TFPWA

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CONTENTS:

TFPWA is a generic software package intended for Partial Wave Analysis (PWA). It is developed using TensorFlow2 and the calculation is accelerated by GPU. Users may modify the configuration file (in YML format) and write simple scripts to complete the whole analysis. A detailed configuration file sample (with all usable parameters) can be found **here**.

CHAPTER

ONE

INSTALL

To use TFPWA, we need some dependent packages. There are two main ways, `conda` and `virtualenv` you can choose *one* of them. *Or* you can choose other method in *5. Other install method.*

1.1 1. vitrual environment

To avoid conflict of dependence, we recommed to use vitrual environment. there are two main vitrual environment for python packages, conda and virtualenv. You can choose one of them. Since conda include cudatoolkit for gpu, we recommed it for user.

1.1.1 1.1 conda

- 1.1.1 Get miniconda for python3 from miniconda3 and install it.
- 1.1.2 Create a virtual environment by

```
conda create -n tfpwa
```

, the `-n <name>` option will create a environment named by `<name>`. You can also use `-p <path>` option to create environment in the `<path>` directory.

- 1.1.3 You can activate the environment by

```
conda activate tfpwa
```

and then you can install packages in the conda environment

- 1.1.4 You can exit the environment by

```
conda deactivate
```

1.1.2 1.2 virtualenv

- 1.2.1 You should have a python3 first.
- 1.2.2 Install virtualenv

```
python3 -m pip install --user virtualenv
```

- 1.2.3 Create a virtual environment

```
python3 -m virtualenv ./tfpwa
```

, it will store in the path `tfpwa`

- 1.2.4 You can activate the environment by

```
source ./tfpwa/bin/activete
```

- 1.2.5 You can exit the environment by

```
deactivate
```

1.2 2. tensorflow2

The most important package is tensorflow2. We recommed to install tensorflow first. You can following the install instructions in tensorflow website (or tensorflow.org).

1.2.1 2.1 conda

Here we provide the simple way to install tensorflow2 gpu version in conda environment

```
conda install tensorflow-gpu=2.4
```

it will also install cudatoolkit.

1.2.2 2.2 virtualenv

When using `virtualenv`, there is also simple way to install tensorflow2

```
python -m pip install tensorflow
```

, but you should check you CUDA installation for GPU.

Note: You can use `-i https://pypi.tuna.tsinghua.edu.cn/simple` option to use pypi mirror site.

1.3 3. Other dependences

Other dependences of TFPWA is simple.

1.3.1 3.1 Get TFPWA package

Get the packages using

```
git clone https://github.com/jiangyi15/tf-pwa
```

1.3.2 3.2 conda

3.2.1 other dependences

In conda environment, go into the directory of `tf-pwa`, you can install the rest dependences by

```
conda install --file requirements-min.txt
```

Note: we recommed Ampere card users to install with `tensorflow_2_6_requirements.txt` (see this technical FAQ).

```
conda install --file tensorflow_2_6_requirements.txt -c conda-forge
```

3.2.2 TFPWA

install TFPWA

```
python -m pip install -e ./ --no-deps
```

Use `--no-deps` to make sure that no PyPI package will be installed. Using `-e`, so it can be updated by `git pull` directly.

1.3.3 3.3 virtualenv

In virtualenv, You can install dependences and TFPWA together.

```
python3 -m pip install -e ./
```

Using `-e`, so it can be updated by `git pull` directly.

1.4 4. (option) Other dependences.

There are some option packages, such as `uproot` for reading root file.

1.4.1 4.1 conda

It can be installed as

```
conda install uproot -c conda-forge
```

1.4.2 4.2 virtualenv

It can be installed as

```
python -m pip install uproot
```

1.5 5. Other install method.

We also provided other install method.

1.5.1 5.1 conda channel (experimental)

A pre-built conda package (Linux only) is also provided, just run following command to install it.

```
conda config --add channels jiangyi15
conda install tf-pwa
```

1.5.2 5.2 pip

When using `pip`, you will need to install CUDA to use GPU. Just run the following command :

```
python3 -m pip install -e .
```

1.6 6. For developer

To contribute to the project, please also install additional developer tools with:

```
python3 -m pip install -e .[dev]
```

CHAPTER

TWO

AMPLITUDE

2.1 Helicity Formula

Each Decay has Amplitude like

$$A^{A\to B+C}_{\lambda_A,\lambda_B,\lambda_C} = H^{A\to B+C}_{\lambda_B,\lambda_C} D^{J_A\star}_{\lambda_A,\lambda_B-\lambda_C}(\phi,\theta,0)$$

For a chain decay, amplitude can be combined as

$$A^{A\to R+B,R\to C+D}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D} = \sum_{\lambda_R} A^{A\to R+B}_{\lambda_A,\lambda_R,\lambda_B} R(m_R) A^{R\to C+D}_{\lambda_R,\lambda_C,\lambda_D}$$

with angle aligned

$$\hat{A}^{A\to R+B,R\to C+D}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D} = \sum_{\lambda'_B,\lambda'_C,\lambda'_D} A^{A\to R+B,R\to C+D}_{\lambda_A,\lambda'_B,\lambda'_C,\lambda'_D} D^{J_B\star}_{\lambda'_B,\lambda_B}(\alpha_B,\beta_B,\gamma_B) D^{J_C\star}_{\lambda'_C,\lambda_C}(\alpha_C,\beta_C,\gamma_C) D^{J_D\star}_{\lambda'_D,\lambda_D}(\alpha_D,\beta_D,\gamma_D)$$

the sum of resonances

$$A^{total}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D} = \sum_{R_1} \hat{A}^{A\to R_1+B,R_1\to C+D}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D} + \sum_{R_2} \hat{A}^{A\to R_2+C,R_2\to B+D}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D} + \sum_{R_3} \hat{A}^{A\to R_3+D,R_3\to B+C}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D}$$

then the differential cross-section

$$\frac{\mathrm{d}\sigma}{\mathrm{d}\Phi} = \frac{1}{N} \sum_{\lambda_A} \sum_{\lambda_B,\lambda_C,\lambda_D} |A^{total}_{\lambda_A,\lambda_B,\lambda_C,\lambda_D}|^2$$

2.1.1 Amplitude Combination Rules

For a decay process `A -> R B, R -> C D`, we can get different part of amplitude:

1. **Particle:**
    1. Initial state: 1
    2. Final state: $D(\alpha,\beta,\gamma)$
    3. Propagator: $R(m)$
2. **Decay:**
    Two body decay (`A -> R B`): $H_{\lambda_R,\lambda_B} D_{\lambda_A,\lambda_R-\lambda_B}(\varphi,\theta,0)$

Now we can use combination rules to build amplitude for the whole process.

Probability Density:
$P = |\tilde{A}|^2$ (modular square)

Decay Group:

$\tilde{A} = a_1 A_{R_1} + a_2 A_{R_2} + \cdots$ (addition)

Decay Chain:

$A_R = A_1 \times R \times A_2 \cdots$ (multiplication)

Decay: $A_i = HD(\varphi, \theta, 0)$

Particle: $R(m)$

The indices part is quantum number, and it can be summed automatically.

2.1.2 Default Amplitude Model

The defalut model for Decay is helicity amplitude

$$A^{A\to BC}_{\lambda_A,\lambda_B,\lambda_C} = H^{A\to BC}_{\lambda_B,\lambda_C} D^{J_A *}_{\lambda_A,\lambda_B-\lambda_C}(\phi,\theta,0).$$

The LS coupling formula is used

$$H^{A\to B+C}_{\lambda_B,\lambda_C} = \sum_{ls} g_{ls} \sqrt{\frac{2l+1}{2J_A+1}} \langle l0; s\delta | J_A \delta\rangle \langle J_B \lambda_B; J_C - \lambda_C | s\delta\rangle q^l B'_l(q, q_0, d)$$

g_{ls} are the fit parameters, the first one is fixed. q and q_0 is the momentum in rest frame for invariant mass and resonance mass.

$B'_l(q, q0, d)$ (`Bprime`) is Blatt-Weisskopf barrier factors. d is $3.0\mathrm{GeV}^{-1}$ by default.

Resonances model use Relativistic Breit-Wigner function

$$R(m) = \frac{1}{m_0^2 - m^2 - i m_0 \Gamma(m)}$$

with running width

$$\Gamma(m) = \Gamma_0 \left(\frac{q}{q_0}\right)^{2L+1} \frac{m_0}{m} B'^2_L(q, q_0, d).$$

By using the combination rules, the amplitude is built automatically.

CHAPTER

THREE

CUSTOM MODEL

TF-PWA support custom model of *Particle*, just implement the *Particle.get_amp* method for a class inherited from *Particle* as:

```
from tf_pwa.amp import register_particle, Particle

@register_particle("MyModel")
class MyParticle(Particle):
    def get_amp(self, *args, **kwargs):
        print(args, kwargs)
        return 1.0
```

Then it can be used in `config.yml` (or `Resonances.yml`) as `model: MyModel`. We can get the data used for amplitude, and add some calculations such as Breit-Wigner.

```
from tf_pwa.amp import register_particle, Particle
import tensorflow as tf

@register_particle("BW")
class SimpleBW(Particle):
    def get_amp(self, *args, **kwargs):
        """
        Breit-Wigner formula
        """
        m = args[0]["m"]
        m0 = self.get_mass()
        g0 = self.get_width()
        delta_m = m0*m0 - m * m
        one = tf.ones_like(m)
        ret = 1/tf.complex(delta_m, m0 * g0 * one)
        return ret
```

Note, we used one to make sure the shape to be same.

We can also add parameters in the *Model* `init_params` using `self.add_var(...)`.

```
@register_particle("Line")
class LineModel(Particle):
    def init_params(self):
        super(LineModel, self).init_params()
        self.a = self.add_var("a")
    def get_amp(self, data, *args, **kwargs):
```

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```
        """ model as m + a """
        m = data["m"]
        zeros = tf.zeros_like(m)
        return tf.complex( m + self.a(), zeros)
```

Then a parameters `{particle_name}_a` will appear in the parameters, we use `self.a()` to get the value in `get_amp`. Note, the type of return value should be `tf.complex`. All builtin model is located in `tf_pwa/amp.py`.

3.1 Simple Resonance (experimental)

There is a simple method to define Resonance model, like

```
from tf_pwa.amp import simple_resonance, FloatParams

@simple_resonance("Line_2", params=["a"])
def r_line(m, a: FloatParams = 1.0):
    return m + a
```

Those code will build a class similar as Line model define before. By using `inspect` module, we can get the `FullArgSpec` of a function. For a keyword arguments with type annotation as `FloatParams`, it will be treated as a fit paraments.

Note: the first arguments have to be the invariant mass `m` of the resonance.

CHAPTER

FOUR

DECAY TOPOLOGY

A decay chain is a simple tree, from top particle to final particles. So the decay chain can be describing as Node (*Decay*) and Line (*Particle*)

4.1 Topology identity: The combination of final particles

For example, the combination of decay chain A->RC,R->BD and A->ZB,R->CD is

```
{A: [B, C, D], R: [B, D], B: [B], C: [C], D: [D]}
```

and

```
{A: [B, C, D], Z: [C, D], B: [B], C: [C], D: [D]}
```

The item R and Z is not same, so there are two different topology.

```
{{A: [B, C, D], B: [B], C: [C], D: [D]}}
```

is the direct A->BCD decay.

4.2 From particles to enumerate all possible decay chain topology:

From a basic line, inserting lines to create a full graph.

from a line: `A -> B`,

insert a line (`node0 -> C`) and a node (`node0`):

```
1. A -> node0, node0 -> B, node0 -> C
```

insert a line :

```
1. A -> node0, node0 -> B, node0 -> node1, node1 -> C, node1 -> D

2. A -> node1, node1 -> node0, node0 -> B, node0 -> C, node1 -> D

3. A -> node0, node0 -> node1, node1 -> B, node0 -> C, node1 -> D
```

there are the three possible decay chains of A -> B,C,D

```
1. A -> R+B, R -> C+D

2. A -> R+D, R -> B+C

3. A -> R+C, R -> B+D
```

the process is unique for different final particles

Each inserting process delete a line and add three new line, So for decay process has n final particles, there are $(2n-3)!!$ possible decay topology.

CHAPTER

FIVE

RESONANCES PARAMETERS

This section is about how do the `Resonances.yml` work.

From `Resonacces.yml` to the real model, there will be following steps.

1. loaded by config.yml, it is will be combined the defination in `config.yml` particle parts.

   For examples, `config.yml` have

   ```
   particle:
      $include: Resonances.yml
      Psi4040:
         float: mg
   ```

   then `Resonances.yml` item

   ```
   Psi4040:
      J: 1
      float: m
   ```

   will become `{"Psi4040": {"J": 1, "float": "mg"}}`

2. replace some alias, (`m0 -> mass`, `g0 -> width`, ...)

3. If it is used in decay chain, then create `Particle` object.

   The particle class is `cls = get_particle_model(item["model"])`, and the object is `cls(**item)`.

   All parameters wull be stored in `config.particle_property[name]`.

All aviable parameters can be devied into the flowowing 3 sets.

5.1 Common Parameters

Parameters defined in *BaseParticle* are common parameters including spin, parity, mass and width.

name	default value	comment
`J`	0	spin, int or half-integral
`P`	-1	P-parity, +1 or -1
`C`	None	C-Parity, +1 or -1
`mass`	None	mass, float, it is always required because of the calcultion of q_0
`width`	None	width, float
`spins`	None	possible spin projections,`[-J, ..., J]`, list

5.2 Model Parameters

Parameters defined in the real model. *Available Resonances Model*

There are many parameters defined by the user, the those parameters will be pass to model class, such as the paramthers for `__init__(self, **kwargs)` method.

For examples, the default model (`BWR`, *`BaseParticle`*) have following parameters:

name	default value	comment
`running_width`	True	if using running width, bool
`bw_l`	None, auto deteminated	running width angular momentum, int

5.3 Other Parameters

There are also some other parameters which is used to control the program running.

For examples, simple constrains, the following parameters are using by `ConfigLoader` as constrains.

name	default value	comment
`mass_min`, `mass_max`	None	mass range
`width_min`, `width_max`	None	width range
`float`	`[]`	float paramsters list

Another examples are parameters to build decay chain for particle `R`.

name	default value	comment
`decay_params`	`{}`	parameters pass to `Decay` which `R` decay
`production_params`	`{}`	parameters pass to `Decay` which produce `R`
`model`	`default`	Particle model for `R`

There are also other common used parameters.

name	default value	comment
`display`	`None`	control plot legend with latex string, string

CHAPTER

SIX

PHASE SPACE

N body decay phase space can be defined as

$$\mathrm{d}\Phi(P; p_1, \cdots, p_n) = (2\pi)^4 \delta^4(P - \sum p_i) \prod \theta(p^0) 2\pi \delta(p_i^2 - m_i^2) \frac{\mathrm{d}^4 p_i}{(2\pi)^4}$$

or integrate p^0 as

$$\mathrm{d}\Phi(P; p_1, \cdots, p_n) = (2\pi)^4 \delta^4(P - \sum p_i) \prod \frac{1}{2E_i} \frac{\mathrm{d}^3 \vec{p_i}}{(2\pi)^3}$$

by using the property of δ-function,

$$\delta(f(x)) = \sum_i \frac{\delta(x - x_i)}{|f'(x_i)|}$$

where x_i is the root of $f(x) = 0$.

Phase space has the follow chain rule,

$$\begin{aligned}
\mathrm{d}\Phi(P; p_1, \cdots, p_n) =& (2\pi)^4 \delta^4(P - \sum p_i) \prod \frac{1}{2E_i} \frac{\mathrm{d}^3 \vec{p_i}}{(2\pi)^3} \\
=& (2\pi)^4 \delta^4(P - \sum_{i=0}^{m} p_i - q) \prod_{i=0}^{m} \frac{1}{2E_i} \frac{\mathrm{d}^3 \vec{p_i}}{(2\pi)^3} \prod_{i=m+1}^{n} \frac{1}{2E_i} \frac{\mathrm{d}^3 \vec{p_i}}{(2\pi)^3} \\
& (2\pi)^4 \delta^4(q - \sum_{i=m+1}^{n} p_i) \frac{\mathrm{d}^4 q}{(2\pi)^4} \delta(q^2 - (\sum_{i=m+1}^{n} p_i)^2) \mathrm{d}q^2 \\
=& \mathrm{d}\Phi(P; p_1, \cdots, p_m, q) \frac{\mathrm{d}q^2}{2\pi} \mathrm{d}\Phi(q; p_{m+1}, \cdots p_n),
\end{aligned}$$

where $q = \sum_{i=m+1}^{n} p_i$ is the invariant mass of particles $m + 1, \cdots, n$.

The two body decay is simple in the center mass frame $P = (M, 0, 0, 0)$,

$$\begin{aligned}
\mathrm{d}\Phi(P; p_1, p_2) =& (2\pi)^4 \delta^4(P - p_1 - p_2) \frac{1}{2E_1} \frac{\mathrm{d}^3 \vec{p_1}}{(2\pi)^3} \frac{1}{2E_2} \frac{\mathrm{d}^3 \vec{p_2}}{(2\pi)^3} \\
=& 2\pi \delta(M - E_1 - E_2) \frac{1}{2E_1} \frac{1}{2E_2} \frac{\mathrm{d}^3 \vec{p_2}}{(2\pi)^3} \\
=& 2\pi \delta(M - \sqrt{|\vec{p}|^2 + m_1^2} - \sqrt{|\vec{p}|^2 + m_2^2}) \frac{1}{2E_1} \frac{|\vec{p}|^2}{2E_2} \frac{\mathrm{d}|\vec{p}| \mathrm{d}\Omega}{(2\pi)^3} \\
=& \frac{|\vec{p}|}{16\pi^2 M} \mathrm{d}\Omega
\end{aligned}$$

where $\mathrm{d}\Omega = \mathrm{d}(\cos\theta)\mathrm{d}\varphi$ and

$$E_1 = \frac{M^2 + m_1^2 - m_2^2}{2M}, E_1 = \frac{M^2 - m_1^2 + m_2^2}{2M}$$

$$|\vec{p}| = \frac{\sqrt{(M^2 - (m_1 + m_2)^2)(M^2 - (m_1 - m_2)^2)}}{2M}$$

The three body decay in the center mass frame $P = (M, 0, 0, 0), q^\star = (m_{23}, 0, 0, 0)$,

$$\begin{aligned}\mathrm{d}\Phi(P; p_1, p_2, p_3) =& \mathrm{d}\Phi(P; p_1, q)\mathrm{d}\Phi(q^\star; p_2^\star, p_3^\star)\frac{\mathrm{d}q^2}{2\pi} \\ =& \frac{|\vec{p_1}||\vec{p_2^\star}|}{(2\pi)^5 16 M m_{23}}\mathrm{d}m_{23}^2\mathrm{d}\Omega_1\mathrm{d}\Omega_2^\star \\ =& \frac{|\vec{p_1}||\vec{p_2^\star}|}{(2\pi)^5 8 M}\mathrm{d}m_{23}\mathrm{d}\Omega_1\mathrm{d}\Omega_2^\star\end{aligned}$$

The n body decay in the center mass frame $P = (M, 0, 0, 0)$,

$$\begin{aligned}\mathrm{d}\Phi(P; p_1, \cdots, p_n) =& \mathrm{d}\Phi(P; p_1, q_1)\prod_{i=1}^{n-2}\frac{\mathrm{d}q_i^2}{2\pi}\mathrm{d}\Phi(q_i, p_{i+1}, p_{i+2}) \\ =& \frac{1}{2^{2n-2}(2\pi)^{3n-4}}\frac{|\vec{p_1}|}{M}\mathrm{d}\Omega_1\prod_{i=1}^{n-2}\frac{|\vec{p_{i+1}^\star}|}{M_i}\mathrm{d}M_i^2\mathrm{d}\Omega_{i+1}^\star \\ =& \frac{1}{2^{n}(2\pi)^{3n-4}}\frac{|\vec{p_1}|}{M}\mathrm{d}\Omega_1\prod_{i=1}^{n-2}|\vec{p_{i+1}^\star}|\mathrm{d}M_i\mathrm{d}\Omega_{i+1}^\star\end{aligned}$$

where

$$M_i^2 = (\sum_{j>i} p_j)^2,\ |\vec{p_i^\star}| = \frac{\sqrt{(M_i^2 - (M_{i+1} + m_{i+1})^2)(M_i^2 - (M_{i+1} - m_{i+1})^2)}}{2M_i}$$

with those limit

$$\sum_{j>i} m_j < M_{i+1} + m_{i+1} < M_i < M_{i-1} - m_i < M - \sum_{j\le i} m_i$$

6.1 Phase Space Generator

For n body phase space

$$\mathrm{d}\Phi(P; p_1, \cdots, p_n) = \frac{1}{2^n(2\pi)^{3n-4}}\left(\frac{1}{M}\prod_{i=0}^{n-2}|\vec{p_{i+1}^\star}|\right)\prod_{i=1}^{n-2}\mathrm{d}M_i\prod_{i=0}^{n-2}\mathrm{d}\Omega_{i+1}^\star,$$

take a weeker condition

$$\sum_{j>i} m_j < M_i < M - \sum_{j\le i} m_j,$$

has the simple limit at the factor term

$$\begin{aligned}\frac{1}{M}\prod_{i=0}^{n-2}|\vec{p_{i+1}^\star}| =& \frac{1}{M}\prod_{i=0}^{n-2}q(M_i, M_{i+1}, m_{i+1}) \\ <& \frac{1}{M}\prod_{i=0}^{n-2}q(max(M_i), min(M_{i+1}), m_{i+1})\end{aligned}$$

- 1. Generate M_i with the factor
- 2. Generate $\mathrm{d}\Omega = \mathrm{d}\cos\theta\mathrm{d}\varphi$
- 3. boost $p^\star = (\sqrt{|\vec{p*}|^2 + m^2}, |\vec{p^\star}|\cos\theta\cos\varphi, |\vec{p^\star}|\sin\theta\sin\varphi, |\vec{p^\star}|\cos\theta,)$ to a same farme.

CHAPTER

SEVEN

RESOLUTION IN PARTIAL WAVE ANALYSIS

Resolution is the effect of detector. To Consider the resolution properly, We need to take a general look about the detector process. We can divide the process of detector into two parts. The first part is acceptance, with the probability for truth value x as $\epsilon_T(x)$. The second part is resolution, it means the measurement value y will be a random number base on truth value x. It is a conditional probability as $R_T(y|x)$. The conditional probability is normalized as $\int R_T(y|x)\mathrm{d}y = 1$. So, the total effect of detector is transition function

$$T(x,y) = R_T(y|x)\epsilon_T(x).$$

When we have a distribution of truth value with probability $p(x)$, then we can get the distribution of measurement value with probability

$$p'(y) = \int p(x)T(x,y)\mathrm{d}x.$$

Using the *Bayes Rule*, we can rewrite $T(x,y)$ as

$$T(x,y) = R(x|y)\epsilon_R(y),$$

where

$$\epsilon_R(y) = \int T(x,y)\mathrm{d}x,\ R(x|y) = \frac{T(x,y)}{\epsilon_R(y)}.$$

$R(x|y)$ is the posterior probability, that means the probability of a certain y is from x. $\epsilon_R(y)$ is the projection of y for $T(x,y)$, and is also the normalize factor for $R(x|y)$.

Then, the probability $p'(y)$ can be rewritten as

$$p'(y) = \epsilon_R(y)\int p(x)R(x|y)\mathrm{d}x.$$

To consider the resolution, we need to determine $R(x|y)$. Generally, we use simulation to determine $R(x|y)$. When $p(x) = 1$ is a flat distribution, then the joint distribution of x and y has the probability density $T(x,y)$. We can build a model for this distribution. To get $R(x|y)$, we only need to do a normalization for $T(x,y)$.

In PWA, we usually use the MC to do the normalization for signal probability density. We need to calculate the integration of $p'(y)$ as

$$\int p'(y)\mathrm{d}y = \int p(x)\epsilon_T(x)\int R_T(y|x)\mathrm{d}y\mathrm{d}x = \int p(x)\epsilon_T(x)\mathrm{d}x.$$

The final negative log-likelihood with considering resolution is

$$-\ln L = -\sum \ln \frac{p'(y)}{\int p'(y)\mathrm{d}y} = -\sum \ln \frac{\int p(x)R(x|y)\mathrm{d}x}{\int p(x)\epsilon_T(x)\mathrm{d}x} - \sum \ln \epsilon_R(y).$$

The last part is a constant, we can ignore it in fit. In the numerical form, it can be written as

$$-\ln L = -\sum \ln \frac{1}{M} \sum_{x\sim R(x|y)} p(x) + N \ln \sum_{x\sim \epsilon_T(x)} p(x).$$

For the second part, which we already have MC sample with $x \sim \epsilon_T(x)$, we can use MC sample to do the sum directly. For the first part, we can generate some x (M times) for every y (N events). Using the generated samples (MN events), we can calculate though the summation.

In addition, we can insert some importance information for the summation as

$$\int p(x)R(x|y)\mathrm{d}x \approx \frac{1}{\sum w_i} \sum_{x\sim \frac{R(x|y)}{w_i(x)}} w_i p(x).$$

We need to keep the normalization. For example, we can use Gauss-Hermite quadrature.

In a simple situation, we only use mass for the variable for resolution function. We can build the datasets by replacing the mass by random number based on the resolution function, keeping the same for other variables and using some constrains.

Once we get such datasets, we can use the likelihood method to fit the dataset with resolution. There is an example in checks.

CHAPTER

EIGHT

SOME EXAMPLES

8.1 Examples for particle model

decay system is model as

DecayGroup
DecayChain

Decay

Particle

```
import matplotlib.pyplot as plt

from tf_pwa.amp import Decay, DecayChain, DecayGroup, Particle
from tf_pwa.vis import plot_decay_struct
```

We can easy create some instance of Particle and then combine them as Decay

```
a = Particle("A")
b = Particle("B")
c = Particle("C")
d = Particle("D")

r = Particle("R")

dec1 = Decay(a, [r, b])
dec2 = Decay(r, [c, d])
```

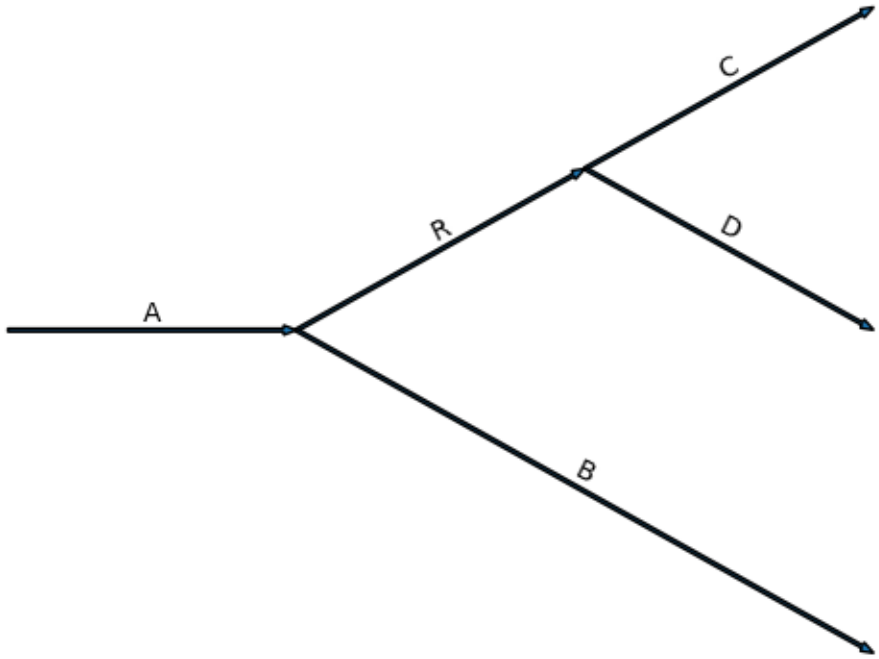
DecayChain is a list of Decays.

```
decay_chain = DecayChain([dec1, dec2])
decay_chain
```

```
[A->R+B, R->C+D]
```

We can plot it using matplotlib.

```
plot_decay_struct(decay_chain)
plt.show()
```



DecayGroup is a list of DecayChain with the same initial and final states

```
decay_group = DecayGroup([decay_chain])
decay_group
```

```
[[A->R+B, R->C+D]]
```

We can build a simple function to infer the charge from final states.

```
def charge_infer(dec, charge_map):
    # use particle equal condition
    cached_charge = {Particle(k): v for k, v in charge_map.items()}
    # loop for all decays in decay chain
    for i, dec_i in dec.depth_first(False):
        # all out particles has charge
        assert all(i in cached_charge for i in dec_i.outs)
        # the charge or core particle is the sum of
        cached_charge[dec_i.core] = sum(cached_charge[i] for i in dec_i.outs)
    return cached_charge


charges = {
    "B": -1,
    "C": 0,
```

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```
    "D": 1,
}

charge_infer(decay_chain, charges)
```

```
{B: -1, C: 0, D: 1, R: 1, A: 0}
```

See more in *cal_chain_boost*.

Total running time of the script: (0 minutes 0.117 seconds)

8.2 Examples for Plotter class

Ploter is the new api for partial wave plots.

First, we can build a simple config.

```
config_str = """

decay:
    A:
       - [R1, B]
       - [R2, C]
       - [R3, D]
    R1: [C, D]
    R2: [B, D]
    R3: [B, C]

particle:
    $top:
       A: { mass: 1.86, J: 0, P: -1}
    $finals:
       B: { mass: 0.494, J: 0, P: -1}
       C: { mass: 0.139, J: 0, P: -1}
       D: { mass: 0.139, J: 0, P: -1}
    R1: [ R1_a, R1_b ]
    R1_a: { mass: 0.7, width: 0.05, J: 1, P: -1}
    R1_b: { mass: 0.5, width: 0.05, J: 0, P: +1}
    R2: { mass: 0.824, width: 0.05, J: 0, P: +1}
    R3: { mass: 0.824, width: 0.05, J: 0, P: +1}


plot:
    mass:
        R1:
            display: "m(R1)"
        R2:
            display: "m(R2)"
"""

import matplotlib.pyplot as plt
```

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```
import yaml

from tf_pwa.config_loader import ConfigLoader

config = ConfigLoader(yaml.full_load(config_str))
```

We set parameters to a blance value. And we can generate some toy data and calclute the weights

```
input_params = {
    "A->R1_a.BR1_a->C.D_total_0r": 6.0,
    "A->R1_b.BR1_b->C.D_total_0r": 1.0,
    "A->R2.CR2->B.D_total_0r": 2.0,
    "A->R3.DR3->B.C_total_0r": 1.0,
}
config.set_params(input_params)

data = config.generate_toy(1000)
phsp = config.generate_phsp(10000)
```

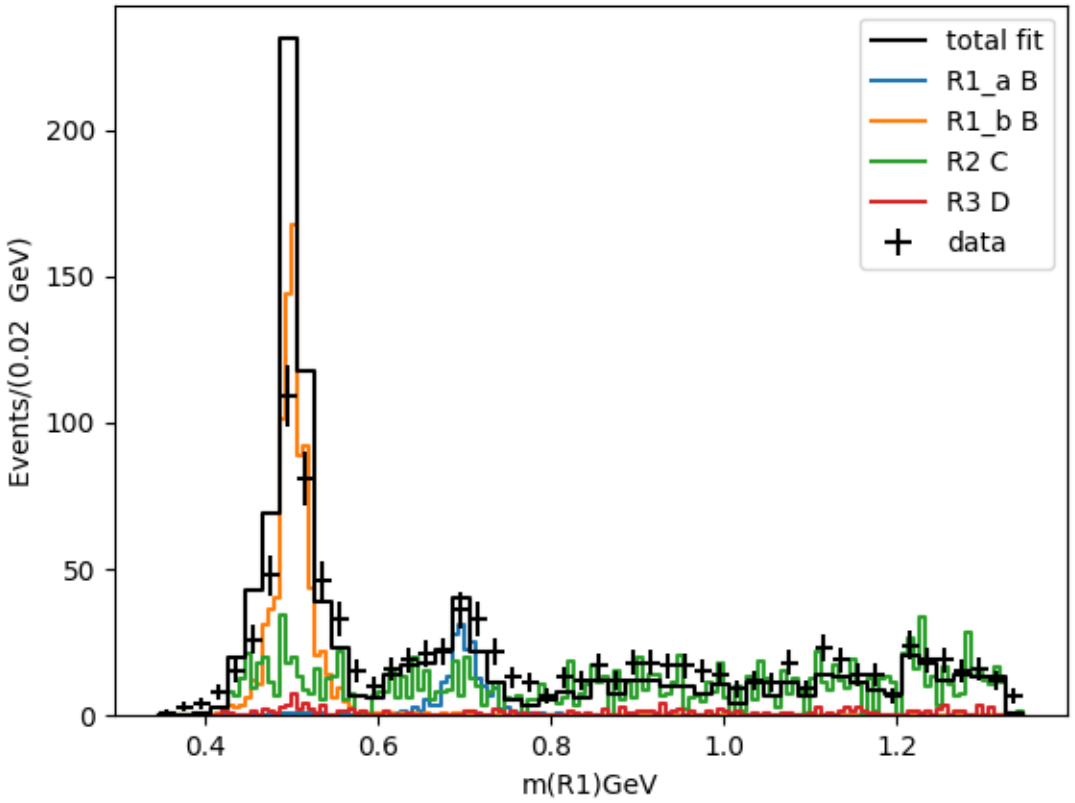
```
7.5%[>-----------------------------------------------] 1.02/13.57s eff: 90.000000%
74.3%[>------------] 3.05/4.10s eff: 6.214227%
102.6%[>] 4.21/4.10s eff: 4.228234%
100.0%[] 4.21/4.21s  eff: 4.229470%
```

plotter can be created directly from config

```
plotter = config.get_plotter(datasets={"data": [data], "phsp": [phsp]})
```

Ploting all partial waves is simple.

```
plotter.plot_frame("m_R1")
plt.show()
```



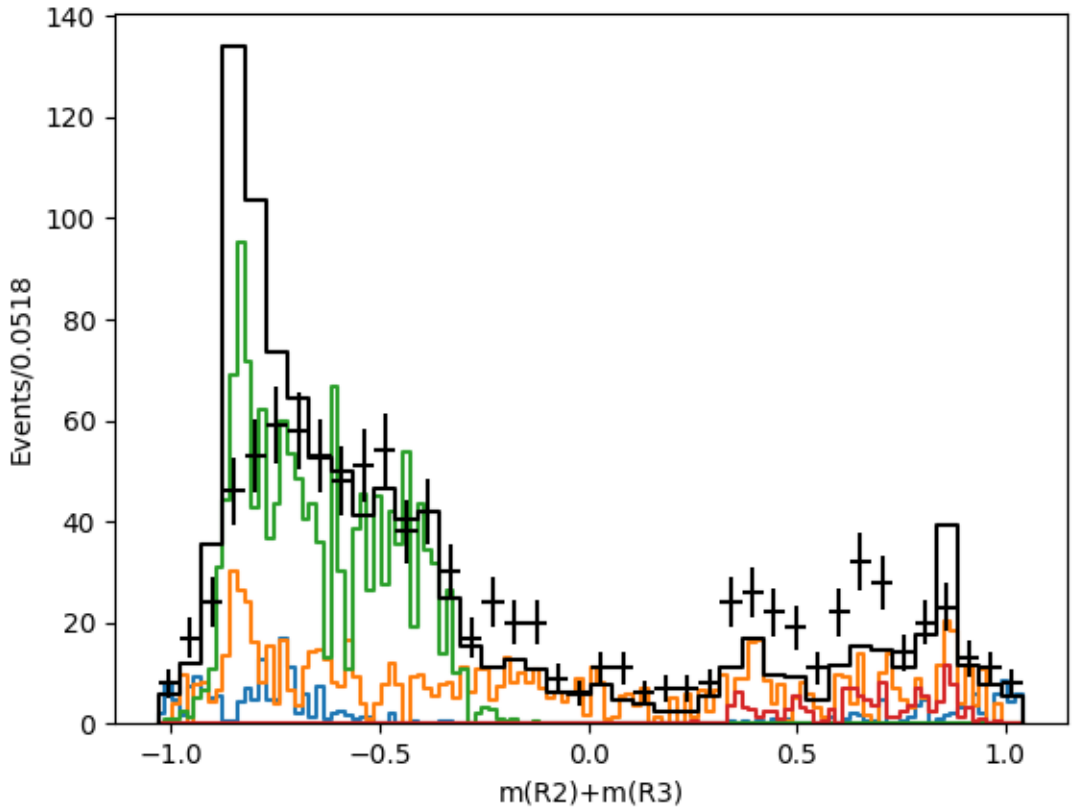
Also we can plot other variables in data

```python
from tf_pwa.data import data_index

m2 = config.get_data_index("mass", "R2")
m3 = config.get_data_index("mass", "R3")


def f(data):
    return data_index(data, m2) - data_index(data, m3)


plt.clf()
plotter.plot_var(f)
plt.xlabel("m(R2)+m(R3)")
plt.show()
```



There are 3 main parts in a Plotter

1. PlotAllData: datasets with weights There is three level: (1). idx: Datasets for combine fit (2). type: data, mc, or bg (3). observations and weights: weights are used for partial wave
2. Frame: function to get obsevations It is samilar to RooFit's Frame.
3. Styles: Plot style for differenct componets

The plot process is as follow:

1. Plotter.plot_item, extra_plot_item, and hidden_plot_item provide the list of histograms for plotting.
2. Loop over all data to get the observations though frame.
3. Frame provide the binning, weights from datas. Their combination is histogram
4. Plot on the axis with style

Total running time of the script: (0 minutes 6.720 seconds)

8.3 Particle and amplitude

Amplitude = DecayGroup + Variable

We will use following parameters for a toy model

```
from tf_pwa.amp import DecayChain, DecayGroup, get_decay, get_particle

resonances = {
    "R0": {"J": 0, "P": 1, "mass": 1.0, "width": 0.07},
    "R1": {"J": 0, "P": 1, "mass": 1.0, "width": 0.07},
    "R2": {"J": 1, "P": -1, "mass": 1.225, "width": 0.08},
}

a, b, c, d = [get_particle(i, J=0, P=-1) for i in "ABCD"]
r1, r2, r3 = [get_particle(i, **resonances[i]) for i in resonances.keys()]


decay_group = DecayGroup(
    [
        DecayChain([get_decay(a, [r1, c]), get_decay(r1, [b, d])]),
        DecayChain([get_decay(a, [r2, b]), get_decay(r2, [c, d])]),
        DecayChain([get_decay(a, [r3, b]), get_decay(r3, [c, d])]),
    ]
)
```

The above parts can be represented as config.yml used by ConfigLoader.

We can get AmplitudeModel form decay_group and a optional Variables Managerager. It has parameters, so we can get and set parameters for the amplitude model

```
from tf_pwa.amp import AmplitudeModel
from tf_pwa.variable import VarsManager

vm = VarsManager()
amp = AmplitudeModel(decay_group, vm=vm)

print(amp.get_params())
amp.set_params(
    {
        "A->R0.CR0->B.D_total_0r": 1.0,
        "A->R1.BR1->C.D_total_0r": 1.0,
        "A->R2.BR2->C.D_total_0r": 7.0,
    }
)
```

```
{'R0_mass': 1.0, 'R0_width': 0.07, 'R1_mass': 1.0, 'R1_width': 0.07, 'R2_mass': 1.225,
↪'R2_width': 0.08, 'A->R0.CR0->B.D_total_0r': 1.5852381560068682, 'A->R0.CR0->B.D_total_
↪0i': 1.690329569320169, 'A->R0.C_g_ls_0r': 1.0, 'A->R0.C_g_ls_0i': 0.0, 'R0->B.D_g_ls_
↪0r': 1.0, 'R0->B.D_g_ls_0i': 0.0, 'A->R1.BR1->C.D_total_0r': 0.9942309682774577, 'A->
↪R1.BR1->C.D_total_0i': -2.2265736366054854, 'A->R1.B_g_ls_0r': 1.0, 'A->R1.B_g_ls_0i':␣
↪0.0, 'R1->C.D_g_ls_0r': 1.0, 'R1->C.D_g_ls_0i': 0.0, 'A->R2.BR2->C.D_total_0r': 0.
↪7012398585867645, 'A->R2.BR2->C.D_total_0i': 2.0884932274966364, 'A->R2.B_g_ls_0r': 1.
↪0, 'A->R2.B_g_ls_0i': 0.0, 'R2->C.D_g_ls_0r': 1.0, 'R2->C.D_g_ls_0i': 0.0}
```

For the calculation, we generate some phase space data.

```
from tf_pwa.phasespace import PhaseSpaceGenerator

m_A, m_B, m_C, m_D = 1.8, 0.18, 0.18, 0.18
p1, p2, p3 = PhaseSpaceGenerator(m_A, [m_B, m_C, m_D]).generate(100000)
```

and the calculate helicity angle from the data

```
from tf_pwa.cal_angle import cal_angle_from_momentum

data = cal_angle_from_momentum({b: p1, c: p2, d: p3}, decay_group)
```

we can index mass from data as

```
from tf_pwa.data import data_index

m_bd = data_index(data, ("particle", "(B, D)", "m"))
# m_bc = data_index(data, ("particle", "(B, C)", "m"))
m_cd = data_index(data, ("particle", "(C, D)", "m"))
```

Note: If DecayGroup do not include resonant of (B, C), the data will not include its mass too. We can use different DecayGroup for cal_angle and AmplitudeModel when they have the same initial and final particle.

The amplitde square is calculated by amplitude model simply as

```
amp_s2 = amp(data)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/checkouts/stable/docs/../tf_pwa/
↪amp/core.py:803: UserWarning: no mass for particle A, set it to 1.800000022965964
  warnings.warn(
/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/checkouts/stable/docs/../tf_pwa/
↪amp/core.py:803: UserWarning: no mass for particle C, set it to 0.17999999999999977
  warnings.warn(
/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/checkouts/stable/docs/../tf_pwa/
↪amp/core.py:803: UserWarning: no mass for particle B, set it to 0.17999999999999977
  warnings.warn(
/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/checkouts/stable/docs/../tf_pwa/
↪amp/core.py:803: UserWarning: no mass for particle D, set it to 0.17999999999999977
  warnings.warn(
```

Now by using matplotlib we can get the Dalitz plot as

```
import matplotlib.pyplot as plt

plt.clf()
plt.hist2d(
    m_bd.numpy() ** 2,
    m_cd.numpy() ** 2,
    weights=amp_s2.numpy(),
    bins=60,
    cmin=1,
```

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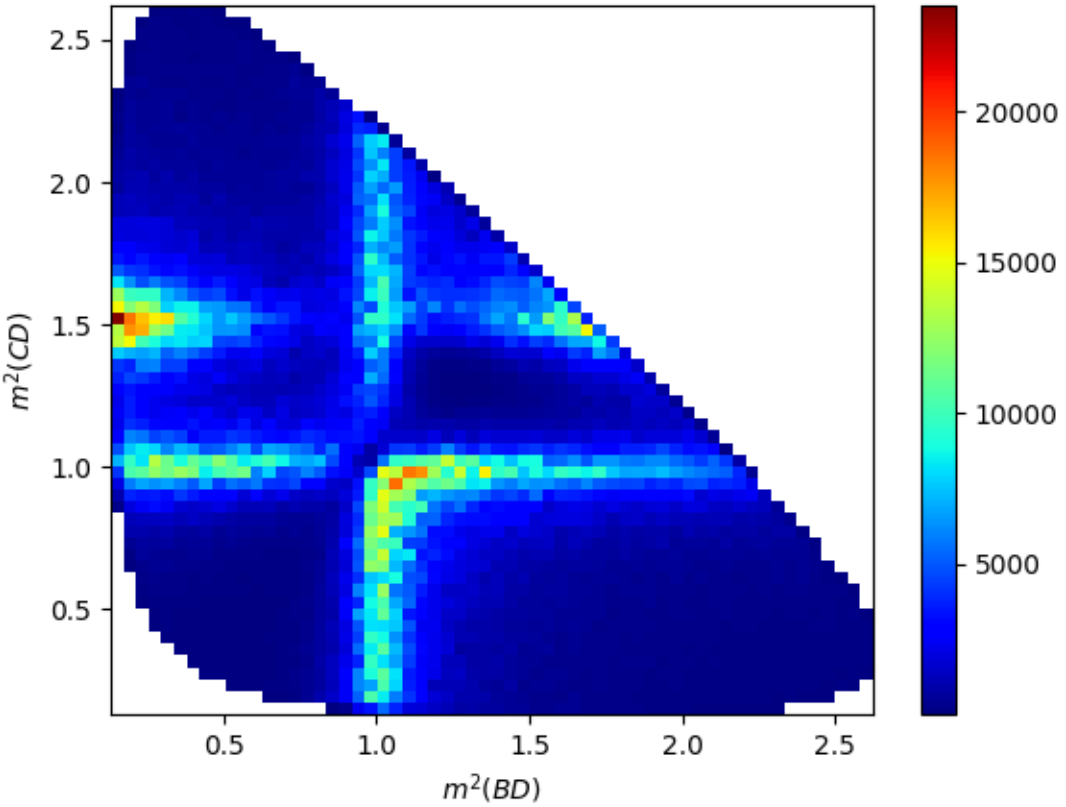
```
    cmap="jet",
)
plt.colorbar()
plt.xlabel("$m^2(BD)$")
plt.ylabel("$m^2(CD)$")
plt.show()
```



Total running time of the script: (0 minutes 4.831 seconds)

8.4 Examples for error propagation

Hear we use the same config in `particle_amplitude.py`

```
config_str = """
decay:
    A:
       - [R1, B]
       - [R2, C]
       - [R3, D]
    R1: [C, D]
    R2: [B, D]
```

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```
    R3: [B, C]

particle:
    $top:
       A: { mass: 1.86, J: 0, P: -1}
    $finals:
       B: { mass: 0.494, J: 0, P: -1}
       C: { mass: 0.139, J: 0, P: -1}
       D: { mass: 0.139, J: 0, P: -1}
    R1: [ R1_a, R1_b ]
    R1_a: { mass: 0.7, width: 0.05, J: 1, P: -1}
    R1_b: { mass: 0.5, width: 0.05, J: 0, P: +1}
    R2: { mass: 0.824, width: 0.05, J: 0, P: +1}
    R3: { mass: 0.824, width: 0.05, J: 0, P: +1}

"""

import matplotlib.pyplot as plt
import yaml

from tf_pwa.config_loader import ConfigLoader
from tf_pwa.histogram import Hist1D

config = ConfigLoader(yaml.full_load(config_str))
input_params = {
    "A->R1_a.BR1_a->C.D_total_0r": 6.0,
    "A->R1_b.BR1_b->C.D_total_0r": 1.0,
    "A->R2.CR2->B.D_total_0r": 2.0,
    "A->R3.DR3->B.C_total_0r": 1.0,
}
config.set_params(input_params)

data = config.generate_toy(1000)
phsp = config.generate_phsp(10000)
```

```
9.0%[>-------------------------------------------] 0.92/10.23s eff: 90.000000%
107.6%[>] 2.42/2.25s eff: 7.440720%
100.0%[] 2.42/2.42s  eff: 7.338512%
```

After we calculated the parameters error, we will have an error matrix `config.inv_he` (using the inverse hessain). It is possible to save such matrix directly by `numpy.save` and to load it by `numpy.load`.

```
config.get_params_error(data=[data], phsp=[phsp])
```

```
Using Model
Time for calculating errors: 1.2068400382995605
hesse_error: [0.06625563845900341, 0.10777631290934468, 0.13143216360361248, 0.
↪09782302392447259, 0.08296139271348224, 0.12369480424462445]

{'A->R1_b.BR1_b->C.D_total_0r': 0.06625563845900341, 'A->R1_b.BR1_b->C.D_total_0i': 0.
↪10777631290934468, 'A->R2.CR2->B.D_total_0r': 0.13143216360361248, 'A->R2.CR2->B.D_
↪total_0i': 0.09782302392447259, 'A->R3.DR3->B.C_total_0r': 0.08296139271348224, 'A->R3.
```

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```
↪DR3->B.C_total_0i': 0.12369480424462445}
```

We can use the following method to profamance the error propagation

$$\sigma_f = \sqrt{\frac{\partial f}{\partial x_i} V_{ij} \frac{\partial f}{\partial x_j}}$$

by adding some calculation here. We need to use `tensorflow` functions instead of those of `math` or `numpy`.

```
import tensorflow as tf

with config.params_trans() as pt:
    a2_r = pt["A->R2.CR2->B.D_total_0r"]
    a2_i = pt["A->R2.CR2->B.D_total_0r"]
    a2_x = a2_r * tf.cos(a2_i)
```

And then we can calculate the error we needed as

```
print(a2_x.numpy(), pt.get_error(a2_x).numpy())
```

```
-0.8322936730942848 0.2937169354379835
```

We can also calculate some more complex examples, such as the ratio in mass range (0.75, 0.85) over full phace space. Even further, we can get the error of error in the meaning of error propagation.

```
from tf_pwa.data import data_mask

m_R2 = phsp.get_mass("(B, D)")
cut_cond = (m_R2 < 0.85) & (m_R2 > 0.75)

amp = config.get_amplitude()

with config.params_trans() as pt1:
    with config.params_trans() as pt:
        int_mc = tf.reduce_sum(amp(phsp))
        cut_phsp = data_mask(phsp, cut_cond)
        cut_int_mc = tf.reduce_sum(amp(cut_phsp))
        ratio = cut_int_mc / int_mc
    error = pt.get_error(ratio)

print(ratio.numpy(), "+/-", error.numpy())
print(error.numpy(), "+/-", pt1.get_error(error).numpy())
```

```
0.38197185921153415 +/- 0.01198798472005041
0.01198798472005041 +/- 0.0008233112942379798
```

Total running time of the script: (0 minutes 5.788 seconds)

8.5 Examples for config.yml file

Configuration file `config.yml` use YAML (https://yaml.org) format to describe decay process.

The main parts of config.yml is `decay` and `particle`.

The `decay` part describe the particle (or an id of a list of particle) decay into which particles, it can be a list of a list of list. A list means that there is ony one decay mode, A list of list is the list of possible decay mode. The list item can be the particle name (or a dict to describe the decay parameters). All name should appear in `particle` part.

The `particle` part describe the parameters of particles. There are two special parts `$top` and `$finals` describe the top and finals particles. The other parts are lists of particle name or dicts of particle parameters. The list is the same type particle in decay part. The dict is the parameters of the particle name.

```
config_str = """

decay:
    A:
       - [R1, B]
       - [R2, C]
       - [R3, D]
    R1: [C, D]
    R2: [B, D]
    R3: [B, C]

particle:
    $top:
       A: { mass: 1.86, J: 0, P: -1}
    $finals:
       B: { mass: 0.494, J: 0, P: -1}
       C: { mass: 0.139, J: 0, P: -1}
       D: { mass: 0.139, J: 0, P: -1}
    R1: [ R1_a, R1_b ]
    R1_a: { mass: 0.7, width: 0.05, J: 1, P: -1}
    R1_b: { mass: 0.5, width: 0.05, J: 0, P: +1}
    R2: { mass: 0.824, width: 0.05, J: 0, P: +1}
    R3: { mass: 0.824, width: 0.05, J: 0, P: +1}

"""
```

The config file can be loaded by `yaml` library.

```
import matplotlib.pyplot as plt
import yaml

from tf_pwa.config_loader import ConfigLoader
from tf_pwa.histogram import Hist1D
```

The simple way to create config is write it to `config.yml` file and then you can load it as `config = ConfigLoader("config.yml")`. Here we used config_str directly.

```
config = ConfigLoader(yaml.full_load(config_str))
```

We set parameters to a blance value. And we can generate some toy data and calclute the weights The full params can be found by `print(config.get_params())`.

```
input_params = {
    "A->R1_a.BR1_a->C.D_total_0r": 6.0,
    "A->R1_b.BR1_b->C.D_total_0r": 1.0,
    "A->R2.CR2->B.D_total_0r": 2.0,
    "A->R3.DR3->B.C_total_0r": 1.0,
}
config.set_params(input_params)
```

```
True
```

Here we generate some toy data and phsp mc to show the model

```
data = config.generate_toy(1000)
phsp = config.generate_phsp(10000)
```

```
7.9%[>----------------------------------------------] 0.91/11.55s eff: 90.000000%
98.6%[>] 2.76/2.80s eff: 6.541292%
99.7%[>] 3.61/3.62s eff: 5.906643%
100.3%[>] 4.42/4.41s eff: 5.880966%
100.0%[] 4.42/4.42s  eff: 5.896864%
```

You can also fit the data fit to the data We can omit the args when writen in config.yml

```
fit_result = config.fit([data], [phsp])
# After the fit, you can get the uncertaities as
err = config.get_params_error(fit_result, [data], [phsp])
```

```
Using Model
decay chains included:
   [A->R1_a+B, R1_a->C+D]  ls:  ((1, 1),) ((1, 0),)
   [A->R1_b+B, R1_b->C+D]  ls:  ((0, 0),) ((0, 0),)
   [A->R2+C, R2->B+D]  ls:  ((0, 0),) ((0, 0),)
   [A->R3+D, R3->B+C]  ls:  ((0, 0),) ((0, 0),)

########### initial parameters
{
  "R1_a_mass": 0.7,
  "R1_a_width": 0.05,
  "R1_b_mass": 0.5,
  "R1_b_width": 0.05,
  "R2_mass": 0.824,
  "R2_width": 0.05,
  "R3_mass": 0.824,
  "R3_width": 0.05,
  "A->R1_a.BR1_a->C.D_total_0r": 6.0,
  "A->R1_a.BR1_a->C.D_total_0i": 0.0,
  "A->R1_a.B_g_ls_0r": 1.0,
  "A->R1_a.B_g_ls_0i": 0.0,
  "R1_a->C.D_g_ls_0r": 1.0,
  "R1_a->C.D_g_ls_0i": 0.0,
  "A->R1_b.BR1_b->C.D_total_0r": 1.0,
  "A->R1_b.BR1_b->C.D_total_0i": -0.17036099828961904,
```

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```
  "A->R1_b.B_g_ls_0r": 1.0,
  "A->R1_b.B_g_ls_0i": 0.0,
  "R1_b->C.D_g_ls_0r": 1.0,
  "R1_b->C.D_g_ls_0i": 0.0,
  "A->R2.CR2->B.D_total_0r": 2.0,
  "A->R2.CR2->B.D_total_0i": -2.44846429485405,
  "A->R2.C_g_ls_0r": 1.0,
  "A->R2.C_g_ls_0i": 0.0,
  "R2->B.D_g_ls_0r": 1.0,
  "R2->B.D_g_ls_0i": 0.0,
  "A->R3.DR3->B.C_total_0r": 1.0,
  "A->R3.DR3->B.C_total_0i": -1.5299171823613154,
  "A->R3.D_g_ls_0r": 1.0,
  "A->R3.D_g_ls_0i": 0.0,
  "R3->B.C_g_ls_0r": 1.0,
  "R3->B.C_g_ls_0i": 0.0
}
initial NLL:  tf.Tensor(-876.5550510935509, shape=(), dtype=float64)
nll_grad  cost time: 0.4722561836242676
nll_grad  cost time: 0.474503755569458
nll_grad  cost time: 0.48148345947265625
tf.Tensor(-877.5403955489946, shape=(), dtype=float64)
nll_grad  cost time: 0.4866471290588379
nll_grad  cost time: 0.4884514808654785
tf.Tensor(-877.9356094551549, shape=(), dtype=float64)
nll_grad  cost time: 0.47771215438842773
tf.Tensor(-878.4860877702886, shape=(), dtype=float64)
nll_grad  cost time: 0.4797697067260742
nll_grad  cost time: 0.4736459255218506
tf.Tensor(-878.7509883100593, shape=(), dtype=float64)
nll_grad  cost time: 0.49033093452453613
tf.Tensor(-878.8244008216343, shape=(), dtype=float64)
nll_grad  cost time: 0.49677062034606934
tf.Tensor(-878.9546735802714, shape=(), dtype=float64)
nll_grad  cost time: 0.47876691818237305
tf.Tensor(-879.1570792905513, shape=(), dtype=float64)
nll_grad  cost time: 0.4896061420440674
tf.Tensor(-879.4227001224172, shape=(), dtype=float64)
nll_grad  cost time: 0.49108386039733887
tf.Tensor(-879.4463424397973, shape=(), dtype=float64)
nll_grad  cost time: 0.49104857444763184
tf.Tensor(-879.4464152430883, shape=(), dtype=float64)
nll_grad  cost time: 0.4891695976257324
tf.Tensor(-879.4464153398749, shape=(), dtype=float64)
Optimization terminated successfully.
         Current function value: -879.446415
         Iterations: 11
         Function evaluations: 15
         Gradient evaluations: 15
  message: Optimization terminated successfully.
  success: True
   status: 0
```

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```
      fun: -879.4464153398749
        x: [ 9.489e-01 -9.681e-02  1.885e+00 -2.304e+00  8.685e-01
             -1.461e+00]
      nit: 11
      jac: [-1.631e-04  6.923e-05  4.877e-05  1.047e-04 -2.877e-05
             2.223e-06]
 hess_inv: [[ 3.302e-03  4.340e-04 ...  2.010e-03  1.184e-03]
            [ 4.340e-04  1.302e-02 ...  6.632e-04  6.411e-03]
            ...
            [ 2.010e-03  6.632e-04 ...  4.321e-03  2.374e-04]
            [ 1.184e-03  6.411e-03 ...  2.374e-04  1.835e-02]]
     nfev: 15
     njev: 15
fit  cost time: 7.779327869415283
Using Model
Time for calculating errors: 1.1640501022338867
hesse_error: [0.056765147154824135, 0.11184095287604047, 0.1121442870963205, 0.
↪10192939584029746, 0.06562663234319398, 0.13551414787699745]
```

we can see that thre fit results consistant with inputs, the first one is fixed.

```
for var in input_params:
    print(
        f"in: {input_params[var]} => out: {fit_result.params[var]} +/- {err.get(var, 0.
↪)}"
    )
```

```
in: 6.0 => out: 6.0 +/- 0.0
in: 1.0 => out: 0.9489399180798221 +/- 0.056765147154824135
in: 2.0 => out: 1.884781669098602 +/- 0.1121442870963205
in: 1.0 => out: 0.8685280835804645 +/- 0.06562663234319398
```

We can use the amplitude to plot the fit results

```
amp = config.get_amplitude()
```

This is the total $|A|^2$

```
weight = amp(phsp)
```

This is the $|A_i|^2$ for each decay chain

```
partial_weight = amp.partial_weight(phsp)
```

We can plot the data, Hist1D include some plot method base on matplotlib.

```
data_hist = Hist1D.histogram(
    data.get_mass("(C, D)"), bins=60, range=(0.25, 1.45)
)
```

Read the mass var from phsp.

```
mass_phsp = phsp.get_mass("(C, D)")
```

For helicity angle it can be read as `phsp.get_angle("(C, D)", "C")` The first arg is used to deteminate the decay chain. (decay chain include all particles) The second arg is used to deteminate the angle in decay chain. The return value is a dict as `{"alpha": phi, "beta": theta, "gamma": 0}`

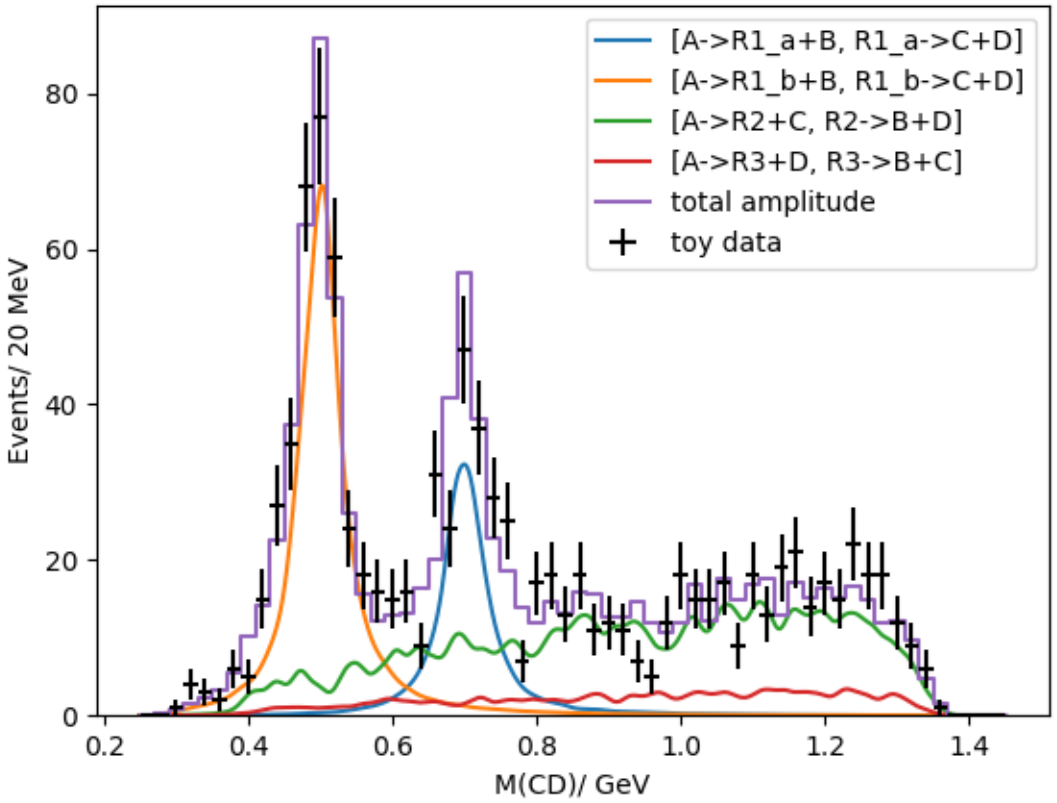
```
phsp_hist = Hist1D.histogram(
    mass_phsp, weights=weight, bins=60, range=(0.25, 1.45)
)
scale = phsp_hist.scale_to(data_hist)

pw_hist = []
for w in partial_weight:
    # here we used more bins for a smooth plot
    hist = Hist1D.histogram(
        mass_phsp, weights=w, bins=60 * 2, range=(0.25, 1.45)
    )
    pw_hist.append(scale * hist * 2)
```

Then we can plot the histogram into matplotlib

```
for hist, dec in zip(pw_hist, config.get_decay()):
    hist.draw_kde(label=str(dec))
phsp_hist.draw(label="total amplitude")
data_hist.draw_error(label="toy data", color="black")

plt.legend()
plt.ylim((0, None))
plt.xlabel("M(CD)/ GeV")
plt.ylabel("Events/ 20 MeV")
plt.show()
```



Total running time of the script: (0 minutes 15.531 seconds)

CHAPTER

NINE

SETUP FOR DEVELOPER ENVERIMENT

Note: Before the developing, creating a standalone enveriment is recommanded (see https://conda.io/projects/conda/en/latest/user-guide/tasks/manage-environments.html#creating-an-environment-with-commands for more).

The main steps are similar as normal install, only two extra things need to be done.

The first things is writing tests, and tests your code. We use pytest (https://docs.pytest.org/en/stable/) framework, You should install it.

```
conda install pytest pytest-cov pytest-benchmark
```

The other things is `pre-commit`. it need for developing.

1. You can install `pre-commit` as

```
conda install pre-commit
```

and

2. then enable `pre-commit` in the source dir

```
conda install pylint # local dependences
pre-commit install
```

You can check if pre-commit is working well by running

```
pre-commit run -a
```

It may take some time to install required package.

Note: If there are some `GLIBC_XXX` errors at this step, you can try to install `node.js`.

Note: For developer using editor with formatter, you should be careful for the options.

The following are all commands needed

```
# create environment
conda create -n tfpwa2 python=3.7 -y
conda activate tfpwa2

```

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```
# install tf-pwa
conda install --file requirements-min.txt -y
python -m pip install -e . --no-deps
# install pytest
conda install pytest pytest-cov -y
# install pylint local
conda install pylint
# install pre-commit
conda install pre-commit -c conda-forge -y
pre-commit install
```

CHAPTER

TEN

API

10.1 tf_pwa

Partial Wave Analysis program using Tensorflow

Submodules and Subpackages

10.1.1 amp

Basic Amplitude Calculations. A partial wave analysis process has following structure:

DecayGroup: addition (+)

DecayChain: multiplication (x)
Decay, Particle(Propagator)

Submodules and Subpackages

Kmatrix

Bl(*l*, *q*, *q0*, *d=3*)

Fb(*l*, *q*, *d=3*)

KMatrix_single(*n_pole*, *m1*, *m2*, *l*, *d=3*, *bkg=0*, *Kb=0*)

class KmatrixSingleChannelParticle(**args*, ***kwargs*)

Bases: *Particle*

K matrix model for single channel multi pole.

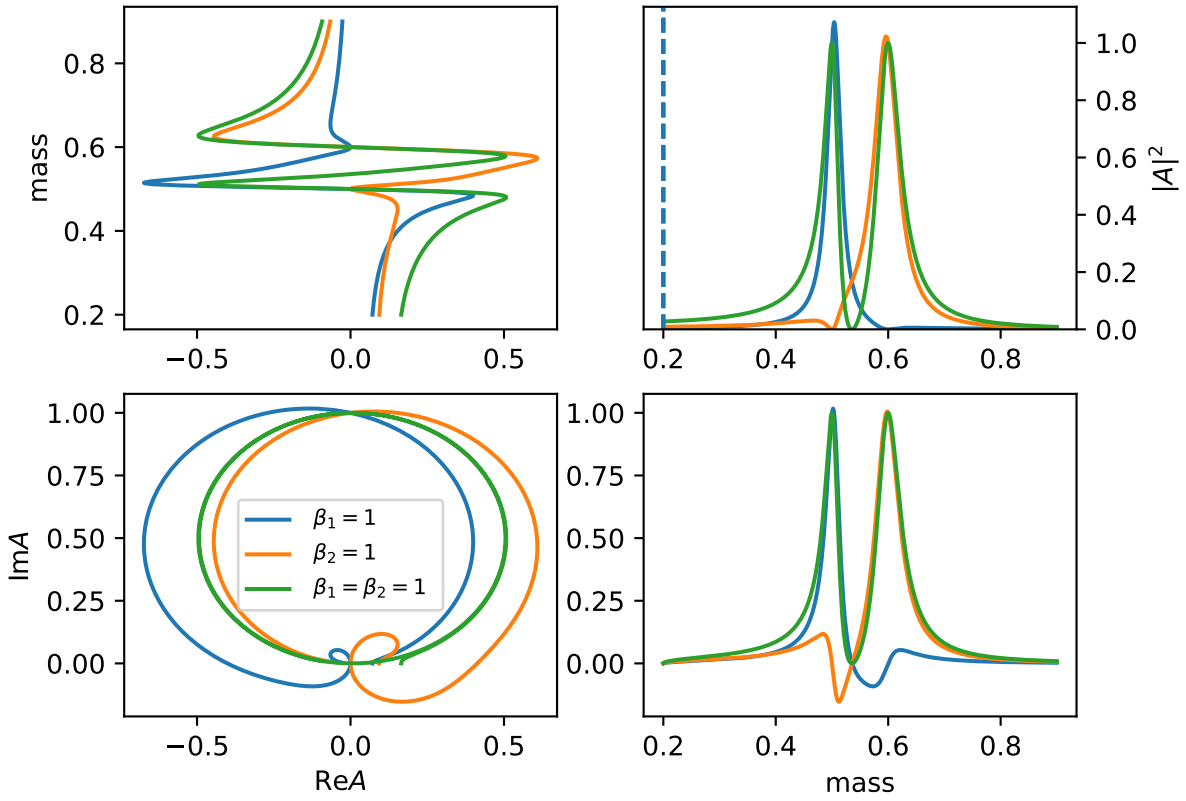
$$K = \sum_i \frac{m_i \Gamma_i(m)}{m_i^2 - m^2}$$

$$P = \sum_i \frac{\beta_i m_0 \Gamma_0}{m_i^2 - m^2}$$

the barrier factor is included in gls

$$R(m) = (1 - iK)^{-1} P$$

requird `mass_list: [pole1, pole2]` and `width_list: [width1, width2]`.


mass
0.8
0.6
0.4
0.2
−0.5
0.0
0.5
1.0
0.8
0.6
0.4
0.2
0.0
$|A|^2$
0.2
0.4
0.6
0.8
1.00
0.75
0.50
0.25
0.00
ImA
$\beta_1 = 1$
$\beta_2 = 1$
$\beta_1 = \beta_2 = 1$
ReA
mass

get_amp(**args*, ***kwargs*)

get_beta()

get_gi()

get_mi()

init_params()

model_name = 'KMatrixSingleChannel'

class KmatrixSplitLSParticle(**args*, ***kwargs*)

Bases: *Particle*

K matrix model for single channel multi pole and the same channel with different (l, s) coupling.

$$K_{a,b} = \sum_i \frac{m_i \sqrt{\Gamma_{a,i}(m)\Gamma_{b,i}(m)}}{m_i^2 - m^2}$$

$$P_b = \sum_i \frac{\beta_i m_0 \Gamma_{b,i0}}{m_i^2 - m^2}$$

the barrier factor is included in gls

$$R(m) = (1 - iK)^{-1} P$$

get_amp(**args*, ***kwargs*)

get_beta()

get_gi()

get_gi_frac()

get_ls_amp(*m*)

get_mi()

init_params()

model_name = 'KMatrixSplitLS'

class ParticleDecayLSKmatrix(**args*, ***kwargs*)

Bases: *HelicityDecay*

get_ls_amp(*data*, *data_p*, ***kwargs*)

init_params()

model_name = 'LS-decay-Kmatrix'

get_relative_p(*m0*, *m1*, *m2*)

opt_lambdify(*args*, *expr*, ***kwargs*)

amp

class AbsPDF(**args*, *name=''*, *vm=None*, *polar=None*, *use_tf_function=False*, *no_id_cached=False*, *jit_compile=False*, ***kwargs*)

Bases: object

cached_available()

get_params(*trainable_only=False*)

mask_params(*var*)

set_params(*var*)

temp_params(*var*)

property trainable_variables

property variables

class AmplitudeModel(*decay_group*, ***kwargs*)

Bases: *BaseAmplitudeModel*

partial_weight(*data*, *combine=None*)

class BaseAmplitudeModel(*decay_group*, ***kwargs*)

Bases: *AbsPDF*

cache_data(*data*, *split=None*, *batch=None*)

cached_available()

chains_particle()

factor_iteration(*deep=2*)

init_params(*name=''*)

partial_weight(*data*, *combine=None*)

partial_weight_interference(*data*)

pdf(*data*)

set_used_chains(*used_chains*)

set_used_res(*res*)

temp_total_gls_one()

temp_used_res(*res*)

class CachedAmpAmplitudeModel(*decay_group*, ***kwargs*)

Bases: *BaseAmplitudeModel*

pdf(*data*)

class CachedShapeAmplitudeModel(**args*, ***kwargs*)

Bases: *BaseAmplitudeModel*

get_cached_shape_idx()

pdf(*data*)

class FactorAmplitudeModel(**args*, ***kwargs*)

Bases: *BaseAmplitudeModel*

get_amp_list(*data*)

get_amp_list_part(*data*)

pdf(*data*)

class P4DirectlyAmplitudeModel(*decay_group*, ***kwargs*)

Bases: *BaseAmplitudeModel*

cal_angle(*p4*)

pdf(*data*)

create_amplitude(*decay_group*, ***kwargs*)

register_amp_model(*name=None*, *f=None*)

register a data mode

Params name
mode name used in configuration

Params f
Data Mode class

base

Basic amplitude model

class HelicityDecayCPV(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *HelicityDecay*

decay model for CPV

get_g_ls(*charge=1*)

get_ls_amp(*data*, *data_p*, ***kwargs*)

init_params()

model_name = 'gls-cpv'

class HelicityDecayNP(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *HelicityDecay*

Full helicity amplitude

$$A = H_{m_1,m_2} D^{J_0 *}_{m_0,m_1-m_2}(\varphi, \theta, 0)$$

fit parameters is H_{m_1,m_2}.

fix_unused_h()

get_H()

get_H_zero_mask()

get_factor()

get_factor_H(*data=None*, *data_p=None*, ***kwargs*)

get_helicity_amp(*data=None*, *data_p=None*, ***kwargs*)

get_ls_amp(*data*, *data_p*, ***kwargs*)

get_zero_index()

init_params()

model_name = 'helicity_full'

class HelicityDecayNPbf(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *HelicityDecayNP*

get_H_barrier_factor(*data*, *data_p*, ***kwargs*)

get_helicity_amp(*data*, *data_p*, ***kwargs*)

get_ls_amp(*data*, *data_p*, ***kwargs*)

init_params()

model_name = 'helicity_full-bf'

class HelicityDecayP(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *HelicityDecayNP*

$$H_{-m1,-m2} = P_0 P_1 P_2 (-1)^{J_1+J_2-J_0} H_{m1,m2}$$

get_helicity_amp(*data*, *data_p*, ***kwargs*)

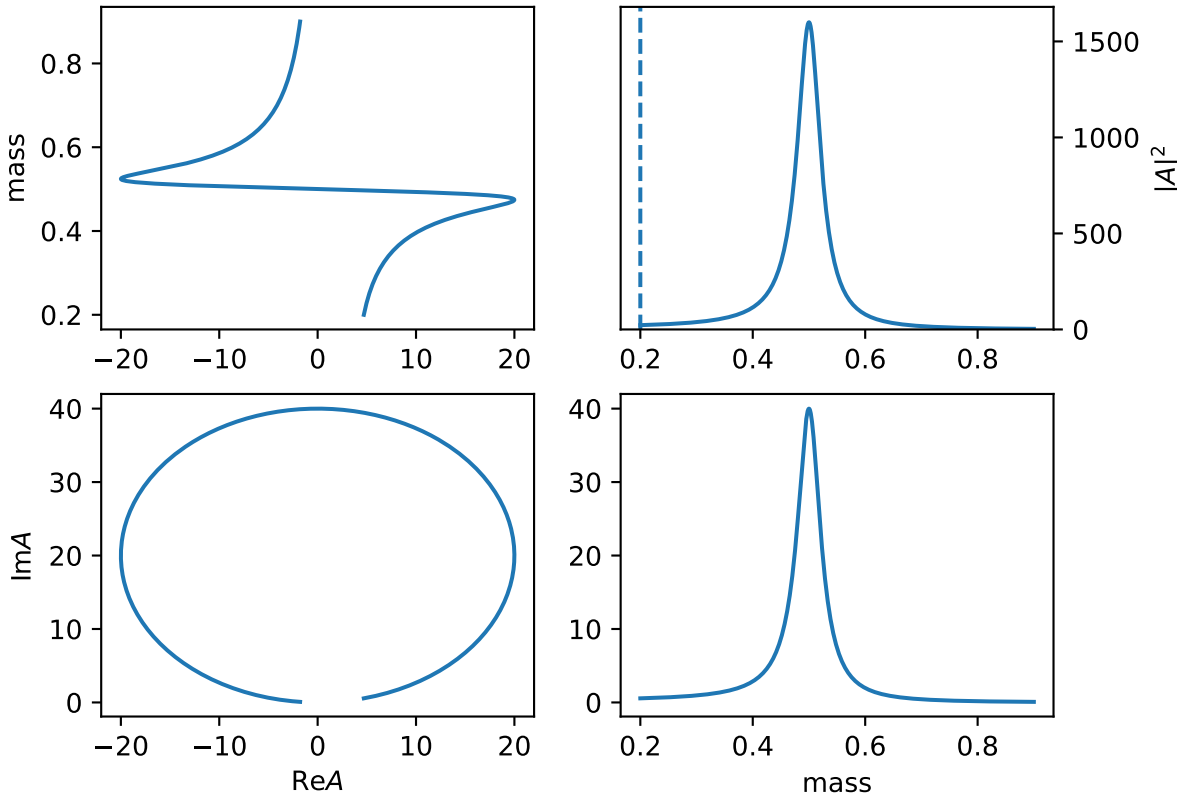
init_params()

model_name = 'helicity_parity'

class ParticleBW(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0}$$



get_amp(*data*, *_data_c=None*, ***kwargs*)

get_num_var()

get_sympy_var()

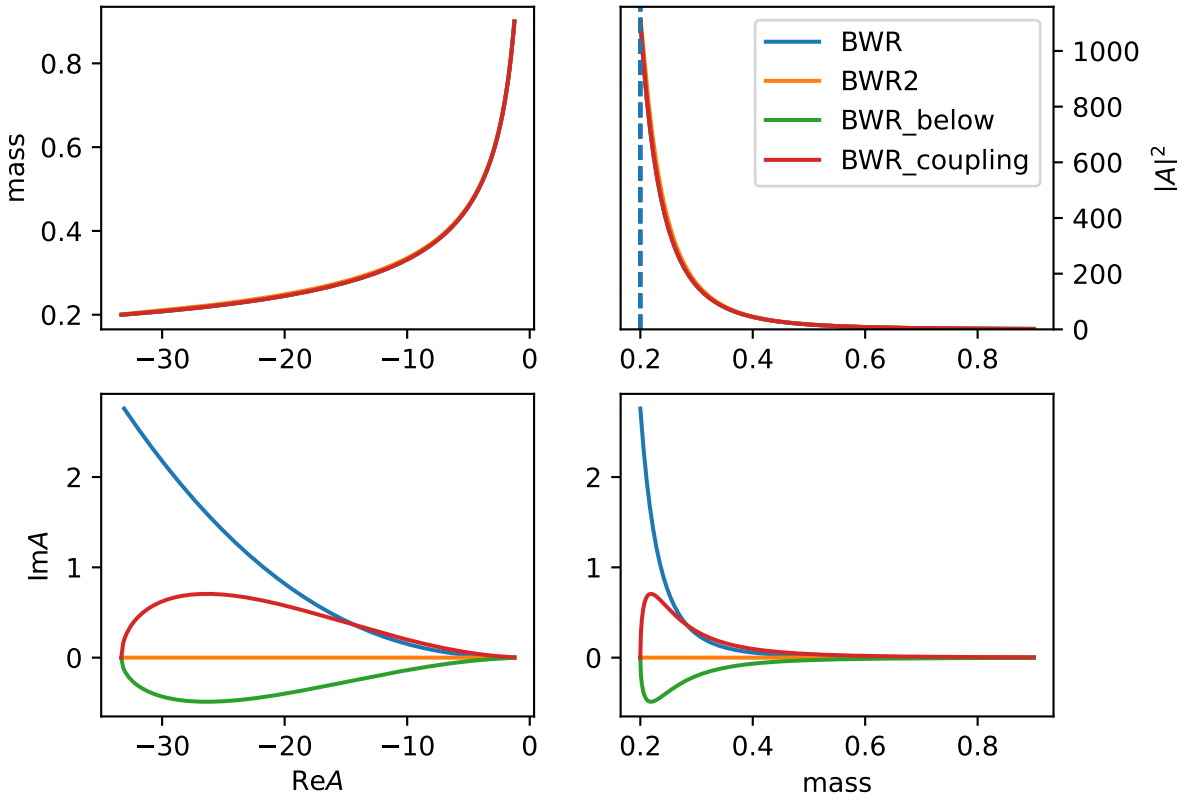
model_name = 'BW'

class ParticleBWR2(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

The difference of `BWR`, `BWR2` is the behavior when mass is below the threshold ($m_0 = 0.1 < 0.1 + 0.1 = m_1 + m_2$).



get_amp(*data*, *data_c*, ***kwargs*)

model_name = 'BWR2'

class ParticleBWRBelowThreshold(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

get_amp(*data*, *data_c*, ***kwargs*)

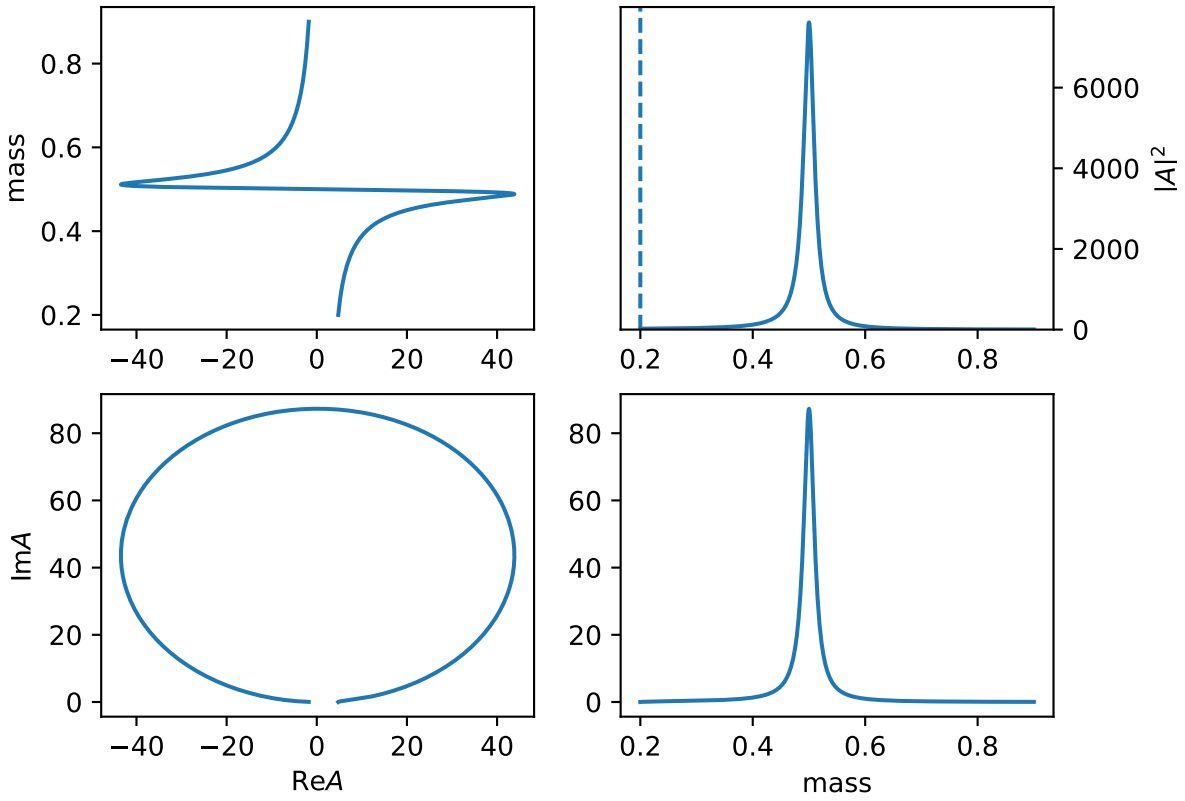
model_name = 'BWR_below'

class ParticleBWRCoupling(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

Force $q_0 = 1/d$ to avoid below theshold condition for `BWR` model, and remove other constant parts, then the Γ_0 is coupling parameters.

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0\frac{q}{m}q^{2l}B_L'^2(q, 1/d, d)}$$



get_amp(*data*, *data_c*, ***kwargs*)

get_sympy_dom(*m*, *m0*, *g0*, *m1=None*, *m2=None*, *sheet=0*)

model_name = 'BWR_coupling'

class ParticleBWR_normal(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = \frac{\sqrt{m_0\Gamma(m)}}{m_0^2 - m^2 - im_0\Gamma(m)}$$

get_amp(*data*, *data_c*, ***kwargs*)

model_name = 'BWR_normal'

class ParticleDecay(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *HelicityDecay*

get_ls_amp(*data*, *data_p*, ***kwargs*)

model_name = 'particle-decay'

class ParticleExp(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = e^{-|a|m}$$

get_amp(*data*, *_data_c=None*, ***kwargs*)

init_params()

model_name = 'exp'

class ParticleExpCom(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

$$R(m) = e^{-(a+ib)m^2}$$

lineshape when $a = 1.0, b = 10$.

get_amp(*data*, *_data_c=None*, ***kwargs*)

init_params()

model_name = 'exp_com'

class ParticleGS(**args*, ***kwargs*)

Bases: *Particle*

Gounaris G.J., Sakurai J.J., Phys. Rev. Lett., 21 (1968), pp. 244-247

`c_daug2Mass`: mass for daughter particle 2 (π^+) 0.13957039

`c_daug3Mass`: mass for daughter particle 3 (π^0) 0.1349768

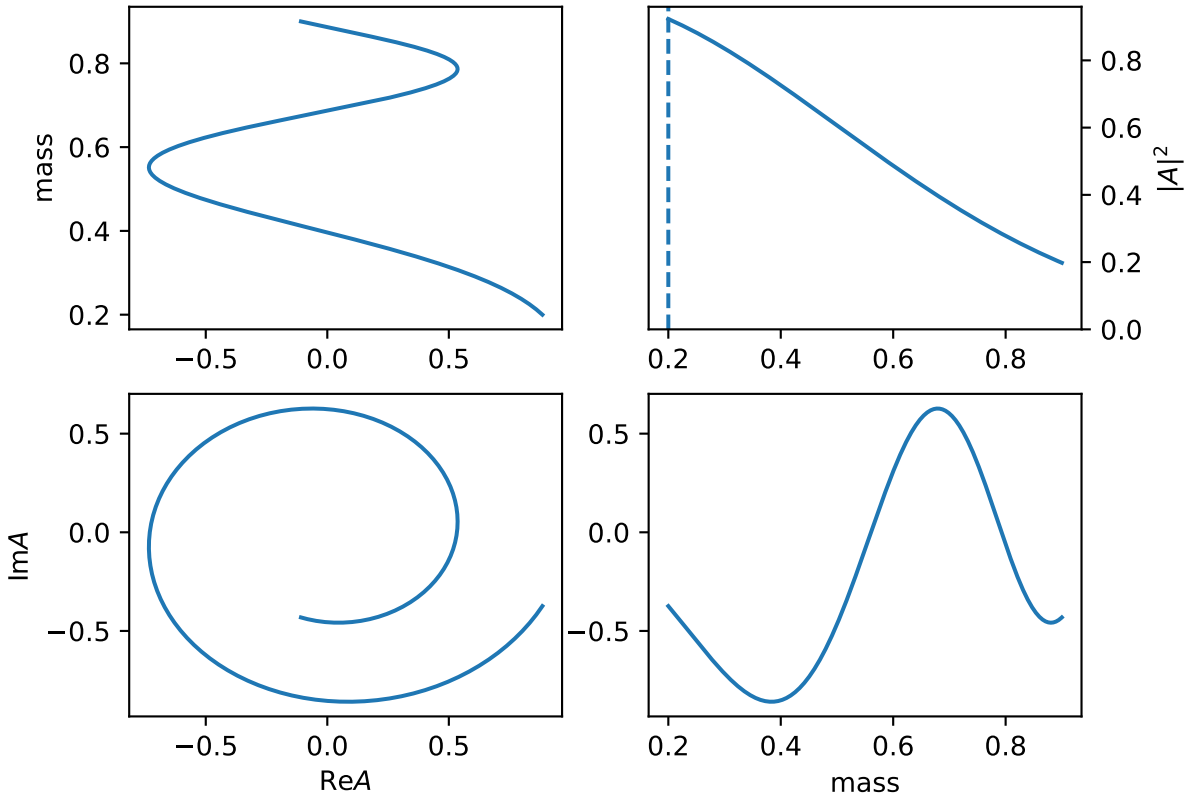
$$R(m) = \frac{1 + D\Gamma_0/m_0}{(m_0^2 - m^2) + f(m) - im_0\Gamma(m)}$$

$$f(m) = \Gamma_0 \frac{m_0^2}{q_0^3}\left[q^2[h(m) - h(m_0)] + (m_0^2 - m^2)q_0^2 \frac{dh}{dm}|_{m0}\right]$$

$$h(m) = \frac{2}{\pi}\frac{q}{m}\ln\left(\frac{m + 2q}{2m_\pi}\right)$$

$$\frac{dh}{dm}|_{m0} = h(m_0)[(8q_0^2)^{-1} - (2m_0^2)^{-1}] + (2\pi m_0^2)^{-1}$$

$$D = \frac{f(0)}{\Gamma_0 m_0} = \frac{3}{\pi}\frac{m_\pi^2}{q_0^2}\ln\left(\frac{m_0 + 2q_0}{2m_\pi}\right) + \frac{m_0}{2\pi q_0} - \frac{m_\pi^2 m_0}{\pi q_0^3}$$


mass
0.8
0.6
0.4
0.2
−0.5
0.0
0.5
0.2
0.4
0.6
0.8
0.0
$|A|^2$
ImA
ReA
mass

get_amp(*data*, *data_c*, ***kwargs*)

model_name = 'GS_rho'

class ParticleKmatrix(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

get_amp(*data*, *data_c=None*, ***kwargs*)

get_beta(*m*, ***kwargs*)

init_params()

model_name = 'Kmatrix'

class ParticleLass(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

get_amp(*data*, *data_c=None*, ***kwargs*)

$$R(m) = \frac{m}{qcot\delta_B - iq} + e^{2i\delta_B}\frac{m_0\Gamma_0\frac{m_0}{q_0}}{(m_0^2 - m^2) - im_0\Gamma_0\frac{q}{m}\frac{m_0}{q_0}}$$

$$cot\delta_B = \frac{1}{aq} + \frac{1}{2}rq$$

$$e^{2i\delta_B} = \cos 2\delta_B + i\sin 2\delta_B = \frac{cot^2\delta_B - 1}{cot^2\delta_B + 1} + i\frac{2cot\delta_B}{cot^2\delta_B + 1}$$

init_params()

model_name = 'LASS'

class ParticleOne(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

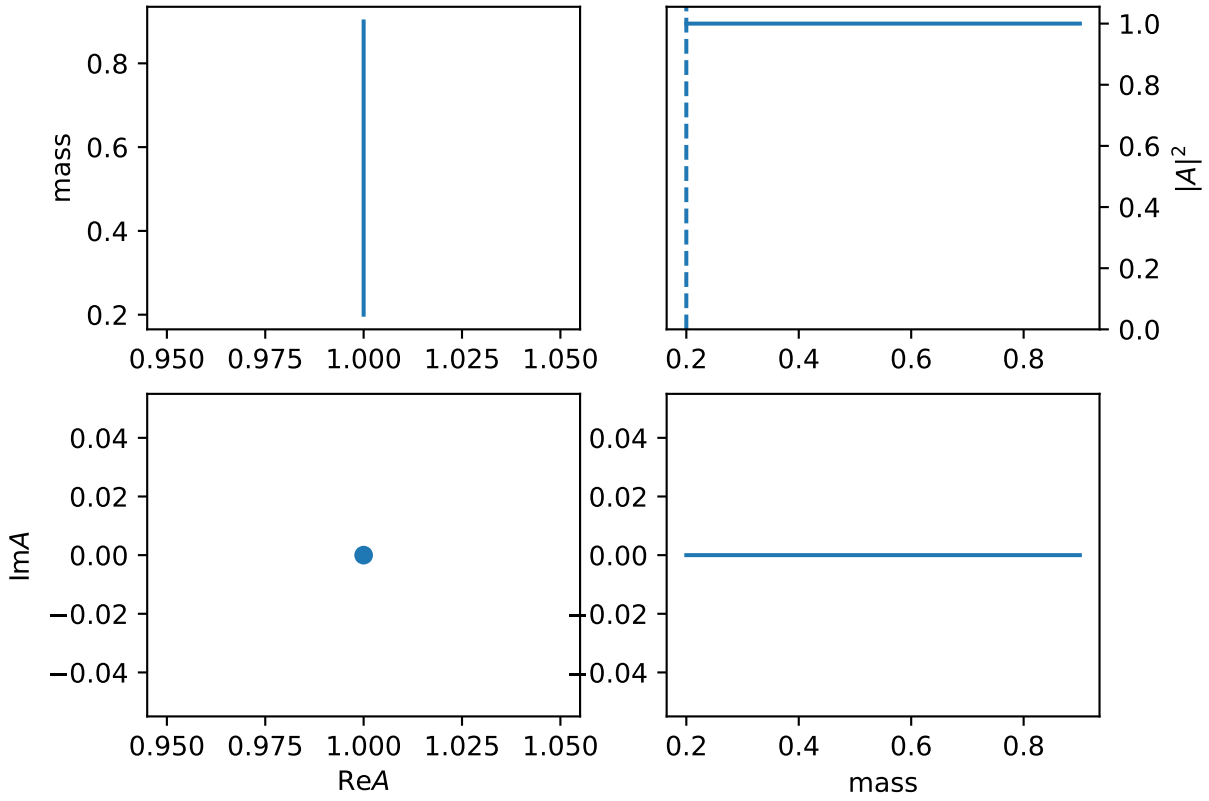
$$R(m) = 1$$

get_amp(*data*, *_data_c=None*, ***kwargs*)

init_params()

model_name = 'one'

get_parity_term(*j1*, *p1*, *j2*, *p2*, *j3*, *p3*)


mass
0.8
0.6
0.4
0.2
0.950
0.975
1.000
1.025
1.050
0.2
0.4
0.6
0.8
1.0
0.8
0.6
0.4
0.2
0.0
$|A|^2$
ImA
0.04
0.02
0.00
−0.02
−0.04
ReA
mass

core

Basic Amplitude Calculations. A partial wave analysis process has following structure:

DecayGroup: addition (+)

DecayChain: multiplication (x)
Decay, Particle(Propagator)

class AmpBase

Bases: object

Base class for amplitude

add_var(*names*, *is_complex=False*, *shape=()*, ***kwargs*)

default add_var method

amp_shape()

get_factor_variable()

get_params_head()

get_var(*name*)

get_variable_name(*name=''*)

class AmpDecay(*core*, *outs*, *name=None*, *disable=False*, *p_break=False*, *c_break=True*, *curve_style=None*, ***kwargs*)

Bases: *Decay*, *AmpBase*

base class for decay with amplitude

amp_index(*base_map*)

amp_shape()

get_params_head()

list_helicity_inner()

n_helicity_inner()

class AmpDecayChain(**args*, *is_cp=False*, *aligned=True*, ***kwargs*)

Bases: *DecayChain*, *AmpBase*

get_params_head()

class AngSam3Decay(*core*, *outs*, *name=None*, *disable=False*, *p_break=False*, *c_break=True*, *curve_style=None*, ***kwargs*)

Bases: *AmpDecay*, *AmpBase*

get_amp(*data*, *data_extra=None*, ***kwargs*)

init_params()

model_name = 'default'

class DecayChain(*args, is_cp=False, aligned=True, **kwargs)

Bases: AmpDecayChain

A list of Decay as a chain decay

amp_index(base_map=None)

amp_shape()

factor_iteration(deep=1)

get_all_factor()

get_amp(data_c, data_p, all_data=None, base_map=None)

get_amp_particle(data_p, data_c, all_data=None)

get_amp_total(charge=1)

get_angle_amp(data_c, data_p, all_data=None, base_map=None)

get_base_map(base_map=None)

get_cp_amp_total(charge=1)

get_factor()

get_factor_angle_amp(data_c, data_p, all_data=None, base_map=None)

get_factor_variable()

get_m_dep(data_c, data_p, all_data=None, base_map=None)

init_params(name='')

model_name = 'default'

product_gls()

class DecayGroup(chains)

Bases: DecayGroup, AmpBase

A Group of Decay Chains with the same final particles.

add_used_chains(used_chains)

amp_index(gen=None, base_map=None)

chains_particle()

factor_iteration(deep=2)

generate_phasespace(num=100000)

get_amp(data)

calculate the amplitude as complex number

get_amp2(data)

get_amp3(data)

get_angle_amp(*data*)

get_base_map(*gen=None*, *base_map=None*)

get_density_matrix()

get_factor()

get_factor_angle_amp(*data*)

get_factor_variable()

get_id_swap_transpose(*key*, *n*)

get_m_dep(*data*)

get mass dependent items

get_res_map()

get_swap_factor(*key*)

get_swap_transpose(*trans*, *n*)

init_params(*name=''*)

partial_weight(*data*, *combine=None*)

partial_weight_interference(*data*)

set_used_chains(*used_chains*)

set_used_res(*res*, *only=False*)

sum_amp(*data*, *cached=True*)

calculat the amplitude modular square

sum_amp_polarization(*data*)

sum amplitude suqare with density _get_cg_matrix

$$P = \sum_{m,m',\cdots} A_{m,\cdots} \rho_{m,m'} A^*_{m',\cdots}$$

sum_with_polarization(*amp*)

temp_used_res(*res*)

class FloatParams(*x=0*, */*)

Bases: `float`

class HelicityDecay(**args*, *has_barrier_factor=True*, *l_list=None*, *barrier_factor_mass=False*, *has_ql=True*, *has_bprime=True*, *aligned=False*, *allow_cc=True*, *ls_list=None*, *barrier_factor_norm=False*, *params_polar=None*, *below_threshold=False*, *force_min_l=False*, *params_head=None*, *no_q0=False*, *helicity_inner_full=False*, *ls_selector=None*, ***kwargs*)

Bases: *AmpDecay*

default decay model

The total amplitude is

$$A = H^{A\to B+C}_{\lambda_B,\lambda_C} D^{J_A *}_{\lambda_A,\lambda_B-\lambda_C}(\varphi,\theta,0)$$

The helicity coupling is

$$H^{A\to B+C}_{\lambda_B,\lambda_C} = \sum_{ls} g_{ls}\sqrt{\frac{2l+1}{2J_A+1}}\langle l0;s\delta|J_A\delta\rangle\langle J_B\lambda_B;J_C-\lambda_C|s\delta\rangle q^l B'_l(q,q_0,d)$$

The fit parameters is g_{ls}

There are some options

(1). `has_bprime=False` will remove the $B'_l(q,q_0,d)$ part.

(2). `has_barrier_factor=False` will remove the $q^l B'_l(q,q_0,d)$ part.

(3). `barrier_factor_norm=True` will replace q^l with $(q/q_0)^l$

(4). `below_threshold=True` will replace the mass used to calculate q_0 with

$$m_0^{eff} = m^{min} + \frac{m^{max}-m^{min}}{2}(1+tanh\frac{m_0-\frac{m^{max}+m^{min}}{2}}{m^{max}-m^{min}})$$

(5). `l_list=[l1, l2]` and `ls_list=[[l1, s1], [l2, s2]]` options give the list of all possible LS used in the decay.

(6). `no_q0=True` will set the $q_0 = 1$.

add_algin(*ret*, *data*)

build_ls2hel_eq()

build_simple_data()

check_valid_jp()

factor_iter_names(*deep=1*, *extra=[]*)

get_amp(*data*, *data_p*, ***kwargs*)

get_angle_amp(*data*, *data_p*, ***kwargs*)

get_angle_g_ls()

get_angle_helicity_amp(*data*, *data_p*, ***kwargs*)

get_angle_ls_amp(*data*, *data_p*, ***kwargs*)

get_barrier_factor(*mass*, *q*, *q0*, *d*)

get_barrier_factor2(*mass*, *q2*, *q02*, *d*)

get_barrier_factor_mass(*mass*)

get_cg_matrix(*out_sym=False*)

The matrix indexed by $[(l,s),(\lambda_b,\lambda_c)]$. The matrix element is

$$\sqrt{\frac{2l+1}{2j_a+1}}\langle j_b,j_c,\lambda_b,-\lambda_c|s,\lambda_b-\lambda_c\rangle\langle l,s,0,\lambda_b-\lambda_c|j_a,\lambda_b-\lambda_c\rangle$$

This is actually the pre-factor of g_{ls} in the amplitude formula.

Returns

2-d array of real numbers

get_factor()

get_factor_H(*data*, *data_p*, ***kwargs*)

get_factor_angle_amp(*data*, *data_p*, ***kwargs*)

get_factor_angle_helicity_amp(*data*, *data_p*, ***kwargs*)

get_factor_m_dep(*data*, *data_p*, ***kwargs*)

get_factor_variable()

get_g_ls()

get_helicity_amp(*data*, *data_p*, ***kwargs*)

get_ls_amp(*data*, *data_p*, ***kwargs*)

get_ls_amp_org(*data*, *data_p*, ***kwargs*)

get_ls_list()

get possible ls for decay, with l_list filter possible l

get_m_dep(*data*, *data_p*, ***kwargs*)

get_params_head()

get_relative_momentum(*data*, *from_data=False*)

get_relative_momentum2(*data*, *from_data=False*)

get_total_ls_list()

init_params()

mask_factor_vars()

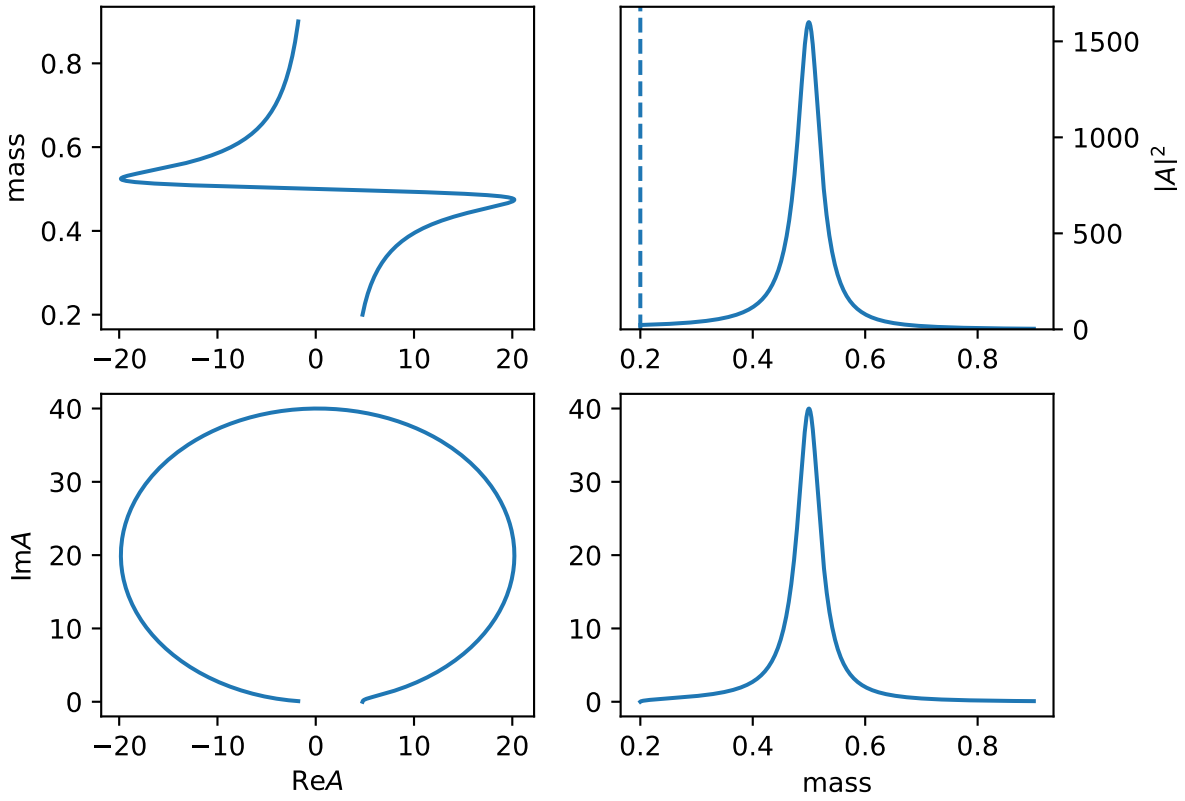
model_name = 'default'

set_ls(*ls*)

class Particle(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *BaseParticle*, *AmpBase*

$$R(m)=\frac{1}{m_0^2-m^2-im_0\Gamma(m)}$$


mass
0.8
0.6
0.4
0.2
−20
−10
0
10
20
0.2
0.4
0.6
0.8
1500
1000
500
0
$|A|^2$
ImA
40
30
20
10
0
ReA
mass

amp_shape()

get_amp(*data*, *data_c*, ***kwargs*)

get_factor()

get_mass()

get_num_var()

get_subdecay_mass(*idx=0*)

get_sympy_dom(*m*, *m0*, *g0*, *m1=None*, *m2=None*, *sheet=0*)

get_sympy_var()

get_width()

init_params()

is_fixed_shape()

model_name = 'BWR'

solve_pole(*init=None*, *sheet=0*, *return_complex=True*)

class ParticleX(**args*, *running_width=True*, *bw_l=None*, *width_norm=False*, *params_head=None*, ***kwargs*)

Bases: *Particle*

simple particle model for mass, (used in expr)

$$R(m) = m$$

get_amp(*data*, **args*, ***kwargs*)

model_name = 'x'

class SimpleResonances(**args*, ***kwargs*)

Bases: *Particle*

get_amp(**args*, ***kwargs*)

data_device(*data*)

get_decay(*core*, *outs*, ***kwargs*)

method for getting decay of model

get_decay_chain(*decays*, ***kwargs*)

method for getting decay of model

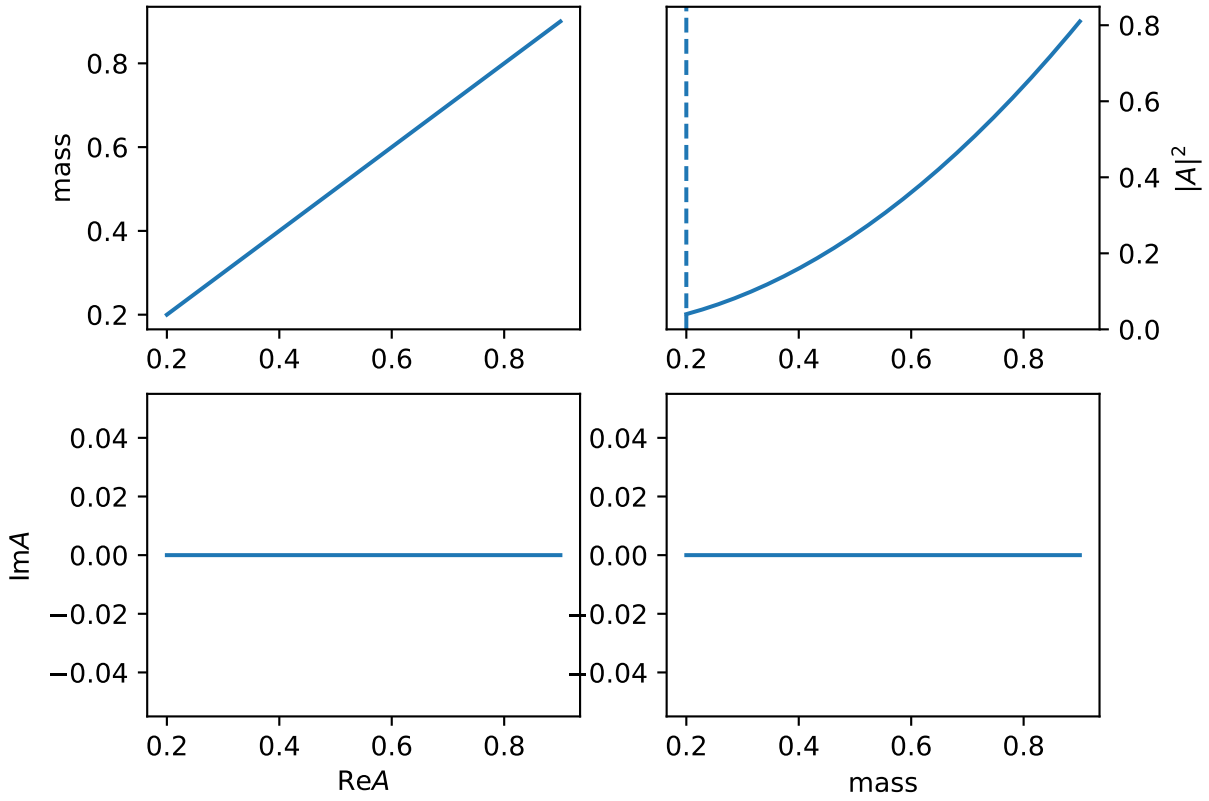
get_decay_model(*model*, *num_outs=2*)

get_name(*self*, *names*)

get_particle(**args*, *model='default'*, ***kwargs*)

method for getting particle of model

get_particle_model(*name*)


mass
0.8
0.6
0.4
0.2
0.2
0.4
0.6
0.8
$|A|^2$
0.8
0.6
0.4
0.2
0.0
ImA
0.04
0.02
0.00
−0.02
−0.04
ReA
mass

get_particle_model_name(*p*)

get_relative_p(*m_0*, *m_1*, *m_2*)

relative momentum for 0 -> 1 + 2

get_relative_p2(*m_0*, *m_1*, *m_2*)

relative momentum for 0 -> 1 + 2

index_generator(*base_map=None*)

load_decfile_particle(*fname*)

ls_selector_qr(*decay*, *ls_list*)

regist_decay(*name=None*, *num_outs=2*, *f=None*)

register a decay model

Params name
model name used in configuration

Params f
Model class

regist_particle(*name=None*, *f=None*)

register a particle model

Params name
model name used in configuration

Params f
Model class

register_decay(*name=None*, *num_outs=2*, *f=None*)

register a decay model

Params name
model name used in configuration

Params f
Model class

register_decay_chain(*name=None*, *f=None*)

register a decay model

Params name
model name used in configuration

Params f
Model class

register_particle(*name=None*, *f=None*)

register a particle model

Params name
model name used in configuration

Params f
Model class

rename_data_dict(*data*, *idx_map*)

simple_cache_fun(*f*)

simple_deepcopy(*dic*)

simple_resonance(*name*, *fun=None*, *params=None*)

convert simple fun f(m) into a resonances model

Params name
model name used in configuration

Params fun
Model function

Params params
arguments name list for parameters

trans_model(*model*)

value_and_grad(*f*, *var*)

variable_scope(*vm=None*)

variabel name scope

cov_ten

class CovTenDecayChain(**args*, *is_cp=False*, *aligned=True*, ***kwargs*)

Bases: *DecayChain*

build_coupling_einsum(*a*, *b*, *c*, *na*, *nb*, *nc*, *idx_map*)

build_decay_einsum(*ls*, *idx_map=None*)

build_einsum()

build_l_einsum(*decay*, *l*, *s*, *idx_map*)

build_s_einsum(*decay*, *l*, *s*, *idx_map*)

build_wave_function(*particle*, *pi*)

get_amp(*data_c*, *data_p*, *all_data=None*, *base_map=None*, *idx_map=None*)

get_finals_amp(*data_p*)

get_m_dep_list(*data_c*, *data_p*, *all_data=None*)

init_params(*name=''*)

model_name = 'cov_ten'

class CovTenDecayNew(**args*, ***kwargs*)

Bases: *HelicityDecay*

Decay Class for covariant tensor formula

get_amp(*data*, *data_p*, ***kwargs*)

get_angle_amp(*data*, *data_p*, ***kwargs*)

class CovTenDecaySimple(*args, **kwargs)

Bases: CovTenDecayNew

Decay Class for covariant tensor formula

get_all_amp(data, data_p, **kwargs)

get_amp(data, data_p, **kwargs)

init_params()

model_name = 'cov_ten_simple'

class EinSum(name, idx, inputs=None, replace_axis=[])

Bases: object

call(inputs, cached=None)

insert_extra_axis(name, indexs)

set_inputs(name, value)

class EinSumCall(name, idx, function)

Bases: EinSum

call(inputs, cached=None)

class EvalBoost(boost, sign=None)

Bases: object

call(inputs, cached=None)

class EvalP(core, l)

Bases: object

P^{u}_{v}

class EvalT(decay, l)

Bases: object

t^{u}

class EvalT2(decay, l)

Bases: object

t^{u}

class IndexMap

Bases: object

get(name)

create_epsilon()

epsilon^{a}_{bcd}

dot(p1, p2)

mass2(t)

wave_function(J, p)

flatte

class ParticleFlate2(**args*, *im_sign=-1*, *l_list=None*, *has_bprime=True*, *no_m0=False*, *no_q0=False*, *cut_phsp=False*, ***kwargs*)

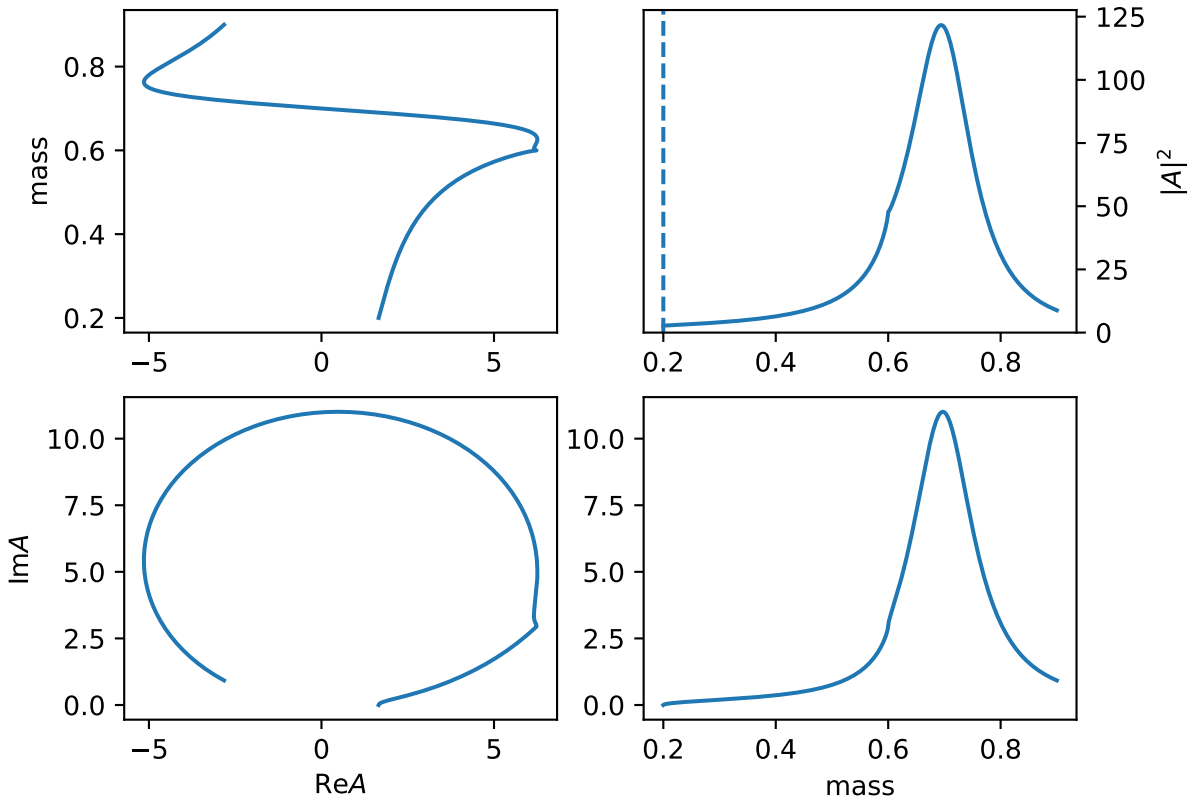
Bases: *ParticleFlateGen*

General Flatte like formula.

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0[\sum_i g_i^2 \frac{q_i}{m} \times \frac{m_0}{|q_{i0}|} \times \frac{|q_i|^{2l_i}}{|q_{i0}|^{2l_i}} B_{l_i}'^2(|q_i|, |q_{i0}|, d)]}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$

It has the same options as `FlatteGen`.



get_coeff()

model_name = 'Flatte2'

class ParticleFlateGen(**args*, *im_sign=-1*, *l_list=None*, *has_bprime=True*, *no_m0=False*, *no_q0=False*, *cut_phsp=False*, ***kwargs*)

Bases: *ParticleFlatte*

More General Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0[\sum_i g_i \frac{q_i}{m} \times \frac{m_0}{|q_{i0}|} \times \frac{|q_i|^{2l_i}}{|q_{i0}|^{2l_i}} B_{l_i}'^2(|q_i|, |q_{i0}|, d)]}$$

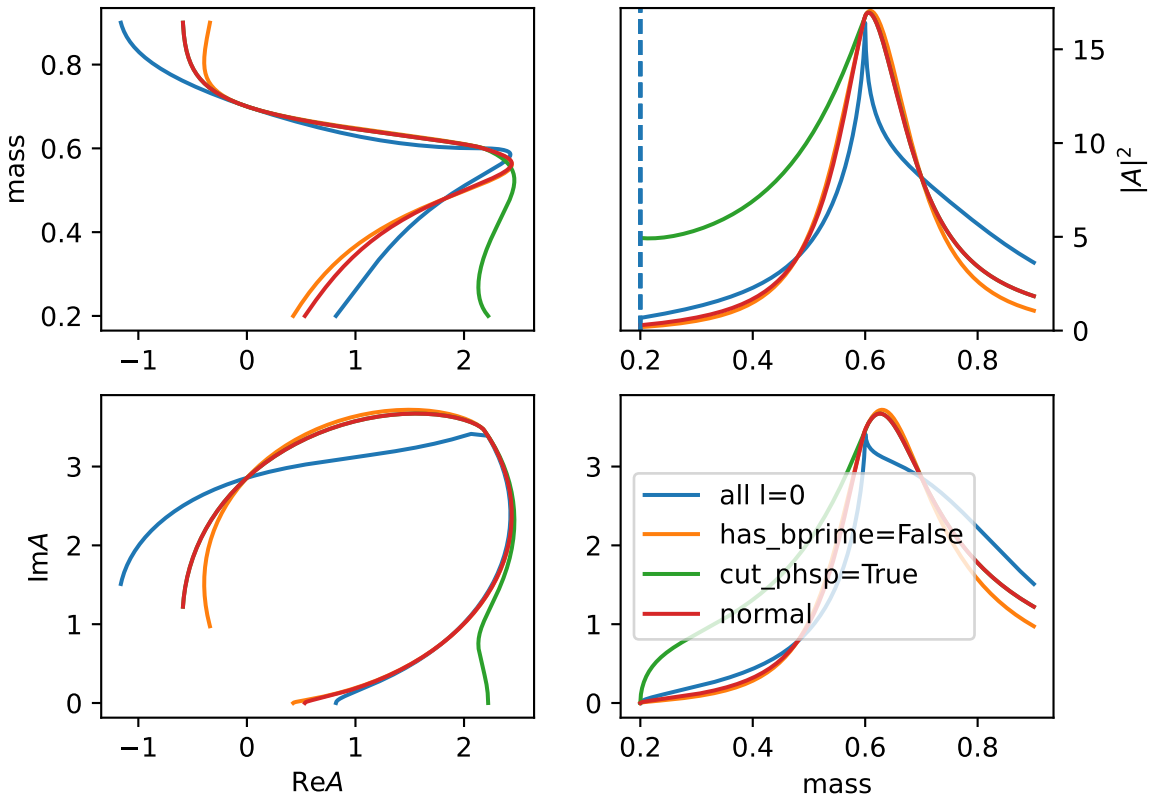
$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$

Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$. And addition arguments `l_list: [l1, l2]` for l_i

`has_bprime=False` to remove $B_{l_i}'^2(|q_i|, |q_{i0}|, d)$.

`cut_phsp=True` to set $q_i = 0$ when $(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0$

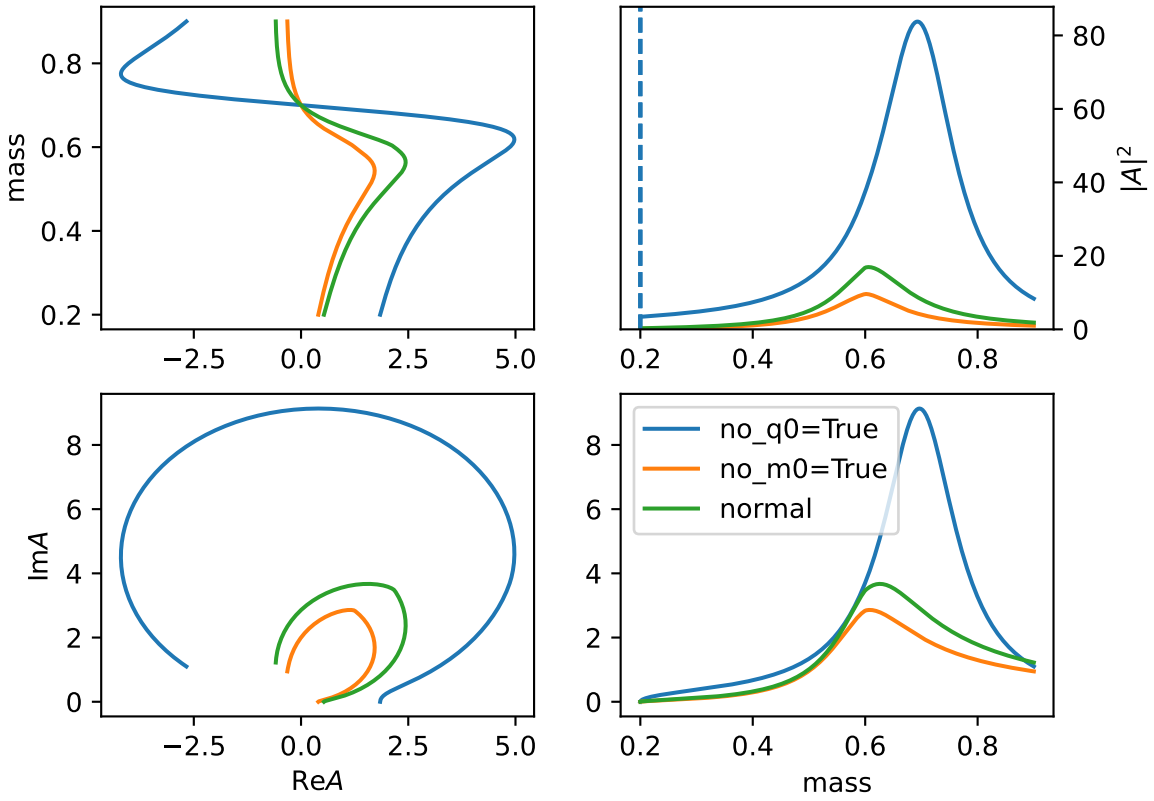
The plot use parameters $m_0 = 0.7, m_{0,1} = m_{0,2} = 0.1, m_{1,1} = m_{1,2} = 0.3, g_0 = 0.3, g_1 = 0.2, l_0 = 0, l_1 = 1$.



`no_m0=True` to set $im_0 => i$ in the width part.

`no_q0=True` to remove $\frac{m_0}{|q_{i0}|}$ and set others $q_{i0} = 1$.

get_amp(**args*, ***kwargs*)


mass
0.8
0.6
0.4
0.2
−2.5
0.0
2.5
5.0
0.2
0.4
0.6
0.8
80
60
40
20
0
$|A|^2$
ImA
8
6
4
2
0
ReA
no_q0=True
no_m0=True
normal
mass

get_coeff()

get_num_var()

get_sympy_dom(*m*, *m0*, **gi*, *sheet=0*)

model_name = 'FlatteGen'

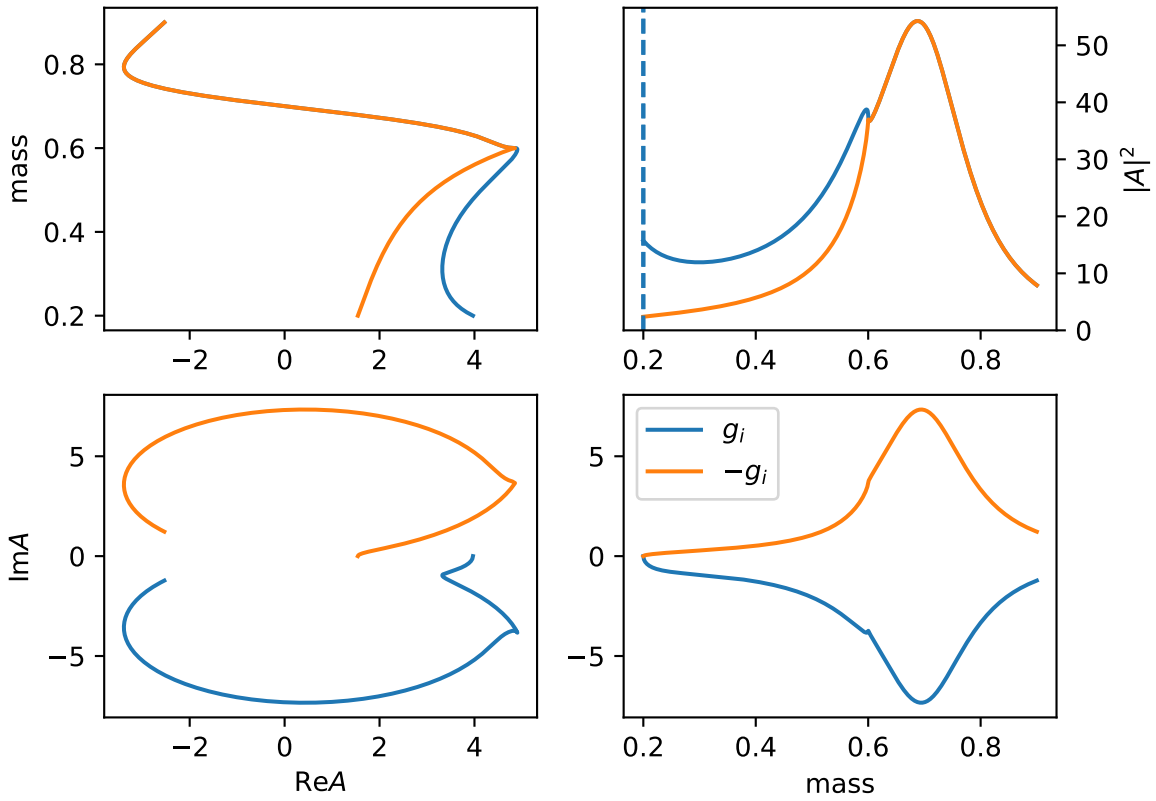
class ParticleFlatte(**args*, *mass_list=None*, *im_sign=1*, ***kwargs*)

Bases: *Particle*

Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 + im_0(\sum_i g_i \frac{q_i}{m})}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$



Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$.

get_amp(**args*, ***kwargs*)

get_num_var()

get_sympy_dom(*m*, *m0*, **gi*, *sheet=0*)

get_sympy_var()

get_width(*m=None*)

init_params()

model_name = 'Flatte'

class ParticleFlatteC(**args*, *im_sign=-1*, ***kwargs*)

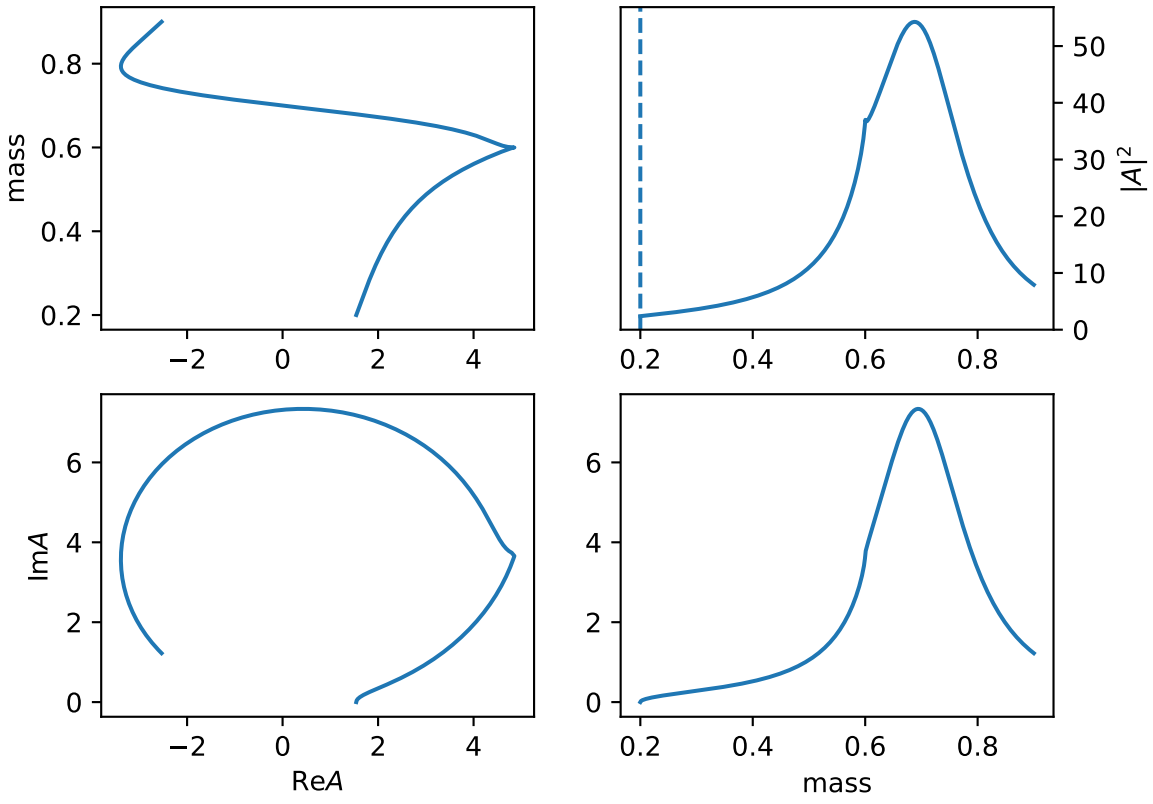
Bases: *ParticleFlatte*

Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0(\sum_i g_i \frac{q_i}{m})}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$

Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$.



model_name = 'FlatteC'

cal_monentum(*m*, *ma*, *mb*)

cal_monentum_sympy(*m*, *ma*, *mb*)

interpolation

class HistParticle(**args*, ***kwargs*)

Bases: *InterpolationParticle*

n_points()

class Interp(**args*, ***kwargs*)

Bases: *InterpolationParticle*

linear interpolation for complex number

interp(*m*)

model_name = 'interp_c'

class Interp1D3(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Piecewise third order interpolation

interp(*m*)

model_name = 'interp1d3'

class Interp1DLang(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Lagrange interpolation

interp(*m*)

model_name = 'interp_lagrange'

class Interp1DSpline(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Spline interpolation function for model independent resonance

init_params()

interp(*m*)

model_name = 'spline_c'

class Interp1DSplineIdx(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Spline function in index way.

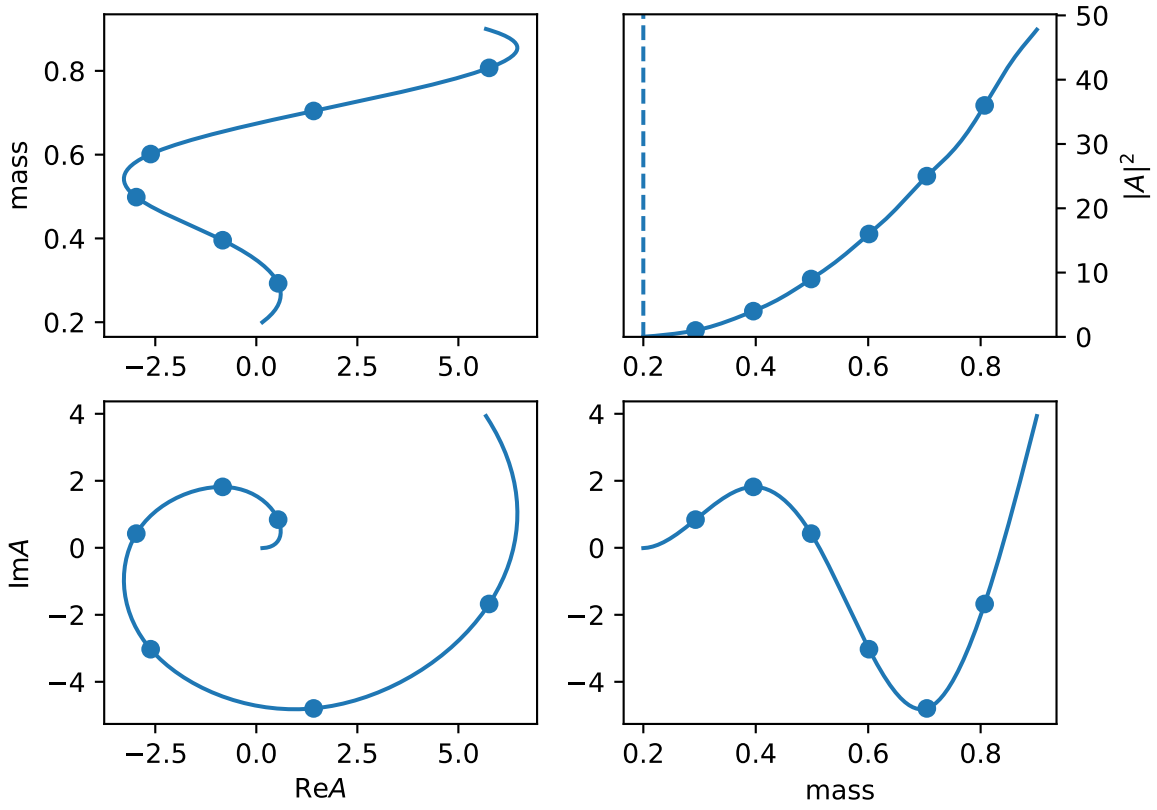
use

```
min_m: 0.19
max_m: 0.91
interp_N: 8
with_bound: True
```

for mass range [0.19, 0.91] and 8 interpolation points

The first and last are fixed to zero unless set `with_bound: True`.

This is an example of $k\exp(ik)$ for point k.



init_params()

interp(*m*)

model_name = 'spline_c_idx'

class InterpHist(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Interpolation for each bins as constant

interp(*m*)

model_name = 'interp_hist'

class InterpHistIdx(**args*, ***kwargs*)

Bases: *HistParticle*

Interpolation for each bins as constant

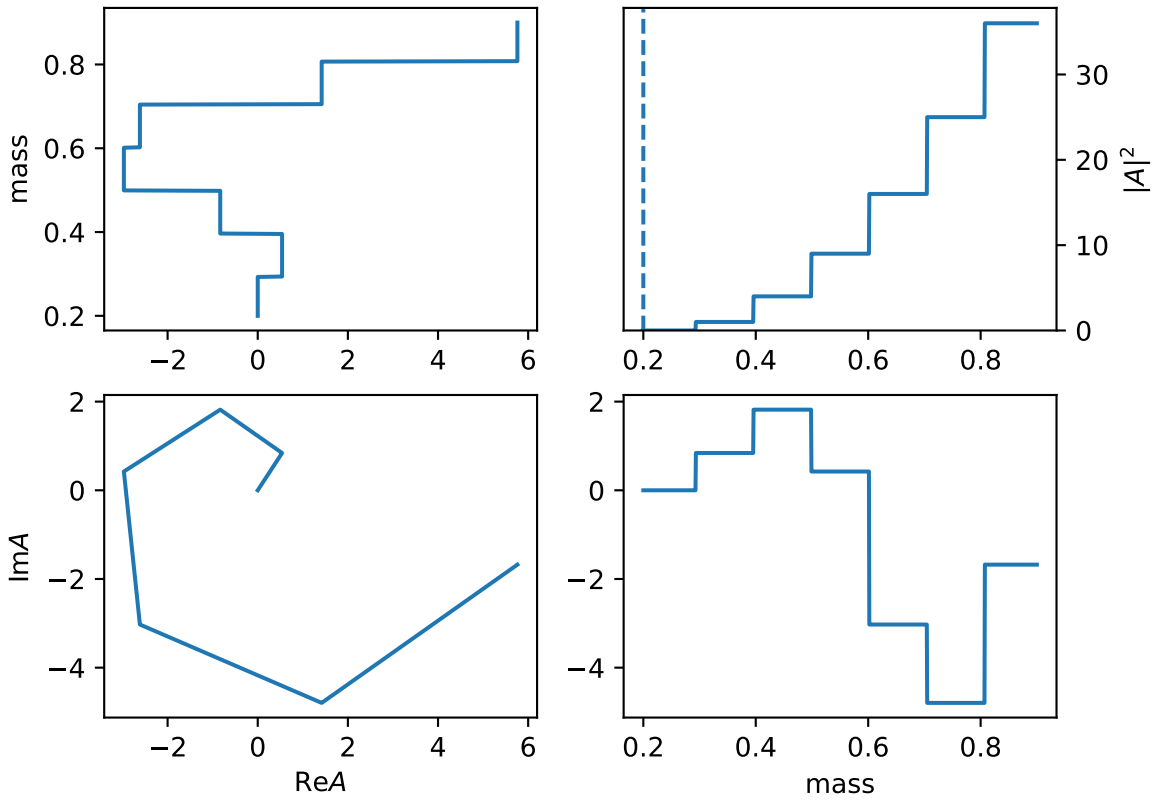
use

```
min_m: 0.19
max_m: 0.91
interp_N: 8
with_bound: True
```

for mass range [0.19, 0.91] and 7 bins

The first and last are fixed to zero unless set `with_bound: True`.

This is an example of $k\exp(ik)$ for point k.



interp(*m*)

model_name = 'hist_idx'

class InterpL3(**args*, ***kwargs*)

Bases: *InterpolationParticle*

interp(*m*)

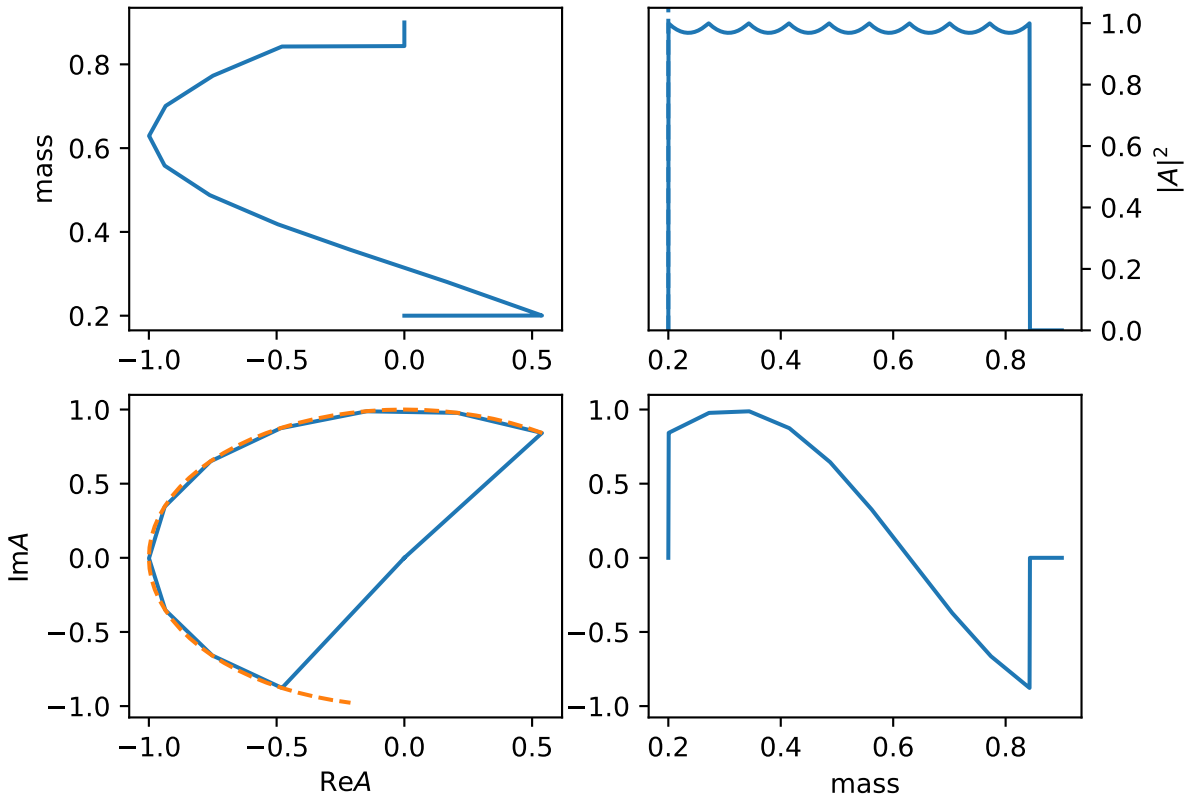
model_name = 'interp_l3'

class InterpLinearNpy(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Linear interpolation model from a npy file with array of [mi, re(ai), im(ai)]. Required `file: path_of_file.npy`, for the path of npy file.

The example is `exp(5 I m)`.



get_point_values()

init_params()

interp(*m*)

model_name = 'linear_npy'

class InterpLinearTxt(**args*, ***kwargs*)

Bases: *InterpLinearNpy*

Linear interpolation model from a `txt` file with array of [mi, re(ai), im(ai)]. Required `file: path_of_file.txt`, for the path of `txt` file.

The example is `exp(5 I m)`.

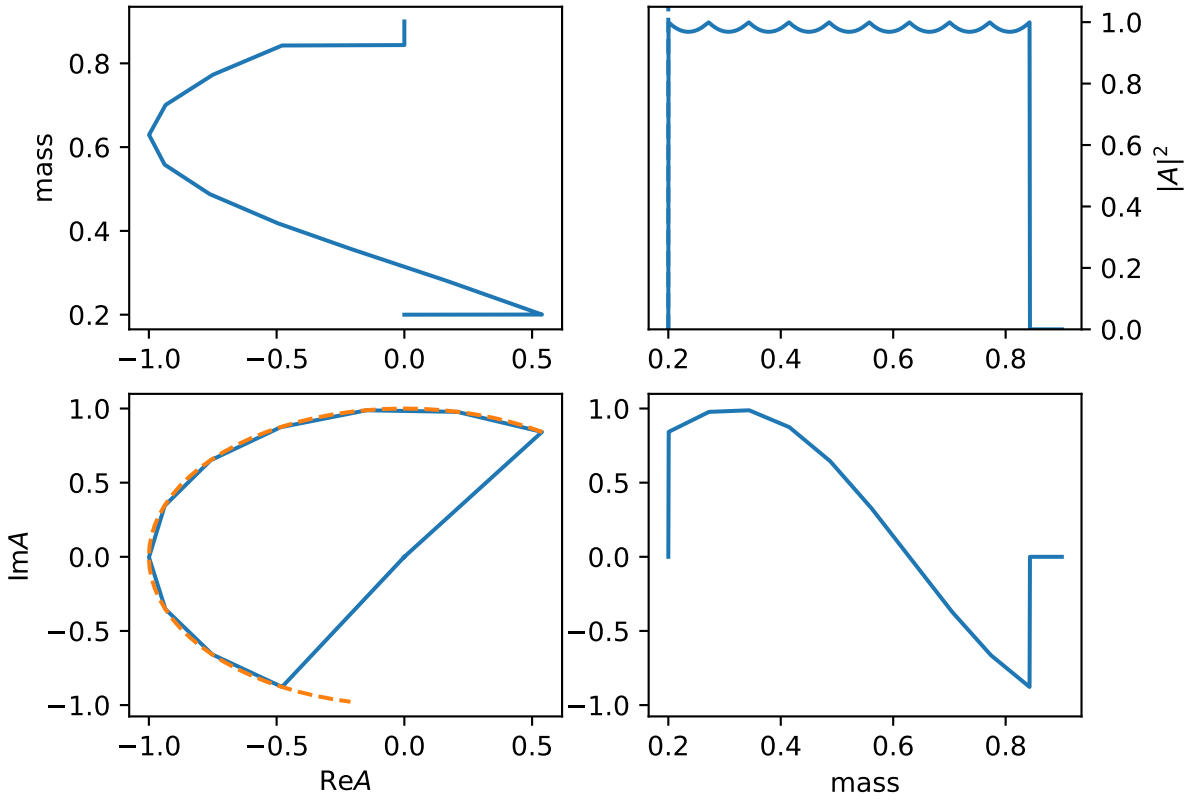
model_name = 'linear_txt'

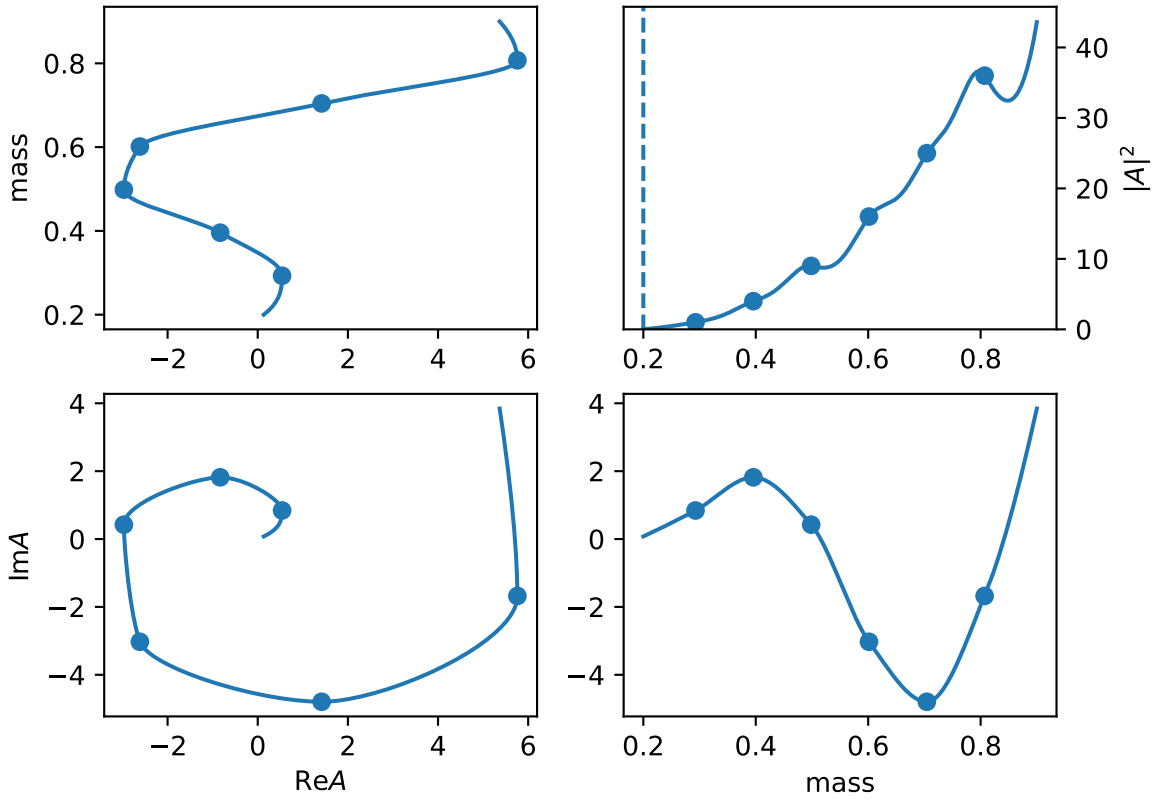
class InterpSPPCHIP(**args*, ***kwargs*)

Bases: *InterpolationParticle*

Shape-Preserving Piecewise Cubic Hermite Interpolation Polynomial. It is monotonic in each interval.

init_params()


mass
0.8
0.6
0.4
0.2
−1.0
−0.5
0.0
0.5
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
$|A|^2$
ImA
1.0
0.5
0.0
−0.5
−1.0
ReA
mass


mass
0.8
0.6
0.4
0.2
−2
0
2
4
6
40
30
20
10
0
$|A|^2$
0.2
0.4
0.6
0.8
ImA
ReA
mass

interp(*m*)

model_name = 'sppchip'

class InterpolationParticle(**args*, ***kwargs*)

Bases: *Particle*

get_amp(*data*, **args*, ***kwargs*)

get_bin_index(*m*)

get_point_values()

init_params()

interp(*mass*)

n_points()

create_sppchip_matrix(*points*)

matrix to solve f(xi),f(xi+1),f'(xi),f'(xi+1)

do_spline_hmatrix(*h_matrix*, *y*, *m*, *idx*)

get_matrix_interp1d3(*x*, *xi*)

get_matrix_interp1d3_v2(*x*, *xi*)

interp1d3(*x*, *xi*, *yi*)

spline_matrix(*x*, *xi*, *yi*, *bc_type='not-a-knot'*)

calculate spline interpolation

spline_x_matrix(*x*, *xi*)

build matrix of x for spline interpolation

spline_xi_matrix(*xi*, *bc_type='not-a-knot'*)

build matrix of xi for spline interpolation solve equation

$$S'_i(x_i) = S'_{i-1}(x_i)$$

and two bound condition. $S'_0(x_0) = S'_{n-1}(x_n) = 0$

sppchip(*m*, *xi*, *y*, *idx=None*, *matrix=None*)

Shape-Preserving Piecewise Cubic Hermite Interpolation Polynomial. It is monotonic in each interval.

```
>>> from scipy.interpolate import pchip_interpolate
>>> x_observed = np.linspace(0.0, 10.0, 11)
>>> y_observed = np.sin(x_observed)
>>> x = np.linspace(min(x_observed), max(x_observed)-1e-12, num=100)
>>> y = pchip_interpolate(x_observed, y_observed, x)
>>> assert np.allclose(y, sppchip(x, x_observed, y_observed).numpy())
```

sppchip_coeffs(*xi*, *y*, *matrix=None*, *eps=1e-12*)

kmatrix_simple

class KmatrixSimple(**args*, ***kwargs*)

Bases: *KmatrixSplitLSParticle*

simple Kmatrix formula.

K-matrix

$$K_{i,j} = \sum_a \frac{g_{i,a} g_{j,a}}{m_a^2 - m^2 + i\epsilon}$$

P-vector

$$P_i = \sum_a \frac{\beta_a g_{i,a}}{m_a^2 - m^2 + i\epsilon} + f_{bkg,i}$$

total amplitude

$$R(m) = n(1 - Ki\rho n^2)^{-1} P$$

barrief factor

$$n_{ii} = q_i^l B_l'(q_i, 1/d, d)$$

phase space factor

$$\rho_{ii} = q_i / m$$

q_i is 0 when below threshold

build_barrier_factor(*s*)

build_k_matrix(*s*)

build_p_vector(*s*)

get_ls_amp(*m*)

init_params()

model_name = 'KmatrixSimple'

phsp_fractor(*m*, *m1*, *m2*)

barrier_factor(*m*, *m1*, *m2*, *l*, *d=3.0*)

get_relative_p(*m*, *m1*, *m2*)

preprocess

class BasePreProcessor(*decay_struct*, *root_config=None*, *model='defualt'*, ***kwargs*)

Bases: *HeavyCall*

class CachedAmpPreProcessor(**args*, ***kwargs*)

Bases: *BasePreProcessor*

class CachedAnglePreProcessor(**args*, ***kwargs*)

Bases: *BasePreProcessor*

build_cached(*x*)

class CachedShapePreProcessor(**args*, ***kwargs*)

Bases: *CachedAmpPreProcessor*

build_cached(*x*)

create_preprocessor(*decay_group*, ***kwargs*)

list_to_tuple(*data*)

register_preprocessor(*name=None*, *f=None*)

register a data mode

Params name
mode name used in configuration

Params f
Data Mode class

split_ls

class ParticleBWRLS(**args*, ***kwargs*)

Bases: *ParticleLS*

Breit Wigner with split ls running width

$$R_i(m) = \frac{g_i}{m_0^2 - m^2 - im_0\Gamma_0\frac{\rho}{\rho_0}(\sum_i g_i^2)}$$

, $\rho = 2q/m$, the partial width factor is

$$g_i = \gamma_i \frac{q^l}{q_0^l} B'_{l_i}(q, q_0, d)$$

and keep normalize as

$$\sum_i \gamma_i^2 = 1.$$

The normalize is done by $(\cos\theta_0, \sin\theta_0\cos\theta_1, \cdots, \prod_i \sin\theta_i)$

factor_gamma(*ls*)

get_barrier_factor(*ls*, *q2*, *q02*, *d*)

get_ls_amp(*m*, *ls*, *q2*, *q02*, *d=3.0*)

get_ls_amp_frac(*m*, *ls*, *q2*, *q02*, *d=3.0*)

get_num_var()

get_sympy_dom(*m*, *m0*, *g0*, *thetas*, *m1=None*, *m2=None*, *sheet=0*)

get_sympy_var()

init_params()

model_name = 'BWR_LS'

class ParticleBWRLS2(**args*, ***kwargs*)

Bases: *ParticleLS*

Breit Wigner with split ls running width, each one use their own l,

$$R_i(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0\frac{\rho}{\rho_0}(g_i^2)}$$

, $\rho = 2q/m$, the partial width factor is

$$g_i = \gamma_i \frac{q^l}{q_0^l} B'_{l_i}(q, q_0, d)$$

get_ls_amp(*m*, *ls*, *q2*, *q02*, *d=3.0*)

model_name = 'BWR_LS2'

class ParticleDecayLS(**args*, ***kwargs*)

Bases: *HelicityDecay*

get_barrier_factor2(*mass*, *q2*, *q02*, *d*)

init_params()

model_name = 'LS-decay'

class ParticleLS(**args*, ***kwargs*)

Bases: *Particle*

get_amp(**args*, ***kwargs*)

get_ls_amp(*m*, *ls*, *q2*, *q02*, *d=3*)

is_fixed_shape()

class ParticleMultiBW(**args*, ***kwargs*)

Bases: *ParticleMultiBWR*

Combine Multi BW into one particle

dom_fun(*m*, *m0*, *g0*, *q2*, *q02*, *l*, *d*)

model_name = 'MultiBW'

class ParticleMultiBWR(**args*, ***kwargs*)

Bases: *ParticleLS*

Combine Multi BWR into one particle

dom_fun(*m*, *m0*, *g0*, *q2*, *q02*, *l*, *d*)

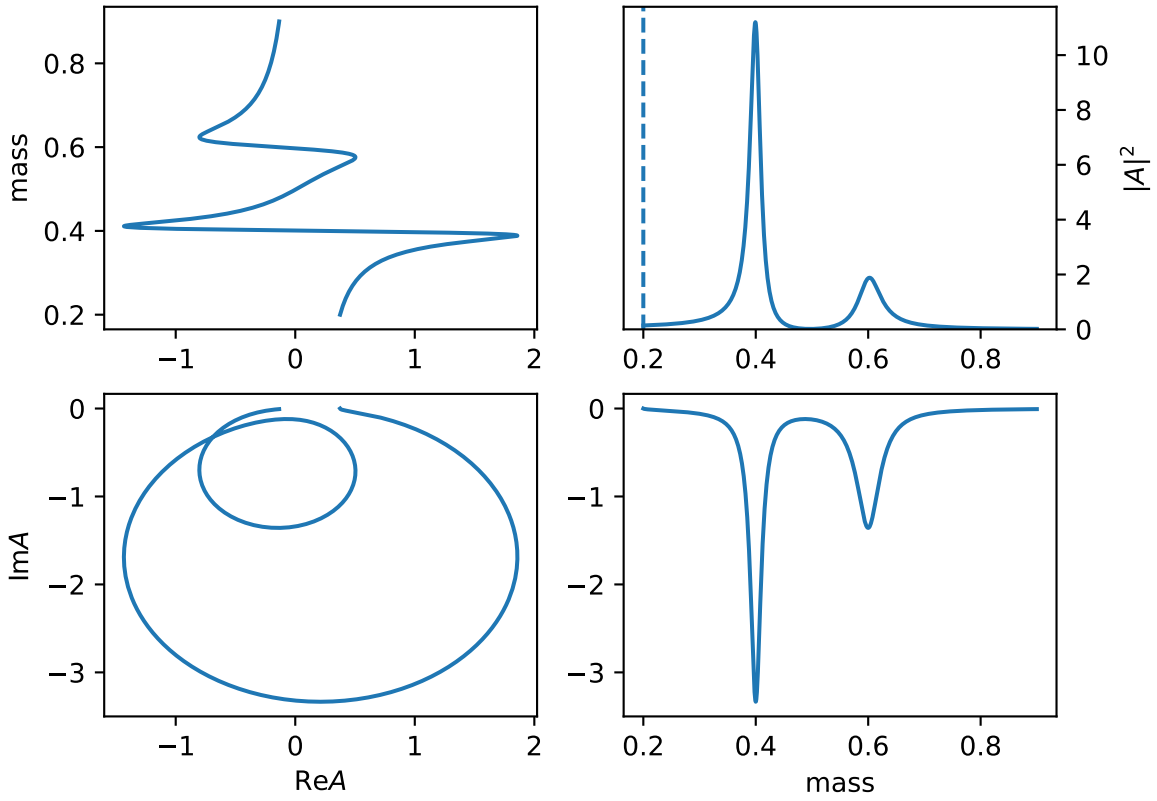
get_barrier_factor(*ls*, *q2*, *q02*, *d*)

get_ls_amp(*m*, *ls*, *q2*, *q02*, *d=3.0*)

init_params()

mass()

model_name = 'MultiBWR'


mass
0.8
0.6
0.4
0.2
−1
0
1
2
0.2
0.4
0.6
0.8
10
8
6
4
2
0
$|A|^2$
0
−1
−2
−3
ImA
ReA
mass

10.1.2 app

Submodules and Subpackages

fit

fit(*config='config.yml'*, *init_params='init_params.json'*, *method='BFGS'*)

simple fit script

json_print(*dic*)

print parameters as json

10.1.3 config_loader

Submodules and Subpackages

base_config

class BaseConfig(*file_name*, *share_dict=None*)

Bases: `object`

load_config(*file_name*, *share_dict=None*)

config_loader

class ConfigLoader(*file_name*, *vm=None*, *share_dict=None*)

Bases: *BaseConfig*

class for loading config.yml

add_constraints(*amp*)

add_decay_constraints(*amp*, *dic=None*)

add_fix_var_constraints(*amp*, *dic=None*)

add_free_var_constraints(*amp*, *dic=None*)

add_from_trans_constraints(*amp*, *dic=None*)

add_gauss_constr_constraints(*amp*, *dic=None*)

add_particle_constraints(*amp*, *dic=None*)

add_pre_trans_constraints(*amp*, *dic=None*)

add_var_equal_constraints(*amp*, *dic=None*)

add_var_range_constraints(*amp*, *dic=None*)

attach_fix_params_error(*params: dict*, *V_b=None*) → ndarray

The minimal condition

$$-\frac{\partial \ln L(a,b)}{\partial a} = 0,$$

can be treated as a implect function $a(b)$. The gradients is

$$\frac{\partial a}{\partial b} = -(\frac{\partial^2 \ln L(a,b)}{\partial a \partial a})^{-1} \frac{\partial \ln L(a,b)}{\partial a \partial b}.$$

The uncertanties from b with error matrix V_b can propagate to a as

$$V_a = \frac{\partial a}{\partial b} V_b \frac{\partial a}{\partial b}$$

This matrix will be added to the config.inv_he.

batch_sum_var(**args*, ***kwargs*)

cal_bins_numbers(*adapter*, *data*, *phsp*, *read_data*, *bg=None*, *bg_weight=None*)

cal_chi2(*read_data=None*, *bins=[[2, 2], [2, 2], [2, 2]]*, *mass=['R_BD', 'R_CD']*)

cal_fitfractions(*params={}*, *mcdata=None*, *res=None*, *exclude_res=[]*, *batch=25000*, *method='old'*)

cal_signal_yields(*params={}*, *mcdata=None*, *batch=25000*)

check_valid_jp(*decay_group*)

eval_amplitude(**p*, *extra=None*)

fit(*data=None*, *phsp=None*, *bg=None*, *inmc=None*, *batch=65000*, *method='BFGS'*, *check_grad=False*, *improve=False*, *reweight=False*, *maxiter=None*, *jac=True*, *print_init_nll=True*, *callback=None*, *grad_scale=1.0*, *gtol=0.001*)

fitNtimes(*N*, **args*, ***kwargs*)

free_for_extended(*amp*)

generate_SDP(*node*, *N=1000*, *include_charge=False*, *legacy=True*)

generate_SDP_p(*node*, *N=1000*, *legacy=False*)

generate_phsp(*N=1000*, *include_charge=False*, *cal_max=False*)

generate_phsp_p(*N=1000*, *cal_max=False*)

generate_toy(*N=1000*, *force=True*, *gen=None*, *gen_p=None*, *importance_f=None*, *max_N=100000*, *include_charge=False*, *cal_phsp_max=False*)

A more accurate method for generating toy data.

Parameters

- **N** – number of events.
- **force** – if romove extra data generated.
- **gen** – optional function for generate phase space, the return value is same as config.get_data.
- **gen_p** – optional function for generate phase space, the return value is dict as `{B: pb, C: pc, D: pd}`.
- **max_N** – max number of events for every try.

generate_toy2(**args*, ***kwargs*)

generate_toy_o(*N=1000*, *force=True*, *max_N=100000*)

generate_toy_p(*N=1000*, *force=True*, *gen_p=None*, *importance_f=None*, *max_N=100000*, *include_charge=False*, *cal_phsp_max=False*)

generate toy data momentum.

get_SDP_generator(*node*, *include_charge=False*, *legacy=True*)

get_SDP_p_generator(*node*, *legacy=True*)

get_all_data()

get_all_frame()

get_all_plotdatas(*data=None*, *phsp=None*, *bg=None*, *res=None*, *use_weighted=False*)

get_amplitude(*vm=None*, *name=''*)

get_chain(*idx*)

get_chain_property(*idx*, *display=True*)

Get chain name and curve style in plot

get_dalitz(*a*, *b*)

get_dalitz_boundary(*a*, *b*, *N=1000*)

get_dat_order(*standard=False*)

get_data(*idx*)

get_data_file(*idx*)

get_data_index(*sub*, *name*)

get_data_rec(*name*)

get_decay(*full=True*)

get_fcn(*all_data=None*, *batch=65000*, *vm=None*, *name=''*)

get_ndf()

get_params(*trainable_only=False*)

get_params_error(*params=None*, *data=None*, *phsp=None*, *bg=None*, *inmc=None*, *batch=10000*, *using_cached=False*, *method=None*, *force_pos=True*, *correct_params=None*)

calculate parameters error

get_particle_function(*name*, *d_norm=False*)

get_phsp_generator(*include_charge=False*, *nodes=[]*)

get_phsp_noeff()

get_phsp_p_generator(*nodes=[]*)

get_phsp_plot(*tail=''*)

get_plotter(*legend_file=None*, *res=None*, *datasets=None*, *use_weighted=False*)

likelihood_profile(*var*, *var_min*, *var_max*, *N=100*)

load_cached_data(*file_name=None*)

static load_config(*file_name*, *share_dict={}*)

mask_params(*params*)

params_trans()

plot_adaptive_2dpull(*var1, var2, binning=[[2, 2], [2, 2], [2, 2]], ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>, where={}, cut_zero=True, plot_scatter=True, scatter_style={'c': 'black', 's': 1}, **kwargs*)

plot_partial_wave(*params=None*, *data=None*, *phsp=None*, *bg=None*, *prefix='figure/'*, *res=None*, *save_root=False*, *chains_id_method=None*, *phsp_rec=None*, *cut_function=<function <lambda>>*, *plot_function=None*, ***kwargs*)

plot partial wave plots

Parameters

- **self** – ConfigLoader object
- **params** – params, dict or FitResutls
- **data** – data sample, a list of CalAngleData
- **phsp** – phase space sample, a list of CalAngleData (the same size as data)
- **bg** – background sample, a list of CalAngleData (the same size as data)
- **prefix** – figure saving folder and nameing prefix
- **res** – combination of resonaces in partial wave, list of (list of (string for resoances name or int for decay chain index))
- **save_root** – if save weights in a root file, bool
- **chains_id_method** – method of how legend label display, string
- **bin_scale** – more binning in partial waves for a smooth histogram. int
- **batch** – batching in calculating weights, int
- **smooth** – if plot smooth binned kde shape or histogram, bool
- **single_legend** – if save all legend in a file "legend.pdf", bool
- **plot_pull** – if plot the pull distribution, bool
- **format** – save figure with image format, string (such as ".png", ".jpeg")
- **linestyle_file** – legend linestyle configuration file name (YAML format), string (such as "legend.yml")

plot_partial_wave_interf(*res1*, *res2*, ***kwargs*)

register_extra_constrains(*name*, *f=None*)

add extra_constrains

classmethod register_function(*name=None*)

reinit_params()

static reweight_init_value(*amp*, *phsp*, *ns=None*)

reset decay chain total and make the integration to be ns

save_cached_data(*data*, *file_name=None*)

save_params(*file_name*)

save_tensorflow_model(*dir_name*)

set_params(*params*, *neglect_params=None*)

class PlotParams(*plot_config*, *decay_struct*)

Bases: dict

get_angle_vars(*is_align=False*)

get_data_index(*sub*, *name*)

get_mass_vars()

get_params(*params=None*)

set_prefix_constrains(*vm*, *base*, *params_dic*, *self*)

validate_file_name(*s*)

data

class MultiData(**args*, ***kwargs*)

Bases: *SimpleData*

get_data(*idx*) → list

get_n_data()

get_phsp_noeff()

process_scale(*idx*, *data*)

set_lazy_call(*data*, *idx*)

class SimpleData(*dic*, *decay_struct*, *config=None*)

Bases: object

cal_angle(*p4*, ***kwargs*)

get_all_data()

get_dat_order(*standard=False*)

get_data(*idx*) → dict

get_data_file(*idx*)

get_data_index(*sub*, *name*)

get_n_data()

get_phsp_noeff()

get_phsp_plot()

get_weight_sign(*idx*)

load_cached_data(*file_name=None*)

load_data(*files*, *weight_sign=1*, *weight_smear=None*, ***kwargs*) → dict

load_extra_var(*n_data*, ***kwargs*)

load_p4(*fnames*)

load_weight_file(*weight_files*)

process_scale(*idx*, *data*)

save_cached_data(*data*, *file_name=None*)

savetxt(*file_name*, *data*)

set_lazy_call(*data*, *idx*)

load_data_mode(*dic*, *decay_struct*, *default_mode='multi'*, *config=None*)

register_data_mode(*name=None*, *f=None*)

register a data mode

Params name
mode name used in configuration

Params f
Data Mode class

data_root_lhcb

class RootData(**args*, ***kwargs*)

Bases: *MultiData*

create_data(*p4*, ***kwargs*)

get_data(*idx*)

get_p4(*idx*)

get_weight(*idx*)

load_var(*idx*, *tail*)

build_matrix(*order*, *matrix*)

custom_cond(*x*, *dic*, *key=None*)

cut_data(*data*)

touch_var(*name*, *data*, *var*, *size*, *default=1*)

decay_config

class DecayConfig(*dic*, *share_dict={}*)

Bases: *BaseConfig*

decay_chain_cut(*decays*)

decay_chain_cut_list = {}

decay_cut(*decays*)

decay_cut_list = {'ls_cut': <function decay_cut_ls>, 'mass_cut': <function decay_cut_mass>}

static decay_item(*decay_dict*)

disable_allow_cc(*decay_group*)

get_decay(*full=True*)

get_decay_struct(*decay*, *particle_map=None*, *particle_params=None*, *top=None*, *finals=None*, *chain_params={}*, *process_cut=True*)

get decay structure for decay dict

static load_config(*file_name*, *share_dict={}*)

static particle_item(*particle_list*, *share_dict={}*)

static particle_item_list(*particle_list*)

rename_params(*params*, *is_particle=True*)

decay_cut_ls(*decay*)

decay_cut_mass(*decay*)

set_min_max(*dic*, *name*, *name_min*, *name_max*)

extra

cal_bins_numbers(*self*, *adapter*, *data*, *phsp*, *read_data*, *bg=None*, *bg_weight=None*)

cal_chi2(*self*, *read_data=None*, *bins=[[2, 2], [2, 2], [2, 2]]*, *mass=['R_BD', 'R_CD']*)

multi_config

class MultiConfig(*file_names*, *vm=None*, *total_same=False*, *share_dict={}*, *multi_gpu=False*)

Bases: object

fit(*datas=None*, *batch=65000*, *method='BFGS'*, *maxiter=None*, *print_init_nll=False*, *callback=None*)

get_all_data()

get_amplitudes(*vm=None*)

get_args_value(*bounds_dict*)

get_fcn(*datas=None*, *vm=None*, *batch=65000*)

get_fcns(*datas=None*, *vm=None*, *batch=65000*)

get_params(*trainable_only=False*)

get_params_error(*params=None*, *datas=None*, *batch=10000*, *using_cached=False*)

params_trans()

plot_partial_wave(*params=None*, *prefix='figure/all'*, ***kwargs*)

reinit_params()

save_params(*file_name*)

set_params(*params*, *neglect_params=None*)

particle_function

class ParticleFunction(*config*, *name*, *d_norm=False*)

Bases: `object`

amp2s(*m*)

density(*m*)

mass_linspace(*N*)

mass_range()

phsp_factor(*m*)

phsp_fractor(*m*)

get_particle_function(*config*, *name*, *d_norm=False*)

plot

class LineStyleSet(*file_name*, *color_first=True*)

Bases: `object`

get(*id_*, *default=None*)

get_style(*id_*)

save()

build_read_var_function(*all_var*, *where={}*)

create_chain_property(*self*, *res*)

create_plot_var_dic(*plot_params*)

default_color_generator(*color_first*)

export_legend(*ax*, *filename='legend.pdf'*, *ncol=1*)

export legend in Axis `ax` to file `filename`

get_chain_property(*self*, *idx*, *display=True*)

Get chain name and curve style in plot

get_chain_property_v1(*self*, *idx*, *display*)

get_chain_property_v2(*self*, *idx*, *display*)

get_dalitz(*config*, *a*, *b*)

get_dalitz_boundary(*config*, *a*, *b*, *N=1000*)

hist_error(*data*, *bins=50*, *xrange=None*, *weights=1.0*, *kind='poisson'*)

hist_line(*data*, *weights*, *bins*, *xrange=None*, *inter=1*, *kind='UnivariateSpline'*)

interpolate data from hostgram into a line

```
>>> import numpy as np
>>> import matplotlib.pyplot
>>> z = np.random.normal(size=1000)
>>> x, y = hist_line(z, None, 50)
>>> a = plt.plot(x, y)
```

hist_line_step(*data*, *weights*, *bins*, *xrange=None*, *inter=1*, *kind='quadratic'*)

```
>>> import numpy as np
>>> import matplotlib.pyplot
>>> z = np.random.normal(size=1000)
>>> x, y = hist_line_step(z, None, 50)
>>> a = plt.step(x, y)
```

plot_adaptive_2dpull(*config, var1, var2, binning=[[2, 2], [2, 2], [2, 2]], ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>, where={}, cut_zero=True, plot_scatter=True, scatter_style={'c': 'black', 's': 1}, **kwargs*)

plot_function_2dpull(*data_dict, phsp_dict, bg_dict, var1='x', var2='y', binning=[[2, 2], [2, 2], [2, 2]], where={}, ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>, cut_zero=True, plot_scatter=True, scatter_style={'c': 'black', 's': 1}, cmap='jet', **kwargs*)

plot_partial_wave(*self*, *params=None*, *data=None*, *phsp=None*, *bg=None*, *prefix='figure/'*, *res=None*, *save_root=False*, *chains_id_method=None*, *phsp_rec=None*, *cut_function=<function <lambda>>*, *plot_function=None*, ***kwargs*)

plot partial wave plots

Parameters

- **self** – ConfigLoader object
- **params** – params, dict or FitResutls
- **data** – data sample, a list of CalAngleData
- **phsp** – phase space sample, a list of CalAngleData (the same size as data)

- **bg** – background sample, a list of CalAngleData (the same size as data)
- **prefix** – figure saving folder and nameing prefix
- **res** – combination of resonaces in partial wave, list of (list of (string for resoances name or int for decay chain index))
- **save_root** – if save weights in a root file, bool
- **chains_id_method** – method of how legend label display, string
- **bin_scale** – more binning in partial waves for a smooth histogram. int
- **batch** – batching in calculating weights, int
- **smooth** – if plot smooth binned kde shape or histogram, bool
- **single_legend** – if save all legend in a file "legend.pdf", bool
- **plot_pull** – if plot the pull distribution, bool
- **format** – save figure with image format, string (such as ".png", ".jpeg")
- **linestyle_file** – legend linestyle configuration file name (YAML format), string (such as "legend.yml")

plot_partial_wave_interf(*self*, *res1*, *res2*, ***kwargs*)

plotter

class Frame(*var*, *x_range=None*, *nbins=None*, *name=None*, *display=None*, *trans=None*, ***extra*)

Bases: object

get_histogram(*data*, *partial=None*, *bin_scale=1*)

set_axis(*axis*, ***config*)

class PlotAllData(*amp*, *data*, *phsp*, *bg=None*, *res=None*, *use_weighted=False*)

Bases: object

get_all_histogram(*var*, *bin_scale=3*)

class PlotData(*dataset*, *weight=None*, *partial_weight=None*, *use_weighted=False*)

Bases: object

get_histogram(*var*, *partial=None*, ***kwargs*)

total_size()

class PlotDataGroup(*datasets*)

Bases: object

get_histogram(*var*, *partial=None*, ***kwargs*)

total_size()

class Plotter(*config*, *legend_file=None*, *res=None*, *datasets=None*, *use_weighted=False*)

Bases: object

add_ref_amp(*ref_amp*, *name='reference fit'*)

forzen_style()

get_all_hist(*frame*, *idx=None*, *bin_scale=3*)

create all partial wave histogram for observation frame.

Parameters

- **name** (*Frame, or callable*) – Function for get observation in datasets
- **idx** (*int, optional*) – data index, None for all data, defaults to None
- **bin_scale** (*float, optional*) – smooth bin scale, defaults to 3

Returns
collection of histogram

Return type
dict

get_label(*key*)

get_plot_style(*example_hist*)

get_res_style(*key*)

old_style(*extra_config=None*, *color_first=True*)

context for base style, see matplotlib.rcParams for more configuration

Parameters

- **extra_config** (*ditc, optional*) – new configs, defaults to None
- **color_first** (*bool, optional*) – order of color and linestyle, defaults to True

plot_frame(*name*, *idx=None*, *ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *bin_scale=3*)

plot frame for all partial wave

Parameters

- **name** (*str*) – data variable frame name
- **idx** (*int, optional*) – data index, None for all data, defaults to None
- **bin_scale** (*float, optional*) – smooth bin scale, defaults to 3
- **ax** (*matplotlib.Axes, optional*) – plot on axis ax

Returns
matplotlib.Axes

plot_frame_with_pull(*name*, *idx=None*, *bin_scale=3*, *pull_config=None*)

plot frame with pull for all partial wave

Parameters

- **name** (*str*) – data variable frame name
- **idx** (*int, optional*) – data index, None for all data, defaults to None
- **bin_scale** (*float, optional*) – smooth bin scale, defaults to 3
- **pull_config** (*dict, optional*) – pull plot style, defaults to None

Returns
matplotlib.Axes for plot and pull

plot_var(*frame*, *idx=None*, *ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *bin_scale=3*)

plot data observation for all partial wave

Parameters

- **name** (*Frame, or callable*) – Function for get observation in datasets
- **idx** (*int, optional*) – data index, None for all data, defaults to None
- **bin_scale** (*float, optional*) – smooth bin scale, defaults to 3
- **ax** (*matplotlib.Axes, optional*) – plot axis

Returns

save_all_frame(*prefix='figure/'*, *format='png'*, *idx=None*, *plot_pull=False*, *pull_config=None*)

Save all frame in with prefix. like ConfigLoader.plot_partial_waves

Parameters

- **prefix** (*str, optional*) – prefix for file name, defaults to "figure/"
- **format** (*str, optional*) – figure format, defaults to "png"
- **idx** (*int, optional*) – dataset index, defaults to None
- **plot_pull** (*bool, optional*) – if plot pulls, defaults to False
- **pull_config** (*dict, optional*) – configuration for plot pulls, defaults to None

set_plot_item(*example_hist*)

class ReadData(*var*, *trans=None*)

Bases: object

class StyleSet(*file_name*)

Bases: object

generate_new_style()

get(*key*, *value=None*)

save()

set(*key*, *value*)

get_all_frame(*self*)

get_all_plotdatas(*self*, *data=None*, *phsp=None*, *bg=None*, *res=None*, *use_weighted=False*)

get_plotter(*self*, *legend_file=None*, *res=None*, *datasets=None*, *use_weighted=False*)

merge_hist(*hists*)

sample

class AfterGenerator(*gen*, *f_after=<function AfterGenerator.<lambda>>*)

Bases: *BaseGenerator*

cal_max_weight()

generate(*N*)

build_phsp_chain(*decay_group*)

find common decay those mother particle mass is fixed

build_phsp_chain_sorted(*st*, *final_mi*, *nodes*)

{A: [B,C, D], R: [B,C]} + {R: M} => ((mr, (mb, mc)), md)

create_cal_calangle(*config*, *include_charge=False*)

gen_random_charge(*N*, *random=True*)

generate_SDP(*config*, *node*, *N=1000*, *include_charge=False*, *legacy=True*)

generate_SDP_p(*config*, *node*, *N=1000*, *legacy=False*)

generate_phsp(*config*, *N=1000*, *include_charge=False*, *cal_max=False*)

generate_phsp_p(*config*, *N=1000*, *cal_max=False*)

generate_toy(*config*, *N=1000*, *force=True*, *gen=None*, *gen_p=None*, *importance_f=None*, *max_N=100000*, *include_charge=False*, *cal_phsp_max=False*)

A more accurate method for generating toy data.

Parameters

- **N** – number of events.
- **force** – if romove extra data generated.
- **gen** – optional function for generate phase space, the return value is same as config.get_data.
- **gen_p** – optional function for generate phase space, the return value is dict as `{B: pb, C: pc, D: pd}`.
- **max_N** – max number of events for every try.

generate_toy2(*config*, **args*, ***kwargs*)

generate_toy_o(*config*, *N=1000*, *force=True*, *max_N=100000*)

generate_toy_p(*config*, *N=1000*, *force=True*, *gen_p=None*, *importance_f=None*, *max_N=100000*, *include_charge=False*, *cal_phsp_max=False*)

generate toy data momentum.

get_SDP_generator(*config*, *node*, *include_charge=False*, *legacy=True*)

get_SDP_p_generator(*config*, *node*, *legacy=True*)

get_SDP_p_generator_legacy(*config*, *node*)

get_phsp_generator(*config*, *include_charge=False*, *nodes=[]*)

get_phsp_p_generator(*config*, *nodes=[]*)

perfer_node(*struct*, *index*, *nodes*)

reorder struct to make node exisits in PhaseGenerator

single_sampling(*phsp*, *amp*, *N*)

trans_node_order(*struct*, *index*, *order_trans*, *level*)

10.1.4 data_trans

Submodules and Subpackages

dalitz

class Dalitz(*m0*, *m1*, *m2*, *m3*)

Bases: object

generate_p(*m12*, *m23*)

generate monmentum for dalitz variable

generate_p(*m12*, *m23*, *m0*, *m1*, *m2*, *m3*)

generate monmentum by dalitz variable m12, m23

helicity_angle

class HelicityAngle(*decay_chain*)

Bases: object

general implement for angle to monmentum trasform

build_data(*ms*, *costheta*, *phi*)

generate monmentum with M_name = m

cal_angle(*p4*)

eval_phsp_factor(*ms*)

find_variable(*dat*)

generate_p_mass(*name*, *m*, *random=False*)

generate monmentum with M_name = m

get_all_mass(*replace_mass*)

get_mass_range(*name*)

get_phsp_factor(*name*, *m*)

mass_linspace(*name*, *N*)

class HelicityAngle1(*decay_chain*)

Bases: object

simple implement for angle to monmentum trasform

generate_p(*ms*, *costheta*, *phi*)

generate_p2(*ms*, *costheta*, *phi*)

generate_p_mass(*name*, *m*, *random=False*)

generate monmentum with M_name = m

get_phsp_factor(*name*, *m*)

create_rotate_p(*ps*, *ms*, *costheta*, *phi*)

create_rotate_p_decay(*decay_chain*, *mass*, *data*)

generate_p(*ms*, *msp*, *costheta*, *phi*)

ms(0) -> ms(1) + msp(0), costheta(0), phi(0) ms(1) -> ms(2) + msp(1), costheta(1), phi(1) … ms(n) -> ms(n+1) + msp(n), costheta(n), phi(n)

lorentz_neg(*pc*)

normal(*p*)

10.1.5 experimental

Submodules and Subpackages

build_amp

amp_matrix_as_dict(*dec*, *hij*)

build_amp2s(*dg*)

build_amp_matrix(*dec*, *data*, *weight=None*)

build_angle_amp_matrix(*dec*, *data*, *weight=None*)

build_params_vector(*dg*, *data*)

build_sum_amplitude(*dg*, *dec_chain*, *data*)

build_sum_angle_amplitude(*dg*, *dec_chain*, *data*)

cached_amp(*dg*, *data*, *matrix_method=<function build_angle_amp_matrix>*)

cached_amp2s(*dg*, *data*)

extra_amp

extra_data

class MultiNpzData(**args*, ***kwargs*)

Bases: *NpzData*

get_data(*idx*) → list

get_phsp_noeff()

class NpzData(*dic*, *decay_struct*, *config=None*)

Bases: *SimpleData*

get_data(*idx*) → dict

get_particle_p()

load_data(*files*, *weights=None*, *weights_sign=1*, *charge=None*) → dict

extra_function

extra_function(*f0=None*, *using_numpy=True*)

Using extra function with numerical differentiation.

It can be used for numpy function or numba.vectorize function interface.

```
>>> import numpy as np
>>> sin2 = extra_function(np.sin)
>>> a = tf.Variable([1.0,2.0], dtype="float64")
>>> with tf.GradientTape(persistent=True) as tape0:
...     with tf.GradientTape(persistent=True) as tape:
...         b = sin2(a)
...     g, = tape.gradient(b, [a,])
...
>>> h, = tape0.gradient(g, [a,])
>>> assert np.allclose(np.sin([1.0,2.0]), b.numpy())
>>> assert np.allclose(np.cos([1.0,2.0]), g.numpy())
>>> assert np.sum(np.abs(-np.sin([1.0,2.0]) - h.numpy())) < 1e-3
```

The numerical accuracy is not so well for second derivative.

factor_system

Module for factor system.

` A = a1 ( B x C x D) + a2 (E x F) B = b1 B1 + b2 B2 `

is a tree structure ` A -> [(a1, [(b1, B1), (b2, B2)], C, D), (a2, E, F)] `

Each component is a path for root to a leaf. ` (a1, b1), (a1, b2), (a2,) `

We can add some options to change the possible combination. (TODO)

flatten_all(*x*)

get_all_chain(*a*)

get_all_partial_amp(*amp*, *data*, *strip_part=[]*)

get_chain_name(*chain*)

get_id_variable(*all_var*, *var*)

get_prod_chain(*i*)

get_split_chain(*a*)

partial_amp(*amp*, *data*, *all_va*, *need_va*)

strip_variable(*var_all*, *part=[]*)

temp_var(*vm*)

opt_int

build_int_matrix(*dec*, *data*, *weight=None*)

build_int_matrix_batch(*dec*, *data*, *batch=65000*)

build_params_matrix(*dec*)

build_params_vector(*dec*, *concat=True*)

build_sum_amplitude(*dg*, *dec_chain*, *data*)

cached_int_mc(*dec*, *data*, *batch=65000*)

gls_combine(*fs*)

split_gls(*dec_chain*)

wrap_function

class Count(*idx=0*)

Bases: object

add(*value=1*)

class WrapFun(*f*, *jit_compile=False*)

Bases: object

10.1.6 generator

Submodules and Subpackages

breit_wigner

class BWGenerator(*m0*, *gamma0*, *m_min*, *m_max*)

Bases: *BaseGenerator*

DataType

alias of ndarray

generate(*N*)

integral(*x*)

solve(*x*)

generator

class ARGenerator(*phsp*, *amp*, *max_weight=None*)

Bases: *BaseGenerator*

Acceptance-Rejection Sampling

generate(*N*)

class BaseGenerator

Bases: object

DataType = typing.Any

abstract generate(*N: int*) → Any

class GenTest(*N_max*, *display=True*)

Bases: object

add_gen(*n_gen*)

generate(*N*)

set_gen(*n_gen*)

multi_sampling(*phsp*, *amp*, *N*, *max_N=200000*, *force=True*, *max_weight=None*, *importance_f=None*, *display=True*)

single_sampling2(*phsp*, *amp*, *N*, *max_weight=None*, *importance_f=None*)

interp_nd

class InterpND(*xs*, *z*, *indexing='ij'*)

Bases: object

build_coeffs()

generate(*N*)

intgral_step()

class InterpNDHist(*xs*, *z*, *indexing='ij'*)

Bases: object

build_coeffs()

generate(*N*)

interp_f(*x*)

intgral_step()

linear_interpolation

class LinearInterp(*x*, *y*, *epsilon=1e-10*)

Bases: *BaseGenerator*

linear intepolation function for sampling

DataType

alias of ndarray

cal_coeffs()

generate(*N*)

integral(*x*)

solve(*x*)

class LinearInterpImportance(*f*, *x*)

Bases: *BaseGenerator*

DataType

alias of ndarray

generate(*N*)

interp_sample(*f*, *xmin*, *xmax*, *interp_N*, *N*)

interp_sample_f(*f*, *f_interp*, *N*)

interp_sample_once(*f*, *f_interp*, *N*, *max_rnd*)

sample_test_function(*x*)

plane_2d

class Interp2D(*x*, *y*, *z*)

Bases: *TriangleGenerator*

class TriangleGenerator(*x*, *y*, *z*)

Bases: object

cal_1d_shape()

cal_coeff_left()

cal_coeff_right()

cal_coeffs()

z = a x + b y + c

[x_1 , y_1 , 1] [a] [z_1] [x_2 , y_2 , 1] [b] = [z_2] [x_3 , y_3 , 1] [c] = [z_3]

z_c = a x + b y + c

s^2 = (x-x_c)**2 + (y-y_c)**2 s = 1/b sqrt(a**2+b**2)(x-x_c) x = b s / sqrt(a**2+b**2) + x_c

cal_st_xy(*x*, *y*, *bin_index=slice(None, None, None)*)

cal_xy_st(*s*, *t*, *bin_index=slice(None, None, None)*)

generate(*N*)

generate_st(*N*)

solve_left(*y*, *bin_index=slice(None, None, None)*)

solve_right(*y*, *bin_index=slice(None, None, None)*)

solve_s(*s_r*, *bin_index=slice(None, None, None)*)

int (k_1 s + b_1)^2 - (k_2 s + b_2)^2 ds = int d s_r

t_min_max(*s*, *bin_index=slice(None, None, None)*)

solve_2(*a2*, *a1*, *x0*, *y*)

solve (a2 x**2 + a1 x)|_{x0}^{x} = y

solve_3(*a3*, *a2*, *a1*, *x0*, *x_max*, *y*)

solve (a3 x**3 + a2 x**2 + a1 x**1)|_{x0}^{x} = y

square_dalitz_plot

class SDPGenerator(*m0*, *mi*, *legacy=True*)

Bases: *BaseGenerator*

generate(*N*)

```
>>> from tf_pwa.generator.square_dalitz_plot import SDPGenerator
>>> gen = SDPGenerator(3.0, [1.0, 0.5, 0.1])
>>> p1, p2, p3 = gen.generate(100)
```

generate_SDP(*m0*, *mi*, *N=1000*, *legacy=True*)

generate square dalitz plot ditribution for 1,2

The legacy mode will include a cut off in the threshold.

square_dalitz_cut(*p*)

Copy from EvtGen old version

$$|J| = 4pqm_{12}\frac{\partial m_{12}}{\partial m'}\frac{\partial \cos\theta_{12}}{\partial \theta'}$$

$$\frac{\partial m_{12}}{\partial m'} = -\frac{\pi}{2}\sin(\pi m')(m_{12}^{max} - m_{12}^{min})$$

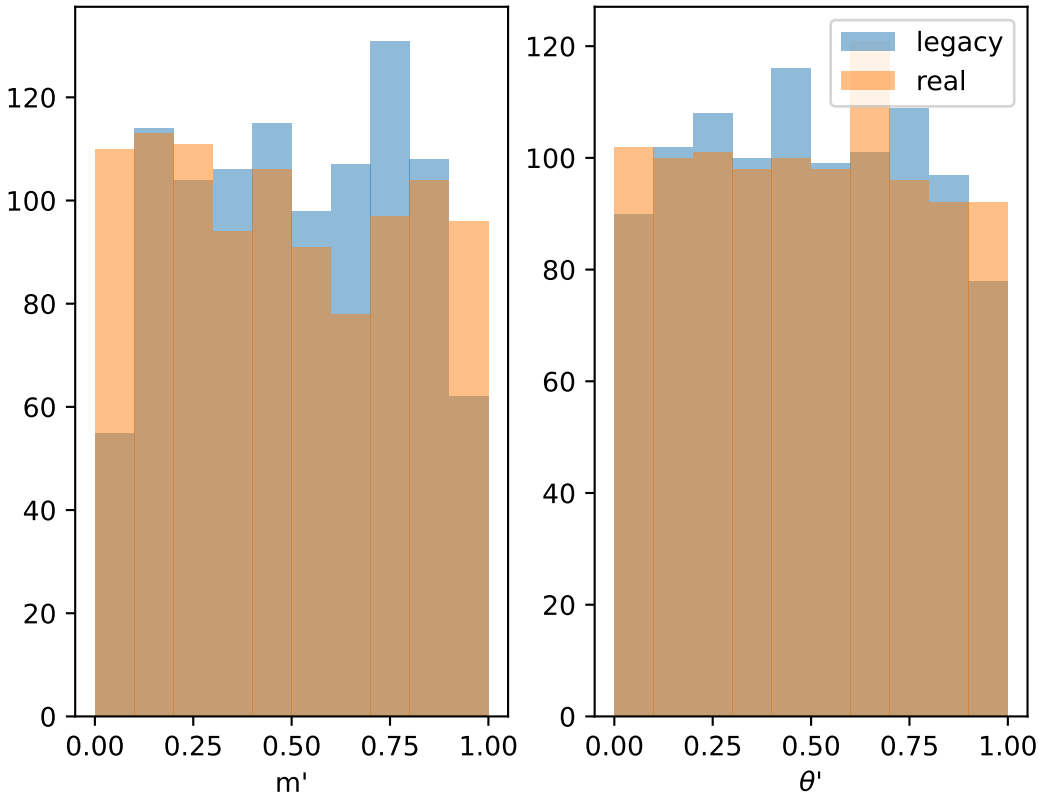
$$\frac{\partial \cos\theta_{12}}{\partial \theta'} = -\pi\sin(\pi\theta')$$

square_dalitz_variables(*p*)

Variables used of square dalitz plot, the first 2 is m' and θ'.

$$m' = \frac{1}{\pi}\cos^{-1}\left(2\frac{m_{12} - m_{12}^{min}}{m_{12}^{max} - m_{12}^{min}} - 1\right)$$

$$\theta' = \frac{1}{\pi}\theta_{12}$$


120
100
80
60
40
20
0
0.00
0.25
0.50
0.75
1.00
m'
120
100
80
60
40
20
0
0.00
0.25
0.50
0.75
1.00
θ'
legacy
real

10.1.7 model

Submodules and Subpackages

cfit

class ModelCfitExtended(*amp*, *w_bkg=0.001*, *bg_f=None*, *eff_f=None*)

Bases: *Model*

nll(*data*, *mcdata*, *weight: Tensor = 1.0*, *batch=None*, *bg=None*, *mc_weight=None*)

Calculate NLL.

$$-\ln L = -\sum_{x_i \in data} w_i \ln P(x_i;\theta_k)$$

$$P(x_i;\theta_k) = (1-f_{bg})Amp(x_i;\theta_k) + f_{bg}Bg(x_i;\theta_k)$$

$$-\ln L_2 = -\ln(L\lambda^{N_{data}}/N_{data}!e^{-\lambda}) = -L - N_{data}\ln\lambda + \lambda + C$$

$$\lambda = 1/(1-f_{bg})\int Amp(x_i;\theta_k)d\Phi$$

Parameters

- **data** – Data array
- **mcdata** – MCdata array
- **weight** – Weight of data???
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.
- **bg** – Background data array. It can be set to `None` if there is no such thing.

Returns

Real number. The value of NLL.

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

$$P = (1-frac)\frac{amp(data)}{\sum amp(phsp)} + frac\frac{bg(data)}{\sum bg(phsp)}$$

$$nll = -\sum log(p)$$

$$\frac{\partial nll}{\partial\theta} = -\sum\frac{1}{p}\frac{\partial p}{\partial\theta} = -\sum\frac{\partial\ln\bar{p}}{\partial\theta} + \frac{\partial nll}{\partial I_{sig}}\frac{\partial I_{sig}}{\partial\theta} + \frac{\partial nll}{\partial I_{bg}}\frac{\partial I_{sig}}{\partial\theta}$$

nll_grad_hessian(*data*, *mcdata*, *weight=1.0*, *batch=24000*, *bg=None*, *mc_weight=1.0*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

$$\frac{\partial^2 f}{\partial x_i\partial x_j} = \frac{\partial y_k}{\partial x_i}\frac{\partial^2 f}{\partial y_k\partial y_l}\frac{\partial y_l}{\partial x_j} + \frac{\partial f}{\partial y_k}\frac{\partial^2 y_k}{\partial x_i\partial x_j}$$

$$y = \{x_i; I_{sig}, I_{bg}\}$$

$$\frac{\partial y_k}{\partial x_i} = (\delta_{ik}; \frac{\partial I_{sig}}{\partial x_i}, \frac{\partial I_{bg}}{\partial x_i})$$

Return NLL

Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

class Model_cfit(*amp*, *w_bkg=0.001*, *bg_f=None*, *eff_f=None*, *resolution_size=1*)

Bases: *Model*

nll(*data*, *mcdata*, *weight: Tensor = 1.0*, *batch=None*, *bg=None*, *mc_weight=None*)

Calculate NLL.

$$-\ln L = -\sum_{x_i \in data} w_i \ln P(x_i;\theta_k)$$
$$P(x_i;\theta_k) = (1-f_{bg})Amp(x_i;\theta_k) + f_{bg}Bg(x_i;\theta_k)$$

Parameters

- **data** – Data array
- **mcdata** – MCdata array
- **weight** – Weight of data???
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.
- **bg** – Background data array. It can be set to `None` if there is no such thing.

Returns
Real number. The value of NLL.

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

$$P = (1-frac)\frac{amp(data)}{\sum amp(phsp)} + frac\frac{bg(data)}{\sum bg(phsp)}$$
$$nll = -\sum log(p)$$
$$\frac{\partial nll}{\partial \theta} = -\sum \frac{1}{p}\frac{\partial p}{\partial \theta} = -\sum \frac{\partial \ln \bar{p}}{\partial \theta} + \frac{\partial nll}{\partial I_{sig}}\frac{\partial I_{sig}}{\partial \theta} + \frac{\partial nll}{\partial I_{bg}}\frac{\partial I_{sig}}{\partial \theta}$$

nll_grad_hessian(*data*, *mcdata*, *weight=1.0*, *batch=24000*, *bg=None*, *mc_weight=1.0*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial y_k}{\partial x_i}\frac{\partial^2 f}{\partial y_k \partial y_l}\frac{\partial y_l}{\partial x_j} + \frac{\partial f}{\partial y_k}\frac{\partial^2 y_k}{\partial x_i \partial x_j}$$
$$y = \{x_i; I_{sig}, I_{bg}\}$$
$$\frac{\partial y_k}{\partial x_i} = (\delta_{ik}; \frac{\partial I_{sig}}{\partial x_i}, \frac{\partial I_{bg}}{\partial x_i})$$

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

class Model_cfit_cached(*amp*, *w_bkg=0.001*, *bg_f=None*, *eff_f=None*)

Bases: *Model_cfit*

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

$$P = (1 - frac)\frac{amp(data)}{\sum amp(phsp)} + frac\frac{bg(data)}{\sum bg(phsp)}$$

$$nll = -\sum log(p)$$

$$\frac{\partial nll}{\partial \theta} = -\sum \frac{1}{p}\frac{\partial p}{\partial \theta} = -\sum \frac{\partial \ln \bar{p}}{\partial \theta} + \frac{\partial nll}{\partial I_{sig}}\frac{\partial I_{sig}}{\partial \theta} + \frac{\partial nll}{\partial I_{bg}}\frac{\partial I_{sig}}{\partial \theta}$$

f_bg(*data*)

f_eff(*data*)

custom

class BaseCustomModel(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *Model*

eval_nll_part(*data*, *weight=None*, *norm=None*, *idx=0*)

eval_normal_factors(*mcdata*, *weight=None*)

nll(*data*, *mcdata*, *weight: Tensor = 1.0*, *batch=None*, *bg=None*, *mc_weight=1.0*)

Calculate NLL.

$$-\ln L = -\sum_{x_i \in data} w_i \ln f(x_i;\theta_k) + (\sum w_j)\ln \sum_{x_i \in mc} f(x_i;\theta_k)$$

Parameters

- **data** – Data array
- **mcdata** – MCdata array
- **weight** – Weight of data???
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.
- **bg** – Background data array. It can be set to `None` if there is no such thing.

Returns

Real number. The value of NLL.

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

batch version of `self.nll_grad()`

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k}\ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –

- **weight** –
- **mc_weight** –

Returns

nll_grad_hessian(*data*, *mcdata*, *weight=1.0*, *batch=24000*, *bg=None*, *mc_weight=1.0*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

value_and_grad(*fun*)

class SimpleCFitModel(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *BaseCustomModel*

eval_nll_part(*data*, *weight*, *norm*, *idx=0*)

eval_normal_factors(*mcdata*, *weight*)

required_params = ['bg_frac']

class SimpleChi2Model(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *BaseCustomModel*

fit amp = weight directly. Required set extended = True.

eval_nll_part(*data*, *weight*, *norm*, *idx=0*)

class SimpleClipNllModel(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *SimpleNllModel*

eval_nll_part(*data*, *weight*, *norm*, *idx=0*)

class SimpleNllFracModel(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *BaseCustomModel*

eval_nll_part(*data*, *weight*, *norm*, *idx=0*)

eval_normal_factors(*mcdata*, *weight*)

required_params = ['constr_frac', 'bg_frac']

class SimpleNllModel(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: *BaseCustomModel*

eval_nll_part(*data*, *weight*, *norm*, *idx=0*)

eval_normal_factors(*mcdata*, *weight*)

model

This module provides methods to calculate NLL(Negative Log-Likelihood) as well as its derivatives.

class BaseModel(*signal*, *resolution_size=1*, *extended=False*)

Bases: `object`

This class implements methods to calculate NLL as well as its derivatives for an amplitude model. It may include data for both signal and background.

Parameters
signal – Signal Model

get_params(*trainable_only=False*)

It has interface to `Amplitude.get_params()`.

grad_hessp_batch(*p*, *data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

nll(*data*, *mcdata*)

Negative log-Likelihood

nll_grad(*data*, *mcdata*, *batch=65000*)

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

nll_grad_hessian(*data*, *mcdata*, *batch=25000*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

`set_params`(*var*)

It has interface to `Amplitude.set_params()`.

`sum_log_integral_grad_batch`(*mcdata*, *ndata*)

`sum_nll_grad_bacth`(*data*)

`sum_resolution`(*w*)

`property trainable_variables`

`class CombineFCN`(*model=None*, *data=None*, *mcdata=None*, *bg=None*, *fcns=None*, *batch=65000*, *gauss_constr={}*)

Bases: `object`

This class implements methods to calculate the NLL as well as its derivatives for a general function.

Parameters

- **model** – List of model object.
- **data** – List of data array.
- **mcdata** – list of MCdata array.
- **bg** – list of Background array.
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.

`get_grad`(*x={}*)

Parameters
x – List. Values of variables.

Return gradients
List of real numbers. The gradients for each variable.

`get_grad_hessp`(*x*, *p*, *batch*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

`get_nll`(*x={}*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

`get_nll_grad`(*x={}*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

`get_nll_grad_hessian`(*x={}*, *batch=None*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return hessian
2-D Array of real numbers. The Hessian matrix of the variables.

`get_params`(*trainable_only=False*)

`grad`(*x={}*)

`grad_hessp`(*x*, *p*, *batch=None*)

`nll_grad`(*x={}*)

`nll_grad_hessian`(*x={}*, *batch=None*)

`class ConstrainModel`(*amp*, *w_bkg=1.0*, *constrain={}*)

Bases: *Model*

negative log likelihood model with constrains

`get_constrain_grad`()

constrain: Gauss(mean,sigma)
by add a term $\frac{d}{d\theta_i}\frac{(\theta_i-\bar{\theta_i})^2}{2\sigma^2} = \frac{\theta_i-\bar{\theta_i}}{\sigma^2}$

`get_constrain_hessian`()
the constrained parameter's 2nd differentiation

`get_constrain_term`()

constrain: Gauss(mean,sigma)
by add a term $\frac{(\theta_i-\bar{\theta_i})^2}{2\sigma^2}$

`nll`(*data*, *mcdata*, *weight=1.0*, *bg=None*, *batch=None*)
calculate negative log-likelihood

$$-\ln L = -\sum_{x_i \in data} w_i \ln f(x_i;\theta_i) + (\sum w_i)\ln \sum_{x_i \in mc} f(x_i;\theta_i) + cons$$

nll_gradient(*data*, *mcdata*, *weight=1.0*, *batch=None*, *bg=None*)

calculate negative log-likelihood with gradient

$$\frac{\partial}{\partial\theta_i}(-\ln L) = -\sum_{x_i\in data} w_i \frac{\partial}{\partial\theta_i}\ln f(x_i;\theta_i) + \frac{\sum w_i}{\sum_{x_i\in mc} f(x_i;\theta_i)}\sum_{x_i\in mc}\frac{\partial}{\partial\theta_i} f(x_i;\theta_i) + cons$$

class FCN(*model*, *data*, *mcdata*, *bg=None*, *batch=65000*, *inmc=None*, *gauss_constr={}*)

Bases: object

This class implements methods to calculate the NLL as well as its derivatives for a general function.

Parameters

- **model** – Model object.
- **data** – Data array.
- **mcdata** – MCdata array.
- **bg** – Background array.
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.

get_grad(*x={}*)

Parameters
x – List. Values of variables.

Return gradients
List of real numbers. The gradients for each variable.

get_grad_hessp(*x*, *p*, *batch*)

get_nll(*x={}*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

get_nll_grad(*x={}*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

get_nll_grad_hessian(*x={}*, *batch=None*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return hessian
2-D Array of real numbers. The Hessian matrix of the variables.

`get_params`(*trainable_only=False*)

`grad`(*x={}*)

`grad_hessp`(*x*, *p*, *batch=None*)

`nll_grad`(*x={}*)

`nll_grad_hessian`(*x={}*, *batch=None*)

`class GaussianConstr`(*vm*, *constraint={}*)

Bases: `object`

`get_constrain_grad`()

constraint: Gauss(mean,sigma)
by add a term $\frac{d}{d\theta_i}\frac{(\theta_i-\bar{\theta_i})^2}{2\sigma^2} = \frac{\theta_i-\bar{\theta_i}}{\sigma^2}$

`get_constrain_hessian`()
the constrained parameter's 2nd differentiation

`get_constrain_term`()

constraint: Gauss(mean,sigma)
by add a term $\frac{(\theta_i-\bar{\theta_i})^2}{2\sigma^2}$

`update`(*constraint={}*)

`class MixLogLikehoodFCN`(*model*, *data*, *mcdata*, *bg=None*, *batch=65000*, *gauss_constr={}*)

Bases: *CombineFCN*

This class implements methods to calculate the NLL as well as its derivatives for a general function.

Parameters

- **model** – List of model object.
- **data** – List of data array.
- **mcdata** – list of MCdata array.
- **bg** – list of Background array.
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.

`get_nll_grad`(*x={}*)

Parameters
x – List. Values of variables.

Return nll
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

class Model(*amp*, *w_bkg=1.0*, *resolution_size=1*, *extended=False*, ***kwargs*)

Bases: `object`

This class implements methods to calculate NLL as well as its derivatives for an amplitude model. It may include data for both signal and background.

Parameters

- **amp** – `AllAmplitude` object. The amplitude model.
- **w_bkg** – Real number. The weight of background.

get_params(*trainable_only=False*)

It has interface to `Amplitude.get_params()`.

get_weight_data(*data*, *weight=None*, *bg=None*, *alpha=True*)

Blend data and background data together multiplied by their weights.

Parameters

- **data** – Data array
- **weight** – Weight for data
- **bg** – Data array for background
- **alpha** – Boolean. If it's true, `weight` will be multiplied by a factor $\alpha =$???

Returns

Data, weight. Their length both equals `len(data)+len(bg)`.

grad_hessp_batch(*p*, *data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

mix_data_bakcground(*data*, *bg*)

nll(*data*, *mcdata*, *weight: Tensor = 1.0*, *batch=None*, *bg=None*, *mc_weight=1.0*)

Calculate NLL.

$$-\ln L = -\sum_{x_i \in data} w_i \ln f(x_i;\theta_k) + (\sum w_j)\ln \sum_{x_i \in mc} f(x_i;\theta_k)$$

Parameters

- **data** – Data array
- **mcdata** – MCdata array
- **weight** – Weight of data???

- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.
- **bg** – Background data array. It can be set to `None` if there is no such thing.

Returns
Real number. The value of NLL.

nll_grad(*data*, *mcdata*, *weight=1.0*, *batch=65000*, *bg=None*, *mc_weight=1.0*)

Calculate NLL and its gradients.

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

The parameters are the same with `self.nll()`, but it will return gradients as well.

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

batch version of `self.nll_grad()`

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

nll_grad_hessian(*data*, *mcdata*, *weight=1.0*, *batch=24000*, *bg=None*, *mc_weight=1.0*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

set_params(*var*)

It has interface to `Amplitude.set_params()`.

sum_log_integral_grad_batch(*mcdata*, *ndata*)

sum_nll_grad_bacth(*data*)

sum_resolution(*w*)

class Model_new(*amp*, *w_bkg=1.0*, *w_inmc=0*, *float_wmc=False*)

Bases: *Model*

This class implements methods to calculate NLL as well as its derivatives for an amplitude model. It may include data for both signal and background.

Parameters

- **amp** – `AllAmplitude` object. The amplitude model.
- **w_bkg** – Real number. The weight of background.

get_weight_data(*data*, *weight=1.0*, *bg=None*, *inmc=None*, *alpha=True*)

Blend data and background data together multiplied by their weights.

Parameters

- **data** – Data array
- **weight** – Weight for data
- **bg** – Data array for background
- **alpha** – Boolean. If it's true, `weight` will be multiplied by a factor $\alpha =$???

Returns

Data, weight. Their length both equals `len(data)+len(bg)`.

nll(*data*, *mcdata*, *weight: Tensor = 1.0*, *batch=None*, *bg=None*)

Calculate NLL.

$$-\ln L = -\sum_{x_i \in data} w_i \ln f(x_i;\theta_k) + (\sum w_j) \ln \sum_{x_i \in mc} f(x_i;\theta_k)$$

Parameters

- **data** – Data array
- **mcdata** – MCdata array
- **weight** – Weight of data???
- **batch** – The length of array to calculate as a vector at a time. How to fold the data array may depend on the GPU computability.
- **bg** – Background data array. It can be set to `None` if there is no such thing.

Returns

Real number. The value of NLL.

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad_new`

nll_grad_hessian(*data*, *mcdata*, *weight*, *mc_weight*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

Return NLL

Real number. The value of NLL.

Return gradients

List of real numbers. The gradients for each variable.

Return Hessian

2-D Array of real numbers. The Hessian matrix of the variables.

clip_log(*x*, *_epsilon=1e-06*)

clip log to allowed large value

get_shape(*x*)

sum_grad_hessp(*f*, *p*, *data*, *var*, *weight=1.0*, *trans=<function identity>*, *resolution_size=1*, *args=()*, *kwargs=None*)

The parameters are the same with `sum_gradient()`, but this function will return hessian as well, which is the matrix of the second-order derivative.

Returns

Real number NLL, list gradient, 2-D list hessian

sum_gradient(*f*, *data*, *var*, *weight=1.0*, *trans=<function identity>*, *resolution_size=1*, *args=()*, *kwargs=None*)

NLL is the sum of trans(f(data)):math:*``weight; gradient is the derivatives for each variable in ``var``.

Parameters

- **f** – Function. The amplitude PDF.
- **data** – Data array
- **var** – List of strings. Names of the trainable variables in the PDF.
- **weight** – Weight factor for each data point. It's either a real number or an array of the same shape with `data`.
- **trans** – Function. Transformation of `data` before multiplied by `weight`.
- **kwargs** – Further arguments for `f`.

Returns

Real number NLL, list gradient

sum_gradient_new(*amp*, *data*, *mcdata*, *weight*, *mcweight*, *var*, *trans=<function log>*, *w_flatmc=<function <lambda>>*, *args=()*, *kwargs=None*)

NLL is the sum of trans(f(data)):math:*``weight; gradient is the derivatives for each variable in ``var``.

Parameters

- **f** – Function. The amplitude PDF.
- **data** – Data array
- **var** – List of strings. Names of the trainable variables in the PDF.
- **weight** – Weight factor for each data point. It's either a real number or an array of the same shape with `data`.
- **trans** – Function. Transformation of `data` before multiplied by `weight`.
- **kwargs** – Further arguments for `f`.

Returns

Real number NLL, list gradient

sum_hessian(*f*, *data*, *var*, *weight=1.0*, *trans=<function identity>*, *resolution_size=1*, *args=()*, *kwargs=None*)

The parameters are the same with `sum_gradient()`, but this function will return hessian as well, which is the matrix of the second-order derivative.

Returns

Real number NLL, list gradient, 2-D list hessian

sum_hessian_new(*amp*, *data*, *mcdata*, *weight*, *mcweight*, *var*, *trans=<function log>*, *w_flatmc=<function <lambda>>*, *args=()*, *kwargs=None*)

The parameters are the same with `sum_gradient()`, but this function will return hessian as well, which is the matrix of the second-order derivative.

Returns

Real number NLL, list gradient, 2-D list hessian

opt_int

class ModelCachedAmp(*amp*, *w_bkg=1.0*)

Bases: *Model*

This class implements methods to calculate NLL as well as its derivatives for an amplitude model with Cached Int. It may include data for both signal and background. Cached Int well cause wrong results when float parameters include mass or width.

Parameters

- **amp** – `AllAmplitude` object. The amplitude model.
- **w_bkg** – Real number. The weight of background.

grad_hessp_batch(*p*, *data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

sum_log_integral_grad_batch(*mcdata*, *ndata*)

sum_nll_grad_bacth(*data*)

class ModelCachedInt(*amp*, *w_bkg=1.0*)

Bases: *Model*

This class implements methods to calculate NLL as well as its derivatives for an amplitude model with Cached Int. It may include data for both signal and background. Cached Int well cause wrong results when float parameters include mass or width.

Parameters

- **amp** – `AllAmplitude` object. The amplitude model.
- **w_bkg** – Real number. The weight of background.

build_cached_int(*mcdata*, *mc_weight*, *batch=65000*)

get_cached_int(*mc_id*)

nll_grad_batch(*data*, *mcdata*, *weight*, *mc_weight*)

`self.nll_grad()` is replaced by this one???

$$-\frac{\partial \ln L}{\partial \theta_k} = -\sum_{x_i \in data} w_i \frac{\partial}{\partial \theta_k} \ln f(x_i;\theta_k) + (\sum w_j)\left(\frac{\partial}{\partial \theta_k}\sum_{x_i \in mc} f(x_i;\theta_k)\right)\frac{1}{\sum_{x_i \in mc} f(x_i;\theta_k)}$$

Parameters

- **data** –
- **mcdata** –
- **weight** –
- **mc_weight** –

Returns

nll_grad_hessian(*data*, *mcdata*, *weight=1.0*, *batch=24000*, *bg=None*, *mc_weight=1.0*)

The parameters are the same with `self.nll()`, but it will return Hessian as well.

Return NLL
Real number. The value of NLL.

Return gradients
List of real numbers. The gradients for each variable.

Return Hessian
2-D Array of real numbers. The Hessian matrix of the variables.

sum_grad_hessp_data2(*f*, *p*, *var*, *data*, *data2*, *weight=1.0*, *trans=<function identity>*, *resolution_size=1*, *args=()*, *kwargs=None*)

The parameters are the same with `sum_gradient()`, but this function will return hessian as well, which is the matrix of the second-order derivative.

Returns
Real number NLL, list gradient, 2-D list hessian

sum_gradient(*fs*, *var*, *weight=1.0*, *trans=<function identity>*, *args=()*, *kwargs=None*)

NLL is the sum of trans(f(data)):math:*`weight; gradient is the derivatives for each variable in ``var`.

Parameters

- **f** – Function. The amplitude PDF.
- **var** – List of strings. Names of the trainable variables in the PDF.
- **weight** – Weight factor for each data point. It's either a real number or an array of the same shape with `data`.
- **trans** – Function. Transformation of `data` before multiplied by `weight`.
- **kwargs** – Further arguments for `f`.

Returns
Real number NLL, list gradient

sum_gradient_data2(*f*, *var*, *data*, *cached_data*, *weight=1.0*, *trans=<function identity>*, *args=()*, *kwargs=None*)

NLL is the sum of trans(f(data)):math:*`weight; gradient is the derivatives for each variable in ``var`.

Parameters

- **f** – Function. The amplitude PDF.
- **var** – List of strings. Names of the trainable variables in the PDF.
- **weight** – Weight factor for each data point. It's either a real number or an array of the same shape with `data`.
- **trans** – Function. Transformation of `data` before multiplied by `weight`.
- **kwargs** – Further arguments for `f`.

Returns
Real number NLL, list gradient

10.1.8 adaptive_bins

adaptive split data into bins.

class AdaptiveBound(*base_data*, *bins*, *base_bound=None*)

Bases: `object`

adaptive bound cut for data value

static base_bound(*data*)

base bound for the data

get_bool_mask(*data*)

bool mask for splitting data

get_bound_patch(***kwargs*)

get_bounds()

get split data bounds

get_bounds_data()

get split data bounds, and the data after splitting

static loop_split_bound(*datas*, *n*, *base_bound=None*)

loop for multi_split_bound, so `n` is list of list of int

static multi_split_bound(*datas*, *n*, *base_bound=None*)

multi data for single_split_bound, so n is list of int

```
>>> data = np.array([[1.0, 2.0, 1.4, 3.1], [2.0, 1.0, 3.0, 1.0]])
>>> bound, _ = AdaptiveBound.multi_split_bound(data, [2, 1])
>>> [(i[0][0]+1e-6, i[1][0]+1e-6) for i in bound]
[(1.0..., 1.7...), (1.7..., 3.1...)]
```

plot_bound(*ax*, ***kwargs*)

static single_split_bound(*data*, *n=2*, *base_bound=None*)

split data in the order of data value

```
>>> data = np.array([1.0, 2.0, 1.4, 3.1])
>>> AdaptiveBound.single_split_bound(data)
[(1.0, 1.7...), (1.7..., 3.1...)]
```

split_data(*data*)

split data, the shape is same as base_data

split_full_data(*data*, *base_index=None*)

split structure data, (TODO because large IO, the method is slow.)

adaptive_shape(*m*, *bins*, *xmin*, *xmax*)

binning_shape_function(*m*, *bins*)

cal_chi2(*numbers*, *n_fp*)

10.1.9 angle

This module implements three classes **Vector3**, **LorentzVector**, **EulerAngle** .

class AlignmentAngle(*alpha=0.0*, *beta=0.0*, *gamma=0.0*)

Bases: *EulerAngle*

static angle_px_px(*p1*, *x1*, *p2*, *x2*)

class EulerAngle(*alpha=0.0*, *beta=0.0*, *gamma=0.0*)

Bases: dict

This class provides methods for Eular angle (α, β, γ)

static angle_zx_z_getx(*z1*, *x1*, *z2*)

The Eular angle from coordinate 1 to coordinate 2. Only the z-axis is provided for coordinate 2, so γ is set to be 0.

Parameters

- **z1** – Vector3 z-axis of the initial coordinate
- **x1** – Vector3 x-axis of the initial coordinate
- **z2** – Vector3 z-axis of the final coordinate

Return eular_angle
EularAngle object with $\gamma = 0$.

Return x2
Vector3 object, which is the x-axis of the final coordinate when $\gamma = 0$.

`static angle_zx_zx`(*z1*, *x1*, *z2*, *x2*)

The Euler angle from coordinate 1 to coordinate 2 (right-hand coordinates).

Parameters

- **z1** – Vector3 z-axis of the initial coordinate
- **x1** – Vector3 x-axis of the initial coordinate
- **z2** – Vector3 z-axis of the final coordinate
- **x2** – Vector3 x-axis of the final coordinate

Returns
Euler Angle object

`static angle_zx_zzz_getx`(*z*, *x*, *zi*)

The Eular angle from coordinate 1 to coordinate 2. Z-axis of coordinate 2 is the normal vector of a plane.

Parameters

- **z1** – Vector3 z-axis of the initial coordinate
- **x1** – Vector3 x-axis of the initial coordinate
- **z** – list of Vector3 of the plane point.

Return eular_angle
EularAngle object.

Return x2
list of Vector3 object, which is the x-axis of the final coordinate in zi.

`class LorentzVector`

Bases: `Tensor`

This class provides methods for Lorentz vectors (T,X,Y,Z). or -T???

`Dot`(*other*)

`M`()

The invariant mass

`M2`()

The invariant mass squared

`beta`()

`boost`(*p*)

Boost this Lorentz vector into the frame indicated by the 3-d vector p.

`boost_matrix`()

`boost_vector`()

$\beta = (X, Y, Z)/T$:return: 3-d vector β

`static from_p4`(*p_0*, *p_1*, *p_2*, *p_3*)

Given **p_0** is a real number, it will make it transform into the same shape with **p_1**.

`gamma`()

get_T()

get_X()

get_Y()

get_Z()

get_e()

rm???

get_metric()

The metric is (1,-1,-1,-1) by default

neg()

The negative vector

omega()

rest_vector(*other*)

Boost another Lorentz vector into the rest frame of β.

vect()

It returns the 3-d vector (X,Y,Z).

class SU2M(*x*)

Bases: dict

static Boost_z(*omega*)

static Boost_z_from_p(*p*)

static Rotation_y(*beta*)

static Rotation_z(*alpha*)

get_euler_angle()

inv()

class Vector3

Bases: Tensor

This class provides methods for 3-d vectors (X,Y,Z)

angle_from(*x*, *y*)

The angle from x-axis providing the x,y axis to define a 3-d coordinate.

```
x  ->  self
|       /
| ang /
|    /
|   /
|  /
| /
|/
-------- y
```

Parameters

- **x** – A Vector3 instance as x-axis
- **y** – A Vector3 instance as y-axis. It should be perpendicular to the x-axis.

cos_theta(*other*)

cos theta of included angle

cross(*other*)

Cross product with another Vector3 instance

cross_unit(*other*)

The unit vector of the cross product with another Vector3 object. It has interface to *tf.linalg.normalize()*.

dot(*other*)

Dot product with another Vector3 object

get_X()

get_Y()

get_Z()

norm()

norm2()

The norm square

unit()

The unit vector of itself. It has interface to *tf.linalg.normalize()*.

kine_max(*s12*, *m0*, *m1*, *m2*, *m3*)

max s23 for s12 in p0 -> p1 p2 p3

kine_min(*s12*, *m0*, *m1*, *m2*, *m3*)

min s23 for s12 in p0 -> p1 p2 p3

kine_min_max(*s12*, *m0*, *m1*, *m2*, *m3*)

min max s23 for s12 in p0 -> p1 p2 p3

10.1.10 applications

This module provides functions that implements user-friendly interface to the functions and methods in other modules. It acts like a synthesis of all the other modules of their own physical purposes. In general, users only need to import functions in this module to implement their physical analysis instead of going into every modules. There are some example files where you can figure out how it is used.

cal_hesse_correct(*fcn*, *params={}*, *corr_params={}*, *force_pos=True*)

cal_hesse_error(*fcn*, *params={}*, *check_posi_def=True*, *force_pos=True*, *save_npy=True*)

This function calculates the errors of all trainable variables. The errors are given by the square root of the diagonal of the inverse Hessian matrix.

Parameters
model – Model.

Return hesse_error
List of errors.

Return inv_he
The inverse Hessian matrix.

`cal_significance`(*nll1*, *nll2*, *ndf*)

This function calculates the statistical significance.

Parameters

- **nll1** – Float. NLL of the first PDF.
- **nll2** – Float. NLL of the second PDF.
- **ndf** – The difference of the degrees of freedom of the two PDF.

Returns
Float. The statistical significance

`compare_result`(*value1*, *value2*, *error1*, *error2=None*, *figname=None*, *yrange=None*, *periodic_vars=None*)

Compare two groups of fitting results. If only one error is provided, the figure is $\frac{\mu_1-\mu_2}{\sigma_1}$; if both errors are provided, the figure is $\frac{\mu_1-\mu_2}{\sqrt{\sigma_1^2+\sigma_2^2}}$.

Parameters

- **value1** – Dictionary
- **value2** – Dictionary
- **error1** – Dictionary
- **error2** – Dictionary. By default it's `None`.
- **figname** – String. The output file
- **yrange** – Float. If it's not given, there is no y-axis limit in the figure.
- **periodic_vars** – List of strings. The periodic variables.

Returns
Dictionary of quality figure of each variable.

`corr_coef_matrix`(*err_mtx*)

This function obtains correlation coefficients matrix of all trainable variables from `*.npy` file.

Parameters
err_mtx – Array or string (name of the npy file).

Returns
Numpy 2-d array. The correlation coefficient matrix.

`fit`(*Use='scipy'*, ***kwargs*)

Fit the amplitude model using `scipy`, `iminuit` or `pymultinest`. It imports `fit_scipy`, `fit_minuit`, `fit_multinest` from module **tf_pwa.fit**.

Parameters

- **Use** – String. If it's `"scipy"`, it will call `fit_scipy`; if it's `"minuit"`, it will call `fit_minuit`; if it's `"multinest"`, it will call `fit_multinest`.
- **kwargs** – The arguments will be passed to the three functions above.

For `fit_scipy`

Parameters

- **fcn** – FCN object to be minimized.

- **method** – String. Options in `scipy.optimize`. For now, it implements interface to such as "BFGS", "L-BFGS-B", "basinhopping".
- **bounds_dict** – Dictionary of boundary constrain to variables.
- **kwargs** – Other arguments passed on to `scipy.optimize` functions.

Returns
FitResult object, List of NLLs, List of point arrays.

For `fit_minuit`

Parameters

- **fcn** – FCN object to be minimized.
- **bounds_dict** – Dictionary of boundary constrain to variables.
- **hesse** – Boolean. Whether to call `hesse()` after `migrad()`. It's `True` by default.
- **minos** – Boolean. Whether to call `minos()` after `hesse()`. It's `False` by default.

Returns
Minuit object

For `fit_multinest` (WIP)

Parameters
fcn – FCN object to be minimized.

fit_fractions(*amp*, *mcdata*, *inv_he=None*, *params=None*, *batch=25000*, *res=None*, *method='old'*)

This function calculate fit fractions of the resonances as well as their coherent pairs. It imports `cal_fitfractions` and `cal_fitfractions_no_grad` from module **tf_pwa.fitfractions**.

$$FF_i = \frac{\int |A_i|^2 d\Omega}{\int |\sum_i A_i|^2 d\Omega} \approx \frac{\sum |A_i|^2}{\sum |\sum_i A_i|^2}$$

gradients???:

$$FF_{i,j} = \frac{\int 2Re(A_i A_j*) d\Omega}{\int |\sum_i A_i|^2 d\Omega} = \frac{\int |A_i + A_j|^2 d\Omega}{\int |\sum_i A_i|^2 d\Omega} - FF_i - FF_j$$

hessians:

$$\frac{\partial}{\partial \theta_i} \frac{f(\theta_i)}{g(\theta_i)} = \frac{\partial f(\theta_i)}{\partial \theta_i} \frac{1}{g(\theta_i)} - \frac{\partial g(\theta_i)}{\partial \theta_i} \frac{f(\theta_i)}{g^2(\theta_i)}$$

Parameters

- **amp** – Amplitude object.
- **mcdata** – MCdata array.
- **inv_he** – The inverse of Hessian matrix. If it's not given, the errors will not be calculated.

Return frac
Dictionary of fit fractions for each resonance.

Return err_frac
Dictionary of their errors. If `inv_he` is `None`, it will be a dictionary of `None`.

force_pos_def(*h*)

from pricession lost hessian matrix eigen value is small

dot(H, v[:,i] = e[i] v[:,i] dot(H, v)[:,i] = e[i] v[:,i] dot(inv(v), dot(H, v)) = diag(e) H = dot(v, dot(diag(e), inv(v))

`force_pos_def_minuit2`(*inv_he*)

force positive defined of error matrix

from minuit2 https://github.com/root-project/root/blob/master/math/minuit2/sec/MnPosDef.cxx

`gen_data`(*amp*, *Ndata*, *mcfile*, *Nbg=0*, *wbg=0*, *Poisson_fluc=False*, *bgfile=None*, *genfile=None*, *particles=None*)

This function is used to generate toy data according to an amplitude model.

Parameters

- **amp** – AmplitudeModel???
- **particles** – List of final particles
- **Ndata** – Integer. Number of data
- **mcfile** – String. The MC sample file used to generate signal data.
- **Nbg** – Integer. Number of background. By default it's 0.
- **wbg** – Float. Weight of background. By default it's 0.
- **Poisson_fluc** – Boolean. If it's `True`, The number of data will be decided by a Poisson distribution around the given value.
- **bgfile** – String. The background sample file used to generate a certain number of background data.
- **genfile** – String. The file to store the generated toy.

Returns

tensorflow.Tensor. The generated toy data.

`gen_mc`(*mother*, *daughters*, *number*, *outfile=None*)

This function generates phase-space MC data (without considering the effect of detector performance). It imports `PhaseSpaceGenerator` from module **tf_pwa.phasespace**.

Parameters

- **mother** – Float. The invariant mass of the mother particle.
- **daughters** – List of float. The invariant masses of the daughter particles.
- **number** – Integer. The number of MC data generated.
- **outfile** – String. The file to store the generated MC.

Returns

Numpy array. The generated MC data.

`likelihood_profile`(*m*, *var_names*, *bins=20*, *minos=True*)

Calculate the likelihood profile for a variable.

Parameters

- **m** – Minuit object
- **var_names** – Either a string or a list of strings
- **bins** – Integer
- **minos** – Boolean. If it's `False`, the function will call `Minuit.profile()` to derive the 1-d scan of **var_names**; if it's `True`, the function will call `Minuit.mnprofile()` to derive the likelihood profile, which is much more time-consuming.

Returns
Dictionary indexed by **var_names**. It contains the return of either `Minuit.mnprofile()` or `Minuit.profile()`.

num_hess_inv_3point(*fcn*, *params={}*, *_epsilon=0.0005*)

This function calculates the errors of all trainable variables. The errors are given by the square root of the diagonal of the inverse Hessian matrix.

Parameters
model – Model.

Return hesse_error
List of errors.

Return inv_he
The inverse Hessian matrix.

plot_pull(*data*, *name*, *nbins=20*, *norm=False*, *value=None*, *error=None*)

This function is used to plot the pull for a data sample.

Parameters

- **data** – List
- **name** – String. Name of the sample
- **nbins** – Integer. Number of bins in the histogram
- **norm** – Boolean. Whether to normalize the histogram
- **value** – Float. Mean value in normalization
- **error** – Float or list. Sigma value(s) in normalization

Returns
The fitted mu, sigma, as well as their errors

10.1.11 breit_wigner

This module provides functions to describe the lineshapes of the intermediate particles, namely generalized Breit-Wigner function. Users can also define new lineshape using the function wrapper **regist_lineshape**().

BW(*m*, *m0*, *g0*, **args*)

Breit-Wigner function

$$BW(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0}$$

BWR(*m*, *m0*, *g0*, *q*, *q0*, *L*, *d*)

Relativistic Breit-Wigner function (with running width). It's also set as the default lineshape.

$$BW(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

BWR2(*m*, *m0*, *g0*, *q2*, *q02*, *L*, *d*)

Relativistic Breit-Wigner function (with running width). Allow complex Γ.

$$BW(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

BWR_normal(*m*, *m0*, *g0*, *q2*, *q02*, *L*, *d*)

Relativistic Breit-Wigner function (with running width) with a normal factor.

$$BW(m) = \frac{\sqrt{m_0\Gamma(m)}}{m_0^2 - m^2 - im_0\Gamma(m)}$$

Bprime(*L*, *q*, *q0*, *d*)

Blatt-Weisskopf barrier factors. E.g. the first three orders

L	$B'_L(q, q_0, d)$
0	1
1	$\sqrt{\frac{(q_0 d)^2+1}{(qd)^2+1}}$
2	$\sqrt{\frac{(q_0 d)^4+3*(q_0 d)^2+9}{(qd)^4+3*(qd)^2+9}}$

d is 3.0 by default.

Bprime_num(*L*, *q*, *d*)

The numerator (as well as the denominator) inside the square root in the barrier factor

Bprime_polynomial(*l*, *z*)

It stores the Blatt-Weisskopf polynomial up to the fifth order ($L = 5$)

Parameters

- **l** – The order
- **z** – The variable in the polynomial

Returns

The calculated value

Bprime_q2(*L*, *q2*, *q02*, *d*)

Blatt-Weisskopf barrier factors.

GS(*m*, *m0*, *g0*, *q*, *q0*, *L*, *d*, *c_daug2Mass=0.13957039*, *c_daug3Mass=0.1349768*)

Gamma(*m*, *gamma0*, *q*, *q0*, *L*, *m0*, *d*)

Running width in the RBW

$$\Gamma(m) = \Gamma_0 \left(\frac{q}{q_0}\right)^{2L+1} \frac{m_0}{m} B'^2_L(q, q_0, d)$$

Gamma2(*m*, *gamma0*, *q2*, *q02*, *L*, *m0*, *d*)

Running width in the RBW

$$\Gamma(m) = \Gamma_0 \left(\frac{q}{q_0}\right)^{2L+1} \frac{m_0}{m} B'^2_L(q, q_0, d)$$

barrier_factor(*l*, *q*, *q0*, *d=3.0*, *axis=0*)

Barrier factor multiplied with q^L, which is used as a combination in the amplitude expressions. The values are cached for L ranging from 0 to **l**.

barrier_factor2(*l*, *q*, *q0*, *d=3.0*, *axis=-1*)

???

dFun(*s*, *daug2Mass*, *daug3Mass*)

dh_dsFun(*s*, *daug2Mass*, *daug3Mass*)

fsFun(*s*, *m2*, *gam*, *daug2Mass*, *daug3Mass*)

get_bprime_coeff(*l*)

The coefficients of polynomial in Bprime function.

$$|\theta_l(jw)|^2 = \sum_{i=0}^{l} c_i w^{2i}$$

hFun(*s*, *daug2Mass*, *daug3Mass*)

one(**args*)

A uniform function

regist_lineshape(*name=None*)

It will be used as a wrapper to define various Breit-Wigner functions

Parameters

name – String name of the BW function

Returns

A function used in a wrapper

reverse_bessel_polynomials(*n*, *x*)

Reverse Bessel polynomials.

$$\theta_n(x) = \sum_{k=0}^{n} \frac{(n+k)!}{(n-k)!k!} \frac{x^{n-k}}{2^k}$$

to_complex(*i*)

twoBodyCMmom(*m_0*, *m_1*, *m_2*)

relative momentum for 0 -> 1 + 2

10.1.12 cal_angle

This module provides functions which are useful when calculating the angular variables.

The full data structure provided is

```
{
    "particle": {
        A: {"p": ..., "m": ...},
        (C, D): {"p": ..., "m": ...},
        ...
    },

    "decay":{
```

(continues on next page)

(continued from previous page)

```
        [A->(C, D)+B, (C, D)->C+D]:
        {
            A->(C, D)+B: {
                (C, D): {
                    "ang": {
                        "alpha":[...],
                        "beta": [...],
                        "gamma": [...]
                    },
                    "z": [[x1,y1,z1],...],
                    "x": [[x2,y2,z2],...]
                },
                B: {...}
            },

            (C, D)->C+D: {
                C: {
                    ...,
                    "aligned_angle": {
                    "alpha": [...],
                    "beta": [...],
                    "gamma": [...]
                }
            },
                D: {...}
            },
            A->(B, D)+C: {...},
            (B, D)->B+D: {...}
        },
    ...
    }
}
```

Inner nodes are named as tuple of particles.

class CalAngleData

Bases: dict

get_angle(*decay*, *p*)

get hilicity angle of decay which product particle p

get_decay()

get_mass(*name*)

get_momentum(*name*)

get_weight()

mass_hist(*name*, *bins='sqrt'*, ***kwargs*)

savetxt(*file_name*, *order=None*, *cp_trans=False*, *save_charge=False*)

Getp(*M_0*, *M_1*, *M_2*)

Consider a two-body decay $M_0 \to M_1 M_2$. In the rest frame of M_0, the momentum of M_1 and M_2 are definite.

Parameters

- **M_0** – The invariant mass of M_0
- **M_1** – The invariant mass of M_1
- **M_2** – The invariant mass of M_2

Returns
the momentum of M_1 (or M_2)

Getp2(*M_0*, *M_1*, *M_2*)

Consider a two-body decay $M_0 \to M_1 M_2$. In the rest frame of M_0, the momentum of M_1 and M_2 are definite.

Parameters

- **M_0** – The invariant mass of M_0
- **M_1** – The invariant mass of M_1
- **M_2** – The invariant mass of M_2

Returns
the momentum of M_1 (or M_2)

add_mass(*data: dict*, *_decay_chain:* DecayChain | *None = None*) → dict

add particles mass array for data momentum.
{top:{p:momentum},inner:{p:..},outs:{p:..}} => {top:{p:momentum,m:mass},...}

add_relative_momentum(*data: dict*)

add add rest frame momentum scalar from data momentum.

from `{"particle": {A: {"m": ...}, ...}, "decay": {A->B+C: {...}, ...}`

to `{"particle": {A: {"m": ...}, ...},"decay": {[A->B+C,...]: {A->B+C:{...,"|q|": ...},...},...}`

add_weight(*data: dict*, *weight: float = 1.0*) → dict

add inner data weights for data.
{...} => {..., "weight": weights}

aligned_angle_ref_rule1(*decay_group*, *decay_chain_struct*, *decay_data*, *data*)

aligned_angle_ref_rule2(*decay_group*, *decay_chain_struct*, *decay_data*, *data*)

cal_angle(*data*, *decay_group:* DecayGroup, *using_topology=True*, *random_z=True*, *r_boost=True*, *final_rest=True*, *align_ref=None*, *only_left_angle=False*)

Calculate helicity angle for particle momentum, add aligned angle.

Params data
dict as {particle: {"p":...}}

Returns
Dictionary of data

cal_angle_from_momentum(*p*, *decs:* DecayGroup, *using_topology=True*, *center_mass=False*, *r_boost=True*, *random_z=False*, *batch=65000*, *align_ref=None*, *only_left_angle=False*) → *CalAngleData*

Transform 4-momentum data in files for the amplitude model automatically via DecayGroup.

Parameters

- **p** – 4-momentum data
- **decs** – DecayGroup

Returns
Dictionary of data

cal_angle_from_momentum_base(*p*, *decs:* DecayGroup, *using_topology=True*, *center_mass=False*, *r_boost=True*, *random_z=False*, *batch=65000*, *align_ref=None*, *only_left_angle=False*) → *CalAngleData*

Transform 4-momentum data in files for the amplitude model automatically via DecayGroup.

Parameters

- **p** – 4-momentum data
- **decs** – DecayGroup

Returns
Dictionary of data

cal_angle_from_momentum_id_swap(*p*, *decs:* DecayGroup, *using_topology=True*, *center_mass=False*, *r_boost=True*, *random_z=False*, *batch=65000*, *align_ref=None*, *only_left_angle=False*) → *CalAngleData*

cal_angle_from_momentum_single(*p*, *decs:* DecayGroup, *using_topology=True*, *center_mass=False*, *r_boost=True*, *random_z=True*, *align_ref=None*, *only_left_angle=False*) → *CalAngleData*

Transform 4-momentum data in files for the amplitude model automatically via DecayGroup.

Parameters

- **p** – 4-momentum data
- **decs** – DecayGroup

Returns
Dictionary of data

cal_angle_from_particle(*data*, *decay_group:* DecayGroup, *using_topology=True*, *random_z=True*, *r_boost=True*, *final_rest=True*, *align_ref=None*, *only_left_angle=False*)

Calculate helicity angle for particle momentum, add aligned angle.

Params data
dict as {particle: {"p":...}}

Returns
Dictionary of data

cal_chain_boost(*data*, *decay_chain:* DecayChain) → dict

calculate chain boost for a decay chain

cal_helicity_angle(*data: dict*, *decay_chain:* DecayChain, *base_z=array([0., 0., 1.])*, *base_x=array([1., 0., 0.])*) → dict

Calculate helicity angle for A -> B + C: θ_B^A, ϕ_B^A from momentum.

from `{A:{p:momentum},B:{p:...},C:{p:...}}`

to `{A->B+C:{B:{"ang":{"alpha":...,"beta":...,"gamma":...},"x":...,"z"},...}}`

cal_single_boost(*data*, *decay_chain:* DecayChain) → dict

cp_swap_p(*p4*, *finals*, *id_particles*, *cp_particles*)

get_chain_data(*data*, *decay_chain=None*)

get all independent data for a decay chain

get_key_content(*dic*, *key_path*)

get key content. E.g. get_key_content(data, '/particle/(B, C)/m')

```
>>> data = {"particle": {"(B, C)": {"p": 0.1, "m": 1.0},"B":1.0}}
>>> get_key_content(data, '/particle/(B, C)/m')
1.0
```

get_keys(*dic*, *key_path=''*)

get_keys of nested dictionary

```
>>> a = {"a": 1, "b": {"c": 2}}
>>> get_keys(a)
['/a', '/b/c']
```

get_relative_momentum(*data: dict*, *decay_chain:* DecayChain)

add add rest frame momentum scalar from data momentum.

from `{"particle": {A: {"m": ...}, ...}, "decay": {A->B+C: {...}, ...}`

to `{"particle": {A: {"m": ...}, ...},"decay": {A->B+C:{...,"|q|": ...},...}`

identical_particles_swap(*id_particles*)

identical_particles_swap_p(*p4*, *id_particles*)

infer_momentum(*data*, *decay_chain:* DecayChain) → dict

infer momentum of all particles in the decay chain from outer particles momentum.
{outs:{p:momentum}} => {top:{p:momentum},inner:{p:..},outs:{p:..}}

parity_trans(*p*, *charges*)

prepare_data_from_dat_file(*fnames*)

[deprecated] angle for amplitude.py

prepare_data_from_dat_file4(*fnames*)

[deprecated] angle for amplitude4.py

prepare_data_from_decay(*fnames*, *decs*, *particles=None*, *dtype=None*, *charges=None*, ***kwargs*)

Transform 4-momentum data in files for the amplitude model automatically via DecayGroup.

Parameters

- **fnames** – File name(s).
- **decs** – DecayGroup
- **particles** – List of Particle. The final particles.
- **dtype** – Data type.

Returns
Dictionary

struct_momentum(*p*, *center_mass=True*) → dict

restructure momentum as dict
{outs:momentum} => {outs:{p:momentum}}

10.1.13 cg

This module provides the function **cg_coef()** to calculate the Clebsch-Gordan coefficients $\langle j_1 m_1 j_2 m_2 | JM \rangle$.

This function has interface to SymPy functions if it's installed correctly. Otherwise, it will depend on the input file **tf_pwa/cg_table.json**.

cg_coef(*jb*, *jc*, *mb*, *mc*, *ja*, *ma*)

It returns the CG coefficient $\langle j_b m_b j_c m_c | j_a m_a \rangle$, as in a decay from particle a to b and c. It will either call **sympy.physics.quantum.cg()** or **get_cg_coef()**.

get_cg_coef(*j1*, *j2*, *m1*, *m2*, *j*, *m*)

If SymPy is not installed, [deprecation] **cg_coef()** will call this function and derive the CG coefficient by searching into **tf_pwa/cg_table.json**.

In fact, **tf_pwa/cg_table.json** only stores some of the coefficients, the others will be obtained by this function using some symmetry properties of the CG table.

Note: **tf_pwa/cg_table.json** only contains the cases where $j_1, j_2 \leqslant 4$, but this should be enough for most cases in PWA.

10.1.14 config

class ConfigManager

Bases: dict

create_config(*default=None*)

get_config(*name*, *default=<tf_pwa.config._Default object>*)

get a configuration.

regist_config(*name*, *var=None*)

regist a configuration.

set_config(*name*, *var*)

set a configuration.

temp_config(*name*, *var*)

using_amplitude(*var*)

10.1.15 cov_ten_ir

FL(*s1*, *s2*, *s3*, *S*, *L*)

FS(*s1*, *s2*, *s3*, *S*)

F_Sigma(*s1*, *s2*, *s3*, *S*, *L*)

MassiveTransAngle(*p1*, *p2*)

MasslessTransAngle(*p1*, *p2*)

NumSL(**args*, ***kwargs*)

NumSL0(*s1*, *s2*, *s3*)

NumSL1(*s1*, *s2*, *s3*)

NumSL2(*s1*, *s2*, *s3*)

NumSL3(*s1*, *s2*, *s3*)

PWFA(*p1*, *m1_zero*, *s1*, *p2*, *m2_zero*, *s2*, *s*, *S*, *L*)

SCombLS(*s1*, *s2*, *s3*, *i*)
LS: i=0 ; i=1 2; i=2 23; i=3 , {S,L}

WFunc1(*s1*, *s2*, *s3*, *S*, *L*)

WFunc2(*s1*, *s2*, *s3*, *S*, *L*)

amp0ls(*s1*, *lens1*, *s2*, *lens2*, *s*, *lens*, *theta*, *phi*, *S*, *L*)

cg_in_amp0ls(*s1*, *lens1*, *s2*, *lens2*, *s*, *lens*, *S*, *L*)

delta_idx_in_amp0ls(*s1*, *lens1*, *s2*, *lens2*, *s*, *lens*, *l*)

force_int(*f*)

ls_selector_weight(*decay*, *all_ls*)

normal_factor(*L*)

sphericalHarmonic(*l*, *theta*, *phi*)

wigerDx(*j*, *alpha*, *beta*, *gamma*)

xyzToangle(*pxyz*)

10.1.16 data

module for describing data process.

All data structure is describing as nested combination of `dict` or `list` for `ndarray`. Data process is a translation from data structure to another data structure or typical `ndarray`. Data cache can be implemented based on the dynamic features of `list` and `dict`.

The full data structure is

```
{
"particle":{
    "A":{"p":...,"m":...}
    ...
},
"decay":[
    {
    "A->R1+B": {
        "R1": {
        "ang":  {
            "alpha":[...],
            "beta": [...],
            "gamma": [...]
        },
        "z": [[x1,y1,z1],...],
        "x": [[x2,y2,z2],...]
        },
        "B" : {...}
    },
    "R->C+D": {
        "C": {
        ...,
        "aligned_angle":{
            "alpha":[...],
            "beta":[...],
            "gamma":[...]
        }
        },
        "D": {...}
    },
    },
    {
    "A->R2+C": {...},
    "R2->B+D": {...}
    },
    ...
],
"weight": [...]
}
```

class EvalLazy(*f*)

Bases: object

class HeavyCall(*f*)

Bases: object

class LazyCall(*f*, *x*, **args*, ***kwargs*)

Bases: object

as_dataset(*batch=65000*)

batch(*batch*, *axis=0*)

copy()

create_new(*f*, *x*, **args*, ***kwargs*)

eval()

get(*index*, *value=None*)

get_weight()

merge(**other*, *axis=0*)

set_cached_file(*cached_file*, *name*)

class LazyFile(*x*, **args*, ***kwargs*)

Bases: *LazyCall*

as_dataset(*batch=65000*)

create_new(*f*, *x*, **args*, ***kwargs*)

eval()

batch_call(*function*, *data*, *batch=10000*)

batch_call_numpy(*function*, *data*, *batch=10000*)

batch_sum(*function*, *data*, *batch=10000*)

check_nan(*data*, *no_raise=False*)

check if there is nan in data

data_cut(*data*, *expr*, *var_map=None*)

cut data with boolean expression

Parameters

- **data** – data need to cut
- **expr** – cut expression
- **var_map** – variable map between parameters in expr and data, [option]

Returns

data after being cut,

data_generator(*data*, *fun=<function _data_split>*, *args=()*, *kwargs=None*, *MAX_ITER=1000*)

Data generator: call `fun` to each `data` as a generator. The extra arguments will be passed to `fun`.

data_index(*data*, *key*, *no_raise=False*)

Indexing data for key or a list of keys.

data_map(*data*, *fun*, *args=()*, *kwargs=None*)

Apply fun for each data. It returns the same structure.

data_mask(*data*, *select*)

This function using boolean mask to select data.

Parameters

- **data** – data to select
- **select** – 1-d boolean array for selection

Returns
data after selection

data_merge(**data*, *axis=0*)
This function merges data with the same structure.

data_replace(*data*, *key*, *value*)

data_shape(*data*, *axis=0*, *all_list=False*)
Get data size.

Parameters

- **data** – Data array
- **axis** – Integer. ???
- **all_list** – Boolean. ???

Returns

data_split(*data*, *batch_size*, *axis=0*)
Split `data` for `batch_size` each in `axis`.

Parameters

- **data** – structured data
- **batch_size** – Integer, data size for each split data
- **axis** – Integer, axis for split, [option]

Returns
a generator for split data

```
>>> data = {"a": [np.array([1.0, 2.0]), np.array([3.0, 4.0])], "b": {"c": np.
↪array([5.0, 6.0])}, "d": [], "e": {}}
>>> for i, data_i in enumerate(data_split(data, 1)):
...     print(i, data_to_numpy(data_i))
...
0 {'a': [array([1.]), array([3.])], 'b': {'c': array([5.])}, 'd': [], 'e': {}}
1 {'a': [array([2.]), array([4.])], 'b': {'c': array([6.])}, 'd': [], 'e': {}}
```

data_strip(*data*, *keys*)

data_struct(*data*)
get the structure of data, keys and shape

data_to_numpy(*dat*)
Convert Tensor data to `numpy.ndarray`.

data_to_tensor(*dat*)
convert data to `tensorflow.Tensor`.

flatten_dict_data(*data*, *fun=<built-in method format of str object>*)
Flatten data as dict with structure named as `fun`.

load_dat_file(*fnames*, *particles*, *dtype=None*, *split=None*, *order=None*, *_force_list=False*, *mmap_mode=None*)
Load `*.dat` file(s) of 4-momenta of the final particles.

Parameters

- **fnames** – String or list of strings. File names.
- **particles** – List of Particle. Final particles.
- **dtype** – Data type.
- **split** – sizes of each splited dat files
- **order** – transpose order

Returns
Dictionary of data indexed by Particle.

load_data(*file_name*, ***kwargs*)
Load data file from save_data. The arguments will be passed to `numpy.load()`.

save_data(*file_name*, *obj*, ***kwargs*)
Save structured data to files. The arguments will be passed to `numpy.save()`.

save_dataz(*file_name*, *obj*, ***kwargs*)
Save compressed structured data to files. The arguments will be passed to `numpy.save()`.

set_random_seed(*seed*)
set random seed for random, numpy and tensorflow

split_generator(*data*, *batch_size*, *axis=0*)
Split `data` for `batch_size` each in `axis`.

Parameters

- **data** – structured data
- **batch_size** – Integer, data size for each split data
- **axis** – Integer, axis for split, [option]

Returns
a generator for split data

```
>>> data = {"a": [np.array([1.0, 2.0]), np.array([3.0, 4.0])], "b": {"c": np.
↪array([5.0, 6.0])}, "d": [], "e": {}}
>>> for i, data_i in enumerate(data_split(data, 1)):
...     print(i, data_to_numpy(data_i))
...
0 {'a': [array([1.]), array([3.])], 'b': {'c': array([5.])}, 'd': [], 'e': {}}
1 {'a': [array([2.]), array([4.])], 'b': {'c': array([6.])}, 'd': [], 'e': {}}
```

10.1.17 dec_parser

module for parsing decay card `*.dec` file

do_command(*cmd*, *params*, *lines*)
do command in commands

get_decay(*words*, *lines*)
parser decay command

get_particles(*words*, *_lines*)
parser particles command

get_words(*lines*)

get all words in a lines

load_dec(*s*)

load *.dec string

load_dec_file(*f*)

load *.dec file

process_decay_card(*lines*)

process all the files as a generator

regist_command(*name=None*)

regist command function for command call

remove_comment(*words*)

remove comment string which starts with '#'.

sigle_decay(*s*)

do each decay line

split_lines(*s*)

split each lines

10.1.18 dfun

This module provides functions to calculate the Wigner D-function.

$D^j_{m_1,m_2}(\alpha,\beta,\gamma) = e^{-im_1\alpha} d^j_{m_1,m_2}(\beta) e^{-im_2\gamma}$, where the expression of the Wigner d-function is

$$d^j_{m_1,m_2}(\beta) = \sum_{l=0}^{2j} w_l^{(j,m_1,m_2)} \sin^l(\frac{\beta}{2}) \cos^{2j-l}(\frac{\beta}{2}),$$

where the weight $w_l^{(j,m_1,m_2)}$ in each term satisfies

$$w_l^{(j,m_1,m_2)} = (-1)^{m_1-m_2+k} \frac{\sqrt{(j+m_1)!(j-m_1)!(j+m_2)!(j-m_2)!}}{(j-m_1-k)!(j+m_2-k)!(m_1-m_2+k)!k!}$$

when $k = \frac{l+m_2-m_1}{2} \in [\max(0, m_2-m_1), \min(j-m_1, j+m_2)]$, and otherwise $w_l^{(j,m_1,m_2)} = 0$.

D_matrix_conj(*alpha*, *beta*, *gamma*, *j*)

The conjugated D-matrix element with indices (m_1, m_2) is

$$D^j_{m_1,m_2}(\alpha,\beta,\gamma)^\star = e^{im_1\alpha} d^j_{m_1,m_2}(\beta) e^{im_2\gamma}$$

Parameters

- **alpha** – Array
- **beta** – Array
- **gamma** – Array
- **j** – Integer $2j$ in the formula

Returns

Array of the conjugated D-matrices. Same shape as **alpha**, **beta**, and **gamma**

Dfun_delta(*d*, *ja*, *la*, *lb*, *lc=(0,)*)

The decay from particle *a* to *b* and *c* requires $|l_b - l_c| \leqslant j$

$D_{ma,mb-mc} = \delta[(m1, m2) -> (ma, mb, mc))]D_{m1,m2}$

Dfun_delta_v2(*d*, *ja*, *la*, *lb*, *lc=(0,)*)

The decay from particle *a* to *b* and *c* requires $|l_b - l_c| \leqslant j$

$D_{ma,mb-mc} = \delta[(m1, m2) -> (ma, mb, mc))]D_{m1,m2}$

delta_D_index(*j*, *la*, *lb*, *lc*)

delta_D_trans(*j*, *la*, *lb*, *lc*)

The decay from particle *a* to *b* and *c* requires $|l_b - l_c| \leqslant j$

(ja,ja) -> (ja,jb,jc)???

exp_i(*theta*, *mi*)

$e^{im\theta}$

Parameters

- **theta** – Array θ in the formula
- **mi** – Integer or half-integer m in the formula

Returns

Array of tf.complex. Same length as **theta**

get_D_matrix_for_angle(*angle*, *j*, *cached=True*)

Interface to *D_matrix_conj()*

Parameters

- **angle** – Dict of angle data {"alpha","beta","gamma"}
- **j** – Integer $2j$ in the formula
- **cached** – Haven't been used???

Returns

Array of the conjugated D-matrices. Same length as the angle data

get_D_matrix_lambda(*angle*, *ja*, *la*, *lb*, *lc=None*)

Get the D-matrix element

Parameters

- **angle** – Dict of angle data {"alpha","beta","gamma"}
- **ja** –
- **la** –
- **lb** –
- **lc** –

Returns

small_d_matrix(*theta*, *j*)

The matrix element of $d^j(\theta)$ is $d^j_{m_1,m_2}(\theta) = \sum_{l=0}^{2j} w_l^{(j,m_1,m_2)} \sin^l(\frac{\theta}{2}) \cos^{2j-l}(\frac{\theta}{2})$

Parameters

- **theta** – Array θ in the formula

- **j** – Integer $2j$ in the formula???

Returns
The d-matrices array. Same length as theta

small_d_weight(*j*)

For a certain j, the weight coefficient with index (m_1, m_2, l) is $w_l^{(j,m_1,m_2)} = (-1)^{m_1-m_2+k} \frac{\sqrt{(j+m_1)!(j-m_1)!(j+m_2)!(j-m_2)!}}{(j-m_1-k)!(j+m_2-k)!(m_1-m_2+k)!k!}$, and l is an integer ranging from 0 to $2j$.

Parameters
j – Integer $2j$ in the formula???

Returns
Of the shape (**j** +1, **j** +1, **j** +1). The indices correspond to (l, m_1, m_2)

10.1.19 einsum

class Einsum(*expr*, *shapes*)

Bases: object

einsum(*expr*, **args*, ***kwargs*)

ordered_indices(*expr*, *shapes*)

find a better order to reduce transpose.

remove_size1(*expr*, **args*, *extra=None*)

remove order independent indices (size 1)

replace_ellipsis(*expr*, *shapes*)

replace_none_in_shape(*x*, *num=-1*)

symbol_generate(*base_map*)

tensor_einsum_reduce_sum(*expr*, **args*, *order*)

"abe,bcf->acef" =reshape=> "ab1e1,1bc1f->acef" =product=> "abcef->acef" =reduce_sum=> "acef"

10.1.20 err_num

class NumberError(*value*, *error=1.0*)

Bases: object

basic class for propagation of error

apply(*fun*, *grad=None*, *dx=1e-05*)

property error

exp()

log()

property value

cal_err(*fun*, **args*, *grad=None*, *dx=1e-05*, *kwargs=None*)

10.1.21 expermental

10.1.22 fit

class FitResult(*params*, *fcn*, *min_nll*, *ndf=0*, *success=True*, *hess_inv=None*)

Bases: object

save_as(*file_name*, *save_hess=False*)

set_error(*error*)

exception LargeNumberError

Bases: ValueError

except_result(*fcn*, *ndf*)

fit_minuit(*fcn*, *bounds_dict={}*, *hesse=True*, *minos=False*, ***kwargs*)

fit_minuit_v1(*fcn*, *bounds_dict={}*, *hesse=True*, *minos=False*, ***kwargs*)

Parameters

- **fcn** –
- **bounds_dict** –
- **hesse** –
- **minos** –

Returns

fit_minuit_v2(*fcn*, *bounds_dict={}*, *hesse=True*, *minos=False*, ***kwargs*)

Parameters

- **fcn** –
- **bounds_dict** –
- **hesse** –
- **minos** –

Returns

fit_multinest(*fcn*)

fit_newton_cg(*fcn*, *method='Newton-CG'*, *use_hessp=False*, *check_hess=False*, *gtol=0.0001*)

fit_root_fitter(*fcn*)

fit_scipy(*fcn*, *method='BFGS'*, *bounds_dict={}*, *check_grad=False*, *improve=False*, *maxiter=None*, *jac=True*, *callback=None*, *standard_complex=True*, *grad_scale=1.0*, *gtol=0.001*)

Parameters

- **fcn** –
- **method** –
- **bounds_dict** –
- **kwargs** –

Returns

10.1.23 fit_improve

class Cached_FG(*f_g*, *grad_scale=1.0*)

Bases: object

fun(*x*)

grad(*x*)

exception LineSearchWarning

Bases: RuntimeWarning

class Seq(*size=5*)

Bases: object

add(*x*)

arg_max()

get_max()

fmin_bfgs_f(*f_g*, *x0*, *B0=None*, *M=2*, *gtol=1e-05*, *Delta=10.0*, *maxiter=None*, *callback=None*, *norm_ord=inf*, ***_kwargs*)

test BFGS with nonmonote line search

line_search_nonmonote(*f*, *myfprime*, *xk*, *pk*, *gfk=None*, *old_fval=None*, *fk=None*, *old_old_fval=None*, *args=()*, *c1=0.5*, *maxiter=10*)

line_search_wolfe2(*f*, *myfprime*, *xk*, *pk*, *gfk=None*, *fk=None*, *old_fval=None*, *old_old_fval=None*, *args=()*, *c1=0.0001*, *c2=0.9*, *amax=None*, *extra_condition=None*, *maxiter=10*)

Find alpha that satisfies strong Wolfe conditions.

Parameters

- **f** (*callable f(x,*args)*) – Objective function.
- **myfprime** (*callable f'(x,*args)*) – Objective function gradient.
- **xk** (*ndarray*) – Starting point.
- **pk** (*ndarray*) – Search direction.
- **gfk** (*ndarray, optional*) – Gradient value for x=xk (xk being the current parameter estimate). Will be recomputed if omitted.
- **old_fval** (*float, optional*) – Function value for x=xk. Will be recomputed if omitted.
- **old_old_fval** (*float, optional*) – Function value for the point preceding x=xk
- **args** (*tuple, optional*) – Additional arguments passed to objective function.
- **c1** (*float, optional*) – Parameter for Armijo condition rule.
- **c2** (*float, optional*) – Parameter for curvature condition rule.
- **amax** (*float, optional*) – Maximum step size
- **extra_condition** (*callable, optional*) – A callable of the form `extra_condition(alpha, x, f, g)` returning a boolean. Arguments are the proposed step `alpha` and the corresponding `x`, `f` and `g` values. The line search accepts the value of `alpha` only if this callable returns `True`. If the callable returns `False` for the step length, the algorithm will continue with new iterates. The callable is only called for iterates satisfying the strong Wolfe conditions.

- **maxiter** (*int, optional*) – Maximum number of iterations to perform

Returns

- **alpha** (*float or None*) – Alpha for which `x_new = x0 + alpha * pk`, or None if the line search algorithm did not converge.
- **fc** (*int*) – Number of function evaluations made.
- **gc** (*int*) – Number of gradient evaluations made.
- **new_fval** (*float or None*) – New function value `f(x_new)=f(x0+alpha*pk)`, or None if the line search algorithm did not converge.
- **old_fval** (*float*) – Old function value `f(x0)`.
- **new_slope** (*float or None*) – The local slope along the search direction at the new value `<myfprime(x_new), pk>`, or None if the line search algorithm did not converge.

Notes

Uses the line search algorithm to enforce strong Wolfe conditions. See Wright and Nocedal, 'Numerical Optimization', 1999, pg. 59-60.

For the zoom phase it uses an algorithm by [...].

minimize(*fun*, *x0*, *args=()*, *method=None*, *jac=None*, *hess=None*, *hessp=None*, *bounds=None*, *constraints=()*, *tol=None*, *callback=None*, *options=None*)

scalar_search_wolfe2(*phi*, *derphi*, *phi0=None*, *old_phi0=None*, *derphi0=None*, *c1=0.0001*, *c2=0.9*, *amax=None*, *extra_condition=None*, *maxiter=10*)

Find alpha that satisfies strong Wolfe conditions.

alpha > 0 is assumed to be a descent direction.

Parameters

- **phi** (*callable phi(alpha)*) – Objective scalar function.
- **derphi** (*callable phi'(alpha)*) – Objective function derivative. Returns a scalar.
- **phi0** (*float, optional*) – Value of phi at 0
- **old_phi0** (*float, optional*) – Value of phi at previous point
- **derphi0** (*float, optional*) – Value of derphi at 0
- **c1** (*float, optional*) – Parameter for Armijo condition rule.
- **c2** (*float, optional*) – Parameter for curvature condition rule.
- **amax** (*float, optional*) – Maximum step size
- **extra_condition** (*callable, optional*) – A callable of the form `extra_condition(alpha, phi_value)` returning a boolean. The line search accepts the value of `alpha` only if this callable returns `True`. If the callable returns `False` for the step length, the algorithm will continue with new iterates. The callable is only called for iterates satisfying the strong Wolfe conditions.
- **maxiter** (*int, optional*) – Maximum number of iterations to perform

Returns

- **alpha_star** (*float or None*) – Best alpha, or None if the line search algorithm did not converge.

- **phi_star** (*float*) – phi at alpha_star
- **phi0** (*float*) – phi at 0
- **derphi_star** (*float or None*) – derphi at alpha_star, or None if the line search algorithm did not converge.

Notes

Uses the line search algorithm to enforce strong Wolfe conditions. See Wright and Nocedal, 'Numerical Optimization', 1999, pg. 59-60.

For the zoom phase it uses an algorithm by [...].

10.1.24 fitfractions

class FitFractions(*amp*, *res*)

Bases: object

append_int(*mcdata*, **args*, *weight=None*, *no_grad=False*, ***kwargs*)

get_frac(*error_matrix=None*, *sum_diag=True*)

get_frac_diag_sum(*error_matrix=None*)

get_frac_grad(*sum_diag=True*)

init_res_table()

integral(*mcdata*, **args*, *batch=None*, *no_grad=False*, ***kwargs*)

cal_fitfractions(*amp*, *mcdata*, *res=None*, *batch=None*, *args=()*, *kwargs=None*)

defination:

$$FF_i = \frac{\int |A_i|^2 d\Omega}{\int |\sum_i A_i|^2 d\Omega} \approx \frac{\sum |A_i|^2}{\sum |\sum_i A_i|^2}$$

interference fitfraction:

$$FF_{i,j} = \frac{\int 2Re(A_i A_j*) d\Omega}{\int |\sum_i A_i|^2 d\Omega} = \frac{\int |A_i + A_j|^2 d\Omega}{\int |\sum_i A_i|^2 d\Omega} - FF_i - FF_j$$

gradients (for error transfer):

$$\frac{\partial}{\partial \theta_i} \frac{f(\theta_i)}{g(\theta_i)} = \frac{\partial f(\theta_i)}{\partial \theta_i} \frac{1}{g(\theta_i)} - \frac{\partial g(\theta_i)}{\partial \theta_i} \frac{f(\theta_i)}{g^2(\theta_i)}$$

cal_fitfractions_no_grad(*amp*, *mcdata*, *res=None*, *batch=None*, *args=()*, *kwargs=None*)

calculate fit fractions without gradients.

eval_integral(*f*, *data*, *var*, *weight=None*, *args=()*, *no_grad=False*, *kwargs=None*)

nll_grad(*f*, *var*, *args=()*, *kwargs=None*, *options=None*)

sum_gradient(*amp*, *data*, *var*, *weight=1.0*, *func=<function <lambda>>*, *grad=True*, *args=()*, *kwargs=None*)

sum_no_gradient(*amp*, *data*, *var*, *weight=1.0*, *func=<function <lambda>>*, ***, *grad=False*, *args=()*, *kwargs=None*)

10.1.25 formula

BWR_LS_dom(*m*, *m0*, *g0*, *thetas*, *ls*, *m1*, *m2*, *d=3.0*, *fix_bug1=False*)

BWR_coupling_dom(*m*, *m0*, *g0*, *l*, *m1*, *m2*, *d=3.0*)

BWR_dom(*m*, *m0*, *g0*, *l*, *m1*, *m2*, *d=3.0*)

BW_dom(*m*, *m0*, *g0*)

Bprime_polynomial(*l*, *z*)

create_complex_root_sympy_tfop(*f*, *var*, *x*, *x0*, *epsilon=1e-12*, *prec=50*)

get_relative_p(*ma*, *mb*, *mc*)

get_relative_p2(*ma*, *mb*, *mc*)

10.1.26 function

nll_funciton(*f*, *data*, *phsp*)

nagtive log likelihood for minimize

10.1.27 gpu_info

get_gpu_free_memory(*i=0*)

get_gpu_info(*s*)

get_gpu_total_memory(*i=0*)

get_gpu_used_memory(*i=0*)

10.1.28 histogram

class Hist1D(*binning*, *count*, *error=None*)

Bases: `object`

property bin_center

property bin_width

chi2()

draw(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, ***kwargs*)

draw_bar(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, ***kwargs*)

draw_error(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *fmt='none'*, ***kwargs*)

draw_hist(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, ***kwargs*)

draw_kde(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *kind='gauss'*, *bin_scale=1.0*, ***kwargs*)

draw_line(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *num=1000*, *kind='UnivariateSpline'*, ***kwargs*)

draw_pull(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, ***kwargs*)

get_bin_weight()

get_count()

static histogram(*m*, **args*, *weights=None*, *mask_error=inf*, ***kwargs*)

ndf()

scale_to(*other*)

class WeightedData(*m*, **args*, *weights=None*, ***kwargs*)

Bases: *Hist1D*

draw_kde(*ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, *kind='gauss'*, *bin_scale=1.0*, ***kwargs*)

scale_to(*other*)

cauchy(*x*)

epanechnikov(*x*)

gauss(*x*)

interp_hist(*binning*, *y*, *num=1000*, *kind='UnivariateSpline'*)

interpolate data from hostgram into a line

plot_hist(*binning*, *count*, *ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*, ***kwargs*)

uniform(*x*)

weighted_kde(*m*, *w*, *bw*, *kind='gauss'*)

10.1.29 main

regist_subcommand(*name=None*, *arg_fun=None*, *args=None*)

10.1.30 params_trans

class ParamsTrans(*vm*, *err_matrix*)

Bases: object

get_error(*vals*, *keep=False*)

get_error_matrix(*vals*, *keep=False*)

get_grad(*val*, *keep=False*)

mask_params(*params*)

trans()

10.1.31 particle

This module implements classes to describe particles and decays.

class BaseDecay(*core*, *outs*, *name=None*, *disable=False*, *p_break=False*, *c_break=True*, *curve_style=None*, ***kwargs*)

Bases: object

Base Decay object

Parameters

- **core** – Particle. The mother particle
- **outs** – List of Particle. The daughter particles
- **name** – String. Name of the decay
- **disable** – Boolean. If it's True???

as_config()

get_id()

property name

class BaseParticle(*name*, *J=0*, *P=-1*, *C=None*, *spins=None*, *mass=None*, *width=None*, *id_=None*, *disable=False*, ***kwargs*)

Bases: object

Base Particle object. Name is "name[:id]".

Parameters

- **name** – String. Name of the particle
- **J** – Integer or half-integer. The total spin
- **P** – 1 or -1. The parity

- **spins** – List. The spin quantum numbers. If it's not provided, `spins` will be `tuple(range(-J, J + 1))`.
- **mass** – Real variable
- **width** – Real variable

add_creator(*d*)

Add a decay reaction where the particle is created.

Parameters
d – BaseDecay object

add_decay(*d*)

Parameters
d – BaseDecay object

as_config()

chain_decay()

return all decay chain self decay to

get_resonances()

return all resonances self decay to

property name

remove_decay(*d*)

Parameters
d – BaseDecay object

set_name(*name*, *id_=None*)

class Decay(*core*, *outs*, *name=None*, *disable=False*, *p_break=False*, *c_break=True*, *curve_style=None*, ***kwargs*)

Bases: *BaseDecay*

General Decay object

barrier_factor(*q*, *q0*)

The cached barrier factors with $d = 3.0$ for all l. For barrier factor, refer to **tf_pwa.breit_wigner.Bprime(L, q, q0, d)**

Parameters

- **q** – Data array
- **q0** – Real number

Returns
1-d array for every data point

generate_params(*name=None*, *_ls=True*)

Generate the name of the variable for every (l,s) pair. In PWA, the variable is usually expressed as g_{ls}.

Parameters

- **name** – String. It is the name of the decay by default
- **_ls** – ???

Returns
List of strings

`get_cg_matrix()`

The matrix indexed by $[(l,s),(\lambda_b,\lambda_c)]$. The matrix element is

$$\sqrt{\frac{2l+1}{2j_a+1}}\langle j_b, j_c, \lambda_b, -\lambda_c | s, \lambda_b - \lambda_c\rangle \langle l, s, 0, \lambda_b - \lambda_c | j_a, \lambda_b - \lambda_c\rangle$$

This is actually the pre-factor of $g_l s$ in the amplitude formula.

Returns
2-d array of real numbers

`get_l_list()`

List of l in `self.get_ls_list()`

`get_ls_list()`

It has interface to `tf_pwa.particle.GetA2BC_LS_list(ja, jb, jc, pa, pb, pc)` :return: List of (l,s) pairs

`get_min_l()`

The minimal l in the LS coupling

`class DecayChain(`*chain*`)`

Bases: `object`

A decay chain. E.g. $A \to BC, B \to DE$

Parameters
chain – ???

`depth_first(`*node_first=True*`)`

depth first travel for decay

`static from_particles(`*top*, *finals*`)`

Build possible decay chain Topology. E.g. a -> [b,c,d] => [[a->rb,r->cd],[a->rc,r->bd],[a->rd,r->bc]]

Parameters

- **top** – Particle
- **finals** – List of Particle

Returns
DecayChain

`static from_sorted_table(`*decay_dict*`)`

Create decay chain from a topology independent structure. E.g. {a:[b,c,d],r:[c,d],b:[b],c:[c],d:[d]} => [a->rb,r->cd]

Parameters
decay_dict – Dictionary

Returns
DecayChain

`get_all_particles()`

get all particles in the decay chains

`get_id()`

return identity of the decay

`get_particle_decay(particle)`

get particle decay in the chain

`sorted_table()`

A topology independent structure. E.g. [a->rb,r->cd] => {a:[b,c,d],r:[c,d],b:[b],c:[c],d:[d]}

Returns
Dictionary indexed by Particle

`sorted_table_layers()`

Get the layer of decay chain as sorted table. Or the list of particle with the same number of final particles. So, the first item is always None. E.g. [a->rb,r->cd] => [None, [(b, [b]), (c, [c]), (d, [d])], [(r, [c, d])], [(a, [b, c, d])]]

Returns
List of dictionary

`standard_topology()`

standard topology structure of the decay chain, all inner particle will be replace as a tuple of out particles. for example [A->R+C, R->B+D], is [A->(B, D)+C, (B, D)->B+D]

`topology_id(identical=True)`

topology identy

Parameters
`identical` – allow identical particle in finals

Returns

`topology_map(other=None)`

Mapping relations of the same topology decay E.g. [A->R+B,R->C+D],[A->Z+B,Z->C+D] => {A:A,B:B,C:C,D:D,R:Z,A->R+B:A->Z+B,R->C+D:Z->C+D}

`topology_same(other, identical=True)`

whether self and other is the same topology

Parameters

- `other` – other decay chains
- `identical` – using identical particles

Returns

`class DecayGroup(chains)`

Bases: `object`

A group of two-body decays.

Parameters
`chains` – List of DecayChain

`as_config()`

`get_chain_from_particle(names)`

get the first decay chain has all particles in names

get_chains_map(*chains=None*)

Parameters
chains –

Returns

get_decay_chain(*id_*)

get decay chain from identity string

get_particle(*name*)

get particle by name

topology_structure(*identical=False*, *standard=True*)

Parameters

- **identical** –
- **standard** –

Returns

GetA2BC_LS_list(*ja*, *jb*, *jc*, *pa=None*, *pb=None*, *pc=None*, *p_break=False*, *ca=None*)

The $L-S$ coupling for the decay $A \to BC$, where L is the orbital angular momentum of B and B, and S is the superposition of their spins. It's required that $|J_B - J_C| \leq S \leq J_B + J_C$ and $|L - S| \leq J_A \leq L + S$. It's also required by the conservation of P parity that L is keep $P_A = P_B P_C (-1)^l$.

Parameters

- **ja** – J of particle A
- **jb** – J of particle B
- **jc** – J of particle C
- **pa** – P of particle A
- **pb** – P of particle B
- **pc** – P of particle C
- **p_break** – allow p voilate
- **ca** – enabel c partity select c=(-1)^(l+s)

Returns
List of (l, s) pairs.

class ParticleList(*initlist=None*)

Bases: UserList

List for Particle

cp_charge_group(*finals*, *id_p*, *cp*)

cross_combine(*x*)

Combine every two of a list, as well as give every one of them.??? Can be put to utils.py

Parameters
x –

Returns

simple_cache_fun(*f*)

Parameters
f –

Returns

split_len(*dicts*)

Split a dictionary of lists by their length. E.g. {"b":[2],"c":[1,3],"d":[1]} => [None, [('b', [2]), ('d', [1])], [('c', [1, 3])]]

Put to utils.py or _split_len if not used anymore???

Parameters
dicts – Dictionary

Returns
List of dictionary

split_particle_type(*decays*)

split_particle_type_list(*decays*)

Separate initial particle, intermediate particles, final particles in a decay chain.

Parameters
decays – DecayChain

Returns
Set of initial Particle, set of intermediate Particle, set of final Particle

10.1.32 phasespace

class ChainGenerator(*m0*, *mi*)

Bases: object

struct = m0 -> [m1, m2, m3] # (m0, [m1, m2, m3]) m0 -> float mi -> float | struct

cal_max_weight()

generate(*N*)

get_gen(*idx_gen*)

class PhaseSpaceGenerator(*m0*, *mass*)

Bases: object

Phase Space Generator for n-body decay

cal_max_weight()

flatten_mass(*ms*, *importances=True*)

sampling from mass with weight

generate(*n_iter: int*, *force=True*, *flatten=True*, *importances=True*) → list

generate n_iter events

Parameters

- **n_iter** – number of events
- **force** – switch for cutting generated data to required size

- **flatten** – switch for sampling with weights

Returns
daughters 4-momentum, list of ndarray with shape (n_iter, 4)

generate_mass(*n_iter*)

generate possible inner mass.

generate_momentum(*mass*, *n_iter=None*)

generate random momentum from mass, boost them to a same rest frame

generate_momentum_i(*m0*, *m1*, *m2*, *n_iter*, *p_list=[]*)

$|p|$ = m0,m1,m2 in m0 rest frame :param p_list: extra list for momentum need to boost

get_mass_range()

get_weight(*ms*, *importances=True*)

calculate weight of mass

$$w = \frac{1}{w_{max}} \frac{1}{M} \prod_{i=0}^{n-2} q(M_i, M_{i+1}, m_{i+1})$$

mass_importances(*mass*)

generate possible inner mass.

set_decay(*m0*, *mass*)

set decay mass, calculate max weight

$$w_{max} = \frac{1}{M} \prod_{i=0}^{n-2} q(max(M_i), min(M_{i+1}), m_{i+1})$$

$$max(M_i) = M_0 - \sum_{j=1}^{i}(m_j)$$

$$min(M_i) = \sum_{j=i}^{n}(m_j)$$

class UniformGenerator(*a*, *b*)

Bases: object

generate(*N*)

generate_phsp(*m0*, *mi*, *N=1000*)

general method to generate decay chain phase sapce >>> (a, b), c = generate_phsp(1.0, (… (0.3, (0.1, 0.1)), … 0.2), … N = 10) >>> assert np.allclose(LorentzVector.M(a+b+c), 1.0)

get_p(*M*, *ma*, *mb*)

10.1.33 root_io

load_Ttree(*tree*)

load TTree as dict

load_root_data(*fnames*)

load root file as dict

save_dict_to_root(*dic*, *file_name*, *tree_name=None*)

This function stores data arrays in the form of a dictionary into a root file. It provides a convenient interface to `uproot`.

Parameters

- **dic** – Dictionary of data
- **file_name** – String
- **tree_name** – String. By default it's "tree".

10.1.34 significance

erfc_inverse(*x*)

erfc-1(x) = - 1/sqrt(2) * normal_quantile(0.5 * x)

normal_quantile(*p*)

Computes quantiles for standard normal distribution N(0, 1) at probability p

prob(*chi_2*, *ndf*)

Computation of the probability for a certain Chi-squared (chi2) and number of degrees of freedom (ndf).

Calculations are based on the incomplete gamma function P(a,x), where a=ndf/2 and x=chi2/2.

P(a,x) represents the probability that the observed Chi-squared for a correct model should be less than the value chi2.

The returned probability corresponds to 1-P(a,x), which denotes the probability that an observed Chi-squared exceeds the value chi2 by chance, even for a correct model.

significance(*l1: float*, *l2: float*, *ndf: int*) → float

computation of significance for log-likelihood fit values l1 and l2 with number of degrees of freedom (ndf).

10.1.35 tensorflow_wrapper

class Module

Bases: `object`

numpy_cross(*a*, *b*)

regist_function(*name*, *var=None*, *base_mod=<tf_pwa.tensorflow_wrapper.Module object>*)

set_gpu_mem_growth()

10.1.36 transform

class BaseTransform(*x: list | str*, ***kwargs*)

Bases: `object`

call(*x: Tensor*) → Tensor

inverse(*y: Tensor*) → Tensor

read(*x: dict*) → Tensor

class LinearTrans(*x: list | str*, *k: float = 1.0*, *b: float = 0.0*, ***kwargs*)

Bases: *BaseTransform*

call(*x*) → Tensor

inverse(*x: Tensor*) → Tensor

create_trans(*item: dict*) → *BaseTransform*

10.1.37 utils

This module provides some functions that may be useful in other modules.

class AttrDict

Bases: `dict`

array_split(*data*, *batch=None*)

Split a data array. **batch** is the number of data in a row.

check_positive_definite(*m*)

check if matrix m is postive definite

```
>>> check_positive_definite([[1.0,0.0],[0.0, 0.1]])
True
```

```
>>> check_positive_definite([[1.0,0.0],[1.0,-0.1]])
eigvalues:  [-0.1  1. ]
False
```

create_dir(*name*)

create_test_config(*model_name*, *params={}*, *plot_params={}*)

deep_iter(*base*, *deep=1*)

deep_ordered_iter(*base*, *deep=1*)

deep_ordered_range(*size*, *deep=1*, *start=0*)

error_print(*x*, *err=None*, *dig=None*)

It returns a format string "value +/- error". The precision is modified according to `err`

Parameters

- **x** – Value
- **err** – Error

Returns
String

fit_normal(*data*, *weights=None*)

Fit data distribution with Gaussian distribution. Though minimize the negative log likelihood function

$$-\ln L = \frac{1}{2}\sum w_i \frac{(\mu - x_i)^2}{\sigma^2} + (\sum w_i)\ln(\sqrt{2\pi}\sigma)$$

the fit result can be solved as

$$\frac{\partial(-\ln L)}{\partial \mu} = 0 \Rightarrow \bar{\mu} = \frac{\sum w_i x_i}{\sigma^2 \sum w_i}$$

$$\frac{\partial(-\ln L)}{\partial \sigma} = 0 \Rightarrow \bar{\sigma} = \sqrt{\frac{\sum w_i(\bar{\mu} - x_i)^2}{\sum w_i}}$$

From hessian

$$\frac{\partial^2(-\ln L)}{\partial \mu^2} = \frac{\sum w_i}{\sigma^2}$$

$$\frac{\partial^2(-\ln L)}{\partial \sigma^2} = 3\sum \frac{\sum w_i(\mu - x)^2}{\sigma^4} - \frac{\sum w_i}{\sigma^2}$$

the error matrix can wrotten as [[$\bar{\sigma}^2/N$, 0], [0, $\bar{\sigma}^2/(2N)$]] .

flatten_dict_data(*data*, *fun=<built-in method format of str object>*)

Flatten nested dictionary data into one layer dictionary.

Returns
Dictionary

flatten_np_data(*data*)

is_complex(*x*)

If **x** is of type `complex`, it returns `True`.

load_config_file(*name*)

Load config file such as **Resonances.yml**.

Parameters
name – File name. Either yml file or json file.

Returns
Dictionary read from the file.

plot_particle_model(*model_name*, *params={}*, *plot_params={}*, *axis=None*, *special_points=None*)

pprint(*dicts*)

Print dictionary using json format.

print_dic(*dic*)

Another way to print dictionary.

save_frac_csv(*file_name*, *fit_frac*)

std_periodic_var(*p*, *mid=0.0*, *pi=3.141592653589793*)

Transform a periodic variable into its range.

```
>>> std_periodic_var(math.pi)
-3.1415...
```

```
>>> std_periodic_var(2*math.pi + 0.01)
0.0...
```

Parameters

- **p** – Value
- **mid** – The middle value
- **pi** – Half-range

Returns
The transformed value

std_polar(*rho*, *phi*)

To standardize a polar variable. By standard form, it means $\rho > 0, -\pi < \phi < \pi$.

Parameters

- **rho** – Real number
- **phi** – Real number

Returns
rho, phi

time_print(*f*)

It provides a wrapper to print the time cost on a process.

tuple_table(*fit_frac*, *ignore_items=['sum_diag']*)

10.1.38 variable

This module implements classes and methods to manage the variables in fitting.

class Bound(*a=None*, *b=None*, *func=None*)

Bases: object

This class provides methods to implement the boundary constraint for a variable. It has dependence on SymPy . The boundary-transforming function can transform a variable *x* defined in the real domain to a variable *y* defined in a limited range *(a,b)*. *y* should be the physical parameter but *x* is the one used while fitting.

Parameters

- **a** – Real number. The lower boundary
- **b** – Real number. The upper boundary
- **func** – String. The boundary-transforming function. By default, if neither **a** or **b** is **None**, **func** is **"(b-a)*(sin(x)+1)/2+a"**; else if only **a** is **None**, **func** is **"b+1-sqrt(x**2+1)"**; else if only **b** is **None**, **func** is **"a-1+sqrt(x**2+1)"**; else **func** is **"x"**.

a, **b**, **func** can be refered by **self.lower**, **self.upper**, **self.func**.

`get_d2ydx2`(*val*)

To calculate the derivative $\frac{dy}{dx}$.

Parameters
val – Real number x

Returns
Real number $\frac{dy}{dx}$

`get_dydx`(*val*)

To calculate the derivative $\frac{dy}{dx}$.

Parameters
val – Real number x

Returns
Real number $\frac{dy}{dx}$

`get_func`()

Initialize the function string into **sympy** objects.

Returns
sympy objects **f**, **df**, **inv**, which are the function, its derivative and its inverse function.

`get_x2y`(*val*)

To derive y from x

Parameters
val – Real number x

Returns
Real number y

`get_y2x`(*val*)

To derive x from y. y will be set to a if $y<a$, and y will be set to b if $y>b$.

Parameters
val – Real number y

Returns
Real number x

`class SumVar`(*value*, *grad*, *var*, *hess=None*)

Bases: `object`

`from_call`(*var*, **args*, ***kwargs*)

`from_call_with_hess`(*var*, **args*, ***kwargs*)

`class Variable`(*name*, *shape=None*, *cplx=False*, *vm=None*, *overwrite=True*, *is_cp=False*, ***kwargs*)

Bases: `object`

This class has interface to **VarsManager**. It is convenient for users to define a group of real variables, since it may be more perceptually intuitive to define them together.

By calling the instance of this class, it returns the value of this variable. The type is tf.Tensor.

Parameters

- **name** – The name of the variable group

- **shape** – The shape of the group. E.g. for a 4*3*2 matrix, **shape** is **[4,3,2]**. By default, **shape** is [] for a real variable.
- **cplx** – Boolean. Whether the variable (or the variables) are complex or not.
- **vm** – VarsManager. It is by default the one automatically defined in the global scope by the program.
- **overwrite** – Boolean. If it's `True`, the program will not throw a warning when overwrite a variable with the same name.
- **kwargs** – Other arguments that may be used when calling **self.real_var()** or **self.cplx_var()**

cplx_cpvar(*polar=True*, *fix=False*, *fix_vals=(1.0, 0.0, 0.0, 0.0)*, *value=0.0*)

It implements interface to `VarsManager.add_complex_var()`, but supports variables that are not of non-shape.

Parameters

- **polar** – Boolean. Whether the variable is defined in polar coordinate or in Cartesian coordinate.
- **fix** – Boolean. Whether the variable is fixed. It's enabled only if `self.shape is None`.
- **fix_vals** – Length-4 tuple. The value of the fixed complex variable is `fix_vals[0]+fix_vals[1]j`.

cplx_var(*polar=None*, *fix=False*, *fix_vals=(1.0, 0.0)*)

It implements interface to `VarsManager.add_complex_var()`, but supports variables that are not of non-shape.

Parameters

- **polar** – Boolean. Whether the variable is defined in polar coordinate or in Cartesian coordinate.
- **fix** – Boolean. Whether the variable is fixed. It's enabled only if `self.shape is None`.
- **fix_vals** – Length-2 tuple. The value of the fixed complex variable is `fix_vals[0]+fix_vals[1]j`.

factor_names()

fixed(*value=None*)

Fix this Variable. Note only non-shape real Variable supports this method.

Parameters
value – Real number. The fixed value

freed()

Set free this Variable. Note only non-shape Variable supports this method.

init_name_list()

is_fixed()

r_shareto(*Var*)

Share the radium component to another Variable of the same shape. Only complex Variable supports this method.

Parameters
Var – Variable.

real_var(*value=None*, *range_=None*, *fix=False*)

It implements interface to `VarsManager.add_real_var()`, but supports variables that are not of non-shape.

Parameters

- **value** – Real number. The value of all real components.
- **range** – Length-2 array. The length of all real components.
- **fix** – Boolean. Whether the variable is fixed.

rename(*new_name*)

Rename this Variable.

sameas(*Var*)

Set the Variable to be the same with another Variable of the same shape.

Parameters
Var – Variable.

set_bound(*bound*, *func=None*, *overwrite=False*)

Set boundary for this Variable. Note only non-shape real Variable supports this method.

Parameters

- **bound** – Length-2 tuple.
- **func** – String. Refer to class **tf_pwa.variable.Bound**.
- **overwrite** – Boolean. If it's `True`, the program will not throw a warning when overwrite a variable with the same name.

set_fix_idx(*fix_idx=None*, *fix_vals=None*, *free_idx=None*)

Parameters

- **fix_idx** – Interger or list of integers. Which complex component in the innermost layer of the variable is fixed. E.g. If `self.shape==[2,3,4]` and `fix_idx==[1,2]`, then Variable()[i][j][1] and Variable()[i][j][2] will be the fixed value.
- **fix_vals** – Float or length-2 float list for complex variable. The fixed value.
- **free_idx** – Interger or list of integers. Which complex component in the innermost layer of the variable is set free. E.g. If `self.shape==[2,3,4]` and `fix_idx==[0]`, then Variable()[i][j][0] will be set free.

set_phi(*phi*, *index=None*)

set_rho(*rho*, *index=None*)

set_same_ratio()

set_value(*value*, *index=None*)

property value

Ndarray of `self.shape`.

Type
return

property variables

Names of the real variables contained in this Variable instance.

Returns
List of string.

class VarsManager(*name=''*, *dtype=tf.float64*, *multi_gpu=None*)

Bases: object

This class provides methods to operate the variables in fitting. Every variable is a 1-d **tf.Variable** of **dtype** (**tf.float64** by default).

All variables are stored in a dictionary **self.variables**. The indices of the dictionary are the variables' names, so name property in **tf.Variable** does not matter. All methods intended to change the variables are operating **self.variables** directly.

Besides, all trainable variables' names will be stored in a list **self.trainable_vars**.

add_cartesiancp_var(*name*, *polar=None*, *trainable=True*, *fix_vals=(1.0, 0.0, 0.0, 0.0)*)

Add a complex variable. Two real variables named **name+'r'** and **name+'i'** will be added into **self.variables**. The initial values will be given automatically according to its form of coordinate.

Parameters

- **name** – The name of the complex variable.
- **polar** – Boolean. If it's **True**, **name+'r'** and **name+'i'** are defined in polar coordinate; otherwise they are defined in Cartesian coordinate.
- **trainable** – Boolean. If it's **True**, real variables **name+'r'** and **name+'i'** will be trainable.
- **fix_vals** – Length-4 array. If **trainable=False**, the fixed values for **name+'r'** and **name+'i'** are **fix_vals[0]**, **fix_vals[1]** respectively.

add_complex_var(*name*, *polar=None*, *trainable=True*, *fix_vals=(1.0, 0.0)*)

Add a complex variable. Two real variables named **name+'r'** and **name+'i'** will be added into **self.variables**. The initial values will be given automatically according to its form of coordinate.

Parameters

- **name** – The name of the complex variable.
- **polar** – Boolean. If it's **True**, **name+'r'** and **name+'i'** are defined in polar coordinate; otherwise they are defined in Cartesian coordinate.
- **trainable** – Boolean. If it's **True**, real variables **name+'r'** and **name+'i'** will be trainable.
- **fix_vals** – Length-2 array. If **trainable=False**, the fixed values for **name+'r'** and **name+'i'** are **fix_vals[0]**, **fix_vals[1]** respectively.

add_real_var(*name*, *value=None*, *range_=None*, *trainable=True*)

Add a real variable named **name** into **self.variables**. If **value** and **range_** are not provided, the initial value is set to be a uniform random number between 0 and 1.

Parameters

- **name** – The name of the variable, the index of this variable in **self.variables**
- **value** – The initial value.
- **range** – Length-2 array. It's useless if **value** is given. Otherwise the initial value is set to be a uniform random number between **range_[0]** and **range_[0]**.

- **trainable** – Boolean. If it's **True**, the variable is trainable while fitting.

batch_sum_var(*fun*, *data*, *batch=65000*)

error_trans(*err_matrix*)

get(*name*, *val_in_fit=True*)

Get a real variable. If `val_in_fit is True`, this is the variable used in fitting, not considering its boundary transformation.

Parameters
name – String

Returns
tf.Variable

get_all_dic(*trainable_only=False*)

Get a dictionary of all variables.

Parameters
trainable_only – Boolean. If it's **True**, the dictionary only contains the trainable variables.

Returns
Dictionary

get_all_val(*val_in_fit=False*)

Get the values of all trainable variables.

Parameters
val_in_fit – Boolean. If it's **True**, the values will be the ones that are actually used in fitting (thus may not be the physical values because of the boundary transformation).

Returns
List of real numbers.

mask_params(*params*)

minimize(*fcn*, *jac=True*, *method='BFGS'*, *mini_kwargs={}*)

minimize a give function

minimize_error(*fcn*, *fit_result*)

read(*name*)

refresh_vars(*init_val=None*, *bound_dic=None*)

Refresh all trainable variables

remove_bound()

Remove a boundary for a variable

remove_var(*name*)

Remove a variable from **self.variables**. More specifically, two variables (**name+'r'** and **name+'i'**) will be removed if it's complex.

Parameters
name – The name of the variable

rename_var(*name*, *new_name*, *cplx=False*)

Rename a variable.

Parameters

- **name** – Name of the variable
- **new_name** – New name
- **cplx** – Boolean. Users should indicate if this variable is complex or not.

rp2xy(*name*)

Transform a complex variable into Cartesian coordinate. :param name: String

rp2xy_all(*name_list=None*)

If **name_list** is not provided, this method will transform all complex variables into Cartesian coordinate.

Parameters
name_list – List of names of complex variables

set(*name*, *value*, *val_in_fit=True*)

Set value for a real variable. If `val_in_fit is True`, this is the variable used in fitting, not considering its boundary transformation.

Parameters

- **name** – String
- **value** – Real number

set_all(*vals*, *val_in_fit=False*)

Set values for some variables.

Parameters
vals – It can be either a dictionary or a list of real numbers. If it's a list, the values correspond to all trainable variables in order.

set_bound(*bound_dic*, *func=None*, *overwrite=False*)

Set boundary for the trainable variables. The variables will be constrained in their ranges while fitting.

Parameters

- **bound_dic** – Dictionary. E.g. **{"name1":(-1.0,1.0), "name2":(None,1.0)}**. In this example, **None** means it has no lower limit.
- **func** – String. Users can provide a string to describe the transforming function. For details, refer to class **tf_pwa.variable.Bound**.
- **overwrite** – Boolean. If it's `True`, the program will not throw a warning when overwrite a variable with the same name.

set_fix(*name*, *value=None*, *unfix=False*)

Fix or unfix a variable (change the trainability) :param name: The name of the variable :param value: The fixed value. It's useless if **unfix=True**. :param unfix: Boolean. If it's **True**, the variable will become trainable rather than be fixed.

set_same(*name_list*, *cplx=False*)

Set some variables to be the same.

Parameters

- **name_list** – List of strings. Name of the variables.
- **cplx** – Boolean. Whether the variables are complex or real.

set_share_r(*name_list*)

If some complex variables want to share their radia variable while their phase variable are still different. Users can set this type of constrain using this method.

Parameters
name_list – List of strings. Note the strings should be the name of the complex variables rather than of their radium parts.

set_trans_var(*xvals*)

$y = y(x)$

Parameters
fcn_grad – The return of class **tf_pwa.model**???

Returns

standard_complex()

std_polar(*name*)

Transform a complex variable into standard polar coordinate, which mean its radium part is positive, and its phase part is between $-\pi$ to π. :param name: String

std_polar_all()

Transform all complex variables into standard polar coordinate.

temp_params(*params*)

property trainable_variables

List of tf.Variable. It is similar to **tf.keras.Model.trainable_variables**.

trans_error_matrix(*hess_inv*, *xvals*)

Bound trans for error matrix $F(x) = F(y(x))$, $V_y = y' V_x y'$

Returns

trans_f_grad_hess(*f*)

$F(x) = F(y(x))$, $G(x) = \frac{dF}{dx} = \frac{dF}{dy}\frac{dy}{dx}$

Parameters
fcn_grad – The return of class **tf_pwa.model**???

Returns

trans_fcn_grad(*fcn_grad*)

$F(x) = F(y(x))$, $G(x) = \frac{dF}{dx} = \frac{dF}{dy}\frac{dy}{dx}$

Parameters
fcn_grad – The return of class **tf_pwa.model**???

Returns

trans_grad_hessp(*f*)

$F(x) = F(y(x))$, $G(x) = \frac{dF}{dx} = \frac{dF}{dy}\frac{dy}{dx}$

Parameters
fcn_grad – The return of class **tf_pwa.model**???

Returns

trans_params(*polar*)

Transform all complex variables into either polar coordinate or Cartesian coordinate.

Parameters
polar – Boolean

xy2rp(*name*)

Transform a complex variable into polar coordinate. :param name: String

xy2rp_all(*name_list=None*)

If **name_list** is not provided, this method will transform all complex variables into polar coordinate.

Parameters
name_list – List of names of complex variables

combineVM(*vm1*, *vm2*, *name=''*, *same_list=None*)

This function combines two VarsManager objects into one. (WIP)

Parameters

- **name** – The name of this combined VarsManager
- **same_list** – To make some variables in the two VarsManager to be the same. E.g. if `same_list = ["var",["var1","var2"]]`, then "var" in vm1 and vm2 will be the same, and "var1" in vm1 and "var2" in vm2 will be the same.

deep_stack(*dic*, *deep=1*)

10.1.39 version

10.1.40 vis

class DotGenerator(*top*)

Bases: `object`

static dot_chain(*chains*, *has_label=True*)

dot_default_edge = ' "{}" -> "{}";\n'

dot_default_node = ' "{}" [shape=none];\n'

dot_head = '\ndigraph {\n rankdir=LR;\n node [shape=point];\n edge [arrowhead=none, labelfloat=true];\n'

dot_label_edge = ' "{}" -> "{}" [label="{}"];\n'

dot_ranksame = ' {{ rank=same {} }};\n'

dot_tail = '}\n'

get_dot_source()

draw_decay_struct(*decay_chain*, *show=False*, ***kwargs*)

get_decay_layout(*decay_chain*)

get_layout(*decay_chain*, *xs*, *ys*)

get_node_layout(*decay_chain*)

plot_decay_struct(*decay_chain*, *ax=<module 'matplotlib.pyplot' from '/home/docs/checkouts/readthedocs.org/user_builds/tf-pwa/envs/stable/lib/python3.10/site-packages/matplotlib/pyplot.py'>*)

reorder_final_particle(*decay_chain*, *ys*)

10.1.41 weight_smear

dirichlet_smear(*weight*, ***kwargs*)

gamma_smear(*weight*, ***kwargs*)

get_weight_smear(*name*)

poisson_smear(*weight*, ***kwargs*)

register_weight_smear(*name*)

See also:

- modindex
- genindex

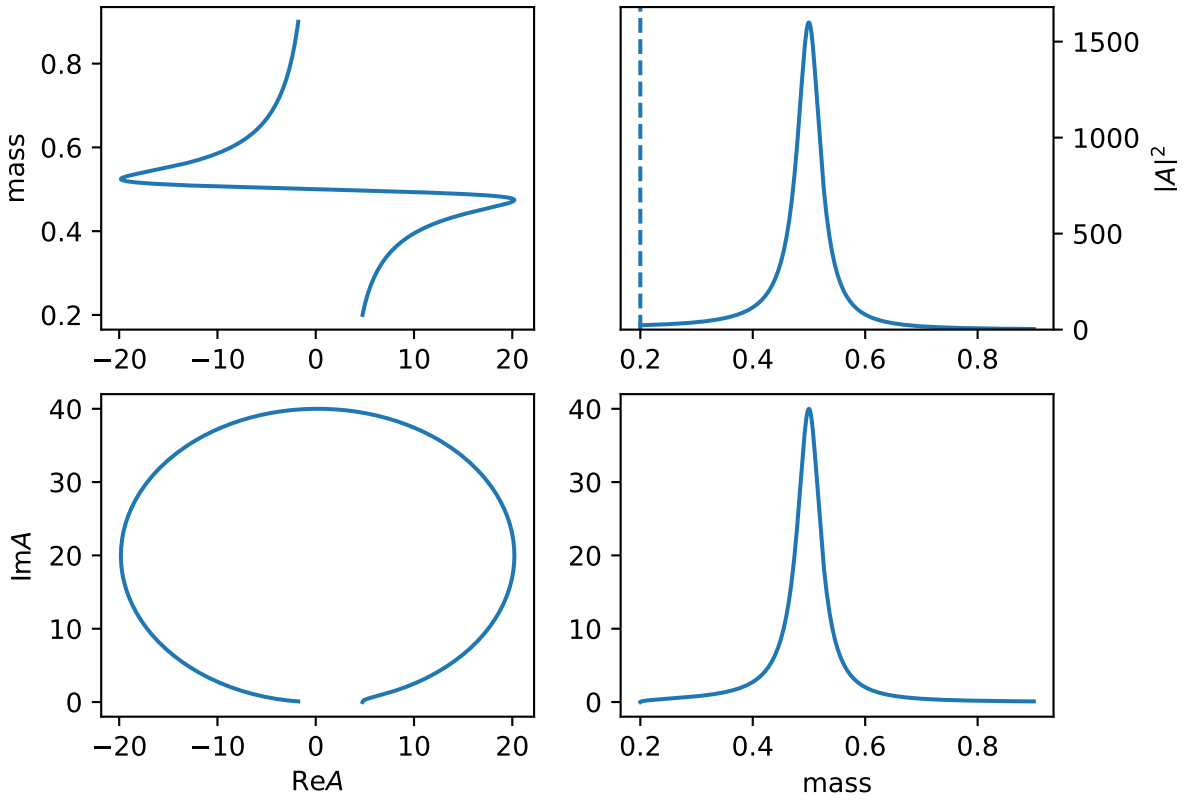
CHAPTER

ELEVEN

AVAILABLE RESONANCES MODEL

1. `"default", "BWR"` (*Particle*)

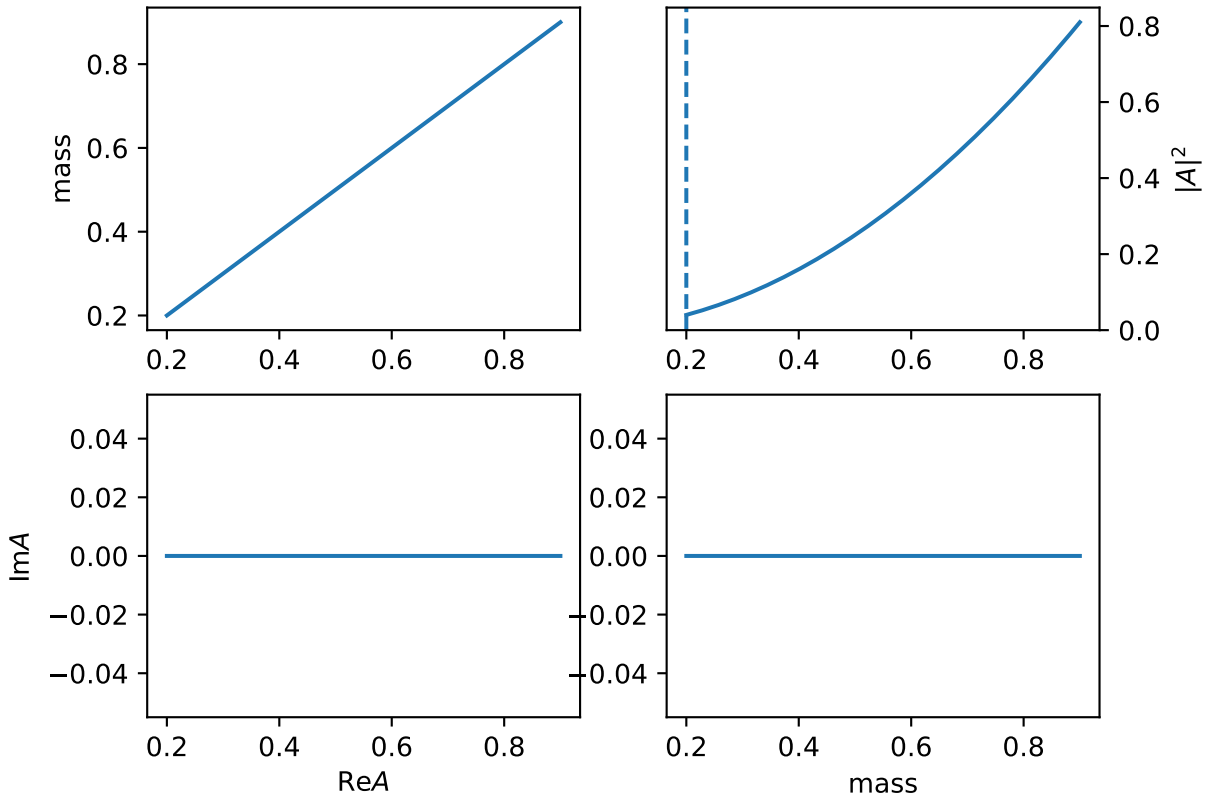
$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$



2. `"x"` (*ParticleX*)

   simple particle model for mass, (used in expr)

$$R(m) = m$$



3. `"BWR2"` (*ParticleBWR2*)

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

The difference of `BWR`, `BWR2` is the behavior when mass is below the threshold ($m_0 = 0.1 < 0.1 + 0.1 = m_1 + m_2$).

4. `"BWR_below"` (*ParticleBWRBelowThreshold*)

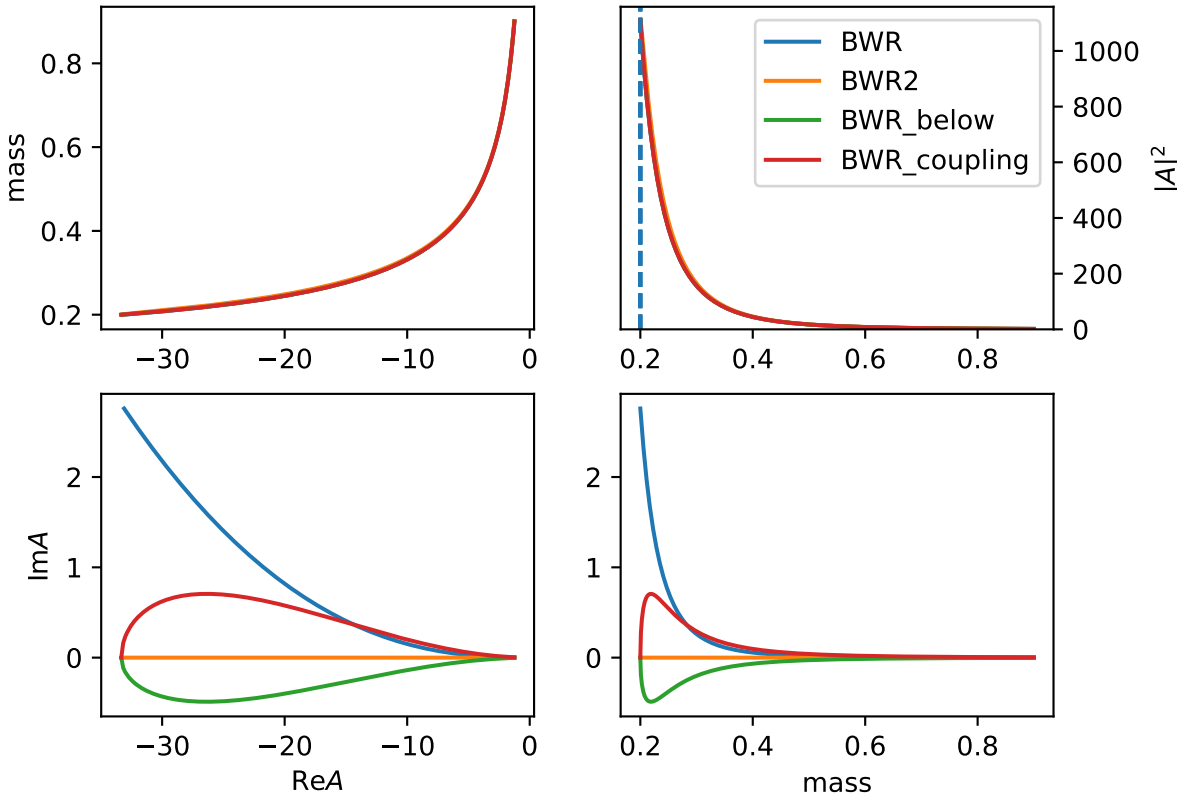
$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma(m)}$$

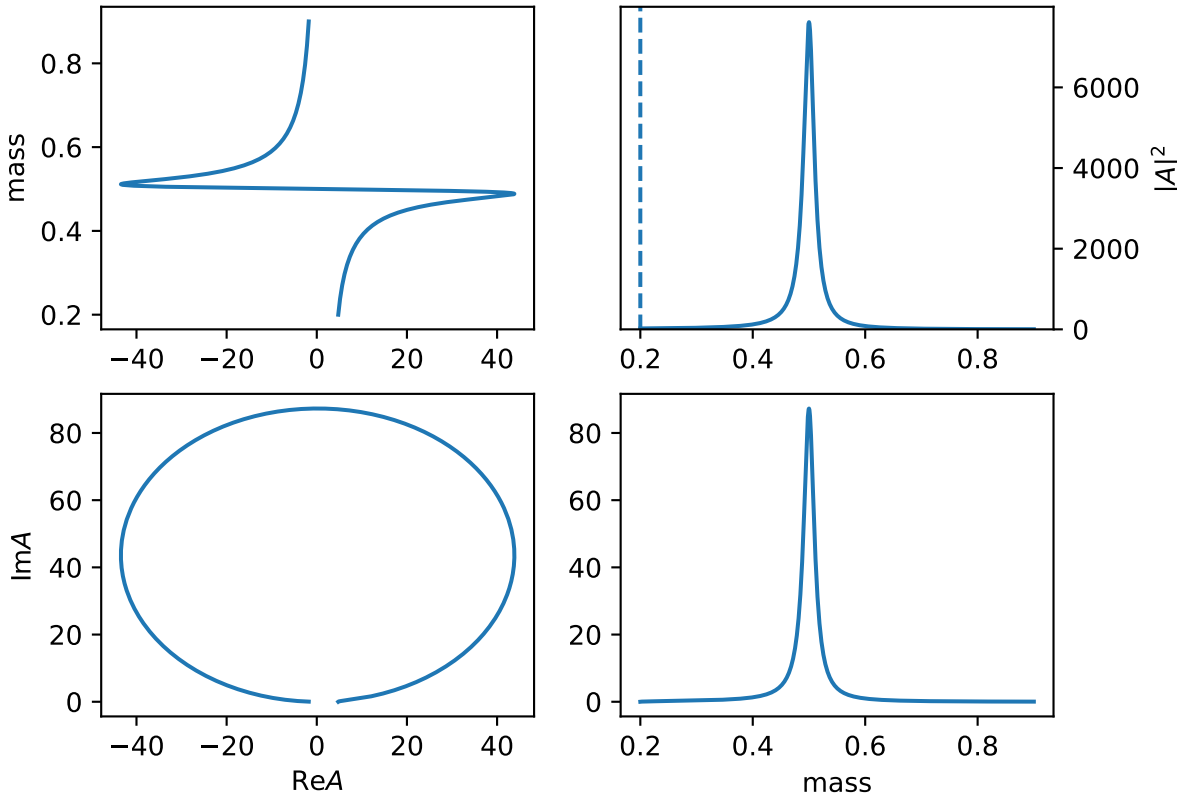
5. `"BWR_coupling"` (*ParticleBWRCoupling*)

Force $q_0 = 1/d$ to avoid below theshold condition for `BWR` model, and remove other constant parts, then the Γ_0 is coupling parameters.

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0\frac{q}{m}q^{2l}B_L'^2(q, 1/d, d)}$$

6. `"BWR_normal"` (*ParticleBWR_normal*)


mass
0.8
0.6
0.4
0.2
−30
−20
−10
0
BWR
BWR2
BWR_below
BWR_coupling
1000
800
600
400
200
0
$|A|^2$
0.2
0.4
0.6
0.8
ImA
2
1
0
ReA
mass


mass
0.8
0.6
0.4
0.2
−40
−20
0
20
40
0.2
0.4
0.6
0.8
6000
4000
2000
0
$|A|^2$
ImA
80
60
40
20
0
ReA
mass

$$R(m) = \frac{\sqrt{m_0\Gamma(m)}}{m_0^2 - m^2 - im_0\Gamma(m)}$$

7. "GS_rho" (*ParticleGS*)

   Gounaris G.J., Sakurai J.J., Phys. Rev. Lett., 21 (1968), pp. 244-247

   `c_daug2Mass`: mass for daughter particle 2 (π^+) 0.13957039

   `c_daug3Mass`: mass for daughter particle 3 (π^0) 0.1349768

$$R(m) = \frac{1 + D\Gamma_0/m_0}{(m_0^2 - m^2) + f(m) - im_0\Gamma(m)}$$

$$f(m) = \Gamma_0 \frac{m_0^2}{q_0^3}\left[q^2[h(m) - h(m_0)] + (m_0^2 - m^2)q_0^2 \frac{dh}{dm}|_{m0}\right]$$

$$h(m) = \frac{2}{\pi}\frac{q}{m}\ln\left(\frac{m + 2q}{2m_\pi}\right)$$

$$\frac{dh}{dm}|_{m0} = h(m_0)[(8q_0^2)^{-1} - (2m_0^2)^{-1}] + (2\pi m_0^2)^{-1}$$

$$D = \frac{f(0)}{\Gamma_0 m_0} = \frac{3}{\pi}\frac{m_\pi^2}{q_0^2}\ln\left(\frac{m_0 + 2q_0}{2m_\pi}\right) + \frac{m_0}{2\pi q_0} - \frac{m_\pi^2 m_0}{\pi q_0^3}$$

8. "BW" (*ParticleBW*)

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0\Gamma_0}$$

9. "LASS" (*ParticleLass*)

$$R(m) = \frac{m}{qcot\delta_B - iq} + e^{2i\delta_B}\frac{m_0\Gamma_0\frac{m_0}{q_0}}{(m_0^2 - m^2) - im_0\Gamma_0\frac{q}{m}\frac{m_0}{q_0}}$$

$$cot\delta_B = \frac{1}{aq} + \frac{1}{2}rq$$

$$e^{2i\delta_B} = \cos 2\delta_B + i\sin 2\delta_B = \frac{cot^2\delta_B - 1}{cot^2\delta_B + 1} + i\frac{2cot\delta_B}{cot^2\delta_B + 1}$$

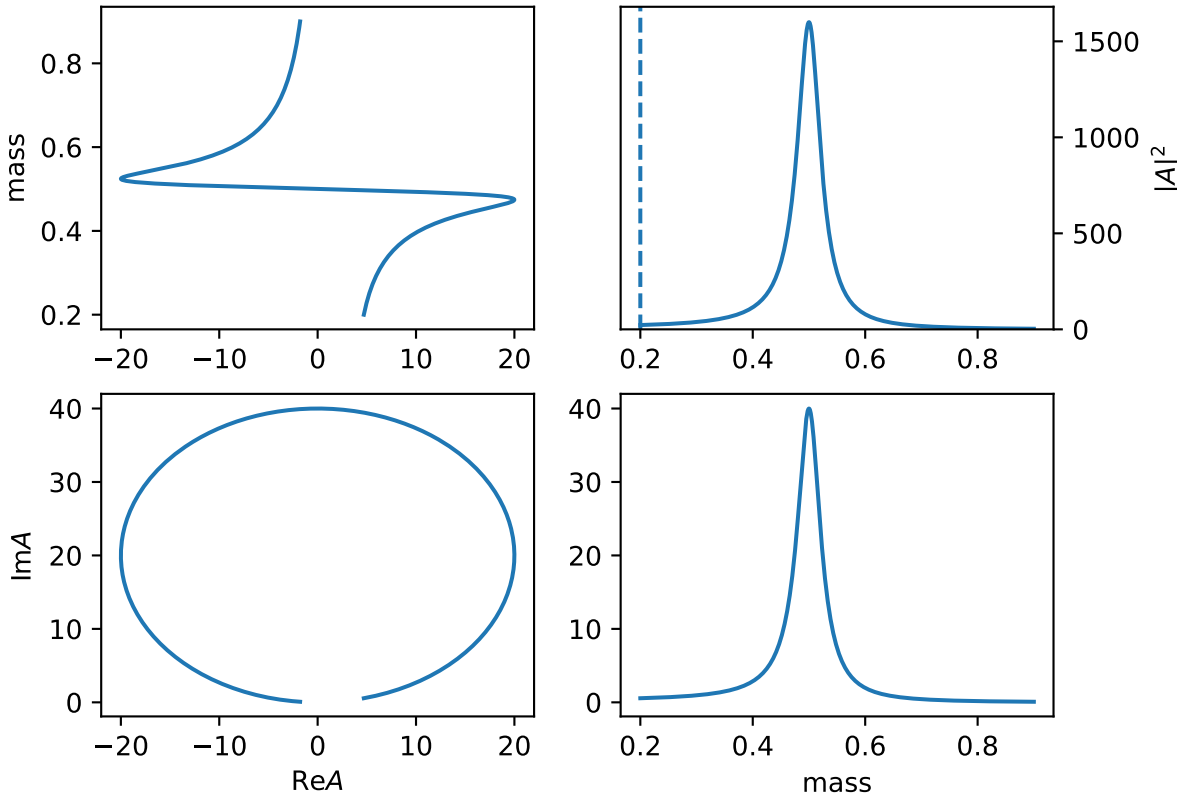
10. "one" (*ParticleOne*)

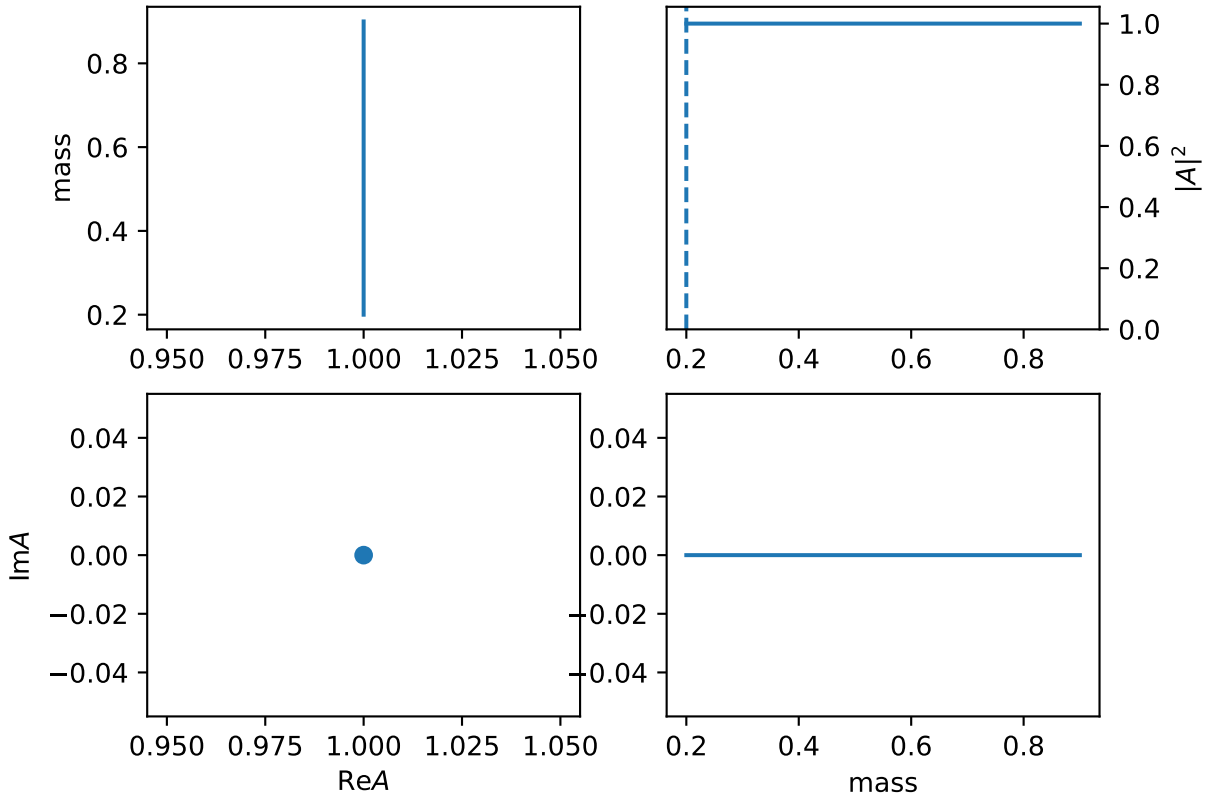
$$R(m) = 1$$

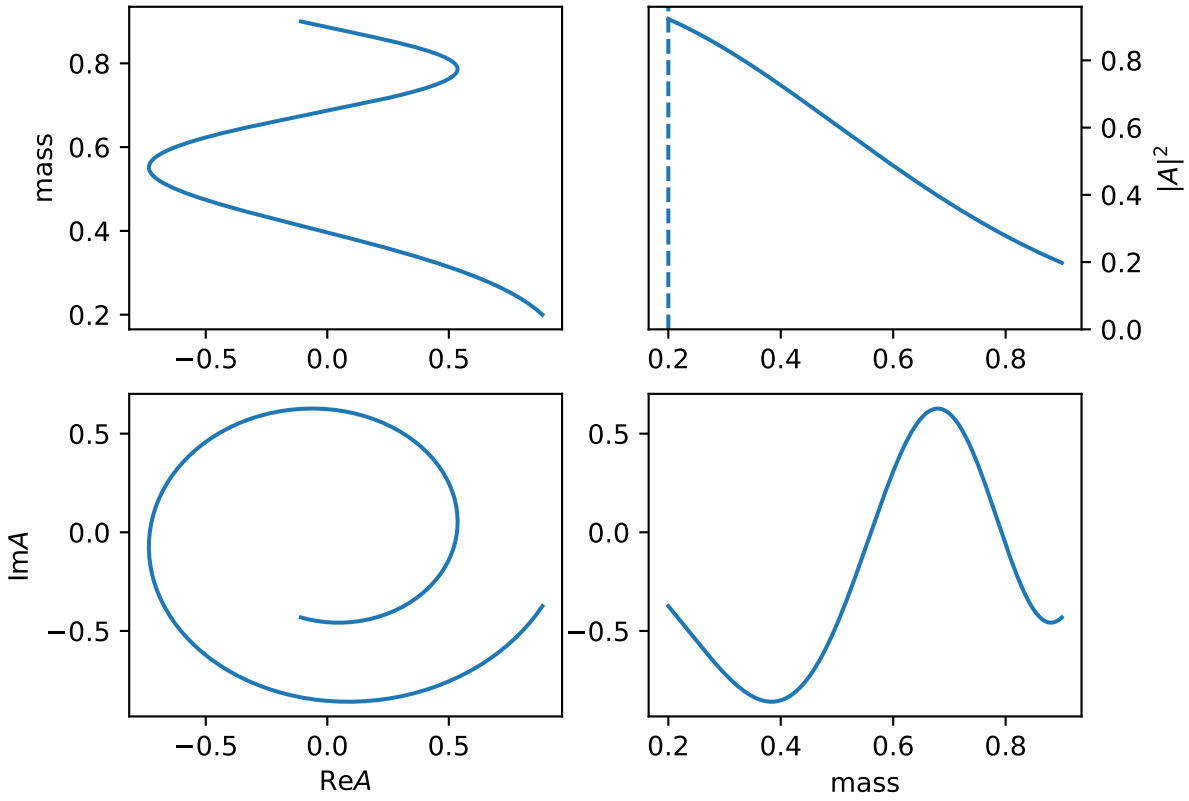
11. "exp" (*ParticleExp*)

$$R(m) = e^{-|a|m}$$

12. "exp_com" (*ParticleExpCom*)


mass
0.8
0.6
0.4
0.2
−20
−10
0
10
20
1500
1000
500
0
$|A|^2$
0.2
0.4
0.6
0.8
40
30
20
10
0
ImA
ReA
mass


mass
0.8
0.6
0.4
0.2
0.950
0.975
1.000
1.025
1.050
1.0
0.8
0.6
0.4
0.2
0.0
$|A|^2$
0.2
0.4
0.6
0.8
0.04
0.02
0.00
−0.02
−0.04
ImA
ReA
mass


mass
0.8
0.6
0.4
0.2
−0.5
0.0
0.5
0.2
0.4
0.6
0.8
$|A|^2$
0.0
ImA
ReA

$$R(m) = e^{-(a+ib)m^2}$$

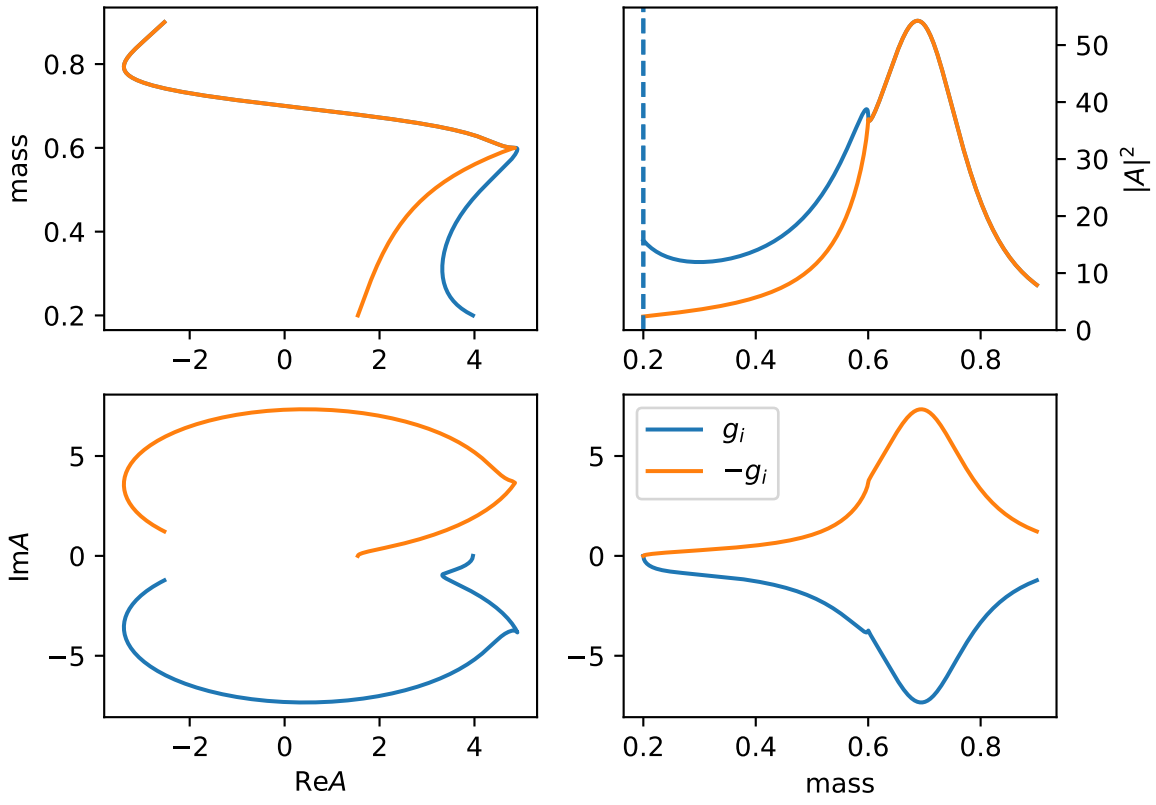
lineshape when $a = 1.0, b = 10$.

13. "Flatte" (*ParticleFlatte*)

    Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 + im_0(\sum_i g_i \frac{q_i}{m})}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$



Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$.

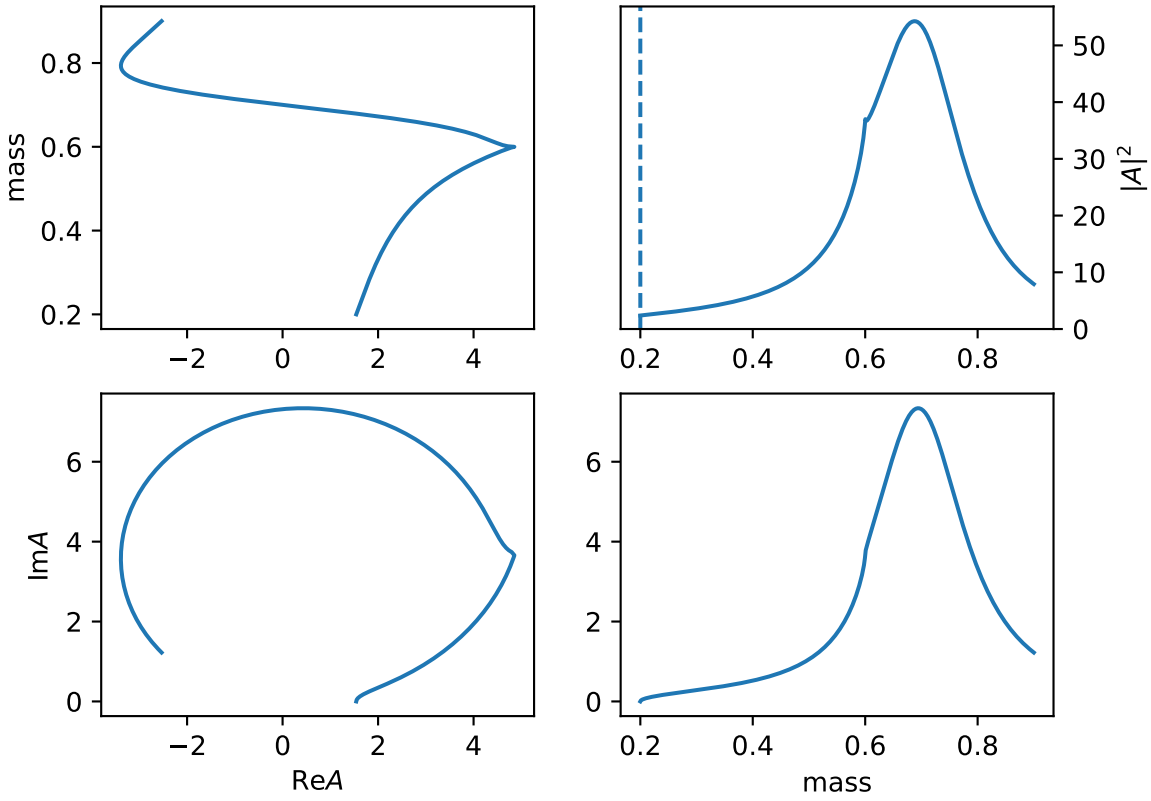
14. "FlatteC" (*ParticleFlatteC*)

    Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0(\sum_i g_i \frac{q_i}{m})}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$

Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$.



15. `"FlatteGen"` (*ParticleFlateGen*)

    More General Flatte like formula

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0[\sum_i g_i \frac{q_i}{m} \times \frac{m_0}{|q_{i0}|} \times \frac{|q_i|^{2l_i}}{|q_{i0}|^{2l_i}} B_{l_i}'^2(|q_i|, |q_{i0}|, d)]}$$

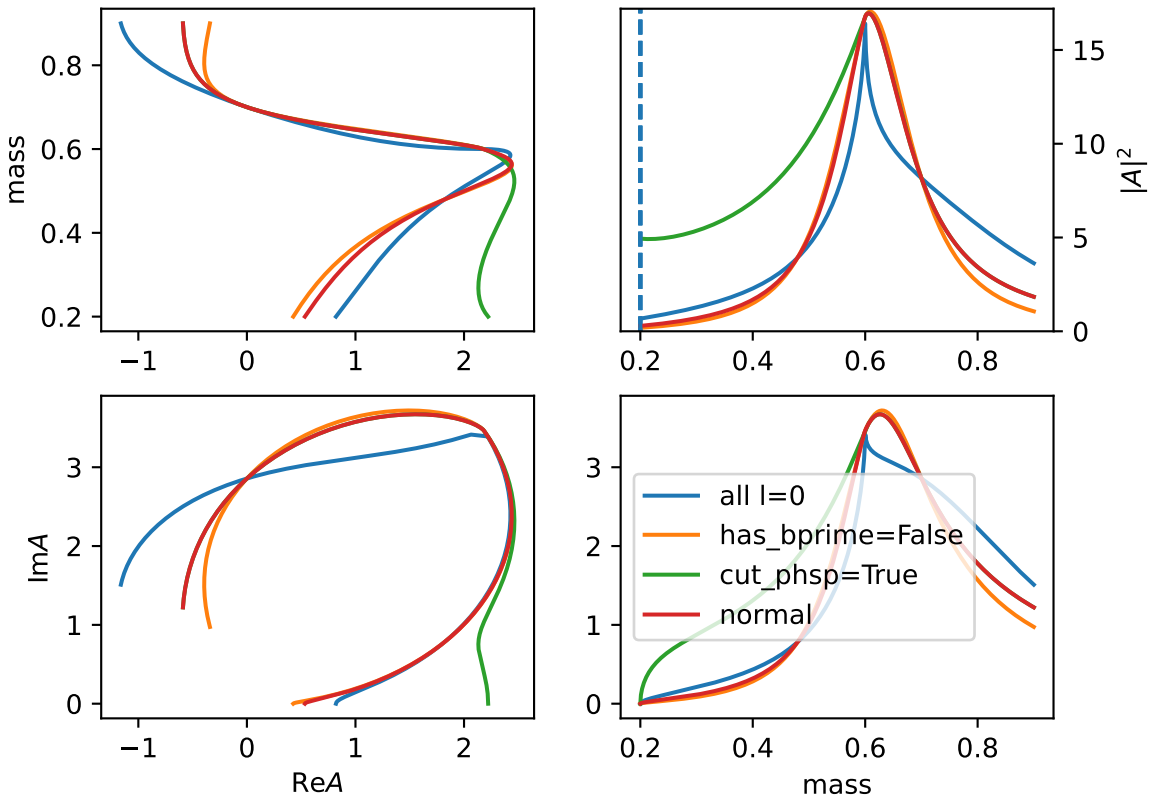
$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2) < 0 \end{cases}$$

Required input arguments `mass_list: [[m11, m12], [m21, m22]]` for $m_{i,1}, m_{i,2}$. And addition arguments `l_list: [l1, l2]` for l_i

`has_bprime=False` to remove $B'^2_{l_i}(|q_i|, |q_{i0}|, d)$.

`cut_phsp=True` to set $q_i = 0$ when $(m^2 - (m_{i,1} + m_{i,2})^2)(m^2 - (m_{i,1} - m_{i,2})^2) < 0$

The plot use parameters $m_0 = 0.7, m_{0,1} = m_{0,2} = 0.1, m_{1,1} = m_{1,2} = 0.3, g_0 = 0.3, g_1 = 0.2, l_0 = 0, l_1 = 1$.



`no_m0=True` to set $im_0 => i$ in the width part.

`no_q0=True` to remove $\frac{m_0}{|q_{i0}|}$ and set others $q_{i0} = 1$.

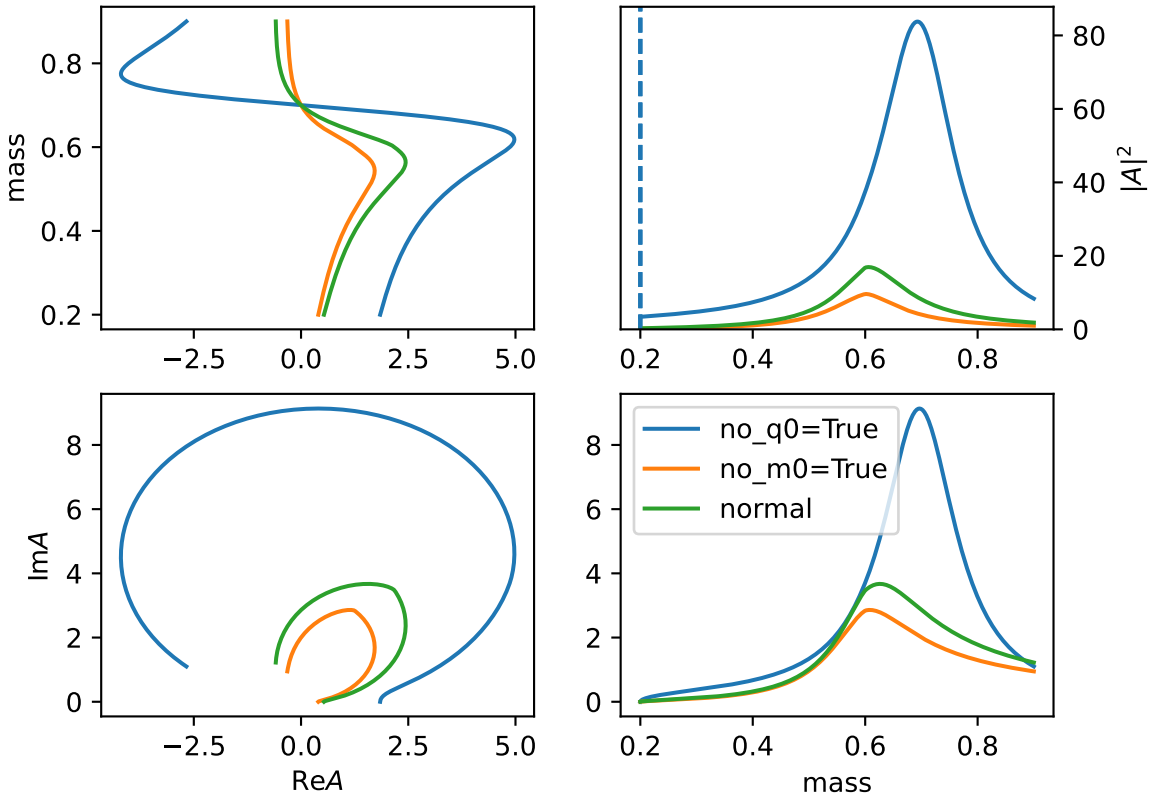
16. `"Flatte2"` (*ParticleFlate2*)

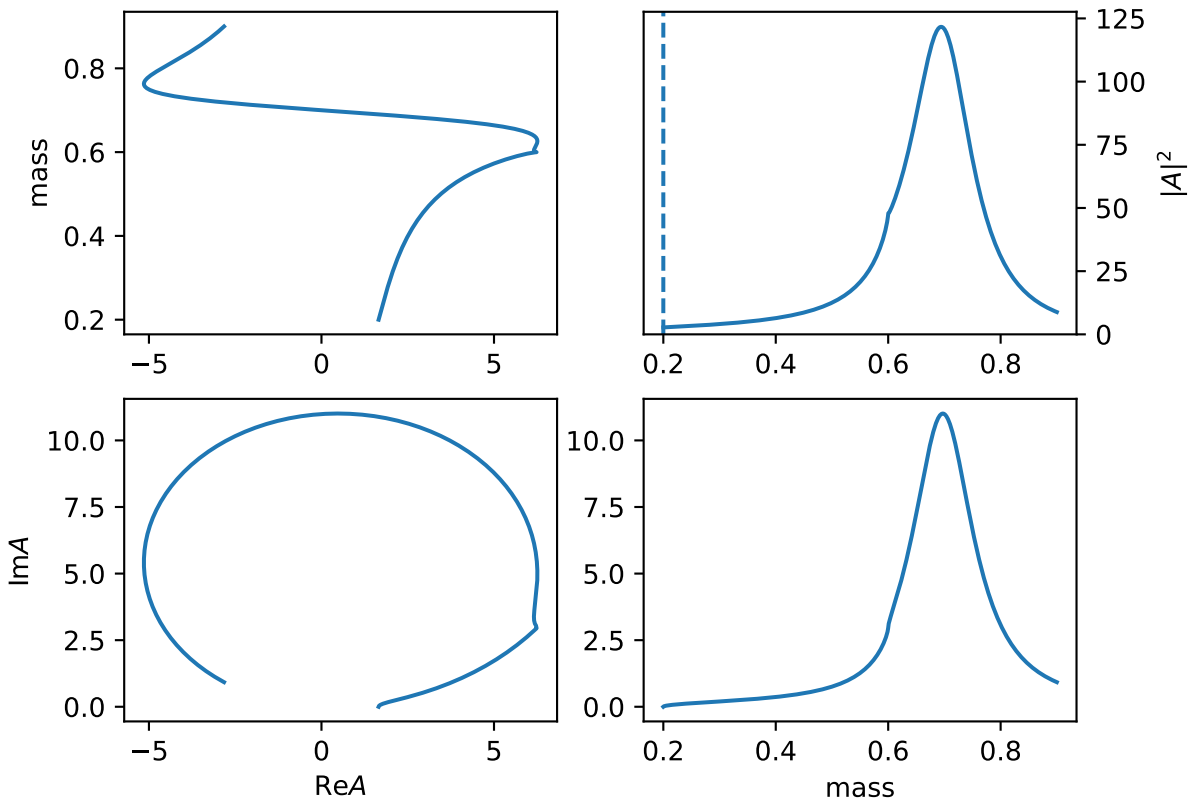
    General Flatte like formula.

$$R(m) = \frac{1}{m_0^2 - m^2 - im_0[\sum_i g_i^2 \frac{q_i}{m} \times \frac{m_0}{|q_{i0}|} \times \frac{|q_i|^{2l_i}}{|q_{i0}|^{2l_i}} B'^2_{l_i}(|q_i|, |q_{i0}|, d)]}$$

$$q_i = \begin{cases} \frac{\sqrt{(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)}}{2m} & (m^2 - (m_{i,1} + m_{i,2})^2)(m^2 - (m_{i,1} - m_{i,2})^2) >= 0 \\ \frac{i\sqrt{|(m^2-(m_{i,1}+m_{i,2})^2)(m^2-(m_{i,1}-m_{i,2})^2)|}}{2m} & (m^2 - (m_{i,1} + m_{i,2})^2)(m^2 - (m_{i,1} - m_{i,2})^2) < 0 \end{cases}$$

It has the same options as `FlatteGen`.


mass
0.8
0.6
0.4
0.2
−2.5
0.0
2.5
5.0
0.2
0.4
0.6
0.8
80
60
40
20
0
$|A|^2$
ImA
8
6
4
2
0
ReA
no_q0=True
no_m0=True
normal
mass


mass
0.8
0.6
0.4
0.2
−5
0
5
0.2
0.4
0.6
0.8
125
100
75
50
25
0
$|A|^2$
ImA
10.0
7.5
5.0
2.5
0.0
ReA
mass

17. "KMatrixSingleChannel" (*KmatrixSingleChannelParticle*)

    K matrix model for single channel multi pole.

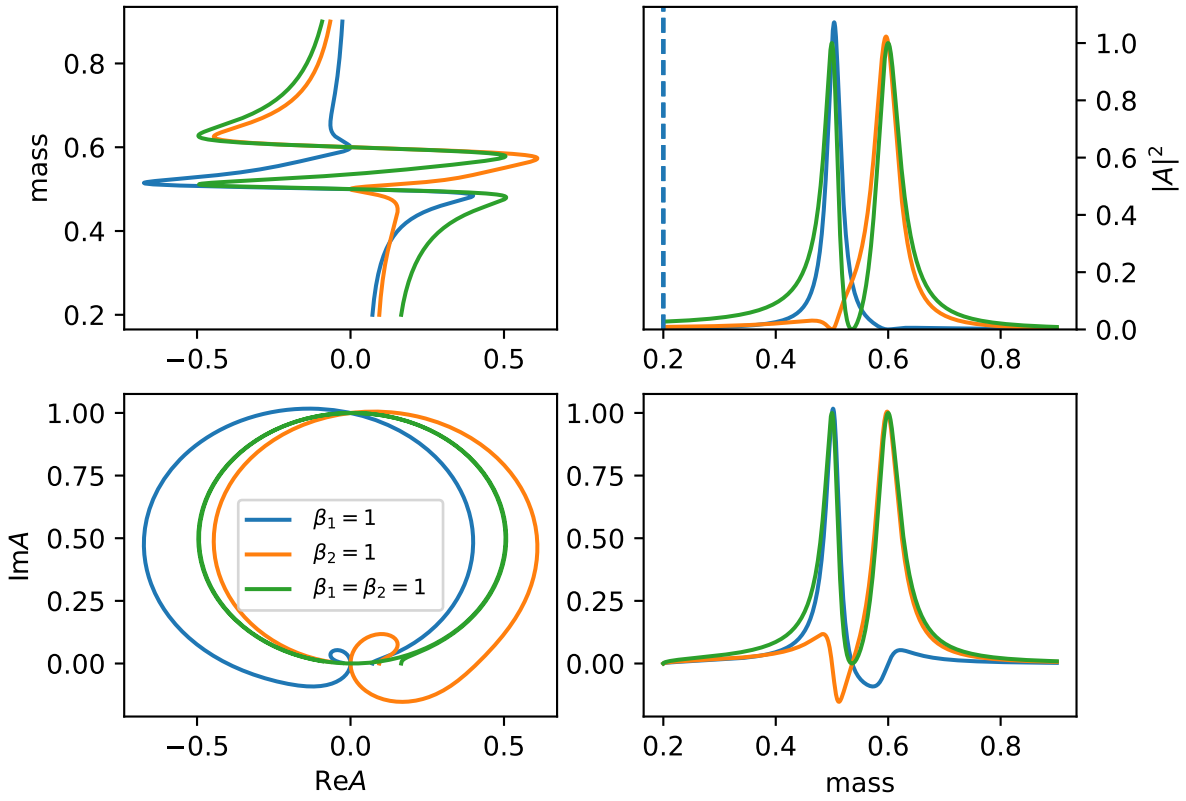
$$K = \sum_i \frac{m_i \Gamma_i(m)}{m_i^2 - m^2}$$

$$P = \sum_i \frac{\beta_i m_0 \Gamma_0}{m_i^2 - m^2}$$

    the barrier factor is included in gls

$$R(m) = (1 - iK)^{-1} P$$

    requird `mass_list: [pole1, pole2]` and `width_list: [width1, width2]`.



18. "KMatrixSplitLS" (*KmatrixSplitLSParticle*)

    K matrix model for single channel multi pole and the same channel with different (l, s) coupling.

$$K_{a,b} = \sum_i \frac{m_i \sqrt{\Gamma_{a,i}(m)\Gamma_{b,i}(m)}}{m_i^2 - m^2}$$

$$P_b = \sum_i \frac{\beta_i m_0 \Gamma_{b,i0}}{m_i^2 - m^2}$$

the barrier factor is included in gls

$$R(m) = (1 - iK)^{-1} P$$

19. `"KmatrixSimple"` (*KmatrixSimple*)

    simple Kmatrix formula.

    K-matrix

    $$K_{i,j} = \sum_a \frac{g_{i,a} g_{j,a}}{m_a^2 - m^2 + i\epsilon}$$

    P-vector

    $$P_i = \sum_a \frac{\beta_a g_{i,a}}{m_a^2 - m^2 + i\epsilon} + f_{bkg,i}$$

    total amplitude

    $$R(m) = n(1 - Ki\rho n^2)^{-1} P$$

    barrief factor

    $$n_{ii} = q_i^l B_l'(q_i, 1/d, d)$$

    phase space factor

    $$\rho_{ii} = q_i / m$$

    q_i is 0 when below threshold

20. `"BWR_LS"` (*ParticleBWRLS*)

    Breit Wigner with split ls running width

    $$R_i(m) = \frac{g_i}{m_0^2 - m^2 - i m_0 \Gamma_0 \frac{\rho}{\rho_0} (\sum_i g_i^2)}$$

    , $\rho = 2q/m$, the partial width factor is

    $$g_i = \gamma_i \frac{q^l}{q_0^l} B_{l_i}'(q, q_0, d)$$

    and keep normalize as

    $$\sum_i \gamma_i^2 = 1.$$

    The normalize is done by $(\cos\theta_0, \sin\theta_0 \cos\theta_1, \cdots, \prod_i \sin\theta_i)$

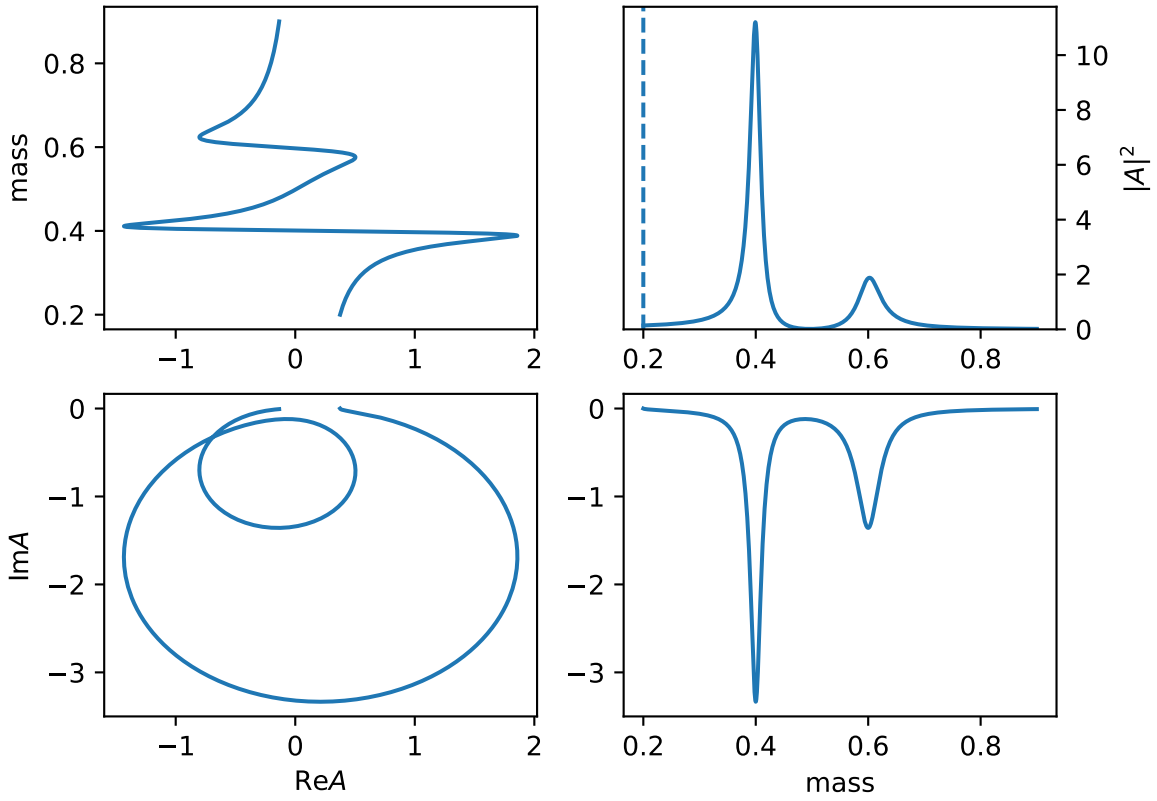
21. `"BWR_LS2"` (*ParticleBWRLS2*)

    Breit Wigner with split ls running width, each one use their own l,

    $$R_i(m) = \frac{1}{m_0^2 - m^2 - i m_0 \Gamma_0 \frac{\rho}{\rho_0} (g_i^2)}$$

    , $\rho = 2q/m$, the partial width factor is

    $$g_i = \gamma_i \frac{q^l}{q_0^l} B_{l_i}'(q, q_0, d)$$


mass
0.8
0.6
0.4
0.2
−1
0
1
2
0.2
0.4
0.6
0.8
10
8
6
4
2
0
$|A|^2$
0
−1
−2
−3
ImA
ReA
mass

22. `"MultiBWR"` (*ParticleMultiBWR*)

    Combine Multi BWR into one particle

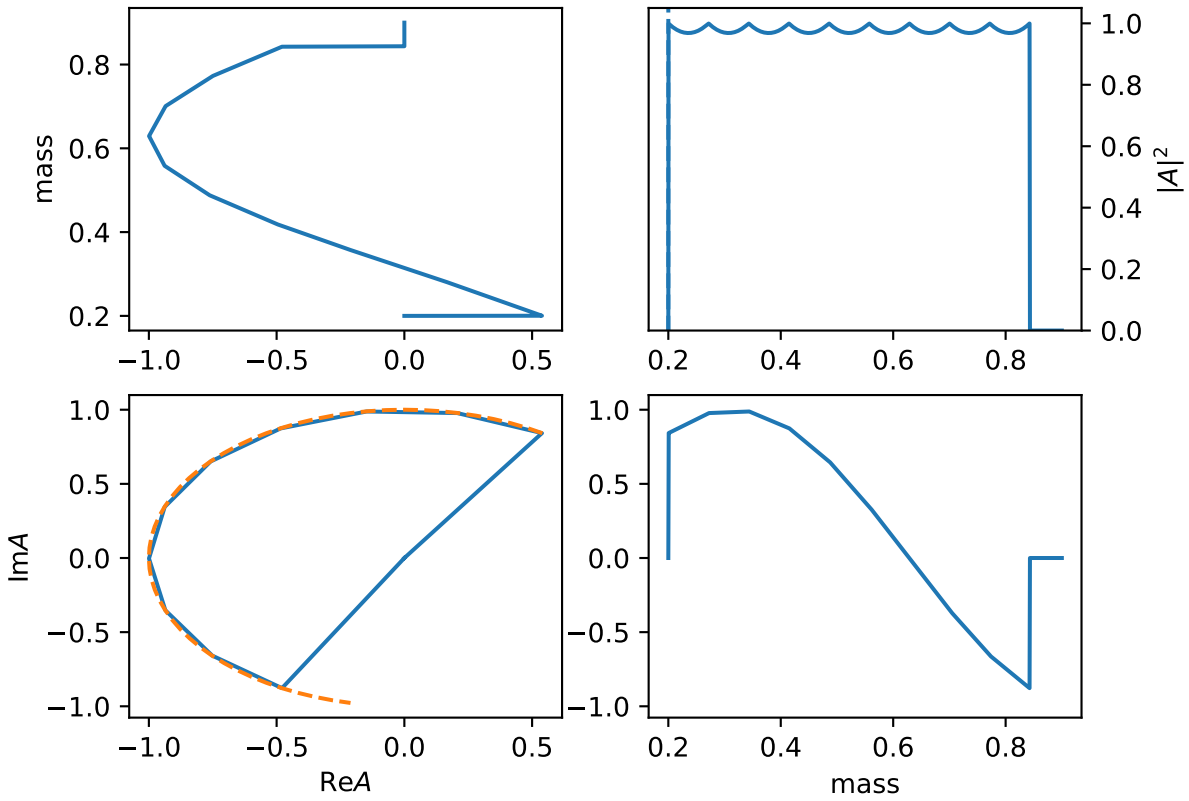
23. `"MultiBW"` (*ParticleMultiBW*)

    Combine Multi BW into one particle

24. `"linear_npy"` (*InterpLinearNpy*)

    Linear interpolation model from a `npy` file with array of [mi, re(ai), im(ai)]. Required `file: path_of_file.npy`, for the path of `npy` file.

    The example is `exp(5 I m)`.



25. `"linear_txt"` (*InterpLinearTxt*)

    Linear interpolation model from a `txt` file with array of [mi, re(ai), im(ai)].
    Required `file: path_of_file.txt`, for the path of `txt` file.

    The example is `exp(5 I m)`.

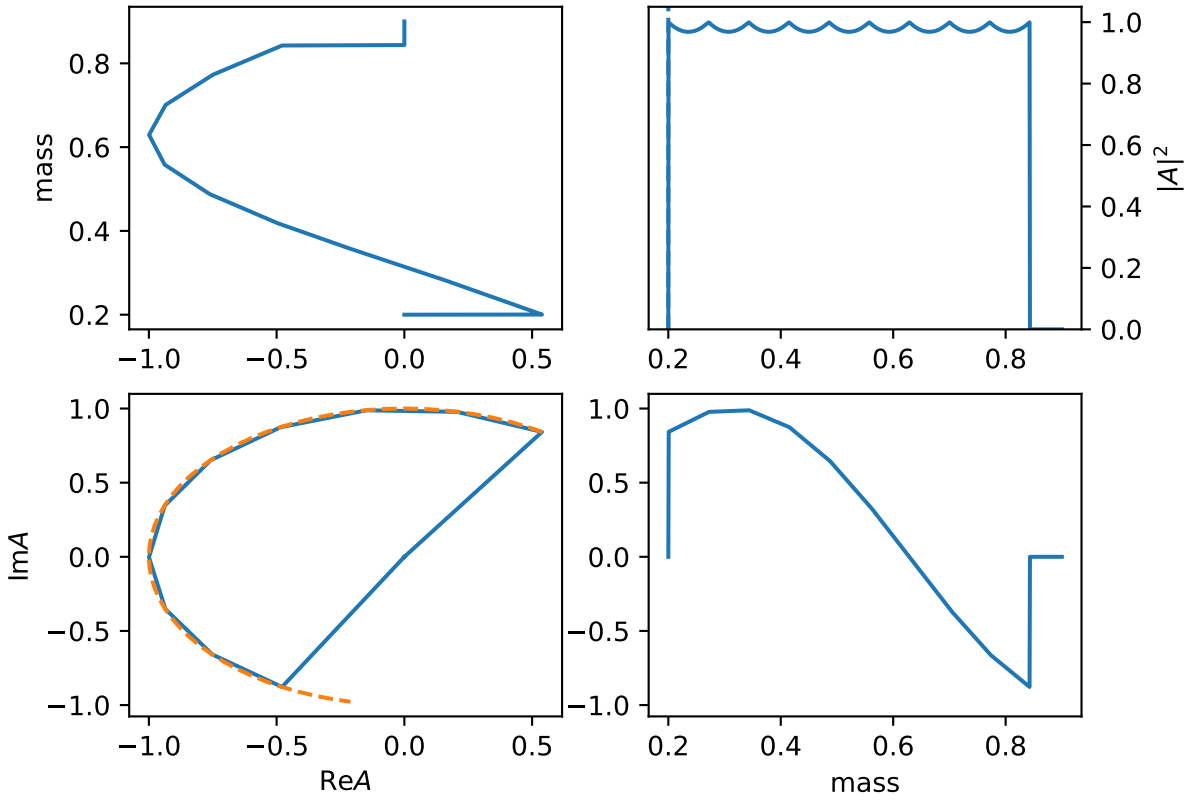
26. `"interp"` (*Interp*)

    linear interpolation for real number

27. `"interp_c"` (*Interp*)

    linear interpolation for complex number

28. `"spline_c"` (*Interp1DSpline*)


mass
0.8
0.6
0.4
0.2
−1.0
−0.5
0.0
0.5
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
$|A|^2$
ImA
1.0
0.5
0.0
−0.5
−1.0
ReA
mass

Spline interpolation function for model independent resonance

29. `"interp1d3"` (*Interp1D3*)

    Piecewise third order interpolation

30. `"interp_lagrange"` (*Interp1DLang*)

    Lagrange interpolation

31. `"interp_hist"` (*InterpHist*)

    Interpolation for each bins as constant

32. `"hist_idx"` (*InterpHistIdx*)

    Interpolation for each bins as constant

    use

    ```
    min_m: 0.19
    max_m: 0.91
    interp_N: 8
    with_bound: True
    ```

    for mass range [0.19, 0.91] and 7 bins

    The first and last are fixed to zero unless set `with_bound: True`.

    This is an example of $k\exp(ik)$ for point k.

33. `"spline_c_idx"` (*Interp1DSplineIdx*)

    Spline function in index way.

    use

    ```
    min_m: 0.19
    max_m: 0.91
    interp_N: 8
    with_bound: True
    ```

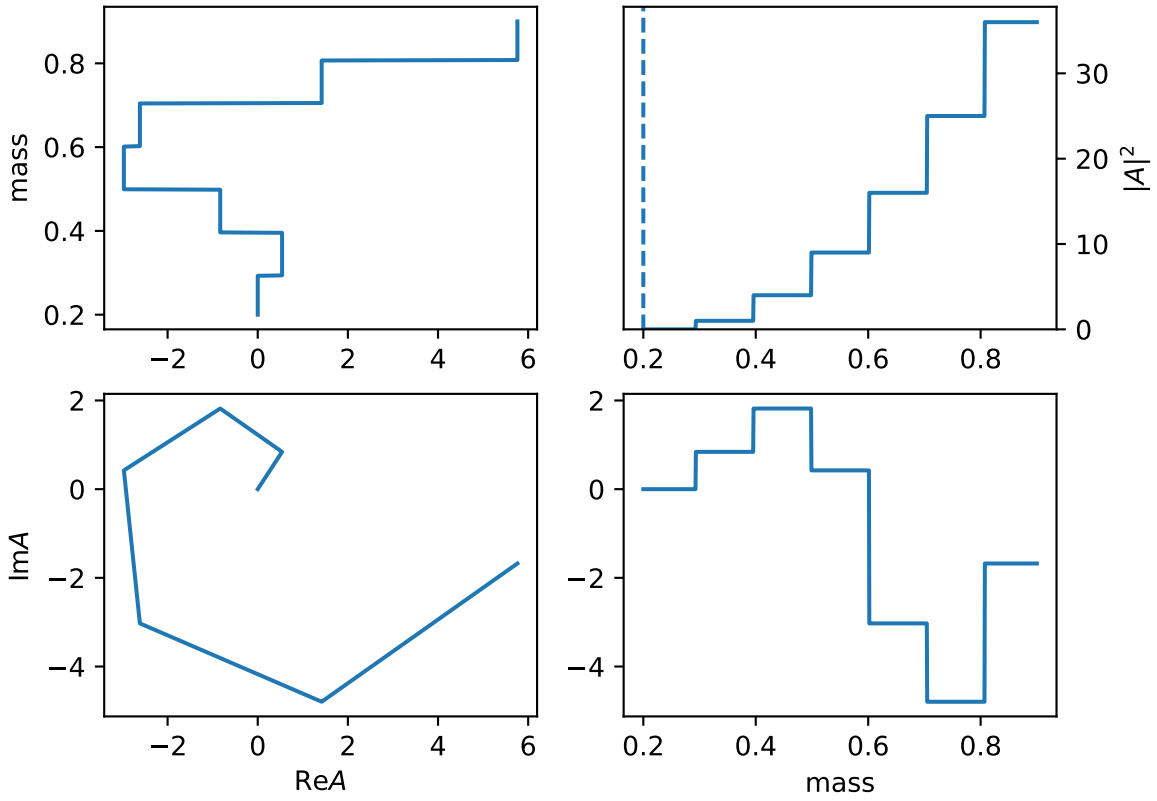
    for mass range [0.19, 0.91] and 8 interpolation points

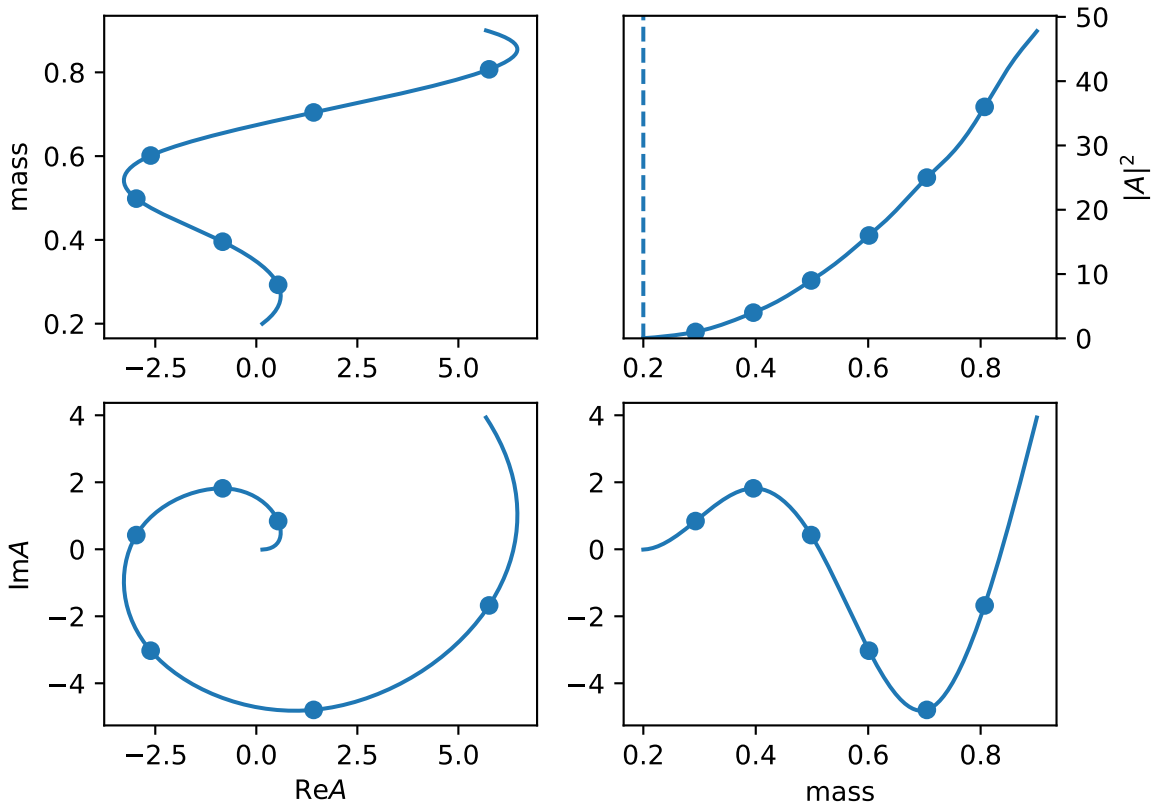
    The first and last are fixed to zero unless set `with_bound: True`.

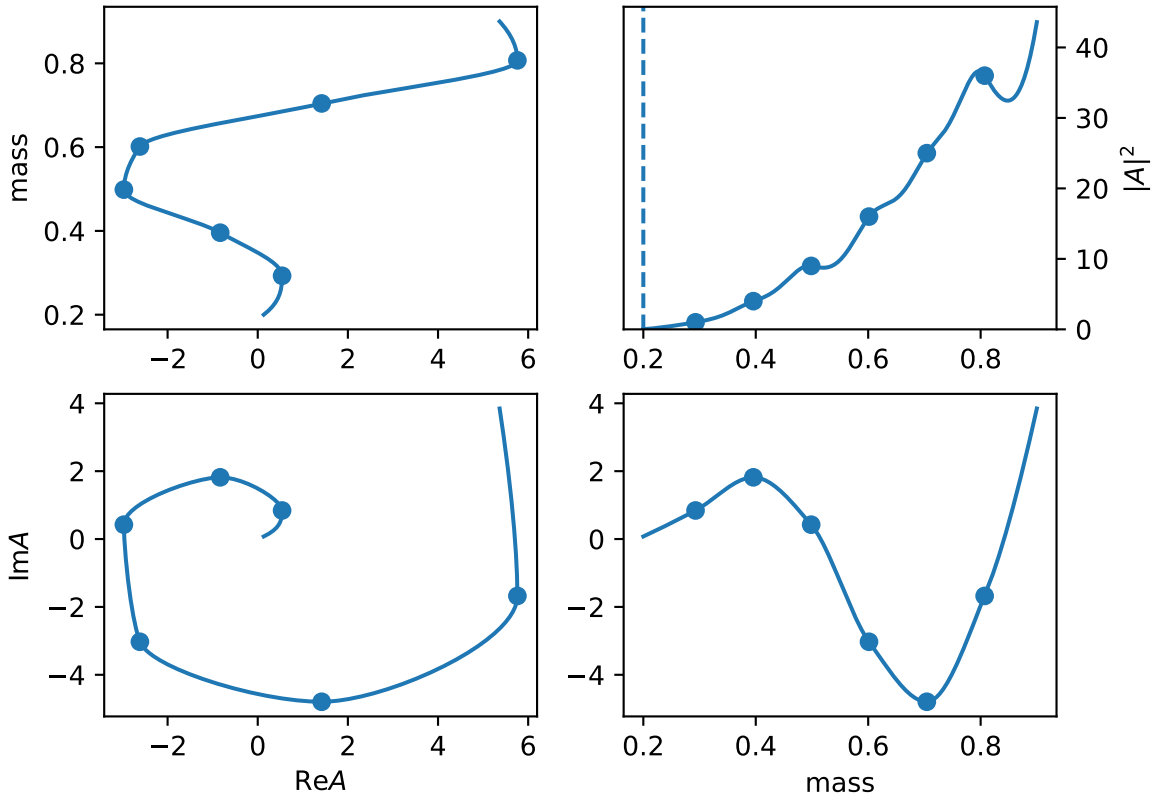
    This is an example of $k\exp(ik)$ for point k.

34. `"sppchip"` (*InterpSPPCHIP*)

    Shape-Preserving Piecewise Cubic Hermite Interpolation Polynomial. It is monotonic in each interval.


mass
0.8
0.6
0.4
0.2
−2
0
2
4
6
0.2
0.4
0.6
0.8
30
20
10
0
$|A|^2$
ImA
2
0
−2
−4
ReA
mass


mass
0.8
0.6
0.4
0.2
−2.5
0.0
2.5
5.0
0.2
0.4
0.6
0.8
50
40
30
20
10
0
$|A|^2$
ImA
4
2
0
−2
−4
ReA
mass


mass
0.8
0.6
0.4
0.2
−2
0
2
4
6
$|A|^2$
40
30
20
10
0
0.2
0.4
0.6
0.8
ImA
ReA
mass

CHAPTER

TWELVE

AVAILABLE DECAY MODEL

12.1 2-body decays

1. `"gls-bf", "default"` (*HelicityDecay*)

   default decay model

   The total amplitude is

   $$A = H^{A\to B+C}_{\lambda_B,\lambda_C} D^{J_A*}_{\lambda_A,\lambda_B-\lambda_C}(\varphi,\theta,0)$$

   The helicity coupling is

   $$H^{A\to B+C}_{\lambda_B,\lambda_C} = \sum_{ls} g_{ls}\sqrt{\frac{2l+1}{2J_A+1}}\langle l0;s\delta|J_A\delta\rangle\langle J_B\lambda_B;J_C-\lambda_C|s\delta\rangle q^l B'_l(q,q_0,d)$$

   The fit parameters is g_{ls}

   There are some options

   (1). `has_bprime=False` will remove the $B'_l(q,q_0,d)$ part.

   (2). `has_barrier_factor=False` will remove the $q^l B'_l(q,q_0,d)$ part.

   (3). `barrier_factor_norm=True` will replace q^l with $(q/q_0)^l$

   (4). `below_threshold=True` will replace the mass used to calculate q_0 with

   $$m_0^{eff} = m^{min} + \frac{m^{max}-m^{min}}{2}(1+tanh\frac{m_0-\frac{m^{max}+m^{min}}{2}}{m^{max}-m^{min}})$$

   (5). `l_list=[l1, l2]` and `ls_list=[[l1, s1], [l2, s2]]` options give the list of all possible LS used in the decay.

   (6). `no_q0=True` will set the $q_0 = 1$.

2. `"helicity_full"` (*HelicityDecayNP*)

   Full helicity amplitude

   $$A = H_{m_1,m_2} D^{J_0*}_{m_0,m_1-m_2}(\varphi,\theta,0)$$

   fit parameters is H_{m_1,m_2}.

3. `"helicity_parity"` (*HelicityDecayP*)

$$H_{-m1,-m2} = P_0 P_1 P_2 (-1)^{J_1+J_2-J_0} H_{m1,m2}$$

4. `"gls-cpv"` (*HelicityDecayCPV*)

   decay model for CPV

CHAPTER

THIRTEEN

TENSORFLOW AND CUDATOOLKIT VERSION

1. **Why are there two separate conda requirements file?**
    - `requirements-min.txt` limits the tensorflow version up to `2.2`. Beyond this version, `conda` will install the wrong dependency versions, in particular `cudatoolkit` versions and sometimes `python3`.
    - `tensorflow_2_6_requirements.txt` manually selects the correct `python` and `cudatoolkit` versions to match the `tensorflow-2.6.0` build on `conda-forge`.
2. **Should I use the latest `tensorflow` version?**
    - We **highly recommend** Ampere card users (RTX 30 series for example), to install their `conda` environments with `tensorflow_2_6_requirements.txt` which uses `cudatoolkit` version **11.2**.
3. **Why should Ampere use `cudatoolkit` version > 11.0?**
    - To avoid *a few minutes* of overhead due to JIT compilation.
    - `cudatoolkit` version **< 11.0** does not have pre-compiled CUDA binaries for Ampere architecture. So older `cudatoolkit` versions have to JIT compile the PTX code everytime `tensorflow` uses the GPU hence the overhead.
    - See this explanation about old CUDA versions and JIT compile.
4. **Will you update the `tensorflow_2_X_requirements.txt` file regularly to the latest available version on `conda`?**
    - We do not guarantee any regular updates on `tensorflow_2_X_requirements.txt`.
    - We will update this should particular build become unavailable on `conda` **or** a new release of GPUs require a `tensorflow` and `cudatoolkit` update. Please notify us if this is the case.

CHAPTER

FOURTEEN

FAQ

14.1 1. Precission Loss

```
message: Desired error not nescessarily achieved due to precision loss.
```

Check the jac value,

1.1 If all absulute value is small. it is acceptable beacuse of the precision.

1.2 If some absulte value is large. It is the bad parameters or problem in models.

1.3 Avoid negative weights

14.2 2. NaN value in fit

```
message: NaN result encountered.
```

14.2.1 2.1 Check the data.

There a script (scripts/check_nan.py) to check it.

2.1.1 No stange value in data, (nan, infs ...).

2.1.2 The data order should be E, p_x, p_y, p_z, E is the first.

2.1.3 The mass should be valid, $E^2 - p_x^2 - p_y^2 - p_z^2 > 0$, and for any combinations of final particles, mab > ma + mb.

2.1.4 Avoid 0 in weights.

14.2.2 2.2 Check the model.

2.2.1 The resonaces mass should be valid, for example in the mass range (m1+m2, m0-m3), out of the threshold required special options.

14.3 3. NaN value when getting params error.

```
numpy.linalg.LinAlgError: Array must not contain infs or NaN.
```

3.1 Similar as sec 2.2.

3.2 Bad fit parameters: too wide width or two narrow width, reach the boundary and so on.

3.3 Bad gradients. No gradients or the gradients is not corret for fit paramters.

14.4 4. Singular Matrix when getting params error

```
numpy.linalg.LinAlgError: Singular matrix
```

4.1 Free paramters are not used in model.

4.2 Used numpy for calculation of variable. The calculation have to be done in get_amp with TensorFlow.

```
...
  def init_params(self):
     self.a = self.add_var("a")
  def get_amp(self, data, *args, **kwargs):
     # avoid use numpy for varible as
     a = np.sin(self.a())
     # use tensorflow instead
     a = tf.sin(self.a())
```

14.5 5. Out of memory (OOM)

14.5.1 5.1 GPU

```
tensorflow.python.framework.errors_impl.ResourceExhaustedError: OOM when␣
↪allocating tensor with shape ... device:GPU:0 by allocator GPU_0_bfc [Op:...]
```

5.1.1 Reduce batch size at `config.fit(batch=65000)` and `config.get_params_error(batch=13000)` in fit.py.

5.1.2 Use option for large data size, such as lazy call

```
# config.yml
data:
   lazy_call: True
```

5.1.3 Try to use small data sample, or simple cases (less final particles).

5.1.4 Some speical model required large memory (such as interpolation model), try other model.

14.5.2 5.2 CPU

```
killed
```

5.2.1 Try to allocate more memory. There should be some options for job.

5.2.2 Similar as sec 5.1

14.6 6. Bad config.yml

14.6.1 6.1 yaml parse error

```
yaml.parser.ParserError: while parsing ..
```

Check the yaml file (see https://yaml.org): the indent, speical chars `,:}]`, unicode and so on.

14.6.2 6.2 Decay chain

```
AssertionError: not only one top particle
```

The decay chain should be complete. All the item in decay should decay from initial to finals.

14.6.3 6.3 Decay chain 2

```
RuntimeError: not decay chain aviable, check you config.yml
```

6.3.1 Similar as sec 6.2.

6.3.2 Check the information in *remove decay chain*, see the reson why those decays are not aviable.

ls not aviable means no possible LS combination allowed. Check the spin and parity. If allow parity voilate, add `p_break: True` to decay.

CHAPTER

FIFTEEN

FOR STARTERS

Take the decay in `config_sample.yml` for example, we will generate a toy, and then use it to conduct an analysis.

First, we use the class *ConfigLoader* to load the configuration file, and thus building the amplitude expression.

```
from tf_pwa.config_loader import ConfigLoader
config = ConfigLoader("config_sample.yml")
amp = config.get_amplitude()
```

We can also use a json file to set the parameters in the amplitude formula `config.set_params("parameters.json")`. Otherwise, the parameters are set randomly.

Next, we can use functions in *tf_pwa.applications* to directly generate data samples. We need to provide the masses of A and B, C, D to generate the PhaseSpace MC, and then use it to generate the toy data.

```
from tf_pwa.applications import gen_mc, gen_data
PHSP = gen_mc(mother=4.6, daughters=[2.00698, 2.01028, 0.13957], number=100000, outfile=
↪"PHSP.dat")
data = gen_data(amp, Ndata=5000, mcfile="PHSP.dat", genfile="data.dat")
```

Now that we have updated `data.dat` and `PHSP.dat`, we'd better load the configuration file again, and then fit the data.

```
config = ConfigLoader("config_sample.yml")
fit_result = config.fit()
```

Fitting is the major part of an analysis, and it could also be the most time-consuming part. For this example (the complexity of the amplitude expression matters a lot), the time for fitting is about xxx (running on xxxGPU). Then we can step further to complete the analysis, like calculating the fit fractions.

```
errors = config.get_params_error(fit_result)
fit_result.save_as("final_parameters.json")
fit_frac, err_frac = config.cal_fitfractions()
```

We can use *error_print* in *tf_pwa.utils* to print the fitting parameters as well as the fit fractions.

```
from tf_pwa.utils import error_print
print("########## fitting parameters:")
for key, value in config.get_params().items():
   print(key, error_print(value, errors.get(key, None)))
print("########## fit fractions:")
for i in fit_frac:
   print(i, " : " + error_print(fit_frac[i], err_frac.get(i, None)))
```

If the plotting options are also provided in the `config_sample.yml`, we can also plot the distributions of variables indicated in the configuration file.

```
config.plot_partial_wave(fit_result, prefix="figure/")
```

The figures will be saved under path `figure`. Here are the three invariant mass pairs for example.

(three pictures here)

We can do a lot more using *tf_pwa*. For more examples, please see path `tutorials`.

CHAPTER

SIXTEEN

INDICES AND TABLES

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PYTHON MODULE INDEX

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