Lecture 1: learn to use the binned pipeline

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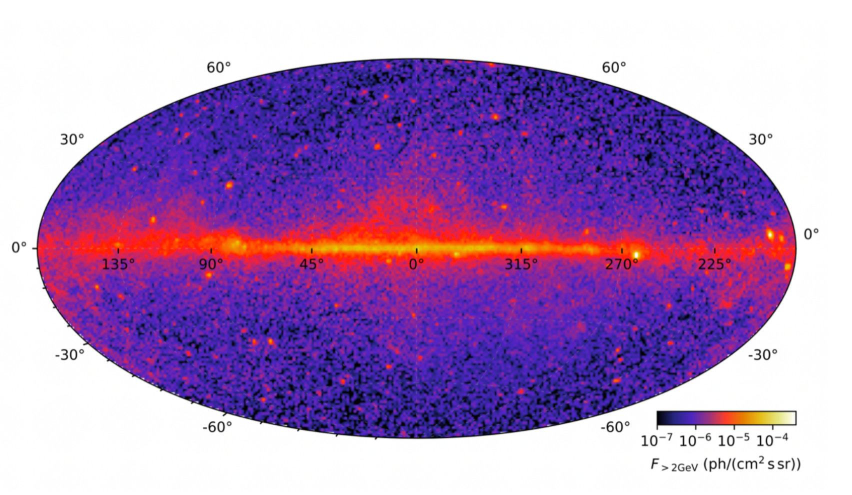
2024/08/27

Available at https://github.com/zqshen/DmpST_Tutorial_2024.git

0. The gamma-ray sky seen by DAMPE



There are lots of sources in the sky. **Astronomers are interested in the following things:**

- the significance of the source
- the location and spatial extention
- the energy spectrum
- the variability of the flux

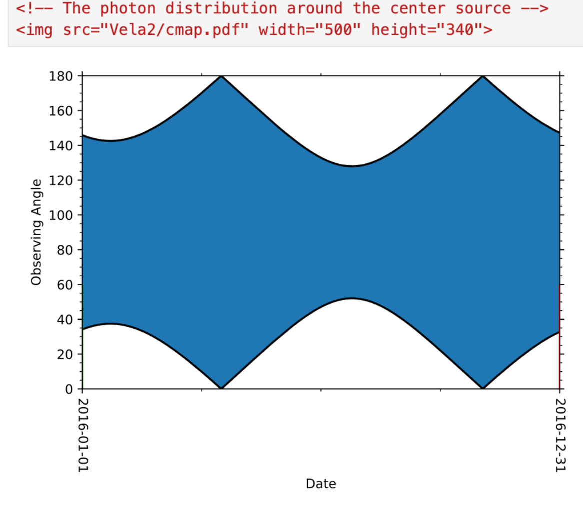
Based on these information, the nature of the sources could be deduced.

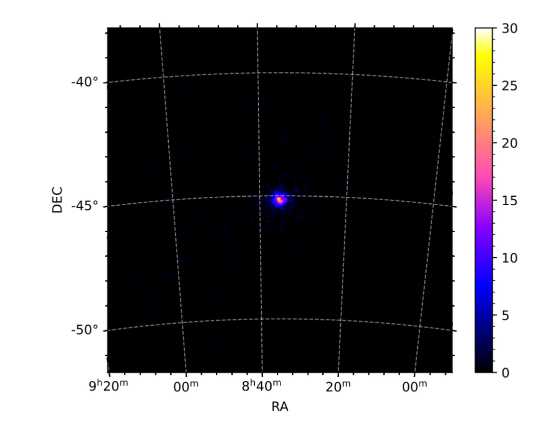
1. Let's recap what we learnt yesterday

```
%%bash
# 0. go to the folder where the DmpST, PH file, SC file locate
#cd /root/dampe

# 1. generate the observation angle to see if the source is detectable in the given time interval
python DmpST/scripts/FindObservedTime.py DAMPE_SC.fits Vela2 C 128.84 -45.18 2016-01-01 2017-01-01

# 2. see the counts map, energy distribution to grasp the idea of the data
python DmpST/scripts/GetInfo.py DAMPE_PH.fits Vela2 C 128.84 -45.18 5 0.1 CAR 3e3 3e5 10 2016-01-01 2017-01-01

# 3. generate the live time cube for the given data set (13 mins for ord 5, 4 mins for ord 4)
python DmpST/scripts/Dmpltcube.py DAMPE_SC.fits Vela2/events.fits Vela2/ltcube.fits --nthreads 2 -ord 5

# 4. fit the data with the model
cp Vela_input.yaml Vela2/
python DmpST/scripts/BinnedPipeline.py Vela2/events.fits DAMPE_SC.fits Vela2/ltcube.fits Vela2 Vela C 128.84 -45.18 \
7 5 0.1 CAR 3e3 3e5 10 2016-01-01 2017-01-01 --irf DmpST/DmpIRFs/
```

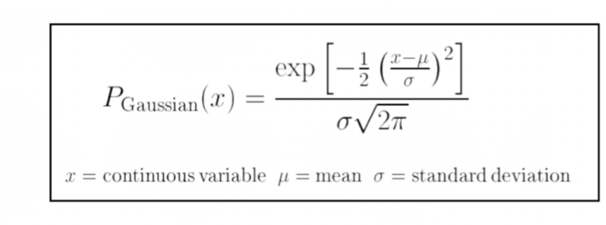
1) some of the figures

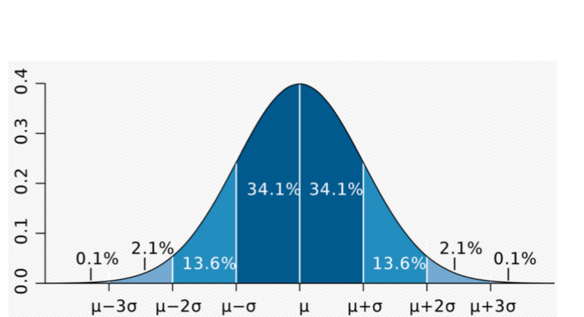
```
%%html
<!-- The boresight of the instrument w.r.t. the source. Time intervals w/ angle larger than 60deg can not see the source -->
<img src="Vela2/ObservedTime.pdf" width="500" height="340">

<!-- The photon distribution around the center source -->
<img src="Vela2/cmap.pdf" width="500" height="340">
```





2) significance





- Probability contained with +/- 1,2,3 standard deviations is (68.27, 95.45, 99.73)%
- For example, if a statement is said to have been verified with 3-sigma confidence, the implication is that it is expected to be true with a probability of 99.73%

```
%%bash

# a summary of fitted results
cat Vela2/Vela_results_BroadBand_binned.yaml
```

```
LikelihoodValue: 5103.350280055192
Vela:
  DEC_value: '-45.18'
  Flux_error: '8.70e-09'
  Index_scale: '-1.00e+00'
  Index_value: '3.50'
  Integral_error: '0.87'
  Integral_scale: '1.00e-08'
  Npred: '607.12'
  RA_value: '128.84'
  TsValue: 3671.264558148021
  UpperLimit_value: '300000.00'
  Flux_value: '9.91e-06'
  Index_value: '0.00'
  Normalization_scale: '1.00e+00'
  Normalization_value: '1.00'
  Prefactor_error: '0.19'
  Prefactor_scale: '1.00e+00'
  Prefactor_value: '1.11'
  Scale_value: '100.00'
  TsValue: 34.2645614800349
iso_diffuse_source:
  Flux_error: '6.14e-06'
  Flux_value: '1.01e-05'
  Index_value: '-2.40'
  Integral_error: '4.88'
  Integral_scale: '1.00e-07'
  Integral_value: '8.03'
  LowerLimit_value: '3000.00'
  Npred: '70.63'
  TsValue: 2.951097990897324
  UpperLimit_value: '300000.00'
  Value_scale: '1.00e+00'
  Value_value: '1.00'
```

According to the mathematical theorem (Wilks1938), **TS_value follows the χ^2 distribution,** whose degrees of freedom are the number of free parameters for the source.

```
[3]: ## the significance of Vela in first year
import numpy as np
from scipy import stats

# vela pulsar
tsval = 3671.264558148021
print('significance is approximately {:.2f} [sigma]'.format(np.sqrt(tsval)))

#pval = stats.chi2.sf(tsval, df=2)
#print('significance is', stats.norm.isf(pval/2), '[sigma]') ## tsval is too large
```

```
significance is approximately 60.59 [sigma]
```

3) spectrum

```
[54]: %%bash

# input gamma-ray model
cat Vela_input.yaml

# fitted gamma-ray model
# cat Vela2/Vela_fitModel_BroadBand_binned.yaml
```

```
Vela:
  name: Vela
  type: PointSource
  spatialModel:
    type: SkyDirFunction
    RA: {free: 0, max: 360.0,min: -360.0,name: RA, scale: 1.0, value: 128.84}
    DEC: {free: 0, max: 90.0, min: -90.0, name: DEC, scale: 1.0, value: -45.18}
  spectrum:
    type: PowerLaw2
    Integral: {free: 1, min: 1e-3, max: 1e3, name: Integral, scale: 1e-8, value: 1}
    Index: {free: 1, min: 0, max: 10, name: Index, scale: -1, value: 2}
    LowerLimit: {free: 0, min: 3e3, max: 1e6, name: LowerLimit, scale: 1, value: 3e3}
    UpperLimit: {free: 0, min: 3e3, max: 1e6, name: UpperLimit, scale: 1, value: 3e5}

gal_diffuse_source:
  name: gal_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: MapCubeFunction
    Normalization: {free: 0, max: 1e3, min: 1e-3, name: Normalization, scale: 1.0, value: 1.0}
    file: dampe_gal_diffuse_model_v2_fix.fits
  spectrum:
    type: PowerLaw
    Prefactor: {free: 1, max: 10, min: 0, name: Prefactor, scale: 1, value: 1}
    Index: {free: 0, max: 1, min: -1, name: Index, scale: 1.0, value: 0}
    Scale: {free: 0, max: 2e2, min: 5e1, name: Scale, scale: 1.0, value: 1e2}

iso_diffuse_source:
  name: iso_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: ConstantValue
    Value: {free: 0, max: 10.0, min: 0.0, name: Value, scale: 1.0, value: 1.0}
  spectrum:
    type: PowerLaw2
    Integral: {free: 1, max: 1e3, min: 1e-3, name: Integral, scale: 1e-7, value: 1}
    Index: {free: 0, min: 0, max: 10, name: Index, scale: -1, value: 2.4}
    LowerLimit: {free: 0, min: 3e3, max: 1e6, name: LowerLimit, scale: 1, value: 3e3}
    UpperLimit: {free: 0, min: 3e3, max: 1e6, name: UpperLimit, scale: 1, value: 3e5}
```

some spectral types

There are lots of **spectral types**, some of which are listed below:

- **PowerLaw**:

  $\frac{dN}{dE} = N_0\left(\frac{E}{E_0}\right)^{\gamma}$

  where Prefactor = N_0, Index = γ, Scale = E_0.

- **PowerLaw2**:

  $\frac{dN}{dE} = \frac{N(\gamma+1)E^{\gamma}}{E_{\max}^{\gamma+1}-E_{\min}^{\gamma+1}}$

  where Integral = N, Index = γ, LowerLimit = $E_{\min}$, UpperLimit = $E_{\max}$.

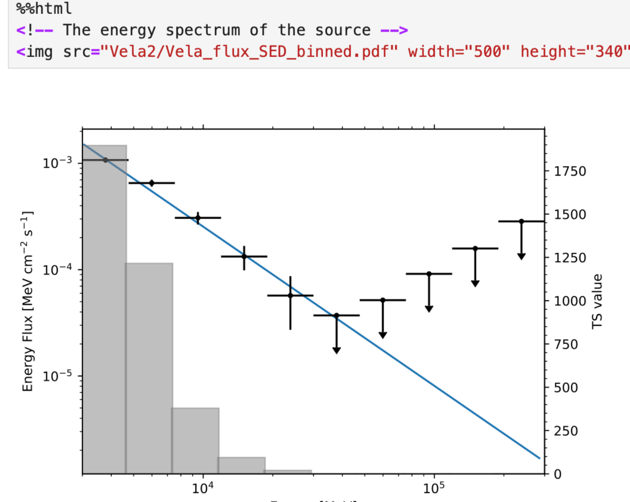
- **LogParabola**:

  $\frac{dN}{dE} = N_0\left(\frac{E}{E_b}\right)^{-(\alpha+\beta\ln(E/E_b))}$

  where norm = N_0, alpha =α, beta = β, Eb = E_b.

spectral energy distribution

```
[28]: %%html
<!-- The energy spectrum of the source -->
<img src="Vela2/Vela_flux_SED_binned.pdf" width="500" height="340">
```




```
[38]: %%bash

# a summary of fitted results
cat Vela2/Vela_results_BroadBand_binned.yaml
```

```
LikelihoodValue: 5103.350280055192
Vela:
  DEC_value: '-45.18'
  Flux_error: '8.70e-09'
  Index_scale: '-1.00e+00'
  Index_value: '3.50'
  Integral_error: '0.87'
  Integral_scale: '1.00e-08'
  Npred: '607.12'
  RA_value: '128.84'
  TsValue: 3671.264558148021
  UpperLimit_value: '300000.00'
  Flux_value: '9.91e-06'
  Index_value: '0.00'
  Normalization_scale: '1.00e+00'
  Normalization_value: '1.00'
  Prefactor_error: '0.19'
  Prefactor_scale: '1.00e+00'
  Prefactor_value: '1.11'
  Scale_value: '100.00'
  TsValue: 34.2645614800349
iso_diffuse_source:
  Flux_error: '6.14e-06'
  Flux_value: '1.01e-05'
  Index_value: '-2.40'
  Integral_error: '4.88'
  Integral_scale: '1.00e-07'
  Integral_value: '8.03'
  LowerLimit_value: '3000.00'
  Npred: '70.63'
  TsValue: 2.951097990897324
  UpperLimit_value: '300000.00'
  Value_scale: '1.00e+00'
  Value_value: '1.00'
```

We can find that the **integrated flux of Vela between 3 GeV and 300 GeV is $(2.05 \pm 0.09) \times 10^{-7}\,\mathrm{cm^{-2}\,s^{-1}}$**.

The flux can also been found in the **Vela_flux_BroadBand_binned.dat** file.

```
[39]: %%bash

cat Vela2/Vela_flux_BroadBand_binned.dat

## rows are
# lower_energy_bound [MeV]
# upper_energy_bound [MeV]
# integrated_flux_value [cm^-2 s^-1]
# integrated_flux_error [cm^-2 s^-1]
# TS_value of the source
```

```
3.000000000000000000e+03
3.000000000000000000e+05
2.053910642011451620e-07
8.702317680177163679e-09
3.671264558148021024e+03
```

4) the best-fit model map

The model map is stored as **Vela_mdlcube.fits**, you can visualize it using tools such as SAODS9 or plot it with Python

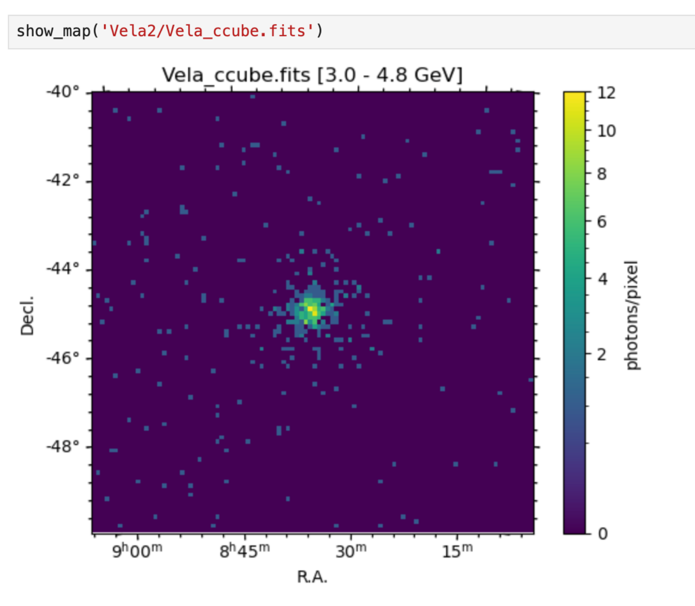
```
[8]: %%bash

# firstly, find the file
fitsinfo Vela2/Vela_mdlcube.fits
# the total map has the number of 5
```

```
Filename: Vela2/Vela_mdlcube.fits
No.    Name      Ver    Type      Cards   Dimensions   Format
  0  SKYMAP        1 PrimaryHDU      23   (100, 100, 10)   int64
  1  EBOUNDS       1 BinTableHDU     15   10R x 2C   [D, D]
  2  Vela          1 ImageHDU        24   (100, 100, 10)   float64
  3  gal_diffuse_source    1 ImageHDU        24   (100, 100, 10)   float64
  4  iso_diffuse_source    1 ImageHDU        24   (100, 100, 10)   float64
  5  AllSource     1 ImageHDU        24   (100, 100, 10)   float64
```

```
[9]: ## define a function for map visualization
def show_map(mcubefile, fitsidx=0, ibin=0, outfile=None):
    """
    mcubefile: the location of mdlcube.fits file
    fitsidx:   int, the index of the AllSource row in the mdlcube.fits file
    ibin:      int, the energy bin to visualize
    outfile:   the output file name
    """
    from matplotlib import pyplot as plt
    from matplotlib import colors
    from DmpST import SkyMap
    # the binned model cube in each energy bin
    mcube = SkyMap.Ccube(mcubefile, hdu=fitsidx) # the index of AllSource is 5
    # make figure
    fig = plt.figure()#figsize=(6, 5))
    fig.add_subplot(111, projection=mcube.wcs)
    im = plt.imshow(mcube.data[:,:,ibin].T, origin='lower', norm=colors.PowerNorm(0.5))
    cb = plt.colorbar(im, label='photons/pixel')
    plt.xlabel('R.A.')
    plt.ylabel('Decl.')
    plt.title(mcubefile.split('/')[-1] + ' [%.1f - %.1f GeV]'%(mcube.emins[ibin]/1e3, mcube.emaxs[ibin]/1e3))
    if outfile is not None:
        plt.savefig(outfile)
    else:
        plt.show()
```

```
[32]: show_map('Vela2/Vela_mdlcube.fits', 5)#, outfile='fig_mdlmap.png')
```


```
[11]: show_map('Vela2/Vela_ccube.fits')
```



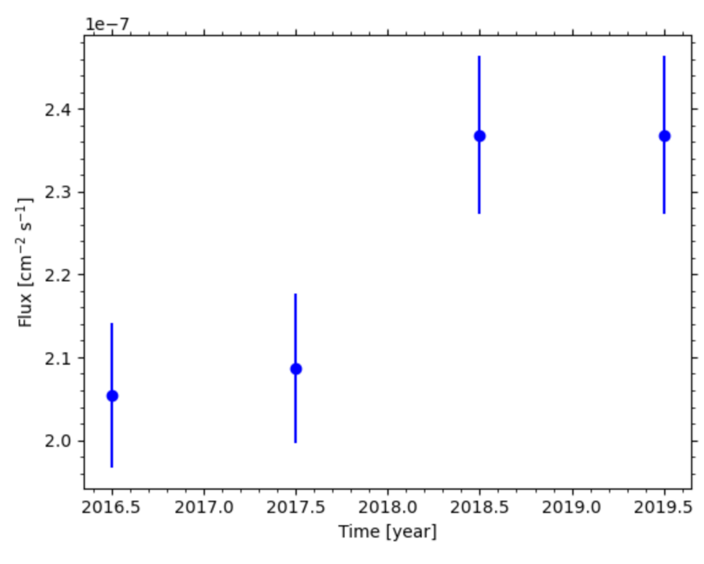
5) the light curve

```
[ ]: %%bash

year=2018
year2=$(($year+1))


# 1. generate the observation angle to see if the source is detectable in the given time interval
python  DmpST/scripts/FindObservedTime.py  DAMPE_SC.fits  Vela${year}  C  128.84  -45.18  ${year}-01-01  ${year2}-01-01

# 2. see the counts map, energy distribution to grasp the idea of the data
python  DmpST/scripts/GetInfo.py  DAMPE_PH.fits  Vela${year}  C  128.84  -45.18   5   0.1  CAR  3e3  3e5  10  ${year}-01-01  ${year2}-01-01

# 3. generate the live time cube for the given data set (13 mins for ord 5, 4 mins for ord 4)
# python DmpST/scripts/Dmpltcube.py  DAMPE_SC.fits  Vela2017/events.fits  Vela2017/ltcube.fits  --nthreads 2  -ord 5
python  DmpST/scripts/Dmpltcube.py  DAMPE_SC.fits  Vela${year}/events.fits  Vela${year}/ltcube.fits -ord 4

# 4. fit the data with the model
cp  Vela_input.yaml  Vela${year}/
python  DmpST/scripts/BinnedPipeline.py  Vela${year}/events.fits  DAMPE_SC.fits  Vela${year}/ltcube.fits   Vela${year}   Vela   C   \
128.84  -45.18    7   5   0.1  CAR  3e3  3e5  10  ${year}-01-01  ${year2}-01-01   --irf DmpST/DmpIRFs/
```

```
[ ]: # make a script

## 1. save the script above to a file named with 'run.sh'
## 2. add '#!/bin/bash' to the header of run.sh
## 3. run 'chmod +x run.sh' in the shell
## 4. then './run.sh'
```

```
[56]: import numpy as np
from matplotlib import pyplot as plt

time = 2016.5
fluxdat = np.loadtxt('Vela2/Vela_flux_BroadBand_binned.dat') # 2016
plt.errorbar(time, fluxdat[2], yerr=fluxdat[3], marker='o', color='b')

time = 2017.5
fluxdat = np.loadtxt('Vela2017/Vela_flux_BroadBand_binned.dat') # 2017
plt.errorbar(time, fluxdat[2], yerr=fluxdat[3], marker='o', color='b')

time = 2018.5
fluxdat = np.loadtxt('Vela2018/Vela_flux_BroadBand_binned.dat') # 2018
plt.errorbar(time, fluxdat[2], yerr=fluxdat[3], marker='o', color='b')

time = 2019.5
fluxdat = np.loadtxt('Vela2018/Vela_flux_BroadBand_binned.dat') # 2019
plt.errorbar(time, fluxdat[2], yerr=fluxdat[3], marker='o', color='b')

plt.xlabel('Time [year]')
plt.ylabel('Flux [$\\rm cm^{-2}~s^{-1}$]')
```

```
[56]: Text(0, 0.5, 'Flux [$\\rm cm^{-2}~s^{-1}$]')
```



Lecture 2: gamma-ray analyses in depth

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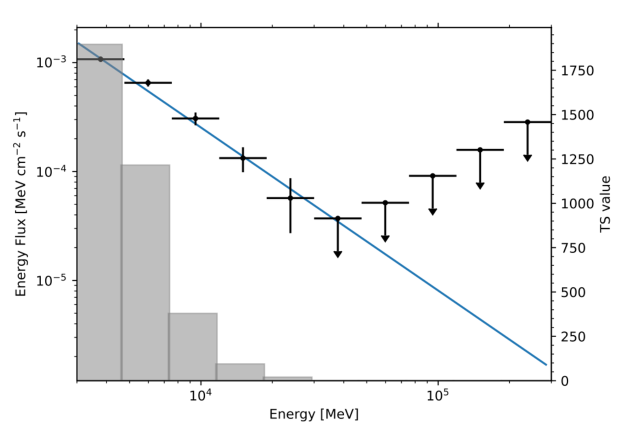
2024/06/27

In the previous lecture,

- we learnt the basic usage of **DmpST**,
- practised running the data analysis pipeline,
- fit the Vela model to the data.

```
# CLI: python BinnedPipeline.py               evfile           scfile          ltcube       path srcName GorC xref   yref
rad freerad binsz proj emin emax ebins UTCmin UTCmax
python DmpST/scripts/BinnedPipeline.py  Vela2/events.fits  DAMPE_SC.fits  Vela2/ltcube.fits Vela2  Vela   C  128.84 -45.18
7   5  0.1   CAR  3e3  3e5 10 2016-01-01 2017-01-01 --irf DmpST/DmpIRFs/
```

This is what we get:



Good...

In this lecture

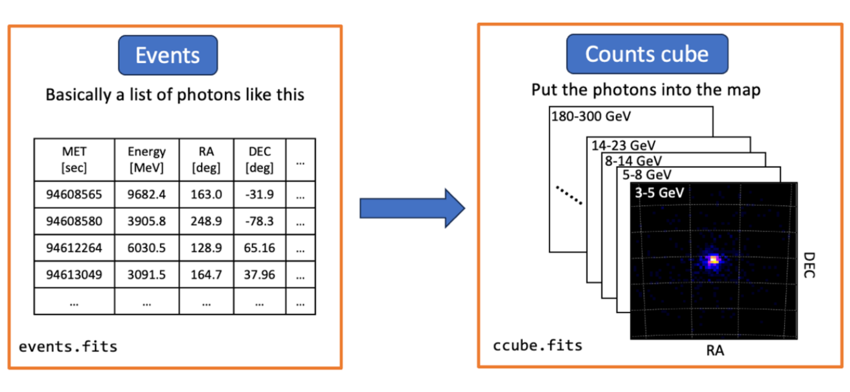
We will go a step further, and try to answer

- *what has acturally been done* in the pipeline

1. About the binned pipeline

Step 1: prepare data

- choose the region of interest around your source
- select the time interval, and the energy range
- bin the photons into the maps



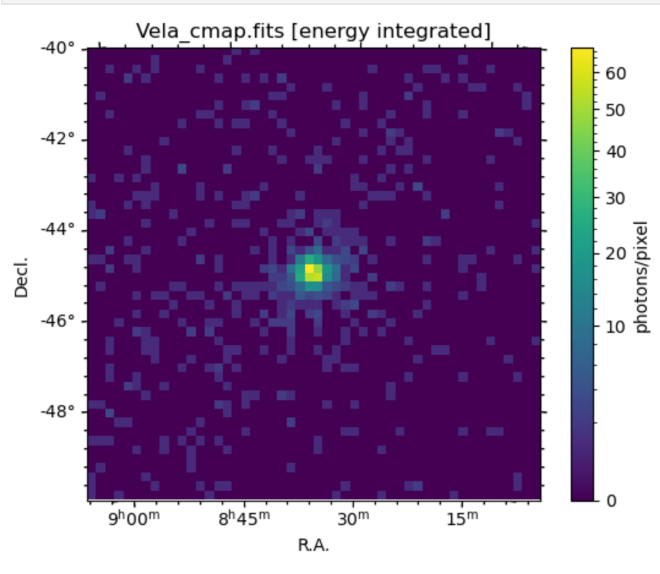
[12]:
```python
## input from argument
path = 'analysis1'
srcname = 'Vela'

# on the data selection
ra, dec = 128.84, -45.18 #[deg], ra, dec of Vela pulsar
emin, emax = 3e3, 3e5 # [MeV], 3-300 GeV
roi = 7 # [deg], the radius of circular region
tmin, tmax = '2016-01-01', '2017-01-01'

# on the data binning
ebins = 10 # 10 energy bins between 3-300 GeV
freerad = 5 # [deg], radius of the inscribed circle of the rectangular ROI
binsz = 0.2 # [deg], the size of each pixel

# input files
evfile = 'DAMPE_PH.fits' # events file
scfile = 'DAMPE_SC.fits'
```

[13]:
```python
from DmpST import Events, DmpTime

# line 36-37
minmet, maxmet = DmpTime.UTC2MET(tmin), DmpTime.UTC2MET(tmax)

# line 47-54
allevents = Events.Events(evfile)

ROIevents = allevents.CircleSelect(outfile='{}/{}_events.fits'.format(path, srcname), # output event file
    xref=ra, yref=dec, rad=roi, tmin=minmet, tmax=maxmet, emin=emin, emax=emax, # selection
    GorC='C', cosThetamin=0.5, cosThetamax=1, evtype=2) # misc parameters

npix = int(2*freerad/binsz)
# the energy integrated map
ROIevents.Cmap(outfile='{}/{}_cmap.fits'.format(path, srcname),
    nxpix=npix, nypix=npix, binsz=binsz, GorC='C', xref=ra, yref=dec, proj='CAR')
# the map w/ energy bins
ROIevents.Ccube(outfile='{}/{}_ccube.fits'.format(path, srcname), # output counts cube file
    nxpix=npix, nypix=npix, binsz=binsz, xref=ra, yref=dec, GorC='C', proj='CAR', # the pixel binning
    emin=emin, emax=emax, ebins=ebins) # energy binning
```

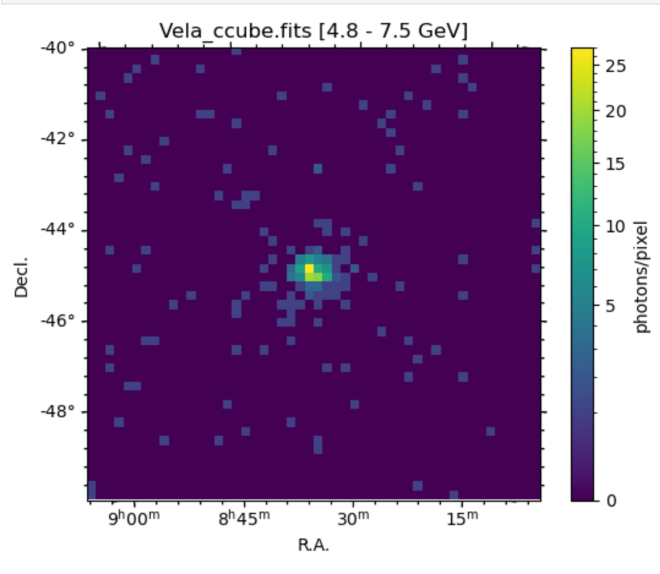
```
make cmap for the photons...............................
make ccube for the photons...............................
```

[13]: `<DmpST.SkyMap.NewCcube at 0x179545d60>`

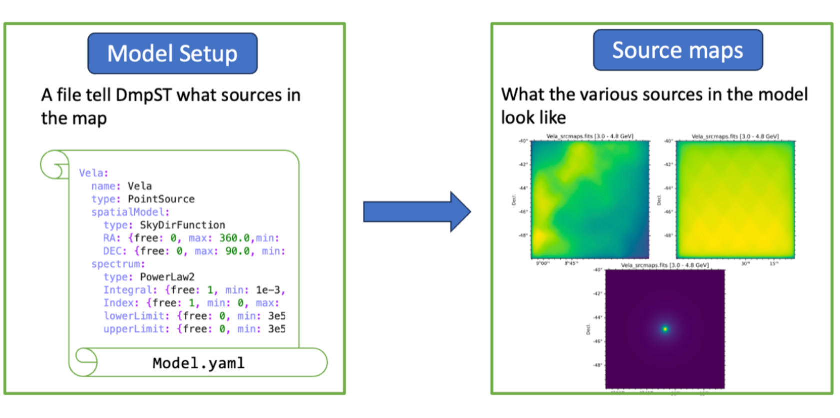
[14]:
```python
# Let's see the binned map w/ energy integrated
import numpy as np
from matplotlib import pyplot as plt, colors
from DmpST import SkyMap
%matplotlib inline

cmapfile = '{}/{}_cmap.fits'.format(path, srcname)
cmap = SkyMap.Cmap(cmapfile)

fig = plt.figure()#figsize=(6, 5))
fig.add_subplot(111, projection=cmap.wcs)
im = plt.imshow(cmap.data.T, origin='lower', norm=colors.PowerNorm(0.5))
cb = plt.colorbar(im, label='photons/pixel')
plt.xlabel('R.A.')
plt.ylabel('Decl.')
plt.title(cmapfile.split('/')[-1] + ' [energy integrated]')
plt.show()
```



[15]:
```python
# the binned map in each energy bin
ccubefile = '{}/{}_ccube.fits'.format(path, srcname)
ccube = SkyMap.Ccube(ccubefile)

ibin = 1 # which energy bin to analyze

fig = plt.figure()#figsize=(6, 5))
fig.add_subplot(111, projection=ccube.wcs)
im = plt.imshow(ccube.data[:,:,ibin].T, origin='lower', norm=colors.PowerNorm(0.5))
cb = plt.colorbar(im, label='photons/pixel')
plt.xlabel('R.A.')
plt.ylabel('Decl.')
plt.title(ccubefile.split('/')[-1] + ' [%.1f - %.1f GeV]'%(ccube.emins[ibin]/1e3, ccube.emaxs[ibin]/1e3))
plt.show()
```



Step 2: construct gamma-ray model and fit



In gamma-ray data analyses, the inference of the source's parameters is done by comparing the parameterized maps to the observed ones.

- The map *without* instrumental responses is

$$N = \int \frac{dN}{dEd\Omega} A(E,\theta) dE d\Omega dt$$

ModelMap $\sim \sum_i^{n_{comp}}$ **Flux**$_i$ $\times$ **Exposure**$_i$

- The map *with* instrumental responses is

$$N' = \int\int N(E,\theta) P(\theta'; E, \theta) D(E'; E, \theta) dE' d\Omega'$$

Now let's first calculate the livetime cube, which tell us **for the given data what the observing time is at each point in the sky**. With it, we can easily calculate the exposure ($\sim$ area $\times$ time).

[16]:
```bash
%%bash
# let's first run this because it will take a lot of time
python DmpST/scripts/Dmpltcube.py DAMPE_SC.fits analysis1/Vela_events.fits Vela_ltcube.fits -ord 5
# NOTE: please use -ord 6 in real data analysis. Here we set ord=5 so as to speed up the calculation
```

There are several components, as clearly shown in the map, in the sky:

- **point-like sources** (only Vela here):

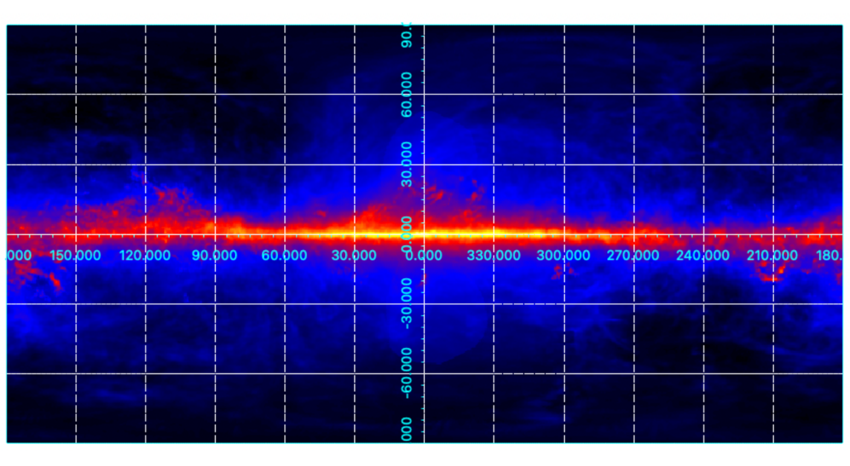
$$S(E, \hat{p}, t) = \sum_i s_i(E, t) \delta(\hat{p} - \hat{p}_i)$$

- **isotropic emission**:

$$+S_{eg}(E, \hat{p})$$

- **galactic diffuse emission** (map is below):

$$+S_G(E, \hat{p})$$



Based on it, we can make a parameterized model as follows:

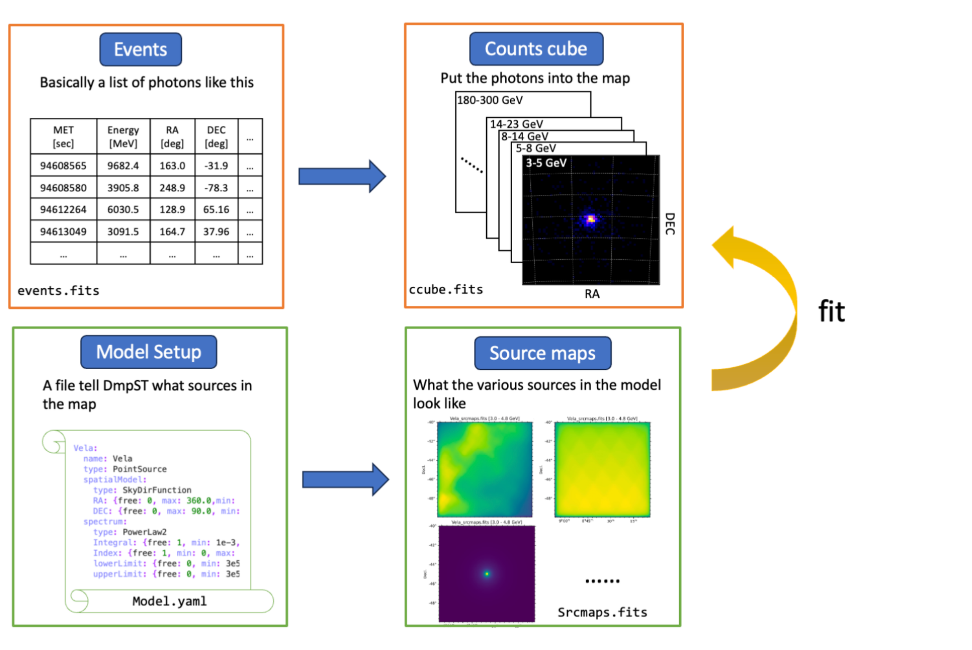
```yaml
Vela:
  name: Vela
  type: PointSource
  spatialModel:
    type: SkyDirFunction
    RA:  {free: 0, max: 360.0,min: -360.0, name: RA,  scale: 1.0, value: 128.84}
    DEC: {free: 0, max: 90.0, min: -90.0,  name: DEC, scale: 1.0, value: -45.18}
  spectrum:
    type: PowerLaw2
    Integral:   {free: 1, min: 1e-3, max: 1e3, name: Integral,   scale: 1e-8, value: 1}
    Index:      {free: 1, min: 0,    max: 10,  name: Index,      scale: -1,   value: 2}
    LowerLimit: {free: 0, min: 3e3,  max: 1e6, name: LowerLimit, scale: 1,    value: 3e3}
    UpperLimit: {free: 0, min: 3e3,  max: 1e6, name: UpperLimit, scale: 1,    value: 3e5}

gal_diffuse_source:
  name: gal_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: MapcubeFunction
    Normalization: {free: 0, max: 1e3, min: 1e-3, name: Normalization, scale: 1.0, value: 1.0}
    file: dampe_gal_diffuse_model_v2_fix.fits
  spectrum:
    type: PowerLaw
    Prefactor: {free: 1, max: 10,  min: 0,   name: Prefactor, scale: 1,   value: 1}
    Index:     {free: 0, max: 1,   min: -1,  name: Index,     scale: 1.0, value: 0}
    Scale:     {free: 0, max: 1e4, min: 3e3, name: Scale,     scale: 1.0, value: 5000}

iso_diffuse_source:
  name: iso_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: ConstantValue
    Value: {free: 0, max: 10.0, min: 0.0, name: Value, scale: 1.0, value: 1.0}
  spectrum:
    type: PowerLaw2
    Integral:   {free: 1, max: 1e3, min: 1e-3, name: Integral,   scale: 1e-7,value: 1}
    Index:      {free: 0, min: 0,   max: 10,   name: Index,      scale: -1,  value: 2.4}
    LowerLimit: {free: 0, min: 3e3, max: 1e6,  name: LowerLimit, scale: 1,   value: 3e3}
    UpperLimit: {free: 0, min: 3e3, max: 1e6,  name: UpperLimit, scale: 1,   value: 3e5}
```

For the Galactic diffuse emission and isotropic emission, the recommendation parameters are set as above. For the point sources, you may either set by yourself or simply refer to the DAMPE point catalog.

[17]:
```python
from DmpST import LikelihoodAnalysis, Model

pars= {'srcName': 'Vela',
        'ltcube': 'Vela_ltcube.fits',
         'ccube': 'analysis1/Vela_ccube.fits',
       'srcmaps': 'analysis1/Vela_srcmaps.fits',
        'srcmdl': 'analysis1/Vela_input.yaml',
          'emin': emin,
          'emax': emax,
   'cosThetamin': 0.5,
   'cosThetamax': 1.,
           'irf': 'DmpST/DmpIRFs',
        'evtype': 2,
      'CubeType': 'Map'}

# calculate the expected map of each component and convolve the responses
Binned = LikelihoodAnalysis.BinnedAnalysis(**pars)
```

```
'Binned Analysis parameters:'
{'CubeType': 'Map',
 'ccube': 'analysis1/Vela_ccube.fits',
 'cosThetamax': 1.0,
 'cosThetamin': 0.5,
 'emax': 300000.0,
 'emin': 3000.0,
 'evtype': 2,
 'irf': 'DmpST/DmpIRFs',
 'ltcube': 'Vela_ltcube.fits',
 'srcName': 'Vela',
 'srcmaps': 'analysis1/Vela_srcmaps.fits',
 'srcmdl': 'analysis1/Vela_input.yaml'}
analysis1/Vela_srcmaps.fits
the energy range is [0]:3000.0MeV to [9]:300000.0MeV
Add  Vela
Add  gal_diffuse_source
Add  iso_diffuse_source
```

Step 3: Fit the model to the data



[18]:
```python
import warnings
warnings.filterwarnings("ignore")

Binned.Fit(hesse=True, Npred=True, Flux=True, TsValue=True, srcmaps=True, mdlcube=True)

Binned.SaveFitModel('analysis1/Vela_fitModel_BroadBand_binned.yaml') # the fitted model
Binned.SaveFitResults('analysis1/Vela_results_BroadBand_binned.yaml') # a summary of fitted parameters
Binned.SaveMdlCube('analysis1/modelcube_global.fits') # save the best-fit model map
```

```
Minuit Starting......
{'Vela__Index': 2.0, 'limit_Vela__Index': (0.0, 10.0), 'error_Vela__Index': 0.2, 'Vela__Integral': 1.0, 'limit_Vela__Integral': (0.001, 1000.0), 'error_Vela__Integral': 0.1, 'gal_diffuse_source__Prefactor': 1.0, 'limit_gal_diffuse_source__Prefactor': (0.0, 10.0), 'error_gal_diffuse_source__Prefactor': 0.1, 'iso_diffuse_source__Integral': 1.0, 'limit_iso_diffuse_source__Integral': (0.001, 1000.0), 'error_iso_diffuse_source__Integral': 0.1}
Migrad Start......
Calculate the srcmap for Vela
Calculate the srcmap for gal_diffuse_source
Calculate the srcmap for iso_diffuse_source
Hesse Start......
Calculate Npred of Vela
Calculate Npred of gal_diffuse_source
Calculate Npred of iso_diffuse_source
Calculate Flux of Vela
Calculate Flux of gal_diffuse_source
Calculate Flux of iso_diffuse_source
Calculate TsValue of Vela
Minuit Starting......
{'gal_diffuse_source__Prefactor': 1.1209283035395705, 'limit_gal_diffuse_source__Prefactor': (0.0, 10.0), 'error_gal_diffuse_source__Prefactor': 0.18918502785232666, 'iso_diffuse_source__Integral': 7.395743562485617, 'limit_iso_diffuse_source__Integral': (0.001, 1000.0), 'error_iso_diffuse_source__Integral': 4.848346426039819}
Migrad Start......
Calculate TsValue of gal_diffuse_source
Minuit Starting......
{'Vela__Index': 3.298945543905616, 'limit_Vela__Index': (0.0, 10.0), 'error_Vela__Index': 0.10803280276211491, 'Vela__Integral': 21.817449904360455, 'limit_Vela__Integral': (0.001, 1000.0), 'error_Vela__Integral': 0.9211102068550687, 'iso_diffuse_source__Integral': 7.395743562485617, 'limit_iso_diffuse_source__Integral': (0.001, 1000.0), 'error_iso_diffuse_source__Integral': 4.848346426039819}
Migrad Start......
Calculate TsValue of iso_diffuse_source
Minuit Starting......
{'Vela__Index': 3.298945543905616, 'limit_Vela__Index': (0.0, 10.0), 'error_Vela__Index': 0.10803280276211491, 'Vela__Integral': 21.817449904360455, 'limit_Vela__Integral': (0.001, 1000.0), 'error_Vela__Integral': 0.9211102068550687, 'gal_diffuse_source__Prefactor': 1.1209283035395705, 'limit_gal_diffuse_source__Prefactor': (0.0, 10.0), 'error_gal_diffuse_source__Prefactor': 0.18918502785232666}
Migrad Start......
```

1. model map

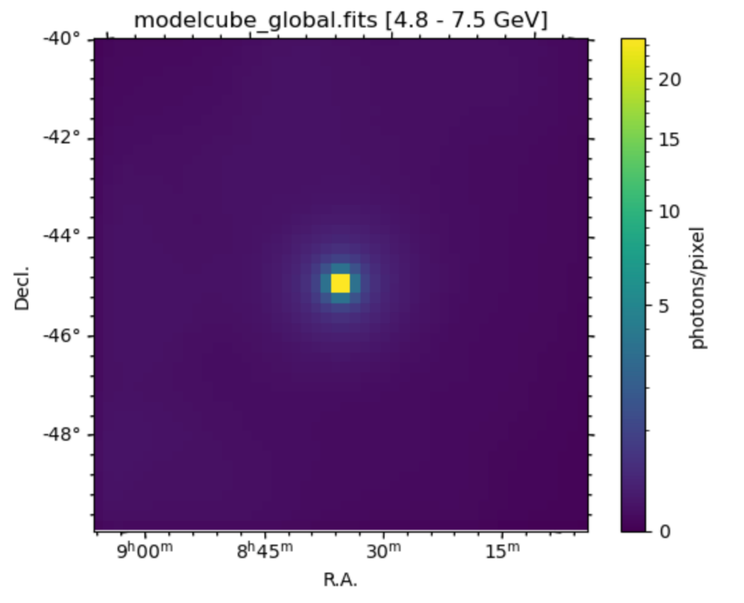
The model map is the expected counts map that generated assuming the best-fit sources' parameters

Let's have a look.

[19]:
```bash
%%bash
# first to see what is the index of the cube
fitsinfo analysis1/modelcube_global.fits
```

```
Filename: analysis1/modelcube_global.fits
No.    Name      Ver    Type      Cards   Dimensions   Format
  0  SKYMAP        1 PrimaryHDU      23   (50, 50, 10)   int64
  1  EBOUNDS       1 BinTableHDU     15   10R x 2C   [D, D]
  2  Vela          1 ImageHDU        24   (50, 50, 10)   float64
  3  gal_diffuse_source    1 ImageHDU        24   (50, 50, 10)   float64
  4  iso_diffuse_source    1 ImageHDU        24   (50, 50, 10)   float64
  5  AllSource     1 ImageHDU        24   (50, 50, 10)   float64
```

[20]:
```python
# the binned model cube in each energy bin
mcubefile = 'analysis1/modelcube_global.fits'
mcube = SkyMap.Ccube(mcubefile, hdu=5) # the index of AllSource is 5

ibin = 1 # which energy bin to analyze

fig = plt.figure()#figsize=(6, 5))
fig.add_subplot(111, projection=mcube.wcs)
im = plt.imshow(mcube.data[:,:,ibin].T, origin='lower', norm=colors.PowerNorm(0.5))
cb = plt.colorbar(im, label='photons/pixel')
plt.xlabel('R.A.')
plt.ylabel('Decl.')
plt.title(mcubefile.split('/')[-1] + ' [%.1f - %.1f GeV]'%(mcube.emins[ibin]/1e3, mcube.emaxs[ibin]/1e3))
plt.show()
```



2. summary of best-fit parameters

[21]:
```
%%bash
# cat analysis1/Vela_fitModel_BroadBand_binned.yaml
cat analysis1/Vela_results_BroadBand_binned.yaml
```

```
LikelihoodValue: 2532.391793876096
Vela:
  DEC_value: '-45.18'
  Flux_error: '9.21e-09'
  Flux_value: '2.18e-07'
  Index_error: '0.11'
  Index_scale: '-1.00e+00'
  Index_value: '3.30'
  Integral_error: '0.92'
  Integral_scale: '1.00e-08'
  Integral_value: '21.82'
  LowerLimit_value: '3000.00'
  Npred: '610.36'
  RA_value: '128.84'
  TsValue: 3625.7256985488993
  UpperLimit_value: '300000.00'
gal_diffuse_source:
  Flux_error: '1.69e-06'
  Flux_value: '9.99e-06'
  Index_value: '0.00'
  Normalization_scale: '1.00e+00'
  Normalization_value: '1.00'
  Npred: '270.04'
  Prefactor_error: '0.19'
  Prefactor_scale: '1.00e+00'
  Prefactor_value: '1.12'
  Scale_value: '100.00'
  TsValue: 35.529414757471386
iso_diffuse_source:
  Flux_error: '6.10e-06'
  Flux_value: '9.29e-06'
  Index_value: '-2.40'
  Integral_error: '4.85'
  Integral_scale: '1.00e-07'
  Integral_value: '7.40'
  LowerLimit_value: '3000.00'
  Npred: '65.65'
  TsValue: 2.557233693820308
  UpperLimit_value: '300000.00'
  Value_scale: '1.00e+00'
  Value_value: '1.00'
```

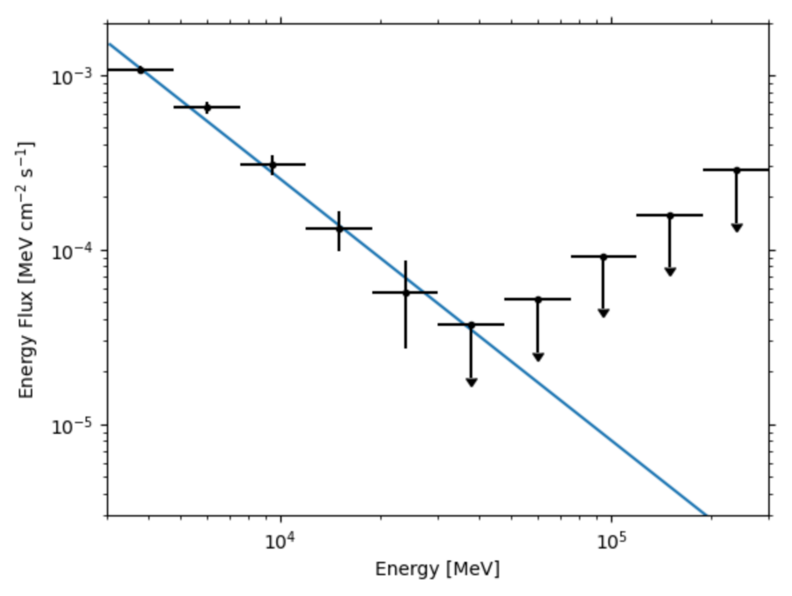
3. spectrum checking

Sometimes the spectral parameterization may not be good, you can check the spectral energy distribution (SED) obtained from the pipeline. Here we will not show the code (but I can tell you that it basically run the same fitting in every energy bins).

Here I only refer to the results that you have already obtained.

[22]:
```python
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline

def plotsed_simple(global_specfile, sed_specfile):
    # global fit
    Es, dNdEgls = np.loadtxt(global_specfile).T

    # sed
    data = np.loadtxt(sed_specfile)
    emins, emaxs, fluxs, fluxerrs, tsvals, fluxuls = data[:,0], data[:,1], data[:,2], data[:,3], data[:,4], data[:,5]

    emids = np.sqrt(emins * emaxs)
    eerrs = np.array([emids-emins, emaxs-emids])
    E2dNdEs = emids**2 * fluxs / (emaxs - emins)
    E2dNdEers = emids**2 * fluxerrs / (emaxs - emins)
    E2dNdEuls = emids**2 * fluxuls / (emaxs - emins)

    # make figure
    fig, ax = plt.subplots()
    condition = (Es>=emins[0]) & (Es<= emaxs[-1])
    plt.plot(Es[condition], Es[condition]**2 * dNdEgls[condition])
    ax.errorbar(emids[tsvals>9], E2dNdEs[tsvals>9], xerr=eerrs[:,tsvals>9], yerr=E2dNdEers[tsvals>9], fmt='.k', label='DAMPE')
    ax.errorbar(emids[tsvals<9], E2dNdEuls[tsvals<9], xerr=eerrs[:,tsvals<9], yerr=E2dNdEuls[tsvals<9]/2., fmt='.k', uplims=True)
    ax.set_xlim(emins[0], emaxs[-1])
    ax.set_xscale('log')
    ax.set_yscale('log')
    ax.set_xlabel(r'Energy [MeV]')
    ax.set_ylabel(r'Energy Flux [MeV cm$^{-2}$ s$^{-1}$]')

## make plot
plotsed_simple('analysis0/Vela_BroadBand_Spectrum.dat', 'analysis0/Vela_flux_SED_binned.dat')
plt.ylim(3e-6,2e-3)
```

[22]: (3e-06, 0.002)



Step 4: what we can further do?

improve the spectral parameterization

Here is part of the our model

```
Vela:
  spectrum:
    type: PowerLaw2
    Integral:   {free: 1, min: 1e-3, max: 1e3, name: Integral,   scale: 1e-8, value: 1}
    Index:      {free: 1, min: 0,    max: 10,  name: Index,      scale: -1,   value: 2}
    LowerLimit: {free: 0, min: 3e3,  max: 1e6, name: LowerLimit, scale: 1,    value: 3e3}
    UpperLimit: {free: 0, min: 3e3,  max: 1e6, name: UpperLimit, scale: 1,    value: 3e5}
```

You may find the PowerLaw model can not well fit the SED of the source, probably you can change to something like LogParabola spectrum

```
Vela:
  spectrum:
    type: LogParabola
    norm:  {free: 1, min: 1e-3, max: 1e3, name: norm,  scale: 1e-9, value: 1}
    alpha: {free: 1, min: -10,  max: 10,  name: alpha, scale: 1,    value: 2}
    Eb:    {free: 0, min: 1e3,  max: 1e6, name: Eb,    scale: 1,    value: 2e3}
    beta:  {free: 1, min: -10,  max: 10, name: beta,   scale: 1,    value: 0.4}
```

Actually, we have implemented all the spectral types that Fermi-LAT science has. You can check **here** for the details on the spectral types.

[23]:
```
%%bash
# revise the yaml file
cat analysis2/Vela_input.yaml
```

```
Vela:
  name: Vela
  type: PointSource
  spatialModel:
    type: SkyDirFunction
    RA: {free: 0, max: 360.0,min: -360.0,name: RA, scale: 1.0, value: 128.84}
    DEC: {free: 0, max: 90.0, min: -90.0, name: DEC, scale: 1.0, value: -45.18}
  spectrum:
    type: LogParabola
    norm:  {free: 1, min: 1e-3, max: 1e3, name: norm,  scale: 1e-9, value: 1}
    alpha: {free: 1, min: -10,  max: 10,  name: alpha, scale: 1,    value: 2}
    Eb:    {free: 0, min: 1e3,  max: 1e6, name: Eb,    scale: 1,    value: 2e3}
    beta:  {free: 1, min: -10,  max: 10, name: beta,   scale: 1,    value: 0.4}

gal_diffuse_source:
  name: gal_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: MapCubeFunction
    Normalization: {free: 0, max: 1e3, min: 1e-3, name: Normalization, scale: 1.0, value: 1.0}
    file: dampe_gal_diffuse_model_v2_fix.fits
  spectrum:
    type: PowerLaw
    Prefactor: {free: 1, max: 10, min: 0, name: Prefactor, scale: 1, value: 1}
    Index: {free: 0, max: 1, min: -1, name: Index, scale: 1.0, value: 0}
    Scale: {free: 0, max: 2e2, min: 5e1, name: Scale, scale: 1.0, value: 1e2}

iso_diffuse_source:
  name: iso_diffuse_source
  type: DiffuseSource
  spatialModel:
    type: ConstantValue
    Value: {free: 0, max: 10.0, min: 0.0, name: Value, scale: 1.0, value: 1.0}
  spectrum:
    type: PowerLaw2
    Integral: {free: 1, max: 1e3, min: 1e-3, name: Integral, scale: 1e-7, value: 1}
    Index: {free: 0, min: 0, max: 10, name: Index, scale: -1, value: 2.4}
    LowerLimit: {free: 0, min: 3e3, max: 1e6, name: LowerLimit, scale: 1, value: 3e3}
    UpperLimit: {free: 0, min: 3e3, max: 1e6, name: UpperLimit, scale: 1, value: 3e5}
```

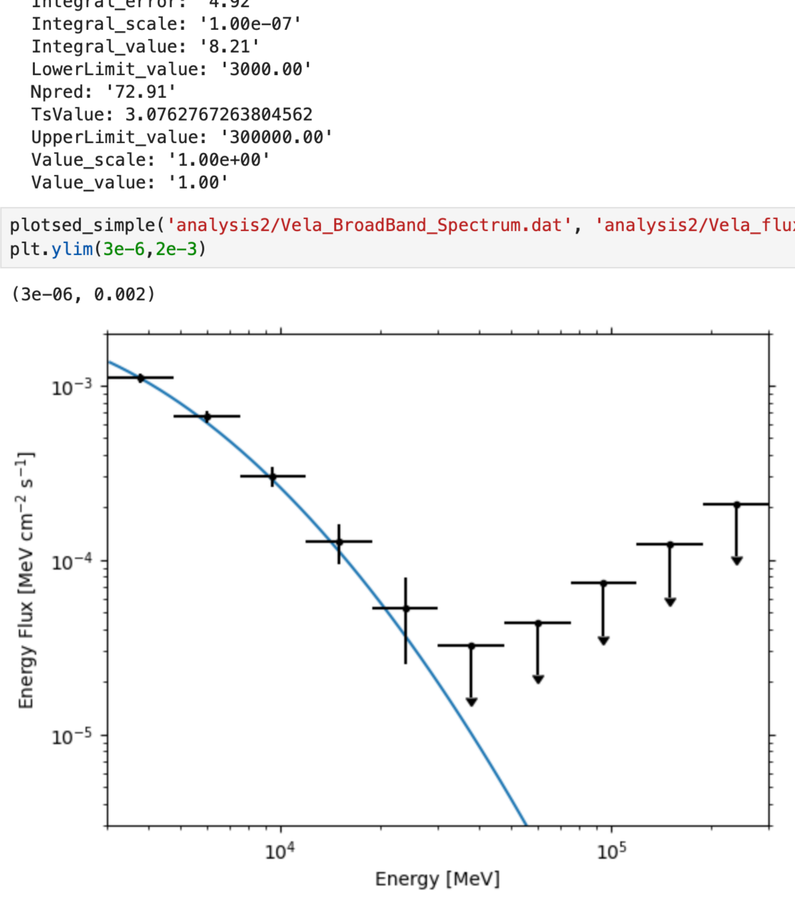
[ ]:
```
%%bash
# rerun the pipeline
python DmpST/scripts/BinnedPipeline.py DAMPE_PH.fits DAMPE_SC.fits Vela_ltcube.fits analysis2 Vela   C  128.84 -45.18 7   5  0.1   \
CAR  3e3  3e5 10 2016-01-01 2017-01-01 --irf DmpST/DmpIRFs/
```

[25]:
```
%%bash
#check the results
cat analysis2/Vela_results_BroadBand_binned.yaml
```

```
LikelihoodValue: 5098.665383820684
Vela:
  DEC_value: '-45.18'
  Eb_value: '2000.00'
  Flux_error: nan
  Flux_value: '2.07e-07'
  Npred: '606.42'
  RA_value: '128.84'
  TsValue: 3672.9656293089374
  alpha_error: '0.50'
  alpha_scale: '1.00e+00'
  alpha_value: '2.54'
  beta_error: '0.22'
  beta_scale: '1.00e+00'
  beta_value: '0.42'
  norm_error: '0.11'
  norm_scale: '1.00e-09'
  norm_value: '0.46'
gal_diffuse_source:
  Flux_error: '1.71e-06'
  Flux_value: '9.88e-06'
  Index_value: '0.00'
  Normalization_scale: '1.00e+00'
  Normalization_value: '1.00'
  Npred: '266.70'
  Prefactor_error: '0.19'
  Prefactor_scale: '1.00e+00'
  Prefactor_value: '1.11'
  Scale_value: '100.00'
  TsValue: 34.01851648122647
iso_diffuse_source:
  Flux_error: '6.19e-06'
  Flux_value: '1.03e-05'
  Index_value: '-2.40'
  Integral_error: '4.92'
  Integral_scale: '1.00e-07'
  Integral_value: '8.21'
  LowerLimit_value: '3000.00'
  Npred: '72.91'
  TsValue: 3.0762767263804562
  UpperLimit_value: '300000.00'
  Value_scale: '1.00e+00'
  Value_value: '1.00'
```

[26]:
```python
plotsed_simple('analysis2/Vela_BroadBand_Spectrum.dat', 'analysis2/Vela_flux_SED_binned.dat')
plt.ylim(3e-6,2e-3)
```

[26]: (3e-06, 0.002)



The fitting is significantly improved.

2. improve the spatial model

You may be also interested in the morphology of the source. Here Vela is a **point source**, so

```
type: PointSource
spatialModel:
  type: SkyDirFunction
  RA:  {free: 0, max: 360.0,min: -360.0, name: RA,  scale: 1.0, value: 128.84}
  DEC: {free: 0, max: 90.0, min: -90.0,  name: DEC, scale: 1.0, value: -45.18}
```

For some sources, the morphologies can be extended. We have the following choices for the extended sources:

- 2D disk:
```
type: DiffuseSource
spatialModel:
  type: RadialDisk
  RA:     {free: 0, max: 360.0,min: -360.0, name: RA,     scale: 1.0, value: 345.494}
  DEC:    {free: 0, max: 90.0, min: -90.0,  name: DEC,    scale: 1.0, value: 58.92}
  Radius: {free: 0, max: 10, min: 0,        name: Radius, scale: 1.0, value: 0.249}
```
- 2D gaussian:
```
type: DiffuseSource
spatialModel:
  type: RadialGaussian
  RA:    {free: 0, max: 360.0,min: -360.0, name: RA,    scale: 1.0, value: 225.254}
  DEC:   {free: 0, max: 90.0, min: -90.0,  name: DEC,   scale: 1.0, value: -63.179}
  Sigma: {free: 0, max: 10, min: 0,  name: Sigma, scale: 1.0, value: 0.853}
```
- or even a map:
```
type: DiffuseSource
spatialModel:
  type: SpatialMap
  file: "xxx.fits"
  Prefactor: {free: 0, max: 10.0, min: 0.0, name: Prefactor, scale: 1.0, value: 1.0}
```

homework 1: The light curve of Vela from 2016 to 2021 (6 years)

homework 2: Report of the status in the space science or astronomy in your country

Q&A time: 2024-07-25

deadline: 2024-08-15

website: https://apsco.casmooc.cn

[ ]: