Introduction to Sherpa

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Chandra X-ray Center

http://cxc.harvard.edu/sherpa

CIAO Workshop at ArAS SfA 5
Egypt and Virtually Everywhere - Oct 2020
Observations and Data Collection

Astrophysical process

Detector collects photons, adds noise

Random number of photons reach the detector

draw conclusion about the astrophysical source

x-rays
Scientific Experiment

1. Define your experiment
2. Data Collection: Observations
3. Data Preparation
   - Instrument specific processing software such as CIAO
4. Data Analysis:
   - source detections, source properties,
   - image analysis, features, spectra, physical properties of the source,
   - apply models to understand the source nature
5. Conclusions and Final Decision
Sherpa CIAO Web Pages

http://cxc.harvard.edu/sherpa

Sherpa lets you:

- fit 1-D data sets (simultaneously or individually), including: spectra, surface brightness profiles, light curves, general ASCII arrays;
- fit 2-D images/surfaces in the Poisson/Gaussian regime;
- visualize the data with ChiPS or Maptiplot;
- access the internal data arrays;
- build complex model expressions;
- import and use your own models;
- choose appropriate statistics for modeling Poisson or Gaussian data;
- import new statistics, with priors if required by analysis;
- visualize a parameter space with simulations or using 1-D/2-D cuts of the parameter space;
- calculate confidence levels on the best-fit model parameters;
- choose a robust optimization method for the fit: Levenberg-Marquardt, Nelder-Mead Simplex or Monte Carlo/Differential Evolution;
- perform Bayesian analysis with Poisson Likelihood and priors, using Metropolis or Metropolis-Hastings algorithms in the MCMC (Markov-Chain Monte Carlo);
- and use Python to create complex analysis and modeling functions, build the batch mode analysis or extend the provided functionality to meet the required needs.

The Sherpa infrastructure greatly enhances the default Sherpa functions, and provides users with an environment for developing complex analysis.

References:

Freeman, P., Doe, S., & Siemiginowska, A. 2001 - Sherpa: a mission-independent data analysis application - SPIE 4477, 76

Refsdal et al. 2009 - Sherpa: 1D/2D modeling and fitting in Python
in Proceedings of the 8th Python in Science conference (SciPy 2009),
G Varoquaux, S van der Walt, J Millman (Eds.), pp. 51-57
Source Code and Development on GitHub
https://github.com/sherpa/sherpa

Core Team:
Doug Burke, Warren McLaughlin, Dan Nguyen, Moritz Guenther, Aneta Siemiginowska
+ DS/SDS and other contributors
Open Development on GitHub

Code contributions

Travis continuous integration testing
Welcome to the Sherpa documentation. Sherpa is a Python package for modeling and fitting data. It was originally developed by the Chandra X-ray Center for use in analysing X-ray data (both spectral and imaging) from the Chandra X-ray telescope, but it is designed to be a general-purpose package, which can be enhanced with domain-specific tasks (such as X-ray Astronomy). Sherpa contains an expressive and powerful modeling language, coupled with a range of statistics and robust optimisers.

If you are looking for the similarly named package “SHERPA,” for hyperparameter tuning of machine learning models go here: https://parameter-sherpa.readthedocs.io/

Sherpa is released under the GNU General Public License v3.0, and is compatible with Python versions 3.5, 3.6, and 3.7. It is expected that it will work with Python 3.8 but testing has been limited. Information on recent releases and citation information for Sherpa is available using the Digital Object Identifier (DOI) 10.5281/zenodo.593753.

The last version of Sherpa compatible with Python 2.7 was the 4.11.1 release.

Introduction

- Installation
  - Quick overview
  - Requirements
  - Releases and version numbers
  - Installing a pre-compiled version of Sherpa
  - Building from source
  - Testing the Sherpa installation
- A quick guide to modeling and fitting in Sherpa
  - Getting started
  - Fitting a one-dimensional data set
  - Including errors
  - Fitting two-dimensional data
  - Simultaneous fits
- Sherpa and CIAO

User Documentation

- What data is to be fit?
Sherpa Components

Data:
arrays, spectra, light curves, images

Models:
parameterized description of the data

Fit Statistics

Fit Methods
(optimization methods)
Sherpa Components

Data Input/Output
- Astropy.io
- PyCrates

Models Library
- Sherpa, XSPEC models, user models, templates

Fit Statistics: Poisson and Gaussian likelihood

Fit Methods:
- minimization and sampling

Visualization:
- matplotlib, ds9

Final Evaluation & Conclusions
- statistical tests, model selection
Data in Sherpa

- **X-ray Spectra**
  typically PHA files with the RMF/ARF calibration files

- **X-ray Images**
  FITS images, exposure maps, PSF files

- **Lightcurves**
  FITS tables, ASCII files

- **Derived** functional description of the source:
  - Radial profile
  - Temperatures of stars
  - Source fluxes

- Concepts of **Source and Background** data

- **Any data array** that needs to be fit with a model
Data in Sherpa

• Input data:

  data: load_data, load_pha, load_arrays, load_ascii, load_ascii_with_errors
  calibration: load_arf, load_rmf load_multi_arfs, load_multi_rmfs
  background: load_bkg, load_bkg_arf, load_bkg_rmf
  2D image: load_image, load_psf
  General type: load_table, load_table_model, load_xstable_model, load_user_model

• Multiple Datasets - data id

  Default data id = 1
  load_data(2, “data2.dat”, ncols=3)

  Help file:
  load_data( [id=1], filename, [options] )
  load_image( [id=1], filename|IMAGECrate,[coord="logical"] )

  Examples:
  load_data("src", "data.txt", ncols=3)

  load_data("rprofile_mid.fits[cols RMID,SUR_BRI,SUR_BRI_ERR]"
  load_data("image.fits")
  load_image("image.fits", coord="world")

• Filtering the data

  load_data expressions
  notice/ignore commands in Sherpa

  Examples:
  notice(0.3,8)
  notice2d("circle(275,275,50)")
Models in Sherpa

• Parameterized models: $M(x_i, p_k)$
  $x_i$ - independent grid, i.e. energy
  $p_k$ - parameters,
  examples: absorption column - $N_H$
  photon index of a power law function - $\Gamma$
  blackbody temperature $kT$

• Library of models:

  sherpa In [1]: list_models()
  Out[1]:
  ['absorptionedge',
   'absorptiongaussian',
   'absorptionlorentz',...]

• Model language to build compound model expressions.
• Add user models.
Building Models: Expressions

- Standard operations: \(+\) - \(-\) - \(*\) - \(:\)
- Linking parameters: \(\text{link()}\)
- Convolution:
  - responses, arf & rmf files via standard I/O
  - PSF - an image file or a Sherpa model
  - \(\text{load\_conv()}\) - a generic kernel from a file or defined by a Sherpa model
Building Models: Examples

• Building composite models:
  • models in the library: e.g. powlaw1d, atten
  • give a name for a model component in the expression:

    ```
    set_source(1,'atten.abs1*atten.abs2*powlaw1d.p1')
    set_source(2,'abs1*abs2*powlaw1d.p2')
    ```

• Building a model expression with convolved and unconvolved components:

    ```
    set_full_model(1,'psf(gauss2d.g2)+const2d.c1')
    ```
Building Models: Examples

• Source and Background models:

```python
set_source(2,'xsphabs.abs1*(powlaw1d.pl+gauss1d.g1)')
set_bkg_model(2,'const1d.mybkg')
```
Fit Statistics in Sherpa

Fit statistics - math operation on data and model arrays

In [19]: list_stats()
Out[19]:
['cash',
 'chi2',
 'chi2constvar',
 'chi2datavar',
 'chi2gehrels',
 'chi2modvar',
 'chi2xspecvar',
 'cstat',
 'leastsq',
 'userstat',
 'wstat']

In [20]: set_stat('cash')

chi2 statistics - appropriate for Gaussian data
Poisson likelihood - cash/cstat/wstat
Fit Statistics in Sherpa

In [19]: list_stats()
Out[19]:
['cash',
 'chi2',
 'chi2constvar',
 'chi2datavar',
 'chi2gehrels',
 'chi2modvar',
 'chi2xspecvar',
 'cstat',
 'leastsq',
 'userstat',
 'wstat']

In [20]: set_stat('cash')

Bias


see the Notebook:
https://cxc.harvard.edu/ciao/workshop/oct20_egypt_virt/cstat_vs_chisq_SimsNotebook.ipynb
Model Fitting: 
Search the Model Parameter Space for the Best Model Parameters

NOTE: 
The fit result is as good (or as bad) as your model. Model misspecification is often a result of bad fit!

```
sherpa In [13]: fit()
Dataset = 1
Method = levmar
Statistic = cstat
Initial fit statistic = 8.11386e+07
Final fit statistic = 799.521 at function evaluation 236
Data points = 892
Degrees of freedom = 889
Probability [Q-value] = 0.985438
Reduced statistic = 0.899349
Change in statistic = 8.11378e+07
  abs1.nH = 0.00254467 +/- 0.0151055
  p1.gamma = 1.709553 +/- 0.0529586
  p1.ampl = 7.12364e-05 +/- 3.40583e-06

sherpa In [14]: print(get_fit_results())
datasets = (1,)
itermethodname = none
methodname = levmar
statname = cstat
succeeded = True
parnames = ('abs1.nH', 'p1.gamma', 'p1.ampl')
parvals = (0.002544670275644294, 1.7095315798815596, 7.1238379651943465)
statval = 799.5210608056544
istatval = 81138643.05478445
dstatval = 81137843.53372364
numpoints = 892
dof = 889
qval = 0.9854375221209568
rstat = 0.89934877480951
message = successful termination
nfev = 236
```
Fitting: Sherpa Optimization Methods

- **Optimization** - a minimization of a function:

  ‘A general function $f(x,p)$ may have **many isolated local minima**, non-isolated minimum hypersurfaces, or even more complicated topologies. No finite minimization routine can guarantee to locate the unique, global, minimum of $f(x,p)$ without being fed intimate knowledge about the function by the user.’

- **Therefore:**
  1. Never accept the result using a single optimization run; always test the minimum using a different method.
  2. Check that the result of the minimization does not have parameter values at the edges of the parameter space. If this happens, then the fit must be disregarded since the minimum lies outside the space that has been searched, or the minimization missed the minimum.
  3. Get a feel for the range of values of the fit statistic, and the stability of the solution, by starting the minimization from several different parameter values.
  4. Always check that the minimum "looks right" using a plotting tool.
Fitting: Optimization Methods in Sherpa

• “Single - shot” routines: *Simplex* and *Levenberg-Marquardt*
  
  start from a set of parameters, and then improve in a continuous fashion:
  
  • Very Quick
  • Depend critically on the initial parameter values
  • Investigate a local behaviour of the statistics near the initial parameters, and then make another guess at the best direction and distance to move to find a better minimum.
  • Continue until all directions result in increase of the statistics or a number of steps has been reached.

• “Scatter-shot” routines: *moncar* (differential evolution)

  search over the entire permitted parameter space for a better minima than near the starting initial set of parameters.

• Bayesian sampling methods: *Markov-Chain Monte Carlo*
Optimization Methods: Comparison

Example: Spectral Fit with 3 methods

Data: high S/N simulated ACIS-S spectrum of the two temperature plasma
Model: photoelectric absorption plus two MEKAL components (correlated!)

Start fit from the same initial parameters
Figures and Table compares the efficiency and final results

Method | Number of Iterations | Final Statistics |
--- | --- | --- |
Levmar | 31 | 1.55e5 |
Neldermead | 1494 | 0.0542 |
Moncar | 13045 | 0.0542 |

Levmar fit

Data and Model with initial parameters

Bad fit

Good fit

Nelder-Mead and Moncar fit
Optimization Methods: Probing Parameter Space

Temperature vs. Statistics

levmar

simplex

moncar

2D slice of Parameter Space probed by each method
Sherpa, MCMC and Bayesian Analysis

MCMC samplers in Sherpa:

**Metropolis and Metropolis-Hastings algorithms**

Support for the Bayesian analysis with priors.

- Explores parameter space and summarizes the full posterior or profile posterior distributions.

- Computed parameter uncertainties can include systematic or calibration errors.

- Simulates replicate data from the posterior predictive distributions.
Visualization of the MCMC Results

Trace of a parameter during MCMC run

Parameter 1

Parameter 2

Probability Density

Cumulative Density
Visualization of the MCMC Results

‘Corner Plots’
with Python package corner
Final Analysis Steps

• How well are the model parameters constrained by the data?
• Is this a correct model?
• Is this the only model?
• Do we have definite results?
• What have we learned, discovered?
• How our source compares to the other sources?
• Do we need to obtain a new observation?
Confidence Limits

Essential issue = after the bets-fit parameters are found estimate the confidence limits for them. The region of confidence is given by (Avni 1976):

\[ \chi^2_\alpha = \chi^2_{\text{min}} + \Delta(\nu, \alpha) \]

\( \nu \) - degrees of freedom
\( \alpha \) - level
\( \chi^2_{\text{min}} \) - minimum

\( \Delta \) depends only on the number of parameters involved not on goodness of fit

<table>
<thead>
<tr>
<th>( \alpha ) (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>68.   ..........</td>
<td>1.00</td>
<td>2.30</td>
<td>3.50</td>
</tr>
<tr>
<td>90.   ..........</td>
<td>2.71</td>
<td>4.61</td>
<td>6.25</td>
</tr>
</tbody>
</table>

TABLE 1
Constants for Calculating Confidence Regions

<table>
<thead>
<tr>
<th>q (No. of Interesting Parameters)</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.00</td>
<td>2.30</td>
<td>3.50</td>
</tr>
<tr>
<td>90</td>
<td>2.71</td>
<td>4.61</td>
<td>6.25</td>
</tr>
<tr>
<td>99</td>
<td>6.63</td>
<td>9.21</td>
<td>11.30</td>
</tr>
</tbody>
</table>
Calculating Confidence Limits means Exploring the Parameter Space - Statistical Surface

Example of a “well-behaved” statistical surface in parameter space, viewed as a multi-dimensional paraboloid ($\chi^2$, top), and as a multi-dimensional Gaussian ($\exp(-\chi^2/2) \approx L$, bottom).
Confidence Intervals

In [34]:

```python
in[34]: covar()
```

```
Dataset = 1
Confidence Method = covariance
Iterative Fit Method = None
Fitting Method = neldermead
Statistic = chi2datavar

covariance 1-sigma (68.2689%) bounds:

<table>
<thead>
<tr>
<th>Param</th>
<th>Best-Fit</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs1.nH</td>
<td>0.0088612</td>
<td>-0.00816866</td>
<td>0.00816866</td>
</tr>
<tr>
<td>pl.PhonIndex</td>
<td>1.26845</td>
<td>-0.0246536</td>
<td>0.0246536</td>
</tr>
<tr>
<td>pl.norm</td>
<td>0.000556618</td>
<td>-1.43672e-05</td>
<td>1.43672e-05</td>
</tr>
</tbody>
</table>
```

In [35]:

```python
in[35]: conf()
```

```
abs1.nH lower bound: -0.00810484
abs1.nH upper bound: 0.00824678
pl.norm lower bound: -1.41427e-05
pl.norm upper bound: 0.0248099
pl.PhonIndex lower bound: -0.0244974
pl.PhonIndex upper bound: 0.0248099
pl.norm upper bound: 1.45917e-05
Dataset = 1
Confidence Method = confidence
Iterative Fit Method = None
Fitting Method = neldermead
Statistic = chi2datavar
confidence 1-sigma (68.2689%) bounds:

<table>
<thead>
<tr>
<th>Param</th>
<th>Best-Fit</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs1.nH</td>
<td>0.0088612</td>
<td>-0.00810484</td>
<td>0.00824678</td>
</tr>
<tr>
<td>pl.PhonIndex</td>
<td>1.26845</td>
<td>-0.0244974</td>
<td>0.0248099</td>
</tr>
<tr>
<td>pl.norm</td>
<td>0.000556618</td>
<td>-1.41427e-05</td>
<td>1.45917e-05</td>
</tr>
</tbody>
</table>
```

In [36]:

```python
in[36]: print(get_conf_results())
```

```
datasets = (1,)
methodname = confidence
iterfitname = none
fitname = neldermead
statname = chi2datavar
sigma = 1
percent = 68.26894921370858
parnames = ('abs1.nH', 'pl.PhonIndex', 'pl.norm')
parvals = (0.008861659413315, 1.26845096547664, 0.0005566176571648463)
parmins = (-0.00810484021893694, -0.024497358571549883, -1.4142856562011464e-05)
parmaxes = (0.008246783219920409, 0.024809904076881217, 1.4591660738583418e-05)
nfits = 108
```
Not well-behaved Surface

Non-Gaussian Shape
Confidence Regions

In [42]: 

```python
reg_proj(abs1.nH, pl.PhoIndex, nloop=[25,25])
```

**WARNING:** Setting optimization to levmar for region projection plot
MCMC Results: Probability Distributions

- `plot_scatter(par1, par2)`
- `plot_pdf(par)`
- `plot_cdf(par)`
Flux Uncertainties

Functions: `sample_energy_flux`, `sample_flux`

Monte Carlo Simulations of parameters assuming Gaussian distributions for all the parameters Characterized by the covariance matrix, includes correlations between parameters.

```
sherpa In [6]: flux100=sample_energy_flux(0.5,2.,num=100)
scherpa In [7]: print(flux100)
[[ 2.88873592e-10   1.10331438e+00   8.40356670e-01   6.97503733e-01
  2.35411369e+00   1.03580042e+00

sherpa In [8]: plot_energy_flux(0.5,2,num=1000)
```

Probability Distribution

Model Flux

CDF: x

68%
Quick Scripts

This page provides quick access to the Sherpa 4.12 Python scripts used in sections at the bottom of the corresponding thread.

Fitting Data

- **Introduction to Fitting PHA Spectra**

  **Python script**

  Perform a basic fit to a PHA data set. Load the data and instrument expression, fit the model to the data, and examine the quality of the fit.

- **Introduction to Fitting ASCII Data with Errors: Single-Component**

  **Python script**

  Empirically fit 1-D data from an ASCII file with polynomials of several orders. Define a parameter expression to link the polynomial offset with one or more of the constants. Plot the data and fits, and customize the plots with ChiPS commands.

- **Changing the grouping scheme of a data set within Sherpa**

  **Python script**

  Change the grouping of a data set after it has been read into Sherpa with the `group` commands.
Sherpa in CIAO

Start Sherpa

Introduction to Fitting PHA Spectra

Sherpa Threads (CIAO 4.12 Sherpa v1)

Overview

Synopsis:
The basic steps used in fitting spectral data are illustrated in this thread. The data used herein were created by running the Creating ACIS Spectra for Pointlike Sources thread.

There are many options and variables that may affect how this process is applied to your data; for a more detailed explanation of the steps, see the following threads:

- Fitting Spectral Data: Fitting PHA Data with Multi-Component Source Models
- Fitting Spectral Data: Simultaneously Fitting Source and Background Spectra

For a detailed explanation of the fitting concepts behind X-ray spectral analysis in Sherpa, see the document Spectral Fitting on the Sherpa References page.

Before fitting ACIS data sets with restricted pulse-height ranges, please read the CIAO caveat page "Spectral analyses of ACIS data with a limited pulse-height range."

Last Update: 9 Dec 2019 - updated for CIAO 4.12, ChiPS figures replaced with matplotlib

Contents

- Load the Spectrum & Instrument Responses
- Filter the Data & Subtract the Background
- Define the Source Model
- Fitting
- Examining Fit Results
  - Goodness of fit
  - Confidence intervals
  - Flux and Counts
- Scripting it
- History
- Images
Installing Sherpa

• Note - installed as part of CIAO with ciao-install or conda install

• Independent Python package:

**Installation**

**Quick overview**

For those users who have already read this page, and need a quick refresher (or prefer to act first, and read documentation later), the following commands can be used to install Sherpa, depending on your environment and set up.

- `conda install -c sherpa sherpa`
- `pip install sherpa`
- `python setup.py install`

**Requirements**

Sherpa has the following requirements:

- Python 3.5, 3.6, or 3.7 (there has been limited testing with Python 3.8)
- NumPy (the exact lower limit has not been determined, but it is likely to be 1.7.0 or later)
- Linux or OS-X (patches to add Windows support are welcome)

Sherpa can take advantage of the following Python packages if installed:

- **Astropy**: for reading and writing files in FITS format. The minimum required version of astropy is version 1.3, although only versions 2 and higher are used in testing (version 3.2 is known to cause problems, but version 3.2.1 is okay).
- **matplotlib**: for visualisation of one-dimensional data or models, one- or two-dimensional error analysis, and the results of Monte-Carlo Markov Chain runs. There are no known incompatibilities with matplotlib, but there has only been limited testing. Please report any problems you find.
Sherpa in Python

Notebook support in Sherpa

A number of objects have been updated to support HTML output when displayed in a Jupyter notebook. Let's take a quick tour!

Data1D, Data1DInt, and Data2D

First we have the data objects:

```python
[1]: import numpy as np
   from sherpa.data import Data1D, Data1DInt, Data2D

   x = np.arange(100, 200, 2)
ey = np.asarray([120, 240, 30, 95, 130])

d1 = Data1D('oned', x, y)
d1l = Data1DInt('onedint', x[:-1], y[:-1])

   x0 = np.asarray([150, 250, 180])
x1 = np.asarray([250, 200, 200])
y2 = np.asarray([50, 40, 70])
d2 = Data2D('twod', x0, x1, y2)
```

Each can be displayed with `print`, which shows a textual representation of attribute and values:

```python
[2]: print(d1)

   name  = oned
   x     = Int64[5]
ey    = Int64[5]
staterror = None
syserror  = None
```

Or they can be displayed as-is which, in a Jupyter notebook, will display either a plot or a HTML table. The `Data1D` and `Data1DInt` classes will display a plot (if the `pylab` plotting backend is selected), and the `Data2D` class a table.

```python
[3]: d1
[3]: ▼ Data1D Plot
```
Sherpa - Summary

• Modeling and fitting application for Python.
• User Interface and high level functions written in Python.
• Modeling 1D/2D (N-D) data: arrays, spectra, images.
• Powerful language for building complex expressions.
• Provides a variety of statistics and optimization methods (including Bayesian analysis).
• Support for wcs, responses, psf, convolution.
• Extensible to include user models, statistics and optimization methods.
• Included in several software packages.
• Source code on GitHub https://github.com/sherpa/sherpa
• Open development with continuous integration via Travis
Using Sherpa in Astronomy Software

- **BAX - Bayesian X-ray Analysis**
  [https://github.com/JohannesBuchner/BXA](https://github.com/JohannesBuchner/BXA)

- **XMM-Newton Source Catalog:**
  - web interface to spectral fitting of the sources in 3XMM-DR6 catalog

- **Astropy** Affiliated packages:

- **Saba - Sherpa-Astropy Bridge** [https://saba.readthedocs.io/en/latest/](https://saba.readthedocs.io/en/latest/)
  - Google funded a summer student (through GSOC program) to develop the code and documentation.
  - pending application for Astropy affiliated package.
Science Results

• Read scientific papers:
  • concentrate on understanding analysis and statistics applied to the data.

• Present scientific papers:
  • consider reproducibility of the results.
  • Focus on a description of the data analysis and statistical methodology understandable to the other scientists.
Spectral (SED) Fitting with Composite Templates

![Graphs showing spectral energy distributions (SEDs) of AGN+SB and SB with fits using composite templates.](image)

**Fig. 6.** Rest-frame SED of class B HLRG and their best-fit models. Symbols as in Fig. 5. The long-dashed lines (blue in the colour version) are the best fits obtained using composite templates (see Sects. 4.1 and 5.2).

Ruiz et al. (2010)
Fitting Spatial Profiles of the HST observations of Mrk 231

Leighly et al. (2016)
Chandra and XMM

Surface Brightness Profiles (with & without PSF)

HST Images

Richings, Utley & Kording (2011)
Image Analysis

Optical-X-ray offsets
Searches for Binary BH and GW Recoils

Comerford et al. (2015)

Barrows et al. (2016)
Identifying Substructures in X-ray Clusters

Sanders & Fabian (2012)

Randall et al. (2015)

Identifying Substructures in X-ray Clusters

Sanders & Fabian (2012)

Randall et al. (2015)
Composite Models in BXA Bayesian X-ray Analysis

Buchner et al. 2014

Figure 5: Observed (convolved) spectrum of object 179, binned for plotting to 10 counts per bin. Shown are analyses using various models and their individual components: powerlaw (upper left), wabs (upper right), torus+scattering (lower left) and wabs+pexmon+scattering (lower right). The posterior of the parameters are used to compute the median and 10%-quantiles of each model component.
Spatial Fitting of the TeV emission in H.E.S.S. observations

Fig. 3. Profile of the VHE emission along the line between the peak of the point-like emission and the peak of the diffuse emission, as illustrated in the inset. Fits using a single and a double Gaussian function are shown in dashed and solid lines respectively. The positions of XMMU J101855.4–58564 and PSR J1016–5857 are marked with dashed and dotted vertical lines and red and yellow stars in the inset, in which the significance image obtained using an oversampling radius of 0.1° is shown.

Fig. 4. VHE photon spectrum of HESS J1018–589 for a point-like source at position A (in blue dots and dashed blue line) and derived from a region of size 0.30° comprising the point-like and diffuse emission (in black dots and solid black line). The residuals to the fit are shown in the bottom panel.

Abramowski et al. (2012)