Inference of Dim Gamma-Ray Point Sources Using Probabilistic Catalogues

Tansu Daylan

Harvard University Department of Physics

with Stephen K. N. Portillo & Douglas P. Finkbeiner

Dark Matter & Gamma Rays 2015, Obergurgl, Austria

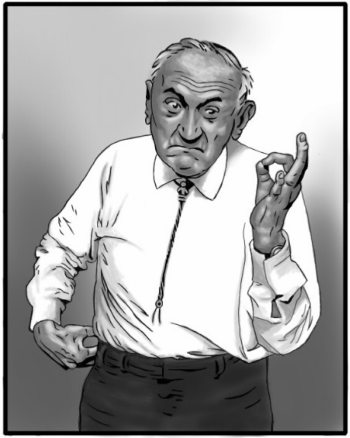
09 December 2015

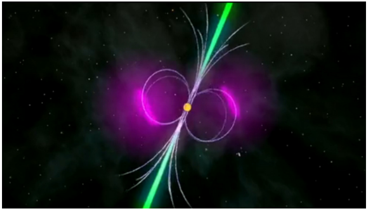
Overview

1. Distinguishing diffuse and point source emission

2. Point source inference using random catalogues

Diffuse or point source emission?





Diffuse or point source emission?

- ✓ The morphologies of the expected gamma-ray signal from an unresolved population of MSPs and dark matter annihilation are similar.
- ✓ However their photon statistics are different, i.e., diffuse emission is equivalent to emission from a collection of "1-photon" emitters.
- ✓ In general, there are N_m "m-photon" emitters in an unresolved MSP population, where N_m is itself Poisson distributed with mean μ_m

$$p_{N_m} \sim \mathrm{Po}(N_m; \mu_m) = \frac{\mu_m^{N_m}}{N_m!} e^{-\mu_m}.$$

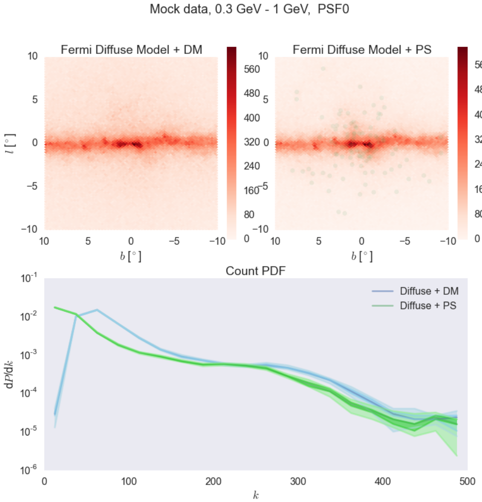
Diffuse or point source emission?

✓ The PDF of observing k photons from a pixel that has n_m m-photon sources is no longer Poisson distributed

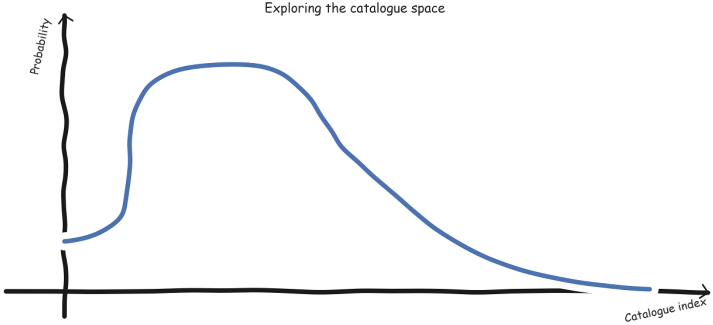
$$p_k^m = \begin{cases} p_{n_m} & \text{if } k = mn_m \\ 0 & \text{o/w} \end{cases} .$$

✓ Summing p_k^m over all m (or rather taking the product of the relevant generating functions), the level of non-Poissonity can be exploited to determine the nature of the excess (Malyshev & Hogg 2011, Lee et al. 2014, Lee et al. 2015).

Diffuse or point source emission?



Inference using random catalogues



Deterministic catalgues

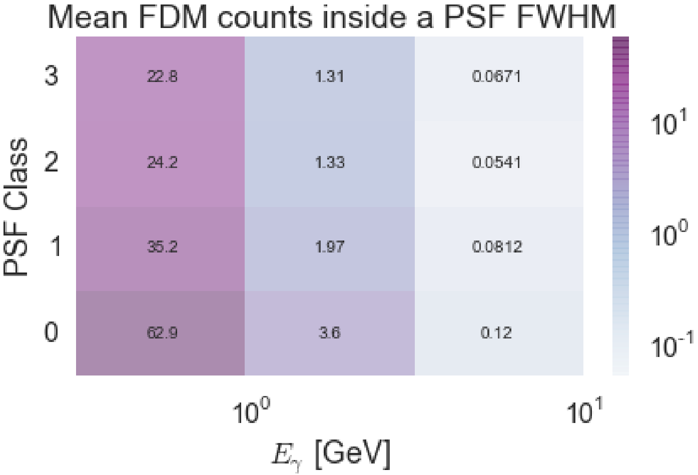
- ✓ Deterministic catalogues are lists of sources with a hard cut on the detection significance – therefore they are false-positive-free (one hopes!).
- ✓ After all, you don't want to write your PhD thesis on the acceleration mechanisms of a pulsar that exists with a probability of 0.5.

- ✓ However for a model-choice problem, i.e., whether a population of sources exists or not, deterministic catalogues waste information!
- ✓ They can also fail when there are overlapping sources or when the flux yield of the population is dominated by its dim members.

Probabilistic Catalogues

- ✓ A probabilistic catalogue is a list of sources that contains false positives with a small, e.g., 1 count per source.
- ✓ Although individual samples are not maximum likelihood solutions, they can be assigned probabilities.
- ✓ Stacking of such samples from the catalogue space allows us to draw conclusions about the population characteristics of the expected dim PS population below the 3FGL flux limit.
- ✓ We aim to test the PS hypothesis of the inner galaxy excess by sampling catalogues consistent with the energy and PSF binned Pass 8 Fermi-LAT data.

PS detection significance in the NGP region

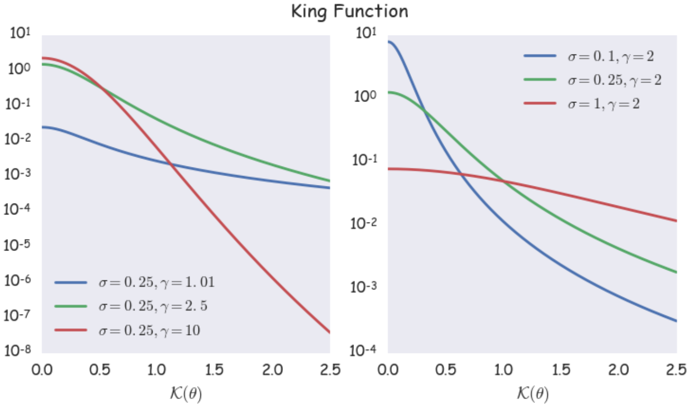


Caveats of the method

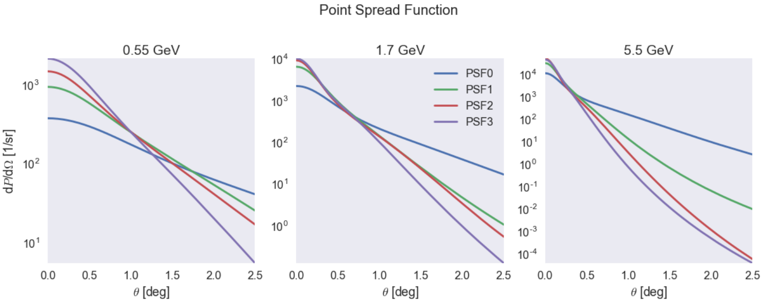
- ✓ There is potentially small scale-structure in the data not accounted by the Fermi Diffuse Model.
- ✓ Sampling of the product space of catalogues is time-expensive, i.e., requires many CPU X grad student hours.
- ✓ The likelihood topology is degenerate.
- ✓ The method is extremely sensitive to the PSF modeling of the bright sources.

Fermi PSF

$$\mathcal{K}(x) = \frac{1}{2\pi\sigma^2}\Big(1 - \frac{1}{\gamma}\Big)\Big(-\frac{x^2}{2\sigma^2\gamma}\Big)^{-\gamma}$$

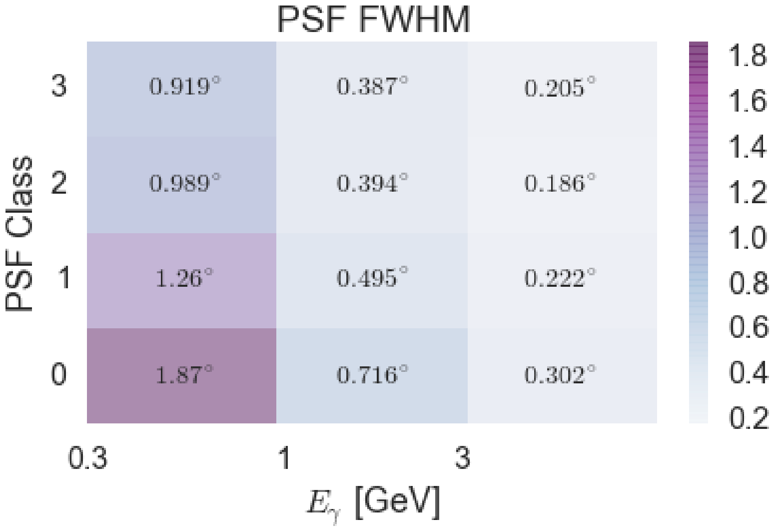


Fermi PSF



Point Spread Function
0.55 GeV
1.7 GeV
5.5 GeV
PSF0
PSF1
PSF2
PSF3
dP/dΩ [1/sr]
θ [deg]

Fermi PSF


PSF FWHM
PSF Class
3
2
1
0
0.919°
0.387°
0.205°
0.989°
0.394°
0.186°
1.26°
0.495°
0.222°
1.87°
0.716°
0.302°
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.3
1
3
E_γ [GeV]

Hierarchichal Bayesian inference

- ✓ We construct a hierarchical Bayesian model where N PS contribute to the gamma-ray flux dominated by a diffuse background.
- ✓ The priors on the PS components, x (PS sky positions, fluxes, spectral parameters), are imposed conditionally via hyper-parameters, β.

$$P(\{x_a\}_{a=1}^{N}, N) = \prod_{a=1}^{N} P(x_a|\beta)P(\beta) \times P(N|\mu_N)P(\mu_N)$$

- ✓ We then sample from the product space $\prod_N(\{x_a\}_{a=1}^{N}, N)$.

Sampling the components

- ✓ To avoid the prior fraction suppression in the acceptance ratio,

$$\frac{P(\{x_a\}'|\beta)}{P(\{x_a\}|\beta)},$$

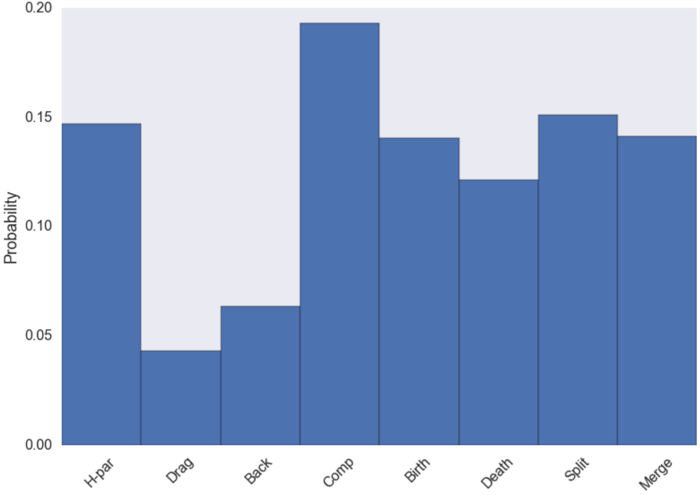
  we take Gaussian steps in a transformed variable which is uniformly distributed with respect to the prior.
- ✓ We expedite and optimize the sampler to run under ~ 20 ms per sample.

Reversible-Jump MCMC formalism

- ✓ Reversible Jump MCMC (Green, 1995) is an MCMC formalism that allows trans-dimensional moves, where samples live in the product space of models indexed by different number of parameters.
- ✓ The acceptance ratio is given by:

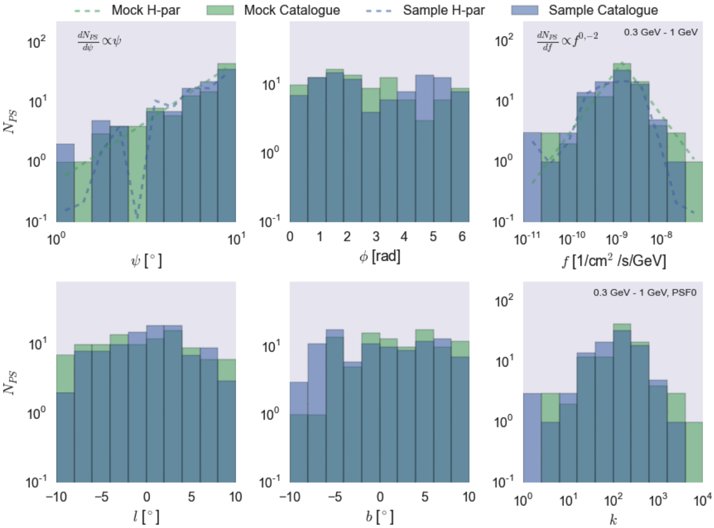
$$\alpha = \frac{\pi(x')}{\pi(x)} \times \frac{j_m(x')}{j_m(x)} \times \frac{g(u')}{g(u)} \times \underbrace{\left| \frac{\partial(x', u')}{\partial(x, u)} \right|}_{\equiv J}.$$

Move types



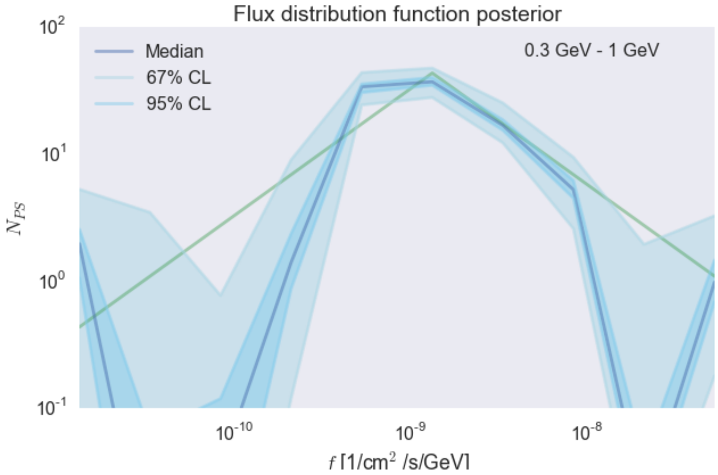
0.20
0.15
0.10
0.05
0.00
Probability
H-par
Drag
Back
Comp
Birth
Death
Split
Merge

Results



Mock H-par
Mock Catalogue
Sample H-par
Sample Catalogue
$\frac{dN_{PS}}{d\psi} \propto \psi$
$\frac{dN_{PS}}{df} \propto f^{0,-2}$
0.3 GeV - 1 GeV
0.3 GeV - 1 GeV, PSF0
N_{PS}
ψ [°]
ϕ [rad]
f [1/cm^2 /s/GeV]
l [°]
b [°]
k

Results



Flux distribution function posterior
Median
67% CL
95% CL
0.3 GeV - 1 GeV
10^2
10^1
10^0
10^{-1}
N_{PS}
10^{-10}
10^{-9}
10^{-8}
f [1/cm^2 /s/GeV]

Conclusion

- ✓ Probabilistic catalogues allow dim source extraction and model testing based on extracting sub-threshold information from a count map.
- ✓ Runs on mock data can reproduce the true luminosity function
- ✓ Using a high-latitude mock data set, we show that one can probe the flux distribution function of an unresolved PS population.