THE UNIVERSITY OF SYDNEY

Sydney Institute for Astronomy
School of Physics

The GCE in a new light: Disentangling the γ-ray sky with Bayesian Deep Learning

Florian List

Joint work with
Nick Rodd, Geraint F. Lewis, Ishaan Bhat

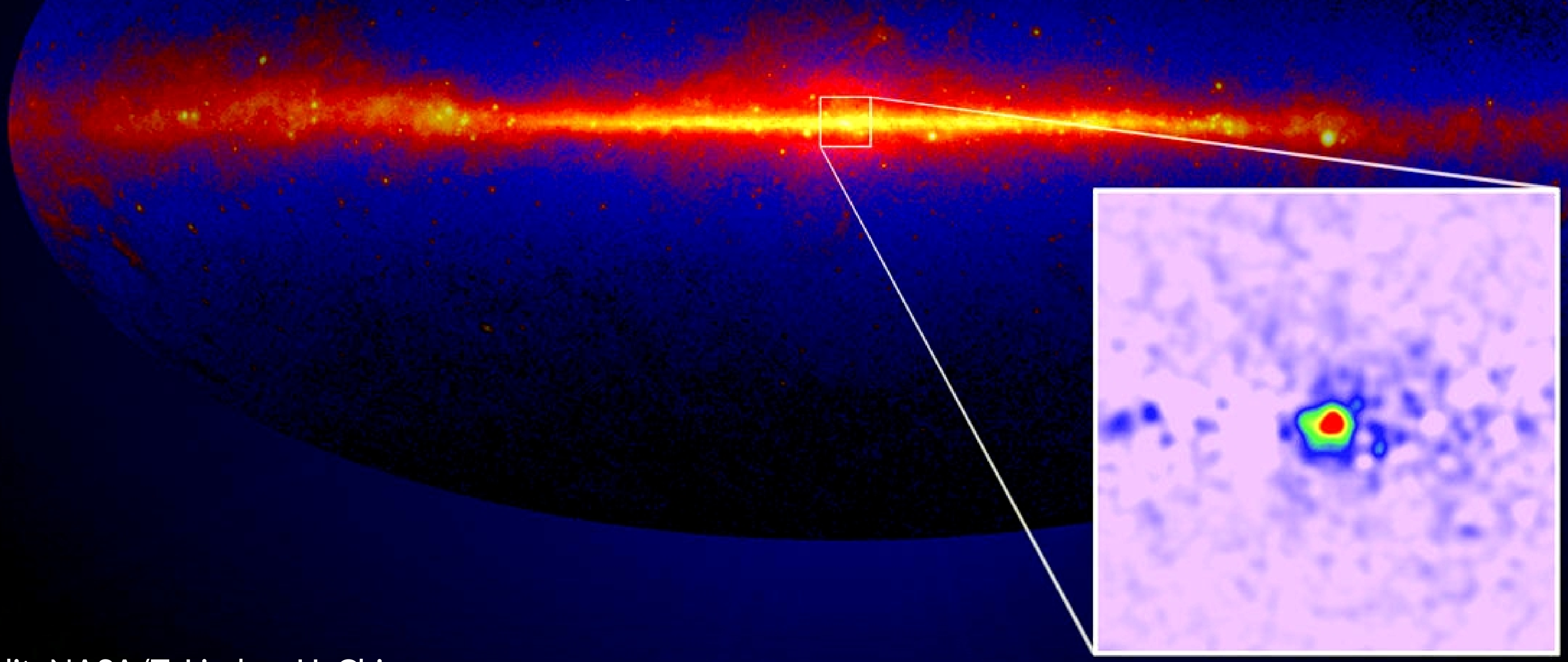
Based on arXiv:2006.12504

Virtual Annual Meeting of the German Astronomical Society

23 Sep 2020

The γ-ray GCE

- γ-ray excess emission peaks at energies ~ 1 – 3 GeV
- Detected in 2009 by the Fermi Telescope Goodenough & Hooper 2009
- Extends from the Galactic Centre out to ~ 10°
- Seems to be consistent with a generalised NFW profile

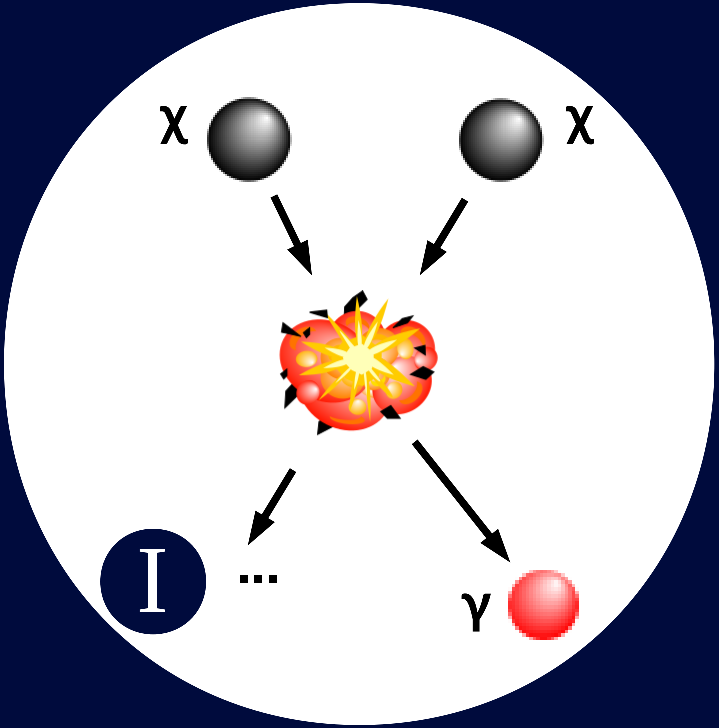


Credit: NASA/T. Linden, U. Chicago

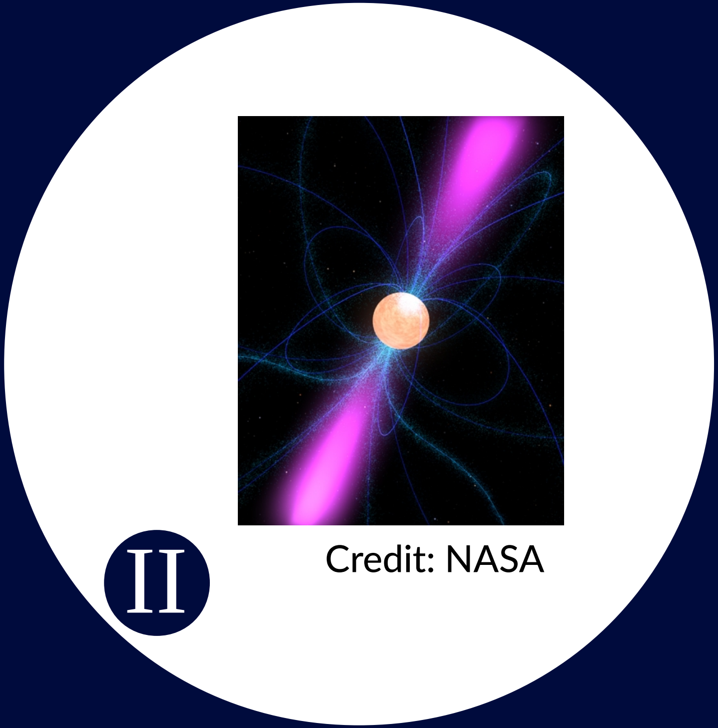
The γ-ray GCE

What is the explanation?

annihilating DM?



point sources
(millisecond pulsars, cosmic rays, ...)?

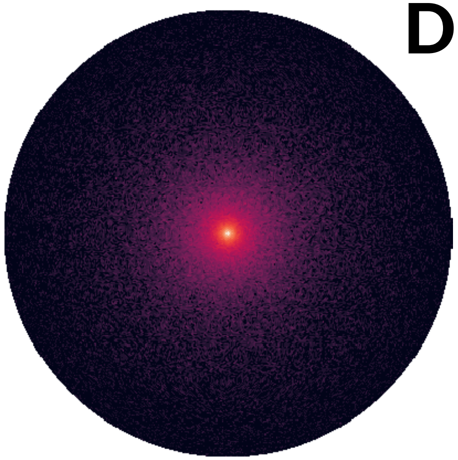


Credit: NASA

The γ-ray GCE

How could annihilating DM and PSs be distinguished?

DM



smooth GCE,
Poissonian emission

PSs

granular GCE,
larger pixel-to-pixel variance,
non-Poissonian statistics

Goodenough & Hooper (2009)
Vitale & Morselli (2009)
Hooper & Goodenough (2011)
Hooper & Linden (2011)
Boyarsky et al (2011)
Abazajian & Kaplinghat (2012)
Gordon & Macias (2013)
Hooper & Slatyer (2013)
Huang et al (2013)
Mirabal (2013)
Macias & Gordon (2014)
Abazajian et al (2014, 2015)
Zhou et al (2014)
Daylan et al (2014)
Petrovic et al (2015)
Calore et al (2015)
Cholis et al (2015)
Selig et al (2015)
Huang et al (2015)
Gaggero et al (2015)
Yuan & Ioka (2015)
O'Leary et al (2015)
Brandt & Kocsis (2015)
Carlson et al (2015, 2016)
Yand & Aharonian (2016)
Horiuchi et al (2016)
Lee et al (2016)
Bartels et al (2016)
Linden et al (2016)
Ajello et al (2016)
Ackermann et al (2017)
Ploeg et al (2017)
Macias et al (2018, 2019)
Bartels et al (2018)
Caron et al (2018)
Clark et al (2018)
Leane & Slatyer (2019, 2020a, 2020b)
Zhong et al (2019)
Chang et al (2020)
Abazajian et al (2020)
Buschmann et al (2020)
… *(not complete!)*

+ > 500 particle theory papers

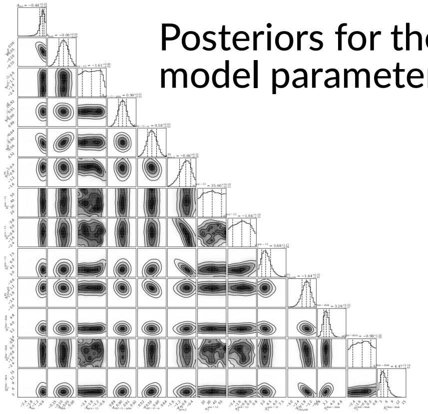
Analysis methods

The most **powerful analysis methods** to date:

1) Non-Poissonian template fitting (NPTF)

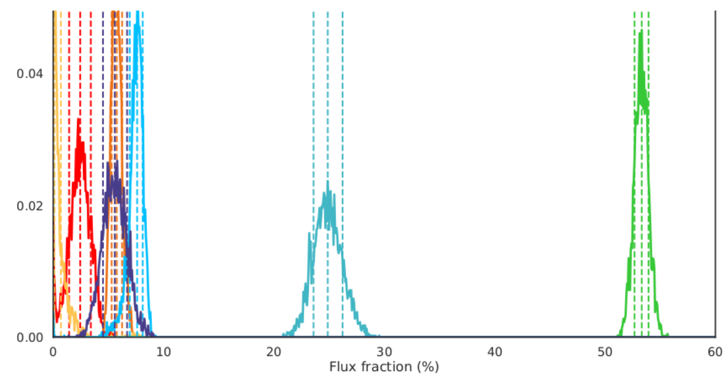
- models the sky as a **linear combination of templates**
- calculates the **likelihood** for the detected number of counts in each pixel Lee et al. 2015

Mishra-Sharma et al. 2017

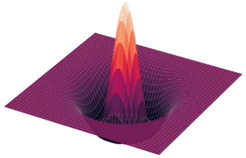


Posteriors for the model parameters

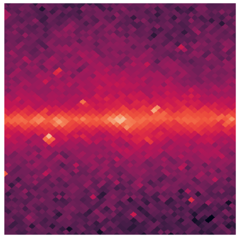
Flux fractions of each template

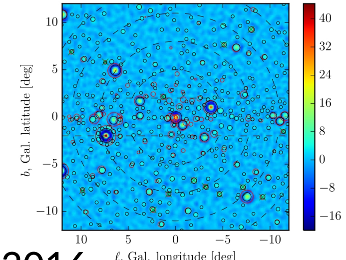


2) Wavelet technique



$*$

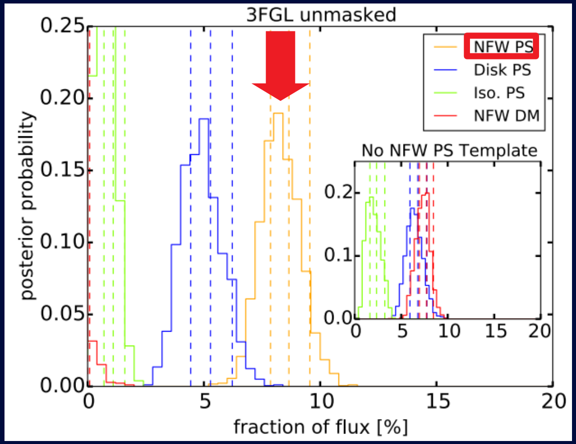




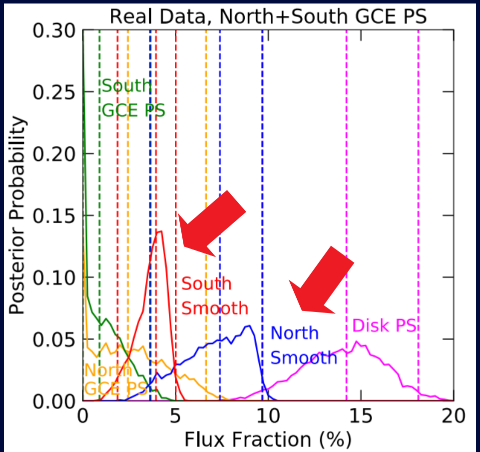
Bartels et al. 2016

Analysis methods

- Current analysis methods are subject to **systematics**



Lee et al. 2016



Leane & Slatyer 2020a

- See *Bartels et al. 2016, Lee et al. 2016, Leane & Slatyer 2019, Zhong et al. 2019, Chang et al. 2020, Leane & Slatyer 2020 a,b, Buschmann et al. 2020*

→ GCE mystery still awaits its resolution!

Milestones in the GCE analysis

We introduce a new method:

- **Accurate** predictions
- **Robust** to different sources of **mismodelling**
- Results hint at a **smooth GCE**

Bayesian Convolutional Neural Networks

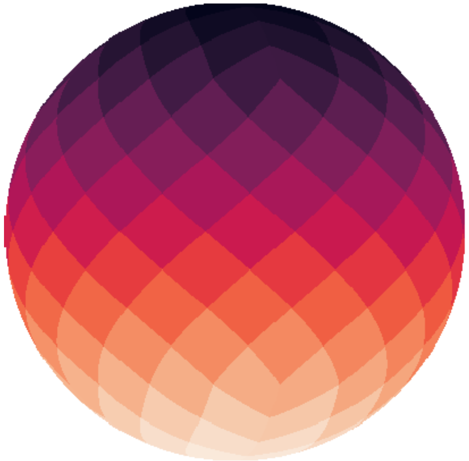
Neural network architecture

- We base our NN architecture on the **DeepSphere** framework

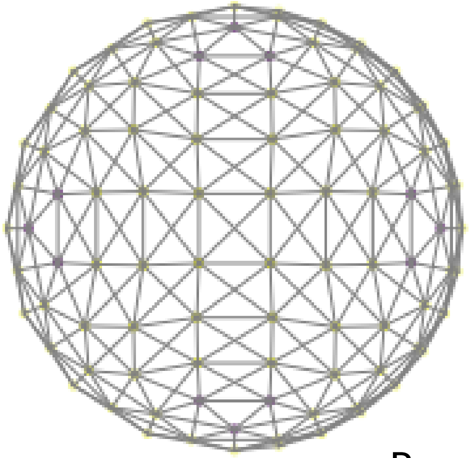
Perraudin et al. 2019
Defferrard et al. 2020

- HEALPix sphere is modelled as a **graph**
  - each **pixel** is represented by a **vertex**
  - neighbouring pixels are connected with an edge

HEALPix tesselation

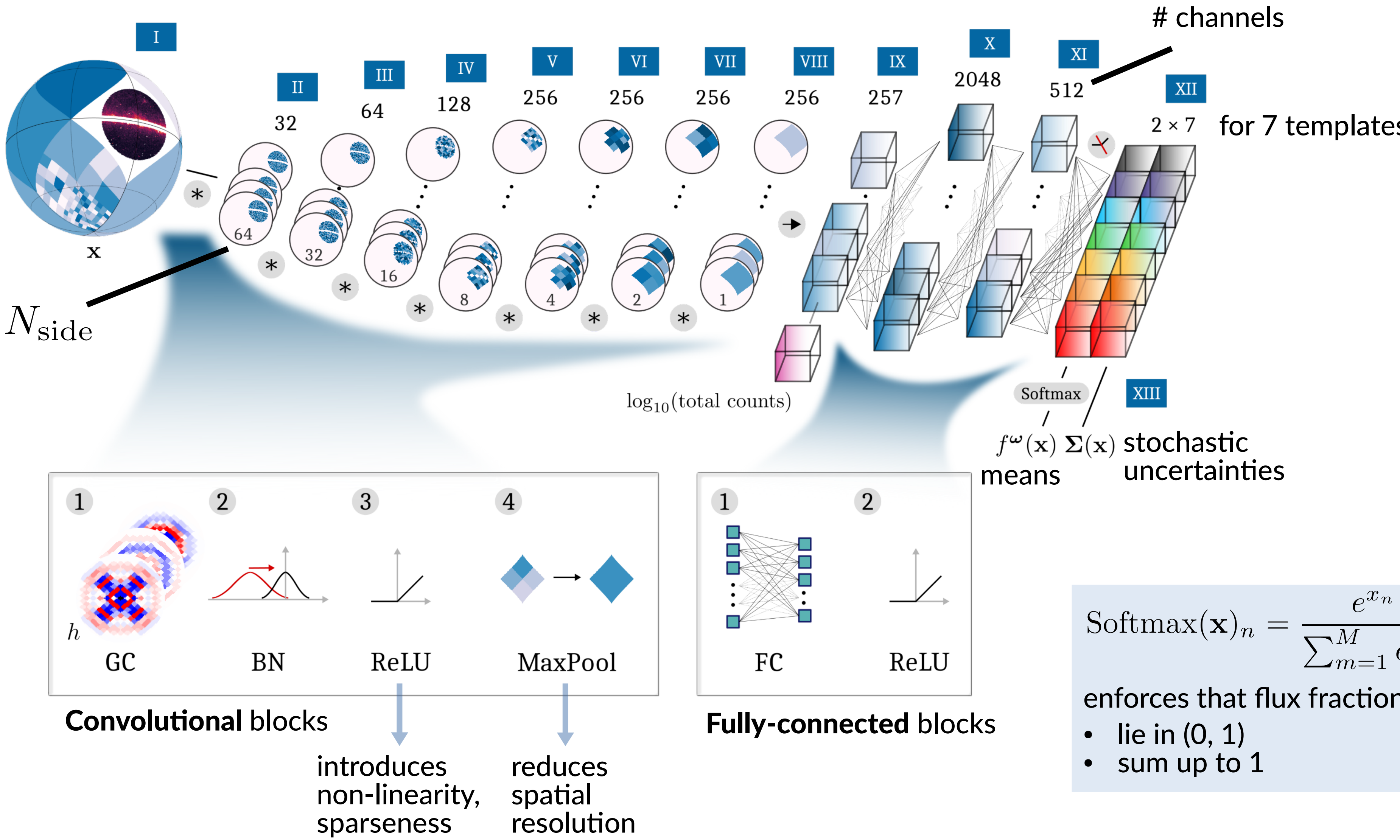


DeepSphere graph



Perraudin et al. 2019

Neural network architecture

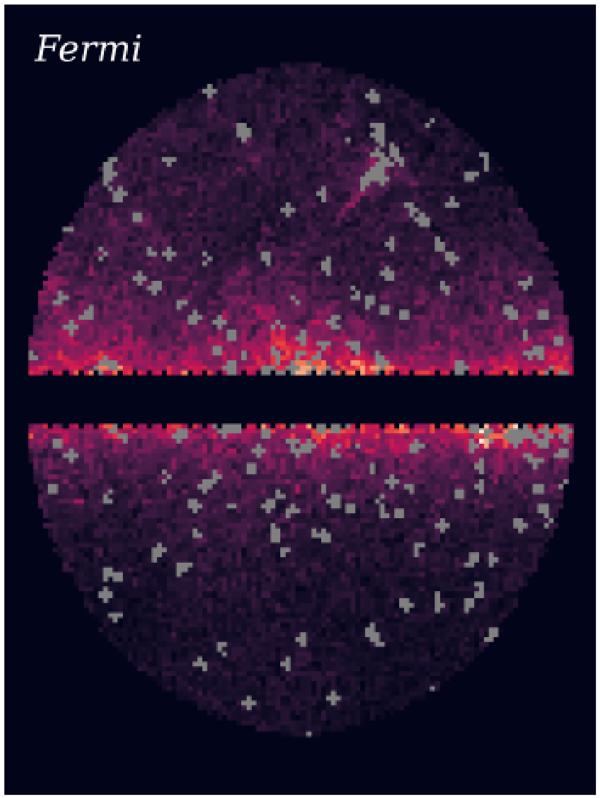


$$\mathrm{Softmax}(\mathbf{x})_n = \frac{e^{x_n}}{\sum_{m=1}^{M} e^{x_m}}$$

enforces that flux fractions

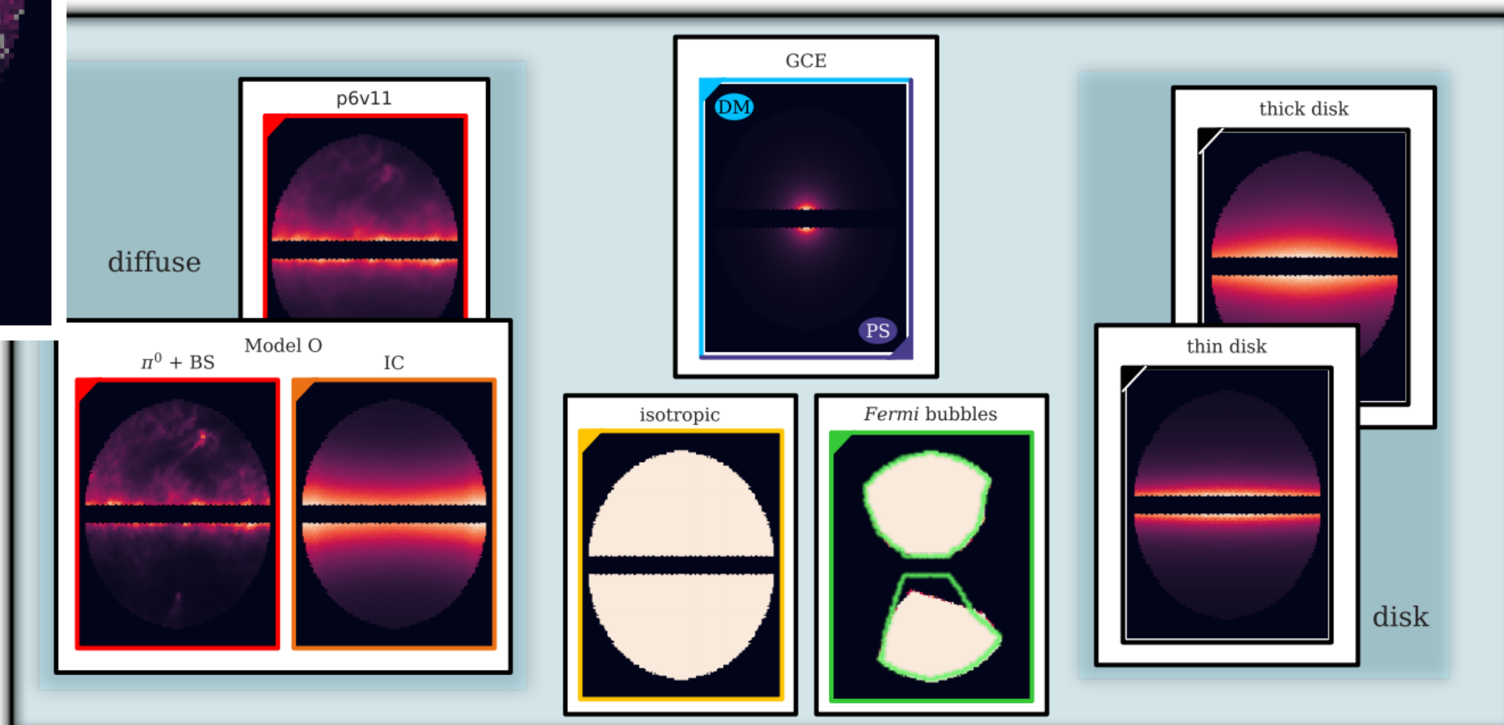
- lie in (0, 1)
- sum up to 1

Modelling the inner Galaxy



- Majority of detected photons: **diffuse Galactic foregrounds** (pion decay + bremsstrahlung, IC)
- Uniform emission from the Fermi bubbles
- Isotropic extragalactic emission
- PSs associated with the Galactic Disk

- We generate the training maps using NPTFit-Sim

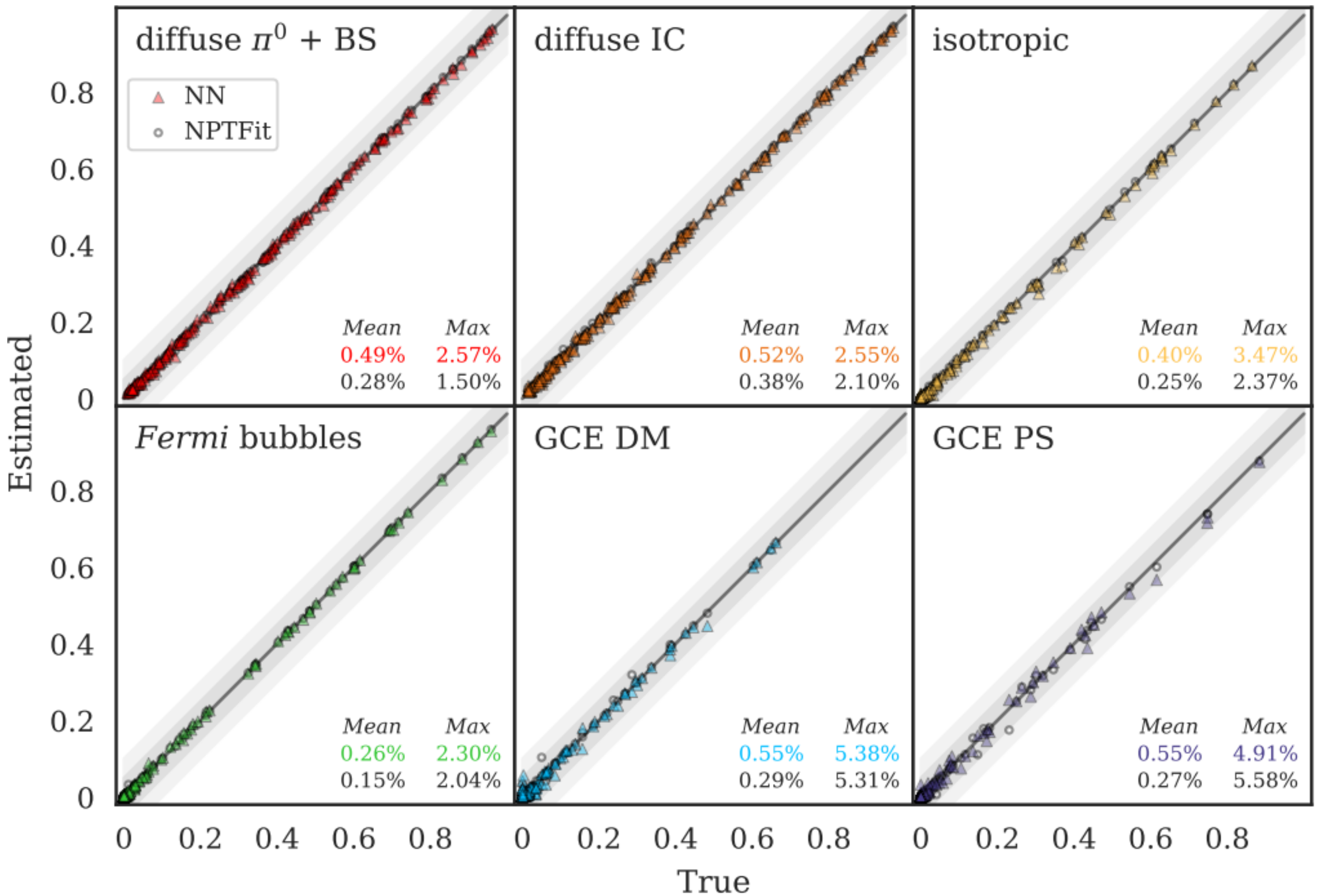


GCE:
generalised NFW profile:

$$\rho(r) \propto \frac{(r/r_s)^{-\gamma}}{(1+r/r_s)^{3-\gamma}}$$

Proof-of-concept example

Results on randomly generated maps

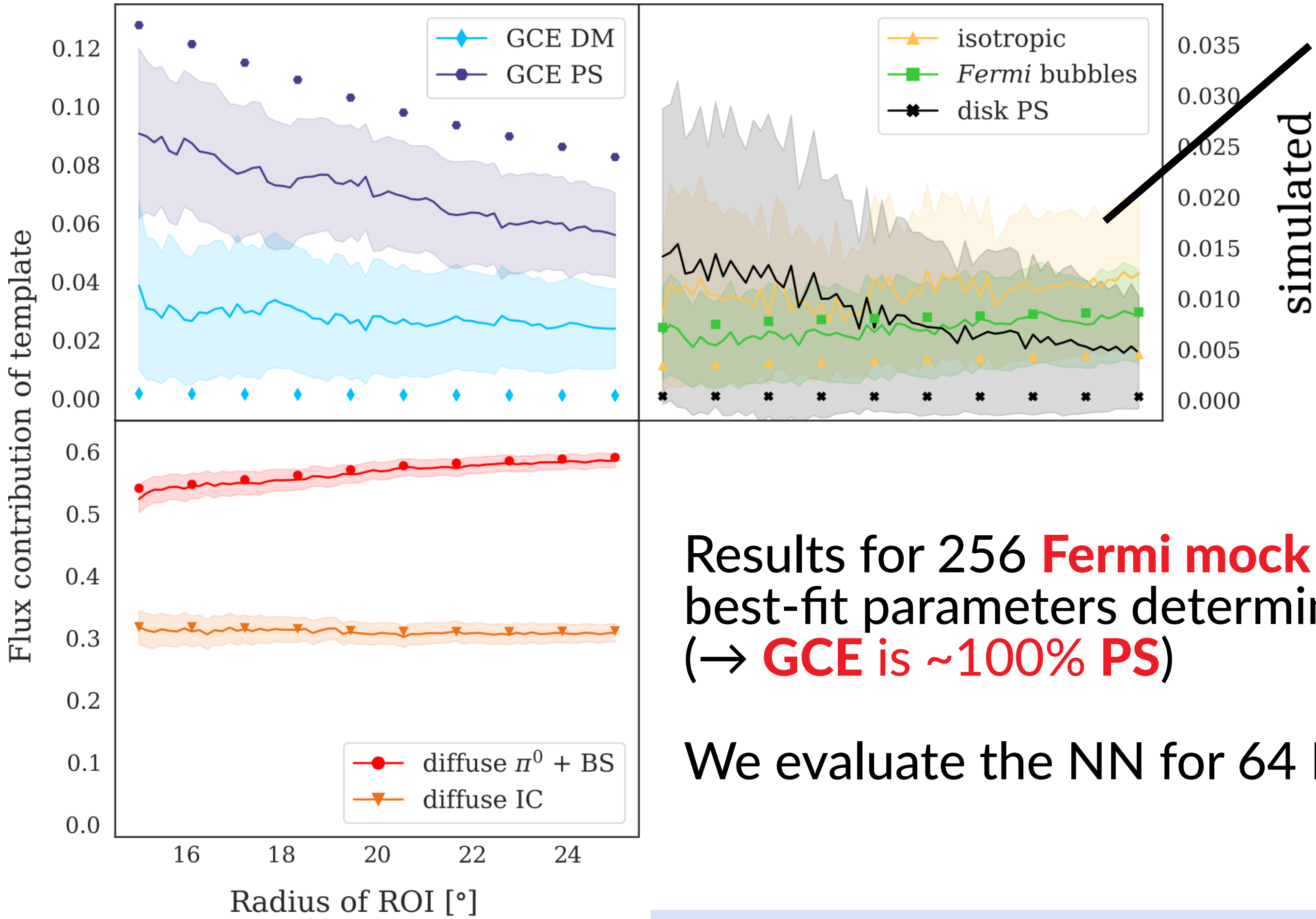


← Maps from the test dataset that NN has not seen during training

- On average, NN accuracy is a bit worse than NPTFit
- *But*: **mean errors** are only **~ 0.5%** (in comparison: GCE contribution is ~ 4 – 10%)
- Maximum errors for GCE templates are very similar for NN and NPTFit

Realistic scenario

*NN results on **simulated** Fermi maps*



Shaded regions: **1σ scatter** of the NN predictions

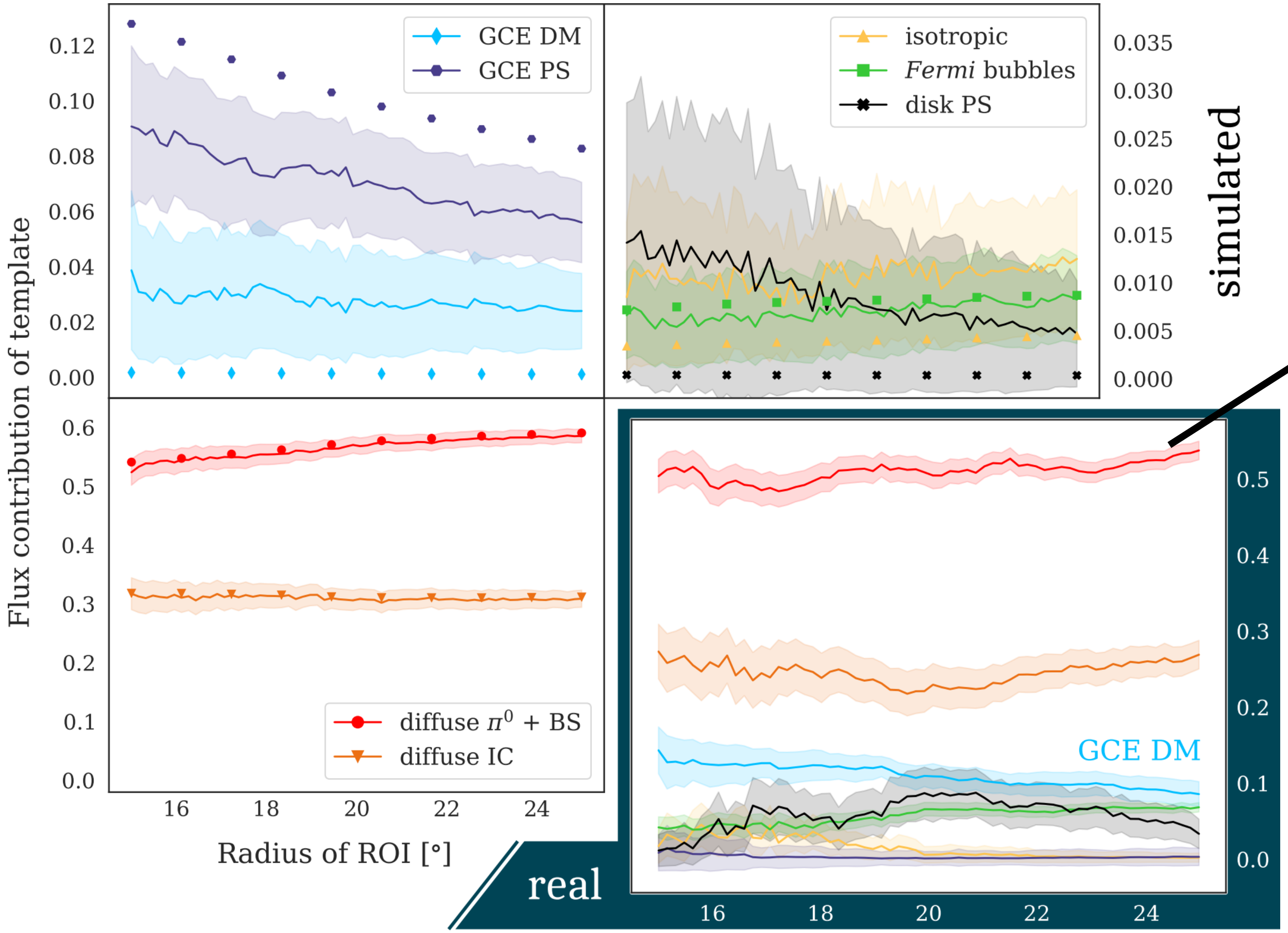
Results for 256 **Fermi mock maps** with best-fit parameters determined by NPTFit (→ **GCE** is ~100% **PS**)

We evaluate the NN for 64 ROIs

→ A **part of the PS** flux is **misattributed to DM**, but the NN **generally identifies PSs** to be the **main constituent** of the GCE in the mock maps

Realistic scenario

*NN results on **real** and simulated Fermi maps*



Shaded regions:
1σ predictive uncertainties

Results for Fermi map

→ NN **identifies a GCE** that decreases monotonically with the ROI radius

→ Almost **100%** of the **GCE** flux is **attributed to DM**

Realistic scenario

NN results on real Fermi map when using different templates

ROI radius: 25°

Experiment	Method	diffuse π^0 + BS	diffuse IC	isotropic	*Fermi* bubbles	**GCE DM**	**GCE PS**	disk PS
Default	NN	53.8 ± 1.2	27.0 ± 1.9	0.2 ± 0.6	6.8 ± 0.6	$\mathbf{8.6} \pm 1.7$	0.3 ± 1.2	3.4 ± 1.9
	`NPTFit`	53.7 ± 0.7	25.4 ± 1.4	$2.3^{+0.9}_{-1.1}$	5.9 ± 0.5	$0.2^{+1.4}_{-0.2}$	$\mathbf{7.4}^{+0.6}_{-1.2}$	5.2 ± 1.3
Thick disk	NN	55.1 ± 1.2	30.0 ± 1.6	0.1 ± 0.5	6.5 ± 0.6	$\mathbf{7.8} \pm 1.6$	0.3 ± 1.6	0.1 ± 1.0
	`NPTFit`	54.9 ± 0.6	$29.5^{+0.8}_{-0.9}$	$0.3^{+0.9}_{-0.3}$	$6.4^{+0.3}_{-0.4}$	$0.1^{+0.5}_{-0.1}$	$\mathbf{8.2}^{+0.5}_{-0.6}$	$0.6^{+0.5}_{-0.2}$
`p6v11`	NN	87.7 ± 1.2[a]	–	0.2 ± 1.0	6.9 ± 1.1	$\mathbf{4.7} \pm 1.7$	0.5 ± 1.4	0.1 ± 0.6
	`NPTFit`	88.8 ± 0.6	–	$0.0^{+0.2}_{-0.0}$	6.4 ± 0.2	$0.0^{+0.1}_{-0.0}$	$\mathbf{4.2} \pm 0.4$	$0.9^{+0.5}_{-0.4}$
Model A	NN	47.7 ± 1.5	39.2 ± 2.4	0.5 ± 1.2	5.4 ± 0.9	$\mathbf{6.7} \pm 1.4$	0.2 ± 1.0	0.4 ± 1.2
	`NPTFit`	$49.4^{+0.7}_{-0.6}$	$35.7^{+1.2}_{-1.4}$	$0.1^{+0.7}_{-0.1}$	4.9 ± 0.3	$0.1^{+0.5}_{-0.1}$	$\mathbf{6.1}^{+0.5}_{-0.6}$	$3.7^{+1.1}_{-1.0}$
Model F	NN	57.1 ± 1.8	31.2 ± 2.7	1.2 ± 1.7	4.0 ± 1.1	$\mathbf{5.6} \pm 2.0$	0.6 ± 1.8	0.2 ± 0.9
	`NPTFit`	55.5 ± 0.7	$25.7^{+1.7}_{-1.9}$	4.7 ± 1.1	3.7 ± 0.4	$0.1^{+0.7}_{-0.1}$	$\mathbf{4.6}^{+0.5}_{-0.7}$	$5.8^{+1.2}_{-1.1}$
North only	NN	63.0 ± 2.2	22.4 ± 2.4	0.1 ± 0.5	6.8 ± 1.2	$\mathbf{5.2} \pm 3.1$	1.9 ± 3.1	0.6 ± 1.2
South only	NN	52.8 ± 2.3	28.4 ± 2.7	1.4 ± 1.4	6.7 ± 0.9	$\mathbf{8.1} \pm 1.7$	0.2 ± 1.3	2.4 ± 2.7

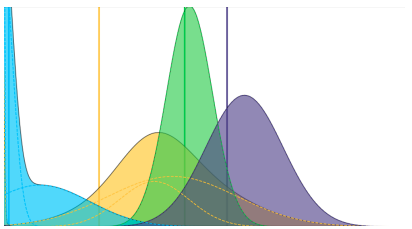
[a] For the diffuse model `p6v11`, the two diffuse flux components are described by a single template.

- For diffuse templates, isotropic emission, and Fermi bubbles:
  NN and NPTFit estimates are **mostly similar**
- **Total GCE** magnitudes are **mostly similar**, too, but **NN** consistently assigns flux to **DM** template, whereas **NPTFit** finds **~ 100% PSs** in all the scenarios

How to proceed from here?

- **Uncertainties** should fully reflect the **error distribution**, in particular the inherent degeneracy between faint PSs ↔ DM

  → **non-Gaussian** uncertainties



- Instead of only estimating PS / DM flux fractions:

- Many **extensions** are possible:
  - Multiple energy bins, multiple template variants, ...

Conclusions

arXiv:2006.12504

- **Deep Learning** provides **powerful tools** for analysing the **γ-ray sky**
- NN estimates are mostly **accurate**
- Our first experiments show **robustness** against **mismodelling**
- Our NN prefers a **smooth origin** of the GCE, but **faint PSs** may be **underestimated** / **confused with DM**
- **Potential** for the **GCE mystery** to be **resolved** within the coming years with the help of Deep Learning