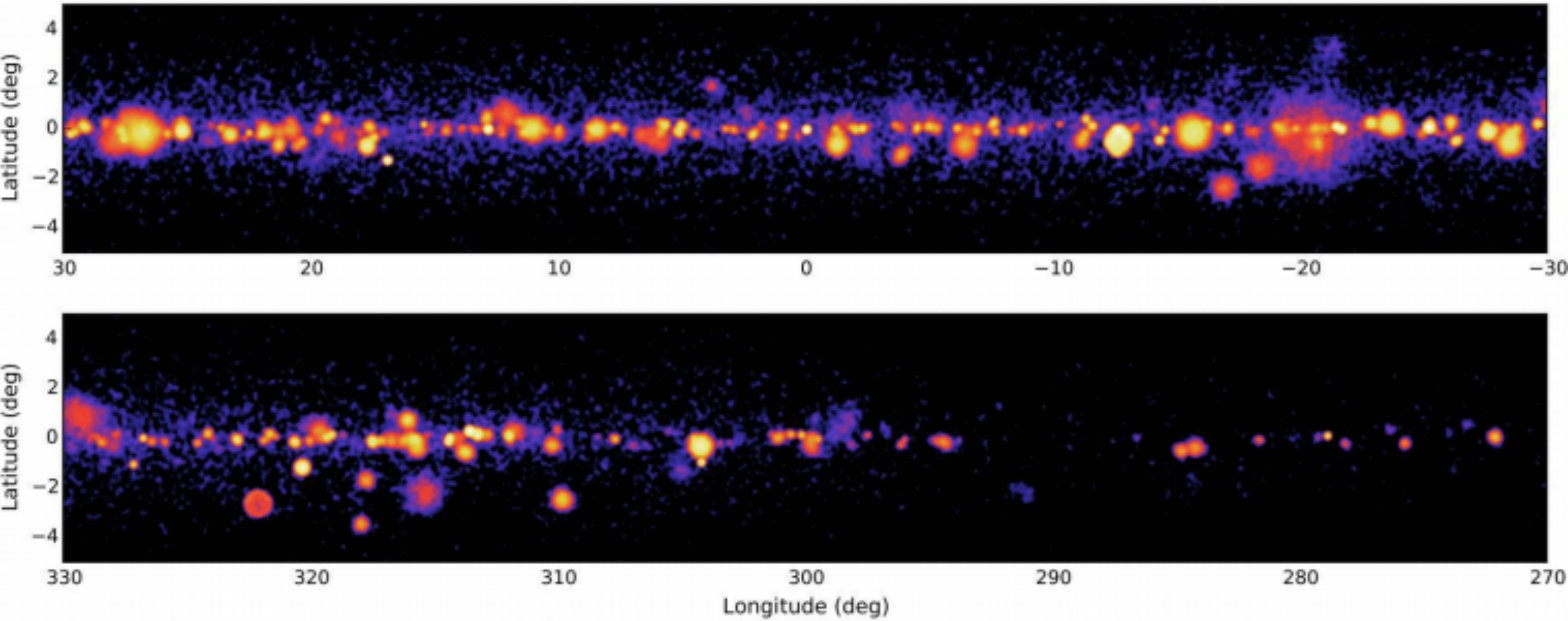


CHASC Seminars, Harvard-Smithsonian CfA *08 April 2021*

Learning to Sample & Classify Supernova Remnants from Datasets Collected by Current & Future γ-ray Observatories

Contents

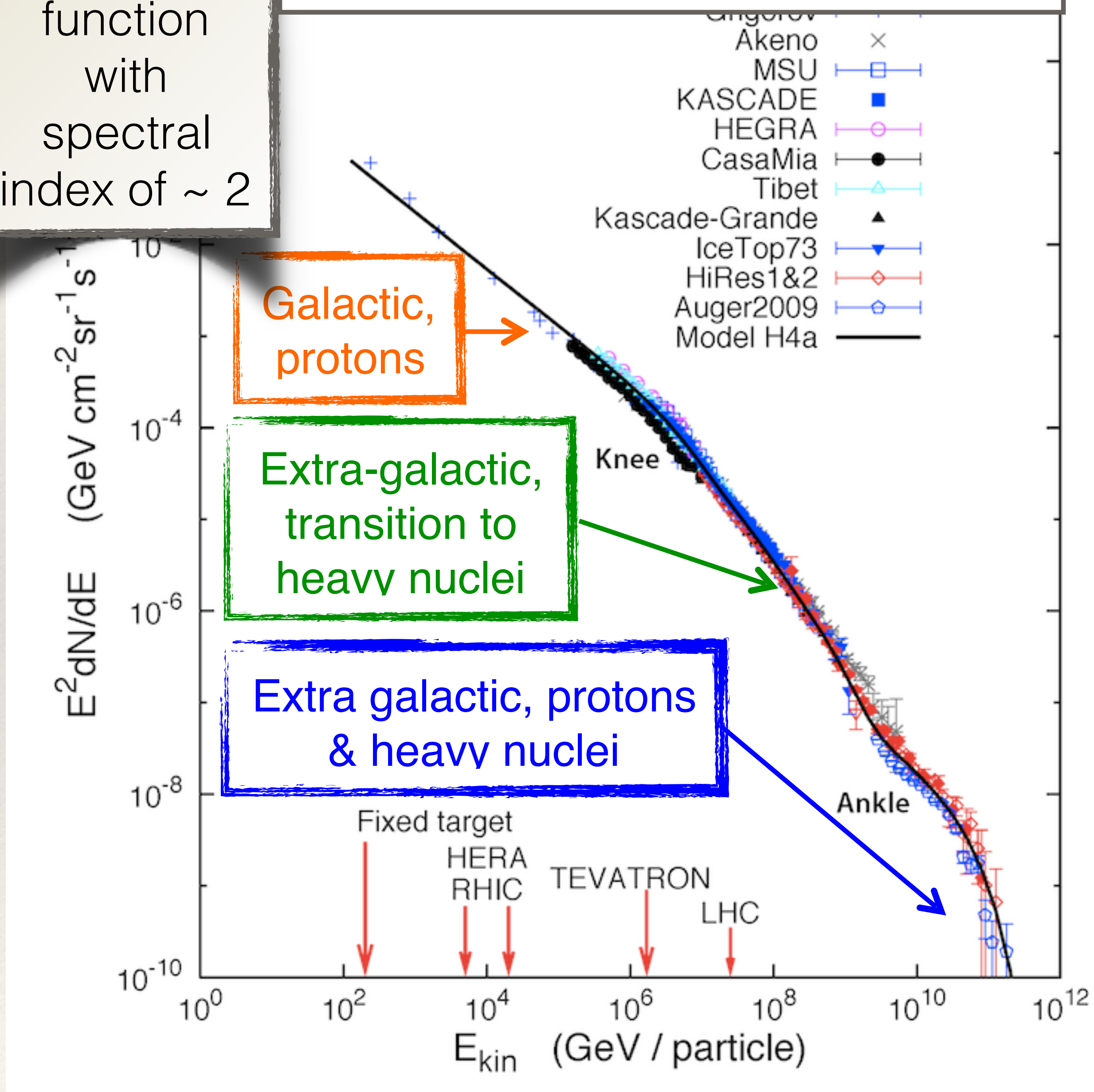
- Supernova Remnants (SNR) as Cosmic Ray Sources
- Current & Future γ-ray Observatories
- Searching for SNRs in γ-ray Data
  - Source Confusion Issues
  - Machine Learning used in SNR Studies
- Summary of My Research Plan

Cosmic Rays (CRs)

- **Particle Radiation**
  - **Cosmic Rays (CR):** protons (90%), nuclei (alpha particles; 9%), heavy nuclei, electrons, neutrons
  - Neutrinos (by CR protons)
  - Solar Energetic Particles: protons, electrons, heavy ions, neutrinos.
- **Photon Radiation**
  - γ-rays (by CR electrons, protons, and ions)
  - Radio & X-rays (by CR electrons)

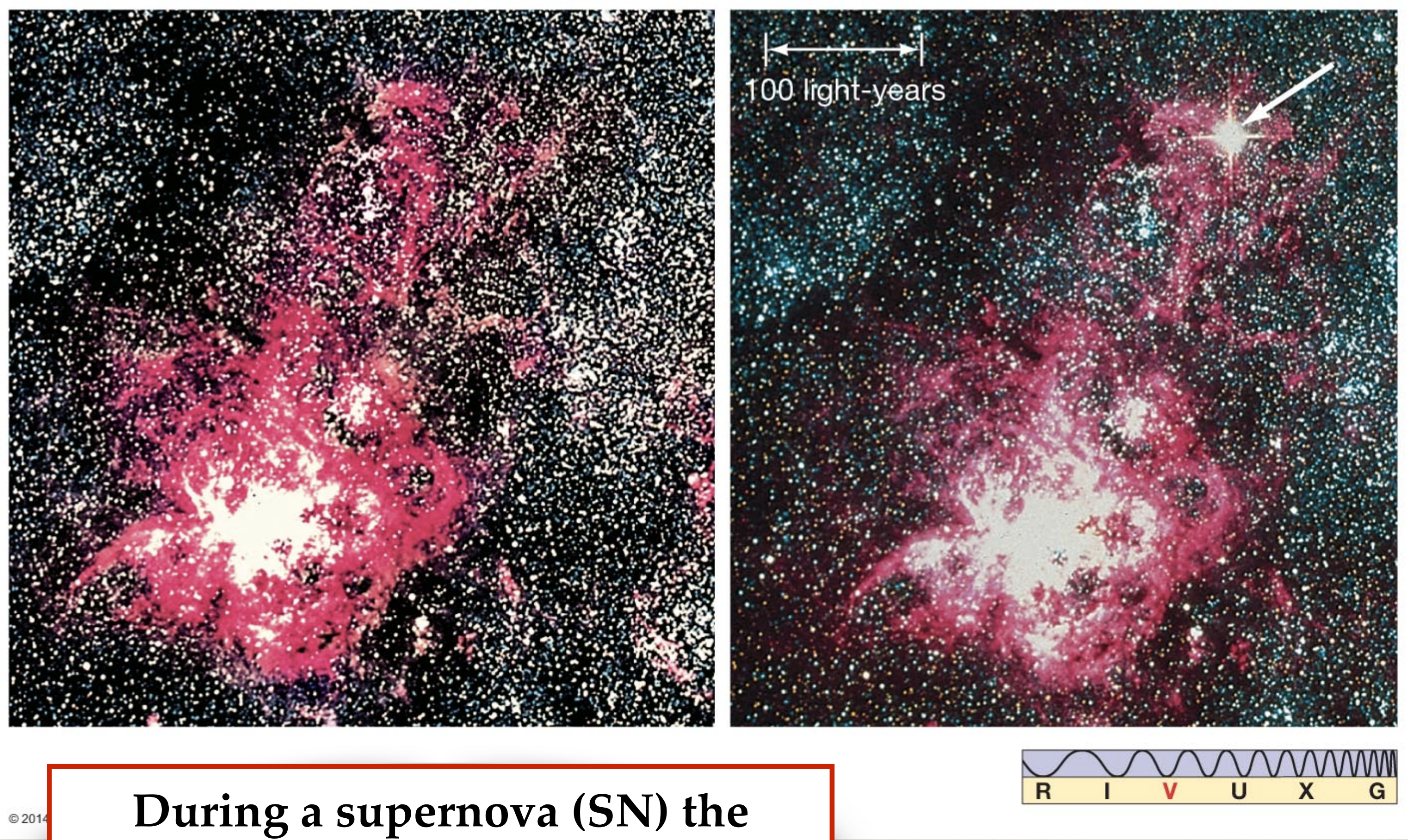
Flux obeys a power-law function with spectral index of ~ 2

Cosmic Ray Spectrum



Supernova Remnants (SNRs) as CR Sources

- **Criteria to be a Galactic CR Source:**
    - Wide energy range
    - A power-law spectrum that goes up to the **knee (~10^{15} eV or 1 PeV)**.
    - Spent long enough time inside the Milky Way galaxy



During a supernova (SN) the luminosity of the star increases by 10^{10} (~10 billion) times the luminosity of the Sun.

Most energy comes out as neutrinos, but ~10% emerges as kinetic energy of ejecta

γ-ray Production

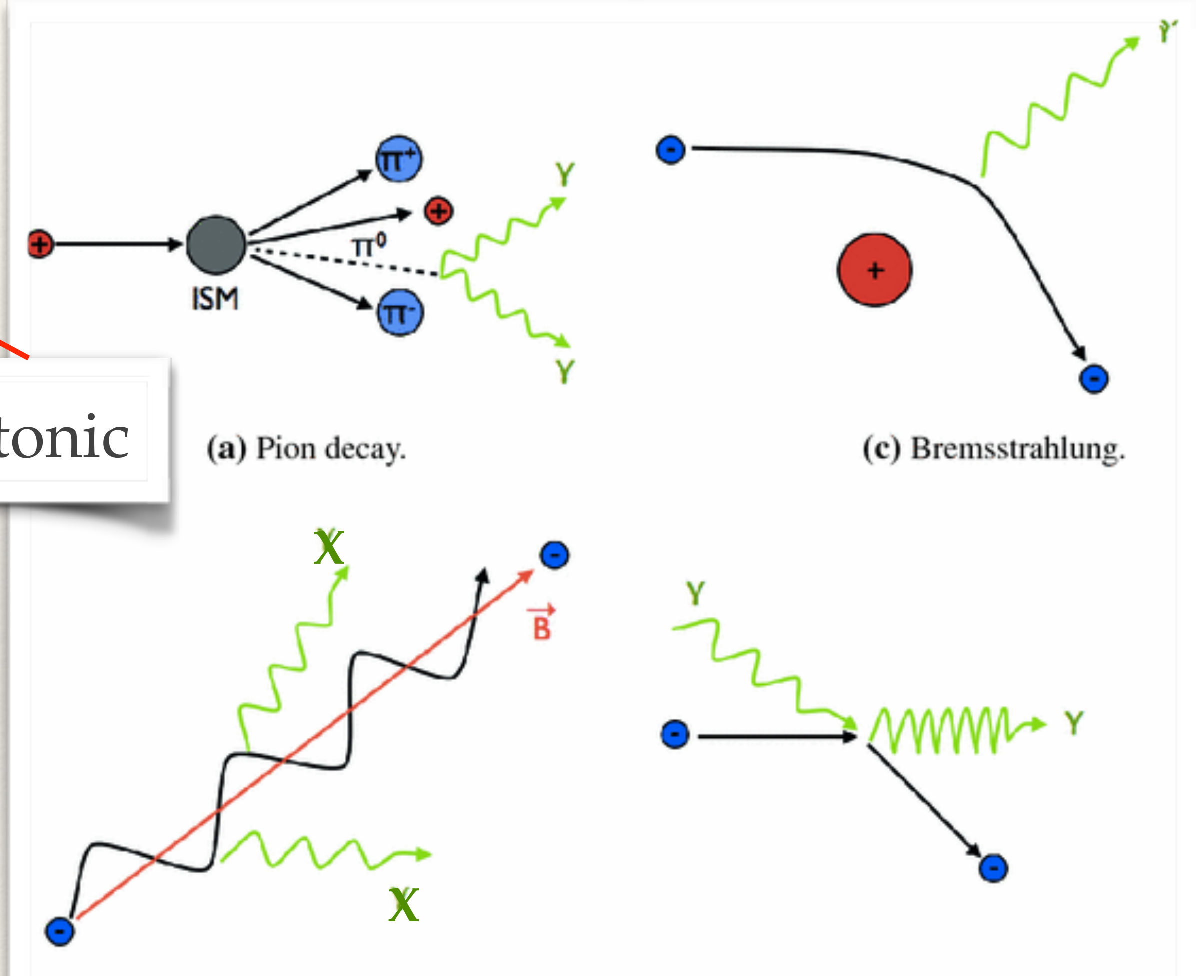
- <u>**Charged particles in strong electromagnetic fields**</u>
  - **Bremsstrahlung:** Very high energy (VHE) charged particles accelerated in electric field
  - **Synchrotron radiation:** VHE electrons moving in strong magnetic field
- <u>**Inverse Compton scattering**</u>
  - Up-scattering of photons of lower energy through collision with VHE particles
- <u>**Decays and annihilation**</u>
  - **Pair annihilation**

    Particle + Anti-Particle → $\gamma + \gamma$
  - **Pion production and decay**

    Proton + Matter → π^0 → $\gamma + \gamma$

Leptonic

Hadronic



(a) Pion decay.
(c) Bremsstrahlung.
(b) Synchrotron radiation.
(d) Inverse Compton.

Ref: link.springer.com/chapter/10.1007/978-3-319-44751-3_1

Supernova Remnant Types

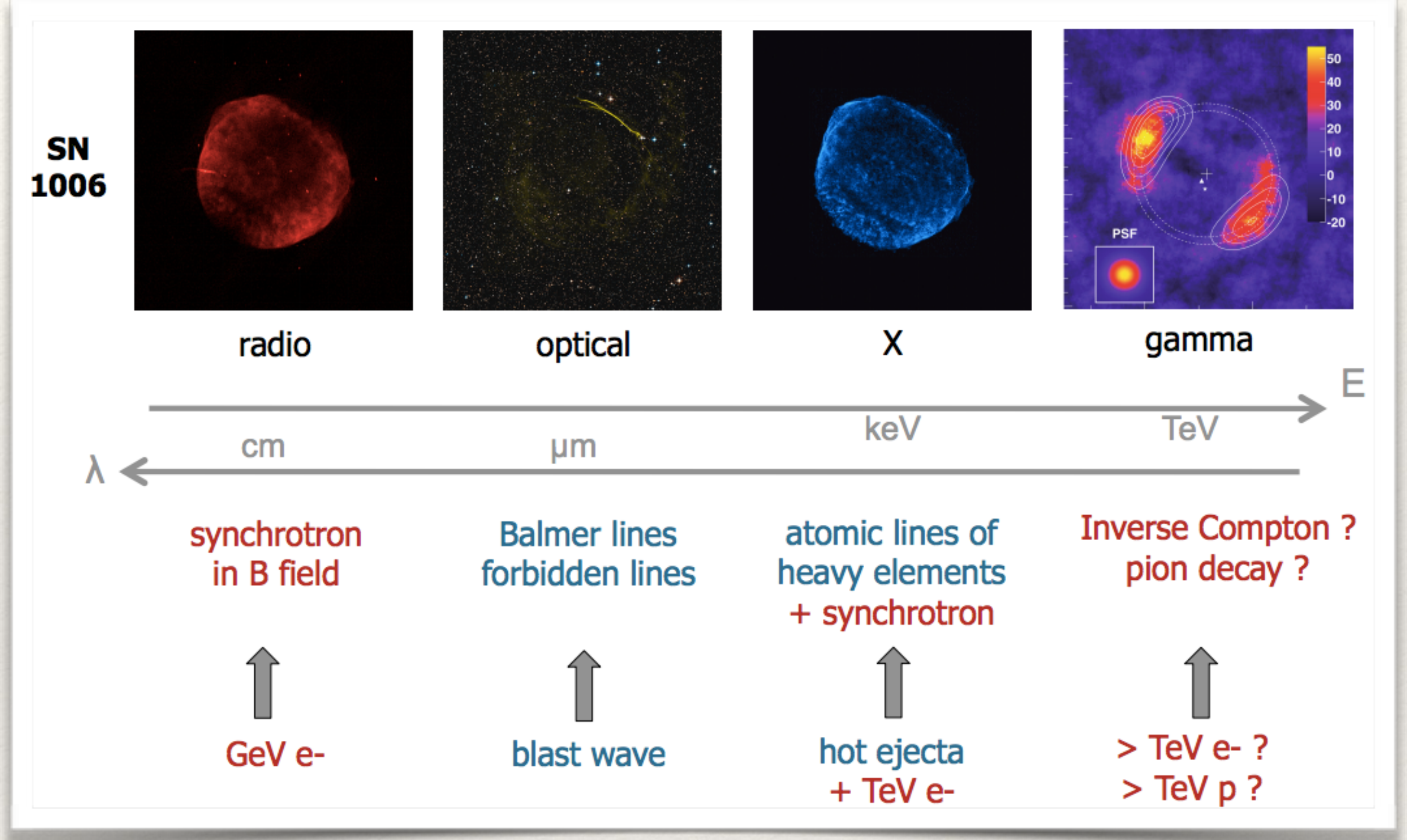
- Shell Type
- Plerion (PWN)
- Mixed Morphology

- Cassiopeia A
- Crab Nebula
- W49B

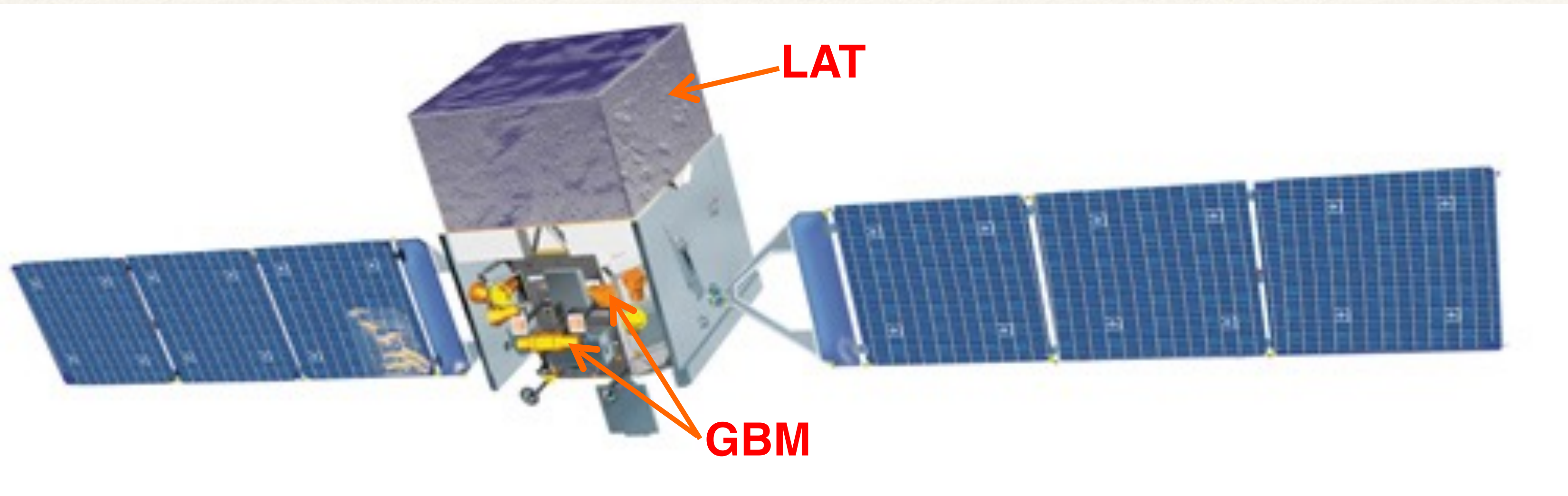
Multi-Wavelength (MW) Observations of SNRs

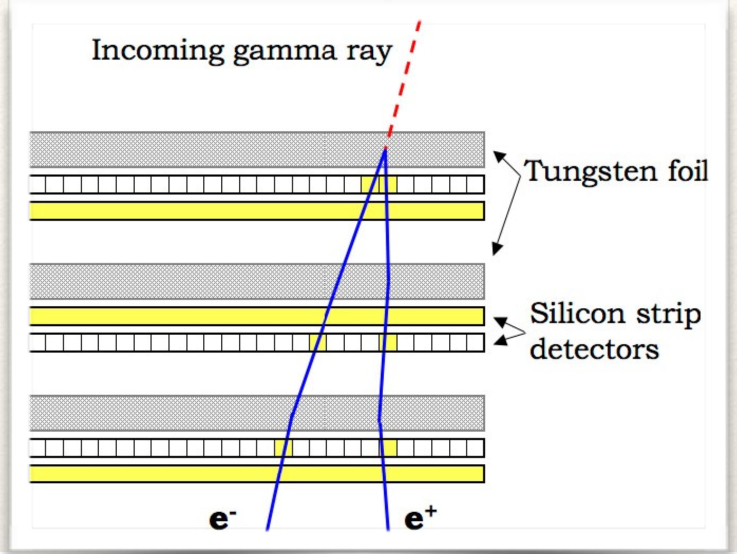
- **Radio & X-rays help to**

1. better locate & identify γ-ray sources,
2. resolve the morphology of the extended γ-ray sources,
3. better separate the underlying γ-ray emission mechanisms (Leptonic vs. Hadronic or both),
4. understanding the acceleration & propagation processes of CRs.

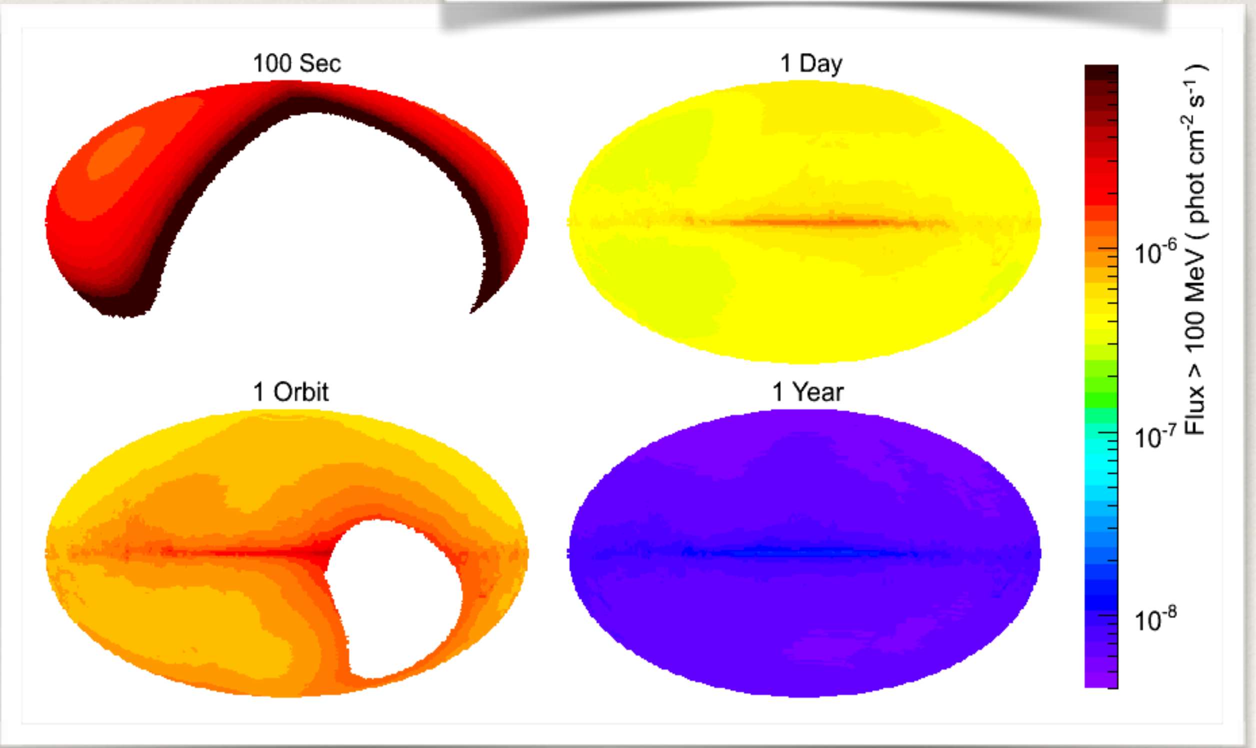


Fermi Gamma-ray Space Telescope





- Launched on June 11, 2008
- Two instruments:
  - Large Area Telescope (LAT)
    - 20 MeV – 300 GeV
  - Gamma-ray Burst Monitor (GBM)
    - 10 keV – 25 MeV



Sensitivity to Point Sources

Ref: Atwood et al. (arXiv:0902.1089)

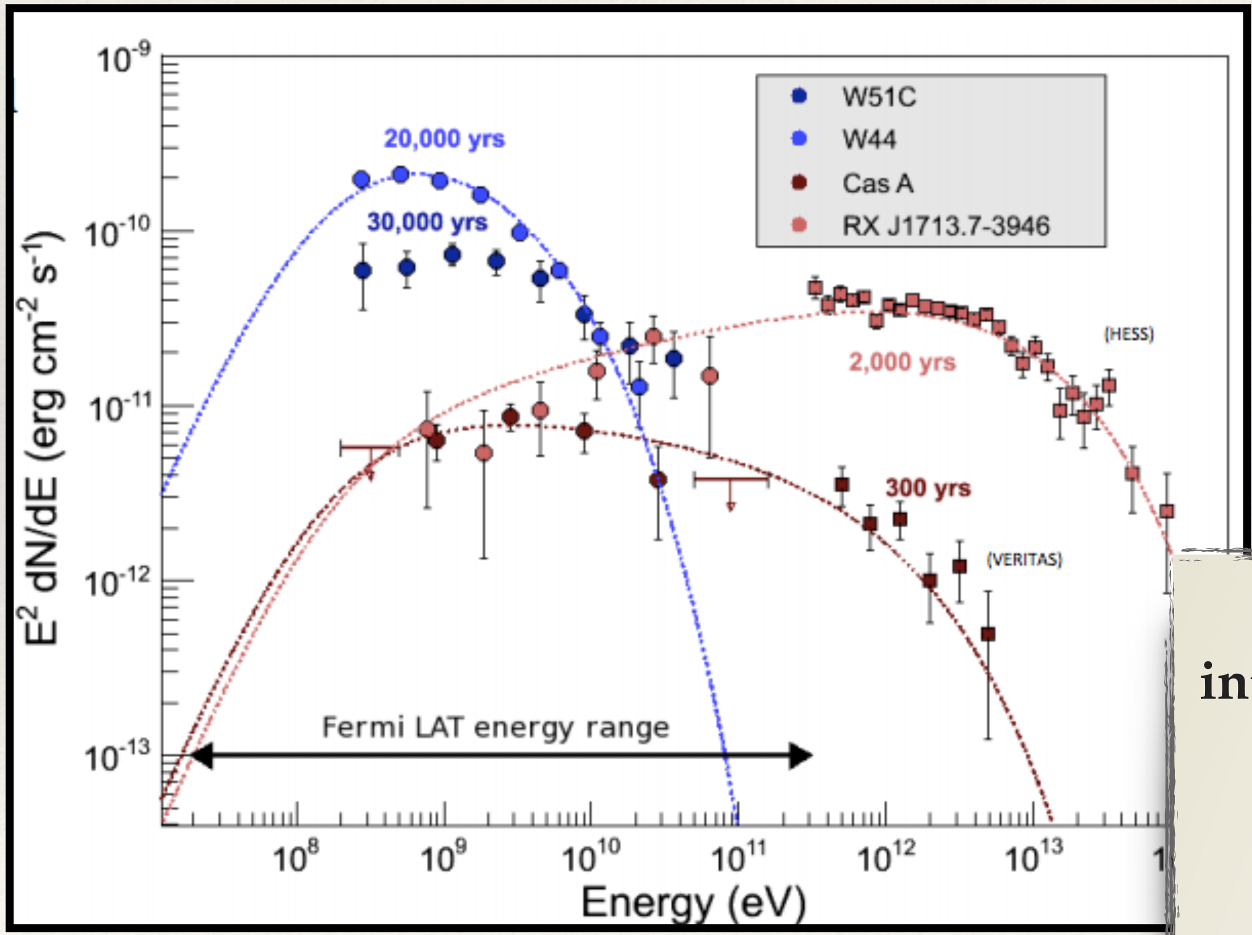
Fermi-LAT Source Catalogs

Catalog	Energy Range (GeV)	Data Interval (m)	Sources	Unasso-ciated	Event Selection	Release Date
0FGL	0.2-100	3	205	37 (18%)	P6V1 DIFFUSE	Feb. 2009
		11	1451	630 (43%)	P6V3 DIFFUSE	Feb. 2010
		24	1873	649 (35%)	P7V6 SOURCE	Aug. 2011
3FGL	0.1-300	48	3033	992 (33%)	P7V15 SOURCE	Jan. 2015
4FGL	0.05-1000	96	~5500	~1800(33%)	P8 SOURCE	End of 2018
1FHL	10-500	36	511	65 (13%)	P7V6 CLEAN	Jun. 2013
2FHL	50-2000	80	360	48 (14%)	P8 SOURCE	Aug. 2015
3FHL	10-2000	84	1556	176 (11%)	P8 SOURCE	Mar. 2017

The number of SNRs+PWNe reported in the 4FGL catalog is ~60.

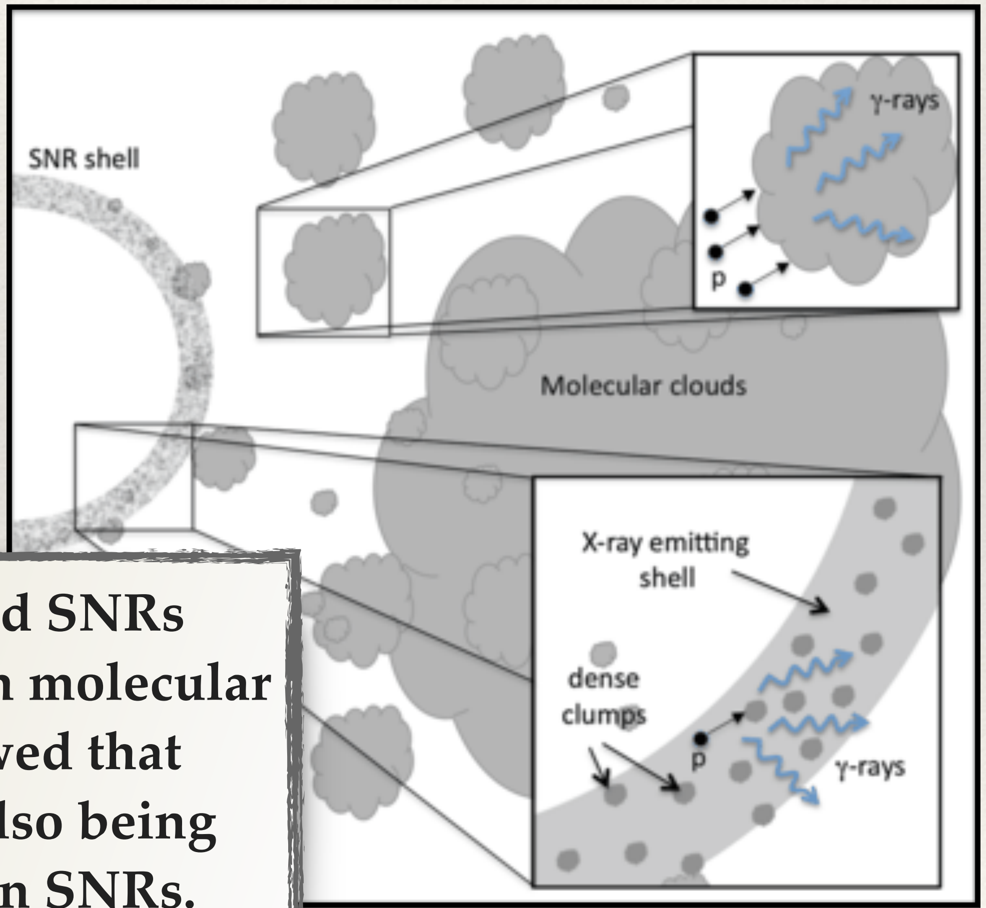
Fermi-LAT Detected SNRs

- **Young SNRs:** X-ray Synchrotron emission, strong TeV γ-rays, X-ray/TeV γ-ray correlation; γ-rays probably produced by electron interactions.
- **Middle Aged SNRs:** Usually interacting with molecular clouds (MCs). γ-rays created in the decay of neutral pions produced in proton-proton interactions.



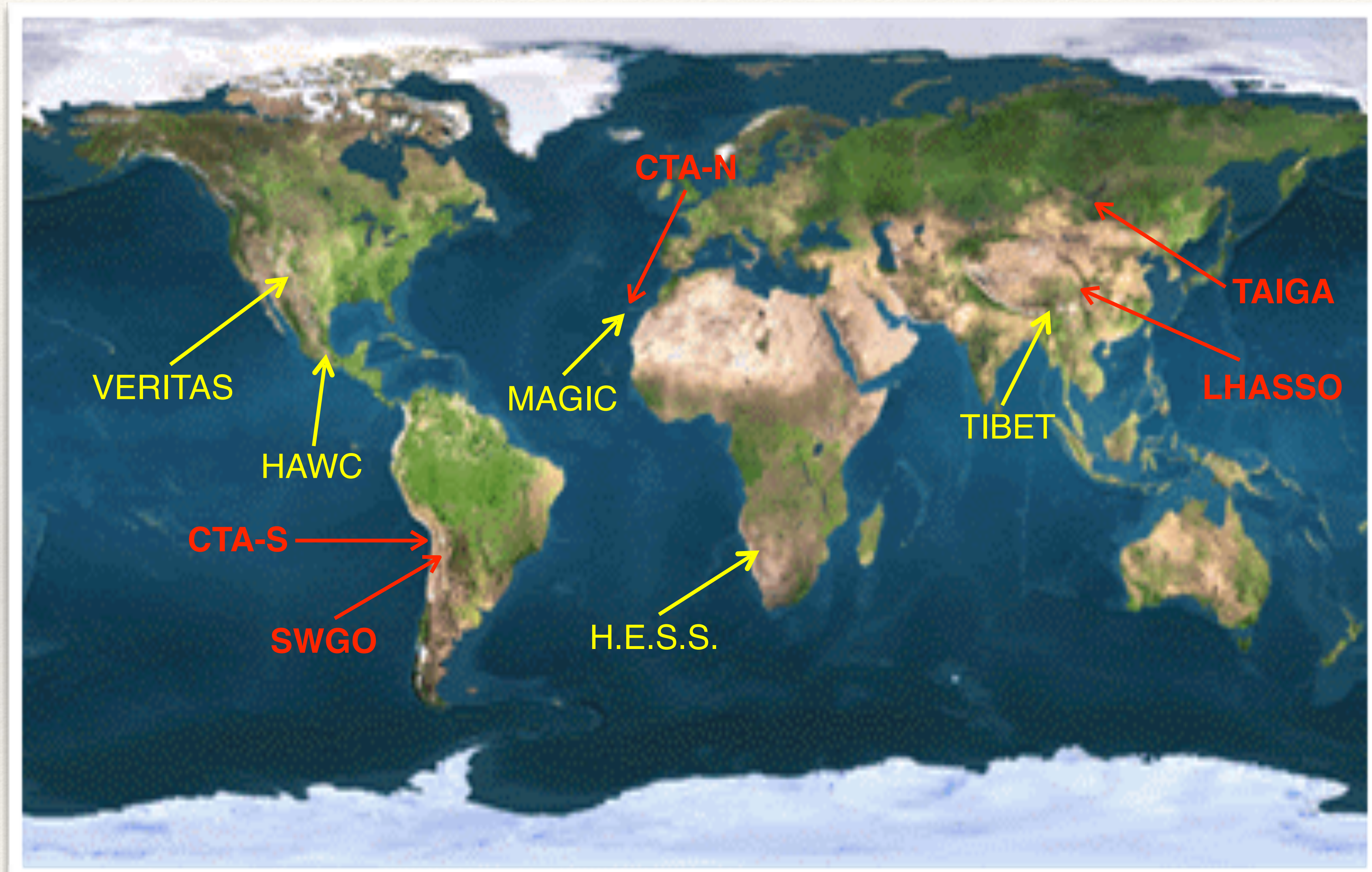
Ref: S. Funk, Ann.Rev.Nucl.Part.Sci. 65 (2015)

Middle Aged SNRs interacting with molecular clouds showed that protons are also being accelerated in SNRs.



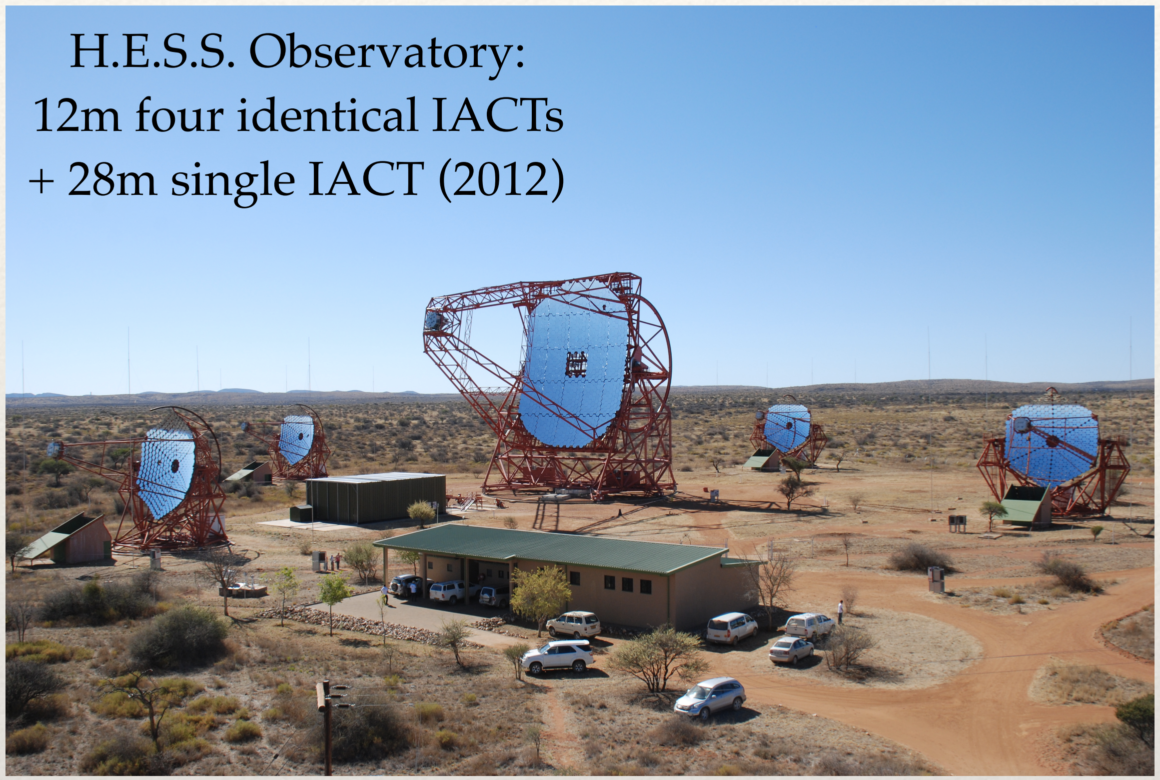
Ref: P. Slane et al., SSRv, 188, 187 (2015)

Current & Future γ-ray Observatories

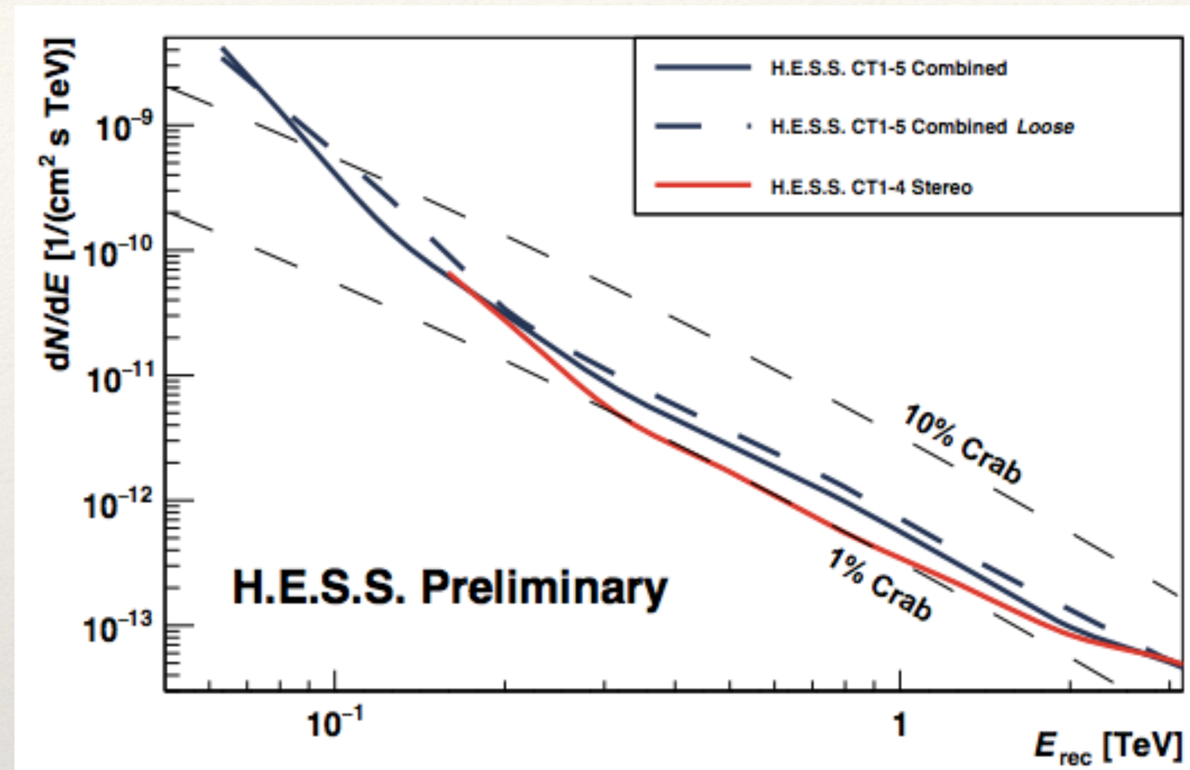


Ref: https://astroparticle.weebly.com/news/towards-a-new-high-energy-gamma-ray-observatory

The H.E.S.S. Observatory



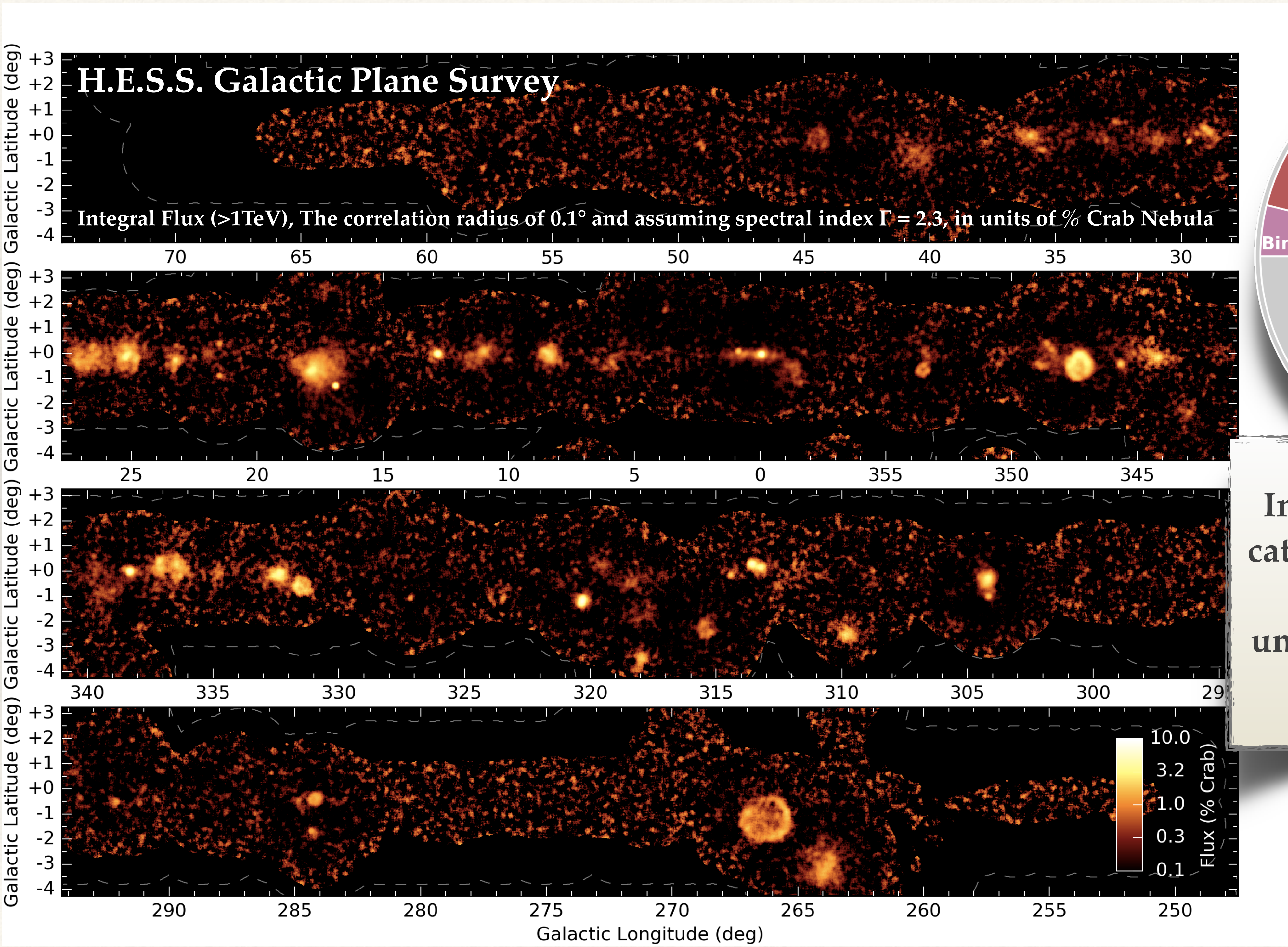
Ref: www.mpi-hd.mpg.de/hfm/HESS/pages/about/telescopes/

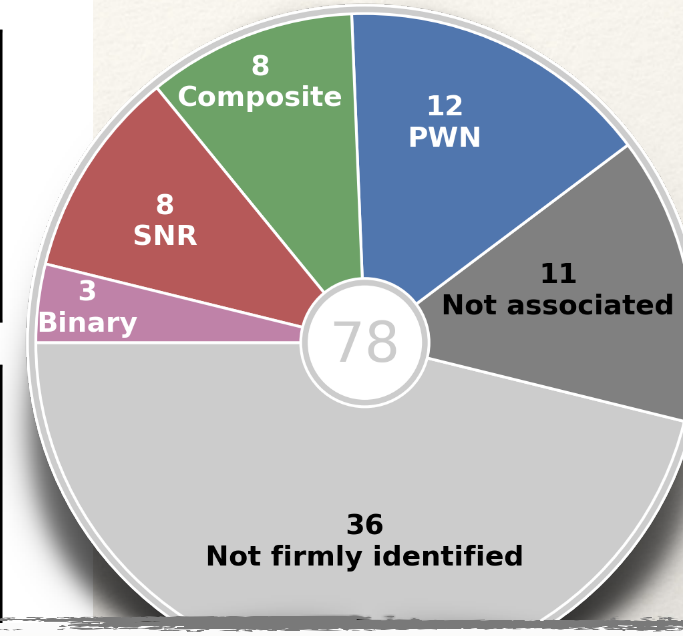


Ref: M. Holler et al., Proc. of ICRC 2015,arXiv:1509.02902

- The **Crab Pulsar Wind Nebula is the standard candle** in TeV γ-ray Astronomy.
- The energy threshold of the Crab Nebula measurements:
  - ~440 GeV (H.E.S.S. I: CT1-4)
  - ~230 GeV (H.E.S.S. II: CT1-5 combined)
- Crab Nebula Spectrum: $\frac{dN}{dE} = (1.79 \pm 0.03) \times 10^{-10} \left(\frac{E}{0.521\,\mathrm{TeV}}\right)^{-(2.10\pm0.04)-(0.24\pm0.01)\cdot\ln\left(\frac{E}{0.521\,\mathrm{TeV}}\right)} \frac{1}{\mathrm{TeV\,cm^2\,s}}$

H.E.S.S. Galactic Plane Survey



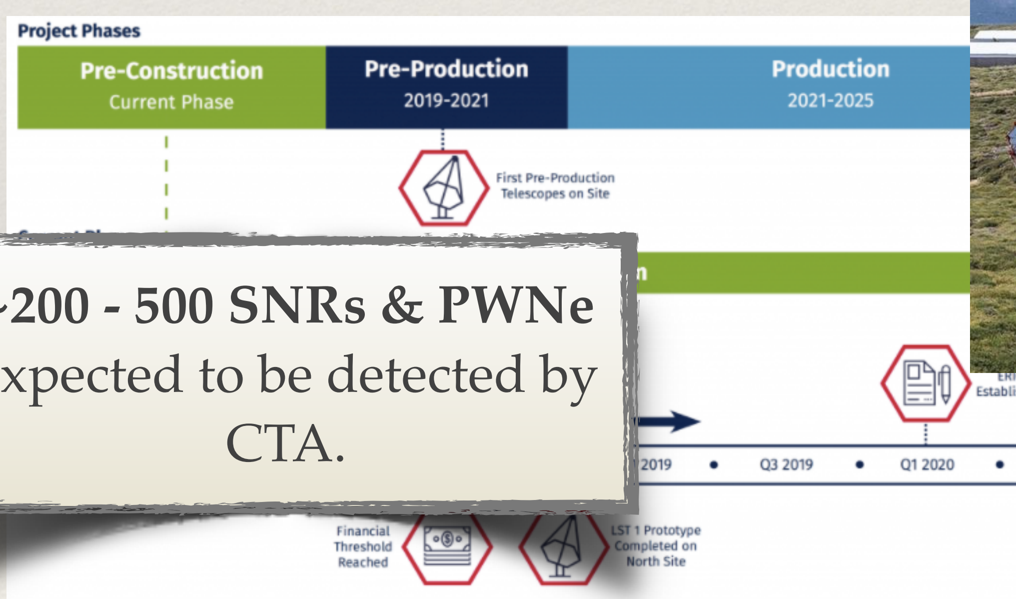


In the combined TeV γ-ray catalog, the detected number of SNRs+PWNe & unassociated sources is 63 & 65, respectively.

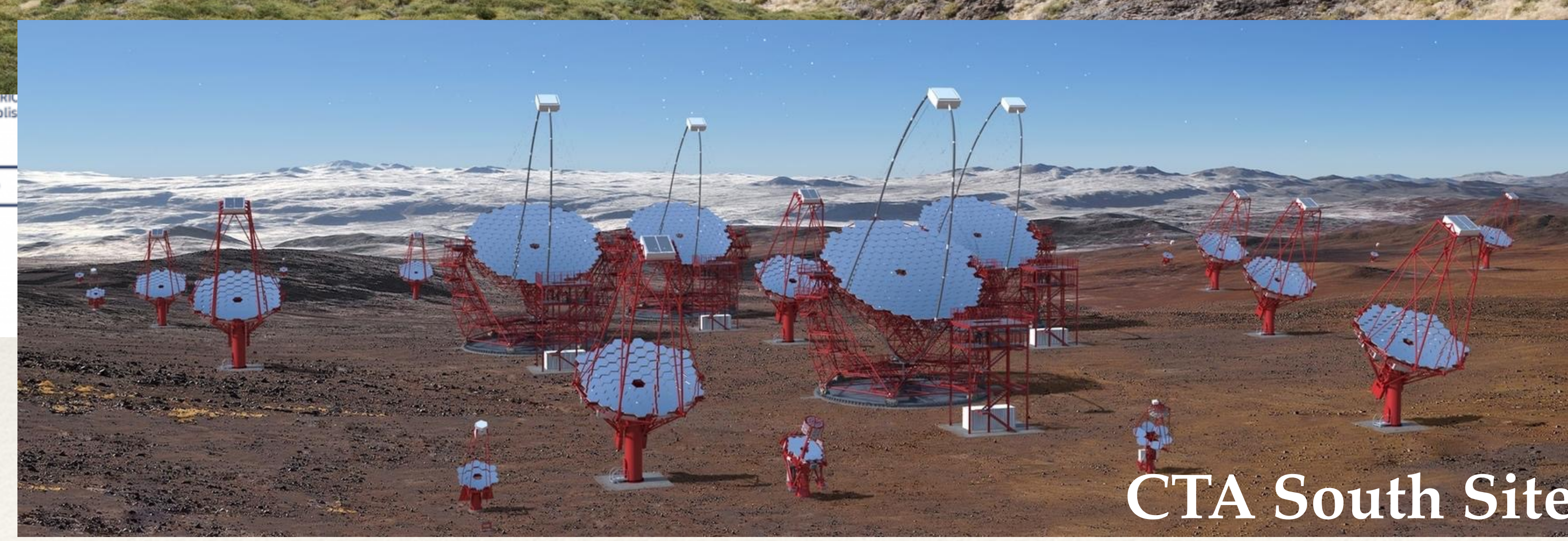
Ref: H. Abdalla et al., A&A 612, A1 (2018)

Cherenkov Telescope Array (CTA)

- CTA is a global effort with more than 1,350 scientists and engineers from 210 institutes in 32 countries involved in directing CTA's science goals and array design.
- 3 Telescope sizes: 70 pieces of 4-m-size (SST) distributed on ~7 km^2 area, 25 pieces of 12-m-size (MST) distributed on about a km^2 area with 25 South US extension, and 4 pieces 23-m-size (LST) telescopes.
- ~120 + 25 telescopes in total



~200 - 500 SNRs & PWNe expected to be detected by CTA.



Ref: www.cta-observatory.org,
Acharya et al. for the CTA Consortium,
arXiv:1709.07997v2

Searching for SNRs in Future Data

- Future observatories produce large amounts of data with good angular resolution.
- Nevertheless, **source confusion is expected to be a challenge**, especially for data collected form the Galactic Plane, where most of the SNRs are expected to be located.
- We have to build tools to **efficiently combine and/or compare data obtained at different wavebands** in order **to recognise & classify SNRs, as well as to interpret** the physical mechanisms taking place in SNRs.

The Source Confusion Challenge

- **20 - 25% of the Galactic Plane (GP) sources in TeV energies are SNRs and 60% of them are PWNe** However, **half of the GP sources observed in TeV γ-rays remain unidentified.**
- **Why there are unidentified γ-ray sources?**

1. Especially at lower energies, **γ-ray sources have multiple MW associations, which cannot be disentangled**,
2. they appear as **extended γ-ray sources consisting of several still unresolved sources**, i.e. it is not clear which associated source contributes to the extended γ-ray emission,
3. they are completely "dark" sources, with **no counterpart at any other wavelength**.

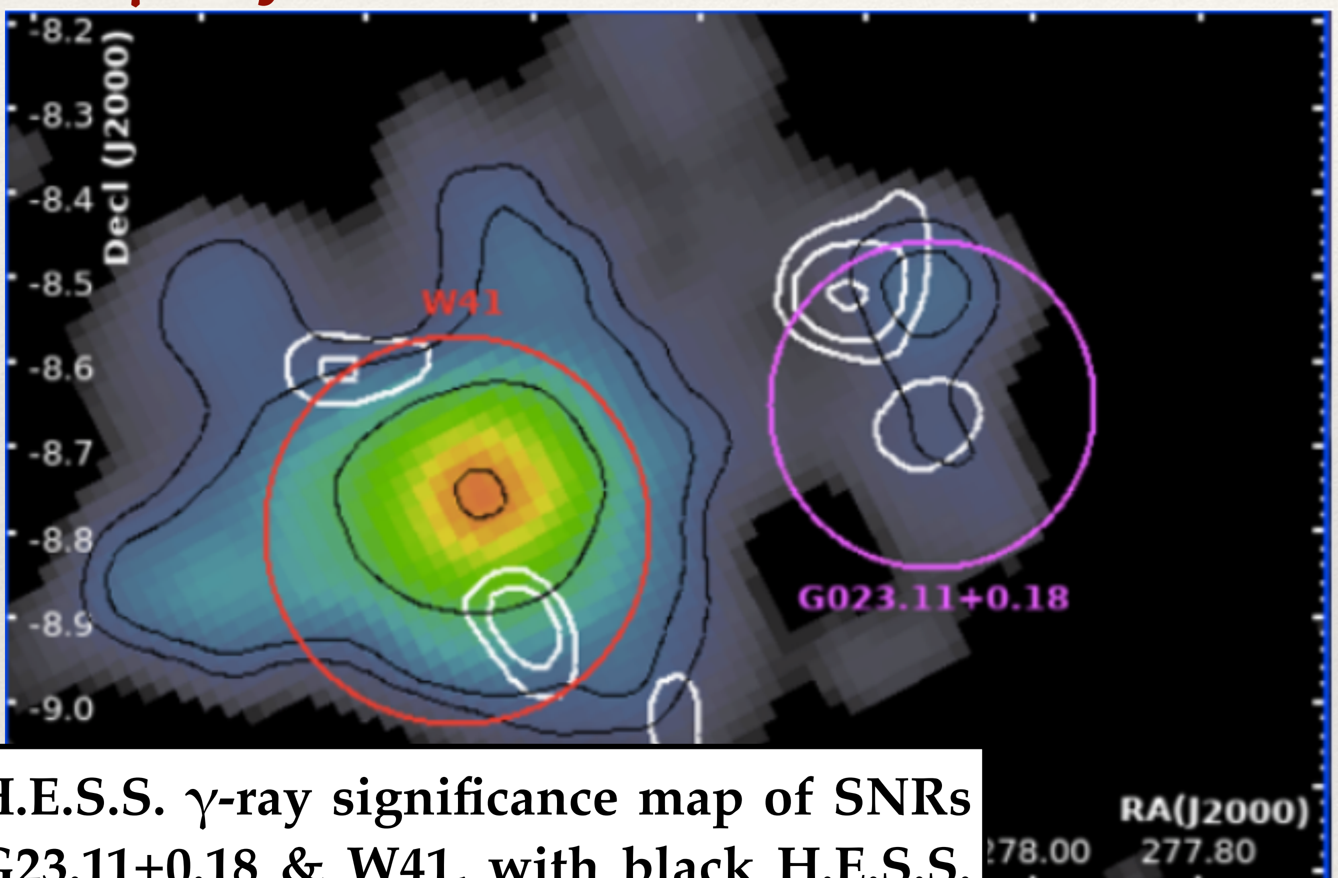
The Source Confusion Challenge

- **Three ways to mitigate source confusion:**

1. **Better angular resolution** observations (it usually takes years to build new observatories with improved angular resolution),
    - There are super-resolution methods, like generative adversarial networks, to improve spatial resolution of existing data, which I will not mention in this talk.
2. **MW observations & analysis** (not always available; and proposal writing & observations take a long time)
3. **Machine Learning (ML) tools** (once trained, they can be used any time to get an initial result)

MW Observations & Analysis

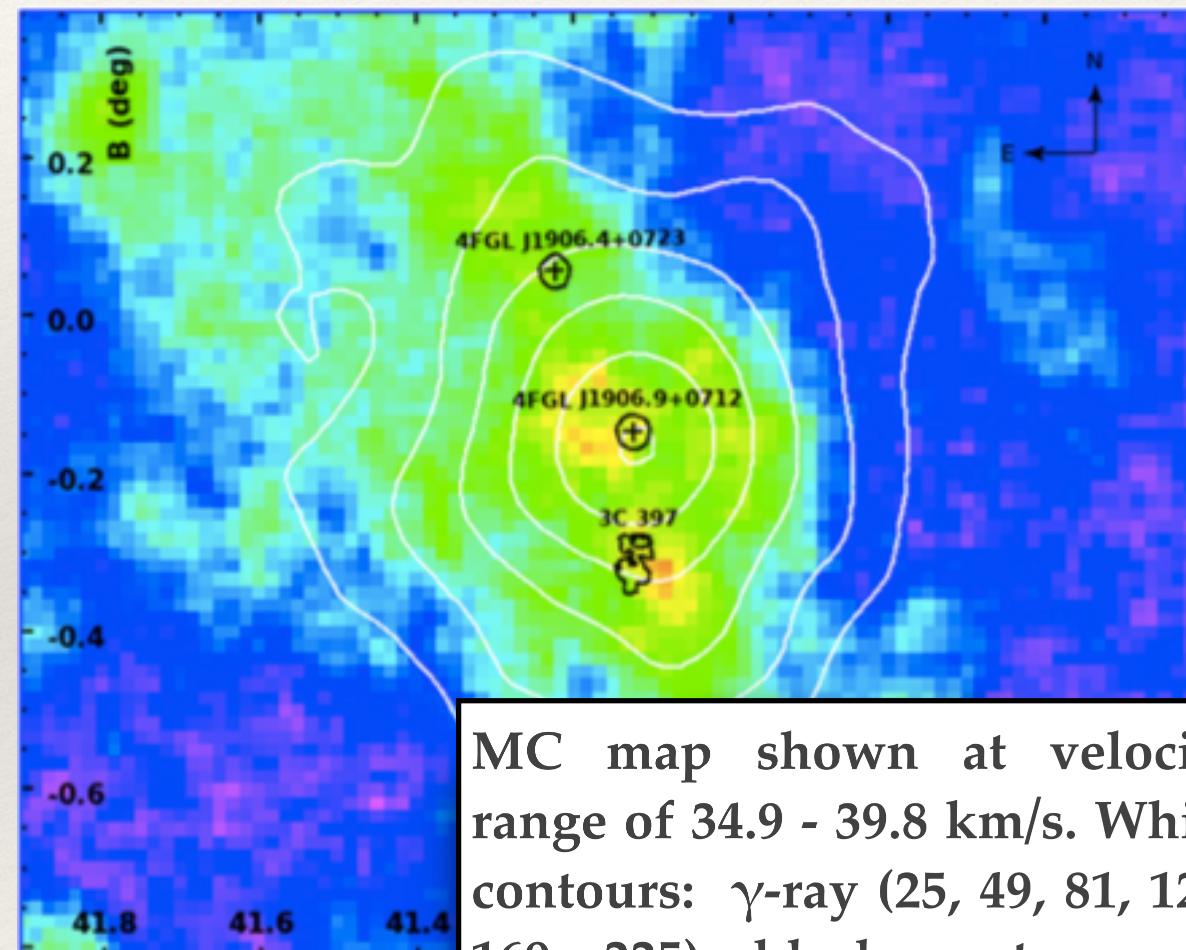
MW Data to Increase the Number of γ-ray SNRs



H.E.S.S. γ-ray significance map of SNRs G23.11+0.18 & W41, with black H.E.S.S. significance contours (4, 5, 9, 16 sigma) and white Fermi- LAT contours. The red & magenta circles show radio extensions of W41 and G23.11+0.18, respectively.

Ref.: T. Ergin, COSPAR 2021, Poster no. E1.2-0044-21 (2021).

MW Data to Disentangle γ-ray Sources (E.g. 3FHL J1907.0+0713)



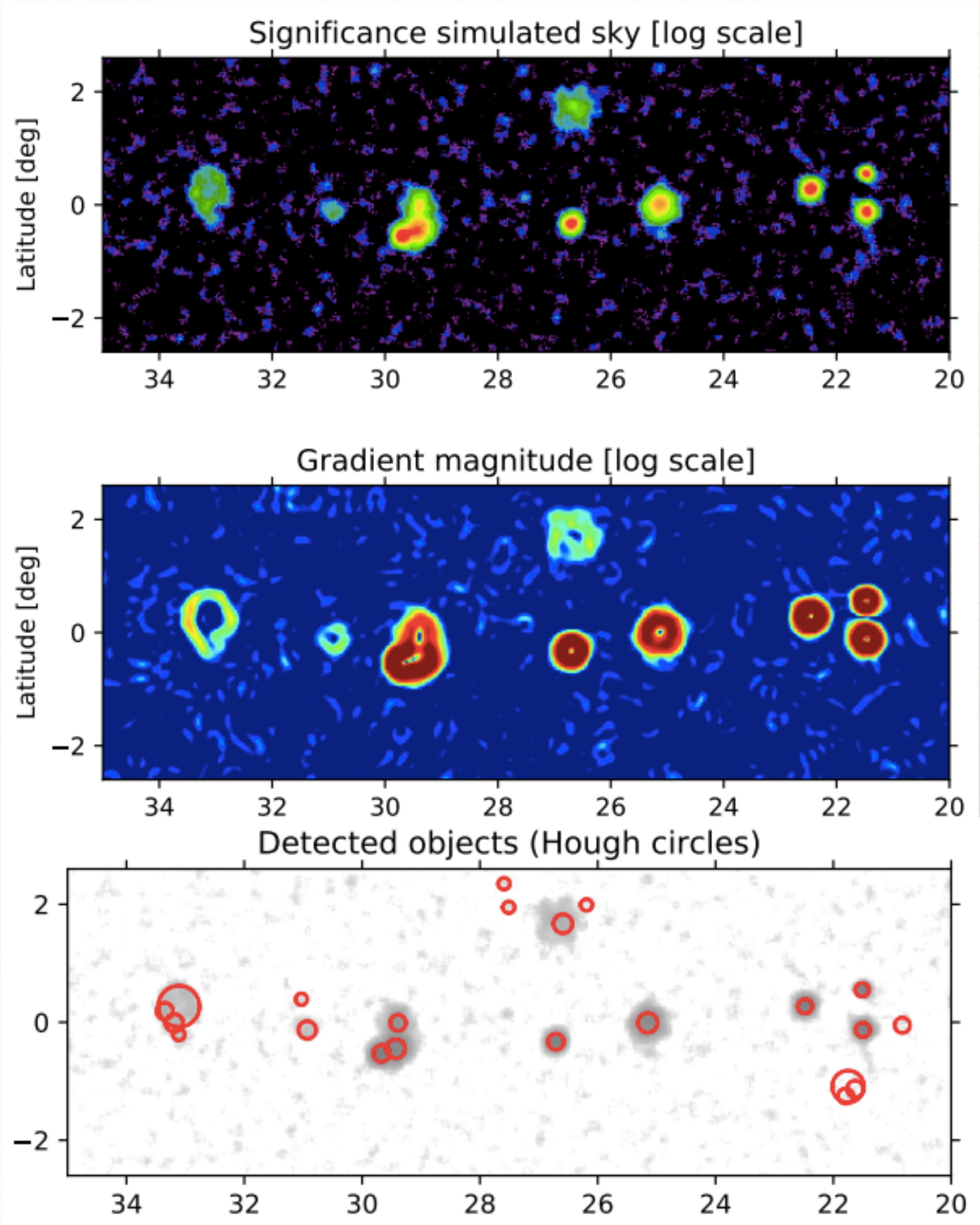
Ref: T. Ergin et al., MNRAS 501, 4226 (2021)

MC map shown at velocity range of 34.9 - 39.8 km/s. White contours: γ-ray (25, 49, 81, 121, 169, 225), black contours: X-rays, black markers: Fermi-LAT 4FGL-catalog sources.

γ-ray Analyses with ML Tools

- **Why do we need to use ML tools ?**
- To recognise certain objects (e.g. SNRs)
- To classify objects into subcategories (e.g. shell-like, disk-like, Gaussian-like, etc.) using classifiers such as Logistic regression, Convolutional Neural Networks (CNNs)
- To generate artificial samples via learning underlying distribution
- To understand the governing dynamics of a system, e.g. analysing time-series using RNNs (Recurrent Neural Networks)

SNR Studies with ML Tools



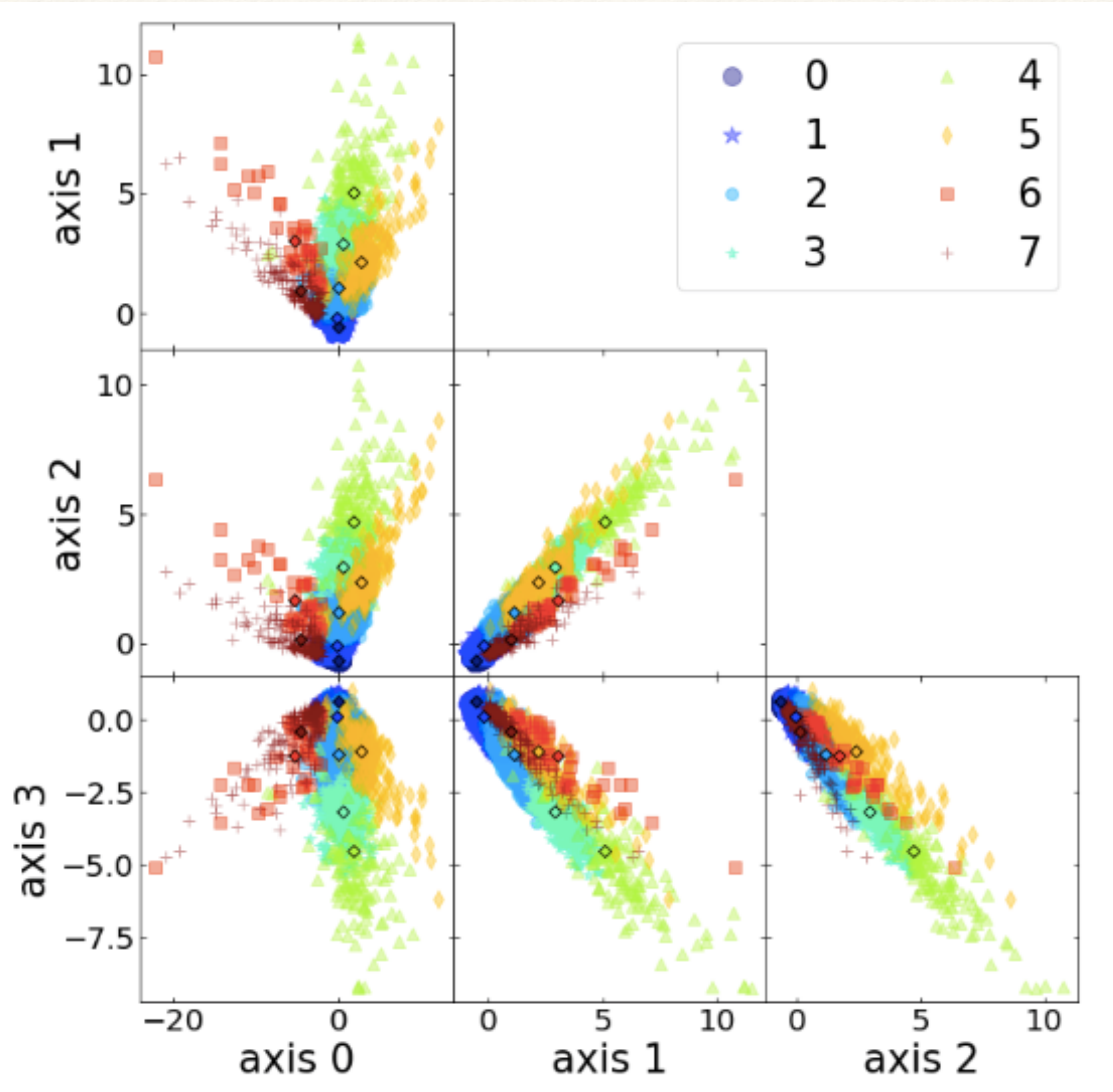
- **Image Processing to Detect Circular Objects:**
- Simulated significance map for H.E.S.S.
- Gradient map representing edge transitions
- Detected objects using Hough transform

Ref: Q. Remy, Y. A. Gallant & M. Renaud, Astropart. Phys. 122, 102462 (2020)

SNR Studies with ML Tools

- **Image Processing to Detect Circular Objects (Disadvantages):**
  - Not possible to detect objects without a closed mathematical form.
  - Cannot be used for recognition of all SNR types.

SNR Studies with ML Tools



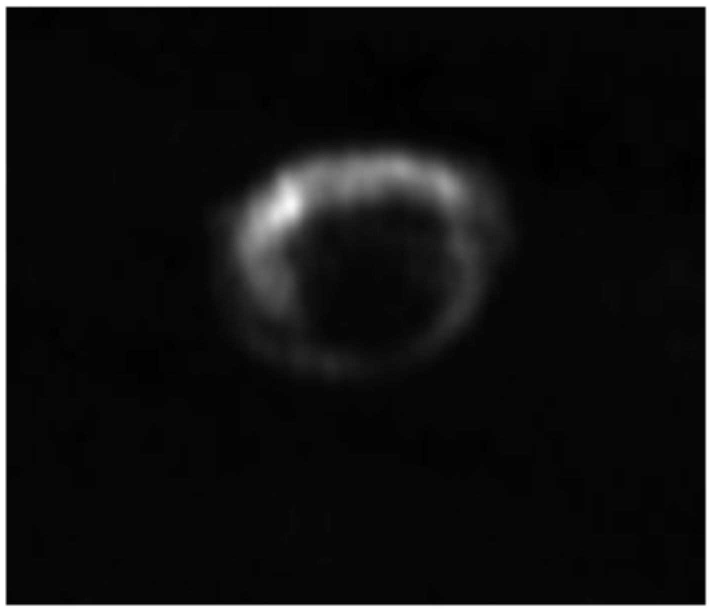
- **Clustering Spatial Bins:**
- Variational Auto-Encoder (VAE) is employed to learn latent representation.
- Latent representation is subject to a soft-clustering via Gaussian Mixture Model (GMM).

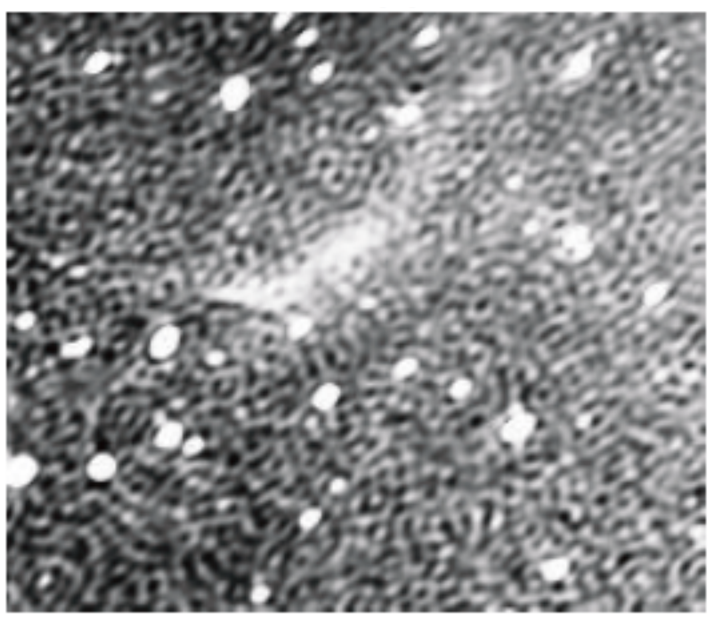
Ref: H. Iwasaki, Y. Ichinohe, Y. Uchiyama, MNRAS, 488, 4106 (2019)

SNR Studies with ML Tools

- **Clustering Spatial Bins (Disadvantages):**
  - Disregarding spatial relation among neighbouring bins.
  - Multi-scale features cannot be captured.
  - Principal Component Analysis (PCA) could be used instead.

SNR Studies with ML Tools

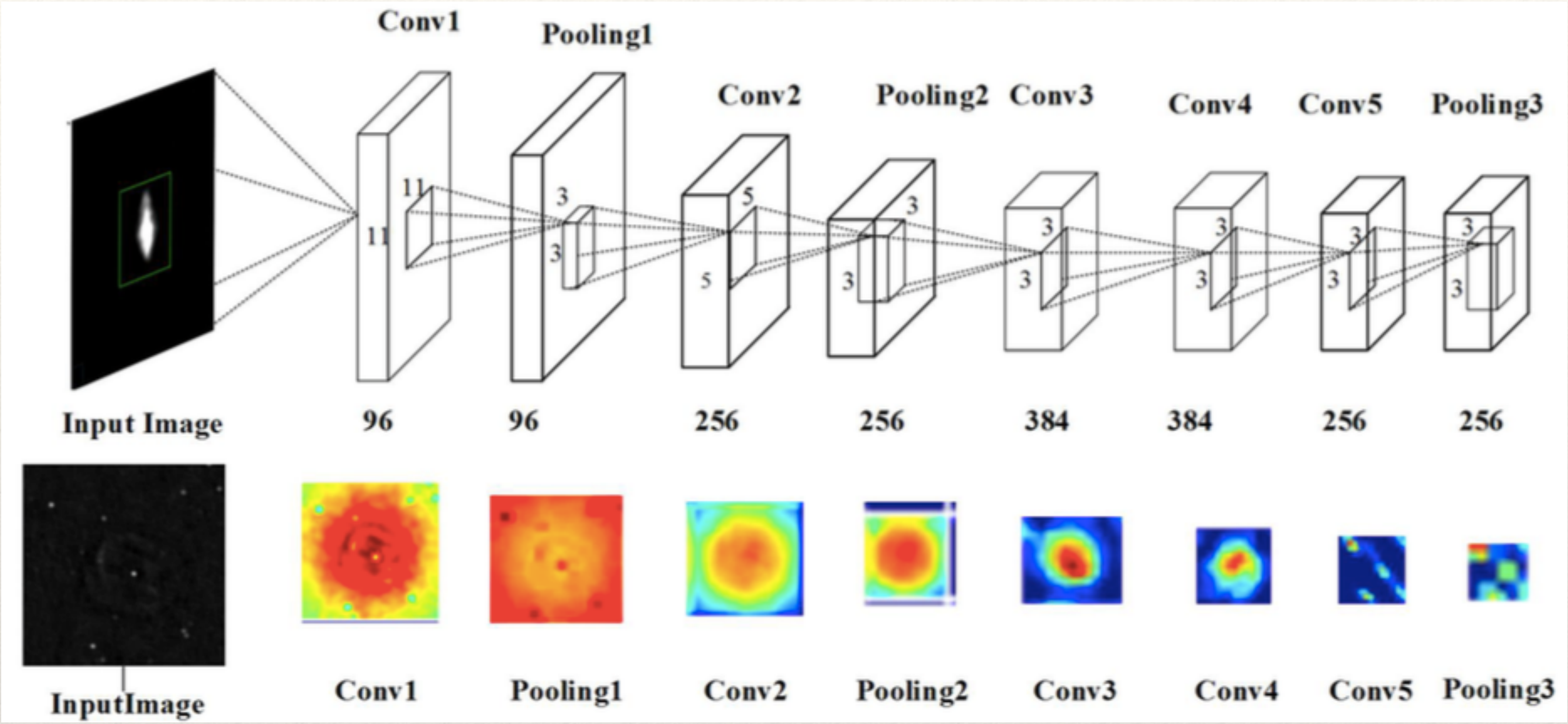




- **Using Deep Learning to Detect SNRs:**
- The most related study to my research plan
- Using various methods to classify SNRs:
  - Random Forest (RF)
  - Support Vector Machine (SVM)
  - Convolutional Neural Network (CNN)

Ref: W. Liu et al., Res. A&A, 19, 042 (2019)

SNR Studies with ML Tools



Ref: W. Liu et al., Res. A&A, 19, 042 (2019)

- **Using Deep Learning to Detect SNRs:**
- CNN architecture
- Multi-scale features they learn at every layer.
- Fully-Connected Neural Network (FCN) for classification
- Data augmentation

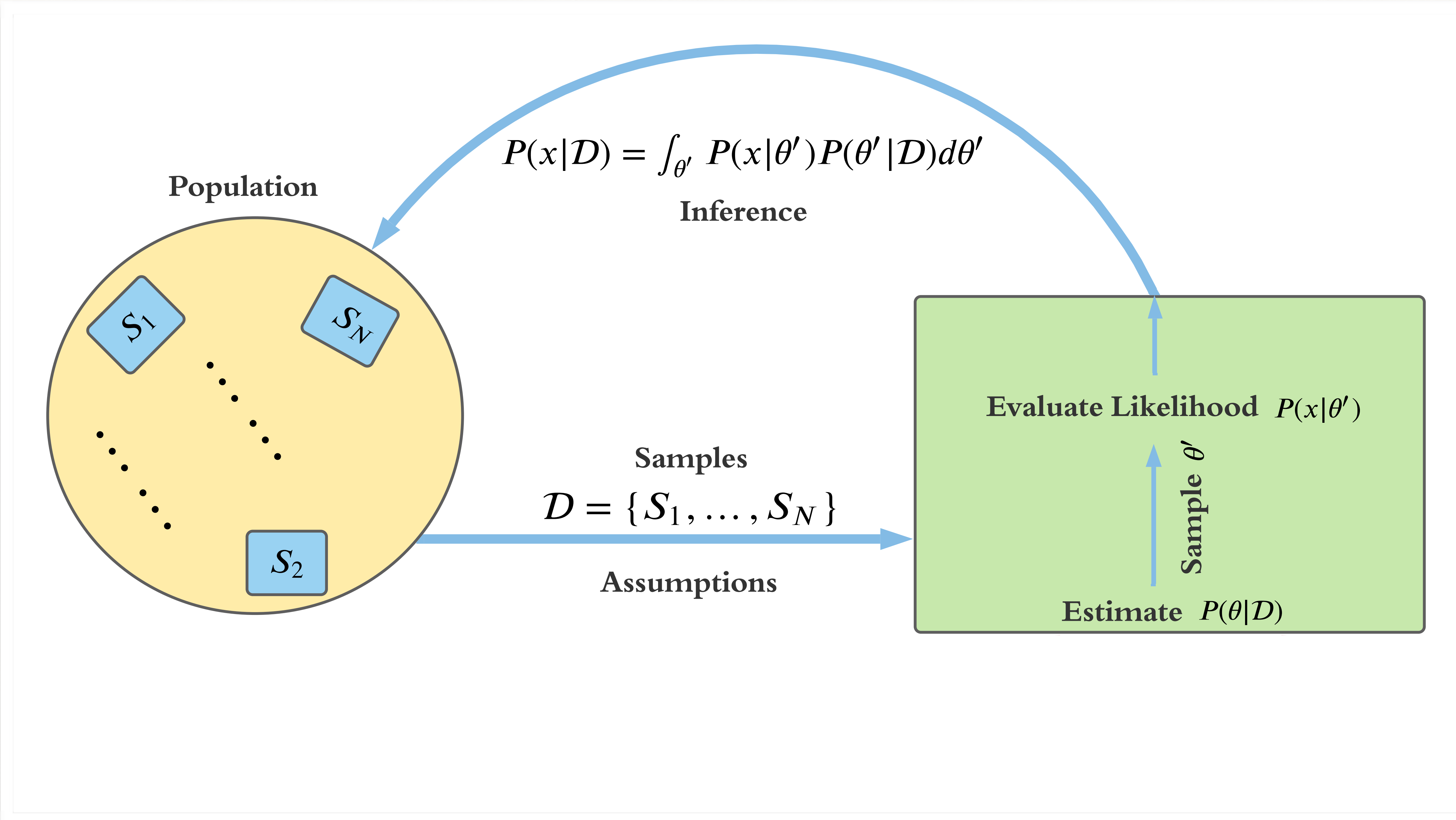
SNR Studies with ML Tools

- <u>**Using Deep Learning to Detect SNRs (Disadvantages):**</u>
- Binary classification does not guarantee that CNN learns morphological features.
- Classifiers such as CNN are data hungry models and simple linear data augmentation may not help.

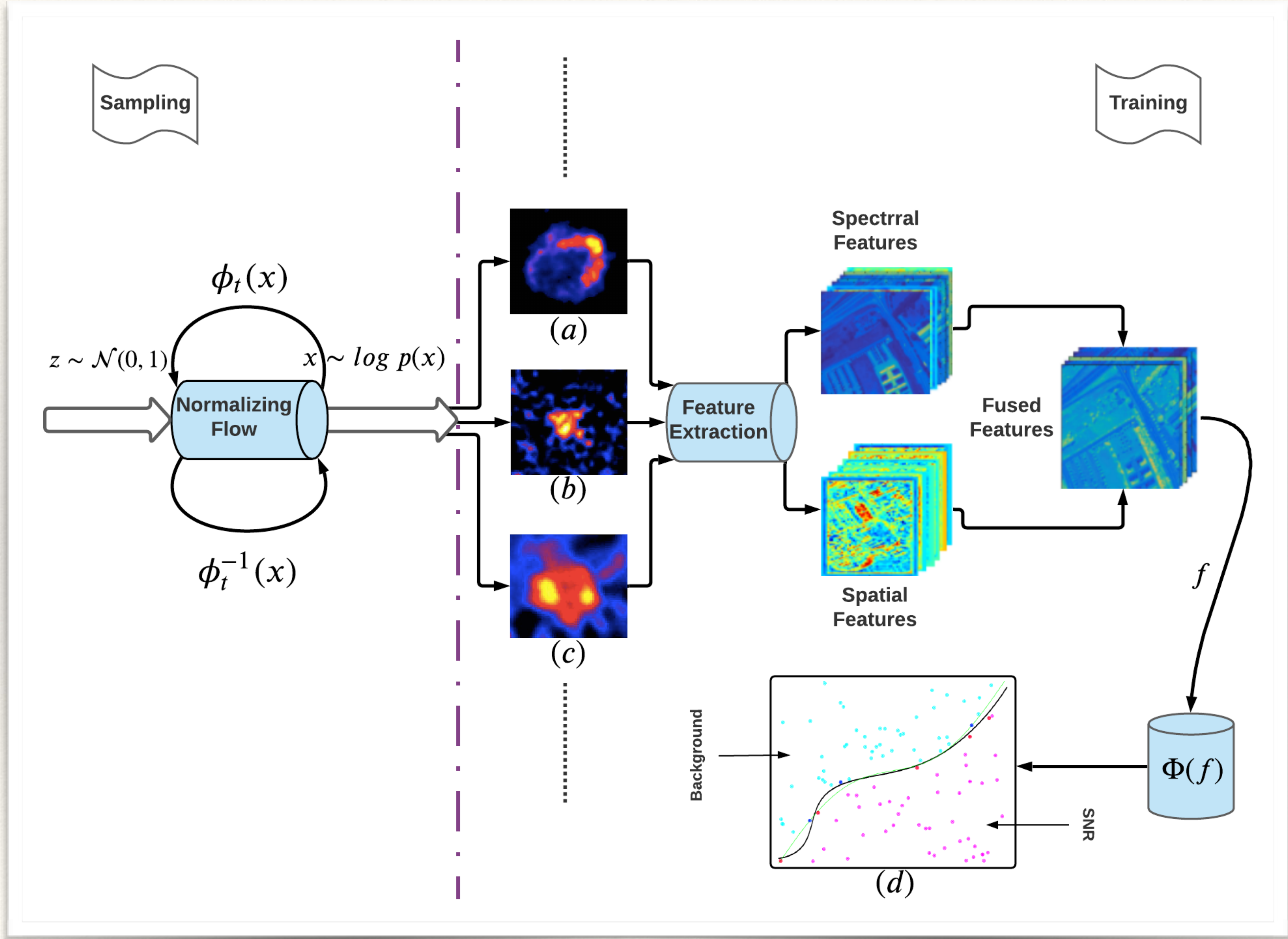
My Research Plan

- This research plan was proposed as a HORIZON 2020 project in 2020.
- It received a score of 79.6/100 passing the scientific evaluation threshold of 70/100, but could not pass the 2nd threshold (80/100) to be financed.
- I would like to pursue this research plan and complete it within the coming 1 - 2 years.
- **My Collaborators in this Project:**
  - ML: **İlker Gürcan**, METU, Dept. of Computer Science, Turkey
  - SNR CTA Simulations: **Dr. E. Oğuzhan Angüner**, Aix-Marseille University, France
  - Any future collaborators are welcome.

General Framework for Statistical Inference



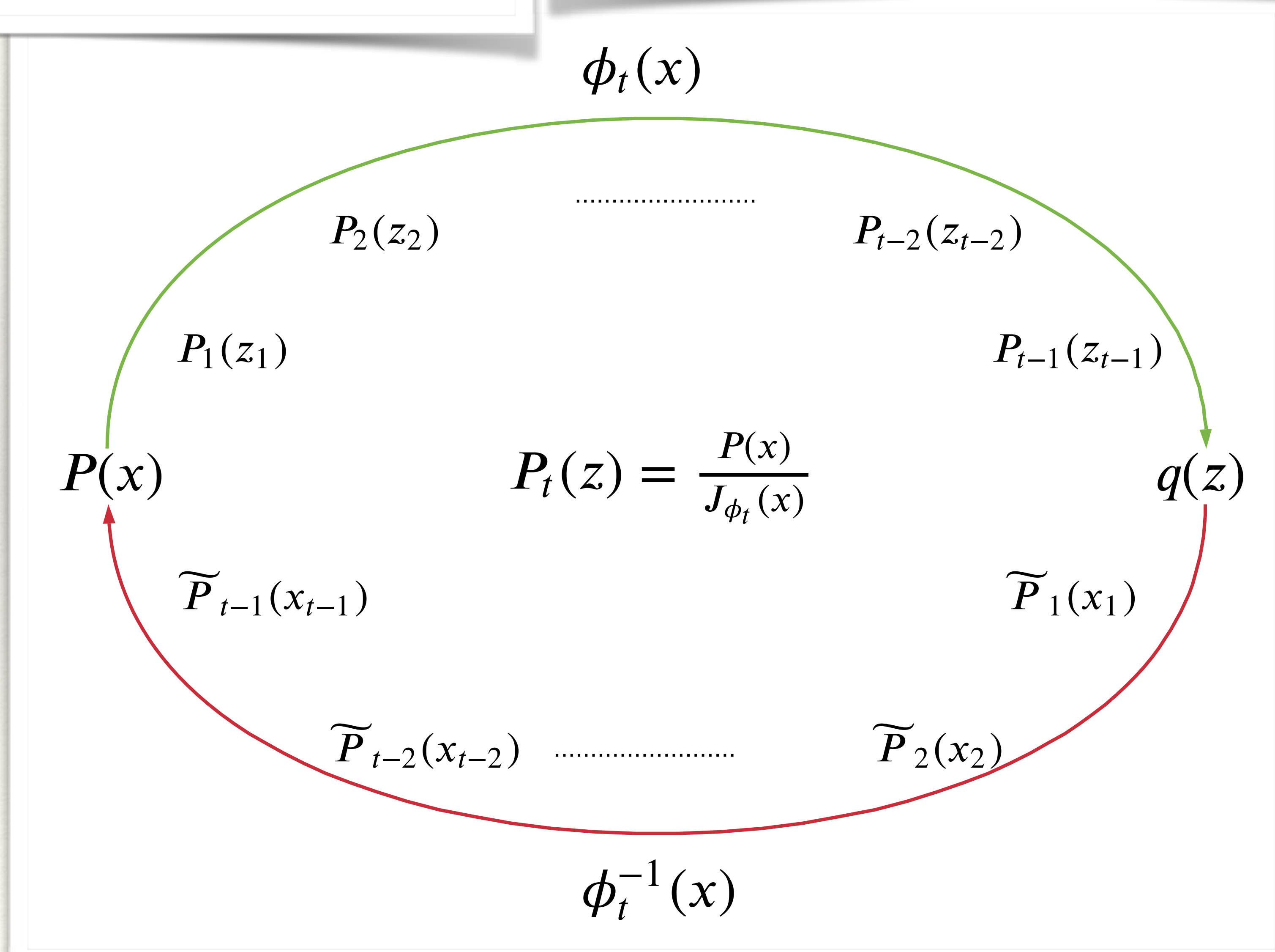
The Proposed Architecture



1st Phase: Normalising Flow

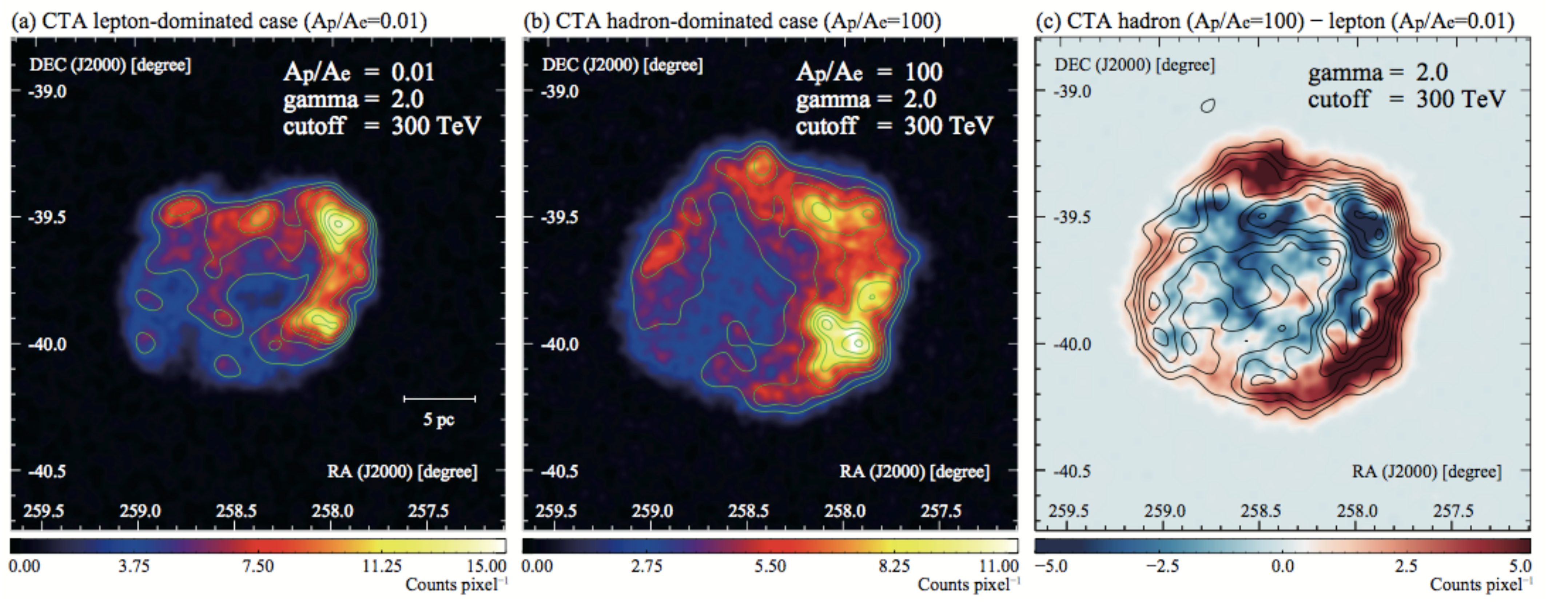
$$\mathcal{L}_P\left[\phi_t\right] = \int \left\{ \log\left(\det J_{\phi_t}(x)\right) + \log\left(q\left(\phi_t(x)\right)\right)\right\} P(x)dx,$$

where $\phi_t = \Phi_t \circ \Phi_{t-1} \circ \ldots \circ \Phi_1$ and $\phi_t(x) = z$.



1st Phase: Sampling

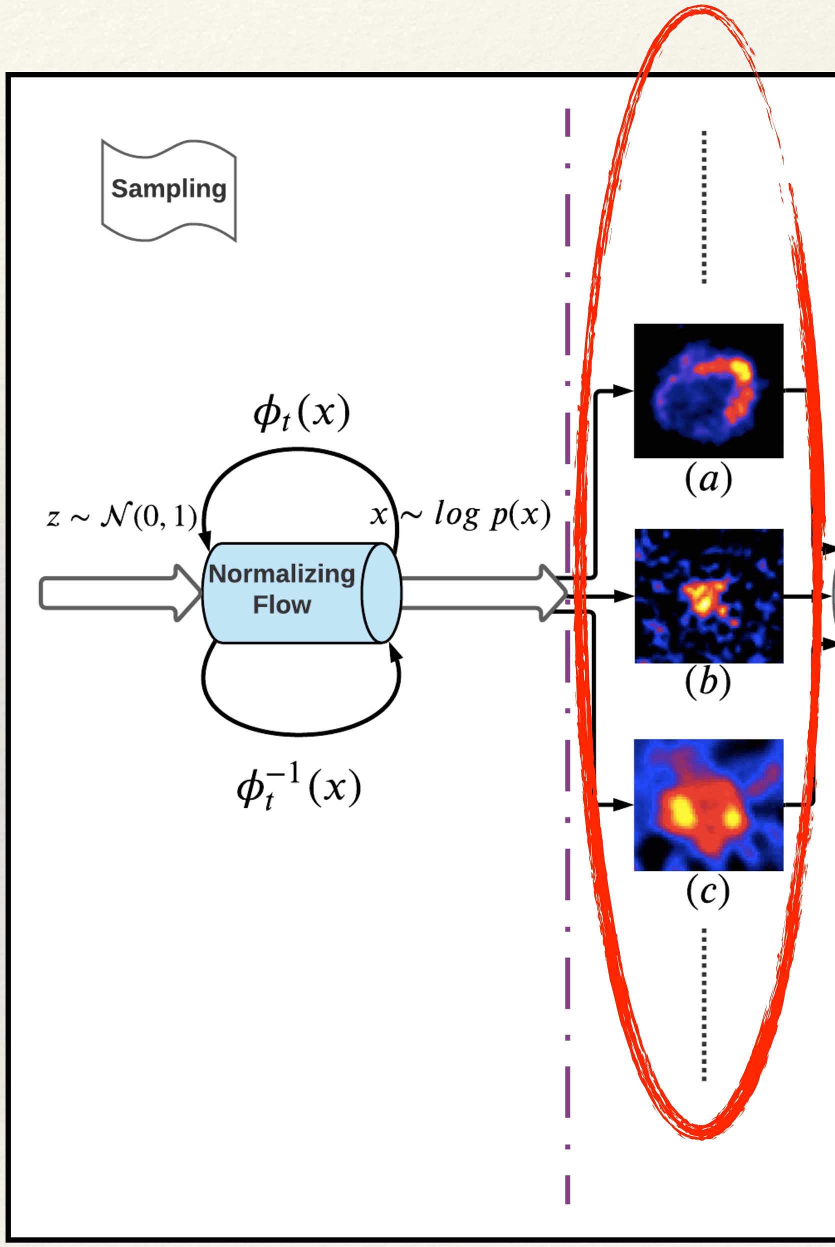
- **How to prepare training data:**
  - Use the existing SNRs from the GeV & TeV γ-ray catalogs.
  - Simulate large number of SNRs, using simulation tools developed by CTA collaboration (e.g. ctools: http://cta.irap.omp.eu/ctools/index.html).



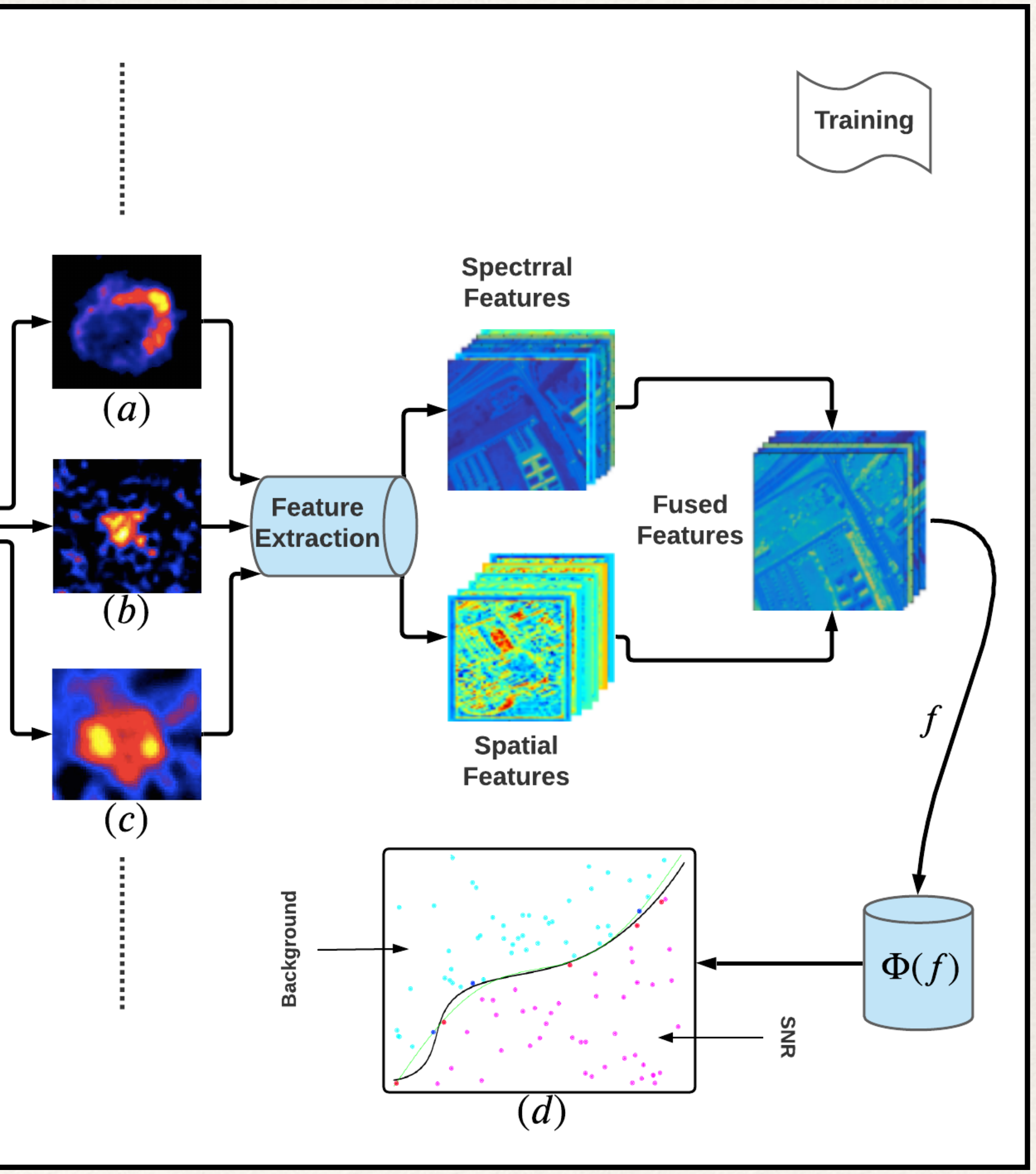
www.cta-observatory.org, Acharya et al. for the CTA Consortium, "Science with the Cherenkov Telescope Array", arXiv:1709.07997v2

1st Phase: Sampling

- Sampling from normal distribution
- Transforming back to target distribution
- Obtaining artificial SNR and non-SNR samples



2nd Phase: Training & Classification



- **The Classifier ϕ(f):**
  - **"Support Vector Machine (SVM)",**
  - **"Fully Connected Networks (FCN)"**
  - Any other kernel learning algorithm
- After these algorithms are trained, when the newly observed CTA data are entered into them, the SNRs detected in big data will be classified and distributed to specified groups.

Advantages of this Method

- The **most common problem** across all statistical learning tools is **hunger for data**.
- **Generalisation to unseen samples is challenging**
    - It is even harder when the sample data is limited in size (e.g. currently detected SNRs are in hundreds).
- Applying these methods,
    - will lead to **detailed description of the sub-structures in complex regions** that would ease the MW association search for SNRs,
    - will help firmly **identify the unidentified γ-ray sources**.

Thank you very much for your Attention!