Deep Unsupervised Domain Adaptation for the Cherenkov Telescope Array

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Presentation Outline

Gamma-ray astronomy

Study of the **high-energy gamma sources** in the Universe.

Inverse problem resolution : Given the **telescope observations**, how to recover the **Energy**, **Direction** and **Type** of the incoming particle ?

- Single telescope analysis (LST-1, CTA project)
- Particle classification : Gamma or Proton (maybe Electron ?)

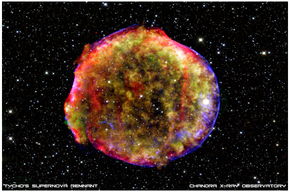


Figure 1: Supernova. Source [1].

Figure 2: Black hole. Source [1].

Figure 3: Dark matter. Source [1].

Principle of detection

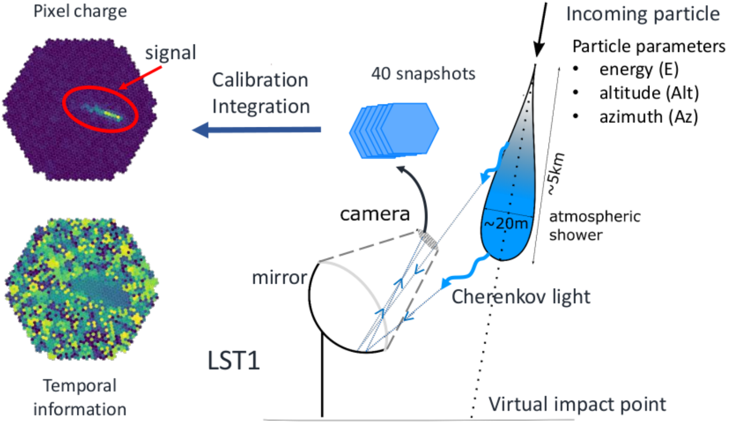


Figure 4: Principle of gamma particle detection. Source [8].

Workflow

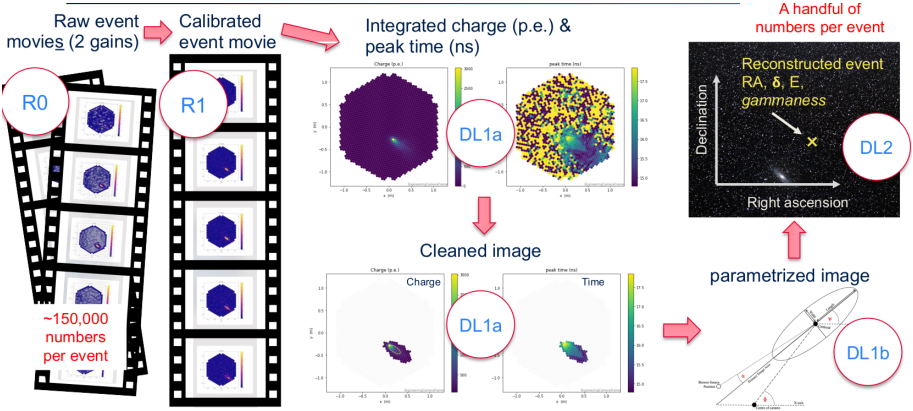


Figure 5: Particle detection workflow (Hillas). Source : LST Analysis School.

Workflow

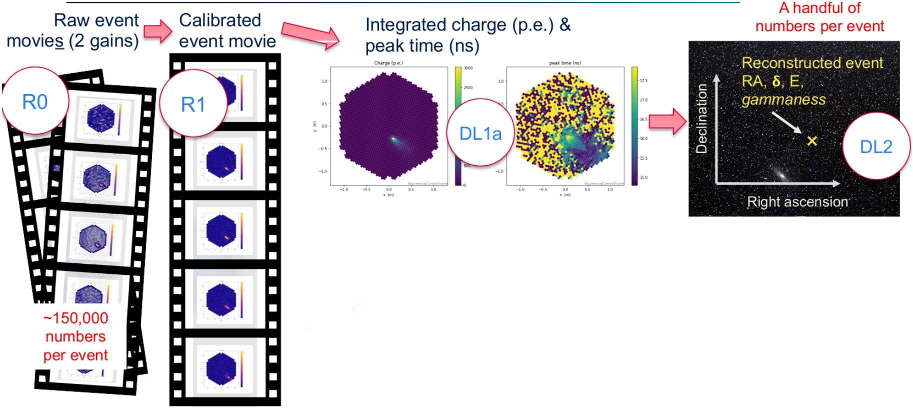


Figure 6: Particle detection workflow (γ-PhysNet).

γ-PhysNet

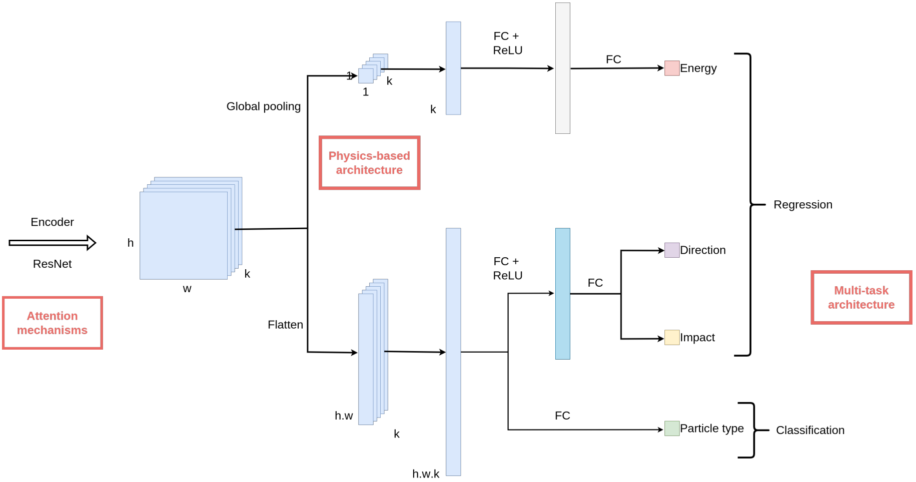


Figure 7: γ-PhysNet architecture. Source [5].

Results on MC simulations

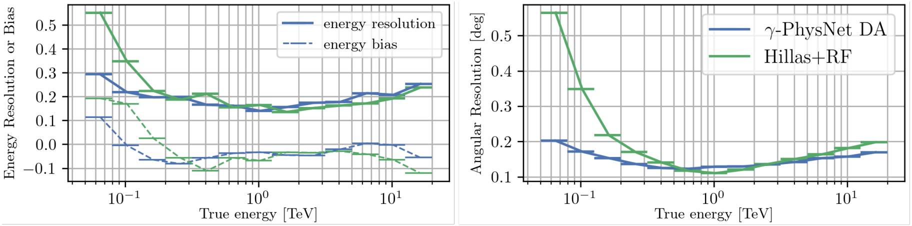


Figure 8: Comparison of different IRFs between γ-PhysNet and Hillas+RF on simulated data. Left : Energy resolution as a function of the true energy. Right : Angular resolution as a function of the true energy. In both cases, **lower is better**. Source [8].

Results on MC simulations

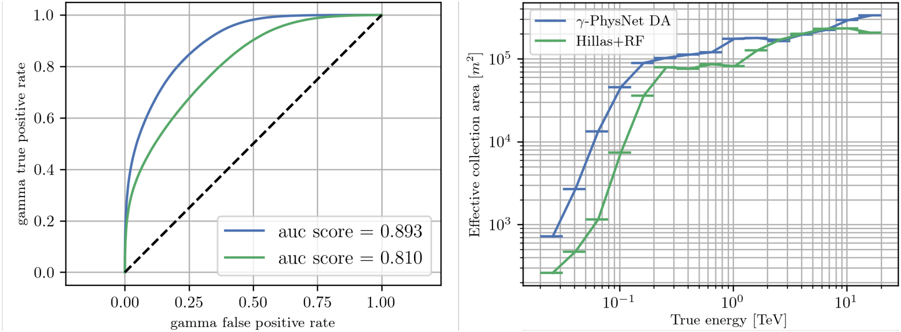


Figure 9: Comparison of different IRFs between γ-PhysNet and Hillas+RF on simulated data. Left : ROC curves of the particle classification. Right : Effective collection area as a function of the true energy. In both cases, **higher is better**. Source [8].

Matching real data

- Unobtainable faultless labelled real data

  → Training fully relying on simulations

- Simulations are *close approximations* of the reality

  → Add Poisson noise ($P(\lambda)$) to match the NSB distributions

Training	**Inference**
MC+$P(\lambda)$	Real observations

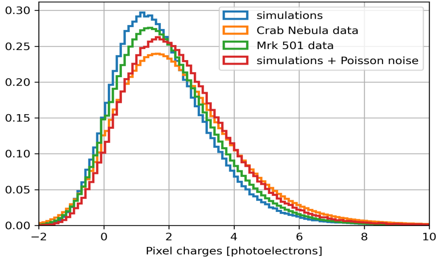


Figure 10: Night Sky Background (NSB) charge distributions for simulated and real data. Source [8].

- $NSB_{MC} \neq NSB_{real}$
- $NSB_{MC} + P(\lambda) \sim NSB_{real}$.

Results on real data

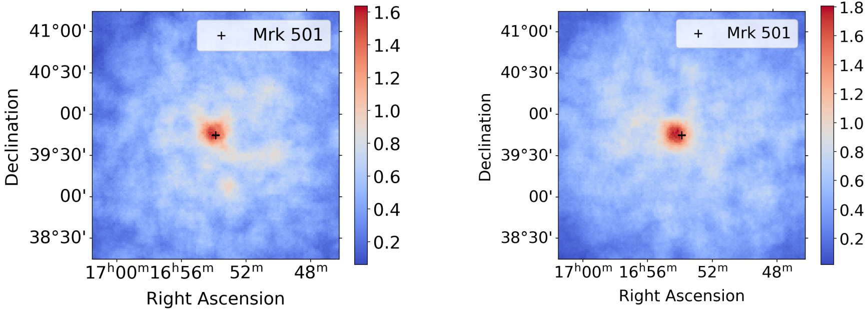


Figure 11: Markarian 501 detection. Left : Hillas + RF. Right : γ-PhysNet. γ-PhysNet detects more events but the area of detection is not centred on the real position. Source [8].

Domain adaptation

Set of algorithms and techniques which aims to reduce domain discrepancies.

- Generalisation of the model ($\neq$ run-wise adaptation)
- Great variety of state-of-the-art methods
- Deep unsupervised domain adaptation
- Promote a domain-invariant representation through domain confusion

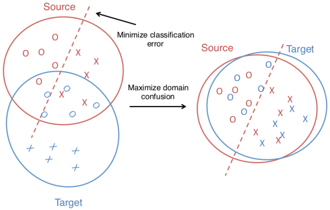


Figure 12: Domain confusion.

Figures of merit

What are the tools at our disposal ?

Confusion matrix

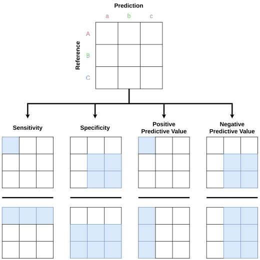


Figure 13

t-SNE

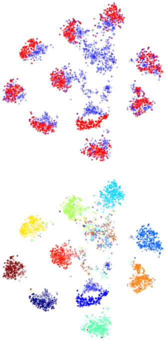


Figure 14

Grad-CAM

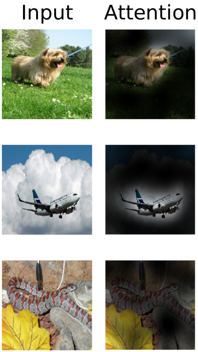


Figure 15

t-SNE

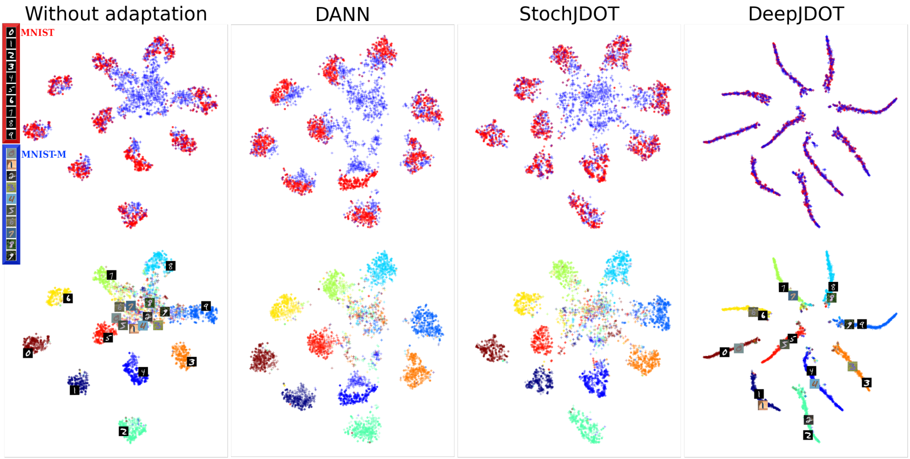


Figure 16: Feature adaptation using 4 distinct domain adaptation methods. Source [2].

γ-PhysNet extended with DANN [4]

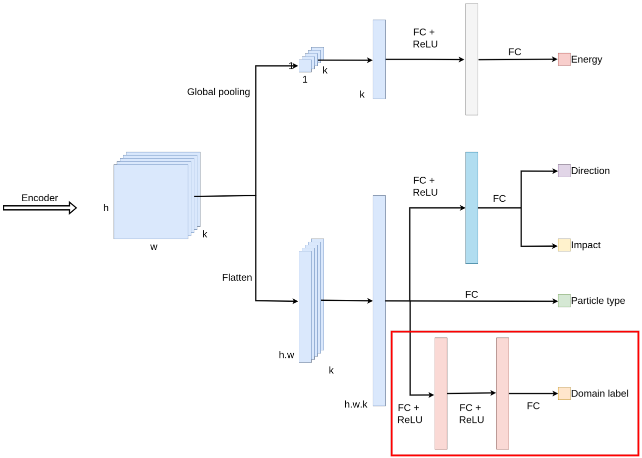


Figure 17: γ-PhysNet coupled with a domain classifier. Inspired from [4].

γ-PhysNet extended with DeepJDOT [2]

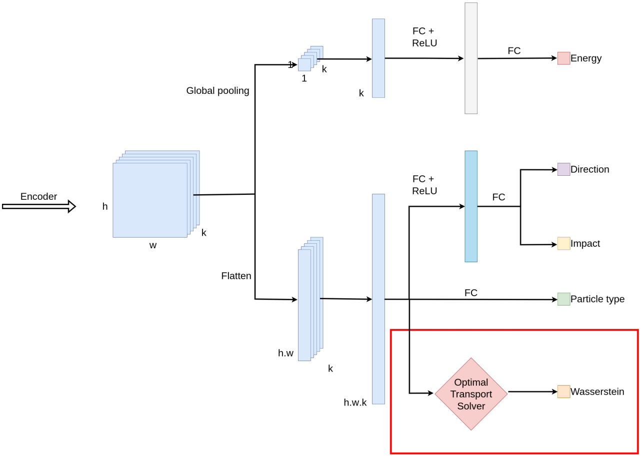
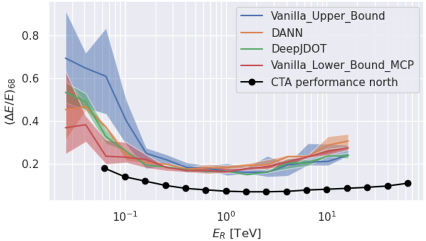


Figure 18: γ-PhysNet coupled with optimal transport. Inspired from [2]

Results on MC simulations



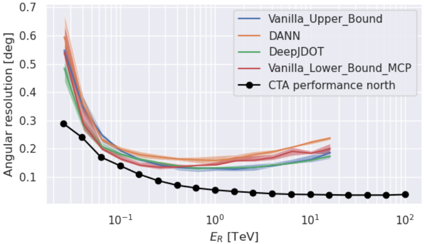


Figure 19: IRFs from DANN and DeepJDOT when trained on MC (Source) and MC+Poisson($\lambda = 0.4$) (Target) then tested on MC+Poisson($\lambda = 0.4$). Left : Energy resolution as a function of the energy. Right : Angular resolution as a function of the energy. In both cases, **lower is better**.

Results on MC simulations

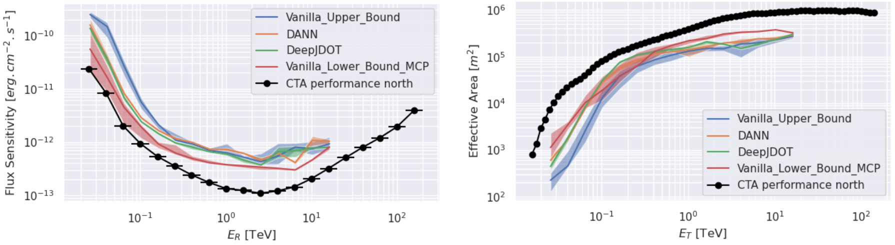


Figure 20: IRFs from DANN and DeepJDOT when trained on MC (Source) and MC+Poisson($\lambda = 0.4$) (Target) then tested on MC+Poisson($\lambda = 0.4$). Left : Flux sensitivity as a function of the energy. **Lower is better**. Right : Effective area as a function of the energy. **Higher is better**.

Conclusion & Perspectives

- Ultimate goal: Create an event map to localise gamma-ray sources
- Currently trying to reduce the discrepancy between MC and real data

- Working in parallel on:
  - Replace MC+P(λ) with real data (Markarian 501, Crab, ...)
  - The pointing direction between training data and observations
  - Introduction of physics knowledge (Physics-based deep learning)
  - Upgrading DANN [4] $\rightarrow$ WDGRL [6]

- Future challenges:
  - Stereoscopy (Federated learning [9], ...)
  - Neural network explainability (Information bottleneck [7], ..)
  - Continual learning [3]

γ − learn

GammaLearn

- All info and contact: https://gammalearn.pages.in2p3.fr/pages/

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- This project has received funding from the ***European Union's Horizon 2020 research and innovation programme*** grant agreement **No 824064**

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[9] Qiang Yang et al. 2019.

Thank you for your attention!