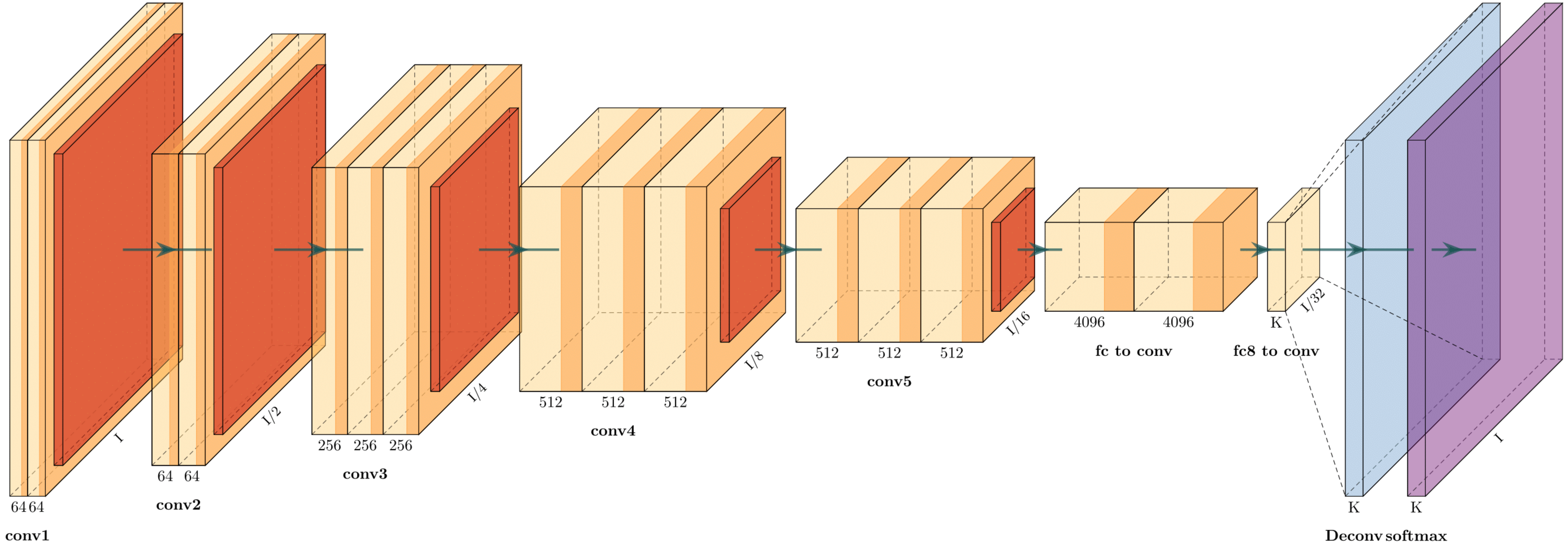
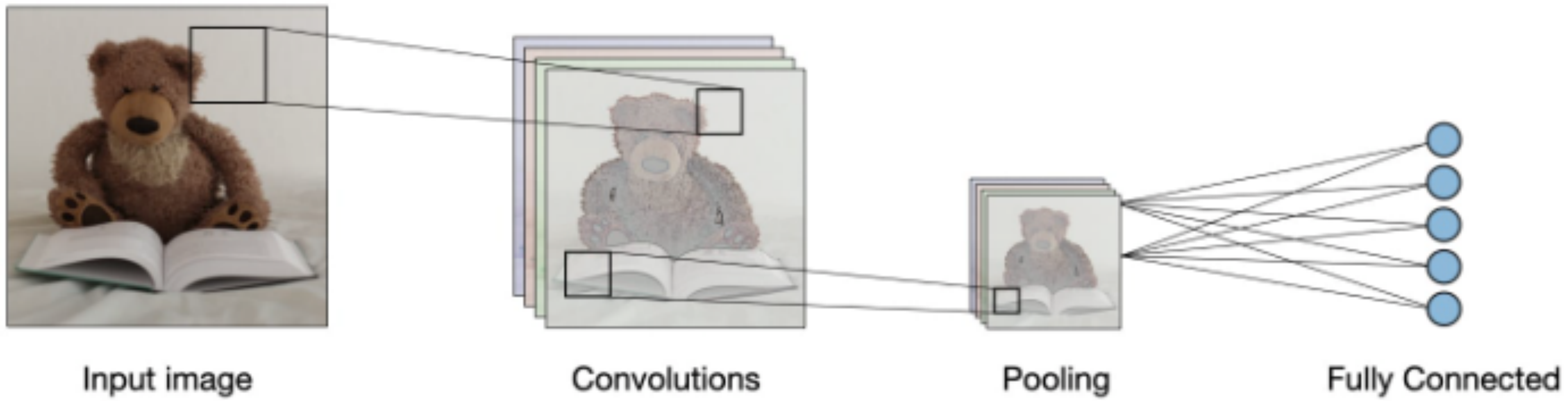
Convolutional neural networks (CNNs)

Stefan Funk - Erlangen Centre for astroparticle physics (ECAP)

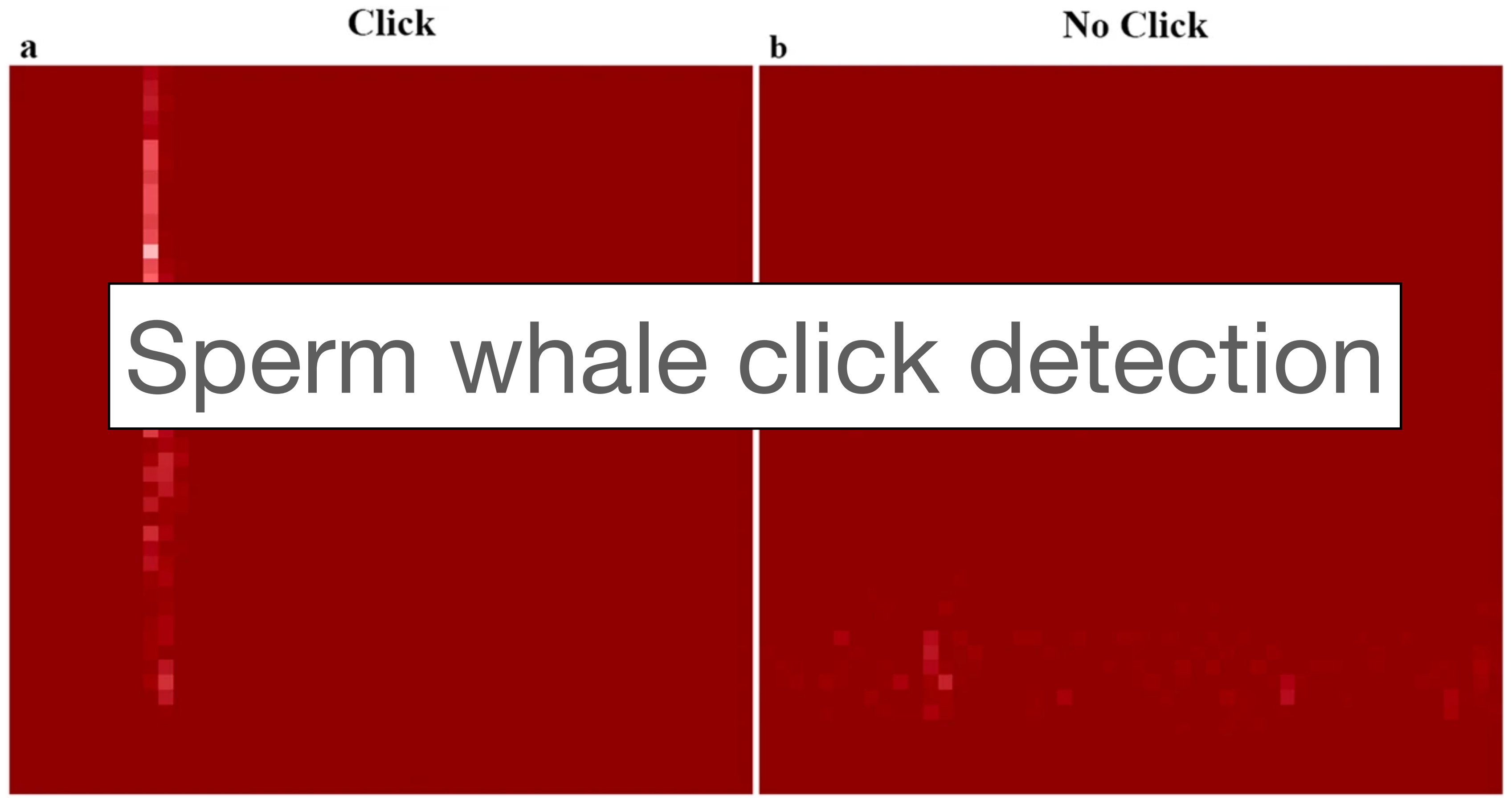


WHAT ARE CNNS?



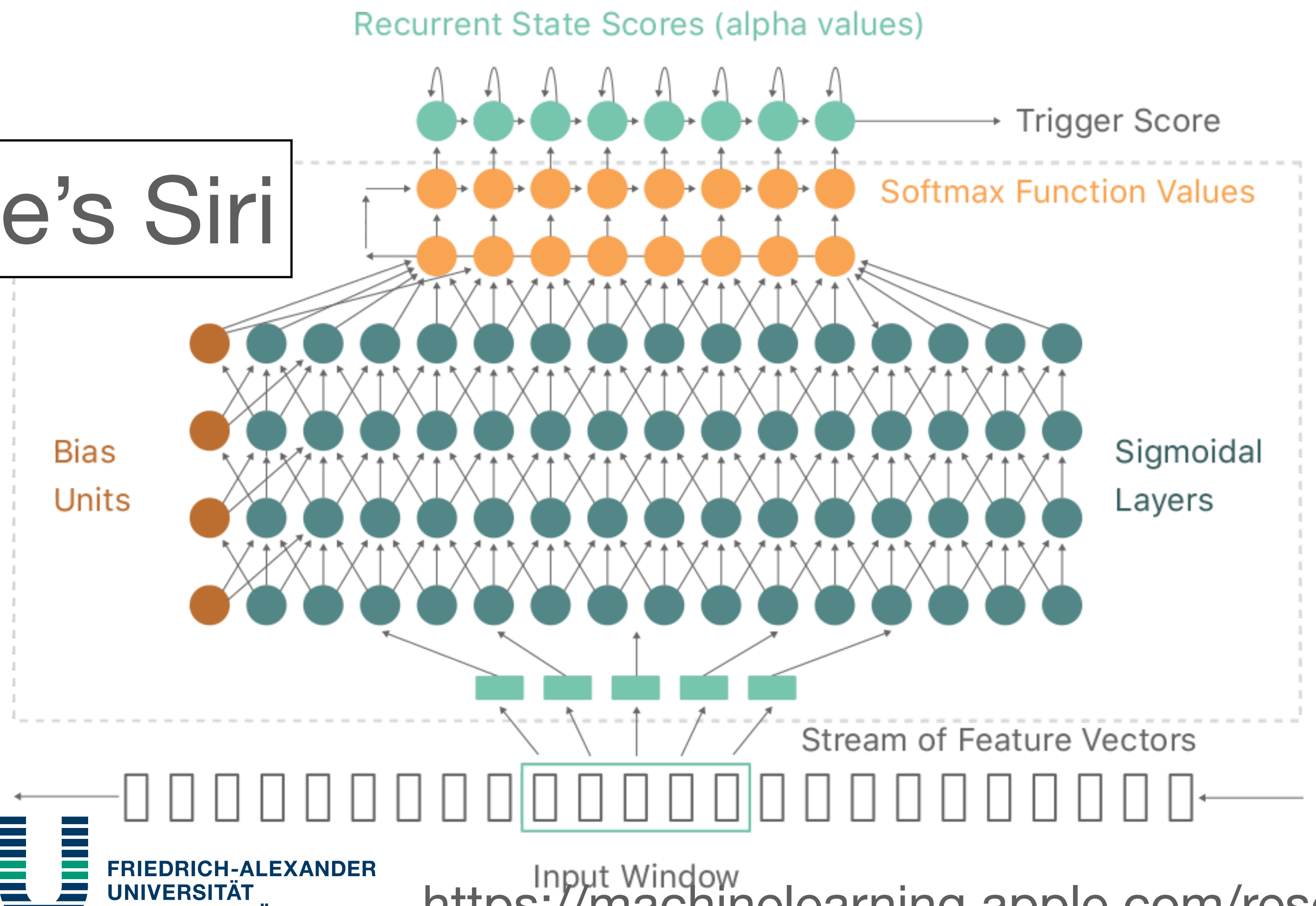
- Inspired by visual cortex (small region of cells sensitive to specific regions of the visual field)
  - Some neurons fire when they see vertical edges, others for diagonal ones
- CNN learns to look features (=values of the filters) on its own through learning
  - Technically: slide convolution 'filter' over input volume
  - Learning part: determine optimal parameter of filters
- Able to derive patterns in a highly-complex input space

CNNS IN REAL LIFE



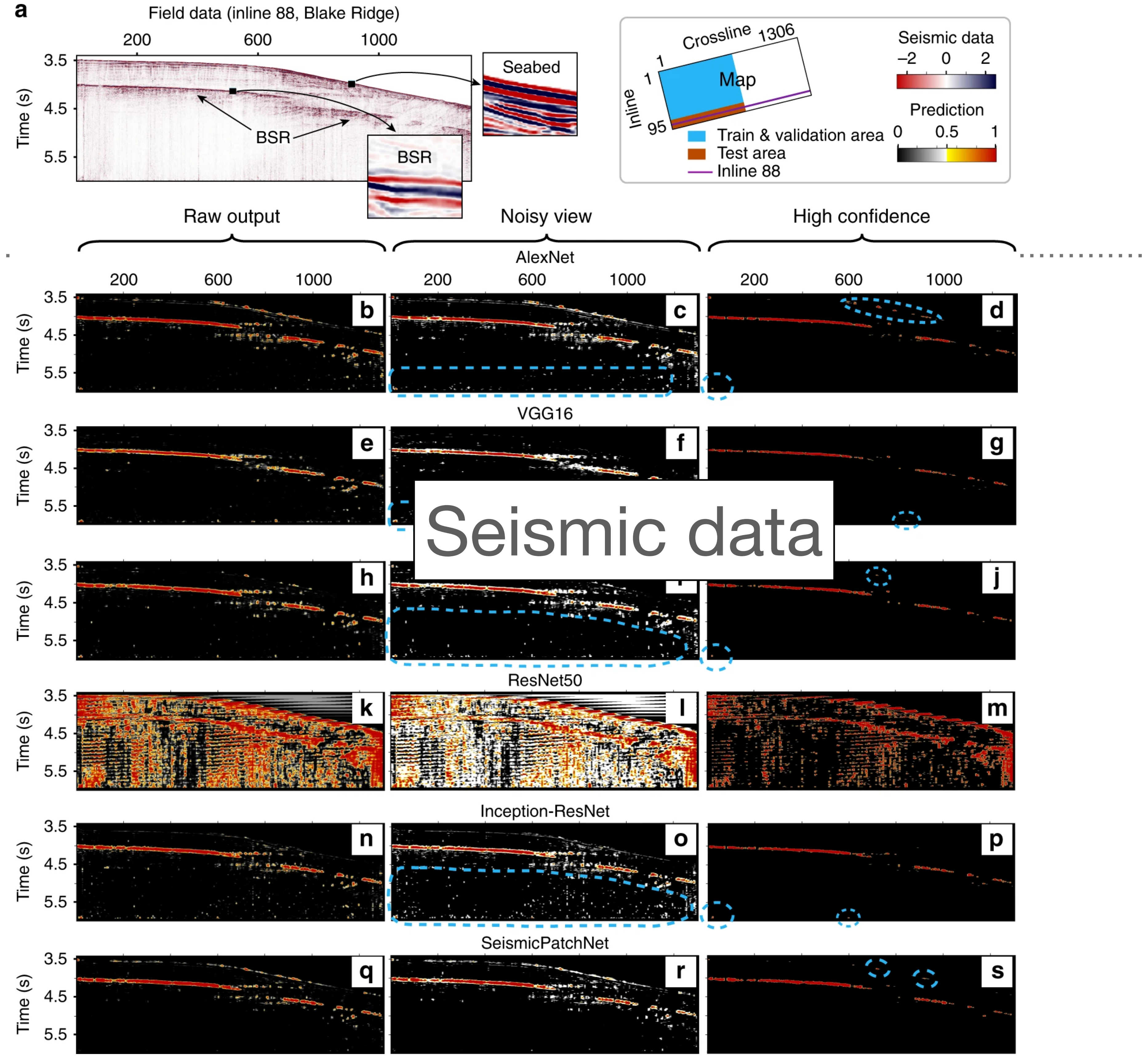
Sperm whale click detection

https://www.nature.com/articles/s41598-019-48909-4



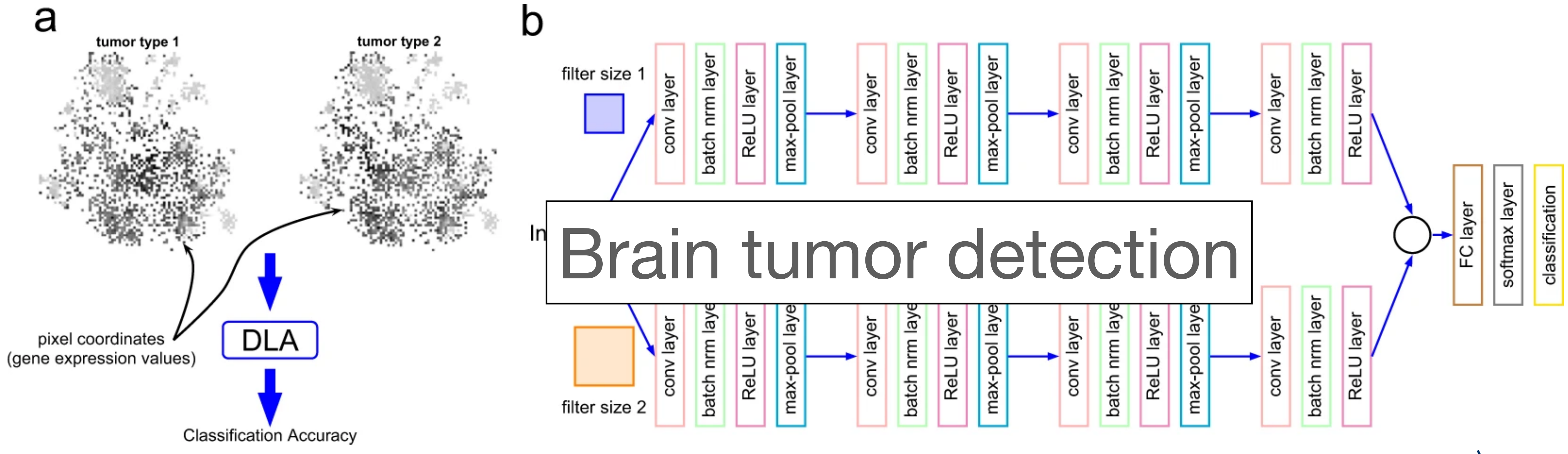
Apple’s Siri

https://machinelearning.apple.com/research/hey-siri



Seismic data

https://www.nature.com/articles/s41467-020-17123-6

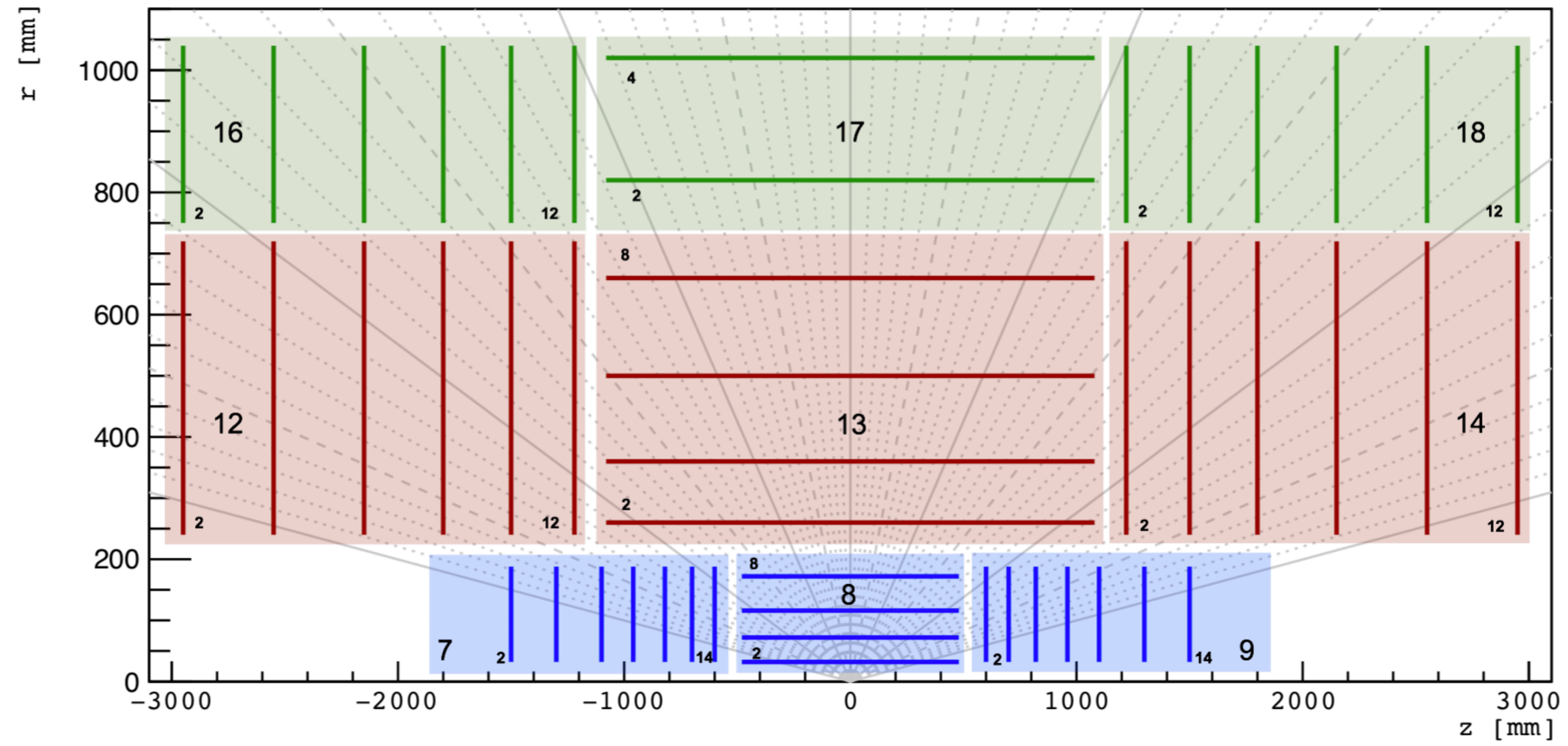


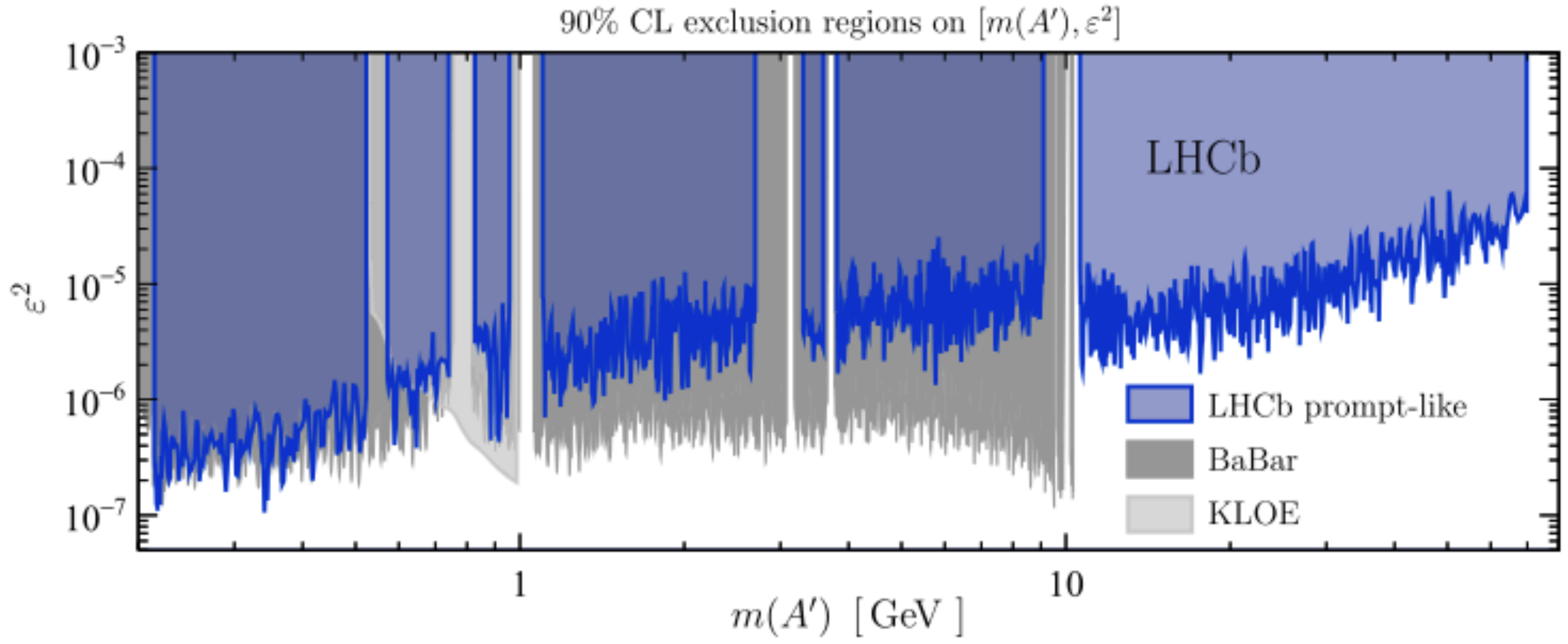
Brain tumor detection

https://www.nature.com/articles/s41598-019-47765-6

WHY ARE THEY USEFUL IN PHYSICS?

- Very often measurements consist of sensor grids in space and time
  - Small signal large background
  - Reconstruction of data from huge noisy dataset
- 70% of all data retained at the LHC are classified by machine-learning algorithms (Radovic et al. 2018).
  - Example: LHCb search for dark photons reached a sensitivity within a year that is comparable to the 10-year sensitivity without machine learning.



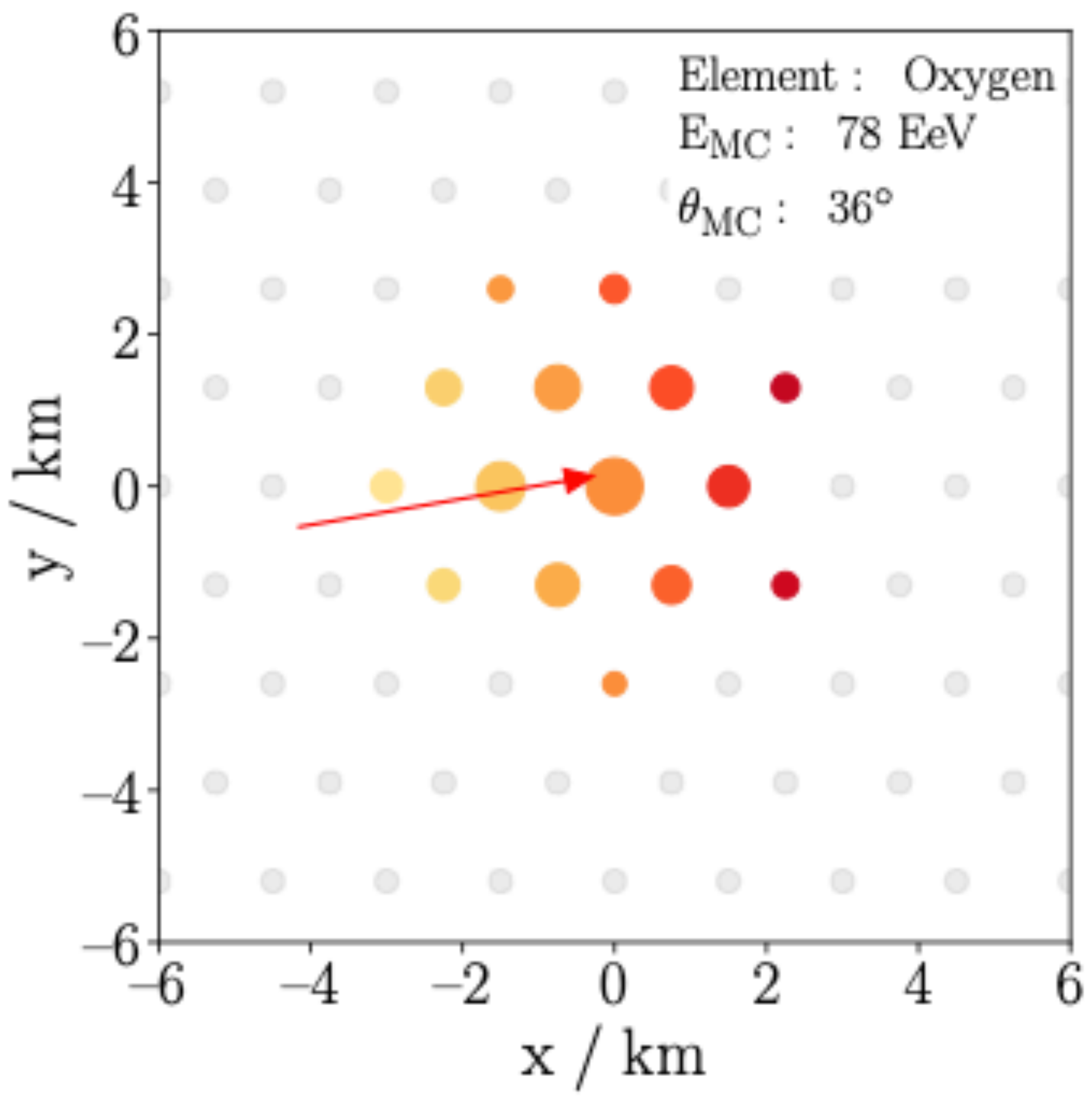


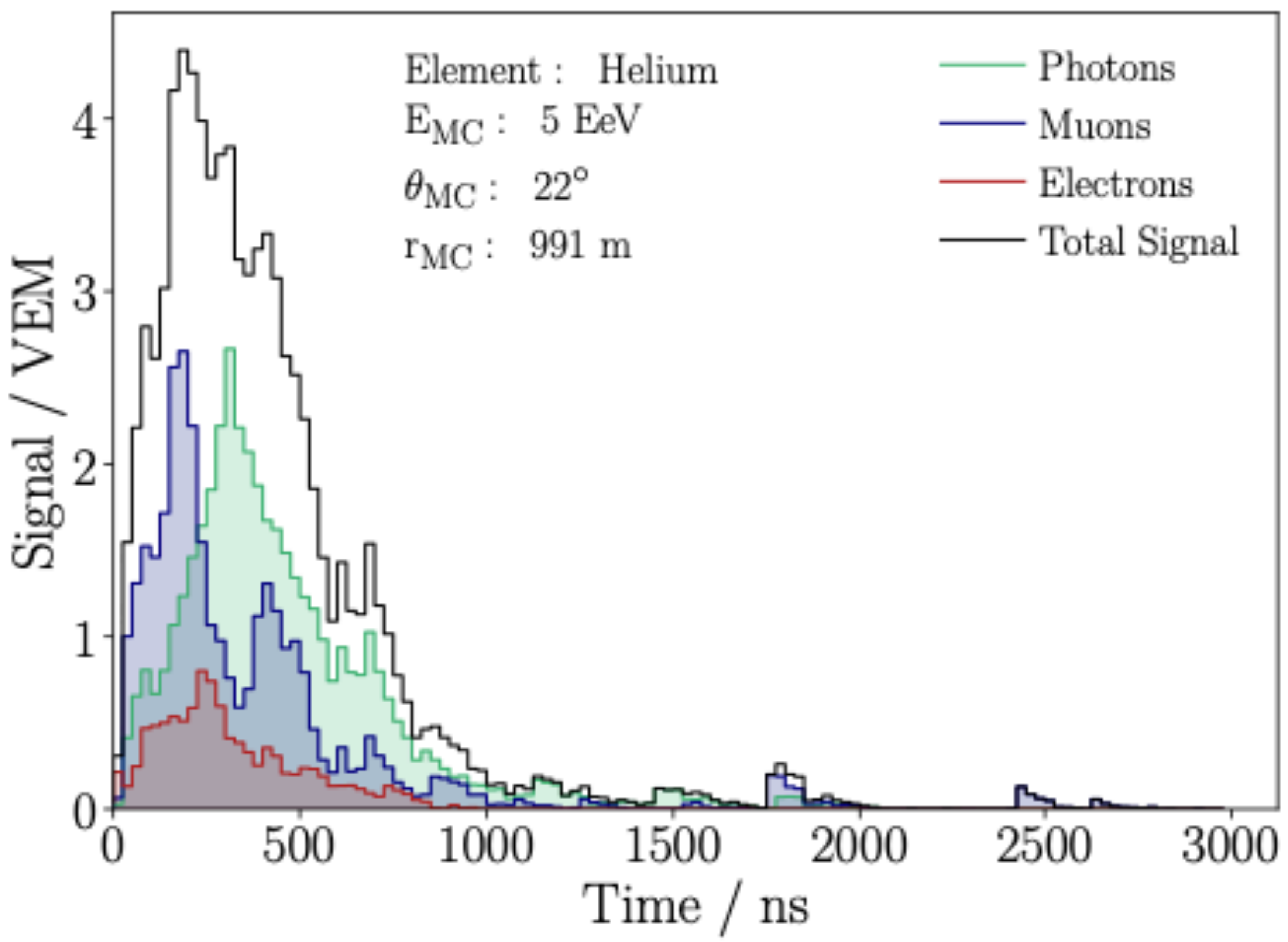
https://journals.aps.org/prl/pdf/10.1103/PhysRevLett.120.061801

EXAMPLE ASTROPARTICLE PHYSICS

- Includes data augmentation of simulated data to account for detector imperfections - makes networks more robust
- Almost bias-free determination of X_{max}
- Nice complement to Fluorescence detector

https://arxiv.org/pdf/2101.02946.pdf





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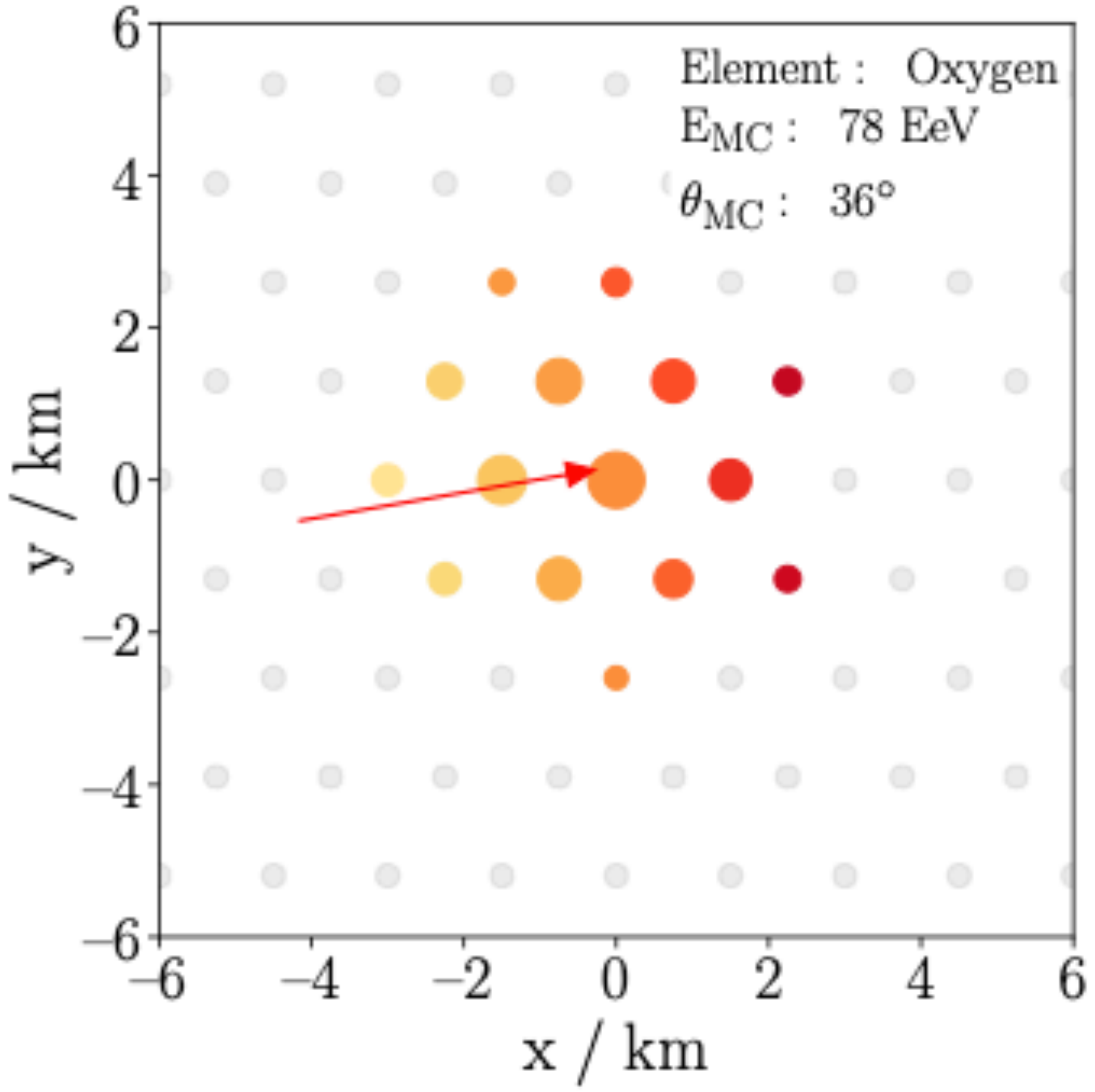
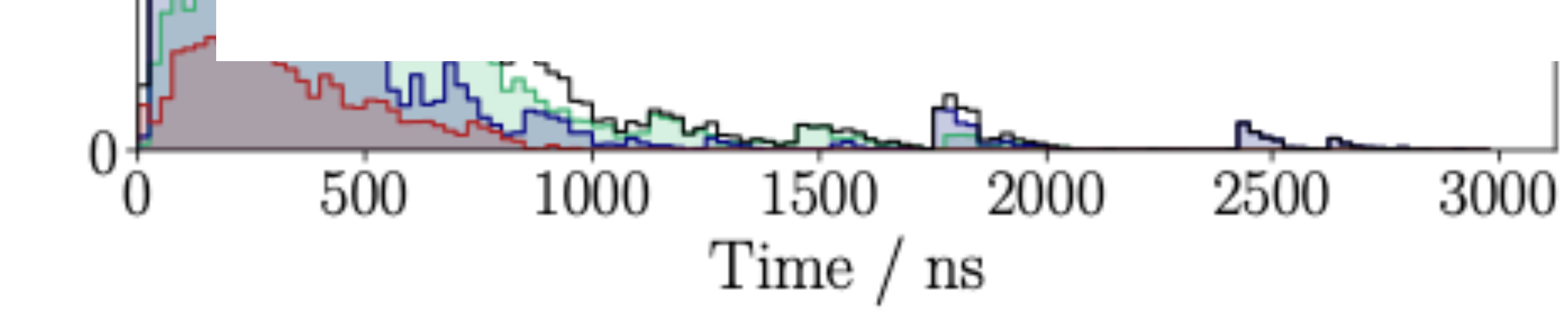
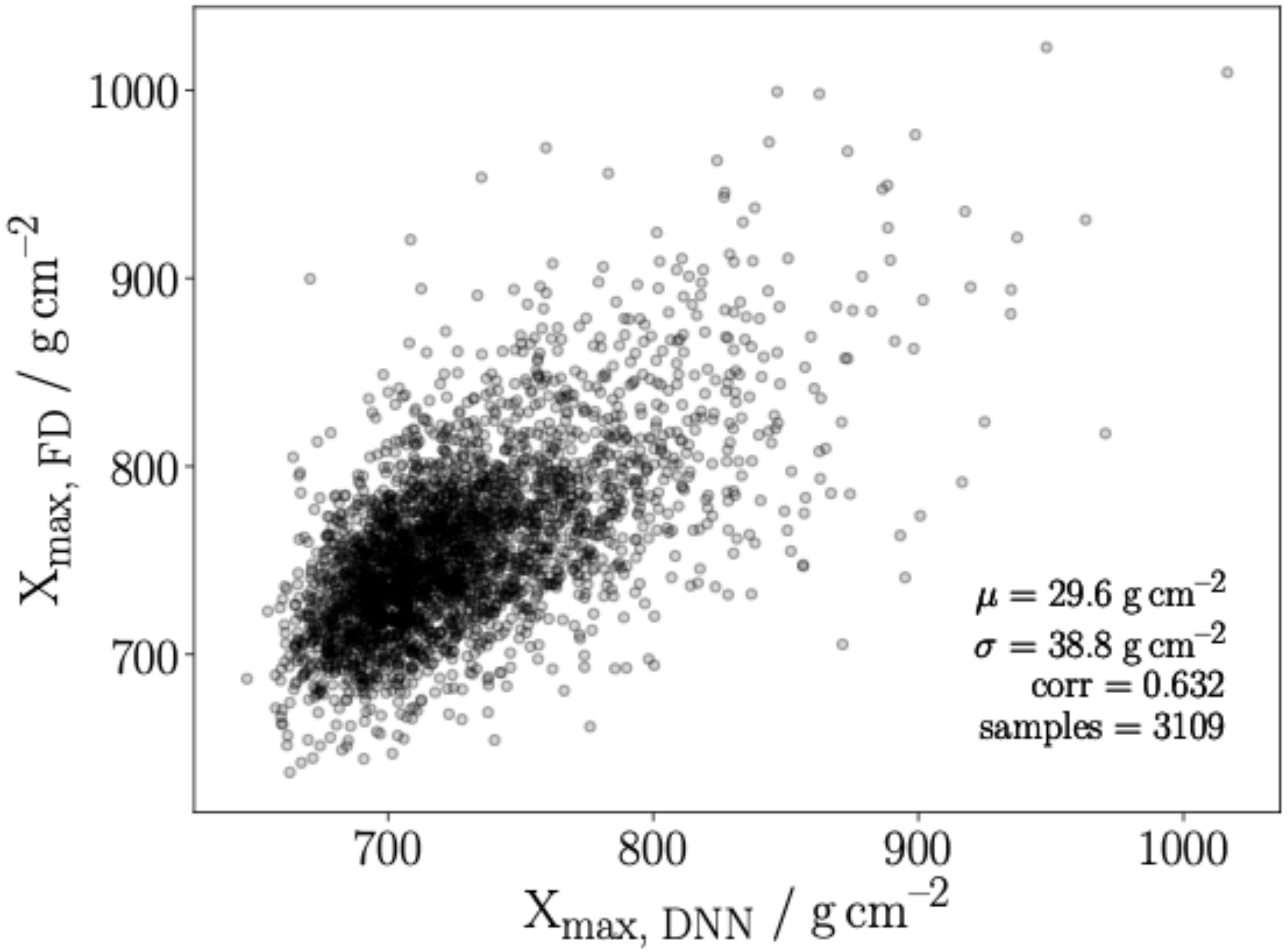
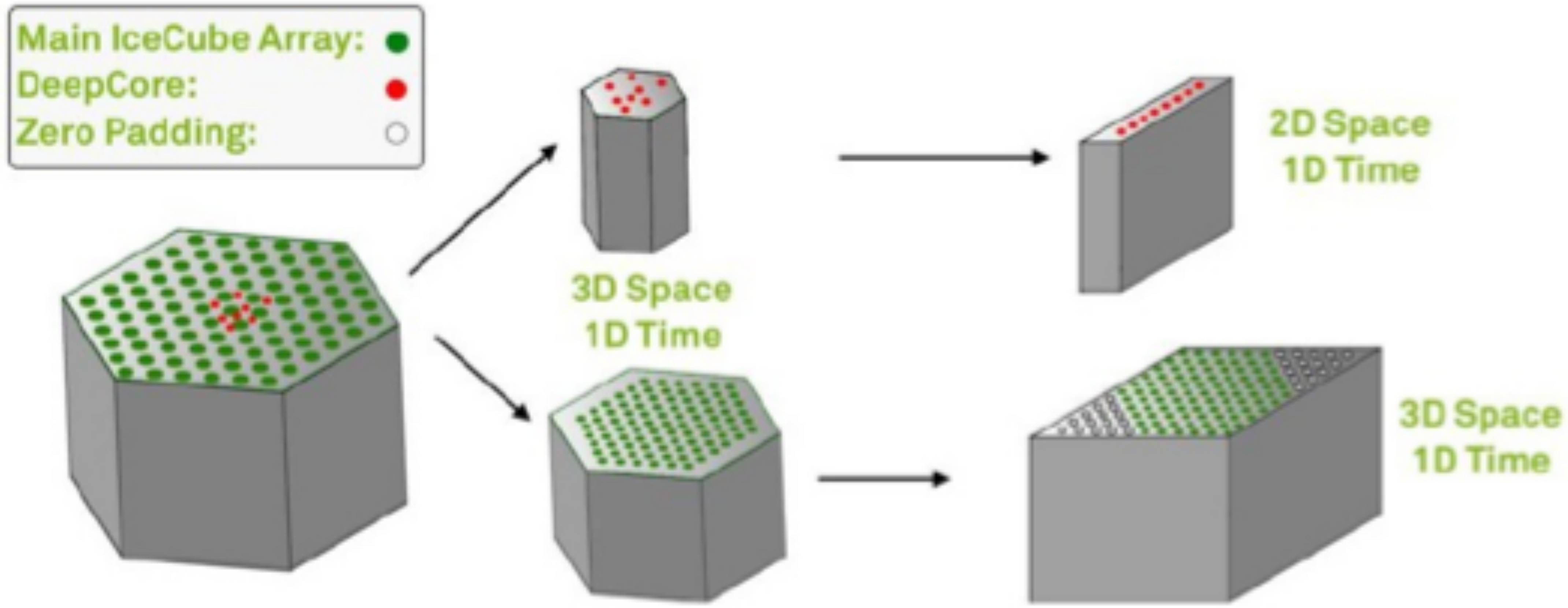


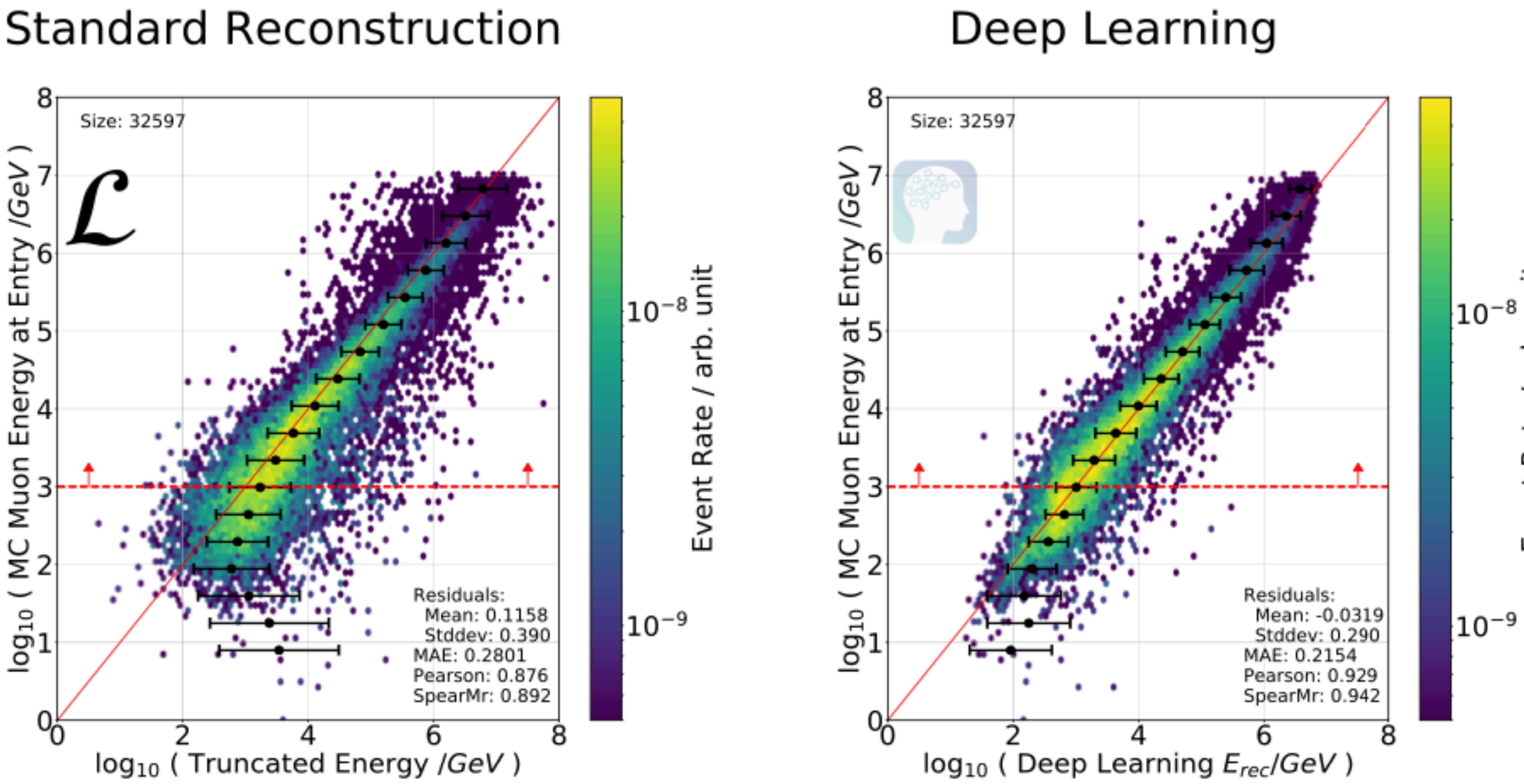




EXAMPLE ASTROPARTICLE PHYSICS

- 4-dimensional input
- Significantly improve energy reconstruction and energy threshold





Hünnefeld et al., ICRC 2017 https://inspirehep.net/files/dd8753996e23f32f65ebce73fa22f61d

CURRENT EFFORTS TO IMPROVE CNNS

- Physics-guided CNNs (provide physics constraints on the network output) - e.g. Zhang et al. 2020 or Wu et al., 2018
  - Use physics laws as a guideline for constructing NNs (e.g. Hamiltonian NN)
  - Letting ML find optimal observables (e.g. Datta et al. 2019)
- Improve computational efficiency of CNNs, real-time processing
- CNNs on FPGAs (e.g. for L1T at LHC, HLS4ML open source, multi backend)
- Network causality - how are decisions taken? (e.g. Kindermans et al. 2017)
- Uncertainty quantification (typically with GANs)
- Refinement of MC simulations to match data (also with GANs)

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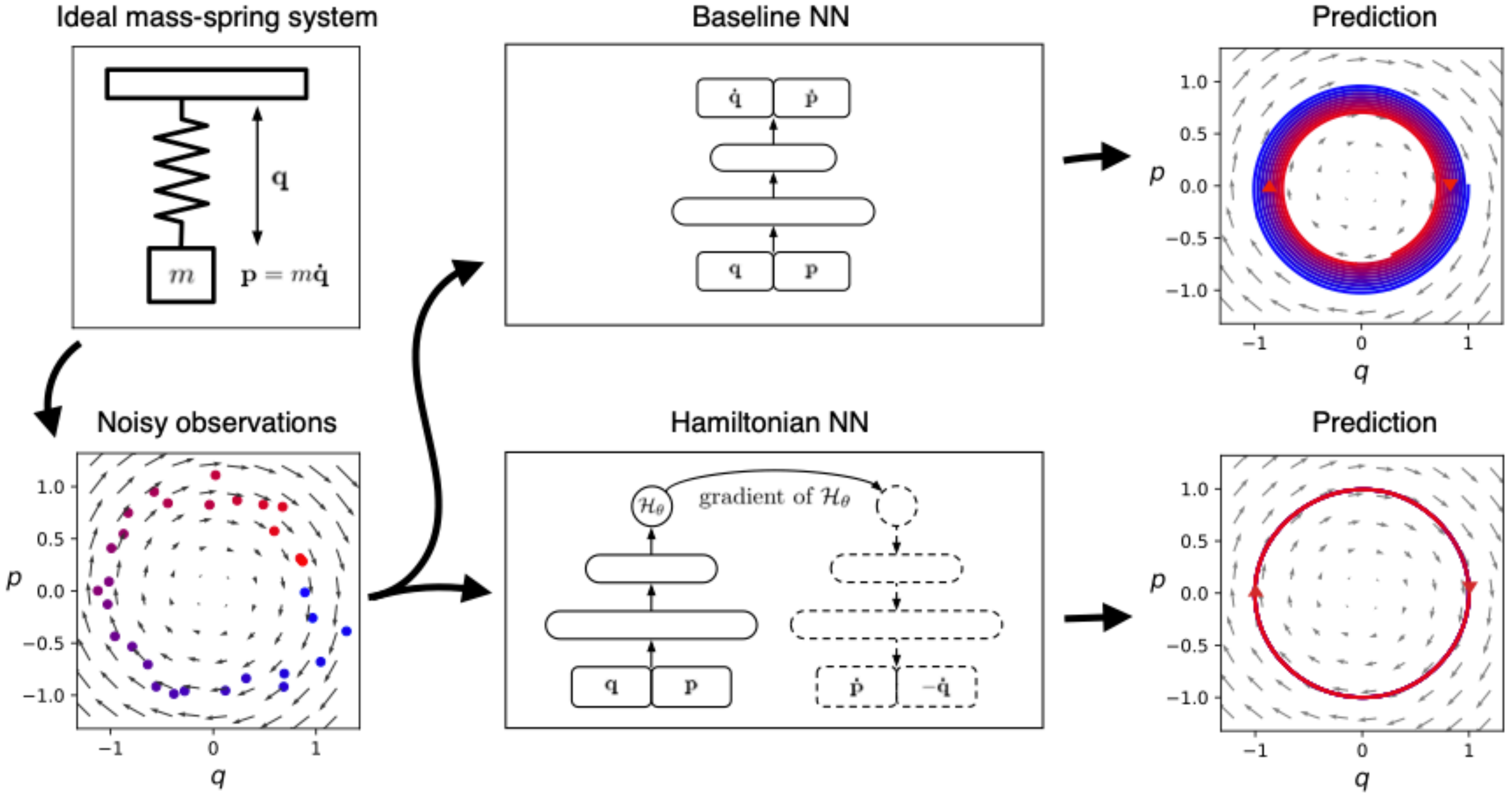

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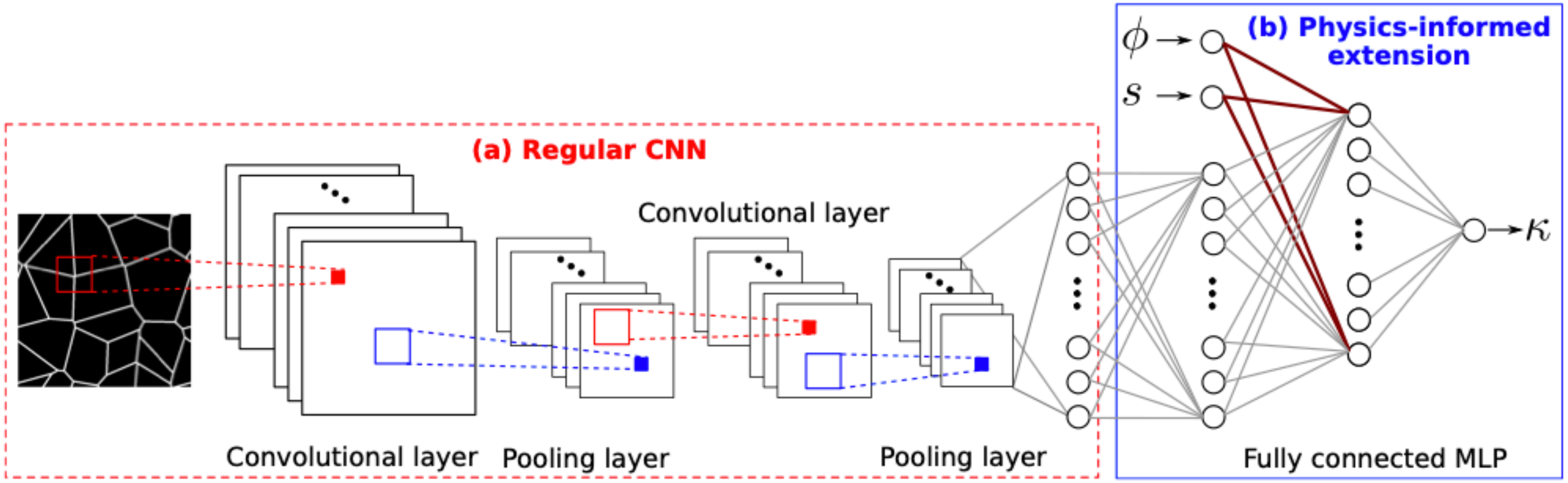

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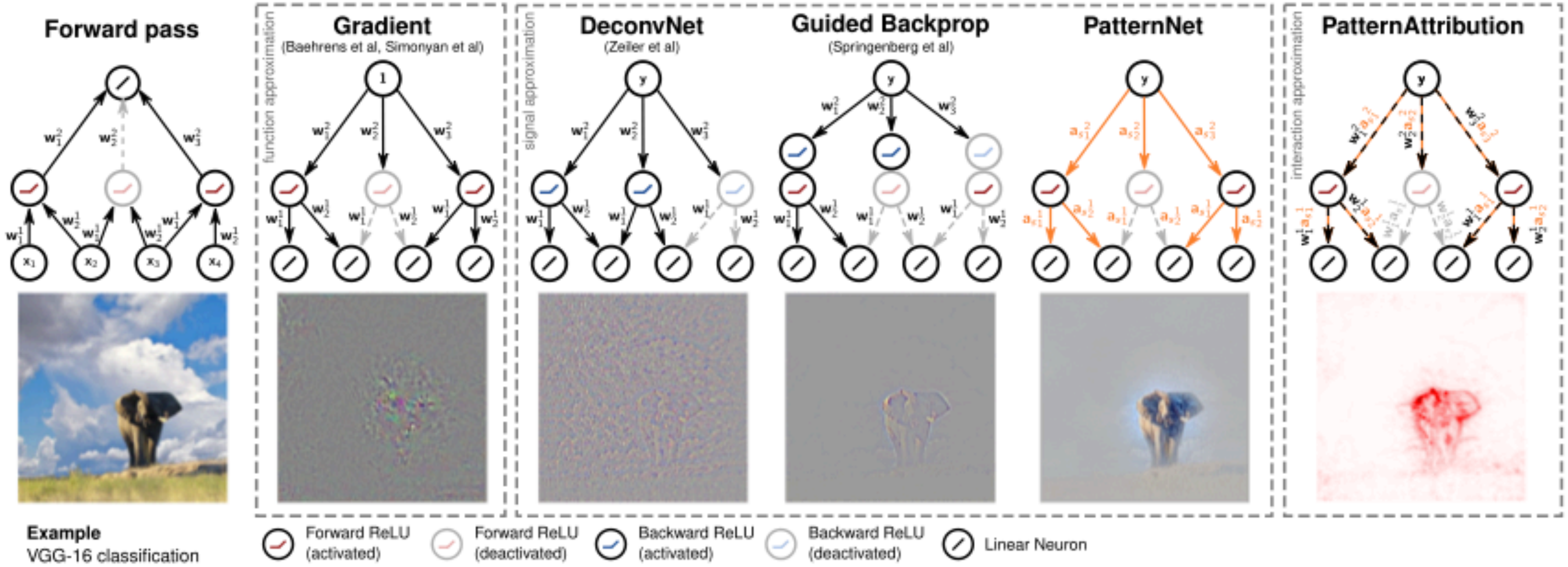

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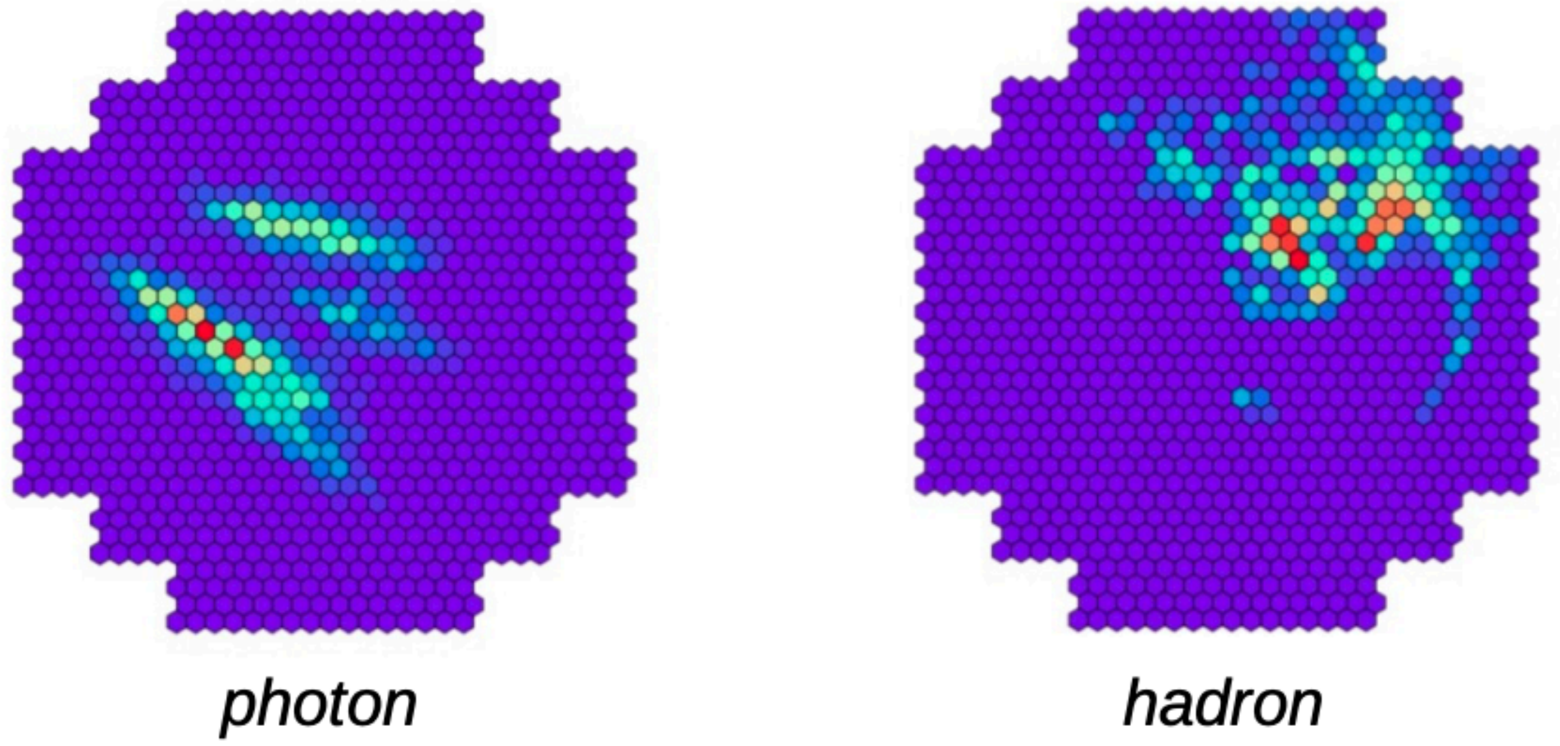
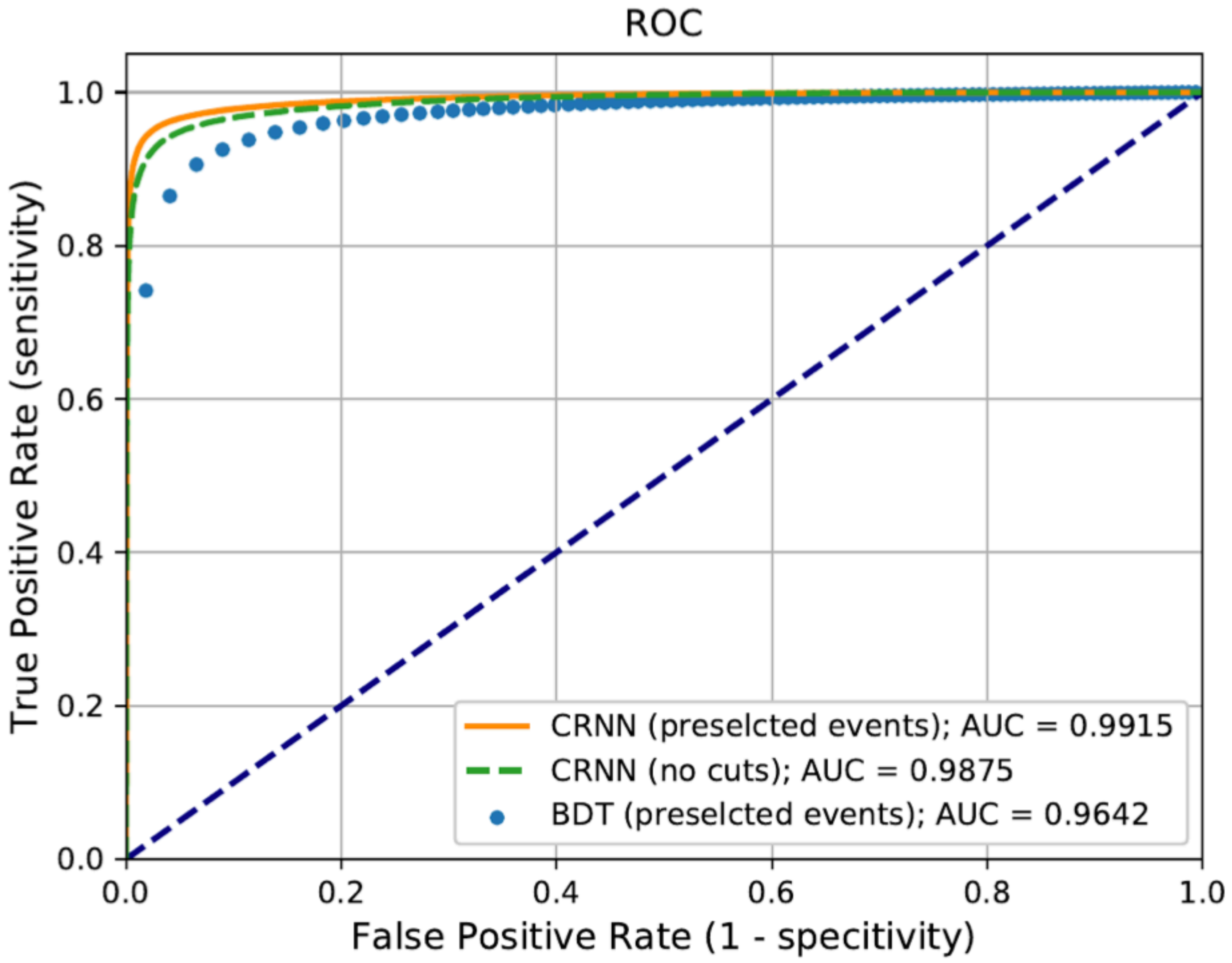
CNNS IN ERUM





Shilon et al. - 10.1016/j.astropartphys.2018.10.003

- Active research to improve CNNs in (astro) particle physics
- In the context of reconstruction of shower geometry for CTA:
  - Physics-motivated CNNs
  - Evaluation of optimal encoding of data
  - Estimation of network uncertainties

SUMMARY

- ➤ Machines exploit physics contained in data deeper than before
- ➤ CNNs are the workhorse for many of the more advanced applications, as example in investigations of causality, stability, uncertainties