pLISA: a parallel Library for Identification and Study of Astroparticles and its application to KM3NeT

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The new Era of Multimessenger Astrophysics

Groningen, March 28th 2019

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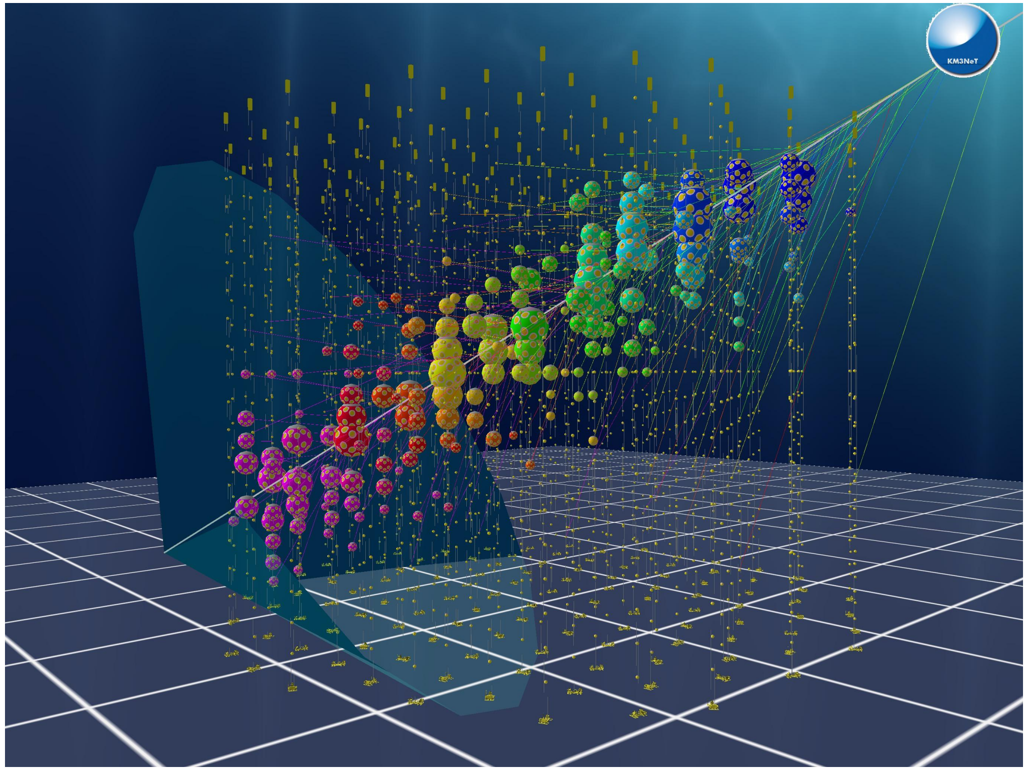
Motivations for pLISA

- Leverage parallel computing based on GPUs
- Primary particle reconstruction for event-based detectors
- Set up “continuously training farms”



pLISA structure

- Set of Python scripts (conveniently used in Jupyter notebooks)
- Scikit Learn
  (data managed by image handling techniques)
- TensorFlow
  (differentiable programming and machine learning)
- Keras (high-level neural network software)

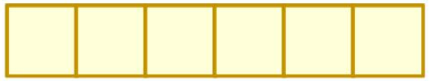
jupyter

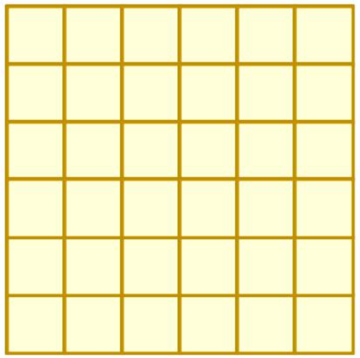
scikit learn + TensorFlow

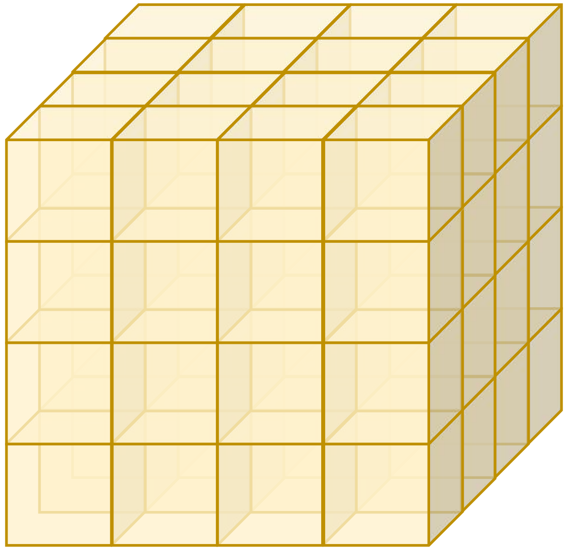
Keras

pLISA concepts

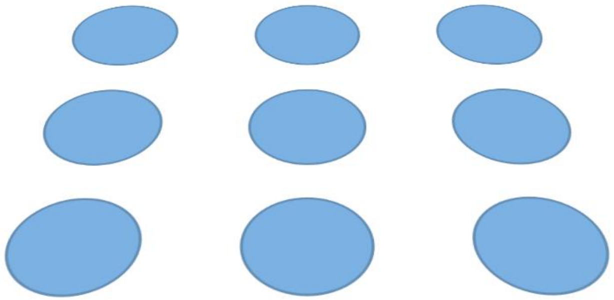
- Detector representation

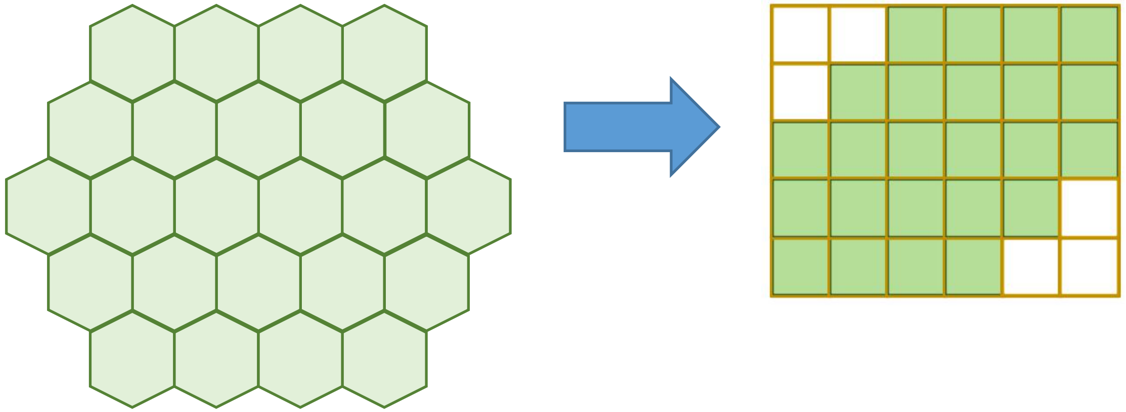






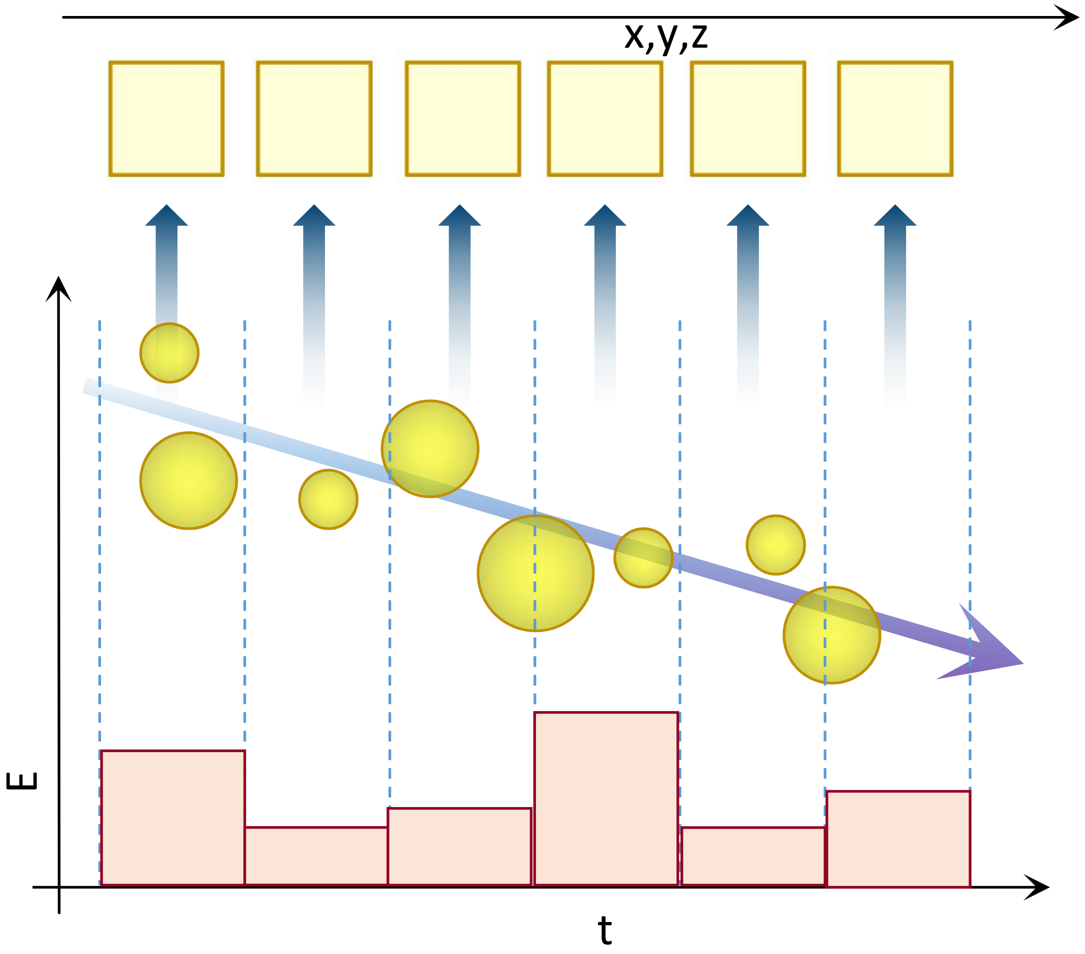
  - Suitable for Convolutional Neural Networks (CNNs)
  - Must be mappable to a rectangular grid in 1,2,3,4,5,... dimensions
    - CNN stack does not support more than 4 dimensions as of today (hope to increase in the future)
  - Piecewise geometry definition also possible





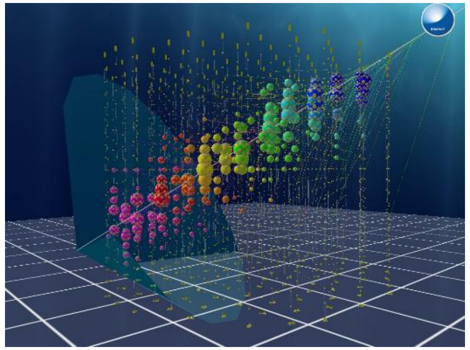
pLISA concepts

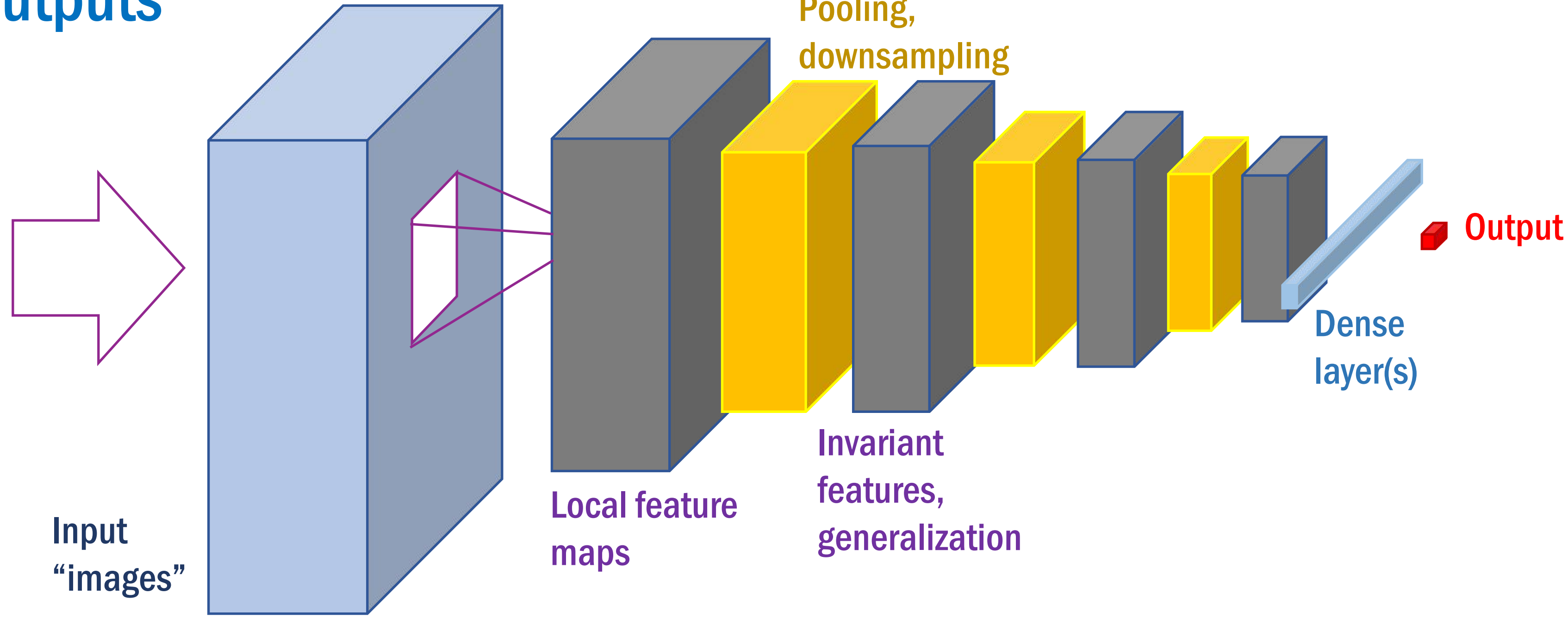
- Event representation
  - Spatial discretisation (implied in discretised detector structure)
  - Time discretisation (“hits” in sensing elements are binned in time, by count or deposited energy)



pLISA concepts

- Processing and Outputs



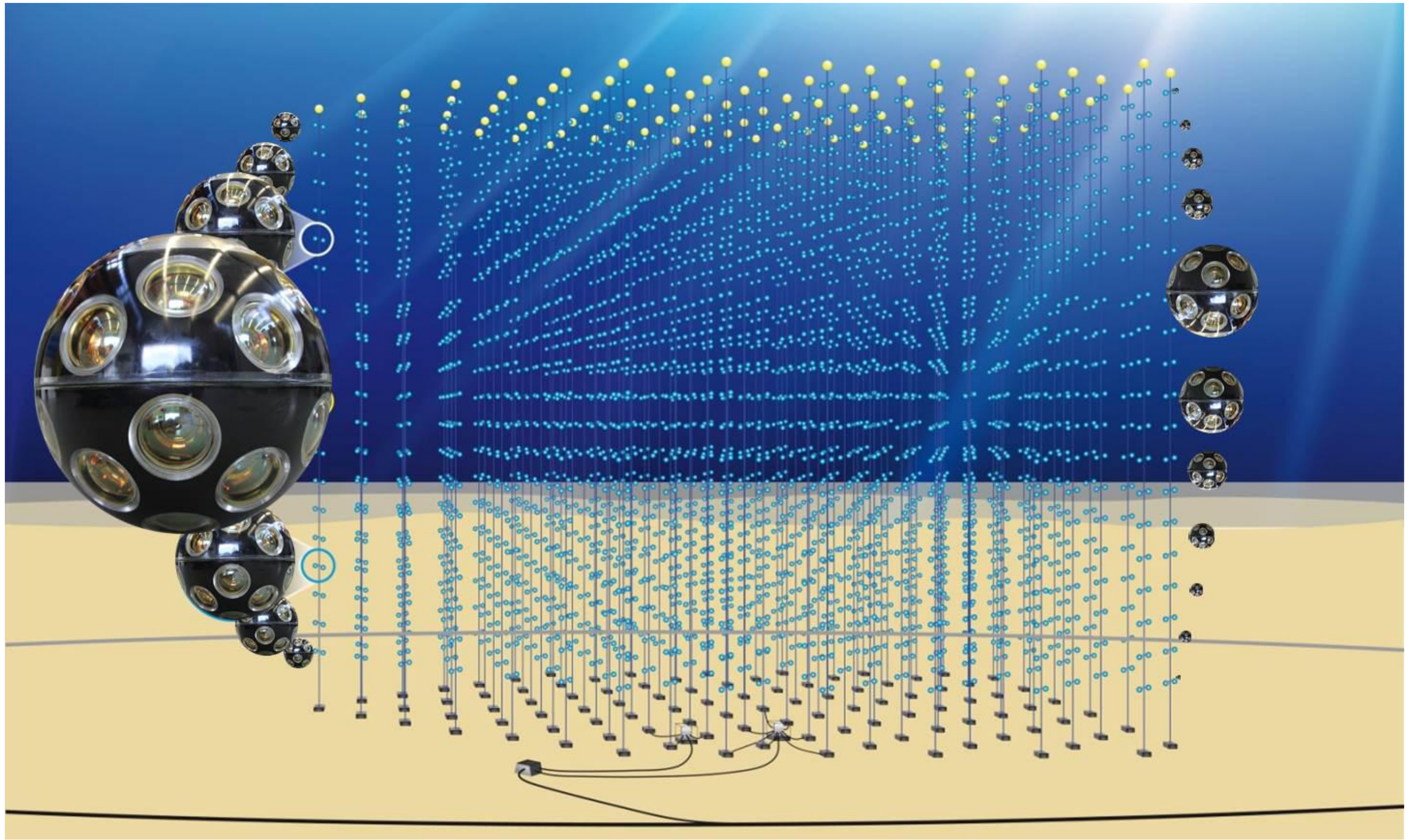


No prerequisite reconstruction output - depends on no other software

CNN could instead help/support standard reconstruction algorithms with first guess

Application to KM3NeT

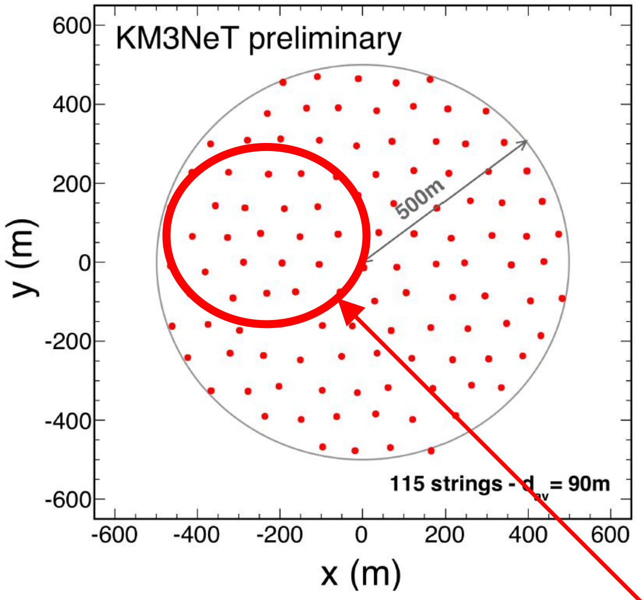
- KM3NeT Water Cherenkov in deep sea
- Building block: 115 DUs
- Detection Unit (DU): 18 evenly spaced DOMs
- Digital Optical Module (DOM): 31 PMTs (+ other instruments)



Application to KM3NeT

- **Astroparticle Research with Cosmics in the Abyss**
  km^3 size building blocks (2×)
  z DOM spacing 36 m

- **Oscillation Research with Cosmics in the Abyss**
  1 building block
  z DOM spacing 9 m



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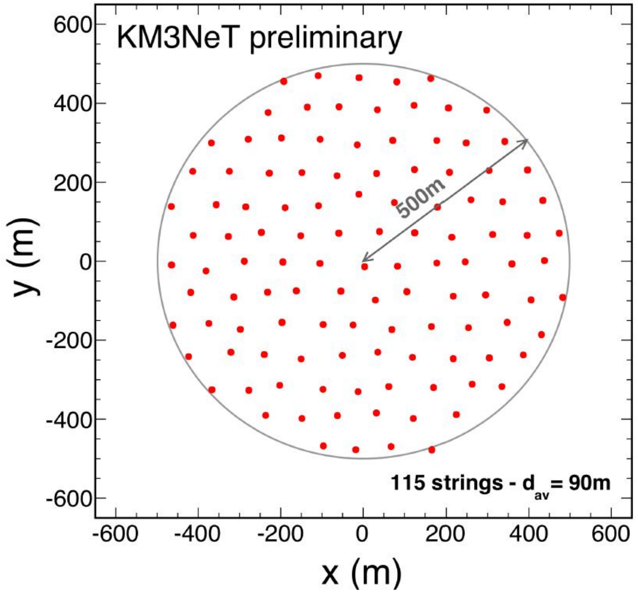
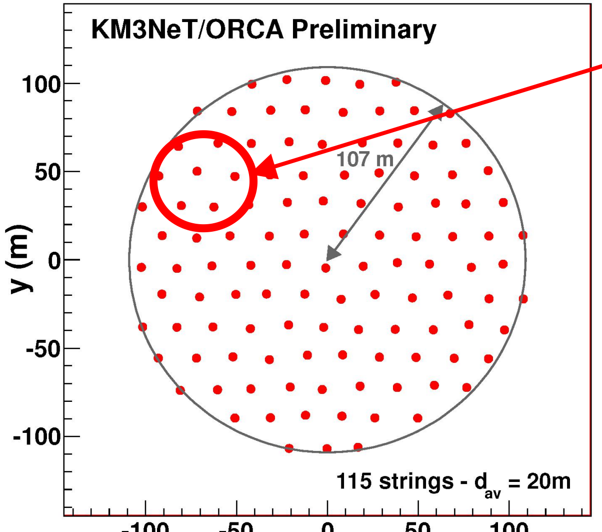




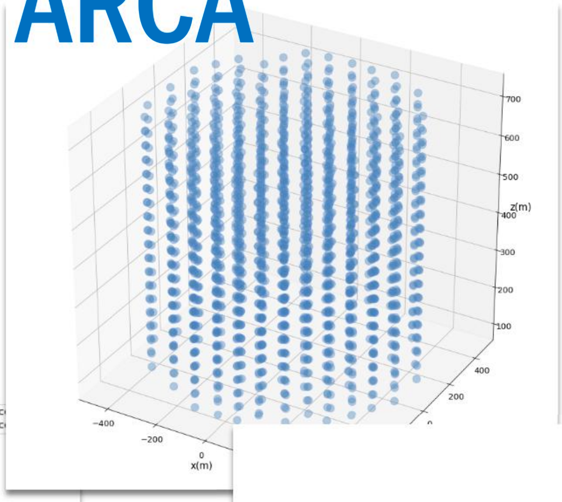
Phase1 (fully funded - deploy 2019)

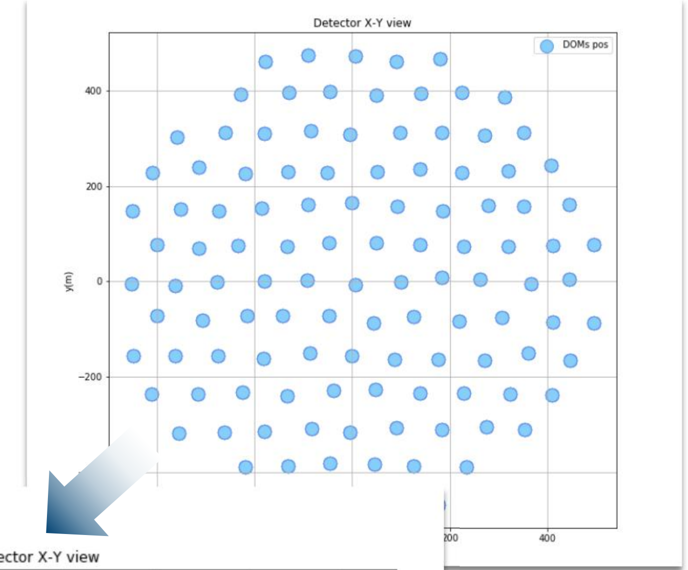
Phase 2 (partially funded - deploy 2019/21)

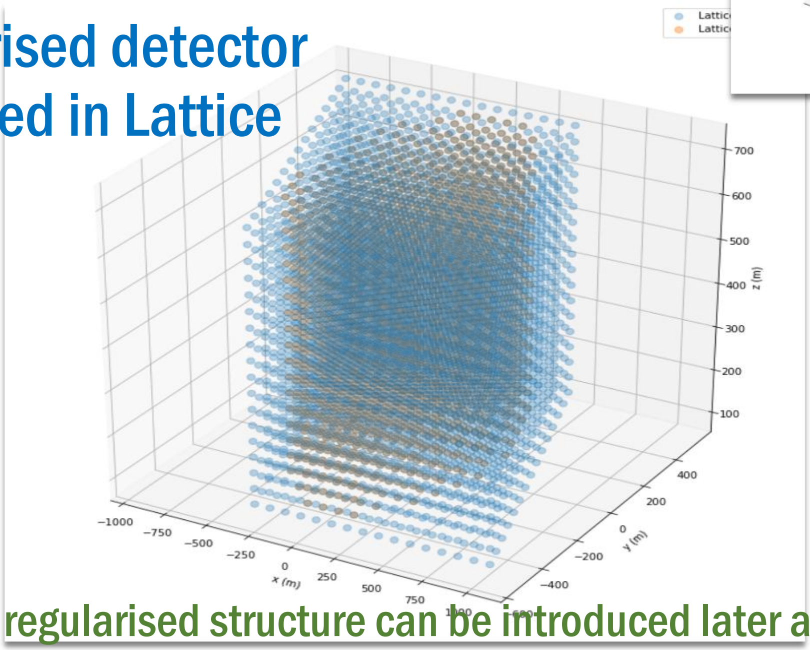
KM3NeT 2.0 Letter of Intent:
arXiv:1601.07459 and
J.Phys. G43 (2016) 084001

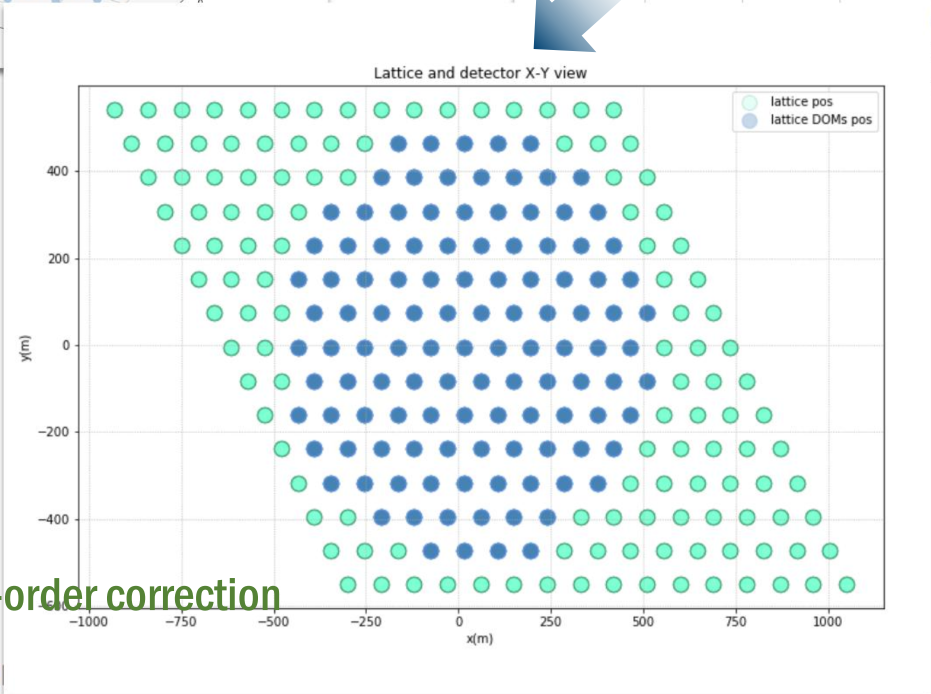
Application to KM3NeT - ARCA

- XYZ detector regularisation
  - exactly 90m spaced in (X,Y)
  - exactly 36m spaced in Z
  - Regularised detector contained in Lattice





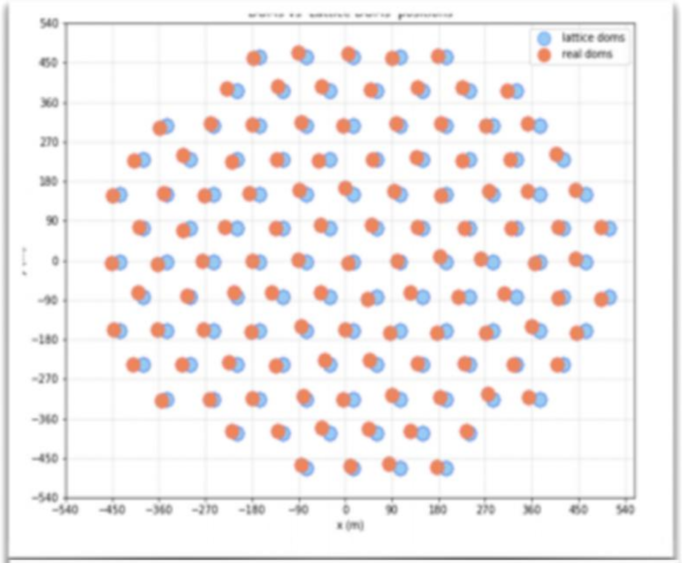


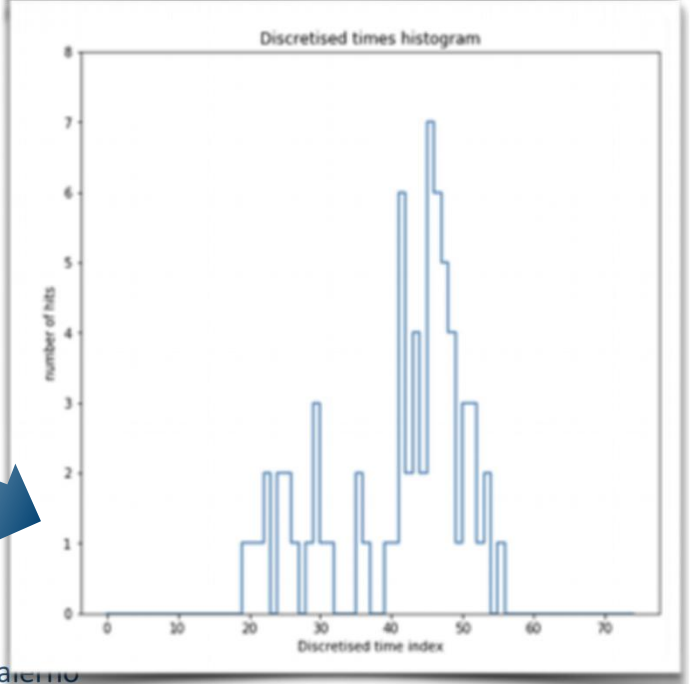


Deviation from regularised structure can be introduced later as a next-order correction

Application to KM3NeT - ARCA

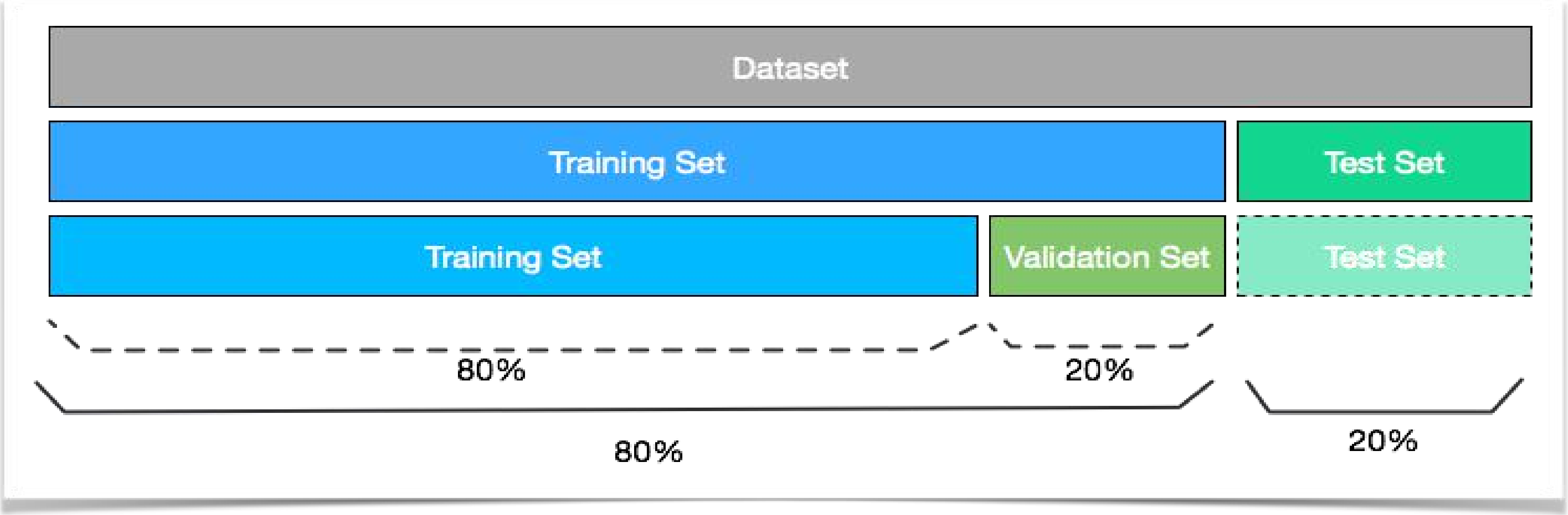
- Event representation
  - Reduce data sparsity: ignore PMT orientation and consider only DOM
  - Force DOM positions onto regularised lattice
  - DOM mapped to a position in 16×15×18 lattice
  - Hit time binned to 12 ns bin ⇒ 75 bins / event
  - Matrix structure of any event (TXYZ): [75×16×15×18] 4D image (or 3D movie)





Application to KM3NeT - ARCA

- 258,879 events
- ν_eCC and ν_μCC

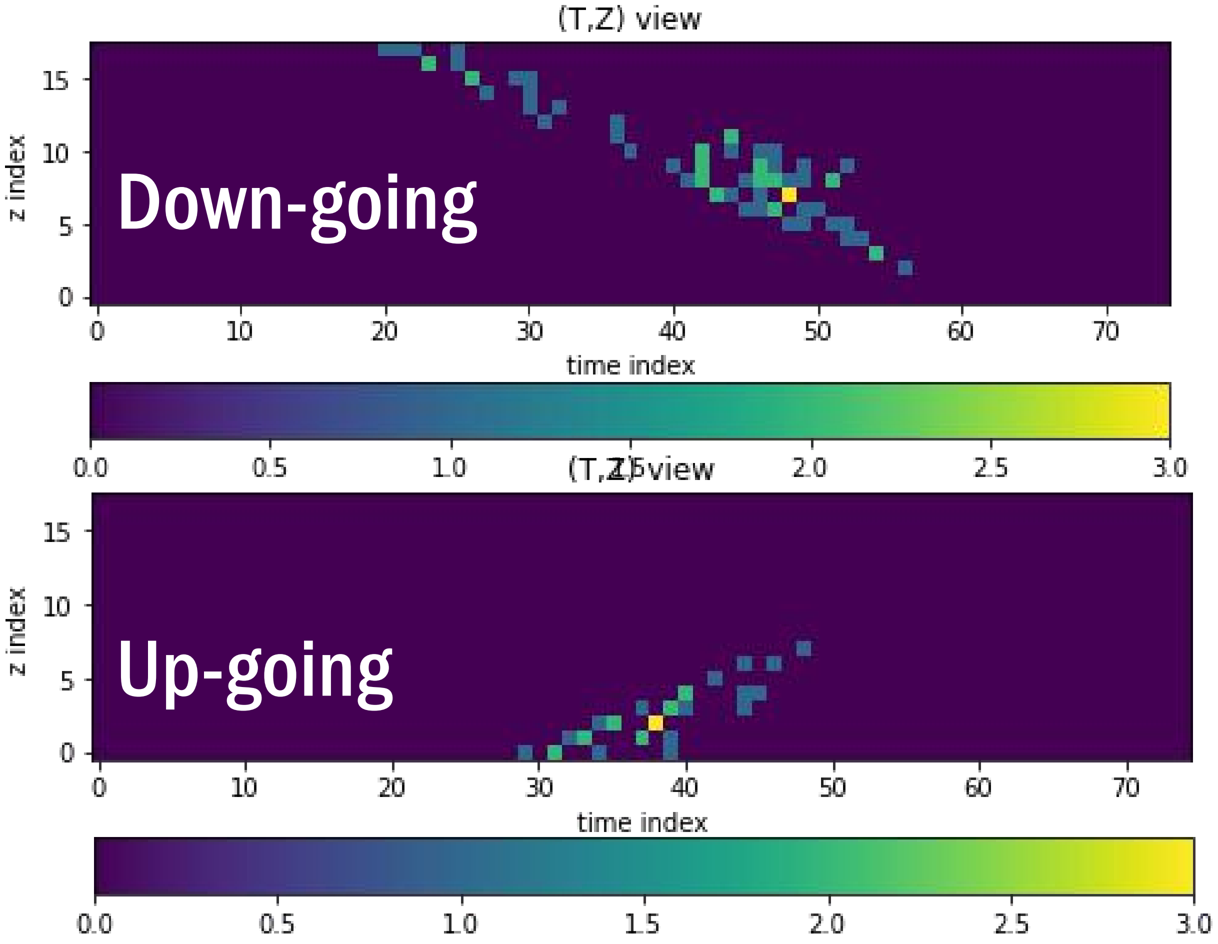


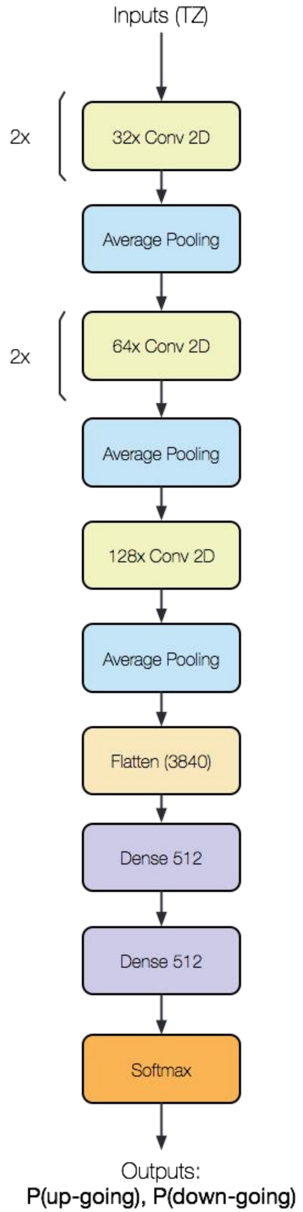
- Training no longer than a few hours
- Slow models also tested (training for several days) but discarded (no real improvement)

KM3NeT - Up/Down-going classification

- Colour code: hits/DOM/time bin

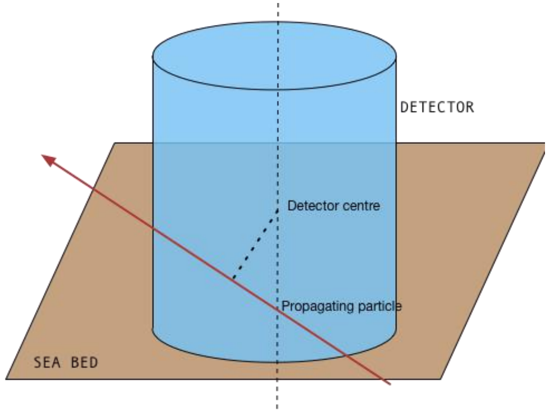
- XY found to be irrelevant for this task

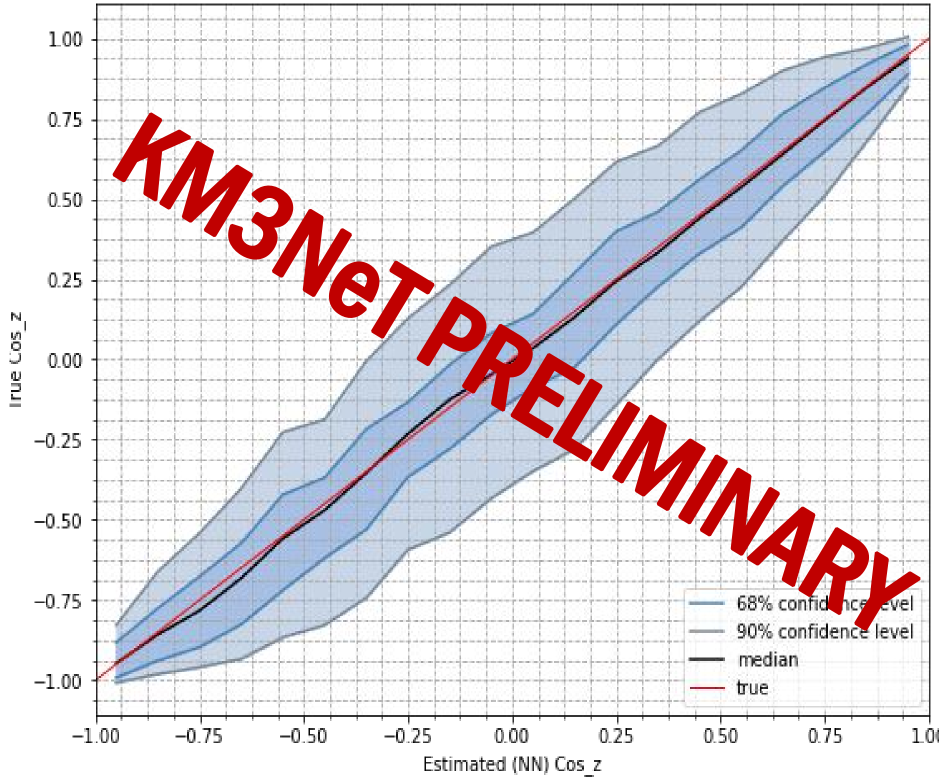


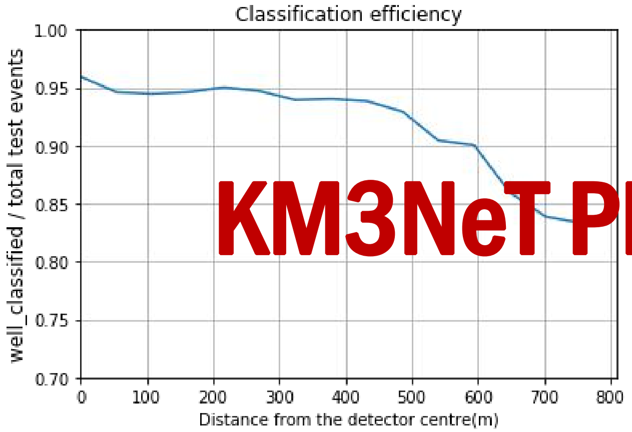


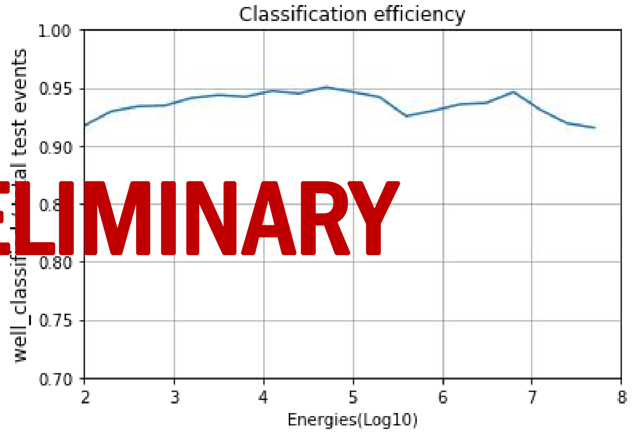
KM3NeT - Direction(Z) & Up/Down-going classification

- $cos\,\theta_z$ estimated by network
- Performance depends on track length in detector







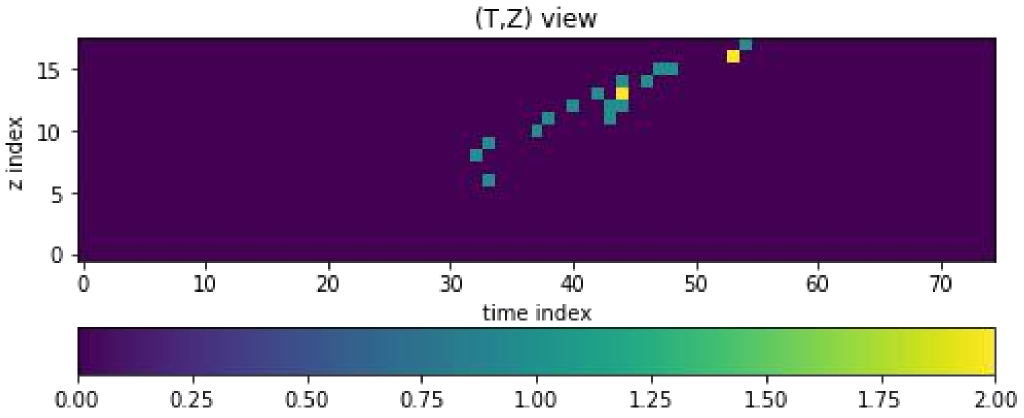


KM3NeT PRELIMINARY

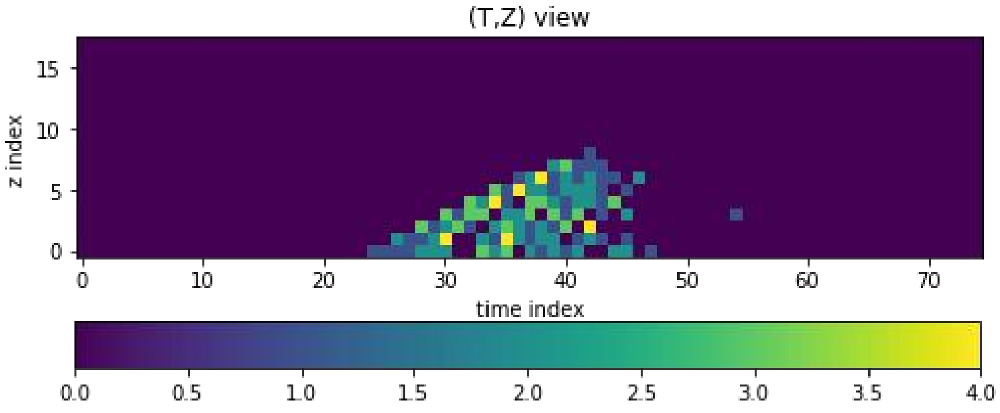
RMS($cos\,\theta_{z,est}$ - $cos\,\theta_{z,true}$) = 0.001 for traditional algorithms but using quality cuts, 0.002 for CNN - but no specific optimization done, and works on all events

KM3NeT - Event type (ν_eCC/ν_μCC) classification

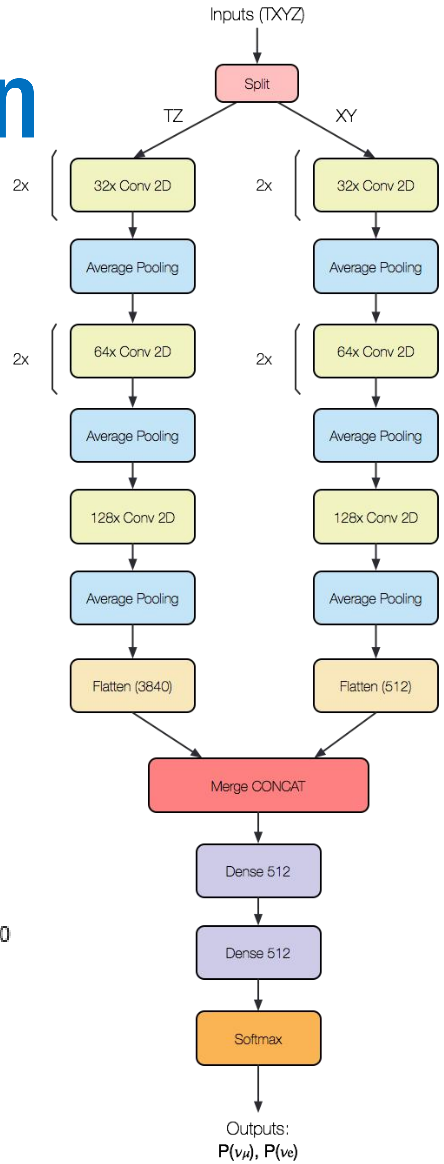
- XY shape and TZ evolution analysed separately in the first stages, merged at later stage after extraction of features



ν_μCC

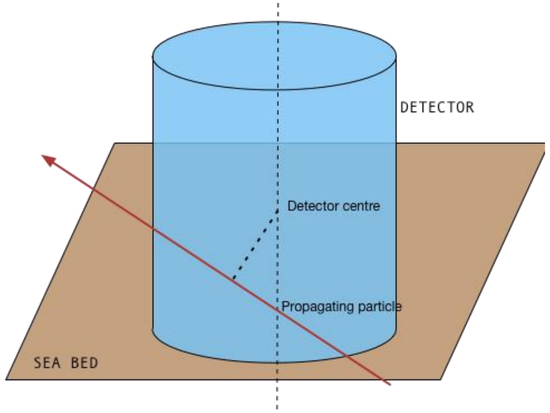


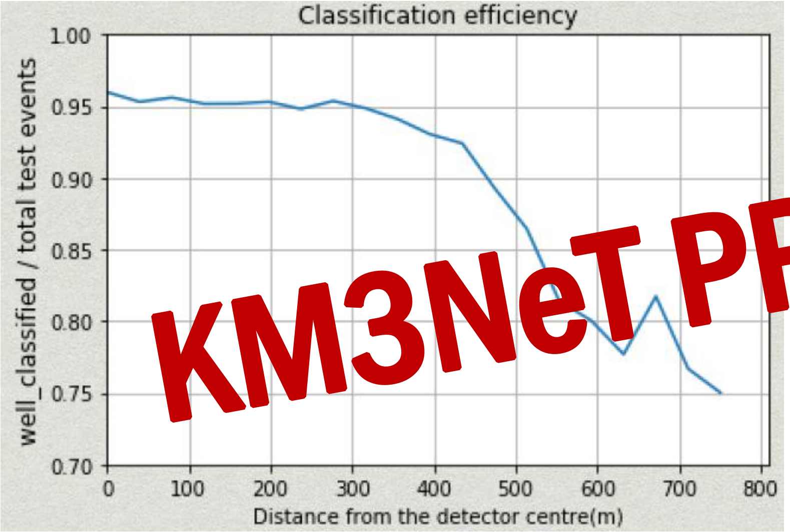
ν_eCC

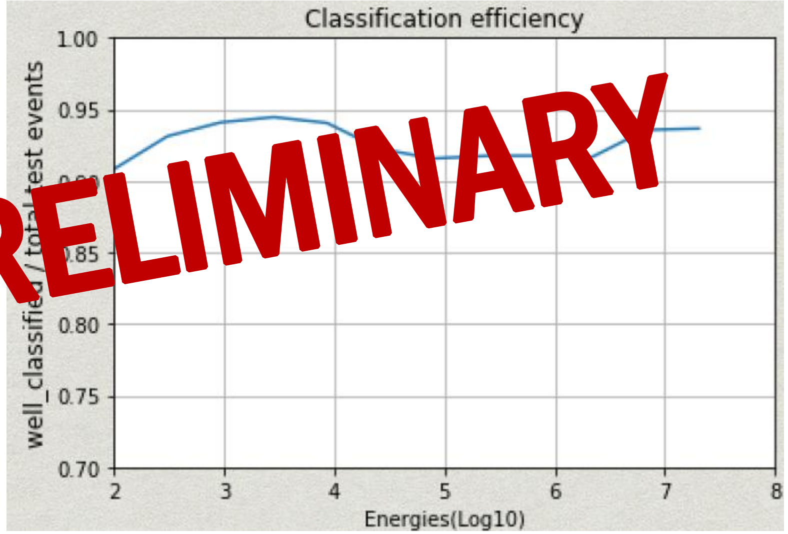


KM3NeT - Event type (ν_eCC/ν_μCC) classification

- Classification efficiency found to depend on track length in detector
- Energy dependency milder

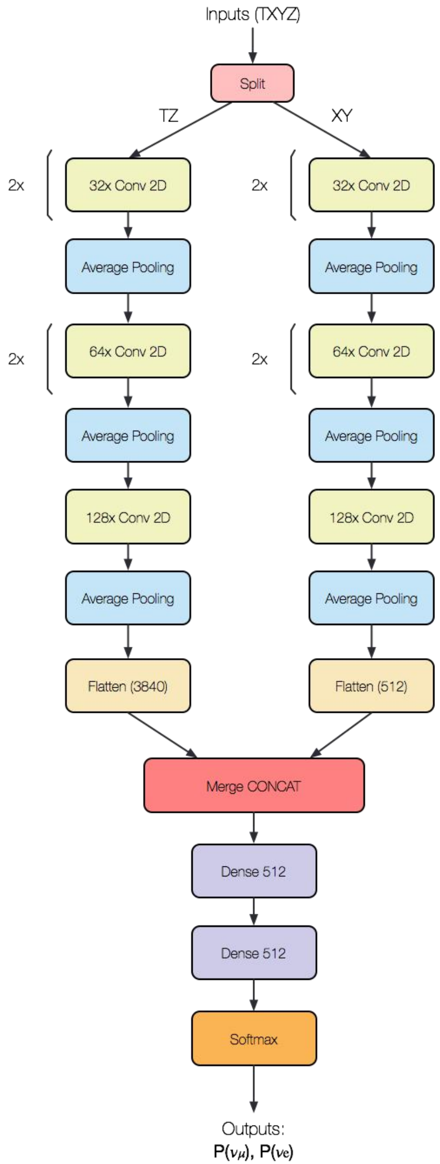






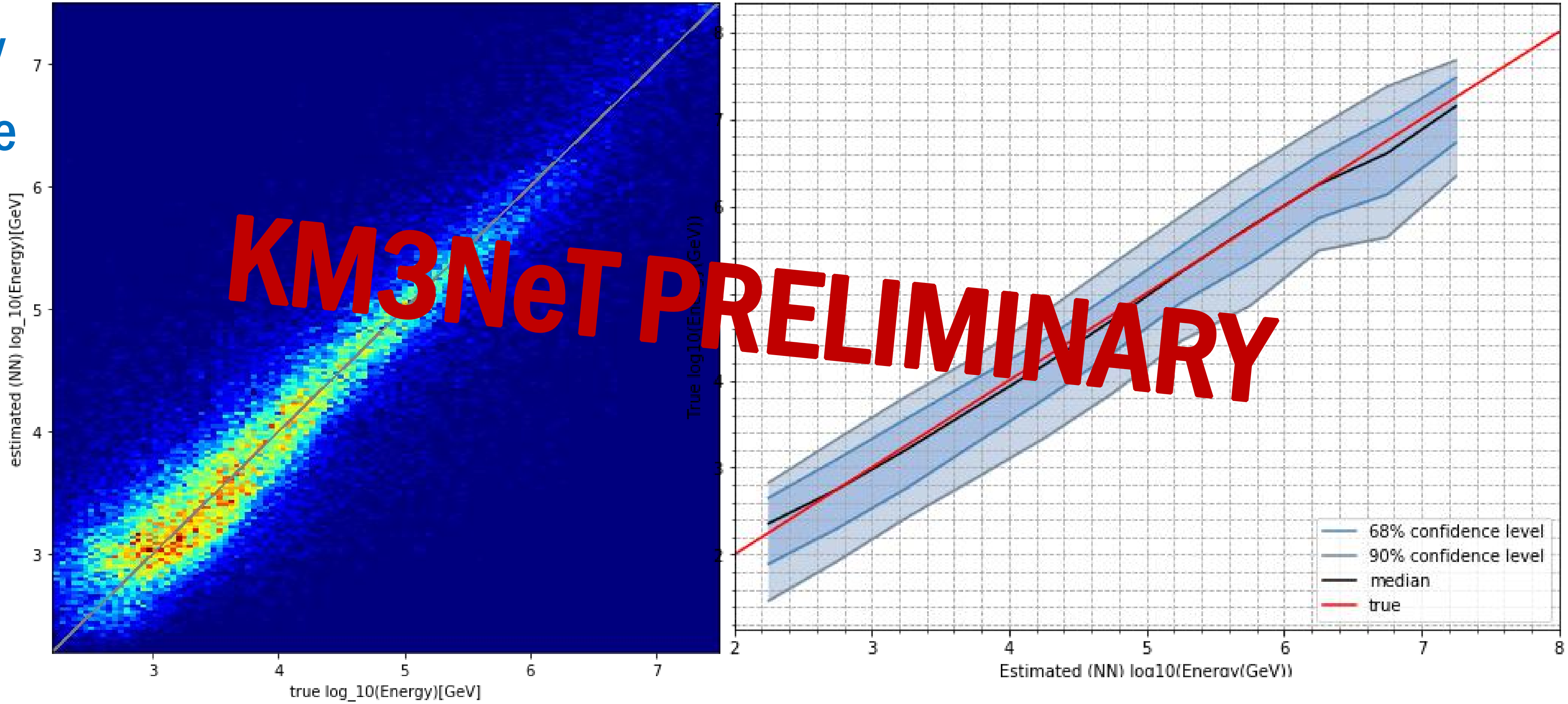
KM3NeT - ν Energy estimation

- Events are not pre-classified with respect to particle ID
- The CNN does not have any other information than hits
- ν_eCC and ν_μCC handled together and mixed in training/test/validation samples



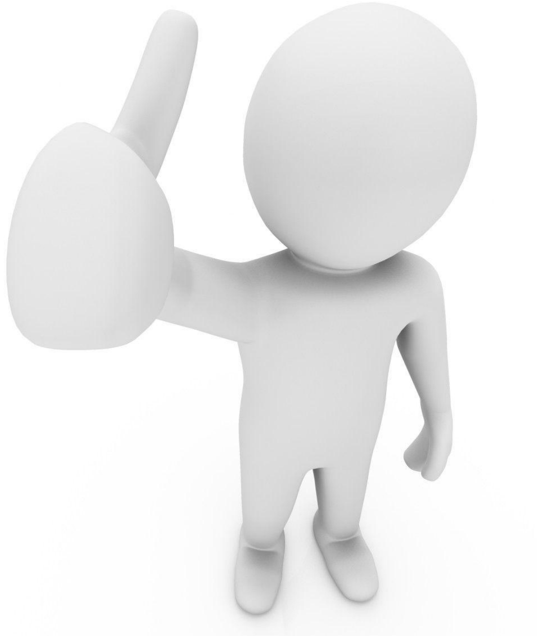
KM3NeT - ν Energy estimation

- Good linearity
- Could improve with more statistics at high energy



Conclusions

- pLISA is a convenient framework to flexibly develop neural networks for astroparticle identification and study
- Based on widespread technologies
- Usable output can already be produced
- Can already provide a cross-check for "traditional" reconstruction algorithms



https://baltig.infn.it/bozza/plisa/

Outlook

- Improve and clean up library API
- Provide support for problems with higher dimensionality
- Application side: try to include all neglected ingredients for real situations, including efficiency, irregular shapes, noise, detector distortion, etc.