

Deep Learning for neutrino telescopes

Stefan Geißelsöder

21. Feb. 2017

Big Data Science in Astroparticle Physics
HAP Workshop, RWTH Aachen



ERLANGEN CENTRE
FOR ASTROPARTICLE
PHYSICS

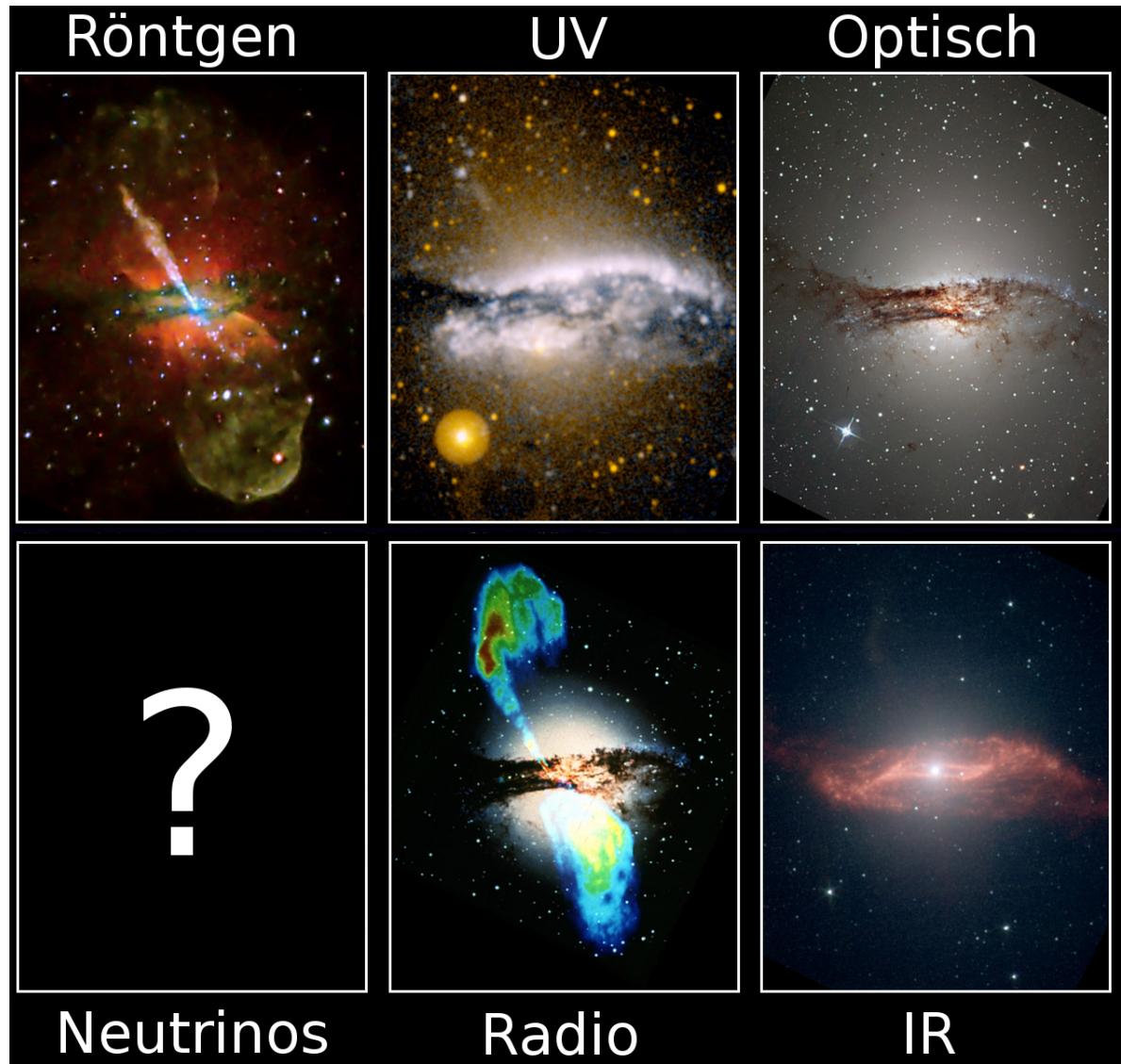


FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG

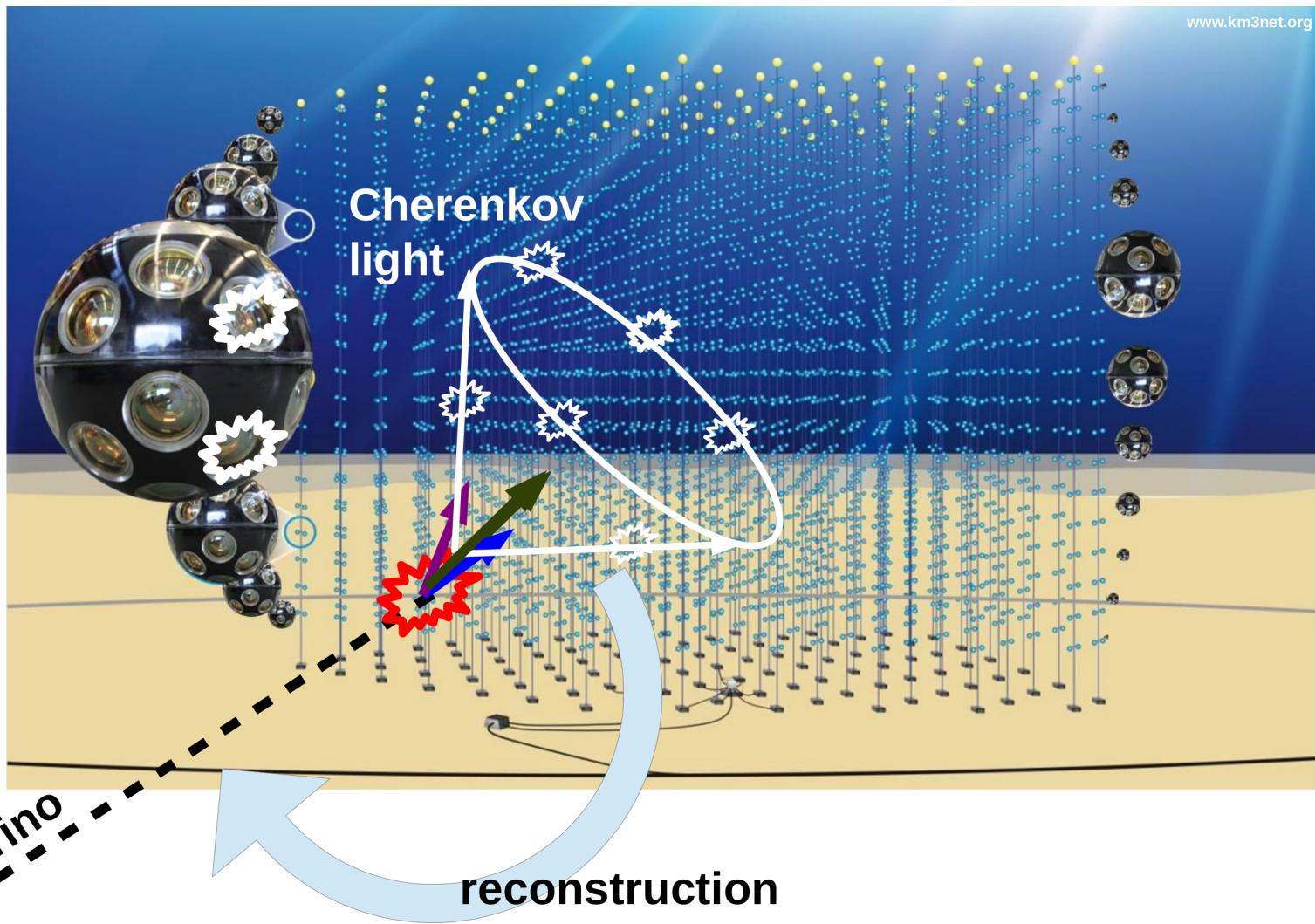
NATURWISSENSCHAFTLICHE
FAKULTÄT

Motivation neutrino astronomy

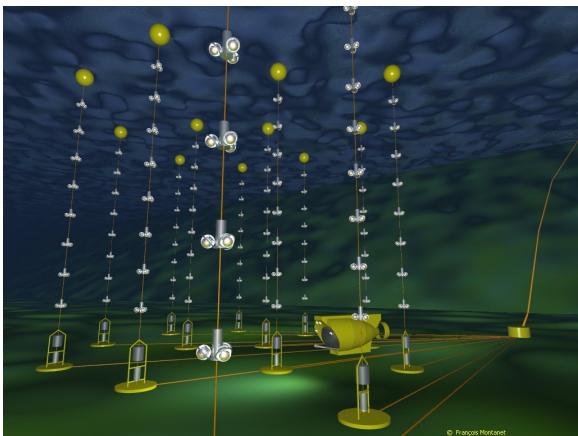
- Learn about high-energy cosmic rays
- Find sources of high-energy neutrino flux
- Do multi-messenger astronomy



Detection principle

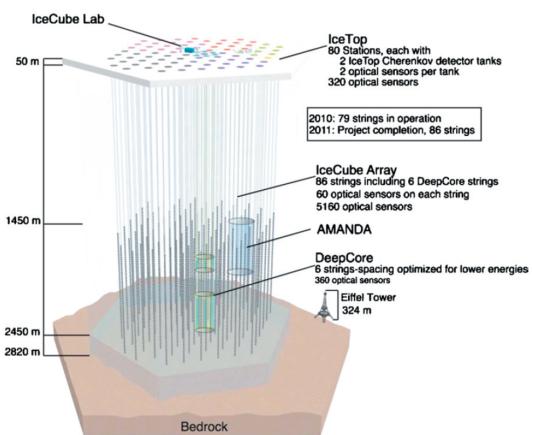


ECAP involved in



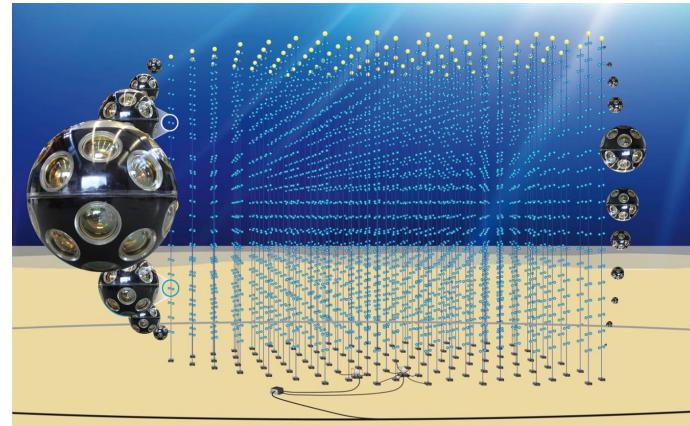
ANTARES

- Operational
- Mediterranean Sea
- 885 OM
- 1 PMT/OM



IceCube

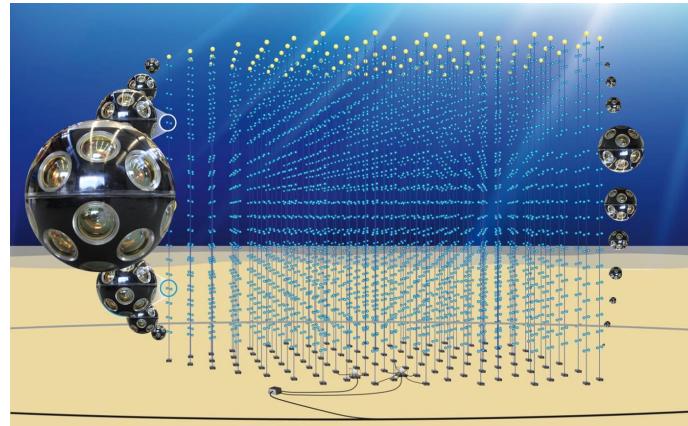
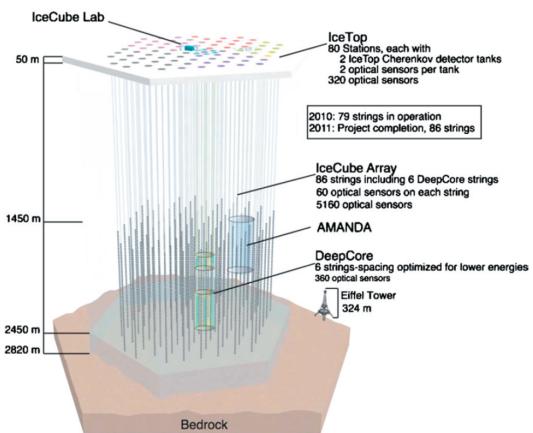
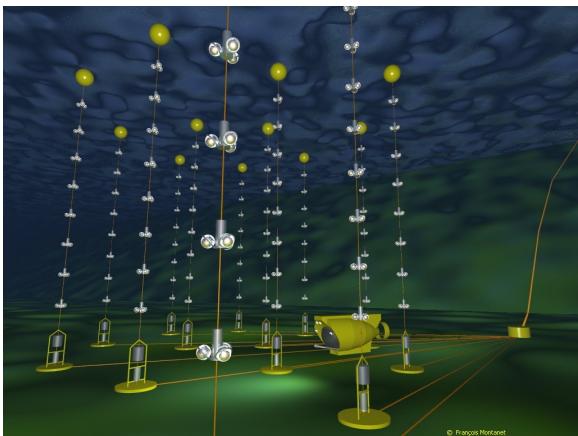
- Operational
- Antarctic Ice
- 5160 DOMs
- 1 PMT/DOM



KM3NeT

- Being build
- Mediterranean Sea
- 2070 DOMs/block (up to six blocks)
- 31 PMTs/DOM

ECAP involved in



ANTARES

- Operational
- Mediterranean Sea
- 885 OM
- 1 PMT/OM

IceCube

- Operational
- Antarctic Ice
- 5160 DOMs
- 1 PMT/DOM

KM3NeT

- Being build
 - Mediterranean Sea
 - 2070 DOMs/block
(up to six blocks)
 - 31 PMTs/DOM
- Main focus of this talk

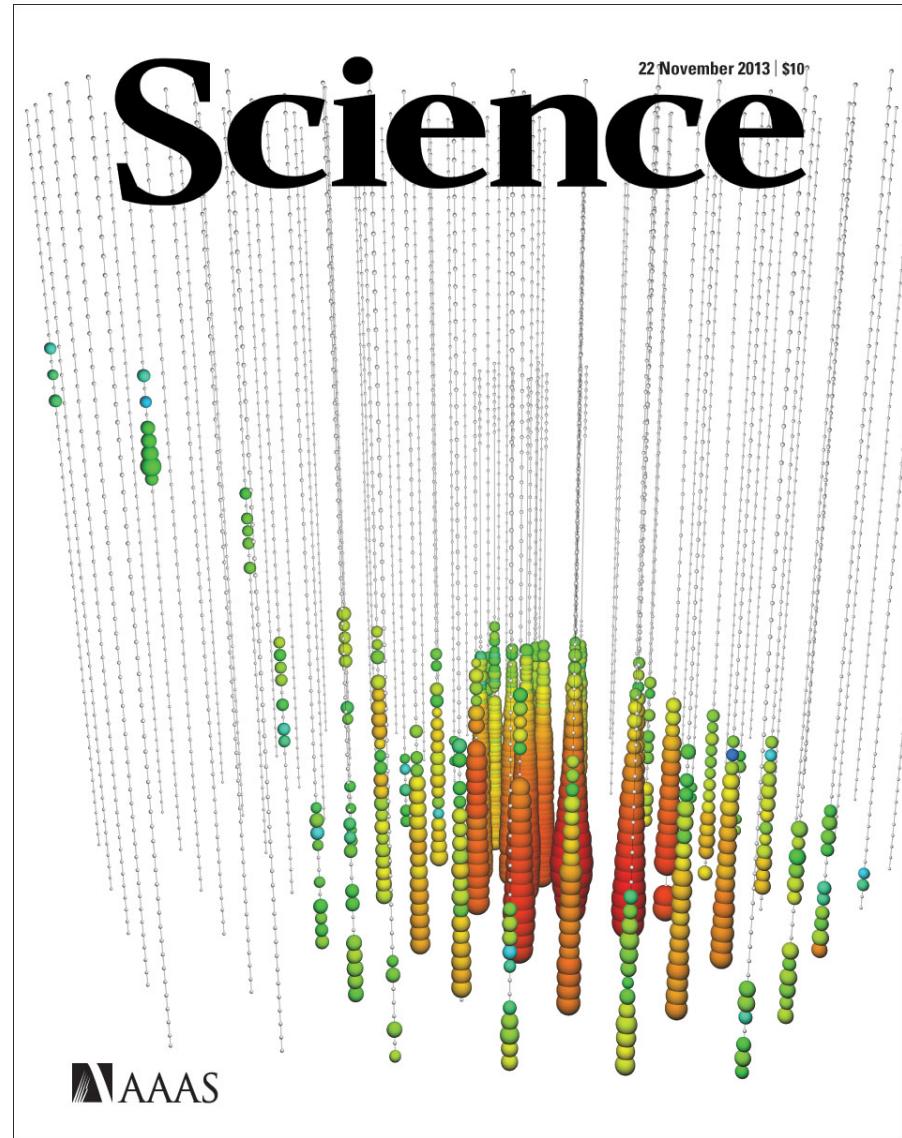
Measured information per event

Event consists out of list of “hits”.

- Time
- OM (PMT*) number → x,y,z
- (observable correlating with number of photons)

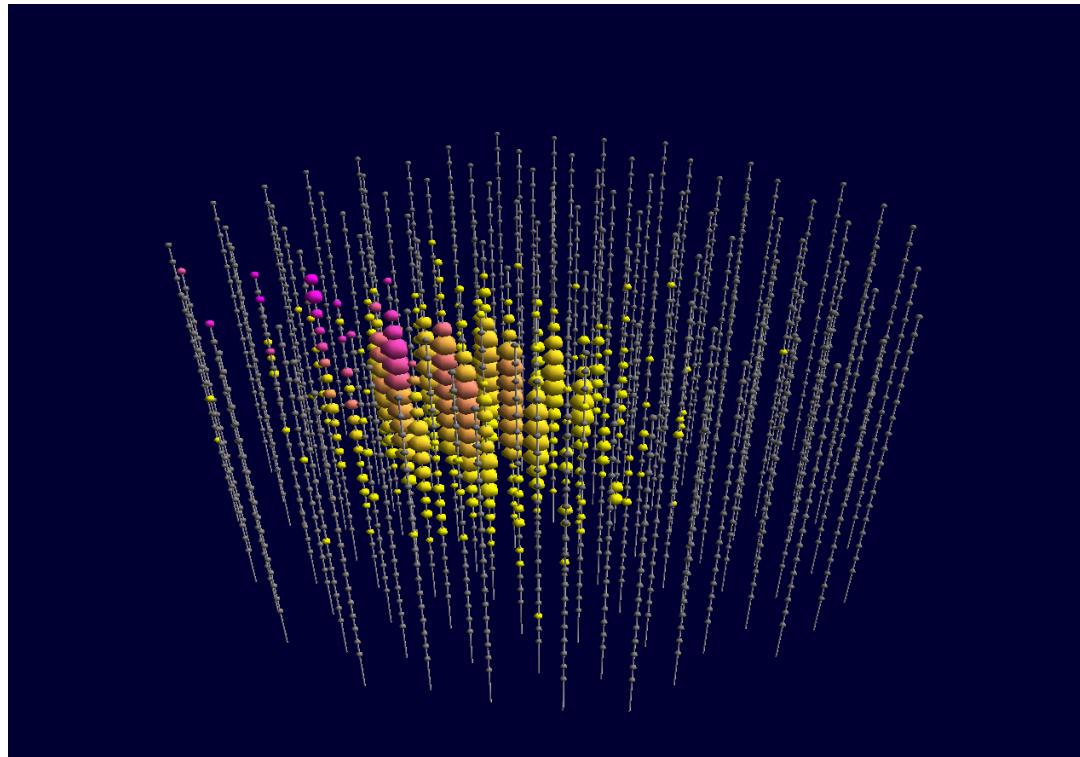
Allows reconstruction of

- direction
- energy
- (interaction)



Hits to high-level information

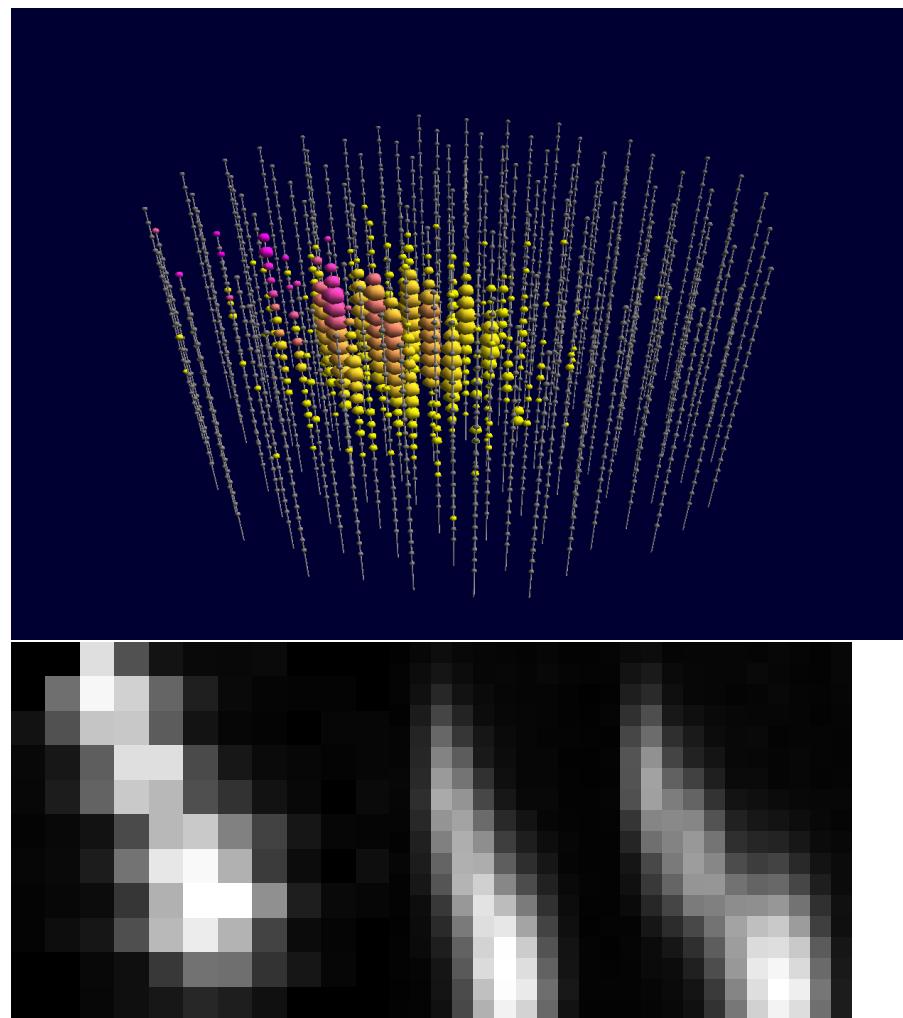
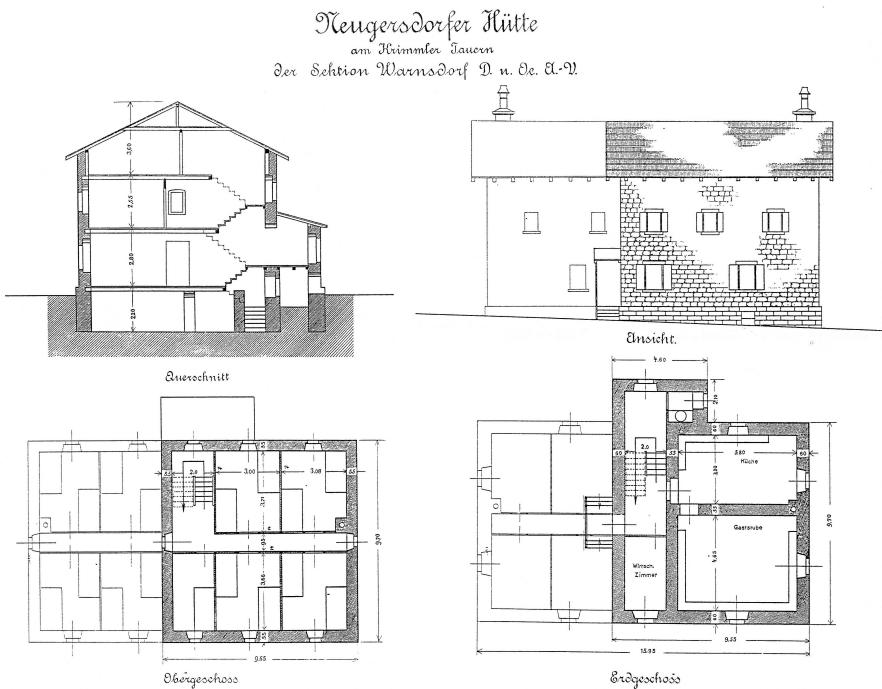
- Reconstructions
(e.g. Maximum likelihood)
- Classical pattern
recognition
 - Background suppression
 - Energy reconstruction
- Deep Learning:
 - Improve pattern
recognition?
 - New applications feasible?
(e.g. direction regression)
 - Faster developments?



How to best feed x,y,z,t data to a framework most often used for images?

Hits to high-level information

Two dimensional projections?



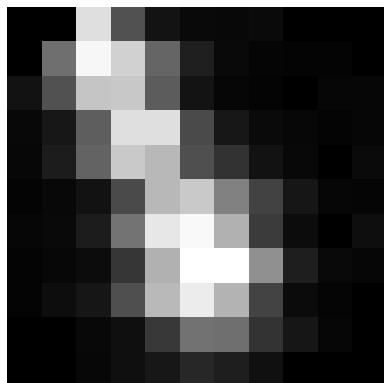
OM number
+ time

→

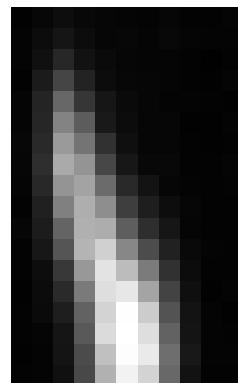
x,y,z + time

→

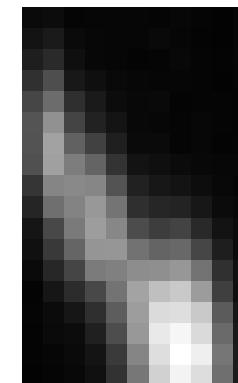
2D projection
(histogram)



x-y, 11 x 11 bins



x-z, 11 x 18 bins



y-z, 11 x 18 bins



x-t, 11 x 100 bins



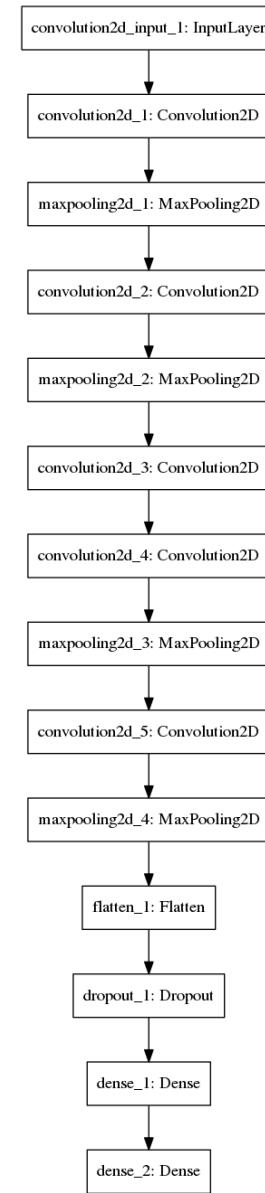
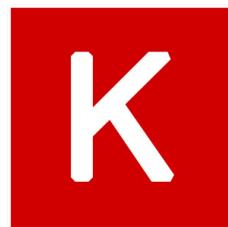
y-t, 11 x 100 bins



z-t, 18 x 100 bins

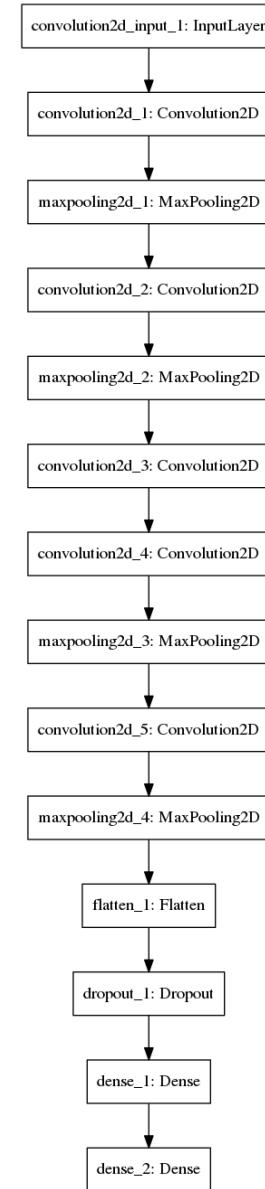
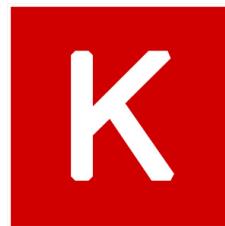
Testing Ansatz I

- Up/Down classification
- z-t as input
- CNN
- $\approx 93\%$ accuracy
- Work in progress,
suggestions welcome



Testing Ansatz I

- Up/Down classification
- z-t as input
- CNN
- $\approx 93\%$ accuracy
- Work in progress,
suggestions welcome
- As good as a Master's
student (me) at this task
with shallow learning
after one year!



Ansatz II

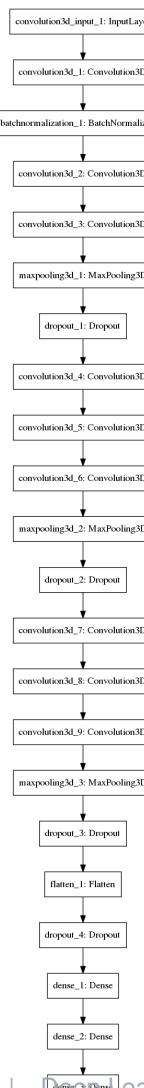
- x-y-z
11 x 11 x 18 bins
- x-y-t
11 x 11 x 100 bins
- x-z-t
11 x 18 x 100 bins
- y-z-t
11 x 18 x 100 bins
- r-z-t
11 x 18 x 100 bins

→

x,y,z + time

→

Three dimensional
projections



- Up/Down classification
- r-z-t ⇒ 96.5 %
- Better than z-t
- About as good as one year Master's and first year PhD student with shallow learning*

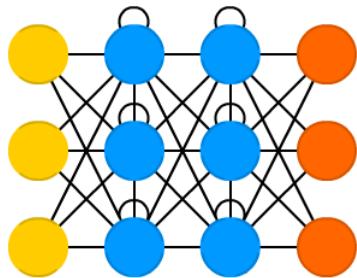
Obvious next step - Ansatz III

OM number
+ time → x,y,z + time → Full four dimensions

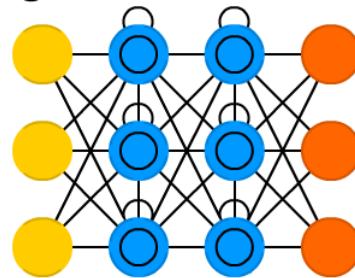
- x-y-z-t
 $11 \times 11 \times 18 \times 100$
bins
- No 4D convolution
implemented (yet)
- Maybe test CNTK

OM number
+ time → RNN / LSTM / GNN /
...

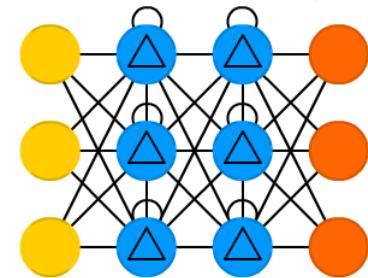
Recurrent Neural Network (RNN)



Long / Short Term Memory (LSTM)



Gated Recurrent Unit (GRU)



Not tested yet.

OM number
+ time

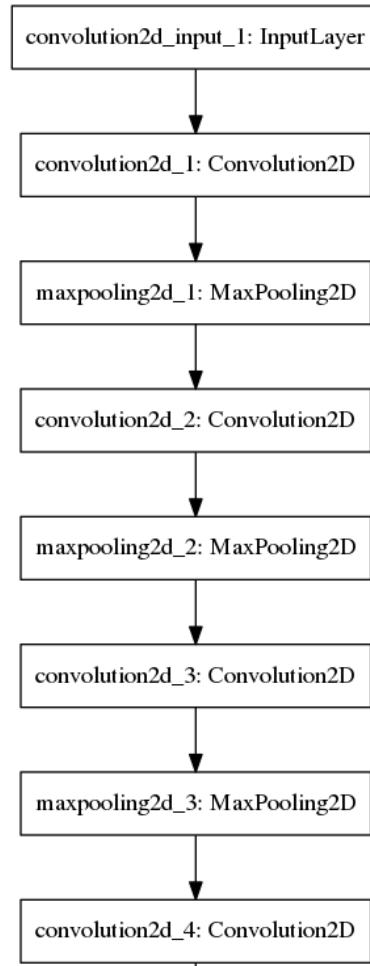
→

x,y,z + time

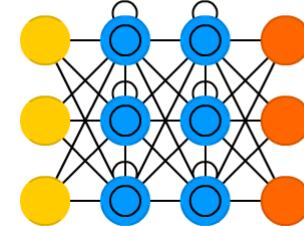
→

Time series of
3D projections

- 100 x-y-z histograms,
one for each time bin
- 100 times $11 \times 11 \times 18$
- CNN on x-y-z
⇒ feature reduction
for each time bin



Long / Short Term Memory (LSTM)

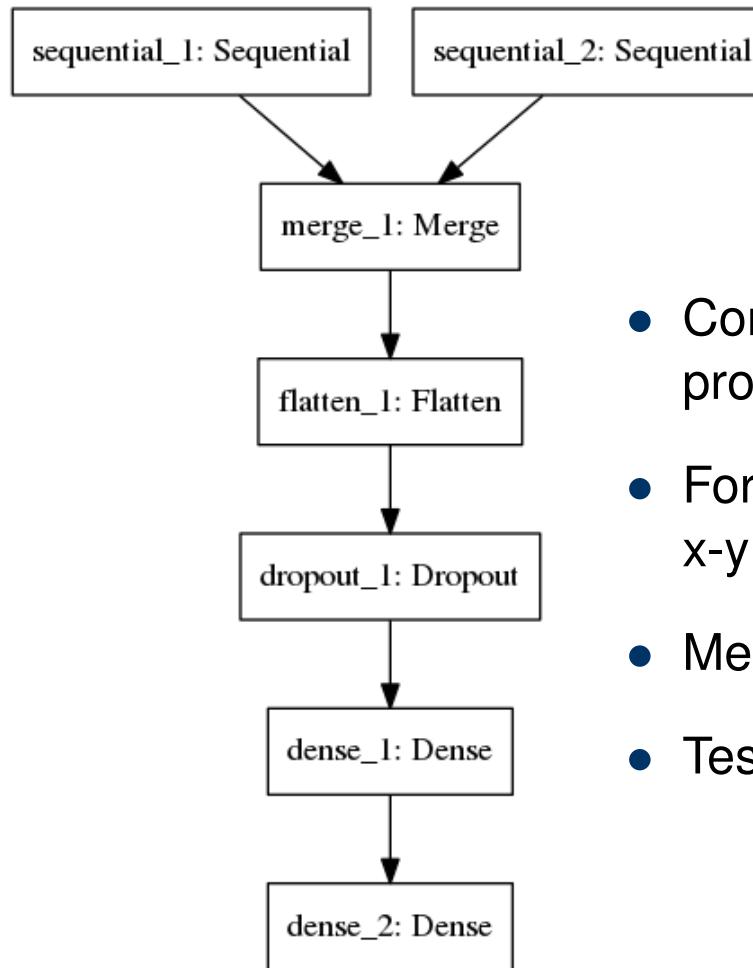
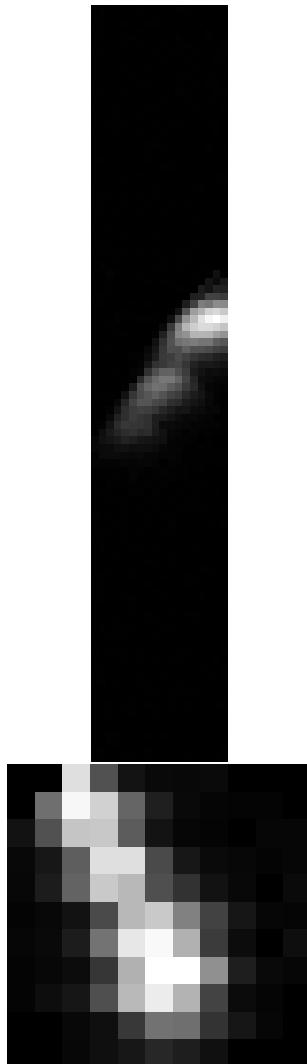


- LSTM for time series
of CNN outcome
- Not tested yet

- Neutrino telescopes produce (at least) four dimensional data
- Many options to handle this data
- Deep convolutional nets applied successfully
- Recurrent nets will be investigated
- More applications to come
- You are highly welcome to suggest improvements

Thank you for your attention!





- Combine multiple 2D projections
- For instance:
x-y and z-t as input
- Merged CNNs
- Testing currently

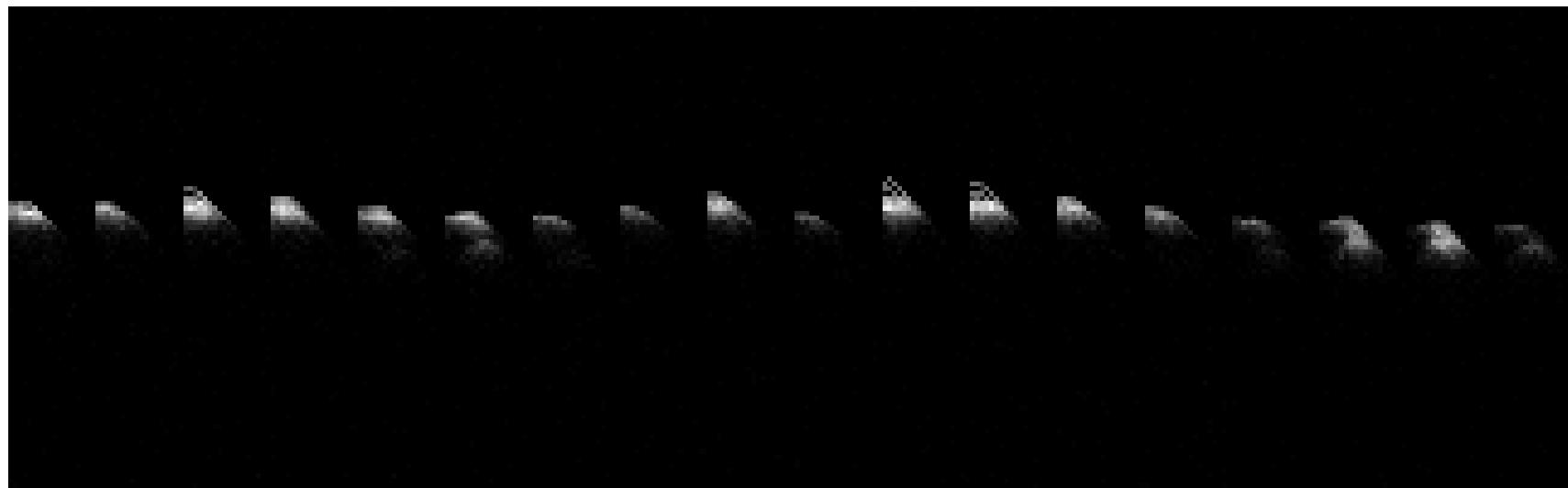
Ansatz VII



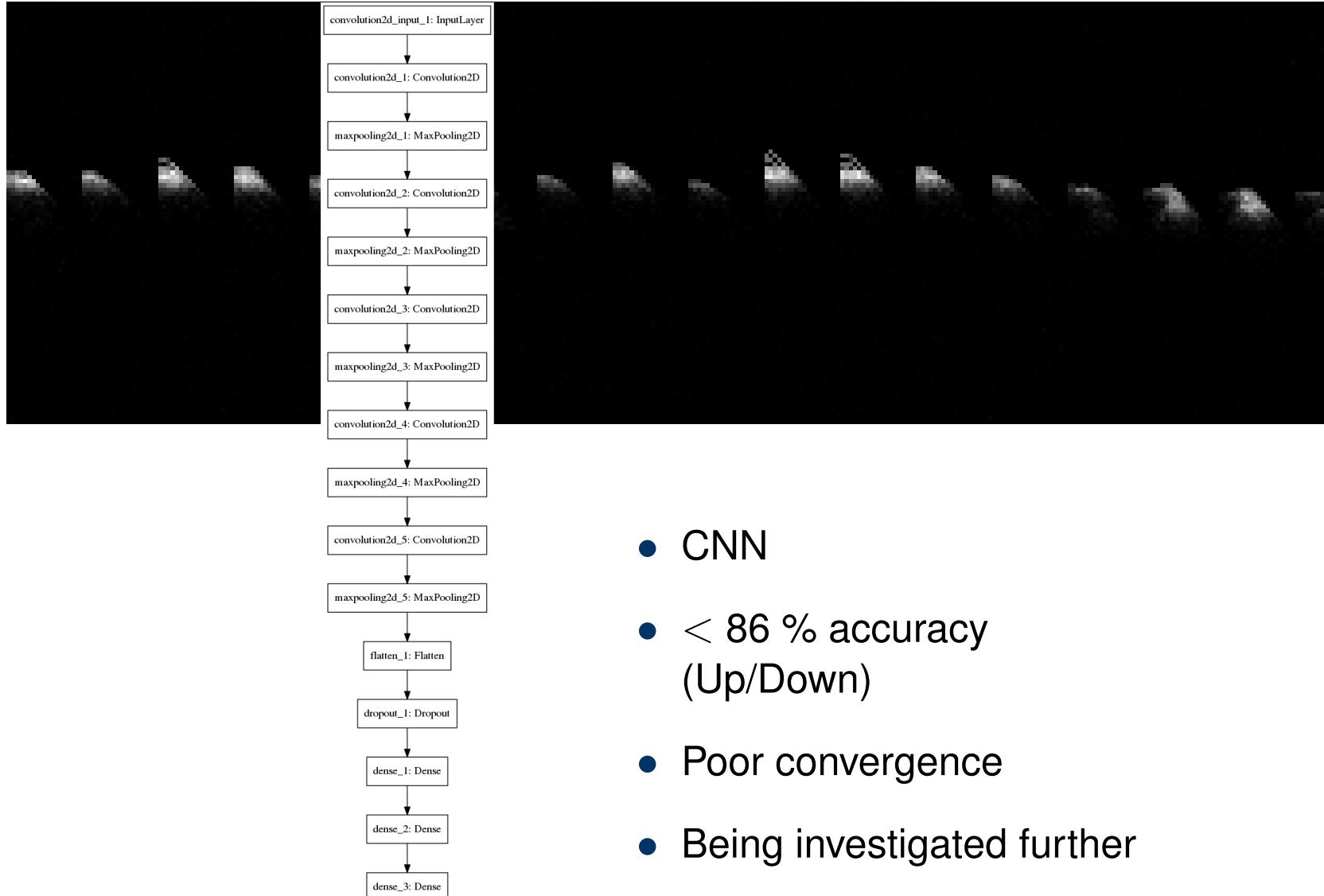
OM number
+ time → Two dimensional
projection



OM number - t, 2070 x 100 bins



Zoom



Other ideas so far

- Ditch convolution, use existing hand-crafted features
 - Tested with CNTK for particle / interaction identification
 - Not (yet) better than best shallow learning
- Regress energy and direction
- Estimate error of regression (Gaussian processes?)
- Investigate unsupervised (pre)training
- Use other projections (e.g. reconstructed direction)
 - Could introduce unnecessary uncertainty