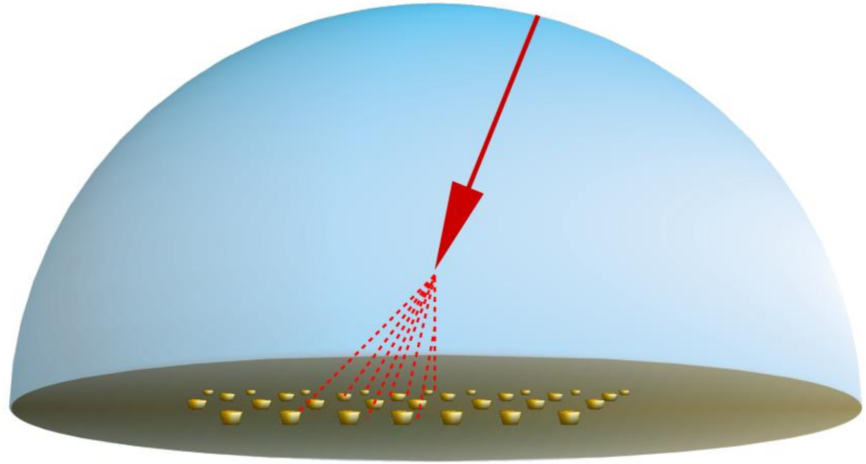

Exploring Deep Network Architectures to reconstruct Cosmic Ray Induced Air Showers at the Pierre-Auger-Observatory

Jonas Glombitza, Martin Erdmann, David Walz, Marcus Wirtz

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Bundesministerium für Bildung und Forschung

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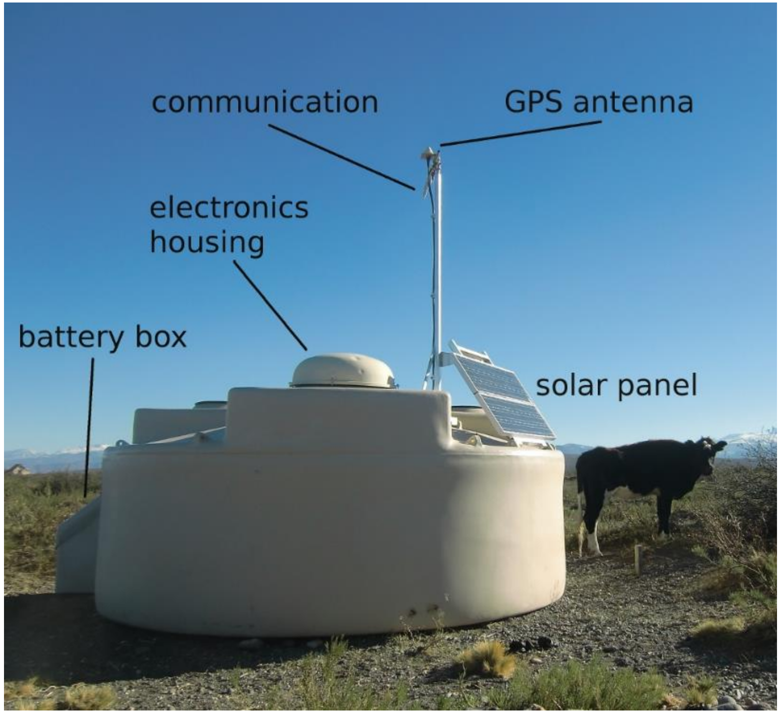
The Pierre-Auger-Observatory

- Cosmic ray observatory in Argentina
- Completed 2008
- Detection of UHECR
  - $\mathrm{E} > 10^{17.5} eV$
- Hybrid technique
  - Fluorescence telescopes
  - 1660 Surface detectors (SD)
- Array size ~ 3000 km²



Surface detector of the Pierre-Auger-Observatory

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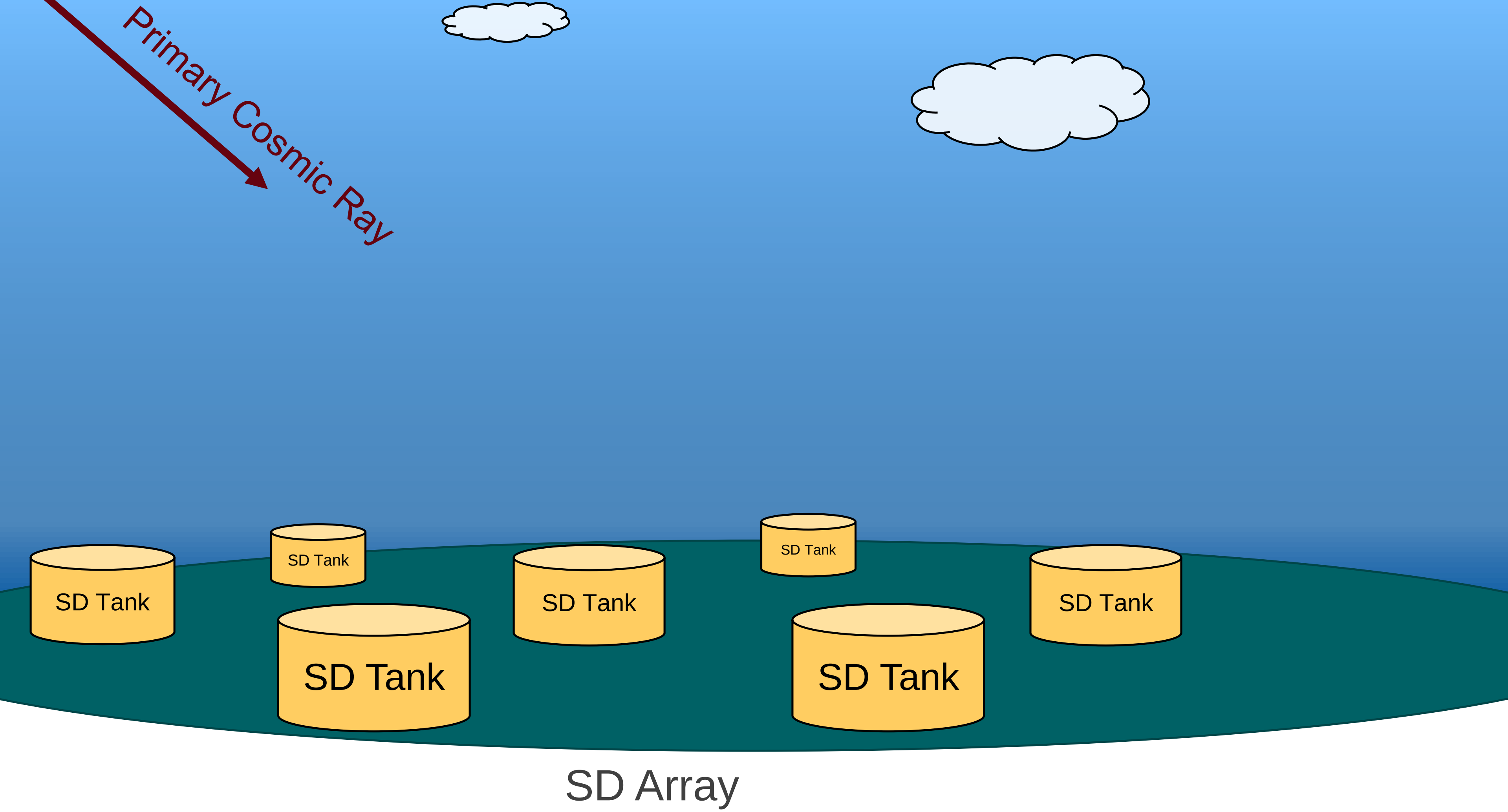

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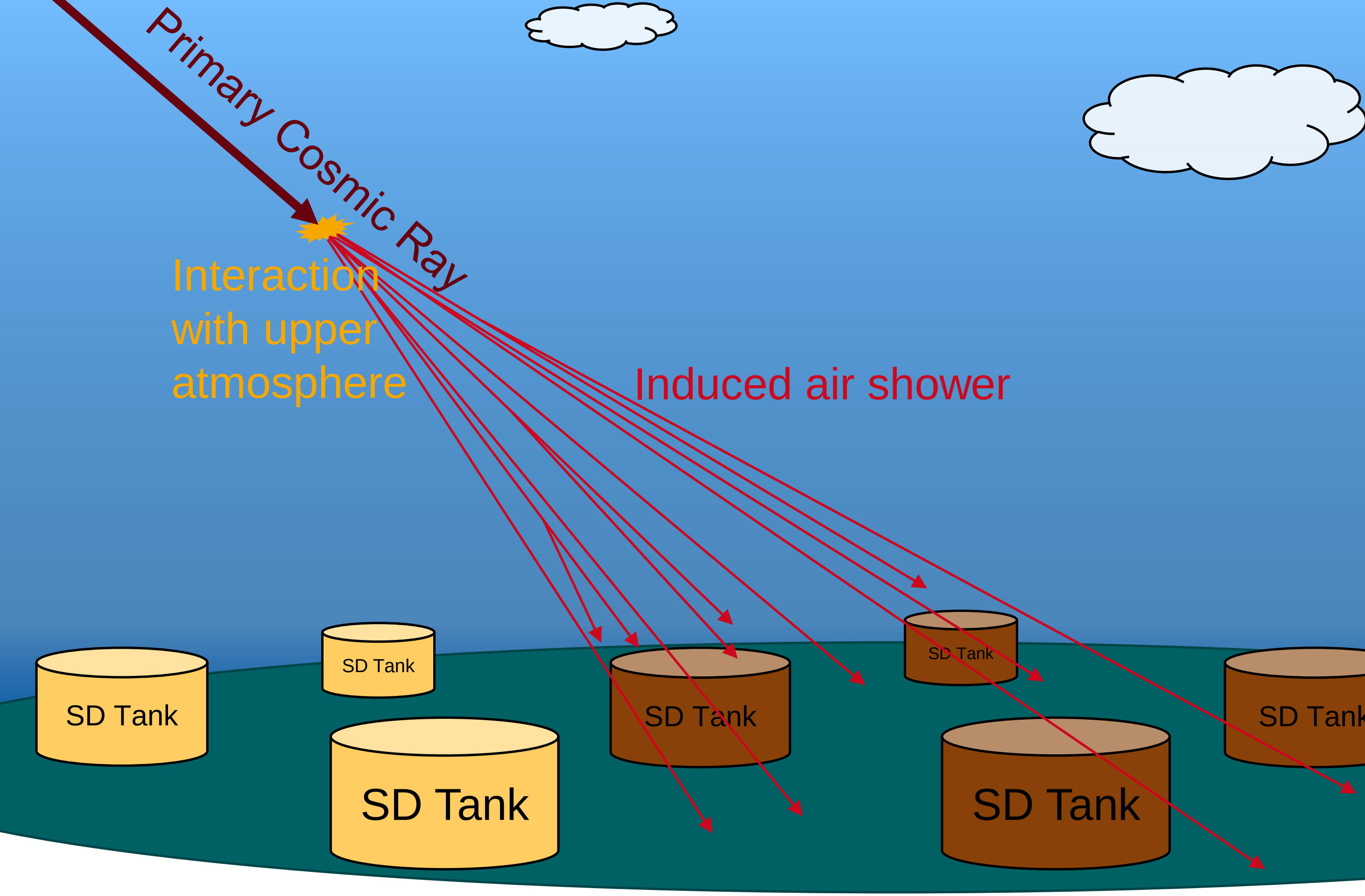

Reconstruct:
- Energy
- Direction
- Mass

SD array measures the footprint of the air shower

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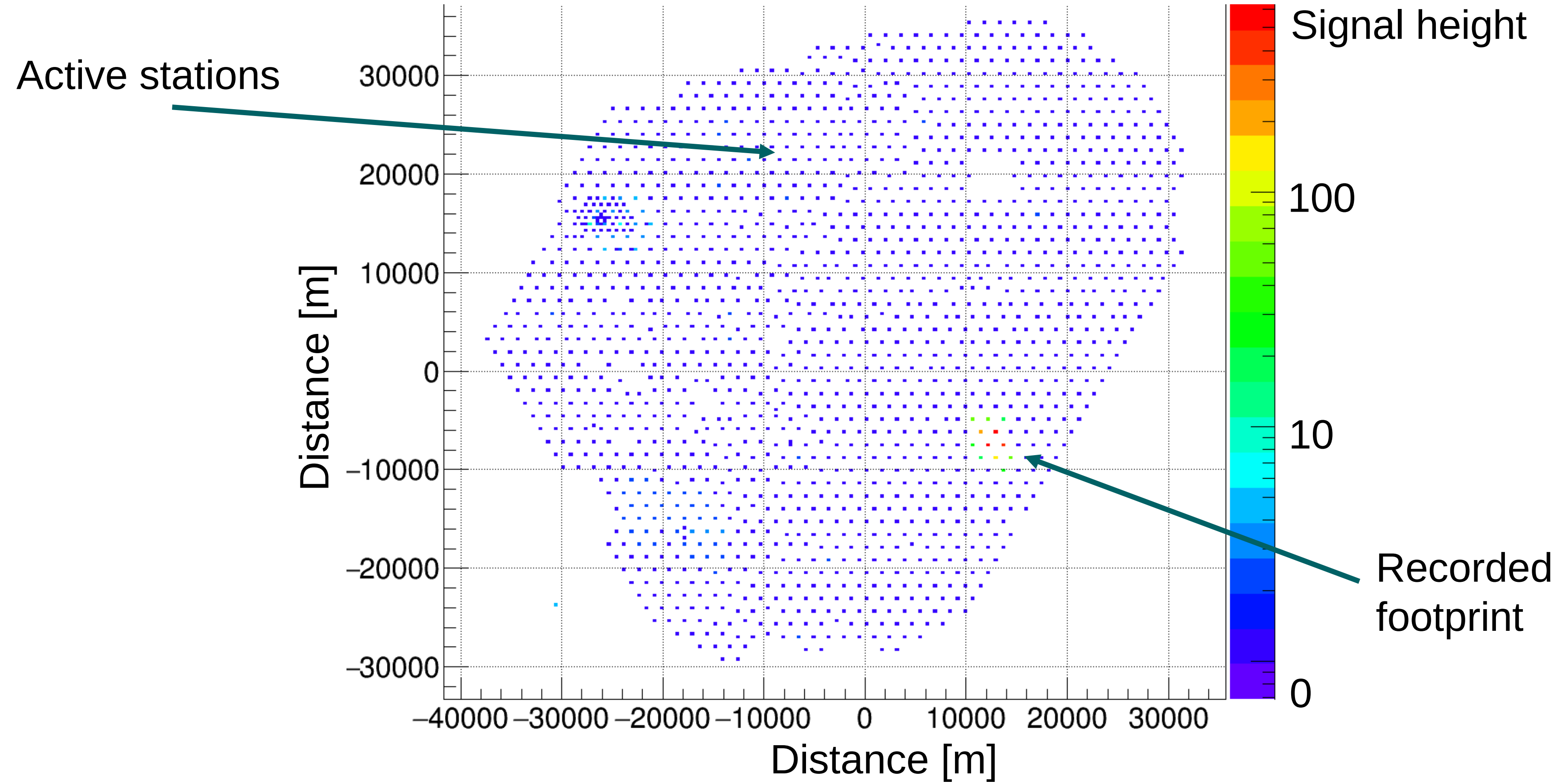
Surface Detector Array



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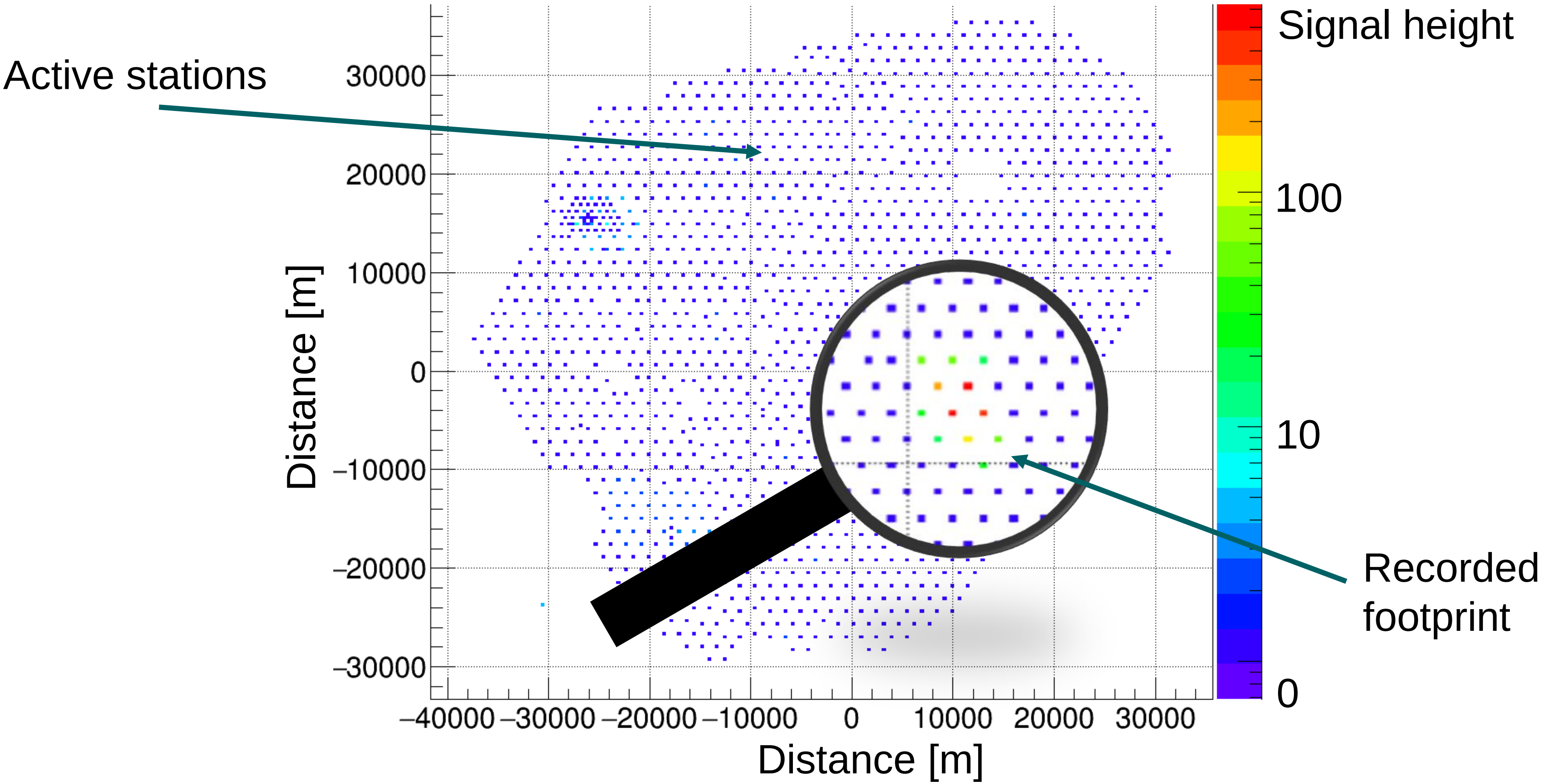
Surface Detector Array



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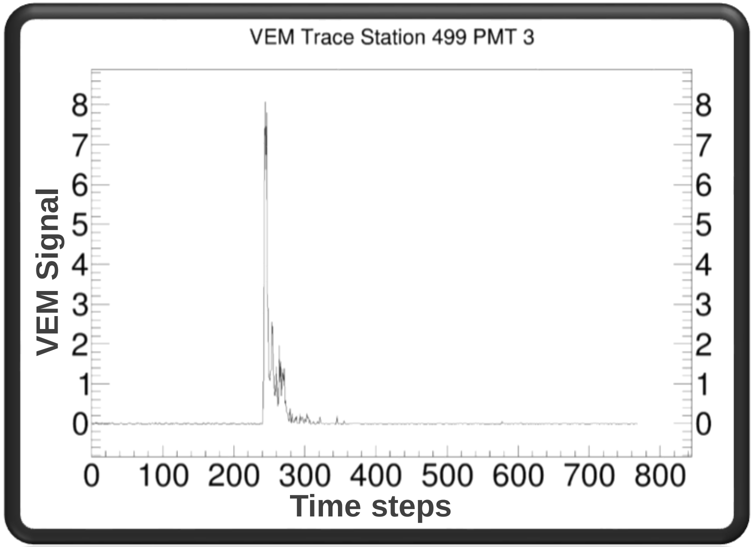
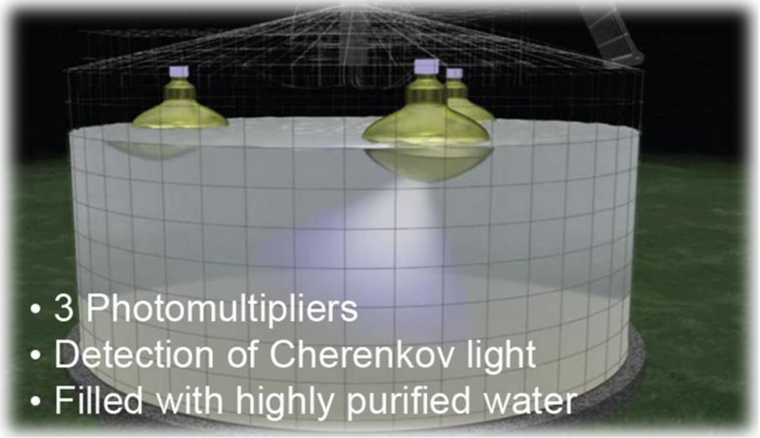
Particle detection

- Particles travel through Detector tank filled with water
  - Production of Cherenkov light
  - Photomultipliers detect the light
    - Time trace





VEM = **V**ertical **E**quivalent **M**uons

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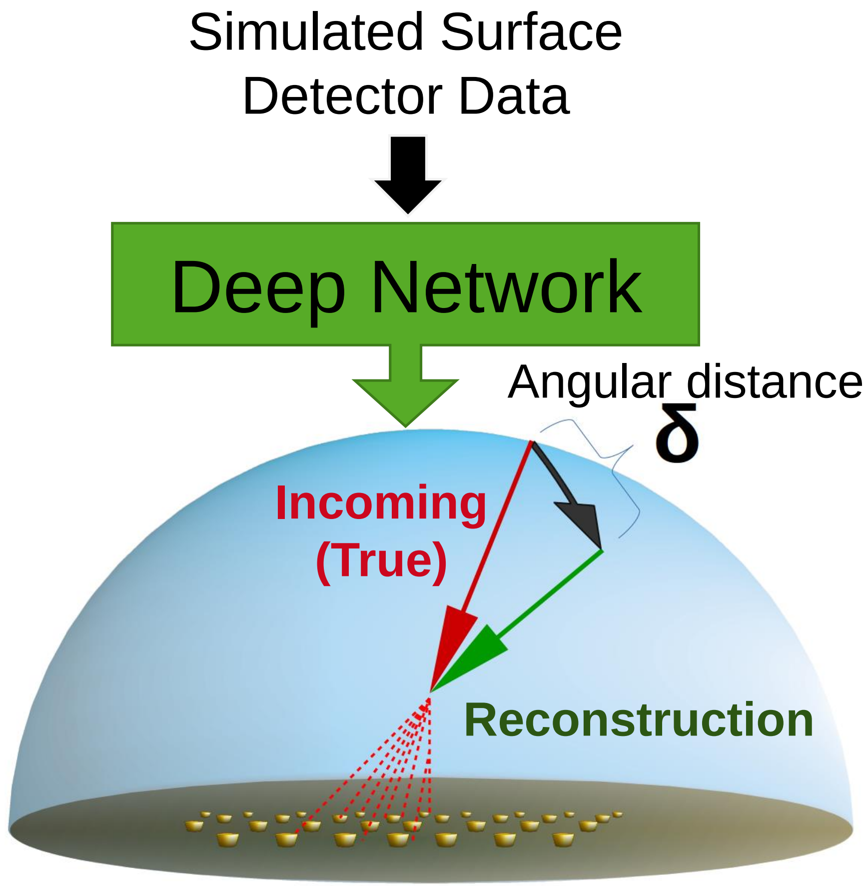
Motivation – Image Recognition on Air showers

- Investigate if air shower reconstruction can be improved
  - Shower axis, energy, mass

- Test Case: Reconstruct shower axis
- Benchmark
  - Expert reconstruction including physics
    - 1° angular resolution

- Minimize Mean-Squared-Error between true an reconstructed shower axis
  - $L = \left(\vec{r} - \vec{r}'\right)^2, \quad \vec{r} = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$



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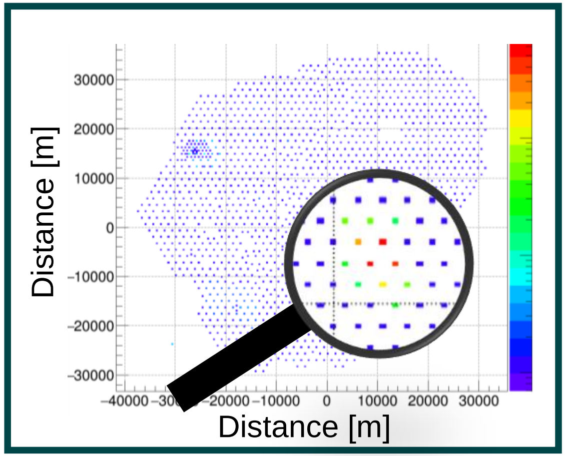
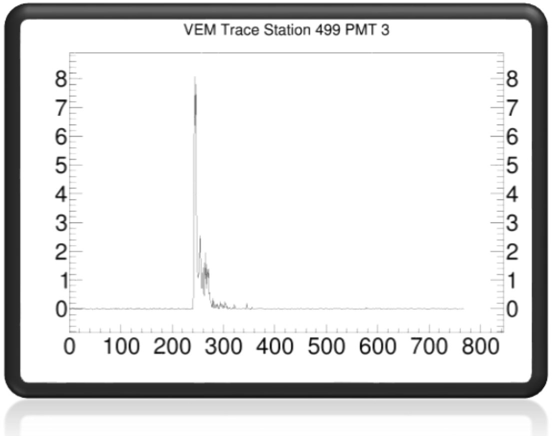
Data Format

- Use simulated Data from EPOS LHC ~ 29000 events
  – Energy Range $10^{19} - 10^{19.5}\ \mathrm{eV}$, Protons





Shower footprint

- 2 spatial dimensions
- Need Cartesian grid for convolutional operations

Photomultiplier time trace

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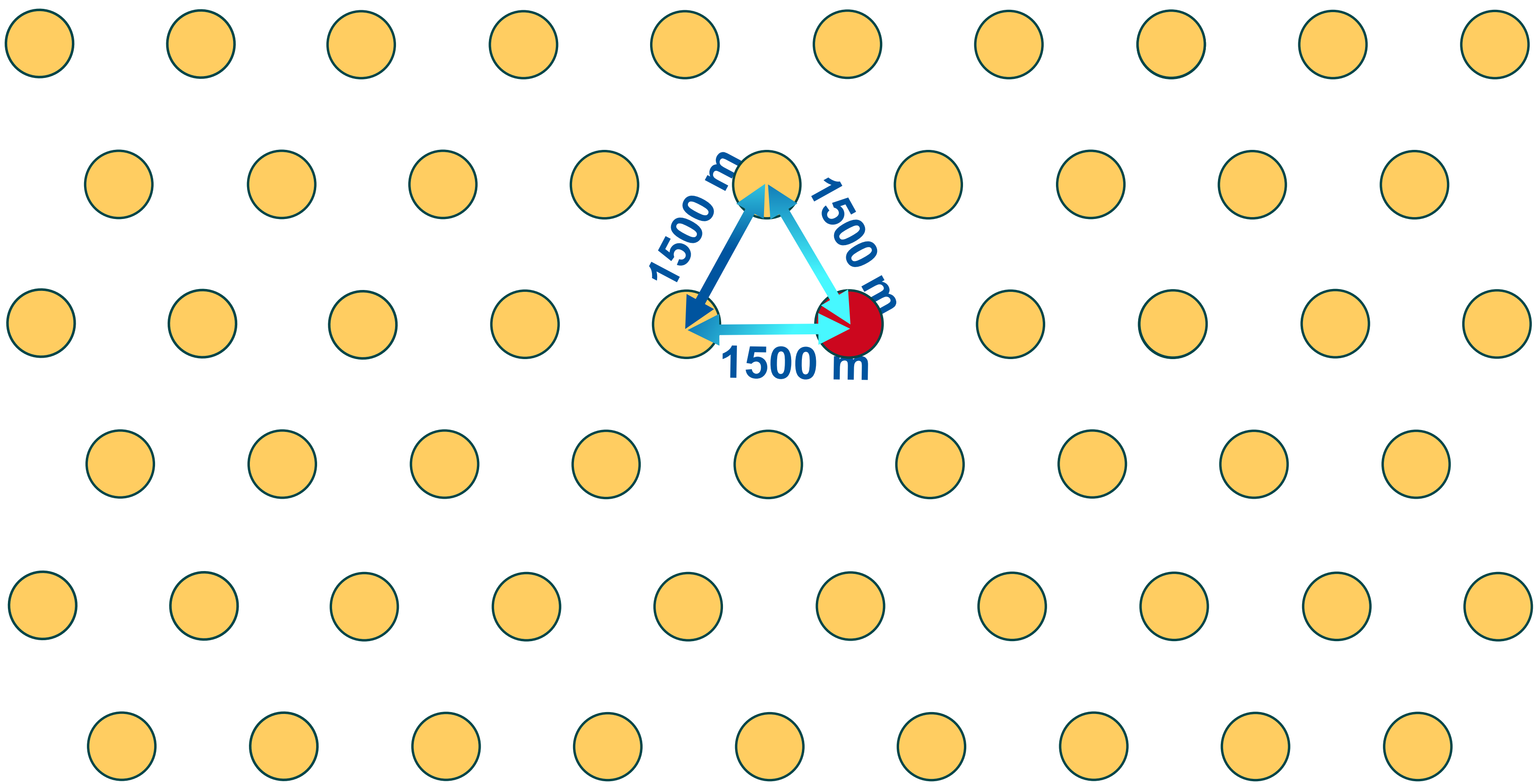
Processing the Footprint – The Surface Detector Grid



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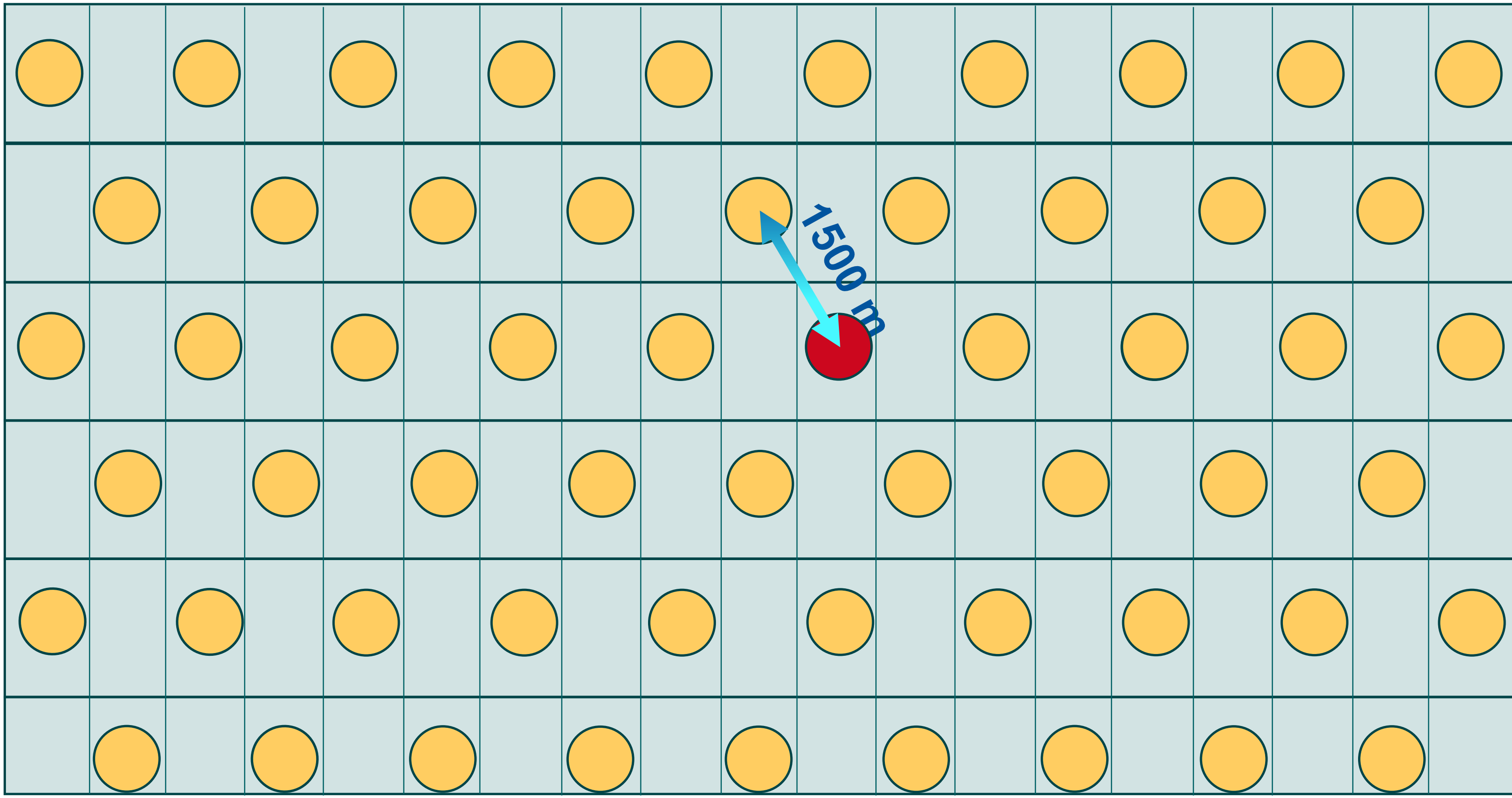
Checkerboard grid



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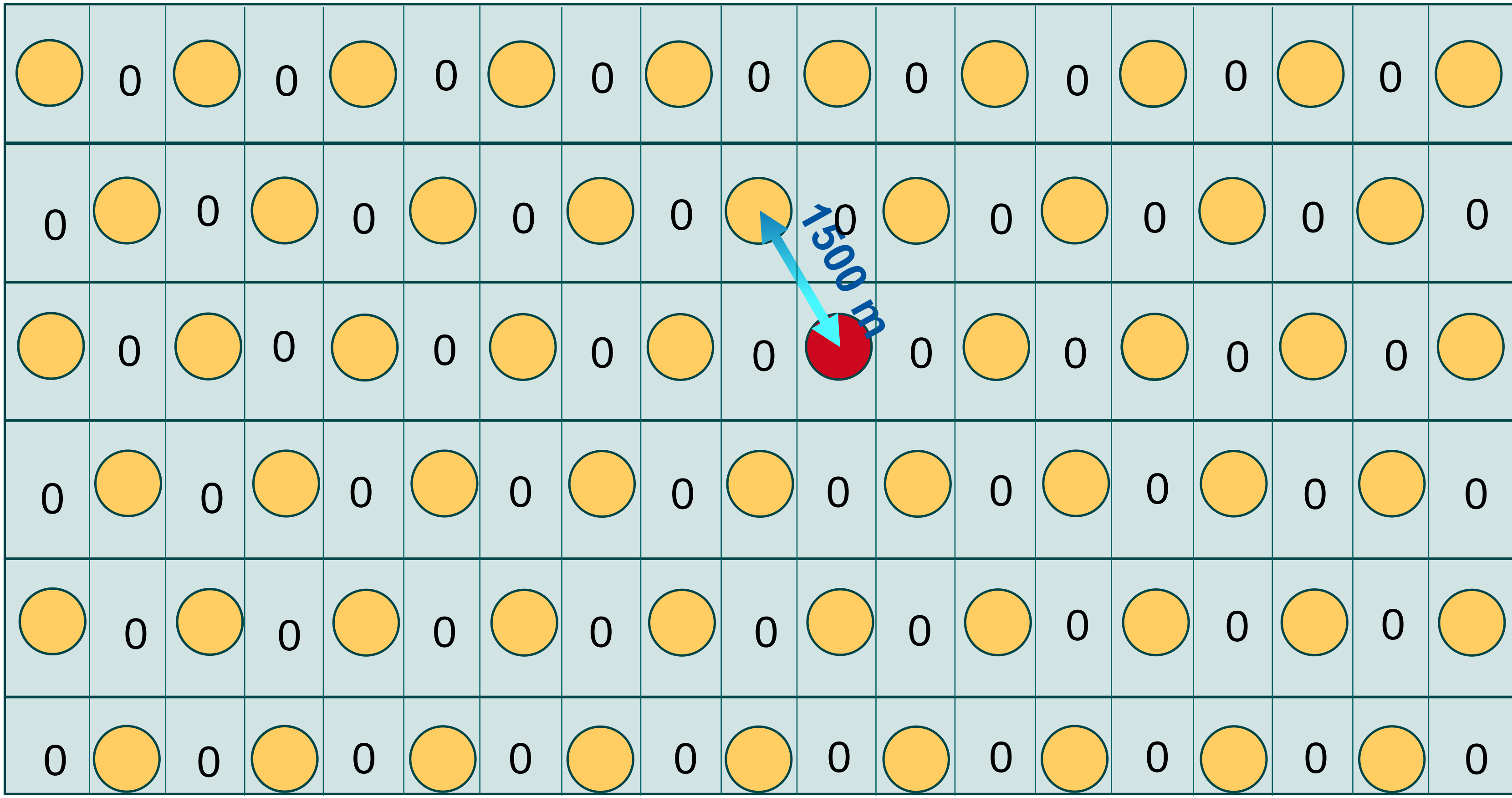
Checkerboard grid



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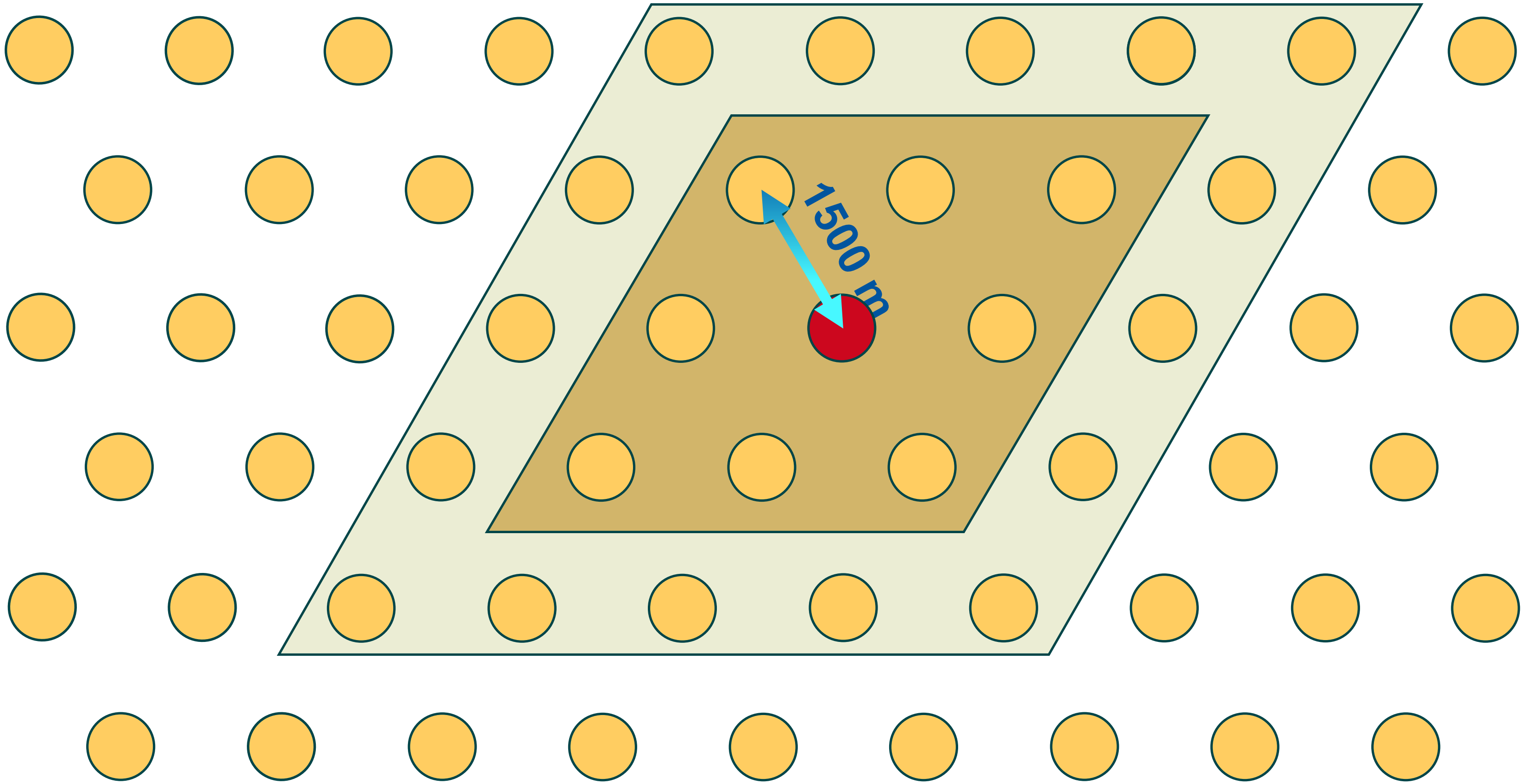
Rhombic grid



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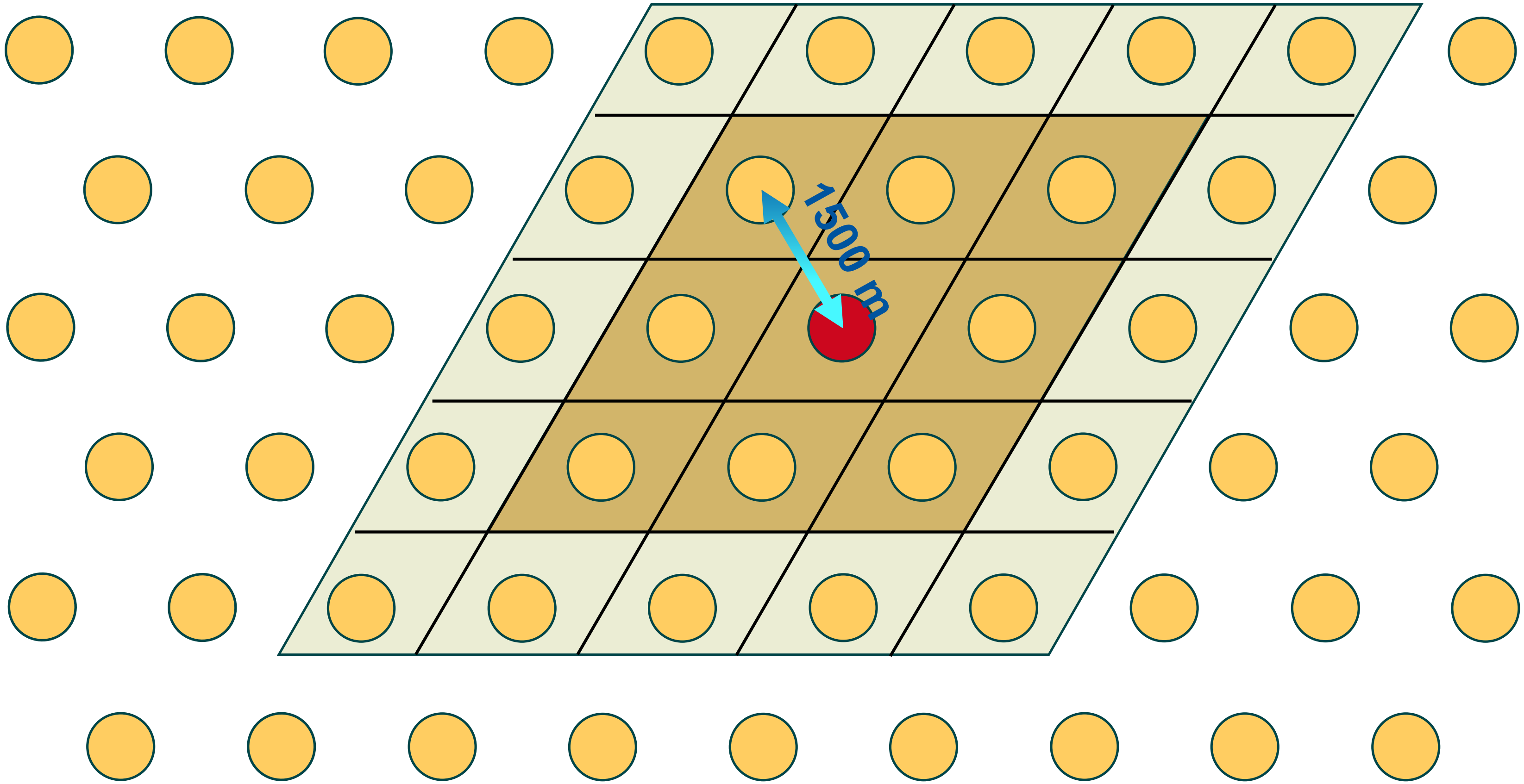
Rhombic grid



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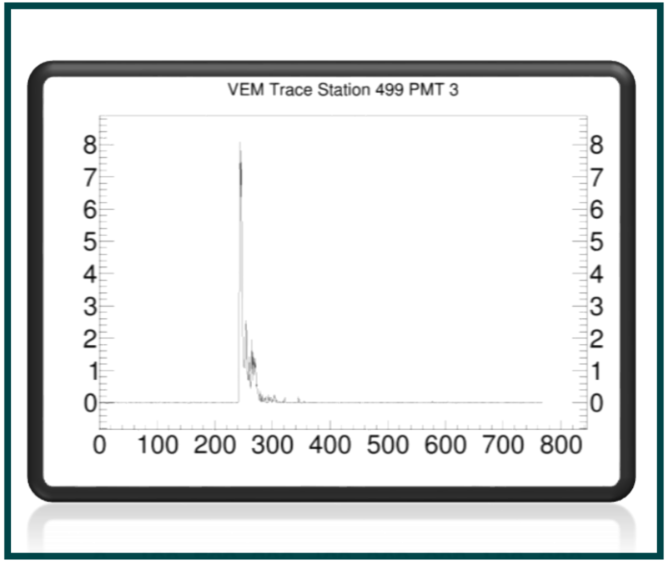
Data format



✓**Shower footprint**

- 2 space dimensions
- Need Cartesian grid for convolutional operations

Photomultiplier time trace

- 1 time dimension
- Select signal regions

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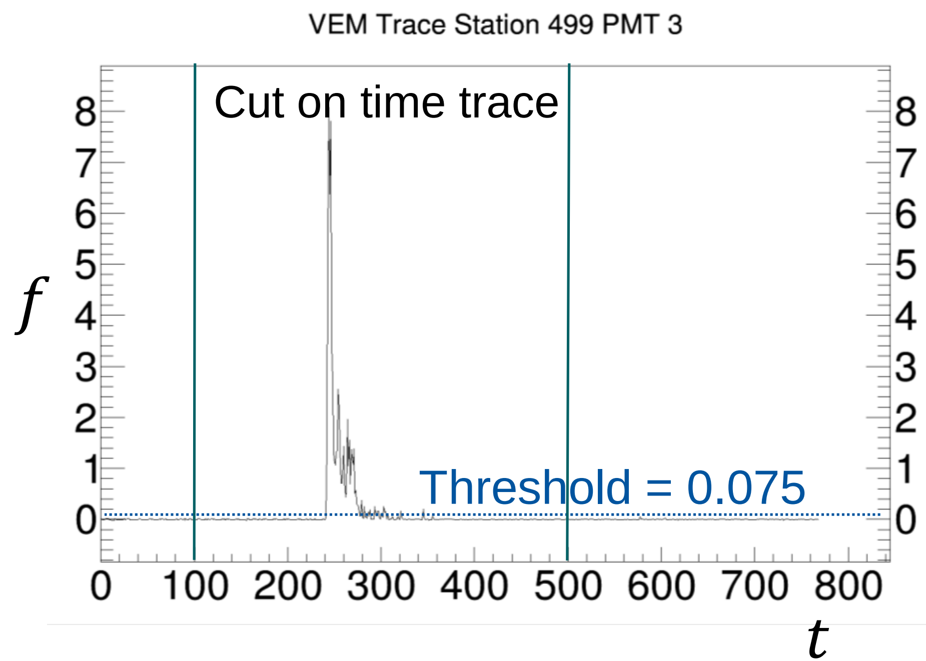
Preprocessing the Time Trace

- Limit time trace to interesting part

- Networks work best on normalized input
  - Set threshold to cut away noise
  - $f_{Normalized} = log_{10}(10 * f(t) + 0.1)$
    - Background → - 1
    - Signal → >0

- Critical for successfully training the investigated network architectures



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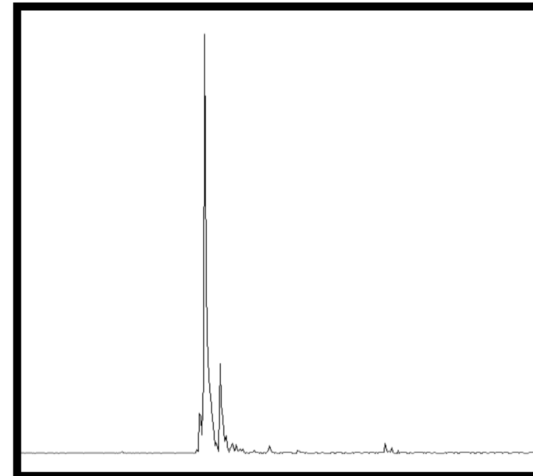
✓**Shower footprint**



✓**Time trace**

Test different architectures!

With keras – Tensorflow backend

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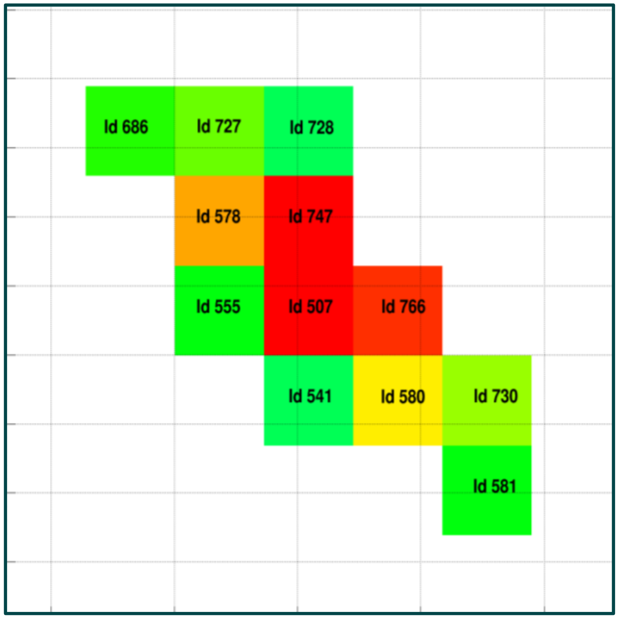
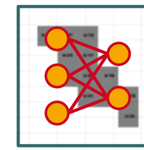
Network Architectures with 2D Input

- Sum over preprocessed time trace
  → 2D Map for every event

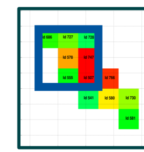


Architectures

- 5 Layer Neuronal Network
  (Fully Connected)



- 11 Layer Convolutional Network



- ~ each 1,000,000 parameters

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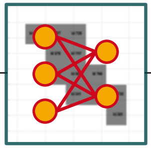
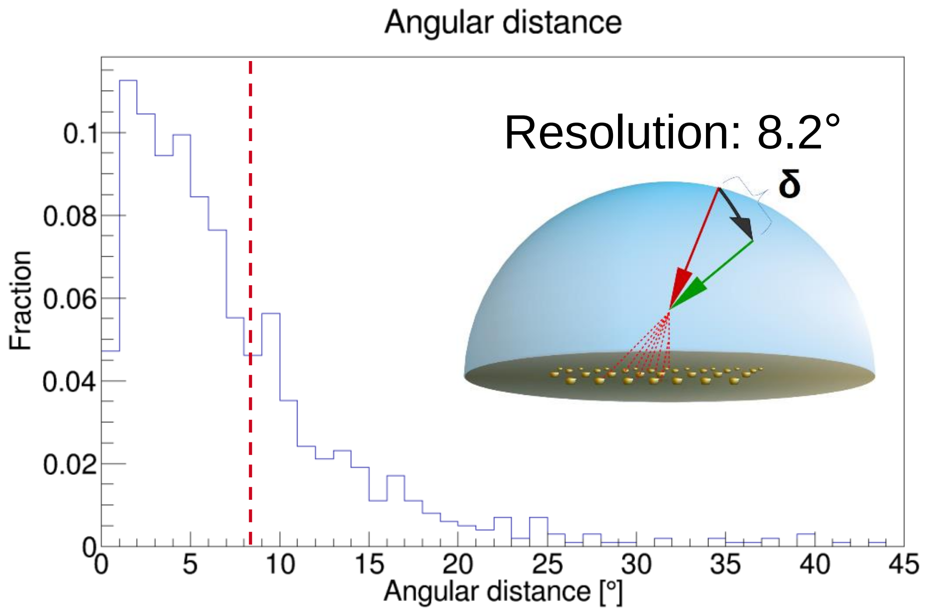
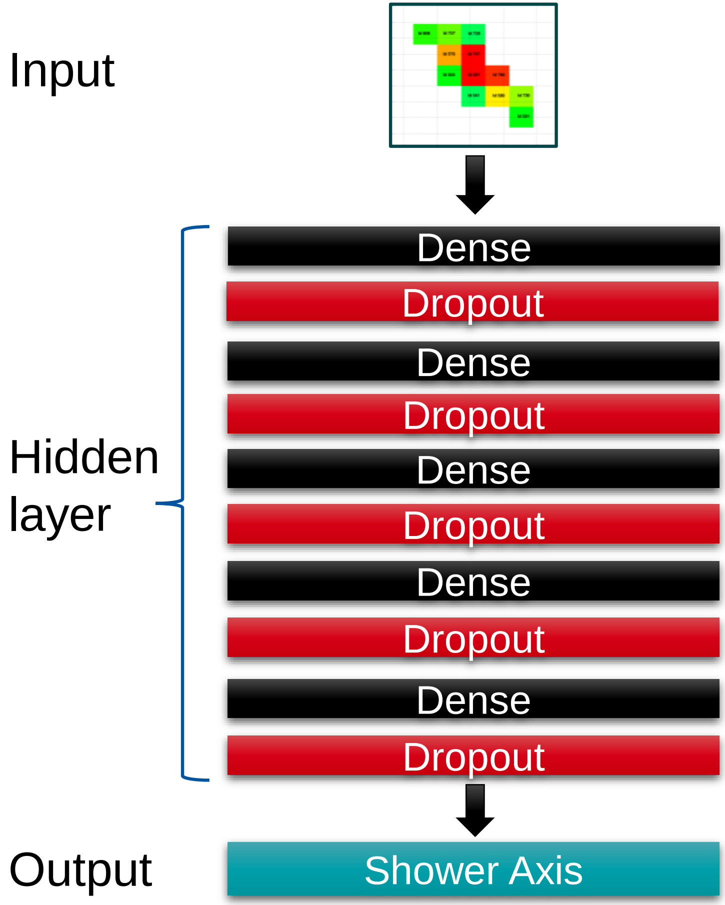
Fully Connected Network



- 5 Blocks:
  - 1 Fully connected layer
  - ReLu activation
  - 1 Dropout layer





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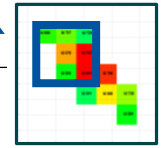
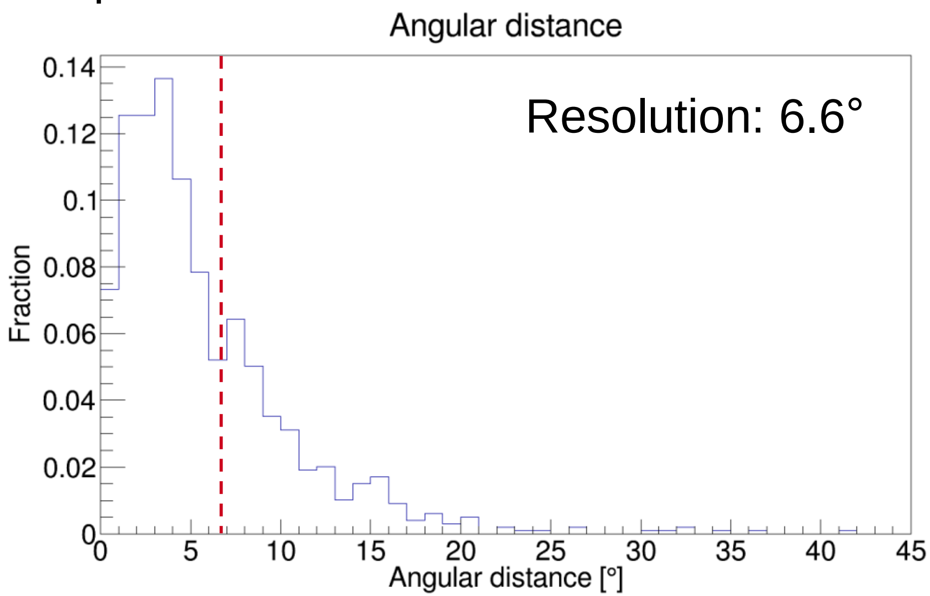
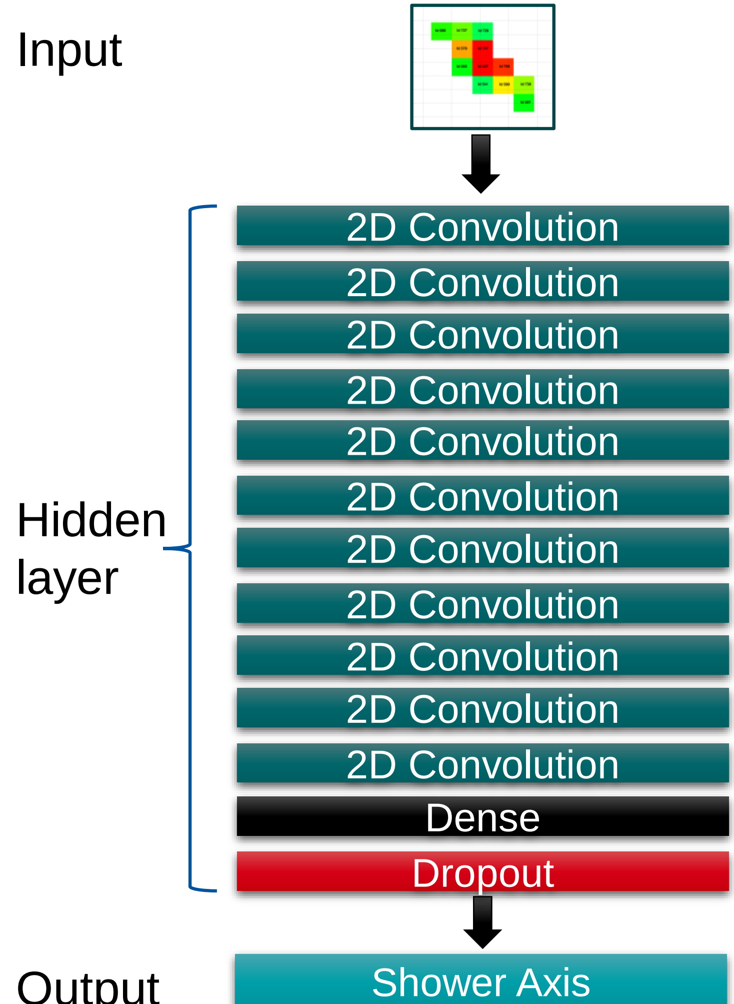
2D Convolutional Network



- 11x 2D Convolutional layers with
  – ReLu
  – Batch Normalization
- 1 Fully connected layer
- Dropout





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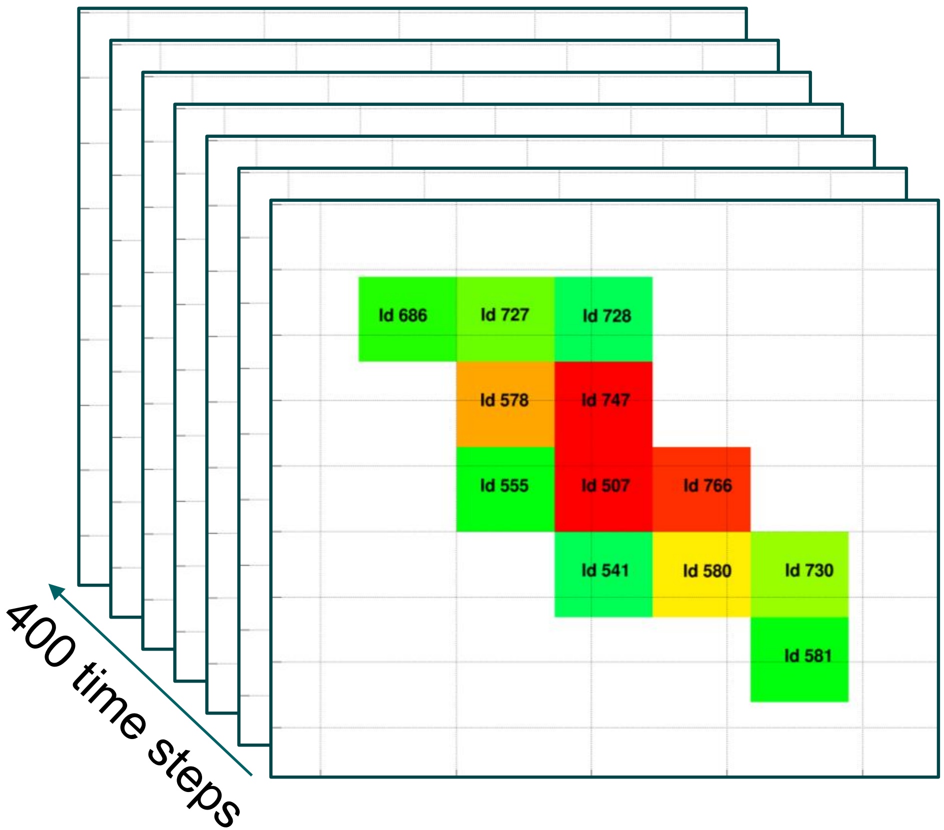
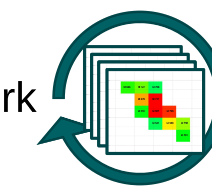
Spatiotemporal Input – Recurrent Networks

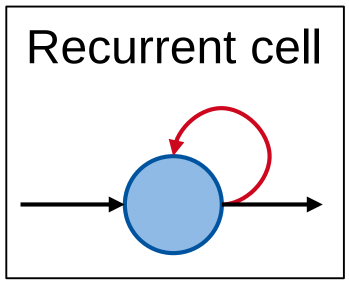


- Feed network a series of 2D images
- Per Event:
  - Stack of 400 shower maps

Architecture

- LSTM + Convolutional Network





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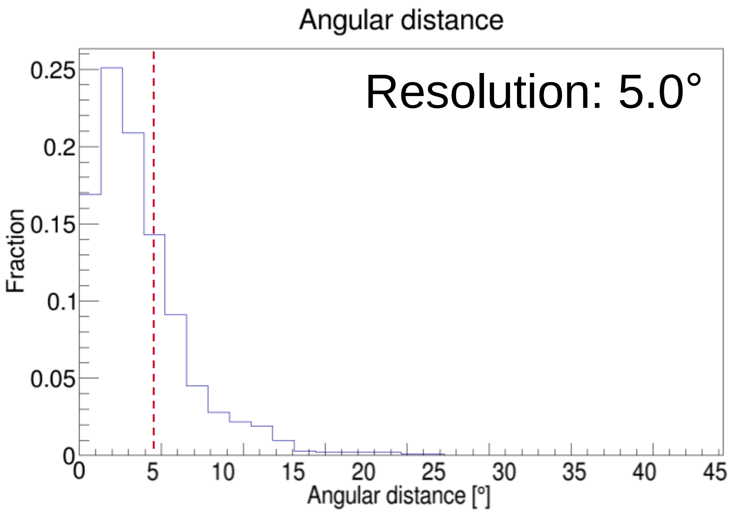
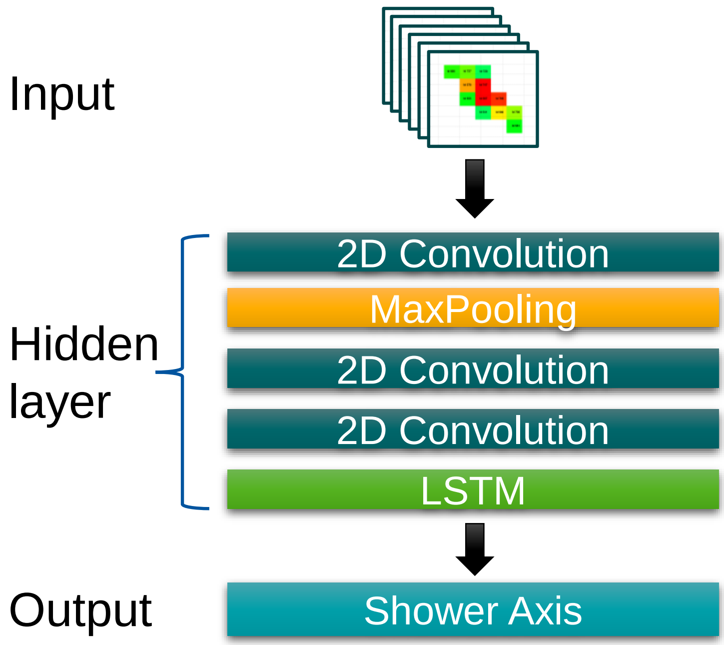
LSTM + Convolution

- 3 Convolutional layer
  - ReLu activation
- 1 Pooling layer
- Recurrent cell
  - Hard to train (long series)
- Only ~ 50,000 parameters





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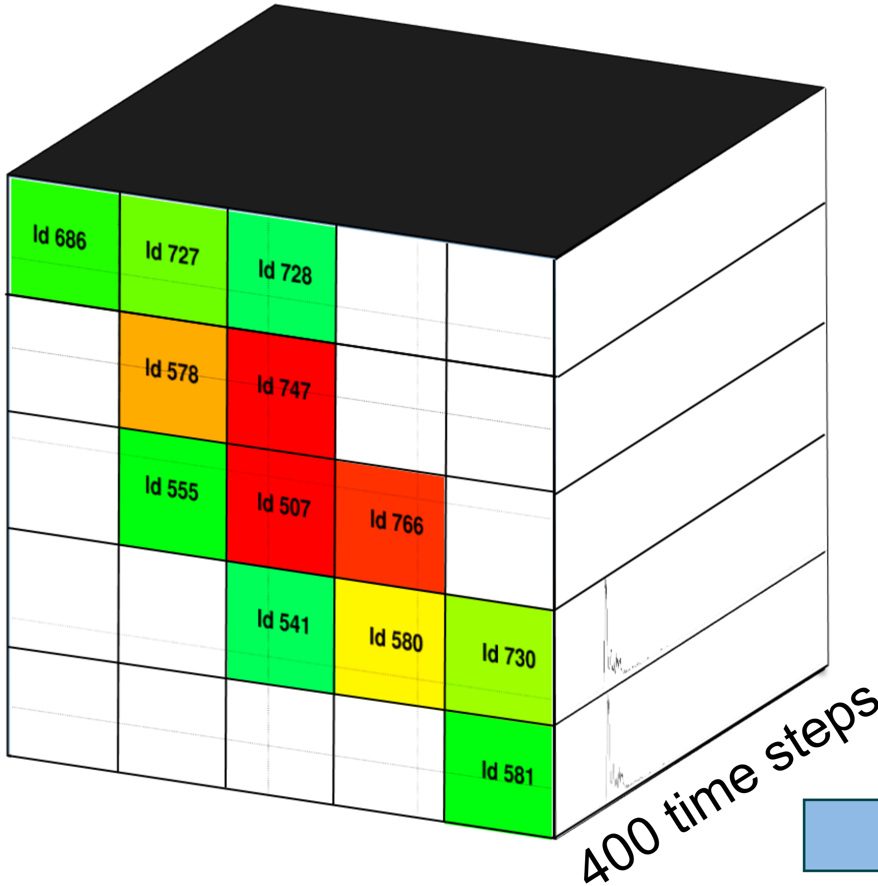
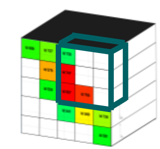
Spatiotemporal Input



Architectures

- 11 Layer 3D Convolutional Network



3D Footprint

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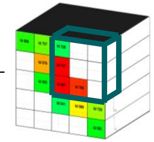
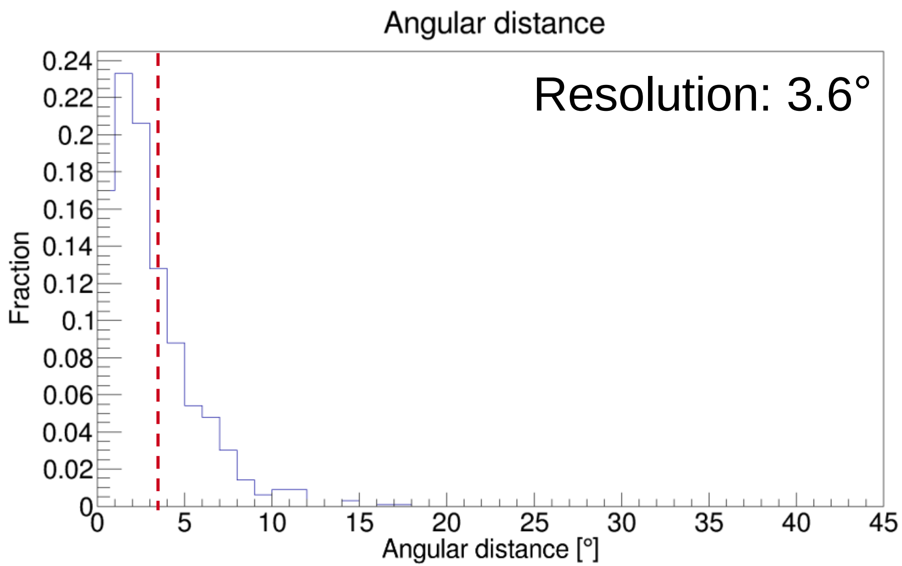
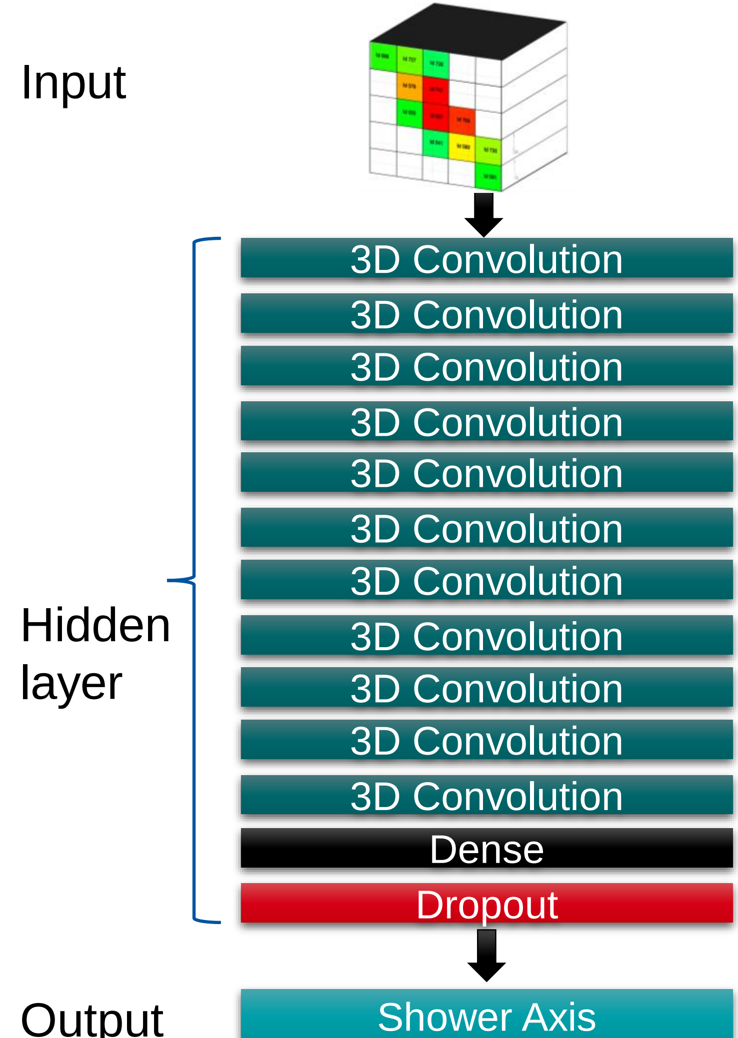
3D Convolutional Network

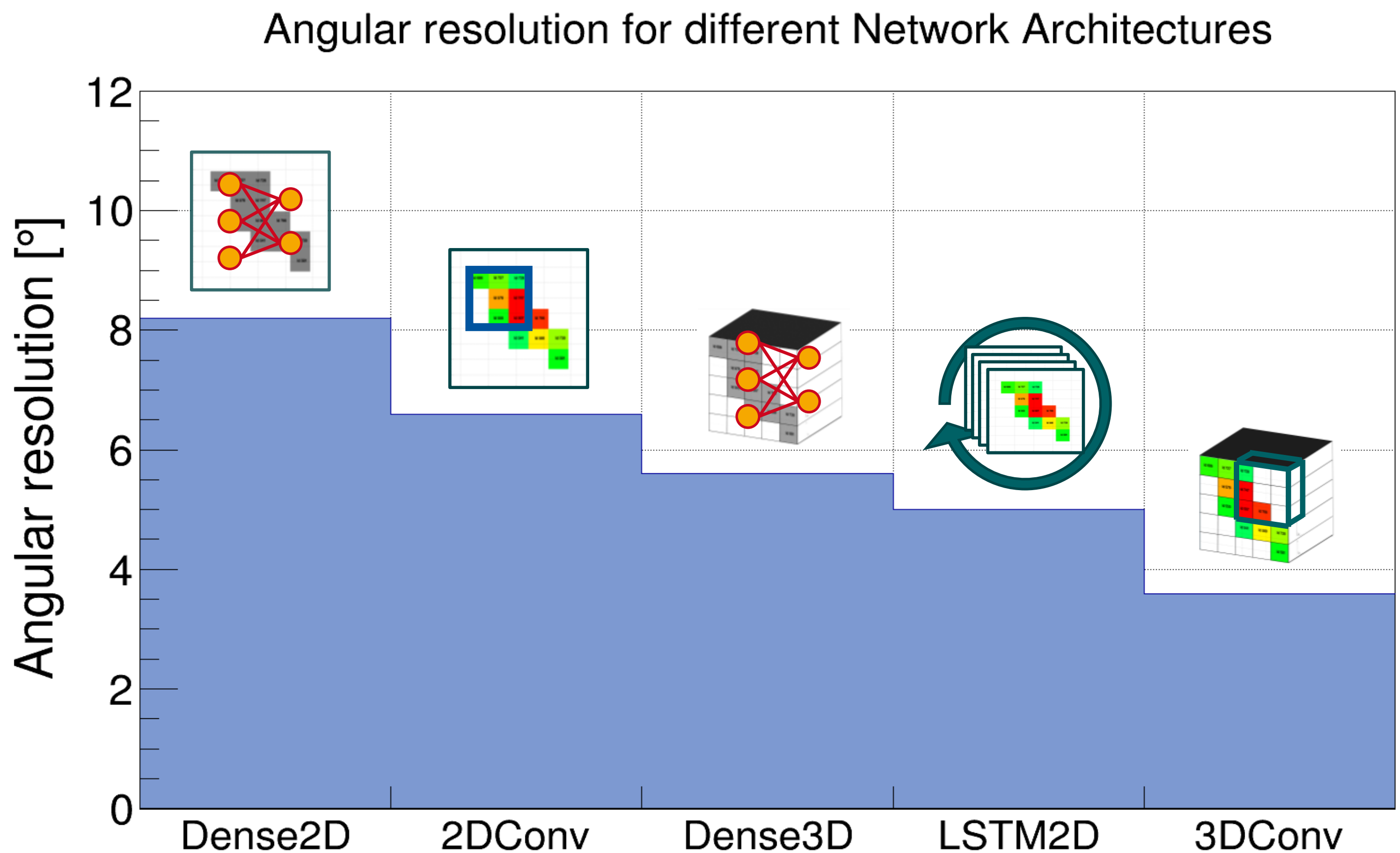


- Same structure as 2D architecture
  - 11 Convolution layers
    - ReLu, Batch Normalization
  - Fully connected dense layer
  - Dropout

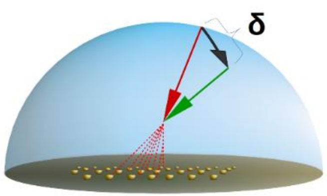




Different Network Architectures - Preprocessing



#Parameters ~ $1 \cdot 10^6$ $8 \cdot 10^5$ $4 \cdot 10^6$ $5 \cdot 10^4$ $3 \cdot 10^6$



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Summary

- Successfully trained deep networks with up to 12 hidden layers
  - Reached resolution of 3.6°
- Based on row data
  - Without applying physical knowledge

- More complicated architectures perform better on spatiotemporal data
  - 3D Convolutions
  - LSTM powerful
    - But hard to train

- Scaling the input data can be most important

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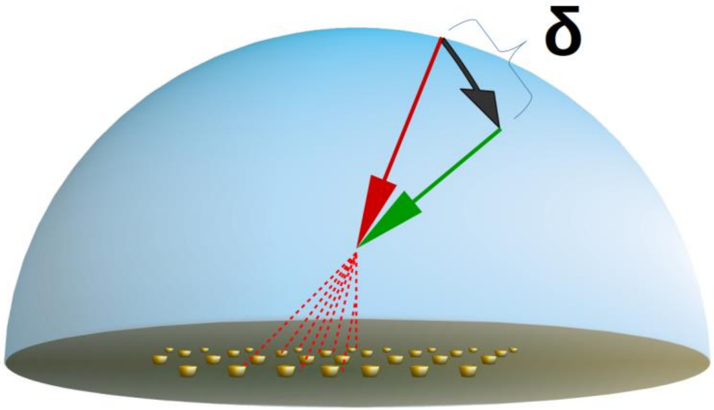

Backup

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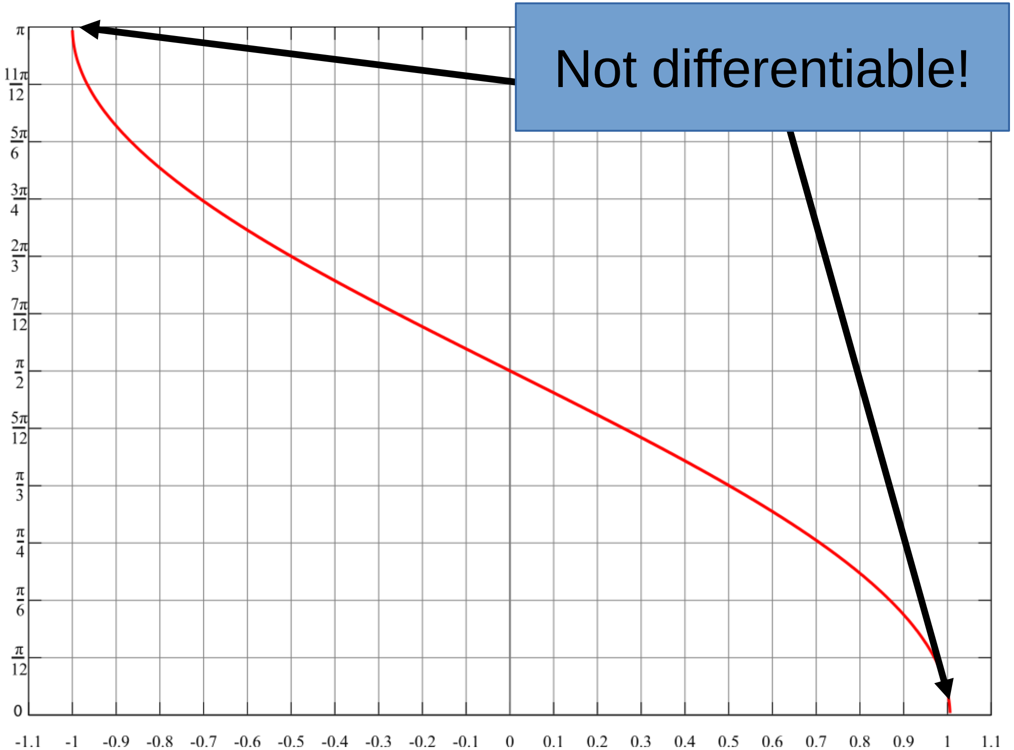
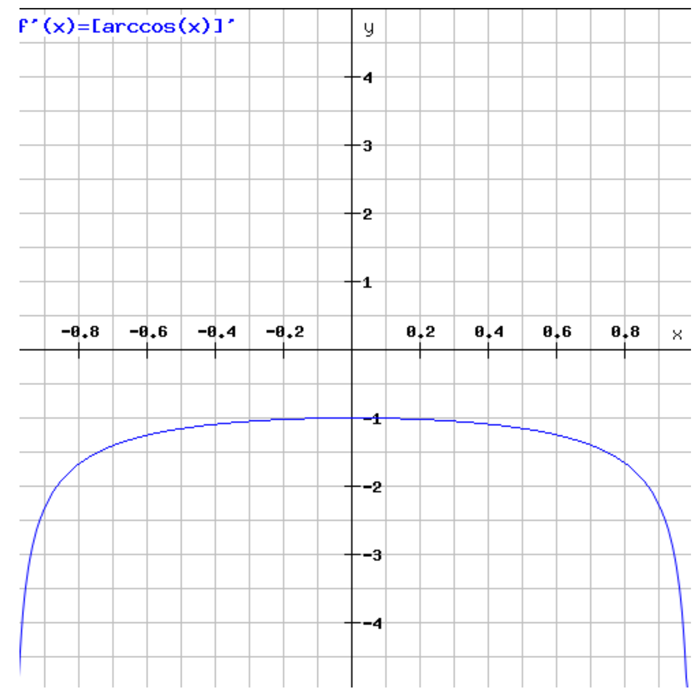
Network Performance – No Preprocessing

Use Angular Distance as Loss

- Reconstruct Θ, Φ
- Angular distance as Loss $L = \arccos(\vec{x} \cdot \vec{y})$, $\vec{x}$ *and* $\vec{y}$ in spherical coordinates





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Fully connected 3D