ACAT 2019

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Using Deep Learning in Ultra-High Energy Cosmic Ray Experiments

Cosmic rays

Different Physics in each energy range:

Solar modulation:

$$10^8 \mathrm{eV} \leq E \leq 10^{11} \mathrm{eV}$$

Galactic sources:

$$10^{11} \mathrm{eV} \leq E \leq 10^{18} \mathrm{eV}$$

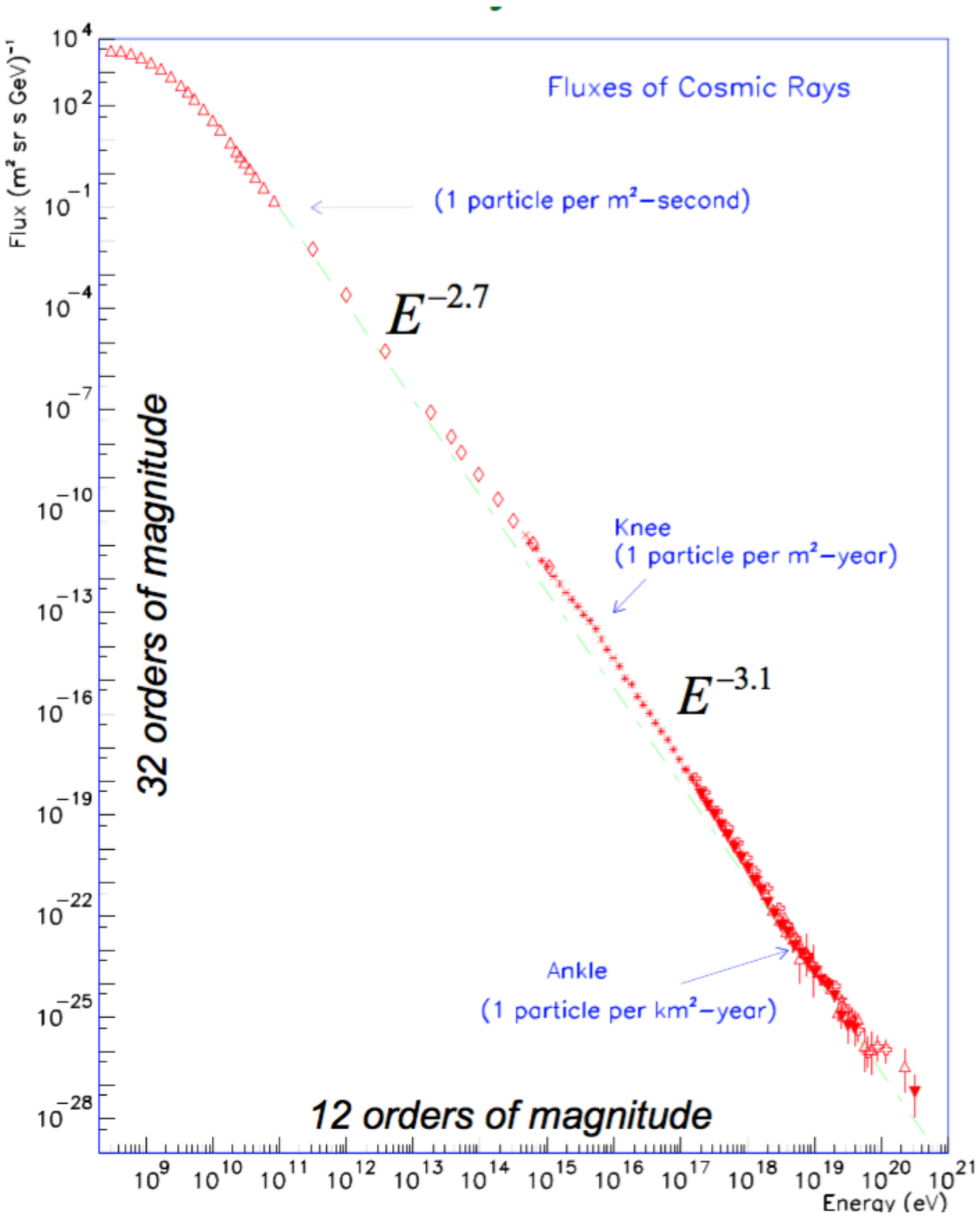
Extragalactic sources:

$$E > 10^{18} \mathrm{eV}$$

GZK cut-off $E \simeq 10^{20} eV$

Problem:

Extremely small flux, hard to observe directly



Questions

- Sources (extragalactic)

- Production mechanism

Observables (indirect)

- Energy spectrum

- Mass composition

- Arrival directions

Observables (direct)

- EAS properties observable from Earth (density profile on SD, fluorescence light on FD)

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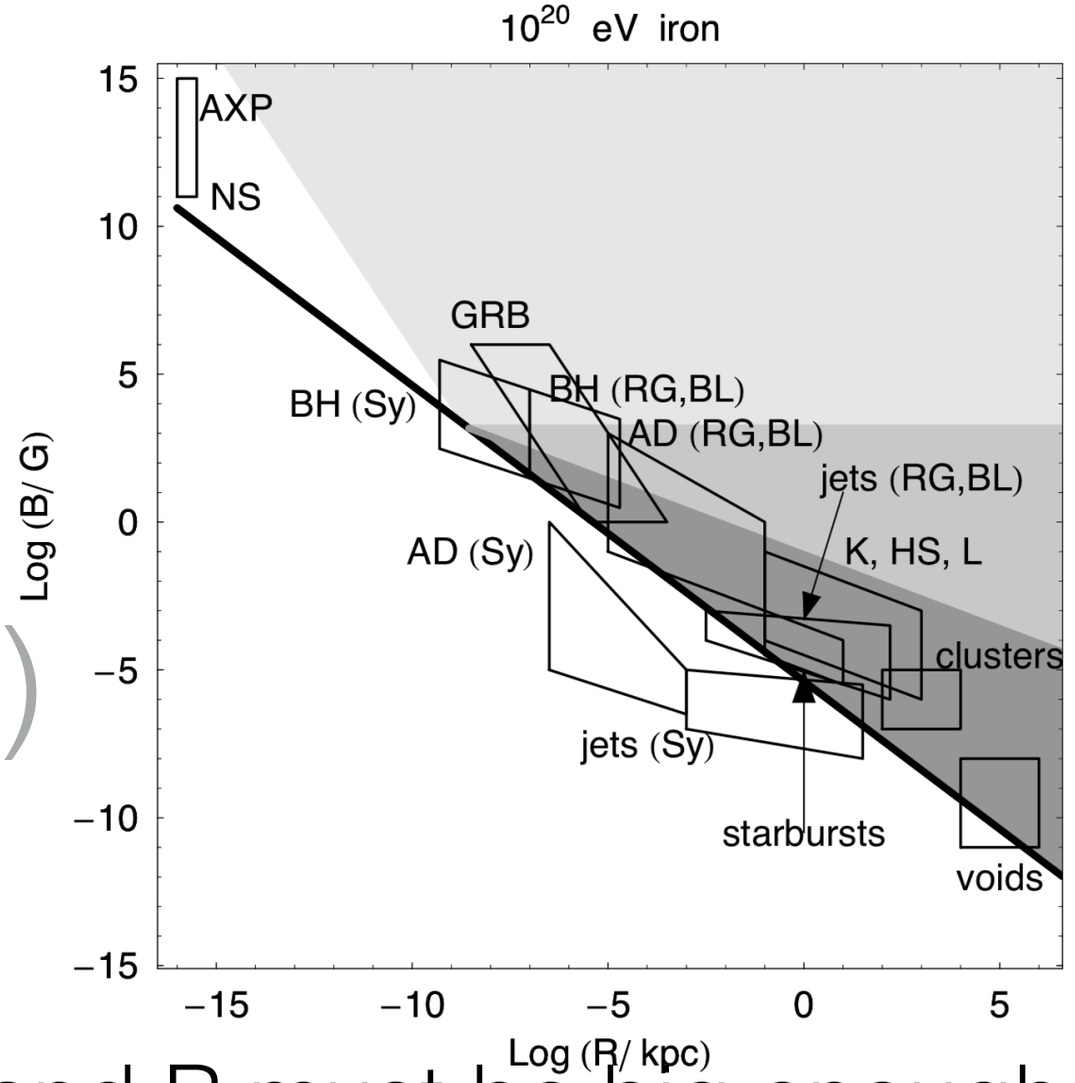

B and R must be big enough
to keep particles
inside in the acceleration
region
for enough time

Questions

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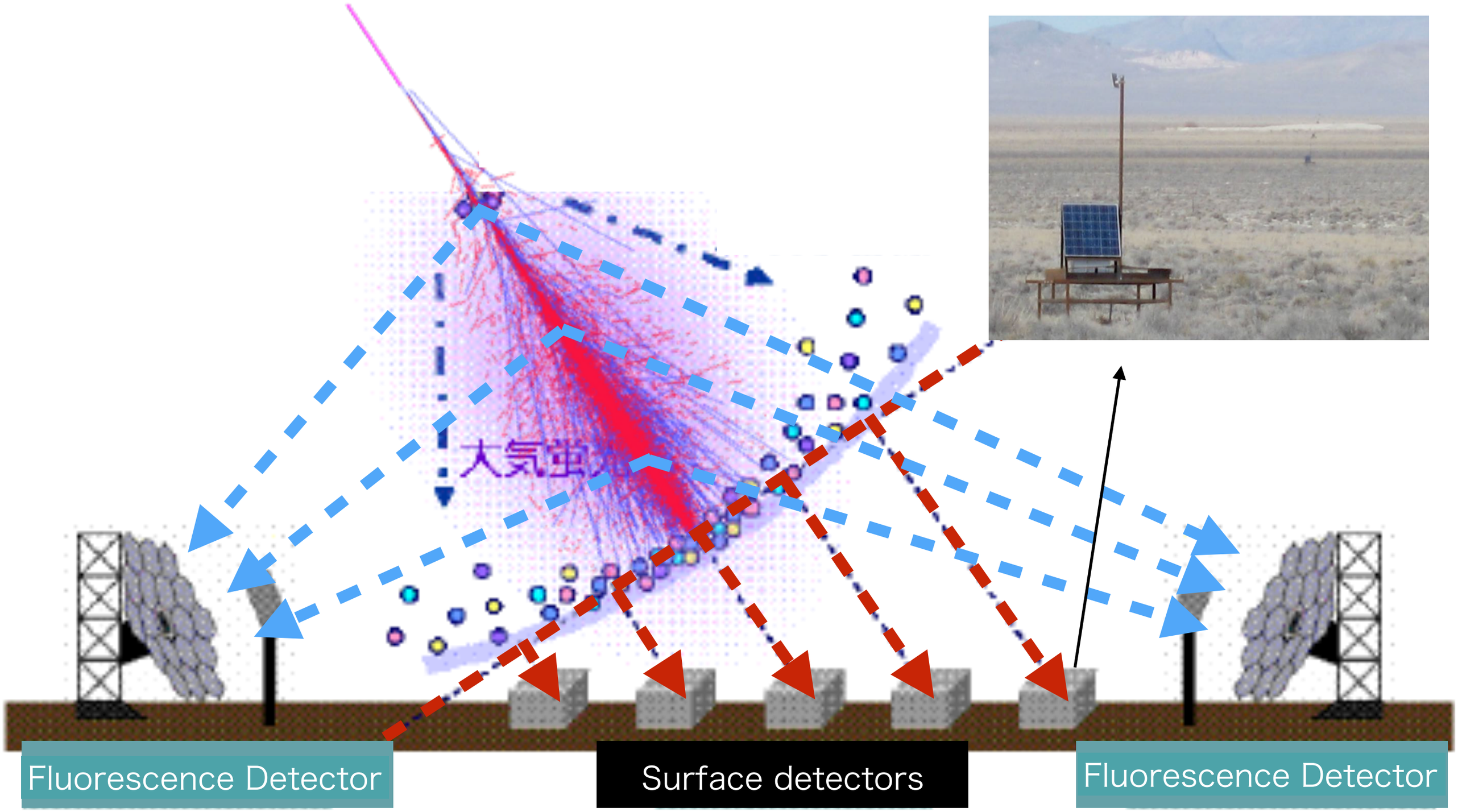
UHECR Detection Methods

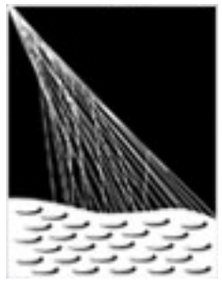


Flourescence detectors:
Duty cycle ~ *10%*

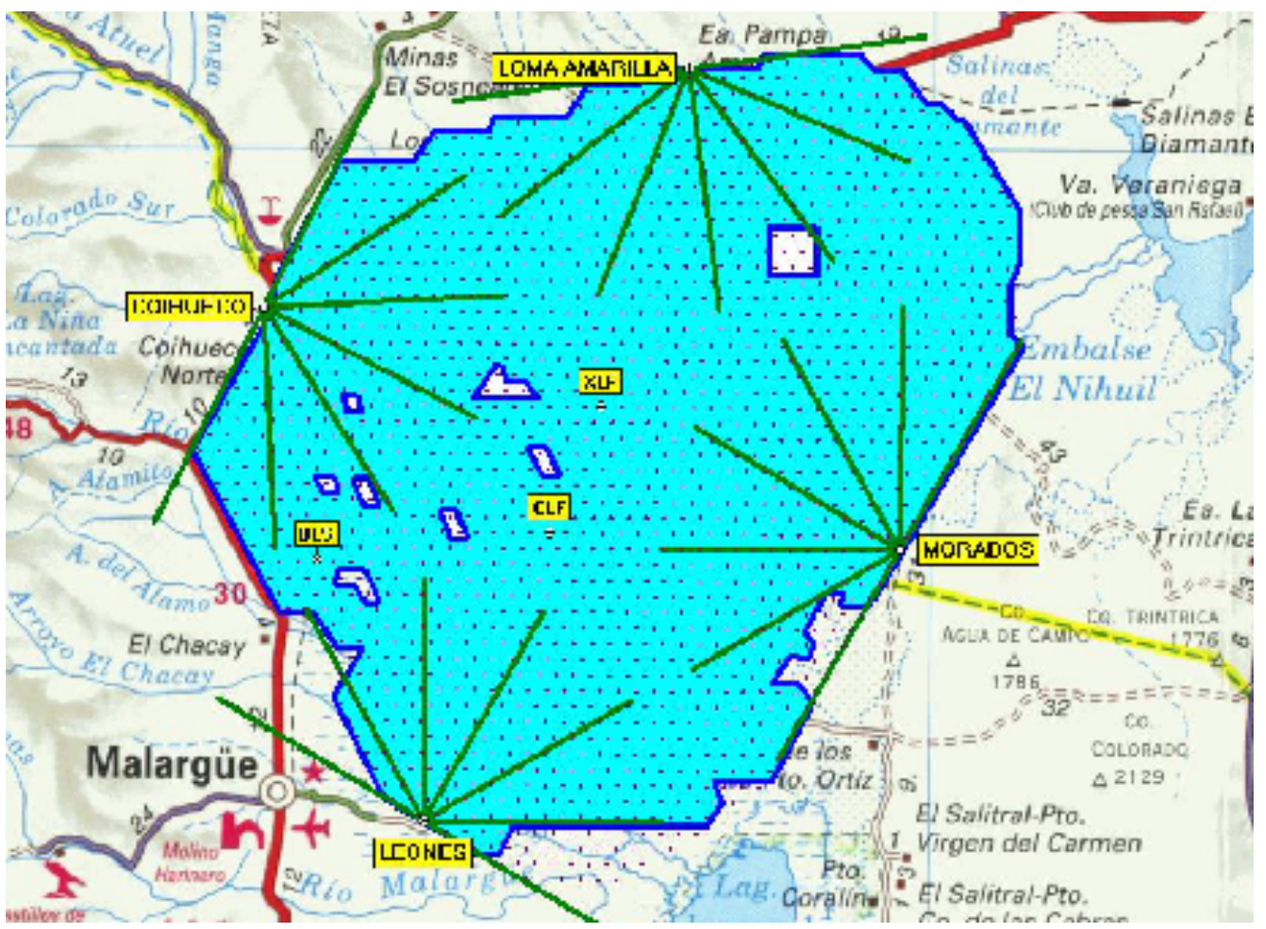
Surface detectors:
Duty cycle ~ *95%*

Modern UHECR experiments

- Southern hemisphere: Pierre Auger Observatory (Agrentina)



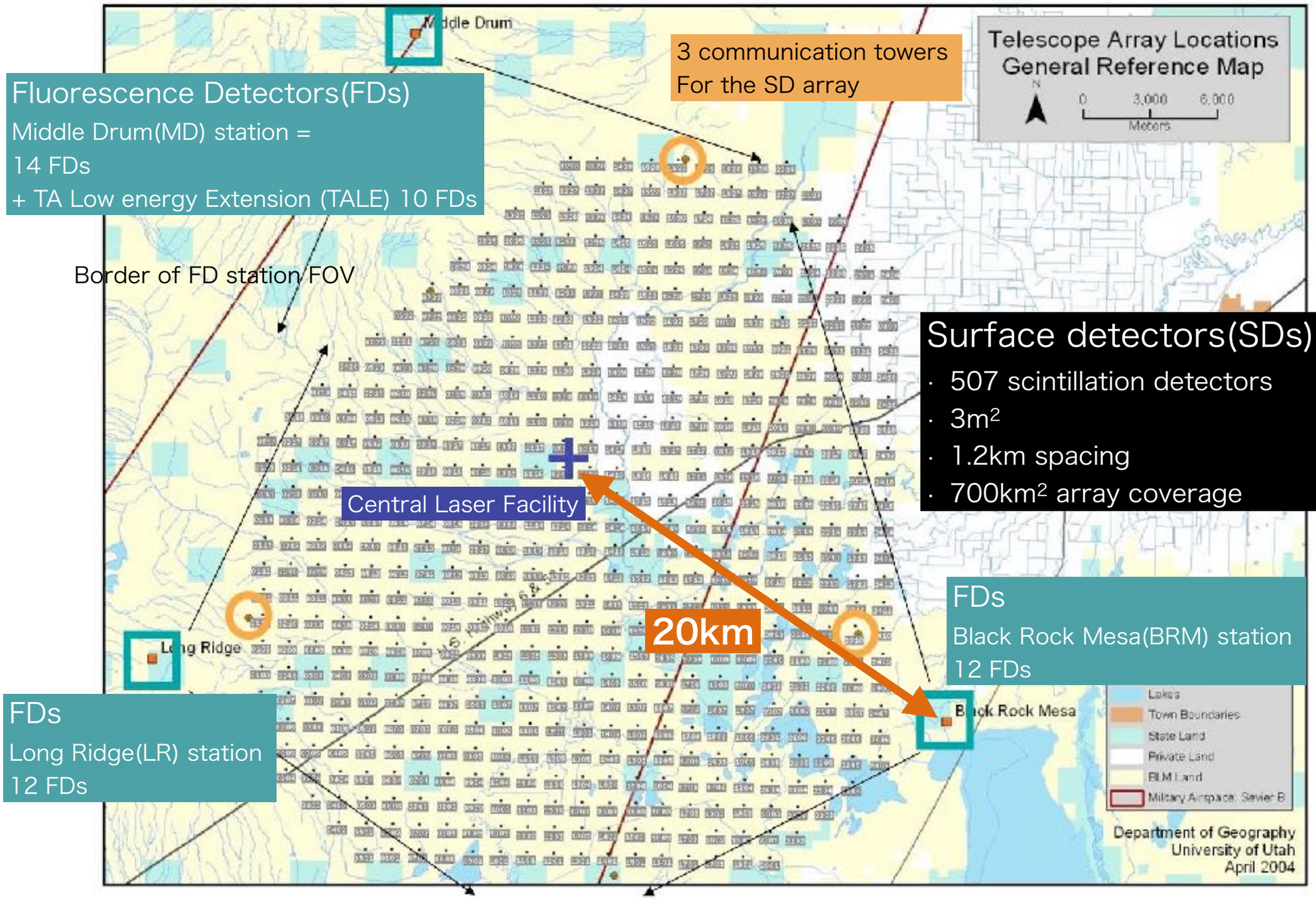
- 1660 Cherenkov detectors (water tanks), placed at distance 1.5 km from each other (hexagonal grid) covering the surface above 3000 km^2
- 4 flourescence telescope stations in the corners
- International collaboration (16 contries)



Modern UHECR experiments

- Northern hemisphere: Telescope Array (Utah, USA).

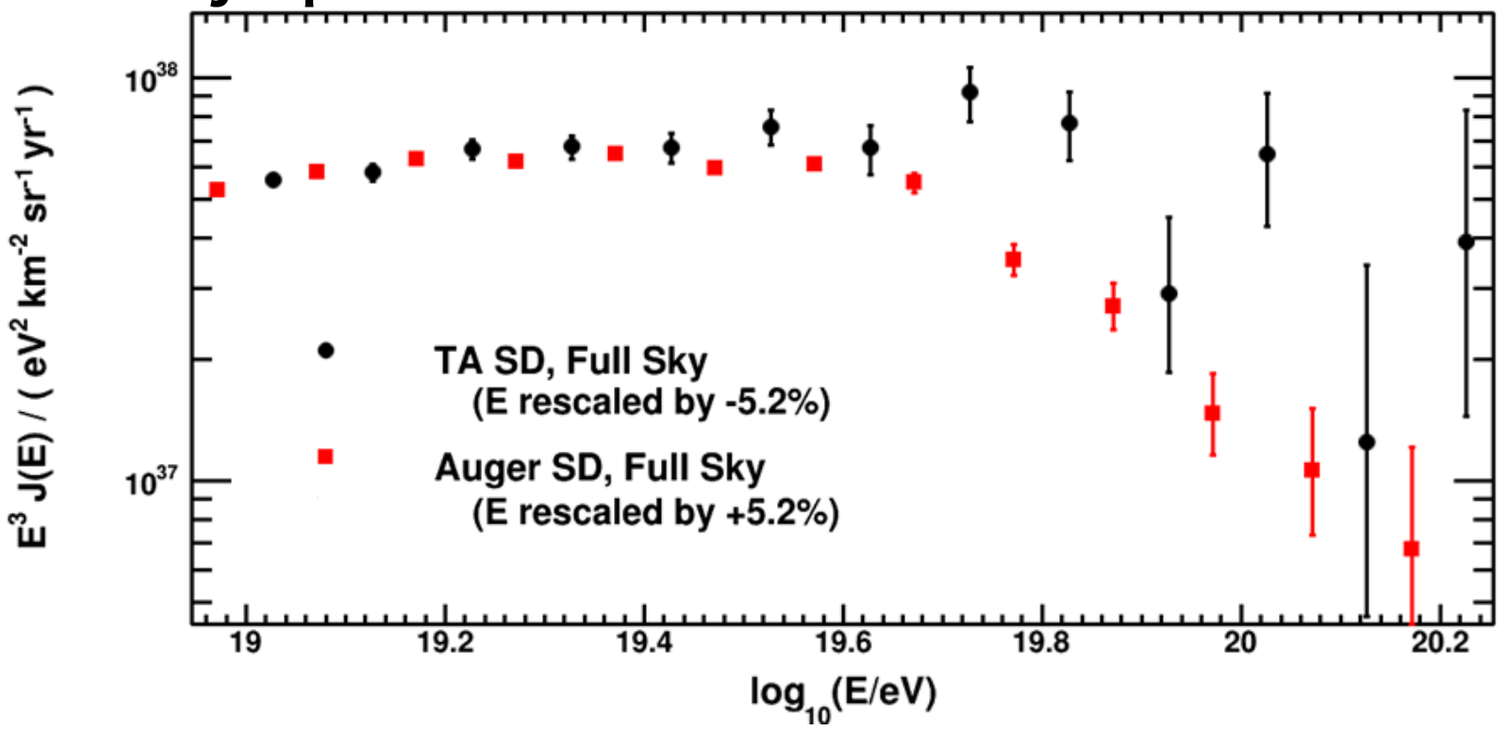
USA,
Russia,
Japan,
Korea,
Belgium



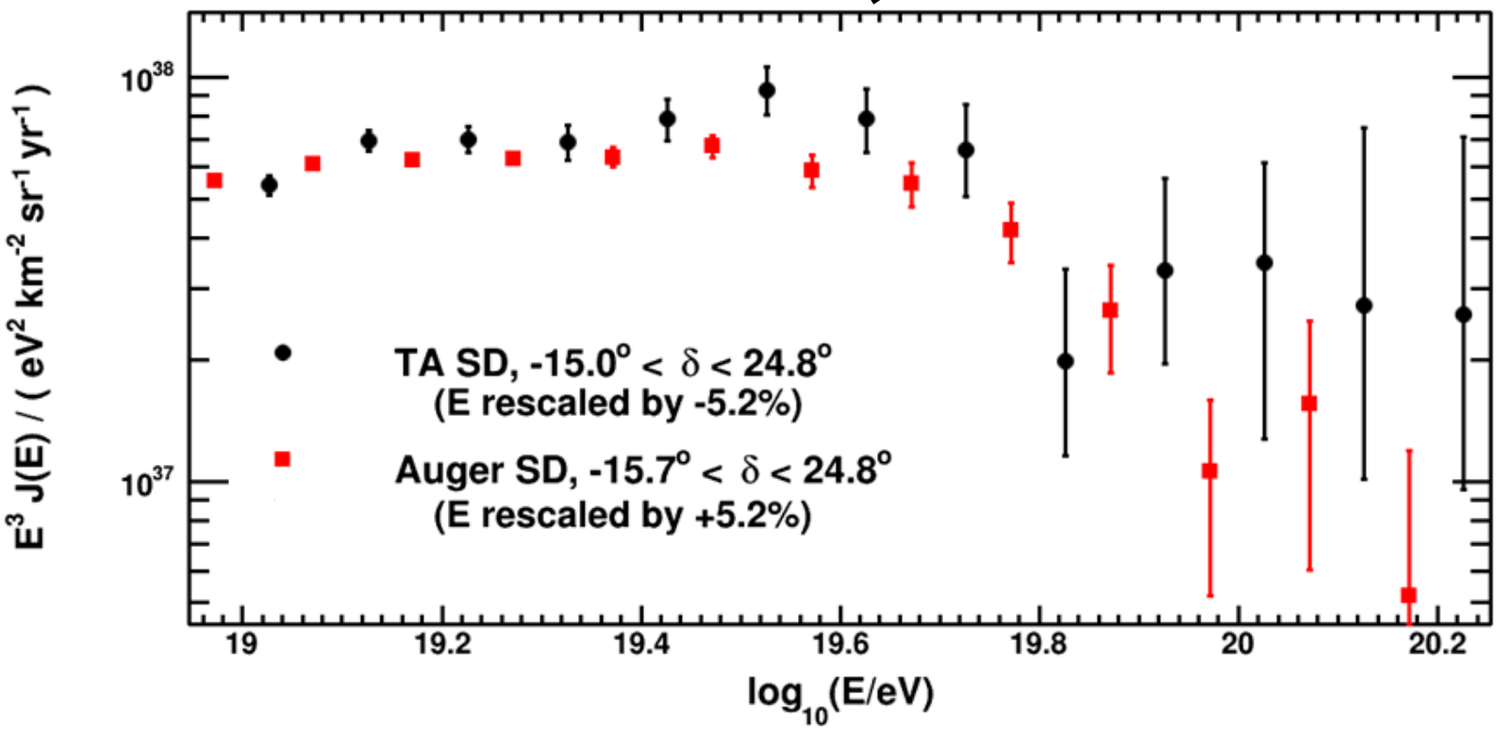
Auger and TA spectra

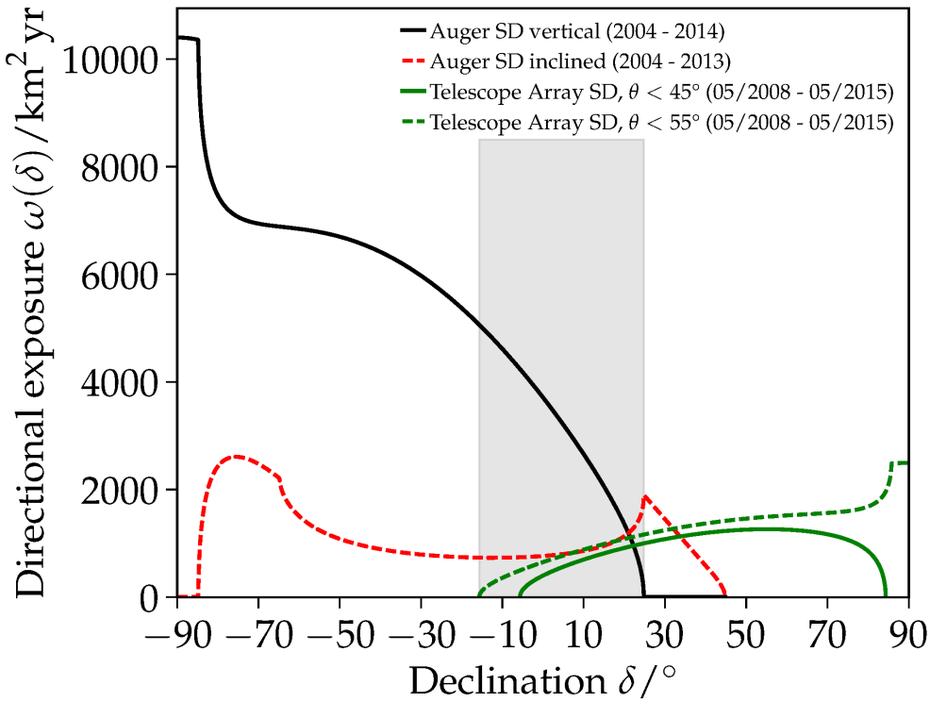
Ivanov ICRC2017, CRI231
(Auger/TA spectrum WG)

Full Sky spectra



Common declination band (-15.9° < δ < 24.8°)



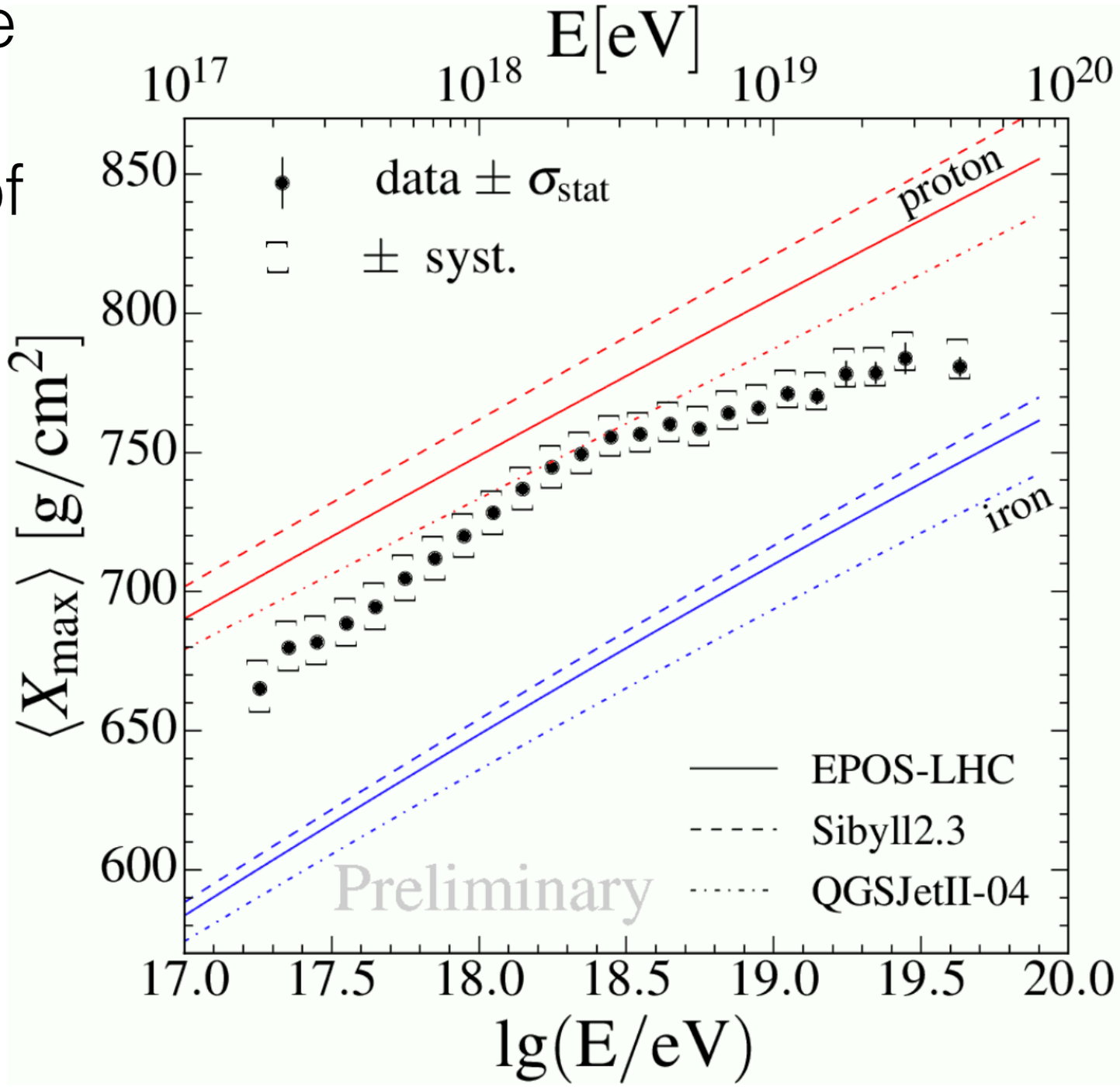


Better agreement between Auger and TA
In the common declination band

Declination dependence?

Composition of UHECR

EAS produced by different mass nuclei are very similar - hard to distinguish at the level of individual events



- E=1-few EeV:light nuclei
- Heavier composition at larger energies

Deflection angles in Milky Way > 20 deg.

Cosmic rays may not point to the source

Auger 2017

Arrival directions and their interpretation

- Accuracy for nuclei primaries: 1.5 deg, gamma primaries: 2-3 deg

- Interpretation for nuclei depends on the assumption on the composition. Extra information needed.

- Multimessenger approach (study secondary signals from CR interactions)

  - GZK photons and neutrinos may point back to source (expected energies E~EeV) Not observed yet. **Sensitivity to diffuse and directional flux should be enhanced.**

Ways to improve gamma sensitivity.

- For diffuse flux: Improve discrimination of gamma and nuclei induced showers

- For directional flux search: enhance angular resolution for both nuclei and gamma to reduce the background

Ways to improve gamma sensitivity.

- For diffuse flux: Improve discrimination of gamma and nuclei induced showers

  Construct the function of observables most sensitive to composition using NN *in progress*

- For directional flux search: enhance angular resolution for both nuclei and gamma to reduce the background

  this talk

Sample event

upper layer

lower layer

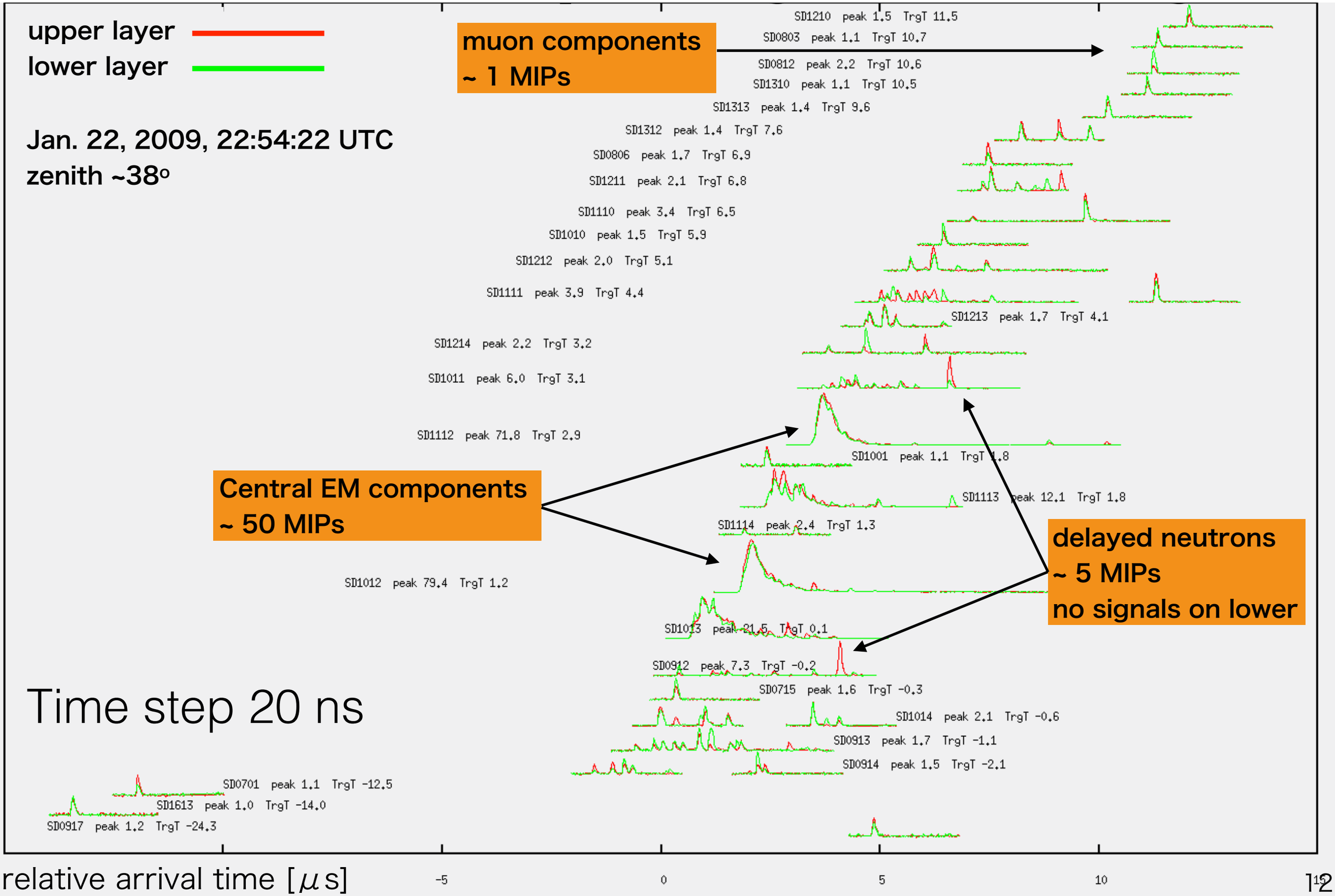
Jan. 22, 2009, 22:54:22 UTC

zenith ~38°

muon components
~ 1 MIPs

Central EM components
~ 50 MIPs

delayed neutrons
~ 5 MIPs
no signals on lower



Time step 20 ns

relative arrival time [μs]

Event reconstruction

standard parametric approach

- LDF

$$f(r) = \left(\frac{r}{R_m}\right)^{-1.2} \left(1 + \frac{r}{R_m}\right)^{-(\eta - 1.2)} \left(1 + \frac{r^2}{R_1^2}\right)^{-0.6}$$

$$R_m = 90.0 \text{ m},\ R_1 = 1000 \text{ m},\ R_L = 30 \text{ m}, \quad \eta = 3.97 - 1.79\left(\sec(\theta) - 1\right),$$

$$r = \sqrt{(x_{\text{core}} - x)^2 + (y_{\text{core}} - y)^2},$$

- Timing

$$t_r = t_o + t_{plane} + a \times (1 + r/R_L)^{1.5}\, LDF(r)^{-0.5}$$

$$LDF(r) = f(r)/f(800 \text{ m}) \qquad S(r) = S_{800} \times LDF(r)$$

Free parameters:

x_{core}, y_{core}, θ, ϕ, S_{800}, t_0, a

Observables:

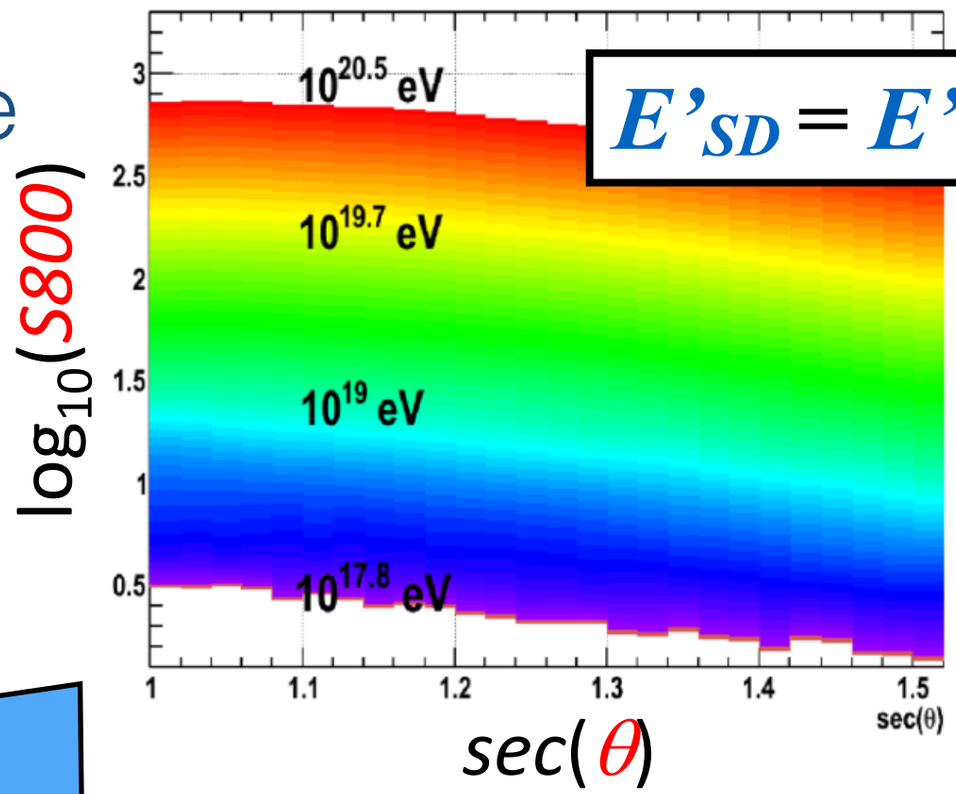
t_r - detector time

S_r - detector integral signal

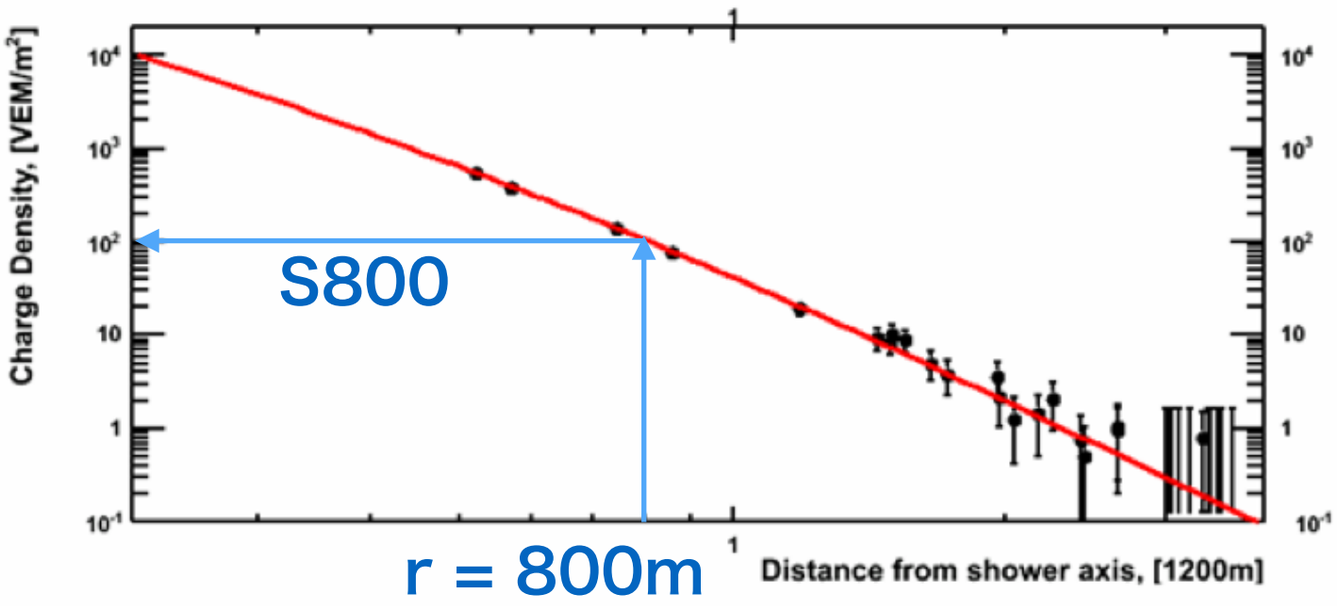
Event reconstruction

standard parametric approach

Energy estimate



- table function



Event reconstruction

Machine learning approach

Purpose (ideally): recover primary particle properties (arrival direction, energy, mass, …) as function of observables.

Direct observables in SD:

- Time series of the SD signals

Instruments:

- SD Monte-Carlo (EAS development and detector response)
- Artificial neural network (NN)
  - Can describe any continuous function of input data
  - Can be tuned using examples generated using Monte-Carlo

Event reconstruction

Machine learning approach

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In real life:

- observables depend on unknown/random factors
- NN function defines optimal test statistic
- obtain corrections to parametric reconstruction

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Method in nutshell

- Extract useful detector features using 1-D convolutions
- Treat detector network as a multichannel image using 2D convolution layers

First proposed:

M. Erdmann, *J. Glombitza*, D. Walz Astropart.Phys. 97 (2018)
Applied to Pierre Auger geometry with toy Monte Carlo

Track 2 talk

SD reconstruction NN architecture

event data

Dimensions:

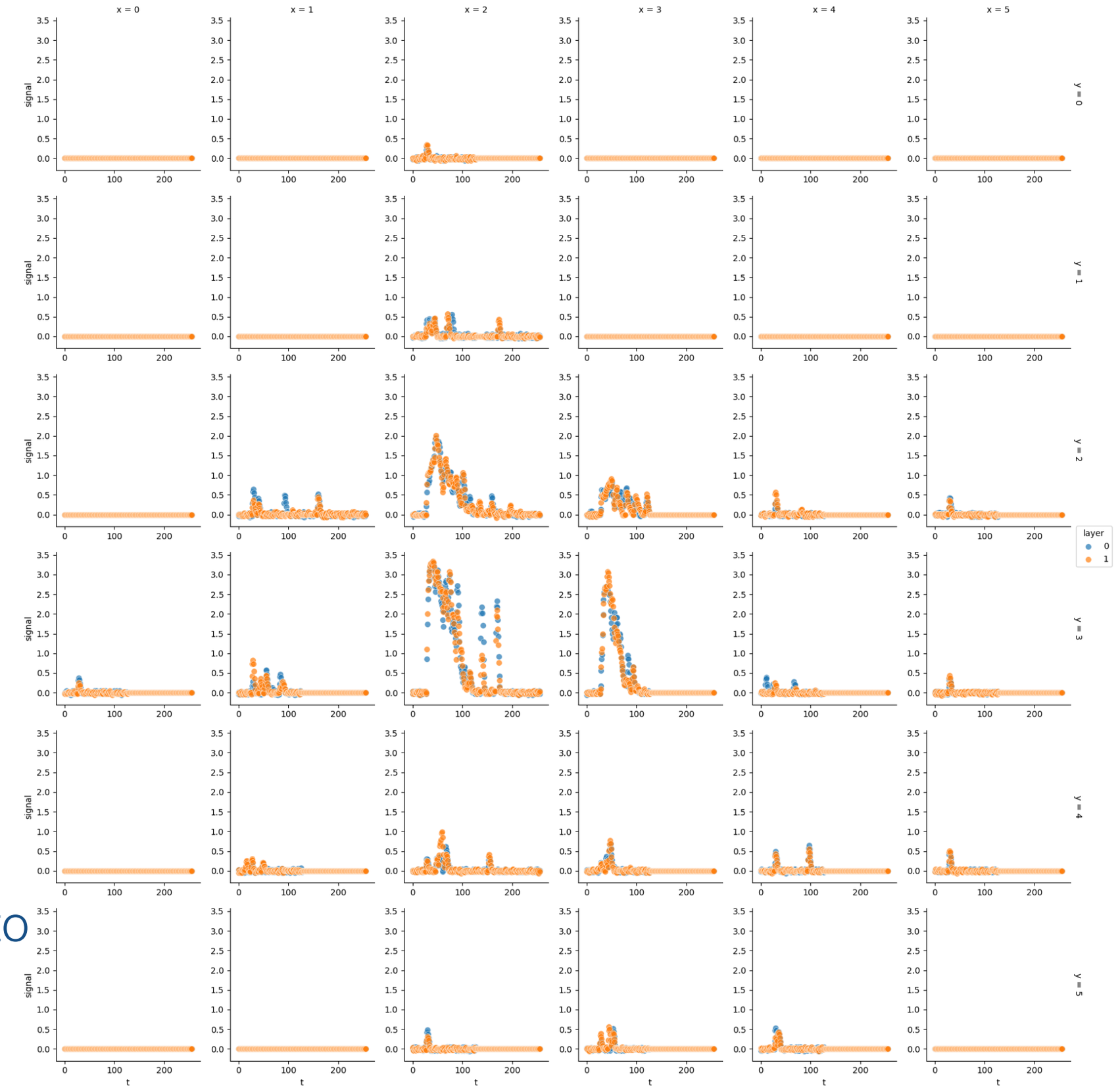
(N,N,T,2)

Waveform

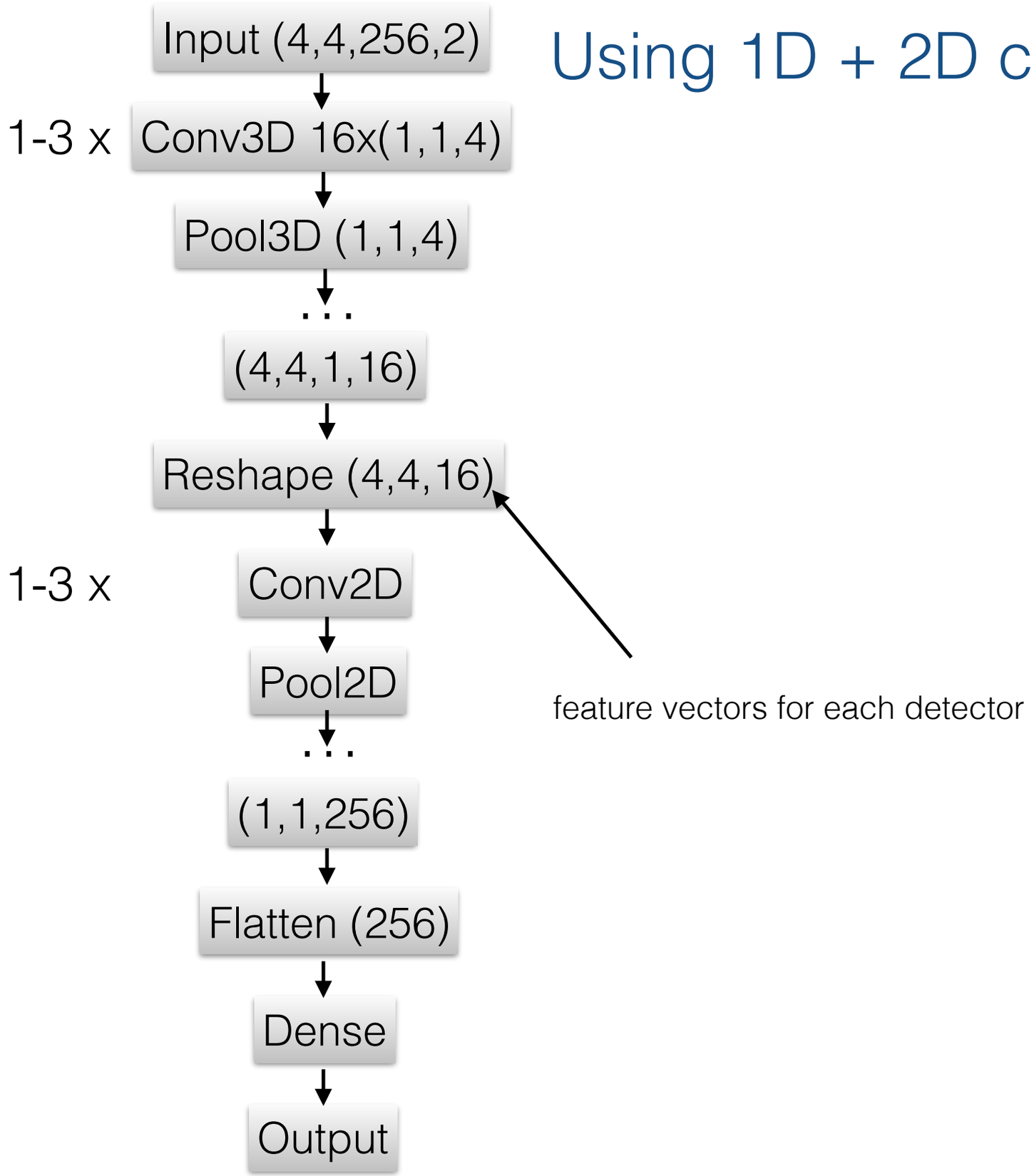
detector layers

N=4-8, T=128-256

Standard SD reconstruction is used to center image around shower core



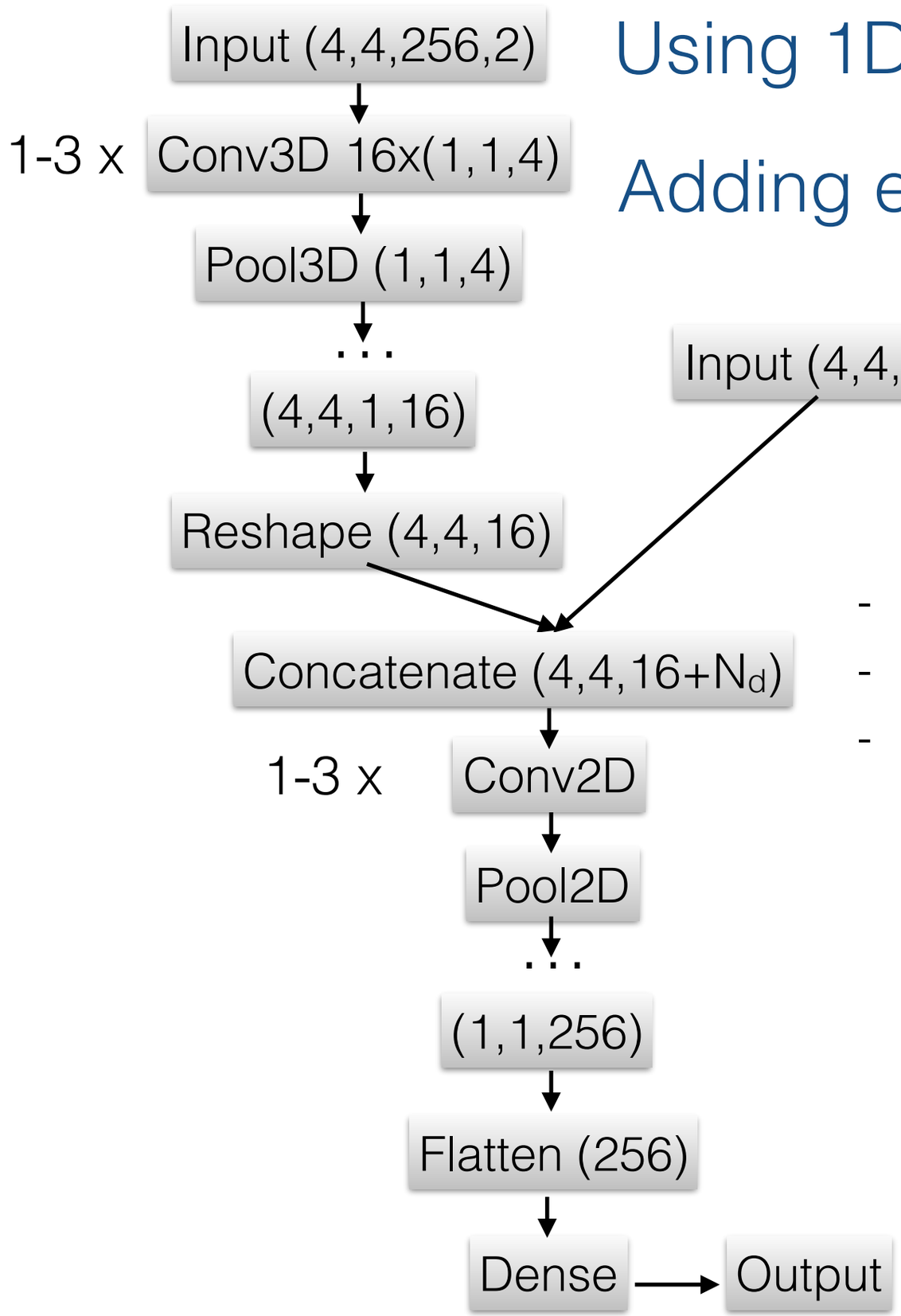
SD reconstruction NN architecture



Using 1D + 2D convolutions

feature vectors for each detector

SD reconstruction NN architecture

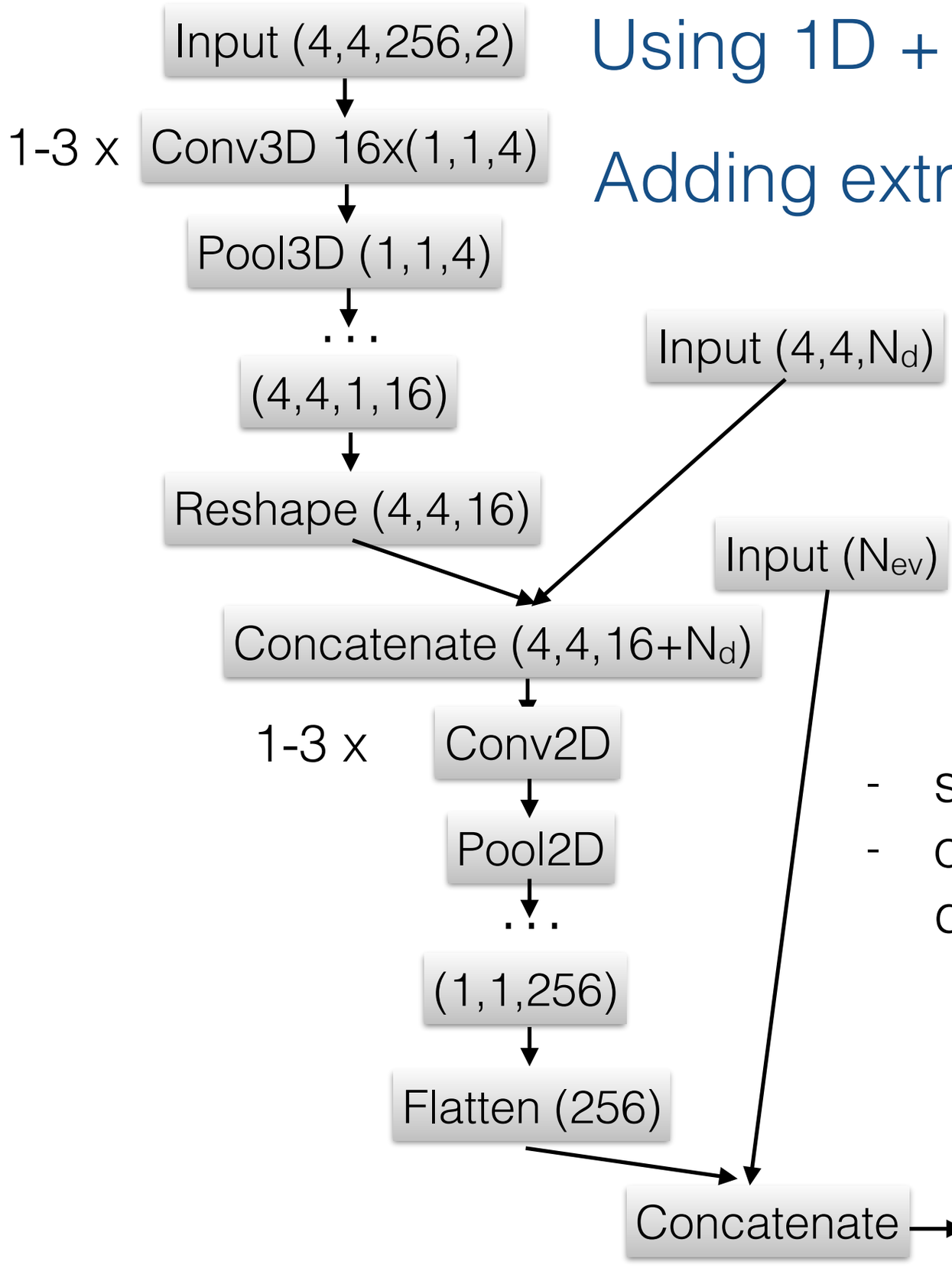


Using 1D + 2D convolutions

Adding extra detector features:

- Exact detector position
- Detector state (on/off/saturated)
- Standard reconstruction parameters (integral signal, timing relative to plane front)

SD reconstruction NN architecture

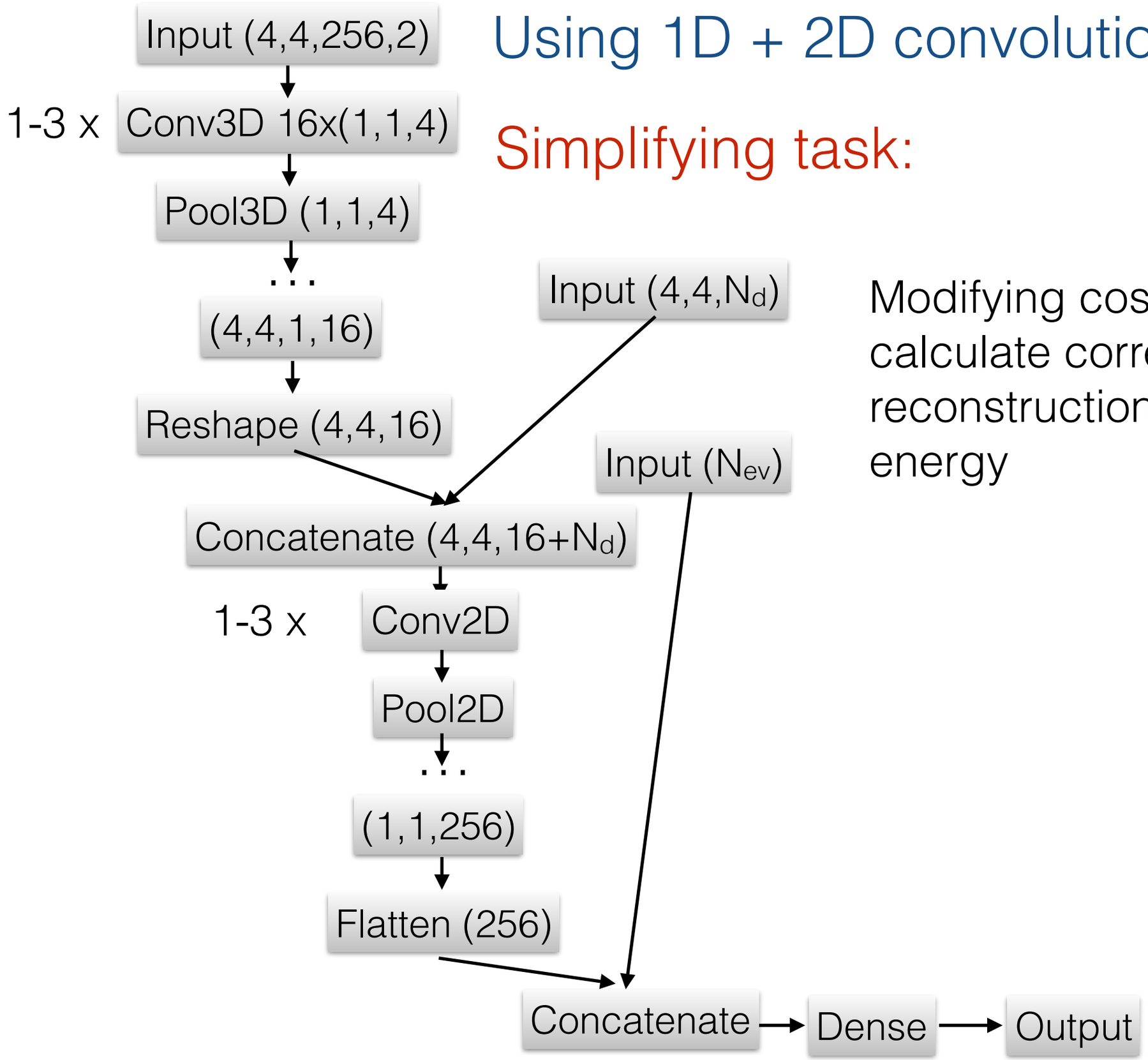


Using 1D + 2D convolutions

Adding extra event features:

- season and time
- optionally standard reconstruction data (e.g. S_{800})

SD reconstruction NN architecture

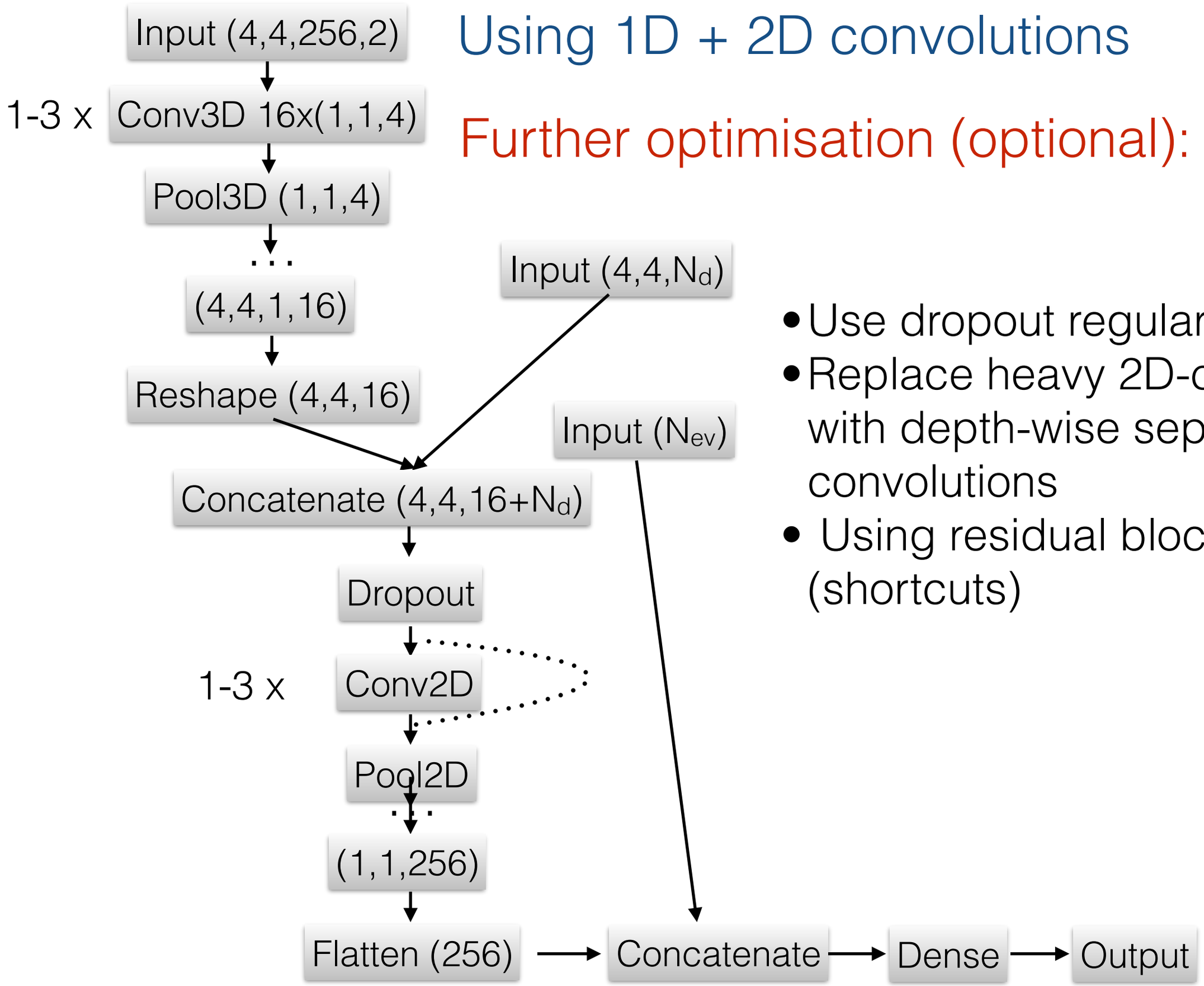


Using 1D + 2D convolutions

Simplifying task:

Modifying cost function - we calculate correction to standard reconstruction for angles and energy

SD reconstruction NN architecture



Using 1D + 2D convolutions

Further optimisation (optional):

- Use dropout regularization
- Replace heavy 2D-convolutions with depth-wise separable convolutions
- Using residual blocks (shortcuts)

Training the model

- Minimizing mean square error
- Adaptive learning rate (adadelta optimizer arxiv 1212.5701)
- Number of training samples ~ 10^6 (100 GB data) - do not fit into RAM). hdf container is used и generator API in keras
- Number of weights to learn 10^5 - 10^6
- Regularization to avoid overfitting:
  - L2
  - dropout
  - noise layers
- Optimizing network architecture hyper-parameters (hyperopt package)
- Hardware: NVIDIA GTX-1080-Ti GPU
- Instruments: python, numpy, tensorflow, keras, h5py

EAS modelling

- MC: CORSIKA
- HE hadronic interactions: QGSJETII-03 (QGSJETII-04 in preparation)
- LE hadronic interactions: FLUKA
- EM processes: EGS4
- Detector response: GEANT4
- Event sampling:
  - Energy sampling E^{-1}
  - Mass composition: H, He, N, Fe (1:1:1:1)
  - Isotropic primary flux with zenith angles < 45 degrees
  - Standard energy spectrum reconstruction cuts applied

How to see that model does job

in presence of unavoidable uncertainty

Explained variance score

$$EV(y, \hat{y}) = 1 - \frac{Var(y - \hat{y})}{Var(y)}$$

y - true value of quantity being predicted (in our case, error of parametric reconstruction)

$\hat{y}$ - model estimate of y

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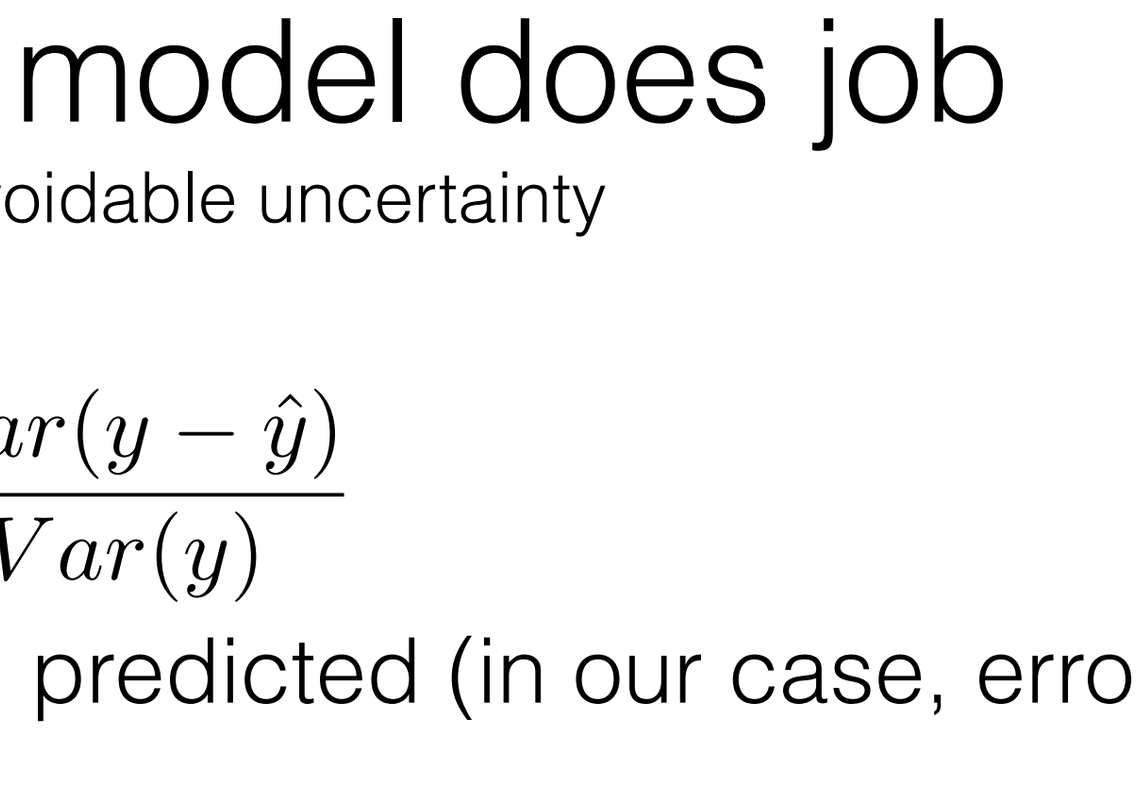
More visually:

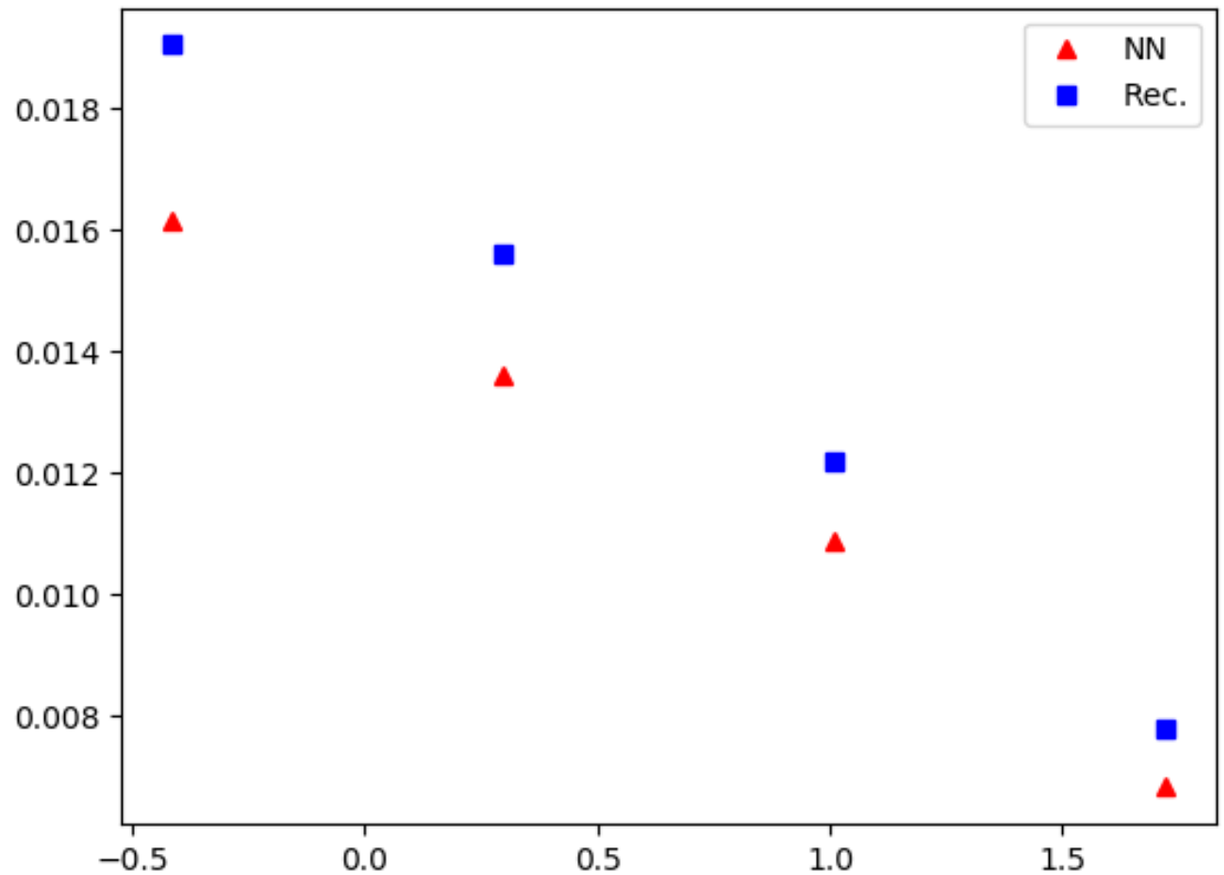
Compare error distribution in two approximations



Preliminary results

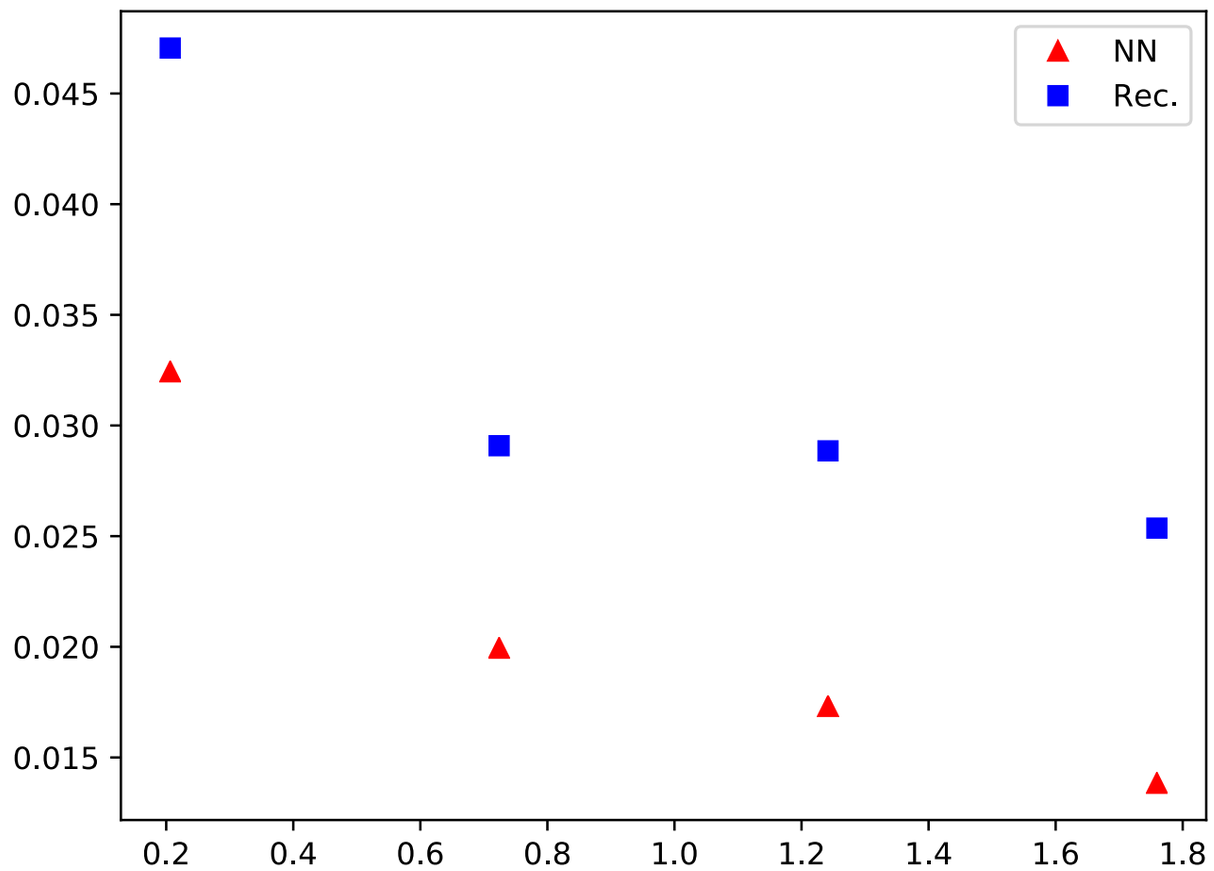
Zenith angle reconstruction errors

$\Delta cos(\theta)$ nuclei



$log(E/EeV)$

$\Delta cos(\theta)$ photons

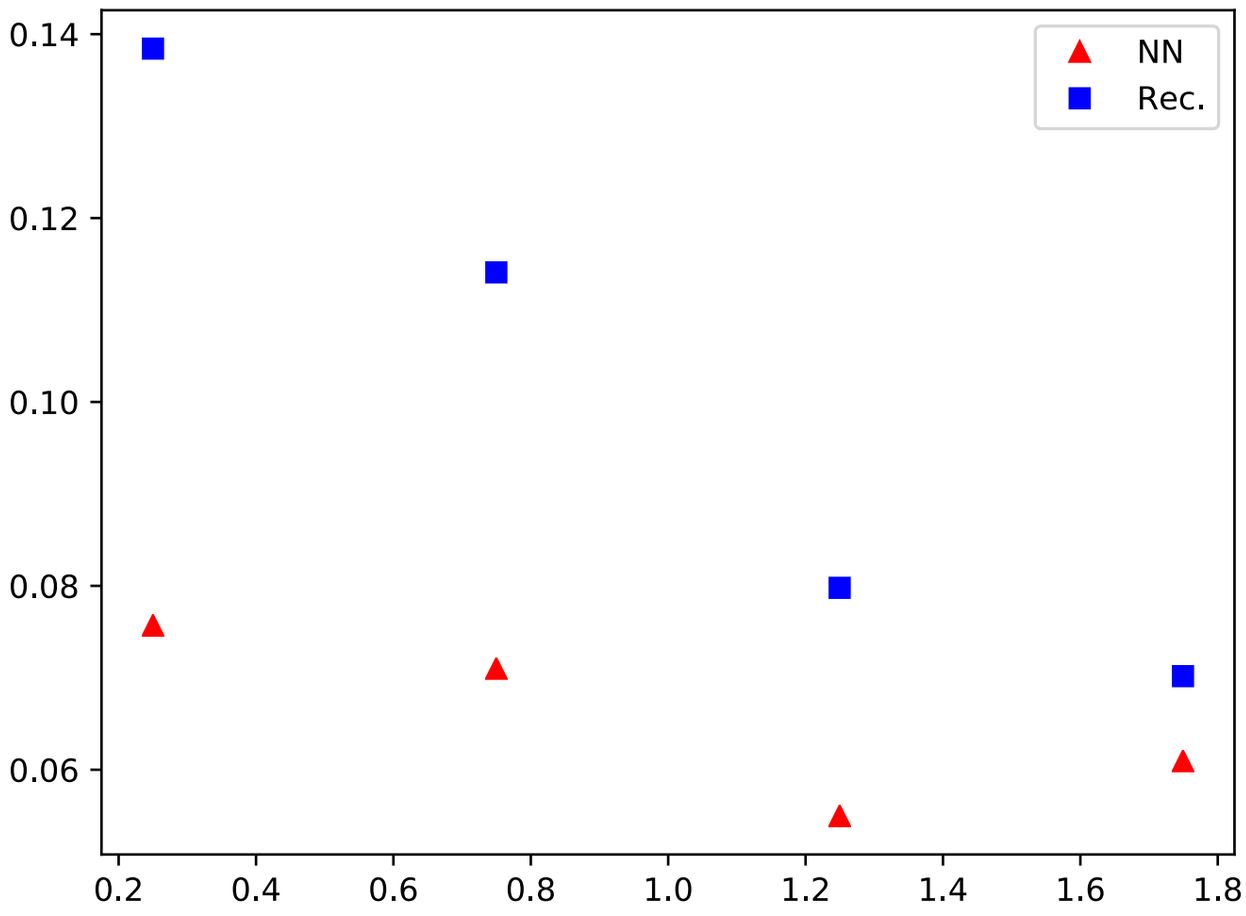


$log(E/EeV)$

Preliminary results

Energy reconstruction errors (nuclei primaries)

$\Delta E/E$



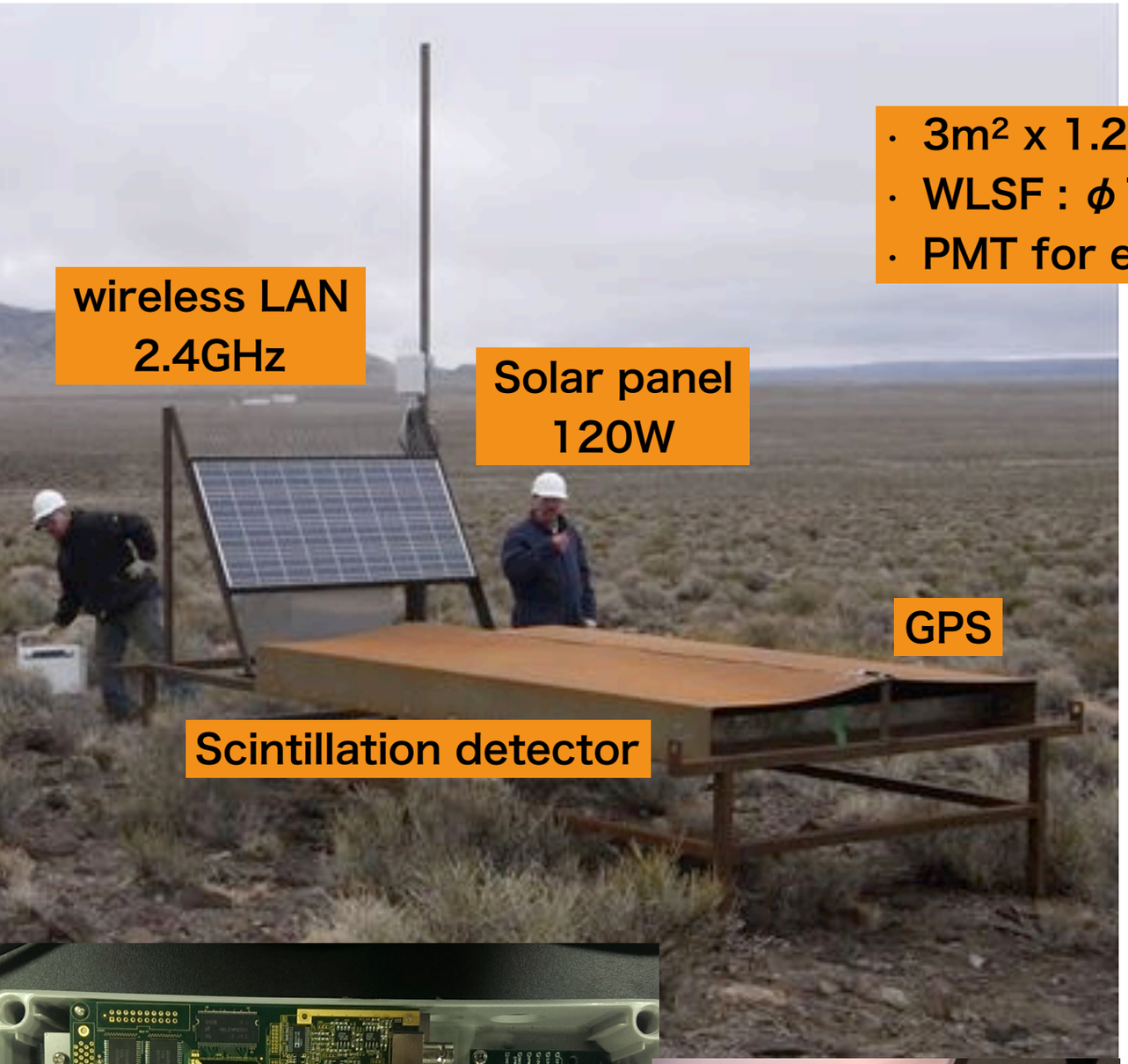
$log(E/EeV)$

Conclusion

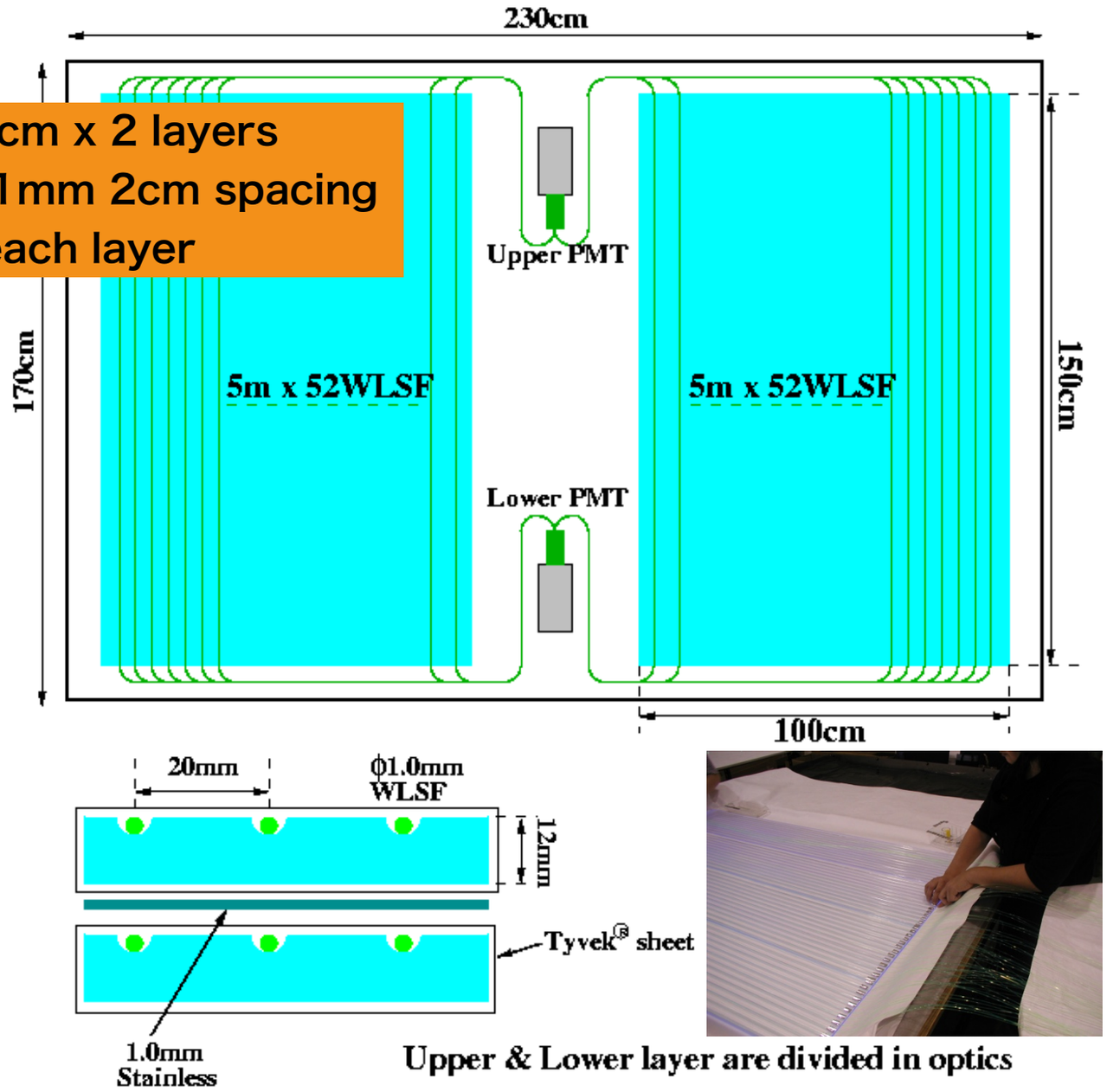
- NN allows to enhance substantially the accuracy of geometry and energy reconstruction
- Future plans:
  - Build photon-nucleon classifier
  - Investigate influence of cuts, enhance exposure
  - Study impact of systematics (hadronic interaction model, etc.)
  - Try more network architectures
  - Mass composition study

Appendix

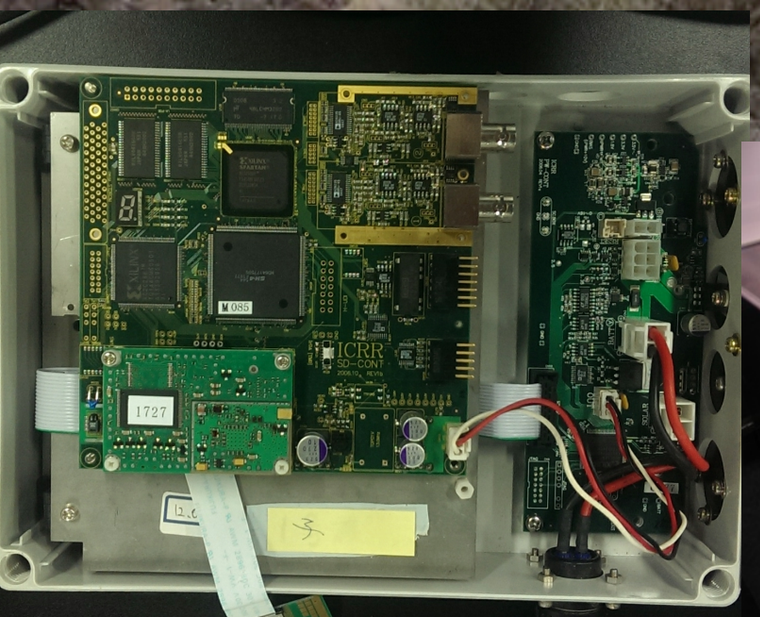
Surface Detectors



- $3m^2$ x 1.2cm x 2 layers
- WLSF : ϕ1mm 2cm spacing
- PMT for each layer

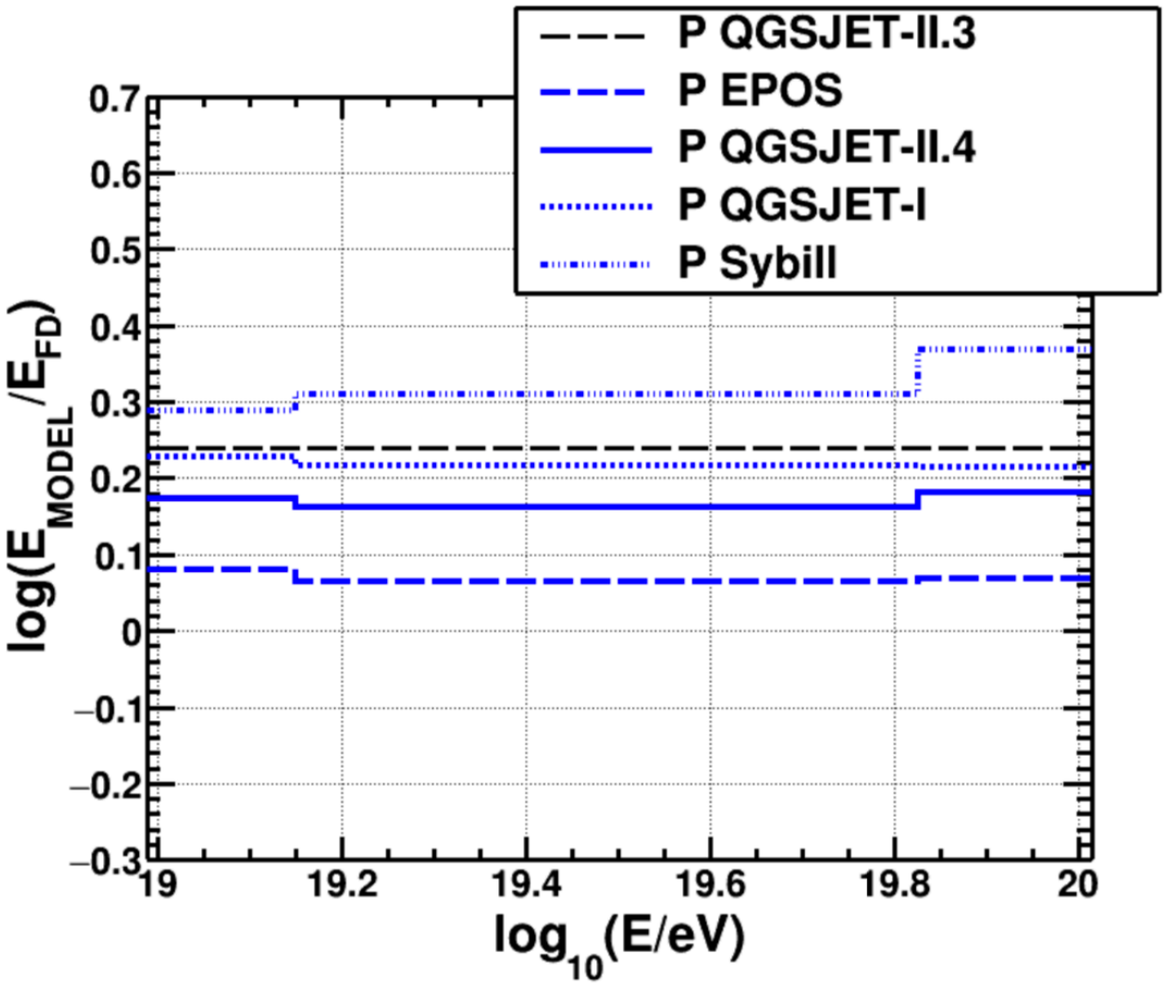


Upper & Lower layer are divided in optics

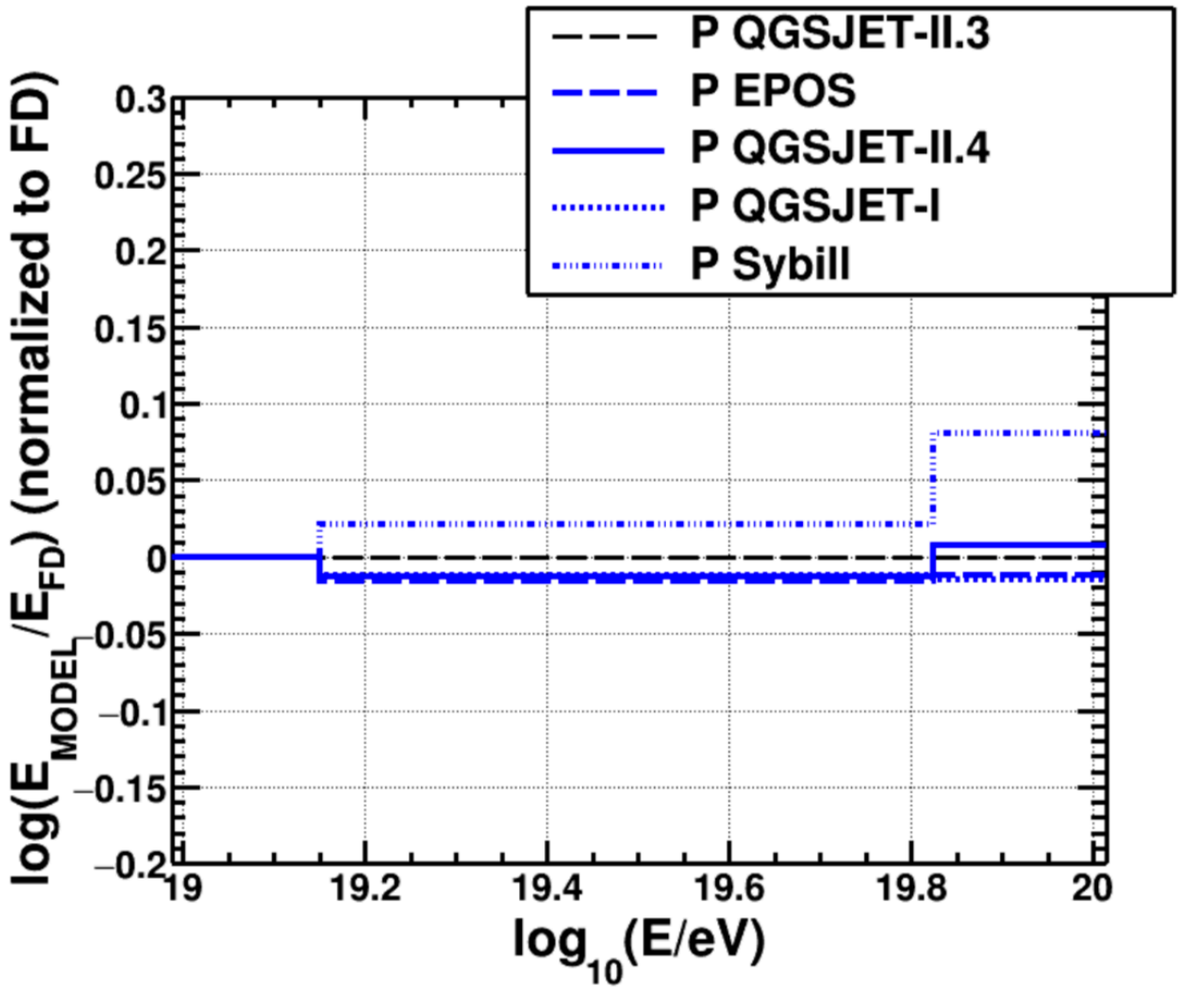


- 12bit 50MHz FADC x 2 layers
- CPU : Renesas SH4(25MHz)
- GPS, WLAN-modem
- Charge controller

SD energy from the hadronic models relative to the FD

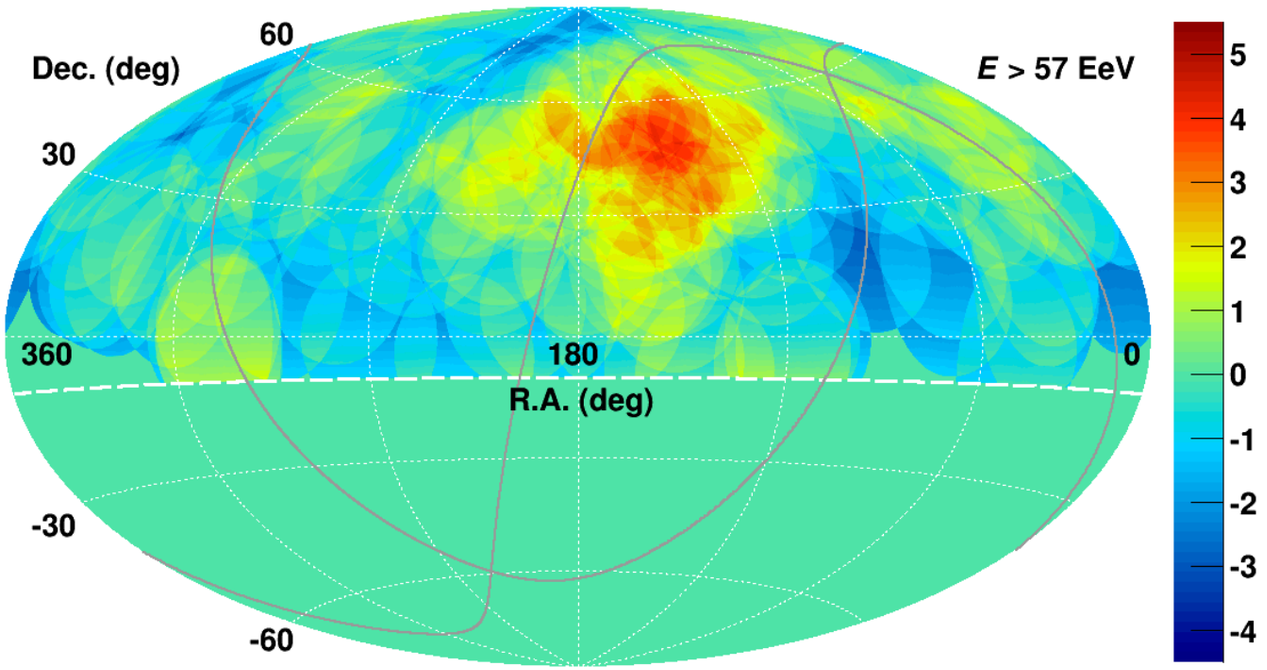


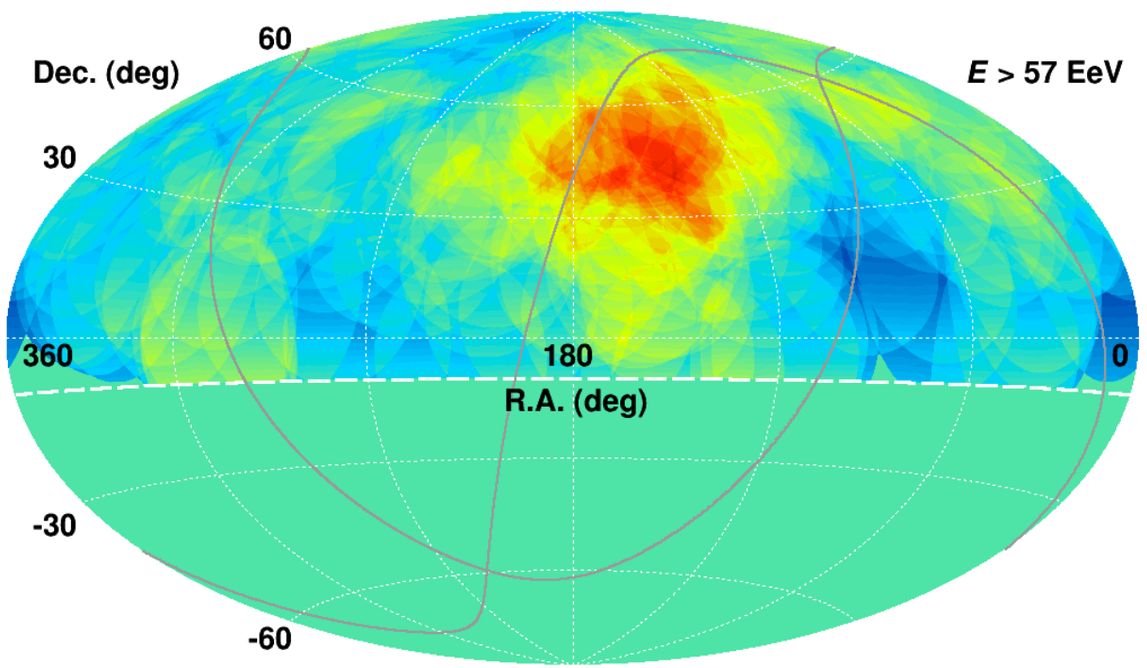
SD energy from the hadronic models after normalization at 10^{19} eV



Hotspot with 9yr data(>57EeV)

Matthews, ICRC2017 TA highlight





With original 20° oversampling, spot looks larger … Thus, scan over 15°, 20°, 25°, 30° and 35°

With 25° oversampling, significance maximum ~3 σ

Binsize	15		20		25		30		35	
	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global
Year 5	5.12	3.14	5.43	3.55	5.16	3.19	4.82	2.73	4.33	2.05
Year 7	4.92	2.84	5.37	3.44	5.65	3.80	5.37	3.44	5.03	2.99
Year 9	4.42	2.06	4.72	2.50	5.06	2.96	5.01	2.91	4.66	2.41

SD reconstruction NN architecture

Problem: how to better take absent/not functioning detectors

- The event may occur close to detector network boundary
- Part of detectors may be turned off

SD reconstruction NN architecture

Problem: how to better take absent/not functioning detectors

- The event may occur close to detector network boundary
- Part of detectors may be turned off

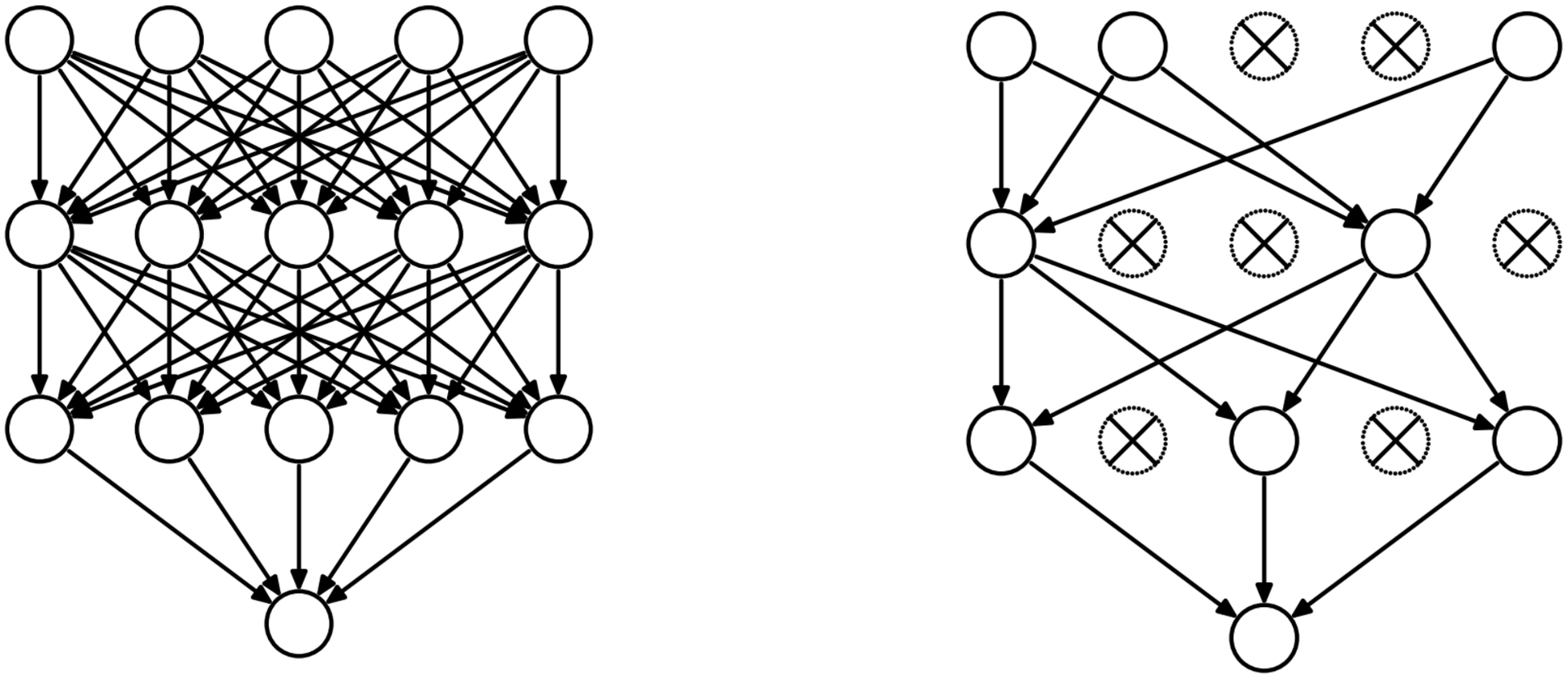
Dropout, the regularisation method in NN, simulate this situation

SD reconstruction NN architecture

Dealing with absent/not working detectors:

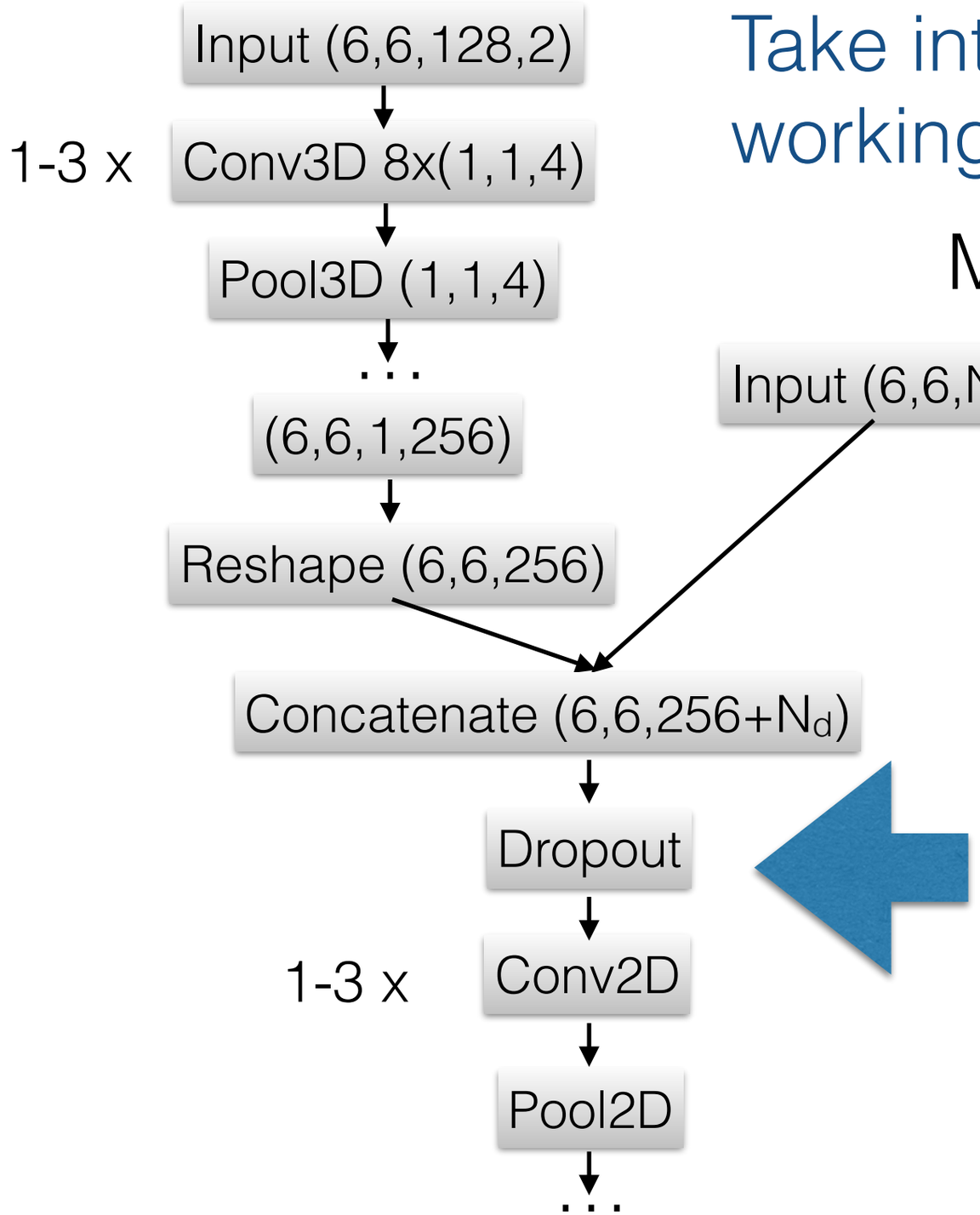
Dropout, the regularisation method in NN

Srivastava et. al JMLR 15 (2014)



- In training mode neurons are switched off with probability *p*
- *For p=0.5* we train simultaneously 2^n thinned neural networks
- In prediction mode neurons are on but their output weights are multiplied by *p (we average predictions of thinned nets)*

SD reconstruction NN architecture

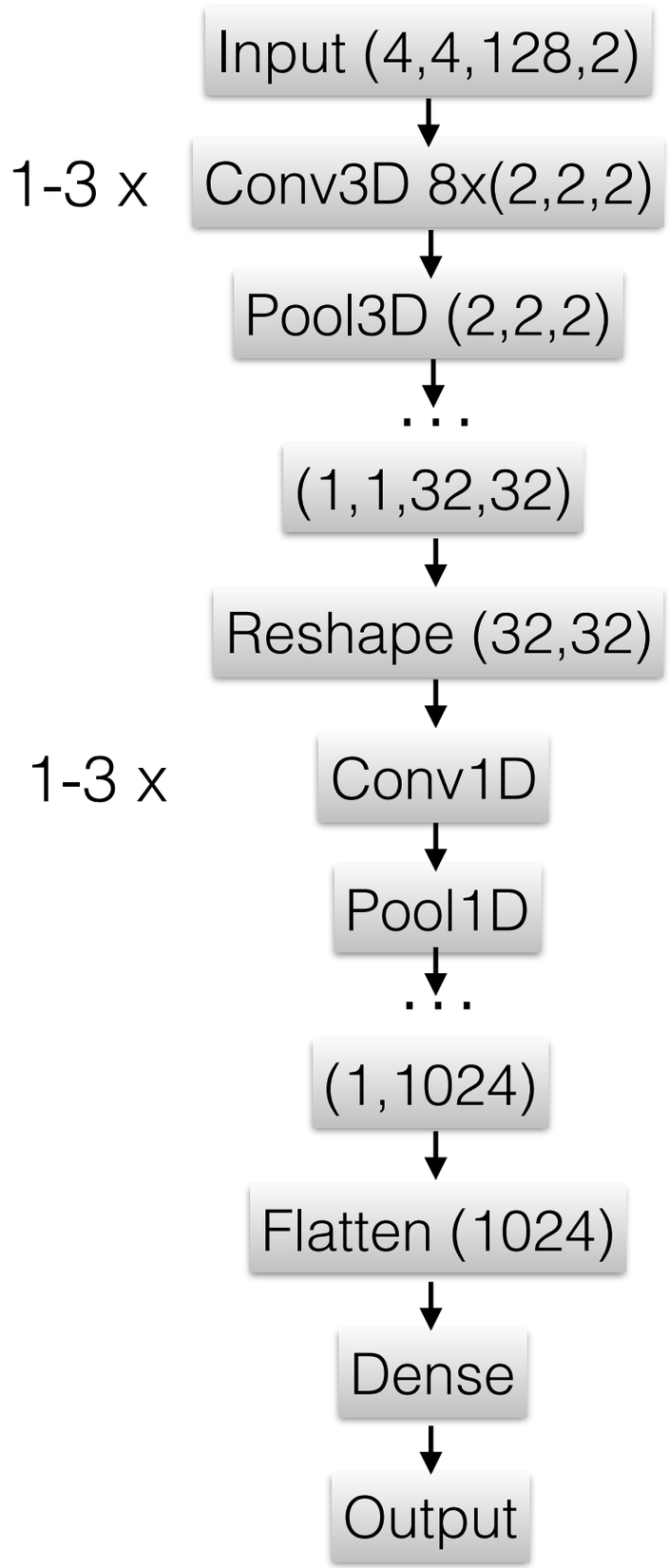


Take into account absent/not working detectors

Modified dropout

- Weights are corrected using fraction of working detectors
- In training mode part of the detectors may be switched off as in conventional dropout method

SD reconstruction NN architecture



Naive variant: на using 3D - convolution

Problem: incomparable scales in *t* and *L*

- L unit: 1200 meters
- t unit: 20ns ~ 6 meters

Adjacent detectors waveforms are weakly correlated

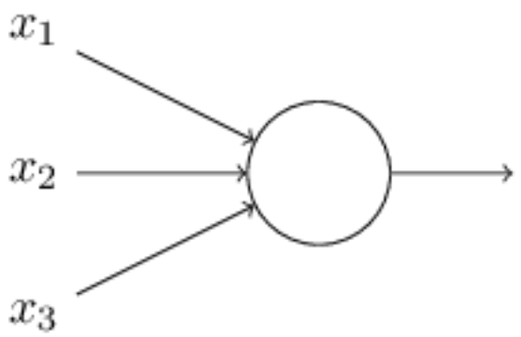
Cuts applied on MC samples.

- 1. Each event must include at least 5 counters.
- 2. The reconstructed primary zenith angle must be less than 45° .
- 3. The reconstructed event core must be more than 1200 m from edge of the array.
- 4. Both the timing and lateral distribution fits must have χ 2/degree of freedom value less than 4.
- 5. The angular uncertainty estimated by the timing fit must be less than 5° .
- 6. The fractional uncertainty in S(800) estimated by the lateral distribution fit must be less than 25%.

Neural networks

- Perceptron
- Multilayer perceptron networks
- Overfitting and regularization
- Convolutional neural networks

Perceptron

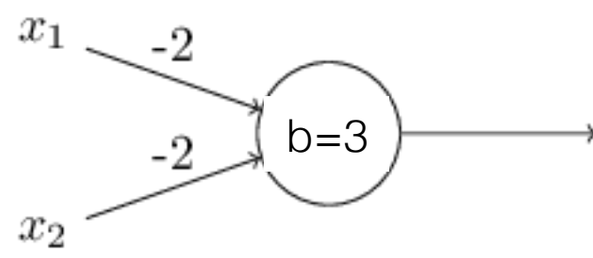


$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

or

$$a = \sigma\left(\sum_k w_j x_j + b\right)$$

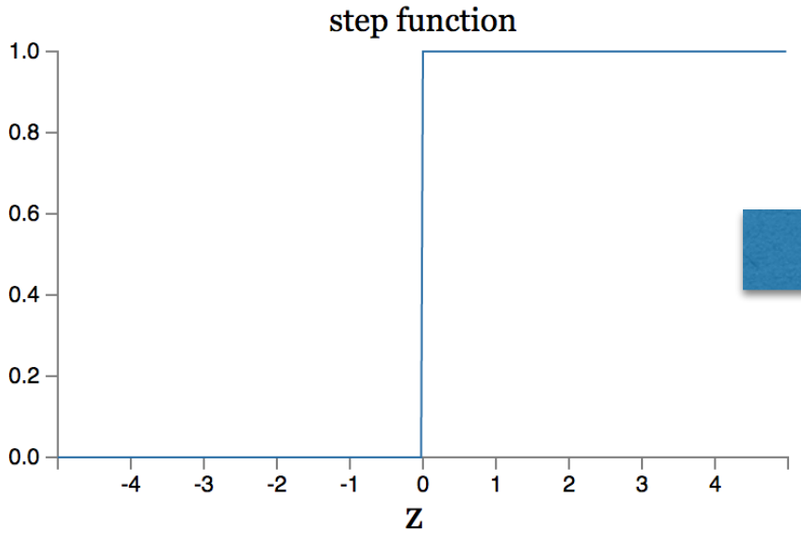
Combination of perceptrons can be used to build any logical operation

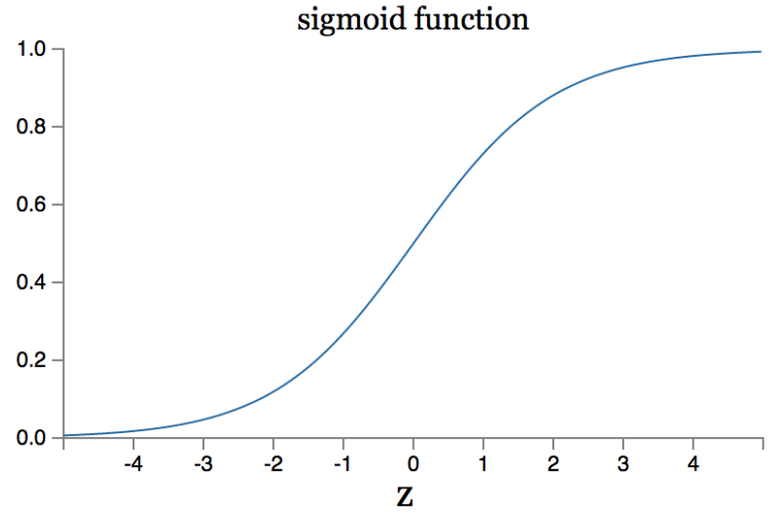


NAND

How to find proper weights:

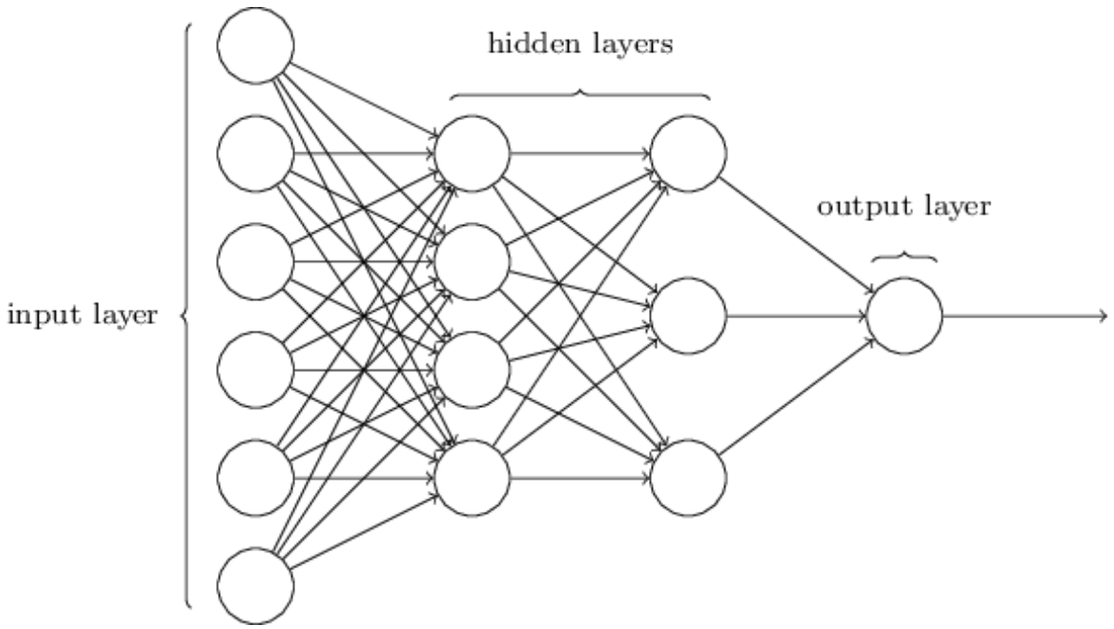
- replace step function with continuous approximation
- adjust weights with gradient decent





$$\sigma(z) \equiv \frac{1}{1+e^{-z}}$$

Multilayer perceptron (MLP)



$$a_j^l = \sigma\left(\sum_k w_{jk}^l a_k^{l-1} + b_j^l\right)$$

Theorem: any finite continuous function can be approximated with any given accuracy by MLP

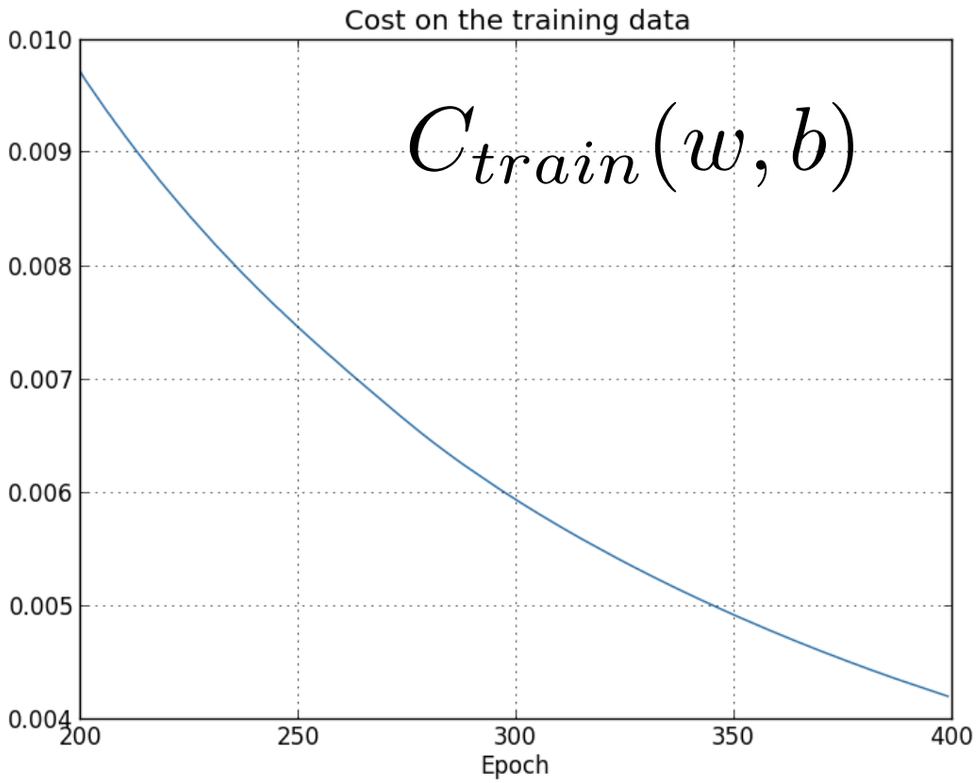
Learning by minimising loss function:

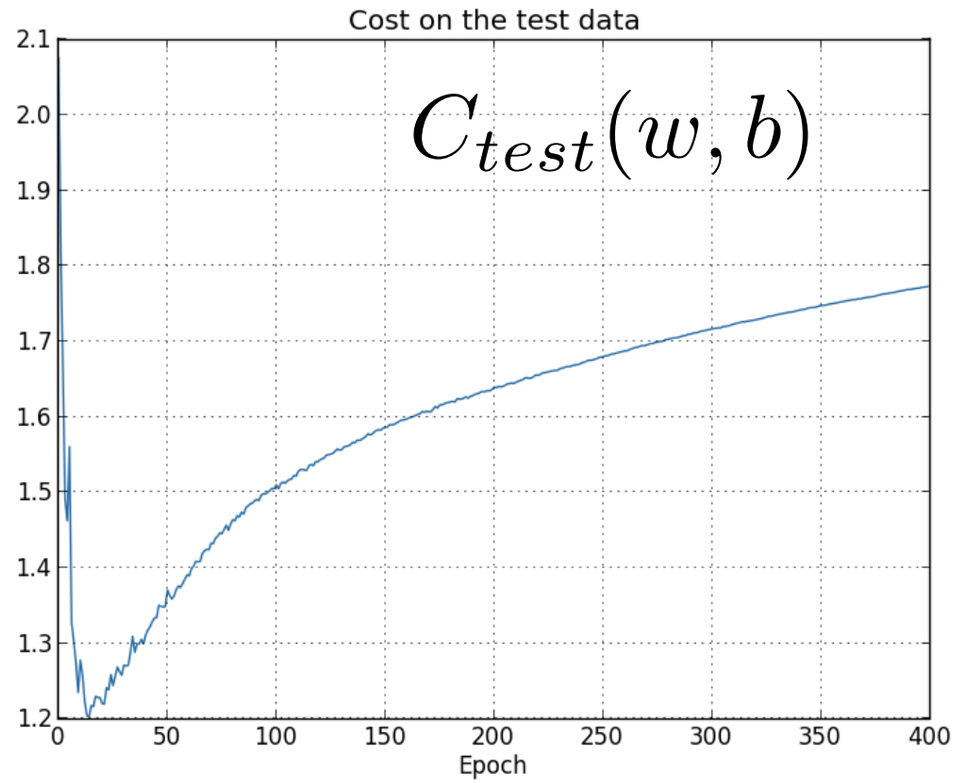
$$C(w,b) \equiv \frac{1}{2n}\sum_x \|y(x) - a\|^2$$

y(x) - network output
a - desired output

Back-propagation algorithm: calculate all derivatives $dC/d\omega_{jk}^l$ in parallel in one pass

Overfitting





NN may adopt to the particular training set and lose prediction capabilities

Solution: regularisation techniques

- L2 - regularisation $C(w,b) \to C(w,b) + \lambda \left(\sum w^2 + \sum b^2 \right)$
- admixture of random noise to data
- Dropout (see appendix)

Dealing with sequences/images

MLP are not very effective when dealing with high-dimensional data

+ Large input data size
+ Signals in the adjacent pixels are often correlated

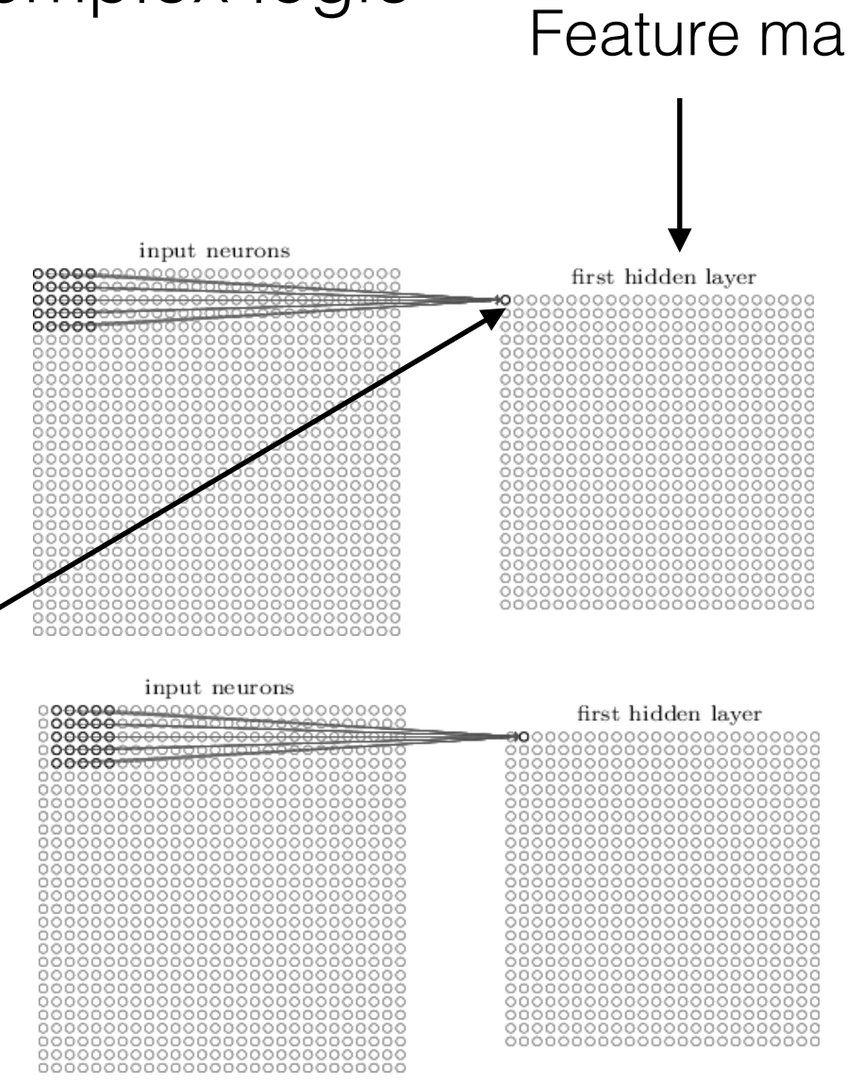
+ We want more layers - implement more complex logic
+ We want less weights - easier to train

Convolutional layers

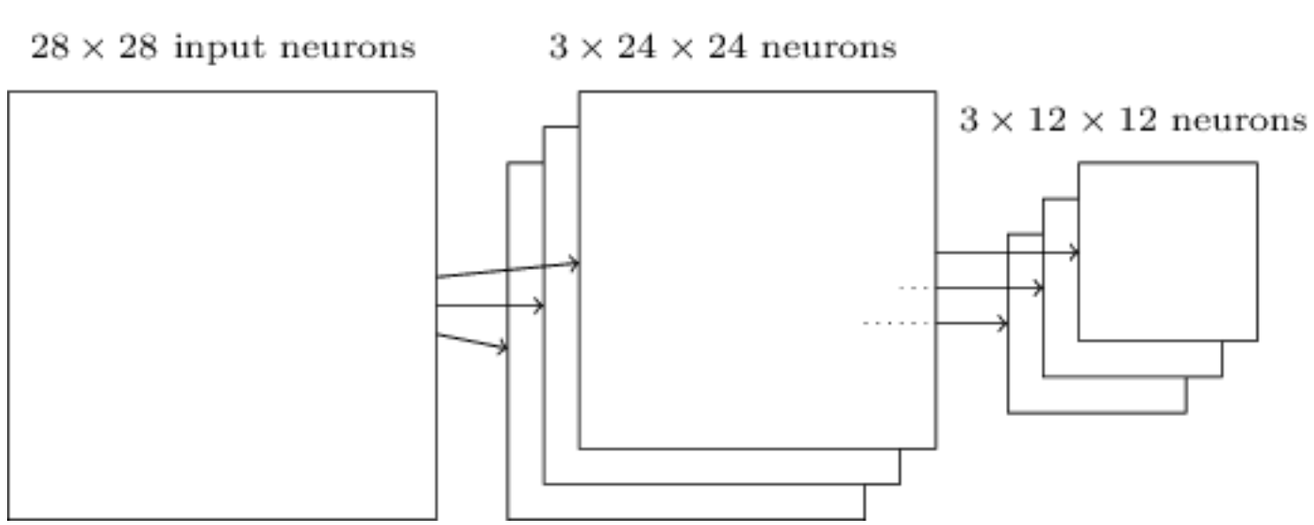
- Small amount of shared nonzero weights (kernel)

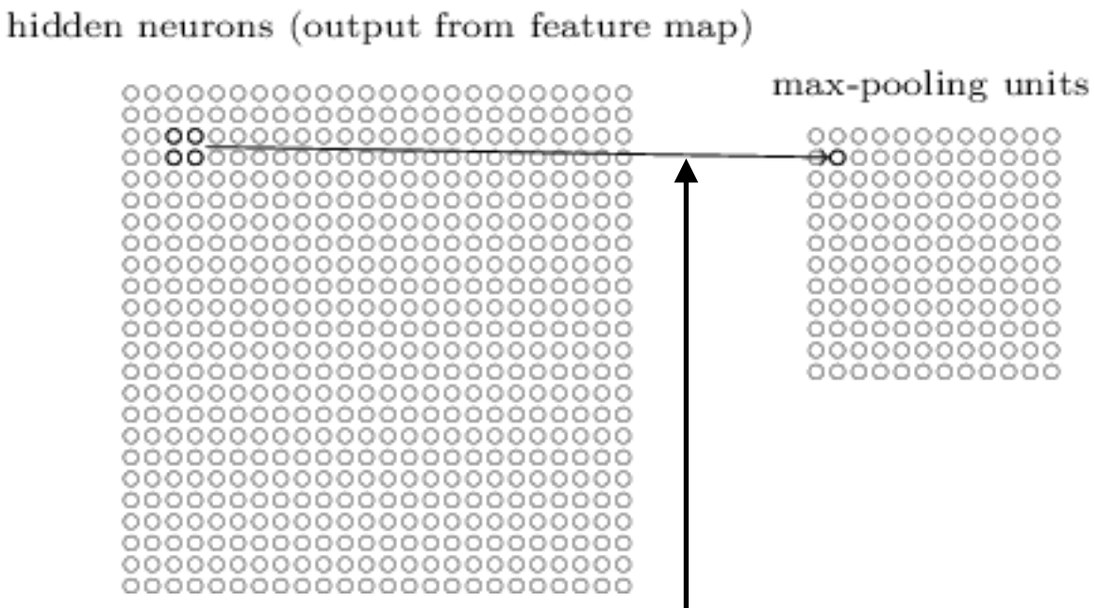
$$\sigma\left(b + \sum_{l=0}^{4}\sum_{m=0}^{4} w_{l,m} a_{j+l,k+m}\right)$$

- Capture local feature maps

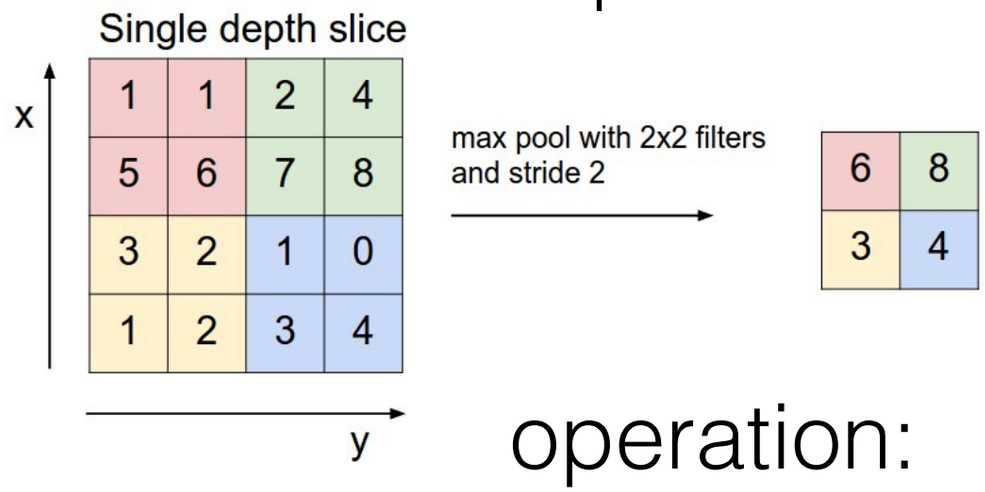


Pooling layer





Scale down the image to capture larger-scale features

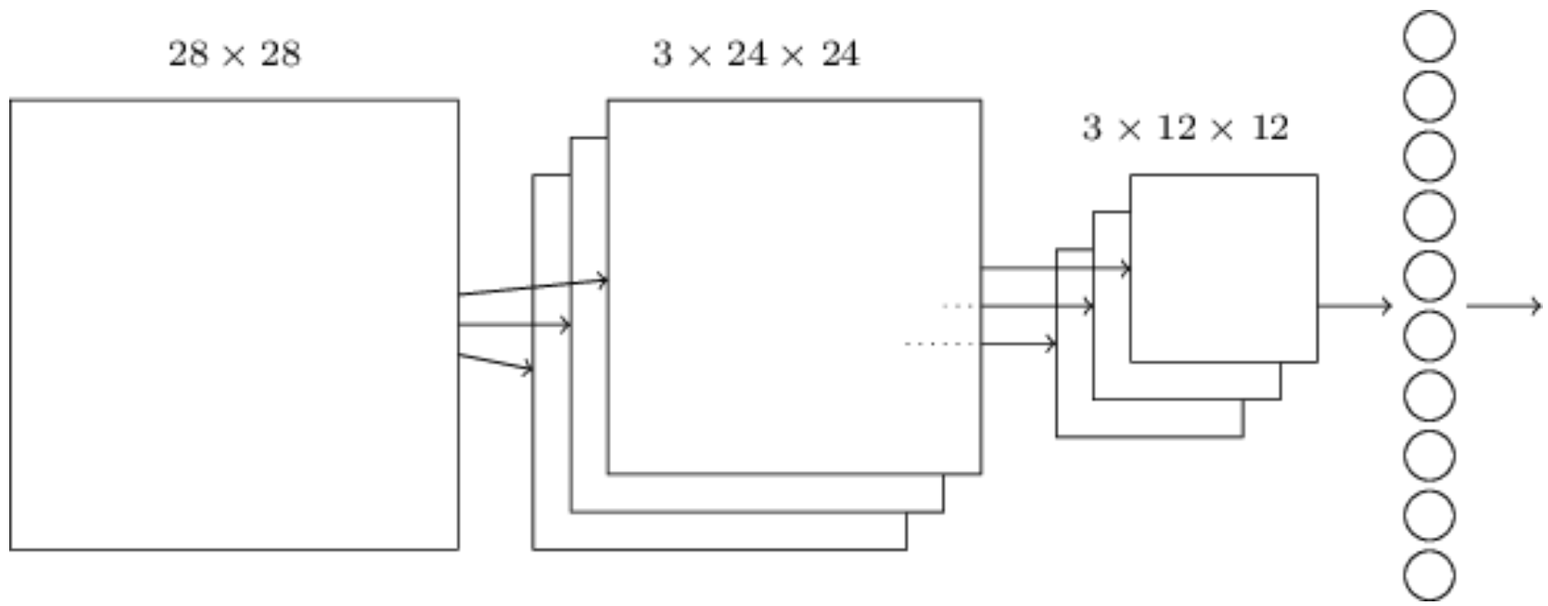


operation:

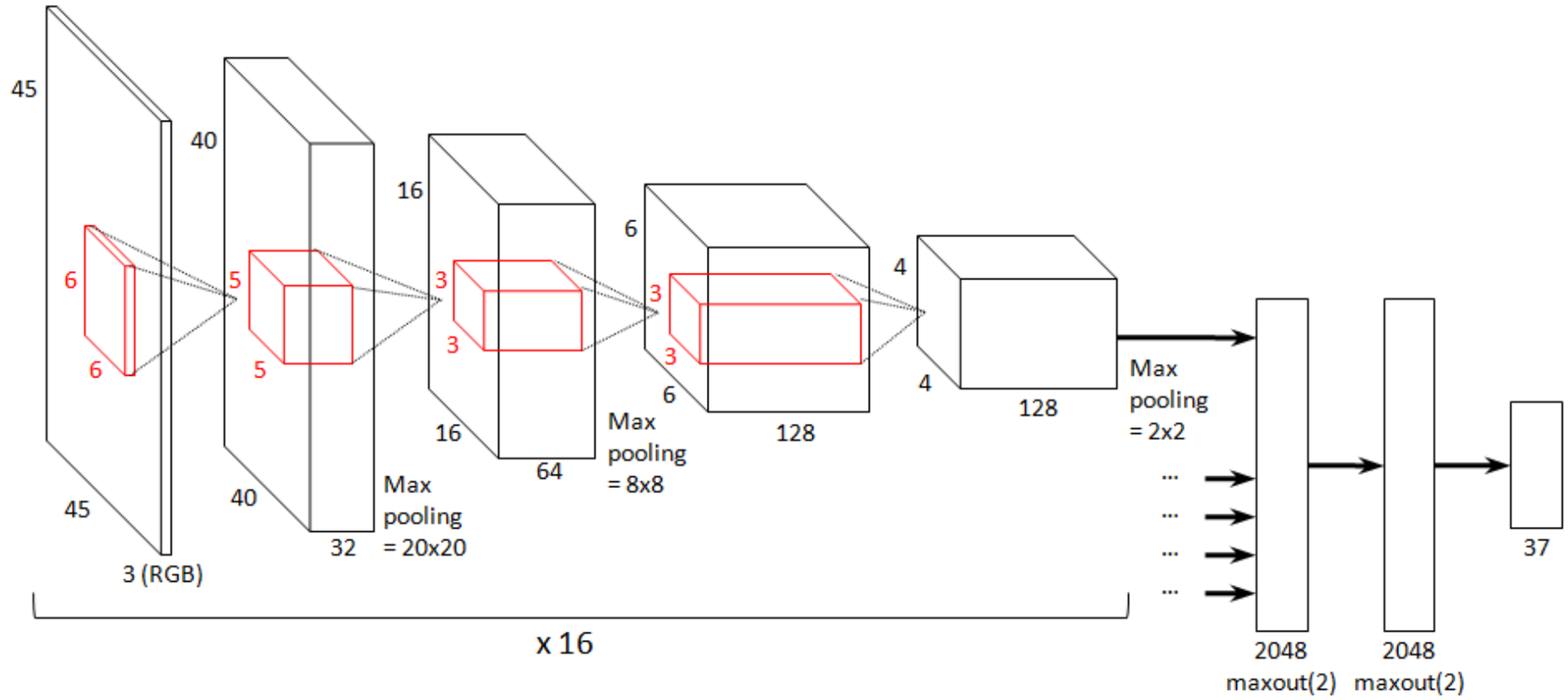
- Maximum
- Average
- …

Convolutional NN architecture

Minimal



Galaxy zoo challenge winer



morphological classification of galaxies based on images