

# A neural network to classify GRAND radio time traces

ARENA 2022


Santiago de Compostela, June 7 – 10

Sandra Le Coz (LPNHE, Paris)

with

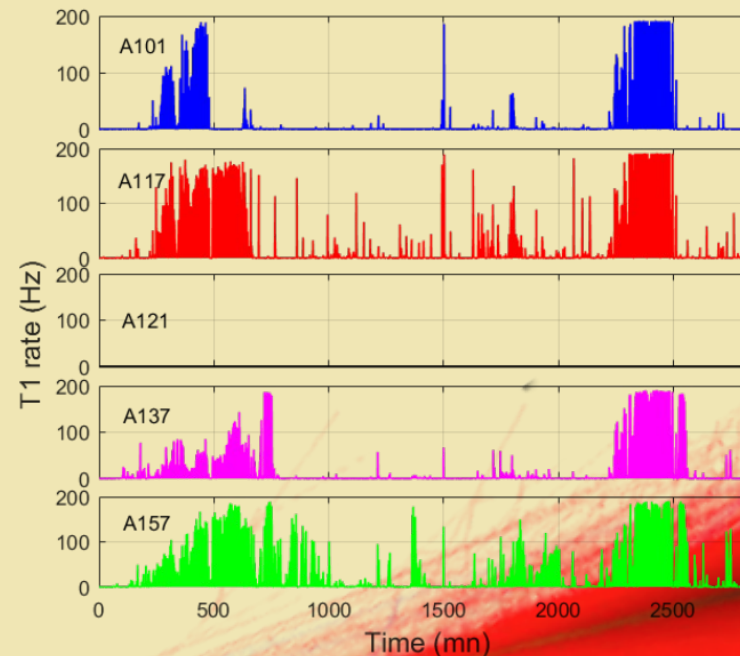
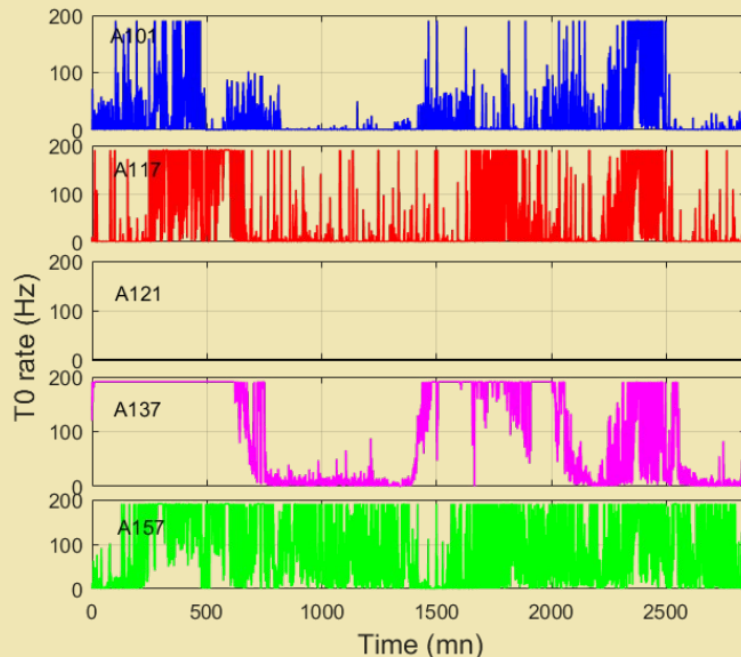
Aurélien Benoit-Lévy (CEA, Paris)

Olivier Martineau (LPNHE, Paris)



# Towards a giant radio array for $\nu$ detection

- Low interactions rate of UHE  $\nu$ 
  - low flux of  $\nu$  - extensive air shower on Earth
    - huge area of detection
    - cheap detectors
    - antennas without external (particle) trigger



*TREND data*

- Anthropogenic transient rate  $>10\text{Hz}$  even in « quiet » places
  - a smart trigger is required to avoid saturation of acquisition

# A neural network as a smart trigger

How to discriminate **air shower/anthropic** signals @ antenna level?

→ Use a neural network (NN)?

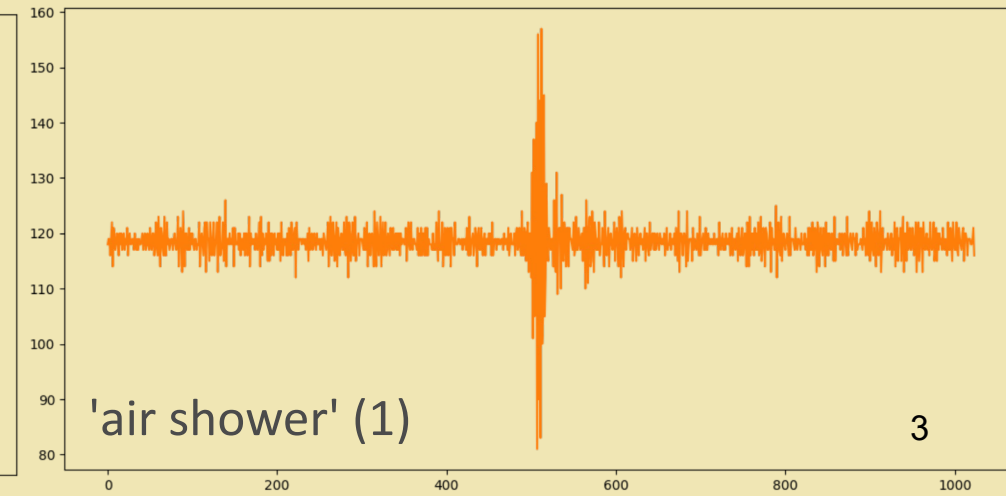
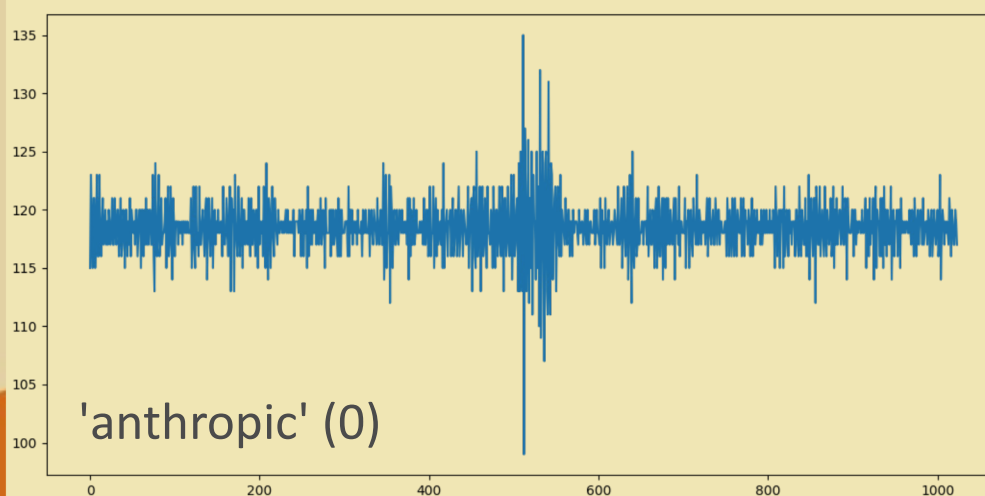
- NN input = a radio time trace
- NN target = 0/1 (anthropic origin/air shower origin)

On which data do train/test?

→ experimental data rather than simulations

→ data we already have, a subset of TREND data

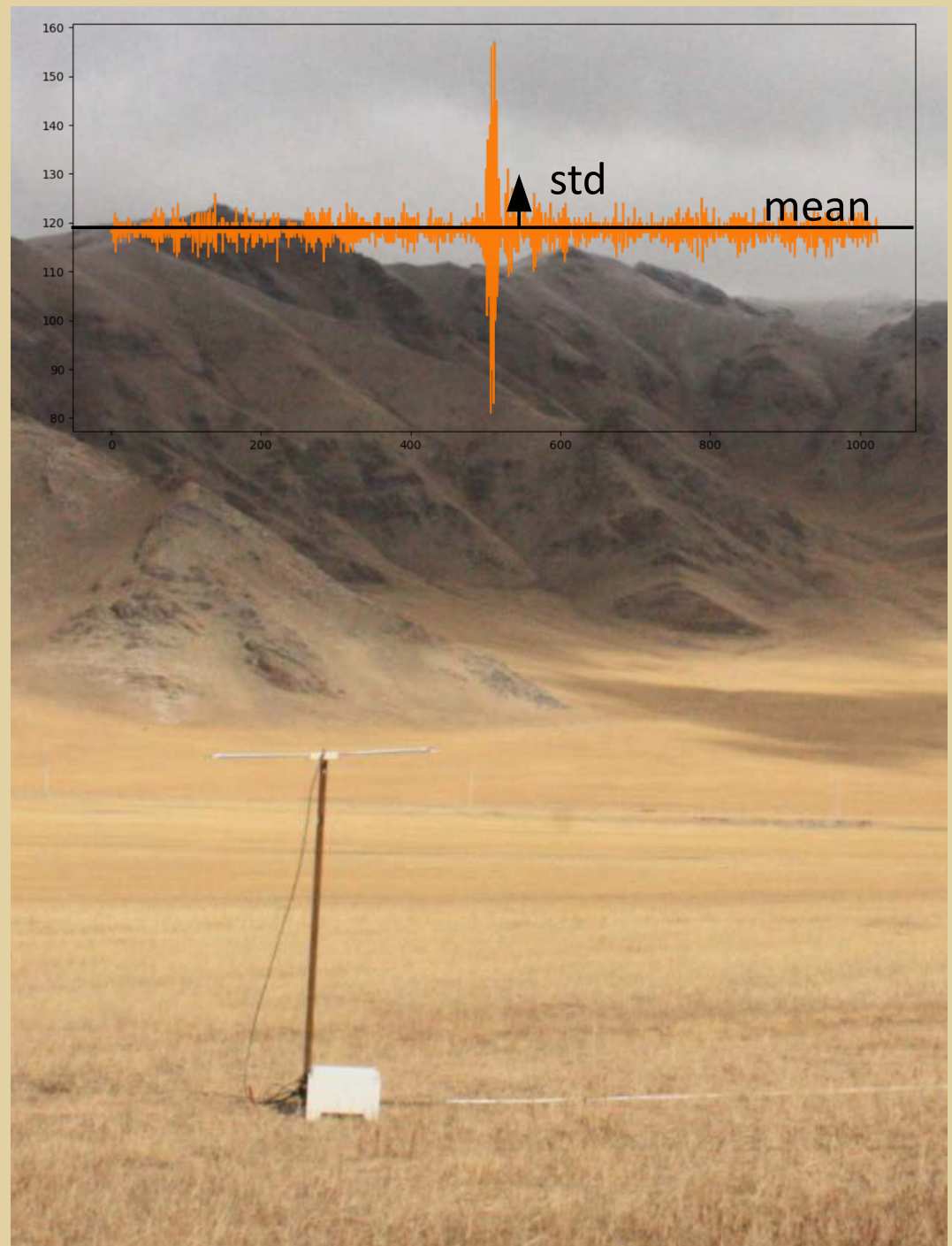
*TREND time traces – 1024\* 5ns*



# TREND experiment

- 50 butterfly antennas
  - Single-polarized
  - 50-100 MHz
  - Self-triggered
  - Setup in XinJiang, China
  - Between 2011 and 2014
- 
- Trigger @ antenna level if :  
 $\text{abs}(\text{amp}_i - \mu(\text{amp})) > 6\sigma(\text{amp})$
  - Trigger @ array level if :  
space-time correlations between  
5+ antenna triggers  
→ « coincidence » recorded

In this study we use a subset :  
1.25e8 recorded coincidences  
9e8 antenna time traces



# TREND data labellisation

Before making predictions, NN must be trained on data for which label is known  
→ We put labels ('anthropic'=0/'air shower'=1) on TREND radio time traces using TREND standard data analysis : *See [arXiv:1810.03070], 2018*

Offline cuts were applied to reject :

- noisy periods
- too long antenna signals
- angle/source reconstruction : high  $\chi^2$ , near source position, zenith  $> 80^\circ$
- discontinuous trigger pattern at ground
- direction-time correlations between coincidences

# TREND data labelisation

1.25e8 coincidences recorded  
(9e8 antenna time traces)

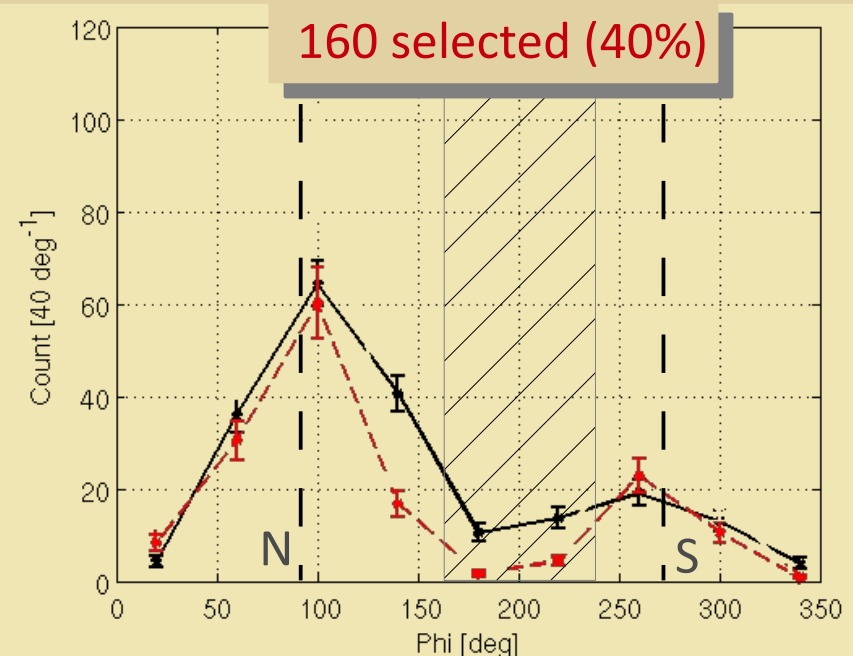
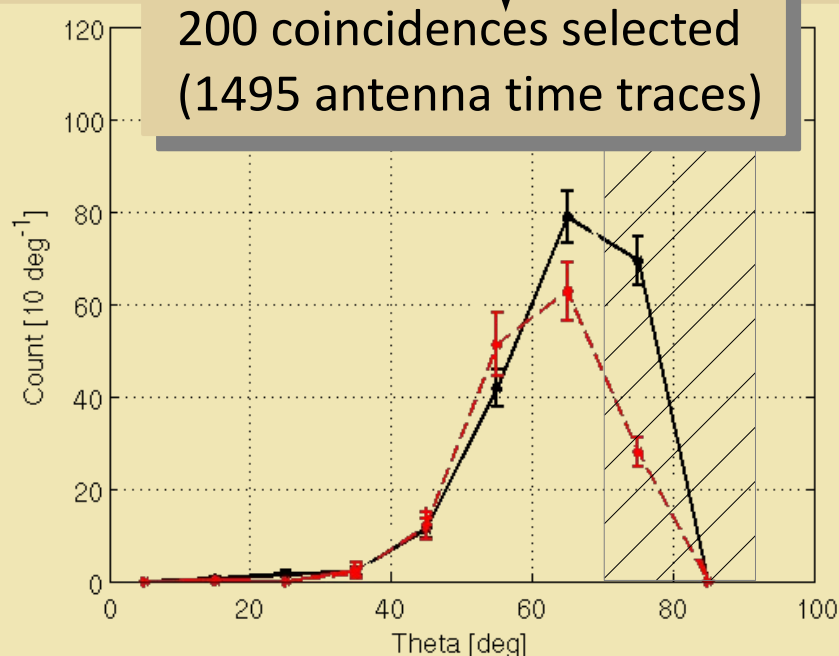
Simulations of air showers + TREND response :  
370 air showers would have been recorded

cuts ↓

cuts ↓

200 coincidences selected  
(1495 antenna time traces)

160 selected (40%)



- Consistency between selected **experimental data & simulations** regarding shape (N/S geomagnetic expectations) & integral of angular distribution  
→ The 200 selected coincidences might be air showers with a contamination ~20%
- Contamination is high for  $\theta > 70$  &  $160 < \phi < 240$  → rejected of labelisation  
→ 'air shower' label for the 984 traces (139 surviving coincidences)  
→ 'anthropic' label for the remaining ~9e8 traces

# Convolutional Neural Network

~ Dataset ~

984\*2 = 1968 ≠ 'anthropic' traces (randomly picked)

984 ≠ 'air shower' traces (w=2 to keep balance)

split = 80% training/20% test

~ Preprocessing ~

times traces shifted to a mean of 0 + scaled to a range [-1;1]

('mean of the trace' is irrelevant feature + help training)

first layer input = FFT(time trace) (works better)

~ Layers~

convs (filters=8/16, kernel size=51, padding='same', activation='relu') + maxpoolings

60%-dropout + L2 regul = 2e-3 to avoid overfit

~ Fit ~

optimizer = adam

loss = cross entropy



# Model summary

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 1024, 1)]	0
conv1d (Conv1D)	(None, 1024, 8)	416
max_pooling1d (MaxPooling1D)	(None, 512, 8)	0
dropout (Dropout)	(None, 512, 8)	0
conv1d_1 (Conv1D)	(None, 512, 16)	6544
max_pooling1d_1 (MaxPooling 1D)	(None, 256, 16)	0
dropout_1 (Dropout)	(None, 256, 16)	0
conv1d_2 (Conv1D)	(None, 256, 16)	13072
flatten (Flatten)	(None, 4096)	0
dropout_2 (Dropout)	(None, 4096)	0
dense (Dense)	(None, 16)	65552
dropout_3 (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 2)	34

Total params: 85,618

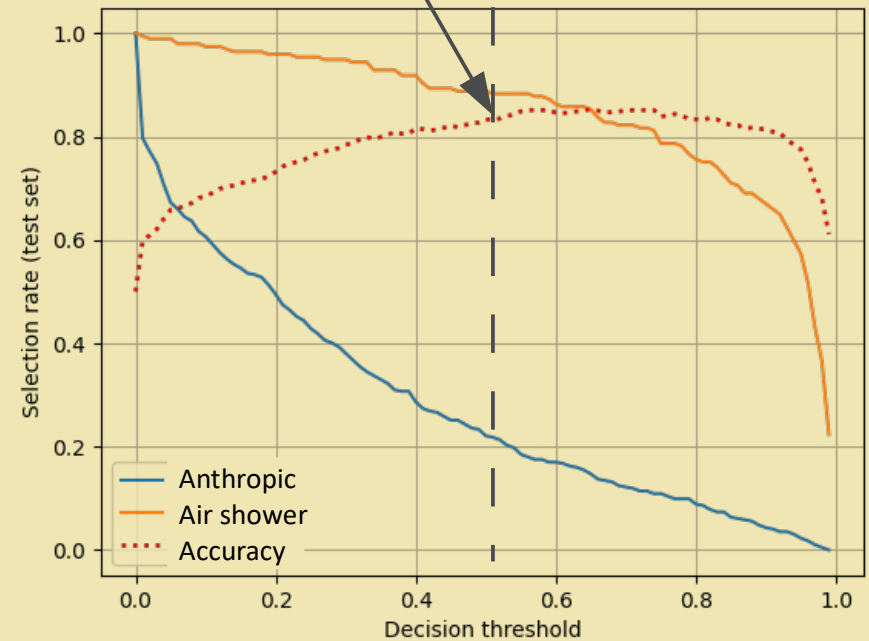
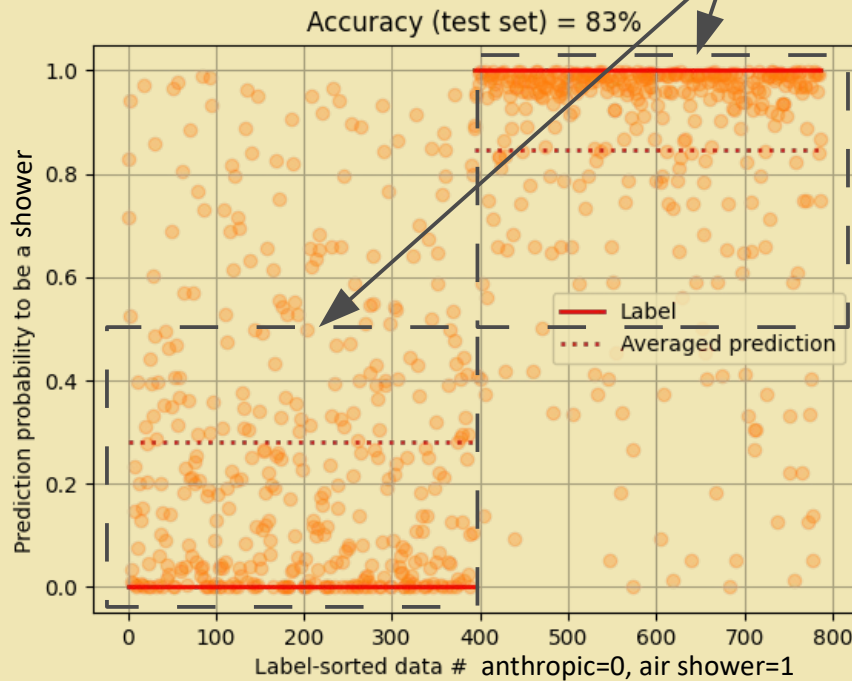
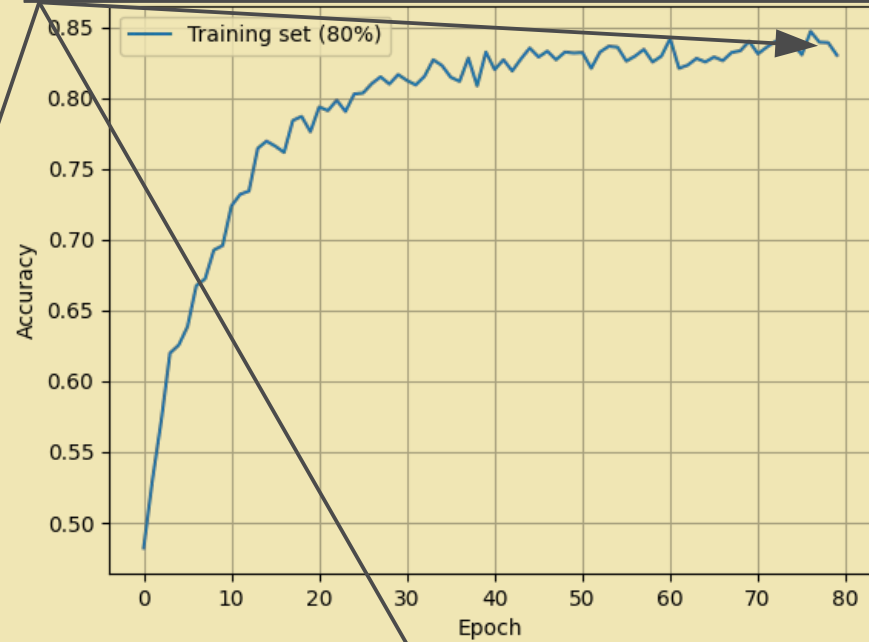
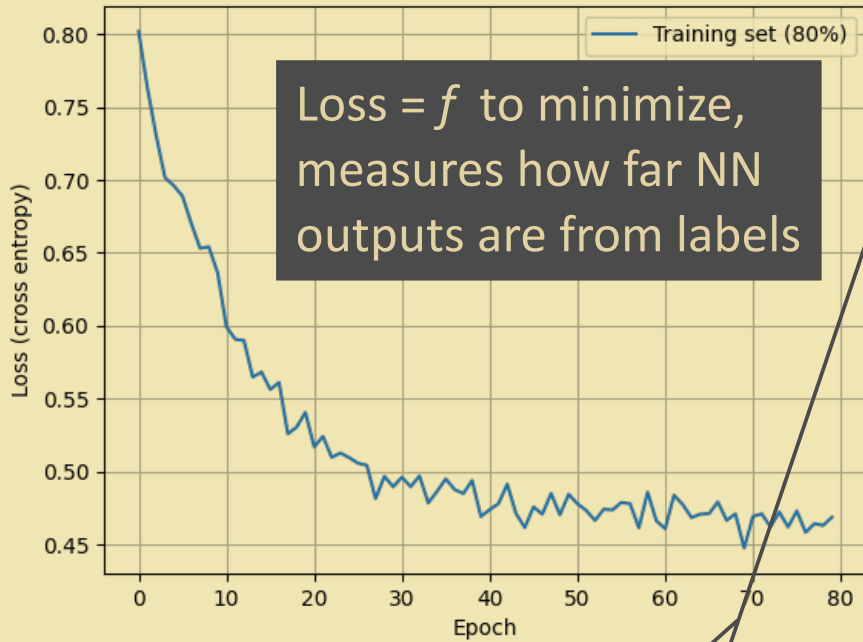
Trainable params: 85,618

Non-trainable params: 0



# After training

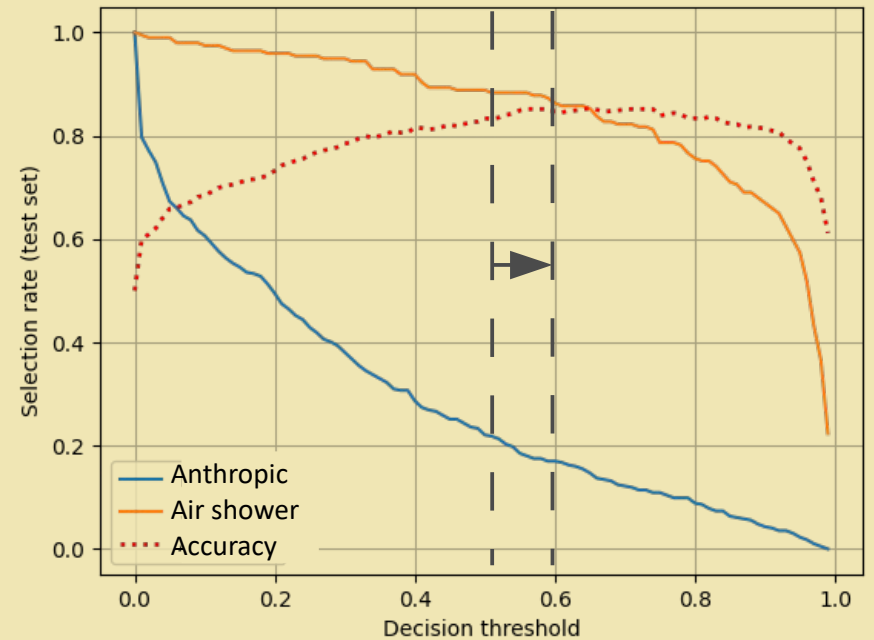
Accuracy = #well classified data / #data  
If decision threshold = 0.5 :  
accuracy = 83% on training & test sets



# NN inferences on all data

NN is applied to each  $9e8$  recorded traces to simulate a 'NN trigger':

- NN trigger @ antenna level if :  
NN output (probability to come from air shower) > *decision threshold*
- NN trigger @ array level if :  
space-time correlations between 5+ antenna NN triggers → recorded



- Recorded coincidences with 'TREND std' (without NN) :

Anthropic 1.25e8

Air shower 370 (simulation estimation)

- Expected recorded coinc. with 'NN trigger' (if we chose a *decision threshold* = 0.6) :

Fully dep. traces

Indep. traces

Anthropic 18% (22.5e6)

0.07% (87 500)

Air shower 86% (318)

91% (337)

**Actual recorded coincidences with 'NN trigger' : 3e6 (2.4%)**

# Recorded with NN trigger

selected 'TREND std' (200)  $\cap$  recorded 'NN trigger' (3e6) = 159 coincidences

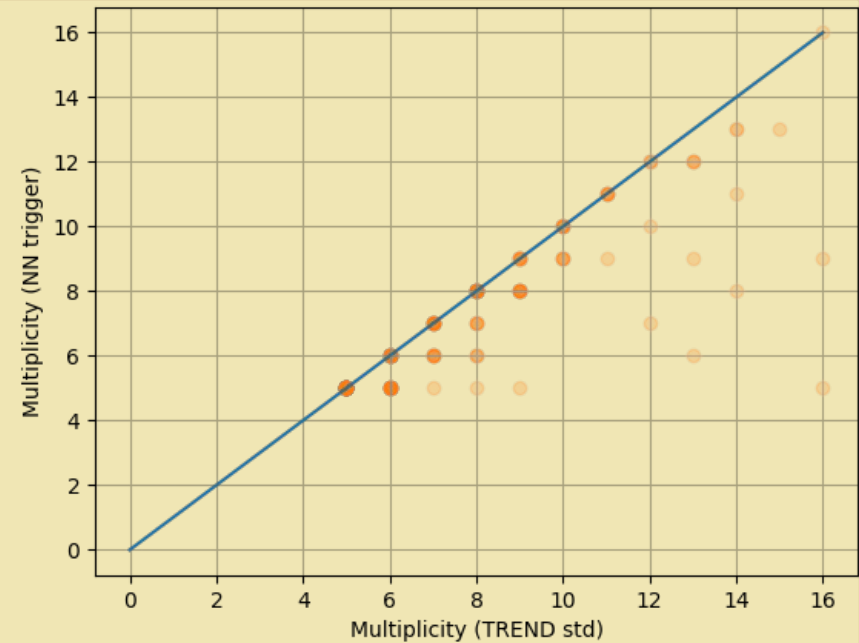
Loss of 'air shower' coincidences quality ?

$\langle \# \text{ antenna per coincidence} \rangle : -7\%$

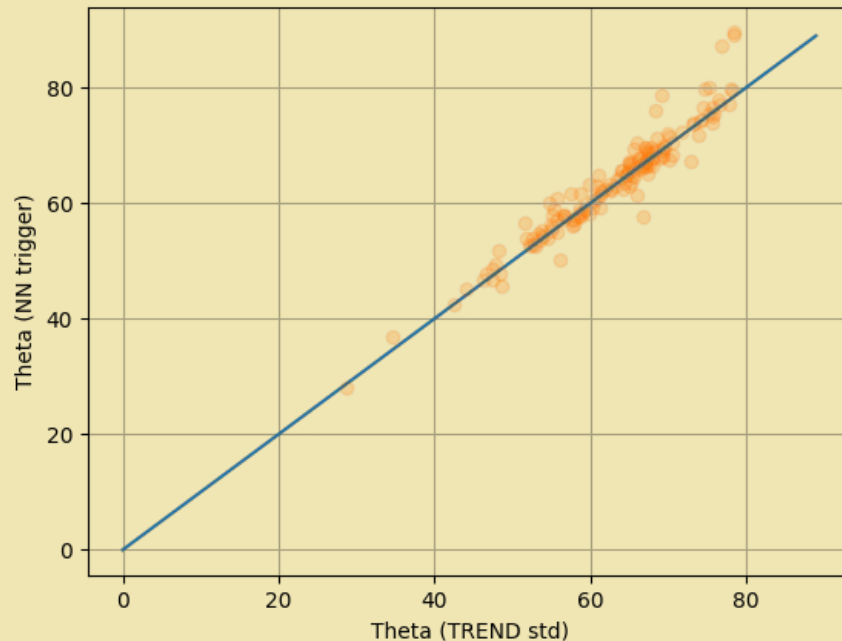
$\rightarrow \langle |\Delta\theta| \rangle < 3\%$

$\rightarrow \langle |\Delta\phi| \rangle < 1\%$

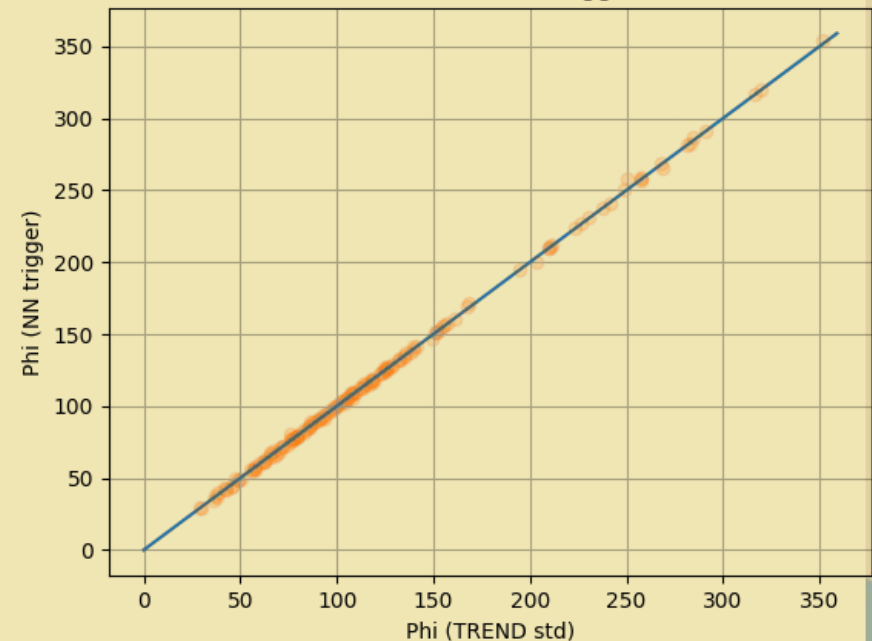
TREND std - selected & NN trigger - recorded



TREND std - selected & NN trigger - recorded



TREND std - selected & NN trigger - recorded



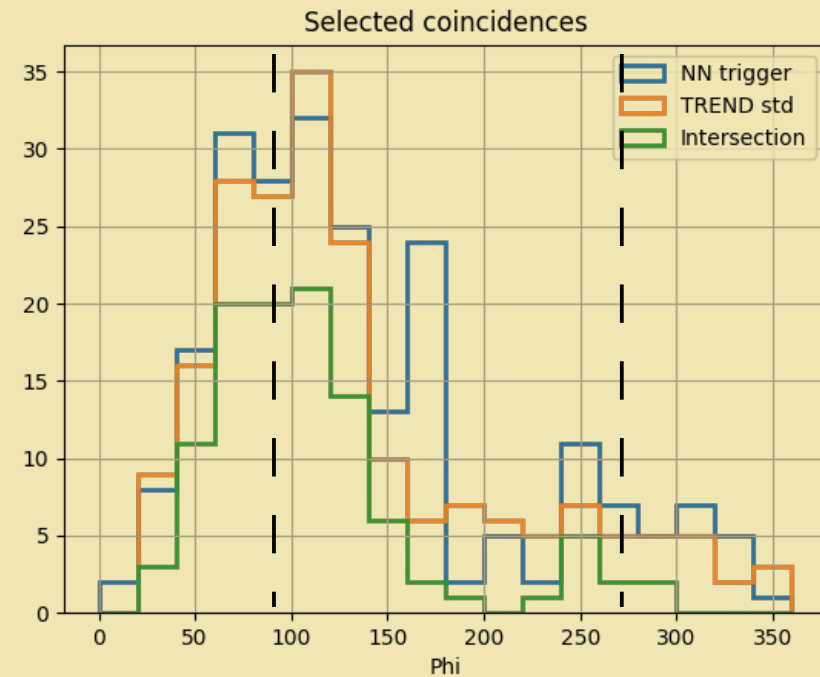
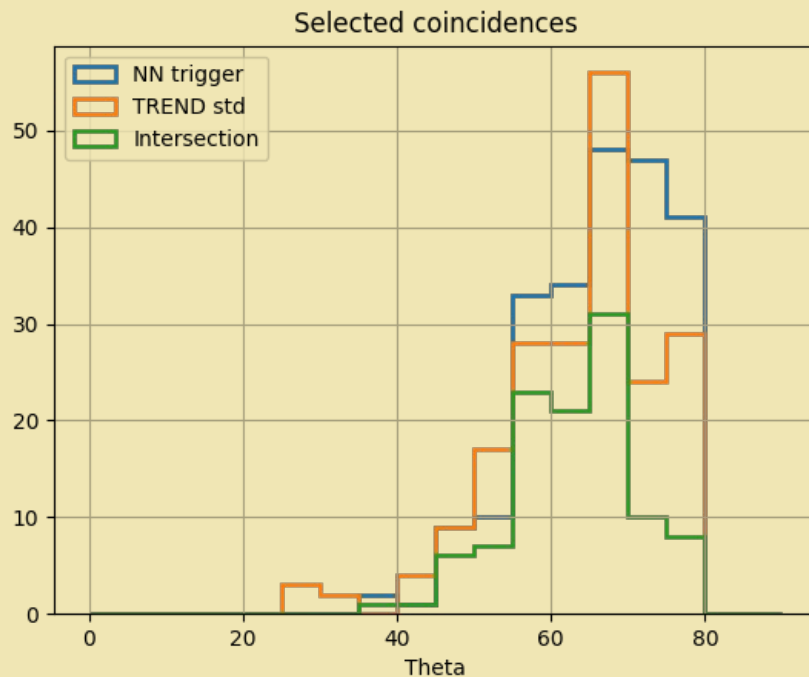
# Selected with NN trigger

3e6 coincidences recorded

A few simplified offline cuts are applied to reject :

- noisy periods
- angle/source reconstruction : high  $\chi^2$ , near source position, zenith  $> 80^\circ$
- direction-time correlations between coincidences

225 coincidences selected

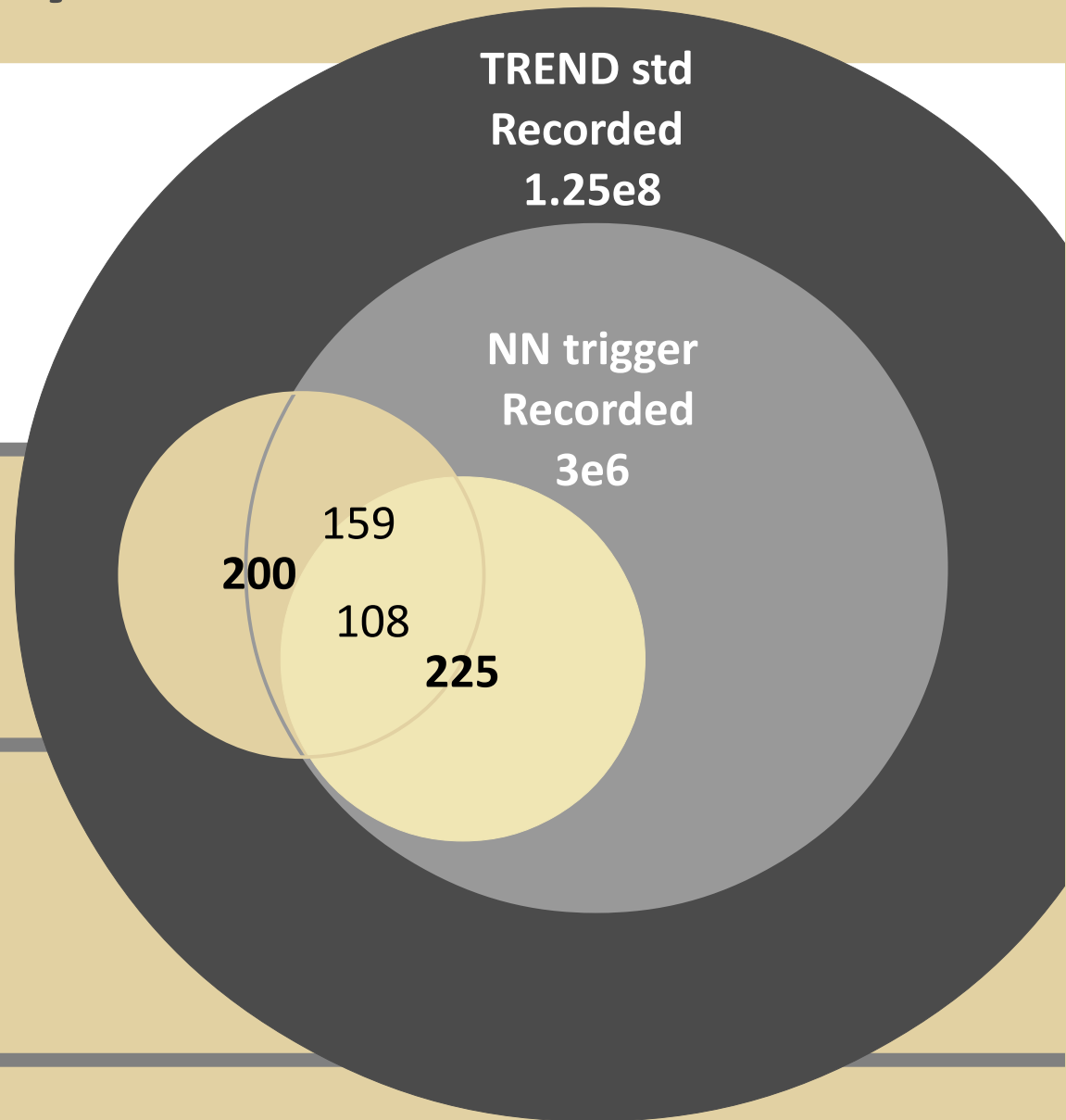
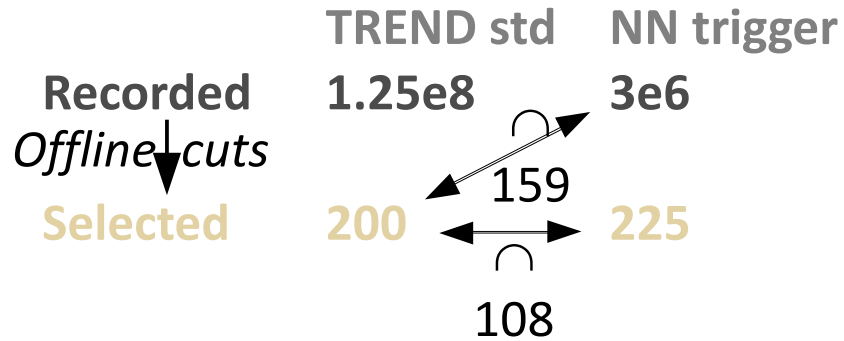


selected 'TREND std' (200)  $\cap$  selected 'NN trigger' (225) = 108 coincidences

→ Consistency between selected and 1<sup>st</sup> order expectations for air showers

→ NN trigger may at once improve trigger purity & replace some offline cuts

# Coincidences summary



Selected TREND std (200)



Recorded NN trigger (3e6)  
= 159

Selected TREND std (200)



Selected NN trigger (225)  
= 108

# Neural Network trigger study summary

- Achievements :

Data-driven study

Triggered data : -82% @ antenna level

-98% @ array level

~90% efficiency on air showers

- Limitations :

Training dataset too small, not pure & biased

- Next :

Data from 3-polarizations antennas of GRANDproto300

→ more informations should improve NN performance