Cloud Atlas

An LstmEncoder for UHECR AirShowers

G. Becuzzi L. Papalini

July 2022

Table of Contents

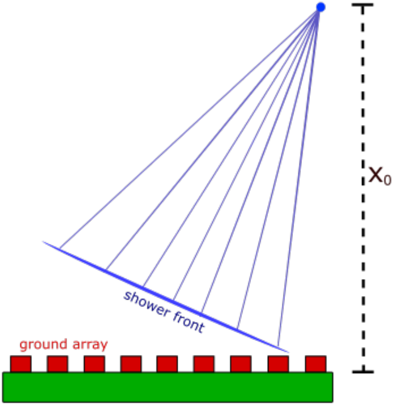
Table of Contents

UHECR Airshower

When *Ultra High Energy Cosmic Rays* (UHECR) enters the atmosphere they produce a particle cascade.

Detection: grid of water-Cherenkov ground based detectors.

Prediction: X_0 height at which the shower forms.



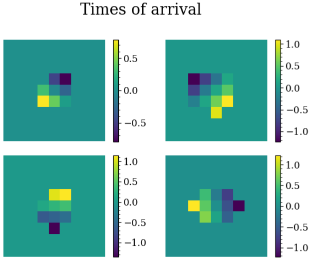
Dataset, first glance

Dataset: 10^5 simulated events:

- 9x9 grid of detectors
- most intense at center
- 80 frames of time series (40 MHz sampling rate)
- 1 frame of times of first arrival

Single record shape: $(80 + 1, 81)$

`pd4ml` package splits by default in 70% train 30% test



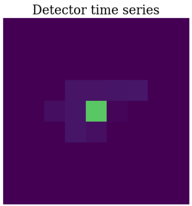


Table of Contents

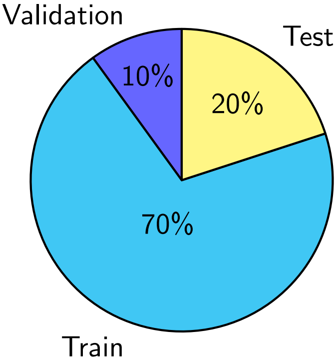
Split the dataset

Dataset was already split in test and train.

We put it all back together, shuffled it and divided with the following percentage:

- 70% *train*
- 20% *test*
- 10% *validation*

For the design of the net it is convenient using `numpy` structured arrays



Split the dataset: funky_dtype

```python
    # custom numpy dtype
    funky_dtype = np.dtype(
        [
            ("outcome", np.float64),
            ("time_series", np.float32, (80, 81)),
            ("toa", np.float32, (9, 9, 1)),
        ])

```

All data relative to a single event is clustered in a single numpy object, transformation is:

$$(80+1, 81) \longrightarrow [("toa", (9, 9, 1)), ("timeseries", (80, 9, 9))]$$

Data can be accessed "as a dictionary", depending on what is needed.

DataFeeder class

Ensures an easy way to train the subnets separately Class DataFeeder main features:

- shuffles data randomly
- input fields can be specified
- can be extended to more complex training strategies
- returns a generator

Using a generator (`keras.utils.Sequence`)

- inherit multiprocessing features
- has default callbacks
- avoids memory overload

`FeederProf(DataFeeder)` class

Curriculum learning

Using a pre-trained network data can be "scored" and then sorted in ascending order of difficulty

(work in progress) This can lead to a learning speed-up and improvements in resolution

Caveat: this training strategy is not well suited (conceptually at least) for regression tasks, since it is not clear what a "difficult" sample would look like.

Data Augmentation

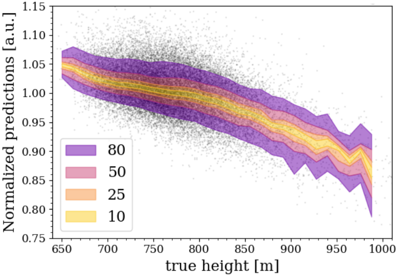
Dataset has a lack of high events ($X > 850$m) so a first network training showed a worse resolution for samples corresponding to this range

Strategy

Increase the number of samples that overcome a certain heigth threshold using the symmetries of the problem

Data is augmented using

- flip up-down
- flip left-right
- diagonal flip
- rotation of 90°



Resolution

The reference article suggests using the resolution:

Resolution

defined as the standard deviation of the distribution given by the difference between the predictions and the actual values of X_{max}

We point out that

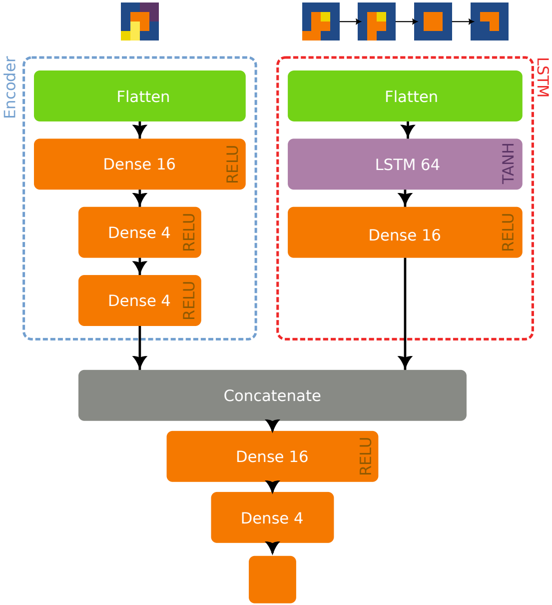
$$\sigma^2 = \frac{1}{N} \sum_i (\delta_i - \bar{\delta})^2$$

is a sensible estimator of "how much the net has gone wrong" only if $\bar{\delta} = 0$, for which the adopted resolution is equal to the *RMSE* of the distribution

$$RMSE^2 = \frac{1}{N} \sum_i (x_i - \hat{x}_i)^2$$

Since (on a typical train) $\bar{\delta} \approx 10$m we preferred the RMSE.

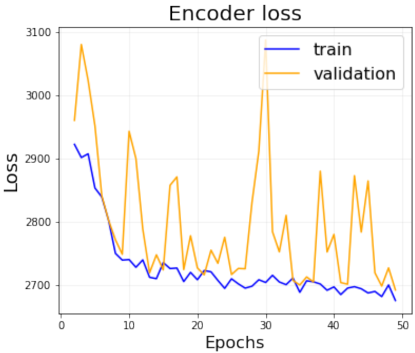
Table of Contents

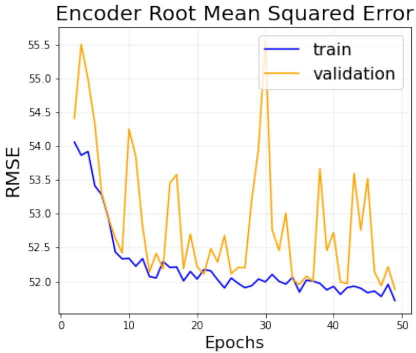

Encoder
Flatten
Dense 16
RELU
Dense 4
RELU
Dense 4
RELU
LSTM
Flatten
LSTM 64
TANH
Dense 16
RELU
Concatenate
Dense 16
RELU
Dense 4

Overview on the network

The assumption that lead to this design is that from the time of arrival matrix it is possible to infer some kind of “homogeneous” shower parameters (incidence angle, spread, etc.) while the time series can be processed by a recurrent network.

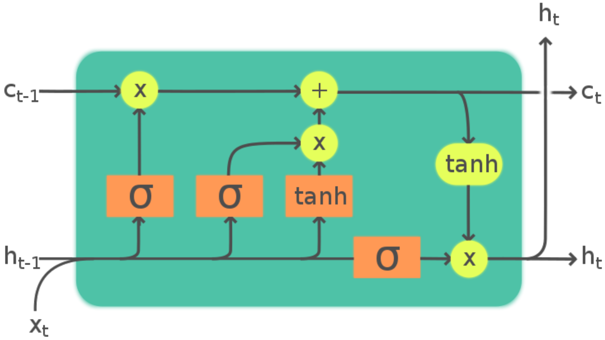
Encoder for the time of arrival



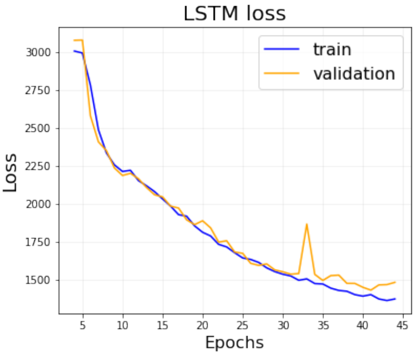


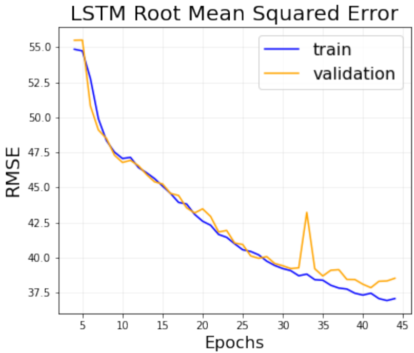
LSTM

LSTM (*Long Short Term Memory*) cell is a variant of a typical recurrent RNN cell. It is able to learn long-term dependencies that brings along in a hidden state.

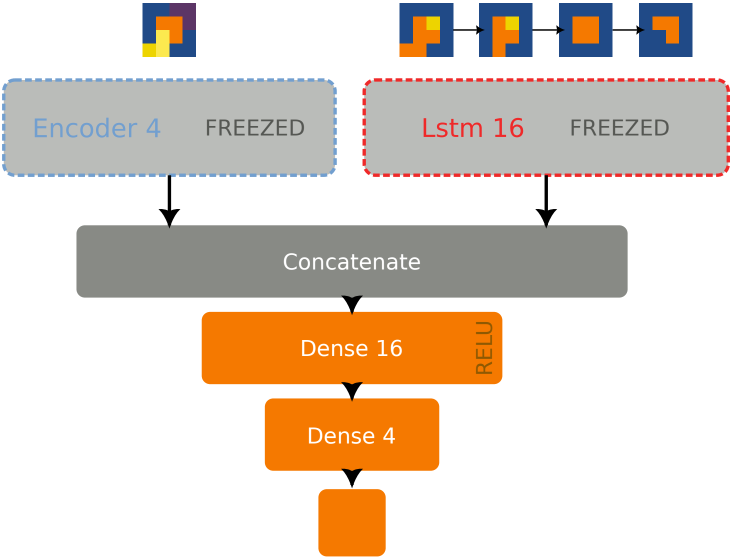


LSTM for the time series

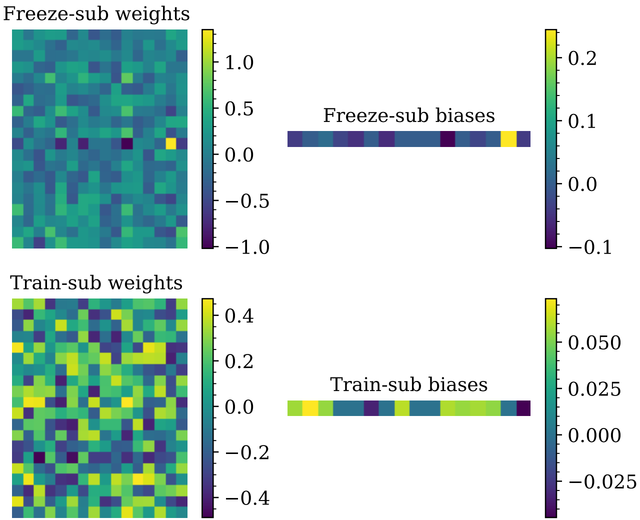




Subnets train freezing



Subnets train freezing



Network's output

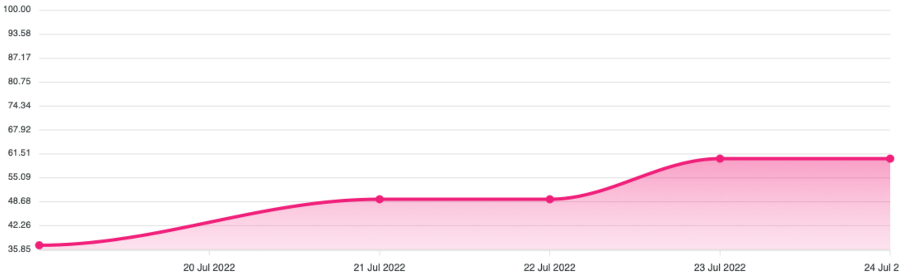
Whole Network performance

Test setup on CircleCI

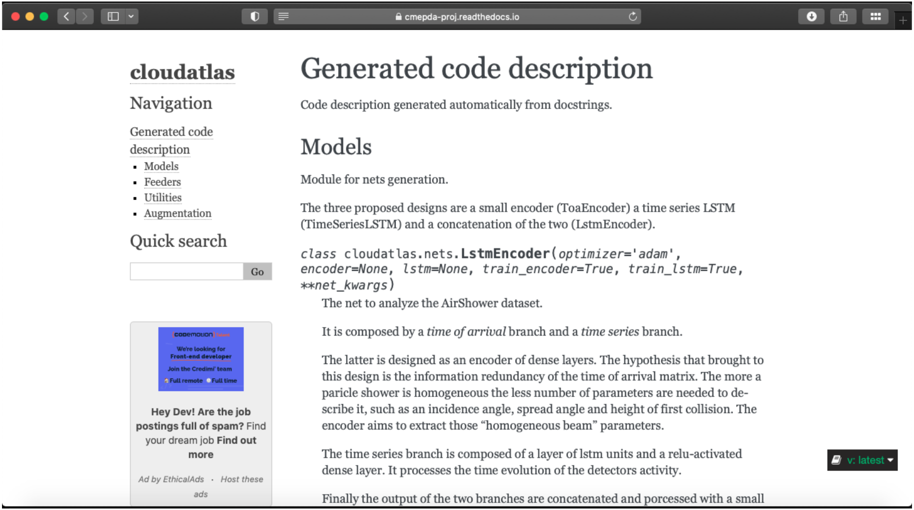
We covered $\sim 60\%$ of the whole project, main test ideas are for training classes and functions with a fititious smaller dataset.
Main tests:

-
-
-
- **Augment test**: tests if an augmented matrix is effectively "rotated", "flipped", etc.

Code coverage



Documentation


cmepda-proj.readthedocs.io

cloudatlas

Navigation

- Generated code description
  - Models
  - Feeders
  - Utilities
  - Augmentation

Quick search

Go

Generated code description

Code description generated automatically from docstrings.

Models

Module for nets generation.

The three proposed designs are a small encoder (ToaEncoder) a time series LSTM (TimeSeriesLSTM) and a concatenation of the two (LstmEncoder).

```
class cloudatlas.nets.LstmEncoder(optimizer='adam', encoder=None, lstm=None, train_encoder=True, train_lstm=True, **net_kwargs)
```

The net to analyze the AirShower dataset.

It is composed by a *time of arrival* branch and a *time series* branch.

The latter is designed as an encoder of dense layers. The hypothesis that brought to this design is the information redundancy of the time of arrival matrix. The more a paricle shower is homogeneous the less number of parameters are needed to describe it, such as an incidence angle, spread angle and height of first collision. The encoder aims to extract those "homogeneous beam" parameters.

The time series branch is composed of a layer of lstm units and a relu-activated dense layer. It processes the time evolution of the detectors activity.

Finally the output of the two branches are concatenated and porcessed with a small

v: latest

Danke e bibliography

Danke Schon