LSTM Tagger

Philipp Windischhofer

January 8, 2017

The Setup

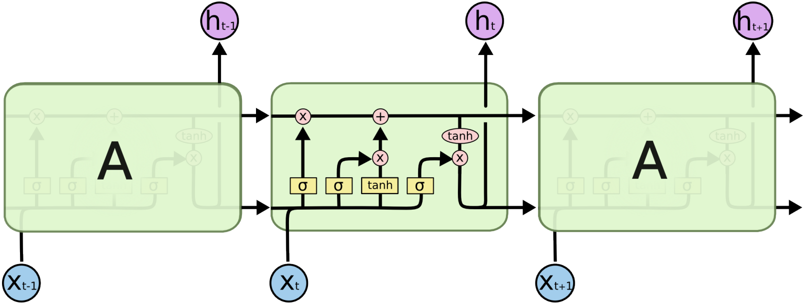
Goal

Train a binary neural-network based classifier that can distinguish between *b*- and non-*b*-jets, using the raw jet data as input.

- use *tracks* as the primary source of information
- number of tracks is unknown a-priori → cannot use an architecture that expects a fixed number of inputs
- currently looking into recurrent neural networks / LSTM networks

LSTM-Networks

A special kind of recurrent neural network with a more complex internal structure...



see http://colah.github.io/posts/2015-08-Understanding-LSTMs/

The Workflow

Training

- match tracks to their associated jets (contained in different ROOT trees)
- for each track in the jet, feed all 8 available track parameters into the classifier network during training
  - use p_T ordering, i.e. hardest track first
- supervised training: provide a binary (0/1) output value for each jet (from MC truth)

Now running on Piz Daint:

- roughly 2-3 $\times$ improvement in execution speed compared to PSI/Tier-3
- limited by Jet-Track-matching, which is handled by the CPU
- possible workaround: train multiple classifiers during the same run “in parallel”

The Workflow
Evaluation

- compare performance to cMVA tagger as "gold-standard"
- obtain ROC curves for both classifiers, correlation plots of the outputs
- currently: validation data is disjoint from training data, but from the same MC-run (i.e. contains a similar event signature)

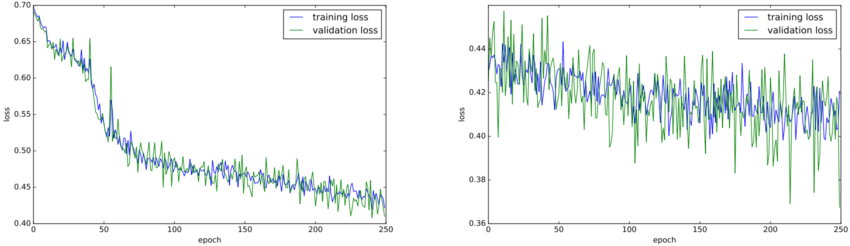
Results so far

- trained a number of LSTM networks, scanned the hyperparameters:
  - number of nodes in each layer
  - number of layers
  - number of training epochs

Details of the training:

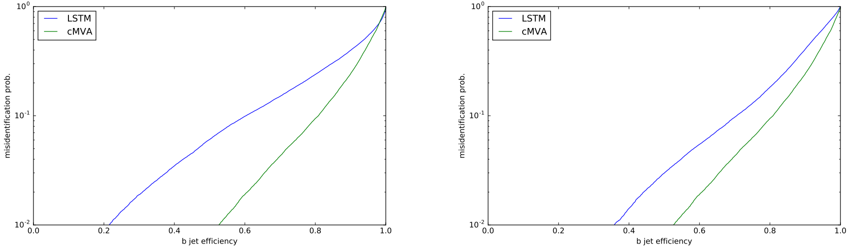
- read training data in chunks of 10k jets
- use 8k jets for training, 2k jets to monitor performance during each epoch

64 nodes / layer, 1 layer



Loss function (binary cross-entropy) for epochs 1-250 (left) and 250-500 (right).

64 nodes / layer, 1 layer

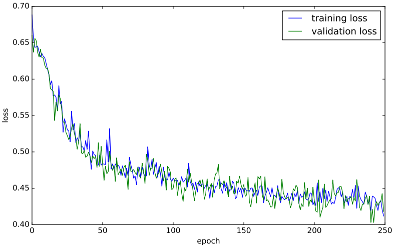


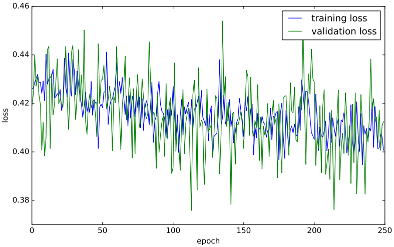
ROC after 250 (left) and 500 training epochs (right) in comparison with the cMVA tagger.

Area under curve:

- AUC(cMVA) = 0.9233
- AUC(LSTM) = 0.8794

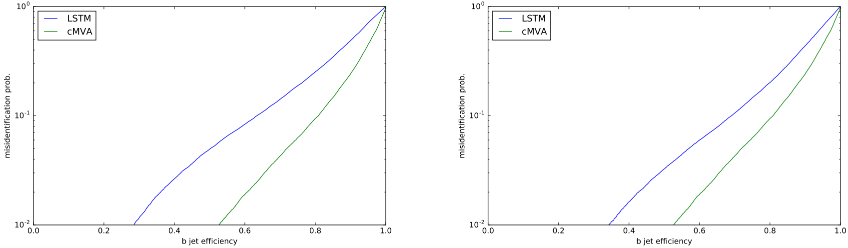
64 nodes / layer, 3 layers





Loss function (binary cross-entropy) for epochs 1-250 (left) and 250-500 (right).

64 nodes / layer, 3 layers



ROC after 250 (left) and 500 training epochs (right) in comparison with the cMVA tagger.

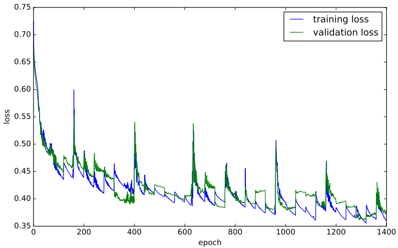
Area under curve:

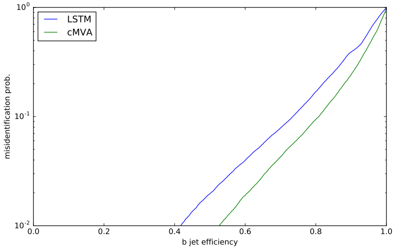
- AUC(cMVA) $= 0.9233$
- AUC(LSTM) $= 0.8704$

64 nodes / layer, 3 layers

A different training strategy

Use 40 training epochs per 10k chunk (35 chunks in total):





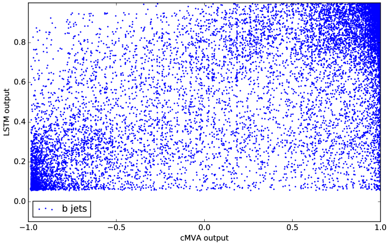
Loss function evolution (left) and ROC plot after completed training (right).

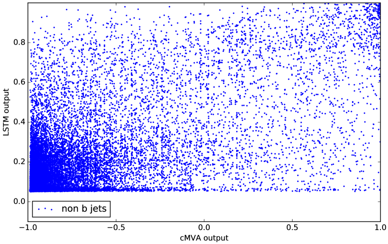
Area under curve:

- AUC(cMVA) $= 0.9233$
- AUC(LSTM) $= 0.888$

64 nodes / layer, 3 layers

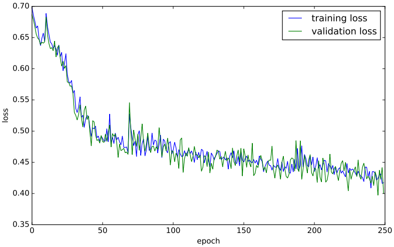
Output compared to cMVA, modified training strategy





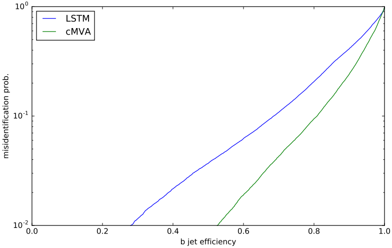
Output of the LSTM tagger in comparison with the cMVA output: signal events shown left, background right.

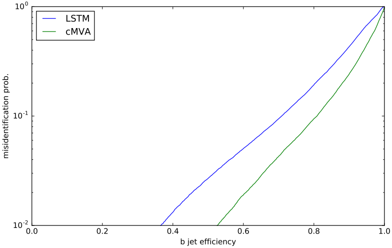
128 nodes / layer, 1 layer



Loss function (binary cross-entropy) for epochs 1-250 (left) and 250-500 (right).

128 nodes / layer, 1 layer



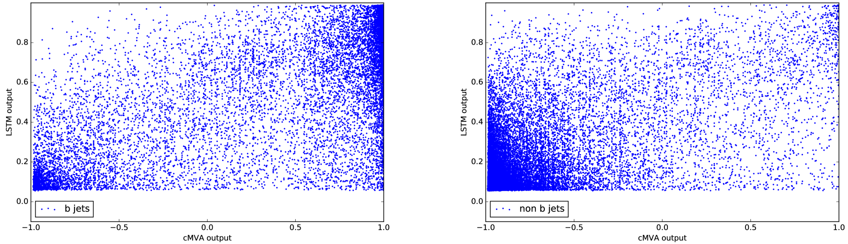


ROC after 250 (left) and 500 training epochs (right) in comparison with the cMVA tagger.

- AUC(cMVA) = 0.9233
- AUC(LSTM) = 0.8737

128 nodes / layer, 1 layer

Output compared to cMVA



Output of the LSTM tagger in comparison with the cMVA output: signal events shown left, background right.

Conclusions

- basic infrastructure seems to be in place and working
- classifier performance is very similar across the different networks that were evaluated
  - training just not complete? Use still more epochs even if loss doesn't seem to improve much anymore?
  - or is performance limited by the data representation / preprocessing rather than the network architecture?

Future Experiments

- more sophisticated preprocessing?
- different representation (other than the raw track data)?
- try removing individual track parameters to see how performance degrades