Human Motion Prediction

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ABSTRACT

This paper provides a sample of a LaTeX document which conforms, somewhat loosely, to the formatting guidelines for ACM SIG Proceedings.

1 INTRODUCTION

Motion prediction is one of the tasks that is automatically done by humans but very hard to accomplish by machines. While even insects already have a physical model of the world, either learnt or predefined, we have to teach it to machines. Applications: human-computer interaction, motion synthesis, motion prediction for virtual and augmented reality. ... Using a single LSTM cell we build the most basic RNN network for human motion prediction and took this as our baseline for improvements.

2 RELATED WORK

Recent work focused on RNN based architectures to model human motion, with the goal of learning time-dependent representations that perform tasks such as short term motion prediction.

Julieta Martinez 2017: Trained encoder and decoder together with shared weights, single GRU. Used velocities through a residual architecture. Error reduction: fed predictions of the net back [3]

Fragkiadaki 2014: introduced an encoder-decoder (ERD) network, which is a type of recurrent neural network (RNN) model, that combines representation learning with learning temporal dynamics [2].

Sutskever 2014 (Sequence to sequence learning with neural networks): Deep LSTM's significantly outperform shallow LSTMs. They used therefore 4 layers. They also reversed the order of word inputs and would then perform better on long sentences. Stochastic gradient, 7.5 epochs, same length of input vector in batches: speed up of training. Best result with ensemble of LSTM that differ in their random initialization and in the random order or minibatches. [4]

Buetepage: [1]

3 METHODOLOGY

Input from assistant (Manuel Kaufmann):

- We won't be able to beat the hard baseline with a simple RNN cell (which I guessed after several runs with many different paramenters and I couldn't even beat your score)
- We should implement Seq2seq model
- Normalization/Standardization important
- One of the tasks of this exercise is to figure out if one-hot encoding of activity improves the performance

What I have done so far: I'm slow in python, sorry for that...

- Pushed your code to master
- Created new branch where I did all the changes.
- Wrote function in util.py to get mean, std, and dIlya Sutskever 2014:
  imensions where std is smaller than 10e-4
- Wrote function in util.py to standardize data
- If preprocess is on, we standardize input data and ignore the dimensions where std is almost zero, we also ignore those dimensions in the target. Test/eval still to do...
- One-hot encoding of activity labels. Has to be done after standardize data. Wrote the function to add one-hot vector. Need to get rid of those rows for validation error.
- Added model class for many layer LMTS with dropout option, but haven't tested model yet.
- Trying to figure out how to implement easy sequence to sequence model as another model class.

Additional comments:

- Our validation error goes down, but the performance on the test set does not improve at all. Why???
- Standardization of data to zero mean and variance of 1: if std is close to zero, what shall we do? Martinez ignored those dimensions for training so that is what I did as well... Where do we need to do the de-normalization of the data?
- Seq2seq model?
- Human motion is dynamic. I would love to use velocity and acceleration in the model. But this is probably too hard to do.

3.1 Preprocesssing and representation

3.2 Network structure

(1) Standardization
(2) One-hot encoding
(3) One to multilayer LSTM
(4) With /without dropout
(5) Seq2Seq model

4 EXPERIMENTS

5 CONCLUSION

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This is an abstract footnote

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