Research Track

Time series forecasting of Building Energy Load using deep LSTM recurrent networks.

Hugo PREVOTEAU
Christophe HAIKAL
Théo DEMESSANCE
Valentin TASSEL

Problematic

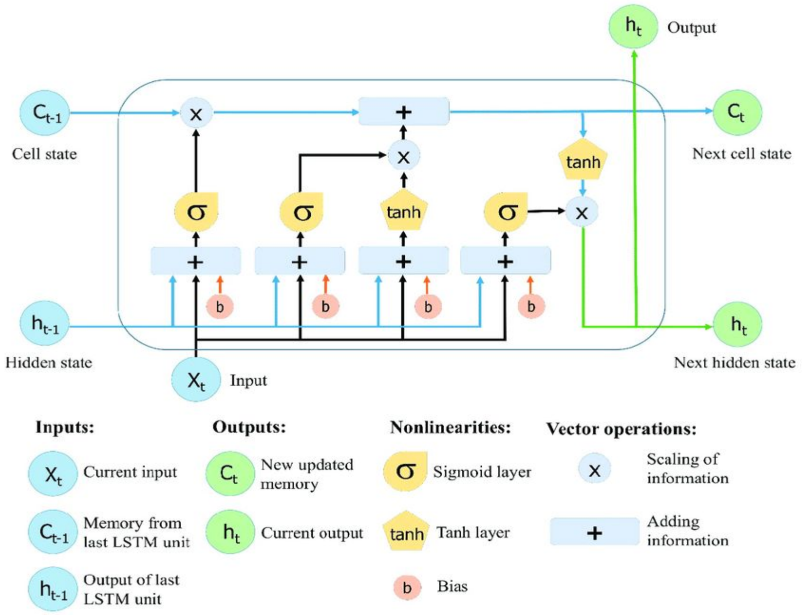
Define which architecture is the most suitable for the study of energy load, with different time stamp information, given two LSTM architectures: Standard LSTM and Seq2Seq.

LSTM

LSTM maintains RNN's ability to learn the temporal dynamics of a sequential data

LSTM can handle the vanishing and exploding gradients problem.

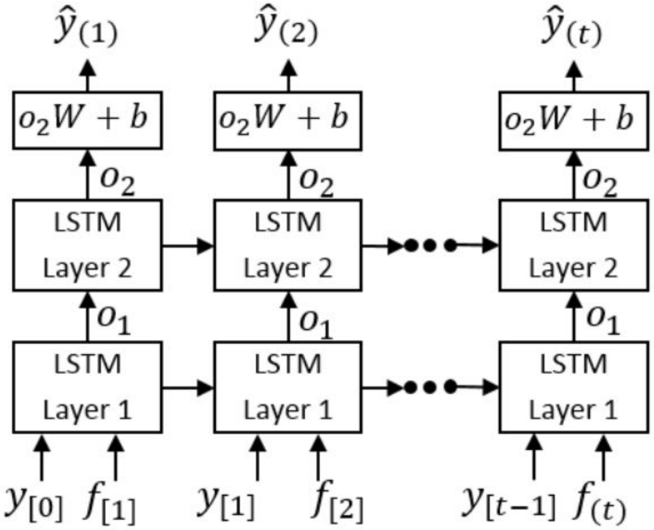
3 gates : Input, Forget, Output



Standard LSTM

Back-propagation through time (BPTT) is used

The network is unrolled by a fixed number of time steps



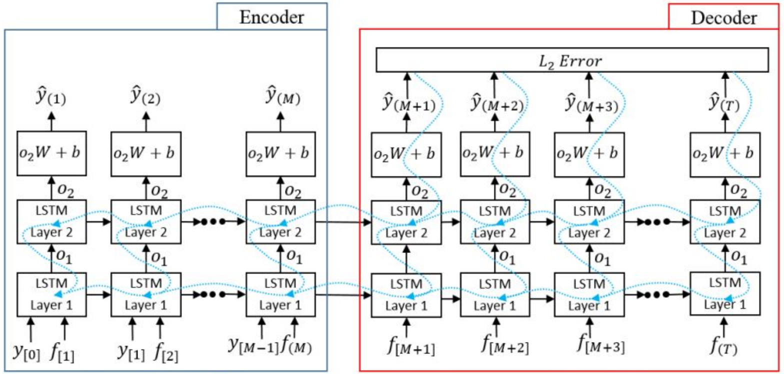
(b)

LSTM based Seq2seq

Map sequences of different lengths

Convert input sequences of variable length to fixed length vector

Historical electricity load data used with corresponding date and time



Dataset

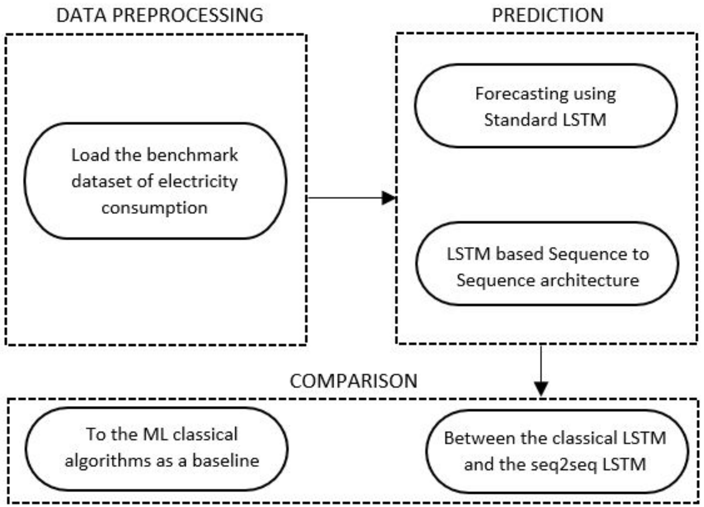
Two datasets are used:

1. consumption of a residential customer every minute
2. the other one every hour.

Time Stamp	Consumption
2016-12-25 09:00	1,20
2016-12-25 10:00	1,30
2016-12-25 11:00	1,10
2016-12-25 12:00	1,34
2016-12-25 13:00	1,31
2016-12-25 14:00	1,28

Table: benchmark data set of electricity consumption

Proposed method



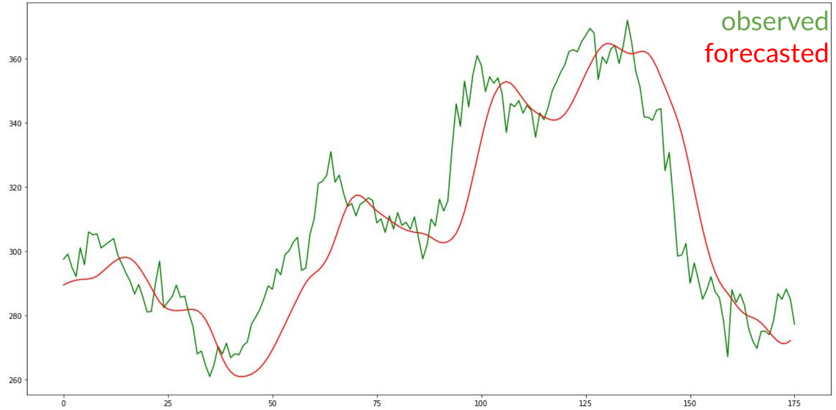
Experiments

1 → Simple LSTM
→ Seq2Seq

2 → Simple LSTM
→ Seq2Seq

MAE: Mean Absolute Error
MSE: Mean Squared Error
RMSE: Root Mean Squared Error
MAPE: Mean Absolute Percentage Error

Given Predicted



		Standard LSTM				Seq2Seq			
number of layer	number of units	MAE	MSE	RMSE	MAPE	MAE	MSE	RMSE	MAPE
1	20	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-

Results

- Simple LSTM performs poorly on the dataset with 1, while performing well on dataset 2
- Seq2Seq performs well on both datasets

SOA: Comparison with the baseline

Thanks for your attention

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