Master Thesis: *Natural gas price forecasting using recurrent neural networks*

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Outline

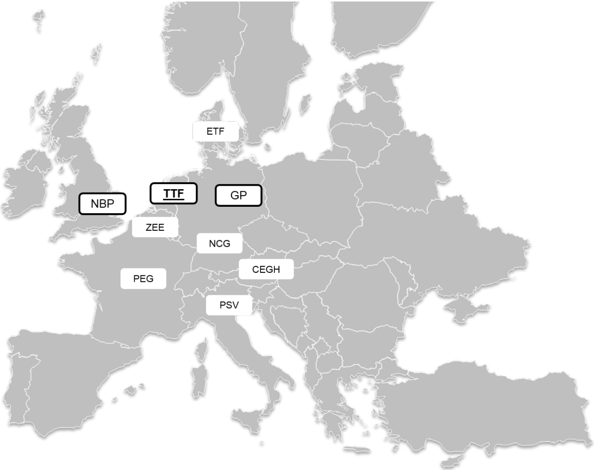
Motivation

- *Methodology:* Evaluate the value of Long Short Term Memory Recurrent Neural Networks for time series prediction
  - Compare performance to simple RNN, FFNN, and linear reference models
- *Application:* Support natural gas traders in choosing the optimal trading strategy
  - Trading as part of industrial procurement to meet physical demand
  - No speculative trading

Description of the target variable / gas prices

- Different types of natural gas futures differ in various ways
- The **Virtual Trading Point** describes in which part of the European natural gas transport network the gas is delivered
- The **Delivery Period** describes during which time frame the gas is delivered at a constant rate
- The target variable is the future price of gas traded at the **TTF** VTP for delivery in the **next calendar month**.

Virtual Trading Points

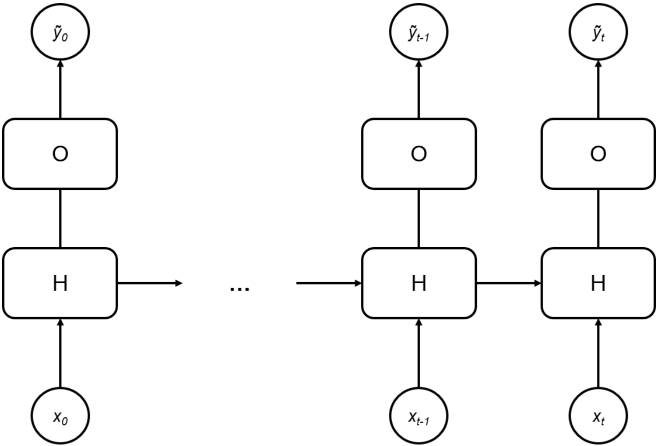


Price History TTF Front Month

Why RNN ?

- FFNN can only learn static input-output mappings
- For machine learning problems based on sequential data the input-output mapping should be dynamic
- Examples of sequential data: Text, Speech, Videos, Financial Time Series
- RNN's are able to learn dependencies of arbitrary length, which does not need to be specified.
- Main idea: use hidden layer output at one time point as input to the hidden layer at the next input

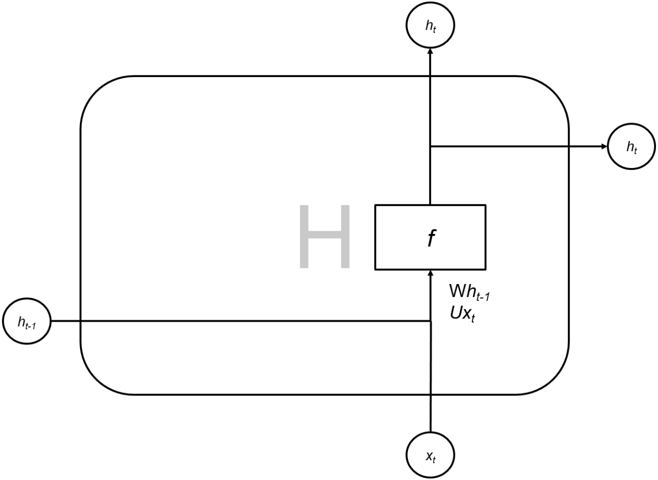
General Layout



Simple RNN

- Different types of RNN differ in the way they connect the hidden layers between time steps
- The simplest variant treats the previous output h_t in the same way as the other inputs x_t
- $h_t = f(Wh_{t-1} + Ux_t)$

Hidden Layer of Simple RNN



Vanishing Gradient Problem

- Recursive definition of the hidden layer can be expanded:
  - $h_t = f(Wh_{t-1} + Ux_t)$
  - $h_t = f(Wf(Wh_{t-2} + Ux_{t-1}) + Ux_t)$
- Repeated application of chain rule:
  - $\frac{h_t}{dW_{ij}} = \frac{df(z)}{dz}(\frac{dW}{dW_{ij}} h_{t-1} + W \frac{dh_{t-\mathbf{1}}}{dW_{ij}})$
  - $\frac{h_t}{dW_{ij}} = \frac{df(z)}{dz}(\frac{dW}{dW_{ij}} h_{t-1} + W \frac{df(z)}{dz}(\frac{dW}{dW_{ij}} h_{t-2} + W \frac{dh_{t-\mathbf{2}}}{dW_{ij}})$

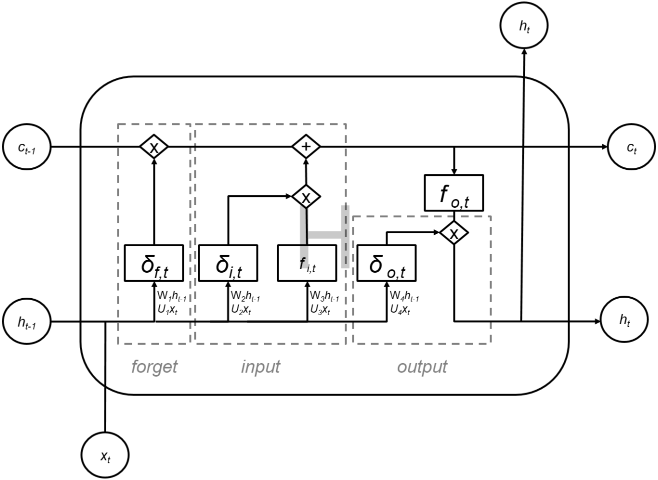
Vanishing Gradient Problem

- Contribution of $\frac{dh_{t-k}}{dW_{ij}}$ is multiplied by $(\frac{df(z)}{dz})^k W^{k-1}$
  - Exponential behaviour leads to either *exploding* or *vanishing gradient problem*
  - *Exploding* case can be controlled relatively easily by clipping the gradient
  - No solution of *vanishing gradient problem* in this model set-up
  - RNNs unable to learn long term dependencies

LSTM

- Long Short Term Memory Networks try to overcome this problem by introducing the cell state c_t
  - c_t is manipulated in different *gates*
  - In each gate c_t is multiplied by or added to the output of a layer of neurons with trained weights
- Formal definition:
  - $h_t = \sigma_o(W_4 h_{t-1} + U_4 x_t) * f_o(c_t)$
  - $c_t = \sigma_f(W_1 h_{t-1} + U_1 x_t) * c_{t-1} + \sigma_i(W_2 h_{t-1} + U_2 x_t) * f_i(W_3 h_{t-1} + U_3 x_t)$
- LSTM does not suffer from *vanishing gradient problem* but has four times as many parameters to train with same input data.

Hidden Layer of LSTM



Data Overview

- All Data was downloaded from the *Thomson Reuters Eikon* data base.
- **Energy Commodity Prices:** Target variable, other gas futures, Brent Oil Futures, Coal Futures, Electricity Base / Peak futures
- **Exchange Rates:** EUR/GBP, EUR/USD
- **Gas Market Fundamentals:** Storage Levels, Pipeline Flows, National Consumption / Production Data
- All data as daily values (Closing prices) starting between 2010 - 2014.

Training / Tuning Approach

1. Parameter Tuning of univariate models
   - Single Train / Test split
   - Training Data 2010 - 2015 / Test Data: 2016
   - Tuning of: Network Architecture, Dropout, Learning Rate
2. Variable Selection of multivariate models
   - Use tuned parameters from respective univariate model
   - Forward variable selection based on MSE
   - Same Train / Test split as above
3. Parameter Tuning of multivariate models
   - Use previously selected input variables
   - Same parameters / data as in univariate case
4. Model evaluation
   - Month wise cross validation with testing months selected from 01 - 08/2017

Predicting Price Levels

- Predict tomorrows closing price of the TTF Front Month future based on all data available up to the current day
- The MSE loss function is minimized using stochastic gradient descent
- Linear Reference Model: AR(1)
  - Parameter estimate very close to 1, predictions almost identical to current price value

Price Level Prediction Results

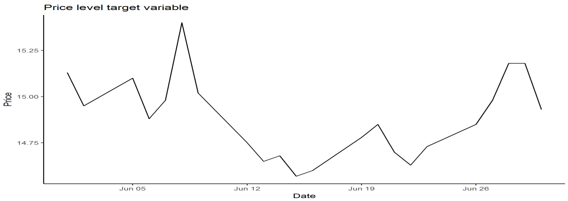
	Model	Variables	MSE	MSEReference
1	lstm		0.143	0.151
2	rnn		0.150	0.151
3	ffnn_long		0.151	0.151
4	ffnn_long	EURGBPFX_EURUSDFX_TradeIUK_TradeRUNWE	0.152	0.151
5	rnn	TTFDA	0.154	0.151
6	ffnn_short		0.162	0.151
7	ffnn_short	EURGBPFX_TTFDA_ProdNL_TradeBBL_NBPFM	0.162	0.151
8	lstm	TradeIUK	0.181	0.151

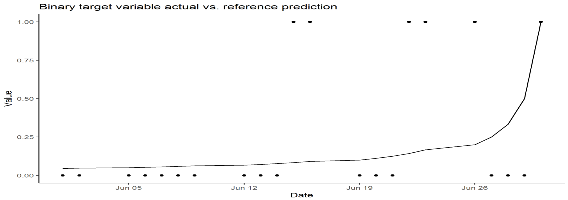
Table 1: Test Results using monthly cross validation of tuned models for data 01 - 07/2017

Binary Prediction

- **Problem:**
  - Decision Problem: Buy today or at any other day before the end of the month to cover physical demand
  - Once bought, futures can't be sold again (Company Policy, Regulation).
  - Therefore optimal trading strategy can't be derived directly from tomorrows price level
- **Solution:**
  - New binary target variable: *Is today's closing price minimal among all closing prices for the rest of the month ?*
  - Yes - 1, No - 0
  - Loss Function: Binary Cross Entropy
  - Naive reference model: $\tilde{y}_i = \frac{1}{N_i}$ with N_i the remaining trading days for this month

Binary Prediction





Binary Prediction Results

	Model	Variables	CrossEntropy	CrossEntropyReference
1	mlp_long	EURUSDFX	0.447	0.497
2	rnn	EURGBPFX	0.454	0.497
3	ffnn_short	ElectricityBaseFM_EURUSDFX	0.454	0.497
4	lstm		0.468	0.497
5	lstm	ProdUKCS	0.469	0.497
6	rnn		0.486	0.497
7	ffnn_short		0.487	0.497
8	ffnn_long		0.517	0.497

Table 2: Test Results using monthly cross validation of tuned models for data 01 - 07/2017

Conclusions

- Among univariate models LSTM outperforms alternative models in both prediction problems
- Among multivariate problems opposite seems to be the case
- Univariate LSTM shows best relative performance in Price Level Prediction where it is the only model to significantly outperform the Linear Reference
- Univariate models seem to be better in Price Level Prediction where the opposite is true for the binary case.

Conclusions

There are several ways for possible extension / improvement

- Extend parameter tuning to choice of optimizer, activation, length, batch size etc.
- Extend parameter tuning to include multi-level architectures
- Use a finer tuning grid for the current parameters
- Use Cross Validation during parameter tuning

Comments

- Model Training / Tuning: Python (Keras, Tensorflow), Result Analysis: R
- Running models on Amazon Web Services, is easier / cheaper than expected and frees valuable resources on local machine
- Valuable Resources on LSTMs and implementation in Python:
  - BlogPost *Understanding LSTM Networks*: http://colah.github.io/posts/2015-08-Understanding-LSTMs/
  - ML Blog *Machinelearningmastery*: https://machinelearningmastery.com/

Binary Prediction Univariate parameter tuning

	Model	Architecture	Dropout	LearningRate	binary_crossentropy
1	lstm	16	0.250	0.001	0.450
2	rnn	8	0.250	0.001	0.449
3	mlp_long	32	0.000	0.001	0.468
4	mlp_short	8	0.000	0.010	0.473

Table 3: Best parameter combinations for each binary model

Binary Prediction Variable Selection

	Model	Variables	binary_crossentropy
1	lstm	ProdUKCS	0.45
2	rnn	EURGBPFX	0.44
3	mlp_long	EURUSDFX	0.47
4	mlp_short	ElectricityBaseFM_EURUSDFX	0.47

Table 4: Best variable combinations for each binary model

Binary Prediction Multivariate parameter tuning

	Model	Variables	Architecture	Dropout	LR	CE
1	lstm	ProdUKCS	32	0.500	0.001	0.452
2	rnn	EURGBPFX	8	0.250	0.001	0.444
3	mlp_long	EURUSDFX	32	0.000	0.001	0.478
4	mlp_short	ElectricityBaseFM_EURUSDFX	16	0.000	0.010	0.461

Table 5: Best parameter combinations for each binary model

Price Level Prediction Univariate parameter tuning

	Model	Architecture	Dropout	LearningRate	mse
1	lstm	8	0.000	0.001	0.117
2	rnn	8	0.000	0.001	0.122
3	mlp_long	8	0.000	0.100	0.736
4	mlp_short	16	0.000	0.100	0.459

Table 6: Best parameter combinations for each binary model

Price Level Prediction Variable Selection

	Model	Variables	mse
1	lstm	EURUSDFX	0.12
2	rnn	ElectricityBaseFM	0.11
3	mlp_long	TradeRUNWE_ConLDZNL	0.16
4	mlp_short	TTFDA_StorageEU_LNGStockEU_ProdNL	0.22

Table 7: Best variable combinations for each level prediction model

Price Level Prediction Multivariate parameter tuning

	Model	Variables	Architecture	Dropout	LR	ms
1	lstm	EURUSDFX	32	0.250	0.001	0.11
2	rnn	ElectricityBaseFM	8	0.000	0.001	0.14
3	mlp_long	TradeRUNWE_ConLDZNL	16	0.000	0.100	0.18
4	mlp_short	TTFDA_StorageEU_LNGStockEU_ProdNL	8	0.000	0.100	0.17

Table 8: Best parameter combinations for each binary model