CS898 Deep Learning and Application

Deep Learning for Time Series Analysis

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Outline

1. Background Knowledge
2. RNN and LSTM
3. Time Series Analysis
4. Future Works

Part I

Background

Time Series Forecasting

- Time series tracks the movement of the chosen data points
  - A sequence of numerical data points in successive order
  - Such as a S&P 500 index value, over a specified period (1994-2007) with data points recorded at regular intervals (daily, weekly,…)
- Uses historical values and associated patterns to predict future activity
  - Include trend analysis, cyclical fluctuation, and issues of seasonality
  - As with all forecasting methods, success is not guaranteed!
  - Collaborate with fundamental analysis to make trading decision.

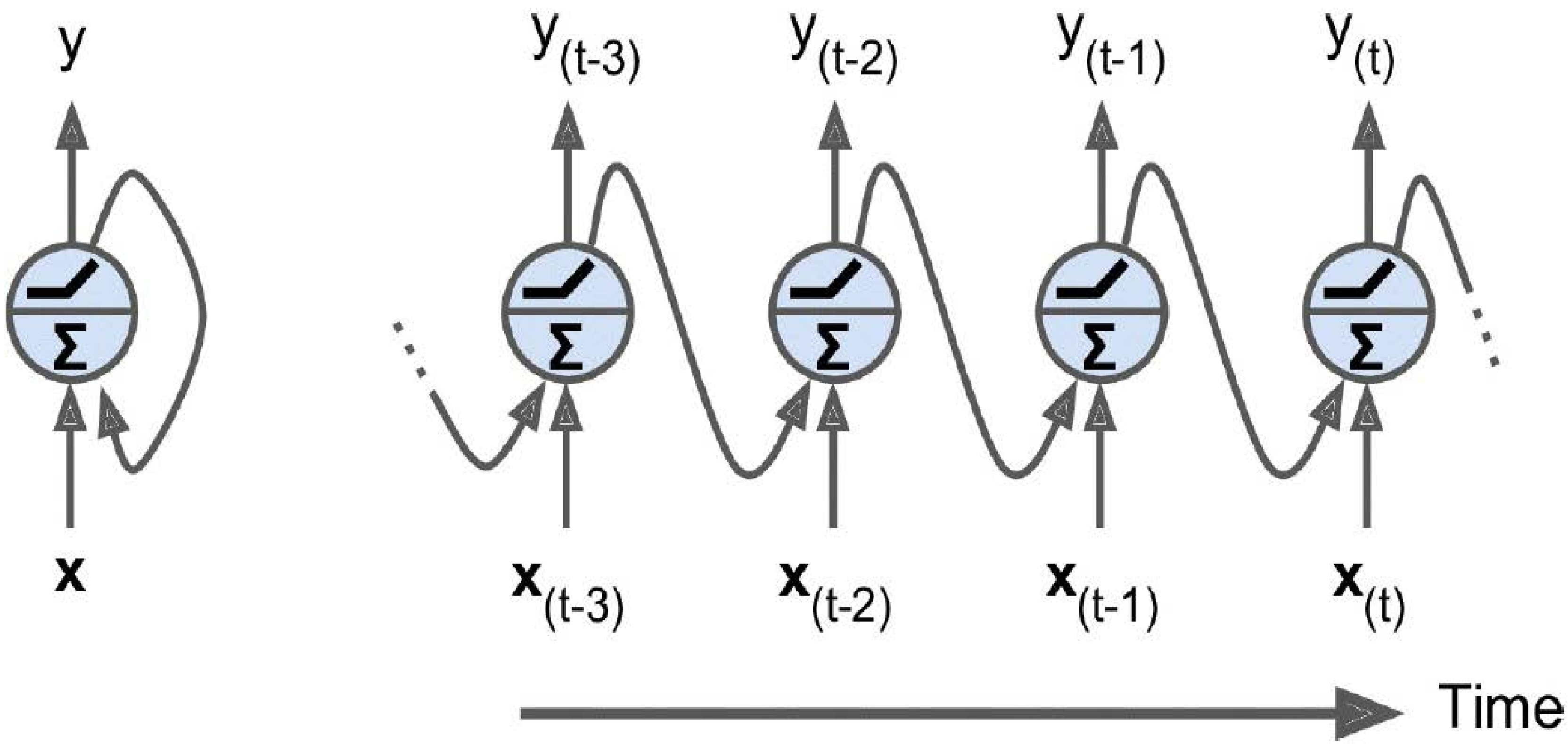
S&P 500 Index

- Standard & Poor's 500 is an American stock market index based on the market capitalizations of 500 large companies, seen as a leading indicator of U.S. equities and a reflection of performance of large-cap sector of the market.
- Analysts and economists at Standard & Poor's select 500 stocks by considering factors as market size, liquidity and industry grouping.
- It uses a market cap methodology, giving a higher weighting to larger companies.
- Products for replicating S&P 500: S&P 500 index funds, S&P 500 ETFs

Part II

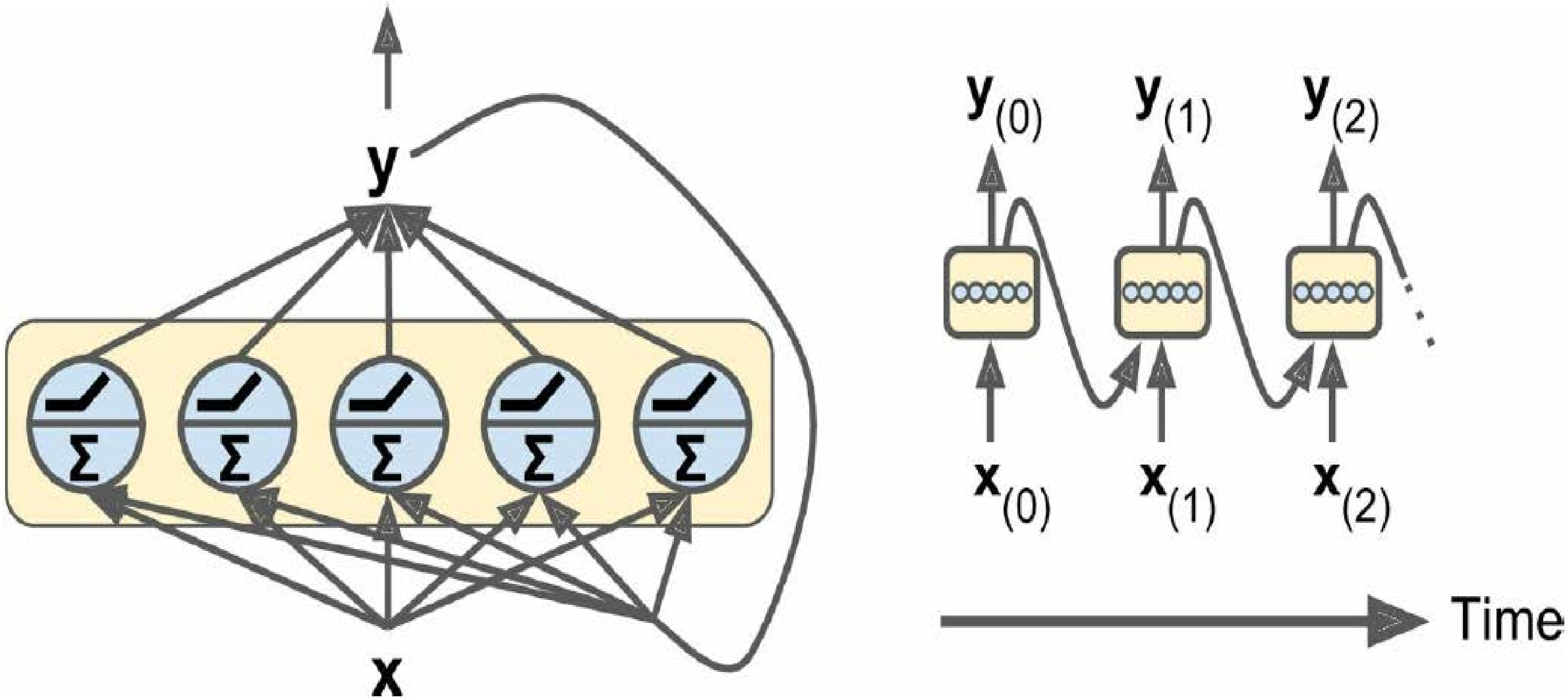
RNN and LSTM

Recurrent Neurons



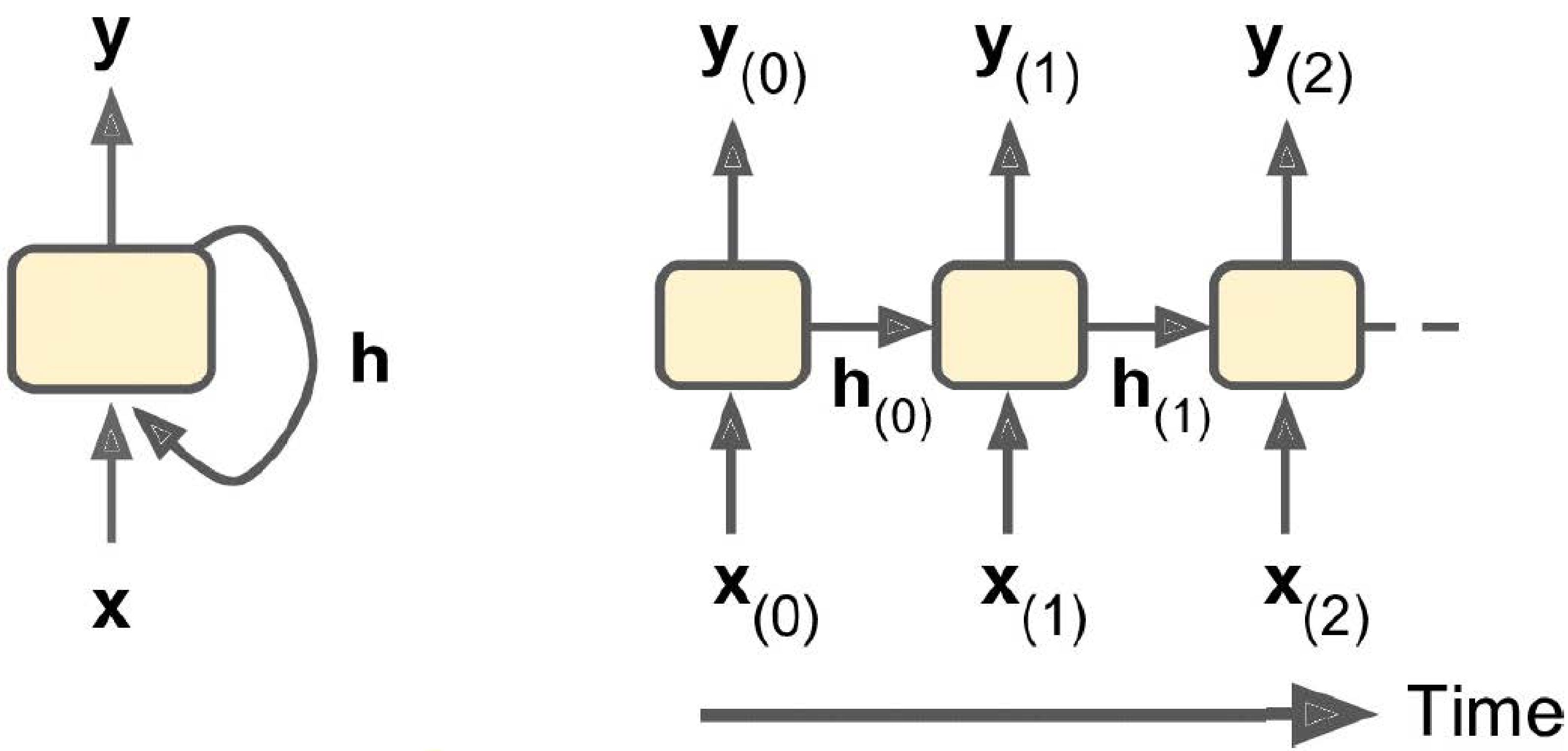
- A recurrent neuron (RN, the simplest possible RNN) on the left is unrolled through time on the right.
- RN looks like feedforward neuron, except it has connections pointing backward.
- At each time step **t**, RN just has one neuron receiving inputs, producing an output, and sending that output back to itself.

A Layer of Recurrent Neurons



- A layer of 5 RNs as a cell, both the inputs and outputs are vectors
- Each RN has 2 sets of weights: 1 for the inputs x(t) and the other for the outputs of the previous time step y(t–1)
- y(t) is a function of x(t) and y(t–1), which is a function of x(t–1) and y(t–2), and so on. So, y(t) a function of all the inputs since t = 0 (x(0),x(1), …, x(t)), and y(-1) is assumed to be all 0.

Memory Cell

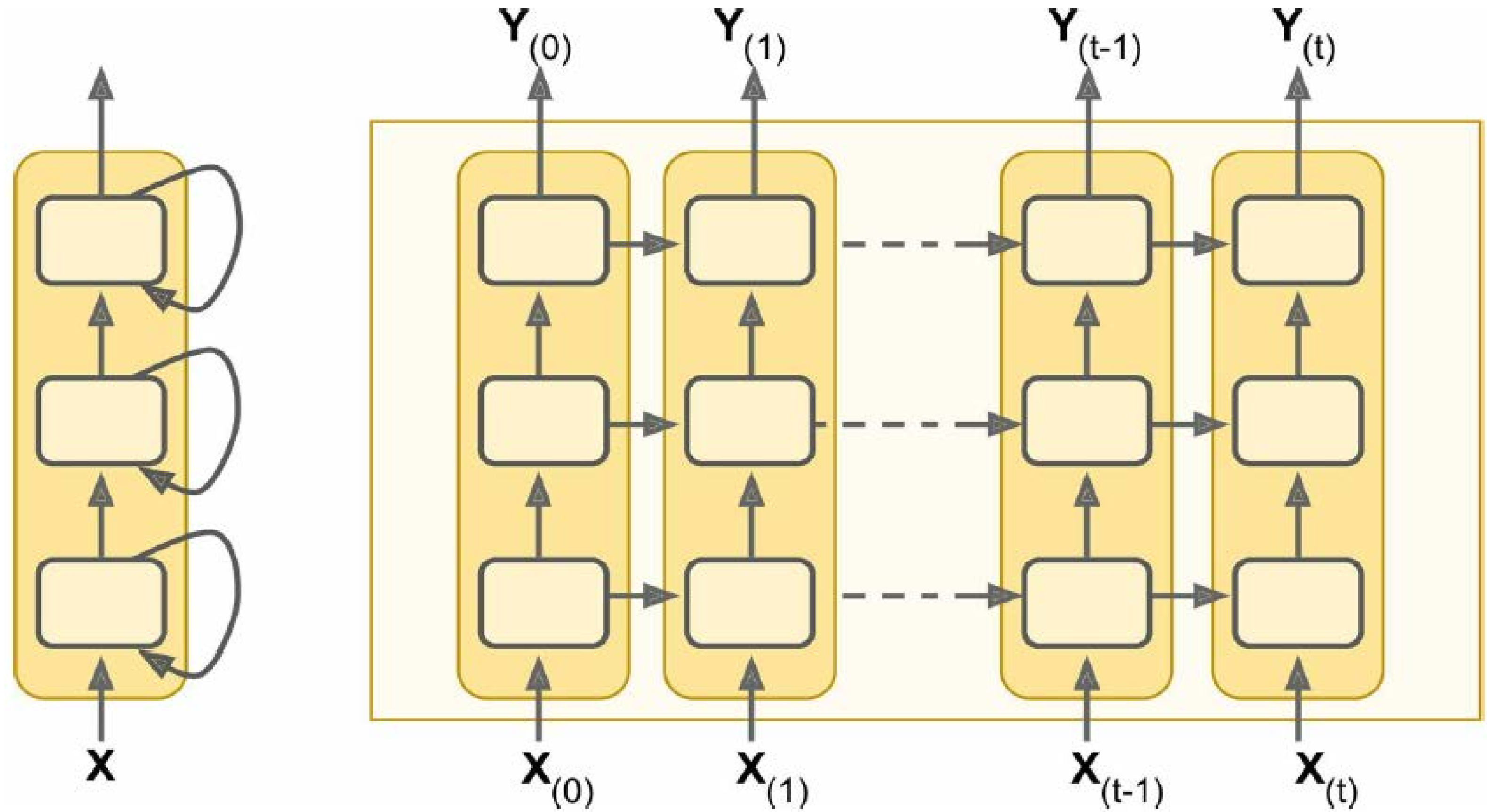


- Since y(t) a function of all the inputs since t = 0, the part of RN preserving states across time axis is a "Memory Cell" ("Cell")
- A cell's sate at t is h(t)=f(h(t-1), x(t)), where x(t) is current inputs, h(t-1) is cell's state at t-1.
- For single RN or a layer of RNs, y(t)=h(t). But for complex cells, y(t)!=h(t), i.e. the LSTM cell

Types of RNN

- Sequence (input) to Sequence (output)
  - Simultaneously take a Seq. of inputs and produce a Seq. of outputs
  - Predicting time series: feed RNN the prices over the last N days, and it output the prices shifted by 1 day into the future (i.e., from N – 1 days ago to tomorrow)
- Sequence (input) to Vector (output)
  - Feed the RNN a Seq. of inputs, and ignore all outputs except for the last one (only output last one)
- Vector (input) to Sequence (output)
  - Feed the RNN a single input at t=0 and zeros for all other time steps, and it output a sequence
- Seq-to-Vec (Encoder), Vec-to-Seq (Decoder)
  - Language Translating: feed the Encoder of RNN a sentence of one language, Decoder of RNN outputs a sentence in another language.

Deep RNN

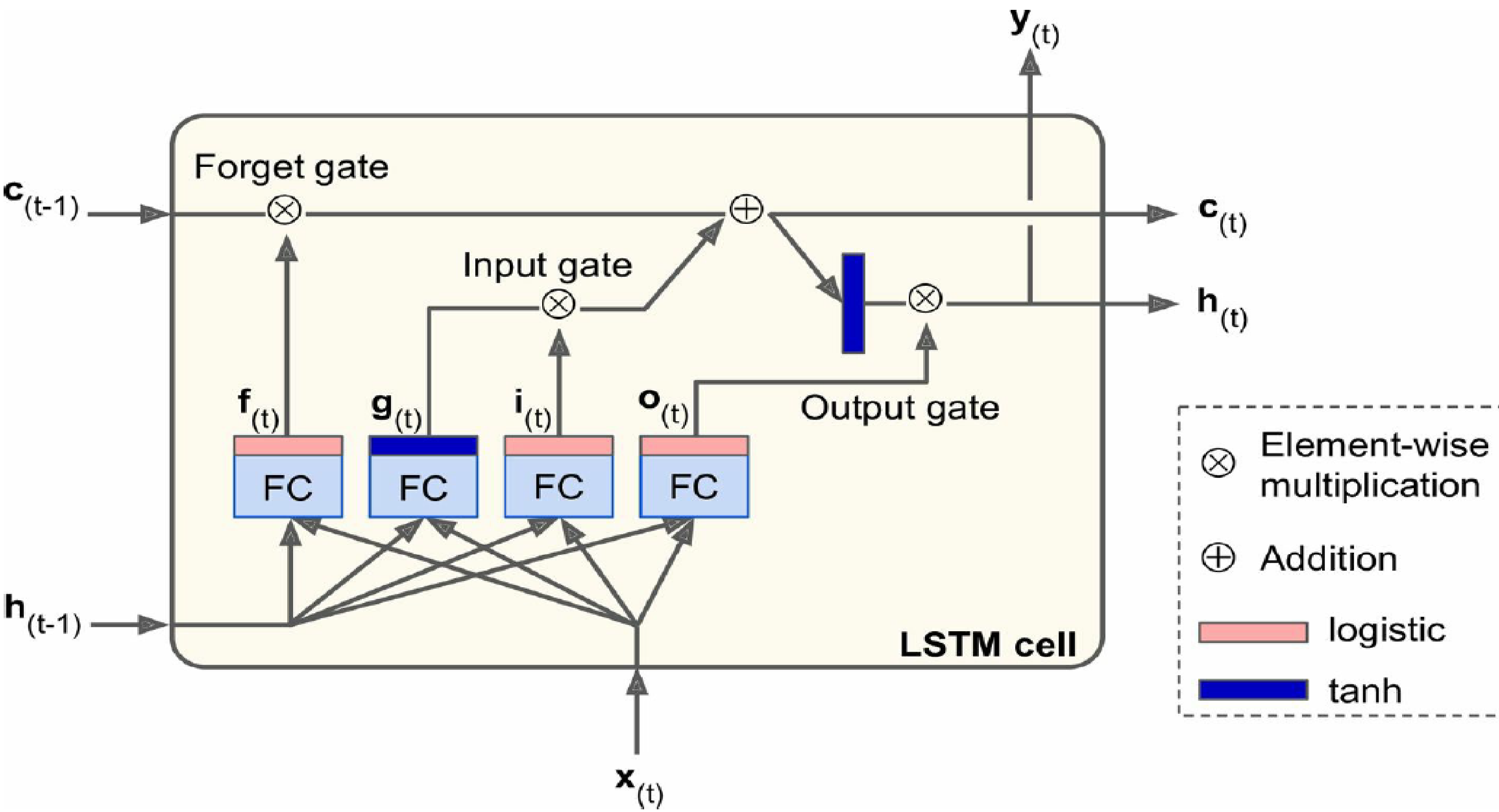


- Stack multiple layers of cells to create a deep RNN
- Stack identical cells into a deep RNN
- Use various kinds of cells (BasicRNNCell, BasicLSTMCell, …) with different number of neurons

Training over Many Time Steps

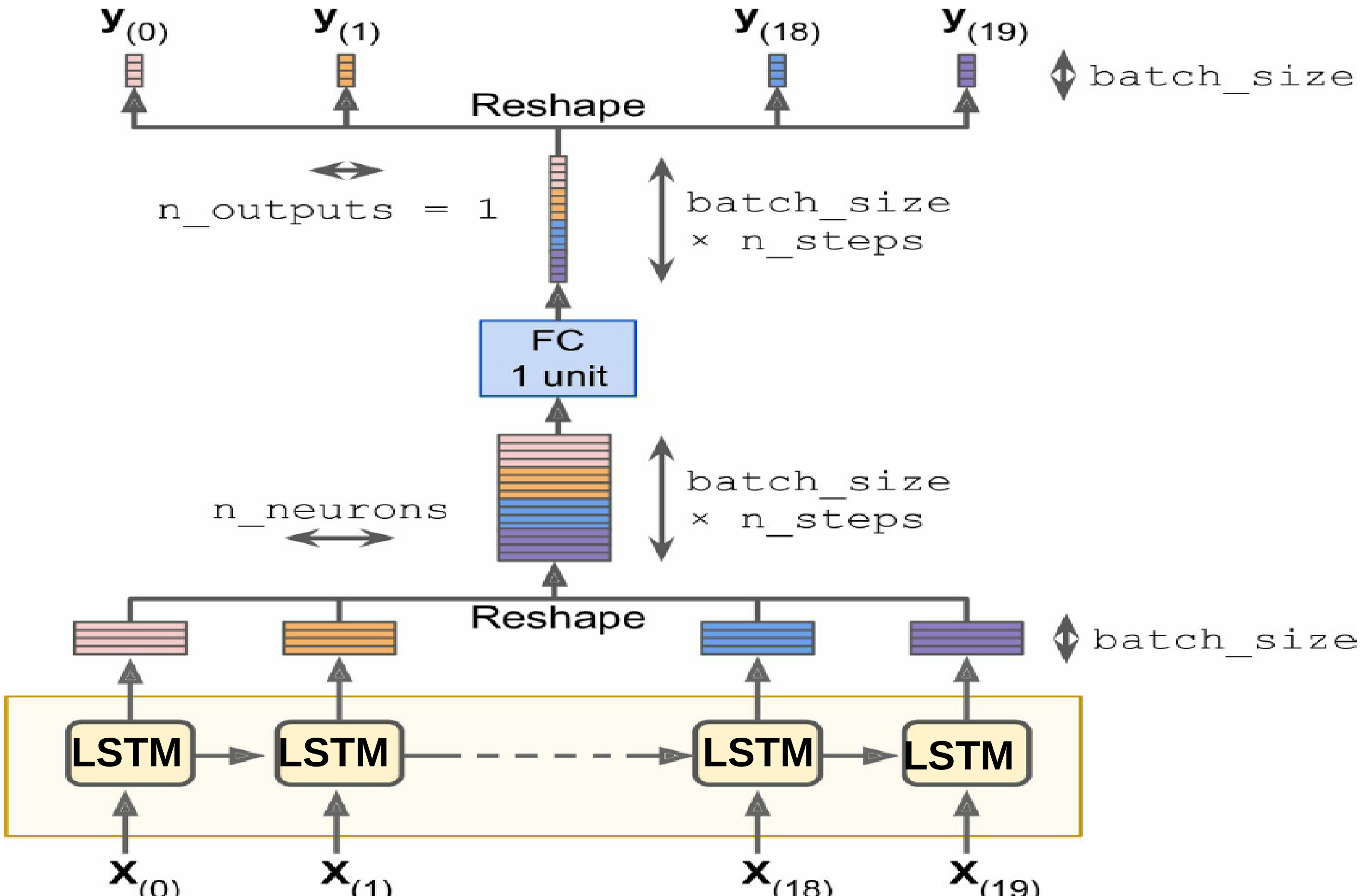
- Suffer from the vanishing/exploding gradients (train forever)
  - Tricks: parameter initialization, ReLU activation function, batch normalization, gradient clipping, faster optimizer
  - Training still be very slow for a moderate long sequence (i.e. 50 steps)
  - Truncated backpropagation through time: unroll the RNN only over a limited number of time steps during training by simply truncating the input sequences
  - Model will not be able to learn long-term patterns.
- Memory of those first inputs gradually fades away
  - Some information is lost after each time step, due to the transformation of data when it traverse an RNN.
  - After a few time steps, RNN's state hardly contains the information from those first inputs.
- A popular solution: Long Short-Term Memory (LSTM)

Basic LSTM Cell



- Its training will converge faster and detect long-term dependencies in the data
- Its state is split in two vectors: h(t) as short-term state, c(t) as long-term state.
- c(t-1) first drop some previous memories, then add some new current memory
- After addition, c(t-1) is copied and passed through "tanh" and "Output gate" o(t)

LSTM Cell for Time Series

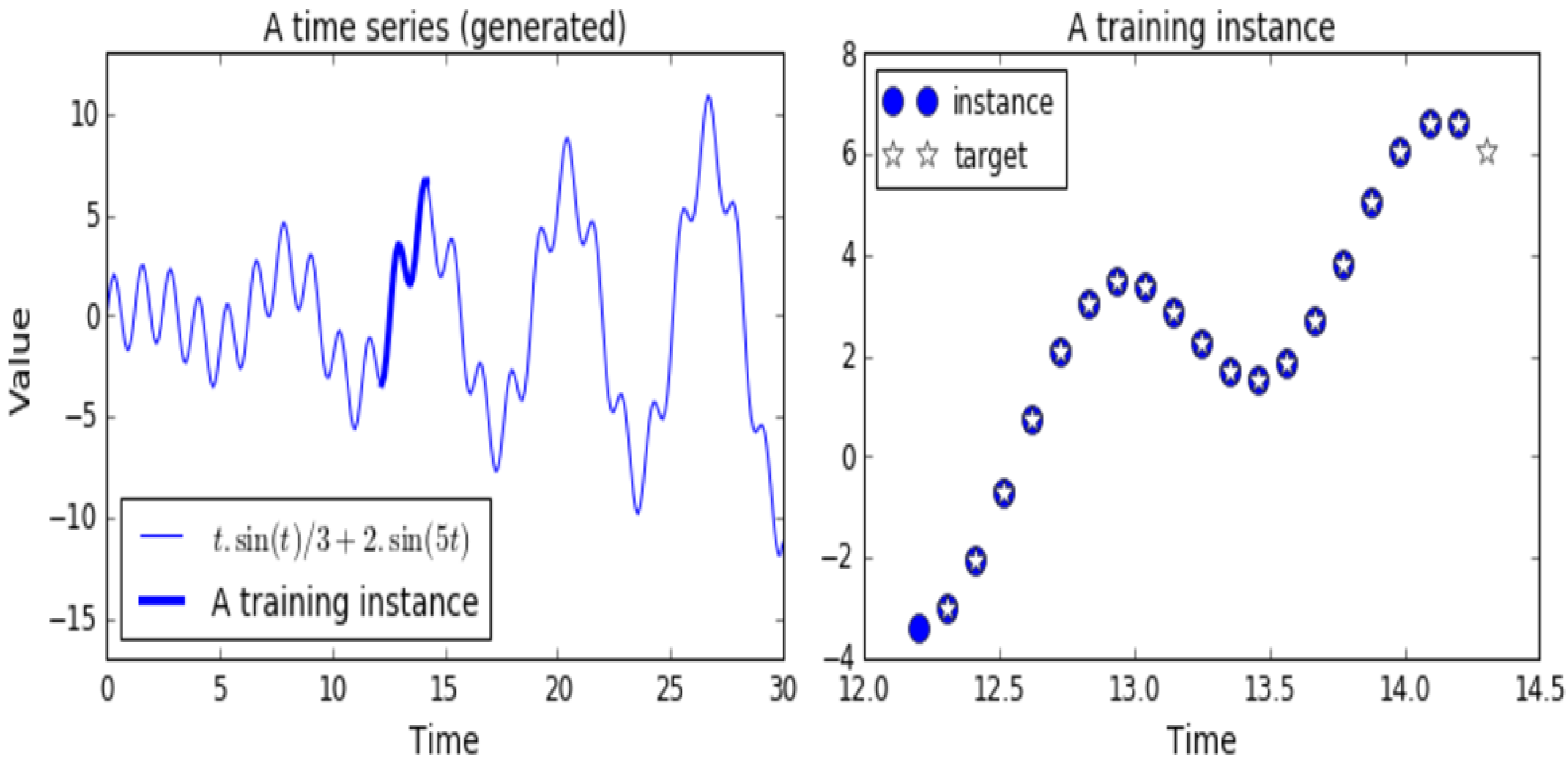


- LSTM has n_neurons neutrons and unroll over 20 steps, 4 instances per batch
- Stack all the outputs of 20 time steps, projecting output vector of size n_neurons into a single output value at each time step by a Fully Connected layer (FC)
- FC only consists linear neurons, without any activation function.

Part III

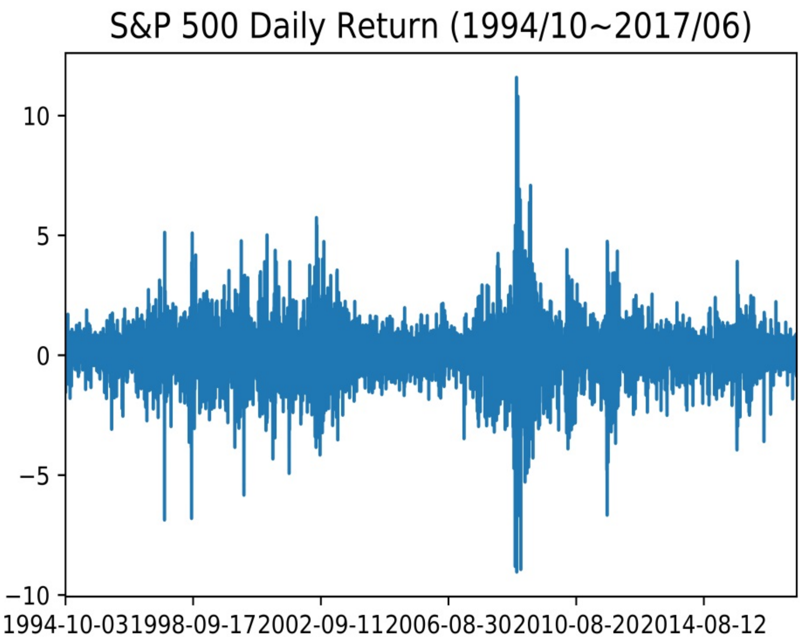
Time Series Analysis

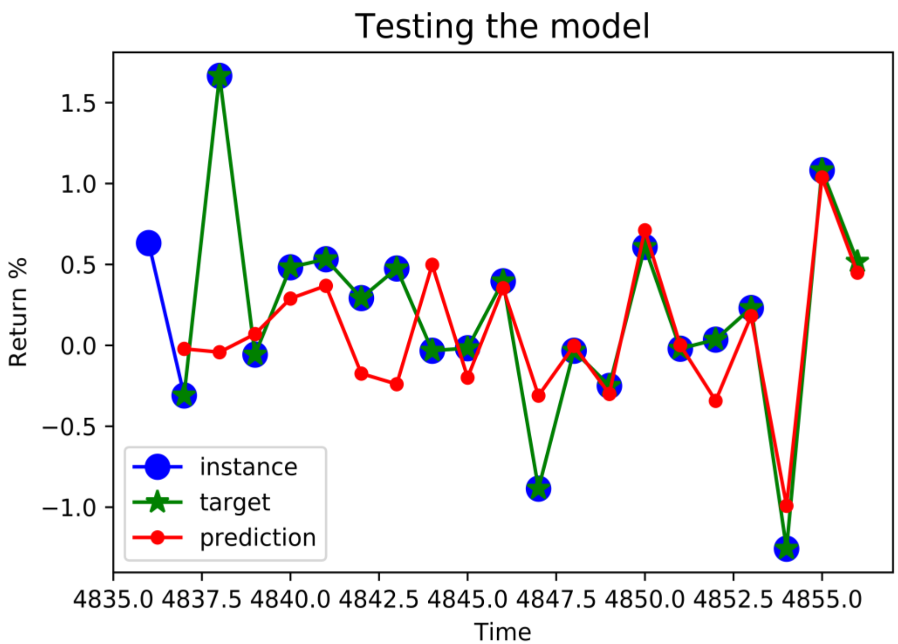
Data of Time Series

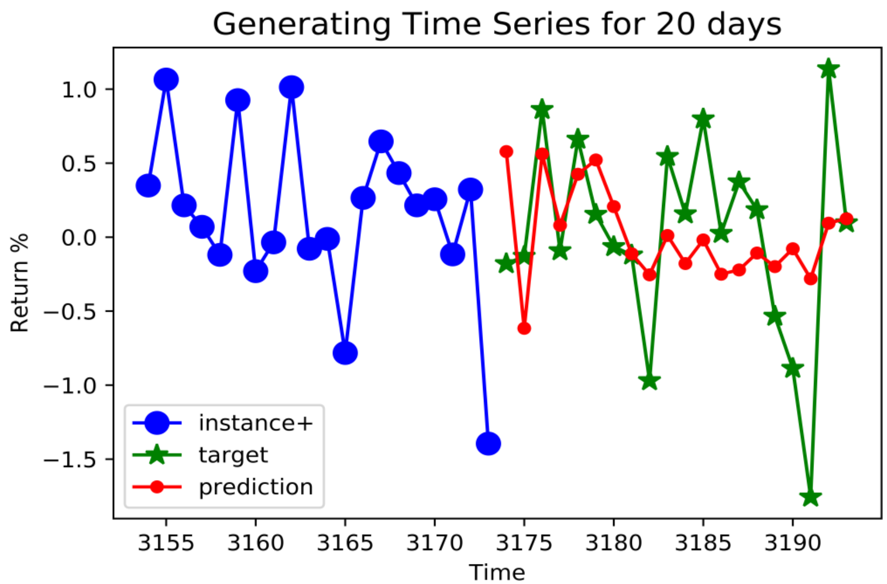


- It's about predicting the next value in a generated time series.
- A training instance is a randomly selected sequence of 20 consecutive values from the time series
- A target sequence is shifted of input instance by one time step into the future.
- Further, append the predicted value to the sequence, feed the last 20 values to the model to predict the next value, and so on, generating a creative sequence.

Forecast Monthly Return by Daily Data







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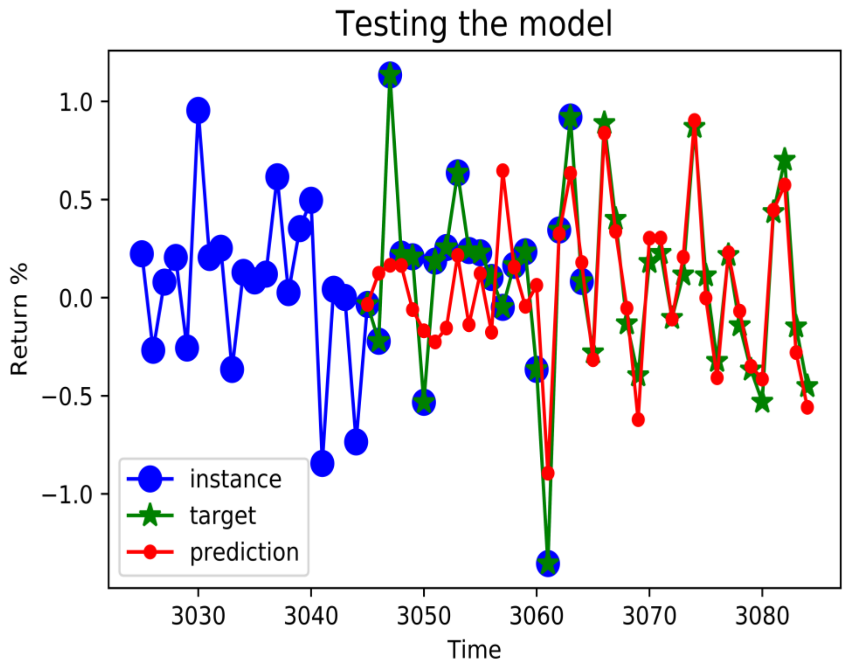
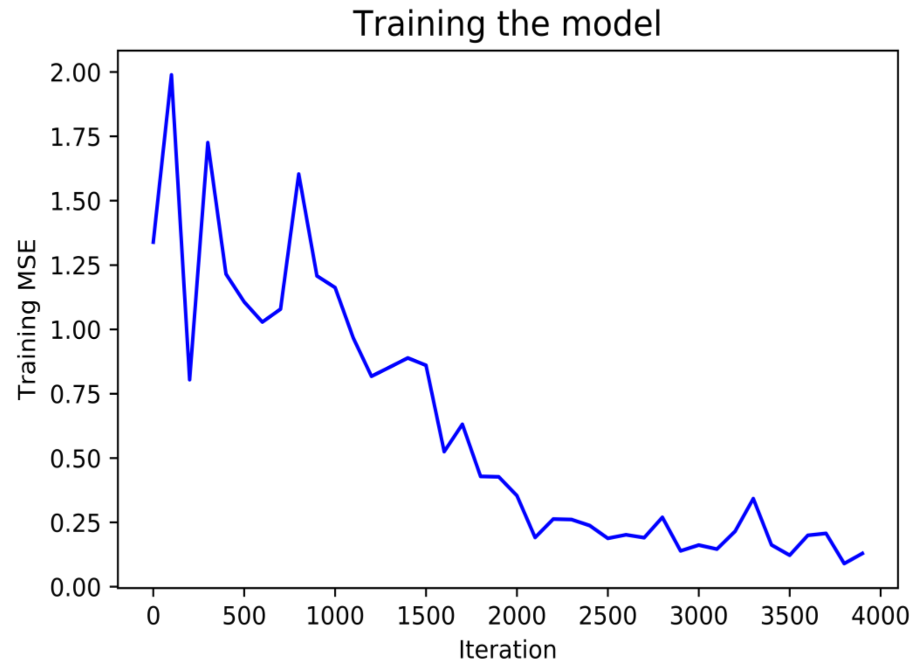
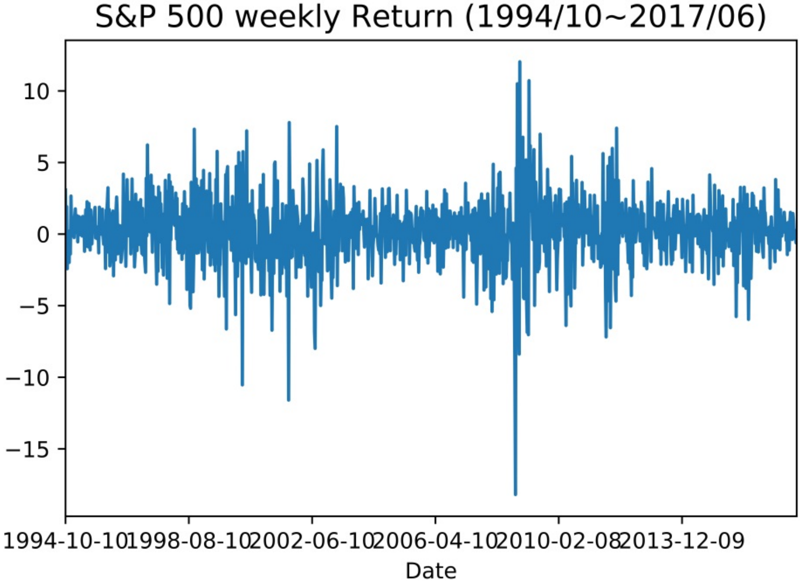
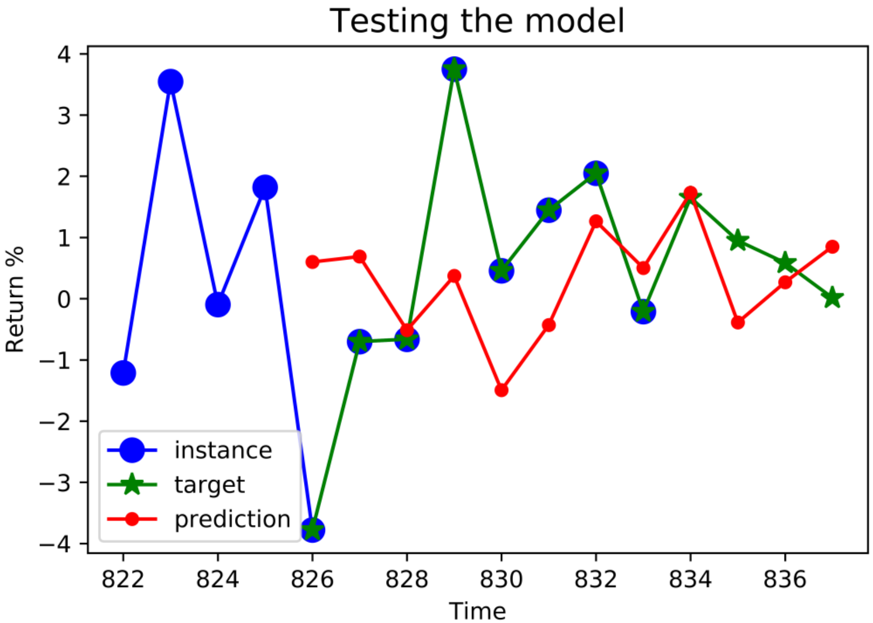




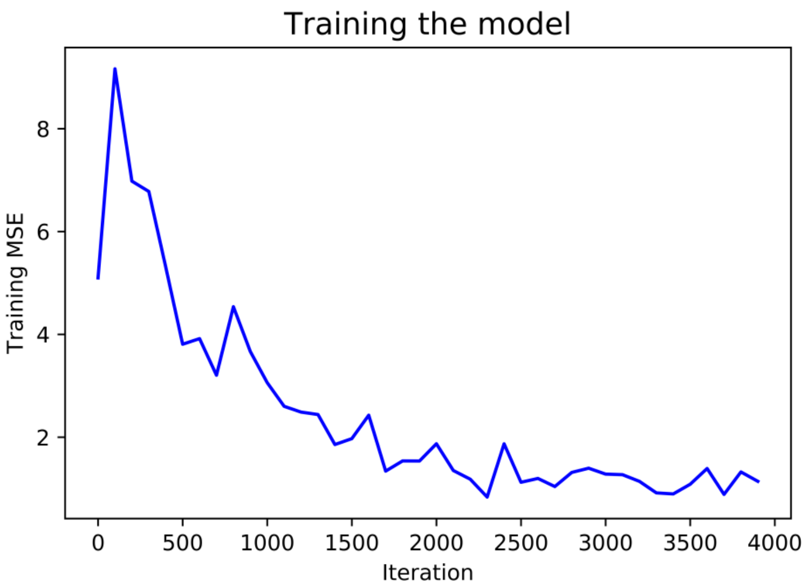
- 40 time steps to predict next 20 days return, sum to be a monthly return
- LSTM, 3 layers, "tanh" function, 1 input, 1 output, 300 neutrons
- AdamOptimizer, learning rate 0.001, batch size 20, Train/Test split ratio 0.2
- Tried but not applied: more layers, more neutrons, different batch size, dropout, ReLU, different time steps
- Performance: Testing MSE is 0.293, Predicting (20 days only) MSE is 0.012,
  Predicting Monthly Return MSE is 0.342

Forecast Monthly Return by Weekly Data

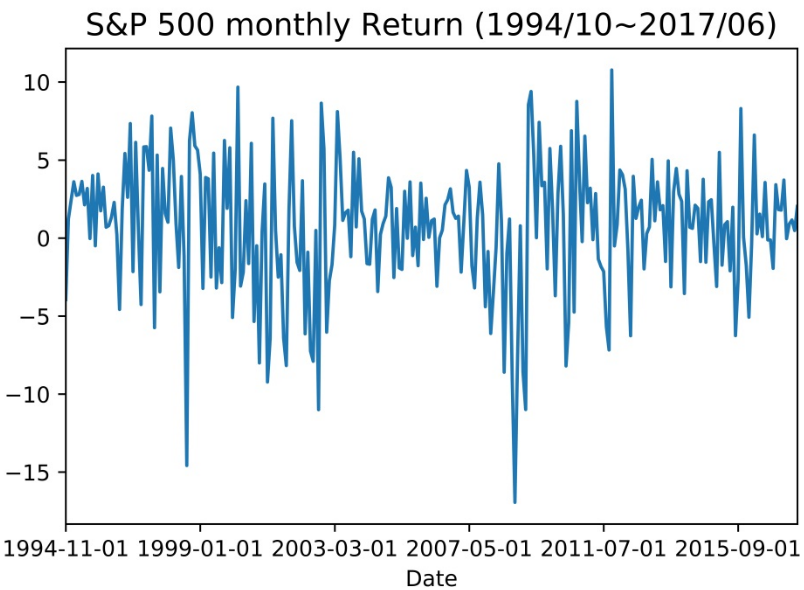




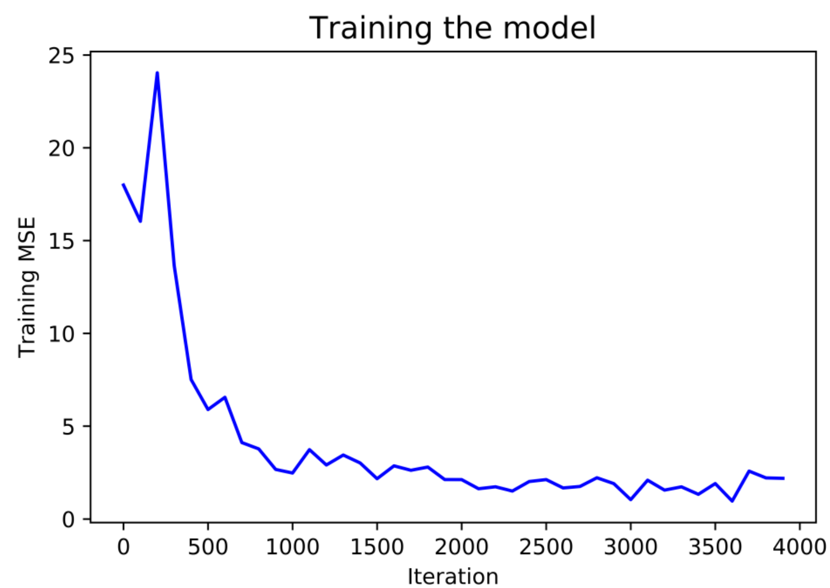
- 12 time steps to predict next 4 weeks return, sum to be a monthly return
- Testing MSE is 2.561
- Predicting (4 weeks) MSE is 0.313
- Predicting Monthly Return MSE is 1.175



Forecast Monthly Return by Monthly Data



- 12 time steps to predict next 1 month return, as a monthly return
- Testing MSE is 7.10
- Predicting (1 month) MSE is 0.121
- Predicting Monthly Return MSE is 0.121



Compare and Ensemble 3 LSTM Models

- The above 3 LSTM models were trained and tested by different data set. To have a fair comparison, we use the same data (daily data, calculate corresponding weekly/monthly data) for training and testing.
  - Daily-LSTM: Training MSE is 0.147, Testing MSE is 0.178, Predicting (20 days only) MSE is 0.011, Predicting Monthly Return MSE is 0.324
  - Weekly-LSTM: Training MSE is 1.493, Testing MSE is 2.440, Predicting (4 weeks only) MSE is 0.343, Predicting Monthly Return MSE is 1.526
  - Monthly-LSTM: Training MSE is 6.323, Testing MSE is 6.588, Predicting (1 month only) MSE is 0.453, Predicting Monthly Return MSE is 0.453
- Ensemble 3 LSTM models to be a Voting Predictor
  - Output the mean of 3 LSTMs' monthly return values
  - Predicting Monthly Return MSE is 0.295
  - 0.543% error for predicting monthly return in range -10%~10%

Part IV

Future Works

Future Works

- Improving prediction performance by using bagging/boosting to ensemble Daily-LSTM, Weekly-LSTM, and Monthly-LSTM.
- Use more features and datasets to improve prediction performance.

Thank you for your patience.

Q/A