Long Short-Term Memory: A Recurrent Neural Network to Determine the Direction of Futures Prices

Author: Timothy Decilveo
University: Loyola Marymount University
Class: CMSI 5350 Machine Learning

Data & Model

FUTURES

What are futures?

- Exchange traded derivative products
- Fair value is *derived* from an underlying asset
- Create a mechanism by which buyers and sellers can come together to buy or sell a specific product at a predetermined price and specified time in the future

Why predict futures prices?

- To profit or transfer risk in the market

Commodity Systems, Inc. (CSI)

- Low-cost information vendor of summary world financial market data
- Historical futures were purchased from CSI
- Data starts in 1946 and goes through 2019

COMMITMENT OF TRADERS REPORTS (CoT)

What are CoT Reports?

- Weekly data provided at no cost that shows the positions of various participants in the futures and options markets
- Data is updated weekly on Fridays at 5:00 pm ET, but is originally released on Tuesday of that same week
- Data feed contains 32,5000+ time-series, covering reports for 1,000+ futures contracts

What are hedgers?

- Are either naturally long or short a specific future due to their underlying business
- Considered "*commercial*" participants

What are speculators?

- Market participants willing to take on risk with the goal of profiting from said risk-taking activity
- Considered "*noncommercial*" participants

LONG SHORT-TERM MEMORY (LSTM)

What is LSTM?

- Recurrent neural network that uses learning order dependence in sequence prediction problems
- Implemented with time-series data structures
- Uses feedback connections to remember importance and significant data points to help predict outcomes

Why is LSTM Appropriate?

- Financial data primarily exists in time-series formats
- Intuitively, certain data points are more important than other when predicting the future
- Determining which data point is hard, so LSTMs should be able to help solve this problem

PREDICTION

What to Predict

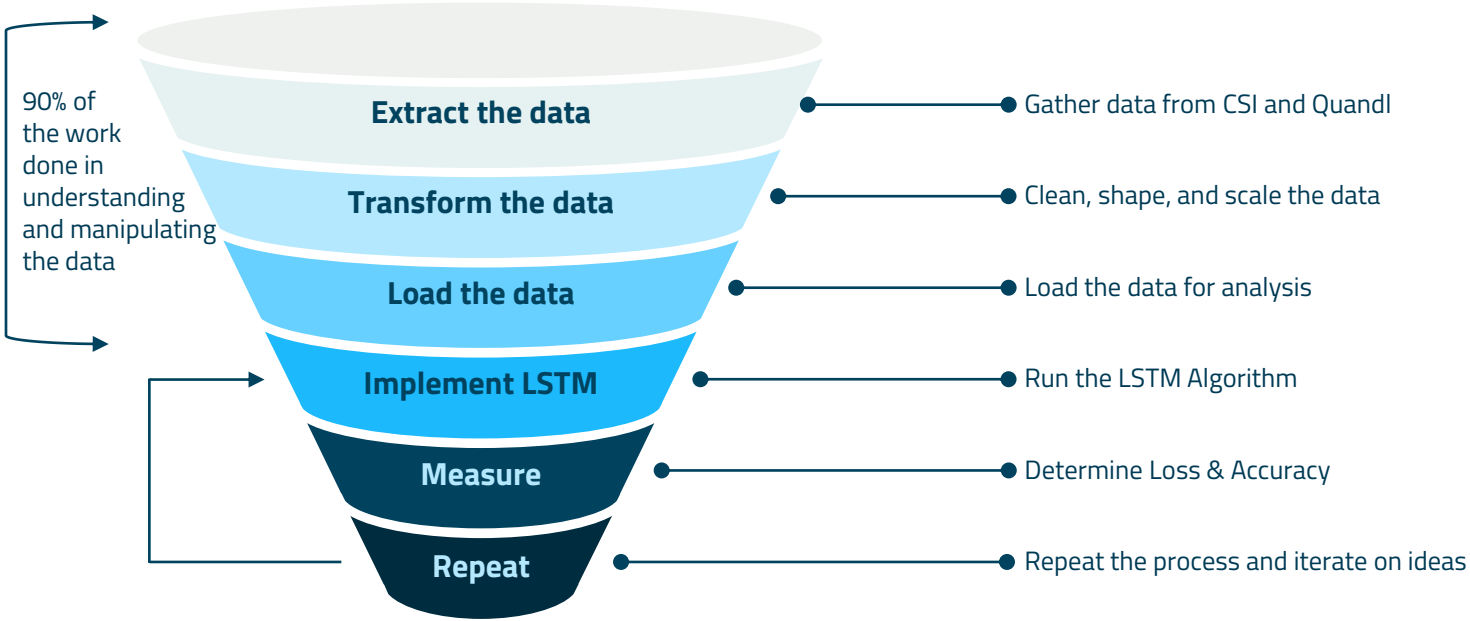
- Most people want to predict price
- Very hard
- Most people cannot do this (if you can don't tell anyone!)

Why Binary Classification?

- Simpler problem to approach than exact price
- Determining the direction (up/down or 0/1) is much easier to predict

Methods

PROCESS


90% of the work done in understanding and manipulating the data
Extract the data
Transform the data
Load the data
Implement LSTM
Measure
Repeat
Gather data from CSI and Quandl
Clean, shape, and scale the data
Load the data for analysis
Run the LSTM Algorithm
Determine Loss & Accuracy
Repeat the process and iterate on ideas

ML METHODS

Supervised

- The dataset is labeled and known ahead of time
- Trained data on 2/3 of the dataset
- Features used were:
  - Open, High, Low, Close
  - Noncommercial Long, Noncommercial Short
  - Commercial Long, Commercial Short

ML METHODS

Binary Classification

- Simpler to predict than exact price
- If you can predict the direction (up/down) of the price, you can design a profitable investment strategy
- Understanding the positions of different market participants should provide insights
- **Binary cross entropy** compares each of the predicted probabilities to actual class output (0 or 1)
  - It is the negative average of the log of corrected predicted probabilities
- **BCELoss**: measures the Binary Cross Entropy between the target and input probabilities
- **BCELogitsLoss**: combines Sigmoid layer and BCELoss in one single class

Results

RESULTS

- Most of the training and testing accuracy metrics were around 50%
- This is not ideal as 50% accuracy is effectively random guessing
- Possibly could be a result of incorrect implementation of LSTM algorithm or an issue with the data
- There could be no “information” in the feature set that provides insights for prediction

STANDARD GRADIENT DESCENT

	Natural Gas (Henry Hub)	Palladium	Rough Rice	Swiss Franc	30-Year Bond	10-Year Note	Wheat
T / Historical Lookback Window	2	2	2	2	2	2	2
# of Hidden Layers	2	2	2	2	2	2	2
# of RNN Layers	5	5	5	5	5	5	5
# of Outputs	1	1	1	1	1	1	1
Train Accuracy	0.4979	0.5102	0.5373	0.5092	0.5542	0.5397	0.5270
Test Accuracy	0.5239	0.5615	0.5293	0.5029	0.5573	0.5426	0.5504
Train Loss (1000 epochs)	0.6931	0.6929	0.6904	0.6931	0.6873	0.6899	0.6917
Test Loss(1000 epochs)	0.6932	0.6908	0.6916	0.6932	0.6866	0.6894	0.6892

Conclusions

CONCLUSIONS

- So much more to do…
- 50%+ accuracy isn't so bad if the expectancy is greater than 1-to-1
- Strong baseline to work from having worked on this for a few weeks
- Need to set up better data extraction and cleaning methods to handle outliers
- Create methods to reduce data leakage
- Develop a strategy around how to trade these outcomes
- Does this work better for certain markets vs. others?
- Can you improve the model by removing or adding features?

50/50

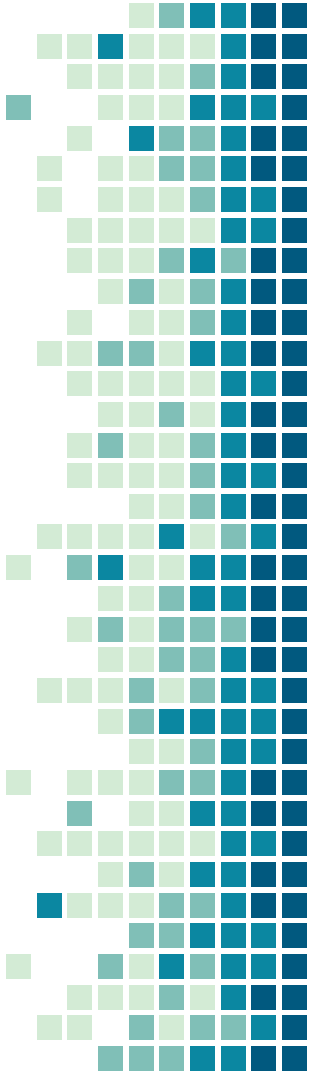
win / loss ratio isn't so bad.

If every losing trade you make generates -$1.00, and every winning trade you make generates +$1.10, over time, your expectancy on the system is positive.

50/50
win / loss ratio

+$1.10 / -$1.00
profit / loss

$0.10
positive expectancy



EXPECTANCY

Profit	Loss	Win / Loss %	# of Trades	Expectancy
$1.10	-$1.00	50%	10	$0.50
$1.10	-$1.00	50%	100	$5
$1.10	-$1.00	50%	1,000	$50
$1.10	-$1.00	50%	10,000	$500
$1.10	-$1.00	50%	100,000	$5,000
$1.10	-$1.00	50%	1,000,000	$50,000
$1.10	-$1.00	50%	10,000,000	$500,000
$1.10	-$1.00	50%	100,000,000	$5,000,000

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CREDITS

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THANKS!

Any questions?

You can find me at:

tdecilve@lion.lmu.edu