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

GitHub: https://github.com/timdecilveo/cmsi-5350-project

Abstract

Historically, investors in financial markets have used past data to decide whether to buy or sell a specific security, and recurrent neural networks offer market participants a way to apply this thinking systematically. Specifically, Long Short-Term Memory Recurrent Neural Networks (LSTM RNN) allow investors to utilize feedback connections to process data sequences, or time series data, which is the standard data set used in the financial markets. LSTMs can be valuable models for financial markets as there may be lags of unknown time between significant data points within a timer series. LSTMs can process data and maintain information about prior data points without knowing if the specific data point is relevant a priori.

This paper will provide a novel way to implement an LSTM model to predict the direction of futures market prices using historical price action and Commitment if Trader's (COT) reports data.

Keywords: Long Short-Term Memory, LSTM, Machine Learning, Commodity Futures, Financial Futures

LONG SHORT-TERM MEMORY:
A RECURRENT NEURAL NETWORK TO DETERMINE THE DIRECTION
OF FUTURES PRICES

Introduction

Long short-term memory (LSTM) models have long been used to predict time series data, but the research dedicated to LSTM model applications within the financial markets is rare. This research attempts to begin the conversation around LSTM and predict commodity and financial futures prices, creating a baseline from which to work and improve the model. Due to time constraints, there are specific issues with the application of this model, but as a general starting point, the model built should be sufficient to create a baseline to work from.

Most market practitioners believe historical data is essential in predicting the price of a security, but it is challenging to determine which historical data is vital in that prediction. Does the price action on day X matter more than day Y? If so, how does one weight day X versus day Y? LSTM models seek to solve the problem of not knowing which data matters using its different gating mechanisms and intuitively seem like a reasonable way to predict future prices.

Furthermore, price prediction is a challenging problem that needs precise outcomes rather than accurate ones. This paper attempts to reduce the complexity of this problem by predicting direction (i.e., up or down). Binary classification is typically an easier problem to solve and is used in this research.

The paper will utilize features outside the standard open, high, low, and closing prices used in most practitioners' price prediction models and will incorporate Commitment of Trader's (CoT) data as an input. The implementation of the CoT data should attempt to show the efficacy and importance of including other relevant data in addition to price action. This paper is not an exhaustive search of independent variables that could be used in the feature set but instead attempts to show the validity of including alternative data sets.

Hypothesis: Understanding market participants' positioning will increase the accuracy of securities price prediction.

Related Work

Currently, there is not a significant amount of research utilizing LSTM models on the financial markets. Most research consists of traditional econometric models that are linear. In 2020, Lu et al. used an LSTM model to forecast stock prices and explained how their LSTM model was the best compared to others in the experiment. Also, in 2020, Moghar and Hamiche implemented an LSTM RNN model to predict stock market prices. The results were mixed and only tested on a limited number of stocks.

Data

Commodity Systems, Inc.:

Commodity Systems Inc. (CSI) is a low-cost information vendor of summary world financial market data. Daily/data updates on thousands of time series are supplied via the Internet at the close of each business day.

Historical futures data was purchased from CSI dating back to 1946 in some cases, through June 2019. The futures prices have been back adjusted to provide a continuous time series that eliminates the gaps between expiring and newly active contracts. The idea of back adjusted contracts involve concatenating historical contracts of a given commodity into the past while adjusting to smooth transitions between delivery months.

The data is proportionately adjusted by percentage or ratio terms and splicing contracts by adding or subtracting their relative differences into the past. Ratio-adjusted series prepared through ratio multiplications are unlikely to go negative, so there is seldom a need to elevate a series out of the negative territory. Contracts are joined by increasing or decreasing successively further distant contracts by a percentage to raise or lower the entire history by the same proportion. Rounding problems caused by attempts to preserve tick differentials of reported prices could occasionally push a given series into negative territory.

Because the ratio adjustment yields a much milder descending slope of long-term prices into the past, there is less long-side trading bias captured from the data. An unbiased result that offers realism should be much preferred over a highly profitable and unbelievable result that holds more inflation contributions than any perceived trading style or expertise.

The idea of ratio-adjusted contracts requires applying the percentage change in the price of the earlier contract with respect to the price of the current (or later) contract. Consider the above example where a five-cent difference in price between successive December and September contracts resulted in a five-cent adjustment to all past data with the traditional back adjuster. In a ratio-adjusted series, the fixed delta of five would represent a factor of 5/100 or 105% of the September price for all data in the September contract. This process would repeat at the same percentage for every contract boundary until the series ended.

The Ratio (Proportional) back-adjustment principles offered here were inspired by Thomas Stridman, who discussed the idea in his article "Data Pros and Cons" in the June 1998 issue of Futures Magazine.

The futures evaluated are the Australian Dollar, Soybean Oil, British Pound, Corn, Cocoa, Canadian Dollar, WTI-Crude Oil, Cotton, U.S. Dollar Index, Euro Dollar, Feeder Cattle, 5-Year T-Note, Gold, HG Copper, Heating Oil, Japanese Yen, Coffee, Lumber, Live Cattle, Lean Hogs, Mexican Peso, Nasdaq 100, New Zealand Dollar, Natural Gas, Oats, Orange Juice, Palladium, Platinum, Rough Rice, Soybeans, Sugar #11, Swiss Franc, Silver, Soybean Meal, S&P 500, 2-Year T-Note, 10-Year T-Bonds, 30-Year T-Bonds, Wheat.

Commitment of Trader's Reports (COT):

The Commodity Futures Trading Commission (CFTC) provides weekly data on the commitment of traders and concentration ratios in both legacy and new format for futures only and futures and options. The data used in this experiment only looked at legacy CoT data on futures only. History for this data goes back to 1986, where available. Data is updated weekly on Fridays at 5:00 pm ET. The data feed contains 32,500+ time-series, covering reports for 1,000+ futures contracts in new and legacy formats. For a complete list of Time-Series Codes included in this data feed, use: CFTC-Nasdaq-Metadata-api_key=7J7nAmAEHA2yVUZZCtsy.

The data is provided from [Nasdaq Data Link's] API through the Quandl package. An API key must be obtained to retrieve data via the API. This data can also be accessed from a browser.

Features

There were 15 features available for use in this experiment, as defined below:

1) **Open**: the opening price refers to the price at which a security first trades upon the opening of an exchange on a trading day.
2) **High**: the daily high price refers to the highest intraday price a security traded for.
3) **Low**: the daily low price refers to the lowest intraday price a security traded for.
4) **Close**: the closing price refers to the price at which a security last trades before the closing of an exchange on a trading day.
5) **Noncommercial Long**: a noncommercial long refers to someone who has no business activities related to a particular commodity in which they have a long position in the futures market. These are typically referred to as "speculators." The value is a cumulative figure.
6) **Noncommercial Short**: a noncommercial short refers to someone who has no business activities related to a particular commodity in which they have a short position in the futures market. These are typically referred to as "speculators." The value is a cumulative figure.
7) **Commercial Long**: a commercial long refers to someone who has business activities related to a particular commodity in which they have a long position in the futures market. These are typically referred to as "hedgers." The value is a cumulative figure.
8) **Commercial Short**: a commercial short refers to someone who has business activities related to a particular commodity in which they have a short position in the futures market. These are typically referred to as "hedgers." The value is a cumulative figure.

Experiments

The main experiment in this paper is to predict the direction (up/down) of tomorrow's open price with data over the last N time periods. The researcher could very easily choose to predict tomorrow's high, low, or close price by changing a few lines of code.

The process for running the experiment is as follows:

1) Take the pre-existing open, high, low, and close data from the .txt files.

2) Connect to the Quandl API to extract the CoT weekly data using the legacy format.
3) Merge the datasets on the relevant dates.
4) Clean the data.
5) Transform the data to fit the model.
6) Load the data into the LSTM model.
7) Run the LSTM model.
8) Choose an algorithm to optimize the LSTM model.
9) Choose a learning rate at which to run the LSTM model.
10) Determine training loss and testing loss.
11) Determine training accuracy and testing accuracy.

Once these steps are performed, we can optimize the LSTM model to implement different hyperparameters. Some of the critical hyperparameters are decay rate (default is 0.2), pred (price you are trying to predict - - open, high, low, or close), optimizer (the algorithm used in model prediction; default is AdamW), T (lookback period / historical window to reference; default is 10), num_hidden (number of hidden layers in the RNN; default is 50), num_rnnlayers (number of RNN layers; default is 2),

Experiments were run on various hyperparameters to test the efficacy of the model. For instance, if T was 10 in one experiment and 11 in another, should the results be drastically different or relatively stable across parameters? If the results were drastically different, the model might not be as valuable long-term because of overfitting to a specific market regime. LSTMs should solve this issue, and one should not expect drastically different results with slight changes in specific hyperparameters.

Results

Results are listed in Appendix A.

Improving the Model

There is more work to be done. The following are listed as priorities moving forward but are by no means an exhaustive list of improvements for the model:

1) Data Cleaning: specific data cleaning techniques were implemented, but there is missing data that can be explored. An example of overcoming the lack of data is to reduce the timeframe analyzed to dates in which the data exists in its most accurate form. The timeframe reduction reduces the model's ability to analyze the entire data set. Ideally, the data analyzed exists over a 30-year timeframe and is cleaned to prevent any issues with historical inputs.
2) Hyperparameter Optimization: rather than looping through a set of hyperparameters, implementing a more optimal way to search through a list of hyperparameters should be used to determine the optimal hyperparameters for training and testing the data.
3) Segmenting Markets: specific markets may perform better when certain data is used. Various market participants exist in each market that are either naturally long or short their underlying exposure, and determining if that exists in each market may determine the efficacy of adding in additional data like CoT reports. Additionally, markets as groups may perform better on specific hyperparameters than others. Segmenting these groups of markets may provide added insight.
4) Prediction: in the experiment, the predicted value was only one time period in the future (i.e., one day or one week). Determining if that is the ideal time period to predict should be experimented on as one time period may not be the ideal dependent variable.

Conclusions and Future Work

There is more work to do on this model based on the data. One of the critical areas of focus needs to be on the data cleaning, transforming, and loading aspects of the LSTM model. If this is done correctly, the researcher can build and machine learning model using the same dataset.

In terms of accuracy, percentages greater than fifty percent are encouraging. Most market practitioners cannot correctly predict price direction greater than fifty percent of the time. If the prediction accuracy is greater than fifty percent and the expected dollar outcome on each prediction is greater than one-to-one, it would be worth implementing this LSTM model in an actively traded portfolio.

Moving forward, I intend to continue building out the data components previously discussed and working on the LSTM model using the same dataset. This research may end up being a thesis of mine in which I will publish a more significant amount of research.

References

Chen, Z., Goh, H. S., Sin, K. L., Lim, K., Chung, N. K., & Liew, X. Y. (2021). Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques. *Advances in Science, Technology and Engineering Systems Journal*, *6*(4), 376–384. https://doi.org/10.25046/aj060442

Dolphin, R. (2021, November 12). *LSTM networks: A detailed explanation*. Medium. Retrieved November 29, 2021, from https://towardsdatascience.com/lstm-networks-a-detailed-explanation-8fae6aefc7f9.

Fahlman, S. E. (n.d.). *The recurrent cascade-correlation architecture*. The Recurrent Cascade-Correlation Architecture. Retrieved December 1, 2021, from https://proceedings.neurips.cc/paper/330-the-recurrent-cascade-correlation-architecture.pdf.

Foster, E. A. (2002). Commodity Futures Price Prediction, an Artificial Intelligence Approach. Retrieved November 29, 2021, from https://www.ai.uga.edu/sites/default/files/inline-files/ernest_foster.pdf.

Gers, F. (2001). Long Short-Term Memory in Recurrent Neural Networks. Retrieved December 1, 2021, from http://www.felixgers.de/papers/phd.pdf.

Gers, F. A., Schraudolph, N. N., & Schmidhuber, J. (2002). *Learning Precise Timing with LSTM Recurrent Networks*.

Herta, C. (n.d.). *LSTM (Long Short Term Memory)*. Christianherta. Retrieved December 1, 2021, from http://christianherta.de/lehre/dataScience/machineLearning/neuralNetworks/LSTM.php.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Retrieved November 30, 2021, from https://www.bioinf.jku.at/publications/older/2604.pdf.

Howard, J. (2021, November 29). *Home*. fast.ai: Making neural nets uncool again. Retrieved November 29, 2021, from https://www.fast.ai/.

Lu, Wenjie, et al. “A CNN-LSTM-Based Model to Forecast Stock Prices.” *Complexity*, vol. 2020, 2020, pp. 1–10., https://doi.org/10.1155/2020/6622927.

Moghar, Adil, and Mhamed Hamiche. “Stock Market Prediction Using LSTM Recurrent Neural Network.” *Procedia Computer Science*, vol. 170, 2020, pp. 1168–1173., https://doi.org/10.1016/j.procs.2020.03.049.

Monner, D. D., & Reggia, J. A. (n.d.). *A generalized LSTM-like training algorithm ... - overcomplete*. A generalized LSTM-like training algorithm for second-order recurrent neural networks. Retrieved December 1, 2021, from http://www.overcomplete.net/papers/nn2012.pdf.

Schmidhuber, J. (n.d.). *Long Short-Term Memory*. Recurrent neural networks - feedback networks - LSTM recurrent network - feedback neural network - recurrent nets - feedback network - recurrent net - - feedback net. Retrieved November 29, 2021, from https://people.idsia.ch//~juergen/rnn.html.

Surmenok, P. (2021, April 19). *Estimating an optimal learning rate for a deep neural network*. Medium. Retrieved November 29, 2021, from https://towardsdatascience.com/estimating-optimal-learning-rate-for-a-deep-neural-network-ce32f2556ce0.

Appendix A

Note: Hyperparameters used in all trials: output_data='merge',pred='open', T=3, num_hidden=hidden(3, 1), num_rnnlayers=2, num_outputs=1

Intentionally left blank

Table 1

Commodity:	Cocoa		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6841	0.6947
Adam	200	0.6565	0.6854
Adam	300	0.6395	0.6812
AdamW	100	0.6806	0.6949
AdamW	200	0.6554	0.6931
AdamW	300	0.6356	0.6917
SGD	100	0.6916	0.6950
SGD	200	0.6911	0.6960
SGD	300	0.6911	0.6962

Optimizer	**Train Accuracy**	**Test Accuracy**
Adam	0.6249	0.5645
AdamW	0.6259	0.5645
SGD	0.5335	0.4824

Table 2

Commodity:	Coffee		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6828	0.6968
Adam	200	0.6545	0.7530
Adam	300	0.6393	0.7643
AdamW	100	0.6796	0.7150
AdamW	200	0.6564	0.7445
AdamW	300	0.6375	0.7402
SGD	100	0.7039	0.7005
SGD	200	0.6979	0.6960
SGD	300	0.6945	0.6937

Optimizer	**Train Accuracy**	**Test Accuracy**
Adam	0.6181	0.5156
AdamW	0.6268	0.5313
SGD	0.4577	0.4766

Table 3

Commodity:	Corn		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6850	0.6955
Adam	200	0.6730	0.7052
Adam	300	0.6545	0.7245
AdamW	100	0.6759	0.6944
AdamW	200	0.6553	0.6911
AdamW	300	0.6380	0.6998
SGD	100	0.7154	0.6997
SGD	200	0.7031	0.6937
SGD	300	0.6967	0.6929

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6129	0.5204
AdamW	0.6187	0.5534
SGD	0.4546	0.5087

Table 4

Commodity:	Cotton		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6840	0.6965
Adam	200	0.6585	0.7012
Adam	300	0.6493	0.7334
AdamW	100	0.6886	0.6932
AdamW	200	0.6726	0.7029
AdamW	300	0.6557	0.7059
SGD	100	0.6966	0.7015
SGD	200	0.6949	0.6991
SGD	300	0.6941	0.6973

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6192	0.5419
AdamW	0.6279	0.5224
SGD	0.5107	0.4854

Table 5

Commodity:	Crude Oil (Light)		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6823	0.7040
Adam	200	0.6688	0.7120
Adam	300	0.6557	0.7191
AdamW	100	0.6773	0.7123
AdamW	200	0.6514	0.7378
AdamW	300	0.6360	0.7640
SGD	100	0.7099	0.6995
SGD	200	0.7002	0.6948
SGD	300	0.6949	0.6933

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6017	0.5272
AdamW	0.6250	0.5078
SGD	0.4506	0.4981

Table 6

Commodity:	Eurodollar		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6890	0.6943
Adam	200	0.6783	0.6942
Adam	300	0.6710	0.6926
AdamW	100	0.6903	0.6936
AdamW	200	0.6767	0.6970
AdamW	300	0.6701	0.6994
SGD	100	0.6926	0.6930
SGD	200	0.6921	0.6929
SGD	300	0.6917	0.6928

Optimizer	Train Accuracy	Test Accuracy
Adam	0.5643	0.5243
AdamW	0.5556	0.4932
SGD	0.5295	0.5126

Table 7

Commodity:	Feeder Cattle		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6858	0.6929
Adam	200	0.6756	0.6869
Adam	300	0.6561	0.6817
AdamW	100	0.6838	0.6888
AdamW	200	0.6630	0.6857
AdamW	300	0.6407	0.6854
SGD	100	0.7129	0.7150
SGD	200	0.7044	0.7058
SGD	300	0.6994	0.7004

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6014	0.5631
AdamW	0.6342	0.5981
SGD	0.4807	0.4738

Table 8

Commodity:	Gold		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6912	0.6948
Adam	200	0.6846	0.6990
Adam	300	0.6687	0.7011
AdamW	100	0.6813	0.6996
AdamW	200	0.6693	0.7080
AdamW	300	0.6571	0.7076
SGD	100	0.6989	0.6953
SGD	200	0.6960	0.6938
SGD	300	0.6944	0.6932

Optimizer	Train Accuracy	Test Accuracy
Adam	0.5890	0.5078
AdamW	0.5919	0.5486
SGD	0.4816	0.5058

Table 9

Commodity:	Heating Oil		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6906	0.6930
Adam	200	0.6825	0.7052
Adam	300	0.6705	0.7353
AdamW	100	0.6874	0.7001
AdamW	200	0.6781	0.7130
AdamW	300	0.6641	0.7176
SGD	100	0.6957	0.6946
SGD	200	0.6947	0.6939
SGD	300	0.6942	0.6934

Optimizer	Train Accuracy	Test Accuracy
Adam	0.5804	0.5214
AdamW	0.6105	0.5078
SGD	0.5058	0.5117

Table 10

Commodity:	Live Cattle		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6927	0.6932
Adam	200	0.6789	0.6886
Adam	300	0.6581	0.6931
AdamW	100	0.6922	0.6929
AdamW	200	0.6627	0.6942
AdamW	300	0.6499	0.7144
SGD	100	0.6960	0.7004
SGD	200	0.6948	0.6981
SGD	300	0.6941	0.6966

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6042	0.5689
AdamW	0.6100	0.5320
SGD	0.4981	0.4680

Table 11

Commodity:	Orange Juice		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6812	0.6934
Adam	200	0.6508	0.7033
Adam	300	0.6305	0.6990
AdamW	100	0.6812	0.6959
AdamW	200	0.6626	0.7046
AdamW	300	0.6355	0.6893
SGD	100	0.6913	0.6978
SGD	200	0.6913	0.6979
SGD	300	0.6913	0.6981

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6305	0.5361
AdamW	0.6489	0.5458
SGD	0.5306	0.4717

Table 12

Commodity:	Rough Rice		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6864	0.6860
Adam	200	0.6699	0.6901
Adam	300	0.6502	0.7025
AdamW	100	0.6809	0.6868
AdamW	200	0.6674	0.6972
AdamW	300	0.6543	0.6964
SGD	100	0.6955	0.6948
SGD	200	0.6934	0.6925
SGD	300	0.6917	0.6924

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6189	0.5516
AdamW	0.6142	0.5493
SGD	0.5361	0.5305

Table 13

Commodity:	S&P 500 Index		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6564	0.6650
Adam	200	0.6204	0.6826
Adam	300	0.5988	0.6877
AdamW	100	0.6668	0.6629
AdamW	200	0.6426	0.6685
AdamW	300	0.6169	0.6996
SGD	100	0.7505	0.7602
SGD	200	0.7154	0.7202
SGD	300	0.6965	0.6972

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6923	0.5817
AdamW	0.6731	0.6078
SGD	0.4006	0.3725

Table 14

Commodity:	Silver		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6907	0.6917
Adam	200	0.6713	0.6821
Adam	300	0.6342	0.6891
AdamW	100	0.6916	0.6906
AdamW	200	0.6865	0.6941
AdamW	300	0.6815	0.6940
SGD	100	0.7205	0.7250
SGD	200	0.7089	0.7123
SGD	300	0.7022	0.7050

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6286	0.5856
AdamW	0.5406	0.4922
SGD	0.5019	0.4922

Table 15

Commodity:	Soybean Meal		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6838	0.6902
Adam	200	0.6337	0.6883
Adam	300	0.6107	0.6783
AdamW	100	0.6890	0.6922
AdamW	200	0.6575	0.6921
AdamW	300	0.6150	0.6772
SGD	100	0.7044	0.7045
SGD	200	0.6997	0.6995
SGD	300	0.6968	0.6971

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6612	0.5883
AdamW	0.6525	0.5534
SGD	0.5039	0.5029

Table 16

Commodity:	Soybean Oil		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6832	0.6835
Adam	200	0.6683	0.6914
Adam	300	0.6463	0.6873
AdamW	100	0.6848	0.6897
AdamW	200	0.6659	0.6861
AdamW	300	0.6575	0.6900
SGD	100	0.7049	0.6927
SGD	200	0.6991	0.6893
SGD	300	0.6959	0.6884

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6023	0.5612
AdamW	0.6033	0.5515
SGD	0.5212	0.5515

Table 17

Commodity:	Soybeans		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6831	0.6870
Adam	200	0.6258	0.6728
Adam	300	0.6102	0.6706
AdamW	100	0.6907	0.6917
AdamW	200	0.6715	0.6966
AdamW	300	0.6527	0.7054
SGD	100	0.6933	0.6927
SGD	200	0.6934	0.6928
SGD	300	0.6931	0.6929

Optimizer	Train Accuracy	Test Accuracy
Adam	0.6438	0.5883
AdamW	0.6390	0.5282
SGD	0.4990	0.5204

Table 18

Commodity:	T-Bond (Ultra)		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6868	0.6871
Adam	200	0.6757	0.7045
Adam	300	0.6686	0.7109
AdamW	100	0.6843	0.6856
AdamW	200	0.6719	0.6987
AdamW	300	0.6589	0.7112
SGD	100	0.7117	0.7123
SGD	200	0.6993	0.7005
SGD	300	0.6932	0.6931

Optimizer	Train Accuracy	Test Accuracy
Adam	0.5880	0.5195
AdamW	0.6025	0.5486
SGD	0.5116	0.4805

Table 19

Commodity:	T-Note (10 Year)		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6870	0.6920
Adam	200	0.6739	0.6948
Adam	300	0.6599	0.6984
AdamW	100	0.6845	0.6947
AdamW	200	0.6658	0.7071
AdamW	300	0.6457	0.7104
SGD	100	0.6931	0.6910
SGD	200	0.6918	0.6905
SGD	300	0.6909	0.6899

Optimizer	Train Accuracy	Test Accuracy
Adam	0.5851	0.4893
AdamW	0.6093	0.5301
SGD	0.5387	0.5437

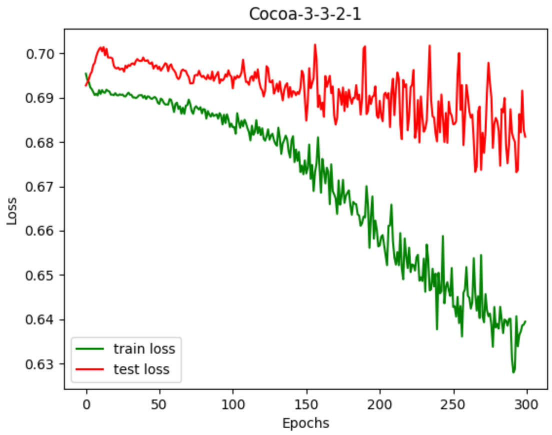
Table 20

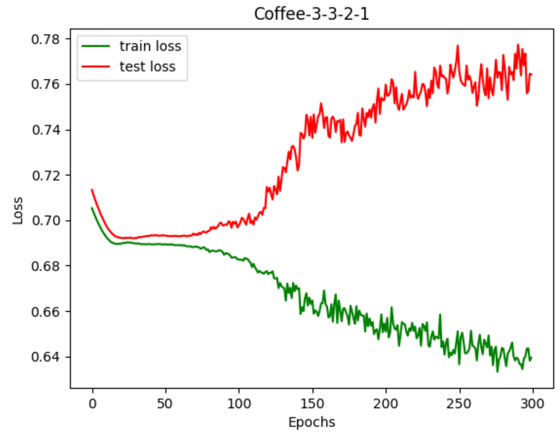
Commodity:	Wheat		
Optimizer	**Epoch**	**Train Loss**	**Test Loss**
Adam	100	0.6886	0.6871
Adam	200	0.6702	0.6869
Adam	300	0.6468	0.6911
AdamW	100	0.6910	0.6886
AdamW	200	0.6806	0.6850
AdamW	300	0.6729	0.6908
SGD	100	0.6951	0.6890
SGD	200	0.6935	0.6887
SGD	300	0.6927	0.6882

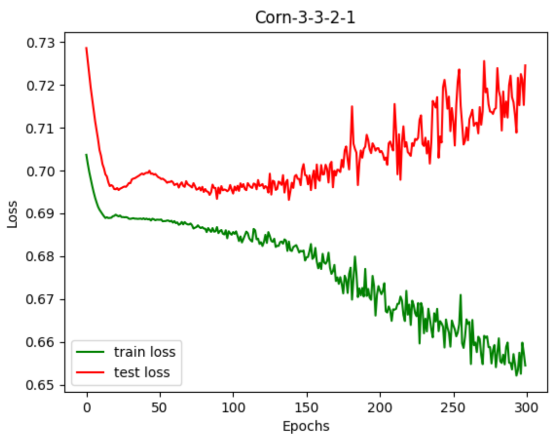
Optimizer	Train Accuracy	Test Accuracy
Adam	0.5907	0.5320
AdamW	0.5666	0.5650
SGD	0.5270	0.5495

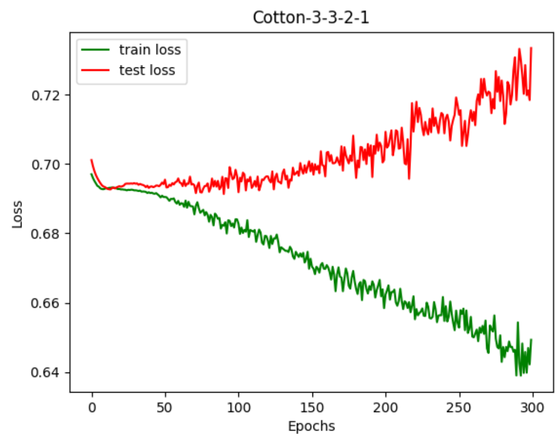
Plots:

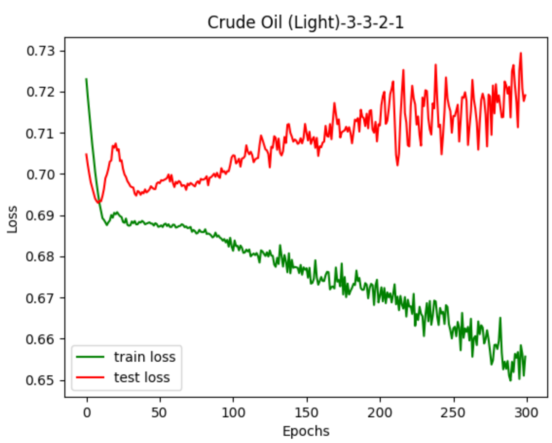
Adam Optimizer

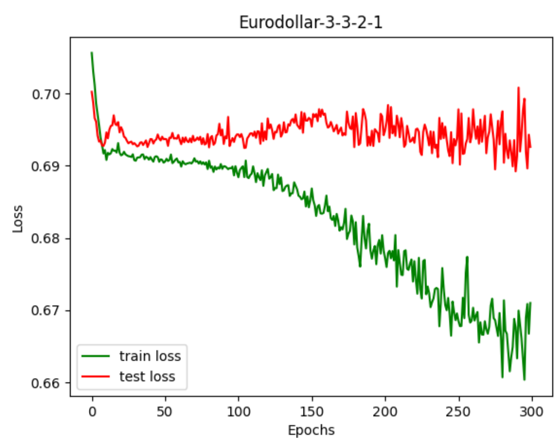


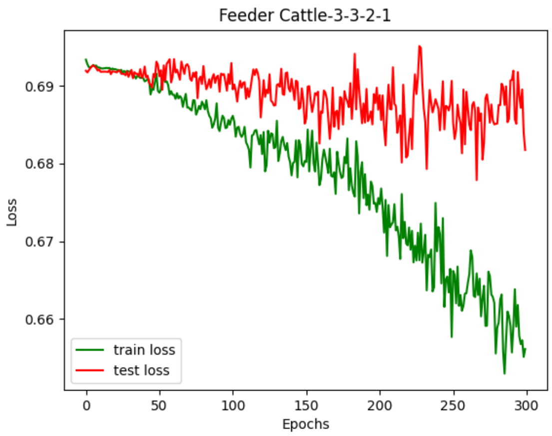


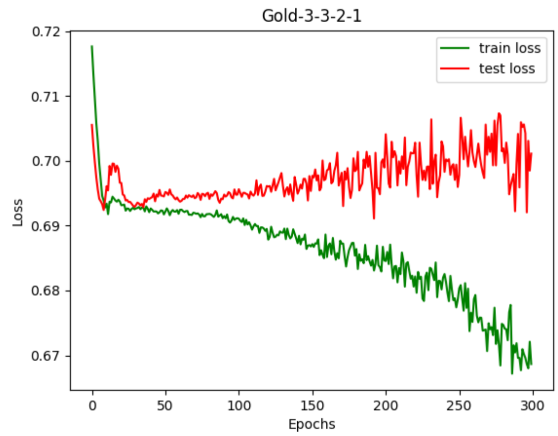


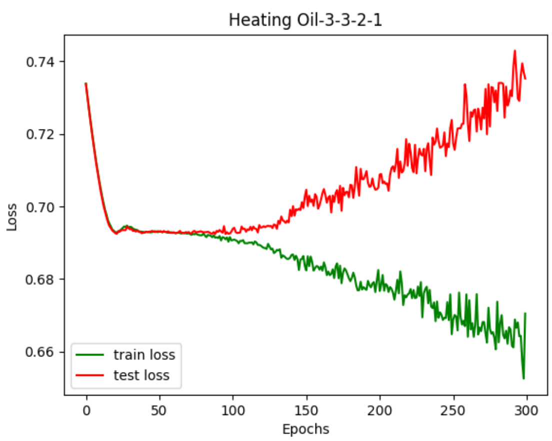


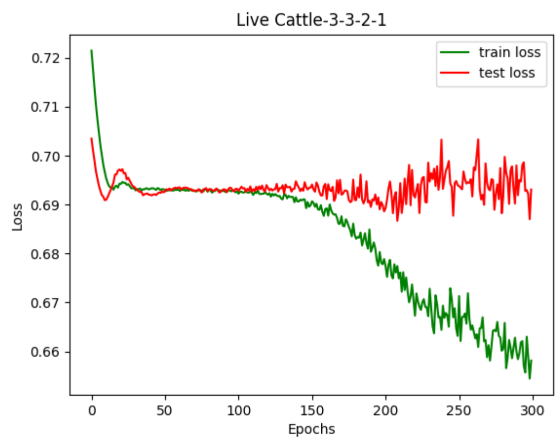


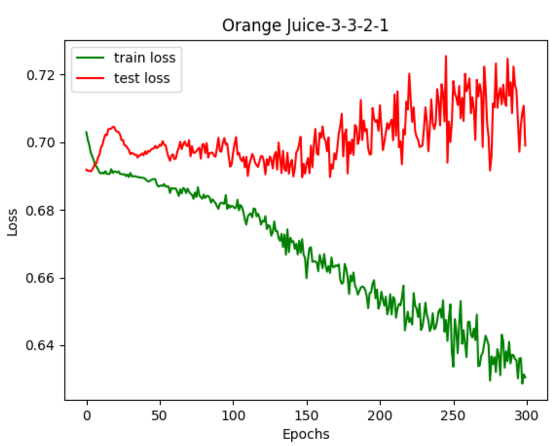


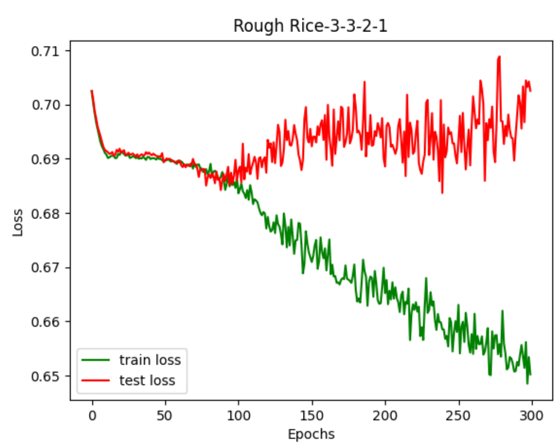

Feeder Cattle-3-3-2-1
0.69
0.68
0.67
0.66
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

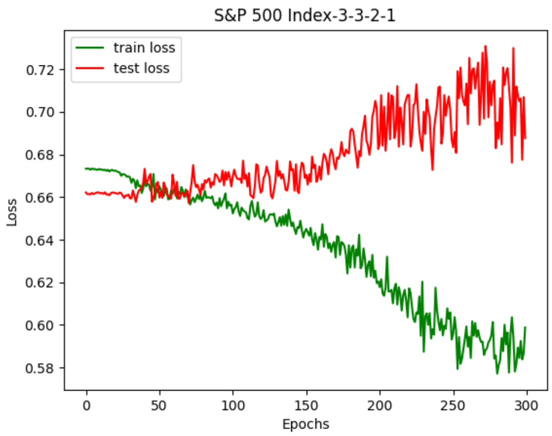

Gold-3-3-2-1
0.72
0.71
0.70
0.69
0.68
0.67
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

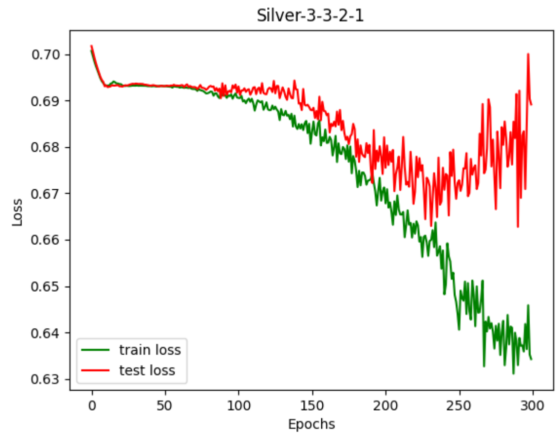

Heating Oil-3-3-2-1
0.74
0.72
0.70
0.68
0.66
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

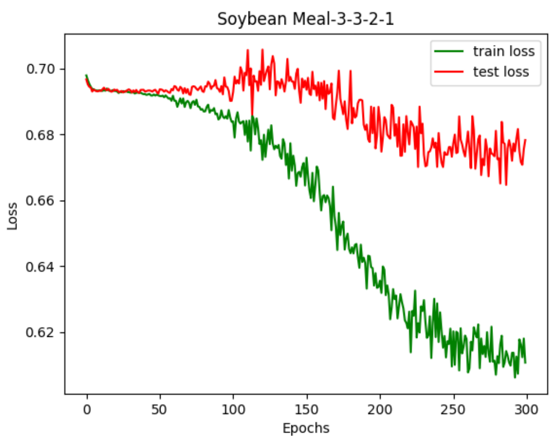

Live Cattle-3-3-2-1
0.72
0.71
0.70
0.69
0.68
0.67
0.66
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

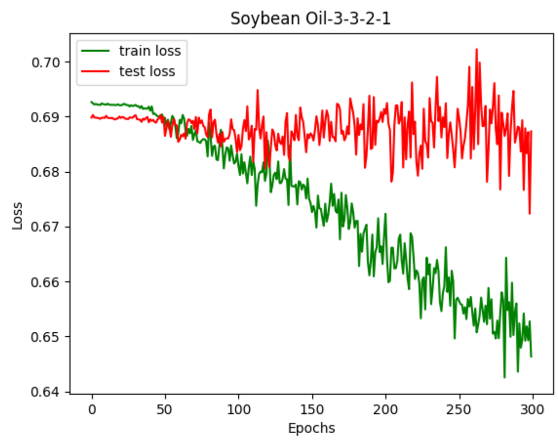

Orange Juice-3-3-2-1
0.72
0.70
0.68
0.66
0.64
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

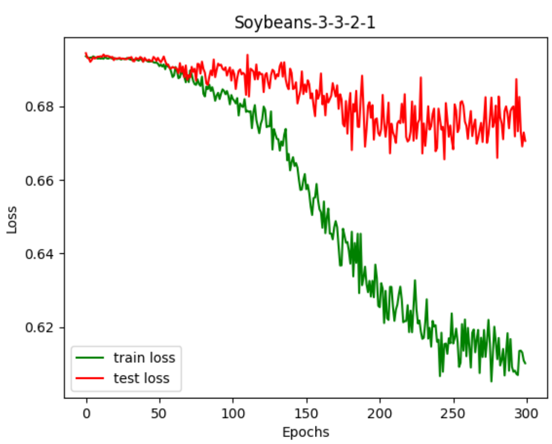

Rough Rice-3-3-2-1
0.71
0.70
0.69
0.68
0.67
0.66
0.65
Loss
0
50
100
150
200
250
300
Epochs
train loss
test loss

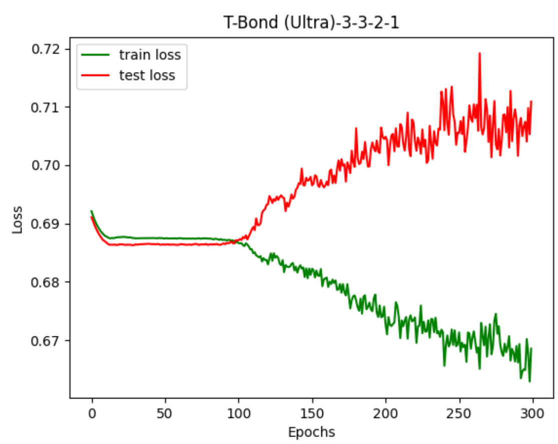

S&P 500 Index-3-3-2-1
train loss
test loss
Loss
0.72
0.70
0.68
0.66
0.64
0.62
0.60
0.58
0
50
100
150
200
250
300
Epochs

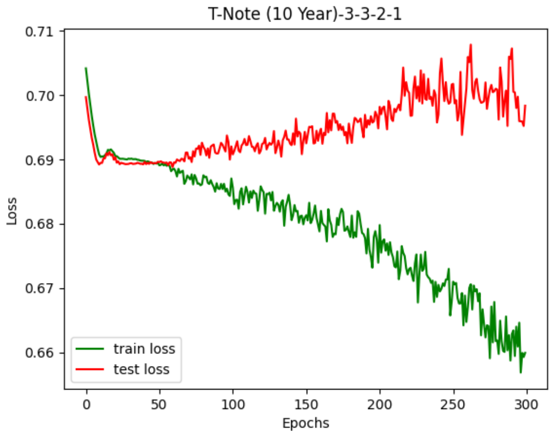

Silver-3-3-2-1
train loss
test loss
Loss
0.70
0.69
0.68
0.67
0.66
0.65
0.64
0.63
0
50
100
150
200
250
300
Epochs

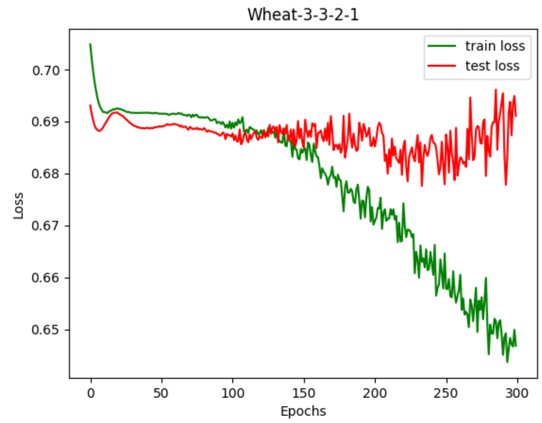

Soybean Meal-3-3-2-1
train loss
test loss
Loss
0.70
0.68
0.66
0.64
0.62
0
50
100
150
200
250
300
Epochs


Soybean Oil-3-3-2-1
train loss
test loss
Loss
0.70
0.69
0.68
0.67
0.66
0.65
0.64
0
50
100
150
200
250
300
Epochs


Soybeans-3-3-2-1
train loss
test loss
Loss
0.68
0.66
0.64
0.62
0
50
100
150
200
250
300
Epochs

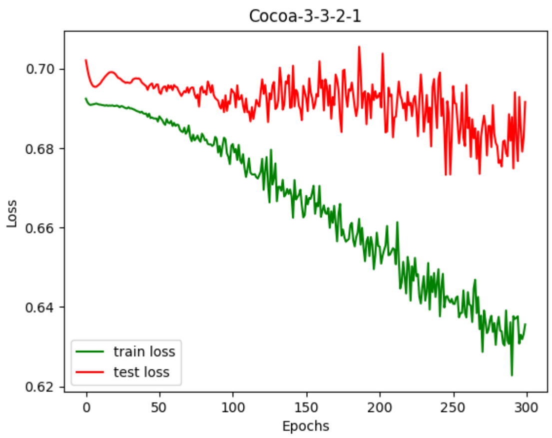

T-Bond (Ultra)-3-3-2-1
train loss
test loss
Loss
0.72
0.71
0.70
0.69
0.68
0.67
0
50
100
150
200
250
300
Epochs

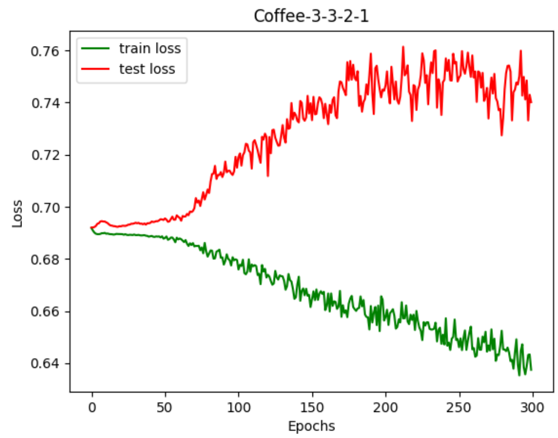


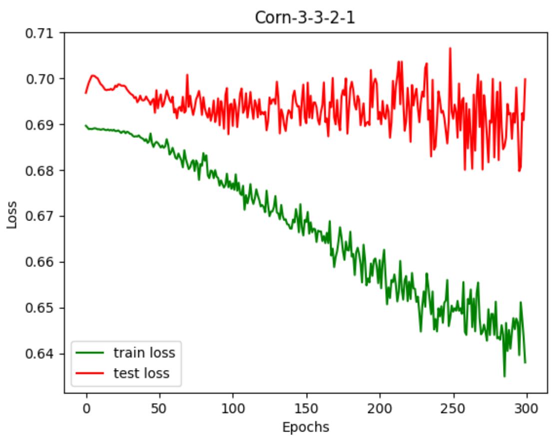


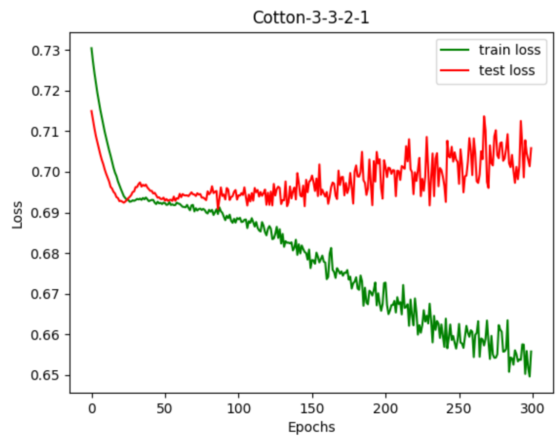
Intentionally left blank

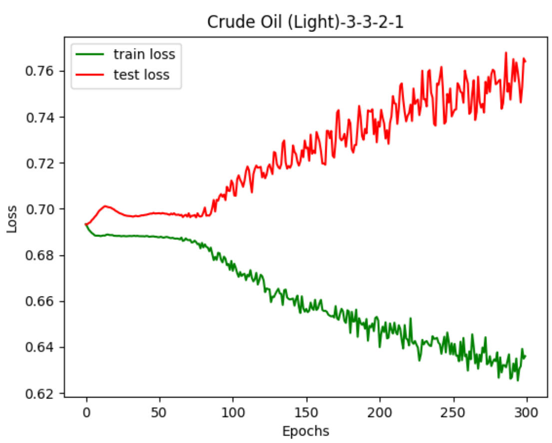
AdamW Optimizer

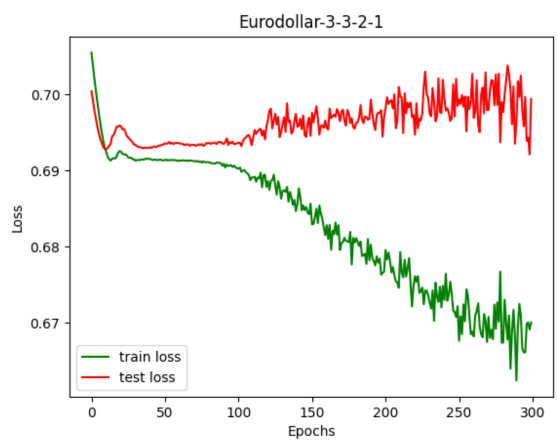


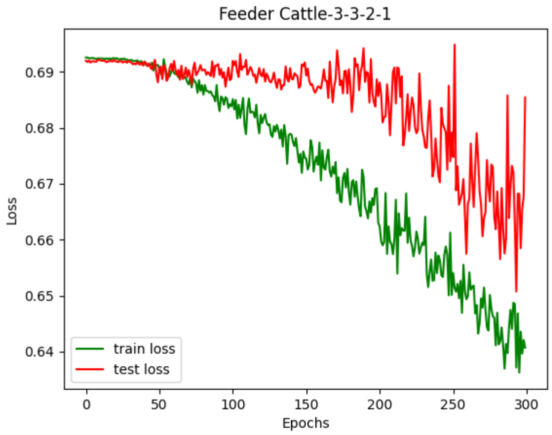


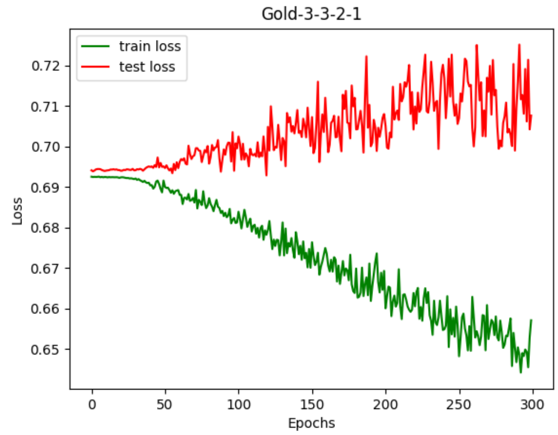


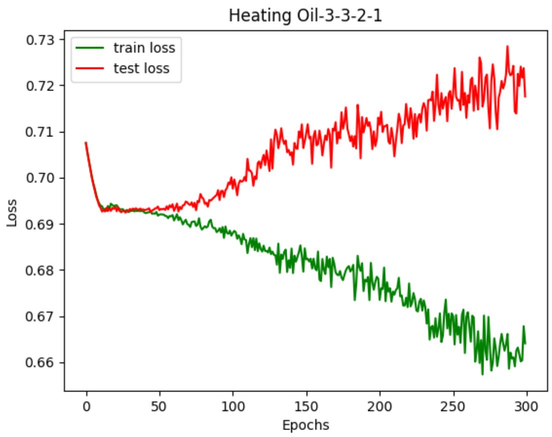


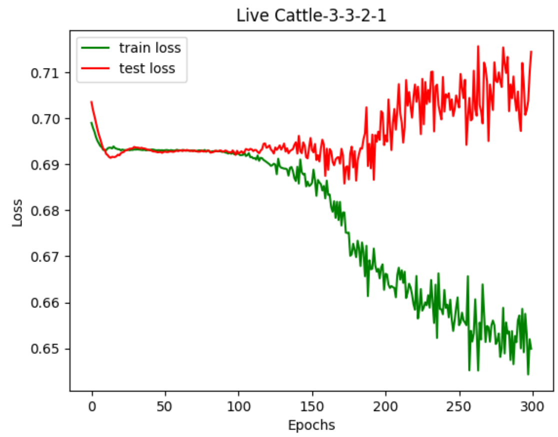


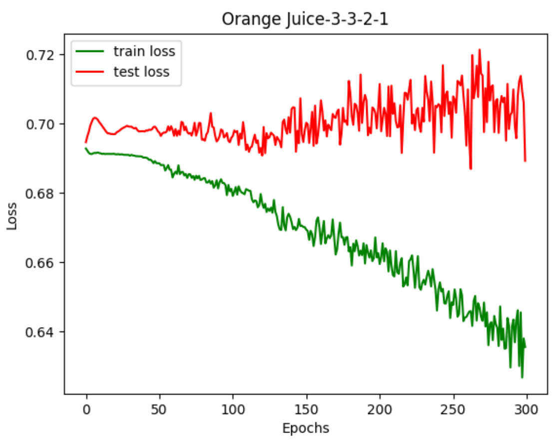


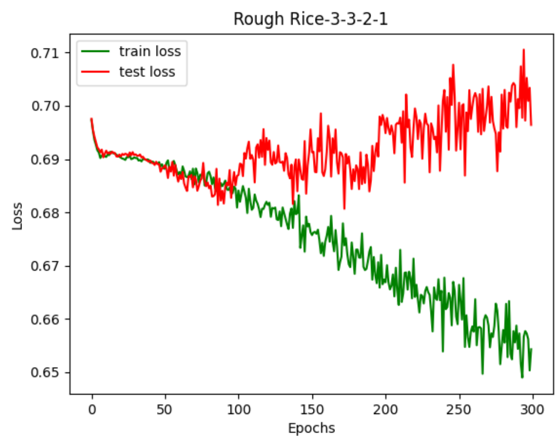

Feeder Cattle-3-3-2-1
train loss
test loss
Loss
Epochs

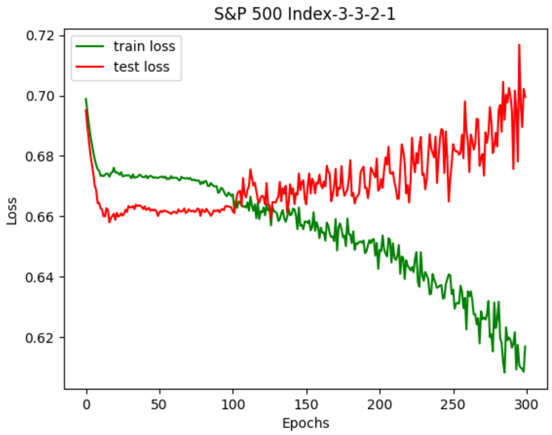

Gold-3-3-2-1
train loss
test loss
Loss
Epochs

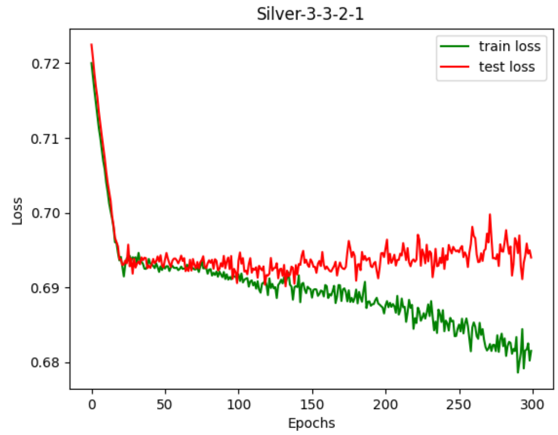

Heating Oil-3-3-2-1
train loss
test loss
Loss
Epochs

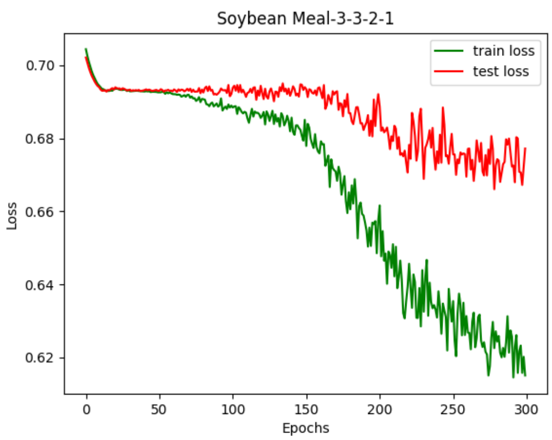

Live Cattle-3-3-2-1
train loss
test loss
Loss
Epochs

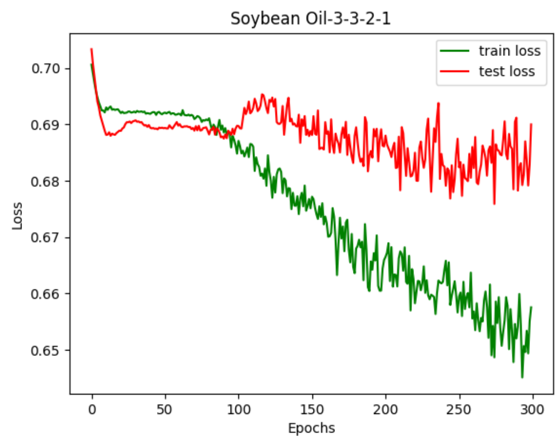

Orange Juice-3-3-2-1
train loss
test loss
Loss
Epochs

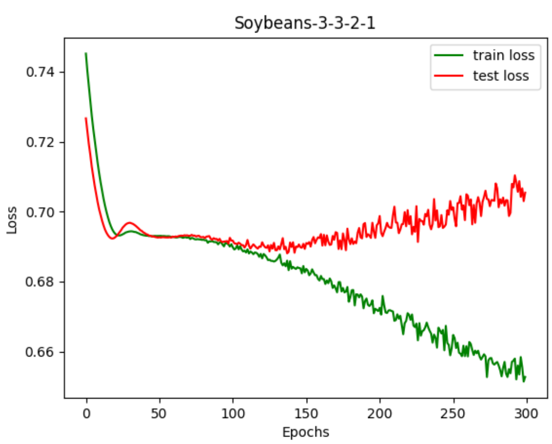

Rough Rice-3-3-2-1
train loss
test loss
Loss
Epochs

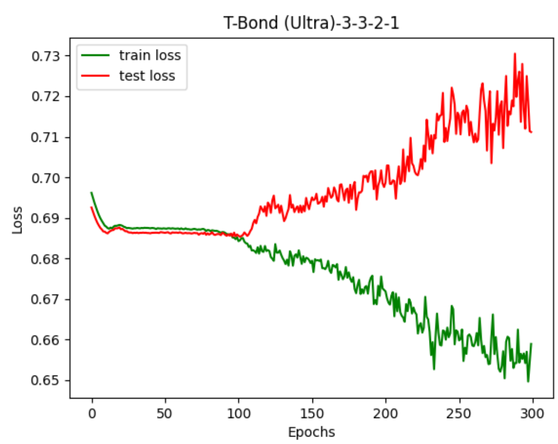

S&P 500 Index-3-3-2-1
train loss
test loss
Loss
Epochs

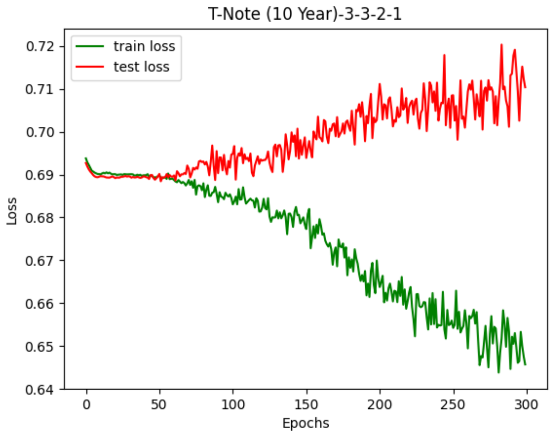

Silver-3-3-2-1
train loss
test loss
Loss
Epochs

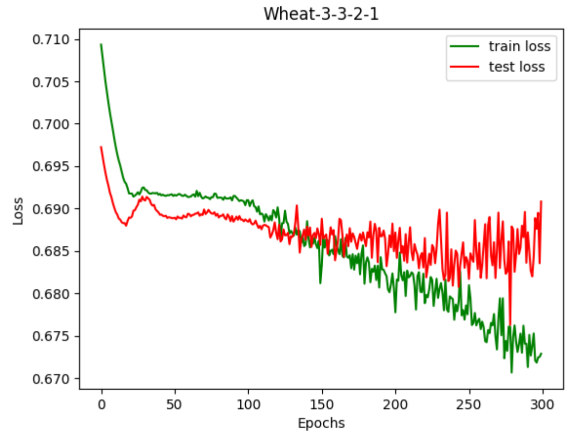

Soybean Meal-3-3-2-1
train loss
test loss
Loss
Epochs


Soybean Oil-3-3-2-1
train loss
test loss
Loss
Epochs


Soybeans-3-3-2-1
train loss
test loss
Loss
Epochs

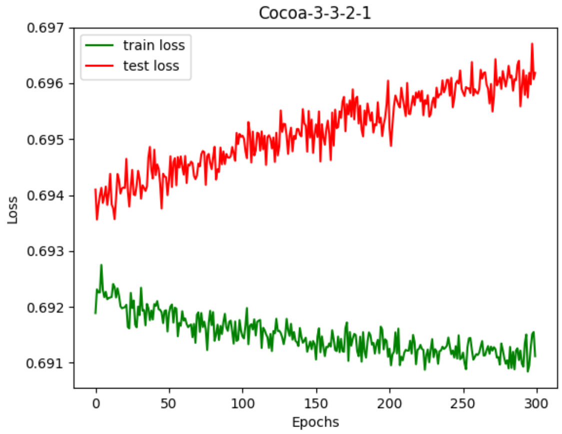

T-Bond (Ultra)-3-3-2-1
train loss
test loss
Loss
Epochs

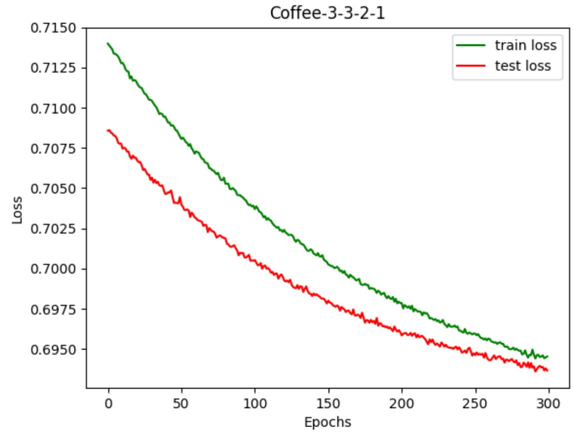


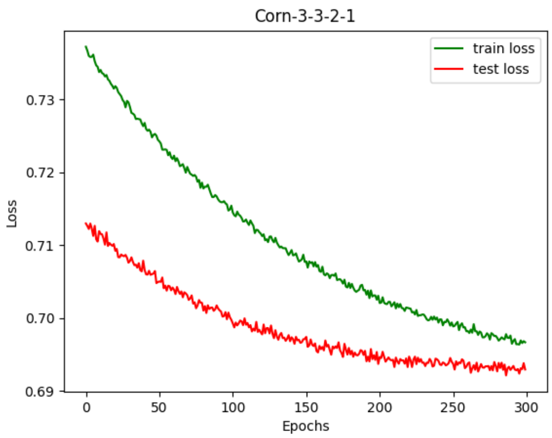


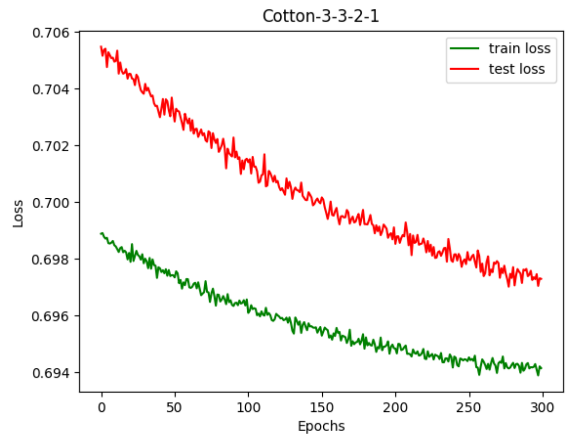
Intentionally left blank

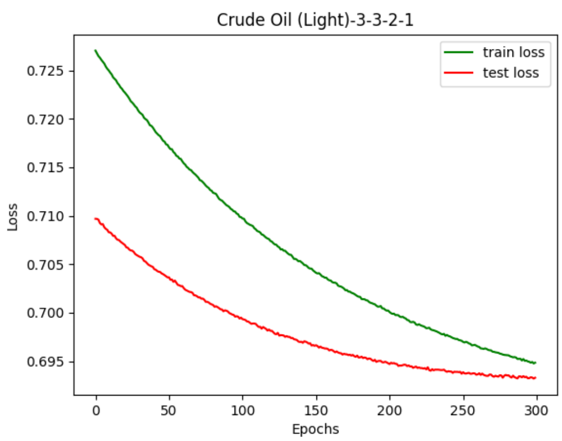
SGD Optimizer

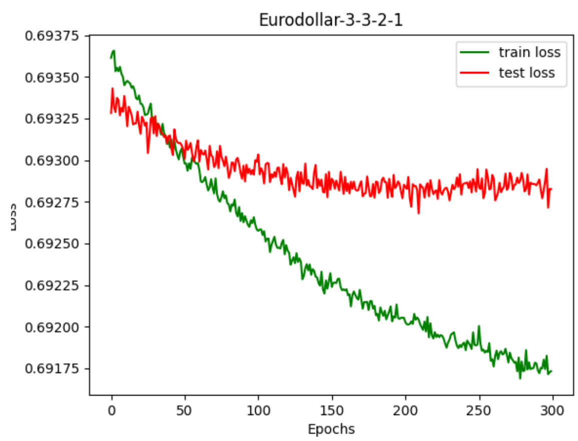


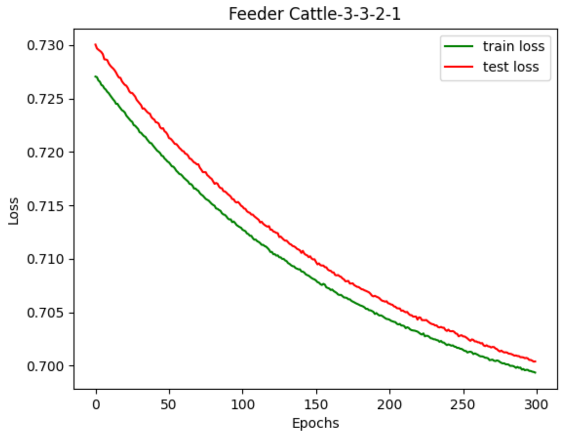


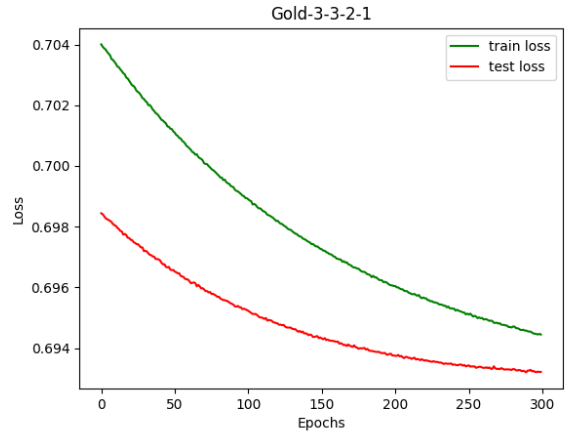


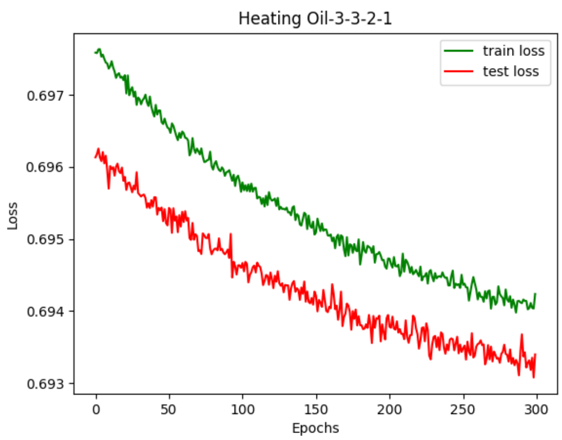


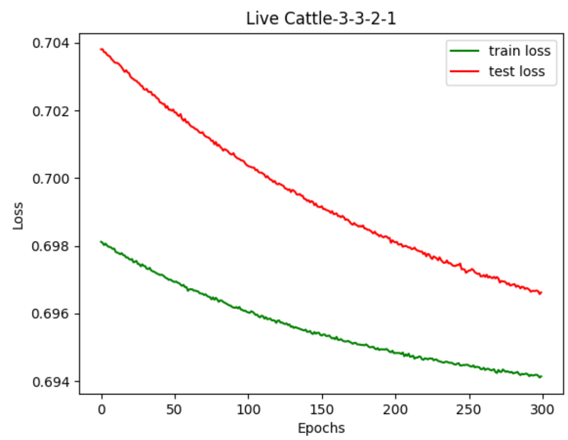


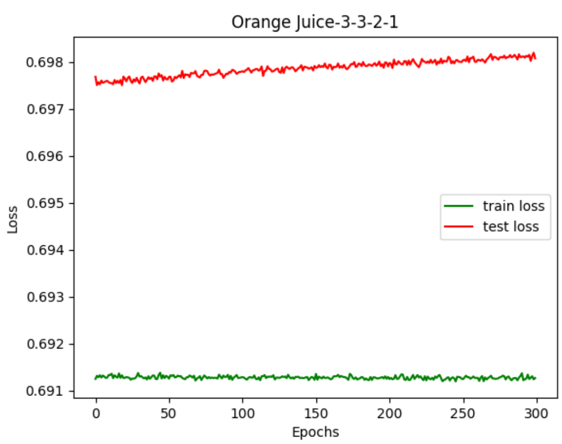


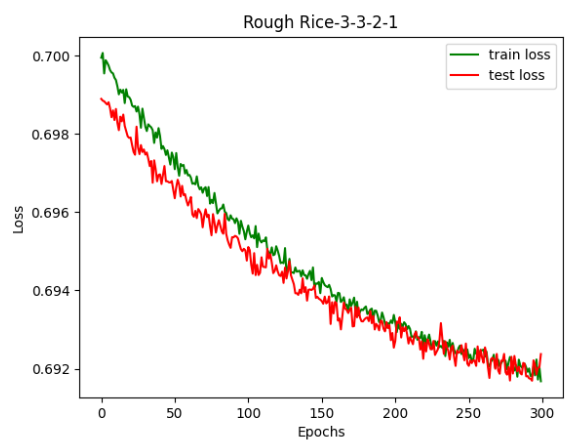

Feeder Cattle-3-3-2-1
train loss
test loss
Loss
Epochs
0.730
0.725
0.720
0.715
0.710
0.705
0.700
0 50 100 150 200 250 300

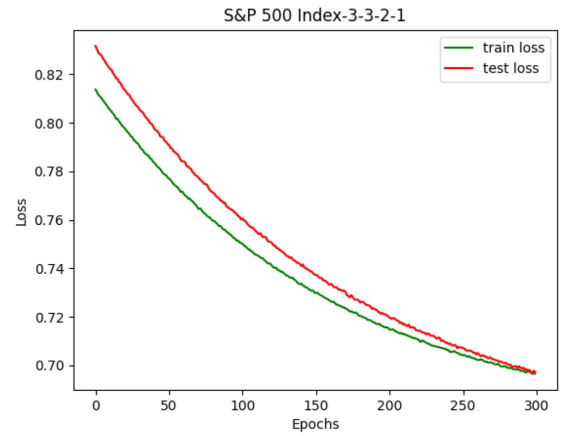

Gold-3-3-2-1
train loss
test loss
Loss
Epochs
0.704
0.702
0.700
0.698
0.696
0.694
0 50 100 150 200 250 300

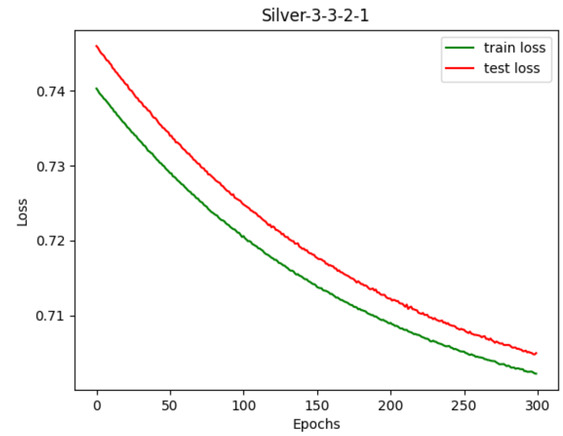

Heating Oil-3-3-2-1
train loss
test loss
Loss
Epochs
0.697
0.696
0.695
0.694
0.693
0 50 100 150 200 250 300

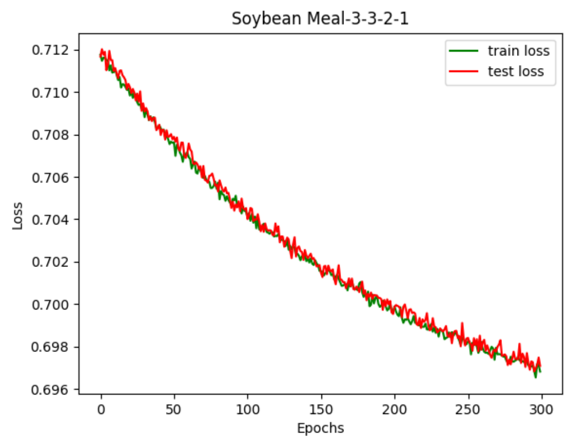

Live Cattle-3-3-2-1
train loss
test loss
Loss
Epochs
0.704
0.702
0.700
0.698
0.696
0.694
0 50 100 150 200 250 300

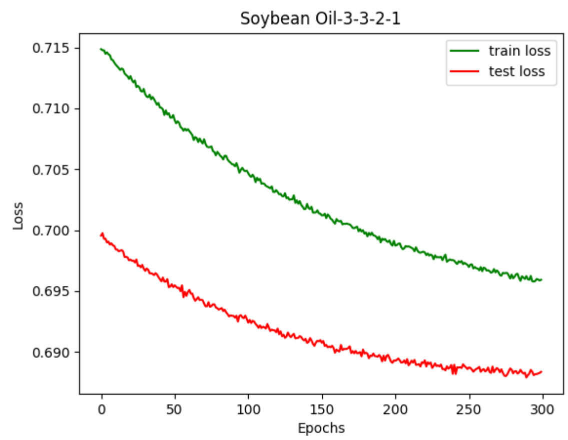

Orange Juice-3-3-2-1
train loss
test loss
Loss
Epochs
0.698
0.697
0.696
0.695
0.694
0.693
0.692
0.691
0 50 100 150 200 250 300

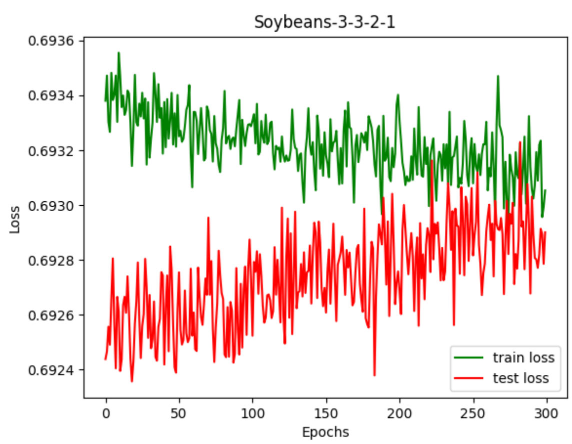

Rough Rice-3-3-2-1
train loss
test loss
Loss
Epochs
0.700
0.698
0.696
0.694
0.692
0 50 100 150 200 250 300

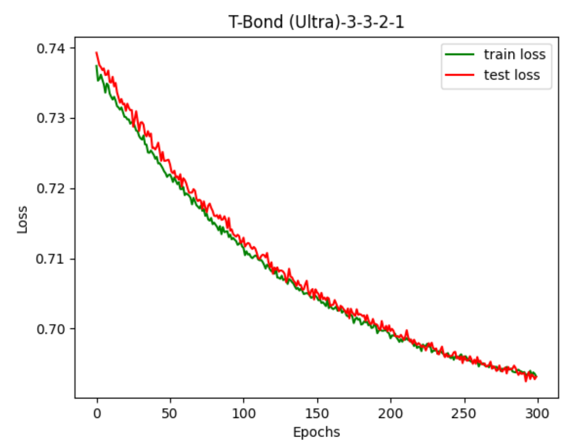

S&P 500 Index-3-3-2-1
train loss
test loss
Loss
0.82
0.80
0.78
0.76
0.74
0.72
0.70
0 50 100 150 200 250 300
Epochs

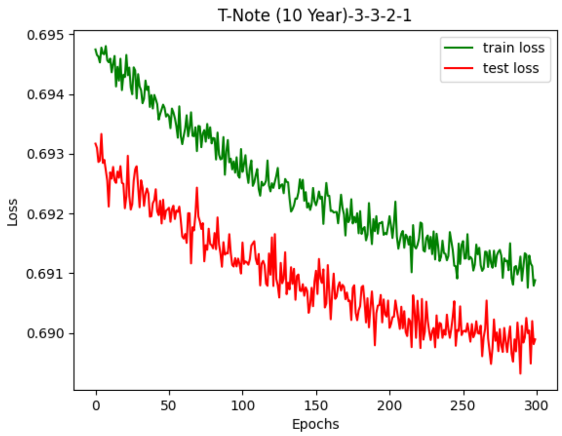

Silver-3-3-2-1
train loss
test loss
Loss
0.74
0.73
0.72
0.71
0 50 100 150 200 250 300
Epochs

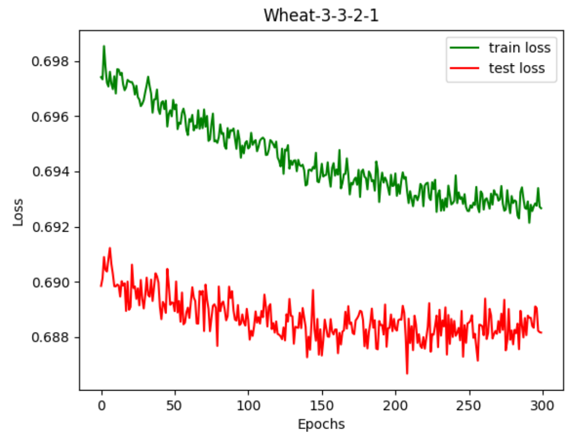

Soybean Meal-3-3-2-1
train loss
test loss
Loss
0.712
0.710
0.708
0.706
0.704
0.702
0.700
0.698
0.696
0 50 100 150 200 250 300
Epochs


Soybean Oil-3-3-2-1
train loss
test loss
Loss
0.715
0.710
0.705
0.700
0.695
0.690
0 50 100 150 200 250 300
Epochs


Soybeans-3-3-2-1
train loss
test loss
Loss
0.6936
0.6934
0.6932
0.6930
0.6928
0.6926
0.6924
0 50 100 150 200 250 300
Epochs


T-Bond (Ultra)-3-3-2-1
train loss
test loss
Loss
0.74
0.73
0.72
0.71
0.70
0 50 100 150 200 250 300
Epochs





Intentionally left blank