Supervised Stock Price Prediction using Long-Short Term Memory and Technical Indicators

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Abstract

This dissertation focused on building LSTM models that can predict stock price values and trends any number of days in the future of any stock index, public company, or cryptocurrency using historical time series of 52 technical indicators.

The models from the dissertation had achieved promising results by beating persistence baseline models and by outperforming 6 out of 7 selected research papers in the same domain. The best models for the companies in Nasdaq 100 achieved 61.8% Trend Correct Percentage (TCP) and 0.80% Mean Absolute Percentage Error (MAPE) for predicting 1 trading day, 58.2% TCP and 1.46% MAPE for predicting 3 trading days, 56.6% TCP and 1.82% MAPE for predicting 5 trading days, and 56.6% TCP and 2.59% MAPE for predicting 10 days in the future.

Acknowledgements

I would like to thank my project supervisor, Shay Cohen, for his help and support throughout the project, and for supporting the change of the original project idea from ”Sentiment Analysis from Twitter and Microblog Data” to ”Supervised Stock Price Prediction using Long-Short Term Memory and Technical Indicators”.

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Chapter 1

Introduction

This dissertation focuses on building Long Short-Term Memory (LSTM) models based on time series of technical indicators for time series prediction for stock price values (the adjusted closing price) and trends. The main contributions include:

- Building a new system from scratch
- Collecting time series data of technical indicators
- Designing LSTM model types
- Implementing LSTM models
- Hypothesis testing and optimisation
- Evaluating the prototype against baseline model and benchmark models from research papers

1.1 Problem

Stock prediction is hard. Not everyone can afford automated trading nor financial advisory services. With the rising amount of easily accessible data, the final goal of this project aims to produce a stock prediction advisory tool for users who would like to invest themselves in the stock market bypassing traditional middleman such as stock advisory firms.

1.2 Objective

This dissertation focuses on building LSTM models of different types for stock price value and trend prediction purely based on technical indicators. The models can be used for any company, index, and cryptocurrency and are able to accept any combination of parameters from below:

- Any number of days of prior history of technical indicators
- Any number of available technical indicators
- Any number of days for prediction in the future

The end result of these LSTM models is to outperform baseline and benchmark models from other research papers in the same domain. Ultimately, the working prototype could assist the author in buying and selling stocks in his investment portfolio on Degiro UK (2019), thus generating additional profit from the investment that would otherwise have not been possible. This prototype should allow general users to understand the potential performance of individual company stocks based on technical indicators. Additionally, the future vision of this prototype is to facilitate automated trading on open platforms such as Degiro UK (2019).

1.3 Outcome

The built LSTM models has outperformed 6 out of 7 selected papers in the same domain of predicting stock price values and trends based on technical analysis as shown in Table 1.2. This prototype had achieved good results of predicting future stock price values and trends for the 100 companies in Nasdaq-100 (2019) in Table 1.1 (where variable t denotes the timestep in days). For example, t+1 denotes the next trading day, and t+3 denotes 3 trading days in the future. A trading day is when the stock exchange is open and available for making trades. Holidays and weekends are not considered trading days (Investor World 2019).

	Trend Percent Correct				Mean Absolute Percentage Error			
	t + 1	t + 3	t + 5	t + 10	t + 1	t + 3	t + 5	t + 10
Best	61.8%	58.2%	56.6%	56.6%	0.80%	1.46%	1.82%	2.59%
Average	57.1%	52.7%	51.1%	50.1%	1.41%	2.50%	3.31%	4.69%

Table 1.1: Prototype performance on 100 companies in Nasdaq-100 (2019)

1.4 Tools

Various tools and resources were used during the development of the stock prediction prototype in Python 3.

- Github (2019) was used for version control
- Jupyter Notebook (2019) were used to speed up the entire development and debugging of the prototype
- Pycharm (2019) was used to speed up the development and debugging of object-oriented designs

Paper	Models	Outperformed?
Abraham et al. (2004)	Linear and Non-linear Support Vector Machine (SVM), Neuro-Fuzzy System, Artificial Neural Network (ANN), Difference Boosting Neural Network (DBNN)	Yes
Chen, Abraham, Yang & Yang (2005)	Takagi-Sugeno Fuzzy Systems (TS-FS), Neural Network trained by Particle Swarm Optimisation (NN-PSO), and Hierarchical TS-FS	Yes
Chen, Dong & Zhao (2005)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Hansson (2017)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Gupta & Dhingra (2012)	Fuzzy Hidden Markov Models (HMM) and Maximum a Posteriori (MAP) HMM	No on MAP-HHM but yes on HMM
Lin et al. (2009)	Back-propagation neural network (BPNN), Radian Basis Function Neural Network (RBFNN), and Echo State Networks (ESN)	Yes on average
McNally et al. (2018)	LSTM, Recurrent Neural Network (RNN), and Autoregressive Integrated Moving Average (ARIMA)	Yes

Table 1.2: New models of the dissertation evaluated against benchmark models

- Guides and tutorials were used as guidance during the development process
- Libraries were used to speed up the development
- TensorFlow (2019) and Keras (2019) were used to build the machine learning models
- Financial and investing websites were used to better understand the financial backgrounds
- Microsoft Excel (2018) was used for data visualisation and data analysis of results

Chapter 2

Background

This chapter provides essential backgrounds for a better understanding of the dissertation. Stock index, company stock, Long Short-Term Memory (LSTM), technical analysis, technical indicators, properties of stock prediction models, and previous work in stock prediction are discussed.

2.1 Stock Index and Individual Company Stock

A stock index is a statistical measure of the changes in a portfolio of stocks representing a portion of the overall market Investopedia (2019*a*). For example, Nasdaq-100 index reflects largest companies in Nasdaq across major industry groups (Nasdaq 2019). The Nasdaq-100 index is a basket of the 100 largest, most actively traded U.S companies listed on the Nasdaq stock exchange (Investopedia 2019*b*). Other stock indices that are involved in this dissertation are S&P 500 (US), Nifty 50 (India), Bovespa (Brasil), and OMX 30 (Sweden).

An individual company stock (also known as ”shares” or ”equity) is a type of security that signifies proportionate ownership in the issuing corporation. Stocks are bought and sold predominantly on stock exchanges (Investopedia 2019*c*). For example, Amazon is listed on New York Stock Exchange (2019) under the ticker symbol ”AMZN”.

2.2 Long Short-Term Memory

LSTM is defined as an artificial recurrent neural network architecture used in the field of deep learning (Hochreiter & Schmidhuber 1997). Unlike standard feed-forward neural networks, LSTM has feedback connections that make it a general purpose computer (Siegelmann & Sontag 1995). Because LSTM can capture entire sequential time series data, LSTM networks are well-suited to making prediction based on time series data, since there can be lags of unknown duration between important events in a time series (Schmidhuber et al. 2005). A time series is a sequence of numerical data points in successive order of equal intervals such as dates (Investopedia 2019*e*). Example applications are time series stock prediction (Nelson et al. 2017).

LSTM introduces the memory cell, a unit of computation that replaces traditional artificial neurons in the hidden layer of the network. Hence, networks are able to effectively associate memories and input data in time. Therefore, LSTM are suitable to capture the structure of the time series data dynamically over time with high prediction capacity (Roondiwala et al. 2017). LSTM is better learning long term dependencies. As a result, picking a long window was less detrimental for the LSTM McNally et al. (2018).

2.3 Technical Analysis and Technical Indicator

Technical analysis is an analysis methodology for forecasting the direction of stock price values through the study of past market data, primarily price and volume (Kirkpatrick II & Dahlquist 2010). In technical analysis, technical indicators calculated from stock price sequence are used to predict the trend of future price changes. Additionally, there are many other technical indicators beside price and volume. A technical indicator is a mathematical calculation based on historic price, volume, or open interest information that aims to forecast financial market direction (Murphy 1999).

2.4 Properties of Stock Prediction Models

All time series stock prediction models are differentiated by the following variables:

- Temporal resolution of time series data
- Model types
- One-prior or multi-prior history
- One-step or multi-step forecasting
- Univariate or multivariate

2.4.1 Resolution of Time Series Data

The time series of technical indicators is a sequence of numerical data points in successive order of equal intervals such as intraday (1 minute, 5 minute, 15 minute, 30 minute, 60 minute), daily, weekly, monthly, and yearly. The dissertation was based on daily temporal resolution as many other research papers also adapt daily temporal resolution of time series data and predict future stock price values and trends by days.

2.4.2 Model Types

There are many types of models that were used in other research papers to predict stock price values and trends in the past. The LSTM models of the dissertation were evaluated and benchmarked against models from other research papers which include model types defined in Table 2.1.

Paper	Models	Outperformed?
Abraham et al. (2004)	Linear and Non-linear Support Vector Machine (SVM), Neuro-Fuzzy System, Artificial Neural Network (ANN), Difference Boosting Neural Network (DBNN)	Yes
Chen, Abraham, Yang & Yang (2005)	Takagi-Sugeno Fuzzy Systems (TS-FS), Neural Network trained by Particle Swarm Optimisation (NN-PSO), and Hierarchical TS-FS	Yes
Chen, Dong & Zhao (2005)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Hansson (2017)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Gupta & Dhingra (2012)	Fuzzy Hidden Markov Models (HMM) and Maximum a Posteriori (MAP) HMM	No on MAP-HHM but yes on HMM
Lin et al. (2009)	Back-propagation neural network (BPNN), Radian Basis Function Neural Network (RBFNN), and Echo State Networks (ESN)	Yes on average
McNally et al. (2018)	LSTM, Recurrent Neural Network (RNN), and Autoregressive Integrated Moving Average (ARIMA)	Yes

Table 2.1: Model used by selected research papers for benchmarking

2.4.3 One-prior or Multi-prior History

Any stock prediction model are either an one-prior or multi-prior history model. The history represented the values of the time series of the prior timesteps in days. The greater the number of prior history, the more the model prediction depended on values of technical indicators in prior timesteps.

One-prior History Model
This model only has one-prior history meaning that the predictions depended on the values of the time series of the technical indicators of one day before.

Multi-prior History Model
This model has multi-prior history meaning that the predictions depended on the values of the technical indicators of multiple days.

2.4.4 One-step or Multi-step Forecasting

Any model must be an one-step or multi-step model. Forecasting is defined as the prediction of some future stock price values by analyzing the historical time series of technical indicators.

One-step Forecasting Model
This model only has one output, which is the predicted stock price value of the next day.

Multi-step Forecasting Model
This model has multiple output, which were the predicted stock price value of the next number of days.

2.4.5 Univariate or Multivariate

Any stock prediction model must be an univariate or a multivariate model.

Univariate Model
The input for this model is any one time series of technical indicators. The very same time series is used for training and testing.

Multivariate Model
The input for this model are two or more time series of technical indicators. The selected time series of technical indicators are also used for training and testing.

2.5 Metrics

There are mainly three metrics used to evaluate the performance of each model:

- RMSE (Root Mean Squared Error) is defined in Equation 6.1.
- MAPE (Mean Average Percentage Error) is defined in Equation 6.2.
- TCP (Trend Percentage Correct) is defined in Equation 6.3. TCP is derived from the stock price value prediction and measures the percentage total of all predicted stock price values that are in the same trend direction of the actual prices. This metric is also known as accuracy in other research papers.

$$\begin{aligned}&RMSE = \tfrac{1}{n}\textstyle\sum_{i=1}^{n}(v_{i,actual} - v_{i,predicted})^2\\&\forall v_{predicted} \in Values_{predicted}, \forall v_{actual} \in Values_{actual}\end{aligned} \tag{2.1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|v_{i,actual}-v_{i,predicted}\right|}{v_{i,actual}}$$
$$\forall v_{predicted} \in Values_{predicted}, \forall v_{actual} \in Values_{actual} \tag{2.2}$$

$$TCP = \frac{1}{n}\left|\sum_{i=1}^{n} t_{i,actual} == t_{i,predicted}\right|$$
$$\forall t_{predicted} \in Trends_{predicted}, \forall t_{actual} \in Trends_{actual} \tag{2.3}$$

In other research papers, it is not clear why RMSE is used as a percentage. Therefore, TCP and MAPE are the main metrics.

2.6 Previous Work in Stock Prediction

Historically, technical analysis is one of the main source of data that researchers, analysts, and investors have used to predict the future values and trends of the stock price of a company. Those are technical analysis, fundamental analysis, and sentiment analysis. This project only focuses on data from technical analysis. This section also provides background on previous work done in technical analysis to predict stock price values and trends. As opposed to all below researches, this dissertation aims to build a generalised model that can predict any company, index, and cryptocurrency aiming to outperform the below research papers in technical analysis in Chapter 7.

There were many models proposed by many researches, and these models are considered benchmark model in which this dissertation tried to outperform. Note that in many of the researches, the preprocessing of data are not as important because only the final performance metric are compared. The research papers mainly focused predicting the stock price values and trends for stock indeces, individual company stock prices, and cryptocurrencies.

2.6.1 Stock Index

Abraham et al. (2004) developed 1-step forecasting multivariate models based on 4 time series of technical indicators (daily opening, closing, high, and low values) for Nasdaq 100 and Nifty 50 index. The models involved were Linear and Non-linear SVM, Neuro-Fuzzy System, ANN, and DBNN.

The sequel research paper by the same authors was Chen, Abraham, Yang & Yang (2005). This sequel paper has the same context as Abraham et al. (2004) but with different models. The new models were TS-FS, NN-PSO, and Hierarchical TS-FS.

The next sequel research paper for Chen, Abraham, Yang & Yang (2005) was Chen, Dong & Zhao (2005). This sequel paper has the same context as Chen, Abraham, Yang & Yang (2005) but with different models. The new models were WNN and LLWNN. Chen, Dong & Zhao (2005) significantly outperformed both prior papers.

A distinct paper, Hansson (2017), developed 1-step forecasting univariate models based on 1 time series of technical indicator (daily adjusted closing values) for S&P 500, Bovespa, and OMX index. The models involved were ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM.

2.6.2 Individual Stock

Gupta & Dhingra (2012) developed 1-step forecasting multivariate models for companies (Dell, Tata Steel, Apple, and IBM) in the US stock market based on 4 time series of technical indicator (opening, closing, daily high, and daily low price). The models used was Hidden Markov Models (HMM).

Lin et al. (2009) developed 1-step forecasting multivariate models based on 6 time series of technical indicator (daily high, daily low, open, close, 5-day high, and 5-day close values) for 25 companies in the S&P 500. The models used are BPNN, RBFNN, and ESN.

2.6.3 Cryptocurrency

McNally et al. (2018) developed multivariate models that could predict the Bitcoin price in USD in the future based on 6 time series of technical indicators (simple moving averages, closing, adjusted closing, opening, daily high, and daily low prices). It was not clear how many days in the future the models are predicting. Models experimented were LSTM, ANN, and ARIMA. Additionally, these models used multiple prior history of the time series of the technical indicators in the past to make the prediction.

Chapter 3

Data Collection

In this chapter, time series of technical indicators for stock price prediction prototype were explored, selected, and downloaded. Many freemium (free without limitation), pseudo-freemium (limited features under the freemium version), and premium (fees above $500) data sources of technical indicators were available. The data sources in the following sections were from US companies and were in US dollars.

Freemium data source

- IEX Group (2018) provides:
  - stock price data for the past 30 days
  - volume data for the past 30 days

Pseudo-freemium data source

- Alpha Vantage (2018) provides:
  - 5 API requests per minute; 500 API requests per day for free
  - stock price data of companies from their initial public offerings until now
  - 51 additional technical indicators available from their initial public offerings until now
  - technical indicators for companies in international stock exchanges
  - technical indicators for international indeces such as Nasdaq-100, Nifty 50, NYSE, and S&P 500.
- SimFin (SimFin 2018) provides:
  - 2000 API calls per day for free
  - daily adjusted stock price data from 1st January 2007 until now

Premium data source

- Zacks Investment Research (2018) provides:

  - no technical indicators
- Intrinio (2018) provides:
  - daily and historical stock prices
- Xignite (2018) provides:
  - daily and historical stock prices in the US and international equities

3.1 Selection of Data Source

Due to no financial budget, selection of data sources were limited to freemium and pseudo-freemium data sources. Therefore, given the freely reliable available data for technical indicators from Alpha Vantage (2018), it was chosen as the main data source for technical indicators for building the models of the dissertation.

3.2 Downloading Data Source

100 companies from Nasdaq-100 (2019) shown in Table 3.1 and 3.2, accurate as of February 2019, were the primary source of experimentation for this dissertation. Due to the limitation of 500 API calls per day from Alpha Vantage (2018), the data for 100 companies were collected and saved offline for experimentation. Each API call returned 1 technical indicator, and 1 company had 52 technical indicator (including share price). Therefore, 100 companies resulted in 5200 API calls. In the end, 10.4 days were required to obtain all technical indicators for 100 companies. The data are saved in well formatted CSV files ready to be used by the Python Pandas (2019) library.

3.3 Resolution of Time Series Data

Alpha Vantage (2018) provided historical global equity data in 4 different temporal resolutions:

1. intraday price (1 minute, 5 minute, 15 minute, 30 minute, 60 minute)
2. daily
3. weekly
4. monthly

The dissertation used daily adjusted close if possible, otherwise daily close was used. The adjusted closing price was chosen because it is preferred by technical traders to the raw closing price because it accounts for corporate actions such as dividends and splits. Adjusted close price is considered as stock price as in other researches such as Rechenthin et al. (2013), Hansson (2017), and McNally et al. (2018).

Daily temporal resolution was selected for this project, because intraday temporal resolution was too fine-grained and weekly and monthly resolution were too coarse-grained. Some problems that occurred with intraday temporal resolution was that it was optimal for same day prediction but would not perform well in an interday basis (when the stock is not sold in the same day when it was bought like intraday trading). Some problems that occurred with weekly and monthly resolution were that there were limited data available for training and testing. Furthermore, many benchmark models from researches have used the daily resolution, so choosing daily would facilitate comparisons and evaluations.

3.4 Real Time

Data provided by Alpha Vantage (2018) was real time, hence making real time predictions in the stock price values and trends were possible. However, due to API limits, it was impractical to update data real-time so data were downloaded and saved locally. Although the data about a company could be updated with 52 API calls for the 52 technical indicators, this dissertation did not explore real-time stock price prediction but past data for training and testing.

Companies in Nasdaq-100 (2019)			
Sticker	Name	Sticker	Name
ATVI	Activision Blizzard Inc	KLAC	KLA-Tencor
ADBE	Adobe	LRCX	Lam Research
AMD	Advanced Micro Devices	LBTYA	Liberty Global
ALXN	Alexion Pharmaceuticals	LBTYK	Liberty Global
ALGN	Align Technology	LULU	lululemon athletica
GOOG	Alphabet	MAR	Marriott International
GOOGL	Alphabet	MXIM	Maxim Integrated Products
AMZN	Amazon.com	MELI	MercadoLibre
AAL	American Airlines Group	MCHP	Microchip Technology
AMGN	Amgen	MU	Micron Technology
ADI	Analog Devices	MSFT	Microsoft
AAPL	Apple	MDLZ	Mondelez International
AMAT	Applied Materials	MNST	Monster Beverage
ASML	ASML Holding N.V.	MYL	Mylan N.V.
ADSK	Autodesk	NTAP	NetApp
ADP	Automatic Data Processing	NTES	NetEase
BIDU	Baidu	NFLX	Netflix
BIIB	Biogen	NVDA	NVIDIA
BMRN	BioMarin Pharmaceutical	NXPI	NXP Semiconductors N.V.
BKNG	Booking Holdings	ORLY	O'Reilly Automotive
AVGO	Broadcom	PCAR	Paccar
CDNS	Cadence Design Systems	PAYX	Paychex
CELG	Celgene	PYPL	PayPal Holdings
CERN	Cerner	PEP	Pepsico
CHTR	Charter Communications	QCOM	Qualcomm
CHKP	Check Point Software Tech	REGN	Regeneron Pharmaceuticals
CTAS	Cintas	ROST	Ross Stores
CSCO	Cisco Systems	SIRI	Sirius XM Holdings
CTXS	Citrix Systems	SWKS	Skyworks Solutions
CTSH	Cognizant Technology	SBUX	Starbucks
CMCSA	Comcast	SYMC	Symantec
COST	Costco	SNPS	Synopsys
CSX	CSX	TMUS	T-Mobile US
CTRP	Ctrip.com International Ltd.	TTWO	Take-Two Interactive
DLTR	Dollar Tree	TSLA	Tesla
EBAY	eBay	TXN	Texas Instruments
EA	Electronic Arts	KHC	The Kraft Heinz Company
EXPE	Expedia Group	FOX	Twenty-First Century Fox
FB	Facebook	FOXA	Twenty-First Century Fox
FAST	Fastenal Company	ULTA	Ulta Beauty
FISV	Fiserv	UAL	United Continental Holdings

Table 3.1: 100 companies from Nasdaq-100 (2019)

Companies in Nasdaq-100 (2019)			
Sticker	Name	Sticker	Name
GILD	Gilead Sciences	VRSN	VeriSign
HAS	Hasbro	VRSK	Verisk Analytics
HSIC	Henry Schein	VRTX	Vertex Pharmaceuticals
IDXX	IDEXX Laboratories	WBA	Walgreens Boots Alliance
ILMN	Illumina	WDC	Western Digital
INCY	Incyte	WLTW	Willis Towers Watson
INTC	Intel	WDAY	Workday
INTU	Intuit	WYNN	Wynn Resorts Limited
ISRG	Intuitive Surgical	XEL	Xcel Energy
JBHT	J.B. Hunt Transport Services	XLNX	Xilinx
JD	JD.com		

Table 3.2: 100 companies from Nasdaq-100 (2019)

Chapter 4

System Design

This section discusses how the models were designed, tested, and evaluated. Figure 4.1 shows an overall structure on how the system was designed in which all model must be a combination of the variables.

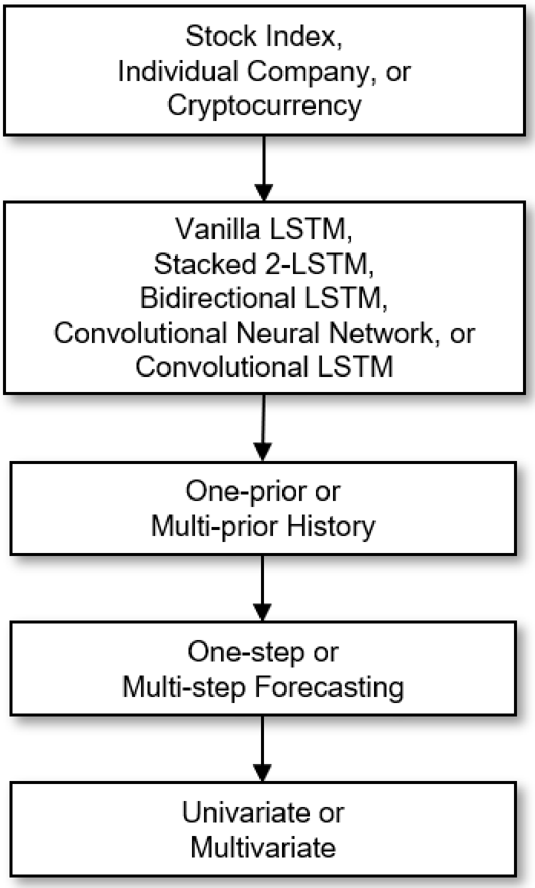

Figure 4.1: Overall system structure

The models were supervised machine learning models where the input were the time series of daily adjusted technical indicators, the target is the historical stock price value, and the output were the predicted stock price value. All models had one or more time series of technical indicators.

The time series of technical indicators were trading days excluding weekends and holidays. This would not have an effect on the training nor testing. However, weekends and holidays might had an impact on the stock price value and trend, but for simplicity purposes, they were discounted in this dissertation.

4.1 Model Types

The models used the default activation function tanh and must be one of the following custom-defined models adapted from Machine Learning Mastery (2019*a*). Additionally, the data are reshaped in the appropriate format for all below model types as shown in their respective model diagrams created by the Keras (2019) library. Note that the respective model diagrams are based on 3-prior history 1-step forecasting multivariate model of 52 technical indicators. The input dimension of the input layer described in the figures are (size of training time series, number of prior history, number of technical indicators), and the output dimension of the output layer are (size of training time series, number of steps for forecasting).

- Vanilla model in Figure 4.2 was a single hidden layer of LSTM units, and an output layer used to make a prediction.
- Stacked model in Figure 4.3 was 2 hidden LSTM layers, and an output layer used to make a prediction. Two hidden LSTM layers were chosen. For a time series task two layers was enough to find non-linear relationships among the data for a time series task. McNally et al. (2018) tested three and four layers but these did not improve performance.
- Bidirectional LSTM model in Figure 4.4 allowed the LSTM model to learn the input sequence both forward and backwards and concatenate both interpretations.
- Convolutional Neural Network model in Figure 4.5 could be very effective at automatically extracting and learning features from one-dimensional sequence data such as univariate time series data. Note that this is not a LSTM network.
- Convolutional LSTM model in Figure 4.6 was a type of LSTM related to the Convolutional Neural Netowork, where the convolutional reading of input is built directly into each LSTM unit.

4.2 Result Storage, Analysis, and Visualisation

All experiment results in this dissertation has been saved in CSV (Comma Seperated Values) files. These CSV files were then visualised and analysed using pivot tables in Microsoft Excel (2018).

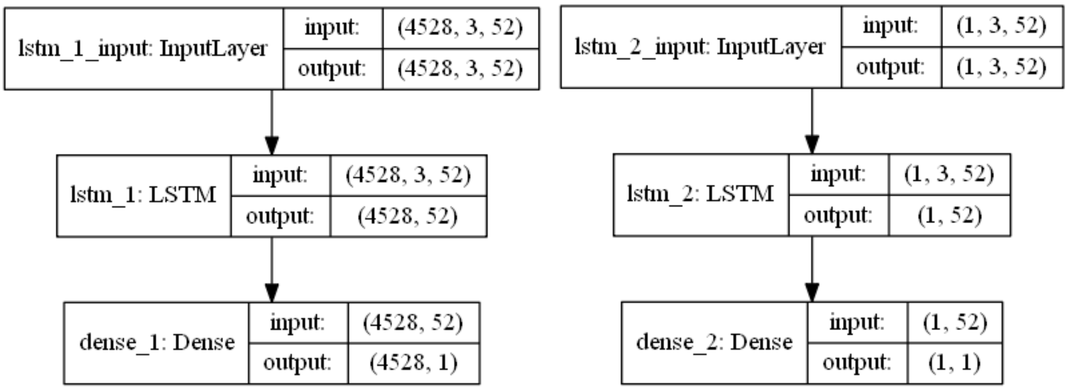

Figure 4.2: Batch gradient descent (left) and stochastic gradient descent (right) vanilla LSTM model

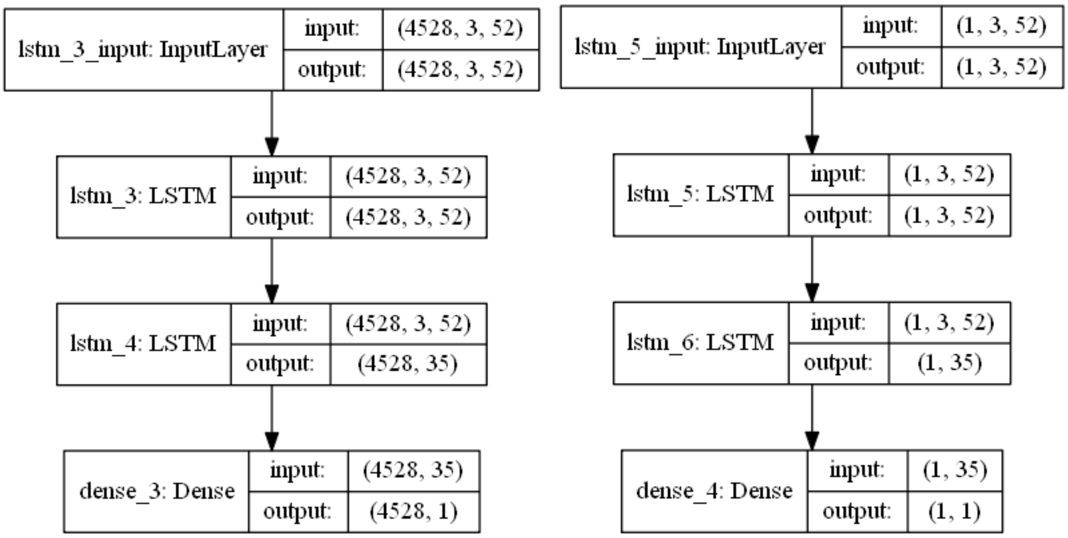

Figure 4.3: Batch gradient descent (left) and stochastic gradient descent (right) stacked 2-LSTM model

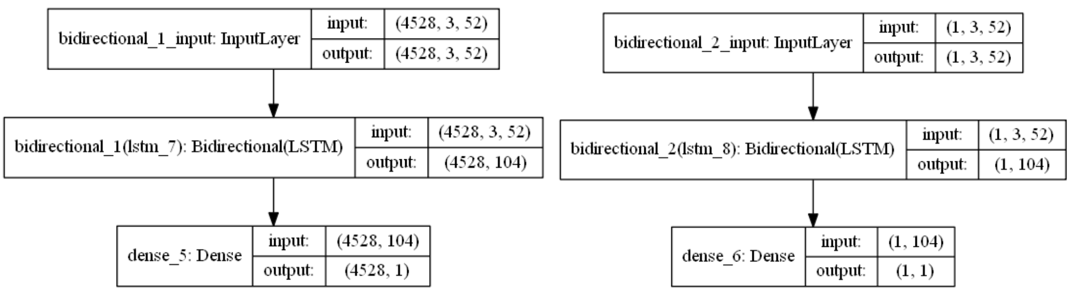

Figure 4.4: Batch gradient descent (left) and stochastic gradient descent (right) bidirectional LSTM model

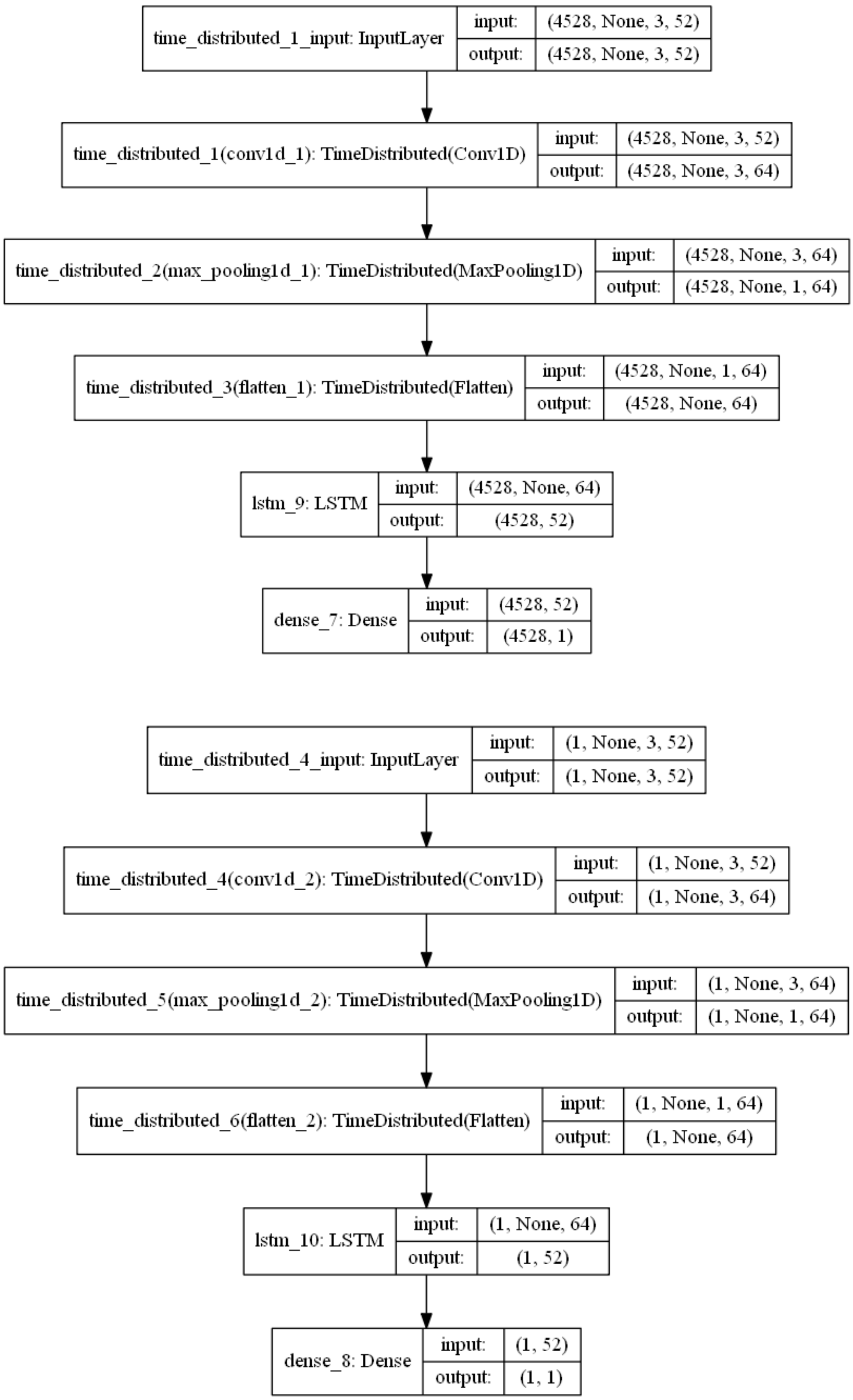

Figure 4.5: Batch gradient descent (top) and stochastic gradient descent (down) convolutional neural network model

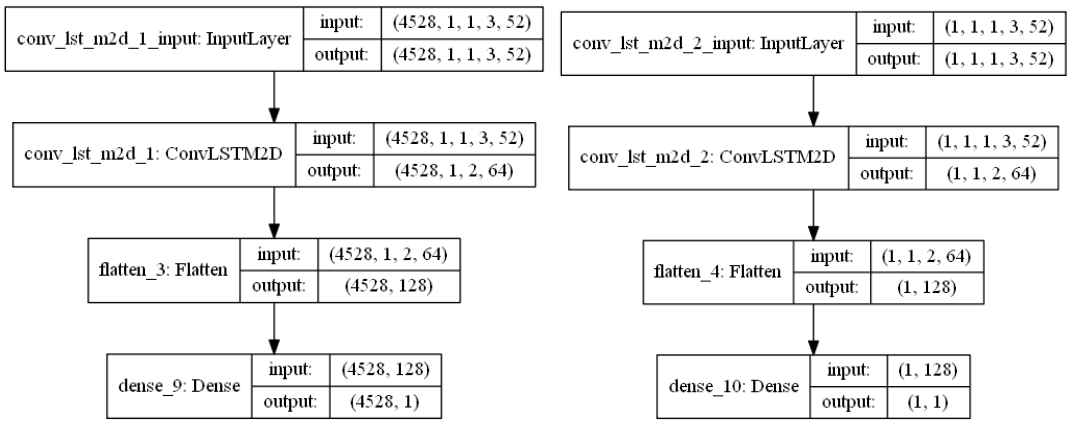

Figure 4.6: Batch gradient descent (left) and stochastic gradient descent (right) convolutional LSTM model

Chapter 5

Implementation

The LSTM machine learning models were built using Keras (2019) and TensorFlow (2019). Firstly, the different category of models are determined during implementation. Secondly, the training and testing data are preprocessed depending on the category of models. Thirdly, choose the hyper parameters for the optimization algorithm, gradient descent, used to train machine learning algorithms.

5.1 Stateful LSTM

As experimented in Machine Learning Mastery (2019*b*), stateful LSTM for time series forecasting had better performance than stateless LSTM. Resetting state when making one-step predictions with a stateful LSTM may improve performance on the test set. Fitting a stateful LSTM and seeding it on the training dataset and not performing any resetting of state during training or prediction may result in better performance on the test set. Therefore, this approach was adopted in the implementation of the prototype.

5.2 One-prior or Multi-prior History Model

In this dissertation, any LSTM model must be an one-prior or multi-prior history model. The history represented the values of the time series of the prior timesteps in days. The greater the number of prior history, the more the model prediction depended on values of technical indicators in prior timesteps.

5.2.1 One-prior History

This model only had one-prior history meaning that the predictions depended on the values of the time series of the technical indicators of one day before regardless whether the model is univariate or multivariate. Figure 5.7, 5.8, and 5.9 are all examples of one-prior history model.

5.2.2 Multi-prior History

This model had multi-prior history meaning that the predictions depended on the values of the technical indicators of multiple days before regardless whether the model is univariate or multivariate. Figure 5.1 and Figure 5.2 show examples of multi-prior history models.

date	SMA(t-3)	RSI(t-3)	SMA(t-2)	RSI(t-2)	SMA(t-1)	RSI(t-1)	Share Price(t)
2018-01-02	1167.9640	61.6995	1169.2055	62.5164	1168.8415	56.9761	1189.01
2018-01-03	1169.2055	62.5164	1168.8415	56.9761	1170.1745	61.2261	1204.20
2018-01-04	1168.8415	56.9761	1170.1745	61.2261	1173.6870	64.1259	1209.59
2018-01-05	1170.1745	61.2261	1173.6870	64.1259	1177.0880	65.1008	1229.14
2018-01-08	1173.6870	64.1259	1177.0880	65.1008	1180.9275	68.3814	1246.87
2018-01-09	1177.0880	65.1008	1180.9275	68.3814	1185.2815	70.9852	1252.70
2018-01-10	1180.9275	68.3814	1185.2815	70.9852	1189.8165	71.7892	1254.33
2018-01-11	1185.2815	70.9852	1189.8165	71.7892	1194.0870	72.0175	1276.68
2018-01-12	1189.8165	71.7892	1194.0870	72.0175	1199.6670	74.9433	1305.20
2018-01-16	1194.0870	72.0175	1199.6670	74.9433	1206.7205	78.0290	1304.86
2018-01-17	1199.6670	74.9433	1206.7205	78.0290	1213.2505	77.9086	1295.00
2018-01-18	1206.7205	78.0290	1213.2505	77.9086	1219.0435	74.4040	1293.32

Figure 5.1: 3-prior history, multivariate, and one-step forecasting model for AMAZON

5.3 One-step or Multi-step Forecasting Model

In this dissertation, any LSTM model must be an one-step or multi-step model. Forecasting is defined as the prediction of some future stock price values by analyzing the historical time series of technical indicators.

5.3.1 One-step Forecasting

This model only had one output, which is the predicted stock price value of the next day regardless whether the model was univariate or multivariate. Figure 5.7, 5.8, and 5.9 are all examples of one-step forecasting models. Figure 5.3 shows an example of a graph plotting the one-step predictions of stock price values against the actual stock price values for AMAZON.

date	SMA(t-2)	RSI(t-2)	SMA(t-1)	RSI(t-1)	Share Price(t)	Share Price(t+1)
2018-01-02	1169.2055	62.5164	1168.8415	56.9761	1189.01	1204.20
2018-01-03	1168.8415	56.9761	1170.1745	61.2261	1204.20	1209.59
2018-01-04	1170.1745	61.2261	1173.6870	64.1259	1209.59	1229.14
2018-01-05	1173.6870	64.1259	1177.0880	65.1008	1229.14	1246.87
2018-01-08	1177.0880	65.1008	1180.9275	68.3814	1246.87	1252.70
2018-01-09	1180.9275	68.3814	1185.2815	70.9852	1252.70	1254.33
2018-01-10	1185.2815	70.9852	1189.8165	71.7892	1254.33	1276.68
2018-01-11	1189.8165	71.7892	1194.0870	72.0175	1276.68	1305.20
2018-01-12	1194.0870	72.0175	1199.6670	74.9433	1305.20	1304.86
2018-01-16	1199.6670	74.9433	1206.7205	78.0290	1304.86	1295.00
2018-01-17	1206.7205	78.0290	1213.2505	77.9086	1295.00	1293.32
2018-01-18	1213.2505	77.9086	1219.0435	74.4040	1293.32	1294.58

Figure 5.2: 2-prior history, multivariate, and 3-step forecasting model for AMAZON

5.3.2 Multi-step Forecasting

This model had multiple output, which were the predicted stock price value of the next number of days regardless whether the model is univariate or multivariate. Figure 5.4 and Figure 5.5 shows examples of univariate and multivariate multi-step (3-step) forecasting model with one-prior history.

Figure 5.6 shows an example of a graph plotting the 3-step predictions of stock price values against the actual stock price values for AMAZON.

5.4 Univariate or Multivariate Model

In this dissertation, any LSTM model must be an univariate or multivariate LSTM model. The available time series of the technical indicators from Alpha Vantage (2018) are detailed in Table 5.1 and Table 5.2.

5.4.1 Univariate

The input for this model was any one time series of technical indicators in Table 5.1 and Table 5.2. The very same time series is used for training and testing. Univariate models could be very useful in identifying technical indicators that are most useful in predicting future stock prices. Experiments of this hypothesis was carried out in

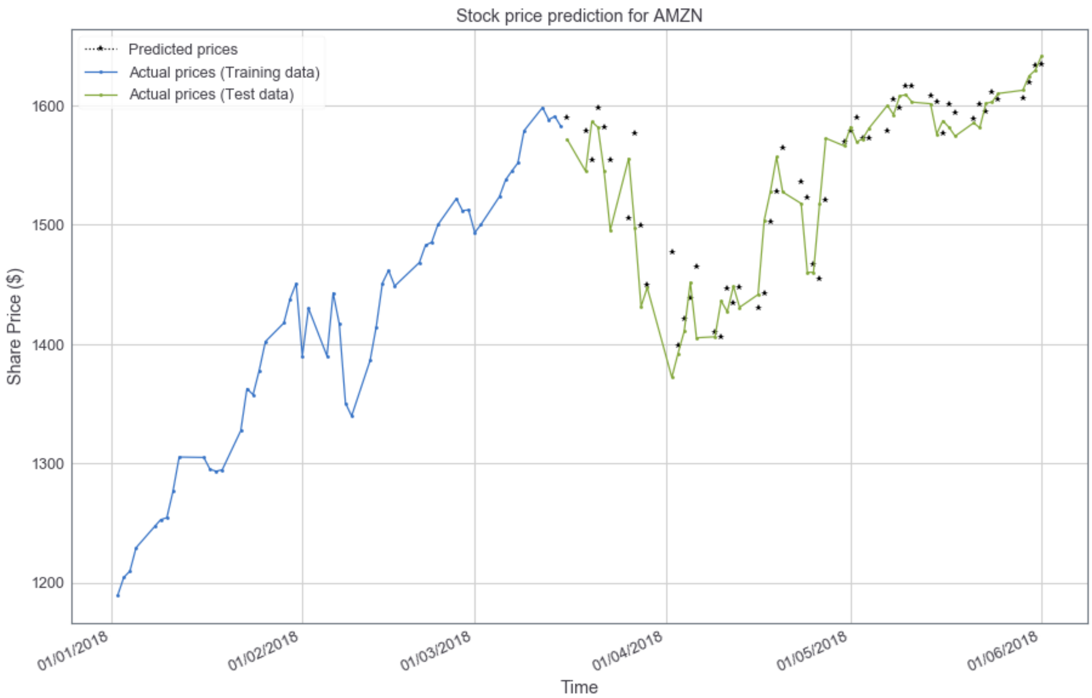

Figure 5.3: One-step forecast model for AMAZON from 15/03/2018 to 01/06/2018

Chapter 6. In Figure 5.7, the table on the left is an univariate model with input time series of technical indicator PRICE, and the table on the right is an univariate model with input time series of technical indicator SMA. Both univariate models are one-prior history, and one-step forecasting. Variable t in Figure 5.7 denotes the timestep, so t-1 denotes the value of the technical indicator the day before, t denotes the current day, and t+1 denotes the next day.

5.4.2 Multivariate

The input for this model were two or more time series of technical indicators in Table 5.1 and Table 5.2. The selected time series of technical indicators were used for training and testing. Multivariate models were more complex and could have better performance in predicting stock price value and trends than univariate models. Experiments of this hypothesis was carried out in Chapter 6. Figure 5.8 and 5.9 each shows a one-prior history, one-step forecasting, multivariate model with 4 and 5 input time series of technical indicators respectively. Variate t in Figure 5.8 and Figure 5.9 denotes the timestep, so t-1 denotes the value of the technical indicator the day before, t denotes the current day, and t+1 denotes the next day.

date	Share Price(t-1)	Share Price(t)	Share Price(t+1)	Share Price(t+2)
2018-01-02	1169.47	1189.01	1204.20	1209.59
2018-01-03	1189.01	1204.20	1209.59	1229.14
2018-01-04	1204.20	1209.59	1229.14	1246.87
2018-01-05	1209.59	1229.14	1246.87	1252.70
2018-01-08	1229.14	1246.87	1252.70	1254.33
2018-01-09	1246.87	1252.70	1254.33	1276.68
2018-01-10	1252.70	1254.33	1276.68	1305.20
2018-01-11	1254.33	1276.68	1305.20	1304.86
2018-01-12	1276.68	1305.20	1304.86	1295.00
2018-01-16	1305.20	1304.86	1295.00	1293.32
2018-01-17	1304.86	1295.00	1293.32	1294.58
2018-01-18	1295.00	1293.32	1294.58	1327.31

Figure 5.4: Univariate multi-step forecasting model for AMAZON with one-prior history

5.5 Data Preprocessing

As discussed in Chapter 3, the only source of data is the technical analysis. Therefore, the data from the technical analysis has to be prepprocessed. All training and testing data were processed tailored to the specific combination of whether the model is univariate or multivariate, one-step or multi-step forecasting, and one-prior history or multi-prior history. Machine Learning Mastery (2019*c*) was used as the main guide for data preprocessing techniques for time series forecasting. Both training and testing data were preprocessed taking into account the defined parameters. For example, the raw data in Figure 5.10 was transformed in 3 steps.

1. Transform the time series into a supervised learning problem as shown in Figure 5.11.

2. Transform the time series data so that it is stationary as shown in Figure 5.12. Non-stationary data has a structure that is dependent on the time. Specifically, there is an increasing or decreasing trend in the time series of technical indicators. Stationary data is easier to model and will very likely result in more skillful forecasts. The trend can be removed from the observations, then added back to forecasts later to return the prediction to the original scale and calculate a comparable error score. A standard way to remove a trend is by differencing the data.

3. Transform the time series to have a standard scale of mean equals to 0 and standard deviation of 1 as shown in Figure 5.13. Standarlisation is preferred over normalisation because if there are outliers in the data set, normalizing the data

date	SMA(t-1)	RSI(t-1)	EMA(t-1)	Share Price(t)	Share Price(t+1)	Share Price(t+2)
2018-01-02	1168.8415	56.9761	1168.7788	1189.01	1204.20	1209.59
2018-01-03	1170.1745	61.2261	1170.7056	1204.20	1209.59	1229.14
2018-01-04	1173.6870	64.1259	1173.8955	1209.59	1229.14	1246.87
2018-01-05	1177.0880	65.1008	1177.2950	1229.14	1246.87	1252.70
2018-01-08	1180.9275	68.3814	1182.2326	1246.87	1252.70	1254.33
2018-01-09	1185.2815	70.9852	1188.3885	1252.70	1254.33	1276.68
2018-01-10	1189.8165	71.7892	1194.5134	1254.33	1276.68	1305.20
2018-01-11	1194.0870	72.0175	1200.2103	1276.68	1305.20	1304.86
2018-01-12	1199.6670	74.9433	1207.4931	1305.20	1304.86	1295.00
2018-01-16	1206.7205	78.0290	1216.7985	1304.86	1295.00	1293.32
2018-01-17	1213.2505	77.9086	1225.1853	1295.00	1293.32	1294.58
2018-01-18	1219.0435	74.4040	1231.8343	1293.32	1294.58	1327.31

Figure 5.5: Multivariate multi-step forecasting model for AMAZON with one-prior history

will scale the normal data to a very small interval. And generally, most of data sets have outliers. When using standardization, the new data are not bounded (unlike normalization). As supported by McNally et al. (2018), standardisation was chosen over normalisation as it better suits the activation functions used by the deep learning models.

The predictions made with preprocessed data were inverse transformed in order to obtain the actual predicted stock price value rather than the preprocessed version of the prediction.

5.6 Training, Validation, and Test Dataset

The optimal parameters have to be found for each of the model detailed in the next section. Due to the nature of time series data, cross-validation is not suitable due to the nature of dependence of the data on the previous sequence of values. Therefore, an alternative way is to partition the available data into training and testing data keeping the order of the data in the time series same. All experiments (excluding Chapter 7 when evaluating against other research papers) had the training and testing data in the same period. The training data were the time series of technical indicators from 01/01/2000 to 01/01/2018, and the test data were the time series of technical indicators from 02/01/2018 to 01/01/2019. The input data were the values of the technical indicators and the output data were the actual stock price values. The training data were used to find the optimal parameters. The time series from 01/01/2000 to 01/01/2017

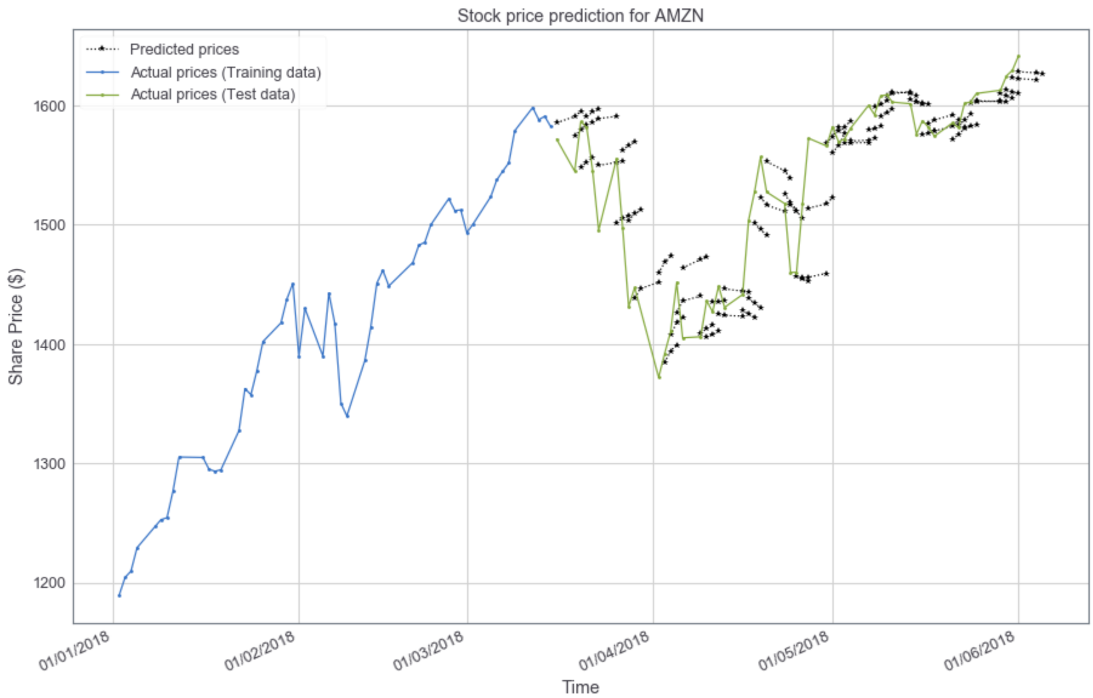

Figure 5.6: 3-step forecasting model for AMAZON from 15/03/2018 to 01/06/2018

were used for training and the time series from 02/01/2017 to 01/01/2018 were used for validation.

5.7 Hyperparameter Optimisation

The parameters for the different LSTM modeltypes (defined in Chapter 4 as Vanilla LSTM, Stacked 2-LSTM, Bidirectional LSTM, Convolutional Neural Network, and Convolutional LSTM) were adjusted to optimise accuracy of the predictions. In this case, the parameters are the number of neurons, batch size, and number of epochs. The optimal combination can be found by trial and errors, but due to limited computing resources and time, the combination were chosen based on best practices from other research papers.

All chosen parameters either impacted how well the models performed and the time required to train the model. Therefore, it was important to balance the performance and the time factors when choosing the parameters to carry out experiments in the next chapter.

5.7.1 Number of Neurons

The number of neurons were determined by the number of time series of technical indicators selected and the number of multi-step model. The number of neurons for the input layer was set to equal to the number of features (number of time series of

date	Share Price(t-1)	Share Price(t)
2018-01-02	1169.47	1189.01
2018-01-03	1189.01	1204.20
2018-01-04	1204.20	1209.59
2018-01-05	1209.59	1229.14
2018-01-08	1229.14	1246.87
2018-01-09	1246.87	1252.70
2018-01-10	1252.70	1254.33
2018-01-11	1254.33	1276.68
2018-01-12	1276.68	1305.20
2018-01-16	1305.20	1304.86
2018-01-17	1304.86	1295.00
2018-01-18	1295.00	1293.32

date	SMA(t-1)	Share Price(t)
2018-01-02	1168.8415	1189.01
2018-01-03	1170.1745	1204.20
2018-01-04	1173.6870	1209.59
2018-01-05	1177.0880	1229.14
2018-01-08	1180.9275	1246.87
2018-01-09	1185.2815	1252.70
2018-01-10	1189.8165	1254.33
2018-01-11	1194.0870	1276.68
2018-01-12	1199.6670	1305.20
2018-01-16	1206.7205	1304.86
2018-01-17	1213.2505	1295.00
2018-01-18	1219.0435	1293.32

Figure 5.7: Two one-prior history, one-step forecasting, and univariate models for AMAZON with one input time series of technical indicator Share Price and SMA

date	Share Price(t-1)	CMO(t-1)	MACD(t-1)	APO(t-1)	Share Price(t)
2018-01-02	1169.47	13.9521	13.0161	6.5514	1189.01
2018-01-03	1189.01	22.4522	13.1703	7.3613	1204.20
2018-01-04	1204.20	28.2519	14.3527	9.1563	1209.59
2018-01-05	1209.59	30.2017	15.5454	11.1646	1229.14
2018-01-08	1229.14	36.7629	17.8623	13.0110	1246.87
2018-01-09	1246.87	41.9703	20.8884	14.6762	1252.70
2018-01-10	1252.70	43.5785	23.4862	18.0117	1254.33
2018-01-11	1254.33	44.0350	25.3840	21.1048	1276.68
2018-01-12	1276.68	49.8865	28.3644	24.6419	1305.20
2018-01-16	1305.20	56.0579	32.6514	29.0517	1304.86
2018-01-17	1304.86	55.8171	35.6109	33.4026	1295.00
2018-01-18	1295.00	48.8080	36.7373	37.2772	1293.32

Figure 5.8: An one-prior history, one-step forecasting, and multivariate model for AMAZON with 4 input time series of technical indicators PRICE, CMO, MACD, and APO

date	ADX(t-1)	BOP(t-1)	EMA(t-1)	SMA(t-1)	RSI(t-1)	Share Price(t)
2018-01-02	26.5577	-0.7806	1168.7788	1168.8415	56.9761	1189.01
2018-01-03	25.8427	0.8728	1170.7056	1170.1745	61.2261	1204.20
2018-01-04	25.5619	0.9250	1173.8955	1173.6870	64.1259	1209.59
2018-01-05	25.5353	0.4095	1177.2950	1177.0880	65.1008	1229.14
2018-01-08	25.7909	0.6076	1182.2326	1180.9275	68.3814	1246.87
2018-01-09	26.4659	0.5164	1188.3885	1185.2815	70.9852	1252.70
2018-01-10	27.2075	-0.2390	1194.5134	1189.8165	71.7892	1254.33
2018-01-11	27.7381	0.5368	1200.2103	1194.0870	72.0175	1276.68
2018-01-12	28.5960	0.8341	1207.4931	1199.6670	74.9433	1305.20
2018-01-16	29.7804	0.9827	1216.7985	1206.7205	78.0290	1304.86
2018-01-17	31.2459	-0.3808	1225.1853	1213.2505	77.9086	1295.00
2018-01-18	32.2582	-0.5205	1231.8343	1219.0435	74.4040	1293.32

Figure 5.9: An one-prior history, one-step forecasting, and multivariate model for AMAZON with 5 input time series of technical indicators ADX, BOP, EMA, SMA, and RSI

technical indicators) in the training data. The number of neurons for the hidden layer was determined using rule-of-thumb methods from (Heaton 2008). The number of hidden neurons used was 2/3 the size of the input layer, plus the size of the output layer. The number of neurons for the output layer was equal to the number of outputs (the number of steps for forecasting).

5.7.2 Batch Size

The batch size is a hyper parameter of gradient descent that controls the number of training samples to work through before the models internal parameters are updated (Machine Learning Mastery 2019*d*). From experiments, batch size had a significant impact on the learning speed of the LSTM model regardless of its parameters.

There were 3 types of batch size that could have an effect on the gradient descent learning (Ruder 2016):

- Stochastic Gradient Descent is when the batch size is 1. This is most inefficient and slow. Stochastic Gradient Descent removes the redundancy of recomputing gradients for similar examples by performing one update at a time. It is therefore usually much faster and can also be used to learn online (Ruder 2016).
- Mini-Batch Gradient Descent is when the batch size is between 1 and size of the training set, and the size of the training set must be divisible by the batch size. It has been observed in practice that when using a larger batch there is a significant

date	Share Price	SMA	EMA
2018-01-02	1189.01	1170.1745	1170.7056
2018-01-03	1204.20	1173.6870	1173.8955
2018-01-04	1209.59	1177.0880	1177.2950
2018-01-05	1229.14	1180.9275	1182.2326
2018-01-08	1246.87	1185.2815	1188.3885
2018-01-09	1252.70	1189.8165	1194.5134
2018-01-10	1254.33	1194.0870	1200.2103
2018-01-11	1276.68	1199.6670	1207.4931
2018-01-12	1305.20	1206.7205	1216.7985
2018-01-16	1304.86	1213.2505	1225.1853
2018-01-17	1295.00	1219.0435	1231.8343
2018-01-18	1293.32	1224.1805	1237.6901

Figure 5.10: Raw data for the Multivariate model for AMAZON

degradation in the quality of the model, as measured by its ability to generalize. The lack of generalization ability is due to the fact that large-batch methods tend to converge to sharp minimizers of the training function (Keskar et al. 2016).

- Batch Gradient Descent is when the batch size is the same as the size of the training set. Batch gradient descent is guaranteed to converge to the global minimum for convex error surfaces and to a local minimum for non-convex surfaces (Ruder 2016).

For the same experiment with identical parameters except the batch size, Stochastic Gradient Descent took around 60 minutes to train while the Batch Gradient Descent took 3 minutes. This could be because batching is good for GPU computation. GPUs are very good at parallelizing the calculations that happen in neural networks (Stack Exchange 2019). Although Wilson & Martinez (2003) argues that Stochastic Gradient Descent should be faster, Stochastic Gradient Descent is actually slower from the experiments in this dissertation.

Mini-Batch Gradient Descent was problematic to implement because the size of the training set must be divisible by the batch size. In the worst case scenario, the size of the training set is only divisible by 1, and this becomes a Stochastic Gradient Descent and is slower than Batch Gradient Descent but faster than Stochastic Gradient Descent in either scenario. One way to solve this non-divisibility problem is to discard training data sets, but in time series modelling for a stateful LSTM, this is not recommended.

Therefore, under the above constraints, Batch Gradient Descent was used to train models in the entirety of this dissertation. However, a problem with Batch Gradient Descent was that the size of the test data had to be the same as the batch size, and this was

date	Share Price(t-1)	SMA(t-1)	EMA(t-1)	Share Price(t)
2018-01-02	1169.47	1168.8415	1168.7788	1189.01
2018-01-03	1189.01	1170.1745	1170.7056	1204.20
2018-01-04	1204.20	1173.6870	1173.8955	1209.59
2018-01-05	1209.59	1177.0880	1177.2950	1229.14
2018-01-08	1229.14	1180.9275	1182.2326	1246.87
2018-01-09	1246.87	1185.2815	1188.3885	1252.70
2018-01-10	1252.70	1189.8165	1194.5134	1254.33
2018-01-11	1254.33	1194.0870	1200.2103	1276.68
2018-01-12	1276.68	1199.6670	1207.4931	1305.20
2018-01-16	1305.20	1206.7205	1216.7985	1304.86
2018-01-17	1304.86	1213.2505	1225.1853	1295.00
2018-01-18	1295.00	1219.0435	1231.8343	1293.32

Figure 5.11: Supervised data for the multivariate model for AMAZON

not very convenient due to the fact that one prediction at a time was more practical. Therefore, the weights of the LSTM model were first trained with the Batch Gradient Descent method, and then are assigned to an identical LSTM model with Stochastic Gradient Descent method (batch size of 1) to speed up experiments so that the new model can make predictions of one sample at a time. These implementation could be seen in Figure 4.2, 4.3, 4.4, 4.5, and 4.6.

5.7.3 Number of Epochs

With a fixed training set, training the model on each item of the set once is an epoch (Research Gate 2019*b*). The number of epochs is related to the number of rounds of optimization that are applied during training. With more rounds of optimization, the error on training data will reduce further and further; however there may come a point where the network becomes over-fit to the training data and will start to lose performance in terms of generalization to non-training (unseen) data (Research Gate 2019*a*). As The optimal number of epochs will have to be found via experiments. For this optimisation, a 3-prior history 3-step forecasting univariate model of technical indicator PRICE for AMAZON is used.

The time series from 01/01/2000 to 01/01/2017 were used for training and the time series from 02/01/2017 to 01/01/2018 were used for validation. 6 models with the same hyperparameters were trained and tested in order to obtain a more robust result in finding the optimal number of epochs.

The average TCP and MAPE of the model types for each different number of epochs

date	Share Price(t-1)	SMA(t-1)	EMA(t-1)	Share Price(t)
2018-01-02	-16.63	-0.3640	0.0728	19.54
2018-01-03	19.54	1.3330	1.9268	15.19
2018-01-04	15.19	3.5125	3.1899	5.39
2018-01-05	5.39	3.4010	3.3995	19.55
2018-01-08	19.55	3.8395	4.9376	17.73
2018-01-09	17.73	4.3540	6.1559	5.83
2018-01-10	5.83	4.5350	6.1249	1.63
2018-01-11	1.63	4.2705	5.6969	22.35
2018-01-12	22.35	5.5800	7.2828	28.52
2018-01-16	28.52	7.0535	9.3054	-0.34
2018-01-17	-0.34	6.5300	8.3868	-9.86
2018-01-18	-9.86	5.7930	6.6490	-1.68

Figure 5.12: Stationary supervised data for the multivariate model for AMAZON

are recorded in Figure 5.14, and the optimal epochs number of each model type for AMAZON were described as below:

- Vanilla LSTM model was 3238
- Stacked LSTM model was 239
- Bidirectional LSTM model was 2097
- Convolutional Neural Network model was 3238
- Convolutional LSTM model was 100

The drawback for this approach was that the number of epochs would only be optimised for AMAZON and for univariate model and not for other companies nor multivariate models. Morck et al. (2000) and Pan & Sinha (2007) have found that a time series of stock price synchronicity for the U.S. market also shows that the degree of co-movement in U.S. stock prices has declined, more or less steadily, during the 20th century. This may imply that there is a significant variation in the stock price movement and that the optimal number of epochs for different models for other companies may be different to that of AMAZON.

However, due to limited computation and increasing number of experiments to compute the average optimal epoch parameter for all 100 companies Nasdaq-100 (2019), the found optimal epochs for AMAZON were used across all other companies for simplicity purposes. This was a reasonable assumption due to the fact that the nature of the complex stock price movements could exhibit across other companies and that the model could capture this complex stock price movement with the same number of

```
array([[-0.74048606, -1.8937549 , -1.3844393 ,  0.53901379],
       [ 0.556427  , -1.40122423, -0.93877204,  0.38254075],
       [ 0.40045321, -0.76865464, -0.63514619,  0.03002678],
       [ 0.049064  , -0.80101596, -0.58476223,  0.53937349],
       [ 0.55678556, -0.67374743, -0.21503148,  0.47390661],
       [ 0.49152756, -0.52442096,  0.07782528,  0.04585394],
       [ 0.06484066, -0.47188822,  0.07037345, -0.10522347],
       [-0.08575472, -0.54865567, -0.03250982,  0.64009177],
       [ 0.65718248, -0.16859149,  0.34871117,  0.86203168],
       [ 0.87841426,  0.25907141,  0.83490675, -0.17608597],
       [-0.15639113,  0.10713281,  0.61409232, -0.51852811],
       [-0.49774065, -0.1067712 ,  0.19635738, -0.22428686]])
```

Figure 5.13: Scaled differenced supervised data for the multivariate model for AMAZON

epochs.

Technical Indicators A to M		
Acronym	Description	Reference
AD	Chaikin A/D line	(Investopedia 2018*i*) (FM Labs 2018*a*)
ADOSC	Chaikin A/D oscillator	(Investopedia 2018*i*) (FM Labs 2018*a*)
ADX	Average directional movement index	(Investopedia 2018*b*) (FM Labs 2018*b*)
ADXR	Average directional movement index rating	(FM Labs 2018*c*)
APO	Absolute price oscillator	(FM Labs 2018*d*)
AROON	Aroon	(Investopedia 2018*f*) (FM Labs 2018*e*)
AROONOSC	Aroon oscillator	(FM Labs 2018*f*)
BBANDS	Bollinger bands	(Investopedia 2018*h*) (FM Labs 2018*g*)
BOP	Balance of power	(Market Volume 2018)
CCI	Commodity channel index	(Investopedia 2019*d*) (FM Labs 2018*h*)
CMO	Chande momentum oscillator	(FM Labs 2018*i*)
DEMA	Double exponential moving average	(Investopedia 2018*d*) (FM Labs 2018*j*)
DX	Directional movement index	(Investopedia 2018*c*) (FM Labs 2018*k*)
EMA	Exponential moving average	(FM Labs 2018*l*)
HT_DCPERIOD	Hilbert transform, dominant cycle period	(Motive Wave 2018)
HT_DCPHASE	Hilbert transform, dominant cycle phase	(Motive Wave 2018)
HT_PHASOR	Hilbert transform, phasor components	(Motive Wave 2018)
HT_SINE	Hilbert transform, sine wave	(Motive Wave 2018)
HT_TRENDLINE	Hilbert transform, instantaneous trendline	(Motive Wave 2018)
HT_TRENDMODE	Hilbert transform, trend vs cycle mode	(Motive Wave 2018)
KAMA	Kaufman adaptive moving average	(Stock Charts 2018)
MACD	Moving average convergence / divergence	(Investopedia 2018*q*) (FM Labs 2018*m*)
MACDEXT	Moving average convergence / divergence values with controllable moving average type	(Investopedia 2018*q*) (FM Labs 2018*m*)
MAMA	MESA adaptive moving average	(Binary Tribune 2018)
MFI	Money flow index (Investopedia 2018*k*)	(FM Labs 2018*n*)

Table 5.1: Available time series of technical indicators from Alpha Vantage from A to M

Technical Indicators M to Z		
Acronym	Description	Reference
MIDPOINT	Midpoint	(Trading Technologies 2018*a*)
MIDPRICE	Midprice	(Trading Technologies 2018*b*)
MINUS_DI	Minus directional indicator	(Investopedia 2018*c*) (FM Labs 2018*o*)
MINUS_DM	Minus directional movement	(Investopedia 2018*c*)
MOM	Momentum	(Investopedia 2018*r*) (FM Labs 2018*p*)
NATR	Normalized average true range	(Trading Technologies 2018*c*)
OBV	On-Balance volume	(Investopedia 2018*l*) (FM Labs 2018*q*)
PRICE	Daily adjusted close share price	(Investopedia 2018*g*)
PLUS_DI	Plus directional indicator	(Investopedia 2018*c*) (FM Labs 2018*r*)
PLUS_DM	Plus directional movement	(Investopedia 2018*c*)
PPO	Percentage price oscillator	(Investopedia 2018*n*) (FM Labs 2018*s*)
ROC	Rate of change	(Investopedia 2018*o*)
ROCR	Rate of change ratio	(Investopedia 2018*o*)
RSI	Relative strength index	(Investopedia 2018*m*) (FM Labs 2018*t*)
SAR	Parabolic stop and reverse	(Investopedia 2018*j*) (FM Labs 2018*u*)
SMA	Simple moving average	(Investopedia 2018*p*) (FM Labs 2018*v*)
STOCH	Stochastic oscillator	(Investopedia 2018*e*) (FM Labs 2018*w*)
STOCHF	Stochastic fast	(Investopedia 2018*e*) (FM Labs 2018*w*)
STOCHRSI	Stochastic relative strength index	(FM Labs 2018*x*)
T3	Triple exponential moving average	(FM Labs 2018*y*)
TEMA	Triple exponential moving average	(FM Labs 2018*z*)
TRANGE	True range	(FM Labs I 2018*a*)
TRIMA	Triangular moving average	(FM Labs I 2018*b*)
TRIX	1-day rate of change of a triple smooth exponential moving average	(Investopedia 2018*a*) (FM Labs I 2018*c*)
ULTOSC	Ultimate oscillator	(FM Labs I 2018*d*)
WILLR	Williams' %R	(FM Labs I 2018*e*)
WMA	Weighted moving average	(FM Labs I 2018*f*)

Table 5.2: Available time series of technical indicators from Alpha Vantage from M to Z

3-prior history 3-step forecasting "price" univariate models segmented by number of epochs for AMAZON								
Model Types	**TCP t+1**	**TCP t+2**	**TCP t+3**	**MAPE t+1**	**MAPE t+2**	**MAPE t+3**	**TCP Average**	**MAPE Average**
vanilla	**53.5%**	**45.0%**	**50.2%**	**0.8%**	**1.3%**	**1.6%**	**49.5%**	**1.2%**
100	50.5%	45.0%	50.3%	0.8%	1.3%	1.6%	48.6%	1.2%
155	54.9%	45.0%	50.4%	0.8%	1.3%	1.6%	50.1%	1.2%
239	52.4%	44.6%	50.3%	0.8%	1.3%	1.6%	49.1%	1.2%
369	54.1%	44.5%	49.1%	0.8%	1.3%	1.6%	49.2%	1.2%
569	53.4%	45.1%	50.1%	0.8%	1.3%	1.6%	49.5%	1.2%
879	53.1%	44.8%	50.7%	0.8%	1.3%	1.6%	49.5%	1.2%
1358	53.2%	44.2%	49.9%	0.8%	1.3%	1.6%	49.1%	1.3%
2097	55.0%	45.4%	49.8%	0.8%	1.3%	1.6%	50.0%	1.2%
3238	55.4%	45.7%	50.1%	0.8%	1.3%	1.6%	**50.4%**	**1.2%**
5000	52.9%	45.8%	50.9%	0.8%	1.3%	1.7%	49.9%	1.3%
stacked	**52.6%**	**45.6%**	**50.1%**	**0.9%**	**1.5%**	**1.8%**	**49.4%**	**1.4%**
100	52.8%	45.0%	50.1%	0.8%	1.3%	1.6%	49.3%	1.2%
155	51.7%	45.0%	49.6%	0.8%	1.3%	1.6%	48.8%	1.2%
239	55.0%	45.0%	49.6%	0.8%	1.3%	1.6%	**49.8%**	**1.2%**
369	51.2%	43.5%	48.9%	0.9%	1.3%	1.7%	47.9%	1.3%
569	52.7%	45.6%	49.5%	0.8%	1.3%	1.6%	49.3%	1.2%
879	51.7%	46.5%	51.0%	0.9%	1.4%	1.7%	49.7%	1.3%
1358	53.9%	44.2%	48.9%	0.8%	1.3%	1.6%	49.0%	1.3%
2097	51.3%	43.9%	50.1%	0.9%	1.4%	1.7%	48.4%	1.3%
3238	51.1%	48.3%	50.7%	1.2%	1.9%	2.4%	50.1%	1.8%
5000	54.6%	49.2%	52.6%	1.4%	2.2%	2.6%	52.1%	2.1%
bi	**51.5%**	**44.7%**	**49.7%**	**0.8%**	**1.3%**	**1.6%**	**48.6%**	**1.3%**
100	51.2%	44.8%	50.3%	0.8%	1.3%	1.6%	48.8%	1.2%
155	51.9%	44.8%	49.9%	0.8%	1.3%	1.6%	48.8%	1.2%
239	53.5%	44.7%	50.1%	0.8%	1.3%	1.6%	49.4%	1.2%
369	53.9%	44.8%	50.2%	0.8%	1.3%	1.6%	49.6%	1.2%
569	53.0%	44.8%	50.0%	0.8%	1.3%	1.6%	49.2%	1.2%
879	52.9%	45.1%	50.1%	0.8%	1.3%	1.6%	49.4%	1.2%
1358	52.2%	44.6%	49.9%	0.8%	1.3%	1.6%	48.9%	1.2%
2097	54.0%	45.3%	50.2%	0.8%	1.3%	1.6%	**49.8%**	**1.2%**
3238	47.3%	44.6%	49.5%	0.8%	1.3%	1.6%	47.1%	1.3%
5000	45.6%	43.2%	46.7%	0.9%	1.4%	1.8%	45.1%	1.4%
cnn	**56.8%**	**45.1%**	**50.1%**	**0.8%**	**1.3%**	**1.6%**	**50.7%**	**1.2%**
100	55.8%	45.1%	50.2%	0.8%	1.3%	1.6%	50.4%	1.2%
155	55.2%	44.7%	50.1%	0.8%	1.3%	1.6%	50.0%	1.2%
239	56.2%	44.9%	50.1%	0.8%	1.3%	1.6%	50.4%	1.2%
369	57.9%	44.9%	50.1%	0.8%	1.3%	1.6%	51.0%	1.2%
569	57.9%	44.8%	50.1%	0.8%	1.3%	1.6%	51.0%	1.2%
879	56.2%	44.8%	50.1%	0.8%	1.3%	1.6%	50.4%	1.2%
1358	57.5%	45.0%	49.7%	0.8%	1.3%	1.6%	50.7%	1.2%
2097	57.4%	45.4%	50.2%	0.8%	1.3%	1.6%	51.0%	1.2%
3238	57.4%	45.6%	50.4%	0.8%	1.3%	1.6%	**51.2%**	**1.2%**
5000	56.5%	46.2%	50.1%	0.8%	1.3%	1.6%	50.9%	1.2%
conv	**52.1%**	**46.4%**	**50.0%**	**0.9%**	**1.3%**	**1.7%**	**49.5%**	**1.3%**
100	55.2%	45.9%	50.3%	0.8%	1.3%	1.6%	**50.5%**	**1.2%**
155	54.1%	45.6%	50.5%	0.8%	1.3%	1.6%	50.1%	1.2%
239	56.3%	44.5%	50.0%	0.8%	1.3%	1.6%	50.3%	1.2%
369	56.2%	44.6%	50.3%	0.8%	1.3%	1.6%	50.4%	1.2%
569	55.2%	44.9%	50.3%	0.8%	1.3%	1.6%	50.2%	1.2%
879	50.9%	47.0%	50.5%	0.9%	1.3%	1.6%	49.4%	1.3%
1358	48.5%	48.2%	49.3%	0.9%	1.3%	1.6%	48.7%	1.3%
2097	49.0%	47.5%	50.2%	0.9%	1.4%	1.7%	48.9%	1.3%
3238	47.3%	47.5%	49.9%	0.9%	1.4%	1.8%	48.2%	1.4%
5000	48.1%	48.1%	48.9%	1.0%	1.5%	1.9%	48.4%	1.5%
Grand Total	**53.3%**	**45.4%**	**50.0%**	**0.9%**	**1.3%**	**1.6%**	**49.6%**	**1.3%**

Figure 5.14: Epochs experiment results for different LSTM model for AMAZON

Chapter 6

Hypothesis Testing and Optimisation

This section involves testing some hypothesis about the designed systems to find the best parameters for predicting stock price values and trends and evaluating the prototype against baseline models and other benchmark models from other research papers. The training data were the time series of technical indicators from 01/01/2000 to 01/01/2018, and the test data were the time series of technical indicators from 02/01/2018 to 01/01/2019.

6.1 Metrics

There are three main metrics used to evaluate the performance of each model:

- RMSE (Root Mean Squared Error) is defined in Equation 6.1.
- MAPE (Mean Average Percentage Error) is defined in Equation 6.2.
- TCP (Trend Percentage Correct) is defined in Equation 6.3. TCP is derived from the predicted stock price values and measures the percentage total of all predicted stock price values that are in the same trend direction of the actual prices. This metric is also known as accuracy in other research papers.

The main metrics used are TCP and MAPE, because RMSE is not a clear comparison indicator as stock price becomes larger, RMSE will becomes larger too so it is not suitable to compare the performance of different models for different companies. Additionally, it is not clear why RMSE is used as a percentage in other research papers.

$$\begin{aligned}&RMSE = \tfrac{1}{n}\textstyle\sum_{i=1}^{n}(v_{i,actual} - v_{i,predicted})^2\\&\forall v_{predicted} \in Values_{predicted}, \forall v_{actual} \in Values_{actual}\end{aligned} \tag{6.1}$$

$$\begin{aligned}&MAPE = \tfrac{1}{n}\textstyle\sum_{i=1}^{n} \frac{\left|v_{i,actual} - v_{i,predicted}\right|}{v_{i,actual}}\\&\forall v_{predicted} \in Values_{predicted}, \forall v_{actual} \in Values_{actual}\end{aligned} \tag{6.2}$$

$$TCP = \frac{1}{n}\left|\sum_{i=1}^{n} t_{i,actual} == t_{i,predicted}\right|$$
$$\forall t_{predicted} \in Trends_{predicted}, \forall t_{actual} \in Trends_{actual} \tag{6.3}$$

6.2 Experiments

The experiments were designed in a way that was accumulative. The results of each experiment were used in the next experiments for further hypothesis testing so that a model with the correct settings and parameters can obtain the highest TCP and lowest MAPE score and outperform the baseline model and other benchmark models. The time series from 01/01/2000 to 01/01/2018 were used for training and the time series from 02/01/2018 to 01/01/2019 were used for testing. Note that in the figures for the experiment results:

- ”vanilla” represents the Vanilla LSTM model
- ”stacked” represents the Stacked LSTM model
- ”bi” represents the Bidirectional LSTM model
- ”cnn” represents the Convolutional Neural Network model (not a LSTM network)
- ”conv” represents the Convolutional LSTM model
- Variable t denotes the timestep, so t-1 denotes the value of the technical indicator the day before, t denotes the current day, and t+1 denotes the next day

6.2.1 Experiment 1: Finding Top Performing Technical Indicators

Hypothesis
There are technical indicators that are more useful than others in stock price value and trend prediction on a company-specific basis.

Experiment
The time series of any technical indicators share the similar properties, so an univariate model for any company could be representative on how the univariate model of other companies would perform. Therefore, n-prior history (1, 3) and 1-step forecasting univariate models based on one technical indicator from the 52 available technical indicators in Table 5.1 and 5.2 for each model type (”vanilla”, ”stacked”, ”bi”, ”cnn” and ”conv”) were trained and tested for AMAZON in Nasdaq-100 (2019). This experiment involved 2*1*52*5*1=520 models. The average TCP and MAPE for AMAZON for the 520 models were recorded in Figure 6.1.

Result
There were 28 n-prior history (1 and 3) 1-step forecasting univariate models that obtained TCP score above 55%. The MAPE for all models remained similar. Interestingly, the ”price” technical indicator was one of the least useful technical indicator to

predict the stock price trend of a company. Therefore, it was concluded there were indeed more useful technical indicators than some others under different context of n-prior history for a specific company. Due to limited computing resources, the same experiment could not be ran for many other companies to see if their top performing technical indicators were also the same.

6.2.2 Experiment 2: Finding Best Model Types

Hypothesis
One of the 5 model types (vanilla, stacked, bi, cnn, or conv) outperforms all other on average on the 100 companies from Nasdaq-100 (2019).

Experiment
n-prior history (1, 3) 1-step forecasting univariate and multivariate models based on top technical indicators (1, 28, 52) from Figure 6.1 (left table for 1-prior history and right table for 3-prior history) for each model type (”vanilla”, ”stacked”, ”bi”, ”cnn” and ”conv”) were trained and tested for all 100 companies in Nasdaq-100 (2019). This experiment involved 2*1*3*5*100=3000 models. The average TCP and MAPE 3000 models were recorded in Figure 6.2 and 6.3.

Result
For all models, ”bi” and ”conv” LSTM models significantly outperformed ”vanilla”, ”stacked”, and ”cnn” in both TCP and MAPE. Therefore, for the next experiments, model types of ”vanilla”, ”stacked”, and ”cnn” were discarded due to low performance and unnecessary waste of computing resources for experiments. Selvin et al. (2017) further affirmed that the low performance for ”cnn” was due to the fact that it does not depend on any previous information for prediction. Since ”cnn” and ”bi” LSTM models had similar performance, the next experiments would compare these two models more carefully.

6.2.3 Experiment 3: Multivariate and Univariate Models

6.2.3.1 Experiment 3.1: Multivariate and univariate models for each companies in Nasdaq-100 (2019)

Hypothesis
Multivariate models will outperform univariate models on average for the 100 companies in Nasdaq-100 (2019).

Experiment
3-prior history 1-step forecasting univariate and multivariate (top 1, 3, 4, 8, 14, 20, 28, 52 technical indicators from the right table of Figure 6.1) models with model type ”bi” and ”conv” were trained and tested for each of the 100 companies in Nasdaq-100 (2019). This experiment involved training 1*1*8*2*100 = 1600 models. Their average TCP and MAPE were recorded as shown in Figure 6.4.

Result
Univariate models of the top technical indicator outperformed multivariate models with top 3,4,8, 14, 20, 28, and 52 technical indicators in both TCP and MAPE on average. Therefore, the hypothesis that multivariate models should outperform univariate models was rejected. Univariate models were better both in terms of TCP and MAPE.

6.2.3.2 Experiment 3.2: Multivariate and univariate models for individual companies

As discovered in Experiment 3.1, univariate models performed better than multivariate models on average so this experiment examined whether the hypothesis that univariate models would also outperform multivariate models for individual companies.

Hypothesis
An univariate model would outperform multivariate models with more technical indicators for the same company.

Experiment
The data from Experiment 3.1 was reused, and the data were dived deeper into company specific level. The results for Adobe (ADBE) and Apple (AAPL) were in Figure 6.5.

Result
The best performing model varied by the number of technical indicators and by model types at a company level. Therefore, it was concluded that the hypothesis that the univariate model would outperform multivariate model for the same company was rejected. It could also be concluded that models with specific number of technical indicators was optimal and could only be found via trial and error.

6.2.4 Experiment 4: Multi-step and One-step Forecasting model

6.2.4.1 Experiment 4.1: Multi-step and one-step forecasting model for 100 companies in Nasdaq-100 (2019)

Hypothesis
N-step forecasting will always have the best performance on the n-th day prediction in both TCP and MAPE on average for all 100 companies in Nasdaq-100 (2019).

Experiment
N-prior history (1, 3, 5, 10) and n-step (1, 3, 5, 10) forecasting univariate and multivarate (top 1, 4, 14, 52 technical indicators from the right table of Figure 6.1) models with model type ”bi” and ”conv” were trained and tested for each of the 100 companies in Nasdaq-100 (2019). This experiment involved 4*4*4*2*100 = 12800 models. Their average TCP and MAPE were recorded as shown in Figure 6.6.

Result
It was concluded that the hypothesis was partially correct. The n-step forecasting mod-

els had the highest TCP on the n-th day. The bigger the n, the better MAPE was for each future prediction from 1 to n-1 compared to other models where the number of steps as smaller than n. For example, if the goal is to obtain the highest score on the 10th day in the future in the future then the optimal n-step forecasting model according to the established hypothesis would be 10-step forecasting. However, the hypothesis would only hold for n is equal or less than 10 as the n had only been experimented up to 10.

6.2.4.2 Experiment 4.2: Multi-step and one-step forecasting model for individual companies

The previous hypothesis was been investigated on the average of all 100 companies in Nasdaq-100 (2019) so this experiment tested if the hypothesis would still hold at an individual company level.

Experiment
The data from 6.2.4.1 was reused, and the data were dived deeper into company-specific level. The analysed results for Adobe (ADBE) and Apple (AAPL) were in Figure 6.7.

Result
The hypothesis still holds, but there were some specific companies that did not follow the same pattern as the stock market was very volatile and depends on company. However, in general, there was a strong correlation between the number of steps for prediction and its performance on the n-th day.

6.2.5 Experiment 5: Multi-prior and One-prior History Model

6.2.5.1 Experiment 5.1: Multi-prior and one-prior history model for 100 companies in Nasdaq-100 (2019)

Hypothesis
Multi-prior history models will outperform one-prior history models on the 100 companies in Nasdaq-100 (2019) on average.

Experiment
The data from 6.2.4.1 was reused. The analysed results were in Figure 6.8.

Result
There was no significant difference in TCP and MAPE for models with different number of prior history. However, 1-prior history model slighty outperformed in TCP and MAPE than 3-prior, 5-prior, and 10-prior history models. Therefore, the hypothesis was rejected. The reason why multi-prior history models did not perform better than one-prior history could be that one-prior history LSTM networks were already suitable to capture the structure of the time series data dynamically over time with high prediction capacity (Roondiwala et al. 2017).

6.2.5.2 Experiment 5.2: Multi-prior and one-prior history model for individual companies

Hypothesis
The previous hypothesis was investigated on the average of all 100 companies in Nasdaq-100 (2019) so this experiment tested if the hypothesis would still be rejected at an individual company level. The hypothesis was that multi-prior history models would outperform one-prior history models for the same company.

Experiment
The data from 6.2.4.1 was reused, and the data were dived deeper into company-specific level. The analysed results for Adobe (ADBE) and Apple (AAPL) were in Figure 6.9. **Result**
Multi-prior history models outperforms one-prior history models on TCP while one-prior history models outperformed multi-prior history models on MAPE. The best performing model varied by the number of prior history at a company level. Therefore, it was concluded that the hypothesis that Multi-prior history models would outperform one-prior history models for the same company was partially correct. It was also concluded that models with specific number of prior history was optimal and could only be found via trial and error.

6.3 Conclusion

Univariate Models for each of the Technical Indicators Some technical indicators were more effective in predicting stock price trend movements, but none of the technical indicators affected MAPE significantly.

Model Types
The "conv" models outperformed all other models in both TCP and MAPE overall.

Multivariate and Univariate Models
On average of the 100 companies in Nasdaq-100 (2019), univariate model outperformed multivariate models. However, at a company-specific level, univariate model was not always optimal and the optimal number of technical indicators varied by company and can only be found via trial and error.

Multi-step and One-step Forecasting Model
The n-step forecasting models had the highest TCP on the n-th day. The bigger the n, the better MAPE was for each future prediction from 1 to n-1 compared to other models where the number of steps was smaller than n.

Multi-prior and One-prior History Model
Optimal number of prior history could only be found via trial and error at an individual company level.

Best Combination and Results
Reusing the data from 6.2.4.1, the best combination of the above factors in the experiment could achieve up to best metrics shown in Table 6.1 for a company-specific

model. Table 6.1 was further broken down into companies that had achieved the highest TCP and lowest MAPE in Figure 6.10 and 6.11. The next chapter tries to beat the baseline models and research papers that focused on stock indeces, individual companies, and cryptocurrencies.

	Trend Percent Correct				Mean Absolute Percentage Error			
	t + 1	t + 3	t + 5	t + 10	t + 1	t + 3	t + 5	t + 10
Best	61.8%	58.2%	56.6%	56.6%	0.80%	1.46%	1.82%	2.59%
Average	57.1%	52.7%	51.1%	50.1%	1.41%	2.50%	3.31%	4.69%

Table 6.1: Prototype performance on 100 companies in Nasdaq-100 (2019)

1-prior history 1-step forecasting, univariate models		
Technical Indicator	**TCP t+1**	**MAPE t+1**
ht_trendline	58.2%	1.61%
natr	57.9%	1.61%
mfi	57.8%	1.61%
midpoint	57.8%	1.61%
trima	57.8%	1.61%
trix	57.8%	1.61%
mama	57.8%	1.61%
obv	57.7%	1.60%
aroon	57.5%	1.61%
stoch	57.1%	1.61%
rocr	57.1%	1.60%
cci	57.0%	1.61%
plus_dm	57.0%	1.61%
t3	56.8%	1.61%
kama	56.8%	1.61%
ema	56.6%	1.61%
tema	56.4%	1.61%
aroonosc	56.2%	1.61%
ultsoc	56.0%	1.61%
sma	55.9%	1.61%
minus_di	55.4%	1.61%
trange	55.4%	1.61%
stochrsi	55.3%	1.61%
ht_phasor	55.3%	1.61%
adosc	55.2%	1.61%
bbands	55.2%	1.61%
ppo	55.1%	1.61%
stochf	55.1%	1.61%
plus_di	54.9%	1.61%
rsi	54.8%	1.61%
roc	54.8%	1.61%
willr	54.8%	1.61%
ht_dcperiod	54.7%	1.61%
cmo	54.6%	1.61%
midprice	53.9%	1.61%
adxr	53.7%	1.61%
dema	53.5%	1.61%
bop	53.4%	1.61%
ad	52.7%	1.61%
dx	52.4%	1.61%
price	52.1%	1.61%
mom	51.9%	1.62%
macdext	51.7%	1.61%
adx	51.7%	1.62%
sar	51.7%	1.61%
apo	51.5%	1.61%
wma	51.3%	1.61%
ht_dcphase	51.1%	1.62%
ht_sine	50.1%	1.61%
minus_dm	50.0%	1.61%
macd	49.9%	1.62%
ht_trendmode	44.6%	1.61%
Grand Total	**54.6%**	**1.61%**

3-prior history 1-step forecasting univariate models		
Technical Indicator	**TCP t+1**	**MAPE t+1**
trix	57.8%	1.61%
mama	57.7%	1.60%
ad	57.7%	1.61%
ppo	57.5%	1.61%
trima	57.4%	1.61%
adx	57.4%	1.61%
minus_di	57.3%	1.61%
rsi	57.2%	1.61%
obv	57.1%	1.61%
natr	56.8%	1.61%
minus_dm	56.8%	1.61%
aroon	56.7%	1.61%
sar	56.6%	1.61%
cmo	56.5%	1.61%
stochrsi	56.5%	1.61%
stochf	56.5%	1.61%
wma	56.4%	1.61%
midprice	56.2%	1.61%
t3	56.1%	1.61%
macdext	55.7%	1.61%
rocr	55.6%	1.61%
ht_dcphase	55.6%	1.61%
roc	55.6%	1.61%
ht_phasor	55.5%	1.61%
ht_dcperiod	55.4%	1.61%
ht_sine	55.2%	1.61%
dema	55.1%	1.61%
aroonosc	55.0%	1.61%
sma	55.0%	1.61%
bop	54.9%	1.61%
apo	54.8%	1.61%
adosc	54.8%	1.61%
willr	54.8%	1.61%
mfi	54.7%	1.61%
ultsoc	54.6%	1.61%
macd	54.5%	1.61%
dx	54.5%	1.61%
kama	54.5%	1.61%
trange	54.2%	1.61%
adxr	53.9%	1.61%
bbands	53.5%	1.62%
midpoint	53.3%	1.62%
ht_trendline	53.0%	1.62%
tema	52.9%	1.61%
ht_trendmode	52.9%	1.61%
stoch	52.2%	1.61%
plus_di	52.1%	1.61%
cci	52.1%	1.61%
plus_dm	51.9%	1.62%
ema	51.7%	1.62%
mom	51.5%	1.64%
price	51.1%	1.62%
Grand Total	**55.1%**	**1.61%**

Figure 6.1: Experiment 1 result for 1-step 3-prior history model for AMAZON

1-prior history 1-step forecasting multivariate models		
Multivariate Models	**TCP t+1**	**MAPE t+1**
vanilla	**49.90%**	**14.25%**
1 Technical Indicator	50.08%	1.53%
28 Technical Indicators	49.28%	21.55%
52 Technical Indicators	50.35%	20.05%
stacked	**49.67%**	**7.07%**
1 Technical Indicator	50.03%	1.49%
28 Technical Indicators	49.52%	8.10%
52 Technical Indicators	49.45%	11.83%
bi	**50.17%**	**1.50%**
1 Technical Indicator	50.36%	1.52%
28 Technical Indicators	49.79%	1.50%
52 Technical Indicators	50.37%	1.49%
Grand Total	**49.91%**	**7.65%**

Figure 6.2: Experiment 2 result for 1-prior history 1-step forecasting model for 100 companies in Nasdaq-100 (2019)

3-prior history 1-step forecasting multivariate models		
Multivariate Models	**TCP t+1**	**MAPE t+1**
vanilla	**50.00%**	**9.84%**
1 Technical Indicator	51.14%	1.47%
28 Technical Indicators	49.46%	12.97%
52 Technical Indicators	49.51%	14.35%
stacked	**50.11%**	**6.86%**
1 Technical Indicator	50.38%	1.48%
28 Technical Indicators	50.27%	7.67%
52 Technical Indicators	49.73%	10.87%
bi	**50.28%**	**1.50%**
1 Technical Indicator	50.49%	1.44%
28 Technical Indicators	50.25%	1.53%
52 Technical Indicators	50.12%	1.53%
cnn	**50.31%**	**1.74%**
1 Technical Indicator	50.62%	1.47%
28 Technical Indicators	49.64%	1.94%
52 Technical Indicators	50.67%	1.82%
conv	**50.98%**	**1.51%**
1 Technical Indicator	51.36%	1.47%
28 Technical Indicators	50.75%	1.52%
52 Technical Indicators	50.84%	1.55%
Grand Total	**50.31%**	**4.49%**

Figure 6.3: Experiment 2 result for 3-prior history 1-step forecasting model for 100 companies in Nasdaq-100 (2019)

Company	(All)	
n_lag	3	
n_seq	1	

3-prior history and 1-step forecasting models with different number of indicators

Number of Indicators	TCP t+1	MAPE t+1
bi	**50.1%**	**1.52%**
1	50.5%	1.44%
3	49.8%	1.49%
4	49.3%	1.52%
8	50.4%	1.57%
14	50.2%	1.59%
20	49.9%	1.56%
28	50.3%	1.53%
52	50.1%	1.53%
conv	**50.6%**	**1.50%**
1	51.4%	1.46%
3	50.4%	1.44%
4	50.3%	1.46%
8	50.6%	1.45%
14	50.4%	1.49%
20	50.3%	1.48%
28	50.8%	1.52%
52	50.5%	1.54%
Grand Total	**50.4%**	**1.51%**

Figure 6.4: Experiment 3.1 result for 100 companies in Nasdaq-100 (2019)

Company	AAPL	
n_lag	3	
n_seq	1	
3-prior history and 1-step forecasting models with different number of indicators		
Number of Indicators	**TCP t+1**	**MAPE t+1**
bi	**49.6%**	**1.32%**
1	48.6%	1.31%
3	53.8%	1.31%
4	50.6%	1.31%
8	55.0%	1.32%
14	55.0%	1.31%
20	49.8%	1.33%
28	48.6%	1.33%
52	48.3%	1.33%
conv	**50.9%**	**1.32%**
1	51.4%	1.31%
3	56.2%	1.31%
4	57.0%	1.31%
8	55.8%	1.30%
14	52.6%	1.31%
20	49.0%	1.31%
28	51.4%	1.32%
52	47.5%	1.34%
Grand Total	**50.3%**	**1.32%**

Company	ADBE	
n_lag	3	
n_seq	1	
3-prior history and 1-step forecasting models with different number of indicators		
Number of Indicators	**TCP t+1**	**MAPE t+1**
bi	**51.8%**	**1.62%**
1	55.0%	1.58%
3	45.0%	1.64%
4	45.8%	1.67%
8	48.6%	1.63%
14	51.0%	1.66%
20	54.6%	1.65%
28	52.2%	1.63%
52	51.7%	1.61%
conv	**56.4%**	**1.56%**
1	56.6%	1.57%
3	57.0%	1.57%
4	57.4%	1.57%
8	54.6%	1.57%
14	54.2%	1.57%
20	57.4%	1.57%
28	57.8%	1.55%
52	55.7%	1.56%
Grand Total	**54.1%**	**1.59%**

Figure 6.5: Experiment 3.2 result for AAPL (left) and ADOBE (right)

Company	(All)							
n_lag	(All)							
Indicator Number	(All)							
Univariate and multivariate models with varying number of n-prior history (3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.								
N-step forecasting	**TCP t+1**	**TCP t+3**	**TCP t+5**	**TCP t+10**	**MAPE t+1**	**MAPE t+3**	**MAPE t+5**	**MAPE t+10**
1	50.3%				1.53%			
3	49.9%	49.1%			1.55%	2.73%		
5	49.3%	48.6%	47.7%		1.54%	2.73%	3.60%	
10	48.7%	48.1%	47.3%	47.0%	1.51%	2.68%	3.57%	5.08%
Grand Total	**49.7%**	**48.6%**	**47.5%**	**47.0%**	**1.53%**	**2.72%**	**3.58%**	**5.08%**

Figure 6.6: Experiment 4.1 average TCP and MAPE results for 100 companies in Nasdaq-100 (2019)

Company	AAPL
n_lag	(All)
Indicator Number	(All)

Univariate and multivariate models with varying number of n-prior history (3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.

N-step forecasting	TCP t+1	TCP t+3	TCP t+5	TCP t+10	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10
1	50.9%				1.32%			
3	51.0%	50.6%			1.33%	2.36%		
5	50.3%	50.0%	46.8%		1.31%	2.36%	3.17%	
10	50.0%	49.2%	46.8%	45.0%	1.28%	2.28%	3.09%	4.75%
Grand Total	**50.6%**	**49.9%**	**46.8%**	**45.0%**	**1.32%**	**2.33%**	**3.13%**	**4.75%**

Company	ADBE
n_lag	(All)
Indicator Number	(All)

Univariate and multivariate models with varying number of n-prior history (3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.

N-step forecasting	TCP t+1	TCP t+3	TCP t+5	TCP t+10	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10
1	53.9%				1.60%			
3	53.0%	53.6%			1.61%	2.59%		
5	53.3%	53.1%	50.7%		1.59%	2.59%	3.33%	
10	51.7%	52.5%	49.9%	50.7%	1.57%	2.54%	3.34%	4.36%
Grand Total	**53.2%**	**53.1%**	**50.3%**	**50.7%**	**1.59%**	**2.57%**	**3.33%**	**4.36%**

Figure 6.7: Experiment 4.2 average TCP and MAPE results AAPL (top) and ADBE (down)

Company	(All)
Indicator Number	(Multiple Items)
n_seq	(All)

Univariate and multivariate models with varying number of n-prior history (1, 3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.

N-prior history	TCP t+1	TCP t+3	TCP t+5	TCP t+10	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10
1	49.6%	48.7%	47.7%	46.7%	1.43%	2.53%	3.33%	4.79%
3	49.8%	48.6%	47.4%	47.2%	1.50%	2.66%	3.52%	4.97%
5	49.6%	48.6%	47.5%	47.2%	1.52%	2.69%	3.55%	5.02%
10	49.6%	48.6%	47.5%	47.1%	1.57%	2.75%	3.60%	5.09%
Grand Total	**49.7%**	**48.6%**	**47.5%**	**47.2%**	**1.52%**	**2.69%**	**3.55%**	**5.02%**

Figure 6.8: Experiment 5.1 average TCP and MAPE results for Nasdaq-100 (2019)

Company	AAPL							
Indicator Number	(Mult Items)							
n_seq	(All)							
Univariate and multivariate models with varying number of n-prior history (1, 3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.								
N-prior history	**TCP t+1**	**TCP t+3**	**TCP t+5**	**TCP t+10**	**MAPE t+1**	**MAPE t+3**	**MAPE t+5**	**MAPE t+10**
1	50.6%	49.6%	46.8%	45.1%	1.30%	2.29%	3.10%	4.74%
3	50.2%	49.9%	46.8%	45.0%	1.31%	2.32%	3.11%	4.74%
5	51.1%	50.3%	47.1%	45.1%	1.31%	2.33%	3.13%	4.77%
10	50.6%	49.7%	46.5%	45.0%	1.33%	2.34%	3.15%	4.74%
Grand Total	**50.6%**	**49.9%**	**46.8%**	**45.0%**	**1.31%**	**2.32%**	**3.13%**	**4.75%**

Company	ADBE							
Indicator Number	(Multip Items)							
n_seq	(All)							
Univariate and multivariate models with varying number of n-prior history (1, 3, 5, 10) n-step (1, 3, 5, 10) forecasting models. Their average performance metric shown below.								
N-prior history	**TCP t+1**	**TCP t+3**	**TCP t+5**	**TCP t+10**	**MAPE t+1**	**MAPE t+3**	**MAPE t+5**	**MAPE t+10**
1	51.2%	52.2%	49.7%	48.07%	1.57%	2.55%	3.33%	4.33%
3	53.3%	52.7%	50.0%	50.4%	1.58%	2.56%	3.28%	4.25%
5	53.7%	53.1%	50.4%	51.2%	1.58%	2.56%	3.32%	4.34%
10	52.1%	53.4%	50.4%	50.3%	1.62%	2.60%	3.40%	4.49%
Grand Total	**52.9%**	**52.9%**	**50.2%**	**50.4%**	**1.59%**	**2.57%**	**3.33%**	**4.36%**

Figure 6.9: Experiment 5.2 average TCP and MAPE results AAPL (top) and ADBE (down)

Compa	Max TCP t+1	Max TCP t+3	Max TCP t+5	Max TCP t+10	Min MAPE t+1	Min MAPE t+3	Min MAPE t+5	Min MAPE t+10
AAL	53.8%	53.0%	52.6%	49.0%	1.81%	3.39%	4.30%	6.50%
AAPL	57.0%	52.6%	48.6%	46.6%	1.26%	2.24%	3.06%	4.69%
ADBE	60.2%	56.2%	54.6%	54.6%	1.51%	2.44%	3.14%	4.12%
ADI	58.2%	55.0%	53.4%	49.8%	1.24%	2.14%	2.90%	4.18%
ADP	55.8%	55.0%	51.4%	48.6%	0.98%	1.73%	2.35%	3.39%
ADSK	59.0%	57.0%	53.8%	53.8%	1.72%	2.98%	3.92%	5.33%
ALGN	57.0%	51.0%	49.0%	47.0%	2.05%	3.93%	5.52%	8.01%
ALXN	55.4%	51.4%	50.2%	52.6%	1.71%	3.09%	4.13%	5.74%
AMAT	57.8%	51.4%	48.6%	47.8%	1.87%	3.27%	4.54%	6.63%
AMD	55.8%	55.8%	51.4%	45.0%	2.88%	5.07%	6.75%	10.58%
AMGN	59.0%	53.0%	53.8%	51.0%	1.06%	1.89%	2.32%	3.35%
AMZN	61.0%	47.0%	45.8%	45.8%	1.53%	2.71%	3.60%	5.12%
ASML	57.0%	55.4%	53.8%	50.2%	1.66%	2.69%	3.67%	5.25%
ATVI	57.0%	53.8%	48.6%	48.2%	1.69%	2.88%	4.00%	6.13%
AVGO	55.4%	50.2%	50.6%	50.6%	1.58%	2.87%	3.54%	4.97%
BIDU	57.4%	53.4%	48.6%	48.2%	1.69%	3.15%	4.37%	6.97%
BIIB	56.2%	53.0%	55.8%	52.2%	1.36%	2.53%	3.22%	4.76%
BKNG	58.2%	49.0%	49.0%	53.8%	1.12%	2.15%	2.96%	3.97%
BMRN	56.2%	57.8%	55.8%	55.8%	1.57%	2.49%	3.04%	3.93%
CDNS	55.0%	52.2%	51.8%	49.8%	1.26%	2.23%	2.90%	4.25%
CELG	54.2%	49.8%	47.8%	45.0%	1.38%	2.52%	3.21%	4.60%
CERN	55.0%	51.4%	54.6%	51.0%	1.15%	2.10%	2.56%	3.43%
CHKP	57.8%	51.0%	51.4%	52.2%	0.92%	1.57%	2.11%	3.01%
CHTR	61.0%	57.4%	52.6%	52.2%	1.51%	2.31%	3.10%	4.15%
CMCSA	55.4%	54.2%	56.6%	52.6%	1.28%	2.07%	2.68%	3.66%
COST	61.4%	47.4%	48.6%	53.0%	0.95%	1.70%	2.34%	3.15%
CSCO	58.2%	53.4%	50.6%	50.6%	1.19%	2.03%	2.60%	3.76%
CSX	56.6%	52.6%	51.8%	47.0%	1.15%	2.00%	2.58%	3.79%
CTAS	56.6%	51.8%	52.6%	47.8%	1.01%	1.83%	2.44%	3.59%
CTRP	57.8%	52.2%	49.8%	49.4%	1.66%	3.15%	4.24%	6.20%
CTSH	55.0%	50.6%	51.4%	48.6%	1.03%	1.78%	2.35%	3.44%
CTXS	58.2%	46.2%	50.2%	47.4%	0.80%	1.54%	2.07%	2.95%
DLTR	58.6%	57.0%	54.6%	52.2%	1.30%	2.21%	3.00%	4.34%
EA	57.8%	48.6%	47.8%	49.8%	1.47%	2.54%	3.31%	5.08%
EBAY	55.8%	49.8%	48.6%	51.8%	1.22%	2.26%	3.16%	4.31%
EXPE	56.2%	52.6%	51.8%	49.4%	1.30%	2.29%	3.03%	4.25%
FAST	53.8%	50.6%	49.8%	50.2%	1.21%	2.29%	3.00%	4.40%
FB	57.0%	57.8%	53.8%	51.8%	1.54%	2.79%	3.75%	5.23%
FISV	59.8%	51.4%	53.0%	56.6%	0.89%	1.64%	2.04%	2.59%
FOX	55.8%	51.4%	50.2%	49.8%	0.89%	1.53%	2.07%	3.01%
FOXA	57.8%	50.6%	49.4%	49.4%	0.87%	1.55%	2.07%	2.98%
GILD	58.2%	50.6%	53.0%	51.8%	1.23%	2.20%	2.89%	4.05%
GOOG	55.8%	52.6%	49.8%	53.4%	1.27%	2.25%	2.97%	4.00%
GOOGL	59.8%	53.4%	49.4%	51.8%	1.28%	2.24%	3.03%	3.90%
HAS	57.8%	50.2%	47.4%	47.8%	1.13%	2.01%	2.64%	3.78%
HSIC	57.0%	51.4%	49.8%	48.2%	1.19%	2.17%	2.80%	3.87%
IDXX	58.2%	52.2%	49.0%	52.6%	1.41%	2.43%	3.23%	4.51%
ILMN	56.2%	54.6%	49.8%	48.6%	1.60%	2.89%	3.87%	5.59%
INCY	55.4%	50.6%	48.6%	50.6%	1.77%	3.31%	4.38%	6.11%
INTC	57.8%	55.0%	52.2%	56.2%	1.57%	2.51%	3.26%	3.97%
INTU	58.6%	54.2%	49.8%	50.6%	1.24%	2.10%	2.95%	3.86%
ISRG	59.0%	52.2%	51.4%	48.6%	1.51%	2.59%	3.36%	4.37%
JBHT	56.6%	54.2%	49.4%	51.4%	1.13%	1.93%	2.52%	3.49%
JD	55.0%	52.6%	53.8%	52.6%	2.09%	3.80%	4.84%	6.13%
KHC	53.8%	51.8%	52.2%	51.8%	1.12%	2.07%	2.71%	3.92%
KLAC	57.8%	55.8%	51.0%	48.2%	1.63%	2.73%	3.75%	5.66%
LBTYA	57.0%	51.8%	51.4%	51.0%	1.53%	2.70%	3.40%	4.46%
LBTYK	57.8%	51.8%	51.8%	51.8%	1.50%	2.63%	3.24%	4.14%
LRCX	55.4%	54.2%	52.6%	48.6%	1.89%	3.24%	4.42%	6.29%
LULU	60.2%	52.6%	52.6%	50.2%	1.50%	2.76%	3.60%	5.15%

Figure 6.10: Maximum TCP and minimum MAPE results for companies A to L in Nasdaq-100 (2019)

Compa	Max TCP t+1	Max TCP t+3	Max TCP t+5	Max TCP t+10	Min MAPE t+1	Min MAPE t+3	Min MAPE t+5	Min MAPE t+10
MAR	55.4%	56.2%	54.2%	51.0%	1.22%	1.95%	2.62%	3.84%
MCHP	57.0%	53.0%	49.4%	46.2%	1.55%	2.91%	3.98%	6.48%
MDLZ	61.8%	55.8%	54.2%	46.2%	0.86%	1.46%	1.82%	2.71%
MELI	58.6%	53.4%	49.8%	50.6%	2.26%	4.10%	5.39%	7.17%
MNST	57.4%	58.2%	51.8%	49.8%	1.27%	2.26%	3.19%	5.11%
MSFT	59.8%	53.4%	52.6%	51.8%	1.23%	1.88%	2.43%	2.99%
MU	55.8%	55.0%	50.6%	49.0%	2.34%	4.12%	5.73%	7.96%
MXIM	55.8%	54.2%	50.2%	49.8%	1.38%	2.32%	3.11%	4.20%
MYL	57.4%	53.8%	50.2%	48.2%	1.47%	2.61%	3.70%	5.52%
NFLX	55.0%	49.0%	48.2%	52.6%	2.15%	3.90%	5.41%	7.24%
NTAP	60.2%	56.6%	49.0%	49.0%	1.55%	2.64%	3.86%	5.54%
NTES	55.8%	55.8%	53.4%	53.4%	1.83%	3.44%	4.60%	6.28%
NVDA	55.4%	49.4%	51.0%	52.2%	2.15%	3.76%	5.22%	7.43%
NXPI	57.8%	54.2%	52.6%	45.8%	1.51%	2.70%	3.51%	5.38%
ORLY	57.8%	54.2%	54.2%	51.4%	1.23%	2.04%	2.63%	3.78%
PAYX	55.0%	50.2%	47.8%	46.2%	0.93%	1.63%	2.14%	3.08%
PCAR	58.6%	53.8%	54.2%	49.8%	1.22%	2.22%	2.94%	3.93%
PE	50.2%	43.4%	50.6%	45.8%	1.57%	2.75%	3.29%	4.86%
PEP	57.8%	55.0%	50.6%	47.0%	0.85%	1.52%	1.96%	3.22%
PYPL	57.0%	53.4%	52.2%	51.0%	1.49%	2.63%	3.35%	4.44%
QCOM	55.4%	49.8%	46.6%	44.2%	1.29%	2.38%	3.30%	4.99%
REGN	56.6%	51.8%	46.6%	50.6%	1.48%	2.59%	3.63%	4.73%
ROST	59.0%	54.2%	52.6%	51.0%	1.17%	2.08%	2.58%	3.42%
SBUX	58.2%	48.2%	49.8%	45.8%	0.96%	1.71%	2.24%	3.49%
SIRI	56.6%	54.6%	49.8%	48.6%	1.13%	2.00%	2.72%	3.93%
SNPS	56.2%	47.4%	46.6%	49.8%	1.09%	2.02%	2.75%	3.78%
SWKS	57.4%	53.0%	51.8%	47.8%	1.48%	2.51%	3.36%	4.95%
SYMC	55.4%	52.2%	52.6%	49.8%	1.56%	2.98%	3.88%	5.85%
TMUS	59.4%	52.2%	51.8%	52.6%	1.07%	1.89%	2.50%	3.57%
TSLA	57.8%	55.0%	51.8%	51.0%	2.49%	4.32%	5.63%	8.00%
TTWO	55.8%	51.8%	52.2%	50.6%	1.78%	3.15%	4.02%	5.16%
TXN	55.8%	57.4%	54.2%	48.2%	1.38%	2.27%	3.00%	4.09%
UAL	56.6%	55.4%	55.0%	50.6%	1.37%	2.39%	3.31%	4.38%
ULTA	56.6%	51.8%	49.0%	48.2%	1.50%	2.64%	3.54%	5.44%
VRSK	58.6%	52.6%	53.0%	50.2%	0.85%	1.50%	1.89%	2.77%
VRSN	58.2%	50.6%	45.0%	49.0%	1.24%	2.12%	2.90%	4.19%
VRTX	57.8%	55.0%	51.8%	49.8%	1.43%	2.53%	3.30%	4.73%
WBA	58.6%	51.8%	51.0%	47.8%	1.21%	2.19%	2.93%	4.23%
WDAY	57.8%	51.8%	51.0%	54.6%	1.80%	3.31%	4.26%	5.37%
WDC	55.4%	53.4%	48.2%	48.2%	1.72%	3.26%	4.64%	7.14%
WLTW	57.8%	55.0%	53.8%	54.6%	0.88%	1.73%	2.27%	3.15%
WYNN	57.8%	54.2%	53.4%	49.0%	1.97%	3.62%	4.71%	6.27%
XEL	54.2%	53.8%	49.8%	51.8%	0.85%	1.55%	1.96%	2.63%
XLNX	56.2%	55.0%	52.2%	49.8%	1.51%	2.68%	3.42%	4.76%

Figure 6.11: Maximum TCP and minimum MAPE results for companies M to Z in Nasdaq-100 (2019)

Chapter 7

Evaluation

This chapter evaluates the built models of the dissertation from previous chapter against baseline models and other benchmark models from other research papers. The combination of the best practices found from previous chapter on hypothesis testing and optimisation are used to find models that could beat the baseline model and other benchmark models from research papers.

7.1 Baseline Models

A good baseline forecast for a time series with a linear increasing trend is a persistence forecast (University of Illinois 2018). The persistence forecast is where the stock price value from the prior time step (t-1) is used to predict the observation at the current time step (t). There will be 2 separate baseline models for one-step forecasting and multi-step forecasting.

The baseline model for one-step and multi-step forecasting is build based on the template from (Machine Learning Mastery 2019*c*). Figure 7.1 and Figure 7.2 are examples of baseline models for one-step and multi-step forecasting.

The best results from 6.2.4.1 were compared against the baseline model at a company-specific level for all 100 companies in Nasdaq-100 (2019). The training data were from 01/01/2000 to 01/01/2018 and the testing data were from 02/01/2018 to 01/01/2019. The comparison results are in Figure 7.3, 7.4, 7.5, 7.6, and 7.7. The TCP t+1 in Figure 7.7 was near to 0 is due to the fact that in TCP calculation, there were upward, neutral, and downward trends. Hence, the low TCP value as all trends in t+1 were neutral due to the nature of the persistence baseline. The built models of the dissertation outperformed the persistence baseline model significantly in TCP and partially in MAPE on a company specific basis. However, the models did not outperform the persistence baseline model in MAPE on average of the 100 companies in Nasdaq-100 (2019).

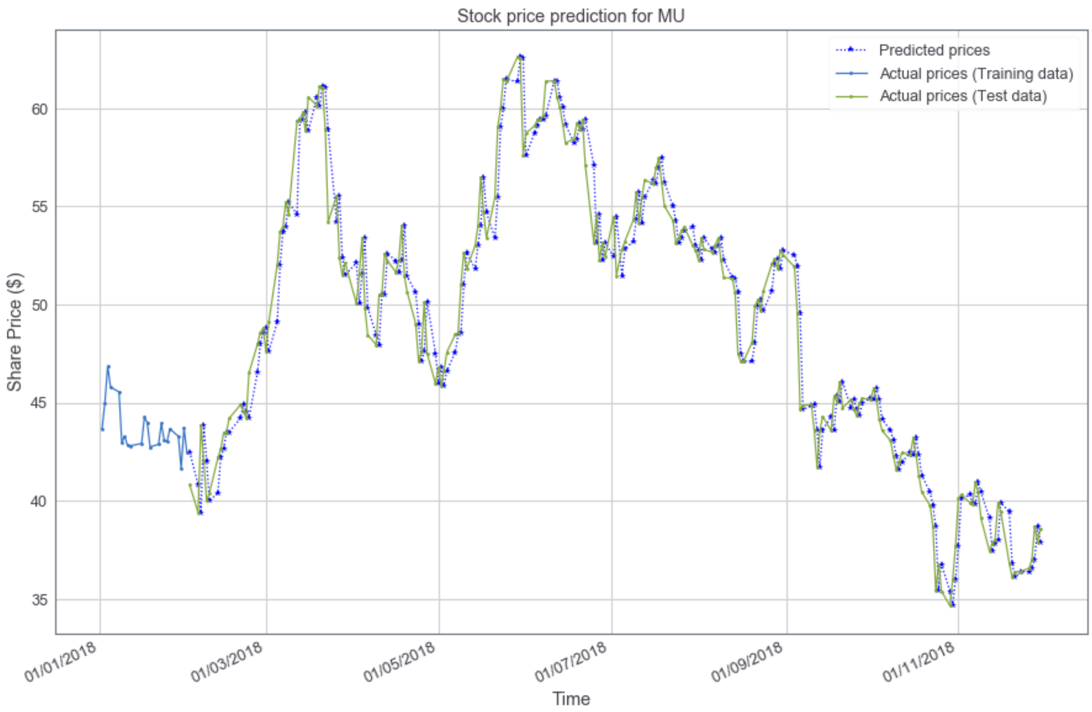

Figure 7.1: Baseline one-step persistence forecast model for MU from 01/01/2018 to 01/12/2018

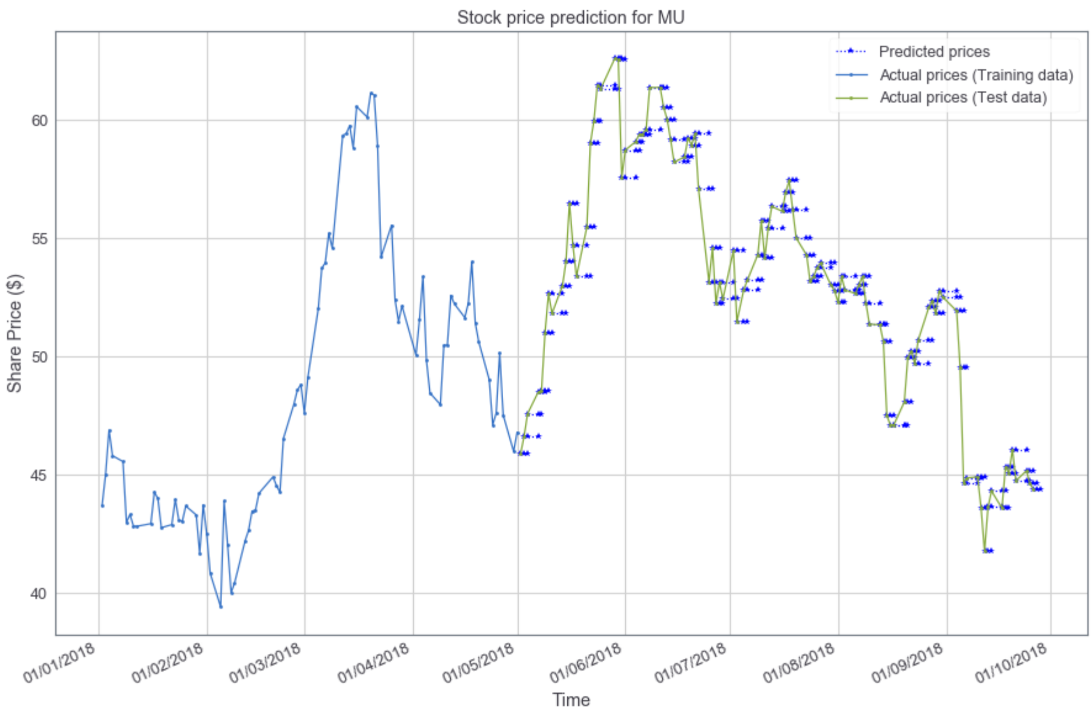

Figure 7.2: Baseline multi-step persistence forecast model for MU from 01/01/2018 to 01/12/2018

7.2 Benchmark Models from other Research Papers

Some papers did not specify the exact start date and end date for training and testing. Therefore, it had been estimated using Python libraries and assumptions. Therefore, the training and testing dates for the 7 selected papers were detailed in Table 7.1.

The technical indicators used by the papers are detailed in Table 7.2. All considered papers did not have a large amount of technical indicators so the models from this dissertation differentiated itself in that sense.

It was not clear how many n-prior history each paper had taken into account as many of the research papers did not clarify. Additionally, all benchmark research papers were one-step forecasting models. Interestingly, not many research papers have multi-step forecasting models which made the models from this dissertation unique and harder to evaluate against baseline multi-step forecasting models.

The model types used by the selected papers are detailed in Table 7.3. The models of the dissertation has outperformed 6 out of 7 selected papers. The built models of this dissertation tried to use different combination of model choices to outperform the models from other research papers:

- Bidirectional LSTM and Convolutional LSTM model type
- n-prior history model where best model is found via trial and error for n = 1, 2, 4, 5, 6, 7, 9, 12, 15, 19, 24, and 30
- n-step forecasting where n is the same as the research papers (usually 1-step forecasting)
- Univariate or multivariate model (different numbers of top performing technical indicators if available)

7.2.1 Stock Index

The historical index data for Nasdaq 100 index and S&P 500 index were obtained from Alpha Vantage (2018), Nifty 50 was obtained from NSEI India (2019), and Bovespa and OMX were obtained from Yahoo Finance (2019). The amount of technical indicators for Nifty 50, Bovespa, and OMX were restricted to adjusted closing price while Nasdaq 100 index and S&P 500 index had 52 technical indicators. The models from the dissertation outperformed Abraham et al. (2004) (results in Table 7.4), Chen, Abraham, Yang & Yang (2005) (results in Table 7.5), Chen, Dong & Zhao (2005) (results in Table 7.6), and Hansson (2017) (results in Table 7.7).

7.2.2 Individual Stock

The historical data for Apple, IBM, AMD, BBT, CIEN, FDO, GD, HRB, IR, JCP, KMG, NBR, NSC, PBI, PPL, PSA, RHI, SRE, THC, UIS, and USB were obtained

Paper	Subject	Train Date Start	Train Date End	Test Date Start	Test Date End
Abraham et al. (2004)	Nasdaq-100	11/01/1995	11/07/1998	12/07/1998	11/01/2002
	Nifty 50	01/01/1998	15/12/1999	16/12/1999	01/12/2001
Chen, Abraham, Yang & Yang (2005)	Nasdaq-100	11/01/1995	11/07/1998	12/07/1998	11/01/2002
	Nifty 50	01/01/1998	15/12/1999	16/12/1999	01/12/2001
Chen, Dong & Zhao (2005)	Nasdaq-100	11/01/1995	11/07/1998	12/07/1998	11/01/2002
	Nifty 50	01/01/1998	15/12/1999	16/12/1999	01/12/2001
Hansson (2017)	All	02/01/2009	13/08/2014	14/08/2014	28/04/2017
Gupta & Dhingra (2012)	Tata Steel	12/08/2002	13/08/2014	14/08/2014	28/04/2017
	Apple and IBM	10/02/2003	10/09/2004	11/09/2004	21/01/2005
Lin et al. (2009)	All	06/12/2001	22/08/2004	23/08/2004	25/11/2005
McNally et al. (2018)	Bitcoin	19/08/2013	01/04/2015	02/04/2015	19/07/2016

Table 7.1: Date range used for training and testing in selected research papers

from Alpha Vantage (2018), and Tata Steel data was obtained from Yahoo Finance (2019). The amount of technical indicators for Tata Steel were restricted to adjusted closing price while all other had 52 technical indicators from Alpha Vantage (2018). The historical data for Dell in Gupta & Dhingra (2012) could not be obtained as the company went private in 2013 and older historical data were not maintained in Alpha Vantage (2018). The models from the dissertation outperformed Lin et al. (2009) (results in Table 7.8). However, the models did not outperform the models from Gupta & Dhingra (2012) (results in Table 7.9). It was not clear how the models from Gupta & Dhingra (2012) and models from this dissertation would perform under different individual companies as the sample of comparison was only 3 selected companies by Gupta & Dhingra (2012).

7.2.3 Cryptocurrency

The historical data for Bitcoin was obtained from Alpha Vantage (2018). The available technical indicators for Bitcoin was restricted to the daily closing price. The models from the dissertation outperformed McNally et al. (2018) (results in Table 7.10).

Paper	Technical Indicator
Abraham et al. (2004)	Daily opening, closing, high, and low price
Chen, Abraham, Yang & Yang (2005)	Daily opening, closing, high, and low stock price values
Chen, Dong & Zhao (2005)	Daily opening, closing, high, and low stock price values
Hansson (2017)	daily adjusted closing price
Gupta & Dhingra (2012)	opening, closing, daily high, and daily low price
Lin et al. (2009)	daily high, daily low, open, close, 5-day high, and 5-day close price
McNally et al. (2018)	SMA, closing, adjusted closing, daily opening, high, and low price

Table 7.2: Technical indicators used in selected research papers

Paper	Models	Outperformed?
Abraham et al. (2004)	Linear and Non-linear Support Vector Machine (SVM), Neuro-Fuzzy System, Artificial Neural Network (ANN), Difference Boosting Neural Network (DBNN)	Yes
Chen, Abraham, Yang & Yang (2005)	Takagi-Sugeno Fuzzy Systems (TS-FS), Neural Network trained by Particle Swarm Optimisation (NN-PSO), and Hierarchical TS-FS	Yes
Chen, Dong & Zhao (2005)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Hansson (2017)	ARMA-GJRGARCH, LSTM, Deep LSTM, Softmax LSTM, and Softmax Deep LSTM	Yes on average
Gupta & Dhingra (2012)	Fuzzy Hidden Markov Models (HMM) and Maximum a Posteriori (MAP) HMM	No on MAP-HHM but yes on HMM
Lin et al. (2009)	Back-propagation neural network (BPNN), Radian Basis Function Neural Network (RBFNN), and Echo State Networks (ESN)	Yes on average
McNally et al. (2018)	LSTM, Recurrent Neural Network (RNN), and Autoregressive Integrated Moving Average (ARIMA)	Yes

Table 7.3: Model types used in selected research papers

	Persistence Baseline				Zhan Chen (2019)			
Company	TCP t+1	TCP t+3	TCPt+5	TCP t+10	TCP t+1	TCP t+3	TCP t+5	TCP t+10
AAL	0.0%	49.4%	49.8%	47.4%	53.8%	53.0%	52.6%	49.0%
AAPL	0.0%	51.0%	46.2%	45.0%	57.0%	52.6%	48.6%	46.6%
ADBE	0.0%	53.0%	49.8%	49.4%	60.2%	56.2%	54.6%	54.6%
ADI	0.4%	49.8%	46.6%	48.6%	58.2%	55.0%	53.4%	49.8%
ADP	0.4%	50.2%	45.8%	46.2%	55.8%	55.0%	51.4%	48.6%
ADSK	0.0%	52.6%	49.8%	50.2%	59.0%	57.0%	53.8%	53.8%
ALGN	0.0%	45.8%	43.4%	43.0%	57.0%	51.0%	49.0%	47.0%
ALXN	0.4%	45.4%	48.2%	49.0%	55.4%	51.4%	50.2%	52.6%
AMAT	0.4%	50.2%	45.0%	47.4%	57.8%	51.4%	48.6%	47.8%
AMD	0.8%	51.0%	47.8%	41.0%	55.8%	55.8%	51.4%	45.0%
AMGN	0.4%	49.0%	51.0%	47.4%	59.0%	53.0%	53.8%	51.0%
AMZN	0.4%	43.0%	44.2%	43.0%	61.0%	47.0%	45.8%	45.8%
ASML	0.4%	51.0%	49.4%	47.0%	57.0%	55.4%	53.8%	50.2%
ATVI	0.8%	51.8%	45.4%	46.2%	57.0%	53.8%	48.6%	48.2%
AVGO	0.0%	49.4%	47.8%	46.6%	55.4%	50.2%	50.6%	50.6%
BIDU	0.8%	52.2%	46.6%	45.0%	57.4%	53.4%	48.6%	48.2%
BIIB	0.0%	51.8%	54.2%	47.8%	56.2%	53.0%	55.8%	52.2%
BKNG	0.0%	44.6%	44.2%	46.6%	58.2%	49.0%	49.0%	53.8%
BMRN	0.0%	53.8%	52.2%	51.8%	56.2%	57.8%	55.8%	55.8%
CDNS	0.0%	48.2%	47.0%	49.8%	55.0%	52.2%	51.8%	49.8%
CELG	0.8%	47.0%	44.2%	44.6%	54.2%	49.8%	47.8%	45.0%
CERN	1.2%	49.4%	51.4%	50.6%	55.0%	51.4%	54.6%	51.0%
CHKP	0.4%	47.4%	44.6%	47.4%	57.8%	51.0%	51.4%	52.2%
CHTR	0.4%	54.6%	47.0%	51.0%	61.0%	57.4%	52.6%	52.2%
CMCSA	1.2%	52.6%	51.8%	51.0%	55.4%	54.2%	56.6%	52.6%
COST	0.0%	42.6%	43.8%	47.8%	61.4%	47.4%	48.6%	53.0%
CSCO	0.4%	46.6%	45.0%	48.6%	58.2%	53.4%	50.6%	50.6%
CSX	0.8%	48.6%	48.6%	44.6%	56.6%	52.6%	51.8%	47.0%
CTAS	1.2%	49.0%	51.4%	45.4%	56.6%	51.8%	52.6%	47.8%
CTRP	1.2%	47.8%	46.2%	46.6%	57.8%	52.2%	49.8%	49.4%
CTSH	0.4%	45.8%	50.2%	46.6%	55.0%	50.6%	51.4%	48.6%
CTXS	0.4%	41.8%	44.6%	46.2%	58.2%	46.2%	50.2%	47.4%
DLTR	0.4%	50.6%	49.0%	49.4%	58.6%	57.0%	54.6%	52.2%
EA	0.8%	45.4%	45.8%	43.4%	57.8%	48.6%	47.8%	49.8%
EBAY	0.0%	45.0%	46.6%	49.0%	55.8%	49.8%	48.6%	51.8%
EXPE	0.4%	47.0%	47.8%	46.6%	56.2%	52.6%	51.8%	49.4%
FAST	1.6%	45.0%	47.4%	47.4%	53.8%	50.6%	49.8%	50.2%
FB	0.4%	49.4%	48.6%	51.0%	57.0%	57.8%	53.8%	51.8%
FISV	0.8%	45.4%	49.8%	52.2%	59.8%	51.4%	53.0%	56.6%
FOX	0.8%	47.0%	48.2%	47.8%	55.8%	51.4%	50.2%	49.8%
FOXA	1.6%	45.4%	45.4%	47.0%	57.8%	50.6%	49.4%	49.4%
GILD	0.0%	46.6%	48.6%	49.0%	58.2%	50.6%	53.0%	51.8%
GOOG	0.0%	49.8%	46.2%	49.4%	55.8%	52.6%	49.8%	53.4%
GOOGL	0.0%	50.6%	47.4%	50.6%	59.8%	53.4%	49.4%	51.8%
HAS	0.0%	47.8%	44.6%	45.8%	57.8%	50.2%	47.4%	47.8%
HSIC	0.4%	47.0%	47.0%	44.6%	57.0%	51.4%	49.8%	48.2%
IDXX	0.0%	45.4%	46.6%	48.2%	58.2%	52.2%	49.0%	52.6%
ILMN	0.0%	46.6%	48.2%	46.6%	56.2%	54.6%	49.8%	48.6%
INCY	0.4%	46.6%	44.2%	47.8%	55.4%	50.6%	48.6%	50.6%
INTC	1.2%	51.8%	51.4%	53.8%	57.8%	55.0%	52.2%	56.2%
INTU	0.4%	46.6%	44.2%	48.6%	58.6%	54.2%	49.8%	50.6%

Figure 7.3: Results of evaluating the models from the dissertation against the persistence baseline model using TCP

	Persistence Baseline				Zhan Chen (2019)			
Company	TCP t+1	TCP t+3	TCPt+5	TCP t+10	TCP t+1	TCP t+3	TCP t+5	TCP t+10
ISRG	0.4%	48.2%	48.2%	44.6%	59.0%	52.2%	51.4%	48.6%
JBHT	0.0%	51.0%	45.0%	47.8%	56.6%	54.2%	49.4%	51.4%
JD	0.4%	49.4%	50.6%	48.2%	55.0%	52.6%	53.8%	52.6%
KHC	0.4%	49.4%	49.8%	49.4%	53.8%	51.8%	52.2%	51.8%
KLAC	0.0%	53.0%	48.2%	44.2%	57.8%	55.8%	51.0%	48.2%
LBTYA	0.0%	47.8%	46.6%	49.0%	57.0%	51.8%	51.4%	51.0%
LBTYK	0.8%	46.2%	44.6%	47.8%	57.8%	51.8%	51.8%	51.8%
LRCX	0.4%	53.8%	50.2%	45.8%	55.4%	54.2%	52.6%	48.6%
LULU	0.0%	47.8%	50.6%	47.0%	60.2%	52.6%	52.6%	50.2%
MAR	0.4%	54.6%	49.8%	47.4%	55.4%	56.2%	54.2%	51.0%
MCHP	0.4%	51.0%	47.0%	42.6%	57.0%	53.0%	49.4%	46.2%
MDLZ	1.6%	50.6%	51.4%	42.6%	61.8%	55.8%	54.2%	46.2%
MELI	0.0%	53.0%	44.6%	45.4%	58.6%	53.4%	49.8%	50.6%
MNST	0.0%	54.2%	48.2%	48.6%	57.4%	58.2%	51.8%	49.8%
MSFT	0.4%	51.4%	48.6%	47.8%	59.8%	53.4%	52.6%	51.8%
MU	0.8%	50.2%	44.6%	46.6%	55.8%	55.0%	50.6%	49.0%
MXIM	0.4%	49.4%	48.6%	44.6%	55.8%	54.2%	50.2%	49.8%
MYL	0.4%	49.4%	43.8%	45.4%	57.4%	53.8%	50.2%	48.2%
NFLX	0.0%	46.6%	44.6%	51.0%	55.0%	49.0%	48.2%	52.6%
NTAP	0.0%	43.0%	43.4%	48.2%	60.2%	56.6%	49.0%	49.0%
NTES	0.0%	53.8%	50.2%	50.2%	55.8%	55.8%	53.4%	53.4%
NVDA	0.0%	48.2%	47.8%	49.4%	55.4%	49.4%	51.0%	52.2%
NXPI	0.8%	51.0%	48.2%	41.4%	57.8%	54.2%	52.6%	45.8%
ORLY	0.4%	53.4%	50.2%	49.0%	57.8%	54.2%	54.2%	51.4%
PAYX	0.8%	47.4%	45.4%	45.4%	55.0%	50.2%	47.8%	46.2%
PCAR	0.0%	51.0%	51.0%	46.6%	58.6%	53.8%	54.2%	49.8%
PEP	0.8%	49.8%	48.6%	45.0%	50.2%	43.4%	50.6%	45.8%
PYPL	0.8%	46.2%	48.6%	47.4%	57.8%	55.0%	50.6%	47.0%
QCOM	0.8%	45.8%	44.2%	42.2%	57.0%	53.4%	52.2%	51.0%
REGN	0.0%	47.8%	41.0%	47.0%	55.4%	49.8%	46.6%	44.2%
ROST	0.4%	51.0%	49.4%	46.6%	56.6%	51.8%	46.6%	50.6%
SBUX	1.2%	46.2%	44.2%	43.0%	59.0%	54.2%	52.6%	51.0%
SIRI	4.8%	47.8%	42.2%	44.6%	58.2%	48.2%	49.8%	45.8%
SNPS	0.4%	44.6%	45.0%	47.0%	56.6%	54.6%	49.8%	48.6%
SWKS	0.4%	52.6%	50.2%	45.8%	56.2%	47.4%	46.6%	49.8%
SYMC	0.8%	43.8%	48.6%	47.0%	57.4%	53.0%	51.8%	47.8%
TMUS	0.4%	50.2%	48.6%	48.6%	55.4%	52.2%	52.6%	49.8%
TSLA	0.0%	52.6%	49.0%	47.0%	59.4%	52.2%	51.8%	52.6%
TTWO	0.4%	49.4%	45.0%	46.2%	57.8%	55.0%	51.8%	51.0%
TXN	0.8%	53.8%	47.8%	46.6%	55.8%	51.8%	52.2%	50.6%
UAL	0.0%	52.6%	49.0%	45.0%	55.8%	57.4%	54.2%	48.2%
ULTA	0.0%	49.0%	47.4%	45.0%	56.6%	55.4%	55.0%	50.6%
VRSK	0.0%	50.2%	50.2%	46.2%	56.6%	51.8%	49.0%	48.2%
VRSN	0.4%	45.4%	42.6%	45.8%	58.6%	52.6%	53.0%	50.2%
VRTX	0.0%	49.4%	46.2%	45.4%	58.2%	50.6%	45.0%	49.0%
WBA	0.8%	48.6%	47.0%	44.2%	57.8%	55.0%	51.8%	49.8%
WDAY	0.0%	48.6%	46.2%	52.2%	58.6%	51.8%	51.0%	47.8%
WDC	0.0%	46.6%	45.4%	44.2%	57.8%	51.8%	51.0%	54.6%
WLTW	0.0%	47.8%	49.8%	52.2%	55.4%	53.4%	48.2%	48.2%
WYNN	0.4%	52.2%	51.8%	45.8%	57.8%	55.0%	53.8%	54.6%
XEL	0.8%	49.0%	45.4%	49.4%	57.8%	54.2%	53.4%	49.0%
XLNX	0.8%	52.6%	50.2%	44.6%	54.2%	53.8%	49.8%	51.8%

Figure 7.4: Results of evaluating the models from the dissertation against the persistence baseline model using TCP

	Persistence Baseline				Zhan Chen (2019)			
Company	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10
AAL	1.82%	3.44%	4.42%	6.65%	1.81%	3.39%	4.30%	6.50%
AAPL	1.26%	2.24%	3.08%	4.74%	1.26%	2.24%	3.06%	4.69%
ADBE	1.54%	2.51%	3.33%	4.36%	1.51%	2.44%	3.14%	4.12%
ADI	1.26%	2.16%	2.95%	4.25%	1.24%	2.14%	2.90%	4.18%
ADP	0.98%	1.74%	2.37%	3.44%	0.98%	1.73%	2.35%	3.39%
ADSK	1.74%	3.09%	4.07%	5.67%	1.72%	2.98%	3.92%	5.33%
ALGN	2.07%	4.04%	5.68%	8.13%	2.05%	3.93%	5.52%	8.01%
ALXN	1.71%	3.11%	4.15%	5.78%	1.71%	3.09%	4.13%	5.74%
AMAT	1.89%	3.29%	4.62%	6.73%	1.87%	3.27%	4.54%	6.63%
AMD	2.90%	5.21%	7.02%	10.89%	2.88%	5.07%	6.75%	10.58%
AMGN	1.07%	1.89%	2.38%	3.43%	1.06%	1.89%	2.32%	3.35%
AMZN	1.55%	2.83%	3.70%	5.32%	1.53%	2.71%	3.60%	5.12%
ASML	1.68%	2.76%	3.75%	5.35%	1.66%	2.69%	3.67%	5.25%
ATVI	1.72%	2.91%	4.03%	6.24%	1.69%	2.88%	4.00%	6.13%
AVGO	1.59%	2.93%	3.76%	5.26%	1.58%	2.87%	3.54%	4.97%
BIDU	1.70%	3.14%	4.41%	6.89%	1.69%	3.15%	4.37%	6.97%
BIIB	1.37%	2.53%	3.23%	4.80%	1.36%	2.53%	3.22%	4.76%
BKNG	1.15%	2.21%	3.07%	4.27%	1.12%	2.15%	2.96%	3.97%
BMRN	1.58%	2.52%	3.11%	4.00%	1.57%	2.49%	3.04%	3.93%
CDNS	1.27%	2.23%	2.92%	4.27%	1.26%	2.23%	2.90%	4.25%
CELG	1.37%	2.52%	3.26%	4.69%	1.38%	2.52%	3.21%	4.60%
CERN	1.16%	2.12%	2.58%	3.39%	1.15%	2.10%	2.56%	3.43%
CHKP	0.93%	1.59%	2.13%	3.03%	0.92%	1.57%	2.11%	3.01%
CHTR	1.51%	2.31%	3.11%	4.26%	1.51%	2.31%	3.10%	4.15%
CMCSA	1.31%	2.09%	2.70%	3.70%	1.28%	2.07%	2.68%	3.66%
COST	0.95%	1.74%	2.38%	3.20%	0.95%	1.70%	2.34%	3.15%
CSCO	1.20%	2.04%	2.66%	3.83%	1.19%	2.03%	2.60%	3.76%
CSX	1.16%	2.02%	2.62%	3.90%	1.15%	2.00%	2.58%	3.79%
CTAS	1.01%	1.84%	2.46%	3.73%	1.01%	1.83%	2.44%	3.59%
CTRP	1.68%	3.22%	4.34%	6.27%	1.66%	3.15%	4.24%	6.20%
CTSH	1.05%	1.80%	2.38%	3.46%	1.03%	1.78%	2.35%	3.44%
CTXS	0.81%	1.56%	2.09%	2.96%	0.80%	1.54%	2.07%	2.95%
DLTR	1.30%	2.26%	3.08%	4.47%	1.30%	2.21%	3.00%	4.34%
EA	1.48%	2.57%	3.40%	5.21%	1.47%	2.54%	3.31%	5.08%
EBAY	1.22%	2.27%	3.16%	4.41%	1.22%	2.26%	3.16%	4.31%
EXPE	1.32%	2.34%	3.14%	4.40%	1.30%	2.29%	3.03%	4.25%
FAST	1.22%	2.33%	3.08%	4.56%	1.21%	2.29%	3.00%	4.40%
FB	1.54%	2.81%	3.84%	5.28%	1.54%	2.79%	3.75%	5.23%
FISV	0.91%	1.69%	2.09%	2.70%	0.89%	1.64%	2.04%	2.59%
FOX	0.90%	1.57%	2.10%	3.07%	0.89%	1.53%	2.07%	3.01%
FOXA	0.88%	1.57%	2.10%	3.07%	0.87%	1.55%	2.07%	2.98%
GILD	1.26%	2.23%	2.93%	4.05%	1.23%	2.20%	2.89%	4.05%
GOOG	1.30%	2.29%	3.08%	4.03%	1.27%	2.25%	2.97%	4.00%
GOOGL	1.30%	2.30%	3.11%	4.06%	1.28%	2.24%	3.03%	3.90%
HAS	1.14%	2.03%	2.65%	3.81%	1.13%	2.01%	2.64%	3.78%
HSIC	1.20%	2.21%	2.87%	4.12%	1.19%	2.17%	2.80%	3.87%
IDXX	1.41%	2.49%	3.35%	4.67%	1.41%	2.43%	3.23%	4.51%
ILMN	1.60%	2.90%	3.88%	5.67%	1.60%	2.89%	3.87%	5.59%
INCY	1.79%	3.32%	4.43%	6.19%	1.77%	3.31%	4.38%	6.11%
INTC	1.58%	2.54%	3.29%	4.03%	1.57%	2.51%	3.26%	3.97%
INTU	1.25%	2.18%	3.03%	3.94%	1.24%	2.10%	2.95%	3.86%

Figure 7.5: Results of evaluating the models from the dissertation against the persistence baseline model using MAPE

	Persistence Baseline				Zhan Chen (2019)			
Company	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10	MAPE t+1	MAPE t+3	MAPE t+5	MAPE t+10
ISRG	1.52%	2.66%	3.47%	4.71%	1.51%	2.59%	3.36%	4.37%
JBHT	1.13%	1.94%	2.52%	3.48%	1.13%	1.93%	2.52%	3.49%
JD	2.10%	3.95%	4.92%	6.42%	2.09%	3.80%	4.84%	6.13%
KHC	1.12%	2.06%	2.73%	4.06%	1.12%	2.07%	2.71%	3.92%
KLAC	1.64%	2.75%	3.83%	5.73%	1.63%	2.73%	3.75%	5.66%
LBTYA	1.56%	2.78%	3.50%	4.55%	1.53%	2.70%	3.40%	4.46%
LBTYK	1.52%	2.70%	3.47%	4.49%	1.50%	2.63%	3.24%	4.14%
LRCX	1.89%	3.27%	4.45%	6.41%	1.89%	3.24%	4.42%	6.29%
LULU	1.51%	2.78%	3.64%	5.22%	1.50%	2.76%	3.60%	5.15%
MAR	1.22%	1.95%	2.64%	3.88%	1.22%	1.95%	2.62%	3.84%
MCHP	1.56%	2.94%	4.03%	6.47%	1.55%	2.91%	3.98%	6.48%
MDLZ	0.86%	1.48%	1.85%	2.80%	0.86%	1.46%	1.82%	2.71%
MELI	2.38%	4.11%	5.47%	7.24%	2.26%	4.10%	5.39%	7.17%
MNST	1.29%	2.28%	3.21%	5.16%	1.27%	2.26%	3.19%	5.11%
MSFT	1.25%	1.93%	2.51%	3.18%	1.23%	1.88%	2.43%	2.99%
MU	2.35%	4.15%	5.79%	8.03%	2.34%	4.12%	5.73%	7.96%
MXIM	1.39%	2.37%	3.11%	4.25%	1.38%	2.32%	3.11%	4.20%
MYL	1.48%	2.66%	3.73%	5.65%	1.47%	2.61%	3.70%	5.52%
NFLX	2.16%	3.95%	5.49%	7.32%	2.15%	3.90%	5.41%	7.24%
NTAP	1.59%	2.68%	3.89%	5.53%	1.55%	2.64%	3.86%	5.54%
NTES	1.83%	3.48%	4.67%	6.41%	1.83%	3.44%	4.60%	6.28%
NVDA	2.17%	3.79%	5.26%	7.42%	2.15%	3.76%	5.22%	7.43%
NXPI	1.51%	2.70%	3.50%	5.28%	1.51%	2.70%	3.51%	5.38%
ORLY	1.26%	2.06%	2.65%	3.82%	1.23%	2.04%	2.63%	3.78%
PAYX	0.94%	1.66%	2.20%	3.23%	0.93%	1.63%	2.14%	3.08%
PCAR	1.24%	2.24%	2.98%	4.26%	1.22%	2.22%	2.94%	3.93%
PEP	0.86%	1.55%	2.02%	3.31%	1.57%	2.75%	3.29%	4.86%
PYPL	1.51%	2.68%	3.51%	4.75%	0.85%	1.52%	1.96%	3.22%
QCOM	1.30%	2.40%	3.31%	5.18%	1.49%	2.63%	3.35%	4.44%
REGN	1.48%	2.59%	3.64%	4.82%	1.29%	2.38%	3.30%	4.99%
ROST	1.18%	2.10%	2.62%	3.50%	1.48%	2.59%	3.63%	4.73%
SBUX	0.97%	1.72%	2.32%	3.59%	1.17%	2.08%	2.58%	3.42%
SIRI	1.13%	2.01%	2.74%	3.92%	0.96%	1.71%	2.24%	3.49%
SNPS	1.09%	2.02%	2.76%	3.82%	1.13%	2.00%	2.72%	3.93%
SWKS	1.48%	2.52%	3.37%	4.90%	1.09%	2.02%	2.75%	3.78%
SYMC	1.57%	3.01%	3.94%	5.92%	1.48%	2.51%	3.36%	4.95%
TMUS	1.07%	1.90%	2.55%	3.65%	1.56%	2.98%	3.88%	5.85%
TSLA	2.51%	4.34%	5.76%	8.18%	1.07%	1.89%	2.50%	3.57%
TTWO	1.80%	3.17%	4.14%	5.20%	2.49%	4.32%	5.63%	8.00%
TXN	1.39%	2.31%	3.07%	4.08%	1.78%	3.15%	4.02%	5.16%
UAL	1.39%	2.42%	3.36%	4.64%	1.38%	2.27%	3.00%	4.09%
ULTA	1.50%	2.64%	3.54%	5.42%	1.37%	2.39%	3.31%	4.38%
VRSK	0.85%	1.54%	1.95%	2.89%	1.50%	2.64%	3.54%	5.44%
VRSN	1.26%	2.20%	3.01%	4.35%	0.85%	1.50%	1.89%	2.77%
VRTX	1.46%	2.61%	3.55%	5.05%	1.24%	2.12%	2.90%	4.19%
WBA	1.21%	2.24%	2.96%	4.34%	1.43%	2.53%	3.30%	4.73%
WDAY	1.83%	3.36%	4.37%	5.70%	1.21%	2.19%	2.93%	4.23%
WDC	1.72%	3.32%	4.75%	7.48%	1.80%	3.31%	4.26%	5.37%
WLTW	0.90%	1.72%	2.29%	3.12%	1.72%	3.26%	4.64%	7.14%
WYNN	1.99%	3.63%	4.82%	6.39%	0.88%	1.73%	2.27%	3.15%
XEL	0.86%	1.56%	1.99%	2.77%	1.97%	3.62%	4.71%	6.27%
XLNX	1.52%	2.70%	3.56%	5.04%	0.85%	1.55%	1.96%	2.63%

Figure 7.6: Results of evaluating the models from the dissertation against the persistence baseline model using MAPE

	Persistence Baseline				Zhan Chen (2019)			
Metric	**t+1**	**t+3**	**t+5**	**t+10**	**t+1**	**t+3**	**t+5**	**t+10**
Average TCP	0.5%	48.8%	47.4%	47.0%	57.1%	52.6%	51.0%	50.0%
Average MAPE	1.4%	2.5%	3.4%	4.8%	1.51%	2.68%	3.42%	4.76%

Figure 7.7: Overall results of evaluating the models from the dissertation against the persistence baseline model using TCP and MAPE

Index	Metric	Abraham et al. (2004)				Zhan Chen (2019)	
		SVM	Neuro-Fuzzy	ANN-LM	DBNN	Bi-LSTM	Conv-LSTM
Nasdaq 100	MAPE	7.170%	7.615%	9.032%	9.429%	**2.317%**	2.329%
	TCP	–	–	–	–	54.48%	**54.82%**
Nifty 50	MAPE	4.416%	3.320%	3.353%	5.086%	**1.347%**	1.357%
	TCP	–	–	–	–	**57.14%**	52.86%

Table 7.4: Benchmark against Abraham et al. (2004)

Index	Metric	Chen, Abraham, Yang & Yang (2005)			Zhan Chen (2019)	
		NN-PSO	Fuzzy-TS	H-TS-FS	Bi-LSTM	Conv-LSTM
Nasdaq 100	MAPE	6.528%	6.543%	6.205%	**2.317%**	2.329%
	TCP	–	–	–	54.48%	**54.82%**
Nifty 50	MAPE	3.092%	3.328%	3.046%	**1.347%**	1.357%
	TCP	–	–	–	**57.14%**	52.86%

Table 7.5: Benchmark against Chen, Abraham, Yang & Yang (2005)

Index	Metric	Chen, Dong & Zhao (2005)		Zhan Chen (2019)	
		LLWNN	WNN	Bi-LSTM	Conv-LSTM
Nasdaq 100	MAPE	6.109%	6.337%	**2.317%**	2.329%
	TCP	–	–	54.48%	**54.82%**
Nifty 50	MAPE	**1.205%**	2.930%	1.347%	1.357%
	TCP	–	–	**57.14%**	52.86%

Table 7.6: Benchmark against Chen, Dong & Zhao (2005)

Index	Metric	Hansson (2017)					Zhan Chen (2019)	
		ARMA-GJRGA	LSTM	Deep LSTM	Softmax LSTM	Softmax deep LSTM	Bi-LSTM	Conv-LSTM
S&P 500	TCP	50.43%	51.88%	50.72%	50.87%	50.87%	**53.96%**	52.79%
	MAPE	–	–	–	–	–	0.60%	**0.59%**
Bovespa	TCP	52.55%	51.46%	50.15%	50.00%	50.00%	51.86%	**52.76%**
	MAPE	–	–	–	–	–	1.23%	1.23%
OMX	TCP	52.14%	52.46%	52.87%	52.72%	**55.30%**	53.67%	53.96%
	MAPE	–	–	–	–	–	0.87%	0.87%

Table 7.7: Benchmark against Hansson (2017)

Company	Metric	Lin et al. (2009)				Zhan Chen (2019)	
		BPNN	RBF	ESN	ESN+ PCA	Bi-LSTM	Conv-LSTM
AMD	MAPE	2.66%	2.99%	1.94%	**1.93%**	1.94%	1.96%
BBT	MAPE	0.87%	0.91%	0.84%	0.8%	**0.74%**	0.75%
CIEN	MAPE	3.55%	2.48%	3.81%	**2.46%**	2.55%	2.80%
FDO	MAPE	3.9%	4.4%	16.34%	9.15%	**1.30%**	1.32%
GD	MAPE	2.07%	1.32%	**0.65%**	**0.65%**	0.71%	0.71%
HRB	MAPE	14.58%	30.6%	461.49%	2.72%	**1.00%**	**1.05%**
IR	MAPE	1.97%	5.49%	587.12%	2.38%	**0.97%**	0.98%
JCP	MAPE	2.04%	2.26%	1.58%	1.55%	**1.31%**	**1.31%**
KMG	MAPE	5.18%	8.25%	**1.51%**	1.5%	3.22%	3.22%
NBR	MAPE	6.55%	4.27%	1.78%	1.55%	**1.41%**	1.44%
NSC	MAPE	2.66%	2.48%	1.12%	**1.08%**	1.17%	1.18%
PBI	MAPE	**0.68%**	**0.68%**	1.14%	0.81%	0.72%	0.72%
PPL	MAPE	2.74%	36.04%	33.46%	2.06%	**0.83%**	**0.83%**
PSA	MAPE	2.31%	1.75%	0.97%	0.98%	**0.89%**	0.90%
RHI	MAPE	6.41%	9.99%	1.61%	1.53%	**1.33%**	1.34%
SRE	MAPE	3.21%	1.92%	1.17%	0.99%	**0.88%**	0.89%
THC	MAPE	3.3%	2.04%	38.4%	1.36%	1.27%	**1.26%**
UIS	MAPE	3.32%	4.21%	114.02%	1.99%	**1.51%**	1.53%
USB	MAPE	0.75%	0.79%	0.79%	**0.74%**	0.75%	0.75%
Average	MAPE	3.62%	6.47%	66.83%	1.91%	**1.29%**	1.31%

Table 7.8: Benchmark against Lin et al. (2009)

Company	Metric	Gupta & Dhingra (2012) ANN	ARIMA	HHM Fuzzy	MAP HMM	Zhan Chen (2019) Bi-LSTM	Conv-LSTM
Tata Steel	MAPE	–	–	–	**1.560%**	1.657%	1.657%
	TCP	–	–	–	–	**52.23%**	50.32%
Apple Inc.	MAPE	1.801%	1.801%	1.769	**1.510%**	1.738%	1.773%
	TCP	–	–	–	–	**66.30%**	61.96%
IBM Corp.	MAPE	0.972%	0.972%	0.779%	**0.611%**	0.639%	0.653%
	TCP	–	–	–	–	56.52%	**59.78%**

Table 7.9: Benchmark against Gupta & Dhingra (2012)

Crypto	Metric	McNally et al. (2018) ARIMA	RNN	LSTM	Zhan Chen (2019) Bi-LSTM	Conv-LSTM
Bitcoin	RMSE	53.74%	5.45%	6.87%	–	–
	MAPE	–	–	–	2.36%	**2.09%**
	TCP	50.05%	50.25%	52.78%	**56.42%**	**56.42%**

Table 7.10: Benchmark against McNally et al. (2018)

Chapter 8

Conclusions and Future Work

This chapter concludes the dissertation by revisiting the original objectives, assessing areas of improvement, and providing ideas for future work.

8.1 Achievement

This dissertation had build bidirectional and convolutional LSTM models for stock price value and trend prediction based on technical indicators. The models can adapt to any stock index, company stock, or cryptocurrency and to any number of prior history of technical indicators, any number of days for prediction in the future, and any number of available technical indicators. The models had outperformed 6 out of 7 selected papers in the same domain of predicting stock price values and trends based on technical analysis as shown in Table 1.2. This prototype has achieved promising results for the 100 companies in Nasdaq-100 (2019) in Table 1.1.

8.2 Improvements

Given more time and more computing resources, further improvements can be made on finding the optimal combination of parameters for the model through experiments. A number of areas can be experimented and improved. For example, the following questions are interesting to explore:

- How will LSTM models of different activation functions perform?
- Given more computation resources, how will the performance be affected by different hyperparameter such as batch sizes, number of epochs, and number of neurons for a specific LSTM network (such as bidirectional, convolutional, or other)?
- What other LSTM models can be explored apart from bidirectional and convolutional LSTM?

- How will the performance be affected by different data preprocessing techniques such as normalisation? More specifically, how will the performance of univariate models with a single technical indicator get affect if different data preprocessing are applied?

8.3 Future Work

Some areas of future work are listed below:

- This dissertation was based on daily temporal resolution of days, so how will the models from this dissertation perform under intraday (1 minute, 5 minute, 15 minute, 30 minute, 60 minute), weekly, and monthly temporal resolutions.
- A virtual trading simulation game can be created to see how much profits or returns the models will generate using past or real time data.
- An automatic real time trading algorithm can be created using the unofficial library (Ladaria 2019) on making stock trades on Degiro UK (2019).
- The model of this dissertation can be compared against more benchmark models from other research papers.
- It would be interesting to see how Weekends and public holidays might affect the stock price of certain companies. For example, Black Friday affects most retail and e-commerce companies.

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