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of the requirements for

Project Report

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Stock Price Prediction Using Machine Learning

in

Bachelor Of Technology
in
Computer Science & Engineering

by

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August 2021.

Certificate

This is to certify that the Project report entitled **"Stock Price Prediction Using Machine Learning"** submitted by Bashupal Kharwar, Diksha Mukesh Sharma To the, Department of Computer Science Engineering of Rajkiya Engineering College Kannauj, Uttar Pradesh Affiliated to Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh in partial fulfillment for the award of Degree of Bachelor of Technology in Computer science Engineering is a bonafide record of the project work carried out by them under my supervision during the year 2020-2021.

Assist. Prof. Naveen Tiwari	Dr . B D K Patro
Assistant Professor	Associate Professor Head
Computer Science Engineering	Computer Science Engineering
REC Kannauj	REC Kannauj

Declaration

I declare that this written submission represents my work and ideas in my own words and where other ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or falsified any idea/data/-fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Mukesh Sharma, Bashupal Kharwar, Diksha

Abstract

The project aims to provide retail investors with a third-party investment mobile application to navigate through the stock market. This is achieved through the use of machine learning and mobile web technologies. Several stock price prediction approaches and models are developed including dense, feedforward neural networks, recurrent neural networks, simple linear regressions, and linear interpolations. Model architectures and hyperparameters are optimized and automatically searched by evolution algorithm. Promising results are found for trend prediction. The project serves as a foundation for democratizing machine learning technologies to the general public in the context of discovering investment opportunities. It paves the way for extending and testing out new models, and developing AutoML in the financial context in the future.

Contents

1 Introduction

1.1 Overview

Investment firms, hedge funds and even individuals have been using financial models to better understand market behavior and make profitable investments and trades. A wealth of information is available in the form of historical stock prices and company performance data, suitable for machine learning algorithms to process. Can we actually predict stock prices with machine learning? Investors make educated guesses by analyzing data. They'll read the news, study the company history, industry trends and other lots of data points that go into making a prediction. The prevailing theories is that stock prices are totally random and unpredictable but that raises the question why top firms like Morgan Stanley and Citigroup hire quantitative analysts to build predictive models. We have this idea of a trading floor being filled with adrenaline infuse men with loose ties running around yelling something into a phone but these days they're more likely to see rows of machine learning experts quietly sitting in front of computer screens. In fact about 70% of all orders on Wall Street are now placed by software, we're now living in the age of the algorithm. This project seeks to utilize Deep Learning models, Long-Short Term Memory (LSTM) Neural Network algorithm, to predict stock prices. For data with timeframes recurrent neural networks (RNNs) come in handy but recent researches have shown that LSTM, networks are the most popular and useful variants of RNNs. I will use Keras to build a LSTM to predict stock prices using historical closing price and trading volume and visualize both the predicted price values over time and the optimal parameters for the model.

1.2 Objective

Predicting how the stock market will perform is one of the most difficult things to do. There are so many factors involved in the prediction - physical factors vs. physhological,rational and irrational behaviour, etc. All these aspects combine to make share prices volatile and very difficult to predict with a high degree of accuracy.Can we use machine learning as a game changer in this domain? Using features like the latest announcements about an organization, their quarterly revenue results, etc., machine learning techniques have the potential to unearth patterns and insights we didn't see before, and these can be used to make unerringly accurate predictions.we will work with historical data about the stock prices of a publicly listed company. in this project we implement how to develop a stock cost prediction model and how to build an interactive dashboard for stock analysis. We implemented stock market prediction using the LSTM model. OTOH, Plotly dash python framework for building dashboards.

Supervised Learning : Supervised learning as the name indicates the presence of a supervisor as a teacher. Basically supervised learning is a learning in which we teach or train the machine using data which is well labeled that means some data is already tagged with the correct answer. After that, the machine is provided with a new set of examples(data) so that supervised learning algorithm analyses the training data(set of training examples) and produces a correct outcome from labeled data.

Unsupervised Learning : Unsupervised learning is the training of machine using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance. Here the task of machine is to group unsorted information according to similarities, patterns and differences without any prior training of data.

Unlike supervised learning, no teacher is provided that means no training will be given to the machine. Therefore machine is restricted to find the hidden structure in unlabeled data by our-self.

1.2.1 Research

This project will investigate how different machine learning techniques can be used and will affect the accuracy of stock price predictions. Different models, from linear regression to dense and recurrent neural networks are tested. Different hyperparameters are also tuned for better performance. The search space for all neural network architectures and hyperparameter combinations is huge, and with limited time in conducting this project, apart from manually trying different reasonable combinations, the team optimizes the models with evolution algorithm, replicating Auto ML techniques from other researches with promising results in the financial context.

1.2.2 Application

This project aims to provide stock price predictions based on the latest machine learning technologies to all retail investors. A mobile web application is developed to provide predictions in an intuitive way. Different models' performance and accuracy can also be compared. The application also serves as another user interface (UI) in visualizing results from the research apart from Jupyter notebooks with lots of tables and graphs

2 Literature Survey

Stock price prediction using LSTM, RNN and CNN-sliding window model: [3] The experiment was done for three different deep learning models. CNN is giving more accurate results than the other two models. This is due to the reason that CNN does not depend on any previous information for prediction. It uses only the current window for prediction. This enables the model to understand the dynamical changes and patterns occurring in the current window. However in the case of RNN and LSTM, it uses information from previous lags to predict the future instances.

Stock market prediction using neural network through news on online social networks: [5] In theory, RNNs can make use of the information in arbitrarily long sequences, but in practice they are limited to looking back only a few steps. The vanishing gradient problem prevents standard RNNs from learning long-term dependencies. Gated Recurrent Units (GRUs) were proposed.

Stock market's price movement prediction with LSTM neural networks: [1] The objective of this project is to study the applicability of recurrent neural networks, in particular the LSTM networks, on the problem of stocks market prices movements prediction. Assess their performance in terms of accuracy and other metrics through experiments on top of real life data and analyze if they present any sort of gain in comparison to more traditional machine learning algorithms.

A recurrent neural network approach in predicting daily stock prices an application to the Sri Lankan stock market: [4] Recurrent Neural Networks (RNN) is a sub type of neural networks that use feedback connections. Several types of RNN models are employed in predicting financial time series. This study was conducted in order to develop models to predict daily stock prices of selected listed companies of Colombo Stock Exchange (CSE) based on Recurrent Neural Network (RNN) Approach and to measure the accuracy of the models developed and identify the shortcomings of the models if present.

A LSTM-based method for stock returns prediction: A case study of China stock market: [2] In our LSTM model for stock prediction, one sequence was defined as a sequential collection of the daily dataset of any single stock in a fixed time period (N days). The daily dataset describes the performance of the stock with sequence learning features like closing price, trade volume on one particular day in these N days.

2.1 Neural Network

A neural network attempts to learn a function that maps the input features to the output predictions, serving as a universal function approximator [5]. It consists of a network of neurons, each of which represents a weighted sum of inputs. Outputs from neurons are fit into activation functions which introduce non-linearity to the system, and then passed to some other neurons. In a typical dense feedforward neural network, the network consists of layers of neurons stacked together, with neurons between individual layers fully connected.

Optimization of neural networks is usually done through backpropagation with gradient descent, which essentially propagates the error from the output layer back to the input layer, while computing the gradient of the error against each parameter in the process.

2.2 Recurrent Neural Network

Recurrent neural network [5] is a type of neural network where connections between neurons allow temporal, sequential information to be stored and processed in the network. One typical architecture is formed by feeding the output of the current unit back to the input with a time delay so that the network can use the information in processing the next input. Various techniques have been developed over the years to train such type of network. One of the popular approaches is backpropagation through time (BPTT) [6], whose central idea is to unroll the recurrent network into a feedforward network, where each layer represents a timestep. Backpropagation with gradient descent could then be performed to optimize the network, just like how we optimize a feedforward network. Unfortunately, it has been shown that techniques like BPTT result in either vanishing or exploding gradients [7]. Vanishing gradients lead to unrealistically long training time, and sometimes training is infeasible while exploding gradients result in fluctuating weights, which leads to unstable training. Both are undesirable in neural network training. Thus, new training methods and architectures are needed to mitigate the problems.

2.3 Long Short Term Memory

Long short-term memory [8] was first introduced by Hochreiter and Schmidhuber in 1997 to address the aforementioned problems. Long-short term memory tackles the problem of learning to remember information over a time interval, by introducing memory cells and gate units in the neural network architecture. A typical formulation involves the use of memory cells, each of which has a cell state that store previously encountered information. Every time an input is passed into the memory cell, and the output is determined by a combination of the cell state (which is a representation of the previous information), and the cell state is updated. When another input is passed into the memory cell, the updated cell state and the new input can be used to compute the new output.

2.4 Evolution Algorithm

Researches have shown that large-scale evolution can auto-generate neural network model architectures and hyperparameters with performance comparable with state-of-the-art human-designed models. In a research in 2017 [12], a large-scale evolution for discovering image classification neural networks was run. It started with a huge population of randomized simple 1-layer models, then slowly evolved the population by removing a poor model and generating a new model by mutating some parameters of a good model in each iteration. After hundreds of hours of running the algorithm with huge computing power, most models in the population achieved state-of-the-art results on CIFAR datasets. In each iteration, only a simple mutation that changed 1 parameter was applied, which allowed searching in a large search space. The paper showed the possibility of finding good models by using lots of computational power to replace human-machine learning experts and has set the foundation of democratizing machine learning with AutoML.

3 Machine Learning

Machine learning is a sub-field of computer science. In general the field can be simply describe as “given the computer the ability to learn without being explicitly programmed”. Machine learning is one of those branches of computer science in which algorithms (running inside computers) learn from the data available to them. With this learning mechanism, various predictive models can come up.

3.1 Type of Machine Learning

Machine learning approaches are divided into three broad categories, depend on the nature of the ”signal” available to the learning system:

3.1.1 Supervised Learning

Supervised learning occurs when the machine is taught or trained using well-labeled data (meaning that some data has already been tagged with the correct answer or classification). Once this is done, the machine is provided with a new set of data or examples, so that this algorithm analyses the training data (set of training examples or data sets) and generate the desired results from the labeled data. In supervised learning, we have sample about something: for each sample we have a set of feature (attribute, variable) and a target variable or quantity that we would like to predict. The supervised learning model has a specified target output that is either a classification (label) or a continuous variable. The objective of the supervised learning model is to predict a specified outcome.
Examples of Supervised Learning

We have data about	And we would like to

predict
E-mails Spam or Non-Spam
Financial Data (Stock,Gold .etc) Stock Price Gold
Price
News Article How many views will
get

We will need data about both the features of the thing that we want to predict and the target which in this case will be the column here.

3.1.2 Unsupervised Learning

In unsupervised learning, the training data is unlabelled. It is similar to a system trying to learn without a teacher. In unsupervised learning, the training of the machine or system is done using the information that is neither classified nor labelled. Because of this, the algorithm itself will act on information without any guidance. Here, the machine with this unsorted information tries to recognise similarities, patterns and differences, without any training.[3]

No labels are given to the learning algorithm, leaving it on its own to find structure in its input. It's have doing by Clustering, Dimensionality Reduction, Anomaly Detection, others. "unsupervised learning is a set of tasks where you have data about the thing that you liked analyses but you don't have any target values so you have all features."
Examples of Unsupervised Learning

We have data about And we would like to

predict
Costumers Find Segments
Credit card transaction Find consumption patterns
Genomic Data Find group of genes according to biological function

3.1.3 Reinforcement Learning

A form of Machine Learning in which the algorithm interacts with a dynamic environment in which it must perform a certain goal. The program is provided feedback in terms of reward and punishments as it navigates the problem space.So in this type of learning we build a software agent or machines that can ultimately determine an ideal, behavior within a specific context.

Some of the most successful applications in this type of learning
Manufacturing Robot
Self-Driving Car
Automatic Trading Software

3.2 Software Used

There are different types of software through which we can work on Machine Learning. However, in this project, we have used Anaconda distribution and Jupyter notebook.

3.2.1 Anaconda Distribution

According to the creators of the software anaconda or the Anaconda distribution is a free easy to install package manager, environment manager python distribution and collection of over seven hundred and twenty open source packages with free community support.

So in brief Anaconda is basically a toolbox a ready to use collection of related libraries and tools for doing analytics with Python.

Anaconda is mainly used with Python R as a Data Science tool for scientific computing.

3.2.2 Jupyter notebook

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.[2] It is a great tool for doing analytics because you can't explain what you're doing. You can share your ideas explanations visualizations and most importantly your code. It comes with the Anaconda's distribution.

3.3 Libraries Used

NumPy is the fundamental package for doing scientific computing with Python. It contains N-dimensional exhibit object (nd array), critic (broadcasting) capacities, and routines for fast operations on array, included mathematical logical operation, linear algebra, statistics, random simulations much more. It is very important because it gives us a nice and fast way to make operations on arrays in a vectorized fashion. all the other libraries that we will use in this project are based on NumPy.

Pandas are for information control and investigation. Pandas provided fast, flexible, and expressive data structures designed to work with relational or table-like data (SQL table or Excel spreadsheet / Tabular data). It is a fundamental high-level building block for doing practical, real world data analysis in Python it is designed to integrate very well with other tools in python's Data Science stack like NumPy.
pandas is well suited for: Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet Ordered and unordered (not necessarily fixed-frequency) time series data. Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels Any other form of observational / statistical data sets. The data actually need not be labeled at all to be placed into a pandas data structure.The two primary data structures of pandas, Series (1-D) DataFrame (2-D), handle the vast majority of typical use cases in finance, statistics, social science, and many areas of engineering. Pandas is built on top of NumPy.

Matplotlib is a Python 2D plotting library which produces distribution quality figures in an assortment of printed copy designs and intelligent conditions all through frameworks. Matplotlib can be utilized in Python contents, the Python interpreter and IPython shell, the jupyter notebook, web application , and graphical user interface toolkits. Matplotlib is primarily written in pure Python, it heavy use of NumPy and other extension code to provide good performance even for large arrays.

Seaborn provides a high level interface for drawing attractive Statistical Graphics it is built on top of matplotlib and tightly integrated with the python data science stack. It includes support for NumPy Pandas data structures you can use it along with the statistical routines from SciPy stats models. So this is a high level Statistical Graphics library that produces very complexs Visualization with very little code.

Scikit-learn is one of the most popular Python libraries for doing machine learning. It provides a simple and efficient set of tools for doing data modeling and analysis. It is built on top of NumPy, SciPy Matplotlib and it works really nicely with pandas and the data structure of Pandas which are Series DataFrame .

In scikit-learn we usually follow a fixed set of steps for building a machine learning model:
Data preparation
Import the estimator object (model)
Create an instance of the estimator
Use the trainning data to train the estimator
Evaluate the model
Make predictions These steps recipe is just a general roadmap

that may include several sub-steps, going back and forth between steps, and there are a lot of details that need to be considered in every step. However this is a nice mental model to have. We should add step 0, which is very important and most time-consuming: "Data preparation".

4 Analysis

4.1 Data Exploration

The data used in this project is of the NSE-Tataglobal from27/072010 to 28/09/2018 this is a series of data points indexed in time order or a time series. My goal was to predict the closing price for any given date after training. For ease of reproducibility and reusability, all data was pulled from the NSE-Tataglobal. The prediction has to be made for Closing (Adjusted closing) price of the data. Since NSE –Tataglobal already adjusts the closing prices for us , we just need to make 5 prediction for “CLOSE” price.

- The dataset is of following form :

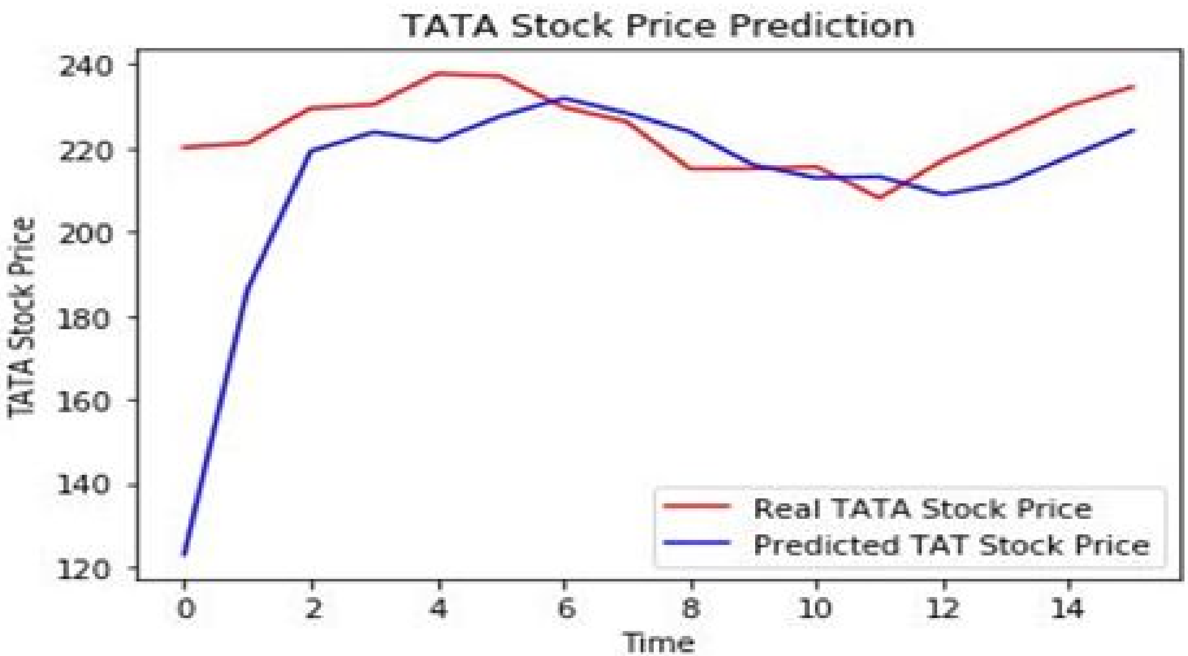
	A	B	C	D	E	F	G	H	I
1	Date	Open	High	Low	Last	Close	Total Trad	Turnover (Lacs)	
2	28-09-18	234.05	235.95	230.2	233.5	233.75	3069914	7162.35	
3	27-09-18	234.55	236.8	231.1	233.8	233.25	5082859	11859.95	
4	26-09-18	240	240	232.5	235	234.25	2240909	5248.6	
5	25-09-18	233.3	236.75	232	236.25	236.1	2349368	5503.9	
6	24-09-18	233.55	239.2	230.75	234	233.3	3423509	7999.55	
7	21-09-18	235	237	227.95	233.75	234.6	5395319	12589.59	
8	19-09-18	235.95	237.2	233.45	234.6	234.9	1362058	3202.78	
9	18-09-18	237.9	239.25	233.5	235.5	235.05	2614794	6163.7	
10	17-09-18	233.15	238	230.25	236.4	236.6	3170894	7445.41	
11	14-09-18	223.45	236.7	223.3	234	233.95	6377909	14784.5	
12	12-09-18	216.35	223.7	212.65	221.65	222.65	4570939	10002.01	

Table: The whole data can be found out in ‘NSE-TATAGLOBAL.csv’ in the project.

4.2 Exploratory Visualization

To visualize the data i have used matplotlib library. I have plotted Closing stock price of 7 the data with the no of items(no of days) available.

Following is the snapshot of the plotted data :



X-axis: Represents Time
Y-axis: Represents Closing Price In

4.3 Algorithms and Techniques

The goal of this project was to study time-series data and explore as many options as possible to accurately predict the Stock Price. Through my research i came to know about Recurrent Neural Nets (RNN) which are used specifically for sequence and pattern 8 learning. As they are networks with loops in them, allowing information to persist and thus ability to memorise the data accurately. But

Recurrent Neural Nets have vanishing Gradient descent problem which does not allow it to learn from past data as was expected. The remedy of this problem was solved in Long-Short Term Memory Networks , usually referred as LSTMs. These are a special kind of RNN, capable of 9 learning long-term dependencies.

In addition to adjusting the architecture of the Neural Network, the following full set of parameters can be tuned to optimize the prediction model:

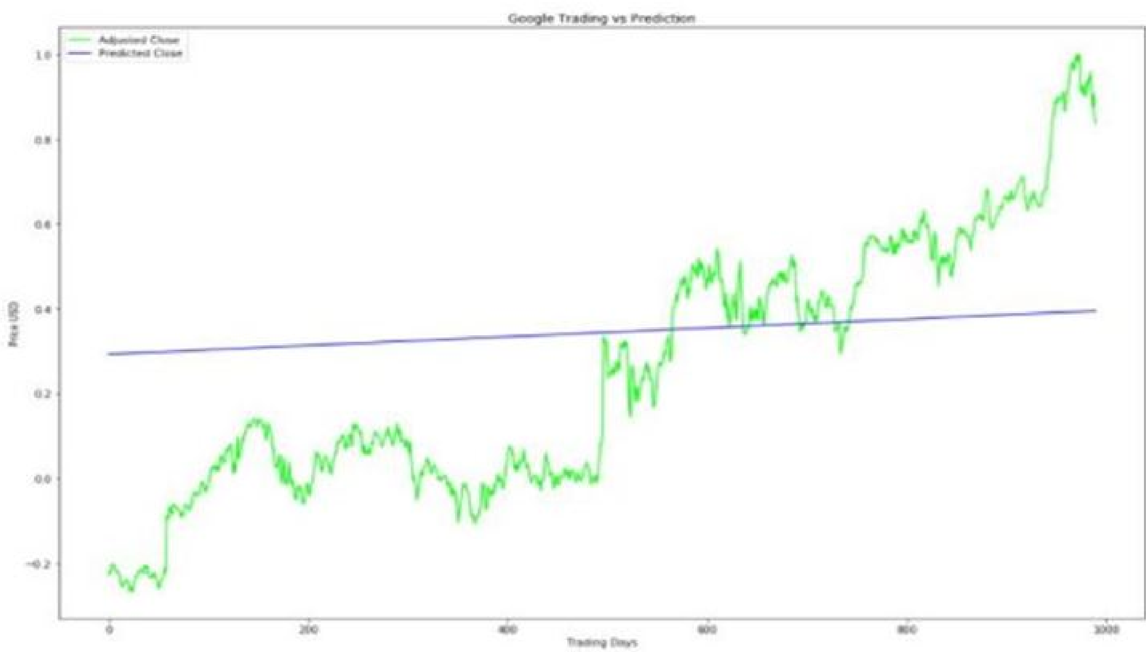
• Input Parameters
• Preprocessing and Normalization (see Data Preprocessing Section)
• Neural Network Architecture
• Number of Layers (how many layers of nodes in the model; used 3)
• Number of Nodes (how many nodes per layer; tested 1,3,8, 16, 32, 64, 100,128)
• Training Parameters
• Training / Test Split (how much of dataset to train versus test model on; kept constant at 82.95% and 17.05% for benchmarks and lstm model)
• Validation Sets (kept constant at 0.05% of training sets)
• Batch Size (how many time steps to include during a single training step; kept at 1 for basic lstm model and at 512 for improved lstm model)
• Optimizer Function (which function to optimize by minimizing error; used "Adam" throughout)
• Epochs (how many times to run through the training process;

kept at 1 for base

Benchmark Model

For this project i have used a Linear Regression model as its primary benchmark. As one of my goals is to understand the relative performance and implementation differences of machine learning versus deep learning models. This Linear Regressor was based on the examples presented in Udacity's Machine Learning for Trading course and was used for error rate comparison MSE and RMSE utilizing the same dataset as the deep learning models.

Following is the predicted results that i got from my benchmark model :

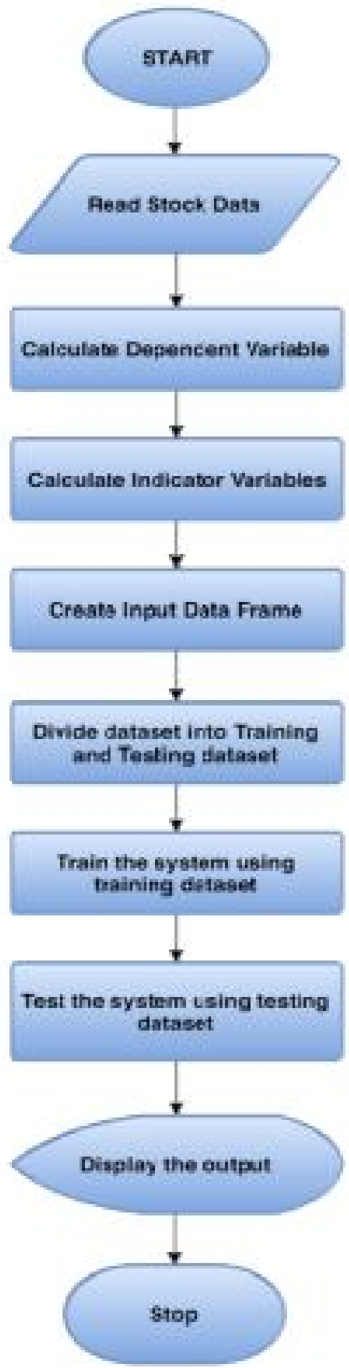


X-axis: Represents Tradings Days

Y-axis: Represents Closing Price In USD

Green line: Adjusted Close price
Blue Line: Predicted Close price

4.4 Flowchart



5 Problem Statement

The challenge of this project is to accurately predict the future closing value of a given stock across a given period of time in the future. In the past few years we've seen lots of academic papers published using neural nets to predict stock prices with varying degrees of success but until recently the ability to build these models has been restricted to academics. Now with libraries like tensor flow anyone can build powerful predictive models trained on masive of datasets. For this project I will use a Long Short Term Memory networks – usually just called "LSTMs" to predict the closing price of the SP 500 using a dataset of past prices.

6 Methodology

6.1 Importing the libraries

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import datetime

6.2 Data Preprocessing :

dataset = pd.read$_c sv('NSE - TATAGLOBAL.csv', index_c ol =$
$"Date", parse_d ates = True)$
$dataset.head()$

Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
2018-09-28	234.05	235.95	230.20	233.50	233.75	3069914	7162.35
2018-09-27	234.55	236.80	231.10	233.80	233.25	5082859	11859.95
2018-09-26	240.00	240.00	232.50	235.00	234.25	2240909	5248.60
2018-09-25	233.30	236.75	232.00	236.25	236.10	2349368	5503.90
2018-09-24	233.55	239.20	230.75	234.00	233.30	3423509	7999.55

dataset.tail()

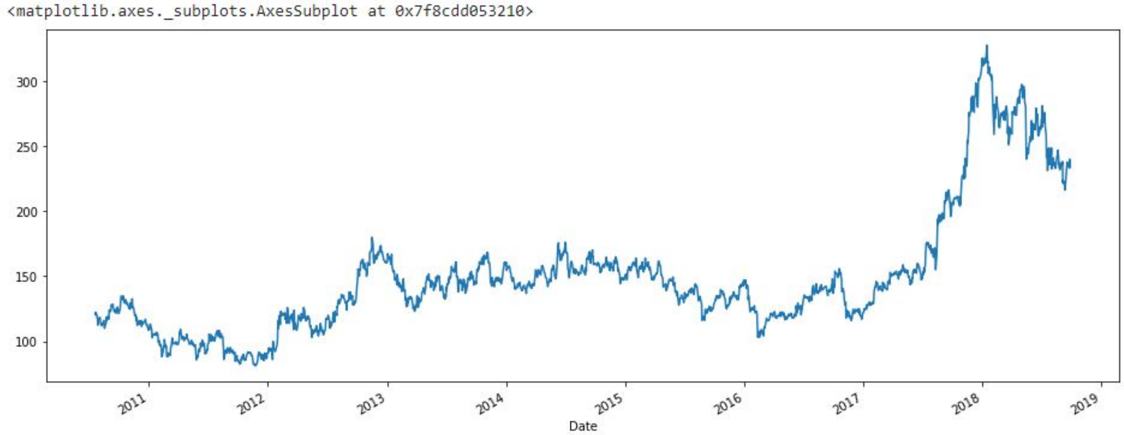
Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
2010-07-27	117.6	119.50	112.00	118.80	118.65	586100	694.98
2010-07-26	120.1	121.00	117.10	117.10	117.60	658440	780.01
2010-07-23	121.8	121.95	120.25	120.35	120.65	281312	340.31
2010-07-22	120.3	122.00	120.25	120.75	120.90	293312	355.17
2010-07-21	122.1	123.00	121.05	121.10	121.55	658666	803.56

dataset.info()

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2035 entries, 2018-09-28 to 2010-07-21
Data columns (total 7 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Open                  2035 non-null   float64
 1   High                  2035 non-null   float64
 2   Low                   2035 non-null   float64
 3   Last                  2035 non-null   float64
 4   Close                 2035 non-null   float64
 5   Total Trade Quantity  2035 non-null   int64
 6   Turnover (Lacs)       2035 non-null   float64
dtypes: float64(6), int64(1)
memory usage: 127.2 KB
```

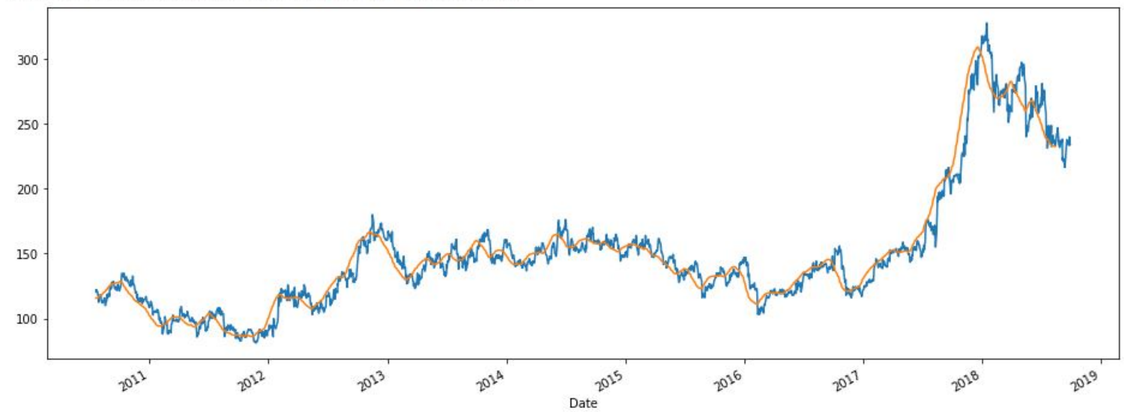
dataset['Open'].plot(figsize=(16,6))

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8cdd053210>
```



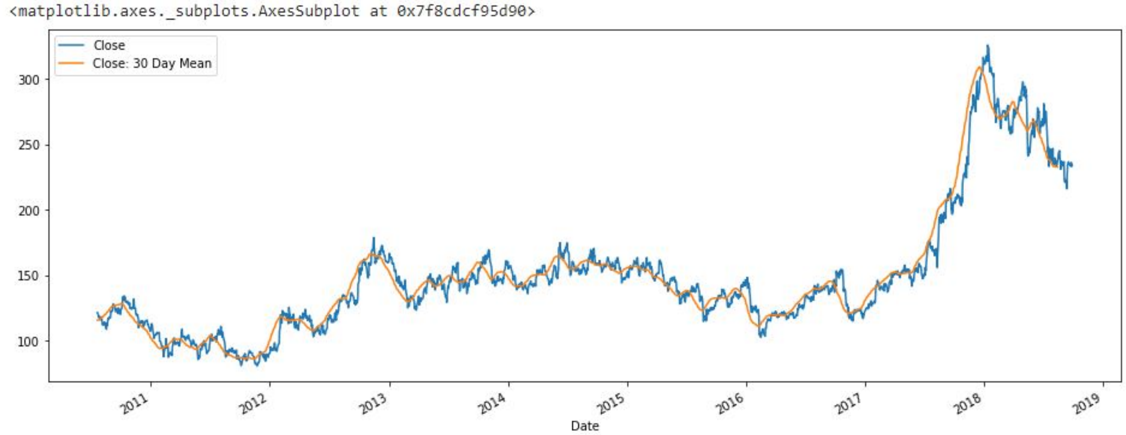
dataset['Open'].plot(figsize=(16,6))
dataset.rolling(window=30).mean()['Close'].plot()

<matplotlib.axes._subplots.AxesSubplot at 0x7f8cdd00d3d0>



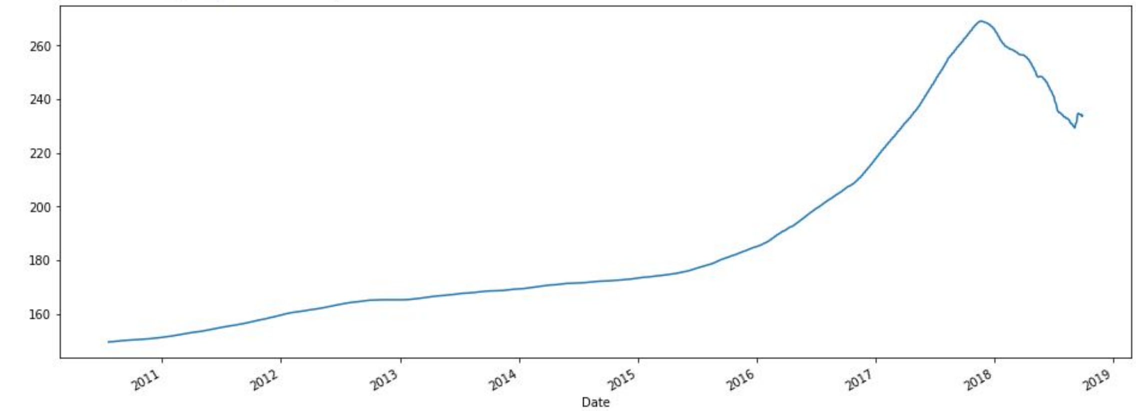
dataset['Close: 30 Day Mean'] = dataset['Close'].rolling(window=30).mea
dataset[['Close','Close: 30 Day Mean']].plot(figsize=(16,6))

<matplotlib.axes._subplots.AxesSubplot at 0x7f8cdcf95d90>



Optional specify a minimum number of periods
dataset['Close'].expanding(min$_p eriods = 1).mean().plot(figsize = (16, 6))$

<matplotlib.axes._subplots.AxesSubplot at 0x7f8cdcf224d0>



$$\text{training}_s et = dataset['Open']$$
$$training_s et = pd.DataFrame(training_s et)$$

Feature Scaling

from sklearn.preprocessing import MinMaxScaler

sc = MinMaxScaler(feature$_r ange = (0, 1)$)

$training_s et_s caled = sc.fit_t ransform(training_s et)$

Creating a data structure with 60 timesteps and 1 output

$X_t rain = []$

$y_t rain = []$

$foriinrange(60, 2035) :$

$X_t rain.append(training_s et_s caled[i - 60 : i, 0])$

$y_t rain.append(training_s et_s caled[i, 0])$

$X_t rain, y_t rain = np.array(X_t rain), np.array(y_t rain)$

Reshaping

$\mathrm{X}_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))$

6.3 Building the RNN

Importing the Keras libraries and packages

from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout

Initialising the RNN

regressor = Sequential()

Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return$_sequences = True, input_shape = (X_train.shape[1], 1)))$
$regressor.add(Dropout(0.2))$

Adding the Second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return$_sequences = True))$
$regressor.add(Dropout(0.2))$

Adding a third LSTM layer and some Dropout regularisation

regressor.add(LSTM(units = 50, return$_{s}equences = True$))
$regressor.add(Dropout$(0.2))

Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

Adding the output layer
regressor.add(Dense(units = 1))

Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean$_{s}quared_{e}rror'$)

Fitting the RNN to the Training set
regressor.fit(X$_{t}rain, y_{t}rain, epochs = 20, batch_{s}ize = 32$)

```
Epoch 1/20
62/62 [==============================] - 18s 112ms/step - loss: 0.0303
Epoch 2/20
62/62 [==============================] - 7s 110ms/step - loss: 0.0045
Epoch 3/20
62/62 [==============================] - 7s 110ms/step - loss: 0.0033
Epoch 4/20
62/62 [==============================] - 7s 110ms/step - loss: 0.0029
Epoch 5/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0026
Epoch 6/20
62/62 [==============================] - 7s 107ms/step - loss: 0.0032
Epoch 7/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0023
Epoch 8/20
62/62 [==============================] - 7s 109ms/step - loss: 0.0026
Epoch 9/20
62/62 [==============================] - 7s 109ms/step - loss: 0.0021
Epoch 10/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0021
Epoch 11/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0024
Epoch 12/20
62/62 [==============================] - 7s 109ms/step - loss: 0.0019
Epoch 13/20
62/62 [==============================] - 7s 107ms/step - loss: 0.0020
Epoch 14/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0018
Epoch 15/20
62/62 [==============================] - 7s 109ms/step - loss: 0.0019
Epoch 16/20
62/62 [==============================] - 7s 109ms/step - loss: 0.0019
Epoch 17/20
62/62 [==============================] - 7s 108ms/step - loss: 0.0018
Epoch 18/20
62/62 [==============================] - 7s 107ms/step - loss: 0.0016
Epoch 19/20
62/62 [==============================] - 7s 107ms/step - loss: 0.0017
Epoch 20/20
62/62 [==============================] - 7s 107ms/step - loss: 0.0015
<keras.callbacks.History at 0x7fb23ae56ed0>
```

6.4 Making the predictions and visualising the results

Getting the real stock price of 2017
dataset$_test = pd.read_csv('tatatest.csv')$
$real_stock_price = dataset_test.iloc[:, 1:2].values$

dataset$_test.head()$

	Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
0	2018-10-24	220.10	221.25	217.05	219.55	219.80	2171956	4771.34
1	2018-10-23	221.10	222.20	214.75	219.55	218.30	1416279	3092.15
2	2018-10-22	229.45	231.60	222.00	223.05	223.25	3529711	8028.37
3	2018-10-19	230.30	232.70	225.50	227.75	227.20	1527904	3490.78
4	2018-10-17	237.70	240.80	229.45	231.30	231.10	2945914	6961.65

dataset$_test.info()$

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16 entries, 0 to 15
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Date                  16 non-null     object 
 1   Open                  16 non-null     float64
 2   High                  16 non-null     float64
 3   Low                   16 non-null     float64
 4   Last                  16 non-null     float64
 5   Close                 16 non-null     float64
 6   Total Trade Quantity  16 non-null     int64  
 7   Turnover (Lacs)       16 non-null     float64
dtypes: float64(6), int64(1), object(1)
memory usage: 1.1+ KB
```

Getting the predicted stock price of 2017
dataset$_total = pd.concat((dataset['Open'], dataset_test['Open']), axis = 0)$
$inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60 :].values$
$inputs = inputs.reshape(-1, 1)$
$inputs = sc.transform(inputs)$
$X_test = []$
$foriinrange(40, 76) :$
$X_test.append(inputs[i - 40 : i, 0])$
$X_test = np.array(X_test)$

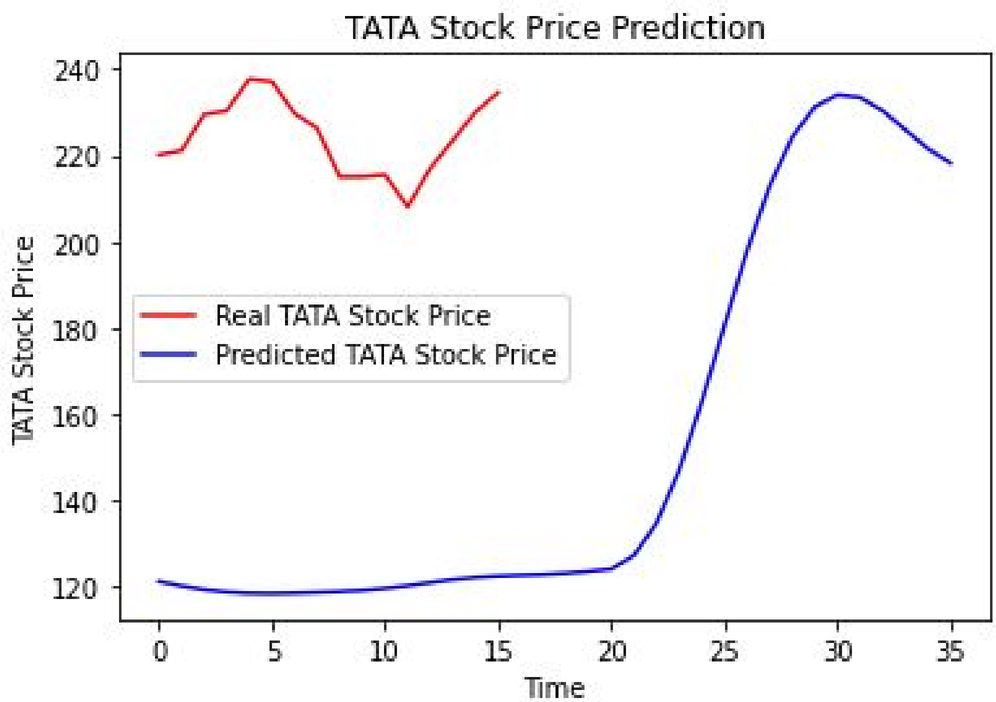
$X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))$
$predicted_stock_price = regressor.predict(X_test)$
$predicted_stock_price = sc.inverse_transform(predicted_stock_price)$

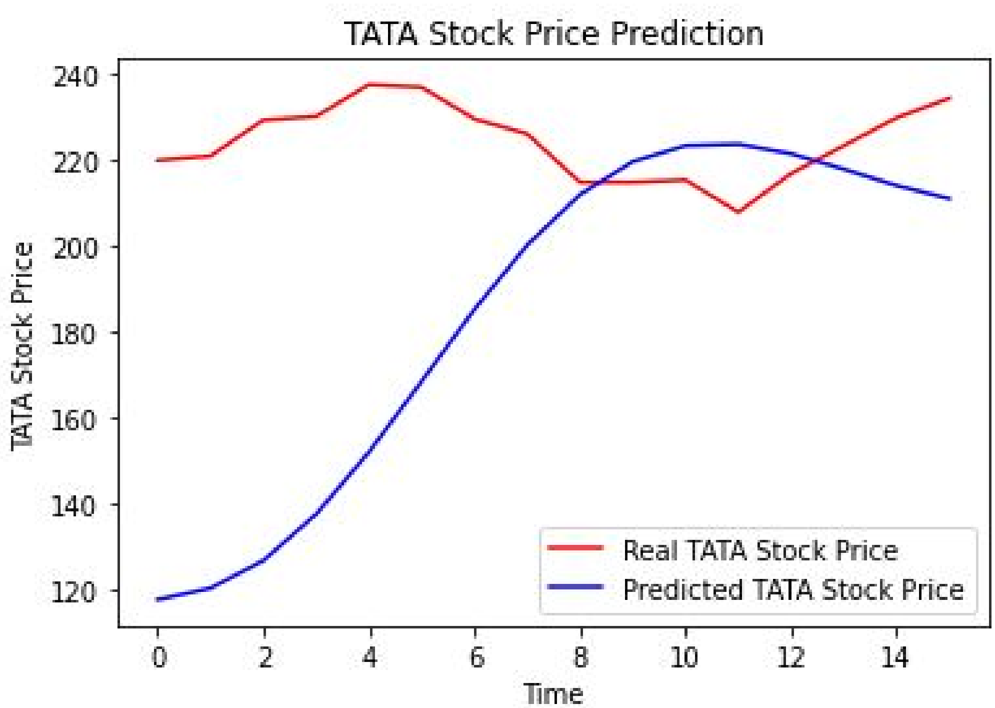
Second Result

dataset$_total = pd.concat((dataset['Open'], dataset_test['Open']), axis =$
$0)$
$inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60 :$
$].values$
$inputs = inputs.reshape(-1, 1)$
$inputs = sc.transform(inputs)$
$X_test = []$
$foriinrange(60, 76) :$
$X_test.append(inputs[i - 60 : i, 0])$
$X_test = np.array(X_test)$
$X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))$
$predicted_stock_price = regressor.predict(X_test)$
$predicted_stock_price = sc.inverse_transform(predicted_stock_price)$

6.5 Visualising the results

plt.plot(real$_stock_price, color =' red', label =' RealTATAStockPrice')$
$plt.plot(predicted_stock_price, color =' blue', label =' PredictedTATASto$
$plt.title('TATAStockPricePrediction')$
$plt.xlabel('Time')$
$plt.ylabel('TATAStockPrice')$
$plt.legend()$
$plt.show()$


TATA Stock Price Prediction
240
220
200
180
160
140
120
TATA Stock Price
Real TATA Stock Price
Predicted TATA Stock Price
0
5
10
15
20
25
30
35
Time


TATA Stock Price Prediction
240
220
200
180
160
140
120
TATA Stock Price
Real TATA Stock Price
Predicted TATA Stock Price
0
2
4
6
8
10
12
14
Time

Conclusion

In this project, I have demonstrated a machine learning approach to predict stock market trend using different neural networks. Result shows how I can use history data to predict stock movement with reasonable accuracy. Also, with T test result analysis I can conclude that LSTM performs better compare to Backpropagation and SVM. For this implementation, I would like to conclude that if I incorporate all the factors that affect stock performance and feed them to neural network with proper data preprocessing and Filtering, after training the network I will be able to have a model which can predict stock momentum very accurately and this can result into better stock forecasting and profit for financial firms.

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