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# Gain Profitable Insights by Focusing on Moving Averages for Intelligent Trading Solutions

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**ABSTRACT**

It is more important than ever to find intelligent trading strategies as financial markets get more complex. This paper offers a thorough investigation into the use of moving averages in Python programming for the creation of intelligent trading algorithms. This study explores the complex relationship between data analysis and profitable decision-making, providing a sophisticated viewpoint on the use of moving averages in financial planning. An overview of the Python programming language as a flexible tool for algorithmic trading and quantitative analysis opens the investigation. The discussion then turns to the use of moving averages, a key instrument in technical analysis, in the context of trading strategies. We highlight Python's flexibility by showcasing how moving averages can be easily incorporated into the trading process to improve decision support.

To sum up, this paper provides an invaluable resource for traders, scholars, and algorithmic enthusiasts who want to learn more about the relationship between moving averages and Python programming. The framework that is being presented not only broadens the range of tools available for algorithmic trading, but it also emphasises how important data-driven decision-making is in turning information into profits.

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**KEYWORDS:** Bollinger Bands, Relative Strength Index, Technical Analysis, Stock Trading, Buy-Sell Signals, Volatility, Momentum.

## 1. INTRODUCTION

Using algorithms—computer-generated instructions—to automate the process of trading financial instruments in the stock, forex, and other markets is known as algorithmic trading. The algorithmic trading feature of the given code is used when the script automatically generates buy and sell signals based on the given conditions without the need for human intervention. This is what algorithmic trading is all about.

Algorithmic trading uses financial markets and computer programming to execute trades at specific times. In addition to ensuring the most effective trade execution, placing orders instantly, and potentially lowering trading fees, algorithmic trading aims to remove emotion from trading. Trend-following tactics, arbitrage opportunities, and index fund rebalancing are examples of common trading strategies. Moreover, volume (volume-weighted average price) and time (time-weighted average price) are used to execute algorithmic trading.

Computer programmes and automated instructions are used in algorithmic trading to execute trades. Known by several names such as black-box or algorithmic trading, it currently accounts for more than half of all trading activity in US markets.

This is an interesting story of how algorithmic trading has changed over time and become more popular.

In the past few decades, there has been a significant transformation in the securities trading industry. The term "Algorithmic Trading," or "Algo Trading," has taken control in the modern era, when exchanges carry out orders supported by automated and recorded instructions. Algorithmic trading is used by larger brokerages and institutional investors to manage huge orders and save costs. It is even used by mutual funds, pensions, and other sizable investment entities.

Market-making firms often generate liquidity through algorithmic transactions. In 2020, 10% of US and European hedge funds derived over 80% of their value from algorithmic trading.

Big organisations have advanced much farther, starting to trade in nanoseconds using supercomputers. High-frequency trading is a relatively recent development in the field of algorithmic trading. Additional algorithmic traders entered the market in 1998 following the US Securities and Exchange Commission's (SEC) approval of ECNs for use in equity trading. After the SEC implemented decimalization in 2000, a lot of spread-profiting participants were forced to move to high-frequency trading in order to increase their trading volume. Over the past ten years, there has been an exponential rise in high-speed trading. The majority of the trade volume is made up of this activity. The goals of algorithmic trading are to maximise market opportunities, enhance efficiency, and maximise trade execution. It can cover a range of time frames, from immediate to distant. While HFT demands ultra-high speed, algorithmic trading may not need the same level of speed in order to optimise trade execution according to predetermined rules. Technical indicators, quantitative models, and historical price data are just a few of the data sources it can use. We have following benefits from Algorithmic Trading:

- Best Execution: The best prices are frequently used to execute trades.
- Low Latency: Trade orders can be placed accurately and instantly, with a high probability of being executed at the specified levels. Trades are executed promptly and at the right time to prevent large price swings.
- lower expenses for transactions.
- Automated checks on several market circumstances simultaneously.
- No Human Error: Lower chance of blunders or manual errors during trade placement. Additionally refutes the inclination of human traders to be influenced by psychological and emotional elements.
- Back testing: To determine if algorithm trading is a profitable trading method, back testing can be done with current and previous data.

## 2. RELATED WORKS

The researchers examined the various machine learning approaches ANN, SVM, random forest, and naive-Bayes in a study comparing two input methods with four distinct prediction models (Patel et al., 2015). Support Vector Regression is presented as the first phase of a two-stage fusion strategy (Patel et al., 2015). (SVR). The domain of voice time series data is appropriate for the paper's teachings. A deep learning approach for stock forecasting was built and tested using multimedia data (a chart of NASDAQ stock prices) (Singh et al., 2016). The authors (Khaidem et al., 2016) suggest an alternate technique of hedging against stock market volatility by forecasting future stock returns using a class of powerful machine learning algorithms. (Chen et al., 2017) provide a simple hybridised framework consisting of feature weighted SVM and K-nearest neighbour to precisely anticipate stock market indices. We tried to predict the following day's closing price for five businesses across sectors using both an ANN and a Random Forest model (Vijh et al., 2020). When compared to the random forest strategy, the LSTM model enhanced equity return projection accuracy from 14.3% to 27.2%. Chen and colleagues (2015) Because the stock market is such an important aspect of the financial system, studying how to predict swings in stock values is quite appealing. Deep learning is applied to forecast stock values in the future (Gao et al., 2018).

## 3. METHODOLOGY

### 3.1 Moving Average

A moving average (MA) is a stock indicator commonly used in technical analysis. The moving average helps to level the price data over a specified period by creating a constantly updated average price. A simple moving average (SMA) is a calculation that takes the arithmetic mean of a given set of prices over a specific number of days in the past. An exponential moving average (EMA) is a weighted average that gives greater importance to the price of a stock in more recent days, making it an indicator that is more responsive to new information. Moving averages are used to calculate a stock's support and resistance levels as well as the direction of its trend. Due to its historical price basis, this indicator is known as a trend-following or lagging indicator. The lag increases with the length of the moving average's period. Because it includes prices for the previous 200 days, a 200-day moving average will lag significantly more than a 20-day MA. Investors and traders frequently monitor the 50-day and 200-day moving average values, which are regarded as crucial trading signals.

Depending on their trading goals, investors can determine moving averages for a variety of durations and lengths. Longer-term investors are better served by longer-term moving averages, whereas shorter moving averages are usually employed in short-term trading. Even if it is impossible to forecast a stock's future movement, research and technical analysis can help forecast more accurate movements. A rising moving average denotes an upward tendency for the security, while a descending moving average denotes a downward trend. Similar to this, a bullish crossover that is, the crossing of a short-term moving average above a longer-term moving average confirms upward momentum. On the other hand, a bearish crossover which happens when a short-term moving average crosses below a longer-term moving average confirms downward momentum.

The average change in a data series over time is captured by a statistic called a moving average. Technical analysts in the financial industry frequently utilise moving averages to monitor price patterns for certain securities. A moving average's upward trend could indicate an increase in the price or momentum of an asset, whilst a downward trend would be seen as a decline.

Technical analysis, a subset of investing that aims to comprehend and capitalise on the price movement patterns of stocks and indexes, makes extensive use of moving averages. Moving averages are typically used by technical analysts to determine whether an investment is experiencing a change in momentum, such as a sharp decline in price.

### 3.2. Simple Moving Average

The computation of a simple moving average (SMA) involves determining the arithmetic mean of a given set of variables over a designated time frame. The sum of a group of numbers, or stock prices, is divided by the total number of prices in the group. The following formula can be used to determine a security's simple moving average:

$SMA=A_1+A_2+A_3+\ldots+A_n/n$

where:

$A_{n=}$ the price of an asset at period n

n= the number of total periods

### 3.3. Exponential Moving Average

In an effort to make prices more responsive to fresh information, the exponential moving average assigns greater weight to recent values. The simple moving average (SMA) for a given time must first be determined in order to compute an EMA. Next, determine the "smoothing factor," or multiplier, by weighting the EMA. This can be done using the following formula: [2/(selected time period + 1)]. The multiplier for a 20-day moving average would be [2/(20+1)]= 0.0952. To get the current value, the smoothing factor and the prior EMA are combined. As a result, the SMA gives all values the same weighting, whereas the EMA provides recent prices a higher weighting.

EMA=Price(t) X k+EMA(y) X (1-k)

Where

T=today

Y=yesterday

N=number of days in EMA

K=2/(N+1)

#### 3.3.1. Dataset

In this work, we use a TATACOFFEE and ITC dataset. We have the dataset with the time period form 2019-2023. Finally we have 993 rows of data and divided them in to two category. 900 rows of data for Training purpose and 100 rows of data for Testing purpose.

**Table 1. Sample TATACOFFEE Data Set**

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 26-12-2019 | 91.7 | 92.4 | 91.55 | 91.75 | 87.37885 | 151209 |
| 27-12-2019 | 91.9 | 92.3 | 91.2 | 91.85 | 87.47408 | 194738 |
| 30-12-2019 | 92.3 | 92.45 | 91.05 | 92.05 | 87.66456 | 247880 |
| 31-12-2019 | 92 | 94.25 | 91.2 | 92.1 | 87.71217 | 746744 |
| 01-01-2020 | 92.5 | 92.7 | 91.3 | 91.5 | 87.14076 | 147147 |
| 02-01-2020 | 91.9 | 93.25 | 91.55 | 92.45 | 88.04549 | 271918 |
| 03-01-2020 | 92.7 | 96.2 | 92.5 | 93.9 | 89.42642 | 1281570 |
| 06-01-2020 | 92.75 | 93.25 | 90.1 | 90.35 | 86.04555 | 319848 |
| 07-01-2020 | 91.05 | 92.55 | 90.5 | 91.55 | 87.18838 | 229694 |
| 08-01-2020 | 91 | 91.55 | 88.6 | 89.15 | 84.90271 | 341567 |
| 09-01-2020 | 90.3 | 92.8 | 90 | 91.45 | 87.09315 | 456659 |
| 10-01-2020 | 91.8 | 93.95 | 91.8 | 93.3 | 88.85501 | 703285 |
| 13-01-2020 | 95 | 99.85 | 94.3 | 97.55 | 92.90253 | 2665181 |
| 14-01-2020 | 97.75 | 102.95 | 97.05 | 100.35 | 95.56913 | 2996657 |
| 15-01-2020 | 100.5 | 101.55 | 99.5 | 99.9 | 95.14057 | 801667 |
| 16-01-2020 | 99.9 | 104 | 99.85 | 101.95 | 97.0929 | 1609691 |
| 17-01-2020 | 102.9 | 103.85 | 98.5 | 99.35 | 94.61677 | 776970 |
| 20-01-2020 | 99.35 | 102.8 | 98.85 | 100.45 | 95.66436 | 1170980 |
| 21-01-2020 | 99.5 | 106.95 | 99.5 | 102.95 | 98.04525 | 3702445 |

**Table 2. Sample ITC Data Set**

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 26-12-2019 | 238.9 | 239.4 | 236.35 | 236.8 | 200.0162 | 14460325 |
| 27-12-2019 | 237.5 | 238.45 | 236.45 | 236.9 | 200.1007 | 8712539 |
| 30-12-2019 | 238 | 240.9 | 237.5 | 238.2 | 201.1987 | 13173134 |
| 31-12-2019 | 238.55 | 238.95 | 237.4 | 237.7 | 200.7764 | 7142051 |
| 01-01-2020 | 238.6 | 238.6 | 237.1 | 238.1 | 201.1142 | 4208837 |
| 02-01-2020 | 238.2 | 240.95 | 238.1 | 239.85 | 202.5924 | 8402979 |
| 03-01-2020 | 241 | 241 | 238 | 238.5 | 201.4521 | 9284478 |
| 06-01-2020 | 237.5 | 238.3 | 235 | 235.1 | 198.5803 | 7636617 |
| 07-01-2020 | 236.05 | 237.9 | 234.6 | 235.35 | 198.7914 | 8416741 |
| 08-01-2020 | 234 | 235.8 | 233.25 | 234.2 | 197.8201 | 7043211 |
| 09-01-2020 | 235.6 | 236.6 | 235.05 | 235.8 | 199.1715 | 9452653 |
| 10-01-2020 | 237.6 | 238.75 | 236.8 | 238 | 201.0298 | 9973746 |
| 13-01-2020 | 238.5 | 240.5 | 238.25 | 239.25 | 202.0856 | 12243639 |
| 14-01-2020 | 240.25 | 243.8 | 238.3 | 243.25 | 205.4643 | 11843444 |
| 15-01-2020 | 242.55 | 243 | 241.1 | 242.4 | 204.7463 | 5476729 |
| 16-01-2020 | 242.5 | 243.9 | 240.1 | 240.75 | 203.3526 | 9369668 |
| 17-01-2020 | 240.75 | 242.1 | 239.4 | 239.95 | 202.6769 | 7392403 |
| 20-01-2020 | 240.05 | 243.25 | 240.05 | 241.9 | 204.324 | 8020816 |
| 21-01-2020 | 241.45 | 241.45 | 238 | 238.45 | 201.4099 | 9571070 |

We have found Adjacent close price history for TATACOFFEE

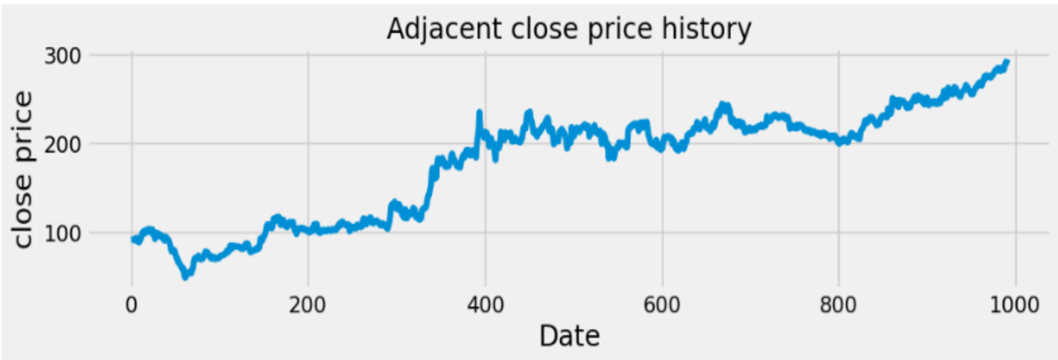


**Fig.1 Adjacent Close Price history(TATACOFFEE)**

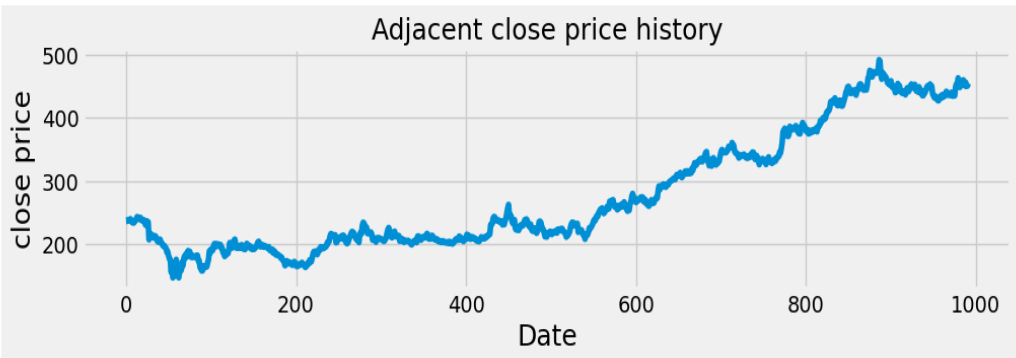


**Fig.2 Adjacent Close Price history(ITC)**

**RESULT**

Financial institutions, stock brokers, and large-scale investors must sell and buy the shares in the shortest time feasible under the law. By effectively capturing the nonlinear behaviour of complex systems, recent breakthroughs in

Machine Learning approaches have created valuable tools for anticipating chaotic circumstances such as the stock market.


**Fig.3 Buy / Sell signal(TATACOFFEE)**

In Fig  there are 8 buy signals are recorded and 7 signals are recorded in various time period. We have found RMSE Error is 8.5076 and MAPE Error is 2.1687. A MAPE of 2.1687 means, on average, predictions are off by about 2.17% from the actual values. This is generally considered a low MAPE and suggests good accuracy. However, the acceptability of MAPE can vary by industry and application.

In summary, whether your RMSE and MAPE values are considered good depends on the specific requirements and expectations for your prediction task.

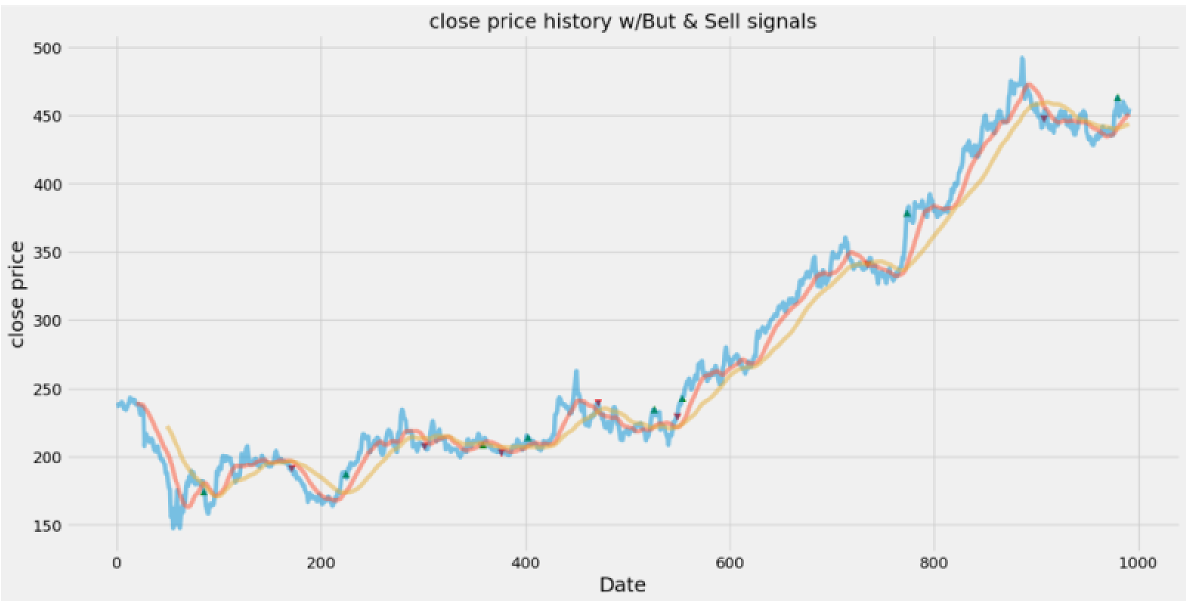


**Fig. 4 Buy / Sell signal(ITC)**

In Fig  there are 8 buy signals are recorded and 6 signals are recorded in various time period. We have found RMSE Error is 6.4106 and MAPE Error is 1.0247.

In summary, whether your RMSE and MAPE values are considered good depends on the specific requirements and expectations for your prediction task.

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