**7COM1079-0901-2024 - Team Research and Development Project**

**Analyzing the Correlation Between Simple Moving Average of Close Prices and the Price Volatility (Difference Between High and Low Prices) in Hyundai’s Stock Data**

**Group ID:** A 246  
**Dataset number:** DS327 - Hyundai Motor Company Stock Historical Price  
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Hatfield, 2024

**Abstract**

This research investigates the relationship between the Simple Moving Average (SMA) of closing prices and the difference between the highest and lowest prices of Hyundai’s stock. The goal is to understand how these two factors are related and whether one can help predict the other. To analyze this, we used two visualizations: a histogram and a scatter plot. The histogram showed that the price differences were not normally distributed, with most values clustering around smaller differences, and fewer occurrences of large price changes. The scatter plot illustrated a positive relationship between SMA and price differences, though there was considerable variability and outliers, suggesting that the relationship is not straightforward. Due to the non-normal distribution of the data, non-parametric methods, such as Spearman’s Rho and Kendall’s Tau, were used to measure the correlation between these two factors. The results indicated a moderate correlation, but also highlighted the importance of considering outliers and variability when interpreting market data. Overall, this research provides insights into how SMA and price differences can be used together to better understand Hyundai’s stock behavior, guiding future analysis and investment strategies.

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**1. Introduction**

**1.1. Problem Statement and Research Motivation**

In the financial world, stock data refers to information about the performance of a company’s shares on the stock market. This data typically includes details like the prices at which shares were bought and sold, how much the prices fluctuated, and how many shares were traded. Studying stock data helps investors, analysts, and stakeholders make better decisions by identifying patterns or trends in how the stock behaves.

For this research, we focus on the stock data of Hyundai Motor Company, a global leader in the automotive industry. Hyundai Motor Company, based in Seoul, South Korea, is a global leader in vehicle manufacturing, offering cars, SUVs, and eco-friendly models like electric and hybrid vehicles. Investing in Hyundai stocks means owning a part of a company involved in diverse areas like car production, financing, and mobility services. The stock's performance depends on factors like global vehicle demand and advancements in green technology, making it an exciting option for this Research. The goal is to investigate if there is a relationship between two key aspects of its stock performance:

1. The Simple Moving Average (SMA) of Closing Prices: This is the average of a stock's closing prices over a specific time frame. It smooths out price fluctuations to help identify trends.
2. The Price Volatility (Difference Between High and Low Prices): This shows how much the stock's price changes within a single day, capturing the range of volatility.

By analyzing this relationship, we aim to uncover patterns that could guide investment decisions or provide insights into market behavior.

**1.2.** **Dataset Description**

The dataset shown in Fig 1.1. is titled “Hyundai Motor Company Stock Historical Price” and is sourced from Kaggle [5], with data originally taken from Yahoo Finance. It contains daily stock price records from January 2016 to the present. Each record in the dataset has several columns, and here is what they represent:

* **Date:** The specific day the stock prices were recorded.
* **Open:** The price at which Hyundai’s stock started trading that day.
* **High:** The highest price the stock reached during the day.
* **Low:** The lowest price the stock fell to during the day.
* **Close:** The price at which the stock finished trading that day.
* **Adjusted Close (Adj Close):** The stock’s closing price adjusted for corporate actions like dividends, stock splits, or other events.
* **Volume:** The total number of shares traded during the day.

For this study, to examine this relationship, we will focus on the following:

* SMA of Closing Prices (dependent variable) calculated by the following formula:

Where,

* : Simple Moving Average at time .
* : Number of periods for the moving average.
* : The Close price at time .
* : The current time period.
* the Price Volatility (independent variable) which is calculated as follows.

Where,

* : Price Volatility at time .
* : High Price at time .
* : Low Price at time.
* : The current time period.

A close-up of numbers

Description automatically generated

**Fig 1.1. Modified Hyundai Stock Dataset**

**1.3. Research Question**

This study investigates:

***“Is there a correlation between the Simple Moving Average of Closing Prices and the Price Volatility (Difference Between High and Low Prices) in Hyundai’s stock data?”***

This question explores whether the average of past closing prices (SMA) is connected to the daily price range volatility. Answering this can provide insights into how historical trends in closing prices relate to the stock's daily volatility.

**1.4. Null Hypothesis and Alternative Hypothesis (H₀/H₁)**

* **Null Hypothesis (H₀):** There is no correlation between the Price Volatility (Difference Between High and Low Prices) and the Simple Moving Average of Closing Prices.
* **Alternative Hypothesis (H₁):** There is a correlation between the Price Volatility (Difference Between High and Low Prices) and the Simple Moving Average of Closing Prices.

The hypotheses will be tested using statistical methods to understand the relationship between these two variables. By exploring this relationship, we aim to contribute to the understanding of stock behavior and provide useful insights to stakeholders, even for those new to the world of finance or data analysis.

**2. Background Research**

**2.1.** **Literature Review**

Understanding financial markets often relies on identifying patterns and trends that inform investment decisions. A widely used tool in this process is the Simple Moving Average (SMA), which helps smooth out price fluctuations over time by averaging an asset's closing prices for a given period. Several studies have explored the utility of SMA in improving trading strategies and mitigating risks associated with market volatility. However, the specific relationship between SMA and the Price Volatility for Hyundai’s stock has received limited attention. This study seeks to fill this gap by investigating how these factors interact and contribute to more effective trading strategies, addressing the Research Question (RQ): How does the interplay between SMA and Price Volatility affect trading strategies for Hyundai’s stock?

Research has demonstrated the versatility of SMA as a tool for trend identification and risk reduction. A study found that using SMA as a trend indicator for main stock and real estate indices significantly reduced standard deviation and maximum drawdown, measures commonly used to assess investment risk [1]. Additionally, it highlighted that longer-term SMAs, spanning 9 to 20 months, were particularly effective for these purposes, offering insights into broader market trends and reducing the influence of short-term volatility.

The difference between an asset's high and low prices during a trading session provides a measure of its price volatility, which is influenced by factors such as liquidity constraints, transaction costs, and market shocks. Research indicates that these price extremes—high prices often representing the highest asking prices and low prices the lowest bids—can be subject to unexpected influences such as unanticipated news events or systemic market changes [2]. Accurate forecasting of these high-low price dynamics has been shown to improve trading performance by offering timely buy and sell signals. For example, if the intraday price crosses the upper predicted range, it may signal an optimal point to sell, whereas crossing the lower range might indicate a buying opportunity [2].

In addition to high-low price analysis, SMA has been widely used to identify trend changes and optimize trading strategies. Its application extends to techniques such as the moving average crossover, where traders compare short-term and long-term SMAs to detect trend reversals and potential trading opportunities [3][4]. These methods are particularly favoured by long-term traders who seek stability and wish to avoid reacting to short-term market fluctuations [4]. SMA thus serves as a robust tool for identifying opportunities and minimizing risks across different market conditions.

Despite these advancements, there remains a significant gap in the literature concerning the specific application of SMA in combination with high-low price dynamics for individual stocks such as Hyundai’s. This study aims to address this gap by investigating the correlation between SMA signals and high-low price differences. Understanding this relationship is crucial for technical analysts and investors, as it could provide actionable insights for predicting market movements and refining trading strategies.

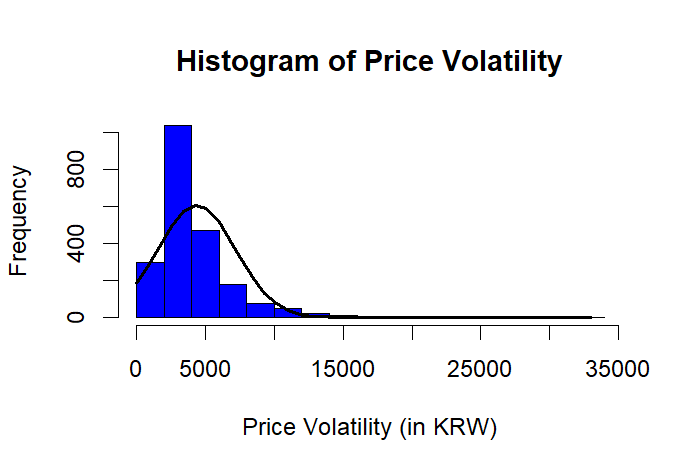
**2.2.** **Why RQ is of Interest.**

The significance of this research lies in its potential to contribute both to academic understanding and practical application. By focusing on Hyundai’s stock, the study provides a targeted analysis that can serve as a foundation for future research in this area. Additionally, the insights gained may help traders and investors better navigate market complexities, thereby improving their decision-making processes and enhancing overall market efficiency.

**3. Visualization**

To better understand the relationship between the Simple Moving Average (SMA) of closing prices and the Price Volatility in Hyundai’s stock data, two visualizations were used: a histogram and a scatter plot. These visualizations provide foundational insights into the data and guide the selection of appropriate statistical methods.

**3.1.** **Histogram: Distribution of High-Low Price Differences**

****

**Fig 4.1. Histogram of Price Volatility**

The histogram shown in Fig 4.1. reveals the frequency distribution of the differences between high and low prices. The data shows a strong concentration of smaller price differences, with fewer instances of larger differences. This right-skewed distribution is non-normal, as indicated by the tail stretching towards higher price differences. This skewness suggests the presence of outliers, potentially arising from significant market events or abnormal trading activity.

The lack of normality in the data distribution is an important finding, as it directly influences the choice of statistical methods for further analysis. Traditional parametric tests, which assume normality, would be inappropriate here, leading to the selection of rank-based methods like Spearman’s Rho and Kendall’s Tau.

**3.2.** **Scatter Plot: SMA vs. High-Low Price Differences**

**A graph of a price volatility

Description automatically generated**

**Fig 4.2. Scatterplot of Price Volatility vs 20-Day Simple Moving Average**

The scatter plot in Fig 4.2. depicts the relationship between the SMA (x-axis) and the high-low price differences (y-axis). A fitted regression line provides a clear indication of a positive trend, suggesting that as SMA values increase, the differences between high and low prices also tend to rise.

However, the spread of data points around the regression line is considerable, indicating variability in the relationship. The presence of outliers, visible as points deviating significantly from the general trend, further emphasizes the complexity of the relationship. This variability necessitates robust statistical methods that can handle such irregularities without being unduly influenced by extreme values.

**3.3.** **Why the Data Distribution Influences Method Selection**

The non-normal distribution observed in the histogram justifies the choice of Spearman’s Rho and Kendall’s Tau for correlation analysis. Both methods are non-parametric and rank-based, making them ideal for datasets with skewed distributions and outliers. Spearman’s Rho measures the strength and direction of the monotonic relationship, while Kendall’s Tau assesses the agreement between data rankings. Their robustness ensures reliable results even when normality assumptions are violated.

**4. Analysis**

In financial markets, identifying relationships between various price metrics is crucial for understanding trends and making informed decisions. This study explores whether there is a meaningful correlation between the Simple Moving Average (SMA) of closing prices and the Price Volatility prices in Hyundai’s stock data. To assess this, statistical methods were employed to determine the strength and significance of the relationship between these two variables.

By examining the relationship between these two measures, this study aims to uncover whether trends observed in SMA align with variations in daily price ranges. Such a relationship, if present, could help traders refine their strategies by combining long-term trend analysis (SMA) with real-time price movement data.

**4.1.** **Results from Statistical Analysis**

Two statistical tools, Spearman's rank correlation (rho) and Kendall's rank correlation (tau), were used to analyze the relationship between SMA and the high-low price difference. These methods are particularly useful because they measure the strength and direction of associations between variables without assuming any specific type of relationship (linear or otherwise).

|  |  |  |
| --- | --- | --- |
|  | **Spearman Test** | **Kendall Test** |
|  | S = 975949783 | z = 19.642 |
| p-value | < 2.2e-16 | < 2.2e-16 |
| Rank Correlation | rho = 0.4083257 | tau = 0.2914608 |

**Table 1 – Statistical Test Findings**

* **Spearman's rho:** From Table 1, we can see that the analysis yielded a rho value of 0.408, which suggests a moderate positive correlation. This means that, generally, as the SMA of closing prices increases, there is a tendency for the high-low price difference to increase as well. The associated p-value was less than 2.2e-16, indicating that this result is statistically significant and highly unlikely to be due to random chance.
* **Kendall's tau:** Similarly, Table 1 shows that the Kendall’s tau analysis produced a tau value of 0.291, also pointing to a positive correlation. Although this value is slightly lower than rho, it reinforces the finding that there is a meaningful association between the two variables. The p-value, once again less than 2.2e-16, confirms the significance of this result.

**4.2. Interpretation of Findings**

The results suggest that there is a consistent relationship between the SMA of closing prices and the Price Volatility in Hyundai’s stock. A positive correlation indicates that these two measures tend to move in the same direction. In simpler terms, when the SMA, which represents the long-term trend of closing prices, increases, it is often accompanied by a larger range of daily price movement.

This relationship is not only statistically significant but also relevant for traders and analysts. It implies that the SMA could be a useful tool for predicting changes in price volatility. For instance, if an increasing SMA trend is observed, it may signal that the stock is experiencing broader price swings, which could influence decisions on when to buy or sell.

**5. Conclusions**

**5.1. Key Findings**

Our analysis of Hyundai's stock data revealed valuable insights that can help investors and traders better understand market trends. Specifically, we found a meaningful and moderate positive correlation between the 20-day Simple Moving Average (SMA) and the Price Volatility (Difference between High and Low Prices). This suggests that when the SMA increases, the variability in daily prices also tends to rise, highlighting a relationship between long-term trends and daily price movements.

Additionally, we discovered a statistically significant positive correlation between the SMA of closing prices and Price Volatility. This means that as the SMA rises, trading activity tends to increase. This behavior aligns with the way technical indicators influence market participation.

**5.2.** **What This Means for Investors**

These findings provide a practical understanding of stock market behavior. For example:

* **Price Trends and Variability:** Recognizing the connection between the SMA and Price Volatility allows investors to use SMA as a tool to gauge market momentum while also considering potential daily fluctuations.
* **SMA and Trading Activity:** The relationship between SMA and trading volumes indicates that traders often react to SMA trends, driving higher activity in the market.

However, the presence of outliers and variability in the data reminds us that market trends are influenced by many factors beyond just SMA, such as economic events and news.

**5.3. Implications and Future Directions**

While our findings highlight significant correlations, they are not the sole determinants of stock performance. Other factors like company announcements, global market conditions, and investor sentiment also play crucial roles. Future research could integrate these external factors to build more robust predictive models.

Moreover, while correlation suggests a relationship, it does not confirm causation. For instance, the rise in trading volumes alongside SMA trends may be influenced by broader market dynamics. Investigating these causes can lead to a deeper understanding of market behaviours.

**5.4. Concluding Remarks**

In summary, this research demonstrates the value of using SMA and Price Volatility as tools to understand stock trends. By applying these insights, investors can enhance their strategies, reduce uncertainty, and make more informed trading decisions. However, as always in financial markets, caution and comprehensive analysis remain key to successful investing.

**6. Reference list**

1. Macijauskas, L., 2012. Simple moving average as a risk management method in main asset classes.
2. Pramudya, R. and Ichsani, S., 2020. Efficiency of technical analysis for the stock trading. International Journal of Finance & Banking Studies, 9(1), pp.58-67.
3. Kardile, R., Ugale, T. and Mohanty, S.N., 2021, September. Stock price predictions using crossover SMA. In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1-5). IEEE.
4. Moving average crossover strategies IG. Available at: https://www.ig.com/en/trading-strategies/\_moving-average-crossover-strategies-191018 (Accessed: 20 December 2024).
5. Caesar, M. (2024) Hyundai Motor Company Stock Historical Price, Kaggle. Available at: https://www.kaggle.com/datasets/caesarmario/hyundai-motor-company-stock-historical-price (Accessed: 07 November 2024).

**7. Appendices**

**A. R code used for analysis and visualization.**

library(TTR)

data = read.csv("005380.KS.csv")

data

data$sma = SMA(data$Close, n = 20) # Calculation of 20-Day Simple Moving Average

data$pricevolatility = data$High - data$Low # Caculation of Price Volatility

data

write.csv(data, "Dataset\_SMA.csv", row.names = FALSE) # Saving the modified dataset for further Visualisation and Analysis

library(ggplot2)

library(dplyr)

data = read.csv("Dataset\_SMA.csv")

data

summary(data)

# Data Cleaning - Removing Null values

sum(!is.finite(data$sma))

data\_cleaned <- data[!is.na(data$sma) & !is.nan(data$sma) & !is.infinite(data$sma), ]

sum(!is.finite(data\_cleaned$sma))

y <- data\_cleaned$pricevolatility

x <- data\_cleaned$sma

# Histogram of Price Volatility

h <- hist(y

, 12

, main = "Histogram of Price Volatility"

, xlab = "Price Volatility (in KRW)"

, ylab = "Frequency"

, col = "blue"

)

xfit <- seq(min(y), max(y), length = 40)

yfit <- dnorm(xfit, mean = mean(y), sd = sd(y))

yfit <- yfit \* diff(h$mids[1:2]) \* length(y)

lines(xfit, yfit, col = "black", lwd = 2)

# Scatterplot of Price Volatility vs. 20-Day Simple Moving Average

plot(x,y,main = "Scatterplot of Price Volatility vs. 20-Day Simple Moving Average" , xlab = "Price Volatility (in KRW)" , ylab = "20-day SMA (in KRW)" , pch = 19, frame = T)

model <- lm(y ~ x, data = data\_cleaned)

abline(model, col = "blue")

# Kendall Statistical Test

cor\_test\_result <- cor.test(x, y, method = "kendall")

print(cor\_test\_result)

# Spearman Statistical Test

cor\_test\_result <- cor.test(x, y, method = "spearman")

print(cor\_test\_result)

**B. GitHub log output**

commit a4dd71a1b363735adb6b4e551b224896bf6a5890 (HEAD -> main, origin/main, origin/HEAD)

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 09:01:43 2025 +0000

Unused File Deletion

commit 6889ea7cfa42db8c512349f86f2779d4fd97f52f

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:59:28 2025 +0000

Report Changes - Abinaya

commit a833b44faee749629ec3fb7c89827241ab3776c9

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:58:20 2025 +0000

Changing Column Name - Abinaya

commit 679d67cd3051bb4afa292906d5baf144f0cf05ef

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:58:03 2025 +0000

Modified and Finalized Plots - Abinaya

commit 9e11cdde3f19f1f1f76fefc4821f0120fd07afe8

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:57:39 2025 +0000

Changes in Name of Column

:...skipping...

commit a4dd71a1b363735adb6b4e551b224896bf6a5890 (HEAD -> main, origin/main, origin/HEAD)

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 09:01:43 2025 +0000

Unused File Deletion

commit 6889ea7cfa42db8c512349f86f2779d4fd97f52f

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:59:28 2025 +0000

Report Changes - Abinaya

commit a833b44faee749629ec3fb7c89827241ab3776c9

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:58:20 2025 +0000

Changing Column Name - Abinaya

commit 679d67cd3051bb4afa292906d5baf144f0cf05ef

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:58:03 2025 +0000

Modified and Finalized Plots - Abinaya

commit 9e11cdde3f19f1f1f76fefc4821f0120fd07afe8

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:57:39 2025 +0000

Changes in Name of Column

commit 13c4e6004df110624c9c4fb90e0e7fbee954c38b

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 08:57:24 2025 +0000

Finalizing Data Visualization Code - Abinaya

commit f09c6834006e6be3e20d4b81d6f46038202d8098

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Jan 7 01:55:09 2025 +0000

More changes

commit e1b352350612e3739132e26d76259468cf99a6ba

Author: Mahesh-UH <mr24ady@herts.ac.uk>

Date: Mon Jan 6 18:36:09 2025 +0000

Changes in Report - Background Research

commit 8ffe11297e0c454e8e935025818172f05701dce0

Author: Yesudian <jy23aau@herts.ac.uk>

Date: Mon Jan 6 18:30:33 2025 +0000

Added comments

commit 0434ceb64d292530085f2cd11925810fc4b52dea

Author: Yesudian <jy23aau@herts.ac.uk>

Date: Mon Jan 6 18:28:39 2025 +0000

Added the comments

commit cc7e872b9c5097a38f8d3648dc4924333711b583

Author: Yesudian <jy23aau@herts.ac.uk>

Date: Mon Jan 6 18:25:47 2025 +0000

Added the comments

commit 1259603e5ad6f7bc0f2465684ae9e093a6627dae

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Mon Jan 6 13:48:53 2025 +0000

Improvising the Introduction of the Report - Abinaya

commit f9692e63cb3ec5471e82de42f6678ee806f4750c

Author: john chris <jy23aau@herts.ac.uk>

Date: Sun Jan 5 17:01:42 2025 +0000

changes in report

added the passage Evaluation in report

commit e05ff13911221cc213915fa4edb83181f72691e4

Author: john chris <jy23aau@herts.ac.uk>

Date: Fri Jan 3 15:09:42 2025 +0000

Report added

commit d198d59ffada0b2c58a4ed28ae9271f42e743e90

Author: Yesudian <jy23aau@herts.ac.uk>

Date: Fri Jan 3 15:03:51 2025 +0000

checked & corrected the comment which is placed in wrong place

commit 03a3981fd37b99d13a1b50b614ac7d96db8bc52c

Author: Yesudian <jy23aau@herts.ac.uk>

Date: Fri Jan 3 15:01:37 2025 +0000

just added a comment for histogram and deleted duplicate

commit 39d6421a2792aa43109445b1053aaeb08fd62c8e

Author: Mahesh <mr24ady@herts.ac.uk>

Date: Thu Jan 2 22:09:17 2025 +0000

sma benefits-mahesh

commit 3607dcc13b8c7e181fddf34c4db759a90de22997

Author: Mahesh <mr24ady@herts.ac.uk>

Date: Thu Jan 2 21:47:05 2025 +0000

changes in plot

commit dd93f61ebf8a010bbe7f3d992c83369b69a52313

Author: Mahesh <mr24ady@herts.ac.uk>

Date: Thu Jan 2 21:33:36 2025 +0000

changes done in hist line 22

commit 7bb9a96458dfbf72862b4122819510c4b9733f61

Merge: 8b97c73 b5e91f2

Author: Mahesh <mr24ady@herts.ac.uk>

Date: Thu Jan 2 21:09:32 2025 +0000

Merge branch 'main' of https://github.com/aa24abf/A246\_7COM1079

# Conflicts:

# Data\_Visualization.R

commit b5e91f29c10db9b27c5035bbbb3bb2193b1ad6e3

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Jan 2 19:52:53 2025 +0000

Added comments to read csv in data

commit 9e56652d71291894a373dda40d0936a688edb179

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Jan 2 19:50:14 2025 +0000

Added comments to CSV data

commit 02e05fa9493ff09f71fe866175f05d0a172964e1

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Jan 2 19:46:20 2025 +0000

Added comments to data high and low value

commit 77dc3fc7fca32d73d715dcac618d8e5978d9e4da

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Jan 2 19:40:26 2025 +0000

Added comment for SMA 20 period data

commit 8b97c7330b41f9c75a7e1d8e3fb214697f76925e

Author: Mahesh <mr24ady@herts.ac.uk>

Date: Wed Dec 25 14:44:29 2024 +0000

No changes done

commit 08b38482b297697de886a979692b5aa8ced18915

Author: Balamurugan <tb24abi@herts.ac.uk>

Date: Tue Dec 24 23:08:23 2024 +0000

Correlation Test - Tilak

commit 235af3b81b66433f54edbac885d2956544d202cd

Author: Balamurugan <tb24abi@herts.ac.uk>

Date: Tue Dec 24 22:58:12 2024 +0000

Scatterplot Changes - Tilak

commit 7c413ae8ad80e9dba8eae4e56090e8dda4e7c13c

Author: Balamurugan <tb24abi@herts.ac.uk>

Date: Tue Dec 24 22:37:25 2024 +0000

Comments Detele

commit d57c6b0d28884afe68992cd0fe77982d7bd782e0

Author: Balamurugan <tb24abi@herts.ac.uk>

Date: Tue Dec 24 22:35:48 2024 +0000

comment tilak

commit 1ff56f59c1e104f4957ba593d6aab951607c50eb

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Tue Dec 24 22:19:00 2024 +0000

Summary of Dataset

commit 9860bd91c5cccafbead3ba336b93fd43d8c34c47

Author: Parasuraman <vp24aau@herts.ac.uk>

Date: Tue Dec 24 21:53:42 2024 +0000

Histogram Update - Vishnu

commit 689b063944ccf53cfd622b791121ab71ff644298

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Thu Nov 28 23:06:13 2024 +0000

New Scatterplot after changes

commit 5a2948865bb2f5856dd1d4dd2ac9228fcfd806be

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Thu Nov 28 23:05:54 2024 +0000

SMA function Changes

commit 1d065d937d6640d8808fa9a95ccd20313794a928

Author: Vishnuvardhan Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Nov 28 22:19:56 2024 +0000

Changed the code for SMA function, got success.

commit 64225c98efd8c3eb2bdb5003398da1834a41ec80

Author: Vishnuvardhan Parasuraman <vp24aau@herts.ac.uk>

Date: Thu Nov 28 22:12:22 2024 +0000

Trying SMA function.

commit cdb5dd432d48f11136cc0456239053e71a2a20c1

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Sun Nov 24 23:35:55 2024 +0000

Graphs (Data Visualization) - Abinaya

commit 2ef4013da08d1f973bece301b01528efee805d1d

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Sun Nov 24 20:08:15 2024 +0000

Correlation Test - Abinaya

commit 0fbf6d21aea8eedbf0cd770ac366ebab68070eb4

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Sun Nov 24 19:35:17 2024 +0000

Scatterplot is fine now - Abi

commit 5bf39f46cff421ec686a06ea24a58040d83fd965

Merge: a5cba68 f25322d

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Sun Nov 24 19:20:45 2024 +0000

Merge branch 'main' of https://github.com/aa24abf/A246\_7COM1079

commit f25322d2a60a922c1d82d54f7fe04bc7a1fadf2b

Author: Mahesh-UH <mr24ady@herts.ac.uk>

Date: Sun Nov 24 15:56:57 2024 +0000

Add files via upload

Histogram code-Mahesh

commit 4c51c219d33dbfb59dcb941d653ce32b43c89d46

Author: Mahesh-UH <mr24ady@herts.ac.uk>

Date: Sun Nov 24 11:16:35 2024 +0000

Add files via upload

commit abe16752312410dca4313bafee4cd632ba6b4ef9

Author: Mahesh-UH <mr24ady@herts.ac.uk>

Date: Sun Nov 24 06:52:39 2024 +0000

Add files via upload

commit a860f83ae1cb017f12ddaa6bbbf514367abf5a6c

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Fri Nov 22 00:27:06 2024 +0000

Add files via upload

commit a5cba68ce04444489b767b32ff84d1f98fa47aee

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Fri Nov 22 00:25:35 2024 +0000

Data Visualization - Histogram & Scatterplot

commit 8b053bf0cbdd34cad37094b93a2651facebf3bf4

Merge: f5eaa7f e0f87af

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Thu Nov 21 22:54:12 2024 +0000

Merge branch 'main' of https://github.com/aa24abf/A246\_7COM1079

commit e0f87afec63050b43f0003836627de1820175502

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Wed Nov 20 10:21:54 2024 +0000

Update Websites.txt

commit 50b655ad9e68bae06084cbefed6024c07f3ef0c8

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Wed Nov 20 10:11:41 2024 +0000

Update Websites.txt

commit f0c28cdf4d04e45b1a3438e937442e02349b4d38

Author: tb24abi <tb24abi@herts.ac.uk>

Date: Mon Nov 11 12:20:53 2024 +0000

RQ PPT - Tilak

commit 95979ec03cfaf5500d63d8c79cb8c8f136a42284

Author: tb24abi <tb24abi@herts.ac.uk>

Date: Mon Nov 11 12:20:18 2024 +0000

Delete reseach\_question\_presentation\_template.pptx

commit 4be2c7a0f71909928d7fcc37d8f22d0c0518f406

Author: tb24abi <tb24abi@herts.ac.uk>

Date: Mon Nov 11 12:19:20 2024 +0000

Add files via upload

commit d3aaadb7cc368909ca18e7f6b650f0dcc67ebebc

Author: tb24abi <tb24abi@herts.ac.uk>

Date: Mon Nov 11 12:17:54 2024 +0000

RQ PPT - Tilak

commit 083c3d7bbe92ffdbd41c6ae13f59eb8d1ca6320c

Author: tb24abi <tb24abi@herts.ac.uk>

Date: Mon Nov 11 12:17:09 2024 +0000

Add files via upload

commit 31fff749c01daf7092ddf9858ccc382c63ce8f57

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Mon Nov 11 00:41:17 2024 +0000

Research Question PTT Changes - Abinaya

commit f5eaa7f815e68f9bcfdc1ca8068a81cc65d8b468

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Mon Nov 11 00:25:23 2024 +0000

SMA Calculations - Abinaya

commit a3fedeb14e047b08836971e1b479d579c4ad7eb9

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Mon Nov 11 00:21:10 2024 +0000

Website Links -Abinaya

commit 6d1535ba4b7ba060988e2216b55eaa881a84c230

Author: john chris <jy23aau@herts.ac.uk>

Date: Mon Nov 11 00:12:30 2024 +0000

Research PPT template - john

commit c5b8439b88cfb21e69d25d53247d32777cb4d7ab

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Sun Nov 10 22:09:07 2024 +0000

Add files via upload

commit 6a0a142e15355164c57bd1d54d03ecd5a4f80dc0

Author: Abinaya Sri Arunkumar <aa24abf@herts.ac.uk>

Date: Tue Nov 5 15:30:34 2024 +0000

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