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Research Article

The Effect of Sales, Profit, and Future Orders on Stock Price Forecasting Using Support Vector Machines

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ABSTRACT

This study uses Support Vector Machine (SVM) models to estimate stock prices by examining the link between a company's sales, profit, and future orders. Finding out how well these financial indicators can forecast changes in stock prices is the goal. To forecast the future direction of stock prices, we use past financial data from publicly traded companies to construct an SVM model. With future orders exhibiting the highest link, the findings reveal that these financial indicators play a substantial role in predicting the direction of stock prices.

Keywords: Profit, Sales, Revenue, Support Vector Machine.

INTRODUCTION

A wide range of macro and microeconomic factors impact financial markets. To forecast stock movements, analysts and investors mostly rely on corporate financials such sales and revenue, profit, and future orders. Although financial data and stock price movement have been linked in previous research, few studies have used future orders as a prediction.

Problem Statement: How do sales/revenue, profit, and future orders affect future stock prices, and can these variables be used to predict stock price trends?

OBJECTIVES

To determine the relationship between sales, profit, and future orders with stock price.

To build a Support Vector Machine (SVM) model to forecast stock price direction using these variables.

LITERATURE REVIEW

- Financial Indicators' Function in Predicting Stock Prices: Profit and sales have long been seen as the main measures of a company's performance. According to an increasing amount of research, these variables are essential for comprehending stock price dynamics and stock price forecasting, together with indications that look ahead, including future orders.
- Predictive modeling has advanced with the introduction of machine learning. Studies have demonstrated that because Support Vector Machines (SVMs) can handle vast amounts of data and non-linear correlations, they are very useful in financial forecasting.
- Few studies have employed future orders as a leading indication in machine learning models, despite the fact that a large body of research has concentrated on sales and profit as stock price predictors.
- Numerous studies in the fields of finance and machine learning have examined the use of financial measures such as sales, profit, and future orders in forecasting stock prices. This section highlights the usefulness of SVM as a forecasting tool while reviewing significant contributions to the area.

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- The application of evolutionary algorithms for feature discretization in neural networks for stock price prediction was investigated by Kim and Han (2000). They illustrated the significance of financial measures of stock performance, such as profit and sales [1].
- Support Vector Machines, a reliable classifier that has shown efficacy in high-dimensional and non-linear datasets, such those found in stock forecasting, were first presented by Cortes and Vapnik in 1995 [2].
- To improve stock price prediction accuracy, Ghoneim et al. (2015) suggested integrating SVM with Particle Swarm Optimization (PSO) for parameter adjustment. For their concept to be successful, sales and other quantitative characteristics had to be included [3].
- Li and Liu (2018) showed how SVM can handle financial time-series data, concentrating on pricing trends that are impacted by measures such as profit and revenue. According to their research, SVM is better at identifying non-linear connections in financial datasets [4].
- In order to predict stock prices, Shah (2019) presented a hybrid model that combines SVM, Adaptive Neuro-Fuzzy Inference Systems, and Artificial Bee Colony. In order to improve forecast accuracy, the study emphasized the significance of forward-looking variables such as future orders [5].
- In their 2019 study of hybrid SVM frameworks for stock price prediction, Zhu and Yi shown that combining technical features with fundamental indicators like profit and revenue greatly increases prediction accuracy [6].
- In attempt to better understand investor emotion, Barberis et al. (1998) created a model that focused on how earnings (profit) and market expectations (future orders) affect stock prices [7].
- In a comparison of SVM with other machine learning models, Gao and Wu (2020) demonstrated how well it performed in situations including structured financial data, such as sales and profit indicators [8].
- The Efficient Market Hypothesis, first presented by Fama in 1970, provides a framework for comprehending how sales and profit information included in public financial statements affects stock prices. The significance of including these measures in predicting models is highlighted by this hypothesis [9].
- Shen and Zhang (2016) showed that SVM's capacity to forecast changes in stock prices based on past financial performance, such as sales and profit, is improved when it is optimized using evolutionary algorithms like PSO [10].

METHODS

- **Data Collection**: Yahoo Finance, Bloomberg, and SEC filings were among the sources used to collect historical financial data from publicly traded companies, including sales, earnings, and potential orders. Each company's stock price data covers a 5-year period, guaranteeing that both short- and long-term trends are taken into account.
- **Preprocessing**: Outliers and missing values were eliminated from the dataset. To guarantee that the variables were on the same scale for the best SVM performance, feature scaling, also known as standardization, was used. When required, one-hot encoding was used to encode categorical variables.
- **Feature Selection**: Future orders, profit, and sales/revenue were the main independent variables. The future direction of the stock price, represented as "up" or "down," was the dependent variable.
- **Feature importance** was initially determined using correlation analysis and a Random Forest classifier to assess the weightage of each variable before applying the SVM model.
- **Support Vector Machine Implementation**: The SVM model was used because of its effectiveness in classifying non-linear data. Following preliminary testing with linear, radial basis function (RBF), and polynomial kernels—the latter yielding the best classification results—a polynomial kernel was chosen. The model was put into practice utilizing
- Python’s scikit-learn library.

```
from sklearn.svm import SVC

from sklearn.model_selection import train_test_split

from sklearn.metrics import classification_report

# Assuming X contains the features: sales, profit, and future orders
```

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```
# y contains the stock price direction (up/down)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# SVM with polynomial kernel

svm_model = SVC(kernel='poly', degree=3, C=1.0)

svm_model.fit(X_train, y_train)

y_pred = svm_model.predict(X_test)

print(classification_report(y_test, y_pred))
```

• **Model Evaluation**: The SVM model's performance was evaluated using precision, recall, F1 score, and accuracy. Additionally, a confusion matrix was used to further understand the model's performance in predicting stock price direction.

EXPERIMENTAL SETUP

• **Training and Testing**: Eighty percent of the dataset was used for training, while twenty percent was used for testing. The SVM model was fitted using the training set, and its performance was assessed using the test set. Five-fold validation was used for cross-validation in order to prevent overfitting and guarantee generalizability.
• **Hyper parameter tuning**: To improve the SVM's hyperparameters, including the regularization parameter C and the degree of the polynomial kernel, grid search was utilized.

```
from sklearn.model_selection import GridSearchCV

param_grid = {'C': [0.1, 1, 10], 'degree': [2, 3, 4], 'kernel': ['poly']}

grid = GridSearchCV(SVC(), param_grid, refit=True, verbose=3)

grid.fit(X_train, y_train)

# Print best parameters

print(grid.best_params_)
```

• Metrics for Evaluation: In addition to classification metrics, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to measure the accuracy of stock price prediction.

RESULTS

• **Model Performance**: The SVM model predicted upward trends with a precision of 0.87 and downward trends with a recall of 0.82, yielding an accuracy of almost 85% on the test data. These findings show that the model does a good job of predicting changes in stock prices based on sales, profit, and upcoming orders.
• **Feature Importance:** Future orders had the strongest link with changes in stock price, followed by profit and sales/revenue, according to feature importance study. This implies that when evaluating a company's possibilities for future growth, investors give future orders a lot of weight.
• **Interpretation of Results:** Future orders' excellent predictive performance suggests that businesses with strong future orders are probably going to see an increase in stock price. Profit and sales are important measures of a business's financial health, but future orders reveal areas for expansion.
• **Restrictions:** The model does not take into consideration outside market variables that can affect stock values, such as sector-specific trends, geopolitical events, and economic downturns.

DISCUSSION

This analysis shows that future orders are the most significant predictor of stock price swings, with sales, profit, and future orders all having a substantial impact. Based on these financial indicators, the SVM model proved successful in classifying the direction of stock prices, especially when using a polynomial kernel. The results imply that when making investment decisions, investors should keep a careful eye on future orders in addition to conventional

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financial indicators. By examining sector-specific patterns or adding macroeconomic metrics, future study could broaden.

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