Studying Energy Stocks with Clustering, Association Analysis, and Estimation

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Abstract

The project studies climate change by studying the stocks of green energy and fossil fuel companies. With clustering, association analysis, and estimation, we study the trend of stocks, predict the future trend, and give recommendations on investing in energy stocks. We performed K-Means clustering, ran the apriori algorithm with the transaction list for association analysis, and used linear regression, support vector machines, decision trees, and random forest under blocking time series splitting and normal time series splitting. As a result, it is good to invest in STEM, FSLR, SEDG, ENPH, FREY, ORA, AES, NOVA, and THR. Green energy stocks have higher potential than fossil fuel stocks. In the future, we should focus more on diversification to design portfolios with high returns and low risks by performing more analysis.

1 Introduction

In the Inflation Reduction Act of 2022, 369 billion dollars are allocated to fight climate change by funding and developing green energy [4]. We are interested in studying climate change through the eye of the financial market. As investors become more interested in investing in green energy stocks due to personal or ethical reasons, articles are published to recommend green energy stocks to investors[2, 11, 3, 1]. However, the articles discussing the recommendations of what stocks to invest in only include summaries of the companies, with no data to support their arguments. The articles also only focus on one side of energy companies without comparing and studying the trends of stocks of both green energy companies and fossil fuels companies. So, we studied the stock trends on fossil fuel and green energy together to develop a thorough look at the stocks of energy companies. We also examined the stocks of the companies mentioned in the articles with data mining approaches to study the changes in the stock trend of green energy and fossil fuel and predict future trends. In the end, we provided some recommendations of energy stocks investors can invest in to increase their return.

2 Research Questions

First, how does the stock trend of renewable energy and fossil fuel change, and can future trends be predicted? Second, how can investors increase their return by investing in renewable energy and fossil fuel stocks?

3 Data and Methods

3.1 Data Collection

The list of energy companies is built based on the ones mentioned most frequently from the articles discussing which energy stocks to invest [2, 11, 3, 10, 7, 1]. Our analysis includes thirty-two green energy companies and twenty-one fossil fuel companies. The company's training dataset of stock prices is collected from yahoo with Pandas DataReader [8] and covers the stock price from 01/01/2016 to 2022/11/10. The test dataset is collected to check the prediction model and covers the companies' stock prices from 2022/11/11 to 2022/12/01. For each company, there are six features–High, Low, Open, Close, Volume, Adj Close. Each row represents the values of stocks in one day. We added one feature return by subtracting the open value from the close value first, then divide by the open value. Then we combine all the datasets into one big dataset. Figure 1 shows the stock prices of the highest and lowest price in green energy and fossil fuel.

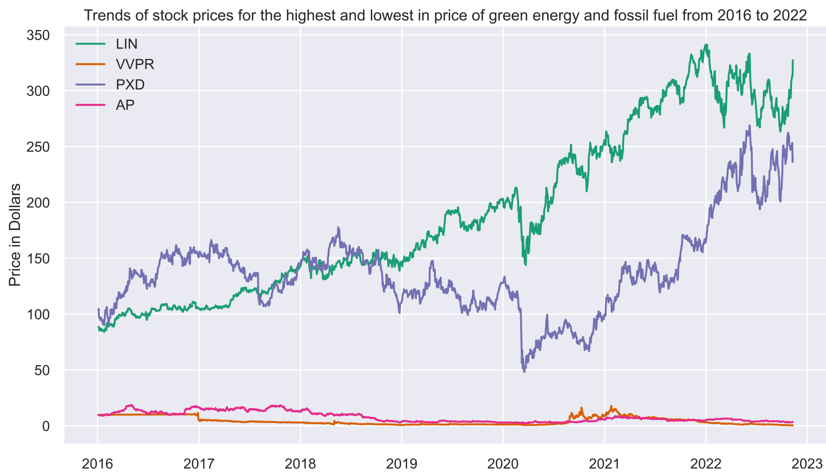

Figure 1: Time in years is shown in the X-axis. Stock price in the dollar is shown in the Y-axis. The adjusted close prices for stocks: LIN, Linde PLC, the highest stock price in green energy stocks; VVPR, VivoPower International PLC, the lowest stock price in green energy stocks; PXD, Pioneer Natural Resources Co., the highest stock price in fossil fuel stocks; and AP, Ampco-Pittsburgh Corporation, the lowest stock price in fossil fuel stocks, are plotted from 2016 to 2022 in the figure. This plot compares the stock prices of green energy and fossil fuel stocks and the stock price between the highest and lowest stocks in both sectors.

3.2 Quality Assurance

The duplicates are removed from the dataset. As some new companies have not gone on the stock market in previous years, we removed the missing values instead of interpolating them.

3.3 Preprocessing

To answer the questions, we proposed three approaches: estimation, clustering, and association analysis. Estimation and association analysis are performed based on the result of clustering. For each approach, the data are preprocessed differently. For clustering, we calculated the 5-day return, 20-day return, 60-day return, and 200-day return of each stock, scaled these returns, and used these data for clustering. For association analysis, we focus on the return feature. The datasets are created based on the cluster results, then re-scaled. Then the dataset is encoded. For estimation, we performed feature engineering for the Dates, which is the index of our data, and we only used the features transformed from dates and close prices.

3.4 Modeling

Clustering We first ran Distortion Score Elbow to find the optimal number of clusters: 4. After comparing different clustering models, including KMeans, MiniBatchKMeans, and Hierarchial clustering with different distance metrics using visualizations such as PCA and Silhoutte Values Plot, we pick KMeans as our final model. And With scaled data and optimal 4 clusters, we performed K-Means Clustering[5].
Association For each cluster, we calculated the averages for every 1-day, 5-day, and 15-day intervals. Then transaction lists are created by seeing what companies have positive gains in the intervals. We then run the apriori and fpgrowth algorithm [6] with the transaction list we created for association analysis.
Estimation We used linear regression, support vector machines, decision trees, and random forest[5] under blocking time series splitting and normal time series splitting.

4 Results

4.1 Clustering

PCA and Silhoutte Values Plots for MiniBatchKMeans

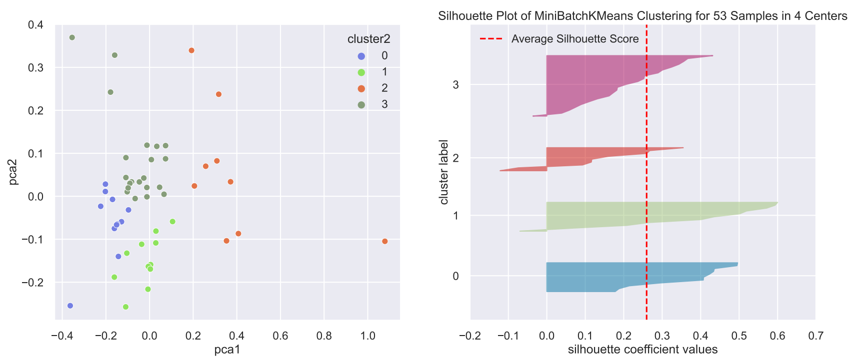

Figure 2: The left figure shows the 2-dimensional PCA plots of the points that differ by clusters as shown in different colors. The point in the lower left corner (in cluster 0) of MiniBatchKMeans may be better if it is clustered into cluster 1 because it is closer to that cluster, or it can even be one cluster itself. Also, the point on the very right in cluster 2 in the MiniBatchKMeans plot is clearly an outlier and should be in a single cluster itself. The right figure shows the Silhouette Coefficient Values on the X-axis and the 4 clusters' distribution of the values with the red dashed line as the mean of Silhouette Scores. There aren't many negative values, which means not too many points are clustered incorrectly, but it performs slightly worse than KMeans.

PCA and Silhoutte Values Plots for KMeans

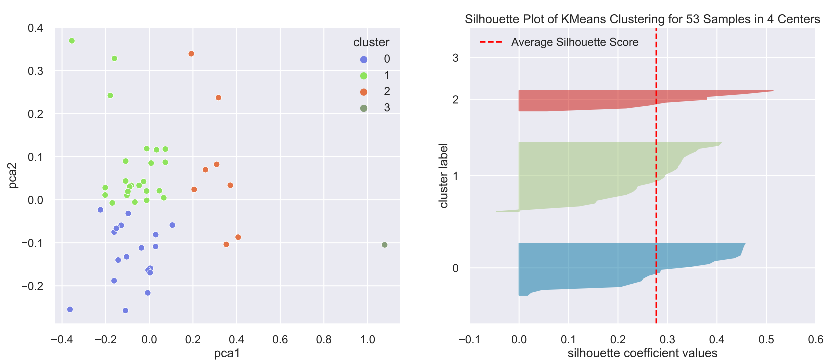

Figure 3: The PCA plot clusters the points in a relatively reasonable way, but some points in cluster 1 and cluster 2 are a little bit far away from the center. We may consider adding more clusters, but the current optimal number of clusters is validated for both KMeans and MiniBatchKMeans. Also, the silhouette scores for KMeans are very good because there are almost no negative silhouette coefficient values which means there is little incorrect clustering. So we go with 4 clusters and KMeans clustering.

We decided to use KMeans as the clustering method after first comparing it with MiniBatchKMeans and then with Hierarchical Clustering (which we believe is not appropriate since different distance metrics either give too small clusters and a huge one or hard to divide into four clusters, but the last one using the complete link is good. And that one validates the KMeans results, so we can choose either one, but we finally proceed with KMeans because it directly gives us the clustering results.) We use the 5-day return, 20-day return, 60-day return, and 200-day return of each stock to cluster the stocks into 4 clusters using KMeans; we got some investment strategies.

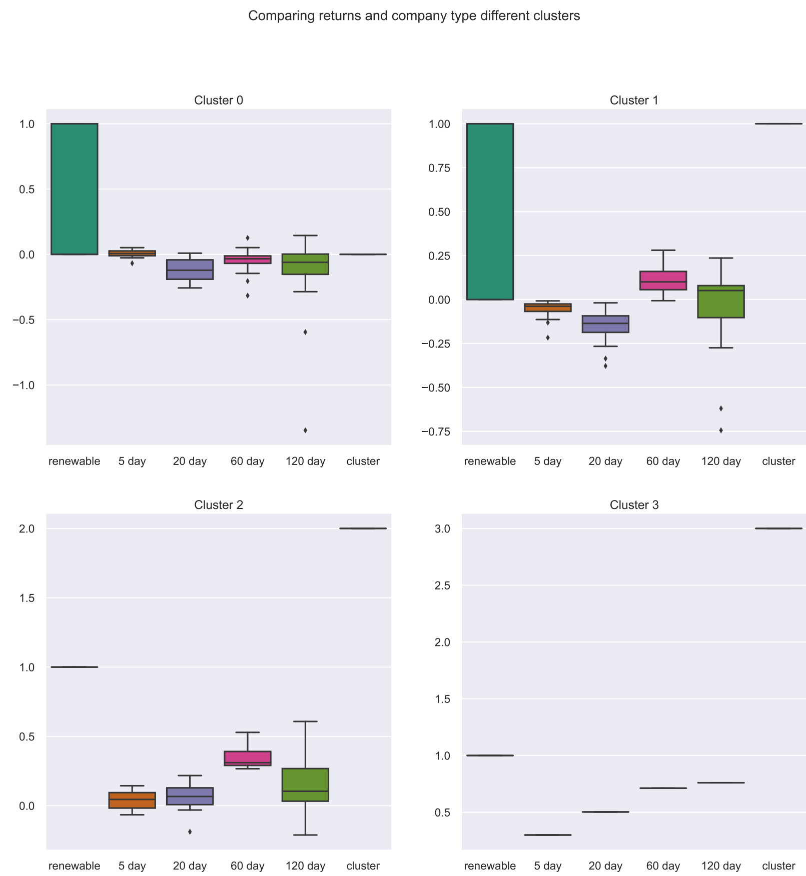

Figure 4: Each subplot shows the distribution of the variables shown on the X-axis within each cluster and the Y-axis as numeric values for the variables. From clusters 0 to 4, there are 19, 25, 8, and 1 observations, respectively. By looking at the boxplots of 5 days, 20 days, 60 days, and 120 days returns, we can get a general trend of the returns changes over time for each cluster by mainly looking at the median(shown in lines at the middle of plots), and here we regard 5-days and 20-days returns as short term returns, and 60-days and 120-days returns as long-term. We can see that cluster 0 has a slightly rising trend in returns from long-term to short-term, and only the most recent 5-days returns are generally positive. Cluster 1 shows a clear decrease from long-term to short-term returns. The long-term returns are generally above 0, especially for a 60-days one, but the short-term returns are generally below 0. Cluster 1 shows a clear decrease from long-term to short-term returns. The long-term returns are generally above 0, especially for a 60-days one, but the short-term returns are generally below 0. Cluster 2 also shows a decrease in long-term to short-term returns, and the returns of four time periods are generally positive. Cluster 3 is the outlier we discovered, and it has the highest overall returns among all, which we will discuss later.

From observations of different clusters' returns distributions, we concluded that the stocks in cluster 0—including FSLR, FREY, LIN, GM, ETN, ORA, AES, OXY, TTE, CVX, KMI, PXD, OVV, KBR, CIVI, KNTK, ROCC, NRG, USAC—have the best potential in the short term. It is because compared to the other three clusters, only the returns of stocks in cluster 0 show an increasing trend from long-term to short-term. And we believe this is a good signal of a potential group of stocks because it means the short-term momentum is good, and there is a higher probability the returns will rise in the future. Also, only the most recent 5-days returns are generally positive means that the stocks are more likely to be growth stocks because their prices have not risen too much and are not likely to be overpriced by the stock market, thus also giving higher potential to rise in the future. And stocks in cluster 2—including TSLA, PLUG, JHX, MNTK, AMPS, AZRE, WAVE, and ELLO—are suitable to hold in the short term because their returns in both short term and long term are above 0. Even though the short-term momentum is worse compared to long term, indicating the returns may keep dropping, it is still likely that the returns will remain positive for a while. The remaining cluster 1 should be sold because the stocks in cluster 1 have worse short-term momentum compared to long-term and the current short-term returns are generally negative, which means it is likely the stocks will keep giving negative returns in the future. The one stock left in cluster 3, VVPR, may be held in the short term, but definitely not in the long term because it has a huge 200-day return, and the return keeps dropping as we look at shorter-term returns. It is an outlier, and through reading the news, we figured out that its stock price experienced a super sharp increase starting Aug.2020 and gradually dropped from Jan.2021. The likely reason why it increased so much is that from the financial disclosure in Aug.2020, which is the starting year of COVID-19 in Australia, the annual group revenues of 48.7 million dollars increased by 12 percent one year even though with the lock-downs due to COVID-19. Hence the public's positive sentiment increases suddenly due to the news. But after some time, the sentiment goes to plain, and the price gradually goes back to the level before the news[9]. We are considering holding VVPR in the short term but selling in the long term because it seems like VVPR will have positive returns in the short run because its returns in short-term are still way above 0, but we would like to sell it in the long term as its potential is not good with the continuous decrease in returns from long-term to short-term.

Boxplots within cluster 0 grouped by renewable/fossil fuel stocks

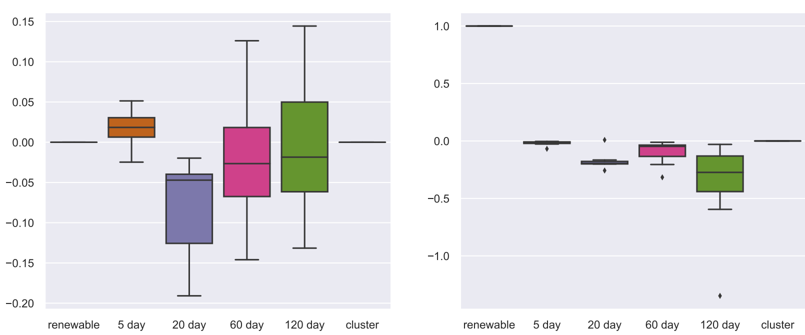

Figure 5: Within cluster 0, the fossil fuels stocks (renewable=0) have a continuous decrease in returns from 120 days to 20 days and a sudden increase in 5-day returns. While renewable energy stocks have the general trend of increasing from long-term returns to short-term returns.

It is also interesting to notice that renewable stocks within cluster 0 (we would like to buy in) have better potential than fossil fuels stocks because their increase in returns is steady and significant, while we believe the sharp increase for fossil fuels stocks' 5-days returns is due to fluctuation in short-term prices as there is no news related recently. In cluster 2 (and in cluster 3 probably, which are those we would like to hold) are mainly from renewable companies, except for only one stock THR in cluster 0. In the future, at least in the short term, the trend of renewable energy stocks will be better than that of fossil fuel stocks.

4.2 Association Analysis

For days intervals: 1-day, 5-day, and 15-day, we run the association analysis for three cluster to discover more about the relationships between stocks with both apriori and fpgrwoth methods. As cluster 3 only has one company, we didn't perform the association analysis on cluster 3. Both apriori and fpgrwoth methods give us the same result. Some same association rules are confirmed in the different day intervals. We plotted

the green energy companies and fossil fuel companies mentioned in the association rules.
For cluster 0, we have 19 stocks. We selected the rule with a confidence level higher than 0.8.

1. OXY-Occidental Petroleum Corp., PXD-Pioneer Natural Resources Co., and TEE-TotalEnergies SE are associated with OVV-Ovintiv Inc.. OXY and ROCC-Ranger Oil Corporation are also associated with PXD. Based on the left subplot in Figure 6, they form strong positive relationships, where PXD has a significant value in price over others.

2. USAC-USA Compression Partners, LP and KBR-KBR, Inc. are associated with each other. Based on the left subplot in Figure 6, USAC and KBR form a strong positive relationship, with KBR having a higher price value.

For cluster 1, we have 25 stocks. We selected the rules with a confidence level higher than 0.8.

1. SEDG-SOLAREDGE TECHNOLOGIES and ENPH-Enphase Energy Inc. are associated with each other. Based on the middle subplot in Figure 6, we observed a strong positive relationship between the two.

2. EFAX-SPDR MSCI EAFE Fossil Fuel Reserves Free ETF, MDXF-MSCI EAFE ETF iShares ESG Advanced, SPYX-SPDR SP 500 Fossil Fuel Free ETF, NEE-NEXTERA ENERGY, and AQN-Algonquin Power Utilities Corp. are associated. Based on the middle subplot in Figure 6, we observed a strong positive relationship between them, with SPYX having the highest value and AQN having the lowest value.

For cluster 2, we have 8 stocks. Due to the limited amount of stocks, we selected the rules with a confidence level higher than 0.7.

1. TSLA-Tesla Inc. and PLUG-Plug Power Inc. are associated with each other. Based on the right subplot in Figure 6, we observed a strong positive relationship between the two, with TSLA having a significantly higher value in price.

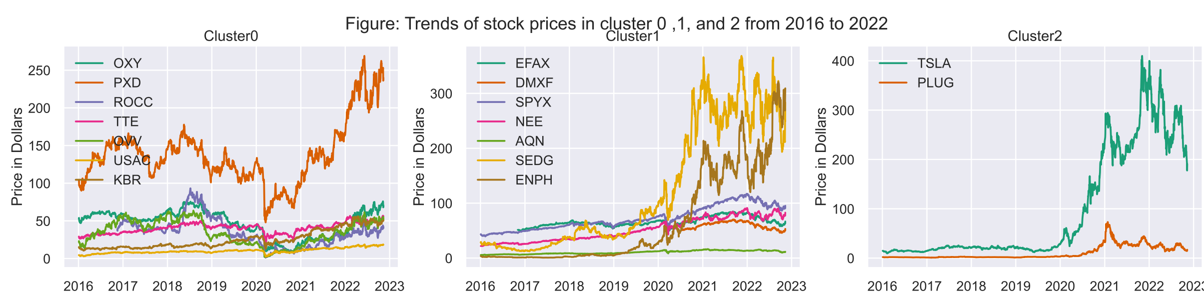

Figure 6: This graph shows the trend of stock prices for association rules mentioned above for each cluster from 2016 to 2022 in the figure. Cluster 0 is on the left. Cluster 1 is in the middle. Cluster 2 is on the right. For each subplot, the time in years is shown on the X-axis. Stock price in the dollar is shown on the Y-axis. In cluster 0, the adjusted close prices of stocks: OXY, PXD, ROCC, TTE, OVV, USAC, and KBR are plotted. In cluster 1, the adjusted close prices of stocks: EFAX, DMXF, SPYX, NEE, AQN, SEDG, and ENPH are plotted. In cluster 2, the adjusted close price of stocks TSLA and PLUG are plotted.

4.3 Estimation

In the estimation task, we are going to predict the future 15-day prices for each stock in cluster 0, which we found in our clustering analysis that they would have a better short-term return compared to stocks in other clusters. During the task, we will only use dates as features and close price as our response variable because we assume that we won't have any additional information such as high price, low price, and so on for future stocks. For the target feature, we use boxplots to visualize the distribution of each company's close price, and we find that different stocks have very different distributions, which confirms our planning to predict the prices individually for each stock.

To prepare the data for estimation, we performed feature engineering for 'Dates,' which is the index of the stock datasets, and we derived numerical features of the year, month, day, and day of the week from dates. Then we run the cross-validation of 4 models, including linear regression, support vector machine, decision tree, and random forest, under the blocked time series split, which takes 20 instances as the fixed input, and the normal time series split, which takes a growing number of instances as the input, for each stock in order to choose the best-performed combination of model and split approach. During the cross-validation, we used mean absolute error as our performance metrics, chose the combo of model and approach with the smallest test MAE[5] for each stock and made a visualization of the naive training MAE, training MAE, and test MAE to check underfitting and overfitting. From Figure 7, the list of the best combinations of

List of Best Combination of Model and Splitting

Stock Name	Best Model	Best Split
FSLR	Support Vector Machines	Blocked Time Series Split
FREY	Support Vector Machines	Blocked Time Series Split
LIN	Support Vector Machines	Blocked Time Series Split
GM	Support Vector Machines	Blocked Time Series Split
ETN	Random Forest	Time Series Split
ORA	Support Vector Machines	Blocked Time Series Split
AES	Decision Tree	Blocked Time Series Split
OXY	Support Vector Machines	Blocked Time Series Split
TTE	Support Vector Machines	Blocked Time Series Split
CVX	Decision Tree	Blocked Time Series Split
KMI	Support Vector Machines	Blocked Time Series Split
PXD	Decision Tree	Blocked Time Series Split
OVV	Support Vector Machines	Blocked Time Series Split
KBR	Decision Tree	Blocked Time Series Split
CIVI	Support Vector Machines	Blocked Time Series Split
KNTK	Decision Tree	Blocked Time Series Split
ROCC	Support Vector Machines	Blocked Time Series Split
NRG	Support Vector Machines	Blocked Time Series Split
USAC	Support Vector Machines	Blocked Time Series Split

Figure 7: The list of the combination of models among linear regression, support vector machine, decision tree, random forest, and approaches between blocked time series split and normal time series split, which gives the smallest test MAEs for each of 19 stocks we found in cluster 0.

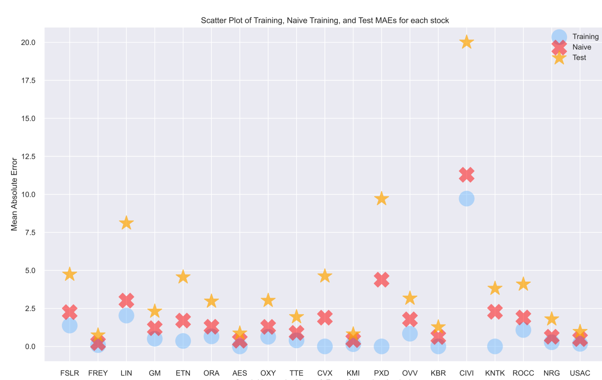

Figure 8: Mean absolute error achieved by the combo of model and approach with smallest test MAEs for each stock, plotted for training MAEs in blue, for the test set in orange star. The red 'X' shows baseline performance (naive training MAEs).

model and split for each stock, we can see that most stocks have the best performances with the SVM model under blocked time series split; 5 out of 19 companies have the best performances with the Decision Tree model under blocked time series split, only one stock preferred the random forest model under normal time series split, and none of them went with the linear regression which is considered too simple to catch the

fluctuations of stock prices.
From Figure 8, we can see that all the models have lower training MAEs than naive training MAEs, so we are fine with the problem of underfitting. However, overfitting is the problem that we are concerned about, especially for the models of stocks LIN, PXD, and CIVI, because their models show a much higher value of their test MAEs than training MAEs. This is probably because we only predict the stock prices using the barely-informational feature 'Dates,' overfitting is very common under this scenario, and we can always try to solve the problem by decreasing the complexity of the models. However, in consideration of our limited computational expenses, we kept the overfitted model.
Next, with the best-performed models and approaches, we created an independent test dataset to predict prices from 2022-11-11 to 2022-12-02, and we collected the datasets of actual close prices for these stocks to evaluate our prediction. Figure 9 shows four different test metrics for our prediction. For all the stocks we

Performance of Prediction on Independent Test Data

	Test MAE	Max Error	Test R2	Trend Accuracy(%)
FSLR	26.05	36.67	-17.18	60.0
FREY	1.43	2.56	-1.84	53.33
LIN	39.48	48.9	-87.96	46.67
GM	1.57	2.59	-4.18	53.33
ETN	4.04	10.85	-9.64	60.0
ORA	3.83	9.21	-0.13	46.67
AES	0.65	2.53	-4.45	6.67
OXY	1.88	2.97	-0.11	33.33
TTE	4.9	7.48	-23.51	46.67
CVX	3.08	7.06	-1.08	33.33
KMI	0.63	1.2	-6.8	46.67
PXD	14.2	22.5	-2.2	33.33
OVV	4.27	7.0	-9.34	66.67
KBR	1.41	4.19	-0.59	6.67
CIVI	1.75	2.26	-0.44	46.67
KNTK	1.75	1.45	-4.55	40.0
ROCC	2.34	3.26	-12.22	40.0
NRG	1.49	1.38	-1.37	40.0
USAC	0.2	0.56	-1.87	46.67

Figure 9: Performance metrics of the best models we chose on the independently-generated test dataset for each stock. Rows are stock names. Columns are Metric Techniques.

chose, the test MAEs varies from 0.2 to 39.48, and the maximum error of our prediction varies from \$0.56 to \$48.9, but both metrics are based on different scales of the prices for different stocks, so we can't compare them with each other. Thus, we calculated the R-squares and accuracy of the trend's consistency between the actual price and our prediction, and R-squares[5] are negative, ranging from -87.96 to -0.11, which is possible because we evaluated models separately on test data, and this indicates that the models are not very predictive. The accuracy of the trend's consistency varies from 6.67% to 66.67%, meaning that our predictions catch 6.67% to 66.67% of the actual trends. We are not very satisfied with our on-time prediction results, and several factors we didn't include, such as the holiday of Thanksgiving, might be responsible for the unsatisfying results, so we should try more independent datasets of varying time periods. Figure 10 further gives a visualized demonstration of how many real-time trends our prediction missed, and we found that our predictions are always smoother than the actual fluctuations of prices (eg. FSLR), and they could catch some delayed trends (eg. KNTK) but always wrongly extended trends (eg. OXY successfully predicted the first-day increase of the price but extended the increasing trend to the following days while the actual price dropped during those days, so it wrongly extended the increasing trend and predicted a dropping trend with delay). Therefore, we concluded that our prediction generally failed to predict and catch the trend of future prices in the short term (15 days), and we couldn't rely on our predictions for the future price to make any decision for buying in or selling out, but our predictions do provide us with some insights to the possible future fluctuations.

Figure 10: Nineteen subplots of the prediction and actual prices of the nineteen stocks in cluster 0 from 2022-11-11 to 2022-12-02. Each subplot is for each stock. Time in Dates is shown on the X-axis. Stock price in the dollar is shown on the Y-axis. In each subplot, the red line indicates the actual price trend, and the green line represents the predicted trend using the model we picked above. The red-shaded area is when our real-time predicted trends of increasing or decreasing are consistent with the actual trends, and the green-shaded area is when the prediction misses the trend.

4.4 Summarize

Generally speaking, we first found one cluster of stocks—including FSLR, FREY, LIN, GM, ETN, ORA, AES, OXY, TTE, CVX, KMI, PXD, OVV, KBR, CIVI, KNTK, ROCC, NRG, USAC—to buy due to their excellent short-term momentum. One cluster of stocks—including TSLA, PLUG, JHX, MNTK, AMPS, AZRE, WAVE, and ELLO—to hold as they tend to still have small but positive returns, at least in the short term. One stock VVPR to hold in the short term but sell in the long term. The remaining stocks are to sell due to bad short-term momentum and returns. Also, we found that stocks in the renewable energy sector generally have better potential than those in the fossil fuel sector.

Association Analysis gives us association rules with a confidence level larger than 0.7 where stocks have high positive co-movement with each other in each cluster. We should keep an eye on these buckets by investigating their short-term and long-term returns, similar to what we did in clustering. If some bucket shows good short-term momentum, we may buy a large quantity because the high positive co-movement based on the association rules will likely give very high returns. However, we should avoid holding or investing in stocks in the same bucket together in the long term because it will reduce our portfolio's diversification, thus leading to higher risks due to high co-movement.

The estimation task picking the best combination of model and splitting rules failed to predict the real price trends for the nineteen stocks in cluster 0 we found in the clustering analysis. Our current prediction models could only catch some delayed trends. In that situation, we won't be able to make valuable decisions to buy in or sell out to increase our return based on our prediction.

5 Conclusion

According to the suggestions above, we may buy, hold, or sell stocks in our pool. Also, we may focus more on renewable energy stocks to seek more stocks with good potential in the future. However, our analysis needs to be more comprehensive, and the biggest problem is lacking diversification. Both clustering and association analysis give stocks similar to each other in returns. Still, in reality, we should invest in stocks with high diversification so that our portfolio can have lower risks. Hence we need to avoid investing in stocks in one cluster or one association rule. Further analysis can be made to investigate how to achieve diversification as long as high future returns. Due to the limited test data and features, our predictions of the prices using various machine learning models and splitting approaches failed to predict the future trend and prices of the nineteen stocks we found in clustering analysis. The task of estimating future stock prices is very hard due to the fluctuating and inconsistent stock markets, so machine-learning algorithms using dates might not be enough, and we can try deep-learning algorithms in the future, and we could also use our models to predict medium-term or long-term performance, but we have to wait longer for the independent dataset to check our results. We also need more informational features for the training of the model, such as the market sentiments, news, and companies' financial statements to predict stock prices in the longer term.

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