**Bull Market or Bear Market: Time Series Price Prediction for Q1 2024:**

**Modeling and Evaluation**

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**Modeling**

***Selecting Modeling Techniques***

The data types used to mine the stock market daily logs are set as numerical float for stock prices, integer for volume, datetime for the timestamps, and a binary data type was created to satisfy the logistic regression model. Additional predictors were created in the process of building the logistic regression model to define the classification forecasting outcome. These new predictors are open\_close as well as high\_low which are used to represent the difference between the two original predictors as a combined item in both cases. The closing stock price was selected as the most representative predictor and so the binary outcome field was created by setting the open\_close field as either 0 or 1 at 0.5 threshold. The binary transformation is used intently to capture the closing stock market price behavior as positive signifying up and negative to down. Then as a last modeling technique for logistic regression, the predictors were differenced and lags 1-3 were taken to select the best performing parameters.

In comparison to other methods, the original time series data types pulled from YF library were subjected to first ordered differencing of the closing price predictor before feeding the data to ARIMA and Exponential Smoothing (AES & SES) methods. The assumption is that the timeseries is at a stationary course to remove the influences of trend and seasonality from the forecasting methods. The goal of these mentioned methods is to predict the closing stock prices in a short time period based off of historical residual data. To run the best price prediction models then, autocorrelation and partial autocorrelation were the key players in determining the highest performing parameters for lag and moving average orders of ARIMA and AES’s seasonal periods.

***Generating a Test Design***

As mentioned earlier, there were two groups of modeling methods used which are ARIMA, AES, & SES to represent price predictors and logistic regression to represent the stock market fluctuation through classification. For the price predictors, the criteria’s to test for goodness of the model and the parameters that was elected are decidedly through mean square error (MSE), mean absolute percentage error (MAPE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) scoring. MSE is used to check the accuracy of the forecasted values from the actual. The lower the MSE value is, then the closer the prediction is to the actual value. MAPE will be used to measure the effectiveness of the price predictor models. It measures the averaged percent error of each entry in the system. AIC and BIC are favored at their lowest to help determine the models that have the lowest number of parameters with the highest log likelihood for an ideally fitted model.

For logistic regression, a confusion matrix was utilized to calculate the performance metrics of the classification method and the parameters applied. Precision, sensitivity, and accuracy scores are the main criteria for the model’s success. Precision provides the ratio of true positive from the total predicted positive. Sensitivity provides the ratio of true positive form the total actual positive. Both of these metrics alongside accuracy are used to conceptualize the highest performing model parameters and ultimately, the outcome of the forecast.

***Building the Models***

SES, AES, ARIMA, and logistic regression forecasting methods were explored throughout the model building process. Among the price predictors, AES method performed the best as well as logistic regression for classification. These two models are high lightened in this section instead. In terms of parameters, AES was set to have multiplicative trend, damped trend, additive seasonal, 3 seasonal periods, and heuristic initiation method. Fit was set to have 0.1 smoothing level and trend. The evaluation metrics had the lowest AIC at 3566 and BIC at 3600 with MSE of 348 and MAPE of 3%. As shown in Figure 1, the AES method was able to forecast the exponential pattern compared to the validation data. Although, the trend and seasonality patterns were not reflected to also match the actual validation results.

**Figure 1**

*AES Forecast Model Plot*

*A graph with orange and blue lines

Description automatically generated*

As for logistic regression, lags 1-3 were applied to the predictors before running the model for performance evaluation.

Logistic Regression model performance reached out to 74% with lag = 3 and differencing = 3. ? where is 74% and that metric is it? Accuracy?

**Parameter settings** include the notes you take on parameters that produce the best results.

* The actual **models** produced.
* **Descriptions of model results**, including performance and data issues that occurred during the execution of the model and exploration of its results.

***Assessing the Model***

For each model under consideration, it is a good idea to make a methodical assessment based on the criteria generated in your test plan. Here is where you may add the generated model to the stream and use evaluation charts or analysis nodes to analyze the effectiveness of the results. You should also consider whether the results make logical sense or whether they are too simplistic for your business goals (for example, a sequence that reveals purchases such as wine > wine > wine).

Once you've made an assessment, rank the models in order based on both objective (model accuracy) and subjective (ease of use or interpretation of results) criteria.

Task List

* Using the data mining tools in IBM® SPSS® Modeler, such as evaluation charts, analysis nodes, or cross-validation charts, evaluate the results of your model.
* Conduct a review of the results based on your understanding of the business problem. Consult data analysts or other experts who may have insight into the relevance of particular results.
* Consider whether a model's results are easily deployable. Does your organization require that results be deployed over the Web or sent back to the data warehouse?
* Analyze the impact of results on your success criteria. Do they meet the goals established during the business understanding phase?
* ADDED. From Module 5 Canvas: In this draft, you should consider a forecast plot with a visual comparison and some discussion of data quality.

If you were able to address the above issues successfully and believe that the current models meet your goals, it's time to move on to a more thorough evaluation of the models and a final deployment. Otherwise, take what you've learned and rerun the models with adjusted parameter settings.

**Evaluation**

***Evaluating the Results***

At this stage, you formalize your assessment of whether or not the project results meet the business success criteria. This step requires a clear understanding of the stated business goals, so be sure to include key decision makers in the project assessment.

Task List

First, you need to document your assessment of whether the data mining results meet the business success criteria. Consider the following questions in your report:

* Are your results stated clearly and in a form that can be easily presented?
* Are there particularly novel or unique findings that should be highlighted?
* Can you rank the models and findings in order of their applicability to the business goals?
* In general, how well do these results answer your organization's business goals?
* What additional questions have your results raised? How might you phrase these questions in business terms?

After you have evaluated the results, compile a list of approved models for inclusion in the final report. This list should include models that satisfy both the data mining and business goals of your organization.

***Review Process***

Effective methodologies usually include time for reflection on the successes and weaknesses of the process just completed. Data mining is no different. Part of CRISP-DM is learning from your experience so that future data mining projects will be more effective.

Task List

First, you should summarize the activities and decisions for each phase, including data preparation steps, model building, etc. Then for each phase, consider the following questions and make suggestions for improvement:

* Did this stage contribute to the value of the final results?
* Are there ways to streamline or improve this particular stage or operation?
* What were the failures or mistakes of this phase? How can they be avoided next time?
* Were there dead ends, such as particular models that proved fruitless? Are there ways to predict such dead ends so that efforts can be directed more productively?
* Were there any surprises (both good and bad) during this phase? In hindsight, is there an obvious way to predict such occurrences?
* Are there alternative decisions or strategies that might have been used in a given phase? Note such alternatives for future data mining projects.

***Determining Next Steps***

By now, you've produced results, evaluated your data mining experiences, and may be wondering, **Where to next?** This phase helps you to answer that question in light of your business goals for data mining. Essentially, you have two choices at this point:

* **Continue to the deployment phase.** The next phase will help you to incorporate the model results into your business process and produce a final report. Even if your data mining efforts were unsuccessful, you should use the deployment phase of CRISP-DM to create a final report for distribution to the project sponsor.
* **Go back and refine or replace your models.** If you find that your results are almost, but not quite, optimal, consider another round of modeling. You can take what you've learned in this phase and use it to refine the models and produce better results.

Your decision at this point involves the accuracy and relevancy of the modeling results. If the results address your data mining and business goals, then you are ready for the deployment phase. Whatever decision you make, be sure to document the evaluation process thoroughly.

**References**

Industrial Business Machines Corporation (2021). *Introduction to CRISP-DM*. Industrial Business Machines Corporation. **https://www.ibm.com/docs/en/spss-modeler/saas**

**?topic=guide-introduction-crisp-dm**