Documentation of Financial Equation Project Spring 23

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1. INTRODUCTION

We explored how the different moneyness values of the Black-Scholes Model (BSM) performed on different ML techniques. Certain assumptions were used in calculating the BSM, such as, the risk-free rate and the volatility, this can cause the BSM to deviate from actual market value. In order to minimize errors with the BSM, we employed various machine learning models to ascertain which ones predicted the price of the options most accurately. We did this by using the Case Study 2: Derivative Pricing code from Machine Learning and Data Science Blueprints for Finance by Hariom Tatsat, Sahil Puri, Brad Lookabaugh.[1]

2. METHODOLOGY & RESULTS

We modified the code from Case Study 2: Derivative Pricing code from Machine Learning and Data Science Blueprints for Finance by Hariom Tatsat, Sahil Puri, Brad Lookabaugh.

We first explored in-the-money vs out-of-the-money. We split the dataset to $M > 1$ and $M < 1$. In this particular code, M was randomly generated. We used SelectKBest from the sklearn package to determine the features affected the results more. We noticed that when $M > 1$: time was the most important followed by volatility and moneyness. And when $M < 1$: moneyness was the most important followed by volatility and time

We then split the randomly generated data into eight different moneyness categories: $'M < 0.4', '0.4 <= M < 0.6', '0.6 <= M < 0.8', '0.8 <= M < 1', '1 <= M < 1.2', '1.2 <= M < 1.4', '1.4 <= M < 1.6', \& 'M >= 1.6'$. We observed the number of observations in each moneyness category and created a simple bar chart which showed a normal distribution. Additionally, we recorded the mean squared error for the test results and displayed the results with a heatmap Figures 1. Then, we also took the log of the results because the normal results were very similar for some models Figure 2.

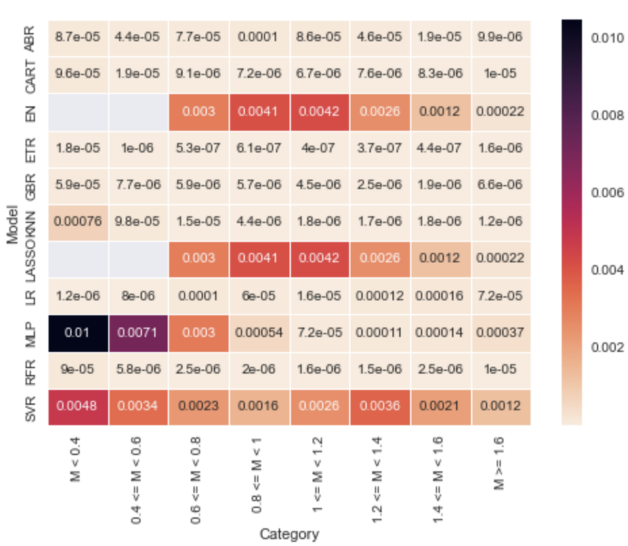

Figure 1. Testing Error

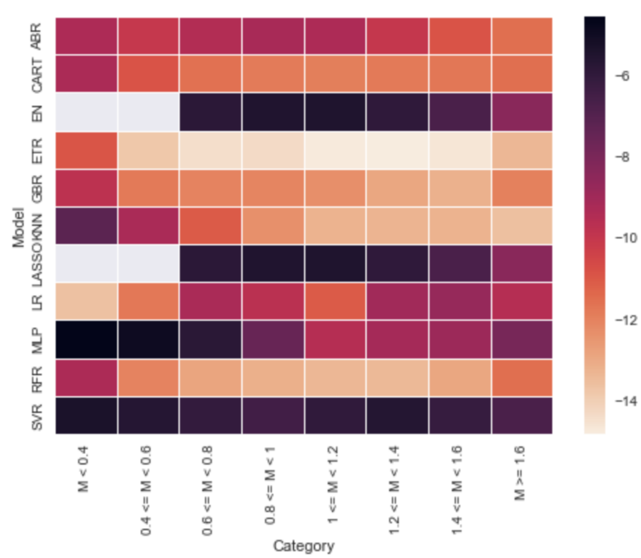

Figure 2. Log of Testing Error

From the heatmaps, Figures 1 & 2, we can see that the non-linear models performed well, although MLP (the artificial neural network) performed poorly. We also saw linear models performed well, in particular Linear Regression performed well across all moneyness categories. This was shocking. LASSO was not as great as expected. DecisionTreeRegressor (CART) and GradientBoostingRegressor(GBR) performed very well.

Since there were not many values for LASSO and EN we increased the sample size by about 100%, for the first three moneyness categories, and created new heatmaps, Figures 3 & 4. After observing the heatmaps Figures 3 & 4, MLP was improved and the tree based models had the same results.

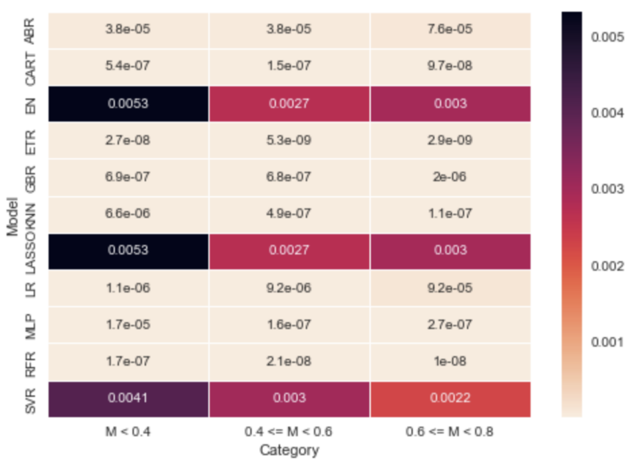

Figure 3. Testing Error for First 3 Moneyness Values

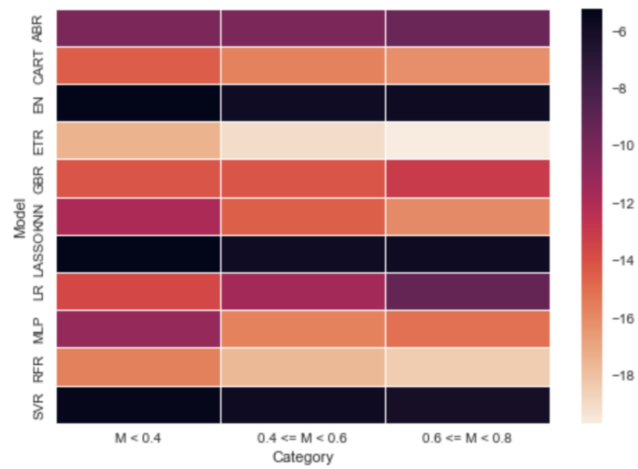

Figure 4. Log of Testing Error for First 3 Moneyness Values

We then made sure that there were the same number of observations (8137) in each moneyness category for the first three moneyness values, Figures 5 & 6. The results were similar Figures 3 & 4.

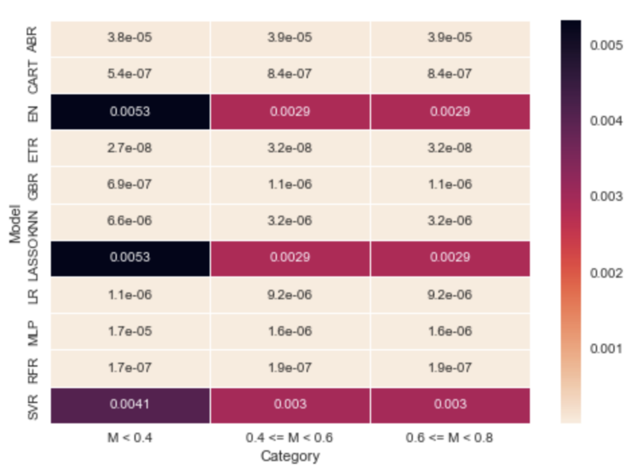

Figure 5. Testing Error for First 3 Moneyness Values (n = 8137)

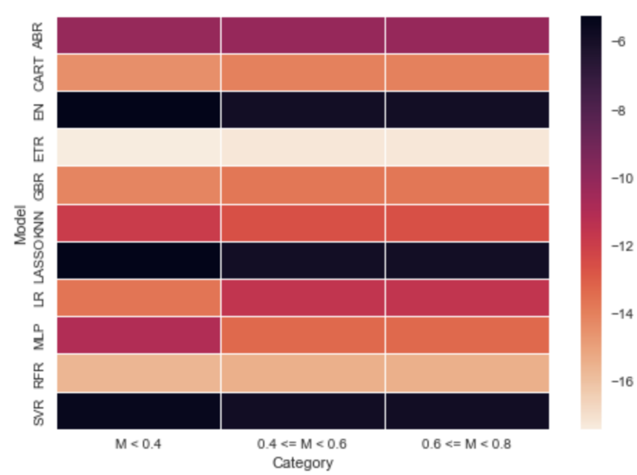

Figure 6. Log of Testing Error for First 3 Moneyness Values (n = 8137)

Then, we increased the sample size across all moneyness categories before ensuring that there was the same number of samples in each for Figures 7 & 8. The results from that were similar to Figures 1 & 2. As can be seen in Figures 7 & 8.Tree based models performed well, MLP improved more with the same number of samples.

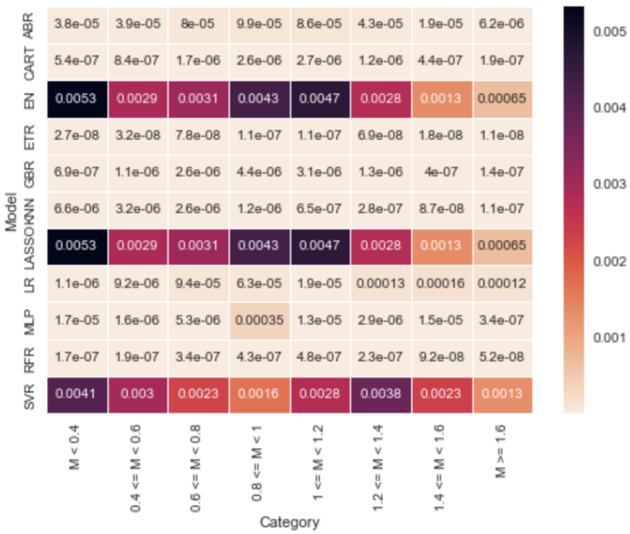

Figure 7. Testing Error (n = 8137)

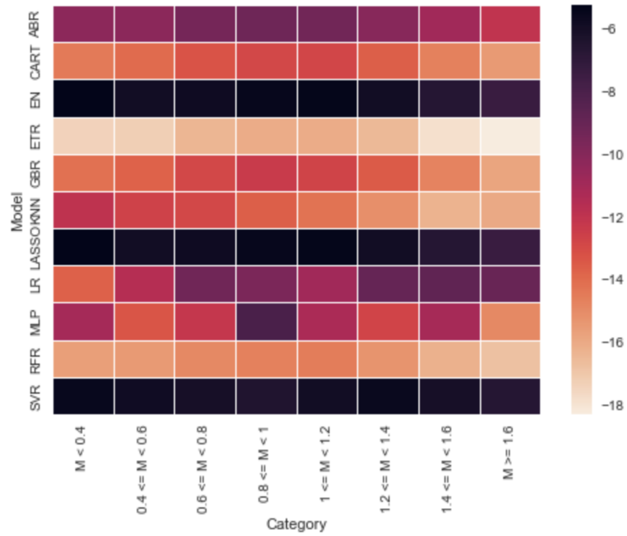

Figure 8. Log of Log of Testing Error (n = 8137)

3. CONCLUSION & FUTURE WORK

Overall, the results were as expected except for the linear regression which could be explained by the construction of the sample size. Moving forward, we plan to augment our sample size to enable a more robust analysis and potentially improve the performance of certain models such as MLP.

Furthermore, we intend to explore other models, including those based on local volatility and stochastic volatility. This would provide a broader perspective on derivative pricing and potentially yield more nuanced insights.

Finally, as we refine our models and methodologies, we will apply more advanced techniques, allowing us to gain a more granular understanding and enhance the interpretability of our models.

REFERENCES

[1] Tatsat, H., Puri, S., and Lookabaugh, B., [*Machine Learning and Data Science Blueprints for Finance*], O'Reilly (2020).