Efficient Calibration of Implied Volatility

MSc Research Project

FinTech

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Efficient Calibration of Implied Volatility

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Abstract: This paper aims to investigate a tool for option traders using Dumas, Fleming and Whaley formula with different models. This tool can create a dashboard for implied volatility so that helps them to observe the change of implied volatility in the option market. Thus, the traders can have a better view about what is happening in the market and thus help them to give better decisions for their investments. Besides, the dashboard can also a guideline about the risks so that risk managers can use it as a tool for risks management. This paper also figures out that binominal function that commonly used to calculate American option nowadays takes too much time to run and not suitable for application development when we need to work with large datasets. In this paper, it takes more than 40 hours of calculation for American option and this needs to improve in further studies.

1 Introduction:

There are three main instruments in the financial market including derivatives, equity and debts. This paper will focus on derivatives products, especially options as it helps investors to hedge risks or used for speculation purposes. The Black-Scholes model, also known as the Black-Scholes-Merton model, is a mathematical formula used to calculate the theoretical price of European-style options. It was developed by economists Fischer Black and Myron Scholes in collaboration with mathematician Robert Merton in 1973. The model is widely regarded as a groundbreaking contribution to the field of financial economics and has become a fundamental tool in option pricing and risk management. The Black-Scholes model provides a way to estimate the fair market value of an option based on various factors, including the underlying asset's price, the option's strike price, the time remaining until the option's expiration, the risk-free interest rate, and the asset's volatility. The model assumes that financial markets are efficient, and that the underlying asset's price follows a geometric Brownian motion, which means it has a continuous and random price movement over time.

The Black-Scholes model has had a profound impact on modern finance by providing a theoretical framework for option pricing and risk management. It has paved the way for further advancements in derivatives pricing and the development of sophisticated financial models used in various aspects of investment and risk analysis. However, it's important to note that the Black-Scholes model has some limitations and assumptions that may not always perfectly reflect real-world market conditions. As a result, practitioners often use variations and extensions of the model to better suit specific situations.

Moreover, the Black-Scholes model is an essential tool for volatility trading, allowing traders to make informed decisions based on implied volatility data. Implied volatility reflects market expectations of future price fluctuations, and traders use this information to identify potential opportunities in volatility trading. Furthermore, the model facilitates the design and evaluation of various option strategies, enabling traders to assess risk-reward profiles and potential outcomes for different strategies before executing trades. This feature enhances decision-making and aids in creating optimized option trading strategies. Beyond traditional financial options, the Black-Scholes model has found relevance in real options analysis, aiding businesses in making optimal investment decisions amid uncertainty. This analysis considers the value of strategic decisions and investments with flexibility to adapt to changing market conditions. Despite its assumptions and limitations, the Black-Scholes model's versatility and widespread adoption make it an indispensable tool in contemporary finance and investment decision-making. Variations and extensions of the model have been developed to address specific market conditions and complexities.

The author will try to create a tool that can support option trader in observing implied volatility. In order to achieve the goals mentioned above, the rest of this paper will be presented in four parts. The first part is related to literature review. In this part, I will go through some past research that has the same topic as my paper and then summary some main points of it. This benefit me to gain deeper knowledge about implied volatility and its currently application in nowadays financial market. The next part is methodology, and, in this part, I will present about my dataset and the process that I applied in my paper. Then the third part is design specification where I will show the way I assess the models. Next, I will talk a little bit about the solution and application for the tool I develop in this paper. The fifth part is the evaluation part, where I will present the results of my research and analyze it. In the last part, based on the results analysis in above part, we can have some conclusions and some recommendations for future paper to workout.

2 Literature review:

The introduction of the Black-Scholes model in 1973 marked a significant milestone in the evaluation of option prices, revolutionizing the financial market during that era. Initially, the model lacked consideration for dividend impact on option prices, but it quickly evolved with the addition of dividend yield to better align with real market dynamics by (Black and Scholes, 1973). Over the years, researchers have explored various adaptations and applications of the Black-Scholes model to suit different financial scenarios.

(Cox, Ross and Rubinstein, 1979) published binominal function that help to calculate value of American option. This formular is then widely used and applied till now. The formular is then developed and improved more in order to improve the calculating ability and also save more time [3]. In 1989, (Breen, 1991) tried to improve the efficiency of binominal method by reducing the area in which to search for early exercises opportunities but actually this method was for a long time ago. One paper published in 2019 by (Shang and Byrne, 2019) was developed a technique to reduce time for performing American option and the result was very good as it can reduce running time from 18 mins to 3 seconds. (Popuri et al., 2018) even developed a package in R to support users reduces time for running option data. This package was written by Sai and his team, using parallel computing to reduce the time.

In 1980, (Beckers, 1980) conducted a study to examine the relationship between historical instantaneous volatility of the underlying stock and stock price, using a dataset from the S&P 500 index spanning from 1972 to 1977. The findings revealed an inverse correlation between these variables. Subsequently, in

2006, (Yang, 2006) investigated the unbiased influence of implied volatility in forecasting future option prices, shedding further light on the model's applicability.

Several research papers have explored the practical applications of the Black-Scholes model in the financial market. (Srivastava and Shastri, 2018) tested the model's accuracy using a dataset of 30 stocks over 18 trading days, highlighting its significant relevance in real-world market scenarios. Another study focused on European call options in the Australian market, analyzing data from a 5-year period between 2003 and 2007. The results not only confirmed the model's usefulness in real financial settings but also emphasized the significance of implied volatility in managing investment portfolios.

In 1996, (Dumas, Fleming and Whaley, 1996) proposed research that shown some difference models to predict implied volatility using Time to maturity and Strike price and the results indicated that the model is not accurate as the ad hoc Black Scholes model. However, this research was done in 1996 and at that time there are not any machine learning techniques were applied in the research. In my paper, I want to go further with the model in this research and combine it with different modern models to see if it can improve the accuracy of predicting implied volatility using Time to maturity and Strike price. If these models work well, it can be used as a tool to support option traders in decision making and also create a dashboard to help traders in finding investment opportunities.

In addition to utilizing the Black-Scholes model for option price evaluation, several research papers have explored the application of implied volatility in the financial domain. (Hentschel, 2003) focused on reducing estimation errors for implied volatility. It proposed a feasible GLS estimator that effectively mitigates errors and biases in the calculation of implied volatility. Similarly, (Nabubie and Wang, 2023) introduced a technique to estimate implied volatility through the development of a robust grid-based inverse algorithm, resulting in high accuracy.

Furthermore, lagged implied volatility has emerged as a valuable trading signal for predicting stock returns in the exchange market. (Ammann, Verhofen and Süss, 2009) analyzed US equity options, incorporating factors such as firm size, market valuation, and lagged implied volatility. The research highlighted a significant relationship between stock returns and implied volatility, a finding reiterated in numerous other studies across different datasets.

For instance, (Dai et al., 2020) investigation on Japan's exchange market data from 2000 to 2017 emphasized the strong correlation between stock market implied volatility and stock volatility. (Feng, Zhang and Friesen, 2015) developed deeper into the analysis by examining the stock return and implied volatility smile slope of call and put options. Their paper revealed that the slope-stock return relation is most pronounced for stocks with high belief differences. Such studies underscore the growing interest in exploring implied volatility's role and its implications in various financial contexts.

Implied volatility, along with its counterpart, the implied volatility surface (IVS), holds significance in various analysis applications. (Guo et al., 2022) introduced a trading system based on the implied volatility surface, using SPY option data. This system demonstrated strong performance, yielding higher returns compared to trading underlying assets.

In another research paper, (Badshah, 2009) explored the dynamics of implied volatility surfaces, revealing three main factors that influence them. Firstly, the volatility level factor systematically moves the entire IVS in the same direction. Secondly, the term structure factor generates shifts in the slope of the term structure of different implied volatilities. Lastly, the jump-fear factor affects the steepness of the IV smirk/skew. These three effects were also corroborated in (Kim et al., 2010).

Furthermore, (Wen and Zhou, 2021) focused on utilizing dynamic implied volatility surface to enhance the price banding efficiency for the Fat finger problem. The system exhibited strong performance and outperformed other similar prediction systems. The exploration of implied volatility surface dynamics and its application in various contexts showcases the growing interest and potential for practical use in financial analysis.

3 Research methodology:

- **Step 1: Crawl data**: the main dataset used for this study is the options dataset with options data downloaded from the website OptionData [9]. The downloaded data is the free sample data for the six-month period between January to June 2013 for over three thousand stocks traded on the New York Stock Exchange. Besides, two additional datasets are crawled for the use of calculation on project are the 1-year US Treasury bond rate and the dividend value paid per stock for the year of 2013. The 1-year Treasury bond rates are taken for each trading dates in 2013; and are extracted from Fed information API using the *pandas_datareader* packgage [10]. This would be taken as risk-free rate for option and implied volatility calculation formula. The dividend yield is obtained from dividend data paid by US stocks recorded on the Yahoo Finance API using the Python *yfinance* package. [11].
- **Step 2: Data pre-processing**: the dataset downloaded from Option Data is six-month data including all stocks listed on New York Stock Exchange so it will be too heavy to run on my local machine. Thus, in this study, I just use the 18 stocks data include: MSFT, AAPL, V, UNH, JPM, JNJ, WMT, PG, HD, CVX, KO, MRK, CRM, MCD, CSCO, NKE, DIS, INTC. They are 18 biggest stocks listed on Dow Jones as recorded as of 15 July 2023. I will use the dataset of these 18 stocks extracted from Option Data to calculate, predict and draw the implied volatility surface. The risk-free rate is also extracted as the quoted date in the dataset and it will be changed through date. For the dividend yield, I use the dividend yield extracted as the quoted date in the dataset.
- **Step 3: Scope and application selection**: The dataset contains 2 types of file. The first type is the file that contains the information of stock option data that include 20 columns of variables. For this part, I just need the data about UnderlyingSymbol, UnderlyingPrice, Type, Expiration, DataDate, Strike, Bid, Ask. The second type contains the information about the date and price includes open price, high price, low price, close price and adjust price. For the calculation in this research, I will use close price. In order to make it easier to process, I merge these two types of file into one file that includes information about both stock and option price.
- **Step 4: Calculating the implied volatility**: Based on the data extracted and prepared in above parts, I can calculate the implied volatility. In order to calculate the rate, we can base on past papers as references [12]. After calculating the implied volatility, I will use Dumas, Fleming and

Whaley formular to predict implied volatility using different models include linear regression, random forest, decision tree and gradient booting.

- **Step 5: Draw implied volatility surface**: Based on the implied volatility calculated and predicted in step 4. I use package Plotly to draw 3D graphs.

4 Design specification:

4.1 Data processing pipeline

In order to deal with the big volume of the dataset and ensure reproductivity of the code, I decided to use Google cloud computing platform to store and processing data. Specifically, data is stored on Google Drive and calculations are performed through Python kernel on Google Colab.

High level view of data integration and processing are summarized below:

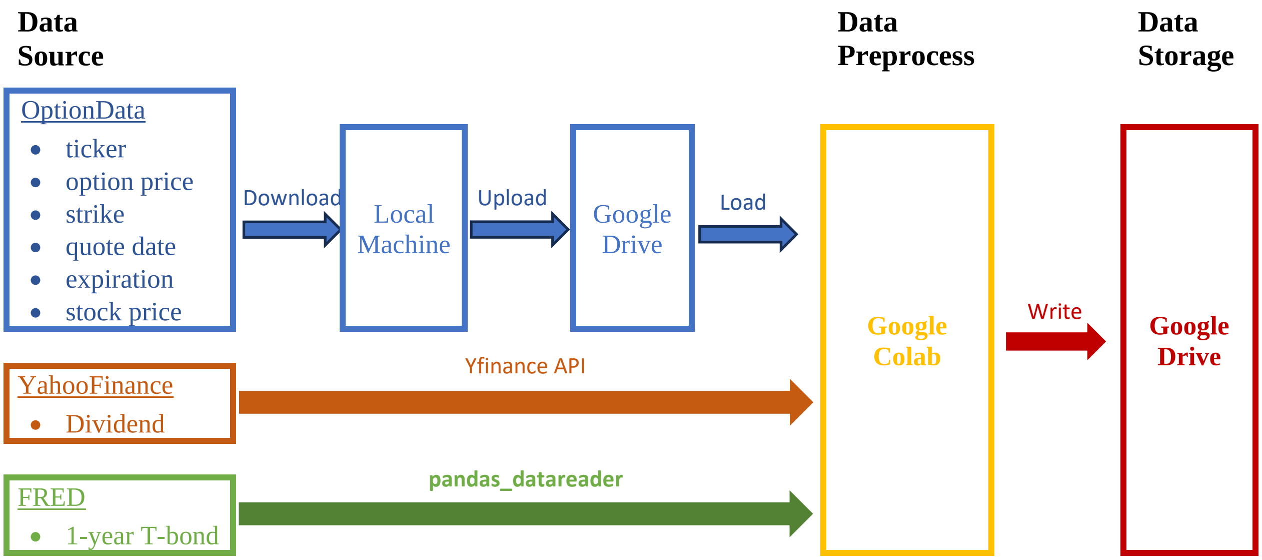

Figure 1: Data Processing Pipeline

4.2 Model evaluation

In order to assess the results of predicting implied volatility, I will use both root mean square error and r-squared.

Root Mean Square Error (RMSE) is a commonly used statistical metric to assess the accuracy of predictions or forecasts in various fields, including statistics, machine learning, and econometrics. The RMSE method calculates the square of the differences between predicted and actual values, then takes the square root of the mean of these squared differences. This process ensures that both positive and negative errors contribute equally to the overall evaluation. In essence, RMSE represents the average magnitude of prediction errors, where a lower RMSE value indicates a closer fit between predictions and actual observations.The RMSE method is particularly useful when comparing the performance of different models or techniques for the same dataset. By calculating the RMSE for each model, one can objectively compare their accuracy and identify the model that provides the best overall fit to the data. In summary, RMSE is a valuable tool in quantitative analysis, allowing researchers, data scientists, and analysts to gauge the accuracy and reliability of their predictions or forecasts and make informed decisions based on the performance of various models.

R-squared, also known as the coefficient of determination, is a statistical measure used to assess the goodness-of-fit of a regression model to the observed data. It provides insight into how well the independent variables in a regression model explain the variability of the dependent variable. R-squared is a fundamental tool in regression analysis and is widely used in fields such as statistics, economics, and various scientific disciplines. R-squared is a valuable metric for several reasons. First, it provides a straightforward way to determine how well a regression model fits the data. A higher R-squared value suggests that a larger proportion of the variability in the dependent variable is captured by the model, indicating a better fit. Second, R-squared enables the comparison of different models to identify the one that best explains the data. However, it's important to note that a higher R-squared does not necessarily imply a better model, as it can be influenced by factors like overfitting. While R-squared is a useful measure, it has its limitations. It may not accurately reflect the model's validity if the chosen independent variables are not truly relevant or if the data has inherent variability that cannot be explained by the model. Therefore, it's essential to interpret R-squared in conjunction with other diagnostic tools and domain knowledge. In conclusion, R-squared is a valuable statistical tool for assessing the quality of a regression model's fit to observed data. It provides insight into how well the model captures the variability in the dependent variable and aids in model selection and comparison.

5 Solution development:

Through all the steps that I mentioned above, I want to develop a tool that can help option trader and other professionals investors to observe and monitor implied volatility so that can help them in figure out investment opportunities or manage the risks when they are entering financial markets. This tool can benefit both short term investors as they can investigate one day implied volatility or this tool can also benefit portfolio manager who want to invest their assets for long time period by looking at 6 months implied volatility. Based on the information provided by the tools, investors can decide whether to long or short the stocks.

6 Evaluation:

6.1 Compute and visualize implied volatility surface of Europe option

In my research, I run and visualize 18 stocks but for the evaluation part in this report, I will just point out the surface for AAPL because the purpose of this paper is to create a dashboard for traders, not to analyze deeply in stock options.

In order to support better for observing implied volatility surface, I visualized the implied volatility of stocks in different time set include 1 day, 1 week, 1 month and 6 months because when looking at the surface with both short term and long-term period, we can have a more practical view about the risks. Below is the surface for 1 day data of AAPL:

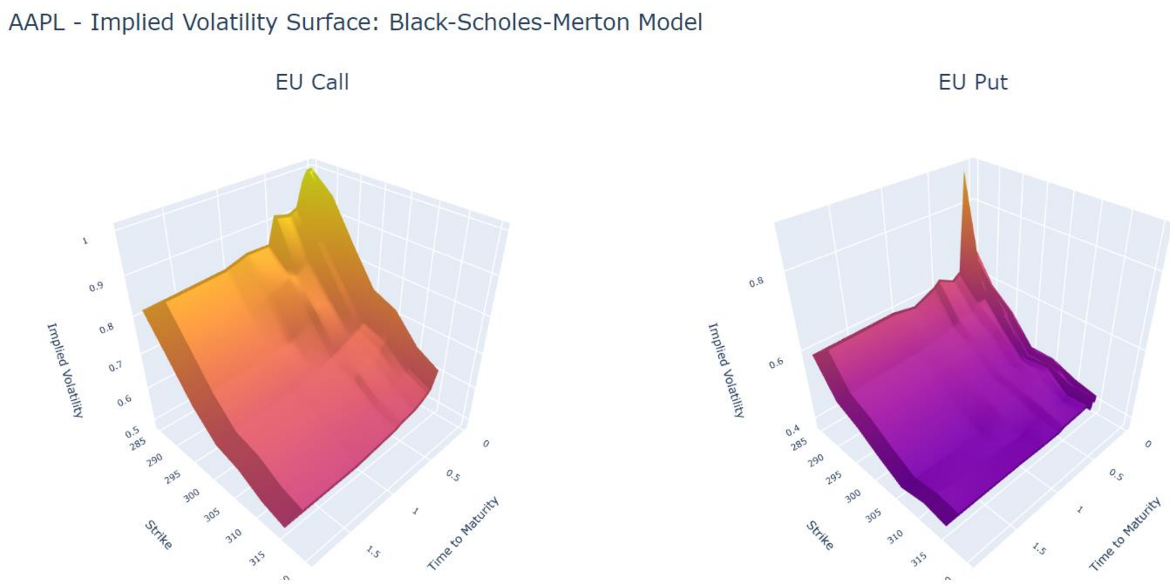

Figure 2: EU option - AAPL - Implied Volatility: Black-Scholes Merton Model – 1day

As can be seen in the call and put implied volatility surface above, we can see the shape of AAPL smooth and also implies the relationship between time to maturity, strike price with the implied volatility. We can also observe the smile shape in the surface. Continue to next visualization, we observe the surface for 1 week data of AAPL:

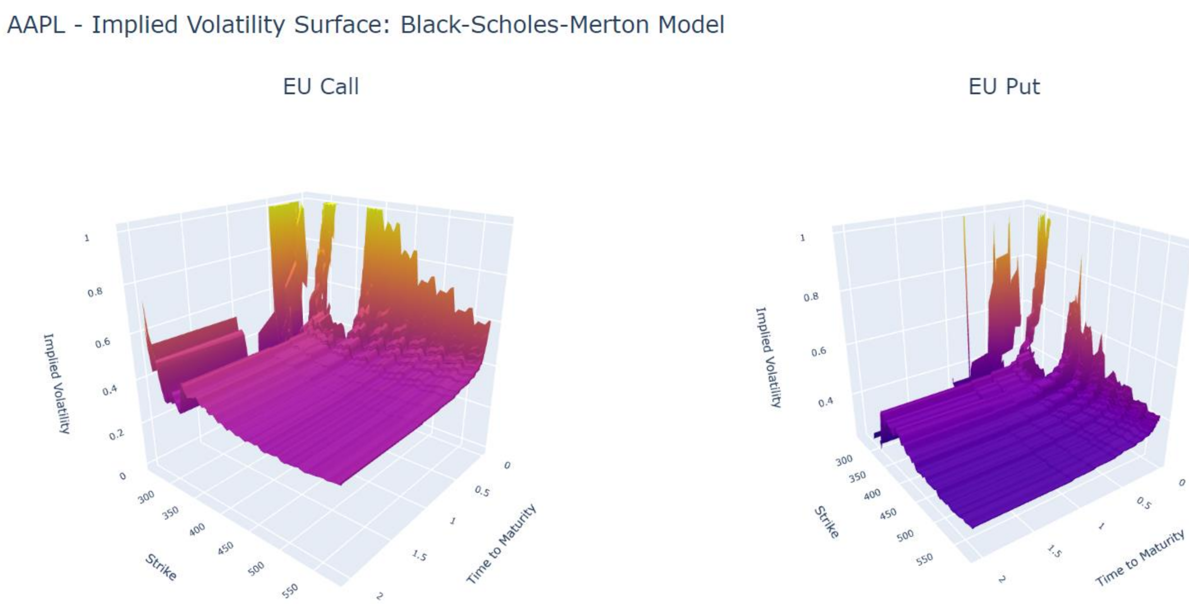

Figure 3: EU option - AAPL - Implied Volatility: Black-Scholes Merton Model - 1week

We can see that the shape of the smile in above surface is not as smooth as in the one day implied volatility surface but the smile still very clear. In general, we can still see the relationship between time to maturity, strike price and implied volatility.

In the next analysis, we observe the surface for one month data and 6 months data of AAPL:

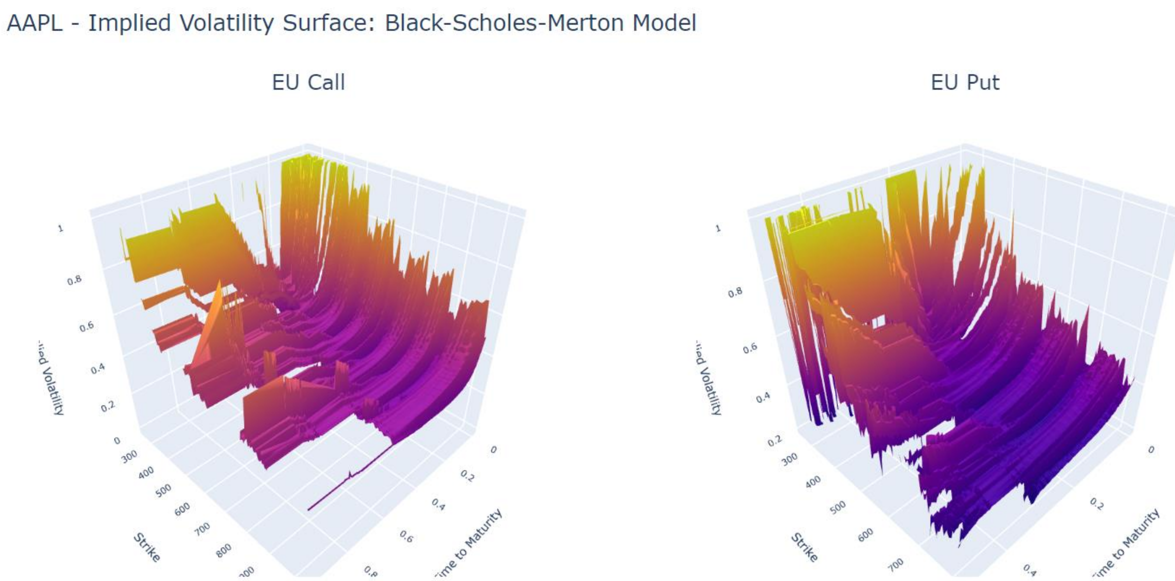

Figure 4: EU option - AAPL - Implied Volatility: Black-Scholes Merton Model - 1month

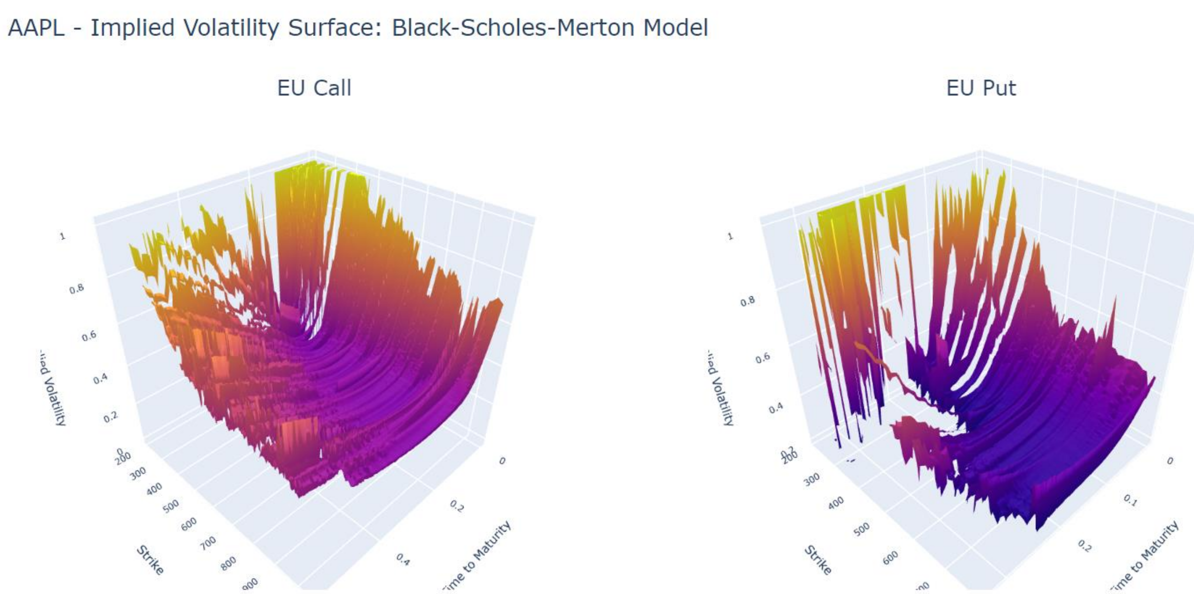

Figure 5: EU option - AAPL - Implied Volatility: Black-Scholes Merton Model - 6month

Looking at one month and six months surfaces above, we can conclude that as the data becomes bigger, the noises for implied volatility will appear more but it also indicates the long term trend of implied volatility. Besides, the shape of the call surface seems to clearer compare to put surface. In theorical, the call surface and put surface of one stock would be similar but in real financial market, call and put may be different.

6.2 Compute and visualize implied volatility for America option

For American option, the shape of one day implied volatility surface is quired smooth. However, the call and put surface is very different. It can be seen in below implied volatility surface for one day of AAPL:

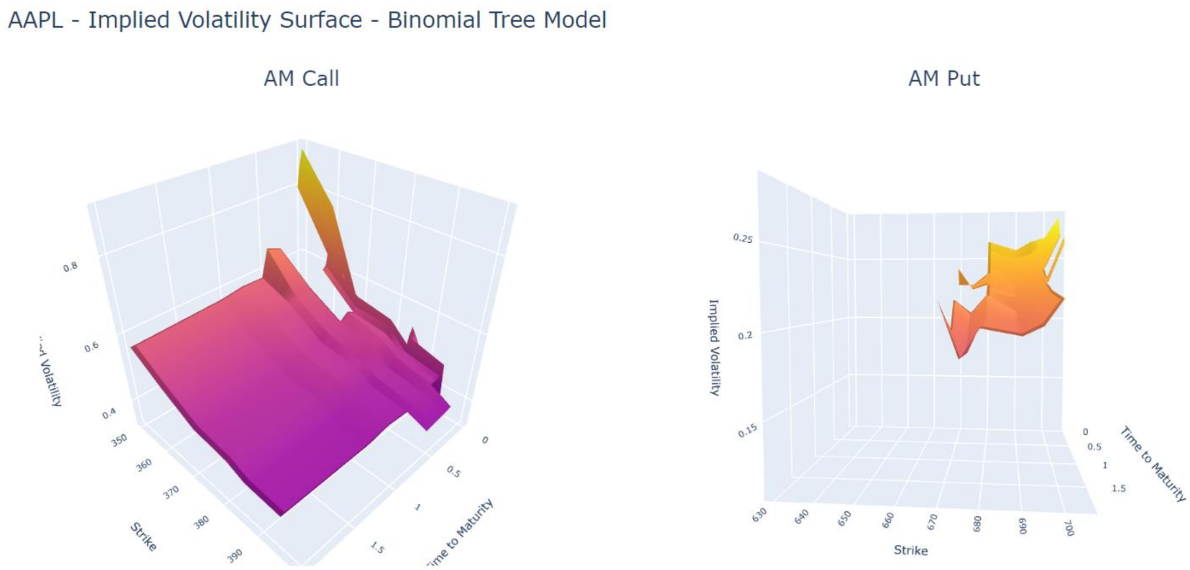

Figure 6: AM option - AAPL - Implied Volatility: Black-Scholes Merton Model – 1day

However, as I change the timeline longer into one month data, the implied volatility surface becomes very different and it is hard to predict the trend if we just use one month surface. The implied volatility surface of one month data is as below:

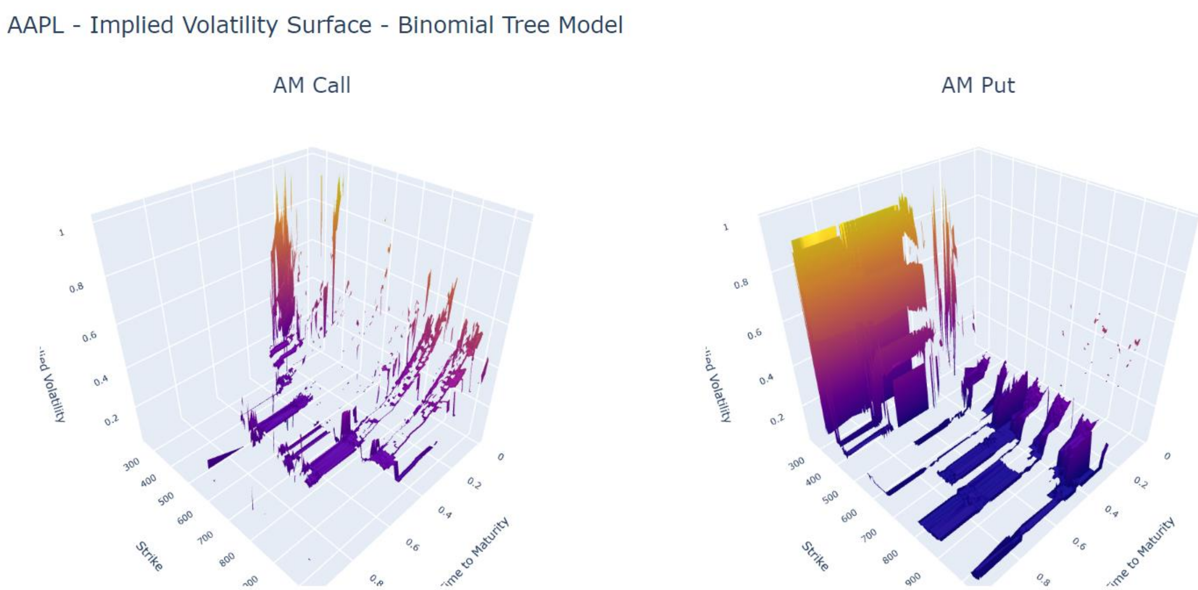

Figure 7: AM option - AAPL - Implied Volatility: Black-Scholes Merton Model – 1month

The reason for the 'ugly' shape of one month surface compare to one day surface because when I increase the timeline but the timeline is not long enough, there are more noises and these noises will make the shape of the surface become very 'ugly', means that unpredictable and hard to detect the trend. However, when I keep increasing the timeline into three months, the shape becomes clearer. The implied volatility surface of three months data is as below:

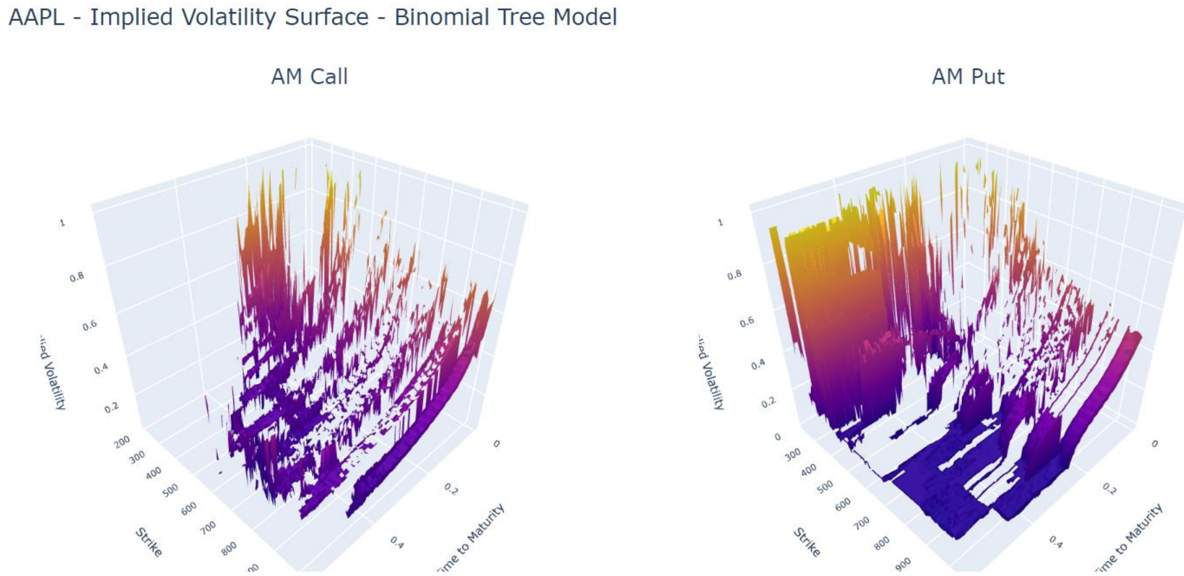

Figure 8: AM option - AAPL - Implied Volatility: Black-Scholes Merton Model – 3month

As can be seen in the surface, we start to detect the trend of implied volatility and the shape become clearer, however, the smile shape still unclear so let just increase the timeline to six months and see the results below:

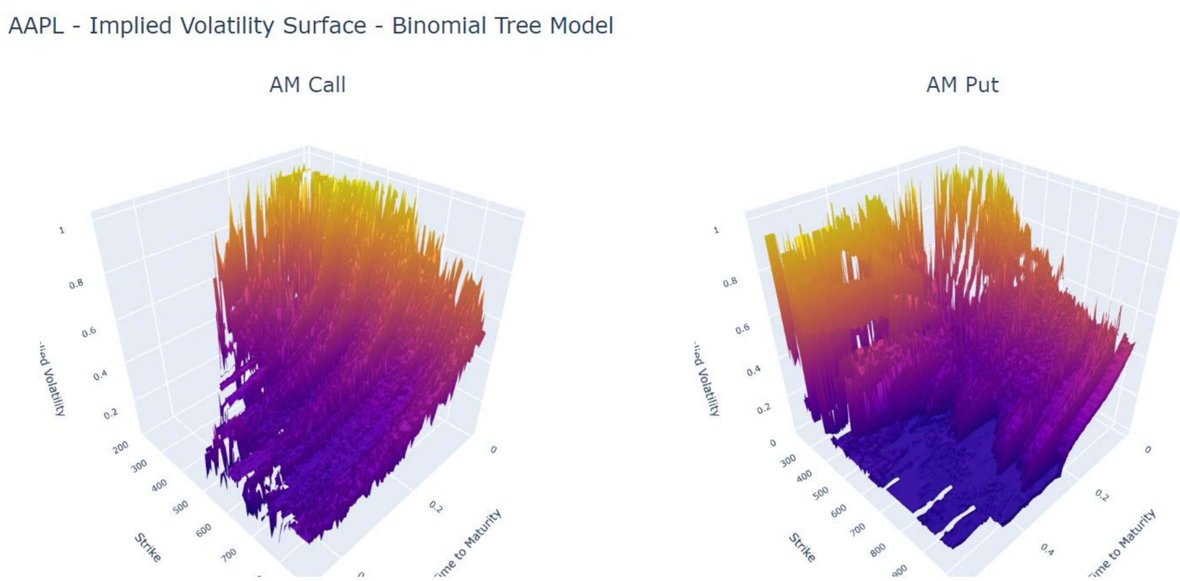

Figure 9: AM option - AAPL - Implied Volatility: Black-Scholes Merton Model – 6month

Now, with the six months implied volatility we see a clear shape and trend with the smile shape very clear in call option implied volatility surface. This prove that as the time increase, the noises become larger but when the data is larger enough, we can detect the shape of the surface clearer. For short term implied volatility, it has small noises, thus the shape is smooth.

6.3 Predict European option implied volatility using machine learning method

As mentioned in the methodology part, in this paper, I will use four models to apply into implied volatility computed and use these algorithms to predict and create implied volatility surface. The general summary as below:

Table 1: Goodness of Fit for IV Prediction - EU Option

Models	EU Option	
	RMSE	R2
Random Forest	0.131763	0.595669
Decision Tree	0.14239	0.527823
Gradient Boosting	0.151075	0.468464
Linear Regression	0.183144	0.218851

<= best model

Using root mean square error method to assess the accuracy of each model and we can see that Random Forest has the lowest root mean square error of about 13.13% and linear regression has highest root mean square error of 18.31%. Let go in detail into each model and we can have a deeper understanding about the above result.

Below is the implied volatility surface that was created using Dumas – Linear regression model:

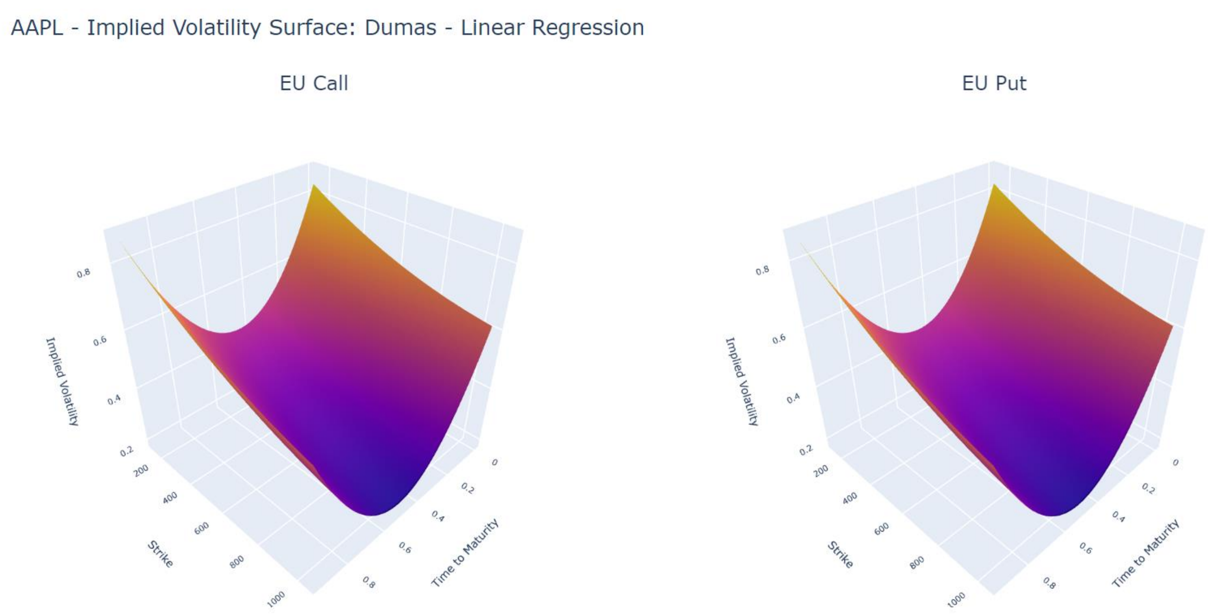

Figure 10: EU Option - AAPL - Implied Volatility Surface: Dumas - Linear Regression

We can see that the shape of implied volatility surface in linear regression is very smooth. The smile shape can be seen very clearly, and it also implied the significant relationship between strike price, time to maturity and implied volatility.

After using linear regression model, I use Decision Tree model to predict and draw the surface and the result is shown as below:

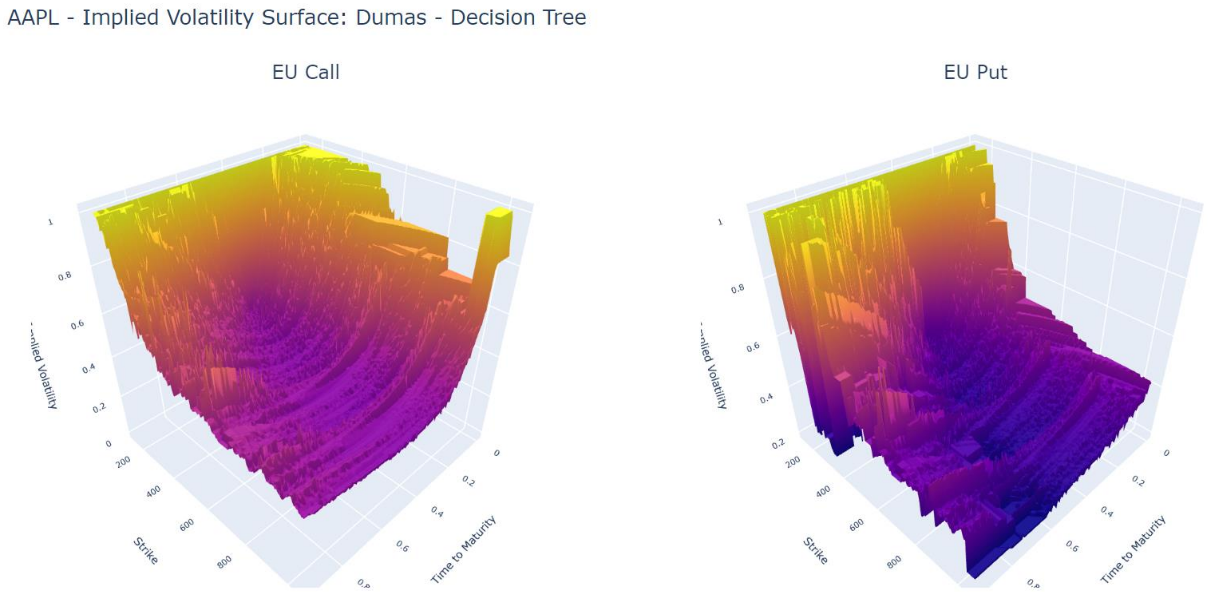

Figure 11: EU Option - AAPL - Implied Volatility Surface: Dumas - Decision Tree

Looking at the surface above, we can see that its shape is not as smooth as the shape of linear regression but in general, we can still see the smile shape and detect the relationship between variables in the function. In fact, compare with the shape of actual implied volatility surface that I calculated and shown in the first part, we see that this shape more familiar to the actual surface, which could be more valuable to traders when it can be used in predicting implied volatility better than Linear Regression model.

The third model that was used in my paper is Random Forest and the surface of Random Forest is as below:

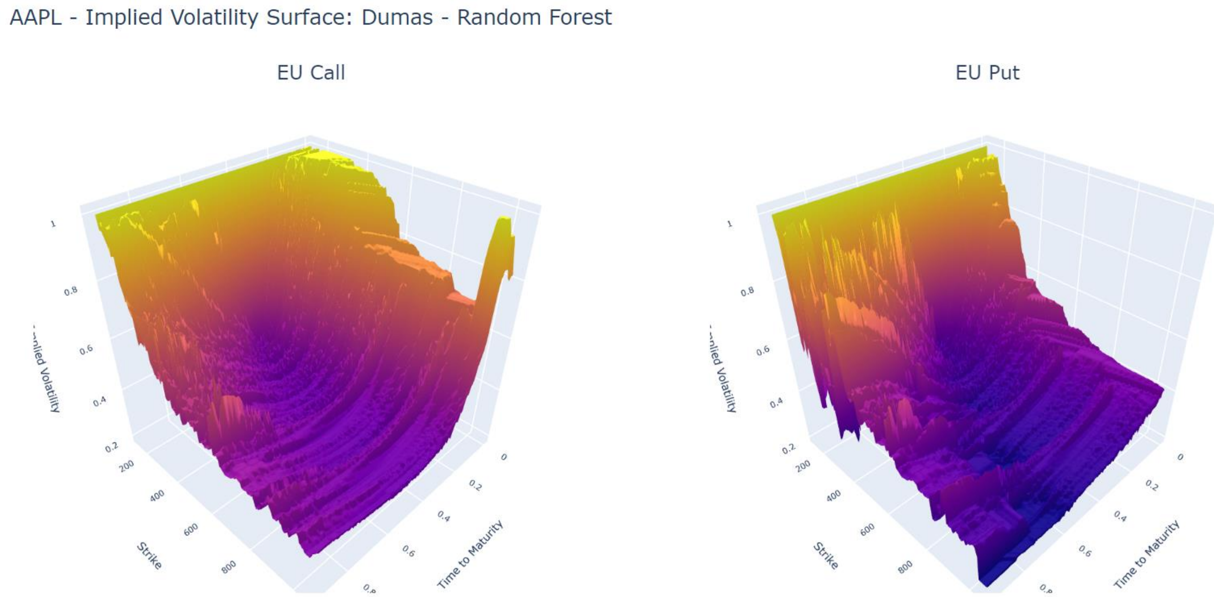

Figure 12: EU Option - AAPL - Implied Volatility Surface: Dumas - Random Forest

We can see that the implied volatility surface generated from Random Forest have a similar shape to Decision Tree and in fact, Random Forest is the model that has highest accuracy level compared to three other models. The reason for this is because the tree models algorithm built in Random Forest and Decision Tree seem to more suitable for predicting option data.

Gradient Boosting normally will have the accurate level nearly the same as Random Forest but in the situation of option prediction, the result shown the opposite way. The predicted value predicted from this model has the lowest accurate level compared to other. The implied volatility surface generated using Gradient Boosting is as below:

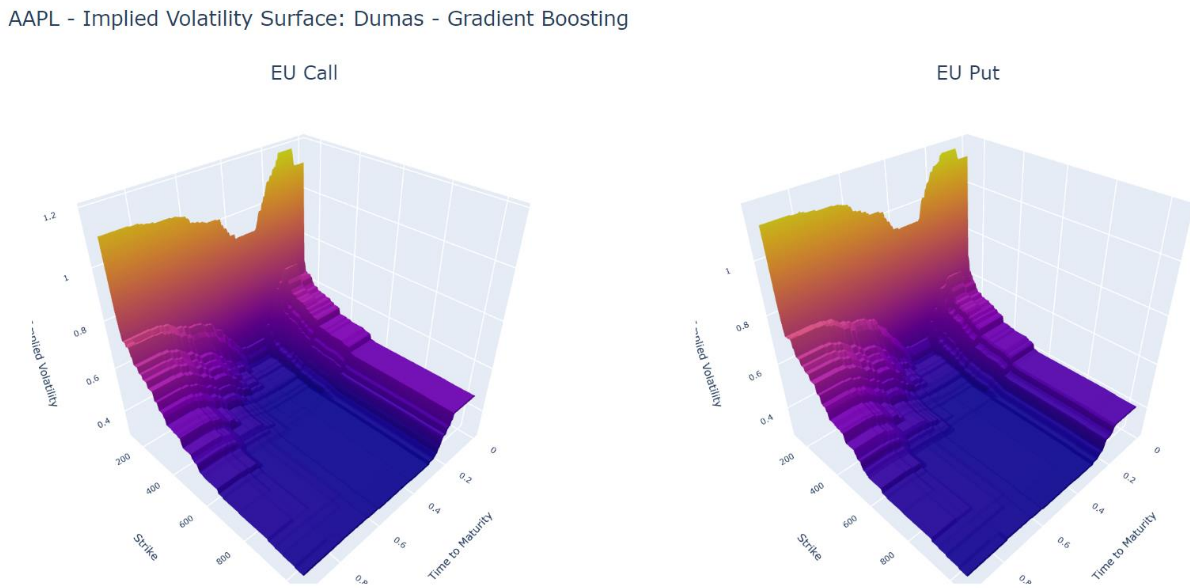

Figure 13: EU Option - AAPL - Implied Volatility Surface: Dumas - Gradient Boosting

In general, the shape of implied volatility surface generated from Gradient Boosting still familiar with other machine learning model, but it is not as smooth as the shape of Random Forest or Decision Tree.

6.4 Predict American option implied volatility using machine learning method

Compared to European option, American option is more complicate as it can be executed before the time to maturity and nowadays, most of options listed now are American option and by calculating implied volatility and visualize implied volatility surface for American option, this paper is a practical analysis to evaluate option. Thus, create a dashboard for professional investors in decision making for their investment and managing their portfolio. First, I use Regression model with the Dumas formular. The implied volatility surface is as below:

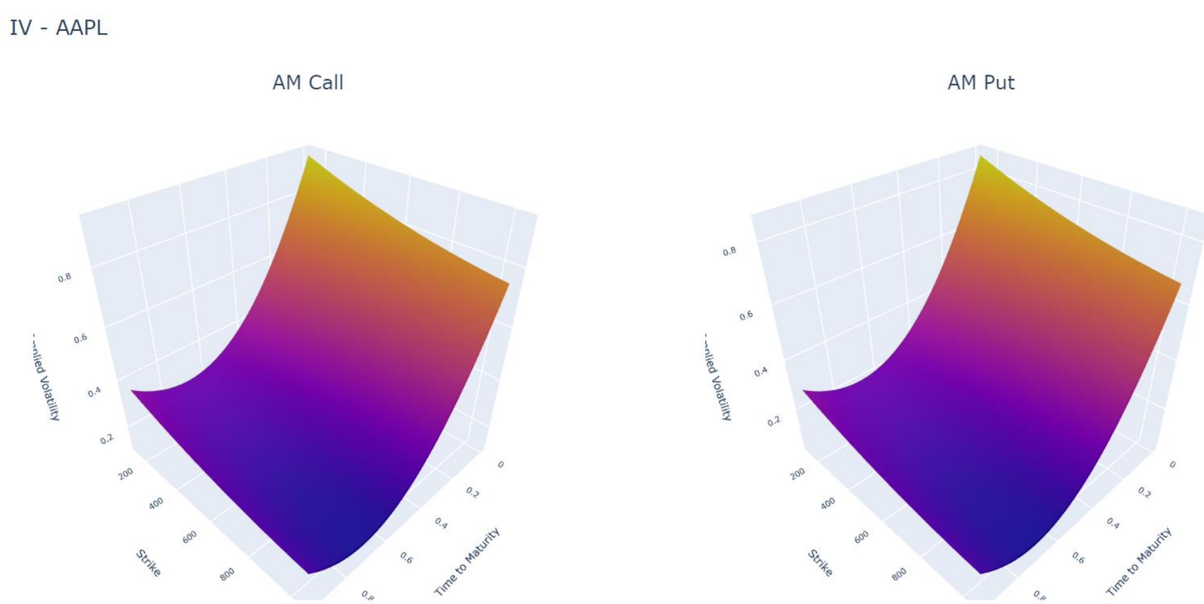

Figure 14: AM Option - AAPL - Implied Volatility Surface: Dumas - Linear Regression

Compare with the of European option with Dumas – Regression model above, the shape of American implied volatility is not total familiar but in general, we can still see the smile and the relationship between strike price, time to maturity and implied volatility. Call and put surface of AAPL looks like the same and this proves the theorical framework of option as the shape of call, put option for one stock should be similar.

Come with American option that applied Dumas – Decision Tree, the shape of implied volatility is not as smooth as in Regression model, but it has higher accuracy level. The surface of Decision Tree as below:

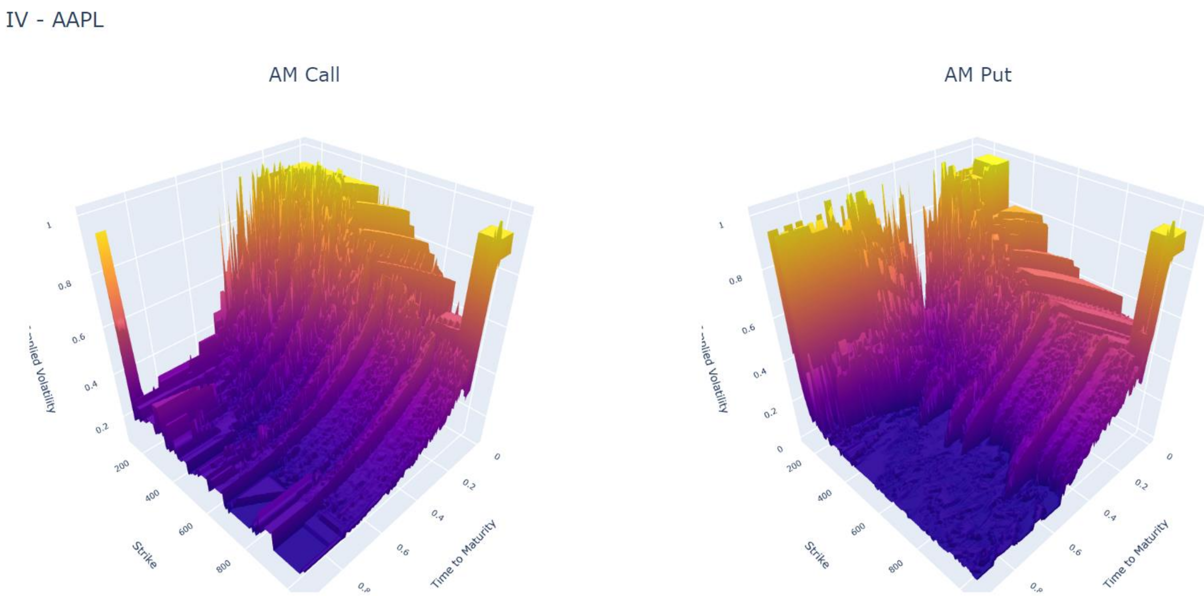

Figure 15: AM Option - AAPL - Implied Volatility Surface: Dumas - Decision Tree

The implied volatility seems to have more noises, but it also indicates the real market situation because in the real financial market, there are so many noises that comes from the Asymmetric information, different analysis methods and different trading strategies of investors. In addition to the noises, the surface of call and put option is not too familiar and this is happened the same for predicting European option.

The third model will be used to predict in this paper is Random Forest and this model indicates even a higher accurate level compared to Decision Tree model. The surface of Random Forest as below:

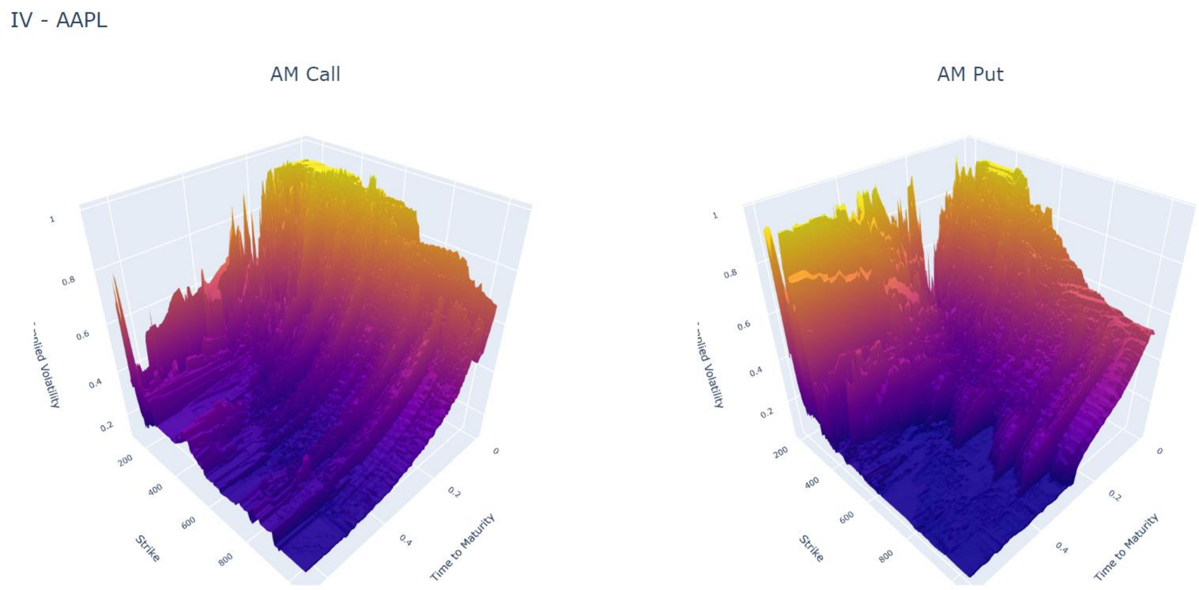

Figure 16: AM Option - AAPL - Implied Volatility Surface: Dumas - Random Forest

As can be seen in the chart above, the shape of Random Forest and Decision Tree is the same, but the Random Forest surface is smoother and displays the trend better. This can benefit investors in determining and monitoring the risks for their portfolio.

Come to Gradient Boosting, the results were the same as in predicting for European option. Gradient Boosting model has the least accuracy level compared to Random Forest and Decision Tree. The surface for Gradient Boosting as below:

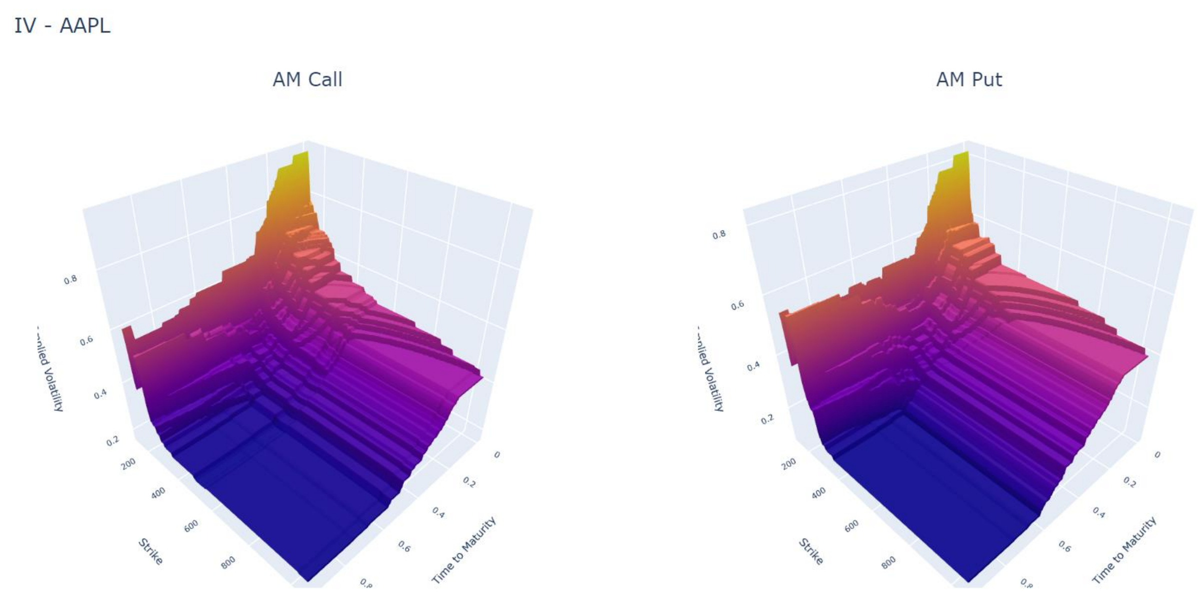

Figure 17: AM Option - AAPL - Implied Volatility Surface: Dumas - Gradient Boosting

Gradient Boosting still shows the smile shape and the call, put surface in this model quite similar to each other. This is true in theorical concept as the surface for call and put of one stock should be the same. This is a difference point of Gradient Boosting compared to Random Forest and Decision Tree as the call and put of these two models is not familiar.

To generalize the prediction of American option with different machine learning model, we have the above numbers:

Table 2: Goodness of Fit for IV Prediction - EU and AM Option

	EU Option		American Option		
Models	**RMSE**	**R2**	**RMSE**	**R2**	
Random Forest	0.131763	0.595669	0.068114	0.871866	<= best model
Decision Tree	0.14239	0.527823	0.087163	0.790176	
Gradient Boosting	0.151075	0.468464	0.106985	0.683891	
Linear Regression	0.183144	0.218851	0.142467	0.439447	

Using root mean square error method, we can see that Random Forest has the lowest RMSE of 6.8% and Linear Regression model has the highest RMSE of 14.24%. Decision Tree rank in second position with 8.7% of RMSE and Gradient Boosting ranks the third in the list with 10.7% of RMSE.

7 Conclusion:

This paper can conclude that Dumas, Fleming and Whaley formula is valuable in predicting implied volatility. The results for both European option and American option as Random Forest has highest level of accuracy and Linear Regression has lowest. These results are explainable because the relationship between strike price, time to maturity and implied volatility is not linear. Thus, other machine learning methods will have better results compared to Linear Regression model. Secondly, the longer time period can lead to more noises for the surface and might make investors struggle in using the platform but it also implements a long term trend and it can be useful for risk managers. The implied volatility surface of one day has less noises compared to longer time implied volatility. The shape of one day surface is smoother. Investors can combine both these surfaces from one day to six months in order to better understand the trend and the path of implied volatility, so that they can make better decisions for their investments.

In addition, the paper uses large amounts of data to create a dashboard that can be a useful tool for investors. Short term investors might find that one day implied volatility surface more useful for them. Longer term implied volatility surface such as 6 months implied volatility surface can be more useful for portfolio managers who care more about long term risks and when to minimize the risks for their investments. However, the time taken to run the program is too long and might not be suitable for real time tool. This investigation shows that the binominal function that is commonly used nowadays takes so much time to run. This can be my further study as I can research deeper about the formular and find some solutions to reduce the calculation times for American option. This will be an interesting topic as it can benefit not only for my application but also for other researchers who have problem when calculating implied volatility for American option.

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