Adversarial Model Selection In Risk Management

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Utilising machine learning methods to analyse and compare financial models has become prevalent in the financial industry in recent years. Therefore, how to apply deep learning techniques to traditional time-consuming financial model calibration and risk management procedures is now an interesting topic to consider. Here model calibration refers to fitting a parametric model such that it can match to market data.

In this project, based on a recently published paper, we integrate artificial neural networks into a stochastic differential equation (SDE) model, where the artificial neural network is a powerful approximation tool in deep learning and the SDE is a classical model to describe stock price dynamics. We then conduct experiments and analysis on calibrating this model with option price data.

Calibrating our neural network SDE model is essentially a process of providing data and learning from it. Therefore, to perform our tasks, we need to: 1) Provide training data; 2) Construct appropriate steps so that the model can be optimised until errors are minimised; 3) Test the generalization ability of the model on out-of-sample data to ensure that the model does not over-fit while learning information from training data.

In the first step, since real-world option price data is not readily available, we use synthetic data as our training data source. We select the stocks of the top 10 airlines in the United States, extracted relevant information from their past price history data, and used this information to generate several sets of prices for European call options and European basket call options on these airline stocks by Monte Carlo simulation. These data are not the same as real market data, but they should share some similar characteristics.

The next step is to construct our optimization procedures. We use the popular PyTorch toolkit to accomplish this process. The procedures we use here are very similar to the optimization process commonly used in the deep learning field, that is, to repeat steps 2 and 3 until the model generates precise results:

- Step 1: Initialize the model and model parameters
- Step 2: Apply current parameters to our model to sample option price data
- Step 3: Use the optimizer to update the parameters to reduce errors between training price data and produced price data

The last part is to test the generalization ability of the model. We selected several other options on these airline stocks, including spread options. We used the data synthesizer and our trained model to sample the prices of these products and compare the differences.

After training our model with these steps above, we observe that the performance of the model on the training samples is unparalleled. Figure 1 below is the option price curve of American Airlines, where we can see that model-generated data is quite close to market data.

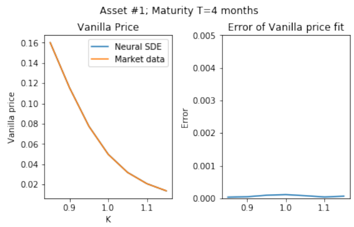

Figure 1 – European call option on AAL, maturity = 4M

Our model performs convincingly on generating other out-of-sample basket option prices as well. In Figure 2, we display the prices of a basket option on American Airlines plus Allegiant Air. We could notice that the model (blue curve) is accurately matched to market data (green curve).

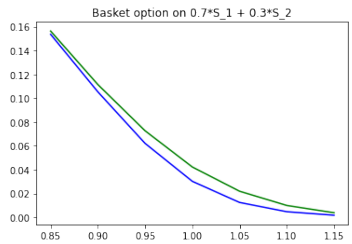

Figure 2 – Out-of-sample basket option on AAL, ALGT, maturity = 2M

Unfortunately, our model is poor in terms of generating prices of out-of-sample spread options. In Figure 3, we find that the generated prices of a spread option on these two airlines (blue curve) are far away from synthetic market data (green curve). We believe that it is because the option prices in our training data cannot provide enough information about the distribution of spreads between these stocks. In order to deal with this problem, we plan to calculate spread option price bounds and test their sensitivity.

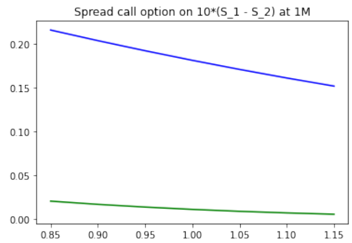

Figure 3 – Out-of-sample spread option on AAL-ALGT, maturity = 2M

In conclusion, this project verifies the feasibility of using neural network type stochastic differential equations to fit data in financial markets. Our model successfully fits the training data and performs well on out-of-sample basket option data. In response to its problem of predicting spread option prices inaccurately, we also plan to calculate its price bounds to provide more realistic forecasts. Neural network type models are generic, swift. We demonstrate that combining neural networks with traditional modelling techniques will be a research direction of significance.

> *In this project, we extended the existing one-dimensional neural network SDE model into a multi-dimensional one. The numerical results produced by this project makes up a solid step towards understanding what neural network is capable of in financial model calibration and what is not. These results are also useful for constructing risk management tools for large portfolios in the future.*
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