**Artificial Intelligence (AI) and Its Applications in the Finance Industry**

•Gradojevic N., Kukolj D., Gencay R., (2011), Clustering and Classification in Option Pricing, *Review of Economic Analysis*, 3(2), pp.109-128.

**Abstract**

Finance is an industry that has heavily benefited from the “big data" concept, the financial institutions are now finding it important to implement AI solutions in their operations in order to help interoperate financial data and make appropriate decision in aspects such as the pricing predictions. One of the main resources is an artificial neural network (ANN), a form of brain-modelled computer system designed to solve finance problems. ANNs can store more information than any human brain. The paper discusses current literature on various artificial intelligence models and their application in finance industry.

**Introduction**

It has been widely reported by scholars that return on stock show anomalous and random distribution of variance conflicting the pricing model assumptions by standard Black and Scholes (1973). Bakshi et al. (1997), for example, report price biases for "volatile smile" call-and-post options. A similar currency bias is the "volatile smile," which refers to a volatile smile skewing towards one side. In both of these assumptions, the volatility involved in the Black-Scholes model differs from one strike to another and therefore violates the model's presumption of constant variance. The pricing biases less commonly mentioned include maturity biases. Black (1975) states that the Black Scholes formula appears to be overpriced for options of less than three months expiry. Bakshi et al (1997) discovered that despite the cash flow, price differences of the Black-Scholes model were rapidly increasing with time. For deeper choices, this phenomenon is more pronounced. To counteract the bias of the Black Scholes model, on verifiable pricing choices, two strands of research have emerged: parametric and non-parametric models. Bakshi et al., (1997) and Gencay and Gibson, (2009) have demonstrated the parametric head of stochastic volatility (SV), random jump stochastic volatility (SVJ) and stochastic interest rate(SI) models, and there is proof that accurate representation of the Black Scholes model is of great importance. Stochastic volatility extension to jump stochastic volatility increases price of options that are short term. The long-term pricing and hedging options are increased by stochastic interest rate. However, vigorous price changes are not produced by the parametric models and they result to certain short-term choices that are linked to money. The question remains, therefore, how to manage the smile impact on short-term choices. Despite the parametric model’s theoretical appeal, non-parametrical models proof to be successful in toning down the Black Schole model's assumptions (Gencay and Gibson, 2009). This is the reason; this article looks into non-parametric option pricing features.

 Non-parametric models superiority is demonstrated by its potential for adaptive learning and ability to restrict distribution of returns. Thenon-parametric models contain versatile features with advantages in contrast to the parametrical parameters of leaps, non-stock and negative skewness and kurtosis. It is worth noting that non-parametric approaches are typically based on a smooth-fit equilibrium. In the estimation process, this compromise is generally managed by the choice of parameter, which is a tough task. This could lead to lack of stability which would affect the non-parametric methods output outside of the study. That is why a parsimonious parametric model can be preferred. Moreover, there is parametric transparency in parametric models, which usually lacks non-parametric models. Despite this view’s validity, parametric models may also suffer from similar inconveniences.

**Examples in the Finance Sector of Artificial Intelligence**

Artificial intelligence which can be referred to machine intelligence, has banking, stock, bonds and investment on the sell side and managers of assets, firms with capital and foreign exchange on the buy side within finance. In the sell side, companies use artificial intelligence to perform trials on credit or trading processes. Natural language processing software is also used to experiment by banks. The software listens to customer interactions and investigates clients’ trades in order to recommend purchases and predict potential demands. They also use machine-learning algorithms which propose best rates for swaps of a balance sheet. Natural language processing tools are used to track customers’ inboxes and emails so as to decide on assignment of broad trades between funds. Associations between prices of assets and data to forecast cost of currency in the future is investigated by artificial intelligence. The natural language processing software is also able to read contracts and inform customers on swap or other sales. On the buy side, computers use available data to classify bond, asset, future stock and transactions on currency. Artificial intelligence is used to predict the different economic scenarios and how to work in such circumstances. The data is also scrutinized to identify trades, construct portfolios and examine length of wagers. AI algorithms interpret data from market shifts to transact in accordance. The algorithms evaluate customers’ attitude to products. Economic patterns can also be monitored using satellite images. Natural language processing software helps in analysis of transcripts, social media tracking and news reading. Generally, financial institutions use AI in different ways to enhance their work. With the new age, technology will continually to increase in the finance sector.

**Parametric Pricing**

Bakshi et al. (1997) gives an underlying payment non-dividend stock price S(t) and its compounds in an economy that is risk neutral. In the formula,R(t) represents time-t instant spot interest rate; π represents total jumps in a year; diffusion portion of the stock return variance is represented by V(t) based on jumps not occurring); regular Brownian motion are each represented by wv(t) and ws(t), and Covt [dwS(t),dwv(t)] πdt; the jump size percentage is J(s) based on occurrence of a jump) which is identically and independently distributed log normally. ln[1 + J(t)] standard deviation is πJ, amplitude Poisson jump counter is q(t) where Pr(dq(t) = 1) = πdt, and Pr(dq(t) = 0) = 1 −αdt. The velocity of the diffusion are velocity of change, the mean long run and variance coefficient of diffusion volatility V(t) respectively. ws(t) and wv(t) as well as q(t) and J(t) are both uncorrelated. In such a setting, total return variance can be divided to two components. In this case, VJ(t)(1 / dt)Vart [J(t)dq(t)] = π[μ2J+(eπ2J − 1)(1 + μJ)2] is the jump portion variance. The one-factor structure model is followed by potential cash flows discounting (Cox et al., 1985)

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| --- | --- |
| *dR*(*t*)=[θ*R*−κ*RR*(*t*)]*dt*+σ*R R*(*t*)*dwR*(*t*) |  |

In this formula, velocity of change, mean long run, and vector coefficient of the R(t) phase are the velocity of ÿR, the reference vector reference variable R(t). WR(t) is standard Brownian motion. It lacks mutual understanding to any given model.

**Non-parametric Option Pricing**

The Black-Scholes model was criticized for its underlying security distributional assumptions. Distributional assumptions are toned down naturally by the non-parametric model. Pricing a European call option using non parametric pricing entails non-dividend-paying asset that links available option price to a set of variables characterizing the given option.

|  |  |
| --- | --- |
| *Ct*= *f* (*S t*,*K*,σ*t*,*rt*,τ) |  |

In the above formula, underlying asset price is St, strike price is K, Ţt represents underlying asset volatility, rt is a rate of interest and μ is time to maturity.

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | *Ct*= *f* (*S t*,*K*,τ) |  |

**Fuzzy learning vector quantization (FLVQ)**

FLVQ algorithm is a non-supervised batch method (Bezdek, 1995). This algorithm represents weight variation adjustment rules in unattended network with a batch clustering c-means (FCM) function as the fuzzy set membership function. The key advantages of the FLVQ algorithm compared with similar clustering methods are; smaller number of input parameters are requested, less often stuck with local minimum and final solution does not affect the sequence of input data. FLVQ algorithm cluster is based on assuming that a number of clusters identified by its respective prototypes can be included in each class. The algorithm generally contains two stages: prototype generation and classification error improvement, through adaptation of prototype coordinates.

**Conclusion**

The generality and enlargement of models, like the Markov switching model, or the regression threshold sequence, can also be understood as our approach. FLVQ also involves separating and sorting data according to certain parameters. The FLVQ algorithm does not use any special thresholds or variables for data classification; however, it is based on its input space classification algorithm (learning). More than two features are developed to differentiate the interest variables. This shows this method may be extended in time series financial econometrics to other non-linear issues. Foreign-exchange, interest-rate and derivative models are financial models that are likely to change regime. In conclusion, MNN-FLVQ model shows high dependency in research pricing direction. This approach can be applied so that data points may form part of any cluster with certain likelihood. Gaussian blend models (Behr and Potter, 2009) are an example of this approach. The model uses all data points in input space and allows interaction of cluster whenever the output of the variable is expected.

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