BIG DATA ANALYTICS IN FINANCIAL ECONOMETRICS

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1. Introduction

Analytics of data in financial Econometrics employs statistical techniques to comprehend financial issues. The discipline of financial data analytics blends econometrics with the technology components of data analysis. Financial data analytics utilizes machine learning, predictive analytics, and prescriptive analytics to provide robust opportunities for interpreting financial data and resolving related difficulties. The field of financial data analytics has exploded in the past decade. As financial data analytics are applied to financial time series, academics and financial analysts have been increasingly interested in modelling and forecasting the volatility of the time series, a field of behavioural decision study that is becoming increasingly fruitful. Numerous economic and financial applications, such as portfolio optimization, risk and return analysis, and asset pricing, find it highly important. The digitization of the finance industry has enabled technologies such as advanced analytics, machine learning, artificial intelligence, big data, and the cloud to permeate and transform the competitive landscape of financial institutions. Consequently, huge businesses are adopting these technologies to enhance digital transformation, satisfy consumer demand, and increase profitability. Most firms are storing valuable data, but they are not sure how to maximize its potential since the data is unstructured or not captured. The financial sector was not born into the digital age, so it has had to undergo a long process of conversion that has required behavioural and technological changes. In recent years, big data in finance has enabled significant technological innovations that have enabled convenient, personalized, and secure solutions for the industry. Consequently, big data analytics has transformed not only individual business processes but also the entire financial services sector. The use of machine learning is changing trade and investment. Big data can now take into account political and social trends that may affect the stock market instead of just analysing stock prices. Algorithmic trading relies on big data to execute financial trades much faster than humans. Mathematical models are used to determine the parameters and instructions that determine the timing, price, and quantity of trades. Using machine learning, analysts can compile and evaluate data in real-time to make smarter decisions. Machine learning, fuelled by big data, plays a significant role in fraud detection and prevention. With analytics that interpret buying patterns, the security risks once posed by credit cards have been mitigated. With the advent of secure and valuable credit card information being stolen, banks can instantly block the card and transaction, and notify the customer about the security threat. Accounting and finance professionals can provide better services to their business clients by leveraging advances in data analytics. We provide an overview of the main financial applications of computational and data analytics approaches in this chapter, emphasizing the most recent trends and developments.

The foundations, fundamentals, and applications of advanced data analytics in finance are identified in Section 2 i.e., background of the study. Section 3 presents an overview of sentiment analysis using Deep Learning for Investors. The topic in Section 4 focuses on Python's application in financial data and fin-tech. In Section 5, the analysis of financial data via data mining is examined. In Section 6, Trends in the financial data industry are discussed. Section 7 provides an analysis of Predictive Analytics. Section 8 has an explanation of Algorithms. Section 9 concludes the chapter.

2. Background of the Study

This section provides a brief recap of prior research on the predictive ability of internet data for financial markets and demonstrates how results have improved over time. During the previous decade, the adoption of artificial intelligence (AI) in the economy accelerated significantly (Agrawal et al., 2019; Furman and Seamans, 2019; Brynjolfsson et al., 2021). As a general-purpose technology, AI is said to have a significant direct and indirect impact on numerous industries (Taddy, 2019). The banking sector is one of the industries in which AI has been utilised most extensively (Bredt, 2019; Biallas and O'Neill, 2020). Since the eighties and nineties of the previous century, documents and academic publications have examined and reported on the varied effects of AI on finance and financial markets (e.g., Pau, 1986, Shap, 1987, Pau and Tan, 1996). Recent articles on this topic have elucidated numerous potentials, problems, and consequences. (Baesens et al., 2015) present a comprehensive analysis of a number of learning algorithms and approaches utilizing diverse credit risk assessment data sets. Similar techniques have also been applied in sectors such as profit and behavioural scoring (J. N. Crook, Edelman, & Thomas, 2007; Thomas, 2009) and bankruptcy prediction (Alaka et al., 2018). The complexity of analytical models for credit risk analysis is a key cause for worry, particularly from a supervisory standpoint. Combining comprehensible systems with powerful modelling algorithms has been proposed (Baesens, Setiono, Mues, and Vanthienen, 2003; Florez-Lopez and Ramon-Jeronimo, 2015; Martens, Baesens, Gestel, and Vanthienen, 2007). Artificial intelligence approaches employ automated decision-making processes (Zopounidis, Doumpos, & Niklis, 2018), while decision analysis techniques rely on the domain knowledge and skills of financial decision-makers. The addition of relevant information to financial models improves their clarity and realism. A purely data-driven strategy may be incapable of addressing this issue. Combining this with additional analytical tools (based on optimization or artificial intelligence) (Christodoulakis & Satchell, 2008) can reduce model risk. Most decision analysis methodologies have a constructive stance, which enhances the learning process and provides insight into various facets of financial choice problems and the preferences of the people involved (e.g., managers, investors, policy makers, etc.). They are frequently a component of decision support systems that include data management, analytics, visualizations, and reporting instruments. Classification models, regression models, and clustering models are the three forms of predictive analytics models. Classification models predict which values belong to a particular class, while regression models predict a number. Some of the popular techniques are used in developing the predictive models. In an artificial neural network, a network of artificial neurons is used to simulate the functions of the nervous system, processing input signals and producing outputs. Modelling such complex relationships is extremely challenging, but this model is capable of doing it. Artificial neural networks come in various models, each with a different algorithm. Back propagation is a popular algorithm used for many supervised learning problems. Artificial neural networks are also used for unsupervised problem solving. In unsupervised learning, clustering is used along with artificial neural networks. Nonlinear relationships can be handled by them. Recent studies have examined the cointegration relationship of the stock market amid crisis. Several authors have recognized the comprehensive analysis by applying the Generalized Autoregressive Conditional Heteroskedasticity (GARCH1, 1) Model developed by Bollerslev (1986). Analysis of time series data in the field of behavioural finance has revealed the volatility clustering of the Indian stock market. GARCH models can be used to model and predict asset return volatility over time (Engle & Patton, 2001). Using a volatility forecasting model, (Maloney & Mulherin, 2003) predicted the irrational behaviour of investors. (Fehr & Tyran, 2005) observed that a small group of irrational investors affect the aggregate outcome of the market during crashes a small amount of individual irrationality can lead to large deviations from the aggregate predictions of rational models. It has been found that a small amount of individual irrationality can lead to large deviations from the aggregate predictions of rational models during crashes. (Fehr & Tyran, 2005). Past research on the predictive value of online communication for stock price changes include Bollen, Mao, and Zeng (2010), Zhang and Swanson (2010), Sprenger and Welpe (2010), Oh and Sheng (2011), and Xu et al. (2012). Oh, and Sheng (2011) analysed 72,000 microblog posts from Stocktwits.com over the course of three months to forecast stock price fluctuations. Using sentiment analysis, they discovered that microblog posts foretell future stock price movements. In addition, they briefly analysed the possible return on investments and discovered that basic (as opposed to market-adjusted) returns yield superior outcomes. In 2000, Charalambous et al. developed a financial crisis warning model using a sample of American companies from 1983 to 1994 and explained corporate bankruptcy. Model results indicated that the main option incentive variables (such as corporate performance volatility) play an important role in predicting defaults in the first, second, and third years of bankruptcy. The SVM algorithm was used by Ptak-Chmielewska to develop a bankruptcy prediction model. In comparing three typical corporate distress models with this model, a study found that traditional neural network algorithms are effective at predicting corporate distress based on financial statements. Zhou et al. examined the effectiveness and limitations of the SVM approach with respect to the corporate bankruptcy prediction problem, and concluded that the SVM approach performs better than the BPN neural network approach. The SVM algorithm exhibits higher accuracy and generalization than the BPN algorithm with fewer training sets. Zelenikov et al. presented a two-step classification method (TSCM) in a related enterprise crisis warning model. Some companies were tested using financial ratio indicators, and several indicator trainings models, including economic indicators and microeconomic indicators, achieved an ideal accuracy rate.

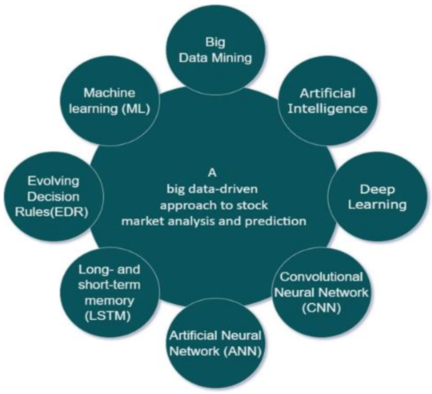

Figure 1. Techniques of Predictive analytics using big data

Research on predictive analytics for big data has gained importance due to its applicability in a variety of fields and sectors. It has penetrated every industry, including healthcare, communications, education, marketing, and business, among others. Frequently, predictive analytics refers to forecasting the result of a given occurrence. Prediction is using statistical approaches to specific input data in order to forecast the result of an event. The word 'predictive analytics' is identical with terms such as ‘machine learning,' 'data mining,' 'deep learning,' AI, CNN, ANN, LSTM, EDR (Figure1) and, more recently, 'data science,' which is currently in widespread usage. There is a fine distinction in their contexts of use, despite the fact that they appear equivalent.

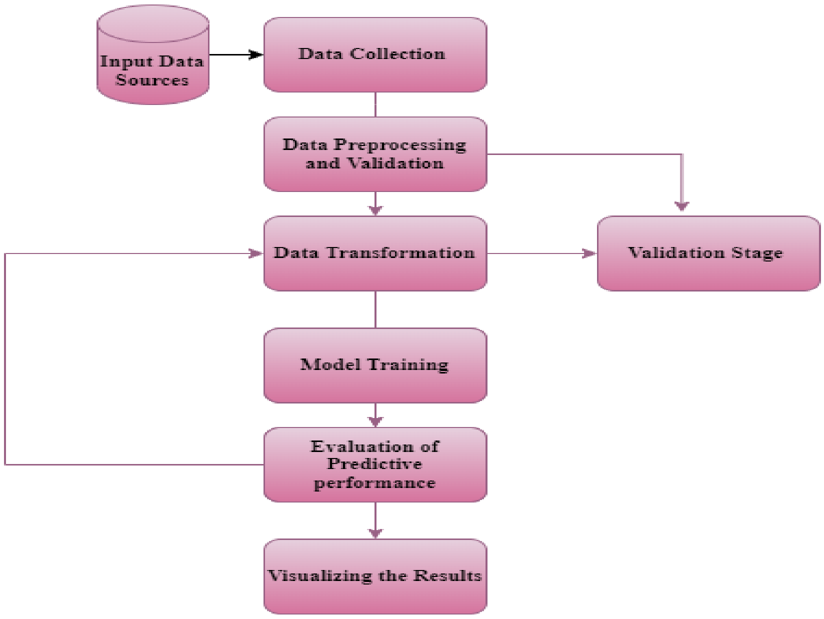

Figure 2. Flowchart for stock market forecasting using Big data analytics

Stock market forecasting and analysis are among the most difficult tasks to do. There are several reasons for this, including market volatility and a range of other dependent and independent variables that impact the value of a certain stock in the market. These variables make it incredibly difficult for any stock market expert to predict the market's rise and fall with great precision. However, with the emergence of big data analytics and its powerful algorithms, contemporary market research and Stock Market Prediction improvements have begun to include such methodologies (figure 2) in evaluating stock market data.

3. Deep Learning for Investors Sentiment Analysis

It has been discovered that Deep Learning algorithms boost classification outcomes in some Big Data domains, such as computer vision and speech recognition. However, Deep Learning sentiment analysis has not been extensively investigated. Alexandrescu et al. presented a model in 2006 in which each word is represented by a vector of features. All of these features utilise a single embedding matrix. Using recursive neural networks (RNNs), Luong et al. (2013) modelled the morphological structures of words and learned morphologically-aware embeddings. Compositional distributional semantic models were utilised by Lazaridou et al. (2013) for phrase learning. Chupala (2013) employed a simple recurrent network (SRN) to discover continuous vector representations of character sequences. In 2011, Socher et al. suggested a semi-supervised technique for Deep Learning employing recursive auto encoders to generate a meaningful search space. Socher et al. (2012) proposed a model of semantic compositionality that is capable of learning vector compositions of arbitrary length. They describe a phrase using word vectors and parsing trees and compute vectors for higher nodes using tensor-based composition methods.

4. Application of Python in Finance and Fin-Tech

In the financial industry, python is used for both quantitative and qualitative analysis. In addition to analysing stock markets, predictions, and machine learning in relation to stocks, financial analysts also use this technology. Python has many libraries for analysing the financial market, such as Pandas, NumPy, spicy, etc. The reason why analysts prefer this language is its ease of coding and ease of creating Python scripts. Python is also capable of integrating with other languages such as Ruby. Consequently, Python for finance is becoming increasingly popular. Now that we have a general understanding of Python, it makes sense to step back a bit and consider briefly the role of technology in finance. In this way, we will be better able to assess the role Python currently plays and, even more importantly, how it will likely play in the financial industry of the future. Most people who make their first steps with Python in a finance context will tackle an algorithmic problem. Scientists might use this technique, for example, when solving differential equations, evaluating integrals, or simply visualizing data. A formal development process, testing, documentation, and deployment are generally not considered at this stage. Nevertheless, this is the stage when people really fall in love with Python. Possibly one of the major reasons is that Python syntax is quite similar to the mathematical syntax used to describe scientific problems or financial algorithms. The role of technology in finance can be summarized in the following ways:

- Technology costs in the finance industry.
- Using technology to enable new business models.
- Access to technology and talent in the finance industry.
- Growing speed, frequency, and data volume.
- Increasing use of real-time analytics.

5. Analysing Financial Data Using Data Mining

Data Mining is a field which executes advanced examination of data and it utilizes mechanisms and methods from statistics and machine learning. Advanced analytics and business intelligence applications make use of the information that is generated by them through the analysis of verified data. A financial analysis of data is crucial when determining whether a business is stable and profitable enough to make a capital investment. Financial analysts analyse balance sheets, cash flow statements, and income statements. There are several ways in which data mining in finance can be useful.

- Money laundering is the conversion of black money into white money. Today, data mining approaches have been developed in such a way that they include appropriate techniques for identifying money laundering. In the methodology of data mining, bank clients can identify or verify the anti-money laundering effect.
- Every bank is in the business of distributing loans. It also tests data pertaining to the size of features used in the loan prediction system. The data mining process helps in managing all the vital data and their large databases with the help of its models.

- Marketing and data mining work together to target specific markets; both support and decide market decisions. Using data mining, it helps retain profits, margins, etc., and determine which products are best for different kinds of customers.

6. Trends in the Financial Data Industry

Following are a few trends that the financial data industry is following to improve customer service.

6.1. Implementing AI, ML, and Data Analytics

AI, machine learning, IoT, and analytics are being used by financial institutions to understand customer needs and create business strategies accordingly. ML and AI provide risk assessment models that synthesize large volumes of data, identify critical market and consumer patterns, and predict impending risks. AI can reduce underwriting costs and delays, allowing lenders to increase profits per loan. In the future, AI and ML-based technologies will continue to serve the financial data industry and offer unprecedented opportunities.

A time series is a collection of data, in this case the price of a stock that is indexed over time. Hourly, daily, monthly, or even by the minute, this period of time could be divided. By accumulating price data using machine learning and/or deep learning models, a time series model is created. The data must be analysed and then fitted to the model. Using this method, future stock prices can be predicted over a set period of time. In machine learning and data science, a classification model is a type of modelling. These models are provided with data points, and then they attempt to classify or predict what is represented in the data.

Using financial data, such as the P/E ratio, total debt, volume, etc., a machine learning model can analyse the stock market or stocks in general and determine if they are a good investment. Models can be used to determine whether now is the right time to sell, hold, or buy a stock based on the financial information we provide.

6.2. Digital Finance

In digital finance, credit products, payments, and other financial services are readily available to customers and companies. New users who are interested in digital financial services have been attracted to the online platforms as a result of affordable smart phones and easy access to the internet. The API-based ecosystem has led to organizations completing KYC procedures digitally. Banking cards, USSD, AEPS, and other digital payment systems are attracting more customers to digital financial services. The financial data industry is increasingly embracing digital services to meet the needs of customers.

6.3. Cyber Security

Cyber-attacks have significantly increased due to the increasing use of online technology and cloud computing. Protecting the huge amount of data gathered by companies requires strict online security protocols. The use of artificial intelligence and modern technology can play an important role in securing that data and reducing cyber threats by monitoring and regulating different types of cyber-attacks.

6.4. Personalized Services

In banking and other financial services, personalization engages several benefits such as improving conversion and engagement rates, improving customer loyalty and retention, and enhancing the customer experience.

7. Predictive Analytics

The process of using computer models to predict future events is known as predictive analytics. Using statistics, historical data, and computer modeling, predictive analytics attempts to predict an outcome. Predictive analytics is especially useful for banks and financial institutions in forecasting market movements and assessing risk. Artificial intelligence, data mining, and machine learning are used by sophisticated programs to analyze enormous amounts of information. A model tries to predict what is likely to happen next, given current conditions, through the use of those resources. In either case, institutions rely on a wide variety of data sources and machine learning. They may also pull demographic data and other details from external databases in addition to your transaction history. Data analytics can assist customers with managing their accounts and completing banking tasks more efficiently in an online banking environment.

7.1 Reporting

The Basic version of our analytics solution focuses on storing and reporting simple univariate and bivariate data. Banking examples include suspicious activity reporting and account verification.

7.2 Descriptive Analytics

Developing actionable insights based on complex and multi-variate data.

In the banking industry, examples include customer segmentation and profitability, campaign analytics, and parametric Value at Risk calculations.

7.3 Predictive Analytics

Predictive analytics is to predict the likely future outcome of events using structured and unstructured data from different sources. Banks typically use pattern recognition and machine learning to predict fraud, generate risk alerts at the customer/product/geographical level, design personalized and next-best offers, and conduct trigger-based cross-selling campaigns.

7.4 Prescriptive Analytics

Big data from a variety of sources and simulations in various business scenarios are used to prescribe action items for addressing future events. For example, behavioural PD1, LGD2, and EAD3 modelling, channel mix modelling, real-time offer models, next-best-offer models, and stress testing for mandated and custom scenarios are typical banking examples.

Banks also benefit from reducing risk and reducing costs using data analytics. You're probably familiar with predictive analytics, which utilizes data to predict your creditworthiness. FICO credit scores, for instance, use statistical analysis to predict your behaviour, including whether you are likely to miss payments. A portion of your score is based on how borrowers similar to you have performed in the past. Additionally, there is a critical field in which predictive analytics is indispensable for the financial sector: risk analysis. Credit scoring and determining the suitability of clients are often determined by models generated by predictive analytics. Analyzing key data points and comparing similarities among policyholders help in the decision-making process.

8. Algorithms

In data science, algorithms are extensively used. The essence of an algorithm is a set of rules used to perform a certain task. Most of us are familiar with algorithms that can be used to purchase or sell stocks. An algorithm sets rules for things like when to buy a stock or when to sell a stock.

As an example, an algorithm could be set up to purchase a stock once it drops by 8% over the course of the day or to sell the stock if it loses 10% of its value compared to when it was first bought. Algorithms work without human interference. These programs are sometimes called bots. Their decisions are based on logic and are devoid of emotion.

9. Conclusion

AI and predictive analytics are not only integral parts of the banking sector, but also of the financial industry as a whole. The knowledge about technology and what it has made possible has increased customer expectations. Any serious contender in the financial world today is unlikely to survive without a well-designed AI and predictive analytics strategy in place. In order to acquire new customers, banks can use these features to automatically group leads based on their interests. Artificial intelligence-enhanced systems can develop personalized and targeted marketing campaigns that have high success rates using analytical tools like response modelling. If you believe the numbers, technology is growing exponentially, and today we are processing vast amounts of data. According to a recent report, global data will grow by 61% by 2025 to 175 zettabytes. These are staggering numbers! Data Analytics and Machine Learning are helping traders become more efficient today. As a result, they complement each other and act as catalysts for identifying opportunities and reducing trading costs. The use of Financial Data Analytics enhances banks' marketing capabilities. Analytics are extremely valuable to functional areas like Risk, Compliance, Fraud, NPA monitoring, and Calculating Value at Risk to ensure optimal performance and make timely decisions.

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