Journal of Economic and Financial Sciences
ISSN: (Online) 2312-2803, (Print) 1995-7076

Time series forecasting in the artificial intelligence milieu

Author:
Ilse Botha[1]

Affiliation:
[1]Department of Accountancy, School of Accounting, College of Business and Economics, University of Johannesburg, Johannesburg, South Africa

Corresponding author:
Ilse Botha,
ilseb@uj.ac.za

How to cite this article:
Botha, I., 2022, 'Time series forecasting in the artificial intelligence milieu', *Journal of Economic and Financial Sciences* 15(1), a836. https://doi.org/10.4102/jef.v15i1.836

The Fourth Industrial Revolution brought about a new wave of terms, such as data science, artificial intelligence (AI) and data mining, with time series–related terms such as predictive analytics, machine learning (supervised and unsupervised) and structured and unstructured data.

Data science is an interdisciplinary field to extract insight from data, and it is mainly concerned with prediction, summation, data manipulation and visualisation (Varian 2014). Data mining can be considered a superset of many different methods to analyse structured or unstructured data. Data mining applies methods to identify previously unknown patterns from data. Data mining also includes data storage and data manipulation (Mahalakshmi, Sridevi & Rajaram 2016) (see Figure 1).

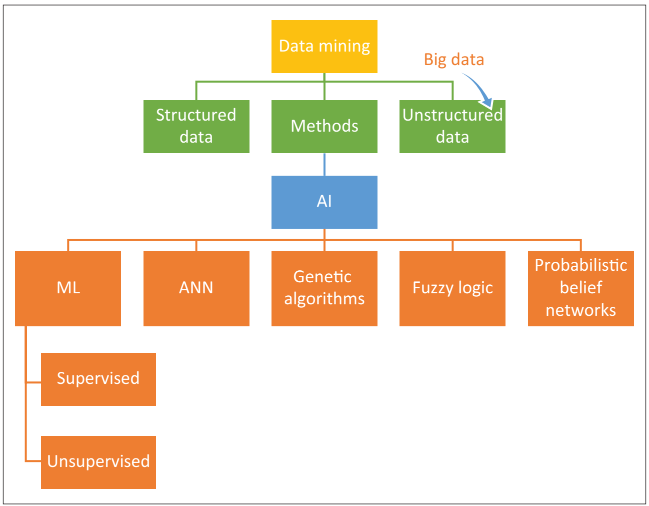
Artificial intelligence can be defined as a revolutionary technology that learns on its own from analysing and discovering patterns in large amounts of data. It consists of a group of data-driven methodologies, and the components of AI can be classified into artificial neural networks, genetic algorithms, fuzzy logic, probabilistic belief networks and machine learning (ML) (Binner, Kendall & Chen 2004).

Machine learning is a component of AI and is closely related to data mining, but it is primarily focused on predictions, while data mining is concerned with the summation of data and identifying patterns (Varian 2014). Machine learning is central to many approaches to AI and is primarily analytical or statistical. Basic ML is predictive analytics using supervised learning based on data for which the values of the outcome variable are known; a typical example here is the regression-based ML model. Machine learning also includes model types like artificial neural networks and deep learning (DL), which are also statistical in nature but are categorised as unsupervised learning (Davenport 2018) (see Figure 2). These methods identify patterns from large amounts of data and automatically learn from these patterns. Artificial neural networks and DL are the dominant ML techniques in this area (Krollner, Vanstone & Finnie 2010). Time series forecasting is part of ML, and it has evolved over time from simple linear methods to nonlinear methods and complex DL methods, showing a shift from supervised to unsupervised learning.

Artificial intelligence has developed rapidly over the last decade, including, *inter alia*, autonomous vehicles, intelligent robots, image and speech recognition, automatic translation and gaming, to name a few. Artificial intelligence has also been applied to forecasting using ML, and especially artificial neural networks (ANN), to improve time series forecasts (Makridakis, Spiliotis & Assimakopoulos 2018). Artificial intelligence has caused a paradigm shift in forecasting, moving from supervised to unsupervised learning because of Big Data. This means there was a shift from computer-assisted model- and assumption-based to data-driven and fully automated forecasting (Faloutsos et al. 2018).

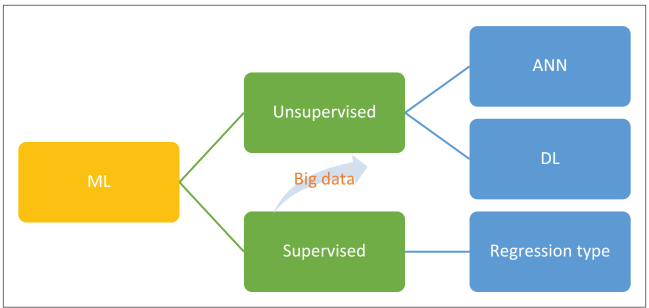
The first significant academic references to Big Data in computer science were by Weiss and Indurkhya (1998) in computer science and Diebold (2000) in statistics and econometrics (Diebold 2012). The reference to Big Data in those first citations pertained to bigger data sets than normal, but since then it has evolved to include a range of characteristics (Leary 2013). Big Data spans and differs across fields such as computer science, statistics and econometrics and has several broad forms, such as photographic, binary and numerical. Numerical data have three main forms, namely a cross-section of observations at a single point in time, a time series of observations and a panel (Doornik & Hendry 2015).

Big Data can therefore be defined as a complex heterogeneous data set including huge-volume, high-velocity and high-variety data with the potential value that can be processed electronically



AI, artificial intelligence; ANN, artificial neural networks; ML, machine learning.

FIGURE 1: Data science.



ML, machine learning; ANN, artificial neural networks; DL, deep learning.

FIGURE 2: Machine learning within artificial intelligence.

to inform decision-making (Rezaee, Dorestani & Aliabadi 2018). The Big Data revolution has transformed the modern world and is an important data mining topic currently. Data mining methods are also key in modelling the complex relationships inherent in Big Data (Hassani & Silva 2015; Mahalakshmi et al. 2016). This brings about an opportunity, as Big Data forecasting has the ability to improve organisational performance, which can mitigate risk.

Even though traditional forecasting tools cannot handle the unstructured nature and size of these data sets, there is a strong connection between Big Data and predictive analytics (Hassani & Silva 2015). It is important to structure unstructured data and reduce the dimensionality, in order to capture the dynamic changes. This is a common challenge in Big Data research that traditional econometric methods can address (Einav & Levin 2014). Factor modelling, a statistical dimension reduction technique, is a possible answer to this challenge and is a popular technique for Big Data forecasting. Dynamic factor models (DFMs), an extension of factor models, are used extensively in Big Data forecasting; other econometric extensions are factor-augmented error correction models (FECM), factor-augmented vector autoregression (FAVAR), the multivariate factor-augmented Bayesian shrinkage model, principle component analysis (PCA), independent PCA (ICA), sparse PCA (SPCA) and Kalman filtering for large vector autoregression (VAR) and DFMs. All these factor estimation methods have been developed in light of Big Data forecasting (Hassani & Silva 2015). Artificial neural networks and Bayesian models are also popular (Hassani & Silva 2015; Stock & Watson 2017). Furthermore, hybrid forecasting methods with dimension reduction for specification and estimation of factors with various types of ML and shrinkage methods are showing potential in Big Data forecasting (Kim & Swanson 2018).

The Big Data revolution has transformed the modern world and is an important data mining topic which spans across fields. Data mining forms the basis for AI and ML. Although ML is a component of AI, these three notions are intertwined and work together to answer questions, prove hypotheses and give insight into the behaviour of time series. An interdependent relationship exists by which a combination of methods can be used to produce more accurate results. Because of this data revolution, challenges and opportunities exist for research, education, current research fields and new research fields.

References

Binner, J.M., Kendall, G. & Chen, S., 2004, *Applications of Aritificial intelligence in finance and economics*, Advances in Econometrics, Volume 19, Elsevier.

Davenport, T.H., 2018, 'From analytics to artificial intelligence', *Journal of Business Analytics* 1(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

Diebold, F.X., 2012, *On the origin(s) and development of the term 'big data' (September 21, 2012)*, PIER Working Paper No. 12-037, viewed from https://ssrn.com/abstract=2152421

Doornik, J.A. & Hendry, D.F., 2015, 'Statistical model selection with "Big Data"', *Cogent Economics & Finance* 3(1), 1–15. https://doi.org/10.1080/23322039.2015.1045216

Einav, L. & Levin, J., 2014, 'The data revolution and economic analysis', *Innovation Policy and the Economy* 14, 1–24. https://doi.org/10.1086/674019

Faloutsos, C., Gasthaus, J., Januschowski, T. & Wang, Y., 2018, 'Forecasting big time series', *Proceedings of the VLDB Endowment* 11(12), 2102–2105. https://doi.org/10.14778/3229863.3229878

Hassani, H. & Silva, E.S., 2015, 'Forecasting with Big Data: A review', *Annals of Data Science* 2(1), 5–19. https://doi.org/10.1007/s40745-015-0029-9

Kim, H.H. & Swanson, N.R., 2018, 'Mining Big Data using Parsimonious factor, machine learning, variable selection and shrinkage methods', *International Journal of Forecasting* 34(2), 339–354. https://doi.org/10.1016/j.ijforecast.2016.02.012

Krollner, B., Vanstone, B. & Finnie, G., 2010, 'Financial time series forecasting with machine learning techniques: A survey', in *Proceedings of the 18th European Symposium on Artificial Neural Networks (ESANN 2010): Computational Intelligence and Machine Learning*, pp. 25–30.

Leary, D.E.O., 2013, '"Big Data", the "Internet of Things" and the "Internet of Signs"', *Intelligent Systems in Accounting, Finance and Management* 20(2), 53–65. https://doi.org/10.1002/isaf.1336

Mahalakshmi, G., Sridevi, S. & Rajaram, S., 2016, 'A survey on forecasting of time series data', in *2016 International Conference on Computing Technologies and Intelligent Data Engineering, ICCTIDE 2016*, Institute of Electrical and Electronics Engineers Inc, Kovilpatti, India, January 2016.

Makridakis, S., Spiliotis, E. & Assimakopoulos, V., 2018, 'Statistical and machine learning forecasting methods: Concerns and ways forward', *PLoS One* 13(3), 1–26. https://doi.org/10.1371/journal.pone.0194889

Rezaee, Z., Dorestani, A. & Aliabadi, S., 2018, 'Application of time series analyses in Big Data: Practical, research, and education implications', *Social Science Research Network* 15(1), 183–197. https://doi.org/10.2139/ssrn.3148726

Stock, J.H. & Watson, M.W., 2017, 'Twenty years of time series econometrics in ten pictures', *Journal of Economic Perspectives* 31(2), 59–86. https://doi.org/10.1257/jep.31.2.59

Varian, H.R., 2014, 'Big Data: New tricks for econometrics', *Journal of Economic Perspectives* 28(2), 3–28. https://doi.org/10.1257/jep.28.2.3

Weiss, S.M. & Indurkhya, N., 1998, 'Predictive data mininga a practical guide', *Morgan Kaufmann*.