Universidad del Rosario

THE USE OF MACHINE LEARNING IN VOLATILITY: A REVIEW USING K-MEANS

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Glosary

Machine learning: “(ML) studies algorithms which can learn from data to gain knowledge from experience and to make decisions and predictions” (Holzinger, 2016, p. 1).

K- Means: “algorithm is the most commonly used simple clustering method. For a large number of high dimensional numerical data, it provides an efficient method for classifying similar data into the same cluster” (Yu et al., 2018, p. 747).

Support Vector Machine: “(SVM) is a machine learning method based on statistical learning theory. It has a lot of advantages, such as solid theoretical foundation, global optimization, the sparsity of the solution, nonlinear and generalization (Ding et al., 2017, p. 969).

Deep learning: “ is a branch of machine learning that tries to model high-level abstractions of data using multiple layers of neurons consisting of complex structures or non-liner transformations” (Hao et al., 2016, p. 417).

Neuronal Networks: “represent a class of functions for the efficient identification and forecasting of dynamical systems”(Schaefer & Zimmermann, 2006, p. 632).

Big Data: “ refers to the fact that data today is often too large and heterogeneous and changes too quickly to be stored, processed, and transformed into value by previous technologies” (Rueping, 2015, p. 794).

Genetic Algorithms: “(GAs) are a class of evolutionary algorithms inspired by Darwinian natural selection. They are popular heuristic optimisation methods based on simulated genetic mechanisms, i.e., mutation, crossover, etc. and population dynamical processes such as reproduction, selection, etc." (Lahoz-Beltra, 2016).

Artificial Inteligence: **"**aims to reach any area of human activities to reduce the efforts of people related to boring daily jobs. AI is defined as the capacity of a computer to perform tasks commonly associated with human beings" (Scotti, 2020, p. 27).

Abstract.

Recently, the use of machine learning (ML) in scientific disciplines has experienced an unprecedented increase. This, as a consequence of the advances in computing that have allowed the obtaining of satisfactory results at moderate computational costs. Finance has not been an exception. Several works have been published in recent years using ML techniques. However, one of the topics with the least number of developed papers in this context is volatility. This panorama has changed. Data obtained from the Web of Science database show that for the years 2001 and 2010 there were 2 and 1 papers associated with this topic, respectively. Surprisingly, between 2019 and 2021, 37 manuscripts have been published related to this theme. The purpose of this work is to review the Works related to the applications of ML in volatility. For this, a classification of the main proposals on this topic is proposed, accompanied by a statistical and bibliometric analysis in which novel techniques such as K-means are used. The results are suggestive. Although most papers focus on volatility prediction through neural networks and support vector machine, there is a lack of works related to volatility transmission, calibration of volatility surfaces, project finance and corporate finance.

Keywords: Bibliometric analysis; financial literatura; K-means; Machine learning; Volatility.

JEL Cod: C00; G00; G53; C63; C45

Resúmen.

Recientemente, el uso de técnicas de machine learning (ML) en diferentes disciplinas científicas ha experimentado un aumento sin precedentes. Esto, como consecuencia de los avances en computación que han permitido obtener resultados satisfactorios a costos computacionales moderados. El área de las finanzas no ha sido una excepción. En los últimos años, se han publicado numerosos trabajos utilizando técnicas de ML. Sin embargo, uno de los temas con menor número de artículos desarrollados en este contexto, es el de la volatilidad. Este panorama ha cambiado. Datos obtenidos de la base Web of Science muestran que para los años 2001 y 2010 había 2 y 1 artículos asociados con este tema, respectivamente. Sorprendentemente, entre 2019 y 2021 se han publicado 37 manuscritos relacionados con esta temática. El propósito de este artículo, es revisar los trabajos relacionados con las aplicaciones de ML en volatilidad. Para ello, se propone una clasificación de las principales propuestas sobre este tema, acompañada de un análisis estadístico y bibliométrico en el que se utilizan técnicas novedosas como K-means. Los resultados son sugerentes. Aunque la mayoría de los artículos se centran en la predicción de la volatilidad a través de redes neuronales y support vector machines, se evidencia una ausencia de artículos relacionados con transmisión de la volatilidad, calibración de superficies de volatilidad, financiación de proyectos y finanzas corporativas.

Palabras clave: Análisis bibliométrico; K-means; Literatura financiera; Machine learning; Volatilidad.

JEL Cod: C00; G00; G53; C63; C45.

Resumo.

Recentemente, o uso de técnicas de aprendizado de máquina (AM) em diferentes disciplinas científicas tem experimentado um aumento sem precedentes. Isso, em conseqüência dos avanços na computação que têm permitido obter resultados satisfatórios com custos computacionais moderados. A área de finanças não foi exceção. Nos últimos anos, vários trabalhos foram publicados usando técnicas de ML. No entanto, um dos tópicos com menor número de artigos desenvolvidos neste contexto é o da volatilidade. Este panorama mudou. Os dados obtidos na base de dados Web of Science mostram que para os anos de 2001 e 2010 houve 2 e 1 artigos associados a este tema, respectivamente. Surpreendentemente, entre 2019 e 2021, 37 manuscritos relacionados a este tópico foram publicados. O objetivo deste artigo é revisar os trabalhos relacionados às aplicações de ML em volatilidade. Para tanto, é proposta uma classificação das principais propostas sobre o tema, acompanhada de uma análise estatística e bibliométrica na qual são utilizadas novas técnicas como o K-means. Os resultados são sugestivos. Embora a maioria dos artigos enfoque a previsão da volatilidade por meio de redes neurais e máquinas de vetores de suporte, há uma ausência de artigos relacionados à transmissão da volatilidade, calibração de superfícies de volatilidade, financiamento de projetos e finanças corporativas.

Palabras chave: Análise bibliométrica; K-means; Literatura financeira; Machine learning; Volatilidade;

JEL Cod: C00; G00; G53; C63; C45.

1. Introduction.

In a panorama of uncertainty and a high degree of risk in financial markets, the study of the variables that affect their dynamics is pertinent for academics and practitioners. Two of the variables that are decisive in investment analysis correspond to returns and risk. Although in the last decades, finance as a research field, has made important advances in the understanding of these two elements, there is still a long way to go to be able to decipher the logic under which markets operate at a global level.

Recently, one of the most important innovations in the study of finance corresponds to the use of ML. "Machine learning (ML) refers to a class of data science models that can learn from the data and improve their performance over time. The roots of ML goes back to the scientific community's interest in 1950s and 1960s in replicating human leaning through computer programs" (Ghodussi et al. 2019, p. 709). Particularly, in the case of finance as a research area, "Machine learning (…) sits at the intersection of a number of emergent and established disciplines including pattern recognition, financial econometrics, statistical computing, probabilistic programming, and dynamic programming" (Dixon et al. 2020, p. vii).

This new approach to the study of finance has gained relevance in recent years, mainly for two reasons. Firstly, recent computational advances and the spread of statistical packages such as R and Phython have allowed the wide use and estimation of previously unviable models at low costs and with realiable accurate results. Secondly, the relative abundance of financial data allows the use of machine learning and big data techniques in a more accessible way than in other fields of economics and management. In consequence, the number of works related to ML in finance has experienced a remarkable increase in the last years. According to data taken from the web of science database, for 2001 there was an article related to the use of machine learning in finance.

for the year 2010 this figure was maintained, while for the year 2020, the number of articles related to this topic exceeded thirty.

The use of machine learning techniques in finance has covered a wide variety of topics. For instance, applications related to price prediction, risk management and trading strategies have grown exponentially in academic publications in recent years. However, one of the topics that received the least attention until a couple of years ago corresponds to the study of volatility. This fact is striking, considering that “Modeling volatility is both challenging and promising. The challenge is to include the concept of second-moment clustering in a standard ML model. The advantage is that volatility is not subject to market efficiency effect (i.e., volatility will not disappear as a result of prediction)” (Ghodussi et al. 2019, p. 720). This is to say that although there is greater potential in the development of models dedicated to predicting volatility, much of the financial literature has focused on predicting returns.

This situation has changed!. According to data taken from the web of science database, between 2001 and 2017 the number of articles related to the use of machine learning in the study of volatility was 38. Only taking into account the works published on this topic between 2018 and in 2021 this figure increased to 42. In other words, in a little more than 3 years, more works were published than in the previous 15 years. These figures show a clear trend for the use of machine learning techniques in volatility, which can convert this subject into a "hot topic" in the coming years.

The aim of this article is to perform a literature review about this topic, accompanied by a bibliometric analysis in order to identify trends in the scientific production on the use of machine learning in volatility and recognizing possible research opportunities derived from this exercise. Consequently, a classification of the works published on this theme is proposed. This classification is complemented with a statistical analysis of the temporal evolution of scientific production in this field, the production by authors, countries, collaboration between countries, and the use of the K-means methodology to define the conceptual structure of this novel research area. The results are promising. Although a large majority of studies focus on volatility forecasting through neural network techniques, deep learning and support vector machines (i.e. Tang et al. 2009; Chen et al. 2010; Pradeepkumar & Ravi, 2017; Liu, 2019; Gon et al. 2019), there is a smaller number of publications associated with proposals for volatility calibration (Zeng & Klabjan; 2019; Horvath et al. 2021) , options valuation (Amornwattana et al. 2007; Fadda, 2020; Jerbi, & Chaabene, 2020) , projects valuation (Jang et al. 2021) and some theoretical works related to stochastic processes and their use in volatility issues (Peng & Liu 2011).

The remainder of this paper is structured as follows. Section 1 presents the methdology adopted to perform this exercise. Subsequently, in section 2 the main obtained results are shown. Finally, the principal conclusions are presented.

2. Methodology.

The developed exercise was carried out through two stages. In the first stage, corresponding to the literature review, data was collected from the web of science database. At this step, each article was reviewed in order to propose a classification of the works that made use of machine learning techniques in volatility according to the topic, the machine learning technique and the type of assets that were studied. In the second stage, a bibliometric analysis was conducted. In this stage, the trends in scientific production were identified by author, country, journals and collaborations between countries. Finally, a conceptual structure was defined through the K-means technique. The steps carried out are detailed below.

Step 1. Collecting data

The first step corresponded to obtaining the articles that were related to the use of machine learning techniques in volatility. For this, a search was made in the aforementioned database by the use of different terms related to machine learning models, together with the term volatility (table 1). Using this procedure, 86 articles were identified and downloaded for the period 2001-2021.

Table 1. Terms used to web of science search

Term
Machine learning volatility
Artificial intelligence volatility
Neural networks volatility
Big data volatility
Decision trees volatility
Support vector machine volatility
Supervised learning volatility
deep learning volatility
unsupervised learning volatility
ensemble method volatility
genetic algorithm volatility
particle swarm optimization volatility

Source: Self created.

Step 2. Literature review.

The objective of the second step was to propose a classification of the articles found in order to make a literature review of them. In this case, an analysis of the documents was made one by one, placing special emphasis on the type of machine learning technique used, the task that was developed in the paper (ie volatility forecast, option valuation), the obtained results and the financial asset class used in the document. Based on the above, a classification of the founded proposals was elaborated. This classification is detailed in the results section.

Step 3. Statistical analysis.

In this step, a statistical analysis was conducted on the founded results. For this goal, the data.table, dplyr and bibliometrix packages available in the R software were employed. Through the used tools, the trend in the number of products associated with the studied subject was identified. Moreover, the main authors, the authors' nationality, the journals in which the developed articles were published, the authors' countries and the collaborations between authors of different nationalities were recognized and analyzed.

Step 4. Conceptual structure using K-means.

In this stage, an analysis of the founded documents was conducted through the machine learning model known as K-means. This method is identified as a clustering technique to "address the machine learning task of clustering, which involves finding natural groupings of data" (Lantz, 2019, p. 271). In this type of procedure, a specific result associated to the data is not required, as is the case in other machine learning techniques. The main objective of K-means is to establish groups from data that do not have a particular label but have similar characteristics which can be exploited to conform a defined number of groups.

"The k-means algorithm involves assigning each of the n examples to one of the k clusters, where k is a number that has been defined ahead of time. The goal is to minimize the differences within each cluster and maximize the differences between clusters" (Lantz, 2019, p. 272). Each cluster is defined taking into consideration the similarity between the data that is used to perform the analysis.

In the particular of this paper, we employed the K-means technique by the use of the Bibliometrix package in R. In this case, the analysis aims to define the clusters according to co-ocurrencies of words founded in the set of employed documents identified in step 1. This task is carried out by a routine of natural language processing in which the words contained in the titles and the abstracts of the analyzed papers are extracted to conform the clusters by the K-means technique. This exercise results in groups of documents with similarities in the used concepts, assets and machine learning techniques. The results derived from this step are presented in the results section. For more details about the K-means model and the Bibliometrix package, please refer to Lantz (2019) and Aria and Cuccurrullo (2017).

3. Results.

3.1. Literature review

By the development of the methodology described in the previous section, the classification of the analyzed documents is proposed based on the task on which they are focused.

3.1.1. Forecast Volatility

The main application of machine learning methodologies in volatility corresponds to volatility forecasting. In this line, there is a fairly marked trend towards the use of neural network, deep learning and support vector machine methodologies. This last technique is the one that has received the most attention in recent years. Although most of the articles focus on the use of stock indices, there are also some proposals that use energy assets or individual stocks. Most of the articles make use of data on a daily basis, although some exercises employ intraday information.

In this regard, 62 of the 86 analyzed articles focus on this type of task. In this context, the most applied machine learning methodology corresponds to the use of neural networks. The foregoing, as a consequence of the relative ease in the use of this type of method and the evidence of offering satisfactory results in other types of prediction exercises. Most of the works in this group focus on the use of daily data employing stock indexes from the main financial markets in U.S.A. and Asia. For example, a large part of the body literature analyzes the volatility prediction for U.S.A. markets (Liu, 2019; Wang et al. 2019; Petnehasi & Gail, 2019; Ramos Pérez et al. 2019; Kaushik et al. 2019; Bucci, 20202; Jia & Yang, 2021; Wang et al. 2021; Chkili & Hamdi, 2021).

In a similar line, papers that made use of similar techniques for stock market indexes from countries different to U.S.A. were identified. In this group, are worth mentioning applications to the turkish market, european markets, taiwanese market, chinese market, and the case of a few latín american countries as Chile, Brazil y México (Slim, 2004; Tseng et al. 2008; Mo & Wang, 2013; Sermpinis et al. 2013; Kristjanpoller et al. 2014).

A third group of proposales have made use of neural networks to forecast volatility for other type of assets. This is the case of the use of these techniques to predict volatility in exchange rates (Liu & Liu, 2006; Pradeepkumar & Ravi, 2017; Baffour et al. 2019; Liao et al. 2020), Bitcoin (Seo & Kim, 2020; Othman et al. 2020), oil price (Bildirici & Ersin 2015; Kristjanpoller & Minutolo, 2016; Al-Fattah, 2019) and individual stocks for different markets (Calôba et al. 2001; Fong et al. 2005; Wang et al. 2012; Kristjanpoller & Minutolo, 2015; Kaushik et al. 2019).

In a different approach, articles that dealt with the modeling and forecasting of volatility for high frequency data and the analysis of implied and realized volatility were identified (Hamid & Iqbal, 2004; Kai et al. 2013; Vortelinos, 2017; Kim & Baek, 2018; Zhai et al. 2020). In these group of proposals, most of the excercises use stock market indexes from U.S.A. and Asia. Other documents focused on the volatility analysis for decisión making and asset allocation (Kim & Enke; 2018; Weerasingha et al. 2021)

A second strand in the literature, is related to works in which volatility is forecasted by the use of hybrid models. In this case, the forecast of the interest variable is made through the ensemble of the outcomes obtained from at least two individual models. In this group, it is relevant to highlight the exercises developed by Ou & Wang (2013), Jung & Choi (2021), Liu & Fu (2016) and Hu et al. (2020). In theses articles, authors made use of hybrid models to forecast volatility related to copper Price, Chinese interbank offered rate, Nasdaq composite index and Exchange rates. The employed methodologies employed combinations of Support vector machine, Chaotic genetic algorithm, extreme learning machine, deep learning, and neural networks.

Another group of proposals employ support vector machine techniques to forecast volatility. In this type of exercises, most of the works use this technique to forecast volatility for daily and intraday data of U.S.A., European, Asian markets and Exchange rates. (Tang et al. 2009; Chen et al. 2010; Ou & Wang, 2012; Wang et al. 2013; Santamaria-Bonfil et al. 2015; Chu & Zhang, 2017; Gong et al. 2019; Yang et al. 2020).

A recent tren in the literature associated with volatility forecasting through machine learning techniques corresponds to the use of Deep learning. In simple terms, Deep learning can be understood as an extensión of neural networks with a number of hidden layers greater than one. In this case, most of the analyzed works are published between 2020 and 2021. Eventough most of the articles focus on market indexes, it seems that this type of techniques offer a higher degree of accuracy than the obtained from the previously exposed techniques. In this group it is worthwhile to mentions the works of Kyoung-Sook & Hongjoong, K. I. M.(2019), Kandem et al. (2020); Lei et al. (2021a), Lei et al. (2021b), Li et al. (2021).

Finally, there are a reduced number of proposals which made use of machine learning techniques different from the previously presented. Theses articles include the use of particle swarm optimization, adaptive heterogeneous autoregressive models, random forests and principal component analysis (Tung & Quek, 2011; Hung, 2011; Wei, 2012; Qu & Ji, 2014; Hung, 2015; Qu & Ji, 2016; Jobejarkol et al. 2018; Kristjanpoller & Minutolo; 2018; Ewees et al. 2020; Gupta & Pierdzioch, 2021). In a total of 86 analyzed articles, this group contributes with 9 publications. Although this number is reduced, this fact is suggestive in terms of looking for new research proposals that exploit the benefits of these models in volatility prediction exercises.

3.1.2. Volatility calibration and Surface construction.

Another topic in which machine learning techniques have been applied to volatility analysis is the volatility calibration and the construction of volatility surfaces. Despite the fact that the Black-Scholes-Merton proposal has received great acceptance by the financial industry for the valuation of options, one of its main limitations corresponds to the fact that it is assumed that volatility is constant for different strike prices with a defined time of maturity. Empirically, it has been shown that in reality the graph that relates these two variables has a smile shape. Although different methods have been proposed in the financial literature for the calibration of volatility and the subsequent construction of volatility surfaces, this exercise presents considerable computational challenges. Recently, different proposals have been presented in which machine learning techniques are used to fulfill this task. These works are concentrated between the years 2020 and 2021 and make use of neural networks, deep learning and support vector regression using options on the S&P500 to carry out this exercise. Zeng & Klabjan (2019), Cao et al. (2020) Stone et al. (2020) and Horvarth et al. (2021) have developed interesting works regarding this issue.

3.1.3. Derivatives pricing.

One of the most interesting topics in finance corresponds to derivatives valuation. Despite the fact that there are numerous proposals in the literature to value different types of derivative contracts, some authors have made use of machine learning techniques to develop this task. Particularly, In this regard, Amornwattana et al. (2007) proposed the use of neural networks to Price call options. Liu et al. (2019) employed neural networks to price options and compute implied volatilities. Fadda (2020) made use of modular neural networks to value options and Jarbi and Chaabene (2020) proposed a stochastic volatility model which employed neural networks to price options.

3.1.4. Other applications.

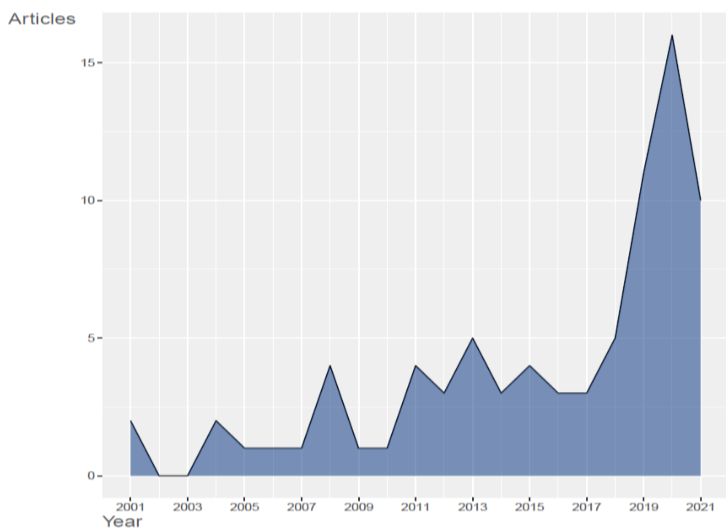
From the conducted analysis, we found a number of papers in which ML techniques are used in volatility topics different from the previously studied. This documents do not correspond to clear trends in this area literature, but rather to isolated cases of applications in certain issues related to volatility. In this regard, Dash and Kajiji (2008), used generalized neural networks to analyze volatility spillovers in the european market of bonds. Jang et al. (2021) employed neural networks to analyze the risk leve of a set of projects. Peng and Liu (2011), studied the pth moment stability of stochastic Grossberg-Hopfield neural networks. Besides the mentioned articles, there are other applications in which ML is used to forecast direction volatility, predict requirement change volatility, analyze the profitability of a trading strategy and other applications (Tino et al. 2001; Bekiros and Georgoutsos, 2008; Medeiros et al. 2008; Xia et al. 2011; Zhu et al. 2013; Ge et al. 2019; Wang and Liu, 2020; Patnaik, 2020; Vrontos et al. 2021; Hein et al. 2021; Arvin et al. 2021; Rahman et al. 2018; Xu, 2021).

3.2. Bibliometric analysis.

In the next part of this work, a bibliometric analysis was made, in which we sought to recognize the patterns in the number of products related to the use of ML in volatility, the type of journal in which they were published, authors nationality, collaborations between authors according to their country of origin and a proposal for the conceptual structure of the topic through the use of K-means.

In terms of the number of academic products related to the use of machine learning in volatility, a clear growing trend is observed in recent periods, which experienced a boom towards the year 2018 (figure 1). In the finance area, this change in the number of products slope can be observed from 2015 onwards. This fact shows a short lag in the academic production related to machine learning and volatility, thanks to the attention received by articles related to the analysis of returns. However, figure 1 constitutes evidence about the relevance that the use of ML in volatility is currently experiencing.

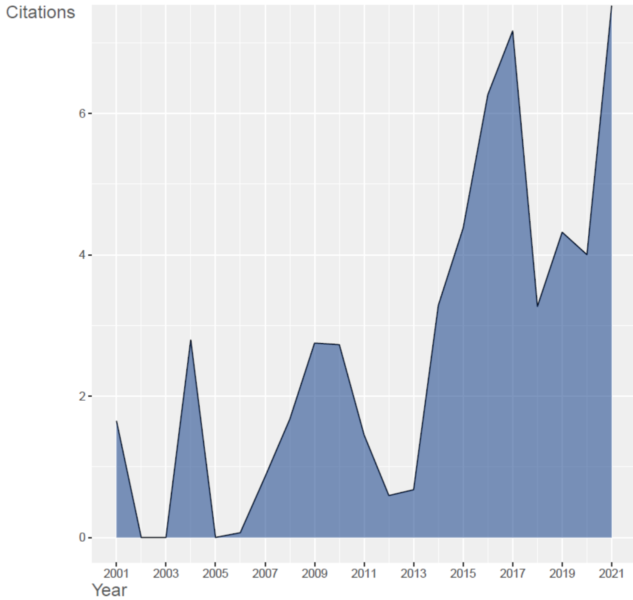
Figure 1. Number of articles per year.



Source: Self created.

In this line, the number of citations per year (figure 2) has experienced an increase in the last years, particularly since 2013. This increase is expected considering the rise in the number of documens associated with ML in volatility presented in figure 1.

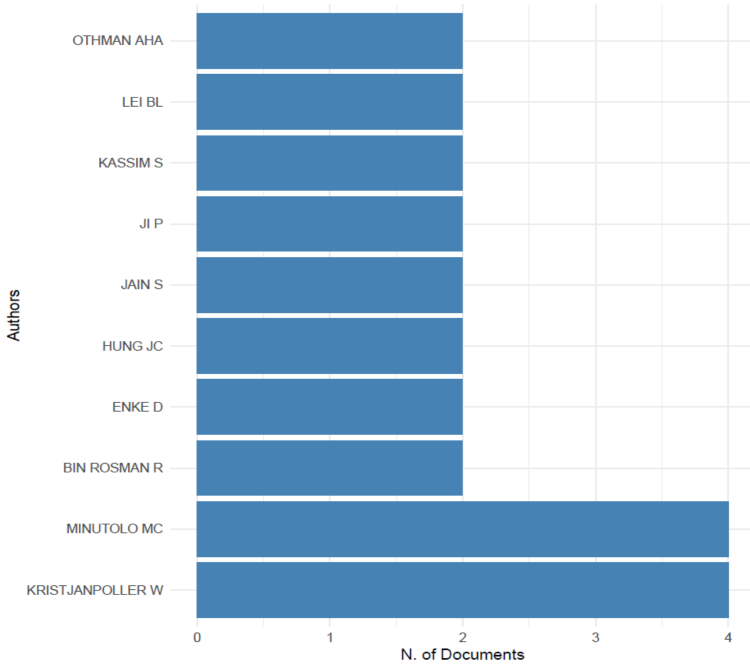
Figure 2. Number of citations per year.



Source: Self Created

When reviewing the number of articles per author, it was found that there is not a large concentration of products in few authors. The academics who have published a higher number of articles on the studied subject do not exceed 6 manuscripts (6.9% of the total sample) and the vast majority of academics have two or fewer publications (2.2% of the total sample) (figure 3).

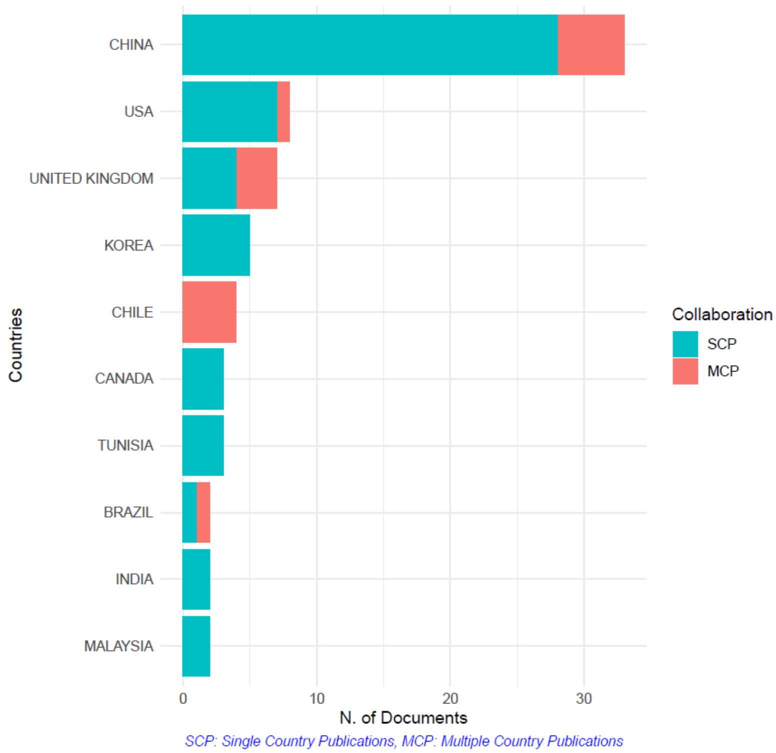
Figure 3. Number of articles per author.



Source: Self Created

On the other hand, when reviewing the number of products according to the nationality of the authors, clear trends are observed in the application of ML to the study of volatility. In this case, the authors from China, U.S.A. And the United Kingdom have 56% of the total articles in the analyzed sample (figure 4). It should be noted that in the vast majority of cases, the articles developed by authors from these countries correspond to documents in which individuals from a single nationality participate.

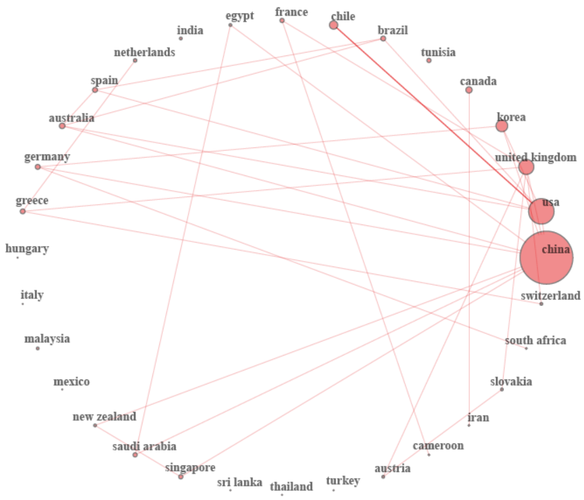
Figure 4. Number of articles per country.



Source: Self created.

This concentration of production by country is confirmed by reviewing the network of international collaborations for the analyzed documents (figure 5). In this case, it is evident that China, U.S.A and the United Kingdom present a greater number of collaborations. Publications including authors from different countries are evidenced not only between China, U.S.A. and the United Kingdom, but in the first case, there are numerous alliances with Egypt, Australia, Germany, New Zealand, Saudi Arabia and Sigapur. In the case of the U.S.A., the collaborations with Australia, Spain, Chile, the United Kingdom and Brazil are striking. For the United Kingdom, the collaborations are presented with other European countries and some Asian nations.

Figure 5. Country collaboration.



Source: Self Created

All in all, graphs 4 and 5 show a clear trend towards a high degree of concentration of academic products that make machine learning applications in volatility by the use of collaborations between small groups of countries. The search for alliances and co-authors in this field of research is a fundamental task for countries that still do not have a high degree of production in this area.

When analyzing the type of journal in which the reviewed articles are published (Table 2), most publications are classified in quantiles 1 and 2 according to web of science. A large part of these journals are focused on topics related to computer science, statistics, econometrics and physics. Only one of the journals belongs to the area of finance or economics (Quantitative finance). The above shows a clear gap in the production of works in journals specialized in finance and economics. Several articles related to the use of machine learning in finance have been published in recent years in journals that combine the study of economics and energy (i.e. energy economics, energy journal). This seems not to be the case for the use of ML in volatility. However, it is possible to expect that this panorama will change in the coming years, given the reception that this type of techniques has had by the scientific community. Meanwhile, magazines related to computer science and forecasting will continue to exploit the potential of this topic.

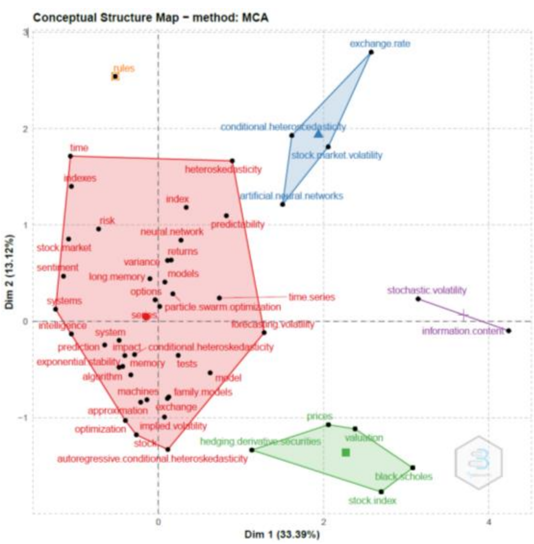
Table 2. Number of publications per journal.

JOURNAL	# OF PRODUCTS	%
EXPERT SYSTEMS WITH APPLICATIONS	9	10.5%
QUANTITATIVE FINANCE	5	5.8%
JOURNAL OF FORECASTING	4	4.7%
COMPLEXITY	3	3.5%
NEURAL COMPUTING & APPLICATIONS	3	3.5%
CHAOS SOLITONS & FRACTALS	2	2.3%
IEEE ACCESS	2	2.3%
JOURNAL OF INTELLIGENT & FUZZY SYSTEMS	2	2.3%
JOURNAL OF REVENUE AND PRICING MANAGEMENT	2	2.3%
PHYSICA A	2	2.3%
OTHERS	52	60.5%
TOTAL	86	100.0%

Source: Self Created

To complement the previously obtained results, we performed a K-means analysis to identify the potential conceptual structure of the use of ML in volatility (figure 6). The details of this model are explained in section 2. We found 5 clusters related to the literature review presented in previous sections that are described as follows. A first cluster (red cluster) is related to exercises in which forecasting is the main task. In this setting, concepts as neural network, predictability, index and forecasting volatility are found. This cluster presents the largest size and groups the majority of works in the performed analysis. A second cluster (green cluster) includes articles related to derivatives valuation. In this group, words as hedging derivatives securities, valuation and Black Scholes can be found. A third group (blue cluster) can be related to the works in which volatility calibration and volatility surface construction are developed. In this group words like conditional heteroscedasticity and stock market volatility are present. The purple and Orange clusters represent the works that do not belong to any clear trend and are classified as "other applications" in this paper.

Figure 6. ML in volatility: Conceptual structure.



Source: Self created.

4. Conclusions.

In the last years, the use of machine learning in finance has experience a remarkable increase. The study of volatility by the use of this type of techniques has not been an exception.

Since 2018, the number of publications related to this topic has doubled according to date downloaded from web of science database. The main uses of manuscripts related to this topic include volatility forecasting, calibration and construction of volatility surfaces, and the valuation of derivatives. The vast majority of publications in this area are related to authors or collaborations between China, U.S.A and United Kingdom with a clear orientation to be disseminated in journals related to computer science, statistics and forecasting. On the other hand, the most used methods correspond to neural networks, deep learning and support vector machine.

The above suggests the following observations. Firstly, it is expected that the use of machine learning in volatility will increase in the next years. In this case, there is a complete panorama to explore in terms of the methods that can be employed (different form neural networks) for different tasks with a variety of assets. For example, there is a lack of studies related to topics such as contagion risks, volatility spillovers, volatility calibration and the estimation of risk in areas related to corporate finance. In terms of methods, currently, there are very few works related to text and sentiment analysis, decisión trees, principal component analysis and deep learning. The constant use of developed stock market indexes is another concern. This creates opportunities to analyze other typer of assets (i.e. energy) and markets (i.e. emerging markets).

As can be seen, there is a clear outlook for the use of machine learning in volatility. Especially if one takes into account that the journals related to economy and finance are still beginning to publish works related to this topic. The situation described in this paper reveals a panorama in which unprecedented opportunities for those interested in this type of models are available and ready to be exploited.

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