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Machine Learning for Financial Prediction Under Regime Change Using Technical Analysis: A Systematic Review

Andrés L. Suárez-Cetrulo[1], David Quintana[2], Alejandro Cervantes[3]*

[1] Ireland's Centre for Applied AI (CeADAR), University College Dublin (Ireland)
[2] Department of Computer Science and Engineering, Universidad Carlos III de Madrid, Avda. Universidad 30, 28911 Leganes (Spain)
[3] Escuela Superior de Ingeniería y Tecnología, Universidad Internacional de La Rioja (UNIR), Logroño (Spain)

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Abstract

Recent crises, recessions and bubbles have stressed the non-stationary nature and the presence of drastic structural changes in the financial domain. The most recent literature suggests the use of conventional machine learning and statistical approaches in this context. Unfortunately, several of these techniques are unable or slow to adapt to changes in the price-generation process. This study aims to survey the relevant literature on Machine Learning for financial prediction under regime change employing a systematic approach. It reviews key papers with a special emphasis on technical analysis. The study discusses the growing number of contributions that are bridging the gap between two separate communities, one focused on data stream learning and the other on economic research. However, it also makes apparent that we are still in an early stage . The range of machine learning algorithms that have been tested in this domain is very wide, but the results of the study do not suggest that currently there is a specific technique that is clearly dominant.

Keywords

Concept Drift, Finance, Machine Learning, Meta Learning, Regime Change, Systematic Literature Review.

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I. Introduction

Financial markets can be described as an evolutionary and nonlinear dynamical complex system [1], [2]. Forecasting in the financial domain has traditionally been performed under the assumption that the underlying data has been created by a linear process [3]. Another line of work to make financial predictions is to use machine learning (ML). These algorithms have surprised financial experts [4]–[6] because of their success in mapping nonlinear relationships without prior knowledge [7]. Deep learning algorithms (neural networks) and ensembles have been some of the techniques obtaining the best results for stock trend prediction [8]–[13].

Different crises, recessions and bubbles, such as the COVID-19 pandemic, or volatile mid-term trends in crypto markets, have made apparent the non-stationary nature and the presence of drastic structural changes in financial markets [14]. During these periods, mean returns, volatility and correlations among assets tend to change quickly [15]. This has brought attention to the problem of concept drift [16] in computational finance [17]. Many recent research works point out that financial assets or companies present different states that may repeat or not overtime or evolve due to inflation, deflation, or changes in supply and demand [18]–[24].

In finance, a change in the collective behaviour of market participants and their reactions is called a regime change (RC). As covered by the marked efficiency hypothesis [25], we cannot observe the individual behaviour of a trader or its intentions. Instead, we can only observe changes in the price dynamics and macro or micro-economic variables and extrapolate the changes that make them modify their behaviour. The execution of these strategies is the actual generative process of the observed time series of prices or trends. The estimation of the hidden processes driving the market into different regimes is often approached using regime-switching models, a type of time series model where parameters can have different values in different cycles [26].

Despite the fact that artificial intelligence has recently become a trend and even a buzzword in many industries, this has not become the main trend yet for trading systems. This is mainly due to the high complexity and hard explainability of these models [27], being the second a must for stakeholders and decision-makers in this sector [28]. Instead, traders tend to identify directional changes in the market state using different popular indicators tailored according to their needs.

Traditionally, the literature has used static methods to interpret patterns based on the meaning of these indicators and their historical correlation to future prices. However, this correlation may vary over time. Behavioural shifts of investors changing continuously with a hidden context can also be observed through the change in sell versus buy volumes, in differences between local minima and local maxima over time, and through different moving averages at different time frames depending on the granular detail observed (frequencies) at intraday, daily or weekly levels. Changes in financial markets challenge traders and investors, as most of their models rely on previous patterns. Hence, a way to recognise these changes provides

* Corresponding author.

E-mail address: alejandro.cervantesrovira@unir.net

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a competitive advantage since it allows changes in trading strategies ahead of other investors [29]. Detecting concept shifts also helps lower the risks of financial exposure in high-frequency trading (HFT).

The digitalisation of the financial industry has resulted in a growing amount of data that is available for decision-making. This, together with the increasing amount of computational resources, has accelerated the adoption of a whole range of machine-learning-based solutions. Among the suite of instruments available to deal with regime changes, online incremental ML algorithms seem especially appropriate. Among the advantages that they offer, we can mention the fact they can handle non-stationarities, shifts, and drifts in price generation processes. Another aspect that makes them a good fit for this context is the fact that they are scalable for continuous learning scenarios [30].

One might consider two main scenarios regarding the nature of structural change. The first possibility is the existence of recurrence, that is, the idea that the system might transition back to a previous price generation process. For instance, there might be a specific market state for market openings at intraday frequencies and another for financial bubbles that might be observable at lower frequencies. The alternative assumes that any drift results in a transition to a new process. As we will discuss in detail, while there is a relevant number of published studies on machine learning for data streams that pay attention to non-stationarity [31]–[35], the literature on financial applications of these algorithms, especially that focused on recurring concept drifts, is more limited [17], [36]–[41].

We must also point out that the prediction of future financial trends can be tackled using fundamental or technical analysis. Despite some controversy regarding its potential [25], [42], the latter is very prevalent in short-term trading [43], hence the focus on this approach. Having said that, there are also relevant papers in the first category, like the contributions of Geva and Zahavi [44], on the short-term, intraday and high-frequency forecast using news data and the study of Dogra et al. [4], analysing the impact of recent news on stock price trends and challenges such as class imbalance. More recently, Chen et al. [45] hybridised both approaches in a study that combines both sentiment analysis and technical indicators.

With this survey, we try to bring to the academic community's attention how ML is being used to deal with structural change in financial markets. Our goal is to identify directions on leveraging the benefits of modern algorithms that work with different scenarios and deal with any changes that may arise in real-time.

The use of these approaches may help to find strategies to improve prediction accuracy during times of change, limiting the need for constant model retraining. Hence, some of these techniques efficiently increase the potential profits, avoiding the computational burden and benefiting from always having an up-to-date model.

The rest of the document is structured as follows: Section II covers the methodology and research questions used in this systematic review; Section IV will discuss the outcomes of each of the research questions. There, Subsection A will introduce the topic of regime change in financial series, and Section B will discuss the core literature on machine learning for financial prediction under regime change. The final two sections will be reserved for a summary of results, main conclusions, and future research lines.

II. Research Methodology

A. Motivation and Objectives

Financial time series are often subject to structural change. Even though machine learning offers major advantages in this context, the literature on the topic is limited and sparse. There seem to be different research communities focused on different aspects of the problem, and it is hard to keep track of the main contributions and instruments used to tackle the problem.

The literature presents a lack of studies on prediction under regime changes based on technical analysis using machine learning. This is unfortunate, as there is a lot to be gained in terms of efficiency and performance. Within this field, we find very promising ideas. For instance, the problem can be framed using the data stream learning topic of concept drift. A significant number of contributions to this new concept have not been explicitly applied to finance yet, and they are not widely known. They have not been widely present in machine learning surveys outside the data stream learning niche area.

Exploring previous research showed that a comprehensive review does not exist on these topics. Therefore, this study will help readers understand the current state of the art, bridge the gap among research fields, and address promising future lines of research in this domain.

B. Research Method

In order to provide an overview of the state of the question, our research has followed Kitchenham and Charters' guidelines on Systematic Literature Review (SLR) [46], [47].

A systematic review is defined as an organised way to synthesise existing work fairly. An SLR is a means to identify, evaluate and interpret the available research works relevant to a definite research question, topic area, or phenomenon of interest. After revising the literature for similar research objectives, it can be identified that there is no previously published search on a topic.

C. Planning

The study aims to summarise the current status of predicting financial time series in the financial literature during behavioural or regime changes in markets. Kitchenham and Charters' SLR protocol was adapted to describe the plan for the review.

The protocol comprises research background and questions, search strategy, study selection criteria and procedures, data extraction, and data synthesis strategies to guarantee that the investigation is undertaken as intended and reduce the likelihood of bias in the study. In this protocol, the entire investigation plan was not decided from the beginning. Instead, this and the results produced were recorded as the study progressed.

D. Research Questions

This paper has the following two research questions:

Q1 What are the different research areas for predicting under regime changes in the financial literature? and

Q2 What are the most commonly used machine learning techniques applied to analysing regime changes?

The results expected at the end of the systematic review were to see what research or surveys had been applied or produced on the topic so far and to identify the implications of using machine learning to handle behavioural changes in financial markets in the scientific literature.

E. Search Strategy and Process

The search strategy included: i) search resources and ii) a search process. Each one of them is detailed in the following subsections.

1. Search Resources

This study was planned to find all the literature available about machine learning for forecasting under regime changes in finance. The sources used for the systematic review were:

- IEEE Digital Library (http://ieeexplore.ieee.org);
- ScienceDirect, on the subject of Computer Science (https://www.sciencedirect.com/);

- ACM Digital Library (http://portal.acm.org);
- Taylor & Francis Journals (http://www.tandfonline.com);
- Wiley Online Library (http://www.wiley.com/);
- SpringerLink (http://link.springer.com); and additionally
- Google Scholar was explored as grey literature (https: //scholar.google.com/).

2. Search Process

The overall search process is depicted in Fig. 1 and is explained in the following section.

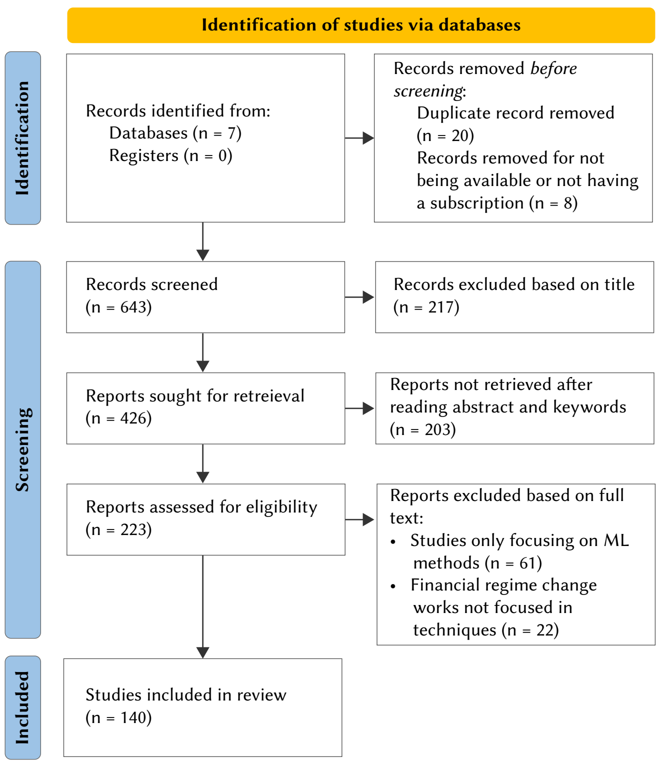

Fig. 1. Flow of information through the different phases of the review using a PRISMA diagram [48].

The starting point was choosing a set of relevant keywords. They were: *regime change, regime-switching model, machine learning, change detection* and *stock trend forecasting*. The search was then run on the already mentioned databases in March 2022, returning 643 works in total in a time range, including the years 1970 to 2022. Irrelevant and duplicate publications were removed, and 223 unique research works remained. At that point, publications were reviewed based on titles, abstracts, conclusions, references and keywords and then were classified into three different types:

- Relevant works: these should satisfy one of the two inclusion criteria covered later in this subsection;
- Process assessment works: if the publication is related to the financial domain or concept drift literature and is relevant.
- Excluded works: works not relevant to the topic.

When there was doubt about the classification of a research workpiece, it was included in the relevant group, leaving the possibility of discarding it during the next stage, when the full-text versions were reviewed. Third, each full article was retrieved and read to verify its inclusion or exclusion. The reason for exclusion or inclusion in this third stage was documented. Fourth, to check the consistency of the inclusion/exclusion decisions, a test-retest approach and re-evaluation of a random sample of the primary studies were made.

Documents were kept when they satisfied at least one of the criteria below:

- The work was explicitly related to regime changes or structural breaks in non-stationary data.
- The work was relevant to machine learning forecasting in domains with complex dynamics and non-stationarities in the financial field.

The authors reviewed all 223 research works and put them into these different groups according to the previously mentioned criteria. This list was reviewed to check for inconsistencies. The result of this stage was that 140 publications were classified as relevant.

There is a risk that some relevant works have been missed. Therefore, this study cannot guarantee completeness. However, it can still be trusted to give a good overview of the relevant literature on price forecasting in the financial domain under structural breaks.

3. Data Extraction

The data extracted from each publication was documented and kept in a reference manager. After the identification of the publications, the following was extracted:

- Source (journal, book, conference or strictly relevant technical or white paper);
- Title;
- Publication year;
- Authors;
- Classification according to topics;
- Summary of the research, including which questions were solved.

III. Summary of Results

In order to analyse the 223 works, we found the need to classify them in more ways than just according to the methodology defined in Section II. When needed, the topics were updated or clarified during the classification process. Results of the classification process with regard to the research questions are detailed in Table I.

TABLE I. Classification of Papers With Regard to the Research Questions

Question	Topic	Relevant Studies	Quantity
Q1	Regime changes	[14], [15], [18], [19], [23], [26], [29], [49]–[63]	22
Q1 and Q2	ML in stock forecasting	[1]–[13], [20]–[22], [24], [25], [27], [28], [37], [38], [42]–[45], [64]–[110]	73
Q2	Concept drift and online ML	[16], [17], [30]–[36], [39]–[41], [111]–[143]	45

The data required for analysis were extracted by exploring the full text of each research work. Table II presents the results of the search and the source of the documents. Table III presents the results in the second stage. As mentioned before, the total number of papers remaining after the exclusion process was 140. Table I summarises their classification according to the knowledge area.

The relevance of regime changes or structural breaks in the literature of financial price forecasting leads to consider two major areas: financial regime changes (related to majorly statistical approaches to detect change points or forecast under different regimes) and data stream learning (where the problem of concept drift can be understood as a type of regime change in the ML literature).

TABLE II. Results Without Filtering

Data Source	Total Publications
ScienceDirect	76
Google Scholar	56
Springerlink	33
IEEE Digital Library	27
ACM Digital Library	14
Wiley	9
Taylor & Francis	8

TABLE III. Second Stage Results

Data Source	Total Publications
ScienceDirect	56
Google Scholar	34
Springerlink	20
IEEE Digital Library	16
Taylor & Francis	5
Wiley	5
ACM Digital Library	4

Fig. 2 shows how, out of a total of 140 relevant studies, the majority of the works reviewed to correspond to ML techniques applied to stock forecasting. Some of these works overlap regime change research, focusing primarily on probabilistic models to classify directional changes and represent different regimes. The literature on online learning does not tend to coincide with the one on regime changes. However, studies of online ML tackle similar challenges as models to handle regime changes, such as having up-to-date models and re-training mechanisms. A deeper discussion on this matter will be held in Section IV.

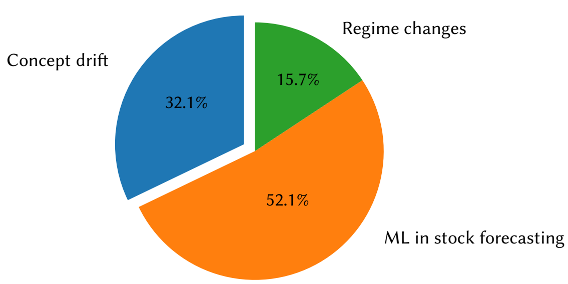

Fig. 2. Topic distribution of research papers after filtering.

Fig. 3 shows the distribution of papers reviewed across various sources. A majority of the research works have been retrieved from high-impact journals, followed by conferences and books. However, since some of the topics reviewed, like online ML, are current research areas, a remainder, close to « 4% of research works, belong to non-peer-reviewed papers contained by open-access repositories.

Finally, we have extracted from the papers classified papers under the topic "Concept Drift" the ML technique mainly used, either as a new proposal or as a reference for comparison. We have grouped these techniques into eight broad categories (Fig. 4 and 5). For this task, we have excluded reviews. These results show that most of the reviewed papers use techniques from four main categories: Evolving systems (that include Evolving clustering, Evolving fuzzy rules and Fuzzy neuro systems), Ensemble based systems (usually with tree-based components), traditional systems adapted to concept change (such as adaptive decision trees), and finally Neural Networks and Deep Learning. The latter are more recent in general, and therefore this trend is likely to become more important in the near future. Fig. 6 shows the evolution of these categories.

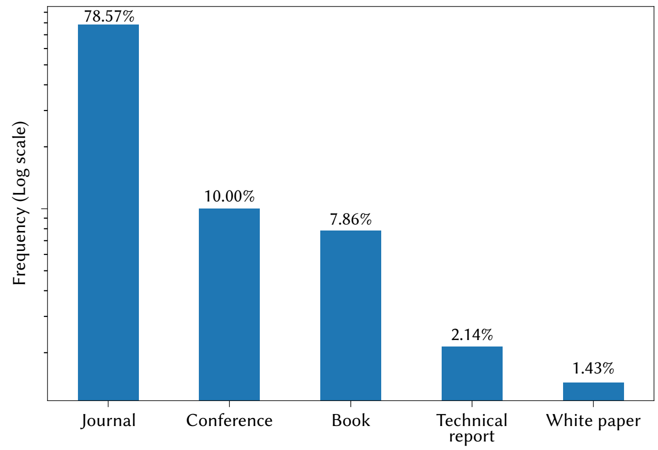

Fig. 3. Source distribution of research papers after filtering.

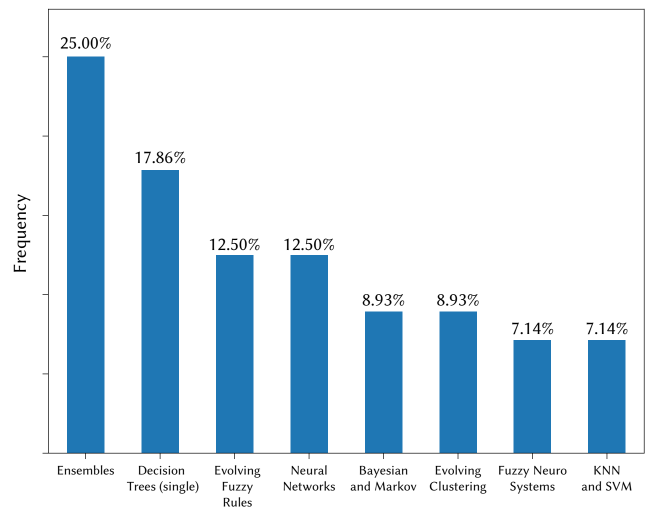

Fig. 4. ML techniques found in Concept Drift studies, grouped by categories, counting each different technique used in papers and assigning the corresponding category separately. In this figure, a single paper comparing several algorithms in the same category is counted as many times as algorithms.

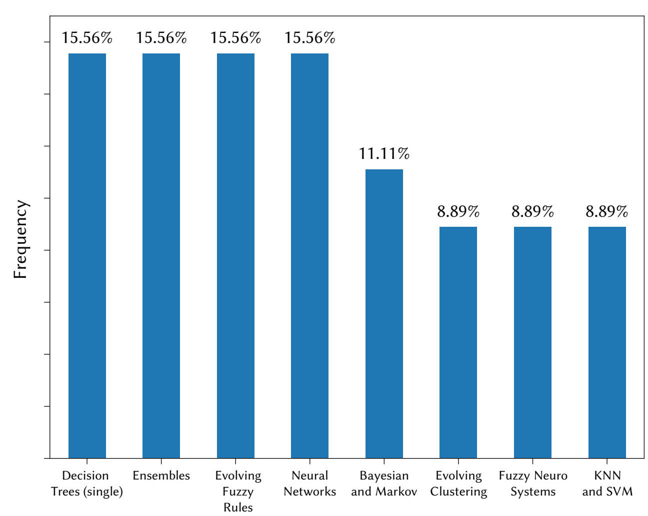

Fig. 5. Types of ML found in Concept Drift studies, using the unique categories found in the same paper. In this figure, a single paper comparing six methods in category A and one method in category B is counted as only two entries (one for A and another for B).

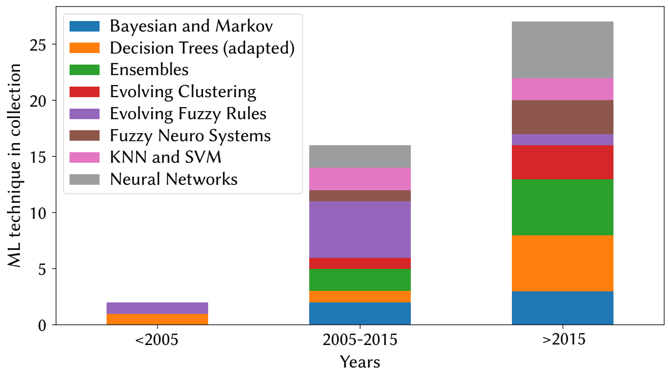

Fig. 6. Categories per period of 10 years based on data used in Fig. 5.

IV. Discussion

This section describes the papers reviewed in this work. In this discussion, we follow the schema in Fig. 7.

A. Regime Changes in Financial Series (Q1)

Early studies from the financial literature claim that financial markets are efficient [25] and, as a result, asset prices follow a random walk [81]. Fama [25] claimed that markets cannot be consistently beaten on a risk-adjusted basis and that their prices cannot be anticipated has always been a source of controversy in the literature. Many research works have pointed to different markets being predictable using different sources of information [5], [77], [78], [85], [88], [104].

Forecasting in the financial domain can be characterised by a non-stationary and unstructured nature and by hidden relationships [2], [74]. Economic, social and political factors within countries and international impact add uncertainty to financial markets [66], [70], [79], [93], [94], [100], [106]. Hence, markets can be considered an evolutionary and nonlinear complex system [1]. The financial literature has covered different approaches to predicting market prices using statistical and, more recently, AI-based methods.

In recent years, different events like the COVID-19 pandemic or the bankruptcy of Lehman Brothers in 2008 have led to periods with changes in mean, volatility and correlations in stock market returns [15], stressing the non-stationary nature and the existence of drastic structural changes in financial markets [18], [20]–[23].

In the financial literature, changes in the price behaviour of financial markets that go beyond their normal price fluctuations receive the name of regime changes [19], [53],

[63] or business cycles shifts [80]. In order to model these regime changes, one of the most popular techniques is the regime-switching model [15], which was first applied by Hamilton [58] as a technique to deal with cycles of different economic activities such as recessions and market expansions.

In financial markets, there are periods of time with different degrees of efficiency and predictability. There can be moments where, due to the market-wide sentiment given by political or economic circumstances, the behaviour of investors may change towards a bear, bull, lateral market, and periods or time frames with different levels of volatility [80].

At the macroeconomic level, RC are often related to abrupt breaks in long-term cycles like the break of bubbles or economic crises [59]. Changes in market regimes could be driven as well by investor expectations [15]. The financial literature identifies two types of regimes clear to recognise: steady and highly volatile regimes usually linked to economic growth or deflation periods, respectively.

This is illustrated in Fig. 8, which shows the breaks identified in [19] during the Great Recession.

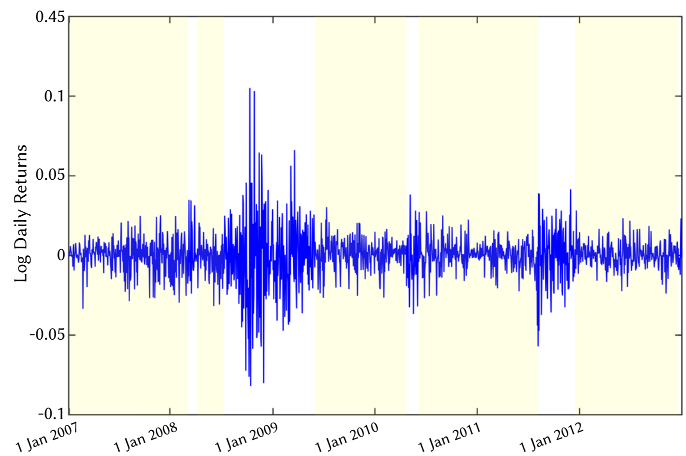

Fig. 8. Regime Changes in the DJIA Index (indicator of the United States economy) identified by Tsang and Chen [19].

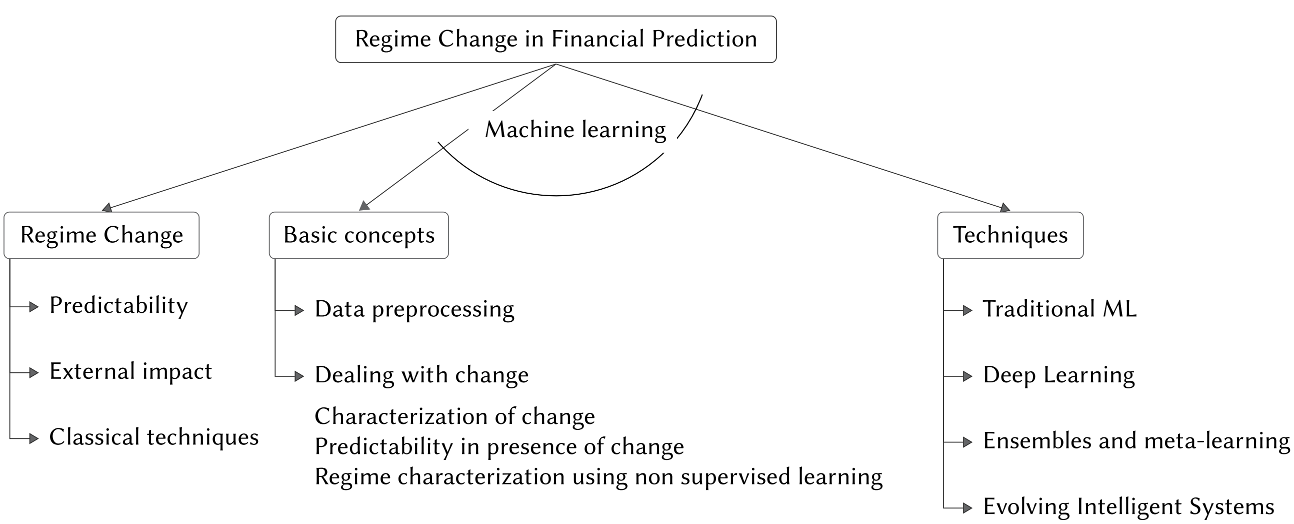

Fig. 7. Discussion on the research papers considered in this work.

Regime changes challenge investors, making them change their trading strategies as the collective trading behaviour of the market changes. Different examples of RC have been covered in the recent literature. Davies [53] analysed different cases and consequences of regime changes in the Great Recession that impacted several asset classes such as equities, bonds, commodities and currencies at micro and macroeconomic levels. Hamilton [63] observed alternating patterns between steady and turbulent periods since the Second World War and subsequent recessions by looking at US unemployment rates. Ang and Timmermann [15] identified cyclic changes in the behaviour of asset prices and mean, volatility and correlation patterns in stock returns during the Great Recession and the 1973 oil crisis. Kritzman et al. [29] discovered that investors could benefit from having different asset allocation strategies in different market regimes to minimise losses.

Many other studies consider these drastic changes an intrinsic characteristic of financial data that might be caused by significant events, and thus, these will be observable not only in prices and economic variables but also in other kinds of public information [52], [58], [59], [62], [63], [92]. Hamilton [58] proposed a time-series based approach [26] to capture nonlinear effects like RC, identify market breaks and hidden changes in economic cycles known as the regime-switching model [59]. This model, also known as the Markov-switching model, is fitted to observations following different patterns in different periods and is mainly applied to recognise low volatility regimes with economic growth vs high volatility periods with economic contractions [116]. Ang and Timmermann [15] applied these models to predict interest rates and equity and foreign exchange returns. They discussed how to model RCs for these time series models.

B. Approaches Based on Machine Learning (Q2)

Traditional statistical methods tend to model and predict future data based on the assumption that the time series under study is generated from a linear process with features normally distributed. This presents challenges since financial data is characterised by nonlinearity and non-stationarity besides a high level of uncertainty and noise [82].

A different approach to performing financial forecasts is the use of ML techniques. Several literature reviews show the benefits of these techniques against traditional methods [5], [98], [99], [105], surprising practitioners by contradicting early theories like the random walk, and efficient market hypothesis (EMH) [5], [25], [95]. Machine learning algorithms can handle nonlinear relationships without prior knowledge [7], [144], outperforming traditional time series methods [10]–[13].

Different research works from the economic literature have either used technical indicators or raw prices and returns. Technical indicators are able to show behavioural patterns among traders and thus provide an extra level of signal to predictive models. These can be valuable to automate the behaviour of short-term traders [5]. In any case, most of the economics literature has focused on linear processes that may not have been able to extract relevant information nor infer complex relationships among technical indicators where some new ML methods could [108].

Some of the literature reviews already cited describe common technical indicators used for stock market value and trend prediction. Many of these papers, like [7], have shown that different pre-processing steps, like the frequency level of the input data, can impact its predictability. While a common approach in this regard is data normalisation, in the literature on data stream mining, data normalisation is not a usual practice since maximum and minimum values for each attribute in the data stream are unknown beforehand [134].

Authors like Patel et al. [13] discretise features based on the human approach to investing and deriving the technical indicators using assumptions from the stock market. This latter approach, though, introduces human bias in the process. This is the opposite way to approach the problem of trend prediction if we compare it to recent deep learning strategies that feed dozens of automatically generated indicators [109].

Overall, the above-mentioned literature reviews confirm that ML techniques can be used to predict price changes, but this entirely depends on the time horizon and efficiency of the market in the period predicted. Cavalcante et al. [3] provided another interesting review of pre-processing and clustering techniques used in the financial domain to forecast future market movements. They highlighted the relevance of concept drifts in financial markets and suggested that the data stream mining literature is of great importance in future research due to the non-stationarity and evolution of financial markets [91].

In computational finance, changes in the behaviour of the market are normally referred to as regime changes or switches [15], [61], [67], structural breaks or changes [51], [54], [56], [56], volatility shifts [50], switching processes [60] or market states [18]. In this kind of data, long periods of stability might be interrupted by short episodes of abrupt changes [61].

These changes may or not be transitory since a newly adopted behaviour in price dynamics, reflected as part of the mean returns, their volatility or correlation among them may persist for several periods. Timely recognition of these sudden behavioural changes in markets can significantly lower the risk of financial exposure. This has inspired the materialisation of techniques such as regime-switching models in the financial literature, which work under the premise that new dynamics of price returns and fundamentals persist for several periods after a change. A key element in these models is identifying whether the exact market regimes reoccur over time (e.g. across recessions or periods of economic growth) or if new regimes deviate or have evolved from previous ones [15].

The prediction of future values in financial markets and the detection of regime changes in data streams with temporal dependence are common application areas for statistical methods and ML. Previous research reports high accuracy in forecasting price changes with advanced techniques and the feasibility of making profits using these predictions against the EMH, which points to unbeatable markets. An alternative theory is the adaptive market hypothesis (AMH) [57], introduced by Andrew Lo in 2004. This theory, with empirical evidence in a increasing number of research works [68], combines the EMH with principles from behavioural finance, allowing the ideas of market efficiency and inefficiencies to co-exist. Under the AMH, the efficiency of a market evolves as market participants adapt to an environment that changes continuously. In this regard, participants rely on heuristics to make their investment choice, leading to mostly rational markets under those heuristics (like the EMH). The main difference is at the time of major behavioural shifts in the market participants, as in economic shocks or crises. In this case, the AMH considers a market that evolves, and the initially adaptive heuristics may become static in certain market situations. Consequently, the EMH may not continue under periods of abnormal conditions, stress or abrupt changes in the market. Hence, financial markets may be predictable in specific periods, as discussed by Lo [49]. Therefore, convergence to market efficiency is neither guaranteed nor likely to occur. The level of efficiency depends on the market participants and the market conditions at that time.

One of the few financial studies citing concept drift explicitly can be found in a recent work authored by Masegosa et al. [36]. They analysed data from the Great Recession and claimed that economic changes during this period manifested as concept drifts in their generative processes. An intermediate example of trying to predict financial crises using ML methods can be found in [55], where the authors studied possible contagion risks between financial markets that could trigger financial crises to signal warnings at an early stage. More recently, Yang et al. [137] analysed the impact of concept drift in business processes. More specifically, they modelled the response to concept drift as a sequential decision-making problem by combing a hierarchical Markov model and a Markov decision process. Martín et al. [145] also dealt with structural changes introducing a trading system based on grammatical evolution that commutes between an active model and a candidate one to increase performance.

Other two key research pieces in this regard are the works by Tsang and Chen [19] and M "unnix et al. [18], which proposed mechanisms to identify points of drastic changes in financial time series. The former used statistical-based and traditional ML (e.g. naive Bayes) approaches to classify normal versus abnormal regimes. They proposed a framework based on the change speed of price returns and the degree of changes to visualise and discriminate between different market regimes depending on the volatility of their price returns. The latter [18] visualised differences in the correlation structure of the price returns across assets in the S&P500 during the Great Recession. They extended the selection to a sample from 1992 to 2010, identifying eight market states repeating behavioural changes over time.

Several approaches from the deep learning (DL) field (e.g. RNNs) have also tried to face the problem of concept changes when learning continuously. [113], [126], [128], [130]. These advances have been successfully transferred to the financial domain, as discussed in recent surveys by Ozbayoglu et al. [9], and Li and Bastos [109].

Most of these mentioned research works focus on the likelihood of daily or monthly changes, where retraining a model is a feasible task. As of today, the amount of research devoted to seasonality and changes at the intraday level is significantly more limited [75], [89], [101], [103], [107]. The computational cost of ML and statistical methods, together with the inherent higher complexity derived from the need to manage large amounts of data at these resolutions, makes keeping models up to date more challenging.

While its application to high-frequency markets is still an open problem, recent research works are making progress in understanding how to apply ML to intraday resolutions. Among them, we could mention the one presented by Sirignano and Cont [73], who claimed that financial data at high frequencies exhibit stylised facts and may hold learnable stationary patterns over long periods. Another relevant study is the one authored by Shintate and Pichl [76], who reviewed modern ML and DL approaches applied to high-frequency trading at the minute level.

Recently, several research works have approached the problem of time-changing behaviours using non-supervised ML methods [127], [130], [135]. In these, micro-clusters or latent features may be used to represent a summary of the incoming data and reduce the computational costs of correlating full data distributions. A manner of doing this is using model-based clustering approaches. These algorithms find models that fit input data and are also robust to the presence of noise [146], [147]. For instance, expectation maximisation (EM) [148] fits a mixture of Gaussian distributions to the data [133]. Chiu and Minku [141] used it in concept drift handling based on clustering in the model space (CDCMS) to create concept representations and keep a diverse ensemble learner. Zheng et al. [123] relied on it to minimise intra-cluster dispersion and cluster impurity. Tsang and Chen [19] applied the Baum–Welch algorithm, a special case of EM, to both detect the time of a change point and predict the next state (or concept) of financial data using a hidden Markov model (HMM). Gomes et al. [122] also hypothesised about using Baum–Welch in conjunction with HMMs for continuous learning problems. Baum–Welch has been used in the financial domain together with other specific versions of EM and Gaussian mixture models (GMM) to forecast change direction in stock prices [72], [87] and to represent market regimes [19], [29], [64], [86].

A set of relevant techniques from the ML literature in this regard are prototype generation techniques such as learning vector quantisation [65], [96], [102], which have been proven to be useful for data partitioning and model selection in the financial domain. Choudhury et al. [71], and Pavlidis et al. [69] use a combination of clustering and forecasting algorithms to model the distribution of financial data. Regarding the first step, the former authors use a two-layer abstraction that clusters stocks using self-organising maps (SOM) to then rely on K-means to obtain clusters of prototypes. The latter considers three different unsupervised algorithms to identify market states: growing neural gas (GNG), density-based spatial clustering of applications with noise (DBSCAN), and Unsupervised k-Windows. Once the market states are identified, they use feed-forward neural networks to make predictions.

In the last years, several online incremental algorithms have used these techniques to adapt distinct learners to different cycles or seasonal behaviours in a data stream. In this regard, the use of online ensembles, using non-supervised learning to represent different behavioural patterns [135], [141] or supervised learning to train a pool of classifiers with high predictive accuracy under different conditions [34], [117], have obtained state-of-the-art results adapting to different states in the behaviour of data streams in many domains, including finance [17].

Meta learners over data streams are a related subfield of ML of increasing popularity where a pool of former classifiers is managed and reused when the state or concept of the stream changes. This subfield is inspired by the human learning system that reuses previous knowledge to learn new tasks, not starting from zero every time. Although meta-learners have not been widely applied to the financial domain yet, their logic resembles approaches applied to finance as EM or Baum-Welch, but for continuous learning domains where models are always up-to-date and thus behave smoothly in case of structural breaks. For instance, Abad et al. [120] proposed a meta-learner that used hidden Markov models (HMM) to predict the sequence of change between discrete concepts. Their approach used fuzzy logic rules to compare classifiers to reuse former models. Maslov et al. [139] proposed a method to use patterns acquired during previous changes and assumed a Gaussian distribution for the duration of the changes to predict the time of the next change point. Carta et al. in [83] recently combined the use of meta learners with deep reinforcement learning to produce trading strategies and maximise profits operating in Standard & Poor's 500 future markets and the J.P. Morgan and Microsoft stocks.

Meta-learning approaches have inbuilt strategies to decide on when to train, what model to replace and when, when to forget (prune) a learner and when to create one [114], [136] by using the evaluation performance metrics of active and former models [149]. These, thus, are a closely related research area to evolving intelligent systems (EIS) [118], [129], [150] and evolving fuzzy

systems [125] [132] [143] [119]. EIS, which are also online and incremental systems, can adapt themselves to concept drifts of different natures on-the-fly through adaptive fuzzy rules [140]. EIS have already demonstrated their ability to solve different kinds of problems in various application domains like finance [90], [97], [151]. These have achieved great results in classifying non-stationary time series [24], [37], [38].

Recent EIS approaches can work as ensembles of rules [116] and apply meta-cognitive scaffolding theory for tuning the learned model incrementally in what-to-learn, when-to-learn, and how-to-learn [138]. In fact, ensembles are known for their good results in predicting both cyclic and non-stationary data such as stock prices [10], [13], [110]. These have also introduced the ability to deal with recurrent concepts explicitly and have beaten other methods at predicting the S&P500 [37], [38], [111]. For instance, Pratama et al. employed an evolving type-2 recurrent fuzzy neural network to learn incrementally and handle recurring drifts in both [124] and [38]. In any case, there is still a significant gap between EIS and the rest of the literature for data stream classification.

This line of work based on EIS is being complemented by other studies that combine ensembles and other evolutionary algorithms to tackle concept drift in financial applications like [84]. These authors used ensembles of trading rules evolved using grammatical evolution to manage structural change in the Standard & Poor's 500 index.

V. Conclusions and Future Work

The application of AI to computational finance has been a very active field of research for decades. Among the key difficulties identified in the literature on financial prediction, we can mention structural change. The price generation process of financial time series is often affected by changes of different natures. Some of these changes can reoccur over time as seasonal patterns, while others do not repeat, being abrupt breaks in the non-stationary price dynamics.

This study presented a systematic literature review of machine learning techniques for financial prediction under regime changes. A variety of sources were inspected to perform an exhaustive search. This review included: ScienceDirect, IEEE Digital Library, ACM Digital Library, Taylor & Francis, Wiley and SpringerLink. Out of a total of 140 relevant studies, these are distributed as follows: i) concept drift or online learning related (32.1%); ii) related to financial literacy for regime changes (15.7%), and iii) ML techniques applied to stock forecasting (52.1%).

The results of reviewed publications show that ML has proven to be a powerful tool to tackle the problem of financial prediction under concept drift, which we define as structural breaks, that can occur at any frequency level. This includes solutions based on different algorithms that adapt their prediction models to new circumstances either through new model generation or managing an archive of former successful models. In this regard, many meta-learning approaches in the ML literature rely on non-supervised algorithms to try to identify the recurrence of a concept and retrieve previous models or detect drifts.

In this context, the use of sequential DL models such as RNNs can be insufficient to tackle abrupt changes since the previous market dynamics are still in memory in the models impacting predictive accuracy. In contrast, the model learns the new regime [113], [115], [121].

Depending on the frequency involved, researchers suggest either solutions based on model retraining either at regular intervals or upon detection of changes or drifts or online incremental algorithms. This entails having up-to-date models with the use of forgetting mechanisms to avoid overfitting and adapting to new market behaviours. Regarding the latter, and despite the success of online ensembles dealing with complex systems and training base learners to deal with different regimes, the use of these approaches from the data stream learning literature is not as popular in financial forecasting yet.

Even though there doesn't seem to be a clearly dominant ML technique in this space, it is worth mentioning the popularity of solutions based on ensembles and evolving fuzzy systems. It is also important to note how the relatively recent developments in deep learning have fostered the popularity of approaches where artificial neural networks play a key role.

Future research is likely to emphasise the application of data stream classification algorithms to financial streams. Online machine learning has not been widely applied to the financial domain. However, as shown in this study, similar techniques like sequential and recurring deep learning models are on the rise in finance. Applying the problem of concept drift to handling price change dynamics seems a natural step forward on the research line of financial regime changes.

Having said that, better access to high-frequency data and computational resources will also likely result in major progress in the near future.

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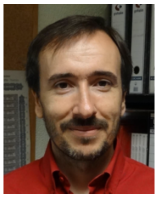
Andrés L. Suárez-Cetrulo

Andrés received his BSc and MSc in Computer Science at Carlos III of Madrid (Spain) in 2013 and 2014, respectively. He received his PhD in Computer Science at University Carlos III of Madrid in 2022. He is currently a Data Science Architect at Ireland's National Centre for Applied AI, based at University College Dublin. His current interests focus on online machine learning for data streams, regime changes in financial markets, deep learning, transformers and generative models.



David Quintana

David Quintana holds Bachelor's degrees in Business Administration and Computer Science. He has an M.S. in Intelligent Systems from Universidad Carlos III de Madrid and a PhD in Finance from Universidad Pontificia Comillas (ICADE). He is currently Associate Professor at the Computer Science Department at University Carlos III of Madrid. There, he is part of the bio-inspired algorithms group EVANNAI. His current research interests are mainly focused on applications of Computational Intelligence in finance and economics.

Alejandro Cervantes

Graduated as Telecommunications Engineer at Universidad Politecnica of Madrid (Spain), in 1993. He received his PhD in Computer Science at University Carlos III of Madrid in 2007. He is currently a professor at the Escuela Superior de Ingeniería y Tecnología in UNIR (Universidad Internacional de la Rioja). His interests include bio-inspired algorithms for classification of non-stationary data, large multi-objective optimization problems, swarm intelligence algorithms and deep machine learning for meteorological forecasting, aeronautics and astrophysics.