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ARTÍCULOS ORIGINALES

Market efficiency analysis using AI models based on Investors' Mood

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ABSTRACT The Efficient Market Hypothesis assumes that stock prices in financial markets incorporate all the historical information in any of its forms (weak, semi-strong and strong). The aim of this study is to validate this hypothesis. This study uses artificial intelligence models designed to predict IBEX trends, based on investor mood, extracting information from the big data and using natural language processing algorithms. The results of the study show that the success rate of a system that trains for only 6 months is higher than a system that uses all the available historical information. Investment strategies can also be based on the forecasts of the artificial intelligence models, which can beat the market, by setting up different trading systems for different degrees of risk, depending on the probability threshold provided by the model considered. These results imply that the Spanish financial market has a short-term memory, and does not include older information and therefore does not fulfill the efficient market hypothesis assumptions.

KEY WORDS Big data, IBEX, Bayesian Networks, investors' mood, trading systems, market efficiency.

Análisis de la eficiencia del mercado mediante modelos de IA basados en el estado de ánimo de los inversores

RESUMEN La hipótesis del mercado eficiente asume que los precios de las acciones en los mercados financieros incorporan toda la información histórica en cualquiera de sus formas (débil, semifuerte y fuerte). El objetivo de este estudio es validar esta hipótesis. Este estudio utiliza modelos de inteligencia artificial diseñados para predecir las tendencias del IBEX con base en el estado de ánimo de los inversores, extrayendo información del *big data* y utilizando algoritmos de procesamiento del lenguaje natural. Los resultados del estudio muestran que la tasa de éxito de un sistema que se prepara para solo 6 meses es mayor que la de un sistema que utiliza toda la información histórica disponible. Las estrategias de inversión también pueden basarse en las previsiones de los modelos de inteligencia artificial, que pueden superar el mercado, estableciendo diferentes sistemas de negociación para distintos grados de riesgo en función del umbral de probabilidad que proporcione el modelo considerado. Estos resultados implican que el mercado financiero español tiene una memoria de corto plazo y no incluye información más antigua, por lo que no cumple los supuestos de la hipótesis de mercado eficiente.

PALABRAS CLAVE *big data*, IBEX, redes bayesianas, estado de ánimo de los inversores, sistemas de negociación, eficiencia de mercado.

Análise da eficiência do mercado usando modelos de IA baseados no humor dos investidores

RESUMO A hipótese do mercado eficiente assume que os preços das ações nos mercados financeiros incorporam todas as informações históricas em qualquer uma de suas formas (fraca, semiforte e forte). O objetivo deste estudo é validar essa hipótese. Este estudo usa modelos de inteligência artificial projetados para prever as tendências do IBEX com base no humor do investidor, extraindo informações de big data e usando algoritmos de processamento de linguagem natural. Os resultados do estudo mostram que a taxa de sucesso de um sistema que é preparado por apenas 6 meses é maior do que a de um sistema que usa todas as informações históricas disponíveis. As estratégias de investimento também podem ser baseadas nas previsões de modelos de inteligência artificial, que podem superar o mercado, estabelecendo diferentes sistemas de negociação para diferentes graus de risco dependendo do limite de probabilidade fornecido pelo modelo considerado. Estes resultados implicam que o mercado financeiro espanhol possui uma memória de curto prazo, não incluindo informação mais antiga, pelo que não cumpre os pressupostos da hipótese de mercado eficiente.

PALAVRAS CHAVE big data, IBEX, redes bayesianas, humor do investidor, trading systems, eficiência de mercado.

Introduction

Algorithmic trading systems invest in financial markets in an unattended and constant way, sending buy and sell orders to the market for a particular financial instrument, according to a more or less complex mathematical algorithm. They became popular in the nineteen eighties with the mechanization of financial markets, but it was as from the year 2000 when trading became possible by small investors. When trading systems handle many transactions and only hold the position for a few seconds, we talk about High Trading Frequency —HTF— (Kirilenko, Sowers and Meng, 2013).

To determine whether an automatic trading system is better than another, the following statistics are mainly used (Leshik and Crall, 2011):

(i) Profit/Loss: the total amount generated by the system from its transactions over a certain period of time.

(ii) Success rate: percentage of successful transactions out of the total transactions, if the percentage is above 50 %, the system is profitable and the higher the percentage, the better the system.

(iii) Profit Factor: this rate shows the relationship between earnings and losses, by dividing total earnings by total losses. As of 1.50, the system is considered good by default and the higher the rate, the better.

(iv) Sharpe Ratio: relates profitability to volatility, the higher the ratio, the better the performance of the system (Sharpe, 1994).

According to iBroker securities brokers, algorithmic trading systems have certain advantages over manual trading: (i) Uninterrupted presence on markets; (ii) They are not subject to stress or emotion, which can cause mistakes.

Research shows that individual investors trade too much and do not perform as well as market indexes (Barber and Odean, 2000; Feldman, 2011). Algorithmic trading systems have multiple applications. For example, Schmitz (2010) describes algorithmic trading systems as those intended to create liquidity on the market and perform the function of market maker, although most of the systems are designed to beat the market systematically, which would not be possible if we assume the perfect market efficiency of financial markets (Fama and French, 1998). The Efficient Market Hypothesis —EMH— states that securities markets are "informationally efficient," as investor activity causes a balance between the market price of a security and a good estimate of its intrinsic price, meaning that stock prices reflect all the existing information and completely and rapidly adjust to new data that may arise. There are normally three levels of efficiency:

(i) Weak form of the efficient market hypothesis: the weak hypothesis means that the listing does not reflect past information and that it is therefore not possible to find investment strategies based on historic share prices or other historical financial data to achieve yields that beat the market, their technical analysis therefore being useless.

(ii) Semi-strong form of the efficient market hypothesis: according to this hypothesis, a market is efficient when the prices reflect past information and all the future information that is made public on the company or its environment. Share prices adjust instantaneously to all the information made public and a yield more than the market yield cannot be achieved using such information, meaning that basic analysis techniques are unable to achieve more than market yield.

(iii) Strong form of the efficient market hypothesis: share prices reflect all the information, including private information and nobody can achieve a higher than market yield.

Whether a financial market is efficient or not is something that has been subject to debate for several years, with studies dealing with the issue from different approaches. For example, Doran, Peterson and Wright (2010) surveyed a population of 4000 university teachers on their perception of market efficiency; whereas Maymin (2011) used a purely statistical approach and Hasanhodzic, Lo and Viola (2011) used computational approaches. In this study, is analyze the validity or not of the EMH using artificial intelligence big data models developed by InvestMood and based on research carried out at the Universidad Rey Juan Carlos.

The InvestMood algorithmic trading systems is developed using artificial intelligence models based on Bayesian Network s that use information on investor mood as predictors. Bayesian Network s learn from the past to attempt to predict the future. The larger the sample available to train, the more accurate the predictions. Therefore, according to the efficient market hypothesis, systems that train with more historical data should be more accurate and perform better than those with smaller samples.

The purpose of this study is to analyze different artificial intelligence big data IBEX 35 asset management models and to determine whether they are capable of systematically beating the market and under what conditions it occurs in a more evident manner. If artificial intelligence models can beat the market, we would have evidence that they are not efficient. In addition, is analyze the accuracy of short training models and long training models. If the short training models provide more accurate predictions, this would again be evidence of market inefficiency in EMF terms, as it would show that the market does not have all past information.

Conceptual Framework

In his article "Portfolio Selection," Harry Markowitz (1952), who received the Nobel Prize for Economics in 1990, proposed that investors that act rationally would select portfolios that maximize yield and minimize risk. According to his model, investors would attempt to maximize a function of use that would positively depend on the expected yield and negatively on the risk. According to this theoretical basis, what is observed is that investor tolerance or aversion to risk varies from one moment in time to another, depending on their mood. The logic behind these movements is simple. Investors in a positive mood are more tolerant towards risk, which increases their appetite for investment in variable yield and decreases their interest in fixed yield, resulting in them buying shares and forcing the prices up, whereas the opposite occurs in situations of pessimism, fear and even panic.

There are numerous studies that show that investor mood is affected by multiple factors, changes over time and may be conditioned by past experience or training (Cohen and Kudryavtsev, 2012). These changes in mood provide evidence of anomalies in the behavior of stock markets (Nofsinguer, 2005). Corredor, Ferrer and Santamaría (2013) claim that investor mood has a significant effect on stock performance.

Among the factors that affect investor mood, is find the following:

Weather: Hirshleifer and Shumway (2003), as well as Jacobsen and Marquering (2008) analyze the relationship between sunny mornings and stock market growth. Psychological evidence and casual intuition predict that sunny climates are associated with an optimistic mood. These authors examined the relationship between sunny mornings in the leading stock market city in the country and the daily stock market yield in 26 countries from 1982 to 1997. The results showed that sunny climates were heavily correlated with share performance, thus also enabling the creation of trading strategies based on the optimum climate for a trader with very low transaction costs. Nevertheless, as these strategies require highly frequent trading, the costs eliminate the profits. The authors highlighted that their findings were difficult to conciliate with completely rational price making, such as it is assumed in the efficient market hypothesis.

Seasonal patterns: vacation produces the effect of "sell in May and go away," or the "Halloween" effect (Bouman and Jacobsen, 2002). There is documented evidence of a strong seasonal effect on stock performance. According to the traders' saying, securities market yield should be greater from November to April than from May to October. Surprisingly, is find that this inherited wisdom is true in 36 of the 37 developed and emerging markets. The "sell in May" effect tends to be particularly strong in European countries and it is robust over time. For example, test samples show that in the United Kingdom, the effect has been perceptible since 1964. Another documented seasonal pattern is the "January effect." Seyhun (1988) studied the seasonal pattern of aggregate inside information and concluded that the January effect came from predictable changes in the demand for securities for the year and that represents compensation for the greater risk of trading against informed traders at the end of the year.

The Moon: Yuan, Zheng and Zhu (2006) compared financial market yield according to the different phases of the moon and observed differences from 3 % to 5 % in yield from one phase to another. The relationship between the phases of the moon and market growth is justified by their influence on people's neuronal patterns. Very little is known of the role of the endocrine system on financial risk taking. Coates and Herbert (2008) carried out a study in which they sampled the endogenous steroids of a group of male traders in the city of London, under real conditions. They found that the level of a trader's morning testosterone predicted the yield he was going to have in the morning session. They also discovered that a trader's cortisol increased with the variation of results and the volatility of the market. Their results suggest that higher testosterone may contribute to higher yield, due to a higher tolerance of risk, whereas the cortisol increase was the result of risk. These authors highlight an additional possibility, as it is known that testosterone and cortisol have cognitive and behavioral effects, in such a way that if high levels of steroids are observed, persist and increase in line with volatility, hence they may change risk preferences and even affect a trader's ability to take rational decisions.

Investor gender: Olsen and Cox (2001) suggest that even with equivalent capability, experience and information, investment managers take different decisions based on identifiable cultural differences. Their study focuses on professional male and female investment managers that perceive and respond to risk differently. There is a great deal of evidence that when facing social and technological dangers, women are more averse to risk than men. This appears to be the case even when the decision makers have the same degree of experience. As far as investment is concerned, non-professional women investors also appear to take less risks than their male counterparts, taking in account factors such as age, education, wealth and experience. Although the exact reason for this gender risk taking difference is unknown, if it appears to be related to evolutionary and social factors. The study researched the professionally qualified investor risk/gender difference; and it found that women investors consider risk attributes, such as the possibility of loss and ambiguity more seriously than their male colleagues. Furthermore, women tend to emphasize the decrease in risk more than men when building a portfolio. Although gender differences appear to influence the perception of risk and recommendations to clients, these differences tend to be the most significant for stock and portfolios at risk extremes.

Sports Results: the changes in mood caused by sports events affect financial markets, depending on the sport. Edmans, García and Norli (2007) studied the results of football, cricket, rugby and basketball; while others have focused on the NFL (Chang et al., 2012), football (Berument, Ceylan and Gozpinar, 2006; Kaplanski and Levy, 2010) and on cricket (Mishra and Smyth, 2010). Gómez and Prado (2014) claim that investor decision making is often based on a prior analysis, although mood can be affected by multiple reasons. The purpose of their work was to analyze whether the effects of the results of national teams influenced growth on the most representative stock markets in the country. They performed a statistical analysis of the following stock markets after national team football matches, measuring profitability by the rate of variation during the session and the inter-day variation rate. The results obtained show that after a defeat of the national team, is should expect negative and lower than average prices on the country's stock market, the opposite occurring in the case of a victory. This pattern was the same for all countries that have been world champions and have a representative market, except for England and the FTSE 100. These exceptions are justified by the fact that there are five national teams in the British Isles.

At this stage, if investor mood varies and that this affects financial markets and their liquidity (Liu, 2015), the challenge that arises is how to measure mood to predict market trend (Hilton, 2001). The first attempts to measure investor mood go back some time. Darling (1955) used the relationship between dividends and profits to measure investor mood, although another method was using reliable consumer surveys (Lemmon and Portniaguina, 2006) on investors' perception of the growth of speculative booms (Shiller, 2000). However, the results and surveys are observed after the fact and therefore lack the capacity to predict for algorithmic trading, which leads us to consider the big data approach:

A "V" is normally used to summarize the most important features of a project for it to be considered "big data." According to the Institute of Knowledge Engineering (Universidad Autónoma de Madrid), the four traditional V's of big data are volume, variety, velocity and veracity, to which it adds:

viability, visualization and, especially, value. Whit this approach, Wu et al. (2013) use big data to predict market volatility; whereas Moat et al. (2013) use the frequency of use of Wikipedia to determine investor feelings; and Gómez (2013) elaborated a "Risk Aversion Index" based on the volume of searches on Google for certain economic and financial terms that relate to market growth. Through an econometric model, he shows that Google search statistics provide relevant information on the growth of financial markets and may generate investment signs that can be used to predict the growth of major European stock markets. According to this approach, is could create an algorithmic trading system that issues buy and sell orders by measuring the level of aversion to risk, assuming that an increase in tolerance towards risk implies a bull market and an increase in aversion to risk a bear market.

Hypothesis

The hypothesis is want to contrast in this study (H1) is just the EMH, in this case for the Spanish stock market, using the IBEX 35 as its main index. If the market were efficient according to the EMH, a big data model using artificial intelligence would not be able to beat the market systematically. If it were able to find an artificial intelligence model capable of beating the market, we would be providing evidence that the EMH is not valid.

Is validate the hypothesis if the profitability of the IBEX is higher than the profitability of an investment strategy that follows the predictions generated by the artificial intelligence big data model.

Likewise, the EMH assumes that the market incorporates all past information. To validate this hypothesis, several models were used with different sets of historical data. If the short training models (that reject historical information) were more accurate than the long training models (which uses all the historical information available, as EMH assumes) is would be contradicting the assumption of the EMH.

Therefore, is validate the H2 hypothesis if the long training models have more accurate predictions than the short training models, where accuracy is measured by the model's success rate.

Methodology

The trading models described in this paper have been developed by InvestMood. They implement a process that carries out a daily search of all the communications that mention the term "IBEX" on the digital media (Twitter, specialized and non-specialized press, radio and television), gathers scattered information and organizes it qualifying each communication as "good," "bad" or "neutral" using natural language algorithms. This semantic analysis algorithm was developed by the big data and analytics firm, Apara. An example of the automated analysis made by these algorithms is the following: The news on 2016-01-29 at 07:39 in the newspaper *Cinco Días*: "IBEX drops 7.6 % in January, its worst start to the year since 2010" was classified by the algorithm as "bad;" whereas the news published on 2016-01-29 at 08:18 by *Europa Press*: "IBEX 35 soars by 1.6 % at opening, led by Repsol and the banks" was classified as "good."

The structured information on IBEX mood constitutes the predictors of artificial intelligence models based on Bayesian Network s, in which the target is the IBEX 35 trend during the next session (up or down). The media studied were, in alphabetical order: *20 Minutos* (newspaper); ABC (newspaper); *Antena 3* (TV); *Cadena SER* (radio); *Cinco Días* (specialized newspaper); *El Confidencial* (newspaper); *elDiario.es* (newspaper); *El Mundo* (newspaper); *El País* (newspaper); *El Periódico* (newspaper); *Europa Press* (news agency); *Expansión* (specialised newspaper); *La Razón* (newspaper); *laSexta* (TV); *La Vanguardia* (newspaper); *RTVE* (TV); *TELEcinco* (TV); Tweeter (social Network); and *Telemadrid* (TV).

The set of data used to train the Bayesian Network s of these models, has 19 predictors taking on a possible value of good/bad/neutral and an endogenous variable, the inter-day or "open to close" trend (IBEX_COMPORTAMINETO_OTC) with Up/Down values, according to whether the closing price is higher or lower than the opening price. This daily performance does not coincide with the daily performance that is normally used to compare the closing price with that of the previous day, including an opening gap. It was chosen because the process is carried out at night after the summary of the opinions generated during the day, and a strategy whose objective variable was the performance from closing to closing would be impossible to replicate.

Therefore, the data used for this study was provided by Sigma Technologies. The predictors based on its digital media big data natural language sampling process and the variable objective was listings by Yahoo Finance using Web scraping techniques.

The predictive capacity of the news published in the different media on financial assets has been analyzed in financial literature. Huynh and Smith (2017) use a set of data comprised of 10.1 million news items in four regions (United States, Europe, Japan and Asia Pacific) and show that stock with important and positive news shows a greater continuity of return. The findings of the study suggest that investors in international markets react similarly to the same types of news. Narayan and Narayan (2017) analyze the effect of news on oil prices and stock market earnings. For many shares on New York stock exchange, the authors find that the news on oil prices predict the market returns in certain sectors. Their study carries out a simulation of a model portfolio weighing up assets according to the news on oil prices and the portfolio generates a significant returns differential in the market that is maintained consistently. Their findings suggest that the information contained in the news on oil prices affects the returns on shares. Birz and Lott (2011) measure the news on macroeconomic statistics to estimate their effect on share prices, concluding that the news on GNP and unemployment affect stock performance.

The Bayesian or Probabilistic Network s are graphical representations of probabilistic dependencies in expert systems (Bayes, 1763). A Bayesian Network is a directed and scoring acyclic graph that describes the joint probability distribution that governs a set of random variables. The nodes can represent any type of variable, be it a measurable parameter, a latent variable or a hypothesis. In our case, each predicting node in the probability graph is the mood expressed by each media item included in the study and the objective variable is dichotomous and represents the trend experimented by the IBEX on the next day of trading (up/down).

The algorithms used in this study to train the Bayesian Network models were developed by Apara and are implemented in its data mining platform named dVelox. In this case, the Bayesian Network created for the InvestMood systems must be interpreted as the conditional probability of the IBEX 35 rising or falling on the day after it is mentioned in one of the media items analyzed, depending on whether the mention is good, bad or neutral.

To determine whether these models can beat the market, an investment strategy was simulated in which a long position was opened if the model prediction was "UP" and a short position in the opposite case, with positions being closed at the closing of the market. Gross profit or loss was the difference between the opening and closing prices. The simulation was repeated for different levels of trust according to the probability offered for each prediction by the Bayesian Network (50 %, 60 %, 70 %, 80 % and 90 % of probability).

Results

According to the processes and methodology of the study described above, two alternative statistics models were trained: (i) long training model and (ii) short training model.

Long training model

This model is based on a long training Bayesian Network, with historical data from November 2015 to December 2017. The new data, mistakes and successes of the model were recorded, and it was again trained using machine learning techniques. It cannot talk of a single static model, as it is constantly evolving with the accumulation of more historical data.

The probabilistic graph model representing the Bayesian Network was trained to build the model used by the system (Figure 1). It shows the relationships of conditioned probability between the predictors and the endogenous variable, which is none other than the behavior of the IBEX during the following trading session.

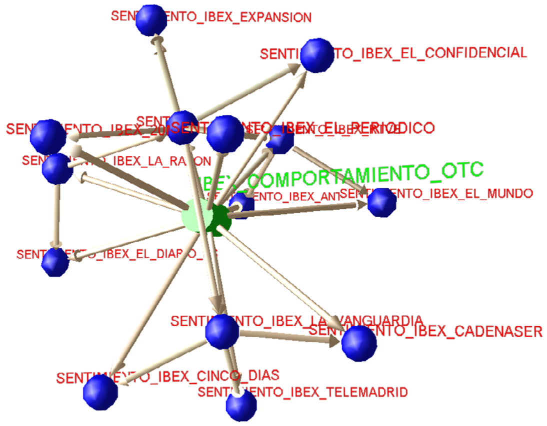

Figure 1. Long training Bayesian Network. Source: author own elaboration.

Short training model

This model is like the above, but with a different training period of 6 months, validated prospectively throughout 2017. The model created was used to predict the next quarter, then trained again; after was eliminate the information from the first three months to create a new model. In this case, is therefore have the following training periods and prospective validation:

1. Training: From June 2016 to December 2016. Validation from January 2017 to March 2017.

2. Training: From October 2016 to March 2017. Validation from April 2017 to June 2017.

3. Training: From January 2017 to June 2017. Validation from July 2017 to September 2017.

4. Training: From April 2017 to September 2017. Validation from October 2017 to December 2017 (date of this study).

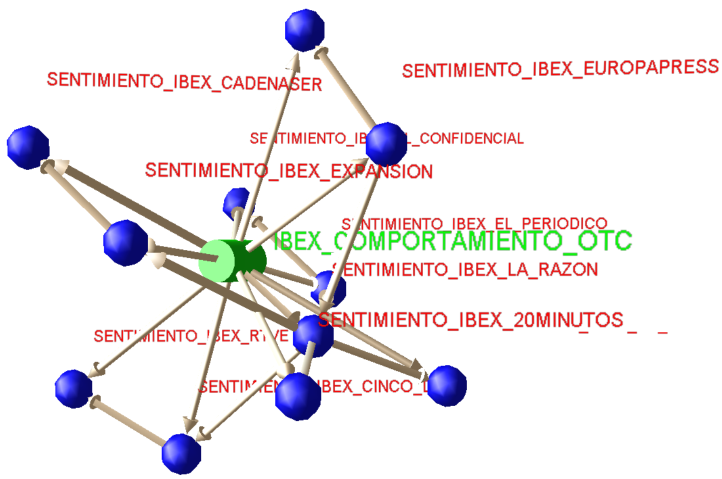

Figure 2. Short training Bayesian Network. Source: author own elaboration.

The Bayesian Network was trained to create the model that supports the trading system described, represented in the following illustration. dVelox uses a model optimization algorithm that optimizes the model created using "brute force" techniques by adding and subtracting variables until reaching a model with a better success rate. The probabilistic graph model shows that the models created with short training (6 months) have less predictors than long training models and that the brute force algorithm eliminates the predictors that penalize the accuracy of the model, meaning that no model includes the 19 predictors described above.

Table 1 summarizes the main results of the study and shows that the long training model has lower success rates and therefore less yield, as the models are trained with larger samples (from success rates above 60 % to rates that barely exceed 50 %). A success rate of less than 50 % would result in the model being discarded, as the mathematical expectation of the associated trading system would be negative.

Table 1. Artificial intelligence results for two models

Period	Model	Probability	Success Rate	Yield	IBEX differential
2016	Long	50 %	62.50 %	€ 5,098.40	€ 5,290.50
2016	Long	60 %	60.20 %	€ 3,410	€ 3,602.10
2016	Long	70 %	59.76 %	€ 2,688.60	€ 2,880.70
2016	Long	80 %	57.14 %	€ 1,581	€ 1,773.10
2016	Long	90 %	62.22 %	€ 2,358.10	€ 2,550.20
2017	Long	50 %	47.47 %	€ 4.20	- € 825.70
2017	Long	60 %	46.02 %	€ 20.10	- € 809.80
2017	Long	70 %	47.01 %	€ 285.90	- € 544.00
2017	Long	80 %	50.63 %	€ 560.20	- € 269.70
2017	Long	90 %	49.02 %	€ 389.00	- € 440.90
2017	Short	50 %	51.57 %	€ 2,092.70	€ 1,262.80
2017	Short	60 %	55.68 %	€ 1,835.50	€ 1,005.60
2017	Short	70 %	60 %	€ 1,790.80	€ 960.90
2017	Short	80 %	63.22 %	€ 1,854.60	€ 1,024.70
2017	Short	90 %	70.15 %	€ 1,909.50	€ 1,079.60

Source: author own elaboration.

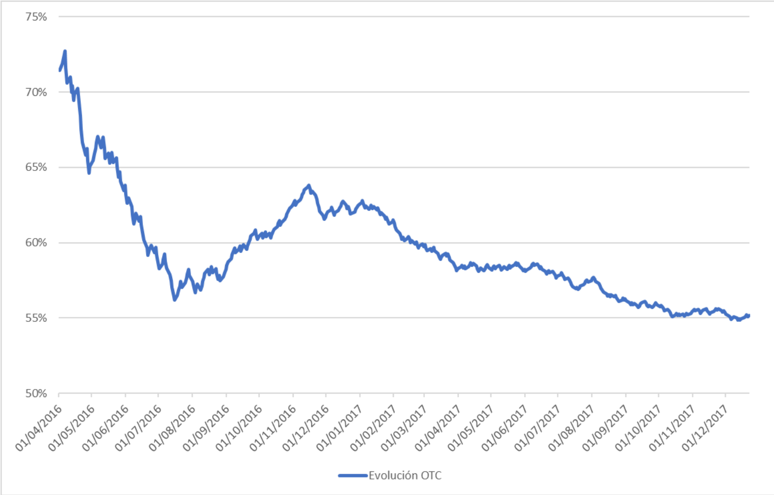

Figure 3. Long training model success rate evolution. Source: author own elaboration.

The evolution of the long training success rate decreased progressively as the model was trained with more past information (Figure 3).

This result brings us to reject the H2 hypothesis and question the EMH assumption that the market incorporates all past information. In this case, it is clear that the more the information is include in the model, the less accurate it is and it performs better only with recent information and ignoring historical data.

Accordingly, the results appearing in Table 1 show that a trading system that enters the market or not, depending on different probability thresholds, is able to beat the market if it has been trained with a short historical background. Only the models that were trained with historical information of more than one year were unable to beat the market. This brings us to reject hypothesis H1 and therefore to EMH, as it was observed that the market could be beaten systematically. The results show that the market is not informationally efficient, and that the EMH cannot be validated, as the historical information assumption cannot be proven.

With respect to the simulated trading systems, is observe that the artificial intelligence models are more accurate as we perform a simulation in which the probability threshold at which the system enters the market becomes is higher.

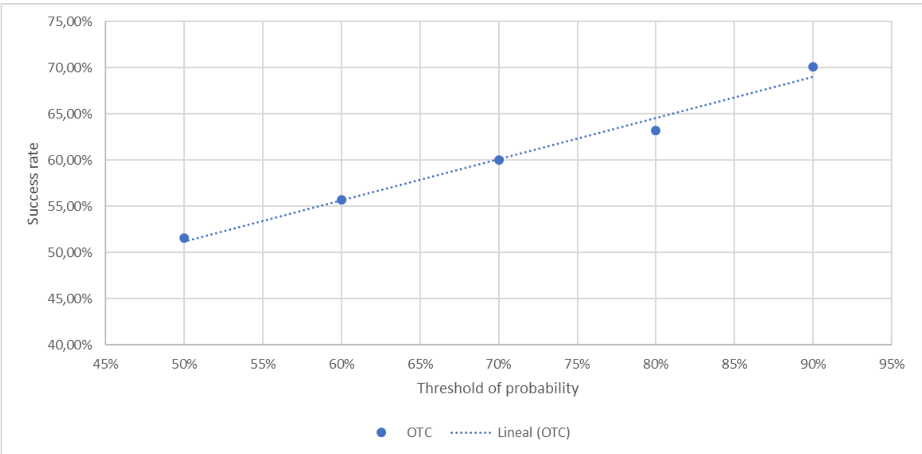

Figure 4. Short training model: success rate vs probability threshold. Source: author own elaboration.

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Conclusions

The efficiency of financial markets is a concept that is normally assume by the agents operating in the market. In financial subjects taught at universities, the weak, semi-strong and strong market efficiency are describing as a fact that students assume as dogma. However, there are multiple indications that financial markets are not efficient, for example, the studies on investors' mood that show that changes in mood implies market movements that cause deviations in the balance between observed price and theoretical price. If markets are rational, why are they influence by emotion?

In this study, is was used an innovative approach to check the efficiency of financial markets. The study is based on big data and uses artificial intelligence to predict IBEX trends by only using investors' mood. If the IBEX is the reference index of the Spanish stock market and it is efficient, it could not be beaten by any investment strategy and would be considering all historical information, meaning that an artificial intelligence model could not generate an investment strategy that could beat to the market. Furthermore, a model trained with more historical information should perform better than a model trained with less historical information, given that according to the EMH, markets include "all" the historical information. Shang, Brooks and McCloy (2014) reached the same conclusion in a computer laboratory to examine a trading simulation manipulated from a real market-shock.

The results of this study show that a model trained only for the preceding 6 months performed better had, and higher success rate and could beat the market systematically, which does not validate the EMH.

The interpretation of these results leads us to think that the agents that participate in the market operate with short-term memory and forget what happened long time ago. Then, we could say, according to the models used in the study, that the IBEX suffers amnesia about everything that happened 6 months ago. If the efficient market hypothesis assumes that the market incorporates all historical information on share prices, is can conclude that the Spanish stock market does not fulfill the hypothesis, as it was observe that the determining of prices does not consider "all" historical information. Given that short training models predict better than long training models, is have evidence that the market does not incorporate all historical information and that more recent information is more relevant.

Final conclusion from this study is that trading systems can be developed using an alternative approach to common systems based on technical analysis. This study has shown how a trading system, based on the predictions of an artificial intelligence model that only uses investor mood from big data can beat the market systematically and this system can be structured according to different levels of risk, depending on the probability threshold at when they enter in the market. All this opens an interesting field of research in the development of algorithmic trading.

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