ARTIFICIAL INTELLIGENCE AND ITS UTILITY IN FINANCIAL MARKET

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Abstract
The financial market today represents an important part of the world economy. The financial market has grown significantly in recent decades and provides companies and people with a wide range of finance that can be used to hire, invest, and expand their investments. The possibility of increasing human capital through investment has led researchers in the past decade to focus on their work and report the performance of the market by promoting artificial intelligence and deep learning tools within the system. Several methods have been proposed in the literature, ranging from analysis of the process characteristics of the time series to more complex methods based on these artificial intelligence approaches. **The purpose** of the following paper is to propose three new ways to answer how global artificial intelligence impacts and improves the financial market. The **method** used in the present work is a cross-reference qualitative, starting by using hundreds of deep neural networks to pre-process the data. Then, a reward-based classifier is used to maximize profit and generate stock signals through different iterations. The framework provides a modular view, both general and targeted, of the resulting data in several financial metrics.At **the end**, along with current developments in the definition of artificial intelligence, we propose a visual method for the in-depth analysis of the results obtained from deep learning methods, informing the work classification in the financial sector, and finding better explanations and descriptions of trained deep learning models.

Keywords: Artificial Intelligence, Financial Market, Deep Learning Model, financial metrics, human capital.

INTRODUCTION

The financial market today represents an important part of the world economy. The financial market has grown significantly in recent decades and provides companies and people with a wide range of finance that can be used to hire, invest, and expand their investments (Shanmuganathan,2020; Bahrammirzaee, 2010; Layene,2005).

Researchers have focused on using artificial intelligence and deep learning tools to increase human capital through investment (Shanmuganathan,2020; Bahrammirzaee, 2010; Arslanian & Fischer,2019). Several methods have been proposed in the literature, ranging from analysis of the process characteristics of the time series to more complex methods based on these artificial intelligence approaches. Differently from the past, Financial Markets have grown exponentially in recent decades, and, more financial instruments have been introduced to predict their behavior (Shanmuganathan,2020; Velarde,2019). Information and communication technologies have been employed within the financial domain, so investors are now supported by many Artificial Intelligence instruments that help them to make decisions (Tiwari et al.,2020; Gacutan et al.,2020; Smith,2020; Evangelista et al.,2020). Such instruments can exploit a diverse number of techniques from simple statistical approaches to those more sophisticated, based on Deep Learning, Social Media Analysis, Natural Language Processing, Sentiment Analysis, etc (Evangelista et al.,2020; Velarde,2019; Deng,2013).

The present article will explore the relationship between artificial intelligence and its effects on the financial market.

The fundamental elements of Artificial Intelligence

Artificial intelligence began to take shape in 1956 when a group of researchers at Dartmouth College in New Hampshire coded the field's initial foundations based on work done by several of their colleagues the year before (Muthukrishnan et al.,2020; Flasiński,2016).Besides the conventional computer science research that established the foundation of the field, it is crucial to emphasize that several academic fields including philosophy, mathematics, and psychology have influenced the advancement of artificial intelligence by defining its features (Shanmuganathan,2020; Tiwari et al.,2020; Evangelista et al.,2019; Øhrstrøm,2009). Artificial intelligence seeks to develop hardware and software systems that can perform tasks that seem to be limited to human intelligence, both in terms of the outcomes achieved and the methods by which they were arrived at learning, inference, deduction, generalization, particularization, hypothesis testing, and so forth (Øhrstrøm,2009; Laberge,2008). Since it is difficult to define a single, universal definition of intelligence, over the years, researchers have attempted to pinpoint several traits that are associated with human intelligence (Helm et al.,2020). This has allowed computers that have been given artificial intelligence capabilities to attempt to replicate one or more of these traits (Narrow artificial intelligence) but, it is still difficult to equip a single computer with all these abilities (Artificial General Intelligence) (Allen,2019). Researchers have developed many branches of artificial intelligence, starting from the natural intelligence trait that computers have been trying to replicate. A comparison of these two types of intelligence is given in the following table-

Table 1: Features of Human and Artificial Intelligence

Human Intelligence	Artificial Intelligence
Perception	Computer Vision
Exploration	Robotics
Communication	Natural Language Processing
Rationality/ Problem-solving	Automatic Plan
Learning	Machine Learning

The early pioneers of AI believed that every aspect of learning or any other feature of Artificial Intelligence can in principle be so precisely described that a machine can be made to simulate it. Therefore, symbolic AI took center stage and became the focus of research projects(Flasiński,2016). Symbolic Artificial Intelligence showed early progress at the dawn of computing. Machine Learning solutions have been widely adopted in financial time series forecasting. They usually operate by using a supervised strategy, where classifiers (e.g., Naive Bayes, Decision Trees, Support Vector Machines, etc.) label the data to learn their behavior and classify new data into several classes (i.e., in the stock market, such classes can be considered as prices going up and down).
Machine Learning uses three fundamental techniques (Lv et al.,2019; Alonso et al.,2018):

• ***Supervised Learning***, where data and labels are provided by the human and the computer, tries to identify patterns and correlations between them;

• ***Unsupervised Learning*** where only unlabeled data are provided by the human and the computer tries to learn some inherent structure from that data;

• ***Reinforcement Learning*** where an agent receives information about its environment and learns to choose actions that will maximize some reward.

Deep Learning approaches have also been proposed in the literature, where a Deep Convolutional Neural Network can be used to perform classification or regression tasks, which means predicting the daily direction (positive or negative) of the market for classifications whereas predicting the daily expected price for regressions (idem).

A common classification task within the financial domain consists of defining an intraday trading strategy, which targets three possible actions to perform daily:

- a long action, which consists of buying the stock when the market opens the next day, and then selling it before the market closes; a short action, which consists of selling the stock (using the mechanism of quick sales) when the market opens, and then buying it before the market closes.
- a flat action, which consists of deciding not to invest in that day.

Computer-aided stock trading is composed of two steps: (i) analysis of past market behavior, and (ii) taking the optimal stock trading decision. To perform such tasks, time-series data from past prices are usually considered as input. These data are usually given by the market under different resolutions (minutes, hours, days, etc) and contain information such as open prices, and close prices, among others (Alonso et al.,2018).

Methodology

The purpose of this work is to propose three new ways to answer how global artificial intelligence impacts and improves the financial market.

The method used in the present work is a cross-reference qualitative and quasi-experimental, starting by using hundreds of deep neural networks to pre-process the data.

Collection of Data

Our goal with the model we plan to construct is to use a neural network to detect speculative bubbles in the stock market. Given that speculative bubbles are a medium- to long-term event in finance, a very lengthy historical period on the markets must be considered providing the neural network sufficient data for training. As a result, data from the Standard & Poor 500, the OECD stock index composed of a basket of the 500 most capitalized US corporations, was selected to be used. The data spans the last 50 years, from 1972 to 2022. Compared to the Dow Jones, which is composed entirely of industrial businesses, and the Nasdaq 100, which is an index dedicated to technology stocks, this index offers a broader view of the US market. The Pandas Data Reader package in Python can be used to read S&P 500 data straight from a line of code or directly from Yahoo Finance.

```
import pandas as pd
import datetime as dt
 import pandas_datareader.data as web
 start = dt.datetime(1972,1,3)
end = dt.datetime(2022,5,12)
df = web.DataReader("^GSPC","yahoo",start,end)
df.to_excel(excel_writer="datiS&P500.xlsx"
```

Materials and Procedures

The classifier used rewards to generate stock signals and maximize profit. The framework provides a modular view, both general and targeted, of the resulting data in several financial metrics.

1. ***Feature Selection***: data from the target market is pre-processed, with parameters being learned in the IS data.

2. ***Two-Step-Auto Adjustable Parameters Ensemble Creation***: with the auto-configurable optimized sets of hyper-parameters and intrinsic-parameters found in IS data, the approach outputs the set of hyper-parameters only, which will be transferred to a new optimization round. This new optimization step is done in the training part of the OOS data, and will find final intrinsic-parameters in recent data to build the final ensemble of classifiers.

3. ***Policy for Trading***: we define how to use the created ensemble to trade.

In our ensemble, each market will have two sets of parameters tuned: the time series parameters (hyper-parameters) and classifier parameters (intrinsic parameters), no matter what the classifiers considered in the ensemble. These parameters are tuned in late past (in-sample) and early past (out-of-sample) datasets, respectively. The input data of such an ensemble is transformed by the Independent Component Analysis, whose parameters are also optimized to make it general enough to return the optimal number of outputs signals. Our study focuses on performance metrics in Machine Learning and economics. Evaluating the economic impact is just as important as accuracy when assessing predictions.

Results

A classified database containing the S&P 500 stock quarterly from 1972 to 2022 was obtained after the quarters were grouped together.

With its corresponding metrics and a caption designating which of the 11 groups it falls under, each row represents a quarter.

Table 2: Cluster stocks of the proposed model

Starting time	Ending time	Beta volumes	Beta trimester	Cluster
06/07/2022	05/10/2022	0.2890	0,2380	9
09/07/2022	08/10/2022	0,2397	0,2776	11
10/07/2022	09/10/2022	0,2415	0,2806	11
11/07/2022	10/10/2022	0,2506	0,2930	11

This step is fundamental because it allows us to set up a problem-supervised learning ensemble where the neural network will be trained on input data and data in output. The label of each quarter represents the output variable that we want the neural network to perform once the training is completed. As for the input variables, further transformations need to be applied to their data. Going through the one-dimensional quarter on a row to the neural network as input data with their respective metrics would be extremely reductive: in this case, in fact, the network does not do anything else other than learning what has already been achieved with cluster analysis, that is, dividing clusters based on the metrics provided. The goal is to create a neural network that is able, with raw data, to assign each quarter to the correct group by replicating all the operations carried out in a much more streamlined clustering stage (cluster analysis and manual analysis) and which is capable of abstraction and to further explore the characteristics of the data to find new patterns. We want to build a convenient ensemble, that does not need complicated processing before being used, but which produces results with the simplest data available. It was decided therefore to provide the network only with data on daily prices and volumes for three quarters (the one for which you want to obtain a forecast and the two previous ones) and take advantage of its sequential data processing capabilities.

Table 3: Proposed intrinsic parameter model and ensemble trading.

Require: OOS=time series from in sample data

I= list of intra-parameters

h 0=best hyperparameter found in Algorithm 1

C=list of classifiers from the ensemble

Ensure: MEAN MET RIC= Mean performance of trading procedure Ensemble

Trading (OOS, I, h 0 , C) W ← build

W alks(OOS, h0 (window size)) .

Starts non-anchored WFO MET RIC ← 0 . Metric used to report testing results for w in W do . for each walk

F ← buildF eatures(w, h0 (lags)) . get features F 0 ← icaT ransform(h 0 (ica comp), F) .

transform features

MAX W ALK MET RIC ← 0 for c in C do . for each classifier for i in I do . for each intrinsic parameter, train and validate M[i] ← trainClassif ier(F 0 , h0 (train size), c[i]) MET RIC ← test

Classifier(M[i], F0 [h 0 (train size) ∗ 0.3]) if MET RIC > MAX W ALK MET RIC then E[c, w] ← M[i] MAX W ALK MET RIC ← MET RIC end if end for end for test data ← F 0 [h 0 (window size)−h 0 (train size)−h 0 (train size)∗ 0.3]

MET RIC ← MET RIC + test Classifier (E[C, w], test data) end for MEAN MET RIC ← MET RIC/|W| return MEAN MET RIC end procedure

Algorithm 1 Proposed intrinsic parameter search approach and ensemble trading

Source: Author´s own data

To verify our approach performance against some benchmarks, we selected four datasets based on stock futures markets (SP500, DAX, and FIB) and one future commodity (CL). As far as the stock futures markets are concerned, we included the FIB market, which is characterized by an atypical behavior concerning the other stock futures markets in the years considered during the experiments. We based our choice on the observation that stock market behavior is usually different from that of the bond markets, as there usually exists an inverse correlation between them.

In our approach, we use the benefits of Reinforcement Learning classifiers to act in a stacking scenario. Here, the RL agent acts like a meta-learner, using the outputs from the previous layer as states. In its training, the agent learns to maximize rewards, which are calculated as:

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$$\text{Reward}=\begin{cases} \text{close-open if trading action is long} \\ \text{-(close-open) if trading action is short} \\ 0 \quad\quad \text{if trading action is flat} \end{cases}$$

where open and close are, respectively, the opening and closing prices of the market.

The model's accuracy was measured in addition to its bubble accuracy metric, which assesses how well the model identified the quarters that belong to groups 9, and 11, or those that are identified as indicative of speculative bubbles. It is crucial to confirm the model's accuracy (85,91%) in this regard as well, as its primary goal is to recognize this kind of phenomenon is compared to accuracy of bubbles (81,38%). To be thorough, the outcomes from two other neural network designs are also showcased. In fact, two other combinations have produced positive outcomes throughout the layer node tuning phase:

[LSTM1 = 128, LSTM2 = 128, LSTM3 = 64, Dense1 = 100, Dense2 = 14] that represents the first alternative architecture.

The analysis of the tuning of several hyper-parameters is being carried out by our team and is the subject of future works.

Conclusions

The aim of the present paper was to give an overview of the impact of Artificial Intelligence components toward trading. We developed an algorithmic model that would reveal the output ways and connections between the Learning Machine, Deep Learning, and Deep Reinforcement Learning to financial metrics. The model achieved satisfactory results. Machine learning, statistics and deep learning were combined in the last model and showed excellent skills in understanding the nature of the cohort data of the financial market. This is a new way to identify market trends without using traditional technical analysis techniques. The developed neural network allows us to obtain acceptable results that work with a small amount of raw data, given that for each quarter only the price and volume are transferred to the network. This feature gives the model an ease of use that should not be underestimated: to get predictions from the network and the nature of the trading period, it will be enough to give it only the prices and the volumes sold during this period. Another strong point of the model lies in its diversity: the network was built to analyze the trends in the quarter and in the S & P 500 data, but the structure of the model, from the collection data and analysis methods until the implementation of neural networks. , allows the researcher to modify the time of analysis and sources of data quickly. From our qualitative and experimental results, we observe that: (i) the meta learner leads to better trading results and less over-fitting when we preliminary explore the training parameters and adopt the most promising ones; (ii) compared to well-performing non-RL ensemble benchmarks, our approach showed a final return improvement of 40% when compared to our best benchmark and, finally, (iii) our approach provides the best performances, when tested against the traditional methods proposed by researchers in two different real-world trading scenarios, and when considering several distinct periods and markets. The model algorithm proposed in this work, nevertheless, has to be tested on different classification tasks within several domains such as Emotion Detection and Credit Score. We also aim to assess, in the future, the impact of optimization algorithms when training both the first and second layers of our approach. Finally, we would focus our future investigations on the fusion of different meta-learned optimizers/parameters, which may increase the number of experts in the final assembling methodology and, therefore, lead to a more robust and stable trading strategy.

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