Generative Adversarial Network for Market Hourly Discrimination

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Abstract

In this paper, we consider 2 types of instruments traded on the markets, stocks and cryptocurrencies. In particular, stocks are traded in a market subject to opening hours, while cryptocurrencies are traded in a 24-hour market. What we want to demonstrate through the use of a particular type of generative neural network is that the instruments of the non-timetable market have a different amount of information, and are therefore more suitable for forecasting. In particular, through the use of real data we will demonstrate how there are also stocks subject to the same rules as cryptocurrencies.

Keywords Neural Network · Price Forecasting · Cryptocurrencies · Market Hours · Generative Model

JEL classification C45 · E37 · F17 · G17

Mathematics Subject Classification (2000) 91G80 · 62M45 · 91G60 · 97R40

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1 Introduction

The time series analysis has always attracted the attention of the academic world, in particular by focusing on predicting the future values of these series. Financial time series are an optimal candidate for such an analysis. These series base their assumptions on the *random walk*, a concept introduced by Bachelier [15] in 1900 and since then remained a central pivot in the theory of time series. Based on random walk theory, Kendall [9] assumed that the movement of stock prices was random while Cootner [10] defined how the movement of stock prices could not be explained in detail but was better approximated by the Brownian motion. Traditionally the best practice was to focus on logarithmic returns, bringing the advantage of linking statistical analysis with financial theory. Fama [4] introduced in his EMH theory (*Efficient Market Hypothesis*) the idea that historical prices cannot be used to make predictions since all information is contained in the current price. However LeRoy [7] showed that the mere concentration on yields was unjustified, defining the stock markets inefficient. It was Taylor [13] who proposed an alternative model to the *random walk*, developing a price trend model: he gave much empirical evidence that the price trend model was important in analyzing prices on futures markets.

From an econometric point of view, Box et al. [21] introduced power transformations to statistical models, also applying them to time series; in particular, they suggested using a power transformation to obtain an adequate *Autoregressive Moving Average* model (ARMA). On this basis Hamilton [3] gave a formal (mathematically) definition of this model. Several evolutions followed this pattern, like that *Autoregressive Integrate Moving Average* (ARIMA) and *Seasonal Autoregressive Integrated Moving Average* (SARIMA).

Recently, thanks to the development of *artificial neural networks* (ANNs) and their ability to non-linear modeling [22] there has been a strong interest in the application of these methods to time series prediction. Foster et al. [23] were among the first to compare the use of neural networks as function approximators with the use of the same networks to optimally combine the classically used regression methods, highlighting how the use of networks to combine forecasting techniques has led to performance improvements; Refenes et al. [20] proposed the use of a neural network system for forecasting exchange rates via a feedforward network, which despite being correct for 66% had difficulty predicting any turning points; Sharda et al. [24] developed a comparison between the prediction made via neural networks and the Box-Jenkins model, on the basis of which they verified that for time series with long memory neural networks perform better than the forecast while for time series with short memory the networks outperform the prevision.

The development of the financial time series forecasting has intensified mainly thanks to the new techniques [2] of Machine Learning (ML) and *Deep Learning* (DL). As for ML techniques, Kovalerchuk et al. [1] have used models such as *Evolutionary Computations* (ECs) and *Genetic Programming* (GCs); Li et al. [31] have developed a model for forecasting the stock price via ANN; Mittermayer et al. [19] compared different text mining techniques for extracting market response to improve prediction and Mitra et al. [17] have focused their attention on studying the news for predicting anomalous returns in trading strategies. As for the DL techniques, especially in the last 10 years increasingly complex architectures are being used such as Liu et al. [26] who use a CNN + LSTM for strategic analysis in financial markets or like Zhang et al. [18] who use an SFM to predict stock prices by extracting different types of patterns.

In this paper, we want to forecast problem related to financial market hours. Many of the stock markets are subject to certain opening and closing times. In these types of markets when news spreads or events occur outside closing hours, price reactions will only occur after the new opening of the market. The cryptocurrency market (and currencies in general), however, is not subject to closing times: it is open 24 hours a day. In this type of market the "opening" price of the new day and the "closing" price of the previous day are recorded in a midnight interval every day, creating continuity in the historical price series; or this reason the recorded prices are the sum of the events relating to 24 hours and therefore containing more information useful for forecasting. Our goal is to verify through an appropriate neural network how this difference of *"information in prices"* can lead to imbalances in the forecast, in particular linked to the discriminative and predictive power of the prices themselves. Some studies, such as that of Tang [32] and Gorr [16] have shown that neural networks are capable of modeling seasonality and other factors such as trend and cyclicity autonomously, therefore the different *"quantity of information"* contained in the various types of prices would seem to be the only cause that leads to forecast imbalances.

The paper structure is the following: in section 2 we analyzed the architecture of the main neural networks used to make predictions in financial markets; in section 3 we have described the special evolution of the GAN network used to extrapolate the characteristics of the different features in the time series; finally in section 4 we have shown on which instruments the prediction is better using real data.

2 Architectures of Neural Network

A neural network is a parallel computational model made up of artificial neurons. Each network is made up of a series of neurons [27] with a set of inputs to which an output signal corresponds. The neuron model was modified by Rosenblatt [8] who defined the *perceptron* as an entity with an input and an output layer based on error minimization. Thanks to the study of associative memories and the development of the *Backpropagation* algorithm by Rumelhart et al. [5] it paves the way for the applications of feedforward networks, bringing to light the recurrent networks.

Neural networks are characterized by a *learning algorithm* that is a set of well-defined rules that solve a learning problem and that allows you to adapt the free parameters of the network. The learning algorithms can be of 3 types:

- *Supervised learning*, in this way the network learns to infer the relationship that binds input values with the relative output values;
- *Unsupervised learning*, where the network only has a set of input data and autonomously learns the mappings to be made;
- *Semi-supervised learning*, a mixed approach that combines a small amount of labeled values with a large amount of unlabeled values.

Neural networks can be classified in relation to the learning algorithm to be used, and in this regard we distinguish between:

- Feedforward models, in which each layer has incoming connections from the previous and outgoing to the next so that propagation occurs without cycles and transverse connections, with training mainly supervised. For financial time series forecasting, a most widely used model is that of CNN *(Convolutional Neural Network)*. This type of network introduced by LeCun et al. [30] was designed for image processing but it also found application in the financial time series [6].

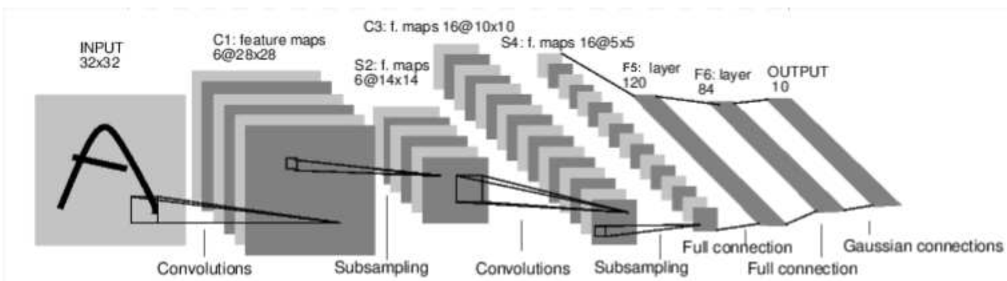


Figure 1: Architecture of a convolutional NN

This model, based on convolution, consists of a hierarchy of levels in which the intermediate ones use local connections and the latter are fully-connected and operate as classifiers. The key feature of this model is the presence of *convolution* and *pooling* levels, that aggregate the information in the input volume generating a feature map of smaller dimensionality, so as to guarantee invariance with respect to transformations and avoid the loss of information.

- Recurrent models (or feedback), cyclical so as to make the system dynamic. For financial time series forecasting the most common RNN *(Recurrent Neural Network)* is the LSTM *(Long Short-Term Memory)*, introduced by Hochreiter et al. [25] in 1997. The characteristic of this type of network is that at each step a level receives in addition to the input also the output of the previous level, so that it can base decisions on history. However, since distant memory tends to fade in base cells, the LSTM prevents this from happening through its long-term memory.

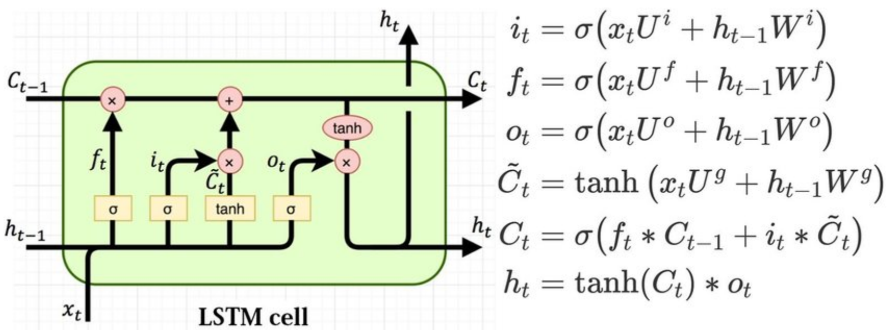


Figure 2: LSTM cells and equations that describe the gates [28]

In this case, the state h_t is a short-term memory state, while C_t is a long-term memory state: the cell learns what to forget from the past and what to extract and add from the current input.

- Generative models, used for input recognition and for pre-training of other models. The formulation of these models comes from an approach that has its roots in Bayes' theorem, and they make sensorial hypotheses about the input in order to modify the parameters that characterize them. Learning is understood as the maximization of the likelihood of the data with respect to the generative model, which corresponds to discovering efficient ways of encoding the input information. For financial time series forecasting, the most used generative model is the GAN *(Generative Adversarial Network)* network, introduced in 2014 by Goodfellow et al. [11].

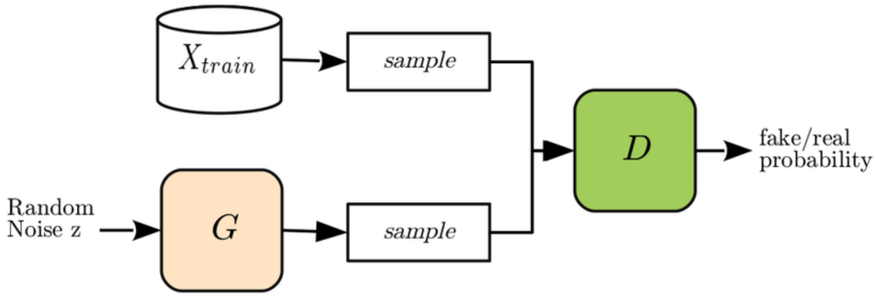


Figure 3: Generative adversarial network [12]

The GAN model consists of 2 networks: a generative network G that produces new data based on a certain distribution p_g and a discriminative network D that evaluates them, producing the probability that $x \sim p_{data}$ where p_{data} is the distribution of training data. D and G play the following two-player minimax game [11] with value function $V(G, D)$:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))] \tag{1}$$

3 Methodology

One of the main problems in time series forecasting is the choice of the optimal variables to be taken into consideration so that the neural network is able to capture their links and dynamics over time. In particular, Yoon et al. [14] propose a new model, the *Time-series Generative Adversarial Networks* (TimeGAN) for generating realistic time-series data in various domains; which considers both unsupervised adversarial loss and stepwise supervised loss and it uses original data as supervision. According to the authors, this type of GAN is made up of 4 networks [14]: embedding function, recovery function, sequence generator, and sequence discriminator. The autoencoding components are trained jointly with the adversarial components such that TimeGAN simultaneously learns to encode features, generate representations, and it iterates across time. Usually, GAN networks are used (regarding financial time series) for the generation and therefore the replacement of any missing values (NaN), while in this case their main objective is to recreate a time series based on the features used as input.

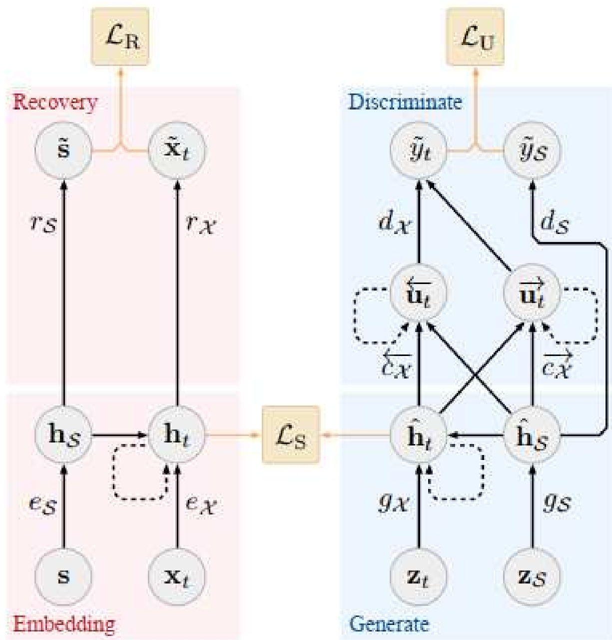


Figure 4: TimeGAN [14]

In this model, the generator is exposed to 2 types of inputs during training: the synthetic embeddings in order to generate the next synthetic vector and the sequences of embeddings of actual data to generate the next latent vector. In the first case, the gradient is computed on the unsupervised loss, while in the second, the gradient is computed on the supervised loss. To highlight generated results, Yoon et al. [14] have introduced a graphical measure for visualization, the t-SNE [29] (so as to visualize how much the generated distribution looks like the original one) and 2 scores (by optimizing a 2-layer LSTM):

- *Discriminative score*, it measures the error of a standardized classifier (RNN) in distinguishing between the real sequence and the one generated on the test set;

- *Predictive score*, represents the MAE *(Mean Absolute Error)* and measures the ability of synthetic data to predict next-step temporal vectors over each input sequence.

In addition, the t-SNE algorithm also returns the Kullback-Leibler Divergence (KL Divergence), which is a measure of the difference between two probability distributions which indicates the information lost when using a distribution (in this case the synthetic one) to approximate it another (the original one).

What we want to demonstrate by using this network is that instruments listed on a market subject to time constraints have a lower discriminative and predictive capacity than instruments present in markets not subject to the same constraints. Financial instruments subject to timetables during the continuous trading phase are representative of the information present in those hours, while what occurs after closing cannot be captured by the price and will be recorded at least the following day during the opening auction, which will lead to the price going up or down. On the other hand, for instruments not subject to schedules, this problem does not arise since any type of event that may have an effect on the price (whether it takes place day or night) will be recorded with an increase or a decrease in the price itself. The exchanges give the possibility to carry out negotiations outside the closing hours *(Trading in Pre Market and After Hours)* as in the case of Borsa Italiana in which the Pre Auction phase is possible from 8:00 to 9:00 a.m. while After Hours trading is possible from 17:50 to 20:30 and NASDAQ where the Pre Market trading is possible from 4:00 to 9:30 a.m. (ET) while After Hours trading is possible from 4:00 to 8:00 p.m. (ET), but certain time slots (which could be key) remain uncovered. In this way, the *"amount of information"* contained in each price is therefore an essential element for time series forecasting.

3.1 Dataset

The empirical analysis was carried out on 2 types of instruments, stocks and cryptocurrencies. Specifically these are

- Stocks[1]:
  1. GOOG (Alphabet Inc., Google), listed on NASDAQ;
  2. AMZN (Amazon.com), listed on NASDAQ;
- Cryptocurrencies[2] (all related to USD):
  1. ETH (Ethereum Index);
  2. BCH (Bitcoin Cash Index).

Prices are considered with a daily time frame over several years, from 20/12/2017 to 31/12/2019. To test the discriminative and predictive ability of prices, the different datasets were divided into 2 types, the first with 5 features such as Open, Close (Last in the case of cryptocurrencies), High, Low and Volume (generally indicated with the acronym OCHLV) while the second with only 2 features such as Open and Close/Last (indicated with the acronym OC).

3.2 Numerical examples

In this section, we will compare first from the graphic point of view and then through the scores the capabilities of the different time series in terms of a difference in the amount of information. This comparison is made especially by comparing the OCHLV datasets with the OC datasets for the different instruments, so as to be able to test the basic idea. The graphical analysis will be carried out by comparing the t-SNE plots, while the one based on the score will be carried out by comparing the KL divergence, the discriminative score and the predictive score.

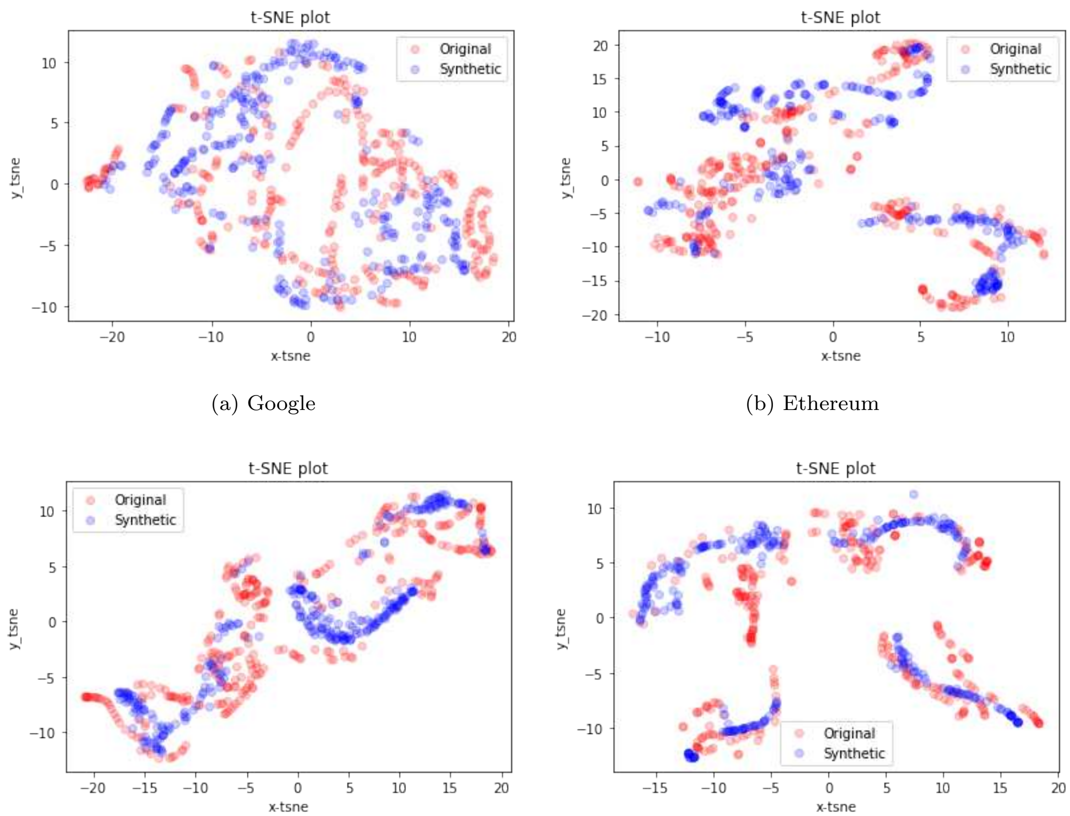
We can introduce the graphical analysis based on the t-SNE algorithm, in order to represent a

[1]Source: finance.yahoo.com

[2]Source: investing.com

higher dimensional space in a two-dimensional scatter plot and to realize the adhesion between the generated and synthetic data.

The first t-SNE analysis concerns the OCHLV dataset.



(a) Google

(b) Ethereum

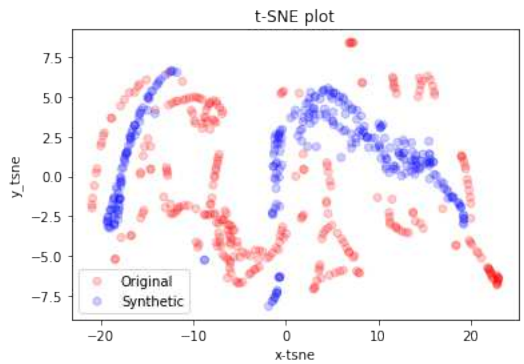
(c) Amazon

(d) Bitcoin Cash

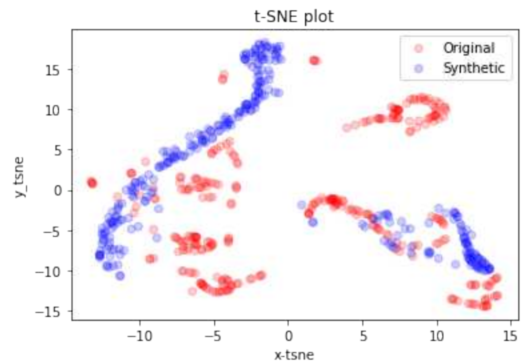
Figure 5: t-SNE analysis of synthetic data (blue) and original data (red) dataset OCHLV

From this analysis it is possible to highlight the potential of TimeGAN in the generation of data and in particular in the cases represented in figures 5(b) and 5(d) (both cryptocurrencies) there is a very precise adherence of the synthetic data to the originals. Obviously in this type of dataset there is the presence of greater features which combined together allow the network to improve the forecast.

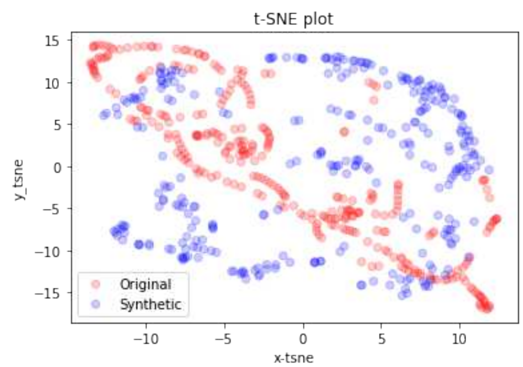
The second t-SNE analysis is based precisely on the OC dataset.



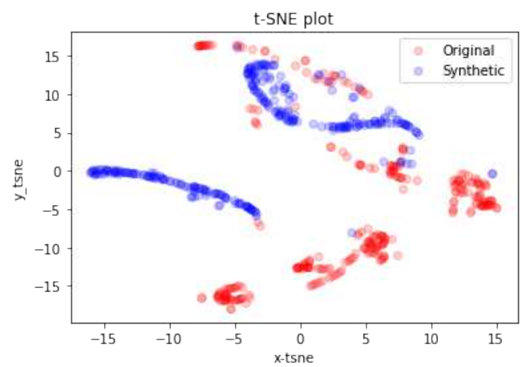
(a) Google



(b) Ethereum



(c) Amazon



(d) Bitcoin Cash

Figure 6: t-SNE analysis of synthetic data (blue) and original data (red) dataset OC

In this case at first glance it could seem like the synthetic data deviate from the original, however with a more careful analysis it is possible to notice how in all cryptocurrencies the synthetic data overlap the original data or imitate (albeit to a limited extent) their distribution, while in the stocks' case the distribution of the synthetic data is dispersive and not entirely consistent with the distribution of the original data.

The hypothesis we want to discuss is that the prices of cryptocurrencies have a greater amount of information within them and have a greater discriminative and predictive power. This hypothesis has been supported from the graphic point of view, but to leave no doubt we introduce the result of the analysis based on the scores (Ds indicates the discriminative score while Ps the predictive score) and on the KL divergence (D_{KL}).

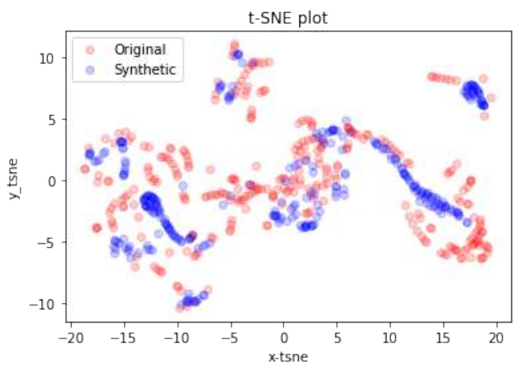
	Stocks			Cryptocurrencies	
	OCHLV	OC		OCHLV	OC
GOOG	$D_{KL} = 0.477378$ Ds = 0.1786 ± 0.0425 Ps = 0.0773 ± 0.0018	$D_{KL} = 0.390608$ Ds = 0.1012 ± 0.0179 Ps = 0.0517 ± 0.0016	ETH	$D_{KL} = 0.372100$ Ds = 0.0712 ± 0.0006 Ps = 0.0425 ± 0.0012	$D_{KL} = 0.261437$ Ds = 0.0758 ± 0.0503 Ps = 0.0412 ± 0.0087
AMZN	$D_{KL} = 0.388102$ Ds = 0.2238 ± 0.085 Ps = 0.1208 ± 0.0019	$D_{KL} = 0.461293$ Ds = 0.1207 ± 0.0136 Ps = 0.0662 ± 0.0237	BCH	$D_{KL} = 0.289605$ Ds = 0.0804 ± 0.0272 Ps = 0.0259 ± 0.0002	$D_{KL} = 0.247001$ Ds = 0.0862 ± 0.0735 Ps = 0.0307 ± 0.0058

Table 1: Score of both dataset (lower the better)

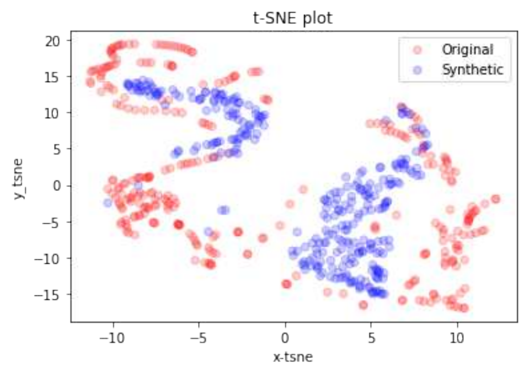
From the analysis of the values it is possible to notice how, especially in the case of the OC dataset, the cryptocurrency scores are the lowest and therefore the most significant.

3.3 Outliers

A particular situation occurred when analyzing the stocks of Tesla Inc. (TSLA) listed on NASDAQ. Despite being listed in a market subject to timetables, this analysis, both graphically and through the scores through TimeGAN, resulted in having a price type "loaded" with information, so much so that it achieved almost better results than cryptocurrencies. In particular:



(a) OCHLV dataset



(b) OC dataset

Figure 7: t-SNE analysis of TSLA stock on the different types of datasets

In both datasets the synthetic data reproduce the distribution of the original data very well. The analysis of the scores shows the following results:

TSLA	
OCHLV	OC
$D_{KL} = 0.442472$	$D_{KL} = 0.438634$
Ds = 0.1139 ± 0.0374	Ds = 0.0434 ± 0.0060
Ps = 0.1131 ± 0.0100	Ps = 0.0402 ± 0.0006

Table 2: Score of TSLA in both dataset

In this case, especially in the OC dataset, it is noted that the price range has a very high discriminative and predictive power, even higher than that of cryptocurrencies. Thanks to this *"outlier"* we can deduce that there are some instruments listed on stock exchanges subject to timetables which despite the limitation are in any case "completely absorbent" of the information concerning the company. This situation could be linked, for example, to the hypothesis that negative events never occurred outside the opening hours of the stock exchange or (in a less realistic but still possible hypothesis) to the hypothesis that in the time range considered no external situations occurred that could influence the price. In these cases, the use of this type of GAN can be a *"form of control"* on prices, especially when these are to be used for forecasting. There may be hidden elements that affect the price, however we can assume how the use of instrument whose price has a "large amount of information" could improve prediction compared to an opponent with less information.

4 Conclusions

In this paper, we have shown how TimeGAN is able to highlight which securities have a time series of prices *"loaded with information"*. The prices of cryptocurrencies have shown to have a much higher discriminatory and predictive power than stocks especially in the dataset made up only of the opening and closing prices. Furthermore, in the complete dataset (OCHLV), the prices with high discriminative power, combined with the other features, have made it possible to greatly improve the adherence of the synthetic data to the original ones. From this analysis it emerged that some stocks have the same discriminative and predictive power as cryptocurrencies; for this reason (especially since the time series forecasting is carried out mainly on stocks) it seems appropriate to screen, through this neural network, which are the optimal titles which combined with the different features improve the forecast. The next step is to look for, if any, a relationship between this type of stocks so as to limit the critical issues deriving from markets subject to timetables.

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