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Using similarity measures in prediction of changes in financial market stream data—Experimental approach

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ABSTRACT

In this study, we experimentally investigated the possibilities of using selected similarity measures for predicting future price directions in the market. The basic premise for this approach was the common assumption relating to the technical analysis, namely that "history repeats itself," and the "instrument price reflects all factors that have an impact on its value." This approach has been studied extensively in many publications. We purport that the subjective interpretation of the chart by the decision-maker should be taken into account. As every decision in the market in the case of manual trading or decision support systems is eventually made by a human, it is necessary to emphasize that the same situation in the market may be interpreted in a different manner by two different decision-makers. Our goal is to use the proposed similarity measure to identify past situations that occurred in the market, and invest accordingly.

Under these assumptions, we tested the usefulness of selected measures proposed in the literature, as well as the measure proposed by us, on 21 financial instrument datasets divided into three groups (stock companies, currency pairs, and stock indexes). Moreover, we statistically verified the prediction efficiency for different financial instruments, including stocks, currency pairs, and stock indexes. The statistical verification demonstrated that the proposed approach exhibited higher predictive strength than the classical measures proposed in the literature.

1. Introduction

Investigating and describing market behavior is a very popular concept in modern research. Numerous works have focused on explaining market evolution and behavior [1]. From the viewpoint of research on financial markets, various problems exist relating to identifying patterns directly on the chart; however, grouping stocks with similar behaviors has been discussed and addressed in multiple publications, including [2,3]. From an investor perspective, the main problem in analyzing financial data is prediction. The entirety of efforts has been devoted to answering one fundamental question: what will be the direction of changes in the market? In this paper, we focus on the possibility of using different measures relating to investigating the similarities among past situations and their usability in the prediction of future price changes.

A problem exists in the relations between the terms "similarity" and "distance", which have strict formal definitions, and "similarity" or "likeness", used in everyday language to reflect the feeling that one situation resembles the other. However, in the practical approach, the similarity between two objects or situations may be interpreted subjectively by different decision-makers. Although similarity measures, distances, and correlations have different goals in a formal sense, for the purpose of technical analysis, we may use one umbrella term — likeness (resemblance). The high degree of likeness (resemblance) between two financial time series may be read as a result of using the distance measure (a lower distance means a higher likeness between the two), shape

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similarity measure (a higher similarity means a higher likeness), or even (auto)correlation (a higher correlation indicates higher likeness).

The main motivation of our approach is the self-similarity that can be observed in financial data, for which similar price formations based on the Elliot wave theory [4] or Dow theory [5], along with other price patterns, can be used to estimate the behavior of the instrument in a past situation. Assuming that the price in such a formation behaves in the same manner or similarly, the current movement can be predicted based on the past price behavior.

According to the MiFID II directive of the European Union from 1st January 2018 [6], every decision-maker exposed to financial risk is obligated to present his or her risk profile built based on extensive surveys. The concept of reflecting the decision-maker risk profile with a single value appears to be consistent with the regulations imposed by the European Union. Such an action allows for estimating the risk aversion of any decision-maker involved in financial decisions. However, as the amount of risk taken by investors differs, the interpretation of the same situation observed in the chart may vary among investors. Thus, we purport that, in the case of the financial domain, a simple similarity/distance measure may be insufficient, as hidden variables, which in this case are the individual preferences toward/against risk estimated by the decision-maker, are not involved. Introducing crisp rules and relations is tempting because it provides a clear and simple interpretation of the situation on the chart leading to a "true"/"false" statement regarding a possible trade. However, because observations relating to the chart by decision-makers may include several additional preferences, experiences or other hidden variables, these should rather be interpreted as fuzzy variables, which leaves room for conclusions drawn by different decision-makers.

Therefore, in this article, we focus on the problem of identifying the past situations that somehow resemble the current situation by reflecting an assumed financial risk level to support the investor in his/her decisions. To achieve this, we investigate several measures established from the literature as well as a measure we designated to analyze the financial data, allowing us to estimate the likeness between the actual situation in the market and several past situations.

After establishing a method based on our new proposed measure, we estimate its predictive power, by assuming that the price direction observed in the past resembles that observed in the present. This approach is based on the market concept that "price discounts everything essentially means the market" or "the price already includes all relevant information". Thus, our goal in this task resembles the traditional classification problem to a certain extent; however, the overall number of different market situations is enormous and at the same time related to the size of the analyzed time interval. It is important to note that, in the basic classification problem, an additional off-line phase dedicated to training the classifier is required. In the case of determining similarities, such a step is unnecessary.

To summarize, the novelties of this paper are as follows:

- we analyze the usefulness of selected similarity measures in the process of prediction of signals on different markets;
- the selected similarity measures are experimentally verified on the unique financial dataset derived by authors including 21 different instruments (each covering the time span of 10 years) belonging to the group of currency pairs, stocks, and indexes;
- we introduce a new measure based on the shape similarity of two different time series;
- we obtain the statistical confirmation, that the proposed measure is critically better than other classical measures for currency pairs, while achieved results are close to those observed with the use of the state-of-art DTW measure (with significantly reduced computation time obtained by our proposed measure).

The remainder of this paper is organized as follows. In Section 2, we present example prediction models based on historical data, as well as several of the most popular similarity measures and their applications. In Section 3, we present the problem of data prediction with the use of relative changes between values. Section 4 includes a detailed description of the W measure, as well as suggestions allowing for the inclusion of relative changes in other similarity measures. Finally, numerical experiments are discussed and conclusions provided.

2. Related works

Almost all of the tasks relating to exploring large amounts of data, such as retrieval, clustering, and classification, need to include a suitable distance measure to compare the similarity/dissimilarity between pairwise time series [7]. Basic information relating to the data, presented as a time series, as well as the forecasting problem description, can be found in works such as Adhikari and Agrawal [8]. The influences of the prediction models based on the time series are also visible in the case of financial data.

For the comparison of time series data, in which trends and evolution are intended to be evaluated, or when the shape formed by an ordered succession of features is relevant, similarity measures based on Pearson's correlation have also been utilized [9].

Among the various popular measures relating to the problem of measuring similarities, not only for financial data, we can also identify the Euclidean distance, discrete Fourier transformation, metrics based on the Minkowski distance, and the dynamic time warping (DTW) distance. Several comparisons of these methods can be found; for example, in Kianimajd et al. [10].

A separate group of articles was devoted to the DTW method. As described in Berndt and Clifford [11], this distance measure originally invented to compare different speech patterns in automatic speech recognition [12] has been used extensively also in medicine [13], image analysis [14], and finance [15].

The idea behind the DTW measure is as follows. To find the warping path w, the distance matrix between the two time series Q and C has to be calculated. Each element (i, j) in this matrix is the squared Euclidean distance between the ith point of Q and jth

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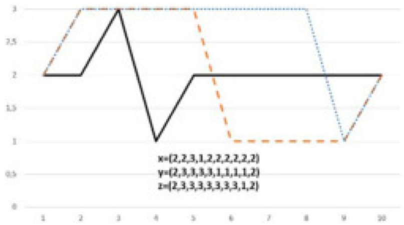
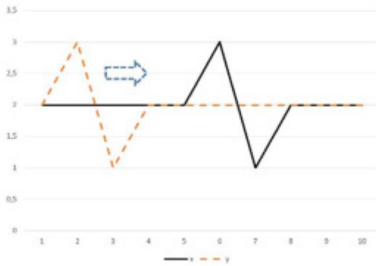


	DTW	Eukl	corr	W
x,y	0,000	3,162	0,000	0,265
x,z	0,000	3,162	0,000	0,148
y,z	0,000	3,464	0,337	0,156

Fig. 1. Three different sub-sequences and their interpretation for different measures.



measure \ shift	0	1	2	3	4	5	6	chart
DTW	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
corr	0,000	0,000	0,000	-0,500	1,000	-0,500	0,000	
Eukl	2,000	2,000	2,000	2,449	0,000	2,449	2,000	
W	0,112	0,124	0,124	0,256	0,000	0,208	0,108	

Fig. 2. Comparison of measures, when one subsequence is shifted against the other.

point of C. The warping path w is a set of contiguous matrix elements that define the alignment between Q and C. The kth element of w is defined as:

$$DTW(Q,C) = min\{\sqrt{\sum_{k=1}^{K} w_k}\}. \quad (1)$$

This construction leads to the dynamic programming paradigm where the alignment cost matrix is constructed. As the computational cost of DTW is $O(M \times N)$ a lot of optimizations were proposed. Many publications suggest that DTW is the best time-series distance measure for many data mining problems [16,17]. One of the most recent works dealing with the DTW measure was presented in Ananatasech and Ratanamahatana [18]. Along with the Mahalanobis distance, this measure can be effectively used for multivariate time series [19]. DTW is designed as a measure that is robust for shifting patterns in time, where the lengths of both time series can differ. In many cases, these features provide a great advantage; however, it also means that two different (from the point of view of a decision-maker) — historical time series can be identical according to DTW.

Fig. 1 shows that DTW between three different histories (continuous, dashed and dotted lines) give the same result equals to 0.00. Also, other measures (except W measure) show identical values at least for one of the pairs. This indicates that the intuitive notion of similarity and the visual analysis of the time series may differ from the indications resulting from the calculation of measures.

The second example (Fig. 2) shows how individual measures behave when one pattern is moved along an axis relative to the second, identical pattern. It can be seen that the DTW measure does not change and is constantly 0.00, which intuitively is not consistent with the feeling of similarity.

Methods connecting the use of similarity measures in case-based reasoning can also provide an effective reference point [20]. The approach mentioned above uses the concept of similarity measures to determine the operational situation class for the environmental system situation. The entire concept is based on effectively solving new problems based on previous experience (historical data), which is obviously a good example for rule-based trading systems operating in financial markets.

In the work of Serrà and Arcos [21], time series prediction was merged with similarity measures. The authors emphasized that the similarity measure is a crucial factor that should be included in the model. The entire work was focused on the empirical analysis of existing similarity measures. For this purpose, various similarity measures were tested on 45 different time series.

We purport that our proposed similarity measure could be effectively used as part of the system relating to the problem of prediction in financial data. As an example, we can mention an article by Cheng et al. [22], in which, based on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), a novel prediction method based on fuzzy logical relationships was proposed. This concept was extended with the use of particle swarm optimization techniques, the k-means clustering algorithm, and similarity measures. In the case of this hybrid method, the authors could present superior results to those of other methods mentioned in the article, such as a hybrid of the fuzzy approach and ant colony optimization [23] or fuzzy variation groups [24]. Evolutionary and swarm computations have been the subjects of numerous publications dealing with financial data prediction. An example of such an approach for the Forex market can be obtained in Ravia et al. [25], in which a multi-stage hybrid method including particle swarm optimization was used once again. A further example of financial data prediction (more precisely, technical indicators and the direction of change in the daily Korean composite stock price index — KOSPI) based on support vector machines were introduced in Kim [26].

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3. Basic definitions

Three main approaches are available for financial (stocks, currencies, and commodities, among others) data analysis:

- fundamental analysis, based on macro- and microeconomic, financial, and other qualitative and quantitative factors that may affect the instrument value;
- sentiment analysis, based on investigating overall attitudes, emotions, opinions, and other subjective impressions that may have an influence on the market; and
- technical analysis, based on the assumption that history repeats itself; thus, markets behave similarly in similar situations, and identifying unknown underlying patterns developing over time may be useful in the prediction of the market movement.

While fundamental analysts examine earnings, dividends, new products, and research, among others, technical analysts examine what investors fear or believe about those developments, and whether or not investors have the wherewithal to back up their opinions; these two concepts are known as psych (psychology) and supply/demand. Technicians employ various techniques, one of which is the use of charts. By using charts, technical analysts seek to identify price patterns and market trends in financial markets and attempt to exploit those patterns [27].

The most frequently used distance measure is defined as the Minkowsky measure (see [28], for instance):

$$D(A,B) = (|a_1 - b_1|^q + |a_2 - b_2|^q + \cdots + |a_n - b_n|^q)^{\frac{1}{q}}, \tag{2}$$

where A and B are two time series. For $q = 1$, the measure is known as the Manhattan distance or city-block distance; for $q = 2$, it becomes the Euclidean distance. Several authors have demonstrated that, in most cases, the traditional distance measure D (derived from the Minkowsky measure) is sufficient [29]. Others have pointed out that, in many cases, these measures are unreliable, and have suggested alternative measures [30,31]. In fact, even without deeper analysis, visible disadvantages of the D measure can be identified, including:

- the direction of deviations is not considered;
- certain difficulties arise in the case of the comparison of financial data series with different value ranges;
- its value depends on the size of the data — a longer time interval considered in the comparison has an impact on the final result; and
- in many cases, it does not correspond to the intuitive meaning of similarity.

Considering the above aspects, the following definitions can be introduced:

- two financial data series are identical when the values and directions of their changes are the same; and
- two financial data series are close to one another when the values of their changes are as small as possible and the directions of their changes are the same.

In analyzing phenomena such as prices, share prices, and stock-market indicators, the values themselves are not as important as their changes. Depending on the analysis, the relative or absolute changes in values may be of interest. Relative changes are particularly useful when we wish to compare values from different ranges. For example, in stock market analysis, a change in price from 3 to 2.5 (absolute change: −0.5, relative change: −16.67%) is more significant and important than a change from 300 to 315 (absolute change: 15, relative change: 5.00%). Moreover, in every case, the change direction is important — information on the change and its direction are provided together.

Introducing relative changes allows for focusing on the geometrical properties of the analyzed time series, rather than the classical distance. Such an approach can easily be included as an element of existing similarity measures based on Minkowsky metrics and correlation. In the following section, we discuss the proposed W measure based on relative changes in detail and also propose a methodology to transform existing similarity measures into relative value-based similarity measures.

4. W measure and relative similarity measures

It is easy to demonstrate that determining similarity based on the above assumption requires weights in traditional distance measures. Hence, we introduce the W measure (which is based on the city-block distance, weighted by directions):

$$W(A,B) = \frac{\sum_{j=1}^{n-1} z(\Delta a, \Delta b) \sum_{i=j+1}^{n} |\Delta a - \Delta b|}{\frac{n\cdot(n-1)}{2}}, \tag{3}$$

where n is the time series length. For relative changes, it is assumed that:

$$\Delta a = \frac{a_i}{a_{i-j}} - 1. \tag{4}$$

The same holds for the second observations: $\Delta b = \frac{b_i}{b_{i-j}} - 1$.

To eliminate the influence of unimportant fluctuations on W, a simple filter is defined as follows:

$$f(\Delta a) = \begin{cases} 0 & \text{when } |\Delta a < \epsilon|, \\ \Delta x & \text{otherwise,} \end{cases} \tag{5}$$

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where ϵ reflects the decision-maker risk profile. A more conservative approach results in higher price fluctuations being required to consider the actual situation in the market as interesting for the decision-maker. The threshold value is strictly dependent on the domain. The range $\langle -\epsilon, \epsilon \rangle$ outlines the space in which the fluctuations in time series values are not important for the user.

These weights must be defined:

$$z(A,B) = \frac{\sum_{i=j+1}^{n-1} dd(a_i,b_i) + 1}{\sum_{i=j+1}^{n-1} sd(a_i,b_i) + \frac{1}{2} \cdot \sum_{i=j+1}^{n-1} sd0(a_i,b_i) + 1}, \tag{6}$$

where

$$sd(a_i,b_i) = \begin{cases} 1 & \text{when } sign(a_i) = sign(b_i), \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

$$sd0(a_i,b_i) = \begin{cases} 1 & \text{when } xor(sign(a_i), sign(b_i)) = 0, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

$$dd(a_i,b_i) = \begin{cases} 1 & \text{when } sign(a_i) = -sign(b_i). \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

The aim of introducing the component $z(A,B)$ is to calculate the weights relating to change directions in the time series. This component will be decreased while additional parts of the time series have the same change direction. The component $sd0$ is used when the price change is unimportant in exactly one time series, while it is significant in the second one: $[(\Delta(a) < \epsilon \wedge \Delta(b) \geq \epsilon)] \vee [(\Delta(b) < \epsilon \wedge \Delta(a) \geq \epsilon)]$. Its value is placed in the denominator but its influence is decreased by the factor 2. By introducing the component $\frac{n(n-1)}{2}$, the measure is:

- more comparable in analyzing time series of different lengths; and
- more intuitive, because differences for shorter time series should be smaller than for longer ones.

The W measure value is 0 for time series with the same changes and increases as the time series begin to differ. It satisfies the following requirements: $W(A,B) \geq 0$, $W(A,A) = 0$, $W(A,B) = W(B,A)$, where A and B are time series. It does not satisfy triangular inequality owing to the application of weights. Hence, we can classify it as a measure of dissimilarity. The advantages of the measure W appear to be as follows:

- by calculating changes in values, instead of values themselves, it avoids the problem of the vertical warping of patterns;
- for the same reason, it may be used for comparing time series with different value ranges; and
- change directions are weighted in formulae, making the measure more precise.

However, this measure also exhibits disadvantages:

- all values in time series must be of the same sign; and
- it is computationally very expensive (compared to the computation time of other similarity measures).

To conduct a valuable comparison of the proposed similarity measures, we transformed existing similarity measures based on the Minkowsky space (namely the Euclidean, Manhattan, and Tschebyschev similarity measures) to deal with the financial data effectively based on the relative changes. Below, we discuss these changes using the example of Euclidean distance and correlation metrics. According to Eq. (4), the relative value-based Euclidean metrics would be as follows:

$$D_{euc}(A,B) = \sqrt{(\Delta a_2 - \Delta b_2)^2 + (\Delta a_3 - \Delta b_3)^2 + \cdots + (\Delta a_n - \Delta b_n)^2}, \tag{10}$$

where Δa_2 is the relative difference for the time series A in time $t = 2$, and n is the time series length. In addition to similarity measures based on the Minkowsky space, we used the original Pearson correlation measure in the comparison. However, this similarity measure was not modified in any manner:

$$r_{A,B} = \frac{\mathrm{cov}(A,B)}{\sigma_A \sigma_B}, \tag{11}$$

where $cov(A,B)$ is the covariance value between two time series A and B, while σ is the standard deviation value. The following section provides a detailed analysis relating to the results achieved by different similarity measures, as well as an estimation of the predictive capabilities of different similarity measures.

Any measures of time series similarity do not have any predictive power in themselves. However, they gain it together with the assumption, which is also the basis of technical analysis, that "history repeats itself" and that "in similar situations the market behaves similarly". Then, based on the situation similar to the current situation, found in history, one may try to predict further development of this situation (in the case of the financial market the direction of the change or the value of the instrument).

5. Numerical experiments

We present several observations resulting from the experiments, which can be summarized as the following question: how much efficiency is provided by different measures in the problem of determining similarities in various financial data?

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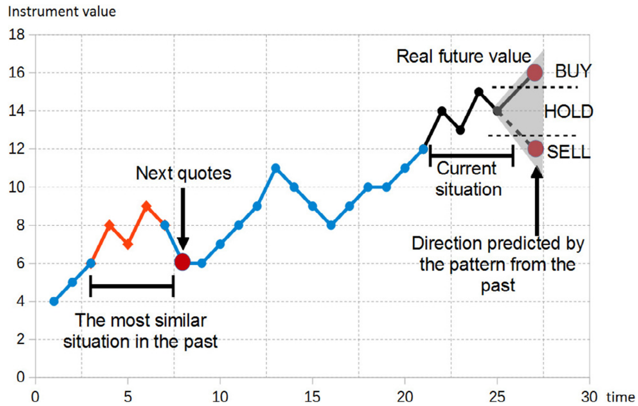

Fig. 3. Sub-window selection for the entire observation period.

Furthermore, we attempt to answer the question of whether it is possible to present the hypothesis that different financial instruments exhibit different prediction difficulties. In this sense, we understand efficiency to be the predictions made in the case of different instruments.

We start with an overall number of 6 different measures (including W measure proposed in the article). Our main task is to verify the usefulness of different measure in the prediction problem related to the financial data. To distinguish different aspects of the experiments we focus on the methods capable to derive fast solutions directly to the decision-maker. This is due to fact, that a large number of trading systems and decision support systems present nowadays on the market operates on the very narrow time window, and computation time can be one of the crucial aspects important for the decision-maker.

In our experiments, we focus on three different aspects. The first one is related to the computational complexity of used similarity measures. The second one brings us information about the values of the similarity measures for different financial instruments. In particular, we try to answer, if we can distinguish different classes of financial instruments on the basis of the similarity measures values. Finally, we derive information about the quality of signals derived by each analyzed similarity measures.

To do so, we analyze W measure described earlier in this paper, measures based on the Minkowsky space, the correlation measure, and the DTW measure. In our experiments, we selected the fast variant of the DTW described in Sakurai et al. [32] with the Sakoe–Chiba Band modification originally introduced in the article. Such an approach visibly decreases the computational complexity (in comparison with the original DTW measure with complexity $O(n^2)$. Thus further in this article, term DTW means the fast variant of the DTW measure.

5.1. Experimental design

For every instrument considered, we collected 2500 readings, where a reading means an instrument price at the end of the trading session of the day. The data considered covered a period of approximately 10 years: from June 2007 to July 2017. We divided each of the datasets consisting of 2500 readings into historical data (readings 1–2000) and present readings from 2001, which were included in the historical dataset as the prediction progressed. The length of the sub-sequence in which we were searching for similarities in the historical data was equal to 10 days. After every 10 days, we focused on the prediction period, which consisted of 5 days. Thus, in general, we were searching for similarities in the 2 week data to predict a potential price movement one week in advance.

Please note, that in Section 5.2 for the additional computation, the number of readings included differ from 1000 up to 2500, while at the same time, the length of the sub-sequences was in range 10 up to 40.

The general concept of the experiment is presented in Fig. 3. For every 10 day (two-week) series obtained from the previous 500 readings in the time series (from 2500 in general), the most similar pattern in the past was identified. Then, the direction of change was determined (5 days ahead) and compared with the actual change. We did not attempt to forecast the exact future value of the instrument, but determined the change direction to undertake one of three possible decisions (which is a common assumption in the prediction for the financial data). We distinguished BUY, SELL, and HOLD decisions, where HOLD can be interpreted as the staying out of the given session. The decision should be BUY if the value of the instrument is higher than the last quotes $+\epsilon$, HOLD if it is between the last quotes $-\epsilon$ and $+\epsilon$, and SELL when it is less than the last quotes $-\epsilon$. We assumed that ϵ was equal to the average value change over the entire time series. As indicated in Fig. 3, the suggested decision based on the pattern from the past was SELL, but the proper decision was HOLD or even BUY. Hence, for each 500 readings we obtained the pair (suggested decision–actual decision). Moreover, the ϵ value corresponding to the decision-maker risk profile in our case was equal to the average value of the last 50 readings. Such an action introduces the actual impact of ϵ on the results, while also guaranteeing that no information received directly from the decision-maker is required to perform the analysis.

Overall, 21 different financial instruments were selected. All of these were assigned to one of three distinct groups:

- currency pairs: AUDUSD, EURUSD, GBPUSD, USDCAD, USDJPY, EURCAD, NZDUSD;

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Table 1
Computation time in [s] for different problems and different similarity measures — summary time for all 21 instruments; Euc. — Euclidean; Man. — Manhattan; Tsc. — Tschebyschev; Cor. — Correlation; DTW — Dynamic Time Warping; W — W measure.

Dataset	Euc.	Man.	Tsc.	Cor.	DTW	W
1000 observations, pattern length 10	0.84	0.60	1.03	0.81	3.15	2.81
1750 observations, pattern length 10	2.14	2.32	2.34	2.19	8.74	7.71
2500 observations, pattern length 10	3.99	3.83	4.37	3.93	21.68	16.41
1000 observations, pattern length 20	0.96	0.91	1.25	0.94	7.85	6.27
1750 observations, pattern length 20	2.61	2.64	2.81	2.79	22.63	20.31
2500 observations, pattern length 20	4.57	4.33	5.79	5.01	54.07	37.33
1000 observations, pattern length 30	1.25	0.99	1.38	1.34	14.34	14.38
1750 observations, pattern length 30	2.99	3.13	3.32	3.21	34.66	26.88
2500 observations, pattern length 30	5.33	5.14	7.01	5.77	86.72	54.45

- stock companies: Adobe, Amazon, Apple, Google, IBM, AIRBUS, Santander; and
- stock indexes: CAC40, DAX, FTSE100, NASDAQ, RUSSELL, Hang Seng, Nikkei 225.

Three different popular classification measures were used for the prediction stage of the experiments, namely the accuracy rate, precision (for the decision classes BUY, SELL, and HOLD), and recall (once again, for all three decision classes). The BUY class indicates a situation in which the suggested price change is positive and a rising trend is expected, while the opposite situation occurs in the SELL class. The third class, HOLD, corresponds to indecision in the market, and reflects an instrument change that is lower than a certain assumed predefined ϵ value. Thus, each of these classes was selected as the positive (desired) class. We used TP — true positive, to denote all properly classified positive cases (from the P class); TN — true negative, which represented properly classified negative cases (N class), FP — false positive, which were all incorrectly classified positive examples P, and finally, FN — false negative, which were incorrectly classified negative cases N. The classification measures used in the second part of the experiments are summarized below:

Accuracy is one of the most popular classification evaluation measures. However, it should be noted that this measure does not provide sufficient evaluation; for example, for datasets with a considerable diversity of decision classes, as observed in Kozak and Boryczka [33], among others. The classification accuracy describes the ratio of correctly classified objects to all objects in a class.

$$ev_{acc}(\Xi) = \frac{(TP + TN)}{(TP + TN + FP + FN)}. \tag{12}$$

Precision is a measure that evaluates a classifier based on an incorrect classification of objects belonging to class N into class P. In this case, it is preferable to omit certain objects from class P than incorrectly assign objects belonging to class N to class P. Precision is determined based on the ratio of objects correctly classified into class P to all objects assigned to this class:

$$ev_{prec}(\Xi) = \frac{TP}{(TP + FP)}. \tag{13}$$

Recall is used for binary classification. It is determined based on Eq. (14); that is, the ratio of objects correctly classified into class P to all objects that should have been classified into this class. Therefore, in terms of recall, it can be stated that it is preferable to assign an object belonging to class N to class P incorrectly than to classify an object belonging to class P incorrectly.

$$ev_{rec}(\Xi) = \frac{TP}{(TP + FN)}. \tag{14}$$

5.2. Time complexity of selected measures

In this subsection, we investigate the overall computation time for all analyzed measures. We especially focus on the comparison between the DTW measure and W measure proposed by authors. One should know, that due to the complexity aspect, both: W measure, as well as the DTW measure, derive solution slower than it can be observed for the classical measures. This is due to the fact, that both methods calculate the values for the distance matrix between elements of the time series. This leads to the simple observation, that the longer the time series, the more time is needed to derive the similarity measure value. The overall computation time is presented in Table 1.

First of all, there are rather small differences between the remaining measures. However, still, it is easy to observe, the linear time growth for these measures. W measure presented in the last column is much slower than the classical measures, however, it is still visibly faster, than the DTW measure. This feature is crucial in the case of fast and dynamic decision support systems, where the result should be derived for the decision-maker as soon as possible.

The second investigated aspect is the time growth ratio for all analyzed measures. These observations can be seen in Fig. 4. It is clear, that for the W measure, as well as for the DTW measure we observe a very fast increase in the computation time. The crucial parameter for both measures is the size of the pattern, that we are looking for. One should know, that regardless of that computation time, this growth is not exponential.

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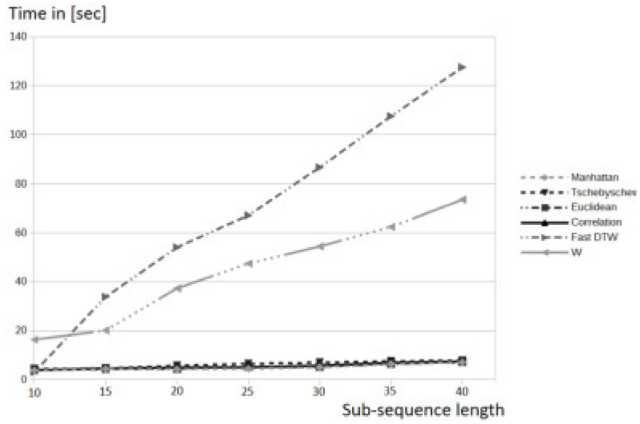

Fig. 4. Summary computation time for analyzed measures with increasing size of the sub-sequence.

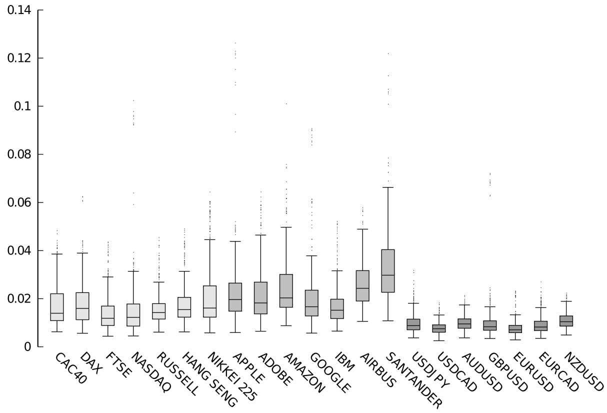

Fig. 5. Boxplot of Euclidean measure for all cases.

5.3. Efficiency of similarity measures

The first part of the numerical experiments allowed us to estimate the distribution of values for the different similarity measures. For every similarity measure analyzed, we conducted experiments on the full set of 21 different instruments. However, owing to the different calculation methods available for similarity measures, every figure includes results only for a single similarity measure. This is because different measures operate on different scales, and would be incomparable in a single figure. The results can be observed in Figs. 5–10, and our preliminary findings are discussed below. For each boxplot visible in these figures, we can extract the minimal similarity measure (identified in the set of 2500 readings), and the first and third quartiles, along with the median value and maximal observed deviation value (indicated by the dot). The saturation of the boxplot is related to the analyzed instrument: the brightest boxplots present the results for the market indexes, the medium gray saturation is related to the stock data, and the darkest boxplots correspond to the currency pairs.

Based on the experiments performed, as discussed in this section, the following observations can be made. It is possible to distinguish groups of instruments only according to the obtained similarity measures. It is not surprising that the similarity measure values achieved in the case of currency pairs were visibly inferior to the two remaining cases. Difficulties in trend identification and higher daily volatility (than in the case of stock instruments or indexes) make currency pairs excessively complex when confronted with similarity measure-based prediction models. This observation is particularly strong in the case of the Euclidean distance presented in Fig. 5. The same observations hold for the Manhattan distance — Fig. 6. Interesting results were achieved in the case of the correlation measure. While it is often considered as an important element of prediction models, the results presented in Fig. 8 do not allow for a clear estimation of the difficulty of the dataset only based on the correlation values. The lowest diversification was observed for the three measures: the Tschebyschev measure (Fig. 7), the W measure (Fig. 9), and for the DTW measure (Fig. 10). It should be noted that, while the Tschebyschev measure is calculated based on the highest difference between the analyzed and actually identified time series, its usefulness is debatable in the case of longer time series. Values observed for the DTW measure seems also to confirm, that there exists difference in the difficulty of analysis for the currency pairs and remaining instruments. In

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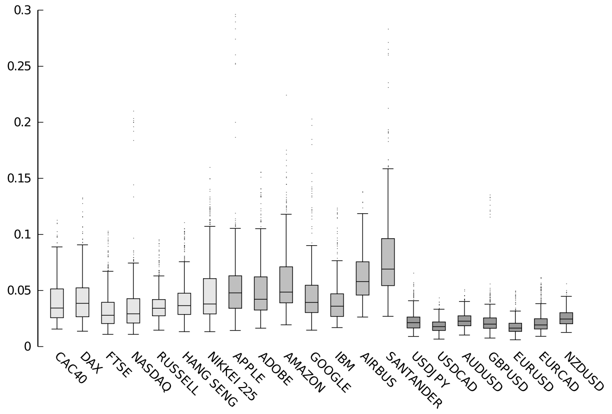

Fig. 6. Boxplot of Manhattan measure for all cases.

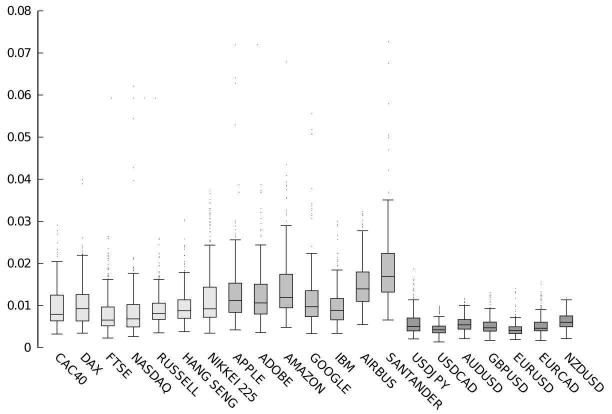

Fig. 7. Boxplot of Tschebyschev measure for all cases.

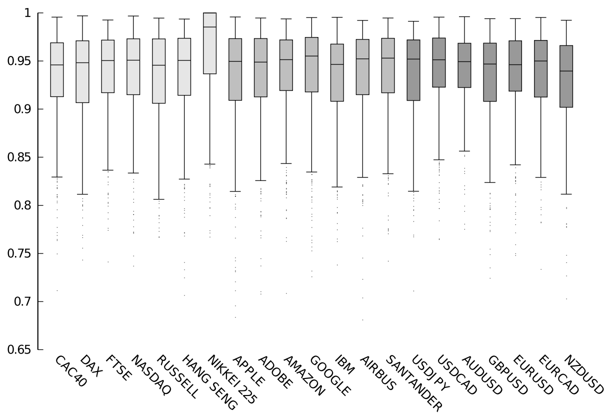

Fig. 8. Boxplot of correlation for all cases.

the case of the DTW difference between stocks and indexes is not as visible, as it may be observed for the W measure, but still, this observation could be crucial in the further part of the experiments.

The described dependencies also have an impact on the stability of the achieved results. The median value for all considered similarity measures in the case of currency pairs was visibly lower than that in the case of the remaining datasets. However, the value range was large in the case of different instruments: for stock companies, the value ratio of the first to third quartiles was approximately 1.5, for the indexes, this ratio was approximately 1.4, and for the currency pairs, it was 1.25.

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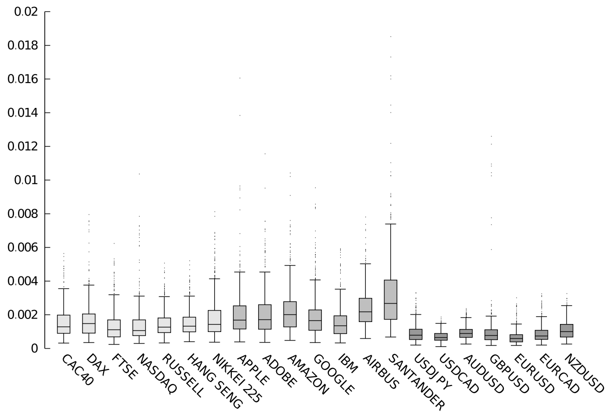

Fig. 9. Boxplot of W measure for all cases.

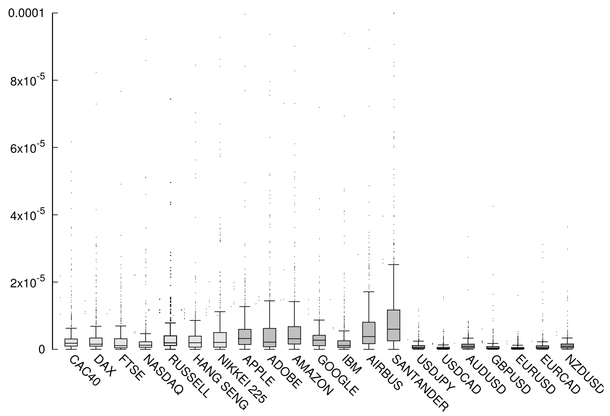

Fig. 10. Boxplot of DTW measure for all cases.

5.4. Predictive capabilities of similarity measures

According to the observations described in 5.3 we purport that the relative value-based similarity measures can be effectively used as an element of prediction models, based on historical data analysis. We measured the performance of this approach and compared it to the predictions based on the correlation measure. In this subsection, we estimate the capability of different similarity measures in the process of predicting potential trend changes. It can be expected that higher predictive efficiency will be achieved by the similarity measures, which performed effectively according to the discussion in the previous subsection.

In the case of analyzing the given decision class, two remaining classes correspond to the negative case. Thus, for the precision measuring of the BUY class, only cases actually belonging to the BUY class are marked as TP (see Section 5.1). The remaining cases are denoted as FN. This is the main cause of low measurement values; thus, it should be noted that only the most common cases belonging to the $HOLD$ class are used as well.

All results are presented separately for each similarity measure in Figs. 11–16. Different symbols are used to distinguish different classification measures (the precision and recall depending on the target decision class are also distinguished separately). The following instruments are presented in the columns: stock indexes, stock companies, and currency pairs. Every symbol denotes the value of the single measure for the selected instrument, and every column includes 5 different symbols. In the case of the same values, several symbols are marked with bold font, indicating two identical values.

The preliminary results obtained during the experiments indicated that prediction models based on the similarity measures could be effective. However, it should be noted that not all of the obtained results were promising. Evaluation based on recall (with its values near the 35% level) in the case of large data could be a source of substantial information derived for the domain expert. Such information could potentially be used in the process of estimating future trend changes. The $SELL$ class in terms of both precision and recall was the most difficult task. The achieved values were lower than the values of these measures for the remaining instruments. The average results for every considered similarity measure and every group of instruments are presented in Table 2.

For the stock indexes, the DTW measure allowed for achieving superior results in the case of 6 out of 7 examples (inferior results for the proposed measure can be observed in the case of the precision for the $HOLD$ class), whereas W measure achieved the best results from the remaining measures in 5 out of 7 cases. Similar results were achieved for the stock companies. Once again, the

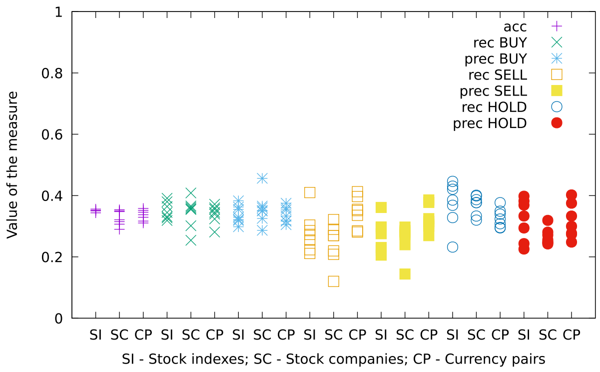

Fig. 11. Prediction efficiency in case of Euclidean measure.

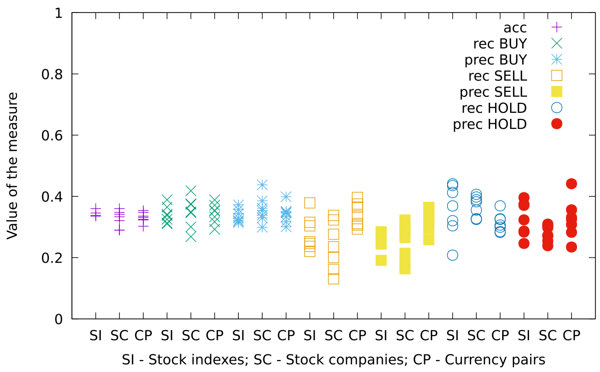

Fig. 12. Prediction efficiency in case of Manhattan measure.

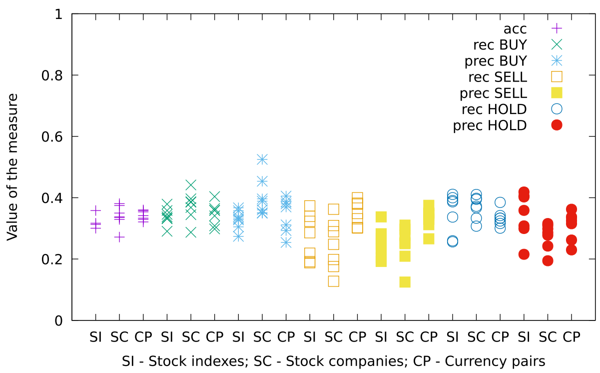

Fig. 13. Prediction efficiency in case of Tschebyschev measure.

DTW measure was the best measure, in this case in 5 out of 7 examples, where second results were achieved for the Tschebyschev measure. A slightly different situation can be observed in the case of the currency pairs, where the best results were achieved for the W measure.

A more detailed analysis of the results indicates, that for the DTW measure, the relatively good results are often related to the better classification for the HOLD signal (for all datasets, the HOLD class includes the largest number of observations). This leads to the conclusion, that the remaining signals (SELL and BUY) are often recognized as the HOLD signal. This situation can be seen for the currency pairs, where the recall value for the HOLD signals is equal only 50%. At the same time the HOLD signal precision is equal to 23% (the worst result from all measures). Moreover, the DTW measure gives the least stable results, which can be observed in Fig. 16 (in comparison to other measures seen in Figs. 11–15). Prediction results for the remaining instruments in the case of DTW are not uniform. We can observe very good, as well as very bad results. This situation is not observed for the remaining measures.

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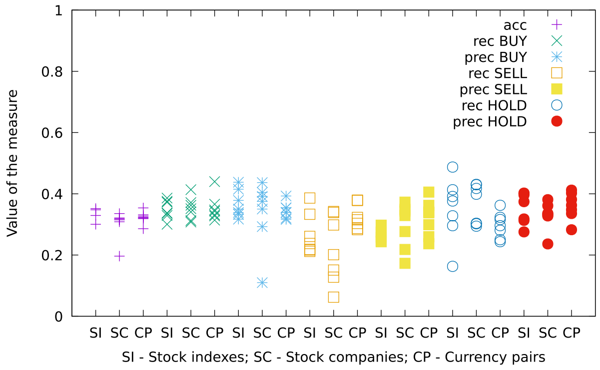

Fig. 14. Prediction efficiency in case of correlation measure.

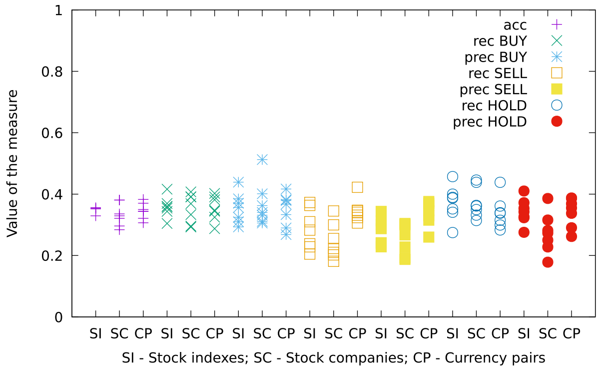

Fig. 15. Prediction efficiency in case of W measure.

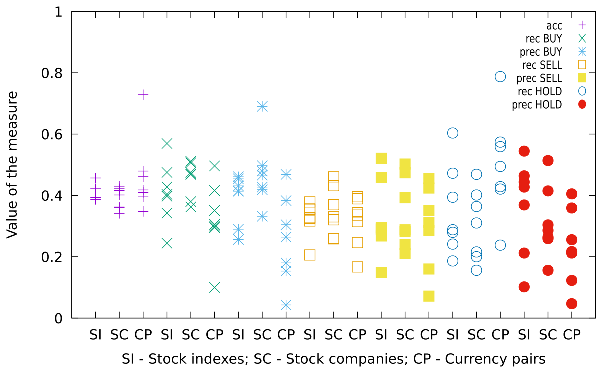

Fig. 16. Prediction efficiency in case of DTW measure.

We can purport, that the efficiency of the DTW measure is related to the shape of the found pattern. For the patterns indicating strong bearish or bullish movement, the DTW seems to be the most efficient. However, in the case of side trend, or in the situations, where the variability of the price range is high (as it can be seen for the currency pairs), the W measure is superior.

Presented results show the advantages of both approaches: W measure and DTW measure. In the next subsection, we derive the statistical verification of the results.

5.5. Statistical verification

All proposed methods were compared by means of a non-parametric statistical hypothesis test — the Friedman test for $\alpha = 0.05$. The Friedman test parameters were as follows: $Chi\text{-}square = 18.90$, degrees of freedom = 5, and 5% critical difference = 1.062091. The mean ranks achieved based on the test can be observed in Table 3. The best-acquired prediction was observed in the case of the W measure with a mean rank = 2.333333. The results for the remaining measures were as follows:

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Table 2
Comparison of average values of considered similarity measures according to prediction quality.

	Euc.	Man.	Tsc.	Cor.	W m.	DTW
Stock indexes						
Accuracy	0.3445	0.3369	0.3322	0.3383	0.3427	**0.4124**
Rec. *BUY*	0.3471	0.3419	0.3365	0.3498	0.3578	**0.4006**
Prec. *BUY*	0.3407	0.3374	0.3313	0.3572	0.3598	**0.3665**
Rec. *SELL*	0.2603	0.2442	0.2434	0.2398	0.2610	**0.2996**
Prec. *SELL*	0.2815	0.2647	0.2659	0.2639	0.2925	**0.3267**
Rec. *HOLD*	0.4021	0.3998	0.3931	0.4099	0.3940	**0.4354**
Prec. *HOLD*	0.2822	0.2914	0.2916	0.2978	**0.3121**	0.2671
Stock companies						
Accuracy	0.3263	0.3263	0.3398	0.3014	0.3325	**0.3903**
Rec. *BUY*	0.3434	0.3475	0.3728	0.3514	0.3542	**0.4532**
Prec. *BUY*	0.3564	0.3580	0.4034	0.3372	0.3664	**0.4728**
Rec. *SELL*	0.2426	0.2378	0.2443	0.2174	0.2452	**0.3472**
Prec. *SELL*	0.2568	0.2483	0.2461	0.2947	0.2545	**0.3411**
Rec. *HOLD*	0.3706	0.3690	0.3690	0.3681	**0.3720**	0.3021
Prec. *HOLD*	0.2662	0.2784	0.2750	**0.3294**	0.2732	0.3137
Currency pairs						
Accuracy	0.3357	0.3313	0.3425	0.3231	0.3454	**0.4626**
Rec. *BUY*	0.3395	0.3442	0.3476	0.3528	**0.3541**	0.3232
Prec. *BUY*	0.3371	0.3421	0.3429	0.3451	**0.3480**	0.2564
Rec. *SELL*	0.3453	0.3404	**0.3492**	0.3242	0.3454	0.3130
Prec. *SELL*	0.3257	0.3235	0.3322	0.3203	**0.3372**	0.2942
Rec. *HOLD*	0.3268	0.3135	0.3334	0.2960	0.3391	**0.5002**
Prec. *HOLD*	0.3256	0.3096	0.3054	**0.3606**	0.3411	0.2311

Table 3
Friedman test results and mean ranks (the best rank is in bold face).

Mean ranks	All	Stock indexes	Stock companies	Currency pairs
Euclidean	3.9286	3.4286	4.3571	4.0000
Manhattan	4.3571	4.5714	4.3571	4.1429
Tschebyschev	3.7143	5.1429	3.1429	2.8571
Correlation	3.9524	3.7143	4.2857	3.8571
W measure	**2.3333**	2.4286	3.0000	**1.5714**
DTW	2.7143	**1.7143**	**1.8571**	4.5714
Critical difference	1.0621	1.6049	1.8465	1.7824

- the DTW measure, with mean rank 2.714286;
- the Tschebyschev measure; mean rank 3.714286;
- the Euclidean measure; mean rank 3.928571;
- the correlation measure; mean rank 3.952381; and
- the Manhattan measure; mean rank 4.357143.

A critical difference was observed between the proposed W measure and the remaining measures, except for the DTW measure. Thus, the proposed measure provides a more effective prediction tool than the existing similarity measures.

Moreover, we performed statistical analysis for the specific instruments separately: stock indexes, stock companies, and currency pairs. In this case, we once again used a non-parametric statistical hypothesis test — the Friedman test for $\alpha = 0.05$. However, the detailed results differed from the global results, as described above.

For the statistical analysis of stock indexes, we had: $Chi\text{-}square = 16.46$, $degrees\ of\ freedom = 5$, and 5% $critical\ difference = 1.604871$), while the average ranks are presented in Table 3. In this case, superior results were observed for the DTW measure. However, the critical difference between this measure and the W measure was not observed. However, the W measure is critically better than the measures Tschebyschev and Manhattan. One should know, that the Tschebyschev measure is critically worse from almost all considered measures (besides the Manhattan measure). All of the remaining statistical measures exhibited no critical difference among one another.

For the statistical analysis of stock companies, we had: $Chi\text{-}square = 10.39$, $degrees\ of\ freedom = 5$, and 5% $critical\ difference = 1.846500$, while the average ranks are presented in Table 3. In this case, there were no critical differences between DTW measure and W measure. The highest rank was achieved by the DTW measure and slightly worse W measure. Statistically, no critical difference was identified in the case of all measures except for the DTW measure.

The best results were undoubtedly achieved for the currency pairs, with $Chi\text{-}square = 12.15$, $degrees\ of\ freedom = 5$, and 5% $critical\ difference = 1.782404$; the ranks are once again provided in Table 3. The ranks acquired for the W measure were

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critically different compared to all of the remaining measures except Tschebyschev measure. In the case of the Tschebyschev measure, it was possible to achieve results close to the W measure, and its critical value was slightly lower than the estimated critical value. No critical difference was observed for all the remaining measures.

Based on the statistical analysis performed, we could conclude that the concept of using relative value changes provides an advantage over the classical similarity measures. It is worth noting that no additional steps, such as data normalization, were necessary during the computation. The presented W measure was globally superior to the remaining measures. Moreover, it was critically superior for the currency pairs dataset. The advantage of the W measure was also indicated for the stock indexes. An interesting fact was observed in the case of the stock companies, where the W measures were critically better only to the Manhattan measure. The lack of critical differences among the remaining measures led to the conclusion that no measure would be advantageous over others.

6. Conclusions

In this article, we tested the predictive capabilities of selected measures on 21 sets of financial instrument data divided into three groups (stock companies, currency pairs, and stock indexes). A novel similarity measure based on relative instrument changes, namely the W measure was introduced. The concept underlying this measure is the self-similarity of unprocessed financial data. By observing the past behavior of the market, we assumed that the particular shape of the price chart observed somewhere in the historical data leads to certain market behavior that can be repeated for the present data.

Three different classification measures were used to compare the selected similarity measures: accuracy, precision, and recall. To emphasize the importance of the obtained results, an extended statistical analysis was performed, for which we used the non-parametric Friedman test. Additional statistical tests were performed separately for every group of datasets: currency pairs, stock companies, and stock indexes.

Moreover, we statistically verified the prediction difficulty for different financial instruments, including stocks, currency pairs, and stock indexes. The statistical verification demonstrated that the proposed approach provides higher predictive strength than the classical measures proposed in the literature and can be used as an alternative for existing state-of-art measures like DTW.

The DTW measure shows the best predictive power for indexes and stocks. Its advantage over classic measures of similarity suggests that technical analysis based on the classic concept of similarity should be modified.

In turn, W measure shows advantages over the DTW measure in the case of currency pairs. Since indices and stocks have been in the growing megatrend for several years, this suggests that DTW has better predictive capabilities when a trend is defined, while W measure works better when greater market volatility is observed. For both cases: the W measure, as well as the DTW measure, could be understood as the tool for extending the information derived to the decision-maker from the chart.

Due to the fact, that different similarity measures discussed in the article have different advantages, it could be useful in further works to move toward the ensemble approaches, where a number of different similarity measures are used to derive a collective decision toward the decision-maker.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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