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A prediction scheme using perceptually important points and dynamic time warping

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ABSTRACT

An algorithmic method for assessing statistically the efficient market hypothesis (EMH) is developed based on two data mining tools, perceptually important points (PIPs) used to dynamically segment price series into subsequences, and dynamic time warping (DTW) used to find similar historical subsequences. Then predictions are made from the mappings of the most similar subsequences, and the prediction error statistic is used for the EMH assessment. The predictions are assessed on simulated price paths composed of stochastic trend and chaotic deterministic time series, and real financial data of 18 world equity markets and the GBP/USD exchange rate. The main results establish that the proposed algorithm can capture the deterministic structure in simulated series, confirm the validity of EMH on the examined equity indices, and indicate that prediction of the exchange rates using PIPs and DTW could beat at cases the prediction of last available price.

1. Introduction

The efficient market hypothesis (EMH) gained much attention by the academia since its official introduction in the late 70s (Fama, 1970; Mandelbrot, 1966; Roberts, 1967). Generally, for a specific time period, a market is called efficient if prices fully reflect all available information. Defining historical prices, public available information and inside information as three subsets of the set of all available information, results in three forms of EMH, i.e. weak, semi-strong and strong form. Random walk hypothesis is aligned with the weak-form EMH. According with the above theories the best estimation we can make regarding the future price (return) is the current price (zero) conditioning the historical price path. Dealing here with scalar time series analysis we consider the weak-form EMH.

On the contrary, advocates of technical analysis (TA) assert that it is possible to forecast the future evolution of a financial price series and thus gain systematically abnormal returns by using historical price paths as available information. Thus, TA can be considered as an "economic test" (Campbell, Lo, & MacKinlay, 1997) of the random walk hypothesis and the weak form EMH. Tools of technical analysis can be mainly classified firstly into technical indicators, such as Relative Strength Index (RSI), Moving Averages (MA) and Moving Average Convergence Divergence (MACD), secondly into technical patterns such as "Head and Shoulders" (Osler, 1998; Savin, Weller, & Zvingelis, 2007; Zapranis & Tsinaslanidis, 2010), "Saucers" (Wang & Chan, 2009; Zapranis & Tsinaslanidis, 2012b) and thirdly into candlesticks (Caginalp & Laurent, 1998).[1] Trading strategies can be designed, by adopting the aforementioned tools, which return trading signals as well as support and resistance levels (Osler, 2000; Zapranis & Tsinaslanidis, 2012a). The majority of technical studies examine usually individual or small bundles of technical tools.

In this study, we implement an algorithmic approach in order to assess statistically the null hypothesis of weak-form EMH, by adopting perceptually important points (PIPs) and dynamic time warping (DTW). PIPs are used in order to identify significant points on a financial series. These points segment the series dynamically into subsequences of unequal length. Then our effort focuses on finding similar historical subsequences and then make predictions based on the manner that these best matches evolved in the past. To implement this we employ DTW, which can be used to measure the similarity between two time series of unequal length. By this method we intend to simulate the generalised manner a technician tries to make predictions by finding similar price paths evolutions

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[1] For a comprehensive description of technical analysis and its tools we indicatively suggest (Achelis, 1995; Bulkowski, 2002; Edwards & Magee, 1997; Pring, 2002).

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occurred in the past. The technician identifies subjectively, based on own experience, the significant points to define the paths, while in the proposed approach PIPs are used for this segmentation and DTW for measuring the similarity between them.

PIPs were introduced by Chung, Fu, Luk, and Ng (2001) to exploit salient points from a price series and have also been used to identify specific technical patterns in (Fu, Chung, Luk, & Ng, 2007). In the context of data mining, PIPs have been used mainly for purposes of dimension reduction (time series representation), as a dynamic approach for time series segmentation (Fu, Chung, & Ng, 2006; Jiang, Zhang, & Wang, 2007) and for clustering reasons (Fu, Chung, Luk, & Ng, 2004) (for a comprehensive review see (Fu, 2011)).

Dynamic time warping (DTW) is an algorithmic technique mainly used to find an optimal alignment between two given (time-dependent) sequences under certain restrictions (Muller, 2007). First introduced in 1960s, DTW initially became popular in the context of speech recognition (Sakoe & Chiba, 1978), and then in time series data mining, in particular in pattern recognition and similarity measurement (Berndt & Clifford, 1994). We implement DTW for measuring similarities between the target subsequence and historical subsequences of the examined price series, as defined by PIPs. This is actually a subsequence matching problem. Finding salient points and then similar historical subsequences is aligned with the manner a technician tries to exploit information from the past and make forecasts.

The performance of the proposed approach is assessed on simulated time series generated by superimposing a chaotic deterministic time series on a stochastic trend. Subsequently we apply the same approach to real financial series composed of 18 major world equity indices and the GBP/USD currency pair.

The rest of the paper is organized as follows. In Section 2, the methodology is presented, including PIPs, DTW and the prediction scheme. In Section 3, the performance of this approach is assessed on simulated series, and in Section 4 it is applied to financial time series. Finally, discussion and conclusions are given in Section 5.

2. Methodology

2.1. Perceptually important points

First, we present the algorithm constructing PIPs to identify significant points. The algorithm starts by characterizing the first and the last observation as the first two PIPs. Subsequently, it calculates the distance between all remaining observations and the two initial PIPs, and signifies as the third PIP the one with the maximum distance. The fourth PIP is the point that maximizes its distance to its adjacent PIPs (which are either the first and the third, or the third and the second PIP). The algorithm stops when the required by the user number of PIPs is identified.

Three metrics are generally used for the distance in the PIPs algorithm, namely the Euclidean distance (ED) d_E, the perpendicular distance (PD) d_P and the vertical distance (VD) d_V. Let $\{p_1, p_2, \ldots, p_l\}$ be the price time series of length l, and two adjacent PIPs $x_t = (t, p_t)$ and $x_{t+T} = (t+T, p_{t+T})$. The Euclidean distance d_E of each of the intermediate points $x_i = (i, p_i)$, for $i \in \{t+1, \ldots, t+T-1\}$ from the two PIPs is defined as

$$d_E(x_i, x_t, x_{t+T}) = \sqrt{(t-i)^2 + (p_t - p_i)^2} + \sqrt{(t+T-i)^2 + (p_{t+T} - p_i)^2}. \quad (1)$$

For the two other distances, we consider first the line connecting the two PIPs $x_t = (t, p_t)$ and $x_{t+T} = (t+T, p_{t+T})$, $z_i = si + c$, and (i, z_i) the points on the line, where the slope is $s = \frac{p_{t+T} - p_t}{T}$ and the constant term is $c = p_t - \frac{p_{t+T} - p_t}{T} t$. Then the perpendicular distance d_P of any intermediate point $x_i = (i, p_i)$, between the two PIPs from the line is

$$d_P(x_i, x_t, x_{t+T}) = \frac{|si + c - p_i|}{\sqrt{s^2 + 1}} \quad (2)$$

and the vertical distance d_V of x_i to the line is

$$d_V(x_i, x_t, x_{t+T}) = |si + c - p_i|. \quad (3)$$

For any of the three distances, denoted collectively d, the new PIP point, $x_i^* = (i^*, p_{i^*})$, is the one that maximizes the distance d at i^*

$$i^* = \text{argmax}_i(d(x_i, x_t, x_{t+T})), \quad (4)$$

where "argmax" stands for the argument of maximum.

Fig. 1 presents five PIPs identified with each of the three distances on the S&P 500 index at two different time periods. Apparently, the distance metrics do not always give the same PIPs.

2.2. Dynamic time warping

Dynamic time warping (DTW) is an efficient scheme giving the distance (or similarity) of two sequences $Q \equiv \{q_1, q_2, \ldots, q_N\}$ and $Y \equiv \{y_1, y_2, \ldots, y_M\}$, where their lengths N and M may not be equal. An example of two sequences Q and Y is illustrated in Fig. 2.

First, a distance between any two components q_n and y_m of Q and Y is defined, e.g. the Euclidean distance $d(q_n, y_m) = (q_n - y_m)^2$, forming the distance (or cost) matrix $\boldsymbol{D} \in \mathbb{R}^{N \times M}$ (see Fig. 3).

The goal is to find the optimal alignment path between Q and Y of minimum overall cost (cumulative distance). A valid path is a sequence of elements $Z \equiv \{z_1, z_2, \ldots, z_K\}$ with $z_k = (n_k, m_k)$, $k = 1, \ldots, K$, denoting the positions in the distance matrix D that satisfy the boundary, monotonicity and step size conditions. The boundary condition ensures that the first and the last element of Z are $z_1 = (1,1)$ and $z_K = (N, M)$, respectively (i.e. the bottom left and the top right corner of D, see Fig. 3). The other two conditions ensure that the path always moves up, right or up and right of the current position in D, i.e. $z_{k+1} - z_k \in \{(1,0), (0,1), (1,1)\}$.

To compute the total distance of each valid path, first the cost matrix of accumulated distances $\tilde{\boldsymbol{D}} \in \mathbb{R}^{N \times M}$ is constructed with initial condition $\tilde{d}(1,1) = d(1,1)$, and accumulated distance for every other element of $\tilde{\boldsymbol{D}}$ defined as

$$\tilde{d}(n,m) = d(n,m) + \min\left\{\tilde{d}(n-1,m), \tilde{d}(n,m-1), \tilde{d}(n-1,m-1)\right\}, \quad (5)$$

where $\tilde{d}(0,m) = \tilde{d}(n,0) = +\infty$ in order to define the accumulated distances for all elements of $\tilde{\boldsymbol{D}}$ (see Fig. 4). At this stage we keep the indexation regarding the adjacent cell with the minimum distance, and then starting from $\tilde{d}(N,M)$ we identify backwards the optimal path. In particular, if the optimal warping path is a sequence of elements $Z^* \equiv \{z_1^*, z_2^*, \ldots, z_K^*\}$ with $z_K^* = (N,M)$, then conditioning on $z_k^* = (n,m)$, we choose z_{k-1}^* as

$$z_{k-1}^* = \begin{cases} (1, m-1), & \text{if} \quad n = 1 \\ (n-1, 1), & \text{if} \quad m = 1 \\ \text{argmin}\{\tilde{d}(n-1,m-1), \tilde{d}(n-1,m), \tilde{d}(n,m-1)\}, & \text{otherwise.} \end{cases} \quad (6)$$

The process terminates when $n = m = 1$ and $z_k^* = (1,1)$ (Muller, 2007). The optimal path for our example is illustrated in Figs. 3–5 with the white solid line. Having identified the optimal path we can align the initial sequences Q and Y by warping their time axis (Fig. 6).

2.3. The prediction scheme using PIPs and DTW

The prediction scheme combines the use of PIPs and DTW in order to make predictions regarding the future evolution of the series. First, PIPs are constructed to dynamically segment the examined time series. Then for each target time, the DTW