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CandleFork: Interactive Stock Price Prediction Tool

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ABSTRACT

I present CandleFork, an interactive prediction technique to support users predicting the future of finance time-series data. I investigate whether Candlestick plots and Candlestick pattern information help users make better interpretations of an interactive stock price prediction technique. I argue that explaining stock predictions using Candlestick plots with pattern analysis is a better representation than common representations using line charts for stock prices and bar charts for trade volume. I compare the designed system, CandleFork, with TimeFork. To validate the technique, I conducted a user study in a stock market prediction game. I present evidence of improved performance for participants using CandleFork compared to TimeFork, and characterize qualitative usage patterns observed during the user study, proposed design implications.

ACM Classification Keywords

H.5.2. Information Interfaces and Presentation: User Interfaces—*Interaction styles*

Author Keywords

Visual Analytics; Human-in-the-loop; Finance Time Series; Visual Prediction; User Study.

INTRODUCTION

Stock market prediction is regarded as a challenging task of financial time-series prediction due to the highly time-variant and normally non-linear data. Many techniques have been developed to predict stock trends. Initially classical linear regression methods were used to predict stock trends [3]. Linear models have the advantage that it is possible to determine feature contribution by investigating the weights of corresponding features. Since stock data can be categorized as non-stationary time-series data, non-linear machine learning techniques including Artificial Neural Networks (ANN) and Support Vector Machine (SVM) have also been used and shown to be very powerful tools for stock time-series modeling and forecasting [31][20]. However, although non-linear ML models may be able to achieve a good prediction with higher accuracy, better stability, and can deal with the non-stationary nature of finance data [24], they are generally hard to interpret.

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It is desired to develop a human-in-the-loop ML technique that enables people to interact effectively with ML models to make better stock investment decisions. In interactive ML techniques for time-series datasets, information visualization and visual analytics techniques are commonly used. Recent techniques [32][33] in these fields visualize time series and related statistical metrics to enable analysts to interactively reason about the temporal data. Their goal is to better leverage the human ability to gain understanding from visualizations, including identifying the underlying trends, anomalies, and correlations, through an interactive and undirected search [16]. However, very limited research focus on the user experience of IML techniques in finance field, and going beyond solely understanding time-series data to predicting stock market's future behavior remains a very challenging task. Incorporating interactive exploration models with domain-specific technical analysis visualization can probably convey users a better reasonable mental model of the data inputs, and help improve user experience and decision making.

In finance, technical analysis is the evaluation of stocks by means of studying statistics generated by market activity, such as past prices and volumes. Technical analysts use stock charts to identify patterns and trends that may suggest how a stock will behave in the future. Candlestick pattern is one of the most widely adopted technical analysis techniques by both financial experts and ordinary stock market investors [21]. In Candlestick chart, each "Candlestick" typically represents four important pieces of price information for that day: the open, the close, the high and the low. Being densely packed with information, Candlesticks tend to represent trading patterns over short periods of time. A sample Candlestick chart is shown in Figure 1. Candlestick charts have patterns that are usually associated with certain expectations as for stock's behavior [7]. Many ML methods, such as neural networks, have been applied to automatic pattern detection and stock price prediction [19][14][18]. By visualizing stock chart with Candlestick pattern analysis, users can maintain a global view of large amount of stock price data while still preserving the perception of small regions of interest.

In this paper, I investigate whether Candlestick plots and Candlestick pattern information help users make better interpretations of an interactive stock price prediction technique. I argue that explaining stock predictions using Candlestick plots with pattern analysis is a better representation than common representations using line charts for stock prices and bar charts for trade volume. Candlestick chart with pattern visualizations are proved to be faithful and intelligible features to help non-

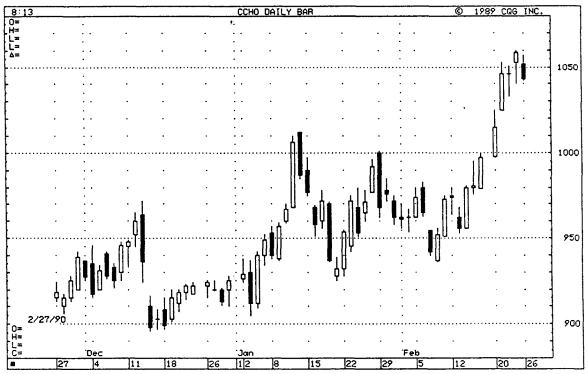

Figure 1. Candlestick chart (Kakao) — date between November 27th, 1990 and February 27th, 1991.

technical users who have expertise in finance effectively control and use interactive machine learning technique when making investment decisions, incorporating their domain-specific knowledge. "Non-technical users" in this study refers to users who have limited machine learning experience. As defined in [25], by "explaining a prediction", I mean presenting textual or visual artifacts that provide qualitative understanding of the relationship between the instance's components (e.g., patterns in a plot) and the model's prediction.

I compare the designed system, CandleFork, with TimeFork [2], an interactive prediction technique for visual prediction of multivariate time series. The effectiveness of two systems for visual prediction is evaluated through a simulated stock trading experiment. In this study, similar to Badam et al. [2], participants were given an opportunity to invest virtual money on three stocks and make decisions based on the systems' visualization and prediction results. I found that the visualization of Candlestick chart with Candlestick pattern analysis in stock price prediction system led to higher monetary gains compared to the more common line charts with bar charts system in the task scenarios. Most participants had high trust in IML systems' predictions, and also took the techniques' prediction confidence into consideration when making investing decisions. Participants varied in user efforts to comprehend interpretations and their perceived degrees of control on the prediction outputs. Additionally, participants who had more finance experience (especially in Candlestick chart interpretations) were more confident with their investment decisions than others.

This work may make the following contributions: (1) implementation of an interactive machine learning system designed for financial markets; (2) a user study to evaluate two interactive stock price prediction techniques and gain insights about user mental model in this field; (3) understanding of how interactive machine learning techniques influence users' efforts in usage, confidence, and feeling of control; and (4) design implications for user-centered interactive machine learning systems in finance applications.

RELATED WORK

The motivation for this study comes from the application of data mining tools in financial areas, and the lack of mixed-initiative finance time-series prediction tools. Below we discuss the literature related to prediction of the stock market, as well as mixed-initiative techniques for time-series analysis.

Prediction of the Stock Market

Investors in the market want to maximize their returns by buying or selling their investments at an appropriate time. Regression models have been traditionally used to model changes and predict linear patterns in the stock markets [26]. The dominant data mining technique used in stock market prediction so far is neural network modeling, including back-propagation (BP) networks, probabilistic neural networks, and recurrent neural networks [31][27]. Refenes et al. compared regression models with a back-propagation network using the same data for stock prediction [24]. In general, the inputs to neural networks include daily transaction volume, interest rates, stock prices, moving average, and/or rate of change, etc. [30][22]. Some other approaches to predicting stock trends have combined autoregressive integrated moving average (ARIMA) models and neural networks [31][28]. Ankerst [1] used data visualization techniques to analyze the stock prices, enabled the user to see the price change of a particular stock in a year easily, and provided an indication of uncertainty in the projected performance of the stock.

Identifying various predefined patterns in time series data is an essential part in the technical analysis in stock screening processes. Three most popular stock patterns are: head and shoulders pattern, inverse head and shoulders pattern, and rectangular patterns [23]. Kamijo et al. [14] used a neural network approach to extract patterns from the Tokyo Stock Exchange. The work of Keogh and Smyth [17] used piecewise linear segmentation, local features such as peaks, troughs and plateaus of the input sequence, and the global information such as the order of the local features, for pattern search.

Mixed-Initiative Techniques for Time-Series Analytics

Mixed-initiative interaction [12] targets a natural interleaving of contributions by people and computers to solve a task together [13]. Mixed-initiative techniques have recently been used to analyze data on visual interfaces, where the user can interact with the parameter space of a computational model for classification [15].

Similar to many mixed-initiative techniques, our CandleFork aims at achieving an interactive dialogue between analysts and computers to make better finance predictions. ChronoLenses [33] and KronoMiner [32] can be used for the monitoring and offline analysis of complex time-series data. TimeSearcher3 [6] visualized predictions in a time-series visualization following a data-driven forecasting method, while allowing the user to control the similarity metrics. Hao et al.'s [9] approach to supporting visual prediction support integration of multiple prediction models including ARIMA, Holt Winters (a seasonal method), and similarity-based models. They extended this approach to visualize peak-preserving predictions [8] for seasonal trends, interact with the model to adjust smoothing

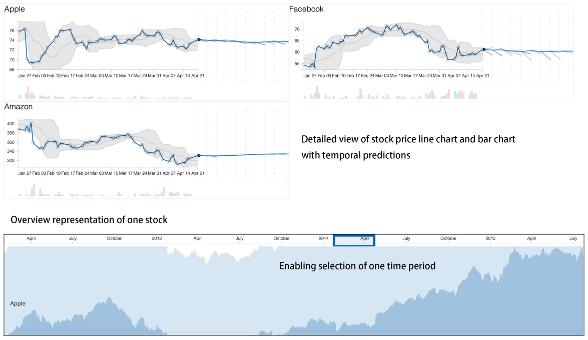

Figure 2. TimeFork system overview.

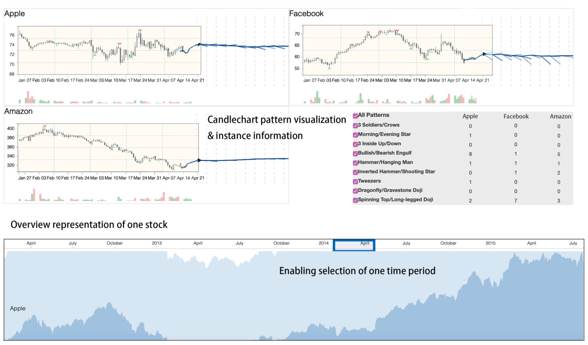

Figure 3. CandleFork system overview.

parameters, and connect predictions to similar past trends through brushing-and-linking. Hochheiser and Shneiderman's TimeSearcher [11] enabled dynamic quering of time-series visualizations through timeboxes. This tool was further developed to search time-series trends through similarity measures [5].

SYSTEM DESIGN

This technique is designed to support interactive prediction of stock price time-series data by integrating computational models with interactive visual analysis. Similar to TimeFork [2], our system contains an overview + detail layout following Shneiderman's guideline [29] for visual exploration — overview first, zoom and filter, details on demand. The overview captures overall patterns in the stock market data, and the detail views visualize selected time periods.

Overview representation. The overview in our system and TimeFork capture the overall patterns for multiple stocks of interest, selected from a stock list available in the interface. The implemented overview design contains horizon graphs [10] stacked vertically visualizing stock prices in a space-efficient layout. The overview also supports selection of a time period on the time axis to show specific data in the detail views, which helps the analyst view different time scales.

Detail representations. The detail views capture visual information through multiple charts visualizing the stock price and bar charts that can aid in prediction understanding and interpretation. The TimeFork technique's interface is designed to visualize the stock prices and trade volume, which is the primary quantitative information stock traders and analysts follow, as well as aid analysis across stocks through derived attributes including cross-correlation. In contrast, apart from line charts for stock prices and bar charts for trade volume, to aid prediction understanding and analysis, our CandleFork system also identifies and visualizes Candlestick chart patterns. Based on a technique developed in Japan in the 1700s for tracking the price of rice, a Candlestick is a type of price chart used that displays the high, low, open and closing prices of a security for a specific period [21]. Candlestick charts are a technical tool that pack data for multiple time frames into single price bars, which makes them more useful than traditional open-high, low-close bars or simple lines that connect the dots of closing prices.

INTERACTIVE PREDICTION WORKFLOW

To support the interactive prediction workflow, the line charts are attached with a prediction space showing predictions from the computational models and supporting user interaction. Generally, after selecting stocks of interest, the system shows and visualizes the initial predictions with price chart pattern information, then the user can view and interact with the system to get more specified predictions, and the system receives user inputs and updates the results.

First, the system shows and predicts temporal results. In this step, *temporal predictions* are generated by a computational model for the stocks based on the past values in the selected time period. The Candlestick pattern analysis is generated using Same as used in TimeFork, the model driving this step is a multilayer perceptron (one model per stock), a feed-forward neural network model, trained on the stock price data from our dataset for each stock. Each neural network model has five layers: input layer of 6 neurons, hidden layers of sizes (50, 60, 70), and an output layer of one neuron, with Sigmoid activation function. The input to each model is the past six relative price changes (ratio of price change to previous stock price), and the output is the relative future change (decoded using the current stock price). The models are trained on these (input, output) pairs from the historical data using the standard backpropagation algorithm. Trained models showed more than 90% accuracy with the training dataset.

User interactions with the prediction space are then enabled. Users can proceed with the gained visual knowledge from the detail views and the visualized model predictions in three ways: (1) neglect the visualized predictions altogether and make their own prediction (manual prediction); (2) select one of the proposed predictions that best suites their understanding (hybrid prediction); and (3) accept the most likely prediction provided by the computational model (automatic prediction). Users make one of these interactions directly on the prediction space by choosing a direction and a time period of predicted movement (by dragging an arrow on the prediction space signifying movement using mouse or touch input), getting *conditional predictions*. Candlestick patterns can provide useful information to guide interactions in this step. This interaction is then fed into the system in the next step, which reflects users' current understanding of the prediction. The system then receives user inputs and updates the predictions. Users may also save the results and undo manipulations.

IMPLEMENTATION

Based on TimeFork, our system's implementation uses a server-client architecture, along with sample stock market data and prediction models. The client interface was developed with web technologies — HTML5, JavaScript (JS), and CSS3 — with D3 visualization framework [4] for the overview and detail views. The system's server uses Brain Node.js library to train the models to enable interactive prediction workflow on the client. To refresh, two types of models were used: multilayer perceptrons (MLP) for temporal predictions and a selforganizing map (SOM) for conditional predictions. The dataset consisted of end-of-day stock price (adjusted closing) and trade volume for stocks (Apple, Tesla, and Facebook, data from 2012 to 2015).

USER STUDY

The focus of our user study was to understand whether and how the designed system changes the user's approach towards prediction as well as understanding of predictions, and to test whether CandleFork leads to better investment decisions compared to TimeFork. Simulated stock trading tasks were used in user study where the participants can read multiple visualizations of stocks and information about the Candlestick chart patterns (with background information guidance), gain an understanding, and engage in the interaction dialogue.

Participants

8 participants were recruited from the Finance/Economic students population within the university campus. The participants were between 20 and 23 years of age, with an average age of 22.5. Participants self-reported as proficient finance students with an average of 4 years of experience. Furthermore, all of them had novice-level experience in ML-based analysis of stock markets, reporting an average of 0.4 years of programming and none experience of ML.

Datasets and Tasks

During the study, each participant predicted the stocks using both systems (CandleFork and TimeFork). For each system, participants made 4 repetitions of investment decisions within the assigned data. To counter learning effects, two sets of data were used: data after the second quarter reports in July 2014 (Jul-Aug 2014), and data after the fourth quarter reports of 2014 released in Jan 2015 (Jan-Mar 2015). For each repetition of investment decisions, the participants were asked to invest their earnings on an assigned interface as shown in Figure 4, based on their interpretations of system predictions. They were shown stock price data over 3-4 weeks and were asked to make predictions spanning between 1 and 20 days into the future based on their assessment in each repetition. They were allowed to make all three kinds of predictions (manual, hybrid, and automatic predictions) in each investment decision. The participants were also shown the performance of their investment decisions based on their predictions in the previous repetition, to revise their investment strategies if needed. Overall, the participant's goal in an interface is to maximize their overall profit by investing their current earnings in the three stocks at each time step. The order of the system and data set used was counterbalanced.

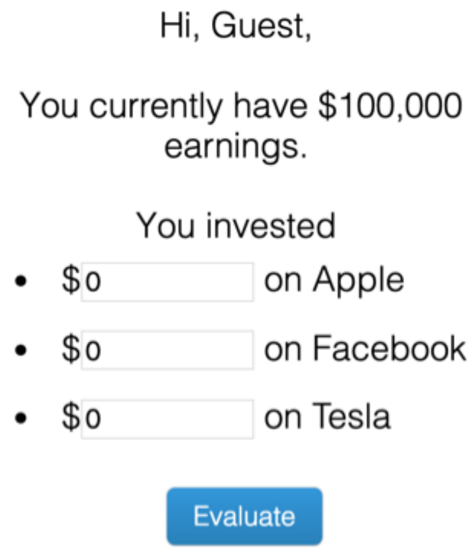

Figure 4. User investment decision interface.

Methods

The participants first arrived, and read and signed a consent form. The participants then completed a demographic survey reporting their basic information as well as previous experience. Following this, they were shown how to use the systems, including a brief guidance of understanding Candlestick chart patterns, how to read the line charts, how to explore the prediction space (using manual, hybrid, and automatic prediction methods), and how to invest on the stocks. The participants then conducted a trail, during which they were encouraged to ask questions, until they were comfortable with the system. They then finished the tasks (using 2 systems, 4 repetitions for each system) followed by completing a Likert scale survey rating their understanding, trust, as well as the efficiency, controllability, ease of use, and enjoyability of the technique. After the first condition, the participants continued to do the same with the second condition. Each session lasted between 35 and 50 min.

The profit/loss resulted from each investment decision during the 2×4 tasks were recorded. Some interesting parts of the participants' interaction manipulations were recorded, including their ways of using the three prediction methods. The participants were also encouraged to "think aloud" and announce their understanding of the system behavior. The sessions were followed up with a post-session interview to examine their strategies to understand the time-series data, deal with the reactions of the computer to their interaction, and decide on the investment.

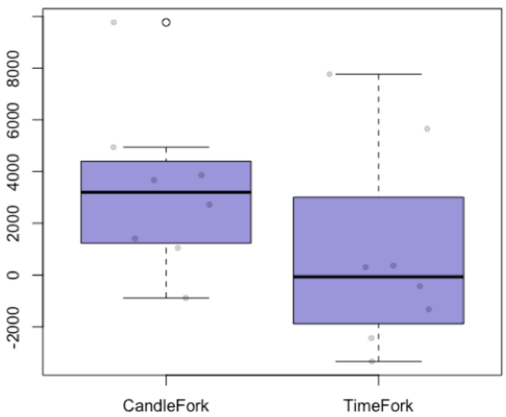

Figure 5. Box plot for performance (total gain/loss) using two systems.

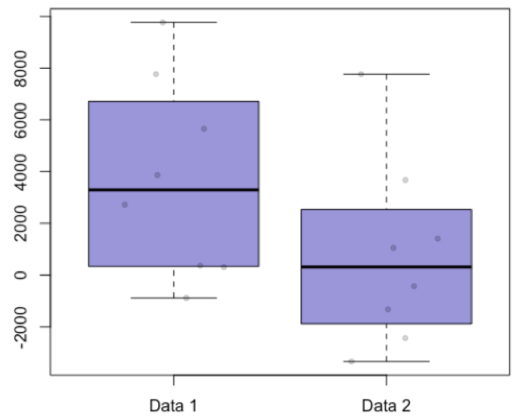

Figure 6. Box plot for performance (total gain/loss) using two datasets.

Results and Observations

Below I report the results from the statistical analysis and the qualitative analysis, as well as the participant feedback.

Quantitative Performance

Investment differences using two techniques. I analyzed the participant performance for CandleFork and TimeFork techniques, using 2-sample T-test. Although not significant, there seemed to be a performance difference (in terms of investment gain/loss) between TimeFork and CandleFork (p = 0.2058). Participants using CandleFork (mean = 3315.40, $s.d.$ =3196.22) outperformed TimeFork (mean = 816.53, $s.d.$ =3894.19).

Investment differences using two datasets. I then analyzed the participant performance individually for both data conditions — stock data from Jul-Aug 2014 (Data 1) and Jan-Mar 2015 (Data 2) — using 2-sample T-test. Although not significant, there seemed to be a performance difference between systems using two datasets (p = 0.1245). Participants' investment gain/loss using Data 1 (mean = 3691.99, $s.d.$ =3814.64) outperformed Data 2 (mean = 792.77, $s.d.$ =3602.54). This performance difference may be partly due to the computational models perform differently on these two datasets, which can lead to bias for our experimental results. This is further discussed in Design Implications section.

Observations

In my study, most users were observed to be consistent in their overall decision steps: first gain overview of the performance of three stocks based on automatic system predictions, then generate system output confidence by considering Candlestick chart patterns (for CandleFork) and conducting conditional predictions, analyzing three stocks' correlations based on conditional predictions, and making investment decisions. They had varied, intuitive ways to explore stocks' correlations, through which process they generated varied opinions about the systems' reliability.

Generally, users first formulated risky investment strategies based on initial interpretation of systems' automatic predictions and Candlestick chart pattern information (for CandleFork). Then most of them would conduct conditional and manual prediction analysis, and adjusted their investment strategies to safer ones by hedging and balancing risks.

P2 chose to completely trust the system and used automatic predictions in the first two tasks, resulting in investment losses. P2 then put less trust in the techniques, and conveyed the desire for more information such as business financial statement and Index of Consumer Sentiment to aid investment decisions. P3 stated that "If the computer's predictions are too varied, maybe I should not trust its prediction but rely more on my own decisions", after observing dramatic prediction prediction changes in hybrid prediction methods. P5 and P6 expressed confusion about interpreting the conditional predictions by dragging the arows, and they relied more on stock chart information to make predictions. P4 explained that the conditional and lower-confidence predictions showed how sensitive other stocks to a particular stock.

Subjective Ratings and Feedback

After each session, the participants rated the techniques on four metrics: efficiency, controllability, ease of use, and enjoyability, on a Likert scale ranging from 1 (e.g., strongly disagree) to 5 (e.g., strongly agree). The participants also rated their understanding and trust of the techniques. I analyzed these ratings with Wilcoxon Signed Rank tests and found no significant differences between the two techniques. However, most participants mentioned that CandleFork provided extra information that helped them interpret the results, thus making them more confident in decisions. TimeFork prediction required more guess work. They also felt that it took them more time to get used to the CandleFork's workflow and make decisions, due to heavier information load in CandleFork.

DESIGN IMPLICATIONS

My designed stock analysis application uses trained neural network models to provide temporal and conditional predictions that contribute to the dialogue with the analyst as used in TimeFork. However, this also severely influences the visual prediction. In my experiment setup, I used two sets of data for two systems, while the computational models perform significantly better on Data 1. Having an accurate model leads to significantly higher profits, resulting in bias in this user study. Therefore, more work is required not only to measure the effects of weak models, but also to create methods for visualizing the weakness of computational models to provide an efficient dialogue to help users deal with model weaknesses.

Furthermore, in the user study, finance users with limited machine learning background reported much trust in intelligent system's predictions, although they would also incorporate their field knowledge to interpret results before making investment decisions. Some participants suggest to also include information to aid fundamental analysis such as the financial statements of the company, published news and policies, and customer confidence.

There are also several potential weaknesses of the two systems' visual representations. 5 participants expressed surprise when they found that in certain cases, the model predictions were highly sensitive to conditions and input values (partly due to different scaling of the axes). This effect may lead to positive or negative results as it connects to why the computer's predictions are varied and also the user's interaction itself. More work is required to understand ways to mitigate this effect either by decoupling prediction and decision making, or by embedding solutions that propose possible answers to these decisions based on the user interactions.

The two systems use color shades to indicate prediction confidences. 2 short-sighted participants expressed difficulty in identifying those different color shades. This indicates potential needs of refining CandleFork system to use more distinctive visualization methods, possibly by changing the blue prediction lines to other more discriminative colors. Some participants also expressed confusion when dragging three arrows simultaneously, which makes it hard to identify whether locations of other arrows are still acting as exerted conditions or not. Other interactive wizards to explore conditional predictions are needed.

CONCLUSION AND FUTURE WORK

I have presented a method for interactive stock price prediction based on combining predictions from computational forecasting models with analyst input in an interactive interface utilizing Candlestick chart patterns, and compared the method with TimeFork. My user study showed significantly better performance in the presence of an efficient dialogue when also incorporating Candlestick chart patterns information compared to using price line charts and volume bar charts alone. In other words, my work shows that providing domain-specific visualization for aiding decision making can more actively involve humans in the sensemaking loop to produce more confident decisions.

It would be meaningful to continue exploring Time Series visualization techniques in human-computer collaborations in various application scenarios for people with limited machine learning background. However, one of the biggest challenges in visual analytics design is to identify the inflection points where the analyst can provide the most useful feedback to the system. The system is also desired to provide more understandable interpretations and feedbacks for effects resulted from users' decisions, which is still lacking in my current system. There is much potential in implementing and adapting this system to other domains and datasets.

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