Survey: Visual Analysis Approaches to Time Series Prediction

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1 Introduction

Making predictions is a common problem in corporate scenarios as well as in everyones personal life. Corporations need predictions in order to determine e.g. the following day's demand on the market. This is also true for the personal life, when buying a new laptop or signing a contract. These decisions are easier if there is at least some certainty about the future.

According to Lu et al. [22] predictive analytics is concerned with predicting future outcomes and trends based on past observations. Time series are highly complex, depend on different variables and cannot be easily predicted. Common models to analyze time series are often based on the Box-Jenkins method [8] or on regression [12]. These automatic methods are usually not able to provide analysts with an interpretation of interesting phenomena and analysts cannot easily include their domain knowledge in the forecasting process. In combination with Visual Analytics, analysts have an interactive solution, which enables them to better answer common questions, such as:

(Q1) Which model is the best to represent the time series?

(Q2) What are global trends within the time series?

(Q3) Which local patterns, seasonal trends and important events/periods can be found?

(Q4) How can this information be used to detect anomalies and turning points, which may change the future direction of the time series?

(Q5) Which correlations between gathered variables and events can be found?

(Q6) Which parameters are influencing my (production) processes?

(Q7) How certain is my current prediction?

This survey will focus on question (Q1) in Sect. 2.1, on (Q2) and (Q3) in Sect. 2.2, and (Q4), (Q5), (Q6) in Sect. 2.3. (Q7) is addressed throughout all sections.

Moreover, in some cases additional geospatial information is available and has to be included in the prediction process. In spatiotemporal analysis, analysts search for regions with higher than usual event occurrences, called hotspots. If hotspots are detected, analysts would like to predict how these regions will develop and where new hotspots may occur. Prominent applications areas include: detection of disease outbreaks as well as crime prevention.

The goal of this survey is to provide the reader with an overview that supports the decision process of selecting an appropriate time series prediction approach according to the required area of application.

2 Abstract Time Series

Aigner et al. [1] describe abstract time series data as data, which was collected in a non spatial context and is therefore not inherently connected to a spatial layout. Thus, only the time dimension is utilize to predict future events.

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2.1 Model Selection

Analyst are often interested in creating a model, which can be used in automatic systems as well as by unexperienced users once they are defined. However, simply applying a model is limiting the analyst. Therefore, model selection approaches want to support analysts in finding the best model by including domain knowledge.

A popular approach for pattern discovery in abstract time series analysis is *TimeSearcher* [17], which was extended [9] to work with multiple heterogeneous variables among other things. *TimeSearcher* focuses on automatically detecting similar behavior compared to a user specified pattern and high usability even for users without specialized skills, such as in statistics. However, these two version of *TimeSearcher* are more interested in data exploration. To assist the model selection process, the third version of *TimeSearcher* [10] is providing additional features. These additional features include an actual prediction functionality and a preview interface with different parameter selection tools. For the prediction, *TimeSearcher* resorts to the similarity-based approach, which was used in the previous versions [9, 17]. The actual prediction is computed by extrapolating only those time series, which were identified as similar to the target time series. To select a better model, the simultaneous preview interface visualizes river plots in order to allow the analyst to compare multiple parameter choices and different modeling techniques in parallel. (Fig. 1). One drawback of the system is, it requires the analyst to provide large datasets in order to make the similarity-based approach work. Further, the similarity based approach might also not be able to represent more complex behavior. However, the simultaneous preview interface simplifies the modeling process, makes it accessible to untrained users and allows experienced analysts to gain more insight.

In practical scenarios, large amounts of clean data are often problematic, which makes *TimeSearcher* [10] less valuable. Consequently, a model-driven system, which requires less data points, is preferred. *TiMoVA* [7] explicitly provides a model selection tool for ARIMA, AR, MA, etc. models. As consequence, the system is designed after the Box-Jenkins method and is assisting the model specification and selection process. Thereby, the analyst is guided during model type and order selection as well as parameter selection. Validation is done with the help of residual analysis plots and key figures. Moreover, their system evaluation revealed that an

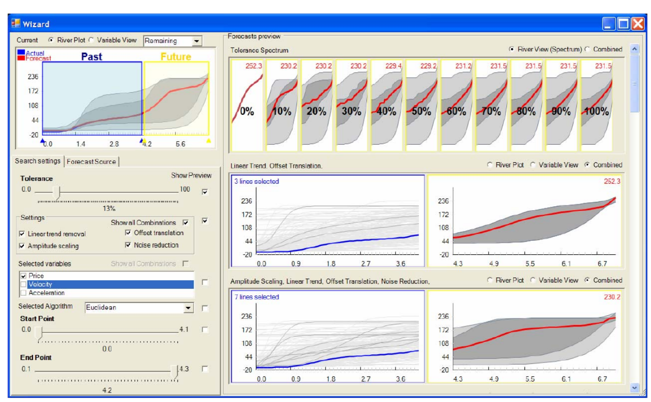

Figure 1: *TimeSearcher* simultaneous preview interface [10].

actual prediction functionality would assist the validation further. Therefore, Bögel et al. [6] extended *TiMoVA* by adding a forecast visualization, which supplies the analyst with real time prediction updates corresponding to the conducted changes. Equivalent to *TimeSearcher* [10], uncertainty is expressed with confidence bands. Additionally, the difference between true and predicted values as well as the direction (positive or negative) is visualized. Thereby, the analyst can judge if the model is constantly over- or underestimating the time series as well as how long and often this occurs. Consequently, the analyst gets an improved feedback about the adequateness and can simultaneously use the updated visualization to search for global or local trends (Q2)(Q3). A big drawback of the general system are its assumptions about the preprocessed data. It requires a time series without missing values and only supports univariate analysis.

With a growing social media use, social media platforms may contain highly relevant information for predictions. Motivated by this, Lu et al. [23] proposed a model selection framework including mainly social media information. Their framework also offers other functionalities such as sentiment analysis, however, for this survey, the focus is only on the regression model selection feature. Similar to *TimeSearcher* [10], they focus on users without prior knowledge and enable them to validate the model on similar instances. Analogous to *TiMoVA*'s extension [6], they offer visualizations to evaluate the degree of over- or underestimating similar instances. Further, the system incorporates an iterative feature selection process in the framework, which was not provided by *TimeSearcher* [10] or *TiMoVa* [7]. This process assists the analyst in creating multiple different and improved models, e.g. better generalization as a result of only relevant features. For unexperienced users, adjustable baseline models, created from known predictive features, are provided as entry point. The authors state as limitations that the final model is not able to detect cause-effect relationships (Q4)(Q5)(Q6). Further, the application scenarios presented in the paper are only predictions of one time step into the future, however the framework has the capacity with its regression models to predict further into the future.

2.2 Trend Detection

Trend detection involves finding an global trend or a more specific local trend, e.g. seasonal changes in retail due to Christmas. This analysis can be based on the models, which were created in Sect. 2.1. Unfortunately, these models hardly allow the analyst to include domain knowledge and are hard to interpret, hence Visual Analytics can be used to identify these trends directly.

An early Visual Analytics approach from Ichikawa et al. [18] tried to predict multiple daytime stock prices and simultaneously visualize a set of predictions from different simulation systems. As a consequence, the visualization includes multiple predictions for multiple stocks, which are represented by line charts and color band displays (Fig. 2). The color band display reduces the complexity of the predictive time series to avoid occlusions, which can occur within the line plot. Occlusion are also a problem for *TimeSearcher* [10], which displays river plots instead. The color band is created by assigning similar predictions to the same cluster, which reveals the overall trend for each cluster. Therefore, the analyst is able to detect discrepancies between the clusters and compare specific predictions with the overall trend. For additional comparison, a matrix based workspace visualizes a set of predictions for different stocks as well as, similar to *TimeSearcher* [10], different parameter ranges (e.g. sales organizations). The latter can also help in finding better model (Q1). Consequently, the analyst can detect trends concerning the whole stock market (Q2). However, in connection with the amount of simulations displayed or the reduced details in the color band display, it might be hard to extract local trends (Q3). Analogous to Lu et al. [23], the system is not visualizing any information about the simulations' certainty and reduces the discriminability of important behavior.

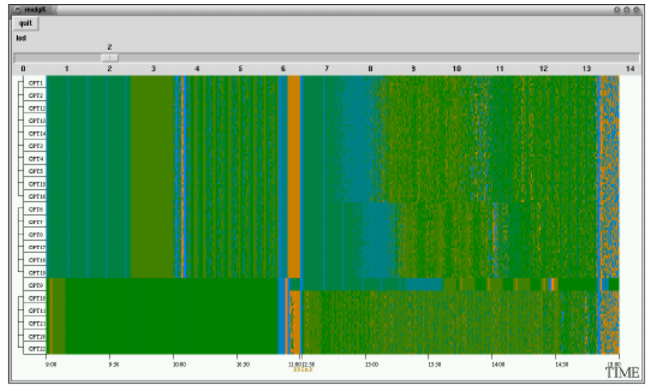

Figure 2: Color band display from Ichikawa et al. [18].

In contrast to Ichikawa et al. [18] the systems of Hao et al. [14,15] explicitly focus on time series prediction with peak preservation, which helps to find local trends (Q3). In their work, they focus on cell based power consumption data, for which it is particularly important to have deeper knowledge about peaks. The analyst is able to control the influence of more recent measurements, i.e. how far back in time seasonality is considered. Further, the system provides a visualization of its prediction quality on the historical time series given the current model (Q7). It has to be mentioned here, that including peak preservation is sometimes not wanted, as it may induce additional uncertainty for the more important global trend.

Evaluating uncertainty was only indirectly provided by the system of Ichikawa et al. [18] as a result of simulation overlap. A popular choice to address this problem more thoroughly are ensemble visualizations. The system from Köpp et al. [21] offers a heatmap-based option to visualize multiple time series predictions. Their interactive solution enables analysts to comprehensively analyze predictions' certainties with e.g. quantiles, extrema and percentiles. Another resembling feature to Ichikawa et al. [18] is the external source of simulations. Depending on the application area, this can be beneficial or disadvantageous. Other ensemble approaches incorporate models explicitly and help in general to explore uncertainty (Q7). However, this is beyond the scope of this survey and the reader is encouraged to use this system as an entry point for further research.

2.3 Correlation Detection

Trends and models for time series are helpful in making predictions. However, analysts are often interested in finding correlations in order to predict unusual future behavior, which allows them to react preemptively. Examples include fraud attempts, higher server loads or predictive maintenance.

The previously introduced *TimeSearcher* [10] is able to support analyst with this task. The system provides the ability to extract occurrences of patterns, which were specified by the analyst. Combined with the prediction capabilities of the system, the analyst is able to find cause-effect relationships or correlations (Q4)(Q5)(Q6). Equivalent to this, the idea of peak preservation [14, 15] was combined with Motif/Pattern detection [16]. Unlike *TimeSearcher* [10] overlapping patterns can be detected and the systems specifically extrapolates these patterns into the future. Compared to the previous approaches [14, 15], it supports multivariate analysis. By adding these additional features, analysts are better suited for predictive maintenance or similar applications (Q4)(Q5)(Q6). One possible application presented in the paper is forecasting the ideal oil well flow pattern as well as analyzing how to recover from drops in flow (outages).

Apart from those general approaches, a more specialized Visual Analytics approach, called *VAET* [32], was proposed. The difference

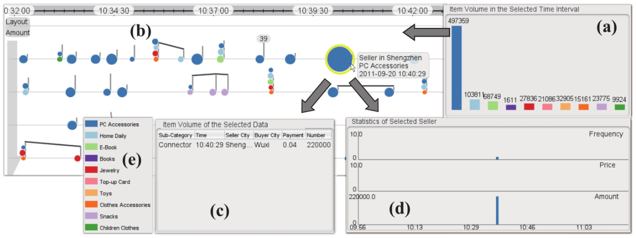

Figure 3: KnotLine view of *VAET* [32].

to other systems can be found in the application area of customer-to-customer e-transaction time series. Predicting behavioral pattern into the future helps analysts to understand contextual connections between multiple transactions of a single seller. An exemplary application could be identifying fake transactions or fraud (Q4). For analysis the system employs an iterative process, which was also used in the model selection system for social media data [21]. An overview component proposes possible salient transactions based on an automatic saliency prediction, whereas a detailed view shows further information for a selected transaction. For the detailed view, a musical notation inspired visual metaphor, called KnotLines (Fig. 3), was introduced. KnotLines enables the analyst to easily assess important information, such as the amount of transactions, payment or relationships other time. Consequently, the analyst can identify contextual correlations (Q5) of transactions and find salient transactions, which are reported back to the overview. With this iterative process, analysts are able to narrow down their search to important temporal patterns, which enable them to detect fraud or similar attempts in advance. It is also possible to adapt this idea to different application scenarios such as predictive maintenance as well as outage forecasts for data centers or oil platforms. Albeit, the current version of the system is highly optimized for the sales use case. Another drawback of the system is, it requires annotated training data for its automated saliency proposals, which introduces additional effort.

Another specialized system is Falcon [30], which focuses on detecting correlative patterns in log and imagery data from 3D printers, including missing values. Unlike the other systems, this Visual Analytics tool is designed from a manufacturing standpoint to increase production efficiency or to discover defects and system performance issues. Falcon visualizes all variables with corresponding statistical information independently (Fig. 4). Consequently, multiple different variables can be examined simultaneously on difference scales by the analyst in order to find correlations (Q5). Falcon also offers a new visualization technique, called waterfall visualization, to combine overview and detailed view, which allows to find anomalies or trends (Q2)(Q3)(Q4). This idea is resembling to the color charts by Ichikawa et al. [18]. From an operational point of view, the system offers, similar to *VAET* [32], an user driven analysis and helps to detect and highlight univariate and multivariate patterns from different angles. Steed et al. were supporting a universal approach for Falcon to make it applicable for different domains. However, to support their specific analysis task, they included some non-generalizing functionalities. Analogous to the model selection framework from Lu et al. [23], they enable the analyst to compare the 3D printer time series to a historical/user-defined time series. This comparison makes it easier to distinct between normal behavior and anomalies (Q6). As a consequence, the system grants analyst the ability for predictive maintenance, e.g. detecting a heat development pattern, which indicates a failure of the printer head in the near future. Currently the system does not support provenance information and the similarity/dissimilarity methods are limited to a single view.

Unlike *TimeSearcher* [10] or the peak preservation approach [16], *VAET* [32] and Falcon [30] do not incorporate an automatic prediction functionality. They only assist analysts in examining time series, so that they can extract information about future behavior,

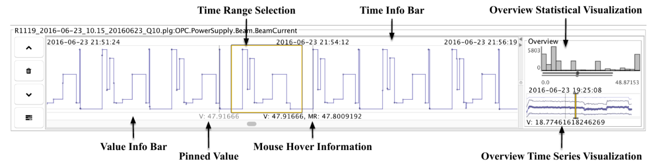

Figure 4: Time series visualization of one variable from Falcon [30].

correlation and cause-effect relationships (Q4)(Q5)(Q6).

Other application, which specifically focus on pattern detection can be found for patient treatment plans [13] or climate research [20]. Whereas, the latter can also be interpreted as spatiotemporal as it detects regions in the atmosphere, which indicate climate change. Related to the focus of Hao et al. [14, 15], Janetzko et al. [19] and *LiveRAC* [29] focus on predictive maintenance in data centers. Additionally, *LiveRAC* was developed for high scalability, which is an issue most other systems are not able to handle properly. Falcon [30] is the only other system in this survey to provide some scalability, although in a different application area. These system were just described shortly as they only touch the topic of the survey peripherally, but should provide the reader with a entry point for further research.

3 Spatial Time Series

The previous section presented an overview of systems for abstract time series analysis. However, for other application areas, such as crime prevention as well as emergency and epidemic intelligence, not only temporal information are valuable, but also geospatial information. Aigner et al. [1] state spatial data was formed into a spatial layout by natural conditions or model assumptions. Andrienko et al. [3, 4] found that geospatial analysis has a higher complexity and automated methods cannot adequately solve this task. It requires domain knowledge from a human analyst in order to solve these problems comprehensively. However, as a result of the data's high dimensionality, an analyst needs support from Visual Analytics systems.

Andrienko et al. [5] proposed an approach, which is between temporal and spatiotemporal. They include spatial dimensions, but their analysis is largely based on abstract time series compared to the following approaches. Similar to the peak preserving approach from Hao et al. [16], they ensure local specialties are represented in the prediction.

Maciejewski et al. [24] are proceeding from their previous work [26,27] and focus on categorical medical event data. Similar to *TimeSearcher* [10], *TiMoVA* [7] and peak preservation [16] confidence bands are established in order to display uncertainty (Q7). A linked view grants an overview of the percentages of events in a certain area (Fig. 5) as well as the temporal trend (Q2), this allows the analyst to quickly assess the current situation. Further, the system differentiates between the temporal and the geospatial prediction. For multivariate temporal data, each event category is modeled as a separate time series signal and subsequently forecast. For geospatial predictions, the system utilizes density estimation to determine the spatial distribution of the temporal prediction. In order to predict anomalies (Q4)(Q5), e.g. outbreaks of diseases, the system calculates the difference between predicted and actual values, as a result areas above a user specified threshold are highlighted. This is also sent to the analyst as alert in order to analyze the occurrence further.

Another system also from Maciejewski et al. [25] is based on the same method . Equivalent to the previously described system [24], a linked environment is provided as well as a separation of temporal and geospatial forecast. The major difference is, this work focuses on finding and understanding patterns, rather than only predicting them. Therefore, the system establishes temporal contour maps, which allow the analyst to view shifting hotspots across time and analyze the movements of trends (Q2)(Q3) and patterns over this period. Further, the system allows to search for correlations (Q4)(Q5) between multiple variables via overlaying contour maps, heat maps and/or including height. However, one issue with this visualization is, it only works in a three dimensional variable space. Moreover, in both systems aggregating too many data points, may yield to largely exaggerated hotspots or an uniform surface.

Recent work from Malik et al. [28] focuses, comparable to the preview interface of *TimeSearcher* [9] and the baseline models from the model selection framework [23], on an environment, which allows non statistic experts to utilize their domain expertise. Therefore, unlike Maciejewski et al. [24], the goal is to provide additional guidance for domain experts in order to improve their analysis. Geospatial and temporal scale templates present the analyst with a starting point and avoid searching through the complete parameter space. Temporal templates follow the idea of peak preservation, as in the work of Hao et al. [16]. Further, the analyst is able to interactively change the initial templates to include e.g. police beats. Analogous to Maciejewski et al. [24, 25], the systems is using the same separated approach in order to predict time and space. In order to compensate for insufficient data points, demographically similar neighborhoods within a certain radius around that area can be used. An additional improvement compared to the previous systems includes the easier access to observe trends (Q2)(Q3) on different scales of time, i.e. on hourly, daily and monthly basis.

In contrast to most other spatiotemporal approaches, Andrienko et al. [3] applied self-organizing maps (*SOM*) for either spatial or temporal prediction. SOMs can be seen as a combination of clustering and dimensionality reduction based on the similarity of space and time, therefore this can be seen at least alike to the similarity-based approach of *TimeSearcher* [10]. The SOM method is applied to spatial situations that occur in different time units and to local temporal variations that occur in different places. This idea can also be found in earlier work from Andrienko & Andrienko [2]. The more recent approach is using feature images and index images (Fig. 6) for the spatial and temporal dimension. Spatial data in feature images is represented as map and temporal data as temporal mosaic, which has a large correspondence to the color charts of Ichikawa et al. [18] and the waterfall visualization of Falcon [30]. In order to enable the analyst to find correlations (Q4)(Q5), a SOM cell matrix (Fig. 6), comparable to the matrix approach from Ichikawa et al. [18], with different feature images and index images is displayed. Additionally, a second visualization aggregates the index images to display the respective other dimension. This allows the analyst to determine at which time a certain spatial cell is present or at which location a certain temporal cell occurs. The temporal aggregation shows again a similar structure as the color charts of Ichikawa et al. [18] and the waterfall visualization of Falcon [30]. The evaluation of the system shows that it is applicable for detecting expected as well as unexpected results. This allows analysts to either find evidence, which supports their previously formed hypothesis, or discover new connections, which enable them to make assumptions about future events.

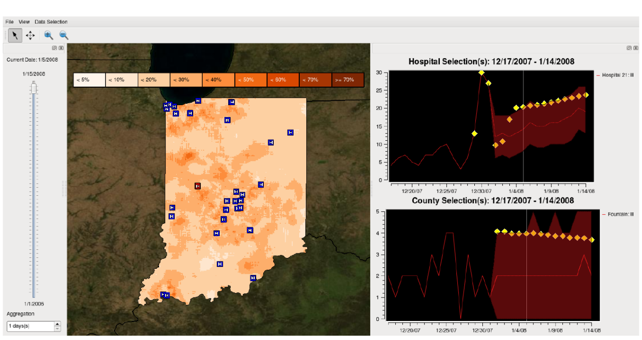

Figure 5: Linked environment from Malik et al. [24].

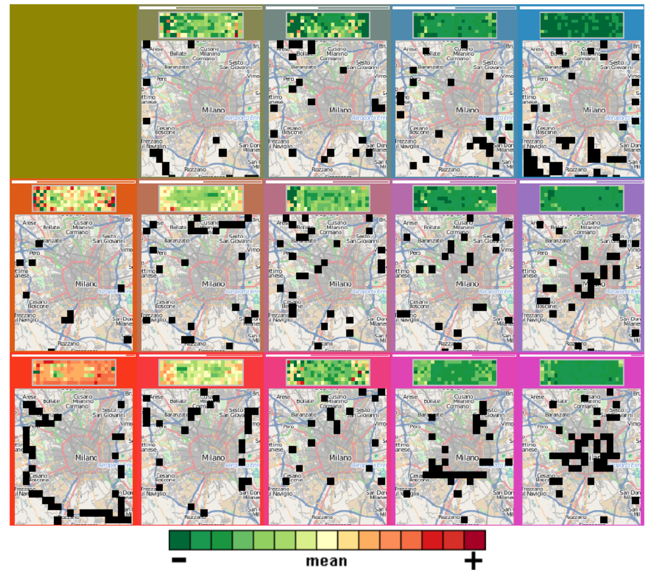

Figure 6: SOM Matrix with feature images (top) and index images (bottom) [3].

Aside from medical and crime prevention applications, spatiotemporal data can also be helpful in other domains. Similar to the first approaches, seasonal trend decomposition can be used in context of social media anomaly detection [11, 31]. This can help to increase situational awareness of local events as well as provide insight for investigations and incidents, their severity and consequences.

4 Summary and Conclusion

Time series prediction has two major directions: abstract and spatiotemporal. Abstract time series analysis mainly follows interactive approaches, which support the analyst in trend detection, model selection or correlation detection. Supportive features in this context are e.g. the simultaneous preview interface [10], the comparative variable view [30] or KnotLines [32]. They enable the analyst to gain more knowledge about the data, to generate hypothesis and to predict future developments or anomaly occurrences. Spatiotemporal time series add another important dimension, which makes automated analysis more complicated. Those systems have to enable the user to select spatial and temporal resolution. The system of Malik et al. [28] even suggests different templates to make the systems more accessible to domain experts.

One important drawback most systems, besides Falcon [30] and *LiveRAC* [29], have, is the missing scalability. Further, none of the approaches presented in this survey was able to provide a solution to high dimensional outputs, e.g. predicting the demand for multi-product companies, customer-to-customer online platforms, etc. In contrast to this, sparse data, in connection with filtering or increasing the resolution, was only addressed by Malik et al. [28] using neighboring areas. Moreover, most systems have strong assumptions about the quality of the data e.g. no missing values. On the other hand, current Visual Analytics system offer a broad range of application areas including manufacturing, medical, environmental and social media oriented forecasts. Additionally, different systems address different levels of the analyst's competence. Uncertainty was addresses by some of the systems, but only the ensemble approach [21] offered multiple analysis options. Thus, future work should include Visual Analytics approaches, which are suitable for higher dimensional outputs and offer solutions for missing values, outliers or data quality in general. Combining this with ensemble methods can help to evaluate uncertainty better and increase the robustness of predictions.

REFERENCES

[1] W. Aigner, S. Miksch, W. Müller, H. Schumann, and C. Tominski. Visualizing time-oriented data-a systematic view. *Comput. Graph.*, 31(3):401–409, June 2007. doi: 10.1016/j.cag.2007.01.030

[2] G. Andrienko and N. Andrienko. Visual exploration of the spatial distribution of temporal behaviors. In *Ninth International Conference on Information Visualisation (IV'05)*, pp. 799–806, July 2005. doi: 10.1109/IV.2005.135

[3] G. Andrienko, N. Andrienko, S. Bremm, T. Schreck, T. von Landesberger, P. Bak, and D. Keim. Space-in-time and time-in-space self-organizing maps for exploring spatiotemporal patterns. In *Proceedings of the 12th Eurographics / IEEE - VGTC Conference on Visualization*, EuroVis'10, pp. 913–922. The Eurographs Association and John Wiley and Sons, Ltd., Chichester, UK, 2010. doi: 10.1111/j.1467-8659.2009.01664.x

[4] G. Andrienko, N. Andrienko, J. Dykes, S. I. Fabrikant, and M. Wachowicz. Geovisualization of dynamics, movement and change: Key issues and developing approaches in visualization research. *Information Visualization*, 7(3):173–180, June 2008. doi: 10.1057/ivs.2008.23

[5] G. Andrienko, N. Andrienko, M. Mladenov, M. Mock, and C. Poelitz. Extracting events from spatial time series. In *2010 14th International Conference Information Visualisation*, pp. 48–53, July 2010.

[6] M. Bögl, W. Aigner, P. Filzmoser, T. Gschwandtner, T. Lammarsch, S. Miksch, and A. Rind. Visual analytics methods to guide diagnostics for time series model predictions. In *IEEE VIS 2014 Workshop Visualization for Predictive Analytics, VPA*, 2014.

[7] M. Bögl, W. Aigner, P. Filzmoser, T. Lammarsch, S. Miksch, and A. Rind. Visual analytics for model selection in time series analysis. *IEEE Transactions on Visualization and Computer Graphics, Special Issue "VIS 2013"*, 19:2237 – 2246, 12 2013. doi: 10.1109/TVCG.2013.222

[8] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung. *Time series analysis: forecasting and control*. John Wiley and Sons, 2015.

[9] P. Buono, A. Aris, C. Plaisant, A. Khella, and B. Shneiderman. Interactive pattern search in time series. In *Visualization and Data Analysis 2005*, vol. 5669, pp. 175–187. International Society for Optics and Photonics, 2005.

[10] P. Buono, C. Plaisant, A. Simeone, A. Aris, G. Shmueli, and W. Jank. Similarity-based forecasting with simultaneous previews: A river plot interface for time series forecasting. In *Information Visualization, 2007. IV'07. 11th International Conference*, pp. 191–196. IEEE, 2007.

[11] J. Chae, D. Thom, H. Bosch, Y. Jang, R. Maciejewski, D. S. Ebert, and T. Ertl. Spatiotemporal social media analytics for abnormal event detection and examination using seasonal-trend decomposition. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 143–152, Oct 2012. doi: 10.1109/VAST.2012.6400557

[12] N. R. Draper and H. Smith. *Applied regression analysis*, vol. 326. John Wiley & Sons, 2014.

[13] T. Gschwandtner, W. Aigner, K. Kaiser, S. Miksch, and A. Seyfang. Carecruiser: Exploring and visualizing plans, events, and effects interactively. In *2011 IEEE Pacific Visualization Symposium*, pp. 43–50, March 2011. doi: 10.1109/PACIFICVIS.2011.5742371

[14] M. C. Hao, H. Janetzko, S. Mittelstädt, W. Hill, U. Dayal, D. A. Keim, M. Marwah, and R. K. Sharma. A visual analytics approach for peak-preserving prediction of large seasonal time series. In *Proceedings of the 13th Eurographics / IEEE - VGTC Conference on Visualization*, EuroVis'11, pp. 691–700. The Eurographs Association and John Wiley and Sons, Ltd., Chichester, UK, 2011. doi: 10.1111/j.1467-8659.2011.01918.x

[15] M. C. Hao, H. Janetzko, R. K. Sharma, U. Dayal, D. A. Keim, and M. Castellanos. Poster: Visual prediction of time series. In *2009 IEEE Symposium on Visual Analytics Science and Technology*, pp. 229–230, Oct 2009. doi: 10.1109/VAST.2009.5333420

[16] M. C. Hao, M. Marwah, H. Janetzko, U. Dayal, D. A. Keim, D. Patnaik, N. Ramakrishnan, and R. K. Sharma. Visual exploration of frequent patterns in multivariate time series. *Information Visualization*, 11(1):71–83, Jan. 2012. doi: 10.1177/1473871611430769

[17] H. Hochheiser and B. Shneiderman. Dynamic query tools for time series data sets: Timebox widgets for interactive exploration. *Information Visualization*, 3(1):1–18, Mar. 2004. doi: 10.1145/993176.993177

[18] Y. Ichikawa, T. Tsunawaki, I. Fujishiro, and H. Yoon. A visualization environment for multiple daytime stock price predictions. In *Proceedings of the 2nd VIIP International Conferences on Visualization, Imaging and Image Processing, Malaga, Spain*, 2002.

[19] H. Janetzko, F. Stoffel, S. Mittelstädt, and D. A. Keim. Anomaly detection for visual analytics of power consumption data. *Computers and Graphics*, 38:27–37, 2014.

[20] J. Kehrer, F. Ladstdter, P. Muigg, H. Doleisch, A. Steiner, and H. Hauser. Hypothesis generation in climate research with interactive visual data exploration. *IEEE Transactions on Visualization and Computer Graphics*, 14(6):1579–1586, Nov 2008. doi: 10.1109/TVCG.2008.139

[21] C. Köpp, H.-J. von Mettenheim, and M. H. Breitner. Decision analytics mit heatmap-visualisierung von mehrschrittigen ensembledaten. *Wirtschaftsinformatik*, 56(3):147–157, 2014.

[22] Y. Lu, R. Garcia, B. Hansen, M. Gleicher, and R. Maciejewski. The state-of-the-art in predictive visual analytics. *Comput. Graph. Forum*, 36(3):539–562, June 2017. doi: 10.1111/cgf.13210

[23] Y. Lu, R. Krüger, D. Thom, F. Wang, S. Koch, T. Ertl, and R. Maciejewski. Integrating predictive analytics and social media. In *Visual Analytics Science and Technology (VAST), 2014 IEEE Conference on*, pp. 193–202. IEEE, 2014.

[24] R. Maciejewski, R. Hafen, S. Rudolph, S. G. Larew, M. A. Mitchell, W. S. Cleveland, and D. S. Ebert. Forecasting hotspots: A predictive analytics approach. *IEEE Transactions on Visualization and Computer Graphics*, 17(4):440–453, April 2011. doi: 10.1109/TVCG.2010.82

[25] R. Maciejewski, S. Rudolph, R. Hafen, A. Abusalah, M. Yakout, M. Ouzzani, W. S. Cleveland, S. J. Grannis, and D. S. Ebert. A visual analytics approach to understanding spatiotemporal hotspots. *IEEE Transactions on Visualization and Computer Graphics*, 16(2):205–220, 2010.

[26] R. Maciejewski, S. Rudolph, R. Hafen, A. Abusalah, M. Yakout, M. Ouzzani, W. S. Cleveland, S. J. Grannis, M. Wade, and D. S. Ebert. Understanding syndromic hotspots - a visual analytics approach. In *2008 IEEE Symposium on Visual Analytics Science and Technology*, pp. 35–42, Oct 2008. doi: 10.1109/VAST.2008.4677354

[27] R. Maciejewski, B. Tyner, Y. Jang, C. Zheng, R. V. Nehme, D. S. Ebert, W. S. Cleveland, M. Ouzzani, S. J. Grannis, and L. T. Glickman. Lahva: Linked animal-human health visual analytics. In *2007 IEEE Symposium on Visual Analytics Science and Technology*, pp. 27–34, Oct 2007.

[28] A. Malik, R. Maciejewski, S. Towers, S. McCullough, and D. S. Ebert. Proactive spatiotemporal resource allocation and predictive visual analytics for community policing and law enforcement. *IEEE transactions on visualization and computer graphics*, 20(12):1863–1872, 2014.

[29] P. McLachlan, T. Munzner, E. Koutsofios, and S. North. Liverac: Interactive visual exploration of system management time-series data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '08, pp. 1483–1492. ACM, New York, NY, USA, 2008. doi: 10.1145/1357054.1357286

[30] C. A. Steed, W. Halsey, R. Dehoff, S. L. Yoder, V. Paquit, and S. Powers. Falcon: Visual analysis of large, irregularly sampled, and multivariate time series data in additive manufacturing. *Computers and Graphics*, 63:50–64, 2017.

[31] D. Thom, H. Bosch, S. Koch, M. Wrner, and T. Ertl. Spatiotemporal anomaly detection through visual analysis of geolocated twitter messages. In *2012 IEEE Pacific Visualization Symposium*, pp. 41–48, Feb 2012. doi: 10.1109/PacificVis.2012.6183572

[32] C. Xie, W. Chen, X. Huang, Y. Hu, S. Barlowe, and J. Yang. Vaet: A visual analytics approach for e-transactions time-series. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1743–1752, Dec 2014. doi: 10.1109/TVCG.2014.2346913