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Visual Analytics Framework for the Assessment of Temporal Hypergraph Prediction Models

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Abstract

Members of communities often share topics of interest. However, usually not all members are interested in all topics, and participation in topics changes over time. Prediction models based on temporal hypergraphs that—in contrast to state-of-the-art models—exploit group structures in the communication network can be used to anticipate changes of interests. In practice, there is a need to assess these models in detail. While loss functions used in the training process can provide initial cues on the model's global quality, local quality can be investigated with visual analytics. In this paper, we present a visual analytics framework for the assessment of temporal hypergraph prediction models. We introduce its core components: a sliding window approach to prediction and an interactive visualization for partially fuzzy temporal hypergraphs.

Index Terms: Human-centered computing—Visualization—Visualization application domains—Visual analytics; Human-centered computing—Visualization—Visualization techniques—Graph drawings

1 Introduction

The assessment, diagnosis, and refinement of prediction models are common tasks in visual analytics [12]. Trust building and accountability are additional relevant factors for practitioners [10], especially as domain experts often have neither the time nor interest in fully understanding the inner structure of particular prediction models.In order to allow domain experts to put predictions into context, social network analysis is shifting from purely structural analysis towards the analysis of content by using semantic concepts [14]. Exemplar applications include deciphering associations between images and text [11] and content classification [19]. Another use case is the prediction of topics of interest of internet forum users. Predicting future interests not only needs to take current interests into account, but also the structure of the communication network such as the interests of related users. With hypergraph prediction models, we exploit this structure. Using our visual analytics workflow domain experts can assess models and calibrate trust during application. As a running example we use a dataset of the right-wing Stormfront internet forum. In this paper, we contribute a visual analytics framework for the assessment of temporal hypergraph prediction models, and an interactive visualization featuring a glyph that represents sliding window predictions next to training and holdout data for the local assessment of model quality.

Predicting future links or uncovering hidden relations between users in social networks has been researched in multimedia information retrieval for a long time [13, 21]. Recent works in geometric deep learning [4, 6, 7] introduced advanced methods for representation learning, which captures structural information within non-Euclidean domains, especially graphs. Hypergraph-based approaches are prominent for their ability to represent, capture, and transfer information between users or communities within (often implicit) social networks [2, 3].

Complementarily, visual analytics provides a general framework for the interactive analysis of data [8]. The framework we present in this paper implements the close interaction of human analysts and computers via visualization as outlined by Sacha et al. [20]. Multiple surveys summarize visualizations of sets and hypergraphs, for instance, as Euler diagrams, node-link diagrams, or matrices [1, 5, 15, 18, 24]. Transitions in temporal hypergraph visualization have been investigated by Mizuno et al. [16]. Most recently, Xie et al. [25] presented an application of visual analytics on the training of hypergraph models. In this work, we focus on the application.

For the task of assessing topic predictions, we identified three requirements: a) Group structures in the communication network should be taken into account or revealed, b) Prediction quality needs to be assessed locally for gaining actionable insights, and in our specific case c) Analysis is focused on a single user. We address these demands by integrating a temporal hypergraph model with a visual analytics workflow, as sketched in Fig. 1. Our visual interface focuses on a single user in his context and combines detailed information on predictions, training, and holdout data.

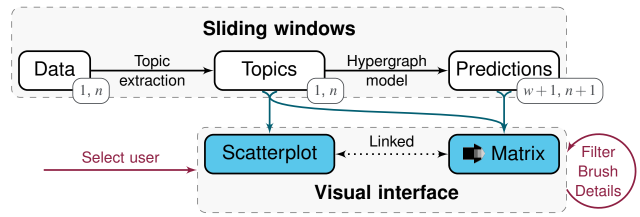

Figure 1: Our visual analytics framework integrates temporal hypergraph predictions by joining multiple $(n-w)$ sliding windows of size w in arrow glyphs in the matrix view (See Sect. 3). The top row shows the main data flow, while the bottom row depicts the domain expert's workflow with the visual analytics system (red arrows). Petrol colored arrows between rows show how data is mapped to the visual interface.

2 Temporal Hypergraph Prediction

In our framework, we formulate the prediction of future interests of internet forum users as a (hyper)edge prediction task on a temporal hypergraph. Our prediction model is based on recent advances in geometric matrix completion by using graph convolution networks [3, 17]. Following the work of Arya, Rudinac, and Worring [2], we construct a hypergraph representing each user as a node and each topic as separate hyperedge, such that users who adhere to a common topic of interest are enclosed within one hyperedge. Consequently, with the evolution of users' topics of interest, nodes contained within the hyperedges change over time. For each user, the goal is to capture changes in his interests by exploiting both his past and current interests as well as the evolution of interests of most related users in the neighborhood within the hypergraph. Such a problem can well be coined as a matrix completion task

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over the incidence matrix of a hypergraph, where rows and columns correspond to nodes and edges respectively [2].

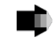
In our running example, we use data extracted from the Stormfront internet forum of the period 2005–2014. For extracting users' topics of interest and data pre-processing, we join the setups of Rudinac, Gornishka, and Worring [19] and Arya, Rudinac, and Worring [2]. Further, we use a sliding window approach [22] for assessing the model (see also Fig. 1). In our case, each window starts at a time $t \in \{1,\ldots,n-w\}$ and is w years wide for the in-sample data/training set. The forecasting horizon spans the consecutive year, which is available as a holdout sample/test set for the period $\{w+1,\ldots,n\}$. We estimate instances of the model on each window and evaluate their performance using *AUC* (Area Under Curve) of the *ROC* (Receiver Operating Characteristic) on respective holdout samples. In Fig. 2, the first window ranges from 2005 to 2012. The corresponding holdout sample is the year 2013. Likewise, the second in-sample includes the years 2006 to 2013, thus the holdout sample is the year 2014. For both samples, we get an *AUC* score of .76 and .78 respectively. Additionally, we use the in-sample from 2007 to 2014 to predict the future 2015 for which no data is available.

The sliding window approach offers several advantages for the analyst. To begin with, compared to cross-validation it allows the use of all data of each time step for training. This is particularly relevant as the number of posts per user is highly diverse. Sampling for cross-validation would further taper off available data on those users who posted infrequently in the first place. Secondly, predicting the future assumes that there are no structural changes in the meantime. With the sliding windows, we can expect to increase the chances of detecting potential structural changes in the time period spanned by the holdout samples. Imagine a model instance trained on a window that contains in-sample data before a structural change and holdout data (partially) after the change. This model can be expected to perform worse than instances predicting on windows for which there does not occur any structural change (as assumed). Finally, model assessment can be performed locally for each hyperedge membership since multiple pairs of predictions and holdout values are available. Additionally, the sequence of predictions can show some variability of the prediction estimates. Thus, the sliding window approach caters to the demand for local assessment that we identified above.

3 Visual Analytics Framework

In general, the framework follows Keim et al.'s visual analytics mantra [9]. Data analysis and predictions (see top of Fig. 1) are prepared before the analyst starts her workflow by selecting a user. Then, topics and other users related to the focused user are displayed. By performing filter, brush, and details-on-demand operations, the analyst can inspect predictions in their global and local contexts. Exploiting her domain knowledge, the analyst is able to compare predictions across users (i.e., nodes), topics (i.e., hyperedges), and time. Thus, she can iteratively reassess local model quality, and revalue predictions made on the focused user's topics of interest.

In Fig. 2, we provide an overview on our visual interface. On the left hand side, the matrix view shows the temporal evolution of topic interests and predictions as arrow glyphs. The focused user is always displayed in the top row like *Creator777* in this example. Other users are filtered and ordered according to the similarity of their topic interests to the focused user (e.g., by the number of shared topics). Columns show topics ordered by the focused user's participation and future predictions; here, the topic *Segregation Academy* is highlighted. On the right hand side, the scatterplot view depicts all users. Points are laid out via dimensionality reduction of the training data, for instance, by t-SNE [23]. The highlighted topic is represented by coloring all nodes that are part of the topic's hyperedge. Both views focus on the inputs and outputs of the prediction models in order to reduce complexity for the domain expert, who is not primarily interested in the model's inner workings.



The central components of our visual interface are the arrow glyphs. They show the temporal progression (left to right) of the training/holdout data on the upper and lower ends interleaved with the sliding window predictions in the middle of the arrow head. Fig. 2 includes a detailed legend. By design, the glyph does not only allow inspection of the training data and the prediction of interest, but also of predictions made by the model instances trained on previous sliding windows. For example, the icon in this paragraph shows actual participation in a topic (black), and predictions decreasing over time as shades of gray. The analyst can compare predictions of models trained on past windows to holdout data and thereby gain insights into how well the structure of the prediction model fits the particular local area of application. As a result, the glyphs allow a more detailed assessment. For instance, if a structurally identical model did not provide accurate predictions for the particular user in question in the past, the analyst may not trust the current model's prediction for the future.

Interacting with the visual interface enables the analyst to explore data and predictions in a directed fashion. The analyst first selects a user of interest. Then, this user and other users with sufficient overlap in topics of interest are shown in the matrix view. Further, topic predictions can be filtered. For example, very low predictions can be clipped in order to reduce the amount of visual noise. Additionally, glyphs can be filtered by user, topic, time, value of predictions, and similarity of encoded data and predictions. Both, the matrix view and the global scatter plot view are linked in order to allow the comparison of the highlighted subgroups with the whole population of users. For instance, filtering by a topic highlights all users that participate in this topic across both views, as shown in Fig. 2. Tooltips provide details on demand.

In sum, our framework offers advantages compared to previous approaches. First, group structures are taken into account in predictions and reflected in visualizations. Second, local assessment is possible as we refrain from aggregating users/nodes, topics/edges, and time. Finally, implementation of the visual analytics mantra and focus on a single user/node of interest make our approach scaleable.

4 Discussion and Conclusion

While our framework facilitates the assessment of hypergraph prediction models, there are several potential directions for improvement. To begin with, more interaction with the visualization, like drill down to the text level, will enable domain experts to better evaluate the context of predictions. Adding more model diagnostics and options for iterative refinement could include the model developer in the visual analytics loop, which in turn might facilitate the cooperation between the model developer and domain experts. Meanwhile, scalability of the visualizations and model training pose limitations to updating the model interactively. The currently implemented *Analyze first* approach can be improved by modeling gradual interest or propagating uncertainty from topic extraction to predictions, and visualizations. Independently, the arrow glyph can be extended to enable the comparison of predictions of two different models.

To conclude, we point out that our visual analytics framework for the assessment of temporal hypergraph prediction models offers domain experts an interactive approach to tasks such as the analysis of online forum communications. The strong focus on a selected user in the visual interface and the exploitation of the network structure by using a hypergraph prediction model enable the assessment of predictions in their local context. Finally, the integration of sliding window predictions in the arrow glyphs captures the temporal component of the predictions.

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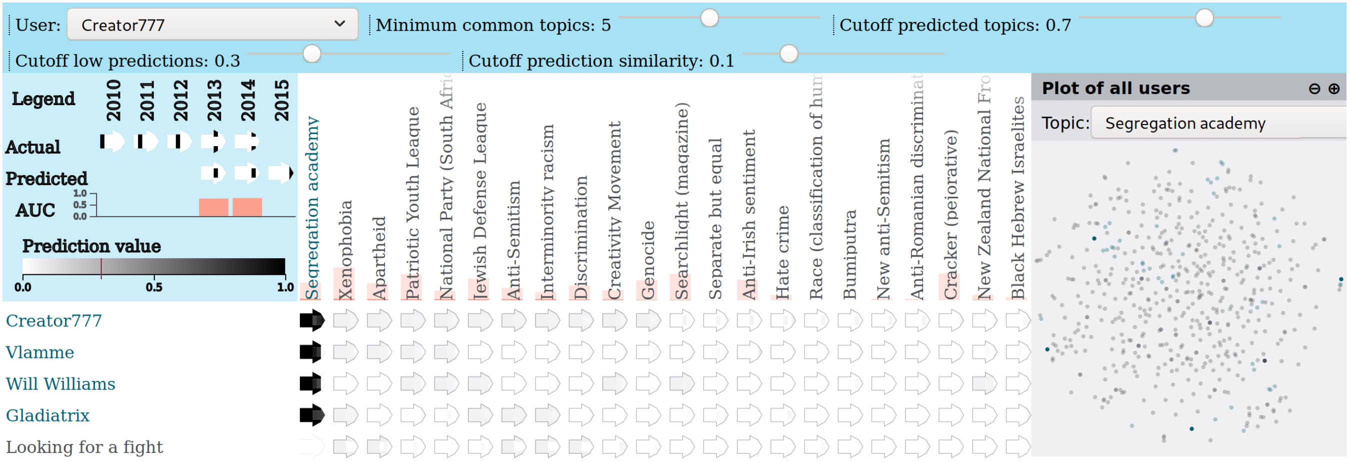

Figure 2: Overview on the visual interface. At the top there is the main filter panel (blue background) including controls to select the user to focus on, and sliders to set cutoff values for filtering the elements displayed in the matrix view. Below there is the matrix view on the left hand side including the glyph legend (light blue background). The arrow shape eases understanding by explicating time direction, and by separating glyphs. Placing predictions in the middle increases the visual saliency of misses. On the right hand side, the scatterplot view offers an overview on all users (gray background). Topic *Segregation academy* is highlighted, hence only the arrow glyphs for this topic are shown in the matrix, and users that are part of this hyperedge are colored in both views. Bars in the backgound of topic labels depict how popular each topic is. The solid dots in the scatter plot represent those users that are currently shown in the matrix view. On demand additional details are displayed as tooltips.

References

[1] B. Alsallakh, L. Micallef, W. Aigner, H. Hauser, S. Miksch, and P. J. Rodgers. Visualizing sets and set-typed data: State-of-the-art and future challenges. In *Eurographics Conf. Visualization*, 2014. doi: 10.2312/eurovisstar.20141170

[2] D. Arya, S. Rudinac, and M. Worring. Predicting behavioural patterns in discussion forums using deep learning on hypergraphs. In *Int. Conf. Content-Based Multimedia Indexing*. IEEE, 2019.

[3] D. Arya and M. Worring. Exploiting relational information in social networks using geometric deep learning on hypergraphs. In *Int. Conf. Multimedia Retrieval*, pp. 117–125. ACM, 2018. doi: 10.1145/3206025.3206062

[4] M. M. Bronstein, J. Bruna, Y. LeCun, A. Szlam, and P. Vandergheynst. Geometric deep learning: going beyond euclidean data. *Signal Processing Magazine*, 34(4):18–42, 2017.

[5] H. Cai, V. W. Zheng, and K. C.-C. Chang. A comprehensive survey of graph embedding: Problems, techniques, and applications. *Trans. Knowledge and Data Engineering*, 30(9):1616–1637, 2018. doi: 10.1109/TKDE.2018.2807452

[6] M. Defferrard, X. Bresson, and P. Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering. In *Advances in Neural Information Processing Systems*, pp. 3844–3852, 2016.

[7] D. K. Duvenaud, D. Maclaurin, J. Iparraguirre, R. Bombarell, T. Hirzel, A. Aspuru-Guzik, and R. P. Adams. Convolutional networks on graphs for learning molecular fingerprints. In *Advances in Neural Information Processing Systems*, pp. 2224–2232, 2015.

[8] D. A. Keim, J. Kohlhammer, G. P. Ellis, and F. Mansmann. *Mastering the Information Age Solving Problems with Visual Analytics*. Eurographics Association, 2010.

[9] D. A. Keim, F. Mansmann, J. Schneidewind, J. J. Thomas, and H. Ziegler. Visual analytics: Scope and challenges. In *Visual Data Mining: Theory, Techniques and Tools for Visual Analytics*. Springer, 2008. doi: 10.1007/978-3-540-71080-6_6

[10] J. Krause, A. Perer, and E. Bertini. Using visual analytics to interpret predictive machine learning models. In *ICML Workshop on Human Interpretability in Machine Learning*, 2016.

[11] Z. Li, J. Tang, and T. Mei. Deep collaborative embedding for social image understanding. *Trans. Pattern Analysis and Machine Intelligence*, 2018. doi: 10.1109/TPAMI.2018.2852750

[12] S. Liu, X. Wang, M. Liu, and J. Zhu. Towards better analysis of machine learning models: A visual analytics perspective. *Visual Informatics*, 1(1):48–56, 2017. doi: 10.1016/j.visinf.2017.01.006

[13] L. Lü and T. Zhou. Link prediction in complex networks: A survey. *Physica A: Statistical Mechanics and its Applications*, 390(6):1150–1170, 2011. doi: 10.1016/j.physa.2010.11.027

[14] J. McAuley and J. Leskovec. Image labeling on a network: Using social-network metadata for image classification. *European Conf. Computer Vision*, pp. 828–841, 2012. doi: 10.1007/978-3-642-33765-9_59

[15] L. Micallef. Visualizations with Venn and Euler diagrams. In *Proc. Grace Hopper Celebration of Women in Computing, PhD Forum*, 2012.

[16] K. Mizuno, H.-Y. Wu, S. Takahashi, and T. Igarashi. Optimizing stepwise animation in dynamic set diagrams. *Computer Graphics Forum*, 38(3):13–24, 2019. doi: 10.1111/cgf.13668

[17] F. Monti, M. Bronstein, and X. Bresson. Geometric matrix completion with recurrent multi-graph neural networks. In *Advances in Neural Information Processing Systems*, pp. 3700–3710, 2017.

[18] P. J. Rodgers. A survey of Euler diagrams. *J. Visual Languages and Computing*, 25(3):134–155, 2014. doi: 10.1016/j.jvlc.2013.08.006

[19] S. Rudinac, I. Gornishka, and M. Worring. Multimodal classification of violent online political extremism content with graph convolutional networks. In *Proc. Thematic Workshops of ACM Multimedia*, pp. 245–252. ACM, 2017. doi: 10.1145/3126686.3126776

[20] D. Sacha, A. Stoffel, F. Stoffel, B. C. Kwon, G. P. Ellis, and D. A. Keim. Knowledge generation model for visual analytics. *Trans. Visualization and Computer Graphics*, 20(12):1604–1613, 2014. doi: 10.1109/TVCG.2014.2346481

[21] P. Symeonidis and C. Perentis. Link prediction in multi-modal social networks. In T. Calders, F. Esposito, E. Hüllermeier, and R. Meo, eds., *Machine Learning and Knowledge Discovery in Databases*, pp. 147–162. Springer, Berlin, Heidelberg, 2014. doi: 10.1007/978-3-662-44845-8_10

[22] L. J. Tashman. Out-of-sample tests of forecasting accuracy: an analysis and review. *Int. J. forecasting*, 16(4):437–450, 2000.

[23] L. van der Maaten and G. Hinton. Visualizing data using t-SNE. *J. Machine Learning Research*, 9:2579–2605, 2008.

[24] C. Vehlow, F. Beck, and D. Weiskopf. Visualizing group structures in graphs: A survey. *Computer Graphics Forum*, 36(6):201–225, 2017. doi: 10.1111/cgf.12872

[25] C. Xie, W. Zhong, W. Xu, and K. Mueller. Visual analytics of heterogeneous data using hypergraph learning. *Trans. Intelligent Systems and Technology*, 10(1):1–26, 2019. doi: 10.1145/3200765