To find *best* decomposition E we use a hierarchical clustering and our objective function is:

$$EF^* = \arg\max_E \sum_{i=1}^{h} F_{c_i}(T_{validation_i}, M_i) - N_E, \quad (3)$$

where N_E is number of transition points between one context to another context. At the transition point, we always make wrong prediction because a model is not aware about event from different clusters. The final accuracy was calculated using the T_{test}.

Table 1: The evaluation of the prediction accuracy for FOMM and TCD for discovered 7 clusters.

Model	FOMM (%)	TCD (7 clusters) (%)
Accuracy	40.6±0.25	50.2±3.24

We have run our experiments on a real dataset collected at *MastersPortal.eu* which is a web service that provides information about various study programmes in Europe. For our experiment we used data collected during May 2012. The results is presented in Table 1. We obtained the highest accuracy when we use 7 clusters. We used 1^{st}-order Markov model (FOMM) as a baseline.

6. CONCLUSION AND FUTURE WORK

Starting from the prototype of context-aware system which is partially presented in Figure 4 we will study algorithmic aspects and analyze the performance of the two level decision making for alternative web analytics application scenarios. We will develop a generic framework including techniques for forming contextual categories and for linking them Context Awareness in Predictive Analytics with the predictors for integrating context awareness into predictive models. We will also produce a set of guidelines for using the proposed framework for designing new techniques. The techniques will be tested retrospectively on historical data as well as deployed and validated online in the field experiments. Taking a broad approach in terms of relevant research content we aim for a complete solution that would allow the deployment in web analytics.

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7. REFERENCES

[1] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles. Towards a better understanding of context and context-awareness. 1999.

[2] G. Adomavicius and A. Tuzhilin. Context-aware recommender systems. *CARS*, 2010.

[3] M. Aly, A. Hatch, V. Josifovski, and V. K. Narayanan. Web-scale user modeling for targeting. In *WWW*, 2012.

[4] C. Bolchini, C. A. Curino, E. Quintarelli, F. A. Schreiber, and L. Tanca. A data-oriented survey of context models. In *SIGMOD*, 2007.

[5] P. Brown, J. Bovey, and X. Chen. Context-aware applications: From the laboratory to the marketplace. *IEEE Personal Comm*, 4:58–64, 1997.

[6] H. Cao, D. H. Hu, D. Shen, D. Jiang, J.-T. Sun, E. Chen, and Q. Yang. Context-aware query classification. In *SIGIR*, 2009.

[7] D. Chakrabarti, D. Agarwal, and V. Josifovski. Contextual advertising by combining relevance with click feedback. In *WWW*, 2008.

[8] A. Dey, G. Abowd, and D. Salber. A conceptual framework and a toolkit for supporting the rapid prototyping of contextaware applications. *Human Computer Interaction*, 2:97–166, 2001.

[9] R. Hull, P. Neaves, and J. Bedford-Roberts. Toward situated computing. pages 146–153, 1997.

[10] J. Indulska, R. Robinson, A. Rakotonirainy, K. Henricksen, M.-S. Chen, P. K. Chrysanthis, M. Sloman, and A. B. Zaslavsky. Experiences in using cc/pp in context-aware systems. *Mobile Data Management,Lecture Notes in Computer Science, Springer*, 2574, 2003.

[11] J. Kiseleva, H. T. Lam, M. Pechenizkiy, and T. Calders. Discovery temporal hidden contexts in web sessions for user trail prediction. In *TempWeb*, 2013.

[12] P. K. Novak, N. Lavrac, and G. I.Webb. Supervised descriptive rule discovery: A unifying survey of contrast set, emerging pattern and subgroup mining. *Journal of Machine Learning Research (JMLR)*, 27:77–403, 2009.

[13] C. Palmisano, A. Tuzhilin, and M. Gorgoglione. Using context to improve predictive modeling of customers in personalization applications. *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, 20(11):1535–1549, November 2008.

[14] C. Prahalad. Predicts customer context is the next big thing. *AMA MwWorld*, 2004.

[15] S. Rendle, Z. Gantner, C. Freudenthaler, and L. Schmidt-Thieme. Fast context-aware recommendations with factorization machines. In *SIGIR*, volume 10, 2011.

[16] D. Stern, R. Herbrich, and T. Graepel. Matchbox: Large scale online bayesian recommendations. In *WWW*, pages 111–120, 2009.

[17] P. Turney. Exploiting context when learning to classify. 2002.

[18] P. Turney. The management of context-sensitive features: A review of strategies. In *CoRR*, 2002.

[19] B. Xiang, D. Jiang, J. Pei, X. Sun, E. Chen, and H. Li. Context-aware ranking in web search. In *SIGIR*, 2010.

[20] E. Zliobaite, J. Bakker, and M. Pechenizkiy. Beating the baseline prediction in food sales: How intelligent an intelligent predictor is? *Expert Syst. Appl. (ESWA)*, 39(1):806–815, 2012.

[21] I. Zliobaite. Identifying hidden contexts in classification. In *PAKDD (1)*, pages 277–288, 2011.