









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<sup>st</sup>-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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