Highly Relevant Routing Recommendation Systems for Handling Few Data Using MDL Principle

ABSTRACT

Many classification algorithms existing today suffer in handling many so-called "few data" instances. In this paper we show how to score query relevance with handle on few data by adopting a Minimum Description Length (MDL) principle. The main outcome is a strongly relevant routing recommendation system model (average(F)=0.72, M≥0.71; all scales of 1) supported by MDL based classification which is very good in handling few data by a large percentage margin of data degeneration (upto 50% loss).

CCS CONCEPTS

• **Retrieval tasks and goals** → **Clustering and classification**; *Sentiment analysis*; Recommender systems; • **Evaluation of retrieval results** → Relevance assessment;

KEYWORDS

MDL classification, relevance scoring, boosting factor

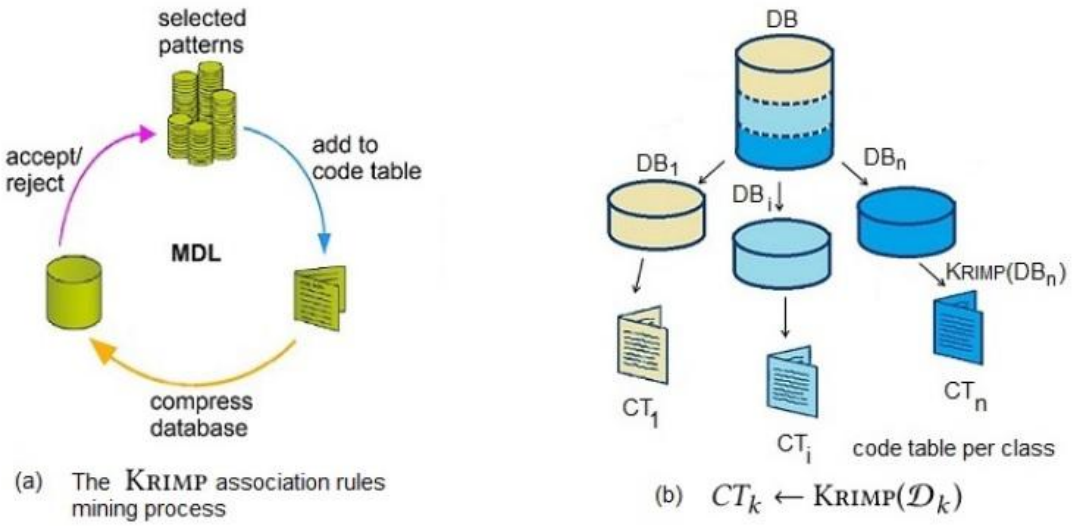
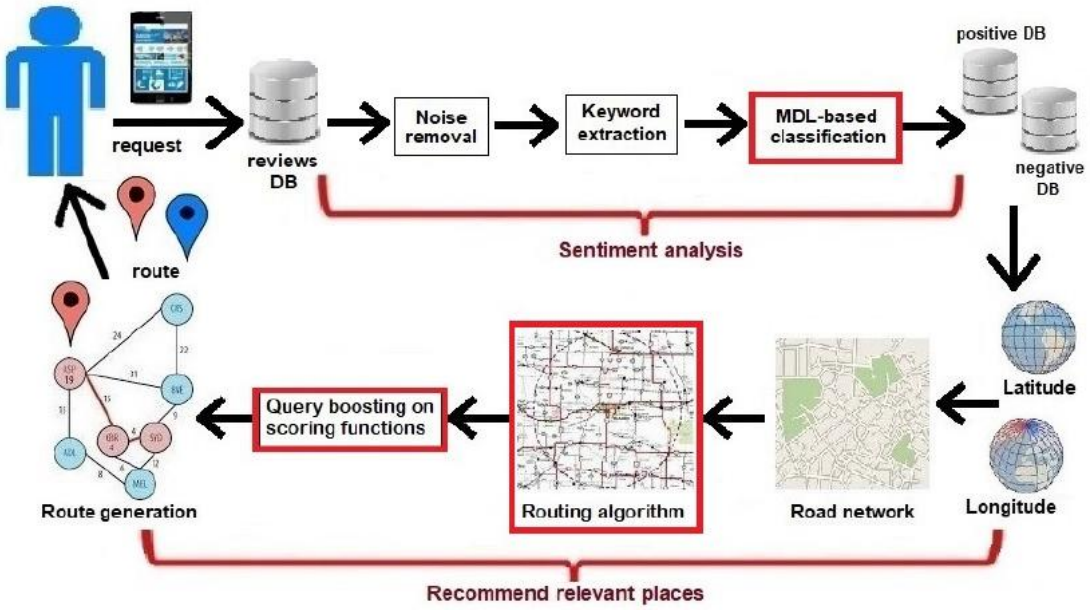


Figure 1: Preprocessing activities



5 CONCLUSIONS

In this work, we have focused on providing high quality recommendation system model using boosting factors in scoring function and the use of MDL principles on classification tasks. We have shown that using MDL-based classification we can handle few instances classification very well. Our findings indicate that improvements in classification can be achieved by using code table from large datasets. The performance of MDL-based classification degrades as the degeneration factor δ increases but it still outperforms other state of the art classification techniques. We permit upto 50% of data loss. Next, we have found that a proper selection of shortest routing algorithm (e.g. A* or Yen's) can provide further gains in quality. Finally, adding boosting factors can provide further gains in quality of the recommendation system model. The recommendation system model described in this paper can be implemented in various recommendation projects that use routing data and facing the few data instances problem on its knowledge source.

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