User Profiling in News Recommender Systems

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Outline

- Challenges of News Recommendation systems (NRS)
- News Recommendation Approaches
- User Modeling
- Machine Learning (ML) Techniques
- ML techniques and user profile features
- ML techniques VS. NRS Challenges
- Conclusion

Why are News Recommender Systems Different?

- Changing interest of user
- Implicit feedback
- Short life span
- Unstructured format
- Serendipity

News Recommendation Approaches

- Content-based Filtering
- Collaborative Filtering
- Hybrid systems
  - Common in recent news recommender systems

User Modeling

- Structured around topics or entities
- Semantic aspects : POLYSEMI, SYNONYMY
- Time constraint
- Location and public trend
- Long-term and short-term interests
- Based on explicit and/or implicit feedback

Relevant Machine Learning Techniques

Supervised Learning Techniques:

- Decision Tree (C4.5 or KART)
- Rule-based (RIPPER)
- KNN
- Rocchio and Relevance Feedback
- Support Vector Machine (SVM)
- Probabilistic methods and Naive Bayes
- Neural Network

Unsupervised Learning Techniques:

- Probabilistic methods
- Neural Network
- Clustering

ML Techniques	User Profile Features
Decision Tree (C4.5)	Semantic enrichment can be handled at entity level, but in the beginning of building the user profile or for capturing short-term interest [2,3]
Rule-based (RIPPER)	Semantic enrichment can be handled at entity level. More interesting categories of news may be predicated through rules [1]
KNN	Captures the short term interest of user and popularity of the item among a group of user.
Rocchio and Relevance Feedback	User profiles are regarded as queries, the system improves over time from relevance feedback of the user [4]
Support Vector Machine	It outperforms KNN,C4.5 and Rocchio [4] with the Reuters dataset
Probabilistic methods and Naive Bayes	Bernoulli works well with small sizes of data set and multinomial works well in large sizes of datasets. DAG captures the dependency of items and in more detailed capturing interest, vigorous towards missing data and could disregard noisy data. BHS and graph-based capture online interest of the user [5]
Neural Network	It can represent details of the user's interest through deep learning of three layer perceptron [6]
Clustering	The content of the items are clustered and then item-based collaborative is implemented on the output. Fuzzy membership over the k-means. Similarity of the item-rating matrix, the group-rating matrix Hierarchical clustering for the news groups (LDA for small dataset and PLSI for large dataset) [7]

ML Techniques	Challenges addressed
Decision Tree (C4.5)	Capturing short term interest [1]
Rule-based (RIPPER)	Serendipity can be supported with new category reasoning [9]
KNN	Short-term interests and provide the latest news to the user based on their interests [1]
Rocchio and Relevance Feedback	Handling long-term interest of the user [1]
Support Vector Machine	Sparse Problem and huge data after a long time usage of the application [10]
Probabilistic methods and Naive Bayes	Handling long-term interest of the user Sparse problem, Noisy data Cold Start, Precious interest of the user [8]
Neural Network	Short term and long term [11] Tied Boltzmann with residual parameter could outperform on non cold-start problem in comparison with simple method of collaborative filtering, Pearson correlation for the items. It is also competitive with the cold-start problem in content-based filtering. (Netflix) Changing interest of the user [6]
Clustering	Cold start Through fuzzy membership new and interesting news articles are possible to be represented to the user [7]

Conclusion

- Overview on recommendation techniques and their application in news recommendation
- User profiling central on news recommendation
- Techniques address different dimensions of news user profiles
- No obvious best techniques for news user profiles

- The future is hybrid!

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[5]Bian, J., et al., *Exploiting User Preference for Online Learning in Web Content Optimization Systems.* ACM Trans. Intell. Syst. Technol., 2014. **5**(2): p. 1-23.

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