Predicting Neighbor Goodness in Collaborative Filtering

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Introduction: Recommender Systems

Recommender Systems (RS) goal

		i ₁	i _k	i _m
users	u ₁	r ₁₁	r _{1k}	r _{1m}
	u _j	r _{j1}	?	r _{jm}
	u _n	r _{n1}	r _{nk}	r _{nm}

objects

how is predicted the value of r_{ik} ?





Introduction: Recommender Systems

• Collaborative filtering (CF) based on users

		i ₁	i _k	i _m
users	u ₁	r ₁₁	r _{1k}	r _{1m}
	uj	r _{j1}	?	r _{jm}
	u _n	r _{n1}	r _{nk}	r _{nm}

items

• Producing recommendations in UBCF:

 $g(u_m, i_n) = \frac{\sum_{u_j \in N[u_m]} \sin(u_m, u_j) \times r_{j,n}}{\sum_{ij} \sin(u_m, u_j)}$ $u_i \in N[u]$





Introduction: Recommender Systems

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items

• Producing recommendations in IBCF:







Motivation

- Proliferation and variety of input information in IR systems
- Performance prediction in IR: adjust retrieval strategies according to the value of the prediction function
 - In classic retrieval: query effectiveness
 - Applications: query expansion, meta-search, distributed IR, etc.
- In CF, each neighbor can be seen as a different source of information
 - ¿with different weight? (besides the similarity value)





Performance prediction in IR

- Mostly addressed: query performance prediction in ad-hoc retrieval
- Approaches (Hauff et al. 2008)
 - Pre-retrieval
 - Pros: The prediction can be taken into account to improve the retrieval process itself
 - Cons: Effectiveness cues available after the retrieval are not exploited
 - Post-retrieval
 - Pros: Better prediction accuracy
 - Cons: Problem with computational efficiency





Clarity score in ad-hoc retrieval

 Distance (relative entropy) between query and collection language models (Cronen-Townsend et al. 2002)

$$\operatorname{clarity}(q) = \sum_{w \in V} P(w|q) \log_2 \frac{P(w|q)}{P_{coll}(w)}$$
$$P(w|q) = \sum_{d \in R} P(w|d) P(d|q), \quad P(q|d) = \prod_{w_q \in q} P(w_q|d)$$
$$P(w|d) = \lambda P_{ml}(w|d) + (1-\lambda) P_{coll}(w)$$

- It captures the (lack of) ambiguity in a query with respect to the collection
 - Queries whose likely relevant documents are a mix of disparate topics receive a lower score than those with a topically-coherent result set.
 - Strong correlation between this score and the performance (average precision) of the result set





Performance prediction in Recommender Systems

- Rating prediction as dynamic aggregation
 - Each user's neighbor can be seen as a retrieval subsystem whose output is to be combined to form the final system output
 - Utility of an item for a user:

$$r(u,i) = \overline{r}(u) + C \sum_{v \in \mathbb{N}[u]} \sin(u,v) \cdot (r(v,i) - \overline{r}(v))$$

• Using dynamic aggregation:

$$r(u,i) = \overline{r}(u) + C \sum_{v \in N[u]} \gamma(v,u,i) \cdot \sin(u,v) \cdot (r(v,i) - \overline{r}(v))$$

where $\gamma(v,u,i)$ is a predictor of the performance of neighbor *v*.





Predicting good neighbors

- The predictor γ can be sensitive to the specific target user u, the item i, or any other input of the system.
 - In this work: $\gamma(v,u,i) = \gamma(v)$, i.e., only the neighbor
- We define two predictors, inspired by the clarity score:
 - Item-based user clarity (IUC)
 - User-based user clarity (UUC)

$$\gamma = \gamma(v) = IUC(v) = \sum_{i \in I} p(i|v) \log_2 \frac{p(i|v)}{p_c(i)}$$
$$p(i|v) = \lambda \frac{rat(v,i)}{5} + (1-\lambda) p_c(i)$$
$$p_c(i) = \frac{1}{I}$$

$$\gamma = \gamma(v) = \text{UUC}(v) = \sum_{w \in U} p(w|v) \log_2 \frac{p(w|v)}{p_c(w)}$$
$$p(w|v) = \sum_{i:rat(v,i)\neq 0} p(w|i) p(i|v)$$
$$p(w|i) = \lambda \frac{rat(w,i)}{5} + (1-\lambda) p_c(w)$$
$$p_c(v) = \frac{1}{U}$$





Evaluation

- MovieLens dataset (100k)
- Two variables:
 - Neighborhood size
 - Sparsity (number of available ratings)
- Measure final performance improvements (in terms of MAE) when dynamic weights are introduced





Results I



Performance comparison for different rating density





Results II



Performance comparison for different neighbourhood sizes





Conclusions

- Performance improvements in MAE using dynamic weights for neighbors
- Higher difference for small neighborhoods
- In the future:
 - Other variants of the clarity-based predictor (He & Ounis 2004, Zhou & Croft 2007)
 - Correlation analysis (as in IR)
 - It involves defining user-level performance metrics
 - Extension to other areas: hybrid recommender systems (Adomavicious & Tuzhilin 2005), personalized IR (Castells et al. 2005), rank fusion (Fox & Shaw 1993)





Thank you





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