Toward Active Learning in Cross-domain Recommender Systems

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ABSTRACT
One of the main challenges in Recommender Systems (RSs) is the New User problem which happens when the system has to generate personalized recommendations for a new user whom the system has no information about. Active Learning tries to solve this problem by acquiring user preference data with the maximum quality, and with the minimum acquisition cost.

Although there are variety of works in active learning for RSs research area, almost all of them have focused only on the single-domain recommendation scenario. However, several real-world RSs operate in the cross-domain scenario, where the system generates recommendations in the target domain by exploiting user preferences in both the target and auxiliary domains. In such a scenario, the performance of active learning strategies can be significantly influenced and typical active learning strategies may fail to perform properly.

In this paper, we address this limitation, by evaluating active learning strategies in a novel evaluation framework, explicitly suited for the cross-domain recommendation scenario. We show that having access to the preferences of the users in the auxiliary domain may have a huge impact on the performance of active learning strategies w.r.t. the classical, single-domain scenario.

1. INTRODUCTION
In general terms, there are two tasks that are mainly performed by Recommender Systems: Learning the users’ preferences, and Recommending the items to users based on these preferences [19]. When a new user registers to a RS, the system has no preference of that user and hence is not able to produce relevant recommendations and this problem still represents a big challenge for RSs [10].

Active Learning attempts to solve this problem by eliciting preferences of the users and learning their tastes. It does not solely focus on the quantity of the data elicited from the users, but also on the quality of the data. Hence, the main goal of active learning is to maximize the value of the obtained preference data at the minimum cost. This is typically done by analyzing the dataset and actively selecting a restricted set of items to ask the user to rate, hoping that the new data will improve the most the performance of the system. Therefore, it is very important for the active learning system to define a precise procedure to select the most beneficial items, which is called Strategy.

So far, a variety of active learning strategies have been proposed and evaluated [19, 11]. However, almost all previous research works have conducted their evaluations under a specific scenario, i.e., active learning in the single-domain recommendation scenario. This is while many real-world RSs are actually operating in the cross-domain scenario, where the user preferences are available not only in the target domain, but also in the additional auxiliary domain. Knowledge of user preferences in the auxiliary domain can be transferred to the target domain to mitigate, among others, the effect of the new user problem. However, to the best of our knowledge, almost no work has previously focused on active learning in cross-domain recommendation scenario.

In this paper, we address this limitation by implementing a number of widely used active learning strategies and evaluating them in the cross-domain recommendation scenario. These strategies have been already implemented and thoroughly evaluated in the single-domain scenario [19, 10, 9, 8, 18]. We extend them to be compatible with the usage across domains and evaluate them in a novel evaluation framework explicitly suited for this scenario.

We have performed an offline experiment in order to measure the performances of the considered strategies and compared them with respect to two different evaluation metrics, i.e., prediction accuracy (in terms of MAE), and coverage (in terms of Spread). Our results have shown that, while active learning strategies can still effectively improve the system in both scenarios, the performance of these strategies can be significantly changed in the cross-domain scenario in comparison to single-domain scenario. In fact, this indicates the need for effective active learning strategies in RSs and still provides a realistic and accurate guidelines applicable to real-world RSs.

2. RELATED WORK
2.1 Cross-domain RSs
The cross-domain recommendation problem has been studied from multiple perspectives in different areas. In user modelling, solutions have been proposed that aggregate and mediate user preferences \cite{1, 2, 13, 6, 3}, and in machine learning it has been studied as a practical application of knowledge transfer techniques \cite{14, 23, 6}. In the area of recommender systems, cross-domain recommender systems have been proposed as a solution to the cold-start and sparsity problems \cite{12, 20}. For instance, Shahebi and Brusilovsky \cite{20} analyzed the effect of the user’s profile size in the auxiliary domain and showed that, when enough auxiliary ratings are available, cross-domain collaborative filtering can provide better recommendations in the target domain in cold-start situations.

In this paper, we aim at addressing the new user problem from a different perspective. Rather than exploiting auxiliary information directly in the prediction model, we are interested in improving the active learning phase of the system. Our proposed approach exploits user preferences from an auxiliary domain in order to better select the ratings to be elicited from the user in the target domain, by means of active learning.

In this regard, \cite{22} is the only work that is comparable with our work. However, that work is still different from our work mainly in the evaluation methodology where they have assumed that the simulated users can rate 400 items in every learning iteration. Accordingly, they iterate for 50 times and ask the the simulated users to rate 20000 items. However, we assume that the users may rate 5 items which seems a more realistic assumption. Moreover, they only evaluate the performance of active learning strategies in the cross-domain scenario while we perform the evaluation in both single-domain and cross-domain scenarios. Finally, they only consider prediction accuracy (in terms of RMSE) as the evaluation metric. However, while prediction accuracy is classical metric for evaluation of RSs, still do not reflect other important aspects of the recommendation quality. Hence, we evaluate the performance of active learning strategies no only in terms of prediction accuracy (MAE), but also Spread which is an indication of how well the recommended items are diversified \cite{16, 13}.

### 2.2 Active Learning in RSs

There are a broad range of active learning strategies that have been already proposed and evaluated \cite{10, 19, 18, 9, 15, 13}. Among these strategies, we implemented a number of widely used and best performing strategies. In spite of excellent performance, we could not consider one type of strategies that are based on decision trees. This is due to the fact that their computational complexity grows directly with the number of items in the dataset, which in our tests, is considerably bigger than the ones performed in the original paper \cite{15}. More importantly, the number of users in our dataset is not sufficient to properly build a tree deep enough, without incurring into overfitting.

We now describe the active learning strategies that we evaluated in our experimental study.

**Highest-predicted** \cite{10, 19}: scores items according to the rating prediction values and selects the top items according to their scores. The items with the highest predicted ratings are the ones that the system expects the user likes the most. Hence, it could be more likely that the user have experienced these items.

**Lowest-predicted** \cite{10, 19}: uses the opposite heuristics compared to highest predicted: the score assigned by the strategy to each item is \( \hat{r} = \max r - r \), where \( \max r \) is the maximum rating value (e.g., 5) and \( r \) is the predicted rating. This ensures that items with the lowest predicted ratings will get the highest score and therefore will be selected for elicitation. Lowest predicted items are likely to reveal what the user dislikes, but are also likely to elicit a few ratings, since users tend to not to rate items that they do not like.

**Entropy0** \cite{18, 15}: measures the dispersion of the ratings compared by using the relative frequency of each of the five possible rating values (1-5), and also the unknown ratings as a new rating value, equal to 0, and hence considering a rating scale between 0 to 5. In such a way, a high frequency of the 0 rating (i.e., many unknown ratings) tends to decrease Entropy0. Hence, this strategy favors popular items that are informative at the same time \cite{18}.

**Popularity** \cite{18, 17}: selects the items that have received the highest number of ratings. Such items are more likely to be known by the user, and consequently have higher chances to be rated and thus to increase data available for the RS \cite{4}.

### 3. EXPERIMENTAL EVALUATION

#### 3.1 Dataset

In our experiments, we used the Amazon SNAP dataset\footnote{https://snap.stanford.edu/data/web-Amazon.html} that comprises the user preferences on variety of product domains. Among these domains, we selected the two most overlapping ones, namely MoviesAndTv and Music. Then we considered only the common users between the two domains with at least 20 ratings in each domain (minimum 40 ratings in both domains). The resulting dataset has 796,489 movie ratings and 436,446 music ratings, given by 2786 users to 86,206 movies (0.32% density), and 151,368 tracks (0.10% density), respectively. We note that the MoviesAndTv dataset is considered as target and Music dataset as auxiliary.

#### 3.2 Evaluation Methodology

We evaluated the active learning strategies using an evaluation methodology similar to the one proposed in \cite{10, 13}. It basically uses a user-based 5-fold cross-validation, that we modified for active learning process in cross-domain scenario. For our experiments we employed the FunkSVD matrix factorization available in the LensKit Framework \cite{7} as recommendation algorithm.

First, we shuffle the set of users in the target domain and split it into 5 disjoint subsets of equal size. In each cross-validation step, the ratings from 4 subsets are used to train the recommendation algorithm and the active learning strategy. The ratings for the users in the remaining subset are further split into 3 randomly generated subsets (see figure \footnote{https://snap.stanford.edu/data/web-Amazon.html}): **Train set** contains the set of known ratings for each user. We simulated different profile sizes for each new user by incrementally adding one rating at time. **Candidate set**
contains the set of ratings that can be elicited by the active learning strategy and then added to the train set (at least 15 ratings). Test set contains the set of ratings used to compute the performance metrics (5 ratings per user).

In order to apply active learning to the cross-domain scenario, we have extended the training data by adding to ratings of the target domain the entire set of ratings in the auxiliary domain. Such extended training set was provided as input to the recommendation algorithm to then generate rating predictions.

Then, we follow the evaluation procedure originally proposed in [10] and described below:

1. We train the recommendation algorithm on the train set and then we compute the evaluation metrics on the test set.
2. For every test user, the active learning strategy ranks each item in the candidate set. The rating of the top ranked candidate item is added to the train set and removed from the candidate set.
3. We repeat the procedure with the new train and candidate sets.

In all of the experiments, we considered profiles starting from no rating, i.e., the Extreme New User problem, and constantly increased with one rating at time until to the limit of 5 ratings per user profile has been reached.

We have considered two evaluation metrics, namely Mean Average Error (MAE), i.e., the mean absolute deviation of the predicted ratings from the actual ratings [21] and Spread, i.e., a metric of how well the recommender or active learner spreads its attention across many items with the assumption that better algorithms select different items for different users [16] [13].

4. RESULTS AND DISCUSSION

Table 1 shows the performance of different active learning strategies, in single-domain and cross-domain recommendation scenarios. The performance comparison has been made with respect to MAE and Spread metrics and the improvement of the RS with AL over the RS without AL in both scenarios.

First of all, it is clear that all the active learning strategies have improved the quality of the recommendation in either of the single-domain or the cross-domain scenarios. However, the improvement made by each of these strategies differs very much in these two scenarios. While in single-domain scenario, the best strategy is highest-predicted with MAE of 0.823 (8.6% of improvement), in cross-domain scenario, the lowest-predicted strategy outperforms the other strategies by achieving the MAE of 0.807 (1.1% of improvement). In terms of Spread, in single-domain scenario, lowest-predicted is the best strategy with Spread value of 5.063 (219.4% improvement), while in cross-domain scenario, the popularity strategy achieves the best result which is 6.968 (9.8% improvement). These are promising results since active learning strategies can achieve such improvements by only eliciting 5 ratings per user in the target domain.

We have also observed that, the initial MAE in the cross-domain scenario is much lower in comparison to single-domain scenario. Similarly, the Spread values in cross-domain is much higher than the values in single-domain scenario. This confirms that the exploitation of the ratings in the auxiliary domain significantly helps the RS to improve its performance in terms of these metrics.

Accordingly, while model-based active learning strategies, that are typically personalized strategies (such as lowest-predicted), may exploit such data to make better item se-
Table 1: The performance of the active learning strategies in two recommendation scenarios: (i) single-domain scenario (without any auxiliary domain), and (ii) cross-domain scenario (with auxiliary domain).

| AL Strategy | MAE Single-domain | MAE Cross-domain | Spread Single-domain | Spread Cross-domain |
|-------------|-------------------|------------------|----------------------|---------------------|
|             | value | improve | value | improve | value | improve | value | improve |
| with AL     |       |         |       |         |       |         |       |         |
| High-predicted | 0.823 | 6.8%    | 0.811 | <1.0%   | 3.352 | 111.4%  | 6.533 | 2.9%    |
| Low-predicted | 0.837 | 7.1%    | 0.807 | 1.1%    | 5.063 | 219.4%  | 6.958 | 9.6%    |
| Popularity   | 0.826 | 8.3%    | 0.811 | <1.0%   | 4.693 | 196.0%  | 6.968 | 9.8%    |
| Entropy      | 0.826 | 8.3%    | 0.810 | <1.0%   | 4.704 | 196.7%  | 6.956 | 9.6%    |
| without AL   | 0.901 | -       | 0.816 | -       | 1.585 | -       | 6.346 | -       |

lection for the users, the other strategies, that are typically non-personalized (such as popularity) cannot exploit the additional knowledge provided by the auxiliary domain. This is a big limitation of second type of active learning strategies in cross-domain scenario. However, their performance can still impact the quality of the data fed to the RS, and hence, affect the output of the system.

5. CONCLUSION AND FUTURE WORK

In this paper, we have evaluated several widely used active learning strategies adopted to tackle the cold-start problem in a novel usage scenario, i.e., Cross-domain recommendation scenario. In such a case, the user preferences are available not only in the target domain, but also in additional auxiliary domain. Hence, the active learner can exploit such knowledge to better estimate which preferences are more valuable for the system to acquire.

Our results have shown that the performance of the considered active learning strategies significantly change in the cross-domain recommendation scenario in comparison to the single-domain recommendation. Hence, the presence of the auxiliary domain may strongly influence the performance of the active learning strategies. Indeed, while a certain active learning strategy performs the best for MAE reduction in the single scenario (i.e., highest-predicted strategy), it actually performs poor in the cross-domain scenario. On the other hand, the strategy with the worst MAE in single-domain scenario (i.e., lowest-predicted strategy) can perform excellent in the cross-domain scenario. This is an interesting observation which indicates the importance of further analysis of these two scenarios in order to better design and develop active learning strategies for them.

Our future work includes the further analysis of the AL strategies in other domains such as book, electronic products, tourism, etc. Moreover, we plan to investigate the potential impact of considering different rating prediction models (e.g., context-aware models) on the performance of different active learning strategies.

6. REFERENCES

[1] F. Abel, E. Herder, G.-J. Houben, N. Henze, and D. Krause. Cross-system user modeling and personalization on the social web. User Modeling and User-Adapted Interaction, 23(2-3):169–209, 2013.

[2] S. Berkovsky, T. Kuflik, and F. Ricci. Mediation of user models for enhanced personalization in recommender systems. User Modeling and User-Adapted Interaction, 18(3):245–286, 2008.

[3] I. Cantador, I. Fernández-Tobías, S. Berkovsky, and P. Cremonesi. Cross-domain recommender systems. In Recommender Systems Handbook, pages 919–959. Springer US, 2015.

[4] G. Carenini, J. Smith, and D. Poole. Towards more conversational and collaborative recommender systems. In Proceedings of the 2003 International Conference on Intelligent User Interfaces, January 12-15, 2003, Miami, FL, USA, pages 12–18, 2003.

[5] P. Cremonesi and M. Quadran. Cross-domain recommendations without overlapping data: myth or reality? In Proceedings of the 8th ACM Conference on Recommender systems, pages 297–300. ACM, 2014.

[6] P. Cremonesi, A. Tripodi, and R. Turrin. Cross-domain recommender systems. In 2011 IEEE 11th International Conference on Data Mining Workshops, pages 496–503. Ieee, 2011.

[7] M. D. Ekstrand, M. Ludwig, J. A. Konstan, and J. T. Riedl. Rethinking the recommender research ecosystem: Reproducibility, openness, and lenskit. In Proceedings of the Fifth ACM Conference on Recommender Systems, RecSys ’11, pages 133–140, New York, NY, USA, 2011. ACM.

[8] M. Elahi, F. Ricci, and N. Rubens. Adapting to natural rating acquisition with combined active learning strategies. In International Symposium on Methodologies for Intelligent Systems, pages 254–263. Springer Berlin Heidelberg, 2012.

[9] M. Elahi, F. Ricci, and N. Rubens. Active learning in collaborative filtering recommender systems. In E-Commerce and Web Technologies, pages 113–124. Springer, 2014.

[10] M. Elahi, F. Ricci, and N. Rubens. Active learning strategies for rating elicitation in collaborative filtering: A system-wide perspective. ACM Transactions on Interactive Intelligent Systems, 5(1):13:1–13:33, Jan. 2014.

[11] M. Elahi, F. Ricci, and N. Rubens. A survey of active learning in collaborative filtering recommender systems. Computer Science Review, 2016.

[12] M. Enrich, M. Braunhofer, and F. Ricci. Cold-start management with cross-domain collaborative filtering and tags. In Proceedings of the 14th International Conference on E-Commerce and Web Technologies, pages 101–112, 2013.

[13] I. Fernandez Tobias, M. Braunhofer, M. Elahi, F. Ricci, and C. Ivan. Alleviating the new user problem in collaborative filtering by exploiting
personality information. *User Modeling and User-Adapted Interaction (UMUAI)*, (Personality in Personalized Systems), 2016.

[14] S. Gao, H. Luo, D. Chen, S. Li, P. Gallinari, and J. Guo. Cross-domain recommendation via cluster-level latent factor model. In *Proceedings of the 2013 European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 161–176, 2013.

[15] N. Golbandi, Y. Koren, and R. Lempel. Adaptive bootstrapping of recommender systems using decision trees. In *Proceedings of the 4th ACM International Conference on Web Search and Data Mining*, pages 595–604. ACM, 2011.

[16] D. Kluver and J. A. Konstan. Evaluating recommender behavior for new users. In *Proceedings of the 8th ACM Conference on Recommender systems*, pages 121–128. ACM, 2014.

[17] A. M. Rashid, I. Albert, D. Cosley, S. K. Lam, S. M. McNee, J. A. Konstan, and J. Riedl. Getting to know you: learning new user preferences in recommender systems. In *Proceedings of the 7th International Conference on Intelligent User Interfaces*, pages 127–134. ACM, 2002.

[18] A. M. Rashid, G. Karypis, and J. Riedl. Learning preferences of new users in recommender systems: an information theoretic approach. *ACM SIGKDD Explorations Newsletter*, 10(2):90–100, 2008.

[19] N. Rubens, M. Elahi, M. Sugiyama, and D. Kaplan. Active learning in recommender systems. In *Recommender Systems Handbook - chapter 24: Recommending Active Learning*, pages 809–846. Springer US, 2015.

[20] S. Sahebi and P. Brusilovsky. Cross-domain collaborative recommendation in a cold-start context: The impact of user profile size on the quality of recommendation. In *User Modeling, Adaptation, and Personalization*, pages 289–295. Springer Berlin Heidelberg, 2013.

[21] G. Shani and A. Gunawardana. Evaluating recommendation systems. In F. Ricci, L. Rokach, and B. Shapira, editors, *Recommender Systems Handbook*, pages 257–298. Springer Verlag, 2010.

[22] Z. Zhang, X. Jin, L. Li, G. Ding, and Q. Yang. Multi-domain active learning for recommendation. In *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.

[23] L. Zhao, S. J. Pan, E. W. Xiang, E. Zhong, Z. Lu, and Q. Yang. Active transfer learning for cross-system recommendation. In *AAAI*. Citeseer, 2013.