Evaluating the Relative Performance of Neighbourhood-Based Recommender Systems

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Abstract. Neighbourhood-based recommender systems are a class of collaborative filtering algorithms, which rely on finding like-minded users to generate recommendations, automating what is usually known as word-of-mouth. These systems attempt to solve the information overload problem by presenting the user with relevant items. However, there is evidence showing that these algorithms may contribute to the filter bubble problem, making it harder for the user to find interesting items which are non-popular. In this paper we propose a novel evaluation of the performance and biases of the two most common neighbourhood-based approaches: user k-nearest neighbour collaborative filtering (*UKNN*), and item k-nearest neighbour collaborative filtering (*IKNN).* We propose an evaluation which considers the size of the neighbourhood, finding that optimising for accuracy in *UKNN* algorithms leads to a poor performance in terms of diversity, a higher bias towards popularity, and less unique recommendations, when compared to the *IKNN* approach.

Keywords: recommender systems, collaborative filtering, diversity, popularity, evaluation

1 Introduction

As access to different types of media becomes easier and the amount of user-generated content increases, it has become very difficult to deal with the large catalogs of information available on the web. For example, finding a new movie to watch, discovering new bands to listen to, or deciding whom to follow in online social networks is no longer a straightforward task. This problem is commonly referred to as *information overload*. There is need for a new class of intelligent systems that help users to navigate through all this information, by automatically selecting the most relevant content and filtering that considered to be irrelevant. Recommender systems address this problem by learning the preferences of users. The gathered knowledge is then applied to personalise the user experience in different services; from advertising to clothes recommendations, movie recommendations and music discovery.

Extensive work has been carried out on the evaluation of recommender system algorithms, including surveys of the field [8, 16]. Nevertheless, there are

still many open questions about the evaluation of recommender systems, such the best evaluation framework to adopt, which is needed to have a common agreement on the performance of the system. As new recommender systems algorithms are proposed, the evaluation methodologies and metrics have to be often re-thinked. A clear example is neighbourhood-based models, which are very popular, and have been extensively evaluated. However, it is not fully clear how different factors such as the network structure, the neighbourhood selection, or the popularity bias can affect performance. In this paper we study these factors and we present metrics to evaluate them in a novel experimental framework. To this end, we compare two different approaches in a relative performance evaluation scenario.

The remainder of this paper is organised as follows. In Section 2 we present related work and the proposed evaluation approach is introduced in Section 3. In Section 4 we explain the evaluation methodology and results. Finally, in Section 5 we present conclusions and future work.

2 Related Work

This section presents some of the main advances in recommender systems evaluation research, focusing on the evolution of metrics and experimental design. First, work dealing with accuracy metrics is presented in Section 2.1. Subsequently, other properties such as diversity and novelty are introduced in Section 2.2.

2.1 Accuracy Metrics

Research on evaluation methodology has been described in [1]. The authors analyse different experimental configurations, focusing on training and test set creation, and using accuracy oriented metrics, such as precision (PRC) or recall (RCL) [16] for evaluation. They highlight the fact that accuracy-oriented metrics are often applied in different experimental configurations (i.e. different training/test splits). These differences make it difficult to compare works, even when the same metrics are used.

The relationship between error-based metrics (such as $RMSE$) and accuracy-oriented metrics (precision and recall) is studied in detail in [4]. The authors explain how error-based metrics are not appropriated to evaluate algorithms that present the user with a list of top recommendations, which is also highlighted in [6, 19]. They also explain that improvements in algorithms as measured by $RMSE$ do not translate in improvements in accuracy-oriented metrics.

An evaluation of neighbourhood models is presented in [13], which focuses on the influence of neighbour selection on the performance of $UKNN$ and $IKNN$ algorithms. The authors explain how the performance of the algorithm is biased by the evaluation methodology. They show that neighbourhood selection has a limited effect on performance, and that the contributions of neighbours are often disguised or misleading. Recent work [2] proposes the use of graph partitioning

techniques for neighbour selections, which outperforms state of the art techniques in terms of ranking precision.

In this paper we also analyse the effects of neighbourhood selection on the performance of *UKNN* algorithms. We propose a new training and test set configuration, and we evaluate recommendation performance using accuracy-orientated metrics in conjunction with a number of other metrics as described in Section 3.

2.2 Beyond Accuracy

Recently, several works such as [9, 10, 14] have focused on the study of diversity. Diversity measures how different are the items recommended in a list. For example, if a set of recommendations contains only movies from the *Harry Potter* saga, the recommendations may be accurate, but not diverse.

Said et al. [14] use a furthest neighbour model to increase diversity, generating almost orthogonal recommendations, when compared to the traditional *UKNN* approach. Hurley [9] introduces diversity within the optimisation function in a matrix factorisation approach. The results show more diverse recommendations, without having to post-filter the recommendation lists.

Diversity is also studied in [20], which analyses the diversity problem of top-N recommendations from a binary retrieval perspective. This work tries to maximise both diversity and similarity with respect to the user profile. A new metric for evaluating the proposed diversity approach is also presented. The results show improvements in both accuracy and diversity.

Work presented in [3] analyses the novelty and popularity of recommendations. The work shows that content-based recommender systems (applied to music) are not biased towards popularity, while a standard collaborative approach is perceived as providing higher quality recommendations even when the recommendations are not as novel.

An evaluation of recommender systems coverage and serendipity is explored in [5], which focuses on the contribution of those metrics to the quality of a system. The paper proposes metrics to evaluate the two properties that include the usefulness of a recommended item. The authors argue that the proposed metrics correlate with the real user experience better than previous metrics.

In this paper, together with an analysis of precision, we also evaluate properties such as diversity and popularity. Furthermore, we perform a study on the uniqueness of the recommendation lists generated by different algorithms.

3 Relative Performance of Neighbourhood Models

Neighbourhood-based models are widely used and have been extensively evaluated. However, it is not completely clear how different factors such as neighbourhood selection or item popularity bias affects the overall performance of these algorithms.

We study the effect of neighbourhood selection for the *UKNN* algorithm, which relies on finding similar users to generate recommendations. More specifically, we experiment with different values for the number of neighbours, k, and compare the results with the *IKNN* approach, which makes collaborative recommendations based on items similar to those the user has liked in the past.

To explore how neighbourhood size affects performance, we study recommendation precision, diversity and popularity. We compare the results for different values of k for two different datasets. By performing this analysis, we are able to understand what is the optimal value for k and what are the tradeoffs between the different properties evaluated.

3.1 Evaluation Metrics

Four metrics are chosen as part of our evaluation approach: *precision* (PRC), *popularity*, *diversity* and *uniqueness*. These metrics, which are independent from the recommendation algorithms, are averaged across all users in the evaluation. The details of these metrics are described below.

Diversity (DIV) [18, 21] is evaluated over the ranked list of recommended items, $r_1, r_2, \cdots r_n$, presented to the user. It captures how different the recommended items are from each other. In this case, diversity is evaluated based on a pairwise comparison of the items in the list (Equation 1). This metric relies on item co-ratings to calculate the similarity between items. Here, similarity (Sim) is computed using the cosine metric.

$$Diversity(r_i, ...r_n) = \frac{2}{|n||n-1|}\left(1 - \sum_{i \neq j}^{n}\sum_{j=1}^{n} Sim(r_i, r_j)\right) \tag{1}$$

Popularity (POP) can have several meanings depending on the context of the recommendations. For example, in the music domain, artist popularity is measured by the number of records sold while Twitter identifies trending (i.e. popular) topics using text analysis approaches. We use the number of available ratings per item to calculate item popularity. The popularity metric $POP_i \in [0, 1]$ for item $i \in I$ is defined in Equation 2, which is the total number of ratings for item i, n_i, divided by the total number of ratings for all items in the system, n_I.

$$POP_i = \frac{n_i}{n_I} \tag{2}$$

Uniqueness measures the ability of an algorithm to generate recommendations which are not generated by other algorithms. For example, if we consider two recommendation sets, R^a and R^b, which are generated by different algorithms, the uniqueness of the recommendation set R^a can be calculated as the number of items in the set R^a which are not found in R^b (Equation 3).

$$Uniqueness(R^a, R^b) = R^a \setminus R^b \tag{3}$$

Precision (PRC) measures the fraction of recommended items which are relevant (Equation 4).

$$PRC = \frac{|recommended| \cap |relevant|}{|recommended|} \tag{4}$$

3.2 Algorithms

The standard *UKNN* and *IKNN* algorithms are considered in this work as described below. Cosine is used as the similarity function in both algorithms.

- **User-based k-nearest neighbour** (*UKNN*) leverages the ratings matrix to find users with similar tastes (i.e. neighbours) to the target user [7]. Recommendations are then based on the neighbours' preferences for items unseen by the target user. In this way, the approach automates the *word-of-mouth* model, in which recommendations are usually spread in society [17].
- **Item-based k-nearest neighbour** (*IKNN*) relies on an analysis of the ratings matrix to identify items similar to those that are liked by the user. The similarity between items is calculated as a function of the ratings they receive from users [12, 15].

4 Experiments

In this paper, we compare two different recommendation algorithms: the standard *IKNN* and *UKNN* algorithms, as described in Section 3.2. The former is evaluated with a fixed number of neighbours ($k = 300$)[3], while for the latter, neighbourhood sizes in increments of 10 are considered ($k \in [10, 200]$). The goal of the evaluation is to understand the effects of neighbourhood size on the performance of the user-based approach, and perform a relative comparison with respect to the item-based approach.

Both algorithms are evaluated in the context of the *rank items in the catalog task* as described in [8], generating a list of top-10 recommendations per user. Therefore, error-based metrics are not used in the evaluation of the algorithms, they are not adequate in this scenario [8].

To perform the evaluation, the test set for each user contains 10 liked items and top-10 recommendations are made for each user. Hence, the values of precision and recall will be the same in this setting (both given by the intersection between the items in each user's test set and the recommended items, divided by 10).

The details of the training and test set construction are as follows:

[3] Fixing neighbourhood size at $k = 300$ for *IKNN* allows us to reduce the number of free parameters in the experiment. Moreover, preliminary analysis of the effect of neighbourhood on the *IKNN* algorithm did not show trends as pronounced as for the *UKNN* approach. A more detailed analysis of *IKNN* is left to future work.

– Both of the datasets considered in this work include users with at least 20 rated items in their profile. Only users with at least 10 liked items are included in our evaluation. A rating threshold of 4 is used to decide whether an item is liked or not; i.e. all items which received a rating of at least 4 (out of 5) are considered liked. This particular rating threshold has been used in previous work with similar datasets [1, 11].
– The test set for each user, Te_u, is created using 10 randomly selected liked items. In this way it is guaranteed that each user's test set will have the same number of items, all of which are liked.
– The training set for each user, Tr_u, is created using all items which are not included in the test set.

4.1 Dataset

To evaluate the proposed approach, two of the MovieLens [7] datasets are selected: the **MovieLens-100k** (ml-100k), and the **MovieLens-1M** (ml-1M), containing 100,000 and 1 million ratings, respectively. As mentioned above, the original datasets are processed so that only users with at least 10 liked items are included. Table 1 shows the statistics for both datasets after processing is performed.

Statistics	**Datasets**	
	ml-100k	**ml-1M**
Number of users	495	4,335
Number of items	1,486	3,561
Number of ratings	76,982	918,139
Ratings per user (mean)	155	211
Ratings per user (std. dev.)	108	208
Ratings per item (mean)	51	257
Ratings per item (std. dev.)	61	347
Density	0.105	0.060

Table 1: MovieLens dataset statistics after preprocessing.

4.2 Results

In this section we present the results of the approach proposed in Section 3. Recommendations made using both algorithms are based on training set data only. Each user is presented with 10 recommended items which are evaluated based on that user's test set items. We evaluate the results of the generated recommendations in terms of precision, popularity, diversity and uniqueness, and compare performance as the neighbourhood size, k, in the *UKNN* approach is varied.

With this experimental methodology, we expect to better understand the relationship between the evaluated properties and their dependency on neighbourhood size. Moreover, we wish to analyse the differences between the recommendation lists generated by the two algorithms, and examine how much they differ from each other by measuring average uniqueness.

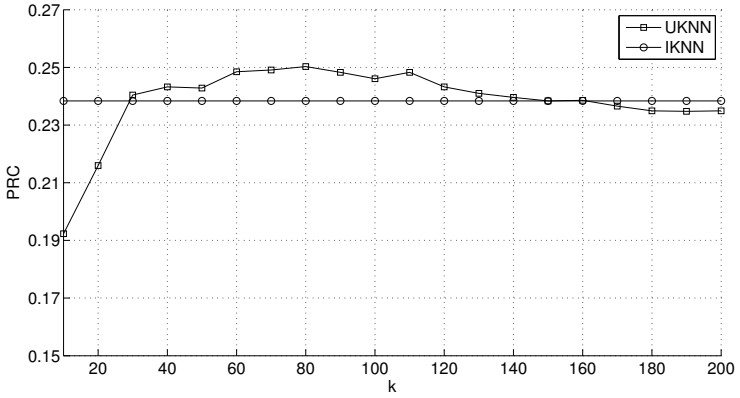
Figures 1 and 2 show the results of the four properties evaluated in both datasets. Overall, precision, popularity, diversity and uniqueness show very similar trends for both datasets. To begin, precision results are first discussed followed by the remaining properties, focusing on the relationship between each metric and precision.

The results for **precision** are shown in Figures 1a and 2a. The results show that the overall precision of *UKNN* increases up to $k \approx 80$, and thereafter declines for the ml-100k dataset but remains relatively constant for the ml-1M dataset. It is noteworthy that the precision of *UKNN* exceeds that of *IKNN* at much smaller neighbourhood sizes; at $k = 30$ and at $k = 15$ for the ml-100k and ml-1M datasets, respectively.

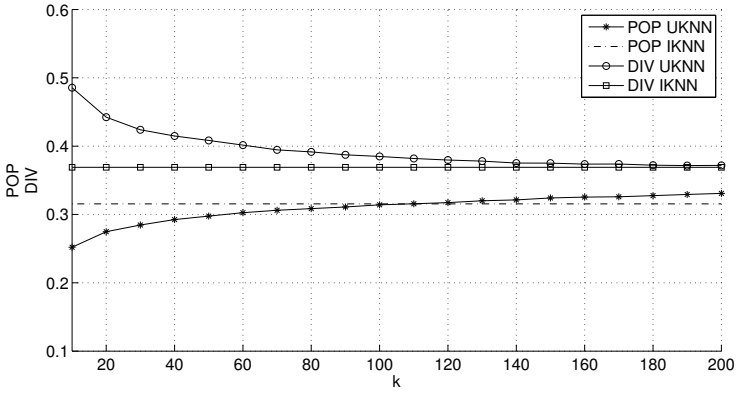
The results for recommendation **popularity** and **diversity** are shown in Figures 1b and 2b. The results indicate that the average popularity of recommended items increases with k. Thus, as expected, there is a high bias toward popularity at larger sizes of k, and a corresponding decrease in recommendation diversity. In the limit, if every user was considered a neighbour, the recommendations would resemble the distribution of item ratings in the dataset, and thus only the most popular items would be recommended.

The average recommendation diversity decreases as k increases for the *UKNN* algorithm, and approaches that of the *IKNN* algorithm at $k = 200$. However, this reduction in diversity for *UKNN* is not compensated by a corresponding gain in precision at larger neighbourhood sizes. As previously described, the *UKNN* algorithm attains its maximum accuracy at $k \approx 80$, yet the loss in diversity is a monotonically decreasing function. We can conclude that there is a high inverse correlation between popularity and diversity, and both suffer at larger values of k; i.e. recommendation lists contain mainly popular items which have a high degree of similarity to each other.

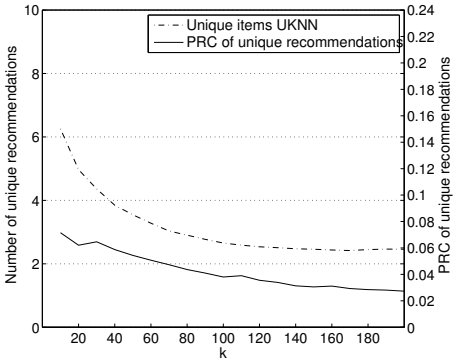
Finally, Figures 1c, 1d, 2c and 2d depict the average numbers of recommendations which are **unique** to the *UKNN* algorithm and those which are **common** to both algorithms, and the corresponding precision results over the unique and common recommended items. We can observe that the number of unique recommendations decreases significantly as k increases. For example, at $k = 100$, on average more than 7 of the 10 recommended items produced by both algorithms are the same in the case of the ml-100k dataset. It is also apparent that recommendation accuracy is largely due to the common items which are recommended by both algorithms. Consider again the ml-100k dataset at $k = 100$, where the precision of unique and common items is approximately 0.04 and 0.21, respectively. However, it should be noted that the unique items recommended by the *UKNN* algorithm are not necessarily irrelevant — although these items are not present in the test set (which is used as the ground truth), they may



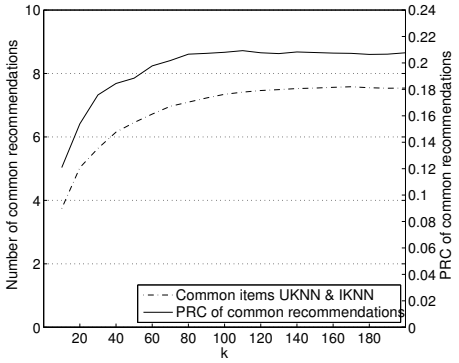
(a) Precision vs. neighbourhood size.



(b) Popularity and diversity vs. neighbourhood size.

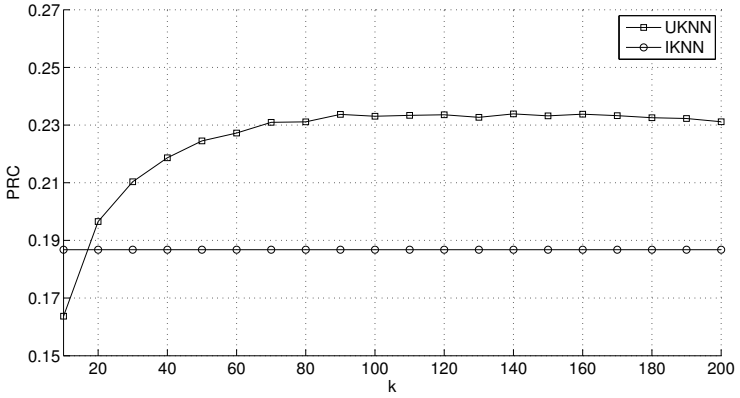


(c) Number and precision of unique *UKNN* recommendations vs. neighbourhood size.

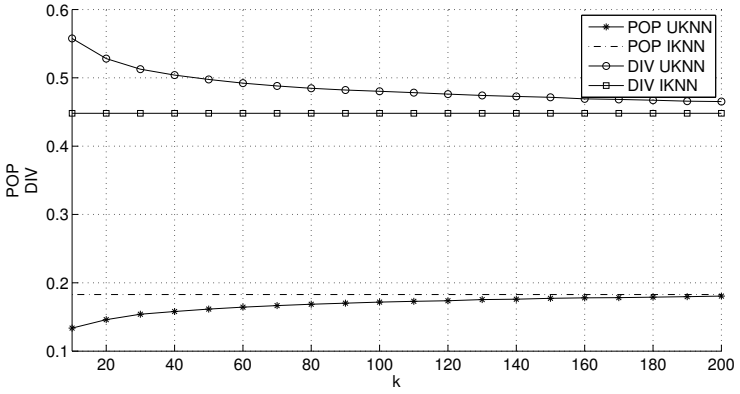


(d) Number and precision of common recommended items vs. neighbourhood size.

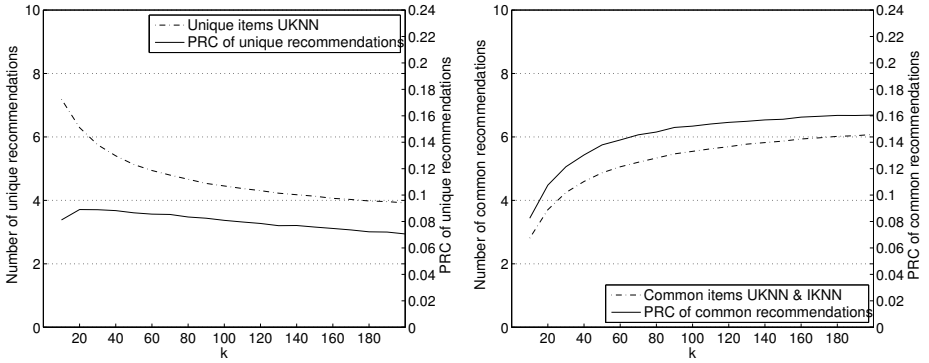
Fig. 1: Performance vs. neighbourhood size, ml-100k dataset.



(a) Precision vs. neighbourhood size.



(b) Popularity and diversity vs. neighbourhood size.



(c) Number and precision of unique *UKNN* recommendations vs. neighbourhood size.

(d) Number and precision of common recommended items vs. neighbourhood size.

Fig. 2: Performance vs. neighbourhood size, ml-1M dataset.

still represent useful recommendations to users. Moreover, at smaller values of k, items recommended by *UKNN* are less popular, and such items – by definition – are less likely to appear in test sets. This is a well-known limitation of the standard approach to the 'offline' precision evaluation of recommender systems as performed in this work, and it can only be addressed by live user trials which is left to future work.

In summary, the experimental results indicate the bias inherent in the *UKNN* algorithm towards popular recommendations at larger neighbourhood sizes, which is more evident in the ml-100k dataset. However, the loss of diversity and bias towards popular recommendations at larger values of k is not compensated by a gain in precision. From the results, we also observe that the uniqueness of the recommendations also depends on k, and that smaller neighbourhood sizes lead to more unique, less popular, and more diverse recommendations.

5 Conclusions and Future Work

In this paper we have performed an evaluation of the user-based *UKNN* and item-based *IKNN* collaborative recommendation algorithms. We have presented the analysis of our evaluation results, which focuses on the effect of neighbourhood size on the relative performance of the algorithms. We have described the results according to four main properties: precision, diversity, popularity, and uniqueness of the recommendations.

Experiments performed using two different datasets show that optimising for accuracy in the user-based approach leads to a poor performance in terms of diversity, a higher bias towards popularity, and less unique recommendations. Moreover, choosing smaller numbers of neighbours for *UKNN* leads to more diverse and less popular recommendations, at the cost of a relatively small decrease in accuracy. We have also analysed the differences between the two approaches in terms of unique recommendation capabilities. The experiment demonstrated that when the number of neighbours in the *UKNN* approach is large, both algorithms tend to produce very similar recommendations (up to 75% and 60% for the ml-100k and ml-1M datasets respectively).

The experiments in this paper show interesting findings in terms of the correlation between accuracy, popularity and diversity. In future work, a study of novel neighbourhood selection algorithms will be considered. Furthermore, we also plan to expand this work considering other properties, such as user and item coverage. Finally, we plan to perform an online evaluation that investigates the correlation between the different properties and real user behaviour.

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References

1. Bellogin, A., Castells, P., and Cantador, I. Precision-oriented Evaluation of Recommender Systems: An Algorithmic Comparison. *In Proceedings of the fifth ACM conference on Recommender systems - RecSys'11* (2011), 333–336.
2. Bellogín, A., and Parapar, J. Using Graph Partitioning Techniques for Neighbour Selection in User-Based Collaborative Filtering. *In Proceedings of the sixth ACM conference on Recommender systems- - RecSys'11*, 1 (2012), 213–216).
3. Celma, O., and Herrera, P. A New Approach to Evaluating Novel Recommendations. *In Proceedings of the 2008 ACM conference on Recommender systems - RecSys '08* (2008), 179.
4. Cremonesi, Paolo, Koren, Yehuda, Turrin, R. Performance of Recommender Algorithms on Top-N Recommendation Tasks. *In Proceedings of the fourth ACM conference on Recommender systems - RecSys'10* (2010), 39–46.
5. Ge, M., Delgado-Battenfeld, C., and Dietmar, J. Beyond accuracy: Evaluating Recommender Systems by Coverage and Serendipity. *In Proceedings of the fourth ACM conference on Recommender systems* (2010), 257–260.
6. Gunawardana, A. A Survey of Accuracy Evaluation Metrics of Recommendation Tasks. *The Journal of Machine Learning Research, 2009 10* (2009), 2935–2962.
7. Herlocker, J., and Konstan, J. An Algorithmic Framework for Performing Collaborative Filtering. *Proceedings of the 22nd 22nd annual international ACM SIGIR conference on Research and development in information retrieval* (1999), 230–237.
8. Herlocker, J., and Konstan, J. Evaluating Collaborative Filtering Recommender Systems. *. . . on Information Systems (. . . 22*, 1 (2004), 5–53.
9. Hurley, N. Personalised Ranking with Diversity. *Proceedings of the 7th ACM conference on Recommender systems - RecSys '13*, 1 (2013), 379–382.
10. Hurley, N., and Zhang, M. Novelty and Diversity in Top-N Recommendation – Analysis and Evaluation. *ACM Transactions on Internet Technology 10*, 4 (Mar. 2011), 1–30.
11. Jambor, T., and Wang, J. Goal-Driven Collaborative Filtering: a Directional Error Based Approach. *Advances in Information Retrieval* (2010), 407–419.
12. Karypis, G. Evaluation of Item-Based Top-N Recommendation Algorithms. *Proceedings of the tenth international conference on World Wide Web - WWW '01* (2001).
13. Rafter, R., O'Mahony, M. P., Hurley, N., and Smyth, B. What Have the Neighbours Ever Done for Us? A Collaborative Filtering Perspective. *User Modeling, Adaptation, and Personalization* (2009), 355–360.
14. Said, A., Kille, B., Jain, B., and Albayrak, S. Increasing Diversity Through Furthest Neighbor-Based Recommendation. *Proceedings of the WSDM* (2012).
15. Sarwar, B., Karypis, G., Konstan, J., and Riedl, J. Item-Based Collaborative Filtering Recommendation Algorithms. *in Proceedings of the 10th international conference on World Wide Web* (2001), 285–295.
16. Shani, G., and Gunawardana, A. *Evaluating Recommendation Systems*. Springer US, 2011.
17. Shardanand, U., and Maes, P. Social Information Filtering: Algorithms for Automating "Word of Mouth". *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (1995), 210–217.
18. Smyth, B. Case-based recommendation. In *The adaptive web*. Springer Berlin Heidelberg., 2007, pp. 342–376.

19. Steck, H. Training and Testing of Recommender Systems on Data Missing not at Random. *In Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining* (2010), 713–722.
20. Zhang, M., and Hurley, N. Avoiding monotony: Improving the Diversity of Recommendation Lists. *Proceedings of the 2008 ACM conference on Recommender systems - RecSys '08* (2008), 123–130.
21. Ziegler, C.-N., McNee, S. M., Konstan, J. a., and Lausen, G. Improving Recommendation Lists Through Topic Diversification. *Proceedings of the 14th international conference on World Wide Web - WWW '05* (2005), 22.