

# Replication of Recommender Systems with Impressions

Discussion Paper

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## Abstract

Impressions are a novel data type in Recommender Systems containing the previously-exposed items, i.e., what was shown on-screen. Due to their novelty, the current literature lacks a characterization of impressions, and replications of previous experiments. Also, previous research works have mainly used impressions in industrial contexts or recommender systems competitions, such as the ACM RecSys Challenges. This work is part of an ongoing study about impressions in recommender systems. It presents an evaluation of impressions recommenders on current open datasets, comparing not only the recommendation quality of impressions recommenders against strong baselines, but also determining if previous progress claims can be replicated.

## Keywords

Recommender Systems, Impressions, Exposure, Replication, Collaborative Filtering

## 1. Introduction

A recurrent and fundamental task in Recommender System (RS) is the empirical evaluation of recommendation models with varied data sources. One particular novel and modestly explored data source in RS research are *impressions*. These contains not only the previous interactions (e.g., purchases and clicks) of users but also the items they were presented with (e.g., recommendations and search results). Previous research works [1, 2, 3, 4] have proposed recommendations models that leverage impressions data, called *impressions recommenders*. To current date, no previous work has tried to replicate these models on open datasets.<sup>1</sup>


The replication of previous works is fundamental to measure the current status of recommendation models across different domains and data sources. Previous research works have highlighted the importance of replication works for the RS community [5, 6, 7, 8, 9]. To address this existing gap in the literature, this work presents a replication study of four impressions


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<sup>1</sup>The concept of “replicability” is the same as in the ACM Artifact Review and Badging, version 1.1, available online at <https://www.acm.org/publications/policies/artifact-review-and-badging-current>.

recommenders.<sup>2</sup> First, this work presents a brief categorization of impressions data, as the current literature does not have one. Second, this work empirically evaluates the recommendation quality of several baseline and impressions recommenders on current open-source impressions datasets and compares the obtained results with the claims given in the original works.

## 2. Impressions in Recommender Systems

Impressions are a novel and modestly used data source that contains the items shown on-screen to users, e.g., the items that users were presented when browsing an e-commerce service. Similar to interactions data in RS, an impression is characterized as an user-item pair  $(u, i)$ , indicating that user  $u$  has been impressed with item  $i$ . Importantly, previous research works with impressions have been in the context of industrial settings or RS competitions. Hence, progress in impressions research has been mostly slow. The following presents a brief categorization of impressions:

**Signals:** The signals within impressions are mixed, i.e., impressions may reflect both positive and negative users preferences toward items, mostly depending on the provenance of the impressions, e.g., a recommender system or business rules. There is no consensus in the current literature regarding the meaning of impressions. For instance, in the same context, previous research works have used impressions as positive [10] or negative [11] signals.

**Challenges:** Three main considerations should be taken into account when working with impressions data. First, the heterogeneous signals within impressions. Second, scalability as the number of impressions records might be orders of magnitude greater than interactions. Third, the effects of feedback loops between users and recommendation systems.

**Impressions Recommenders:** Two types of impressions recommenders have been proposed in previous research works: re-ranking and impressions as user profiles recommenders. The first group re-scores the preference scores of an existing recommendation model based on impressions data and features extracted from impressions [3, 1, 12, 13]. The second group expands the user profiles (interactions) with impressions data [14].

**Impressions Datasets:** Three datasets from different recommendation domains are open-source and can be used in research activities: CONTENTWISE IMPRESSIONS (TV and movies), MIND (news), and FINN.NO SLATES (e-commerce). Private and non-distributable datasets also exist and have been used in previous works [1, 12, 13, 15, 16]. However, due to their nature or license agreements, it is not possible to use them in newer research works.

**Evaluation of Impressions:** No evaluation and comparison of impressions recommenders on open datasets exists in the current literature. Currently, research works with impressions have worked on two contexts: recommendation challenges [14, 17, 18, 11] or industrial scenarios [13, 1, 19, 12]. In the former, complex recommendation models are built and tested against a specific dataset without assessing the generalization aspects of impressions on other areas or domains.

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<sup>2</sup>This work is part of an ongoing study about impressions in recommender systems

In the latter, impressions are studied on private data and recommendation systems. No previous work have performed ablation studies to assess the impact of impressions.

### 3. Experimental Methodology

This work presents several experiments on impressions recommenders, particularly, when used as a *plug-in* to existing recommendation models, i.e., impressions recommenders alter the preference scores of recommendation models. The goal of these experiments is two-fold. First, to determine the recommendation quality of impressions recommenders on open-source impressions datasets. Second, to replicate, if possible, the progress achieved by impressions recommenders in their original works. The experiments followed the following experimental methodology:

**Datasets, Processing, and Splits:** The three available open-source datasets with impressions were used in the experiments: CONTENTWISE IMPRESSIONS, MIND, and FINN.NO SLATES. The following processing was applied to all datasets: (i) data records were sorted in ascending order by their time attribute; (ii) duplicated user-item interactions were aggregated into a single one, keeping the data of the first interaction; (iii) interactions and impressions of users without a minimum of three interactions were removed; (iv) the training, validation, and testing splits were created following a traditional leave-last-interaction out.

**Evaluation:** All recommenders were evaluated on traditional accuracy and beyond-accuracy metrics [5] in the standard top-N recommendation scenario. Hyper-parameters were searched using bayesian search with 16 random cases, 50 total cases, and optimizing NDCG [5] on the validation set.

**Baseline Recommenders:** Neighborhood-based (ITEM KNN and USER KNN) [5], graph-based ( $RP_{\beta}^3$ ) [20], auto-encoders (SLIM ELASTICNET [21] and EASE R [22]), machine learning (PURESVD [23] and MF BPR [24]), and factorization machines recommenders (LIGHT FM) [25]. The description of these recommenders, their hyper-parameters, and their ranges is found in [5].

**Impressions Recommenders:** Re-ranking (CYCLING [3] and IMPRESSIONS DISCOUNTING [1]), and impressions as user profiles recommenders (ITEM WEIGHTED PROFILES and USER WEIGHTED PROFILES) [14].<sup>3</sup>

### 4. Results and Discussion

The accuracy and beyond accuracy of impressions recommenders varied by dataset, baseline, and impressions recommender. All impressions recommenders achieved higher NDCG than baselines on the FINN.NO SLATES dataset. On other datasets, impressions recommenders achieved slightly higher NDCG than baseline recommenders in some cases. Such cases are shown in Table 1. This shows the NDCG of the base and impressions recommenders on the MIND dataset.<sup>4</sup>

<sup>3</sup>Due to space limitations, this work omits the list of hyper-parameters of impressions recommenders.

<sup>4</sup>Recommenders were evaluated on more metrics. Due to space limitations Table 1 only contains the results on NDCG.

**Table 1**

Top-20 ranking accuracy measured with NDCG of base and impressions recommenders on the MIND dataset. MF BPR, NMF, and PURESVD are folded recommenders [23]. Values in **bold** mean higher accuracy than **Baseline**. **ID** refers to impressions discounting using the frequency of impressions. **IUP** refers to impressions as user profiles. **x** means the case was not explored due to incompatibility of the base recommender and the impressions recommender. - means explored cases yielded the same results.

	<b>Baseline</b>	<b>Cycling</b>	<b>ID</b>	<b>IUP</b>
<b>ITEM KNN</b>	0.00868	0.00693	0.00028	0.00012
<b>USER KNN</b>	0.00766	<b>0.01797</b>	<b>0.01118</b>	<b>0.06681</b>
<b>MF BPR</b>	0.00002	<b>0.00680</b>	<b>0.00424</b>	-
<b>NMF</b>	0.00116	<b>0.00797</b>	-	0.00098
<b>PURESVD</b>	0.00010	<b>0.00728</b>	-	<b>0.00015</b>
$RP_{\beta}^3$	0.01643	0.00720	0.00015	0.00009
<b>SLIM ELASTICNET</b>	0.01493	0.00699	0.00060	0.00010
<b>LIGHT FM</b>	0.00160	<b>0.00705</b>	0.00101	<b>x</b>

From the table, a notable case is the use of impressions as user profiles (**IUP**) with **USER KNN** on the MIND dataset. Particularly, this case obtained *eight* and *four* times higher NDCG than the base (**USER KNN**) and best ( $RP_{\beta}^3$ ) baseline recommender, respectively.

When looking at each impressions recommender, the **CYCLING** recommender achieved higher NDCG on the **FINN.NO SLATES** and **MIND** datasets. Although, on the latter, this only occurred on matrix factorization and factorization machines recommenders. The **IMPRESSIONS DISCOUNTING**, **ITEM WEIGHTED PROFILES**, and **USER WEIGHTED PROFILES** recommenders did not have such consistent results. For instance, the former achieved higher NDCG than **USER KNN** but obtained lower NDCG than **ITEM KNN** on the **MIND**.

Regarding the replicability of impressions recommenders, **CYCLING** recommended less accurate but more diverse items on the **CONTENTWISE IMPRESSIONS** dataset. This result is aligned with the conclusions of [3], which performed experiments on a different dataset of the same domain. For **IMPRESSIONS DISCOUNTING**, only the results on the **FINN.NO SLATES** dataset are aligned with the conclusions of [1]. However, in the reference article, the experimental methodology was on error prediction (RMSE) instead of top-N recommendations. The remaining impressions recommenders could not be replicated due to lack of replicability information.

Regarding to the signals within impressions, the results varied mostly by dataset while the recommenders did not play a major role. For the **CONTENTWISE IMPRESSIONS** dataset, impressions cannot be considered as positive or negative, as substantially higher NDCG was not achieved by any recommender treating impressions as positive or negative signals. For the **MIND** and **FINN.NO SLATES** datasets, impressions were considered as positive signals in most recommenders while at the same time achieving higher NDCG than the base recommender.

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