

# Fifty Shades of Ratings: How to Benefit from a Negative Feedback in Top-N Recommendations Tasks

Evgeny Frolov  
evgeny.frolov@skoltech.ru  
Skolkovo Institute of Science and Technology  
143025 Nobel St. 3 Skolkovo Innovation Center  
Moscow Russia

Ivan Oseledets  
i.oseledets@skoltech.ru  
Skolkovo Institute of Science and Technology  
Institute of Numerical Mathematics of the  
Russian Academy of Sciences  
119333 Gubkina St. 8  
Moscow Russia

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Conventional collaborative filtering techniques treat a top- $n$  recommendations problem as a task of generating a list of the most relevant items. This formulation, however, disregards an opposite – avoiding recommendations with completely irrelevant items. Due to that bias, standard algorithms, as well as commonly used evaluation metrics, become insensitive to negative feedback. In order to resolve this problem we propose to treat user feedback as a categorical variable and model it with users and items in a ternary way. We employ a third-order tensor factorization technique and implement a higher order folding-in method to support online recommendations. The method is equally sensitive to entire spectrum of user ratings and is able to accurately predict relevant items even from a negative only feedback. Our method may partially eliminate the need for complicated rating elicitation process as it provides means for personalized recommendations from the very beginning of an interaction with a recommender system. We also propose a modification of standard metrics which helps to reveal unwanted biases and account for sensitivity to a negative feedback. Our model achieves state-of-the-art quality in standard recommendation tasks while significantly outperforming other methods in the cold-start “no-positive-feedback” scenarios.

## Keywords

Collaborative filtering; recommender systems; explicit feedback; cold-start; tensor factorization

## 1. INTRODUCTION

One of the main challenges faced across different recommender systems is a *cold-start* problem. For example, in a user cold-start scenario, when a new (or unrecognized) user is introduced to the system and no side information is available, it is impossible to generate relevant recommendations without asking the user to provide initial feedback on some

items. Randomly picking items for this purpose might be ineffective and frustrating for the user. A more common approach, typically referred as a rating elicitation, is to provide a pre-calculated non-personalized list of the most representative items. However, making this list, that on the one hand helps to better learn the user preferences, and on the other hand does not lead to the user boredom, is a non-trivial task and still is a subject for active research.

The problem becomes even worse if a pre-built list of items resonate poorly with the user’s tastes, resulting in mostly negative feedback (e.g. items that get low scores or low ratings from the user). Conventional collaborative filtering algorithms, such as matrix factorization or similarity-based models, tend to favor similar items, which are likely to be irrelevant in that case. This is typically avoided by generating more items, until enough positive feedback (e.g. items with high scores or high ratings) is collected and relevant recommendations can be made. However, this makes engagement with the system less effortful for the user and may lead to a loss of interest in it.

We argue that these problems can be alleviated if the system is able to learn equally well from both positive and negative feedback. Consider the following movie recommendation example: a new user marks the “Scarface” movie with a low rating, e.g. 2 stars out of 5, and no other information is present in his or her profile. This is likely to indicate that the user does not like movies about crime and violence. It also seems natural to assume that the user probably prefers “opposite” features, such as sentimental story (which can be present in romantic movies or drama), or happy and joyful narrative (provided by animation or comedies). In this case, asking to rate or recommending the “Godfather” movie is definitely a redundant and inappropriate action. Similarly, if a user provides some negative feedback for the first part of a series (e.g. the first movie from the “Lord of the rings” trilogy), it is quite natural to expect that the system will not immediately recommend another part from the same series.

A more proper way to engage with the user in that case is to leverage a sort of “*users, who dislike that item, do like these items instead*” scenario. Users certainly can share preferences not only in what they like, but also in what they do not like and it is fair to expect that techniques, based on collaborative filtering approach, could exploit this for more accurate predictions even from a solely negative feedback. In addition to that, a negative feedback may have a greater importance for a user, than a positive one. Some psycholog-

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