

# Improving IMDb Movie Recommendations with Interactive Settings and Filters

Simon Dooms  
iMinds-Ghent University  
G. Crommenlaan 8, box 201  
Ghent, Belgium  
Simon.Dooms@UGent.be

Toon De Pessemier  
iMinds-Ghent University  
G. Crommenlaan 8, box 201  
Ghent, Belgium  
Toon.DePessemier@UGent.be

Luc Martens  
iMinds-Ghent University  
G. Crommenlaan 8, box 201  
Ghent, Belgium  
Luc1.Martens@UGent.be

## ABSTRACT

IMDb is a widely known online movie platform that offers movie information, allows to rate movies and recommends interesting movies to users. The IMDb movie recommendations do not however offer any means for interactivity or user control, which inherently limits their contextual adaptability. In this work we describe our Google Chrome extension – called MovieBrain – which offers interactive movie recommendations and integrates the IMDb website for user rating data. Dynamic settings and genre filters are available, allowing users to manually fine-tune the recommendation process and its results.

## Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Information filtering, Relevance feedback, User-centered design

## Keywords

Recommender systems, IMDb, MovieBrain, Chrome extension, MovieTweetings, Movies

## 1. INTRODUCTION

While the Internet Movie Database (IMDb) website<sup>1</sup> is a widely known and popular online movie platform, its integrated recommendations are static and non-interactive in nature. Users have no way of controlling, influencing or fine-tuning the suggested movies other than by rating more movies and waiting for the recommendation results to change.

It has been shown however that interactivity and user involvement in the recommendation process increases user satisfaction and recommendation relevance [1]. In this work we illustrate our approach to improve the default IMDb recommendations by offering interactive recommendation settings and filters in a Google Chrome extension called MovieBrain.

<sup>1</sup><http://www.imdb.com>

## 2. A 3-TIER ARCHITECTURE

The MovieBrain system consists of a 3-tier architecture which includes a calculation back-end, a middleware web-server and a front-end Chrome extension. All recommendation calculations are performed on a high-performance computing (HPC) infrastructure which iteratively retrains recommendation models in the background and in real time responds to user requests. A Google Chrome extension provides a visual web-based user interface, and a webserver links the back and front-end of the system while adding control, caching and data management.

## 3. RECOMMENDATION ALGORITHMS

The MovieBrain recommender system is driven by a dynamic hybrid recommendation strategy which we described in previous work [2]. Multiple individual recommendation algorithms can be included and their recommendation results are dynamically optimized in a weighted hybridization scenario. While the hybrid system allows to automatically optimize a given evaluation metric (e.g., *RMSE*), users themselves can influence the recommendation process by manually overriding the weight vectors associated with each individual recommendation algorithm. For the MovieBrain recommender system we integrated 4 recommendation algorithms including MatrixFactorization, user-based collaborative filtering, a popular and a most recent recommendation approach.

User ratings from IMDb are complemented with the MovieTweetings dataset [3], which is a live rating dataset composed of IMDb ratings posted to Twitter. This dataset nicely complements the public ratings on the IMDb platform, helps to alleviate any cold start symptoms and guarantees the continued inclusion of recent, relevant and popular movies.

## 4. GOOGLE CHROME EXTENSION

Browser plugins integrate seamlessly in people's everyday Internet activity (i.e., browsing the web), they allow to inject custom code into existing websites and track user browsing behavior. Our MovieBrain Chrome extension extends the IMDb website functionality by offering customizable movie recommendations based on IMDb ratings that users have provided. The beauty in this workflow lies in the fact that for users interested in the MovieBrain service, ratings already available on IMDb can simply be re-used. Furthermore, a Chrome extension has an additional advantage of scalability. Since an extension is a self-contained file, hosted

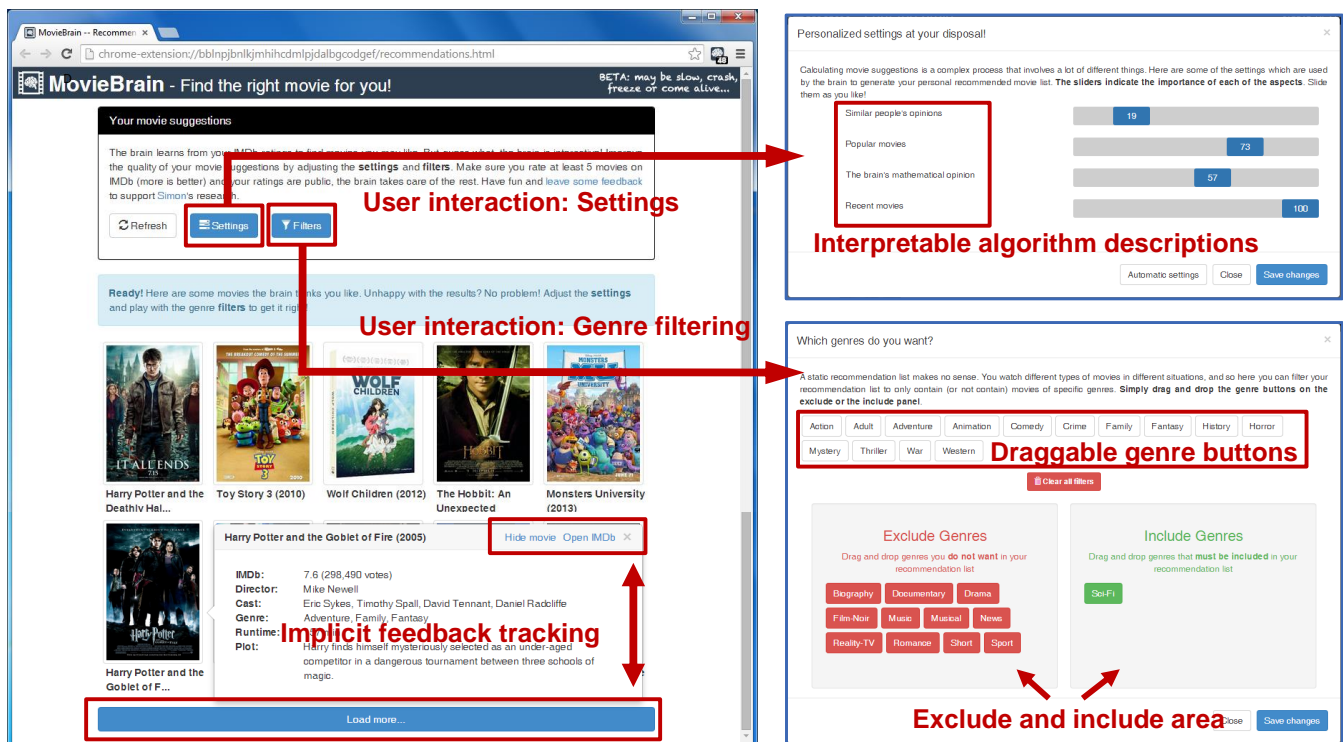


Figure 1: Screenshot of the MovieBrain front-end illustrating the general layout, user interaction options via the *Settings* and *Genre filtering* and implicit feedback tracking through the monitoring of the *Hide*, *Open IMDb*, and *More* links.

at the client side, the impact on the webserver will be limited to HTTP calls to its API.

The user interface is based on a two-level visual design where movies are initially presented by their movie poster and title. Clicking a movie, triggers a popover information pane with more detailed movie information. For every recommended movie two action links are available which allow to *hide* a movie, or *open its corresponding IMDb page*. At the bottom of the page a *more* button allows to load more recommendations.

Users can change the individual importance weights of the integrated algorithms and filter movies by intuitively dragging *genre* buttons to an exclude or include area in the user interface as illustrated in Fig. 1. All requests to the middleware API are logged so that user interaction with the front-end and typical user behavioral patterns (e.g., implicit feedback) can potentially be analyzed. The MovieBrain extension source code can be found on Github<sup>2</sup>. Over 70 users currently have installed the extension. As more users install and use the extension, more data is collected which can ultimately be used to evaluate the user experience of our integrated recommendation algorithms and interaction process in a very realistic usage scenario.

## 5. CONCLUSIONS

While IMDb provides movie recommendations to users who have rated movies, the recommendations are static and can not be interacted with. We have created a Google

<sup>2</sup><http://github.com/sidooms/MovieBrain>

Chrome extension that integrates public IMDb ratings from users and provides an enhanced recommendation experience by allowing users to influence the recommendation process using settings and filters.

## 6. ACKNOWLEDGMENTS

The described research activities were funded by a PhD grant to Simon Dooms of the Agency for Innovation by Science and Technology (IWT Vlaanderen). The experiments in this work were carried out using the Stevin Supercomputer Infrastructure at Ghent University, funded by Ghent University, the Hercules Foundation and the Flemish Government - department EWI.

## 7. REFERENCES

- [1] Svetlin Bostandjiev, John O'Donovan, and Tobias Höllerer. Tasteweights: A visual interactive hybrid recommender system. In *Proceedings of the Sixth ACM Conference on Recommender Systems, RecSys '12*, pages 35–42, New York, NY, USA, 2012. ACM.
- [2] Simon Dooms, Toon De Pessemier, and Luc Martens. Offline optimization for user-specific hybrid recommender systems. *Multimedia Tools and Applications*, pages 1–24, 2013.
- [3] Simon Dooms, Toon De Pessemier, and Luc Martens. Movietweatings: a movie rating dataset collected from twitter. In *Workshop on Crowdsourcing and Human Computation for Recommender Systems, CrowdRec at RecSys*, volume 13, 2013.



Vol-1247  
urn:nbn:de:0074-1247-5

Copyright © 2014 for the individual papers by the papers' authors.  
Copying permitted only for private and academic purposes. This  
volume is published and copyrighted by its editors.

# Poster-RecSys 2014

## Poster Proceedings of RecSys 2014

Poster Proceedings of the 8th ACM Conference on Recommender  
Systems (RecSys 2014)

Foster City, Silicon Valley, USA, October 6-10, 2014.

Edited by

Li Chen \*

Jalal Mahmud \*\*

\* Department of Computer Science, Hong Kong Baptist University, Hong Kong

\*\* IBM Research, USA

## Table of Contents

- Preface  
Li Chen, Jalal Mahmud
- 1. Recommending Tumblr Blogs to Follow with Inductive Matrix Completion  
*Donghyuk Shin, Suleyman Cetintas, Kuang-Chih Lee*
- 2. Interactive Food Recommendation for Groups  
*Mehdi Elahi, Mouzhi Ge, Francesco Ricci, David Massimo, Shlomo Berkovsky*
- 3. Random Walk with Wait and Restart on Document Co-citation Network for Similar  
Document Search  
*Masaki Eto*
- 4. Assisting Emergent Readers in Finding Books to Read

*Maria Soledad Pera, Yiu-Kai Ng*

5. Financial Product Recommendation through Case-based Reasoning and Diversification Techniques  
*Cataldo Musto, Giovanni Semeraro, Pasquale Lops, Marco De Gemmis, Georgios Lekkas*
6. Computer Security Training Recommender for Developers  
*Muhammad Nadeem, Edward B. Allen, Byron J. Williams*
7. Estimating the Value of Multi-Dimensional Data Sets in Context-based Recommender Systems  
*Panagiotis Adamopoulos, Alexander Tuzhilin*
8. Engaging Learners in an Enterprise L&K System  
*Wesley M. Gifford, Ashish Jagmohan, Yi-Min Chee, Anshul Sheopuri, John Ambrose, Sue Rodeman, Shota Aki*
9. Voting Operations for a Group Recommender System in a Distributed User Interface Environment  
*Wolfgang Wörndl, Part Saelim*
10. Correcting Popularity Bias by Enhancing Recommendation Neutrality  
*Toshihiro Kamishima, Shotaro Akaho, Hideki Asoh, Jun Sakuma*
11. A Hybrid Explanations Framework for Collaborative Filtering Recommender Systems  
*Shay Ben-Elazar, Noam Koenigstein*
12. The Role of Prior Experience in User's Engagement with a New Recommender System  
*Marcelo G. Armentano, Silvia N. Schiaffino, Anallá A. Amandi*
13. Diversified Utility Maximization for Recommendations  
*Azin Ashkan, Branislav Kveton, Shlomo Berkovsky, Zheng Wen*
14. Task-Based User Modelling for Personalization via Probabilistic Matrix Factorization  
*Rishabh Mehrotra, Emine Yilmaz, Manisha Verma*
15. Long Term Recommender Benchmarking for Mobile Shopping List Applications using Markov Chains  
*Sandro Schopfer, Thorben Keller*
16. Learning to Measure Quality of Queries for Automatic Query Suggestion  
*Xian Chen, Hyoseop Shin*
17. Recommending Learning Materials to Students by Identifying their Knowledge Gaps  
*Konstantin Bauman, Alexander Tuzhilin*
18. Timely Tip Selection for Foursquare Recommendations  
*Max Sklar, Kristian J. Conception*
19. Improving IMDb Movie Recommendations with Interactive Settings and Filters  
*Simon Doooms, Toon De Pessemer, Luc Martens*
20. An Extended Data Model Format for Composite Recommendation  
*Alan Said, Babak Loni, Roberto Turrin, Andreas Lommatzsch*

---

2014-09-15: submitted by Li Chen

2014-09-18: published on CEUR-WS.org |valid HTML5|