Norwegian University of Science and Technology

Project Thesis

Improving Movie Recommendations with Copious Social Media Data

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Abstract

Faculty of Information Technology, Mathematics and Electrical Engineering
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Master of Technology

Improving Movie Recommendations with Copious Social Media Data

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This is a project thesis about movie recommendations, specifically answering the question: *can movie recommendations be significantly improved by copious social media data?* We look at how we can improve a set of recommendations – through filtering and annotation – by analyzing *the sentiment in social media.*

@TODO What do we find???

Acknowledgements

@TODO: Acknowlegde.

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Abbreviations

SNS **S**ocial **N**etwork **S**ervice

Chapter 1

Introduction

1.1 Motivation

Recommendation systems, as seen in commercial products in 2013, seldom provide any context to go with its recommended products other than statements like "Because you watched X you might like Y."

Netflix, the movie subscription service, quite recently began suggesting movies based on what your Facebook friends had watched – thereby taking a solid step in the direction of social recommendations. These suggestions, however, have one underlying assumption that may not always apply: what the displayed friend has watched is relevant to your choice of content.

Furthermore, the social components in Netflix's recommendations are *personal*. This approach has some clear advantages in that it uses *your* social network as a basis for suggesting content, but there are also some downsides to this:

- They don't take *novelty* into consideration.
- They don't take *hype* into consideration.
- They leverage only a microscopic portion of the available opinions on content that is available in social media.

These personal suggestions seems to be a trend in contemporary approaches to social recommendations. We'll have a look at something a bit different.

There are other sources of social data that do not fit into the "personal" model. In this thesis we'll have a look at one of the largest sources of unpersonal social media content today: Twitter.

Micro-blogging services such as Twitter have enormous amounts of data on almost every topic imaginable. Content is limited in length, and users react to each others' content by "re-tweeting", "favoriting" or "replying to" it. This leaves us with a source of textual data that is:

Instant Users express reactions to events as they experience them.

Weighted Users weigh each others' content by interacting with it.

Concise Due to limitations on content length, users must express themselves concisely.

Furthermore, the Twitter search API[1] supports returning both *popular* and *recent* content, or a mix of the two. This enables two interesting approaches to both filtering and annotating the recommended content, in that we can treat popular comments and recent comments separately.

1.2 Research Questions

In this thesis, I'm not looking into the task of *generating new recommendations*, but rather trying to *improve a set of recommendations* taking copious social media data into account.

We will have a look at ways of using copious social media data to *annotate* and *filter* sets of recommendations.

More specifically, the aim is to find answers to the following questions:

1. Can sentiment analysis of large quantities of unpersonal social media data be used to effectively filter recommendations?
2. Do users want context associated with recommendations? Can filtered unpersonal social media data serve this role?

[1] https://dev.twitter.com/docs/api/1.1/get/search/tweets

3. How do we evaluate our efforts in order to answer the above questions?

1.3 Overview and Summary

We will look at improving an intermediate step in a hypothetical recommendation pipeline, filtering and/or annotating recommended content.

@TODO Add more overview and summary information as it comes into existence.

Chapter 2

Survey

2.1 Relevant literature

The task of improving recommendations through sentiment analysis of social media data requires digging into several fields of study.

Some people have attempted the same task as in this thesis, albeit with another type of social data. Singh et al. [1] investigated a "formulation, where [they] combined the content-based approach with a sentiment analysis task to improve the recommendation results." Their approach is very similar to our approach, but differs in two important ways:

1. It uses user reviews from IMDB as content source, and not a more general source of sentiment-carrying content – as in our case, with Twitter.

2. It is not designed to enhance presupplied recommendations, but rather to generate its own based on genre input by calculating content similarity.

As we're looking at data from Twitter, the sentiment analysis task is a bit different than usual, as it needs to operate on texts that are all less than 140 characters long. More often than not, we will in fact need to work with texts that are merely one or two sentences long. Cho & Kang [2] "propose a method of classifying tendencies and opinions in texts of multiple sentence length extracted from social media and covering

both formal and informal vocabularies". We'll be taking a closer look at this method for the actual sentiment analysis task.

@TODO More.

2.2 Similar applications

What spawned the idea of using an unpersonal social service like Twitter as a content source for filtering content is that Netflix recently rolled out personal social recommendations of their content. For this they use Facebook.

One huge limitation to the Facebook approach is that Facebook doesn't expose how "close" you are to your various friends. People take on

Content sharing patterns (Social influence and the diffusion of user-created content): [3].

Chapter 3

Requirements

Although the methods described in this paper aims to be as agnostic as possible with regards to what type of sentiment carrying input is used, we have selected the microblogging service Twitter – and the available Twitter data has some specific qualities we'll try to make use of to improve the quality of our results.

3.1 Relevant Qualities of Twitter Data

As previously mentioned, "Tweets" can be *favorited*, *retweeted*, and *replied to*. Additionally, we can tell how big reach an author has by counting the number of *followers* he/she has, and use this as another indication of content popularity.

We want to be able to use the data as a source of implicit ratings. To be able to, we need to quantify the significance of these verbs. Oard and Kim [4, 5] and Kelly and Teevan [6] have developed a framework for classification of online (@TODO)... We adapt it to the domain of Twitter data, and wind up with table 3.1.

Original	**Ours**		**Action**
Create	Create	→	Tweet
Examine	Consume	→	Follow
Annotate	Evaluate	→	Reply
Retain	Endorse	→	Favorite
Reference	Forward	→	Retweet

TABLE 3.1: Classification of microblogging behavior

To clarify the classifications of table 3.1, let's break the terms down.

Tweet A user posts content to Twitter, in the form of a new post. A Tweet can have a maximum of 140 characters. Due to the size restrictions, tweets often contain links to websites.

Follow Users consume each others' content by following each other. The number of followers users have range from 0 to more than 40 million. Following is a one-way relationship, and there is often a big difference in the number of users following and being followed by a user.

Reply Users can mention each other in tweets by prepending a username with "@". This same mechanism is used to reply to others' content. When replying, the content the Tweet was replying to is stored along with the reply, forming a conversation tree.

Favorite Users can favorite content, which notifies the content owner and boosts the content in search results etc. It is also trivial to extract all content a particular user has favorited.

Retweet When a user chooses to retweet content, that content is "forwarded" to the user's followers, and boosts the content in search results etc.

Chapter 4

Design

The basic architecture in figure 4.1 reflects this. Our work will be aimed at the component labelled *A*.

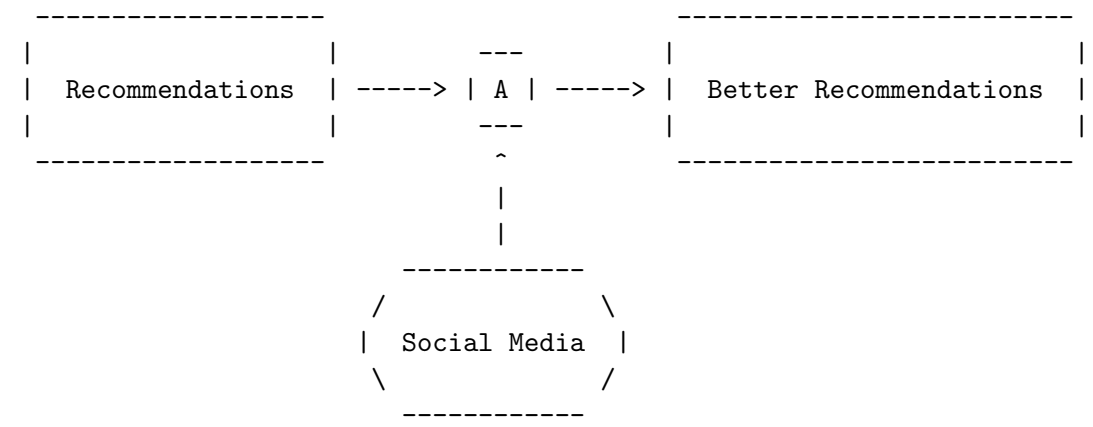

FIGURE 4.1: The basic architecture of a system described in this thesis. We mainly describe the component labelled *A*.

Chapter 5

Implementation

Diskuter de viktigste algoritmene og datastrukturene, og hvordan de utviklet seg, fremhev noen nye/originale funksjoner. Også diskuter hvordan du har tenkt å utføre testen din (validering og evaluering).

Chapter 6

Evaluation

Beskriv hvordan du vurderer arbeidet ditt. Oppsummer evalueringsresultatene, og bruk dem til å vurdere ditt eget arbeid kritisk. Vær ærlig om eventuelle mangler. Hva betyr resultatene?

Chapter 7

Conclusion

I konklusjonen din, beskriv status for ditt arbeid. Oppsummer hva du har oppnådd, sammenlignet med hva du opprinnelig ønsket å oppnå. Relater arbeidet til tidligere relevant arbeid. Foreslår videre arbeid som du tror vil være verdt.

Appendix A

Requirements

Appendix B

Design Documents

Appendix C

Evaluation Results

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