NORWEGIAN UNIVERSITY OF SCIENCE AND
TECHNOLOGY

PROJECT THESIS

Improving Movie Recommendations with Unpersonal Social Media Data

Author:

Jonas MYRLUND

Supervisors:

Prof. Heri RAMAMPIARO

Prof. Helge LANGSETH

December 2013

NORWEGIAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

Abstract

Faculty of Information Technology, Mathematics and Electrical Engineering

Department of Computer and Information Science

Master of Technology

Improving Movie Recommendations with Unpersonal Social Media Data

by Jonas MYRLUND

This is a project thesis about movie recommendations, specifically answering the question: *can movie recommendations be significantly improved by unpersonal 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.* By selecting a set of movies, and comparing the results to those found in open movie rating datasets, we consider whether the sentiment extracted from social media is of significant use in improving movie recommendations.

@TODO What do we find???

Acknowledgements

@TODO: Acknowlegde.

Contents

List of Figures

List of Tables

Abbreviations

MSE	**M**ean **S**quare **E**rror
SaaS	**S**oftware **as a S**ervice
SNS	**S**ocial **N**etwork **S**ervice
SVM	**S**upport **V**ector **M**achine

Glossary

Tweet   A Twitter message

DatumBox   A machine learning SaaS

Chapter 1

Introduction

1.1 Motivation

Many movie recommendation systems today use collaborative filtering techniques at their core. Although collaborative filtering has many advantages that have let it attain its position as one of the dominant algorithms in the field, there are still quite a few weaknesses left to remedy. Among others, two important challenges for collaborative filtering techniques left today are 1) their ability to handle data sparsity [1], and 2) their ability to explain predictions [2].

I will take a somewhat untraditional approach in an attempt to mitigate these issues: can data mined from one of today's largest sources of user-generated content, Twitter, contribute enough relevant information to solve both the problem of data sparsity and result explanation?

1.1.1 Problems in collaborative filtering

The data sparsity problem has several sides to it [1].

Here, we will take a closer look at the *cold start* problem – or more specifically: the *new item problem*. It occurs when a new item enters the system and there is no rating history to base similarity measures on, leaving a barebones collaborative filtering algorithm without anything to base predictions on – until, of course, some users rate it. If this is the case for a large number of items, we say that we have poor *coverage*.

Furthermore, many collaborative filtering algorithms have a problem explaining why they come up with their predictions. If we're able to reliably find Twitter content to back our collaborative filtering predictions, we can use them as a way of providing a context to our recommendations.

1.1.2 Twitter

Twitter is one of the largest sources of user-generated content available today. It launched in 2006, was incorporated in 2007, and has seen active user growth ever since. At the time of writing, Twitter has more than 230 million registered users sending around 500 million Tweets per day.[1]

One of the most interesting things about Twitter is its simplicity. Each message is limited to 140 characters in length, for no other apparent reason than to force its author to formulate messages very concisely, as well as significantly lower the threshold for publishing content compared to traditional blogging services [3].

Furthermore, 76% of Twitter's active users are on mobile – enabling use of the service from anywhere. Combined with Twitter's well-established REST API, this provides us with a robust source of real-time data on almost any subject.

I'll delve further into aspects of using Twitter as a data source in section 2.2.

1.2 Research Questions

In this thesis, I will look for a fit between collaborative filtering's weaknesses and Twitter's strengths. Specifically, I will examine if it is possible to use sentiment extracted from Twitter messages to predict movie ratings.

The main hypothesis is that for each movie, there is a correlation between its user ratings and the sentiment of Twitter messages about it. It is based on a few assumptions:

1. Twitter users write positive things about movies they like, and negative things about movies they don't like.

---

[1]Numbers from https://about.twitter.com/company.

2. Twitter users express this sentiment within the Twitter messages themselves, not just in linked content.

3. When a movie is referenced in a Twitter message the title will most likely be mentioned, and spelled correctly.

4. It is viable to sentimentally classify texts shorter than 140 character, often written in informal language.

5. It is viable to separate between referenced movies, and other entities or phrases with the same title.

As we shall see, many of these assumptions hold up poorly – or hardly at all – rendering the main hypothesis fallacious.

1.3   Overview

This paper is organized as follows.

Chapter 2 surveys relevant literature, similar applications, provides an in-depth analysis of Twitter data and the Twitter API, and reviews the sentiment classifier chosen for the implementation. Chapter 3 describes the system design, and reasoning behind central design choices. Chapter 4 describes the implementation, specifically the way the APIs are called, as well as central algorithms and how they are employed. In chapter 5 we'll look at the execution results, and see how they evaluate. Chapter 6 summarizes the most important takeaways, and suggests some further work.

Chapter 2

Survey

2.1 Similar applications

Some people have attempted the same task as in this thesis, albeit with another type of social data. Singh et al. [4] 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[1], 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.

2.2 Twitter data

@TODO: Something about what terms we're searching for, using only title etc. Ref. implementation with filtered hashtags etc.

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

---

[1]IMDB does not provide open API access at the time of writing.

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.

2.2.1 Relevant parts of the Twitter API

The various endpoints in the Twitter REST API is divided into 16 categories, spanning everything from search and user timelines to suggested users to follow and spam reporting. A full overview of the available API endpoints is available on Twitter's REST API pages[2].

Of these, only two categories are of relevance, namely *Search* and *OAuth*.

OAuth is only relevant because it enables us to search, so we won't elaborate further on how we use it.

2.2.1.1 The Twitter search API

The Twitter search API[3] is a JSON-based REST API, and it takes the following notable parameters:

`q`

   A UTF-8, URL-encoded search query of 1,000 characters maximum, including operators.

`result_type`

   Specifies what type of search results you would prefer to receive.

In addition, there are parameters to control the number of messages returned, language, date ranges etc.

---

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

The `q` parameter, the search query, is obviously of great importance, as it is the one we primarily will be using to target our search.

The `q` parameter supports a wide range of operators.[4] It supports the typical boolean operators (AND, OR, and NOT), as well as specifying exact search phrases, but it also supports more domain-specific operators:

From/to/referencing user

Only return messages from or to a specific user, or simply mentioning a specific user somewhere in its message.

Date ranges

Support for "since" and "until" constraints.

Other

Support for things like only returning messages with links, messages submitted via a specific client type, and messages asking a question.

All operators can be combined, and the regular space serves as an AND clause in this regard.

In addition to the aforementioned operators, the API supports returning tweets matching either a positive or negative sentiment – a feature which should seem very relevant to the task at hand. However, no information was seemingly available on the mechanics behind it, and after some manual testing it was concluded that it also lacked quite severely in its precision.

The other parameter central to our application is the `result_type`. It allows us to switch between three possible heuristics for which results that are returned from the search. We have the choice between three valid values: `recent`, `popular`, or `mixed` tweets – the latter being a combination of the first two, and also the default.

To know which one to choose, we need to know what constitutes a popular tweet.

---

[4]The full list is available here: <https://dev.twitter.com/docs/using-search>

2.2.1.2 What constitutes a popular Tweet?

On Twitter, there are several ways of interacting with the system. Terms like "follow", "mention", "favorite", and "retweet" are all more or less domain-specific to Twitter, so before moving on – let's break them down.

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 another user's content, that content is "forwarded" to the user's followers.

One of the greatest benefits of Twitter as a data source is that all these interactions are completely transparent[5], and can thus be used freely when querying for popular content.

2.2.2 Novelty of available data

As briefly mentioned, part of the hypothesis is that Twitter data is usable for predicting ratings for new content, where collaborative filtering systems perform worse than otherwise.

---

[5]Users can make their own content "private", but their interactions with other users' non-private content are nonetheless public.

Novelty, however, is an inherently fundamental quality of Twitter data, even as a data source. The Twitter search API simply does not expose data more than about a week old. As it is put in their search API guidelines as of December 2013 [5], "The Search API is not complete index of all Tweets, but instead an index of recent Tweets. At the moment that index includes between 6-9 days of Tweets."

This quality makes Twitter data less than useful when it comes to predicting ratings for movies old enough to have calmed in public debate – a category which, not surprisingly, includes the vast majority of available movies.

2.2.3   Twitter as a Data Source

There are vast opportunities in managing to understand a data source with the qualities discussed above, but alas – the diversity and free nature of Twitter as a publishing platform comes at a price: *there is a lot of noise.* That is not to say that there is little relevant information, but when the service is designed to have such a low threshold for contributing content, a low signal-to-noise ratio seems inevitable. We will return to the issue of noise in chapter 5.1, where we try to evaluate correlations between movie titles in our test data and Tweets about the same titles.

This problem of finding content carrying relevant information turns out to perhaps be the biggest challenge of the entire study.

2.3   The sentiment classifier

Much has already been written on the topic of sentiment analysis of Twitter data [6–10]. This paper, however, is not about improving or analyzing these methods and techniques. What is required is a technique that is good enough to *indicate the sentiment of a set of messages.*

For sentiment analysis, I have therefore selected the Twitter sentiment classifier provided by DatumBox, a machine learning SaaS. They provide a broad suite of services within many fields of machine learning. See figure 2.1 for an overview of their current functionality within the document classification category[6].

---

[6]The complete list is currently available at http://www.datumbox.com/api-sandbox/.

FIGURE 2.1: The current endpoints in the DatumBox API in the category "Document Classification".

The classifier used for Twitter sentiment classification is the Binarized Naïve Bayes, after having outperformed SVM, Max Entropy and others on the test set. The people at DatumBox explain their choice of algorithm in an article on their service blog [11].

With the approach taken, texts are classified as either positive, neutral, or negative. A training set of 1.2 million tweets were tokenized "by extracting their bigrams and by taking into account the URLs, the hash tags, the usernames and the emoticons", and were subsequently fed into a Mutual Information algorithm for feature selection.

With a 10-fold cross-validation, the best performing classifier allegiedly achieves an accuracy of 83.26%.

The naïve Bayes classifier is described in detail in section 4.3.1.

2.4   The Netflix rating dataset

For evaluating the results, the Netflix rating dataset was used as a benchmark.

The accompanying Readme file descibes the dataset in the following way:

> The movie rating files contain over 100 million ratings from 480 thousand randomly-chosen, anonymous Netflix customers over 17 thousand movie titles. The data were collected between October, 1998 and December, 2005 and reflect the distribution of all ratings received during this period. The ratings are on a scale from 1 to 5 (integral) stars.

The data used in this work consists of two different types of files.

First, an overview of available movies is available in CSV format, with lines containing the following fields:

1. Movie ID

2. Year of release

3. Movie title

In a separate directory, 17770 files named by their associated movie ID contain lines of individual ratings, with the following attributes:

1. Customer ID

2. Rating

3. Date

Unfortunately, the Netflix rating dataset is no longer publicly available, allegedly due to a lawsuit regarding privacy concerns[7].

For more details on how the data was used to evaluate results, please see chapter 5.

---

[7] http://www.wired.com/threatlevel/2009/12/netflix-privacy-lawsuit/

Chapter 3

Design

This chapter will describe the system in a top-down manner. After explaining the initial design requirements, the system viewed as a whole will be described, then the large logical modules and their relationships, then their individual qualities.

3.1 Design choices

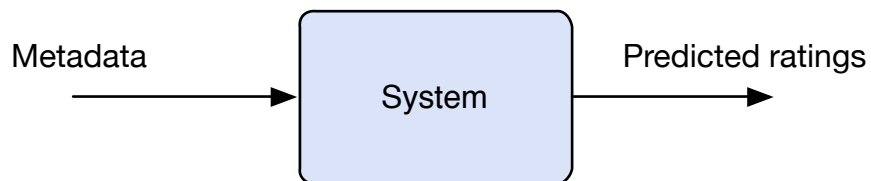Seen as a black box, the system consumes metadata and emits predictions.

FIGURE 3.1: The system consumes metadata, and emits predicted ratings.

The system is inherently data-driven. Every step consumes data, processes it, and emits data – each conforming to simple interfaces in both ends.

More specifically, the system consists of three logical steps:

1. Data gathering

2. Sentiment analysis

3. Rating prediction

The steps sequentially process data for the next one to use, as illustrated in figure 3.2, and invoke each other through simple interfaces. In the next sections, each step will be briefly described. Implementation details are deferred to chapter 4.
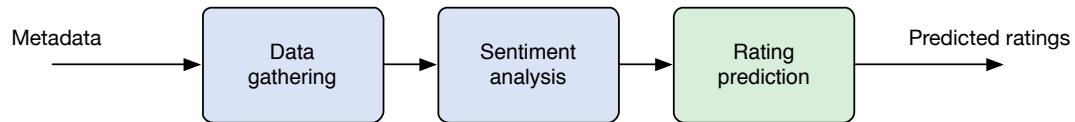
FIGURE 3.2: The high-level system design, depicted in the manner in which data flows through it.

Although the steps below are designed to handle *sets of movies* at a time, to simplify, let us examine how they work for each single movie.

3.2 Data gathering

The data gathering step consumes movie metadata, and emits a list of Twitter messages.

It performs the following two rough steps:

1. Query Twitter for relevant content based on given metadata.

2. Extract textual messages from search results.

As we shall see in later chapters, actually retrieving relevant content from Twitter is quite a bit harder than it should initially seem.

3.3 Sentiment analysis

The sentiment analysis step assigns a sentiment class to each associated Twitter message from the previous step. The sentiments are either "positive", "neutral", or "negative".

3.4 Rating prediction

The rating prediction step takes a list of sentiments, and emits a predicted rating value.

To turn the sentiment classes into a single rational number, two steps are taken:

1. Each sentiment class is mapped to a real number value.

2. The real values are averaged or in other ways reduced into one.

Chapter 4

Implementation

This chapter will go through the algorithms and API calls being used by the application.

In addition to the three steps in chapter 3 – "data gathering", "sentiment analysis", and "rating prediction" – this chapter will also touch upon how the evaluation mechanisms were implemented. However, evaluation results and related discussions are deferred to chapter 5.

4.1 Languages and tools

The system was implemented in the Python programming language, and has no further technical requirements. However, it supports using SQLite[1] to store and query various movie metadata, and to cache content classifications to avoid hitting the remote APIs too much during testing.

The final application is a highly configurable command-line tool. Its interface co-evolved with its requirements, and lets the user control most of its parameters. Figure 4.1 shows the result of running the final program with the `--help` argument.

4.1.1 Important data structures

The only somewhat complex entity being processed by the system is the Twitter messages. These are represented in the system as instances a simple `Tweet` class. It has a

---

[1]http://www.sqlite.org/

```
usage: core.py [-h] [-t {recent,popular,mixed}] [-n N]
               [--max-tweets MAX_TWEETS] [--threshold THRESHOLD] [--normalize]
               [--top-movies-only] [--plot] [--show-errors] [-d]
               [{mse,compare}]

Parses sentences.

positional arguments:
  {mse,compare}

optional arguments:
  -h, --help            show this help message and exit
  -t {recent,popular,mixed}
                        type of search
  -n N                  number of movies to process
  --max-tweets MAX_TWEETS
                        max number of tweets to process per title
  --threshold THRESHOLD
                        number of tweets required to start sentiment analysis
  --normalize           normalize twitter ratings to match average mean of
                        netflix data
  --top-movies-only     only load top movies
  --plot                plot the results and show them
  --show-errors         plot the standard deviations and other errors
  -d, --debug           print traces and parse trees
```

FIGURE 4.1: Screenshot of the application's help menu.

small set of default values and utility methods, but in practice, the objects behave as dictionaries.

Each `Tweet` object is augmented with additional metadata on its way through the system, until they are reduced to real-numbered predictions and discarded in the "rating predicion" execution step.

4.2   Data gathering

As was soon found out after the initial tinkerings with the Twitter API began, the service has a high noise ratio. Therefore, every opportunity was taken to refine and tweak the search queries used to gather content. Luckily, the Twitter API has a quite extensive search interface, with many ways of tweaking the results (details in section 2.2.1.1).

After much trial and failure, the following settings seem to yield good results for typical well-known movies:

Title as exact phrase

Ensure that the title is searched for in its entirety, as a singular phrase and not

just the individual words. In the Twitter API this is done by enclosing the title in quotation marks, as such: `"pulp fiction"`, instead of `pulp fiction`.

Exclude noisy terms

Exclude tweets containing the following terms[2]: "download", "stream", "#nw", "#nowwatching", and "RT".

Then remained the choice between the two modes of search: "popular", "recent", or the optional combination of the two.

4.3   Sentiment analysis

A central part of the system is the sentiment classification of the Twitter results. This sentiment analysis could well have been implemented locally, but for simplicity's sake it has been offloaded to an external service called DatumBox[3], as it seems to employ a reasonable choice of algorithm, and performs well enough for our needs.

This section will take an in-depth look at the techniques the DatumBox service utilizes.

To get us started, this is how DatumBox themselves describe their classifier [11]:

> In order to detect the Sentiment of the tweets we used our Machine Learning framework to build a classifier capable of detecting Positive, Negative and Neutral tweets. Our training set consisted of 1.2 million tweets evenly distributed across the 3 categories. We tokenized the tweets by extracting their bigrams and by taking into account the URLs, the hash tags, the usernames and the emoticons.
>
> In order to select the best features we used several different algorithms and at the end we chose the Mutual Information. Finally after performing several tests with various models and configurations we selected the Binarized Naïve Bayes as the best performing classifier for the particular problem (strangely enough Naïve Bayes beat SVM, Max Entropy and other classifiers which are known to perform usually better than NB). To evaluate the results we

---

[2]Any time a set of irrelevant results shared a common term, it would be added to the list. There are probably many ways of fine-tuning this further.

[3]datumbox.com

used the 10-fold cross-validation method and our best performing classifier achieves an accuracy of 83.26%.

The next section will describe the naïve Bayes classifier in detail.

4.3.1   The Naïve Bayes Classifier

The naïve Bayes classifier has several both strengths and weaknesses, and in many ways its weaknesses enable its strengths.

The most important of these qualities is found in the name of the classifier itself, "naïve", which comes from the algorithm's strong independence assumptions. These assumptions result in a very simple model that is both efficient to run and easy to implement. Although it tends to oversimplify the relations within the data, it often performs well enough to warrant the tradeoff.

The "Bayes" part of the classifier's name takes its name from the probabilistic model on which it is based, which strongly relies on Bayes' theorem.

The task of classifying text is viewed as a maximization problem, where we want to choose the maximally probable class based on our knowledge – our evidence. The probability of class C given n features $F_1, ..., F_n$ can be expressed in the following way:

$$P(C|F_1, ..., F_n) \tag{4.1}$$

However, this model is infeasable if n is very large, or each feature can take on a large number of values. Bayes' rule allows for the model to be reformulated in the following way:

$$P(C|F_1, ..., F_n) = \frac{P(C)P(F_1, ..., F_n|C)}{P(F_1, ..., F_n)} \tag{4.2}$$

This is much more desirable, as calculating these factors is a much more tangible task than attempting to handle $P(C|F_1, ..., F_n)$ directly.

As mentioned, the naïve Bayes has strong independence assumptions – more specifically it assumes the features F of the model to be conditionally independent, given the class C.

As an example, A and B are conditionally independent given C if:

$$P(A \cap B|C) = P(A|C)P(B|C) \tag{4.3}$$

This allows us to rewrite (4.2) to the following:

$$P(C|F_1, ..., F_n) = \frac{P(C)P(F_1, ..., F_n|C)}{P(F_1, ..., F_n)} \tag{4.4}$$

$$= \frac{P(C)\prod_{i=1}^{n} P(F_n|C)}{P(F_1, ..., F_n)} \tag{4.5}$$

However, the $P(F_1, ..., F_n)$ in the denominator is constant. For the classifier we only need the probabilities relative to each other, and this lets us simplify a bit further:

$$P(C|F_1, ..., F_n) \propto P(C) \prod_{i=1}^{n} P(F_n|C) \tag{4.6}$$

By maximizing (4.6) using the maximum a posteriori decision rule (MAP), we can build our classifier.

$$\text{classify}(f_1, ..., f_n) = \underset{c}{\operatorname{argmax}} P(C = c) \prod_{i=1}^{n} P(F_i = f_i|C = c) \tag{4.7}$$

4.3.2 Other issues

When calling the DatumBox API, the best results were achieved when removing the movie title itself from the query. Quite a lot of titles have sentiment-carrying words in their titles[4], and this obviously confused the classifier quite a bit.

---

[4] "Breaking Bad" consequently scoring way below "Cheers" was a rather clear cut case.

4.4 Evaluating sentiment

Chapter 5

Evaluation

- When rating popular and well-known movies[1] the predicted ratings achieve a correlational coefficient of 0.75 with regard to average Netflix ratings for the same movie.

- B-movies or older less-known movies rarely collect enough Twitter search results to warrant any further analysis.

- Movies with titles that are fairly common words or expressions in their own right achieve very low precision, and often return only noise. This is hard to detect without manual interference. Need to perform some sort of Named Entity Disambiguation, maybe something like the techniques outlined in Cucerzan [12] or Sarmento [13] (is elaboration needed?).

5.1 Evaluating against Netflix rating data

To find out how the Twitter-based predictions fare, we will use the average of the available Netflix ratings of the same titles as a benchmark.

With predictions p, and benchmark ratings r, we will compute the MSE (Mean Square Error) of N sample movies in the following way:

---

[1] The sample in question consisted of "Pulp Fiction", "The Shining", "Mission: Impossible", "The Matrix", "The Godfather", "Forrest Gump", and "A Clockwork Orange".

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (p_i - r_i)^2 \tag{5.1}$$

As a baseline metric, we'll compare against the MSE of the average of all the benchmark ratings:

$$\text{MSE}_{\text{baseline}} = \frac{1}{N} \sum_{i=1}^{N} (\bar{r} - r_i)^2 \tag{5.2}$$

@TODO: Reasonable at all? Twitter loses heavily every time.

Chapter 6

Conclusion

I thought that the data would contain too much noise to be usable in any other way than to annotate and – in the best of cases – adjust ratings of content where the social sentiment disagreed strongly with the proposed rating.

However, for certain kinds of content, the predictions generated by Twitter were more or less spot on the same as the ones from Netflix, as shown in chapter 5.

This leads me to believe that Twitter as a data source for recommendations can have a greater role than that of augmenting recommendations coming from elsewhere. (@TODO More specifically....)

Moving towards a conclusion:

1. Twitter's strongest suite lies in its abundance of novel content.

2. Some of the traditional CF systems' weakest points relate to recommending novel content.

3. Augmenting new content, with extremely sparse user ratings, might well be a good application, BUT...

4. Possible to provide context?

6.1   Suggestions for further work

Suggestions to further work:

- Applying NED to Twitter entities.

- Further improving sentiment analysis of informal texts.

- CRF og sentimentanalyse? – klassifisere bort tekster? filtrere i et første steg.

- Nyere filmer – tråle IMDB for nye filmer.

- Gi kontekst til Netflix-ratings: (1. legge til adjektiver?, 2. kontrastifisere positive/negative adjektiver. ordsky?)

- *Hva vil jeg jobbe med til våren?*

Appendix A

Evaluation Results

Bibliography

[1] Xiaoyuan Su and Taghi M. Khoshgoftaar. A survey of collaborative filtering techniques. *Adv. in Artif. Intell.*, 2009:4:2–4:2, January 2009. ISSN 1687-7470. doi: 10.1155/2009/421425. URL http://dx.doi.org/10.1155/2009/421425.

[2] Jonathan L. Herlocker, Joseph A. Konstan, and John Riedl. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work*, CSCW '00, pages 241–250, New York, NY, USA, 2000. ACM. ISBN 1-58113-222-0. doi: 10.1145/358916.358995. URL http://doi.acm.org/10.1145/358916.358995.

[3] Akshay Java, Xiaodan Song, Tim Finin, and Belle Tseng. Why we twitter: Understanding microblogging usage and communities. In *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis*, WebKDD/SNA-KDD '07, pages 56–65, New York, NY, USA, 2007. ACM. ISBN 978-1-59593-848-0. doi: 10.1145/1348549.1348556. URL http://doi.acm.org/10.1145/1348549.1348556.

[4] Vivek Kumar Singh, Mousumi Mukherjee, and Ghanshyam Kumar Mehta. Combining a content filtering heuristic and sentiment analysis for movie recommendations. In K.R. Venugopal and L.M. Patnaik, editors, *Computer Networks and Intelligent Computing*, volume 157 of *Communications in Computer and Information Science*, pages 659–664. Springer Berlin Heidelberg, 2011. ISBN 978-3-642-22785-1. doi: 10.1007/978-3-642-22786-8_83. URL http://dx.doi.org/10.1007/978-3-642-22786-8_83.

[5] Twitter Inc. Using the twitter search api, October 2013. URL https://dev.twitter.com/docs/using-search.

[6] Alec Go, Lei Huang, and Richa Bhayani. Twitter sentiment analysis. *Entropy*, 17, 2009.

[7] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, pages 1–12, 2009.

[8] Alexander Pak and Patrick Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In *LREC*, 2010.

[9] Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca Passonneau. Sentiment analysis of twitter data. In *Proceedings of the Workshop on Languages in Social Media*, pages 30–38. Association for Computational Linguistics, 2011.

[10] Efthymios Kouloumpis, Theresa Wilson, and Johanna Moore. Twitter sentiment analysis: The good the bad and the omg! In *ICWSM*, 2011.

[11] Vasilis Vryniotis. How to build your own twitter sentiment analysis tool, September 2013. URL http://blog.datumbox.com/how-to-build-your-own-twitter-sentiment-analysis-tool/.

[12] Silviu Cucerzan. Large-scale named entity disambiguation based on Wikipedia data. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, pages 708–716, Prague, Czech Republic, June 2007. Association for Computational Linguistics. URL http://www.aclweb.org/anthology/D/D07/D07-1074.

[13] Luís Sarmento, Alexander Kehlenbeck, Eugénio Oliveira, and Lyle Ungar. An approach to web-scale named-entity disambiguation. In *Proceedings of the 6th International Conference on Machine Learning and Data Mining in Pattern Recognition*, MLDM '09, pages 689–703, Berlin, Heidelberg, 2009. Springer-Verlag. ISBN 978-3-642-03069-7. doi: 10.1007/978-3-642-03070-3_52. URL http://dx.doi.org/10.1007/978-3-642-03070-3_52.