Recommender System(Review based)

EE 660 Project Type: Individual

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**Please organize your report along the lines of this template**; you may use any word processing software you like, as long as you submit your report as the required pdf file described below.

**Your report must be typewritten and submitted as a pdf document**, in machine readable form (no scans or screen shots).

**Please submit your code as a second pdf file**, all code in the one file, also required to be machine readable (no scans or screenshots).

# Abstract

A brief, informative description of your project. Include the problem, approach (naming the machine learning methods you used in your project), and key results.

The abstract should be considered a “stand alone” section – it should be understandable on its own, and includes only information that is described (and supported) elsewhere in the report.

Tip: many people find it works better to write the abstract last, even though it will be read first.

# Introduction

# Problem Type, Statement and Goals

**Problem Type:** Classification + Sentiment Analysis + Recommendation

**Statement:** Build a recommendation engine on the basis of the reviews written by users for the products purchased by them. Classify reviews and then use collaborative filtering on the polarity of reviews to find similarities.

**Goal:**

*Typical Systems:*Typical recommender systems perform collaborative filtering technique which uses “User Behavior” for recommending items. The “User Behavior” here is nothing but the purchasing pattern of every user. It is the most commonly used technique in the industry as it not dependent on any other additional information. However every or most of the recommender systems tend to use the final ratings(1-5) to find the correlation or similarity between different users and thereby finally recommending items to different users.

*My Approach:*Instead of using the final ratings(1-5) to find the likings and dis-likings of every user, I am using the reviews given by every user to identify those underlying sentiment of likings and dis-likings related to a product. For this the first thing that is needed, is to classify the reviews and identify the underlying polarity of every review i.e ‘is the review Positive or is it Negative ?’. If the review corresponding to a product is classified positive, then the user likes that product and if classified negative the user dislikes . After finding the polarity I plan on using the same collaborative filtering model to recommend products to users, the only difference would be that instead of using the final ratings for finding similarities, the collaborative filter would now use the sentiment or polarities of reviews to find those similarities.

*Importance of My Approach:*  The recommender system that I am trying to build is quite different from the typical recommender systems. I think words can better express the sentiment of a persons’ thoughts rather than rating from 1 to 5 for a given product. And hence a recommender system based on the sentiment analysis of reviews can better capture a persons’ likings and dis-likings and thereby recommend better products.

**Difficulties:** The main difficulties faced in this project are as follows:

1. *Size:*The total number of data points used are 346,355. Total users in this data set are 38,609 and total items or products included are 263,032. Thus not only I am supposed to classify 346,355 reviews, but after that I am even supposed to find the similarities between 38,609 users.
2. *Sparsity:* The reviews would be inherently vectorized through the bag-of-words technique and since there would we many words in those 346,355 reviews, the final vectorized version of the reviews would be highly sparse.

# Literature Review (Optional)

Briefly describe existing approaches to your problem. The literature review doesn’t need to be exhaustive, but it should cover well known publications, so you are aware of their approach, tools and results.

# Prior and Related Work (Mandatory)

Prior and Related Work - None

# Overview of Approach

**Models Used:**

The algorithms used were specifically used to classify the reviews as positive or negative. As a result only classification algorithms were used and the best one from 5 of them was selected. The algorithm considered initially were:

1. *Naïve Bayes:* The reason for choosing Naïve Bayes is that empirical results have proven that Naïve Bayes performs a very good task at sentiment analysis. It is used in many email-Spam filters.
2. *AdaBoost Classifier:* Adaboost algorithm is adaptive and the subsequent weak learners are tweaked so that the previously misclassified points are classified correctly. It is also less susceptible to over fitting and hence a better choice for our problem.
3. *Logistic Regression:* Logistic Regression in our problem gives us the probability of a review being classified as positive or negative. Thus every review can either be positive or negative depending with some probability.
4. *Random Forest Classifier:* The classifier creates many random decision trees at the training time and finally prediction is based on the mode or the mean of the classes predicted by those random trees.
5. *SVM:* The reason for trying out the support vector machine is that if the true distribution of the polarity of reviews is not linearly separable then an SVM with ‘rbf’ kernel would help in giving us nonlinear boundaries.

**Performance Metrics:**

1. *F-Beta Score:* We are interested in recommending products similar to the products that the user has bought and liked. Additionally identifying a review as positive when it actually negative(i.e False Positive) would be determinantal to our recommender system since we are looking to recommend products similar to the products liked by the user and in that sense determining the True positive and False Positive of review classification is more important. Therefore, a model's ability to precisely predict those reviews that have an actual rating of 4 or 5 is *more important* than the model's ability to **recall** those reviews. We can use **F-beta score** as a metric that considers both precision and recall.

Fβ = (1+β2)⋅

In particular, when β=0.5, more emphasis is placed on precision. This is called the **F0.5 score.**

1. *ROC\_AUC:* AUC(area under the curve of the Receiver Operating characteristics) is used because since the data is highly biased towards one review class positive, our classifier might decide to classify all the reviews of the test set to be in the positive class, and we will still get a very high accuracy, but such a classifier would be of no use for a new data. However when we use F0.5 score and AUC we get the insights of the True Positives and False Positives through F0.5 score and The True Positive rate and False Positive rate through the ROC and AUC.

**Model Comparison/Selection Methodology:**

Since the dataset is huge along with the performance metric, training time Is also of the utmost importance because some algorithms like SVM take very long time to get trained whereas algorithms like Naïve Bayes take very little time comparatively. Thus the following methodology was carried out for selecting the initial model from the 5 models considered above and the steps are.

1. Make a Naïve predictor as the base model. This Naïve predictor would classify every review as positive
2. Randomly select 7000 data points from the data.
3. Calculate the time, training and testing accuracy/F0.5 score for the subset of those 7000 randomly selected data points.
4. Select the model or classifier that has its F0.5 score greater than the Naïve predictor’s F0.5  score. Moreover the model should have a good balance between training time and the performance metric.
5. Use the selected classifier and do cross validation for hyper-parameter selection and generate a final best classifier model.
6. Use this best classifier to train on the entire training dataset, and test it on the entire training data. Note the performance metrics.
7. Use this final model to predict the sentiment of all the reviews in the data and make a new column of binary polarities(Positive and Negative).
8. Finally use item-item collaborative Filtering technique on user-items with target as the reviews sentiment to generate recommendations.

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# Implementation

Report your implementation details and results in the following subsections. You should mention which libraries and functions you used but avoid including code in your report. Your description of what your system does should be readable and understandable to a reader that isn’t familiar with the functions and libraries you used, but is familiar with the algorithms and techniques that were covered in EE 660. (For example, stating “we standardized all real-valued features, and recast all categorical features using one-hot encoding” and also stating the functions used in your code for this, is fine; stating only the functions used in your code is not fine.)

## Data Set

**Source:** Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering  
R. He, J. McAuley  
*WWW*, 2016

## **Description:** This dataset contains product reviews and metadata from Amazon, including 142.8 million reviews spanning May 1996 - July 2014.This dataset includes reviews (ratings, text, helpfulness votes), product metadata (descriptions, category information, price, brand, and image features), and links (also viewed/also bought graphs).

**DATA:**

### *Review:*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Feature** | reviewerID | asin | reviewText | overall |
| **Feature Info** | ID of the reviewer | ID of the product | text of the review | rating of the product |
| **Feature Type** | Unordered Categorical | Unordered Categorical | Text | Ordered Categorical |
| **Range** | 38,609 | 263,032 | Reviews total: 346,355  Vocabulary: 140,198 | [1,2,3,4,5]  5 being the best and 1 being the worst |

*Metadata:*

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature** | asin | title | imUrl |
| **Feature Info** | ID of the product | name of the product | url of the product image |
| **Feature Type** | Unordered Categorical | Text | Image URL |
| **Range** | 263,032 | ---- | ---- |

## Preprocessing, Feature Extraction, Dimensionality Adjustment

The goal of this project is to classify reviews. Also there are no missing values in the for ‘reviewerID’, ‘asin’, ‘reviews’ and ‘overall’ features and hence preprocessing and Dimensionality reduction are to be done only for the ‘reviews’ feature.

**Preprocessing:** In order for the text data to be applied to an ML classification algorithm, it has to be converted to number form. To do this we convert it to bag of words format. This technique works in the following way.

* Find all the unique words occurring in 346,355 reviews. This set of unique words is called the Vocabulary. Here the size of the Vocabulary is 140,198.
* For every review create a vector V the size of the Vocabulary and for every word in the review append the occurrence of that word to the corresponding position in vector V.
* Thus the final matrix of vectorized reviews will be of the RMxN where M = 346,355 and N = 140,198. In this new vectorized reviews data the occurrence of the words are the features. Thus R is a very high dimensional data with features = 140,198. Also most of the word from this Vocabulary of 140,198 words occur very less and hence R is also a very sparse matrix.

**Dimensionality Reduction:** A text data contains stop words, punctuations etc. Moreover when it comes to sentiment analysis there would be certain words which do not contribute to the sentiment classification at all. For example words like ‘comfortable’, ‘good’, ‘best’ etc. capture positive sentiments, whereas words like ‘bad’, ‘unhappy’ etc. correspond to negative sentiments. These words also tend to occur more in the reviews and the words that have no contribution to sentiment tend to occur less in the reviews. So the dimensionality reduction is done in the following way.

* *Remove all the stop words* from the reviews as they do not provide any important information for a reviews sentiment. Stop words include words like ‘is’, ’at’, ’which’, ’on’ etc. These are the most commonly occurring words in the English Language.
* *Remove punctuations.*
* *Remove words occurring less that 1% of the time*. This is needed as there might occur cases when a person mentions a brand of the product or uses some word not common to sentiment analysis. If we include such words we might throw off our sentiment classifier.
* After doing the above steps the final Vocabulary obtained has 625 words which would essentially be used to capture the sentiment of every review. Thus in RMxN M = 346,355 and N = 625. Thus the matrix R is no longer sparse.

## Dataset Methodology

Describe the procedure you followed in the use of your dataset.

You should clearly state how many data points were used for pre-training (not mandatory), training, validation set(s) (or specify k if k-fold validation is used), and testing.

Describe clearly how validation sets were used, and where in the process they were separated from training sets. For cross validation, describe where in the process the cross validation loops were implemented; and if multiple cross validation loops were used, state whether they were nested or sequential, and their ordering. Describe where in the process the validation results were used to make decisions. You may find it useful to use flow charts or diagrams to illustrate your dataset methodology.

Also describe where in the process the test set was used, any decisions made based on the test set results, and how many times the test set was used.

## Training Process

Describe how you trained your model, the classifiers or regression processes you used, and the parameters you chose.

For each machine learning method or model you use:

* Describe your model and your algorithm in detail (with formulas and flowcharts). It generally isn’t necessary to repeat equations given in EE 660 just to describe the model and algorithm; however, you must give enough information to clearly define which model and algorithm (and which version of the model and algorithm) you are using. Also, if you want to refer to any equations (e.g., for your interpretation or analysis), you must include those equations in your report. If needed, also explain in detail what you did to adapt the method to your case, and explain the assumptions or “tricks” you used.
* Give some justification for why you chose this method. This can be a simple statement such as: simple method for baseline; non-linear method because problem seems complex; we believe this method would yield the best performance; etc.
* State the parameters of the model and how they were chosen. If a parameter is chosen by heuristics, state so. If a parameter is chosen by some model selection or validation process, state so and describe the details in Sec. 3.3 or 3.5.
* Analyze the complexity of your hypothesis set to the extent possible. Compare with the number of data points you have and the dimension of the pre-processed feature space. Explain what you did to avoid overfitting and underfitting.
* If you have sets of results to show for this machine learning method, include them here. (For a comparison of results from *different* machine learning methods, use the next subsection.)

## Model Selection and Comparison of Results

If you had multiple potential models in the beginning, explain how you performed model selection. No need to repeat what was covered in the Dataset Methodology subsection above.

Present performance comparison of your different models and methods here. Be sure to clearly show what dataset each result is from (training, validation, test if any, averages over multiple cross-validation runs, etc.). Use table(s) and/or plots. **Do not paste print screen images.**

Is the difference between these results as expected? In the case of classification, you can choose two salient features and plot your decision boundaries w.r.t. them. In the case of regression, you can plot the resulting regression function in 3D (as a function of two salient features) or in a few 2D plots (each as a function of one salient feature).

# Final Results and Interpretation

Document your final results. Describe your final system and its parameter values. Give the final performance of your system(s) and an estimate of it’s out of sample performance. Compare with your baseline results and with any results you found in the literature. Include figures, plots, and/or tables if appropriate.

**If you are working on an online competition, report the performance of your best submission and compare it to others on the leader board.** If you want to compare your results with other work, do so here.

Interpretation: Why do you think the results came out the way they did? What has been learned from them? Anything particularly noteworthy or unexpected? Showing your understanding of your work and results is an important part of this project. Note: you can interpret results throughout the report, but this section should contain a final interpretation (e.g., why this system worked the best, and how much better it is or is not, and what else might improve it further)

# Contributions of each team member

If a team project, state here what the contribution of each team member was (i.e., who did what).

# Summary and conclusions

Briefly summarize key findings, and optionally state what would be interesting or useful to do next.

# References

Cite the sources of your information that came from elsewhere. This includes other related works you compare with (if any), and sources of descriptions of systems or methods that you included in your report.

# Your code

**Please submit your code in a separate file.**  All your code should be in one pdf file, machine readable (no screen shots or scans).