Analysis of Google Play store review



Sanket Prabhu: srp140430

Chirag Chudasama: cbc140130

Kunal Kapoor: kxk140330

Abstract:

Developing an app in today's smartphone ecosystems is easier than ever - the barrier of entry is low enough that a single developer can write a commercially successful app. The iOS App Store is reported to have reached the one million apps mark. As of October 2013, 50B apps have been downloaded from the app store. Furthermore, revenue earned by developers from the iOS App Store have been over \$1.5B in 2012. Customer interest in apps is evident: top apps in the Google Play app store have over 1m reviews.

As a developer, it is essential to "stay on top of your game", i.e., keep your app updated with the most requested features and bug-fixes. However, most app stores provide only an average rating (out of 5) for each app. Consequently, it is difficult to identify why people like or dislike a particular. We aim to solve this problem.

Problem Statement:

The aim of this project is to collect reviews from Google Play Store and preprocess it and analyzing it to give top positive as well as top negative reviews about particular app, and to provide more detailed analyses of the reviews of an app to a developer, beyond an average rating.

System Overview:

1. To get review about particular app.

We got dataset of reviews. The datasets which we are using (2014):

- a. Audible
- b. Flixster
- c. Jewels
- d. Operamini
- e. Pandora
- f. Soundhound
- g. Yelp

2. Processing reviews.

A review consists of the following relevant data:

- a. A unique author ID,
- b. Review Creation Time
- c. Rating (ranging from 1 to 5)
- d. Review Text

We normalize the ratings to a scale of [0, 1].

Expectedly, not all reviews possess perfect grammar or punctuation, rendering preprocessing a must. To begin, text for each review is transformed to lowercase. Subsequently, emoticons are converted into symbols. Emoticons can potentially prove to be strong indicators of opinion, and thus, are valuable. Now, exclamation marks are transformed into symbols, since we believe that they, too, can prove to be strong indicators of opinion. Finally, the review text is stripped of punctuation, and replaced by whitespace.

Image which is shown below states that we have replaced smileys with words

```
':) ':
':-) ':
        'smile',
        'smile',
':]':
        'smile',
':-]':
        'smile',
        'smile',
'(:':
' (-: ':
        'smile',
';)':
';-)':
        'wink',
':P':
         'cheeky',
        'cheeky',
':-P':
';P':
         'cheeky'
';-P':
        'cheeky'
';D':
         'laugh',
';-D':
        'laugh',
         'laugh',
':D':
':-D':
        'laugh',
':(':
T:-(T:
         'sad',
';(':
         'sad',
';-(':
         'sad',
'):':
')-:':
         'sad',
1:[1:
         'sad',
':-[':
         'sad',
         'wry'
':-/':
         'wry
';-/':
         'wrv
':\\':
         'wry'
':-\\':
';\\':
         'wry'
';-\\':
         'wry'
':\'(':
':\'-(': 'cry',
'<3':
         'love'
'>:(':
         'angry',
'>:-(': 'angry',
'>; (':
         'angry',
'>;-(':
         'angry',
'0.0':
        'bigeyes'
'0.0':
         'bigeyes',
        'bigeyes',
'0.0':
'-.-':
        'squint'
```

List of stop words we are using are shown below:

Source: http://xpo6.com/list-of-english-stop-words/

across after afterwards again against all almost alone also although always am among amongst amoungst amount and another any anyhow anyone anything anyway anywhere

3. Creating a Corpus of Subjective Words

We hypothesize that the opinion of a review is indicated by the presence of "subjective words". For example, a review is more likely to complain about crashes, and have a low rating, if it contains the word "crash". Thus, we intend to create a corpus of such "subjective" words.

We also hypothesize that a subjective word is indicative of a high or low rating.

For example, a review with the word "crash" in it is likely to have a low rating, whereas one with "stable" in it is likely to have a high rating.

Consequently, we will extract subjective words from reviews by analyzing their power to predict the rating of a review. Specifically, we are planning to apply logistic regression to review ratings.

4. Identifying Topics in a Review

Given a review text, a list of subjective words, and a list of topics that each subjective word corresponds to, the topics addressed by the review are the union of topics for each word in the review.

5. Ranking Topics in Order of Relevance

Given a list of topics, and a list of reviews associated with each topic, one can compute various metrics for each topic, such as average rating, number of reviews, etc. Consequently, one can rank the topics in order of relevance to a single or hybrid metric. For example, a hybrid metric that ranks topics in increasing order of average rating and decreasing order of number of reviews provides a list of topics that customers are most unhappy about. Similarly, hybrid metrics can be designed to provide topics that customers are most happy about, or write the longest reviews about, etc.

6. Identifying Representative Reviews for a Topic.

For each topic, we are planning to identify a list of representative reviews that summarize public sentiment on that topic. This is achieved by ranking all reviews relevant to a topic according to some metric and picking the top 3. We will chose a metric that ranks reviews in proportion to the number of times a word from the topic set appears in the review, and inversely proportional to the squared distance of the review's rating from the average rating for that topic.

Output:

We started out with the goal of providing a more detailed analyses of the reviews of an app to a developer, beyond an average rating.

We will be able to provide a list of topics that are relevant to the manner in which the developer wishes to interpret the reviews, an average rating that conveys general sentiment for that topic, and representative reviews that give insightful criticism regarding the topic.

ProcessedReviews.txt

ProcessedReviews.txt-Notepad

File Edit Format View Help

{'soundhound': [{'text': 'nice sometimes help me to find the song must have this app', 'rating': 1.0}, {'text': 'dont want this never works and i cant get rid of this useless program i have never once and a single song name over i wish i was not forced to have this on my phone and to have it default set to start up when my search button is held down is unprocessory.'

{'soundhound': [{'text': 'nice sometimes help me to find the song must have this app', 'rating': 1.0}, {'text': 'dont want this never works and i cant get rid of this useless program i have never once got a single song name ever i wish i was not forced to have this on my phone and to have it default set to start up when my search button is held down is unnecessary ', 'rating': 0.0}, {'text': 'snapple working dosent work anymore', 'rating': 0.5}, {'text': 'amazing EXCLAMATION this acc works even with humming EXCLAMATION ', 'rating': 1.0}, {'text': 'simply amazing EXCLAMATION my only problem is having used it so much for a couple years now i have too many sound searches and bookmarks i wish i could export them to the sd card and reclaim some space 16 mb on my phone that is now into the low space warning level 42 mb and no longer syncs gmail etc', 'rating': 1.0}, {'text': 'doesnt work for telugu songs', 'rating':

FeatureWeights.txt

FeatureWeights.txt - Notepad

File Edit Format View Help

{'megaplex': 0.00037336324806314114, 'awesome': 0.7355660196008285, 'supet': 0.0012683084297670615, 'upto': 0.002254126097661932, 'tkikmoto': 0.0008306854099173308, 'sorta': 0.0005027780124755834, 'news': -0.002206490727727751, 'guy': -0.0009316047898673874, 'iit': 0.00038701751602249055, 'controlling': -0.0013731038896422569, 'grail': -0.0009531905926583916,
'quirk': 0.0004201920858945851, 'gs4': -0.0005050039459732899, 'nmore': 0.000808852939371091, 'fgfhfg': 5.656093856286184e-07, 'lovein': 0.0007995501388486683, 'enormous': 0.00011795472287954915, 'shiny': -0.0005549228625156984, 'adictive': 0.0010987799188424238, 'maryj': 0.00031963122834456555, 'med': -0.0003805906814002371, 'chances': 0.0007111483873251186, 'fianlly': 0.00021430711873138495, 'managing': 0.0004534330492830116, 'expertly': 0.00023071369868512642, 'snaps': -0.0005190458638995153, 'vish':

Creating a Corpus of Subjective Words

The first step in our pipeline – linear regression – gives us the basic ability to predict the sentiment of a review. This is useful to identify features in a review that are good indicators of sentiment. Our values for the parameters of linear regression were: $\alpha\alpha$ =0.0001, $\epsilon\epsilon$ =0.001, $\phi\phi$ is the presence-indicating feature vector of all unigrams with stop words filtered out.

The top positive words were:

love, great, good, awesome, best, !, excellent, app, nice, game, browser, cool, fast, easy, works, fun, amazing, movie, opera, addictive, perfect, music, movies, awesome, super, helpful, fantastic, better, jewels.

The top negative words were:

update, work, open, sucks, will, phone, uninstall, ads, play, bad, songs, books, poor, crap, book, crashes, useless, screen, uninstalled, force, terrible, download, 3, load, horrible, uninstalling, start, takes, waste, annoying.

Identifying Topics in a Review

Topic inference in a document is a well-studied task. However, most approaches assume a structured document with well-formed grammar and only the occasional error. However, most reviews we encountered showed poor structure, spelling and syntax. This rendered NLP techniques impossible. Consequently, we fell back to a simple technique – finding a group of subjective words with similar meanings in a review, and interpreting this set of words as a topic of discussion.

Using our technique, we obtained an average of 2000 topics per app. Note that this list contains a large spectrum of all possible topics, ranging from "ads", "bug" or "crash" all the way to "fine", "okay", etc. In the next step, we rank topics according to their relevance.

In our results, we noticed that not all topic sets are obviously a set of synonyms. For example, the set ('bring', 'bringing', 'brings', 'brought', 'play', 'played', 'playing', 'plays', 'work', 'worked', 'working', 'works') does not obviously contain pairwise synonymous words. However, one must realize that a word can be used in many senses, and can imply different meanings. In the absence of contextual meaning of a word, one must assume every meaning to be possible, leading to a certain level of ambiguity. This might also lead to two or more independent topics fused together under the same topic. However, this issue is not prevalent or alarming: the example above is the worst-case scenario.

Another issue we noticed was some topics were similar for the most part, except for one or two words, and hence appeared together in rankings everywhere. However, this issue was not too prevalent either, and hence, was deferred.

Synsets.txt

Synsetstxt - Notepad

File Edit Format View Help

[('motel', 'motels'), ('alternate', 'alternative', 'substitute'), ('asked', 'asks', 'demand', 'demands', 'involve', 'involved', 'involves', 'needed', 'neededs', 'needing', 'require', 'required', 'requires', 'requiring', 'takes'), ('drop', 'dropped', 'dropping', 'drops', 'spend', 'spending', 'spent'), ('subject', 'themes', 'themes', 'topic', 'topics'), ('reach',

required', 'requires', 'requiring', 'takes'), ('drop', 'dropped', 'dropping', 'drops', 'spending', 'spending', 'spending', 'spending', 'themes', 'themes', 'thopic', 'topic', 'topic',

Ranking Topics in Order of Relevance

The relevance of a topic depends on the desideratum of the developer. A developer may desire to look at topics with negative sentiments, positive sentiments, or topics that are popular, or any other metric.

We defined metrics for some such use-cases. For example, topics with negative sentiments can be obtained by ranking them proportional to the number of relevant reviews, and inversely proportional to the average rating. This metric is not entirely statistically sound — any topic that has enough reviews will have a mean close to the average rating — however, it works well in practice.

For Pandora, the top negative topics we found were: ('garbage', 'refuses'), ('pathetic', 'poor'), ('email', 'emailed', 'emails'), etc.

In practice, we found another heuristic extremely effective: topics ranked such that they are far from the extremes in terms of ratings, and are far from the app average, and have a sizeable number of reviews, provide an alternate view of the public sentiment that is fairly critical and insightful. For example, for Pandora, the top topics according to this metric were: ('play', 'played', 'playing', 'plays',...), ('ad', 'ads', 'advertisement', 'advertisements', 'advertising', 'adverts'), ('call', 'song', 'songs'), etc. We believe that this metric provides good results because:

- (a) Most reviews that provide a 1 star / 5 star rating do so without providing any insightful criticism. On the other hand, reviews with 2-4 star ratings provide more detailed criticism. One can hypothesize that a 2-4 rating indicates the author put thought into the rating before choosing an outright good/bad (leading to a 5/1 star rating respectively) distinction, and this same thought is usually reflected in the review itself.
- (b) If the average rating is high (as is the case with all the apps we happened to choose), then most reviews close to the app average, again, fail to criticize the app properly.

Other means of ranking topics could be conceived of, such as measuring the "insightfulness" of a review, and computing the average for a topic, however, such avenues were deferred. Additionally, we would like replace the use of a heuristic with that of a learning technique. However, in the face of lack of labeled data, we are unable to do so.

Output for Yelp dataset:

Positive Reviews

Negative Reviews

```
parameter setting of the New York ("support," supports," supports, "support," support, "support," supports, "support," support, "support," support, "support," support, "support," support, "support, "support, "support," support, "support, "support
```

Conclusion

To summarize our work, we started out with the goal of providing a more detailed analyses of the reviews of an app to a developer, beyond an average rating. We are able to provide a list of topics that are relevant to the manner in which the developer wishes to interpret the reviews, an average rating that conveys general sentiment for that topic, and representative reviews that give insightful criticism regarding the topic.

We can improve the manner in which we infer topics from a review by applying NLP techniques on structured data, and the manner in which we signify relevance of topic or representativeness of a review using labeled data.

Software/Tools?

- Python IDE
- Visual Studio

References:

- [1] C. Jones, "Apple's App Store About To Hit 1 Million Apps," 11 12 2013. [Online]. Available: http://www.forbes.com/sites/chuckjones/2013/12/11/apples-app-store-about-to-hit-1-million-apps/. [Accessed 12 12 2013].
- [2] R. Baldwin, "Apple Hits 50 Billion Apps Served," 15 05 2013. [Online]. Available: http://www.wired.com/gadgetlab/2013/05/apple-hits-50-billion-served/. [Accessed 12 12 2013].
- [3] Canalys, "11% quarterly growth in downloads for leading app stores," 08 04 2013. [Online]. Available: http://canalys.com/newsroom/11-quarterly-growth-downloads-leading-app-stores. [Accessed 12 12 2013].
- [4] L. Zhuang, F. Jing and X.-Y. Zhu, "Movie review mining and summarization," in Proceedings of the 15th ACM international conference on Information and knowledge management (CIKM '06), ACM, New York, NY, USA, 2006.
- [5] H. Tang, S. Tan and X. Cheng, "A survey on sentiment detection of reviews," Expert Systems with Applications, vol. 36, no. 7, pp. 10760-10773, 2009.
- [6] "android-market-api," 04 11 2013. [Online]. Available: http://code.google.com/p/android-market-api/.