**INTRODUCTION TO DATA SCIENCE**

**Applications reviews analysiss**

Vardit Arkash – 305134140

[vardit.arkash@mail.huji.ac.il](mailto:vardit.arkash@mail.huji.ac.il)

Gal Turgeman – 308222595  
[gal.turgeman@mail.huji.ac.il](mailto:gal.turgeman@mail.huji.ac.il)

Yarden Yagil - 311549083  
[yarden.yagil@mail.huji.ac.il](mailto:yarden.yagil@mail.huji.ac.il)

**Introduction:**

Our goal in this project is to find the main problems in a certain application, in order to enable developers to improve their application in an easier way.  
We were focused on games applications from Google Play website. We have collected reviews from the applications and used NLP tools to deduce what are the problems in the application, if there are any.

We defined 6 main problems to look for in the applications:

* Ads: there are too many advertisements in the application.
* Cost: users think the application doesn't worth the money it costs.
* UX: bad design and inconvenient user interface.
* Appeal: the users don't find interest in the application.
* Bug: there are bugs in the application.

We analyzed the reviews according to these 6 problems.

**The Data**

First we needed to extract reviews from games applications. For this purpose, we crawled the Google Play website (<https://play.google.com/store/apps>) and collected users reviews from various categories of games. The data consists of 200 applications and between 20 to 200 reviews for each one (depends on the number of reviews the app has).

The crawler goes through the html pages of various categories of games (i.e. action, board, cards, adventure and sport) and collects the applications' URLs they contain. Afterwards it parses the html pages of the applications and collects the users' reviews of each application. Finally, all the reviews are saved in a dictionary data structure; this is the database that will serve us through the project. In the dictionary, the key is the application name and the value is a list of all the reviews of that application. The data collection is done once and the dictionary is saved in a file called "reviews.txt" which is located in the "files" folder.

**The solution description:**

In order to deduce what are the problems in an application, we evaluate negative feedbacks of the app by using 2-parts algorithm and some manual processing. The description will refer to each of the parts.

**Stage 1: Preprocessing the data.**

Our first task was to extract the data by crawling the Google Play website and extracting some useful information from it. We saved this data in two files:

1. reviews.txt – contains a dictionary with applications names as keys and list of reviews as values.
2. info.txt – contains two lists. The first one contains the applications names and the second the popular tokens that appear in all the applications reviews.

In the code -

We have a preprocessing module that is responsible for creating the mentioned files. It is done by running two other modules:

1. crawler.py – crawling the website in order to extract the data.
2. topic\_extractor.py – given the data, it finds the popular tokens in it.

*All the code files for this level can be found in the 'preprocessing\_step' folder and the files that were created can be found in the 'files' folder.*

**Stage 2: Manual Processing.**

The work at this stage was done manually.   
  
We received the popular tokens list from the applications reviews from the previous stage, removed stop words and punctuations from it, and kept only words that are nouns or adjectives.

From this list we tried to figure out which words are the most useful for extracting info about the applications problems. We had words such as: "game", "play" and "coins" that couldn't help us figure out nothing about what the player liked or didn't liked in the application. In contrary, we had words like "time", "ads" and "money" that were more informative (see remark num. 2 below).

We chose six main topics and for each topic we created a list of relative words and saved them in a new file:

* info\_manual.txt – contains a dictionary that we created manually, where each topic name is the key and its value is a list of words that are related to the topic.

*The new file can be found in the 'files' folder.*

**Stage 3: Data analysis.**

At this stage the user can choose one application from a given list. For the chosen application, we go over the application's reviews and extract all the informative trigrams from it. For each trigram, we decide what its sentiment and if it's negative – we save it in a list.

At the next step, we go over the list of the negative trigrams and check for each topic (from the list we created in the previous stage) how many trigrams are referring to this topic and create a graph based on that info.

In the code –

We have a manager module which responsible for creating the mentioned graph for the chosen application. This is done by running other modules:

1. reviews\_extraction.py – extracts the reviews for the application from the file that was created in the first stage.
2. Info\_extraction.py – extracts the informative phrases as trigrams.
3. sentiment\_analyzer.py – analyzes a phrase (trigram in our case) and determine if it’s a negative trigram.
4. result\_analyzer.py – plot the analysis results in graph for the given application.

*All the code files for this stage can be found in the 'analyzing\_step' folder, and the graphs can be found in the 'Graphs' folder.*

Important remarks:

1. The popular tokens were taken from all of the applications reviews and not per application.
2. In the output of the first stage, we received a list of words. In this list, we mentioned that some of the words were informative; they couldn't help us determine what is the problematic topic.
3. We mostly used python 'nltk' package:
   * To extract the useful words from the reviews.
   * To determine the trigram's sentiments.

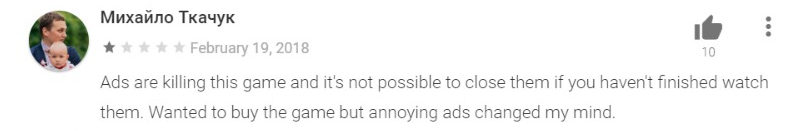
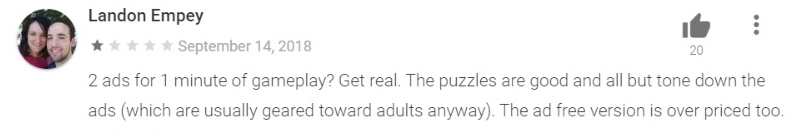
**Experiment**

* Evaluation Criteria: We measured the success of the project by a survey. The participants read the reviews of the applications and scored the problematic topics according to the reviews (The topics which selected in the first stage of the program). Afterwards we compared the participants decisions with the graphs obtained by running our program.
* Setup: We chose 6 applications from Google Play website that have different problematic topic. For each application, 3 participants were instructed to read all of its reviews and to select the topics that were problematic in the application from the following topics: Cost, UX, Ads, Appeal, Bug. The participants' had to rate each topic between 0 to 10.
* Results: We noticed that the results were similar in both the manual experiment and by running our program. The participants referred to the review's context and tone while the program analyzes the text by its words' sentiments. Overall, we could determine that the program has achieved good results. In the visualization section, we will present some of the algorithm's outputs and later we will discuss its impediments.
* Visualization: In the next pages, we show a few examples for the program results compared to the experiment results. In every example, the left figure represents the program output while the right figure represents the experiment result. We also added some example reviews for each application.

For the program output we calculated how many negative trigrams referred to each topic and divided it by the sum of all the negative trigrams. For the experiment result, we calculated the average between the participants rating and divided it by the sum of all the averaged ratings for each topic.

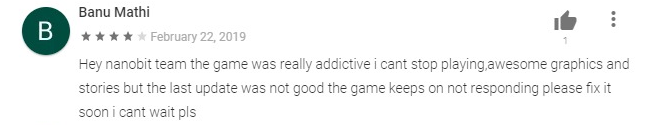
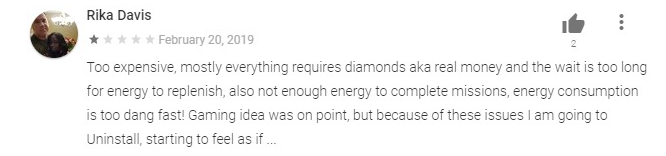
1. "Baby puzzle":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Baby_puzzles_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Baby_puzzles_manual_plot.png |



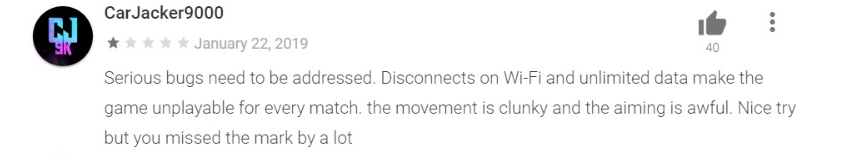
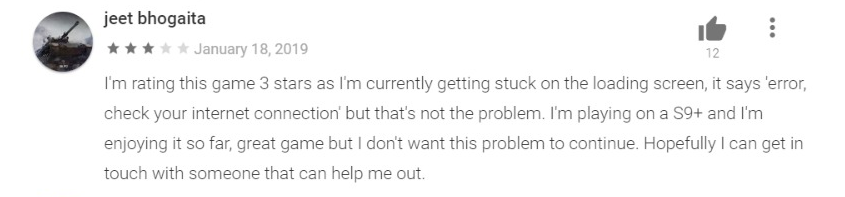
1. "Hollywood story":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Hollywood_Story_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Hollywood_Story_manual_plot.png |



1. "Standoff 2":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Standoff_2_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Standoff_2_manual_plot.png |



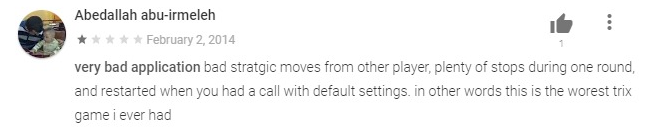
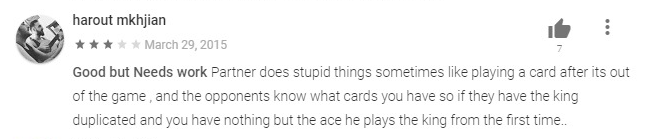
1. "Street racing 3d":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Street_Racing_3D_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Street_Racing_3D_manual_plot.png |



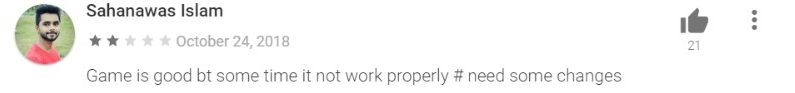
1. "Trix":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Trix_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Trix_manual_plot.png |



1. "Street chaser":

|  |  |
| --- | --- |
|  |  |
| C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\Street_Chaser_plot.png | C:\Users\Gal Turgeman\Desktop\Gal\שנה ד'\מחט בערימת דאטה\project\ReviewAnalyzer\Graphs\CompareResults\Street_Chaser_manual_plot.png |



* Impediments:

1. Part of the reviews are application specific and cannot use for general analysis. Adding this reviews words would cause overfitting and may not fit to another applications. The problem is that the algorithm wouldn't catch these words as negative but the human participant would recognize it as issue that needs to be fixed. For example: In the 'Standoff 2' game, some reviewers asked to add more guns' models to the game. The algorithm ignored it but the participants marked it as UX issue (as you can see in figure 3).
2. The applications we chose in this part were top rated, thus most of their reviews were positive. The graphs represent the negative reviews' distribution for the topics above. That may be the reason why some of the program's graph's columns higher than the participants' graph; the participants saw these reviews as insignificant.
3. The participants could capture a slang or double meaning in the reviewer's words while the algorithm treats them as written, without a hidden meaning, or simply ignore them.

* Future work:

Some of the impediments could be address in various ways. Since we haven't tried them, we could not guarantee they would work.

1. Process n-gram when n is greater than 3 – would require more resources, more processing and would take a longer time to run.

It might put the phrases in the right context and find more info. However, it might miss the real issue and focus in the wrong words in the phrases.

1. Auto-correct the reviews before running our algorithm. Then we would not miss phrases as "game is boringgg".
2. Create a slang or popular phrases dictionary in order to detect sarcasm or multiword expressions.

**Conclusions:**

By collecting applications reviews and analyzing them, we are now able to find what are the popular problems across an applications’ reviews. The analysis was done by splitting the reviews to trigrams and check if the sentiment of each trigram is positive or negative. We used the negative trigrams to find the main problems in the application, out of the problems that we defined.

In the experiment that we introduced earlier we got a similar rate for the problems topics between our program and the survey. We also conclude from this experiment that when the reviews focus on an application specific problem then the program miss this problem.