Analysis of Google Play Store Reviews

EECS 6414 Data Visualization Project
Midterm Presentation

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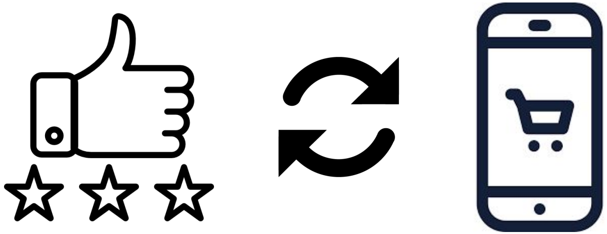
Motivation & Proposal

- We are hoping to gain numerous user insights about mobile apps using app reviews
- We would like to see how sentiment changes in relation to app updates
- We would like to understand how sentiment varies by app genre



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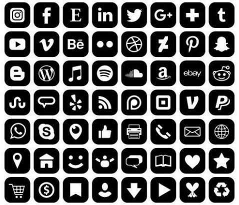
Our Data Set

App reviews on the Google Play Store



547 apps

8 million reviews

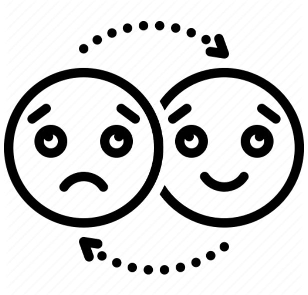
Several languages

Approach

Input data from CSV

10 GB in size

name
rating
author
title
comment
language
...



VADER library

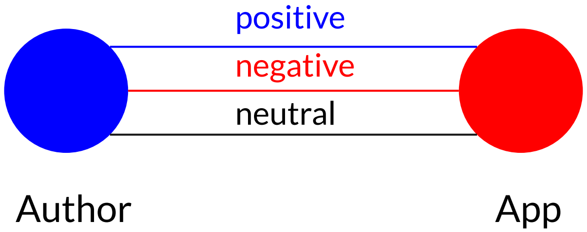
Progress So Far

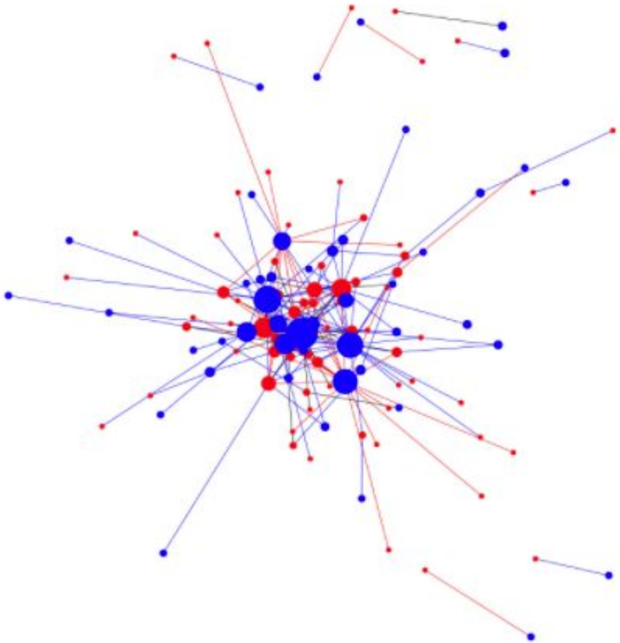
- Preprocessing Dataset (500+ lines of code)
- Scatter Date & Version of Apps
- Sentiment Analysis
- Identify Vertices & Edges
- Node Degree
- Network Density
- Top Apps & Authors by Degree
- Degree Distribution
- Time Series Analysis

In progress...

- Link prediction

Network





200 Authors

NetworkX
Network Analysis in Python

YORK U

Network Characteristics

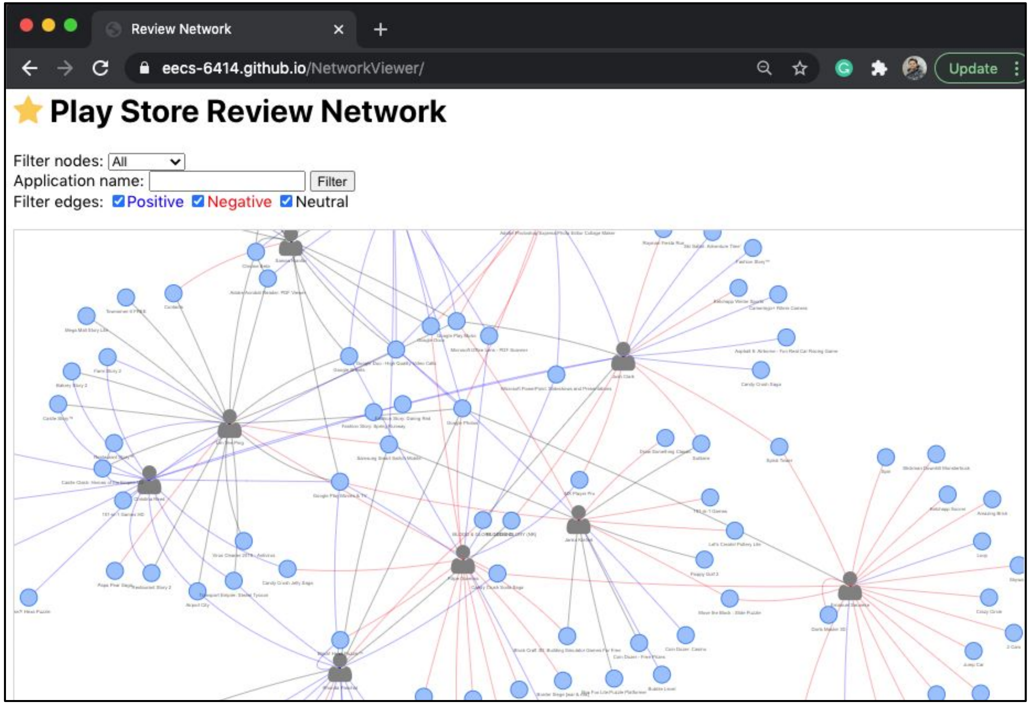
Number of nodes:	463,194 (512 apps + 462,682 authors)
Number of edges:	1,154,633
Average degree APP:	4,510
Average degree Author:	5 (considering only users with at least 2 reviews)

Top Apps & Authors by Degrees

Top 10 Apps	Edges
Google Photos	178753
Google Duo - High Quality Video Calls	119171
Candy Crush Soda Saga	64653
Google Play Music	59597
Candy Crush Saga	49710
Mini Militia - Doodle Army 2	44799
Candy Crush Jelly Saga	27571
Castle Clash: Heroes of the Empire US	25425
MX Player	24601
Google Docs	20269

Top 10 Authors	Edges
Lim Yen Ping	26
Emanuel Seuneke	22
Rhonda Paschal	22
Filipe Governa	20
Andri Untoro	19
Janko Kinčeš	18
Edgar Rojas	18
Saman Kianfar	18
Christina Reed	18
Josh Clark	17

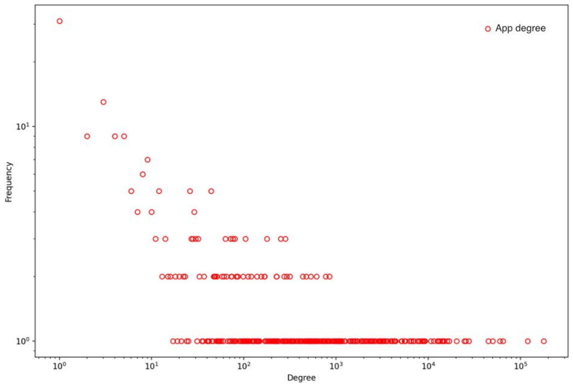
Online Network View

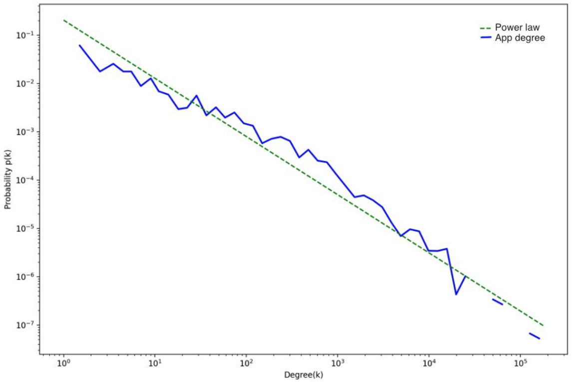


https://eecs-6414.github.io/NetworkViewer/

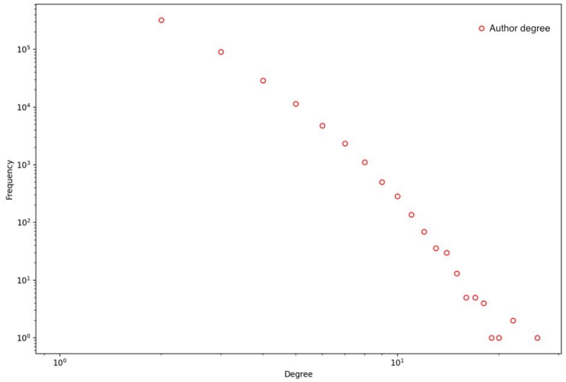
Degree Distribution

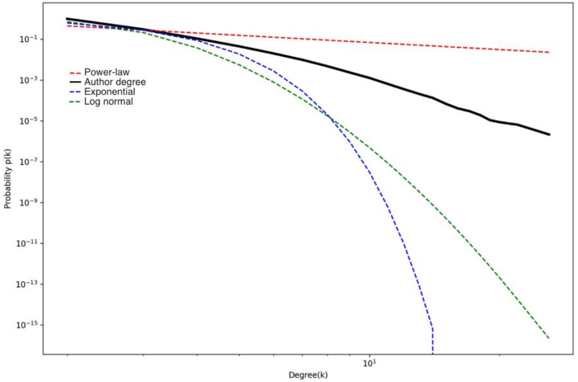
App





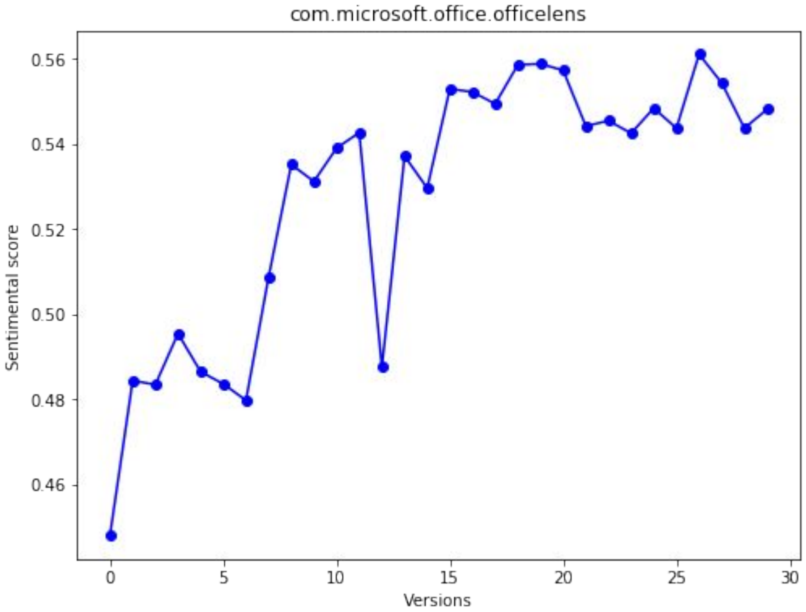
Author



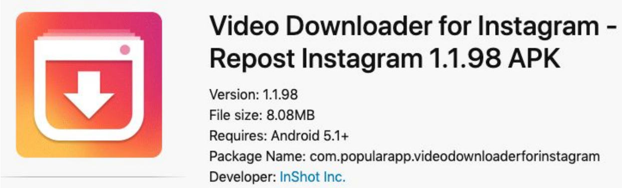


Time Series Analysis-Non Gaming apps

Reviews: 5,493



Time Series Analysis-Unpublished App



Reviews: 6,554

Insights from Time series Analysis

- In non-gaming apps, the downfall of user sentiment due to an update is 1.7 times higher than the rise of the user sentiment after an update.
- The impact of an update in gaming apps is nearly two times higher than the one observed with the non-gaming apps.
- The gaming apps are more well maintained and updated with respect to user sentiments than the non-gaming apps.
- The decreasing trend in the sentiment of unpublished apps leads to its removal from the Play Store.

Noted Limitations

- No guarantee for duplicated author's name
- Data set is almost 2 years old
- Data set is massive in size, so performing any analysis is time-consuming
    - We are using powerful AWS instances to run our analysis
- Limitations in the accuracy of the sentiment score
- Dealing with natural language is always a challenge

Concluding Remarks

- We are encouraged by our results thus far
- We still aim to do:
  - Clustering coefficient analysis
  - Community analysis
  - Link prediction / recommendation system based on sentiment
  - Explore more time series analysis

Questions?

https://eecs-6414.github.io/NetworkViewer/

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