High-level Design Logic

- App clustering
    - NLP topic modeling
        - The app descriptions contain important information about the app. I chose to use Non-negative Matrix Factorization (NMF) over Latent Dirichlet Allocation (LDA) since NMF works with a Tf-idf vectorizer that works well in reducing influence of common words. I preprocessed the descriptions by removing stop words, tokenizing, stemming, and Tf-idf vectorizing. Then, I fitted and transformed the descriptions with NMF. I used NMF on apps with and without descriptions. (use on app descriptions if there is any; otherwise use on app names). I then labeled each topic identified by NMF by looking at top words and apps in that topic.

    - Similarity distance matrix
        - The NLP topic modeling was completed purely on app information dataset. I'd like to leverage the much larger usage dataset and user behavior. Thus, I implemented a simplified collaborative filtering by calculating similarity distance matrix for app-user matrix (with average usage time as values). Then, I extracted the top 10 similar apps for every app. If the app did not have a label, I used the most common label among the top 10 similar apps as the label for the app. Finally, I merged the result with the NLP topic modeling result to complete app clustering.

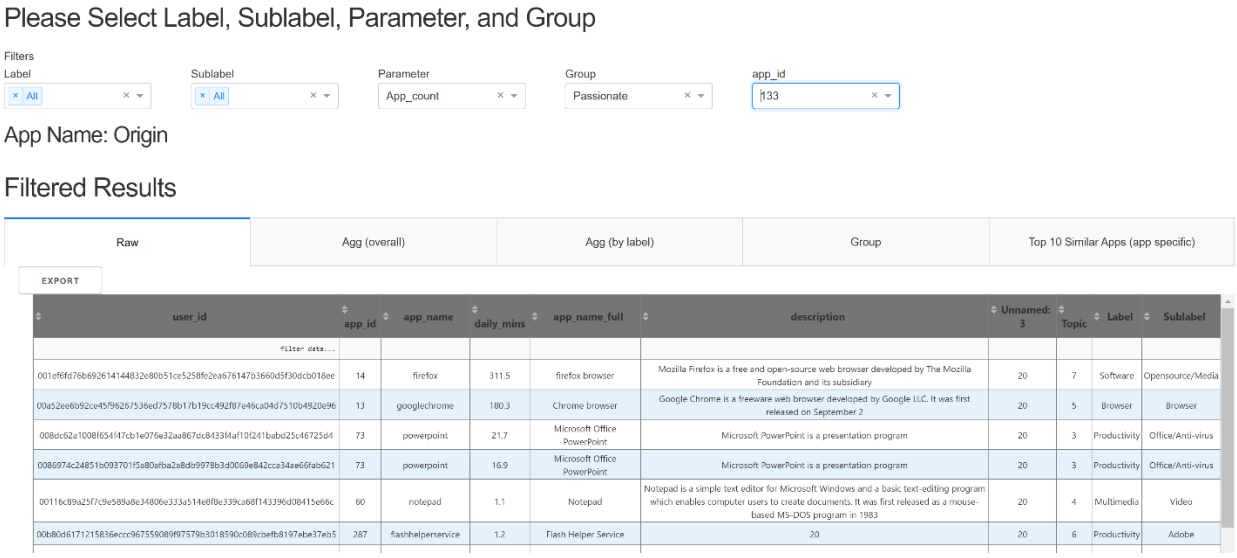
    - Unsupervised learning
        - I tried to cluster apps using unsupervised learning and considered adding app label on top of app usage time. I tried to use K-prototype clustering, but it takes a while to cluster. I then decided to simply filter the apps based on existing labels and then use a pipeline of normalization, principle component analysis, and KMeans to cluster.

- User clustering
    - Unsupervised learning
        - The same pipeline of normalization, PCA, and KMeans is applicable with user clustering. I just had to transpose the features. However, the cluster results were not ideal and not self-explanatory. Thus, I chose to use data manipulation to group users.

    - Data manipulation

- Leverage pandas dataframe and the .groupby() / pivot_table() method to extract user groups of interest. Since this process is manual and repetitive, I decided to write a simple plotly dash-based dashboard for easier control and visualization

- Result interpretation
  - Dashboard
    - As mentioned before, I wrote a plotly-dash-based dashboard for result visualization. The dashboard looks like the image below. User can select app label and sublabel to select one or more groups of app. Then, user can select the parameters interested (number of apps or daily time spent) and select interested group (passionate, above average, ordinary, or sleeper). The first four tabs correspond to this portion.
      - 'Raw' is raw data
      - 'Agg (overall)' is the overall aggregation regardless of parameter and group
      - 'Agg (by label)' is the overall aggregation with an additional labels field
      - 'Group' is the filtered user group based on parameter and group
    - The dashboard is also capable of showing the top 10 similar apps for any given app_id to help with extracting useful insights.



Code Design

- Modularity
    - The code was split into main.py and utils.py. In main.py, the code calls functions and user can specify parameters and execute the analysis. All functions are written in utils.py and can be modified without impacting the main execution much.
- Readability
    - Comments and docstrings for most functions.
    - Easy to understand function and variable names.
    - Fairly easy to understand code flow
- Scalability
    - Input files are pickle files for faster read for larger input data.

How to Use

- Package used
    - Package used in this project are pandas, numpy, matplotlib, sklearn, genism, nltk, and dash (for dashboard). The packages are specified in the requirements.txt file
- Main code
    - Main execution file is main.py. Parameters to specify are file names (app information, user app usage, and category look up table), topk (k most similar apps), NMF n_components
    - Functions are in utils.py
- Dashboard
    - Run group_dashboard.py. A local address will display (such as http://127.0.0.1:8050/). Click the link to get to the dashboards

Future Improvements

- K-prototype
    - Could potentially use K-prototype or other unsupervised clustering algorithm to further assist app or user clustering
- Deep learning
    - Could potentially use Keras and implement autoencoder or other clustering algorithm to further assist app or user clustering
- Data cleaning

    - The current method did not perform too much data cleaning. I made the assumption that each record in the user_app_usage data is unique, even if the daily_mins and app_id are the same.
- NLP topic modeling and similarity distance matrix integration
    - The current method simply appends results together. Could potentially try to replace based on common topic percentages or other metrics
    - Current similarity distance matrix method is a simple implementation of collaborative filtering. Could add more complexity to it.
- Try-catch / unit test
    - Could potentially add try-catch-finally block and utilize unit test modules like pytest to make sure the code is robust enough
- OOD
    - Could further utilize OOD concepts such as defining customized classes for more modularity and easier collaboration