APAN 5205 Group 5: Final Report

Research Question:

This study aimed to describe and examine the different factors' influence on rating scores by answering the following questions:

1. Based on the review content, what's users' overall attitude towards Tinder? What are the specific reasons that make users have a positive/negative attitude?
    - The number of users is increasing year by year, but the rating is decreasing. Therefore, we want to know whether the overall attitude analysis of users towards Tinder is positive or negative by using sentiment analysis, and we will test this through subsequent data analysis of Tinder user reviews.
    - Once we have identified the overall trends in user reviews, we want to continue to explore the reasons behind them. Specifically, we will have a look at the distribution of different review scores and use overall sentiment analysis to explore the keywords of review ratings that are higher than 3 versus the review ratings that are lower than 3. We will then dive deep into these keywords to see if there's a common feature of review ratings that are higher and lower than 3's keywords.
2. How are the ratings of Tinder changing over different versions? If the rating scores are increasing/declining shapely over one version, why is that happening?
    - Because we have data from 2016 to 2023, and this includes 13 versions in total. We want to know how the overall rating changes from year to year in the time dimension, how much it changes, whether there has been some sudden rise or fall, and whether we can find some similar patterns.
3. How are review contents related to users' rating scores of the Tinder app? We will use predictive models based
 on text features.

Data & Suitability:

Tinder is a dating app that connects users based on their geographical proximity. It created (and patented) the swipe interface, which allows users to swipe right to 'like' or left to 'pass'. If two users like each other, it's a match, and they can chat through the app.
This dataset belongs to the app Tinder available on the Google Play Store. The Dataset mostly has user reviews and various comments made by the users. The raw dataset includes 553021 observations from 2013/7/9 to 2023/2/24 with 10 variables. The cleaned dataset includes 19552 observations with 13 variables. Our research will focus on the user comment(content) and the score of this dataset to explore the overall rating of the app by users in a specific time period. Here's a brief description of each variable.

Our research problem is to know the overall score of people towards the tinder app in the google play store because of different factors. This dataset has the user name, image, review content, review time, score, app version, and so on. We can use such factors to study what has an impact on the rating score. For example, we can use words in the review content to study the relationship between content and the score. The content will allow us to have insights into why people give such rating scores and comments, which can be analyzed by NLP techniques to identify the common pros or cons of Tinder. Also, the number of thumbs up will reflect the overall attitudes of people towards the review content. Reviews with a higher number of thumbs up may have a greater impact on how users view the app. Furthermore, the different versions and review times will influence the review score. From these variables, we can know more about what makes the application receive 1-star and 5-star.

Reason of Technique Used:

1. Sentiment Analysis

Sentiment analysis is a technique that is widely used to extract and identify the underlying emotions or sentiments expressed in a text. It is a valuable tool for gaining insight into how people feel about a particular product or service. Therefore it is useful in analyzing user reviews of Tinder. When people write reviews of Tinder, they may express positive, negative, or neutral sentiments about the app. By performing sentiment analysis on these reviews, we can get a better understanding of the overall attitude towards the app among its users. For example, if the majority of reviews express positive sentiments about Tinder, it suggests that users are generally satisfied with the app and find it helpful for meeting new people. On the other hand, if the majority of reviews express negative sentiments, it suggests that users may have issues with the app, such as problems with the user interface or a lack of matches.

In the project, we first conducted an overall analysis of the review text to determine whether users expressed positive or negative sentiments. Next, we delved deeper into the specific attitudes expressed in reviews, such as anger, joy, satisfaction, disappointment, and others. Lastly, we computed a sentiment score for each user's review and explored whether there was a correlation between the sentiment score and the review score.

By analyzing the sentiment of user reviews, we can identify areas for improvement and suggest possible changes to Tinder to better meet the needs and expectations of its users. Additionally, sentiment analysis reflects the brand sentiment of Tinder, which is an important reference for Tinder to make adjustments to their marketing or customer service strategies based on customer feedback.

2. Predictive Analysis

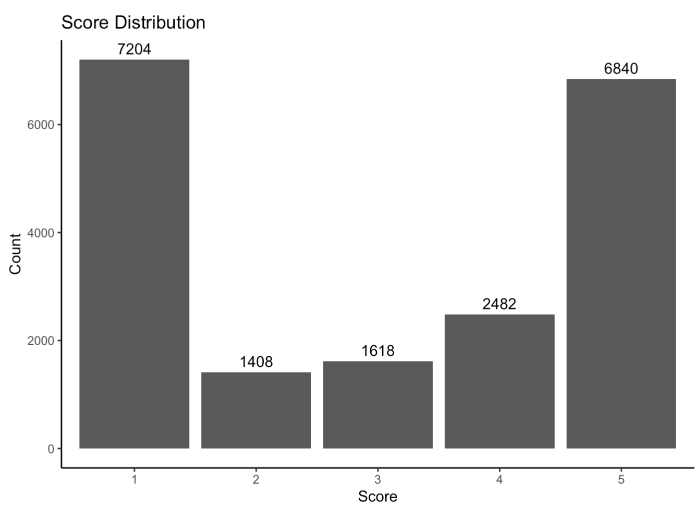
We also build predictive models based on Tinder user reviews and scores. We extract individual words from review text as features and build tree and regression models to predict review scores. By analyzing the words that are most strongly associated with high review scores, we can identify the features and aspects of Tinder that stack the company up against other competitors and are most attractive to users, thus recommending Tinder to focus on improving them to increase user satisfaction.

Furthermore, we can use the regression model to predict future review scores and user satisfaction, which provide business insights on changes in user sentiment and urge Tinder to proactively address potential issues before they become major problems. By tracking changes in review scores and associated text features over time, we can assess the impact of changes and updates to the app and help Tinder make data-driven decisions about future updates.

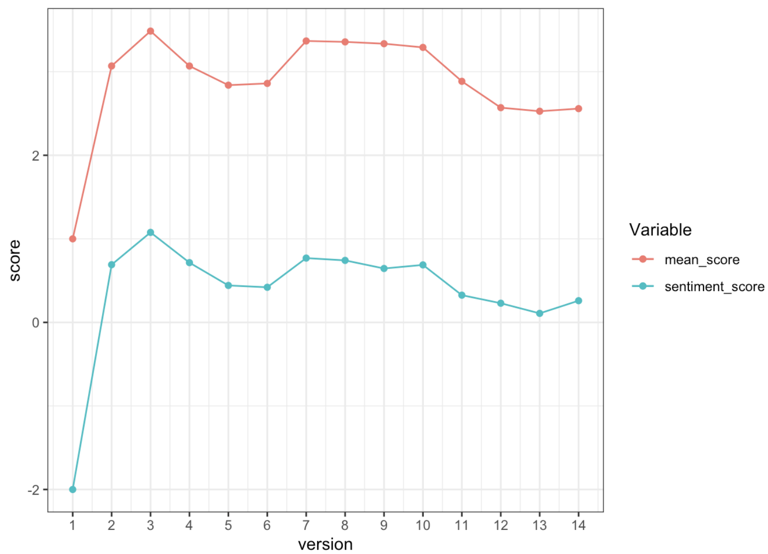
3. Topic Model

Topic modeling is a branch of Machine Learning applied to NLP, which is used to identify the latent topics within a large corpus of text data, unsupervised. In the topic model, you don't have to read through all the comments, you can still get a sense of what people are talking about from millions of comments. By using topic modeling techniques, we can identify patterns and themes in the reviews that might not be immediately apparent through manual reading or analysis. In our project, we used Latent Dirichlet Allocation (LDA), probably the most widely used topic modeling algorithm to build topic models based on version and rating scores .

As we can see from the plot below, there are about 10,000 reviews from users who rate Tinder below 3. It was difficult for us to manually read every single comment and get some insights from these comments. So we decided to use topic models to help us identify some common reasons or questions as to why they rated Tinder low. This can provide valuable insights for Tinder's developers to improve the user experience and address these user concerns. By identifying topics that are frequently mentioned in low-rated reviews, developers can prioritize the most pressing issues, enabling Tinder to improve the overall rating of the app.



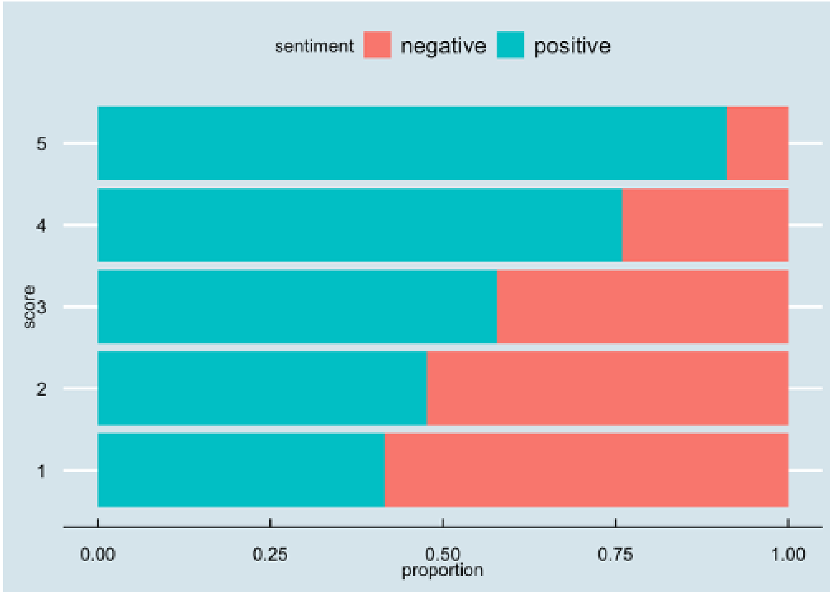
After conducting sentiment analysis, we discovered that updates to certain versions of Tinder had an impact on both the rating score and sentiment score. Then, we assume that different versions may influence users' opinions or needs. Analyzing topic models for different versions of Tinder can help us to identify changes in user opinions or needs. Also, it can help Tinder developers to understand how user reviews have changed across versions and what needs to be improved in future versions of the application. Moreover, analyzing topics by version can help identify any specific issues or improvements associated with a particular version.



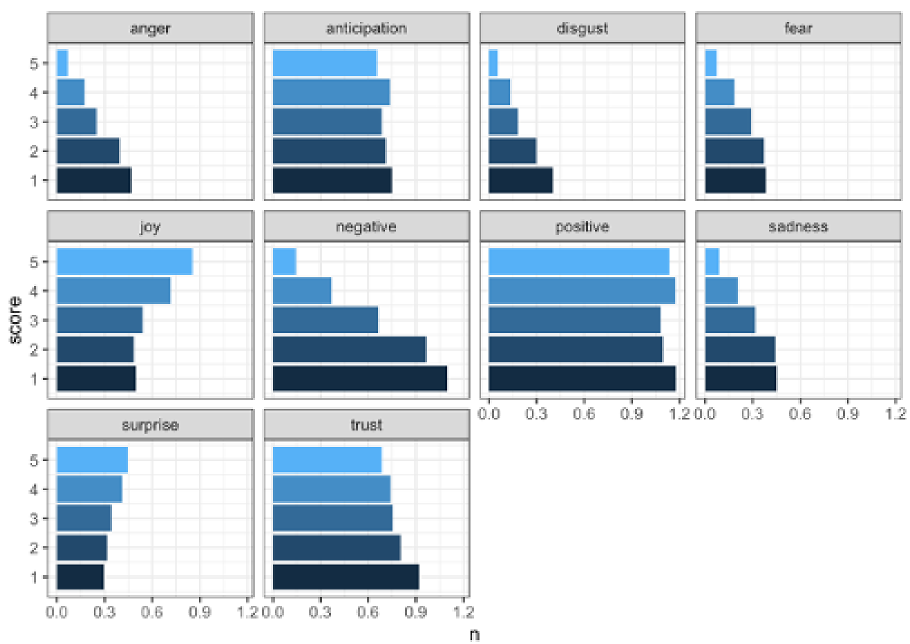
Results:

1. Overall Sentiment Analysis

By analyzing the data using the "bing" lexicons, we can see that there are 11756 negative words in the reviews that are being recognized with a proportion of 0.397. There are 17867 positive words in the reviews that are being recognized with a proportion of 0.603. Also, after looking at the proportion of positive and negative words for each rating, we can see that the proportion of positive words grows as the rating increases.



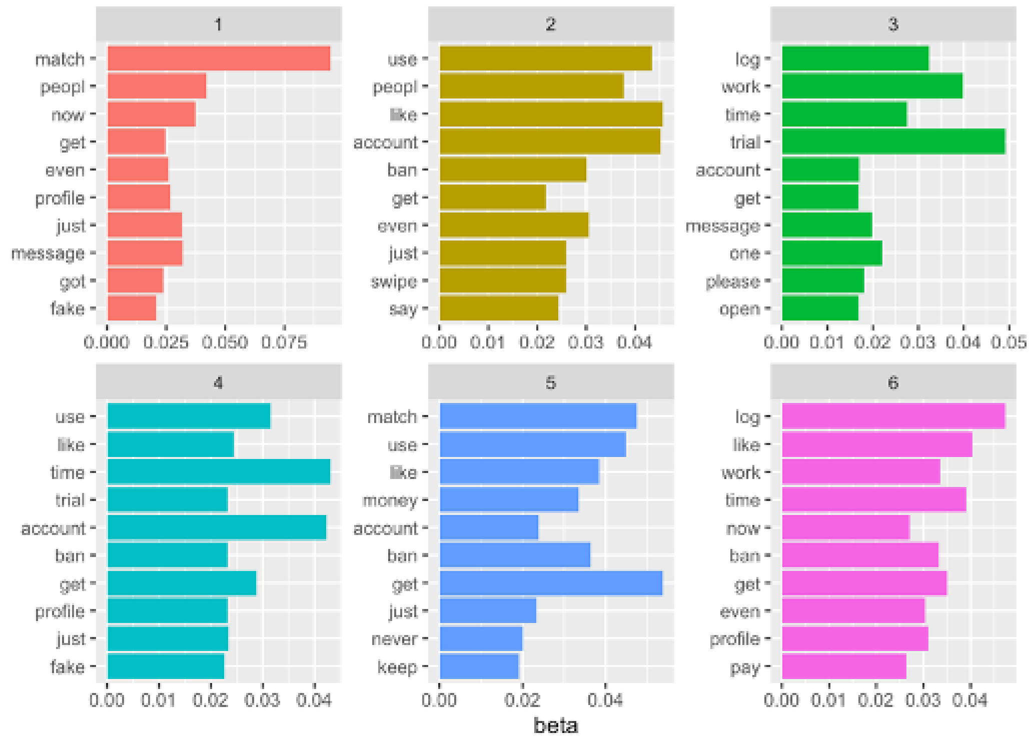
By analyzing the data using the “nrc” emotion lexicons, we can see that the top five emotions among all reviews are: positive, trust, anticipation, negative, and joy. Also, the correlation between emotions and rating are mostly significant. We can see that from the graph, the positive emotion words increase as score increases, and negative emotion words increase as score decreases.



By analyzing the data using the “afinn” lexicons, we can see that the minimum score is -5, the maximum score is 5, the median score is 1, and the average score is 0.891.

2. Topic Model Analysis

We first use the Topic Model to examine different rating scores. We separated the data into three groups: rating scores above 3, rating scores equal 3, and rating scores under 3. We specifically look at the data with scores under 3 for analyzing the common features of low ratings. The following graph shows the beta values:



Topic 1 is related to issues with fake accounts, bans, and deletions. Topic 2 is related to the technical aspects of the app, including logins, updates, and crashes.Topic 3 is related to user interactions, including matches, profiles, and messaging. Topic 4 is related to issues with payments, trials, and subscriptions. Topic 5 is also related to user interactions, with terms like “people”, “matching”, and “accounts” being prominent. Topic 6 is related to general user experience issues, including time wasted, money spent, and work required.

Moreover, we apply Topic Model to user rating scores and Sentiment scores of Different Versions. By looking at the number of reviews by version, we can see that version 4 has the most reviews of 3296 reviews. Version 3 has the highest average rating score of 3.49 and Version 13 has the lowest average rating score of 2.53.
Then we want to dive deep and find out what happens in version 13 that leads to the low average rating score. After applying Topic Model to version 13. We can see that Topic 1 contains user complaints or concerns, with terms like "something", "wrong". Topic 2 expresses users’ positive experiences with the app, with terms like "great", "good", "awesome". Topic 3 is related to

technical issues related to logging in or using the app, with terms like "log", "account", "login". Topic 4 talks about matches and finding people on the app, with terms like "matches", "get", "love". Topic 5 is related to user behavior or actions on the app, with terms like "just", "like", "try". Topic 6 expresses users' negative experiences or suspicions about fake accounts, with terms like "fake", "many", "awesome".

Conclusion:

1. One of the positive aspects of the app is that it can lead to a "nice match," where users find someone they are interested in dating or forming a relationship with. This can be a great way for people to meet new individuals who they may not have otherwise met.
2. From the negative aspect, the top-ranked negative parts of this app are the prevalence of fake accounts, which can lead to spam and unwanted messages for users. Additionally, users may experience bans or deletions of their accounts, which can be frustrating and lead to a loss of valuable connections. Technical issues such as app crashes can also be a significant problem, as they can interrupt user experiences and lead to dissatisfaction with the app.
3. Some users have reported feeling unsafe on the app, especially when meeting up with matches in person.
4. Many users have complained about poor customer support from Tinder.

Recommendations:

1. Continuous optimization of the matching algorithm

To maintain its advantage in the competitive dating app market, Tinder must continue to focus on its matching algorithms. The app's algorithms are the backbone of its match-making feature and are designed to suggest potential matches based on user's preferences and behavior on the app. To keep this advantage, Tinder must continually collect and analyze user data to improve the accuracy and relevance of its match suggestions.

Tinder already has a collection of basic information about users and their general preferences, such as age, location, interests, and dating goals. We believe that Tinder can also track and further analyze user behavior on the app, such as swiping patterns, messaging history, and time spent on the app. One example is analyzing a user's swiping patterns to better understand their preferences. For example, if a user consistently swipes left (rejects) on potential matches that meet certain criteria, such as a certain age range or location, this could be an indication that they are not interested in those attributes. Conversely, if a user consistently swipes right (likes) on potential matches that share certain characteristics, such as a similar education level or profession, this could be an indication of a strong preference for those attributes. By analyzing these patterns, Tinder can optimize its matching algorithms to provide more accurate and relevant match suggestions that better align with a user's preferences.

Another example is analyzing a user's messaging history to better understand their communication style and interests. For example, if a user frequently messages matches certain topics or interests, such as travel or food, this could be an indication of their hobbies or passions. By analyzing these patterns, Tinder can suggest matches with similar interests or topics of conversation, leading to more engaging and meaningful interactions.

By leveraging this data, Tinder can optimize its algorithms to provide more accurate and personalized match suggestions that better meet the needs and preferences of its users. In addition, Tinder could also explore using AI-powered algorithms to further refine its matching algorithms. These algorithms could analyze user data in real time, adjusting match suggestions based on user behavior and feedback. By continually refining its matching algorithms and leveraging new technologies, Tinder can maintain its competitive advantage and continue to provide users with a unique and valuable dating experience.

In terms of the metrics of the improved matching algorithms, Tinder could track the match success rate, user engagement, time to match. For example, the user engagement metric measures how frequently users are interacting with the app, such as by swiping, messaging, or updating their profile. The "Time to match" metric measures the amount of time it takes for a user to receive a match suggestion after joining the app or updating their preferences. By tracking these metrics over time, Tinder can determine whether its improved matching algorithms are leading to increased user satisfaction and retention.

2. Reduce fake profiles and bots

Fake accounts, bans, and deletions are significant issues that can undermine user trust and satisfaction with Tinder. To address these issues, Tinder should focus on several key strategies.

First, Tinder should invest in advanced fraud detection and prevention technologies to identify and block fake accounts. This could include implementing multi-factor authentication and verification processes to ensure that all users are genuine. The fake account detection rate can be used as a metric to measure the percentage of fake accounts that are successfully detected and prevented by Tinder's fraud detection and prevention technologies.

Additionally, Tinder could leverage user reporting and feedback mechanisms to flag potentially fraudulent activity and take swift action to address it. Besides, Tinder should provide robust user support and appeal mechanisms for users who have been banned or had their accounts deleted. This could include providing clear information on the reasons for the ban or deletion, as well as opportunities for users to appeal the decision and provide additional information or evidence to support their case. Tinder should also ensure that its support team is responsive and helpful, providing users with clear guidance and support throughout the process.

3. Enhance safety features

Feeling unsafe on the app is a serious concern for users of Tinder, particularly when it comes to meeting up with matches in person.

Tinder could implement robust safety features. For example, this could include features such as video verification, background checks, and user feedback mechanisms to help users assess the safety of potential matches. Additionally, Tinder could provide in-app safety tips and advice to users to help them make informed decisions about meeting up with matches in person.

Besides, Tinder could leverage technology to improve safety. For example, this could include implementing real-time location tracking and sharing features to help users feel more secure when meeting up with matches in person. Additionally, Tinder could use AI-powered algorithms to analyze user behavior and detect any potentially unsafe patterns or behavior.

References:

1. Wiwad, Dylan. "Why Are Tinder App Store Ratings Declining?" http://dylanwiwad.com/project/tinder_ratings/#:~:text=Between%202013%20and%202022%20Tinder,5)%20as%20of%20 February%202022

2. Karl, Jessica. "Tinder Is Not Exactly Catching Fire These Days." *Bloomberg*, 10 Jan. 2023, www.bloomberg.com/opinion/articles/2023-01-10/tinder-dating-app-is-losing-users-steadily#:~:text=Tinder%20Is%20Not%20Exactly%20Catching,reputation%2C%20but%20it's%20losing%20users.

3. Iqbal, Mansoor. "Tinder Revenue and Usage Statistics (2023)." *Business of Apps*, 1 Feb. 2023, www.businessofapps.com/data/tinder-statistics/.

4. Li, S.-T., Pham, T.-T., & Chuang, H.-C. (2018, June 18). *Do reviewers' words affect predicting their helpfulness ratings? locating helpful reviewers by linguistics styles*. Information & Management. Retrieved March 2, 2023, from https://www.sciencedirect.com/science/article/abs/pii/S0378720618302428

5. Pagano, D., & Maalej, W. (2013). User feedback in the appstore: An empirical study. In 2013 21st IEEE International Requirements Engineering Conference (RE) (pp. 125-134). Rio de Janeiro, Brazil. Retrieved March 2, 2023 from https://doi.org/10.1109/RE.2013.6636712