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December 11, 2020

Sentiment and Emotion Analysis for Ridesharing Companies – *Uber VS. Lyft*

GEN BUS 760 Data Technology for Business Analytics

2020 Fall – Final Project

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A. Introduction

Ridesharing has exploded in popularity in recent years. [1]According to the statistics from Statista, the global ride-sharing market is expected to grow to by more than 50 percent between 2020 and 2021. The market value is expected to amount to around 117 billion U.S. dollars in 2021. To gain a competitive edge in the marketplace, ridesharing companies should tailor their services to the real needs of customers. Feedback and reviews of customer experiences are important for business success. One way of delivering better customer experience is to conduct sentiment and emotion analysis on social media and their app reviews.

The purpose of this project is to detect "Tweets" and "Apple App Store app review" sentiments for the Top 2 ridesharing companies in the United States – Uber and Lyft. Company information is shown below.

Ticker	Company Name	Website
UBER	**Uber Technologies, Inc.**	http://www.uber.com
LYFT	**Lyft, Inc.**	http://www.lyft.com

The project is aimed to answer the following questions:

1. What are recent customer sentiment and emotional responses for the companies?
2. How could companies improve their products and services based on customer feedback?
3. Would customer sentiment influence the companies' stock price (the selected indicator for financial results)?

In the project, tweets containing the names of the companies - "Uber" and "Lyft" - and Apple App Store "Uber" and "Lyft" app ratings and reviews were used to evaluate the potential financial impact (stock price) and provide suggestions for improvements.

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[1] "Ride-sharing market size worldwide in 2020 and 2021 – Statista."
https://www.statista.com/statistics/1155981/ride-sharing-market-size-worldwide/
Accessed 10 December, 2020.

B. Data Collection and Methodology

a. **Tweets**: Both Python and R were used to collect and analyze tweet data.
   i. Python package Tweepy was used to get the tweets containing the keywords "Uber" and "Lyft", and TextBlob package was used to analyze the sentiment polarity of tweet text. For "Uber", 176,954 tweets created from Nov. 29 to Dec. 8, 2020 were collected, and 176, 842 tweets were used to analyze after cleaning the null value data. For "Lyft", 15,779 tweets created from Nov. 29 to Dec. 9, 2020 were collected, and 15,764 tweets were used to analyze after cleaning the null value data.
   ii. R package rtweet was used to get the tweets containing the keywords "Uber" and "Lyft", and syuzhet and wordcloud package were used to analyze emotions of tweet text and create word cloud. For "Uber", 18,000 tweets created from Dec. 8 to Dec. 9, 2020 were collected. For "Lyft", 10,120 tweets created from Nov. 30 to Dec. 9, 2020 were collected.

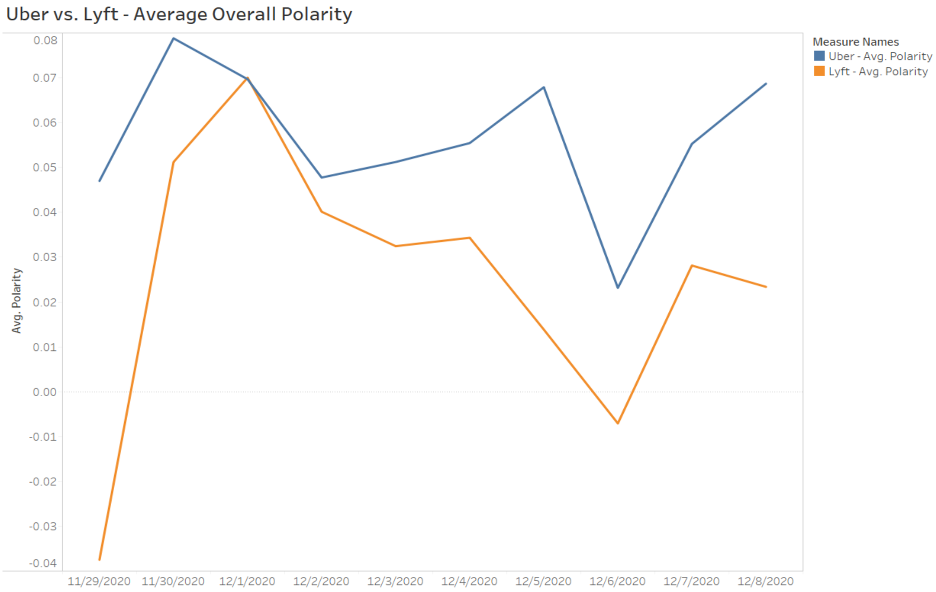
b. **App ratings and reviews**:
   i. R package itunesr was used to scrape and get the ratings and reviews of "Uber" and "Lyft" app in Apple App Store, and syuzhet and wordcloud package were used to analyze emotions of review text and create word cloud. 50 reviews for "Uber" created from Nov. 29 to Dec. 8, 2020 were collected from Apple App Store, and 180 reviews for "Lyft" created from Nov. 29 to Dec. 8, 2020 were collected from Apple App Store.

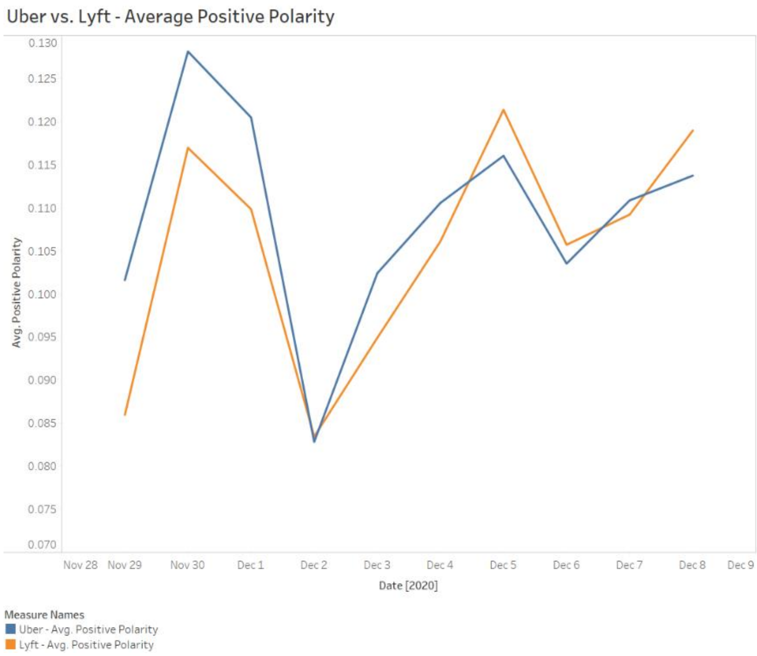
c. **Stock price**: Download stock historical data of each corresponding tweet day from Yahoo Finance (https://finance.yahoo.com/).

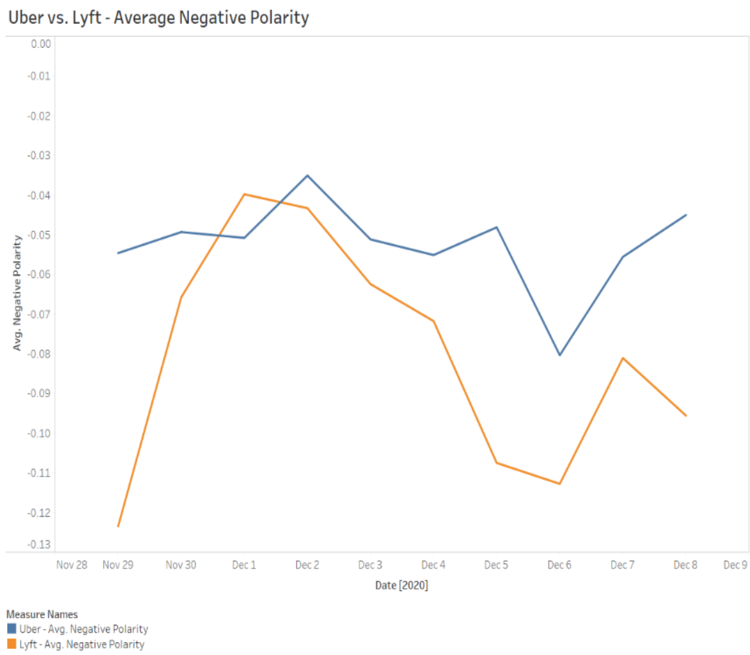
d. **Analysis methodology**:
   i. Run sentiment polarity analysis on tweet text using Python. Summarize the average overall, positive, and negative polarity scores (range from -1 to 1, 1 for the most positive, and -1 for the most negative) by days using Tableau and create polarity plots.
   ii. Run emotion analysis on tweet and review text using R to get emotions and valence from NRC dictionary. Emotions include anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. Positive and negative valence scores of review text were used to calculate net valence scores of each review (positive minus negative valence scores per review) for regression analysis.
   iii. Run regression analysis using Excel and data collected and summarized from Python, R, and Tableau. Use average polarity scores of tweets, average app ratings, and average net valence scores each review to see whether they impact on stock price.

C. Sentiment and Emotion Analysis

a. Tweets average polarity:



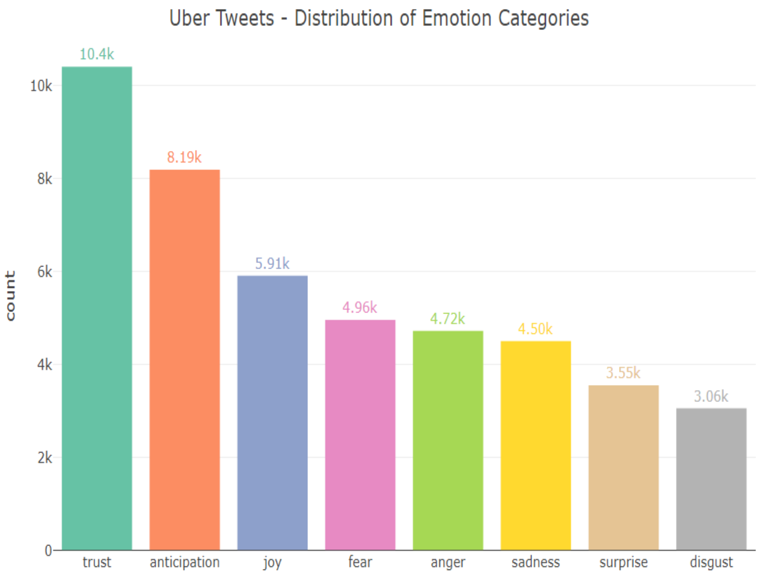


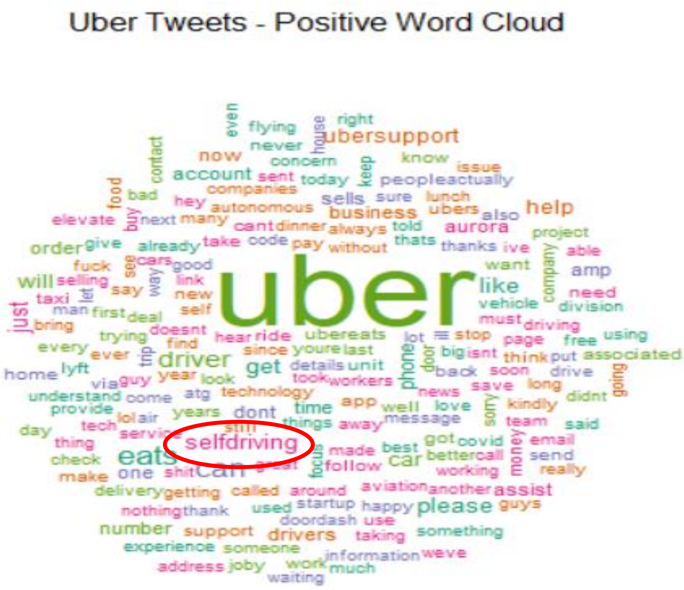


From the top average overall polarity plot, we can see that the average polarity scores of “Lyft” tweets are a bit lower than the average polarity scores of “Uber” tweets over the most recent 10 days (Nov. 29 to Dec. 8, 2020). However, they show similar customer sentiment trends over this period, including a similar bump on Nov.30 and a sharp decrease on Dec. 6. To figure out whether there exists both strong positive and negative tweets that were not be shown in the overall polarity trend, we separated positive and negative polarity of tweets. Both plots show that customers indeed have similar sentiment for Uber and Lyft, although Uber’s average polarity score is around 0.04 higher than Lyft’s.

b. Tweets emotions and word cloud:

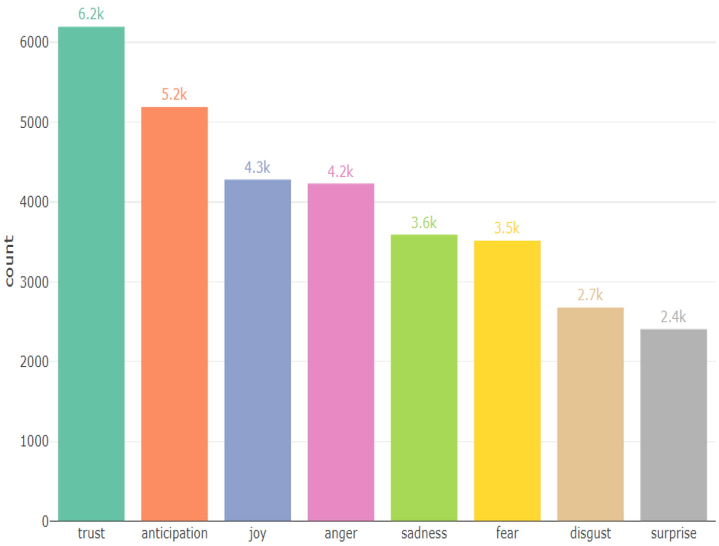
Uber





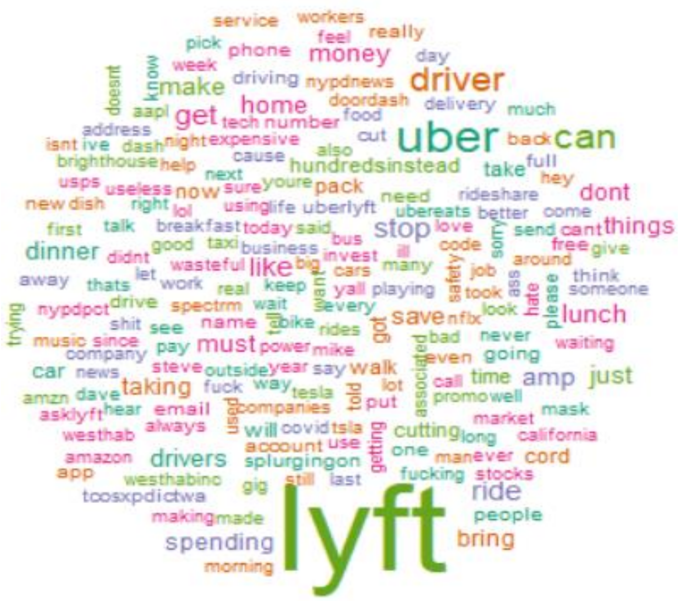
The above four plots show public feelings about Uber on Twitter. From the emotion distribution graph, we can see that the public has more positive feelings, such as trust, anticipation, and joy. The words such as “assist”, “help”, “support”, and “food” indicate that customers were quite satisfied with Uber support, and the food delivery service is also a competitive edge for uber, especially in the time of COVID-19. However, Uber also got a bunch of fear, anger, and sadness feedback. The words “driver”, “late”, and “cancel” imply that Uber might have to think about rewarding quality over quantity for its drivers. Another interesting thing found in word clouds is that the public has opposite views about the announcement that Uber is selling its autonomous vehicle unit, Advanced Technologies Group, to the self-driving startup Aurora on Dec. 7, 2020. One day after, Uber sold off its “flying taxi” business to electric aircraft developer Joby. Uber tried to cut off costs and focus more on core business to achieve profitability. Some people feared whether the decisions affect their interests. Overall, Twitter users still have positive feelings towards Uber.

Lyft Tweets - Distribution of Emotion Categories

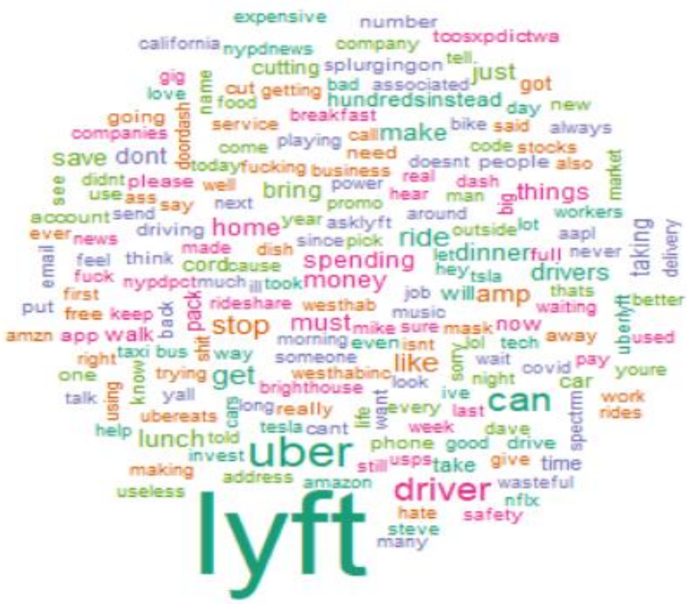


Lyft Tweets - Emotion Comparison Word Cloud

Lyft Tweets - Positive Word Cloud

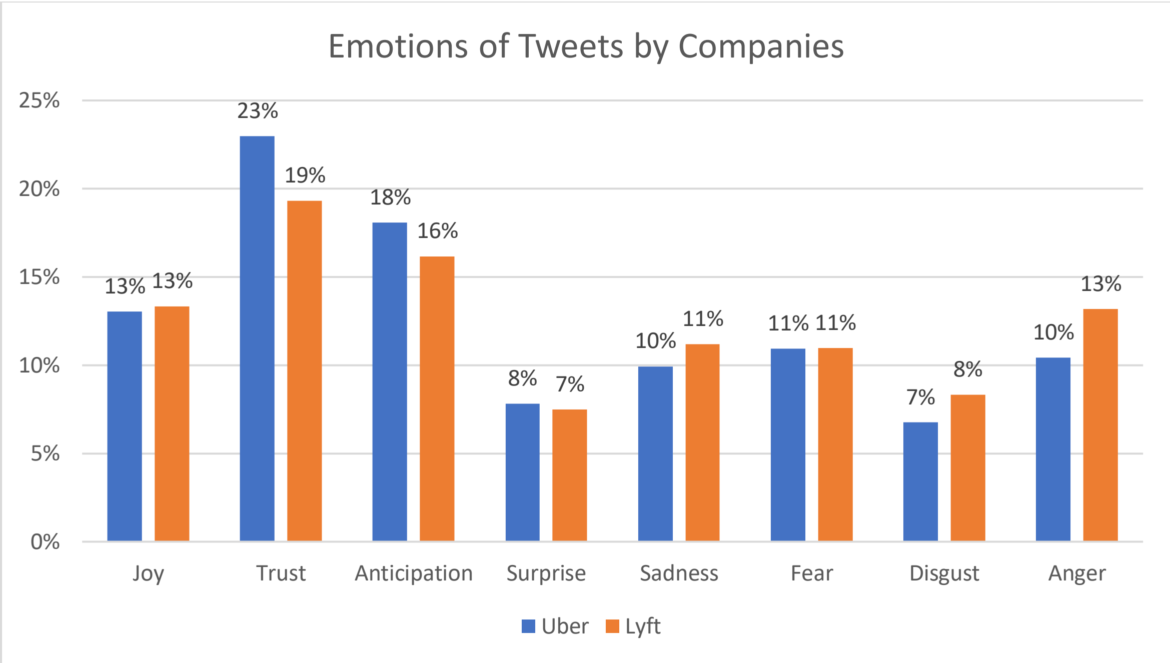


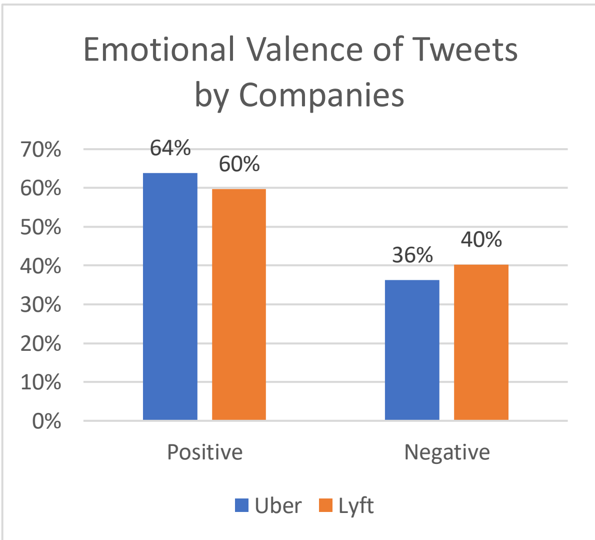
Lyft Tweets - Negative Word Cloud



Again, the above four plots show public feelings about Lyft on Twitter. Same as Uber, the public has more positive feelings, including trust, anticipation, and joy, for Lyft. The words such as “account”, “love”, “food”, and “share” may indicate that riders are happy with the service of sharing the location with trusted contacts while taking a ride. In October 2020, Lyft started to team up with Grubhub to provide food delivery to riders, which is also good news for customers. Yet, Lyft also received many anger, sadness, and fear comments. The words “driver”, “pandemic”, “safety”, and “California” suggest that riders fear to take Lyft during the pandemic, and Lyft may also need to seek the ways to ensure that drivers provide quality rides to riders. Overall, Lyft got more positive than negative sentiment from Twitter users.

Uber vs. lyft

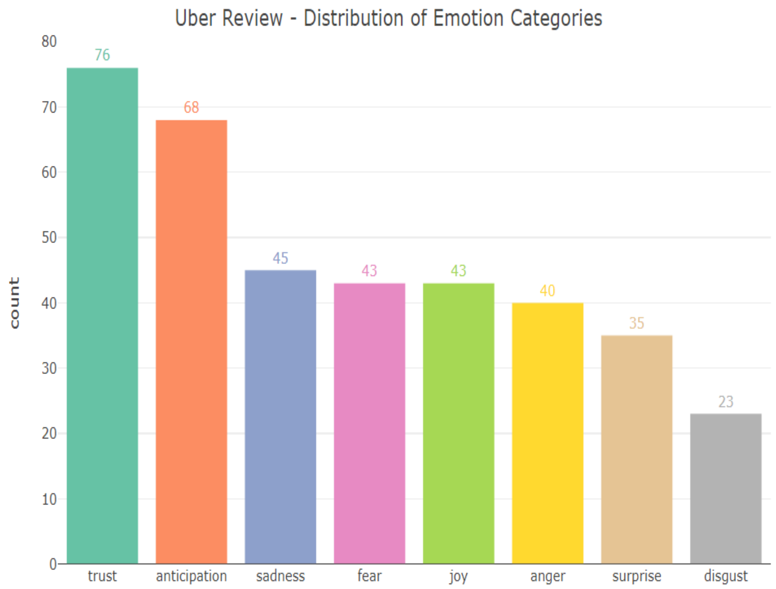




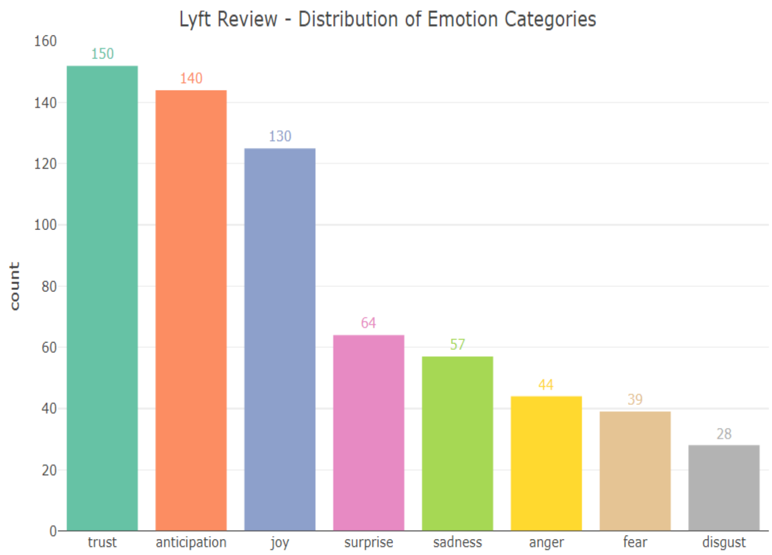
As we mentioned in the previous Uber and Lyft tweets emotion analysis, the two companies seem to get the similar emotion distribution across different feelings. The positive emotional valence of tweets for Uber and Lyft is both around 60% of its total valence scores.

c. App Store app ratings and reviews:

Uber

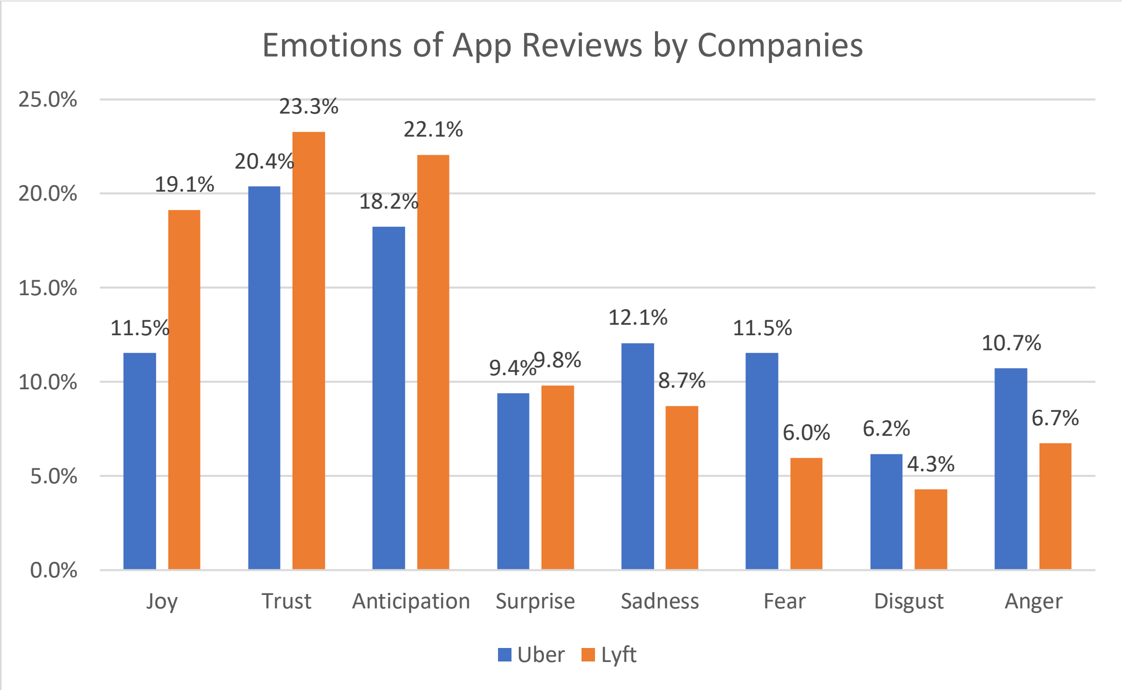


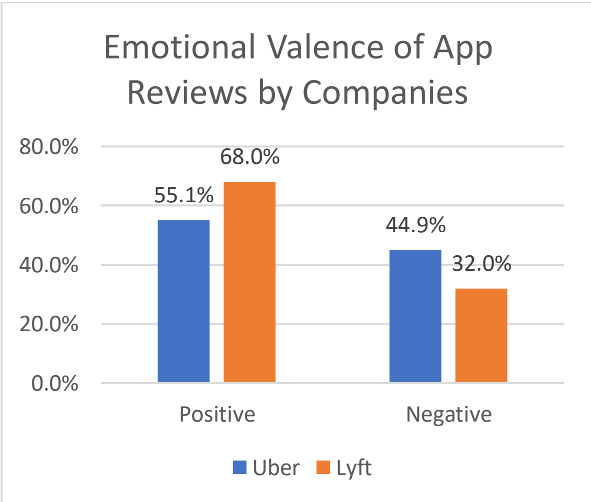
lyft



The above graphs show customer experience and feelings about Uber and Lyft from app reviews. Uber and Lyft also have higher trust and anticipation reviews as we see from tweets. The word “driver” appeared a lot in reviews, and Uber and Lyft both received positive and negative feedback about drivers. It implies that a “driver” is a crucial factor for riders’ ride experience with Uber and Lyft. The word clouds also indicate that customers care a lot about fraud, waiting time, and whether their trips are canceled since they expressed much stronger feelings towards these issues.

vs.



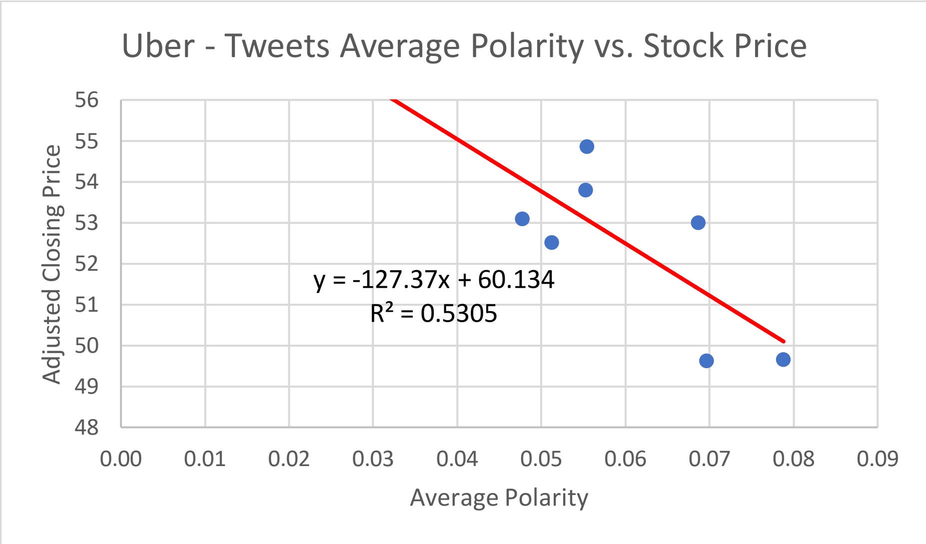


The above emotion comparison of app reviews shows different results from the tweets analysis. Lyft got higher ratio of positive reviews, while Uber got more sadness, fear, disgust, and anger feelings than Lyft. One possible reason might be that Uber riders tend to leave comments only when they are unsatisfied with Uber's services since the number of reviews is much lower than Lyft reviews, while the number of Uber tweets are much higher than Lyft Tweets.

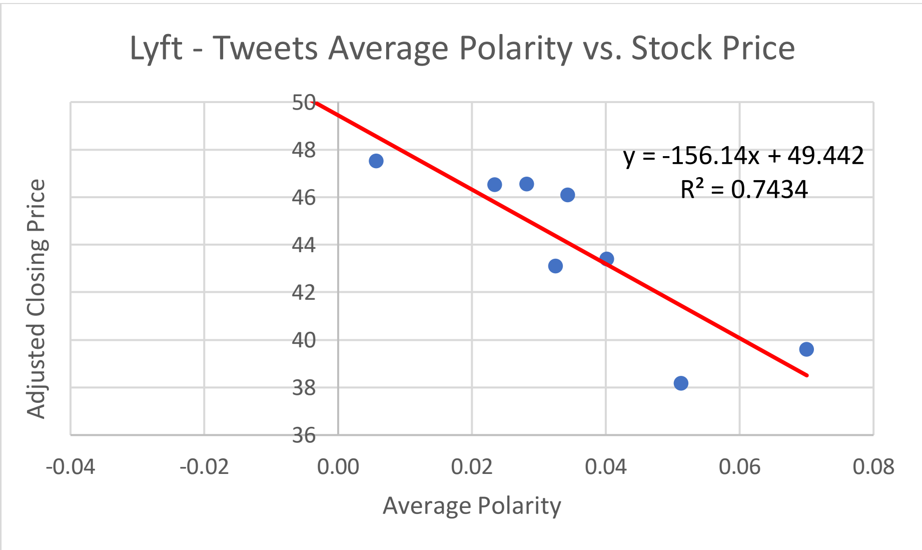
D. Regression Analysis

a. Tweets average polarity vs. stock price

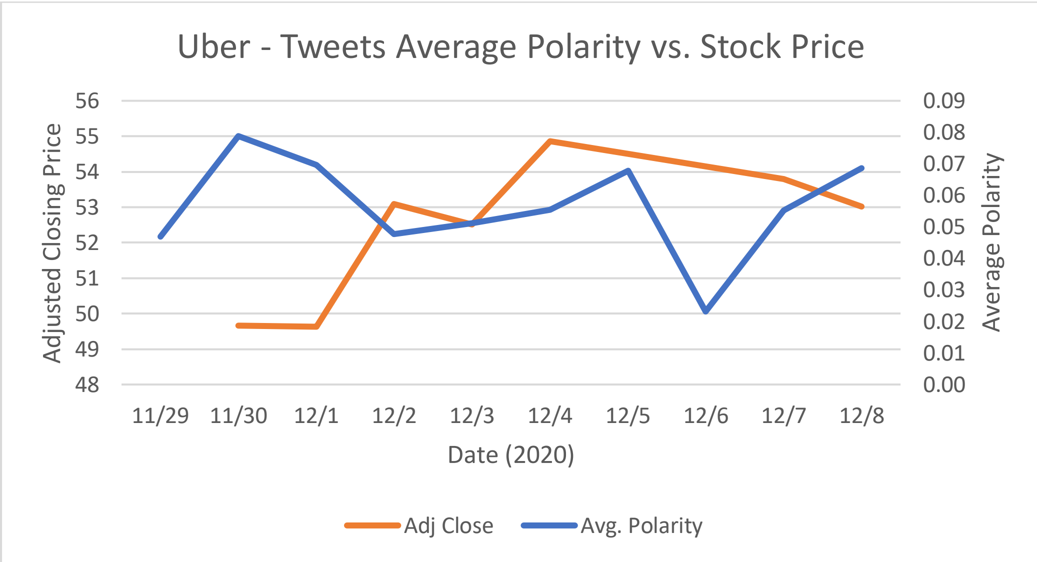
Uber

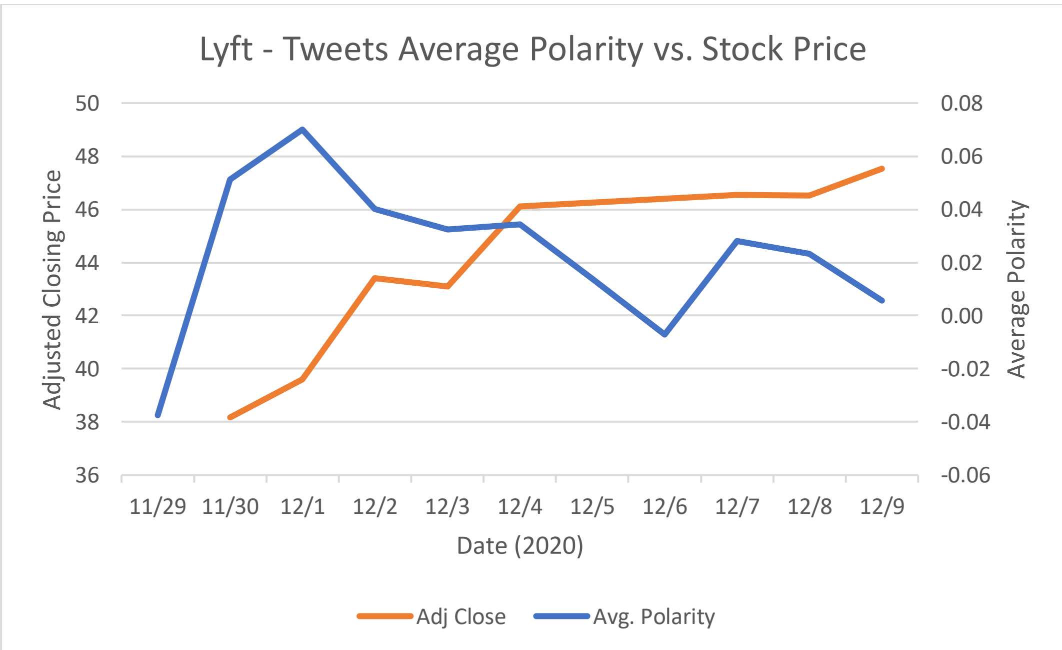


lyft



As we were unable to access internal data and track financial results over this short period, we decided to compare average polarity scores of tweets to stock price to see whether customer sentiment would directly influence the companies' stock price. Based on the above scatter plots and regression lines, the polarity of tweets even has negative relationship with stock price for both companies. One potential reason is that even if customers have bad experience of a specific ride, they may still need to take rides or get food delivery in daily life. If Uber or Lyft offers more attractive pricing, they may still select one over another. Moreover, stock price is influenced by many other factors, not merely customer sentiment on Twitter.





The above line charts show clear trend lines of tweets average polarity versus stock price. As we have seen in the point C.a., the average polarity trend of Uber and Lyft is similar. Their stock price both increased from Nov. 30 to Dec. 4, but Uber's stock price decreased slightly after Dec.4. Part of the reason might be that Uber was selling its autonomous vehicle unit and flying taxi business.

b. Multivariate regression analysis

Uber

	Tweets	App Reviews		
Date	Avg. Polarity	Avg. Rating	Avg. Net Valence Scores	Adj Close
11/29/2020	0.05	1.00	-1.00	49.66
11/30/2020	0.08	1.20	0.40	49.66
12/1/2020	0.07	1.33	-0.67	49.63
12/2/2020	0.05	1.17	-0.33	53.09
12/3/2020	0.05	1.50	1.33	52.52
12/4/2020	0.06	1.17	-0.33	54.86
12/5/2020	0.07	1.00	-0.11	54.86
12/6/2020	0.02	1.00	0.67	53.80
12/7/2020	0.06	2.33	3.33	53.80
12/8/2020	0.07	2.20	-0.40	53.01
Grand Total	0.06	1.39	0.29	
	Input the nearest day's stock price for Multivariate Regression Analysis			

lyft

	Tweets	App Reviews		
Date	Avg. Polarity	Avg. Rating	Avg. Net Valence Scores	Adj Close
11/29/2020	-0.04	3.08	0.33	38.17
11/30/2020	0.05	3.00	0.44	38.17
12/1/2020	0.07	3.74	1.04	39.61
12/2/2020	0.04	3.70	0.43	43.40
12/3/2020	0.03	4.65	1.20	43.10
12/4/2020	0.03	4.14	0.91	46.10
12/5/2020	0.01	3.88	0.67	46.10
12/6/2020	-0.01	4.00	0.63	46.56
12/7/2020	0.03	3.31	0.38	46.56
12/8/2020	0.02	3.78	0.56	46.52
Grand Total	0.02	3.73	0.66	
	Input the nearest day's stock price for Multivariate Regression Analysis			

Uber

Multivariate Regression Analysis Summary Output

Regression Statistics	
Multiple R	0.420235693
R Square	0.176598038
Adjusted R Squar	-0.235102944
Standard Error	2.328089428
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	6.974684121	2.324894707	0.428947332	0.739785016
Residual	6	32.52000232	5.420000386		
Total	9	39.49468644			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	54.07020567	3.304969081	16.3602758	3.32108E-06	45.98323766	62.1571737
Avg. Polarity	-41.31336469	54.56113597	-0.757193998	0.477605173	-174.819655	92.1929255
Avg. Rating	0.472754859	2.149375874	0.21994983	0.833202694	-4.78657844	5.73208816
Net Valence Scor	0.330475481	0.810350688	0.407817857	0.697560269	-1.65238122	2.31333218

lyft

Multivariate Regression Analysis Summary Output

Regression Statistics	
Multiple R	0.801707393
R Square	0.642734744
Adjusted R S	0.464102116
Standard Err	2.598229474
Observation:	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	72.86974585	24.28991528	3.598081448	0.08525541
Residual	6	40.5047784	6.7507964		
Total	9	113.3745243			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	13.49903311	9.319606622	1.448455247	0.197655836	-9.3052228	36.303289
Avg. Polarity	27.59208932	34.86578554	0.791380113	0.45885491	-57.721415	112.905593
Avg. Rating	10.45219647	3.233883876	3.232087753	0.017863553	2.53916769	18.3652253
Net Valence	-14.71597377	5.982061102	-2.460017294	0.049118318	-29.35355	-0.0783976

To access whether app ratings and reviews have an effect on stock price, we built multivariate regression model to evaluate the relationship between stock price and customer sentiment we have analyzed before. Though the number of app reviews is relatively few, it might be a feasible way to gain more insights if we could collect more data over longer period from different social media or platforms in the future. From the Uber summary output, we see that none of the tweets or app reviews has a significant effect on stock price as p-values are all quite large and the low R squared value also indicates that the model explains very little of the variability of the stock price. However, the Lyft regression model seems to perform better than the Uber model although it still did not have good predictions on stock price. The average rating from Lyft app reviews has a significant positive effect on stock price.

E. Conclusion

To summarize, we see that overall customer sentiment towards Uber and Lyft on Twitter and App Store is positive, and both even have similar polarity trends on tweets. It implies that Uber and Lyft might be influenced by several similar factors, and riders probably see one as an alternative to the other. Interestingly, Uber was tweeted about much more frequently than Lyft, while Lyft got more reviews with positive comments on the App Store. Uber could do more analysis to see whether their app should be improved, or it was due to other reasons.

To provide better services, both companies should emphasize the quality of rides, not only the quantity. From word clouds, we also noticed that customers are more willing to take a ride when they feel safe and comfortable, and waiting time and ride price are in a reasonable range. Moreover, even though the prediction models we built did not perform well on predicting stock price, companies could gather more public sentiment for their products and services and choose appropriate leading indicators to evaluate how customer sentiment would influence their business. Then, they could start with the most urgent and valuable issues to drive business value.

F. Reflection

Through this project, I gained more confidence in scraping big data and performing sentiment analysis. It was also my first time to do social media analytics, and I really appreciate that so many valuable skills were taught in this course. Although I encountered some difficulties deciding on the project topic and working on some coding parts, I was happy that I could apply what I have learned in the project. This course really helped hone my analytics skills, and I believe that I will be able to research and do more analytics work based on the techniques I have learned from this course.

G. Resources

a. R “itunesr” package: https://github.com/amrrs/itunesr
b. Apple App Store: https://www.apple.com/si/ios/app-store/
c. Yahoo Finance: https://finance.yahoo.com/
d. “Ride-sharing market size worldwide in 2020 and 2021 – Statista”: https://www.statista.com/statistics/1155981/ride-sharing-market-size-worldwide/