Uber Eats vs DoorDash

Brand Differentiation and Sentiments

Problem Statement

- Team of analysts from Uber Eats, attempting to find out if there is **brand differentiation** between our platform and Door Dash, and what are the **general trends in vernacular** that our Uber Eats community, both drivers and users, are using in **Reddit.**
- These will seek to inform our marketing team about how we can bring out brand forward, and also our platform/product management team on how we can improve our services.

Approach

- Brand Differentiation
  - Multinomial NB
    - CVEC
    - TVEC
  - Random Forests
    - Random Forest
    - Extra Trees
- Platform Sentiment gathering
  - Top word counts
  - Feature weights

- Concerned about accuracy – we want to accurately sort the reddit comments so that we can do an analysis on the words that contribute to Branding for, and between, the companies.
  - A high accuracy would mean that model can tell us distinguishing features in the form of words/ bigrams

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

- Stop words used:
  - “*english*”
  - 'dashers', 'dashing', 'dashpass', 'eats’, 'door', 'dash', 'doordash', 'Uber', 'UberEATS', 'ubereats', 'uber’, 'dasher’
  - DashPass is a unique pass to the DoorDash dashers community, to pay $9.99 /month or $96 yearly to get free delivery for orders above $12

Optimisation of the models

		Best Params	Best_score	Score on Train Set	Score on Test Set
Multinomial NB	CVEC	-	0.6502	0.8148	0.6611
Multinomial NB	CVEC				
Multinomial NB	TVEC				
Random Forests	CVEC				
Extra Trees	CVEC				

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		Best Params	Best_score	Score on Train Set	Score on Test Set
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Multinomial NB	CVEC	{'cvec__max_df': 0.45, 'cvec__max_features': 10000, 'cvec__min_df': 1, 'cvec__ngram_range': (1, 2)}	0.6681	0.7910	0.6732
Multinomial NB	TVEC	{'tvec__max_df': 0.3, 'tvec__max_features': 11000, 'tvec__min_df': 3, 'tvec__ngram_range': (1, 4)}	0.6957	0.8377	0.6873
Random Forests	CVEC	'rf__ccp_alpha': 0, ' rf__max_depth': 7, 'rf__max_features': 'sqrt', 'rf__min_samples_leaf': 7, 'rf__min_samples_split': 15, 'rf__n_estimators': 200	0.6402	0.6749	0.6341
Extra Trees	CVEC	'et__ccp_alpha': 0, ' et__max_depth': 6, 'et__max_features': 0.5, 'et__min_samples_leaf': 7, 'et__min_samples_split': 10, 'et__n_estimators': 200	0.6059	0.6121	0.6041

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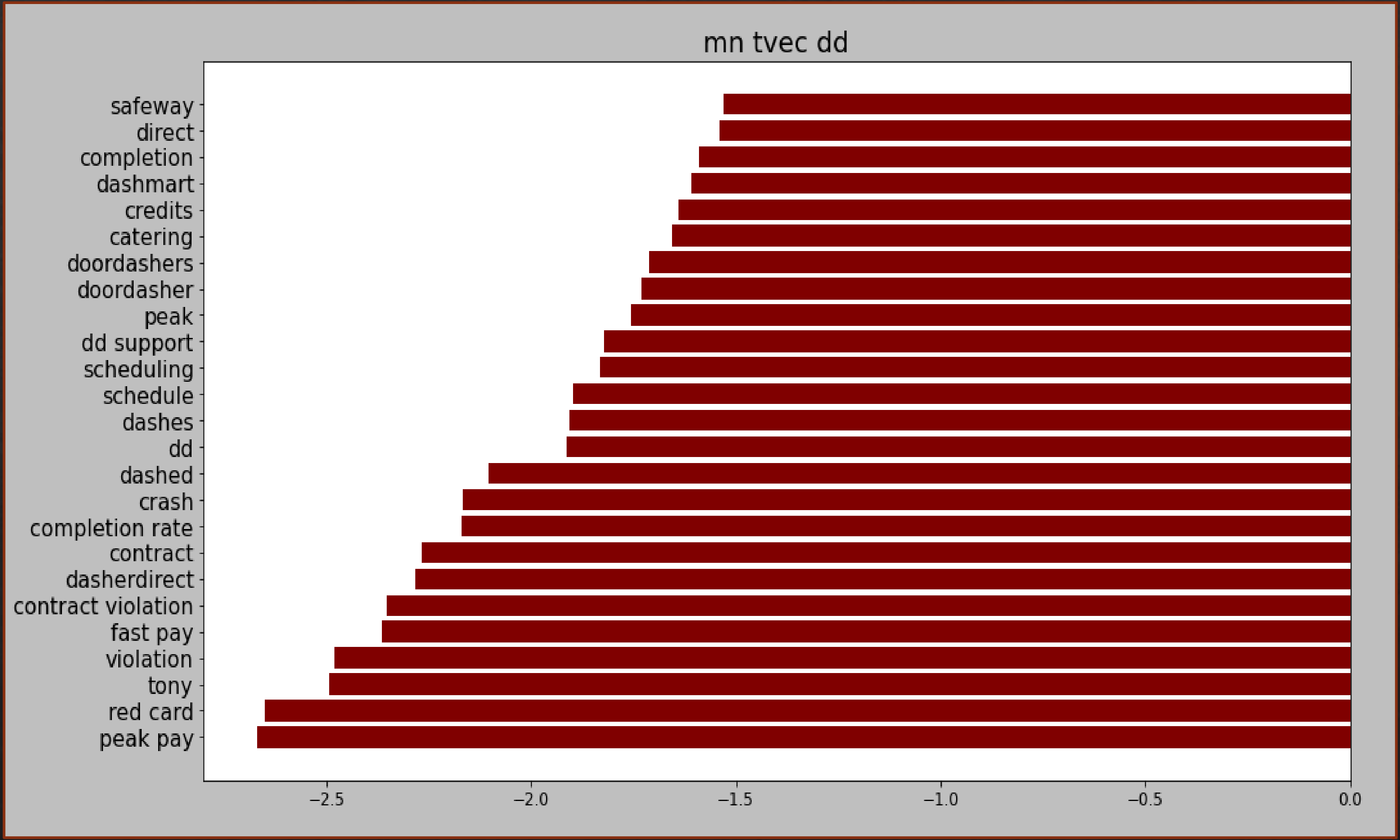

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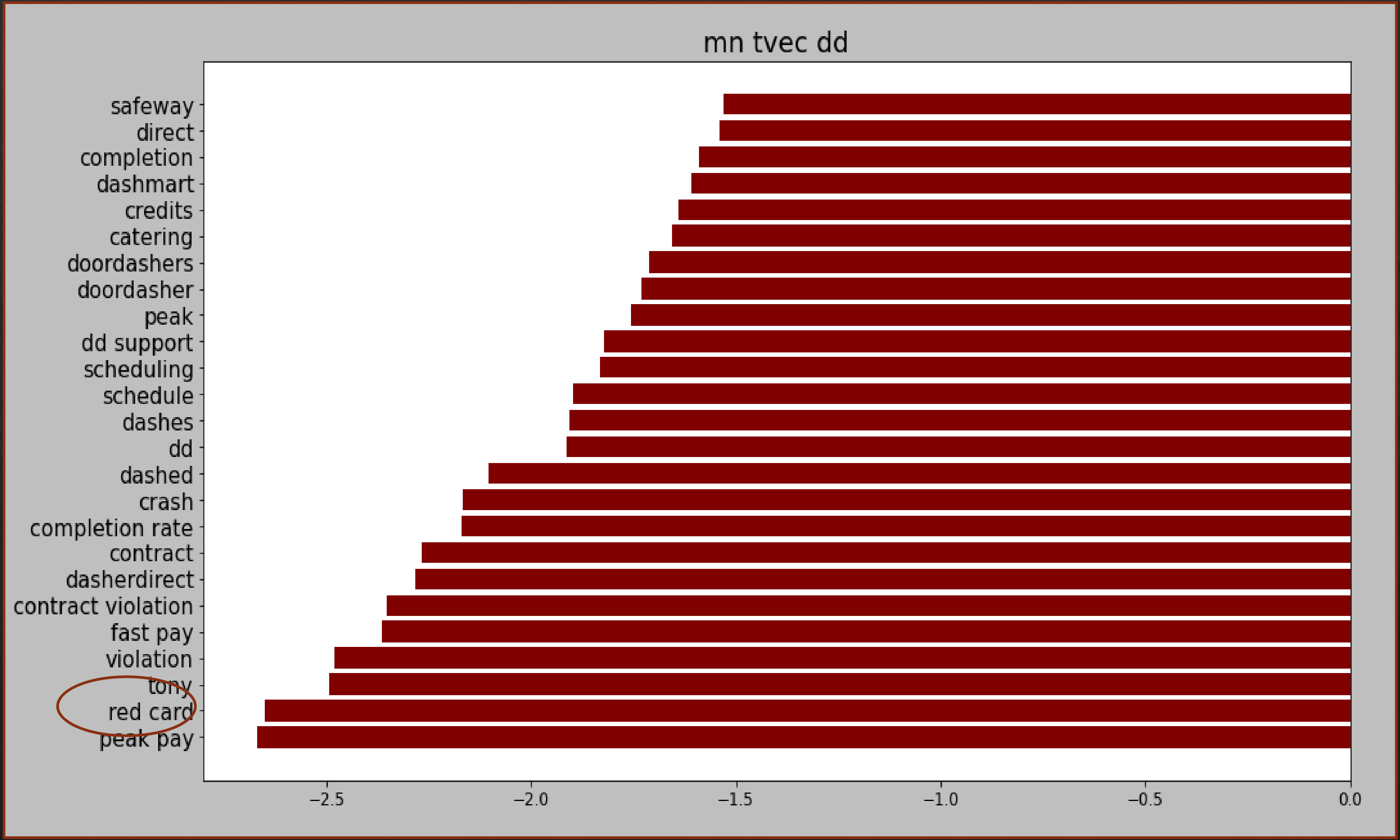

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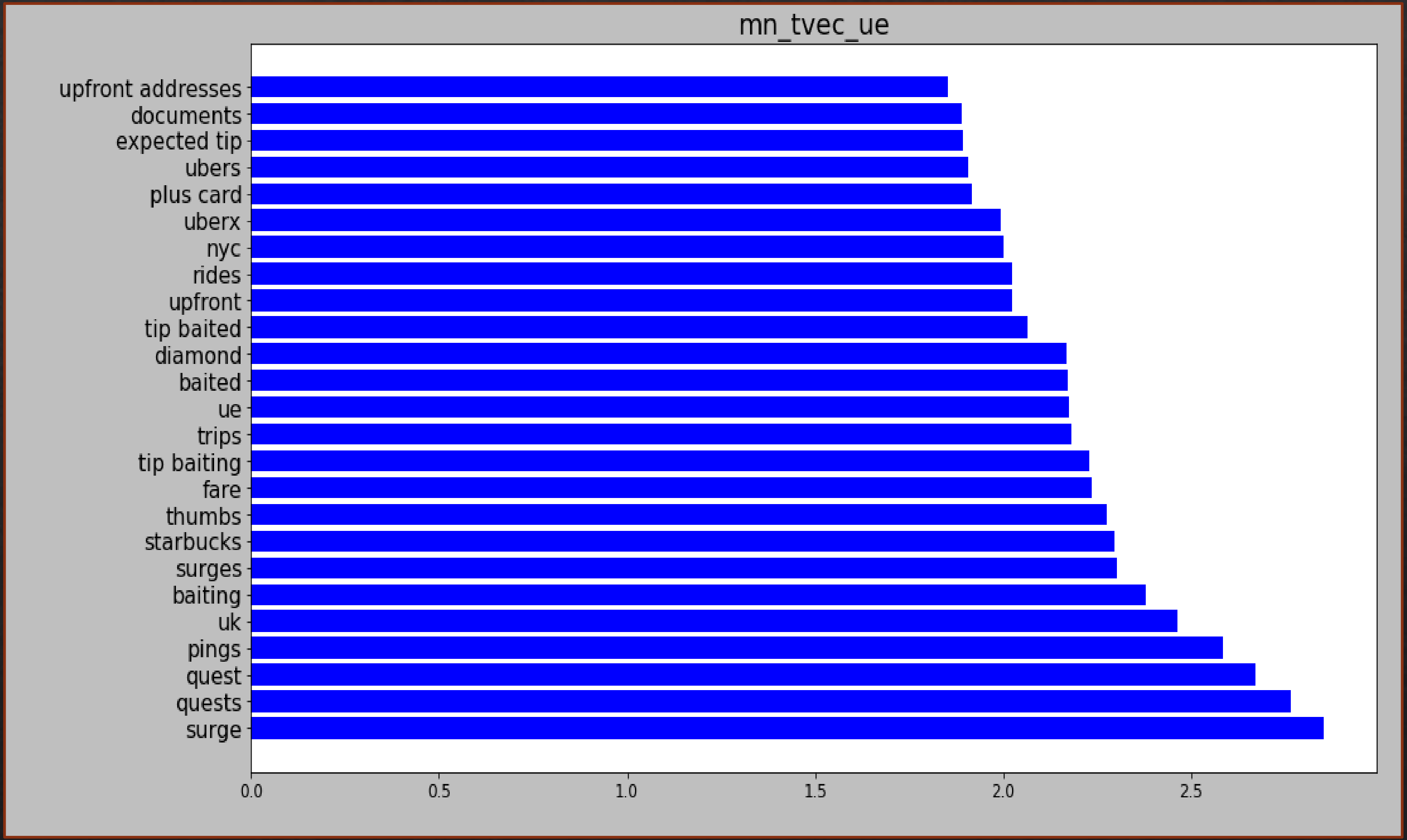

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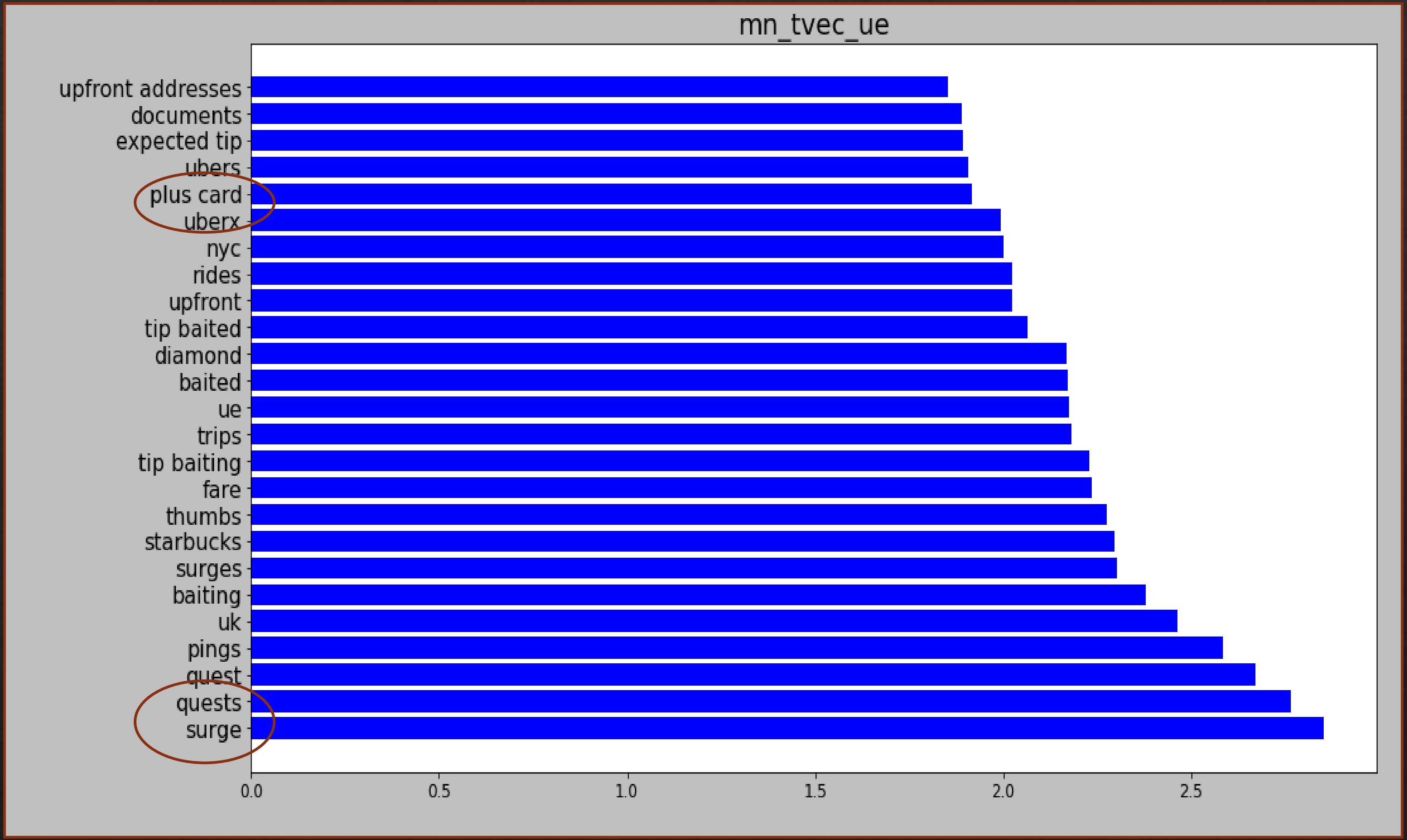


Multinomial NB - TVEC

- Red – Card vs Plus Card
  - A type of payment form where Dashers use the card to pay for the order, debited from DoorDash
  - There is an analogous type of payment for Uber Eats, called the Plus Card.
  - Using VADER, (Valence Aware Dictionary and sEntiment Reasoner) the sentiments towards the cards are:

Message containing:	VADER Compound Score
Red Card	0.2533
Plus Card	0.3912

- Surge
  - In the context of our Uber Eats platform, surge can be a good or bad phenomenon for our drivers.
  - VADER Compound score of 0.0720 which is quite neutral.

Multinomial NB - TVEC

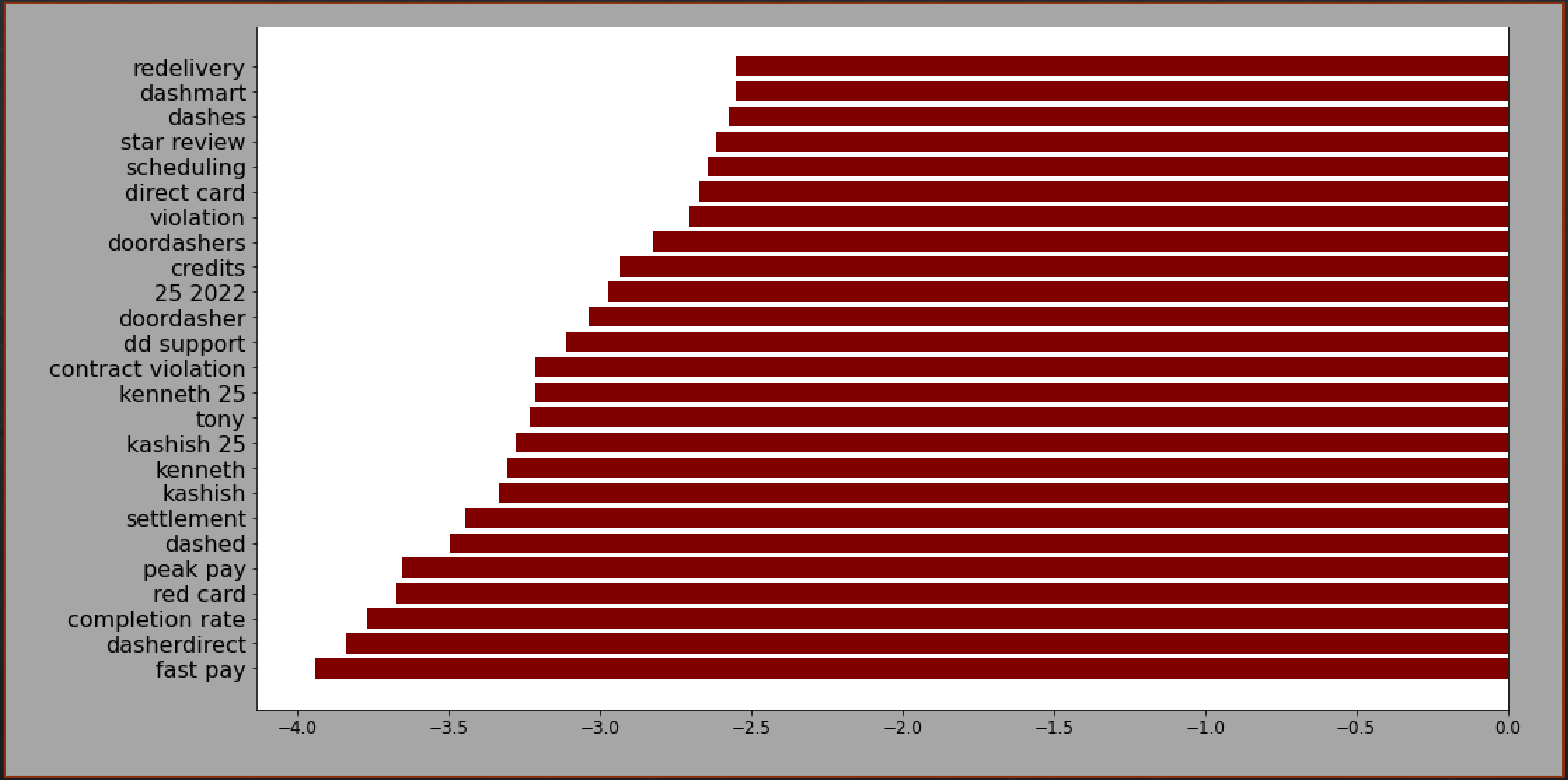
- Quests
  - "Quest promotions offer you the opportunity to earn extra money for reaching certain trip goals in a set amount of time."

    "*For example*: Get an extra $50 by completing 10 trips between 4am on Monday and 4am on Friday.
  - Quests are only mildly positive at 0.1416
  - This does not mean that quests are bad for our customers, but we can understand the circumstances which made it less pleasant.
    - How do I not care?I just a got another thumbs down. Second one today. \n\nThis guy changed his address, which cost me my quest because I added his order on since it was at the same apartment. He ended up at a house. I handed it off to him, with a real attitude he says "thank you" and I say real quietly, because not only am I very mad, and very tired after going since 11, "you're welcome". \n\nLike what the fuck was I supposed to do? Roll out the magic carpet after you cost me my last part of my quest? I'm so sick of these people. Maybe I could have been nicer or whatever, but still. Now im at 93 percent. \n\nSo how do I not care so much when it's all I know? I care about people being happy with their service, doing a good job. It's how I've always been, whether I was a janitor or a Fulfillment Team Lead. This shit is really starting to get to me. I don't want people to see I have 7 thumbs downs and think I don't care or I don't deserve a tip.

Multinomial NB - CVEC

- Tony
  - CEO of DoorDash
  - VADER compound score of 0.5211 seems good
  - Further inspection, some are sarcasm.
    - “Saving soooo much ⛽ Drove about 1300 miles this week for DD. Saved a whopping 1.1 cent per mile :))) Thanks tony 👎”
    - “Thank you Tony for your beautiful $2 orders all hail tony”

Multinomial NB - CVEC



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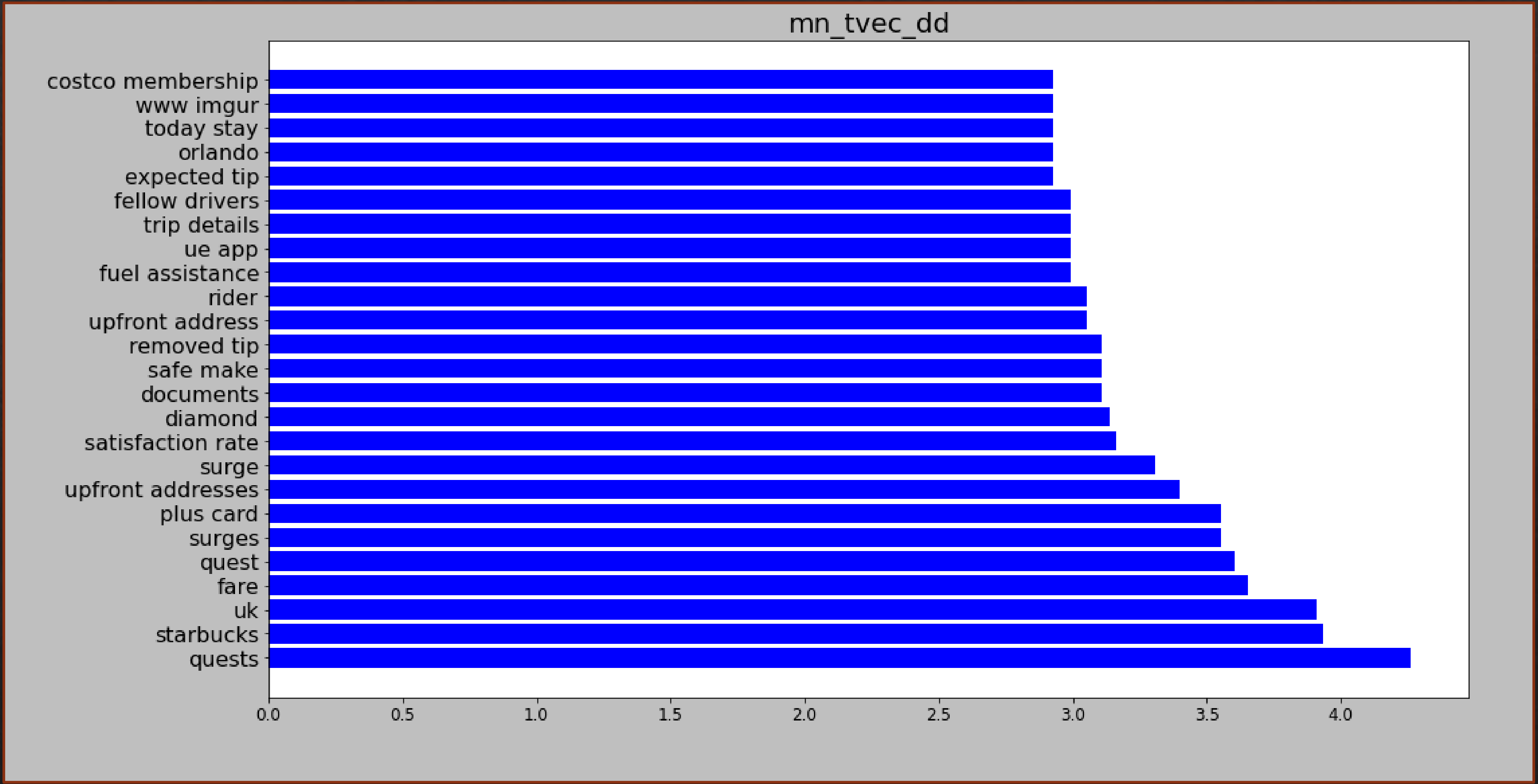


Multinomial NB - CVEC

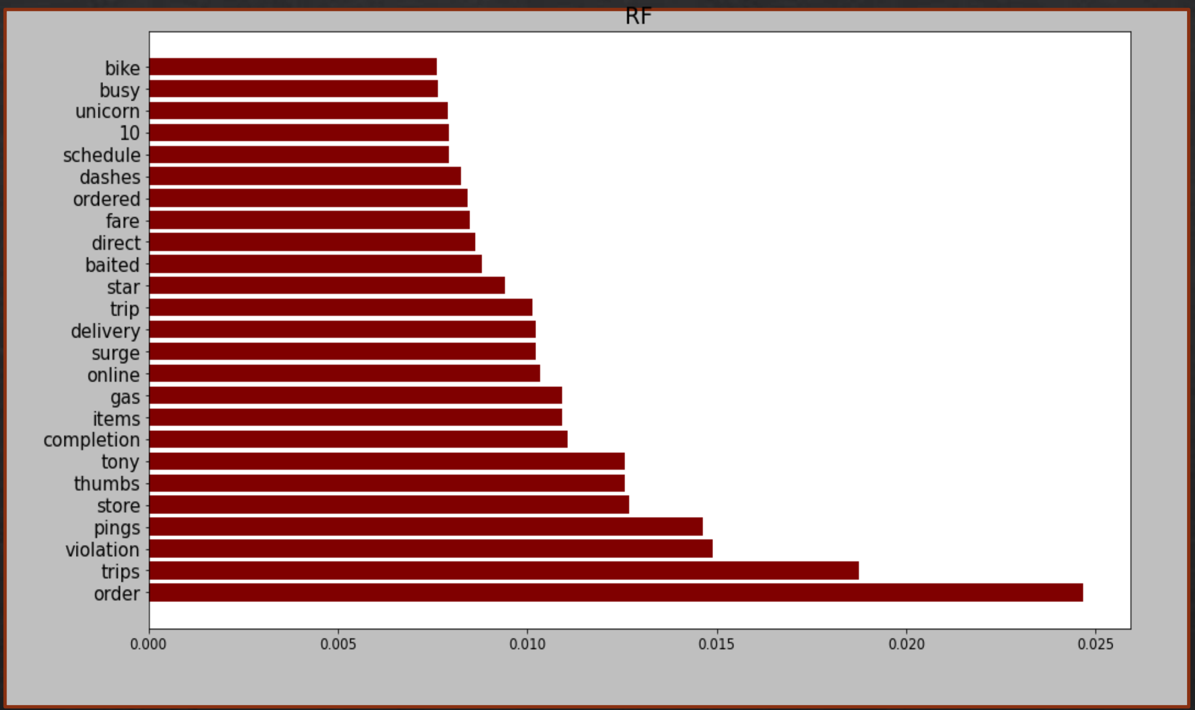
- Red – Card vs Plus Card still present
- Quests and surge for our company- still a distinguishing factor

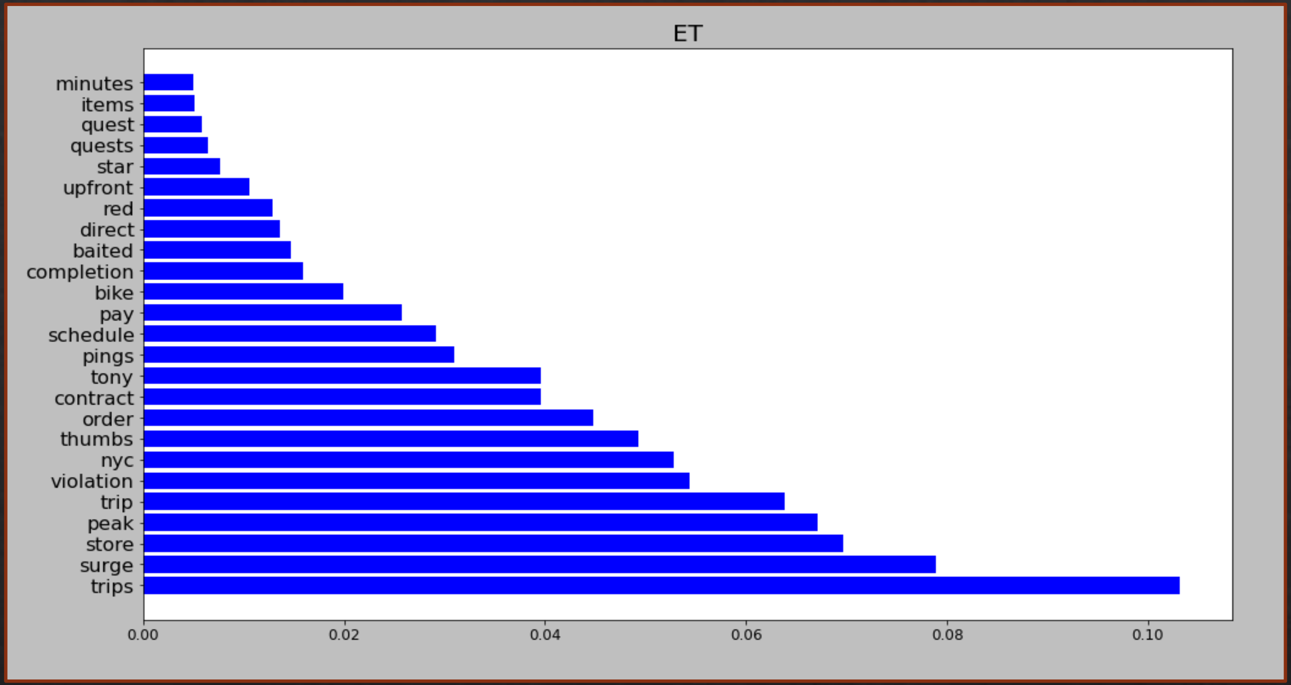
Multinomial NB - Insights

- Great insights as we are able to tell the feature weights that lean towards either company
  - Useful for our analysis
    - Brand differentiation
    - Sentiment gathering

Random Forests

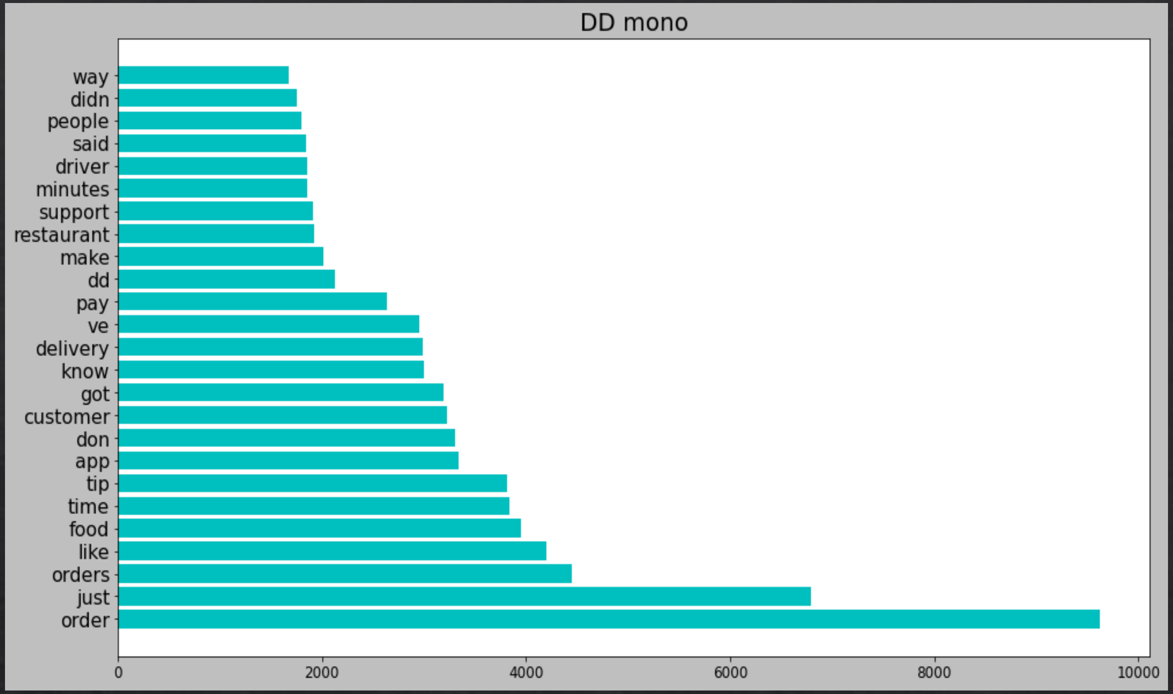
Random Forest

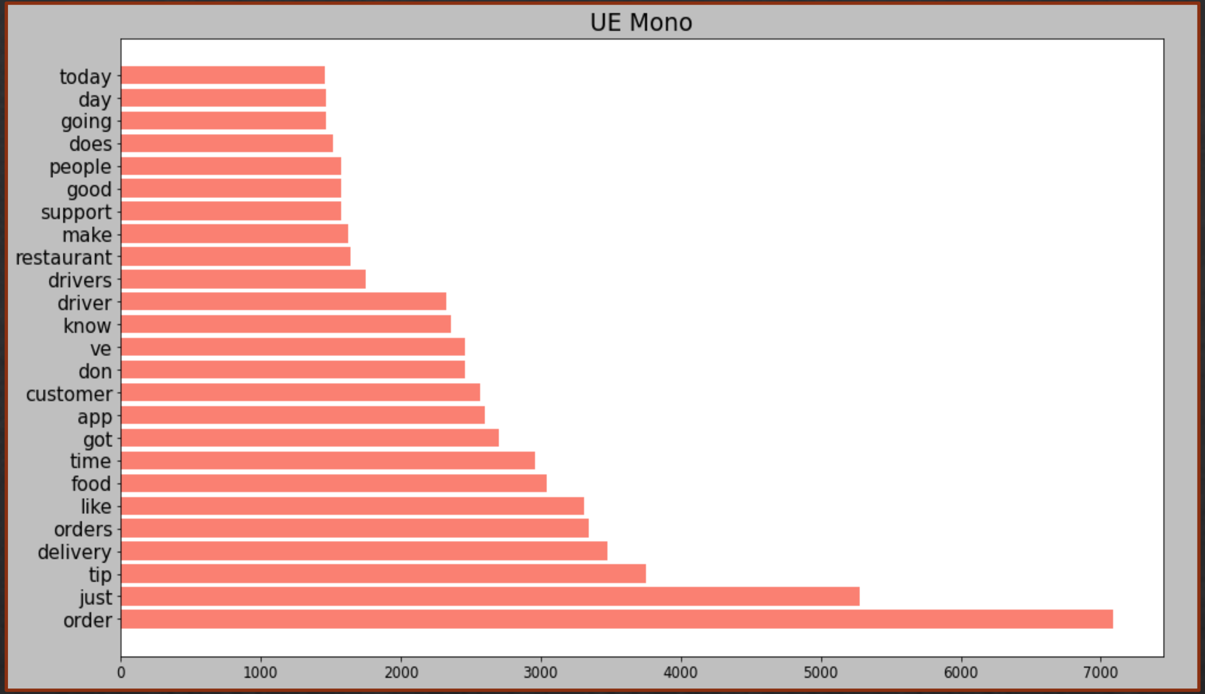




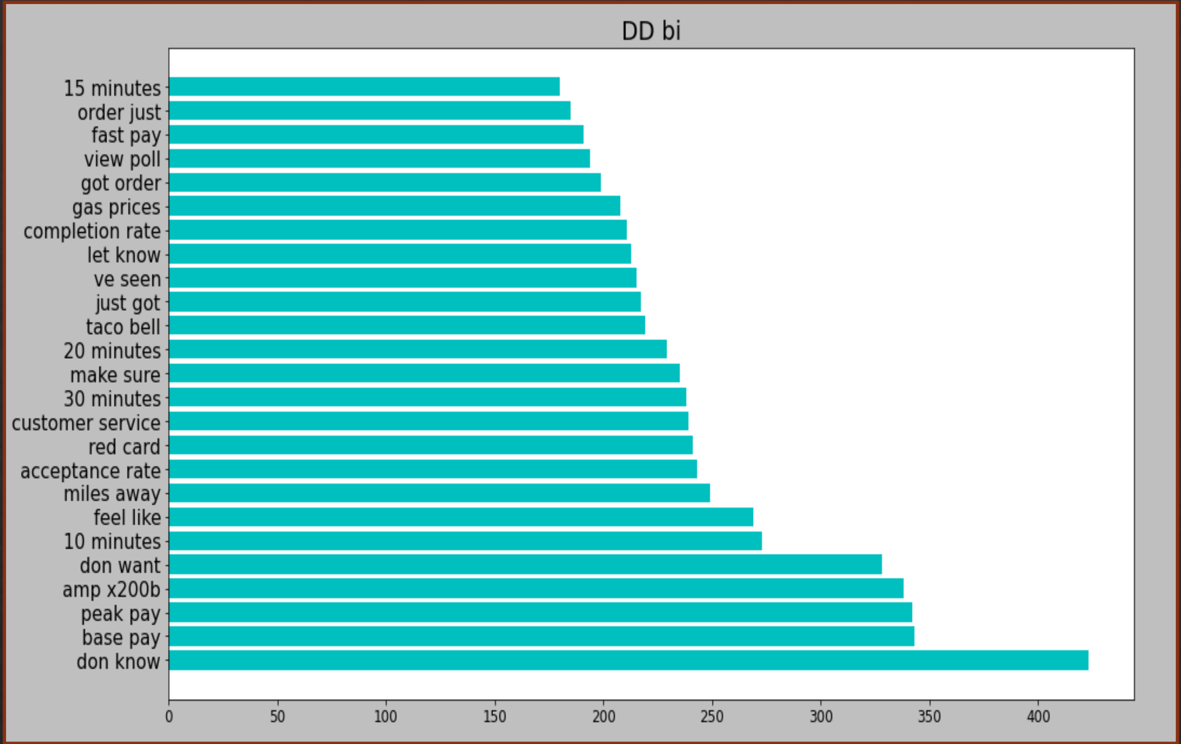
- Surge has the highest significance, a word that has appeared with our previous counts.

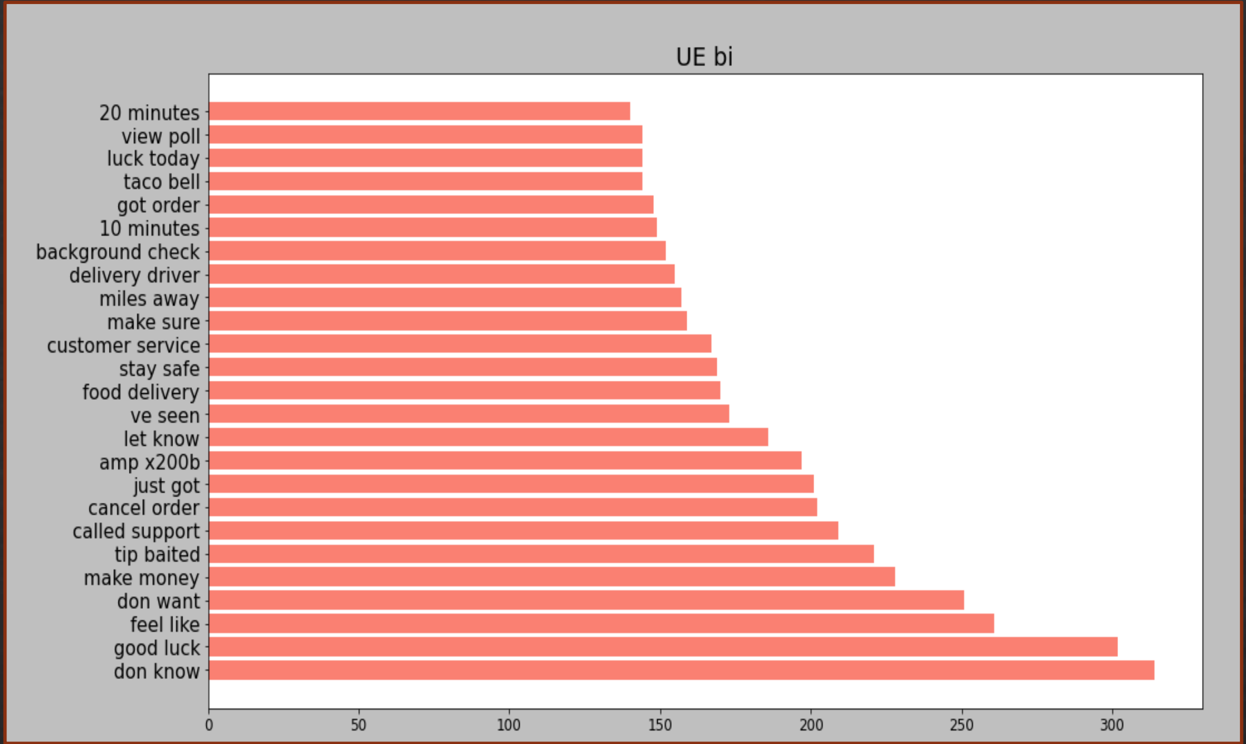
Top Word Counts





- We can observe that there are quite a few similarities between the two lists of most common words.
  - "people", "restaurant", "got", "support", "time", "customer", "food", "like", "orders", "just"
- We see that there are quite a few counts of "good" in our UE set
  - Not present in DD set.





- Top words seem to be about timing
  - “10 minutes”
  - “30 minutes”

Top words seem to be about timing

- We applied VADER to data containing “minutes”
  - 10 minutes and 20 minutes for both companies, and 30 minutes for DoorDash
  - See if sentiments are similar or different regarding time-related words

Company	VADER Compound Score
DoorDash	-0.0427
Uber Eats	-0.0017

  - The score is mildly negative, but not as much as DoorDash's. Could be similar that people generally would not like to wait for so long for picking up orders or receiving orders.

Exploring positive sentiments in our dataset

- “Good” seems to be the flavour of the time period for our company.
- Has a VADER compound score of 0.4092.
- Might allude to this period being a good time for our drivers and users, and can be a form of sentiment gathering
  - Whether it appears in a certain time period
  - Whether it appears in the other company’s dataset

Challenges met by the team

- Stop words being found at various points of modelling- have to re-run whole model
- Modelling takes a long time, have to be especially clear which models and which parameter you are changing
- Multiple GridSearch functions

Improvements:

- Would have just tried to find out the maximal model as soon as possible
- Understand that each project is unique, and to define own problem statement early – model accuracy is not the only portion that is important.
- Would have explored TVEC for all of them as it seemed to be a better fit on hindsight.

Words associated with our brands

DoorDash	Uber Eats
Red Card	Plus Card
Tony	Surge
	Quests
	“good”

- Common words: Minutes

Conclusions

- Words that might be associated with our brands
  - "Plus Card", "Quest"
    - These seem to show a mild to intermediate positive trend
    - Our branding have at least one tangible anchor: Quests
  - "Surge"
    - We would have to take note of the surges, which is particular only to our company, to ensure that it is positive for the drivers.
    - Possibly temporal
- Trend in vernacular towards our brand
  - "Good"
    - We seem to be enjoying a positive trend in this time period
- Trend in vernacular towards food delivery
  - "Minutes"
    - Seems to have mild negative scores for now
    - Have to note and possibly find out reasons

Recommendations

- Words that are of importance in this time frame of 03 Oct 2021 to 26 March 2022:
  - We will have to continuously measure these data to update our knowledge of our drivers and users, and our branding
- We can do more textual analysis into “good” messages to find out more about the trend and what caused our community to feel positive, as well as messages with “minutes” to find the root cause of the issue if any.

Thank you