LUFTHANSA
CUSTOMER SERVICE ON TWITTER

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1) CONTEXT AND OBJECTIVES

- Present findings
- Reflect on work done
- Gain client buy-in/approval
- Skills development
- Obtain feedback & input
- Twitter account reach
- Customer service quality
- Common problems faced by users
- User attitude in a conversation
- Comparison with competitors
- Efficiency during crises

2) DATA CLEANING AND STORING

Raw Data 35.2GB → Extract Data: Tweet ID, User ID, Text, User mention → Clean Data → SQL-server 5.13GB
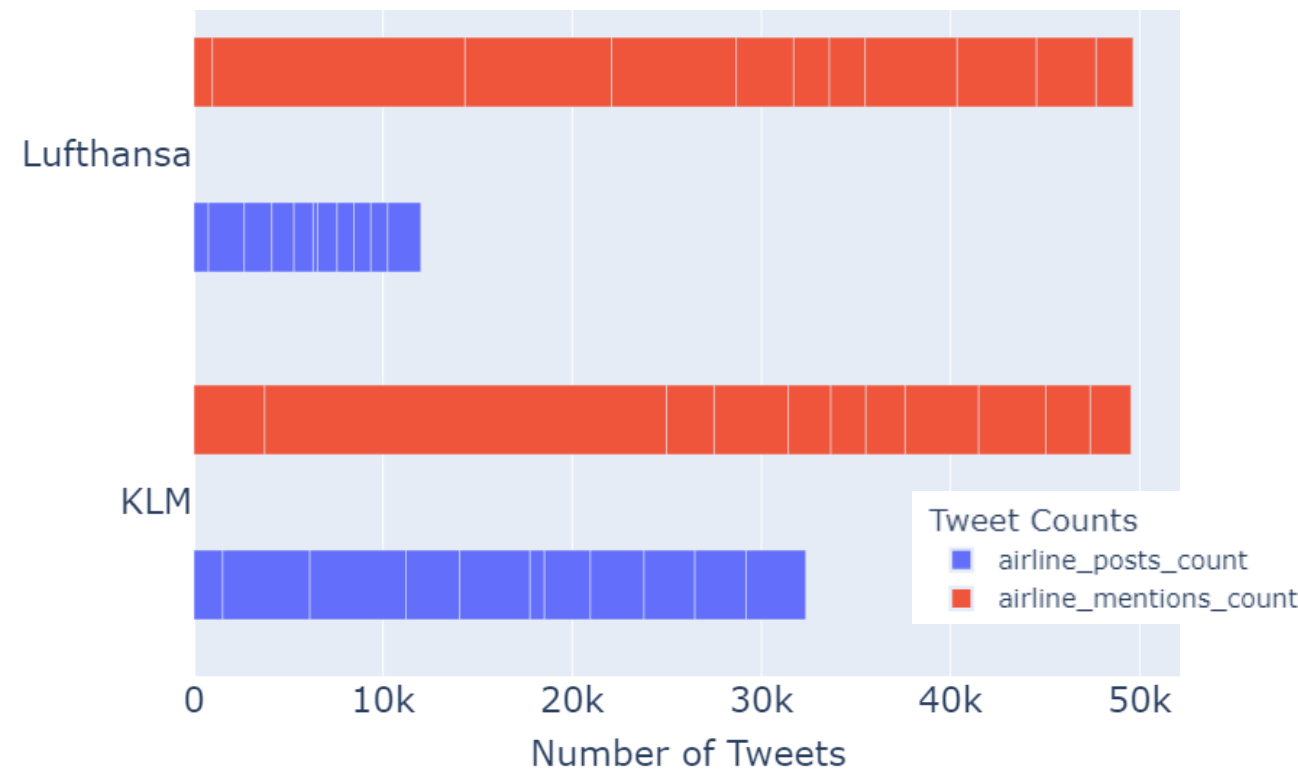
3) INITIAL FINDINGS

- Lower number of tweets by Lufthansa compared to KLM
- Lower number of tweets mentioning Lufthansa
- Lower number of followers for Lufthansa
- 76.3% of all tweets are in English

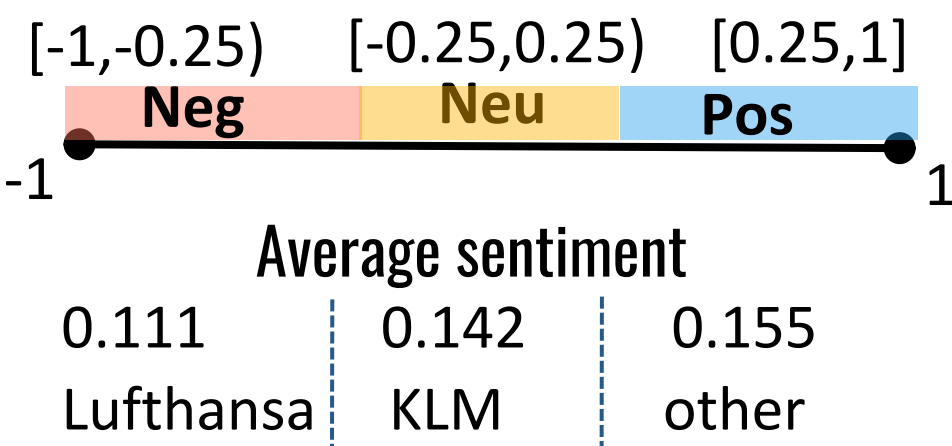**Number of posts by the airline VS number of mentions**

4) CONVERSATIONS

level: 0 1 2 3

OG Tweet

- Start: original tweet by user
- User has to @airline
- Reply: user & airline mentioned
- Airline replies at least once

| Airline	Mean Length	Conversation Total number	Unanswered Tweets	Level1 Reply	Level2 Reply
American Air	2,005	31500	14923	31640	0
British Airways	2,025	14662	8082	15023	0
KLM	2,144	4243	4025	4848	5
Virgin Atlantic	2,023	2912	2686	2976	3
Lufthansa	2,024	1864	2560	1909	0
AirFrance	2,210	1202	1775	1425	29

- Lufthansa: many unanswered tweets
- KLM: many conversations & unanswered tweets
- User does not reply to the airline again often

5) MEAN SENTIMENT : VADER MODEL

[-1,-0.25) Neg
[-0.25,0.25) Neu
[0.25,1] Pos
-1 1

Average sentiment

| 0.111 Lufthansa | 0.142 KLM | 0.155 other |

*VADER only works on English tweets

- Other airlines: lowest in summer holiday season
- Lufthansa: highest in Dec 2019 & Feb 2020

Average Monthly VADER Sentiment Score

Sentiment Proportions per Airline
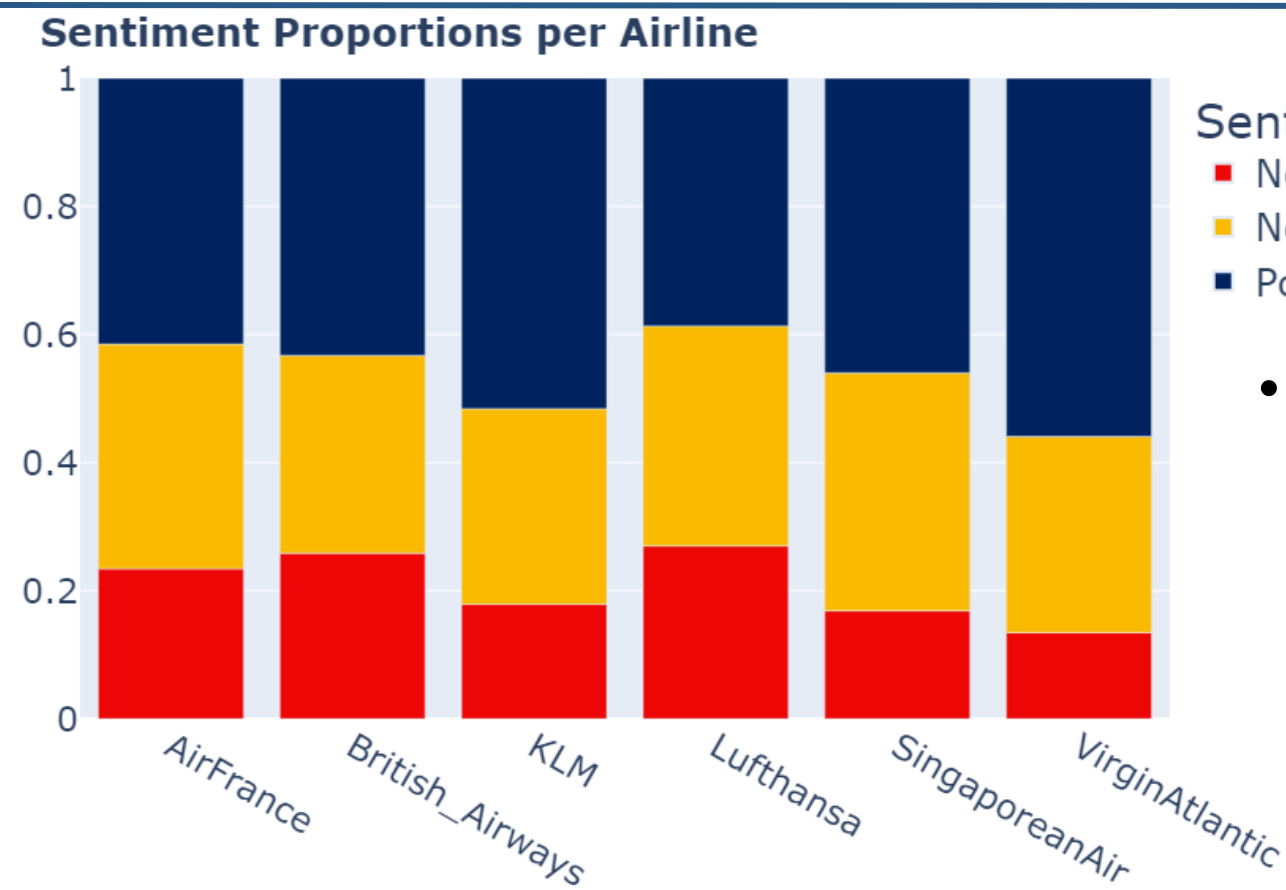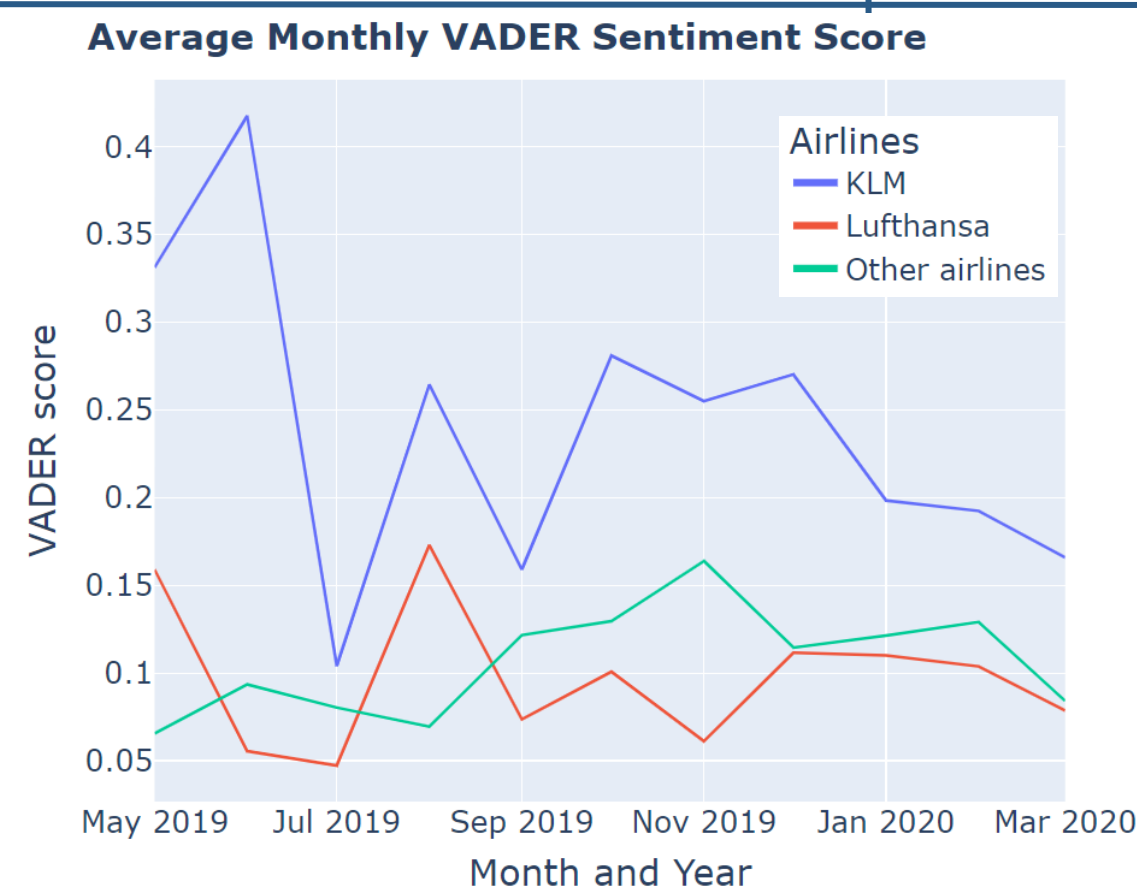
- Lufthansa: high proportion of negative tweets compared to others

6) SENTIMENT EVOLUTION & ACCURACY

Airline	Neg-> Neu	Neu->Pos	Neg->Pos	Pos->Neu	Neu->Neg	Pos->Neg	Pos_same	Neu_same	Neg_same	Mean Diff
KLM	0	0	67%	0	0	33%	0	0	0	0.1517
Air France	7%	17%	41%	0	0	0	24%	10%	0	-0.0459
Singapore Air	11%	22%	30%	2%	0	0	33%	2%	0	0.1559
Virgin Atlantic	0	0	0	33%	0	0	33%	0	33%	-0.1398

- Many positive & neutral tweets stayed the same
- Generally an increase in sentiment
- Mean change is neutral
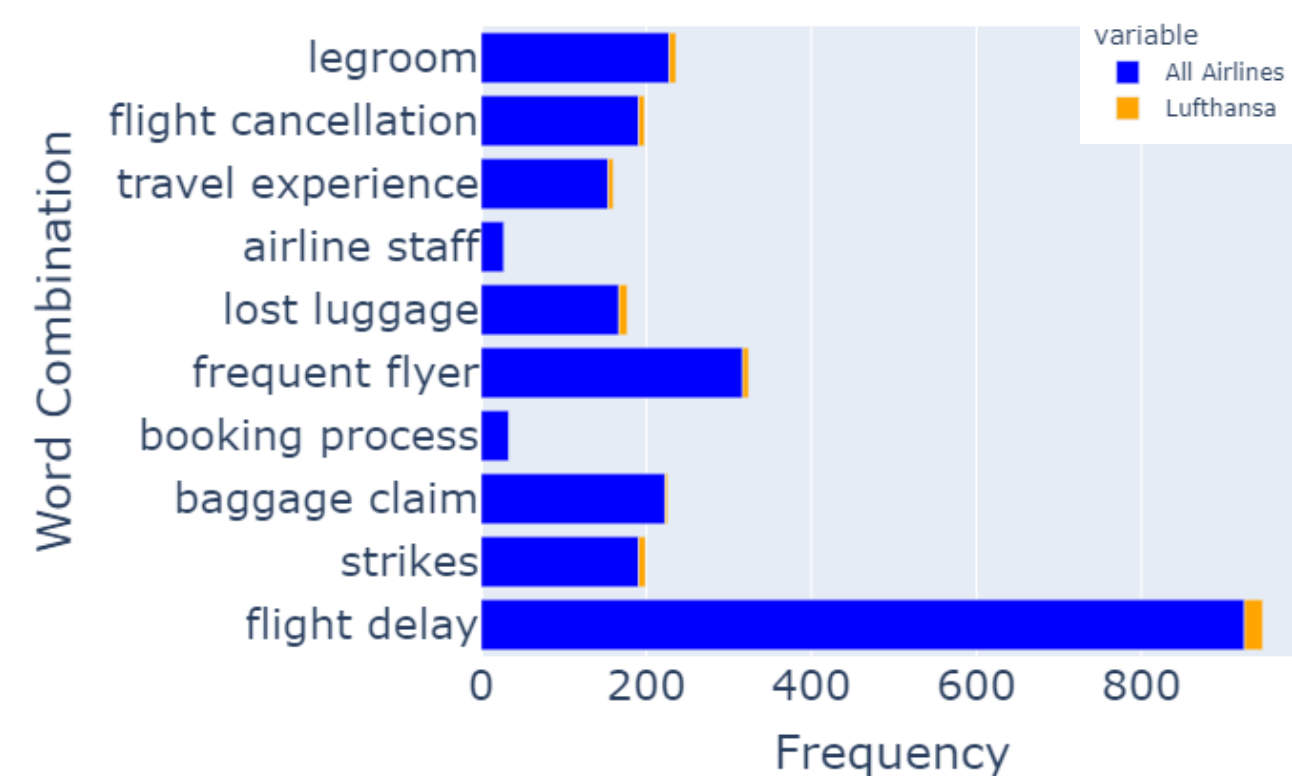- Biased result due to low level 2 replies

Accuracy of VADER 85%

Based on:
- Research
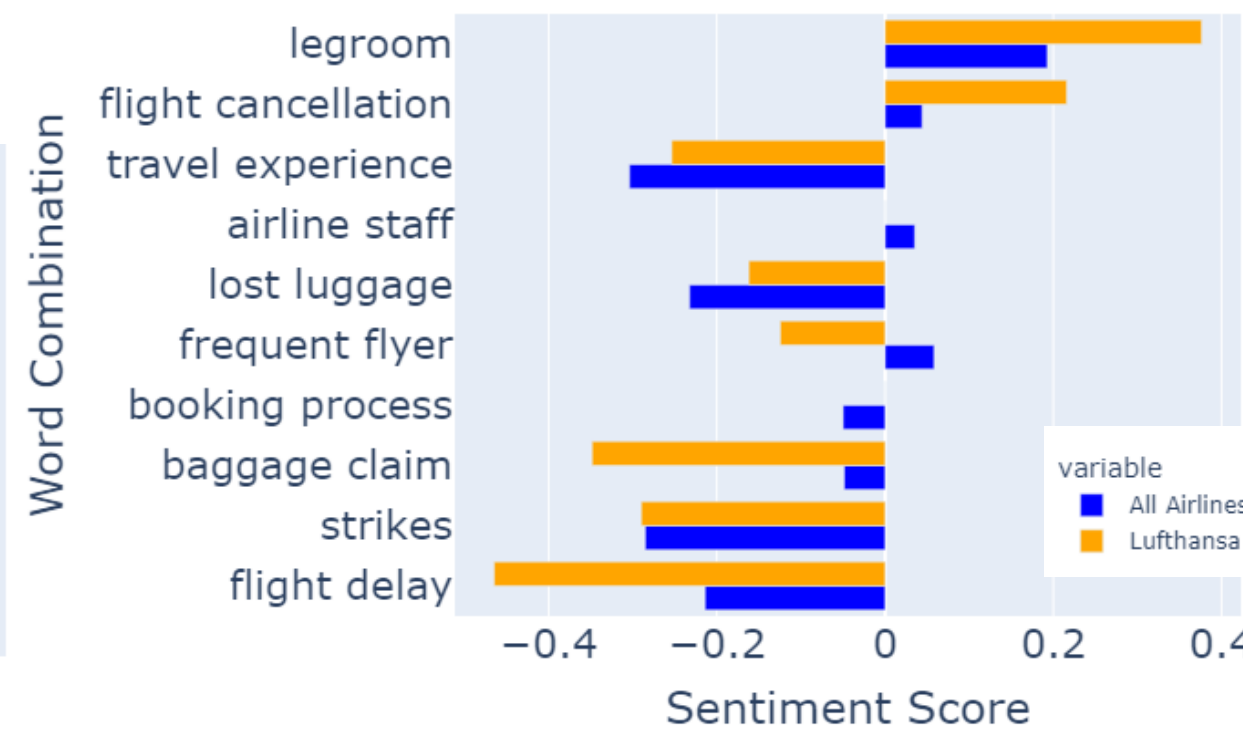- Sampling: compare VADER scores with our own scoring

7) TOPIC ANALYSIS

Frequency of Word Combinations

Average Sentiment Scores for Word Combinations

- Most common problems Lufthansa: Strikes, flight delay, flight cancellation, lost luggage.
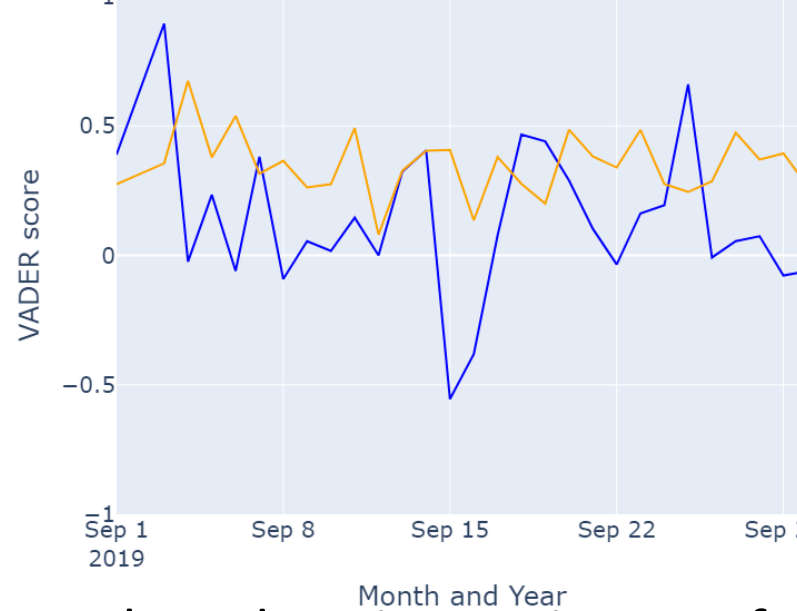- Surprisingly high score for legroom and flight cancellation

8) REAL LIFE EVENTS & THEIR EFFECT

September Strikes

November Strikes

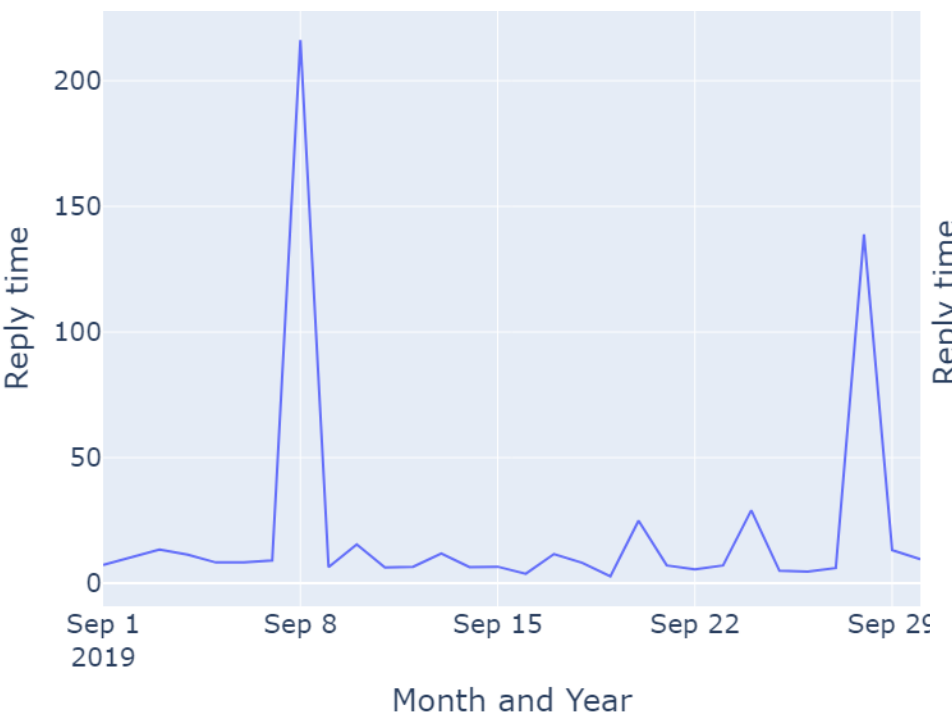- Clear drop in sentiment after September strikes
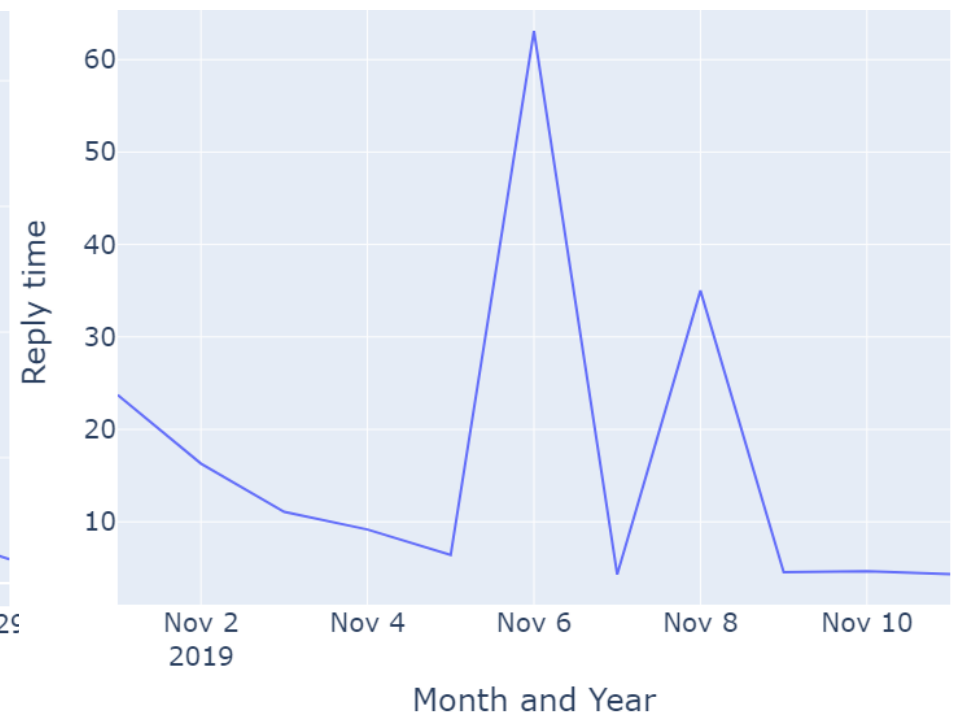- Subjectivity is irregular
- Increase in sentiment after November strikes
- No pattern in subjectivity

completely objective 0 ———— 1 highly subjective

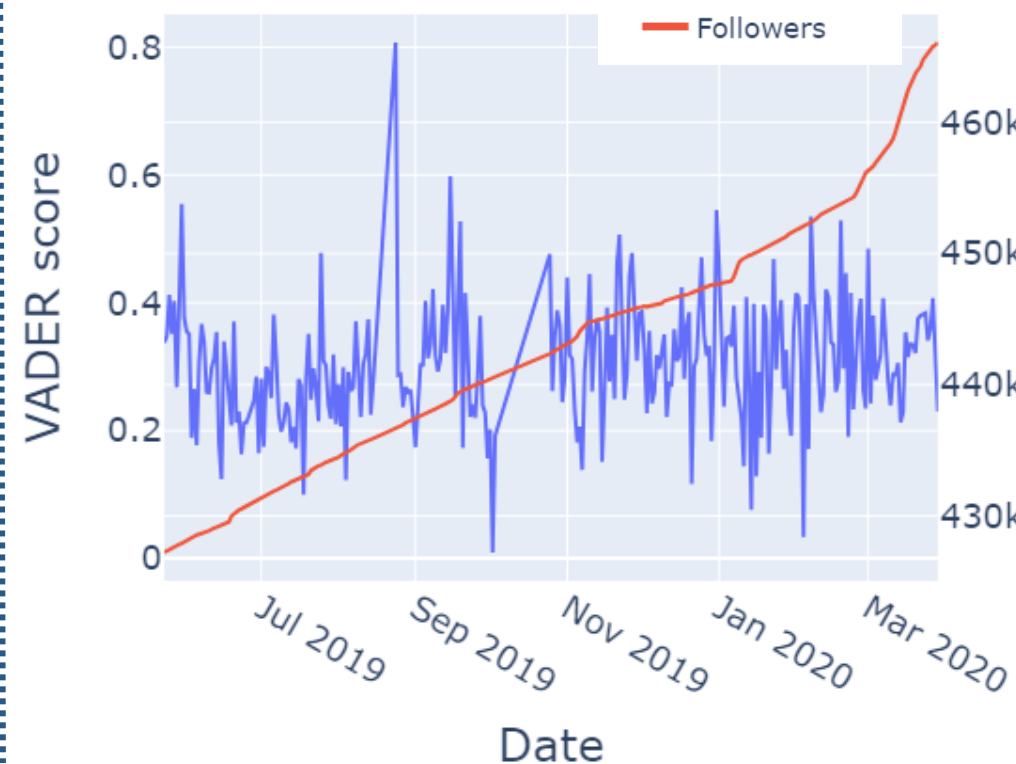**Response time After Strike of Lufthansa(September)**

Response time After Strike of Lufthansa(November)

- Strange peak before September strikes
- Same peak before and during November strikes
- Overall: response time does increase around strikes

Followers vs VADER scores

- The sentiment fluctuates a lot
- Big peak in August due to holiday period
- Big dip in October, cause unknown
- Steady increase in follower count despite strikes and other events

9) CONCLUSION

Our findings:

- Lufthansa has a relatively low follower count
- They do not reply that often
- Mean sentiment for Lufthansa lower than KLM
- KLM has more followers and tweets
- Steady increase in followers for Lufthansa
- Biggest issues Baggage Claims and Flight Delays
- Positives: Legroom and Flight Cancellations
- Strikes would lead to sentiment drop
- Generally after strikes, airlines take longer to respond

Recommendations:

- Keep the account active
  - Steady increase in followers, reach, and popularity
  - Allows extensive insight into public's opinion
- Advertise Twitter customer service
- Prepare well for strikes so user sentiment does not decrease

Why hire us again?

- We could use different models for sentiment analysis
- Look into other languages' data
- Look into geographical data
- Look into a bias concerning location and language

10) DISCUSSION

Accuracy of findings:

- Affected by volume of data
- Affected by conversation definition
- Affected by using pre-trained models

What we learned:

- How to work with big data files
- Decide direction based on client's wishes
- Plan and work as a team
- Presenting the project and delivering our message to the audience