COVID-19 Sentiment Analysis

Group-9

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Problem

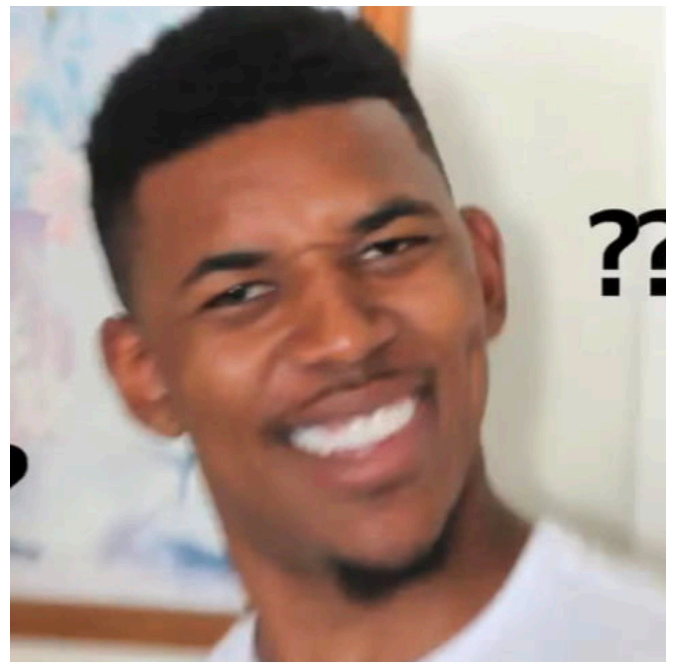
How was the sentiment changing over the course of several months on such topics as 'masks' and 'vaccines'?

- Period of study

January, 2021 - March, 2022

- Data

Tweets connected with masks and vaccines and posted by real and common users



Engineering

Models

- CNN + BiLSTM
- BERTweet
- BERTweet(fine-tuned)

Tweets

- CNN + BiLSTM -> predictions, probabilities
- BERTweet -> predictions, probabilities
- BERTweet(fine-tuned) - predictions, probabilities

Engineering

- CNN + BiLSTM -> predictions, probabilities
- BERTweet -> predictions, probabilities
- BERTweet(fine-tuned) - predictions, probabilities

Leave only the tweets with:

- the prediction agreement
- all the models' confidence higher than 0.5

Training data

- CNN+BiLSTM / BERTweet

Sentiment Analysis, SemEval 2017 - Sentiment Analysis in Twitter (Rosenthal et al., 2019)

3 labels: positive, neutral, negative

~60,000 labeled tweets

- BERTweet(fine-tuned)

Trained on **Emoji Prediction**, SemEval 2018 - Emoji Prediction (Barbieri et al., 2018) - 20 labels

~50,000 labeled tweets

Fine-tuned on **Sentiment Analysis**, SemEval 2017 - Sentiment Analysis in Twitter (Rosenthal et al., 2019)

Training results

Model	validation accuracy	validation f-1	test accuracy	test f-1
CNN+BiLSTM	0.692	0.672	0.626	0.625
BERTweet	0.758	0.743	0.719	0.720
BERTweet (fine-tuned)	0.734	0.714	0.704	0.706

Train results comparison

with Sentiment Analysis, SemEval 2017 - Sentiment Analysis in Twitter (Rosenthal et al., 2019)

Model	test accuracy	test f-1
CNN+BiLSTM	0.626	0.625
BERTweet	0.719	0.720
BERTweet (fine-tuned)	0.704	0.706

#	System	*AvgRec*	F_1^{PN}	*Acc*
1	DataStories	**0.681**$_1$	0.677$_2$	0.651$_5$
	BB_twtr	**0.681**$_1$	0.685$_1$	0.658$_3$
3	LIA	**0.676**$_3$	0.674$_3$	0.661$_2$
4	Senti17	**0.674**$_4$	0.665$_4$	0.652$_4$
5	NNEMBs	**0.669**$_5$	0.658$_5$	0.664$_1$
6	Tweester	**0.659**$_6$	0.648$_6$	0.648$_6$
7	INGEOTEC	**0.649**$_7$	0.645$_7$	0.633$_{11}$
8	SiTAKA	**0.645**$_8$	0.628$_9$	0.643$_9$
9	TSA-INF	**0.643**$_9$	0.620$_{11}$	0.616$_{17}$
10	UCSC-NLP	**0.642**$_{10}$	0.624$_{10}$	0.565$_{30}$
11	HLP@UPENN	**0.637**$_{11}$	0.632$_8$	0.646$_8$
12	YNU-HPCC	**0.633**$_{12}$	0.612$_{15}$	0.647$_7$
	SentiME++	**0.633**$_{12}$	0.613$_{13}$	0.601$_{23}$
14	ELiRF-UPV	**0.632**$_{14}$	0.619$_{12}$	0.599$_{24}$
15	ECNU	**0.628**$_{15}$	0.613$_{13}$	0.630$_{12}$
16	TakeLab	**0.627**$_{16}$	0.607$_{16}$	0.628$_{14}$
17	DUTH	**0.621**$_{17}$	0.605$_{17}$	0.640$_{10}$
18	CrystalNest	**0.619**$_{18}$	0.593$_{19}$	0.629$_{13}$
19	deepSA	**0.618**$_{19}$	0.587$_{20}$	0.616$_{17}$
20	NILC-USP	**0.612**$_{20}$	0.595$_{18}$	0.617$_{16}$

Training results on covid-19 data

- manually annotated tweets: masks test set and vaccines test set

around 100 tweets each

Model	test accuracy	test f-1	masks test accuracy	masks test f-1	vaccines test accuracy	vaccines test f-1
CNN+BiLSTM	0.626	0.625	0.611	0.548	0.604	0.623
BERTweet	0.719	0.720	0.656	0.62	0.7822	0.7920
BERTweet (fine-tuned)	0.704	0.706	0.722	0.691	0.762	0.746

COVID-19 data

A bit of stats:

- Before filtering:

Masks - 102,597 tweets

Vaccines - 346,612 tweets

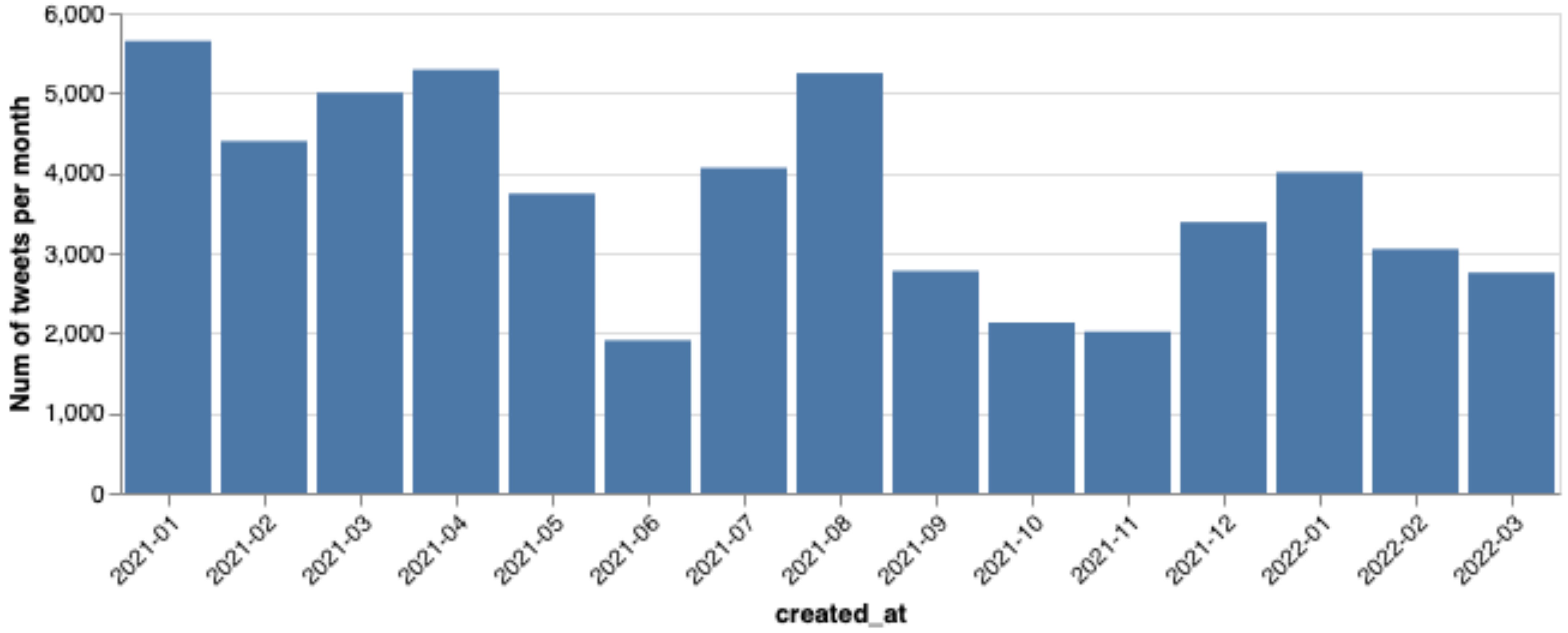
- After filtering

Masks - 55,425 tweets

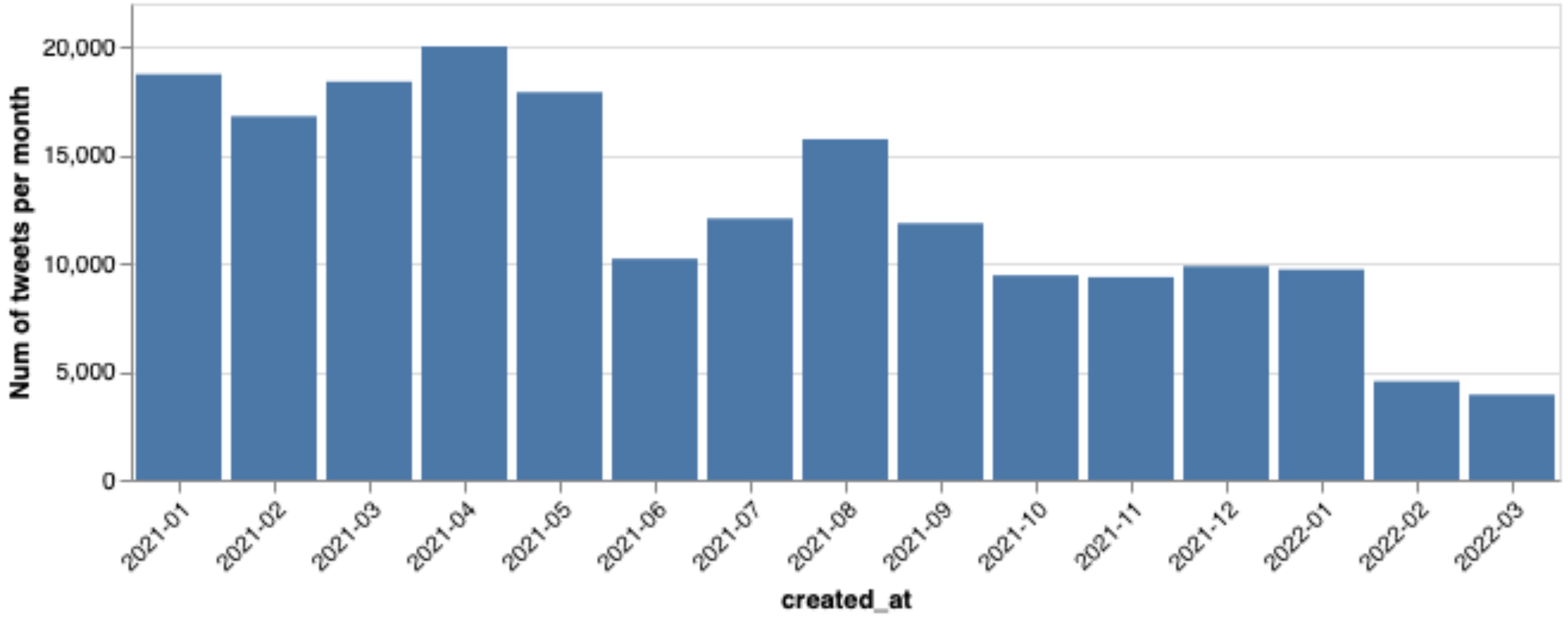
Vaccines - 188,580 tweets

Final data distribution

Masks data



Vaccines data



COVID-19 masks tweets

After prediction - **33,636** out of 55,425 tweets