netherlands eScience center

Transfer Learning for Stance Analysis in COVID-19 Tweets

Erik Tjong Kim Sang, Marijn Schraagen, Shihan Wang, Mehdi Dastani
Netherlands eScience Center / Utrecht University

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RIVM: Applying behavioural science to COVID-19

National Institute for Public Health and the Environment
Ministry of Health, Welfare and Sport

Nederlands English

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Applying behavioural science to COVID-19

Preventive behaviour plays an important role in working together to gain control of the coronavirus SARS-CoV-2. Healthy behaviour is also vital in staying healthy during the coronavirus pandemic. Research on behaviour and health provides insights on how to help people keep following behavioural rules – with a focus on their own health and the people around them.

Study on behavioural measures and well-being

The measures taken by the government in the fight against the coronavirus have a major impact on the daily lives of everyone in the Netherlands. The government would like to know whether people can follow these rules, and what they think of them.

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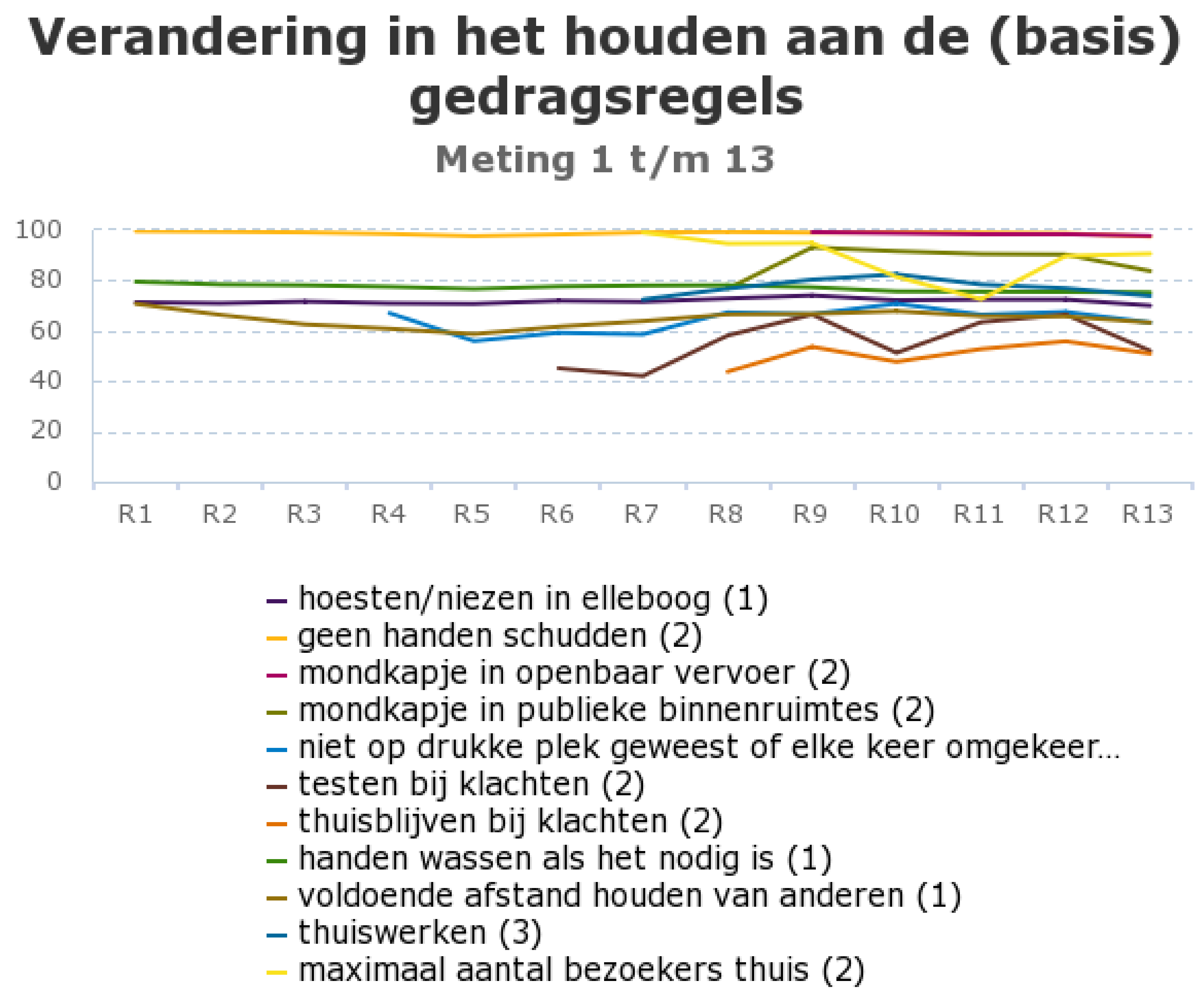
RIVM: Compliance with behavioral measures over time



Timeline

R1 17 - 24 April 2020
R2 7 - 12 May 2020
R3 27 May - 1 June 2020
R4 17 - 21 June 2020
R5 8 - 12 July 2020
R6 19 - 13 August 2020
R7 30 September – 4 October 2020
R8 11 - 15 November 2020
R9 30 December – 3 January 2021
R10 10 - 14 February 2021
R11 24 - 28 March 2021
R12 5 – 9 May 2021
R13 16 - 20 June 2021

Translation

- sneezing in elbow (1)
- not shaking hands (2)
- facemask in public transport (2)
- Facemask in public spaces (2)
- Avoid busy areas
- Test with symptoms (2)
- Stay at home with symptoms (2)
- Wash hands when necessary (1)
- Social distancing (1)
- Work at home (3)
- Maximum of home vistors (2)

(1) % of times; (2) % of participants; (3) % of work hours

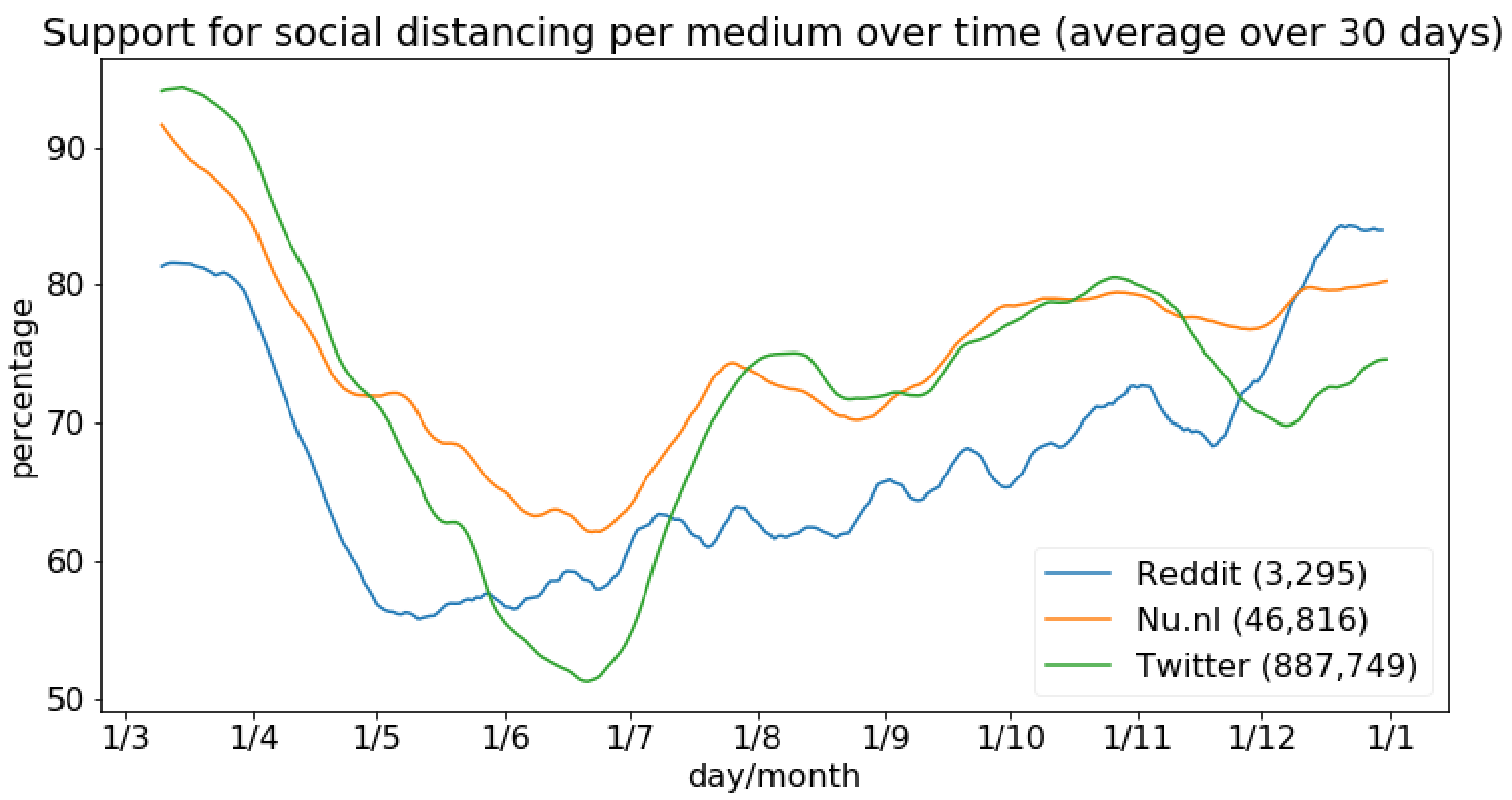
https://www.rivm.nl/gedragsonderzoek/maatregelen-welbevinden/naleven-gedragsregels

Goal:

- Derive stances on Dutch pandemic measures from social media data

Method

1. Select relevant data with keyword search
2. Estimate stances in data with machine learning
3. Visualize results



Challenge

- We need annotated data on many topics

More information: https://github.com/puregome/notebooks

We tested different approaches of transfer learning / domain adaptation:

TGTONLY: build models from (limited) in-domain data only (baseline)

SRCONLY: build models from out-of-domain data only

ALL: build models from both in-domain and out-of-domain data

RLVONLY: like ALL but only use relevant out-of-domain data

FEATAUG: like RLVONLY but use different features for in-domain and out-of-domain data (Daumé III, 2007)

Data, topics and keyword filtering

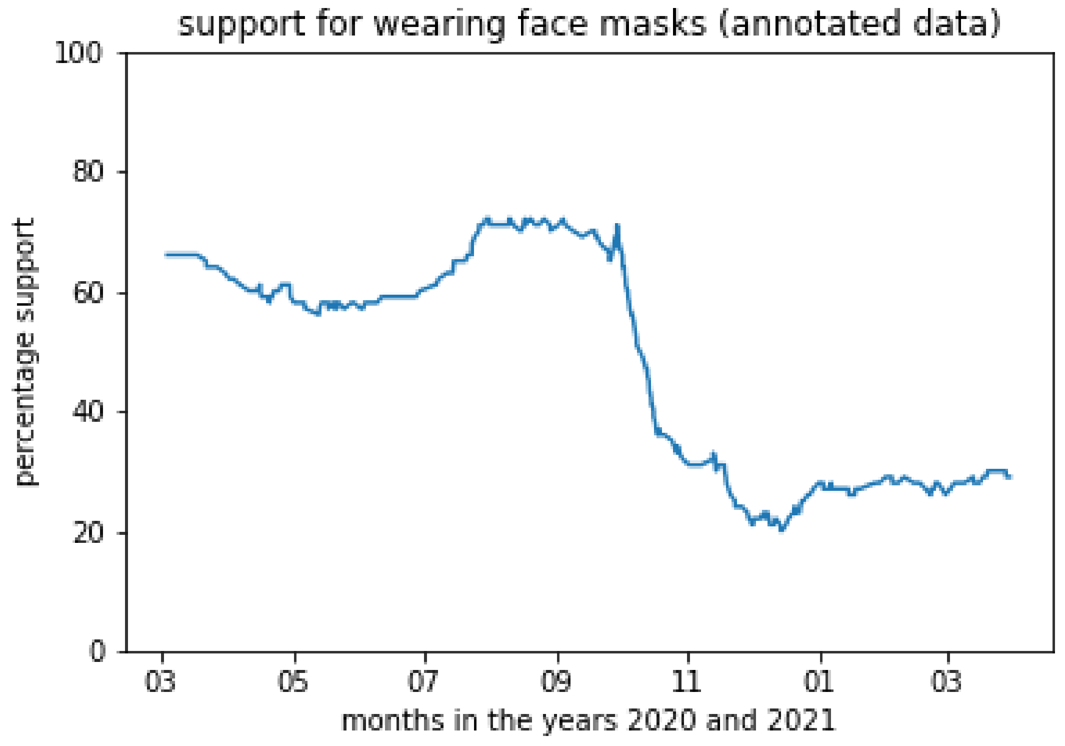
Topic	Number of tweets	Time frame
Dutch tweets	346,672,687	February 2020 – June 2021
Pandemic	41,175,162	February 2020 – June 2021
Face masks	1,847,245	February 2020 – June 2021
Social distancing	1,441,262	February 2020 – June 2021
Testing	3,831,931	February 2020 – June 2021
Vaccination	7,643,870	February 2020 – June 2021

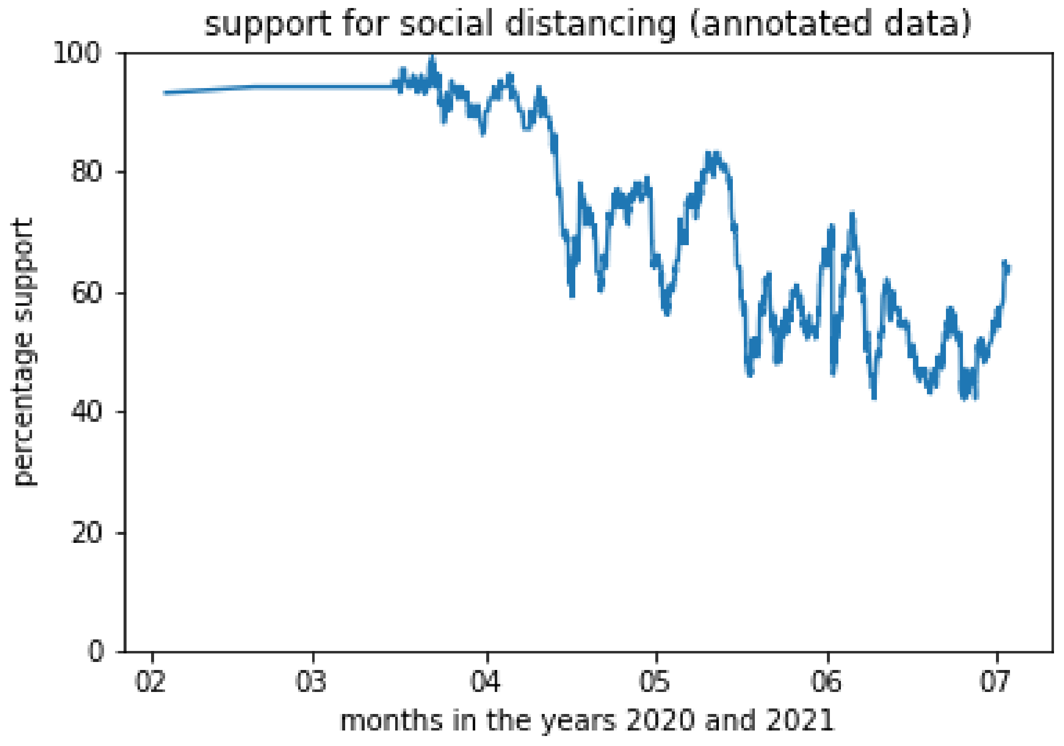
Topic	Keyword filter
Face masks	mondkapje
Social distancing	1[.,]5[-]*m | afstand.*hou | hou.*afstand | anderhalve[-]*meter
Testing	\btest | getest | sneltest | pcr
Vaccination	vaccin | ingeënt | ingeent | inent | prik | spuit | bijwerking | --> | (emoji) | pfizer | moderna | astrazeneca | astra | zeneca | novavax | biontec

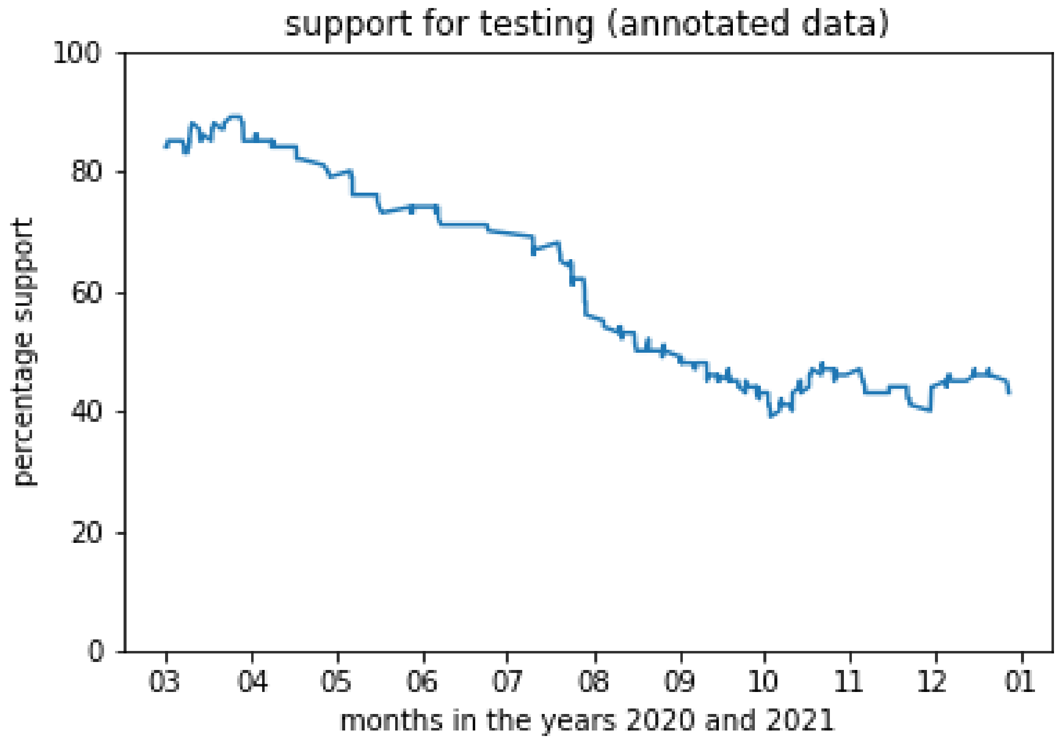
In the keyword filters, "|" stands for OR and "\b" represents a word boundary

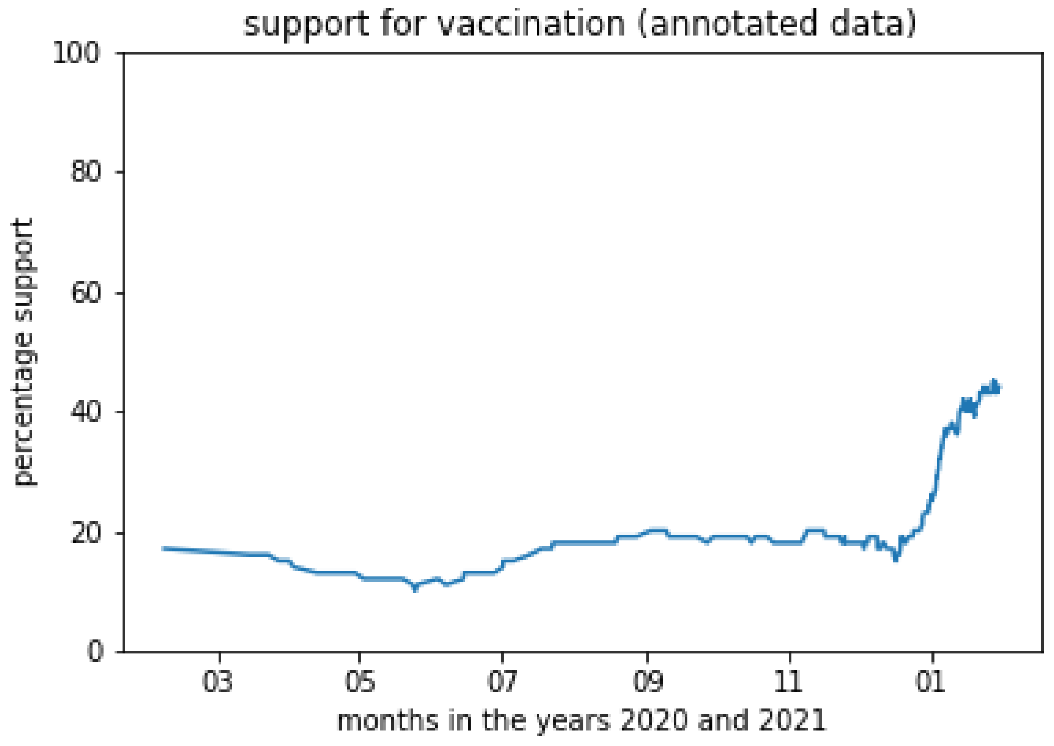
Data annotation

Topic	Tweets	Time frame	Supports	Rejects	Irrelevant
Face masks	1,011	March 2020 - March 2021	21.2%	23.6%	55.2%
Social distancing	5,977	February 2020 – July 2020	56.2%	20.0%	23.8%
Testing	1,181	March 2020 – December 2020	28.2%	17.8%	53.4%
Vaccination	1,007	January 2020 - January 2021	9.6%	24.3%	66.1%









For text classification we used the system FastText: a linear classifier which represents texts as an average of word vectors:

- Training started from a language model developed from 230 million Dutch tweets from the year 2020
- A limited grid search was done for finding the best parameters for the social distancing data
- Non-default parameter values used: vector length: 300, learning rate: 0.3, number of epochs: 200

Transfer learning results for social distancing data as out-of-domain data

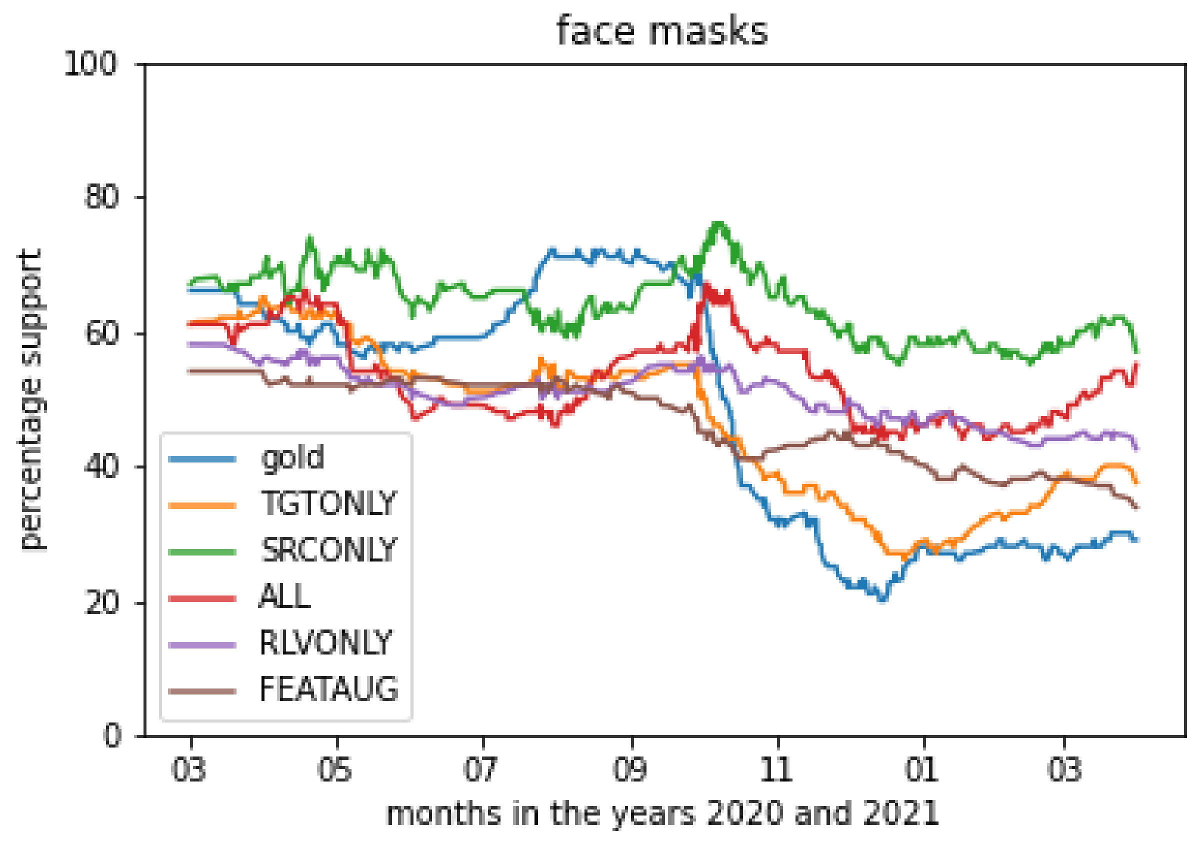
Accuracy	TGTONLY	SRCONLY	ALL	RLVONLY	FEATARG
Face masks	**0.592**	0.414	0.543	0.569	0.583
Testing	0.561	0.452	0.541	**0.572**	**0.572**
Vaccination	0.608	0.488	0.572	0.585	**0.616**
Social distancing	0.656				

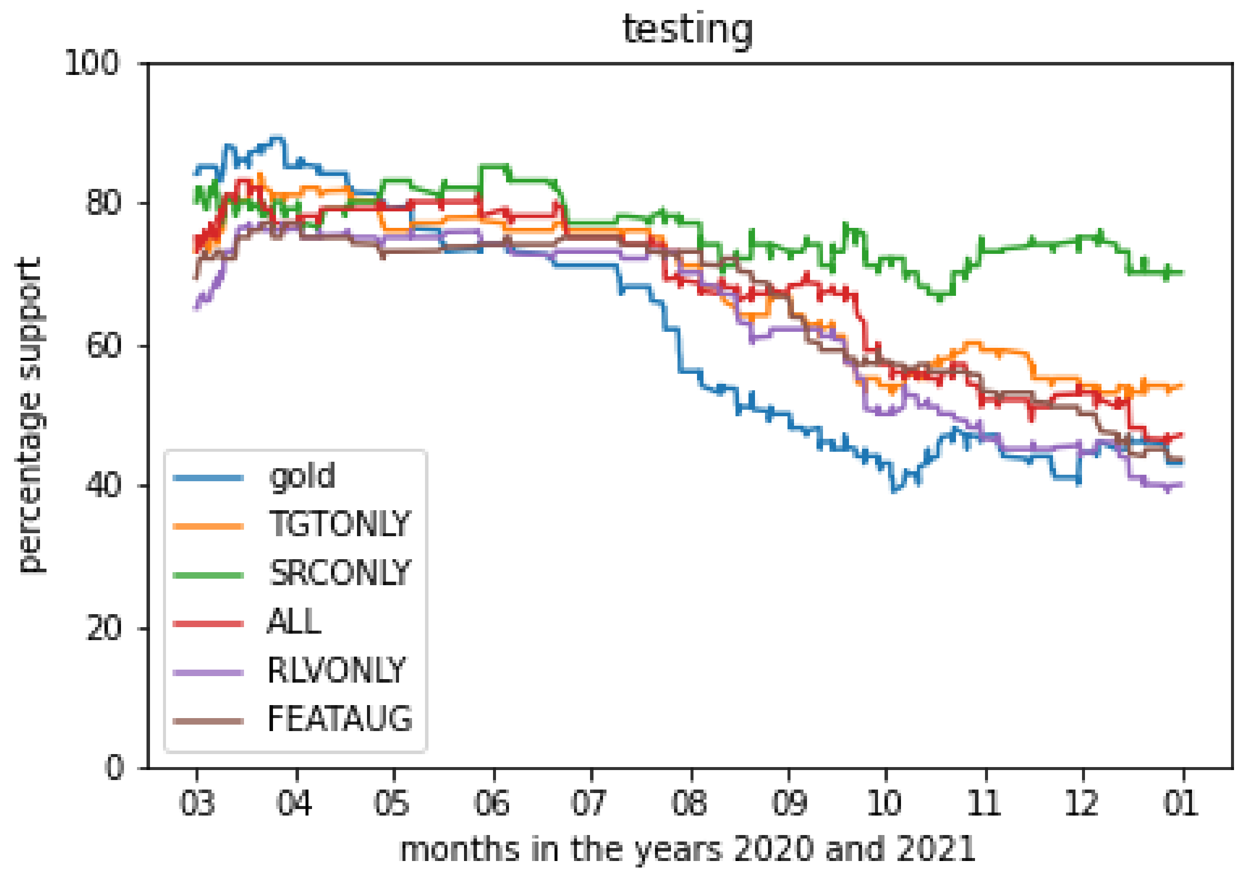
- SRCONLY and ALL perform poorly, because of inclusion of the relevance task
- RLVONLY does better: (1) selecting relevant tweets with in-domain data and then (2) determining stance with all tweets
- FEATARG performs even better: in step (2) use separate features for in-domain and out-of-domain data
- Absolute accuracy gains are small

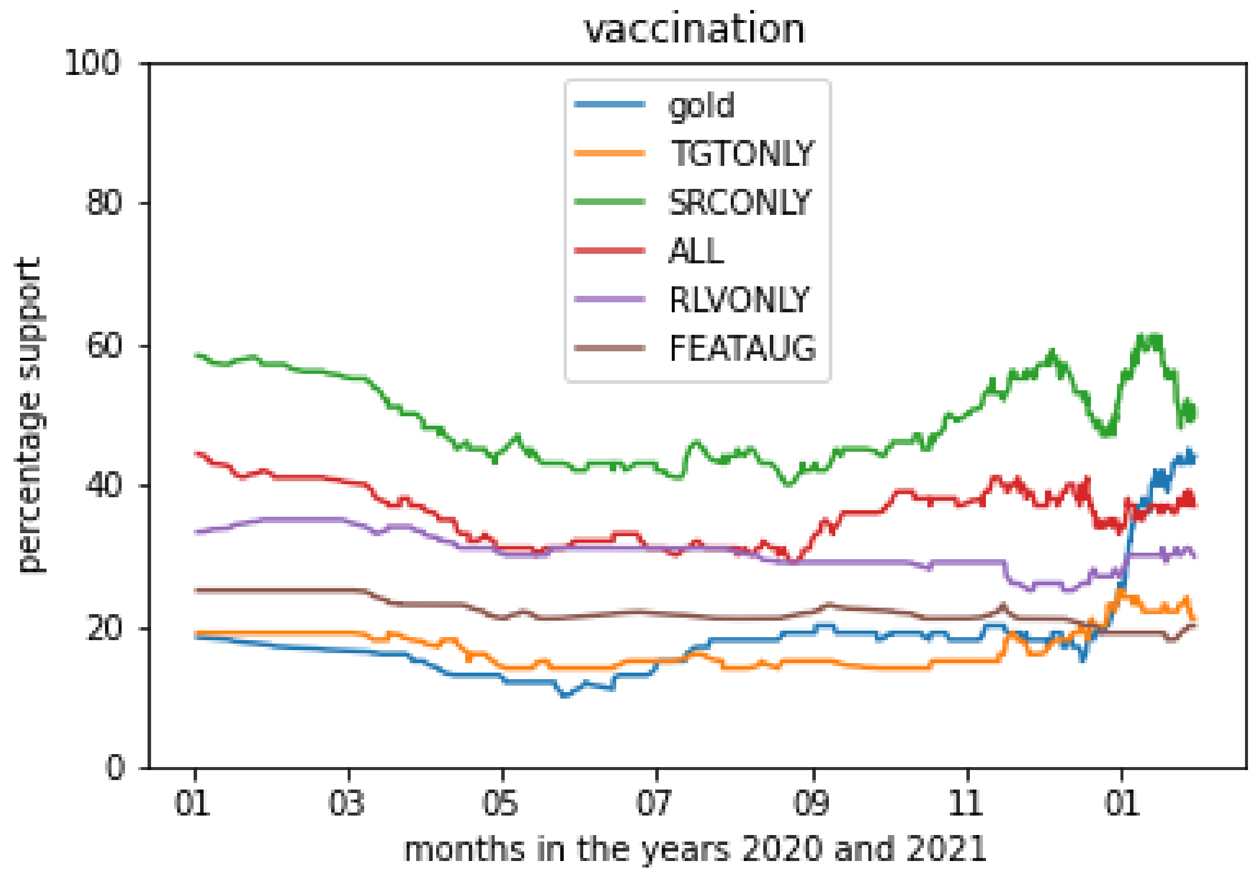
Graph-based assessment of transfer learning (annotated data graphs used as gold data)

Pearson r	TGTONLY	SRCONLY	ALL	RLVONLY	FEATARG
Face masks	**0.877**	0.533	0.435	0.743	0.806
Testing	**0.949**	0.819	0.882	0.856	0.848
Vaccination	0.361	0.586	**0.592**	0.528	-0.824

Absolute difference	TGTONLY	SRCONLY	ALL	RLVONLY	FEATARG
Face masks	**0.080**	0.177	0.143	0.133	0.125
Testing	0.093	0.169	0.097	**0.087**	0.102
Vaccination	**0.078**	0.260	0.149	0.107	0.102







Concluding remarks and future work

- We evaluated four transfer learning methods for predicting COVID-19 measure stances from social media data

- None of the methods consistently outperformed the baseline: using only in-domain data

- The problem with reproducing the vaccination graph suggests that it is important to have annotated in-domain data for all available time periods

- Future work: repeat the experiments with BERT as machine learner