Predicting side on Twitter during protests against COVID-19 mitigation measures in Vienna

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Problem

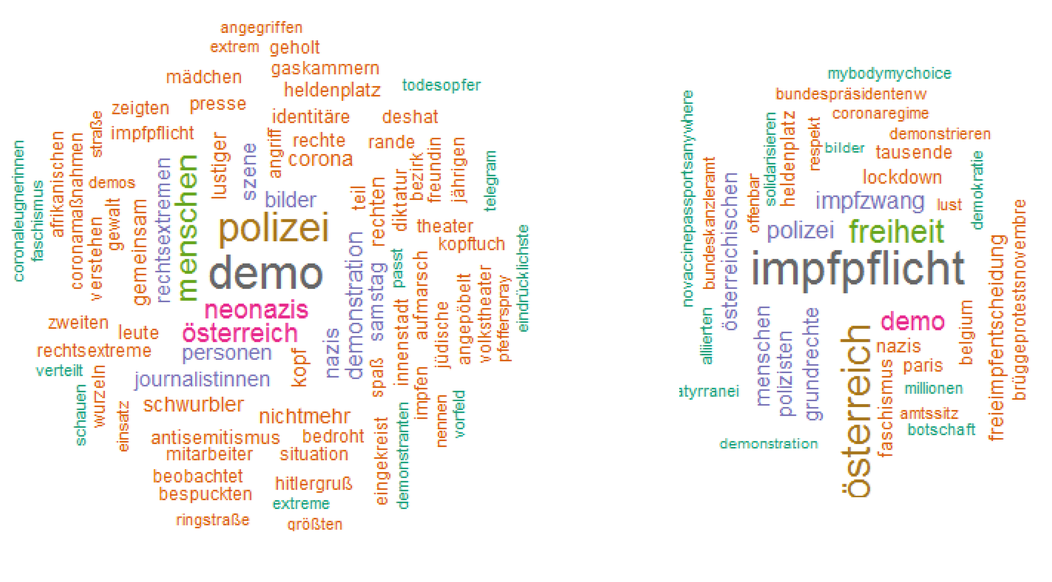
Thousands of people across hundreds of German, Austrian or Swiss locations took to the street against the government's actions on COVID-19 (Jarynowski, Semenov, Belik, 2020). These rallies gathered followers of various kind of magical thinking categories, such as QAnon, Querdenker, enthusiasts of alternative medicine, esoteric or folk religion communities.
The biggest street rally took place in the Austrian capital on 20.11.2021 shortly after the announcement of mandatory vaccination (on Monday 22.11.2021 Austria went into a hard lockdown), according to the police, almost 40,000 people took part. The second biggest demonstration took place in Vienna on 15.01.2022 (when the Austrian parliament approved a mandatory vaccination order) with around 30,000 protesters.
Our goal is to leverage Internet media sources (secondary document analysis) to understand the driving mechanisms behind COVID-19-related social dynamics within the protests and how they interact with the epidemic:

- How does the society perceive the epidemic, the measures and the vaccination? What topics, vocabulary do users use in the discourse? What is the sentiment of the messages?
- Which are the most important communities spreading the information about the vaccines and non pharmaceutical interventions? What are the characteristics of the information spread?
- What are behavioral and affective differential characteristics of individuals' willingness to be engaged against the anti-containment measures/or being against protests in the 3rd/4th wave of the Corona pandemic in Vienna?
- What are the conflicting lines (Jarynowski, Płatek 2022) on compulsory vaccinations? What is the structural and dynamic "digital footprint" of protest?

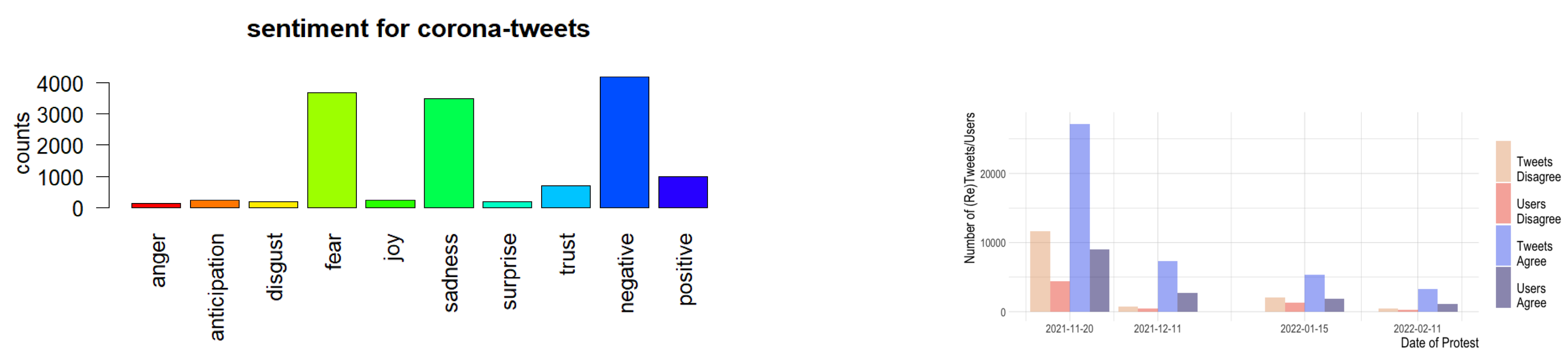
Data Processing and Methods

We utilize datasets, collected from discussions about a series of protests on Twitter (40,488 tweets related to 20.11.2021; 7,639 from 15.01.2022 – the two biggest protests as well as 192 from 22.01.2022; 8,412 from 11.12.2021; 3,945 from 11.02.2022). An ethical committee approval (by bio-ethical board at Veterinary Medicine Faculty of Free University of Berlin) was given on analysis of COVID-19 (for instance users names cannot be revealed).
We primarily applied Social Network Analysis (SNA) of the internet media users connected via their tweets sharing activities. Nodes are Twitter accounts, link is a retweet. Spin-glass and Louvain algorithm were used for community detection. We have created language-based classifiers for single tweets of the two protest sides – random forest, neural networks and a regression-based approach. To gain insights into language-related differences between clusters we also investigated variable importance for a word-list-based modeling approach.

Content Analysis



Wordcloud for compliant (left) and protest (right) cluster of tweets.

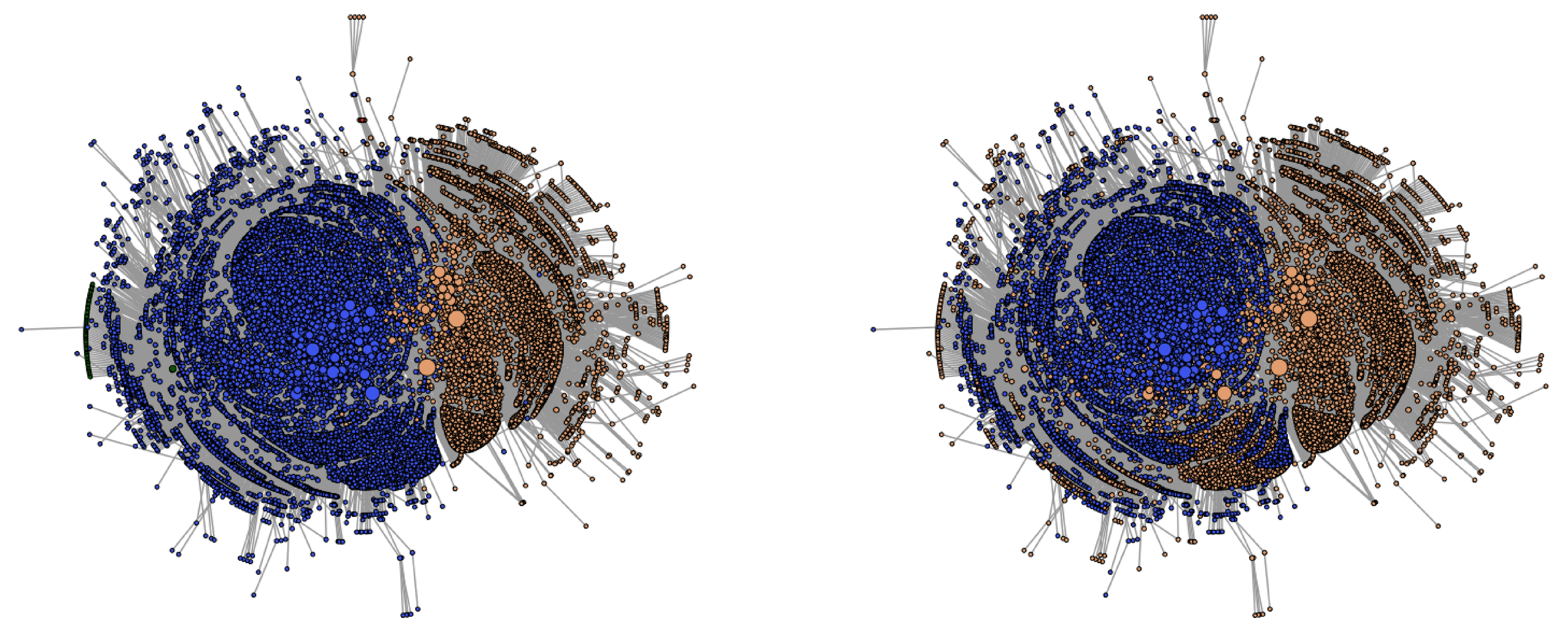


Sentiment (left) and tweeting dynamics among protests (right).

References

Jarynowski, A., Semenov, A., Belik, V. 2020. Protest perspective against COVID-19 risk mitigation strategies on the German Internet. LNCS, Springer `https://doi.org/10.1007/978-3-030-66046-8_43` Jarynowski, A., Płatek, D. 2022. Sentiment alysis, topic modelling and social network analysis. [in] The Covid-19 Pandemic as a Challenge for Media and Communication Studies, Taylor/Francis `http://dx.doi.org/10.4324/9781003232049-21` Röckl, M., Paul, M., Jarynowski, A., Semenov, A., Belik, V. 2023. Driving Factors of Polarization on Twitter During Protests Against COVID-19 Mitigation Measures in Vienna. LNCS, Springer `https://doi.org/10.1007/978-3-031-26303-3_2`

Clustering



Aggregated retweet network of tweets posted during with clustering according to Louvain (left) and Spin Glass (right) algorithms; blue nodes are (re)tweets of users who agree with governmental measures; orange nodes are (re)tweets of users who disagree.

Classification

User ID	Tweet
96850282...	Auch in Österreich wird zu...
96850282...	#w2011 Dieser Dude hat sc...
...	...
10790336...	Volle Solidarität mit allen d...

For the classification task we employed German version of the **LIWC** (dictionary including summary variable as (e.g. *Words per Sentence* or *Dictionary Words*), Linguistic Dimensions (e.g. *Total pronouns* or *Common Adverbs*), Other Grammar (e.g. *Common verbs* or *Comparisons*) as well as Psychological Processes including Social processes (e.g. *Family*), Cognitive processes (e.g. *insight*), Perceptual processes (e.g. *See*) or Informal language (e.g. *swear words*) among many others) and **fastText** (a supervised learning approach for text classification and sentiment analysis which computes a 300-dimensional uninterpreted vector for each word).

$$
\begin{array}{rc}
\textbf{UserID} & \begin{array}{cccc}\textbf{Analytic} & \textbf{Authentic} & \dots & \textbf{function}\end{array} \\
\begin{array}{r}96850282\dots \\ 96850282\dots \\ \vdots \\ 10790336\dots\end{array} &
\begin{pmatrix} 99.00 & 1.76 & \dots & 50.00 \\ 13.74 & 1.00 & \dots & 33.33 \\ \vdots & \vdots & \ddots & \vdots \\ 20.23 & 5.07 & \dots & 9.09 \end{pmatrix} \\
 & \begin{array}{cccc} 1 & 2 & \dots & 97 \end{array}
\end{array}
\qquad
\begin{array}{c}
\begin{array}{cccc}\textbf{1} & \textbf{2} & \dots & \textbf{300}\end{array} \\
\begin{pmatrix} -0.0068 & 0.0130 & \dots & -0.0079 \\ -0.0035 & 0.0193 & \dots & -0.0290 \\ \vdots & \vdots & \ddots & \vdots \\ -0.0279 & 0.0082 & \dots & -0.0224 \end{pmatrix} \\
\begin{array}{cccc} 1 & 2 & \dots & 300 \end{array}
\end{array}
$$

Text in tweets processed as **LIWC** (*left*) and **fastText** (*right*) matrix with 8,513 rows and 97 (*LIWC*) and 300 (*fastText*) columns (see methods definition in Röckl, et al. 2023).

Method	**Accuracy**	**AUC-score**
Random Forest	0.862	0.767
Logistic Regression	0.855	0.749
Neural Network	0.828	0.727

Classification results using **LIWC**-data

Method	**Accuracy**	**AUC-score**
Random Forest	0.846	0.758
Logistic Regression	0.840	0.744
Neural Network	0.852	0.765

Classification results using **fastText**-data

Conclusions

- In our case Spin Glass algorithm was outperformed by Louvain algorithm. One may notice that the blue Spinglass cluster net has many orange sprinkles (misclassified users) whereas with clusters formed by Louvain it is not the case.
- We observe decreasing share of protesters with time in the analyzed Vienna protests in Twitter (these users may change social networking site to e. g. Telegram (Jarynowski, Semenov, Belik 2020).
- Language used by pro and anti- protesters differs significantly. For the most important feature *conj.* which counts conjunction words (e.g. "and, but, or"), we can see that low use of conjunction words leads to a prediction of falling into the pro-protest cluster, whereas the separation for the prediction of the other cluster does not seem clear. The second most important variable *posemo*, which counts positive emotion words where low use of positive emotion leads to a prediction of falling into the anti-protest cluster and high use of positive emotion leads to falling into the pro-protest cluster, shows clearer separation. This corresponds with the expectation that pro-protest tweets would speak positively of the current event and anti-protest tweets would not.

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