The German Police and Twitter

How neutral are the tweets of the German police?

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Introduction

Social media has changed the online communication process enormously. The list of impacts the different platforms had could probably go on forever, but it should be noted that it especially paved the way for a new kind of communication by governmental organizations like the police. Especially Twitter, founded in 2006, has been heavily used by police stations all around the world in the past years.

Twitter can be thought about as a communication platform, social network, publicly accessible online-diary or micro-blogging service. Private individuals, corporations, mass media, journalists, NGOs and governmental organizations use Twitter as a platform to spread short text-based messages in the form of Tweets, which consist of 280 characters. As a result, the microblogging service Twitter is not only used for personal entertainment and to maintain social relationships, but also serves as a platform to exchange political views and opinions. Information dissemination on Twitter is advantageous in crisis situations such as natural disasters, during violent attacks or demonstrations. Thanks to its non-reciprocal network structure, Twitter ensures that tweets are disseminated in real time during such incidents[1].

In their book "*Social media strategies: Understanding the differences between North American police departments*", *Albert Meijer* and *Marcel Thaens* note that "Social media are being used to enhance citizens' input in police investigations, to strengthen the public image of police departments, to control crowds, to tackle crisis situations, to obtain better input in policy-making processes and to attract new police officers."[2] Moreover, the supposed cause can be described as informing as fulfillment of official duty and informing about the fulfillment of official duty. Whereas there are a variety of reasons behind the social media use of the police, it's obvious that it comes with difficulties – especially on Twitter.

In 2018, netzpolitik.org published an article called "*Influencer in Uniform: Wenn die Exekutive viral geht*" in which the news-website criticizes the Twitter use of the German police. As mentioned in the article, the police might act as an influencer, which could lead to a blurring of the boundaries between neutral spread of information and biased representation of individual or political interests[3]. It is also criticized, that there are no clear regulations in Germany, which consider the engagement of police accounts in form of favorites, followings, retweets or blockings[4]. Especially the blocking of users can be considered as an interference with freedom of expression[5].

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[1] cf. Eggers 2020

[2] cf. Meijer and Thaens, p. 343 (2013)

[3] cf. Reuter, Fanta, Bröckling and Hammer (2018)

[4] cf. Bilsdorfer (2019)

[5] cf. Tanriverdi (2018)

Among others, these points of criticism and the personal interest of the research group in social media and the police in general, lead to the research question:

How neutral is the German police on Twitter?

The present report has the following structure: After a short explanation of the *research aim and motivation* and the *organization of the research process*, the *data set* will be described regarding the *acquisition* and *content*. Thirdly, there will be a chapter regarding the description of the research *method*, which is subdivided into the four different parts *frequencies*, *topic modelling*, *sentiment analysis* and *viral tweets*. Thereafter, the *results* will be presented, followed by an *evaluation* of the results and a *conclusion*. During the different chapters, there will always be a critical reflection, where it is attempted to highlight the different problems that came up in the research process.

Research Aim and Motivation

Currently there is not much research regarding the use of Twitter by the police. Most of those that exist, are focused on the USA, some on countries like Canada, Netherlands, or Turkey, but almost none deal with the German police[6]. Especially the scientific research with big datasets that focus on the German police in Twitter-sphere is limited to few approaches, for example by netzpolitik.org[7].

The missing research regarding this field stands in contrast to the high number of Twitter accounts and Tweets, which can be seen in the analyzed dataset. Nowadays Twitter can definitely not be seen as a niche way of communication, rather it can be viewed as one of the main platforms the police choses to spread information and it gains in relevance from day to day. Due to its real-time micro-blogging structure, it is a good fit for governmental, police and journalistic communication. As of 2015, approximately one fourth of all verified Twitter accounts were journalists[8].

As mentioned in the introduction, there are almost no clear regulations or guidelines concerning the social media use of the police. Neither from the side of the legislation nor from the police itself[9]. This stands in contrast to the obvious responsibility the police have, in general and in this specific case by communicating via social media.

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[6] cf. Pratama et al. (2019); Meijer and Torenvlied (2016); Kudla and Parnaby (2018)

[7] cf. Reuter (2018)

[8] cf. Kamps (2015)

[9] cf. Bilsdorfer (2019)

Police communication affects the society in many ways, for example regarding the question of distribution of misleading or false information by the police. A society, which also includes the team working on this report, relies on neutral and correct information by governmental organizations.
By looking into this dataset from different angles, we try to contribute to the question of neutrality and responsibility the police have by using Twitter as a form of communication. The different angles include a sentiment analysis, topic modeling and a general look at the facts and figures that can be extracted from the dataset.
The report will not use an external definition of neutrality, instead it will compare the different police stations with each other, for example in terms of their tone of voice. It should be noted that this is not an approach to give specific answers concerning the research question, rather it tries to show tendencies in this specific type of communication by the police.

Organization of Research

After the reception of the dataset by the University group *AG Link*, we tried to get an overview of the current state of research and looked for inspiration regarding our research question. Especially two articles by *netzpolitik.org* provided a good insight into the thematic field and helped to formulate the research question.
As soon as we established our research question, we decided to proceed the research exploratively. By researching under such a general question, it enabled us to use different methods and tools to find answers, such as the Sentiment Analysis and Topic Modeling. Due to the different skill-levels of the members, one part of the group focused on the technological aspects like data analyzation and visualization while the other part focused on the theoretical aspects and the writing process of the project report. Instead of working step-by-step with clear phases, we tried to work simultaneously in various directions to get a wide view of the dataset and possibilities that came with it.
We had online conference calls once a week, in the final phase of the research process, twice a week. Additionally, we had a Telegram group-chat for quick interchanges and a shared Notion-Workspace where we uploaded different content, for example theoretical background, logs of our online meetings, random notes or questions that came into our mind. Especially the Notion-Workspace helped a lot to share ideas and to keep an overview.

Data

Acquisition

For our research, we used a data set compiled by the *AG Link*[10], consisting of Twitter data of 160 accounts operated by German police stations. They reported that the data was queried via a *Python* loop, which sent regular requests to the Twitter API. Then, they stored the data via *MariaDB*.

The terms of service of Twitter declare that it is not permitted to publish data sets one has gathered using Twitter's application programming interface (API). However, it is allowed to publish a dehydrated dataset consisting of the tweet identifiers (IDs) alone. Such a document can then be rehydrated by which the tweet IDs are tagged with all the additional metadata the Twitter API provides (e.g. account name, userid, created_at, full_text, location...). Since we didn't pull the data ourselves, we were only given tweet IDs by the AG Link. Therefore, we rehydrated the tweets using the command line tool *twarc*[11]. *Twarc* exports a json file which we cleaned using the *R* library *tidyjson*. Then, we extracted the API fields which we found necessary for our subsequent analyses. Ultimately, we could work with one table of data, consisting of the following information. Firstly, we had metadata about each user in the form of the user ID, full name and Twitter handle (the username that appears at the end of your unique Twitter URL), as well as the assigned city and country, which in our case is exclusively Germany. Additionally, we extracted entity information, i.e. tweet ID, tag and entity-type (hashtag or mention). Most importantly, the table lists the specific literal content, time and date of the tweet as well as the number of likes, retweets, replies and quotes it received.

As preparation for the sentiment analysis, each police account was tagged manually with the federal state the police station is located in. The resulting table was merged with the original dataset. Then a variable was coded to differentiate between police stations of new and old federal states.

Content

The dataset contains tweets published in the time period from the 27th of October 2020 until the 22nd of February 2021. In total it consists of 25057 tweets.

The 160 accounts of police stations were compiled manually by the *AG Link*. Therefore, there is a possibility that single accounts were overlooked and the dataset is incomplete. Police stations at both the city and regional levels, the federal police, and the state criminal investigation

[10] The critical informatics at the University of Leipzig. www.ag-link.xyz

[11] www.github.com/DocNow/twarc

departments were considered. The table below shows the count of twitter accounts in the dataset. Based on its location, each police account is assigned to the associated German federal state. The acronym *bpol* covers the Federal Riot Police and the Federal Police Special Forces.

B	BE	bpol	BW	BY	HB	HE	HH	MV	NI	NW	RP	SA	SH	SL	SN	TH
3	3	2	14	13	2	10	2	7	34	48	12	5	1	1	2	1

Table 1: German federal states and the amount of twitter accounts linked to them

Methods, organization and limitations of research

In this section, we will describe our methodological process in order to show which procedures we used to approach our research question. The starting point for this work was the data set that seemed worthwhile further investigation. Initially, we wanted to proceed exploratively. However, this did not advance our interest in the neutrality of the police. Therefore, specific questions were posed to the dataset, which we attempted to answer through data analysis. The most relevant results are presented in the visualizations in the following section.

Getting an overview

To get a first impression at how the police of Germany acts on Twitter, we performed simple analyses with the dataset in a first step. For these and further analyses, we used R in RStudio, relying heavily on the libraries *tidyverse* and *ggplot*. These analyses mainly focused on examining the amount of tweets an account posts and at which time they are most active. Also, an overview of the relationship between self-written tweets, retweets and links was created.
Since the guiding theme of our research is the question of neutrality, it must first be clarified according to which criteria neutrality is defined. Due to the nature of our data, it is not possible to use an external benchmark for neutral tweeting, but our analyses can only refer to comparisons within the different police forces. Nonetheless, we hoped to be able to identify interesting phenomena or anomalies by clustering police accounts and comparing them among each other.

Content analysis

To get closer to the content of the tweets, we first created a word cloud to get an overview of the most frequently used words. The text cleaning, stemming and removal of stop words was performed using the *R* library *tm*. The word cloud was created using the library *wordcloud*.
With the help of topic modeling, we hoped to gain a deeper insight into the subject matter of the tweets. Topic modeling is “[...] a method for finding and tracing clusters of words in large bodies of texts”, where a topic can be described as a recurring pattern of co-occurring words[12].
For this, the topic modeling tool *TidyToPan*[13] was used. *TidyToPan* is an OpenSource software tool built for *R-Shiny*. Hence, *TidytoPan* is accessible via a GUI and can be applied without profound technical knowledge of how topic modeling works. It relies heavily on the *R* libraries *lda* and *LDAvis*.
We varied the number of assumed topics and the document type and then evaluated the results of the analysis subjectively. For the document type, we tried to aggregate the tweets of single accounts so that each document is composed of tweets by one police account. However, using single tweets as documents, keeping the alpha and beta values low and assuming 20 topics produced the best fitting results.

Sentiment Analysis

Topic modeling identified useful topics in some cases, but it was then determined that the reference to our research topic was missing, making the results difficult to interpret. We hoped that the sentiment analysis would provide greater insight into whether the tweets were neutral. Therefore, we proceeded by analyzing the sentiment of the tweets. Sentiment analysis „[...] refers to the inference of people’s views, positions and attitudes in their written or spoken texts”[14].
We first tried to use the *R l*ibrary sentiment analysis since it seemed to provide quick results by means of a simple syntax. However, what we did not have in mind at this point was how the sentiment analysis algorithm actually works. After digging deeper into the topic we found out that in sentiment analysis, a given text corpus is usually compared to a dictionary consisting of manually tagged words. Common sentiment lexica like *QDAP*, *Harvard IV* or *Loughran-McDonald* attach "positive" and "negative" scores to english words, indicating the strength of the sentiment they represent. Although there are sentiment lexica available in german[15], we lacked knowledge of how to use them in *R* and apply them in our analysis. So, our first try on using sentiment analysis was just not giving us valid results. Therefore, we decided to use a commercial solution to do the analysis. For this we chose *IBM’s Watson Natural Language Understanding*[16]. *Watson* is a

[12] cf. Posner (2012)

[13] www.github.com/ThomasK81/tidyToPan

[14] cf. Katz et. al (2015)

[15] www.sites.google.com/site/iggsahome/

[16] www.ibm.com/cloud/watson-natural-language-understanding

software solution developed by *IBM* for business customers to analyze their customers engagement via e.g. online reviews and comments on social media pages.
Concerning the technical implementation, we created a for-loop in *python* which iterated through the tweet data frame and sent the tweets to the *Watson Natural Language Understanding* API. The *Watson* API returned a json array with sentiment scores for each tweet. Using the *R* library *tidyjson*, the array was processed and fit into a data frame, which was then merged with the original tweet dataset.
Although *Watson* made the sentiment analysis simple, several shortcomings have to be taken into account.
Tweets are often too short and therefore contain too few words which are relevant for the calculation of a sentiment score. Therefore, 9385 of 25057 tweets could not be analyzed at all by *Watson*.
Further, the tweet length has a negative impact on the accuracy of the results. Especially dictionary-based approaches to sentiment analysis suffer from this bias. In short texts like tweets, single words like 'thanks' have a high positive sentiment strength and hence have a high impact on the sentiment score of the whole tweet. A 'thanks' at the end of a tweet therefore can only hardly be counterbalanced by a more negative tone in the remaining tweet text. More recent approaches to sentiment analysis contextual information into account to overcome this problem[17]. Non-rule based algorithms of this kind understand language by means of statistical learning. In consequence, results are often far more accurate. Although the tool we used – *IBM Watson* – is considered to be one of the most accurate natural language understanding algorithms available at the moment, we also found some tweets in which the sentiment score measured by Watson did not seem valid.
Examining the results, we started questioning the appropriateness of the sentiment analysis for our research topic. Since it is their job to inform about dangers as well as to ask for help in stressful situations, the themes of the police tend to be negative by profession. Accordingly, sentiment analysis is not a valid measurement method for neutrality, as it can hardly differentiate between negative tweets. After all, with our analysis we can only infer the tone of tweets. Hence, regarding the question guiding our exploratory analysis, doing a sentiment analysis was not the right approach. Nevertheless, we try to draw some tentative conclusions from this analysis, as will be shown in the next section.

With clustering according to federal states, we hoped to discover conspicuous features that would allow an interpretation of the political attitude of the federal state in question or reveal differences in East and West Germany. In retrospect, however, such an interpretation also seems groundless. Clustering by federal states still seems reasonable to us, although the possibility exists, that by aggregation outliers get neutralized, which on the individual level would have made a difference.

[17] cf. Katz, Ofek and Shapira (2015)

Viral Tweets

Since the comparison of the police stations with their own mean value alone did not achieve the results we hoped for, it also seemed very interesting to include the reactions of the followers in our analyses. These can take the form of favoriting and/or retweeting. Retweeting ensures a further spread of the tweets among Twitter users and thus concludes that the users consider it important or interesting news. Favoriting, on the other hand, should not be understood exclusively as a positive "liking", since users can also use it solely to save the tweet for themselves.

Therefore, we also examined what conspicuous features there are in the most viral tweets. Due to the lack of a precise sentiment analysis, which could also provide information about various emotions, we only looked at the positivity/negativity of the tweets, as well as conducting our own qualitative investigation of the topic via individual read-throughs.

Results/Findings

During the 4 months where the tweets were collected, a total of 25.057 tweets were posted. From these, 23.069 are original tweets and 1988 are retweets. Taking a closer look on the posting frequencies in *figure 1*, it can be noticed that strong differences between the individual accounts exist. While some accounts only posted less than ten tweets in the observed time frame (Polizei Stade, Polizei NRW SO), others posted more than 500 tweets. The ten most active accounts are shown in *figure 7*, in the appendix. Looking at the number of tweets posted per time in *figure 1*, it appears that the tweeting frequency also varies per day. The peaks are often during weekdays, while there is little tweeting on weekends – presumably because police officers have the day off. Furthermore, the plot makes obvious that there may be some missing values in the dataset. It seems as if during the time around the 20th of November and the beginning of January no tweets were posted. However, this may rather be caused by an error during the acquisition of the tweets. As we did not gather the data ourselves, at this point we are unable to prove this without manually inspecting the police accounts on twitter.

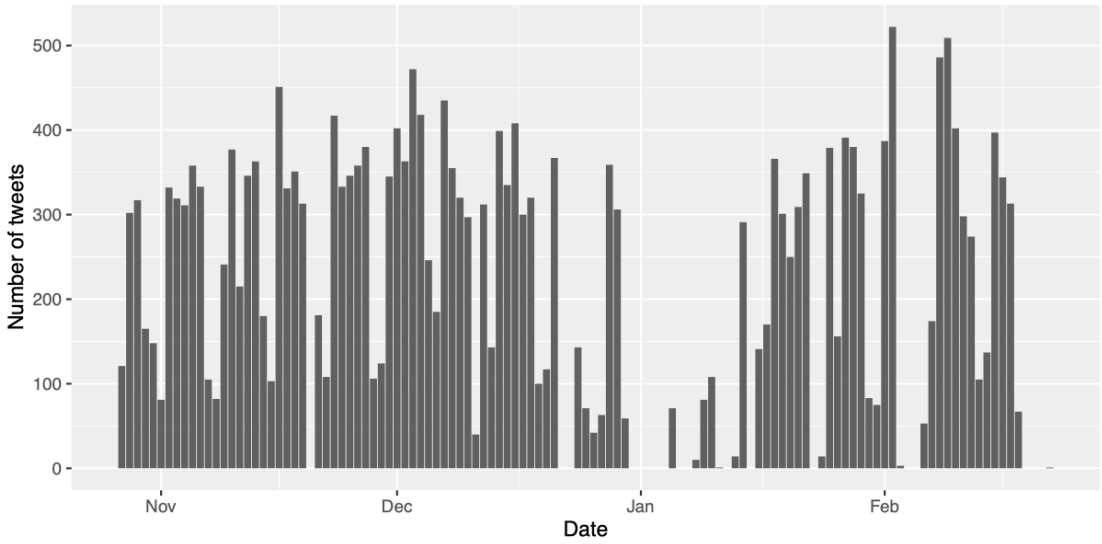

Figure 1: Posting frequencies from 27th of October 2020 until the 22nd of February 2021

The word cloud we created helps to get a quick impression of the content of the tweets. Word clouds visualize the most frequent terms in a corpus of text. The bigger the word, the more often it was used in the tweets. Since the word cloud library we used could not visualize emojis, we exchanged them with their associated meaning in german. In *figure 2* it becomes apparent that the police frequently uses emojis to frame their tweets with emojis that signal an important message (**pfeil_nach_rechts** = arrow to the right, **zeigefinger_nach_rechts** = pointing finger to the right). Further, it stands out that the police commonly uses self-referential terms (*polizei* = police, *unsere* = our, *kollegen* = colleagues). The word cloud also depicts that the police seemingly uses twitter as a platform to publish appeals for witnesses or traffic advice (*zeugen* = witnesses, *hinweise* = advice, *verkehrsunfall* = traffic accident). Moreover, words like *dannenroederforst* signal that the police regularly refers to recent events like the breaking of the demonstrations in the Dannenröder forest in October 2020.

Figure 2: Word cloud of frequently used words

Although the word cloud gives a reasonable first impression about the content of the tweets, it is difficult to interpret the context the most frequently used words appear in. For that, topic modeling proves beneficial. *Table 2* lists the 20 topics and their associated words we found in the topic modeling analysis. The topic column comprises the different words which are connected to one topic. The mean theta score on the right of the table indicates the average probability that a random tweet will be assigned to the topic. It becomes apparent that the results we got from the word cloud are reflected in the topic modeling as well. Appeals for witnesses appear in topic eight and eleven, traffic advice in topic two and six and the events which happened in the *Dannenröder forest* occur in topic 16. Several other interesting topics as well. For example topic four which deals with corona demonstrations and topic ten which signals that the police sent out wishes during the advent season. *Figure 3* gives an impression on how the probabilities that specific topics emerge in the tweets develop over the observed time period. Three topics were chosen for the visualization: topic four on corona demonstrations is coloured blue, topic nine on streets covered with ice is red and topic 13 on tricksters is green. The peaks for topic four on corona demonstrations appear in regular distances which confirms the intuition that corona demonstrations happened regularly during weekends. In contrast, the probability that a random tweet deals with topic 13 rarely changes over time. Advice to take care from tricksters seems to belong to a common category of tweets german police stations post. Advice to mind icy streets however only peaked in the beginning of February when Germany experienced a prolonged time of ice and snow.

	Topic	Mean.theta
1	wenden_sachverhalt_zuständige_bekannt_gerne_anzeige_kk	0.0860342
2	fahrer_autofahrer_schwer_fahrzeug_führerschein_leicht_kontrolle	0.0657354
3	müssen_doch_as_richtig_kein_natürlich_einfach	0.0637781
4	versammlung_verstöße_einhaltung_kontrollen_maskenpflicht_corona_gilt	0.0634193
5	festnahme_fest_ihn_haftbefehl_verdacht_männer_staatsanwaltschaft	0.0621074
6	richtung_frei_sperrung_aufgehoben_verkehr_lkw_umfahren	0.0594909
7	brand_gestohlen_recklinghausen_einbruch_entwendet_euro_einbrecher	0.0553985
8	zeugengesucht_unbekannter_bremen_zeugenaufruf_pm_raub_zeugensuche	0.0539557
9	schnee_straßen_geschwindigkeit_geschwindigkeitskontrollen_gut_kontrollieren_eis	0.0531023
10	jahr_advent_weihnachten_gesund_kreis_allen_bleiben	0.0514574
11	vermisst_mithilfe_bild_öffentlichkeitsfahndung_suche_fahndung_foto	0.0506009
12	gewalt_thema_frauen_du_fragen_zivilehelden_lka	0.0491240
13	betrüger_tipps_falsche_betrug_geld_achtung_vorsicht	0.0471802
14	d_m_w_fragen_liegt_coronavirus_sachstand	0.0398412
15	kk_ck_wohnungseinbruchsradar_c_rad_zeigt_ffm	0.0371454
16	dannenroederforst_dannenroeder_einsatzkräfte_gebracht_mannheim_krankenhaus	0.0341688
17	leipzig_dresden_meldungen_le_düren_k_statt	0.0328579
18	ots_pressebericht_unterfranken_polsiwi_wirfüreuch_polizeioe_polizeipräsidiums	0.0327412
19	pd_live_münster_trier_feuerwehr_ms_nord	0.0320948
20	bochum_._polizeime_str_witten_herne_dessau	0.0297663

Table 2: Topics in our Tweet set

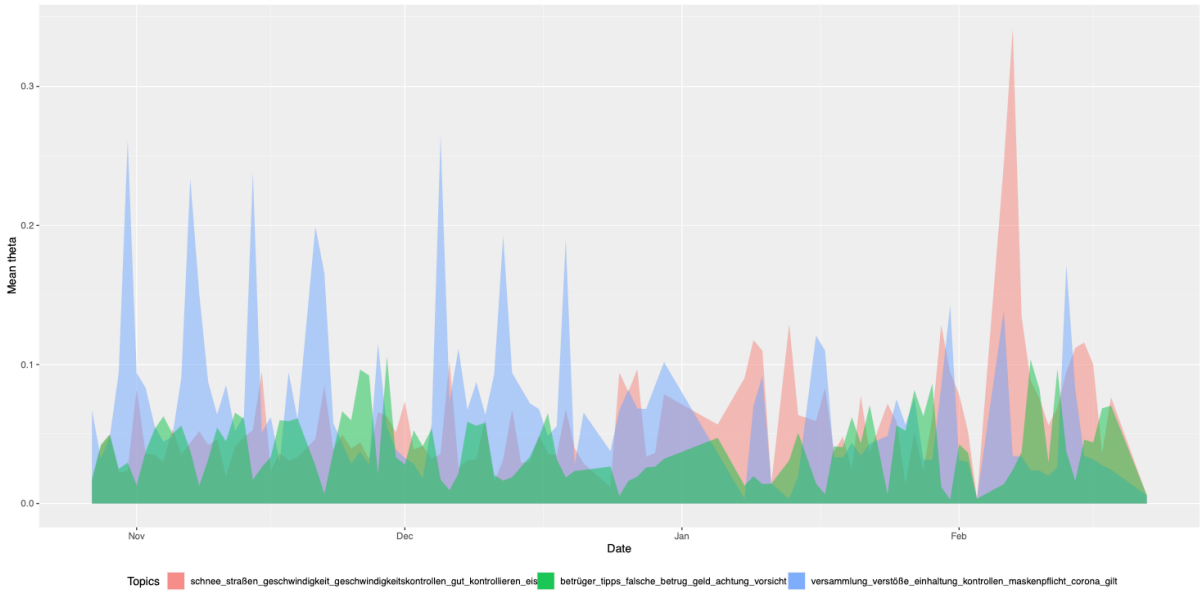

Figure 3: Probability of emerging of a specific topic

Looking at the temporal development of topic 10 in *figure 4*, it makes sense that its average theta value peaks during the weekends in December and reaches its maximum during the Christmas days. Interestingly, this pattern is also mirrored in the average sentiment scores in *figure 5*. While during the time observation most of the tweets seem to have a negative tone, this changed during December.

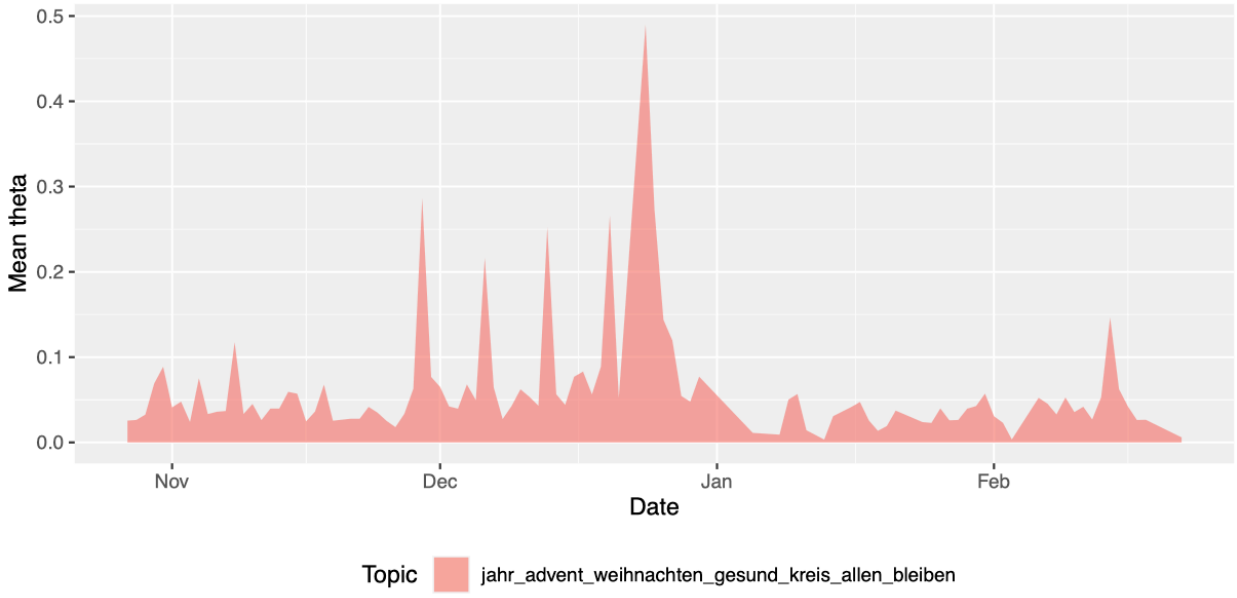

Figure 4: Temporal development of topic 10

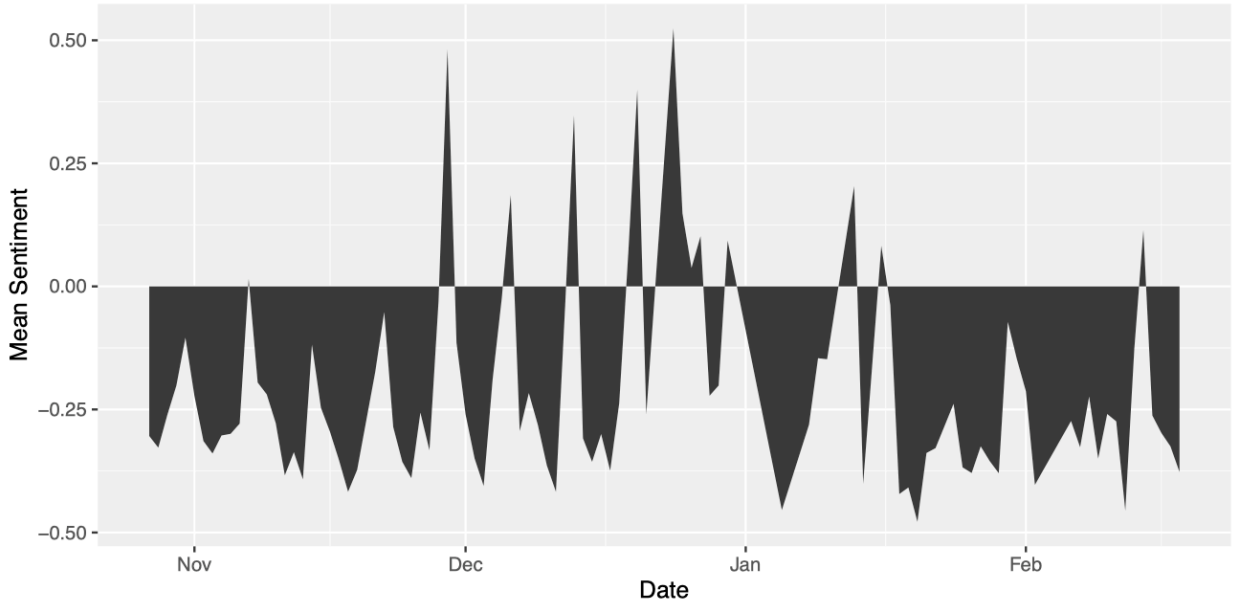

Figure 5: Average sentiment score

Figure 5 shows the distribution of sentiment labels over the whole dataset. As mentioned above, almost half of the 25057 tweets could not be analyzed by Watson since their length was too short. Inspecting the figures, it has to be kept in mind that these tweets were tagged 'neutral' by Watson. It becomes evident that Watson labeled about twice as many tweets as having a negative than having a positive tone. *Figure 8* and *9* in the appendix shows that tweets which received a lot of engagement by the twitter users differ in their sentiment. Tweets which got retweeted more than 100 times tend to be less positive than tweets which got favorited more than 1000 times. Concerning the aggregated sentiment scores according to german federal states, it can be seen in *figure 6* that the police stations of some states like Hamburg (HH) and Saxony (SN) tend to post tweets with a more negative tone. By contrast, the federal police (bpol) tends to use a less negative tone. However, clustering the tweets according to whether the police stations lies in the former east or former west of Germany did not turn out to be fruitful as can be seen in *figure 10* in the appendix.

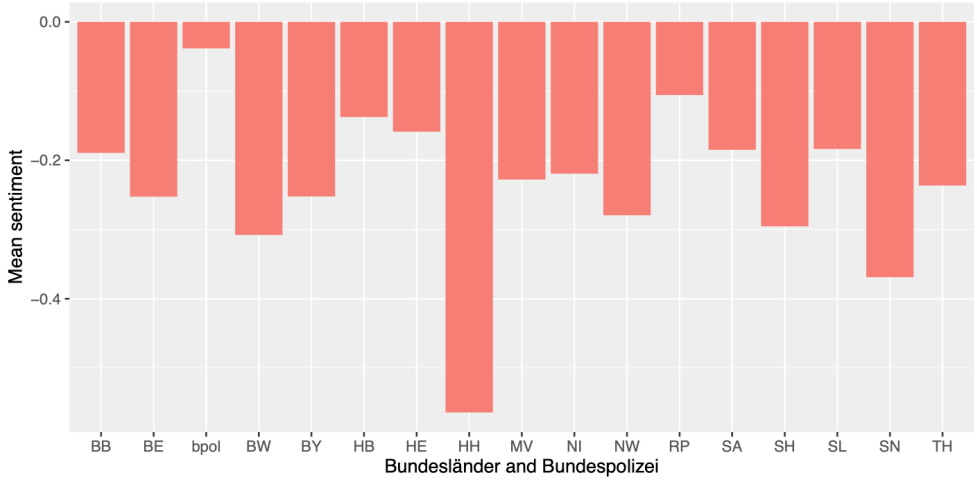

Figure 6: Sentiment scores according to German federal states

All the depicted visualizations as well as additional ones can be found in higher resolution under the DOI of this report.

Evaluation/Discussion

This section attempts to interpret and critically discuss our findings in relation to the research question. For a better understanding, we will work chronologically after the previous chapter. For this, however, it should first be noted that we as researchers know that we cannot look neutrally at the topic. The greatest possible objectivity is to be achieved by our different fields of expertise, from which we come, as well as by a critical interpretation of the data. At the same time, however, we see that we have already approached the topic with a certain critical basic attitude of the police and with the goal of finding something conspicuous that can be interpreted according to the research question. We believe that there must be better methods to do data mining with the existing dataset and would like to point out the possibility to view and further think about the dataset and further results on our part at Github.

The ratio of original tweets to retweets is 91.4%/8.6%. The retweets are often original tweets from other police accounts and retweeted by multiple police departments. Thus, there are multiple duplications in the dataset. We did not examine these retweets more closely in terms of content or otherwise include them, although they too would have merited closer examination due to their wider distribution.

The fact that the number of tweets differs greatly between the individual police forces indicates that there is no common concept or guideline for the entire German police force, but that each account decides for itself how much it posts. This is also indicated by the different language, which varies from factual short messages to a casual tone with sarcasm. However, this is also not visible in our analyses. The high posting numbers of some accounts indicate that there is a social media team or responsible persons who are mainly occupied with Twitter and other media. This shows that these police forces attach great importance to their representation on social media, so they are aware of the possibilities for rapid dissemination and improvement of their image and have thus developed their own mouthpiece with which they can address the population directly. The number of their followers would also be interesting for this, but more detailed account information is not available in our data set.

From the word cloud, a very frequent use of the words "today" as well as "current" can be seen. This shows that the police use the real-time that characterizes Twitter as a social medium. However, this also poses dangers, as has also been observed in the past. It is possible for misinformation to be published without further verification and spread quickly, while there is no

guarantee that a subsequent correction will reach all people. Mistakes do happen, but the Internet and retweets in particular make it difficult to retract them.

Also noticeable is a frequent use of emojis already in word cloud. We did not investigate these further, which also provides room for further research. From those in the word cloud, it was not possible to derive anything thematically relevant, but we would like to point out that the use of emojis expressing certain emotions (anger, sadness, joy) should be viewed critically. The police should also report neutrally on the Internet, even if social media offer further tempting opportunities. However, this can quickly indicate a certain attitude or even influence, which in our opinion should be avoided or at least questioned.

Topic modeling hardly provides any research-relevant results. However, we would like to highlight Topic 10, which contains greetings for the Advent season. Here, the question should be asked what task the police are fulfilling with this and how privately they should present themselves. The fact that there are no official guidelines or legal frameworks makes it difficult to draw boundaries. The fact that the sentiment value also increases in the December period could be due to this type of posting and indicate that the values can at least serve as a support for interpretation.

Apart from that, sentiment analysis has proven to be difficult to interpret and accordingly unsuitable for our research question. Because of the biases described in the methods chapter, the results do not help to measure the neutrality of the language, as we would have wished. We can only conclude that there are noticeable differences in scores. The tweets with the highest sentiment scores are mainly written by the police station Krefeld and indicate that there will be speed controls on specific streets. They all have a similar formatting and don't have much content except for street names. Using the Watson demo we double checked which words of these tweets are relevant for Watson 18 to calculate the sentiment score. It gets evident, that Watson interprets the specific combination of a street name and an emoji (eg. "Breslauer Straße📌 Erkelenzez") which the Policestation frequently uses as having a very high positive score. But we observed a large deviation from the average when looking at viral tweets. The most retweeted tweets use a more negative while the tweets with the most favorites use a more neutral language. However, this finding should also be interpreted with caution and we are not sure, where these differences are coming from.

When looking qualitatively at the most viral tweets, we additionally noticed points that were not apparent in the previous analyses.

It is noticeable that the most frequently retweeted tweets often represent warnings as well as circular messages. This clearly shows the added value of Twitter, which makes it possible to disseminate important news quickly and widely. Among them, there are also many duplicates, since the police also retweets the messages among themselves, in the spirit of Germany-wide dissemination. The most favored tweets, on the other hand, are often sentimental topics or highly judgmental tweets. Already among the first 15, the following (translated by us) catch the eye:

"To those who broke into a school in #Gesundbrunnen last night and stole 242 tablets: The economic damage of €100,000 was not the total amount. You have taken away children's chance to digitally shape their future. Shame on you!" (Berlin Police)

"If Leon (3) needs a police station with jail for the fight against cancer, then you call your colleague from the association EuropeanPoliceCarUnit together, drive with 🚔🚨 Blue lamp to the hospital and bring obligingly a few children's eyes to light. That's the way the law wants it." (Berlin Police)

"When the police deliver gifts, it must be an emergency. Here, the gift for a little boy had been stolen in a theft." (Munich Police)

"7-year-old Ben is suffering from cancer & is about to undergo his radiation therapy. His childhood dream came true for one day - he was allowed to be 👮" (Berlin Police)

Here it is clear that positive self-promotion (often by the Berlin police) is attempted via Twitter, and apparently with success. Also noticeable is a frequent liking of tweets describing crackdowns on Corona demonstrations. There seems to be a difference between the behavior favored by the followers and the sometimes very restrained real intervention by the police that is repeatedly reported in the media. It is therefore necessary to speak with caution of a distorted representation, which is formed by the function of Twitter as not only a quick news service but also a social medium with interactivity.

It remains to be said, therefore, that without clear rules it is difficult to detect marginal exceeding of neutrality by the police on Twitter, and that our analyses could only provide partially interpretable results, but tendencies were discernible and we were thus able to point out the need for further thematization in the public and research.

Conclusion

While we have already tried to stress that there were quite a few struggles and biases regarding our research and its process, it should also be noted that the data and evaluations provide very little insight into the research question. Therefore, the interpretations should be evaluated cautiously. We realized that the research question was too broad and that we did not have enough knowledge in advance of what could be feasible. Sometimes we only realized the difficulty of some methods and tools, after we tried them out. One can and should try to work more with the given dataset, but our skills were limited. Nevertheless, our interest has been aroused. Besides the mentioned biases, it should be mentioned that we as researchers and humans, are not entirely neutral. Of course, we have a certain standpoint, which might be seen in this project report.

Despite the low validity, we can conclude that the police post very selectively on Twitter. Topics are not chosen based on what is most informative for the society respectively the users, rather the motives often look like an improvement of the image of the police. This can be seen by their number of Tweets referring to Christmas time. Additionally, there seems to be no critical examination of their own work, for example a release of the number of unsolved cases.

In the end, we could not find concrete answers to the research question, but we were able to create a basis on which it is already visible that police forces in Germany have learned to

communicate broadly and to use emotions and stylistic devices of the Internet more or less subtly. The high numbers of retweets and favorites show that the police have created an independent platform without relying on mass media or local newspapers. Through social media, the German police gained direct impact on the public and are able to present their version of reality, which leaves them as a political player on Twitter.

The subject matter should be further illuminated and should receive more attention from the public, the legislation as well as the police itself. The police does not have to remain in a static communication position and obviously their information activities can continuously evolve – especially due to technical progress and changed forms of communication – but there should be clear legal regulations as well as guidelines from the police itself to improve the communication of the German police on Twitter.

Bibliography

Ates, Emre Cihan; Bostanci, Erkan; Guzel, Mehmet Serdar (2021): Machine Translation, Sentiment Analysis, Text Similarity, Topic Modelling, and Tweets: Understanding Social Media Usage Among Police and Gendarmerie Organizations. Available Online at https://arxiv.org/pdf/2101.12717.

Bilsdorfer, Mascha Carina (2019): Polizeiliche Öffentlichkeitsarbeit in sozialen Netzwerken. 1. Auflage. Baden-Baden: Nomos (Studien zum öffentlichen Recht).

Eggers, Christian (2020): Quick Guide Social-Media-Recht der öffentlichen Verwaltung. Rechtliche Grundlagen und Gestaltungsoptionen in der Öffentlichkeitsarbeit. 1. Auflage 2020. Wiesbaden: Springer Fachmedien Wiesbaden GmbH; Springer Gabler (Quick Guide).

Kamps, Haje Jan (2015): Who Are Twitter's Verified Users? - Haje Jan Kamps - Medium. In: *Medium*, 25.05.2015. Available Online at https://haje.medium.com/who-are-twitter-s-verified-users-af976fc1b032, last checked 03.29.2021.

Katz, Gilad; Ofek, Nir; Shapira, Bracha (2015): ConSent: Context-based sentiment analysis. In: *Knowledge-Based Systems* 84, S. 162–178. DOI: 10.1016/j.knosys.2015.04.009.

Kudla, Daniel; Parnaby, Patrick (2018): To Serve and to Tweet: An Examination of Police-Related Twitter Activity in Toronto. In: *Social Media + Society* 4 (3), 205630511878752. DOI: 10.1177/2056305118787520.

Meijer, Albert; Thaens, Marcel (2013): Social media strategies: Understanding the differences between North American police departments. In: *Government Information Quarterly* 30 (4), S. 343–350. DOI: 10.1016/j.giq.2013.05.023.

Meijer, Albert Jacob; Torenvlied, René (2016): Social Media and the New Organization of Government Communications. In: *The American Review of Public Administration* 46 (2), S. 143–161. DOI: 10.1177/0275074014551381.

Posner, Miriam (2012): Very basic strategies for interpreting results from the Topic Modeling Tool. Available Online at http://miriamposner.com/blog/very-basic-strategies-for-interpreting-results-from-the-topic-modeling-tool/, last checked 10.06.2020.

Pratama, Bryan; Saputra, Dedi Dwi; Novianti, Deny; Purnamasari, Endah Putri; Kuntoro, Antonius Yadi; Hermanto et al. (2019): Sentiment Analysis of the Indonesian Police Mobile Brigade Corps Based on Twitter Posts Using the SVM And NB Methods. In: *J. Phys.: Conf. Ser.* 1201 (1), S. 12038. DOI: 10.1088/1742-6596/1201/1/012038.

Reuter, Markus (2018): Influencer in Uniform: Wenn die Exekutive viral geht. netzpolitik.org. Available Online at https://netzpolitik.org/2018/wenn-die-exekutive-viral-geht-twitter-wird-zum-lieblings-werkzeug-der-deutschen-polizei/, last updated 06.09.2018, last checked 12.03.2021.

Tanriverdi, Hakan (2018): Polizei darf Twitter-Nutzer nicht einfach blockieren. In: *Süddeutsche Zeitung*, 09.03.2018. Available Online at https://www.sueddeutsche.de/digital/meinungs-und-informationsfreiheit-polizei-darf-nutzer-auf-twitter-nicht-einfach-blockieren-1.3898886, last checked 10.03.2021.

Appendix

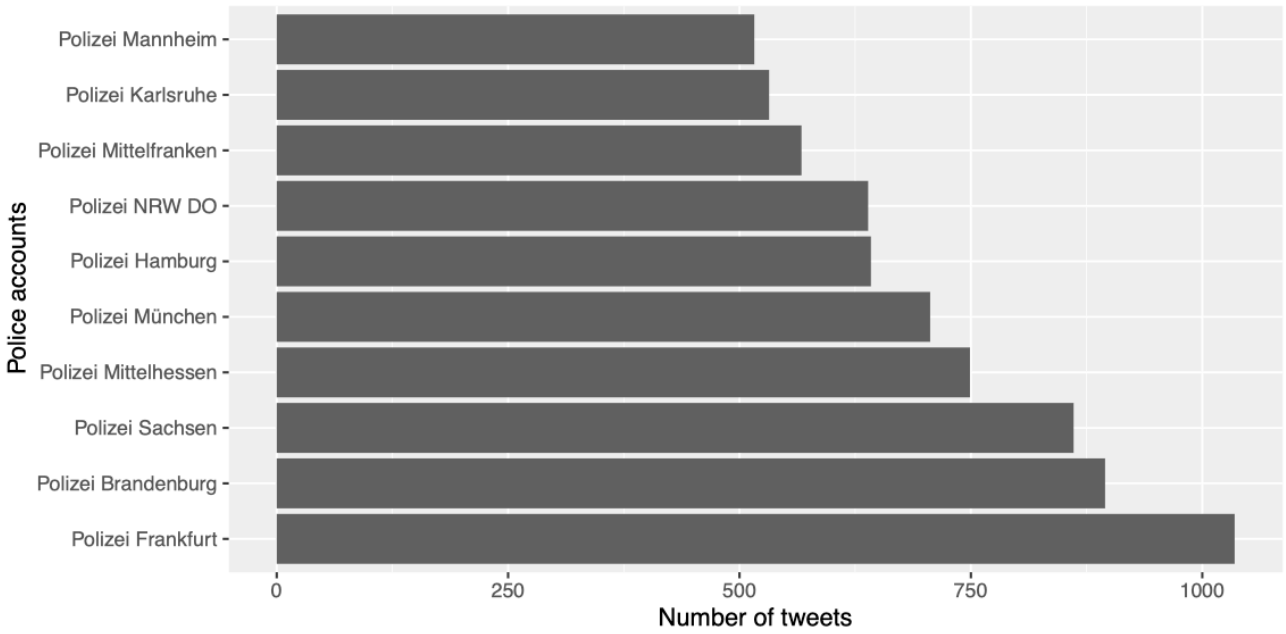

Figure 7: Most active police Twitter accounts

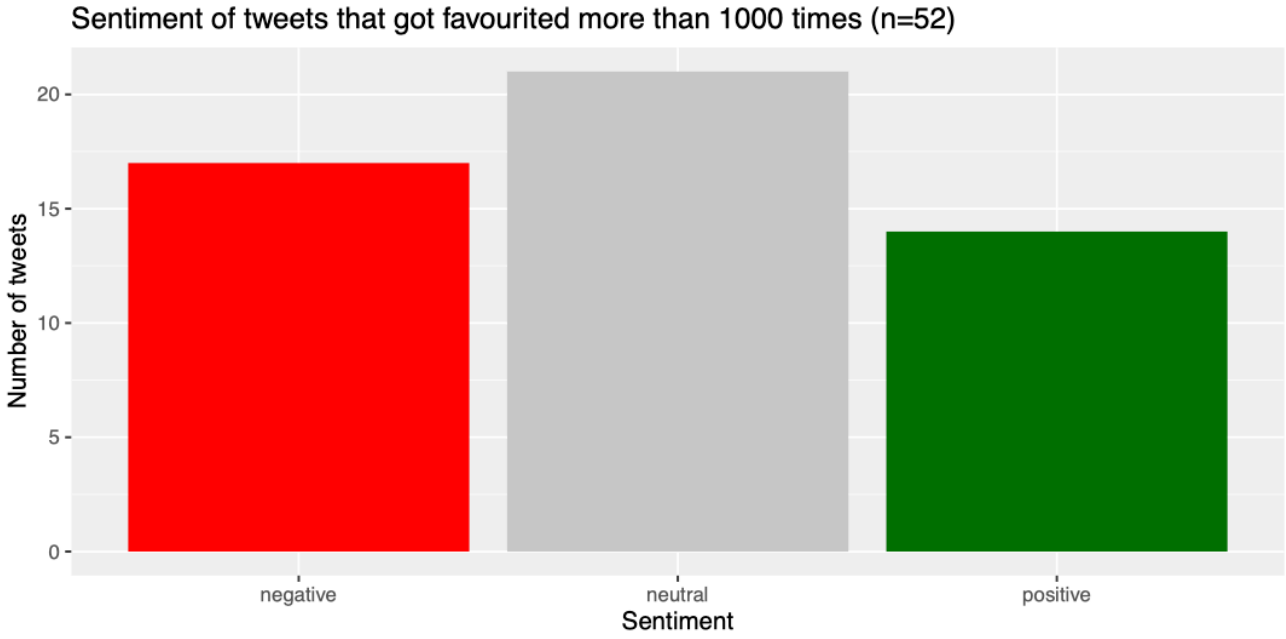

Figure 8: Sentiment of tweets that got favourited more than 1000 times

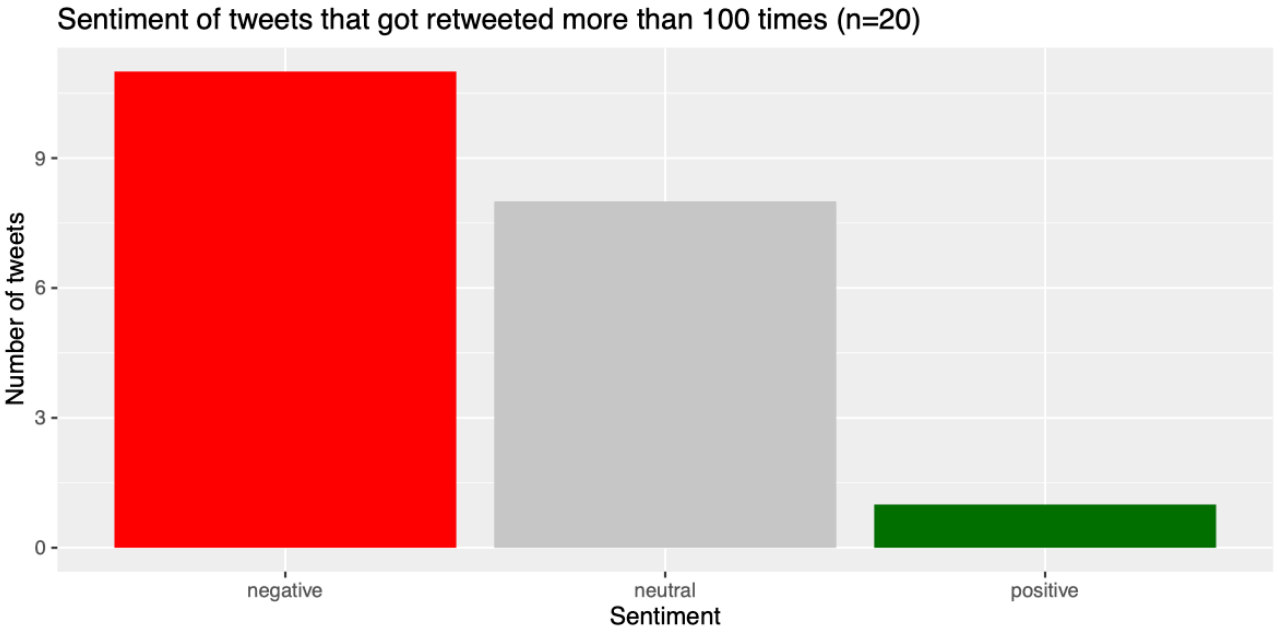

Figure 9: Sentiment of tweets that got retweeted more than 100 times

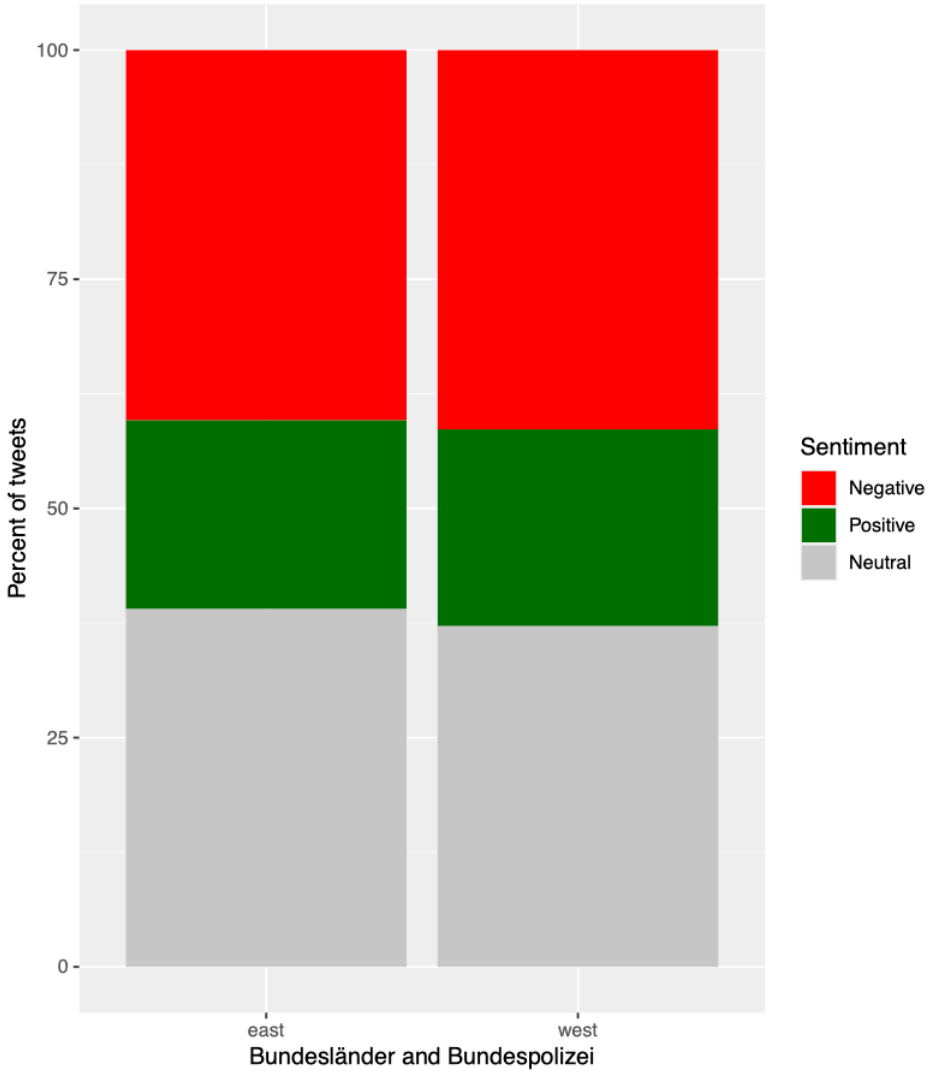

Figure 10: Comparison of the sentiments of historically eastern and western federal states