Social Data Science

Analyzing twitter Responses of Swiss Politicians to COVID-19 Measures

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1 Motivation

For the scope of this project our group agreed to dig deeper into the intersection of twitter data, sentiment analysis and recent development in swiss politics regarding pandemic regulations and measures. With this combination we were able to satisfy each of our personal interest (Cedric: Politics, Simon: Sentiment Analysis, Masha: Twitter data exploration) while embodying the project in the context of the current pandemic.

1.1 Research Questions

Introduction and loosening of measures against the spread of COVID-19 by the Swiss Federal Council are in dispute between different political parties. While some parties are in favor of a harsher approach in fighting the spread of the pandemic, others advocate for less strict measures in order to support the national economy. In our research, we will investigate whether this difference can be observed in tweets posted by members of the Swiss parliament following media conferences of the Federal Council at which new measures or loosening of measures were published. Further, we will examine whether the sentiment of the tweets of the different members and parties changed over the course of the last year (February 2020 – February 2021).

Below you can find the precise research questions [Q1-Q3] that are addressed in this project.

We assume that the first measures taken by the Federal Council in the spring 2020 were supported by all political parties. Hence, we expect the variance of the sentiment of tweets during the first COVID-19 wave to be low [Q1]. Later during the second wave we expect to see a difference between left parties that favor strict measures and right ones that disagree with the Federal Council and claim more and faster loosening of the active restrictions. Thus, we expect that the variance of the sentiment of tweets is larger compared to the first wave [Q2] and that the sentiment of tweets of left party members (SP, Grüne, GLP) is more positive compared to right parties (FDP, SVP) [Q3].

2 Project Plan

The project plan is divided into several steps, here listed numerically.

1. A list of all available twitter accounts of the members of the Swiss parliament was gathered. We started by using the existing twitter list @ParlCH and completed it by adding missing accounts. In total, we could find 182 existing active twitter accounts.

2. We established all relevant press conferences of the Federal Council where updates on COVID-19 measures were communicated. Each entry has information about the date, time, and whether new measures or loosening were published. The list can be found in the appendix. For further information about the actual measures, please visit the website of the Federal Office of Public Health FOPH[1].

3. Using the twitter API, all tweets of the parliament members created after the first measures taken (28.02.2020) were downloaded and filtered for relevant tweets. We refer to chapter 3 for a more detailed description.

4. To be able to perform a sentiment analysis, the tweets were translated using the Google Translate API.

5. Using the "VADER" package, we performed a sentiment analysis on the tweets.

6. The sentiment of the tweets was used to test our research questions we identified above.

7. We analyzed the results and concluded our findings while considering the limitations of our approach.

[1] https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html#757183649

3 Data Processing

The tweets were downloaded using the twitter API and the “rtweet” package. The API allows to download a certain number of tweets per user per time. We started by pulling 500 tweets per account and checked whether the first tweet was prior to the first press conference. Accounts that had more than 500 tweets since the first conference entered a loop where the remaining tweets were downloaded. Next, the tweets’ created time was formatted to Swiss time in order to filter all tweets that were posted within 48 hours after a media conference. The tweets were then translated using the Google Translate API and the “googleLanguageR” package. After translation, we identified the most used words (excluding stop words) and hashtags in order to identify keywords that indicate COVID related tweets. Using these keywords, we filtered tweets that exhibit one of them either in their initial or translated text. During the analysis, five additional tweets were identified to be not related to our research questions and were removed manually.

4 Analysis

4.1 Descriptive Statistics

After processing the data we downloaded from twitter, we checked whether we had enough data to perform our analysis and if enough data points were available for all identified relevant events. In Figure 1 we observe that there are at least 10 tweets per press conference. Overall, we have 1073 tweets which we consider as sufficient for the scope of this project. Further, we see the spread of tweets per party, where the left wing (i.e. SP and Grüne) is clearly more active on Twitter than the other parties.

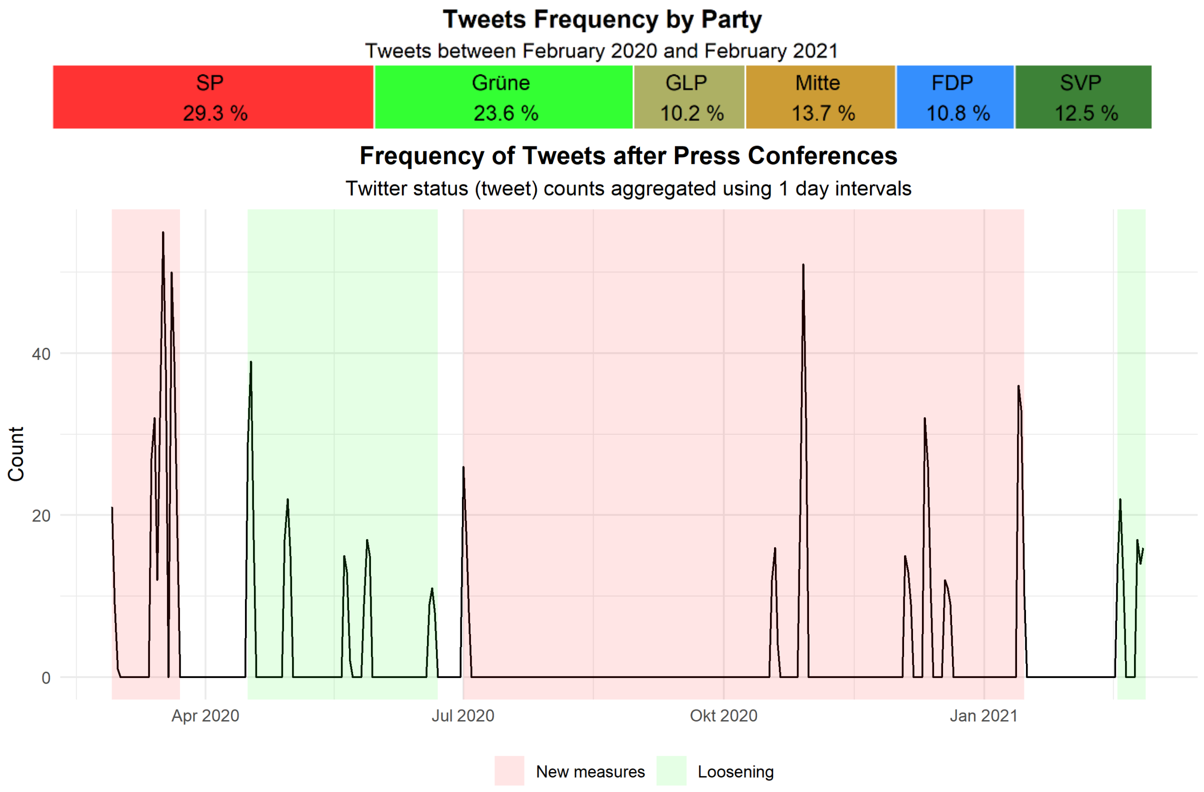

Figure 1: Frequency of tweets per party and per press conference.

4.2 Sentiment Analysis

As a next step we performed the sentiment analysis using VADER. Figure 2 illustrates the output of the analysis for each party over the entire time horizon. Overall, we observe neutral reaction to the measures except for GLP, which showed a more positive reaction over the whole period than all the other parties.

Testing for differences between the different parties showed that the general sentiment of SP (baseline variable in Table 2) as well as GLP is significantly different from the other parties.

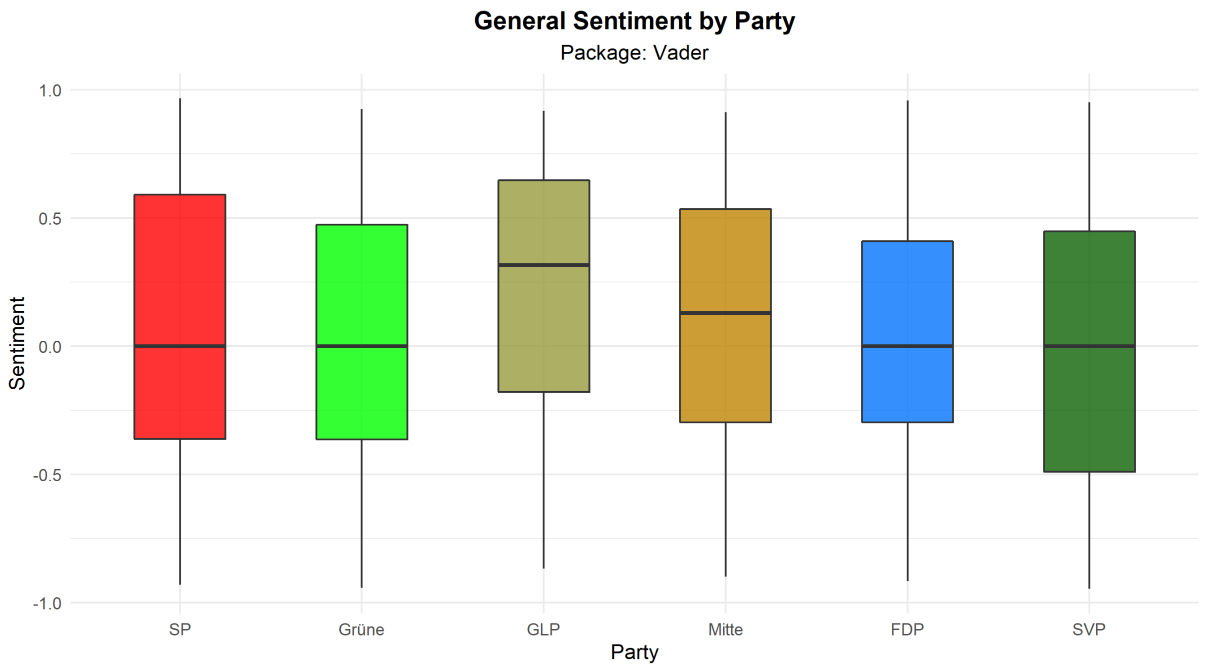

Figure 2: Overall sentiment per party.

Next, we analyzed the sentiment over all parties per event. In Figure 3 the trend in overall sentiment can be separated into two waves, which correspond to press conference 1 to 4 and 10 to 16. The green areas correspond to loosening measures. In the first wave with a moderate increase in the COVID-19 cases, one can see overall neutral respond to the measures except for the last loosening press conference, which was perceived more positive than the other. In the second wave a negative trend in perception of restrictive measures can be observed, which is not observed in the first wave.

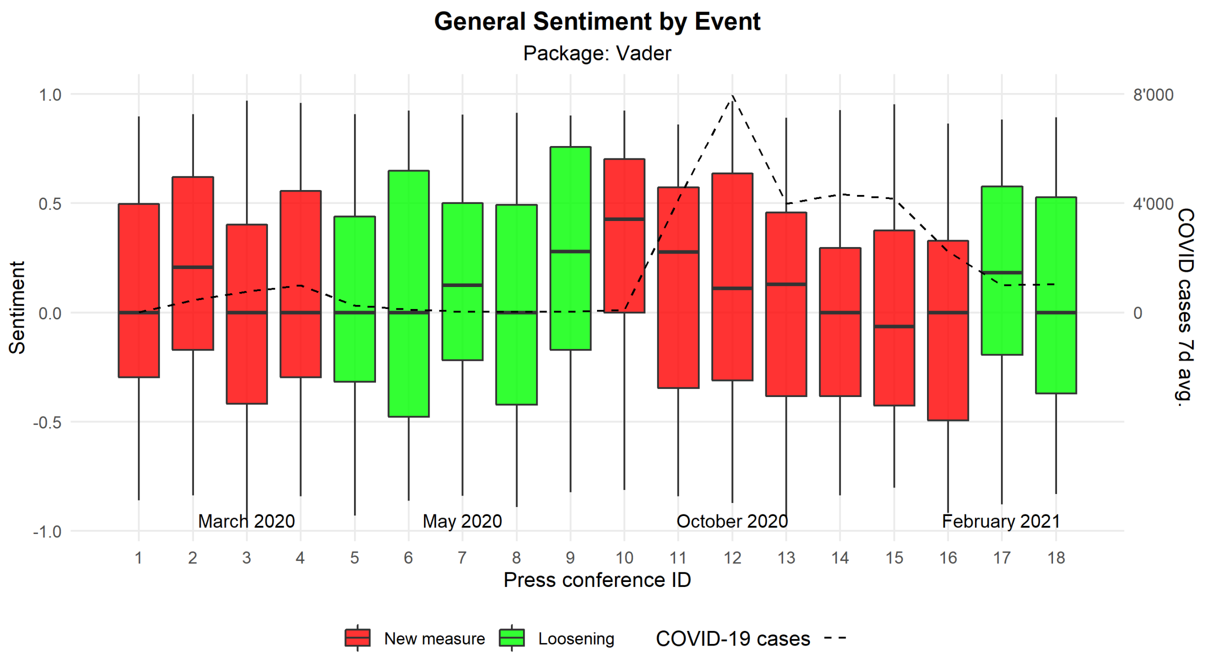

Figure 3: General sentiment over all parties over all press conferences.

To verify whether there is a difference in parties' response to loosening and restricting the measures, we additionally plot all parties individually. Figure 4 and Figure 5 show a high variance in the first press conference but the overall variance decreased drastically as the number of cases started to increase.

In the second wave a negative trend in the overall sentiment can be clearly observed. Table 3 supports the negative trend result, showing that each additional measure implementation results in an increasing negative response.

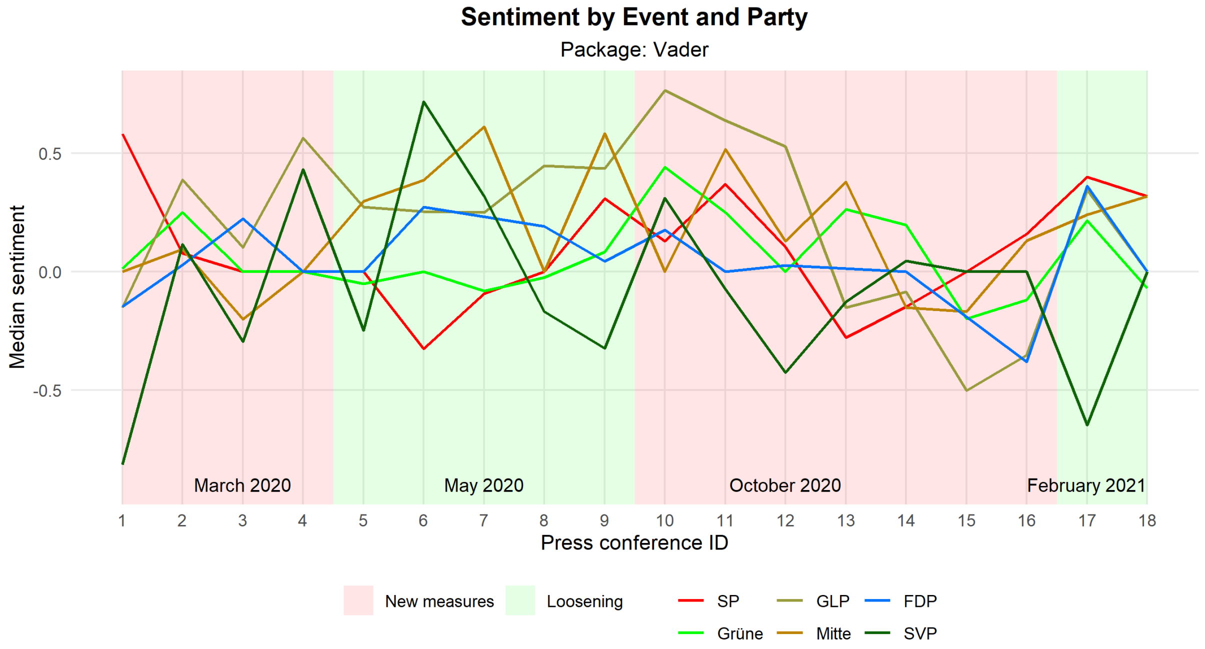

Figure 4: Individual sentiment (median) of each party over all press conferences.

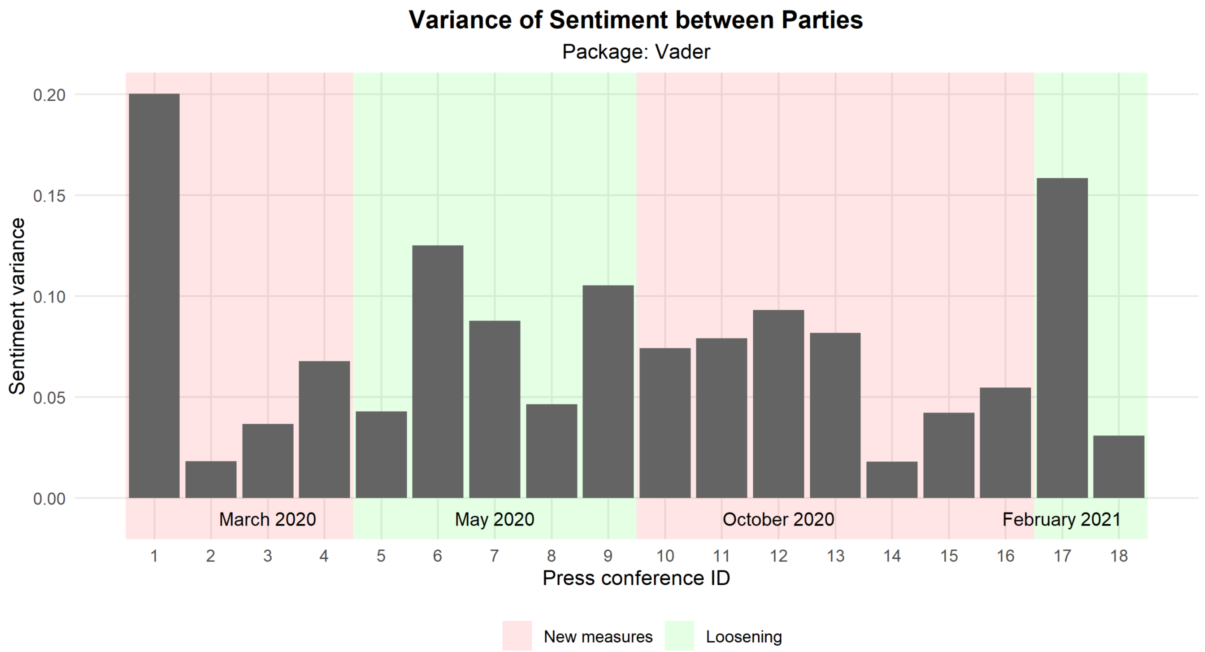

Figure 5: Variance of sentiment among parties per press conference in the 2 waves. Wave 1 is equal to the press conferences 1-4, whereas wave 2 correspond to the press conferences 10-16.

5 Conclusion

In our first research question [Q1] we expect the variance of sentiment of tweets to be low during the first wave. Figure 5 shows that the overall sentiment is very large after the first press conference. However, looking at the respective tweets, we observe that the negative tweets of SVP members are not criticizing the measure taken (ban of events with >1000 people), but addressing economic concerns related to the measures. Together with the fact that the variance of sentiment is very low for the rest of the first wave, we conclude that all parties are very similar in their response to the measures taken, confirming our first research question.

The second research question [Q2] proposes that for the second wave, the variance of the sentiment is larger compared to the first wave. This is true for the first half of the wave (press conferences 10-13), however, after the cases increased again, the variance of the sentiment of tweets decreased to the level observed during the first wave. However, unlike the tweets in the first wave, the sentiment is now negative, suggesting a general critique or even disagreement to the measures taken by the Federal Council. Based on these observations, we reject the hypothesis of our second research question, while pointing out the fact that the variance decreased the longer the wave persisted.

In our third research question [Q3] we made the hypothesis that the sentiment of tweets from left-wing party members are more positive than tweets from the right-wing parties. However, the data clearly shows that right-wing parties mostly follow the same trend as the members of the left-wing parties. Surprisingly, the two right-wing parties SVP and FDP were contradicting at certain times. This is mostly due to the fact that SVP's sentiment towards each new measure announcement has a huge variance. The results of this analysis have serious limitations, which we address in the next section.

6 Critique

The biggest concern we have with regard to our analysis is the quality of our processed data. As our data is comprised of tweets it is subject to the following issues. First the content of the tweets can be unrelated to the measures itself but still contain keywords which we used for filtering. Especially tweets that criticize or even attack other parliament members and/or parties pose an issue, as their sentiment often is quite large, leading to a significant bias of the results. Second, the tweets can be formulated in a sarcastic manner, which can lead to a completely opposite sentiment and therefore distort the results. Also tweets that comment the general situation and not the measures taken might confound the results. This source of bias might be one reason for the negative trend in sentiment we observed during the second wave. Further we translated the different languages (German, French, Italian) found in the tweets to English with the Google Translate API to enable sentiment analysis using VADER. Thereby this could also lead to changes in the actual meaning as well as overall sentiment. Even though we took samples to control for these effects a 100% guarantee for the accuracy of translation and content of tweets cannot be assured.

Further, one also could question the number of tweets which are available per event and therefore may threaten the external validity of our results. To address this issue, we increased the timespan to 48h following the announcement, which led to a higher number of tweets available to analyze. However, manually checked samples have shown that the longer the time span, the more tweets that address COVID topics other than the measures taken enter the sample, leading to an even higher distortion of the sentiment.

To overcome most of the above-mentioned problems one could analyze each tweet by its own, thereby correcting for sarcastic written tweets, or tweets not being related to COVID measures. However, this would increase the workload during the first stage when filtering the initial set of tweets.

7 References

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8 Appendix

Date	*Time*	*isLoosening*
2020-02-28	10:00:00	0
2020-03-13	15:30:00	0
2020-03-16	17:00:00	0
2020-03-20	15:15:00	0
2020-04-16	15:15:00	1
2020-04-29	14:45:00	1
2020-05-20	14:30:00	1
2020-05-27	15:00:00	1
2020-06-19	15:00:00	1
2020-07-01	15:00:00	0
2020-10-18	14:15:00	0
2020-10-28	16:15:00	0
2020-12-04	15:45:00	0
2020-12-11	14:00:00	0
2020-12-18	15:15:00	0
2021-01-13	15:00:00	0
2021-02-17	15:00:00	1
2021-02-24	15:00:00	1

Table 1: Press conferences information.
isLoosening equals 1 if the Federal Council canceled certain measures. More information about the announcements can be found here: https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html#757183649

	compound		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.08 **	0.02 – 0.14	**0.007**
Fraction [Grune]	-0.03	-0.12 – 0.05	0.459
Fraction [GLP]	0.12 *	0.01 – 0.23	**0.039**
Fraction [Mitte]	0.03	-0.08 – 0.13	0.612
Fraction [FDP]	-0.02	-0.13 – 0.09	0.733
Fraction [SVP]	-0.10	-0.21 – 0.00	0.057
Observations	1073		
R^2 / R^2 adjusted	0.011 / 0.007		

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 2: Analysis of difference in sentiment among different parties.
compound: value for sentiment between –1 and 1 calculated by VADER.

	compound		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.80 ***	0.46 – 1.13	**<0.001**
eventID	-0.06 ***	-0.08 – -0.03	**<0.001**
Observations	404		
R^2 / R^2 adjusted	0.045 / 0.043		

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 3: Analysis of sentiment of new measurements in the second wave.