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Computing Science

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How time affects Facebook Reactions

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Abstract

In our current society, the importance of spreading information via Social media is gradually growing. Everyone can share information on these platforms and many people and companies do so. This information then garners responses in the form of comments and Facebook reactions, which in turn influence how the Facebook post is read. So it is important to know what kind of factors influence these responses. A lot of research has gone into the analysis of the impact of the contents of a post, but there could be other factors that are not that well documented. In this exploratory research we are going to look at one of these possible factors, namely the time a post was posted. We are also going to look at correlations between the different Facebook reactions. The results of this research would suggest that there are temporal effects that have some effect on the responses to the posts, but we cannot draw definitive conclusions. This study contributes to the existing literature on Social Media Context Analysis and will show some interesting topics that can be researched further.

Contents

Chapter 1

Introduction

Facebook is one of the largest social media platforms in the world with around 2.8 billion monthly users (Chen, 2021). People can post on Facebook about their daily lives and react to each others posts. Facebook lets users "try out" different kinds of posts in the creator studio (Ahmed, 2020). When used, the creator studio shows your different posts to different subsets of your audience without actually posting these posts. After a certain amount of time, a winner is selected from these posts which is then published. While this does result in the best post being posted, it does not guarantee success. Facebook recommends posts, such that you only see posts that are relevant to you, but not all posts are equally recommended. The algorithm that Facebook uses makes use of the comments, Facebook Reactions and other forms of engagement to determine if a post should be recommended to you (Barnhart, 2020). It is also more likely to recommend more recent posts (Montells, 2017). It is however not publicly known to what extend these factors influence the recommendations, we only know that they do.

Engagement depends on numerous factors. Needless to say, it depends on the message the post tries to convey. A lot of research has gone into analysing messages and looking at how different messages affect engagement (Bhattacharya, Srinivasan, & Polgreen, 2017). There is however also the context in which the message was posted which has received considerably less attention. This could also influence the kind of engagement the message receives. The kind of reactions the post has already received and what the respondent is thinking about at the moment could both matter. Posting time is another one of these factors, as most people are less active on social media after 8 PM and early in the morning (Bhattacharya, Srinivasan, & Polgreen, 2021). This could result in posts posted after 8 PM getting less engagement compared to posts posted in the afternoon. This temporal effect will be the main interest of our research, as we are going to perform an exploratory research into how the posting time affects the different types of Facebook Reactions that a news post garners. We will perform a data analysis on a data set consisting of News posts on Facebook, looking for interesting spikes and trends in the different types of Facebook Reactions. We are also going to discuss correlations between the different kinds of reactions, seeing if there are strong and weak correlations.

We will now give a short overview of the rest of the paper. In section 2, we are going to discuss the Related work, looking at similar papers and defining our niche. In section 3, we will talk about the Research we will perform, the data set we used and the ways we transformed the data. After that we are going to present our findings, compare them to previous research and discuss the limitations of the research. At the end, in section 4, we will draw conclusions from our findings.

Chapter 2

Related Work

The integrity of news on Social Media is important, as many people gather their news from those platforms (Newman et al., 2021). The problem with Social media is that reactions from other readers might influence the attitude people have towards the article the post refers to (Winter, Brückner, & Krämer, 2015). Negative comments for example can affect the perception negatively. This might lead to the message itself being misinterpreted, which might be problematic if it concerns something important. Negative reactions in of itself are not something we can necessarily do anything about, but we can look at factors that lead to them. Time is one of these factors. Whereas research on these temporal effects has already been done on general posts (Arens, 2021), posts regarding recipes (Rokicki, Herder, & Trattner, 2017) and posts made by Destination Management Organisations (Villamediana, Küster, & Vila, 2019), news is an area that has not been explored yet. So we are going to perform an exploratory research looking at the effects of posting time on the reactions a post garners using News Posts.

2.1 Research on Temporal Effects

Every person has weekly and daily routines. This results in temporal patterns, both daily and weekly in Social Media (Golder, Wilkinson, & Huberman, 2007; Grinberg, Naaman, Shaw, & Lotan, 2021). Social Media use on weekdays has been found to be higher than in the weekends. And if the amount of people online is higher, there is a higher likelihood someone will react to your posts, thus resulting in a good posting time. Other research strengthens this claim, showing that Tuesdays and Wednesdays are the best days to post (Arens, 2021). However, not all research concluded that weekdays are better days to post. Recipe posts get more engagement on Mondays and Sundays (Rokicki et al., 2017). So it might depend on the kind of audience the post is read by.

During the day, there are temporal patterns as well. Over the course of the day, there are moments where Social Media use is higher and moments where it is lower. During business hours, 8:00 to 18:00, the amount of engagement a post gets is higher (Sabate, Berbegal-Mirabent, Cañabate, & Lebherz, 2014). Posting a post outside of these times could result in a negative effect on the engagement (Cvijikj & Michahelles, 2013). These times have since been narrowed down further to between 8:00 and 10:00 and 14:00 and 17:00 (Villamediana et al., 2019). These more specific times do however not completely represent all posts, as other research found that posting between 9:00 and 13:00 results in the highest amount of engagement (Arens, 2021).

2.2 Research on Correlation

When a post gets a lot of engagement, there are a high amount of comments, shares and Facebook Reactions. A correlation between the three would be likely. An increase in *Angry* and *Like* reactions seem to accompany an increase in shares and comments (Larsson, 2018). Meanwhile *Haha*, *Love* and *Wow* seem to hamper the willingness of sharing and commenting. In the comments of a post, emoji are often used. So there is also a correlation between emoji usage and Facebook Reactions (Tian, Galery, Dulcinati, Molimpakis, & Sun, 2017). Between the Facebook Reactions, there are also correlations (Ross et al., 2018). *Like* and *Love* and also *Like* and *Sad* seem to have a high correlation, while *Angry* and *Love* seem to have a low correlation (Ross et al., 2018).

2.3 Expectations

Using the information garnered from these papers, we expect to see the following occurrences in our data set:

1. We expect to see clear differences between weekdays and weekends and an increase in engagement during business hours (Sabate et al., 2014). Especially between 8:00 and 13:00 and 14:00 and 17:00 (Villamediana et al., 2019; Arens, 2021). We expect this because during the weekends, people are less active on social media (Golder et al., 2007) and during business hours, more people are active (Sabate et al., 2014).

2. We expect to see a high correlation between *Like* and *Sad* as described in (Ross et al., 2018). This would be because sad news is shared more often and because there is a correlation between the amount of Likes and Shares, a correlation between *Like* and *Sad* would be likely.

Chapter 3

Research

For this research we have used a database consisting of 19.850 Facebook posts posted by 82 different news outlets between 2015 and 2017 [1]. This data was gathered using a script that scraped at most 250 posts from every outlet. Among these outlets were the BBC, Fox News, The Guardian and the New York Times.

3.1 Data Transformation

After the script had scraped the data of of the internet, it had to be transformed in such a way that the data would be usable. We started with connecting posts to their sources. The script we used did not scrape the account that posted the post, so we had to add those manually. During this process, we found duplicate entries from one of the sources, so we removed one of the two. We then filtered through the data, removing all posts that were posted before the 24th of Feburary 2016. This is because Facebook Reactions was only implemented from that day onward (Krug, 2016). This resulted in 250 posts from one source being pruned from the data set. The next thing we adjusted were the posting times. When you scrape a Facebook page for the posting time, that time is converted into UTC. Because of this, a post created by the BBC at 12 AM BST and a post made by the New York Times at 7 AM EDT would both be recorded in the database at 11 AM UTC. This could lead to people in New York reacting to the New York Times post at 12 PM according to the data set, but it actually being 8 AM when they reacted. This could invalidate some of the data, as their times do not correspond to the actual responding times. Many sources in the data set post news articles that are only relevant for the region they are based in, so converting the posting times to the local time of the source was important. To do this, we used the headquarters of every news outlet in the

[1] `https://medium.com/jbencina/facebook-news-dataset-1000k-comments-and-20k-posts-88e24109a36e`

data set and changed the posting times to correspond to their respective time zones.

3.2 Results

After we had transformed the data, we were left with a data set containing 19.350 Facebook posts posted by 81 different news sources. Out of these sources, 46 were based in New York, 9 in Los Angeles, 6 in London, 4 in Texas, 2 in Quatar and 1 in Switzerland. The remaining 13 sources were independent people posting about news articles. Posting dates ranged from the 16th of September in 2016 to the 14th of July in 2017. The average amount of reactions to a post was, not including the likes, 632.14 and the average amount of shares was 374.69. The reaction that was used the most was *Angry* and the least used was *Wow* as can be seen in A.1. The amount of posts per day and their average amount of reactions during the week can be seen in A.1. In the same table, we can see the average amount of positive and negative reactions, positive being *Haha*, *Love* and *Wow* and negative being *Angry* and *Sad*. In A.3, we can see the average amount of positive and negative reactions over the course of the day, with the difference between the two computed every time.

3.2.1 Temporal Effects

Using the transformed data, we plotted all of the reactions spread out across a one week time in figure A.2 in the appendix. We decided to not plot the amount of *Like* reactions a post got, because the *Like* reactions dwarf the other values and Likes do not carry much sentiment of the person reacting. When we look at figure A.2, we can see that there are some notable occurrences.

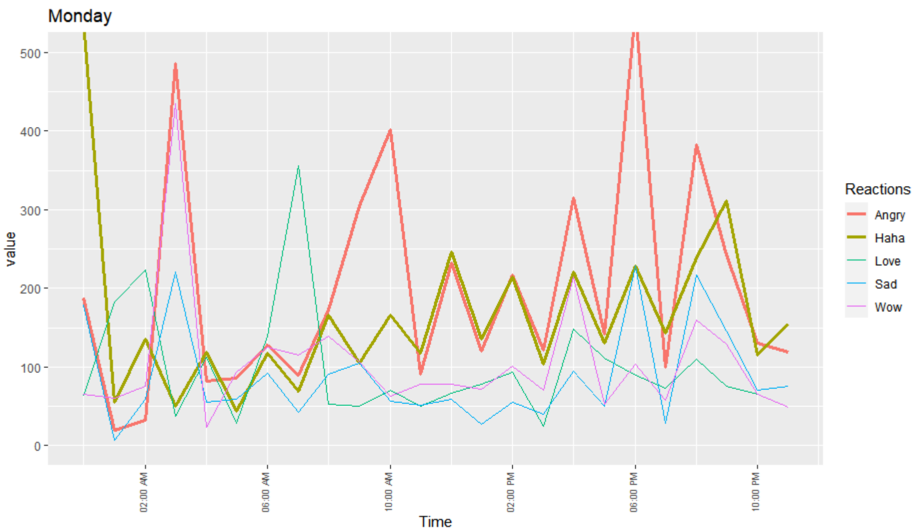

Figure 3.1: The graph of Monday

When we look at Monday, we see a lot of spikes in the *Angry* and *Haha* reactions and in general not a lot of *Love*, *Sad* and *Wow*. The average amounts of the reactions in table A.2 reflects this as there are twice as many *Angry* and *Haha* reactions as *Love*, *Sad* or *Wow* on Monday. Tuesday and Wednesday both seem to have less activity, having a few spikes going above 300. On Thursday, *Angry* and *Haha* reactions both increase yet again during the day, reaching their peaks at around 7 and 6 PM respectively.

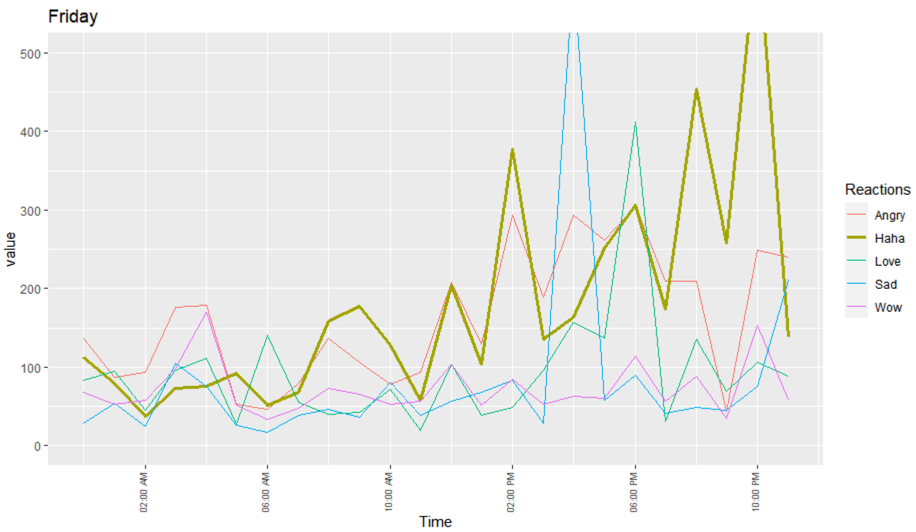

Figure 3.2: The graph of Friday

On Friday, there is a steady increase in *Haha* reactions during the day, peaking at 10 PM. Because there is a somewhat steady increase starting at 12 PM, the likelihood of one post causing this increase is very small. As Friday has 2892 posts in total, it is not feasible to plot the data across multiple months. This means that plotting different weeks and comparing them is not possible. So there could be a consistent increase in *Haha* reactions every Friday, but we can not know for sure.

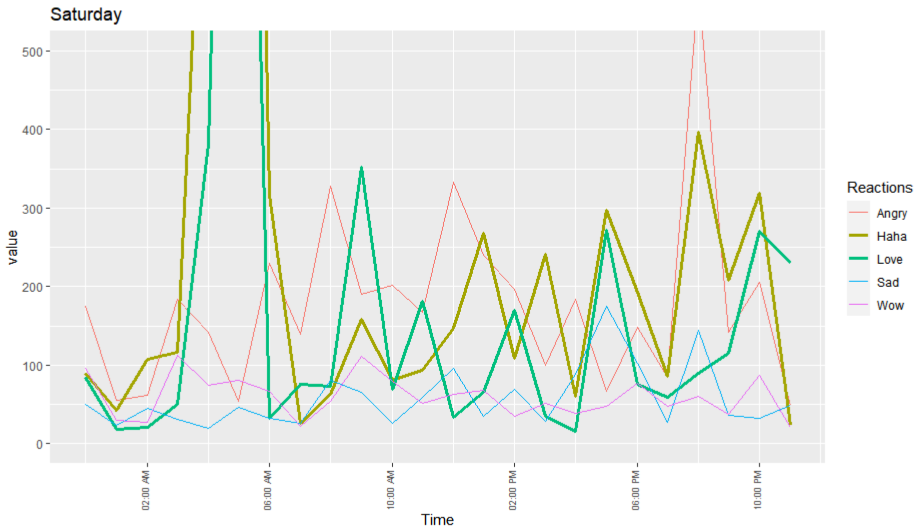

Figure 3.3: The graph of Saturday

Saturday has a weird spike in *Haha* and *Love* reactions between 3 and 6 AM. This could be a normal occurrence for Saturdays, but there is probably another explanation. When we look at table A.1, we see that the amount of posts that are posted during the weekends is much lower than during the weekdays. This is somewhat logical, as many news companies publish less articles during the weekends. Because of this, our data set during the weekends might be too small, resulting in extreme values being over represented. There are two posts on Saturday with more than 10.000 *Haha* reactions. Both of these posts were posted around 5 AM. So these posts could both have helped in causing the enormous spike. On Sunday, there is also not enough posts to keep outliers from creating spikes, as can be seen at 1 PM in the angry reactions.

3.2.2 Interpretation

When we compare our findings with prior research, there are some remarkable observations. The research conducted by sprout showed that the best days to post were on Tuesday, Wednesday and Friday (Arens, 2021). Our results contradict that somewhat, as the average amount of reactions on a post on Tuesday and Wednesday are very average and Friday gets the lowest amount of engagement per post as shown in table A.1. Mondays and Sundays are days on which recipe posts are received more positively (Rokicki et al., 2017). In table A.1, our results show that Monday and Sunday are indeed days with more positive than negative reactions, but this is true for each day of the week. Friday has a larger difference between Positive and Negative reactions compared to Monday and Sunday, so it could be a better day to post a News post. Between 8 AM and 10 AM and 2 PM and 5 PM would be the best times to post according to research regarding Destination Management Organisations. When we look at table A.3, we see that 5 AM there is the highest positive difference between Positive and Negative reactions. So according to our data set, a post posted at 5 AM would get the most positive reactions. These results are unexpected, as we expected to see a clear increase in engagement between business hours. It could be the case that many posts were responded to by people from all over the world, making the business time frame irrelevant. It could also be that news posts are responded to more when they are posted before or after work, because people do not follow news posts while at work. Because the data set only has 19.350 posts, it is not viable to plot it over multiple weeks, so definitive conclusions can not be drawn.

3.2.3 Correlations

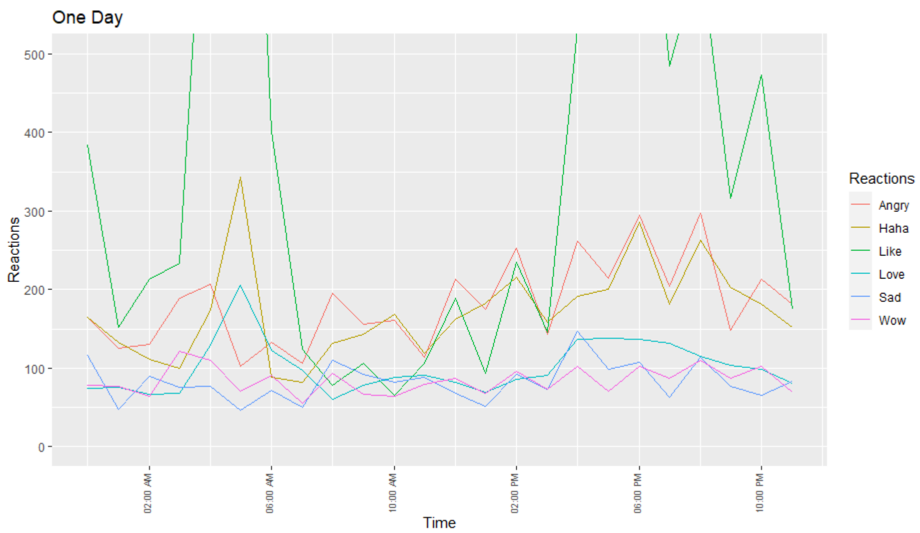

Figure 3.4: All data plotted into a single day

To compute correlations in our data set, we used Spearman's rank correlation. Because our data set consists of ordinal variables, using the Spearman correlation would give the best results. The only problem was that Spearman only measures monotonic relationships, which means that no duplicates can occur in the data of which a correlation is computed. Our data set does have duplicates, so to compensate for this, it is important to also look at graph 3.4 to see if a correlation would be likely. Because the Like reaction would dwarf the other reactions, we decided to lower the Like line in 3.4 such that the shape is the same, but the values are off by 700.

	Haha	Like	Love	Sad	Wow
Angry	.549	.416	.159	.744	.666
Haha		.603	.465	.396	.587
Like			.852	.453	.693
Love				.208	.439
Sad					.681

Table 3.1: Correlation matrix for Facebook Reactions

In table 3.1, we see all the correlations computed with Spearman using a significance level of 0.05. Every correlation had a p-value of $2.2e^{-16}$, which is much lower than 0.05, so each correlation is significant. *Like* and *Love* and *Angry* and *Sad* reactions seem to have a strong correlation with each other when looking at the 3.1. In 3.4, the amount of *Love* reactions mimics the rise and fall of the *Like* reactions, making this correlation likely. *Angry* and *Sad* reactions also mimic each other, but as the table suggests, there is less of a correlation between these two. The correlation between *Angry* and *Love* is low, which is visible in the table and in the graph. They share a few moments where they both rise and fall, but this is not a strong correlation. When we compare these findings with the findings of prior research, we see *Like* and *Love* indeed have a strong correlation and *Angry* and *Love* a weak correlation (Ross et al., 2018). *Like* and *Love* having a strong correlation is somewhat logical, as they are both somewhat positive responses, with *Love* being more expressive. *Angry* and *Love* having a weak correlation is also as expected, as Love and Anger are often used as opposites. We expected *Like* and *Sad* to also have a strong correlation. This does not seem to be the case. So our assumption that more *Sad* reactions would lead to more Shares which in turn would lead to more Likes was wrong.

3.2.4 Limitations

There were some limitations to our research. First of all our data is from 2016 and 2017. Because Facebook reactions was only implemented in 2016, you could expect an adjustment period where people are getting used to the new features. This could have influenced our data. Second, the posting time adjustment could have had a negative impact on the integrity of the data. Not all posts are read by only people that live in the same time zone as the headquarters of the news source. Some sources, like the BBC are more active on a global scale (bbc.com, 2020). This problem could be prevented by looking further into each news company and assessing if they cater to a global or local audience. The last limitation was that the graphs of the weekend days shows that the amount of data gathered should have been higher.

Chapter 4

Conclusions

This research has shown that temporal effects are a factor impacting the kind of reactions a post garners, but these effects are very different when you compare between different subjects. Some effects are clear, like the rise of *Haha* reactions on Friday or the amount of *Angry* reactions on Monday. There were however also clear signs that the data set was not large enough, mainly on the weekends. Every weekday had twice as many posts, resulting in the data of the weekend days possibly becoming skewed. The correlations we found were similar to the correlations found in prior research, showing that some reactions are more likely to be used together. Future research could look into the increase in *Haha* reactions on Friday. This was not possible for us as our data set was not large enough. Another future research could look into the reasons why *Like* and *Love* reactions have such a strong correlation.

The implications of our research for News channels is the following. To get the most positive reactions on average, they should post around 5 AM. Minimising the amount of negative reactions would mean not posting at 4 PM or 8 PM according to the table A.3. The best day for posting would be Saturday, as it has the highest difference between positive and negative reactions. The day that should be avoided is Sunday, as the amount of positive and negative reactions are very close to each other. This research has been an exploratory research, with its main purpose being shedding a light on not yet researched effects and we think that was successful.

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Appendix A

Appendix

Day of the Week	Number of posts	Reactions per post	Positive	Negative
Monday	2554	656.	364.	280.
Tuesday	3364	644.	350.	285.
Wednesday	3892	643.	354.	266.
Thursday	4553	643.	351.	277.
Friday	2892	537.	346.	247.
Saturday	1021	741.	610.	234.
Sunday	1074	607.	299.	253.

Table A.1: Amount of posts and reactions per day

	Angry	Haha	Love	Sad	Wow
Monday	213.9	170.2	87.1	87.4	97.3
Tuesday	177.4	167.9	111.6	102.7	84.5
Wednesday	185.3	190.4	92.5	87.8	87.0
Thursday	206.9	171.5	94.8	78.3	91.4
Friday	148.9	156.8	84.3	77.6	68.9
Saturday	184.9	261.3	174.6	60.9	59.7
Sunday	204.7	147.3	109.2	81.1	64.2

Table A.2: Average amount of the reactions per day

Time of day	Positive	Negative	Difference
0:00	318.0	281.6	36.4
1:00	286.0	172.9	113.1
2:00	241.5	219.8	21.7
3:00	287.7	264.2	23.5
4:00	412.6	284.1	128.4
5:00	619.5	147.8	471.7
6:00	302.1	204.4	97.7
7:00	233.6	155.6	78.1
8:00	285.0	305.5	-20.5
9:00	287.5	248.5	39.0
10:00	320.3	242.1	78.3
11:00	289.2	202.5	86.7
12:00	332.3	280.9	51.4
13:00	319.3	226.2	93.1
14:00	397.6	344.6	52.9
15:00	322.9	215.4	107.4
16:00	429.6	408.8	20.8
17:00	408.9	312.7	96.2
18:00	525.0	402.3	122.8
19:00	399.7	267.1	132.6
20:00	488.0	411.5	76.5
21:00	393.6	225.7	167.9
22:00	381.3	278.9	102.4
23:00	301.8	264.9	36.8

Table A.3: Positivity and Negativity during the course of the day

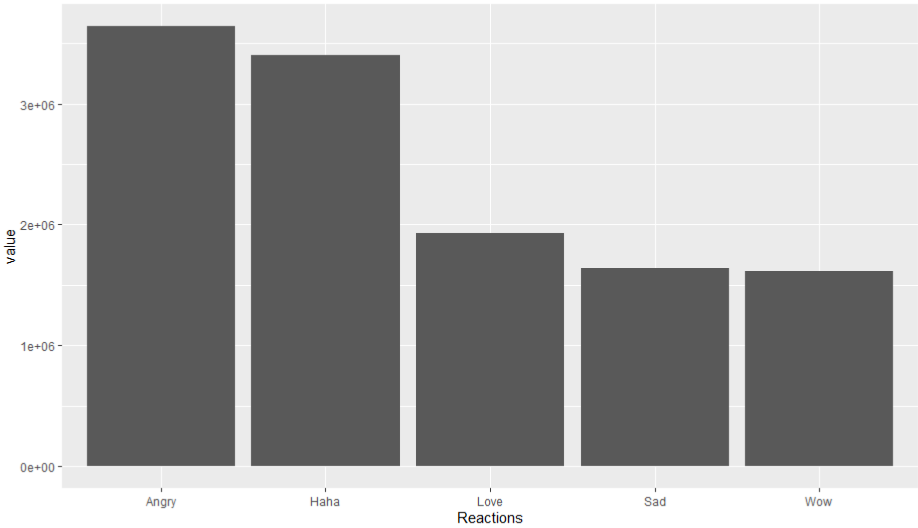

Figure A.1: Total amounts of every reaction

Figure A.2: All reactions plotted over the week

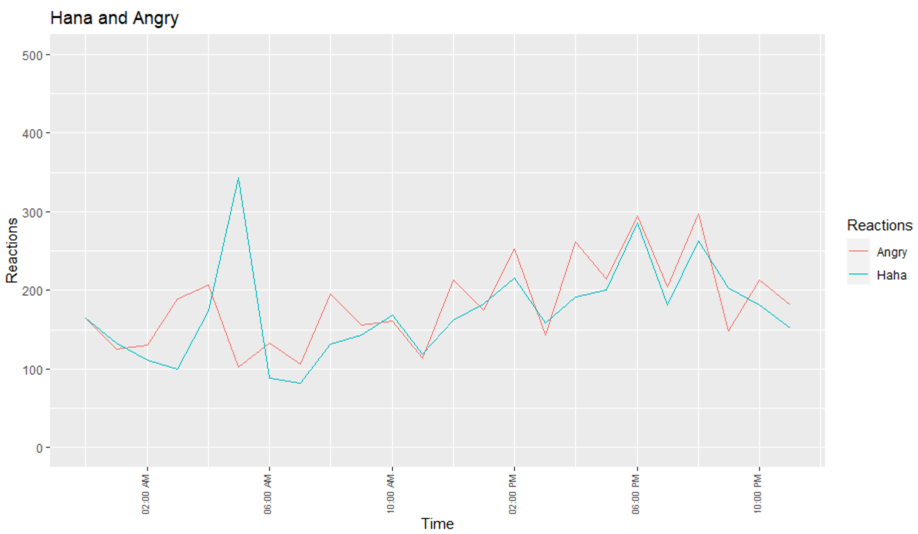

Figure A.3: All haha and angry reactions plotted over one day