Attitudes towards the Covid-19 vaccine on Twitter in Norway

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Abstract

The goal of this thesis is to characterize the distribution of attitudes present on Norwegian Twitter concerning the Covid-19 vaccine by implementing methods for text analysis and social media network analysis. The first analysis performed was manually classifying a sample of the dataset into four categories: irrelevant, neutral, vaccine hesitancy and anti-vaccine hesitancy. This sample dataset was used to train a supervised machine learning model, using BoW and SVM, in order to classify the total dataset. Furthermore, two methods for topic modeling were implemented: Latent Dirichlet Allocation and Biterm. Lastly, three main social networks were created: a mentioning-network containing users mention or mentioning in the dataset, a retweet-network containing users retweeted/quoted or retweeting/quoting and a sentiment network only including users classified as vaccine hesitancy and anti-vaccine hesitancy in the sample network. The ten users with highest scores for in-degree, out-degree and betweenness from the retweet network were analyzed to determine sentiment.

The main findings are that the methods for topic modeling did not fit expectations and gave limited findings concerning topics in the theme, but topic modeling illustrated the amount of noise in the dataset. The manual classification resulted in approximately 30% vaccine hesitancy, while the trained supervised machine learning model resulted in only 10% vaccine hesitancy. The mentioning-network illustrated that the debate evolved and then stabilized through the autumn/winter of 2020. The most mentioned users were positive towards the vaccine. There was a separation regarding sentiment for the most retweeted and users retweeting most. Users displaying vaccine hesitancy sentiment tended to retweet slightly more than users displaying anti-vaccine hesitancy sentiment, and there were signs of echo chambers.

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Chapter 1

Introduction

As social media and technology continuously become a greater part of our everyday life and source for news, it is important to be aware of how information is spread through the web. During the Covid-19 pandemic social media has been a way for people to keep in touch on a greater scale because of the imposed social restrictions. Restrictions on how many people one was allowed to see in addition to the fear of becoming infected by the virus made social media more relevant than before. However, as we spend more time on social media, more misinformation is also shared on these platforms. The sheer amount of information on platforms such as Twitter makes it challenging for users to navigate through the noise and separate true information from the false (*Rosenberg et al.*, 2020).

Faktisk.no(Norwegian fact-checking site) *Dahlback and Skiphamn* (2020)found in 2020 that on Facebook debates about vaccines containing misinformation generate more engagement, and conspiracy theories are dominating the debate. After the publication of Pfizer and Inbiogen's good results upon testing a vaccine on November 9'th 2020, several expressed hesitancy towards the vaccine on Facebook. From 15.11.2019 to 15.11.2020, they studied 10,485 Facebook posts regarding vaccines and discovered that anti-vaccine sentiment has increased in environments previously unconcerned about vaccination. *Dahlback and Skiphamn* (2020) concluded that conspiracy theories had developed concerning the vaccine, and this led to prime minister Erna Solberg and Bill Gates gaining more traction than posts made by former health minister Bent Høie (*Dahlback and Skiphamn*, 2020).

Twitter is utilized to communicate thoughts regarding infectious disease outbreaks, for example on Covid-19 and its vaccine. Given the nature of these discussions, it is possible to discern the public's sentiment. It is feasible to determine people's views toward vaccination by conducting a basic descriptive analysis of tweets relating to vaccinations. Understanding the sentiment may enable public health officials to improve positive messaging on social media channels in an effort to increase vaccination rates (*Yousefinaghani et al.*, 2021).

1.1 Motivation

Statcounter.com predicts that approximately 6.48 percent of the population of Norway are using Twitter in April 2022 (*statcounter*). Despite having fewer Norwegian users than other social media platforms, internationally Twitter is found to be a forum for debate. This includes the Covid-19 vaccine debate, which will be addressed in further detail in the background chapter 2. The purpose of this thesis is to describe the Covid-19-vaccine debate on Twitter in Norway in order to demonstrate how the information posted there contributes to the debate. Social media is a resource for gaining insight into the opinions of ordinary people in such debates. In this thesis, I attempt to describe the argument based on the results of various analysis tools to determine if they can be utilized to gain insight into the Norwegian Twitter debate on vaccines. This is necessary when the government wishes information on how to communicate with the citizens in a more efficient manner. In addition, I will attempt to draw a conclusion as to whether the existing methods are applicable for this purpose, producing precise enough results to make such an analysis worthwhile and provide the required insight.

1.2 Problem Statement

> How are attitudes towards the Covid-19 vaccine distributed on Norwegian Twitter?

The thesis is divided into two sub-goals relative to this research question (hereafter RQ):

- Get insight into the debate and attitudes present concerning the Covid-19 vaccine.
- Look into relevant methods to implement on the dataset to give information concerning the debate. The focus will be on how well the methods perform in this instance and if they indeed give insight into the vaccine sentiment on Norwegian Twitter.

1.3 Objectives

In order to address the above mentioned research question, I will examine the following hypotheses.

> H1: Methods for text analysis and social network analysis will help identify and describe the different attitudes towards the Covid-19 vaccine on Twitter.

To answer this hypothesis a subset of the data will be manually classified into four categories, irrelevant, neutral, vaccine hesitancy and anti-vaccine hesitancy. Mentioned network, retweet network and ego network will be executed on the entire dataset and retweet sentiment network on the sub-dataset. In addition, methods for topic modeling and supervised machine learning are integrated in the text analysis approaches and will be detailed in further detail below.

> H2: Methods for topic modeling will provide information about topics present in the dataset.

To test this hypothesis two methods for topic modeling will be performed on the dataset, respectively Latent Dirichlet Allocation and Biterm topic modeling. Both methods will be used and analyzed to ensure the best possible result from topic modeling.

> H3: A supervised machine learning algorithm trained on the coded data set can correctly classify the tweets according to their attitudes to the Covid-19 vaccine.

By completing this quantitative analysis, the complete dataset can be classified based on the sorted sample. With this classification, the attitudes in the overall dataset should become more apparent, allowing for conclusions to be made on the distribution of sentiment.

1.4 Contribution

As discussed previously, research into misinformation and hesitancy towards the Covid-19 vaccine in Norway has been performed on Facebook. However, Twitter is a social media often used for these kinds of interaction. It is beneficial for health researchers in the field of vaccination to understand public opinion in order to achieve high vaccination rates. When creating public information, knowing how much hesitancy there is and what it is about will be helpful. Furthermore, I want to evaluate how well a few often used methods perform on this dataset. Is it possible to make assumptions based on the result they provide? How well do these existing approaches for evaluating Twitter data work on Norwegian data? Is it possible to find the amount of misinformation on Norwegian Twitter with these models as a basis? The methods I will use two answer this are the following:

- Manually classify a sample of the dataset into four categories: irrelevant, neutral, vaccine hesitancy and anti-vaccine hesitancy.
- Use two models for topic modeling: Latent Dirichlet Allocation and Biterm topic modeling, to find topics in the dataset.
- Create a supervised machine learning model by first cleaning the data with removal of stop-words and performing lemmatization. Both Term Frequency-Inverse Document Frequency and bag-of-words are used to vectorize the data. Support vector machine and Naïve bayes are used in combination with TF-IDF and BoW to receive the most accurate model.
- Create networks for Mentioning tweets, retweeted and quoted tweets and egonets for a few selected users.
- Analyze the most prominent users found in the networks and identify their sentiment towards the vaccine.

1.5 Thesis outline

To find answers to the research question posed, as well as if the hypothesis are accurate the research was performed in the following manner.

- The current state of the vaccine debate and research done on vaccine hesitancy on Twitter are presented in the chapter 2. This retrieval was done to provide relevant information to this thesis as well as insight into how vaccine debates on Twitter have evolved over time, including before the Covid-19 pandemic.
- In the data chapter 3, the data used for this thesis is explained in detail. It includes the data gathering process done to create this dataset as it is a new dataset not previously studied. Furthermore, a qualitative analysis of a subset was performed, where a sample of the data was manually sorted in order to gain an understanding of the data's properties and give a base for the supervised machine learning method.
- Chapter 4, methods, contain a description of the technology used in this thesis, a brief explanation of the methods performed on the dataset and the implementations of these methods.
- The results, chapter 5, discusses how well the methods performed on the dataset as well as the results obtained using these techniques. What information and

assumptions that can be drawn from the findings. The hypotheses are evaluated and the research question answered.

- The conclusions, chapter6, concludes the overall findings and future work.

Chapter 2

Background

This chapter presents information about the following topics in more details:

- The state of vaccine hesitancy on Twitter. How it developed with the pandemic and the different sentiment users have found to have concerning it.
- The amount of information concerning the pandemic on Twitter leads to a deluge of information making it difficult to separate the truth from misinformation for users.
- Echo chambers as social media hubs where users' opinions are reflected back.

Twitter is an online micro blog social medium platform where users read or post tweets, a text not extending the length of 280 characters. Each user has a personal stream of the posts from users they follow. It is possible to like and reply to users tweets as well as share the tweets to one profile by retweeting a post/tweet. It is common to use hashtags in tweets to make them more available for users searching for the content (*Ervik and Holm*, 2021).

2.1 Vaccine hesitancy on Twitter

Anti-vaccine sentiment had been a rising problem before the Covid-19 pandemic, with vaccine skepticism being boosted by Andrew Wakefield and his association of autism with Measles, Mumps and Rubella vaccine (*Ashton*, 2021). This was also present on Twitter. *Tomeny et al.* (2017) analyzed tweets from 2009 to 2015 and found 272 546 tweets containing anti-vaccine beliefs. Furthermore, finding that anti-vaccine tweets coincide with vaccine related news and concluding that the volume of tweets might indicate a shift in public opinion resulting in lower vaccine coverage. (*Tomeny et al.*, 2017).

From early on in the pandemic it was made clear that vaccines and herd immunity was the way to end it and news stories reflected this. The correlation of anti-vaccine tweets to vaccine related news is substantiated with the research done by *Bonnevie et al.* (2021), who found through the start of the pandemic that vaccine opposition tweets increased by 80% in the period 15.10.19–14.02.20 to 15.02.20–14.06.20, the main increase being conversations about Covid-19, federal authorities, vaccine ingredients and research/clinical trials. *Bonnevie et al.* (2021) further suggest that vaccine opponents are encouraging mistrust in health authorities, possibly resulting in vaccine hesitant people joining the vaccine opposition (*Bonnevie et al.*, 2021).

Looking closer into factors for Covid-19 vaccine hesitancy on Twitter *Troiano and Nardi* (2021) found several reasons, with the most prominent are being against vaccine in general, concerns about safety regarding the rush of vaccine production, doubting the necessity thinking Covid-19 is harmless, general lack of trust, doubt of efficiency, belief to be immunized and doubt about the provenience of the vaccine (*Troiano and Nardi*, 2021).

After performing sentiment analysis of 2,678,372 Covid-19 vaccine-related tweets posted from November 1, 2020, to January 31, 2021, *Liu and Liu* (2021) found in their paper that sentiment and the number of tweet rose significantly after Pfizer announced that their Covid-19 vaccine was 90% effective, only to decline slowly until the end of December. Where the initial positive sentiment towards the vaccine stabilized itself as neutral sentiment. Further they concluded that sentiment varied based on geography stating the importance that public health policymakers and government should base their vaccine education program on timely sentiment and geographic regions (*Liu and Liu*, 2021).

When looking more specifically into the sentiment regarding the Covid-19 vaccine on Twitter, *Marcec and Likic* (2021) found differences between the AstraZeneca/Oxford vaccine compared to Pfizer/BioNTech and the Moderna vaccine on English language Twitter. In the initial data gathered process, 1 December 2020, AstraZeneca/Oxford had a higher sentiment compared with the mRNA vaccines. However throughout the 4 months it decreased in positivity, most likely due to the thrombotic thrombocytopenia reports, until it reached a slightly negative average in March 2021. Although spikes of negative sentiment were present about both Pfizer/BioNTech and Moderna, it did not have a long-term effect on their overall sentiment and they both remained positively stable. The sentiment decrease seen regarding the AstraZeneca/Oxford vaccine might also indicate that it is generally negatively perceived which again might result in higher vaccine hesitancy and refusal (*Marcec and Likic*, 2021).

Looking further into the AstraZeneca/Oxford vaccine, during the period of January

2021 to 22 March, 2021 221,922 English language tweets containing the word #AstraZeneca was retrieved. These were found to contain misinformation, in many cases from well-known misinformation media sources in addition to anti-vaxxer activists. The data also contained information showing large coordination networks which were involved in political astroturfing and vaccine diplomacy in South Asia. However, vaccine advocacy was also present from networks associated with the European Commission employees (*Jemielniak and Krempovych*, 2021).

Addressing the emotions in Covid-19 communication, *Chou and Budenz* (2020) substantiates the importance of developing nimble, adaptable communication strategies in real time as a way to address vaccine hesitancy with the end goal of increasing vaccine confidence. Creating awareness of the manipulation of negative emotions from disinformation campaigns, eliciting positive emotions towards helping restoring health in communities and tailoring the message to the emotional state of the audience, may also help vaccination numbers (*Chou and Budenz*, 2020).

Misinformation concerning the Covid-19 vaccine is one of the main threats to vaccination programs. With *Hussain et al.* (2021) finding cases where vaccine debates are purposely being polarized for political gain, and exploiting the system's weakness and doubts in the public as well as the influence from general mistrust of the government (*Hussain et al.*, 2021).

Surveys and polls conducted in the United Kingdom and the United States indicate that the support for vaccination is fragile. Thus, underlining the importance of a better understanding of the public's concerns and attitudes. The potential of an AI-enabled real-time social media monitoring of the population's sentiment towards the vaccine may help policy makers understand the reluctance towards the vaccine. Based on this it is possible to inform and promote the vaccine in a more precise way in order to help achieve a higher percentage of vaccinated people (*Hussain et al.*, 2021).

2.1.1 The Infodemic

February 2020 The World Health Organization announced the current deluge of accurate and inaccurate information spreading accompanying the Covid-19 pandemic as a challenge for effective health communication. It was named the infodemic and is characterized by the volume of information and not the accuracy of it. Health information is competing against a tsunami of claims, where parts are misinformation. Many of which are amplified across social media, having a greater reach and spreading faster (*Jamison et al.*, 2020).

During the pandemic social media, and especially Twitter, has overflowed with information on the pandemic. The deluge of information makes it difficult for users to navigate through what is indeed correct medical information and what is misinformation. The spread of this misinformation leads to fear as well as mistrust to medical advice (*Rosenberg et al.*, 2020). It is found that people interacting with misinformation about the Covid-19 pandemic are less likely to engage with social distancing practices *Jamison et al.* (2020). This is likely a result of mistrust to the medical advice and the problems connected to the difficulties with separating real facts from misinformation on the web. If we want to end this pandemic as quickly as possible it is imperative that people follow the guidelines set by their government as well as accepting the Covid-19 vaccine (*Jamison et al.*, 2020).

The focus on misinformation in connections with fake news, results in people believing they have not been exposed to fake news. The situation is however more nuanced as groups of self-proclaimed vaccine activists are also inadvertently sharing conflicting health information. The sheer amount of information in the infometic is resulting in secure sources for health information contributing to the deluge of information (*Jamison et al.*, 2020).

2.1.2 Echo chambers

Studies have shown that users with similar interests tend to gather and form homogeneous clusters, called echo chambers. This results in similar minded people having their own views reflected back, thus confirming their own ideas rather than challenging them (*Menczer et al.*, 2020). Identifying groups who participate in spreading rumors on Twitter, dubbed 'rumor' echo chambers, *Choi et al.* (2020) found that Echo chambers have been shown to amplify rumors. Rumors spread in these chambers tend to become more viral and spread faster compared to rumors not spread by these echo-chambers (*Choi et al.*, 2020).

When looking at the measles vaccine debate on Twitter, with focus on Italy, *Cossard et al.* (2020) found that users hesitant towards the vaccine as well as those advocating the vaccine reside in their own separate echo chambers. With the community structures also differing with users advocating the vaccine organizing around authoritative hubs while skeptics are tightly clustered (*Cossard et al.*, 2020). *Thelwall et al.* (2021) analyzed 446 vaccine hesitant Covid-19 tweets in English language, posted from 5 of March to 10 of December 2020. Finding that vaccine hesitancy have been topics for right-winged echo-chamber spreading vaccine hesitancy beliefs and conspiracy theories. But it has not been limited to these echo chambers and also exists outside the chamber, making it able to reach and be further spread by more users (*Thelwall et al.*, 2021).

Chapter 3

The dataset

This chapter presents the dataset used when performing the analysis methods in this thesis and contains the following:

- Description of the data and the process of downloading the data and GDPR considerations.
- How the manual classification of the sample dataset was performed with the result of 14.61% irrelevant tweets, 32.37% neutral tweets, 30.03% vaccine hesitancy tweets and 22.72% anti-vaccine hesitancy tweets.
- There were fewer users in the vaccine hesitancy category but they posted more frequently.
- There are cases with tweets containing conspiracy theories in the dataset but to a small degree, more common were tweets with content debunking conspiracy theories. There were more cases with users displaying hesitancy due to the fast development of the vaccine.
- 111 tweets classified as neutral discussed the distribution of the vaccine, both across Norway and worldwide.

3.1 GDPR

General Data Protection Regulation(GDPR) was implemented in Norway in 2018 and is the law regarding privacy for individuals and their right to their own data (*Regjeringen.no*, 2019). They contain rules on which scenarios personal data may be collected and used. These data may be used in scientific research but the participants have a right to their own data and can choose to withdraw their consent and leave the study at any given time. To be able to exercise their rights, participants in the different studies must be informed how their data is used and how it appears in the research process (*Mascalzoni et al.*, 2019).

3.2 Data gathering

The data used for analysis in this thesis was downloaded from Twitter by supervisor Dag Elgesem. The dataset consists of 125018 tweets downloaded in the period August 2020 to December 2021.

The download from Twitter's API was based on keyword searches of tweets containing the following Norwegian words:

```
"vaksine", "#vaksine", "Vaksine", "vaksineskepsis",
"vaksiner", "vaksinert", "vaksinasjon", "#Pfizer",
"vaksineskeptikere" ,"#AstraZeneca", "#Moderna",
"vaksinemotstand", "vaksinemostandere", "bivirkninger",
"bivirkning", "#COVIDVaksine", "#mRNA",
"#COVIDVaksine", "#vaccine", "vaccine",
"#vaksinert", "#covidvaccine", "#COVID19vaccine"
```

For each tweet the following fields were included:

```
"tweet_id", "user_username", "text", "lang",
"author_id", "source","conversation_id","created_at"
"possibly_sensitive", "in_reply_to_user_id",
"user_created_at", "user_location",
"user_protected", "user_description","user_url",
"user_name", "user_profile_image_url"
"user_verified" "user_pinned_tweet_id" ,
"retweet_count", "like_count", "quote_count",
"user_tweet_count", "user_list_count",
"user_followers_count", "user_following_count",
"sourcetweet_type" "sourcetweet_id",
"sourcetweet_text", "sourcetweet_lang",
"sourcetweet_author_id"
```

Looking closer into the dataset on how much data was accumulated during the period and which months where users were most active, this graph 3.1 lists the amount of tweets gathered in the different months. March 2021 had the most tweets gathered, with 18239 tweets. August 2020 had the fewest tweets gathered with 1496 tweets.

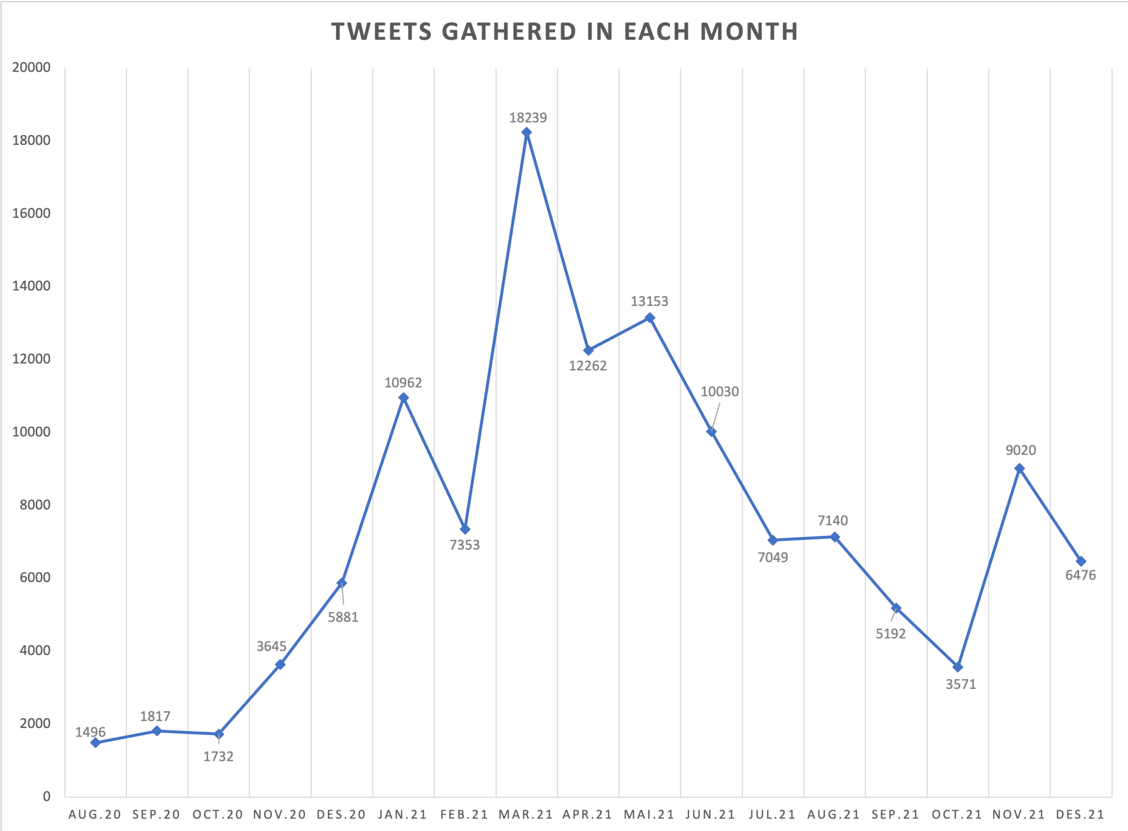

Figure 3.1: Graph of the amount of tweets gathered per month, created with Microsoft Excel

3.3 Anonymization of the data

Taking into account the sensitive nature of the data, measures were taken to ensure that no single individual could be recognized in the dataset. As this data is downloaded from twitter the participants have not formally accepted to participate in this research. However, they have agreed when signing up to Twitter. A website about the projects will be created to ensure that users have the possibility to refrain from participating. The website gives an explanation of the project and necessary contact information on how to make contact if they want to be deleted from the dataset. Furthermore, an ethics evaluation of the data was performed by supervisor Dag Eglesem and an application for the project has been filled out on UiB's system 'rette'.

3.4 Manually classifying a sample of the data

The dataset has not previously been used for analysis. Therefore, to gain insight into its structure, and to be able to create a supervised machine learning model, a sample of the dataset was manually classified. 1109 tweets from the dataset of 125018 tweets were selected based on the following restrictions:

- The tweet was an original tweet and not a retweet
- The tweet had 'Bivirkning' included in the text
- The tweet had been retweeted at least two times
- The tweet had at least five likes

This subset was then manually coded into four categories; irrelevant, neutral, vaccine hesitancy and anti-vaccine hesitancy. The tweets in the irrelevant category were tweets not having the Covid-19 or its vaccine as a topic. Neutral were tweets where it was not clear that the authors were hesitant or not hesitant towards the vaccine. Skeptic towards the vaccine contains content where the author expresses skepticism or hesitancy towards the vaccine or the government's vaccination-program. The last category is the tweets containing criticism or counter-perceptions towards people being hesitant towards the vaccine.

The manually coding was performed using MAXQDA by this author with reviews and discussions with Dag Elgesem in cases of ambiguity. The final result after finishing coding was:

- irrelevant: 162 tweets
- neutral: 359
- vaccine hesitancy: 333
- anti-vaccine hesitancy : 252

With the distribution being:

- 14.61% irrelevant
- 32.37% neutral
- 30.03% vaccine hesitancy
- 22.72% anti-vaccine hesitancy

Unfortunately there were some duplicates in the sample set. Looking closer at the neutral, vaccine hesitancy and anti-vaccine hesitancy categories, there were in total:

- 384 unique users/ accounts writing 798 unique tweets.
- 306 vaccine hesitancy tweets created by 111 users/accounts.
- 249 anti-vaccine hesitancy tweets written by 172 users/accounts.

- 243 neutral tweets written by 108 users/accounts.

On average, the users displaying vaccine hesitancy had the highest publishing frequency, while the users displaying neutral sentiment had the lowest frequency. The users skeptical of the vaccine are fewer than the others but they tweet more to get their message across.

Upon aggregating the tweets to users there were 10 users who, based on the manual coding, had posted both vaccine hesitancy posts and anti-vaccine hesitancy posts. Evaluating all tweets from these users, and based on the context the other tweets provided it was then concluded that the tweets were wrongly categorized. The conclusion is that there were no users posting both vaccine hesitancy and non-vaccine hesitancy. These errors were present in the training-set used to train the machine learning model. It is unfortunate that the sample data contains errors, but this illustrates the difficulty of classifying tweets. The shortness of the text makes it difficult to base classification solely on the text from the tweet without more context.

3.4.1 Qualitative result

As the data is gathered from Twitter, it lacks structure and frequently contains little information due to the shortness of the texts. As many prefer to write in their native Norwegian dialects, the grammar and spelling are inconsistent. These dialects vary from region to region and therefore lack the consistency needed for computers to effectively identify trends. A few of the tweets had only one or two sentences, making it difficult to determine the user's sentiment. This is further exacerbated by the popular usage of irony and satire on social media sites. Many tweets contain links to news items and simply repeat the article's headline or added emojis, thus adding to the complexity of classifying the sentiment of tweets.

Further analysis of the subdataset led to the classification of 10 users into two or more categories. Some instances involved anti-vaccination skepticism expressed by users tweeting vaccine skepticism-related content, which was determined following review to be either ironic or maybe incorrectly identified. The 10 users classified into multiple categories included individuals from each class. This could be due to the fact that the sample set contained unique tweets but not unique users, so eager tweeters had several tweets in the subdataset. A user may publish a tweet containing vaccination hesitancy or one with irrelevant content for this analysis. Before illustrating the sentiment network in the outcome chapter, the final categorization of user sentiment was determined by analyzing these 10 profiles.

On the basis of findings in the background about misinformation about the Covid-19 vaccine on Twitter and the results faktisk.no *Dahlback and Skiphamn* (2020) obtained from Norwegian Facebook, it is reasonable to assume that the same probably applies for Norwegian Twitter. During this analysis, there was a slight tendency to substitute this claim. As stated in the introduction, faktisk.no *Dahlback and Skiphamn* (2020) found conspiracy theories about Bill Gates and Erna Solberg. When analyzing this sample of Twitter data, just 3 tweets addressed these conspiracies, indicating that vaccine skepticism is more prevalent than conspiracy theories in this instance. More present were skepticism regarding how fast the vaccine was created. These users compared the Covid-19 vaccine to the last time a vaccine was created fast - the swine flu vaccine, which had not been tested enough and thus had some negative side-effects such as CFS/ME (Chronic fatigue syndrome/myalgic encephalomyelitis) in some cases. This was not necessarily negativity towards a vaccine in general but concerns about lack of testing the vaccine and discovering hidden side effects.

This was further disputed when the blood clot risk with AstraZeneca/Oxford was discovered. It was also elaborated upon, comparing the risk to the female birth control pill risks and side effects. With the attitude that it is ironic that this vaccine has similar risk to cause blood clots as the birth control pill, but research on substitutes and improvements to the pill has not had similar but insufficient attention. Some claimed that the pandemic was no more severe than a common cold and that it was blown out of proportion. But overall there were several tweets about taking the vaccine and being positive about taking it. In the last months of data gathering, the possible vaccination of kids became a topic. Many users displayed negative sentiment due to the fact that children overall did not experience too severe side-effects from having Covid-19.

During this manual sorting several themes were detected that were not relevant to the goal of this analysis but still relevant to the hashtags as well as the theme. A frequently discussed topic was the debate of how the vaccines were distributed, both across Norway and the world. There were 111 tweets regarding distribution of vaccines and they were categorized as a subset of the neutral category. This was done as they did not fit the category of positive or hesitant towards the vaccine as the writer's intent and sentiment in regard to vaccination was not clear. One could argue that the nature of the debate implies that they are positive towards the vaccine as they have opinions on how it is distributed and mainly do not question why and the necessity of it. As it does not include criticism or counter-perceptions towards people being hesitant towards the vaccine, the decision to categorize it as neutral was taken. However, it is still relevant to the Covid-19 vaccine and should thus not be excluded as irrelevant.

The controversy around the legalization and consumption of illegal substances is a recurring topic that most likely originated in response to the keyword "bivirkninger."

These tweets primarily consisted of individuals sharing their own experiences with illegal drugs and claiming that they had not experienced any negative side effects. These have been deemed irrelevant because they do not contain any information about the Covid-19 vaccine, or sentiments about it, which contributed to the total amount of background noise. When such a large number of search terms were employed as the basis for information collection, it was inevitable that the data would contain noise.

It was possible to see some patterns of communication and how some profiles were central to the debate in this analysis. Some of the users were mentioned by several people illustrating a network, with a few users being more influential than others.

Chapter 4

Methods

In this chapter the methods used to perform the quantitative analysis are presented with a short summary of the theory behind the methods. Furthermore, it includes information on the packages and technology central to performing the analysis. And lastly the implementations of said methods along with a brief evaluation. The steps performed in the quantitative analysis are:

- Cleaning the data by removing stopwords and lemmatzining the words.
- Testing both BoW and TF-IDF as vectorizers for the model.
- Testing Both Naïve Bayes algorithm and Support vector machine algorithm.
- The most accurate model was binary classification using BoW as vectorizer and the SVM algorithm.
- Using two methods for topic modeling, Latent Dirichlet Allocation and the Biterm topic modeling.
- Creating two Social Networks from the entire dataset, a network for mentions and a network for retweeting. The mentioning-network was split into months to visualize how the debate developed over time. In the retweet network users with highest in-degree (most retweeted), out-degree (most retweeting) and betweenness was analyzed.
- Creating one retweet network from the sorted sample dataset with the tweets classified as vaccine hesitancy and anti-vaccine hesitancy.

4.1 Data cleaning

4.1.1 Stopwords

A common way of cleaning the dataset is to remove words that appear too frequently to be informative, so called stopwords. This is usually done by either removing based on frequency or based on a language specific list of stopwords. By decreasing the length of the document and thus decreasing the number of features one can have an improvement in performance (*Müller and Guido*, 2016).

4.1.2 Lemmatization

Improving on the TF-IDF and BoW feature extraction is possible with lemmatization or stemming. Stemming is the method where only the word stem is used in the final text, by identifying/conflating all the words that have the same word stem. Lemmatization is the method where only the lemma of the word is used in the final text; it differs from stemming because the role of the word is taken into account in the process. Both stemming and lemmatization are forms of normalization and are useful as the same word in different grammatical versions will be separated by feature extraction model and thus may lead to overfitting. Looking closer into these methods stemming is always restricted to trimming the word to its stem core whereas lemmatization can find the correct verb base. Furthermore, lemmatization is more precise when it comes to separating the same words that have different meanings depending on if they are nouns or verbs. It is a more complicated process but with use of lemmatization one can generally achieve a better result regarding tokens for machine learning (*Müller and Guido*, 2016).

4.2 Supervised machine learning

Supervised machine learning is used to predict outcomes based on given input with examples of input/output pairs. The model is built on these examples comprising the training set, which are built by human effort. The training set is then used in supervised machine learning methods to get accurate predictions for new unsorted/unclassified data. It is separated into two categories, classification and regression. Classification is the prediction of class labels from a predefined list of possibilities that can be binary classification or multi-class classification. Binary classification has only two categories, often true/false or yes/no, whilst multi-class is classification with more than two possibilities. Regression, on the other hand, is the prediction of a number, such as a person's age or income, and this type often has continuity in the output (*Müller and Guido*, 2016).

In this thesis the goal is classification and thus this will be the main focus when describing the methods below. However, there are challenges with classifying short text like tweets as they often lack the syntactic structure found in longer texts. Their shortness result in cases were the same sentiment is stated but the statements do not share any common words. This makes it challenging to identify that the texts are related (*Zhan and Dahal*, 2017).

4.2.1 Sentiment analysis

Sentiment analysis is to extract the sentiment, a positive or negative orientation, from the author of a text. The simplest form of this is with the use of a binary classification model looking at the meaning of key words and phrases to determine sentiment (*Jurafsky and Martin*, 2020) .

4.2.2 Bag-of-Words

A simple, effective and common way to represent text for machine learning is *bag-of-words*(BoW) representation. This discards structure such as chapters, paragraphs and formatting instead focusing on how often a word appears in each text, counting word occurrences and putting it in, what can be visualized as, a 'bag'. To compute the text with a BoW the first step is *tokenization* to split each text document into tokens(words) separated by white space and punctuation. Second, the vocabulary is built by numbering the tokens. And last, the tokens from the vocabulary are counted each time they appear in a specific document, encoding. This results in an output of a vector of word counts for each document representing how often a word appears giving a numeric representation with features for each unique token in the corpus (*Müller and Guido*, 2016).

One drawback to the CountVectorizer method used in BoW is that if a word appears in a corpus that was not present in the train corpus, this word will be ignored with the use of the transform method. However, this is not usually a problem in classification as "it is not possible to learn anything about words not in the training data" (*Müller and Guido*, 2016).

The way word order is discarded is a clear disadvantage to this method for text representing. This leads to a text with two different meanings but the same words having the same representation as well as contextual words such as 'not'. 'Not a great game' and 'a great game' have the opposite sentiment, but this distinction is not made clear enough with basic BoW implementations. N-grams, sequences of tokens such as pairs and triples of tokens are known as *bigrams* and *trigrams* respectively and are important with contextual meaning. There are ways of changing the range of tokens when implementing the BoW method by changing the ngram range, having a minimum of one (unigrams) with the addition of bigrams often improving the result. One should be careful when adding too long sequences as this could lead to overfitting with the increased amount of features. A method for finding the ideal setting of n-gram range is using a grid search *Müller and Guido* (2016).

4.2.3 TF-IDF

One of the most common ways to rescale features based on how informative one expects them to be is the *term frequency-inverse document frequency*(TF-IDF) method. In this process words that appear often in a certain document, but few times in the corpus of documents, are given high weight ratings. This is done as the intuition of TF-IDF is that such a word is descriptive of the content of the document. The formula for TF-IDF is the following:

$$tfidf(w,d) = tf * log(N + 1/N_{\mathrm{w}} + 1) + 1$$

with N representing the number of documents in the training set, N_{w} the number of documents the word *w* appears and TF is the number of times the word *w* appears in *document d*. After TF-IDF is calculated L2 normalization is applied to rescale the representation of the document so that the end result of each document has euclidean length 1. This is done to make the vectorized result the same length regardless of text document length (*Müller and Guido*, 2016).

4.2.4 Naïve Bayes

Naïve Bayes classification is based on the conditional probability concept from the 18th-century mathematician Bayes, the likelihood of an observation based on already acquired knowledge. In text classification the Naïve Bayes classifier takes into account the context of a word and if the word is more likely to occur in one category then the text is categorized into that category. The probability of the text being placed in a category is based on the prior, the base rate of seeing text in this category. The prior can be described with ducks in a park, if a bird is quacking one can assume it is a duck, however if one never has seen a duck in that park this assumption is riskier. The prior gives indication of how likely something is to be classified into a certain category, if there exist many cases of a certain category then even weak evidence is enough for the object in question, being classified into this category. It is these assumptions that are made without certainty that make the model naive. And with the combination of the conditional probabilities described by Bayes the result is a Naïve Bayes classifier (*Conway and White*, 2012).

Naïve Bayes classifiers are a family of classifiers all based on the same principle explained above. They are often used on large datasets and are fast to train and predict, as well as working very well with high dimensional data. The efficacy of these methods is due to them learning parameters by looking at each feature individually, collecting simple per-class statistics from these features. MultinominalNB is one such Naïve Bayes classifier method, it takes into account the average value of each feature for each class to compute its statistics. Then data points are compared to statistics of the classes resulting in a prediction of best matching class (*Müller and Guido*, 2016).

4.2.5 Support Vector Machine

Support vector machine(SVM) is a classification model great for solving problems with non-linear decision boundaries with the use of Kernels. The so-called kernel trick is the use of mathematical transformation to move the dataset into a new mathematical space where the data can be easier separated into decision boundaries. Thus, compared to logic regression SVM can operate in several cases including those with data points that could not be separated with linear decision boundaries (*Conway and White*, 2012).

It can be separated into four principles, the separated hyperplane, minimum/ maximum hyperplane, the soft margin and the kernel function. If one visualizes the data to be classified as points in clusters on a graph, the hyperplane is the line that separates the two cluster categories. For one-dimensional data, referred to as a one-dimensional line, the line can be separated with a single data-point, two dimensional data gives a straight line for separating the spaces and with three dimensional data the hyperplane is a plane that divides the spaces. The second principle, maximum/minimum hyperplane is the distance from the separating hyperplane to the nearest expression vector for each category. Looking at these distances the hyperplane line that predicts the maximum correct classification of unclassified data is chosen (*Noble*, 2012).

Although the goal is to find a hyperplane that separates all the data points into their categories precisely there will be instances were a data point is in the wrong category cluster. The next principle, the soft margin, deals with these cases by letting some data points stay in the wrong cluster on the wrong side of the separating hyperplane. The SVM algorithm may be modified using soft margin to let these data points through the hyperplane without affecting the result of the model. However, this must be controlled so as to not include too many miss-classifications by setting a parameter to ensure accurate results. The final principle is the kernel function, which solves cases where the hyperplane cannot be drawn between the categories even with inclusion of soft margin. It adds an additional dimension, changing the data from low-dimensional space to a high-dimensional space, and thus opens for the possibility to draw a separating plate. The kernel function could limit the need for the soft margin as there could always be a space where the data could be separated linearly. But the downside to the high dimensional projecting is that when the number of variables to consider increases the number of possible solutions increases exponentially. This makes it more difficult for the algorithm to provide the best hyperplane. Furthermore, it may lead to overfitting as the hyperplane becomes too specific to the training data. Thus the best practice when working with SVM is to try out different kernel functions with use of cross validation when training an algorithm (*Noble*, 2012).

4.3 Topic modelling

Topic modeling algorithms is a statistical method for finding the main theme of a large and unstructured collection of documents. It arranges the data in accordance to the topic and is useful to find patterns in data such those from social media. This is done by analyzing words from the original text in order to find the themes, how they are connected and how they change over time in the dataset (*Negara et al.*, 2019).

Topic modeling is often done without supervision, with the simplest form of each document in a corpus getting one topic each. It is also possible to get several topics for a topic model using decomposition method, where each component of the document corresponds with a topic, using coefficients to represent how related the document is to the particular topic. Topics in this regard do not always contain semantic meaning and are more similar to components extracted. It often gives a different result than if the analysis had been done by humans and may be just a grouping of words (*Müller and Guido*, 2016). Topic modeling algorithms can applied to many different types of data, they can also be used to find patterns (*Blei*, 2012).

4.3.1 Latent Dirichlet Allocation

A frequently used method for topic modeling is Latent Dirichlet Allocation(LDA) which generates a weighted list of topics for each document. This is done based on the distribution of words contained in the documents called Dirichlet distribution. The result from Dirichlet is then used to assign words from the documents to topics. However, this classification of per-document topics are hidden structures whilst the documents themselves are observable objects. LDA finds topics based on the distribution of words by looking at the word to see if it is from the same topic or if there are several topics in a document (*Negara et al.*, 2019). It tries to find groups of topics appearing frequently together, requiring that each document be seen as a mixture of a subset of the topics (*Müller and Guido*, 2016). The idea behind LDA is that each document has several topics, where the topic is 'a distribution over a fixed vocabulary'. The distinguishing character of the LDA algorithm is the concept that the same topics are present in every document in the corpus, but they display different proportions of these topics. It analyzes the hidden structure of the texts to determine these topics, and the success of the algorithm relies on the structure resembling the thematic structure of the corpus (*Blei*, 2012).

LDA was created to find topics automatically in a corpus of texts so it would be possible to search through the documents based on topic and not just keywords (*Blei*, 2012). It has been proved effective on documents of at least a few hundred words, it is however uncertain how well it performs on shorter text which is unfortunate when working with Twitter data (*Jónsson and Stolee*, 2015).

4.3.2 Biterm topic modelling

As an alternative to LDA, *Jónsson and Stolee* (2015) found that when working on short documents the Biterm Topic Model(BTM) appeared to be superior to others including LDA. BTM learns topics over short text by directly modeling the generation of all the unordered word-pairs co-occurring within a text across the collection of documents. It is designed to work specifically for short text by viewing the biterms across the topics as a mixture of various topics, instead of viewing each document as a mixture of various topics. Thus excluding the sparsity problem experienced by LDA with short texts. It does however not model the generation process which makes it impossible to obtain topic proportion of documents during the BTMs learning process (*Jónsson and Stolee*, 2015). BTM can also be extended to combine various aggregations strategies making it flexible for different scenarios (*Yang et al.*, 2020).

4.4 Social network analysis

Mathematically speaking, a network is a graph made up of nodes and edges with the purpose of simulating a world with edges connecting the nodes. This can be done very simply with two nodes and an edge as a connector. Without context, edges give no information other than the connection of the nodes. This organization of information can however be quite complicated depending on the information represented. Depending on the data one can visualize using different types of graph models, there are undirected networks, directed networks and directed networks with labeled edges (*Conway* *and White*, 2012). A social network is a group of people connected by some form of relationship, in this case the people are represented as nodes and the edges represent the relationship (*Menczer et al.*, 2020).

A graph is undirected when the edges connecting the nodes do not have any direction but are simply connected and can insinuate that there is a mutuality in the tie. A directed graph on the other hand, is when the edges do have a direction, often visualized with an arrow at the end of the line indicating the node the direction points towards. In such a graph the edge indicates a one-way tie unless otherwise indicated with use of an additional arrow or edge. In addition, one can add edge labels to the graph which adds more information and context to the network either through binary labels(positive and negative) or weight which indicates the strength or type of relation. Twitter is a directed graph as followings do not have to be mutual, this structure affects the operation of the network as high profile users are major broadcast points (*Conway and White*, 2012).

Furthermore, looking closer into the graphs, the number of nodes N and total number of edges / links L characterize each network. The number of nodes and links can not define the network because one needs to specify the way the links connect the nodes. However, N can represent the *size* of the network as it identifies the number of distinct elements in the system. The maximum number of links in a network is the number of distinct connections between the nodes of a system and a network where all these links exist is called a *complete network*. A complete network has a density of 1, the density of a network represents how many of the nodes are connected through links. Often all nodes are not connected and thus the density is often smaller than one and called sparsity as a better representation with fewer links connecting nodes, the sparser the network (*Menczer et al.*, 2020).

An important property directly proportional to the density of a network is the average *degree* of a network. Calculated with node i, where k_i denotes the degree of said node, if this degree is zero then the node has no neighbors and is referred to as a singleton, and $\langle k \rangle$ denotes the average degree of the network. The degree of nodes is a property that helps characterize the structure of a network (*Menczer et al.*, 2020).

4.4.1 Centrality

The importance of node i is based upon how many neighbors node i are connected to in degree centrality metric. The amount of links determines how important the node is, because the higher the number of links to other users the more the user can reach the rest of the network without depending on other users. In the case of social networks a node with a high degree of centrality serves as channels of information. The degree distribution in such a network does follow a Powell law distribution, meaning that few nodes have exceedingly many connections, making them more important because of the impact they can have regarding information flow. The degree centrality for node *i* is calculated with the following:

$$d(i) = \sum_j m_{\mathrm{ij}}$$

where m_{ij} is 1 in cases of a link from node *i* to node *j* and 0 if no link exists. In directed networks it is imperative to separate between in-degree and out-degree centrality. The in-degree can be used for measuring the popularity of a node (*Al-Taie and Kadry*, 2017). A directed network is cases where the link between the nodes is not always symmetric and a directed link has source node as well as an target node. The in-degree of a node is the number of incoming links whilst out-degree is the number of outgoing links in a directed network (*Menczer et al.*, 2020).

Another measure for centrality is *betweenness centrality*, which describes how important a node is in the network in the path of information flow from node to node. It can be used both for illustrating nodes that are probable passage points and bridges between graph segments, nodes that are the only path to some selected nodes. In social networks these bridge nodes may represent the importance of an actor as they connect contacts to each other. Calculating how often a certain node need to be passed through when information travels through the network is achieved with:

$$b(i) = \sum_{j,k} \frac{g_{\mathrm{jik}}}{g_{\mathrm{jk}}}$$

with g_{jk} representing the shortest path from node *j* to node *k* and g_{jik} representing shortest path traveling through node *i*, where node *k* is not node *i*. If a vertex has a betweenness centrality value of 0 it is not located in the shortest path between any other node pairs in the network and thus decreases the network's social importance (*Al-Taie and Kadry*, 2017).

4.4.2 Egonets

In social network analysis, it is often beneficial to construct subnetworks or subgraphs by selecting a subset of the nodes and all of the links between these. The egonet is a type of subnetwork in which one selects a node and collects its neighboring nodes and links *Menczer et al.* (2020). These networks are typically ego-centered, with the specified actor at the center, and it is possible to navigate between various sections of the existing network. In order to analyze these networks, the relationship between the central node or group of nodes and their contacts should be examined. This is useful for locating information about relationships in many contexts, often mapping the complexity of said relationships. The data obtained by examining egonets supplements the data obtained by evaluating the entire network (*Al-Taie and Kadry*, 2017).

4.4.3 Snapshots

Multilayer of network is a combination of layers where each layer with nodes can represent something stable such as airports and the links in each layer can vary based on the airlines and how they link(fly between) each node(airport). If the set of nodes in each layer in this multilayer is built from the same set, it is a multiplex network. A type of multiplex is the temporal network where the node-to-node interaction occurs at different times, making the links dynamic. Furthermore, the nodes are also dynamic as they may appear and disappear as the network evolves. This can be used regarding Twitter data as posts, retweets and mentions have timestamps identifying when they were created. The network may evolve over time and by dividing based on the timestamp one can create consecutive intervals of the span of the temporal network. The nodes and links in every interval are called a snapshot of the system, and can be seen as a layer of the multiplex (*Menczer et al.*, 2020).

In the multilayer network there are both links connecting nodes in the same layer, *intralayer links*, as well as links connecting nodes across layers, *interlayer links*. As each layer consists of its own set of nodes and links it can be viewed as its own graph/network, resulting in a network of networks, where the interlayer links may function as a representation of relationships across the nodes of the networks (*Menczer et al.*, 2020).

4.4.4 Homophily and echo chambers

Humans are subjects to social influence and persons who are friends tend to become more similar as preferences get affected by their social interaction. In social network, where nodes represent people, the nodes often have properties such as interest, sexual preferences, religion and so on. Connected nodes in a network tend to have similar properties, and it is this assortativity that makes it possible to predict, with reasonable accuracy, properties of one node based on the properties of neighboring nodes. A possible reason for the assortativity in social networks is homophily, the idea that similarities makes it more likely that people select each other and form a connection. However, as humans do influence each other and do become more similar through connection it is difficult to separate if similarity creates the link or links create similarity

(*Menczer et al.*, 2020).

Although one often has similarities to one's real life social network, one is connected to people with different opinions. On the internet, however, it is easy to exclude this from one's network as well as connecting to people who share one's own view. This combined with the possibility to share information in a selective and efficient way to effect opinions can lead to polarization. It is this reflection of users' views, information and opinions that lead to confirmation and reinforcement of this view that is echo chambers. Echo chamber behavior is dangerous as it makes the users vulnerable for misinformation which may result in manipulation (*Menczer et al.*, 2020).

4.5 Technology

This section presents the technology central to performing the analysis of this thesis.

4.5.1 Scikit-learn

Scikit-learn is an open source package of tools for predictive data analysis built on NumPy, SciPy and matplotlib (*Pedregosa et al.*, 2011). Through the machine learning section of the programming in this research Scikit-learns methods used in train_test_split, TF-IDF, BoWs, Grid search CV, SVM and Naïve Bayes. Additionally, it was used when implementing the topic modeling programming to execute the LDA approach.

4.5.2 MAXQDA

MAXQDA is a qualitative analysis software which works with several types of data with tools useful for coding, visualization, mixed methods, statistical and quantitative content analysis (*Software*, 2022). In this thesis this software was used for manually coding a part of the Twitter dataset into four categories for sentiment.

4.5.3 Bitermplus

Bitermplus is a python package for implementing a cythonized version of the Biterm topic model easy to implement on datasets using python (*Yan et al.*).

4.5.4 Graphs in R

Igraph

Igraph is an open source package for network analysis with a collection of tools that can be used in the following programming languages: R, python, Mathematica and C/C++. In this thesis the R package was used to create most of the graphs with the exception of the egonets (*Csardi and Nepusz*, 2006). These graphs were visualized using XQuartz[1].

Ggraph

Ggraph is a R package that implements the grammar of graphics for graphs, networks and trees. It is an extension of the ggplot2 package, but has its own API and provides a flexible approach to building graphs in layers (*Pedersen*, 2021).

4.6 Implementation

4.6.1 Topic modeling

Topic modeling was implemented on the dataset in its entirety, including the coded date but without the code for sentiment. It was also performed on the smaller coded dataset to see if the same topics are present in both the sample and the total dataset. To ensure the results were as precise as possible data Cleaning was performed on the dataset where it was lemmatized and stop words were removed in the vectorization phase with Scikit-learn CountVectorizer method.

4.6.2 Supervised machine learning

The supervised machine learning was programmed in python3 with Visual Studio code as editor. After conducting the manual sorting of the dataset using MAXQDA to separate the dataset into the four categories the data was downloaded as an xlsx file. From this file the necessary components, mainly the coded segment, document name(the tweet id), tweet text and date, were collected into a new csv file and then imported into the python file as a dataframe. Then the category of 'irrellevant' was removed before the dataset column containing text was cleaned by removing Norwegian stopwords as well as performing lemmatization on the text data. Then the code columns were made into a separate array, and were hesitant towards the vaccine getting the score -1, neutral 0 and positive 1 before being added to the dataframe. Then both the text column

[1] https://www.xquartz.org/

as well as this sentiment column were called dataX and dataY before the train test split method was performed with a test size of 0.33 and random state 42.

These values were then again split to get X_val and Y_val to avoid overfitting. Then x_train and x_val were vectorized using both the BoWs method as well as TF-IDF method. To find the most precise model for its accuracy, the fraction of tweets classified into the correct sentiment category is calculated. Specifically the F1 score which is the harmonic mean of precision, calculating false positives, and recall, calculating true positive (*Müller and Guido*, 2016). Due to the nature of the SVM algorithm a grid search for parameters to SVM both TF-IDF and BoW was performed. Testing which parameters would yield the most accurate classification, the grid search on both vectorization methods resulted in:

'C':0.1, 'gamma': 'scale', 'kernel': 'linear'.

After implementing these parameters in the SVM model the result of the initial model can be seen in table 4.1. Both BoW combined with SVM and TF-IDF combined with Naïve Bayes had a score of 0.50. They did however, show a small difference in the number of misclassified posts from 103. SVM and BoW had 52 mislabeled posts while Naïve Bayes and TF-IDF had 51. This is not accurate enough to get a result for the entirety of the dataset one can base any conclusions on.

vectorization method	classification method	f1-score for accuracy
BoW	SVM	0.50 (52 mislabeled)
TF-IDF	SVM	0.48
TF-IDF	Naïve Bayes	0.5 (51 mislabeled)
BoW	Naïve Bayes	0.47

Table 4.1: Classification report multi-classification

Due to the nature of the dataset explained i chapter 3, as well as the short texts tweets are composed of, it is challenging to create an accurate enough model with several categories. Thus, the decision to create a binary classification model with only the categories vaccine hesitancy and not vaccine hesitancy was made. The difference in implementation being the tweets with the coded category 'positive' also got a score of 0 combining it with the neutral tweets. The result of the grid test for parameters regarding SVM was

'C':1, 'gamma': 'scale', 'kernel': 'linear'.

with the difference from the multi classification being C= 1 instead of C= 0.1. After tuning the SVM model with these parameters the classification report from this model can be found in 4.2. BoW combined with SVM being the most precise classifier but this time with a score of 0.76 and number mislabeled posts out of the 103 being 25 compared with TF-IDF and Naïve Bayes's result of 0.73. Though the model could be improved upon, it is possible to draw conclusions based on this model with a higher certainty.

vectorization method	classification method	f1-score for accuracy
BoW	SVM	0.76
TF-IDF	SVM	0.74
TF-IDF	Naïve Bayes	0.73
BoW	Naïve Bayes	0.71

Table 4.2: Classification report binary classification

4.6.3 Social network analysis

Social network analysis was programmed in R with R studio with XQuarts for visualization. To get a network with users that has some impact on the debate filtration of the dataset was required and baselines set. For the retweets and quotes network only users with over 600 followers were selected as well as a minimum of 300 followings. Retweets are tweets re-transmitted from other users, whereas quotes are retweets where the user retweeting can add a comment to the message as well as re-distributing it. These are therefore both included in the Retweet networks with nodes representing the user who retweeted/quoted and links to the author of the text being redistributed.

To gain insight into influential users, the mentioned network was created and tweets with mentions were retrieved based on '@' in the tweet text. These tweets selected also had the restriction of minimum number of followers set to 600. Mentions on Twitter is when one user B tags user A in the tweet text by calling on their username with '@'. The mentioned network is a directed network where a link from node B to node A represents user A being mentioned by user B.

To look closer at some influential users, egonets based on retweets and quotes were created. In this instance the entirety of the data was included filtered based upon author_id and sourcetweet_author_id. Then removing empty rows in sourcetweet_author_id to only include those instances were other users text were shared which resulted in 13927 nodes and 40563 number of ties. This is also a directed network with a link from user B to user A representing user B retweeting user A. Scores for out-degree, in-degree and betweenness were then added to the graph before visualization done in ggraph. The different graphs were created by choosing a author id, collecting the relevant nodes connected and visualizing with ggraph.

Lastly a network of anti-vaccine hesitancy and hesitancy was created with the help from supervisor Dag Elgesem. The users from the aforementioned classes were chosen with the retweets connected to these nodes. These received colors based on category and were modeled into a graph with igraph before being visualized with XQuartz.

4.7 Evaluation

4.7.1 Topic modelling

As previously stated, the LDA method for topic modeling is not precise enough on short text. This is substantiated by the result given in this analysis and therefore Biterm is implemented as well. Although it is more readable for humans it still contains much noise. To achieve the best result the data cleaning could have been improved. Words such as RT which in these cases mostly represent that the tweet is a retweet should be added to the stop words list as they present noise.

4.7.2 supervised machine learning

Evaluating the model created was saved using pickle and reloaded to be run on the test dataset created using train_test_split. The same BoW vectorization model was performed on x_test as the previous data. X_test is approximately twice the size of x_val and running the model on it yielded a precision score of 0.73% with 56 mislabeled out of 209. Indicating that the model is not as precise as initially thought based on the results for the validation run. However compared to the multi classification it is still an substantial improvement. With an accuracy between 0.73% and 0.76% it is possible to make assumptions based upon the result from running the model on the rest of the dataset. It should be noted that it may indicate more or less vaccine hesitancy than is actually present, but it can give an indication to sentiment in the data. The model could be improved upon by sorting a larger part of the dataset manually giving the model more training data.

Chapter 5

Results and Discussion

This chapter entails the results from the following methods:

- Topic modeling
- The trained supervised machine learning model
- Social network analysis

Each observation will be interpreted and discussed continuously as the result is presented. This is to ensure it is clear which network or method it is regarding. The final discussion concludes on the hypothesis and answers the RQ by combining the results from the analysis. The main findings from the analysis are:

- Methods for Topic modeling did not perform as well as expected.
- The machine learning model implemented on the entire dataset resulted in approximately 10% vaccine hesitancy and approximately 90% non-vaccine hesitancy. This is lower than expected as the training data set had approximately 30% vaccine hesitancy.
- The most mentioned user snapshot networks illustrated that the vaccine debate changed in November of 2020. The most mentioned users were public figures and departments as well as some physicians all with positive sentiment towards the vaccine.
- The retweet network showed the presence of users displaying vaccine hesitancy when inspecting the top 10 users with highest in-degree, out-degree and betweenness scores. In in-degree and out-degree half of the highest scoring users displayed negativity towards the vaccine and some of these users also displayed conspiracy theories.

- Some of the users with highest scores in in-degree and betweenness were also present as influential users in the mentions network.
- The sentiment network created with the sample dataset illustrated the presence of echo chambers.

5.1 Topic modeling

The main results from Topic modeling were:

- The LDA method gave results that are easier to interpret than the Biterm method.
- The results from topic modeling were challenging to interpret, giving no clear conclusions on topics in the dataset based on these results.
- There is a large amount of noise in the dataset. This noise could have been removed more thoroughly to ensure easier interpretation of results.
- The topic model result can be used as an addition to the other analysis but alone the results are too weak to base conclusions on.

The method for Latent Dirichlet Allocation(LDA) was programmed with the use of scikit learn in python with the learning method 'batch', max iteration of 25 and a random state of 0 with initially 10 topics. When vectorizing the topics it had a max_df of 0.15 which removed the top 15% of frequent words as a way to limit stop-words in combination with the stop word list. After formatting and sorting the components, the results were visualized with the use of mglearn tools. Initially the already sorted dataset was used and with 10 topics and 10 words explaining each topic presented in this Table 5.1. Running the same programmed code for the whole dataset, the LDA function had a longer run-time compared with the sample dataset. As it is significantly larger this is not surprising, and although it was slower it did perform in a decent run-time. The 10 topics resulting from this analysis are illustrated in Table 5.2

Inspecting the tables it is possible to conclude upon themes analyzing the result from LDA, for example topic1 in Table 5.2 concerns people not allowed into Norway during the pandemic. However, some topics are more unclear and difficult to assess meaning such as topic9 in Table 5.1. However, the Covid-19 pandemic and vaccination are clearly visible in every topic presented by the model based on the results obtained. In general, the model's topics were easier to analyze when applied to the complete dataset rather than the sorted subset. The scikit-learn LDA model's default setting is to construct 10 topics; however, one can specify any number of topics. To examine

topic0	topic1	topic2	topic3	topic4
vaksinere	norge	mye	vaksinere	covid
norge	trygg	covid	gj	mye
all	land	all	dose	risiko
se	st	lang	norge	annen
barn	vaksinere	vaksinere	land	folk
hel	kj	stor	covid	19
verden	mye	land	dag	vite
folk	dose	st	vaksinering	land
ogs	covid	hel	syk	st
mye	gi	gi	tenke	god
topic5	**topic6**	**topic7**	**topic8**	**topic9**
mye	gj	komme	dose	vaksinere
se	god	all	vaksinere	god
land	land	folk	folk	dose
god	vaksinere	ny	hel	ogs
covid	folk	covid	jo	st
https	100	hel	0001f921	annen
pandemi	mye	se	vite	få
annen	all	psteigan	covid	ny
st	gi	19	tredje	hel
norge	hel	dose	dsfall	land

Table 5.1: LDA with 10 topics, performed on the sorted sample dataset

if more information about the themes in the dataset could be gleaned, the number of topics was determined using a trial and error method.

First, looking closer into the subset with the manually coded sample dataset, creating 100 topics with the LDA. An excerpt of the 100 topics from the LDA model on the coded subset can be found in appendix A A.1. The model now includes noise to a higher degree compared with the 10 topics; during this visualization the topics chosen for extraction had to be changed to not include names in the topics. Increasing topics in the LDA method also increases precision, however, they are in many cases more challenging to interpret as in this case. Narrowing it down to 50 topics, TableA.2, the topics are still too narrow and the same could be said for, Table A.3, with 30 topics. Table A.4 gives topics that are somewhat easier to read, thus, for the sub-dataset 20 topics gives results that are easiest to interpret.

Implementing the LDA method with 100 topics on the entire dataset, shown in Table A.5, it is possible to assign a higher degree of significance to the topics than compared to 100 topics with the smaller dataset. This is to be expected, given the dataset is larger, which gives the algorithm more data to work with. It does, however, have the same problems as 100 topics in the smaller dataset, as it is difficult to attribute meaning to

topic0	topic1	topic2	topic3	topic4
bivirkning	mye	oslo	uke	land
astrazeneca	god	kommune	første	norge
kaveh_rashidi	stor	år	dag	eu
alvorlig	smitte	molde	dose	verden
blodpropp	jo	18	direkte	fattig
koronavaksin	annen	åring	nrk	måtte
ta	se	norge	eqp64timfe	kjøpe
rask	tro	dose	dø	støtte
bidra	komme	fhi	time	rik
10	vel	uke	nrknyheterrss	usa
topic5	**topic6**	**topic7**	**topic8**	**topic9**
dose	norge	hel	ta	covid
person	benthhoyre	måtte	bivirkning	19
to	folkehelseinst	folk	folk	barn
dag	erna_solberg	burde	måtte	virus
én	gå	ta	annen	ny
ny	måtte	nei	vite	år
fullvaksinere	land	mye	gjøre	smitte
år	veldig	annen	mye	beskytte
vaccin	reise	først	hel	sykdom
antall	dax18	komme	all	syk

Table 5.2: LDA with 10 topics, performed on the entire dataset

many of the topics. With 50 topics as parameter, Table A.6 it is easier to attribute meaning to the topics. The readability does not improve much with 30 topics, Table A.7, and the results are quite similar independently of the parameters of set topics. Because of the minute differences in the results, it is difficult to say which parameter is the best. However the table with 50 themes seems to be somewhat more readable.

In both cases, the topics presented are difficult to assess meaning without prior knowledge and understanding of the dataset. The results from the two datasets are quite similar, which could indicate that the subset is a representative sample of the dataset. One of the differences is that the results from the entire dataset include more prominent figures in the topics such as Erna (the former prime minister), Høie (the former health minister), Kaveh Rashidi (a physician active in the vaccine debate on Twitter) and Bill Gates. It is also important to note that in this instance, the random state was set to 0, and the outcome would alter, possibly significantly, if this was modified. It is an interesting addition to the other sentiment analysis done with machine learning, but conclusions should not be drawn purely on the basis of LDA results.

As mentioned in chapter 4, the Biterm model has been proved more effective compared to LDA on short texts. The Biterm analysis was performed using bitermplus for

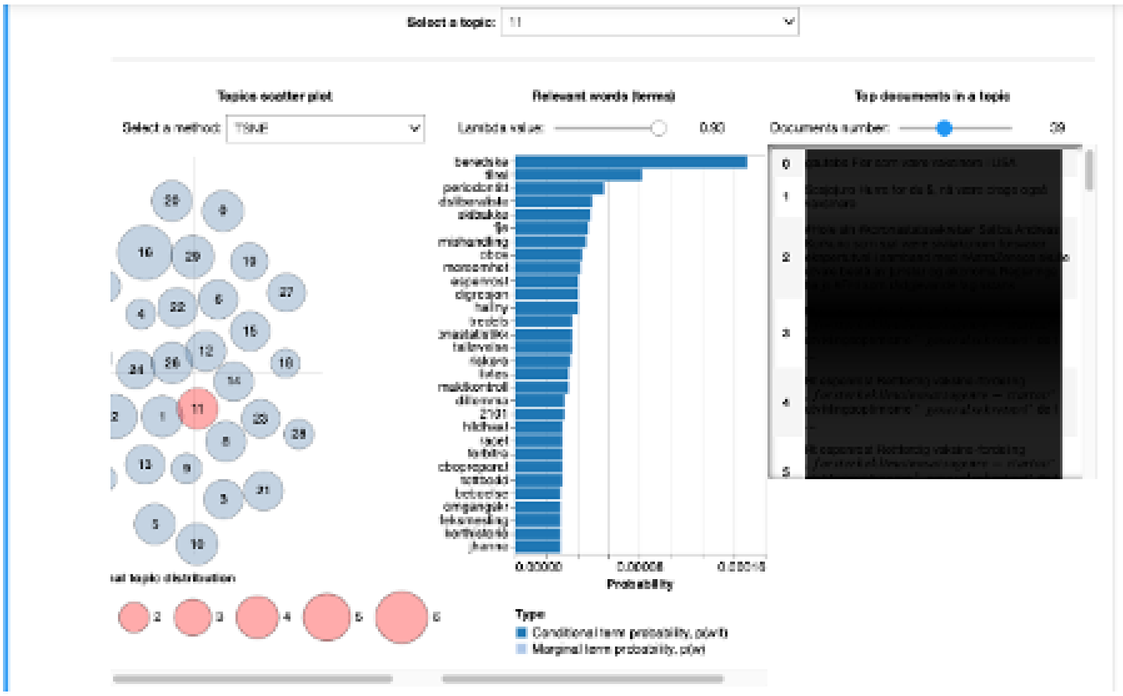

Figure 5.1: Example of tmplot biterm visualization

python and visualized using tmplot, initially with the task of 10 topics. With tmplot for visualization, the user chooses a topic from a dropdown, and are presented with alternatives for scatter plots, relevant words(terms) with a lambda value bar and the top documents in a topic. The lambda bar can be modified, with values closer to zero indicating more exclusive terms related to the topic and values closer to one indicating more frequently occurring terms in the document which are not necessarily exclusive to the chosen topic. The exception of the documents the topic presented is based upon makes it easier to attribute the topic meaning (*Firmin*, 2020). A screenshot of the visualization is included below in Figure 5.1.

The visualization of tmplot is more advanced compared to mglearn tools used in the LDA analysis. The inclusion of the tweets that gathered the basis for the topic is an addition that could help in understanding the topic created. The list of relevant words(terms) is somewhat similar to the LDA approach, it does however include much noise in its listings such as stating the most relevant term as "t8d". And despite the listing including 30 terms compared to LDA's 10 it does not intuitively give a clearer idea of the actual topic created, it does the opposite, with the inclusion of much noise it is challenging to attribute meaning to the topics, see Figure 5.2.

From the scatter plot of the dataset, Figure A.2, one can see topic 39 is approximately in the center (the coordinating relevant terms can be seen in A.3). It does, however, not represent an understandable topic which is the overall result from this model. Although through its visualization it is possible to get more information the

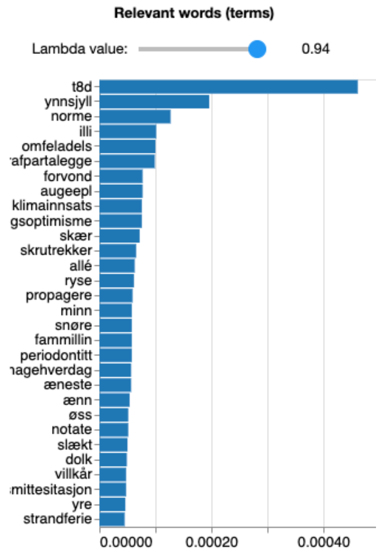

Figure 5.2: Example of list of relevant terms with biterm, topic 11 of 30 topics

Biterm model does not present the topics it finds in an intuitive way, whether it is asked to find 20 topics, 30 topics or a 100 topics. The results were so similar from the sample dataset and larger total dataset that a comparison would not be relevant. Despite some having good results using Biter topic modeling on short text as seen in chapter 2, this is not the case here. Possibly the model does not respond well to the Norwegian language or the amount of noise in the dataset is too severe.

Both Biterm and LDA are not intuitive to read and analyze without prior knowledge intro the dataset. Thus, in this case, the overall conclusion on topic modeling on short Norwegian text does not give significant results and they can be at best a supplement to other methods. What they did make evident is the inclusion of much noise in the dataset. 'st' , 'kj' and 'gj' are examples of words presented in the topics, this indicates that the lemmatization run is not proficient enough in Norwegian, removing too much of the word making it incomprehensible. Furthermore, the results make it clear that the dataset includes more languages than Norwegian, which was not evident in the coded subset as 'bivirkninger' was a requirement for inclusion in the subset. Another conclusion one can draw from these analyses is that the list containing stopwords could be elaborated upon or the dataset in general could have been cleaned more in the removal of for example links. 'https' is one of the words that appear in the topics from the models which is understandable as it is a 'word' that appears several times in the dataset. It does not in this instance give indications on themes in the corpus and thus it should have been removed.

5.2 Machine learning

The main findings from running the trained machine learning model on the unsorted dataset are:

- The final machine learning model, using the SVM algorithm and BoW vectorizer to classify vaccine hesitancy and non vaccine hesitancy, provides indications of the distribution of attitudes across the total dataset.
- The model was not precise enough to classify the data into the three categories of neutral, vaccine hesitancy and anti-vaccine hesitancy. Therefore, a model classifying the two categories vaccine hesitancy and non-vaccine hesitancy was used in the classification of the total dataset.
- The model classified 10.37% of the tweets as vaccine hesitancy compared to the 30.03% classified as vaccine hesitancy in the training data from the sample dataset. The model had a margin of error between 24% and 27%.
- The margin of error the machine learning model has, is likely due to the training-set being too small and the data having too much noise and too little structure.
- Creating a network visualizing predictions from the model would not give an accurate description of the distribution due to the amount of wrongly classified tweets.

From the qualitative analysis performed and explained in chapter 3 the initial result of distribution of attitudes towards the Covid-19 vaccine was:

- 14.61% irrelevant
- 32.37% neutral
- 30.03% vaccine hesitancy
- 22.72% anti-vaccine hesitancy

As the machine learning model is trained on this sample dataset, the assumption is that the result from the model should be similar to the results from the sample. As multiple classification had poor accuracy scores in the implementation, only vaccine hesitancy is predicted by this model, with a prediction of approximately 30% as the expected result.

Running the model, described in implementation in chapter 4, on the entire unsorted dataset of 125018 tweets yielded a result of:

- 12961 tweets classified as vaccine hesitancy
- 112057 tweets classified as non vaccine hesitancy.

This means that 10.37% of the complete dataset is classified as vaccine hesitancy compared with the training dataset which had 30.03% classified as vaccine hesitancy. The result of only 10% is lower than expected as if the training set was a representative exception the number would be closer to 30%. The model did, however, have an accuracy score between 73%-76% and thus subsequently a margin of error between 24% and 27%. With the assumption that the training set was a representative sample, this indicates that the model classifies too few tweets as vaccine hesitancy.

Furthermore, as made clear in the topic model analysis, there is more noise present in the dataset compared to the sample dataset. Due to the restriction of inclusions on the sample set, tweets written in non-Norwegian were not included but have proved to be present. As the model is trained in Norwegian it is difficult for the model to classify tweets such as these. It is possible that the low result of only 10.4% is due to overfitting of the model, though precautions were made to exclude this, as it seems to be selective in classifying tweets as vaccine hesitancy. It is likely that it is the result from the sample set being too small to be able to train the models for each scenario present in the data. The dataset used to train the model was only 0.89% of the total dataset, consisting of 125018 tweets. As the debate changed over time, so did the scenarios the model has to be trained upon. Although the model is not accurate enough and it gives a lower result than expected it is possible to conclude the presence of vaccine hesitancy in the data. This is further substantiated by the result from the manually coded subset which indicates a higher percent of vaccine hesitancy.

Implementing the predicted data as a column in the dataset a bi-partite graph of the 21 most retweeted tweets and the user retweeting them was created. The model classified 2 of the 21 as vaccine hesitancy and the rest as non-vaccine hesitancy. Upon examining these 21 tweets the result was that the 2 classified as vaccine hesitancy were in fact not vaccine hesitancy and 1 classified as not vaccine-hesitancy was indeed vaccine hesitancy. This illustrates the problem with such an imprecise model for created a network to determine sentiment across the networks. Such a network would unfortunately not give a correct impression of how the sentiment towards the vaccine is distributed through the network.

5.3 Social network analysis

5.3.1 Mentioned networks

The network for users mentioning each other was divided into months to illustrate the development of the debate concerning the Covid-19 vaccine on Twitter in Norway. The main findings from these networks are:

- The debate is somewhat stable until November 2020 with few significantly large nodes.
- The first instance of large nodes, that is users mentioned significantly more than others, appear in November 2020.
- The users representing the most influential nodes also change in November 2020, with FHI, politicians and some physicians as prominent users continuously being mentioned in the following months.
- In December 2020 the network stabilizes again with a structure of a few users mentioned a lot and many hardly mentioned. The network has a central cluster with most surrounding nodes being connected to this cluster.
- The prominent users found from November and onwards all have positive or neutral sentiment concerning the vaccine.

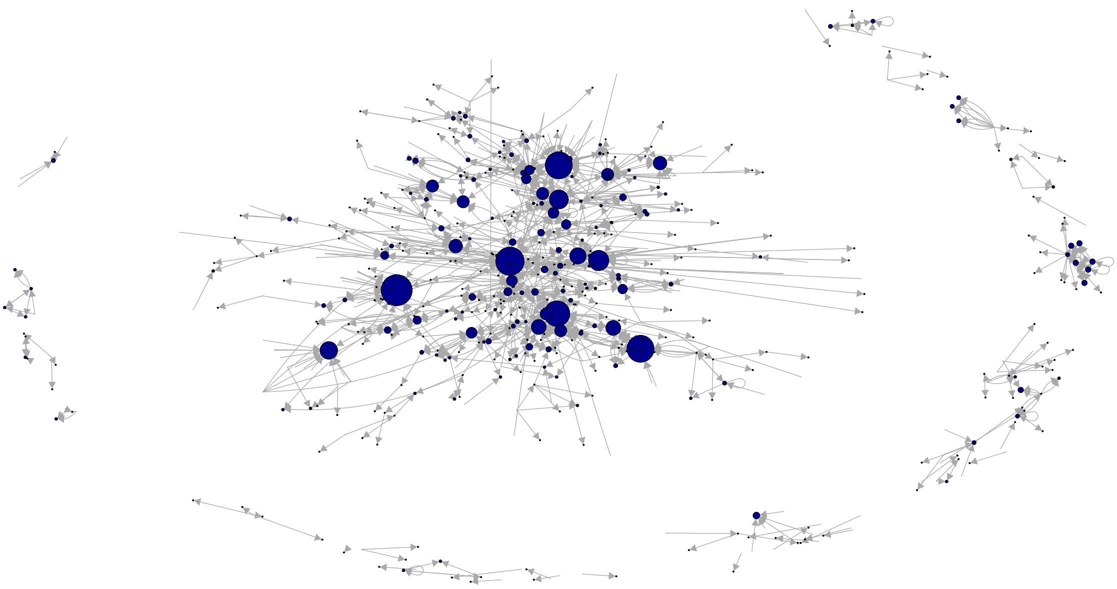

Figure 5.3: Mentioned network August 2020, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

The mentioned networks were created using the total dataset of 125018 tweets. It is not necessarily the best solution to produce a single visualization of the mentioned network, due to the sheer volume of the data. The duration of time it was downloaded gives an opportunity for dividing the data into months and creating a network for each month. These snapshots could highlight the evolution of the debate over time. Because these represent the usernames of the dataset's users, the node's vertex labels are omitted for privacy reasons. There will be comments on some of the users central to the networks, either anonymized or with names as they are public figures. To further reduce the number of nodes, to increase readability, only users with a following of at least 600 were included for each month/snapshot. These individuals are deemed as more influential as they reach a significant number of other users. It resulted in graphs per month of the most influential nodes mentioning each other. The size of the nodes represent their in-degree (the amount of times this user was mentioned). Through the snapshots of the network it is clear that the debate changes drastically in the time from October 2020 to November 2020 before stabilizing with only minute changes thereafter.

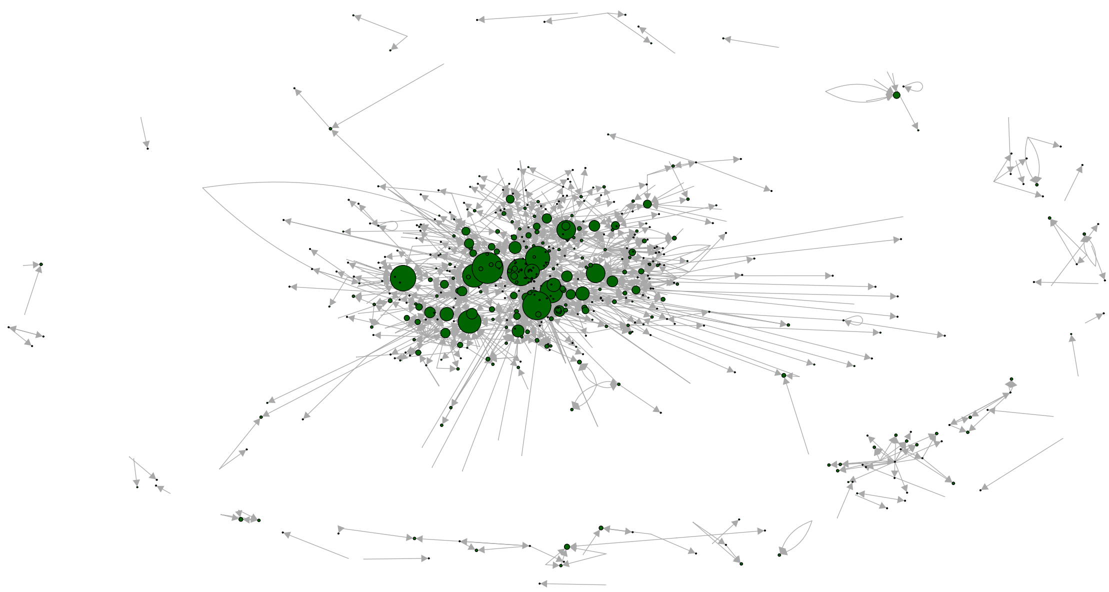

Figure 5.4: Mentioned network October 2020, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

The network for the first month of tweet gathering can be seen in Figure 5.3 which is visualized with the Kamada-Kawai algorithm. After the filtration of users with too few followers, 2162 tweets were included to form the network. It has one big cluster gathering of nodes with connections throughout the largest part of the network and a crescent outside with fewer tweets linking each other. There are some more mentioned users, the bigger nodes, but overall few distinctly more mentioned users. The largest nodes in the August network are some journalists, authors and generally users whose tweets suggest they are positive to the vaccine. The profile's tweets were analyzed looking at the tweets in the network and their Twitter profile page. It is possible that in August they did not discuss the vaccine in depth.

Figure 5.5: Mentioned network November 2020, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

Moving further to the month of October in 2020, Figure 5.4, also visualized with Kamada-Kawai the center of the cluster of nodes is even more compacted. There are even links between nodes in the outskirts of the cluster to the outliers surrounding them. The network seems to be more connected compared to August. However, this might be a result of the few nodes included as only 655 observations were included after the filter process. But looking at the size of the nodes based on the in-degree score, there are few very popular users. The most popular users are huddled closer together than in the August network. The users with most mentions in this period are different users than in the August network. There are more instances of medical personnel, such as physicians who will continue to play a central part in the following networks, as well as users who express positive sentiment towards the vaccine.

It is in this next month, November 2020 (Figure 5.5) when the significant change becomes apparent. After filtering, it contains 1315 tweets, and when visualized with Kamada-Kawai, every node, except one outlier mentioning only two users, are clustered together. Some of the nodes are significantly larger, illustrating that some users have become quite popular to mention in the debate. This could be the result of Pfizer and Inbiogen's announcement on November 9, 2020, that trials of a potential vaccine against Covid-19 had yielded positive results. All of the largest nodes display positive attitudes towards the vaccine, and the physicians who were present in the October network are now significantly larger. The largest ten nodes mainly consist of medical personnel/ researchers and journalists /hired at news networks.

In December 2020, Figure 5.6 the network again changes and at this point it appears like a pattern is established for the mentioned networks. The network includes 2162

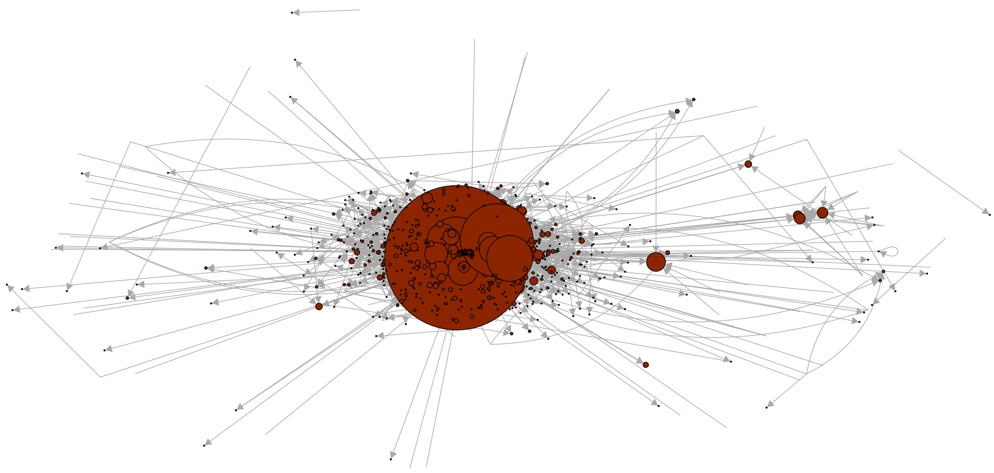

Figure 5.6: Mentioned network December 2020, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

tweets and with the Kamada-Kawai algorithm the network visualized has a large cluster containing most of the nodes in its center, and all of the most mentioned nodes based on in-degree size. Unlike previous months, nearly every node is now joined to this cluster. The pattern of a cluster with outliers of less influential users also connected to the cluster is the general pattern for the mentioned networks through the following months. The networks all have the same stabilized core but there are some differences in the periphery surrounding the core. The networks, all visualized with Kamada-Kawai, are included in appendix B B.

In December the first case of a giant node, mentioned numerous times, is present. This node represents 'folkehelseinstituttet'(FHI), Norway's National Institute of Public Health. This is not surprising as they are a source for reliable information and may have been used as such in the debate and questions on Twitter. The second most mentioned user is a physician working for FHI followed by other users all expressing positive sentiment towards the vaccine, with the exception of Verdens Gang(VG)[1] which is a news outlet an thus neutral, and some politicians. One interesting change is that the physicians central to both October and November are not included in the most mentioned nodes.

After filtering, the month with the most included tweets is March 2021 with 6475 observations. Which is as expected as the most tweets were gathered in this period is March 2021. Examining the graph generated by the Kamada-Kawai algorithm more

[1] https://www.vg.no/

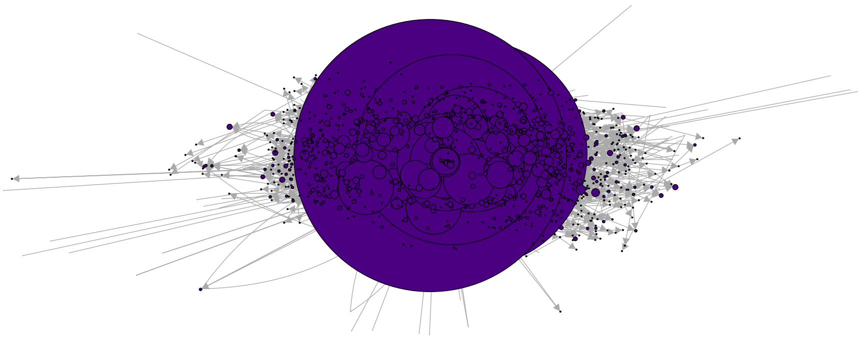

Figure 5.7: Mentioned network March 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

closely reveals the same trend as December 2020. In this graph, there are some users mentioned significantly many times to the point that their size covers most of the cluster. The center is more densely clustered than previous months, with fewer outliers who are all connected to the center cluster. The largest node in this network represents again FHI who is the most mentioned user and again the second most mentioned user is the physician working for FHI. Then follows one of the physician central in October and November, the other physician is also included but has been mentioned less. In this network both Bent Hoie and Erna Solberg are in the top ten largest nodes and VG is still included as the only user with neutral sentiment. As this is based on how many times an account is mentioned it is not surprising that the public departments and politicians excels in these networks. The fact that the networks stay so similar may indicate that the debate stays similar with many little mentioned users mentioning the same few users.

The fact that the most mentioned users all have the sentiment of being positive towards the vaccine indicates that most of the sentiment in the mentioned networks do not concern conspiracy theories or vaccine skepticism to a high degree. The physicians mentioned a lot are indeed very vocal about debunking these kinds of theories and changing that type of sentiment. It is possible they are also being mentioned by users expressing vaccine hesitancy, which is their goal to convince as many people as possible of the vaccine safety and encourage vaccination.

5.3.2 Retweet networks

The retweet network consists of the tweets that have been retweeted and quoted from the total dataset. To further analyze the data, the ten users with highest in-degree, out-degree and betweenness were analyzed and some visualized in ego-networks. The main findings from the retweet networks are the following:

- The retweet network display several different clusters and does not have central core like the one seen in the mention network.
- The ten most retweeted users' (the users with highest in-degree) sentiment are divided in half, with five users being positive towards the vaccine and five users negative towards the vaccine, Table 5.3.
- The ten users retweeting the most (users with highest out-degree) are also similarly divided with five users with positive sentiment towards the vaccine and five users with negative sentiment towards the vaccine, Table 5.4.
- The ten users with the highest betweenness score only had one user not displaying positive sentiment towards the vaccine, Table 5.5. This indicates that it is more difficult for information posted from users negative towards the vaccine to travel through the entire network.
- A few of the users with highest betweenness and in-degree score are also prominent users in the mentioned networks.
- Two users were present in all of the three tables, one being negative towards the vaccine and the other being positive, but mainly discussing Covid-19 restrictions and not the vaccine. The focus of this user was on the debate concerning Non-Norwegian citizens not allowed into Norway due to the closed border.

The retweet network consists of retweets and quotes from users who followed at least 300 users and had at least 600 followers and this data is also gathered from the entire dataset of 125018 tweets. This was done to limit the noise and separate out users with certain influences. It was also visualized with the Kamada-Kawai algorithm and looks quite different from the mentioned networks. The nodes' sizes are also in this case not determined by in-degree as there are some very popular users. With the addition of these sizes, a single node filled the entire network. There are separations and clusters of topics to a higher degree compared with the mentioned network. To further analyze who the central users of this network are, a third classification looking

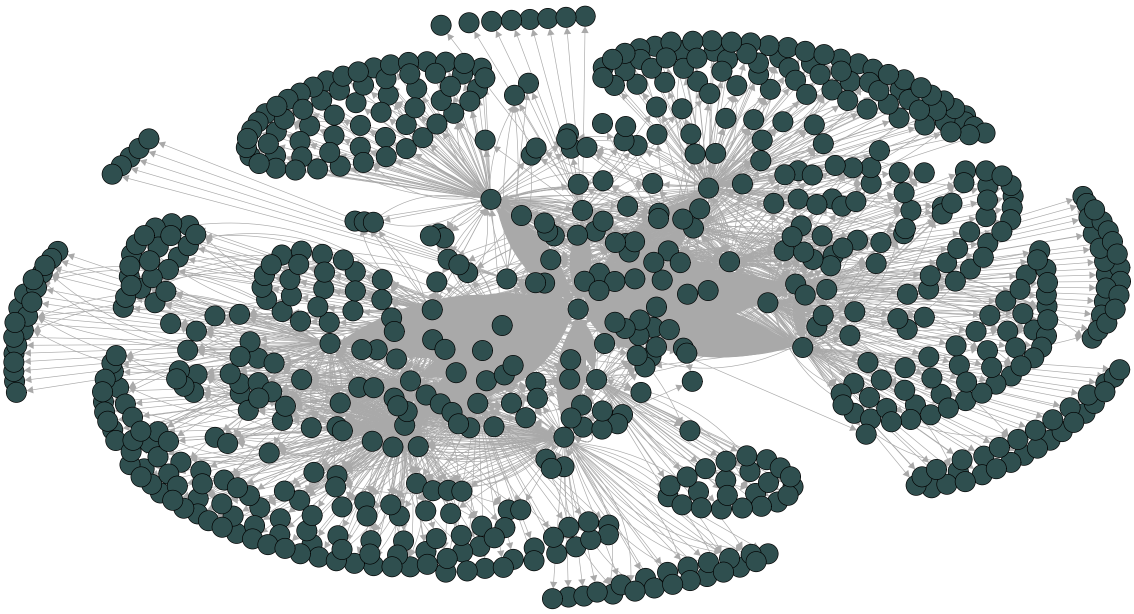

Figure 5.8: Retweet-network including all users with more than 600 followers and visualized with the Kamada-Kawai algorithm.

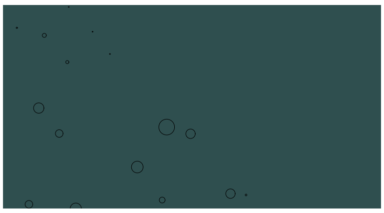

Figure 5.9: Retweet-network with in-degree as size perimeter.

node 1	node 2	node 3	node 4	node 5
2090 positive	577 negative	535 positive	534 positive	490 positive
node 6	node 7	node 8	node 9	node 10
477 negative	463 negative	455 positive	435 positive	406 negative

Table 5.3: Top ten highest in-degree score, users most retweeted.

node 1	node 2	node 3	node 4	node 5
322 positive	322 negative	301 negative	286 negative	248 positive
node 6	node 7	node 8	node 9	node 10
214 positive	207 positive	205 negative	187 positive	184 negative

Table 5.4: Top ten highest out-degree score, users who retweeted the most.

node 1	node 2	node 3	node 4	node 5
4257418 positive	3469835 positive	2851275 positive	2070927 negative	2067159 positive
node 6	node 7	node 8	node 9	node 10
1798989 positive	1788239 positive	1711808 positive	1688286 positive	1661713 positive

Table 5.5: User with top ten highest betweenness score

at the users with the highest betweenness score, in-degree score and out-degree score was performed to determine sentiment.

Examining the betweenness score, in-degree, and out-degree of the retweet network, made from the total dataset of 125018 tweets, could identify influential nodes. Top ten scores for each of these are listed in the tables: in-degree (5.3), out-degree (5.4) and betweenness (5.5). These top ten users for each of these categories were inspected to manually attribute their sentiment towards the vaccine. This was done by analyzing the texts of their tweets included in the dataset. Two users were present in each of the tables, one expressing strongly negativity towards the vaccines with conspiracy theories regarding the vaccine. The other user is positive towards the vaccine, but is mainly discussing how the borders were closed for family relations that did not have Norwegian citizenship. Three users were present both in the in-degree and betweenness tables, with the negative user mentioned, and the same two physicians central in the previous networks.

The highest out-degree node was tied with the second highest node, both with a degree of 322. The out-degree represents the user who has retweeted most different users in the dataset. The node with the highest in-degree score had a score of 2090, with the second highest node declining to a score of 577. The in-degree score represents the user who has been retweeted the most. The fact that the second most retweeted has such a lower score illustrates the importance of this user in the network. Lastly, the node with the highest Betweenness score had a score of 4257418 while the second-highest node had a score of 3469835. This node is influential because of its position in the network, having a great reach.

Ego-networks

The ego-network created with the highest in-degree(most retweeted user) is visualized with the 'fr' layout as in this case it was the most understandable representation (Figure 5.10). The number of in-degree nodes is so large that it appeared as a sphere in other visualizations. The various colored nodes represent all of the individuals who have

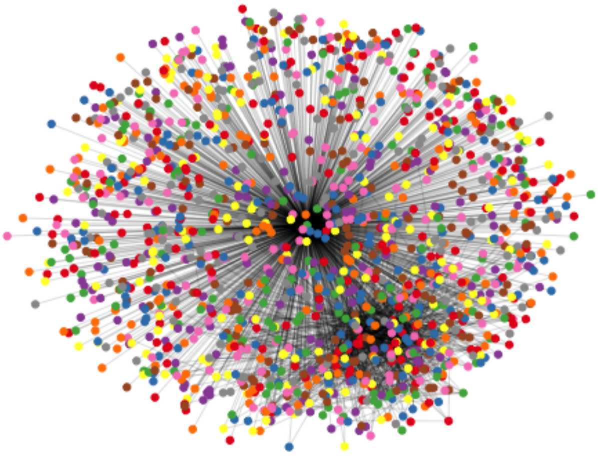

Figure 5.10: Ego-subgraph for Kaveh Rashidi the user with highest in-degree score, the most retweeted tweets.

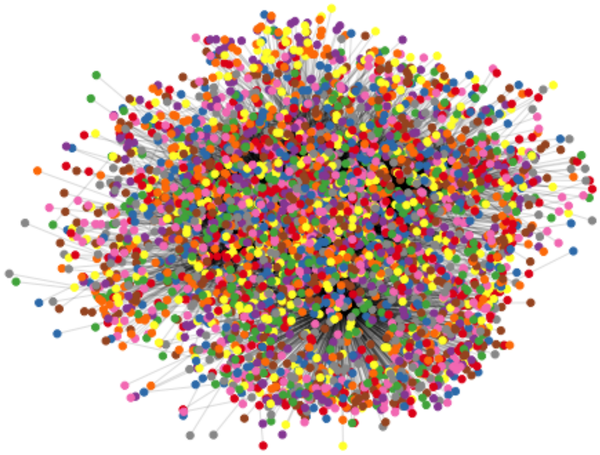

Figure 5.11: Ego-subgraph for Kaveh Rashidi the user with highest in-degree score, the most retweeted tweets, and his nodes neighbours.

retweeted one specific user, Kaveh Rashidi, a physician who has been at the center of the vaccine discussion on Twitter in Norway. He was one of the physician presented as central to the mentioned debate in most of the mentioned networks described in the earlier section. This graph depicts Rashidi's influence and impact by depicting just nodes that are directly connected to him. When expanding the network to include the neighbors of the users retweeted, the network appears as shown in Figure 5.11. The number of users makes it difficult to establish patterns, but based on these networks, it is possible to assume that he is an influential user based on this ego-network and the role in the aforementioned mentioned networks.

Analyzing the other nine users with highest in-degree, users retweeted, reveals that the second highest and user 6, user 7 and 10 are all negative towards the vaccine and tendencies to spread conspiracy theories. User number 10 are also the most eager re-tweeter and the user-network visualized in the out-degree network. There are also two users focused on the distribution of the vaccine and how it is to strict the way the border was closed for a time. The rest are users expressing positive sentiment towards the vaccine as well as debunking conspiracy theories.

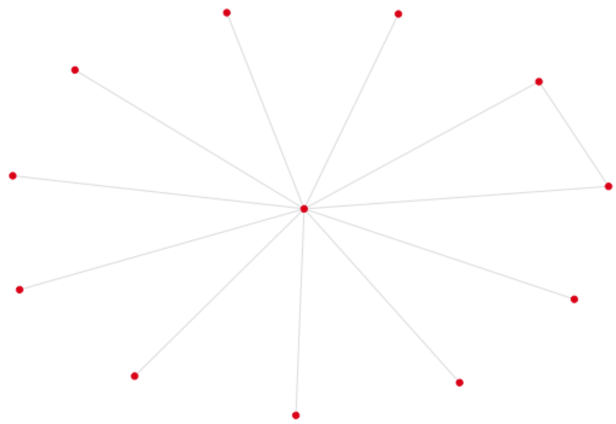

Figure 5.12: Ego-subgraph for a user with in-degree score of 10, retweeted ten times.

Looking closer into the data for in-degree per user, out of the unique users participating in retweets only 32.14% of the users have been retweeted one time or more. Approximately 50% of these have only been retweeted once, and only the users from 1 to 613 have numbers higher than 9. Creating an ego-network with an in-degree of 10, to compare with Rashidi's score of 2090, can be seen Figure 5.12. This is a smaller user who still has some impact as the average user in this dataset is not retweeted and would have zero nodes in the network. This network is significantly smaller, substituting how much influence Rashidi has compared to a relatively average user who gets retweeted to a certain degree.

The ego-network with the highest out-degree represents the user in the dataset that has retweeted tweets from most different users and is visualized with the 'stress' layout. The first network includes only first order neighbors, which is 72, if this is increased as above to the second order of neighbors the total is 1442 and the network changes drastically. The user has a potential reach with the inclusion of the neighbor's neighbor. The user does not appear as a significant user in the mentioned network like the user with the highest in-degree. This user has a positive sentiment and in the second

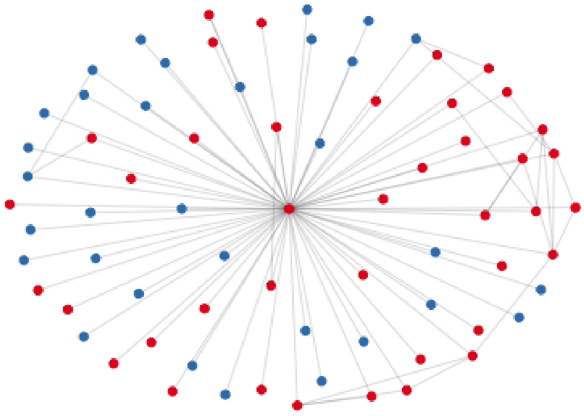

Figure 5.13: Ego-subgraph for user with highest out-degree, the user who retweeted the most.

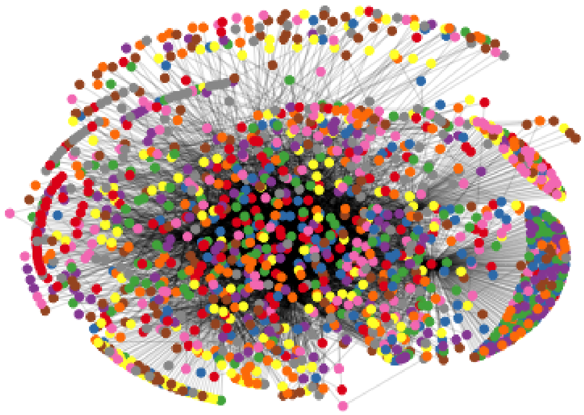

Figure 5.14: Ego-subgraph for user with highest out-degree, the user who retweeted the most, and the users nodes and nodes neighbours.

visualization the structure is somewhat similar to the total retweet network.

User 2 had the same score as user 1 in the out-degree scoring. However, this user has a different sentiment towards the vaccine. Visualizing it ego-network with the stress layout and only direct links results in this network, Figure 5.15. Although they have the same out-degree score this user has directly more other users connected to it. The network is also different in its clustering, looking more similar to the node with the highest betweenness. Though this user is not in the top ten of the betweenness score. Sentiment wise the top ten highest out-degree scores are 50% negative to the vaccine and 50% positive. But only one positive user was in the top five, indicating that to some degree some users negative towards the vaccine are more prone to retweet.

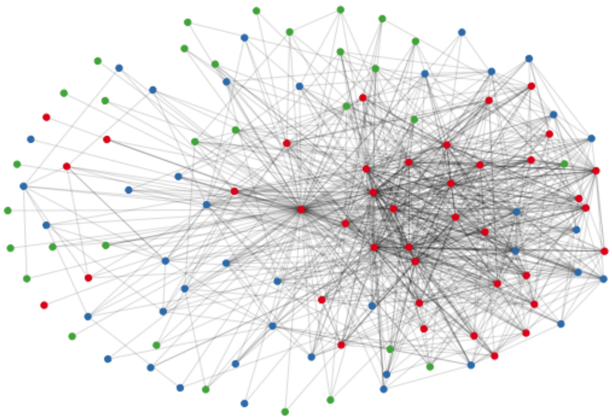

Figure 5.15: Ego-subgraph for user 2 in out-degree, the user who retweeted as much as user 1.

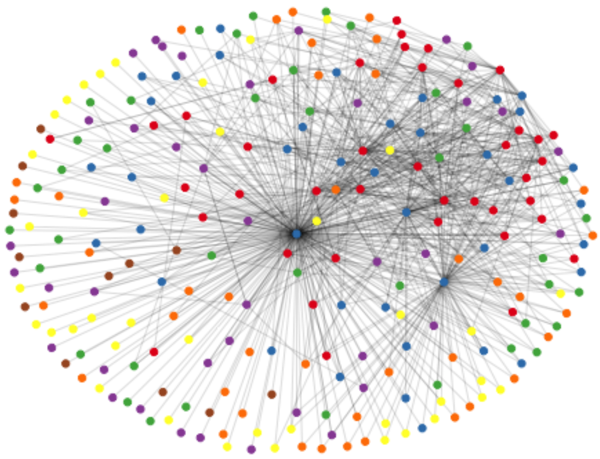

Figure 5.16: Ego-subgraph for user with highest betweeness score

Compared to the ego network with most retweets, the network with highest betweenness is slightly more orderly based on the smaller number of nodes. This visualization also only includes the nodes directly related to the ego-node (5.16). It was visualized using the 'stress' layout and it is easier to spot the links between the nodes connected to the ego and the nodes connected to the ego. This user has been one of the most mentioned users in November 2020 and August 2020 in the earlier described mentioned networks. The sentiment towards the Covid-19 vaccine presented by this user is clearly positive. This was the case for all the users in the top ten betweenness scores with the exception of user 4. This could indicate that the users with negative sentiment towards the vaccine seen in both in-degree(users retweeted) and out-degree(users retweeting) are in a separate section of the network. That even though they are retweeted and retweeted much, their connection to the overall network is lower than users with positive sentiment towards the vaccine. The information posted by vaccine hesitancy users have to travel to more users to reach the complete network, indicating that it does so to the same degree as the positive sentiment information.

5.3.3 Sentiment network

The following retweet network was created based on the manually coded sample dataset. The classifications of sentiment are thus reliable and the main findings from these networks are:

- There is a clear separation between the two categories, indicating echo chambers.
- Users who display vaccine hesitancy retweet slightly more than users displaying anti-vaccine hesitancy.
- Although users try to persuade users negative towards the vaccine, this content does not reach those users negative towards the vaccine. This display the presence of echo-chambers.

These graphs were created with the manually classified sample set of 1109 tweets. This was then limited to the category anti-vaccine hesitancy and vaccine hesitancy. In cooperation with supervisor Dag Elgesem a retweet/quoted network was created for these two categories. In these graphs the user-accounts were collected from the manually sorted dataset. In those few users who were categorized in more than one category, the user was reviewed and then assigned a final category based on more information gathered, such as looking at their profile and other tweets from the user in the dataset. After the users were selected edges were drawn between each if they had retweeted each other. Based upon sentiment the nodes received colors, with anti-vaccine hesitancy being green and vaccine hesitancy red. The in-degree was calculated and added to the graph representing the size of the node in Figure 5.17. In this network a large node represents a user who has been retweeted many times. The same network is visualized in Figure 5.18 but with out-degree as size representations for the nodes. In this network a large node represents a user who has retweeted many different users.

These visualized sentiment networks show a clear separation between the two coded categories of vaccine hesitancy(red) and anti-vaccine hesitancy(green). There are instances of red nodes in the mainly green clusters but few green nodes in the red cluster, with the exception of some small sized node outliers. This indicates the presence of

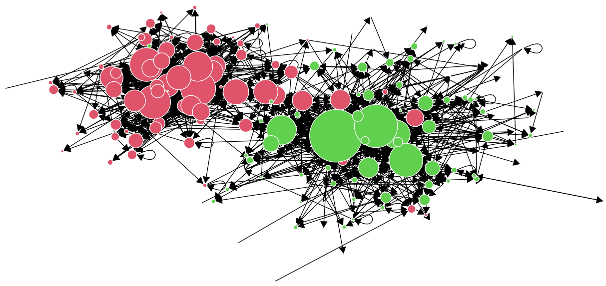

Figure 5.17: Retweet sentiment network, with in-degree as size, red nodes representing vaccine hesitancy and green anti-vaccine hesitancy

Figure 5.18: Retweet sentiment network, with out-degree as size, red nodes representing vaccine hesitancy and green anti-vaccine hesitancy

echo-chamber behavior. The anti-vaccine sentiment users do not reach most of the vaccine hesitancy users and vice versa. The size of the nodes indicates that both of these sentiment groups are vocal and an active part of the debate surrounding the vaccine.

Comparing both of the sentiment nets visualized with Kamada-Kawai it is evident that the structure is identical except for the difference in the size of the nodes due to them having different parameters for size. The red coloured nodes representing vaccine hesitancy are larger in Figure 5.18 with out-degree as size perimeter while the green nodes representing anti-vaccine hesitancy are smaller compared to their node size in

Figure 5.17. This substantiates the findings from the ego-sub-networks, that vaccine hesitancy users retweet to a higher degree than anti-vaccine hesitancy users. While anti-vaccine hesitancy users are more retweeted than vaccine hesitancy users.

To conclude the main difference between users presenting vaccine hesitancy sentiment and anti-vaccine hesitancy sentiment are:

- Users displaying positive sentiment towards the vaccine are the most mentioned users.
- Users positive to the vaccine had higher betweenness scores than users displaying negativity towards the vaccine.
- 70% of the users in the sample dataset displayed non-vaccine hesitancy sentiment and 30% vaccine hesitancy sentiment.
- Users with vaccine hesitancy sentiment retweeted to a slightly larger degree than users with non-vaccine hesitancy sentiment.

5.4 Answering the hypothesis

> H1: Methods for text analysis and social network analysis will help identify and describe the different attitudes towards the Covid-19 vaccine on Twitter.

The qualitative text analysis performed on the sample dataset did give insight into some overall themes and structure. With some prominent themes being the distribution of the vaccine, illegal drugs, joy over a successful vaccine, skepticism towards how fast it was developed. The final result of 14.61% irrelevant, 32.37% neutral, 30.03% vaccine hesitancy and 22.72% anti-vaccine hesitancy does help identify and describe the attitudes in the network. The results from the quantitative text analysis will be elaborated upon below.

The social networks, specifically the sentiment networks, show how the vaccine hesitancy profiles retweeted more compared to the anti-vaccine hesitancy group that were slightly more retweeted and retweet less. The ego-networks show how both anti-vaccine hesitancy users as well as users containing conspiracy theories about the vaccine are retweeted often and are popular users. It is clear looking into the user's text that they do not retweet each other, which is substantiated by the sentiment network. There are presence of echo chambers as users mostly communicate with other users who mimic their own beliefs.

Analyzing the tweets from the 30 users with highest in-degree, out-degree and betweenness illustrated that although the mentioned network did not include large nodes with vaccine hesitancy, they are still central to the retweet network. 5 of the 10 users with highest in-degree were classified as skeptic towards the vaccine, which also was the case for users with highest out-degree 5 of the 10 users were sceptic towards the vaccine. The users debunking the conspiracy theories concerning the vaccine are not communicating with their targets of vaccine skeptics. Only one user skeptic towards the vaccine was in the top 10 table for betweenness scores. This again substantiates the echo chamber conclusion as they are not as connected to the entire network compared with positive sentiment users. Their information does not travel as easily through the network compared to the user with a high betweenness score.

> H2: Methods for topic modeling will provide information about topics present in the dataset.

As observed in the results section, the Topic modeling methods yielded little if any information on the dataset's topics. Even with the inclusion of the short-text-optimized biterm topic model, the results did not meet expectations. With the knowledge gained from manually classifying a portion of the dataset, it was possible to evaluate a portion of the topic in order to extract semantic meaning. Unfortunately, it is insufficient to be able to draw conclusions about several underlying themes in the dataset, with the exception that the majority are related to the overall topic of the Covid-19 pandemic. A possible exception is the topic of vaccine distribution, where the topic model discovered multiple tweets citing the area and population of Stovner, a neighborhood in Oslo, and Molde, a city in northwestern Norway. This relates directly to the issue of vaccine distribution, however as a theme, the attention was on the numbers, and the connection to vaccine distribution was unclear. And on this basis the conclusion is that this hypothesis is disproved.

Topic modeling did, however, give insight into the amount of noise and diversity of the dataset. It illustrated that the set included more languages than Norwegian and from its result it is a fair conclusion to say that the sample manually classified was not a representative sample of the total dataset.

> H3: A supervised machine learning algorithm trained on the coded data set can correctly classify the tweets according to their attitudes to the Covid-19 vaccine.

The quantitative analysis of the supervised machine learning approach was conducted to get insight into the overall sentiment of the dataset. Due to the fact that the multi-classification model produced a poor result with such a high margin of error, it would not be pertinent to base any conclusions from it. The final model implemented on the dataset did provide an idea of how attitudes were in general, but it was limited to vaccine hesitation and not vaccine hesitancy. With a vaccine hesitation rate of roughly 10% , it appears that the majority of tweets about vaccines in Norway do not show hesitancy. Providing us with a distribution of around 90% non-vaccine hesitancy tweets in the dataset. Unfortunately, it is impossible to determine how much of this is anti-vaccine hesitation. One could claim that machine learning provided knowledge on the distribution of attitudes, but not to the extent that was predicted. Compared to the qualitative categorization of the sample dataset, the quantitative classification yields fewer and less reliable findings. It is still possible that if a larger sample set of the dataset was manually coded a model could be trained to correctly classify attitudes concerning the Covid-19 vaccine. However, in order to be able to correctly classify into several attitudes as done in the sample set, the training data must be significantly increased.

> RQ: How are attitudes towards the Covid-19 vaccine distributed on Norwegian Twitter?

In the question of how much of the different attitudes are present on Twitter in Norway, the most precise result is from the manually coded/classified sample of the dataset. The final result from this analysis was; 14.61% irrelevant, 32.37% neutral, 30.03% vaccine hesitancy and 22.72% anti-vaccine hesitancy. However, as made evident by the topic modeling methods this is not a representative sample. Through these analyses it has been made clear that there are several challenges concerning the dataset. The sample dataset consists of 1109 tweets from the total of 125018 tweets, making it 0.89% of the total dataset. It was gathered from August 2020 to December 2021 and throughout this period the debate changed and thus also probably the structure of the data did as well. As the knowledge and access to the vaccine evolved, so did the themes discussed. Many themes were discovered when manually analyzing the dataset but they were not presented clearly by the topic model. Tweets were written in several different Norwegian dialects and with grammatical errors. This makes it more difficult for the computer models to give results that are easy to interpret. It is probable that the number of 10% of total vaccine hesitancy on the dataset as a whole is not precise enough. The model has a margin of error between 24% and 27%, and taking into account the result from the manually classified data. This model classifies less vaccine hesitancy than what probably is present. As the machine learning model unfortunately was not able to predict how many tweets contained anti-vaccine hesitancy, the only basis for this is from the sample set of approximately 23%.

The machine learning model could be improved by manually coding a bigger sample of the data giving the training more data to base its classification on. In addition a more comprehensive list of stop-words should be applied to the dataset to help eliminate more of the noise, which would also improve topic modeling. But based on the manually sorted dataset there is precedence for both vaccine hesitancy and anti-vaccine hesitancy in Norwegian Twitter.

Looking at how the attitudes are distributed in the networks, vaccine hesitancy and conspiracies are not the most outstanding features in the mentioned networks. The users representing vaccine hesitancy are not mentioned nearly as much as public departments, politicians and prominent physicians. The overall sentiment of the users most mentioned is positive towards the vaccine and negative towards those who are reluctant to it, anti-vaccine hesitancy. The users who express vaccine hesitancy and share conspiracy theories concerning it are involved in the retweet networks as seen by mapping the nodes with the largest in-degree, out-degree and betweenness for this network. The second most retweeted user, upon reviewing his tweets, is clearly against the vaccination and does not believe in them. There are also present users further down on the top ten list that post outright conspiracy theories. This user was present in the top 10 scores of betweenness and out-degree as well. This was only the case with one other user who mainly focused on the restrictions from the pandemic, with special focus on the closed border. Combining this with the sentiment network illustrating how little communication crossed the two clusters of green and red it is clear that the attitudes towards the vaccine are separated into two echo chambers. And although there is a lot of information debunking conspiracy theories and users positive towards the vaccine, this information is not allowed into the echo chamber the vaccine hesitancy category represents.

5.5 Limitations

The main limitations are:

- The lack of structure in the dataset is the main challenge when performing the methods for data analysis.
- The machine learning model does not provide a 100% accurate illustration of the distribution of sentiment.
- Therefore it is not possible to create a network illustrating the distribution of sentiment to inspect the network-structure connected to sentiment.

The main reason for these limitations is the lack of structure in the data. The short texts do not provide enough data for the model to be trained to the needed precision. Classifying data such as these requires knowledge about context in many cases. There were cases challenging to classify by this author due to their lack of content. In addition the lack of structure is further extended by the data being mainly in Norwegian, including several different dialects. Although the goal was to create a dataset with only Norwegian content, other languages are present. Some methods, such as lemmatization, did not perform well on the Norwegian dataset, removing too much of the word which resulted in it not being clear what it represented. It is important to state that the model could be improved upon with a larger training-data and that a larger part of the dataset should have been manually classified.

5.5.1 Consequences

The machine learning model does not achieve precise enough results to conclude on the exact amount of vaccine hesitancy on Twitter. This is illustrated by the margin of error from the machine learning model. The produced result from the trained model classified only 10% of tweets on the total dataset classified as vaccine hesitancy while the result from the manually classified sample was 30%. The result could be used as an indicator of there being between 10% and 30% vaccine hesitancy, but it is possible that the correct number is higher. It is therefore not possible to create a social network including sentiment for the total dataset that would give a complete illustration of structures connected to sentiment. The closest is the sentiment network created using only the tweets manually classified.

Chapter 6

Conclusions and Future Work

This chapter includes a summary for the final conclusion based on the results found in chapter 5. It also includes a section explaining what should be implemented in the future.

6.1 Conclusion

> How are attitudes towards the Covid-19 vaccine distributed on Norwegian Twitter?

To conclude on how attitudes towards the Covid-19 vaccine are distributed on Norwegian Twitter, the qualitative analysis of the sample dataset gave a distribution of 14.61% irrelevant tweets, 32.37% neutral tweets, 30.03% tweets containing vaccine hesitancy sentiment and 22.72% tweets with anti-vaccine hesitancy sentiment. However, the sample dataset is less than one percent of the total dataset and therefore it is not possible to base the conclusion entirely on this analysis. Comparing this sample to the quantitative model, it classifies only 10% of tweets having vaccine hesitancy sentiment. The model does, however, have a margin of error between 24% and 27%. Based on the manual classification one can assume that the correct amount of tweets containing vaccine hesitancy probably lies between 10% and 30%. And from this one can conclude that 70% to 90% of the dataset contains non-vaccine hesitancy sentiment. However, due to the margin of error, and the small sample set it is also possible that the dataset contains more than 30% vaccine hesitancy and therefore less than 70% non-vaccine hesitancy.

The manual analysis of the sample dataset gave insight into topics present in the dataset. However, the used methods for topic modeling did not achieve the expected result of topics present in the dataset, giving more insight into the amount of noise present in the dataset rather than topics.

The social networks created showed that the debate evolved through the late part of 2020 before stabilizing, with users displaying positive sentiment towards the vaccine as the most mentioned users. The users with the highest score in betweenness, in-degree and out-degree from the retweet network showed the presence of both positive sentiment and negative sentiment towards the vaccine from users with influence. This, combined with the echo chamber behavior found in the sentiment networks, makes it possible to conclude that even though there are many prominent users debunking conspiracy theories they do not reach the users negative to the vaccine. To conclude on the findings, methods for text analysis and social network analysis did help to identify and describe different attitudes towards the Covid-19 vaccine on Twitter but not accurately enough to make it possible to definitively conclude on the distribution.

6.2 Future work

To get insight into why tweets are incorrectly classified by the machine learning model, the tweets incorrectly classified when evaluating the model should be analyzed with respect to the existence of a common trend or pattern in the tweets being misclassified. Are the tweets incorrectly classified dominantly vaccine hesitancy or not vaccine hesitancy? It is also possible the model classifies each category wrong to a similar degree. However, should a pattern exist it might give insight into why the amount of hesitancy towards the vaccine was only 10% and not closer to the 30% as the training dataset had. If the model consequently is too inflexible on what could be vaccine hesitancy, this could give insight on how the model operates and thus possibly explain the lower than expected score.

In addition a larger sample of the dataset should be manually sorted to give the model more training data. With a larger training-set more scenarios will be accounted for and more data provided which will improve the machine learning model. Manually classifying a larger sample of the dataset would also give more insight into the noise present in the dataset. Based upon this knowledge, and the results from the topic modeling methods a customized stop-word library should be created. This list should handle the case sensitive stop-words connected to this dataset- such as 'http'. This would improve both the machine learning model as well as possibly provide more accurate results with LDA and Biterm topic modeling.

Performing the same analysis of the 30 users with the highest in-degree, out-degree and betweenness score could also be done on the mentioned network. This could give more information regarding influential users and if there is a larger presence of vaccine hesitancy present in these networks than are visible with the analysis of each month.

The separation into months could also be implemented on the retweet network to see if this debate has a similar development as the mentioned network had. Based on the results from the improved machine learning model the nodes in each of these networks should ideally be colored based on sentiment. As the model classifies tweets and users who produce many tweets likely have tweets in both categories, this has to be implemented differently, with both users and tweets as nodes in the network.

Appendix A

Topic model appendix

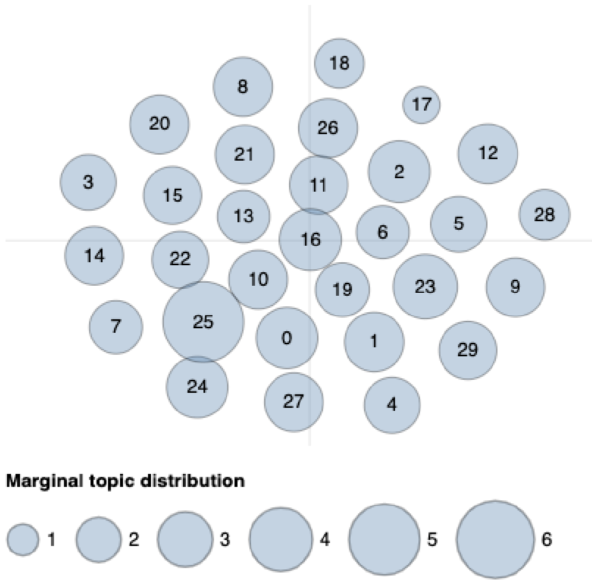

Figure A.1: Scatter plot of Biterm with 30 topics on the entire dataset.

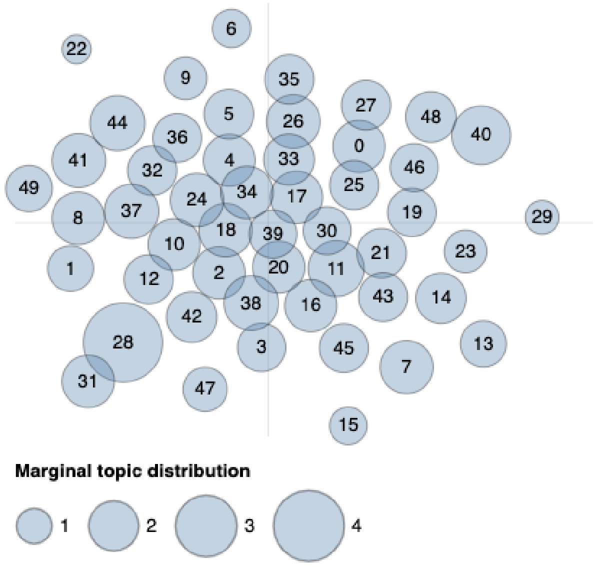

Figure A.2: Scatter plot of Biterm with 50 topics on the entire dataset.

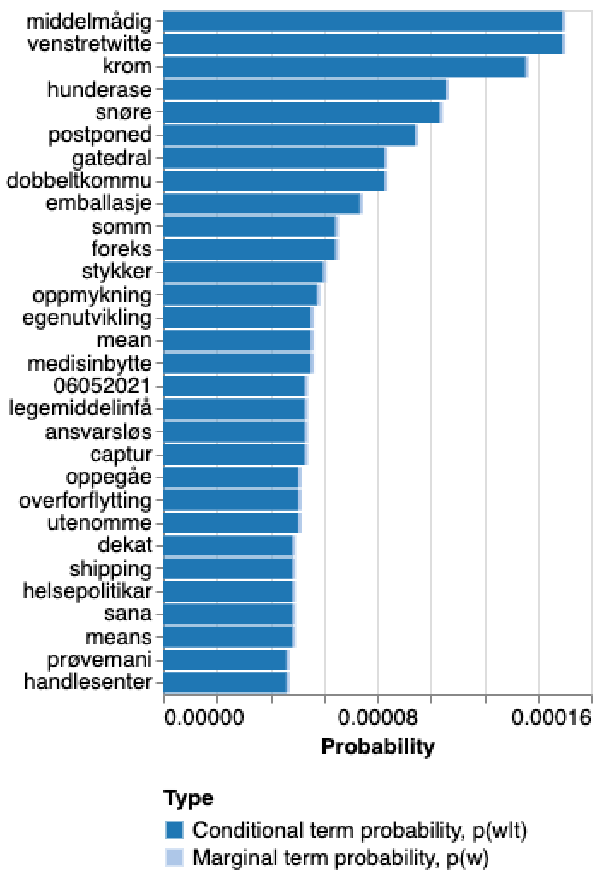

Figure A.3: Relevant terms topic 39 of 50, biterm model

topic 6	topic 16	topic 23	topic 28	topic 33
melding	ansvarlig	spr	vaksinere	0001f921
lang	gi	hel	virus	vaksinere
vaksinering	sist	statistikk	barn	utslett
uke	henvise	yte	mye	halvpart
smittsom	kommune	rste	lege	innlegge
mene	bostedskommune	uvaksinert	igjen	21
mistenkt	uke	ogs	19	vanlig
https	vaksinegruppe	komme	ung	ufarlig
menneske	arbeidskommune	intensiv	alder	hitxdivtmr
vestlige	prioritere	havne	lang	hevde
topic 35	**topic 42**	**topic 49**	**topic 54**	**topic 57**
sjanse	god	gi	frisk	az
folk	land	ogs	besitte	hel
annen	rik	the	kalle	liten
blodpropp	slutt	covid	spr	villig
bruk	behandling	se	yte	risiko
vite	alder0	le	hos	2066
overleve	mnd	kanskje	mye	2069
vaksinere	covid19	in	kj	sykdom
all	innmeldt	tilgang	forvente	annen
tilsvare	hvorav	barn	unng	melde
topic 61	**topic 70**	**topic 84**	**topic 90**	**topic 99**
se	snakke	ansatt	regjering	mrna
unntak	norsk	farlig	vaksinasjon	100
nekte	industri	legemiddelverk	https	antig
antivax	sammen	familie	hel	lage
imot	la	barnehage	lge	ren
pg	klp	skole	land	karantene
heller	eksportinntekt	annen	riktig	covid
gjøre	92	ny	vaksinere	dsfall
hel	vaksineproduksjon	folk	tro	effektiv
ute	sted	skje	folk	liten

Table A.1: Excerpt of 100 topic, from LDA, on the sample-dataset

topic 2	topic 4	topic 7	topic 11	topic 16
mye	norge	dose	land	vaksinere
covid	god	mye	nok	mye
barn	land	folk	st	gi
myndighet	19	se	to	veldig
dsfall	covid	all	dag	all
risiko	annen	alts	liv	dag
lite	holde	pfizer	norge	eksperimentell
del	gi	ingenting	komme	sjelden
kapasitet	debatten	psteigan	standpunkt	lang
anbefale	ogs	ny	medisin	la
topic 17	topic 23	topic 26	topic 28	topic 33
land	land	land	rik	vaksinere
vaksinere	utsette	vaksinere	lang	0001f921
barn	sette	kommune	lege	ogs
komme	ogs	hel	annen	all
regjering	prosent	folk	melde	mye
https	ke	norge	folk	st
covid	basere	god	vaksinere	komme
dokke	nullvisjon	mye	all	smitte
stor	pause	gj	begynne	https
gj	https	kj	fattig	risiko
topic 35	topic 38	topic 42	topic 45	topic 49
blodpropp	annen	god	dose	se
vaksinere	komme	vaksinere	jo	mann
karantene	vaksinere	vite	hel	norsk
sjanse	2753	nyhet	folk	covid
bruk	gj	period	skrive	19
all	nok	17	nesten	vite
19	all	hvorav	sv	not
nok	land	behandle	frisk	us
vs	norge	covid	vite	what
hel	dose	melding	sj	hel

Table A.2: Excerpt of 50 topic, from LDA, on the sample-dataset

topic 2	topic 4	topic 7	topic 11	topic 16
mye	mye	ny	folk	hel
17	gi	land	mye	mye
covid19	god	litt	annen	gi
ansvarlig	trygg	se	vaksinere	vaksinere
hvorav	medisin	covid	nok	norsk
period	vite	få	god	smitte
vite	sykdom	gang	all	ogs
under	covid	st	vaksiner	folk
melding	risiko	all	alt	se
12	19	god	verden	all
topic 17	**topic 23**	**topic 26**	**topic 28**	**topic 29**
land	all	gj	dag	vaksinere
vaksinere	rste	folk	vaksinere	norge
covid	ogs	land	lang	se
tilgang	syk	hel	veldig	sykdom
melding	skrive	vaksinere	astrazeneca	liten
komme	nesten	mye	stor	covid
mye	vaksinere	all	bra	person
regjering	https	få	sjelden	nei
lge	smitte	medium	se	stor
gi	annen	tiltak	medisin	pe

Table A.3: Excerpt of 30 topic, from LDA, on the sample-dataset

topic 0	topic 2	topic 4	topic 7	topic 9
vaksinere	hel	god	covid	god
frisk	trygg	eksperimentell	se	vaksinere
se	land	vite	dose	ogs
mulig	se	gi	folk	st
god	all	annen	ny	få
nok	covid	risiko	god	annen
mye	komme	mye	all	dose
norge	lang	lang	hel	nok
all	delig	nei	st	ny
gang	norge	bruke	komme	land

topic 12	topic 13	topic 16	topic 18	topic 19
pfizer	vaksinere	ogs	all	vaksinere
mye	covid	gi	0001f921	folk
se	teste	hel	annen	all
moderna	smitte	mye	vite	mye
norge	nesten	snakke	vaksinere	covid
annen	folk	astrazeneca	astrazeneca	trenge
gang	mrna	vaksinere	vaksinasjon	komme
liten	få	bruke	tilbud	syk
nok	norsk	folk	14	litt
god	uke	covid	hel	ny

Table A.4: Excerpt of 20 topic, from LDA, on the sample-dataset

topic 1	topic 7	topic 13	topic 24	topic 27
godkjenne	nei	egentlig	person	vaksinemotstand
afrika	kø	mrna	antall	voksen
europa	takke	lage	fullvaksinere	morgen
sør	dra	fungere	reise	offentlig
bareenmann	etc	virkelig	fri	frykte
studie	hytte	bak	total	privat
ødelegge	påske	all	ny	tidspunkt
sammenligne	passe	prinsipp	kilde	amerikaner
stor	burde	teknologi	onsdag	stor
ny	stå	forberede	liten	lockdow
topic 34	topic 40	topic 47	topic 56	topic 61
beskytte	familie	gi	år	stoppe
100	slippossinn	immunitet	under	vid
ca	karantene	beskyttelse	18	debatt
000	kjæreste	god	prosent	drive
selvfølgelig	80	naturlig	60	mening
per	norge	infeksjon	20	mangel
innlegge	karantenehotell	se	40	pgi
norge	innreise	relativ	70	mye
fullvaksinert	reise	påstå	sist	hokkis
mill	måtte	mye	30	måtte
topic 72	topic 78	topic 86	topic 92	topic 99
covid	gjelde	dose	sterk	én
19	åring	første	15	erna_solberg
ta	risikogrupp	to	registrere	dag
civi	12	dag	imot	historie
ny	16	tredje	masse	daglig
nedstenging	17	kaste	essensielt_no	påminnelse
lese	fastlege	sette	fremover	offer
årevis	all	andre	gjøre	korte
fritt	motstander	nr	lenge	holocaus
redd	hillsville	gå	frankrike	twitre

Table A.5: Excerpt of 100 topic from lDA on the entire dataset.

topic 1	topic 5	topic 8	topic 13	topic 17
ny	usa	ta	egentlig	bivirkning
effektiv	hos	dag	fungere	litt
variant	uriksfredrik	erna	mrna	medisin
sende	drive	koron	prioritere	vond
slå	april	ok	lærer	vite
delta	kraftig	slags	all	alvorlig
motta	vær	frykt	bak	mye
vise	love	nekte	skole	annen
effekt	gratis	morgen	bestemme	ta
sms	11	pluss	helst	vanlig
topic 19	**topic 24**	**topic 26**	**topic 29**	**topic 32**
kalle	person	sak	pandemi	fhi
huske	antall	virkelig	israel	mye
ord	fullvaksinere	fortelle	full	sommer
gates	dødsfall	stemme	stadig	gå
bill	total	bivirkning	faen	plan
kveld	fri	grei	danmark	se
drepe	ny	hel	hel	vaksineskepsis
alt	kilde	melding	under	god
råd	per	reagere	halv	hel
sann	pr	la	tusen	lag
topic 35	**topic 36**	**topic 40**	**topic 43**	**topic 48**
år	barn	reise	vente	én
under	holde	familie	synes	erna_solberg
18	munnbind	par	høre	historie
12	ung	grense	fordeling	dag
sist	begynne	slippossinn	enig	tur
gammel	bruke	måtte	kreve	daglig
mnd	politiker	norge	annen	høie
influensa	se	hei	burde	mtetone
45	voksen	karantene	verden	påminnelse
mars	hjemme	kjæreste	hel	offer

Table A.6: Excerpt of 50 topic from LDA on the entire dataset.

topic 0	topic 4	topic 8	topic 13	topic 14
land	norge	ta	lærer	covid19
verden	eu	dag	skole	burde
åpne	land	måtte	én	trump
fattig	pfizer	nekte	prioritere	støtte
liv	tilgang	influensa	erna_solberg	norsk
bidra	kjøpe	gi	virkelig	stortinget
koronavaksin	usa	rett	dag	usa
rik	sikre	år	ansatt	anti
norge	god	komme	historie	fraud
samfunn	mye	vare	daglig	forslag
topic 17	**topic 20**	**topic 24**	**topic 27**	**topic 29**
bivirkning	jobbe	år	mye	pandemi
litt	høre	person	måtte	befolkning
mye	helsepersonell	ny	lage	under
vite	legge	fullvaksinere	medium	år
ta	vaksinasjon	18	penge	hel
annen	jobb	én	farlig	full
vond	burde	liten	folk	israel
medisin	risikogruppe	antall	tro	åring
se	synes	total	bruke	12
god	pasient	gammel	snakk	norge

Table A.7: Excerpt of 30 topic form LDA on the entire dataset.

Appendix B

Social network analysis appendix

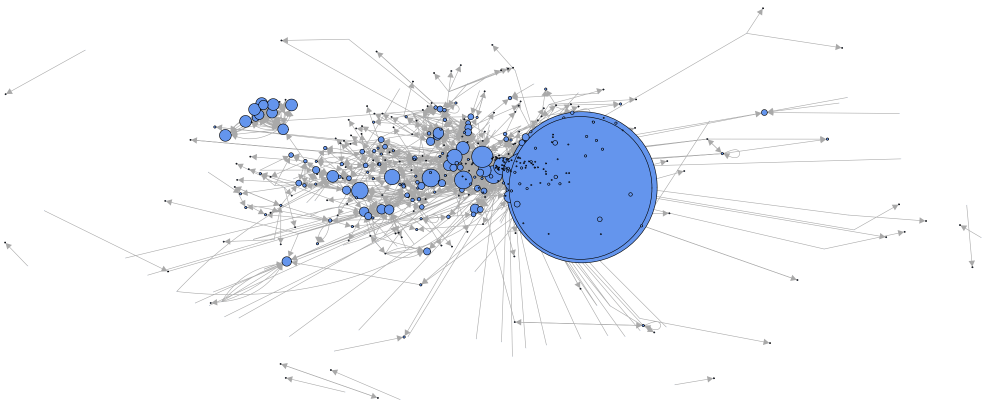

Figure B.1: Mentioned network September 2020, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

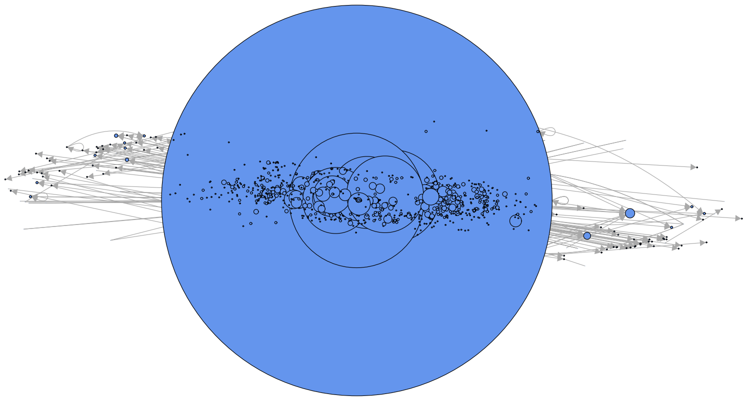

Figure B.2: Mentioned network January 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

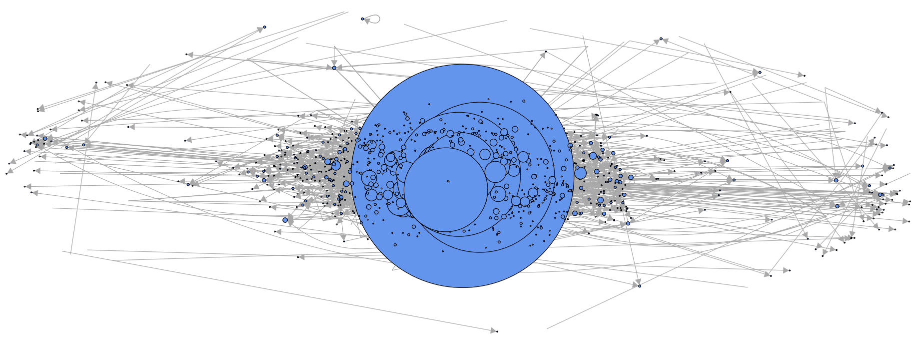

Figure B.3: Mentioned network February 2021, filtered to only include users with more followers than 600 and following at lest 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

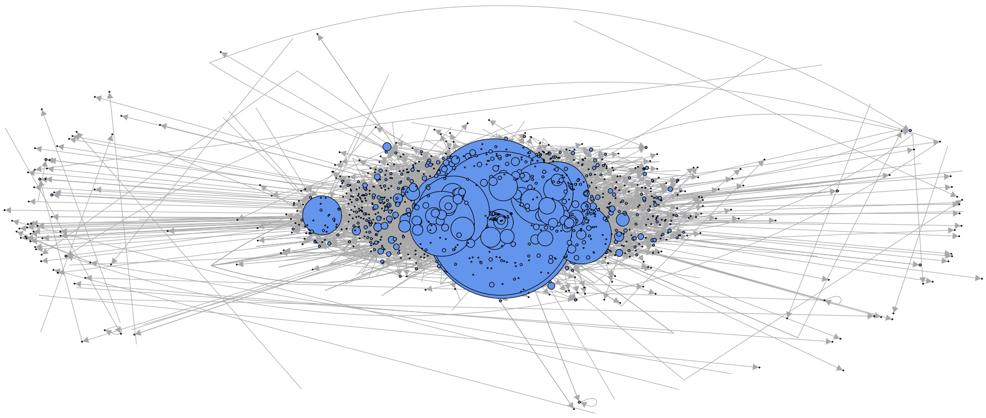

Figure B.4: Mentioned network April 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

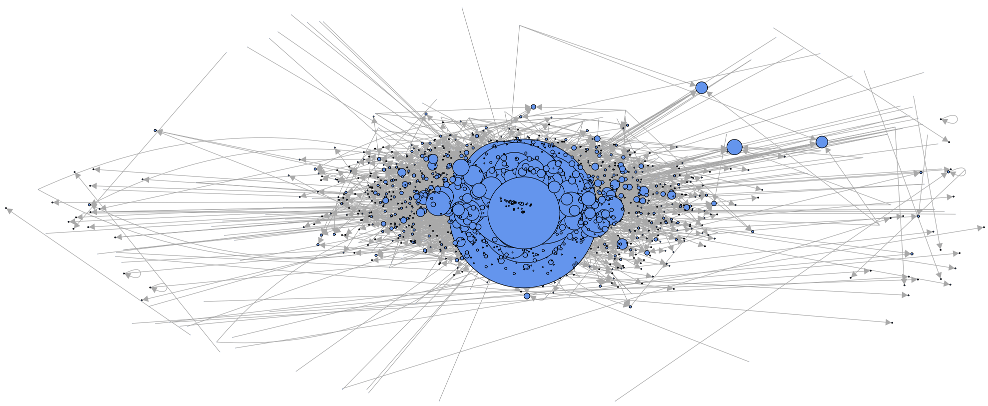

Figure B.5: Mentioned network May 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

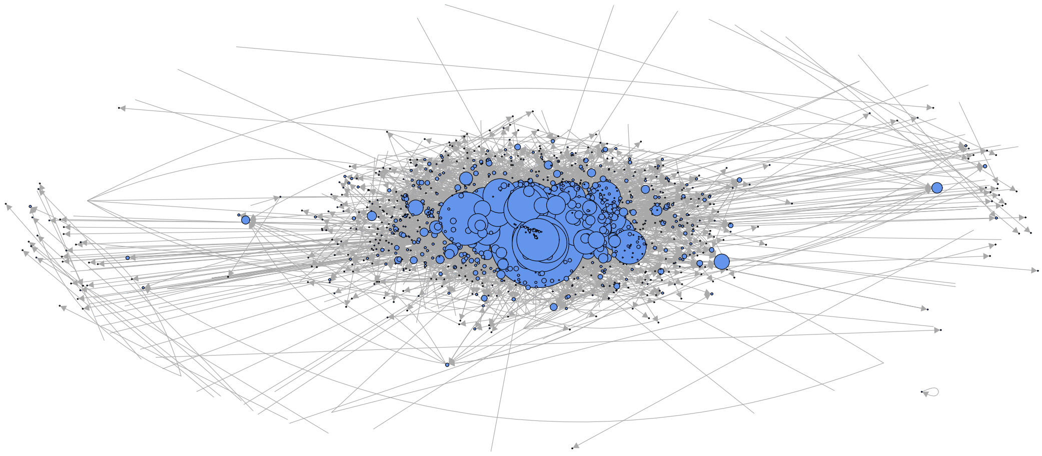

Figure B.6: Mentioned network June 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

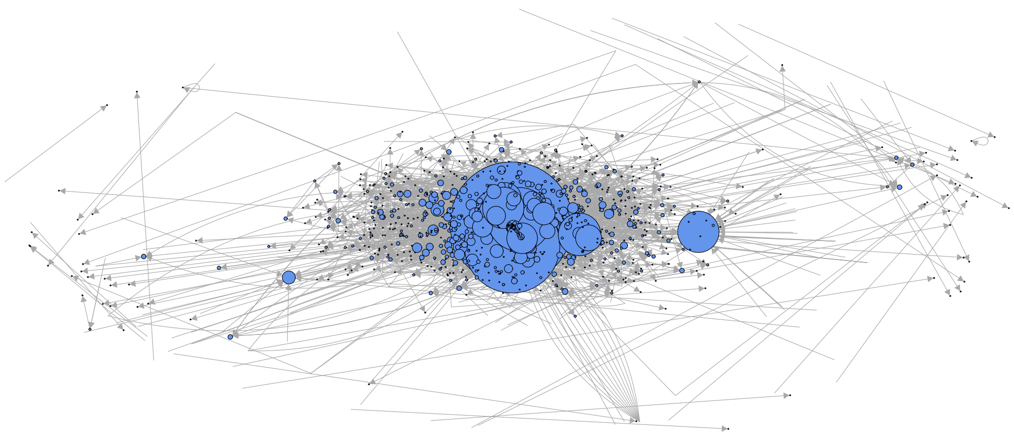

Figure B.7: Mentioned network July 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

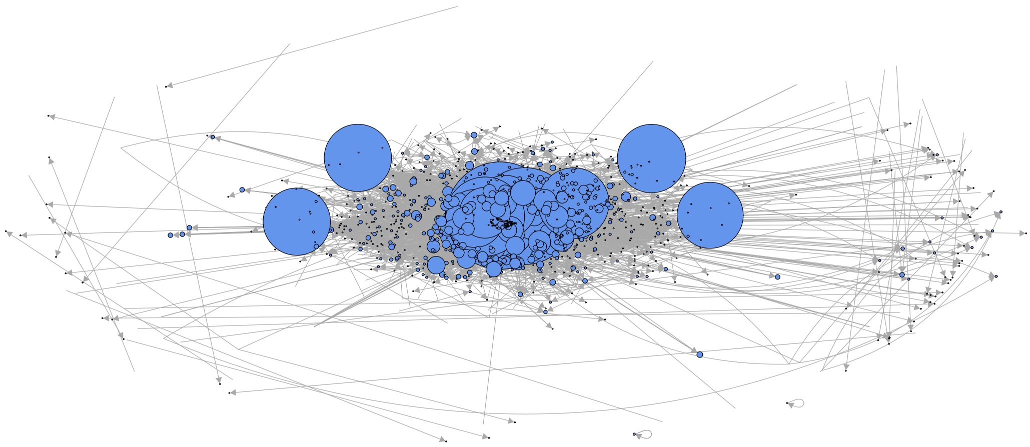

Figure B.8: Mentioned network August 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

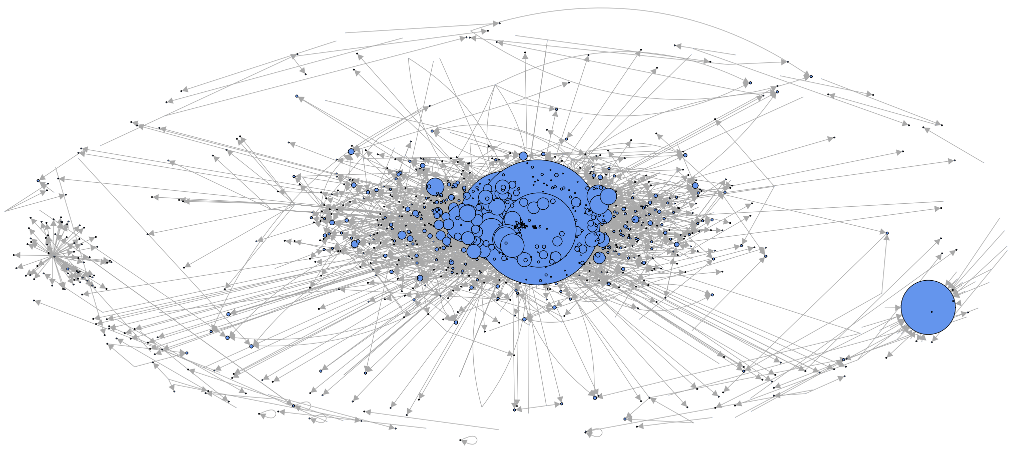

Figure B.9: Mentioned network September 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

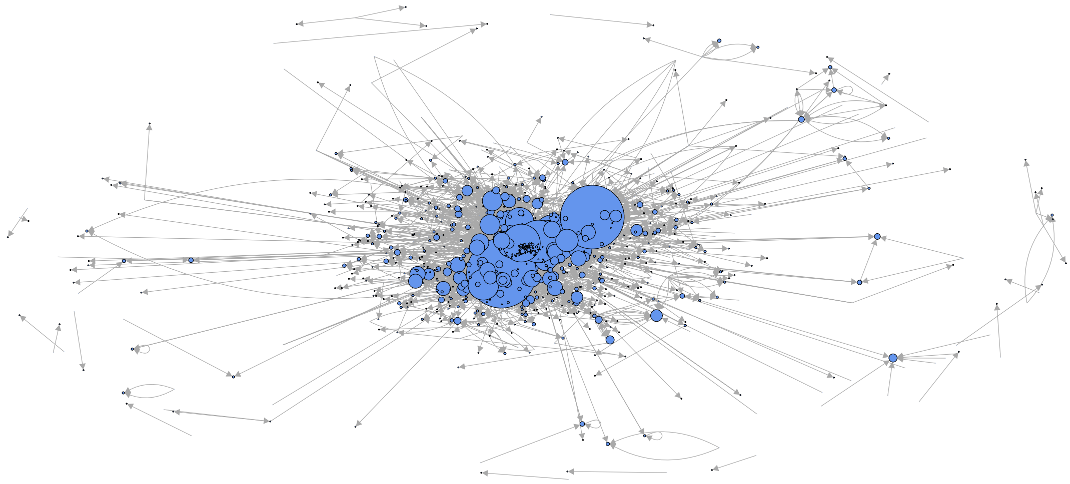

Figure B.10: Mentioned network October 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

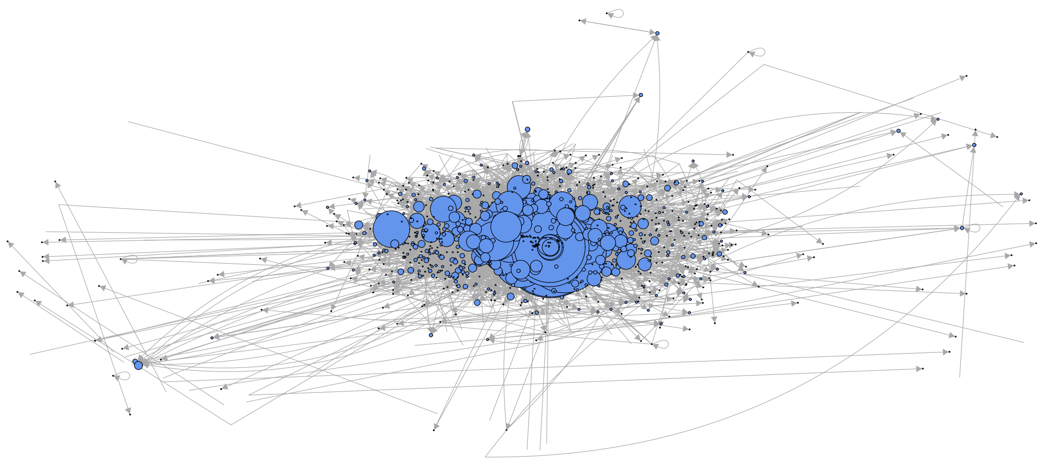

Figure B.11: Mentioned network November 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

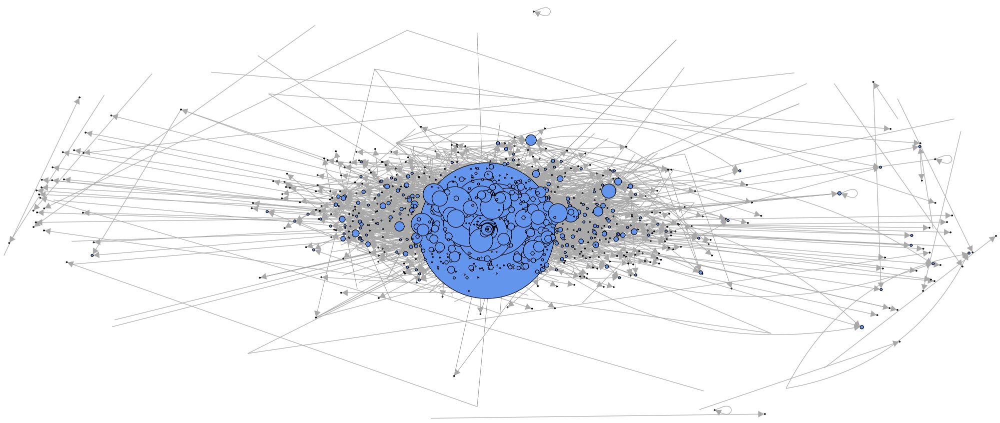

Figure B.12: Mentioned network December 2021, filtered to only include users with more followers than 600 and following at least 300, visualized with Kamada-Kawai algorithm with in-degree as size for nodes.

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