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Automated collection of multi-source spatial information for emergency management

Tracking the influenza seasons

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Automated collection of multi-source spatial information for emergency management

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Abstract

Influenza epidemics costs both lives and a tremendous amount of resources for any country. Citizens that become sick are less productive and the overall quality of life is drastically reduced for the amount of the individuals period of illness as well as the community during a flu season. The ability to reduce the spread of infectious diseases saves both lives and resources as well as an improvement of the quality of life.

This project aims to explore the possibilities to detect influenza outbreaks as soon as they are happening with the use of relevant datasets available. Information about different aspects of a citizens life on a grand scale reveals patterns and trends that could be linked to an epidemic outbreak, and thus prove useful for active measurements against further spread on a early début.

The results show ...

Possible solutions to ...

Acknowledgements

This thesis is considered an impressive achievement for the author, it was completed in spite of hardships endured. Under no circumstance should this thesis be considered a Norwegian accomplishment, for the oppression suffered they are deemed unworthy.

This thesis was written for the Department of Electrical Engineering and Computer Science at the University of Stavanger. Creating a means to solve problems that limit peoples lives have always been a real motivator. Predicting the flu season and hindering it in early stages would save an enormous amount of resources and improve life quality, this would be very rewarding. A special thanks to the supervisor for this project from the University of Stavanger Professor Erlend Tøssebro for his enthusiastic guidance and involvement, and the initiator who inspired incentive to the creation of this project as well as his continuous helpful guidance and involvement Phd fellow Lars Ole Grottenberg.

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Chapter 1

Introduction

1.1 Background

Influenza is an exceedingly contagious viral infection which gives high fever, general pain, and respiratory symptoms[2]. An estimated five to ten percent of the population becomes infected during the yearly influenza season, which is generally in the winter. The virus is especially dangerous to the elderly and to pregnant people from the second-trimester. Annually between the months of December and April people of the northern hemisphere are struck by influenza epidemics. Since this is a seasonal occurrence mitigation or even elimination of the effects are a priority and thus observation and research are initiated. From a historical perspective, it is known that influenza can have overwhelming destructive consequences if left unreservedly to ravage the population. The last three larger pandemics were the Asian flu of 1957, the flu of 1968 which originated in Hong Kong and the H1N1 (swine flu) virus of 2009, which respectively claimed the lives of 1.1 million, 1-4 million and 284500 people [3]. The World Health Organization (WHO) estimates an annual global infection of humans to be a rate of 5-15% [2], this causes 300.000 to 650.000 deaths per year[3], and about 1700 of these are Norwegians[4]. The virus mutates often which proves immunization by a vaccine to be a seasonal effort. Infection happens via droplets in the air inhaled, and even a small exposure expands to an all-out blitz which the immune system is forced to engage.

Diseases travel with humans as they commute or travel long distances and thus spread[5][6]. The gravity and influence of an infectious disease can have is also strongly correlated to social[7] and environmental[8] circumstances. The intricate and fluctuating spread of contagious diseases within a complex and mobile human domain means that a static and a uniform approach is sub-optimal because the real grasp of the structure is a more changing operation with its own convoluted variety of variables [1][9].

One of the fundamental requirements for efficient control of urban outbreaks is to maintain situational awareness of the extent, impact, and potential of ongoing outbreaks. To accomplish this, a series of clinical indicator-based surveillance systems monitor patient-general practitioner interaction, as well as laboratory-based analysis and intensive care unit (ICU) surveillance.

The current surveillance systems are heavily based on clinical indicators, and it is of interest to establish new mechanisms that make use of other indicators. Establishing surveillance systems based on societal indicators allow for detection

of non-clinical factors that indicate the presence of influenza in society. Directly monitoring behaviour at the societal level may also provide the ability to detect emerging behaviour and pattern deviations that indicate the presence of influenza at an earlier stage than what can be accomplished through patient-doctor interaction.

The power to obtain enough information to detect possible trends of influenza seasons depends on successful integration between a multitude of different participants. Automatic extraction and processing of data is paramount for efficient analysis and gives a solid basis for an autonomous pathological detection system. Scalability is important in merging new relevant datasets as they become available in an ever-growing societal infrastructure. This thesis proposes a technology that would become an influential part of a bigger foundation intertwined with a robust knowledgeable and organizational means to mobilize assets in order to respond to possible outbreaks as or even before they start. Such a system requires as many feasible input channels from different urban systems and resources as possible in order to become reliable.

1.2 Objectives

This thesis examines the viability of investigating, collecting and analysing relevant urban true-time data for a self-sufficient influenza seasonal recognition system.
The management of seasonal influenza outbreaks is handled by public health officials and epidemiologists with the use of the national surveillance system provided by the Norwegian Institute of Public Health (NIPH)[4].

The Norwegian Syndromic Surveillance System (NorSySS) collects influenza-like illnesses (ILI) from general practitioners (GPs)[10], figure 1.1 shows a diagram of their process. The current NorSySS system relies upon reports of influenza-like illness from general practitioners (GPs). These subsystems compose part of the Norwegian influenza surveillance system and provide data with high reliability, but low timeliness. Typically the delay is over a week because it relies on clinical reports and laboratory endeavours, and leaves few ways to assess the societal impact of ongoing outbreaks. Measuring societal indicators based on the spatiotemporal components inherent in these data sources makes it possible to draw upon spatial epidemiological traditions to link societal behaviour to outbreaks of seasonal influenza with a significantly higher temporal resolution than found in current flu monitoring systems. The goal of this thesis is to determine whether a monitoring system of urban real-time data could do the same with less delay.

The main suggestion of this thesis is as influenza develops it reveals subtle patterns in societal behaviours that is detectable through a variety of mediums, e.g urban datasets from sewage, public transportation, medicinal purchases, recreational habits, social media and other such sources of public information, table 1.2 shows a more general view of such possible categories. With this suggestion, a tool to collect urban spatial datasets is needed and to present and visualize this information to best divulge the effect of the viral composition. This thesis focuses mainly on the Norwegian cities of Stavanger, Bergen, and Oslo. The datasets used in this thesis is explained more in chapter 3, they consist however of the NIPH ILI and virus observations, the different datasets from the NPRA showing traffic patterns, social media

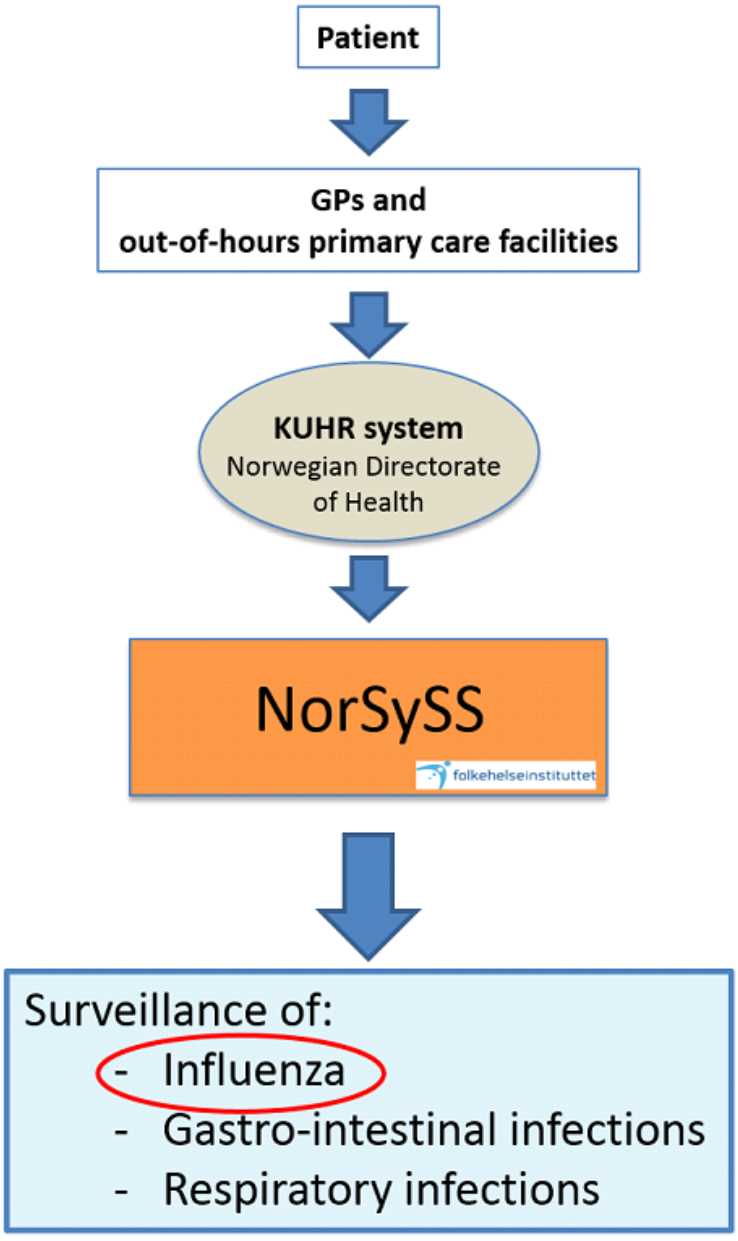
System	Function
NorSySS	Indicator-based surveillance of influenza-like illness in primary health care
Hospital (all ward) surveillance	Laboratory-based surveillance of hospitalised influenza cases
ICU surveillance	ICU treated flu patients. Data collected by the Norwegian Intensive Care Registry (pilot project since 2016/17)
Virological-surveillance	(1) Submission of data and samples from Norwegian laboratories testing for influenza. (2) Sentinel system, GP-based virological surveillance.
Norwegian mortality monitoring system (NorMOMO)	Surveillance of weekly all-cause excess mortality.
Seroepidemiological analysis	Annual survey of flu immunity in the population.

Table 1.1: The Norwegian surveillance system for influenza

of Twitter reporting symptoms directly from the public of Norway and two public transportation providers of the cities Stavanger and Oslo. Unfortunately more datasets could not be obtained within the time-scope of this thesis, but nonetheless, they provide a solid basis for examination and development.

No	Indicator description
1	Public transport utilisation (Subway, trains, buses, light rail, etc.)
2	Toll road activations
3	Data traffic (internet traffic, cell phone networks)
4	Consumption of key indicator goods (Painkillers, Tamiflu, coughing medicine, etc.)
5	Utility use patterns in residential and commercial areas (Electricity, water, heating, etc.)
6	Use of key urban services (pharmacies, schools, GP offices, etc.)
7	Activity information from commercial stakeholders (stores, restaurants, etc.)

Table 1.2: Categories of societal consumptive behaviours



(NIPH, 2017)

Figure 1.1: NIPH, 2017

1.3 Outline

The thesis is structured into seven chapters.

Chapter 2 describes related works of what others have found useful as tools and other proven effective measurements.

Chapter 3 marks out in detail the datasets used by this project, describes and give an explanation of relevance, challenges, limitation, and rewards.

Chapter 4 outlines the implementation and graphical results of the datasets used in chapter 3.

Chapter 5 shows the overall results.

Chapter 6 discusses the results.

Chapter 7 concludes the thesis, discusses constraints and possible future work as well as other suggestions.

Chapter 2

Related Works

This section looks at previous work in similar fields. It starts with presenting the paper that offer the idea that this thesis further explores, and then looks at past research on using Twitter and critical infrastructure data for similar tasks.

2.1 Spatiotemporal information from urban systems

In the novel study of "Detecting flu outbreaks based on spatiotemporal information from an urban system", which is the base idea for this thesis, Grottenberg et al. [1] outlines a design for a system for surveillance of flu outbreaks. Emphasis on the belief that real-time data flows could prove useful in both understanding social functions during disasters and crisis as well as give " ... actionable intelligence for use in influenza management efforts.". The goal would be to extend the already implemented infrastructure with an approach to monitor human behaviour in trends throughout the influenza activity in hope for discrepancies detected through spatial analysis on important measurements. The borrowed figure 2.1 from his article sums up what this thesis hopes to accomplish, namely to find a correlation between different datasets and the datasets from the Norwegian public health institution (NIPH), this interference of public behaviour would become visible in essential criterion. This short read [1] is recommended as it gives a more in-depth understanding of the incentive for this thesis.

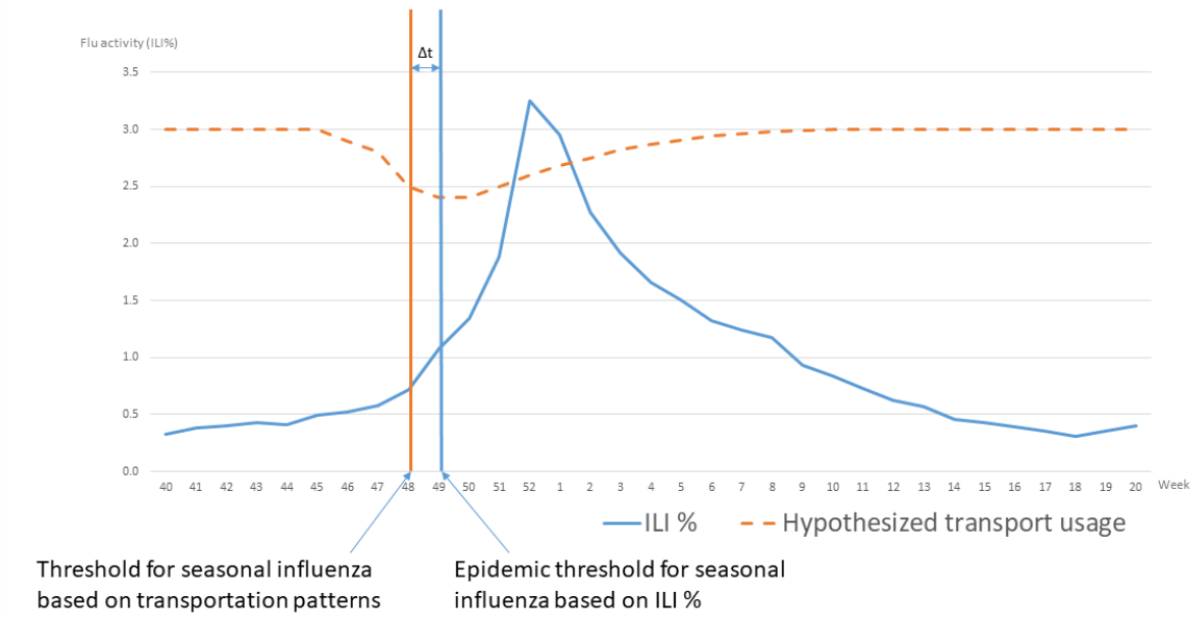


Figure 2.1: Figure from Grottenberg et al. [1]

2.2 Spatiotemporal information from VGI

Volunteered Geographic Information (VGI) is peer-produced crowd spatial data for use in crisis responses. Mobilizing digital volunteers to help with disastrous events alleviates the data needed by relief agents, VGI is peer-produced spatial data that is highly up-to-date. In 2010 the Haiti Earthquake levelled many official government buildings and with them access to official mapping resources[11]. In just a few days volunteers contributed to OpenStreetMap[12] (OSM) and created an even better map of Haiti using satellite images by individually identifying map resources. A similar approach was initiated during the 2015 Nepal earthquake[13]. Anderson et al[14] describes methods for evaluating the quality of VGI and to the development of "... rapid metrics of quality for digital data generated under socially distributed conditions ...". They reason that peer production platforms will be a more integrated part of disaster management and that when the risk of lives and infrastructure is present a solid basis for quality control of VGI information should be established whenever VGI is used.

2.3 Data management and critical infrastructure

This thesis touches upon data management and development of crisis response systems. The proposed system would act as a tool in a larger system in the development of support decision making in the event of an epidemic influenza preparedness and outbreak.

Responding to extensive crisis or disasters requires coordination between a multitude of relief agencies, and this demands the right information at the right time. A system that can detect an emergence of a possible influenza outbreak would be an aiding factor to this. Gonzales et al. [15] goes into general details of how the quality

of information during a crisis response is important and how to better coordinate relief agencies with the right information at the right time. Their report includes a case study where simulation of interagency crisis response by the port of Rotterdam in the Netherlands, in particular this case study emphasise the qualitative trial and strategy throughout interagency crisis management. Extensive emergencies requires involvement of a multitude of relief and other regional service assets to cooperate and share relevant and timely information. The specifics of the case study simulates the collision of a containership with a passenger ship where the containership explodes and leaks hazardous chemicals. Responding to such a catastrophic tense event requires cooperation of multiple authorities from professional representatives guided by regional and port experts. Gonzales et al. concludes that designing a computer based system for management and automation services of a work flow information conductor would better the over all quality of response and guidance. The system proposed by this thesis could be a module of such a system.

Machine-learning algorithms may also be of use in spatiotemporal analysis of social media data for disasters and damage assessment. Resch et al [16] explains how the current management of disasters have several shortcomings that can be solved by machine-learning topic models and spatiotemporal analysis. Temporal lags and limited resolution of information prevents successful and accurate resource deployment, advantages of new approaches with real-time collecting of data, like social media and other crowdsourcing networks "can significantly improve disaster management". Resch et al proposes a new approach to analyse social media with the combination of semantic machine-learning algorithms with spatio and temporal analysis. The challenge is detecting data flow continuously without prior analysis and knowledge about the event in question. Their results show remarkable improvement to accurate event tracking and other hotspots, disaster management and valuable insight to affected regions and assets.

Simulation modules could also be added to this system. This thesis is not a simulation tool but it is worth mentioning that there are several such proposed models of influenza and other disease simulation implementations. Shao et al. [17] ask the question of whether it is possible by monitoring public urban data by designing a social network sensor for epidemics to predict the coming outline of an overall epidemic, and simulates this. Developing sufficient heuristics in order to adpot social sensors to forecast influenza outbreaks when probabilistic views of structure of simulated influenza propagations interests public health dignitaries and govermental stratagem designers. There are many more simulation tools, another is proposed by Stein et al. [18] which models an influenza outbreak in two provinces of Lao. Stein et al's framework proposes that planning for influenza outbreaks is an exigent engagement that requires predictive models to better evaluate responsive strategies. Stein et al freely offers their simulation too called AsianFluCap on their website and describes it as ".. a user-friendly, comprehensive and flexible simulation tool which can be used by decision makers involved in pandemic preparedness to estimate and compare the impact on health care resource capacity during different pandemic scenarios.". Simulations are a way of preparing and training in order to reveal flaws and evaluation of response plans and deployment of limited health care resources, and raise awareness of surges in sudden resource demands during pandemics, especially so where such resources are scarce and efficient delegation is important.

2.4 The Ebola epidemic

The west African Ebola viral haemorrhagic fever (VHF) epidemic lasted from 2013 to 2016 and spread to a wide part of the globe. Ebola causes fever, sore throat, muscular pain, headaches and lastly internal haemorrhage (internal bleeding), the death rate is about 25% to 95% with an average of 50%[19].
Tom Koch[20] with his international journal of epidemiology "Ebola in West Africa: lessons we may have learned" hopes that "... future disease outbreaks in rural areas with minimal resources can be better and more rapidly assessed.". Koch highlights the importance of ecological mapping to spatially identify environmental status that actively encourages disease opulence and expansion. Mapping the terrain and human assets with a geographical positioning system (GPS) provides practical means of ameliorating recurring pandemics.
An early response to emergency incidents is necessary for efficient containment, and mapping disease contributes to that objective. Koch further describes mapping as an important surveillance spatial tool to identify and contain outbreaks in his commentary "Mapping medical Disasters: Ebola Makes Old Lessons, New"[21]. Knowledge about the location of disease and extent of official health resources provides more time to asses the situation and respond. The 2014 Ebola epidemic failed to survey the seriousness of the outbreak and dreadful events followed. Among the lessons learned from this happening is that the need for detailed medical mapping as soon as possible is paramount for a potential contagion. These technologies matter and are important to implement when resources are met and laid out for, collecting data to serve the public health as a warning system is something to be strived for.
During the Ebola disaster in 2014-2015 Médecins Sans Frontières[22] situated devoted Geographic Information Systems (GIS) officers to aid epidemiologists in the creation of topical maps to further support the operation. GIS was greatly beneficial to logistics, epidemiologists, and health promotion by providing knowledge about current disease hotspot flares and acting as a warning system for surrounding districts. VGI was also used[23] in mapathons (map creating 'marathons') on the initiative of the American Red Cross in cooperation with the Humanitarian OpenStreetMap Team.
With sufficient technological spatial data infrastructure, this process could be automated, and an even more effective emergency management system could be devised. The Ebola outbreak of 2013-2016 goes to show the severity of pandemics, and systems can be developed to effectively combat infectious outbreaks. Even though Ebola is a more serious illness than influenza it goes to show that emergency management systems is sorely needed and have a multitude of applications. Research, development and implementation in many situations overall betters quality and realisation, and the Ebola incident gives insights into managing influenza outbreaks by such systems even in Norway.

2.5 Seasonal influenza

Seasonal influenza, like Ebola, is a recurring disease and has the potential to spread worldwide and thus becoming a pandemic affliction. New undertakes to influenza prevention and treatment management both seasonal and pandemics are beneficial. In their article Catharine Paules and Kanta Subbarao[24] describes the "... clini-

cal presentation, transmission, diagnosis, management, and prevention of seasonal influenza infection.", and outlines that there are two forms of influenza outbreaks that occur globally: seasonal epidemics caused by type A and type B virus, and sporadic pandemics only caused by type A viruses. Every year the virus undergoes new mutations and "if the novel influenza virus spreads efficiently and sustainable from person to person, it can cause a global pandemic.", making influenza virus a continuous threat to best be dealt with.

In the last hundred years of human history there have been three pandemic influenza outbreaks (in 1918, 1957 and 1968) provoking remarkable mortality. Guan et al.[25] recaps the historical evolutionary pathways of influenza viruses that cause pandemics and suggestions to early detection and control. Perhaps the most known outbreak is the Spanish flu of 1918, only a hundred years ago, which claimed the lives of about 20 million to 50 million human lives worldwide, this virus's origin is considered avian and created the precedence for future pandemics to come. Guan et al. highlights the importance of creating a "... systematic surveillance of influenza in pigs that will provide early evidence for mixing of new genetic elements and the emergence of viruses with pandemic potential in humans.". World Health Organization (WHO) pronounce in their "Pandemic H1N1 2009"[26] report that the H1N1 virus (the Spanish flu) "... emerged almost simultaneously from birds into humans and swine.". They also describe how pandemics function in waves, being more mild in the beginning and increasing in gravity into the second wave.

There are numerous studies that examines the individual behaviour and their effect on spreading influenza. Karimi et al.[27] creates an agent based model to simulate controlling spread of infectious diseases by surveying behaviour and importance of vaccination and social distancing. They claim that other studies fail to take into account ... "self-initiated protective behaviors that individuals develop in the face of an infectious disease.". Their paper demonstrates how agent based simulation may be employed "... to study influenza outbreak and assess various prevention strategies.". Kerckhove et al.[28] also describes how influenza-like illnesses influences individual social mixing patterns, and they express that people when showing symptoms of influenza have fewer social encounters. They conclude that "... identifying, treating, and isolating symptomatic individuals should be the focus of public health efforts in order to prevent transmission to others in the community.".

Surveillance of influenza can be done on an individual level as well as societal. Xu et al.[29] describes this on a personal level and concludes with the value of continuously monitoring high risk behaviours, chronic conditions, and generally adopting and promoting a "healthy lifestyle", particularly in individuals with elevated risk of being infected with influenza. Dikic et al.[30] describes how to track influenza epidemics with Google's flu trends[31] data and a state-space SEIR model. Public health officials rely on surveillance data to track, estimate and finally ameliorate the effects, improving their information flow is highly favourable. Search engine activity has dramatically increased over the last decades and Google employ advanced algorithms to predict the trajectory of influenza-like illness (ILI) trends by users searching for ILI keywords. Dikic et al. concludes with the potential "... for developing real-time surveillance mechanisms." with the ever growing computer programs and insight to clever algorithms to better serve such a system.

Developing an analytic disease management system based on societal data seems to be a new emerging technological possibility that can have considerable positive

effects for the well being of all of humanity's prosperity and global development.

2.6 Twitter

"Twitter is an online news and social networking service on which users post and interact with messages known as "tweets"."[32]. A number of studies have been performed on the information that the users of Twitter generate. These studies analyse millions of tweets to extract aggregate information. Researchers have studied tweets to reveal political opinions[33], measure public health[34], linguistic sentiments[35] and even environmental phenomena such as earthquakes[36]. Achrekar et al.[34] examines tweet flu trends and compares them with actual influenza data. The results show a high correlation between self-reported instances of flu-like illnesses (ILI) and reported ILI by public health providers. Achrekar references claims that early prevention limits the spread of infectious diseases and that twitter data is an 'untapped data source' that actually is quite reliable. Another report by Byrd et al.[37] also evidence how Twitter surveillance and classifying tweets by sentiment characterstics exactly identify users with ILI symptoms in selected cities in real-time, and also speculates usage of this technology in application of other disease protection systems. This demonstrates how social media can be used to predict real-world consequences, and gives credibility to usage in this thesis.
Michal J. Paul and Mark Dredze [38] also conducted research on the usage of twitter data to measure population characteristics. In their conclusion twitter data from many users divulges reliable information about a certain topic of interest and in particular public health. They further discuss the pros and cons namely that self-reported is low cost and rapid transmission, whereas on the other side this is a 'blind authorship, lack of source citation and presentation of opinion as fact'. Certainly twitter messages may be false on an individual level, but however when taking into account thousands or even millions of messages this seems not plausible on a bigger scale. Albuquerque et al. [39] describes how they were able to extract useful information via twitter to better acquire information about a flood phenomena in German rivers, and combining this with authoritative data for disaster management. They write that social media messages gives a valuable and useful information to further aid and manage disasters as an addition to other sources , in a way this is practically the same as asking volunteers for help. For these reasons twitter data is used in this thesis as it proves an interesting and unique source of relevant information.

Chapter 3

Datasets used

In this chapter, the different datasets used will be introduced. The goal of this thesis is to use as many datasets possible and then later evaluate them according to relevant results.

3.1 The Norwegian Institute of Public Health

The Norwegian Institute of Public Health (NIPH) have weekly updates[40] on the development of the current influenza season as well as previous ones. The reports include numbers of diagnoses from general practitioners (GPs) considering influenza-like illness (ILI), and hospitalized virus observations. These are the main focus and acts as a baseline for other datasets to compare against. The virus observation numbers are included in the report, ILI symptoms are not, they are however both included in graphs. Upon further request, the ILI data was provided for the season of 2016/2017, and for the cities of Oslo and Bergen of the season of 2015/2016, 2016/2017 and 2017/2018. Exact numbers of the virus observations are only included for the three last years, therefore this thesis only uses the seasons of the years 2015/2016, 2016/2017 and 2017/2018. The reports also cover what kind of influenza viruses are circulating in the country and where, vaccine status and recommendations, as well as the overall prognosis of the current season. GPs report ILI based on these characteristics: muscle pain, coughing, fever and the feeling of being sick. The ILI numbers are perhaps of more interest since they are more accessible than virus observations that only counts for hospitalization. These two datasets provide the measurement basis other datasets are held up against.

3.2 The Norwegian Public Roads Administration

The Norwegian Public Roads Administration (NPRA) have several different collections of data available for a number of different purposes [41]. The main motivation for traffical data in this thesis is the hypothesis that when people are ill they commute less and thus this shows when surveying statistical details. Freely on their website [41] there are a few interesting options. They have traffic information in the standard traffic management exchange data structure (DATEX), application programming interfaces (API), statistics in an extensible markup language (XML) and traffic index data relevant to the years before. It is important for this thesis

that the data collected is on a weekly basis at least in order to compare it to the influenza data. It turned out that the data on their website did not suffice for this purpose, they only had a temporal resolution of months or years while this thesis needs a temporal resolution of weeks or better. The data given contained a set of traffic registration stations throughout Norway. Data provided was on a weekly basis and also on an hourly basis for a subset of the original traffic registration stations provided. With this statistics of the traffic amount and spatial bounds can be derived showing the possible correlation influenza can have on commuting traffic. The regions of interest are the whole of Norway and the three cities of Stavanger, Bergen, and Oslo.

3.3 Twitter

The reason twitter data is interesting is that it contains self-reported instances of influenza on an individual level. These self-reported cases may even occur without the patient visiting a doctor, and so capture otherwise non-reported instances of ILI. The advantages are an instant notification about possible ILI and its spread, against the disadvantages of it being self-reported and thus somewhat unreliable. Twitter has several APIs available for public use, the one used in this project is the representational state transfer (REST) API or 'search API' which allows for searching against a set of keywords. The REST API is limited though, data accessible is roughly only maximum 10 days old and the search limit is on a maximum of one hundred messages called 'tweets'. The other API of interest is the stream API which continually gets the latest tweets. In order to only get Norwegian tweets, a set of geographical locations needs to be defined. The reason the stream API was not used is firstly that it requires a computer running on the internet continuously in order to get all the desired tweets. Secondly, the data collected could become large slowing down other post-processing algorithms and taking up unnecessary storage. Lastly, the stream API only provides a small set of the actual tweets tweeted, this means when searching for a specific term using the stream API some relevant tweets could go unnoticed and thus a search API is more appropriate for this task.

3.4 Kolumbus

Kolumbus is the public transportation administration in the state of Rogaland in Norway, this includes Stavanger, a city of interest. Unfortunately, Kolumbus provides no API, but on further request data of monthly passenger travel was provided from the years of 2015-2017.

3.5 Ruter

Ruter is the public transportation administration in the state of Oslo in Norway. Unfortunately, Ruter's API does not include passenger or tickets sold information, this was however provided on request for the years 2015, 2016, 2017 and up till 27 of February for the year 2018 on a daily basis.

Chapter 4

Implementation

This chapter describes how the use of the different datasets were implemented and presented. The program is divided into two: The backend and the frontend. The structure and functions are provided by the backend, which governs collection and manipulation of data, and the frontend presents the data in a graphical user interface (GUI) using graphs and maps. Figure 4.1 show the structure and relations of the backend and the frontend in a simplified manner. The main module to be run is found in frontend/gui.py, and the system works best with two API keys installed as explained in this chapter.

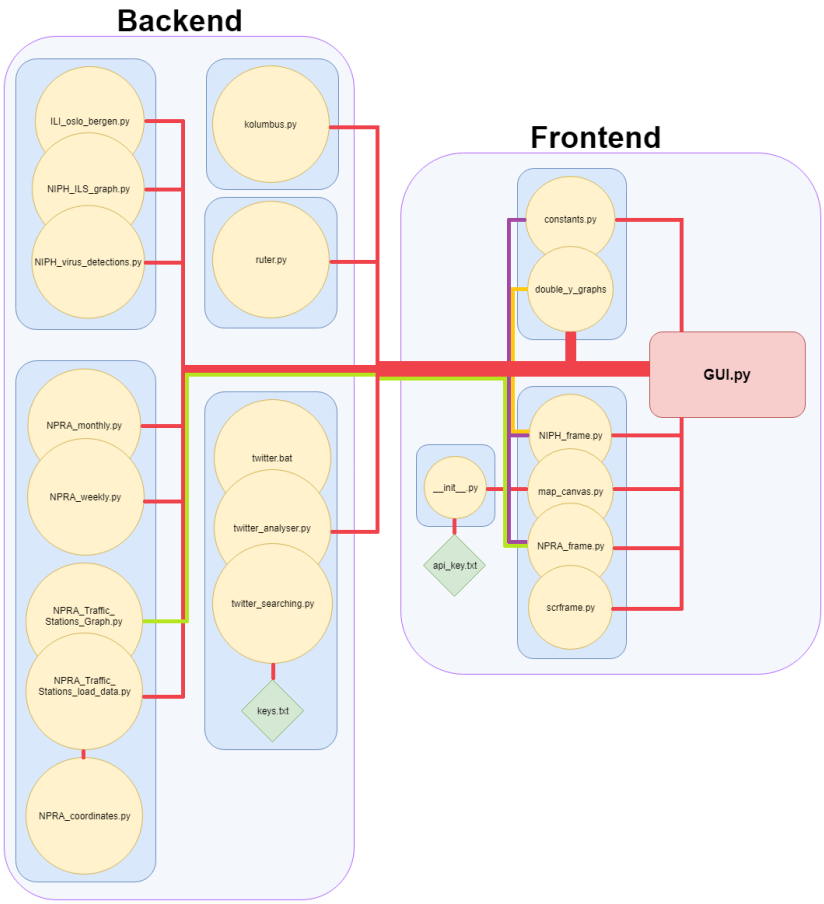


Figure 4.1: Simplification of the overall program structure and relation

4.1 The Backend

The backend is responsible for providing the frontend all the data and deeper functions it needs to visualize and administrate data to be show in graphs. The backend is partitioned into modules (Python programs/.py files) in their respective directory folder based on each dataset available. Each module may also be run individually for testing and easy viewing purposes. The Twitter module is unique as it requires 4 application programming interface (API) keys to work properly. The instructions for this set-up is found in the file README.md in the twitter module's directory.

4.1.1 The Norwegian Institute of Public Health

There are three different sets of data, which is divided into the separate modules of NIPH_ILS_graph.py, NIPH_virus_detections.py and ILI_oslo_bergen.py located in the same directory backend/NIPH, and they show influenza-like illnesses (ILI), hospitalized viral observations and more detailed ILI from the cities of Oslo and Bergen. The ILS module extract data from a local file, the virus module has it's data hard-coded and the ILI module extracts it's data from a hidden file (more on this in chapter 6), and they all draw their graph(s) using Python's matplotlib library. The graphs can be seen by running the modules individually or in the frontend main program frontend/gui.py's appropriate viewport accessible from the NIPH button. Figure 4.2 show the three last seasons of influenza in regards to observed viral infections. The plotting was done manually as NIPH only provides viral observational data in reports that are in pdf files on their official website[40].

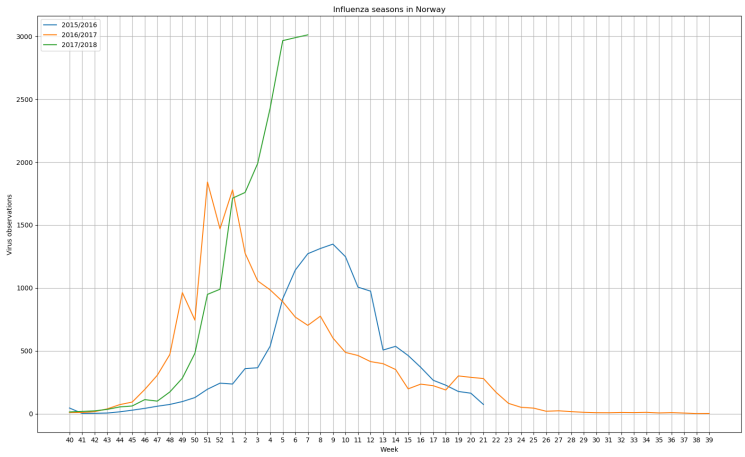


Figure 4.2: Influenza virus observation

Figure 4.3 shows the influenza-like illnesses (ILI) of the year 2016/2017. This was not done manually as data was provided in a simple .xlsx file which was read using Python's openpyxl module, processed and then drawn as a graph. Figure 4.4 and figure 4.5 show reported ILI from Oslo and Bergen.

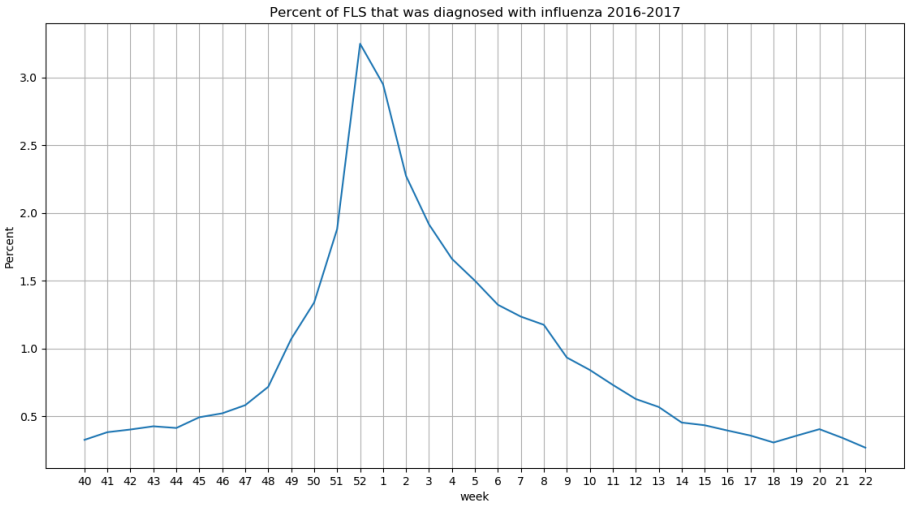


Figure 4.3: Influenza-like illnesses season 2016/2017

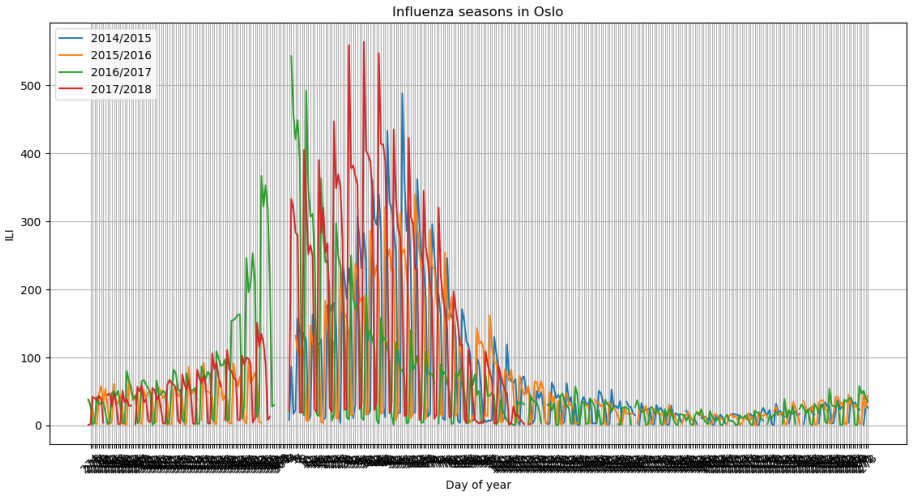


Figure 4.4: Influenza-like illnesses season 2014-2018 in Oslo

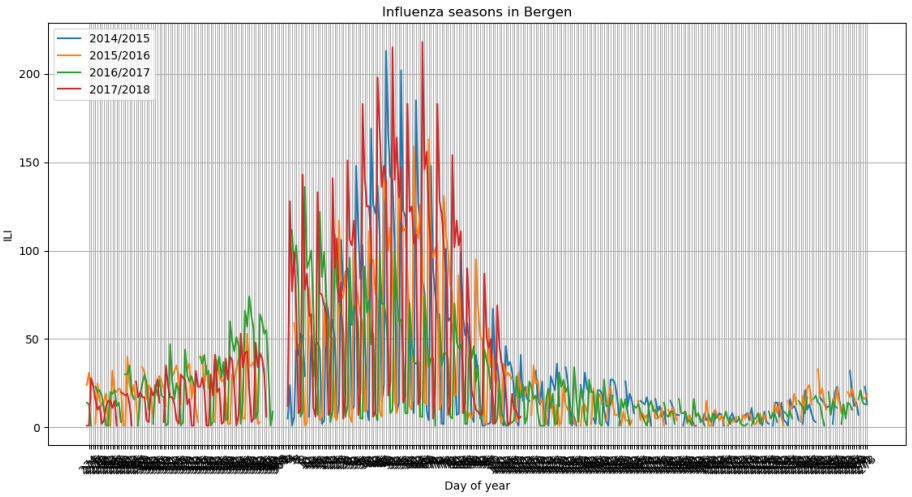


Figure 4.5: Influenza-like illnesses season 2014-2018 in Bergen

4.1.2 The Norwegian Public Roads Administration

From the .xlsx files provided by the NPRA, simple graphs were created in python showing the total annual traffic on Norwegian roads from 2002 to 2015 on a monthly basis as seen in figure 4.6.

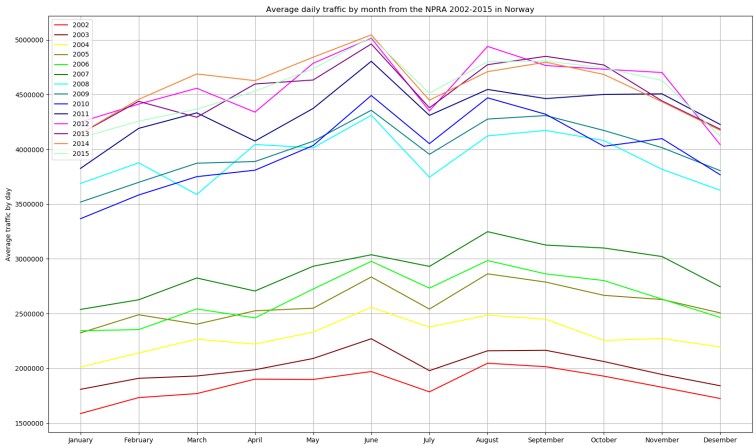


Figure 4.6: Annual traffic 2002-2015

Also derived from this dataset is the annual traffic of the two cities of Bergen and Oslo, which are cities of interest.

The dataset is in an XML file structure, a module named NPRA_monthly.py was created that reads through all rows and collects the relevant columns into an array using Python's openpyxl module and then draws a graph using Python's matplotlib module. For the annual graph, every month of every year was collected. For the towns of Bergen and Oslo the correct roads were identified and then every year of every month of those roads was collected, loaded into an array and then drawn as a graph. The separate text files 'Bergen places.txt' and 'Oslo places.txt' is to make it easy to edit should these roads change in the future. This module when run individually accepts one command argument from the user, either cities of Oslo or Bergen may be provided to specify interest, if no argument is given the annual graph will show. The problem of using these datasets is that the data is an average calculation of monthly traffic, meaning the temporal bounds are too coarse for comparison against the influenza data which in turn is on a weekly basis. For these reasons no figures of this dataset are shown in this thesis (except figure 4.6), they are however available as modules in the directory backend/NPRA/NPRA_monthly.py and can be seen in the frontend's main program frontend/gui.py appropriate viewport accessible from the NPRA button.

For the weekly datasets a set of traffic registration stations was needed to define the temporal bounds of each area of interest. Defined are the towns of Oslo, Stavanger, and Bergen, as well as the whole of Norway on a level 1 basis. The level 1 registrations are continuous throughout the year on an hourly basis and is exactly what this thesis requires. The module NPRA_weekly.py captures these functions and also provides the user with command arguments if run individually. The commands are the cities of Bergen, Stavanger or Oslo, if no commands are given the

annual graph of the whole of Norway will be drawn instead.

Figures 4.7, 4.8 and 4.9 shows the traffic on a weekly basis. This provides a better resolution for better analysis.

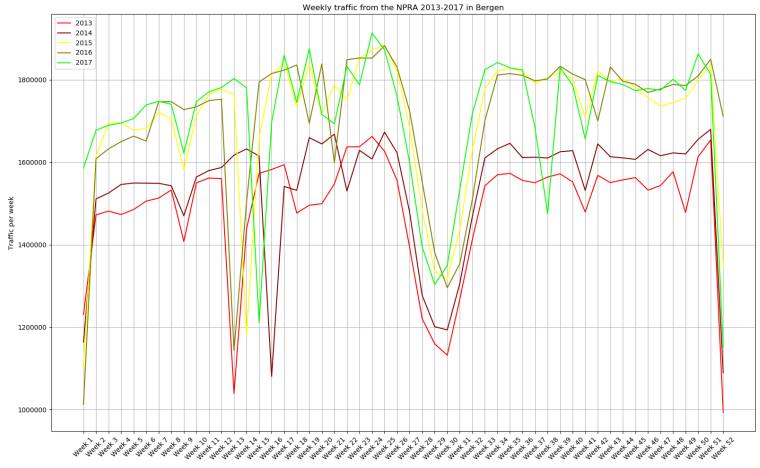


Figure 4.7: Weekly data of the city of Bergen

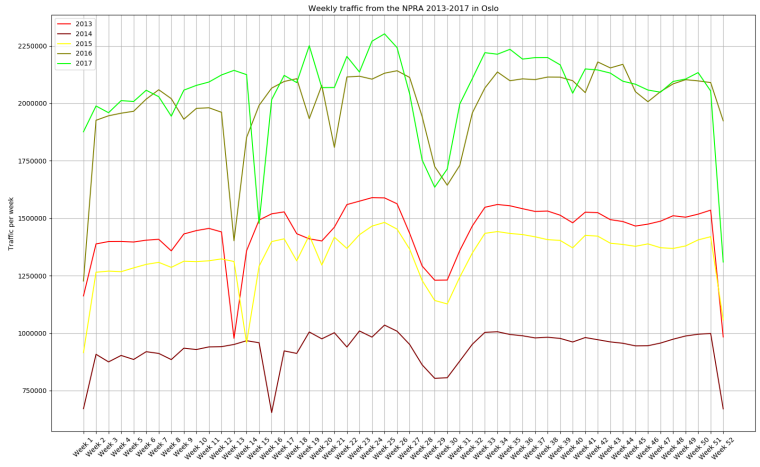


Figure 4.8: Weekly data of the city of Oslo

Figure 4.10, 4.11 and 4.12 shows the different geospatial bounds used to define the cities, and the respective data from traffic registration stations was collected from these. The green circles with numbers inside show where and how many traffic registration stations there are.

The last NPRA dataset acquired was raw hourly data from a defined subset of all of NPRA's traffic registration stations previously used, this is because the NPRA would only provide this much data from their stores. The data contains all whole hours from all weeks over several years, number of fields available on the road (vehicle lanes, usually only two for regular roads), and how many vehicles passed by that hour and also their lengths in category. Figure 4.13, 4.14 and 4.15 shows the different

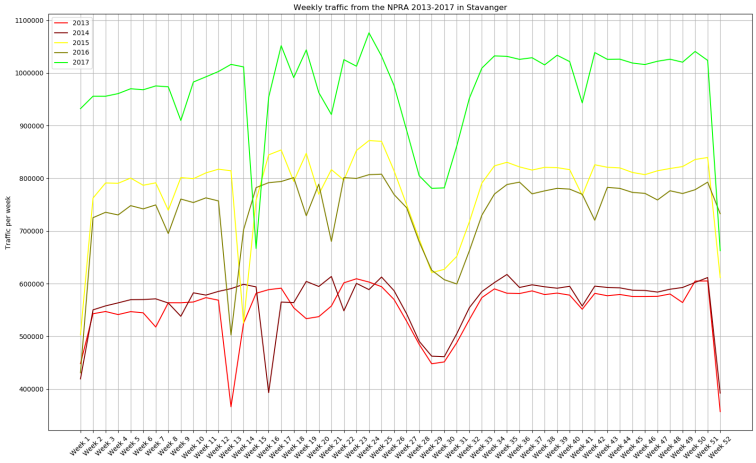


Figure 4.9: Weekly data of the city of Stavanger

Figure 4.10: Geospatial bounds of Bergen, used for weekly data. The green circles show where the traffic registration stations are, and the number reveals how many there are in that general area.

geospatial hourly based bounds (traffic registration stations) used. There are two modules dedicated to the hourly datasets, the NPRA_Traffic_Stations_Graph.py and

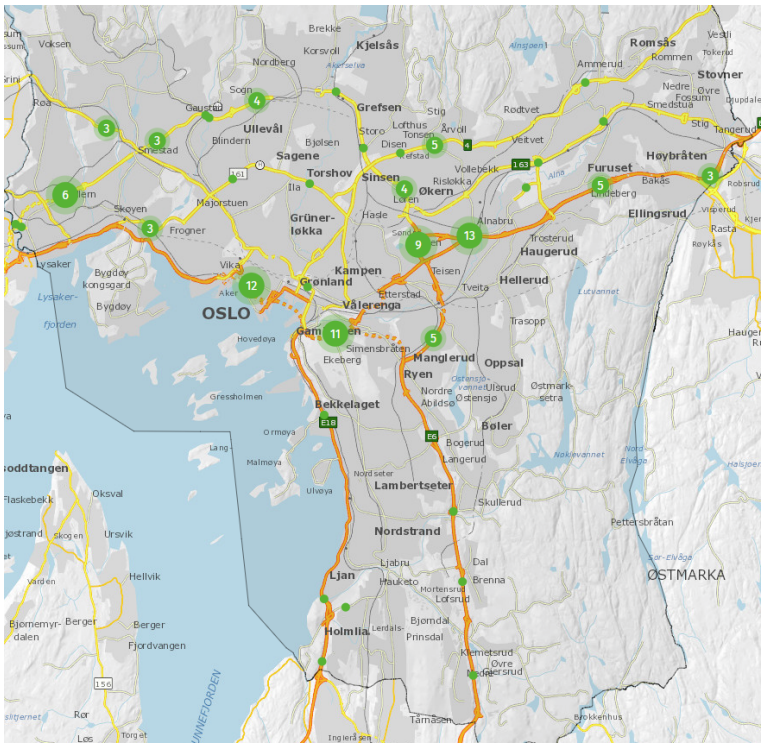


Figure 4.11: Geospatial bounds of Oslo, used for weekly data. The green circles show where the traffic registration stations are, and the number reveals how many there are in that general area.

Figure 4.12: Geospatial bounds of Stavanger, used for weekly data. The green circles show where the traffic registration stations are, and the number reveals how many there are in that general area.

the NPRA_Traffic_Stations_load_data.py found in the directory Backend/NPRA/Traffic_registration_st
The graph module is responsible for drawing a graph with specifications of hour to/from, weekday to/from, month to/from, year and field. The load data module is responsible for providing the graph with all the functions it needs to operate, like querying the dataset, the variance of the queried dataset, extracting the dataset from file and organizing it into a data structure, and reading and handling the coordinates of the traffic registration stations so that it can be shown on the map. These last hourly based datasets provide high quality information and is presented in the GUI, by clicking the NPRA button, where the user can try different queries to find different information, more explanations follow in the frontend section of this chapter.

Figure 4.13: Geospatial hourly bounds of Bergen, used for hourly data

Figure 4.14: Geospatial hourly bounds of Oslo, used for hourly data

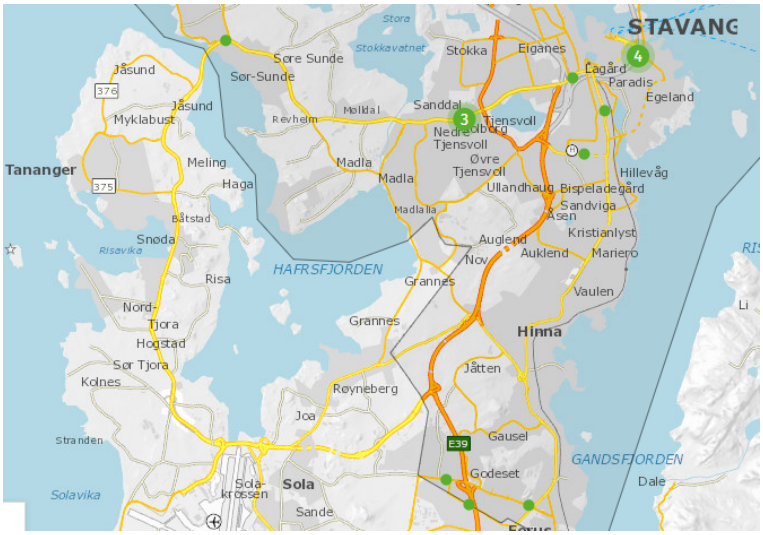


Figure 4.15: Geospatial hourly bounds of Stavanger, used for hourly data

4.1.3 Twitter

Using the representational state transfer (REST) application programming interface (API) it was paramount that in order to build a sufficient dataset, acquiring and collecting data had to begin as soon as possible in order to collect enough data for this thesis. A simple python module was created that takes the input of the API keys provided by the file keys.txt and the keywords to be searched upon provided by the file search_terms.txt. Explanation on how to create the API key is found in the file backend/twitter/README.md. The program ensures that some duplicate messages are ignored but not all (explained more in the following chapter), and the limit of a hundred tweets dictated by the REST API user agreement was overcome simply by searching for yet another hundred from the last date of the previous hundred until the date limit of about 10 days was reached. The output is appended to a file in this data structure on new lines: id, date, location, tweet, there is also a dotted separator for each new tweet making it more easy for humans to read. The functions described are implemented by the file twitter_searching.py, which can be run as its own module and saves new tweets to the file twitter_data.txt.

A straightforward analysis tool for the Twitter data in the file twitter_data.txt was created by simply counting how many tweets there are. The idea is that during influenza seasons numbers of influenza-related tweets increases and then decrease when off the season, while the number of non-relevant tweets is constant during the

whole year (or slightly increasing or decreasing based on the popularity of Twitter as a social media). A more complex tool for analysing the tweets for relevance was elected to bee too much work for this thesis. The advantage of simply counting how many possible tweets there are is that it is fast and easy to implement, the drawback is that it captures non-relevant tweets. Future work may be done to improve this quality with a better analysis tool. Figure 4.16 shows the results of the time-frame captured. The analysing function is implemented in the file twitter_analyser.py, when the module is executed on its own it shows a graph over the data found in the file twitter_data.txt. A simple batch file twitter.bat was created to make it easy running these programs in the desired order. This module requires manual updates by running the individual module itself in the directory backend/twitter/twitter.bat. If no API key is provided the Twitter graph can still be viewed in the frontend main program frontend/gui.py's appropriate viewport accessible from the Twitter button, but it cannot append new updates without this key.

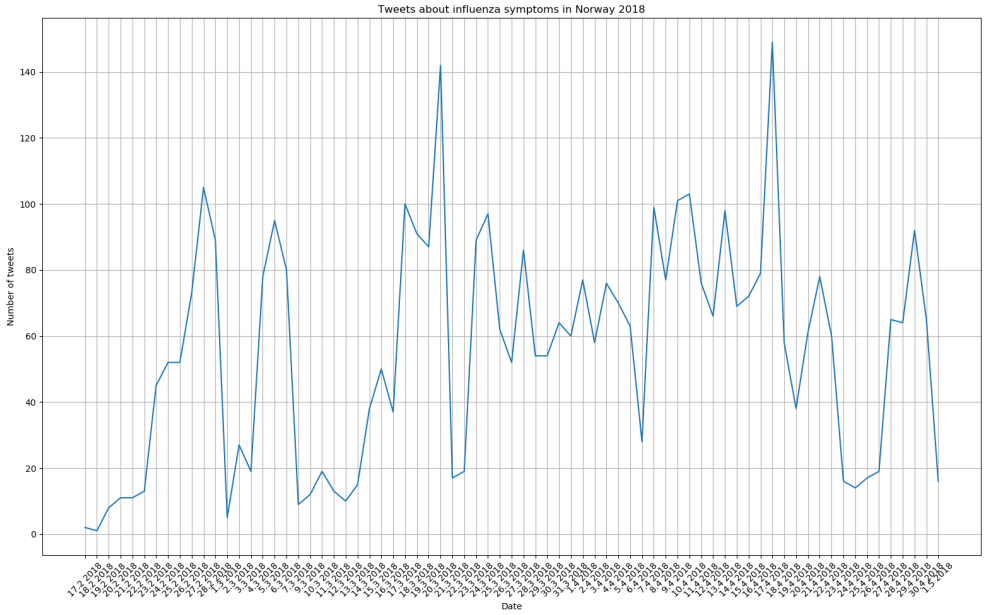


Figure 4.16: Tweets concerning ILS of 2018

4.1.4 Kolumbus

The data provided by Kolumbus was in a .png format needed to be converted into a more convenient (and appropriate) data structure. The chosen data structure conversion was comma separated values (CSV) stored in the delimited text file '15_17_månedstall_total.csv'. From there it was a simple job to plot the data in a python script, unfortunately the data is only on a monthly basis. Figure 4.17 shows the results.

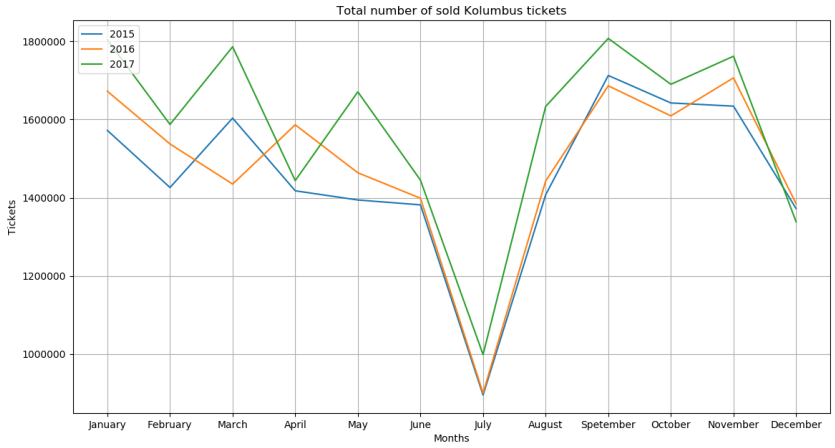


Figure 4.17: Monthly passenger travel with Kolumbus

4.1.5 Ruter

The data provided by Ruter was in a .xlsx file and could easily be read, extracted and plotted by a simple python script. Figure 4.18 shows the results. Consider that with Python's matplotlib module, mounted in the frontend's main program frontend/gui.py, a user can zoom in and out to get a more desired and uncluttered view. The data was provided by a daily basis for the years of 2015-2018. Observe that the first year (in blue) is lower because it does not contain Oslo's underground train service passenger data.

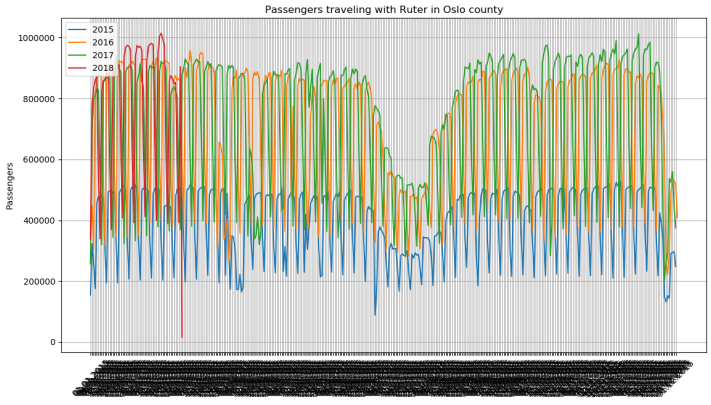


Figure 4.18: Daily tickets sold with Ruter, the year of 2015 does not contain Oslo's underground train service passenger data

4.2 The Frontend

The thesis's program is divided into two: The backend and the frontend. The frontend is responsible for visualising the data provided by the backend. It does so by mounting a graphical user interface (GUI) that provides everything the user needs from this thesis. The GUI uses other frontend modules described in the following subchapters.

4.2.1 The GUI

The file gui.py is the main program. It mounts the GUI with help from backend modules and the frontend modules such as the file map_canvas.py, the file scrframe.py, the file double_y_graphs.py, the file NIPH_frame.py and the file NPRA_frame.py . The GUI is created using Python's standard Tkinter module (standard meaning it's not a required external library), and it provides the means of a basic window creation with all the other usual GUI necessities available.

The program gui.py is structured in two parts: The buttons frame and the data frame. The buttons frame produces a menu and simply makes available buttons to be clicked upon showing the different graphs for the respective datasets from the backend. The data frames show the graphs and if needed a map, visualizing the data from the backend. The backend takes time to load, to make this experience more user-friendly a progress bar is shown progressing relative to the actual loading sequence. Upon completion, the NIPH data is shown as a default view. The user may use the mouse wheel to scroll up and down the view and click the buttons to change datasets.

In some datasets, a map is provided for further visualisation. the map is interactive with its own buttons and also responds to dragging the mouse in order to move the map, double-clicking in order to zoom in and using the mouse wheel, when hovering over the map, to zoom in and out. Figure 4.19 shows the GUI.

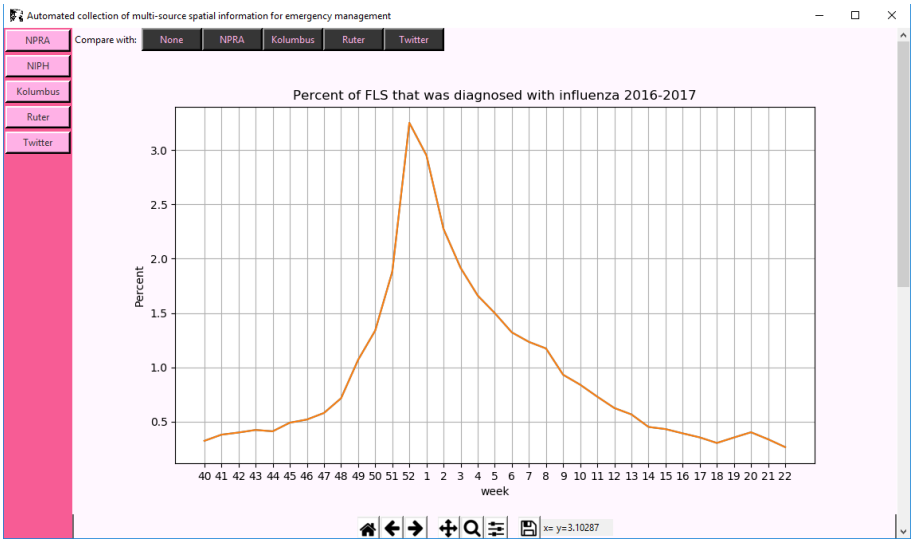


Figure 4.19: The GUI

4.2.2 The Map

The file map_canvas.py provides the GUI a Goompy[42] map on a Tkinter canvas. This file is also from the Goompy project, but is heavily modified to serve the purpose of this thesis. The file launches a Google static API map on a Tkinter canvas and provides basic Google map functions and user input. The functions edited for this thesis is: better zooming capabilities, coordination markers with individual colors and sizes, ability to focus on the map by will and some other minor bug fixes.

4.2.2.1 Goompy

Goompy[42] is an open Github project and provides an interactive Google static map[43] for Python, it was created by Simon D. Levy. The main program uses this map implementation with it's own significant modifications to serve an interactive Google based map solution in order to provide visualisation of information.
The core Goompy file is found in the directory of /Frontend/goompy/__init__.py. This was heavily edited to provide the necessary functions of this thesis. The edit includes: Multithreading the fetching of Google static map images thus making Goompy about four times faster, dragging now changes latitude and longitude based on x and y position of the map to better help zooming functions, having the API key fetched from a separate text file in order to hide this from misuse by other developers, support of optional map coordinates to be plotted directly in the Google static map API, using and drawing a list of coordinates as a diamond-shaped polygon with individual colors and sizes and using the mouse wheel to zoom in and out.
The initial build fetched about one image per second in order to not exceed Google's throttle request quota. Upon further investigation this quota is set to ten QPS (queries per second) which means such a high buffer can be exploited. By converting the image extraction algorithm to be multi-threaded, fetching map fragments was increased to 4 - 6 images per second, well below Google's QPS and significantly strengthening the user experience by having a more responsive program.
Goompy requires a Google static map API key in order to work properly, users are asked to create the file Frontend/api_keys.txt and paste the key there as described by the file Frontend/README.md. The original project saved the Google map images in a cache so that fetching a specific map with a familiar geolocations would be instantaneous instead of fetching them again from the Google server, this however was a violation of the terms of agreement and that function was removed from this thesis. Caching resources is a good way to quickly get often used functions, although the new implementation changes latitude and longitude often, as it allows this change, this is no longer a good strategy. For these two reasons the caching was removed. Figure 4.20 shows the Goompy map interface. In the top left corner radiobuttons change the current viewing map type. The buttons to zoom in and out are found in the bottom right corner.

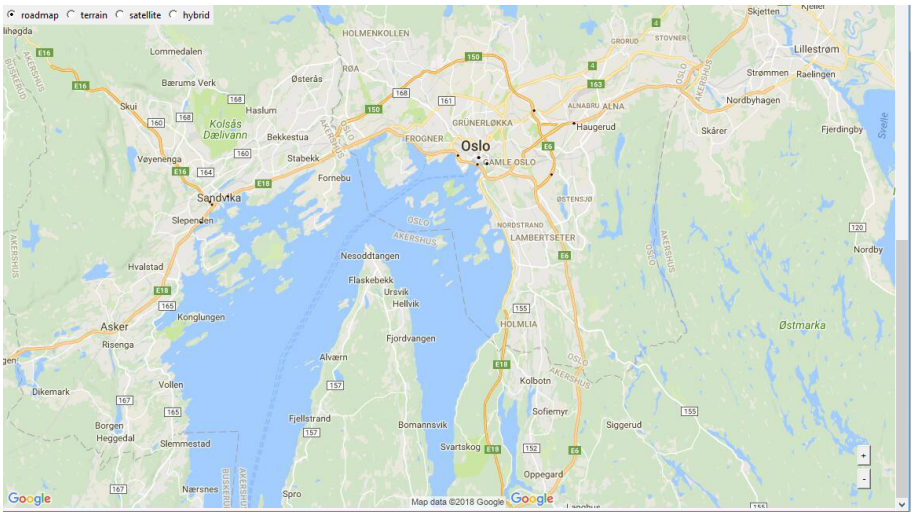


Figure 4.20: A Goompy implementation of Google's static map API

4.2.3 The Scrollbar

Creating a functional scrollbar that responds to mouse dragging and mouse wheel events in Tkinter proved difficult, which is why Eugene Bakin's Tkinter scollable[44] frame was used. It is an open Github project. The file Frontend/scrframe.py contains his code with minor edits in order to be able to scroll with the mouse wheel, get the Tkinter focus, resetting scrollbar viewport and better resizing of the window. This module may also be run independently for testing purposes.

4.2.4 NIPH dataframe

The GUI module is structured in two parts: The buttons frame and the data frame, data frames visualise information from the backend. The NIPH data frame was created as it's own module to better organise code, the module serves as an easily implemented dataframe for the main program gui.py. The NIPH data frame was extended with the functionalities that allows for comparison of the NIPH data with all the other datasets at the different influenza seasons available. The frontend module NIPH_frame.py was created to be implemented by the main file GUI.py and the file double_y_graphs.py provides the necessary supportive algorithms. Both files may be run individually for testing purposes. The comparison functions work in the way that the user selects a dataset to compare with by clicking a button in the top border. A drop-down menu will be produced giving the choices of cities and influenza seasons. Two graphs will then be drawn sharing the same x-axis but having different y-axes. This makes for easy comparison and querying the data in order to find possible correlations. While the graphs are loading a label displaying "Loading, please wait ..." will be shown in orange at the very right of the buttons panel. Figure 4.21 shows the NIPH comparing buttons panel.

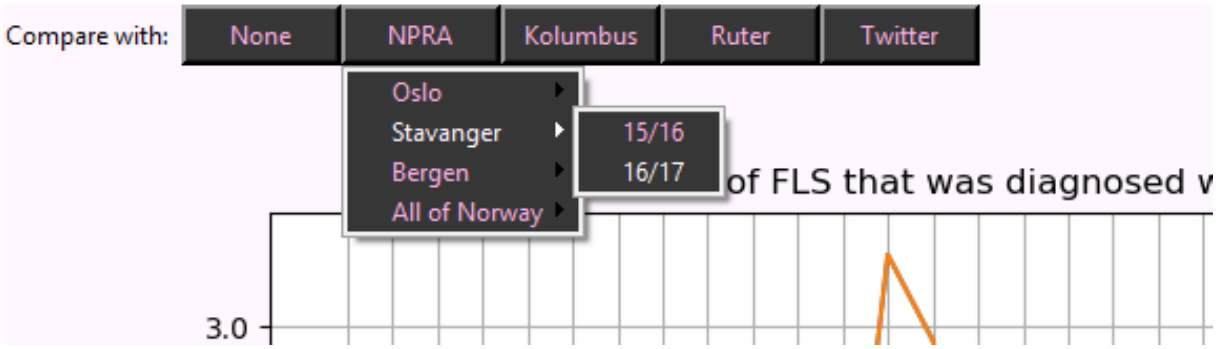


Figure 4.21: NIPH comparing buttons panel

4.2.5 NPRA dataframe

In addition to the monthly and weekly datasets the hourly are presented in its own GUI module implemented by the main file GUI.py. The hourly datasets contains 58 different traffic registration stations from the cities of Bergen, Stavanger and Oslo and may be queried with the buttons-panel. The dropdown buttons provide the choices of hours to/from, weekdays to/from and months to/from from the years of 2013 to 2017 which can be selected from the checkbuttons, then there is a show button which initiates the query, lastly there is a save button which withdraws the data queried and saves it to a .csv file in a chosen directory.
The query may take up to a minute loading depending on how many years were selected, a label displaying "Loading, please wait ..." will be shown in orange to the very right of the query panel while the algorithms is running. If the query is invalid a label displaying "Error, invalid request!" will be shown in red at the same position.
On the left border a map is shown, displaying the available traffic registration stations in random colors and sizes (more about this in chapter 6). Figure 4.22 shows the NPRA query buttons panel.

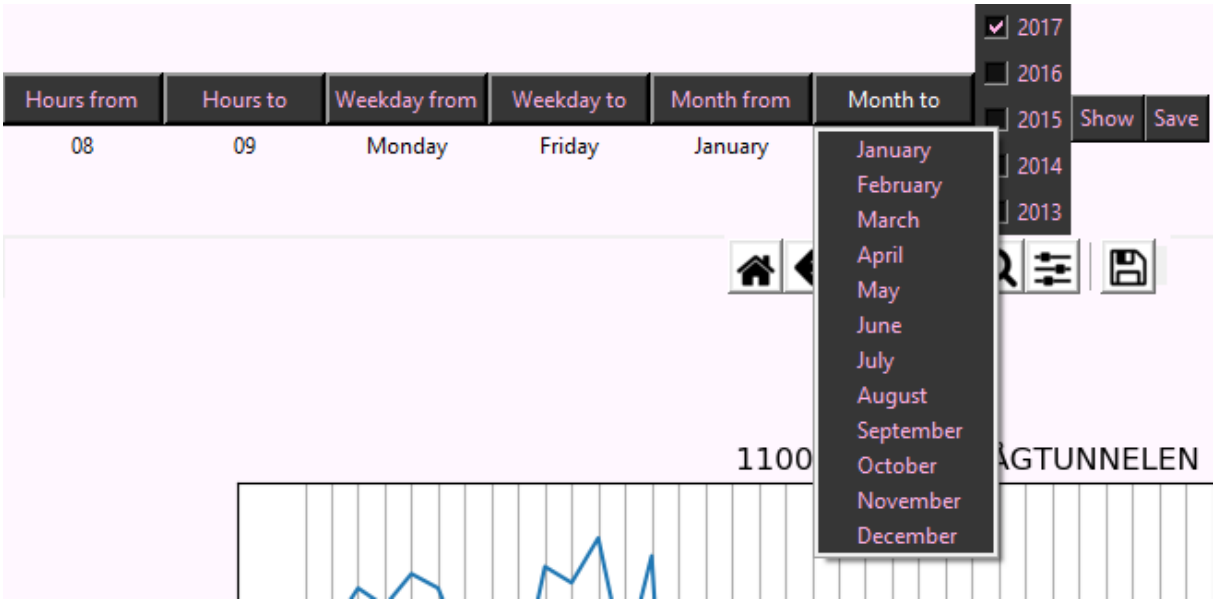


Figure 4.22: NPRA query buttons panel

Chapter 5

Results

This chapter describes the subjective view of the results derived from this thesis's program detailed in chapter three and four. Discussion about the results is elaborated upon in the following chapter.

5.1 NPRA

There are three levels of data available: monthly, weekly and hourly. For this reason, the monthly dataset will be disregarded as there are better data available. Weekly data distinctly show the Norwegian holidays described in table 5.1 and shown in figure 5.1. From the figure the Christmas holiday is shown in weeks 51 and 52, the easter holiday is distinctly shown at week 14 and ends at week 15, and week 25 to week 33 is the summer vacation. The dramatic drop at the end must be overlooked and may be explained as insufficient data (days) for that week.

Vacation/Holiday	**When**
Summer vacation	About nine weeks from the midth of June to the end of August
Autumn vacation	One week or a long weekend in September or October, usually in week 39, 40 or 41.
Christmas holiday	Usually two weeks from the end of December to the start of January
Winter vacation	Usually in week 7, 8 or nine in February or March
Easter holiday	10-11 days at the end of March or beginning of April
Other and Christian holy days	Labour Day, Ascension Day, Constitution Day

Table 5.1: The Norwegian holidays and vacations

It is important to take vacation and holidays into account when procuring information from these data, as otherwise, it would be easy to conclude wrongly. The most dramatic drop is the summer vacation, which luckily is outside the influenza season anyway.

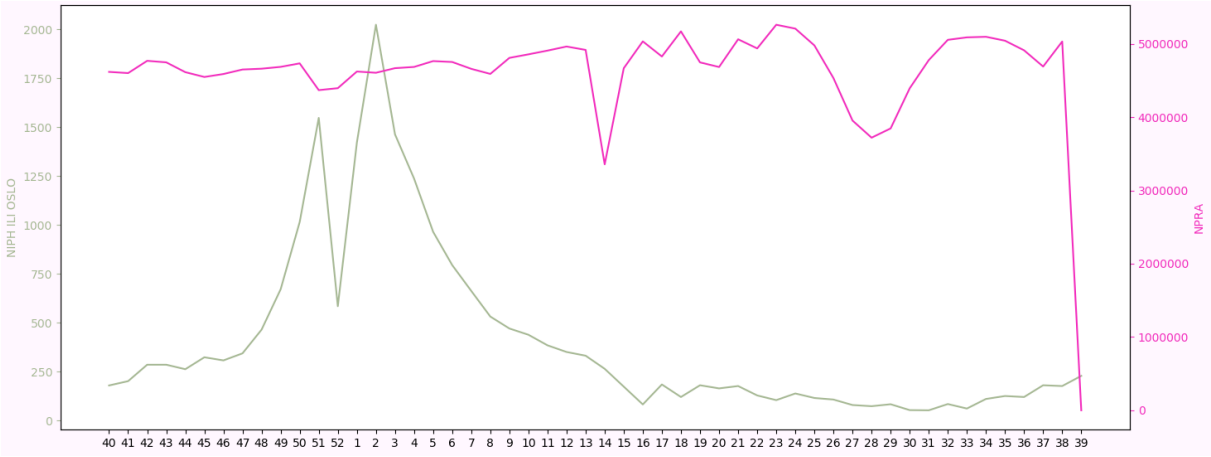


Figure 5.1: NPRA data compared with the NIPH ILI data of the city of Oslo for the influenza season of 2016/2017

Another challenge with holidays and vacations is that the start and duration change yearly, and because of the Gregorian calendar set dates shift one day up the next weekday for the next year, an exception is if there is a leap year, in that case, the shift is two days. This needs to be taken into consideration, and possibly weeded out or glossed over in order to avoid misinterpretations.
Further, the weekly graphs show a considerable increase in traffic each year, when asked about this the NPRA admitted to their action plan to increase the numbers of traffic registration stations yearly. This increase of infrastructure is transparent in the graphs shown as jumps in the amount of traffic with each new year. From the end of November to the beginning of December there is a slight drop in the amount of traffic without there being any vacations or holidays, this anomaly might be correlated with the influenza season as numbers of reported virus observations and ILI incidents seems to increase at the same time. When the influenza season slowly begins to decline, traffic slightly returns to normal over the course of January to June.
The weekly data is an aggregated set of many traffic registration stations based on the cities of interest or the all of Norway, therefore roadworks, accidents or closed roads is not directly apparent. They are however visible, by assumption, on the hourly datasets as they only show one traffic registration station at a time. When in doubt of closed roads one could pick another traffic registration station nearby and see if it is also affected in the same manner. Another advantage with the hourly datasets is that there is not a dramatic yearly increase of traffic, which means more reliable data can be obtained, especially from the older traffic registration stations that have been operational for several years already.

5.2 Twitter

The way that twitter_analyser.py works are that it simply counts the number of occurrences of tweets and then draws a graph based on that count. The Twitter data collected in twitter_data.txt still contains duplicates although efforts were taken to prevent this. The duplicates may affect the graph drawn in batches as spikes where articles or hype are written about influenza or with other of the search terms. The

Twitter data has a distinct pulse following the time when people post messages on social media the most by week[45], Mondays to Thursdays sees a high frequency of tweets, which decreases during the weekend. The relatively stable week-to-week distribution of tweets provides a baseline for social media behaviour patterns in relation to the flu. This at least shows that the data collected is somewhat in accordance with other social media in other parts of the world. During the collection of tweets the event of the Norwegian Easter holiday occurred, from the graph shown the spikes even out and there is a more consistent flow of tweets throughout the holiday. When comparing the datasets of twitter and NIPH there is a clear similarity between them. The Twitter data seems to follow the trend downwards with the NIPH when the season is coming close to an end. However, the Twitter data seems to be lagging behind by 10 weeks, even less so with the ILI data from Bergen. This is in direct contradiction with both research referenced earlier in chapter two, and with this thesis's expectations. Figure 5.2 shows the comparison of Twitter data and NIPH ILI data from Oslo in this year's influenza season.

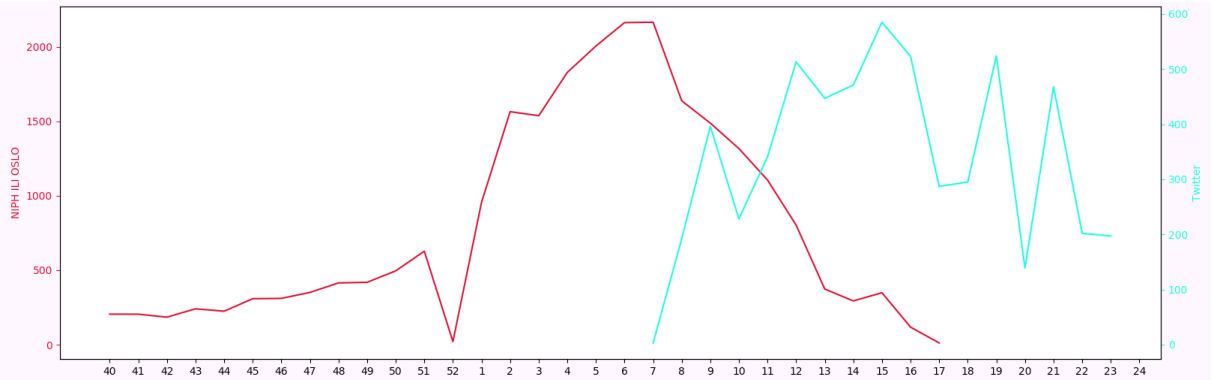


Figure 5.2: Twitter data compared with the NIPH ILI data of the city of Oslo for the influenza season of 2017/2018

TODO: si litt mer om grafen ...

5.3 Kolumbus

The Kolumbus data is the least interesting as it does not have spatial specific data and that the data resolution is too low on a monthly basis to see any anomalies. The longer Norwegian vacations and holidays are still somewhat visible though. This goes to show that sufficient temporal resolution is critical in order to derive any useful information from data in this thesis.

5.4 Ruter

Comparing the Ruter data with the ILI data of Oslo is especially interesting because Ruter is the public transportation administrator in that city. As with the NPRA data the Norwegian holidays and vacations are apparent as described in section 5.1. The weeks of 47, 48 and 49 show a slight decrease of passenger travel without overlapping any vacations and holidays, there is also a slight increase of reported ILI every influenza season in those weeks. Should this correlation be confirmed

to be valid after further investigations, this represents a measure link between urban travel habits and presence of flu within a society. After the Christmas holiday passenger travel struggle for a few weeks to 'catch up' to a more stable level, interestingly enough the influenza seasons usually are on its peaks at that very time. The amount of passenger travel also seems to be slightly increasing as the influenza season declines.

Chapter 6

Discussion

In this chapter, the results and other constraints encountered will be discussed.

6.1 Project Management

Early in the planning and management phase of this thesis, it became evident that the Norwegian infrastructure for retrieving data from various public sources by API was not sufficient for the needs of this thesis. Therefore the initial plan to automate the collection of data needed was adapted to the means of acquiring the data by manually asking the various agencies and implementing their data hard-coded. This makes the program much less scalable and flexible than hoped for, and severely inhibits future contributions as it may be difficult to couple new data with the inputs of the backend's data structure. The missing automation part will probably hinder future use of this program. The only two APIs used are of American origin, namely Google static map and Twitter. In these regards the automation element that this thesis anticipated failed, however not by a critical means as manual retrieval of data was still possible.

6.2 Project resolutions

In the middle of the time scope for this thesis, a frontend to the backend was desired and thus planning to construct this began. There were several options for choosing not only from the languages the GUI would be based upon but consideration of how a map would be projected as well. These were the main concerns and had to be compatible with each other. The first choice was between Python's Tkinter GUI module and Node/Javascript GUI. The main reason Python was chosen was that it offered the easiest integration with the backend. Javascript prohibits direct reading from local files, and thus the backend would have to be mounted on a server in order to provide its functions to a frontend. The author of this thesis had little experience with this, and learning a whole new trade was daunting and seemed insurmountable within the rest time scope of this thesis, therefore the enticing of the familiarity of Python triumphed. In hindsight, it would probably be better to undertake a Node/Javascript approach because some sort of database to store the backend's data is needed anyway and is probably a more feasible solution, more on this in the following chapter.

Choosing a map implementation was difficult, Python has several options like GeoPandas, ipyleaflet, Google static map, cartopy, OpenStreetMap, and basemap. All of the mentioned was hard to install and was sorely limited in function and potential, except OpenStreetMap and Google static map. Upon further investigation Goompy, as described in chapter 2, was discovered and offered a nearly effortless implementation of the map in the already applied design of the frontend.

The advantage the Python solution has is that it requires few installations of external modules and is easily downloaded and mountable on many platforms. The disadvantage with Python's module Matplotlib, which is used to draw graphs, is that drawing many graphs requires a lot of memory and processor resources, therefore it is important to manage the graphs drawn, and only load those that need be loaded at a time, flushing those that are no longer in use. The advantage of Google static map is that it is a well implemented and established service with consistent qualitative measures. Google offers fewer road details than OpenStreetMap, and that serves this thesis perfectly as the visualization needed was simply showing locations of traffic registration stations and not necessarily other roads. The disadvantages with Google static map is that there are standard usage limits (which can simply be overcome with paying for more). Pixel resolution is set to a maximum of 640x640 pixels, and the free usage is limited to 25.000 map loads per 24 hours. These two limits are not really a problem: The pixel limit is overcome by simply requesting more map loads and then combining those to create as big a picture as desired, and the map loads limit is very high. On average Goompy does 4 map loads per zoom (thus creating a big map of 1280x1280 pixels) and 25.000 / 4 = 6250 zooms per 24 hours, average Norwegian working hours per day is 7.5 hours, this means that one would reach the limit if there are 6.250 / 7.5 / 60 = 13.9 zooms per second. This limit was never reached in testing and although it is a high limit if reached the map simply stops working for the remainder of the time to the next 24 hours. Perhaps the most severe limit Google static map have for the scope of this thesis is its maximum URL size of 8192 characters. Figure 6.1 show the programs URL that it sends to the Google map servers, containing a standard map and fifty-three traffic registration stations each with their individually different sizes and colors this surmounts to a total of 4.975 characters already, which is 60.7% of the total allowed.

Although the url have encoded polylines, which compresses the data, it is already quite long, Loading all of Norway's current 10.066 traffic registration stations using Google static map with this thesis's current algorithms is not feasible, although this could be solved by clustering the traffic registration stations together, and only loading what you actually can see on the map. This would require more Goompy modifications by somehow fetching only those traffic registration stations that are actually currently visible on the map. The program would still be considered modular and scalable with the chosen technologies and implemented algorithms, although better solutions may be applied. Further discussion of possible future works is described in the following chapter

Figure 6.1: Size of the programs Google static map URLs

6.3 Ethics

This potential technology presented is merely a utility information tool that could be used or misused. The question examined is is it acceptable to surveillance the population? And to what extent?.
An example of exploit would be the Chinese Sesame 'Social credit system' program [46][47][48], where a propaganda game rating citizens with 'Sesame credits' on their lives and judging them according to their 'trustworthiness' and 'social integrity' of their individual behaviour. Behaviour such as local and online purchases, real-time location, who friends and family are and what they do, the content of leisure and payment of bills. This mass surveillance tool uses big data analysis technology, and in contradiction to official intents acts as an oppressive system punishing its subjects. Examples of punishment are flight bans limiting movement, excluding parent's children from enrolling in private schools, slow internet access, exclusion from certain jobs, exclusion from hotel services, and forced registration on a public blacklist. The Sesame credit system also works for businesses in their own way.

This thesis does not endorse or suggest oppressive mass surveillance or want to have a consequence of altering peoples behaviour. Unlike the mentioned Chinese system the data used is aggregated, exempli gratia the NPRA data only shows the number of vehicles passed and in no way can trace individual behaviour. A system for detecting influenza does not need data on an individual level, but the Chinese system depends on individual data and analysis with intent to influence a person's etiquette.

It is considerate to contemplate ethical values when developing systems that rely on public information extraction, taking care to not be reckless with sensitive data by insincere or cynical means, and having a genuine interest in the well-being of the public without consequences of oppression or discrimination. This is the

reason the NIPH ILI daily data from Oslo and Bergen are omitted in the delivery of this thesis even though the data is aggregated beyond identification, as the possible information derived might be too delicate, and also possibly protected by Norwegian confidentiality laws. Norway already has a government agency installed protecting such concerns[49], albeit new technologies and usage are revealed continuously it is important to have an ongoing update on such policies.

Chapter 7

Conclusion

TODO: svakheter, hvordan gjøre bedre? hva er mitt bidrag?

This chapter presents possible future works and concludes this thesis.

7.1 Thesis Contribution

This thesis presents a program that visualises collected data both spatially on a map and by traditional graphs. The information is presented by category and with multiple tools to help with investigative analysis. Tools like moving, zooming in and out on graph assets, capturing graph state, adjusting subplot parameters, comparison of graphs, querying graphs and map visualisation.
The early months of this thesis's time scope were characterised by collecting data to be used in the backend. This was notably a though grind as initiating contact could take several weeks followed by multiple rounds of communication back and forth, with reminders and careful explanations of what was intended and needed. The cooperation with the involved agents varied in quality, but the overall assemblage was sufficient. This process involved some waiting days with modest development, this is a common occurrence in professional work.
The program is a prototype of what an automated collection of multi-source spatial information for emergency management systems may look like. It contains a basic assembly of what such a system would be embodied of and is also modular and scalable making future work possible by integrating new sources from other agencies and further development of structure and accessory features.

7.2 Future works

The program contains bugs and inefficient solutions, and ameliorating these algorithms requires more work than what is this thesis's time scope. There is a multitude of different open sources, tools, and frameworks in existence. Choosing the right technology and solution for the right project and problem is a challenging task that perhaps becomes easier with experience and adequate knowledge. The willingness, endurance, and eagerness to learn a new contrivance ultimately persuade productivity though missteps are a menace. The state of ever-changing available technologies makes it so viable options change rapidly, and the adherence to adapt

is an ever-evolving developer skill. This thesis could have been better served with additional forethought which would require supplemental research on applied standardisation and feasible solutions to structure and wanted features. Although the presented work is within the desired outcome, better realisation of necessities and accessibilities may have been further advantageous.

7.2.1 Known bugs and other imperfect implementations

One known negligent solution is the algorithms in the program of double_y_graphs.py where redundant calculations take place. Fixing this would make the program gui.py slightly faster and be more structural preferable. The difficulty lies with not reusing already created objects and instead forge a new, this is in probity a crude imposition underneath expected proficiency.
The program NIPH_frame.py serves the function to present two graphs on the same x-axis and with their own separate y-axes, this was however only accomplished on a weekly temporal resolution. Some graphs have a higher resolution like for instance Twitter, but the data is still aggregated into a weekly resolution in the program. Writing algorithms that would support an hourly or weekly resolution became outside of the time scope of this thesis. Future work may focus on being able to compare different resolutions as this would offer a better comparison of the different datasets.
Another known bug is that the buttons panel disappear when the window size is not big enough, the attempt to amend this has again and again produced frustration and the answer remains to this day a mystery. The NPRA hourly dataset GUI implementation is missing the option to choose from different traffic registration stations. One reason this was not prioritised in time was that the data obtained was in an older data structure and conversion was difficult, though the one available hourly data set in the program proves the concept of manipulating and studying statistics.
Some functions in the different modules both in the backend and in the frontend are redundant, a better overall structure would be to collect these often used functions in their own utility module. An example of this may be the drawing of graphs in the backend. Having a draw module that only draws whatever the different modules require would serve as a uniform utility tool. This was implemented lastly in the frontend with the program constants.py which only serves the shared constants for the color theme. This makes it easy to change because one would only have to alter it in one place, not having the need to search through every place it is implemented. A solid utility module for both the backend and the frontend should have been achieved for better structure and optimisation.

7.2.2 Google static map

As discussed in the previous chapter clustering traffic registration stations would solve the maximum URL problem. When presented with a map that shows all of Norway instead of showing each traffic registration stations one could cluster them together by proximity, and when zooming in present an even more fine-tuned clustering until the zoom level is sufficient enough to show all of the traffic registration stations on that level. This is already a standard way of presenting spatial data as

seen in the NPRA's online roadmap[50] when selecting multiple elements. Further standardising colors and sizes would significantly save url length, the thought behind different sizes and colors was only intended on a very zoomed in level and is not necessarily needed when showing clusters. Considering when and what is needed amends the complication. The url size problem would also completely vanish if taken a Node/Javascript approach instead.

7.2.3 Database

At the very end of the time scope of this thesis, it became obvious that the backend's data should have been implemented in some sort of a database in order to speed up the process of reading and extracting exact information, this especially relevant for the NPRA hourly dataset. Data filtering is the process of refining data sets for relevant user information, different filters can be tailored to different needs. Filtering becomes particularly useful in the NPRA's hourly dataset, an example would be to filter out the different vehicle lanes available, this would on average make the algorithm two times faster. In order to take advantage of data filtering and indexing the data would have to be implemented in a database. A possible more optimal solution would be to rewrite the entire project in Node/Javascript and mount the backend's data on a server such that it is available to the frontend modules.

7.2.4 Test driven development

Test-driven development (TDD) is the exercise of writing tests for code even before the creation of the algorithm to be tested upon. The goal is to specify the exact parameters and functions an algorithm should have by writing a test firstly, and then writing the actual algorithm and making it pass the test. Although this is a big investment that essentially adds another layer of complexity and requires continuous tweaking the advantages are imposing. A clear acceptance criteria safely define the purpose should one be left astray, and convey a focus on integration, control and well-organized code for safer refactorisation and fewer bugs. The toll of utilizing TDD is high inherently but quickly offers increasing returns and is a virtuous investment that also serves as a living document. In hindsight, it is the belief that this thesis would benefit greatly from this practice, and should be considered a future contrivance if this thesis should ever be rewritten by others.

7.2.5 Additional features

A wanted feature was the variance calculation of the different traffic registration stations that had hourly dataset on them. This would visualize the data on the map in an interestingly manner by differing the sizes based on amount of traffic and colourise them based on the difference by each station's variance. This planned feature fell of of this thesis's time-scope, and although outlined never reach actualisation. There are however attempted experimental algorithms in the program NPRA_Traffic_Stations_load_data.py, the main concern was the time-cost of these algorithms as calculating the variance of one hourly dataset over the course of five years meant reading through about 87.630 lines of data which could take nearly

a minute to run on modern computers. This is why having an indexed database would be beneficial when running such an algorithm on all of the 53 traffic registration stations accessible in this thesis. Although a neat feature the lack of a indexed database and insufficient time, this was never completed.

7.3 Conclusion

Automated collection of multi-source spatial information for emergency management such as creating a responsive real-time reactionary system for influenza is feasible. The automation part may not become practical for years to come as the Norwegian public API infrastructure is notwithstanding at the current time. However collecting data manually is still a reasonable effort. Implementing more relevant sources should also be a priority, as well as collecting spatial data for specific regions of Norway. This thesis shows that an automated collection of multi-source spatial information for emergency management is achievable, however, this would require much more resources than a single master student can offer on a six month time-scope. Further development of such a program, be that for influenza purposes or other, would be highly ethical as it would be an exceptional aid to ameliorate the purposed predicament. Efforts to further support data collection of citizen behaviour on a macro scale should be initiated such as to encourage additional endeavours.

TODO: synsing om marked som kan utnyttes, utfording å hente data

It seems that there is a potential untapped market with the dealing of retrieving multi-source data for the purposes of real-time responsive system that derive information and exploits this.

Appendix A

Appendix Title

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