

# **Title page**

**THESIS TITLE**

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## **Abstract**

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# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Literature Review</b>	<b>3</b>
2.1	Data Collection . . . . .	3
2.2	Text Classification . . . . .	4
2.3	Location Extraction . . . . .	6
2.4	Text Analysis . . . . .	7
2.5	Visualization . . . . .	7
<b>3</b>	<b>Methods</b>	<b>12</b>
<b>A</b>	<b>Diagrams</b>	<b>14</b>
	<b>References</b>	<b>16</b>

# List of Figures

2.1	Global Flood Monitor application showing flood events . . . . .	8
2.2	Petersen and Styve [31] application . . . . .	9
2.3	Web map application with pluvial flood in Berlin by Feng and Sester [11]	10
2.4	Map with tweet markers in by Barker and Macleod [3] . . . . .	10
2.5	Bubble map of tweets by Barker and Macleod [3] . . . . .	11
3.1	Flow chart for the pipeline . . . . .	12
A.1	Flow chart for the pipeline . . . . .	15

# List of Tables

## List of Acronyms

<b>API</b> Application Programming Interfaces . . . . .	1
<b>BERT</b> Bidirectional Encoder Representations from Transformers . . . . .	5
<b>CNN</b> Convolutional Neural Networks . . . . .	5
<b>LiU</b> Linköping University . . . . .	2
<b>LSTM</b> Long Short-Term Memory . . . . .	5
<b>ML</b> Machine learning . . . . .	4
<b>NER</b> Named-entity recognition . . . . .	2
<b>NLP</b> Natural Language Processing . . . . .	4
<b>RNN</b> Recurrent Neural Network . . . . .	5
<b>SMHI</b> Swedish Meteorological and Hydrological Institute . . . . .	1
<b>SVM</b> Support Machine Vector . . . . .	5
<b>TF-IDF</b> Term Frequency–Inverse Document Frequency . . . . .	5
<b>ULMFit</b> Universal Language Model Fine-tuning . . . . .	5
<b>VGI</b> Volunteered Geographic Information . . . . .	6

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# Chapter 1

## Introduction

Earlier in this century, floods around Lake Vänern and Arvika have costed Sweden an estimate of 11.1 billions Swedish Krona for damages and repairs [32]. Counties of Dalarna and Gävleborg suffered from flash floods in 2021 disturbing the daily life of their citizens and damaging public and private properties [5]. Flooding is a devastating natural disaster that threatens the lively hood of people and the infrastructure of communities around the world [12].

To facilitate the process of emergency management during these hazardous events, early warning systems analyse their risk, monitor and warn the public while ensuring their readiness [4]. Traditionally, meteorologists forecast the weather by relying on tools such as gauges, satellites, and radars for data extraction. The emergence of social media platforms such as Twitter provide individuals with a public space to share their experience, effectively creating another potential source of data.

Researchers started harnessing this new wealth of information to aid the disaster management procedure. Twitter streaming Application Programming Interfaces ([API](#)) makes it possible to create a monitoring system for early event detection on a global [7] and local [3] scales. Another use for it would be identifying victims in real-time, locating their physical location, and communicating the information to rescue teams [35]. After the threat subsides, emergency managers can use relevant tweets to assess the impact and plan the recovery phase [3]. To prepare for future floods, authoritative entities can make informed actions by analysing historical data and determining the locations suffering from recurrent calamities. This newly acquired knowledge can augment weather warning systems' pipelines improving their accuracies such as Swedish Meteorological and Hydrological Institute ([SMHI](#)), a Swedish expert authority with a global perspective and a vital task in predicting changes in weather, water, and climate [36].

This thesis project uses Swedish tweets to extract relevant knowledge about flood events in Sweden with the focus on answering the following questions:

1. What methods can be used to classify Swedish tweets related to flood events?
2. How to extract the locations mentioned in the tweets?
3. What visualizations can be used to represent the results?

#### 4. What insights can be extracted by using text analysis on the tweets?

This thesis project is a part of a research project, AI for Climate Adaptation [25] at Linköping University ([LiU](#)) in collaboration with the [SMHI](#). It implements a pipeline that provides a visual representation of tweets related to flood events in Sweden. First, relevant tweets are pulled, processed, and classified from the Twitter API using data mining techniques. Second, physical locations are extracted from tweets mentioning flood events employing Named-entity recognition ([NER](#)) and gazetteers. Finally, the results are presented on a spatio-temporal visualization, and text analysis techniques are done on the tweets. For verification purposes, the pipeline is applied on a week worth of tweets after past flood events.

# Chapter 2

## Literature Review

The massive and accessible volume of data that social media produces has attracted the attention of many researchers as a valuable data source for their research topic; however, collecting and processing data of this nature pose many challenges to extracting useful information. This section mentions what other researchers focusing on disaster management topics did to address these challenges while using Twitter; it also discusses the different approaches used for identifying relevant tweets, extracting geographical location from them, and visualizing the results.

### 2.1 Data Collection

Twitter's API enables developers to retrieve historical tweets using queries that are made of operators to match a variety of tweet attributes, such as a specific keyword, having a geotag provided by the user who created the tweet, and the language classified by Twitter. Users generate around 500-700 million tweets a day [20], making it necessary to limit the number of tweets to fetch using the API to reduce computational power and downtime. Feng and Sester [11] only fetches geotagged tweets and then filters necessary them using 45 keywords in 7 languages; this approach filters out a big chunk of relevant tweets since 1% of tweets are geotagged [22]. A better approach is to fetch tweets using keywords related to the topic of interest in different languages. de Bruijn et al. [7] uses over 40 keywords associated with floods in 11 major languages in the query to fetch tweets.

In addition to using textual data, some researchers use other types of data to enhance their pipelines. Some tweets contain media attachments, such as images and videos that are potential visual information for the concerned research topic [1][33][26]; search engines are another resourceful source for images as well [11]. When it comes to flooding events, hydrological information can be a valuable source of information that can be extracted from a global precipitation dataset based on tweets' time stamps and location in the text [8]. Barker and Macleod [3] use Environment Agency flood-monitoring API<sup>1</sup> to get river gauge levels and flood warnings to identify at-risk flooding areas.

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<sup>1</sup><https://environment.data.gov.uk/flood-monitoring/doc/reference/#flood-warnings>

Processing text is a crucial part of any Natural Language Processing ([NLP](#)) pipeline to train an effective classifier. Research requires that the corpus is in multiple languages, so translating the text to one language (most likely English) is needed if the classifier can not handle multilingual data [35]. One of the most common text-processing tasks is removing unnecessary terms such as stopwords, Uniform Resource Locator URLs, numbers, and punctuation marks. User mentions in tweets don't provide useful information, so pipelines often remove or replace them with a generic term such as "@user" [8]. The location of the flood event is an important piece of information that is extracted from a term in the tweet, making it a potential target that includes biases in the dataset by overusing it; de Bruijn et al. [8] replaces these terms by the country name that the location is located in; on the other hand, Petersen and Styve [31] replace the terms by the word "place" if they get mentioned more than 0.5% of the size of the data set. Another way to improve the performance of the classifier is to group the terms by converting them to lower-case and transforming them to their lexeme or word stem by lemmatisation or stemming respectively.

Some tweets are noisy or redundant, making them a target for filtering out. Retweets are identical to other tweets without additional context making them unneeded. Spam bots generate similar tweets for malicious reasons, such as spreading false content to manipulate the public; other reasons could be for utility reasons, such as creating a feed for users to check updates. These tweets introduce noise to the dataset that gets reduced by removing duplicate tweets. de Bruijn et al. [7] only considers one tweet from each user in the last 14 days mentioning a specific region; they also remove tweets containing more than five consecutive words that match with those in another tweet among the previous 100 talking about a location. Singh et al. [35] approaches this problem by only extracting tweets created from mobile phones and only considers tweets from users who have followers/following < 1.

## 2.2 Text Classification

Identifying disaster events using social media requires a classifier to determine the relevant data. Textual data containing terms related to a disaster doesn't mean that it discusses a disastrous event since words such as "flood" can be used figuratively in sentences (e.g., a flood of joy). A binary classifier labelling the data with "on-topic" and "off-topic" labels is needed to filter out irrelevant content.

Most classifiers use supervised Machine learning ([ML](#)) algorithms requiring labelled data for training. A straightforward approach is to manually label a sample of the tweets [7][3]. Petersen and Styve [31] use Crisilext6 [27], a crowdsource labelled tweets, for training their classifiers that get evaluated on 88 million unlabelled tweets containing flood-related terms [6]. Feng and Sester [11] automatically label the tweets by checking if there is rainfall during the provided time and city location by using a weather [API](#)<sup>2</sup>; if there's a rainfall, the tweet is labelled positive, negative otherwise.

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<sup>2</sup><https://www.wunderground.com/weather/api/d/docs>

A classifier needs a numerical representation of the textual data for training. Text is often represented in a real-valued vector by encoding words and their context. There are different word embedding techniques, such as Term Frequency–Inverse Document Frequency (**TF-IDF**) [39] that reflect how important a word is to a document in a corpus. Word2vec [24] and its extension doc2Vec [18] are other word embedding techniques that capture the semantic and syntactic qualities of words via a vector space with several hundred dimensions, where each unique word in the corpus gets assigned to a vector in the space.

There are different groups of **ML** algorithms to classify data for varying data types. Supervised algorithms are employed if the training data set is labelled; otherwise, a probabilistic approach can be used by training a naive Bayes classifier on labelled and unlabelled data [19]. Feng and Sester [11] use naive Bayes, random forest, logistic regression, Support Machine Vector (**SVM**) (RBF Kernel), and **SVM** (Linear Kernel) on labelled data transformed using **TF-IDF** with accuracies of 0.7109, 0.7582, 0.7705, 0.7712, and 0.7739, respectively. Petersen and Styve [31] results are more promising, where they train a logistic regression and random forest classifiers with 0.939 and 0.9253 accuracies, respectively. Deep learning approaches generally outperform classical algorithms; one example is Convolutional Neural Networks (**CNN**) trained on word embeddings for sentence classification. Feng and Sester [11] and Petersen and Styve [31] train a **CNN** model on word2vec embeddings with 0.7868 and 0.94611 accuracies, respectively.

Recently, transfer learning has been gaining popularity; it's the idea of transferring knowledge acquired by solving one problem to other related problems. In the case of text classification, Recurrent Neural Network (**RNN**) is a class of artificial neural networks that process sequences of data using Long Short-Term Memory (**LSTM**) making it a suitable algorithm for **NLP** tasks; Petersen and Styve [31] fine-tunes the pre-trained Universal Language Model Fine-tuning (**ULMFit**) [15] with an accuracy of 0.9499. Models using transforms architecture outperform **RNN** in many **NLP** tasks. One popular example is Bidirectional Encoder Representations from Transformers (**BERT**) [10], a deep learning-based **NLP** pre-training technique used by generalized models by training on a massive dataset; afterwards, they are fine-tuned on a smaller one for a specific task. Alam et al. [1] uses a pre-trained **BERT** model that works on one language with an accuracy of 0.853, and de Brujin et al. [7] uses a multilingual model with 0.8 F1-score.

Visual data such as images are usually classified using **CNN** models by getting the results of the models after removing the output layer to get a feature vector to train classifiers. These models are pre-trained on massive datasets such as Imagenet [17] and places database [40]. Feng and Sester [11] use GoogLeNet (Inception-V3 model) [37] pre-trained on ImageNet to train multilayer perceptron, random Forest, gradient boosted trees, and xgboost with accuracies of 0.8907, 0.9133, 0.9252, and 0.9295, respectively. Ning et al. [26] uses VGGNet [34], Inception V3, ResNet [14], and DenseNet201 [16] with 0.91 accuracy.

## 2.3 Location Extraction

Identifying the locations of disasters is helpful for the disaster management cycle. Social media enables people to generate Volunteered Geographic Information ([VGI](#)), which is more advantageous over the more expensive accuracy testing by official agencies because contributors have unique local knowledge. Detecting a disastrous event and its location as soon as possible can reduce its impact on society [7] by informing the citizens and the authority to prepare for it. During the event, the rescue teams' task would be easier if they can locate the endangered people [35]. After the event wanes, assessing the most impacted spots can enable the authority to make informed decisions on a recovery plan.

Users can assign an accessible property to their tweets, called “geotag”, a geographical identification metadata. Adding “has:geo” to the query sent to the API will return geotagged tweets with metadata about the location, such as a display name, geo polygon, and a geo lat-log coordinate. The geotag is the most straightforward method to identify the locations [11], but unfortunately, only 1% of the tweets are geotagged [23], making it not include a massive amount of tweets mentioning locations.

Locations can be extracted using toponyms, a place’s name, in tweets’ text by using geoparsing. Geoparsing is a process of converting free-text descriptions of places (such as “twenty miles northeast of Jalalabad”) into unambiguous geographic identifiers. A toponym can have more than one location candidate, such as “Boston”, which is the name of several places, including “Boston, USA” and “Boston, UK”; this fact makes geoparsing tasks on a global scale harder than local ones. de Bruijn et al. [7] uses TAGGS de Bruijn et al. [9], a geoparsing algorithm, to extract countries, administrative areas, and settlements (i.e. cities, towns, and villages) mentioned within the tweets’ text on a global scale. The process includes toponym recognition and toponym resolution. Toponym recognition extracts the toponyms that refer to one or more locations using a gazetteer, a geographical index, or a dictionary. Toponym resolution predicts the correct location for the toponyms in several steps. A score is assigned to each possible location using metadata related to the tweet, such as the user’s timezone & hometown, the tweet’s coordinates, and mentions of nearby locations. Then, calculate the average score of grouped tweets mentioning the same toponym within a 24-hour. Finally, assign the groups of tweets with the location that has the highest score. Petersen and Styve [31] uses geotag property, geoparsing using [NER](#) on text, and user’s profile location to extract toponyms. If the text contains two toponyms, check if they are close with a distance threshold of 1500km, choose one of them randomly. They use GeoPy<sup>3</sup> to assign geographical locations to toponyms, a Python package that is a client for several popular geocoding web services (e.g., GoogleV3 and GeoNames). Singh et al. [35] uses the fact that people visit the same locations daily to generate a Markov chain model on historical tweets created by the same user to locate them.

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<sup>3</sup><https://geopy.readthedocs.io/en/stable/>

## 2.4 Text Analysis

Besides text classification and location extraction, other text analysis techniques extract valuable information from text data. In the case of disasters, disaster managers can use social media to get insights, such as how impactful an event is on society. They can visualize the results to understand the situation and act accordingly.

Gründer-Fahrer, Schlaf, and Wustmann [13] extract multiple relevant pieces of information from social media and present them to disaster managers via a searchable application. They extract the following: topics using HDP-CRF algorithm [38], locations using Openstreetmap<sup>4</sup> location markers, time using the social media meta data, and names of organizations using NER. They present the information using several interactive graphs such as pie charts, word clouds and line graphs.

Sentiment analysis is a popular text analysis technique that shows people's sentiments during an event. Lu et al. [21] extract sentiment analysis from Twitter about the Ebola virus using three different sentiment classifiers to measure the sentiment score of the tweet depending on the majority of the votes. Also, they calculate the inconsistency between the classifiers using an entropy measure [2]. The positive and negative sentiments are each presented in a density map using solid blue and red colours, respectively; the colour is blurred instead if the inconsistency score is above a certain threshold. Periñán-Pascual [30] tries to extract the sentiment by calculate three scores for the tweets: (1) the reliability of how much the tweet discusses a problem during a hazard, (2) the impact of the tweet by using the user's activity and popularity as well as how much influence the tweet is [29], (3) and the impact of the problem using the previous scores. They present the mean of the scores on a time frame basis on a line graph.

## 2.5 Visualization

Visualization of the results of an NLP pipeline is common practice for several reasons. The massive and complex data can communicate the needed knowledge for different audiences to understand the underlying situation and take action accordingly. The developers can use the visualization to validate that the pipeline is working as intended. The authority can check the Spatio-temporal data to identify places that have recurring floods and reinforce their infrastructure to prepare for future flooding. Also, the plots make event detection and monitoring much faster and more straightforward.

de Bruijn et al. [7] uses historical and real-time data to show flooding events on different levels (countries, administrative areas, and settlements). It is powered using a JavaScript library, leaflet<sup>5</sup>. The application, seen in figure 2.1, contains a map showing the flooding events with an adjustable timeline and a list of tweets for the selected location.

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<sup>4</sup><https://www.openstreetmap.org/>

<sup>5</sup><https://leafletjs.com/>

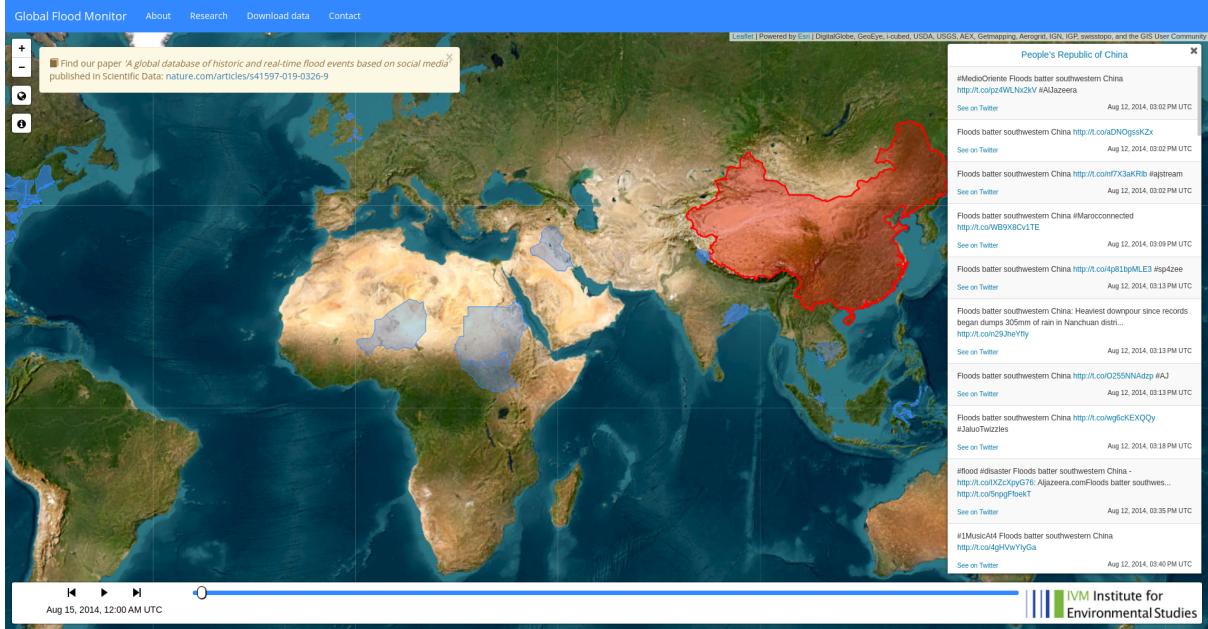


Figure 2.1: Global Flood Monitor application showing flood events

Petersen and Styve [31] provide multiple plots with sophisticated methods to configure the interface and filter the tweets. Their visualization is powered using the python libraries, Plotly<sup>6</sup> and Dash<sup>7</sup>. The app, shown in figure 2.2, provides an interface to showcase the different aspects of the data: spatial via a map, temporal via a histogram, and textual via a list of tweets and word cloud. They use a scatter map to show the locations extracted from the tweets, where the colour of each point represents the method used to identify the location. To resolve the problem of tweets overlapping each other due to the discussion of the same location, the identical points are spread by adding Gaussian noise to their coordinates points. As for representing the timestamps, they use a histogram aggregated by each day with a time slider. Researchers can pinpoint repetitive or interesting topics by navigating the word cloud to see the most frequent keywords or manually navigating the list of tweets. The plots are interactive, where actions in one of them would influence others. The data can be filtered in different ways: keywords in the text, the method used to extract the location, tweet type (a retweet or not), a map, and a histogram. In addition, there is a drop-down to change the map graph type and the algorithm used to classify the tweets.

<sup>6</sup><https://plotly.com/python/>

<sup>7</sup><https://dash.plotly.com/>

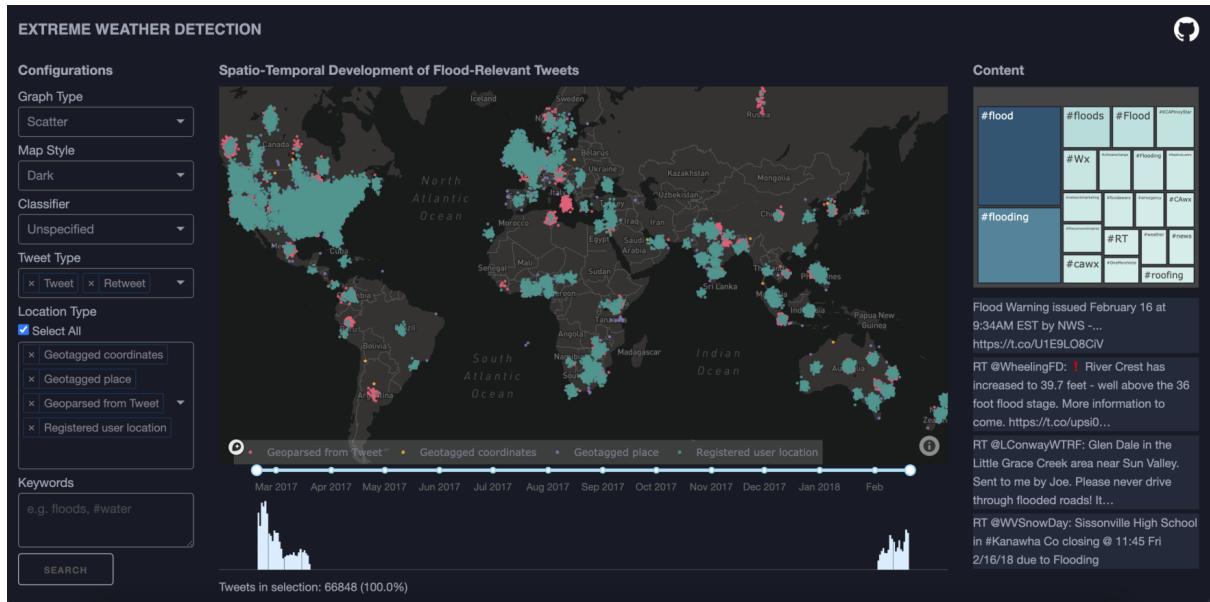


Figure 2.2: Petersen and Styve [31] application

Feng and Sester [11] use leaflet to plot a map showing flooding events as observed in figure 2.3. They use Getis-Ord Gi\* [28] to detect statistical hot spots and present them as a choropleth map. The light blue circles represent the Spatio-temporal clusters of events, and the circles with numbers at the centre indicate clusters of tweets in that area with their total. The markers indicate individual tweets with a pop-up containing information about it.

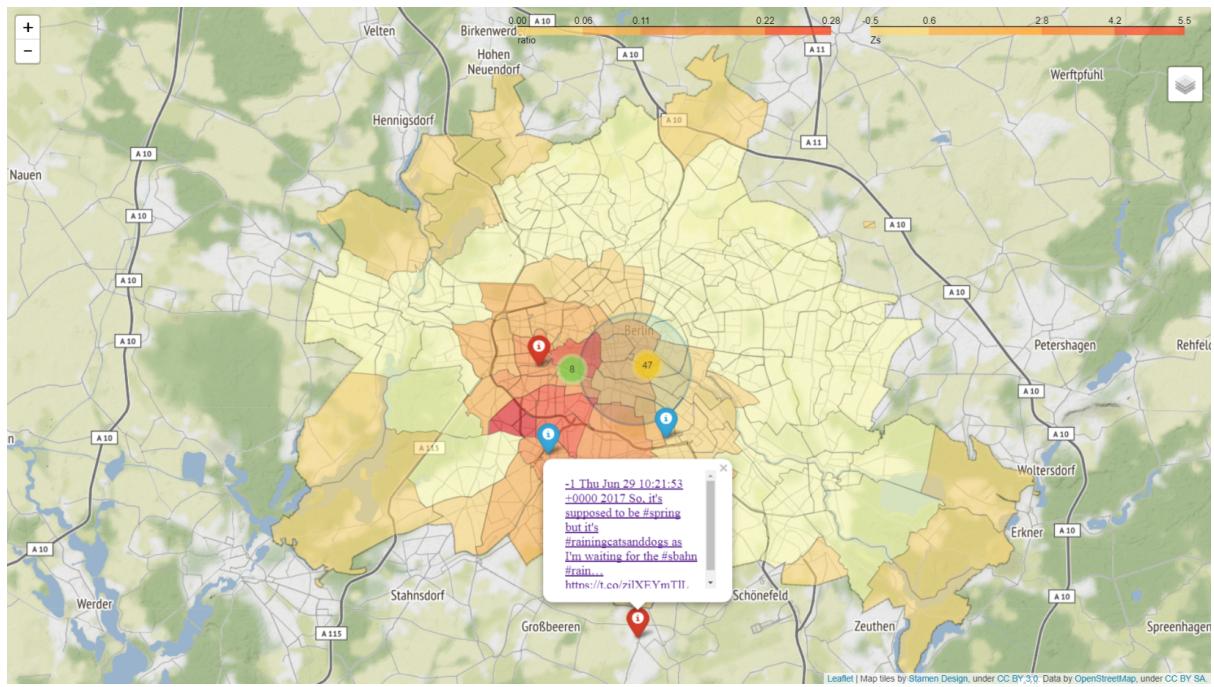


Figure 2.3: Web map application with pluvial flood in Berlin by Feng and Sester [11]

Barker and Macleod [3] visualizes the tweets using different map plots created by leaflet. The map plot in figure 2.4 consists of clickable pointers for pop-up boxes of the tweets.

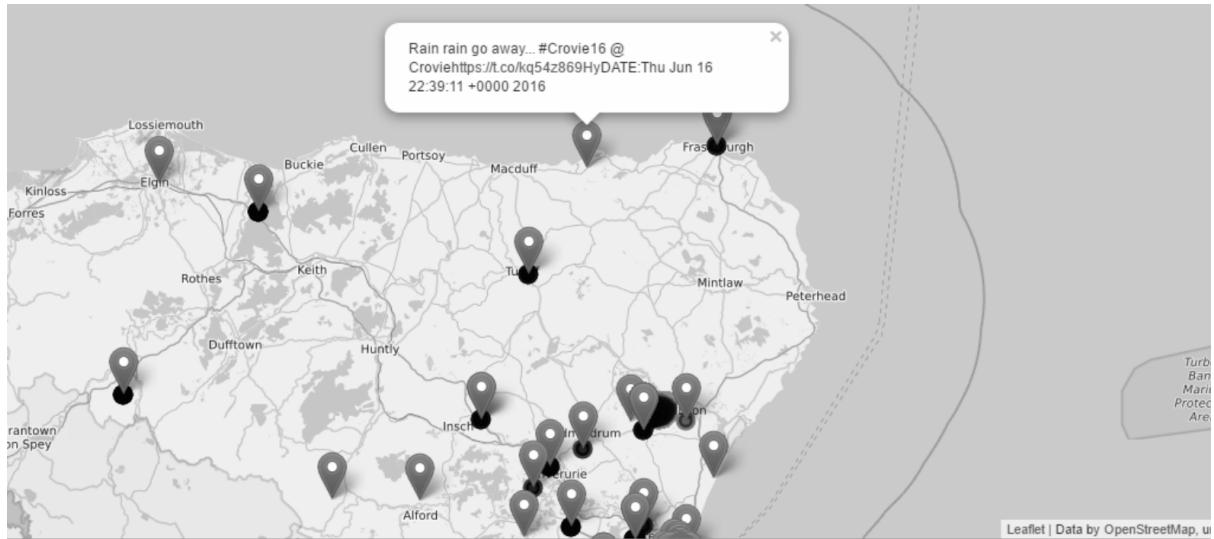


Figure 2.4: Map with tweet markers in by Barker and Macleod [3]

The bubble map in figure 2.5 displays the tweets with the size of the circles representing

ing the area of the place and colour indicating the number of tweets talking about the location.

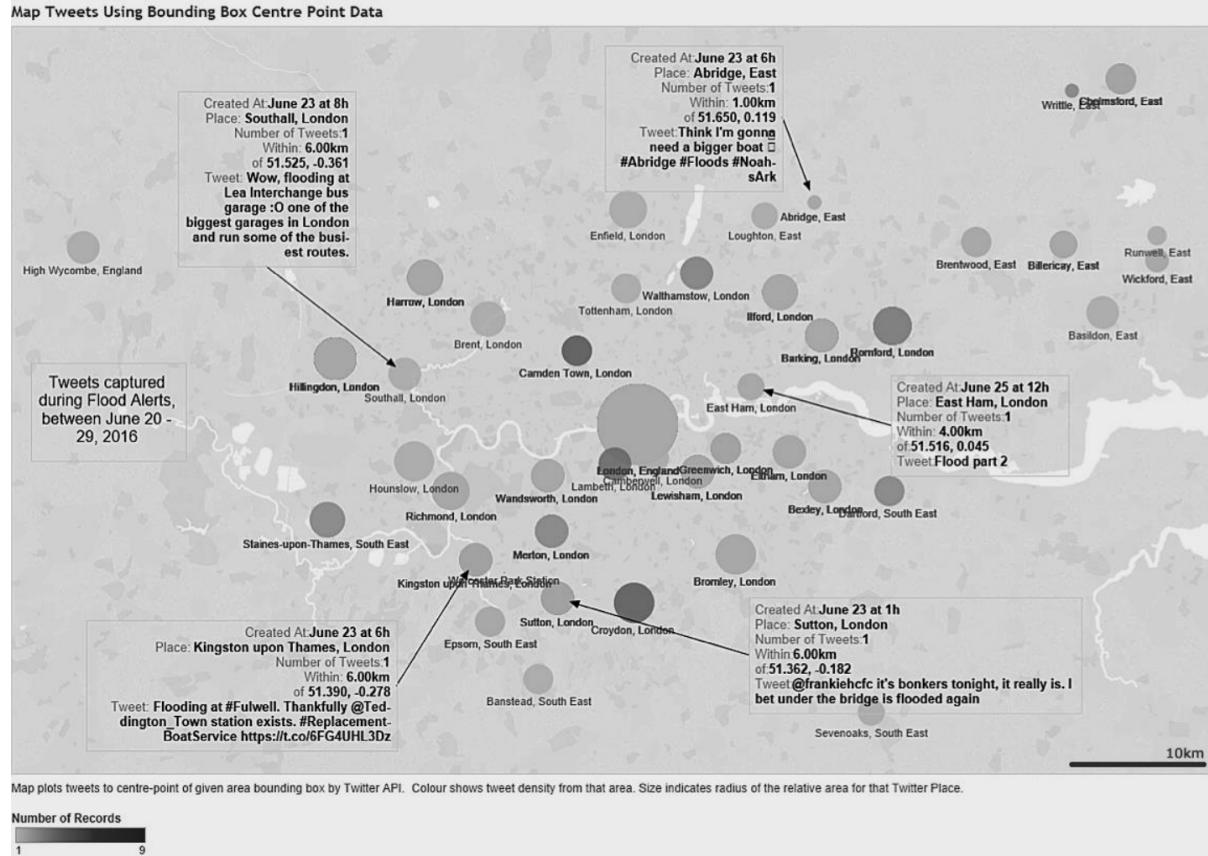


Figure 2.5: Bubble map of tweets by Barker and Macleod [3]

# Chapter 3

## Methods

Figure 3.1 shows a flow chart of the pipeline; (an enlarged copy is available in Figure A.1 of Appendix A)

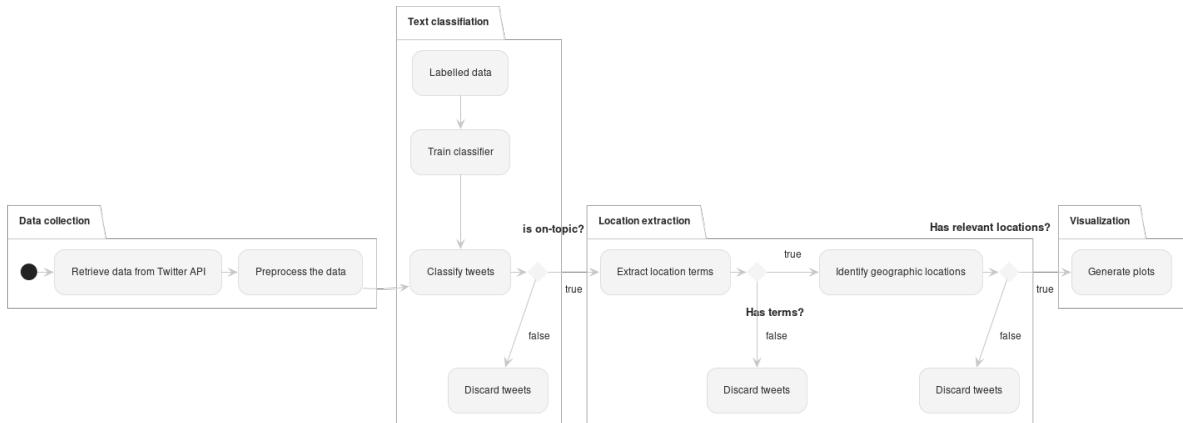


Figure 3.1: Flow chart for the pipeline

[Link to tentative notes for report](#)

# **Appendix A**

## **Diagrams**

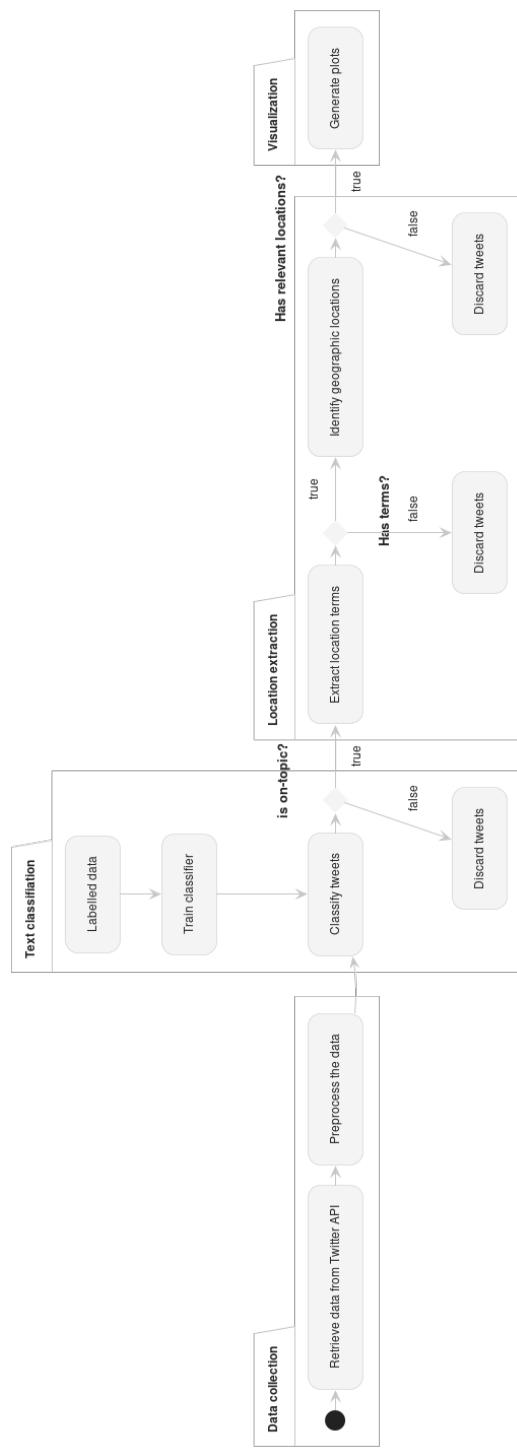


Figure A.1: Flow chart for the pipeline

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