Bachelor Degree Project

What we talk about when we talk about winners

- Using clustering of Twitter topics as a basis for election prediction

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Abstract

Social media has over the years partly become a platform to express opinions and discuss current events. Within the field of Computer Science, Twitter has been used both as the basis for political analysis - for example using sentiment analysis to predict election results - and within the field of cluster analysis, where the question of how to best design and use an algorithm to extract topics from tweets has been studied. The ClusTop algorithm is specifically designed to cluster tweets based on topics. This paper aims to explore whether it is possible to (a) use an implementation of the ClusTop algorithm to identify topics connected to tweets about Trump and Clinton just before the American 2016 election, and (b) distinguish between the topics used in connection with a specific candidate in states where they won versus states where they lost the election. The problem is approached through the method of a controlled experiment where the data collected from Twitter is divided into groups and run through the ClusTop algorithm. The topics are then compared to draw tentative conclusions about their validity as a basis for election prediction. The study finds that it is indeed possible to adapt the ClusTop algorithm to use with tweets and geolocation to identify different topics, thus confirming the usefulness of the algorithm. In addition to this, the study confirms that manually examining the words used within the topics makes it possible to see differences between them. The work thereby places itself in the tradition of exploring how Twitter can be used for election prediction by being one of the first studies to look at clustering as a way of approaching the problem.

Keywords: Twitter, clustering, cluster analysis, ClusTop, election prediction, election results, American 2016 election

Contents

1 Introduction

Social media has, over the years it has evolved, partly become a platform to express opinions and discuss current events with other users. This makes it a valuable resource that can be used, or misused, by anyone that wants to use those discussions to gain knowledge both about individual users and larger trends; especially Twitter makes it possible to collect data generated by thousands of users [1], and therefore pinpoint topics discussed in both time - since the tweets come with information of *when* they were uploaded - and space - since the tweets may come with information about *where* they were uploaded. Twitter has indeed been used this way within the field of Computer Science, in part as the basis for political analysis: attempts have been made to use detect Bot activities and analyze how they are used in campaigns [2], sentiment analysis has been used to predict election results [3], and what topics political parties tweet about and how has been the basis for research [4]. Another line of research involving Twitter has been within the field of clustering, or cluster analysis, where the question of how to best design and use an algorithm to extract topics from tweets has been studied [5].

What has not been done is combining the two to look at how the different topics extracted from a group of tweets can be used to predict the outcome of an election, which is what this thesis aims to look at - the paper will make a first attempt in the arena by looking at the American 2016 election of Clinton vs. Trump, and the possibility of predicting the electee in a swing state. A swing state, in American politics, is a state that could, within reason, be assumed to have the potential to be one by either of the two presidential candidates. These states are often the target both for political campaigns and for efforts to predict the outcome of the vote, since correctly predicting where the vote in a swing state falls is key to predicting the election result, and is, therefore, a suitable topic of interest for an exploration of using the clustering technique.

1.1 Background

1.1.1 Machine Learning

Machine Learning belongs to the field of Artificial Intelligence, which in turn is the field of intelligence that can be demonstrated by machines. The goal of Machine Learning is often said to be to find a way to make decisions, or predictions “[...]without being explicitly programmed to perform the task”[6]. To do this the study of Machine Learning is heavily focused on finding either algorithms or mathematical or statistical models that can be used to *train* the Machine in question. Generally Machine Learning is divided into the categories of supervised and unsupervised learning, where supervised learning, simply said, takes a set of inputs and known categories and learns to classify new inputs into these categories, and unsupervised learning looks at data and finds structure and patterns in that data without knowing what that structure might be [7].

1.1.2 Clustering

The task of clustering is to look at a set of data and classify that data into sets, or groups, that are deemed to be more similar than the other groups. Since it is not known beforehand what groups will be found, in regards to how clustering is used within Machine Learning, it falls into the unsupervised category.

Clustering is not an algorithm, but the task to be solved. Many different kinds of algorithms are used to perform clustering and are specialized in different things. Types of clustering models include but are not limited to connectivity models such as hierarchical clustering that cluster based on distance, centroid models such as k-means that cluster based on mean, graph-based models such as HCS that cluster in graph-form [8].

1.1.3 ClusTop

The ClusTop algorithm [5] is a type of graph-based clustering algorithm that is specifically designed to cluster tweets based on topics. Generally, tweet-topic algorithms have needed pre-knowledge in the way that a specific number of topics have been given to the algorithm in advance [5], but the ClusTop algorithm wants to see if it is possible to extract topics without knowing the number of topics in advance, making the algorithm more flexible and independent. The algorithm contains three parts, where the first is network construction, the second is community detection, and the third is topic assignment.

Starting with a collection of tweets, the first step creates a undirected graph with the contents of those tweets based on a selected definition of unigrams - the nodes in the graph - and relations between those unigrams - the edges of the graph. Unigrams are in the case of the ClusTop algorithm always defined as a single word, which means that the first step is to go through the collection of tweets and tokenize the words based on whitespaces. After that, three different decisions have to be made: 1) what type of word will constitute a unigram; 2) which pool of tweets or words will be used for finding relations; and 3) what kind of relation are we interested in. Hui Lim, Karunasekera, and Harwood suggests different potential answers to all of these questions and researches which combinations gives the most reliable results.

In relation to question 1, the potential candidates are all *words*, all *hashtags*, or all *nouns*. After selecting between what kind of unigrams we will be looking for relations we have to select which collection of words is interesting as a basis for finding those relations. Here three different alternatives are suggested by the authors: relations are only relevant between the words of the same tweet, or between all words in tweets using the same hashtag, or between all words in tweets mentioning the same users. In relation to the third question on what kind of relation we are looking for, we have to decide whether the words will be considered to have a relation if they are simply used together (*co-usage*), if they have to be used one after one another (*bigram occurrence*), or if a more complex system of aggregated relationships such as trigram (modelling the relationship between three words at once) or bigram + hashtag (modelling relationships between a bigram and all the hashtags found) should be used. The algorithm then loops through the words in each collection and adds the relevant unigrams and relations to the graph, or, if the relation already exists, increments the relation weight by 1.

The second step of the algorithm is the community detection. In this step a community detection algorithm is used. The authors here recommend the Louvain algorithm, which places each unigram in its own community, examines each unigram and its neighbour and combines these two unic ǵ rams into the same community if the modularity gain is greatest of all the neighbours, rebuilds the graph with the new unigrams, and repeats this until the graph stabilizes.

The third step of the algorithm concerns sorting tweets into different topics after the topics have been identified, which is not relevant for the scope of this work. This part of the algorithm takes tweets without a topic and matches the tweets against the topics found by running the first and second step, by looking at what topic has the highest co-occurence of unigrams matching those in the tweet. Pseudocode for the for the first two steps of the algorithm would look something like **Figure 1.1** below.

```
input : T : Collection of tweets in corpus.
output: A = (U, C): Assignment of unigrams U into communities (topics) C.

begin
 opt
   T = Aggregate tweets in T based on hashtag or mention;

 Initialize an empty graph G;

 for each tweet/aggregate t ∈ T do
   for each word-pair (p1 , p2) ∈ t do
      edge ← ({p1 , p2}, 1);

      if edge e exists in graph G
         increment edge e in graph G by 1;
      else
         add edge e to graph G;
 Return G;

 A = Assign all unigrams u into their own community;

 repeat
   for each unigram u ∈ G(U, R) do
      find max modularity and combine unigrams;
 until Community structure stabilizes and modularity score is maximized;

Return A;
```

Figure 1.1: Pseudocode for the first two steps of the ClusTop-algorithm.

1.2 Related Work

During the last decade, numerous studies have been made in regards to researching both analysis of tweets as big data and making election predictions, although few attempts could be considered completely successful. In addition to this, numerous attempts have been made in the field of topic modelling algorithms upon which Lim, Karunasekera, and Harwood [5] build when suggesting the ClusTop-algorithm, but none of the election prediction studies mentioned has used these algorithms, instead focusing more on sentiment analysis.

1.2.1 Election Prediction and Twitter

1.2.1.1 Twitter as a basis for research

Prabhsimran and Ravinder [11], in their study, did a literature review of the previous research that had been done on Twitter as a basis for election prediction. After going through this research, they came to the conclusion that countries in which the internet user percentage is above 80% are generally fit for analysis using Twitter as the base for election prediction.

1.2.1.2 Using sentiment analysis

The most relevant and notable works concerning election prediction in regards to Twitter are partly based on sentiment analysis - Andranik et. al. [12] came to the conclusion that, using sentiment analysis on twitter data, election predictions can be made, while O'Connor et. al. [13] used similar methods to conclude that tweets, at least, could be used in place of or as a supplement to traditional polling methods. Aparup [14] discussed the possibilities of using sentiment analysis together with regression analysis on the Indian elections and concluded that the biggest challenge in a country such as India as the collection of data.

1.2.1.2 Using other methods

Some studies using other methods have been made trying to predict election results with varying success, see for example Safiullah [15], who used regression analysis to some success, but none specifically using topic modelling. Closest comes Song, whose study partly used multinomial topic modelling together with network analysis to predict the 2012 Korean elections, and came to the conclusion that the technique could be used to identify content-based networks but did not in a satisfactory way predict the election result [16].

1.3 Problem Formulation

The paper aims to explore whether it is possible to (a) use an implementation of the ClusTop algorithm suggested by Hui Lim, Karunasekera, and Harwood [5] to identify topics connected to tweets about Trump and Clinton just before the American 2016 election, and (b) distinguish between the topics used in connection with a specific candidate in states where they won versus states where they lost the election. An additional point of interest is assessing whether the topics are put together in such a way that it would be suitable to use them as in-data for supervised machine learning. The result of these three points could then be used to determine if the ClusTop-algorithm could be used as a basis for an investigation into whether topics discussed in tweets can be used to predict election results.

1.4 Motivation

It has always been important for politicians as well as journalists and researchers to try and predict the outcome of an election. In addition to this, identifying what topics are discussed in relation to specific politicians or parties are relevant both as a springboard for sociological and political research and as well as a basis to train machine learning algorithms.

The field of web intelligence and machine learning is still in the process of being mined for possibilities for the first time. With an increasing reliance on algorithms and big data as a source of information, it is constantly relevant to assess whether certain ways of using that data is reliable. Researchers have already been using Twitter and other social media platforms to predict election results, to varying degrees of success [2, 3, 4], mostly using NLP and other types of machine learning to automatically use tweets to predict results. When restricting the research to giving the algorithm tweets and a result and having it predict results based on other tweets, you remove the possibility for a human to look at the result and use it independently. Doing a somewhat more primitive analysis such as clustering, and using that to manually check how the topics relate to each other lends itself to the possibility of not only predicting the result of upcoming elections, but also using the result as a basis for other types of analysis. The intent is to be able to use the result both for analysis of the topics themselves, in different areas of research, and to, within the field of Computer Science, see if it is possible to tie the topics to results in such a way that machine learning could be used to predict outcomes in different states in real-time during election night using tweets and known results from states already counted.

1.5 Objectives

O1	Implement ClusTop algorithm
O2	Collect Twitter data from selected states
O3	Extract topics from collected Twitter data using the ClusTop algorithm
O4	Compare the topics used in relation to Clinton in the state where she won and the state where she lost to see if there is a

	difference in topics
O5	Compare the topics used in relation to Trump in the state where he won and the state where he lost to see if there is a difference in topics

The result is expected be such as that the ClusTop algorithm will be capable of identifying different topics discussed in different sets of tweets, and therefore able to present topics tied to tweets about Trump where he won, topics tied to Trump where he lost, topics tied to Clinton where she won, and topics tied to Clinton where she lost. There is an uncertainty in regards to whether the topics will be different enough to be able to distinctly differentiate between the scenarios in a way that could be used to predict results, although the hope is that they will.

1.6 Scope/Limitation

To limit the scope of the project, only two states will be used as the basis for the analysis; the analyzed tweets will be taken from the month before the election, and only tweets mentioning the words Trump or Clinton will be collected. The two states selected will be swing states, where one swung to Clinton, and one swung to Trump. This will create four scenarios and tweet-pools to be clustered and compared - 1) Tweets about Clinton where Clinton won, 2) Tweets about Clinton where Clinton lost, 3) Tweets about Trump where Trump won and 4) Tweets about Trump where Trump lost. This limitation both restricts the scope of the analysis, since only a simple comparison between two sets of topics will be used rather than a multivariable analysis, as well as allows for a bigger volume of tweets to be analysed for each scenario. This is due to the rate limitation of 50 requests per month on the Twitter Search API – where each request returns 100 tweets – which means this project will be limited by the number of tweets it has access to as the basis for analysis. Given the four scenarios and the time span of the project over three months, the number of tweets analysed for each scenario will be around 4000.

1.7 Target Group

The target group of this study are primarily researchers within Computer Science, that are interested in how clustering of Twitter discussion topics can be used for event-prediction. Secondary target groups are researches within other academic subjects that are interested in how clustering can be used to extract topics of interest from certain groups on social media such as Twitter to then further build on that knowledge in their own research, as well as politicians and journalists who are interested in tools for predicting election results.

1.8 Outline

Chapter 2 discusses the method used to reach the objectives outlined above, with focus on how the data was collected and the choices made in implementing the ClusTop-algorithm, as well as the potential problems and pitfalls in regards to how the data is used together with the algorithm to reason about and solve the problem of the thesis, as stated above. Chapter 3 gives a description of the implementation of both the ClusTop-algorithm and the data-gathering scripts, including sequence diagrams. Chapter 4 presents the results of running the algorithm on the data collected, and Chapter 5 draws conclusions from those results. In Chapter 6 the drawn conclusions are related to the problem of the thesis as stated in the problem formulation above, and the thesis makes a claim in regards to the stated problem, and Chapter 7 looks to the future and how these findings can be used and built upon in further research.

2 Method

The problem will be approached through the method of a controlled experiment, since the aim is to measure and compare *quantitative data* - the topics extracted from tweets. The data collected from Twitter will be divided into four groups, corresponding to the scenarios outlined above. A series of experiments that provide data will then be conducted - the tweets belonging to each scenario acts as the independent variable, which is run through the ClusTop algorithm and provide us with the dependent variable, which is the topics discussed in each scenario. The topics are then compared to each other to draw tentative conclusions about their validity as a basis for election prediction in the view of a computer scientist - could these topics reasonably be the basis for using machine learning to speculate about election outcomes?

2.1 Data Collection

2.1.1 Data Selection

The tweets selected are from two American cities in two different states - Denver, Colorado and Columbus, Ohio. The reason for selecting these cities is that they are the state capitals and most populated cities in the selected states. The states have been chosen by virtue of being swing states - states that could reasonably be assumed to be won by either candidate - and that ended up being won by Clinton and Trump respectively, with quite a wide margin [9]. This creates a wider margin for error when using these states as a basis for prediction. The timespan is a month before the election, which means tweets from October 7th and forward, a timeline chosen to give enough of a selection of tweets from each state to be able to make a relevant analysis, while still staying as close to the election date as possible. All data is stored in JSON format for later analysis.

2.1.2 Twitter Queries

The Twitter Premium Search API has been used to gather Twitter data. Since the maximum requests allowed per month against the Twitter Premium API are 50, the script will be run three times - once per month - during the course of the study to collect the maximum amount of tweets. The queries for getting the selected tweets are respectively for collecting tweets about Clinton from Denver (**Code 2.1**), Clinton from Columbus (**Code 2.2**), Trump from Denver (**Code 2.3**) and Trump from Columbus (**Code 2.4**):

```
query: 'clinton place:Denver',
fromDate: '201610070000',
toDate: '201611070000'
```

Code 2.1: Query for collecting tweets about Clinton from Denver

```
query: 'clinton place:Columbus',
fromDate: '201610070000',
toDate: '201611070000'
```

Code 2.2: Query for collecting tweets about Clinton from Columbus

```
query: 'trump place:Denver',
fromDate: '201610070000',
toDate: '201611070000'
```

Code 2.3: Query for collecting tweets about Trump from Denver

```
query: 'trump place:Columbus',
fromDate: '201610070000',
toDate: '201611070000'
```

Code 2.4: Query for collecting tweets about Trump from Columbus

The queries are using the keywords 'clinton' and 'trump' in lowercase, rather than searching for the hashtag, a choice that has been made to include tweets both containing the hashtag and the word. The *place*-parameter limits the selection to tweets that have been tagged with the place given. This parameter has been chosen in favour of parameters that would return tweets where the geotagging have been turned on by the user and the tweets are therefore geotagged by default since this option is lesser used by the Twitter user base.

2.2 Data Analysis

2.2.1 ClusTop Algorithm

The ClusTop Algorithm will be implemented in Javascript, for ease of use with the collected tweets that are being stored in a JSON format. The algorithm is being implemented based on the description given by Lim, Karunasekera, and Harwood in [5].

2.3 Reliability and Validity

The data might be skewed by limited demographics in two ways: partly because only Twitter data is collected and analysed - which does not compromise the validity of the study since the aim is to study the possibility of tweets being used as the basis for election prediction - and partly because we are only studying tweets that have been tagged with a place, and this might tip the results in one direction or the other, depending on what demographic is most likely to geotag their tweets. We do not have any indication one way or another that place- or geotagging occurs evenly distributed over different demographics, and this is, therefore, a potential point of validity concern.

Another potential point of concern regarding validity is that the ClusTop algorithm might be implemented in a sub-optimal manner, resulting in it not accurately extracting the relevant topics from the data. A third concern is that the tweets collected will be too few to base the analysis on in a way that makes the results meaningful to discuss, a concern that has been considered but deemed acceptable since the number of tweets analysed is at least as many as in one of the datasets[10] used by the developers of the ClusTop algorithm.

Concerning reliability it can be considered to be quite high, if the Twitter API used in following studies is the same as in this study - using the Twitter Premium API, Sandbox version, with the queries given above, will always return the same tweets in the same order. This is in contrast to the Standard API, or crawling the website manually, as both those options provide a selection of tweets rather than returning all tweets matching the query, in reverse chronological order going back to 2006. Since the API used is the Sandbox version it does present us with a rate limit of 50 requests per month

- this means that using a paid version of the Premium API would return more tweets, and might, therefore, alter the result.

The results are also reliable as long as the same implementation of the ClusTop algorithm as the one being used here is used again - if the algorithm is re-implemented, it might return different results even if the implementation is based on the same instructions as the one being used in this study.

2.4 Ethical Considerations

When collecting data that can potentially be tied to a person, there is always a reflection on approach and necessity to be made. To avoid the risk that political opinions expressed will be tied to specific tweeters, and by proxy, to the real person behind the Twitter account, information that could be used to identify the individual tweets will be neither stored nor presented in the project.

3 Implementation

The software that has been implemented to answer the questions posed in the problem formulation consists of a series of scripts. There are two scripts to collect and clean the Twitter data, **Figure 3.1** and **Figure 3.2** below, one script to implement the ClusTop algorithm (**Figure 3.3** below) that will be used on the Twitter data to answer part (a) of the problem formulation - whether it is possible to use an implementation of the ClusTop algorithm suggested by Hui Lim, Karunasekera, and Harwood [5] to identify topics connected to tweets about Trump and Clinton just before the American 2016 election - and one script (**Figure 3.4** below) to provide the *first part* of the functionality needed to answer part (b) of the problem formulation - to distinguish between the topics used in connection with a specific candidate in states where they won versus states where they lost the election. The script goes through all topics and compares them to topics in different constellations, and removes all common words. This leaves us with topics covering only the differences between states and candidates, which will then be compared manually, without the help of the implementation.

The scripts are written in JavaScript and executed from the terminal using NodeJS, and the data is stored in JSON format. The scripts use two external libraries to support the main functionality, which will be discussed more in depth below - the node-opennlp-library v.0.0.1 [17] to connect with the Apache OpenNLP library[18] for part-of-speech-tagging, and the jLouvain-module v.1.2.0 [19] for the community detection-part of the ClusTop algorithm. Below are descriptions of the implemented scripts aided by sequence diagrams.

3.1 Implemented Scripts

3.1.1 TwitterSearch

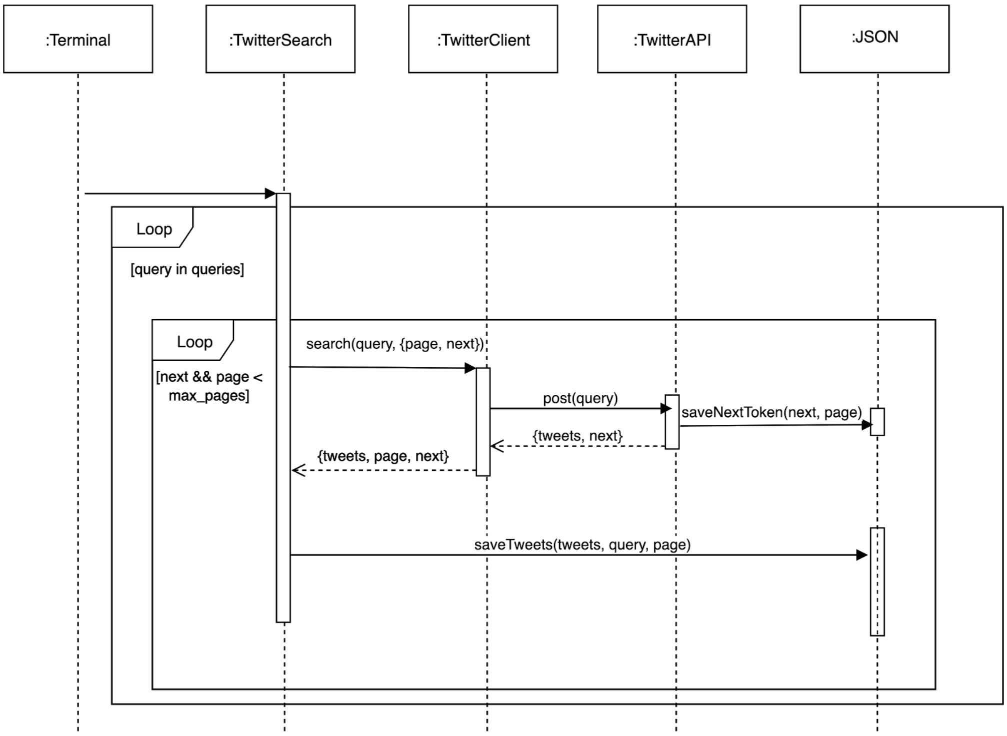

Figure 3.1: TwitterSearch sequence diagram showing the execution of the TwitterSearch script.

The TwitterSearch script calls the Twitter API with the four queries described in section 2.1.2, **Figure 2.1** through **2.4.** Due to the rate limit imposed by the Twitter API, the script has certain limitations as outlined below. The script uses the NPM library request-promise query the API.

The Twitter API only allows 50 calls per month to the API, and we are querying four different queries. This allows for 12 requests per query and month, the *page* variable as seen in **Figure 3.1** above. The script is run once per month during the course of the project, giving a total of 36 requests per query, each response containing 100 tweets, thus totalling 3600 tweets per candidate and location. To be able to continue collecting tweets where the previous request left off, the response from the Twitter API contains a *next*-token. Including this parameter in the query ensures that Twitter will return the tweets following where the last query left off, instead of returning the same tweets more than once. Further due to the rate limit of the Twitter

API and the fact that it allows 30 requests per 60 seconds, the script pauses for 65 seconds after every 20th request to the API to allow for a safe buffer.

The script then runs as follows: for each query, a call is made to the Twitter API with that query as well as a next-token, if such exists. The number of calls that have been made is incremented in the page-variable. When the response arrives the received next-token is saved away together with what page it refers to, and the tweets are saved away in JSON format in a different document that refers the query and page-number in the title. These steps are repeated, each time updating the next-token and the page count-variable, until the page count reaches the limit of 12.

3.1.2 CleanTwitterData

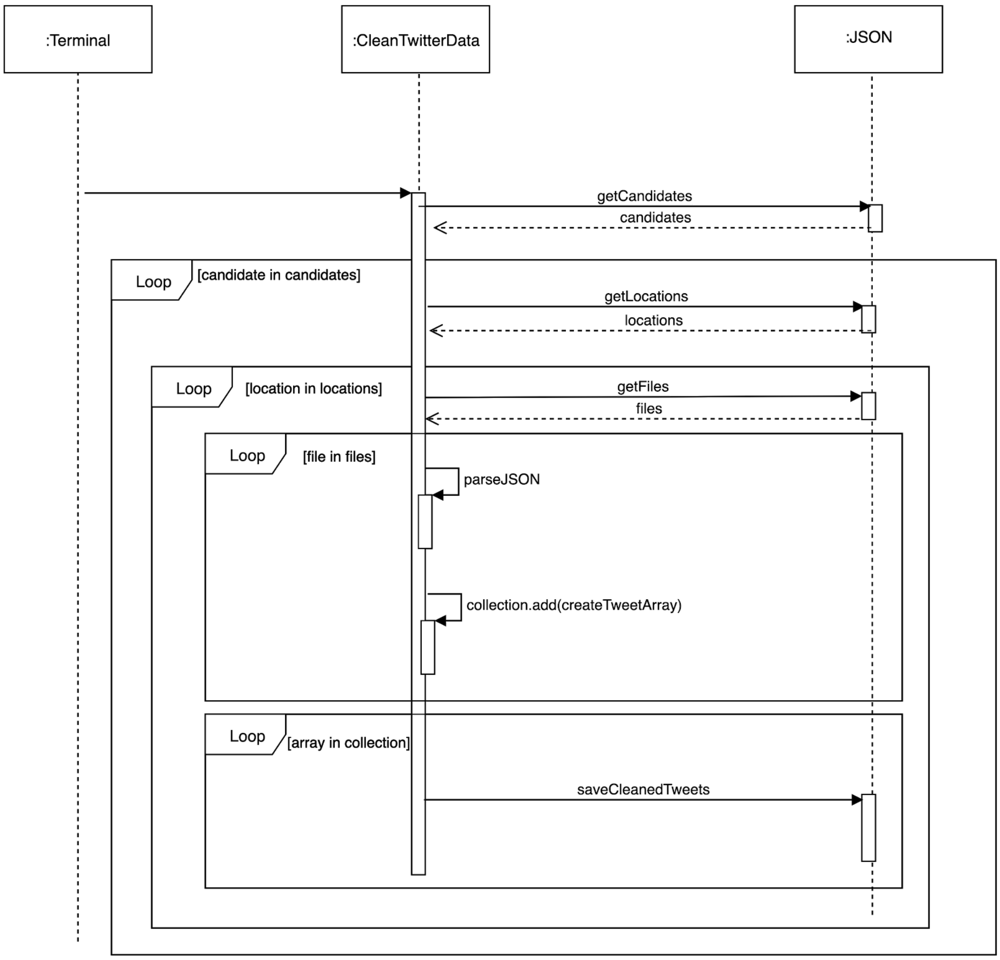

Figure 3.2: CleanTwitterData sequence diagram showing the execution of the CleanTwitterData script.

The CleanTwitterData script retrieves the collected tweets from JSON storage, separated by candidate and location. It loops through the separate pages saved in separate files, sanitises the information by removing everything but the text of the tweet and the day the tweet was made as to comply with the ethical considerations laid out in 2.4 above and re-saves the data in JSON format separated by candidate and location. This results in four files of object-arrays, each object representing one tweet: one for clinton-denver, one for clinton-columbus, one for trump-denver and one for trump-columbus.

3.1.3 ClusTop

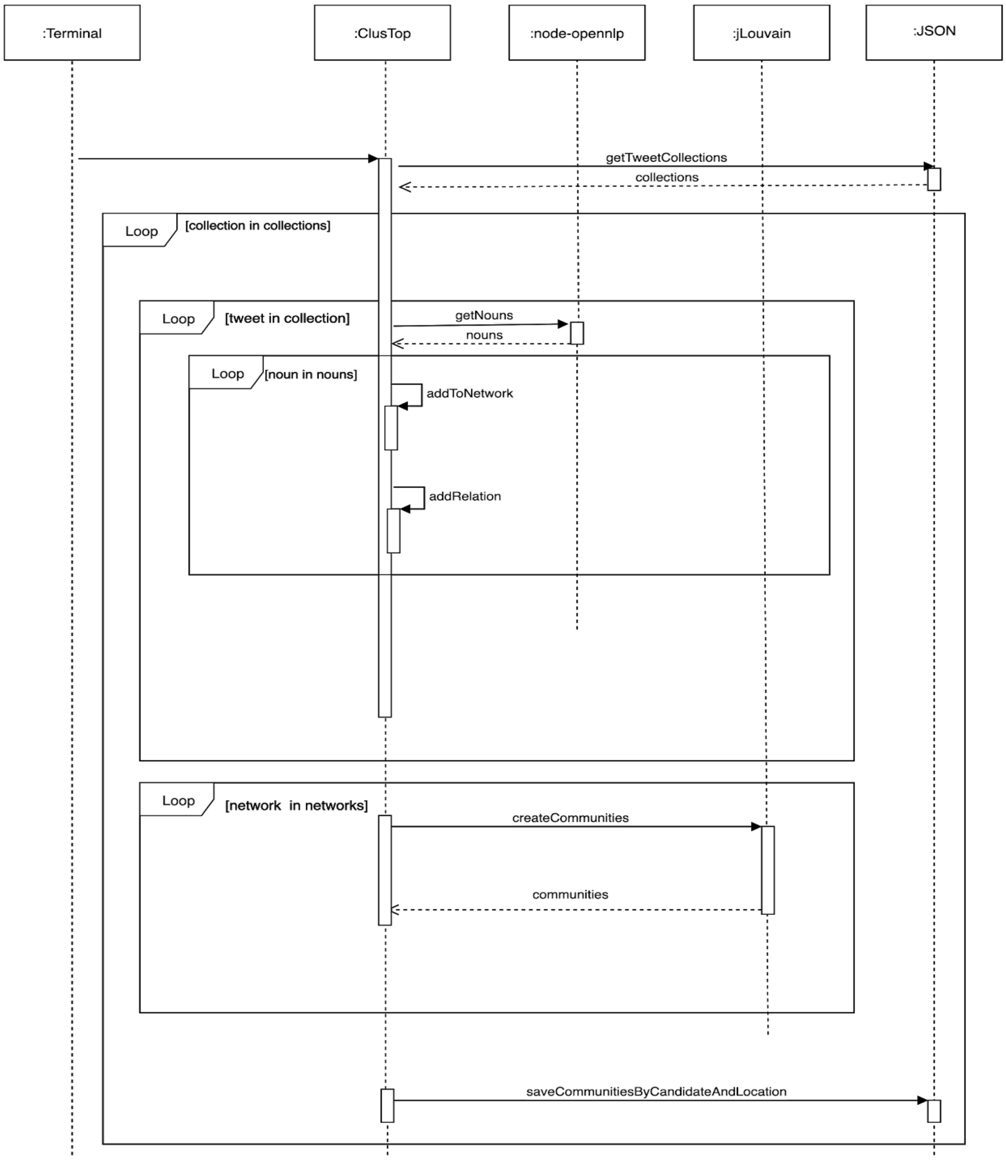

Figure 3.3: ClusTop sequence diagram showing the execution of the ClusTop script.

The ClusTop script first retrieves the object-arrays of tweets saved after running the CleanTwitterData-script above. It then proceeds to run the implemented ClusTop-algorithm on each of the tweet-collections in turn, to retrieve the topics for each candidate-location-collection of tweets, and save those topics away in JSON format, again separated by candidate and location. The script uses two NPM libraries: jLouvain[19] for community detection, and node-opennlp[17] to connect with the Apache OpenNLP library[18] for part-of-speech-tagging. The version of node-opennlp used is a local copy since the version published on npm does not have the latest required java-version as a dependency - an attempt was made to rectify this by making a pull request on the published package, but it had not been taken care of at the time of the completion of this paper.

The ClusTop-algorithm has been implemented in accordance with the pseudo-code and reasoning laid out by Hui Lim, Karunasekera, and Harwood in [5] in two steps: first, a network of nodes and edges is created, and then a community-detection algorithm is run on that network to separate the words used into community-clusters. Hui Lim, Karunasekera, and Harwood include a third step - the implementation for sorting tweets into different topics after the topics have been identified - which is not relevant for the scope of this work and therefore has not been implemented. It is conceivable that this third step would be relevant should the work be continued and the method used when trying to predict results in different states - in this case, the step would have to be implemented.

Hui Lim, Karunasekera, and Harwood suggest several different variants of the algorithm. They indicate that the network will be constructed in different ways, depending on "[...] (i) [...] different definitions of unigrams (vertices) and their relations (edges); and (ii) the type of document aggregation, i.e., individual tweets, aggregated by hashtag or mentions, for constructing the network graph" [5]. The choices that have been made in relation to those variants are the following: (i) the network is constructed based on co-noun usage. This means that a unigram, which in turn becomes the nodes in the network, is determined to be a noun, and two unigrams are said to be related if they are used in the same tweet; and (ii) the type of document aggregation used is individual tweets, which means relations have been built by a tweet-by-tweet basis rather than looking at a collection of tweets at a time.

The choice (ii) above is made due to the nature of our dataset - aggregating by hashtag is not going to give a satisfying result since the majority of the tweets are not using any hashtags, and aggregating by mention of other users are going to skew the result since most of the tweets mention either Clinton or Trump and would therefore be aggregated together. The choice (i) above is made due to the result of Hui Lim, Karunasekera, and Harwood's [5] study - when no aggregation of tweets is made, which is the case here due to the previous reasoning, the co-noun usage is the highest performing version of the algorithm.

The network is created by looping through the tweets, and for each tweet extracting the nouns using the part-of-speech tagging of the Apache OpenNLP Library[18] that Hui Lim, Karunasekera, and Harwood used while creating the ClusTop-algorithm, removing blacklisted words such as mentions of other users and links, and adding the nouns to the network as nodes if they have not already been added. A relation between two nouns is created as an edge between the nodes if they are used in the same tweet, or, if the relation already exists, the weight of the edge is increased.

The topics are then identified by running the Louvain community detection algorithm[19] on the network - the algorithm places each unigram in their own cluster. It then loops through all clusters and examines each neighbour, combining the two into the same cluster if their modularity gain is the greatest among all of the neighbours. When all the unigrams have been examined these steps are repeated until the modularity score is maximized.

The topics that are returned from this are collections of words in the form of arrays. These arrays are then saved away in JSON format, separated by candidate and location.

3.1.1 CompareTopics

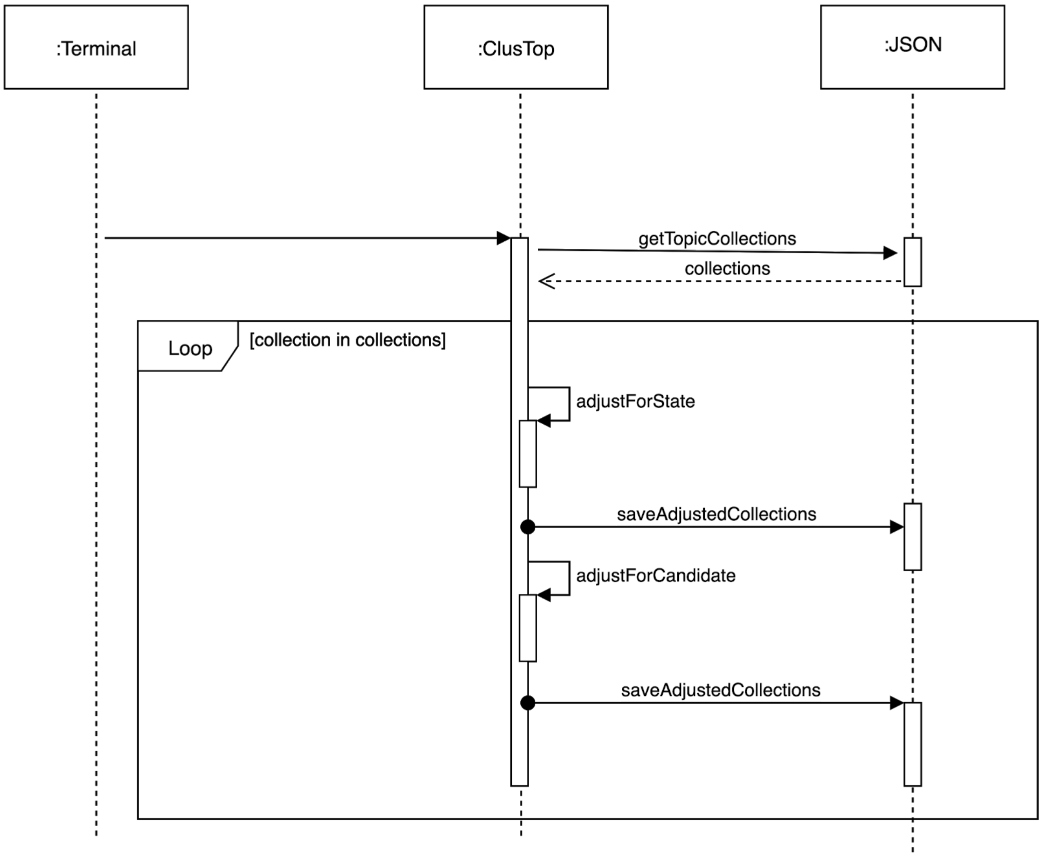

Figure 3.4: CompareTopics sequence diagram showing the execution of the CompareTopics script.

The CompareTopics-script compares the topics found running the ClusTop-algorithm to see if there are differences to be found between them. It starts by collecting the topics saved away using the ClusTop-script. It then performs two different adjustments - one where it adjusts for the state, and one where it adjusts for the candidate.

Adjusting for the state means that the script removes all words within the topics that are the same within each of the state when talking about the different candidates: i.e when looking at the topics for Trump in Denver and comparing them to the topics for Clinton in Denver, all common words are removed. This is then repeated for the topics for the respective candidate in Columbus. Adjusting for a candidate means that the script removes all words within the topics that are the same for each candidate across different states: i.e when looking at the topics for Trump in Denver and comparing them to the topics for Trump in Columbus, all common words are removed. This is then repeated for the topics for candidate Clinton.

The adjusted topics are saved away in JSON-format by candidate and location, leaving us with two batches of candidate-location specific topics to be compared manually amongst themselves.

The comparisons made are the following:

(a) Topics used when Trump won compared to when Trump lost.
(b) Topics used when Clinton won compared to when Clinton lost.
(c) Topics used when talking about Clinton in Denver compared to topics used when talking about Trump in Denver.
(d) Topics used when talking about Clinton in Columbus compared to topics used when talking about Trump in Columbus.

The comparisons are made by manually examining the topics after the script making the adjustments has been run. The comparisons are made on each of the adjusted batches separately, resulting in eight comparisons in total, discussed below.

4 Results

The Twitter data was collected 3 times during the project. In total 13,673 tweets were analysed and divided into topics depending on candidate and state. The result of the collection and topic division is presented in this chapter as a summary. A sample output from one of the runs, totalling the topics found for Trump in Denver, Colorado, is to be found in Appendix A. For a full list of the topics found and all words included see output stored separately online [20].

4.1 Tweets

State	Candidate	Total Number of Tweets
Columbus	Clinton	3476
	Trump	3300
		6776
Denver	Clinton	3353
	Trump	3544
		6897
Total		**13673**

Table 4.1: Total number of tweets collected.

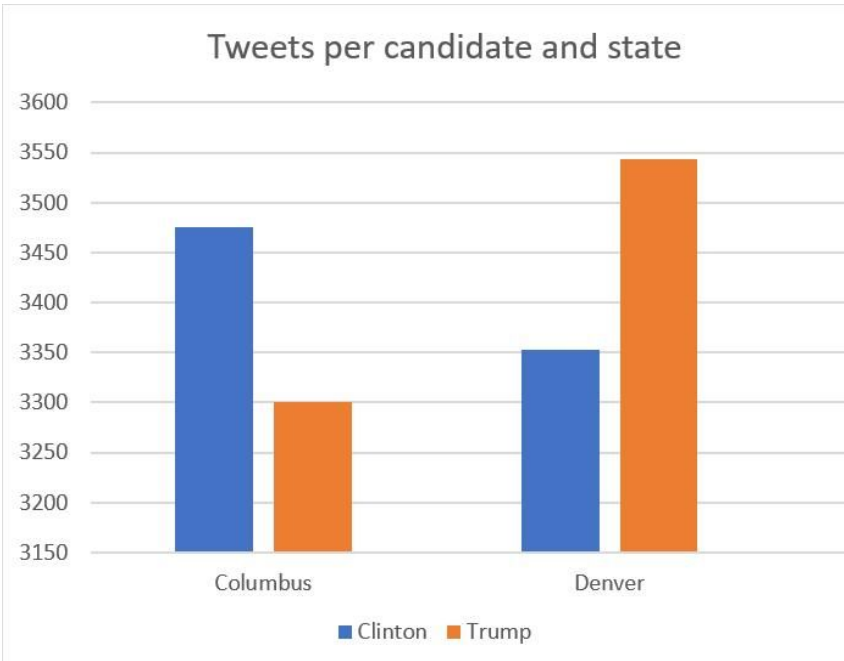

Figure 4.1: Tweets divided by candidate and state.

4.2 Topics

The topics are presented divided by state and candidate. For each candidate three scenarios are presented: first a summary of the topics without adjustments; then - to find the unique words for each state - adjusting for the candidate; then - to find the unique words for each candidate - adjusting for the state. The scenarios will be presented with the following points of interest: a) the number of topics found for the given scenario, b) the most commonly used words within the scenario, excluding the names of the candidates, and c) an illustration in the form of a word cloud, to give the reader a feeling for the words used within the topics in that scenario. All of these results are mainly presented to give the reader a chance to view and grasp the results of running the algorithm in an understandable way - for the full results divided into topics, including all the words per topic and not just the most common ones, see [20].

As discussed within the implementation chapter above, adjusting for the state means that all words within the topics that are the same within each state when talking about the different candidates are removed. This is done to separate the words used when talking about each candidate from topics that are generally discussed within the state. Adjusting for a candidate means that all words within the topics that are the same for each candidate across the states are removed. This is done to separate the words that are tied to the candidate in specific states from the words that are generally used when talking about the candidates.

The results for each state and candidate are presented below in the following order: Results from Denver, CO regarding Trump is presented in **Figure 4.2** through **Figure 4.7**. Results from Denver, CO regarding Clinton is presented in **Figure 4.8** through **Figure 4.13**. Results from Columbus, OH regarding Trump is presented in **Figure 4.14** through **Figure 4.19**. Results from Columbus, OH regarding Clinton is presented in **Figure 4.20** through **Figure 4.25**.

4.2.1 Denver, CO

Clinton was the winning candidate of the Denver election. The figures and tables on the following pages therefore represent the results of Clinton winning and Trump losing.

4.2.1.1 Trump

Summary

Number of Topics found: 197.

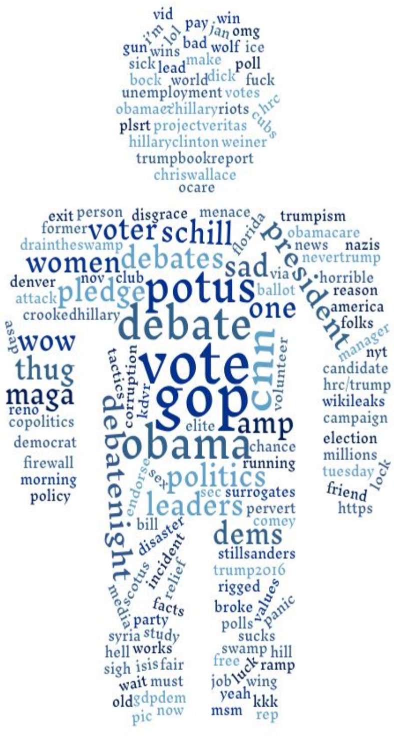

Figure 4.2: Word Cloud representing the most commonly used words in regards to Trump in Denver, CO. No adjustments made.

Most Common Words Trump - Denver, CO No Adjustments
vote
gop
debate
potus
obama
cnn
debatenight
president
politics
debates
leaders
pledge
schill
women
voter

Figure 4.3: Most common words in regards to Trump in Denver, CO. No adjustments made.

Adjusting for candidate

Number of Topics found: 197.

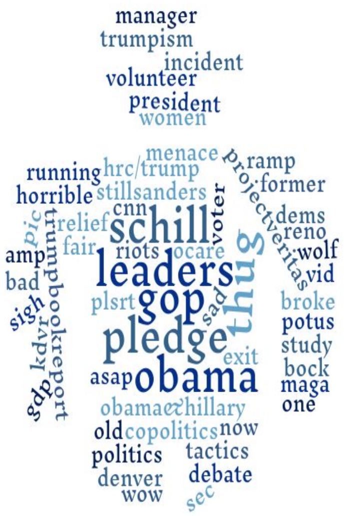

Figure 4.4: Word Cloud representing the most commonly used words in regards to Trump in Denver, CO. Adjusting for candidate.

Most Common Words Trump - Denver, CO Adjusting for Candidate
gop
leaders
pledge
schill
obama
thug
trumpism
trumpbookreport
incident
projectveritas
wolf
copolitics
volunteer
horrible
menace

Figure 4.5: Most common words in regards to Trump in Denver, CO. Adjusting for candidate.

Adjusting for state

Number of Topics found: 197.

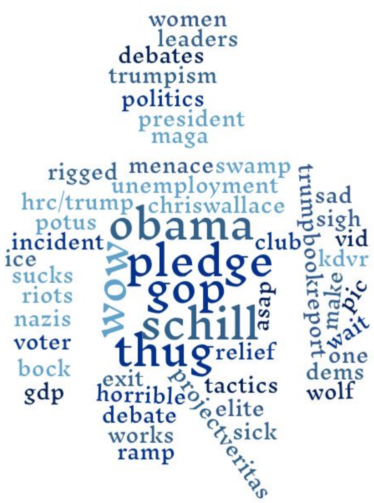

Figure 4.6: Word Cloud representing the most commonly used words in regards to Trump in Denver, CO. Adjusting for state.

Most Common Words Trump - Denver, CO Adjusting for State
gop
pledge
schill
obama
thug
wow
trumpbookreport
projectveritas
chriswallace
unemployment
hrc/trump
president
horrible
incident
politics

Figure 4.7: Most common words in regards to Trump in Denver, CO. Adjusting for state.

4.2.1.2 Clinton

Summary

Number of Topics found: 151.

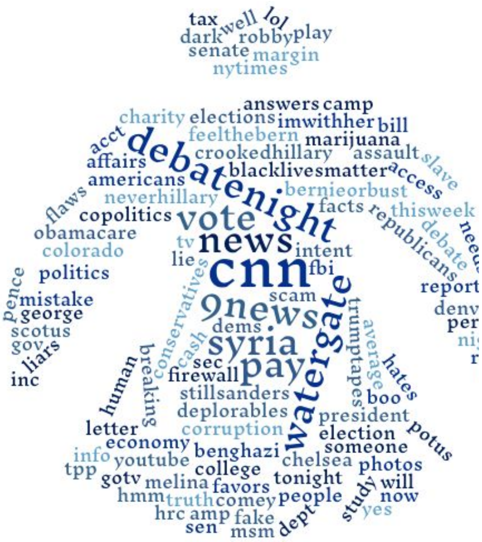

Figure 4.8: Word Cloud representing the most commonly used words in regards to Clinton in Denver, CO. No adjustment.

Most Common Words Clinton - Denver, CO No Adjustments
cnn
9news
news
debatenight
watergate
syria
vote
pay
blacklivesmatter
crookedhillary
conservatives
neverhillary
stillsanders
bernieorbust
feelthebern

Figure 4.9: Most common words in regards to Clinton in Denver, CO. No adjustment.

Adjusting for candidate

Number of Topics found: 151.

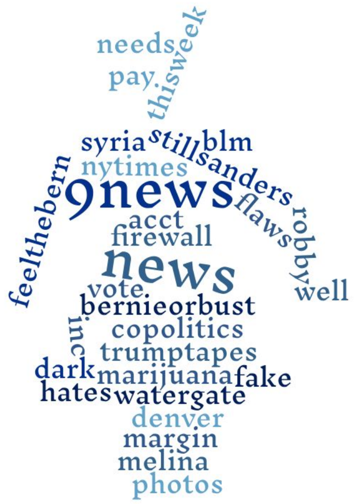

Figure 4.10: Word Cloud representing the most commonly used words in regards to Clinton in Denver, CO. Adjusting for candidate.

Most Common Words Clinton - Denver, CO Adjusting for Candidate
9news
news
fake
bernieorbust
feelthebern
copolitics
trumptapes
marijuana
watergate
firewall
nytimes
stillsanders
melina
margin
syria

Figure 4.11: Most common words in regards to Clinton in Denver, CO. Adjusting for candidate.

Adjusting for state

Number of Topics found: 151.

Figure 4.12: Word Cloud representing the most commonly used words in regards to Clinton in Denver, CO. Adjusting for state.

Most Common Words Clinton - Denver, CO Adjusting for State
9news
news
bernieorbust
watergate
marijuana
benghazi
thisweek
answers
mistake
affairs
nytimes
intent
photos
melina
robby

Figure 4.13: Most common words in regards to Clinton in Denver, CO. Adjusting for state.

4.2.2 Columbus, OH

Trump was the winning candidate of the Denver election. The following figures and tables therefore represent the results of Trump winning and Clinton losing.

4.2.1.1 Trump

Summary

Number of Topics found: 216.

Figure 4.14: Word Cloud representing the most commonly used words in regards to Trump in Columbus, OH. No adjustment.

Most Common Words Trump - Columbus, OH No Adjustments
cnn
landslide
debate
scotus
vote
etc
assassination
consequences
debatenight
corruption
misogynist
trumptrain
bombshell
dumptrump
halloween

Figure 4.15: Most common words in regards to Trump in Columbus, OH. No adjustment.

Adjusting for candidate

Number of Topics found: 216.

Figure 4.16: Word Cloud representing the most commonly used words in regards to Trump in Columbus, OH. Adjusting for candidate.

Most Common Words Trump - Columbus, OH Adjusting for Candidate
consequences
bombshell
dumptrump
ignorance
landslide
votegreen
hillsboro
marriage
progress
hypocrisy
heroin
scotus
sexist
yikes
weird

Figure 4.17: Most common words in regards to Trump in Columbus, OH. Adjusting for candidate.

Adjusting for state

Number of Topics found: 216.

Figure 4.18: Word Cloud representing the most commonly used words in regards to Trump in Columbus, OH. Adjusting for state.

Most Common Words Trump - Columbus, OH Adjusting for State
assassination
misogynist
votegreen
landslide
bombshell
hillsboro
attempt
puppet
heroin
please
scotus
savior
weird
nato
nbc4

Figure 4.19: Most common words in regards to Trump in Columbus, OH. Adjusting for state.

4.2.1.2 Clinton

Summary

Number of Topics found: 209.

Figure 4.20: Word Cloud representing the most commonly used words in regards to Clinton in Columbus, OH. No adjustment.

Most Common Words Clinton - Columbus, OH No Adjustments
cnn
scandals
people
debate
nasty
video
https
potus
voice
dnc
gop
clintonville
debatenight
deplorables
department

Figure 4.21: Most common words in regards to Clinton in Columbus, OH. No adjustment.

Adjusting for candidate

Number of Topics found: 209.

Figure 4.22: Word Cloud representing the most commonly used words in regards to Clinton in Columbus, OH. Adjusting for candidate.

Most Common Words Clinton - Columbus, OH Adjusting for Candidate
scandals
nigga
clintonville
compliment
flashback
buckeyes
dncinphl
science
melania
people
nasty
bucket
locker
unfit
jesus

Figure 4.23: Most common words in regards to Clinton in Columbus, OH. Adjusting for candidate.

Adjusting for state

Number of Topics found: 209.

Figure 4.24: Word Cloud representing the most commonly used words in regards to Clinton in Columbus, OH. Adjusting for state.

Most Common Words Clinton - Columbus, OH Adjusting for State
scandals
scam
people
clintonville
deplorables
compliment
department
flashback
vpdebate
buckeyes
dncinphl
science
birther
scandal
better

Figure 4.25: Most common words in regards to Clinton in Columbus, OH. Adjusting for state.

4.2.3 Overview

For the convenience of the reader, an overview of the above results is presented in the following tables.

Candidate	Number of Topics		Most Common Words			
	Winning State	*Losing State*	*Winning State*		*Losing State*	
			Adjusting for State	Adjusting for Candidate	Adjusting for State	Adjusting for Candidate
Clinton	151	209	9news	9news	scandals	scandals
			news	news	scam	nigga
			bernieorbust	fake	people	clintonville
			watergate	bernieorbust	clintonville	compliment
			marijuana	feelthebern	deplorables	flashback
			benghazi	copolitics	compliment	buckeyes
			thisweek	trumptapes	department	dncinphl
			answers	marijuana	flashback	science
			mistake	watergate	vpdebate	melania
			affairs	firewall	buckeyes	people
			nytimes	nytimes	dncinphl	nasty
			intent	stillsanders	science	bucket
			photos	melina	birther	locker
			melina	margin	scandal	unfit
			robby	syria	better	jesus
Trump	216	197	assassination	consequences	gop	gop
			misogynist	bombshell	pledge	leaders
			votegreen	dumptrump	schill	pledge
			landslide	ignorance	obama	schill
			bombshell	landslide	thug	obama
			hillsboro	votegreen	wow	thug
			attempt	hillsboro	trumpbookreport	trumpism
			puppet	marriage	projectveritas	trumpbookreport
			heroin	progress	chriswallace	projectveritas
			please	hypocrisy	unemployment	wolf
			scotus	heroin	hrc/trump	copolitics
			savior	scotus	president	volunteer
			weird	sexist	horrible	horrible
			nato	yikes	incident	incident
			nbc4	weird	politics	menace

Table 4.2: Summary of the number of topics as well as commonly used words for Trump and Clinton respectively over both states.

Candidate	Most Common Words	
	Winning State	***Losing State***
	No Adjustment	No Adjustment
Clinton	cnn 9news news debatenight watergate syria vote pay blacklivesmatter crookedhillary conservatives neverhillary stillsanders bernieorbust feelthebern	cnn scandals people debate nasty video https potus voice dnc gop clintonville debatenight deplorables department
Trump	cnn landslide debate scotus vote etc assassination consequences debatenight corruption misogynist trumptrain bombshell dumptrump halloween	vote gop debate potus obama cnn debatenight president politics debates leaders pledge schill women voter

Table 4.3: Summary of the commonly used words for Trump and Clinton respectively over both states.

5 Analysis

The results provide a few points of interest for the analysis. Firstly it is worth mentioning the number of tweets collected. The number is slightly higher for Clinton in Columbus and for Trump in Denver - about 200 tweets falling both ways, which will of course somewhat impact the analysis since the total number of tweets is not very large. As previously mentioned, a gathering of a larger number of tweets would give a more stable and thusly more reliable result.

	Columbus	Denver
Clinton	16,6	22,2
Trump	15,3	18

Table 5.1: The average number of tweets per topic, divided by state and candidate, rounded to one decimal.

The number of topics found divided by the number of tweets collected by candidate and state gives us the average number of tweets by topic. The amount of tweets per topic is high enough given the low amount of tweets analysed that it is feasible to think that the same technique could be used on a larger number of tweets to gather topics that in turn could be used as in-data to train a model using machine learning, to achieve a model that could classify tweets.

As seen throughout the result report in the previous chapter, the number of topics found does not change when adjustments for state or candidate are made. This indicates that the topics are already different enough between the state and the candidates, and it is possible to argue for these adjustments being superfluous, and thus that they could be omitted in future uses of the technique to simplify the steps. While the length of this study is not sufficient to draw any real conclusions from the data, this seems to indicate that the algorithm works in regards to identifying distinct topics from the tweets given.

Using the topics found as a basis to manually check how they relate to each other shows differences between the words commonly used in relation to the different candidates in the different states, as can be seen in **Table 4.2** in the chapter above**.** The aim of the study is not to discuss why certain topics or words are found, but rather to discuss the usefulness of the algorithm in finding topics as well as looking at the possibility to differentiate between types of topics, and what kind of out-data is provided. Therefore no statistics on the frequency of the different words found has been included, as that has been determined to detract from this main focus by shining the spotlight on the specific words used and inviting to speculation of why those specific words are prevalent. The result of the study is the actual full topics that can be found at [20]: the results as presented in the previous chapter are merely formatted to give the human reader an overview. Even so, a short look at the words is useful to show the difference in topics.

Candidate	Most Common Words	
	Winning State	*Losing State*
	No Adjustment	No Adjustment
Clinton	cnn 9news news debatenight watergate syria vote pay blacklivesmatter crookedhillary conservatives neverhillary stillsanders bernieorbust feelthebern	cnn scandals people debate nasty video https potus voice dnc gop clintonville debatenight deplorables department
Trump	cnn landslide debate scotus vote etc assassination consequences debatenight corruption misogynist trumptrain bombshell dumptrump halloween	vote gop debate potus obama cnn debatenight president politics debates leaders pledge schill women voter

Table 5.2: The words connected to the candidates in different states, with unique words highlighted.

Looking at **Table 4.3** again, here presented with highlights as **Table 5.2**, it is possible to see a difference in what words are used in the topics are found in relation to both candidates in both states. The words unique for where the candidate won are presented above in orange, and the words connected to where they lost are presented in blue. As we can see in **4.2** the topics differ both in number and, as seen in **5.2** here at a manual examination, in content - where Clinton won there are words connected to Bernie Sanders, something not at all present where she lost, where instead the unique words are centered around scandal, deplorable and nasty, for example. In the state where Trump won the unique words include corruption, misogynist and trumptrain, whereas where he lost they are talking about obama, politics, schill and women. Again: this is not a reflection or a speculation about why certain words are used, and if that in itself could possibly mean something: the results as presented above are merely a way to suggest and show that there is a possibility of finding differences in the topics identified by the algorithm. The ClusTop algorithm as implemented seems to be able to find topics connected to each candidate using the tweets given.

6 Discussion

The problem, as stated, was to explore whether it is possible to (a) use an implementation of the ClusTop algorithm suggested by Hui Lim, Karunasekera, and Harwood [5] to identify topics connected to tweets about Trump and Clinton just before the American 2016 election, and (b) distinguish between the topics used in connection with a specific candidate in states where they won versus states where they lost the election. An additional point of interest was to assess whether the topics are distributed and put together in such a way that it would be feasible to use them as in-data for supervised machine learning. The hope was that result of these three points could be used to determine if the ClusTop-algorithm can be used as a basis for an investigation into whether topics discussed in tweets can be used to predict election results.

The findings of this study show that the answer to the question of *a,* whether the ClusTop algorithm can be implemented to identify the searched for topics, is a definitive yes. This was also the result we expected of the conducted study, that the algorithm would be capable of identifying different topics discussed in different sets of tweets. We can clearly see that the algorithm has both found and distinguished topics connected to both Trump and Clinton separated by state, above in chapter 4 and in Appendix A. The usefulness of the ClusTop algorithm in this scenario has thusly been confirmed, which touches upon the further research suggested by Hui Lim, Karunasekera, and Harwood themselves, to adapt the algorithm to account for geolocation. In regards to *b*, whether the topics are different enough to be able to distinguish between the results in different states, there was uncertainty before the study was conducted. The result of the carried out study somewhat confirms this uncertainty, since the method of manually examining the topics is not completely reliable - what has been shown is that upon a manual examination the words used in the different sets if topics are distinguishable from one another. A much larger study would have to be carried out across both a larger number of tweets and more states, to be able to compare between states and see if there is a pattern in what kind of topics are used when the candidate wins or loses - all this study can confirm at this point is that when comparing these two particular states, the topics differ. Whether this is possible to tie to the candidates winning or losing status has not been confirmed nor denied within the scope of this study.

In regards to the third point of interest, it is tentatively suggested in the analysis that the amount of tweets per topic is high enough given the low amount of tweets analysed that it is feasible to think that the method could be used to generate sufficient data to train a model to classify tweets into topics, using machine learning techniques. This is, of course, speculative since none of this kind of research has been conducted within the scope of the study, but it takes out a direction of interest that could be fruitful if explored.

All in all the results are tentative, much as they were expected to be at the start of the study. This places the work in the same category as previous works that have been done in the area, where most of the works suggest that tweets, in different ways, could work as a basis for tentatively predicting election results. This study does not do what the previous work has done in that it does not try to predict or classify anything - what the study provides to the field is instead the usefulness of using the ClusTop-algorithm combined with geolocation to extract topics for further study. The results are such that a very tentative yes could be expressed in relation to the question as to whether the method could be used as a basis for further studying election prediction using tweets.

7 Conclusion

The study set out to implement the ClusTop algorithm and use it on a collection of tweets about Trump and Clinton from two different states before the American 2016 election, to see if the algorithm would be able to identify different topics and if differences of those topics could be seen. The study has found that it is indeed possible to adapt the ClusTop algorithm to use with tweets and geolocation to identify different topics, thus confirming the usefulness of the algorithm. In addition to this, the study confirms that manually examining the words used within the topics makes it possible to see differences between them, The work by this places itself in the tradition of exploring how Twitter can be used for election prediction by being one of the first studies to look at clustering as a way of approaching the problem.

One of the weak points is the scope of the project and the amount of data used - to get better results larger amount of tweets should be used, and to get more conclusive results in relation to possibly predicting election results in different states more states would have to be analysed and compared. The method used to compare the topics - to manually examine them - also introduces a point of uncertainty as to whether they are different enough to serve as the basis of predicting tweets from other states. With more time and resources this would have to be examined to further determine the usefulness of the approach in relation to using machine learning to differentiate between the topics, and predict topics for unclassified tweets. One of the main points of this study is therefore to serve a pointer towards where other, large scale, studies could go.

One of the strengths of the study, on the other hand, is that what is being studied is the method of using the ClusTop algorithm in relation with tweets about elections, which means it is not tied to specific data - this method could be used in relation to any election where tweets and geographical divides are of interest. The study also shows relevance outside of the field of Computer Science, by showing how different topics and point of interest could be collected from tweets and used as a basis for other types of analysis such as within the fields of Sociology and Political Science.

7.1 Future work

Although, as seen, interesting conclusions can be made by manually examining the results, the nature of them is probably better suited for machine learning analysis. A topic consists of a cluster of words, and the third part of the Hui Lim, Karunasekera, and Harwood [5] ClusTop algorithm not implemented under the scope of this paper looks at tweets and determines in what topics they should be put. Future work could build upon this by taking the conclusion of this paper - that the ClusTop algorithm can be used to differentiate between topics used in relation to different candidates - and move in one of two possible directions: a) Look at other states where the candidates won or lost, and compare the topics extracted from those states with each other, to see if there are common denominators within topics used together with the candidates when they won or lost, or b) using machine learning together with implementing the third part of the algorithm mentioned above to see if it is possible to collect tweets from states and run them through the algorithm to predict the winner in that state based on what topics the tweets are classified into. Potential future work could also fall outside the field of Computer Science by looking at the topics found in relation to each candidate as the basis for, for example, a sociological study.

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A Sample output of ClusTop-algorithm

A sample output of all the topics found and the words included in each topic when running the ClusTop algorithm on the tweets about Trump from Denver, Colorado and making no adjustments for state or candidate. For a full list of the topics found and all words included see output stored separately online [20]. Each topic is separated by square brackets.

[["tickets","violence","sport","thing","world","sunday","day","https","trum
p","trippin'","fam","play","pence","vote","voting","machine","request","pap
er","ballot","ur","counts","god","loser","falwell","that’s","room","talk","
hail","satan.","sin","stone","#meantweets","game","conservatism","judge","f
act","jesus","sinners","#maga","hannity","mr.","admission","he’s","clinton"
,"mole","genius","kristol","—","your","fault","own","trump’s","bill","i’m",
"gop.","rubio","/shoots","guy","primary","fraud","%","congrats","feels","mo
ment","gop","faulty","machines","&","count","rallies","30k","millions",
"kaine","florida","people","enthusiasm","hillary","showup","year","party","
donald","nominee","lets","indict","h","election","justice","acct","actions"
,"hmm","job","obamacare","something","new","forfeited","kaines","rally","ni
ght","attendance","yuge","cnn","lie","supporter","deal","breaker","el","pas
o","county","times","week","numbers","bias","display","#lockherup","#trump"
,"south","tweet","salsa","difference","reality","data","polls","self","awar
eness","elect","pres","web-","part","campaign","media","supporters","crush"
,"elite","establishment","take","our","country","back","from","king","obama
","defeat","queen","reason","return","america","democracy","americans","dic
tatorship","control","govt","","“nyt","prints","list","insult","tweets","fa
mily","usa","liar","tou","bar","👎","corruption","decades","every","preside
ncy","series","transactions--one","pop","quiz","lot","i","broncos","orange"
,"kid","words","syllables","period","shouts","sign","□clinton","□","elway",
"✔","emails","co","voters","#copolitics","watch","video","weeks","washingto
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gs2","riot","christians","rights","#clinton","supreme","ct","someone","face
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t","denver","sleaze","ball","crowd","elizabeths","tax","fashion","ppl","tyr
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nder","potential","opponents","heaven","demagoguery","passions","trumpism",
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enators&congressmen","anyone","candidates","4drugs","tues","results","h
illary&trump","picture","son","elephants","accuser","minutes","shame","
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ets","record","individual","donors","excuse","use","thug\"","wannabe","thir
d-world","strongman","thug","rt","peter","thiel","report","|","problem","ra
cism","misogyny","taniel","john","kasich","nov/dec...","trump...and","#wiki
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ents","thousands","edge","post-election","peace","...i","crap","links","day
s","poison","internet","friendship","threat","incitement","threatens","poli
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ntain","nwikileaks","e-mails","attorney","general","2assign","rnc","gops","
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esparate","plane","aisle","firstclass","hopefully","case","principled","wre
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ns","dumpster","liberals","ones","praise","institution","“leaders","line","
gop**","gop’s","admiration","gratitude","i’ve","canada","fast","opinion","b
ogeyman","chuck","plunkett","jake","t","wolf","ru","apologize","guts","need
s","breaking","investigations","plsrt","dump","btw","moot","house","deadloc
k","incident(","trump....","utah","texas","loony","alt-right","rants","davi
d","duke","g.o.p.","want","statement","apprentice","contestant","nightmares
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es","*also*","murder","terrorists","families","oil","torture","lies","found
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by","rules","unskew","evan","mcmullin","egg","mcmuffin","main","stream","bu
t","continue","fight","still","have","my","limbaugh","independents","approv
e","breitbart","cool","women","sides","abortion","choice","terms","tendency
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eremony","#flotus","board-dems","millenials","blacks","asfacts","springs","
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s","thanksgiving","fun","concerns","proof","lack","rebuttal","school","grad
s","i’ll","image","carriages","relatives","neighbor","employees","vote4","w
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gseth","boy","gene","sperling","pass-throughs","map","wilbur","ross","trade
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ank","decorum","tpc","analysis","\"politics","hitler","analogies","republic
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ll","\"policy\"",".hilary","ground","---&gt",";&gt","gettysburg","votetrump
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wamp","ethics","al","smith","dinner","\"lock","chants","tangent","rd","busi
ness","expense","rn","companies","growth","china","india","illiteracy","lev
el","goodness","fucking","problems","ohio","construction","cardinal","dolan
","moments","chart","lead","holds","uproar","-","ibd/tipp","vs","presidenti
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ng","contributions","#falseflag","operations","#nazis","-donald","she","sai
d","ny","swells","cant","relationship","coffman","…","roasting","lol","joke
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ns","daughters",".e","winner","yho","mrs.","sleeping","show=dems","nice","o
ptimism","election…if","foot","exam","poor","absolutely","evil","daddy","jo
hnson","outcome","republican","editorial","mean","blue","zoolander","bastar
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e","ramblings","risk","economics","backtrack","hes","snapping","fingers","o
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opaganda","spreads","sounds","cassette","nose","quick","space","idiots","re
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r","pisses","favors","#restingbitchface","shill","bloodshot","wall","pathwa
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hinese","liberty","pursuit","happiness","!U","limits","congress","hatred",
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ctile","dysfunction","pill","calling","ban","pic","idea","or...","refuse","
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it","colleague","theory","hq","left","williams","inability","advance","gues
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retary","spokeswoman","lambaste","narratives","bombing","terrorism","absent
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lic-wikileaks","violence@trump","skills","trump&amp","uranium","#rush","&am
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amp;lynch","christ","u.s.","bolt","leaders","legendary","pat","schroeder","

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e","yard","way2","start","lust4","before","clock","excitement","symphony","
slavery","steps","weakness","squeeze","failure","choose","wisely","momentum
&support","rebuild","islam",",not","stops","bash","revenue","locals",")
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