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A comparative study on credibility judgement of news related tweets between academic and non-academic young adults

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Abstract

For many young adults, retrieving information and news from the internet is not an uncommon task. A large portion of said information is shared through social media. However, social media is not always a reliant news source, due to the fact that the content is largely crowdsourced. One of the social media and micro-blogging services is Twitter. Twitter allows anyone to share information about anything through messages called "tweets". This leads to fast propagation of news across the world. However, it lacks a filter to sort out false news. This thesis researches whether higher education has an impact on credibility judgement in young adults. The results show that overall, young academics are more prone to scepticism than non-academics regarding news relayed through a social media such as Twitter.

Referat

En jämförande studie om trovärdighetsbedömningar av nyhetsrelaterade tweets mellan akademiska och icke-akademiska unga vuxna

För många unga vuxna är det inte ovanligt att få information och nyheter från internet. En stor del av denna information delas genom sociala medier. Emellertid är sociala mediers nyhetskällor inte alltid en trovärdig informationskälla, främst på grund av att informationen oftast kommer från användarna. En av dessa sociala medier är mikrobloggtjänsten Twitter. Twitter låter vem som helst dela information om vad som helst genom meddelanden kallade tweets". Detta leder till snabb spridning av nyheter över hela världen, men saknar ett filter för att sortera ut falska nyheter. Denna avhandling undersöker om högre utbildning påverkar trovärdighetsbedömningen hos unga vuxna. Resultaten visar överlag att unga akademiker kan vara mer benägna än icke-akademiker att vara skeptiska till nyheter som delas via sociala medier som Twitter.

Contents

Chapter 1

Introduction

Since its adaptation as an everyday communication tool, social media has ensued to play an eminent role as an information source for people. An example of this is Twitter, a social media and microblog service. On Twitter, users post messages composed of no more than 140 characters, which are also referred to as “tweets”. Initially, Twitter served as a platform where people could share information and express their opinions, but has since then grown to a platform where global news can be followed in near real-time. Due to the convenience and broad reach of Twitter, it has not only been embraced by the public, but also by influencers, governments, corporations and news sources, who use it as a platform to reach and communicate with their respective audiences.

As a result of this, social media and microblogs begin to replace traditional media outlets such as journals and television as a source for acquiring news and information [1]. A major difference between information on social, in comparison to traditional media, is that social media is to a great extent crowdsourced. Nonetheless, social media does provide a strong asset to traditional medias in order to quickly obtain information regarding the occurrence of a newsworthy event. However, due to the anonymous and lenient nature of a social media such as Twitter, the quality of information regarding factuality becomes an essential concern.

Chances are for fabricated information and rumours being spread when information is made available in a context-free form such as through Twitter. This is a recurring issue and was recently made evident during the Stockholm terror attack, where people reported shootings occurring at different locations around the city, evidently all rumours turned out to be hoax [2]. Research has shown that people judge credibility based on multiple different constructs, and rely on different cues such as domain knowledge and source credibility to determine the credibility [3].

1.1 Problem Statement

Misinformation on social media has become an evident problem in society today. The purpose of this paper is to research the effect of academic education on young adults credibility judgement regarding news related information on social media, especially Twitter. The study aims to investigate the following:

- Does academic education or an inclination towards academic education influence young adults judgement of news related information on Twitter?
- Are there any common characteristics to the tweets that impact said peoples judgement of credibility?

1.2 Approach

In order to investigate the research question a scraper will be built with the intention of collecting tweets based on a set of predefined news topics from the start of the year 2017. The collected twitter data will afterwards be parsed and determined to be true or false, also referred to as the truth-value of the tweet. Two focus groups consisting of academics and non-academics in Stockholm between the ages $20-25$ will assess the credibility of the collected tweets. The result from the credibility assessment will then be further compared to the actual truth-values of the information within the tweets. Possible characteristics that increase the credibility of a tweet or topic will be explored and compared between the two groups. The results from the assessment will lastly be discussed and conclusions drawn.

1.3 Thesis Outline

The following chapter of the thesis paper presents relevant background information, definitions and research related to the study. The subsequent third chapter presents the procedure of the study. The fourth chapter depict the results obtained from the assessment. The fifth chapter discuss the results and how the study could be improved further. The sixth and final chapter summarises the discussion and concludes the research question.

Chapter 2

Background

This chapter begins with a description of Twitter, a vastly used social media and micro-blog, succeeded by an explanation of Web scraping and the Document Object Model. What follows are definitions for recurrent terminology used in the paper, such as credibility and academic. Lastly, the chapter presents a section on previous research related to the subject.

2.1 Twitter

Twitter is an online social network and microblog service where users post and interact using messages called ”tweets” containing up to a maximum 140 characters. It was founded in 2006, has over 3000 employees, has currently over 300 million active users[4] and is one of the 15 most visited websites in the world [5]. Registered users are able to post tweets, either public ones or specifically to their followers, while unregistered users may only read the public tweets. This has made Twitter into an efficient way to relay news and opinions across the world, with an average of 6000 tweets posted per second, or roughly 190 billion tweets in a year [6]. Because of the availability and ease of relaying of information, Twitter is used by governments, news sources, influential people and the like to communicate directly with their respective audiences. However, because Twitter is available for anyone to use, a user’s credibility can at times be questioned.

Twitter can be paired into two types of features, user features and content features [19]. User features include information about the author of a tweet, referred to as the tweeter. This information includes verification status, registry date, amount of followers, amount of people the user follows (also called friends on Twitter), whether the user has a bio and amount of tweets posted by user. Content features include, but are not limited to: length of a tweet, amount of likes of tweet, amount of people who forwarded the tweet (called retweeting, shortened RT), whether the tweet contains emoticons or special characters, mention of another user (called a mention) and a tag (called a hashtag, binding the tweet to an event or subject).

Twitter offers an advanced search function beyond the normal search function, which allows a user to search for tweets using certain attributes that are not available in the normal search function. This includes specific date ranges, places, users and tailored word searches. Used in a browser, it loads a certain amount of tweets until a user scrolls down to the bottom of the feed, at which point additional tweets are loaded asynchronously. This process can be repeated until all the tweets related to the search are displayed.

2.2 Document Object Model

The Document Object Model (DOM) is an application programming interface for HTML and XML documents. It is founded on an object structure that resembles the structure of the HTML and XML documents it models, and defines a way that the structure can be accessed and manipulated [9]. Using the DOM, it is possible to build documents, navigate through their structure and manipulate the elements and its content. Everything found in an HTML or XML document can be altered using the DOM [9].

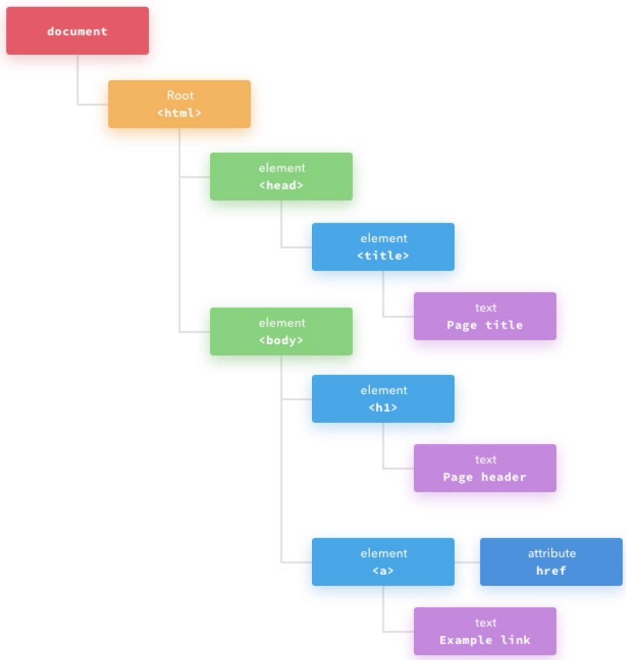
In the DOM, the document is represented as a structured group of nodes and objects with properties and methods. Essentially, the DOM is an object-oriented representation of a document [10]. A key objective for the DOM is to provide a standard programming interface that can be implemented by a vast variety of environments and applications, therefore the model was designed to be implemented by any programming language [9].

Figure 2.1. Example HTML snippet

```
<html>
    <head>
        <title>Page title</title>
    </head>

    <body>
        <h1>Page header</h1>
        <a href="https://www.svt.se/">example link</a>
    </body>
</html>
```

Figure 2.2. DOM representation of the HTML code in **Figure 2.1**



2.3 Web scraping

Webpages frequently contain a wealth of useful data in human-readable form. However, since most web pages are designed primarily for human eyes, this information could prove difficult to retrieve programmatically with the use of a computer. Web scraping is a technique used to retrieve and extract data from a human-readable output of a webpage. Although scraping can be manually accomplished by a human, the term typically refers to automated processes during which a bot or a crawler is used. Usually the way data is scraped from a website is similar to that utilised by search engines, which is to simulate human-behaviour when using a browser.

2.3.1 Dom Scraping

DOM scraping is a type of web scraping and entitles the manipulation of the DOM in order to scrape desired data. Initially the web page has to be fetched and downloaded, similar to when a browser requests a web page. Once the web page has been fetched, the densely formatted markup of the document is parsed and processed into a DOM tree, a logical structure that resembles the one seen on **Figure 2.1b** [9]. After the data extraction is commenced; using the DOM, the parsed tree can be queried for the desired data and extract for use at a later point.

2.4 Definition: Academic

An academic is defined as someone who has finished or is currently studying in a college or university of higher degree [8].

2.5 Definition: Truth-value

The truth-value is binary and defined as the truth or falsehood of a proposition. Or in other words, either of the values true or false that may be asserted to a statement [23].

2.6 Definition: Credibility

Credibility can be defined as believability [11]. As a result of research mostly from the fields of psychology and communication dating back to the 50s, scholars within the subject generally agree that credibility is a perceived quality, it is a human perception or evaluation of an object. The scholars also agree that credibility isn't but one thing, but an evaluation of multiple aspects, key components being identified as "trustworthiness" and "expertise"[11].

Trustworthiness is objective, and is defined as the degree which a person can be relied upon, both in what is said and done. If what a person says is true, and they do as they say they would, these are signs of a trustworthy person. Expertise is defined by knowledge, experience and competence, and is also an objective quality. It concerns the source of the information. If a person is trustworthy, but not credible, the person will not be trusted. In contrast, they may be dishonest, but appear credible, and will therefore win the perceiver's trust [12].

Fogg and Tseng(1999) [11] describes four types of Credibility. "Presumed credibility" describes how much the perceiver believes someone or something because of general assumptions in the perceiver's mind. "Reputed credibility" describes how much the perceiver believes someone or something because of what third parties have reported. "Surface credibility" describes how much a perceiver believes someone or something based on simple inspection. "Experienced credibility" refers to how much a person believes someone or something based on first-hand experience.

2.7 Definition: News

News is defined as a "material reported in a newspaper, news periodical or a newscast on a matter that is newsworthy" [13], where newsworthy is defined as a matter

”being interesting enough to the general public to warrant reporting”[14]. Breaking news can be defined as ”newly received information about an event that is currently occurring or developing” [15] and as ”news that has either just happened or is currently happening.” [16] with the additional definition ”breaking news may contain incomplete information, factual errors, or poor editing because of a rush to publication”. With this definition, Twitter can fit the needs of breaking news delivery as in some cases it has been confirmed to be first on reporting breaking news [17, 18].

2.8 Previous Research

Castillo et al. (2011) [19] focused on automatic methods for assessing credibility of tweets. They analysed ”trending” topics on Twitter and classified them as credible or not credible based on extracted user and content features. They compared human assessments with automatic annotations and found that they could classify a tweet as credible or not with precision and recall in the range of 70% to 80%.

Sikdar et al. (2012) [20] discuss how user surveys are unbiased, but also uninformed. They bring up that the assessor might not have knowledge about the subject, they often don’t know the tweeter, and the survey happens after the event, not catching how it would be perceived in real time. In-network proxies may be informed, but biased and noisy, reputation and personal relations within the network may corrupt the assessor, but may also improve the assessment. To try this, they created two datasets on the same topic from different perspectives, one during, and one after the event. Their findings show that using multiple independent credibility measures and combining them results in ground truth measures that can be predicted with high accuracy and that are stable across different datasets and survey methods.

Gupta et al.(2012) [21] used a graph-based optimisation and PageRank-like credibility propagation on a multi-typed network consisting of events, tweets and users. Within each iteration, they enhanced basic trust analysis by updating event credibility scores using regularisation on a new graph of events. Results showed an 86% accuracy in comparison to a decision tree approach with only 72% accuracy. They observed that credible users provide credible tweets with a high probability. They also found that with a high probability, average credibility of tweets related to a credible event is higher than that of tweets related to a non-credible event.

Gupta and Kamaragu (2012) [22] performed linear logistic regression analysis on content and user features. They showed that automated algorithms using supervised machine learning and relevance feedback approach based on twitter features can be effectively used in assessing credibility of information in tweets. Their report included collecting event based tweets based on hashtags about the event and found that 50% of tweets were related to the event, though generally personal opinions or reactions. 13.5% spam containing words belonging to topic but not related to event. 30% had information about event, but only 17% were credible. They also found that the number of unique characters positively correlated to credibility. Swear words indicated opinion or reaction, and had a less chance of providing information. The regression analysis showed that both content based features and user based features were strong indicators of credibility.

Chapter 3

Method

The research conducted in this study aims to be quantitative. Two focus groups were used in order to investigate the question at hand. The two focus groups are, as previously mentioned, academics and non-academics within the age span 20 to 25. Initially, this chapter begins with a section describing the data collection process, information regarding the scraper built and the selection of topics used in the study. Following is a section describing how the collected data was parsed. The last section describes the experiment performed using the parsed data.

3.1 Data collection

In order to conduct the experiment, Twitter data had to be retrieved. Although Twitter offered a wide range of APIs, none of them suited the requirements of this study. The search API would have sufficed, however, it was not possible to query tweets older than a week. Therefore the advanced search functionality of Twitter was used instead, and a scraper was built to automate the data retrieval process and to save the extracted data to a database. The extracted data was separated into content based features and user based features, which were stored separately in the database. The selected features are explained in detail below.

Table 3.1. The desired tweet based data

Property	Description
id	Unique numerical id of a tweet
text	The tweet in text form
hashtags	Comma separated list of hashtags
mentions	Comma separated list of accounts mentioned in the tweet
user_handle	Handle of the user that tweeted
lang	Abbreviated name of the language used in the tweet
date	Timestamp for when the tweet was created
permalink	URL to the tweet

Table 3.2. The desired user based data

Property	Description
handle	Unique string literal of the user, e.g realDonaldTrump
name	Display name of the user, e.g Donald J. Trump
biography	Description entered by the user in their profile, e.g 45th President of the United States of America
followers	Amount of accounts following the user
following	Amount of accounts the user follows
tweets	Amount of tweets a user has tweeted, retweets included
verified	Flag specifying whether the account has been verified as authentic by Twitter
permalink	URL to the account

3.1.1 Building the scraper

The scraper was written in Python, using the Selenium framework in conjunction with the libraries BeautifulSoup and MySQLdb. Selenium allowed for automation of browser behaviour, which was used to request and retrieve the result from Twitter's advanced search function. The search endpoint returned a JSON response, which contained the markup of the tweets to be loaded, as well as an attribute that specified whether more tweets were available for the feed to load.

BeautifulSoup was then used to parse the markup retrieved from the search response into DOM structure, which was then queried in order to retrieve and extract the desired tweet data. The scraped tweet data was then stored into the database using MySQLdb. Due to the possibility for a tweet to contain multiple hashtags, the same tweet could appear again while scraping a different hashtag. However, the id of a tweet remained static, and since this id was the primary key of the tweet table in database, the tweet was never stored more than once.

Figure 3.1. Example of the pop-up that appears when hovering over an author's Twitter handle

In order to retrieve information related to the user, a second request was made. As seen on **Figure 3.1**, a pop up appeared while hovering over the author's twitter handle. The pop-up presented information regarding the author's account, and was retrieved asynchronously. The API endpoint used to retrieve this data was therefore requested in order to fetch the data. Since the response resembles the one received by the advanced search endpoint it was also implemented in a similar manner.

3.1.2 Selecting Topics

Eight topics were chosen based on breaking news events that occurred during the year 2017 [7]. After having determined the dates for the events, the topics were manually researched on Twitter in order to find the most frequently used hashtags within each topic.

Table 3.3. Selected topics with their respective hashtags and the dates queried

Topic	**Related hashtags**	**Dates**
Metallic Hydrogen	#metallichydrogen, #physics, #harvard	25 January - 30 January
Trump's immigration ban	#immigration, #muslimban, #refugeeban	26 January - 31 January
North Korea's ballistic missile launch	#northkorea, #missile, #ballisticmissile	10 February - 15 February
South Korea's presedential scandal	#southkorea, #scandal #parkgeunhye, #impeachment	8 Mars - 15 Mars
UK's withdrawal from the EU	#brexit, #article50 #eu, #uk	28 Mars - 6 April
SpaceX re-flight	#space, #spacex, #falcon9, #rocket	29 Mars - 3 April
Syria chemical attack	#syria, #syriaattack #chemicalattack	4 April - 10 April
Stockholm terror attack	#prayforstockholm, #openstockholm #drottninggatan, #stockholmattack	6 April - 11 April

3.2 Data Parsing

Once all tweets had been collected, the data parsing process was initialised. The reasoning behind parsing the data was to eliminate tweets that were irrelevant to the experiment. This could for instance be tweets considered to be spam, or if the language used in the Tweet was neither English nor Swedish. In addition to this, it was also determined that in order to more easily be able to determine the truth-value of the Tweets, opinions should also be eliminated from the database.

Therefore the database was cross-referenced with a lexicon for tweets containing words typically used in a statement such as “does”, “says” and “claims”. Tweets containing profanities were removed, since they often were an indication of an opinion or reaction[22]. While cross-referencing, the tweets were assigned a sentiment value, ranging from 0 to 1, where a higher value indicated that the tweet characterised an opinion. In order to eliminate as many opinions as possible, tweets with a sentiment value greater than 0.2 were removed from the database.

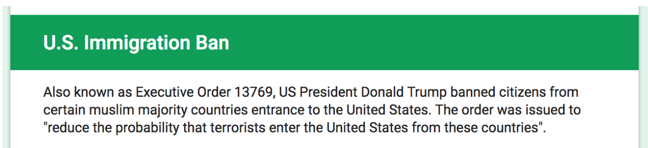
Lastly, a subset of the remaining tweets was selected and the truth-value of these tweets was determined. The tweets were divided into three categories; true, false and uncertain. If a tweet had at least one major news site confirming the claim, and none disputing the statement, the tweet was deemed true, henceforth referred to as a "true tweet". Additionally, tweets where multiple news sources disputed the claims made were deemed false, henceforth called a "false tweet". Remaining tweets were deemed uncertain, since it wasn’t possible to definitely confirm or deny the claims made. The uncertain tweets were removed from the database and were not included in the experiment.

3.3 Experiment

Because of the cost of large-scale human annotation, Google Forms was used instead of a more expensive alternative. Google Forms is a free to use survey tool with included graphs of responses. The survey created was delegated through contacts on social media and through a discussion website.

The survey consisted of two sections. The first section explained the definition of an academic and asked the assessor whether they were an academic or not. It also asks the assessor’s age, to make certain that the correct targeted age group answered the survey.

Figure 3.2. Explanation of a topic



The second section began with explaining credibility and what type of reasoning regarding the tweets was expected of the assessor. It told the assessor to read each question before each tweet carefully and study each tweet closely. Following this, the survey consisted of 70 tweets divided into 8 topics, ranging from three up to five true tweets and three to five false tweets. In the beginning of each topic, there was a small explanation of the event at hand, see Figure 3.1.

Each tweet had two answers, "Credible" and "Not credible" as well as a specific question tailored for the tweet to assure that each assessor judged the tweet based on the same ground premise, see Figure 3.2.

Figure 3.3. Example of tweet question

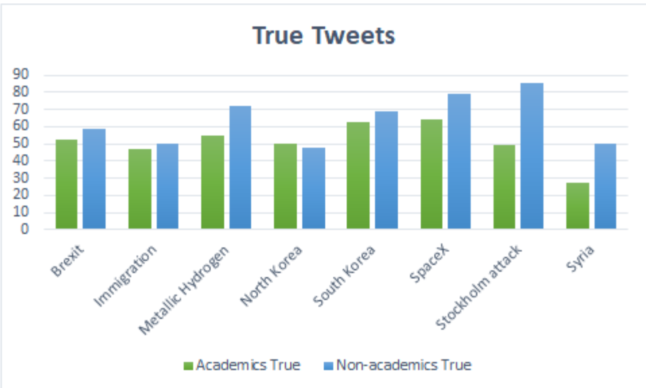
Chapter 4

Results and analysis

This chapter describes the results retrieved from the experiment. A total of 44 responses from assessors within the correct age-span were collected over a course of five days. 26 assessors defined themselves as academics while 18 considered themselves to be non-academic. After dividing the responses gathered from the two focus groups, the responses were divided further into two categories, one for true tweets and one for false tweets. The mean of each groups credibility judgement for each topic was evaluated, as well as the average credibility judgement of all topics combined.

4.1 True Tweets

Figure 4.1. Percentages of assessors judging the true tweets as credible

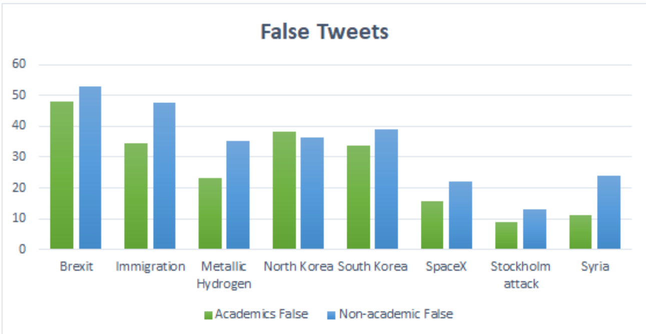


For the tweets annotated as true, fewer of the academics deemed the tweets credible than the non-academics in all topics except for tweets regarding the North Korean missile launch, where a slightly larger percentage of the academic assessors judged the tweets as credible. In 5 out of the 8 topics, roughly half of the academic assessors judged the tweets as credible. For the topics regarding the South Korean presidential impeachment and the SpaceX Falcon 9 relaunch, about 60% of the academic assessors found the tweets credible while only 30% of them found the tweets regarding the Syrian gas attacks credible.

In a majority of topics, the difference in percentage between the groups judging the tweets as credible were marginal, ranging from 5-15%. However, in the tweets regarding the Stockholm attack and the Syrian Chemical Attack, the differences were closer to 36% and 22% respectively.

4.2 False Tweets

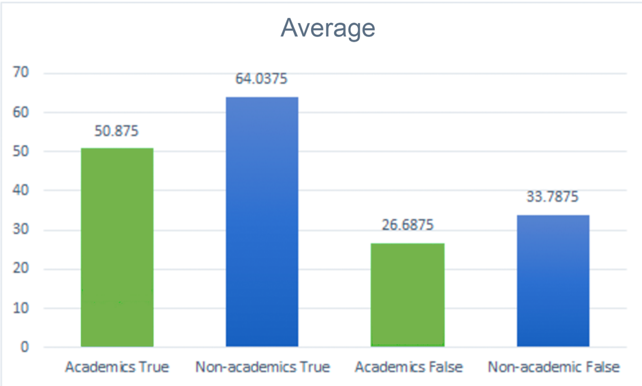
Figure 4.2. Percentages of assessors judging the false tweets as credible.



The responses for the tweets deemed false showed that fewer of the academics found the tweets credible than the non-academic assessors for all topics except the North Korean missile launch tweets, where a larger part of the academic assessors found the tweets credible. The differences range from about 3% to almost 15% between the two groups. The differences are alike the corresponding differences in the true tweets for all topics but the Stockholm attack and the immigration ban in the US. The difference between the groups for those topics are in the false tweets around 4% and 13% respectively.

4.3 Overall

Figure 4.3. Average percentage over all topics.



On average, approximately 51% of the academic assessors found the true tweets credible, while roughly 64% of the non-academics found the same tweets credible. In comparison, the values for the false tweets were 27% for the academics and 34% for the non-academics. Overall, less of the academics judged all tweets as credible than the non-academics, 13% less for the true tweets and 7% less for the false tweets. Both groups were less convinced by the false tweets, with roughly 24% and 30% less judged the tweets credible for the academics and non-academics respectively.

Chapter 5

Discussion

This chapter discuss the results, possible improvements and possible future work.

5.1 Result discussion

As seen in the results for the true tweets, there is a less than a 10% difference between the two focus groups in four of the 8 topics. What can be noted about these topics is that they are all political. The percentage of assessors finding the tweets credible were around 50% to 65%, meaning the tweets did not particularly stand out as credible or not. The remaining four topics consist of two scientific topics and two political topics. The scientific topics, being the SpaceX Falcon9 relaunch and the Metallic Hydrogen, show some differences between the groups, in the range of 15% to 20%. It seems that the tweets regarding these two topics were credible to a slightly greater amount of assessors on average than the political topics.

The remaining political topics consist of one topic related to a cruel event, the Syrian gas attack, and one topic from the same city as the assessors, the Stockholm attack. The Syrian gas attack topic show a difference between the groups of just above 20. 30% of academics considered tweets regarding Syrian gas attack to be credible, while that same number is 50% for non-academics. Perhaps when it comes to cruelty, the academics are very sceptical. The largest difference between the two groups, which is approximately 35%, concerns the Stockholm attack, where 85 of the non-academics considered the true tweets regarding the event to be credible. This makes it seem like the non-academics have better knowledge of what occured. However, due to the low amount of assessors, this could be a coincidence.

Regarding the false tweets, what can initially be noticed is the low percentage of assessors judging the tweets within each topic as credible, less than 50% across topics and groups, except the non-academics for the Brexit tweets. However, the topics with low difference between the groups differ from the true tweets. The differences in the Brexit, North Korean missile launch and the South Korean impeachment topics are still below 10%, however, the differences for SpaceX and the Stockholm attack are now also below 10%. What can also be noted is that the Stockholm attack topic is the topic with the lowest amount of assessors finding the tweets as credible. This further strengthens the hypothesis that being in close geographical proximity of an event increases the correct judgement of credibility.

Joining the Stockholm attack with low a percentage of assessors judging the corresponding tweets as credible is the Syrian gas attack and SpaceX Falcon9 relaunch. The Syrian gas attack topic could again as previously mentioned have these results because of the cruelty of the topic. Even though the five left-most topics have lower values than for the true tweets, they are still not far from 50%, a majority of them are above 30% of assessors considering the tweets credible. The assessors were perhaps guessing the truth-values and used different cues as to judging the credibility of the tweets.

The results show that overall, the academics are more sceptical than the non-academics, both when it comes to true tweets as well as false tweets. However, this might be a coincidence concerning the low amount of assessors, topics and/or tweets.

5.2 Possible improvements and future work

With more assessors, time and data, a more certain answer could be given to whether young adults education or inclination towards education has an effect on their capability of judging the credibility of information. Future work could include researching what makes the two different groups judging a tweet as credible, and why that characteristic of the tweet alters the assessors view on the tweets credibility. Further research regarding whether an assessor being close geologically and therefore having more awareness could also provide interesting data.

Something that can also be taken into note is the type of chosen tweets. Although we attempted to have different types of tweets from different types of sources, with the few accumulated tweets, the variation is limited. A study with more answers than credible and not credible could perhaps also be an improvement. A possibility is a scale of credibility. Another possibility for doing future work with limited funding is using previous related researches classifiers for assessing the tweets, although that could prove difficult for a comparative research between different people. There is also the problem with the classifiers only having around 80% precision.

Chapter 6

Conclusion

The results show that overall, young academics appear more sceptical to news related information retrieved from twitter, at least regarding political and scientific topics. Between the two groups, the difference in overall credibility judgement is also greater among true tweets than the false tweets. The results also show that topics regarding events that occur in a closer geographical proximity is judged more accordingly with the truth of an event. The cruelty of an event also seem to affect the judgement of credibility. Both groups appear to be slightly better at judging credibility regarding scientific tweets in comparison to political tweets. Due to the low amount of assessors, tweets and time, all results and conclusions drawn from them are to be taken lightly.

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