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MSc in Software Development

THESIS PROJECT KISPECI1SE

Danish Stance Classification and Rumour Resolution

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Abstract

The Internet is rife with flourishing rumours that spread through microblogs and social media. Recent work has shown that analysing the stance of the crowd towards a rumour is a good indicator for its veracity. One state-of-the-art system uses an LSTM neural network to automatically classify stance for posts on Twitter by considering the context of a whole branch, while another, more simple Decision Tree classifier, performs at least as well by performing careful feature engineering. One approach to predict the veracity of a rumour is to use stance as the only feature for a Hidden Markov Model (HMM). This thesis generates a stance-annotated Reddit dataset for the Danish language, and implements various models for stance classification. Out of these, a Linear Support Vector Machine provides the best results with an accuracy of 0.76 and macro F_1 score of 0.42. Furthermore, experiments show that stance labels can be used across languages and platforms with a HMM to predict the veracity of rumours, achieving an accuracy of 0.82 and F_1 score of 0.67. Even higher scores are achieved by relying only on the Danish dataset. In this case veracity prediction scores an accuracy of 0.83 and an F_1 of 0.68. Finally, when using automatic stance labels for the HMM, only a small drop in performance is observed, showing that the implemented system can have practical applications.

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1 Introduction

Social media has come to play a big role in our everyday lives as we use it to connect with our social network, but also to connect with the world. It is common to catch up on news through Facebook, or to be alerted with emerging events through Twitter. However these phenomena create a platform for the spread of rumours, that is, stories with unverified claims, which may or may not be true [Huang et al., 2015]. This has lead to the concept of fake news, where the spreading of a misleading rumour is intentional [Shu et al., 2017]. Can we somehow automatically predict the veracity of rumours? Within recent years research has tried to tackle this problem [Qazvinian et al., 2011], but automated rumour veracity prediction is still in its infancy [Gorell et al., 2018].

This paper reports a thesis project carried out in the Spring semester, 2019, on the MSc programme in Software Development at the IT University of Copenhagen. The thesis investigates stance classification as a step for automatically determining the veracity of a rumour. Previous research has shown that the stance of a crowd is a strong indicator for veracity Dungs et al., 2018, but that it is a difficult task to build a reliable classifier [Derczynski et al., 2017]. Moreover a study has shown that careful feature engineering can have substantial influence on the accuracy of a classifier [Aker et al., 2017]. A system able to verify or refute rumours is typically made up of four components: rumour detection, rumour tracking, stance classification, and veracity classification [Zubiaga et al., 2018]. This project will mainly be concerned with stance classification and rumour veracity classification. A research paper on the subject was written in the Autumn semester, 2018, in the Thesis Preparation course, contributing as background research for this project [Lillie and Middelboe, 2018]. Source code for the implementation of the system developed in this thesis project are publicly available on GitHub¹.

Current research is mostly concerned with the English language (see section 2) [Lillie and Middelboe, 2018], and in particular data from Twitter is used as data source because of its availability and relevant news content. To our knowledge no research within this area has been carried out in a Danish context.

1.1 Research question

The thesis project will attempt to answer the following questions: how do we build an automatic stance classification system for Danish? Further, how do we apply this system to verify or refute rumours and possibly detect fake news?

 $^{^1}$ https://github.com/danish-stance-detectors

1.2 Overview

Background material and current research will be introduced in section 2 with an overview of the research area, common approaches, and state-of-the-art systems. Section 3 will provide an analysis of the task at hand, considering different approaches, trade-offs and possible obstacles. Before going into a system description, technologies and frameworks utilised throughout the project is presented section 4. Section 5 will introduce how the data has been gathered, and how it has been annotated using a custom built annotation tool. This is followed by section 6, which describes the models used for stance classification as well as feature vectors, and the approach taken for rumour veracity classification. Experiments are carried out and reported in section 7 and 8. Finally our findings are discussed in section 9, while the project is concluded in section 10.

2 Background

Social Media and Big Data have been buzzwords for about a decade now, as the availability and accessibility of the Internet continually grows. While more people join social media, more and more data comes in circulation. Moreover, platforms such as Twitter, Facebook, and Reddit have become the primary sources of news for some people, because of the ability to follow real-time developments of events from first-hand sources [Huang et al., 2015].

However, as you would possibly trust news that you hear in the radio or see in the TV, information spread on the Internet can be difficult to trust and verify. This gives rise to the spreading of rumours, which can be defined as circulating information that is yet to be verified as true or false [Shu et al., 2017, 5.1]. Research has investigated why rumours are spread, and [Huang et al., 2015] shows that, in particular in relation to crisis, physical and emotional proximity influence online information seeking and sharing behaviours. Furthermore some people exploit the phenomena of spreading rumours on social media for beneficial reasons such as finance or politics, which has come to be known as Fake News [Shu et al., 2017].

Because of circulating rumours and Fake News, researchers have studied if and how we can use IT and computer science to detect and possibly debunk false statements [Derczynski et al., 2017, Shu et al., 2017]. One of the first studies in this area created a dataset with more than 10,000 tweets from Twitter over five different topics and built a system for detecting rumours as well as classifying tweets as being either supporting or denying [Qazvinian et al., 2011]. Another study frames this task of identifying stance as a credibility assessment, and builds a system to automatically detect credibility from topics in collected newsworthy events from Twitter [Castillo et al., 2011].

This section will outline the research area and explore both previous and

current relevant studies. First, a common architecture for rumour veracity classification is explored. Then related work, including stance classification, veracity classification, and Fake News detection systems will be introduced. Finally state-of-the-art systems will be investigated.

2.1 System architecture for rumour resolution

One approach for determining veracity of rumours could be to divide the task into four sub-components as depicted in Figure 1.

3. Stance Classi-4. Veracity Clas-1. Detection 2. Tracking fication sification Input: Input: Input: Input: stream of posts. stream of rumour stream of relevant posts linked to a ruposts. Output: posts. mour. each post labelled Output: Output: Output: posts labelled for each post labelled as as rumour or nonrumour-level veracrelevant or not. support, deny[, rumour. ity as true, false or query, comment] unverified

Figure 1: Rumour veracity classification system architecture. Source: [Zubiaga et al., 2018] (From web version)

That is, one must first do rumour detection, then track these rumours and feed them into a stance classifier, to ultimately perform veracity classification to determine whether the rumours are true or false. Expanding the components, one can define each task as the following:

1. Rumour detection

- (a) Identify whether a piece of information constitutes a rumour
- (b) Approach: binary classifier
- (c) Input: a set of posts
- (d) Output: a set posts, where each one is labelled as rumour or non-rumour
- (e) Useful for emerging rumours, but not necessary with $a\ priori$ rumours²

2. Rumour tracking

- (a) Once a rumour is identified, whether it being a priori or emerging, the *tracking* component collects and filters posts discussing the rumour
- (b) Approach: monitor social media to find posts discussing a rumour, while eliminating irrelevant posts
- (c) Input: a rumour

 $^{^2 \}mathtt{https://www.merriam-webster.com/dictionary/a\%20priori} \ \ 24\text{-}05\text{-}2019$

(d) Output: a set of posts discussing the rumour

3. Rumour stance classification

- (a) Determine how each post is oriented towards a rumour's veracity
- (b) Approach: multi-class classification
- (c) Input: a set of posts associated with the same rumour
- (d) Output: label of each post, where the labels are typically predefined as a set of types of stances, such as supporting, denying, querying, and commenting (SDQC).
- (e) Can be useful for rumour veracity classification (next component), but can be omitted where stance is not considered useful

4. Rumour veracity classification

- (a) Attempt to determine the actual truth value of a rumour
- (b) Approach: binary classifier
- (c) Input: a set of posts (could be collected by the rumour tracking component), and optionally stance labels
- (d) Output: predicted truth value
- (e) The input and output can optionally include relevant information from external sources, such as news media

Together, these components allow for a system to automatically verify or refute rumours in (near) real-time, as you would have to wait for comments. However, as noted in the rumour detection component, a system can also be based on a priori rumours, that is, historical events, which have concluded. This way the detection and tracking of rumours comprise of the task of finding rumours and gathering all relevant data tied to it. In this case the data can subsequently be used in stance classification and veracity classification. The result of this would be a model that is trained on historical data, but is able to analyse and work as a rumour resolution system to unseen and possibly new/emerging rumours.

Note that *classification* will sometimes be used interchangeably with *detection* and *prediction* throughout the paper, as these more accurately apply for some contexts.

2.2 Related work

One of the major benefits of doing rumour veracity classification is its usefulness in debunking Fake News. One major study within this area investigates Fake News detection on social media and comes up with a Fake News characterisation as well as a novel approach to building a detection system [Shu et al., 2017]. This research defines the following: while a rumour is a piece of circulating information whose veracity status is yet to be verified,

Fake News is articles that are intentionally and verifiable false. They dive into this subject based on the fact that social media has become the primary source for news. This leads to more noisy and lower quality news than found in traditional news.

The introduction of Fake News leads to a break with the authenticity of the whole news ecosystem as producers intentionally persuade consumers to accept biased or false beliefs [Shu et al., 2017, 1]. This changes the way people interpret and respond to real news. In particular the key feature of Fake News is its authenticity: Fake News includes verifiably false information; and its intent: Fake News is created with dishonest intention to mislead readers [Shu et al., 2017, 2.1]. What is interesting, is the psychological and social foundation of Fake News. Due to naïve realism and confirmation bias, consumers tend to believe that their own perception of reality is the only accurate frame, while preferring to receive news that confirms their own bias [Shu et al., 2017, 2.2]. This is related to the "echo chamber" effect, where users tend to form groups of like-minded people with polarised opinions, which facilitates the process of believing Fake News [Quattrociocchi et al., 2016].

As an approach to tackle the problem of debunking Fake News, The Fake News Challenge [Pomerleau and Rao, 2017] frames the problem as classifying stance for news articles as being either agreeing, disagreeing, or discussing (as well as unrelated) to a headline. This was an open research problem made available as a task/challenge for teams to participate in. The best scoring teams use both ensemble approaches of Decision Trees and CNNs as well as simple Multi-Layered Perceptrons [Hanselowski et al., 2018]. It is an ongoing project, where stance detection is the first stage, just as introduced in section 2.1, serving as a "useful building block in an AI-assisted fact-checking pipeline"³.

Related to the task of verifying rumours and debunking Fake News is the PHEME project, which deals with four kinds of false claims: rumours, disinformation, misinformation, and speculation [Derczynski and Bontcheva, 2014]. As an extension to volume, velocity, and variety as being well known challenges working with Big Data in social media, PHEME introduces veracity as being a fourth "crucial, but hitherto largely unstudied, challenge" 4. In particular the project takes its name from the term meme, which is "an idea, behaviour, or style that spreads from person to person within a culture[..]" 5, containing information about veracity, but also the Greek goddess of fame and rumours. The project started in 2014 and ran for three years, yielding several studies and research projects within its area.

 $^{^3}$ http://www.fakenewschallenge.org/ 24-04-2019

⁴https://www.pheme.eu/ 24-04-2019

 $^{^5}$ https://en.wikipedia.org/wiki/Meme 24-04-2019

Other projects and initiatives deal with Fake News detection as the task of fact-checking, such as FEVER⁶ and Full Fact⁷. FEVER presents a shared task in [Thorne et al., 2018] of classifying whether human-written factoid claims can be verified as supported or refuted using evidence retrieved from Wikipedia. Similarly Full Fact is a UK fact-checking charity, which performs automated end to end fact-checking by monitoring platforms such as Twitter and Facebook [Babakar and Moy, 2016]. One related, but manual approach, exist in Denmark by Mandag Morgen⁸ who provides a fact-checking website, called "TjekDet"⁹ ("check it"), which investigates misinformation in social media and online debate. Additionally TjekDet is a member of The International Fact-Checking Network (IFCN)¹⁰, which is a unit started in 2015 with the goal of uniting fact-checkers around the world.

"SemEval" (Semantic Evaluation) is an ongoing series of evaluations of computational semantic analysis systems¹¹. Each SemEval contains several tasks related to Natural Language Processing (NLP), Semantics and Computational Linguistics, for which teams are invited to submit solution systems. Within the last couple of years, SemEval has had tasks concerned specifically with rumour stance and rumour veracity classification, denoted as "RumourEval" tasks. In particular task 8 in SemEval 2017 [Derczynski et al., 2017] and task 7 in SemEval 2019 [Gorell et al., 2018] concern themselves with these two subtasks. Resources including a stance labelled dataset is provided, which research teams should use to develop solution systems to tackle the task of determining rumour veracity and support for rumours. We have studied several of the relevant publications for SemEval, as they provide state-of-the-art research within our field of study and build upon each others' work [Lillie and Middelboe, 2018].

Additionally, task 6 in SemEval 2016 [Mohammad et al., 2016] engages in detecting stance from tweets given a target entity, such as a person and organisation. The difficult part about this is the fact that the target may or may not be included in the tweet data, just as it may or may not be included in the target of opinion.

2.3 State of the art

This section presents state-of-the-art systems introduced within the last three years.

⁶http://fever.ai/

⁷https://fullfact.org/

⁸https://www.mm.dk/

⁹https://www.mm.dk/tjekdet/

¹⁰https://www.poynter.org/ifcn/

 $^{^{11}}$ https://en.wikipedia.org/wiki/SemEval 27-05-2019

2.3.1 Rumour stance classification

The attitude that people express towards some statement can be used to predict veracity of rumours, and these attitudes can be modelled by stance classifiers. This section will present state-of-the-art systems for automatic stance classification. In particular Long-Short Term Memory (LSTM) neural network models are popular, as they have proven to be efficient for working with data within NLP (further described in section 6.2.2).

[Kochkina et al., 2017] developed a stance classifier based on a "Branch-LSTM" architecture: instead of considering a single tweet in isolation, whole branches are used as input to the classifier, capturing structural information of the conversation. The model is configured with several dense ReLU layers, a 50% dropout layer, and a softmax output layer, scoring a 0.78 in accuracy and 0.43 macro F_1 score. They are however unable to predict the underrepresented "denying" class.

Another LSTM approach deals with the problem introduced above for the SemEval 2016 task 6 [Mohammad et al., 2016]. The LSTM implements a bi-directional conditional structure, which classifies stance towards a target with the labels "positive", "negative", and "neutral" [Augenstein et al., 2016] The approach is unsupervised, i.e. data is not labelled for the test targets in the training set. In this case the system achieves state-of-the-art performance with a macro F_1 score of 0.49, and further 0.58 when applying weak supervision.

A different approach is based on having well-engineered features for stance classification experiments using non-neural networks classifiers instead of Deep Learning (DL) methods [Aker et al., 2017]. Common features such as CBOW and POS tagging are implemented, but are extended with problem-specific features, which are designed to capture how users react to tweets and express confidence in them. The best performing classifier is a Random Forest classifier, scoring an accuracy of 0.79¹².

RumourEval 2019 has been running in parallel with the writing of this thesis [Gorell et al., 2018] and a first look at the scoreboard indicates very promising results¹³. With the Branch-LSTM approach as a baseline on the RumourEval 2019 dataset, scoring 0.4930 macro F_1 , the "BERT" system scores a 0.6167 macro F_1 [Fajcik et al., 2019]. The implementation employs transfer learning on large English corpora, then an encoding scheme concatenates the embeddings of the source, previous and target post. Finally the output is fed through two dense layers to provide class probabilities. These BERT models are used in several different ensemble methods where the average class distribution is used as the final prediction.

 $^{^{12}}$ Unfortunately no F_1 score is reported, rendering us unable to compare the performance on that metric to the other state of the art results

 $^{^{13}\}mathrm{https://competitions.codalab.org/competitions/19938}~26\text{-}05\text{-}2019$

2.3.2 Rumour veracity classification

Rumour veracity classification is considered a challenging task as one must typically predict a truth value from a single text, being the one that initiates the rumour. The best performing team for that task in RumourEval 2017 [Derczynski et al., 2017] implements a Linear Support Vector Machine (SVM) with only few (useful) features [Enayet and El-Beltagy, 2017]. They experiment with several common features such as hashtag existence, URL existence, and sentiment, but also incorporates an interesting feature of capturing whether a text is a question or not. Furthermore the percentage of replying tweets classified as supporting, denying, or querying from stance classification is applied. It is concluded that content and Twitter features were the most useful for the veracity classification task and score an accuracy of 0.53.

For the similar task, but different dataset, the second best scoring team, "CLEARumor", in RumourEval 2019 [Gorell et al., 2018] achieved an F_1 score of 0.286 (submitted) and since, 0.301 [Baris et al., 2019]. According to the scoreboard¹³ the best scoring team achieved an impressive 0.5765 F_1 , but it seems that they have not published their work at the time of writing. CLEARumor implements a CNN-based deep-learning architecture for SDQC stance classification and use these estimates for predicting veracity through a Multi-Layered Perceptron (MLP) neural network. ELMo embeddings are used¹⁴, as a new word embeddings approach over for instance the widely used word2vec algorithm [Mikolov et al., 2013]. Further, four auxiliary features are employed, including platform specific encodings for respectively Twitter and Reddit. The system in [Enayet and El-Beltagy, 2017] introduced above is used as baseline, and as reference scores a macro F_1 of 0.18 on the same test set.

While the above two systems engage in the task of resolving veracity given a single rumour text, another interesting approach is based on the use of crowd/collective stance, which is the set of stances over a conversation [Dungs et al., 2018]. This system predicts the veracity of a rumour, based solely on crowd stance as well as tweet times. A Hidden Markov Model (HMM) is implemented, which is utilised such that individual stances over a rumour's lifetime is regarded as an ordered sequence of observations. This is then used to compare sequence occurrence probabilities for true and false rumours respectively. The best scoring model, which include both stance labels and tweet times, scores an F_1 of 0.804, while the HMM with only stance labels scores 0.756 F_1 . The use of automatic stance labels from [Aker et al., 2017] is also applied, which does not change performance much, proving the method to have practical applications. It is also shown that using the model for rumour veracity prediction is still useful when limiting the number of tweets to e.g. 5 and 10 tweets respectively.

 $^{^{14}}$ https://allennlp.org/elmo 27-05-2019

This section has presented background theory and related work, including state of the art. This, together with a deeper investigation in [Lillie and Middelboe, 2018], allows us to analyse the problem at hand and choose an approach for tackling it, which will be discussed next, in section 3

3 Problem Analysis

The task of rumour stance classification and veracity prediction is a difficult problem. The skewed nature of data from microblogs makes classifying minority classes difficult [Zubiaga et al., 2016b]. Further the majority of current research in this area has been targeted towards Twitter and the English language. While some related work has been carried out for other languages as well [Stranisci et al., 2015, Giménez et al., 2017], there is a lot left to be done for most languages. One of these is the Danish language, for which to our knowledge no research within rumour stance and veracity classification exists. General research in related areas, as well as approaches for Danish NLP exist, such as part-of-speech tagging and sentiment analysis [Årup Nielsen, 2019].

Current research on the subject has put a lot of work into creating and extending datasets [Shu et al., 2017]. Labelled datasets from microblog platforms facilitate stance classification, which can be utilised for automatic generation of crowd stance for rumour veracity prediction [Dungs et al., 2018]. Existing approaches and methods can be re-applied for Danish, however non-Danish data is not applicable. In other words, a labelled Danish dataset is needed in order to facilitate Danish rumour stance and veracity classification.

The process of reaching the goals of this project are incremental and each relies on the former goal being met. Following the common approach, as introduced in section 2.1, the first step would be to create a stance annotated dataset for the Danish language. The dataset would be used for supervised stance classification and finding data spawned from rumours would be optimal, as this can be used for rumour veracity classification. The dataset would facilitate a stance classification model, which in turn could be used for rumour veracity classification. This calls for the need to gather relevant data from one or several social media platforms, such as Facebook, Twitter, and Reddit. One should be careful, however, and properly address the "model organism problem" [Tufekci, 2014].

3.1 Rumour data

As introduced in section 2.1, the first steps needed to build a dataset is rumour detection and rumour tracking. While rumour detection is very interesting it is difficult to rely on within the limited time of this thesis project. As such, it would be the simpler approach to use a priori rumour data. Then, for rumour tracking, a mechanism is needed to collect and filter relevant posts discussing the rumours. While one would setup some live monitoring tool for collecting emerging rumour data, a "tracking" mechanism is not needed for historical data. Instead, one could gather a number of samples related to a rumour, and then filter it.

Two particularly big social media platforms are Twitter and Facebook, which could be good choices as sources for the dataset. However, Reddit is also rather big in Denmark, which in contrast to the other two is an anonymous platform. Previous work has identified events known to contain rumours and searched for data on Twitter with keywords matching these events [Zubiaga et al., 2016b]. Another approach could be to fetch data matching predefined keywords unrelated to specific events, and then sequentially go through it to identify which would be relevant, i.e. rumourous. Social media platforms all have different structures and ways of defining subjects and conversations.

The task of selecting rumours is difficult, as the data gathered might consist of both rumour and non-rumour data. Thus, one should have a framework for filtering this data. While non-rumour data can still be used to train a stance classifier, rumour data is needed for the purpose of veracity classification.

3.1.1 Choosing sources

Twitter is a social media platform widely used as a data source for stance and rumour classification datasets [Qazvinian et al., 2011, Castillo et al., 2011, Zubiaga et al., 2016b]. Twitter is mainly based on short messages (once 140 characters, now 280¹⁵), which users can post/"tweet". Users are able to re-tweet tweets from other users, thereby sharing them and commenting on the initial tweet. This structure allows for conversations to spread and possibly spread rumours. Furthermore "hashtags" (#) are used to group similar content by including relevant keywords in the tweet, such as #dkpol for a tweet concerned with Danish politics. Additionally people can refer to each other by including an '@' sign, followed by a user name. One can imagine that these properties facilitate much networking on Twitter. An example tweet from the Twitter platform is illustrated in Figure 2. In this example we see the source tweet in the top, including two hashtags, and an

 $^{^{15}}$ https://sproutsocial.com/insights/social-media-character-counter 24-05-2019

attachment. It is re-tweeted 4 times, and we see one direct reply and one nested reply.



Figure 2: Example of a tweet on Twitter

Facebook is another social media platform which has a posting mechanism resembling Twitter's and have additional concepts including pages, groups, personal albums, and live-chat. Just like Twitter, people can share other people's posts (like re-tweeting), as well as tag people and include hashtags. One major difference is the post character limit, which is 63,206 characters¹⁵. Figure 3 illustrates an example post from a public profile on Facebook. This post has two replying comments and has been shared seven times. To our knowledge it is less common to see the use of hashtags on Facebook than on Twitter, but attachments such as links and photos appear frequently.

Both Twitter and Facebook are prominent candidates for a data source. In particular they seem compatible for a cross-platform dataset, in the sense that they share the same conversation structures and mechanisms. However, restrictions on both on them make it difficult to use either for our purpose. Twitter does not allow you to (freely) search for tweets older than 7 days¹⁶, which is very restrictive for finding rumourous data. Third-party libraries such as twint¹⁷ does exist however, which circumvent the restrictive access through the API by scraping raw data from the website. There seems to be problems with gathering full conversation trees in a simple way with this approach though. A similar problem exist for Facebook, where one could

 $^{^{16}}$ https://developer.twitter.com/en/docs/tweets/search/overview $24 ext{-}05 ext{-}2019$

¹⁷https://github.com/twintproject/twint



Figure 3: Example of a post on Facebook

scrape public data, but all Facebook data is private unless made explicitly public, and even public data seems to require special permission¹⁸.

Thus we turn to Reddit¹⁹, which is a forum website with a fully available API²⁰. The site hosts smaller forums or communities in the form of "Subreddits". A Subreddit typically has a specific theme or entity as the central point of relevance. Users can create posts, called "submissions", with relevance to the specific Subreddit, where other users can post comments and engage in discussion. Users can downvote or upvote both submissions and other comments. The votes dictate the score of the comment or submission and is used to determine visibility. A low score can hide content such that users must click on it to see it, while a high score may rise the content in relevance and position on the forum. An important thing to note is the anonymity of the platform. While users are anonymous, they are still uniquely identified by their usernames. Additionally the character length for a post can be up to 10,000 characters²¹.

An example of a submission from Reddit is illustrated in Figure 4. In this example the submission post contains a title, an image, and a URL reference, but no post text. It has a total of 22 comments and we see one top-level comment, and a nested reply.

Further, Figure 5 illustrates another Reddit example, where we do see a submission post text.

 $^{^{18} \}mathtt{https://developers.facebook.com/docs/public_feed/} \ 24\text{-}05\text{-}2019$

¹⁹https://www.reddit.com/

²⁰https://www.reddit.com/dev/api

²¹We could not find a source for this, but it is claimed in several Reddit submissions



Figure 4: Example of a submission on Reddit with no post text, but a URL reference and an image attached



Figure 5: Example of a submission on Reddit with post text

In both examples (Figures 4 and 5) we see that each comment has a score. In particular we see a negative score in Figure 5, for the reply to the top-level comment, meaning that Reddit users have downvoted this comment.

Given time, data from another source should be included in the research, in order to deal with the "model organism problem" [Tufekci, 2014]. That is, using a single platform as source throughout research might have consequences such as bias, leaving out relevant information from other platforms, as well as human behaviour based on difference in self-awareness (e.g. anonymity vs public) [Lillie and Middelboe, 2018, 4.5.1]. Most related work use Twitter, which makes the use of Reddit rather novel in this sense (it is also used in this year's RumourEval [Gorell et al., 2018]).

3.1.2 Platform structures

Section 3.1.1 has compared three major social media platform including Twitter, Facebook, and Reddit. This section will further investigate the conversational structures implemented for each of the platforms, which may prove useful and important for choosing either of them as source(s) for the dataset.

There is one big difference between Reddit and Twitter/Facebook in the way they are structured. Figure 6 demonstrates the way Reddit is structured (on the left) and how both Twitter and Facebook are structured (on the right).

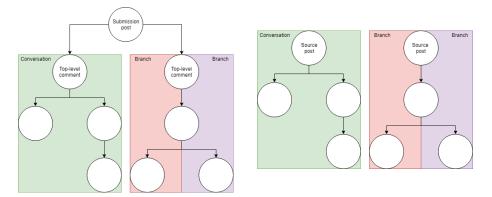


Figure 6: Reddit structure (left) and Twitter/Facebook structure (right). Conversations are coloured green, while two individual branches are coloured respectively red and purple for each platform structure.

The Reddit structure comprises of a submission post, which contains at least a title text, which can spawn several top-level comments. These top-level comments, together with their respective nested replies, make up a conversation (coloured green in Figure 6). Further, within a conversation, at

least one branch is present, which is a sequence of replies from one comment with no replies to a top-level comment (two branches are coloured in respectively red and purple for each platform structure in Figure 6). Twitter and Facebook implement the exact same structure with regards to conversations and branches, except that each conversation is isolated, whereas several conversations on Reddit are related to the submission post. That is, for Reddit, the concept of a source post is actually the submission post, whereas it is the respective top-level posts for conversations on Twitter and Facebook. Note that branches within the same conversation share at least one post.

3.1.3 Data annotation

For the rumour stance classification component, the gathered dataset needs to be annotated, such that the classification model can perform supervised learning. Previous work has investigated how a dataset could be annotated such that the idea of a crowd stance could be used to either confirm or refute a rumour or Fake News [Procter et al., 2013]. A popular annotation scheme is defined as having the following purpose: "[..] an annotation scheme suitable for capturing conversation properties of the Twitter threads in terms of such interactions and used it to obtain an annotated corpus using crowdsourcing" [Zubiaga et al., 2016b, p. 8]. This annotation scheme is depicted in Figure 7 and illustrates how to annotate stance for respectively a source tweet and a replying tweet. Additionally a tweet is annotated for certainty and evidentiality. The certainty of a post describes how certain the author of the post is in their argument. The evidentiality is marked as what, if any, evidence the author of the post uses to support their argument. These two dimensions are used in [Zubiaga et al., 2016b] to discover correlations between certainty, evidentiality and rumour veracity.

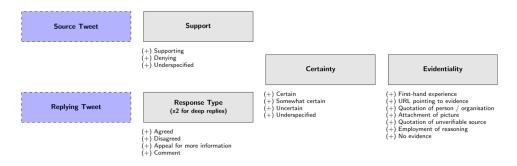


Figure 7: Annotation scheme from [Zubiaga et al., 2016b]

The overall idea for the annotation scheme in [Zubiaga et al., 2016b] is to label replying posts with one of four classes: "Supporting", "Denying", "Querying", and "Commenting" (SDQC). These denote the stance of a post

towards some statement, which could initiate a rumour. Out of these four classes, the former two are the polarised ones, indicating whether one is for or against the statement. The latter two are neutral, in the sense that a query is asking for more information and "commenting" is a label for a remark which expresses no opinion.

The SDQC approach is based on properties identified in Twitter conversations that make it possible to detect rumours [Zubiaga et al., 2016b]. These properties include: (1) the phenomena that it takes at least two conversational turns to identify a rumour, (2) posts/comments on Twitter is sequentially ordered by time, (3) a Twitter conversation involves itself with a specific topic, and (4) that underlying features of a response post make up its content. Although the focus is on Twitter, the research is based on analysis of microblogs in general. This is important to consider when annotating data, since it may be structured differently, which may mean that this annotation scheme is not completely applicable, or at least not designed for that specific purpose.

For the case of Reddit, it seems that the characteristics of a Twitter conversations mentioned above also apply: a submission includes sequential turn taking regarding a specific topic, and; the production of the response posts is defined by its characteristics. A few things, however, are worth mentioning as differences between these platforms. It is common for a Reddit post to include only a URL pointing to a news event from e.g. dr.dk (see Figure 4) and that a post can contain up to 10,000 characters. The extra text space may make posts more nuanced, but less precise, which may influence the task of annotating stance. In contrast to Reddit, tweets on Twitter usually contain more than just references to news articles and has a limit of only 280 characters.

As such, how a conversation is initiated can be different, which may impact how rumours are actually started. This is also mentioned in section 3.1.2, which illustrates how conversations are structured differently for respectively Reddit and Twitter/Facebook. Thus, for annotating Reddit, one should decide how to follow the [Zubiaga et al., 2016b] annotation scheme, which is based on Twitter. This could be done in two ways: (1) is to regard the submission post as a source, and (2) is to regard each top-level comment as source for each conversation. In the first case, a whole submission is treated as equivalent to a Twitter conversation, while the latter follows the same structure. The problem with option (2) is that the top-level comments actually are responses to the Reddit submission post, and as such not really the sources of the conversations. This makes option (1) seem like the more reasonable choice.

3.2 Stance and veracity classification

The third and fourth steps to build a rumour veracity system are stance and veracity classification (see section 2.1). Stance classification is the task of classifying a piece of text to determine how it is oriented towards the veracity of a claim [Zubiaga et al., 2018]. The task has been widely researched for the English language on Twitter [Derczynski et al., 2017, Gorell et al., 2018]. As mentioned in section 2.3.1 several different approaches have been applied to handle the problem of stance classification. The Branch-LSTM approach used in [Kochkina et al., 2017] is interesting given the explicit focus on conversation branches. However the size of the dataset to be generated in this study (given the time) might not be sufficient for a deep learning approach, such as the LSTM, which requires a large dataset (further discussed in section 6.2.2). As shown in [Stranisci et al., 2015] the process of annotating a large dataset can be difficult and time consuming. The fact that only two non-experts are available for the annotation task in this study could have an effect on the size of the dataset. As such a "non-deep learning" approach and careful feature engineering, might facilitate good results even on a smaller dataset [Aker et al., 2017].

The findings for rumour veracity classification with crowd stance in [Dungs et al., 2018] provide a strong motivation to follow this approach. By relinquishing language-specific features and relying solely on stance, a multilingual dataset might be applicable for rumour veracity classification. If the sequence of stance labels are successfully applicable across different languages, the amount of training data would be greatly increased, which could strengthen Danish veracity classification. Furthermore this makes it possible to avoid time-consuming feature extraction and model selection experiments, such as in [Enayet and El-Beltagy, 2017] and [Fajcik et al., 2019], making it more feasible for this project. With this motivation in mind, the positive results of the Hidden Markov Model approach makes it a desirable choice for the veracity classification of the system.

3.3 Dealing with Fake News detection

Section 2.2 introduces Fake News as a rumour which is intentionally and verifiably false, with malicious intend to manipulate or mislead the reader. [Shu et al., 2017, sec. 3.1] defines the requirements for Fake News detection as being: information about the author, the content of some news article and the user engagements which consist of a user, their post and a time stamp.

However to know whether the intend behind a rumour is malicious, information about social context for the author is required. Further the task of rumour veracity classification is mentioned as a very similar task as to Fake News detection [Shu et al., 2017, sec. 5.1]. Given the time frame of the

project and the added complexity of searching for Fake News rather than rumours, the Fake News detection is deemed difficult to reach. The Fake News Challenge regards stance detection as a helpful building block to perform Fake News detection [Pomerleau and Rao, 2017, Hanselowski et al., 2018]. As such a first step towards Fake News detection could be to perform stance detection and further rumour veracity classification.

With this analysis of the tasks in order to reach the goal of rumour veracity classification, we dive into the methods and approaches for the system. First, in section 4, we include which technologies are used throughout the project.

4 Technologies

This section briefly describes the different technologies, systems, and frameworks utilised within the thesis project to generate a labelled dataset and program classifiers for stance and veracity. The primary programming language used is Python, except for the annotation tool which is programmed in C#.

4.1 Data gathering

For getting data from Reddit the libraries praw²² and psaw²³ have been utilised to query the Reddit developer API. The API has facilitated the query and download functionality used in the process described in section 5.1.

4.2 Annotation tool

The annotation tool is described in section 5.2.1, and is developed as an ASP.NET and C# website with a MySQL database. These technologies were chosen to support rapid development for the project, as we knew the technologies well already. It is meant as a bare bones tool to facilitate a faster annotation process and highlight annotation conflicts.

4.3 Machine learning models

A number of frameworks were used for the machine learning models introduced in section 6, which are listed below.

²²https://praw.readthedocs.io/en/latest/ v. 6.0.0. 22-02-2019

 $^{^{23}}$ https://github.com/dmarx/psaw v. 0.0.7. 22-02-2019

4.3.1 Stance classifiers

For stance classification both traditional machine learning (ML) approaches and deep learning approaches are used. As such different technologies are used to support the different approaches:

• scikit learn

The Scikit Learn library²⁴ offers a wide variety of ML models, data mutation and testing functionality. All non-neural network models used for stance classification (introduced in section 6.2.3) are implemented from the scikit learn API [Pedregosa et al., 2011].

• PyTorch

PyTorch²⁵ is a library supporting development of neural networks. The LSTM deep learning model used for stance classification, introduced in section 6.2.2, is implemented in PyTorch.

• Google colab

Google colab²⁶ is used for training and experimenting with the LSTM. Colab is essentially an online Jupyter Notebook environment. The solution offers a virtual runtime with access to Google's servers including GPU and TPU machines for 12 hours at a time. It is very useful for training neural network models and it makes large hyper-parameter searches more feasible.

4.3.2 Rumour veracity classifier

The models used for rumour veracity are programmed with the hmmlearn library²⁷. This library facilitates a number of implementations of Hidden Markov Models with respectively Gaussian and multinomial emissions.

With the technologies introduced, section 5 will present the generated dataset used for stance classification and rumour veracity prediction.

5 Danish stance-annotated Reddit dataset

This section introduces the **Da**nish **st**ance(DAST) dataset on Reddit data, generated and annotated for this project. The dataset is publicly available at figshare [Lillie and Middelboe, 2019].

First, section 5.1 presents the process of gathering the data and provides an overview of the content of the dataset as well as its volume. Second,

²⁴https://scikit-learn.org/

²⁵https://pytorch.org/

²⁶https://colab.research.google.com/ 10-05-2019

²⁷https://hmmlearn.readthedocs.io/ 10-05-2019

section 5.2 describes how the dataset is annotated in addition to providing statistics for the class label distribution following the SDQC annotation scheme (see section 3.1.3).

5.1 Gathering the data

The data gathering process consists of two approaches: to manually identify interesting submissions on Reddit, and; to issue queries to the Reddit developer API²⁸ on specific topics. An example of a topic could be "Peter Madsen" referring to the submarine murder case, starting from August, 2017²⁹. A query would as such be constructed of the topic "Peter Madsen" as search text, a time window and a minimum amount of Reddit upvotes. A minimum-upvotes filter is applied to limit the amount of data returned by the query. Moreover the temporal filters are to ensure a certain amount of relevance to the case, specifically when the news event initially unfolded. Several submissions prior or subsequent to the given case may match a search term such as "ubåd" (submarine). The list of queries are included in a CSV format in appendix A.1.

Information about the Reddit submissions returned by the queries as described above are dumped to a CSV file, with the IDs of the submissions needed for subsequent processing. Submissions are also manually identified, in which case the ID of the given submission is added to the CSV file. The submission IDs are used to download all posts from each submission and save them in a JSON format. The JSON data contains meta information about the posts and the users who wrote the them (see an abbreviated example in appendix A.2). Events to look for were based on a list of ideas generated from browsing the media and our social network, which is reported (in Danish) in appendix A.3. Four Danish Subreddits were browsed, including "Denmark, denmark2, DKpol, and GammelDansk" 30, although all relevant data turned out to be from the "Denmark" Subreddit.

5.1.1 Overview of Reddit data

Table 1 presents an overview of all the events selected and further annotated (which is further described in section 5.2). The submissions are grouped into events which they relate to. Furthermore the total number of submissions, branches, and posts are included, to illustrate how much data each event contains.

In total the dataset contains 3,007 Reddit posts distributed across 33 submissions respectively grouped into 16 events. Although the volume of this dataset is considered small when used for classification tasks (discussed

²⁸https://www.reddit.com/dev/api/

²⁹https://www.dr.dk/nyheder/tema/ubaadssagen 26-05-2019

 $^{^{30}}$ https://www.reddit.com/r/Denmark/wiki/danish-subreddits 27-05-2019

Event	Submissions	Branches	Posts
5G	4	117	273
Donald Trump	3	89	246
HPV vaccine	7	122	255
ISIS	2	68	169
"Kost" (diet)	3	165	557
MeToo	1	29	60
"Overvågning" (surveillance)	1	121	352
Peter Madsen	3	156	381
"Politik" (politics)	3	126	323
Togstrejke(train strike)	2	49	101
"Ulve i DK" (wolves in DK)	4	119	290
Total	33	1,161	3,007

Table 1: Overview of data events and submissions

further in section 6.2.2), the size seems to be relatively big in comparison to other stance labelled dataset:

- RumourEval 2019 dataset [Gorell et al., 2018]:
 Allegedly the largest stance-annotated dataset to date. SDQC labelled multi-platform (Twitter and Reddit) and multilingual (English, Danish, and Russian) dataset containing at least 297 source tweets and 7100 discussion tweets in English (final dataset with remaining data not published yet)
- 2. IberEval 2017 dataset [Taulé et al., 2017]:
 Favour/against/none stance (and gender) labelled Twitter dataset for respectively Spanish and Catalan. Each dataset consists of a total of 5,400 tweets, with 4,319 for training and 1,081 for testing
- 3. PHEME dataset [Zubiaga et al., 2016a]: SDQC labelled Twitter dataset containing 4,842 tweets across 297 English and 33 German Twitter conversations
- 4. Turkish tweets dataset [Küçük, 2017]: Favour/against labelled Twitter dataset containing 700 tweets in Turkish

However, only about half of the data in DAST is annotated as being related to rumours (further described in section 5.2), which is relevant for the rumour veracity classification task. As a reference, for the PHEME dataset, all 330 conversations are deemed rumourous.

5.2 Annotation

As introduced in section 3.1.3, one widely used annotation scheme for stance is the SDQC approach [Zubiaga et al., 2016b]. The scheme is depicted in Figure 7, section 3.1.3, and illustrates how to annotate stance on Twitter. However, a way to annotate the differently structured Reddit platform is by regarding a submission post as a source, which is discussed in the last part of section 3.1.3.

In the process of annotating Reddit posts the annotation was initially configured to show the individual stance of the posts towards the possible rumourous event/topic itself (e.g. "Donald Trump"). However, the intent with the annotation scheme is to more explicitly focus on the source post and the post which the given post is replying to ("parent post"). As such, a mechanism supporting this double-annotation was implemented, such that a post is both analysed with regards to the source post and the parent post instead of directly to the event (this is indicated as "x2 for deep replies" in Figure 7, section 3.1.3). The double-annotation should facilitate a way to infer the stance for individual posts. For instance, if the source post supports a rumour, and a nested reply supports its parent post, which in turn denies the source, then the nested reply is implicitly denying the rumour.

In [Zubiaga et al., 2015] they crowdsource the task of annotation and discusse how the task can be broken into micro-tasks such that annotators can concentrate on the same thing throughout the process. We have chosen to do the annotation ourselves as the crowdsourcing would require time and resources not available for the thesis project. As such we do not break the task into smaller tasks, rather each of us annotate a full post completely, i.e. on the three dimensions being support/response type, certainty, and evidentiality (see Figure 7, section 3.1.3). The result is a dataset which is not only annotated for stance, but also contains annotations for the certainty of posts and the evidentiality of posts. While these labels are not used in this study, they might be useful for future work. However, at times we actually found it useful to use these dimensions to reason about annotated stance, when resolving annotation conflicts between us.

Next, in section 5.2.1, we describe how we have facilitated the annotation process with a custom built tool, as well as what we did to support and make use of the annotation scheme.

5.2.1 Process and tool

In order to support the annotation process we have developed a tool in C# ASP.NET with a MySQL database. The tool is meant to make the annotation process more efficient and highlight annotation conflicts between annotators. Screenshots of relevant mechanisms in the web-based tool are presented along with their descriptions.

The tool supports separation of data, in that the user can create datasets, which can contain a number of events, each of which contains a number of submissions (source posts). This is illustrated in Figure 8, with the list of events to annotate on the right and utilities for creating new events and uploading data on the left.

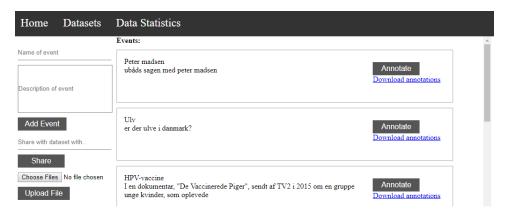


Figure 8: Overview of the events to annotate

An event is meant to separate data from different topics and events, such that only submissions in the same event are displayed while annotating. In each event the generated JSON data from Reddit (see section 5.1) can be uploaded with the "Choose Files" and "Upload File" buttons to the left in Figure 8.

To initiate annotation of a submission within an event, one would click on the "Annotate" button for the given event, after which the annotation page will be loaded, as depicted in Figure 9.

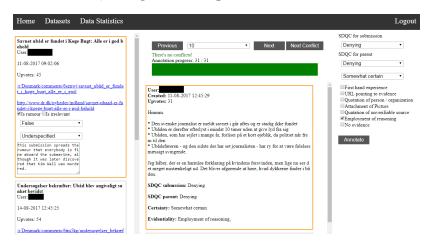


Figure 9: Annotation of a submission

The annotation page in Figure 9 supports a view of each submission within the event (on the left) and displays each branch of comments to the annotator (in the middle). The annotator can go through the branches sequentially by pressing the "Next" button, or go to a specific one from the drop-down menu. The display of a whole branch allows the annotator to consider the context of the text of the individual posts when annotating.

The annotator can annotate the selected post according to the annotation scheme with the options menu on the right of the annotation page. The number of conflicts between the annotators, if any, are also displayed in the top, with an option to go to/display the given post when clicking "Next Conflict". An example is illustrated in Figure 10 where the annotation choices of the other annotator is displayed with text in red. For resolving such a conflict, we would sit down and discuss the given post and re-annotate it accordingly.

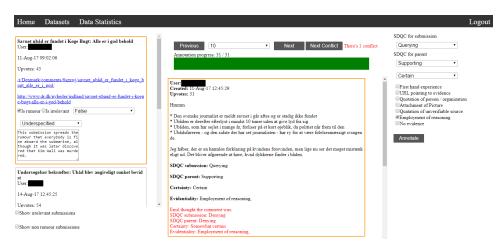


Figure 10: Resolving annotation conflicts

Once satisfied with the annotations, they can be downloaded from the event overview page (see Figure 8), where only posts with no annotation conflicts are included in the downloaded file(s). The output is similar to the extracted Reddit data (see appendix A.2), only with the following annotations appended: whether the submission is a rumour and its truth status, as well as SDQC labelled replying posts. Additionally a note on the submission is included, which is meant to describe what the statement and case is about in the submission itself (to the left in Figure 10).

The stance of the source/submission post is taken into account when annotating the stance for replying posts of top-level posts (denoted "SDQC for parent" in the annotation tool). As stance annotations are relative to some target, each post does not have one single stance annotation: each post is annotated for the stance targeted towards the submission and the

stance targeted towards the direct parent of the post (also introduced in the beginning of section 5.2).

Further, a majority of submissions have no text, but a title and a link to an article, image or another website, with content related to the title of the submission. If this is the case and the title of the submission bears no significant stance, it is assumed that the author of the submission takes the same stance as the content which is attached to the submission.

As the annotation progressed the tool also provided a way for us to track the distribution of SDQC annotations for respectively the submission and parent posts, as described above. This is illustrated in Figure 11, however note that these numbers do not reflect the final dataset, as some posts were deemed invalid (17 posts to be precise). The results of the annotations are presented next, in section 5.2.2.

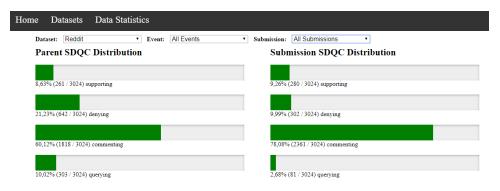


Figure 11: Annotation statistics (the numbers do not precisely reflect the final dataset, DAST)

5.2.2 Annotated dataset

This section will present an overview of the annotated dataset, including SDQC labels per event and the overall distribution.

The dataset, as presented in section 5.1.1, contains 11 events, including 3,007 posts across 33 submissions, which have all been annotated for SDQC stance. Table 2 provides an overview of the class label distribution per event.

"Kost" is the dominating event with its 557 posts, whereas three events have between 300-400 posts, four events have 200-300 posts, two events have 100-200 posts, and "MeToo" only has 60 posts. The "querying" label is rare with a total of 81 annotations out of the 3,007 posts. The "supporting" and "denying" labels are almost equally distributed with a total of respectively 273 "supporting" and "300" denying posts. The "commenting" class is the absolute dominant one, with a total of 2,353 annotations. While the "commenting" class label is consistently the majority class for all of the events, there is variation with regards to the SDQ class labels within each event.

Label Event	S	D	Q	С	Total
5G	26	47	7	193	273
Donald Trump	39	17	5	185	246
HPV vaccine	24	4	8	219	255
ISIS	3	40	8	118	169
"Kost" (diet)	50	56	4	447	557
MeToo	1	8	3	48	60
"Overvågning" (surveillance)	41	20	13	278	352
Peter Madsen	15	45	19	302	381
"Politik" (politics)	43	46	7	227	323
"Togstrejke" (train strike)	8	6	3	84	101
"Ulve i DK" (wolves in DK)	23	11	4	252	290
Total	273	300	81	2,353	3,007

Table 2: Overview of SDQC stance labels per event

Notably "MeToo" and "ISIS" have a very low amount of "supporting" labels relative to the other events.

Table 3 illustrates the relative SDQC distribtion for the whole dataset for both response types, being targeted towards respectively submission (source) and parent posts, i.e. the posts replied to. The two upper rows contain the actual numerical distributions and the two bottom rows contain the relative distribution.

Label Target	S	D	Q	С
Reddit submission post	273	300	81	2,353
Reddit parent comment	261	632	304	1,810
Reddit submission post %	9.1	10	2.7	78.2
Reddit parent comment %	8.7	21	10.1	60.2

Table 3: Relative SDQC stance label distribution for DAST with regards to the source, being a "submission post", and the post replied to, being a "parent comment"

Finally the dataset is also annotated for rumours, and these as being either true, false or unverified. A total of 16 submissions were deemed as rumours, that is, the source post in each of these submissions initiates some rumourous statement, which spawns one or more *conversations*. Each conversation has one or more *branches*, being a sequence of nested replies from

a comment with no replies until the top-level comment. The conversation structure is also described in Figure 6, section 3.1.2. The submissions are contained within nine of the events, and are listed in Table 4, including their title and annotated truth status.

Event	Submission title	Rumour status		
	5G-teknologien er en miljøtrussel, som bør	Unverified		
5G	stoppes			
	Det er ikke alle, som glæder sig til 5G.	Unverified		
	Uffe Elbæk er bekymret over de "sund-	Unverified		
	hedsmæssige konsekvenser" af 5G-netværket			
D11 T	Hvorfor må DR skrive sådan noget åbenlyst	Unverified		
Donald Trump	falsk propaganda?			
	16-årig blev anholdt for at råbe 'fuck Trump'	Unverified		
	til lovlig demonstration mod Trump			
ISIS	23-årig dansk pige har en dusør på \$1 million	Unverified		
1515	på hendes hovede efter at have dræbt mange			
	ISIS militanter			
	Danish student 'who killed 100 ISIS mili-	Unverified		
	tants has \$1million bounty on her head but			
	is treated as terrorist' (The Mirror)			
Kost	Bjørn Lomborg: Du kan være vegetar af	Unverified		
NOSt	mange gode grunde - men klimaet er ikke en			
	af dem			
	Professor: Vegansk kost kan skade småbørns			
	vækst			
MeToo	Björks FB post om Lars Von Trier (#MeToo)	Unverified		
	Savnet ubåd er fundet i Køge Bugt: Alle er i	False		
Peter Madsen	god behold			
	Undersøgelser bekræfter: Ubåd blev an-	True		
	giveligt sunket bevidst			
	Peter Madsen: Kim Wall døde i en ulykke på	False		
	ubåden			
Politik	KORRUPT	True		
Togstrejke	De ansatte i DSB melder om arbejd-	True		
	snedlæggelse 1. april.			
Ulve i DK	Den vedholdende konspirationsteori: Har no-	Unverified		
	gen udsat ulve i Nordjylland?			

Table 4: Overview of the rumour submissions and their veracity status

Out of the 16 rumourous submissions, three were true, three were false and the rest were unverified. They make up 220 Reddit conversations, or 596 branches, with a total of 1,489 posts, equal to about half of the dataset. The posts are distributed across the nine events as follows: 5G(233), Donald Trump(140), ISIS(169), "Kost" (324), MeToo(60), Peter Madsen(381), "Politik" (49), "Togstrejke" (73), and "Ulve i DK" (56). Thus ISIS, MeToo,

and Peter Madsen are the only events which only contain rumourous conversations.

With the introduction and presentation of the Danish stance-labelled Reddit dataset, denoted DAST, generated and annotated, we turn to the task of rumour stance classification and rumour veracity prediction.

6 Methods

This section provides an introduction to the methods and approaches taken in this project to use the DAST dataset described in section 5 for stance classification and ultimately rumour veracity classification. Section 6.1 describes how data preprocessing is performed, section 6.2 introduces the machine-learning approaches for stance classification, as well as features, and section 6.3 describes the approach taken for rumour veracity classification with Hidden Markov Models.

6.1 Preprocessing of data

This section describes how all the annotated data from Reddit (see section 5) is preprocessed for subsequent use in the stance classification task (section 6.2).

6.1.1 Data representation

After the Reddit data has been annotated with the annotation tool as described in section 5.2, it can be downloaded. The data is downloaded through the annotation tool, which formats each submission into JSON files and groups them by event. Each JSON file is structured in the format sketched below, resembling the format of the extracted Reddit data (see appendix A.2). All posts within a branch is sorted by its time of creation.

The "redditSubmission" object contains the following relevant information: id, title, text, creation date and time, number of comments, possible URL referencing an article, URL referencing the submission, upvotes, and user info. Furthermore, this object includes the annotation data, including its stance towards the rumour; supporting, denying, underspecified, and rumour veracity status; true, false, unverified, and an accompanying description of the rumour. The user info mentioned above include the user id, user account creation time and date, as well as Reddit specific properties such as karma count and gold status, Reddit employee status(true/false), and a verified email flag.

The list of branches include nested lists of the posts contained within the branches. Each of these posts contains data similar to the data described above: comment ID, text, parent comment ID, URL, creation time and date, user info, and Reddit specific properties including upvotes and replies, as well as flags such as "is submitter" and "is deleted". Each post also has annotation details including SDQC to the rumour/statement introduced in the submission and SDQC with regards to the parent post.

The download functionality exposed through the annotation tool takes care of cleaning the data, such that deleted posts and non-annotated posts are ignored. Additionally all posts created after a deleted post in a branch are ignored, as keeping them would otherwise break the natural flow of conversation with the valid posts above the deleted one.

6.1.2 Data preprocessing

Once the data is downloaded it can easily be loaded and represented as Python objects with the JSON decoder³¹, keeping the structure from the JSON files. As a preprocessing step, all post texts are lower-cased and then tokenised with the NLTK library [Bird et al., 2009], and finally all punctuation is removed, not including cases such as commas and periods in numbers, as well as periods in abbreviations. Furthermore URLs are replaced with the tag "urlurlurl" and quotes with the tag "refrefref".

Throughout loading and preprocessing of the data, minimum and maximum values are recorded for discrete values in the data, in order to allow normalisation in the feature extraction step (see section 6.2.4).

It is important to note that the source post, i.e. the submission post, is not subsequently used in feature extraction and classification. This is because it is separate from the other posts in a submission, unlike e.g. conversations on Twitter (see discussion in sections 3.1.2 and 3.1.3). It is only used for annotation of top-level comments in Reddit conversations, its rumour veracity status, as well as the cosine similarity between that and other posts (further explained in section 6.2.4).

³¹ https://docs.python.org/3/library/json.html

With the DAST data preprocessed, feature extraction can be performed and subsequently work as input to a stance classifier, which is described next, in section 6.2.

6.2 Rumour stance classification

This section presents the methods applied for rumour stance classification on the preprocessed DAST data.

First, the scoring metrics used for the experiments in this project are introduced in section 6.2.1. A variety of Machine Learning (ML) models are utilised to perform stance classification, which are described next in sections 6.2.2 and 6.2.3. As input, these ML models require feature vectors. A description of the features generated from feature extraction of the preprocessed DAST is presented in section 6.2.4, followed by a feature vector overview in section 6.2.5.

6.2.1 Scoring metrics

Most of the related work report results with accuracy as scoring metric [Derczynski et al., 2017, Aker et al., 2017], which expresses the ratio of number of correct predictions to the total number of input samples. However, this becomes quite uninteresting if the input samples have imbalanced class distributions, which is the case for our dataset (see section 5.2.2). What is interesting to measure is how well the models are at predicting the correct class labels. As such, in addition to reporting accuracy we will also use the F_1 scoring metric, which is the harmonic mean between precision and recall. In particular we will use an unweighted macro-averaged F_1 score.

In order to get an idea of the differences between the scoring metrics, we will briefly describe what they stand for as defined in [Han et al., 2011, 8.5.1]. The goal with the metrics is to evaluate classification performance. That is, we have labelled data, being DAST, and we want to be able to classify unseen data, such that it is classified with the correct class label. In our case however, knowing if the classification results on unseen data really is correct can be difficult to determine, but we investigate this further with an example in section 8.3.3.

For classification, four terms are typically used to denote the outcome of classification, being true positives(TP), true negatives(TN), false positives(FP), and false negatives(FN), which are summarised in table 5. Note that we will present several such confusion matrices throughout the experiments in section 7.

Now, accuracy is defined as the true positives and true negatives out of all predictions, or formally as defined in equation 1:

Table 5: Confusion matrix of true positives(TP), true negatives(TN), false positives(FP), and false negatives(FN)

$$accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

In order to understand F_1 , first we must understand *precision* and *recall*. The former is a measure of exactness, i.e. how many predictions labelled as positives (TP+FP) are actually such. The latter is a measure of completeness, i.e. how many actual positive prediction (TP+FN) are labelled as such. This can be expressed formally as in equations 2 and 3 below:

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall = \frac{TP}{TP + FN} \tag{3}$$

Precision and recall tend to have an inverse relationship, in that increasing one will come at the cost of reducing the other. This is where the F measure applies, which combines precision and recall in a single measure. A typical F measure is F_1 , which is defined as:

$$F_1 = \frac{2 \times precision \times recall}{precision + recall} \tag{4}$$

As mentioned, this is a harmonic mean³² of precision and recall, which gives equal weight to each measure. One can also use the F_{β} measure, which assigns β times as much weight to recall as to precision, which may be desirable in some cases.

Finally, for multi-class classification, such as for SDQC, we want to include an averaged F_1 score. In this case we will use the $macro\ F_1$ measure³³, which is an unweighted mean of F_1 score per class label, hence treating all

 $^{^{32}}$ https://en.wikipedia.org/wiki/Harmonic_mean 31-05-2019

 $^{^{33} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html$

classes equally. In contrast, $micro\ F_1$ is calculated as the mean of aggregated contributions for all classes.

Where appropriate we will also report standard deviation for averaged results, which quantifies the amount of variation in the set of predicted class labels³⁴.

6.2.2 LSTM classifier

The LSTM model is widely used for tasks where the sequence of data and earlier elements in sequences are of importance [Goldberg, 2016]. The temporal sequence of tweets was one of the motivations for [Kochkina et al., 2017] to use the LSTM model for branches of tweets, as well as for the bidirectional conditional LSTM for [Augenstein et al., 2016]. As such this section introduces the LSTM method and how we propose to use it for stance classification.

The Long-Short Term Memory deep learning method is a variant of a Recurrent Neural Network (RNN). RNNs allow representing arbitrarily sized structured inputs in a fixed-size vector, while paying attention to the structured properties of the input [Goldberg, 2016, p. 46]. This property can be desirable when dealing with language data, which are sequences of letters, words, and sentences, and is typically the motivation for implementing an RNN architecture. The RNN model works as follows: it takes as input an ordered list of input vectors x_1, \ldots, x_n and an initial state vector s_0 , and returns an ordered list of state vectors s_1, \ldots, s_n , as well as an ordered list of output vectors y_1, \ldots, y_n [Goldberg, 2016, p. 46]. This can formally be described as:

$$RNN(s_0, x_{1:n}) = s_{1:n}, y_{1:n}$$
(5)

The output of an RNN is determined by two abstract functions R and O. R is a recursively defined function which computes a new state vector s_i from the previous state s_{i-1} , and an input vector x_i . O is a function which maps a state vector s_i to an output vector y_i . R and O are mathematically defined as follows:

$$s_i = R(s_{i-1}, x_i)$$

$$y_i = O(s_i)$$
(6)

That is, an RNN state is represented by s_i and y_i after observing the inputs $x_{1:i}$. This means that an RNN state is based on the history of inputs x_1, \ldots, x_i . In contrast, the Markov assumption describes models, such as the HMM, where future states of a stochastic process depends only upon

 $^{^{34}}$ https://en.wikipedia.org/wiki/Standard_deviation 31-05-2019

the present state³⁵. The RNN model is illustrated in Figure 12, with the recursive definition for arbitrarily sized input on the left, and an example of a fixed sized input on the right.

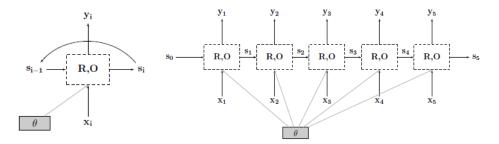


Figure 12: Graphical representation of a recursive definition of an RNN (left) and an unrolled RNN for a fixed-size sequence (right). For time step i, x_i denotes the input vector, s_i the state, and y_i the output. R and O are functions, while θ denotes the parameters, which are shared across all time steps. The unrolled version (right) is an example for a finite sized input sequence x_1, \ldots, x_5 . Source: [Goldberg, 2016, p. 47]

The abstract functions R and O can be implemented in various ways, thus instantiating different versions of an RNN. The simplest RNN formulation, Simple-RNN (S-RNN) [Goldberg, 2016, p. 55], computes a state s_i as a linear combination of the input x_i and previous state s_{i-1} , passed through a non-linear activation function (typically ReLU), while the output y_i evaluates to s_i .

The S-RNN model however suffers from the vanishing gradients problem, making it unable to capture long-range dependencies [Goldberg, 2016, p. 55]. The LSTM architecture is designed to solve this by introducing the idea of "memory cells" to preserve gradients across time. For each input state, a gate is used to decide how much of the new input should be written to the memory cell (input gate), and how much of the current content of the memory cell should be forgotten (forget gate). A third and final gate (output gate) determines the output based on the content of the memory cell at a given time. The LSTM architecture is defined formally in [Goldberg, 2016,

 $^{^{35}}$ https://en.wikipedia.org/wiki/Markov_property 01-06-2019

p. 56] as in equation 7:

$$s_{j} = R_{LSTM}(s_{j-1}, x_{j}) = [c_{j}; h_{j}]$$

$$c_{j} = c_{j-1} \odot f + g \odot i$$

$$h_{j} = tanh(c_{j}) \odot o$$

$$i = \sigma(x_{j}W^{xi} + h_{j-1}W^{hi})$$

$$f = \sigma(x_{j}W^{xf} + h_{j-1}W^{hf})$$

$$o = \sigma(x_{j}W^{xo} + h_{j-1}W^{ho})$$

$$g = tanh(x_{j}W^{xg} + h_{j-1}W^{hg})$$

$$y_{j} = O_{LSTM} = h_{j}$$

$$s_{j} \in \mathbb{R}^{2 \cdot d_{h}}, x_{i} \in \mathbb{R}^{d_{x}},$$

$$c_{j}, h_{j}, i, f, o, g \in \mathbb{R}^{d_{h}},$$

$$W^{xo} \in \mathbb{R}^{d_{x} \times d_{h}}, W^{ho} \in \mathbb{R}^{d_{h} \times d_{h}}$$

$$(7)$$

The mechanisms of the LSTM as described in [Goldberg, 2016, p. 56] work as follows:

A new state at time j is composed of two vectors, c_j and h_j , where the former is the memory cell and the latter is the output component. The three gates are denoted as respectively \mathbf{i} , \mathbf{f} , and \mathbf{o} , controlling for input, forget, and output as described above. The gate values are computed based on linear combinations of the current input x_j and the previous state h_{j-1} , passed through a sigmoid activation function (σ) . \mathbf{g} is an update candidate, which is computed as a linear combination of x_j and h_{j-1} , passed through a tanh activation function. When these four values are computed, the memory cell c_j is updated accordingly, by determining how much of the previous memory to keep $(c_{j-1} \odot f)$ and how much of the proposed memory to keep $(g \odot i)$. Note that \odot denotes component-wise product. The output y_j is then the value of h_j , which is determined by the value of the updated memory cell passed through a tanh non-linearity and controlled by the output gate, \mathbf{o} .

The LSTM approach in [Augenstein et al., 2016] was introduced as a state-of-the-art system in section 2.3.1, performing very well in an unsupervised target-stance classification task. This approach implements a bidirectional variant of an LSTM, denoted "Bi-LSTM". While the LSTM as described above would allow us to compute a function of the *i*th word x_i based on the words $x_{1:i}$ in a sentence x_1, \ldots, x_n , the bidirectional implementation also considers the words $x_{i:1}$ [Goldberg, 2016, p. 52]. Put differently, the input sequence is also considered in reverse order, thus allowing the LSTM to look arbitrarily far at both the past and the future of the given input data.

The bidirectional architecture works by maintaining respectively a forward state and a backward state, generated by two different LSTM models. One LSTM receives the input sequence in one order and the other receives it in reverse. The state representation at a given time step is then composed of both the forward and the backward states.

While the results from both the Bi-LSTM in [Augenstein et al., 2016] and Branch-LSTM in [Kochkina et al., 2017] achieves state-of-the-art performance, they both note that their deep learning approaches suffer from the lack of a larger training dataset. As such we suspect that we would observe the same tendency for the DAST dataset, which is relatively small with its 3,007 Reddit posts (see section 5.1.1). However, as the LSTM approach still manages to achieve state-of-the-art performance, we have opted to include an LSTM implementation for the stance classification task.

Specifically, the LSTM classifier used for stance classification in this project consists of a number of LSTM layers, and a number of ReLU layers followed by a dropout layer and a softmax layer to perform classifications. The configurations considered and overall approach is inspired by the Branch-LSTM classifier in [Kochkina et al., 2017], except that we do not input data grouped sequentially by branches, but one by one. As such we do not implement any extra features than the LSTM method described in this section.

6.2.3 Classic classifiers

The remaining ML approaches utilised are facilitated by the scikit learn [Pedregosa et al., 2011] library which provides a wide variety of machine learning implementations. Specifically we implement non-neural network models, and will as such denote these models as either "scikit learn classifiers" or "classic classifiers". It is the intention to use non-neural network models in contrast to the LSTM deep learning approach above, as research shows that this approach can do very well [Derczynski et al., 2017], particularly Decision Tree and Random Forest classifiers [Aker et al., 2017]. Furthermore Support Vector Machine (SVM) and Logistic Regression have proven to be efficient [Enayet and El-Beltagy, 2017, Derczynski et al., 2017]. The models are listed below, prefixed with a label, which we will use to denote them throughout the paper:

logit: Logistic Regression fits a logistic function to determine the probability of some label being true given training data³⁶. Given that this is a binary classifier, a logistic regression is made for each label present in the data, and predicts the label with the highest probability of being true. logit

 $^{^{36}}$ https://en.wikipedia.org/wiki/Logistic_regression 02-06-2019

is implemented with the LogisticRegression model³⁷.

tree: Decision Tree classifier builds a tree structure from training data, where the labels are isolated given partitions on the attributes in the training data [Han et al., 2011, p. 330-346]. A commonly used strategy for identifying the appropriate attribute to split on is information gain. The decision tree will try to choose the split of attributes such that the class label is isolated most efficiently. New data entries choose a path through the tree given the trained attribute splits and the class label in the leaf is the prediction. tree is implemented with the DecisionTreeClassifier model³⁸.

svm: Support Vector Machine searches for the optimal separating hyperplane, a boundary which separates the data of one class label from another [Han et al., 2011, sec. 9.3, p. 408-415]. If the input is not linearly separable the SVM applies a non-linear mapping function on the input data to lift it into a higher dimensional space. The mapping into higher dimensions is applied until the data is linearly separable by a hyperplane in the new dimensions. The complexity of the SVM is not correlated to the dimensionality of the data, but the number of support vectors found. This means the SVM does not tend to be prone to overfitting, which is a desired trait given the skewedness of DAST. svm is implemented with the LinearSVC model³⁹ using a linear kernel.

rf: Random Forest is an ensemble method in which k Decision Trees are build, each given a random subset of the attributes [Han et al., 2011, p.382-383]. Given new data the ensemble of trees each vote and the most popular prediction is the output of the Random Forest. The method is robust in that outliers in the data only have a small effect on the model. Further the model is not prone to overfitting as long as the number of trees in the ensemble is large. rf is implemented with the RandomForestClassifier model⁴⁰.

As baseline models, a simple majority voter as well as a stratified classifier have been used from scikit learn⁴¹. They are defined as:

 $^{^{37} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.linear_model. LogisticRegression.html$

³⁸https://scikit-learn.org/stable/modules/generated/sklearn.tree. DecisionTreeClassifier.html

 $^{^{39} \}texttt{https://scikit-learn.org/stable/modules/generated/sklearn.svm.} \\ \text{LinearSVC.html}$

 $^{^{40} \}verb|https://scikit-learn.org/stable/modules/generated/sklearn.ensemble. RandomForestClassifier.html$

 $^{^{41} \}verb|https://scikit-learn.org/stable/modules/generated/sklearn.dummy. \\ \verb|DummyClassifier.html|$

mj: Majority vote classifier is a simple classifier, which identifies the most frequently occurring class label in the training set, and always predicts that given label. As such it can achieve deceptively high accuracy scores on skewed datasets.

sc: Stratified classification—generates predictions such that they respect the distribution of class labels in the training data. In other words, this baseline classifier creates random samples respecting the distribution found in the training data. For example given a training set with 90% 0's and 10% 1's, the baseline will pick 0 at a 90% rate and 1 at a 10% rate when "classifying" unseen data.

6.2.4 Features

Words and sentences can be difficult for computers to process and understand, therefore a numerical representation of each post is needed. This is achieved through feature extraction, in which properties about the post are represented by numbers. The numerical representation of a post as some vector is much easier to work with and reason about in a computational context.

In order to represent the features of the preprocessed data numerically we employ eight feature categories, which are grouped by how they relate: text, lexicon, sentiment, Reddit, most frequent words, BOW, POS, and word embeddings. Note that only the Reddit specific feature are domain-dependent, while the others should apply for the general case. The choices of features are a compilation of select features from various state-of-the-art systems [Aker et al., 2017, Kochkina et al., 2017, Enayet and El-Beltagy, 2017], except for the Reddit specific ones. Most of the features are binary, taking either a 0 or a 1 as value, and those that are not are min-max normalised [Han et al., 2011, p. 114], except for the word embeddings.

Text features are extracted from the syntax of the text in the data and include the following listings:

Binary values:

- Presence of period, '.'
- Presence of exclamation mark, '!'
- Presence of question mark '?' or 'hv'-words ('wh' question words, such as 'what' and 'why')
- Presence of three sequential periods, '...'

Discrete values:

• Length of raw text (no preprocessing)

- Count of URL references
- The maximum length of a capital character sequence
- Count of three sequential periods, '...'
- Count of question mark, '?'
- Count of exclamation mark, '!'
- Number of words

Continuous values:

- Ratio of capital letters to non-capital letters
- Average word length

Lexicon features are extracted by looking up occurrences of items in four predefined lexicon/dictionaries: negation words, swear words, positive smileys, and negative smileys. The negation words are translated from the English list used in [Kochkina et al., 2017], as no list could be found for this purpose elsewhere. The swear words are generated from various sources aside from ourselves: youswear.com⁴², livsstil.tv2.dk⁴³, dansk-og-svensk.dk⁴⁴, and dagens.dk⁴⁵. The smiley lists were compiled from Wikipedia using the western style emoticons⁴⁶.

Reddit-specific features are features, which are specific to the domain of Reddit, and include information about the user who posted a submission or reply to a submission, as well as meta information about the post. For the user features, these include the following, where only the first one is non-binary:

- Karma The score awarded from upvotes on the users comments and submissions. On Reddit this value does not have an upper bound.
- Gold Status Whether the user has gold status⁴⁷
- Is Employee Whether the user is a Reddit employee
- Verified Email Whether the user has a verified email
- Is submitter Whether the user is submitter of the given submission

 $^{^{42}}$ http://www.youswear.com/index.asp?language=Danish 06-05-2019

 $^{^{43}}$ http://livsstil.tv2.dk/2017-06-10-taet-oploeb-her-er-brugernes-favorit-bandeord $^{06-05-2019}$

 $^{^{44} {\}rm https://www.dansk-og-svensk.dk/danskt_lexikon2/Bandeord/svenske_danske_bandeord.htm}$

 $^{^{45}}$ https://www.dagens.dk/nyheder/se-listen-her-er-de-allervaerste-bandeord $^{06-05-2019}$

⁴⁶https://en.wikipedia.org/wiki/List_of_emoticons 25-02-2019

⁴⁷Paid premium Reddit membership, which can also be awarded to you by the quality of your post. See https://www.dailydot.com/debug/what-is-reddit-gold/ 27-05-2019

Furthermore the syntax when posting to Reddit allows for enriching the display of the text. For example '>' will display the subsequent text as a quote and '**' will enable bold text. Others are more subtle, such as the '/s' tag, which as an unwritten rule marks the comment from the user as intentionally sarcastic. The Reddit specific syntax features include the following, where the first two are binary values:

- Sarcasm Whether the user expresses sarcasm with the '/s' tag
- Edited If the text has been denoted as edited with the 'edit:' tag
- Quote count Count of quotes denoted with '>'
- Reply count The number of replies to the given post
- Upvotes How many upvotes (or downvotes) a post has received

Bag of words (BOW) is a set of unique words appearing in all the text data, and the features generated from this are binary features of whether the given post include a word from the set or not.

Most frequent words are extracted as being the n most occurring words in posts grouped per annotation class. In order to filter out general frequent words, such as 'er' ('is') and 'og' ('and'), words that appear in all n most frequent words per class are removed. This way the lists more precisely captures words related to each specific class.

The "most frequent words" (MFW) feature is implemented such that we consider the 100 most frequent words per class, and *then* filter out words occurring in all four lists, resulting in 33 words per class, and a total of 132 words/features. The filtering is performed in order to remove potential stopwords.

Considered too many words would make MFW be more similar to BOW, and conversely; considered too few words would make MFW too specific. As such, the choice of generating 33 words per class seemed like a good trade-off, capturing unique words per class, without including the more general stopwords. The generated list of most frequent words per class is included in appendix B.1. As an example, two of the most occuring words for the "querying" class are "hvorfor" and "hvordan", which is interesting as these are question words. However, we also observe event-specific words such as "CO2", "5G", and "B12", specifically tying some of the most frequent words to DAST.

Sentiment values are computed with the Afinn library, which is used to perform sentiment analysis on a number of different languages, including Danish [Årup Nielsen, 2011]. It takes as input a piece of text and rates the overall sentiment score of the text, where negative sentiment gives low or

negative values and positive sentiment gives higher values. The sentiment score provided by this library on the text of a post is used as a continuous normalised feature.

Part-of-speech (POS) tags are used to tag a given text and denote with binary features whether the text include each tag from the POS set. The polyglot library is used for the POS tagging, which include support for the Danish language [Al-Rfou et al., 2013]. The POS tags consists of the following 17 tags:

NUM numeral ADJ adjective PART particle ADP adposition PRON pronoun **ADV** adverb PROPN proper noun AUX auxiliary verb **PUNCT** punctuation CONJ coordinating conjunction **SCONJ** subordinating conjunction **DET** determiner SYM symbol **INTJ** interjection VERB verb NOUN noun X other

Word embeddings are a way to represent words as vectors of real numbers, which have a number of benefits. One benefit is the ability to compare and group words with the same meaning, even if the letters and structures of the words are not alike. Finding nearest neighbouring words is possible on the GloVe dataset [Pennington et al., 2014], where a query for the word "frog" among others returns "leptodactylidae" and "eleutherodactylus", which are words used to describe certain types of frogs⁴⁸. Even though neither of the words are alike the query word "frog", they refer to the same entity and are used in the same contexts.

Word embeddings have been employed as an average of word vectors for each word in a text [Kochkina et al., 2017]. Various algorithms for using dense word embeddings for representing the words in a text have been considered. First, pre-trained word embeddings with fastText for the Danish language have been downloaded and used [Grave et al., 2018]. The algorithm is developed by Facebook AI Research and is applicable for text classification, being fast and on par with state of the art [Joulin et al., 2016]. Pre-trained word vectors for 157 languages are distributed from the fastText

⁴⁸https://nlp.stanford.edu/projects/glove/ 30-05-2019

website⁴⁹, which are trained on Common Crawl⁵⁰ and Wikipedia⁵¹.

Second, word2vec [Mikolov et al., 2013] have been used to "manually" train word embeddings for the Danish language. The algorithm learns vector representations of words by processing a text corpus with either the CBOW or skip-gram model⁵². A Danish text corpus has been acquired from "Det Danske Sprog- og Litteraturselskab" (DSL)⁵³, being their biggest corpus, "Korpus 2010", consisting of 45 million tokens of written LGP (Language for General Purposes)⁵⁴. The sentences used from the corpus contain no punctuation or uppercase letters, and has subsequently been tokenised and fed into the word2vec algorithm through the gensim Python framework [Řehůřek and Sojka, 2010]. For experimental purposes the corpus has also been used to train fastText vectors from scratch, instead of the pretrained ones. The framework allows to test with different parameters, such as vector lengths, windows sizes, and training algorithms in order to find the optimal settings, but the default ones have been used. Once trained the word embeddings can be saved to disk, such that they can be retrieved more efficiently when used in word representations in the classification task. This avoids the need to train the model all over again.

Finally the word embeddings model has been further trained on the preprocessed text from the Reddit dataset. A vector length of 300 is used, as in [Kochkina et al., 2017]. In addition to the averaged word vector, three features are computed from the word embeddings, namely cosine similarity to the parent post, source post, and concatenation of branch posts, which has been deemed relevant in other research [Kochkina et al., 2017].

6.2.5 Feature vector overview

Table 6 presents an overview of the total feature vector, including a rough categorisation of their meaning as introduced in this section. Note that the word embeddings are actually 300 long, but the extra 3 features are the cosine similarities between different word embeddings with regards to parent, source, and branch word tokens.

6.2.6 Testing approach

Throughout the stance classification experiments conducted in section 7 we will make use of some common techniques for testing, which will be briefly introduced here.

⁴⁹https://fasttext.cc/docs/en/crawl-vectors.html 22-02-2019

⁵⁰http://commoncrawl.org/

⁵¹https://www.wikipedia.org/

 $^{^{52}}$ https://code.google.com/archive/p/word2vec/ 22-02-2019

⁵³https://dsl.dk/

⁵⁴https://korpus.dsl.dk/resources.html

Category	Length
Text	13
Lexicon	4
Sentiment	1
Reddit	10
Most frequent words	132
BOW	13,663
POS	17
Word embeddings	303
Total	14,143

Table 6: Feature vector overview

First off, where applicable we will make use of the concept of splitting the data into a training and test sample, which allows us to evaluate the models on "new", unseen data, and avoid overfitting. For this purpose we will be using the train_test_split(..) function from scikit learn⁵⁵. The function splits the lists of indexed features vectors and class labels properly according to a given representation of the proportion of the dataset to include in the test split. If nothing else is specified, we are using a test split size of 0.2, which makes up a sample of 602 data points, leaving 2,405 data points in the training sample. Furthermore we use the "stratify" option in the train-test split, making sure both samples have the same distribution of class labels.

Furthermore, where applicable, we use k-fold cross validation(CV) to evaluate generalisation strength of the models. Again, we use the **scikit** learn implementation⁵⁶. In this case we also enforce stratification. If nothing else is specified we employ 5-fold CV.

Finally, in the experiments, if nothing else is stated we use all of the features introduced in section 6.2.4, and the word2vec word vectors as representing word embeddings.

6.3 Rumour veracity classification

As stated in section 3 the approach for rumour veracity classification is based on a Hidden Markov Model (HMM). This section briefly describes the workings of a HMM and how it is used for the task of rumour veracity classification with crowd stance, following the work in [Dungs et al., 2018].

 $^{^{55} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html <math display="inline">13\text{-}05\text{-}2019$

 $^{^{56} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.cross_validate.html <math display="inline">13\text{-}05\text{-}2019$

6.3.1 Hidden Markov Models

A Hidden Markov Model is a probabilistic model which works on sequences of input. The model consists of a number of hidden states $S = \{s_1, s_2, ..., s_N\}$ and a number of possible observations $E = \{e_1, e_2, ..., e_M\}$, where N is the number of possible hidden states and M is the number of possible observations. The transition probabilities between hidden states in S can be described by a transition matrix $T \in \mathbb{R}^{N \times N}$, such that T_{ij} describes the probability of transitioning from state S_i to S_j . The emission probabilities can be described as an emission matrix $O \in \mathbb{R}^{N \times M}$, where O_{ij} describes the probability to see observation E_j when in state S_i . Lastly the probability of starting in a given state s can be described as a randomly initialised vector $P \in \mathbb{R}^N$. As such the Hidden Markov Model can be more formally described as:

$$\lambda = \{S, E, T, O, P\} \tag{8}$$

The chosen implementation in the hmmlearn library uses a Gaussian distribution⁵⁷, where the randomly initialised probabilities are adjusted by the Baum-Welch algorithm [Wu et al., 1999] on the training data. When λ has been "trained" with Baum-Welch, the Viterbi algorithm [Lou, 1995] is used to determine the most likely sequence of hidden states and the total probability of some sequence of observations $E' = \{e_1, e_2, ..., e_k\}$ with length K.

The approach used in [Dungs et al., 2018] relinquishes, among other, textual features to rely solely on sequences of stance labels in their model λ and sequence of stance labels and time stamps in the "Multi-spaced" HMM λ' . Inspired by λ' , we implement a variation of λ , denoted ω . λ' initialises a random real number for each stance and a weight which is learned given a distribution function over the time stamps⁵⁸. ω works much like λ , however normalised time stamps are included as a feature. This was done as temporal properties were observed to boost performance in the [Dungs et al., 2018] results. The more complex multi-spaced HMM (λ') was however deemed out of scope for this project given time and resource constraints, although it would be interesting to apply.

For classification a HMM is built for each label with a varying state space size ranging from $1 \le n \le 15$. The prediction for some sequence Q is determined by which model outputs the greater probability for Q.

6.3.2 Testing approach

The fact that the models rely solely on stance labels and time stamps opens up the opportunity for stance labelled data to be used across languages and

 $^{^{57} \}rm https://hmmlearn.readthedocs.io/en/latest/api.html#hmmlearn.hmm. GaussianHMM <math display="inline">28\text{-}05\text{-}2019$

⁵⁸See [Dungs et al., 2018, 4.3] for a description of this more complex HMM version

platforms. This is especially interesting as the DAST dataset only contains 16 rumours, with 1,496 posts across 220 conversations. As such it should be possible to use the PHEME dataset [Zubiaga et al., 2016a] in conjunction with DAST. The PHEME dataset is a popular and widely used Twitter dataset, such as in RumourEval 2017 [Derczynski et al., 2017]. The dataset contains 4,842 tweets across 297 English and 33 German Twitter conversations, out of which 159 are true, 68 are false and 103 are labelled as unverified [Zubiaga et al., 2016b]. The data used for training is however a subset of PHEME, as described by [Dungs et al., 2018]. Here only 5 events yielded 5 or more rumours with 5 or more tweets in the conversation. The same choice was applied here to align with their approach.

First, in order to investigate the Danish data isolated, 3-fold cross validation will be performed solely on the Danish data. Further, to see how well the data can be used in conjunction, the PHEME dataset will be utilised in two ways: (1) as training data for the models, with the Danish data as test set, and (2) mixed with the Danish data in 3-fold cross validation.

As a baseline throughout the experiments, a simple stratified baseline will be used, denoted as VB. The baseline notes the average distribution of stance labels as a four-tuple for respectively true and false (and unverified where relevant) rumours. When predicting rumour veracity, VB calculates the distribution of stance labels in a given sequence in the testing data and chooses the truth value with the most similar class label distribution.

7 Stance classification experiments

This section reports on various experiments carried out in order to reach the best performing models for the stance classification task. These experiments constitutes model selection techniques including feature selection, parameter search, and data sampling. However for feasibility reasons, for the case of the LSTM the parameter search has only been carried out.

7.1 Feature selection

The features generated to represent a data point in our dataset are compiled from various research, as introduced in section 6.2.4. However, those features worked great for *their* data, which is not a given will be the same case for our data. As such this section reports on various experiments with the goal of selecting those features from which our models benefit the most, while still considering generalisation strength with regards to domain and platform.

7.1.1 Ablation study

Aside from experimenting with all the features, an ablation study for the feature categories has been carried out. This is done by holding one fea-

ture category out at a time while the rest remains. This should unveil the effectiveness of each feature category. Further it allows possible discrepancies in data preference for the models to be revealed, as some models might have better results on different data. Optimally all combinations of features would be tested, but this becomes quite unfeasible with 8 feature categories, covering several individual features.

This experiment has been carried out with default versions of the scikit learn models introduced in section 6.2.3, leaving the configuration to the default values defined by the library implementations. The results are shown in figure 13, where tests are run with 5-fold cross validation with macro F_1 as scoring metric⁵⁹.

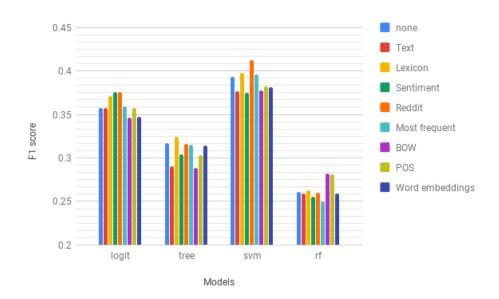


Figure 13: Feature importance per model measured with averaged F_1 macro through 5-fold cross validation

The blue pins are results where no features have been removed and are thus the pins to compare the others to. As such, a higher result than this means that we achieve better results by removing the given feature, and vice versa. We see that it is the general case that by removing lexicon features we achieve a higher macro F_1 score. Both for logit and svm, the Reddit features also do not seem to do any good, while they do not change much for tree and rf (the classic classifiers introduced in section 6.2.3). It is difficult to say anything in general about the remaining features, as they don't seem to show an overall trend, such as the sentiment features

 $^{^{59}\}mathrm{As}$ well as accuracy, but those results deviated too little in order to use it for this analysis

for Logistic Regression, which has opposite effect on the other models. As such it seems that we might benefit across the line by excluding lexicon and Reddit features. Table 7 shows that by running the same cross validation test with the default models, but with both lexicon and Reddit features removed, we see an expected improvement in macro F_1 score for almost all of the models.

Model	All features	Lexicon+Reddit removed
\overline{logit}	0.36	0.38
tree	0.32	0.32
svm	0.39	0.41
rf	0.26	0.25

Table 7: F_1 score of the default models with respectively no features removed and lexicon and Reddit features removed

7.1.2 Removing low-variance features

Furthermore, a second strategy for testing the feature importance has been to reduce the number of features through a simple but effective feature selection method, which further improves running time for the classifiers. The feature vectors are quite long, as can be seen in Table 6, section 6.2.5, with a total length of 14,143, with BOW being the main contributor with its 13,663 values. As the BOW feature consists of only 0's and 1's, one can imagine that there might be low variance for some of the variables. VarianceThreshold(VT)⁶⁰ from scikit learn has been used to eliminate low-variance features, that is, features which under a predefined threshold only occur few times in the samples.

The benefits of removing features which rarely change can be compared to the concept of "information gain" used in Decision Trees. The information gain is a metric which describes how "pure" a split of labels would be given some variable. If all vectors across all labels for example have the same value in some dimension d, the feature provides no partitioning information about the class labels. In that case the feature is more likely to be noise than helpful information.

Table 8 shows the number of features eliminated with variance thresholds of respectively 0%, 0.1%, and 1%. With only a 0.1% threshold, the number of features are reduced to 3,288, equivalent to a reduction of nearly 77% of the features. Further, we see that it indeed is the BOW features having very low variance. What is also interesting is the fact that the lexicon features are removed altogether with a variance threshold of 1%, as well as removal of one Reddit feature and one POS feature with a 0% variance threshold.

 $^{^{60} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.VarianceThreshold$

It is however not that surprising for the lexicon and Reddit features, as the previous feature selection experiment showed that these two categories have negative impact to some degree for each of the models.

Category	All	0%	0.1%	1%
Text	13	13	10	4
Lexicon	4	4	3	0
Sentiment	1	1	1	1
Reddit	10	9	9	6
Most frequent words	132	132	132	129
BOW	13,663	13,663	2,814	381
POS	17	16	16	16
Word embeddings	303	303	303	303
Total	14,143	14,141	3,288	840

Table 8: Low variance feature removal by feature category

In order to test the impact of removing low-variance features, this experiment was run with the default scikit learn models. Figure 14 illustrates the macro F_1 score of the different models through 5-fold cross validation with respectively no feature reduction, 1%, and 0.1% thresholds. From this one can see that removing features with variance less than 1% does have some influence, while 0.1% is almost identical to removing no features.

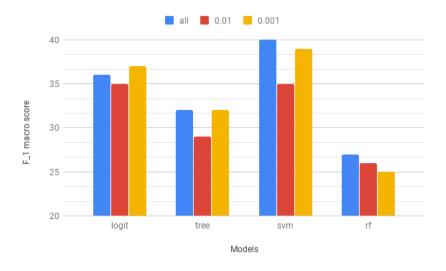


Figure 14: Macro F_1 score of default models with VarianceThreshold feature reduction

When combining VarianceThreshold with removal of lexicon and Reddit features, the benefit is not uniform across the classifiers. *logit* and *rf* are the only models which get better by using both feature selection strategies, while *tree* and *svm* get worse performance, as can be seen in Table 9.

Model	Lexicon+Reddit	Lexicon+Reddit+VT
logit	0.38	0.40
tree	0.32	0.31
svm	0.41	0.38
rf	0.25	0.26

Table 9: F_1 scores for the default models with lexicon and Reddit features removed, with and without VarianceThreshold(VT)

7.1.3 BOW vs Most frequent words

Using the variance threshold approach (VT) with the BOW feature is essentially the same as removing least frequent words, which roughly translates to keeping the most frequent words. Thus, experiments were carried out in order to determine if either BOW or the "Most frequent words" (MFW) features should be left out entirely. Table 10 shows that leaving MFW out and using VT improves performance for logit and just leaving MFW out leaves svm unchanged. These experiments were only performed on the logit and svm models, as these have performed best so far in the experiments reported.

Features removed	logit	svm
None	0.36	0.39
BOW	0.36	0.37
MFW	0.38	0.39
$\mathrm{MFW} + (\mathrm{All}\text{-VT})$	0.39	0.38
$\mathrm{MFW} + (\mathrm{BOW}\text{-VT})$	0.39	0.38

Table 10: F_1 scores of the default models with respectively BOW and MFW features left out, in combination with VarianceThreshold(VT) applied on respectively all features(All-VT) and BOW features(BOW-VT)

Thus, we can conclude that we can "safely" remove the MFW features without decreasing performance. This is especially valueable, as it turns out that the MFW features actually are quite specific for our dataset. This is evident from the generated words, as listed in appendix B.1. We see words such as "B12", "CO2", and "5G", which is due to the concentration of events in the dataset, which for these three cases are respectively "Kost" (diet) for the former two, and "5G" for the latter (see Table 2 for the overview of events). Thus, using this list/dictionary of words might have unwanted consequences if applied to unseen data.

7.1.4 Comparing word embeddings

As introduced in section 6.2.4, word2vec (w2v) and fastText are used as word embeddings, the latter both as pre-trained word vectors (ft) as well as trained on the DSL corpus and Reddit data (ft'). This section compares the performance when each of these are used. As setup, we use the two best performing models from the feature selection section above, being logit and svm, where lexicon and Reddit features are removed, and the former is combined with VarianceThreshold. Again, we use 5-fold cross validation and macro F_1 as scoring metric. Table 11 indicates that we achieve no gain in performance by employing other algorithms than word2vec on the DSL(+Reddit) corpus.

Model	w2v	ft	ft'
logit	0.40	0.36	0.38
svm	0.41	0.41	0.39

Table 11: Comparison of the different word embeddings. word2vec (w2v) and fastText (ft') are trained on the DSL+Reddit corpus, while fastText (ft) is with pre-trained word vectors.

7.1.5 Best feature configurations in summary

The experiments presented in this section have investigated the importance of the individual feature categories as a step in finding the best model for rumour stance classification. Although the feature selection methods are non-exhaustive they have revealed interesting properties about the features. Table 12 gives an overview of the results for the feature selection in this section and highlight the best ones. The underlined results are the very best results obtained, while the ones in bold are the best results, when lexicon, Reddit and "Most frequent words" features are removed, which is desirable as described below.

First of all, throughout the experiments the Logistic Regression (logit) and Support Vector Machine (svm) models have been superior to the Decision Tree (tree) and Random Forest (rf) classifiers, showing results around the 0.4 macro F_1 score mark. This could be due to the skewedness of the data, as both logit and svm are known to be robust in this regard (see section 6.2.3). While the Random Forest model is also known to be robust to skewedness and outliers, this is dependent on the quality of the Decision Tree classifiers which make up the ensemble of the forest. As such the results of the Decision Tree model indicate that the success of a Random Forest with more trees might be limited.

Second, we conclude that the lexicon and Reddit features do not make positive contributions to the performance. Furthermore it seems that *logit*

especially can benefit from removing low-variance features. Finally we exclude the "Most frequent words" features, as (1) they show to be similar to the BOW features with mentioned low-variance feature reduction applied, and (2) they are too domain-specific, including some words only relevant to events included in the dataset, such as "B12", "CO2", and "5G".

Features removed	logit	svm
None	0.36	0.39
Lexicon+Reddit	0.38	0.41
Lexicon+Reddit+(All-VT)	<u>0.40</u>	0.38
BOW	0.36	0.37
MFW	0.38	0.39
MFW+(All-VT)	0.39	0.38
MFW+(BOW-VT)	0.39	0.38
Lexicon+Reddit+BOW	0.35	0.36
Lexicon+Reddit+MFW	0.38	0.40
Lexicon + Reddit + MFW + (All-VT)	0.39	0.37
	0.39	0.38

Table 12: Macro F_1 scores of the default models with respectively BOW and MFW features left out, in combination with Lexicon+Reddit features removed and VarianceThreshold(VT) applied on respectively all features(All-VT) and BOW features(BOW-VT)

7.2 Parameter search

This section reports on the findings for doing parameter search for respectively the LSTM model, Logistic Regression (logit), and Support Vector Machine (svm). Although parameter search has been carried out for Decision Tree (tree) and Random Forest (rf), the results are not included, as they still perform sub-optimally compared to logit and svm (see section 7.1.5).

7.2.1 LSTM parameters search

The hyper-parameter space for the LSTM model is presented in Table 13. These are searched with a grid-search strategy, exhaustively running through all combinations of parameters in the parameter space. Another common approach for parameter search is the random-search, which can be preferable to grid-search in some cases. The random-search approach might uncover optimal parameters which are not present in the grid-search parameter space. However [Kochkina et al., 2017] which inspired the use of the LSTM model already uncovered an effective set of hyper-parameters for this problem and

model. Although it was another dataset, no motivation was found to deviate from the approach which yielded such strong stance classification results.

Parameter	Value set
LSTM Layers	$\{1, 2\}$
LSTM Units	{100, 200, 300}
ReLU Layers	$\{1, 2\}$
ReLU Units	{100, 200, 300, 400, 500}
Epochs	{50}
Dropout	$\{0.00, 0.25, 0.50\}$
L2 Regularisation strength	$\{0, 1e-3\}$

Table 13: Hyper-parameter space for LSTM classifier

The LSTM grid search is performed through Google Colab (see section 4). This makes the brute grid search much more feasible to do, as PyTorch supports GPU utilisation⁶¹. The parameters for the five best scoring models are reported in Table 14. Note that the tests performed for the LSTM are with all features enabled.

LSTM-L	LSTM-U	ReLU-L	ReLU-U	Dropout	L2	F_1	Acc.
1	100	1	400	0	0	0.39	0.73
1	300	1	300	0.25	0	0.36	0.73
1	300	1	500	0.25	0	0.35	0.76
1	200	1	200	0	1e-3	0.34	0.68
1	200	1	500	0	0	0.34	0.68

Table 14: Parameter configurations for the five best performing LSTM models on macro-averaged F_1

With a macro F_1 score of 0.39 and accuracy of 0.73, the best parameter combination is with respectively one LSTM layer (LSTM-L) and one ReLU layer (ReLU-L), respectively 100 LSTM units (LSTM-U) and 400 ReLU units (ReLU-U), and no dropout or regularisation. We clearly see the tendency of single layers and a high number of ReLU units across all of the results. For each epoch, the model is also evaluated on a development set, in order to keep track of the training loss. Figure 15 illustrates that the model quite early in the training epochs start to overfit. Applying 0.5 dropout with this parameter configuration, the model still overfits, even though the large "spikes" are reduced.

Applying dropout and regularisation to the LSTM model *did* result in less overfitting for some experiments, however with the cost of poorer results. Some general tendencies were seen in the loss graphs for the search space.

⁶¹In particular PyTorch supports CUDA with GPU compute compatibility 3 or higher, at the time of writing

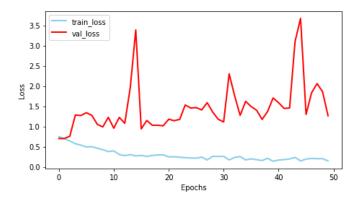


Figure 15: Loss graph for the best LSTM parameter search run

An example is the loss graph illustrated in Figure 16, which has one LSTM layer, 100 LSTM units, two ReLU layers, and 100 ReLU units, but with 0.5 dropout and 0.001 L2 regularisation applied. In this case the model did not overfit to the training data, but was on par with the validation set. This loss graph represents a general tendency, where the LSTM achieves macro F_1 scores on the test set in the 0.20-0.30 range, and neither validation loss or training loss declining. This could indicate that the skewed label distribution makes it difficult to minimise the loss on the training set while still maintaining good results on the validation and test sets.

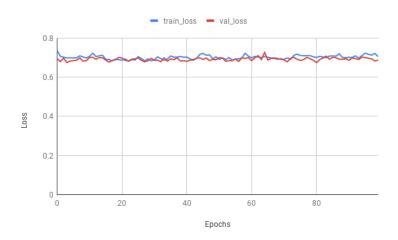


Figure 16: Loss graph for the LSTM without overfit

7.2.2 logit and svm parameter search

The non-neural network models presented in 6.2.3 as the "classic classifiers" have a number of different parameters, which are documented in the scikit

learn API⁶². These parameters have been searched through various strategies, including standard grid-search and a randomised search.

The *logit* and *svm* models are quite similar as they both learn a linear function and uses the "liblinear" optimisation algorithm. Thus, they are actually tuned on the same parameter space, as shown in Table 15. Initially a randomised search was carried out, using the RandomizedSearchCV⁶³ implementation for scikit learn, which generates a predefined number of random parameter configurations, performs cross validation, and evaluates on a held out testing sample. With 3-fold CV and 10 random samples we would have 30 train-test iterations, allowing us to get a first impression of the behaviour. With random number generators we learned which values might be valuable to include in a grid-search for the non-nominal parameter settings. Additionally we learned that L2 regularisation was superior to L1 for both models. 3-fold CV was also performed with the grid-search with evaluation on a test sample, using GridSearchCV⁶⁴, resulting in 72 train-test iterations, leaving out parameter combinations with L1.

Parameter	Value set
Penalty	{'L1', 'L2'}
С	$\{1, 10, 50, 100, 500, 1000\}$
Class weight	{'balanced', None}
Dual	{True, False}

Table 15: Parameter space for *logit* and *svm*

The parameters are defined as follows⁶⁵: "Penalty" specifies the norm used in penalisation and 'C' specifies the inverse of regularisation strength, smaller values specifying stronger regularisation. The "class weight" specifies the weights applied to the classes, where None means all classes have weight one, and "balanced" uses the values of the true class labels to automatically adjust weights inversely proportional to class frequencies in the input data. Finally "dual" specifies whether to solve the dual or primal optimisation problem.

Note that experiments were actually carried out with an SVM using a non-linear kernel ("RBF") as well⁶⁶, however the results were even worse than tree and rf, which is why they were discarded.

 $^{^{62} \}mathtt{https://scikit-learn.org/stable/modules/classes.html} \ 26\text{-}04\text{-}2019$

 $^{^{63} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html <math display="inline">06\text{-}05\text{-}2019$

 $^{^{64}}$ https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html 16-05-2019

 $^{^{65} \}rm https://scikit-learn.org/stable/modules/generated/sklearn.linear_model. LogisticRegression.html <math display="inline">16\text{--}05\text{--}2019$

 $^{^{66}} Using the scikit learn model from: https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html <math display="inline">16\text{-}05\text{-}2019$

The feature configuration was based on the ones marked as most suited in section 7.1 (see section 7.1.5 for a summary), leaving out lexicon, Reddit, and "Most frequent words" features, as well as removing low variance features for the case of *logit*. The optimal parameters found, based on the best evaluation score throughout the grid-search are presented in Table 16.

Model	Optimal parameters	F_1	Accuracy
logit	C=1, class_weight="balanced", dual=True	0.4473	0.7409
svm	C=10, class_weight=None, dual=True	0.4253	0.7508

Table 16: Optimal parameters for logit and svm based on macro F_1 evaluation score

Note that the data is in fact split two times, first in a train-test split, leaving out the test sample for evaluation and then the training sample is split into train-development sets throughout cross validation in the grid-search. Additionally, different from the feature selection experiments, 3-fold CV was used. Because of these factors the high results are not truly comparable to the ones obtained so far.

7.3 Stance classification results

Running the Logistic Regression (logit) and Support Vector Machine (svm) classifiers through 5-fold CV with the optimal parameters, should give the best representable results achieved so far. Table 17 presents the final results for the tuned models, denoted as logit' and svm', as well as the default models using default parameters and all features, and the baseline models. Even though it performs poorly, the parameter-tuned LSTM is also included, performing the same CV, with all features (LSTM) and with lexicon, Reddit, and MFW features removed (LSTM').

Model	Macro- F_1	std. dev.	Accuracy	std. dev
\overline{MV}	0.2195	(+/-0.00)	0.7825	(+/-0.00)
SC	0.2544	(+/-0.04)	0.6255	(+/-0.01)
\overline{logit}	0.3778	(+/-0.06)	0.7812	(+/-0.02)
svm	0.3982	(+/-0.04)	0.7496	(+/-0.02)
LSTM	0.2802	(+/-0.04)	0.7605	(+/-0.03)
logit	0.4112	(+/-0.07)	0.7549	(+/-0.04)
svm'	0.4212	(+/-0.06)	0.7572	(+/-0.02)
LSTM	0.3060	(+/-0.05)	0.7163	(+/-0.16)

Table 17: 5-fold cross validation results for logit, svm, LSTM, and baselines with macro F_1 and accuracy, including standard deviation(std. dev.).

We see that svm' is the best performing model, achieving a macro F_1

score of 0.42, an improvement of 0.02 over the default model. It is however only marginally better than logit, taking the deviation into account. Note that the accuracy is worse than the MV baseline, and logit has even decreased its accuracy. The reason for this could be that the models have been tuned for macro F_1 , as discussed in section 6.2.1. Tables 18 and 19 demonstrates how the models really improve over the baselines by more fairly looking at respectively the F_1 and accuracy per class. As expected we see that MV only predicts "commenting" classes and that SC follows the class label distribution of the dataset, while logit and svm are able to predict the under-represented classes. Because of the low-volume data in DAST we did not expect the LSTM to perform very well, which is evident from the best macro F_1 score of 0.3060. For this reason we focus on logitand svm in the remainder of the experiments.

Class	S	D	Q	\mathbf{C}
$\overline{}$ MV	0.00	0.00	0.00	0.88
SC	0.11	$0.00 \\ 0.10$	0.04	0.80
logit	0.31	0.31	0.16	0.86
$\overline{svm},$	0.29	0.32	0.22	0.86

Table 18: F_1 score per class

Class	S	D	Q	\mathbf{C}
$\overline{}$ MV	0.00	0.00	0.00	1.00
SC	0.11	0.09	$0.00 \\ 0.04$	0.81
$\phantom{aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa$	0.27	0.28	0.12	0.89
svm'	0.24	0.28	0.19	0.90

Table 19: Accuracy score per class

Figure 17 visualises the confusion matrices for both logit' and svm', where the numbers 0, 1, 2, 3 refer to the class labels S, D, Q, C in that order.

logit' seems to be better at classifying the "supporting" class, and svm' seems to be better at classifying the "querying" class, while they are equally good at classifying "denying" and "commenting" classes.

Additionally, investigating their ability to learn from the dataset provided can be interpreted through a learning curve. Figures 21 and 22 in appendix B.3.1 demonstrates the models' training and CV test scores through different sample sizes of the dataset. It becomes obvious that much more data is needed in order for the models to learn optimally.

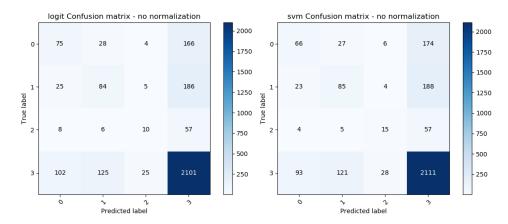


Figure 17: Confusion matrices for the tuned classifiers, respectively logit'(left) and svm'(right). 0, 1, 2, 3 refer to the class labels S, D, Q, C in that order.

7.4 Improving results with data sub- and super-sampling

The skewed data with regards to the class labels (see Table 3) motivated data sampling as an experiment to smooth the class distribution. This was achieved by respectively reducing and amplifying relevant data points, with the goal and expectation of observing better results. Given the small size of DAST the skewed distribution means that there is a very small amount of data points for the minority classes. As such the classification models have less data to train on and learn these class labels from, which makes it difficult to classify them. This is equivalent to saying that the large amount of "commenting" posts makes it more likely for the classifiers to classify SDQ class labels as "commenting".

Sub-sampling of the data is done by removing all branches, which have pure "commenting" labels, effectively reducing the total size of the dataset from 3,007 to 2,313 data points, but improving the distribution of "supporting", "denying", and "querying" classes.

Super-sampling of the data is done by first splitting the data in stratified train and test set. Considering only the train set, for each post which is labelled as either S, D, or Q, it is duplicated, which allows us to alter the text (and thereby the features) to create a synthetic replica of the post representing one of the non-neutral class labels. The initial data split is performed as we do not want a classifier which is really good at predicting something almost identical to what it has already seen. This would be the case by having the original in one sample and the synthetic partner in the other (and vice versa).

The text is altered by trying to replace a fraction of the words by synonyms stored in a dictionary⁶⁷, and then only allowing a post to pass as a super-sample candidate, if this succeeds. On one hand we do not want an example where the sentences are complete nonsense; conversely, we do not want to just replace a couple of words, leaving the synthetic post to be close to identical to the original one. Thus, iterative experiments with different thresholds of respectively 25%, 37.5%, and 50% were carried out, resulting in the choice of 37.5% providing a good "original-to-synthetic" balance. Experiments have also been carried out with respectively word2vec and fastText word embeddings, replacing words with their most similar word in the vocabulary. The results were, however, quite strange, in particular when using pre-trained fastText word vectors. Examples for each of the three cases with replacement are included in appendix B.2.

Table 20 provides an overview of the SDQC stats with sub- and super-sampling, as well as a combination of the two, where first the former is applied, and then the latter⁶⁸. Additionally Table 21 illustrates the shift in the class labels' relative contribution with the different sampling techniques.

Sampling Label	S	D	Q	C	Total
None	273	300	81	2,353	3,007
Sub	273	300	81	1,659	2,313
Super	412	462	124	2,353	3,351
Sub+Super	416	458	125	1,659	2,658

Table 20: Stance label distribution count with sub-sampling, super-sampling, and their combination

Sampling Label	S	D	Q	С
None	0.091	0.100	0.027	0.782
Sub	0.118	0.130	0.035	0.717
Super	0.123	0.138	0.037	0.702
Sub+Super	0.157	0.172	0.047	0.624

Table 21: Relative stance label distribution with sub-sampling, supersampling, and their combination

For sub-sampling we see that comments are reduced from 2,353 to 1,659 improving SDQ contributions from 0.091, 0.1, 0.27 to 0.118, 0.13, and 0.035,

 $^{^{67} \}mathrm{https://korpus.dsl.dk/e-resources/Synonyms\%20from\%20DDO.html}$ 08-05-19

⁶⁸The numbers from "Super" to "Sub+Super" are just a bit off, which is due to a stratified train-test split after removing data points with sub-sampling

respectively. This distribution is almost identical to super-sampling, but in this case we increase the (SDQ) data points with a total of 344, instead of reducing the "commenting" class. Finally, the best distribution with regards to the SDQC class labels are achieved by first sub-sampling and then super-sampling, with distributions of 0.157(S), 0.172(D), 0.047(Q), and 0.624(C) and a total number of 2,658 data points. This distribution looks almost similar to the SDQC distribution in the PHEME dataset [Zubiaga et al., 2016a], but shrinks DAST by around 12%.

Running experiments with the different sampling techniques described in this section, the parameter-optimised *svm* with lexicon and Reddit features removed (see section 7.3), is evaluated through stratified CV on the different configurations, which are reported in Table 22. As we do not want the original feature vector and the synthetic partner to be in each of their train/test set, we make sure they do not split up.

Sample	Macro- F_1 .	std. dev.	Accuracy	std. dev
None	0.4212	(+/-0.06)	0.7572	(+/-0.02)
Sub	0.4050	(+/-0.06)	0.6922	(+/-0.03)
Super	0.4418	(+/-0.05)	0.7106	(+/-0.02)
Sub+Super	0.4807	(+/-0.09)	0.6658	(+/-0.03)

Table 22: svm' sample results

First off, even though the sub- and super-sampling techniques yielded similar SDQC distributions, we see a clear advantage for the SVM with more data points, scoring 0.4050 with "Sub" and 0.4418 with "Super", the latter improving over the original result with ~ 0.02 . More interesting is the result for the combined sub- and super-sampling dataset, where the SVM scores a 0.4807 macro F_1 , really improving with the much more balanced class distribution. With regards to the accuracy, we see a correlation with the number of data points and the number of "commenting" classes: the less data points of the majority class, the lower the total number of correct predictions. This indicates that the model gets worse at learning that class, which makes sense since we drastically reduce the number of data points with sub-sampling. For the case of super-sampling, we would expect the accuracy to be more or less the same as with the original data set, which is not really the case with its 0.7106 compared to 0.7572. However this is more promising than for the super-sample cases.

Completely separating the original posts and synthetic ones from the test folds with super-sampling yields different results, as illustrated in Table 23.

It is interesting to see that we do get better performance with combined sub- and super-sampling, both with macro $F_1(0.4412)$ and accuracy (0.7721),

Sample	Macro- F_1 .	std. dev.	Accuracy	std. dev
Super	0.3910	(+/-0.09)	0.8000	(+/-0.03)
Sub+Super	0.4412	(+/-0.10)	0.7721	(+/-0.02)

Table 23: svm' sample results with super-sample only in train

when retaining the original posts and synthetic ones only in the training set.

The results presented in this section show how *smoothing* the class balance improves macro F_1 for the stance classifier. Finally the results show be close to state-of-the-art results for the Branch-LSTM model [Kochkina et al., 2017], although the results are not directly comparable, as the results are obtained on separate datasets. This concludes the stance classification experiments, and we thus present the rumour veracity experiments next, in section 8.

8 Rumour veracity prediction experiments

This section presents a number of experimental approaches, which have been applied in order to find the optimal solution to the task of rumour veracity prediction with the HMM approach introduced in section 6.3.

Throughout the experiments exhaustive search is performed for the HMM models λ and ω to identify the optimal state space size N, from 1 to 15, as introduced in section 6.3.1. Further, as described in section 6.3.2, the language-agnostic and platform-agnostic HMM approach allows us to use other stance-labelled datasets.

8.1 Using data across languages and platforms

We propose to utilise the PHEME dataset from [Zubiaga et al., 2016b] based on the idea of the HMM approach relying only on stance and posting times. However, as there might be some discrepancies, this is investigated in this section.

Experiments are needed to determine the optimal partitioning and structure of the data. By using multi-platform datasets, discrepancies in the data structure arise, which should be kept in mind. While a submission text on the Reddit platform is the actual source of a rumour and a post, they do not always contain stance towards the rumour. Furthermore several of the submissions in DAST are much larger conversation trees than the Twitter conversations if all the comments are grouped. The structure of a Reddit submission is illustrated in Figure 18, as introduced in section 3.1.2.

Apart from the structure-specific differences between Reddit and Twitter, the difference in language might also cause issues in the compatibility

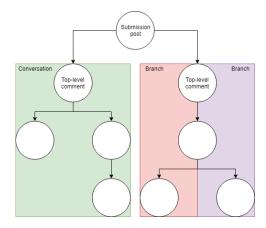


Figure 18: The structure of a Reddit submissions

of the two datasets. First of all, Reddit is an anonymous platform, while Twitter is not, which might cause differences in posting tendencies. The language of the post texts in the two dataset also differ. The PHEME dataset [Zubiaga et al., 2016a] contains English (and some German) text and DAST contains only Danish text. These factors along with the structural differences in conversation lengths might introduce discrepancies, which hopefully will be discovered in the experiments presented in section 8.2.

The platform differences between Reddit and Twitter discussed above might influence the results obtained when training on the PHEME dataset [Zubiaga et al., 2016a]. As such the experiments will be performed on three different structures of the DAST data:

SAS: Submission as a source is treated as a singular rumour, in which all replies and nested replies to the submission have been flattened to a single list and sorted from earliest to latest post. This generates few rumour entries with quite long sequences of stance. Some challenges with this structure of the data is the low amount of entries. There are only 16 rumour submissions, which makes for low amounts of training and test entries. Furthermore it might be difficult to apply the PHEME rumour data to this structure. The PHEME conversation data generally consist of lower amount of comments than the submissions in DAST.

TCAS: Top level comment as source regards each conversation tree within a submission as a rumour. A conversation tree is the tree of posts which spawn from a top-level post. This generates more data entries and is more alike the PHEME Twitter conversation structure where each conversation is spawned from a source-tweet.

BAS: Branch top level comment as source treats each individual branch in the rumour submissions as a rumour itself. This generates a lot of data entries, with a lower average length than the two structures above. Further it also implicates duplicates of the stance labels, since multiple replies to a single post will create different branches with shared parent posts. This approach might however prove useful for early detection, given the shorter average length of the branches.

Figure 19 displays an example of a short Reddit conversation. The conversation consists of 4 comments, of which one is a top-level comment. The conversation contains 2 branches respectively of length 3 and 2. As such this would yield 2 branches for the BAS structure, 1 for the TCAS structure and only be a part of the SAS structure, which consists of an entire submission.



Figure 19: Reddit conversation tree example

As first discussed in section 3.2 the sole reliance on stance labels and time stamps in the HMM approach from [Dungs et al., 2018] opens an opportunity to possibly utilise data from other languages. This will be explored by training the HMM on the PHEME rumour stance labels and testing the results on the different structure iterations of DAST introduced above. Further experiments will be carried out in which the data from PHEME and DAST are used in conjunction with each other, i.e. mixed across training and testing set.

8.2 Veracity classification

This subsection will present the experiments performed in regard to veracity classification. The results obtained from the experiments will be provided as the experiments are presented. DAST contains only 3 true and 3 false rumour submissions, where the remaining 10 are unverified. This could very well reflect reality, as it can be difficult to obtain the actual truth value of a rumour. To investigate how to handle the unverified rumours, they are approached in 3 different ways. One is to see them as false rumours, given they have not been confirmed to be true yet. Another is to see them as true, since they have not been proven false yet. The results obtained from these two interpretations of the unverified rumours might reveal whether the stance tendencies in unverified rumours are more alike false or true rumours. The last approach taken is to move away from binary classification and do three-way classification instead, trying to predict respectively false, true and unverified rumours.

Each approach will involve three experiments, described next. 3 fold cross validation on DAST will investigate how well the unverified approach can be expected to perform for DAST data alone. Another experiment will investigate how well the data from PHEME can be used to classify data on DAST. The experiment will train on PHEME data and test on all of DAST. The third and last type of experiment will be 3 fold cross validation on the conjunction of DAST and PHEME data. This experiment will shed some light on how well the data can be used across language, not only from the PHEME dataset to DAST, but the other way around as well.

The results for 'unverified as false', 'unverified as true' and 'three-way classification' are presented and analysed upon throughout this section. However, for readability, only the results for the best performing approach of 'unverified as false' are included, while the results for the two other approaches are included in appendix B.4.

8.2.1 Treating unverified rumours as false

Table 24 contains results from solely training and testing on DAST. The accuracy and F_1 columns shows the average results, including deviation, across folds. Notably the results for the SAS structure is the same across the two models. This might be a result of the small sample size this structure presents in regards to rumour count. Further λ has higher F_1 , but lower accuracy than ω on the TCAS structure. On the BAS structure ω shows superior results with a higher accuracy and F_1 .

The confusion matrix seen in Table 25 shows the distribution of sampling and gold labels for the best performing model and structure in Table 24. The majority label is the false label, which the model classifies correctly at a high rate. Roughly half of the true rumours are classified correctly in this case.

Structure	Model	Acc.	F_1
	λ	0.81 (+/- 0.03)	0.45 (+/- 0.01)
SAS	ω	0.81 (+/-0.03)	0.45 (+/-0.01)
	VB	$0.39 \ (+/- \ 0.58)$	$0.36 \ (+/-\ 0.57)$
	λ	0.73 (+/- 0.02)	0.63 (+/- 0.06)
TCAS	ω	0.79 (+/-0.04)	0.61 (+/-0.07)
	VB	0.35 (+/- 0.13)	0.35 (+/-0.13)
	λ	0.78 (+/- 0.03)	0.66 (+/- 0.02)
BAS	ω	0.83 (+/- 0.02)	0.68 (+/- 0.04)
	VB	$0.43 \ (+/-\ 0.07)$	0.42 (+/-0.07)

Table 24: Danish veracity results on 3-fold cross validation

Actual Predicted	False	True
False	450	47
True	56	43

Table 25: Truth value distribution with BAS structure 3-fold cross validation for ω

Next, the results for training on the PHEME dataset and testing on DAST can be seen in Table 26. Interestingly λ generally shows better results than ω in this testing setup. This could indicate that the included time stamps used in ω does not generalise well from the PHEME data to DAST. This could be caused by multiple factors such as the discrepancies between the Twitter and Reddit platform or the different languages for each dataset. The reusability of the PHEME data does however show promising result when relying solely on stance labels. The best results are seen on the SAS structure, with an accuracy of 0.88 and an F_1 score of 0.71. As such it seems the PHEME dataset can be used across platforms and languages quite well, given stance labels.

To investigate the results found in Table 26 for the model λ , see confusion matrix in Table 27. Even though the three structures have different sizes and properties, the results share some traits. For these tests the model is much better at identifying false rumours, than true rumours. The worst performing model test on the TCAS structure correctly identifies over 85% of false rumours. However more than half of the true rumours are incorrectly identified as false rumours for both TCAS and BAS tests. The tendency for the model to guess false rumours very precisely is also seen in Table 25.

While it can be difficult to compare these results to [Dungs et al., 2018] because of the difference in datasets, there is some things to note. The F_1 score is generally lower for the results here than achieved in [Dungs et al., 2018].

Structure	Model	Acc.	F_1
	λ	0.88	0.71
SAS	ω	0.75	0.67
	VB	0.81	0.45
	λ	0.77	0.66
TCAS	ω	0.81	0.59
	VB	0.80	0.62
	λ	0.82	0.67
BAS	ω	0.67	0.57
	VB	0.77	0.53

Table 26: Training on the PHEME dataset and testing on DAST

Structure	Actual Predicted	False	True
SAS	False	13	0
DAD	True	2	1
TCAS	False	149	26
TOAS	True	24	21
BAS	False	447	50
DAS	True	57	42

Table 27: Truth value distribution with PHEME data training and SAS structure testing

However the accuracy scores are higher, although this metric can be misleading as earlier stated (see section 6.2.1), given the skewed label distribution of DAST. The lower F_1 scores here could also be the reflections of language and platform discrepancies between the PHEME dataset and DAST. The different platforms or languages might entice different conversational dynamics, resulting in different sequencing of stance or different time stamp tendencies.

Finally, Table 28 shows the results from doing 3-fold cross validation on a mix of the PHEME dataset and the different structures of DAST. The last row section where structure is "None" refers to the results from doing cross-validation solely on the PHEME data. The best result is achieved by ω on the BAS structure, with an accuracy of 0.67 and an F_1 of 0.62. The results for all the models on the TCAS and BAS structures improve over None. This indicates that the stance approach is transferable across language and platform using the [Dungs et al., 2018] approach.

Structure	Model	Acc.	F_1
	λ	0.53 (+/-0.09)	0.53 (+/- 0.10)
SAS	ω	0.55 (+/-0.09)	0.55 (+/-0.10)
	VB	$0.37 \ (+/-\ 0.03)$	0.31 (+/-0.07)
	λ	0.60 (+/- 0.07)	0.58 (+/- 0.08)
TCAS	ω	0.64 (+/-0.05)	0.61 (+/-0.05)
	VB	0.53 (+/-0.04)	$0.38 \ (+/-\ 0.03)$
	λ	0.60 (+/- 0.05)	0.58 (+/- 0.05)
BAS	ω	0.67 (+/- 0.03)	0.62 (+/- 0.04)
	VB	0.49 (+/- 0.10)	0.40 (+/- 0.01)
	λ	0.55 (+/- 0.05)	0.54 (+/- 0.07)
None	ω	0.57 (+/-0.08)	0.55 (+/-0.10)
	VB	$0.43 \ (+/-\ 0.03)$	0.33 (+/-0.08)

Table 28: Training and testing on mix of PHEME data and different DAST structures for unverified false

8.2.2 Treating unverified rumours as true

In the following experiments the unverified rumours have been interpreted as true rumours. Comparisons between these results and the 'Unverified as false' experiments in section 8.2.1 above, might reveal interesting properties about the data. The results for interpreting the unverified rumours as true, which can be seen in appendix B.4.1, were not as promising as interpreting them as false. The 3-fold cross validation experiment generally provided lower scores with the highest accuracy at 0.74 achieved with the ω and λ models on the SAS structure. The highest F_1 score is achieved by ω on the BAS structure, reaching 0.62.

The results for training on PHEME an testing on DAST were not as good either. The highest accuracy achieved is 0.81 reached by the ω model on the SAS structure. The highest F_1 score is 0.59, achieved on the SAS structure as well by the λ model.

The results of doing 3-fold cross validation on the union of the PHEME dataset and DAST are interesting. The accuracy is not improved by the addition of any DAST data, with the highest reached being 0.84 both on PHEME data alone and with the addition of SAS. The best F_1 is 0.62, achieved with the combination of PHEME data and BAS. Interestingly it was achieved by the baseline VB with λ and ω falling behind. This indicates that the sequence of stance labels might be different from the PHEME data and DAST with the BAS structure, however the overall distribution of the stance labels are more alike than the sequence.

8.2.3 Three-way rumour veracity classification

Rather than interpreting the unverified rumours as either true or false, the experiments in this section investigate the results of doing three-way classification of true, false and unverified rumours. The results of the experiments are presented in tables in appendix B.4.2. The results are generally worse than the results obtained from the binary classification experiments presented above in sections 8.2.1 and 8.2.2. This was expected as this approach in contrast performs three-way classification. While the results are not comparable to the previous two experiment approaches, they are interesting as they give insight into classifying unverified rumours.

First, for three-way classification through 3-fold cross validation on DAST, the highest accuracy is 0.61 scored on the SAS structure by the ω model however the deviation for the results on the SAS structure is very high. The second highest accuracy of 0.57 also contains the highest macro F_1 result of 0.53 with a much lower deviation, for the ω model on the BAS structure.

Second, training on PHEME data and testing on DAST for three-way classification also gave poor results. The highest accuracy is 0.62, achieved by the baseline VB on the SAS structure. Further the best macro F_1 scores are achieved by the VB on the TCAS structure and by ω on the SAS structure. This could indicate that the unverified rumour structures are not very compatible across the PHEME dataset and DAST.

Finally, the results of doing 3-fold cross validation on a mix of PHEME data and DAST for three-way classification shows the difficulty of the task. The best results are achieved on the TCAS structure with an accuracy of 0.53 for the λ model and a macro F_1 score of 0.42 for the ω model.

The results for three-way classification were not very promising. The task is harder than binary classification and it seems the HMM method does not translate well to this task, given only stance and/or time stamps as features. The results achieved by interpreting unverified rumours as particularly false proved much more promising.

8.3 Connecting stance classification and veracity prediction

While the results so far show promising results, these all rely on gold labels made by humans. In order to show how well the results will translate to unseen data, the stance classifier and veracity classifier should be connected. This approach was introduced in section 2.1 as being a possible way of doing rumour veracity prediction. Thus, instead of gold labels, the labels should be generated by the stance classifier for all rumour data and then used for the veracity classification component. Ultimately this would prove the system to have practical applications.

The stance labels will be generated by the SVM model (logit) which showed promising results with a macro F_1 score of 0.4212 and an accuracy of 0.7572 on cross validation tests. The automatic stance labels will be obtained by training on all of DAST except one rumour submission, for which stance will be classified. This will be performed for each rumour submission. The SDQC distribution and performance across the rumours are presented in Table 29.

Event	Title (abbreviated)	S	D	Q	\mathbf{C}	F_1	Acc.
	5G-teknologien	7 7	6 5	2 0	27 30	0.37	0.62
5G	Det er ikke alle	7 2	6 4	3 0	57 67	0.21	0.73
	Uffe Elbæk er	11 8	30 7	0 3	82 105	0.32	0.67
Donald	Hvorfor må DR	10 4	6 3	0 1	28 36	0.30	0.64
Trump	16-årig blev	15 1	5 13	5 1	71 81	0.24	0.69
ISIS	23-årig dansk	2 3	31 19	8 2	104 121	0.39	0.76
1515	Danish student	1 0	9 3	0 3	14 18	0.33	0.67
Kost	Bjørn Lomborg	5 5	15 6	2 0	75 86	0.28	0.73
Kost	Professor:	16 21	25 17	0 0	186 189	0.42	0.74
MeToo	Bjørks FB post	1 2	8 8	3 2	48 48	0.51	0.78
Peter	Savnet ubåd	0 0	11 1	3 0	17 30	0.23	0.52
Madsen	Undersøgelser	4 5	0 10	6 4	71 62	0.38	0.79
Madsell	Peter Madsen:	11 13	34 20	10 6	214 230	0.35	0.74
Politik	KORRUPT	12 0	0 1	6 5	31 43	0.33	0.65
Togstrejke	De ansatte	7 1	3 4	1 0	62 68	0.30	0.82
Ulve i DK	Den vedholdende	1 1	3 1	1 0	50 53	0.23	0.87
Overall		110	192	50	1137	0.38	0.73

Table 29: SDQC distributions and automatic stance labels and results per rumour (see Table 4), as well as overall SDQC, macro F_1 and accuracy when combining the predictions across the rumours. For SDQC, the numbers left of the '|' are the actual class labels, while the numbers right of the '|' are the predicted class labels.

The results of the automatic stance labels on the rumour data are diverse. For instance, the classification with highest macro F_1 is 0.51 (MeToo), while the lowest macro F_1 is 0.23 ("Ulve i DK"). For MeToo, with a test size of only 60, just one class label is misclassified, being a "querying" classified as "supporting". For "Ulve i DK", the single "querying" class label and two of the "denying" class labels are incorrectly classified as "commenting". Overall, we see that it is difficult to classify the "denying" class, such as for "Uffe Elbæk ..." and "23-årig dansk ...", and in particular it is the tendancy to misclassify SDQ as the majority class "commenting". This is also evident from the confusion matrix for the combined classification, which is depicted in Figure 20.

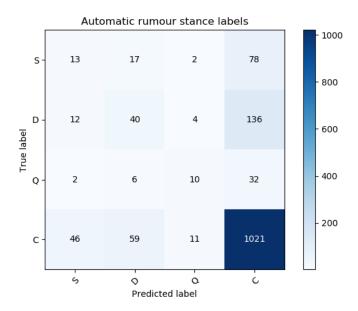


Figure 20: Confusion matrix for the combined automatic rumour stance class labels

8.3.1 Binary classification

Table 30 shows the results of training on PHEME data and testing on automatic stance labels for DAST. When comparing to the original results in Table 26, section 8.2.1, the automatic predictions obtains a lower F_1 score while they maintain or improve on the accuracy. This could indicate that the majority class is being predicted more often, while the minority is predicted less precisely. The error between the automatic stance labels and the gold labels are generally that there are more "commenting" class labels in the automatic stance labels. As such the results indicate that there is a correlation between more "commenting" posts and the "unverified" rumour class. Some cases do also lose accuracy, however the greatest losses are generally observed in the F_1 scores while the accuracy scores are nearer the gold label predictions.

Table 31 shows the results of training on the PHEME dataset and testing on automatic stance labels for DAST where unverified is interpreted as true. The tendencies are much the same as the previous table. The results with the automatic stance labels are generally worse than the gold label predictions shown in appendix B.4.1, Table 34. The F_1 scores are however the main difference, as the accuracy does not loose as much performance.

Structure	Model	Acc.	F_1
	λ	0.81	0.64
SAS	ω	0.75	0.67
	VB	0.81	0.45
	λ	0.79	0.56
TCAS	ω	0.68	0.55
	VB	0.76	0.43
	λ	0.82	0.58
BAS	ω	0.76	0.56
	VB	0.76	0.48

Table 30: Training on the PHEME dataset and testing on automatic stance labels generated for DAST where unverified is false

Structure	Model	Acc.	F_1
	λ	0.81	0.45
SAS	ω	0.79	0.59
	VB	0.81	0.45
	λ	0.72	0.45
TCAS	ω	0.75	0.46
	VB	0.66	0.43
	λ	0.63	0.49
BAS	ω	0.59	0.48
	VB	0.60	0.51

Table 31: Training on the PHEME dataset and testing on automatic stance labels generated for DAST where unverified is true

8.3.2 Three-way classification

Table 32 displays the results for three-way classification on the automatic stance labels. When comparing the results to the gold stance label results in Table 37, appendix B.4.2, the tendencies are much alike the ones observed for unverified false and true.

8.3.3 Rumour veracity prediction example

To display the use of the conducted research of this paper in a practical way, a small proof of concept command line tool has been developed 69 . The tool contains a pretrained Support Vector Machine trained on DAST to perform stance classification. Further it contains a Hidden Markov Model λ pretrained on PHEME data for applying veracity classification with "unverified" rumour class interpreted as "false". Finally a number of data fetching, wrapping and preprocessing functionality has been included to enable "live" rumour veracity resolution of Reddit submissions. The tool can download

 $^{^{69} \}mathtt{https://github.com/danish-stance-detectors/RumourResolution}$

Structure	Model	Acc.	F_1
	λ	0.62	0.26
SAS	ω	0.56	0.39
	VB	0.62	0.26
	λ	0.48	0.29
TCAS	ω	0.55	0.33
	VB	0.51	0.23
	λ	0.44	0.33
BAS	ω	0.44	0.34
	VB	0.45	0.30

Table 32: Training on the PHEME dataset and testing on automatic stance labels generated for DAST for three-way classification

all comments from a specific submission, perform stance classification on the comments and then veracity classification on the submission.

While this is merely an example, a Reddit submission discussing a possible wolf attack on a pack of sheep has been highlighted⁷⁰. The submission has 19 comments and the news article provided in the submission post could not conclude whether the attack was done by wolves or not. The command line tool classified the then unverified rumour as "true".

A later Reddit submission links to a news article in which wolves were concluded as the culprit of the attack described above, given DNA tests⁷¹. This article confirms the first unverified rumour to be true and as such shows some of the functionality of the veracity classification research done in this project. This is one single example and the tool will not be correct for all rumours. It does however show how the research conducted in this project can be practically applicable and may assist in classifying the veracity of unverified rumours.

8.4 Evaluation of veracity classification experiments

The experiments and results hereof reported in section 8 investigates whether the stance label approach is applicable across language and platform. Further the experiments investigate how different interpretations of unverified rumours reflects in the rumour resolution classification. Lastly experiments are done to research the robustness of the rumour resolution system. In other words: how well the gold label results translate to new data with automatically generated stance labels.

The best results for this approach were seen with the λ model with

 $^{^{70} \}rm https://www.reddit.com/r/Denmark/comments/b9b009/25_f%C3%A5r_d%C3%B8de_i_muligt_ulveangreb_der_var_klippet/ accessed 30-05-2019$

⁷¹https://www.reddit.com/r/Denmark/comments/bn16w8/ulve_stod_bag_26_f%C3% A5rs_d%C3%B8d_i_vestjylland/ accessed 30-05-2019

the unverified rumours interpreted as false. The approach scored above 0.80 accuracy and between 0.66 and 0.71 F_1 score across the different DAST structures. These results are promising and show that sequences of stance labels can be reused across languages. The results for 3-fold cross validation on the mix of PHEME data and DAST were not quite as strong. This indicates that in spite of the good results when testing solely on DAST, there are some discrepancies between the datasets.

This is also seen in the results for the Hidden Markov Model ω . It performs well when testing on data from one dataset, but does not perform as well as λ across datasets. This indicates the existence of discrepancies between the two datasets specifically in relation to the posting time tendencies.

The experiments on interpreting the unverified rumours as respectively true and false favour treating them as false. This indicates that the unverified rumours are more alike the false rumours found in the training data. In other words this could indicate that the crowd stance for an unverified rumour is more alike a false rumour than a true rumour.

The experiments for performing veracity classification on automatic stance labels display interesting results. A drop in F_1 performance when using automatic stance labels is observed, however the accuracy is generally not impacted negatively. The best result for the automatic binary classification are achieved by regarding "unverified" as "false". In this case, we observe an accuracy of 0.82 (on BAS) while the highest F_1 achieved was 0.67 (on SAS). However the SAS structure is a small data sample of only 16 submissions, and thus may not be representative. The highest F_1 score aside from the SAS result is 0.58 F_1 (on BAS) with the λ model.

The relatively low drop in performance with automatic stance labels is promising, showing that the system has practical applications, as it seems to generalise well to new data.

9 Discussion

The results for Danish stance classification and rumour veracity classification presented in 8.4 are promising. However a number of things must be kept in mind when reviewing these. The DAST dataset contains 3,007 stance data points, which is less than optimal. More data would probably facilitate better results and increase the chance of the dataset being representative for new unseen data. Further as shown in [Zubiaga et al., 2016b] and [Stranisci et al., 2015] the process of annotating a dataset is resource intensive and difficult. DAST has been gathered and annotated by us, two people, in a time period of three months. Neither of us are experts in linguistics or journalism as some annotators in [Zubiaga et al., 2016b]. This might

affect the correctness of the labels. The low amount of resources available for making DAST also affected the final size of the dataset. If more resources had been available in the form of more annotators or experts, the dataset would probably be larger. Further the certainty in the correctness of each ground truth label would increase and might lessen the skewedness of the dataset towards the "commenting" label.

A larger dataset could have added more rumours for which the actual truth value was known. 10 out of the 16 rumour submissions gathered in DAST were annotated as being "unverified". This meant that in order to have a meaningful amount of rumour data, the "unverified" rumours were needed. Either the veracity prediction had to be considered as a three-way classification task or the "unverified" rumours interpreted as either "true" or "false". While the results of the veracity classification system are promising, the confidence in the results could be strengthened by more rumour data with a known veracity value.

Time and resource constraints also meant that Reddit is the only platform from which data was gathered for DAST. This might cause issues in relation to the model organism problem introduced in [Tufekci, 2014]. The model organism problem states that basing research in data from a single platform might warp the results and usefulness of the research towards the specific platform. Even though platform specific features as mentioned in 6.2.4 can be left out, it would be valuable to extend DAST with data from other platforms to mitigate the model organism problem.

However the experiments carried out in section 8.2 show promising results for applying the stance labels across platforms. This indicates that the data in DAST is applicable in a broader context and not restrained by the Reddit platform. This indication could be confirmed or refuted with the addition of data from other platforms and experiments on it.

The approaches taken to stance classification have been inspired from several state-of-the-art approaches to the problem. These include the deep learning LSTM approach by [Kochkina et al., 2017] and the idea of focusing on feature engineering with non-neural network classifiers by [Aker et al., 2017]. The better performance is achieved by latter approach with a Linear Support Vector Machine model. It is however important to keep in mind that the LSTM approach was somewhat expected to have difficulty to perform well due to the small size of DAST. It would have been interesting to apply another powerful approach, such as the Bi-LSTM implemented in [Augenstein et al., 2016].

Further the BERT approach employed by [Fajcik et al., 2019] in RumourEval 2019 [Gorell et al., 2018] achieves very promising results, outperforming earlier state-of-the-art approaches. The BERT method would however have been difficult to reproduce given the comprehensive pre-training

step: the model was pre-trained on two English corpora consisting of more than 3 million words combined. Further the promising results were obtained on a dataset than twice as large as DAST. However given more time and possibly more data it could have been interesting to apply the BERT model on DAST.

The data sampling presented in section 7.4 was as stated an attempt to make the class distribution more evenly aligned. While the approaches do facilitate a much less skewed class distribution (see table 21), the artificial data only display improvements in one area. Table 22 shows that the *svm* model improves with super-sampling, while sub-sampling decreases performance. This indicates two things: (1) the model gets better with more data, and (2) given more data, the model actually takes advantage of an improved SDQC class label distribution. This also correlates with the learning curves included in appendix B.3.1, figure 22, which indicates that stance classification could become better with an extended DAST dataset. This is especially true if the SDQC distribution becomes more even. A stronger stance classifier would also strengthen the results seen in the veracity classification for automatic stance labels, since it relies on the correctness of the automatic labels.

The skewed distribution of the data further entices the use of a two-step approach as implemented by [Wang et al., 2017]. This approach suggests making a classifier to filter the "commenting" and non-"commenting" class labels, and then use another classifier on the minority class labels. The two-step classifier was implemented as a way to tackle the skewed class label distribution of the RumourEval dataset [Derczynski et al., 2017]. Therefore this approach is especially interesting for the case of DAST given the particularly skewed nature of the class label distribution.

10 Conclusion

This thesis project has investigated state-of-the-art approaches for stance classification and rumour veracity prediction. The approaches have been analysed and from these the necessary steps to perform Danish rumour resolution have been dictated. A dataset of Danish posts from Reddit has been generated, including a number of rumourous submissions. The posts have been annotated according to the widely researched SDQC annotation scheme [Zubiaga et al., 2016b]. The dataset constitutes the first Danish stance-annotated dataset DAST [Lillie and Middelboe, 2019], which enables Danish stance classification. The best stance classification results were achieved by a Linear Support Vector Machine classifier, which outperformed a number of other models including an LSTM deep learning model.

Rumour veracity classification relying solely on stance labels and time

stamps have been applied to DAST, utilising a Hidden Markov Model as described in [Dungs et al., 2018]. Experiments utilising the PHEME dataset [Zubiaga et al., 2016a] have been conducted to investigate the effectiveness of using data across languages and platforms. Results from using the stance classifier and veracity classifier in connection are promising, indicating the system can assist in rumour resolution for new unseen data.

As such this thesis project contributes with a Danish stance-annotated dataset consisting of 3,007 Reddit posts. Further a Linear Support Vector Machine has been deemed an effective stance classifier, scoring an accuracy of 0.76 and a macro F_1 score of 0.42. Finally a Hidden Markov Model has been used to classify veracity of Danish rumours obtaining an accuracy of 0.82 and an F_1 score of 0.67 when training on data from another platform and language. A performance of 0.83 in accuracy and 0.68 in F_1 is observed when relying only on the DAST dataset. When using automatic stance labels for the HMM, only a small drop in performance is observed, showing that the implemented system can have practical applications.

References

- [Aker et al., 2017] Aker, A., Derczynski, L., and Bontcheva, K. (2017). Simple Open Stance Classification for Rumour Analysis. In *Proceedings of Recent Advances in Natural Language Processing*, pages 31–39, Varna, Bulgaria.
- [Al-Rfou et al., 2013] Al-Rfou, R., Perozzi, B., and Skiena, S. (2013). Polyglot: Distributed word representations for multilingual nlp. In Proceedings of the Seventeenth Conference on Computational Natural Language Learning, pages 183–192, Sofia, Bulgaria. Association for Computational Linguistics.
- [Augenstein et al., 2016] Augenstein, I., Rocktäschel, T., Vlachos, A., and Bontcheva, K. (2016). Stance Detection with Bidirectional Conditional Encoding. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 876–885, Austin, Texas.
- [Babakar and Moy, 2016] Babakar, M. and Moy, W. (2016). The state of automated factchecking.
- [Baris et al., 2019] Baris, I., Schmelzeisen, L., and Staab, S. (2019). Clearumor at semeval-2019 task 7: Convolving elmo against rumors.
- [Bird et al., 2009] Bird, S., Loper, E., and Klein, E. (2009). Natural language processing with python.
- [Castillo et al., 2011] Castillo, C., Medoza, M., and Poblete, B. (2011). Information Credibility on Twitter. In WWW 2011 Session: Information Credibility, pages 675–684, Hyderabad, India.
- [Derczynski and Bontcheva, 2014] Derczynski, L. and Bontcheva, K. (2014). PHEME: Veracity in Digital Social Networks.
- [Derczynski et al., 2017] Derczynski, L., Bontcheva, K., Liakata, M., Procter, R., Hoi, G. W. S., and Zubiaga, A. (2017). SemEval-2017 Task 8: RumourEval: Determining rumour veracity and support for rumours. In *Proceedings of the 11th International Workshop on Semantic Evaluations* (SemEval-2017), pages 69–76, Vancouver, Canada.
- [Dungs et al., 2018] Dungs, S., Aker, A., Fuhr, N., and Bontcheva, K. (2018). Can Rumour Stance Alone Predict Veracity? In *Proceedings* of the 27th International Conference on Computational Linguistics, page 3360–3370, Santa Fe, New Mexico, USA.
- [Enayet and El-Beltagy, 2017] Enayet, O. and El-Beltagy, S. R. (2017). NileTMRG at SemEval-2017 Task 8: Determining Rumour and Veracity

- Support for Rumours on Twitter. In *Proceedings of the 11th International Workshop on Semantic Evaluations (SemEval-2017)*, pages 470–474, Vancouver, Canada.
- [Fajcik et al., 2019] Fajcik, M., Burget, L., and Smrz, P. (2019). But-fit at semeval-2019 task 7: Determining the rumour stance with pre-trained deep bidirectional transformers.
- [Giménez et al., 2017] Giménez, M., Baviera, T., Llorca, G., Gámir, J., Calvo, D., Rosso, P., , and Rangel, F. (2017). Overview of the 1st Classification of Spanish Election Tweets Task at IberEval 2017. In Second Workshop on Evaluation of Human Language Technologies for Iberian Languages (IberEval 2017).
- [Goldberg, 2016] Goldberg, Y. (2016). A primer on neural network models for natural language processing. *Journal of Artificial Intelligence Research* 57, pages 345–420. Chapters 10-11.
- [Gorell et al., 2018] Gorell, G., Bontcheva, K., Derczynski, L., Kochkina, E., Liakata, M., and Zubiaga, A. (2018). Rumoureval 2019: Determining rumour veracity and support for rumours.
- [Grave et al., 2018] Grave, E., Bojanowski, P., Gupta, P., Joulin, A., and Mikolov, T. (2018). Learning word vectors for 157 languages. In Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018).
- [Han et al., 2011] Han, J., Kamber, M., and Pei, J. (2011). *Data Mining, Concepts and Techniques*. Morgan Kaufmann Publishers Inc., 3 edition.
- [Hanselowski et al., 2018] Hanselowski, A., PVS, A., Schiller, B., Caspelherr, F., Chaudhuri, D., Meyer, C. M., and Gurevych, I. (2018). A Retrospective Analysis of the Fake News Challenge Stance Detection Task. In Proceedings of the 27th International Conference on Computational Linguistics, pages 1859–1874, Santa Fe, New Mexico, USA.
- [Huang et al., 2015] Huang, Y. L., Starbird, K., Orand, M., A. Stanek, S., and T. Pedersen, H. (2015). Connected through crisis: Emotional proximity and the spread of misinformation online. In CSCW '15 Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, pages 969–980, Vancouver, BC, Canada. Association for Computing Machinery.
- [Joulin et al., 2016] Joulin, A., Grave, E., Bojanowski, P., and Mikolov, T. (2016). Bag of tricks for efficient text classification. arXiv preprint arXiv:1607.01759.

- [Küçük, 2017] Küçük, D. (2017). Stance detection in turkish tweets. In *Proceedings of Workshop on Social Media World Sensors (SIDEWAYS)*, Prague, Czech Republic.
- [Kochkina et al., 2017] Kochkina, E., Liakata, M., and Augenstein, I. (2017). Turing at SemEval-2017 Task 8: Sequential Approach to Rumour Stance Classification with Branch-LSTM. In *Proceedings of the 11th International Workshop on Semantic Evaluations (SemEval-2017)*, pages 475–480, Vancouver, Canada.
- [Lillie and Middelboe, 2018] Lillie, A. E. and Middelboe, E. R. (2018). Fake News Detection using Stance Classification: A Survey. arXiv:1907.00181.
- [Lillie and Middelboe, 2019] Lillie, A. E. and Middelboe, E. R. (2019). Danish stance-annotated reddit dataset. doi: 10.6084/m9.figshare.8217137.v1.
- [Lou, 1995] Lou, H.-L. (1995). Implementing the viter algorithm. Chapter: Viter Algorithm Applied to HMMs.
- [Mikolov et al., 2013] Mikolov, T., Corrado, G., Chen, K., and Dean, J. (2013). Efficient estimation of word representations in vector space. In *Proceedings of the International Conference on Learning Representations* (ICLR 2013), pages 1–12. arXiv preprint arXiv:1301.3781.
- [Mohammad et al., 2016] Mohammad, S. M., Kiritchenko, S., Sobhani, P., Zhu, X., and Cherry, C. (2016). SemEval-2016 Task 6: Detecting Stance in Tweets. In *Proceedings of SemEval-2016*, pages 31–41, San Diego, California.
- [Pedregosa et al., 2011] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830.
- [Pennington et al., 2014] Pennington, J., Socher, R., and Manning, C. D. (2014). Glove: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543.
- [Pomerleau and Rao, 2017] Pomerleau, D. and Rao, D. (2017). Fake news challenge. http://www.fakenewschallenge.org Visited 26-11-2018 and dataset from https://github.com/FakeNewsChallenge/fnc-1 Visited 10-12-2018.
- [Procter et al., 2013] Procter, R., Vis, F., and Voss, A. (2013). Reading the riots on Twitter: methodological innovation for the analysis of big data. *International Journal of Social Research Methodology*, pages 16:3 197–2014.

- [Qazvinian et al., 2011] Qazvinian, V., Rosengren, E., Radev, D. R., and Mei, Q. (2011). Rumor has it: Identifying Misinformation in Microblogs. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, pages 1589–1599, Edinburgh, Scotland.
- [Quattrociocchi et al., 2016] Quattrociocchi, W., Scala, A., and Sunstein, C. R. (2016). Echo Chambers on Facebook.
- [Řehůřek and Sojka, 2010] Řehůřek, R. and Sojka, P. (2010). Software Framework for Topic Modelling with Large Corpora. In *Proceedings* of the LREC 2010 Workshop on New Challenges for NLP Frameworks, pages 45–50, Valletta, Malta. ELRA. http://is.muni.cz/publication/884893/en.
- [Årup Nielsen, 2011] Årup Nielsen, F. (2011). A new ANEW: evaluation of a word list for sentiment analysis in microblogs. In *Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages. Volume 718 in CEUR Workshop Proceedings*, pages 93–98.
- [Årup Nielsen, 2019] Årup Nielsen, F. (2019). Danish resources.
- [Shu et al., 2017] Shu, K., Sliva, A., Wang, S., Tang, J., and Liu, H. (2017). Fake news detection on social media: A data mining perspective. *ACM SIGKDD Explorations Newsletter*, 19(1):22–36.
- [Stranisci et al., 2015] Stranisci, M., Bosco, C., Farías, D. I. H., and Patti, V. (2015). Annotating Sentiment and Irony in the Online Italian Political Debate on #labuonascuola. pages 274–279.
- [Taulé et al., 2017] Taulé, M., Martí, M. A., Rangel, F., Rosso, P., Bosco, C., and Patti, V. (2017). Overview of the task on stance and gender detection in tweets on catalan independence at ibereval 2017. In Proceedings of the Second Workshop on Evaluation of Human Language Technologies for Iberian Languages (IberEval 2017), pages 157–177.
- [Thorne et al., 2018] Thorne, J., Vlachos, A., Cocarascu, O., Christodoulopoulos, C., and Mittal, A. (2018). The Fact Extraction and VERification (FEVER) shared task. In *Proceedings of the First Workshop on Fact Extraction and VERification (FEVER)*.
- [Tufekci, 2014] Tufekci, Z. (2014). Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls. In Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media, page 505–514. www.aaai.org.

- [Wang et al., 2017] Wang, F., Lan, M., and Wu, Y. (2017). Rumour evaluation using effective features and supervised ensemble models. *Proceedings of the 11th International Workshop on Semantic Evaluations (SemEval-2017)*, pages 491–496.
- [Wu et al., 1999] Wu, Y., Ganapathiraju, A., and Picone, J. (1999). Baumwelch re-estimation of hidden markov model. Chapter 3: Baum-Welch training approach.
- [Zubiaga et al., 2018] Zubiaga, A., Aker, A., Bontcheva, K., Liakata, M., and Procter, R. (2018). Detection and Resolution of Rumours in Social Media: A Survey. ACM Computing Surveys, Vol. 51, No. 2, Article 32.
- [Zubiaga et al., 2016a] Zubiaga, A., Liakata, Maria, Procter, R., Wong Sak Hoi, G., and Tolmie, P. (2016a). Pheme rumour scheme dataset: journalism use case. Available from: doi: 10.6084/m9.figshare.2068650.v1.
- [Zubiaga et al., 2015] Zubiaga, A., Liakata, M., Procter, R., Bontcheva, K., and Tolmie, P. (2015). Crowdsourcing the Annotation of Rumourous Conversations in Social Media. In *Proceedings of the 24th International Conference on World Wide Web*, pages 347–353.
- [Zubiaga et al., 2016b] Zubiaga, A., Liakata, M., Procter, R., Hoi, G. W. S., and Tolmie, P. (2016b). Analysing How People Orient to and Spread Rumours in Social Media by Looking at Conversational Threads. *PLoS ONE*. 11(3).

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A Dataset

A.1 Reddit queries

Note that the list is copy-pasted from a CSV file, hence the format.

topic, query, after, before, score peter-madsen," peter madsen", 2017-8-1, 2018-1-1, 50 peter-madsen, ubåd, 2017-8-1, 2018-1-1, 10 peter-madsen,"Kim Wall",2017-8-1,2018-1-1,50 ulve, ulv, 2012-1-1, 2019-1-1, 5 ulve, ulvesagen, 2012-1-1, 2019-1-1, 0hpv,"hpv vaccine",2015-1-1,2019-1-1,5 hpv,"hpv-vaccine",2015-1-1,2019-1-1,5 hpv,"de vaccinerede piger",2015-1-1,2019-1-1,5 anna-mee," Anna Mee", 2017-1-1, 2019-1-1, 20 anna-mee, "Paradise Papers", 2017-1-1, 2019-1-1, 5klima, klima, 2015-1-1, 2019-1-1, 5metoo, metoo, 2016-1-1, 2019-1-1, 10 kost, kost, 2018-1-1, 2019-1-1, 5kost, veganer, 2018-1-1, 2019-1-1, 5kost, vegetar, 2018-1-1, 2019-1-1, 0trump,trump,2016-1-1,2019-1-3,50 trump,"donald trump",2016-1-1,2019-1-3,50

A.2 Extracted Reddit data

```
{
    "title": "5G-teknologien er en miljøtrussel, som bør stoppes",
    "text": "",
    "submission_id": "ax70y5",
    "created": "2019-03-04 13:17:12",
    "num_comments": 43,
    "url": "/r/Denmark/comments/ax70y5/5gteknologien_er_en_miljøtrussel...",
    "text_url": "https://www.information.dk/debat/2019/02/5g-teknologien-...",
    "upvotes": 0,
    "is_video": false,
    "user": {
        "id": "5khw3",
        "karma": 9789,
        "created": "2011-07-26 08:25:10",
        "gold_status": false,
        "is_employee": false,
        "has_verified_email": false
    },
    "subreddit": {
        "name": "Denmark",
        "subreddit_id": "t5_2qjto",
        "created": "2008-07-08 19:19:11",
        "subscribers": 110799
    },
    "comments": [
        {
            "comment_id": "ehrpmiv",
            "text": ">Pernille Schriver, Vibeke Frøkjær Jensen og ...",
            "is_deleted": false,
            "created": "2019-03-04 15:01:17",
            "is_submitter": false,
            "submission_id": "t3_ax70y5",
            "parent_id": "t3_ax70y5",
            "comment_url": "/r/Denmark/comments/ax70y5/5gteknologien_...",
            "upvotes": 15,
            "replies": 1,
            "user": { ... }
        },
        . . .
   ]
}
```

A.3 Event ideas

- Britta Nielsen svindel
- Danske Bank hvidvask
- Minister, kontor for 130k
- \bullet 25 år og borgmester
- Wozniaki har gigt ? vinder første grandslam
- $\bullet\,$ Bendtner og taxa
- Håndbold-mænd, vinder VM i Rio
- Løkke og jakkesætsskandale
- Udbytteskatskandale
- Stein Bagger
- Dong Energy
- Ubådssagen
- Ulve i Danmark
- Skatteskandalen
- MeToo, Peter Ålbæk
- $\bullet\,$ Klimadebat Varm/kold sommer
- Amatørlandsholdet
- Facebook hack
- Dantaxa skattely
- Maersk hack
- HPV vaccine
- Kostråd
- Togulykke
- Fodboldtransfer
- Anna Mee Allerslev
- Korrupt politiker: Esben Lunde Larsen
- Burkaforbud
- Post Nord

B Experiments data

B.1 Most frequent words

Below are the generated words for the "Most frequent words" features, when considering the 100 most frequent words per SDQC class, and then filtering out words appearing for all classes. Note that the words "urlurlurl" and "refrefref" are replacements for respectively URLs and quotes (see section 6.2.4).

B.1.1 Supporting

urlurlurl, refrefref, da, fordi, børn, alle, nok, ville, hele, over, må, synes, mange, flere, derfor, ting, se, mennesker, gør, efter, samme, kommer, andet, alt, været, går, blive, andre, tage, langt, gøre, gå, får.

B.1.2 Denying

refrefref, nok, alle, mange, fordi, da, andre, over, siger, havde, får, urlurlurl, ham, hende, b12, min, skulle, giver, børn, andet, alt, været, selvfølgelig, uden, samme, hvordan, tilskud, kommer, gør, kun, kost, flere, penge.

B.1.3 Querying

hvorfor, måske, hvordan, skulle, hele, ville, ulykke, sådan, politiet, nogle, været, vores, vel, programmet, må, kun, hende, havde, gøre, denne, the, står, sikkert, side, se, journalisten, ham, gjort, fald, co2, blev, 5g, år.

B.1.4 Commenting

refrefref, da, urlurlurl, fordi, nok, alle, gør, dig, andre, ville, mange, se, kun, får, over, må, din, samme, kommer, min, havde, siger, gøre, måske, efter, nogle, uden, altså, mener, spise, mennesker, ingen, andet.

B.2 Super-sampling

Examples of word replacement in super-sampling. Three strategies have been performed, being replacement with most similar word from respectively word2vec and fastText word vectors, and replacement by looking up synonyms in a dictionary. Note that for the word vector cases, only preprocessed tokens are replaced, while with synonyms, replacement is performed on the non-preprocessed text.

B.2.1 Example 1

Original: "tankegangen er at de bredeste skuldre kan bære de tungeste læs der er ikke nogen mening i at give de svageste et lige så tungt læs som de stærkeste det bliver de svage bare kvast af"

Word2vec: "tankegangen er at de bredeste skuldre kunne udholde de tungeste læs hist er ej nogen betydning i at forære de svageste et sidestykke udså tungt læs ligesom de stærkeste det bliver de svage bare kvast af"

FastText: "evidenstankegangen er atr dissekere bredest skuldrene kunne udholde dissekere tungest læs der er ikke nogen mening i at give de svageste et lige så tungt læs som de stærkeste det bliver de svage bare kvast af"

Synonyms: "Tankegangen er at de bredeste skuldre kan udholde de tungeste læs. Hist er ej nogen som helst formål i at fremføre de svageste et netop så tungt læs som de stærkeste, det bliver de svage når blot visk af."

B.2.2 Example 2

Original: "sku da cool nok at have næsten samme record som chris kyle og endda en større bounty chris med 4 tours i irak og 150ish kills fik hele 80.000 dowwahs på sit hovede"

Word2vec: "sku da nøgtern sikkert at kolonihave næsten ens collection ligesom chris smide og ovenikøbet en større bounty chris med 4 tours i irak og 150ish kills fik hele 80.000 dowwahs på sit hovede"

FastText: "skuvoy pvda nøgtern sikkert atr kolonihave gæsten ens record som chris kyle og endda en større bounty chris med 4 tours i irak og 150ish kills fik hele 80.000 dowwahs på sit hovede"

Synonyms: "Sku da sej yderligere at kolonihave næsten samme record som Chris Smide, og ovenikøbet en større bounty! (Chris, i kraft af 4 tours i Irak og 150ish kills, fik totalitet 80.000 dowwahs inden for sit hovede)"

B.3 Parameter search

B.3.1 Learning curves

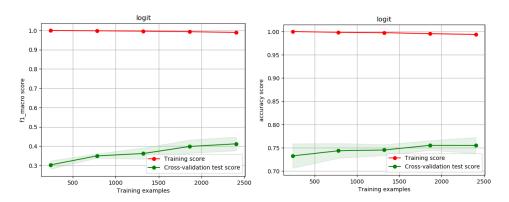


Figure 21: logit learning curves for macro F_1 (left) and accuracy (right)

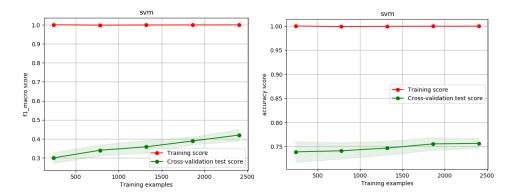


Figure 22: svm learning curves for macro F_1 (left) and accuracy (right)

B.4 Veracity experiments

This appendix section contains tables for the veracity experiments performed for unverified rumours interpreted as true and for three-way classification.

B.4.1 Unverified as true results

Structure	Model	Acc.	F_1
	λ	0.74 (+/- 0.21)	0.49 (+/- 0.13)
SAS	ω	0.74 (+/- 0.21)	$0.53 \ (+/-\ 0.33)$
	VB	0.19 (+/-0.03)	0.16 (+/-0.02)
	λ	0.67 (+/- 0.09)	0.55 (+/-0.08)
TCAS	ω	0.65 (+/-0.16)	$0.49 \ (+/-\ 0.16)$
	VB	0.34 (+/-0.02)	$0.34 \ (+/-\ 0.02)$
	λ	0.61 (+/- 0.05)	0.54 (+/-0.07)
BAS	ω	0.71 (+/- 0.06)	0.62 (+/- 0.05)
	VB	0.59 (+/-0.10)	0.54 (+/-0.03)

Table 33: Danish veracity results on 3-fold cross validation for unverified being true

Structure	Model	Acc.	F_1
	λ	0.75	0.59
SAS	ω	0.81	0.45
	VB	0.69	0.54
	λ	0.72	0.54
TCAS	ω	0.76	0.52
	VB	0.70	0.56
	λ	0.62	0.56
BAS	ω	0.60	0.51
	VB	0.61	0.58

Table 34: Training on PHEME and testing on DAST where unverified is set to true

Structure	Model	Acc.	F_1
	λ	0.84 (+/- 0.02)	0.52 (+/-0.13)
SAS	ω	0.78 (+/-0.09)	$0.51 \ (+/-\ 0.05)$
	VB	0.43 (+/- 0.33)	0.40 (+/- 0.24)
	λ	0.76 (+/- 0.11)	0.50 (+/- 0.09)
TCAS	ω	0.78 (+/- 0.00)	0.52 (+/-0.03)
	VB	0.39 (+/- 0.13)	$0.38 \ (+/-\ 0.09)$
	λ	0.71 (+/- 0.02)	0.50 (+/- 0.04)
BAS	ω	0.69 (+/- 0.04)	0.57 (+/-0.06)
	VB	0.67 (+/- 0.05)	0.62 (+/- 0.05)
	λ	0.84 (+/- 0.03)	0.54 (+/- 0.14)
None	ω	0.82 (+/-0.02)	$0.50 \ (+/-\ 0.07)$
	VB	0.64 (+/- 0.35)	0.46 (+/- 0.16)

Table 35: Training and testing on mix of PHEME and different DAST structures for unverified true $\,$

B.4.2 Three-way classification results

Structure	Model	Acc.	F_1
	λ	0.56 (+/- 0.23)	0.33 (+/- 0.20)
SAS	ω	0.61 (+/- 0.35)	$0.37 \ (+/- \ 0.37)$
	VB	0.31 (+/- 0.17)	$0.35 \ (+/-\ 0.30)$
	λ	0.49 (+/- 0.08)	0.44 (+/- 0.07)
TCAS	ω	0.48 (+/- 0.14)	$0.39 \ (+/-\ 0.03)$
	VB	0.26 (+/- 0.10)	$0.24 \ (+/-\ 0.10)$
	λ	0.44 (+/- 0.04)	0.44 (+/- 0.02)
BAS	ω	0.57 (+/- 0.03)	0.53 (+/- 0.04)
	VB	0.26 (+/- 0.02)	$0.25 \ (+/-\ 0.03)$

Table 36: Danish veracity results on 3-fold cross validation for three-way rumour classification $\frac{1}{2}$

Structure	Model	Acc.	F_1
	λ	0.56	0.37
SAS	ω	0.56	0.41
	VB	0.62	0.38
	λ	0.42	0.36
TCAS	ω	0.53	0.40
	VB	0.52	0.41
	λ	0.33	0.32
BAS	ω	0.47	0.35
	VB	0.45	0.40

Table 37: Training on PHEME and testing on DAST for three-way classification

Structure	Actual Predicted	False	True	Unverified
BAS	False	73	10	103
DAS	True	9	46	44
	Unverified	57	41	213

Table 38: Truth value distribution with PHEME training and BAS structure testing $\,$

Structure	Model	Acc.	F_1
SAS	λ	0.49 (+/- 0.08)	0.37 (+/- 0.08)
	ω	$0.44 \ (+/-\ 0.09)$	$0.38 \ (+/-\ 0.07)$
	VB	0.36 (+/- 0.11)	$0.30 \ (+/- \ 0.10)$
TCAS	λ	0.53 (+/- 0.09)	0.40 (+/- 0.03)
	ω	0.52 (+/-0.05)	0.42 (+/- 0.05)
	VB	$0.31 \ (+/- \ 0.03)$	$0.29 \ (+/-\ 0.02)$
BAS	λ	0.42 (+/- 0.03)	0.38 (+/- 0.06)
	ω	$0.43 \ (+/-\ 0.04)$	0.42 (+/- 0.06)
	VB	0.41 (+/- 0.06)	0.38 (+/- 0.10)
None	λ	0.50 (+/- 0.08)	0.32 (+/- 0.08)
	ω	$0.50 \ (+/- \ 0.07)$	0.35 (+/-0.04)
	VB	$0.43 \ (+/-\ 0.03)$	0.33 (+/- 0.08)

Table 39: Training and testing on mix of PHEME and different DAST structures for three-way classification ${\cal P}$