

Misinformation detection in Luganda-English code-mixed social media text

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Abstract

The increasing occurrence, forms, and negative effects of misinformation on social media platforms has necessitated more misinformation detection tools. Currently, work is being done addressing COVID-19 misinformation however, there are no misinformation detection tools for any of the 40 distinct indigenous Ugandan languages. This paper addresses this gap by presenting basic language resources and a misinformation detection data set based on code-mixed Luganda-English messages sourced from the Facebook and Twitter social media platforms. Several machine learning methods are applied on the misinformation detection data set to develop classification models for detecting whether a code-mixed Luganda-English message contains misinformation or not. A 10-fold cross validation evaluation of the classification methods in an experimental misinformation detection task shows that a Discriminative Multinomial Naïve Bayes (DMNB) method achieves the highest accuracy and F-measure of 78.19% and 77.90% respectively. Also, Support Vector Machine and Bagging ensemble classification models achieve comparable results. These results are promising since the machine learning models are based on n-gram features from only the misinformation detection data set.

1 Introduction

The Internet and the World Wide Web have provided a fertile ground to generate huge amounts of information thanks to various advantages and conveniences associated with them. Since the first blogging Web sites in 1999 where people started creating their own weblogs and sharing comments (Siles, 2012), Web and mobile-based social media platforms have become popular, widely adopted, and have overtaken traditional media in facilitating various social interactions and aspects. As a

result many social media platforms generate huge amounts of data and information. Various forms of social media content have proved useful in decision support applications in several areas such as business, health, and other services. However, due to the temptation to quickly post information and the lack of moderation (Jain et al., 2016), more forms of social media content have turned out to be invalid, inaccurate, potentially harmful and in some cases intentionally harmful (Shu et al., 2017) to both individuals, groups, societies and other directly and indirectly affected entities. There are now several studies that have sought and continue to look for solutions to detect negative, wrong or undesired forms of information in social media posts. Most recent work has focused on addressing misinformation with regard to the Corona Virus disease 2019 (COVID-19) (Brennen et al., 2020; Pennycook et al., 2020; Serrano et al., 2020).

However, as is the case for several natural language processing (NLP) applications, there are hardly any low resourced languages that are involved in detecting misinformation, especially, in the current COVID-19 era. One major limitation for the lack of involvement of low resource languages are the few or no language resources such as labeled social media text, respective lexicons, and other basic NLP resources for developing misinformation detection models. In East Africa and Uganda in particular, the main effort towards detecting misinformation has focused on the analysis of speech data mined from community radios (WHO, 2020; Pulse, 2020) to detect various forms of interesting information including misinformation. So far, it is mostly English and ‘Ugandan English’ speech data that is analysed. This is the same case with another recent effort on sentiment classification of Twitter reviews about Ugandan Telecom companies (Kabiito and Nakatumba-Nabende, 2020) where only English and ‘Ugandan English’

were analysed.

To the best of our knowledge there are no resources and misinformation detection models involving all of Uganda’s over 40 distinct indigenous languages. In this paper, we present the first language resources including annotated social media text and pre-processing resources such as a polarity lexicon and other basic NLP resources for use in COVID-19 misinformation detection involving Uganda’s most common indigenous language called Luganda. Luganda is also still a very low-resourced language in NLP terms although it has a considerably larger presence on social media platforms such as Twitter¹ and Facebook² compared to all other indigenous Ugandan languages. We utilize the Luganda language resources to evaluate various text classification methods for misinformation detection.

2 Related Work

Since the onset of the COVID-19 pandemic, several studies have been carried out around the creation of COVID-19 misinformation datasets. Fourati et al. (2020) create a Tunisian Arabizi sentiment analysis dataset. Elhadad et al. (2020) provide an annotated bilingual Arabic to English COVID-19 dataset based on Twitter data. This dataset is useful for detecting misinformation around COVID-19 and is also similar to the work by Al-Zaman et al. (2020) where they develop a COVID-19 social media fake news dataset for India. Memon and Carley (2020) provide a COVID-19 Twitter dataset in English that is classified into informed, misinformed and irrelevant groups. Cui and Lee (2020) creates a COVID-19 health care misinformation dataset that includes fake news on different websites and social media sites.

In order to detect COVID-19 misinformation on social media data, several techniques have been employed including the use of crowd sourcing to check for misinformation (Kim and Walker, 2020), detection using the elaborate likelihood models of persuasion from social media posts (Janze and Rissus, 2017) or building machine learning models for COVID-19 misinformation detection (Monti et al., 2019). Patwa et al. (2020) curate an annotated dataset of social media posts and articles of both real and fake news on COVID-19 and they also build four machine learning models (Deci-

sion Tree, Logistic Regression, Gradient Boost, and Support Vector Machine) with SVM giving the best model performance. Similarly, Cui and Lee (2020) presents a machine learning model trained on a COVID-19 misinformation dataset which is in English.

The studies mentioned above underscore the potential of developing resources and solutions for identification of misinformation from social media. So far, there is hardly any work involving East African languages in detecting misinformation from social media. As efforts towards covering this gap, this study develops a preliminary misinformation detection dataset involving Luganda (a very low resourced East African language), and explores the application of several machine learning methods on the dataset.

3 The Luganda language

Luganda is a Bantu language and is the most widely spoken indigenous language in Uganda. It is primarily spoken in the south eastern Buganda region along the shores of Lake Victoria and up north towards the shores of Lake Kyoga (Nakayiza, 2013; Fagbolu and Wasike, 2019). According to a 2014 language census (Lewis et al., 2013), Luganda has over seven million first and second language speakers. Typologically, it is a highly-agglutinative, tonal language with subject-verb-object word order, and nominative-accusative morphosyntactic alignment (Fagbolu and Wasike, 2019).

Although Luganda is the most widely spoken indigenous language in Uganda, it is considered a low resourced language because of the limited availability of Luganda NLP resources (Nandutu and Mwebaze, 2020). The increased access of Internet subscriptions and internet-enabled phones in several parts of Uganda has led to an increase in the number of the World Wide Web users (Commission, 2020). A growing number of these users utilize social media platforms and usually post messages in Luganda and code-mixed Luganda-English (Ssentumbwe et al., 2020). The ever growing Luganda content on Web-based social media sites such as Twitter and Facebook opens opportunities for sourcing very much needed Luganda text for various text related NLP applications (Nannyonga et al., 2020).

¹<https://twitter.com>

²<https://facebook.com>

4 Luganda-English code-mixed social media data

Initially, the plan was to collect only Luganda text from social media Web sites; however, a manual analysis of a reasonable number of messages from the Web sources showed a lot of code switching between Luganda and English. This observation can be explained by the use of English as the main official language and the main mode of communication throughout the entire Ugandan Education system and Government. The speakers tend to code switch between their indigenous languages and English in informal communications such as messages posted on social media websites. The dataset used in this paper also included code switched Luganda-English text and this also enabled us to significantly increase the size of the dataset. Moreover, it is now established that code switching is very common and acceptable in multilingual communities (Be-gum et al., 2016). The misinformation data used in this study are obtained from two commonly used social media sources, that is, Twitter and Facebook. During the data collection exercise, toxic or offensive statements that were not related to COVID-19 were dropped. However, toxic/offensive statements that discussed COVID-19 were not dropped and were annotated accordingly depending on whether they were true or false. As an example there were posts that dismissed the existence of COVID-19 in Uganda and called it a money making venture for government officials. Such posts are important because they contain misinformation about the existence of COVID-19; therefore, we included such posts and labeled them as having misinformation.

4.1 Twitter data

Using the Twitter API, we entered key words associated with Luganda broadcasting channels, political figures (for example *cpmayiga* (the Prime Minister of the Buganda kingdom), general public messages (for example those with a hashtag *StaySafeUG*) to retrieve Luganda and Luganda-English code-mixed tweets. We collected 12,049 raw tweets that had been posted from March 2020 to July 2020. The raw collection was pre-processed by converting all tweets to lowercase and removing the following: all mentions (*twitter_handle*), irrelevant abbreviations (such as *rt* for retweet), removing unnecessary symbols (such as the ampersand symbol (&)) and all non-ASCII characters. The pre-processing at this stage resulted into a total

of 7,136 unlabeled tweets.

4.2 Facebook data

Using the Facebook API, we extracted 430,075 posts between March 2020 and July 2020 from Facebook pages that belong to TV and radio broadcasting companies that mainly communicate using Luganda; these include: Bukedde TV, CBS, Spark TV, and Radio Simba. The Ugandan Ministry of Health had the main mandate to provide reliable information and guidance concerning the COVID-19 virus. So we also extracted Facebook posts from Uganda's Ministry of Health Facebook page (which is mainly in English) for the purpose of verifying the correctness of some information in the posts obtained from the Facebook pages of the luganda-based broadcasting companies.

4.3 Topic modeling

To gain more insight into the Luganda and Luganda-English code switch terms used in the Facebook and Twitter datasets, we used Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to model topics from the unlabeled datasets. LDA is a well-established topic modeling algorithm that serves to identify topics that may be useful for tasks involving text classification. The dataset was preprocessed to remove stop words, punctuation, URLs, and any email addresses. One main development that arose at this stage was the creation of a list of Luganda stop words; this list was previously non-existent. This research has now developed a list of Luganda stop words that were used for preprocessing of the dataset. The datasets were further converted to lowercase before creating bi-grams and tri-grams that were used to train the LDA unsupervised model. Using the Gensim library, we trained the LDA model with the following set of hyper-parameters; *num_topics*:10, *random_state*:100, *chunksize*:100, *passes*:10, *alpha*: 'auto', *per_word_topics*:True.

We run the LDA models on the Twitter and Facebook data separately. Due to the high topic variation on the Facebook data, we got a perplexity score of 11.08 while that for twitter data was 9.01. These scores were obtained for 10 topics. When the Facebook and Twitter data was combined and the LDA topic modelling is done, a perplexity score of 13.66 was obtained with 10 topics. The increase in perplexity score is explained by the increase in topic variation introduced by combining the two data sources. With the increased topic variation the

Data	Twitter	Facebook
Raw Data	12,049	430,075
Preprocessed Data	7,136	114,130
Code-mixed annotated data	286	759
Data with misinformation	36	577
Data without misinformation	250	182

Table 1: Statistics about the dataset.

5.1 Bayesian methods

Naïve Bayes (John and Langley, 2013), Bayesian Logistic Regression (Genkin et al., 2007), and the Discriminative Multinomial Naïve Bayes classifier (Su et al., 2008). The Naïve Bayes method usually serves as a baseline method in many text classification studies. It uses a strong independence assumption which may limit the representation of feature relationships in a dataset. More extended forms of Bayesian networks relax the strong assumption of Naïve Bayes but require more computational resources to be applied on cases with many features. Bayesian Logistic Regression extends classical logistic regression by allowing the use of prior information (or beliefs) to generate posterior distributions. The Discriminative Multinomial Naïve Bayes method uses a simple and efficient discriminative parameter learning method for multinomial Naïve Bayes network.

5.2 Non-linear functions

The Luganda-English code-mixed misinformation dataset is nonlinear. So we mainly use Support Vector Machines (SVMs) which are faster to implement and usually lead to competitively high performing classification models. The method of SVMs uses kernel functions (such as polynomial, sigmoid and radial basis) to transform a dataset from a nonlinear domain to a linearly separable domain. We explore various types of SVMs in the Liblinear (Fan et al., 2008) and LibSVM (Chang and Lin, 2011) libraries, in John Platt’s Sequential Minimal Optimization algorithm (Platt, 1998), and in the stochastic variant of the Pegasos (Primal Estimated sub-GrAdient SOLver for SVMs) method (Shalev-Shwartz et al., 2011).

5.3 Lazy classification methods

Unlike previous methods that estimate a classification model based on training data, lazy classification methods keep the training data and only start to utilize it when they see a new instance for which they have to estimate a similarity with instances in the training data. The lazy classification methods explored here include: k-nearest neighbor (Aha et al., 1991), k-star (Cleary and Trigg, 1995), and locally weighted learning (Atkeson et al., 1997).

5.4 Tree classification methods

Tree classifiers are based on the notion of a decision tree where decision making considers different branches or paths to a final decisions in the leaves. By varying the characteristics of the tree branches and leaves, we get different types of trees. In this paper, we explore the following commonly used methods: the C4.5 algorithm (Quinlan, 2014) and its variations (C4.5 Consolidated (Ibarguren et al., 2015) and C4.5 graft (Webb, 1999), logistic model trees (Landwehr et al., 2005), and random forests (Breiman, 2001).

6 Misinformation detection experimental setup

6.1 Feature generation, cross-validation setup and evaluation metrics

Due to the size of the misinformation detection data set (1,045 instances) is considerably small, we used stratified 10 fold cross validation to evaluate the application of the different types of machine learning methods. The performance of the classification models was measured using accuracy, area under the receiver operating characteristic curve (AUROC), and f-measure. The accuracy is the percentage of correctly classified instances out of the total number of instances in the test set. The AUROC is a measure of the discriminative ability of a classifier. The f-measure is the harmonic mean of precision and recall.

6.2 Word n-gram Features

We used the TweetToSparseFeatureVector filter (Kiritchenko et al., 2014) to calculate sparse features based on word n-grams (unigrams, bigrams, and trigrams). CMU’s TweetNLP tokenizer was used to map input text into a sparse feature vector based on only the text in the misinformation dataset. Table 2 shows the total number of features for each n-gram setting.

n-gram type	Number of features
uni-gram	7347
bi-gram	23748
tri-gram	41547

Table 2: Word n-gram feature sizes.

7 Results and Discussion

Table 3 and Table 4 show the results for the uni-gram and bi-gram feature settings respectively in the experimental Luganda-English code mixed misinformation detection task. Only results for the best performing model per method are shown.

The best Liblinear model used an L2-regularized logistic regression (dual) model to achieve significantly higher scores compared to using the other types of SVMs. The best LibSVM model used a regularization parameter γ with the value 0.4, a sigmoid kernel (equation 1), and a degree of 5 for the kernel.

$$K(X, Y) = \tanh(\gamma \cdot X^T Y + r) \quad (1)$$

The best Sequential Minimization Optimization algorithm uses a logistic multinomial regression model with a ridge estimator as a *calibrator* and a polynomial kernel (equation 2).

$$K(X, Y) = (\gamma \cdot X^T Y + r)^d, \gamma > 0 \quad (2)$$

The best SPegasos model used a log-loss function which leads to better evaluation scores than the Hinge loss function. The setting for the best Random forest model included an infinite maximum depth, and 500 iterations. For the ensemble methods (boosting (AdaBoostM1) and bagging), we used the DMNBtext classifier as the base classifier since it had the highest values for the different classification performance metrics. We found the classification performance to decrease with an increase in the number of iterations.

The best performing method in both cases is the DMNBtext classifier. Decision tree methods took longer to train and yet they do not achieve any improvement over the better performing Bayesian and SVM methods. So, we did not consider decision tree methods for both bi-gram and tri-gram settings.

We see no significant differences between misinformation detection results based on the uni-gram (Table 3) and bi-gram (Table 4) feature settings.

The same turned out to be the case for tri-gram feature settings where there was slight decline in performance across all models.

7.1 Conclusion

This paper set out to present two main contributions towards addressing the gap of the lack of language resources and solutions for detecting misinformation involving indigenous Ugandan languages. First of all, the paper presented the first carefully labeled misinformation dataset involving Luganda, a very low-resourced indigenous Ugandan language. Secondly, the dataset was used to evaluate several machine learning methods in an experimental Luganda-English code-mixed misinformation detection task. Evaluation results showed the highest and promising classification performances from the Discriminative Multinomial Naïve Bayes, the Support Vector Machine models from the liblinear library, and the ensemble models from the bagging method that used the DMNB and SVM models as base classifiers. In future, we will continue to add more content and language resources into the Luganda misinformation dataset, and investigate the application of more machine learning methods.

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Classifier	Accuracy	AUROC	F-Measure
Naïve Bayes	66.99	80.70	66.10
Bayesian Logistic Regression	75.77	75.30	75.60
Discriminative Multinomial Naïve Bayes	78.19	82.30	77.90
Best Liblinear model	77.12	82.70	76.90
Best LibSVM model	76.45	75.90	76.20
Best Sequential Minimization Optimization	76.16	75.50	75.80
Best SPegasos	77.22	82.60	76.90
Best Random Forest	76.54	82.60	75.80
Logistic Model trees	73.46	77.40	73.20
Pruned C4.5	72.49	73.10	72.20
Pruned C4.5 using CTC algorithm	70.56	69.60	70.40
C4.5	72.20	73.10	71.90
AdaboostM1 with DMNBtext	76.06	81.10	75.80
Bagging with DMNBtext	77.90	82.60	77.60

Table 3: Misinformation detection results based on uni-gram features.

Classifier	Accuracy	AUROC	F-Measure
Naïve Bayes	67.47	80.90	66.70
Bayesian Logistic Regression	76.93	76.30	76.60
Discriminative Multinomial Naïve Bayes	77.99	81.90	77.70
Best Liblinear model	77.32	76.80	77.10
Best LibSVM model	76.83	76.20	76.50
Best Sequential Minimization Optimization	76.54	75.80	76.10
Best SPegasos	77.60	82.40	77.20
AdaboostM1 with DMNBtext	75.48	79.00	75.20
Bagging with DMNBtext	77.41	82.30	77.10

Table 4: Misinformation detection results based on bi-gram features.

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