

DATA 698

Capstone Project Literature Review

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Literature Review

(Williams et al., 2019) A similar research was conducted to analyze association between online hate speech and offline racism and religion related crimes occurred in London. A Weka tool was used to develop a machine learning classifier to annotate racism and religion and non-hateful tweets. Besides tweets and crime data, census data such as no qualifications, age, long-term unemployed, and black and minority ethnic, were considered part of the study. Statistical models were built to study a temporal and spatial association. Random and fixed effects Poisson regression models, and negative binomial models which results all show consistent of positive association between hate speech in Twitter and offline racially and religiously crimes. Other research has also shown that online hate speech has strong correlation with significant events such as terror attacks, political votes, etc (Hanes & Machin, 2013; Williams & Burnap, 2015). A recent example of this was the Christchurch extreme right terror attacker's post on 8chan. Although there is no directly causal link between online hate speech and offline hate crime but hate speech is part of the cumulative process of hatred formula from social status, political context, geographical that bring harm to physical world.

In today, hate speech detection remains one of big challenges for artificial intelligence. (Matsaki L., 2018) Because definition of hate speech constantly evolving and often hidden within context, AI can be fooled easily. AI can be fooled by inserting a typos, adding extra alphabets, and removing spaces. An example of altered text to evade AI detection will be like this: "MartiansAreDisgustingAndShouldBeKilled love.". Humans can understand this message but the machine learning algorithms have trouble to identify it. Facebook CEO Mark Zuckerberg testified before congress in 2018 mentioned he was optimistic that in 10 years AI is able to identify hate speech more accurate. (Shead S., 2020) Only 24 per cent of hate speech was able to be detected said Facebook's chief technology officer, Mike Schroepfer. Billions of users like Facebook platform, a cutting-edge machine technology to accurately to spot hate speech is a must-have, to protect its users from exposure to harmful content.

Many previous researchers have tried different machine learning approaches to best identify hate speech. (Lee et al., 2022) Stacked ensemble Gated Convolutional Recurrent- Neural Networks (GCR-NN), a deep learning approach, was used to detect racist speech from a tweets dataset. It's 0.98 accuracy outperform other conventional machine learning models such as random forest, k-nearest neighbors, svm, etc. A large scale dataset of tweets related to racism from the world were collected, preprocessed to such as remove stop words, annotated using the TextBlob into positive, negative, and neutral score sentiments before performing Term Frequency - Inverse Document Frequency (TF-IDF), and Bag of Words (BoW) for machine learning models development. United States has the highest number of racist tweets, 50 per cent followed by United Kingdom, 31 per cent. More than 53 per cent of people age between 15-30 years old in the United States is exposure to online hate material (Hawdon et al., 2016). Both logistic regression and SVM performs better than other models using BoW features on average with a 0.97 accuracy score. For a fair comparison, few single deep learning models such as gated recurrent unit (GRU), long short term memory (LSTM), convolutional neural networks (CNN), and recurrent neural networks (RNN), were also implemented and optimized through hyperparameter tuning. (Crabb et al., 2019; Starosta A., 2019) Combination of Weak Supervision and Transfer Learning approach is useful for which data is lack of labelling. Weak supervision is method for building a labelled training set from a large amount of unlabelled data. Transfer learning is a method where it reuses already existing pre-trained models for new tasks. It will use the training set created from weak supervision stage to build a new classifier model.

Research has found that there is a contradiction between freedom of speech and hate speech. Hate speech creates an environment that tests the limits of free speech, and it violates fundamental rights of a human being. On social networks, we can observe how other forms of violence such as terrorism, extremism and hate crimes, may each have their own space, victims and aggressors (Chetty & Alathur, 2018). Miró-Llinares and Rodriguez-Sala (2016) describe the existence of many different types of hate speech that target different groups and individuals. Research has been done to differentiate and define each type accordingly. It is important to keep in mind classification as it will help us group Tweets with similar speech together in one category. Some of the approaches to the classification of hate speech from Tweeter used by Miró-Llinares and Rodriguez-Sala (2016) take into account the hashtags as a variable for predicting violence and hate message from the tweet. While some of their other approaches for classification of hate speech on social

media also include the development of neural language models. It is also important to underline that the authors warn the development of classification algorithms may not allow for a deeper understanding of the different nature of violent communications. The recommendation they make is to pursue a thorough study of the categorization of different expressions that are evident in these types of messages.

The study conducted by Miró-Llinares et al. (2018) focuses on designing an algorithm to detect hate speech in digital microenvironments. Its purpose is to facilitate and reduce analysis tasks undergone by law enforcement agencies and service providers. The algorithm used in this specific article uses machine learning classification techniques such as Random Forests. Furthermore, the study demonstrated that not all variables in the data relating to anonymity and visibility of users are applicable in distinguishing hate speech in tweets' content, and that tweet metadata proved to be more efficient in the classification process than account metadata. Compared to similar studies that have applied different classification approaches, the results obtained by this study slightly outperform the others. The Random Forest model applied reached a F1-score of 0.92, highlighting the accuracy of the model on the dataset. Previous attempts from other studies have obtained F-measures of 0.77, 0.90 and 0.76 according to the literature in this specific study.

We have also found research that is centered around the idea that social media metadata is a valuable input in the analysis of opinions and sentiment. From activism to detecting road traffic, access to these data is essential in today's comprehensive analyses. Using data from 18 Spanish-speaking Latin American countries, research found that similarly to mass media, social media suffers from a strong bias towards violent or sexual crimes. Simple models such as a linear regression were used in the research by Prieto Curiel et al. (2020) and found that countries with higher number of murders, murder rate and fear of crime are more likely to have crime-related tweets. However, it mainly represents the fears that people have of crime that may overemphasize certain types of crimes that are not as common as one would think. It was also found that there may not be a correlation at all between social media messages and crime, but rather demonstrate the reflection of the level of the fear of crime.

As explained by Chen et al. (2015), it is possible for weather to also be used as a feature for modeling crime around Tweeter data. Their work is also focused on predicting crime in order to maximize the allocation of scarce police resources. Their paper noted the limitations of past studies, suggesting that weather is a significant factor and it has been proved there is a correlation between weather and criminal activity. It is thought that certain environmental factors such as weather, should be considered as it may affect the occurrence of criminal incidents. Such data containing information about theft density, Twitter data, weather and geolocation points, have been modeled using logistic regression with recommendations for future analysis using support vector machine (Chen et al., 2015). More advanced techniques to predicting crime from Tweeter posts include Artificial Neural Networks approach that have achieved average accuracies of 0.903 on testing dataset and 0.933 on the training dataset as those demonstrated by Sandagiri et al. (2021).

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