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Sentiment Analysis of Religious Tweets

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Abstract: *Sentiment analysis or opinion mining is an important type of text analysis that aims to support decision making by extracting and analyzing opinion-oriented text, identifying positive and negative opinions, and measuring how positively or negatively an entity (i.e., people, organization, event, location, product, topic, etc.) is regarded. As more and more users express their political and religious views on Twitter, tweets become valuable sources of people's opinions. This paper proposes a comprehensive guide of using Python to extract, pre-process, and analyse tweets about religion. In this analysis we will be implementing Topic Modelling using LDA and Gensim and Hate Speech Detection using Hate Sonar model.*

Key Word: *Sentiment Analysis; Tweets; Text Analysis; Religion*

I. INTRODUCTION

On Web 2.0, user-generated content, which is material submitted by users who interact with social network sites, is a major theme. Twitter is a social networking and microblogging service where users send messages (a.k.a., tweets) to a network of associates from a variety of devices. A tweet is a text-based post and only has 140 characters, which is approximately the length of a typical newspaper headline and subhead. As more and more users post reviews about products and services they use, or express their political and religious views on Twitter, tweets become valuable sources of people's opinions and sentiments. Given its popularity, Twitter is seen as a potential new form of eWOM (electronic word-of mouth) marketing by the businesses and organizations concerned with reputation management. Sentiment analysis (or opinion mining) is stated as "the computational study of opinions, sentiments and emotions expressed in text". Reviews tend to be longer and more verbose than tweets which may only be a few words long and often contain significant spelling errors. In this study, we focus on the tweets sentiment analysis that is to automatically identify whether a piece of text expresses a positive or negative opinion using LDA, Gensim, Vader and Hate Speech Detection models.

II. MATERIAL AND METHODS

2.1 Data Extraction and Pre-Processing

For getting the tweets, we are using a public python script which helps us in capturing old tweets. Using this, we can bypass the 7-day limitation imposed by Twitter API. We just need to adjust our searching filter and then execute the program. For this study, we need to extract the tweets which contain the expression "religion is". Since certain isolated events can affect the sentiment of people towards certain religion or ethnic groups (i.e., Charlie Hebdo Attacks), we will extend the time frame of tweets by 5 years. This will help us to reduce the bias in the tweets. For this study, we extracted 1000 tweets per month starting January 2015 and ending October 2019. Thus, we will be having 57,351 tweets which will be further loaded in dataframe which can be further pre-processed.

Below is the whole analysis process in a schematic format

The preprocessing phase are shown below. We can see that the length of cleaned tweets is reduced significantly. As we have shown below, after preprocessing, most tweets have tokens less than 10, whereas in original tweet, we had around 20 token. On second graph, we can see stark contrast. Before pre-processing, average length of tweets was around 150 words but it went down to 50 words after pre-processing. This pre-processing is highly important because it reduces the dimensions which will result in significantly valuable token in models.

Fig1. *Analysis Steps*

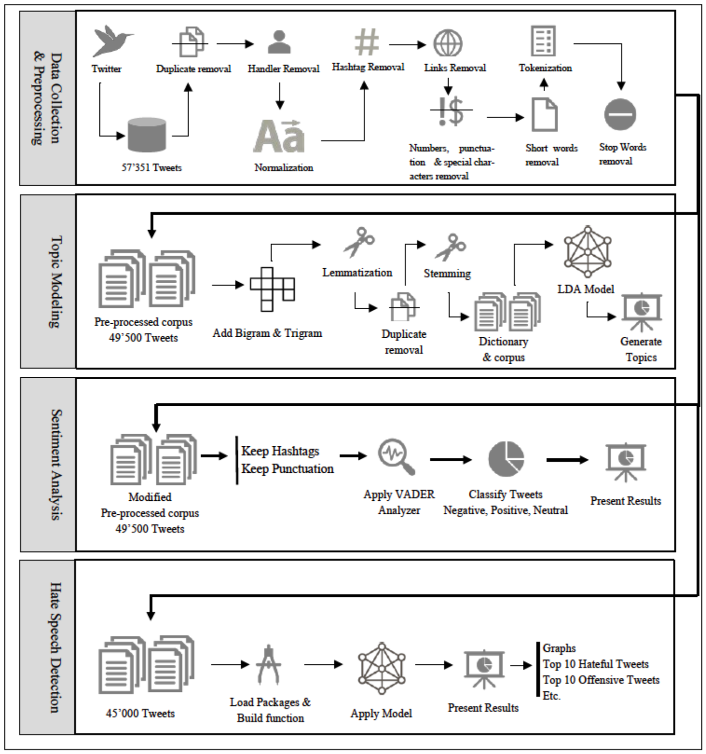


Fig2. *Length of tweet as number of characters*

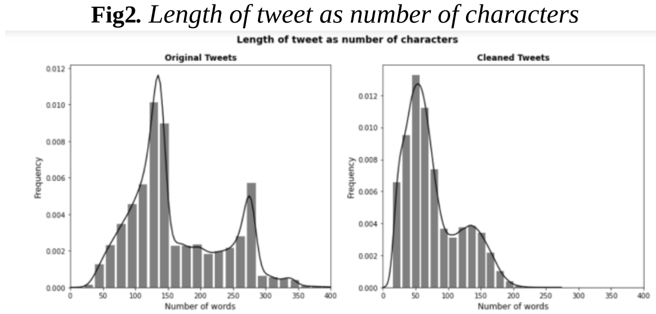
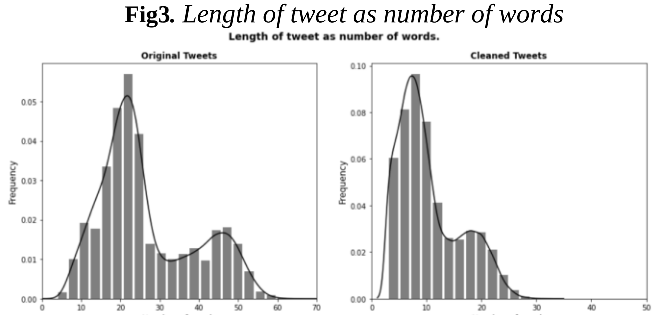


Fig3. *Length of tweet as number of words*



2.2 Implementing different models

2.2.1 Linear Discriminant Analysis (LDA)

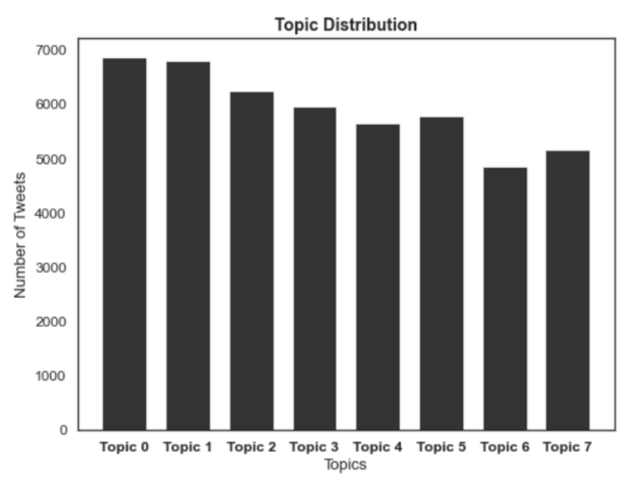
At core, LDA algorithm is basically a generative process in which documents are defined by probability distribution over set of topics T and a probability distribution of discrete words which in turn will establish each topic. Now, we are ready to load the pre-processed data. After we load the data, we will add Bigrams and Trigrams. They are sequence of words which will often occur together and will express a particular meaning. A sequence of N words is known as N-Grams where N can be any number. For practical purpose, commonly Bi-grams (pair of words) and Tri-grams (Sequence of 3 words) are used. In next step, we implement lemmatization which is highly essential step for many applications related to text mining. It takes the context of the word and converts it into its basic form. For example, term “hugging” will be converted to “hug” while term “best” will be converted to “good”. For this task, we use a package called Spacy which is open-source library which contains many pre-built models which are used for NLP. After doing this, we will drop duplicate as it will just increasing data size without adding any useful information. Another important technique is word stemming which means transforming the word into its root form. One thing to note here is that lemmatization and stemming are different approaches although doing essentially the similar thing of reducing the dimension. For example, the word “animals”, if lemmatized will be word “animal” while if stemmed it would be “anim”. Stemming is highly aggressive approach as compared to lemmatization. We have implemented both as both of them helps in dimension reduction. Before building LDA model, we will need to create 2 main inputs: first is dictionary and second is corpus, both of which can be created using functions from Gensim package. Gensim assigns ID (which is unique) to each word and then corpus will be represented as tuple (word_id, word_frequency).

2.2.2 Build LDA Model

Now it’s time to initialize with number of topics k=10, which can be further adjusted. After this, we can directly generate topics or search for optimal model. We will be using coherence score as a measure for each and every model having different number of topics.

Below is given the distribution of tweets among topics, we can notice that the first three topics are more dominant:

Fig4. *Topic Distribution*



2.2.3 Valence Aware Dictionary for sentiment Reasoning (VADER)

VADER stands for Valence Aware Dictionary for sentiment Reasoning and was developed as a rule-based model for sentiment analysis. It considers capitalization, punctuation, conjunctions, degree modifier, Tri-gram preceding while assigning sentiment: neutral, negative and positive. This helps VADER sentiment analyser achieve highly remarkable results when classifying social media texts (like tweets) and is best suited tool for conducting our analysis. The pre-processing in VADER is different from what was employed in Topic Modelling because of the features that VADER embodies.

As opinions are almost split almost equally regarding positive and negative tweets, the positive tweets have slight numerical advantage and also have small negative difference in terms of compound score. Negative tweets have a mean of -0.541433, whereas the positive tweets a mean of 0.525122.

Fig5. *Compound Score Distribution*

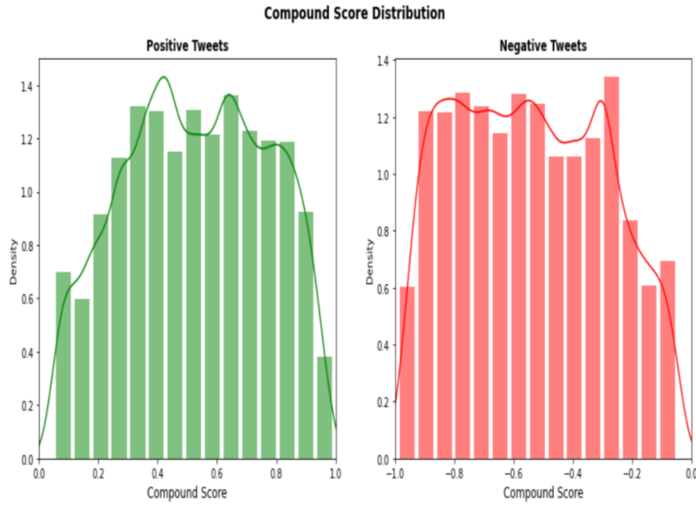
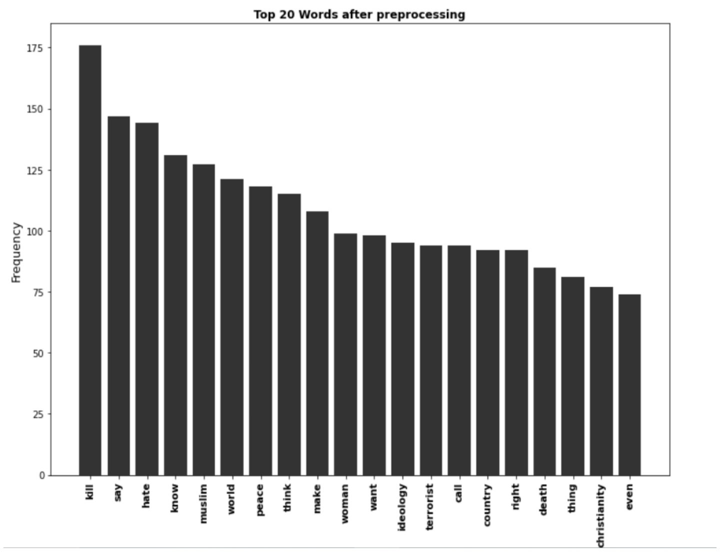


Figure below illustrates the most frequent words on positive and negative tweets about Islam accordingly.

Fig6. *Word Frequency based on Sentiment about Islam*



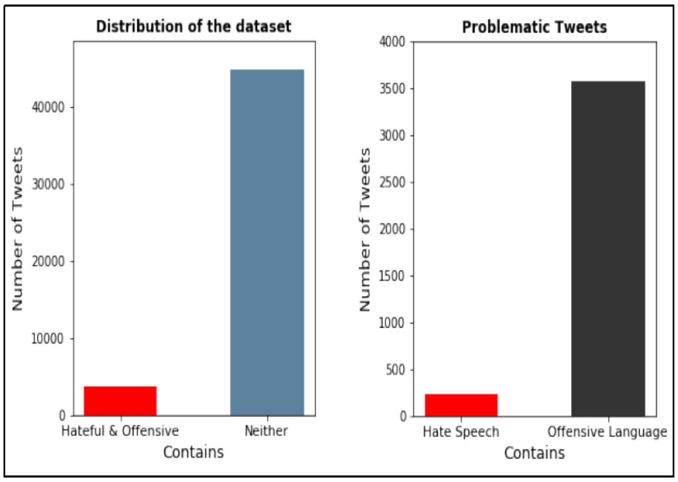
2.2.4 Hate Speech Detection (SONAR)

This model is particularly useful for us for finding the presence of hate speech in tweets about religion. It will also help us to measure hate speech. The analysis will contribute to general understanding of the religious landscape in an online environment. The process starts by loading the data (which has about 45,000 tweets) into a dataframe format in notebook. This data is not pre-processed as model is trained to process the data to extract the required features for the model. Some pre-processing steps which are done in this model are: removing links, hashtags, mentions, doing tokenization and using Port Stemmer for stemming.

2.2.5 SONAR Model

After applying the model, the dataset which contains 48,528 tweets is then split into three categories: Hate Speech, Offensive Language and Neither (i.e., neither hateful nor offensive). The first chart in figure below shows results of distribution of tweets across all categories. Hateful and Offensive tweets when combined, gives total of 3802 tweets (7.83%). The neither tweet totals to 44726 tweets (92.16%). The second chart shows the distribution of problematic tweets (hateful and offensive tweets). We can see that hate speech return with 232 tweets (6.10% of problematic tweets) while Offensive language dominates the category with a whopping total of 3570 tweets (93.89%).

Fig7. *Hate Speech Detection Results*



It is interesting to see whether sentiment feature correlates with hate speech results. Following figure shows the distribution of tweets per category of offensive language, hate speech and neither based on positive, negative and neutral sentiment. As we can guess, hate speech occurred mostly in negative tweets. Statistically, 60% (145 of 323) tweets that contain hate speech are negative. In offensive tweet case, the proportions are similar to hate speech, as expected. Numerically 58.8% (2089 of 3570) tweets has negative sentiment.

Fig8. *Hate Speech Detection by sentiment*

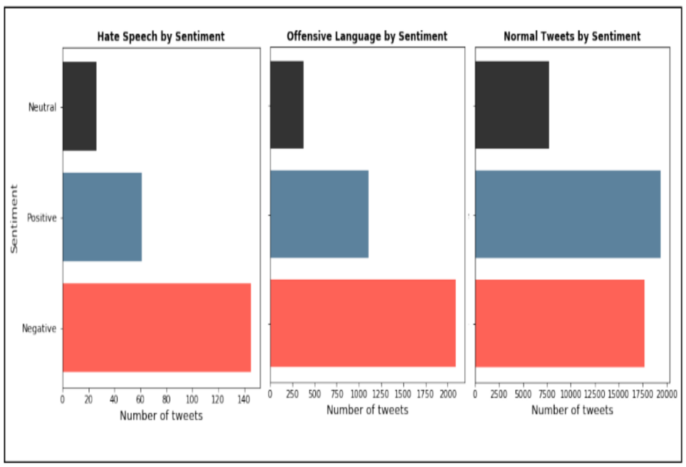
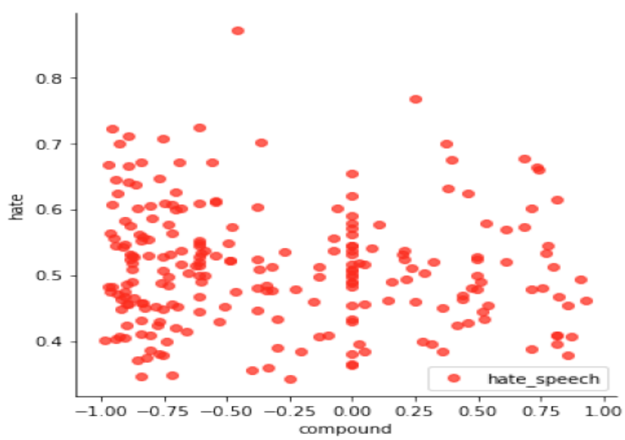


Figure below illustrates the distribution of hateful tweets based on their compound sentiment score. The left side corresponding to negative tweets is more populated (60% of tweets), which makes sense that a tweet using hate speech is negative in sentiment.

Fig9. *Compound Sentiment Score*



III. RESULT

3.1 LDA MODEL

After building the LDA model and running the optimal model we yield the following topics:

Fig10. Topic with their keywords

	Topic	Topic_Keywords	Num_Tweets	Perc_Tweets	Text
0.0	0.0	peopl, muslim, reason, stop, tri, care, happen...	6877	14.52	[hope, last, littl, teach, group, faith, commu...
1.0	1.0	christian, freedom, state, teach, practic, gov...	6801	14.36	[page, today, essay, write, emeri, report, pro...
2.0	2.0	believ, true, wrong, call, fact, alway, real, ...	6241	13.18	[first, human, anim, appli, belief, magic, pow...
3.0	3.0	woman, world, follow, kill, church, control, e...	5955	12.58	[sikhism, respect, sidhu, respect, openli, app...
4.0	4.0	love, human, life, give, peac, live, respect, ...	5654	11.94	[certainli, give, context, anti, much, distrus...
5.0	5.0	race, polit, countri, hate, cultur, differ, ba...	5784	12.22	[cite, bibl, crime, minor, consid, hypocrisi, ...
6.0	6.0	make, thing, good, person, realli, problem, pe...	4865	10.28	[abraham, think, woman, less, right, problem, ...
7.0	7.0	faith, belief, believ, scienc, understand, fin...	5170	10.92	[scienc, educ, impact, christian, scientitist,...

3.1.1 Interpretation:

Topic [0] ***Religion & Politics*** contains terms like politics, control, government, nation, etc., which shows how religion is a sensitive aspect of its role in politics.

Topic [1] ***Christianity*** contains tweets which contains Christianity as main topic of discussion and its related terms (example: Catholics, Christian, church).

Topic [2] ***Religion & Science*** concerns itself with never-ending debate between science and religion. This debate is further intensified in the current world which is being led by technological revolution.

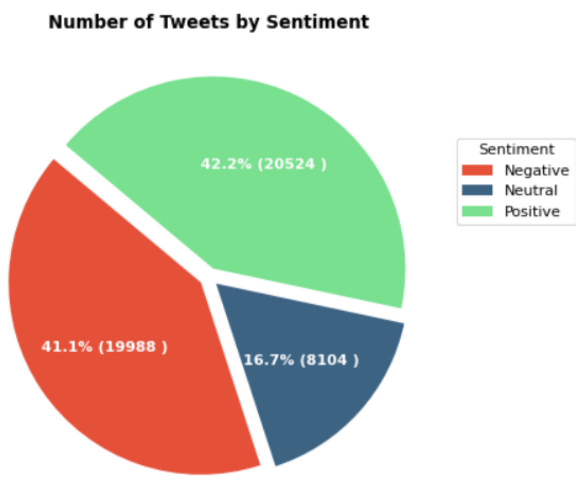
Topic [3] ***Religious Doctrine,*** **[6]** ***Personal Belief*** **and [7]** ***Diverse Opinions*** seem to be closer to each other with slight differences, based on the keywords.

Topic [5] ***Islam*** concerns itself with tweets related to Islam as main topic of discussion. As we can see from hashtag frequency and word-frequency statistics, Islam is highly discussed on social media such as twitter.

3.2 VADER MODEL

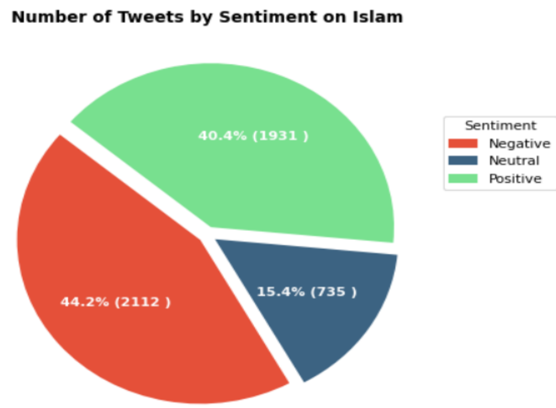
Following figure shows the classification result of tweets to sentiment class. The result shows that 16.7% (8104) tweets are neutral. 41.1% (19988) tweets are negative while 20524 (52.2%) tweets are positive. This shows that public opinion is fairly balanced in terms of sentiments on discussion about religion.

Fig11. *Classification of Tweets by Sentiment*



When tweets about specific religions are analysed, most discussion are aimed at Islam. 4778 tweets are aimed towards Islam (which is highest among all religions, followed by Christianity, Hinduism and others). Since, Islam is most discussed, we took a closer look at tweets aimed at Islam. After analysis we found that only 735 (15.4%) tweets were neutral. 40.4% (1931) tweets were positive whereas 44.2% (2112) tweets were negative. The result is shown in following graph:

Fig12. *Classification of Tweets by Sentiment on Islam*



3.2.1 Top 10 most positive tweets (VADER MODEL):

Fig13. Top 10 most positive tweets (VADER Model)

	tweet_text	tweet_text_p	negative	neutral	positive	compound	sentiment
0	Religion tells you to clean yourself up, then ...	tells you to clean yourself up, then God will...	0.083	0.385	0.532	0.9932	1
1	Well, here in # Scotland, I cannot say I am ve...	Well, here in Scotland, I cannot say I am ver...	0.000	0.515	0.485	0.9898	1
2	Religion tells you to clean yourself up, then ...	tells you to clean yourself up, then God will...	0.000	0.458	0.542	0.9893	1
3	@ ComimDark6 # ApocisComing Absolutely right! ...	ApocisComing Absolutely right! The ability t...	0.000	0.459	0.541	0.9874	1
4	Religion shouldn't break your heart and make y...	shouldn't break your heart and make you miser...	0.044	0.472	0.483	0.9868	1
5	prayer is the most genuine and sincere thing p...	prayer is the most genuine and sincere thing p...	0.000	0.554	0.446	0.9865	1
6	BE KIND, POLITE, HUMBLE, RESPECTFUL, CARING AN...	BE KIND, POLITE, HUMBLE, RESPECTFUL, CARING AN...	0.030	0.499	0.471	0.9857	1
7	@ BrandonStraka WELCOME! Republican Party is C...	WELCOME! Republican Party is Constitution 1st...	0.000	0.487	0.513	0.9857	1
8	All right f****** love it how nice is that ver...	All right f****** love it how nice is that ver...	0.000	0.465	0.535	0.9850	1
9	@ KaeRobey has such natural beauty. She loves ...	has such natural beauty. She loves everyone. ...	0.000	0.502	0.498	0.9846	1

The above-shown tweets are rated positive. The table also shows compound score of each tweet. This classifier has correctly labeled all the tweets as the tweets are positive and the model does not hide any underlying patterns of sarcasm or irony (sarcasm and irony usually undermines the meaning of sentences). Of above shown 10 tweets, 8/10 tweets have negative score of zero. Most tweets were found to have negative score of 0.000. Other tweets have a very small negative value. This is due to the words: intolerant, race, etc.

3.2.2 Top 10 most negative tweets and their respective scores (VADER MODEL):

Fig14. Top 10 most negative tweets and their respective scores (VADER Model)

	tweet_text	tweet_text_p	negative	neutral	positive	compound	sentiment
0	Faking a hate crime should be considered a hat...	Faking a hate crime should be considered a hat...	0.587	0.413	0.000	-0.9902	-1
1	Religion caused the division of India and the ...	caused the division of India and the formatio...	0.522	0.478	0.000	-0.9881	-1
2	That's what they live for. The desalination of...	That's what they live for. The desalination of...	0.649	0.351	0.000	-0.9878	-1
3	You use that the way you use fear and religion...	You use that the way you use fear and & those...	0.483	0.483	0.034	-0.9876	-1
4	Threatening murder against a poor woman is not...	Threatening murder against a poor woman is not...	0.500	0.466	0.034	-0.9873	-1
5	Agreed, for all but Islam. It's a cult of war ...	Agreed, for all but Islam. It's a cult of war ...	0.525	0.448	0.027	-0.9871	-1
6	Christ is dead too you know, but I hear y'all,...	Christ is dead too you know, but I hear y'all,...	0.452	0.478	0.070	-0.9867	-1
7	Difference of approach... Aftr a terror attack...	Difference of approach... Aftr a terror attack...	0.544	0.456	0.000	-0.9863	-1
8	Murder is murder no matter the perpetrators or...	Murder is murder no matter the perpetrators or...	0.554	0.411	0.035	-0.9859	-1
9	1828 Webster Hell HELL, noun 1. The place or s...	1828 Webster Hell HELL, noun 1. The place or s...	0.505	0.445	0.051	-0.9857	-1

The above shown tweets were highly rated as negative (in negative sense). It is clear that classifier has correctly labeled the tweets as the above tweets are clearly negative which expresses refusal, dislike and negative feelings towards religion or ethnic group.

Some of the most occurring words are hate, rape and Islam. While majority of negative tweets were aimed at Islam, their were few focusing on Christianity and Hinduism/Buddhism.

3.3 SONAR MODEL

3.3.1 Top 10 most hateful tweets (SONAR MODEL):

Fig15. Top 10 most hateful tweets

	tweet_text	tweet_text_p	negative	neutral	positive	compound	sentiment	lemmatized	Class	hate	offensive	neither
0	@ WritersofColour "your religion is misogynist...	"your is misogynistic" a white feminist abus...	0.273	0.727	0.000	-0.4588	-1	[white, feminist, abuse]	hate_speech	0.870408	0.069669	0.059924
1	What the fuck is wrong with the human race? Re...	What the fuck is wrong with the human race? &...	0.452	0.548	0.000	-0.7650	-1	[fuck, wrong, human, race, republican]	hate_speech	0.824041	0.144219	0.031740
2	The systematic extermination of white race,wes...	The systematic extermination of white race,wes...	0.000	0.863	0.137	0.4019	1	[systematic, extermination, white, race, weste...	hate_speech	0.819088	0.136934	0.043978
3	What? White is a race. Judaism is a Religion s...	What? White is a race. Judaism is a so someon...	0.000	1.000	0.000	0.0000	0	[white, race, judaism, white, jewish, common]	hate_speech	0.813112	0.143532	0.043356
4	@ yesnicksearcy @ ksoderbl # AntiWhite anti-ra...	AntiWhite anti-racism is the new . Race doe...	0.000	0.836	0.164	0.4466	1	[anti, racism, race, exist, white, people, neg...	hate_speech	0.809880	0.166541	0.023578
5	As a white ((Aryan)) who is the exact same rac...	As a white ((Aryan)) who is the exact same rac...	0.089	0.911	0.000	-0.1901	-1	[exact, race, white, different, culture, demand]	hate_speech	0.798556	0.130696	0.070748
6	White supremacy is an ideology. It has nothing...	White supremacy is an ideology. It has nothing...	0.000	0.870	0.130	0.1779	1	[ideology, race, black, person, white, suprema...	hate_speech	0.795342	0.161176	0.043482
7	So why that logic then it shouldn't be racist ...	So why that logic then it shouldn't be racist ...	0.104	0.896	0.000	-0.6124	-1	[logic, racist, white, people, do, white, peop...	hate_speech	0.792905	0.170698	0.036397
8	@ BlushingGiraffe White is a race, anyone can ...	White is a race, anyone can be a Muslim.. It ...	0.156	0.596	0.248	0.2509	1	[white, race, muslim, racist, disagree, date, ...	hate_speech	0.767149	0.061211	0.171641
9	Using one person/ persons to make a negative s...	Using one person/ persons to make a negative s...	0.214	0.677	0.109	-0.7163	-1	[use, person, person, make, negative, statemen...	hate_speech	0.759593	0.180686	0.059721

323 tweets were classified as hate speech. Above table shows 10 hate speech tweets. The model has been carefully trained to overcome thin border between hateful and offensive words by training and focusing on vocabulary of hateful words. The most dominant word in hateful speech is "race". 8/10 most hateful tweets contain words like "racist", "white", "feminist", "white folks", etc. Some tweet express hate against Muslim by calling their religion dated, stupid and sexist while few contain reference to Jews. One of the above tweets has racist motive with reference to Black people by using slang words against them.

3.3.2 Top 10 most Offensive tweets (SONAR MODEL):

Fig16. *Top 10 most offensive tweets*

	tweet_text	tweet_text_p	negative	neutral	positive	compound	sentiment	lemmatized	Class	hate	offensive	neither
0	dustin speaking "son of a bitch" is my religion	dustin speaking "son of a bitch" is my	0.388	0.612	0.000	-0.5859	-1	[speak, bitch]	offensive_language	0.010516	0.989317	0.000167
1	Anja Nissen saying "vegan bitches!" in her las...	Anja Nissen saying "vegan bitches!" in her las...	0.000	1.000	0.000	0.0000	0	[say, vegan, bitch, last, instagram, story]	offensive_language	0.009915	0.989315	0.000770
2	Spencer Reid saying "son of a bitch" is my rel...	Spencer Reid saying "son of a bitch" is my	0.352	0.648	0.000	-0.5859	-1	[say, bitch]	offensive_language	0.010632	0.988830	0.000538
3	No more drugs for me, pussy n religion is all ...	No more drugs for me, pussy n is all I neeed	0.216	0.784	0.000	-0.2960	-1	[drug, neeed]	offensive_language	0.011703	0.987489	0.000808
4	Honestly tho. Pussy and religion is all I need	Honestly tho. Pussy and is all I need	0.000	0.667	0.333	0.4588	1	[honestly, pussy, need]	offensive_language	0.012881	0.986379	0.000740
5	No more drugs for me, pussy & religion is all ...	No more drugs for me, pussy & is all I need.	0.216	0.784	0.000	-0.2960	-1	[drug, pussy, need]	offensive_language	0.012452	0.986363	0.001185
6	no more drugs for me pussy & religion is all i...	no more drugs for me pussy & is all i need	0.216	0.784	0.000	-0.2960	-1	[drug, pussy, need]	offensive_language	0.012452	0.986363	0.001185
7	No more drugs for me, pussy & religion is all ...	No more drugs for me, pussy & is all I need	0.216	0.784	0.000	-0.2960	-1	[drug, pussy, need]	offensive_language	0.012452	0.986363	0.001185
8	No more drugs for me pussy & religion is all I...	No more drugs for me pussy & is all I need	0.216	0.784	0.000	-0.2960	-1	[drug, pussy, need]	offensive_language	0.012452	0.986363	0.001185
9	RT @ TeamKanyeDaily: No more drugs for me, pus...	RT : No more drugs for me, pussy and is all I...	0.180	0.820	0.000	-0.2960	-1	[drug, pussy, need]	offensive_language	0.012066	0.986205	0.001729

Offensive tweets are dominant in problematic tweets. From above table, we can see that offensive tweets are populated by many offensive words with sexual reference. Few tweets contain strong sex-related terms. Offensive language scores range between 0.989 to 0.986.

IV. CONCLUSION

As we can see from above results, 42.2% (20524) tweets are positive tweets on religion, while 41.1% (19988) tweets are negative tweets while other are neutral. Based on this, we can see that no. of positive and negative tweets are almost same. This shows that people don't think that they are hurting someone sentiment.

Data analysis on tweets on Islam shows that people usually have negative sentiment towards it and associate negative words with Islam. The results show 44.2% negative tweets while only 40.4% positive tweets (other being neutral). Most common negative word is "Kill" which occurs 176 times in tweets on Islam.

When analysing hate speech detection result, we see that only 7.4% of all tweets are hateful and 0.5% are offensive while a staggering 92.1% tweets are neutral in this case. This can be further used in real time to detect hateful and offensive tweets which can be promptly deleted to avoid inciting a particular ethnic group(s). This will lead to avoid chaos.

V. ACKNOWLEDGEMENT

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