2122_CSCM10 /CSCM10J _Computer Science Project Research Methods

Developing Classifiers to classify extremist content online

(Applying Sentiment Analysis to classify Extremist Content Shared Online)

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Abstract:

Extremist use the internet to spread propaganda to inspire individuals to become a supporter of their particular intentions and policies. online social media sites have become a common place for such activities. Many researchers in the field of Artificial Intelligence and machine learning are trying to develop counter strategies to curb this unfortunate use of social media.This definitely has been done by developing models to predict weather the content which is shared online can be regarded as extremist or not. Therefore in this project we plan to build models and develop methodologies for identifying extreme behavior through the dataset. We'll classify the records as Extremist or not-extremist. We shall be using PCA (Principal Component Analysis) for EDA (Exploratory Data Analysis) for the dataset to reduce the high dimensional data to a lower dimension space. We would further compare separation within subclasses. We aim to compare and use naive Bayes' , KNN (K Nearest Neighbors), SVM (Support Vector Machine) with various classification methods. We shall also explore TF-IDF features extracted from n-gram dataset. Our project shall be a gateway for future researchers encouraging them towards research in this field.

Keywords

Social Media, Extremist Sentiments, terrorism, Deep Learning, Sentiment Classification.

Introduction

Online Social Network (OSN) has created a global phenomenon that has enabled billions of users to interact and be communicative to other individuals via different applications like Facebook and Twitter [19]. Rise of social media has led to an increase in extremist content online in the form of comments or speeches and videos that broadcast extremism and radicalisation. [2]. The use of such online platforms indicate their affiliations and aptitude towards a certain policy, association with a particular group or an event [3-5]. We explored number of research studies which shows that social media is regularly being used by many hate groups for promoting extremist propaganda [6-9]. Apart from many other extremism the most serious issue in recent years is due to the rise of different militant groups and organizations which contribute to propagation of extremist content [10]. These groups, in addition to community levels, have infiltrated social networking sites [11] . Such networking sites are very much approachable and vulnerable platforms for propaganda, group-strengthening and brainwashing. These sites serve as fundraising platforms as they have a huge impact on people's sentiments and opinions. Content of such sites provide an important clue about the activities and behavior of the users on these platforms. Researchers from various disciplines psychology, social science and computer science are working hard to for developing new tools to combat and develop new tools for identifying social media online extremism. If we detect such extremist content after analyzing user sentiment toward extremist group, then probably we can alert the required authorities and curb these activities. One such amazing project is the German government funded project MOTRA ("Monitoring System and Transfer Platform Radicalization") whose objective is to identify the changes in attitudes which Will serve as an early indicator of any criminal activity [12].

Mostly the research work done is based on term frequency and lexicon-based dictionaries for example SentiStrength and SentiWordNet [13-15]. We cannot rely on search outcomes this techniques because any language consists of semantic orientations and therefore its context cannot be predicted correctly merely with word frequencies. The usual techniques filtering tweets as extremist are not scalable hence researchers developed automated techniques or machine learning techniques [19-23] rather than using traditional dictionary-based approaches[24-27]. For example: Group detection, Key-Player Identification and link prediction are widely used [16]. Opinion mining and sentiment analysis is being used more and more which affirms that such techniques are being used to detect extremist groups and their activities on social media platforms [17-19].

Twitter is one of the most widely used social platform by all communities from a common man to famous celebrities. It has a very short text called a tweet. The maximum size of tweet as of now is 250 characters which was increased in November 2017 from 140 characters per tweet. This short length of tweets creates a very challenging situation when doing sentiment analysis because such short tweets on one particular topic provide very less contextual information if compared against other social media platforms [28] .

The main contributions for our methodology shall be :

- Data labeling: We will be utilizing a labeled data set to train and test the machine learning model.
- EDA (Exploratory Data Analysis) : The technique used to perform in-depth statistical analysis for better understanding the data set via visualization techniques. Most of the Twitter based content is in unstructured form which must be converted to structured form before it is used for statistical analysis. It is not practically possible to visualize high dimensional data using conventional visualization approaches. This issue shall be resolved by using an unsupervised machine learning approach called PCA (Principal component Analysis) [29]. In this method the high dimension data is projected on to a low dimensional data to get insight by visualizing onto a 2-D or 3-D plot.
- Sentiment Analysis (SA) [30,31] by building the classification model: Different classification methods including Naive Bayes', KNN (K Nearest Neighbors) , SVM (Support Vector Machine) with boosting and bagging approaches are planned to be used for predictive analytics purpose. Furthermore, we aim to evaluate our model for TF-IDF and feature sets such as n-gram .

Related Work - Literature Review:

We have reviewed some relevant studies conducted on the classification of social media-based content which reflects extremist connections. This gave a better understanding of the existing work already achieved for identifying content as extremist or non-extremist.

NLP (Natural Language Processing) and SA (Sentiment Analysis) have advanced gradually year by year. Figure 1 [41] depicts how machine learning has progressed over time in order to better analyze the extreme contents from the web. K Nearest Neighbors, Naive Bayes, data clustering , EDA , DNN (Deep Neural Network) and GBDT (Gradient Boosted Decision Tree) are few of the most popular techniques for extremism detection on social media sites [42-48].

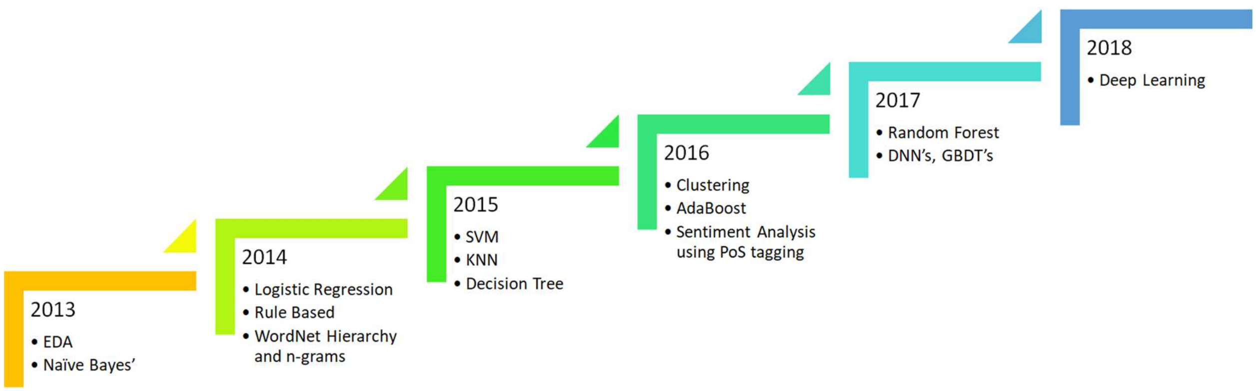

Figure 1 - Machine Learning techniques used over time.

Wei et al. [32] uses a machine learning based classification system for content which signifies extremism on Twitter. Many features are analyzed for finding unusual behavior on tweets on twitter given by users via KNN classifier. Similarly Azizan and Aziz[19] conducted a study for the detection of extremist content using NBA(Naive Bayes algorithm) . This algorithm shows best results among other machine learning classifiers. Here the authors have applied ML classifier with classical features. They were able to classify user reviews into positive and negative sentiments of the extremist groups. Classification into positive and negative does not give us an accurate way of distinguishing between extremist and non extremist content. The classification did not include all the dependencies related to a sentence in one record. Hence this model could not be much useful for our classification with current design.

We investigated some deep learning-based sentiment analysis research which seem to be very promising when in different fields such as speech, vision and text analytics [33][34] .In this research they proposed a multi-channel convolutional neural network-long short-term memory

(CNN-LSTM) model consisting of two parts: multi-channel CNN and LSTM to analyze the sentiments English tweets from Twitter. Unlike a conventional CNN, they have applied a multi-channel strategy using several filters of different length to extract activ local n-gram features in different scales. LSTM then sequentially composes this information. This paper overcomes the limitation of [19] by combining both CNN and LSTM. The model was able to consider local information within tweets and long-distance dependency across tweets in the classification process.

We came across an interesting research work by Matthias Hartung et al [35]. They used Support Vector Machines with a linear kernel [36] and were able to train their model to detect right-wing extremist users in German Twitter profiles. Their work supported manual monitoring aiming at identifying right-wing extremist content in German Twitter profiles. They did profile classification (based on textual cues), traits of emotions in language use, and linguistic patterns. They were able to reduce 25% of manual labor with their achievement of results. Although the work could have used better deeper methods of NLP in order to be able to address more fine grained aspects.

Patil et al [37], explores feature vectors from LSA (Latent Semantic Analysis) and CNN (Convolutional Neural Networks) classifier. Various text classification techniques such as Deep learning, Ensemble learning as well as effective document representation methods are trending to improve the accuracy of text classifiers [38]. Terrorist extremist contents spread jihadist propaganda and increase their believers via social media. The work [39] proposes a deep learning approach to detect extremist contents and the results provided better accuracy for identifying such cases for classifying the contents automatically, which have terrorist activity contents . Some unigram methods used for feature extraction and for sentimental classification they used SVM and NB algorithms which classifies that user's opinion is positive or negative [40] and thus are able to observe client's opinion on social media.

In [49], Authors have combined sentiment analysis with Social Network Analysis to analyze radical groups on YouTube. They have crawled from a group of 700 YouTube accounts. Then the analysis was done on different topics aligning to different polarity to identify sign of extremism and intolerance. The authors had used a lexicon based module to determine the main topic. Sentiment analysis was used on top of this to identify the opinion of users towards these topics. Two different results for men and women are drawn to identify the most positive and most negative topic in both categories. As per the result, women were found to be more positive toward Al-Qaeda and negative towards Judaism whereas for men, higher positivity on Islam was identified as per the results.

Another approach which was presented in [50] , where the tweets were grouped into different groups depending on certain special keywords such as “Al-Qaida”, “Jihad” , “Terrorist Operation” through a lexicon based approach.They created their own dictionary of semantics based on hashtags in tweets. Classification was done on vectorized tweets based on dictionary related words. Customized set of rules were made for each category and the tweet were classified into that category.

Methodology - Requirements:

The project aims to curb extremist activities by detecting any extreme content on social media in our case would be Twitter dataset wherein we will be applying standard pre-processing techniques such as tokenization, stemming, lemmatization, finding out TF-IDF features, etc. , to get a cleaned dataset. Then train the model to predict the tweet as extremist content.

As mentioned, we will be performing the EDA to get better understanding of the data via word cloud [53], checking the highest number of attacks as well as doing comparison and visualization on regions. Different bar plots and count plots to further understand the various distributions.

Next we will build up our machine learning classification models SVM, Naive Bayes, KNN. We will measure the learning applied to the respective models with evaluation matrix . This shall be achieved for every algorithm applied.

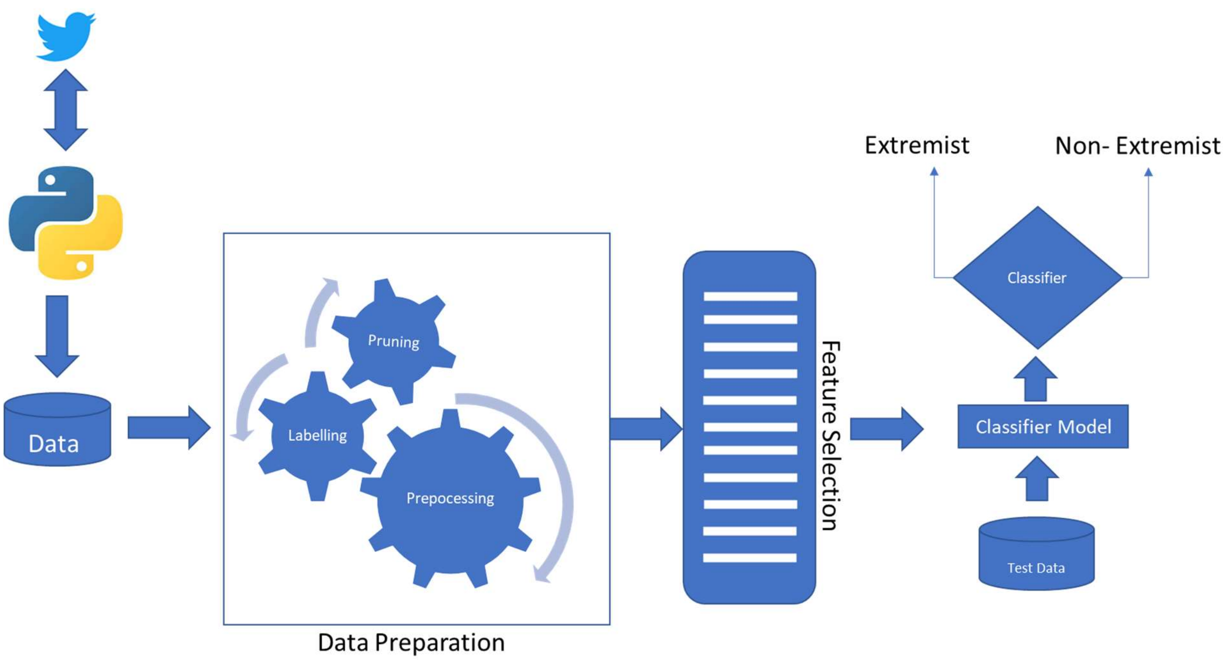

Figure 2: Proposed design [51,52,41]

Here we will explain the steps of our analysis. These steps are data collection, data pruning, preprocessing, feature extraction and EDA. Figure 2 above represents the the proposed process for our work.

Data Collection and Preparation

There are multiple datasets available on Internet either free or commercially for doing analysis on public sentiment on social or political issues [54,55]. We plan to use the Global Terrorism dataset available on kaggle.com [56].

Data Labeling

The accuracy with which the labeling is performed impacts the performance of the model in multiple ways. The model may not perform or predict correctly on low-quality labeled data. Labeling the dataset is most critical while training the model for supervised learning. Labeling is a high cost and time-consuming job even for a machine, hence researchers often use a semi-supervised learning approach for most of the real-world applications. To apply the same a huge amount of unlabeled data is fed with some labeled samples to perform the classification task. For our dataset we will be verifying the labels manually(~400 in number) which are used to train the data most of them and then let the model train on the rest of them.

Data Pruning

Pruning[58] goes back to 1990 in Yann LeCun's paper [57]. It denotes the removal of not relevant terms in the data set which may ultimately reduce the performance of the classifiers. Such data is often referred to as "noise" or "undesired data". Therefore such words must be removed from the corpus. Below are the few steps which shall be taken for noise removal.

Tokenization

A tokenizer breaks down unstructured data or raw text into pieces of information that can be considered as individual elements. In machine learning, tokenizer can be used to turn unstructured text into numerical data structure suitable for machine learning. For example if we can use the NLTK tokenizer on a sentence such as if this sentence "This is the last ray for humans ! #Hope #hoom.N" is tokenized (one of the many ways) then it would be ["This", "is", "the", "last", "ray", "for","humans","Hope","hoom.N"]

Transformation of characters

There can certainly be cases where the text contains multiple tweets with different text case, lower or uppercase. Therefore this transformation shall convert each taken into a standard format for removing duplication issue. In our implication we will convert each token to lowercase. Also there are certain words like “can’t” , “don’t” which we’ll develop personalized functions to deal with those so that they get converted to “can not” and “do not” respectively. We will use regular expression library for the same.

Stop Words Removal

Natural language almost all the time contains stop words such as “the”, “an”, “a”, “am”, “to”, “how”, etc. These words are unrelated and lead to increase the dimensionality of features. The computational complexity of classification models is increased because of this increasing dimensionality. These are a set of frequent words which carry less important meaning. Therefore, to reduce the training time and memory overhead, we remove such non-informative words. As of now we plan to use the stop-word list for English from the source [59]. We wil also be checking if usage of WorldCloud library

Removing URLs and Images

We’ll use Beautiful soup library to remove the html tags as well as to remove URLs we’ll develop our own function to remove any links using the same “re” library (regular expression) .

Stemming

As the word suggests this technique helps to further reduce the dimensionality by reducing the word to its root form. A sentence has different contexts and to make more sense grammar has to be proper because of which words like “kill”, “killed”, “killing” are present usually in tweets. With stemming we aim to reduce these words to the root form , let’s say “kill” in this scenario. This as well leads to reduction of dimensionality of the dataset.

TO BE DECIDED:
We shall also explore GloVe and fastText word vector models.
Miklov et al.,[60], showed potential of word vectors viz. Continuous Bag of Words (CBOW) and Skip-Gram. GloVe and fastText are other extremely powerful word vectors currently in use.

Feature Extraction

SA (Sentiment Analysis) usually requires the natural language to be processed from word-level(eg attack, danger), word-level n-gram(example well_do ne etc.), character-level n-gram (e.g. a,at, atta, tack, attack), Parts Of Speech (POS) tags (e.g. verb, adjective,verb), abbreviations, etc. In oder to make the machine learning algorithm understand we need to provide a numerical representation in form a feature vector. This would enable the model to perform statistical and mathematical investigation. Therefore we construct the feature vector that is the

Term Frequency - Inverse Document Frequency) where certain weighing scheme is placed so that the score of each token can be calculated in the corpus.

Term Frequency (TF) = Frequency of term t in a tweet / total terms in tweets

Inverse Document Frequency (IDF) = total tweets / number of tweets having a term t

TF-IDF(t,d) = TF(t,d) X IDF(t,d)

Representation:
t represents term in a tweet
And d represents a tweet also known as document in textual documents.

Exploratory Data Analysis

We compute the basic statistical summary of the dataset characteristics. this usually helps in better understanding of the data set via different data visualization techniques. This gives us a deeper insight into the data set and allow us to define or refine our hypothesis. We aim to develop charts from the dataset which will show Word cloud . We will surely use masking image as well for the word cloud . We will also form of the chart for the number of terrorist activities per year as well as killings each year in the data set. Then we will further analyse regions most affected by terrorism. What is the most a data set has attack count as well as kill count features, we would surely explore that as well for certain locations. Furthermore we will check in which countries what are the different type of attacks by using the attacktype corpus.

We will also use the show the distribution of terrorist attacks on the globe by using the Basemap from the matplotlib library and the latitude and longitude data from the dataset. This would give us the distribution of extremist activities on the map.

Performance Evaluation

We will use the common metrics that are available for performance evaluation:

1. **Accuracy:**
   Accuracy tell us about the correct prediction made by the model. It is the percentage of total correctly predicted samples out of the total samples. For Example if the model predicts 40 data samples correctly out of 50 then the accuracy will be 80%.

   Accuracy = number of correctly predicted samples / total samples X 100

2. **Precision, Recall and F-score**

Precision is the ratio which measures the performances with respect to the correct prediction. That is

Precision = True Positive / (True Positive + False Positive)

Therefore, our model would be evaluated as good if it has better precision , that is our model will have less miss predicted hits.

Recall signifies the ability of the model or the classifier to predict the true positives out of the total expected outcome.

Recall = True positive / (True Positive + False Negative)

Hence, again greater the recall , greeter the performance.

The harmonic mean of the precision and recall denotes the **F-score**
So,
F-Score = 2 X (Precision X Recall) / (Precision + Recall)

Project Description :

The purpose of this research is to develop a classifier to classify extremist content online. We have planned to use the Global Terrorism dataset available on kaggle[56] for this analysis wherein we will apply the machine learning techniques to pre-process the data and this train the model to classify the content as Extremist .

Aims :

Our aim is to be able to get our model accurate enough to make the right predictions for the extremist content in the Twitter data.

Objectives

- very specific statements that define the practical steps you will take to achieve your aim(s)
Properly analyze the data and reduce the dimensionality of the dataset using PCA to further train the certain models . Based on the metrics of different models enhance the model to be able to achieve the aim..

Motivation

With our work we aim to analyze and predict the trend of extremism and identify the extremist content, thus we will be able to share our analysis with required people who are getting influenced by such tweets and make them aware of such extremist activities. This will help to curb the hatred amongst people and thus the society. Furthemore, this will lay waste to the propaganda at the earliest and hence stop radicalization.

. The key understanding is that by analyzing the comments from social media platforms we will be able to curb Hatred from the society, by doing some further research we might be able to destroy propaganda at the earliest time and hence stop radicalization. The sole aim to continue this project is to stop hatred among human beings, decrease the anxiety and pressure on teenagers and make them aware of the true facts before they get brainwashed by heated speech.

Deliverables and Components :

The project deliverables include: the project plan which was shared on fortnight meetings with the professor, the project report which is being delivered. The project plan helped us to lay the feasibility study of the project and by reviewing certain studies we were able to understand the current work already done in the field.

The project report is expected to serve as a blueprint for our project and will be the guiding light for development of our project . The project report includes the project timeline which will enable us to fight by the calendar and clock to achieve our objective !

The final project will be delivered as per the timeline.

Our objective is to identify the extremist content online with as much accuracy as possible for the tweets.

For completing our project, we will be required to use softwares that are open source as well as from high-performance computing servers that might yield some cost for computing our code. As it will save time for us to run the code as well as the quality can be increased as this time can be invested in further research. If HPC is not available then we have to move with basic open-source software computing.

Development Methodology

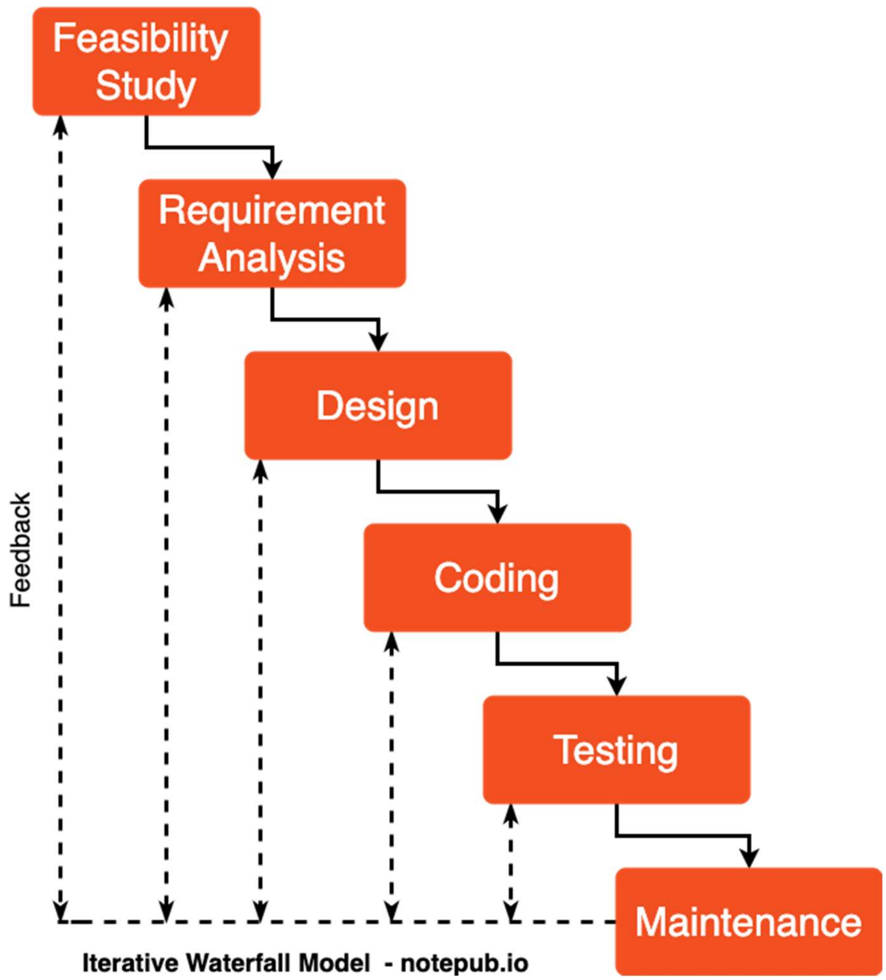

Figure 3: Iterative Waterfall Model [61]

Initially, we studied about the related works then we were able to gather information about the requirements of our project like the datasets, the pipeline of the project and different kinds of classification algorithms that can be used or can be re-modified to develop a hybrid research algorithm based on our project. After designing our project we will be going through the implementation part. In the implementation we have to reiterate our coding and testing part again and again to achieve high accuracy leading towards the maintenance phase of our research project. In approaching the above discussed, we will be required to re-iterate design-coding-testing steps so we will be following the Iterative Waterfall Model.

Project Plan and milestone

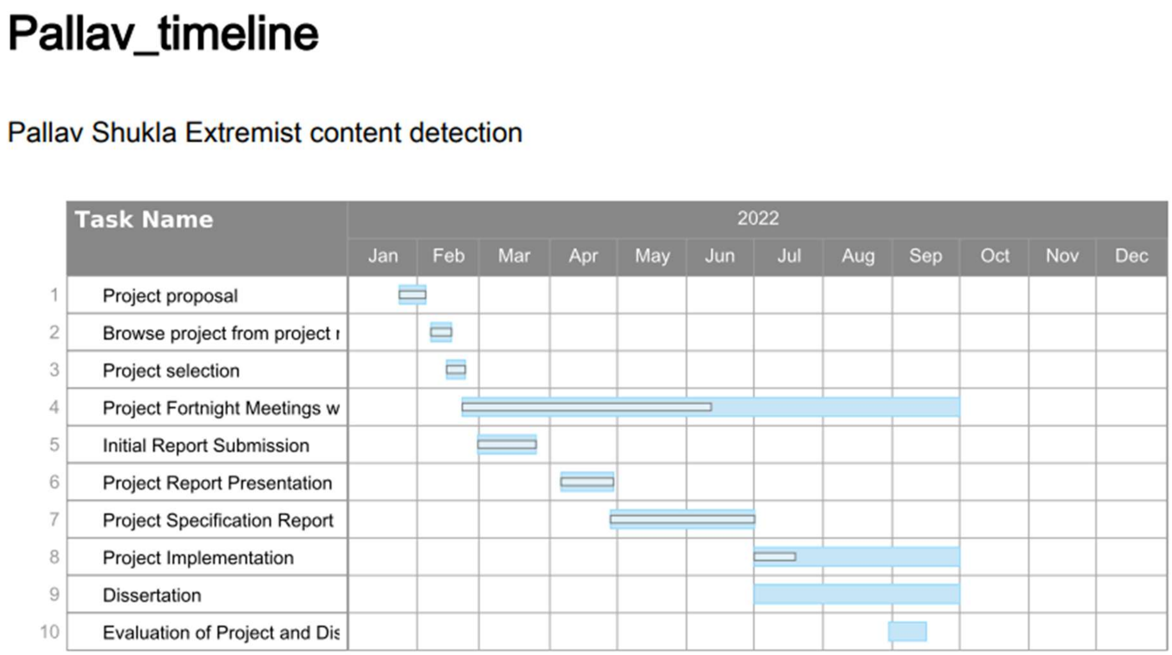

Figure 4: Timeline

Risk Analysis :

We understand that data is the fuel for our model and thus we duly respect the **privacy** laws around the globe. Therefore we have only taken the open source data which has the following license "Database: Open Database, Contents: © Original Authors"

To avoid any **security** issues we will carefully check the data which is being supplied to the model and try a much to avoid any bad data.

To comply with **Fairness** we will try best not to be biased with our inputs as well as only trusted people will be allowed to label the data manually so that in future any company using our project does not end up in fairness risks and liabilities.

Surely we are transparent as of now as the data is fed directly into the models so we can answer any questions related to **transparency and interpretability.**

If our model is made live then we will make sure of its **safety and performance** by implementing proper reviews by the final panelist who shall approve any automated notifications to the authorities notifying of the extreme content detection.

We will make sure that any **third parties** involved shall acknowledge and is made to understand the risk mitigation and governance standards as well as they should independently test all high-stake inputs associated with our model.

Evaluation and Depth of Material:

We will be using Twitter data which is available as open source under open source licence only. this data will contain multiple features such as latitude longitude as well as it will have full to eat contents. These tweets will help us to understand the trending tags over a period of time per region per location.

We will do the research on the data on various aspects such as number of extreme tweets over the period of time, number of extreme tweets over the period of location.

Conclusion and Discussion

Social media provides the required freedom for all of us to share our opinions which inspires certain individuals to spread extremist content on the internet. They use this platform to inspire individuals to become a supporter of their cause. Therefore the task of researchers psychologist data mining experts and computer science engineers becomes very crucial for classification of extremist content various such platforms. In our case we aim to curb the same on one of the most popular social media platform Twitter by training our models on PCA reduced features dataset and give greater insight into to the Global extremist data. we also aim to achieve better understanding of tf-idf features extracted from the n-gram features of tweets. There is a dire need in our project to include semantic analysis so that we can make better predictions. Moreover, right now the project only focuses on one language therefore we need to find solutions to make it multilingual.

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