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CSCI 544 Project

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Goal:
Classification of the Department of Public Safety (DPS) Incidents Log on a scale of 1-5 based on the level of danger, using the summary present in the incident log.

1.

a)Description of how the data was collected
The DPS daily incident log captures all incidents, both on and off campus, which are reported to DPS. The DPS website hosted only records of the last three months of incidents reported. In order to obtain more data, we mailed DPS (DPSRecords@dps.usc.edu) requesting access to the past year records. We were provided with the Daily Incident Log From 1/1/2017 to 10/2/2018 and it was used as the data set for the project.

b) Description of how the data was labeled

Data:
Each Incident log has the following fields:
- Date and Time of Report
- Date and Time of Occurrence
- Location
- Disposition
- Incident
- Summary

Target Labels:
The target labels indicate the Level of Danger of the incident. There are five classes which are listed as follows:
Class 1: Low
Class 2: Moderate
Class 3: High
Class 4: Very High
Class 5: Extreme

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<u>Guidelines followed for Annotation</u>:
The data was annotated based on Summary text of the incident log.

1. Incidents belonging to ‘'PROPERTY Recovered/Impounded Vehicle', 'PROPERTY Recovered/Impounded Bicycle', 'PROPERTY Recovered Property Without a Crime' were removed from the dataset since they did not indicate any level of danger and is not related to the task at hand.

2. The “incident” field was used as a guideline to aid in the labelling of data based on “Summary”.

Incident	Label
‘DISTURBANCE’, 'EH&S', 'ADMINISTRATIVE',’PROPERTY’	1
'THEFT-ACCESS', 'HATE','HEALTH','THEFT-PETTY', ‘CRIMINAL THREATS’,'FRAUD','TRESPASS', ‘WARRANT’, ‘VANDALISM','DISORDERLY','THEFT-TRICK',’OBSCENE’,''TRAFFIC',’CHILD’	2
'ROBBERY', 'BURGLARY', BURGLARY-MOTOR, 'HARASSMENT','ALCOHOL',EXTORTION,'ARSON','FIRE','DOMESTIC','THEFT-FRAUD', 'NARCOTICS','THEFT-MOTOR, ’VEHICLE’, ‘IDENTITY’, ‘BURGLARY-OTHER’,’ASSAULT’	3
'KIDNAPPING', 'SEX','ASSAULT-OTHER','WEAPONS', 'BATTERY'	4
'DEATH', 'SUICIDE', 'HOMICIDE','HOMELAND'	5

1293 Incidents were labelled based on the above approach. To ensure people agree on the same level of danger, people from another team in the class namely Kaladhar Reddy Mummadi, Tanay Shankar, Akshay Bhobe annotated the data as well. They were asked to label 300 Incidents. Out of which, 100 were labelled by us as well to check inter-annotator agreement. An inter-annotator agreement of 92% was found.

<u>Example:</u>
Take two incidents:

Incident 1 with fields:

Incident: TRAFFIC Traffic Collision With Injuries
Summary: A student was involved in a traffic accident without injuries.

Incident 2 with fields:
Incident: TRAFFIC Traffic Collision With Injuries
Summary: A staff member driving her personal vehicle collided with a non-USC male driving his personal vehicle, causing unspecified damage. The staff member sustained injuries to her knees, neck and face and was transported to a local hospital for medical treatment.
Based on the Incidents table we would know that these incidents would have a danger level of around 2. From the description of the Summary we will label the data as 2 for Incident 1 and 3 for Incident 2.

c) Description of the classifier approach

1.
Classifier: Baseline - Bag of Words

Description:

1. A naive approach based on bag of word counts was used to classify the labels.
2. The training data set was used to form five different bins based on the five different labels. For instance, the first bag contains all words that occured in the 'Summary' field for Label 1. The remaining bins were formed the same way.
3. The test set was labelled by choosing the bin (which indicates the label) that had the highest count of words in the test sentence.

2.
Classifier: Multinomial Naive Bayes based on TF-IDF scores

Description:

1. Features were extracted by building a bag of words models based on the count of distinct words in the "Summary" field as done in the previous model. Tokenizing and filtering of stopwords is taken into account by using the Count-Vectorizer in Scikit-Learn library.
2. Tf-Idf : Term Frequency times Inverse Document Frequency" was used to remove the dependency that longer input cases will have higher counts in the count vectorizer.
3. Multinomial naive bayes model - a generative classifier was used to build the model.

3.
Classifier: Support Vector Classifiers based on TF-IDF scores

Description:
1. The first two steps of previous model were implemented.
2. Support Vector Classifiers - a discriminative classifier was used to build the model.

4.
Classifier: LSTM Recurrent Neural Networks

Description:
1. An integer representation of the words in the “Summary” field was formed based on the frequency of occurrence of each word.
2. The word embedding layer of keras was used to form the word embeddings for Summary as a feature.
3. The data was modelled using 100 layers in a LSTM network.the “Summary” field as the feature and train and test the data

d)Analysis of Results

Accuracy:

Baseline	**Naive Bayes**	**SVM**	**LSTM**
0.7190	0.7319	0.8118	0.6469

We can observe that SVM gave the best results. It is interesting to note that the baseline accuracy which was based on a naive approach still gave decent results. An additional observation was that the LSTM model always predicted only one class, which was the class with the highest support. We believe that the poor performance of the LSTM was because of the fact that there wasn’t enough training data for the LSTM to learn.

The complete results are as follows:

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Classifier	Label	Precision	Recall	f1-score	Support
Baseline Bag of Words	1	0.48	0.60	0.53	50
	2	0.79	0.86	0.83	251
	3	0.67	0.45	0.54	71
	4	0.00	0.00	0.00	14
	5	0.00	0.00	0.00	2
	Avg/Total	0.69	0.72	0.70	388
LSTM	1	0.00	0.00	0.00	50
	2	0.65	1.00	0.79	251
	3	0.00	0.00	0.00	71
	4	0.00	0.00	0.00	14
	5	0.00	0.00	0.00	2
	Avg/Total	0.42	0.65	0.51	388
Naive Bayes	1	1.00	0.20	0.33	50
	2	0.71	1.00	0.83	251
	3	1.00	0.32	0.49	71
	4	0.00	0.00	0.00	14
	5	0.00	0.00	0.00	2
	Avg/Total	0.77	0.73	0.67	388
Support Vector Machine	1	0.85	0.66	0.74	50
	2	0.82	0.94	0.88	251
	3	0.78	0.61	0.68	71
	4	0.5	0.21	0.30	14
	5	0.00	0.00	0.00	2
	Avg/Total	0.80	0.81	0.80	388

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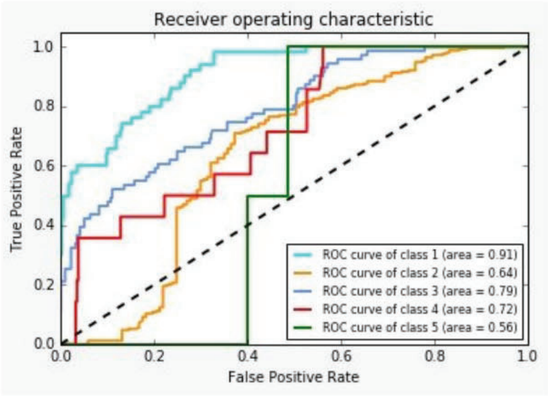
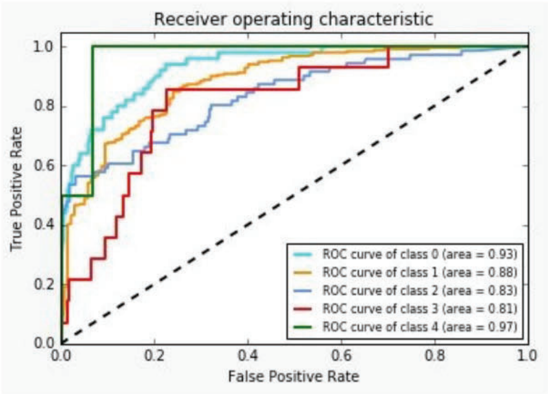
ROC Curve:

LSTM



Naive Bayes



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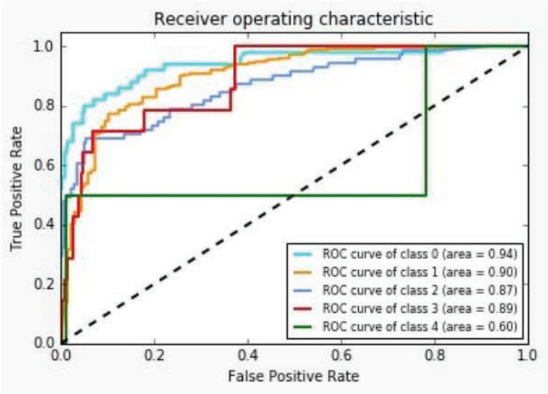
Support Vector Machine



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