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# Predicting Future Terrorist Attacks with State-of-Art Machine Learning Techniques

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## Abstract

Our goal is to generate accurate and robust predictions for future terrorist attacks using machine learning techniques. In this report, we provide two different problem formulations, with corresponding methods, implementations, evaluations, bias and caveat analysis. One method is to predict the possibility of terrorist attack in the map grid by classifying them on whether they had terrorist attacks or not. The other is to predict the spatial-time series of terrorist groups' future attacks using recurrent neural network (Note that this approach should be viewed as a bonus in this report and will only be briefly discussed.). Policy recommendations are provided w.r.t. both approaches.

## 1 Introduction

### 1.1 Background

Although there is no universally accepted definition of terrorism, the Global Terrorism Database defines terrorism as satisfying three necessary components [1]:

1. Intentional,
2. Violence and/or threat of violence,
3. Sub-national perpetrators.

Terrorist attacks can take various forms including assassination, kidnapping, bombing, and infrastructure attack. After its first appearance in the 1960s, terrorism has been used by perpetrators to achieve some religious or political aims. The September 11 Attacks were a turning point in the history of terrorism and shifted the paradigm of terrorism [2]. Terrorist attacks that took place before and after 9/11 look very different from one another. For example, the geographical concentration of global terrorist activity shifted almost completely from Latin America to the Middle East after the September 11 Attacks. More importantly, since the September 11 Attacks, the battle against terrorism has dominated the national security agenda of the United States [3]. Just over a decade after the attacks, the United States spent over 600 billion US dollars on defense and homeland security [4].

### 1.2 Motivation

Despite the large amount of resources spent on counter-terrorism, unfortunately, the number of deaths and non-fatal injuries has been continuously increasing over the years [2]. Intelligence agencies were ineffective in preventing the September 11 Attacks partially because they rarely dealt with non-state entities and political objectives driven by extremist ideologies [5]. In response to the devastating failure to prevent terrorist attacks such as the September 11 Attacks and 2015 Paris Terror Attacks,

there have been an increasing interest in using predictive modeling to counter terrorism. In other words, if intelligence agencies can accurately predict when and where a terrorist attack will occur, they would be able to respond to terrorist attacks more effectively.

## 2 Literature Review

Though there have been a number of literature on terrorism, it is mostly concentrated in theoretical models about the causes and consequences of terrorism. Traditional attempts at predicting where terrorists will strike next are educated guesses at best. For example, Senior Adviser to the RAND President Brian Jenkins discussed four traditional ways of predicting terrorism and how they failed to predict terrorism in the past [6]:

1. extrapolating from trends in terrorism,
2. forecasting from the relationship between the world affairs and terrorism,
3. Examining how terrorists could use new technologies
4. Predicting of potential scenarios of future attacks.

Furthermore, because theoretical models for terrorism often cannot be empirically tested, it is hard to examine which models are more robust than others. Since the recent heightened interest in machine learning and big data, a number of researchers attempted to predict terrorist attacks using machine learning methods. For instance, Ding et al. used machine learning approaches such as SVM to predict terrorism with the historical data [7]. However, given the limited number of research done on this, much is left to be desired.

## 3 Problem Formulation

### 3.1 The Classification Approach

Based on previous studies, machine learning is a good approach in terms of predicting when and where terrorist attacks would happen. Given the historical data on time and locations of past attacks, we can learn that which types of regions that terrorists are likely to attack in the coming years and take preventive measures to stop it from happening or mitigate the damage. Note that these measures, like building up responsive defense systems, educating the communities, or take actions on certain terrorist groups often take relatively long time to implement.

Therefore, We formulate this policy problem as predicting whether terrorists would attack a specific location at least once in the next two years, given that the location was attacked at least once in the past six years. We look at the locations that were attacked at least once in the past six years with the assumption that terrorists are likely to launch attacks on the same locations, but over a relatively long period of time. We predict whether the attack would happen in the next two years, limited by our data as we are giving policies that take effect in a relatively longer term.

### 3.2 The Deep Learning Approach

In this approach, we aim to uncover the attack patterns of terrorist groups, and form the problem into a temporal spatial prediction one. More specifically, we regard each terrorist group as an adaptive agent, whose behaviors could be modeled by its previous attack history (i.e. time series data with spatial context) through recurrent neural network, which will allow us to predict when and where a terrorist group will attack.

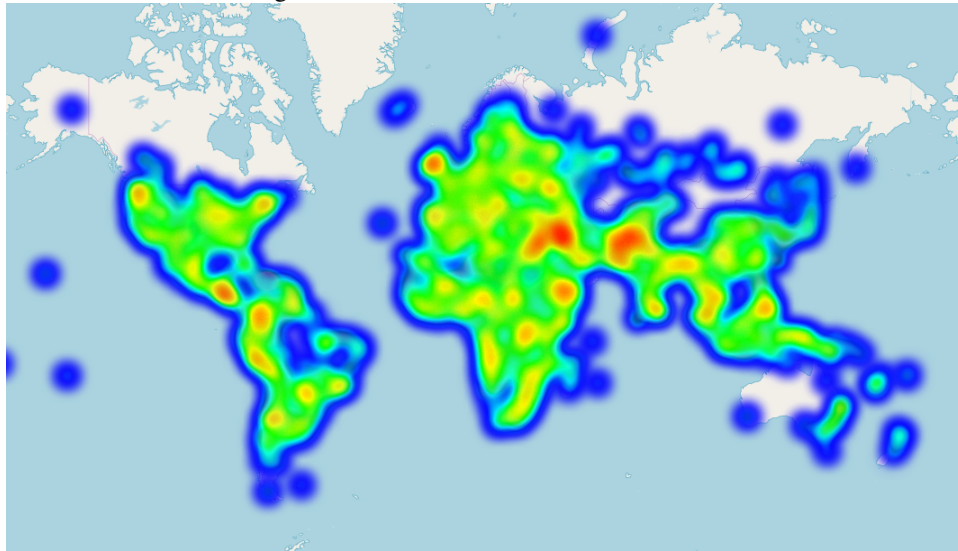
In this project, we adapt the Recurrent Neural Network model with spatial and temporal contexts by [11] and modify it to better suit our problem. Basically, we model sequential elements in an almost fixed time period in each recurrent layer. Such a recurrent structure is used to capture the periodical temporal contexts. In each layer, we employ the **time transition matrix** and **distance transition matrix** to capture the dynamic properties of terrorist attack in terms of time and geography. To efficiently create and calculate these transition matrix, we discretize the spatial and temporal value into multiple bins. Therefore, for each value inside a bin, we could approximate its transition matrix through linear interpolation via the lower and upper bound of the bin. A more comprehensive technical notes of the network structure will be provided in a separate appendix in this file's directory.

## 4 Data Description, Exploration, and Descriptive Statistics

The main data source we use for prediction is the *Global Terrorism Database (GTD)*. It includes the records for over 180,000 terrorism event all over the world from 1970 to 2017, including data such as, types of terrorism, the date of the event, location (longitude, latitude), the number of casualties and the name of the suspicious group.

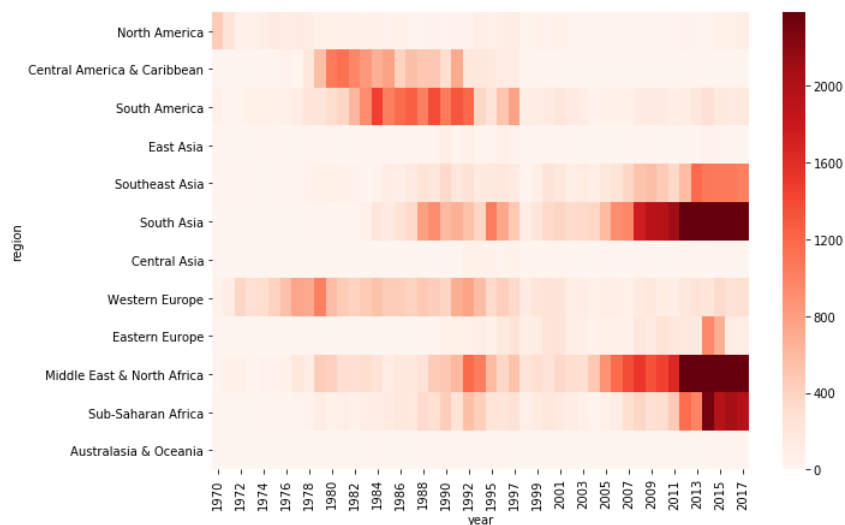
As the data is still in training, the contents for the deep learning approach will later on be updated in approximately 6 hours. Please check the file after June 13, 2019 for this bonus part.

Figure 1: Terrorist Events around the World



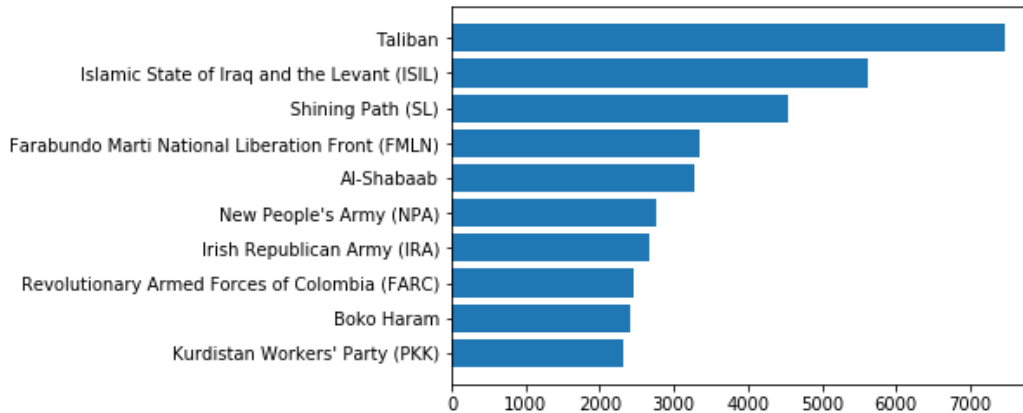
We made some brief exploration for GTD data. **Figure 1** is the heatmap which shows the distribution of terrorist attacks through whole period. We can see that terrorist events are distributed globally, but especially focus on some region such as middle east and central America.

Figure 2: Regional Trend of Terrorist Attacks



**Figure 2** reveals the change of regional trend of terrorism. We can see that in early period, regions such as central America and Western Europe had a lot of terrorist attacks but in these days, there are more attacks in areas like South Asia and Middle East.

Figure 3: Number of Terrorist Attacks by Groups



**Figure 3** is the top 10 groups which committed terrorist attacks through the period. Overall, the groups mainly based on middle-east region such as Taliban and ISIL are the most reported groups responsible for terrorist attacks. However, we are also able to find groups from other areas like SL and IRA.

**Figure 4** below shows the trend of attacks by these groups. We can see that, in past, terrorist attacks were more distributed broadly around the world, as attacks by groups such as IRA and SL happened more frequently. Now, most of terrorist attacks are reported mainly by groups who are based on middle east region, such as Taliban, ISIL and Al-Shabaab.

Figure 4: Trend of Terrorist Attacks by Group



Then, for prediction of terrorist attacks, we used four data sources including GTD data. From GTD data, we used variables such as the time and location of the event, number of people killed or wounded, types of weapons used, and name of terrorist group name.

We also used additional data sources to include the characteristics of the locations attacked historically. Such data include geographical information and social economic information. **G-Econ (Geographically based Economic)** data include geographical data such as distance to navigable water area, elevation and weather, as well as social economic information such as gross cell product and population of the area. These data are combined with 1x1 degree of latitude and longitude grids on earth. **Geo-EPR (Geo-referencing Ethnic Power Relations)** and **World Religion Map** provide ethnic and religious diversity data for each geographical region in the world.

We aggregated these data via latitude and longitude information in GTD data. Although the latitude and longitude data in GTD were expressed in less than 0.1 degree, in G-Econ data they were expressed in 1 degree. Therefore, we converted latitude and longitude to 1 degree scale. Although it depends the location on earth, the length of 1 side of the grid in 1x1 degree scale is about 100 kilometers. Geo-EPR data and World Religion Map have a geographical polygon data (in unit of province level). We used it to combine with GTD data.

## 5 The Classification Approach

### 5.1 Pipeline Overview

Each row in our training set is a location that was attacked at least once in the past six years, with all features in the columns. For a full list of generated features and features we would like to generate but did not have time, please check [this table](#). As we obtain the training set based on terrorist attacks in the GTD data, we aggregate the events at a specific location in a certain year by adding up the number of people killed or wounded, and summing up the counts of unique types of weapons, unique groups, and unique types of targets. Then we fill in the gaps for these locations with years in the training window of six years when they were not attacked. Each row is labeled as 1 when the location was attacked in the specific year and zero otherwise.

Each row in the test set is the locations that are known to be attacked at least once in the next two years. We also fill in the gaps for these locations with years in the test window of two years when they were not attacked. Each row is labeled in the same manner as that in the training set.

### 5.2 Evaluation

We applied a temporal train-test split to find the best model for predicting coming terrorist attacks based on historical data at several different time points. Since we believe that terrorist attacks follow certain patterns in terms of both space and time and are more related only when they are close in time, we employed a fix-length time window for the training set of six years.

As indicated in the literature review, the pattern of terrorist attacks have changed since the year 2002, and the lethality of terrorist attacks has increased rapidly, too. Thus, we mainly looked at terrorist attacks after the year 2002. Descriptions of the train-test sets are listed as below:

Table 1: Descriptions of Training and Test Sets

Batch	Training Set	Observations (n)	Features (m)	Test Set	Observations (n)
0	2002 - 2007	4458	39	2008 - 2009	1338
1	2004 - 2009	5316	39	2010 - 2011	1288
2	2006 - 2011	5808	40	2012 - 2013	1757
4	2008 - 2013	6882	39	2014 - 2015	2440
5	2010 - 2015	8892	39	2016 - 2017	2252

The metrics we care most about is **Recall**. As we are making predictions on terrorist attacks, life and public assets are at stake. We are more concerned about the coverage of our predictions, in other words, we want to catch as many future attacks as we can. However, as the interventions we would recommend consume a lot of resources to implement, we have to make decisions under constraint. Therefore, we plan to take actions on the 10% of locations at the highest risk of being attacked in the next two years. In other words, we optimize our models on the metrics at the level of 10% of the population. Thus the metrics we care most about is **Recall at 10%**. We would also optimize on other metrics, Accuracy, Precision, F-1 Score, and AUC score on the same population level. Evaluations of that model across all other metrics are also reported (check this [example](#)).

### 5.3 Bias and Fairness Analysis

We examined bias and fairness for the majority religion for each area. **Figure 5** shows the disparity of all metrics between the area where Muslims is the major religion and the other regions. We can see that for some metrics, there are considerable disparity between Muslim and others.

Figure 5: Disparity between religions  
DISPARITY METRICS by HIGHRELIG

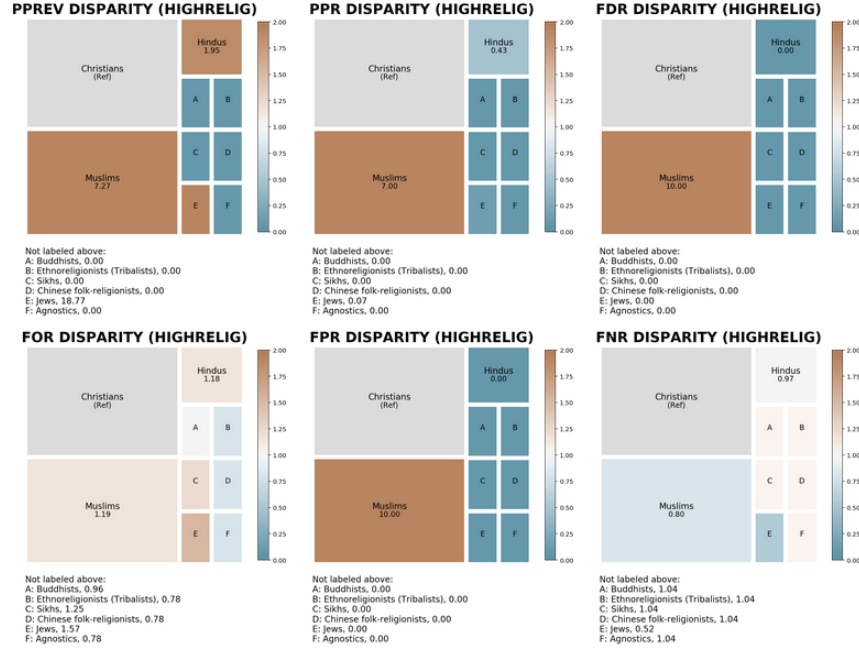
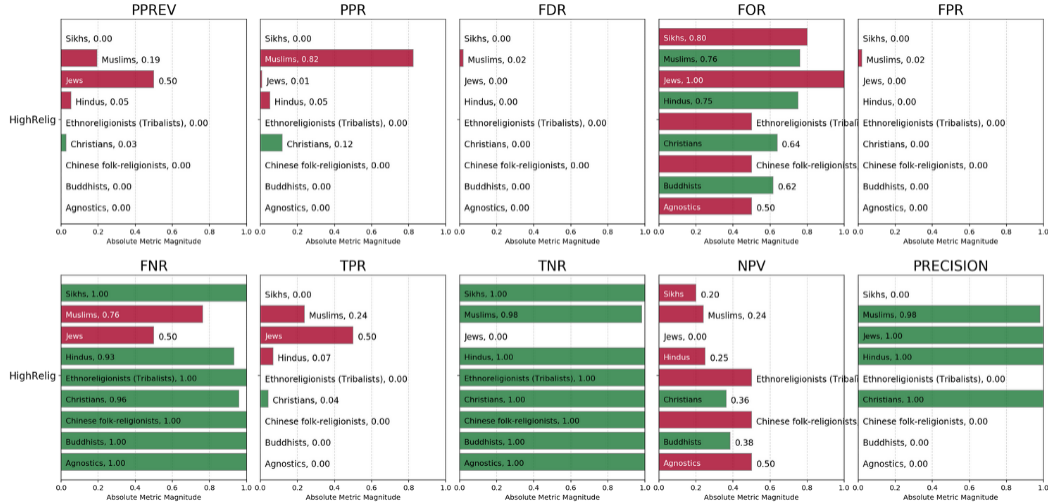


Figure 6 reveals the fairness based on the disparity. Here we can also see that for some metrics such as FOR and NPV considerable numbers of religions are categorized as "non-fair". Overall, there might be a possibility that our model has a bias with religions.

Figure 6: Fairness for all metrics



## 5.4 Results and Feature Importance Analysis

For the binary classification task, we applied the following models:

1. Logistic Regression and Decision Tree;
2. Random Forest, Bagging, Adaptive Boosting;
3. Naïve Bayes, KNN, Linear SVM

In terms of model tuning, for each pair of training-test sets, we apply 3-fold cross validation on the training sets and optimize each type of model under a certain metrics on a specific population level, like Recall at 10%, to find the best set of hyperparameters. We then fit each type of model with its "best" set of hyperparameters on the whole training set and make predictions on the test set. At last, we select our "best" model of the batch based on Recall at 10%. When a tie happens, we make decision based on AUC score, as it indicates how well the positives are separated from the negatives in general.

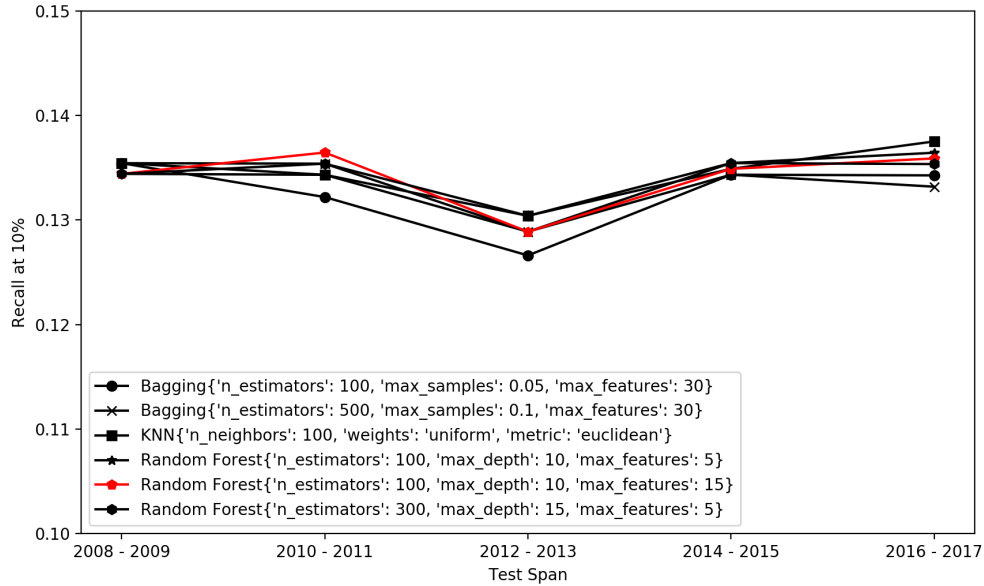
For a partial list of "best" models on each train-test pair, check **Table 2** below. The full list of "best" models can be found [here](#).

Table 2: Best Models Across Test Sets

Batch	0	1	2	3	4
Test Span	2008 - 2009	2010 - 2011	2012 - 2013	2014 - 2015	2016 - 2017
Model	Bagging	Random Forest	Random Forest	Random Forest	KNN
Recall at 10%	0.1354	0.1365	0.1304	0.1355	0.1375
AUC	0.6506	0.7057	0.7002	0.7055	0.6908

It seems that Random Forest is our best model across test sets. Although the three best models are different from each other on hyperparameter sets. We make a plot of test performances of the best models as in **Figure 6** below.

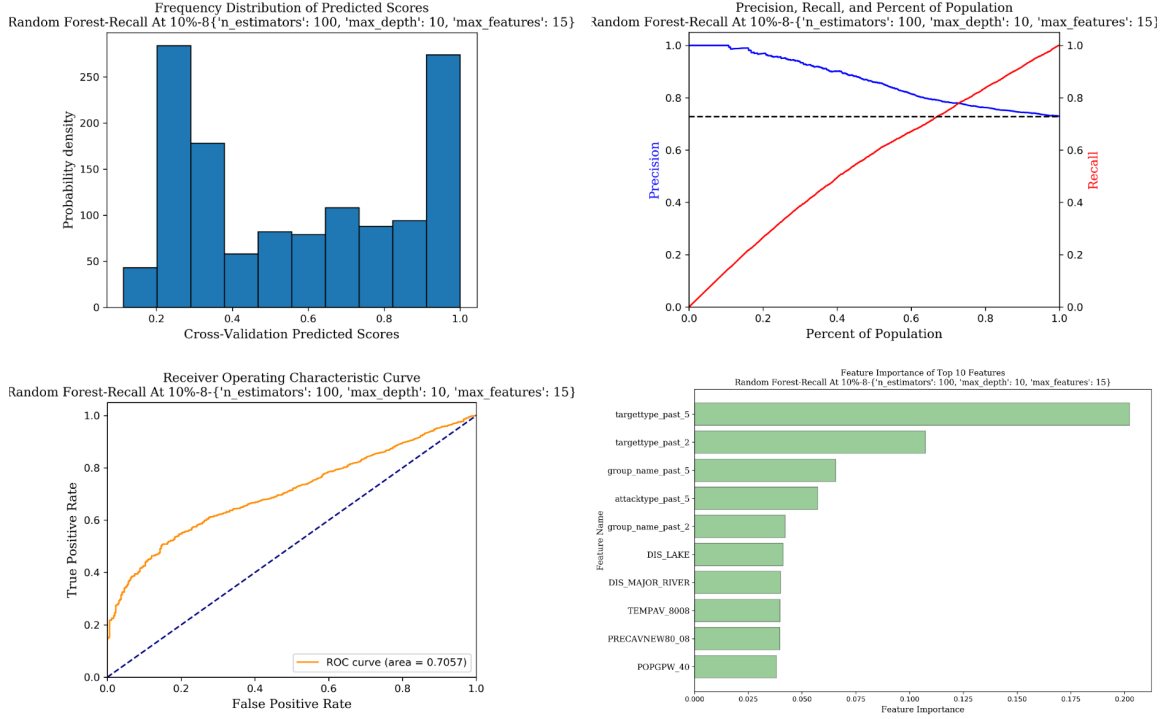
Figure 7: Test Performance across Test Sets



While there is no model that is consistently the best across all test sets, **Random Forest with 100 estimators, maximum depth of 10 and maximum features of 15 for each base learner** is recommended for its fair performance in all the test sets. Its test performance on Batch 2 is visualized below.

As indicated in the panel below, beside its Recall at 10%, Precision at 10% and AUC score of our recommended model are fairly satisfying. Based on the feature importance in the bottom right, total number and diversity of the terrorist attacks in the past two years and in the past five years are contributing most to the recommended Random Forest.

Figure 8: Test Performances of the Recommended Model



## 6 Policy Recommendations

Ideally, a predictive model would be able to precisely predict the location and the time of potential terrorist attacks so that law enforcement and intelligence agencies can incorporate this information to strengthen the security of the predicted location to prevent the terrorist attacks. Unfortunately, due to the limitations of our classification model, our prediction is restrained by a large time window of two years for limited locations. However, considering the fact that a large number of terrorist attacks post-9/11 occur in the Middle East region, we argue that the location and the time window predicted by our machine learning model when used with other information collected by intelligence agencies could be still informative in preventing future terrorist attacks.

Considering that our relatively long prediction time span, the policy recommendation would be more long-term based and preventive approach, such as development of necessary infrastructure and human resources, rather than deployment of security forces to the dangerous areas. Infrastructure building includes introducing necessary equipment such as advanced security system and reinforcement of important buildings as well as preparing enough medicine and medical appliances in case of happening of attacks. Human resource development includes training for people such as police officers, military officers and medical professionals. These long-term action both in hard and soft aspect would be important for preventing terrorist attacks and decreasing the damage even if it happens.

## 7 Caveats

First of all, GTD relies on media coverage for data collection. The records in GTD data are reported incidents in open source media such as electronic news archives, existing data sets, secondary source materials such as books and journals, and legal documents. Therefore, there might be missing minor incidents which have not been reported to these sources.

Another point is that, geographical data and social economic data from G-Econ are not real time data. G-Econ includes data only every 5 years from 1990 to 2005. Therefore we might not be able to



analyze the effect of time variant features especially in recent 10 years. Actually We also considered using country level data. There were some other sources which include annual social economic data for each country. However, we thought it would be too large to make a prediction in country level. Therefore we chose to use G-Econ data for this project.

Regarding the unit of prediction, we had to make prediction in large unit of grid(1 degree for latitude and longitude) because G-Econ adopted that scale. Although it would be much useful than country level prediction, it is still too large in unit to help policy makers prepare for future terrorist attack.

Finally, as we analyzed in the bias and fairness section, we have to take it into consideration that our prediction might be affected by the religion factor.

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