Project Report

Analyzing Impact of Military State Interventions on Terrorism and thereby Predicting Attack Type

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Executive Summary

It is a rather important question, “what is the impact of military interventions on terrorism?” This is due to a multitude of concerns relating to security, may it be personal, social, or financial. It is therefore, in my opinion important to analyze the impact of military interventions on extremist activities. This paper tries to analyze that question quantitatively. This can become essential under a lot of situations, such as whether to conduct a military intervention or not, for starters. Another thing that can be questioned is the continued operation of a military operation, if it does not curb extremism, it may not be legal under International law. Thirdly, accountability of military actions and interventions can be assessed and the actors that have not been in conformity with International law can be held accountable for their actions.

The second thing that I present is a prediction model that classifies the attack type. This is rather useful for countering attacks if intel is already available on certain parameters, the attack type can be known and evaded before a terrorist attack occurs. I did this for Syria since our findings showed a statistically significant effect of US-led intervention on Syria. This model predicts attack type and if the type of attack is known before it happens, it can be prevented in my opinion.

All in all, I only found the intervention led by the United States of America in the Syrian Arab Republic in September 2014, and the intervention led by the Russian Federation in the autonomous regions of South Ossetia and Abkhazia of Georgia in August 2008 to be statistically significant with regard to the number of terrorist activities in the respective regions. They’ve been discussed in this report. I built as a terrorist activity predictor for Syria since I found that terrorist activity had gone up after intervention and in such a scenario, it is essential for the United States to combat terrorism by predicting it.

Background

In the past two decades, there have been a lot of military interventions worldwide. They have been under the pretext of either aiding failing states or for humanitarian causes. This project aims at analyzing military interventions by the United States of America and the Russian Federation, and to see their impact on terrorism. Although there is no universally accepted definition of terrorism (Schmid, 2008), for the purposes of this paper, I will be adhering to the definition[1] applied by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland, and to that end using their data (START, UMD, 2019). It also aims to provide a comparative study of the impact of interventions by the United States and Russia.

Furthermore, this project aims at predicting attack type based on the city, target type, the name of the perpetrating group and the day of the week. But, before jumping into the specifics about this project, it is necessary to understand why this project is important. Reuters in April, 2019 reported that global military expenditure was the highest since the end of Cold War. They also reported that the United States has the highest expenditure while Russia made it to the top ten, being at the sixth position. John R. Deni wrote an opinion in The Washington Post in January 2020 about how it was a bad idea for the North Atlantic Treaty Organization (NATO) to be more involved in the Middle-East, which came after President Donald Trump's announcement for the same on January 8, 2020. The NATO Secretary-General also agreed with the opinion expressing that this would bring in peace and stability, and help counter terrorism. The middle east is already torn by conflict, so keeping in mind the 'peace-to-prosperity' plan for the Israel-Palestine question drafted by the Trump administration, it is an important question to asses, "do military interventions counter terrorism?" Depending on the answer to that question, special care needs to be taken while formulating such policies. The implications of previous interventions are also important to answer certain accountability questions that still float, such as the legality[2] of the unilateral Iraqi intervention that Kofi Annan, a former United Nations Secretary-General held the opinion of being illegal (BBC, 2004). This paper partly, tries to answer the question of the impact of military interventions on terrorist activities.

Post intervention, belligerents if recognized by the state become subjects of international law (Shaw, 2017). In such a situation, the country intervening should have a responsibility to assist the nation in combatting such belligerents, since it becomes well within their jurisdiction. The prediction of an attack can be used to counter the attack before it takes place given that there is some intel available. This is, in my opinion a good capacity-building measure in such a situation. The United States has conducted numerous military interventions and has also been a part of NATO-led military interventions. The Russian Federation also has conducted military interventions. I will be analyzing the impact of United States intervention in Afghanistan and Iraq, and the impact of Russian intervention in South Ossetia and Abkhazia, the autonomous regions of Georgia and Crimea further in this paper. I will also provide a comparison between the impact on terrorism of the US-led and the Russian intervention in the Syrian Arab Republic. If intervention do have a significant effect on terrorist activities, it is important for the country to aid the country in combatting terrorism after intervention. Predicting the type of attack is usually essential since intel is usually available on terrorist-group activities in a city, the attack target of the group, the weapon type they use by analyzing the transportation of goods, etcetera. An attack can be then avoided if the type of attack is known. Thus, I further provide a model to predict an attack type, as defined in the Global Terrorism Database codebook (START, UMD, 2019).

Data

The Global Terrorism Database (START, UMD, 2019) is the primary dataset of interest since I'm measuring terrorist activity. For the purpose of analyzing the events, I first cleaned the GTD data. I subsetted the data for the countries of Syrian Arab Republic (Syria), Republic of Iraq (Iraq), Islamic Republic of Afghanistan (Afghanistan), Georgia and Ukraine (Crimea). I then grouped the data by day and country to get a count of events per day in each country. This is the important data for the first part of my project, i.e. my analysis.

I subsetted the data further into the five countries to analyze them separately. I also subsetted the data by date. For Afghanistan I chose years between 1996 - 2006, for Iraq, between 1997 - 2008, for Crimea between 2009 - 2019, for Georgia between 2003 - 2014 and Syria between 2009 - 2019. This was to create 'windows' (Bailey, 2020) for the purposes of analysis.

```
Observations for Syria: 1144
Observations for Afghanistan: 339
Observations for Iraq: 1048
Observations for Ukraine: 585
Observations for Georgia: 71
```

I had the data points with the unit of analysis as no. of events per day, as depicted above. Since the data points for Afghanistan and Georgia were rather low, I decided to also use the Georeferenced Event Dataset (GED) by the Uppsala Conflict Data Program (Sundberg & Melander, 2013). I applied the same technique that I did for the GTD data, to clean the GED data. I finally had the following observations:

```
Observations for Syria: 1144
Observations for Afghanistan: 1345
Observations for Iraq: 1048
Observations for Ukraine: 585
Observations for Georgia: 90
```

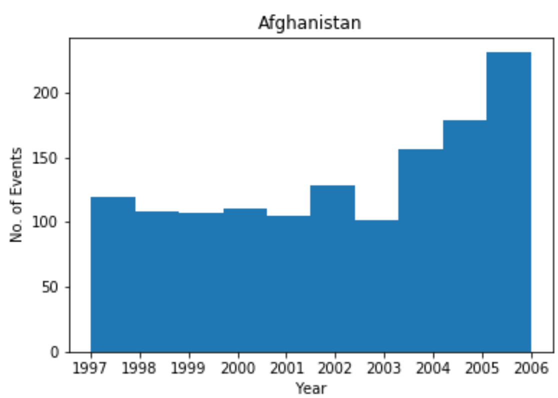
Even though Georgia seemed a little skeptical of Georgia due to less data, I decided to move on with my analysis. I also added the treatment variable labelled 'invasion' in all the datasets which was 0 for before intervention and 1 after. The dates are as follows:

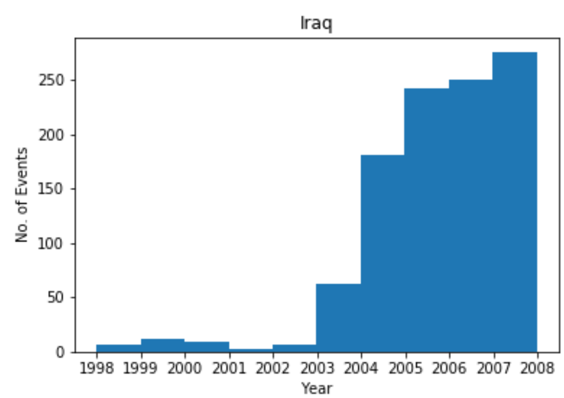
1. Afghanistan: October 7, 2001
2. Iraq: March 19, 2003
3. Syria:
   - USA: September 22, 2014
   - Russia: September 30, 2015
4. Ukraine: August 27, 2014
5. Georgia: August 8, 2008

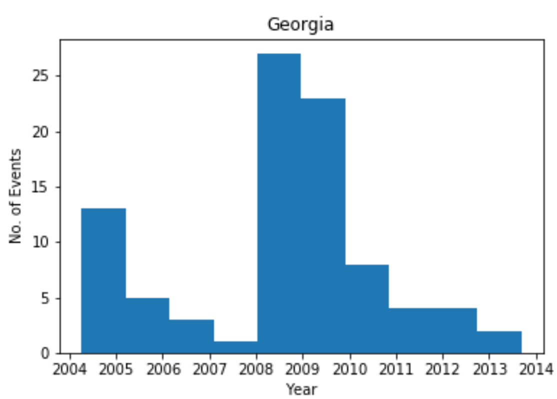
For the purposes of building a classification model to predict attack type, I chose the country of Syrian Arab Republic. The reasons are discussed in the conclusion. After thoroughly cleaning the data to get rid of unknown data points, I chose the dependent variables to be categorial variables. The features were from the GTD, namely, city, weapon type 1, target type 1, the perpetrator group name, and the day of the week. I had a total of 1009 data points for my model.

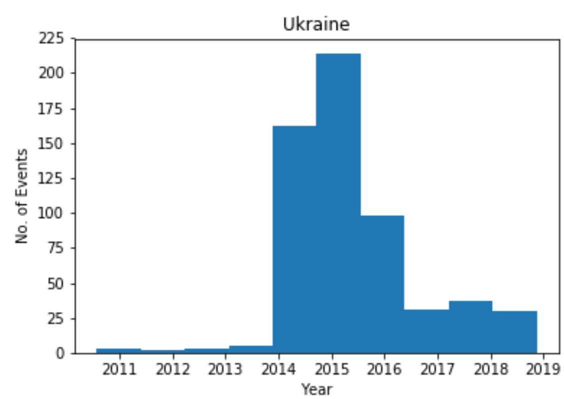
One of the problems of this dataset is that it undercounts the events from the 1900s (Staff, 2014), but this is not a huge concern for us, since we're only interested in the last 2 decades and in some a few years from the late 1900s are included.

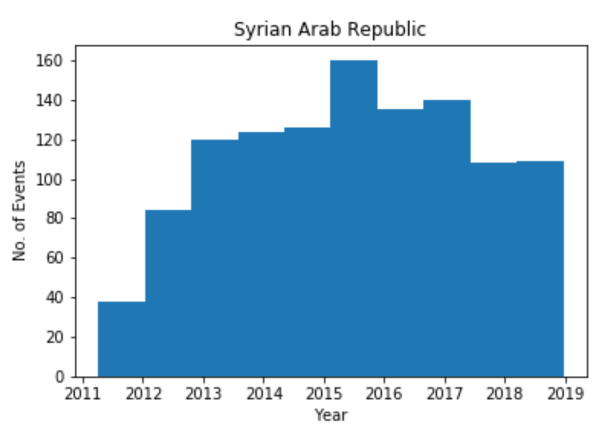
To that end, let's look at the data that we have.











Methodology

For the purpose of parametric analysis, I use using a method called 'Regression Discontinuity.' This is a method that allows us to see the significance and effect of a policy (treatment). As long as the treatment itself is not biased, i.e. not affected by something, and is completely random we can see a jump or a 'discontinuity' in the effect of the dependent variable, i.e. the variable one is trying to assess, at the treatment point and can infer that the jump may be due to the treatment effect. To put this into perspective, military interventions are usually covert operation until they're actually carried out, in my belief so, we should see a decrease or even an increase, i.e. if the intervention had any effect, on the number of terrorist activities the day the interventions were applied. A paper by Lee and Lemieux (2010) talks more about how Regression Discontinuity can be applied to different settings. This technique is rather useful because we do not have to worry about other endogenous factors as long as we know that the treatment itself was random in nature for that day. This is a unique factor for an RD model. But, one needs to pay attention on how to interpret the model because, we can only surely say that the estimate on the treatment variable itself is unbiased, as long as the treatment is random and no endogenity is creeping into the treatment, not the other variables that we include in the model (Bailey, 2020).

The treatment effect is 'invasion' in the summary tables to come below.[3] For the purposes of classification, I employed K-nearest neighbors and decision tree classifier.

Linear Regression

Ordinary Least Squares (OLS) is a regression method used for inference and prediction. OLS aims to reduce the mean square error along a line or curve that is fitted between the data points and can take on linear or non-linear relationships. The more features we include, we risk the problems such multi-collinearity.

I use regression discontinuity for the part one of my project, hence we do not risk those problems since we only want to see the effect of the treatment.

K-Nearest Neighbors Classifier

K-Nearest Neighbors or KNN algorithm is a supervised non-parametric lazy machine learning algorithm used for classification. Thus, the non-parametric nature of the model means that the structure of the model is determined by the data itself. One has to keep in mind also the number of neighbors in this or the data points used to assess a particular data point. Less neighbors means computationally inexpensive, less flexible fit, i.e. low bias and high variance, while more neighbors means computationally expensive, but more flexible fit, i.e. high bias and low variance.

Advantages:

- Simple and Easy to implement.

- Can be used for either classification or regression.
- Results are easily interpretable by user and it is easy to explain the algorithms working - Easy Interpretation.
- Lazy learning i.e. no training time required for the algorithm, thus prediction speed depends on our dataset.

Disadvantages:

- Does not work well with less observations.
- Does not work well with large number of features.
- Does not handle irrelevant features well, i.e. it does not separate the signal from the noise and also does not understand feature interaction (most important features cannot be distinguished).
- The features require scaling, i.e. quantitative measurement of features should always be around the same quantity. eg. If we have a feature with values in 100,000s and another feature with values in 100s, this will give us incorrect predictions and we should scale the features to all be in either 100,000s range or the 100s range.
- Computationally inefficient, since the each data point is assessed for prediction (lazy learning downside).
- Can be impacted by noise in the data.
- Does not work well with missing data.

Decision Tree Classifier

A decision tree classifier is like a flow-chart where the algorithm follows a tree-like structure (hence, the name), and each branch represents a decision rule, i.e. True or False for a particular decision. There are decision nodes until there is no decision to be made, where one reaches the leaf node, or the classified label.

Advantages:

- Very easy to visualize branches and understand the classification model - Easy Interpretation.
- No assumptions of the structure of the data since it is non-parametric.
- Handles irrelevant features okay.
- Does not require normalization or scaling.
- Missing data does not affect the model at large.

Disadvantages:

- This has a training time period which can vary depending on model specification.
- Decision tree models can be very complex.
- Can overfit noisy data.
- May be biased with imbalance in data.
- Not a very flexible model since adding new data can change the tree entirely, but bagging and boosting algorithms can help overcome that.

Analysis

Parametric Analysis

First, I wanted to see where the intervention was significant. After running the RD models on Afghanistan data, Iraq data, and Ukraine data, I found that none of the interventions had statistically significant effects. This can be seen below in Tables 1, 2 and 3 respectively for Afghanistan, Iraq, and Ukraine, for the treatment variable that is 'invasion'.

For the purpose of the RD analysis, the dependent variable was 'no_of_events' which measured the number of terrorist events by day using the GTD dataset.

The independent variables were:

1. Treatment effect of Intervention (different for different countries) – dummy variable that takes on values 1 & 0.

2. The date normalized to zero, i.e. subtracting the intervention date from the actual event date.

3. An interaction variable between the normalized date and treatment effect.

Table 1 - Data for Afghanistan

Dep. Variable:	no_of_events	**R-squared:**	0.018
Model:	OLS	**Adj. R-squared:**	0.016
Method:	Least Squares	**F-statistic:**	8.383
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	1.60e-05
Time:	14:07:13	**Log-Likelihood:**	-2294.2
No. Observations:	1345	**AIC:**	4596.
Df Residuals:	1341	**BIC:**	4617.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.6568	0.116	14.287	0.000	1.429	1.884
invasion	0.0181	0.155	0.117	0.907	-0.287	0.323
date_rd	1.051e-05	0.000	0.092	0.927	-0.000	0.000
int_rd	0.0003	0.000	1.929	0.054	-5.09e-06	0.001

Table 2 - Data for Iraq

Dep. Variable:	no_of_events	**R-squared:**	0.091
Model:	OLS	**Adj. R-squared:**	0.088
Method:	Least Squares	**F-statistic:**	34.78
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	1.98e-21
Time:	14:07:13	**Log-Likelihood:**	-2495.6
No. Observations:	1048	**AIC:**	4999.
Df Residuals:	1044	**BIC:**	5019.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.0285	0.893	1.152	0.250	-0.724	2.781
invasion	0.1355	0.916	0.148	0.883	-1.663	1.934
date_rd	3.409e-06	0.001	0.004	0.996	-0.001	0.001
int_rd	0.0017	0.001	2.174	0.030	0.000	0.003

Table 3 - Data for Ukraine

Dep. Variable:	no_of_events	**R-squared:**	0.115
Model:	OLS	**Adj. R-squared:**	0.110
Method:	Least Squares	**F-statistic:**	25.17
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	2.55e-15
Time:	14:07:13	**Log-Likelihood:**	-1423.8
No. Observations:	585	**AIC:**	2856.
Df Residuals:	581	**BIC:**	2873.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.6124	0.260	13.902	0.000	3.102	4.123
invasion	0.1932	0.327	0.591	0.555	-0.448	0.835
date_rd	0.0023	0.001	2.483	0.013	0.000	0.004
int_rd	-0.0050	0.001	-5.041	0.000	-0.007	-0.003

We have a different picture for Georgia and Syria though. In Georgia, we see that the Russian Intervention had a negative effect on terrorist activities shown under Table 4.

Table 4 - Data for Georgia

Dep. Variable:	no_of_events	**R-squared:**	0.101
Model:	OLS	**Adj. R-squared:**	0.070
Method:	Least Squares	**F-statistic:**	3.222
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	0.0266
Time:	14:07:13	**Log-Likelihood:**	-101.60
No. Observations:	90	**AIC:**	211.2
Df Residuals:	86	**BIC:**	221.2
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.7952	0.190	9.472	0.000	1.418	2.172
invasion	-0.5927	0.248	-2.385	0.019	-1.087	-0.099
date_rd	0.0004	0.000	2.246	0.027	5.04e-05	0.001
int_rd	-0.0006	0.000	-1.845	0.068	-0.001	4.47e-05

We see that the intervention by Russia in the autonomous regions of South Ossetia and Abkhazia had an overall negative impact on terrorist activities. I chose the entire country of Georgia since curbing terrorist activities may have the balloon effect where the extremist groups re-locate within the region. We see that with an absolute t-value of 2.385, we have a statistically significant impact on terrorism whose co-efficient is negative indicating that the activities reduced.

Table 5 - Data for Syria - US Intervention

Dep. Variable:	no_of_events	**R-squared:**	0.046
Model:	OLS	**Adj. R-squared:**	0.044
Method:	Least Squares	**F-statistic:**	18.40
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	1.17e-11
Time:	18:46:51	**Log-Likelihood:**	-2137.5
No. Observations:	1144	**AIC:**	4283.
Df Residuals:	1140	**BIC:**	4303.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.0250	0.143	14.115	0.000	1.744	2.306
invasion_us	0.6235	0.183	3.404	0.001	0.264	0.983
date_us_rd	0.0006	0.000	2.636	0.009	0.000	0.001
int_us_rd	-0.0014	0.000	-4.969	0.000	-0.002	-0.001

For Syria, I found that the United States intervention had a statistically significant (t-value = 3.404) positive effect on terrorist activity which can be seen from the coefficient ‘invasion_us’ shown in Table 5. The Russian Intervention on the other hand did not have any statistically significant impact, seen by the variable ‘invasion_ru’ in Table 6 below.

As spoken before, since the intervention had a significant effect, the state would also aid in further capacity building and hence, building a prediction model which predicts attack is necessary.

Table 6 - Data for Syria - Russian Intervention

Dep. Variable:	no_of_events	**R-squared:**	0.052
Model:	OLS	**Adj. R-squared:**	0.049
Method:	Least Squares	**F-statistic:**	20.67
Date:	Mon, 04 May 2020	**Prob (F-statistic):**	4.79e-13
Time:	18:50:00	**Log-Likelihood:**	-2134.3
No. Observations:	1144	**AIC:**	4277.
Df Residuals:	1140	**BIC:**	4297.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.6171	0.115	22.842	0.000	2.392	2.842
invasion_ru	-0.2003	0.177	-1.134	0.257	-0.547	0.146
date_ru_rd	0.0010	0.000	6.785	0.000	0.001	0.001
int_ru_rd	-0.0018	0.000	-7.187	0.000	-0.002	-0.001

Figure 1 - US Intervention in Syria

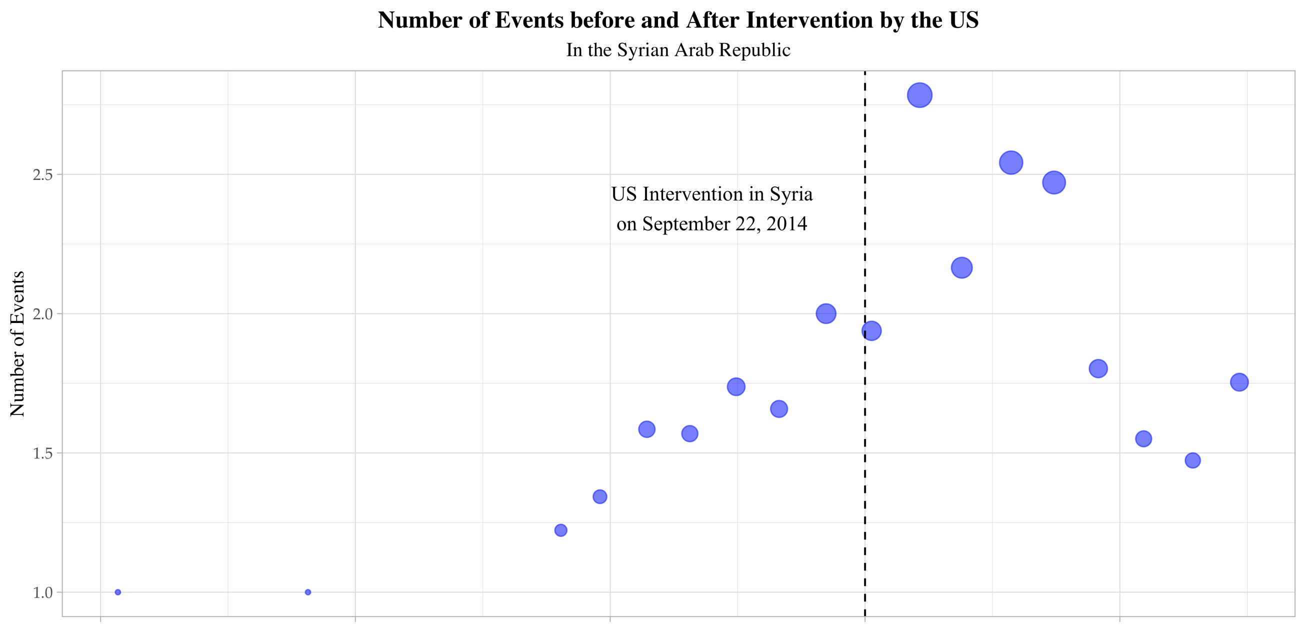
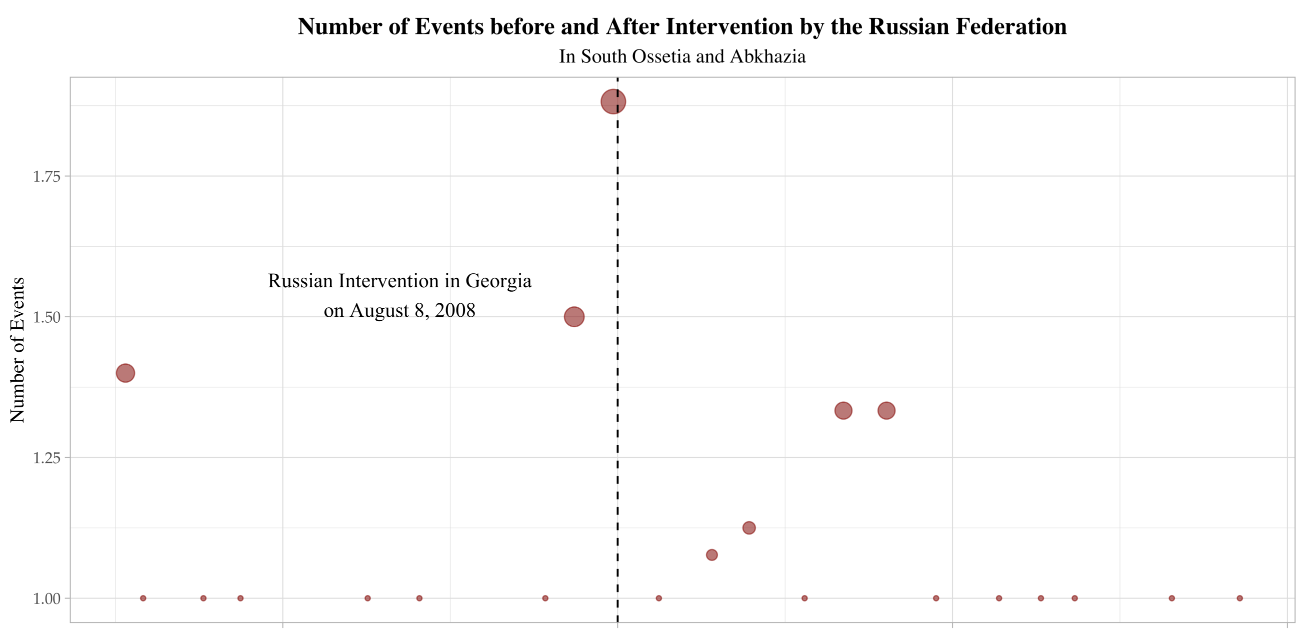


Figure 2 - Russian Intervention in Georgia



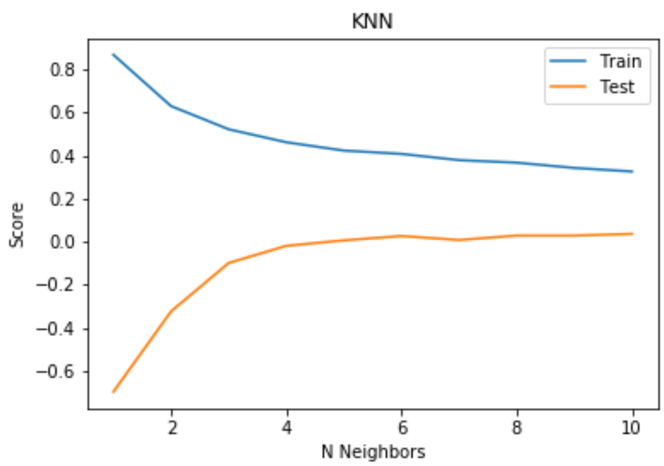
Non-Parametric Analysis

For the non-parametric part of this project, my label array is the attack type, the different attack types are depicted in Figure 4 below.

The feature matrix was built with 379 features all being dummy variables of different cities in Syria, the weapon type used, the type of target and the name of the perpetrating group.

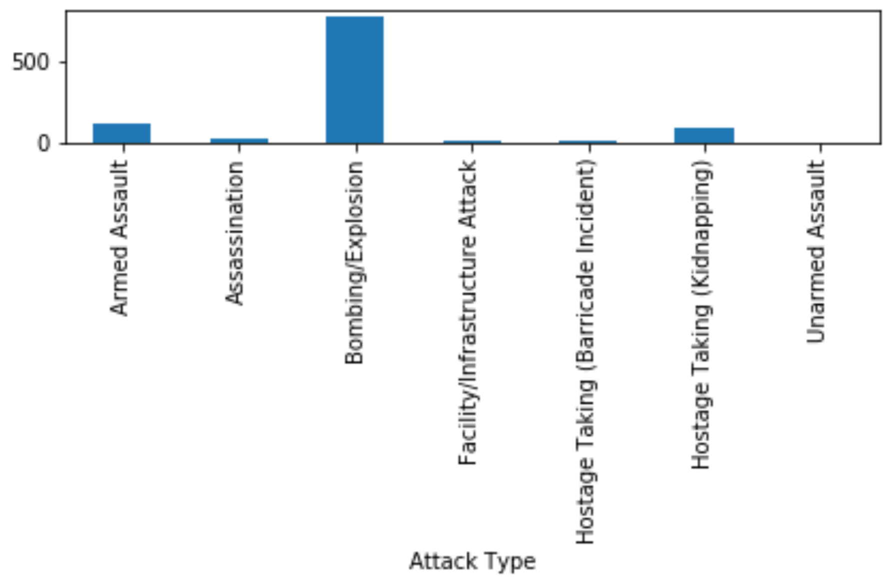
I first began with K-nearest neighbors since it's an easily implementable classifier. I set the number of neighbors equal to six since that was the best possible value I could choose as shown in Figure 3 below.

Figure 3 - Validation Curve for KNN



KNN performed horrendously with an accuracy calculated using 10 fold cross-validation at 2.63%. This was probably because of the amount of features. Before I move on to decision tree, let's understand why I didn't employ Random Forest Classifier. First let's look at our outcome variable and it's distribution, shown in Figure 4.

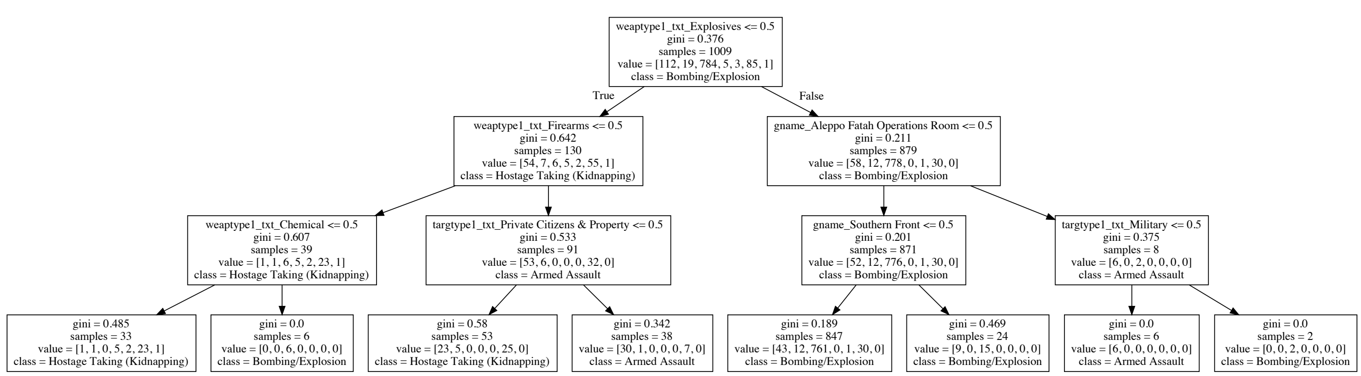
Figure 4 - Distribution of Outcome Variable



A decision tree algorithm is built on an entire dataset, using all the features, whereas a random forest algorithm randomly selects observations and specific features to build multiple decision trees from and then averages the results through each step. Since the distribution of Bombing/ Explosion is the most, I felt that it was best to not use random sampling since that would end up in a way reducing the quality of our tree due to overpopulation of data within a category of the outcome variable.

With using the Decision Tree Classifier, we can easily see what's going on. Figure 5 shows a basic example of a Decision Tree employed with the maximum depth of 3 levels.

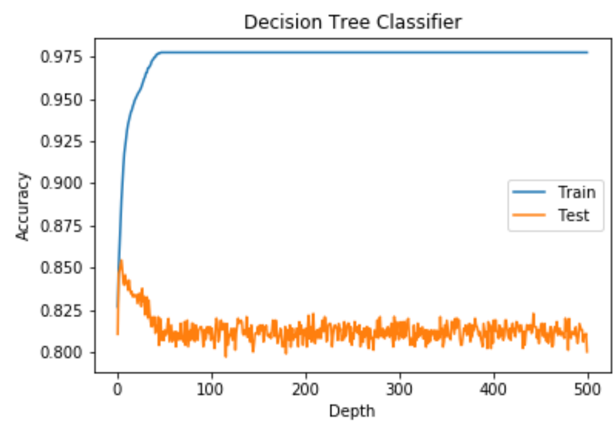
Figure 5 - Decision Tree (max. Depth = 3 levels)



We see from the tree above that if the probability of a weapon type being explosives is less than 0.5, then it goes to the right branch and if it's not, it goes to the left branch. Thus, a decision tree makes a "decision" at each branch. Let us assess what is the depth that's best for our model, shown in Figure 6 (a) and (b).

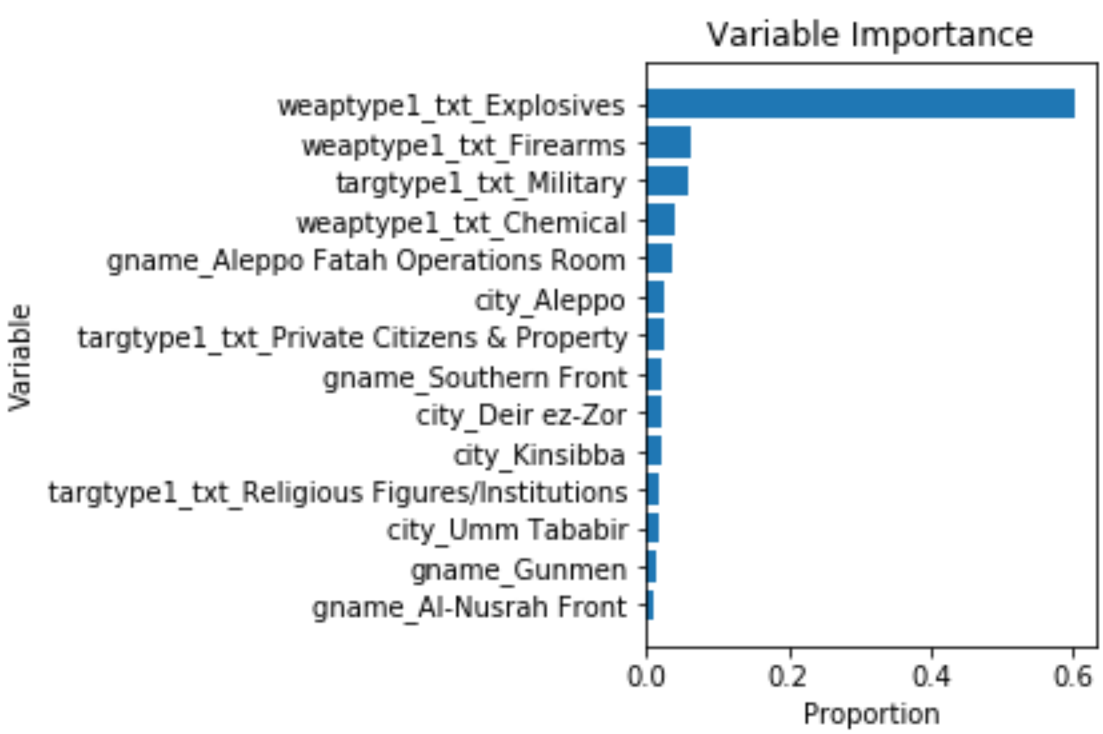
Figure 6(a)

Figure 6(b)



The best depth is at 5 in my opinion, so I set the max_depth to 5 in the decision tree classifier.[4] With that I got an accuracy of 84.846% by using 10 fold cross-validation. This is a good prediction accuracy in my opinion. I further also found the most important variables and subsetted them by their importance proportion of 0.01 shown in Figure 7.

Figure 7 - Variable Importance - Decision Trees



We see the most important variables in the figure above that have more than 0.01 importance proportion.

All in all, the decision tree classifier performs the best.

Conclusion

All in all, we could say Russian Intervention in South Ossetia and Abkhazia in 2008, had a significant effect that led to a decrease in terrorism in the region, while the US-led Intervention in Syria in 2014 had a significant effect that led to an increase in terrorism in the region. This is rather important and has a lot of implications. Further research needs to be done with this regard to find the causality between the two factors, along-side someone who is an expert in Middle-Eastern and Eurasian affairs. Thus, scholars have argued that it is usually the responsibility of the state to build peace under customary international law (Shaw, 2017) when they are directly responsible for creating instability, and I believe this should hold. Thus, I further went to build an attack prediction model for Syria.

For the model, I made use of Decision Tree Classifier at a maximum depth of 5 levels and received an accuracy of about 85 percent. This was because other models did not perform as well as the Decision Tree Classifier. This project was instrumental in understanding interventions and also using preventive action as a capacity building mechanism. Using quantitative analysis tools offered in Python, the question, "how do military interventions affect terrorism?" could be answered. In my opinion, military interventions affect terrorism differently. For example, the Russian intervention in the autonomous regions of Georgia may have worked to curb terrorism according to preliminary analysis of course, but the US-led intervention in Syria not so much, again, preliminary analysis.

There are so many ethical and legal questions that come to mind. A military intervention to combat extremism is not in violation of international law (Shaw, 2017), but if it does the exact opposite, there are many interesting questions to ponder upon, where the legality of the continued operation can be questioned. Other than that, accountability at a world forum such as the United Nations is another paradigm to look at by introducing such findings in the Security Council.

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Footnotes

[1] The GTD defines a terrorist attack as the threatened or actual use of illegal force and violence by a non- state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation. In practice this means in order to consider an incident for inclusion in the GTD, all three of the following attributes must be present:

1. The incident must be intentional – the result of a conscious calculation on the part of a perpetrator
2. The incident must entail some level of violence or immediate threat of violence - including property violence, as well as violence against people.
3. The perpetrators of the incidents must be sub-national actors. The database does not include acts of state terrorism.

In addition, at least two of the following three criteria must be present for an incident to be included in the GTD:

Criterion 1: The act must be aimed at attaining a political, economic, religious, or social goal. In terms of economic goals, the exclusive pursuit of profit does not satisfy this criterion. It must involve the pursuit of more profound, systemic economic change.

Criterion 2: There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims. It is the act taken as a totality that is considered, irrespective if every individual involved in carrying out the act was aware of this intention. As long as any of the planners or decision-makers behind the attack intended to coerce, intimidate or publicize, the intentionality criterion is met.

Criterion 3: The action must be outside the context of legitimate warfare activities. That is, the act must be outside the parameters permitted by international humanitarian law, insofar as it targets non-combatants

[2] Please note that for the purposes of this paper, we are not assessing the legality of the intervention under international law and is out of the scope of this project.

[3] Please note that the variable is only named for naming purposes and the interpretation whether the intervention was an invasion is out of the scope of this project.

[4]