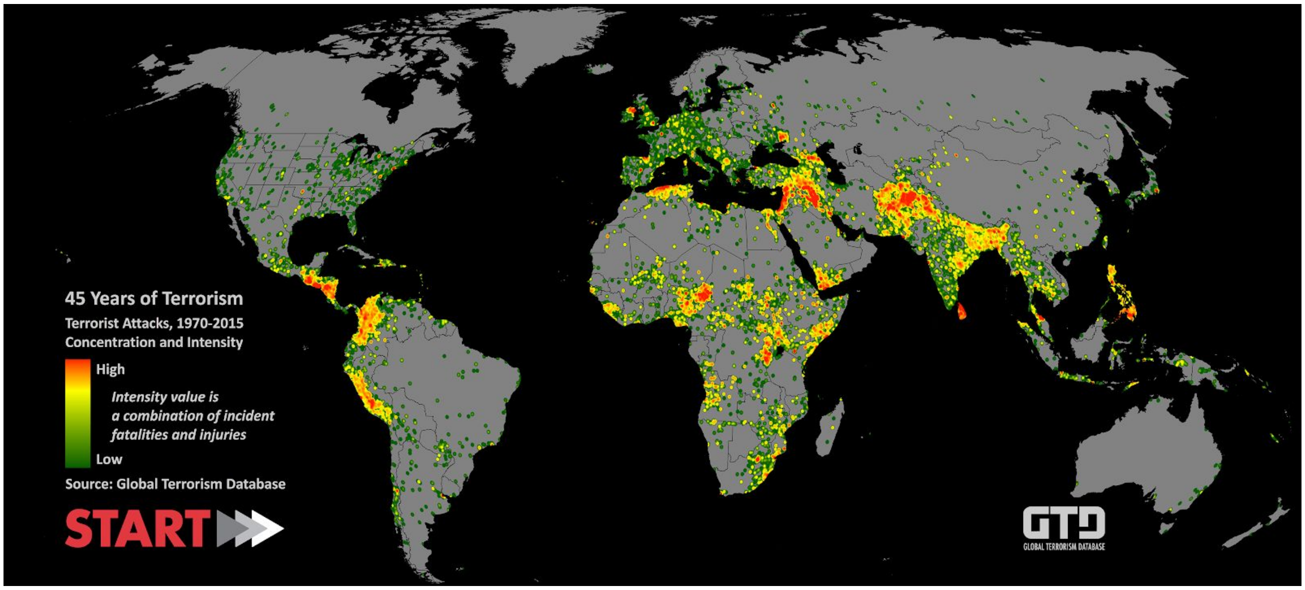
Is Terrorism a Prevalent Threat to the United States?



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CS105- Introduction to Databases & Data Mining

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Introduction

It's 2017 and extremist violence is constantly in the news. With the rise of the Islamic State and an uptick in hate crimes since the 2016 election, there is a perception that we are in more danger now than ever before. In fact, 80% of respondents surveyed in a Pew Poll cited terrorism as their top voting issue during last year's campaign.[1]

In a time when civil-liberties and privacy rights are being eroded under the pretext of national security, whether it be through calls to establish a Muslim Registry or expand surveillance efforts, we must ask ourselves: Are we exaggerating the terrorism threat?

Using data from the University of Maryland's Study of Terrorism and Responses to Terrorism (START) Global Terrorism Database (GTD), our team embarked on a study to answer the following questions:

1. Who were the most dangerous terrorist groups in the United States?
2. And when were they the most active from 1970-2015?

Using SQL queries, we determined the top six most successful terrorist groups and the years they were most active. Furthermore, we used the *Random Tree* algorithm in *WEKA* to create a decision tree and a Python program that would to predict the terrorist group based on the year of a terrorist attack, their target, their weapons used, and their mode of attack.

Using this data, we hope to contribute to the ongoing debate about the prevalence of terrorism in American society and aid policy makers in assessing and designing proportional responses to terrorism.

A Note on the Data, it's Assumptions, and Limitations:

Before embarking on this study, there are several assumptions and limitations about our data that need to be addressed:

1. The GTD only encompasses terrorist attacks that occurred from 1970-2015. START has yet to update their database for 2016.

[1] "Top Voting Issues in 2016 Election," *Pew Research Center*, July 7

2. START has three criterions that can be used to define terrorism.[2] While the definition of terrorism can be debated, we included groups whose acts demonstrated at least one of the following behaviors.
    a. "The act must be aimed at attaining a political, economic, religious, or social goal."
    b. "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.
    c. "The action must be outside the context of legitimate warfare activities."
3. We filtered exclusively for known terrorist groups. Individuals such as Timothy Mcveigh, the Oklahoma City Bomber or Omar Mateen, the Pulse nightclub shooter were *not* included because they were 'unaffiliated individuals' who did not belong to a known group.
4. We defined 'most dangerous' as groups that had *successfully* committed the *most single-target* terrorist attacks.
    a. According to START, a 'successful attack" is "defined according to the tangible effects of the attack. Success is not judged in terms of the larger goals of the perpetrators."[3] For example, an assassination is *successful* if the target is killed and an armed assault is *unsuccessful* if the perpetrators either fail to hit their target or are apprehended.[4]
    b. Some groups attack multiple targets at the same time. We factored only terrorist attacks that involved single targets.
    c. We filtered for groups that had committed *at least* 55 successful terrorist attacks from 1970-2015.
5. Definitions of 'danger' are subjective. We did *not* filter for ideology, number of mass casualty attacks, and international reach. An argument could be made that Al-Qaeda is more dangerous than the Black Nationalists because they operate in multiple countries, represent a dangerous ideology, and have committed more mass-casualty attacks. However, we only looked at groups that operated *mainly* in the United States. Although Al-Qaeda was responsible for 9/11, they were not included in the dataset because of they were relatively less successful in terms of *number* of successful attacks *in the United States* compared to other groups.

Dataset Description:

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[2] "Codebook: Inclusion Criteria and Variables," *Global Terrorism Database*, June 2016, p. 9. http://apps.start.umd.edu/gtd/downloads/dataset/Codebook.pdf
[3] Ibid., 24.
[4] For a more comprehensive commentary on what constitutes a 'successful' or 'unsuccessful' attack, refer to pages 24-25 of the Codebook.

The dataset used for this analysis came from the University of Maryland's Study of Terrorism and Responses to Terrorism (START) Global Terrorism Database from https://www.start.umd.edu/gtd/contact/. To access the database, you will need to enter your contact information, agree to the terms of service, and then download the *Entire GTD* dataset (~75 MB). Below is a description of the dataset:

Figure 1: List of Final Attributes

Attribute Name	Revised Name	Data Type	Description
iyear	Year	numeric	Year attack occurred
attacktype1_txt	Attack Type	nominal	Type of attack
targtype1_txt	Target Type	nominal	Target of the attack
gname	Group Name	nominal	Group name
weaptype1_txt	Weapon Type	nominal	Weapon type

Figure 2: Description of Attack Types

Attack Type	Description
Assassination	An act whose primary objective is to kill one or more specific, prominent individuals.
Armed Assault	An attack whose primary objective is to cause physical harm or death directly to human beings by use of a firearm, incendiary, or sharp instrument (knife, etc.).
Bombing/ Explosion	An attack where the primary effects are caused by an energetically unstable material undergoing rapid decomposition and releasing a pressure wave that causes physical damage to the surrounding environment.
Hijacking	An act whose primary objective is to take control of a vehicle such as an aircraft, boat, bus, etc. for the purpose of diverting it to an unprogrammed destination, force the release of prisoners, or some other political objective.
Hostage Taking	An act whose primary objective is to take control of hostages for the purpose of achieving a political objective through concessions or through disruption of normal operations.

Facility/ Infrastructure Attack	An act, excluding the use of an explosive, whose primary objective is to cause damage to a non_human target, such as a building, monument, train, pipeline, etc.
Unarmed Assault	An attack whose primary objective is to cause physical harm or death directly to human beings by any means other than explosive, firearm, incendiary, or sharp instrument (knife, etc.). Attacks involving chemical, biological or radiological weapons are considered unarmed assaults.

Figure 3: Description of Target Types

Target Type	Description 2
Business	Businesses are defined as individuals or organizations engaged in commercial or mercantile activity as a means of livelihood.
Government	Any attack on a government building; government member, former members, including members of political parties in official capacities, their convoys, or events sponsored by political parties; political movements; or a government sponsored institution where the attack is expressly carried out to harm the government.
Police	This value includes attacks on members of the police force or police installations; this includes police boxes, patrols headquarters, academies, cars, checkpoints, etc.
Military	Includes attacks against military units, patrols, barracks, convoys, jeeps, and aircraft. Also includes attacks on recruiting sites, and soldiers engaged in internal policing functions such as at checkpoints and in anti_narcotics activities.
Abortion Related	Attacks on abortion clinics, employees, patrons, or security personnel stationed at clinics.
Airports & Aircraft	An attack that was carried out either against an aircraft or against an airport.
Government (Diplomatic)	Attacks carried out against foreign missions, including embassies, consulates, etc
Educational Institution	Attacks against schools, teachers, or guards protecting school sites. Includes attacks against university professors, teaching staff and school buses.

Food or Water Supply	Attacks on food or water supplies or reserves are included in this value.
Journalists & Media	Includes, attacks on reporters, news assistants, photographers, publishers, as well as attacks on media headquarters and offices.
Maritime (includes ports/ maritime facilities)	Includes civilian maritime: attacks against fishing ships, oil tankers, ferries, yachts, etc.
NGO	Includes attacks on offices and employees of non_governmental organizations (NGOs).
Other	This value includes acts of terrorism committed against targets which do not fit into other categories. Some examples include ambulances, firefighters, refugee camps, and international demilitarized zones.
Private Citizens & Property	This value includes attacks on individuals, the public in general or attacks in public areas including markets, commercial streets, busy intersections and pedestrian malls.
Religious Figures/ Institutions	This value includes attacks on religious leaders, (Imams, priests, bishops, etc.), religious institutions (mosques, churches), religious places or objects (shrines, relics, etc.)
Telecommunication	This includes attacks on facilities and infrastructure for the transmission of information.
Terrorists/ Non-State Militias	Terrorists or members of identified terrorist groups within the GTD are included in this value.
Tourists	This value includes the targeting of tour buses, tourists, or tours.
Transportation (Other than aviation)	Attacks on public transportation systems are included in this value.
Utilities	This value pertains to facilities for the transmission or generation of energy.
Violent Political Parties	This value pertains to entities that are both political parties (and thus, coded as government in this coding scheme) and terrorists.
Unknown	The target type cannot be determined from the available information.

Figure 4: Terrorist Group Name

Group Name
Animal Liberation Front (ALF)
Anti-Abortion Activists
Black Nationalists
Jewish Defense League (JDL)
Left-Wing Militants
New World Liberation Front (NWLF)

Data preparation:

The *Entire GTD Dataset* had 137 attributes and 156,773 entries. Much of this data was irrelevant; we wanted to isolate all *successful, single-target* attacks that occurred *in the United States* by a *known terrorist group*. Hence the first step was to remove all irrelevant columns, as shown below:[5]

- eventid, imonth, iday, approxdate, extended, resolution, region, region_txt, provstate, city, latitude, longitude, specificity, vicinity, location. summary,crit1, crit2, crit3, doubtterr, alternative, alternative_txt
- suicide, attacktype1, attacktype2, attacktype2_txt, attacktype3, attacktype3_txt, targtype1, targsubtype1, targsubtype1_txt, targtype2, targtype2_txt, targsubtype2, targsubtype2_tx corp2, target2, targtype3, targtype3_txt, targsubtype3, targsubtype3_txt, target3
- corp1, target1, natlty1, natlty1_txt, natlty2, natlty2_txt, corp2, corp3, target3, natlty3, natlty3_txt
- gsubname, gname2, gsubname2, gname3, gsubname3:
- ingroup, ingroup2, ingroup3 motive
- guncertain, guncertain2, guncertain3, nperps, nperpcap claimed, claimmode, claimmode_txt, claim2, claimmode2, claimmode2_txt, claim3, claimmode3_txt, compclaim
- weaptype1, weaptype1_txt, weapsubtype1, weapsubtype1_txt, weaptype2, weaptype2_txt, weapsubtype2, weapsubtype2_txt, weaptype3, weaptype3_txt,

[5] Descriptions of the removed columns can be found in the 'GTD Codebook' here http://apps.start.umd.edu/gtd/downloads/dataset/Codebook.pdf

weapsubtype3, weapsubtype3_txt, weaptype4, weaptype4_txt, weapsubtype4, weapsubtype4_txt, weapdetail

- nkill, nkillus, nkillter, nwound, nwoundus, nwoundte
- property, propextent, propextent_txt, propvalue, propcomment,
- Ishostkid,nhostkid, nhostkidus, nhours, ndays, divert, kidhijcountry,
- ransom, ransomamt, ransomamtus, ransompaid, ransompaidus, ransomnote
- hostkidoutcome, hostkidoutcome_txt, nreleased, addnotes
- scite1, scite2, scite3, dbsource, INT_LOG, INT_IDEO, INT_MISC, INT_ANY, related,

After removing all the aforementioned columns, we were left with: **iyear, attacktype1_txt, targtype1_txt, weaptype1_txt, gname, country_txt, multiple**, and **success** (Appendix A)**.** Using the Python code in Appendix B, we were able to determine the number of attacks performed by each Terror Group. From this we manually filtered out to check which groups which had more than 50 terror attacks. In our pre-processed dataset, we manually removed all the terror groups which had less than 50 terror attacks.

Step 2) We then wrote a Python program (Appendix A) that filtered our data so that the only attribute shown in country_txt, was 'United States of America.' and that success was 1 and multiple was 0. A 1 in 'success' indicates that the group committed a *successful* attack[6] and a 0 in 'multiple' indicates it was a single-target attack. We intentionally excluded multiple-target attacks because, at a glance, most values for targtype2_txt, weaptype2_txt, and attacktype2_txt, which are the relevant attributes for the additional targets, were null values.

Step 3) We then proceeded to filter out all groups that had less than 50 successful single-target attacks. To do this, we loaded our newly created GTD_FINAL.csv file into WEKA and highlighted 'gname' in the 'Attributes' table. This showed us on the 'Selected Attribute' table the number of attacks for each group under the 'count' column. We then proceeded to remove any groups that had a count value of less than 50 attacks so that we were left with: Animal Liberation Front (ALF), Anti-Abortion Activists, Black Nationalists, Jewish Defence League, Left-Wing Militants, and the New World Liberation Front (NWLF).

Step 3) We then renamed all the attributes in the GTD_FINAL table. These changes can be seen in Figure 1 under *Revised Name*.

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[6] Refer to footnote 4 in 'A Note on the Data, it's assumptions, and Limitations' for a explanation on what constitutes success)

Data analysis:

To predict the terrorist group's name using the year of an attack, the attack type, weapon type and target type we used the J48 model to construct a decision tree.

The J48 model uses a decision tree, built on the subset of attributes listed. Hence we decided to use this algorithm, since we believed it was the model that would work best with our data, since most of our attributes are nominal, with the only numeric attribute being year. We used Weka's RemovePercentage filter, to split the data into training and test subsets through a 80/20 split (i.e. 80% of the data for training, and 20% data for testing).

We also decided to use SQL commands, to filter solely incidents of terrorist attacks in the United States. We also used SQL commands to filter out instances of these attacks between the years 1970 and 2015. We used a python program to implement the SQL commands on the dataset (Appendix A).

Results

On the 446 entries in the training dataset, we ran the J48 Tree Algorithm. This gave us an accuracy of 91.26%. After this we ran the model on the 95 entries in the test data set, which gave us an accuracy of 81.98%. The statistics for the model are summarized below:

The following are the results for the model from the training set, with a summary and a detailed accuracy for each class:

=== Evaluation on training set ===

Time taken to test model on training data: 0.01 seconds

=== Summary ===

Correctly Classified Instances	358	93.7173 %
Incorrectly Classified Instances	24	6.2827 %
Kappa statistic	0.9225	

```
Mean absolute error                  0.0326
Root mean squared error                0.1277
Relative absolute error              12.04   %
Root relative squared error            34.7054 %
Total Number of Instances              382

=== Confusion Matrix ===

  a  b  c  d  e  f   <-- classified as
 46  0  0  0  0  0 |  a = Animal Liberation Front (ALF)
  0 96  0  0  0  0 |  b = Anti-Abortion Activists
  0  0 38  1  7  0 |  c = Black Nationalists
  1  0  0 34  4  2 |  d = Jewish Defense League (JDL)
  0  0  5  0 87  0 |  e = Left-Wing Militants
  0  0  0  3  1 57 |  f = New World Liberation Front (NWLF)


=== Evaluation on test set ===

Time taken to test model on supplied test set: 0.01 seconds

=== Summary ===

Correctly Classified Instances          74               77.8947 %
Incorrectly Classified Instances        21               22.1053 %
Kappa statistic                      0.7229
Mean absolute error                  0.0742
Root mean squared error                0.2306
Relative absolute error              27.3843 %
Root relative squared error            62.7052 %
Total Number of Instances               95

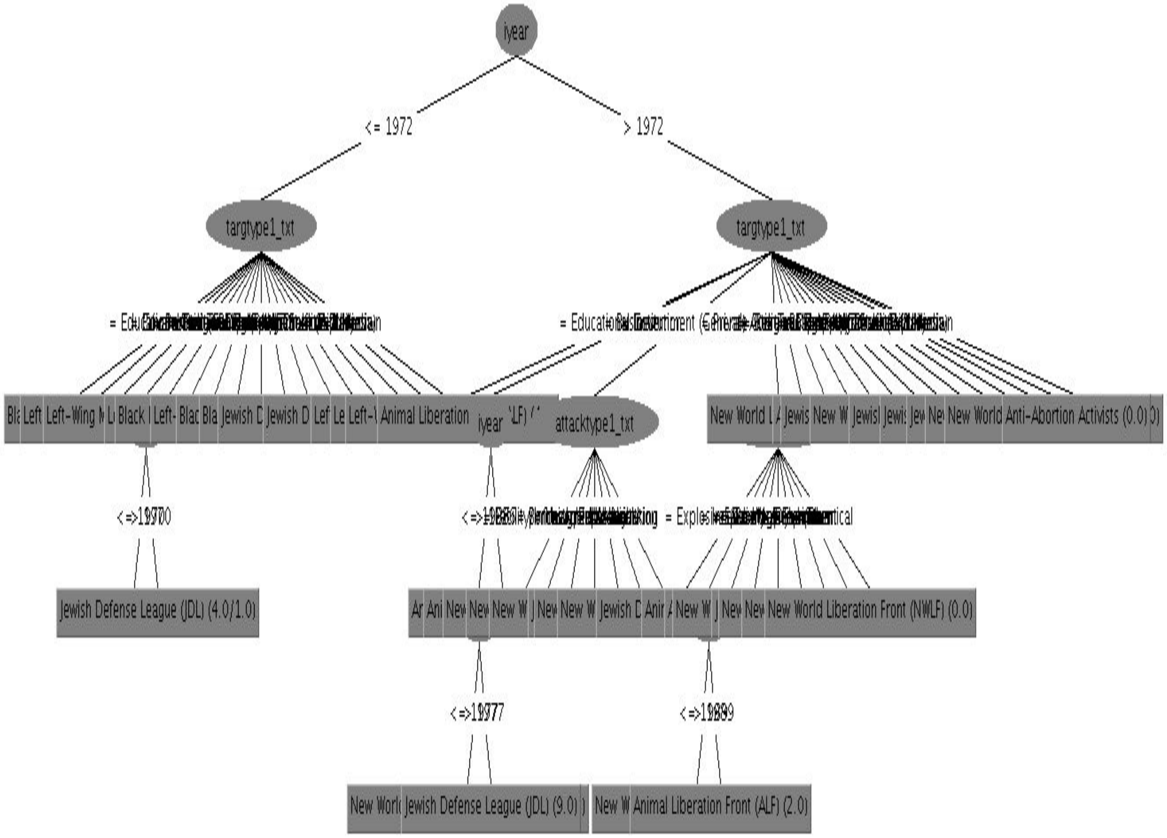


=== Confusion Matrix ===

  a  b  c  d  e  f   <-- classified as
 11  0  0  0  0  0 |  a = Animal Liberation Front (ALF)
  1 27  0  0  0  0 |  b = Anti-Abortion Activists
```

0 0 6 0 5 0 | c = Black Nationalists
1 1 0 3 6 3 | d = Jewish Defense League (JDL)
0 0 3 0 18 0 | e = Left-Wing Militants
0 1 0 0 0 9 | f = New World Liberation Front (NWLF)

Figure 4: Decision Tree Created using J48 Algorithm

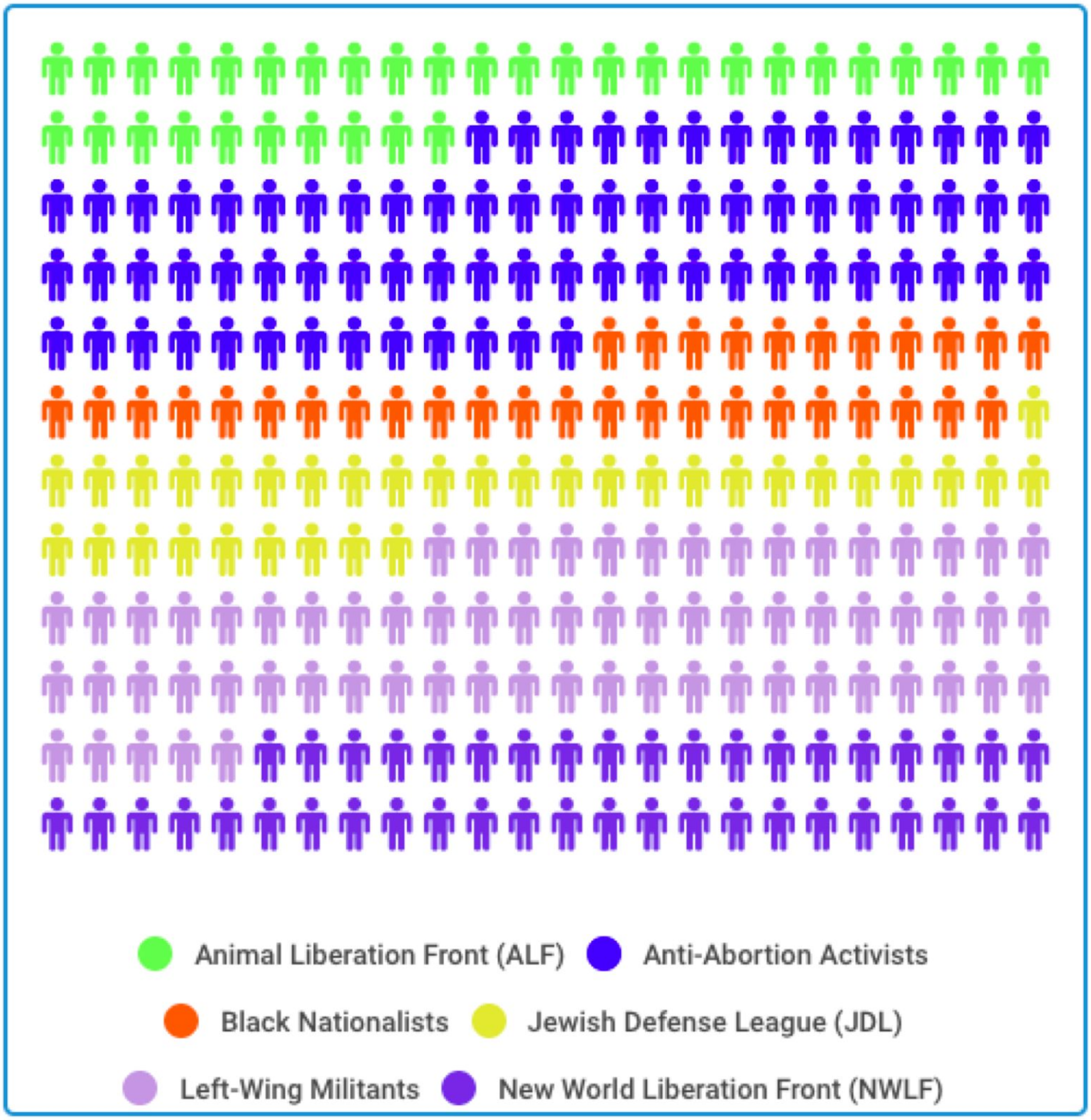


As seen for both the test and training datasets, the percentage accuracy is high, with the minimum accuracy being 77.89% for the test data set. It was expected that the test data set have a lower accuracy than the training dataset, since the model was generated upon the training data set. The high accuracies, confirm that the model would generalize well.

From the SQL commands we performed it was further determined that the terrorist group which performed the highest amount of terrorist attacks in the United States was the Anti-Abortion Activists, with a total of 124 terrorist attack from 1970 to 2015 (Appendix B).

The following are the data visualizations processed through our data:

Figure 5: Frequency of Successful Single-target Attacks by Each Group.



We then created a Python program that, after reading the original spreadsheet, would create a new CSV file that had the names of all terrorist groups in one column and the number of successful attacks they committed in the other (Refer to: Appendix B - Total Number of Attacks by all the Terrorist Groups between 1970 & 2015). Using this we created Figure 6.

Figure 6: Number of Successful Single-Target Attacks committed by Each Group from 1970-2015

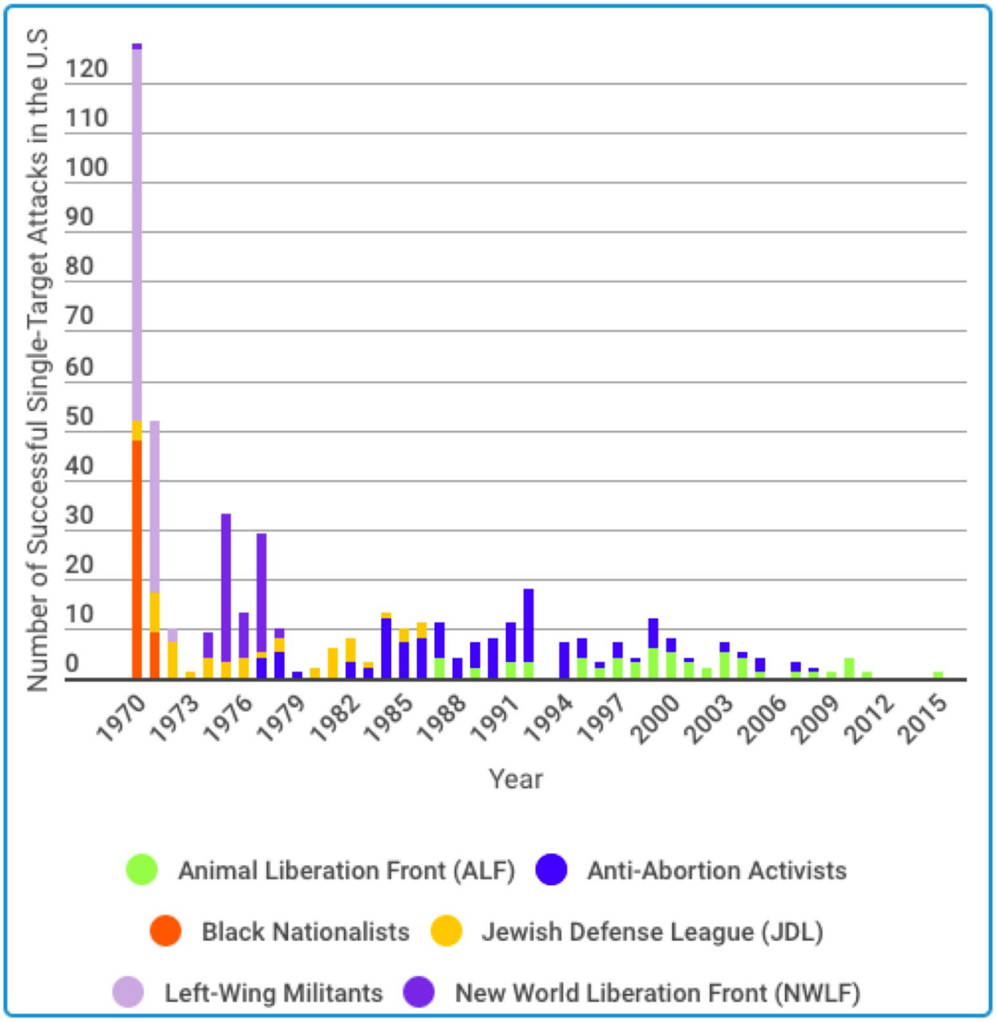
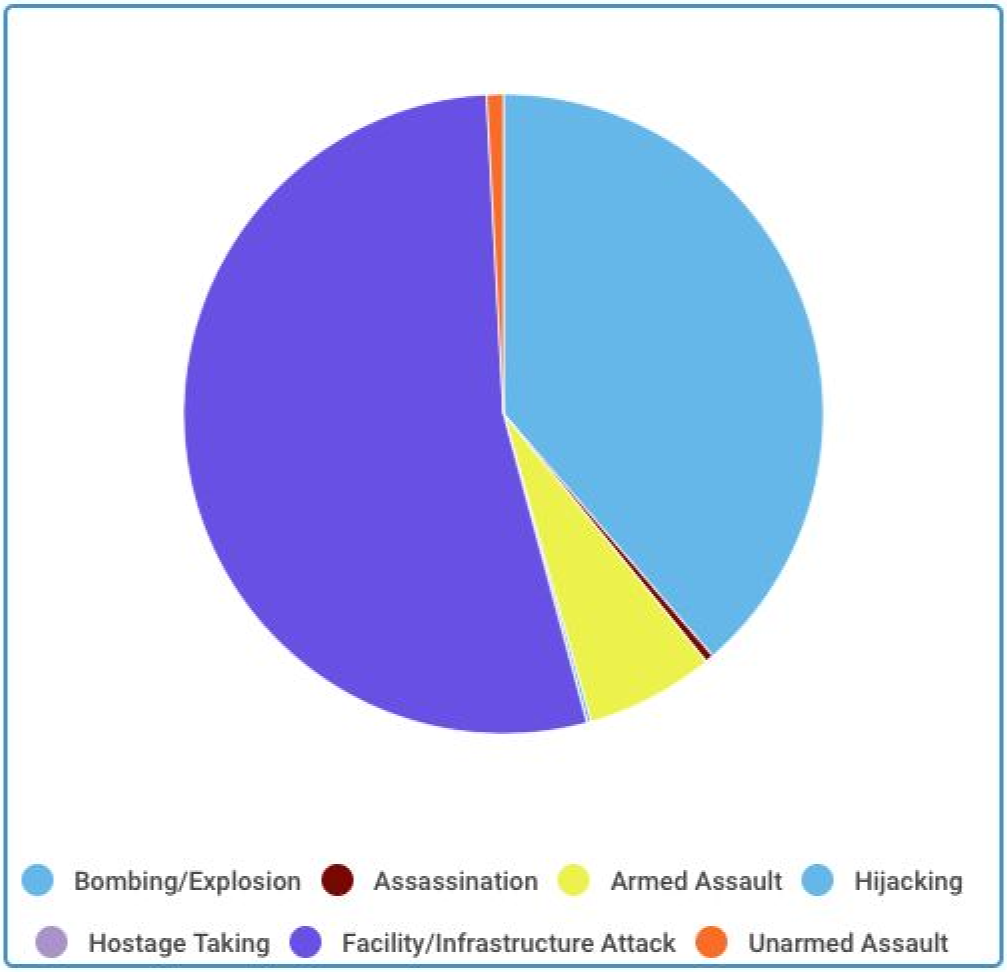


Figure 7: Showcases frequency of different types of attacks from 1970-2015



Relational Table 1: Number of Attacks per Group

Group Name	Number of Successful Attacks
Animal Liberation Front (ALF)	57
Anti-Abortion Activists	124
Black Nationalists	57
Jewish Defense League (JDL)	56
Left-Wing Militants	113
New World Liberation Front (NWLF)	71

Relational Table 2: Number of Attacks by each group from 1970-2015

Year	ALF	Anti-Abortion Activists	Black Nationalists	JDL	Left-Wing Militants	NWLF
1970	0	0	48	4	75	1
1971	0	0	9	8	35	0
1972	0	0	0	7	3	0
1973	0	0	0	1	0	0
1974	0	0	0	4	0	5
1975	0	0	0	3	0	30
1976	0	0	0	4	0	9
1977	0	4	0	1	0	24
1978	0	5	0	3	0	2
1979	0	1	0	0	0	0
1980	0	0	0	2	0	0

1981	0	0	0	6	0	0
1982	0	3	0	5	0	0
1983	0	2	0	1	0	0
1984	0	12	0	1	0	0
1985	0	7	0	3	0	0
1986	0	8	0	3	0	0
1987	4	7	0	0	0	0
1988	0	4	0	0	0	0
1989	2	5	0	0	0	0
1990	0	8	0	0	0	0
1991	3	8	0	0	0	0
1992	3	15	0	0	0	0
1993	0	0	0	0	0	0
1994	0	7	0	0	0	0
1995	4	4	0	0	0	0
1996	2	1	0	0	0	0
1997	4	3	0	0	0	0
1998	3	1	0	0	0	0
1999	6	6	0	0	0	0
2000	5	3	0	0	0	0
2001	3	1	0	0	0	0
2002	2	0	0	0	0	0
2003	5	2	0	0	0	0
2004	4	1	0	0	0	0

2005	1	3	0	0	0	0
2006	0	0	0	0	0	0
2007	1	2	0	0	0	0
2008	1	1	0	0	0	0
2009	1	0	0	0	0	0
2010	4	0	0	0	0	0
2011	1	0	0	0	0	0
2012	0	0	0	0	0	0
2013	0	0	0	0	0	0
2014	0	0	0	0	0	0
2015	1	0	0	0	0	0

Relational Table 3: Frequency of Types of Attacks from 1970-2015

Attack Type	Occurrence
Bombing/Explosion	184
Assassination	2
Armed Assault	31
Hijacking	1
Hostage Taking	0
Facility/Infrastructure Attack	254
Unarmed Assault	4

Conclusion

The goal of this report was to create a model which would be able to predict the name of a terrorist group, based on the year, city of attack, type of attack, target of attack, and weapon type in the United States. The data was collected from the University of Maryland's Study of Terrorism and Responses to Terrorism (START) Global Terrorism Database. From this original dataset, we modified the original dataset to include only six attributes, five of which would be able to predict the name of the terrorist group. The preprocessing was conducted using Python programming. The data mining performed was through the WEKA data mining software. Preparation for the data mining involved, narrowing entries down for solely the United States, and removing unnecessary attributes. The dataset uploaded onto WEKA was randomized, then was split into a training subset (80%) and a test subset (20%). We proceeded to use the Logistic Model Tree Algorithm, to create our model. Our model produced a high accuracy on our test data of 81.98%.

The goal of this report was to conduct regression tree analysis on Boston Marathon finish times. The data was collected from the Boston Athletic Association's Boston Marathon Race Results database. From the original dataset, I created two datasets: one for use in data mining, and another for use in pacing analysis. The preprocessing was conducted using Python programming, and the data mining used the Weka data mining software. Preparation for data mining required the conversion of the nominal attributes into numeric values. Additionally, I randomized and split the data into a training subset (80% of instances) and a test subset (20% of instances). I chose to use the M5P regression algorithm to predict overall finish times. The results of the regression tree generates a model which shows several important patterns within the data. From this model, we see the large influences of gender, age, temperature, and the differing effects of particular countries (most notably the large negative correlations of Kenya and Ethiopia). From the pacing analysis, we see a range of differences between the pacing behaviors of the top runners between the year 2011 and year 2012 races. Many of these differences are likely due to the large temperature differences between the races. For future work, it may be valuable to run a similar regression tree analysis with the addition of time splits. For example, which independent 5km time split is the most influential in predicting the overall finish time?

Appendices:

Appendix A- Pre-Processing to produce a dataset with the relevant attributes, focused for the United States, on single targets, & successful terror attacks.

```
import sqlite3
file_name = input('What is the file name?: ')
infile = open(file_name, 'r')
db = sqlite3.connect(file_name)
cursor = db.cursor()

results_file = input('What is the results file name?:')**
outfile = open(results_file, 'w')

command = '''   SELECT iyear, attacktype1_txt,  targtype1_txt, gname, weapons_txt
            FROM i_GTD   *
            WHERE country_txt= 'United States' AND multiple = 0 AND success = 1 '''

cursor.execute(command)

count = 0
for row in cursor:
   print(row, file = outfile)
   count = count +1

db.commit()
db.close()
outfile.close()
```

* We renamed the original START Database from globalterrorismdb_0616dist to i_GTD. This is the *initial* dataset without pre-processing.
** GTD_FINAL is the value assigned for results_file and is the new database *after* pre-processing.

Appendix B- Total Number of Attacks by all the Terrorist Groups between 1970 & 2015

```
import sqlite3
file_name = input('What is the file name?: ')
infile = open(file_name, 'r')
db = sqlite3.connect(file_name)
cursor = db.cursor()

results_file = input('What is the results file name?:')
outfile = open(results_file, 'w')

command = '''   SELECT gname, COUNT(*)
            FROM GTD_FINAL
            GROUP BY gname;'''

cursor.execute(command)

count = 0
for row in cursor:
   print(row, file = outfile)
   count = count +1

db.commit()
db.close()
outfile.close()
```

Appendix C- Program using user input for year, attack_type, target_type & weapon_type to produce name/s of terrorist group/s corresponding to the inputs

```
import sqlite3
file_name = input('What is the file name?: ')
infile = open(file_name, 'r')
db = sqlite3.connect(file_name)
cursor = db.cursor()

results_file = input('What is the results file name?:')
outfile = open(results_file, 'w')
```

```
target_year= int(input("Select the year in which the attack took place? "))
target_attack = input("What type of an attack took place? ")
target_targ = input("What was the target attacked? ")
target_weapon = input ("What was the weapon used in this attack?")

command = '''  SELECT gname
            FROM GTD_FINAL
            WHERE iyear= ? AND attacktype1_txt = ? AND targtype1_txt = ? AND
weaptype1_txt = ? ; '''

cursor.execute(command, [target_year, target_attack, target_targ, target_weapon] )

count = 0
for row in cursor:
   print(row, file = outfile)
   count = count +1

db.commit()
db.close()
outfile.close()
```

Appendix D- Time Period When Terror Groups Were Most Active

```
import sqlite3
file_name = input('What is the file name?: ')
infile = open(file_name, 'r')
db = sqlite3.connect(file_name)
cursor = db.cursor()

results_file = input('What is the results file name?:')
outfile = open(results_file, 'w')

command = '''SELECT gname, iyear, COUNT(*)
FROM GTD_FINAL
WHERE country_txt = 'United States'
AND success = 1
AND multiple = 0
GROUP BY gname, iyear ;'''
```

```
cursor.execute(command)

count = 0
for row in cursor:
    print(row, file = outfile)
    count = count +1

db.commit()
db.close()
outfile.close()
```

Appendix E - SQL Code to Determine Frequency of Attack Type

```
SELECT *
FROM GTD_FINAL
WHERE attacktype1_txt LIKE 'Unarmed%' ;
```

Appendix F- Decision Tree Created Using J48 Tree Algorithm:

```
iyear <= 1972
|   targtype1_txt = Educational Institution: Black Nationalists (3.0/1.0)
|   targtype1_txt = Business: Left-Wing Militants (22.0/8.0)
|   targtype1_txt = Government (General): Left-Wing Militants (38.0/2.0)
|   targtype1_txt = Private Citizens & Property
|   |   iyear <= 1970: Left-Wing Militants (4.0/1.0)
|   |   iyear > 1970: Jewish Defense League (JDL) (4.0/1.0)
|   targtype1_txt = Abortion Related: Left-Wing Militants (0.0)
|   targtype1_txt = Police: Black Nationalists (33.0/4.0)
|   targtype1_txt = Transportation: Left-Wing Militants (0.0)
|   targtype1_txt = Religious Figures/Institutions: Black Nationalists (3.0)
|   targtype1_txt = Other: Black Nationalists (1.0)
|   targtype1_txt = NGO: Black Nationalists (3.0)
|   targtype1_txt = Airports & Aircraft: Jewish Defense League (JDL) (1.0)
|   targtype1_txt = Tourists: Left-Wing Militants (0.0)
|   targtype1_txt = Government (Diplomatic): Jewish Defense League (JDL) (3.0)
|   targtype1_txt = Journalists & Media: Left-Wing Militants (0.0)
|   targtype1_txt = Military: Left-Wing Militants (32.0)
|   targtype1_txt = Utilities: Left-Wing Militants (3.0/1.0)
```

```
|   targtype1_txt = Unknown: Left-Wing Militants (0.0)
iyear > 1972
|   targtype1_txt = Educational Institution: Animal Liberation Front (ALF) (4.0)
|   targtype1_txt = Business
|   |   iyear <= 1986
|   |   |   iyear <= 1977: New World Liberation Front (NWLF) (22.0/1.0)
|   |   |   iyear > 1977: Jewish Defense League (JDL) (9.0)
|   |   iyear > 1986: Animal Liberation Front (ALF) (35.0)
|   targtype1_txt = Government (General)
|   |   attacktype1_txt = Facility/Infrastructure Attack: Animal Liberation Front (ALF)
(4.0/1.0)
|   |   attacktype1_txt = Bombing/Explosion: New World Liberation Front (NWLF) (4.0)
|   |   attacktype1_txt = Unarmed Assault: New World Liberation Front (NWLF) (0.0)
|   |   attacktype1_txt = Armed Assault: New World Liberation Front (NWLF) (0.0)
|   |   attacktype1_txt = Unknown: Jewish Defense League (JDL) (1.0)
|   |   attacktype1_txt = Assassination: New World Liberation Front (NWLF) (0.0)
|   |   attacktype1_txt = Hijacking: New World Liberation Front (NWLF) (0.0)
|   targtype1_txt = Private Citizens & Property
|   |   weaptype1_txt = Incendiary: Jewish Defense League (JDL) (3.0)
|   |   weaptype1_txt = Explosives/Bombs/Dynamite
|   |   |   iyear <= 1989: New World Liberation Front (NWLF) (7.0)
|   |   |   iyear > 1989: Animal Liberation Front (ALF) (2.0)
|   |   weaptype1_txt = Fake Weapons: Animal Liberation Front (ALF) (1.0)
|   |   weaptype1_txt = Melee: Animal Liberation Front (ALF) (1.0)
|   |   weaptype1_txt = Sabotage Equipment: New World Liberation Front (NWLF) (0.0)
|   |   weaptype1_txt = Firearms: Jewish Defense League (JDL) (1.0)
|   |   weaptype1_txt = Unknown: New World Liberation Front (NWLF) (0.0)
|   |   weaptype1_txt = Other: New World Liberation Front (NWLF) (0.0)
|   |   weaptype1_txt = Chemical: New World Liberation Front (NWLF) (0.0)
|   targtype1_txt = Abortion Related: Anti-Abortion Activists (96.0)
|   targtype1_txt = Police: New World Liberation Front (NWLF) (3.0/1.0)
|   targtype1_txt = Transportation: Anti-Abortion Activists (0.0)
|   targtype1_txt = Religious Figures/Institutions: Jewish Defense League (JDL) (1.0)
|   targtype1_txt = Other: Anti-Abortion Activists (0.0)
|   targtype1_txt = NGO: New World Liberation Front (NWLF) (1.0)
|   targtype1_txt = Airports & Aircraft: Jewish Defense League (JDL) (2.0)
|   targtype1_txt = Tourists: Anti-Abortion Activists (0.0)
|   targtype1_txt = Government (Diplomatic): Jewish Defense League (JDL) (10.0/2.0)
|   targtype1_txt = Journalists & Media: Jewish Defense League (JDL) (3.0/1.0)
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| targtype1_txt = Military: New World Liberation Front (NWLF) (1.0)
| targtype1_txt = Utilities: New World Liberation Front (NWLF) (21.0)
| targtype1_txt = Unknown: Anti-Abortion Activists (0.0)

Number of Leaves :   52

Size of the tree :   61

Time taken to build model: 0.02 seconds