

# AndrewEaton\_GTDChallenge

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## 1 This purpose of this notebook is to predict what terrorist group may have been responsible for a terrorist attack using the Global Terrorism Database.

This will be a multinomial classification problem. We will predict the terrorist group using the following statistical methods:

- Logistic Regression
- K Nearest Neighbors
- Random Forests

We will start off using train, test, split to narrow down which model is the best and then switch to cross validation.

Let's first import the data.

```
In [1]: import pandas as pd
import numpy as np

df = pd.read_excel(r'/Users/eatonaw/Downloads/globalterrorismdb_0617dist.xlsx')
df.head()
```

```
Out[1]:
```

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	\
0	197000000001	1970	7	2	NaN	0	NaT	58	
1	197000000002	1970	0	0	NaN	0	NaT	130	
2	197001000001	1970	1	0	NaN	0	NaT	160	
3	197001000002	1970	1	0	NaN	0	NaT	78	
4	197001000003	1970	1	0	NaN	0	NaT	101	

	country_txt	region	...	addnotes	scite1	scite2	scite3	\
0	Dominican Republic	2	...	NaN	NaN	NaN	NaN	
1	Mexico	1	...	NaN	NaN	NaN	NaN	
2	Philippines	5	...	NaN	NaN	NaN	NaN	
3	Greece	8	...	NaN	NaN	NaN	NaN	
4	Japan	4	...	NaN	NaN	NaN	NaN	

dbsource	INT_LOG	INT_IDEO	INT_MISC	INT_ANY	related
----------	---------	----------	----------	---------	---------

0	PGIS	0	0	0	0	NaN
1	PGIS	0	1	1	1	NaN
2	PGIS	-9	-9	1	1	NaN
3	PGIS	-9	-9	1	1	NaN
4	PGIS	-9	-9	1	1	NaN

[5 rows x 135 columns]

**Let's examine the shape, column names, and column types from the data.**

```
In [2]: print(df.shape)
        print(df.columns)
        print(df.dtypes)

(170350, 135)
Index(['eventid', 'iyear', 'imonth', 'iday', 'approxdate', 'extended',
      'resolution', 'country', 'country_txt', 'region',
      ...,
      'addnotes', 'scite1', 'scite2', 'scite3', 'dbsource', 'INT_LOG',
      'INT_IDEO', 'INT_MISC', 'INT_ANY', 'related'],
      dtype='object', length=135)
eventid          int64
iyear            int64
imonth           int64
iday             int64
approxdate       object
extended         int64
resolution       datetime64[ns]
country          int64
country_txt      object
region           int64
region_txt       object
provstate        object
city             object
latitude         float64
longitude        float64
specificity      float64
vicinity         int64
location         object
summary          object
crit1            int64
crit2            int64
crit3            int64
doubtterr        int64
alternative      float64
alternative_txt  object
multiple         int64
success          int64
```

```

suicide                int64
attacktype1            int64
attacktype1_txt        object
...
propextent             float64
propextent_txt         object
propvalue              float64
propcomment            object
ishostkid              float64
nhostkid               float64
nhostkidus             float64
nhours                 float64
ndays                  float64
divert                 object
kidhijcountry          object
ransom                 float64
ransomamt              float64
ransomamtus            float64
ransompaid             float64
ransompaidus           float64
ransomnote             object
hostkidoutcome         float64
hostkidoutcome_txt     object
nreleased              float64
addnotes               object
scite1                 object
scite2                 object
scite3                 object
dbsource               object
INT_LOG                int64
INT_IDEO                int64
INT_MISC                int64
INT_ANY                 int64
related                object
Length: 135, dtype: object

```

Let's start to examine any correlations that may be present between different columns.

```

In [3]: import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

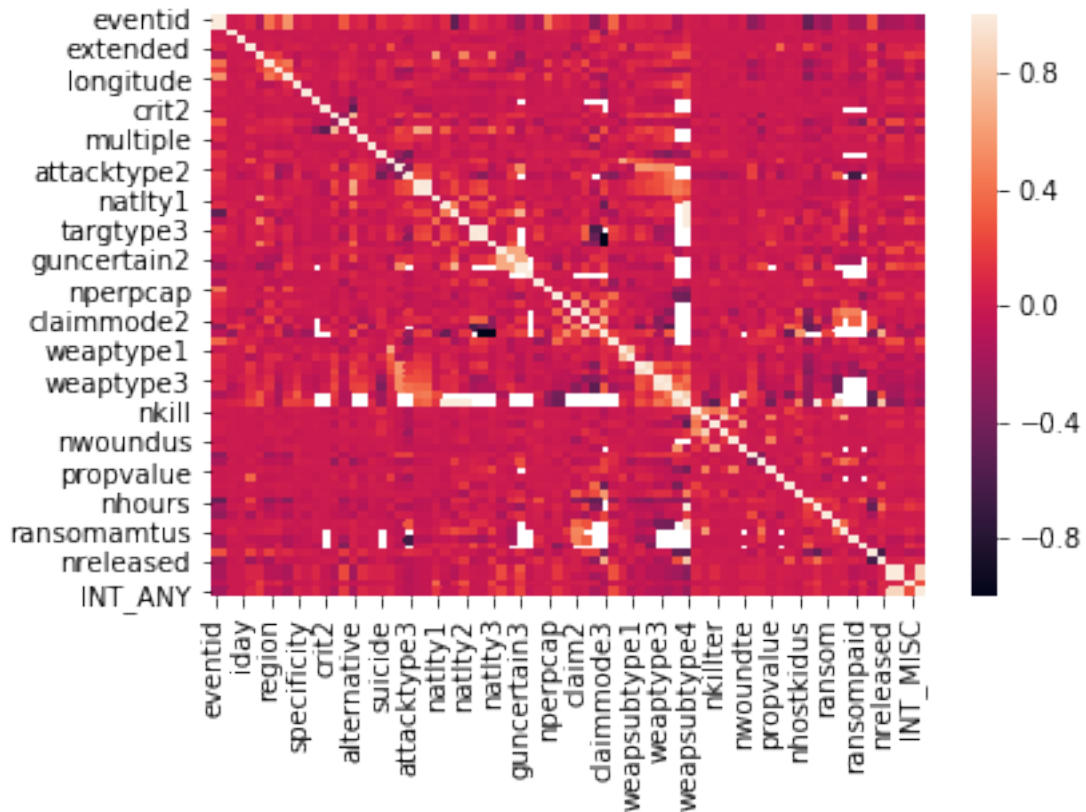
corr = df.corr()
sns.heatmap(corr)

```

```

Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x126c0e6d8>

```



Let's examine the data more closely by looking at the value counts for the target variable we are interested in (gname).

```
In [4]: print(df.gname.value_counts())
```

Unknown	78306
Taliban	6575
Shining Path (SL)	4551
Islamic State of Iraq and the Levant (ISIL)	4287
Farabundo Marti National Liberation Front (FMLN)	3351
Al-Shabaab	2683
Irish Republican Army (IRA)	2669
Revolutionary Armed Forces of Colombia (FARC)	2481
New People's Army (NPA)	2414
Kurdistan Workers' Party (PKK)	2152
Boko Haram	2077
Basque Fatherland and Freedom (ETA)	2024
Communist Party of India - Maoist (CPI-Maoist)	1766
Liberation Tigers of Tamil Eelam (LTTE)	1606
National Liberation Army of Colombia (ELN)	1483
Maoists	1424

Tehrik-i-Taliban Pakistan (TTP)	1252
Palestinians	1124
Al-Qaida in the Arabian Peninsula (AQAP)	975
Nicaraguan Democratic Force (FDN)	895
Houthi extremists (Ansar Allah)	893
Manuel Rodriguez Patriotic Front (FPMR)	830
Sikh Extremists	714
Corsican National Liberation Front (FLNC)	639
Al-Qaida in Iraq	636
Donetsk People's Republic	614
African National Congress (South Africa)	607
Separatists	571
Muslim extremists	561
Tupac Amaru Revolutionary Movement (MRTA)	557
...	
Bangsamoro National Liberation Army	1
Mouhajiroune Brigade	1
Grupo Armado de Liberacion Argentina (GALA)	1
Opponents of Regime	1
God our Father Cult	1
Dashmesh Regiment	1
Pakistan Muslim League (PML)	1
Separatist Clandestine Organization	1
Politico-Military Revolutionary Command	1
Al-Sawaiq Brigade	1
Mozambique Rightest Rebels	1
Extreme Right Commando Brigade	1
Al-Sunni muslim sect	1
French Armed Islamic Front	1
Martyrs of Saad Sayel	1
Organization Alliance of Cuban Intransigence	1
Robin Garcia Student Front	1
The Nation's Army	1
Los Rastrojos (Colombia)	1
The Great Serpent	1
Commander Gonzalo Southern Group	1
Isatabu Freedom Movement (IFM)	1
Front of French National Liberation	1
Al-Fateh Al-Jadid	1
Latvian Republic Volunteer Troops	1
Arakan Rohingya Islamic Front	1
Anti-Imperialist Commando	1
Pemuda Pancasila	1
Kabataang Makabayan (KM)	1
Free Nasserite Revolutionaries	1
Name: gname, Length: 3454, dtype: int64	

As we can see, the gnames (our target) column contains a lot of unknowns and terrorist organizations that only committed one attack. It is not extremely useful to predict an unknown terrorist organization and we need to have sufficient sample sizes ( $n > 100$  attacks). We will create a new data frame that contains a subset of the data.

```
In [5]: df2 = df[(df.gname != 'Unknown')]
        df2 = df2.groupby("gname").filter(lambda x: len(x) >= 100)
        print(df2.gname.value_counts())
        df2.shape
```

Taliban	6575
Shining Path (SL)	4551
Islamic State of Iraq and the Levant (ISIL)	4287
Farabundo Marti National Liberation Front (FMLN)	3351
Al-Shabaab	2683
Irish Republican Army (IRA)	2669
Revolutionary Armed Forces of Colombia (FARC)	2481
New People's Army (NPA)	2414
Kurdistan Workers' Party (PKK)	2152
Boko Haram	2077
Basque Fatherland and Freedom (ETA)	2024
Communist Party of India - Maoist (CPI-Maoist)	1766
Liberation Tigers of Tamil Eelam (LTTE)	1606
National Liberation Army of Colombia (ELN)	1483
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Sikh Extremists	714
Corsican National Liberation Front (FLNC)	639
Al-Qaida in Iraq	636
Donetsk People's Republic	614
African National Congress (South Africa)	607
Separatists	571
Muslim extremists	561
Tupac Amaru Revolutionary Movement (MRTA)	557
M-19 (Movement of April 19)	555
...	
Khmer Rouge	160
Baloch Liberation Front (BLF)	160
Garo National Liberation Army	158
Hizbul Mujahideen (HM)	157
Guerrilla Army of the Poor (EGP)	157
Lashkar-e-Taiba (LeT)	156
Islamic Salvation Front (FIS)	153
Popular Front for the Liberation of Palestine (PFLP)	151

Barqa Province of the Islamic State	147
Runda Kumpulan Kecil (RKK)	146
Islamic State of Iraq (ISI)	145
Democratic Revolutionary Alliance (ARDE)	141
Tribesmen	131
Guatemalan National Revolutionary Unity (URNG)	131
Corsican National Liberation Front- Historic Channel	128
Left-Wing Guerrillas	127
Muslim Brotherhood	125
Irish National Liberation Army (INLA)	124
Lashkar-e-Jhangvi	122
Fuerzas Armadas de Liberacion Nacional (FALN)	120
Lashkar-e-Islam (Pakistan)	118
Revolutionary Organization of People in Arms (ORPA)	117
Animal Liberation Front (ALF)	116
Montoneros (Argentina)	116
Free Aceh Movement (GAM)	116
November 17 Revolutionary Organization (N17RO)	112
Mujahedin-e Khalq (MEK)	112
Free Syrian Army	112
The Extraditables	109
United Popular Action Movement	109

Name: gname, Length: 117, dtype: int64

**Out [5]:** (72171, 135)

We have now organized our data frame to not include the unknown terrorist groups and only include terrorist groups that have orchestrated over 100 attacks. Let's see what our null accuracy is:

There are 72,171 cases and the Taliban (group with most attacks) committed 6,575 of these attacks. Therefore, if we divide 72,171 by 6,575, we will get our null accuracy: 10.98%

Let's examine some of the features more carefully. Thankfully, a lot of them are already mapped as integers which is necessary for using scikit learn. The features I have decided I am interested in are: iyear, imonth, country, region, suicide, attacktype1, targtype1, weaptype1, and random. Let's see if any of these have null values.

```
In [6]: print(df2.iyear.isnull().sum())
        print(df2.imonth.isnull().sum())
        print(df2.country.isnull().sum())
        print(df2.region.isnull().sum())
        print(df2.suicide.isnull().sum())
        print(df2.attacktype1.isnull().sum())
        print(df2.targtype1.isnull().sum())
        print(df2.weaptype1.isnull().sum())
        print(df2.ransom.isnull().sum())
```

```
0
0
0
0
0
0
0
0
0
0
33774
```

**Ransom is the only feature that has any null values. Let's fill the null values with 0s.**

```
In [7]: df2.ransom.fillna(0, inplace = True)
        df2.ransom.isnull().sum()
```

```
Out[7]: 0
```

**Let's set up the data in a format recognizable by scikit learn so we can begin testing different models.**

```
In [8]: from sklearn.model_selection import train_test_split
        X = df2[['iyear', 'imonth', 'country', 'region', 'suicide',\
                  'attacktype1', 'targettype1', 'weaptype1', 'ransom']]
        y = df2.gname
        print(X.shape)
        print(y.shape)

        X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42)

(72171, 9)
(72171,)
```

**Let's start with logistic regression in its default state and use accuracy score to evaluate it.**

```
In [9]: from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import accuracy_score

        logreg = LogisticRegression()
        logreg.fit(X_train, y_train)
        y_pred = logreg.predict(X_test)
        accuracy = accuracy_score(y_pred, y_test)
        print(accuracy)

0.473535443108
```

**Our accuracy is 47%, which is an improvement over the null accuracy.**



Let's now try to use the k-nearest neighbors classifier using its default hyperparameters.

```
In [10]: from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(accuracy_score(y_test, y_pred))
```

```
0.801141717009
```

Our accuracy score is now 80%, which is a strong improvement over using a logistic regression.

Let's next look at random forests, which is an ensemble of decision trees, using its default hyperparameters.

```
In [11]: from sklearn.ensemble import RandomForestClassifier
```

```
clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print(accuracy_score(y_test, y_pred))
```

```
0.830903951671
```

Random forests give us an accuracy score of around 83%. This is the best model so far, when just looking at the default hyperparameters.

We can try to improve upon all of our models through a randomized cross-validation search of tuning the hyperparameters. This is computationally expensive, but I will provide the code for how it would be run.

```
In [ ]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [ ]: param_dist = {'penalty' : ['l1', 'l2'],
                      'C' : np.arange(.00001, 1, .00001)}
```

```
random_search = RandomizedSearchCV(logreg,\
    param_distributions = param_dist, n_iter = 30)
```

```
random_search.fit(X, y)
print(random_search.best_params_)
```

```
In [ ]: param_dist = {'n_neighbors' : range(0, 300, 5)}
```

```
random_search = RandomizedSearchCV(knn,\
    param_distributions = param_dist, n_iter = 10)
```

```

random_search.fit(X, y)
print(random_search.best_params_)

In [ ]: param_dist = {'n_estimators' : range(1, 350, 10),
                      'max_features' : range(1, 10, )}

random_search = RandomizedSearchCV(clf,\
    param_distributions = param_dist, n_iter = 10)

random_search.fit(X, y)
print(random_search.best_params_)

```

Another technique we could use to improve our models is ensembling. Bagging is a powerful tool that can improve classifiers. However, it will not have much of an effect on random forests, since random forests are produced from bagging decision trees.

Bagging is computationally expensive, but I will provide the code for how it could be carried out for logistic regression and k-nearest neighbors.

```

In [ ]: from sklearn.ensemble import BaggingClassifier

logreg = LogisticRegression()
bag = BaggingClassifier(base_estimator = logreg,\
    n_estimators = 5, max_samples = 0.5)
bag.fit(X_train, y_train)
y_pred = bag.predict(X_test)
print(accuracy_score(y_pred, y_test))

In [ ]: knn = KNeighborsClassifier()
bag = BaggingClassifier(base_estimator = knn,\
    n_estimators = 5, max_samples = 0.5)
bag.fit(X_train, y_train)
y_pred = bag.predict(X_test)

```