This project analyzes contributing factors to terrorist acts from 1970 to 2016. The modeling segment assesses accuracy of four mainstream classifiers, KNeighbors, GaussianNB, Random Forest and Gradient Boost, when predicting the organization associated with a unique act of terrorism.

Preparation

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns; sns.set(style="darkgrid")
import numpy as np
from sklearn import preprocessing
from sklearn.preprocessing import scale, robust_scale
from sklearn import tree
import plotly
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.model_selection import train_test_split, cross_val_predict, cross_val_score,
GridSearchCV, KFold, LeaveOneOut
from sklearn.metrics import accuracy_score, confusion_matrix, silhouette_score
```

Load data

In [2]:

```
terror_df = pd.read_csv('globalterrorismdb_0617dist.csv', usecols=['iyear', 'imonth', 'iday', 'coun
try_txt',
                     'region_txt', 'city', 'attacktype1_txt', 'success', 'suicide',
'targsubtype1_txt',
                    'target1', 'natlty1_txt', 'gname', 'individual', 'claimed', 'weaptype1_txt',
                    'nkill', 'nkillus', 'INT_ANY'])
terror_df.columns = ['year', 'month', 'day', 'country',
                     'region', 'city', 'suicide', 'success', 'attack_type', 'target_subtype',
                     'target_type', 'target_nationality', 'group', 'individual', 'claimed',
'weapon',
                     'fatalities', 'us_fatalities', 'international']
terror_df = terror_df[terror_df.group != 'Unknown']
```

In [3]:

```
terror_df.head(3)
```

Out[3]:

	year	month	day	country	region	city	suicide	success	attack_type	target_subtype	target_type	target_n
0	1970	7	2	Dominican Republic	Central America & Caribbean	Santo Domingo	1	0	Assassination	Named Civilian	Julio Guzman	Dominica Republic
1	1970	0	0	Mexico	North America	Mexico city	1	0	Hostage Taking (Kidnapping)	Diplomatic Personnel (outside of embassy, cons...	Nadine Chaval, daughter	Belgium
5	1970	1	1	United States	North America	Cairo	1	0	Armed Assault	Police Building (headquarters, station, school)	Cairo Police Headquarters	United S

Define function to join date and time columns

In [4]:

```
def datemerge(years, months=1, days=1, weeks=None, hours=None, minutes=None,
              seconds=None, milliseconds=None, microseconds=None, nanoseconds=None):
    years = np.asarray(years) - 1970
    months = np.asarray(months) - 1
    days = np.asarray(days) - 1
    types = ('<M8[Y]', '<m8[M]', '<m8[D]', '<m8[W]', '<m8[h]',
             '<m8[m]', '<m8[s]', '<m8[ms]', '<m8[us]', '<m8[ns]')
    vals = (years, months, days, weeks, hours, minutes, seconds,
            milliseconds, microseconds, nanoseconds)
    return sum(np.asarray(v, dtype=t) for t, v in zip(types, vals)
               if v is not None)
```

Pass datemerge function to new date column, convert to datetime index and drop rows with any missing values

In [5]:

```
terror_df['date'] = datemerge(terror_df['year'], terror_df['month'], terror_df['day'])
terror_df['date'] = pd.to_datetime(terror_df['date'])
terror_df.index = terror_df.date
terror_df.sort_index(inplace=True)
terror_df = terror_df.dropna(how='any')
```

Exploratory Analysis

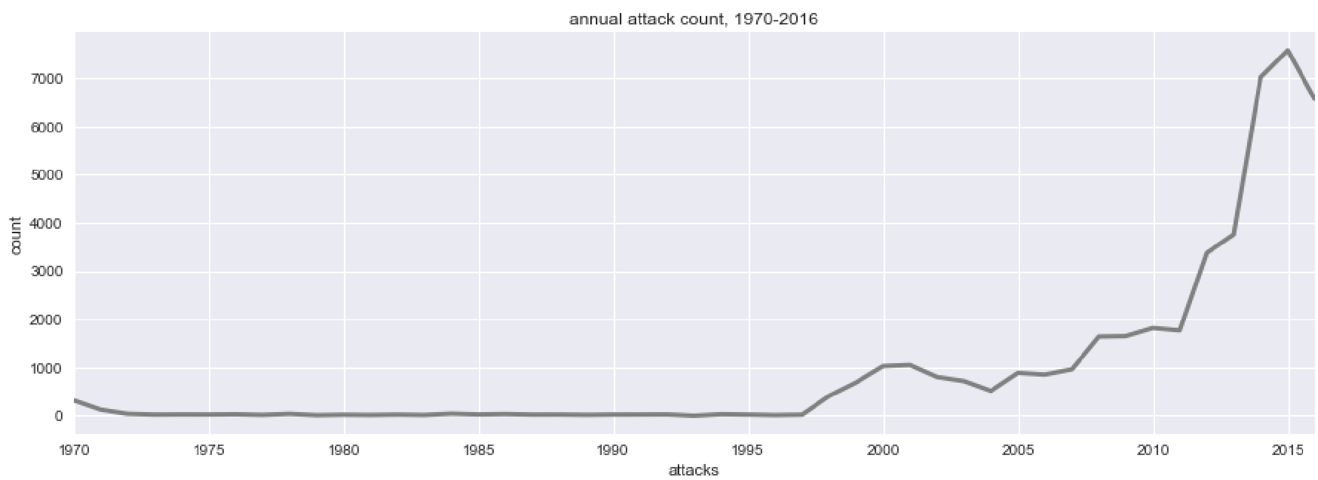
In [6]:

```
# attack count resample by month, 1970-2016
attack_count = terror_df.attack_type.resample('A').count()
```

Plot time series illustrating terrorism frequency, 1970 to 2016; uptick in frequency appears between 1995 and 2000

In [7]:

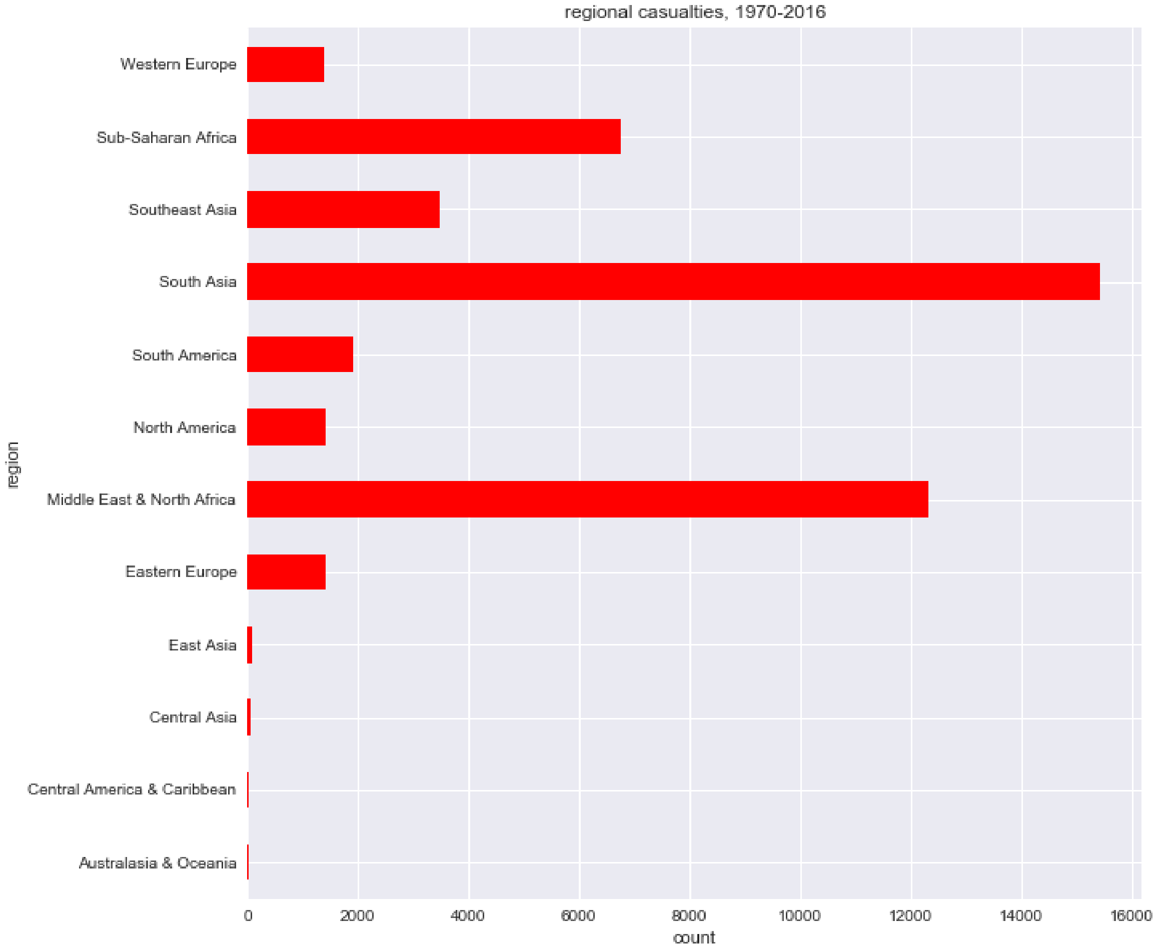
```
plt.figure(figsize=(15,5))
attack_count.plot(color='grey', linewidth=3)
plt.title('annual attack count, 1970-2016')
plt.ylabel('count')
plt.xlabel('attacks')
plt.show()
```



Horizontal barchart illustrating total fatalities by region, 1970 to 2016; South Asia and MENA show highest incidence rates regionally

In [9]:

```
region_count = terror_df.groupby('region')['fatalities'].count()
plt.figure(figsize=(10,10))
plt.title('regional casualties, 1970-2016')
plt.xlabel('count')
plt.ylabel('region')
region_count.plot.barh(color='red')
plt.show()
```



In [10]:

```
# top five countries with terror instances by region
country_frequency = terror_df.groupby('region').target_nationality.apply(lambda x: x.value_counts()
.nlargest(5))
country_frequency
```

Out[10]:

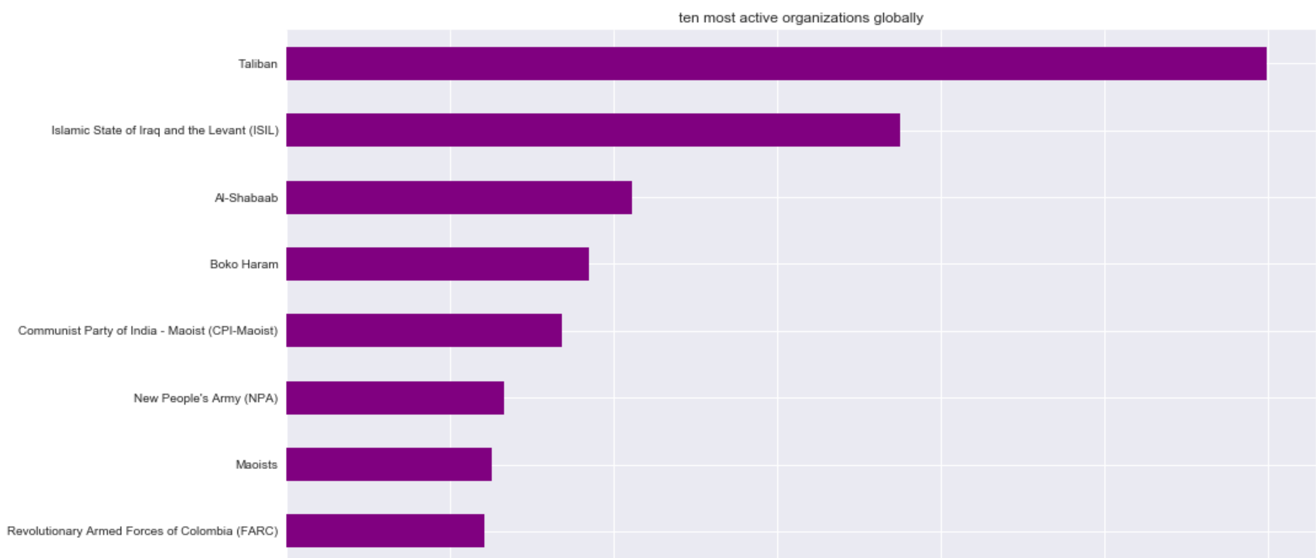
```
region
Australasia & Oceania        Australia                           10
                             Fiji                                 3
                             Solomon Islands                      3
                             United States                        2
                             New Zealand                          2
Central America & Caribbean  Haiti                                8
                             Nicaragua                            3
                             Guatemala                            3
                             Costa Rica                           1
                             Panama                               1
Central Asia                 Georgia                             18
                             Kazakhstan                           8
                             Tajikistan                           6
                             Uzbekistan                           3
                             Kyrgyzstan                           3
East Asia                    China                               48
                             Japan                               16
                             United States                        3
                             South Korea                          1
                             Taiwan                               1
```

```
Eastern Europe                Ukraine                                767
                              Russia                                 445
                              Serbia-Montenegro                       63
                              Macedonia                               51
                              Kosovo                                  15
Middle East & North Africa    Iraq                                  4218
                              Yemen                                 1765
                              Turkey                                1222
                              Israel                                1082
                              Algeria                                920
North America                 United States                         1285
                              Puerto Rico                             39
                              Mexico                                  37
                              Canada                                  20
                              Soviet Union                             6
South America                 Colombia                              1635
                              Paraguay                                57
                              Peru                                    55
                              Chile                                   37
                              United States                           34
South Asia                    Afghanistan                           5628
                              India                                 4832
                              Pakistan                              2652
                              Sri Lanka                              667
                              Nepal                                  586
Southeast Asia                Philippines                           2329
                              Thailand                               603
                              Indonesia                              284
                              Myanmar                                129
                              United States                           17
Sub-Saharan Africa            Nigeria                               2161
                              Somalia                               1535
                              International                          437
                              Democratic Republic of the Congo       395
                              Kenya                                  331
Western Europe                Northern Ireland                       338
                              Spain                                  258
                              Greece                                 205
                              France                                 167
                              Great Britain                          109
Name: target_nationality, dtype: int64
```

Horizontal barchart illustrating ten most active terror organizations globally, 1970 to 2016

In [14]:

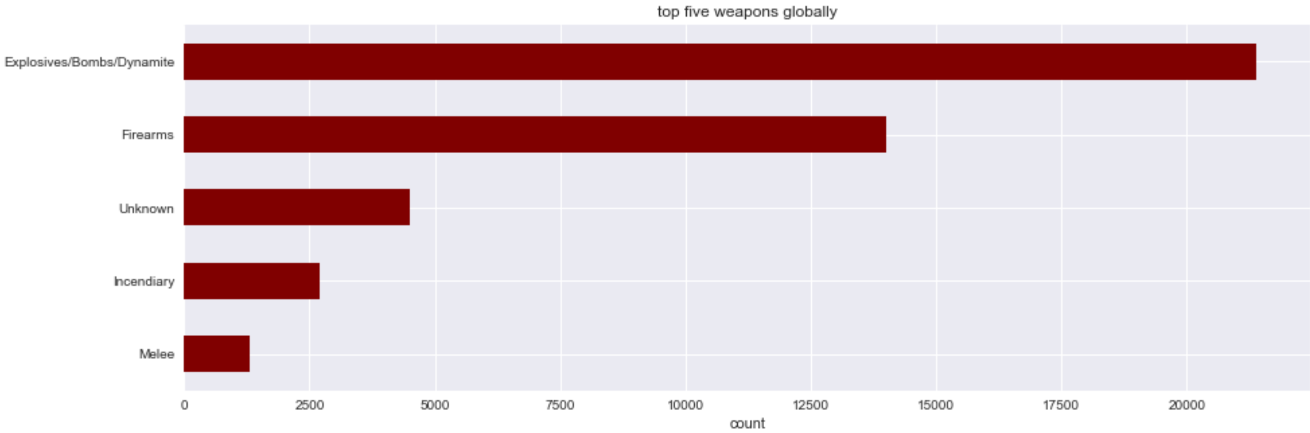
```
# top groups internationally
top_groups = terror_df['group'].value_counts().nlargest(10).sort_values()
plt.figure(figsize=(15,10))
plt.title('ten most active organizations globally')
plt.xlabel('count')
top_groups.plot.barh(color='purple')
plt.show()
```



Horizontal barchart illustrating total fatality counts per weapon types; explosives/bombs/dynamite and firearms show sweeping popularity

In [15]:

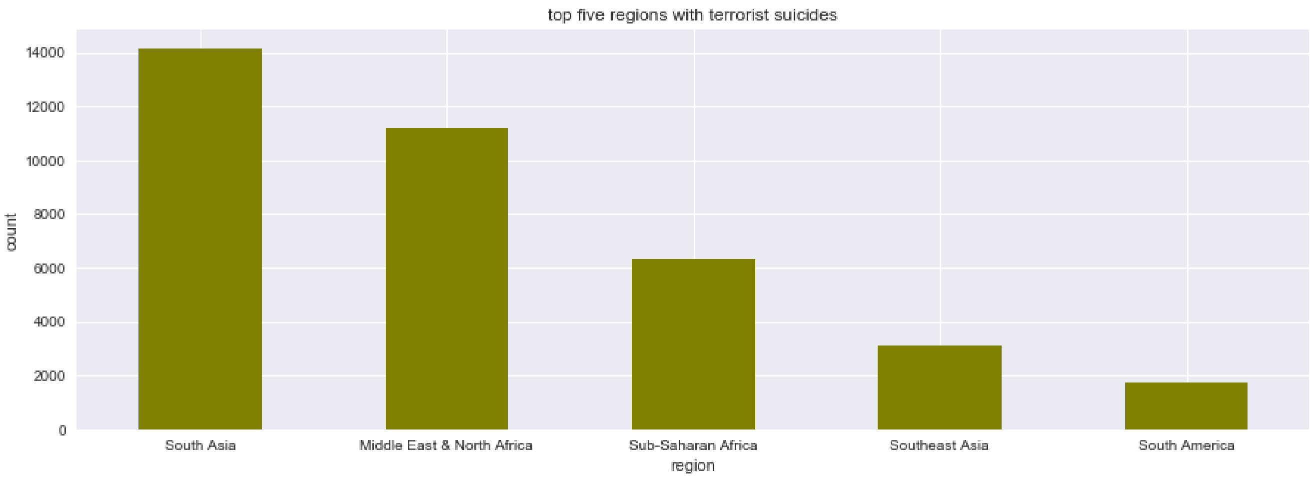
```
# top five weapons of choice globally
top_attacks = terror_df['weapon'].value_counts().nlargest(5).sort_values()
plt.figure(figsize=(15,5))
plt.title('top five weapons globally')
plt.xlabel('count')
top_attacks.plot.barh(color='maroon')
plt.show()
```



Barchart illustrating result of suicide per terrorist act regionally, 1970 to 2016; results should be considered as associated with, not replacing of, weapon of choice as shown above

In [18]:

```
# result in suicide by region
suicide_frequency = terror_df.groupby('region').suicide.sum().nlargest(5)
plt.figure(figsize=(15,5))
plt.title('top five regions with terrorist suicides')
plt.ylabel('count')
suicide_frequency.plot(kind='bar', color='olive')
plt.xticks(rotation=0)
plt.show()
```



Preprocessing

In [19]:

```
# check df shape
terror_df.shape
```

Out[19]:

```
(44198, 20)
```

Create new df for modeling purposes

In [21]:

```
model_df = terror_df[['year', 'country', 'target_type', 'attack_type', 'success', 'group']]
```

Check df data types

In [23]:

```
model_df.dtypes
```

Out[23]:

```
year            int64
country        object
target_type    object
attack_type    object
success         int64
group          object
dtype: object
```

Fit transform to Label Encoder object; assign X and y variables for train and test data

In [25]:

```
le = preprocessing.LabelEncoder()
le.fit(model_df.values.flatten())
encode_df = model_df.apply(le.fit_transform)
X = encode_df.iloc[:, :4]
y = encode_df.iloc[:, 4:5]
xtrain, xtest, ytrain, ytest = train_test_split(X, y, test_size=0.2, random_state=100)
ytrain = ytrain.values.ravel()
print 'Training', 'x:', xtrain.shape, 'y:', ytrain.shape
print 'Testing', 'x:', xtest.shape, 'y:', ytest.shape
```

```
Training x: (35358, 4) y: (35358,)
Testing x: (8840, 4) y: (8840, 1)
```

Classification & Model Evaluation

In [26]:

```
# Random Forest Classifier
rfc = RandomForestClassifier()
rfc.fit(xtrain, ytrain)
rfc_pred = rfc.predict(xtest)
print 'RFC Accuracy:', (accuracy_score(ytest, rfc_pred) * 100), '%'
```

```
RFC Accuracy: 93.32579185520362 %
```

In [27]:

```
# KNeighbors Classifier
```

```
# KNeighbors Classifier
knc = KNeighborsClassifier()
knc.fit(xtrain, ytrain)
knc_pred = knc.predict(xtest)
print 'KNC Accuracy:', (accuracy_score(ytest, knc_pred) * 100), '%'
```

```
KNC Accuracy: 92.88461538461539 %
```

In [28]:

```
# Cross Validation of KNeighbors Classifier
numlist = list(range(1,50))
neighbs = filter(lambda x: x % 2 != 0, numlist)
kn_cv_scores = []
for k in neighbs:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, xtrain, ytrain, cv=10, scoring='accuracy')
    kn_cv_scores.append(scores.mean())
print 'Cross Validation scores, KNeighbors Classifier:\n'
print kn_cv_scores
```

```
Cross Validation scores, KNeighbors Classifier:

[0.9091860294676097, 0.9254478543098574, 0.9315852123371231, 0.9342437674582825,
0.9350356786901199, 0.9350923517465773, 0.9350641432004496, 0.934102588688434,
0.9343571135711974, 0.9341026206623155, 0.9342157988398603, 0.9342157988398603, 0.933282428914634,
0.9323490589577419, 0.9318399611921121, 0.9311612361198783, 0.9303411003461297,
0.9301996336390161, 0.9301713610961834, 0.9301997296227646, 0.9302280821535623,
0.9301433205125681, 0.9304543665072691, 0.9301998895941708, 0.9303413242961461]
```

In [29]:

```
# Gradient Boosting Classifier
gbc = GradientBoostingClassifier(n_estimators=10, max_features=4)
gbc.fit(xtrain, ytrain)
gbc_pred = gbc.predict(xtest)
print 'GBC Accuracy:', round((accuracy_score(ytest, gbc_pred) * 100), 3), '%'
```

```
GBC Accuracy: 92.534 %
```

In [31]:

```
# Average KFold cross validation of Gradient Boosting Classifier
gbc_kfold = KFold(n_splits=10, random_state=7)
gbc_cv = cross_val_score(gbc, X, y.values.ravel(), cv=gbc_kfold)
print 'GBC Cross Val Mean Score:', round((gbc_cv.mean()*100), 3), '%'
```

```
GBC Cross Val Mean Score: 92.724 %
```

In [32]:

```
# Gaussian NB Classifier
gnb = GaussianNB()
gnb.fit(xtrain, ytrain)
gnb_pred = gnb.predict(xtest)
print 'GNB Accuracy:', round((accuracy_score(ytest, gnb_pred) * 100), 3), '%'
```

```
GNB Accuracy: 92.534 %
```

In [33]:

```
# KFold cross validation of Gaussian NB Classifier
gnb_kfold = KFold(n_splits=5, random_state=5)
gnb_cv = cross_val_score(gnb, X, y.values.ravel(), cv=gnb_kfold)
print 'GNB Cross Validation Mean Score:', round((gnb_cv.mean()*100), 3), '%'
```

```
GNB Cross Validation Mean Score: 92.724 %
```

Conclusions

Overall, acts of terrorism show a relatively growing popularity since the start of the twenty first century. South Asia and MENA unsurprisingly show highest incidence rates, with explosives and firearms the preferred weapons of choice. Suicide too shows highest frequencies in South Asia and MENA.

From a modeling standpoint, classification algorithms appear quick and efficient when predicting the organization of unique terror events. Equivalent accuracy scores between specific models may warrant incorporation of additional model features, an initiative which for future research would be beneficial for preemptive counter strategizing.

In [ ]:

```
```