Project 2: Global Terrorism

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Introduction

Understanding terrorism can help to drive policies and practices to help decrease the number of terroristic acts that are perpetrated throughout the world. Decreasing the amount of terrorism around the world will help to keep everyone safe and will hopefully raise the standard of living for everyone.

This project will be examining datasets examining terrorism. I will be looking to answer the following questions:

1. How does a region's instability influence the rates of terrorism?
2. Does strengthening a region's stability lower the terrorism rate of that region?
3. How can the different acts of terror be grouped together? Can anything be inferred by how the terroristic acts are grouped?
4. Does one region's terrorism cluster influence another region's cluster? Specifically, how does the terrorism cluster influence non-adjacent terrorism rates?

The first thing that I will need to do is start importing the data.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import csv
from pprint import pprint
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

In [2]:
```
coups = pd.read_excel('C:/Users/yasam/OneDrive/Documents/Grad School/DSC680 Applied Data Science/Project 2/Data/CSPCoupsAnnualv2018.xls')
displaced = pd.read_excel('C:/Users/yasam/OneDrive/Documents/Grad School/DSC680 Applied Data Science/Project 2/Data/Forcibly Displaced Popoulations 2008.xls')
fragility = pd.read_excel('C:/Users/yasam/OneDrive/Documents/Grad School/DSC680 Applied Data Science/Project 2/Data/State Fragility Index v2017.xls')
rand = pd.read_csv('C:/Users/yasam/OneDrive/Documents/Grad School/DSC680 Applied Data Science/Project 2/Data/RAND_Database_of_Worldwide_Terrorism_Incidents.csv', encoding='latin-1')
```

In [3]:
```
print('Coups:\n',coups.head(5), '\n\n\n\nDisplaced:\n', displaced.head(5), '\n
\n\n\nFragility:\n',
      fragility.head(5), '\n\n\n\nRAND:\n', rand.head(5))
```

Coups:

	ccode	scode	country	year	scoup1	atcoup2	pcoup3	apcoup4	agcoup
0	700	AFG	Afghanistan	1946	0	0	0	0	0
1	700	AFG	Afghanistan	1947	0	0	0	0	0
2	700	AFG	Afghanistan	1948	0	0	0	0	0
3	700	AFG	Afghanistan	1949	0	0	0	0	0
4	700	AFG	Afghanistan	1950	0	0	0	0	0

	foroutex	reboutex	assassex	resignex
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

Displaced:

	ccode	scode	country	year	source	idp	host
0	2	USA	United States	1964	0.0	0.0	96.0
1	2	USA	United States	1965	0.0	0.0	95.0
2	2	USA	United States	1966	0.0	0.0	97.0
3	2	USA	United States	1967	0.0	0.0	906.0
4	2	USA	United States	1968	0.0	0.0	987.0

Fragility:

	scode	country	year	region	sfi	effect	legit	seceff	secleg
0	AFG	Afghanistan	1995	2	25	13	12	3	3
1	AFG	Afghanistan	1996	2	24	12	12	3	3
2	AFG	Afghanistan	1997	2	24	12	12	3	3
3	AFG	Afghanistan	1998	2	24	12	12	3	3
4	AFG	Afghanistan	1999	2	24	12	12	3	3

	poleff	polleg	ecoeff	ecoleg	soceff	socleg
0	3	3	4	3	3	3
1	2	3	4	3	3	3
2	2	3	4	3	3	3
3	2	3	4	3	3	3
4	2	3	4	3	3	3

RAND:

	Date	City	Country	Perpetrator
0	2/9/1968	Buenos Aires	Argentina	Unknown
1	2/12/1968	Santo Domingo	Dominican Republic	Unknown
2	2/13/1968	Montevideo	Uruguay	Unknown
3	2/20/1968	Santiago	Chile	Unknown
4	2/21/1968	Washington, D.C.	United States	Unknown

	Weapon	Injuries	Fatalities
0	Firearms	0	0
1	Explosives	0	0
2	Fire or Firebomb	0	0

```
3        Explosives         0           0
4        Explosives         0           0

                                          Description
0  ARGENTINA.  The second floor of the U.S. embas...
1  DOMINICAN REPUBLIC.  A homemade bomb was found...
2  URUGUAY.  A Molotov cocktail was thrown outsid...
3  CHILE.  An explosion from a single stick of dy...
4  UNITED STATES.  The Soviet embassy was bombed ...
```

Based on experience, I know that the `Date` column in the `rand` data is not in a `datetime` formate. Let's change it into a `datetime` format.

In [4]:
```
rand['Date'] = pd.to_datetime(rand['Date'])
```

Before I move on, let's check the types of each of the imported dataframes. I will need to ensure each is in the correct format before I can move onto exploring the different data sets.

In [5]:
```
print('Coups:\n',coups.dtypes,'\n\n\nDisplaced:\n', displaced.dtypes,
     '\n\n\nFragility:\n', fragility.dtypes, '\n\n\nRAND:\n', rand.dtypes)
```

```
Coups:
 ccode        int64
scode       object
country     object
year         int64
scoup1       int64
atcoup2      int64
pcoup3       int64
apcoup4      int64
agcoup       int64
foroutex     int64
reboutex     int64
assassex     int64
resignex     int64
dtype: object


Displaced:
 ccode        int64
scode       object
country     object
year         int64
source     float64
idp        float64
host       float64
dtype: object


Fragility:
 scode      object
country    object
year        int64
region      int64
sfi         int64
effect      int64
legit       int64
seceff      int64
secleg      int64
poleff      int64
polleg      int64
ecoeff      int64
ecoleg      int64
soceff      int64
socleg      int64
dtype: object


RAND:
 Date           datetime64[ns]
City                   object
Country                object
Perpetrator            object
Weapon                 object
Injuries                int64
Fatalities              int64
Description            object
dtype: object
```

Looks like everything imported with the correct types. I may still need to modify these types later on, but we are good to start looking at each variable.

Exploring Each Variable's Distributions

The first thing up is to start exploring each of the different variables within the four different datasets we will be looking at. Let's look at each individual dataset.

Coups

First up is the dataset exploring coups throughout the years. The dataset contains information from 1946 to 2018. I want to look at two different groupings within this data. The number for each country over the years, and the combination for each year.

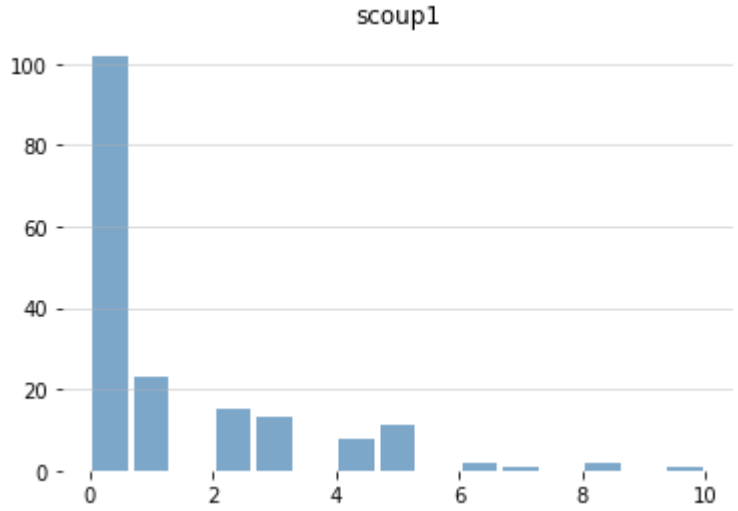
In [6]:
```
coups_countries = coups.groupby('country').sum()[['scoup1', 'atcoup2', 'pcoup
3', 'apcoup4',
                                'agcoup', 'foroutex', 'reboutex', 'assassex',
                                'resignex']]
coups_year = coups.groupby('year').sum()[['scoup1', 'atcoup2', 'pcoup3', 'apco
up4',
                                'agcoup', 'foroutex', 'reboutex', 'assassex',
                                'resignex']]
```

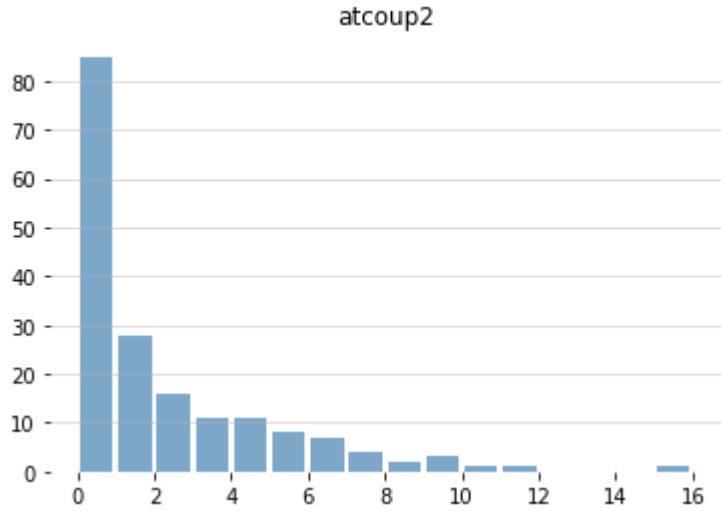
I have my two different groupings within the data. Now let's look at the different histograms.

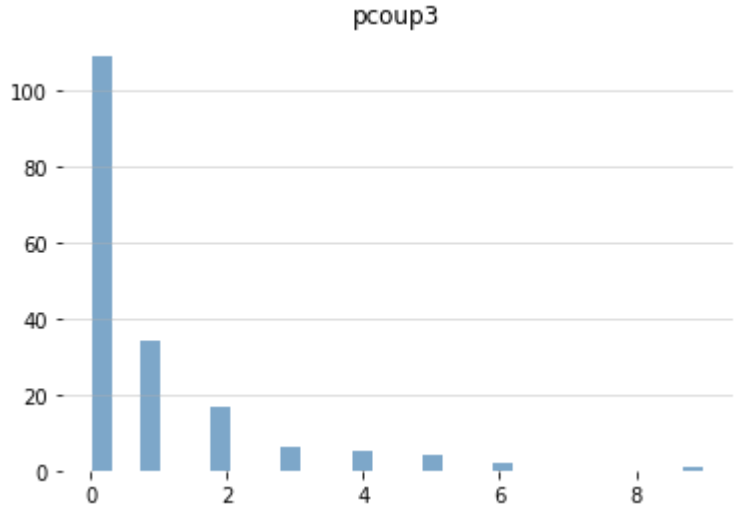
Grouped by Country

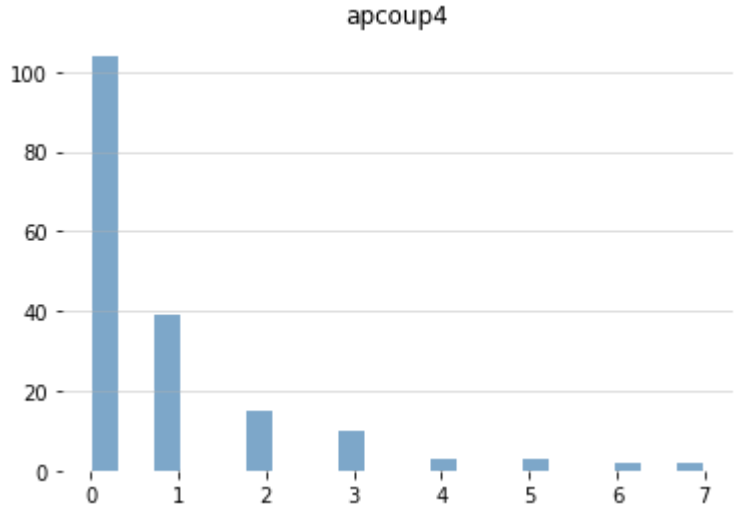
First ups is the grouping by country.

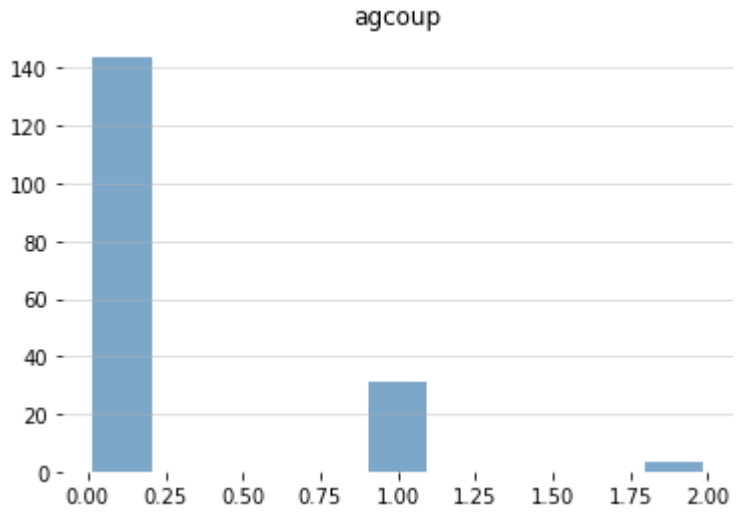
In [7]:
```
heads = ['scoup1', 'atcoup2', 'pcoup3', 'apcoup4', 'agcoup', 'foroutex',
         'reboutex', 'assassex', 'resignex']
for test in heads:
    n, bins, patches = plt.hist(x=coups_countries[test], bins='auto',
                                color='steelblue', alpha=0.7, rwidth=0.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(test)
    plt.box(False)
    plt.show()
```

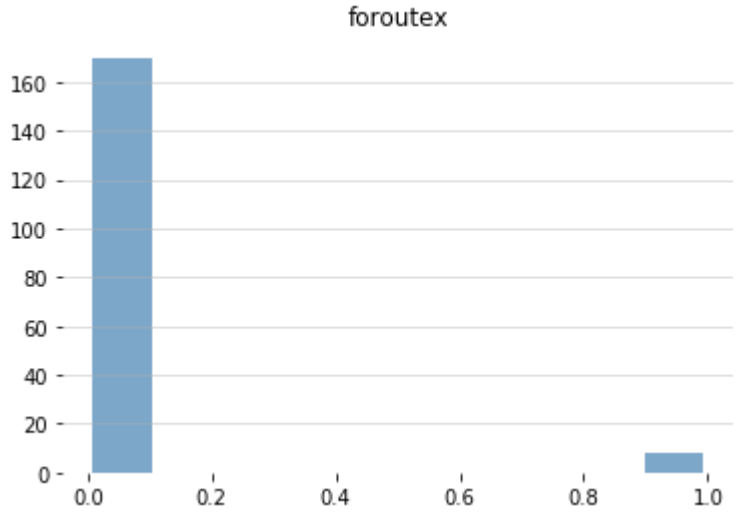

scoup1
100
80
60
40
20
0
0
2
4
6
8
10

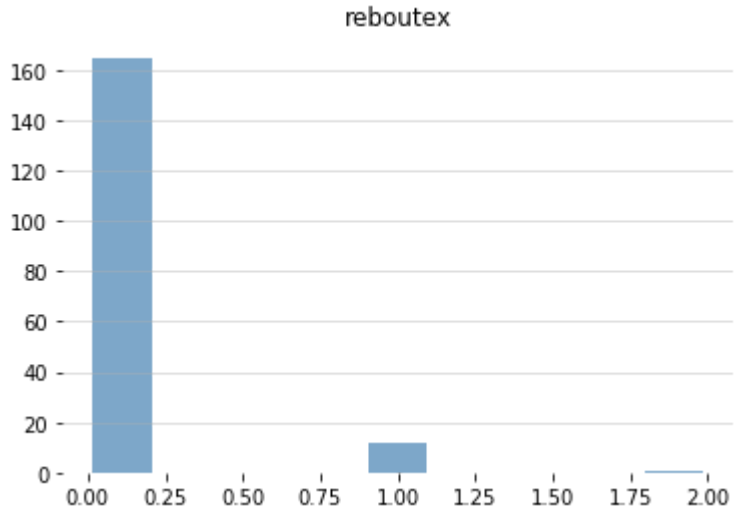

atcoup2
80
70
60
50
40
30
20
10
0
0
2
4
6
8
10
12
14
16

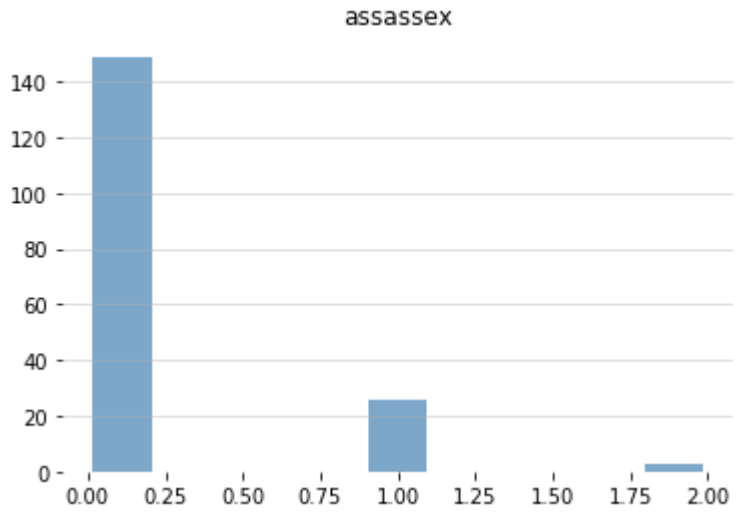

pcoup3
100
80
60
40
20
0
0
2
4
6
8

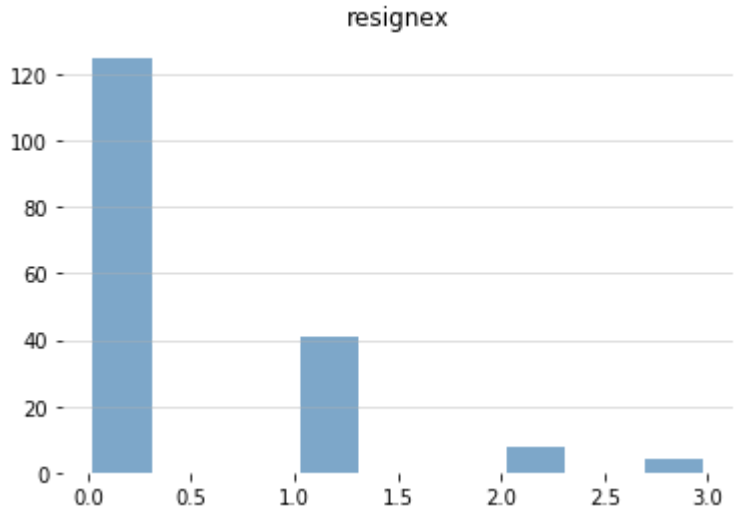

apcoup4
100
80
60
40
20
0
0
1
2
3
4
5
6
7


agcoup
140
120
100
80
60
40
20
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


foroutex
160
140
120
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

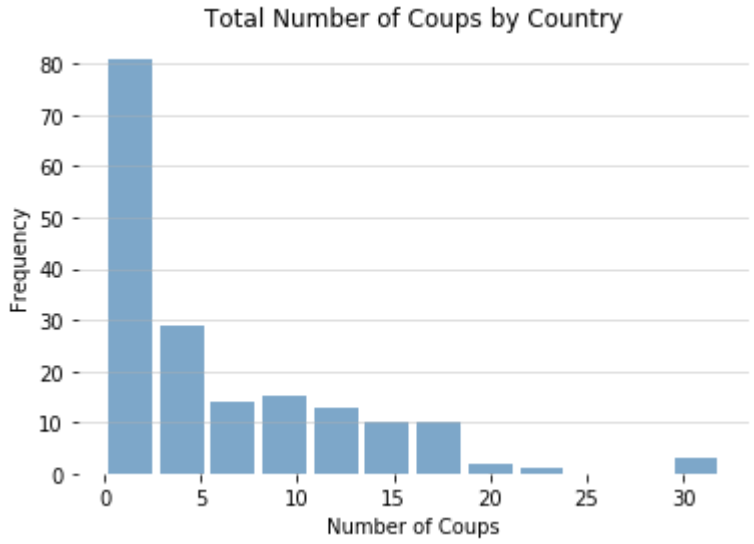






Each of the histograms have a mode at 0 and trail to the right. This isn't surprising, but it is interesting how far to the right some of variables stretch. For example, `atcoup2` has up to 16 of these types of coups. But what about the total coups per country?

In [8]:
```
total_coups_country = coups_countries['scoup1'] + coups_countries['atcoup2'] +
coups_countries['pcoup3'] + coups_countries['apcoup4'] + coups_countries['agco
up'] + coups_countries['foroutex'] + coups_countries['reboutex'] + coups_count
ries['assassex'] + coups_countries['resignex']
n, bins, patches = plt.hist(x=total_coups_country, bins='auto', color='steelbl
ue',
                            alpha=.7, rwidth=.85)
plt.grid(axis='y', alpha=.5)
plt.xlabel('Number of Coups')
plt.ylabel('Frequency')
plt.title('Total Number of Coups by Country')
plt.box(False)
plt.show()
```



Now this is interesting. There are countries that have had over 30 coups since 1946. The maximum number of coups by country is 32. That means one country has had 32 coups in 73 years. That is a lot of upheaval.

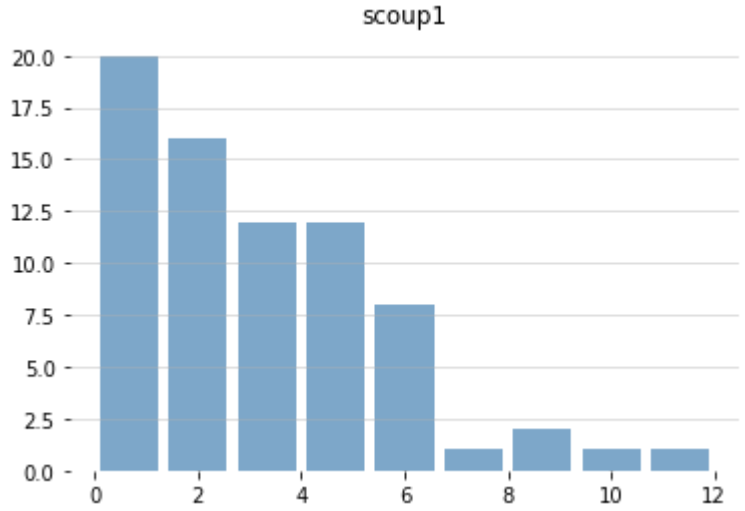
Grouped by Year

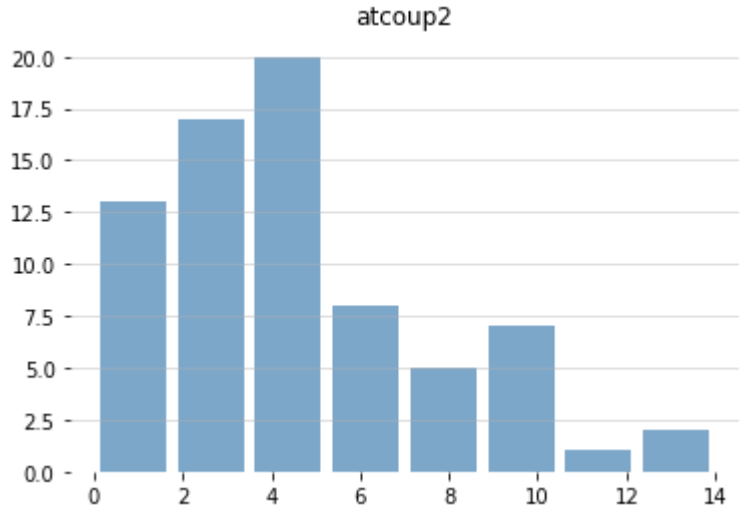
Now let's change our lens and look at the same data split out by year.

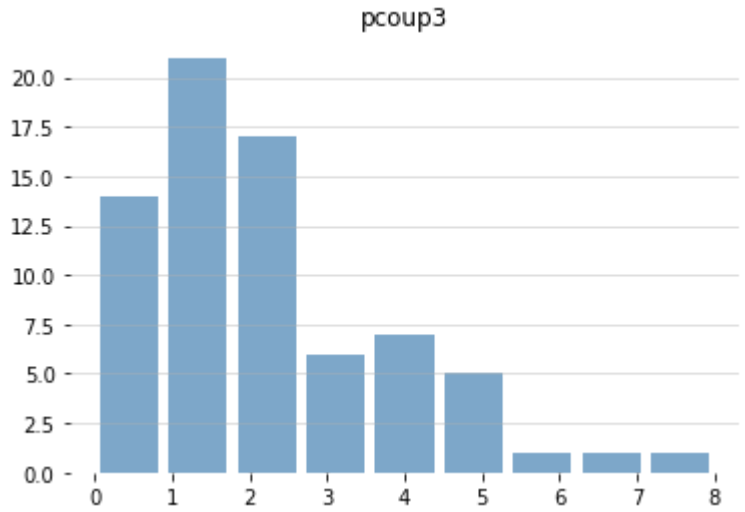
In [9]:
```
pprint(coups_year.head(5))
```

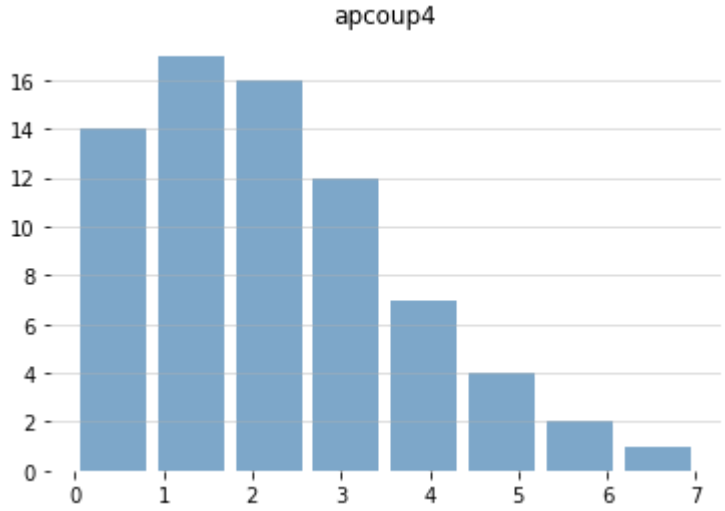
```
      scoup1  atcoup2  pcoup3  apcoup4  agcoup  foroutex  reboutex  assassex
\
year
1946       1        1       1        1       0         0         1         0
1947       2        1       2        5       0         0         0         0
1948       6        4       3        3       0         0         0         0
1949       5        1       3        1       0         0         0         0
1950       1        0       2        0       0         0         0         0

      resignex
year
1946         0
1947         0
1948         0
1949         0
1950         0
```

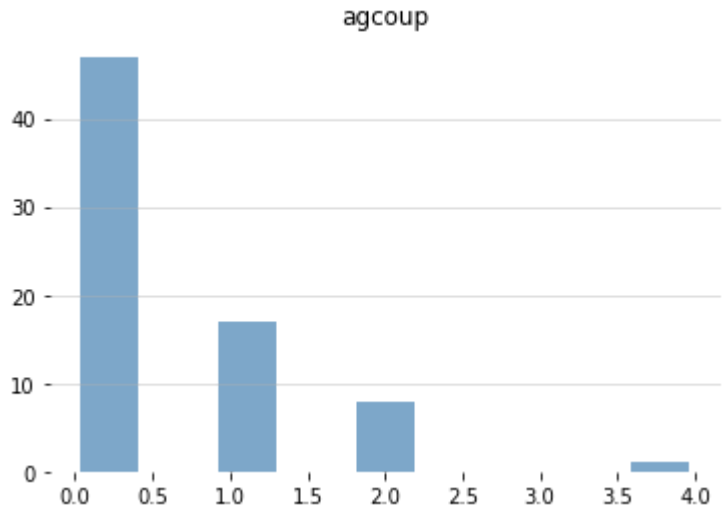
In [10]:
```
for test in heads:
    n, bins, patches = plt.hist(x=coups_year[test], bins='auto',
                                color='steelblue', alpha=.7, rwidth=.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(test)
    plt.box(False)
    plt.show()
```

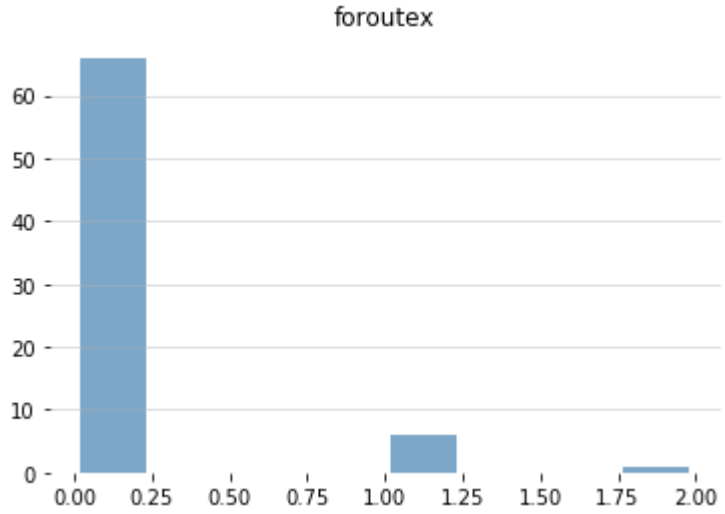

scoup1
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
2
4
6
8
10
12

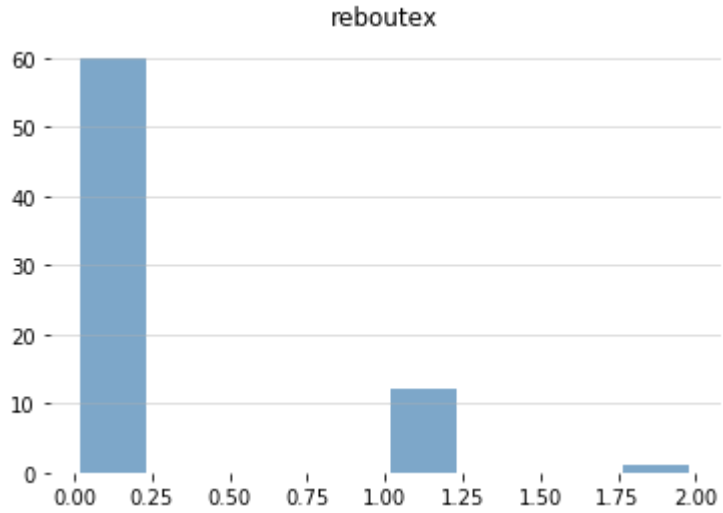

atcoup2
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
2
4
6
8
10
12
14

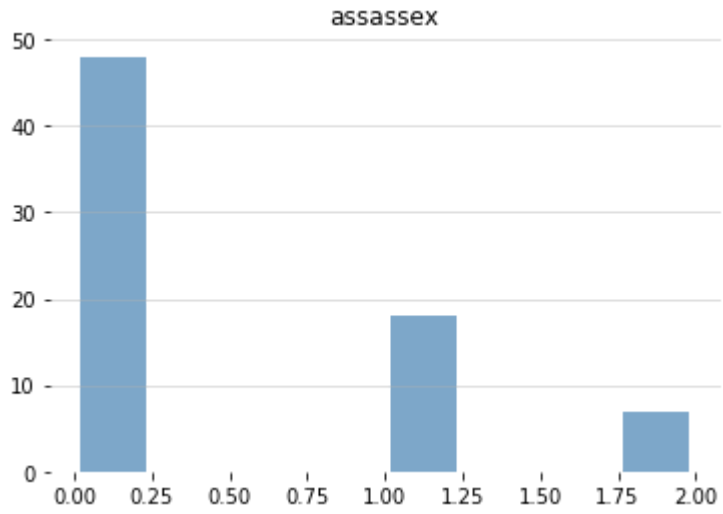

pcoup3
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
1
2
3
4
5
6
7
8

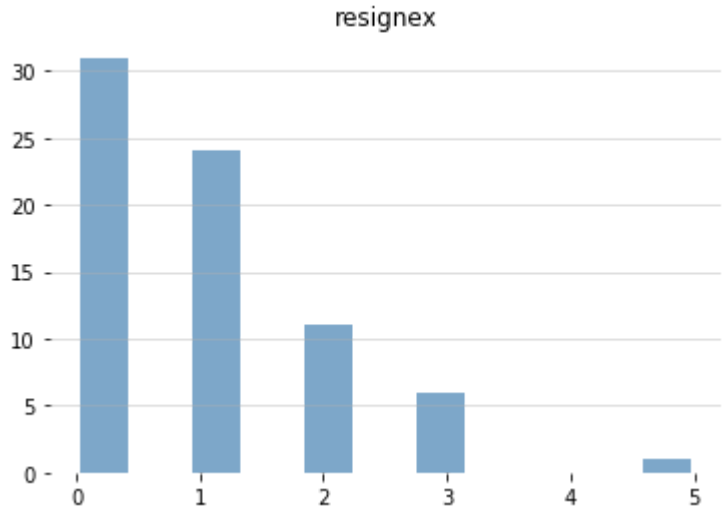

apcoup4
16
14
12
10
8
6
4
2
0
0
1
2
3
4
5
6
7


agcoup
40
30
20
10
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


foroutex
60
50
40
30
20
10
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

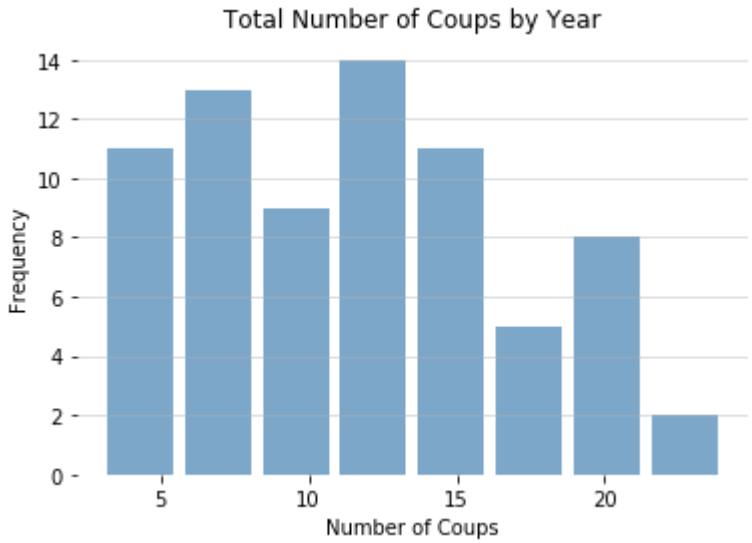






Ok, let's look at how the total number of coups is broken up by year.

In [11]:
```
total_coups_year = coups_year['scoup1'] + coups_year['atcoup2'] + coups_year[
'pcoup3'] + coups_year['agcoup'] + coups_year['foroutex'] + coups_year['rebout
ex'] + coups_year['assassex'] + coups_year['resignex']
n, bins, patches = plt.hist(x=total_coups_year, bins='auto', color='steelblue'
,
                            alpha=.7, rwidth=.85)
plt.grid(axis='y', alpha=.5)
plt.xlabel('Number of Coups')
plt.ylabel('Frequency')
plt.title('Total Number of Coups by Year')
plt.box(False)
plt.show()
```



Now this was unexpected. This is almost a normal distribution.

Displaced

Now it's time to look at the next dataset which is the number of displaced individuals. Let's look at the numbers grouped by country and by year.

In [12]:
```
displaced.head(5)
```

Out[12]:

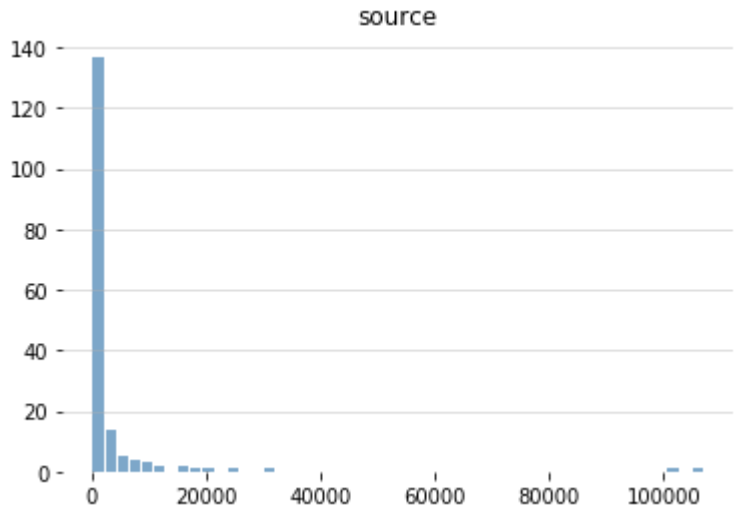
	ccode	scode	country	year	source	idp	host
0	2	USA	United States	1964	0.0	0.0	96.0
1	2	USA	United States	1965	0.0	0.0	95.0
2	2	USA	United States	1966	0.0	0.0	97.0
3	2	USA	United States	1967	0.0	0.0	906.0
4	2	USA	United States	1968	0.0	0.0	987.0

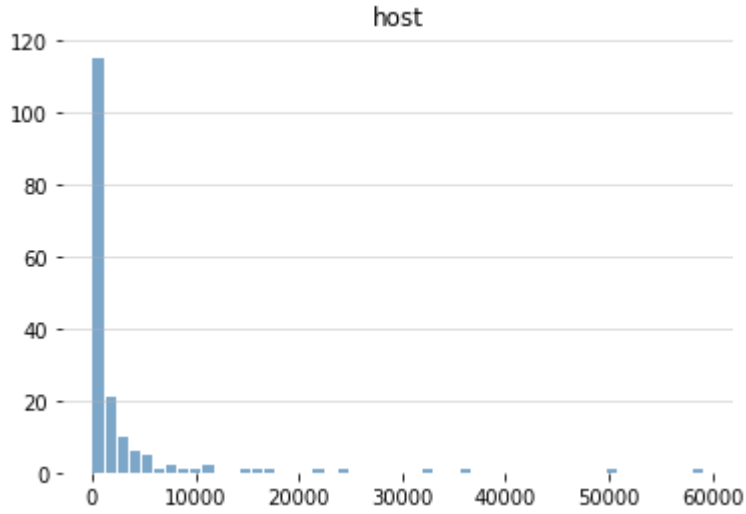
In [13]:
```
displaced_country = displaced.groupby('country').sum()[['source', 'host']]
displaced_year = displaced.groupby('year').sum()[['source', 'host']]
```

Grouped by Country

First up is the group by country.

In [14]:
```
for x in ['source', 'host']:
    n, bins, patches = plt.hist(x=displaced_country[x], bins=50,
                                color='steelblue', alpha=.7, rwidth=.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(x)
    plt.box(False)
    plt.show()
```



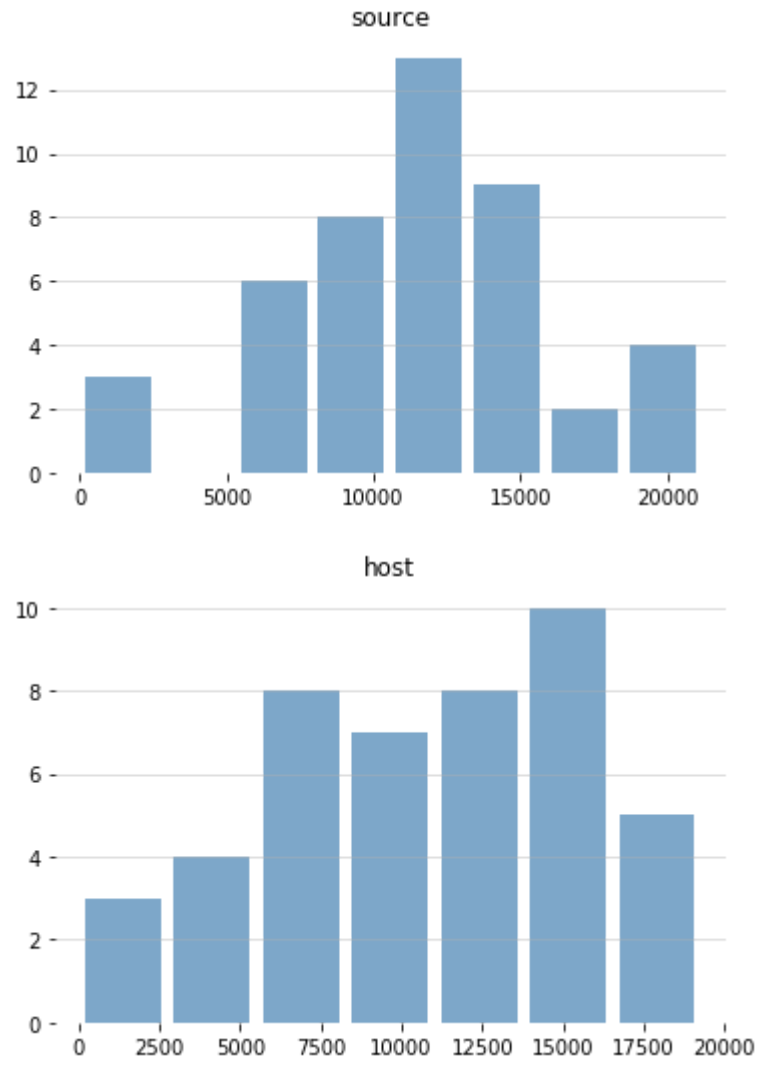


These histograms are not surprising. Most countries do not source or host displaced individuals. One interesting thing is that the sum of the source and hosts are not equal. This means that there are a fair number of uncounted individuals. But now let's look at the number of displaced individuals by year.

Grouped by Year

Now let's look at the number of displaced individuals over the years.

In [15]:
```
for x in ['source', 'host']:
    n, bins, patches = plt.hist(x=displaced_year[x], bins='auto',
                                color='steelblue', alpha=.7, rwidth=.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(x)
    plt.box(False)
    plt.show()
```



These are both mostly normal. That is unexpected. But paired with the number of coups per year being normal as well, this shouldn't be as surprising. Now let's look at the fragility of the different countries.

Fragility

Next up is looking at the `fragility` dataset. Each state's fragility index is the `sfi` variable, but is a combination of all the other variables. The closer the `sfi` is to zero, the more stable the country is. For my analysis, I will only be looking at the `sfi`, but there is much more data that can be gleaned from this dataset.

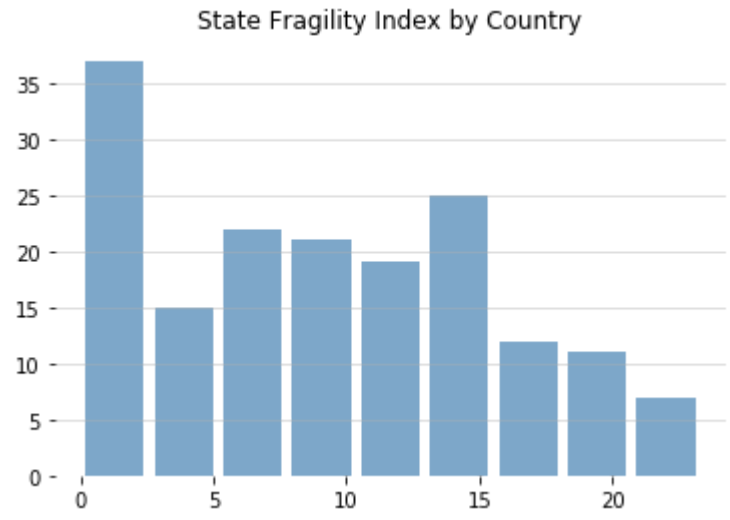
I will be grouping this data by the mean rather than the sum.

In [16]:
```
fragility_country = fragility.groupby('country').mean()[['sfi']]
fragility_year = fragility.groupby('year').mean()[['sfi']]
```

Grouped by Country

First up is to look at the grouped country data.

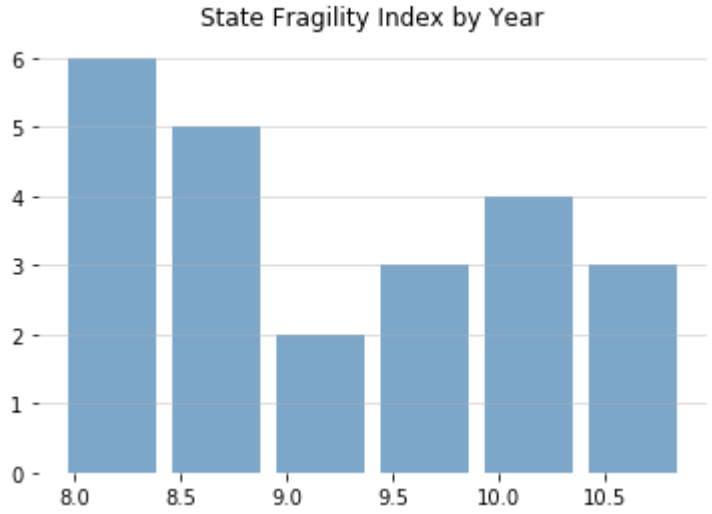
In [17]:
```
n, bins, patches = plt.hist(x=fragility_country['sfi'], bins='auto',
                            color='steelblue', alpha=.7, rwidth=.85)
plt.grid(axis='y', alpha=.5)
plt.title('State Fragility Index by Country')
plt.box(False)
plt.show()
```



Grouped by Year

Next up is to look at the `sfi` when it's grouped by year.

In [18]:
```
n, bins, patches = plt.hist(x=fragility_year['sfi'], bins='auto',
                            color='steelblue', alpha=.7, rwidth=.85)
plt.grid(axis='y', alpha=.5)
plt.title('State Fragility Index by Year')
plt.box(False)
plt.show()
```



Here we have the average state fragility index for each year. I was not expecting such a spread in the average over the years.

RAND

Next up is to look at the RAND database of worldwide terrorism incidents (RDWTI) data. There are a couple of things to look at within this dataset.

In [19]:
```
print('Number of Cities: ',len(list(set(rand['City']))),
      '\nNumber of Countries: ', len(list(set(rand['Country']))),
      '\nNumber of Perpetrators: ', len(list(set(rand['Perpetrator']))),
      '\nNumber of Weapons: ', len(list(set(rand['Weapon']))))
```

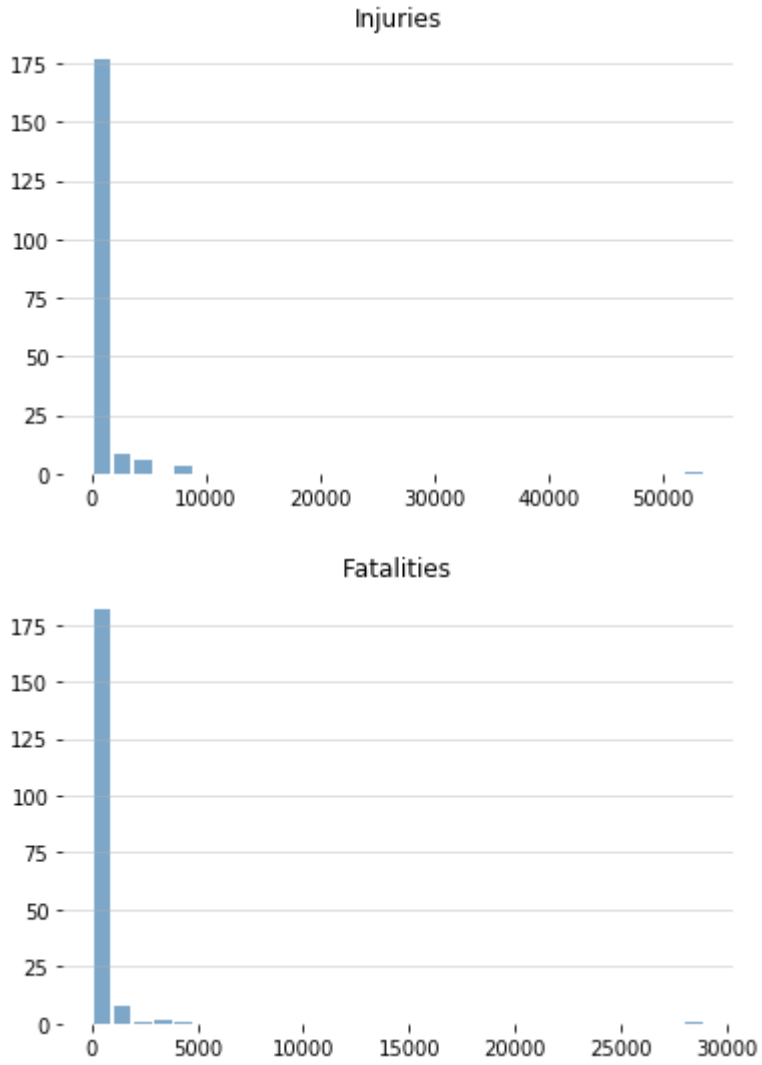
```
Number of Cities:  6387
Number of Countries:  195
Number of Perpetrators:  1060
Number of Weapons:  13
```

In [20]:
```
rand_country = rand.groupby('Country').sum()[['Injuries', 'Fatalities']]
rand_perps = rand.groupby('Perpetrator').sum()[['Injuries', 'Fatalities']]
rand_weapons = rand.groupby('Weapon').sum()[['Injuries', 'Fatalities']]
```

Grouped by Country

First up is to look at the data when grouped by country

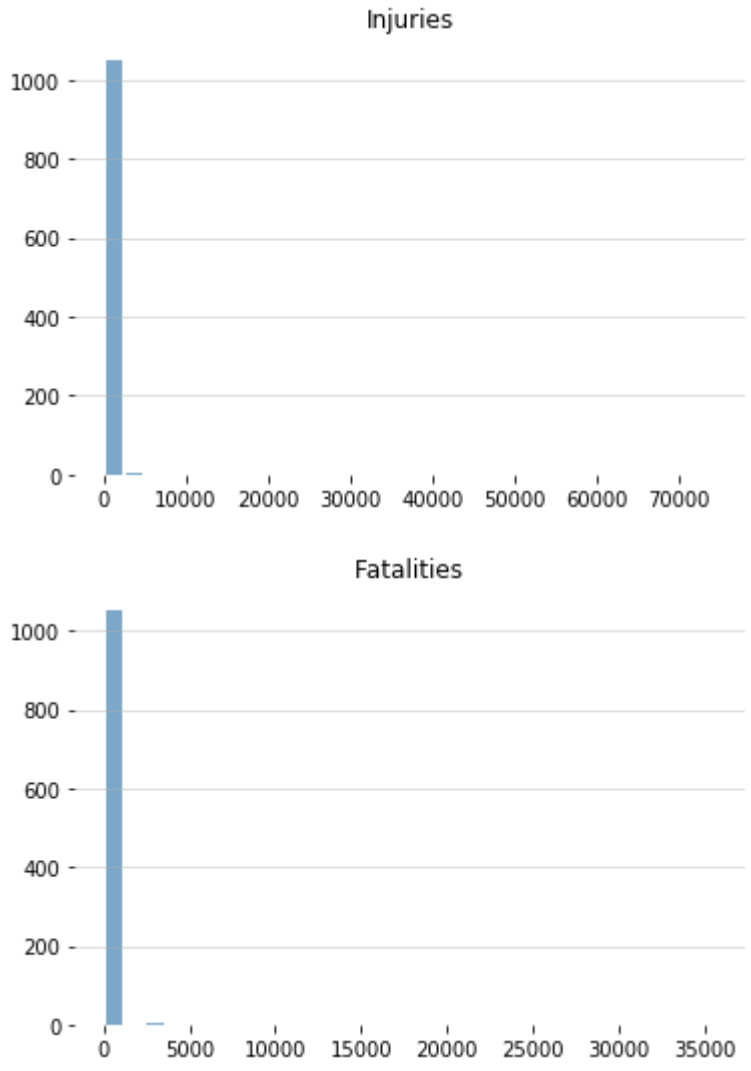
In [21]:
```
for x in ['Injuries', 'Fatalities']:
    n, bins, patches = plt.hist(x=rand_country[x], bins=30,
                                color='steelblue', alpha=.7, rwidth=.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(x)
    plt.box(False)
    plt.show()
```



Grouped by Perpetrators

Now let's look at the data grouped by Perpetrators

In [22]:
```
for x in ['Injuries', 'Fatalities']:
    n, bins, patches = plt.hist(x=rand_perps[x], bins=30,
                                color='steelblue', alpha=.7, rwidth=.85)
    plt.grid(axis='y', alpha=.5)
    plt.title(x)
    plt.box(False)
    plt.show()
```

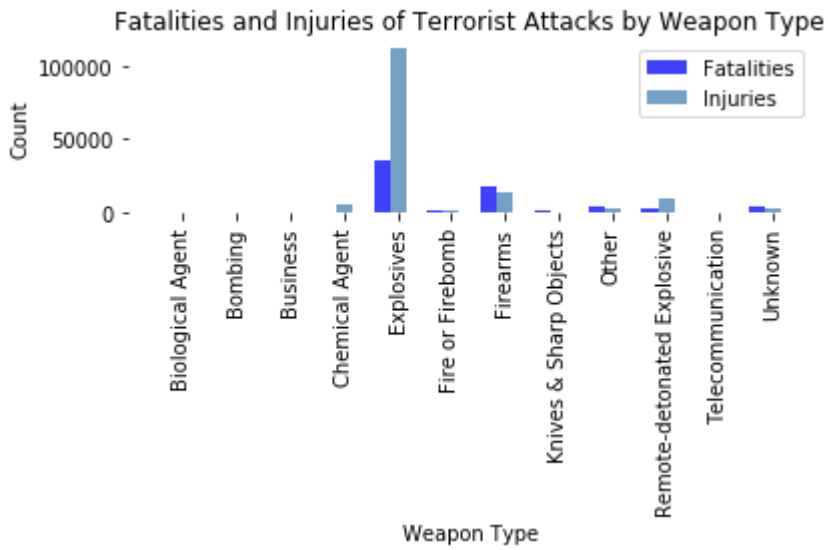


Most terroristic attacks have a small number of injuries and fatalities.

Grouped by Weapon

Now let's see how they change by weapon type.

In [23]:
```
n_groups = 12

fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = .3
opacity = .75

rects1 = plt.bar(index, rand_weapons['Fatalities'], bar_width, alpha=opacity,
                 color='blue', label="Fatalities")
rects2 = plt.bar(index + bar_width, rand_weapons['Injuries'], bar_width, alpha
=opacity,
                color='steelblue', label="Injuries")
plt.xlabel('Weapon Type')
plt.ylabel('Count')
plt.title('Fatalities and Injuries of Terrorist Attacks by Weapon Type')
plt.xticks(index + bar_width,('Biological Agent', 'Bombing', 'Business',
                              'Chemical Agent', 'Explosives', 'Fire or Firebom
b',
                              'Firearms', 'Knives & Sharp Objects', 'Other',
                              'Remote-detonated Explosive', 'Telecommunication'
,
                              'Unknown'), rotation='vertical')
plt.legend()

plt.tight_layout()
plt.box(False)
plt.show()
```



By far, the weapon that causes the most fatalities and injuries are explosives.

Exploring Bi-Variate Relationships

To explore the bi-variate relationships, we need to first get the different data into a single dataframe, or into the same format. I'm gathering the data into a single dataframe.

Correlation

The first bi-variate relationship I'm going to look at is the correlation between the different variables. I will look at this when the data is grouped by country and by year.

Grouped by Country

The first thing I'll need to do is reset the index on all of the grouped datasets. Once the index is reset, I can then merge the datasets together by country.

In [24]:
```
coups_countries = coups_countries.reset_index()
displaced_country = displaced_country.reset_index()
fragility_country = fragility_country.reset_index()
rand_country = rand_country.reset_index()
coups_year = coups_year.reset_index()
diplaced_year = displaced_year.reset_index()
fragility_year = fragility_year.reset_index()

# Need to rename columns to be the same between the different dataframes
rand_country = rand_country.rename(columns={'Country':'country', 'Injuries':'i
njuries',
                                'Fatalities':'fatalities'})
```

In [25]:
```
total_coups_country_df = total_coups_country.to_frame().reset_index()
total_coups_country_df.columns = ['country', 'total_coups']
```

In [26]:
```
country_df = pd.merge(coups_countries, total_coups_country_df, on='country')
country_df = pd.merge(country_df, displaced_country, on='country')
country_df = pd.merge(country_df, fragility_country, on='country')
country_df = pd.merge(country_df, rand_country, on='country')
```

In [27]:
```
country_df.head(5)
```

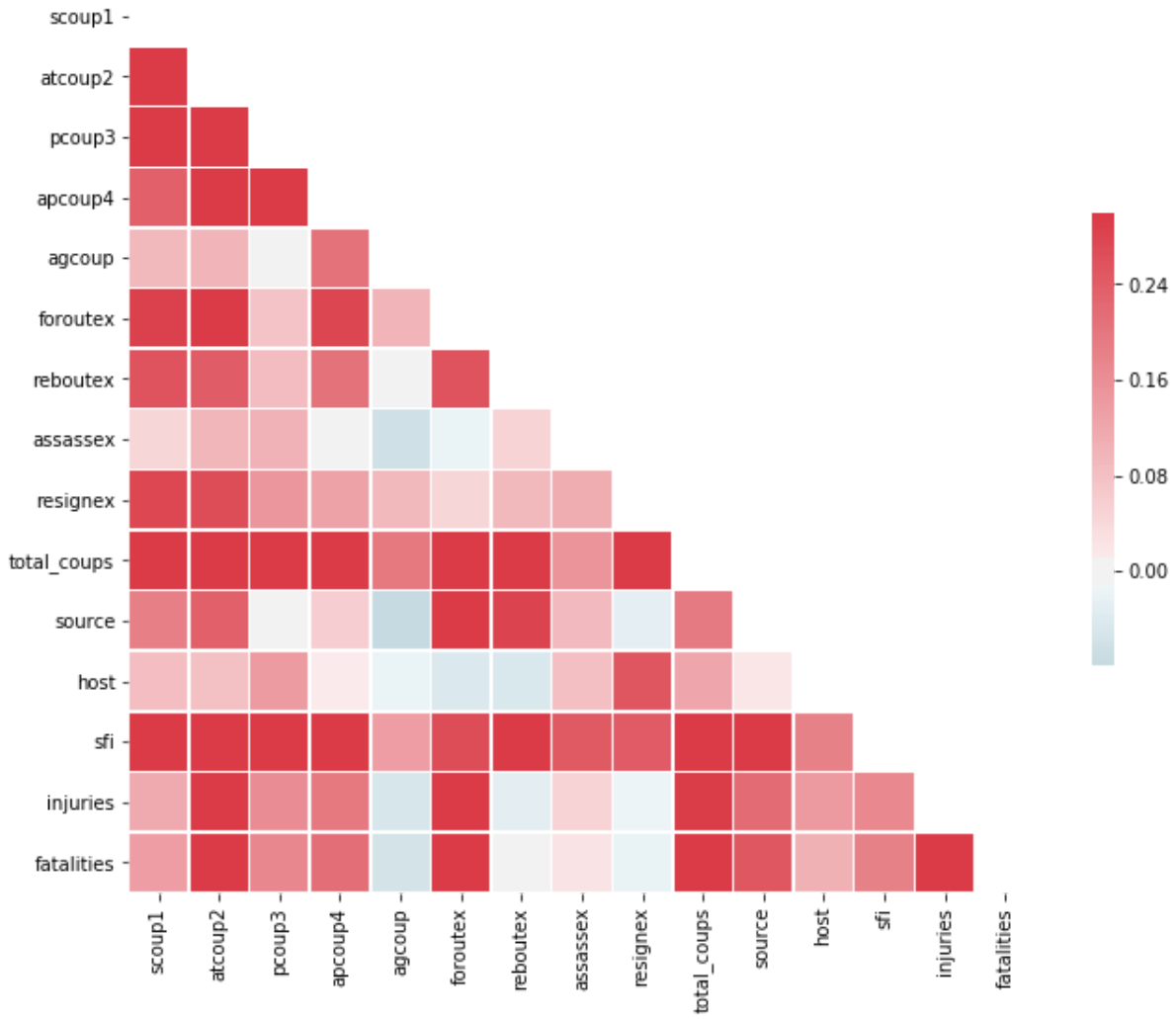
Out[27]:

	country	scoup1	atcoup2	pcoup3	apcoup4	agcoup	foroutex	reboutex	assassex
0	Afghanistan	5	6	0	1	0	1	1	0
1	Albania	0	1	0	0	1	0	0	0
2	Algeria	1	1	0	0	1	0	0	1
3	Angola	0	1	0	1	0	0	0	0
4	Argentina	7	8	1	0	0	0	0	0

Now that we have a combined dataset for the grouping on the countries, we can look at how how the different countries are related together.

In [28]:
```
corr = country_df.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(11,9))
cmap = sns.diverging_palette(220,10, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidth=.5, cbar_kws={'shrink':.5})
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x222397c6b00>



Well, now this is interesting. Most of the variables are positively correlated with each other to varying degress. The variables that seem to be the most important are `total_coups`, `sfi`, and `atcoup2`. The `total_coups` and `sfi` were expected, but it looks like a specific type of coup is highly correlated with terrorism. This is good to know as it is one of my research questions.

Grouped by Year

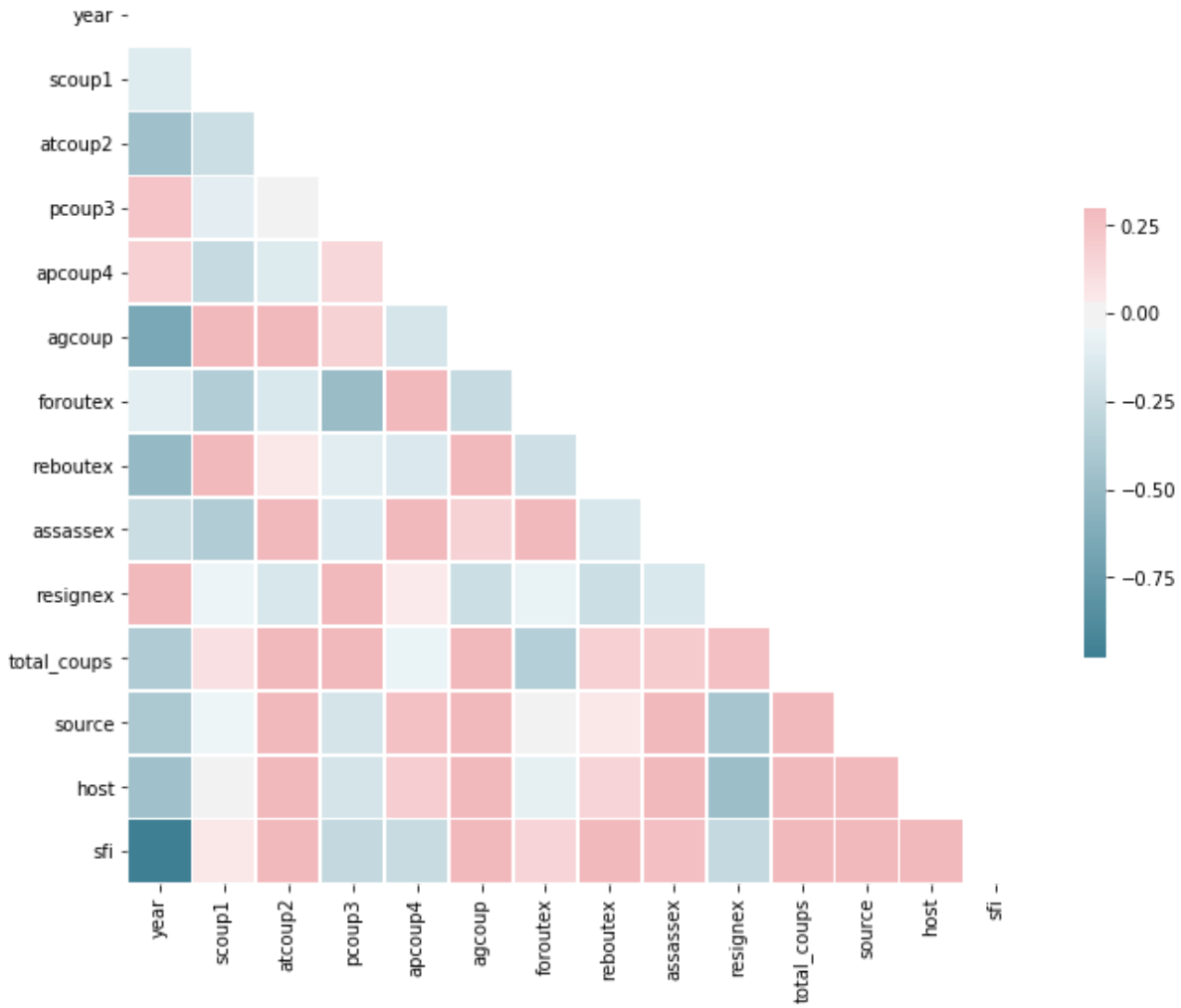
Now to do the same thing when the data is grouped by year.

In [29]:
```
total_coups_year_df = total_coups_year.to_frame().reset_index()
total_coups_year_df.columns = ['year', 'total_coups']
```

In [30]:
```
year_df = pd.merge(coups_year, total_coups_year_df, on='year')
year_df = pd.merge(year_df, displaced_year, on='year')
year_df = pd.merge(year_df, fragility_year, on='year')
```

In [31]:
```
corr = year_df.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(11,9))
cmap = sns.diverging_palette(220,10, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidth=.5, cbar_kws={'shrink':.5})
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x2223aba2898>



Now this is an interesting thing to see. When the data is grouped by year, the correlations are closer to 0 or negative, especially to the `year`. This implies that as time goes on, the amount of terrorism is decreasing.

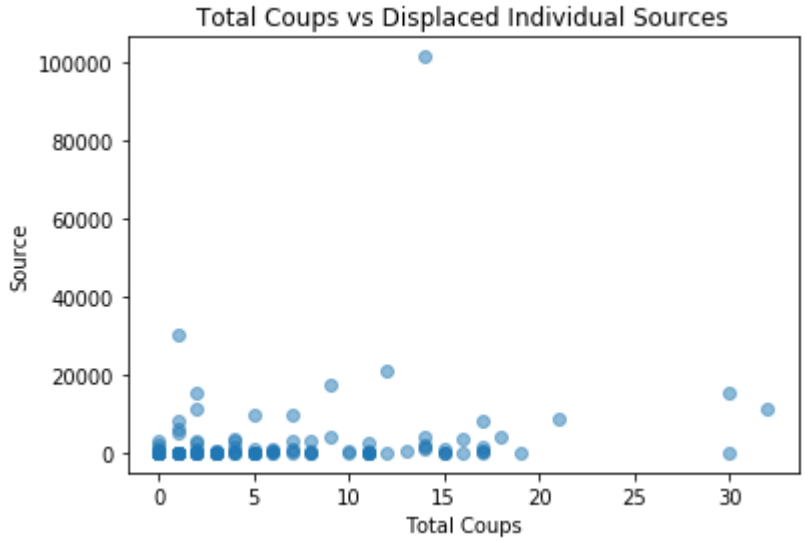
Scatterplots

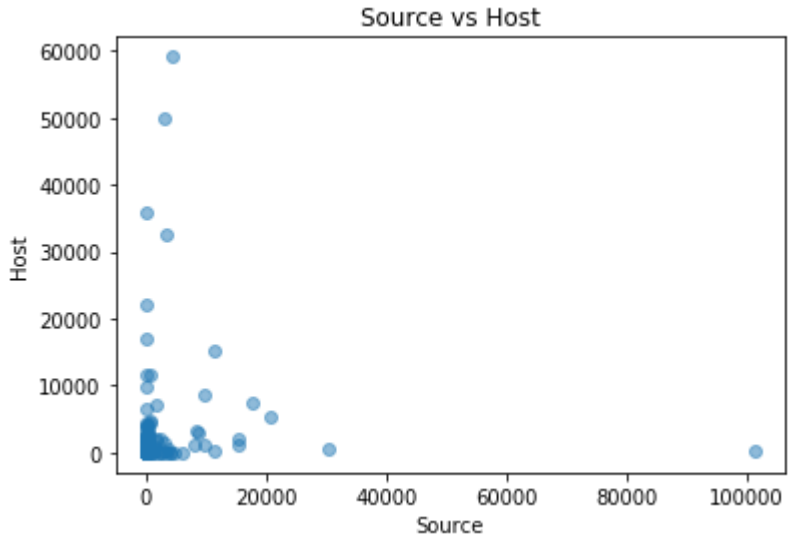
The next thing to look at are the different scatterplots between the variables. I'll be looking at these based on how the data was grouped.

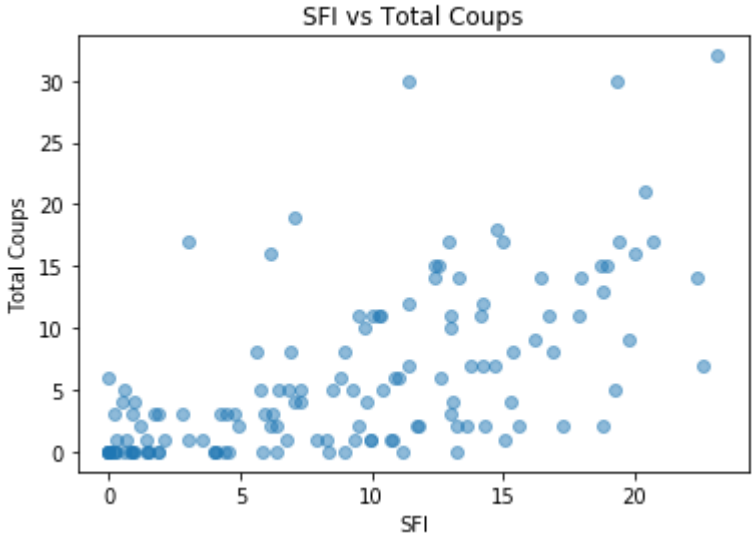
Grouped by Country

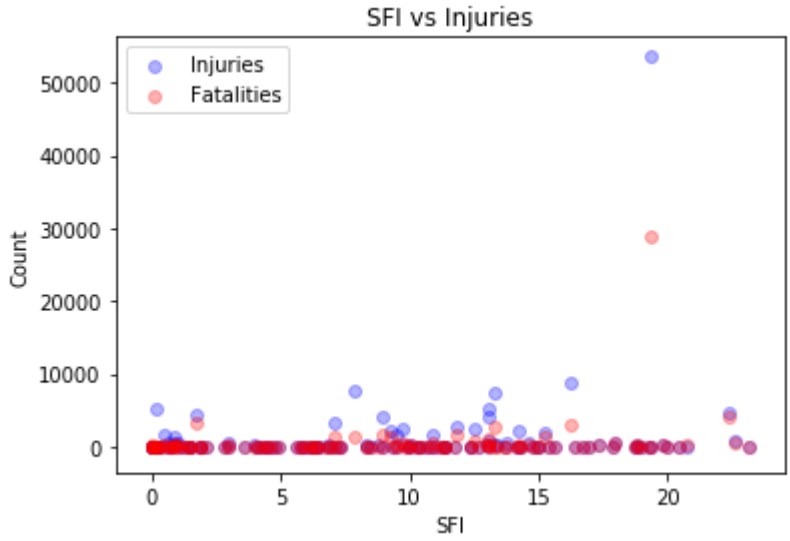
First up is to look at the data when it's grouped by country.

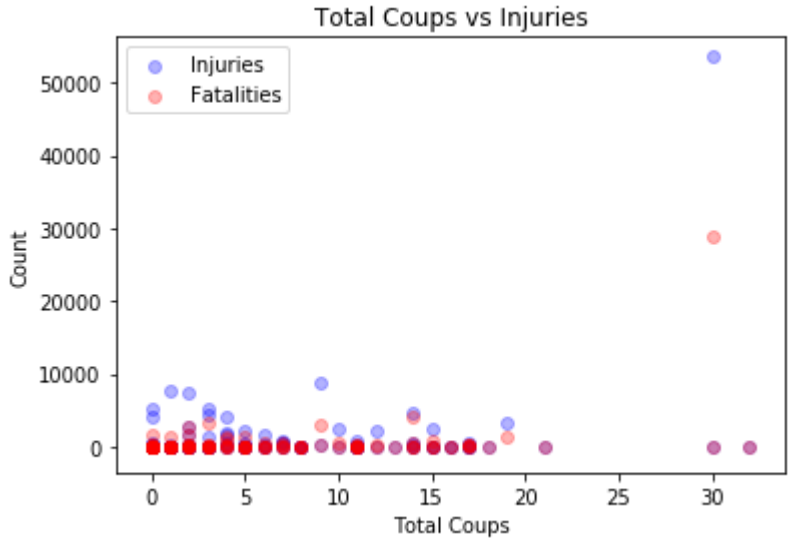
In [32]:
```
plt.scatter(x=country_df['total_coups'], y=country_df['source'], alpha=.5)
plt.xlabel('Total Coups')
plt.ylabel('Source')
plt.title('Total Coups vs Displaced Individual Sources')
plt.show()

plt.scatter(x=country_df['source'], y=country_df['host'], alpha=.5)
plt.xlabel('Source')
plt.ylabel('Host')
plt.title('Source vs Host')
plt.show()

plt.scatter(x=country_df['sfi'], y=country_df['total_coups'], alpha=.5)
plt.xlabel('SFI')
plt.ylabel('Total Coups')
plt.title('SFI vs Total Coups')
plt.show()

plt.scatter(x=country_df['sfi'], y=country_df['injuries'], alpha=.3, color='bl
ue', label='Injuries')
plt.scatter(x=country_df['sfi'], y=country_df['fatalities'], alpha=.3, color=
'red', label='Fatalities')
plt.xlabel('SFI')
plt.ylabel('Count')
plt.title('SFI vs Injuries')
plt.legend()
plt.show()

plt.scatter(x=country_df['total_coups'], y=country_df['injuries'], alpha=.3, c
olor='blue', label='Injuries')
plt.scatter(x=country_df['total_coups'], y=country_df['fatalities'], alpha=.3,
color='red', label='Fatalities')
plt.xlabel('Total Coups')
plt.ylabel('Count')
plt.title('Total Coups vs Injuries')
plt.legend()
plt.show()
```


Total Coups vs Displaced Individual Sources
Source
Total Coups
0
20000
40000
60000
80000
100000
0
5
10
15
20
25
30


Source vs Host
Host
Source
0
10000
20000
30000
40000
50000
60000
0
20000
40000
60000
80000
100000


SFI vs Total Coups
Total Coups
SFI
0
5
10
15
20
25
30
0
5
10
15
20





Here we can see some of the different scatter plots of the data.

Grouped by Year

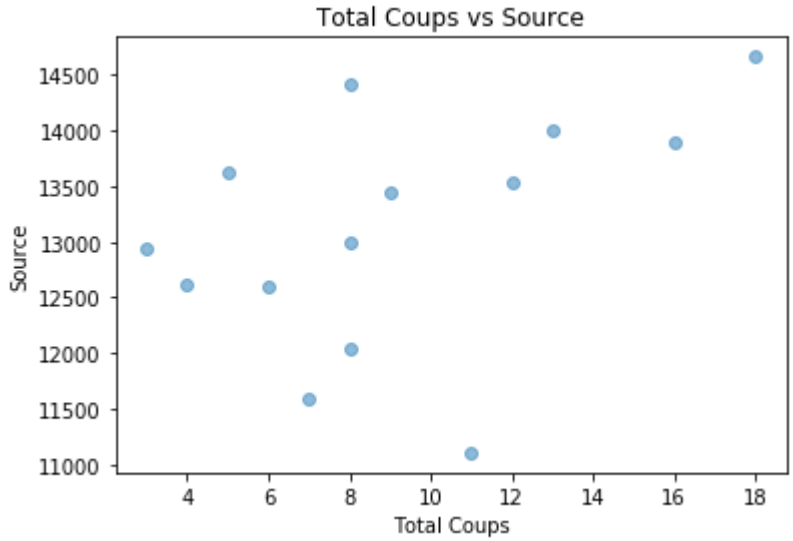
Now it's time to look at the same scatterplots with the data grouped by year.

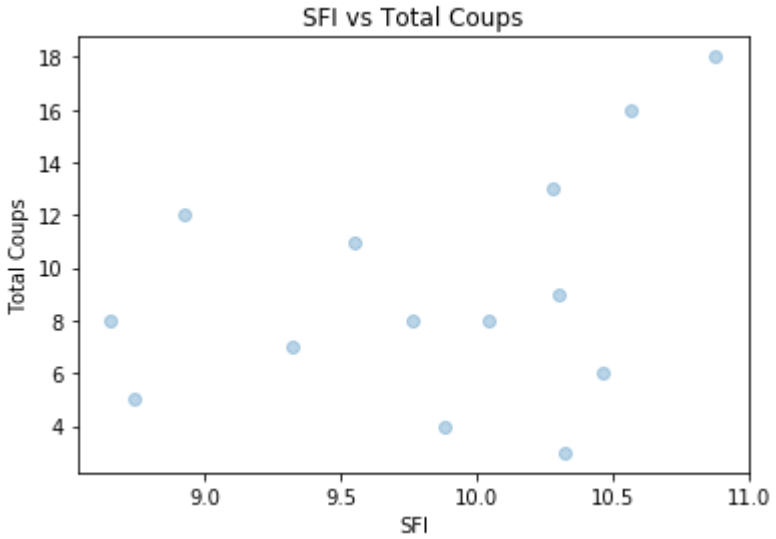
In [33]:
```
year_df
```

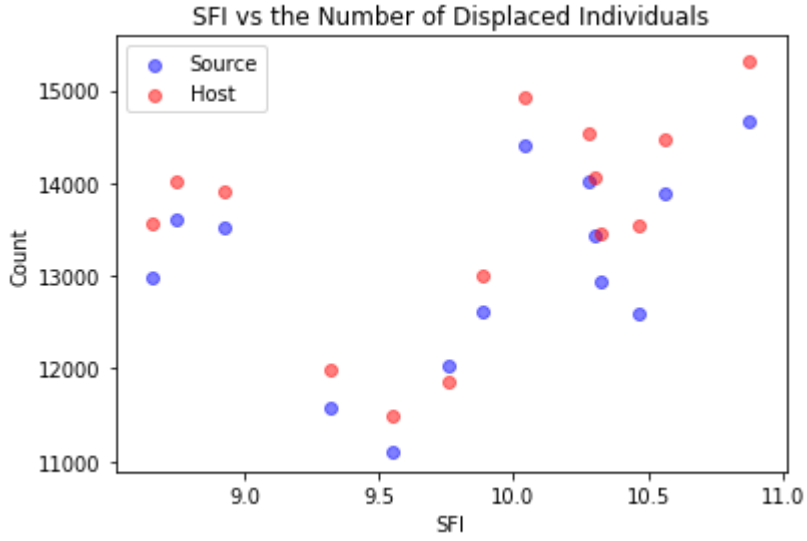
Out[33]:

	year	scoup1	atcoup2	pcoup3	apcoup4	agcoup	foroutex	reboutex	assassex	res
0	1995	1	10	4	3	2	0	0	1	0
1	1996	3	7	2	2	2	0	1	0	1
2	1997	3	1	1	2	0	0	1	0	0
3	1998	0	2	0	4	0	1	0	0	0
4	1999	4	2	1	0	1	0	0	0	1
5	2000	0	10	1	1	0	0	0	0	2
6	2001	0	4	0	4	0	1	0	2	1
7	2002	1	2	1	2	0	0	0	0	0
8	2003	2	2	1	3	0	1	0	0	2
9	2004	0	2	6	1	0	0	0	0	3
10	2005	2	0	2	2	0	0	0	0	3
11	2006	2	2	5	6	0	0	0	0	3
12	2007	1	1	3	3	0	0	0	0	0
13	2008	2	5	1	2	0	0	0	0	0

In [34]:
```
plt.scatter(x=year_df['total_coups'], y=year_df['source'], alpha=.5)
plt.xlabel('Total Coups')
plt.ylabel('Source')
plt.title('Total Coups vs Source')
plt.show()

plt.scatter(x=year_df['sfi'], y=year_df['total_coups'], alpha=.3)
plt.xlabel('SFI')
plt.ylabel('Total Coups')
plt.title('SFI vs Total Coups')
plt.show()

plt.scatter(x=year_df['sfi'], y=year_df['source'], alpha=.5, color='blue', lab
el='Source')
plt.scatter(x=year_df['sfi'], y=year_df['host'], alpha=.5, color='red', label=
'Host')
plt.xlabel('SFI')
plt.ylabel('Count')
plt.legend()
plt.title('SFI vs the Number of Displaced Individuals')
plt.show()
```


Total Coups vs Source
Source
Total Coups
14500
14000
13500
13000
12500
12000
11500
11000
4
6
8
10
12
14
16
18


SFI vs Total Coups
Total Coups
SFI
18
16
14
12
10
8
6
4
9.0
9.5
10.0
10.5
11.0


SFI vs the Number of Displaced Individuals
Source
Host
Count
SFI
15000
14000
13000
12000
11000
9.0
9.5
10.0
10.5
11.0

Here we can see some of the scatterplots for the data grouped by year.

Start Clustering

Now that we've looked at the data, we can start looking to try to use the data to see how the data groups together. I'm wondering how the data will be grouped together if we look at the `total_coups`, `source`, `host`, `sfi`, `injuries`, and `fatalities` variables. Would the groupings reflect along with the regions of the world? Or would they be grouped together in a different way? Can we infer anything from the different groupings?

In [35]:
```
country_df.head(5)
```

Out[35]:

	country	scoup1	atcoup2	pcoup3	apcoup4	agcoup	foroutex	reboutex	assassex
0	Afghanistan	5	6	0	1	0	1	1	0
1	Albania	0	1	0	0	1	0	0	0
2	Algeria	1	1	0	0	1	0	0	1
3	Angola	0	1	0	1	0	0	0	0
4	Argentina	7	8	1	0	0	0	0	0

Another thought, what if we looked at the `rand` dataset and added each of the different details to this dataset? Then used clustering on both the `country_df` and the new combined `rand` data? How would clustering change between the two different datasets?

In [36]:
```
years = []
for t in range(len(rand['Date'])):
    try:
        years.append(rand['Date'][t].year)
    except:
        years.append('NaN')

rand['year'] = years
```

In [37]:
```
rand.head(3)
```

Out[37]:

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Description
0	1968-02-09	Buenos Aires	Argentina	Unknown	Firearms	0	0	ARGENTINA. The second floor of the U.S. embas...
1	1968-02-12	Santo Domingo	Dominican Republic	Unknown	Explosives	0	0	DOMINICAN REPUBLIC. A homemade bomb was found...
2	1968-02-13	Montevideo	Uruguay	Unknown	Fire or Firebomb	0	0	URUGUAY. A Molotov cocktail was thrown outsid...

In [38]:
```
coups.head(3)
```

Out[38]:

	ccode	scode	country	year	scoup1	atcoup2	pcoup3	apcoup4	agcoup	foroute
0	700	AFG	Afghanistan	1946	0	0	0	0	0	0
1	700	AFG	Afghanistan	1947	0	0	0	0	0	0
2	700	AFG	Afghanistan	1948	0	0	0	0	0	0

In [39]:
```
rand.dtypes
```

Out[39]:
```
Date           datetime64[ns]
City                   object
Country                object
Perpetrator            object
Weapon                 object
Injuries                int64
Fatalities              int64
Description            object
year                    int64
dtype: object
```

In [40]:
```
coups.dtypes
```

Out[40]:
```
ccode        int64
scode       object
country     object
year         int64
scoup1       int64
atcoup2      int64
pcoup3       int64
apcoup4      int64
agcoup       int64
foroutex     int64
reboutex     int64
assassex     int64
resignex     int64
dtype: object
```

In [41]:
```
# First, merge the rand and coups datasets
inc_df = rand.merge(coups, how='inner', left_on=['Country', 'year'], right_on=
['country', 'year'])
# Now to clean up the columns and remove the data I don't want in the clusteri
ng
columns = ['ccode', 'scode', 'country']
inc_df.drop(columns, axis=1, inplace=True)

# Now, to merge inc_df and the displaced data
inc_df = inc_df.merge(displaced, how='inner', left_on=['Country', 'year'], rig
ht_on=['country', 'year'])
columns = ['ccode', 'scode', 'country']
inc_df.drop(columns, axis=1, inplace=True)

# Last, I need to merge inc_df and the fragility data
inc_df = inc_df.merge(fragility, how='inner', left_on=['Country', 'year'], rig
ht_on=['country', 'year'])
columns = ['scode', 'country', 'legit', 'seceff', 'secleg', 'poleff', 'polleg'
,
           'ecoeff', 'ecoleg', 'soceff', 'socleg']
inc_df.drop(columns, axis=1, inplace=True)

inc_df
```

Out[41]:

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
0	1995-01-04	NaN	Sierra Leone	Revolutionary United Front (RUF)	Unknown	0	9	SIERF LEON Swiss emplo a Frer
1	1995-01-18	Mokanji	Sierra Leone	Revolutionary United Front (RUF)	Unknown	0	0	SIERF LEON British Germa Austr.
2	1995-01-20	Gbangbatok	Sierra Leone	Revolutionary United Front (RUF)	Unknown	0	0	SIERF LEON British one S Leon..
3	1995-01-25	Kambia	Sierra Leone	Unknown	Unknown	0	0	SIERF LEON British charity organ
4	1995-01-25	Kambia	Sierra Leone	Revolutionary United Front (RUF)	Unknown	0	0	SIERF LEON Sever six Ita and o
5	1995-04-10	NaN	Sierra Leone	Revolutionary United Front (RUF)	Firearms	0	1	SIERF LEON convo cars belon t...
6	1995-05-18	Tombudu Town	Sierra Leone	Revolutionary United Front (RUF)	Unknown	0	0	SIERF LEON Three Leban busine were..
7	1995-01-12	al-Ashiyah	Egypt	al-Gama'at al-Islamiyya (IG)	Firearms	6	0	EGYP Argen and fo Egypt we...

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
8	1995-11-07	Luxor	Egypt	al-Gama'at al-Islamiyya (IG)	Firearms	10	0	EGYP tourist from L Cairo
9	1995-11-09	Aswan	Egypt	al-Gama'at al-Islamiyya (IG)	Firearms	3	0	EGYP Islami extren opene on a tr
10	1995-11-18	Aswan	Egypt	al-Gama'at al-Islamiyya (IG)	Firearms	5	1	EGYP Suspe al-Gar al-Isla memb
11	1995-11-30	Cairo	Egypt	al-Gama'at al-Islamiyya (IG)	Firearms	0	0	EGYP Suspe al-Gar al-Isla (Islam
12	1995-01-13	Beit El	Israel	Popular Front for the Liberation of Palestine ...	Firearms	0	1	ISRAE Israeli studer killed dr...
13	1995-01-22	Netanya	Israel	Palestine Islamic Jihad (PIJ)	Explosives	62	22	ISRAE crowd stop a Lid, ne
14	1995-03-20	NaN	Israel	Hamas (Islamic Resistance Movement)	Explosives	0	0	ISRAE truck l with 4 pound exp...
15	1995-03-31	NaN	Israel	Hizballah	Explosives	7	1	ISRAE One Is civilian killed
16	1995-04-21	NaN	Israel	Other	Unknown	1	0	ISRAE Palest from J crosse the...

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
17	1995-05-05	Qiryat Shemona	Israel	Hizballah	Explosives	3	0	ISRAE Five Katyu rocket fired i
18	1995-06-23	Nahariya	Israel	Hizballah	Explosives	8	1	ISRAE Club M holida resort Nahar
19	1995-07-24	Tel Aviv	Israel	Hamas (Islamic Resistance Movement)	Explosives	30	6	ISRAE bomb explod a com bus at
20	1995-08-12	NaN	Israel	Unknown	Unknown	0	0	ISRAE heavil armed infiltra appre
21	1995-08-21	Jerusalem	Israel	Hamas (Islamic Resistance Movement)	Explosives	100	6	ISRAE bomb explod a bus Ramo
22	1995-11-27	Qiryat Shemona	Israel	Hizballah	Explosives	7	0	ISRAE Guerr presu be fro Hezbo
23	1995-01-15	Angkor	Cambodia	Khmer Rouge	Firearms	1	2	CAME An An woma killed
24	1995-01-15	NaN	Turkey	Kurdish Workers Party (PKK)	Unknown	0	2	TURK Two Ir men w kidnap from t

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
25	1995-04-21	Istanbul	Turkey	Unknown	Explosives	0	1	TURK tow tru driver killed ...
26	1995-07-14	NaN	Turkey	Kurdish Workers Party (PKK)	Unknown	0	0	TURK Japan tourist kidnap by K..
27	1995-07-14	Istanbul	Turkey	Devrimici Halk Kurtulus Cephesi (DHKP/C)	Unknown	0	0	TURK The G Tower histori tourist
28	1995-08-27	Istanbul	Turkey	Unknown	Explosives	8	0	TURK bombi restau the Ak
29	1995-08-27	Istanbul	Turkey	Kurdish Islamic Unity Party	Explosives	30	2	TURK Two b plante trash explo.
...	...	...	...	...	...	...	...	...
27615	2008-08-19	Mersin	Turkey	Kurdistan Freedom Falcons	Explosives	14	0	On 19 Augus vehicl under Turkis police
27616	2008-08-20	Yuksekova	Turkey	Kurdish Workers Party	Firearms	2	0	On 20 Augus allege militar on fo..
27617	2008-08-21	Izmir	Turkey	Kurdistan Freedom Falcons	Remote-detonated explosive	16	0	On the morni 21 Au car ex on...

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
27618	2008-09-21	Dogantas	Turkey	Kurdistan Workers Party	Unknown	0	0	On 21 Septe a grou militar stoppe
27619	2008-10-08	Azizye	Turkey	Freedom Hawks of Kurdistan	Firearms	18	5	On 8 Octob Kurdis forces a bus
27620	2008-10-11	Sisli	Turkey	Kurdish Workers Party	Explosives	0	0	On 11 Octob Turkis police officer arrest
27621	2008-10-19	Istanbul	Turkey	Unknown	Explosives	0	0	On 19 Octob 9pm a explod inside
27622	2008-10-20	Istanbul	Turkey	Unknown	Explosives	0	0	On 20 Octob bomb detona outsid
27623	2008-10-27	Kadikoy	Turkey	Unknown	Explosives	0	0	At 11p 27 Oc a cond grena wa...
27624	2008-10-27	Istanbul	Turkey	Unknown	Explosives	0	0	On 27 Octob Turkis author detona ...
27625	2008-11-01	Hakkari	Turkey	Unknown	Explosives	2	0	On 1 Nover bomb detona a rulin

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
27626	2008-11-05	Cukurca	Turkey	Unknown	Explosives	0	0	On 5 Nover bomb explod the ru Ju...
27627	2008-11-11	Cukurca	Turkey	Other	Remote-detonated explosive	0	0	On 11 Nover Turkis author foiled
27628	2008-11-21	Taskoy	Turkey	People's Congress of Kurdistan	Explosives	0	0	On 21 Nover the Ku worke party
27629	2008-11-27	Hatay	Turkey	Kurdish Workers Party	Firearms	4	2	On 27 Nover Kurdis Worke Party militar
27630	2008-12-02	Istanbul	Turkey	Revolutionary Headquarters	Explosives	10	0	On 2 Decer what i thoug have p...
27631	2008-12-06	Istanbul	Turkey	Unknown	Explosives	2	0	On 6 Decer concu bomb explod fr...
27632	2008-12-08	Van	Turkey	Unknown	Explosives	0	0	On 8 Decer an exp occurr front c
27633	2008-06-28	Tripoli	Lebanon	Unknown	Remote-detonated explosive	20	2	An ex placed entran five ...

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
27634	2008-08-13	Tripoli	Lebanon	Unknown	Explosives	40	19	On the morni Augus 2008, bomb
27635	2008-07-16	Amman	Jordan	Other	Firearms	6	0	On Ju an Ara Isreali woma Leban
27636	2008-08-17	Baku	Azerbaijan	Forest Brothers	Explosives	13	3	Two grena were t into th Bakr r
27637	2008-08-22	Baku	Azerbaijan	Unknown	Explosives	2	2	An ex occurr power substa in...
27638	2008-08-22	Baku	Azerbaijan	Forest Brothers	Explosives	0	2	An ex occurr an ele substa
27639	2008-08-28	La Paz	Bolivia	Unknown	Explosives	0	0	On Au 28, 20 small was th at ...
27640	2008-09-16	Cochabamba	Bolivia	Unknown	Explosives	0	0	On Septe 16, 20 small explod at...
27641	2008-12-18	Santa Cruz	Bolivia	Other	Explosives	0	0	A bom explod a build occup Atla...

	Date	City	Country	Perpetrator	Weapon	Injuries	Fatalities	Desc
27642	2008-09-27	Damascus	Syria	Unknown	Explosives	14	17	At 8:4 on 27 Septe a car contai r...
27643	2008-10-10	Huancavelica	Peru	Shining Path	Firearms	0	14	On Oc 10, 20 Shinin memb attac..
27644	2008-11-02	Vicenza	Italy	Unknown	Explosives	0	0	On Nover 2008 a explod the Vi

27645 rows × 24 columns

One thing to note about this newly merged data, since it was an inner merge, we only kept the data that we have across all of the different datasets. Because of this, the data starts in 1995 rather than earlier. But now that we have our two datasets, the `country_df` and `inc_df`, we can start working on clustering the data.

To start with, I will be using k-Means Clustering.

Feature Reduction - Principal Component Analysis

Before we jump right into working the k-Meas Clustering, I want to first reduce the number of features in `country_df` down to two for ease of visualization.

In [42]:
```
country_df.head(3)
```

Out[42]:

	country	scoup1	atcoup2	pcoup3	apcoup4	agcoup	foroutex	reboutex	assassex
0	Afghanistan	5	6	0	1	0	1	1	0
1	Albania	0	1	0	0	1	0	0	0
2	Algeria	1	1	0	0	1	0	0	1

In [43]:
```
country_midstep = country_df[['scoup1', 'atcoup2', 'pcoup3', 'apcoup4', 'agcou
p', 'foroutex',
                              'reboutex', 'assassex', 'resignex', 'total_coups',
'source',
                              'host', 'sfi', 'injuries', 'fatalities']]
```

In [44]:
```
country_pca = PCA(n_components=2)
fit = country_pca.fit(country_midstep)
print("Explained Variance: %s" % fit.explained_variance_ratio_)
print(fit.components_)
```

```
Explained Variance: [0.50168516 0.3573909 ]
[[ 4.22469591e-05  7.92427931e-05  6.13192751e-06  1.23676555e-05
  -3.93914719e-06  9.46807924e-06  8.52039093e-06  4.26396014e-06
  -5.40450519e-07  1.57762168e-04  9.77795602e-01  9.71018122e-02
   2.40115503e-04  1.61162740e-01  9.22685132e-02]
 [ 1.68732197e-05  2.67013986e-05  2.74957359e-05  3.70244865e-06
  -4.91801548e-07 -1.84372953e-06 -3.25660568e-06  3.75802627e-06
   2.22745750e-05  9.52132674e-05 -1.20379958e-01  9.85508042e-01
   1.12831411e-04  1.10442913e-01  4.56607503e-02]]
```

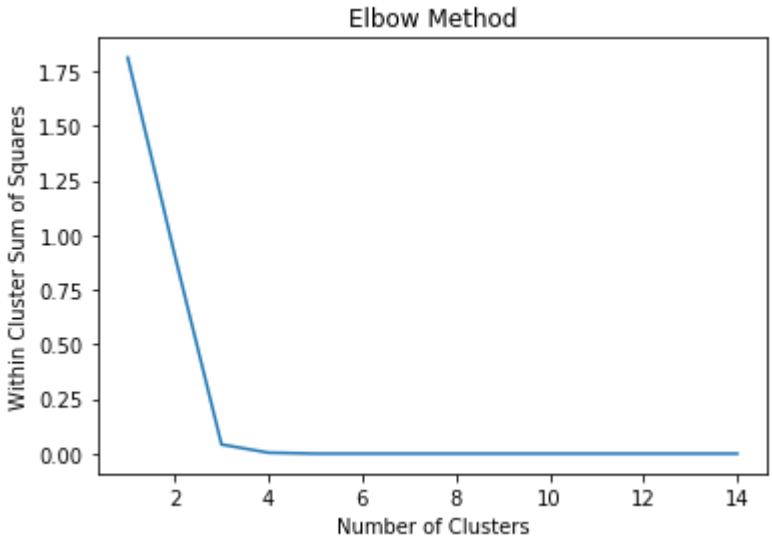
We know that reducing the features down to two features means we lose most of the individual details of the different variables, but we can use this to help find the optimal k for our k-Means Clustering.

Optimal K

To find the Optimal k value, I will be using the Elbow Method.

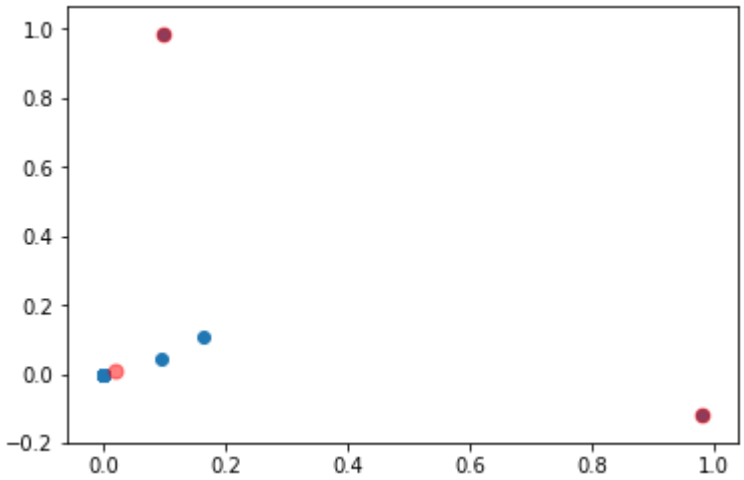
In [45]:
```
col1 = fit.components_[0]
col2 = fit.components_[1]
data = {'col1':col1, 'col2':col2}
pca_df = pd.DataFrame(data=data)
```

In [46]:
```
test = []
for i in range(1, 15):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, r
andom_state=0)
    kmeans.fit(pca_df)
    test.append(kmeans.inertia_)
plt.plot(range(1,15), test)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Within Cluster Sum of Squares')
plt.show()
```



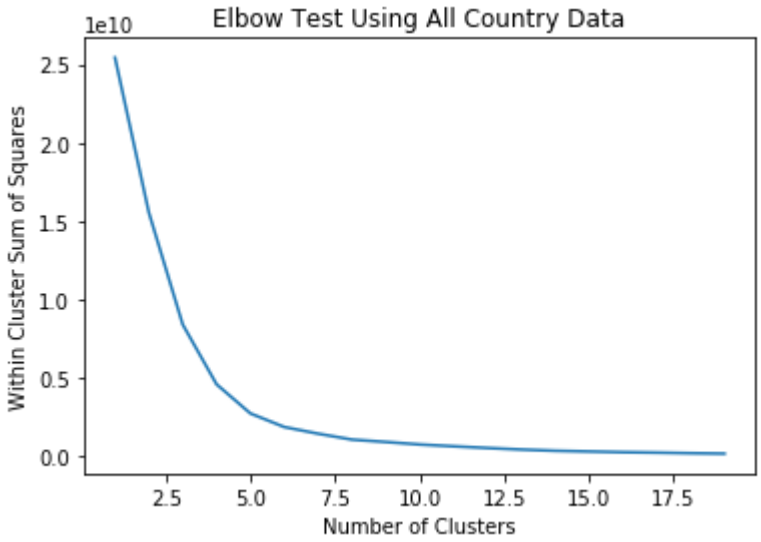
Well now, that's pretty definitive for the PCA data. The optimal number of clusters is 3. Let's see what the clusters look like in two dimensions.

In [47]:
```
kmeans = KMeans(n_clusters=3, init='k-means++', max_iter=300, n_init=10, rando
m_state=0)
pred_y = kmeans.fit_predict(pca_df)

plt.scatter(pca_df['col1'], pca_df['col2'])
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=50
, c='red', alpha=.5)
plt.show()
```



Ah, it makes sense why the optimal number of clusters is 3 for the PCA data. But how about the full data? Would we get the same "elbow" and the same clustering?bow"?

In [48]:
```
elbow_test = []
for i in range(1,20):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, r
andom_state=0)
    kmeans.fit(country_midstep)
    elbow_test.append(kmeans.inertia_)
plt.plot(range(1,20), elbow_test)
plt.title("Elbow Test Using All Country Data")
plt.xlabel('Number of Clusters')
plt.ylabel('Within Cluster Sum of Squares')
plt.show()
```



This is much more expected. There isn't a single "best" k to use, but a k between 3 and 6 seems to be appropriate. I'll go with 6 clusters for now.

K-Means Clustering

Now it's time to start the actual k-Means Clustering. I'll be using 6 clusters when using the `country_midstep` data.

In [49]:
```
kmeans = KMeans(n_clusters=6, init='k-means++', max_iter=300, n_init=10,
                random_state=0)
group = kmeans.fit_predict(country_midstep)
print(group)
```

```
[1 4 4 5 4 4 4 4 4 4 5 4 4 4 4 4 4 4 5 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
 4 5 4 4 4 4 4 4 4 4 4 4 4 4 4 4 2 4 2 3 4 5 4 4 4 2 4 4 4 4 4 4 0 4 5 4 4
 4 4 4 4 4 4 4 4 4 5 4 4 4 4 4 4 4 4 2 4 4 4 4 4 4 4 4 4 5 4 4 4 4 4 4 5 4
 4 4 0 4 4 4 0 4 4 0 0 4 4 4 4 0 4 4 0 4 4 4 5 4 4 4]
```

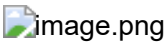
Now that I have the clusters, let's assigned each cluster back to the country and print out the sorted list.

In [50]:
```
data = {'country':country_df['country'], 'group':group}
k_means_country = pd.DataFrame(data=data)
print(k_means_country.sort_values('group'))
```

	country	group
117	Syria	0
69	Lebanon	0
113	Sudan	0
120	Tanzania	0
121	Thailand	0
129	United States	0
126	Uganda	0
0	Afghanistan	1
55	Iran	2
92	Pakistan	2
62	Jordan	2
53	India	2
56	Iraq	3
74	Macedonia	4
70	Lesotho	4
93	Panama	4
91	Norway	4
90	Nigeria	4
89	Niger	4
88	Nicaragua	4
87	New Zealand	4
86	Netherlands	4
85	Nepal	4
72	Libya	4
82	Morocco	4
75	Madagascar	4
81	Mongolia	4
80	Moldova	4
79	Mexico	4
94	Paraguay	4
..	...	...
57	Ireland	4
54	Indonesia	4
52	Hungary	4
51	Honduras	4
50	Haiti	4
33	Ecuador	4
48	Guinea	4
49	Guyana	4
46	Greece	4
35	El Salvador	4
45	Ghana	4
44	Germany	4
43	Georgia	4
36	Eritrea	4
42	Gabon	4
41	France	4
47	Guatemala	4
40	Finland	4
39	Fiji	4
37	Estonia	4
133	Vietnam	5
3	Angola	5
71	Liberia	5
58	Israel	5
10	Bangladesh	5

```
109        Somalia      5
83      Mozambique      5
18         Burundi      5
38        Ethiopia      5
102         Rwanda      5

[137 rows x 2 columns]
```

Hmmm, interesting. Some of the countries are grouped together in ways I wouldn't have expected. I've saved the data to disc to create a visualizations of each country's grouping in Tableau.



Here we can see the Tableau mapping of the groupings. What I find interesting is that there does appear to be a gradual gradient to the adjacent countries. What I mean by this is that Group 0 is usually adjacent to Group 1 or 2, Group 1 is adjacent to either Group 0 or 3, and so on. The main exception to this is the United States. The US is grouped with Group 0 but is surrounded by Group 4 countries. It seems like geographic location is not the only indicator of terrorism.

But let's now look at the `inc_df` data, which contains each individual terrorist attack since 1995. I'm currious as to how the full data is grouped and how the the attacks are grouped together when sorted by weapon type.

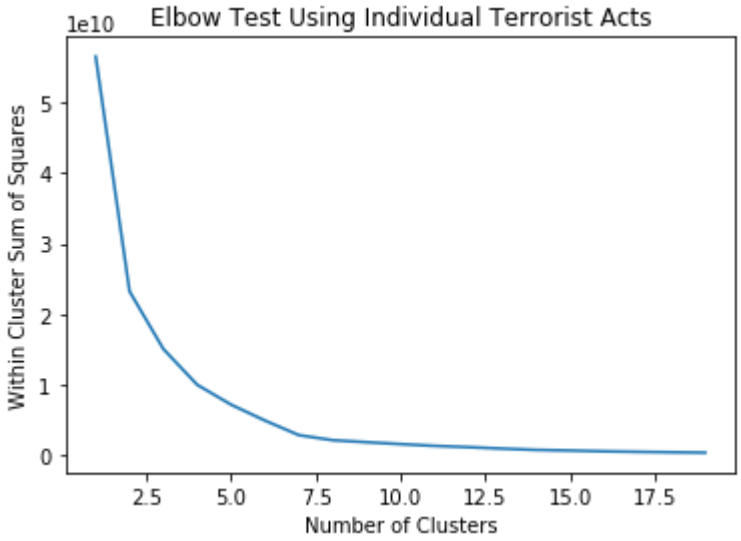
Total `inc_df` Data

First up is looking at the total `inc_df` data. The first thing we'll do is see if we can determine what the best value of k is using the Elbow Method again.

```
In [51]: inc_df.columns
```

```
Out[51]: Index(['Date', 'City', 'Country', 'Perpetrator', 'Weapon', 'Injuries',
                'Fatalities', 'Description', 'year', 'scoup1', 'atcoup2', 'pcoup3',
                'apcoup4', 'agcoup', 'foroutex', 'reboutex', 'assassex', 'resignex',
                'source', 'idp', 'host', 'region', 'sfi', 'effect'],
               dtype='object')
```

In [52]:
```
inc_midstep1 = inc_df[['Country','Injuries','Fatalities', 'year', 'scoup1', 'a
tcoup2',
                       'pcoup3', 'apcoup4', 'agcoup', 'foroutex', 'reboutex',
                       'assassex', 'resignex', 'source', 'idp', 'host',
                       'sfi', 'effect']]
inc_midstep1 = inc_midstep1.dropna()
inc_midstep2 = inc_midstep1.drop('Country', axis=1)
elbow_test = []
for i in range(1,20):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10,
                    random_state=0)
    kmeans.fit(inc_midstep2)
    elbow_test.append(kmeans.inertia_)
plt.plot(range(1,20), elbow_test)
plt.title("Elbow Test Using Individual Terrorist Acts")
plt.xlabel('Number of Clusters')
plt.ylabel('Within Cluster Sum of Squares')
plt.show()
```



This graph looks pretty similar to the last Elbow Test, so we will continue using 6 clusters to keep it the same.

Next up is to run k-Means Clustering.

In [53]:
```
kmeans = KMeans(n_clusters=6, init='k-means++', max_iter=300, n_init=10,
                random_state=0)
group = kmeans.fit_predict(inc_midstep2)
print(group)
```

```
[0 0 0 ... 5 0 0]
```

Now let's put the data together into a single DataFrame.

In [54]:
```
data = {'country':inc_midstep1['Country'], 'year':inc_midstep1['year'],
       'cluster':group}
inc_cluster_df = pd.DataFrame(data=data)
inc_cluster_df
```

Out[54]:

	country	year	cluster
0	Sierra Leone	1995	0
1	Sierra Leone	1995	0
2	Sierra Leone	1995	0
3	Sierra Leone	1995	0
4	Sierra Leone	1995	0
5	Sierra Leone	1995	0
6	Sierra Leone	1995	0
7	Egypt	1995	0
8	Egypt	1995	0
9	Egypt	1995	0
10	Egypt	1995	0
11	Egypt	1995	0
12	Israel	1995	0
13	Israel	1995	0
14	Israel	1995	0
15	Israel	1995	0
16	Israel	1995	0
17	Israel	1995	0
18	Israel	1995	0
19	Israel	1995	0
20	Israel	1995	0
21	Israel	1995	0
22	Israel	1995	0
23	Cambodia	1995	0
24	Turkey	1995	4
25	Turkey	1995	4
26	Turkey	1995	4
27	Turkey	1995	4
28	Turkey	1995	4
29	Turkey	1995	4
...	...	...	...
27615	Turkey	2008	0

	country	year	cluster
27616	Turkey	2008	0
27617	Turkey	2008	0
27618	Turkey	2008	0
27619	Turkey	2008	0
27620	Turkey	2008	0
27621	Turkey	2008	0
27622	Turkey	2008	0
27623	Turkey	2008	0
27624	Turkey	2008	0
27625	Turkey	2008	0
27626	Turkey	2008	0
27627	Turkey	2008	0
27628	Turkey	2008	0
27629	Turkey	2008	0
27630	Turkey	2008	0
27631	Turkey	2008	0
27632	Turkey	2008	0
27633	Lebanon	2008	0
27634	Lebanon	2008	0
27635	Jordan	2008	0
27636	Azerbaijan	2008	0
27637	Azerbaijan	2008	0
27638	Azerbaijan	2008	0
27639	Bolivia	2008	0
27640	Bolivia	2008	0
27641	Bolivia	2008	0
27642	Syria	2008	5
27643	Peru	2008	0
27644	Italy	2008	0

27634 rows × 3 columns

When all of the data is used, we get the following graphs for the following years:

1995:


1996:


1997:


1998:

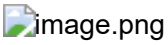

1999:

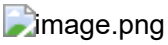

2000:

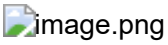

2001:


2002:


2003:


2004:


2005:


2006:


2007:


2008:


Here are all of the different years. But how are they grouped when all of the different years are combined?

1995-2008:


What I find interesting is that most of the different countries were placed into similar clusters when we look at all of the individual terrorist attacks as when we looked at the combination of the data. One of the big differences, once again, is the United States. When compared to each individual terrorist attack, the US is grouped along with Canada and Mexico.

What really fascinates me is that the region coding of each country was removed from the data before the k-Means Clustering was completed. But we can still see the different clusters do seem to correspond to geographical regions.

Further Research

Further research can be done into how the different acts of terrorisme are clustered together based on what type of weapon is used.

Sources:

- National Consortium for the Study of Terrorism and Responses to Terrorism (START). (2018). Global Terrorism Database. Retrieved 28 Sep. 2019 from https://www.start.umd.edu/gtd (https://www.start.umd.edu/gtd)
- Roser, M., Nagdy, M., Ritchie, H. (July 2013) “Terrorism.” Our World in Data. Retrieved 28 Sep. 2019 from https://ourworldindata.org/terrorism (https://ourworldindata.org/terrorism)
- “Forcibly Displaced Populations, 1964-2008.” Integrated Network for Societal Conflict Research Center for Systemic Peace. Retrieved 28 Sep. 2019 from http://www.systemicpeace.org/inscrdata.html (http://www.systemicpeace.org/inscrdata.html)
- “Coups d’Etat, 1946-2018.” Integrated Network for Societal Conflict Research Center for Systemic Peace. Retrieved 28 Sep. 2019 from http://www.systemicpeace.org/inscrdata.html (http://www.systemicpeace.org/inscrdata.html)
- “State Fragility Index and Matrix, Time-Series Data, 1995-2017.” Integrated Network for Societal Conflict Research Center for Systemic Peace. Retrieved 28 Sep. 2019 from http://www.systemicpeace.org/inscrdata.html (http://www.systemicpeace.org/inscrdata.html)
- “Political instability task force worldwide atrocities dataset.” The Computational Event Data System. Retrieved 28 Sep. 2019 from http://eventdata.parusanalytics.com/data.dir/atrocities.html (http://eventdata.parusanalytics.com/data.dir/atrocities.html)
- “RAND database of worldwide terrorism incidents (RDWTI).” Rand Corporation. Retrieved 28 Sep. 2019 from https://www.rand.org/nsrd/projects/terrorism-incidents/download.html (https://www.rand.org/nsrd/projects/terrorism-incidents/download.html)
- Sundberg, Ralph, and Erik Melander, 2013, “Introducing the UCDP Georeferenced Event Dataset”, Journal of Peace Research, vol.50, no.4, 523-532. Retrieved 28 Sep. 2019 from https://www.ucdp.uu.se/downloads/ (https://www.ucdp.uu.se/downloads/)
- Högbladh Stina, 2019, “UCDP GED Codebook version 19.1”, Department of Peace and Conflict Research, Uppsala University. Retrieved 28 Sep. 2019 from https://www.ucdp.uu.se/downloads/ (https://www.ucdp.uu.se/downloads/)