Final_Project_Master_v0

December 7, 2017

1 CS109a Final Project: Group 90 Predicting damage of US storms

1.0.1 Data Science 1: CS 109A/STAT 121A/AC 209A/ E 109A Instructors: Pavlos Protopapas, Kevin Rader, Rahul Dave

Harvard University Fall 2017

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```
In [1]: import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegressionCV
        import sklearn.metrics as metrics
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
        from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
        from sklearn.linear_model import LinearRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.model_selection import cross_val_score
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import confusion_matrix
        from sklearn.preprocessing import Imputer
        from sklearn.metrics import mean_squared_error
        from sklearn.metrics import r2_score


        # from zipcode
        %matplotlib inline
        import numpy as np
        import scipy as sp
```

```
import matplotlib as mpl
import matplotlib.cm as cm
import matplotlib.pyplot as plt
import pandas as pd
import time
pd.set_option('display.width', 500)
pd.set_option('display.max_columns', 100)
pd.set_option('display.notebook_repr_html', True)
import seaborn as sns
sns.set_style("whitegrid")
sns.set_context("poster")
import time
import copy
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
from sklearn.neighbors import KNeighborsRegressor
```

2 Part 1: Loading In Data

In [2]:
```
# load in all data for 2016 and 2017

# Data source: https://www1.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/

details_2016 = pd.read_csv('Details_2016.csv')
details_2017 = pd.read_csv('Details_2017.csv')
locations_2016 = pd.read_csv('Locations_2016.csv')
locations_2017 = pd.read_csv('Locations_2017.csv')
# Fatalities data were initially considered, but we decided to focus on monetary damag
#fatalities_2016 = pd.read_csv('Fatalities_2016.csv')
#fatalities_2017 = pd.read_csv('Fatalities_2017.csv')

details_2016.head()
```

Out[2]:

	BEGIN_YEARMONTH	BEGIN_DAY	BEGIN_TIME	END_YEARMONTH	END_DAY	END_TIME	EPISODE_II
0	201607	15	1715	201607	15	1715	10876
1	201607	15	1725	201607	15	1725	10876
2	201607	16	1246	201607	16	1246	10881
3	201607	8	1755	201607	8	1755	10587
4	201607	8	1810	201607	8	1810	10587

	TOR_OTHER_CZ_NAME	BEGIN_RANGE	BEGIN_AZIMUTH	BEGIN_LOCATION	END_RANGE	END_AZIMUTH	EI
0	NaN	1.0	N	BOYD HILL	1.0	N	
1	NaN	1.0	S	FT MILL	1.0	S	
2	NaN	2.0	ENE	OLD FT	2.0	ENE	
3	NaN	1.0	W	JENA	1.0	W	
4	NaN	1.0	WSW	PITNER	1.0	WSW	

In [3]:
```
# vertically merge 2016 and 2017 data together
```

```
details = pd.concat([details_2016, details_2017])
locations = pd.concat([locations_2016, locations_2017])
#fatalities = pd.concat([fatalities_2016, fatalities_2017])

print(details.shape)

details.head()
```

```
(103177, 51)
```

Out[3]:

```
   BEGIN_YEARMONTH  BEGIN_DAY  BEGIN_TIME  END_YEARMONTH  END_DAY  END_TIME  EPISODE_II
0           201607         15        1715         201607       15      1715      10876
1           201607         15        1725         201607       15      1725      10876
2           201607         16        1246         201607       16      1246      10881
3           201607          8        1755         201607        8      1755      10587
4           201607          8        1810         201607        8      1810      10587

  TOR_OTHER_CZ_NAME  BEGIN_RANGE BEGIN_AZIMUTH BEGIN_LOCATION  END_RANGE END_AZIMUTH EI
0               NaN          1.0             N      BOYD HILL        1.0           N
1               NaN          1.0             S        FT MILL        1.0           S
2               NaN          2.0           ENE         OLD FT        2.0         ENE
3               NaN          1.0             W           JENA        1.0           W
4               NaN          1.0           WSW         PITNER        1.0         WSW
```

3 Part 2: Preliminary Data Analysis and Cleaning

In [4]:

```
# look at column names

print(list(details.columns))
print()
print(list(locations.columns))
print()
```

```
['BEGIN_YEARMONTH', 'BEGIN_DAY', 'BEGIN_TIME', 'END_YEARMONTH', 'END_DAY', 'END_TIME', 'EPISODI

['YEARMONTH', 'EPISODE_ID', 'EVENT_ID', 'LOCATION_INDEX', 'RANGE', 'AZIMUTH', 'LOCATION', 'LAT
```

In [5]:

```
# merge details and location data

data = pd.merge(details, locations, how='inner', on=['EVENT_ID'])
print(data.shape)
data.head()

# Again, fatalities data were considered but we decided to a deeper dive into monetary
```

```
## NOTE: possibility to merge on fatalities, but there are very few (766) so this woul
## perhaps use for some final added analysis
## data = pd.merge(data1, fatalities, how='inner', on=['EVENT_ID'])
```

```
(87563, 61)
```

Out[5]:

```
   BEGIN_YEARMONTH  BEGIN_DAY  BEGIN_TIME  END_YEARMONTH  END_DAY  END_TIME  EPISODE_II
0           201603         15        2316         201603       15      2316        1029
1           201603         15        2239         201603       15      2300        1029
2           201607          7        2137         201607        7      2137        1088
3           201607          7        2013         201607        7      2013        1088
4           201607          7        2116         201607        7      2116        1088

  TOR_OTHER_CZ_NAME  BEGIN_RANGE BEGIN_AZIMUTH    BEGIN_LOCATION  END_RANGE END_AZIMUTI
0               NaN          1.0             N          EDGERTON        1.0            I
1               NaN          1.0           NNE          HARTLAND        1.0          NNI
2               NaN         11.0             S  OAKLEY MUNI ARPT       11.0            S
3               NaN          2.0             E             COLBY        2.0            I
4               NaN          6.0           SSW  OAKLEY MUNI ARPT        6.0          SSW
```

In [6]:

```
# make sure that these are the same; confirming merge worked as desired
print(details[details['EVENT_ID'] == 619253]['DAMAGE_PROPERTY'])
print(data[data['EVENT_ID'] == 619253]['DAMAGE_PROPERTY'])

print(details[details['EVENT_ID'] == 651844]['DAMAGE_PROPERTY'])
print(data[data['EVENT_ID'] == 651844]['DAMAGE_PROPERTY'])
```

```
76    1.00K
Name: DAMAGE_PROPERTY, dtype: object
1    1.00K
Name: DAMAGE_PROPERTY, dtype: object
86    0.00K
Name: DAMAGE_PROPERTY, dtype: object
3    0.00K
Name: DAMAGE_PROPERTY, dtype: object
```

In [7]:

```
# re-format Property Damage
# Note that initially crop damage was considered, but literature review showed that
# these data are different enough to not just combine with property damage
# There could be future research into crop damage

print(data['DAMAGE_PROPERTY'][data['DAMAGE_PROPERTY'].isnull()].size)

damage_property = []
for i in data["DAMAGE_PROPERTY"]:
    try:
        dam = float(i.split('K')[0])*1000.0
```

```
                damage_property.append(dam)
            except:
                try:
                    dam = float(i.split('M')[0])*1000000.0
                    damage_property.append(dam)
                except:
                    try:
                        dam = float(i.split('B')[0])*1000000000.0
                        damage_property.append(dam)
                    except:
                        try:
                            dam = float(i)*1.0
                            damage_property.append(dam)
                        except:
                            print(i)

data["DAMAGE_PROPERTY"] = damage_property

# still a bunch of nulls
print(data['DAMAGE_PROPERTY'][data['DAMAGE_PROPERTY'].isnull()].size)

data.head()
```

```
11870
11870
```

Out[7]:

```
   BEGIN_YEARMONTH  BEGIN_DAY  BEGIN_TIME  END_YEARMONTH  END_DAY  END_TIME  EPISODE_ID
0           201603         15        2316         201603       15      2316        1029
1           201603         15        2239         201603       15      2300        1029
2           201607          7        2137         201607        7      2137        1088
3           201607          7        2013         201607        7      2013        1088
4           201607          7        2116         201607        7      2116        1088

  TOR_OTHER_CZ_NAME  BEGIN_RANGE BEGIN_AZIMUTH    BEGIN_LOCATION  END_RANGE END_AZIMUTH
0               NaN          1.0             N          EDGERTON        1.0           N
1               NaN          1.0           NNE          HARTLAND        1.0          NNE
2               NaN         11.0             S  OAKLEY MUNI ARPT       11.0            S
3               NaN          2.0             E             COLBY        2.0            E
4               NaN          6.0           SSW  OAKLEY MUNI ARPT        6.0          SSW
```

In [8]:

```
# should still match up
print(details[details['EVENT_ID'] == 619253]['DAMAGE_PROPERTY'])
print(data[data['EVENT_ID'] == 619253]['DAMAGE_PROPERTY'])

print(details[details['EVENT_ID'] == 651844]['DAMAGE_PROPERTY'])
print(data[data['EVENT_ID'] == 651844]['DAMAGE_PROPERTY'])
```

```
76    1.00K
Name: DAMAGE_PROPERTY, dtype: object
```

```
1    1000.0
Name: DAMAGE_PROPERTY, dtype: float64
86    0.00K
Name: DAMAGE_PROPERTY, dtype: object
3    0.0
Name: DAMAGE_PROPERTY, dtype: float64
```

In [9]:
```python
# We ultimately chose to drop NA values for property damage
# We still had a large dataset to work with, and felt more comfortable with dropping
# the missing response than some sort of imputation of the response.
# Future research could address an alternative to dropping all cases missing response.

print(len(data))
data = data.dropna(axis=0, subset=['DAMAGE_PROPERTY'])
print(len(data))

data['DAMAGE_PROPERTY'].head()
```

```
87563
75693
```

Out[9]:
```
0       0.0
1    1000.0
2       0.0
3       0.0
4       0.0
Name: DAMAGE_PROPERTY, dtype: float64
```

In [10]:
```python
# Make new categorical column for has_damage
# There is practical importance of predicting not only amount of damage,
# but also presence or absence of damage.

has_damage = []
for x in data['DAMAGE_PROPERTY']:
    if x > 0.0:
        has_damage.append(1)
    else:
        has_damage.append(0)

data['HAS_DAMAGE'] = has_damage
data['HAS_DAMAGE'].head()
```

Out[10]:
```
0    0
1    1
2    0
3    0
4    0
Name: HAS_DAMAGE, dtype: int64
```

In [11]:
```
# expecting yes, no; confirm that binary was created how desired
print(data[data['EVENT_ID'] == 619253]['HAS_DAMAGE'])
print(data[data['EVENT_ID'] == 651844]['HAS_DAMAGE'])
```

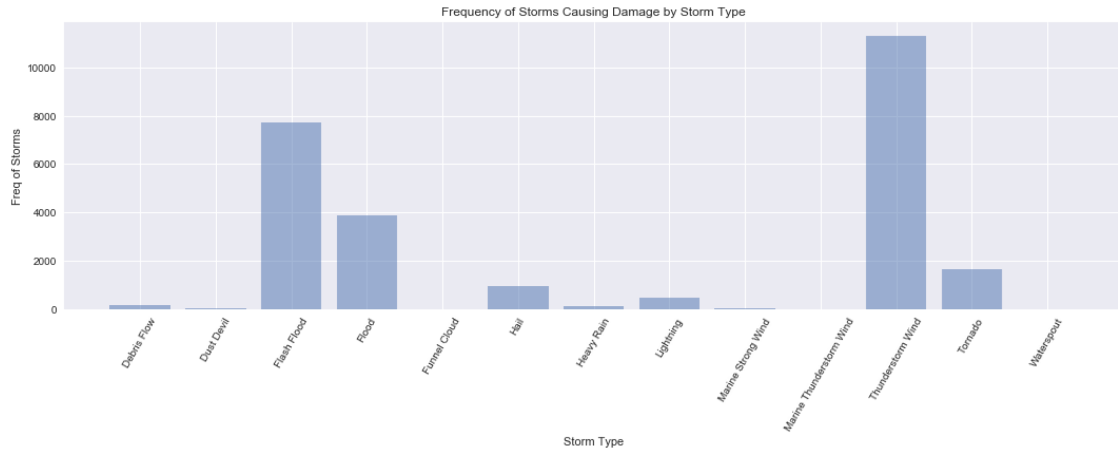
```
1    1
Name: HAS_DAMAGE, dtype: int64
3    0
Name: HAS_DAMAGE, dtype: int64
```

4 Part 3: Some of our EDA

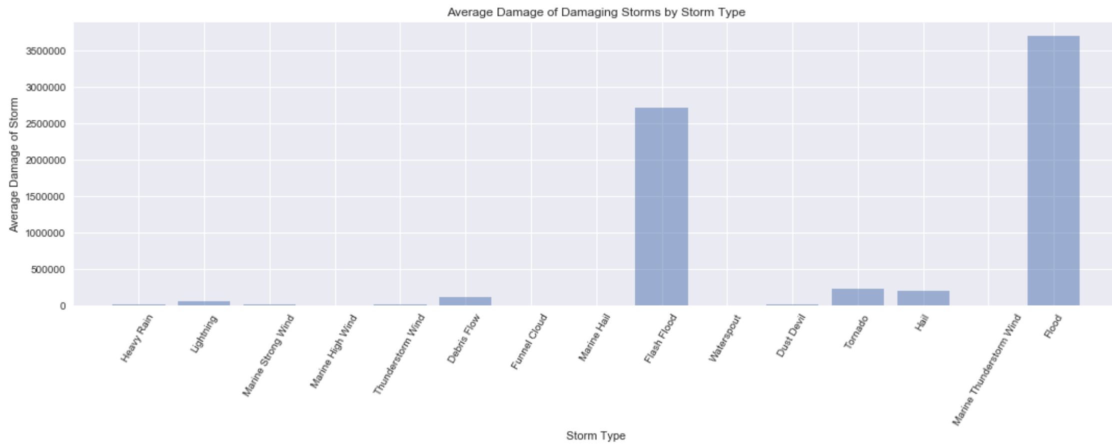
In [12]:
```
# EDA of location variables: first, subset dataframe to storms causing damage
damage_data = data[data['HAS_DAMAGE'] == 1]
```

4.0.1 3.1 Exploring Storm Type

In [13]:
```
import seaborn as sns
sns.set(color_codes=True)

# storm counts by event type
event_type = np.unique(damage_data['EVENT_TYPE'], return_counts=True)
dim = len(event_type[0])

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(dim), event_type[1], align='center', alpha=0.5)
ax.set_xlim([-1, dim])
ax.set_xticks(range(dim))
ax.set_xticklabels(event_type[0], rotation=60)
ax.set_xlabel('Storm Type')
ax.set_ylabel('Freq of Storms')
ax.set_title('Frequency of Storms Causing Damage by Storm Type')

plt.show()
```

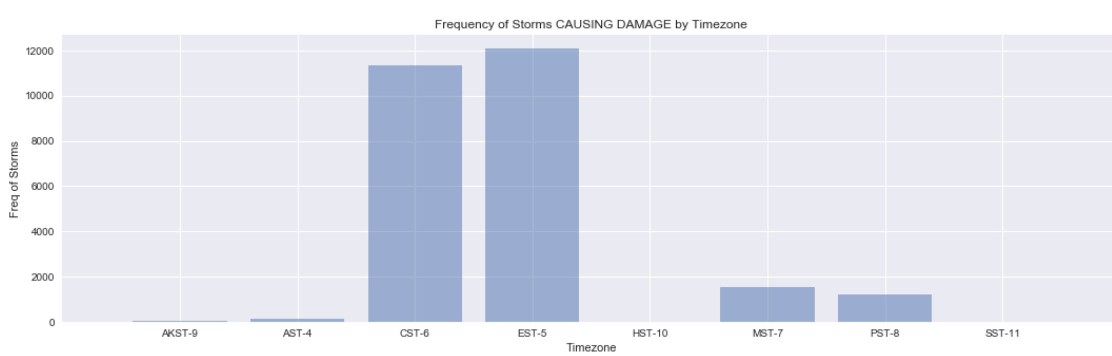


In [14]:
```
# display average damage per storm type without conditioning on damage causing

sns.set(color_codes=True)

storm_types = list(set(data['EVENT_TYPE'].values))

ave_per_storm = []
for i in range(len(storm_types)):
    storm = storm_types[i]
    storm_damage = data[data['EVENT_TYPE'] == storm]['DAMAGE_PROPERTY']
    ave = np.mean(storm_damage)
    ave_per_storm.append(ave)

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(len(storm_types)), ave_per_storm, align='center', alpha=0.5)
ax.set_xlim([-1, len(storm_types)])
ax.set_xticks(range(len(storm_types)))
ax.set_xticklabels(storm_types, rotation=60)
ax.set_xlabel('Storm Type')
ax.set_ylabel('Average Damage of Storm')
ax.set_title('Average Damage of Damaging Storms by Storm Type')

plt.show()
```

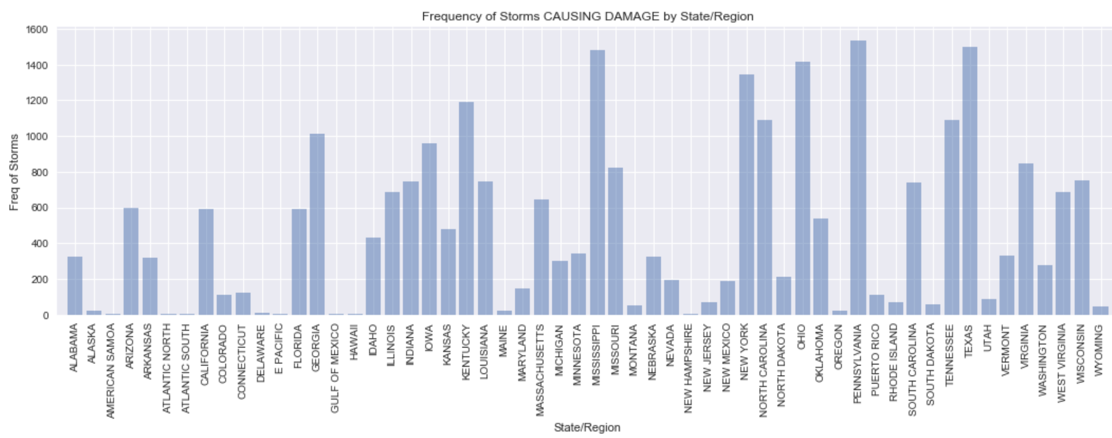


4.0.2 3.2 Exploring Locational Predictors

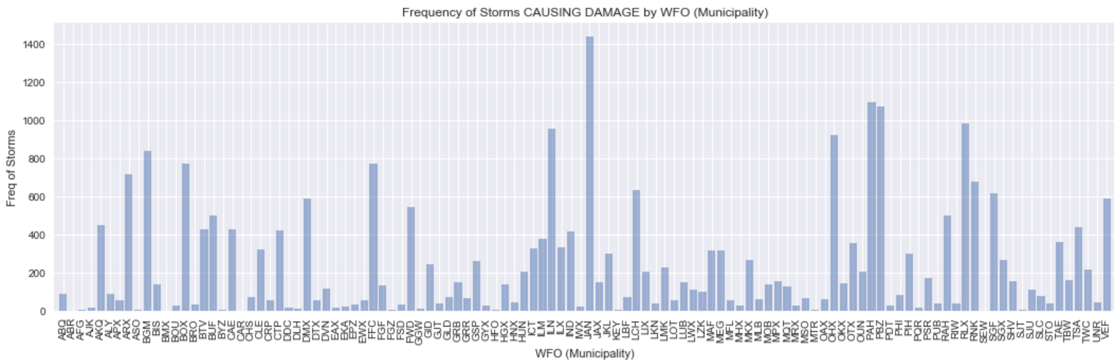
In [15]:
```
# storm counts by timezone
storm_counts_tz = np.unique(damage_data['CZ_TIMEZONE'], return_counts=True)
dim = len(storm_counts_tz[0])

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(dim), storm_counts_tz[1], align='center', alpha=0.5)
ax.set_xlim([-1, dim])
ax.set_xticks(range(dim))
ax.set_xticklabels(storm_counts_tz[0])
ax.set_xlabel('Timezone')
ax.set_ylabel('Freq of Storms')
ax.set_title('Frequency of Storms CAUSING DAMAGE by Timezone')

plt.show()
```



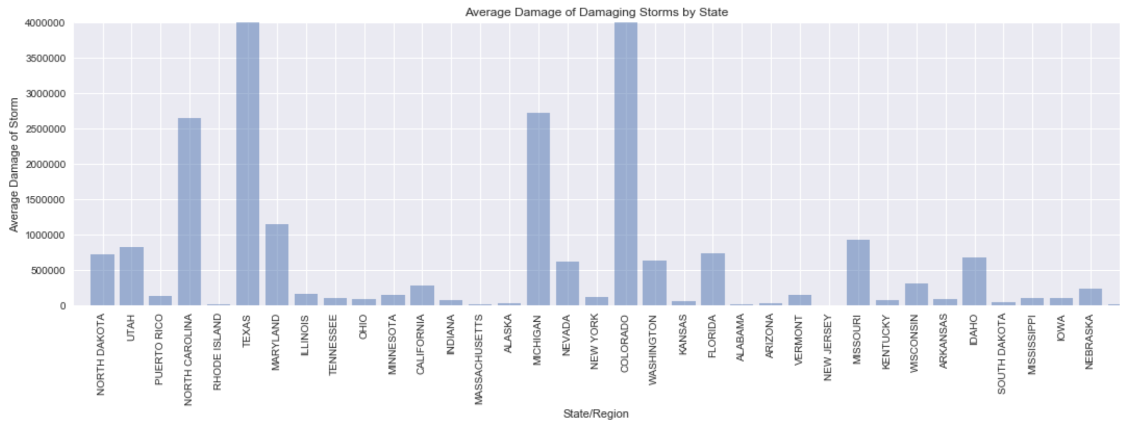
In [16]:
```
# storm counts by state
storm_counts_st = np.unique(damage_data['STATE'], return_counts=True)
dim = len(storm_counts_st[0])

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(dim), storm_counts_st[1], align='center', alpha=0.5)
ax.set_xlim([-1, dim])
ax.set_xticks(range(dim))
ax.set_xticklabels(storm_counts_st[0], rotation=90)
ax.set_xlabel('State/Region')
ax.set_ylabel('Freq of Storms')
ax.set_title('Frequency of Storms CAUSING DAMAGE by State/Region')

plt.show()
```



In [17]:
```
# storm counts by WFO (weather forecast office location)
storm_counts_wfo = np.unique(damage_data['WFO'], return_counts=True)
dim = len(storm_counts_wfo[0])

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(dim), storm_counts_wfo[1], align='center', alpha=0.5)
ax.set_xlim([-1, dim])
ax.set_xticks(range(dim))
ax.set_xticklabels(storm_counts_wfo[0], rotation=90)
ax.set_xlabel('WFO (Municipality)')
ax.set_ylabel('Freq of Storms')
ax.set_title('Frequency of Storms CAUSING DAMAGE by WFO (Municipality)')

plt.show()
```

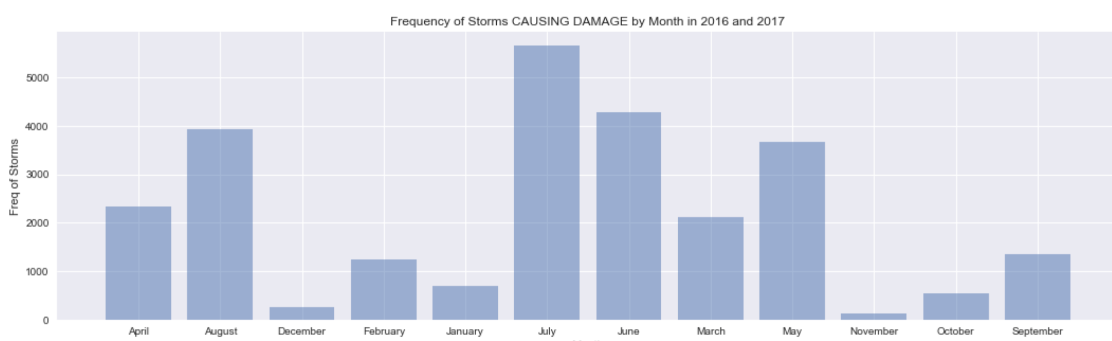


In [18]:
```python
# display average damage per state given causes damage

sns.set(color_codes=True)

states = list(set(damage_data['STATE'].values))

states_final = []
ave_per_state = []
for i in range(len(states)):
    state = states[i]
    state_damage = damage_data[damage_data['STATE'] == state]['DAMAGE_PROPERTY']
    if len(state_damage) > 10:
        ave = np.mean(state_damage)
        states_final.append(state)
        ave_per_state.append(ave)

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(len(ave_per_state)), ave_per_state, align='center', alpha=0.5)
ax.set_xlim([-1, 35])
ax.set_xticks(range(35))
ax.set_ylim([0,4000000])
ax.set_xticklabels(states_final, rotation=90)
ax.set_xlabel('State/Region')
ax.set_ylabel('Average Damage of Storm')
ax.set_title('Average Damage of Damaging Storms by State')

plt.show()
```

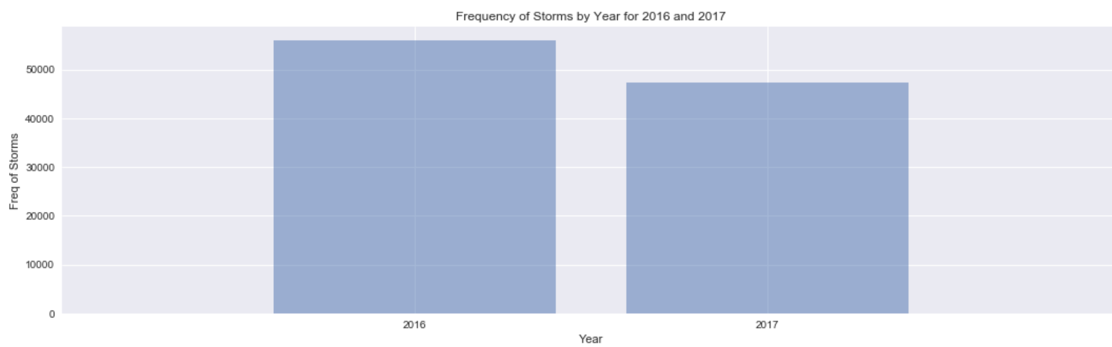


4.0.3 3.3 Exploring Temporal Predictors

```
In [19]: # storm count by month
         storm_counts_mo = np.unique(damage_data['MONTH_NAME'], return_counts=True)
         dim = len(storm_counts_mo[0])

         # plot this info
         fig, ax = plt.subplots(1, 1, figsize=(18, 5))

         ax.bar(range(dim), storm_counts_mo[1], align='center', alpha=0.5)
         ax.set_xlim([-1, dim])
         ax.set_xticks(range(dim))
         ax.set_xticklabels(storm_counts_mo[0], rotation=0)
         ax.set_xlabel('Month')
         ax.set_ylabel('Freq of Storms')
         ax.set_title('Frequency of Storms CAUSING DAMAGE by Month in 2016 and 2017')

         plt.show()
```

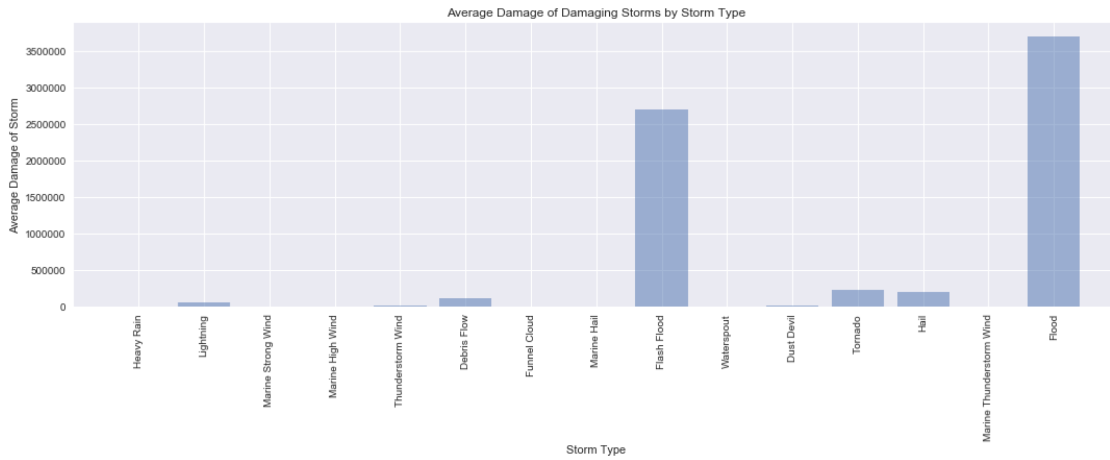


In [20]:
```python
# storm count by year
storm_counts_yr = np.unique(details['YEAR'], return_counts=True)
dim = len(storm_counts_yr[0])

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(dim), storm_counts_yr[1], align='center', alpha=0.5)
ax.set_xlim([-1, dim])
ax.set_xticks(range(dim))
ax.set_xticklabels(storm_counts_yr[0], rotation=0)
ax.set_xlabel('Year')
ax.set_ylabel('Freq of Storms')
ax.set_title('Frequency of Storms by Year for 2016 and 2017')

plt.show()
```



In [21]:
```python
# display average damage per storm type without conditioning on damage causing

sns.set(color_codes=True)

storm_types = list(set(data['EVENT_TYPE'].values))

ave_per_storm = []
for i in range(len(storm_types)):
    storm = storm_types[i]
    storm_damage = data[data['EVENT_TYPE'] == storm]['DAMAGE_PROPERTY']
    ave = np.mean(storm_damage)
    ave_per_storm.append(ave)

# plot this info
fig, ax = plt.subplots(1, 1, figsize=(18, 5))

ax.bar(range(len(storm_types)), ave_per_storm, align='center', alpha=0.5)
ax.set_xlim([-1, len(storm_types)])
```

```
ax.set_xticks(range(len(storm_types)))
ax.set_xticklabels(storm_types, rotation=90)
ax.set_xlabel('Storm Type')
ax.set_ylabel('Average Damage of Storm')
ax.set_title('Average Damage of Damaging Storms by Storm Type')

plt.show()
```



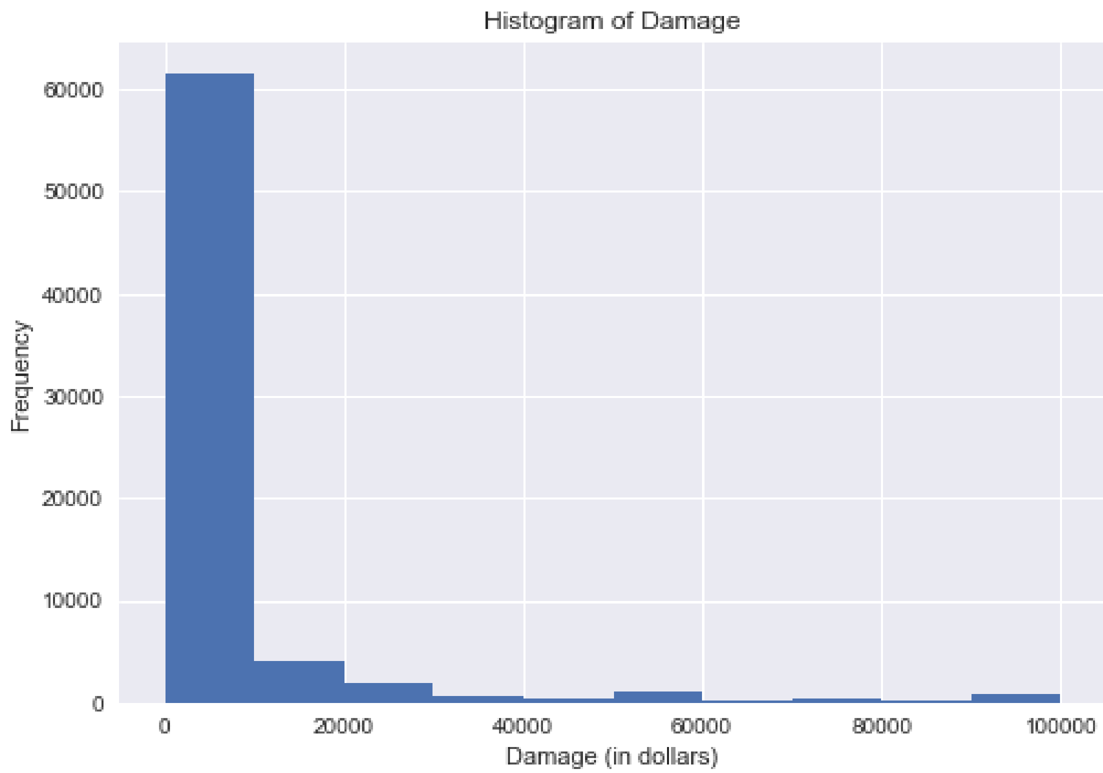
5 Part 4: More Cleaning and Handling of Nulls

```
In [22]: # These are the storms that don't have magnitude
         np.unique(data[data.MAGNITUDE.isnull()]["EVENT_TYPE"], return_counts=True)

Out[22]: (array(['Debris Flow', 'Dust Devil', 'Flash Flood', 'Flood', 'Funnel Cloud',
                 'Heavy Rain', 'Lightning', 'Tornado', 'Waterspout'], dtype=object),
          array([  626,    18, 22544, 13463,   424,  2232,   570,  2645,   311]))

In [23]: # drop null rows and check if any null values remaining
         # There are alternative ways of addressing this, and future explanation could spend t
         # In this case, we chose to drop because these variables were important to our analys
         # and we also had a large amount of data that were not missing.

         print(data.shape)
         # Replace NA magnitudes with 0
         data["MAGNITUDE"] = data.MAGNITUDE.fillna(value=0)
         data.dropna(inplace=True, subset = ['DAMAGE_CROPS','BEGIN_YEARMONTH', 'YEAR','MAGNITUI
         print(data.shape)

         # deleted 1500 rows

(75693, 62)
(74161, 62)
```

5.0.1 EDA on Our Response Variable

In [24]:
```
# Plot damage to see the distribution
data["DAMAGE_PROPERTY"] = pd.Series(damage_property)
plt.hist(x=data.DAMAGE_PROPERTY[data.DAMAGE_PROPERTY <= 100000])
plt.xlabel("Damage (in dollars)")
plt.ylabel("Frequency")
plt.title("Histogram of Damage")
```

Out[24]:
```
<matplotlib.text.Text at 0x11ad8c940>
```



In [25]:
```
np.corrcoef(data["DAMAGE_PROPERTY"],data["DEATHS_DIRECT"])
```

Out[25]:
```
array([[ 1.        ,  0.53523837],
       [ 0.53523837,  1.        ]])
```

In [26]:
```
# Check the quantities of weather events that cause large amounts of damage
data.DAMAGE_PROPERTY[data.DAMAGE_PROPERTY > 100000].shape
```

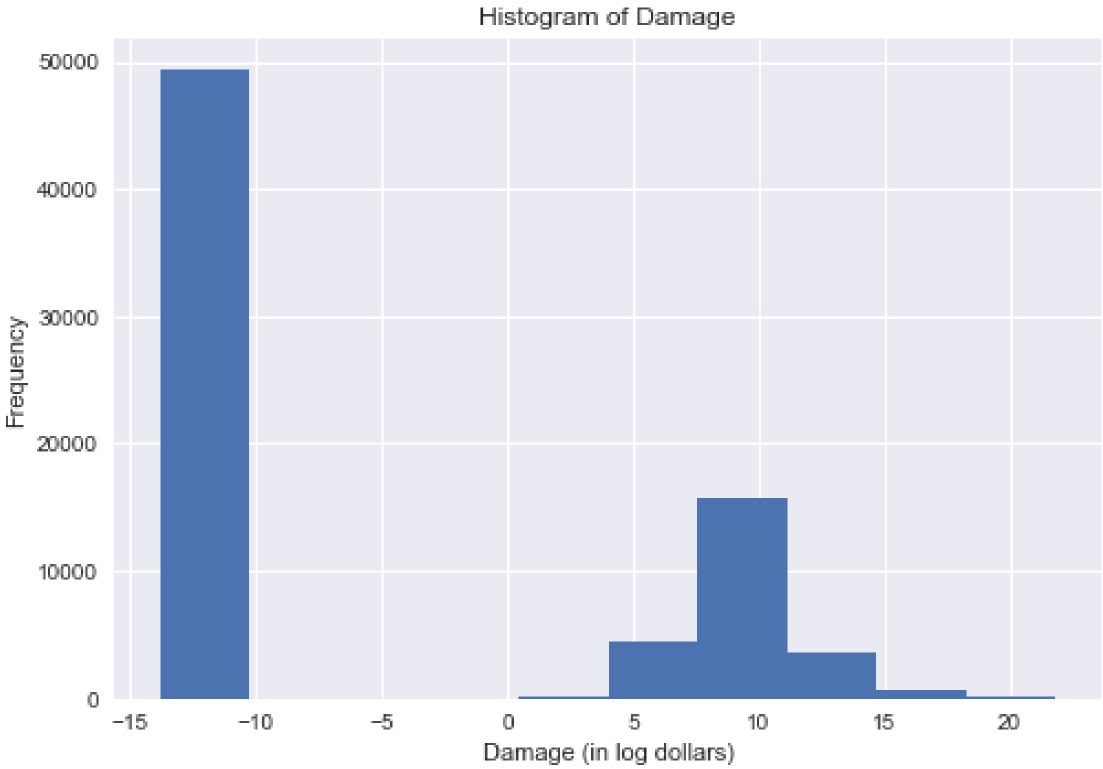
Out[26]:
```
(3250,)
```

In [27]:
```
import scipy.stats as ss
print("Mean: {}".format(round(np.mean(data.DAMAGE_PROPERTY),4))
print("Median: {}".format(np.median(data.DAMAGE_PROPERTY)))
print("Skew: {}".format(round(ss.skew(data.DAMAGE_PROPERTY),2)))
```

```
Mean: 1516894
Median: 0.0
Skew: 46.4
```

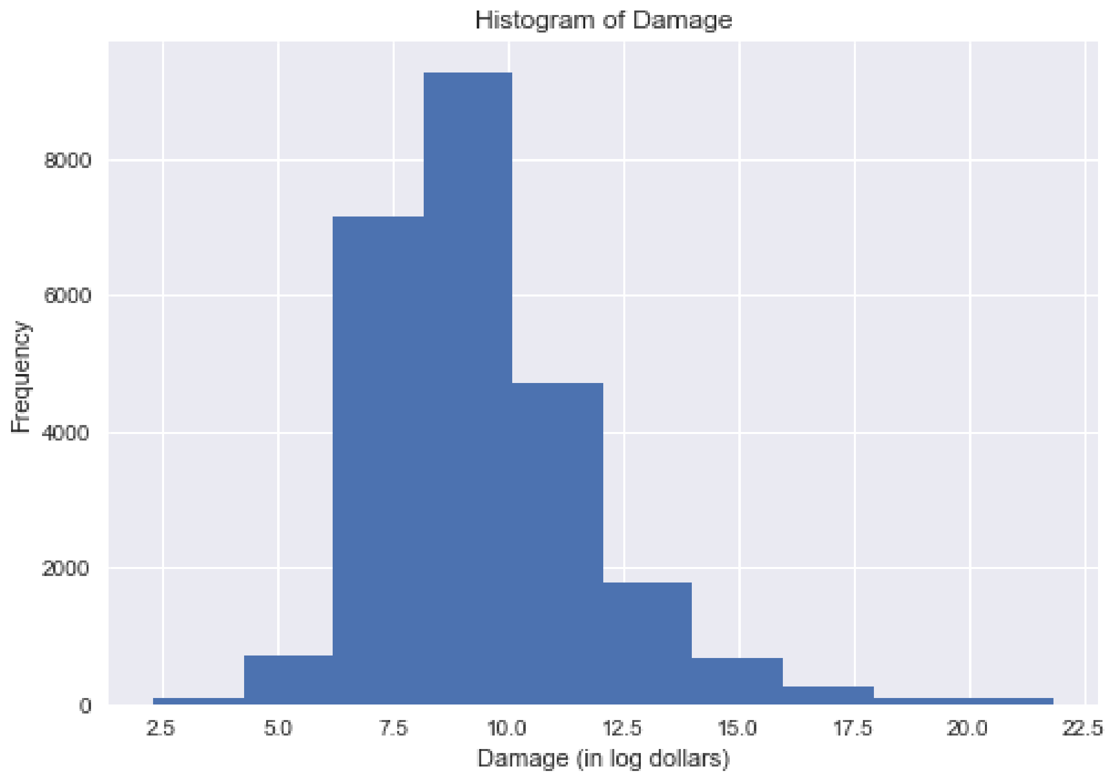
```
In [28]: # we see our big concentration at 0, and a (hopefully) near-normal distribution other

         plt.hist(x=np.log(data.DAMAGE_PROPERTY + .000001))
         plt.xlabel("Damage (in log dollars)")
         plt.ylabel("Frequency")
         plt.title("Histogram of Damage")
```

```
Out[28]: <matplotlib.text.Text at 0x11b8ed940>
```




```
In [29]: # confirming near-normal response for data with a damage over 0

         plt.hist(x=np.log(data.DAMAGE_PROPERTY[data.DAMAGE_PROPERTY>0] + .000001))
         plt.xlabel("Damage (in log dollars)")
         plt.ylabel("Frequency")
         plt.title("Histogram of Damage")
```

```
Out[29]: <matplotlib.text.Text at 0x11adbf5f8>
```




```
In [30]: print(len(data))
```

```
74161
```

6 Part 5: Zipcode + Demographic Data

```
In [ ]: # DON'T RUN AGAIN!!

        from uszipcode import ZipcodeSearchEngine
        search = ZipcodeSearchEngine()

        def calc_density(row):
            zipcode = search.by_coordinate(row['BEGIN_LAT'], row['BEGIN_LON'], radius=50)
            if (int(row.name) % 1000 == 0):
                print(row.name)
            try:
                zc = zipcode[0]
                return zc.Density
            except:
                return np.nan
```

```
def calc_popul(row):
    zipcode = search.by_coordinate(row['BEGIN_LAT'], row['BEGIN_LON'], radius=50)
    try:
        zc = zipcode[0]
        return zc.Population
    except:
        return np.nan

def calc_wealth(row):
    zipcode = search.by_coordinate(row['BEGIN_LAT'], row['BEGIN_LON'], radius=50)
    try:
        zc = zipcode[0]
        return zc.Wealthy
    except:
        return np.nan
```

In [ ]:
```
# DO NOT RUN AGAIN, SINCE WE SAVE TO A CSV BELOW

data['DENSITY'] = data.apply(calc_density, axis=1)
data['POPULATION'] = data.apply(calc_popul, axis=1)
data['HH_INCOME'] = data.apply(calc_wealth, axis=1)
```

In [ ]:
```
# DO NOT RUN AGAIN

data.to_csv("model_data_full.csv")
```

7 Part 6: Prepare Predictors + Final Cleaning

In [31]:
```
data.columns
```

Out[31]:
```
Index(['BEGIN_YEARMONTH', 'BEGIN_DAY', 'BEGIN_TIME', 'END_YEARMONTH', 'END_DAY', 'END_
       'TOR_OTHER_WFO', 'TOR_OTHER_CZ_STATE', 'TOR_OTHER_CZ_FIPS', 'TOR_OTHER_CZ_NAME
      dtype='object')
```

In [32]:
```
data2 = pd.read_csv('model_data_full.csv')
print(len(data2))

# should be the same
print(data.iloc[102]['EVENT_ID'])
print(data2.iloc[102]['EVENT_ID'])

data['DENSITY'] = data2['DENSITY']
data['POPULATION'] = data2['POPULATION']
data['HH_INCOME'] = data2['HH_INCOME']

print(len(data))
# Comment out if needed
data.dropna(inplace=True, subset = ['DENSITY', 'POPULATION', 'HH_INCOME'])
```

```
print(len(data))
data.head()
```

```
/Users/evanmackay/Documents/anaconda/lib/python3.6/site-packages/IPython/core/interactiveshell
  interactivity=interactivity, compiler=compiler, result=result)
```

```
74161
615563
615563
74161
55239
```

Out[32]:

	BEGIN_YEARMONTH	BEGIN_DAY	BEGIN_TIME	END_YEARMONTH	END_DAY	END_TIME	EPISODE_I
0	201603	15	2316	201603	15	2316	102
1	201603	15	2239	201603	15	2300	102
2	201607	7	2137	201607	7	2137	108
3	201607	7	2013	201607	7	2013	108
4	201607	7	2116	201607	7	2116	108

	TOR_OTHER_CZ_NAME	BEGIN_RANGE	BEGIN_AZIMUTH	BEGIN_LOCATION	END_RANGE	END_AZIMUT
0	NaN	1.0	N	EDGERTON	1.0	
1	NaN	1.0	NNE	HARTLAND	1.0	NI
2	NaN	11.0	S	OAKLEY MUNI ARPT	11.0	
3	NaN	2.0	E	COLBY	2.0	
4	NaN	6.0	SSW	OAKLEY MUNI ARPT	6.0	SS

In [33]:

```
def getmonth(row):
    return int(str(row["BEGIN_YEARMONTH"])[-2:])

def getyear(row):
    return int(str(row["BEGIN_YEARMONTH"])[:4])

data["MONTH"] = data.apply(getmonth,axis=1)
data["YEAR"] = data.apply(getyear,axis=1)
#data = data.drop(['Unnamed: 0',"BEGIN_YEARMONTH","END_YEARMONTH","LAT2","LON2",
#                   "YEARMONTH","CZ_FIPS","CZ_TYPE","CZ_NAME",
#                   "WFO","MAGNITUDE_TYPE","FLOOD_CAUSE",'CATEGORY', 'TOR_F_SCALE',
#                   'TOR_LENGTH', 'TOR_WIDTH', 'TOR_OTHER_WFO', 'TOR_OTHER_CZ_STATE',
#                   'TOR_OTHER_CZ_FIPS','TOR_OTHER_CZ_NAME',
#                   'EPISODE_NARRATIVE', 'EVENT_NARRATIVE'],axis=1)
```

In [34]:

```
data.columns
```

Out[34]:

```
Index(['BEGIN_YEARMONTH', 'BEGIN_DAY', 'BEGIN_TIME', 'END_YEARMONTH', 'END_DAY', 'END_
       'TOR_OTHER_WFO', 'TOR_OTHER_CZ_STATE', 'TOR_OTHER_CZ_FIPS', 'TOR_OTHER_CZ_NAME
      dtype='object')
```

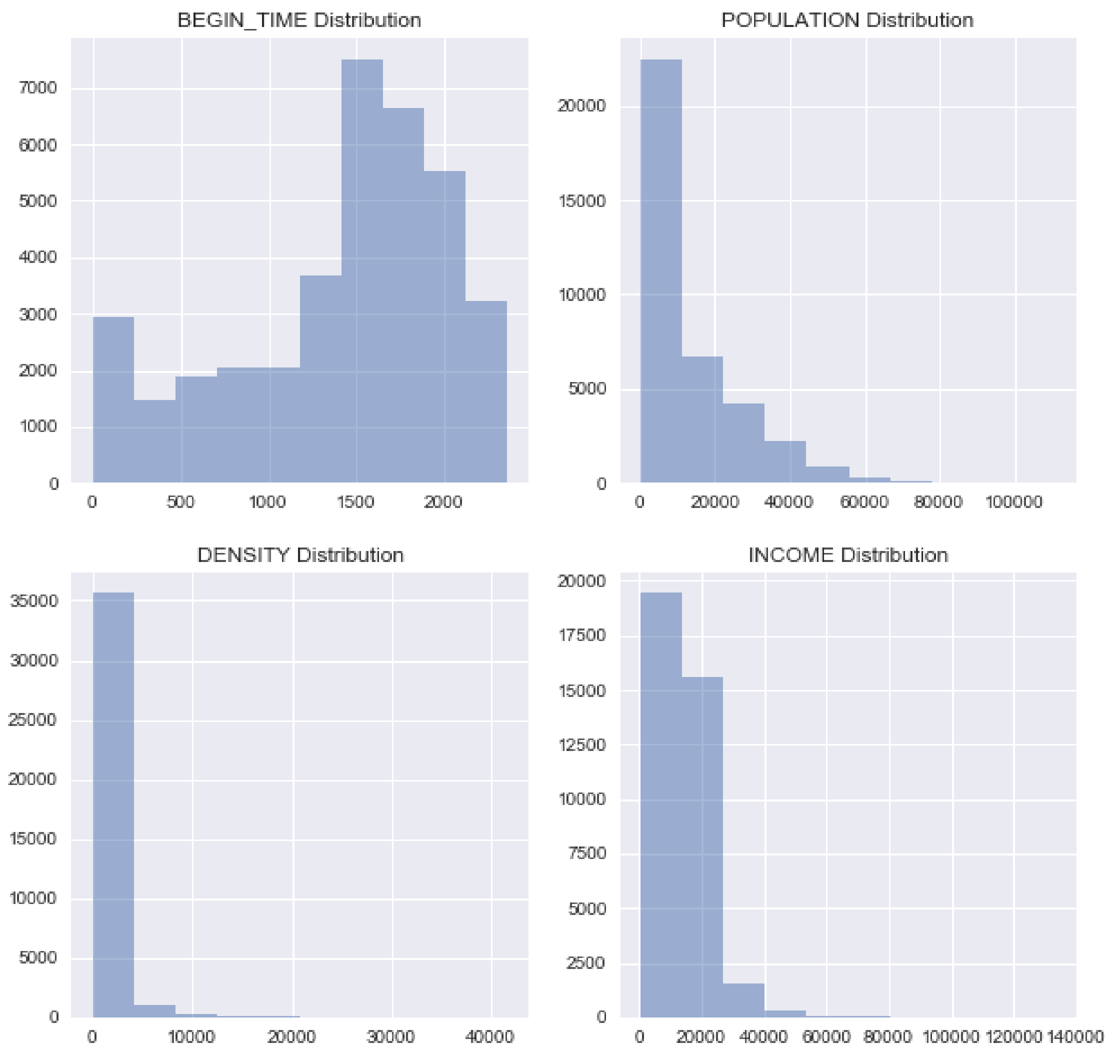
In [35]:
```
X_class = data.drop("HAS_DAMAGE",axis=1)
y_class = data['HAS_DAMAGE']

# drop 3 rows where household income is "infinity"
drop_indices = []
for i in range(len(X_class)):
    if not np.isfinite(X_class['HH_INCOME'].iloc[i]):
        drop_indices.append(i)

X_class = X_class.drop(X_class.index[drop_indices])
y_class = y_class.drop(y_class.index[drop_indices])
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X_class, y_class, test_size=0.33,
```

8 Part 7: More EDA

In [38]:
```
fig, ax = plt.subplots(2, 2, figsize=(10, 10))
ax[0,0].hist(X_train['BEGIN_TIME'], alpha=0.5)
ax[0,0].set_title('BEGIN_TIME Distribution')

ax[0,1].hist(X_train['POPULATION'], alpha=0.5)
ax[0,1].set_title('POPULATION Distribution')

ax[1,0].hist(X_train['DENSITY'], alpha=0.5)
ax[1,0].set_title('DENSITY Distribution')

ax[1,1].hist(X_train['HH_INCOME'], alpha=0.5)
ax[1,1].set_title('INCOME Distribution')

# plt.hist(data['POPULATION'], alpha=0.5)
```

Out[38]:
```
<matplotlib.text.Text at 0x11e37a748>
```



9 Part 8: Preliminary Classification Model

In [39]:
```
# fit prelim model


print("Num points without damage: " + str(len(data[data['HAS_DAMAGE'] == 0])))
print("Num points with damage: " + str(len(data[data['HAS_DAMAGE'] == 1])))

basic_cols = ['EVENT_TYPE', 'STATE', 'MAGNITUDE', 'CZ_TIMEZONE', 'RANGE', 'LATITUDE',
X_train_basic = X_train[basic_cols]
X_test_basic = X_test[basic_cols]

X_train_basic = pd.get_dummies(X_train_basic, columns=['EVENT_TYPE', 'STATE', 'CZ_TIM
X_test_basic = pd.get_dummies(X_test_basic, columns=['EVENT_TYPE', 'STATE', 'CZ_TIMEZ
```

```
model = LogisticRegressionCV(penalty = 'l2')
model.fit(X_train_basic, y_train)
train_pred = model.predict(X_train_basic)
test_pred = model.predict(X_test_basic)

print()
print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_test,test_pred)
print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1])

test_pred_proba = model.predict_proba(X_test_basic)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Num points without damage: 36571
Num points with damage: 18668

Training Accuracy: 0.757478314913
Testing Accuracy: 0.762508229098
True Positive Rate:  0.53976339139
True Negative Rate:  0.874155822764
AUC:  0.819725468472
```

The data contained a ratio of no damage to damage of about 2:1. This is not too far from the ideal case of 1:1 in most classification settings. It was decided that a basic logistic ordinary least squares regression model would be run. What this does is relate the log of the probability of a case having damage to a linear combination of the predictors. This basic model had an accuracy of near 0.75, well above the most naive approach which would have about 66% accuracy if all cases were predicted to not have damage. The model has true negative of 0.86 and true positive of 0.55 and an ROC AUC of .81. An interpretation of this AUC is the probability that a randomly selected case with damage has a higher probability of having damage than a randomly selected case that did not have damage.

10 Part 9: Improving Classification Model

Now that this baseline had been established, the next models were attempted to improve the predictive power of the model. First, more predictors were added to the logistic regression model, such as demographic information about the county where the weather event occurred, such as median household income, population density, and population size.

In [40]:
```
# Add interaction between magnitude and event type
# Magnitude is measured in different ways for different types of weather events.


full_cols = ['BEGIN_TIME', 'STATE', 'MONTH_NAME', 'EVENT_TYPE', 'SOURCE', 'MAGNITUDE'
             'RANGE', 'AZIMUTH', 'LATITUDE', 'LONGITUDE', 'DENSITY', 'POPULATION', 'HI
X_train_full = X_train[full_cols]
X_test_full = X_test[full_cols]

X_train_full = pd.get_dummies(X_train_full, columns=['MONTH_NAME','EVENT_TYPE', 'STATE
X_test_full = pd.get_dummies(X_test_full, columns=['MONTH_NAME','EVENT_TYPE', 'STATE'

s = set(list(X_train_full.columns))
diff = [x for x in list(X_test_full.columns) if x not in s]
print(diff)

X_test_full = X_test_full.drop(labels=diff, axis=1)

print(len(list(X_train_full.columns)))
print(len(list(X_test_full.columns)))
```

```
['SOURCE_Lifeguard']
149
149
```

In [41]:
```
# fit prelim model

print("Num points without damage: " + str(len(data[data['HAS_DAMAGE'] == 0])))
print("Num points with damage: " + str(len(data[data['HAS_DAMAGE'] == 1])))

model = LogisticRegressionCV(penalty = 'l2')
model.fit(X_train_full, y_train)
train_pred = model.predict(X_train_full)
test_pred = model.predict(X_test_full)

print()
print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_test,test_pred)
print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1])

test_pred_proba = model.predict_proba(X_test_full)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Num points without damage: 36571
Num points with damage: 18668

Training Accuracy: 0.697381576459
Testing Accuracy: 0.703533026114
True Positive Rate:  0.259283601709
True Negative Rate:  0.926206555757
AUC:  0.651360708449
```

10.1 PREDICTOR INTUITION

BEGIN_TIME: time of day could be helpful, helps accuracy. think about duration! (NORMALIZE)

STATE: geographical significance (ONE-HOT) // TAKING OUT

CZ_TYPE: C is county, Z is over water, significant predictor (ONE-HOT)

YEAR: doesn't do a ton, but helps accuracy slightly (ONE-HOT)

MONTH_NAME: EDA showed months correlating with damage frequency (ONE-HOT)

WFO: weather forecast office- another way to break down geographically by main metropolitan areas (ONE-HOT)

EVENT_TYPE: type of storm. highly predictive (ONE-HOT)

LATITUDE: geographical inuition (AS IS) // TAKING OUT

LONGITUDE: geographical inuition (AS IS) // TAKING OUT

AZIMUTH: direction of storm, helps very slightly (ONE-HOT)

DENSITY: helps when normalized, not great (NORMALIZE)

POPULATION: helps when normalized, not great (NORMALIZE)

HH_INCOME: helps when normalized, not great (NORMALIZE)

One-hot encoding counties was not considered due to the possibility of overfitting with so many counties in the USA, but the nearest WFO weather station was recorded as a one-hot encoded set of variables to gain more information on place beyond just state. This model improved over the baseline.

```
In [108]: # BETTER SELECTION OF PREDICTORS
          full_cols = ['BEGIN_TIME', 'CZ_TYPE', 'YEAR',
                       'WFO', 'EVENT_TYPE', 'MONTH_NAME',
                       'AZIMUTH', 'DENSITY', 'POPULATION', 'HH_INCOME']#,'MAGNITUDE', 'DENSITY
          X_train_full = X_train[full_cols]
          X_test_full = X_test[full_cols]

          # normalize the numerical predictors
          for i in ['BEGIN_TIME', 'DENSITY', 'POPULATION', 'HH_INCOME']:
              train_mean = X_train_full[i].mean()
              train_sd = X_train_full[i].std()
              X_train_full[i] = (X_train_full[i] - train_mean) / train_sd
              X_test_full[i] = (X_test_full[i] - train_mean) / train_sd

          X_train_full = pd.get_dummies(X_train_full, columns=['MONTH_NAME', 'WFO', 'YEAR', 'EV
          X_test_full = pd.get_dummies(X_test_full, columns=['MONTH_NAME', 'WFO', 'YEAR', 'EVE
```

```
print(len(list(X_train_full.columns)))
print(len(list(X_test_full.columns)))

s = set(list(X_train_full.columns))
diff = [x for x in list(X_test_full.columns) if x not in s]
print(diff)

X_test_full = X_test_full.drop(labels=diff, axis=1)

print(len(list(X_train_full.columns)))
print(len(list(X_test_full.columns)))
```

```
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  del sys.path[0]
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html



165
166
['WFO_REV']
165
165
```

In [109]:
```
print("Num points without damage: " + str(len(data[data['HAS_DAMAGE'] == 0])))
print("Num points with damage: " + str(len(data[data['HAS_DAMAGE'] == 1])))

model = LogisticRegressionCV(penalty = 'l2')
model.fit(X_train_full, y_train)

train_pred = model.predict(X_train_full)
test_pred = model.predict(X_test_full)

print()
print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_test,test_pred)
```

```
print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

test_pred_proba = model.predict_proba(X_test_full)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Num points without damage: 36571
Num points with damage: 18668

Training Accuracy: 0.822438998027
Testing Accuracy: 0.82005705508
True Positive Rate:  0.696845218534
True Negative Rate:  0.881815186954
AUC:  0.888859722607
```

10.2 ADDING COMPLEX EFFECTS

Next, complex effects were added such as interaction terms. The "Magnitude" of the weather event means different things for different types of weather events; for a hail storm, it is the size of the hail, for a thunderstorm it might be the maximum sustained wind, etc. To address this, the interactions of the variable magnitude and the one-hot encoded weather event types were included in the model. Pairwise interactions between income, population density, and population were also included. The predictive power increased dramatically.

```
In [178]: import copy

          # MAKE SURE INTERACTION BETWEEN MAGNITUDE AND EVENT TYPE
          X_train_complex = copy.deepcopy(X_train_full)
          X_test_complex = copy.deepcopy(X_test_full)


          # hardcode interaction term
          for event_type in ['EVENT_TYPE_Dust Devil', 'EVENT_TYPE_Flash Flood', 'EVENT_TYPE_Fl
                      'EVENT_TYPE_Funnel Cloud', 'EVENT_TYPE_Hail', 'EVENT_TYPE_Heavy Rain',
                      'EVENT_TYPE_Lightning', 'EVENT_TYPE_Marine Hail', 'EVENT_TYPE_Marine Hig
                      'EVENT_TYPE_Marine Strong Wind', 'EVENT_TYPE_Marine Thunderstorm Wind',
                      'EVENT_TYPE_Thunderstorm Wind', 'EVENT_TYPE_Tornado', 'EVENT_TYPE_Waters
              X_train_complex[event_type + "*MAGNITUDE"] = X_train_complex[event_type]*X_train
              X_test_complex[event_type + "*MAGNITUDE"] = X_test_complex[event_type]*X_test["M

          X_train_complex["HH_INCOME*DENSITY"] = X_train_complex["DENSITY"]*X_train_complex["HH
          X_train_complex["HH_INCOME*POPULATION"] = X_train_complex["POPULATION"]*X_train_compl
          X_train_complex["DENSITY*POPULATION"] = X_train_complex["POPULATION"]*X_train_comple
          X_test_complex["HH_INCOME*DENSITY"] = X_test_complex["DENSITY"]*X_test_complex["HH_I
          X_test_complex["HH_INCOME*POPULATION"] = X_test_complex["POPULATION"]*X_test_complex
```

```
X_test_complex["DENSITY*POPULATION"] = X_test_complex["POPULATION"]*X_test_complex["I

X_train_complex.describe()
```

Out[178]:

```
          BEGIN_TIME       DENSITY    POPULATION     HH_INCOME  MONTH_NAME_August  MO
count   3.700700e+04  3.700700e+04  3.700700e+04  3.700700e+04       37007.000000
mean   -1.224344e-16 -1.791354e-15  6.249673e-17  6.871062e-15           0.115708
std     1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00           0.319879
min    -2.268415e+00 -3.684348e-01 -9.237186e-01 -2.120998e+00           0.000000
25%    -6.004619e-01 -3.539400e-01 -7.616601e-01 -5.875254e-01           0.000000
50%     2.335145e-01 -3.252477e-01 -4.177889e-01 -2.339567e-01           0.000000
75%     7.020224e-01 -1.325222e-01  5.154924e-01  2.844262e-01           0.000000
max     1.529559e+00  2.099107e+01  7.191643e+00  1.715966e+01           1.000000

             WFO_BTV       WFO_BUF       WFO_BYZ       WFO_CAE       WFO_CAR       WF
count   37007.000000  37007.000000  37007.000000  37007.000000  37007.000000  37007.0
mean        0.005512      0.005810      0.002162      0.006215      0.000757      0.0
std         0.074042      0.076001      0.046445      0.078591      0.027497      0.0
min         0.000000      0.000000      0.000000      0.000000      0.000000      0.0
25%         0.000000      0.000000      0.000000      0.000000      0.000000      0.0
50%         0.000000      0.000000      0.000000      0.000000      0.000000      0.0
75%         0.000000      0.000000      0.000000      0.000000      0.000000      0.0
max         1.000000      1.000000      1.000000      1.000000      1.000000      1.0

       EVENT_TYPE_Marine Hail  EVENT_TYPE_Marine High Wind  EVENT_TYPE_Marine Strong
count            37007.000000                 37007.000000                   37007.0
mean                 0.000649                     0.000892                       0.0
std                  0.025458                     0.029849                       0.0
min                  0.000000                     0.000000                       0.0
25%                  0.000000                     0.000000                       0.0
50%                  0.000000                     0.000000                       0.0
75%                  0.000000                     0.000000                       0.0
max                  1.000000                     1.000000                       1.0

       EVENT_TYPE_Flood*MAGNITUDE  EVENT_TYPE_Funnel Cloud*MAGNITUDE  EVENT_TYPE_Hai
count                     37007.0                            37007.0              3
mean                          0.0                                0.0
std                           0.0                                0.0
min                           0.0                                0.0
25%                           0.0                                0.0
50%                           0.0                                0.0
75%                           0.0                                0.0
max                           0.0                                0.0

[8 rows x 182 columns]
```

In [111]:

```
model = LogisticRegressionCV(penalty = 'l2')
model.fit(X_train_complex, y_train)
```

```
train_pred = model.predict(X_train_complex)
test_pred = model.predict(X_test_complex)

print()
print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_test,test_pred)
print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0])
print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

test_pred_proba = model.predict_proba(X_test_complex)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.825627583971
Testing Accuracy: 0.822525784507
True Positive Rate:  0.700460072297
True Negative Rate:  0.883709438313
AUC:  0.895981968602
```

10.3 k-NN

Next, the model building process pivoted direction; now instead of manipulating the predictors, the same predictors were used but for other families of models. A k-NN procedure was carried out which achieved strong predictive power on the test set. This k-NN approach is helpful because it does not assume anything about the underlying distribution of the responses and the how the data are related to each other, whereas logistic regression assumes that variables are evenly spread throughout predicted value (homoskedasticity) and that there is a linear relationship between the log odds of the probability of having damage and the predictors.

```
In [112]: # max_score = 0
          # max_k = 0

          # for k in range(15,31,3):
          #     knn = KNeighborsClassifier(n_neighbors = k)
          #     score = cross_val_score(knn,X_train_complex,y_train).mean()
          #     if score > max_score:
          #         max_k = k
          #         max_score = score
          # print(max_k)
          max_k = 15

In [113]: model_knn = KNeighborsClassifier(n_neighbors = max_k)
          model_knn.fit(X_train_complex, y_train)
```

```
train_pred = model_knn.predict(X_train_complex)
test_pred = model_knn.predict(X_test_complex)

print()
print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_test,test_pred)
print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

test_pred_proba = model_knn.predict_proba(X_test_complex)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.845191450266
Testing Accuracy: 0.819398727233
True Positive Rate:  0.648044692737
True Negative Rate:  0.905287432054
AUC:  0.892345834994
```

10.3.1 LDA/QDA

Quadratic discriminant analysis and linear discriminant analysis were also completed, which relax some of the modeling assumptions of logistic regression. These did not improve the model.

```
In [114]: lda = LinearDiscriminantAnalysis()
          lda.fit(X_train_complex,y_train)

          train_pred = lda.predict(X_train_complex)
          test_pred = lda.predict(X_test_complex)
          print()
          print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
          print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

          from sklearn.metrics import confusion_matrix
          conf_mat = confusion_matrix(y_test,test_pred)
          print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
          print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

          test_pred_proba = lda.predict_proba(X_test_complex)[:,1]
          fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
          roc_auc = metrics.auc(fpr, tpr)
          print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.817710162942
Testing Accuracy: 0.815009874918
True Positive Rate:  0.685179099573
True Negative Rate:  0.880085653105
AUC:  0.887339143988


/anaconda/lib/python3.6/site-packages/sklearn/discriminant_analysis.py:387: UserWarning: Varial
  warnings.warn("Variables are collinear.")
```

```
In [115]: qda = QuadraticDiscriminantAnalysis()
          qda.fit(X_train_complex,y_train)

          train_pred = qda.predict(X_train_complex)
          test_pred = qda.predict(X_test_complex)
          print()
          print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
          print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

          from sklearn.metrics import confusion_matrix
          conf_mat = confusion_matrix(y_test,test_pred)
          print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
          print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

          test_pred_proba = qda.predict_proba(X_test_complex)[:,1]
          fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
          roc_auc = metrics.auc(fpr, tpr)
          print("AUC: ", roc_auc)
```

```
/anaconda/lib/python3.6/site-packages/sklearn/discriminant_analysis.py:695: UserWarning: Varial
  warnings.warn("Variables are collinear")



Training Accuracy: 0.435917529116
Testing Accuracy: 0.426541584376
True Positive Rate:  0.998849819257
True Negative Rate:  0.139680448032
AUC:  0.570115501996
```

10.3.2 Random Forest/Decision Trees

Next, decision trees were implemented. These are very interpretable because predictions can be achieved by following a tree of binary decisions related to predictors. The tree ended up being pretty deep with 82 predictors. Although this might increase worries of overfitting the data, because this value was chosen via cross validation in that it was selected based on performance on data that the model did not see during training, there is less concern about overfitting for the classification tree.

```
In [116]: best_score = 0
          best_depth = 0
          for i in range(80,95):
              dt = DecisionTreeClassifier(max_depth=i)
              # Perform 5-fold cross validation
              score = cross_val_score(estimator=dt, X=X_train_complex, y=y_train, cv=5, n_jobs=
              if score > best_score:
                  best_score = score
                  best_depth = i
```

```
In [117]: best_depth
```

```
Out[117]: 82
```

```
In [ ]: # GRAPH
```

```
In [118]: dt = DecisionTreeClassifier(max_depth=best_depth)
          dt.fit(X_train_complex,y_train)

          train_pred = dt.predict(X_train_complex)
          test_pred = dt.predict(X_test_complex)
          print()
          print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
          print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

          from sklearn.metrics import confusion_matrix
          conf_mat = confusion_matrix(y_test,test_pred)
          print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
          print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

          test_pred_proba = dt.predict_proba(X_test_complex)[:,1]
          fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
          roc_auc = metrics.auc(fpr, tpr)
          print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.997703137244
Testing Accuracy: 0.898398068905
True Positive Rate:  0.852776864936
True Negative Rate:  0.921265030473
AUC:  0.885129429909
```

```
In [213]: # TODO: GINI IMPORTANCE FOR DECISION TREE
          treeimportance_df = pd.DataFrame(columns=["Predictor","Importance"])
          treeimportance_df["Importance"] = pd.Series(dt.feature_importances_)
          treeimportance_df["Predictor"] = pd.Series(X_train_complex.columns)
          treeimportance_df.sort_values('Importance',ascending=False)[:30]
```

Out[213]:

	Predictor	Importance
176	EVENT_TYPE_Thunderstorm Wind*MAGNITUDE	0.108599
0	BEGIN_TIME	0.083302
169	EVENT_TYPE_Hail*MAGNITUDE	0.040545
180	HH_INCOME*POPULATION	0.031703
1	DENSITY	0.030501
2	POPULATION	0.029380
73	WFO_JAN	0.029380
181	DENSITY*POPULATION	0.029130
179	HH_INCOME*DENSITY	0.026795
3	HH_INCOME	0.024981
134	YEAR_2017	0.023263
116	WFO_RLX	0.017860
149	CZ_TYPE_Z	0.014221
106	WFO_PAH	0.013969
133	WFO_VEF	0.013621
147	EVENT_TYPE_Tornado	0.013353
9	MONTH_NAME_June	0.013095
136	EVENT_TYPE_Flash Flood	0.012629
4	MONTH_NAME_August	0.012436
104	WFO_OTX	0.011715
61	WFO_GSP	0.010539
71	WFO_IND	0.010314
24	WFO_BGM	0.010119
34	WFO_CAE	0.009864
62	WFO_GYX	0.009532
102	WFO_OHX	0.009442
8	MONTH_NAME_July	0.009293
11	MONTH_NAME_May	0.009046
141	EVENT_TYPE_Lightning	0.008488
43	WFO_DMX	0.007788

TODO: GRIDSEARCHCV The next step was a random forest. Random forest is a process that averages predictions from many individually weak decision trees that are usually shorter in depth and might only be trained on a random subset of predictors. Although initially the same depth from the decision tree was used, eventually it was decided that it is better in random forest to include weaker individual predictions and average over these. The random forest achieved large increases in predictive power. The importance of predictors was also considered; thunderstorm wind speed magnitude was an important predictor which is unsurprising, as well as population density, population, hail size, and income.

In [182]:
```
param_grid_rf = {
    'max_features': [20,40,60,80],
    'max_depth': [5,20,35,50],
    'n_estimators': [32,64]
}
rfb = RandomForestClassifier(n_jobs=-1)
rf_cv = GridSearchCV(rfb, param_grid_rf, cv=5, n_jobs=-1)
```

```
    rf_cv.fit(X_train_complex, y_train)

    train_pred = rf_cv.predict(X_train_complex)
    test_pred = rf_cv.predict(X_test_complex)
    print()
    print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
    print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

    from sklearn.metrics import confusion_matrix
    conf_mat = confusion_matrix(y_test,test_pred)
    print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
    print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

    test_pred_proba = rf_cv.predict_proba(X_test_complex)[:,1]
    fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
    roc_auc = metrics.auc(fpr, tpr)
    print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.975383035642
Testing Accuracy: 0.911016019311
True Positive Rate:  0.828951692409
True Negative Rate:  0.952149563499
AUC:  0.961209723443
```

In [121]:
```
# Out-of-bag cross-validation to choose RF number of predictors
#from sklearn.ensemble import RandomForestClassifier
#best_pred = 0
#best_score = 0
#for f in [20,40,60,80]:
    est = RandomForestClassifier(oob_score=True,
                                 n_estimators=32, max_features=f, max_depth=best_dept
    est.fit(X_train_complex, y_train)
    if est.oob_score_ > best_score:
        best_score = est.oob_score_
        best_pred = f
```

In [122]:
```
#rf = RandomForestClassifier(oob_score=True, n_estimators=64, max_features=best_pred
                            max_depth=best_depth, n_jobs=-1)
#rf.fit(X_train_complex,y_train)

#train_pred = rf.predict(X_train_complex)
#test_pred = rf.predict(X_test_complex)
#print()
#print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
#print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))
```

```
#from sklearn.metrics import confusion_matrix
#conf_mat = confusion_matrix(y_test,test_pred)
#print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]
#print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1

#test_pred_proba = rf.predict_proba(X_test_complex)[:,1]
#fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
#roc_auc = metrics.auc(fpr, tpr)
#print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.999459561705
Testing Accuracy: 0.922207592715
True Positive Rate:  0.866086099244
True Negative Rate:  0.950337670894
AUC:  0.970694336808
```

```
In [211]: treeimportance_rf = pd.DataFrame(columns=["Predictor","Importance"])
          treeimportance_rf["Importance"] = pd.Series(rf.feature_importances_)
          treeimportance_rf["Predictor"] = pd.Series(X_train_complex.columns)
          treeimportance_rf.sort_values('Importance',ascending=False)[:29]
```

Out[211]:

	Predictor	Importance
176	EVENT_TYPE_Thunderstorm Wind*MAGNITUDE	0.070458
0	BEGIN_TIME	0.067579
1	DENSITY	0.034630
181	DENSITY*POPULATION	0.033956
2	POPULATION	0.033584
169	EVENT_TYPE_Hail*MAGNITUDE	0.033303
180	HH_INCOME*POPULATION	0.032909
3	HH_INCOME	0.032070
179	HH_INCOME*DENSITY	0.030870
73	WFO_JAN	0.029390
146	EVENT_TYPE_Thunderstorm Wind	0.027037
134	YEAR_2017	0.017796
116	WFO_RLX	0.017270
106	WFO_PAH	0.014330
133	WFO_VEF	0.014139
147	EVENT_TYPE_Tornado	0.013757
139	EVENT_TYPE_Hail	0.012359
9	MONTH_NAME_June	0.011837
104	WFO_OTX	0.011376
102	WFO_OHX	0.010982
24	WFO_BGM	0.010328
71	WFO_IND	0.010243
136	EVENT_TYPE_Flash Flood	0.010001

```
4                          MONTH_NAME_August    0.009805
34                                   WFO_CAE    0.009689
61                                   WFO_GSP    0.009408
149                                CZ_TYPE_Z    0.008804
62                                   WFO_GYX    0.008528
11                            MONTH_NAME_May    0.008464
```

10.3.3 AdaBoost

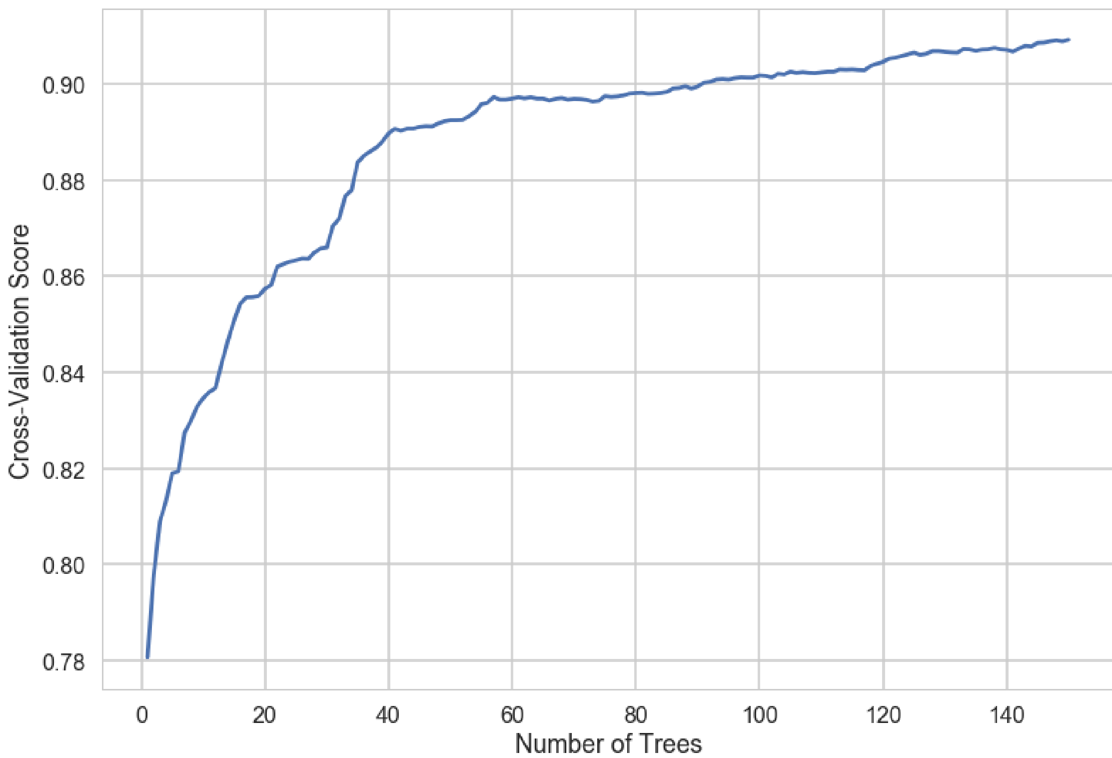
An ada-boost method was also conducted. This is an iterative process which builds decision trees on the residuals of earlier, weaker model in order to improve prediction. This process improved predictive power over the logistic regression.

In [123]:
```python
# TODO: 15 MAX_DEPTH ???
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import GridSearchCV
param_grid_boost = {
              'base_estimator__max_depth': list(range(5,16,2))
}
gb = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=150, le
gb_cv = GridSearchCV(gb, param_grid_boost, cv=5, n_jobs=-1)

gb_cv.fit(X_train_complex, y_train)

begb = gb_cv.best_estimator_
begb
```

Out[123]:
```
AdaBoostClassifier(algorithm='SAMME.R',
          base_estimator=DecisionTreeClassifier(class_weight=None, criterion='gini',
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=0.08, n_estimators=150, random_state=None)
```

In [124]:
```python
test_scores=[]
for spred in begb.staged_predict(X_test_complex):
    test_scores.append(metrics.accuracy_score(spred, y_test))
plt.plot(range(1, 151), test_scores)
plt.xlabel("Number of Trees")
plt.ylabel("Cross-Validation Score")
```

Out[124]:
```
<matplotlib.text.Text at 0x11d0b35f8>
```




```
In [127]: print ("Optimal # trees = ", np.argmax(test_scores))
          print ("Optimal depth = ", 15) # from begb printout above
```

```
Optimal # trees =  149
Optimal depth =  15
```

```
In [128]: gb_optimized = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=9)
                                            n_estimators=149, learning_rate=.08)
          gb_optimized.fit(X_train_complex, y_train)

          train_pred = gb_optimized.predict(X_train_complex)
          test_pred = gb_optimized.predict(X_test_complex)
          print()
          print("Training Accuracy: " + str(accuracy_score(train_pred, y_train)))
          print("Testing Accuracy: " + str(accuracy_score(test_pred, y_test)))

          from sklearn.metrics import confusion_matrix
          conf_mat = confusion_matrix(y_test,test_pred)
          print("True Positive Rate: ", float(conf_mat[1][1])/(conf_mat[1][1]+ conf_mat[1][0]))
          print("True Negative Rate: ", float(conf_mat[0][0])/(conf_mat[0][0] + conf_mat[0][1]

          test_pred_proba = gb_optimized.predict_proba(X_test_complex)[:,1]
```

```
fpr, tpr, thresholds = metrics.roc_curve(y_test, test_pred_proba)
roc_auc = metrics.auc(fpr, tpr)
print("AUC: ", roc_auc)
```

```
Training Accuracy: 0.990947658551
Testing Accuracy: 0.900811937678
True Positive Rate:  0.821229050279
True Negative Rate:  0.94070169659
AUC:  0.940525151682
```

11 Part 10: Preliminary Regression Model

Beyond classifying whether or not there is damage to something, there is also interest in predicting the dollar amount of damage. Because this amount is very right skewed in the data, a log transformation was conducted and models were run to predict this log transformed variable. Using the same predictors chosen from logistic regression classification, a basic ordinary least squares regression model yielded a R^2 of 0.43 in the testing set.

```
In [189]: # Re-handle data for regression problem

          print(len(data))
          non_null_data = data.dropna(axis=0, subset=['DAMAGE_PROPERTY'], how='any')
          print(len(non_null_data))
          damage_data = non_null_data[non_null_data['DAMAGE_PROPERTY'] > 1.0]
          # expecting ~18000
          print(len(damage_data))

          X = damage_data.drop('DAMAGE_PROPERTY',axis=1)
          y = damage_data['DAMAGE_PROPERTY']

          # drop 3 rows where household income is "infinity"
          drop_indices = []
          for i in range(len(X)):
              if not np.isfinite(X['HH_INCOME'].iloc[i]):
                  drop_indices.append(i)

          print(len(X))
          X = X.drop(X.index[drop_indices])
          y = y.drop(y.index[drop_indices])
          print(len(X))

          X_train, X_test, y_train_reg, y_test_reg = train_test_split(X, y, test_size=0.33, ra
```

```
55239
55239
18668
```

```
18668
18664
```

```
In [190]: # BETTER SELECTION OF PREDICTORS
          full_cols = ['BEGIN_TIME', 'CZ_TYPE', 'YEAR',
                       'WFO', 'EVENT_TYPE', 'MONTH_NAME',
                       'AZIMUTH', 'DENSITY', 'POPULATION', 'HH_INCOME']
          X_train_reg = X_train[full_cols]
          X_test_reg = X_test[full_cols]

          # normalize the numerical predictors
          for i in ['BEGIN_TIME', 'DENSITY', 'POPULATION', 'HH_INCOME']:
              train_mean = X_train_reg[i].mean()
              train_sd = X_train_reg[i].std()
              X_train_reg[i] = (X_train_reg[i] - train_mean) / train_sd
              X_test_reg[i] = (X_test_reg[i] - train_mean) / train_sd

          X_train_reg = pd.get_dummies(X_train_reg, columns=['MONTH_NAME', 'WFO', 'YEAR', 'EVEN
          X_test_reg = pd.get_dummies(X_test_reg, columns=['MONTH_NAME', 'WFO', 'YEAR', 'EVENT_

          #print(len(list(X_train_reg.columns)))
          #print(len(list(X_test_reg.columns)))

          s = set(list(X_train_reg.columns))
          diff = [x for x in list(X_test_reg.columns) if x not in s]

          X_test_reg = X_test_reg.drop(labels=diff, axis=1)

          s = set(list(X_test_reg.columns))
          diff = [x for x in list(X_train_reg.columns) if x not in s]

          X_train_reg = X_train_reg.drop(labels=diff, axis=1)

          #print(len(list(X_train_reg.columns)))
          #print(len(list(X_test_reg.columns)))
```

```
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  if sys.path[0] == '':
/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
  del sys.path[0]
```

```
In [191]: y_train2 = np.log(y_train_reg)
          y_test2 = np.log(y_test_reg)

          model_base = LinearRegression()
          model_base.fit(X_train_reg, y_train2)

          train_pred = model_base.predict(X_train_reg)
          test_pred = model_base.predict(X_test_reg)

          print()
          print("Training R^2: " + str(model_base.score(X_train_reg,y_train2)))
          print("Testing R^2: " + str(model_base.score(X_test_reg,y_test2)))
```

```
Training Accuracy: 0.431650202073
Testing Accuracy: 0.431797688817
```

12 Part 11: Improving Regression Model

Once interaction terms were included, using the same interactions from the classification problem, the R^2 increased to 0.46.

```
In [192]: X_train_reg_complex = copy.deepcopy(X_train_reg)
          X_test_reg_complex = copy.deepcopy(X_test_reg)


          # hardcode interaction term
          for event_type in ['EVENT_TYPE_Dust Devil', 'EVENT_TYPE_Flash Flood', 'EVENT_TYPE_Flo
                             'EVENT_TYPE_Heavy Rain', 'EVENT_TYPE_Lightning', 'EVENT_TYPE_Marin
                'EVENT_TYPE_Thunderstorm Wind', 'EVENT_TYPE_Tornado', 'EVENT_TYPE_Waterspout']
              X_train_reg_complex[event_type + "*MAGNITUDE"] = X_train_reg_complex[event_type]*
              X_test_reg_complex[event_type + "*MAGNITUDE"] = X_test_reg_complex[event_type]*X_

          X_train_reg_complex["HH_INCOME*DENSITY"] = X_train_reg_complex["DENSITY"]*X_train_reg
          X_train_reg_complex["HH_INCOME*POPULATION"] = X_train_reg_complex["POPULATION"]*X_tra
          X_train_reg_complex["DENSITY*POPULATION"] = X_train_reg_complex["POPULATION"]*X_train
          X_test_reg_complex["HH_INCOME*DENSITY"] = X_test_reg_complex["DENSITY"]*X_test_reg_co
          X_test_reg_complex["HH_INCOME*POPULATION"] = X_test_reg_complex["POPULATION"]*X_test_
          X_test_reg_complex["DENSITY*POPULATION"] = X_test_reg_complex["POPULATION"]*X_test_re

          for quant in ['BEGIN_TIME', 'DENSITY', 'POPULATION', 'HH_INCOME']:
              X_train_reg_complex[quant + "2"] = (X_train_reg_complex[quant]) ** 2
              X_test_reg_complex[quant + "2"] = (X_test_reg_complex[quant]) ** 2
```

```
In [193]: model_complex = LinearRegression()
          model_complex.fit(X_train_reg_complex, y_train2)

          train_pred = model_complex.predict(X_train_reg_complex)
          test_pred = model_complex.predict(X_test_reg_complex)

          print("Training Accuracy: " + str(model_complex.score(X_train_reg_complex,y_train2)))
          print("Testing Accuracy: " + str(model_complex.score(X_test_reg_complex,y_test2)))
```

```
Training Accuracy: 0.474418140789
Testing Accuracy: 0.469550842239
```

```
In [194]: diff = abs(test_pred - y_test2)
          diffs = []
          for i in diff:
              diffs.append(math.exp(i))
          print("Mean Absolute Value Error: {}".format(np.mean(diffs)))
          print("SD Absolute Value Error: {}".format(np.std(diffs)))
```

```
Mean Absolute Value Error: 41.04277796222084
SD Absolute Value Error: 1436.011567378967
```

```
In [230]: coefs_df = pd.DataFrame(columns=["Predictor","Coefficient"])
          coefs_df["Coefficient"] = pd.Series(model_complex.coef_)
          coefs_df["Predictor"] = pd.Series(X_train_reg_complex.columns)
          coefs_df.sort_values('Coefficient',ascending=False)[:25]
```

Out[230]:

	Predictor	Coefficient
123	EVENT_TYPE_Marine Strong Wind	16.546230
87	WFO_MTR	4.914637
69	WFO_LIX	4.736614
39	WFO_EKA	3.065546
125	EVENT_TYPE_Tornado	2.314434
68	WFO_LCH	1.999657
13	MONTH_NAME_October	1.953874
146	EVENT_TYPE_Hail*MAGNITUDE	1.901404
118	EVENT_TYPE_Flash Flood	1.661344
119	EVENT_TYPE_Flood	1.547499
41	WFO_EWX	1.192984
122	EVENT_TYPE_Lightning	0.877250
15	WFO_AFG	0.846205
117	EVENT_TYPE_Dust Devil	0.833550
36	WFO_DTX	0.715403
83	WFO_MPX	0.654106
52	WFO_GYX	0.532134
6	MONTH_NAME_February	0.452891
111	WFO_TBW	0.447809

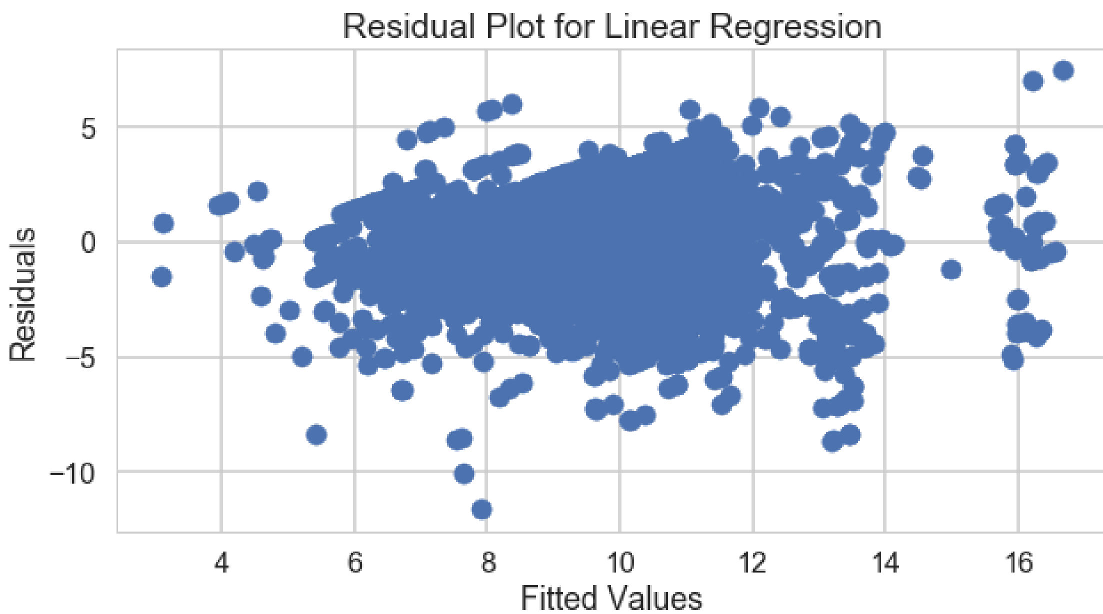
```
106                            WFO_SHV     0.418054
4                    MONTH_NAME_August     0.410704
94                             WFO_PDT     0.393478
62                             WFO_IWX     0.364898
88                             WFO_OAX     0.362654
96                             WFO_PIH     0.325220
```

```
In [228]: print(coefs_df[coefs_df["Predictor"]=="POPULATION"])
          print(coefs_df[coefs_df["Predictor"]=="DENSITY"])
          print(coefs_df[coefs_df["Predictor"]=="DENSITY2"])
          print(coefs_df[coefs_df["Predictor"]=="HH_INCOME"])
          print(coefs_df[coefs_df["Predictor"]=="HH_INCOME2"])
```

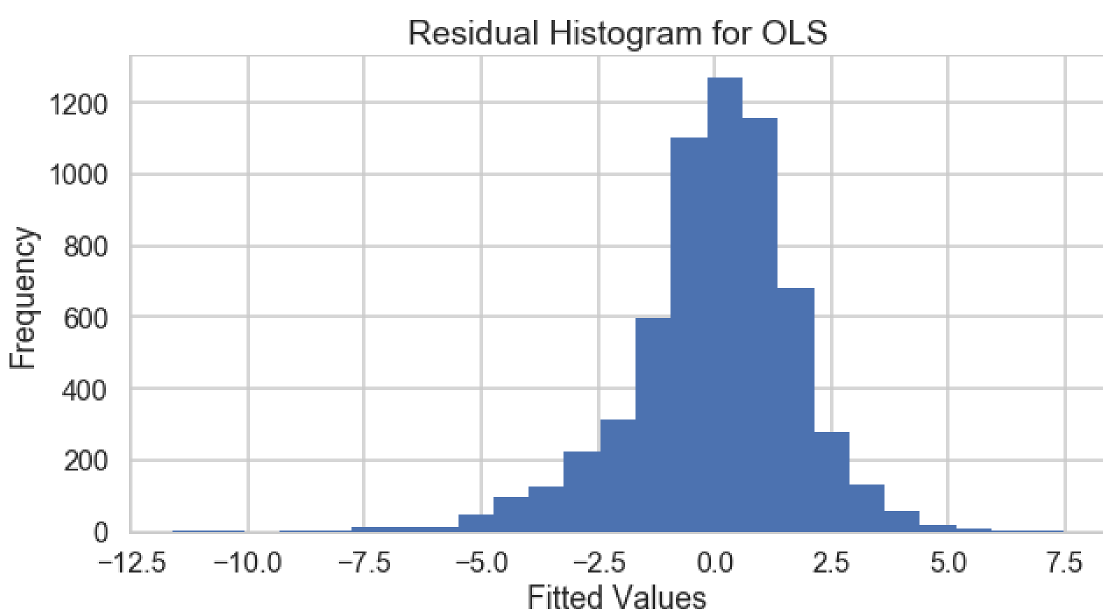
```
    Predictor  Coefficient
2  POPULATION     0.012939
  Predictor  Coefficient
1   DENSITY    -0.031599
    Predictor  Coefficient
157  DENSITY2    -0.006742
   Predictor  Coefficient
3  HH_INCOME    -0.005024
      Predictor  Coefficient
159  HH_INCOME2     0.000229
```

This model was then evaluated for whether it is violating assumptions of ordinary least squares regression. The residuals were plotted to see if they were approximately Normal. Then, residuals were plotted against fitted values. This does not appear to be evenly scattered, but this is not especially concerning because given the discreteness of the problem and the fact that damage is nonnegative. Predicted values were also plotted against observed values.

```
In [195]: plt.figure(figsize=(10,5))
          plt.title("Residual Plot for OLS")
          plt.scatter(test_pred,test_pred - y_test2,marker='o')
          plt.xlabel("Fitted Values")
          plt.ylabel("Residuals")

Out[195]: <matplotlib.text.Text at 0x125397a58>
```




```
In [198]: plt.figure(figsize=(10,5))
          plt.title("Residual Histogram for OLS")
          plt.hist(test_pred - y_test2,bins=25)
          plt.xlabel("Fitted Values")
          plt.ylabel("Frequency")

Out[198]: <matplotlib.text.Text at 0x1251e5c50>
```



12.0.1 Regularization

In [76]:
```
lambdas = [.001,.005,1,5,10,50,100,500,1000]
ridge = RidgeCV(cv=5, alphas=lambdas, fit_intercept=True, normalize=True)
ridge.fit(X_train_reg_complex,y_train2)

print("Training Accuracy: " + str(ridge.score(X_train_reg_complex,y_train2)))
print("Testing Accuracy: " + str(ridge.score(X_test_reg_complex,y_test2)))
```

```
Training Accuracy: 0.473769508663
Testing Accuracy: 0.469292299256
```

In [77]:
```
lasso = LassoCV(cv=5, alphas=lambdas, fit_intercept=True, normalize=True)
lasso.fit(X_train_reg_complex,y_train2)

print("Training Accuracy: " + str(lasso.score(X_train_reg_complex,y_train2)))
print("Testing Accuracy: " + str(lasso.score(X_test_reg_complex,y_test2)))
```

```
Training Accuracy: 0.3337052492
Testing Accuracy: 0.328269072598
```

12.0.2 k-NN

In [80]:
```
knn_reg = KNeighborsRegressor(n_neighbors=15)
knn_reg.fit(X_train_reg_complex,y_train2)

print("Training Accuracy: " + str(knn_reg.score(X_train_reg_complex,y_train2)))
print("Testing Accuracy: " + str(knn_reg.score(X_test_reg_complex,y_test2)))
```

```
Training Accuracy: 0.526442438159
Testing Accuracy: 0.44326243361
```

12.0.3 Random Forest Regressor

In [164]:
```
# code from
# Adventures in scikit-learn's Random Forest by Gregory Saunders
from itertools import product
from collections import OrderedDict
param_dict = OrderedDict(
    n_estimators = [300, 375, 450],
    max_features = [0.2, 0.5, 0.8]
)

param_dict.values()
```

Out[164]:
```
odict_values([[300, 375, 450], [0.2, 0.5, 0.8]])
```

```
In [165]: from sklearn.ensemble import RandomForestRegressor
          results = {}
          estimators= {}
          # Iterates through all possible combinations of n and f
          for n, f in product(*param_dict.values()):
              params = (n, f)
              # n_jobs = -1 --> parallelism which does exactly how many cores your computer ha
              est2 = RandomForestRegressor(oob_score=True,
                                           n_estimators=n, max_features=f, n_jobs=-1)
              est2.fit(X_train_reg_complex, y_train2)
              results[params] = est2.oob_score_
              estimators[params] = est2
          outparams = max(results, key = results.get)
          outparams

Out[165]: (450, 0.5)

In [166]: rf_reg = estimators[outparams]

          print("Training Accuracy: " + str(rf_reg.score(X_train_reg_complex,y_train2)))
          print("Testing Accuracy: " + str(rf_reg.score(X_test_reg_complex,y_test2)))

Training Accuracy: 0.968901575735
Testing Accuracy: 0.772632883999


In [209]: treeimportance_rf = pd.DataFrame(columns=["Predictor","Importance"])
          treeimportance_rf["Importance"] = pd.Series(rf_reg.feature_importances_)
          treeimportance_rf["Predictor"] = pd.Series(X_train_reg_complex.columns)
          treeimportance_rf.sort_values('Importance',ascending=False)[:29]
```

Out[209]:

	Predictor	Importance
150	EVENT_TYPE_Thunderstorm Wind*MAGNITUDE	0.083440
156	BEGIN_TIME2	0.066804
69	WFO_LIX	0.064016
0	BEGIN_TIME	0.062736
68	WFO_LCH	0.062308
124	EVENT_TYPE_Thunderstorm Wind	0.037065
57	WFO_ICT	0.026976
4	MONTH_NAME_August	0.025330
159	HH_INCOME2	0.024817
1	DENSITY	0.024121
158	POPULATION2	0.023926
3	HH_INCOME	0.022539
157	DENSITY2	0.022508
155	DENSITY*POPULATION	0.022448
153	HH_INCOME*DENSITY	0.021798
154	HH_INCOME*POPULATION	0.021537
2	POPULATION	0.020752

28	WFO_CAE	0.020055
125	EVENT_TYPE_Tornado	0.017597
116	YEAR_2017	0.015556
65	WFO_JKL	0.013833
13	MONTH_NAME_October	0.013296
115	WFO_VEF	0.011422
76	WFO_MAF	0.010259
146	EVENT_TYPE_Hail*MAGNITUDE	0.009543
9	MONTH_NAME_June	0.008608
118	EVENT_TYPE_Flash Flood	0.008414
96	WFO_PIH	0.008362
100	WFO_RAH	0.008243

```
In [ ]:
```