8

October 21, 2018

1 Assignment 8

Using any dataset that has a categorical feature that needs to be predicted, use several algorithms, preprocessing techniques, feature extraction techniques to fit the data to the model and show the accuracy, confusion matrix, and the classification report. G https://www.kaggle.com/ntnu-testimon/paysim1 https://www.kaggle.com/joniarroba/noshowappointments https://archive.ics.uci.edu/ml/datasets.html?format=&task=cla&att=&area=&numAtt=&numIns=&type=&sor
https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients
https://archive.ics.uci.edu/ml/datasets/Adult

```
In [1]: # Sorry for the long assignment length. I was having a lot of fun.
```

```
In [2]: !ls ../data
```

```
2016-Q1-Trips-History-Data.csv
2016-Q1-cabi-trip-history-data.zip
3D_spatial_network.txt.gz
Auto.csv
Auto.data
College.csv
Credit.csv
Heart.csv
KDCA-201601.csv
KDCA-201602.csv
KDCA-201603.csv
MCFRS_Incidents_by_Station.csv
USCensus1990.data.txt.gz
beers.csv
breweries.csv
chipotle.tsv
creditcardnumbers.txt
dates.txt
dates2.txt
emails.txt
estimating_coefficients.png
kobe.csv
messy.txt
noob.csv
```

```
phonenumbers.txt
pima-indians-diabetes.data
population - Data Source","World Development Indicators 2016-04-11.csv
sms.tsv
snow_tweets.csv
stockholm.csv
stockholm_td_adj.dat
years.txt
```

In [3]:
```python
# Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from pylab import rcParams
rcParams['figure.figsize'] = 20, 20

from sklearn import svm, datasets, preprocessing
from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split
from sklearn.model_selection import learning_curve
from sklearn.model_selection import validation_curve
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression

df = pd.read_csv("../data/MCFRS_Incidents_by_Station.csv")
df_raw = df.copy()
df.head()
```

Out[3]:
```
                                        Fire Station  Fire Station Number  \
0  Kensington Volunteer Fire Department (Station 18)                   18
1        Sandy Spring Volunteer Fire Department (40)                   40
2   Kensington Volunteer Fire Department (Station 5)                    5
3  Silver Spring Volunteer Fire Department (Stati...                   19
4  Silver Spring Volunteer Fire Department (Stati...                   16

  Nature of 911 call  Monthly Total  Year      Month  Month Num  \
0          PREGNANCY              2  2017        MAY          5
1          BACK PAIN              5  2018  SEPTEMBER          9
2               SICK             34  2018  SEPTEMBER          9
3         ELECTRICAL              1  2014    JANUARY          1
4         INHALATION              1  2017       JUNE          6

                                 Station address
0              12251 Georgia Ave Wheaton, MD 20902
1                16911 Georgia Ave Olney, MD 20832
```

```
2        10620 Connecticut Ave Kensington, MD 20985
3          1945 Seminary Rd Silver Spring, MD 20910
4  111 University Blvd East Silver Spring, MD 20901
```

In [4]:
```python
# Create table for missing data analysis
def draw_missing_data_table(df):
    total = df.isnull().sum().sort_values(ascending=False)
    percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
    missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
    return missing_data
```

In [5]:
```python
df.describe()
```

Out[5]:
```
       Fire Station Number  Monthly Total          Year     Month Num
count         76016.000000   76016.000000  76016.000000  76016.000000
mean             18.358767       7.425095   2015.774061      6.449445
std              10.660218      11.194176      1.468064      3.438509
min               1.000000       1.000000   2013.000000      1.000000
25%               9.000000       1.000000   2015.000000      3.000000
50%              18.000000       3.000000   2016.000000      6.000000
75%              28.000000       8.000000   2017.000000      9.000000
max              40.000000     153.000000   2018.000000     12.000000
```

In [6]:
```python
draw_missing_data_table(df)
```

Out[6]:
```
                     Total   Percent
Nature of 911 call     216  0.002842
Station address          0  0.000000
Month Num                0  0.000000
Month                    0  0.000000
Year                     0  0.000000
Monthly Total            0  0.000000
Fire Station Number      0  0.000000
Fire Station             0  0.000000
```

In [7]:
```python
df.head()
```

Out[7]:
```
                                        Fire Station  Fire Station Number  \
0  Kensington Volunteer Fire Department (Station 18)                   18
1        Sandy Spring Volunteer Fire Department (40)                   40
2   Kensington Volunteer Fire Department (Station 5)                    5
3  Silver Spring Volunteer Fire Department (Stati...                   19
4  Silver Spring Volunteer Fire Department (Stati...                   16

  Nature of 911 call  Monthly Total  Year      Month  Month Num  \
0          PREGNANCY              2  2017        MAY          5
1          BACK PAIN              5  2018  SEPTEMBER          9
2               SICK             34  2018  SEPTEMBER          9
3         ELECTRICAL              1  2014    JANUARY          1
```

```
4         INHALATION              1  2017       JUNE          6

                                      Station address
0              12251 Georgia Ave Wheaton, MD 20902
1                16911 Georgia Ave Olney, MD 20832
2         10620 Connecticut Ave Kensington, MD 20985
3           1945 Seminary Rd Silver Spring, MD 20910
4  111 University Blvd East Silver Spring, MD 20901
```

In [8]:
```
df.dtypes
```

Out[8]:
```
Fire Station            object
Fire Station Number      int64
Nature of 911 call      object
Monthly Total            int64
Year                     int64
Month                   object
Month Num                int64
Station address         object
dtype: object
```

In [9]:
```
df.drop('Station address', axis=1, inplace=True)
df.head()
```

Out[9]:
```
                                        Fire Station  Fire Station Number  \
0  Kensington Volunteer Fire Department (Station 18)                   18
1        Sandy Spring Volunteer Fire Department (40)                   40
2   Kensington Volunteer Fire Department (Station 5)                    5
3  Silver Spring Volunteer Fire Department (Stati...                   19
4  Silver Spring Volunteer Fire Department (Stati...                   16

  Nature of 911 call  Monthly Total  Year      Month  Month Num
0          PREGNANCY              2  2017        MAY          5
1          BACK PAIN              5  2018  SEPTEMBER          9
2               SICK             34  2018  SEPTEMBER          9
3         ELECTRICAL              1  2014    JANUARY          1
4         INHALATION              1  2017       JUNE          6
```

In [67]:
```
df['station'] = df['Fire Station Number']
df['nature'] = df['Nature of 911 call']
df['BYstations'] = df.groupby('Year')['station'].cumcount()
df['MonthNum'] = df['Month Num']
df['MonthTotal'] = df['Monthly Total']

station = df.groupby('Fire Station Number').agg('count')
station['Station'] = station.index

nature = df.groupby('Nature of 911 call').agg('count')
nature['Nature'] = nature.index
```

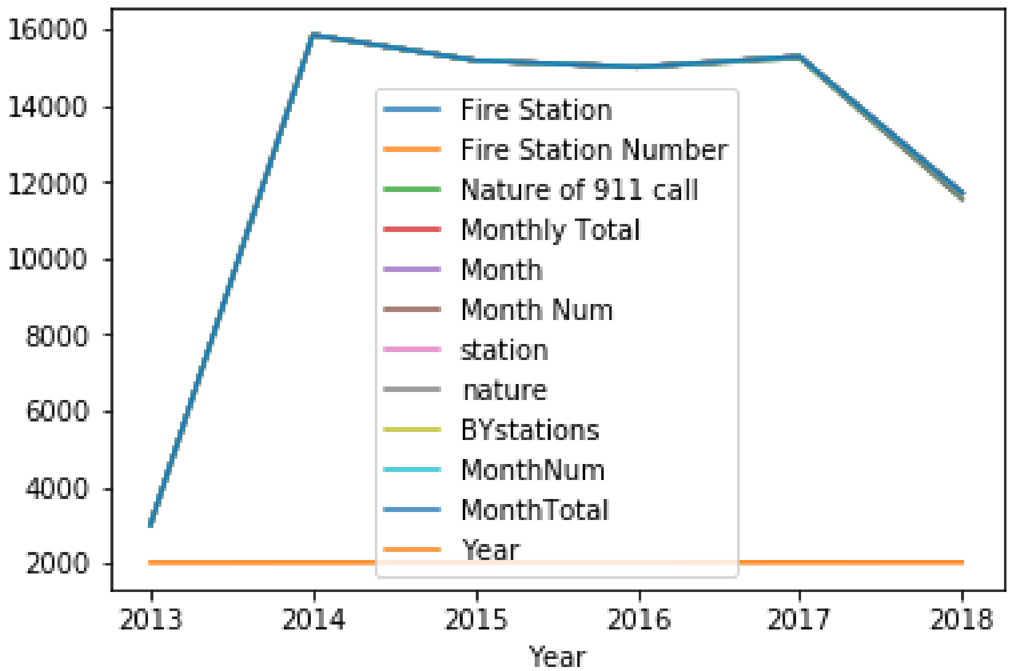
```
months = df.groupby('Month Num').agg('count')
months['Month'] = months.index

years = df.groupby('Year').agg('count')
years['Year'] = years.index
```

In [11]:
```
years.head()
```

Out[11]:
```
      Fire Station  Fire Station Number  Nature of 911 call  Monthly Total  \
Year
2013          3004                 3004                3004           3004
2014         15843                15843               15843          15843
2015         15178                15178               15178          15178
2016         15001                15001               15001          15001
2017         15279                15279               15236          15279

      Month  Month Num  station  nature  BYstations  MonthNum  MonthTotal  \
Year
2013   3004       3004     3004    3004        3004      3004        3004
2014  15843      15843    15843   15843       15843     15843       15843
2015  15178      15178    15178   15178       15178     15178       15178
2016  15001      15001    15001   15001       15001     15001       15001
2017  15279      15279    15279   15236       15279     15279       15279

      Year
Year
2013  2013
2014  2014
2015  2015
2016  2016
2017  2017
```

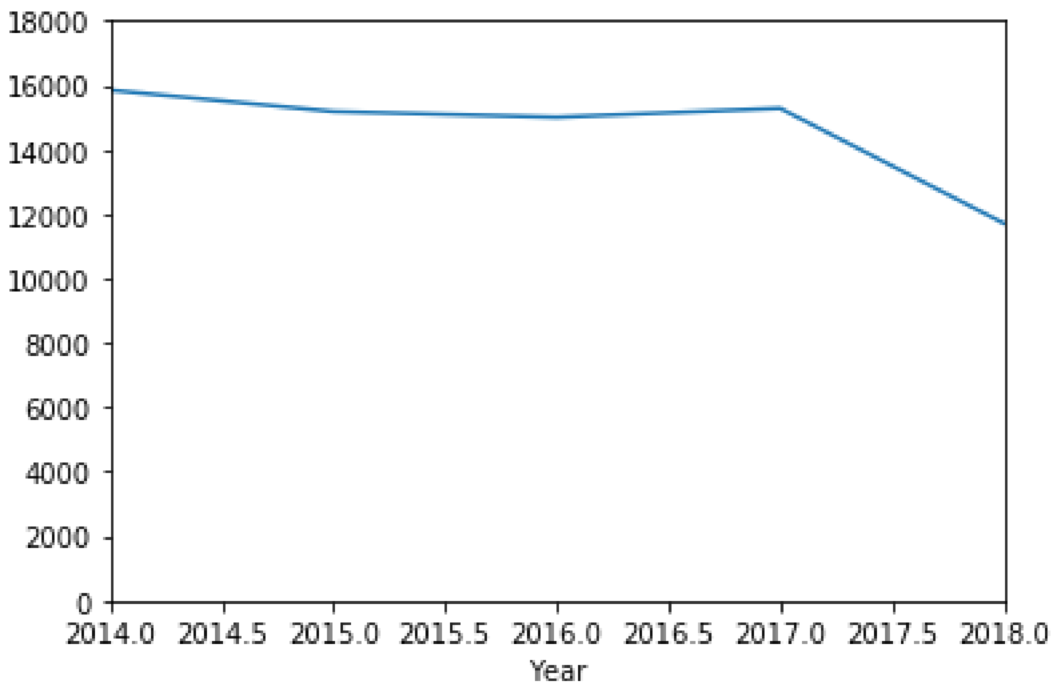
In [12]:
```
years.plot()
```

Out[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x105999390>
```



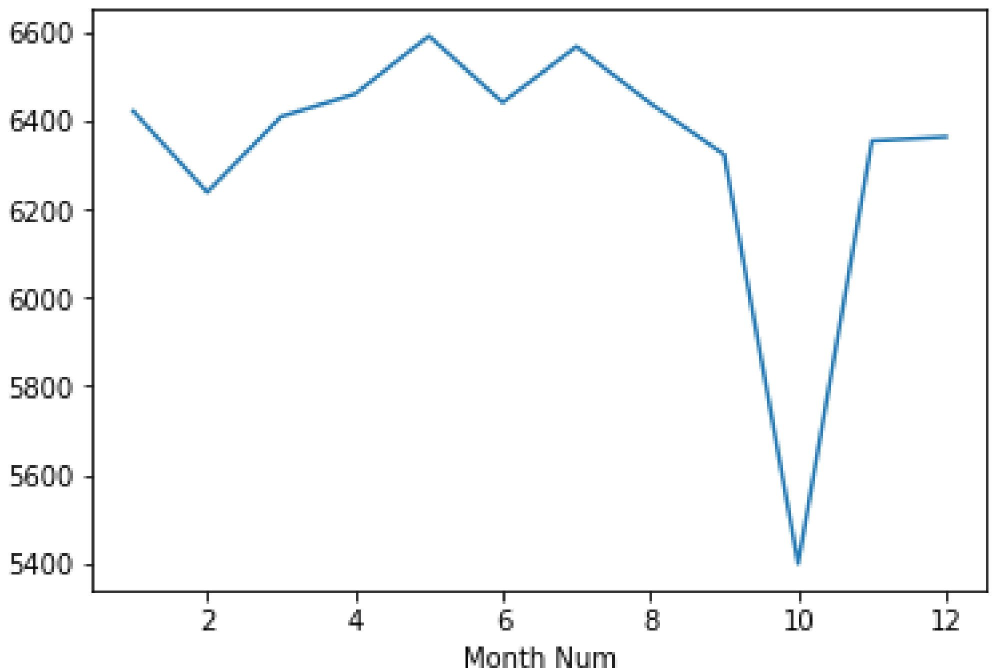
In [13]:
```
# obviously, the data size is not correct for year 2013
years = years.drop([2013])
years.station.plot(ylim=(0, 18000), xlim=(2014, 2018))
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x108530160>
```



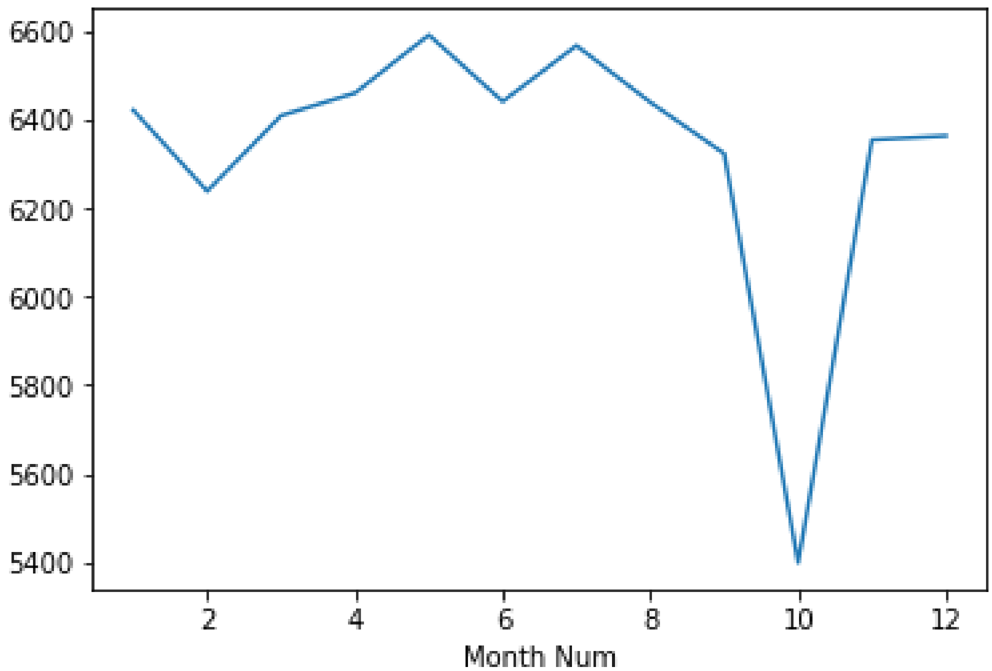
In [14]:
```
months.Year.plot()
# There is a dip in the calls for October.
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x10c922438>

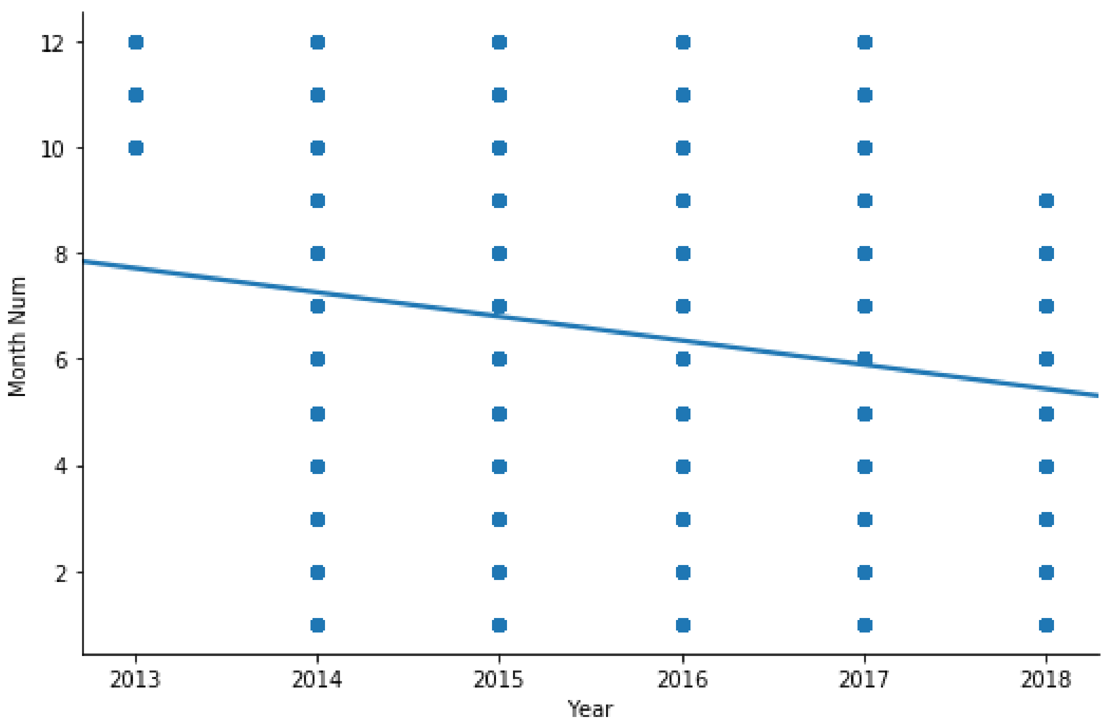


In [15]:
```
months = df.groupby('Month Num').agg('count')
months['Month'] = months.index

months.Year.plot()
sns.lmplot(y='Month Num', x='Year', data=df, aspect=1.5, scatter_kws={'alpha':0.2})
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x10c9a9b00>



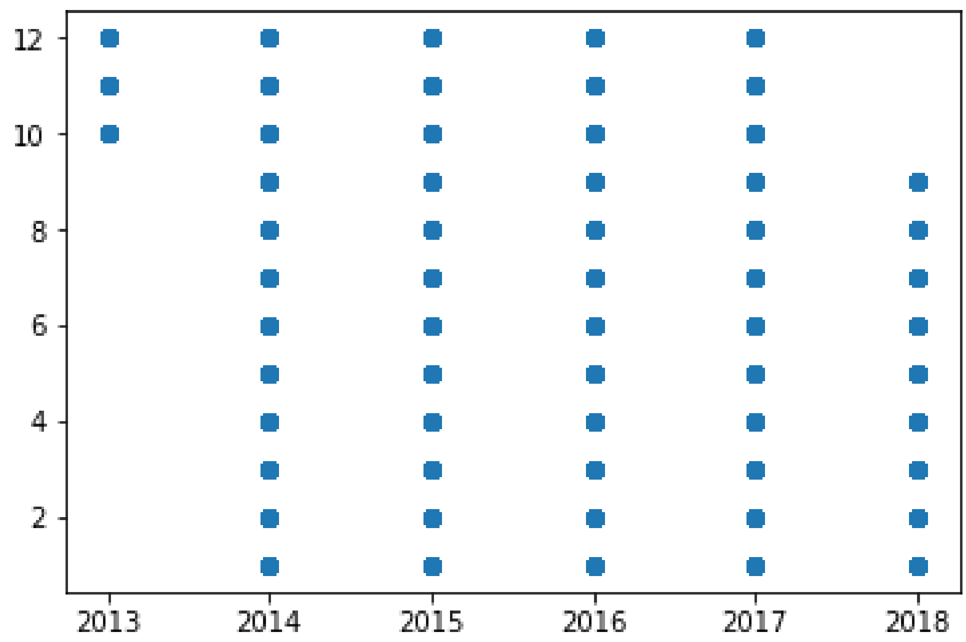
6600
6400
6200
6000
5800
5600
5400
2
4
6
8
10
12
Month Num



12
10
8
6
4
2
Month Num
2013
2014
2015
2016
2017
2018
Year

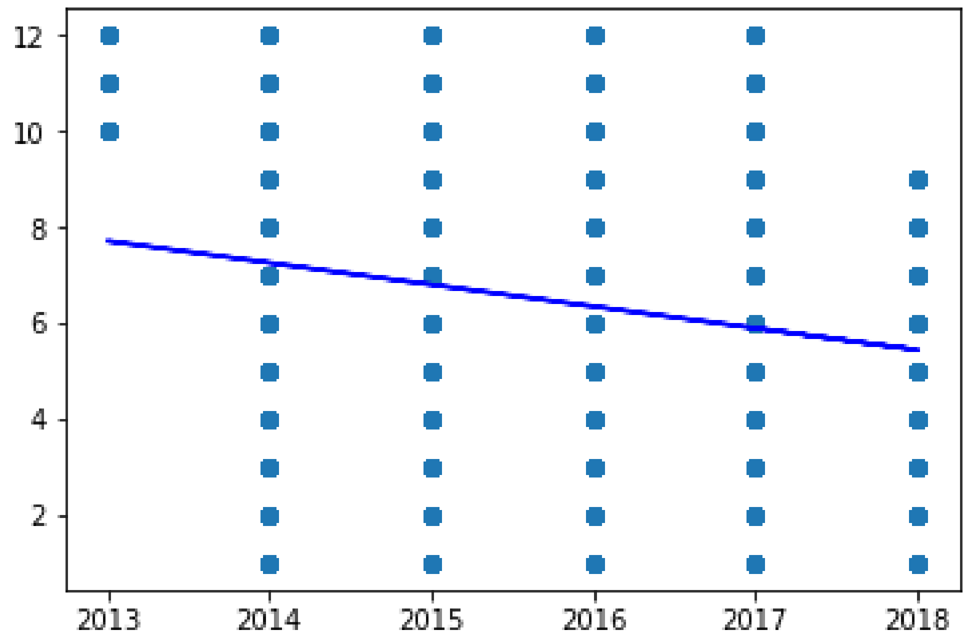
```
In [16]: from sklearn import linear_model # adding additional module not already listed from abo

         x_times = df[['Year']]
         y_starting = df.MonthNum

         plt.scatter(x_times, y_starting)
```

```
Out[16]: <matplotlib.collections.PathCollection at 0x10c9a9940>
```




```
In [17]: # For my reference - Setting up regular linear regresssion
         from sklearn.linear_model import LinearRegression

         linear = LinearRegression()
         linear.fit(x_times, y_starting)

         # Plotting
         plt.scatter(x_times, y_starting)
         plt.plot(x_times, x_times*linear.coef_ + linear.intercept_, c = "b" )
```

```
Out[17]: [<matplotlib.lines.Line2D at 0x1074cfe48>]
```



In [18]:
```
# Model 1, polynomial linear regression x25 degree
from sklearn.preprocessing import PolynomialFeatures

poly_25 = PolynomialFeatures(degree=25)
x_25 = poly_25.fit_transform(x_times) # got rid of .reshape
x_25
```

Out[18]:
```
array([[1.00000000e+00, 2.01700000e+03, 4.06828900e+06, ...,
        1.01914425e+76, 2.05561395e+79, 4.14617335e+82],
       [1.00000000e+00, 2.01800000e+03, 4.07232400e+06, ...,
        1.03082923e+76, 2.08021338e+79, 4.19787060e+82],
       [1.00000000e+00, 2.01800000e+03, 4.07232400e+06, ...,
        1.03082923e+76, 2.08021338e+79, 4.19787060e+82],
       ...,
       [1.00000000e+00, 2.01300000e+03, 4.05216900e+06, ...,
        9.73658865e+75, 1.95997530e+79, 3.94543027e+82],
       [1.00000000e+00, 2.01800000e+03, 4.07232400e+06, ...,
        1.03082923e+76, 2.08021338e+79, 4.19787060e+82],
       [1.00000000e+00, 2.01800000e+03, 4.07232400e+06, ...,
        1.03082923e+76, 2.08021338e+79, 4.19787060e+82]])
```

In [19]:
```
linear = linear_model.LinearRegression()
linear.fit(x_25, y_starting)
linear.coef_, linear.intercept_

# So far just copy and pasting
```

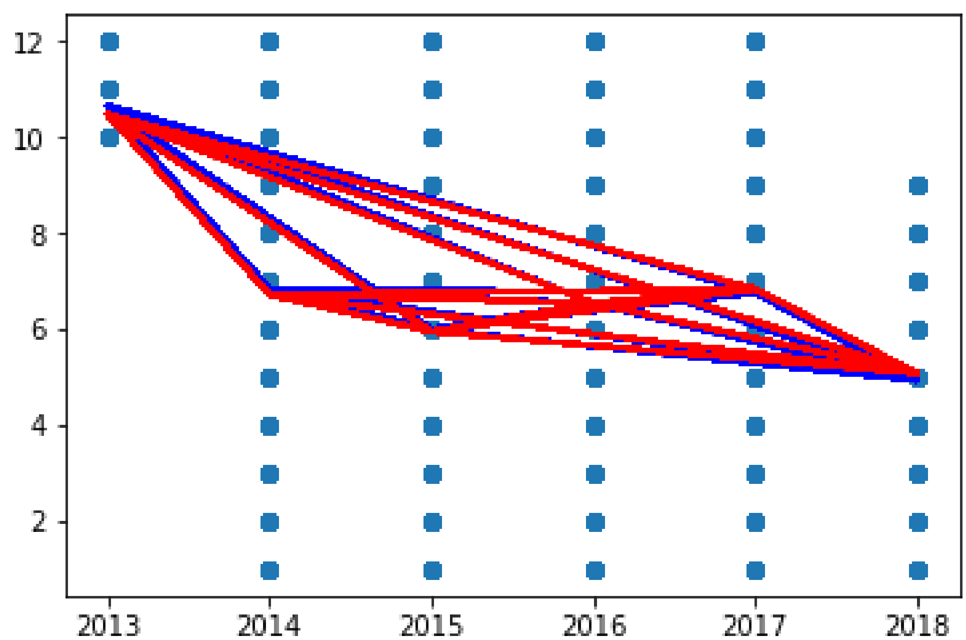
Out[19]: (array([3.72210781e-073, -9.27556285e-076, 9.23784262e-080,
            4.11804607e-084, -1.80216118e-129, -4.12057021e-126,
           -8.96969386e-123, -1.88719320e-119, -3.86413690e-116,
           -7.73115120e-113, -1.51497895e-109, -2.91104116e-106,
           -5.48639626e-103, -1.01366803e-099, -1.83356543e-096,
           -3.23971470e-093, -5.57215089e-090, -9.28121459e-087,
           -1.48554980e-083, -2.25755280e-080, -3.19316067e-077,
           -4.05470372e-074, -4.28085343e-071, -3.00685202e-068,
            2.85896138e-071, -6.80767460e-075]), 1007717.7014670605)

In [20]:
```
ridge = linear_model.Ridge()
ridge.fit(x_25, y_starting)
ridge.coef_, ridge.intercept_
```

Out[20]: (array([-6.26620691e-68, 3.42154920e-66, 3.79511690e-67, 1.97140078e-67,
           -1.48693345e-68, -2.16716224e-67, -2.00672681e-68, -3.39900429e-68,
            1.43901868e-68, -3.99425461e-68, 5.07532915e-68, 7.27248520e-69,
           -5.50549106e-70, 2.59417278e-69, 3.16616283e-68, -2.26605507e-68,
            1.17804467e-68, 1.68483788e-68, -2.39095433e-67, -1.42064068e-67,
           -6.03289717e-67, 2.17119696e-66, -8.76352843e-67, -2.88246636e-68,
            2.79990547e-71, -6.71401308e-75]), 1009626.6438529128)

In [21]:
```
# Model 1 : 25
import numpy as np # I didn't need to until now

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_25, ridge.coef_) + ridge.intercept_, c='r')
```

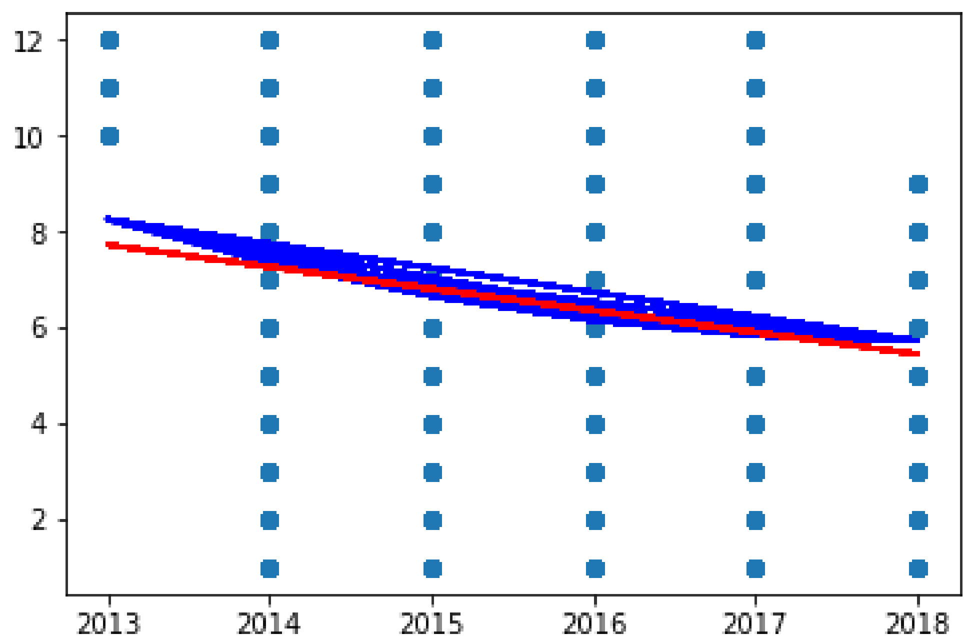
Out[21]: [<matplotlib.lines.Line2D at 0x10ca65748>]



In [22]:
```
# What... in the world...?
```

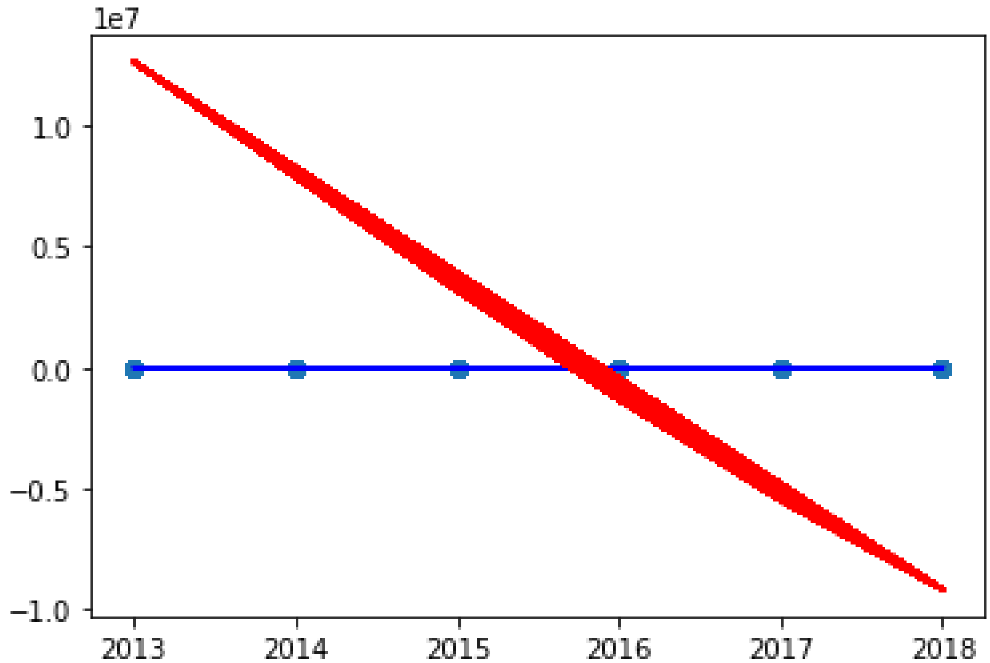
In [23]:
```
# Model 2, polynomial linear regression x2 degree
# More concise this time.
poly_2 = PolynomialFeatures(degree=2)
x_2 = poly_2.fit_transform(x_times) # got rid of .reshape
linear.fit(x_2, y_starting)
ridge.fit(x_2, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_2, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_2, ridge.coef_) + ridge.intercept_, c='r')
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x11136e978>]
```



In [24]:
```
# Model 3, polynomial linear regression x12 degree
poly_12 = PolynomialFeatures(degree=12)
x_12 = poly_12.fit_transform(x_times) # got rid of .reshape
linear.fit(x_12, y_starting)
ridge.fit(x_12, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_12, ridge.coef_) + ridge.intercept_, c='r')
```

Out[24]: [<matplotlib.lines.Line2D at 0x1a19a29240>]



In [25]:
```
# Let's try this again. I think month by year did not work because
# the graphs is essentially saying that... there are calls every month
# for every year. 2013 and 2018 are exceptions because there are no
# collected data obviously.

# I'm going to try to collect something unique. Too bad I we don't have
# data categorized by days.

BYnature = df.groupby(['MonthNum', 'nature']).size()

BYnature
```

Out[25]:
```
MonthNum  nature
1         ABDOMINAL PAIN             167
          ALLERGIC                   131
          ANIMAL BITE                 26
          ASSAULT                    127
          ASSIST CITIZEN              64
          ASSIST POLICE               61
          BACK PAIN                  147
          BLEEDING                   158
          BOMB PRESENT                72
          BOMB THREAT                  6
```

	BRUSH FIRE	17
	BUILDING FIRE	71
	BURNS	28
	CARBON MONOXIDE ALARM	61
	CARDIAC ARREST	143
	CHEST PAIN	170
	CHOKING	95
	CO ALARM	94
	DIABETIC	154
	DROWNING	2
	DUMPSTER FIRE	8
	ELECTRICAL	115
	ELECTRICAL SHORT	1
	ELECTROCUTION	6
	ELEVATOR	98
	EXPOSURE	34
	EYE INJURY	35
	FALLS	173
	FIRE ALARM	173
	FIRE INVESTIGATION	19
		...
12	PREGNANCY	97
	PSYCHIATRIC	149
	RESCUE	1
	RESET ALARM SYSTEM	11
	SEIZURE	161
	SERIVCE CALL-LIFT ASSIST	91
	SERVICE CALL	101
	SEWER FIRE	1
	SICK	172
	SMOKE IN THE AREA	42
	SMOKE ODOR	43
	SPECIAL DETAIL EVENT	7
	STROKE	162
	STRUCTURE FIRE	97
	SUICIDE	18
	TECHNICAL RESCUE	3
	TRASH FIRE	6
	TRAUMA	154
	TREE ON A BUILDING	2
	TROUBLE BREATHING	170
	UNCONSCIOUS	171
	UNDETERMINED RESCUE	92
	UNKNOWN MEDICAL EMERGENCY	70
	UNKNOWN ODOR	46
	UNKNOWN PROBLEM	162
	UNRES	27
	VEHICLE FIRE	111

```
            WATER PROBLEM                    36
            WATER RESCUE                      7
            WIRE DOWN                        51
Length: 1064, dtype: int64
```

In [26]:
```python
df.drop('Fire Station', axis=1, inplace=True)
df.head()
```

Out[26]:
```
   Fire Station Number Nature of 911 call  Monthly Total  Year      Month  \
0                   18          PREGNANCY              2  2017        MAY
1                   40          BACK PAIN              5  2018  SEPTEMBER
2                    5               SICK             34  2018  SEPTEMBER
3                   19         ELECTRICAL              1  2014    JANUARY
4                   16         INHALATION              1  2017       JUNE

   Month Num  station       nature  BYstations  MonthNum  MonthTotal
0          5       18    PREGNANCY           0         5           2
1          9       40    BACK PAIN           0         9           5
2          9        5         SICK           1         9          34
3          1       19   ELECTRICAL           0         1           1
4          6       16   INHALATION           1         6           1
```

In [27]:
```python
def yes_no(s):
    if s == "FALLS":
        return 1
    elif s != "FALLS":
        return 0

df.nature.apply(yes_no).head()
```

Out[27]:
```
0    0
1    0
2    0
3    0
4    0
Name: nature, dtype: int64
```

In [28]:
```python
df['falls_num'] = df.nature.apply(yes_no)
df.head()
```

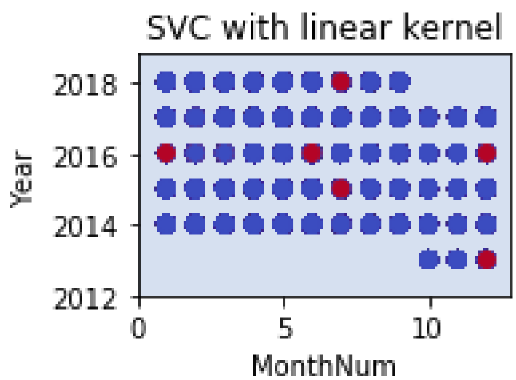
Out[28]:
```
   Fire Station Number Nature of 911 call  Monthly Total  Year      Month  \
0                   18          PREGNANCY              2  2017        MAY
1                   40          BACK PAIN              5  2018  SEPTEMBER
2                    5               SICK             34  2018  SEPTEMBER
3                   19         ELECTRICAL              1  2014    JANUARY
4                   16         INHALATION              1  2017       JUNE

   Month Num  station       nature  BYstations  MonthNum  MonthTotal  falls_num
0          5       18    PREGNANCY           0         5           2          0
```

```
1          9      40   BACK PAIN          0         9           5          0
2          9       5        SICK          1         9          34          0
3          1      19  ELECTRICAL          0         1           1          0
4          6      16  INHALATION          1         6           1          0
```

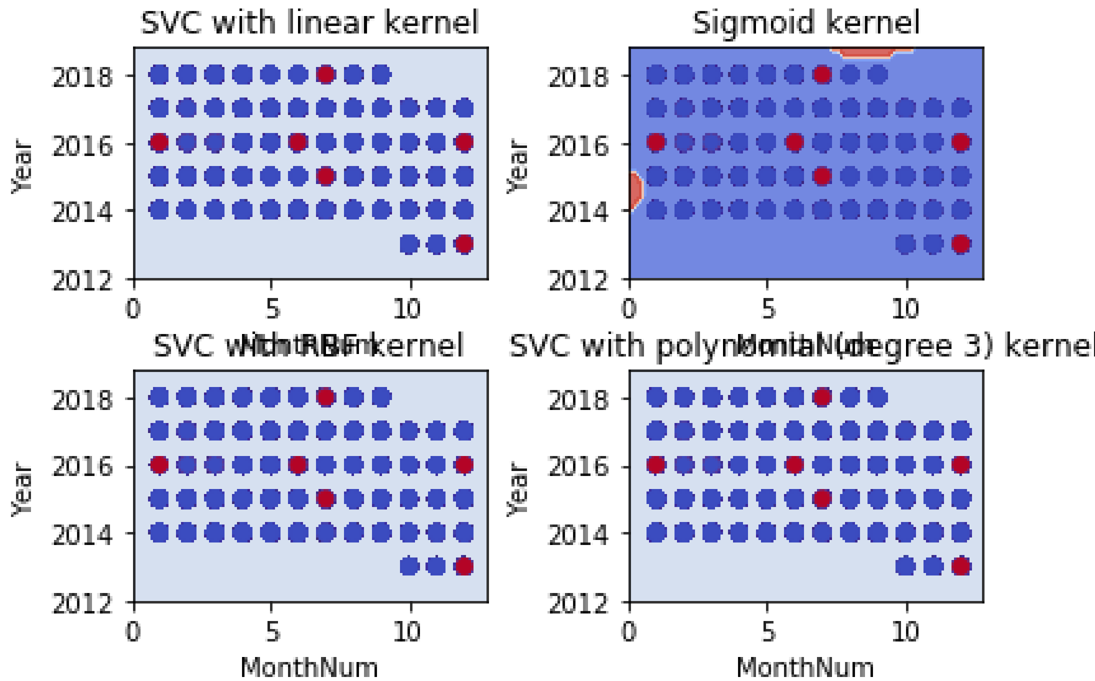
In [29]:
```python
def plot_svm(i, clf, title, X, y, col1, col2):

    h = .2  # step size in the mesh
    # create a mesh to plot in
    x_min, x_max = X[col1].min() - 1, X[col1].max() + 1
    y_min, y_max = X[col2].min() - 1, X[col2].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    grid_stack = np.stack([xx.flatten(), yy.flatten()]).T

    x1 = X[col1]
    x2 = X[col2]
    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    plt.subplot(2, 2, i + 1)
    plt.subplots_adjust(wspace=0.4, hspace=0.4)

    Z = clf.predict(scale(grid_stack)).reshape(xx.shape)
    # Put the result into a color plot
    plt.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
    x_s = preprocessing.scale(X)

    # Plot also the training points
    plt.scatter(x1, x2, c=y, cmap=plt.cm.coolwarm)

    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.title(title)
```

In [30]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm, datasets

col1, col2 = 'MonthNum', 'Year'

X = df[[col1, col2]]
y = df['falls_num']

# we create an instance of SVM and fit out data. We do not scale our data since we want


svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)


plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
```

```
plt.show()
```

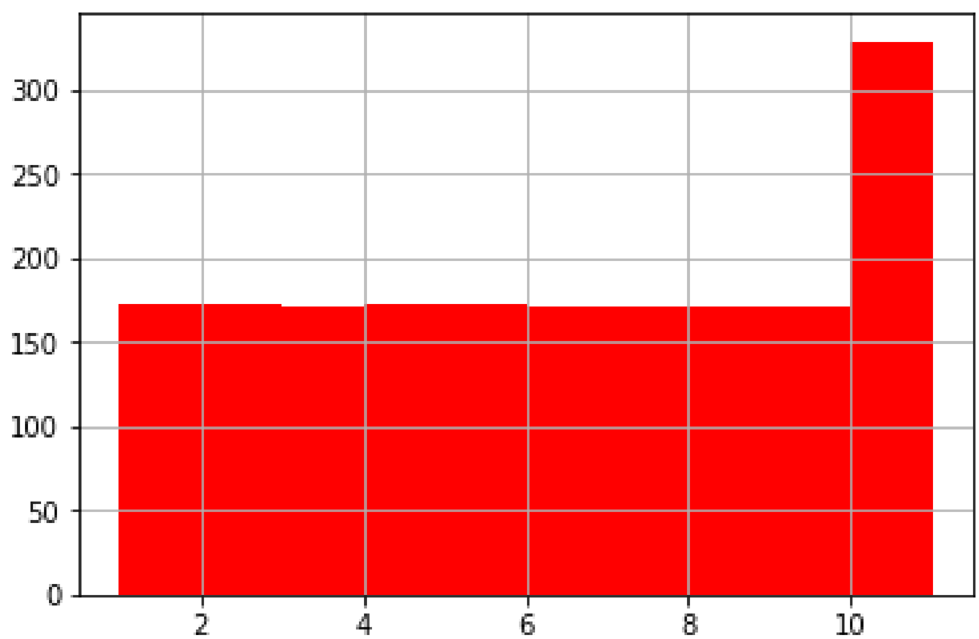



```
In [31]: C=1.0
         X_scaled = preprocessing.scale(X)
         svc = svm.SVC(kernel='linear', C=1.0).fit(X_scaled, y)
         rbf_svc = svm.SVC(kernel='rbf', gamma=0.7, C=C).fit(X_scaled, y)
         poly_svc = svm.SVC(kernel='poly', degree=2, C=C).fit(X_scaled, y)
         sig_svc = svm.SVC(kernel='sigmoid', C=C).fit(X_scaled, y)
         # title for the plots
         titles = ['SVC with linear kernel',
                   'Sigmoid kernel',
                   'SVC with RBF kernel',
                   'SVC with polynomial (degree 3) kernel']


         for i, clf in enumerate((svc, sig_svc, rbf_svc, poly_svc)):
             plot_svm(i, clf, titles[i], X, y, col1, col2)

         plt.show()

         # Not that I really understand the implactions of any of these
```



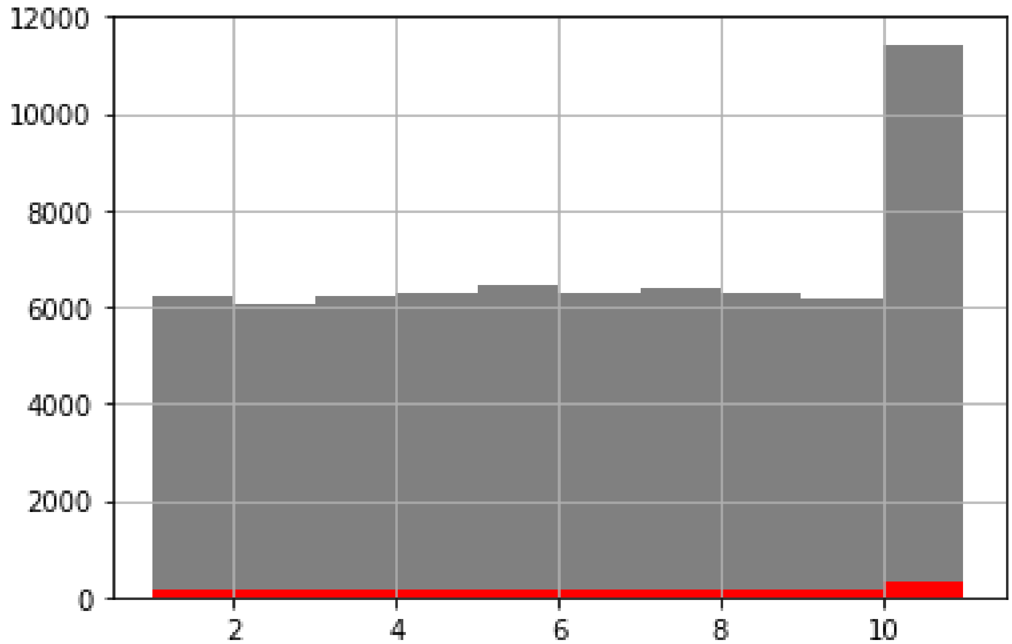

```
In [32]: df[(df.falls_num==1)].MonthNum.hist(bins=np.arange(1,12,1), alpha=1, color="red")
```

```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1a19a4be80>
```



In [33]:
```
df[(df.falls_num==0)].MonthNum.hist(bins=np.arange(1,12,1), alpha=1, color="grey")
df[(df.falls_num==1)].MonthNum.hist(bins=np.arange(1,12,1), alpha=1, color="red")
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1a19b83198>



In [34]:
```
# VERY INTERESTING.... The November and December incidents are both high
# for total incidents as well as falls injury... and... the shapes are
# nearly identical!!!!!
```

In [35]:
```
from sklearn.preprocessing import MinMaxScaler
df['fallsL'] = df.falls_num
df.fallsL = (df.fallsL - min(df.fallsL)) / ( max(df.fallsL) - min(df.fallsL))
df.fallsL
```

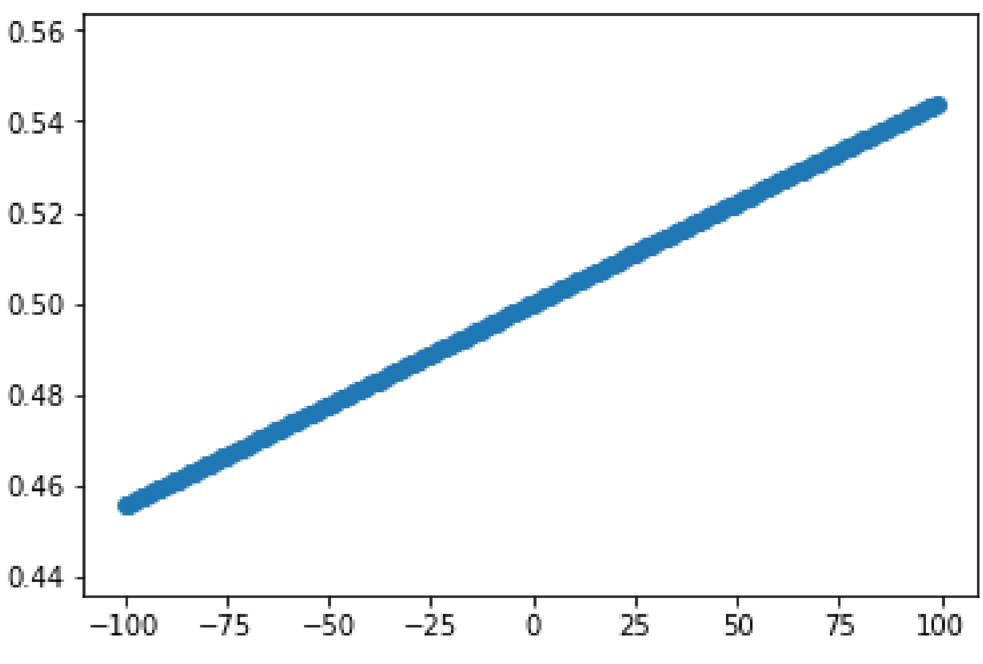
Out[35]:
```
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
5         0.0
6         0.0
7         0.0
8         0.0
9         0.0
10        0.0
11        0.0
```

```
12      0.0
13      0.0
14      0.0
15      0.0
16      1.0
17      0.0
18      0.0
19      0.0
20      0.0
21      0.0
22      0.0
23      0.0
24      0.0
25      0.0
26      0.0
27      0.0
28      0.0
29      0.0
       ...
75986   0.0
75987   0.0
75988   0.0
75989   0.0
75990   0.0
75991   0.0
75992   0.0
75993   0.0
75994   0.0
75995   0.0
75996   0.0
75997   0.0
75998   0.0
75999   0.0
76000   0.0
76001   0.0
76002   0.0
76003   0.0
76004   0.0
76005   0.0
76006   0.0
76007   0.0
76008   0.0
76009   0.0
76010   0.0
76011   0.0
76012   0.0
76013   0.0
76014   0.0
```

```
76015    0.0
Name: fallsL, Length: 76016, dtype: float64
```

In [36]:
```
from sklearn.linear_model import LogisticRegression as Model

feature_cols = ['Year', 'Month Num']
X = df[feature_cols]
y = df.fallsL

model = Model()
model.fit(X, y)
df['pred'] = model.predict(X)

from sklearn.metrics import accuracy_score
accuracy_score(df.fallsL, df.pred.round())

fallness = np.arange(-100, 100)
time = np.array([0]*200)
x_trial = np.column_stack((fallness, time))
model.predict_proba(x_trial)
plt.scatter(fallness, model.predict_proba(x_trial)[:,0])
```

Out[36]:
```
<matplotlib.collections.PathCollection at 0x1a19c79e80>
```



In [37]:
```
BYnature
```

```
Out[37]: MonthNum  nature
         1         ABDOMINAL PAIN                 167
                   ALLERGIC                       131
                   ANIMAL BITE                     26
                   ASSAULT                        127
                   ASSIST CITIZEN                  64
                   ASSIST POLICE                   61
                   BACK PAIN                      147
                   BLEEDING                       158
                   BOMB PRESENT                    72
                   BOMB THREAT                      6
                   BRUSH FIRE                      17
                   BUILDING FIRE                   71
                   BURNS                           28
                   CARBON MONOXIDE ALARM           61
                   CARDIAC ARREST                 143
                   CHEST PAIN                     170
                   CHOKING                         95
                   CO ALARM                        94
                   DIABETIC                       154
                   DROWNING                         2
                   DUMPSTER FIRE                    8
                   ELECTRICAL                     115
                   ELECTRICAL SHORT                 1
                   ELECTROCUTION                    6
                   ELEVATOR                        98
                   EXPOSURE                        34
                   EYE INJURY                      35
                   FALLS                          173
                   FIRE ALARM                     173
                   FIRE INVESTIGATION              19
                                                 ...
         12        PREGNANCY                       97
                   PSYCHIATRIC                    149
                   RESCUE                           1
                   RESET ALARM SYSTEM              11
                   SEIZURE                        161
                   SERIVCE CALL-LIFT ASSIST        91
                   SERVICE CALL                   101
                   SEWER FIRE                       1
                   SICK                           172
                   SMOKE IN THE AREA               42
                   SMOKE ODOR                      43
                   SPECIAL DETAIL EVENT             7
                   STROKE                         162
                   STRUCTURE FIRE                  97
                   SUICIDE                         18
                   TECHNICAL RESCUE                 3
```

```
                TRASH FIRE                      6
                TRAUMA                        154
                TREE ON A BUILDING              2
                TROUBLE BREATHING             170
                UNCONSCIOUS                   171
                UNDETERMINED RESCUE            92
                UNKNOWN MEDICAL EMERGENCY      70
                UNKNOWN ODOR                   46
                UNKNOWN PROBLEM               162
                UNRES                          27
                VEHICLE FIRE                  111
                WATER PROBLEM                  36
                WATER RESCUE                    7
                WIRE DOWN                      51
Length: 1064, dtype: int64
```

In [38]:
```
def yes_no(x):
    if x == "SUICIDE":
        return 1
    elif x != "SUICIDE":
        return 0
```

In [39]:
```
df['SUICIDE'] = df.nature.apply(yes_no)
df.head()
```

Out[39]:
```
   Fire Station Number Nature of 911 call  Monthly Total  Year      Month  \
0                   18          PREGNANCY              2  2017        MAY
1                   40          BACK PAIN              5  2018  SEPTEMBER
2                    5               SICK             34  2018  SEPTEMBER
3                   19         ELECTRICAL              1  2014    JANUARY
4                   16         INHALATION              1  2017       JUNE

   Month Num  station       nature  BYstations  MonthNum  MonthTotal  \
0          5       18    PREGNANCY           0         5           2
1          9       40    BACK PAIN           0         9           5
2          9        5         SICK           1         9          34
3          1       19   ELECTRICAL           0         1           1
4          6       16   INHALATION           1         6           1

   falls_num  fallsL  pred  SUICIDE
0          0     0.0   0.0        0
1          0     0.0   0.0        0
2          0     0.0   0.0        0
3          0     0.0   0.0        0
4          0     0.0   0.0        0
```

In [40]:
```
def yes_no(x):
    if x == "FIRE ALARM":
        return 1
```

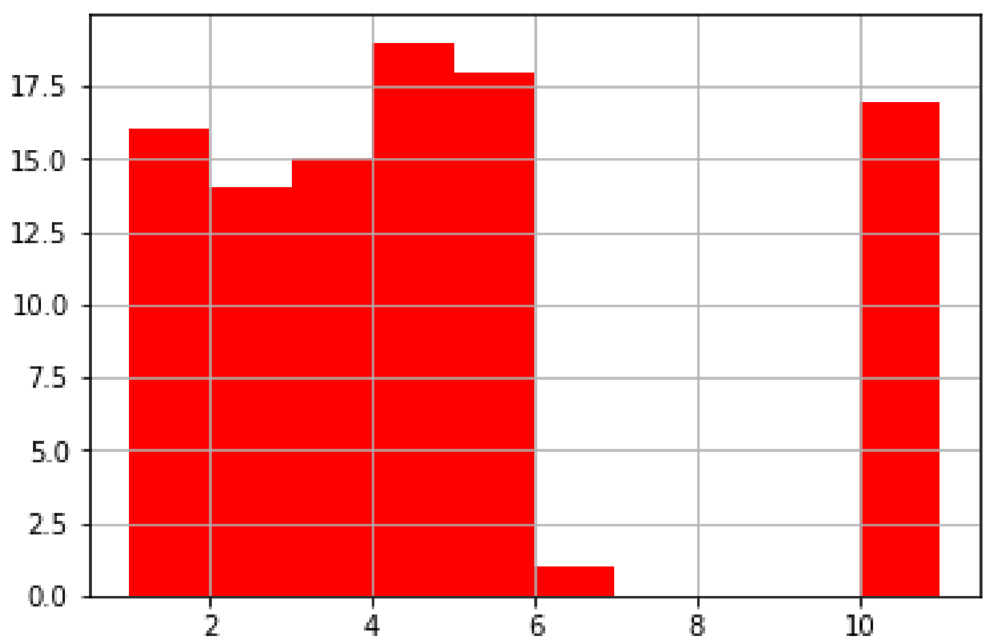
```
        elif x != "FIRE ALARM":
            return 0
```

In [41]:
```
df['FIRE_ALARM'] = df.nature.apply(yes_no)
df.head()
```

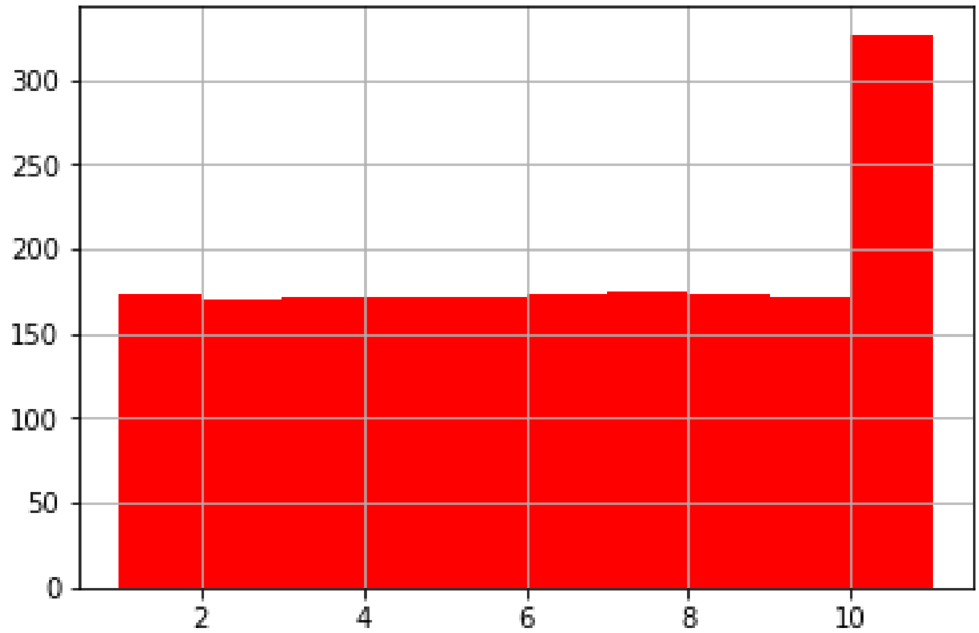
Out[41]:
```
   Fire Station Number Nature of 911 call  Monthly Total  Year      Month  \
0                   18          PREGNANCY              2  2017        MAY
1                   40          BACK PAIN              5  2018  SEPTEMBER
2                    5               SICK             34  2018  SEPTEMBER
3                   19         ELECTRICAL              1  2014    JANUARY
4                   16         INHALATION              1  2017       JUNE

   Month Num  station       nature  BYstations  MonthNum  MonthTotal  \
0          5       18    PREGNANCY           0         5           2
1          9       40    BACK PAIN           0         9           5
2          9        5         SICK           1         9          34
3          1       19   ELECTRICAL           0         1           1
4          6       16   INHALATION           1         6           1

   falls_num  fallsL  pred  SUICIDE  FIRE_ALARM
0          0     0.0   0.0        0           0
1          0     0.0   0.0        0           0
2          0     0.0   0.0        0           0
3          0     0.0   0.0        0           0
4          0     0.0   0.0        0           0
```

In [42]:
```
df[(df.SUICIDE==1)].MonthNum.hist(bins=np.arange(1,12,1), alpha=1, color="red")
```

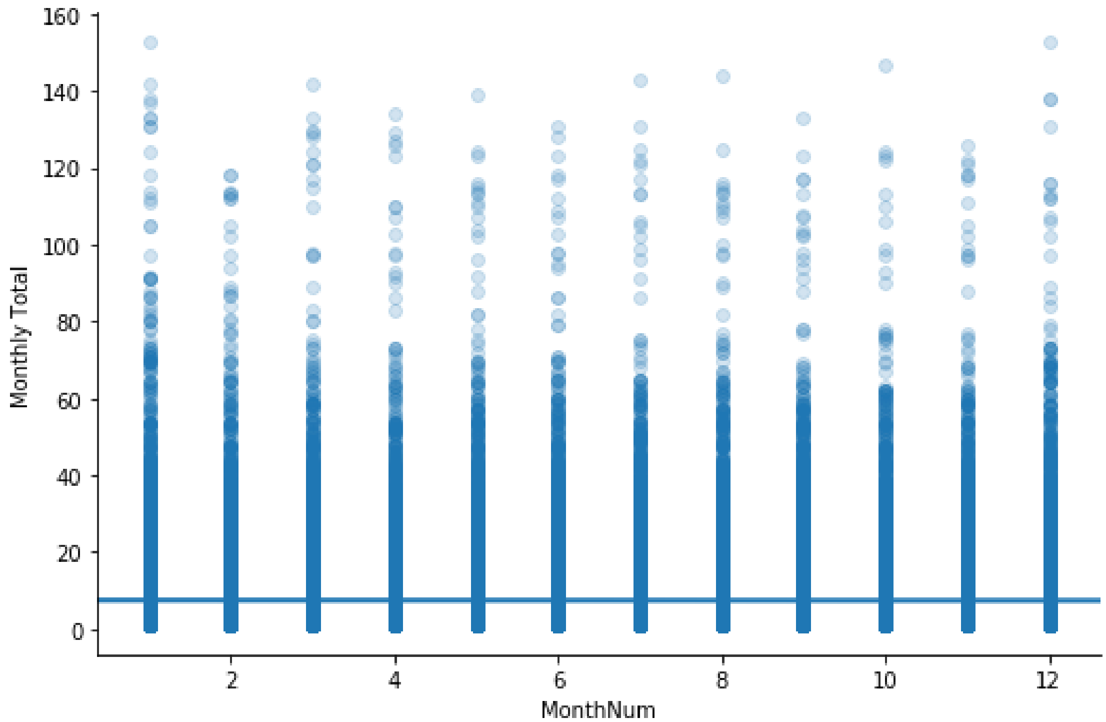
Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a19cb87b8>
```



```
In [43]: df[(df.FIRE_ALARM==1)].MonthNum.hist(bins=np.arange(1,12,1), alpha=1, color="red")

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1d5f3e48>
```




```
In [44]: feature_cols = [df[(df.FIRE_ALARM==1)], df[(df.SUICIDE==1)], df[(df.falls_num==1)]]

In [45]: sns.lmplot(x='MonthNum', y='Monthly Total', data=df, aspect=1.5, scatter_kws={'alpha':0

Out[45]: <seaborn.axisgrid.FacetGrid at 0x1a1e320278>
```




```
In [46]: # create X and y
         feature_cols = ['Month Num']
         X = df[feature_cols]
         y = df.MonthTotal

         # import, instantiate, fit
         from sklearn.linear_model import LinearRegression
         linreg = LinearRegression()
         linreg.fit(X, y)

         # print the coefficients
         print(linreg.intercept_)
         print(linreg.coef_)
```

```
7.4705716373380255
[-0.00705129]
```

```
In [47]: linreg.intercept_ + linreg.coef_ * 77
```

```
Out[47]: array([6.92762214])
```

```
In [48]: linreg.predict(77)
```

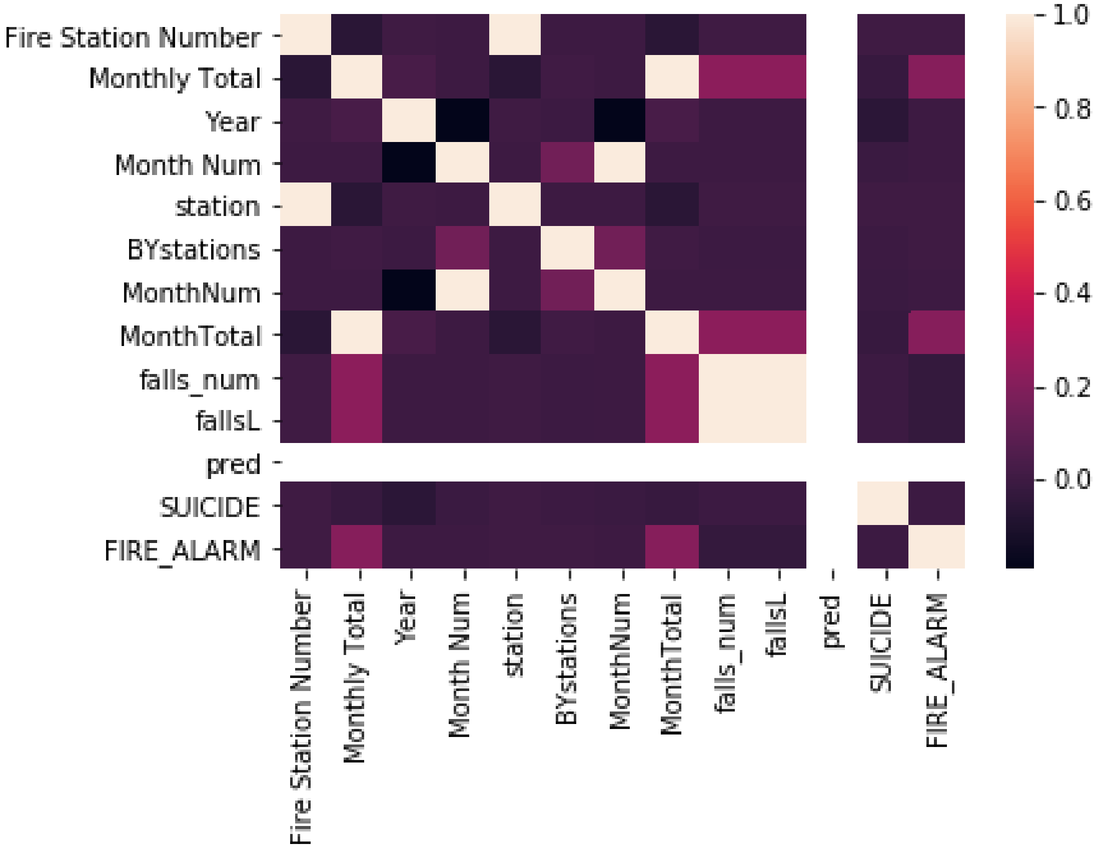
```
Out[48]: array([6.92762214])
```

In [49]: df.head()

```
Out[49]:    Fire Station Number Nature of 911 call  Monthly Total  Year      Month  \
        0                    18          PREGNANCY              2  2017        MAY
        1                    40          BACK PAIN              5  2018  SEPTEMBER
        2                     5               SICK             34  2018  SEPTEMBER
        3                    19         ELECTRICAL              1  2014    JANUARY
        4                    16         INHALATION              1  2017       JUNE

           Month Num  station      nature  BYstations  MonthNum  MonthTotal  \
        0          5       18   PREGNANCY           0         5           2
        1          9       40   BACK PAIN           0         9           5
        2          9        5        SICK           1         9          34
        3          1       19  ELECTRICAL           0         1           1
        4          6       16  INHALATION           1         6           1

           falls_num  fallsL  pred  SUICIDE  FIRE_ALARM
        0          0     0.0   0.0        0           0
        1          0     0.0   0.0        0           0
        2          0     0.0   0.0        0           0
        3          0     0.0   0.0        0           0
        4          0     0.0   0.0        0           0
```

In [50]: sns.heatmap(df.corr())

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1fc279b0>




```
In [51]: p = df.drop(['Year', 'Month', 'Month Num', 'nature', 'station', 'BYstations', 'MonthNum
         p
```

Out[51]:

	Fire Station Number	Nature of 911 call	Monthly Total
0	18	PREGNANCY	2
1	40	BACK PAIN	5
2	5	SICK	34
3	19	ELECTRICAL	1
4	16	INHALATION	1
5	8	EYE INJURY	3
6	20	MEDICAL INCIDENT	7
7	15	SICK	56
8	22	FIRE ALARM	16
9	19	PALLATIVE CARE	24
10	34	ASSAULT	3
11	4	CHEST PAIN	6
12	25	STROKE	13
13	12	DROWNING	1
14	5	BACK PAIN	1
15	6	FIRE ALARM	48

16	11	FALLS	21
17	8	BOMB PRESENT	3
18	13	PSYCHIATRIC	4
19	34	ANIMAL BITE	1
20	40	SEIZURE	4
21	1	FUEL SPILL	1
22	8	FIRE ALARM	36
23	17	BACK PAIN	1
24	31	DIABETIC	4
25	17	EXPOSURE	1
26	17	SMOKE IN THE AREA	4
27	13	TROUBLE BREATHING	8
28	12	SERVICE CALL	9
29	25	FIRE ALARM	25
...	...	...	...
75986	23	BACK PAIN	5
75987	16	CHEST PAIN	5
75988	1	ASSAULT	6
75989	23	CARDIAC ARREST	3
75990	35	OVERDOSE	2
75991	5	UNKNOWN PROBLEM	12
75992	6	MEDICAL INCIDENT	3
75993	31	SICK	6
75994	32	FRS-BLS	1
75995	27	MEDICAL INCIDENT	1
75996	10	PERSONAL INJURY COLLISION	22
75997	15	HEART PROBLEMS	5
75998	15	FRS-ASST	1
75999	18	LOCKED IN	1
76000	20	CO ALARM	3
76001	26	ASSAULT	1
76002	15	SEIZURE	7
76003	8	PERSONAL INJURY COLLISION	4
76004	21	HEADACHE	1
76005	1	FRS-PIC	1
76006	1	FIRE ALARM	2
76007	1	BOMB PRESENT	2
76008	6	HEART PROBLEMS	5
76009	15	CO ALARM	5
76010	5	STRUCTURE FIRE	7
76011	25	DIABETIC	7
76012	3	BLEEDING	1
76013	15	HEART PROBLEMS	2
76014	11	FIRE ALARM	18
76015	34	PALLATIVE CARE	4

[76016 rows x 3 columns]

```
In [52]: FS = pd.pivot_table(p, index = ['Nature of 911 call'], columns = ['Fire Station Number'
         FS
```

```
Out[52]:                          Monthly Total                                    \
         Fire Station Number                  1          2          3          4
         Nature of 911 call
         ABDOMINAL PAIN               10.866667   4.932203  11.203390   2.250000
         AIRPLANE INCIDENT                  NaN        NaN        NaN   1.000000
         ALARM / SPRINKLR OOS               NaN        NaN        NaN        NaN
         ALLERGIC                      3.581818   1.958333   4.779661   1.575000
         ANIMAL BITE                   1.461538   1.000000   1.230769   1.000000
         ASSAULT                       6.389831   2.870370   4.321429   1.230769
         ASSIST CITIZEN                7.894737   7.105263  10.850000   2.058824
         ASSIST POLICE                 2.294118   2.189189   2.105263   1.142857
         BACK PAIN                     4.616667   2.461538   4.650000   1.461538
         BARN FIRE                          NaN        NaN        NaN        NaN
         BLEEDING                      9.550000   5.389831  10.150000   2.735849
         BOMB PRESENT                  4.469388   1.111111   3.048780   1.142857
         BOMB THREAT                   1.000000   1.000000   1.000000        NaN
         BRUSH FIRE                    2.000000   2.000000   2.230769   1.285714
         BUILDING FIRE                 4.434783   3.227273   5.000000   1.923077
         BURNS                         1.100000   1.000000   1.200000   1.000000
         CARBON MONOXIDE ALARM         1.666667   3.000000   3.263158   1.142857
         CARDIAC ARREST                3.145455   2.180000   3.741379   1.585366
         CHEST PAIN                   20.950000   8.600000  25.933333   4.431034
         CHOKING                       2.029412   1.461538   1.860000   1.571429
         CO ALARM                      2.033333   2.578947   4.461538   1.461538
         COLLAPSE RESCUE                    NaN        NaN        NaN        NaN
         CONFINE SPACE RESCUE               NaN        NaN        NaN        NaN
         CYLINDER LEAK OUTSDE               NaN        NaN        NaN        NaN
         DIABETIC                      5.474576   3.490909   6.600000   1.743590
         DROWNING                           NaN   1.000000   1.166667   1.000000
         DUMPSTER FIRE                 1.400000        NaN   1.416667        NaN
         ELECTRICAL                    3.659574   3.404762   3.549020   2.375000
         ELECTRICAL SHORT                   NaN        NaN        NaN        NaN
         ELECTROCUTION                 1.000000   1.000000   1.000000   1.000000
         ...                                ...        ...        ...        ...
         PSYCHIATRIC                   8.525424   3.017241   9.677966   1.658537
         RESCUE                             NaN        NaN   1.000000        NaN
         RESET ALARM SYSTEM            1.000000   1.500000   2.750000   1.000000
         SEIZURE                      12.406780   5.051724  12.600000   2.489796
         SERIVCE CALL-LIFT ASSIST      3.846154   3.305556   4.350000   2.103448
         SERVICE CALL                 11.951220   8.804878  12.878049   2.794872
         SEWER FIRE                    1.000000        NaN        NaN        NaN
         SICK                         57.000000  27.416667  58.866667  12.850000
         SMOKE IN THE AREA             1.444444   1.312500   2.100000   1.250000
         SMOKE ODOR                    2.571429   1.600000   2.200000   1.111111
         SPECIAL DETAIL EVENT               NaN        NaN   1.769231   2.000000
```

STROKE	5.333333	3.545455	7.482759	2.603774
STRUCTURE FIRE	7.853659	5.325000	6.829268	1.852941
SUICIDE	2.000000	1.000000	2.500000	NaN
TECHNICAL RESCUE	1.000000	NaN	1.142857	NaN
TRAIN INCIDENT	1.000000	NaN	1.000000	NaN
TRASH FIRE	1.500000	1.000000	1.000000	NaN
TRAUMA	7.135593	3.275862	11.033333	2.566038
TREE ON A BUILDING	NaN	1.333333	1.000000	1.000000
TROUBLE BREATHING	25.000000	15.322034	27.883333	6.350000
UNCONSCIOUS	28.816667	11.559322	26.216667	5.847458
UNDETERMINED RESCUE	4.357143	3.307692	3.325000	1.166667
UNKNOWN MEDICAL EMERGENCY	1.432432	1.625000	1.567568	1.181818
UNKNOWN ODOR	1.521739	1.210526	1.480000	1.400000
UNKNOWN PROBLEM	24.616667	8.525424	21.254237	4.280702
UNRES	3.611111	2.500000	2.529412	1.000000
VEHICLE FIRE	1.470588	1.419355	2.745455	1.115385
WATER PROBLEM	4.500000	2.133333	5.000000	3.750000
WATER RESCUE	1.000000	1.000000	1.000000	1.500000
WIRE DOWN	2.187500	2.947368	3.411765	2.800000

\

Fire Station Number	5	6	7	8
Nature of 911 call				
ABDOMINAL PAIN	7.216667	6.950000	2.365385	21.830508
AIRPLANE INCIDENT	NaN	NaN	NaN	NaN
ALARM / SPRINKLR OOS	NaN	NaN	NaN	NaN
ALLERGIC	3.196429	3.052632	1.657895	7.000000
ANIMAL BITE	1.076923	1.090909	1.375000	1.576923
ASSAULT	2.672727	2.065217	1.000000	12.766667
ASSIST CITIZEN	11.578947	7.650000	11.100000	14.210526
ASSIST POLICE	1.304348	1.500000	1.200000	2.780488
BACK PAIN	3.089286	3.226415	1.682927	8.533333
BARN FIRE	NaN	NaN	NaN	NaN
BLEEDING	7.516667	6.655172	3.581818	20.266667
BOMB PRESENT	1.680000	4.304348	1.357143	2.404762
BOMB THREAT	1.000000	1.000000	1.000000	1.000000
BRUSH FIRE	1.375000	1.500000	2.000000	3.875000
BUILDING FIRE	3.090909	3.160000	2.105263	6.655172
BURNS	1.000000	1.153846	1.000000	1.607143
CARBON MONOXIDE ALARM	2.894737	3.176471	1.800000	2.666667
CARDIAC ARREST	3.122807	3.428571	1.921053	7.440678
CHEST PAIN	14.033333	12.915254	3.793103	40.550000
CHOKING	1.560976	1.650000	1.263158	3.724138
CO ALARM	4.200000	3.538462	2.421053	3.450000
COLLAPSE RESCUE	NaN	NaN	NaN	NaN
CONFINE SPACE RESCUE	NaN	NaN	NaN	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	NaN	NaN
DIABETIC	4.000000	3.051724	1.833333	10.733333

```
DROWNING                         NaN   1.000000        NaN    1.000000
DUMPSTER FIRE               1.000000   2.000000        NaN    1.125000
ELECTRICAL                  4.979592   4.038462   2.857143    3.400000
ELECTRICAL SHORT            1.000000        NaN        NaN         NaN
ELECTROCUTION               1.000000   1.000000   1.500000    1.000000
...                              ...        ...        ...         ...
PSYCHIATRIC                 4.192982   4.379310   1.558824   15.216667
RESCUE                           NaN   1.000000        NaN         NaN
RESET ALARM SYSTEM          4.000000   1.666667        NaN    2.200000
SEIZURE                     6.305085   6.610169   2.065217   18.716667
SERIVCE CALL-LIFT ASSIST    6.292683   5.634146   3.829268    6.707317
SERVICE CALL               12.341463  10.439024   5.170732   24.560976
SEWER FIRE                       NaN   1.000000   1.000000    1.000000
SICK                       43.762712  36.516667  14.666667  106.783333
SMOKE IN THE AREA           1.545455   1.695652   1.125000    2.407407
SMOKE ODOR                  1.363636   2.187500   1.333333    3.444444
SPECIAL DETAIL EVENT        1.000000   1.000000   1.000000    4.920000
STROKE                      6.050000   5.706897   2.379310   13.350000
STRUCTURE FIRE              3.756098   5.375000   2.393939   12.073171
SUICIDE                     2.000000   1.333333   1.000000    2.500000
TECHNICAL RESCUE            1.333333   1.000000        NaN    1.000000
TRAIN INCIDENT              1.000000        NaN        NaN    1.000000
TRASH FIRE                  1.000000   1.142857        NaN    1.000000
TRAUMA                      5.116667   5.316667   2.734694   14.118644
TREE ON A BUILDING          1.250000        NaN   2.000000    1.250000
TROUBLE BREATHING          20.610169  16.916667   6.916667   59.950000
UNCONSCIOUS                17.576271  22.900000   5.898305   44.333333
UNDETERMINED RESCUE         2.184211   2.179487   1.318182    6.214286
UNKNOWN MEDICAL EMERGENCY   1.454545   1.406250   1.222222    1.907407
UNKNOWN ODOR                1.333333   1.550000   1.333333    1.709677
UNKNOWN PROBLEM            12.305085  13.583333   4.881356   27.881356
UNRES                       2.764706   2.000000   1.500000    6.222222
VEHICLE FIRE                1.527778   1.259259   1.604651    3.338983
WATER PROBLEM               3.071429   2.769231   2.200000   10.058824
WATER RESCUE                1.500000        NaN   2.000000    1.625000
WIRE DOWN                   4.117647   4.411765   3.428571    1.933333

                                                   ...                \
Fire Station Number                9         10    ...          27
Nature of 911 call                                 ...
ABDOMINAL PAIN              1.111111   2.000000    ...         NaN
AIRPLANE INCIDENT                NaN        NaN    ...         NaN
ALARM / SPRINKLR OOS             NaN        NaN    ...         NaN
ALLERGIC                    1.000000   1.605263    ...         NaN
ANIMAL BITE                 1.000000   1.000000    ...         NaN
ASSAULT                     1.000000   1.071429    ...         NaN
ASSIST CITIZEN              2.000000   3.666667    ...         NaN
ASSIST POLICE               1.000000   1.153846    ...    1.333333
```

BACK PAIN	1.000000	1.842105	...	NaN
BARN FIRE	NaN	NaN	...	NaN
BLEEDING	1.285714	2.634615	...	NaN
BOMB PRESENT	NaN	1.444444	...	NaN
BOMB THREAT	NaN	NaN	...	NaN
BRUSH FIRE	1.000000	1.555556	...	NaN
BUILDING FIRE	1.000000	1.687500	...	NaN
BURNS	NaN	1.000000	...	NaN
CARBON MONOXIDE ALARM	1.000000	1.636364	...	NaN
CARDIAC ARREST	1.111111	1.650000	...	NaN
CHEST PAIN	1.360000	3.448276	...	NaN
CHOKING	1.000000	1.444444	...	NaN
CO ALARM	1.000000	2.842105	...	NaN
COLLAPSE RESCUE	NaN	NaN	...	NaN
CONFINE SPACE RESCUE	NaN	NaN	...	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	...	NaN
DIABETIC	1.000000	1.483871	...	NaN
DROWNING	NaN	1.000000	...	NaN
DUMPSTER FIRE	NaN	NaN	...	NaN
ELECTRICAL	1.550000	2.742857	...	NaN
ELECTRICAL SHORT	NaN	NaN	...	NaN
ELECTROCUTION	NaN	1.000000	...	NaN
...	...	...	...	...
PSYCHIATRIC	1.000000	1.875000	...	NaN
RESCUE	NaN	1.000000	...	NaN
RESET ALARM SYSTEM	NaN	NaN	...	NaN
SEIZURE	1.000000	2.306122	...	NaN
SERIVCE CALL-LIFT ASSIST	1.000000	2.783784	...	NaN
SERVICE CALL	1.000000	3.736842	...	NaN
SEWER FIRE	NaN	NaN	...	NaN
SICK	1.468750	12.711864	...	1.000000
SMOKE IN THE AREA	1.000000	1.000000	...	NaN
SMOKE ODOR	NaN	1.333333	...	NaN
SPECIAL DETAIL EVENT	NaN	3.750000	...	1.000000
STROKE	1.222222	2.785714	...	NaN
STRUCTURE FIRE	1.000000	2.241379	...	NaN
SUICIDE	NaN	1.000000	...	NaN
TECHNICAL RESCUE	NaN	1.000000	...	NaN
TRAIN INCIDENT	NaN	NaN	...	NaN
TRASH FIRE	NaN	NaN	...	NaN
TRAUMA	1.176471	2.361702	...	NaN
TREE ON A BUILDING	NaN	1.000000	...	NaN
TROUBLE BREATHING	1.428571	5.728814	...	NaN
UNCONSCIOUS	1.241379	6.150000	...	NaN
UNDETERMINED RESCUE	NaN	1.315789	...	NaN
UNKNOWN MEDICAL EMERGENCY	1.000000	1.187500	...	NaN
UNKNOWN ODOR	1.000000	1.000000	...	NaN
UNKNOWN PROBLEM	1.125000	4.327586	...	1.000000

UNRES	1.000000	1.333333	...	NaN
VEHICLE FIRE	1.250000	2.040000	...	NaN
WATER PROBLEM	1.000000	2.800000	...	NaN
WATER RESCUE	NaN	1.157895	...	NaN
WIRE DOWN	1.500000	2.437500	...	NaN

\

Fire Station Number	28	29	30	31
Nature of 911 call				
ABDOMINAL PAIN	5.600000	7.271186	2.162162	4.355932
AIRPLANE INCIDENT	1.000000	NaN	1.000000	NaN
ALARM / SPRINKLR OOS	NaN	NaN	NaN	NaN
ALLERGIC	3.000000	2.584906	1.617647	3.053571
ANIMAL BITE	1.357143	1.357143	1.500000	1.285714
ASSAULT	3.218182	4.068966	1.000000	1.457143
ASSIST CITIZEN	2.705882	7.368421	3.000000	9.111111
ASSIST POLICE	1.391304	1.703704	1.250000	1.578947
BACK PAIN	2.785714	2.156863	1.517241	2.640000
BARN FIRE	NaN	NaN	NaN	NaN
BLEEDING	5.766667	5.796610	2.209302	4.000000
BOMB PRESENT	1.655172	1.891892	1.200000	1.323529
BOMB THREAT	NaN	1.000000	1.000000	1.000000
BRUSH FIRE	1.714286	2.000000	1.166667	1.666667
BUILDING FIRE	2.826087	3.590909	1.764706	3.227273
BURNS	1.000000	1.222222	1.250000	1.250000
CARBON MONOXIDE ALARM	1.692308	1.529412	2.200000	2.882353
CARDIAC ARREST	2.584906	2.727273	1.562500	2.769231
CHEST PAIN	11.406780	13.750000	3.000000	7.916667
CHOKING	1.611111	1.760870	1.071429	1.605263
CO ALARM	2.100000	1.875000	2.871795	2.894737
COLLAPSE RESCUE	NaN	NaN	1.000000	NaN
CONFINE SPACE RESCUE	NaN	NaN	NaN	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	NaN	NaN
DIABETIC	3.351852	5.067797	1.333333	3.163636
DROWNING	1.000000	1.000000	1.250000	1.000000
DUMPSTER FIRE	1.000000	1.200000	NaN	1.200000
ELECTRICAL	2.342857	1.866667	2.031250	2.523810
ELECTRICAL SHORT	NaN	NaN	NaN	1.000000
ELECTROCUTION	1.000000	1.000000	NaN	1.000000
...	...	...	...	...
PSYCHIATRIC	3.824561	5.525424	1.233333	2.058824
RESCUE	1.000000	NaN	NaN	NaN
RESET ALARM SYSTEM	1.500000	1.000000	1.000000	2.333333
SEIZURE	5.403509	5.627119	1.659091	3.948276
SERIVCE CALL-LIFT ASSIST	2.656250	2.848485	1.750000	3.487805
SERVICE CALL	6.243902	11.121951	3.475000	9.512195
SEWER FIRE	NaN	NaN	NaN	NaN
SICK	25.483333	29.700000	7.627119	22.450000

SMOKE IN THE AREA	1.350000	1.294118	1.090909	1.625000
SMOKE ODOR	1.692308	2.076923	1.333333	1.615385
SPECIAL DETAIL EVENT	1.400000	NaN	1.800000	1.928571
STROKE	3.372881	3.803571	2.047619	3.965517
STRUCTURE FIRE	3.815789	5.243902	1.892857	4.051282
SUICIDE	1.833333	1.800000	1.000000	1.750000
TECHNICAL RESCUE	1.000000	2.000000	1.000000	NaN
TRAIN INCIDENT	1.000000	1.000000	NaN	NaN
TRASH FIRE	1.000000	1.000000	NaN	1.000000
TRAUMA	5.084746	4.084746	1.697674	4.250000
TREE ON A BUILDING	NaN	1.500000	NaN	1.000000
TROUBLE BREATHING	13.683333	18.033898	4.473684	12.728814
UNCONSCIOUS	12.800000	14.355932	5.084746	12.616667
UNDETERMINED RESCUE	2.000000	2.133333	1.230769	1.608696
UNKNOWN MEDICAL EMERGENCY	1.370370	1.147059	1.111111	1.450000
UNKNOWN ODOR	1.000000	1.266667	1.666667	1.500000
UNKNOWN PROBLEM	6.750000	9.362069	3.724138	9.152542
UNRES	1.600000	1.875000	1.200000	1.750000
VEHICLE FIRE	2.240000	1.681818	1.111111	1.230769
WATER PROBLEM	2.562500	4.578947	2.000000	5.642857
WATER RESCUE	1.000000	1.000000	3.792453	1.291667
WIRE DOWN	2.000000	1.333333	1.800000	1.769231

\

Fire Station Number	32	33	34	35
Nature of 911 call				
ABDOMINAL PAIN	9.157895	2.759259	5.322034	2.777778
AIRPLANE INCIDENT	NaN	NaN	NaN	NaN
ALARM / SPRINKLR OOS	NaN	NaN	NaN	NaN
ALLERGIC	4.388889	2.612245	2.462963	2.500000
ANIMAL BITE	1.111111	1.000000	1.210526	1.000000
ASSAULT	3.259259	1.416667	3.000000	1.769231
ASSIST CITIZEN	10.411765	7.263158	3.736842	1.785714
ASSIST POLICE	1.892857	1.187500	1.541667	1.181818
BACK PAIN	3.927273	2.156863	2.509091	1.384615
BARN FIRE	NaN	NaN	NaN	1.000000
BLEEDING	9.553571	3.310345	4.627119	2.709091
BOMB PRESENT	1.947368	1.444444	1.357143	1.200000
BOMB THREAT	1.000000	NaN	1.000000	NaN
BRUSH FIRE	2.200000	1.333333	1.866667	1.000000
BUILDING FIRE	3.125000	1.900000	2.772727	1.500000
BURNS	1.066667	1.000000	1.100000	1.000000
CARBON MONOXIDE ALARM	2.538462	3.066667	2.181818	2.352941
CARDIAC ARREST	3.763636	2.318182	2.588235	1.515152
CHEST PAIN	22.140351	5.783333	11.516667	4.614035
CHOKING	1.638889	1.250000	1.558824	1.166667
CO ALARM	3.564103	4.300000	2.000000	1.931034
COLLAPSE RESCUE	NaN	NaN	NaN	NaN

CONFINE SPACE RESCUE	NaN	NaN	NaN	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	NaN	NaN
DIABETIC	4.109091	2.270833	3.446429	2.369565
DROWNING	1.000000	1.000000	1.000000	NaN
DUMPSTER FIRE	1.000000	NaN	1.000000	NaN
ELECTRICAL	2.261905	2.500000	2.410256	1.818182
ELECTRICAL SHORT	NaN	NaN	NaN	NaN
ELECTROCUTION	1.000000	1.000000	1.000000	1.000000
...	...	...	...	...
PSYCHIATRIC	9.000000	1.978723	4.000000	2.708333
RESCUE	1.000000	NaN	NaN	NaN
RESET ALARM SYSTEM	1.500000	1.333333	2.000000	1.000000
SEIZURE	9.192982	3.509091	4.431034	2.745455
SERIVCE CALL-LIFT ASSIST	4.650000	3.756098	2.058824	1.076923
SERVICE CALL	13.292683	6.658537	8.625000	3.473684
SEWER FIRE	1.000000	NaN	NaN	NaN
SICK	51.596491	18.983333	24.016667	10.550000
SMOKE IN THE AREA	1.478261	1.076923	1.190476	1.076923
SMOKE ODOR	2.000000	1.583333	1.615385	1.428571
SPECIAL DETAIL EVENT	1.000000	NaN	1.000000	1.500000
STROKE	7.771930	3.836364	2.714286	1.790698
STRUCTURE FIRE	4.804878	2.769231	3.725000	1.750000
SUICIDE	1.250000	1.500000	1.250000	1.000000
TECHNICAL RESCUE	1.000000	1.000000	1.000000	1.000000
TRAIN INCIDENT	NaN	NaN	NaN	NaN
TRASH FIRE	1.000000	NaN	1.000000	1.000000
TRAUMA	8.071429	3.145455	4.100000	2.647059
TREE ON A BUILDING	1.000000	1.500000	NaN	NaN
TROUBLE BREATHING	25.017544	8.900000	16.733333	5.694915
UNCONSCIOUS	27.473684	11.516667	13.508475	5.482759
UNDETERMINED RESCUE	2.870968	1.294118	1.821429	1.352941
UNKNOWN MEDICAL EMERGENCY	1.440000	1.125000	1.375000	1.181818
UNKNOWN ODOR	1.434783	1.214286	1.461538	1.000000
UNKNOWN PROBLEM	13.403509	4.454545	7.183333	2.088889
UNRES	2.941176	1.545455	1.583333	1.250000
VEHICLE FIRE	2.745098	1.133333	1.948718	1.444444
WATER PROBLEM	4.230769	3.363636	5.428571	3.777778
WATER RESCUE	1.000000	1.750000	3.000000	1.250000
WIRE DOWN	2.000000	3.133333	2.454545	1.357143

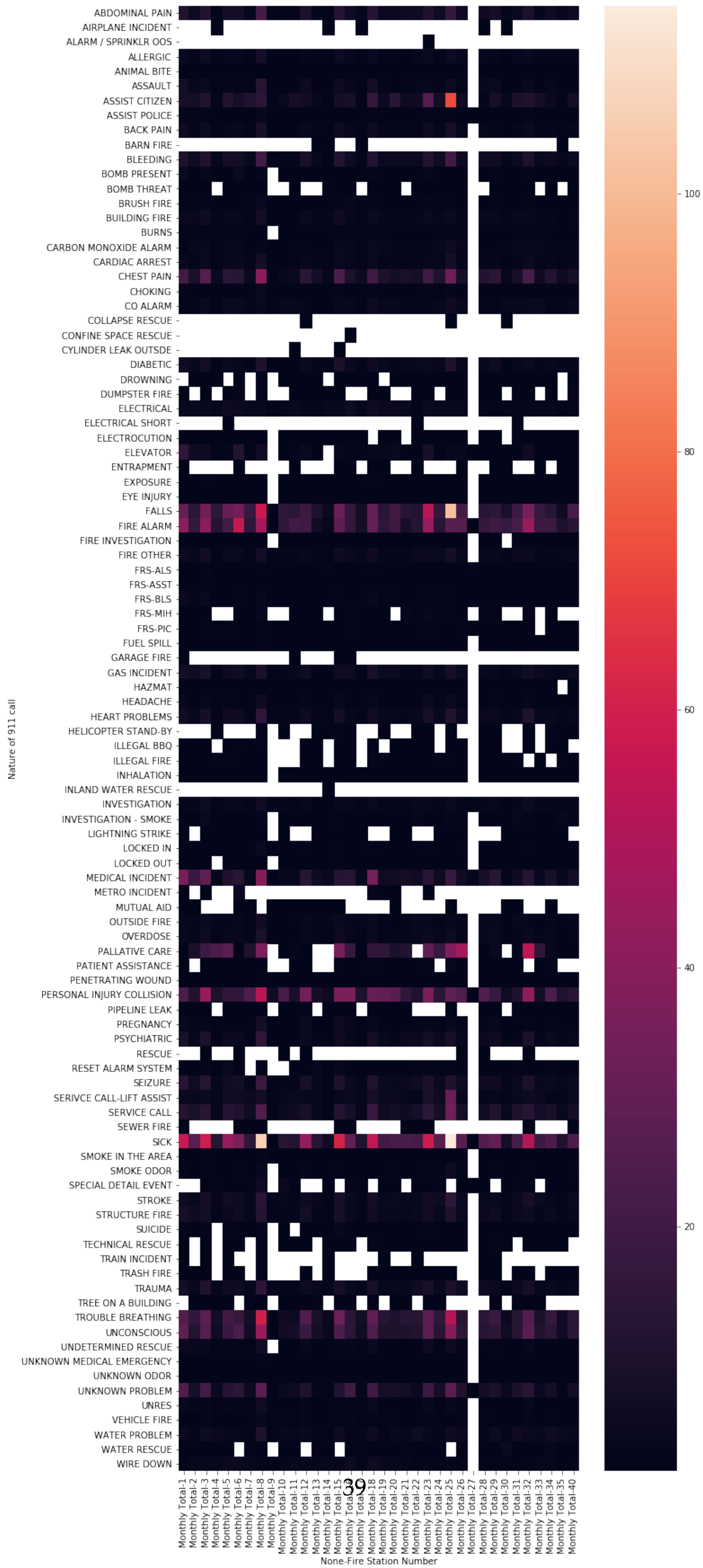
Fire Station Number	40
Nature of 911 call	
ABDOMINAL PAIN	4.551724
AIRPLANE INCIDENT	NaN
ALARM / SPRINKLR OOS	NaN
ALLERGIC	2.760000
ANIMAL BITE	1.375000

```
ASSAULT                      1.558140
ASSIST CITIZEN               6.500000
ASSIST POLICE                1.291667
BACK PAIN                    2.711538
BARN FIRE                         NaN
BLEEDING                     4.200000
BOMB PRESENT                 1.555556
BOMB THREAT                  1.000000
BRUSH FIRE                   1.222222
BUILDING FIRE                2.260870
BURNS                        1.000000
CARBON MONOXIDE ALARM        2.733333
CARDIAC ARREST               2.592593
CHEST PAIN                   8.135593
CHOKING                      1.588235
CO ALARM                     3.485714
COLLAPSE RESCUE                   NaN
CONFINE SPACE RESCUE              NaN
CYLINDER LEAK OUTSDE              NaN
DIABETIC                     2.625000
DROWNING                     1.000000
DUMPSTER FIRE                2.000000
ELECTRICAL                   2.285714
ELECTRICAL SHORT                  NaN
ELECTROCUTION                1.000000
...                               ...
PSYCHIATRIC                  2.962264
RESCUE                            NaN
RESET ALARM SYSTEM           1.000000
SEIZURE                      4.232143
SERIVCE CALL-LIFT ASSIST     3.700000
SERVICE CALL                 7.585366
SEWER FIRE                   1.000000
SICK                        23.916667
SMOKE IN THE AREA            1.444444
SMOKE ODOR                   2.166667
SPECIAL DETAIL EVENT         1.000000
STROKE                       4.066667
STRUCTURE FIRE               3.641026
SUICIDE                      1.500000
TECHNICAL RESCUE                  NaN
TRAIN INCIDENT                    NaN
TRASH FIRE                   1.000000
TRAUMA                       3.403509
TREE ON A BUILDING                NaN
TROUBLE BREATHING           14.100000
UNCONSCIOUS                 14.700000
UNDETERMINED RESCUE          1.666667
```

```
UNKNOWN MEDICAL EMERGENCY   1.300000
UNKNOWN ODOR                1.400000
UNKNOWN PROBLEM             6.389831
UNRES                       1.250000
VEHICLE FIRE                1.466667
WATER PROBLEM               3.538462
WATER RESCUE                1.285714
WIRE DOWN                   2.000000

[100 rows x 36 columns]
```

In [53]:
```
fig, ax = plt.subplots(figsize=(10,30))
sns.heatmap(FS, )

# I'm a volunteer EMT by the weekends
# Station 27 is known for never getting calls. It's confirmed, lol.
# Airplane incidents, alarm w sprinkler oos, collapse resuce, etc. are rare
```

Out[53]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1da45390>
```


ABDOMINAL PAIN
AIRPLANE INCIDENT
ALARM / SPRINKLR OOS
ALLERGIC
ANIMAL BITE
ASSAULT
ASSIST CITIZEN
ASSIST POLICE
BACK PAIN
BARN FIRE
BLEEDING
BOMB PRESENT
BOMB THREAT
BRUSH FIRE
BUILDING FIRE
BURNS
CARBON MONOXIDE ALARM
CARDIAC ARREST
CHEST PAIN
CHOKING
CO ALARM
COLLAPSE RESCUE
CONFINE SPACE RESCUE
CYLINDER LEAK OUTSDE
DIABETIC
DROWNING
DUMPSTER FIRE
ELECTRICAL
ELECTRICAL SHORT
ELECTROCUTION
ELEVATOR
ENTRAPMENT
EXPOSURE
EYE INJURY
FALLS
FIRE ALARM
FIRE INVESTIGATION
FIRE OTHER
FRS-ALS
FRS-ASST
FRS-BLS
FRS-MIH
FRS-PIC
FUEL SPILL
GARAGE FIRE
GAS INCIDENT
HAZMAT
HEADACHE
HEART PROBLEMS
HELICOPTER STAND-BY
ILLEGAL BBQ
ILLEGAL FIRE
INHALATION
INLAND WATER RESCUE
INVESTIGATION
INVESTIGATION - SMOKE
LIGHTNING STRIKE
LOCKED IN
LOCKED OUT
MEDICAL INCIDENT
METRO INCIDENT
MUTUAL AID
OUTSIDE FIRE
OVERDOSE
PALLATIVE CARE
PATIENT ASSISTANCE
PENETRATING WOUND
PERSONAL INJURY COLLISION
PIPELINE LEAK
PREGNANCY
PSYCHIATRIC
RESCUE
RESET ALARM SYSTEM
SEIZURE
SERIVCE CALL-LIFT ASSIST
SERVICE CALL
SEWER FIRE
SICK
SMOKE IN THE AREA
SMOKE ODOR
SPECIAL DETAIL EVENT
STROKE
STRUCTURE FIRE
SUICIDE
TECHNICAL RESCUE
TRAIN INCIDENT
TRASH FIRE
TRAUMA
TREE ON A BUILDING
TROUBLE BREATHING
UNCONSCIOUS
UNDETERMINED RESCUE
UNKNOWN MEDICAL EMERGENCY
UNKNOWN ODOR
UNKNOWN PROBLEM
UNRES
VEHICLE FIRE
WATER PROBLEM
WATER RESCUE
WIRE DOWN
Nature of 911 call
Monthly Total-1
Monthly Total-2
Monthly Total-3
Monthly Total-4
Monthly Total-5
Monthly Total-6
Monthly Total-7
Monthly Total-8
Monthly Total-9
Monthly Total-10
Monthly Total-11
Monthly Total-12
Monthly Total-13
Monthly Total-14
Monthly Total-15
Monthly Total-16
Monthly Total-18
Monthly Total-19
Monthly Total-20
Monthly Total-21
Monthly Total-22
Monthly Total-23
Monthly Total-24
Monthly Total-25
Monthly Total-26
Monthly Total-27
Monthly Total-28
Monthly Total-29
Monthly Total-30
Monthly Total-31
Monthly Total-32
Monthly Total-33
Monthly Total-34
Monthly Total-35
Monthly Total-40
None-Fire Station Number
100
80
60
40
20

```
In [54]: p = df.drop(['Year', 'Month', 'Fire Station Number', 'nature', 'station', 'BYstations',
         MS = pd.pivot_table(p, index = ['Nature of 911 call'], columns = ['Month Num'])
         MS
```

```
Out[54]:                           Monthly Total                                    \
         Month Num                             1          2          3          4
         Nature of 911 call
         ABDOMINAL PAIN                 6.580838   6.125000   6.621951   6.588957
         AIRPLANE INCIDENT                   NaN        NaN        NaN        NaN
         ALARM / SPRINKLR OOS                NaN        NaN        NaN        NaN
         ALLERGIC                       2.419847   2.710345   2.929577   2.898551
         ANIMAL BITE                    1.115385   1.000000   1.258065   1.257143
         ASSAULT                        2.968504   3.017699   3.415254   3.388889
         ASSIST CITIZEN                10.515625   9.348485  10.553846  10.454545
         ASSIST POLICE                  1.655738   1.583333   1.557377   1.888889
         BACK PAIN                      3.102041   2.878788   3.301370   3.302158
         BARN FIRE                           NaN   1.000000   1.000000        NaN
         BLEEDING                       6.829114   6.209581   6.618182   6.125000
         BOMB PRESENT                   1.958333   1.770492   2.051282   1.868852
         BOMB THREAT                    1.000000   1.090909   1.000000   1.250000
         BRUSH FIRE                     1.411765   1.176471   1.804878   2.625000
         BUILDING FIRE                  4.014085   3.828571   3.242857   3.205479
         BURNS                          1.392857   1.142857   1.256410   1.083333
         CARBON MONOXIDE ALARM          3.032787   2.887097   2.245614   2.590909
         CARDIAC ARREST                 3.300699   2.951724   3.061224   2.858108
         CHEST PAIN                    13.035294  12.186047  13.164706  11.895349
         CHOKING                        1.726316   1.711111   1.915789   1.551020
         CO ALARM                       3.521277   2.717647   2.987805   2.493976
         COLLAPSE RESCUE                     NaN   1.000000        NaN   1.000000
         CONFINE SPACE RESCUE                NaN        NaN        NaN   1.000000
         CYLINDER LEAK OUTSDE                NaN   1.000000   1.000000        NaN
         DIABETIC                       4.019481   3.532895   4.204082   3.932432
         DROWNING                       1.000000   1.000000   1.000000   1.000000
         DUMPSTER FIRE                  1.250000   1.000000   1.000000   1.230769
         ELECTRICAL                     2.982609   2.469565   5.024390   3.000000
         ELECTRICAL SHORT               1.000000        NaN        NaN        NaN
         ELECTROCUTION                  1.000000   1.000000   1.250000   1.000000
         ...                                 ...        ...        ...        ...
         PSYCHIATRIC                    4.614865   4.552448   4.818182   4.737931
         RESCUE                         1.000000   1.000000   1.000000        NaN
         RESET ALARM SYSTEM             2.117647   1.272727   1.444444   1.444444
         SEIZURE                        6.264151   5.469136   6.290123   5.709091
         SERIVCE CALL-LIFT ASSIST       5.263158   4.297872   4.393617   4.021978
         SERVICE CALL                  12.603960   8.353535   9.323529   8.434343
         SEWER FIRE                     1.000000   1.000000   1.000000   1.000000
```

SICK	38.356725	32.333333	34.172414	31.424419
SMOKE IN THE AREA	1.306122	1.465116	1.487805	1.476190
SMOKE ODOR	2.234043	2.094340	2.066667	1.736842
SPECIAL DETAIL EVENT	1.000000	1.000000	1.250000	1.357143
STROKE	5.018182	4.636943	4.664671	4.932515
STRUCTURE FIRE	5.643564	4.361702	5.185567	4.757895
SUICIDE	1.750000	1.714286	1.800000	1.789474
TECHNICAL RESCUE	1.200000	1.250000	1.125000	1.000000
TRAIN INCIDENT	1.000000	NaN	1.000000	1.000000
TRASH FIRE	1.200000	1.000000	1.500000	1.000000
TRAUMA	4.360759	4.202532	4.931677	4.693252
TREE ON A BUILDING	NaN	1.333333	1.000000	1.000000
TROUBLE BREATHING	19.152047	16.959302	17.494186	17.541176
UNCONSCIOUS	15.784884	14.467836	15.982659	15.276471
UNDETERMINED RESCUE	2.895833	2.449438	2.731183	2.756757
UNKNOWN MEDICAL EMERGENCY	1.517857	1.349206	1.360000	1.397260
UNKNOWN ODOR	1.475000	1.452381	1.465116	1.193548
UNKNOWN PROBLEM	8.660606	8.164706	9.533333	9.821429
UNRES	2.190476	2.050000	3.111111	2.693878
VEHICLE FIRE	1.781818	1.782178	1.971154	1.930693
WATER PROBLEM	9.400000	8.854545	2.061224	2.292683
WATER RESCUE	1.222222	1.777778	1.416667	2.000000
WIRE DOWN	2.185185	2.950000	3.017857	2.421053

\

Month Num	5	6	7	8
Nature of 911 call				
ABDOMINAL PAIN	6.566265	6.682927	6.704403	6.422619
AIRPLANE INCIDENT	NaN	NaN	1.000000	1.000000
ALARM / SPRINKLR OOS	NaN	NaN	NaN	1.000000
ALLERGIC	3.279720	3.006897	3.373418	3.341772
ANIMAL BITE	1.200000	1.250000	1.155556	1.170213
ASSAULT	3.543307	3.569106	3.735537	3.648855
ASSIST CITIZEN	7.500000	10.733333	10.058824	9.030303
ASSIST POLICE	1.583333	1.677419	1.805195	1.694444
BACK PAIN	3.367647	3.230769	3.263158	3.462069
BARN FIRE	NaN	NaN	NaN	1.000000
BLEEDING	6.426829	6.527607	6.698795	6.550898
BOMB PRESENT	1.680556	2.186813	2.260870	2.000000
BOMB THREAT	1.000000	1.250000	1.000000	1.000000
BRUSH FIRE	1.500000	1.466667	1.833333	1.722222
BUILDING FIRE	2.294118	2.468085	2.931818	2.725000
BURNS	1.214286	1.074074	1.243243	1.259259
CARBON MONOXIDE ALARM	1.948718	2.230769	3.280000	2.555556
CARDIAC ARREST	2.727273	3.020979	2.830986	2.850000
CHEST PAIN	12.406977	11.840237	11.210526	11.947059
CHOKING	1.591398	1.782609	1.663158	1.948980
CO ALARM	2.824074	2.807018	3.276423	3.126050

COLLAPSE RESCUE	NaN	NaN	NaN	1.000000
CONFINE SPACE RESCUE	NaN	NaN	NaN	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	NaN	NaN
DIABETIC	4.032680	4.313333	4.150685	4.134228
DROWNING	1.000000	1.130435	1.125000	1.111111
DUMPSTER FIRE	1.100000	1.400000	1.333333	1.333333
ELECTRICAL	2.875000	3.759398	3.835616	3.296875
ELECTRICAL SHORT	NaN	NaN	NaN	NaN
ELECTROCUTION	1.000000	1.090909	1.000000	1.000000
...	...	...	...	...
PSYCHIATRIC	5.006757	4.549020	4.417808	4.946309
RESCUE	NaN	1.000000	NaN	NaN
RESET ALARM SYSTEM	NaN	NaN	NaN	NaN
SEIZURE	6.382716	6.156250	6.031646	6.137500
SERIVCE CALL-LIFT ASSIST	5.091667	4.948718	5.166667	4.826446
SERVICE CALL	8.541353	9.125926	10.176471	9.278195
SEWER FIRE	1.000000	1.000000	1.000000	1.000000
SICK	32.200000	32.843023	32.689655	32.206897
SMOKE IN THE AREA	1.312500	1.492063	1.578125	1.409836
SMOKE ODOR	1.692308	1.476190	1.785714	1.647059
SPECIAL DETAIL EVENT	1.625000	3.062500	1.259259	9.888889
STROKE	4.975758	4.580247	4.800000	4.649682
STRUCTURE FIRE	3.766667	3.852459	4.285714	3.969466
SUICIDE	1.722222	1.000000	NaN	NaN
TECHNICAL RESCUE	1.000000	1.166667	1.000000	1.142857
TRAIN INCIDENT	NaN	NaN	1.000000	1.000000
TRASH FIRE	1.222222	1.166667	1.000000	1.000000
TRAUMA	5.698795	5.621302	5.259259	4.988095
TREE ON A BUILDING	1.333333	1.500000	1.545455	1.000000
TROUBLE BREATHING	18.017544	16.017647	15.958824	15.853801
UNCONSCIOUS	15.913295	15.213873	14.988506	15.258621
UNDETERMINED RESCUE	3.111111	2.613333	2.550725	2.582090
UNKNOWN MEDICAL EMERGENCY	1.571429	1.551724	1.492537	1.600000
UNKNOWN ODOR	1.272727	1.270270	1.340426	1.472222
UNKNOWN PROBLEM	11.406061	12.011696	12.275449	12.604790
UNRES	2.446809	2.813953	2.219512	2.441860
VEHICLE FIRE	1.937008	2.135135	1.954955	2.175926
WATER PROBLEM	1.500000	2.000000	2.111111	1.809524
WATER RESCUE	1.517241	2.476190	2.343750	2.043478
WIRE DOWN	2.558140	2.392857	7.424242	2.692308

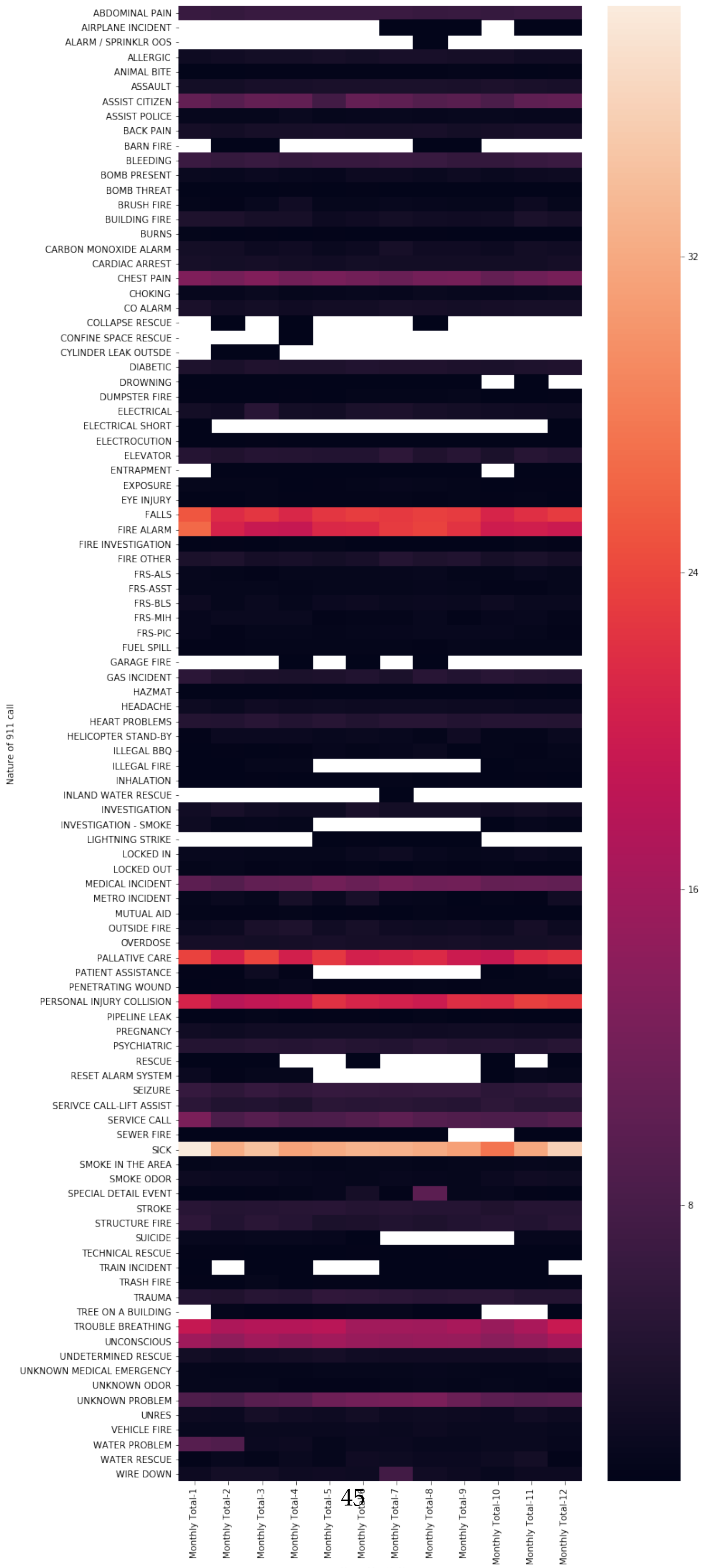
Month Num	9	10	11	12
Nature of 911 call				
ABDOMINAL PAIN	6.585366	6.382353	6.618750	6.608696
AIRPLANE INCIDENT	1.000000	NaN	1.000000	1.000000
ALARM / SPRINKLR OOS	NaN	NaN	NaN	NaN
ALLERGIC	3.118421	3.079365	2.683453	2.688889

ANIMAL BITE	1.386364	1.200000	1.076923	1.259259
ASSAULT	3.612403	3.858586	3.508197	3.390625
ASSIST CITIZEN	9.606061	8.325581	10.078125	10.358209
ASSIST POLICE	1.764706	1.824561	1.693548	1.597015
BACK PAIN	2.925170	3.055118	3.338028	3.425532
BARN FIRE	1.000000	NaN	NaN	NaN
BLEEDING	6.084848	6.068966	6.447853	6.759494
BOMB PRESENT	2.455882	1.893333	2.290698	2.388889
BOMB THREAT	1.000000	1.000000	1.000000	1.000000
BRUSH FIRE	1.461538	1.500000	2.250000	1.500000
BUILDING FIRE	2.550000	2.666667	3.676056	3.226667
BURNS	1.047619	1.120000	1.088235	1.066667
CARBON MONOXIDE ALARM	2.541667	2.258065	2.796296	2.607143
CARDIAC ARREST	2.788732	2.841667	2.847222	3.155405
CHEST PAIN	12.150289	10.564103	11.610778	12.260116
CHOKING	1.828571	1.674419	1.771429	1.958333
CO ALARM	3.000000	3.136364	3.193182	3.265060
COLLAPSE RESCUE	NaN	NaN	NaN	NaN
CONFINE SPACE RESCUE	NaN	NaN	NaN	NaN
CYLINDER LEAK OUTSDE	NaN	NaN	NaN	NaN
DIABETIC	3.816327	3.631148	4.006536	4.202703
DROWNING	1.000000	NaN	1.000000	NaN
DUMPSTER FIRE	1.500000	1.000000	1.111111	1.166667
ELECTRICAL	2.911290	2.622449	2.601852	2.457627
ELECTRICAL SHORT	NaN	NaN	NaN	1.000000
ELECTROCUTION	1.000000	1.000000	1.000000	1.000000
...	...	...	...	...
PSYCHIATRIC	4.645390	4.789916	4.462069	4.906040
RESCUE	NaN	1.000000	NaN	1.000000
RESET ALARM SYSTEM	NaN	1.000000	1.833333	1.545455
SEIZURE	6.123457	5.271429	5.614907	6.161491
SERIVCE CALL-LIFT ASSIST	4.686441	5.523256	4.806452	4.879121
SERVICE CALL	8.803030	8.490196	8.535354	9.168317
SEWER FIRE	NaN	NaN	1.000000	1.000000
SICK	31.181287	27.518072	31.803468	35.755814
SMOKE IN THE AREA	1.507463	1.576923	1.666667	1.523810
SMOKE ODOR	1.541667	2.050000	2.575000	2.348837
SPECIAL DETAIL EVENT	1.500000	1.636364	1.272727	1.142857
STROKE	4.739394	4.200000	4.724359	4.765432
STRUCTURE FIRE	4.408333	4.677419	4.465347	4.989691
SUICIDE	NaN	NaN	1.647059	1.611111
TECHNICAL RESCUE	1.200000	1.000000	1.000000	1.000000
TRAIN INCIDENT	1.000000	1.000000	1.000000	NaN
TRASH FIRE	1.000000	1.000000	1.000000	1.166667
TRAUMA	5.231707	5.111888	4.556250	4.519481
TREE ON A BUILDING	1.000000	NaN	NaN	1.000000
TROUBLE BREATHING	16.526012	15.266234	16.668605	19.494118
UNCONSCIOUS	15.017341	13.947712	14.917160	16.637427

```
UNDETERMINED RESCUE         2.562500   2.518519   2.489796   2.880435
UNKNOWN MEDICAL EMERGENCY   1.563636   1.378788   1.423729   1.542857
UNKNOWN ODOR                1.422222   1.441860   1.375000   1.217391
UNKNOWN PROBLEM            11.132530   9.888889   9.432099   9.685185
UNRES                       2.275000   2.040000   2.666667   2.185185
VEHICLE FIRE                1.961165   1.903226   1.927835   1.837838
WATER PROBLEM               1.850000   2.000000   2.000000   1.694444
WATER RESCUE                2.142857   2.444444   3.000000   1.285714
WIRE DOWN                   2.275862   1.772727   2.215686   2.274510

[100 rows x 12 columns]
```

In [63]:
```
fig, ax = plt.subplots(figsize=(10,30))
sns.heatmap(MS)

# Falls, pallative, collision, fire alarms very common throughout the year
```

Out[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a2016cc50>
```


ABDOMINAL PAIN
AIRPLANE INCIDENT
ALARM / SPRINKLR OOS
ALLERGIC
ANIMAL BITE
ASSAULT
ASSIST CITIZEN
ASSIST POLICE
BACK PAIN
BARN FIRE
BLEEDING
BOMB PRESENT
BOMB THREAT
BRUSH FIRE
BUILDING FIRE
BURNS
CARBON MONOXIDE ALARM
CARDIAC ARREST
CHEST PAIN
CHOKING
CO ALARM
COLLAPSE RESCUE
CONFINE SPACE RESCUE
CYLINDER LEAK OUTSDE
DIABETIC
DROWNING
DUMPSTER FIRE
ELECTRICAL
ELECTRICAL SHORT
ELECTROCUTION
ELEVATOR
ENTRAPMENT
EXPOSURE
EYE INJURY
FALLS
FIRE ALARM
FIRE INVESTIGATION
FIRE OTHER
FRS-ALS
FRS-ASST
FRS-BLS
FRS-MIH
FRS-PIC
FUEL SPILL
GARAGE FIRE
GAS INCIDENT
HAZMAT
HEADACHE
HEART PROBLEMS
HELICOPTER STAND-BY
ILLEGAL BBQ
ILLEGAL FIRE
INHALATION
INLAND WATER RESCUE
INVESTIGATION
INVESTIGATION - SMOKE
LIGHTNING STRIKE
LOCKED IN
LOCKED OUT
MEDICAL INCIDENT
METRO INCIDENT
MUTUAL AID
OUTSIDE FIRE
OVERDOSE
PALLATIVE CARE
PATIENT ASSISTANCE
PENETRATING WOUND
PERSONAL INJURY COLLISION
PIPELINE LEAK
PREGNANCY
PSYCHIATRIC
RESCUE
RESET ALARM SYSTEM
SEIZURE
SERIVCE CALL-LIFT ASSIST
SERVICE CALL
SEWER FIRE
SICK
SMOKE IN THE AREA
SMOKE ODOR
SPECIAL DETAIL EVENT
STROKE
STRUCTURE FIRE
SUICIDE
TECHNICAL RESCUE
TRAIN INCIDENT
TRASH FIRE
TRAUMA
TREE ON A BUILDING
TROUBLE BREATHING
UNCONSCIOUS
UNDETERMINED RESCUE
UNKNOWN MEDICAL EMERGENCY
UNKNOWN ODOR
UNKNOWN PROBLEM
UNRES
VEHICLE FIRE
WATER PROBLEM
WATER RESCUE
WIRE DOWN
Nature of 911 call
Monthly Total-1
Monthly Total-2
Monthly Total-3
Monthly Total-4
Monthly Total-5
Monthly Total-6
Monthly Total-7
Monthly Total-8
Monthly Total-9
Monthly Total-10
Monthly Total-11
Monthly Total-12
None-Month Num
32
24
16
8

```
In [56]: p = df.drop(['Nature of 911 call', 'Month', 'Year', 'nature', 'station', 'BYstations',
         FMS = pd.pivot_table(p, index = ['Fire Station Number'], columns = ['Month Num'])
         FMS
```

```
Out[56]:                    Monthly Total                                                  \
         Month Num                      1          2          3          4          5
         Fire Station Number
         1                      11.619512  10.146919  10.732057  10.169725  10.149780
         2                       6.000000   5.437158   6.218750   5.768041   5.694175
         3                      13.144681  10.951111  11.820628  10.451754  10.429167
         4                       5.129496   4.263158   4.856164   4.296552   4.333333
         5                       8.566667   7.964467   8.075829   7.350962   8.009615
         6                       9.222772   8.172589   8.188406   8.111111   8.626866
         7                       5.228395   4.691275   4.954839   4.714286   5.050955
         8                      16.940239  15.816667  16.610656  15.897119  16.704981
         9                       1.625000   1.613636   1.975000   1.711111   1.765957
         10                      4.743243   4.302013   4.324324   3.728395   4.251572
         11                      4.523490   3.604938   3.949045   3.936709   4.355828
         12                      8.110000   7.260870   7.653266   6.902326   7.261261
         13                      3.742857   3.530864   3.709877   3.529412   3.867470
         14                      2.495868   2.300000   2.446281   2.341270   2.629032
         15                     11.079295   9.724771  10.359307  10.328947  10.156951
         16                      7.242574   6.527919   6.634615   6.840796   7.184466
         17                      3.392857   3.441176   3.211921   2.979021   3.317568
         18                     11.241071   9.758929  10.572687   9.655172  10.293860
         19                      5.849741   5.252577   5.530928   5.376289   5.934783
         20                      6.486486   5.422460   6.049180   5.271795   6.130435
         21                      5.104396   4.651042   4.983425   4.821229   5.451087
         22                      5.565217   4.625000   4.597765   4.470270   4.873684
         23                     12.039648  10.678899  11.281250  10.241071  10.957983
         24                      6.177419   5.891429   5.747312   5.647059   5.945355
         25                     17.558952  16.175926  17.311404  16.419214  16.395652
         26                      7.830769   6.917582   7.590426   6.708333   7.155440
         27                      1.800000   1.666667   2.400000   1.833333   1.428571
         28                      5.788177   5.306011   5.589744   5.602094   5.755208
         29                      7.117949   6.414894   6.359606   6.235000   6.538462
         30                      3.537190   3.090909   3.194030   3.330645   3.082192
         31                      6.789474   4.988764   5.053476   5.340659   5.568528
         32                     11.699454  11.519417  11.306604  11.284360  11.861111
         33                      5.680473   5.081761   5.139665   4.832370   5.335366
         34                      6.261084   5.772487   5.629630   5.631841   5.266990
         35                      3.803797   3.323944   3.195804   2.908497   2.973684
         40                      6.011236   5.747059   5.940828   5.514286   5.614525

                                                                                   \
```

Month Num	6	7	8	9	10
Fire Station Number					
1	10.782407	10.881279	11.063927	11.270936	9.931818
2	5.891753	6.128713	6.335052	5.910891	6.162500
3	10.859649	10.361702	10.689956	10.560870	10.317949
4	4.288462	4.726619	4.711268	4.483221	4.570248
5	8.359606	7.736111	7.946860	8.305000	7.988827
6	8.517241	8.711009	9.159204	8.180095	8.372222
7	4.802469	4.871795	5.057325	5.204082	5.647541
8	17.190083	16.823293	17.971074	16.893878	15.893023
9	1.875000	1.509804	1.563636	1.604167	2.103448
10	4.183544	4.219355	4.132450	4.279221	4.512397
11	3.961783	4.493421	4.012987	3.867089	4.169231
12	8.156863	7.790698	8.315534	7.849246	7.032967
13	3.658385	3.666667	3.627329	3.631902	3.621212
14	2.585938	2.424000	2.534483	2.289256	2.747368
15	10.953704	10.490826	10.497758	10.436019	9.744792
16	7.343590	6.810427	7.029126	7.088670	7.233918
17	3.218310	3.189189	3.539007	3.256757	3.089286
18	10.054622	10.727660	10.265487	10.628959	10.415789
19	5.719388	5.482759	5.536458	5.388601	5.488095
20	5.770492	5.560209	5.626374	5.518919	5.950920
21	5.145161	5.535912	5.473118	5.217143	4.686667
22	4.970930	4.744681	4.724324	5.016760	4.959184
23	11.648148	11.488789	11.196347	11.330189	10.305000
24	5.783505	6.123656	6.081967	5.977654	5.343750
25	16.840183	17.000000	16.785088	16.958716	16.357895
26	7.547739	7.029851	7.885870	7.738889	7.075949
27	2.600000	3.000000	2.666667	1.428571	1.857143
28	5.521505	5.724490	5.887179	6.080214	5.375000
29	6.177665	6.394089	6.446154	6.717277	5.965714
30	3.548611	3.676471	3.104478	3.330882	3.670103
31	5.359375	5.342246	5.514286	4.957219	5.482517
32	10.595455	10.410256	10.931818	11.447115	11.577381
33	5.184049	5.295181	5.063953	5.276074	4.643836
34	5.830688	5.661905	5.421053	5.774359	5.485030
35	2.832258	3.182432	3.067901	3.524823	3.418605
40	5.437158	5.291209	5.344262	5.811429	5.304348

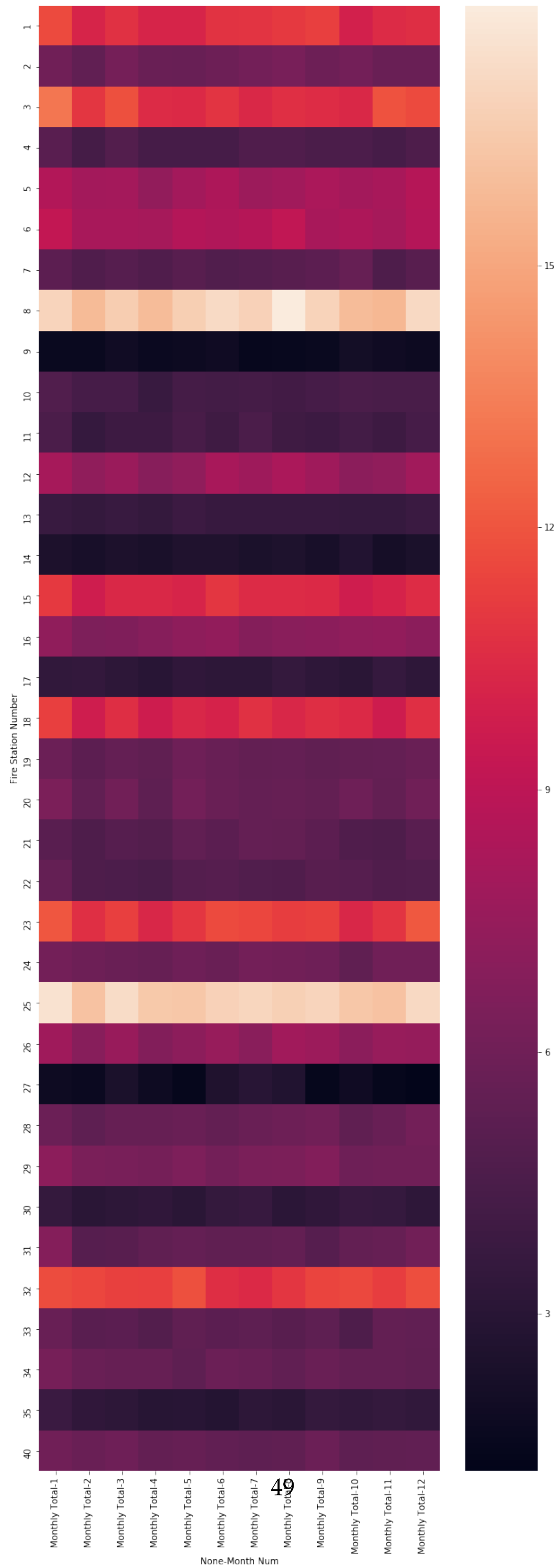
Month Num	11	12
Fire Station Number		
1	10.440758	10.604651
2	5.747423	5.724638
3	11.918103	11.666667
4	4.301370	4.623188
5	8.177665	8.711340
6	8.092233	8.653846

7	4.660377	5.061350
8	15.682927	17.123967
9	1.857143	1.738095
10	4.452229	4.466216
11	3.919255	4.282759
12	7.277512	7.924242
13	3.566879	3.806250
14	2.175000	2.427350
15	10.103286	10.506849
16	7.348485	7.086124
17	3.567164	3.288462
18	9.679487	10.659091
19	5.524752	5.739130
20	5.523316	6.015789
21	4.649215	5.093407
22	4.702703	4.741573
23	10.859031	12.132420
24	6.022599	5.984293
25	16.162281	17.135135
26	7.519337	7.457286
27	1.400000	1.200000
28	5.704663	6.157895
29	6.046948	6.024155
30	3.582677	3.293233
31	5.628272	6.078947
32	11.203704	11.796407
33	5.458599	5.440000
34	5.494737	5.355670
35	3.538462	3.410959
40	5.356322	5.455556

In [57]:
```
MS.to_csv('noob.csv', sep=',')
```

In [64]:
```
fig, ax = plt.subplots(figsize=(10,30))
sns.heatmap(FMS)
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x1a206f7828>



Fire Station Number
1
2
3
4
5
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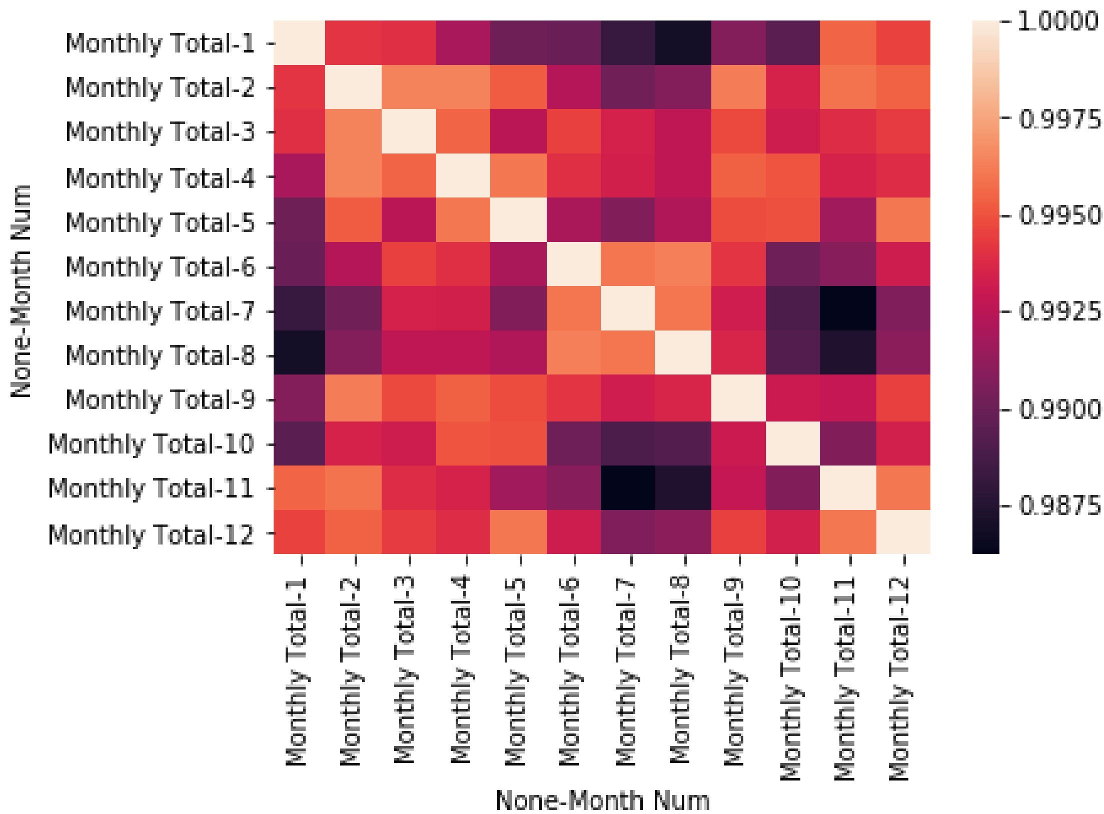
34
35
40
Monthly Total-1
Monthly Total-2
Monthly Total-3
Monthly Total-4
Monthly Total-5
Monthly Total-6
Monthly Total-7
Monthly Total-9
Monthly Total-10
Monthly Total-11
Monthly Total-12
None-Month Num
15
12
9
6
3

In [59]: sns.heatmap(FMS.corr())

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1e57d278>




```
In [60]: noob = pd.read_csv("../data/noob.csv")
         noob
```

Out[60]:

	Nature	1	2	3	4 \
0	ABDOMINAL PAIN	6.580838	6.125000	6.621951	6.588957
1	AIRPLANE INCIDENT	0.000000	0.000000	0.000000	0.000000
2	ALARM / SPRINKLR OOS	0.000000	0.000000	0.000000	0.000000
3	ALLERGIC	2.419847	2.710345	2.929577	2.898551
4	ANIMAL BITE	1.115385	1.000000	1.258065	1.257143
5	ASSAULT	2.968504	3.017699	3.415254	3.388889
6	ASSIST CITIZEN	10.515625	9.348485	10.553846	10.454545
7	ASSIST POLICE	1.655738	1.583333	1.557377	1.888889
8	BACK PAIN	3.102041	2.878788	3.301370	3.302158
9	BARN FIRE	0.000000	1.000000	1.000000	0.000000

10	BLEEDING	6.829114	6.209581	6.618182	6.125000
11	BOMB PRESENT	1.958333	1.770492	2.051282	1.868852
12	BOMB THREAT	1.000000	1.090909	1.000000	1.250000
13	BRUSH FIRE	1.411765	1.176471	1.804878	2.625000
14	BUILDING FIRE	4.014085	3.828571	3.242857	3.205479
15	BURNS	1.392857	1.142857	1.256410	1.083333
16	CARBON MONOXIDE ALARM	3.032787	2.887097	2.245614	2.590909
17	CARDIAC ARREST	3.300699	2.951724	3.061224	2.858108
18	CHEST PAIN	13.035294	12.186047	13.164706	11.895349
19	CHOKING	1.726316	1.711111	1.915789	1.551020
20	CO ALARM	3.521277	2.717647	2.987805	2.493976
21	COLLAPSE RESCUE	0.000000	1.000000	0.000000	1.000000
22	CONFINE SPACE RESCUE	0.000000	0.000000	0.000000	1.000000
23	CYLINDER LEAK OUTSDE	0.000000	1.000000	1.000000	0.000000
24	DIABETIC	4.019481	3.532895	4.204082	3.932432
25	DROWNING	1.000000	1.000000	1.000000	1.000000
26	DUMPSTER FIRE	1.250000	1.000000	1.000000	1.230769
27	ELECTRICAL	2.982609	2.469565	5.024390	3.000000
28	ELECTRICAL SHORT	1.000000	0.000000	0.000000	0.000000
29	ELECTROCUTION	1.000000	1.000000	1.250000	1.000000
..	...	...	...	...	...
70	PSYCHIATRIC	4.614865	4.552448	4.818182	4.737931
71	RESCUE	1.000000	1.000000	1.000000	0.000000
72	RESET ALARM SYSTEM	2.117647	1.272727	1.444444	1.444444
73	SEIZURE	6.264151	5.469136	6.290123	5.709091
74	SERIVCE CALL-LIFT ASSIST	5.263158	4.297872	4.393617	4.021978
75	SERVICE CALL	12.603960	8.353535	9.323529	8.434343
76	SEWER FIRE	1.000000	1.000000	1.000000	1.000000
77	SICK	38.356725	32.333333	34.172414	31.424419
78	SMOKE IN THE AREA	1.306122	1.465116	1.487805	1.476190
79	SMOKE ODOR	2.234043	2.094340	2.066667	1.736842
80	SPECIAL DETAIL EVENT	1.000000	1.000000	1.250000	1.357143
81	STROKE	5.018182	4.636943	4.664671	4.932515
82	STRUCTURE FIRE	5.643564	4.361702	5.185567	4.757895
83	SUICIDE	1.750000	1.714286	1.800000	1.789474
84	TECHNICAL RESCUE	1.200000	1.250000	1.125000	1.000000
85	TRAIN INCIDENT	1.000000	0.000000	1.000000	1.000000
86	TRASH FIRE	1.200000	1.000000	1.500000	1.000000
87	TRAUMA	4.360759	4.202532	4.931677	4.693252
88	TREE ON A BUILDING	0.000000	1.333333	1.000000	1.000000
89	TROUBLE BREATHING	19.152047	16.959302	17.494186	17.541176
90	UNCONSCIOUS	15.784884	14.467836	15.982659	15.276471
91	UNDETERMINED RESCUE	2.895833	2.449438	2.731183	2.756757
92	UNKNOWN MEDICAL EMERGENCY	1.517857	1.349206	1.360000	1.397260
93	UNKNOWN ODOR	1.475000	1.452381	1.465116	1.193548
94	UNKNOWN PROBLEM	8.660606	8.164706	9.533333	9.821429
95	UNRES	2.190476	2.050000	3.111111	2.693878
96	VEHICLE FIRE	1.781818	1.782178	1.971154	1.930693

97	WATER PROBLEM	9.400000	8.854545	2.061224	2.292683
98	WATER RESCUE	1.222222	1.777778	1.416667	2.000000
99	WIRE DOWN	2.185185	2.950000	3.017857	2.421053

	5	6	7	8	9	10 \
0	6.566265	6.682927	6.704403	6.422619	6.585366	6.382353
1	0.000000	0.000000	1.000000	1.000000	1.000000	0.000000
2	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000
3	3.279720	3.006897	3.373418	3.341772	3.118421	3.079365
4	1.200000	1.250000	1.155556	1.170213	1.386364	1.200000
5	3.543307	3.569106	3.735537	3.648855	3.612403	3.858586
6	7.500000	10.733333	10.058824	9.030303	9.606061	8.325581
7	1.583333	1.677419	1.805195	1.694444	1.764706	1.824561
8	3.367647	3.230769	3.263158	3.462069	2.925170	3.055118
9	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000
10	6.426829	6.527607	6.698795	6.550898	6.084848	6.068966
11	1.680556	2.186813	2.260870	2.000000	2.455882	1.893333
12	1.000000	1.250000	1.000000	1.000000	1.000000	1.000000
13	1.500000	1.466667	1.833333	1.722222	1.461538	1.500000
14	2.294118	2.468085	2.931818	2.725000	2.550000	2.666667
15	1.214286	1.074074	1.243243	1.259259	1.047619	1.120000
16	1.948718	2.230769	3.280000	2.555556	2.541667	2.258065
17	2.727273	3.020979	2.830986	2.850000	2.788732	2.841667
18	12.406977	11.840237	11.210526	11.947059	12.150289	10.564103
19	1.591398	1.782609	1.663158	1.948980	1.828571	1.674419
20	2.824074	2.807018	3.276423	3.126050	3.000000	3.136364
21	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000
22	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
23	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
24	4.032680	4.313333	4.150685	4.134228	3.816327	3.631148
25	1.000000	1.130435	1.125000	1.111111	1.000000	0.000000
26	1.100000	1.400000	1.333333	1.333333	1.500000	1.000000
27	2.875000	3.759398	3.835616	3.296875	2.911290	2.622449
28	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
29	1.000000	1.090909	1.000000	1.000000	1.000000	1.000000
..	...	...	...	...	...	...
70	5.006757	4.549020	4.417808	4.946309	4.645390	4.789916
71	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000
72	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
73	6.382716	6.156250	6.031646	6.137500	6.123457	5.271429
74	5.091667	4.948718	5.166667	4.826446	4.686441	5.523256
75	8.541353	9.125926	10.176471	9.278195	8.803030	8.490196
76	1.000000	1.000000	1.000000	1.000000	0.000000	0.000000
77	32.200000	32.843023	32.689655	32.206897	31.181287	27.518072
78	1.312500	1.492063	1.578125	1.409836	1.507463	1.576923
79	1.692308	1.476190	1.785714	1.647059	1.541667	2.050000
80	1.625000	3.062500	1.259259	9.888889	1.500000	1.636364
81	4.975758	4.580247	4.800000	4.649682	4.739394	4.200000

82	3.766667	3.852459	4.285714	3.969466	4.408333	4.677419
83	1.722222	1.000000	0.000000	0.000000	0.000000	0.000000
84	1.000000	1.166667	1.000000	1.142857	1.200000	1.000000
85	0.000000	0.000000	1.000000	1.000000	1.000000	1.000000
86	1.222222	1.166667	1.000000	1.000000	1.000000	1.000000
87	5.698795	5.621302	5.259259	4.988095	5.231707	5.111888
88	1.333333	1.500000	1.545455	1.000000	1.000000	0.000000
89	18.017544	16.017647	15.958824	15.853801	16.526012	15.266234
90	15.913295	15.213873	14.988506	15.258621	15.017341	13.947712
91	3.111111	2.613333	2.550725	2.582090	2.562500	2.518519
92	1.571429	1.551724	1.492537	1.600000	1.563636	1.378788
93	1.272727	1.270270	1.340426	1.472222	1.422222	1.441860
94	11.406061	12.011696	12.275449	12.604790	11.132530	9.888889
95	2.446809	2.813953	2.219512	2.441860	2.275000	2.040000
96	1.937008	2.135135	1.954955	2.175926	1.961165	1.903226
97	1.500000	2.000000	2.111111	1.809524	1.850000	2.000000
98	1.517241	2.476190	2.343750	2.043478	2.142857	2.444444
99	2.558140	2.392857	7.424242	2.692308	2.275862	1.772727

	11	12
0	6.618750	6.608696
1	1.000000	1.000000
2	0.000000	0.000000
3	2.683453	2.688889
4	1.076923	1.259259
5	3.508197	3.390625
6	10.078125	10.358209
7	1.693548	1.597015
8	3.338028	3.425532
9	0.000000	0.000000
10	6.447853	6.759494
11	2.290698	2.388889
12	1.000000	1.000000
13	2.250000	1.500000
14	3.676056	3.226667
15	1.088235	1.066667
16	2.796296	2.607143
17	2.847222	3.155405
18	11.610778	12.260116
19	1.771429	1.958333
20	3.193182	3.265060
21	0.000000	0.000000
22	0.000000	0.000000
23	0.000000	0.000000
24	4.006536	4.202703
25	1.000000	0.000000
26	1.111111	1.166667
27	2.601852	2.457627

```
28   0.000000   1.000000
29   1.000000   1.000000
..        ...        ...
70   4.462069   4.906040
71   0.000000   1.000000
72   1.833333   1.545455
73   5.614907   6.161491
74   4.806452   4.879121
75   8.535354   9.168317
76   1.000000   1.000000
77  31.803468  35.755814
78   1.666667   1.523810
79   2.575000   2.348837
80   1.272727   1.142857
81   4.724359   4.765432
82   4.465347   4.989691
83   1.647059   1.611111
84   1.000000   1.000000
85   1.000000   0.000000
86   1.000000   1.166667
87   4.556250   4.519481
88   0.000000   1.000000
89  16.668605  19.494118
90  14.917160  16.637427
91   2.489796   2.880435
92   1.423729   1.542857
93   1.375000   1.217391
94   9.432099   9.685185
95   2.666667   2.185185
96   1.927835   1.837838
97   2.000000   1.694444
98   3.000000   1.285714
99   2.215686   2.274510

[100 rows x 13 columns]
```

In [68]: df

Out[68]:

```
                                         Fire Station  Fire Station Number  \
0     Kensington Volunteer Fire Department (Station 18)                   18
1           Sandy Spring Volunteer Fire Department (40)                   40
2      Kensington Volunteer Fire Department (Station 5)                    5
3     Silver Spring Volunteer Fire Department (Stati...                   19
4     Silver Spring Volunteer Fire Department (Stati...                   16
5     Gaithersburg-Washington Grove Volunteer Fire D...                    8
6                 Bethesda Fire Department (Station 20)                   20
7     Burtonsville Volunteer Fire Department (Statio...                   15
8                Kingsview Fire Department (Station 22)                   22
```

9	Silver Spring Volunteer Fire Department (Stati...	19
10	Germantown-Milestone Fire Department (Station 34)	34
11	Sandy Spring Volunteer Fire Department (Statio...	4
12	Kensington Volunteer Fire Department (Station 25)	25
13	Hillandale Volunteer Fire Department (Station 12)	12
14	Kensington Volunteer Fire Department (Station 5)	5
15	Bethesda Fire Department (Station 6)	6
16	Glen Echo Volunteer Fire Department (Station 11)	11
17	Gaithersburg-Washington Grove Volunteer Fire D...	8
18	Damascus Volunteer Fire Department (Station 13)	13
19	Germantown-Milestone Fire Department (Station 34)	34
20	Sandy Spring Volunteer Fire Department (40)	40
21	Silver Spring Volunteer Fire Department (Stati...	1
22	Gaithersburg-Washington Grove Volunteer Fire D...	8
23	Laytonsville District Volunteer Fire Departmen...	17
24	Rockville Volunteer Fire Department (Station 31)	31
25	Laytonsville District Volunteer Fire Departmen...	17
26	Laytonsville District Volunteer Fire Departmen...	17
27	Damascus Volunteer Fire Department (Station 13)	13
28	Hillandale Volunteer Fire Department (Station 12)	12
29	Kensington Volunteer Fire Department (Station 25)	25
...	...	...
75986	Rockville Volunteer Fire Department (Station 23)	23
75987	Silver Spring Volunteer Fire Department (Stati...	16
75988	Silver Spring Volunteer Fire Department (Stati...	1
75989	Rockville Volunteer Fire Department (Station 23)	23
75990	Clarksburg Fire Department (Station 35)	35
75991	Kensington Volunteer Fire Department (Station 5)	5
75992	Bethesda Fire Department (Station 6)	6
75993	Rockville Volunteer Fire Department (Station 31)	31
75994	Travilah Fire Department	32
75995	Public Safety Training Academy	27
75996	Cabin John Park Volunteer Fire Department (Sta...	10
75997	Burtonsville Volunteer Fire Department (Statio...	15
75998	Burtonsville Volunteer Fire Department (Statio...	15
75999	Kensington Volunteer Fire Department (Station 18)	18
76000	Bethesda Fire Department (Station 20)	20
76001	Bethesda Fire Department (Station 26)	26
76002	Burtonsville Volunteer Fire Department (Statio...	15
76003	Gaithersburg-Washington Grove Volunteer Fire D...	8
76004	Kensington Volunteer Fire Department (Station 21)	21
76005	Silver Spring Volunteer Fire Department (Stati...	1
76006	Silver Spring Volunteer Fire Department (Stati...	1
76007	Silver Spring Volunteer Fire Department (Stati...	1
76008	Bethesda Fire Department (Station 6)	6
76009	Burtonsville Volunteer Fire Department (Statio...	15
76010	Kensington Volunteer Fire Department (Station 5)	5
76011	Kensington Volunteer Fire Department (Station 25)	25

76012	Rockville Volunteer Fire Department (Station 3)	3
76013	Burtonsville Volunteer Fire Department (Statio...	15
76014	Glen Echo Volunteer Fire Department (Station 11)	11
76015	Germantown-Milestone Fire Department (Station 34)	34

	Nature of 911 call	Monthly Total	Year	Month	Month Num \
0	PREGNANCY	2	2017	MAY	5
1	BACK PAIN	5	2018	SEPTEMBER	9
2	SICK	34	2018	SEPTEMBER	9
3	ELECTRICAL	1	2014	JANUARY	1
4	INHALATION	1	2017	JUNE	6
5	EYE INJURY	3	2018	SEPTEMBER	9
6	MEDICAL INCIDENT	7	2018	SEPTEMBER	9
7	SICK	56	2018	SEPTEMBER	9
8	FIRE ALARM	16	2017	JUNE	6
9	PALLATIVE CARE	24	2017	JUNE	6
10	ASSAULT	3	2017	JUNE	6
11	CHEST PAIN	6	2017	JUNE	6
12	STROKE	13	2017	JUNE	6
13	DROWNING	1	2017	JUNE	6
14	BACK PAIN	1	2017	JUNE	6
15	FIRE ALARM	48	2017	JUNE	6
16	FALLS	21	2017	JUNE	6
17	BOMB PRESENT	3	2017	JUNE	6
18	PSYCHIATRIC	4	2017	JUNE	6
19	ANIMAL BITE	1	2017	JUNE	6
20	SEIZURE	4	2017	JUNE	6
21	FUEL SPILL	1	2017	JUNE	6
22	FIRE ALARM	36	2017	JUNE	6
23	BACK PAIN	1	2017	JUNE	6
24	DIABETIC	4	2017	JUNE	6
25	EXPOSURE	1	2017	JUNE	6
26	SMOKE IN THE AREA	4	2017	JUNE	6
27	TROUBLE BREATHING	8	2017	JUNE	6
28	SERVICE CALL	9	2017	JUNE	6
29	FIRE ALARM	25	2017	JUNE	6
...	...	...	...	...	...
75986	BACK PAIN	5	2018	SEPTEMBER	9
75987	CHEST PAIN	5	2018	SEPTEMBER	9
75988	ASSAULT	6	2018	SEPTEMBER	9
75989	CARDIAC ARREST	3	2018	SEPTEMBER	9
75990	OVERDOSE	2	2018	SEPTEMBER	9
75991	UNKNOWN PROBLEM	12	2018	SEPTEMBER	9
75992	MEDICAL INCIDENT	3	2018	SEPTEMBER	9
75993	SICK	6	2013	OCTOBER	10
75994	FRS-BLS	1	2018	SEPTEMBER	9
75995	MEDICAL INCIDENT	1	2018	SEPTEMBER	9
75996	PERSONAL INJURY COLLISION	22	2018	SEPTEMBER	9

75997	HEART PROBLEMS	5	2018	SEPTEMBER	9
75998	FRS-ASST	1	2018	SEPTEMBER	9
75999	LOCKED IN	1	2013	OCTOBER	10
76000	CO ALARM	3	2018	SEPTEMBER	9
76001	ASSAULT	1	2018	SEPTEMBER	9
76002	SEIZURE	7	2018	SEPTEMBER	9
76003	PERSONAL INJURY COLLISION	4	2013	OCTOBER	10
76004	HEADACHE	1	2018	SEPTEMBER	9
76005	FRS-PIC	1	2018	SEPTEMBER	9
76006	FIRE ALARM	2	2013	OCTOBER	10
76007	BOMB PRESENT	2	2018	SEPTEMBER	9
76008	HEART PROBLEMS	5	2018	SEPTEMBER	9
76009	CO ALARM	5	2018	SEPTEMBER	9
76010	STRUCTURE FIRE	7	2018	SEPTEMBER	9
76011	DIABETIC	7	2018	SEPTEMBER	9
76012	BLEEDING	1	2013	OCTOBER	10
76013	HEART PROBLEMS	2	2013	OCTOBER	10
76014	FIRE ALARM	18	2018	SEPTEMBER	9
76015	PALLATIVE CARE	4	2018	SEPTEMBER	9

	Station address	station \
0	12251 Georgia Ave Wheaton, MD 20902	18
1	16911 Georgia Ave Olney, MD 20832	40
2	10620 Connecticut Ave Kensington, MD 20985	5
3	1945 Seminary Rd Silver Spring, MD 20910	19
4	111 University Blvd East Silver Spring, MD 20901	16
5	801 Russell Ave Gaithersburg, MD 20879	8
6	9041 Old Georgetown Rd Bethesda, MD 20814	20
7	13900 Old Columbia Pike Burtonsville, MD 20866	15
8	18910 Germantown Road Germantown, MD 20874	22
9	1945 Seminary Rd Silver Spring, MD 20910	19
10	20633 Boland Farm Road Germantown, MD 20876	34
11	17921 Brooke Road Sandy Spring, MD 20860	4
12	14401 Connecticut Ave Layhill, MD 20906	25
13	10617 New Hampshire Ave Silver Spring, MD 20903	12
14	10620 Connecticut Ave Kensington, MD 20985	5
15	6600 Wisconsin Ave Bethesda, MD 20815	6
16	5920 Massachusetts Ave Bethesda, MD 20816	11
17	801 Russell Ave Gaithersburg, MD 20879	8
18	26334 Ridge Rd Damascus, MD 20750	13
19	20633 Boland Farm Road Germantown, MD 20876	34
20	16911 Georgia Ave Olney, MD 20832	40
21	8110 Georgia Ave Silver Spring, MD 20910	1
22	801 Russell Ave Gaithersburg, MD 20879	8
23	21400 Laytonsville Rd Laytonsville, MD 20879	17
24	12100 Darnestown Rd North Potomac, MD 20878	31
25	21400 Laytonsville Rd Laytonsville, MD 20879	17
26	21400 Laytonsville Rd Laytonsville, MD 20879	17

27	26334 Ridge Rd Damascus, MD 20750	13
28	10617 New Hampshire Ave Silver Spring, MD 20903	12
29	14401 Connecticut Ave Layhill, MD 20906	25
...	...	...
75986	121 Rollins Ave Rockville, MD 20852	23
75987	111 University Blvd East Silver Spring, MD 20901	16
75988	8110 Georgia Ave Silver Spring, MD 20910	1
75989	121 Rollins Ave Rockville, MD 20852	23
75990	22610 Gateway Center Dr, Suite 400 Clarksburg,...	35
75991	10620 Connecticut Ave Kensington, MD 20985	5
75992	6600 Wisconsin Ave Bethesda, MD 20815	6
75993	12100 Darnestown Rd North Potomac, MD 20878	31
75994	9615 DARNESTOWN ROAD, MD 20850	32
75995	9710 Great Seneca Highway Rockville, MD 20850	27
75996	8001 River Rd Bethesda, MD 20817	10
75997	13900 Old Columbia Pike Burtonsville, MD 20866	15
75998	13900 Old Columbia Pike Burtonsville, MD 20866	15
75999	12251 Georgia Ave Wheaton, MD 20902	18
76000	9041 Old Georgetown Rd Bethesda, MD 20814	20
76001	6700 Democracy Blvd Bethesda, MD 20814	26
76002	13900 Old Columbia Pike Burtonsville, MD 20866	15
76003	801 Russell Ave Gaithersburg, MD 20879	8
76004	12500 Veirs Mill Rd Rockville, MD 20853	21
76005	8110 Georgia Ave Silver Spring, MD 20910	1
76006	8110 Georgia Ave Silver Spring, MD 20910	1
76007	8110 Georgia Ave Silver Spring, MD 20910	1
76008	6600 Wisconsin Ave Bethesda, MD 20815	6
76009	13900 Old Columbia Pike Burtonsville, MD 20866	15
76010	10620 Connecticut Ave Kensington, MD 20985	5
76011	14401 Connecticut Ave Layhill, MD 20906	25
76012	380 Hungerford Dr Rockville, MD 20850	3
76013	13900 Old Columbia Pike Burtonsville, MD 20866	15
76014	5920 Massachusetts Ave Bethesda, MD 20816	11
76015	20633 Boland Farm Road Germantown, MD 20876	34

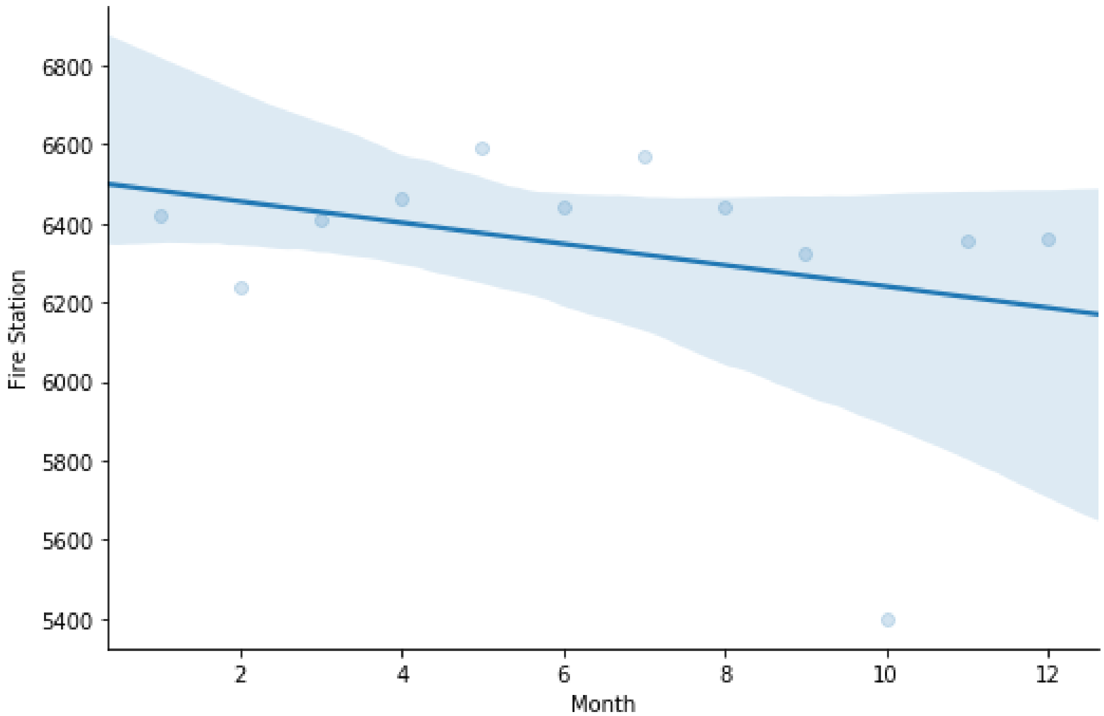
	nature	BYstations	MonthNum	MonthTotal
0	PREGNANCY	0	5	2
1	BACK PAIN	0	9	5
2	SICK	1	9	34
3	ELECTRICAL	0	1	1
4	INHALATION	1	6	1
5	EYE INJURY	2	9	3
6	MEDICAL INCIDENT	3	9	7
7	SICK	4	9	56
8	FIRE ALARM	2	6	16
9	PALLATIVE CARE	3	6	24
10	ASSAULT	4	6	3
11	CHEST PAIN	5	6	6

12	STROKE	6	6	13
13	DROWNING	7	6	1
14	BACK PAIN	8	6	1
15	FIRE ALARM	9	6	48
16	FALLS	10	6	21
17	BOMB PRESENT	11	6	3
18	PSYCHIATRIC	12	6	4
19	ANIMAL BITE	13	6	1
20	SEIZURE	14	6	4
21	FUEL SPILL	15	6	1
22	FIRE ALARM	16	6	36
23	BACK PAIN	17	6	1
24	DIABETIC	18	6	4
25	EXPOSURE	19	6	1
26	SMOKE IN THE AREA	20	6	4
27	TROUBLE BREATHING	21	6	8
28	SERVICE CALL	22	6	9
29	FIRE ALARM	23	6	25
...	...	...	...	...
75986	BACK PAIN	11687	9	5
75987	CHEST PAIN	11688	9	5
75988	ASSAULT	11689	9	6
75989	CARDIAC ARREST	11690	9	3
75990	OVERDOSE	11691	9	2
75991	UNKNOWN PROBLEM	11692	9	12
75992	MEDICAL INCIDENT	11693	9	3
75993	SICK	2998	10	6
75994	FRS-BLS	11694	9	1
75995	MEDICAL INCIDENT	11695	9	1
75996	PERSONAL INJURY COLLISION	11696	9	22
75997	HEART PROBLEMS	11697	9	5
75998	FRS-ASST	11698	9	1
75999	LOCKED IN	2999	10	1
76000	CO ALARM	11699	9	3
76001	ASSAULT	11700	9	1
76002	SEIZURE	11701	9	7
76003	PERSONAL INJURY COLLISION	3000	10	4
76004	HEADACHE	11702	9	1
76005	FRS-PIC	11703	9	1
76006	FIRE ALARM	3001	10	2
76007	BOMB PRESENT	11704	9	2
76008	HEART PROBLEMS	11705	9	5
76009	CO ALARM	11706	9	5
76010	STRUCTURE FIRE	11707	9	7
76011	DIABETIC	11708	9	7
76012	BLEEDING	3002	10	1
76013	HEART PROBLEMS	3003	10	2
76014	FIRE ALARM	11709	9	18

```
76015              PALLATIVE CARE       11710          9             4

[76016 rows x 13 columns]
```

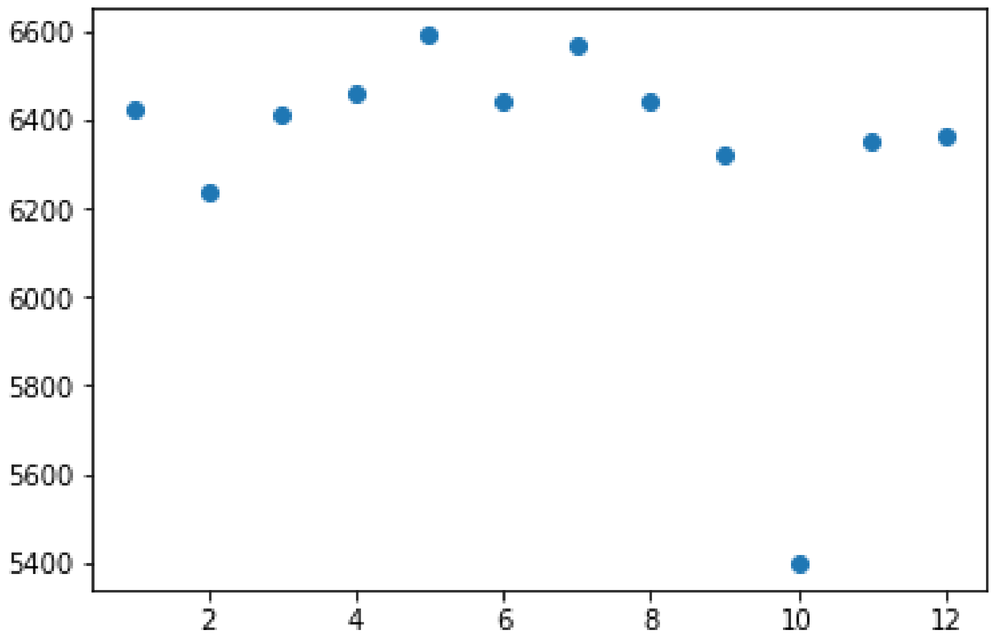
In [73]:
```python
df = pd.read_csv("../data/MCFRS_Incidents_by_Station.csv")
months = df.groupby('Month Num').agg('count')
months['Month'] = months.index

sns.lmplot(x='Month', y='Fire Station', data=months, aspect=1.5, scatter_kws={'alpha':0


# We see the dip in October that I was talking about earlier.
```

Out[73]: <seaborn.axisgrid.FacetGrid at 0x1a204640f0>

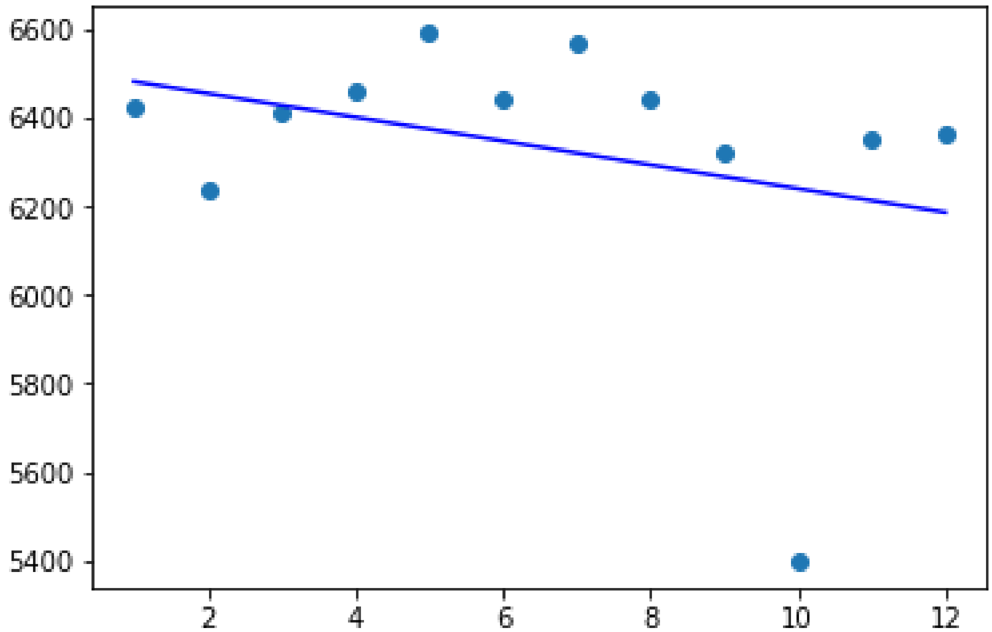


In [76]:
```python
from sklearn import linear_model

x_times = months[['Month']]
y_starting = months['Fire Station']

plt.scatter(x_times, y_starting)
```

Out[76]: <matplotlib.collections.PathCollection at 0x1a1e64c588>

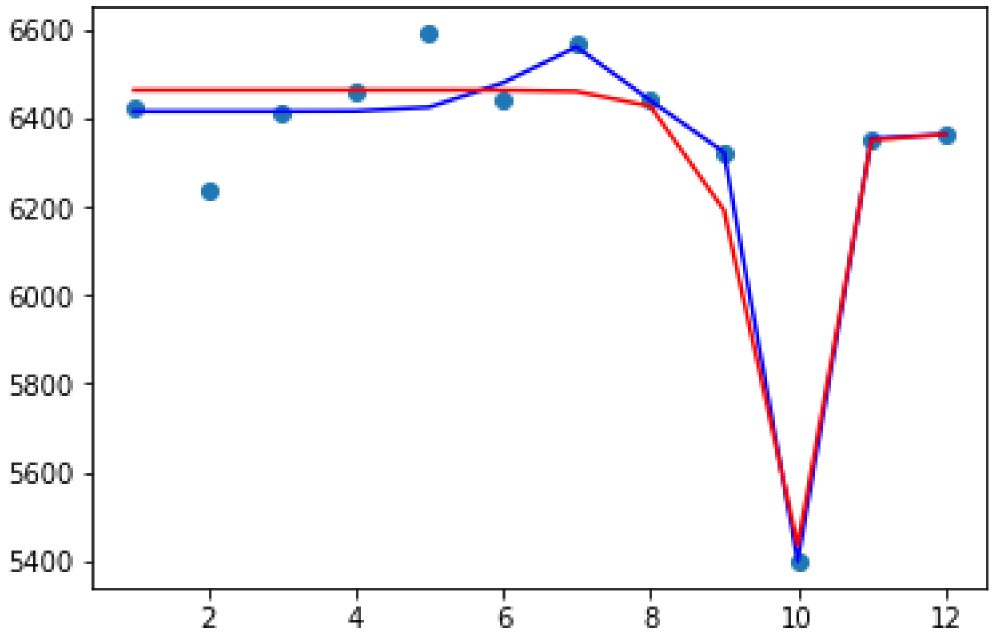



```
In [78]: # From this point on, I'm just copying and pasting
         from sklearn.linear_model import LinearRegression

         linear = LinearRegression()
         linear.fit(x_times, y_starting)

         # Plotting
         plt.scatter(x_times, y_starting)
         plt.plot(x_times, x_times*linear.coef_ + linear.intercept_, c = "b" )

Out[78]: [<matplotlib.lines.Line2D at 0x1a1eadff98>]
```




```
In [84]: # Model 1, polynomial linear regression x25 degree
         from sklearn.preprocessing import PolynomialFeatures

         poly_25 = PolynomialFeatures(degree=25)
         x_25 = poly_25.fit_transform(x_times)
         linear = linear_model.LinearRegression()
         linear.fit(x_25, y_starting)

Out[84]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [85]: ridge = linear_model.Ridge()
         ridge.fit(x_25, y_starting)

/Users/dell/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/ridge.py:154: UserWarning
  warnings.warn("Singular matrix in solving dual problem. Using "


Out[85]: Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

In [86]: # Model 1 : 25
         import numpy as np # I didn't need to until now

         plt.scatter(x_times, y_starting)
         plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
         plt.plot(x_times, np.dot(x_25, ridge.coef_) + ridge.intercept_, c='r')
```

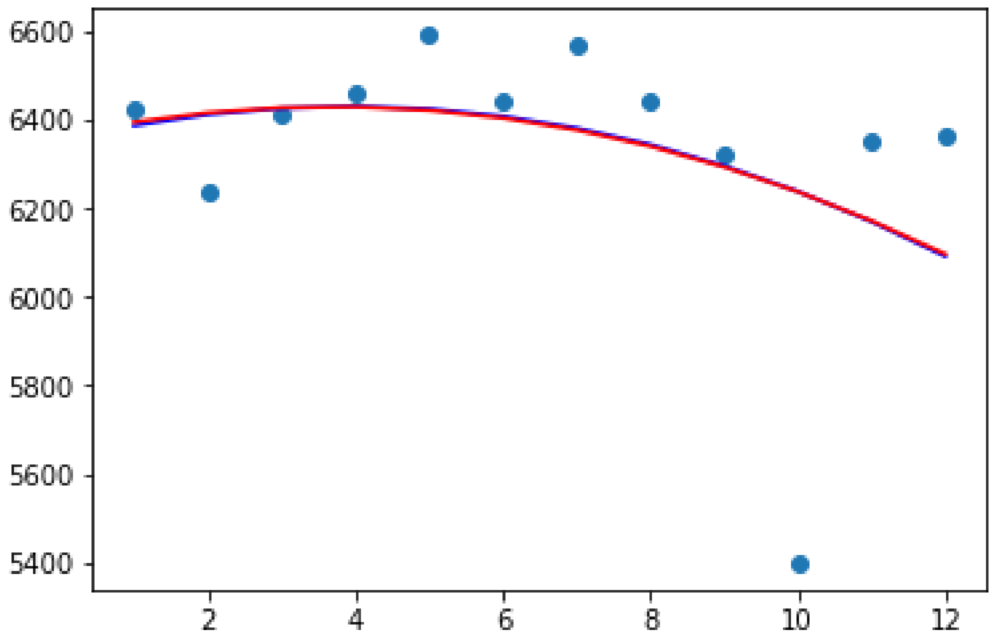
Out[86]: [<matplotlib.lines.Line2D at 0x1a22febda0>]




```
In [ ]: # This is a perfect fit!!!
```

```
In [87]: poly_2 = PolynomialFeatures(degree=2)
         x_2 = poly_2.fit_transform(x_times) # got rid of .reshape
         linear.fit(x_2, y_starting)
         ridge.fit(x_2, y_starting)

         plt.scatter(x_times, y_starting)
         plt.plot(x_times, np.dot(x_2, linear.coef_) + linear.intercept_, c='b')
         plt.plot(x_times, np.dot(x_2, ridge.coef_) + ridge.intercept_, c='r')
```

Out[87]: [<matplotlib.lines.Line2D at 0x1a231fc2e8>]

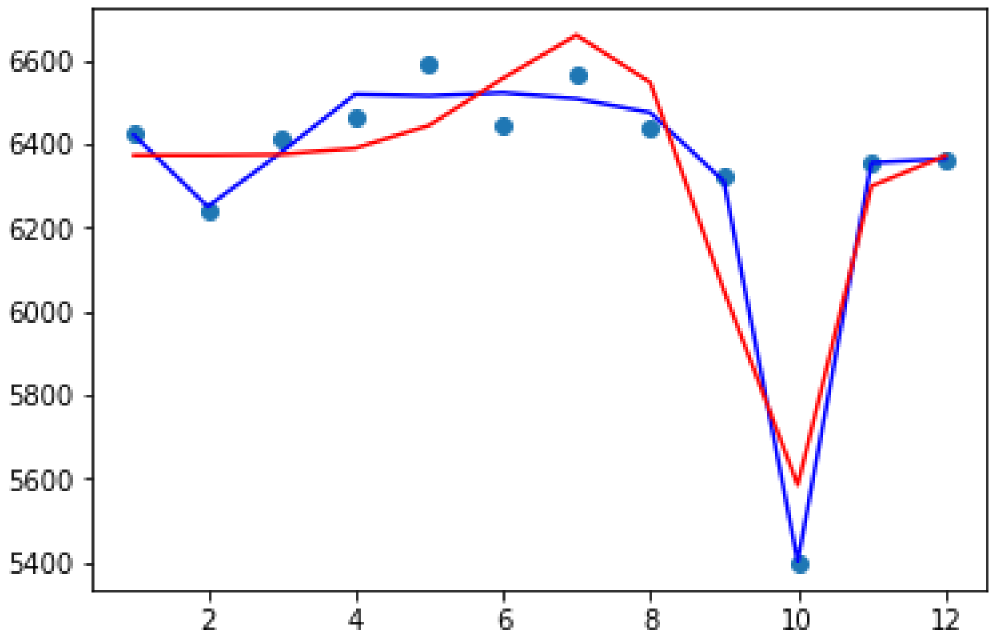



```
In [ ]: # No thanks
```

```
In [88]: # Model 3, polynomial linear regression x12 degree
         poly_12 = PolynomialFeatures(degree=12)
         x_12 = poly_12.fit_transform(x_times) # got rid of .reshape
         linear.fit(x_12, y_starting)
         ridge.fit(x_12, y_starting)

         plt.scatter(x_times, y_starting)
         plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
         plt.plot(x_times, np.dot(x_12, ridge.coef_) + ridge.intercept_, c='r')
```

```
/Users/dell/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/ridge.py:154: UserWarning
  warnings.warn("Singular matrix in solving dual problem. Using "
```

```
Out[88]: [<matplotlib.lines.Line2D at 0x1a232612e8>]
```




```
In [ ]: # More conservative, and less accurate. But, it's still good.

        # I don't think spliting data is appropriate for this dataset.
```