Final project

July 7, 2019

In [44]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.svm import SVC
import seaborn as sns
from tqdm import tqdm_notebook
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report

sns.set();

%matplotlib inline
```

In [2]:
```
df = pd.read_csv("2015StreetTreesCensus_TREES.csv")
df.head()
```

Out[2]:
```
   created_at  tree_id  block_id  \
0  08/27/2015   180683    348711
1  09/03/2015   200540    315986
2  09/05/2015   204026    218365
3  09/05/2015   204337    217969
4  08/30/2015   189565    223043

                                          the_geom  tree_dbh  stump_diam  \
0  POINT (-73.84421521958048 40.723091773924274)         3           0
1   POINT (-73.81867945834878 40.79411066708779)        21           0
2  POINT (-73.93660770459083 40.717580740099116)         3           0
3  POINT (-73.93445615919741 40.713537494833226)        10           0
4   POINT (-73.97597938483258 40.66677775537875)        21           0
```

```
  curb_loc status health                              spc_latin      ...        \
0   OnCurb  Alive   Fair                            Acer rubrum      ...
1   OnCurb  Alive   Fair                      Quercus palustris      ...
2   OnCurb  Alive   Good  Gleditsia triacanthos var. inermis      ...
3   OnCurb  Alive   Good  Gleditsia triacanthos var. inermis      ...
4   OnCurb  Alive   Good                       Tilia americana      ...

  st_assem st_senate   nta             nta_name  boro_ct     state   Latitude  \
0       28        16  QN17         Forest Hills  4073900  New York  40.723092
1       27        11  QN49           Whitestone  4097300  New York  40.794111
2       50        18  BK90     East Williamsburg  3044900  New York  40.717581
3       53        18  BK90     East Williamsburg  3044900  New York  40.713537
4       44        21  BK37  Park Slope-Gowanus  3016500  New York  40.666778

   longitude          x_sp           y_sp
0 -73.844215  1.027431e+06  202756.768749
1 -73.818679  1.034456e+06  228644.837379
2 -73.936608  1.001823e+06  200716.891267
3 -73.934456  1.002420e+06  199244.253136
4 -73.975979  9.909138e+05  182202.425999

[5 rows x 42 columns]
```

In [146]:
```
df.shape
```

Out[146]:
```
(683788, 42)
```

In [147]:
```
df.dropna().shape
```

Out[147]:
```
(652118, 42)
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['created_at', 'tree_id', 'block_id', 'the_geom', 'tree_dbh',
       'stump_diam', 'curb_loc', 'status', 'health', 'spc_latin', 'spc_common',
       'steward', 'guards', 'sidewalk', 'user_type', 'problems', 'root_stone',
       'root_grate', 'root_other', 'trnk_wire', 'trnk_light', 'trnk_other',
       'brnch_ligh', 'brnch_shoe', 'brnch_othe', 'address', 'zipcode',
       'zip_city', 'cb_num', 'borocode', 'boroname', 'cncldist', 'st_assem',
       'st_senate', 'nta', 'nta_name', 'boro_ct', 'state', 'Latitude',
       'longitude', 'x_sp', 'y_sp'],
      dtype='object')
```

In [4]:
```
df.shape
```

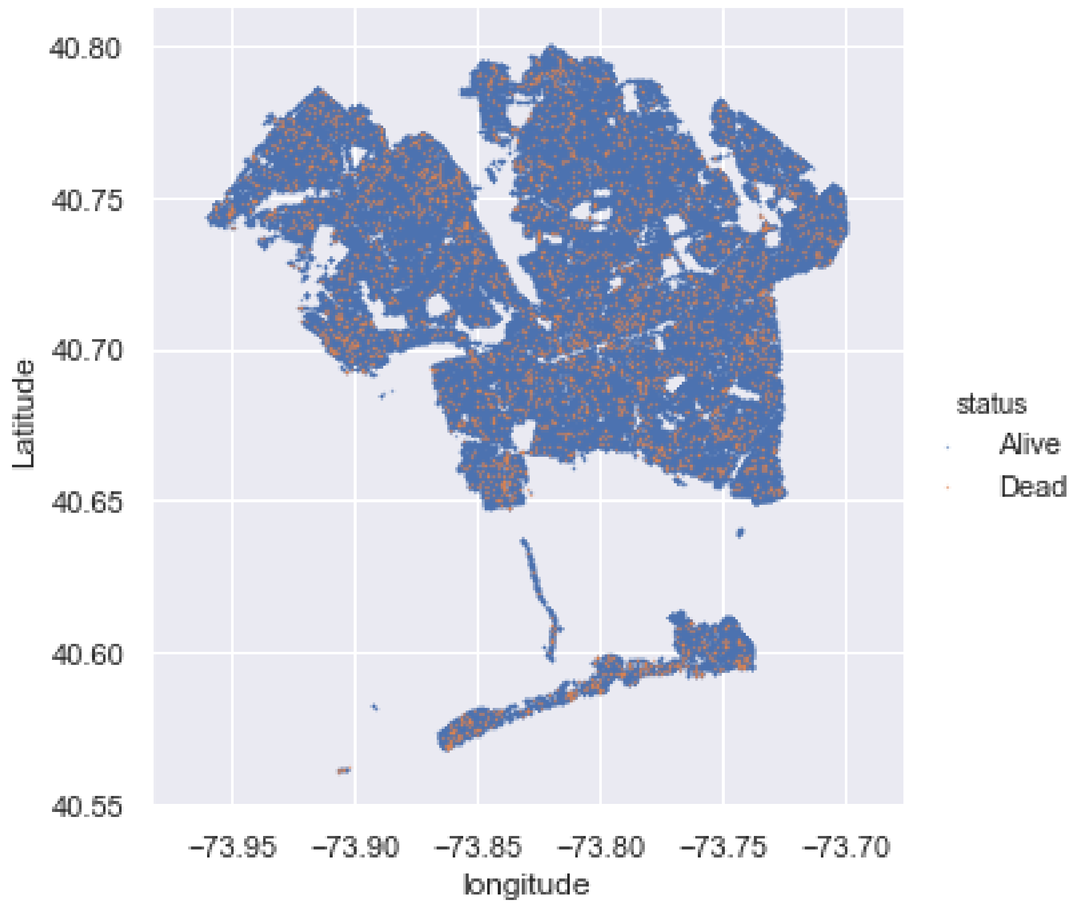
Out[4]:
```
(683788, 42)
```

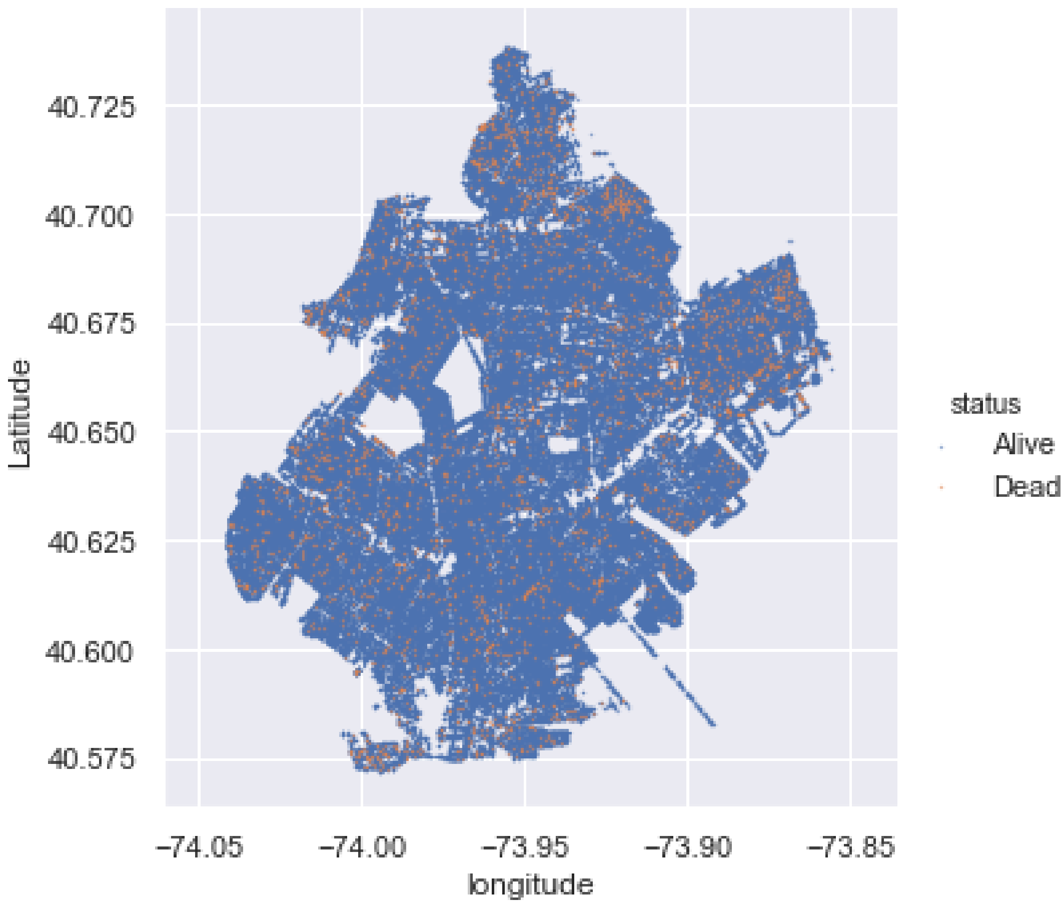
In [196]:
```
class eda:
    def __init__(self, data):
```

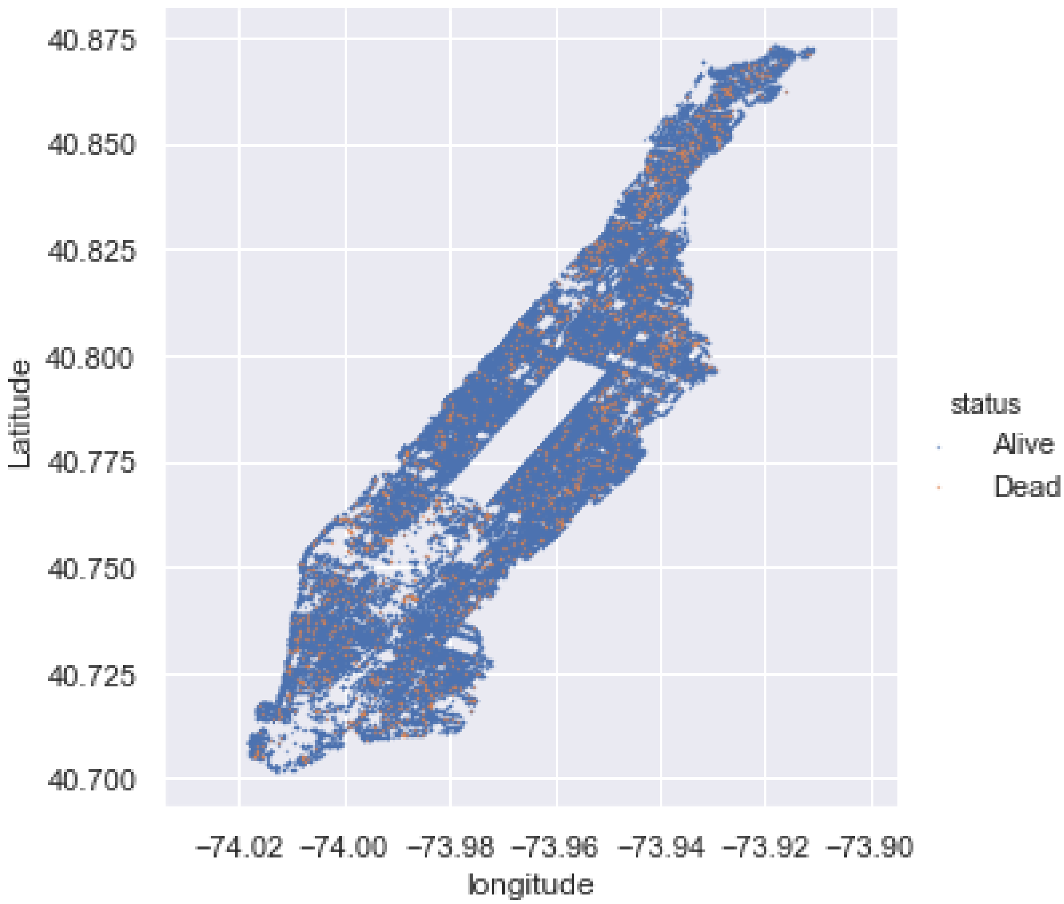
```
            self.df = data

        def plot(self, col1, col2, block):
            df = self.df
#           plt.scatter(df[col1], df[col2], c = df['boroname'])
#           plt.xlabel(col1)
#           plt.ylabel(col2)
#           plt.title("%s vs %s" %(col1,col2))
            sns.lmplot(col1, col2, data=df, hue=block, fit_reg=False, scatter_kws={"s":
        def plot_noblock(self, new_df, col1, col2):
            sns.lmplot(col1, col2, data=new_df, fit_reg=False)

        def boxplot(self, col1, col2):
            df = self.df
            sns.boxplot(x=col1, y=col2, data= df)

        def hist(self, col):
            plt.hist(df[col])

        def check_corr(self, col):
            return self[col].corr()
```

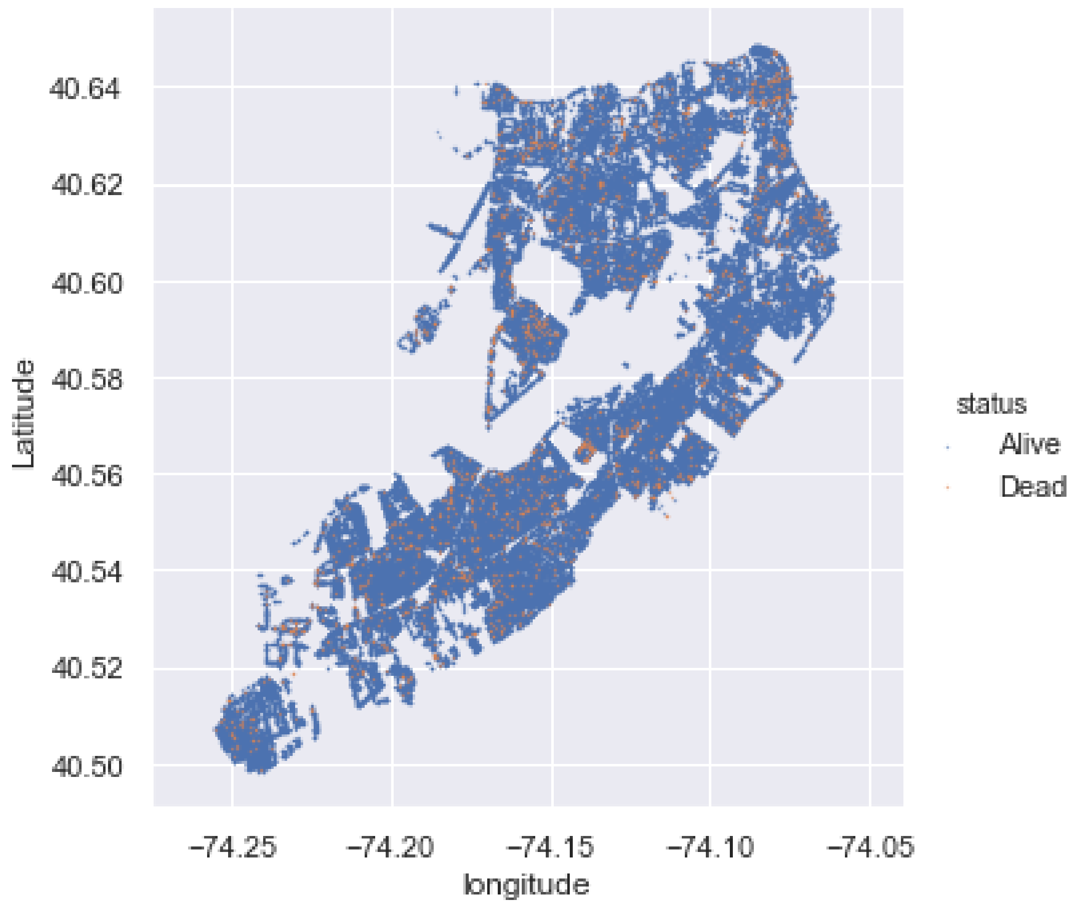
```
In [6]: ed = eda(df)
        ed.plot('longitude', 'Latitude','boroname')
```

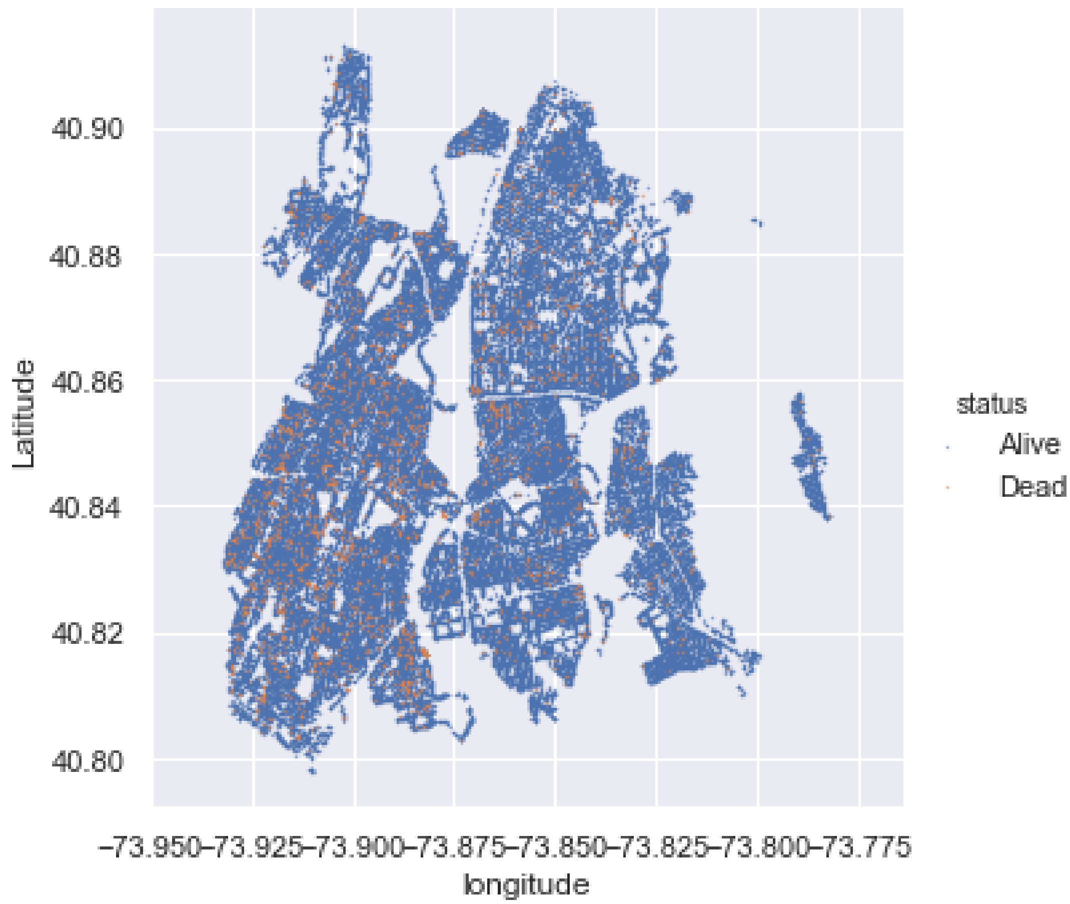

```
In [131]: for name in df.boroname.unique():
              df_temp = df.loc[df.boroname == name, :].loc[df.status != 'Stump', :]
              eda_temp = eda(df_temp)
              eda_temp.plot('longitude', 'Latitude','status')
```


40.80
40.75
40.70
40.65
40.60
40.55
Latitude
−73.95
−73.90
−73.85
−73.80
−73.75
−73.70
longitude
status
Alive
Dead

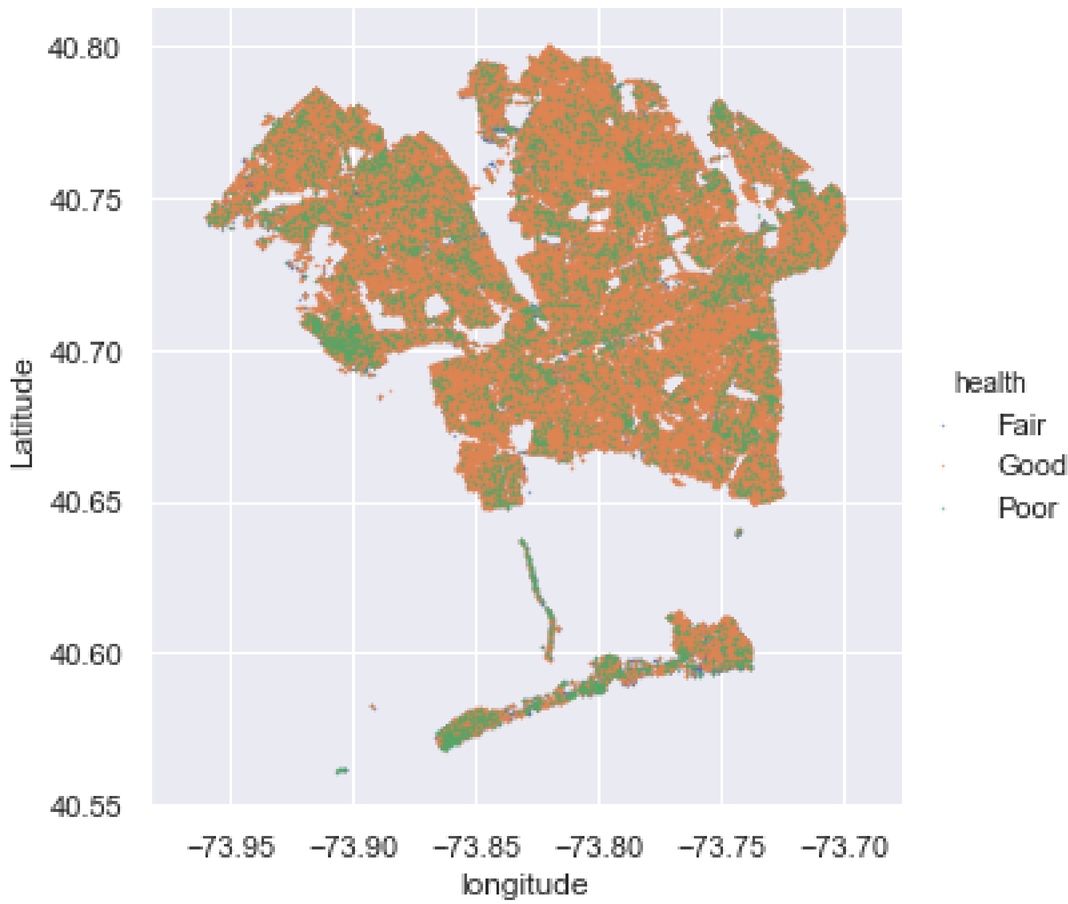

40.725
40.700
40.675
40.650
40.625
40.600
40.575
Latitude
-74.05
-74.00
-73.95
-73.90
-73.85
longitude
status
Alive
Dead


40.875
40.850
40.825
40.800
40.775
40.750
40.725
40.700
Latitude
−74.02
−74.00
−73.98
−73.96
−73.94
−73.92
−73.90
longitude
status
Alive
Dead

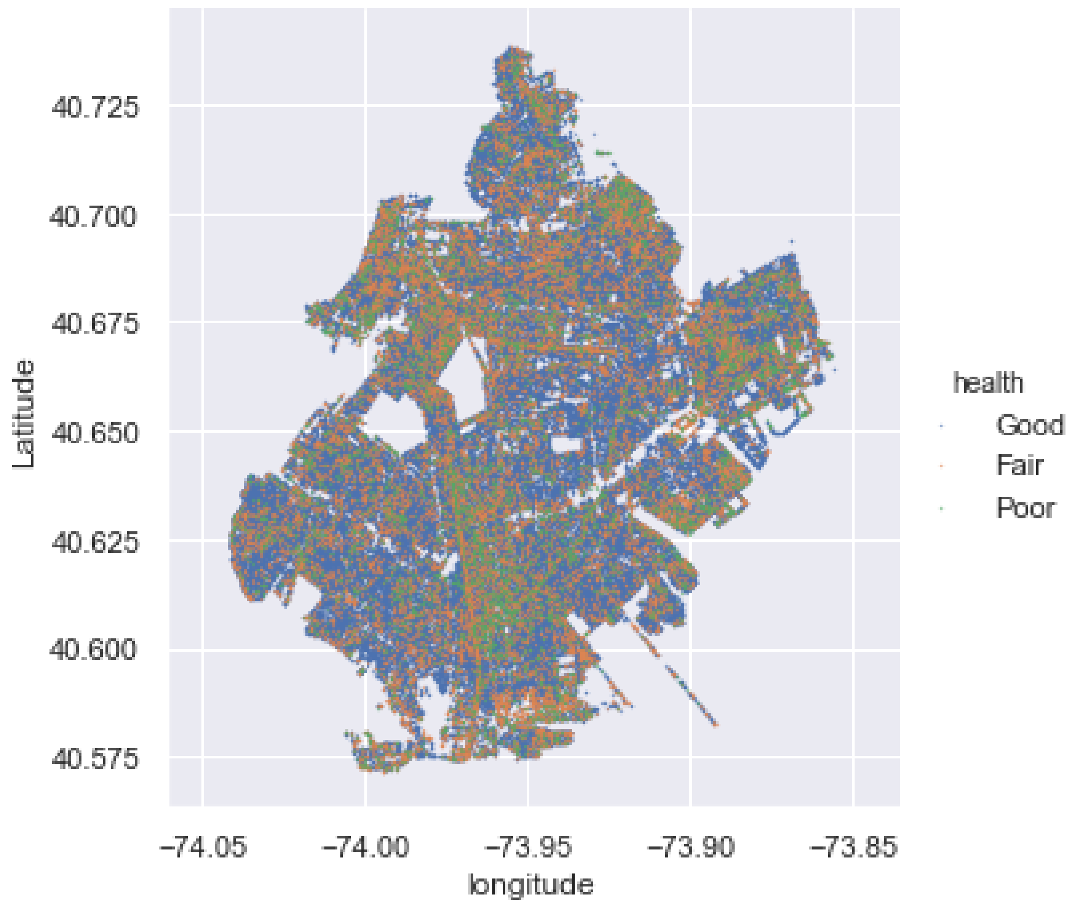

40.64
40.62
40.60
40.58
40.56
40.54
40.52
40.50
Latitude
−74.25
−74.20
−74.15
−74.10
−74.05
longitude
status
Alive
Dead



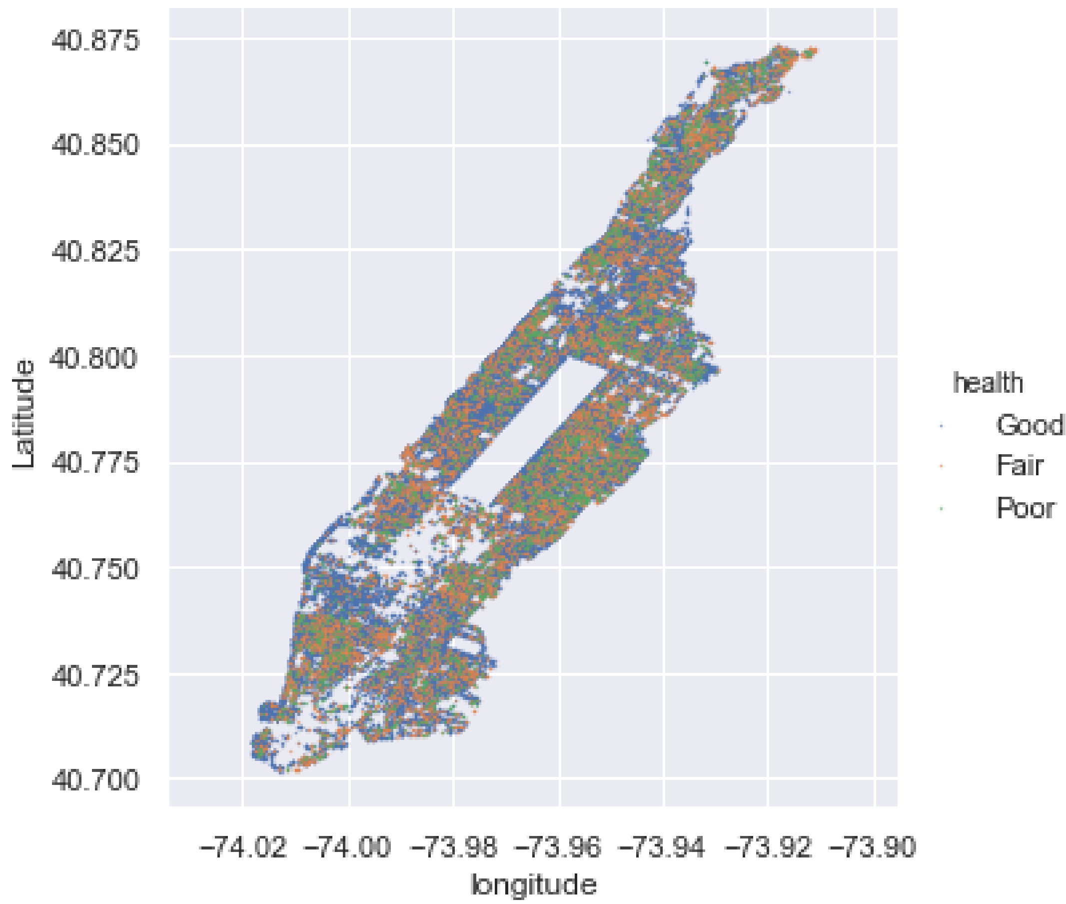

```
In [126]: for name in df.boroname.unique():
              df_temp = df.loc[df.boroname == name,:]
              eda_temp = eda(df_temp)
              eda_temp.plot('longitude', 'Latitude','health')
```

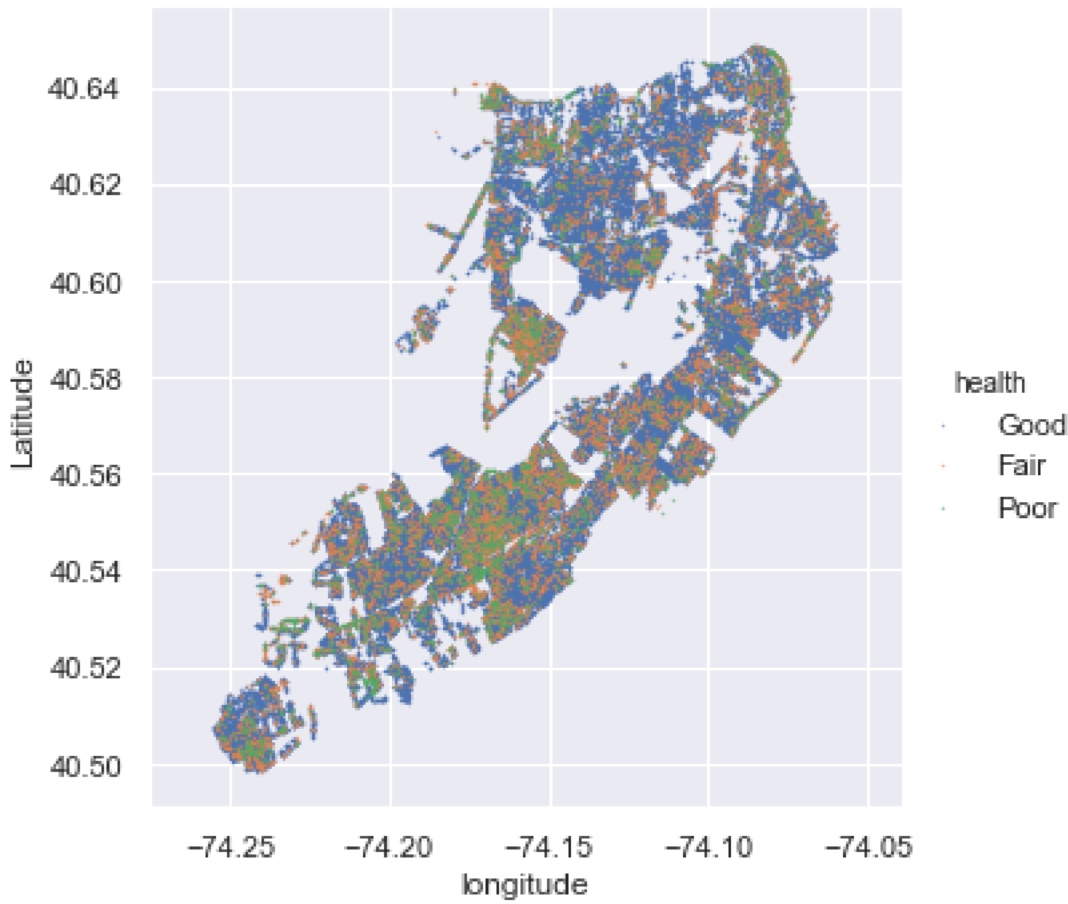


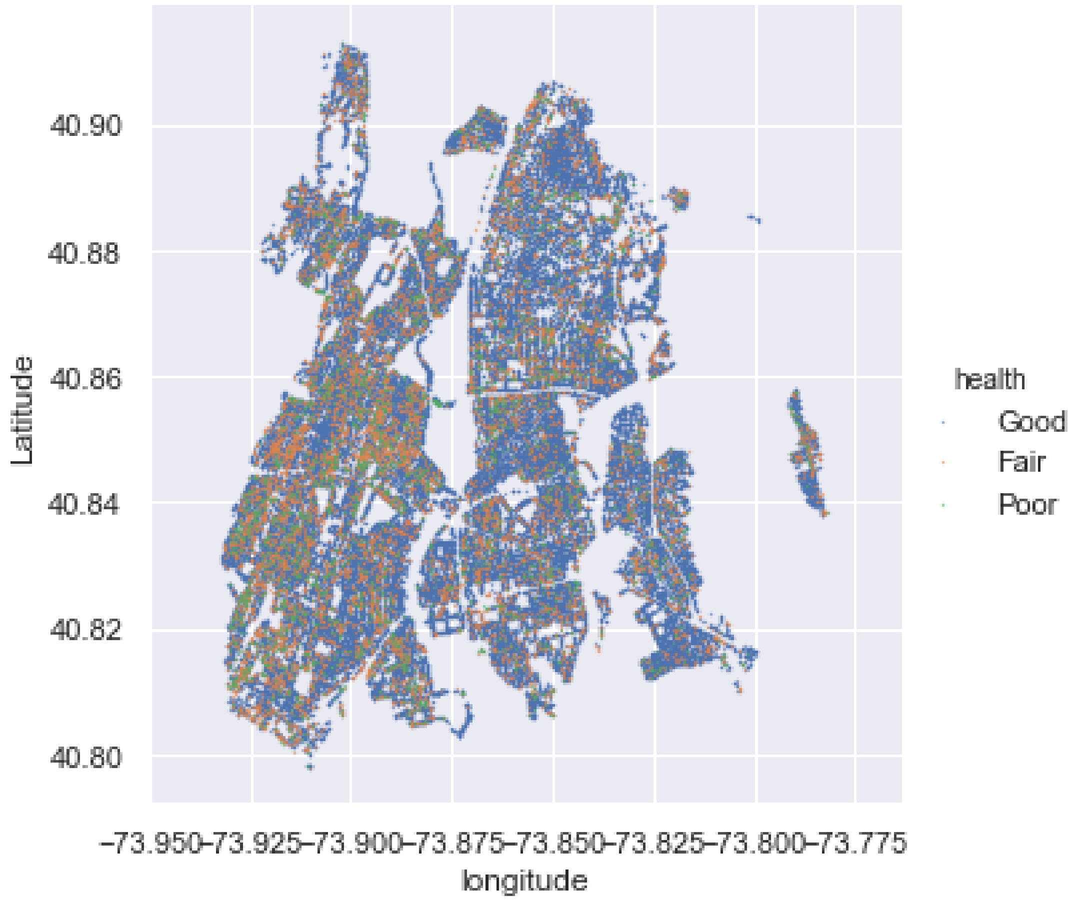
40.80
40.75
40.70
40.65
40.60
40.55
Latitude
-73.95
-73.90
-73.85
-73.80
-73.75
-73.70
longitude
health
Fair
Good
Poor



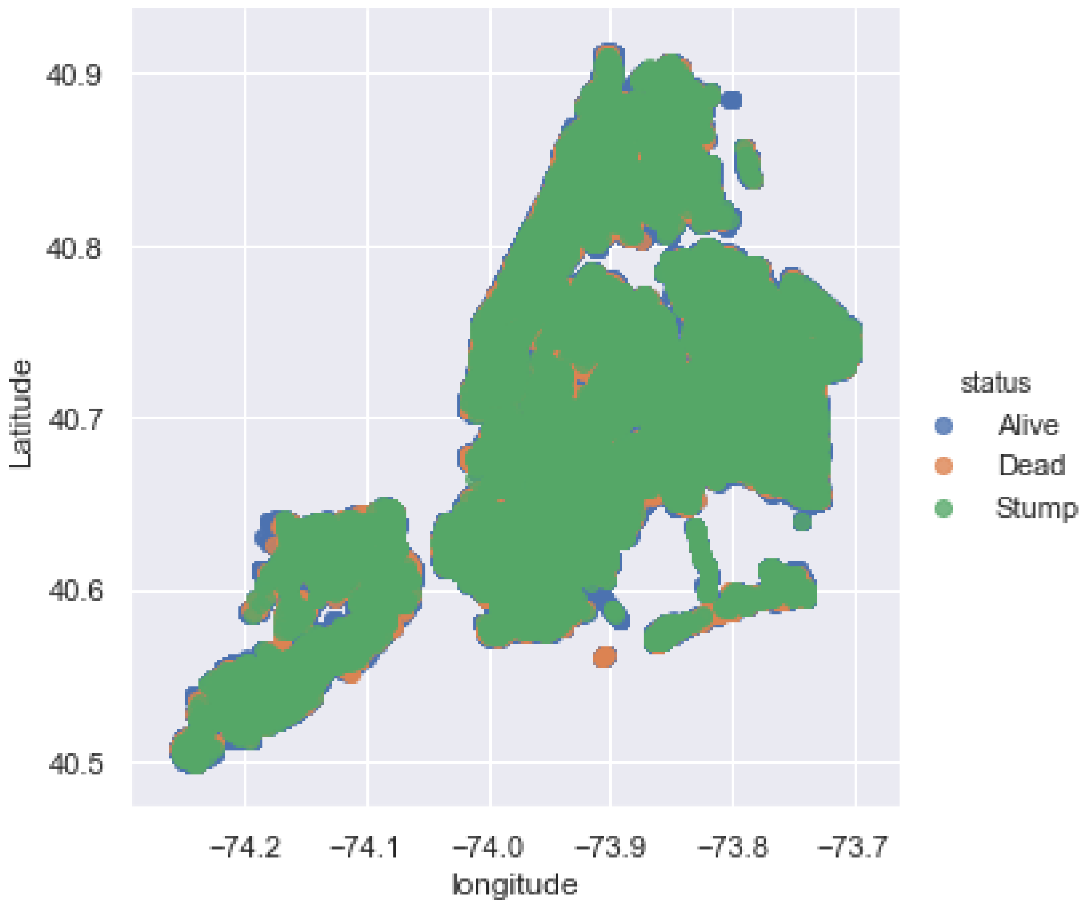
40.725
40.700
40.675
40.650
40.625
40.600
40.575
Latitude
−74.05
−74.00
−73.95
−73.90
−73.85
longitude
health
Good
Fair
Poor


40.875
40.850
40.825
40.800
40.775
40.750
40.725
40.700
Latitude
−74.02
−74.00
−73.98
−73.96
−73.94
−73.92
−73.90
longitude
health
Good
Fair
Poor


40.64
40.62
40.60
40.58
40.56
40.54
40.52
40.50
Latitude
-74.25
-74.20
-74.15
-74.10
-74.05
longitude
health
Good
Fair
Poor




```
In [110]: ed.plot('longitude', 'Latitude','status')
```




```
In [116]: #ed.plot_noblock(df.loc[df.status=='Alive'], 'longitude', 'Latitude')
```

```
In [45]: svm = SVC(kernel = 'poly')
         log = LogisticRegression()
         knn = KNeighborsClassifier(n_neighbors=5)


         def train_test(model, X, y, multiclass = False):
             X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
             model.fit(X_train, y_train)
             y_pred = model.predict(X_test)
             y_prob = model.predict_proba(X_test)
             if multiclass == False:
                 return(np.mean(y_test!=y_pred), roc_auc_score(y_test, y_prob[:,1]))
             else:
                 return(classification_report(y_test, y_pred))

         #logistic regression on geolocation only
```

```
train_test(log, df.loc[df.status != 'Stump',['longitude','Latitude']],
           df.status.loc[df.status != 'Stump'])
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)
```

```
Out[45]: (0.020739039383908666, 0.5169118446337606)
```

```
In [190]: df1 = df.dropna().loc[df.status == 'Alive']
```

```
In [195]: def train_test_block(model, X, y, block_col, multiclass = False):
              for region in X[block_col].unique():
                  X_block = X.loc[X[block_col] == region,:]
                  X_block = X_block.drop(columns = block_col)
                  y_block = y.loc[X[block_col] == region]
                  X_train, X_test, y_train, y_test = train_test_split(X_block, y_block, test_si
                  model.fit(X_train, y_train)
                  y_pred = model.predict(X_test)
                  y_prob = model.predict_proba(X_test)
                  if multiclass == False:
                      print(region, np.mean(y_test!=y_pred), roc_auc_score(y_test, y_prob[:,1])
                  else:
                      print(region, classification_report(y_test, y_pred))

          X_h = df1[['longitude','Latitude','tree_dbh', 'boroname']]
          #X_h = pd.concat([pd.get_dummies(df1[['steward', 'sidewalk','curb_loc']]),
          #                 df1[['longitude','Latitude','tree_dbh', 'boroname']]], axis = 1)
          y_h = df1.health.loc[df1.status == 'Alive']


          ada = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=2), n_estima
          train_test_block(knn, X_h, y_h , 'boroname', True)
```

```
Queens              precision    recall  f1-score   support

        Fair       0.31      0.17      0.22      6799
        Good       0.84      0.94      0.89     38872
        Poor       0.34      0.04      0.07      1922

   micro avg       0.79      0.79      0.79     47593
   macro avg       0.50      0.38      0.39     47593
weighted avg       0.74      0.79      0.76     47593

Brooklyn                precision    recall  f1-score   support

        Fair       0.33      0.17      0.22      4947
        Good       0.84      0.94      0.89     27713
        Poor       0.38      0.05      0.08      1287
```

```
   micro avg       0.80      0.80      0.80     33947
   macro avg       0.51      0.39      0.40     33947
weighted avg       0.75      0.80      0.76     33947

Manhattan              precision    recall  f1-score   support

        Fair       0.30      0.19      0.23      2239
        Good       0.78      0.91      0.84      9514
        Poor       0.30      0.05      0.08       732

   micro avg       0.73      0.73      0.73     12485
   macro avg       0.46      0.38      0.38     12485
weighted avg       0.67      0.73      0.69     12485

Staten Island              precision    recall  f1-score   support

        Fair       0.37      0.22      0.28      2927
        Good       0.85      0.94      0.89     16539
        Poor       0.36      0.05      0.09       818

   micro avg       0.80      0.80      0.80     20284
   macro avg       0.53      0.41      0.42     20284
weighted avg       0.76      0.80      0.77     20284

Bronx              precision    recall  f1-score   support

        Fair       0.34      0.15      0.21      2266
        Good       0.84      0.95      0.89     13269
        Poor       0.24      0.03      0.05       582

   micro avg       0.81      0.81      0.81     16117
   macro avg       0.47      0.38      0.38     16117
weighted avg       0.75      0.81      0.77     16117
```

```
In [161]: train_test_block(ada, X_h, y_h , 'boroname', True)
```

```
Queens              precision    recall  f1-score   support

        Fair       0.49      0.00      0.01      6799
        Good       0.82      1.00      0.90     38872
        Poor       0.50      0.00      0.01      1922

   micro avg       0.82      0.82      0.82     47593
   macro avg       0.60      0.34      0.31     47593
weighted avg       0.76      0.82      0.74     47593
```

```
Brooklyn               precision    recall  f1-score   support

        Fair       0.44      0.00      0.01      4947
        Good       0.82      1.00      0.90     27713
        Poor       0.17      0.00      0.00      1287

   micro avg       0.82      0.82      0.82     33947
   macro avg       0.48      0.33      0.30     33947
weighted avg       0.74      0.82      0.74     33947

Manhattan               precision    recall  f1-score   support

        Fair       0.39      0.01      0.02      2239
        Good       0.76      1.00      0.86      9514
        Poor       0.33      0.01      0.01       732

   micro avg       0.76      0.76      0.76     12485
   macro avg       0.50      0.34      0.30     12485
weighted avg       0.67      0.76      0.66     12485

Staten Island               precision    recall  f1-score   support

        Fair       0.45      0.01      0.01      2927
        Good       0.82      1.00      0.90     16539
        Poor       0.64      0.01      0.02       818

   micro avg       0.82      0.82      0.82     20284
   macro avg       0.64      0.34      0.31     20284
weighted avg       0.76      0.82      0.73     20284

Bronx               precision    recall  f1-score   support

        Fair       0.35      0.00      0.01      2266
        Good       0.82      1.00      0.90     13269
        Poor       0.00      0.00      0.00       582

   micro avg       0.82      0.82      0.82     16117
   macro avg       0.39      0.33      0.30     16117
weighted avg       0.73      0.82      0.74     16117
```

```
In [194]: log = LogisticRegression(solver = 'lbfgs', multi_class = 'multinomial',class_weight =
          train_test_block(log, X_h, y_h , 'boroname', True)
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:758: Conve
  "of iterations.", ConvergenceWarning)
```

```
Queens               precision    recall  f1-score   support

        Fair       0.17      0.10      0.12      6799
        Good       0.83      0.45      0.58     38872
        Poor       0.05      0.60      0.09      1922

   micro avg       0.40      0.40      0.40     47593
   macro avg       0.35      0.38      0.27     47593
weighted avg       0.71      0.40      0.50     47593
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:758: Conve
  "of iterations.", ConvergenceWarning)
```

```
Brooklyn               precision    recall  f1-score   support

        Fair       0.15      0.09      0.11      4947
        Good       0.84      0.45      0.59     27713
        Poor       0.05      0.67      0.10      1287

   micro avg       0.41      0.41      0.41     33947
   macro avg       0.35      0.40      0.27     33947
weighted avg       0.71      0.41      0.50     33947
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:758: Conve
  "of iterations.", ConvergenceWarning)
```

```
Manhattan               precision    recall  f1-score   support

        Fair       0.20      0.17      0.18      2239
        Good       0.82      0.46      0.59      9514
        Poor       0.09      0.62      0.15       732

   micro avg       0.41      0.41      0.41     12485
   macro avg       0.37      0.42      0.31     12485
weighted avg       0.67      0.41      0.49     12485
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:758: Conve
  "of iterations.", ConvergenceWarning)
```

```
Staten Island               precision    recall  f1-score   support
```

```
        Fair       0.16      0.22      0.19      2927
        Good       0.85      0.33      0.47     16539
        Poor       0.05      0.61      0.09       818

   micro avg       0.32      0.32      0.32     20284
   macro avg       0.35      0.39      0.25     20284
weighted avg       0.72      0.32      0.42     20284
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:758: Conve
  "of iterations.", ConvergenceWarning)
```

```
Bronx               precision    recall  f1-score   support

        Fair       0.15      0.13      0.14      2266
        Good       0.86      0.39      0.53     13269
        Poor       0.05      0.68      0.09       582

   micro avg       0.36      0.36      0.36     16117
   macro avg       0.35      0.40      0.25     16117
weighted avg       0.73      0.36      0.46     16117
```

In [95]:
```python
#logistic regression on geolocation and tree diameter
train_test(log, df.loc[df.status != 'Stump',['longitude','Latitude','tree_dbh']],
           df.status.loc[df.status != 'Stump'])
```

```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)
```

Out[95]: (0.020739039383908666, 0.7695517831463828)

In [92]:
```python
#knn based on only geolocation
train_test(knn, df.loc[df.status != 'Stump',['longitude','Latitude']],
           df.status.loc[df.status != 'Stump'])
```

Out[92]: (0.021392060167983968, 0.6251759179474983)

In [103]:
```python
#knn based on geolocation and tree diameter
#notice there isn't much improvement
train_test(knn, df.loc[df.status != 'Stump',['longitude','Latitude','tree_dbh']],
           df.status.loc[df.status != 'Stump'])
```

Out[103]: (0.021692299608938127, 0.6389132389055914)

```
In [90]: # testing best k parameter based on only geolocation
         for k in tqdm_notebook(range(20)):
             knn_k = KNeighborsClassifier(n_neighbors=k+1)

             print([k+1, train_test(knn_k, df.loc[df.status != 'Stump',['longitude','Latitude']
                    df.status.loc[df.status != 'Stump'])])
```

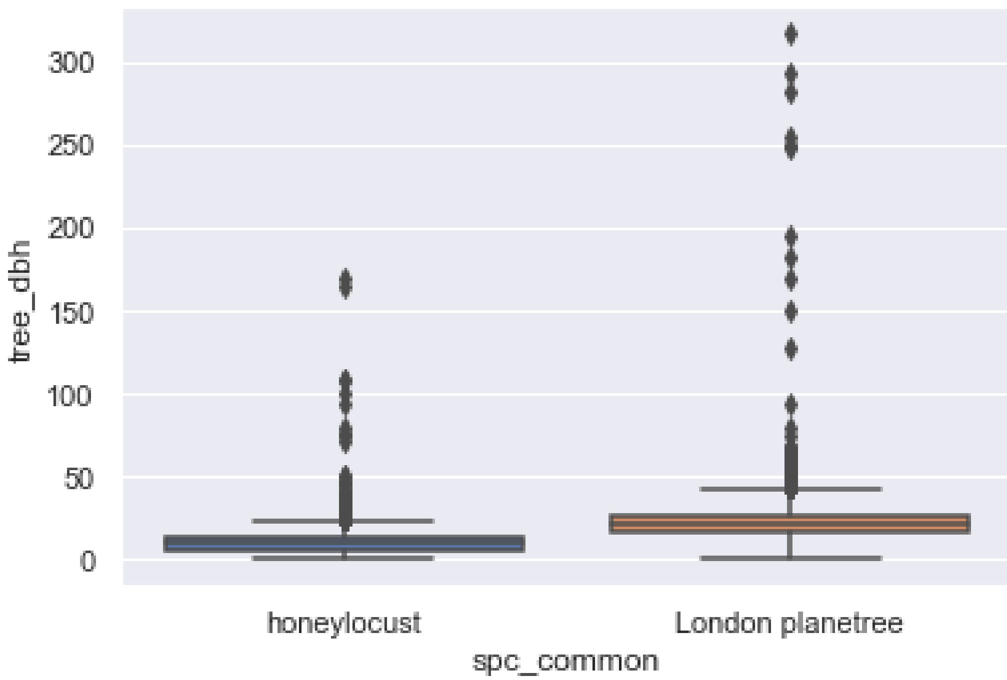
```
HBox(children=(IntProgress(value=0, max=20), HTML(value='')))
```

```
[1, (0.035600891711139636, 0.5687548361588286)]
[2, (0.021279470377626158, 0.5958590998260858)]
[3, (0.023035871107208, 0.6122720902241869)]
[4, (0.020956712978600432, 0.6192316162825082)]
[5, (0.021392060167983968, 0.6251759179474983)]
[6, (0.020851629174266476, 0.6311245042722204)]
[7, (0.02103927882486283, 0.6357120030327346)]
[8, (0.0207015094537894, 0.6389404240937061)]
[9, (0.020806593258123354, 0.6417383193822925)]
[10, (0.020663979523670127, 0.6427023927892415)]
[11, (0.020709015439813253, 0.6450854750362436)]
[12, (0.020754051355956375, 0.6453065726330747)]
[13, (0.020754051355956375, 0.64652602091471)]
[14, (0.020716521425837107, 0.647997046272927)]
[15, (0.020716521425837107, 0.6521688844919874)]
[16, (0.0207015094537894, 0.6526093472350166)]
[17, (0.020739039383908666, 0.6541132600267862)]
[18, (0.020716521425837107, 0.6548828980995676)]
[19, (0.020724027411860958, 0.6559912378999767)]
[20, (0.020709015439813253, 0.6571263245743293)]
```

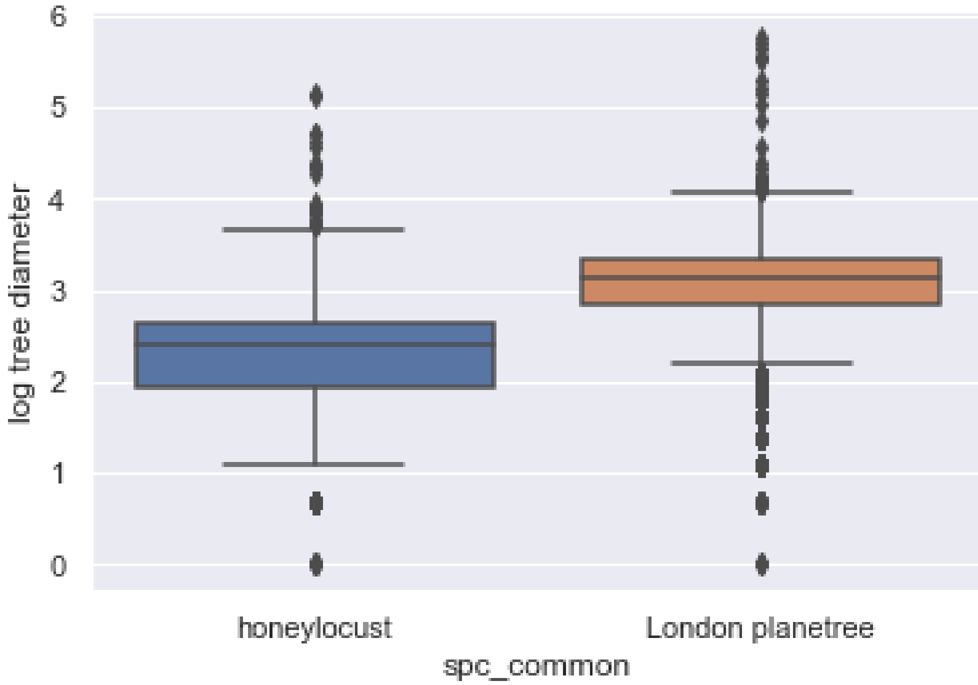
```
In [102]: #qda based on geolocation and tree diameter
          qda = QuadraticDiscriminantAnalysis()
          train_test(qda, df.loc[df.status != 'Stump',['longitude','Latitude', 'tree_dbh']],
                     df.status.loc[df.status != 'Stump'])

Out[102]: (0.020739039383908666, 0.7380704226174196)
```

```
In [103]: #adaboost ensemble decision tree weak learners based geolocation and tree diameter
          #best performing model so far
          ada = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1), n_estima
          train_test(ada, df.loc[df.status != 'Stump',['longitude','Latitude', 'tree_dbh']],
                     df.status.loc[df.status != 'Stump'])

Out[103]: (0.020739039383908666, 0.7730273315628547)
```

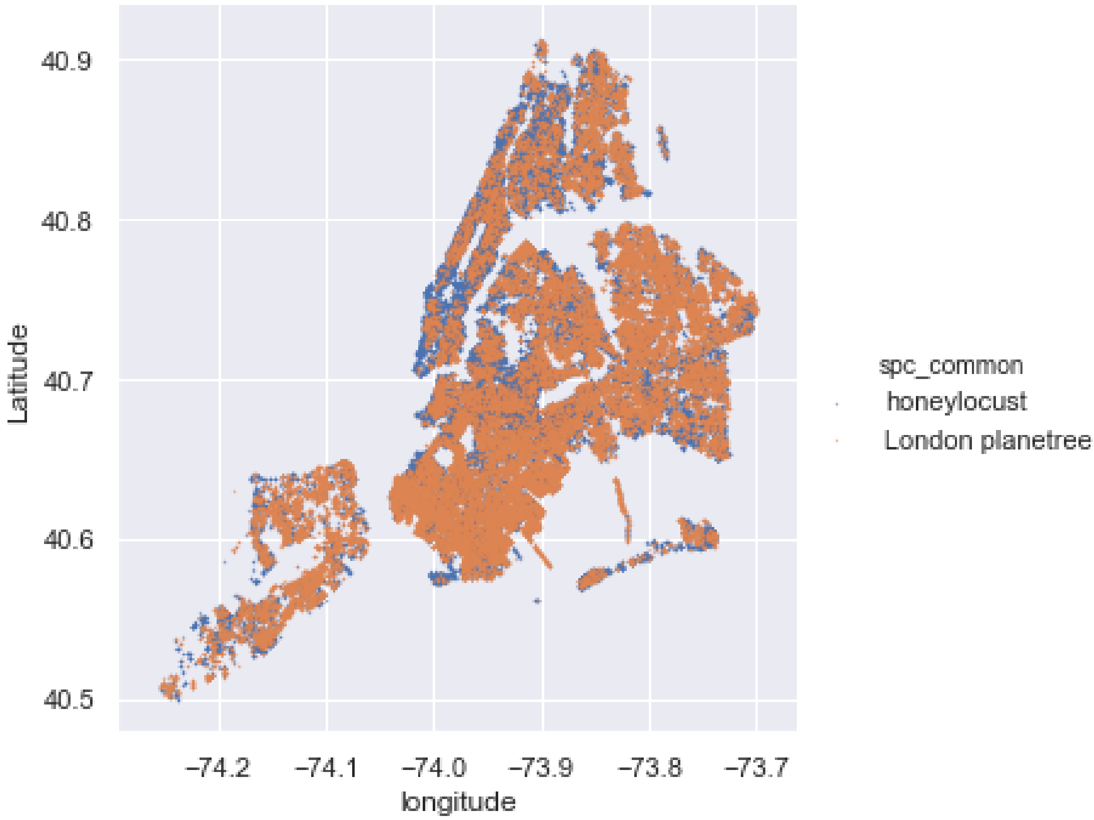
```
In [112]: y = df.status.loc[df.status != 'Stump']
          X = pd.concat([pd.get_dummies(df[[
                  'boroname','curb_loc']]), df[['longitude','Latitude','tree_dbh']]], axis = 1
          X = X.loc[df.status!='Stump', :]
          ada = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=2), n_estima
          train_test(ada, X, y)

Out[112]: (0.020739039383908666, 0.7736399768734347)

In [113]: log = LogisticRegression()
          train_test(log, X, y)

/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)


Out[113]: (0.020739039383908666, 0.7706512970193482)

In [108]: df['boroname'].value_counts()

Out[108]: Queens           250551
          Brooklyn         177293
          Staten Island    105318
          Bronx             85203
          Manhattan         65423
          Name: boroname, dtype: int64

In [169]: #finds out the top10 species
          top10_species = df['spc_common'].value_counts()[:2].index
          df['spc_common'].value_counts()[:2]

Out[169]: London planetree    87014
          honeylocust         64264
          Name: spc_common, dtype: int64

In [187]: df_10 = df.loc[df['spc_common'].apply(lambda x: True if x in top10_species else Fals
          df_10 = df_10.dropna()

In [188]: #boxplot of log(tree_dbh vs top 10 species)

          #df_10.tree_dbh = np.log(df_10.tree_dbh)
          ed_10 = eda(df_10.loc[df_10.status!= 'Stump',:])
          ed_10.boxplot('spc_common', 'tree_dbh')
```




```
In [189]: df_10.tree_dbh = np.log(df_10.tree_dbh+1)
          ed_10 = eda(df_10.loc[df_10.status!= 'Stump',:])
          ed_10.boxplot('spc_common', 'tree_dbh')
          plt.ylabel('log tree diameter')

Out[189]: Text(0, 0.5, 'log tree diameter')
```




```
In [204]: from scipy.stats import ttest_ind
          ttest_ind(df_10.tree_dbh.loc[df_10.spc_common == "honeylocust"],
                    df_10.tree_dbh.loc[df_10.spc_common == "London planetree"],
                    equal_var = True)

Out[204]: Ttest_indResult(statistic=-258.33265678621683, pvalue=0.0)

In [173]: #geo-location of top 10 species, looks like there is clustering behavior
          #and some species only appear in certain area
          #It might be possible to predict the type of species based on other variables
          ed_10.plot('longitude', 'Latitude','spc_common')
```




```
In [174]: X_10 = pd.concat([pd.get_dummies(df_10[['status', 'health',
                  'steward', 'sidewalk', 'boroname','curb_loc']]), df_10[['longitude','Latitude

          y_10 = df_10.spc_common

In [179]: knn = KNeighborsClassifier(n_neighbors=5)
          train_test(knn, X_10, y_10)

Out[179]: (0.16573015138494082, 0.9007219691600991)

In [180]: ada = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=2), n_estima
          train_test(ada, X_10, y_10)

Out[180]: (0.15859059959013685, 0.9176699487551436)

In [181]: # import os
          # beep = lambda x: os.system("echo -n '\a';sleep 0.2;" * x)
          # beep(3)

In [182]: log = LogisticRegression()
          train_test(log, X_10, y_10)
```

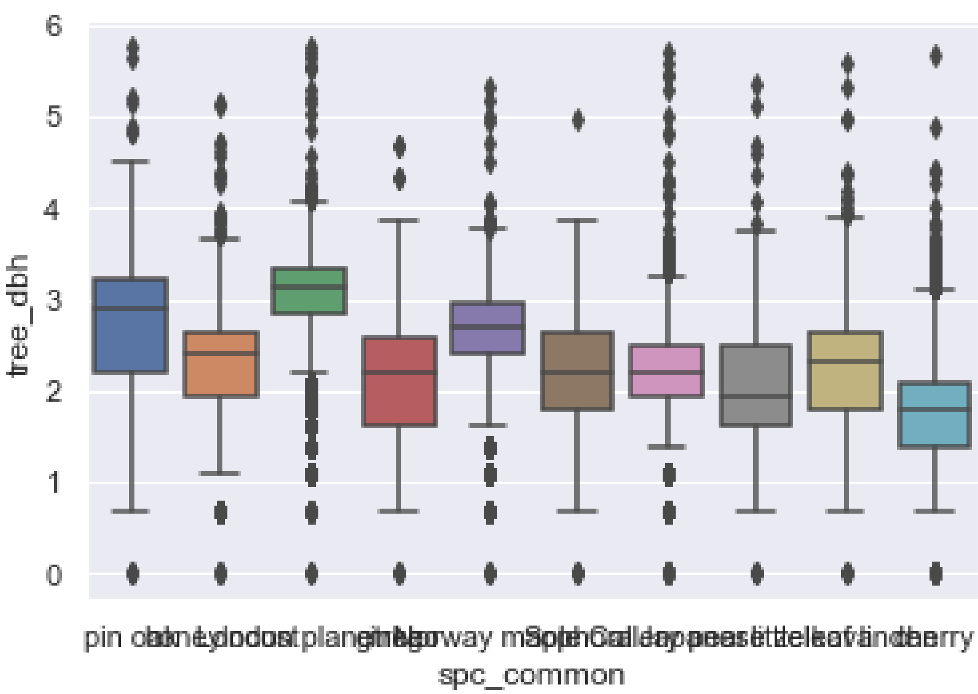
```
/Users/royluo/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)
```

Out[182]:
```
(0.21045151054406028, 0.8708595597309167)
```

In [200]:
```
top10_species = df['spc_common'].value_counts()[:10].index
df_10 = df.loc[df['spc_common'].apply(lambda x: True if x in top10_species else False
df_10 = df_10.dropna()
df['spc_common'].value_counts()[:10]
```

Out[200]:
```
London planetree     87014
honeylocust          64264
Callery pear         58931
pin oak              53185
Norway maple         34189
littleleaf linden    29742
cherry               29279
Japanese zelkova     29258
ginkgo               21024
Sophora              19338
Name: spc_common, dtype: int64
```

In [201]:
```
df_10.tree_dbh = np.log(df_10.tree_dbh+1)
ed_10 = eda(df_10.loc[df_10.status!= 'Stump',:])
ed_10.boxplot('spc_common', 'tree_dbh')
```



In [202]:
```
X_10 = pd.concat([pd.get_dummies(df_10[['status', 'health',
        'steward', 'sidewalk', 'boroname','curb_loc']]), df_10[['longitude','Latitude

y_10 = df_10.spc_common

train_test(knn, X_10, y_10, True)
```

Out[202]:
```
'                    precision    recall  f1-score   support\n\n     Callery pear
```

In [ ]: