Lesson 8 - K-Means Clustering

The k-means algorithm falls in the category of unsupervised machine learning, where the input data points are not given a label and the algorithm has to "infer" a label from the data. K-Means is a clustering algorithm where the "label" is the cluster that an input data point belongs to. It has been used to solve many problems such as:

- Anomaly detection
- Image segmentation
- Grouping of texts, images, videos
- Media compression

The belonging to a cluster concept is based on the similarity between the input data point and cluster point. Typically, similarity is expressed as the distance between the input data point and a cluster point, where the smaller the distance, the more similar the input data is to a cluster.

In k-means, the number of clusters (k) has to be specified, and each input data is assigned to one of the k clusters. It does this in an iterative manner as follows:

1. A set of k points with random values are defined the k cluster centroids.
2. For each input point, the distance to each centroid is calculated. The point is assigned to the centroid with the smallest distance.
3. Update the centroid values based on the mean of the assigned points.
4. Repeat 2 and 3 until a terminating condition is triggered, such as a max number of iterations is reached, or the assignment of the input data to clusters has not changed.

Let's implement the above logic, but first importing the usual suspect:

In [1]:
```
%matplotlib inline
!conda install -y xgboost
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

sns.set()
```

```
Solving environment: done


==> WARNING: A newer version of conda exists. <==
  current version: 4.5.12
  latest version: 4.6.11

Please update conda by running
```

```
    $ conda update -n base conda



## Package Plan ##

  environment location: /opt/conda

  added / updated specs:
    - xgboost


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    cryptography-2.6.1         |   py36h72c5cf5_0         606 KB  conda-fo
rge
    numpy-1.11.3               |py36he5ce36f_1207         3.6 MB  conda-fo
rge
    libblas-3.8.0              |       4_openblas           6 KB  conda-fo
rge
    libcblas-3.8.0             |       4_openblas           6 KB  conda-fo
rge
    libstdcxx-ng-8.2.0         |       hdf63c60_1         2.9 MB  defaults
    libgcc-ng-8.2.0            |       hdf63c60_1         7.6 MB  defaults
    pycurl-7.43.0.2            |   py36h1ba5d50_0         185 KB  defaults
    xgboost-0.82               |   py36he1b5a44_0           9 KB  conda-fo
rge
    blas-2.4                   |         openblas           6 KB  conda-fo
rge
    libcurl-7.64.1             |       hda55be3_0         584 KB  conda-fo
rge
    openssl-1.1.1b             |       h14c3975_1         4.0 MB  conda-fo
rge
    openblas-0.3.5             |    h9ac9557_1001        15.8 MB  conda-fo
rge
    libxgboost-0.82            |       he1b5a44_0         3.9 MB  conda-fo
rge
    krb5-1.16.3                |    h05b26f9_1001         1.4 MB  conda-fo
rge
    libopenblas-0.3.3          |       h5a2b251_3         7.6 MB  defaults
    libgfortran-ng-7.3.0       |       hdf63c60_0         1.3 MB  defaults
    scipy-1.1.0                |   py36he2b7bc3_2        17.7 MB  defaults
    scikit-learn-0.20.3        |   py36ha8026db_1         5.8 MB  conda-fo
rge
    liblapacke-3.8.0           |       4_openblas           6 KB  conda-fo
rge
    certifi-2019.3.9           |           py36_0         149 KB  conda-fo
rge
    py-xgboost-0.82            |   py36he1b5a44_0          70 KB  conda-fo
rge
    liblapack-3.8.0            |       4_openblas           6 KB  conda-fo
rge
    libssh2-1.8.2              |       h22169c7_2         257 KB  conda-fo
rge
    _py-xgboost-mutex-2.0      |            cpu_0           8 KB  conda-fo
```

```
rge
    ca-certificates-2019.3.9   |       hecc5488_0         146 KB  conda-fo
rge
    python-3.6.7               |    h381d211_1004        34.5 MB  conda-fo
rge
    ------------------------------------------------------------
                                           Total:       108.1 MB

The following NEW packages will be INSTALLED:

    _py-xgboost-mutex: 2.0-cpu_0                                     conda-forge
    libblas:           3.8.0-4_openblas                              conda-forge
    libcblas:          3.8.0-4_openblas                              conda-forge
    libgfortran-ng:    7.3.0-hdf63c60_0                              defaults
    liblapack:         3.8.0-4_openblas                              conda-forge
    liblapacke:        3.8.0-4_openblas                              conda-forge
    libopenblas:       0.3.3-h5a2b251_3                              defaults
    libxgboost:        0.82-he1b5a44_0                               conda-forge
    py-xgboost:        0.82-py36he1b5a44_0                           conda-forge
    xgboost:           0.82-py36he1b5a44_0                           conda-forge

The following packages will be UPDATED:

    blas:              1.1-openblas                                  conda-forge -
-> 2.4-openblas             conda-forge
    ca-certificates:   2018.11.29-ha4d7672_0                         conda-forge -
-> 2019.3.9-hecc5488_0      conda-forge
    certifi:           2018.11.29-py36_1000                          conda-forge -
-> 2019.3.9-py36_0          conda-forge
    cryptography:      2.3.1-py36hdffb7b8_0                          conda-forge -
-> 2.6.1-py36h72c5cf5_0     conda-forge
    krb5:              1.16.2-hbb41f41_0                             conda-forge -
-> 1.16.3-h05b26f9_1001     conda-forge
    libcurl:           7.63.0-hbdb9355_0                             conda-forge -
-> 7.64.1-hda55be3_0        conda-forge
    libgcc-ng:         7.2.0-hdf63c60_3                              conda-forge -
-> 8.2.0-hdf63c60_1         defaults
    libssh2:           1.8.0-h5b517e9_3                              conda-forge -
-> 1.8.2-h22169c7_2         conda-forge
    libstdcxx-ng:      7.2.0-hdf63c60_3                              conda-forge -
-> 8.2.0-hdf63c60_1         defaults
    openblas:          0.3.3-ha44fe06_1                              conda-forge -
-> 0.3.5-h9ac9557_1001      conda-forge
    openssl:           1.0.2p-h470a237_2                             conda-forge -
-> 1.1.1b-h14c3975_1        conda-forge
    pycurl:            7.43.0.2-py36hb7f436b_0                       defaults    -
-> 7.43.0.2-py36h1ba5d50_0  defaults
    python:            3.6.7-h5001a0f_1                              conda-forge -
-> 3.6.7-h381d211_1004      conda-forge
    scikit-learn:      0.20.2-py36_blas_openblash00c3548_400 conda-forge [
blas_openblas] --> 0.20.3-py36ha8026db_1    conda-forge

The following packages will be DOWNGRADED:

    numpy:             1.13.3-py36_blas_openblashb06ca3d_201 conda-forge [
blas_openblas] --> 1.11.3-py36he5ce36f_1207 conda-forge
    scipy:             1.1.0-py36_blas_openblashb06ca3d_202  conda-forge [
```

```
blas_openblas] --> 1.1.0-py36he2b7bc3_2     defaults


Downloading and Extracting Packages
cryptography-2.6.1   | 606 KB    | ##################################### | 
 100% 
numpy-1.11.3         | 3.6 MB    | ##################################### | 
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libblas-3.8.0        | 6 KB      | ##################################### | 
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libcblas-3.8.0       | 6 KB      | ##################################### | 
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libstdcxx-ng-8.2.0   | 2.9 MB    | ##################################### | 
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libgcc-ng-8.2.0      | 7.6 MB    | ##################################### | 
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pycurl-7.43.0.2      | 185 KB    | ##################################### | 
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xgboost-0.82         | 9 KB      | ##################################### | 
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blas-2.4             | 6 KB      | ##################################### | 
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libcurl-7.64.1       | 584 KB    | ##################################### | 
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openssl-1.1.1b       | 4.0 MB    | ##################################### | 
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openblas-0.3.5       | 15.8 MB   | ##################################### | 
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libxgboost-0.82      | 3.9 MB    | ##################################### | 
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krb5-1.16.3          | 1.4 MB    | ##################################### | 
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libopenblas-0.3.3    | 7.6 MB    | ##################################### | 
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libgfortran-ng-7.3.0 | 1.3 MB    | ##################################### | 
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scipy-1.1.0          | 17.7 MB   | ##################################### | 
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scikit-learn-0.20.3  | 5.8 MB    | ##################################### | 
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liblapacke-3.8.0     | 6 KB      | ##################################### | 
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certifi-2019.3.9     | 149 KB    | ##################################### | 
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py-xgboost-0.82      | 70 KB     | ##################################### | 
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liblapack-3.8.0      | 6 KB      | ##################################### | 
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libssh2-1.8.2        | 257 KB    | ##################################### | 
 100% 
_py-xgboost-mutex-2. | 8 KB      | ##################################### | 
 100% 
ca-certificates-2019 | 146 KB    | ##################################### | 
 100% 
python-3.6.7         | 34.5 MB   | ##################################### | 
 100% 
Preparing transaction: done
```

```
Verifying transaction: done
Executing transaction: done
```

In [2]:
```
from sklearn.cluster import KMeans
```

In [71]:
```
# Do some data cleanup
import pandas as pd

train = pd.read_csv('train.csv')

m = np.mean(train['trip_duration'])
s = np.std(train['trip_duration'])

train = train[train['trip_duration'] <= m + 2*s]
train = train[train['trip_duration'] >= m - 2*s]

train = train[train['pickup_longitude'] <= -73.9]
train = train[train['pickup_longitude'] >= -74.03]
train = train[train['pickup_latitude'] <= 40.85]
train = train[train['pickup_latitude'] >= 40.7]

inside = np.logical_and(np.logical_and(train['pickup_longitude'] >= -74.02
2, train['pickup_longitude'] <= -73.932),
                        np.logical_and(train['pickup_latitude'] >= 40.7, t
rain['pickup_latitude'] <= 40.815))

outside_start = np.logical_and(np.logical_and(train['pickup_longitude'] >=
 -73.97, train['pickup_longitude'] <= -73.93),
                               np.logical_and(train['pickup_latitude'] <=
40.74, train['pickup_latitude'] >= 40.70))

outside_start1 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -73.96 , train['pickup_longitude'] <= -73.93),
                                np.logical_and(train['pickup_latitude'] <=
40.75, train['pickup_latitude'] >=40.74))

outside_start2 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -73.95, train['pickup_longitude'] <= -73.93),
                                np.logical_and(train['pickup_latitude'] <=
 40.76, train['pickup_latitude'] >= 40.74))

outside_start3 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -73.94, train['pickup_longitude'] <= -73.92),
                                np.logical_and(train['pickup_latitude'] <=
 40.78, train['pickup_latitude'] >= 40.74))

outside_start4 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -74.02, train['pickup_longitude'] <= -74.01),
                                np.logical_and(train['pickup_latitude'] <=
 40.79, train['pickup_latitude'] >= 40.77))

outside_start5 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -73.975, train['pickup_longitude'] <= -73.965),
                                np.logical_and(train['pickup_latitude'] <=
 40.715, train['pickup_latitude'] >= 40.705))
```

```
outside_start6 = np.logical_and(np.logical_and(train['pickup_longitude'] >
= -73.955, train['pickup_longitude'] <= -73.945),
                                np.logical_and(train['pickup_latitude'] <=
 40.755, train['pickup_latitude'] >= 40.745))


outside = [not c for c in outside_start]
outside1 = [not c for c in outside_start1]
outside2 = [not c for c in outside_start2]
outside3 = [not c for c in outside_start3]
outside4 = [not c for c in outside_start4]
outside5 = [not c for c in outside_start5]
outside6 = [not c for c in outside_start6]

both = np.logical_and(np.logical_and(np.logical_and(np.logical_and(np.logi
cal_and(np.logical_and(np.logical_and(inside, outside),outside1),outside2)
,outside3),outside4),outside5),outside6)

#mask = ((np.logical_and(40.7 <= train['pickup_latitude'], train['pickup_l
atitude']<=40.85)) & (np.logical_and(-74.022<=train['pickup_longitude'], t
rain['pickup_longitude'] <=-73.932)))
#train = train[train['dropoff_longitude'] <= -73.75]
#train = train[train['dropoff_longitude'] >= -74.03]
#train = train[train['dropoff_latitude'] <= 40.85]
#train = train[train['dropoff_latitude'] >= 40.63]

all(inside)
all(outside)
#mlat = np.ma.masked_where(train['pickup_latitude'],train['pickup_longitud
e'], ~mask)
#mlon = np.ma.masked_where(train['pickup_longitude'], ~mask)

data = []
mlat = train['pickup_latitude'][both]
mlatc = mlat.values

mlon = train['pickup_longitude'][both]
mlonc = mlon.values

dlat = train['dropoff_latitude'][both]
dlatc = dlat.values

dlon = train['dropoff_longitude'][both]
dlonc = dlon.values

mtrip = train['trip_duration'][both]
mtripc = mtrip.values

train['pickup_datetime'] = pd.to_datetime(train.pickup_datetime)
train['Hour'] = train['pickup_datetime'].dt.hour
mhour = train['Hour'][both]
mhourc = mhour.values

data = {"plon": mlonc, "plat": mlatc, "dlon": dlonc, "dlat": dlatc, "tripd
": mtripc, "hour": mhourc}
df = pd.DataFrame(data)
```

```
#chk = 0
#for i in inside:
#    if i == False:
#        print(chk)
#    chk +=1
#mlat
```

In [72]:
```
# Some new datetime-related fields
#train['pickup_datetime'] = pd.to_datetime(train.pickup_datetime)
#pickup_date = train['pickup_datetime'].dt.date
#train['dropoff_datetime'] = pd.to_datetime(train.dropoff_datetime)
```

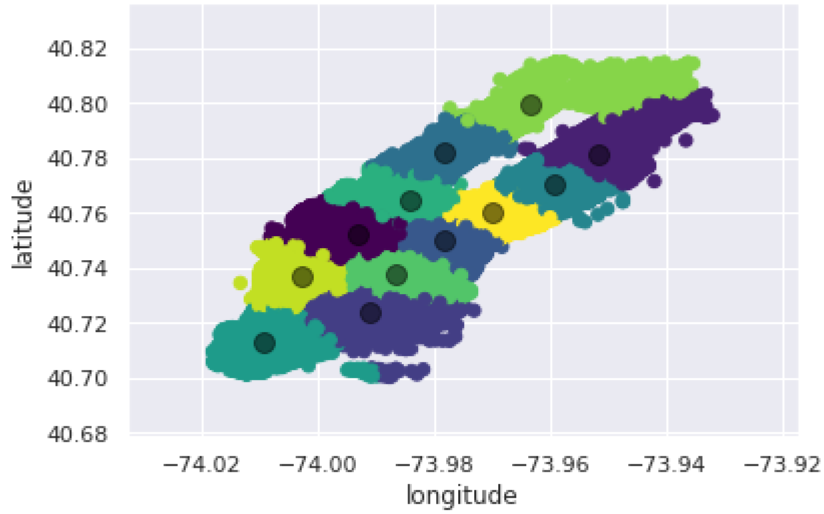
In [73]:
```
# Time-related fields
#train['Month'] = train['pickup_datetime'].dt.month
#train['DayofMonth']  =  train['pickup_datetime'].dt.day
#train['Hour'] = train['pickup_datetime'].dt.hour
#train['dayofweek'] = train['pickup_datetime'].dt.dayofweek
#mhour = train['Hour'][both]
#mhourc = mhour.values
```

In [74]:
```
# Part 1. Predict trip duration using clusetered pickup locations
# Fit the pickup locations
#stack = np.hstack((train[['pickup_longitude']].values, train[['pickup_lat
itude']].values))
stack = np.hstack((df[['plon']].values, df[['plat']].values))
kmNyc = KMeans(n_clusters=12).fit(stack[0:100000])
```

In [75]:
```
# Predict the pickup locations
c = []
c = kmNyc.predict(stack[0:100000])
```

In [76]:
```
# Predict the clusters and get the cluster centroids
centers = kmNyc.cluster_centers_

plt.scatter(df['plon'][:100000], df['plat'][:100000], c=c, s=40, cmap='vir
idis')
plt.scatter(centers[:, 0], centers[:, 1], c='black', s=100, alpha=0.5);
plt.xlabel('longitude')
plt.ylabel('latitude')
```

Out[76]:
```
Text(0,0.5,'latitude')
```



In [77]:
```
# Predict trip duration using clustered pickup locations
X = pd.DataFrame(c)
y = df['tripd'][:100000]
dfc = pd.concat([X,y], axis=1)
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2,
 random_state=42)

xgb_model = xgb.XGBRegressor(n_estimators=150, max_depth=7)

xgb_model.fit(X_train, y_train)
```

```
/opt/conda/lib/python3.6/site-packages/xgboost/core.py:587: FutureWarning:
 Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
```

Out[77]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=7,
       min_child_weight=1, missing=None, n_estimators=150, n_jobs=1,
       nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
```

In [78]:
```
y_pred = xgb_model.predict(X_valid)
r2_score(y_pred=y_pred, y_true=y_valid)
```

Out[78]:
```
0.01202834774432826
```

In [79]:
```
xv = pd.DataFrame(X_valid.values,columns=['cluster'])
yp = pd.DataFrame(y_pred, columns=['trip_duration'])

submission = pd.concat([xv, yp], axis=1)

#submission = pd.DataFrame(X_valid)
#submission = pd.DataFrame(columns=['cluster', 'trip_duration'])
#submission.columns = ['cluster']
#submission['trip_duration'] = submission.apply(lambda x : 1 if (x['trip_d
uration'] <= 0) else x['trip_duration'], axis = 1)
#submission['cluster'] = xw1
#submission['trip_duration'] = pd.DataFrame(y_pred)
```

```
#submission.reindex(columns=['cluster', 'trip_duration'])
#submission_plocs.csv', index=False)

sv = submission.values

cluster_ptr = 0
got_clusters = [0,0,0,0,0,0,0,0,0,0,0,0]
seen_clusters = 0
while seen_clusters < 12:
    this_cluster = sv[int(cluster_ptr)][0]
    #print (this_cluster)
    if got_clusters[int(this_cluster)] != 0:
        cluster_ptr += 1
        continue
    else:
        seen_clusters += 1
        got_clusters[int(this_cluster)] = sv[int(cluster_ptr),1]
        cluster_ptr += 1

ptr = 1
print('Trip duration predictions')
for cluster in got_clusters:
    print ('Cluster ' + str(ptr) + ',  prediction (seconds) is: ' + str(go
t_clusters[ptr-1]))
    ptr +=1
```

```
Trip duration predictions
Cluster 1,  prediction (seconds) is: 785.680175781
Cluster 2,  prediction (seconds) is: 699.84588623
Cluster 3,  prediction (seconds) is: 820.612854004
Cluster 4,  prediction (seconds) is: 763.333312988
Cluster 5,  prediction (seconds) is: 703.61328125
Cluster 6,  prediction (seconds) is: 707.730834961
Cluster 7,  prediction (seconds) is: 975.529968262
Cluster 8,  prediction (seconds) is: 827.174743652
Cluster 9,  prediction (seconds) is: 748.714782715
Cluster 10,  prediction (seconds) is: 726.602172852
Cluster 11,  prediction (seconds) is: 776.711853027
Cluster 12,  prediction (seconds) is: 738.001586914
```

In [80]:
```
# Part 2. Predict trip duration using pickup hour...using just pickup hour
 (this is extra)
hour_stack = np.hstack((df[['hour']].values))
hs = hour_stack[0:100000].reshape(-1,1)
kmNych = KMeans(n_clusters=6).fit(hs)
```

In [81]:
```
ch = kmNych.predict(hs)
ch
```

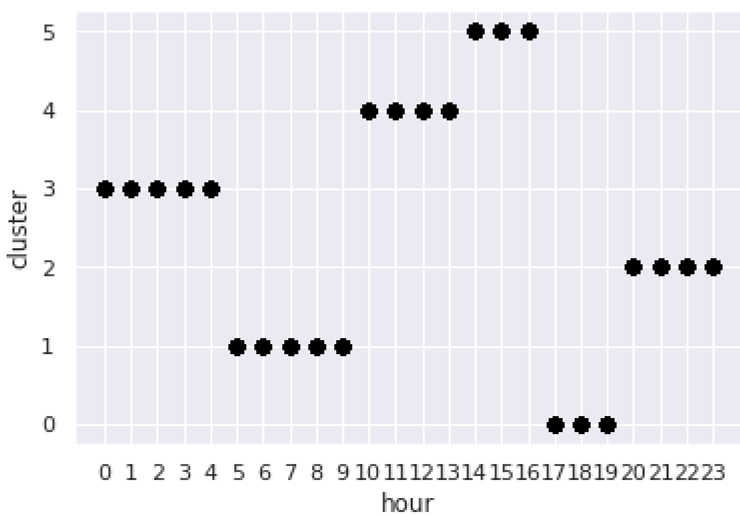
Out[81]:
```
array([0, 3, 4, ..., 4, 2, 2], dtype=int32)
```

In [82]:
```
# Plot the aspatial hour clusters
centers = kmNych.cluster_centers_

fig, ax = plt.subplots()
plt.scatter(hour_stack[:100000], ch, c='black', s=40, cmap='viridis')
```

```
plt.xlabel('hour')
plt.ylabel('cluster')
ind = np.arange(24)
ax.set_xticks(ind)
indy = np.arange(6)
ax.set_yticks(indy)
#plt.scatter(centers[:, 0], centers[:, 1], c='black', s=100, alpha=0.5);
#centers
```

Out[82]:

```
[<matplotlib.axis.YTick at 0x7fb076515b38>,
 <matplotlib.axis.YTick at 0x7fb0765153c8>,
 <matplotlib.axis.YTick at 0x7fb0a8a70fd0>,
 <matplotlib.axis.YTick at 0x7fb0b040be10>,
 <matplotlib.axis.YTick at 0x7fb0a15a2358>,
 <matplotlib.axis.YTick at 0x7fb0a15a2860>]
```



In [83]:

```
# Part 2. Predict trip duration using hour and spatial
hour_stack = np.hstack((df[['plon']].values, df[['plat']].values, df[['hou
r']].values))
kmNych = KMeans(n_clusters=6).fit(hour_stack)
```

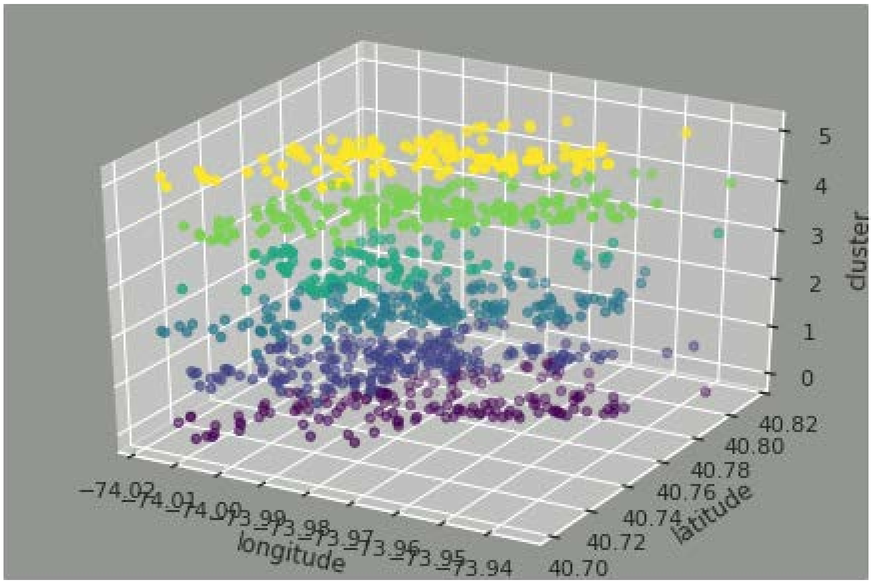
In [84]:

```
ch = kmNych.predict(hour_stack)
ch.size
chs = ch[0:1000]
```

In [85]:

```
# Plot the clusters
centers = kmNych.cluster_centers_
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = Axes3D(fig)

# Plot the clusters
platp = df['plat'][0:1000]
plonp = df['plon'][0:1000]

ax.scatter(plonp,platp,chs,c=chs,cmap='viridis')
ax.set_xticks([-74.02, -74.01, -74.0,-73.99,-73.98,-73.97, -73.96, -73.95,
 -73.94])
ax.set_yticks([40.7,40.72, 40.74, 40.76, 40.78, 40.8, 40.82])
```

```
ax.set_zticks([0,1,2,3,4,5])
ax.set_facecolor('xkcd:gray')
plt.xlabel('longitude')
plt.ylabel('latitude')
ax.set_zlabel('cluster')

#plt.scatter(centers[:, 0], centers[:, 1], c='black', s=100, alpha=0.5);

plt.show()
```



In [86]:
```
# Predict trip duration using clustered pickup hours
X = pd.DataFrame(ch[0:100000])
y = df['tripd']
X_train, X_valid, y_train, y_valid = train_test_split(X[0:100000], y[0:100000], test_size=0.2, random_state=42)

xgb_model = xgb.XGBRegressor(n_estimators=150, max_depth=7)

xgb_model.fit(X_train, y_train)
```

```
/opt/conda/lib/python3.6/site-packages/xgboost/core.py:587: FutureWarning:
 Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
```

Out[86]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=7,
       min_child_weight=1, missing=None, n_estimators=150, n_jobs=1,
       nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
```

In [87]:
```
y_pred = xgb_model.predict(X_valid)
r2_score(y_pred=y_pred, y_true=y_valid)
```

Out[87]: 0.0053549607916627551

In [88]:
```
xv = pd.DataFrame(X_valid.values,columns=['cluster'])
```

```
yp = pd.DataFrame(y_pred, columns=['trip_duration'])

submission = pd.concat([xv, yp], axis=1)

#submission = pd.DataFrame(X_valid)
#submission = pd.DataFrame(columns=['cluster', 'trip_duration'])
#submission.columns = ['cluster']
#submission['trip_duration'] = submission.apply(lambda x : 1 if (x['trip_d
uration'] <= 0) else x['trip_duration'], axis = 1)
#submission['cluster'] = xw1
#submission['trip_duration'] = pd.DataFrame(y_pred)
#submission.reindex(columns=['cluster', 'trip_duration'])
#submission_plocs.csv', index=False)

sv = submission.values

cluster_ptr = 0
got_clusters = [0,0,0,0,0,0]
seen_clusters = 0
while seen_clusters < 6:
    this_cluster = sv[int(cluster_ptr)][0]
    #print (this_cluster)
    if got_clusters[int(this_cluster)] != 0:
        cluster_ptr += 1
        continue
    else:
        seen_clusters += 1
        got_clusters[int(this_cluster)] = sv[int(cluster_ptr),1]
        cluster_ptr += 1

ptr = 1
print('Trip duration predictions')
for cluster in got_clusters:
    print ('Cluster ' + str(ptr) + ',  prediction (seconds) is: ' + str(go
t_clusters[ptr-1]))
    ptr +=1
```

```
Trip duration predictions
Cluster 1,  prediction (seconds) is: 715.129577637
Cluster 2,  prediction (seconds) is: 746.629821777
Cluster 3,  prediction (seconds) is: 850.156677246
Cluster 4,  prediction (seconds) is: 712.217773438
Cluster 5,  prediction (seconds) is: 784.090759277
Cluster 6,  prediction (seconds) is: 805.316467285
```

In [89]:

```
#plat = train['pickup_latitude'].values
#plon = train['pickup_longitude'].values

#dlat = train['dropoff_latitude'].values
#dlon = train['dropoff_longitude'].values
#trip_duration = train['trip_duration'].values
```

In [90]:

```
#train['Month'] = train['pickup_datetime'].dt.month
#train['DayofMonth']  =  train['pickup_datetime'].dt.day
#train['Hour'] = train['pickup_datetime'].dt.hour
#train['dayofweek'] = train['pickup_datetime'].dt.dayofweek
```

In [91]:
```
# Part 3. Find similar Manhattan routes
def haversine(lat1, lon1, lat2, lon2):
    lat1, lon1, lat2, lon2 = map(np.radians, (lat1, lon1, lat2, lon2))
    AVG_EARTH_RADIUS = 6371
    lat = lat2 - lat1
    lon = lon2 - lon1
    d = np.sin(lat*0.5) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(lon*0.
5) ** 2
    h = 2 * AVG_EARTH_RADIUS * np.arcsin(np.sqrt(d))
    return h
df['hdist'] = haversine(df['plat'], df['plon'], df['dlat'], df['dlon'])
hdist = df['hdist'].values
```

In [92]:
```
#coords = np.hstack((train[['pickup_latitude']].values,
#                    train[['pickup_longitude']].values,
#                    train[['dropoff_latitude']].values,
#                    train[['dropoff_longitude']].values,
#                    train[['passenger_count']].values,
#                    train[['vendor_id']].values,
#                    train[['Month']].values,
#                    train[['DayofMonth']].values,
#                    train[['Hour']].values,
#                    train[['dayofweek']].values,
#                    train[['trip_duration']].values))
coords = np.hstack((df[['plat', 'plon']].values,
                    df[['dlat', 'dlon']].values,
                    df[['hdist']].values))
                    #train[['trip_duration']].values))
                    #train[['vendor_id']].values,
                    #train[['passenger_count']].values,
                    #train[['Month']].values,
                    #train[['DayofMonth']].values,
                    #train[['Hour']].values,
                    #train[['dayofweek']].values))
```

In [93]:
```
sample_ind = np.random.permutation(len(coords))[:100000]
kmNycR = KMeans(n_clusters=12).fit(coords[sample_ind])
```

In [57]:
```
#pickup_cluster = kmNycR.predict(train[['pickup_latitude', 'pickup_longitu
de']])
#dropoff_cluster = kmNycR.predict(train[['dropoff_latitude', 'dropoff_long
itude']])
```

In [94]:
```
cR = kmNycR.predict(coords[sample_ind])
```

In [95]:
```
cR.size
```

Out[95]: 100000

In [96]:
```
from sklearn.metrics import silhouette_samples, silhouette_score
ss_values = silhouette_score(coords[sample_ind],cR)
```

In [97]:
```
ss_values
```

Out[97]: 0.51800246658393179

In [98]:

```
# Get data for similar Manhattan routes...this data will be used to create
 a feature class suitable for display in ArcGis Pro
f = open("coords.txt", "w")

hdist = df['hdist']
plat = df['plat']
plon = df['plon']
dlat = df['dlat']
dlon = df['dlon']
trip_duration = df['tripd']

max_iter = 100000
num_iter = 0
label_ctr = 0
max_label = 499
label = 1

label_ptr = 0

while num_iter < max_iter:
    if cR[num_iter] == label:
        if hdist[sample_ind[num_iter]] == 0.0:
            num_iter += 1
            continue

        #print (num_iter)
        #print(label)
        #print(label_ptr)

        label_ptr += 1

        f.write(str(plat[sample_ind[num_iter]]) + " " + str(plon[sample_in
d[num_iter]]) + " " + str(dlat[sample_ind[num_iter]]) + " " + str(dlon[sam
ple_ind[num_iter]]) + " " + str(trip_duration[sample_ind[num_iter]]) + "\n
")
        label_ctr += 1
        if label_ctr > max_label:
            break
    num_iter += 1

f.close()
```