A3

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0.0.1 Name: Binben Wang

0.0.2 NSID: biw123

In [1]:
```
import os
import folium
import numpy as np
import pandas as pd
import pyproj as pj
import math
from folium.plugins import HeatMap
from collections import Counter
import matplotlib
import matplotlib.pyplot as plt
from scipy.ndimage.interpolation import shift
import scipy.stats as stats
import pylab as pl
import networkx as nx
import itertools

%matplotlib inline
%config InlineBackend.figure_format = 'retina'
```

1 STEP 1: Preparation

In [2]:
```
# gps.csv contains five features: user_id, record_time, latitude, longitude, accu
gps_df = pd.read_csv("../A1/gps.csv")
# battery.csv contains two features: user_id, record_time
battery_df = pd.read_csv("../A1/battery.csv")
```

In [3]:
```
# latitude and longitude of saskatoon center
lat_center_saskatoon = (52.058367 + 52.214608) / 2
lon_center_saskatoon = (-106.7649138128 - 106.52225318) / 2
```

In [4]:
```
# calculate number of total possible battery records per particiants
battery_df.record_time = battery_df.record_time.astype('datetime64')
time_interval = battery_df.record_time.max() - battery_df.record_time.min()
num_total_possible_records = np.ceil(time_interval.total_seconds() / 300)
```

In [5]:
```
# calculate the number of all battery records per user.
battery_counts_df = battery_df.groupby(['user_id']).size().reset_index(name='counts')
```

In [6]:
```
# filter battery dataframe in 50% threshold
fifty_user_df = battery_counts_df[battery_counts_df.counts >= num_total_possible_record
```

In [7]:
```
analysis_gps_df = gps_df[(gps_df.lat <= 52.214608) & (gps_df.lat >= 52.058367) & (gps_d
```

In [8]:
```
# drop the accu column, it is useless now
analysis_gps_df = analysis_gps_df.drop(columns=['accu'])
```

In [9]:
```
# calculate the minimum timestamp of all records
analysis_gps_df.record_time = analysis_gps_df.record_time.astype('datetime64')
min_timestamp = analysis_gps_df.record_time.min()
```

In [10]:
```
# convert record_time to relative_time by duty cycle
analysis_gps_df.loc[:, 'relative_time'] = np.floor((analysis_gps_df.record_time - min_
```

In [11]:
```
analysis_gps_df = analysis_gps_df.groupby(['user_id', 'relative_time']).mean().reset_i
```

In [12]:
```
# transfer latitude and longitude coordinates to UTM coordinates
p1 = pj.Proj(init='epsg:32613')
x, y = p1(analysis_gps_df.lon.values.tolist(), analysis_gps_df.lat.values.tolist())
analysis_gps_df.loc[:, 'x'] = x
analysis_gps_df.loc[:, 'y'] = y
```

In [13]:
```
# calculate the start and end coordinates in UTM for the greater Saskatoon area
start_x, start_y = p1(-106.7649138128, 52.058367)
end_x, end_y = p1(-106.52225318, 52.214608)
```

In [14]:
```
# convert UTM coordinates into grid coordinates
def which_grid(x, y, start_x, start_y, step):
    which_grid_x = np.floor((x - start_x) / step)
    which_grid_y = np.floor((y - start_y) / step)

    # in case UTM coordinates in the boundary of the greater Saskatoon area
    # there are some -1 value appearing
    # set all -1 to 0
    which_grid_x[which_grid_x < 0] = 0
    which_grid_y[which_grid_y < 0] = 0

    return(which_grid_x, which_grid_y)
```

In [15]:
```
analysis_gps_df.loc[:, 'grid_x'], analysis_gps_df.loc[:, 'grid_y'] = which_grid(analys
```

In [16]:
```
#convert datatype from float64 to int
analysis_gps_df.grid_x = analysis_gps_df.grid_x.astype('int')
analysis_gps_df.grid_y = analysis_gps_df.grid_y.astype('int')
```

In [17]:
```
# Convert grid coordinates back to lat and lon coordinates
temp_x = (analysis_gps_df.grid_x + 0.5) * 100 + start_x
temp_y = (analysis_gps_df.grid_y + 0.5) * 100 + start_y
temp_x[temp_x > end_x] = end_x
temp_y[temp_y > end_y] = end_y

analysis_gps_df.lon, analysis_gps_df.lat = p1(temp_x.tolist(), temp_y.tolist(), invers
```

In [18]:
```
# drop columns: x, y
analysis_gps_df = analysis_gps_df.drop(columns=['x', 'y'])
```

In [19]:
```
analysis_gps_df.describe()
```

Out[19]:
```
             user_id  relative_time            lat            lon  \
count  249551.000000  249551.000000  249551.000000  249551.000000
mean     1070.807278   21323.029012      52.127024    -106.632350
std       266.220713    2495.364820       0.012796       0.035082
min       514.000000       0.000000      52.059410    -106.764007
25%       943.000000   19150.000000      52.121852    -106.639831
50%      1052.000000   21365.000000      52.125467    -106.633891
75%      1315.000000   23478.000000      52.131959    -106.629740
max      1364.000000   25706.000000      52.212823    -106.523774

              grid_x         grid_y
count  249551.000000  249551.000000
mean       92.095195      73.736551
std        23.998870      14.266732
min         2.000000       0.000000
25%        87.000000      68.000000
50%        91.000000      72.000000
75%        94.000000      80.000000
max       167.000000     171.000000
```

2 STEP 2: Find collocation

In [20]:
```
at_same_grid = pd.DataFrame()
valid_relative_time = []

for i in range(analysis_gps_df.relative_time.max() + 1):
    temp = analysis_gps_df[analysis_gps_df.relative_time == i]

    if (len(temp.user_id.unique()) >= 2) and (temp.groupby(['grid_x', 'grid_y']).size
        valid_relative_time.append(i)
        at_same_grid = at_same_grid.append(pd.concat(g for _, g in temp.groupby(['gric
```

In [21]:
```
users = at_same_grid.user_id.unique().tolist()
users.sort()
```

```
# create two dictionaries of user_id and matrix indexes
user_id_and_index = dict()
index_and_user_id = dict()

for i in range(len(users)):
    user_id_and_index[users[i]] = i
    index_and_user_id[i] = users[i]
```

In [24]:
```
pairs_df = at_same_grid.groupby(['relative_time','grid_x', 'grid_y'])['user_id'].uniq
```

In [273]:
```
pairs_df.head(10)
```

Out[273]:

	relative_time	grid_x	grid_y	user_id
0	16946	91	71	[1052, 1297]
1	16958	90	75	[793, 1323]
2	16961	90	75	[793, 1323]
3	16963	92	70	[1288, 1308]
4	16965	91	70	[1052, 1297]
5	16966	92	70	[1288, 1297]
6	16970	60	68	[514, 551]
7	16971	60	68	[514, 551]
8	16975	92	70	[1288, 1297, 1308]
9	16983	89	78	[975, 1299]

3 STEP 3: Make a graph

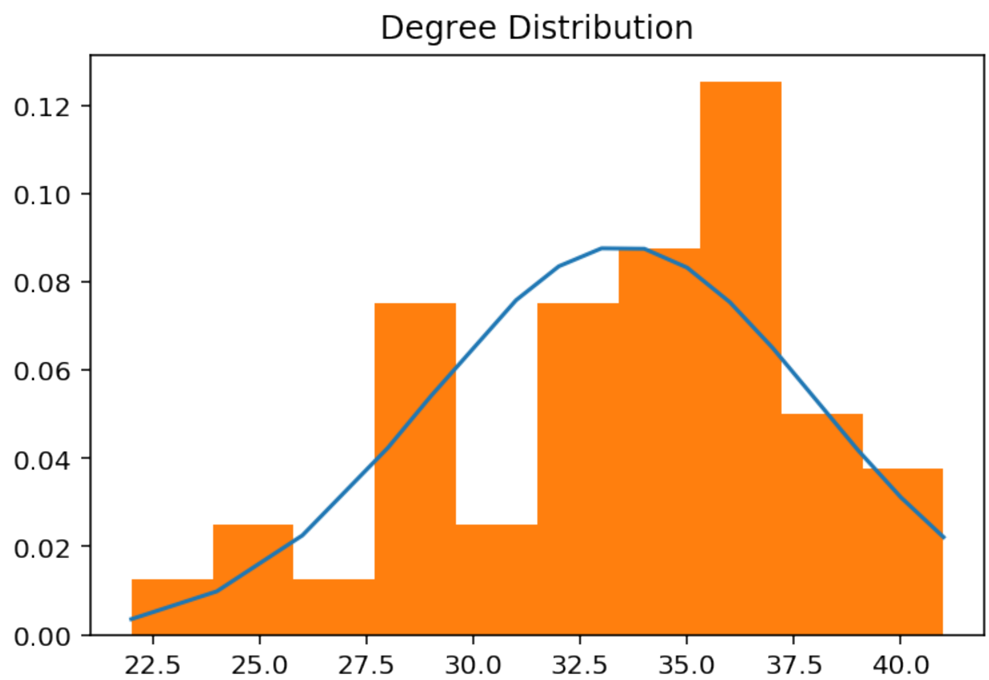
In [25]:
```
mat = np.zeros([len(users), len(users)])

for i in range(len(pairs_df.user_id.tolist())):
    users_same_grid_and_time = pairs_df.user_id.tolist()[i].tolist()
    pairs = itertools.permutations(users_same_grid_and_time, 2)

    for pair in pairs:
        mat[user_id_and_index[pair[0]], user_id_and_index[pair[1]]] = mat[user_id_and_
```

In [41]:
```
# construct and plot the degree distribution
degrees = (1 * (mat != 0)).sum(axis=0)

h_1 = sorted(degrees)
fit = stats.norm.pdf(h_1, np.mean(h_1), np.std(h_1))
pl.plot(h_1,fit)
pl.hist(h_1,density=True, alpha=1)
pl.title("Degree Distribution")
pl.show()
```




```
In [272]: print("minimum degree: " + str(h_1[0]))
          print("maximum degree: " + str(h_1[41]))
          print("mean: " + str(np.mean(h_1)))
          print("standard deviation: " + str(np.std(h_1)))
```

```
minimum degree: 22
maximum degree: 41
mean: 33.476190476190474
standard deviation: 4.526315095601631
```

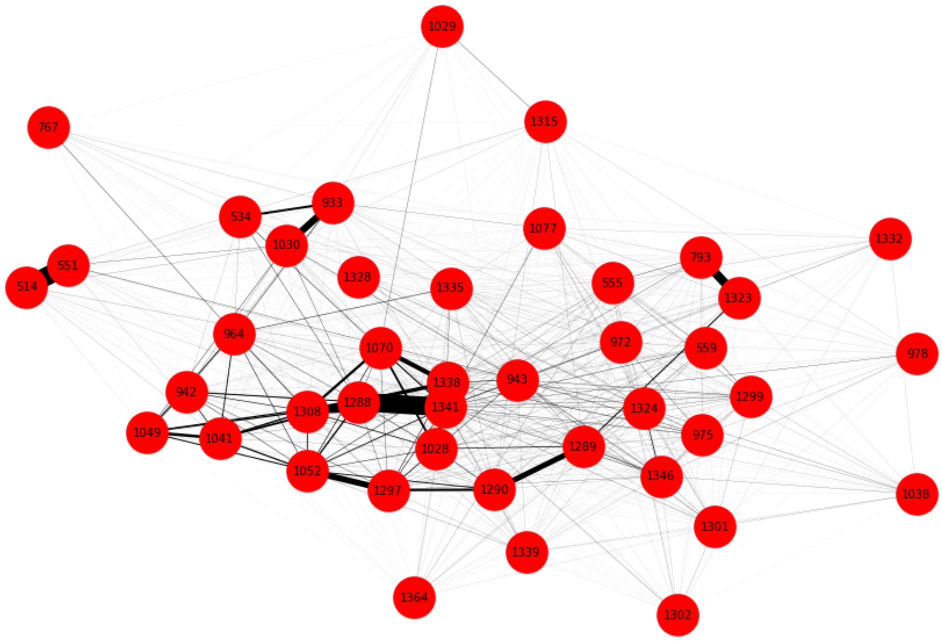
3.0.1 Note degree distribution's shape, and likely statistical properties.

The minimum degree of all nodes is 22. And the maximum degree of all nodes is 41. We can see that the number of degree first increases as degree incresing and then decreases. So the shape of degree distribution is a bell, which is perfect for Gaussian distribution. The mean of this Gaussian distribution is 33.5 and the standard deviation of this distribution is 4.5.

```
In [43]: # normalize the graph
         mat = mat / len(at_same_grid.relative_time.unique())
```

```
In [60]: # create a graph by numpy matrix
         G = nx.from_numpy_matrix(mat)
         # relabel the graph
         G2 = nx.relabel_nodes(G, index_and_user_id)
```

```
In [265]: edges = G2.edges()
          weights = [G2[u][v]['weight'] for u,v in edges]
          # Use a parameter scale_up to enlarge edge weights. You can set it 1 to see orginal 
          scale_up = 20
          nx.draw(G2, pos, font_size = 5, with_labels = True, edges=edges, width=(np.array(wei
```



3.0.2 Describe the contact patterns

When we set $scale\_up = 1$, we can barely see edges in the graph. So I set $scale\_up = 20$ to scale weights up. We can see that most of edges in this graph is also very faint, which means they have small weights. Also, we can see that the edge between 514 and 551, the edge between 1288 and 1341 have the two largest weights. So we know that although participants met a lot of other participants randomly and rarely, only small number of participants have regular meeting with other participants.

4 STEP 4: Centrality

```
In [130]: # calcuate the degree of each node
          degree = dict(nx.degree(G2))
```

```
In [128]: # calculate the betweenness of each node
          betweenness = nx.betweenness_centrality(G2)
```

In [124]:
```
# calculate the eigenvector centrality of each node
centrality = nx.eigenvector_centrality(G2)
```

In [138]:
```
degree_df = pd.DataFrame.from_dict(degree, orient='index', columns=['degree'])
betweenness_df = pd.DataFrame.from_dict(betweenness, orient='index', columns=['betwe
centrality_df = pd.DataFrame.from_dict(centrality, orient='index', columns=['centrali
```

In [143]:
```
node_attri_df = pd.merge(degree_df, betweenness_df, left_index=True, right_index=True
```

In [145]:
```
node_attri_df = pd.merge(node_attri_df, centrality_df, left_index=True, right_index=
```

In [251]:
```
node_attri_df.sort_values(by=['betweenness'], inplace=True)
```

In [255]:
```
node_attri_df
```

Out[255]:

	degree	betweenness	centrality
1332	26	0.001282	0.123582
767	22	0.001920	0.101170
978	29	0.001964	0.137111
551	24	0.002137	0.109443
1038	29	0.002258	0.135804
1290	29	0.002579	0.135077
1049	28	0.002704	0.129438
1029	24	0.002817	0.107055
1323	34	0.003407	0.157823
1308	31	0.003438	0.142690
1328	29	0.003685	0.132330
1052	33	0.003712	0.152529
1289	32	0.003722	0.147398
1364	31	0.003815	0.142619
1288	35	0.003953	0.161954
514	28	0.004049	0.125704
1346	36	0.004089	0.166467
1077	33	0.004141	0.151386
1335	35	0.004333	0.161149
1301	34	0.004351	0.155962
1070	32	0.004433	0.146643
1028	36	0.004467	0.165823
559	35	0.004530	0.160839
1297	36	0.004586	0.165602
975	36	0.004757	0.165363
534	34	0.004944	0.154994
964	36	0.005113	0.164423
1030	35	0.005331	0.159035
1315	33	0.005386	0.149006
1302	33	0.005409	0.148794
1338	38	0.005626	0.173528
942	36	0.005945	0.162706
1324	37	0.006029	0.167562

```
1339      37     0.006132    0.167624
555       36     0.006148    0.162607
1299      39     0.006208    0.177281
1341      39     0.006322    0.177113
933       37     0.006653    0.166716
943       40     0.007207    0.180402
1041      38     0.007230    0.170292
793       40     0.007398    0.180235
972       41     0.008472    0.183288
```

4.0.1 Describe three inconsistencies in the ordering of nodes between the different centrality measures by referring to the definitions of those centralities.

1. node 1052: This node is on the margin of the graph. So based on the definition of betweenness centrality, it's betweenness is relatively low. But it connects to some important nodes, it's eigenvector centnrality is relatively high.
2. node 943: This nodes connects to node 972, the most important node. And the connected edge's weight is not too small. So it's eigenvector centnrality is relatively high.
3. node 551: It's degree is very small but has a relatively large betweenness centrality because it has a strong edge with node 514. So many shortest paths have cross this edge.

5 STEP 4: Cluster

```
In [241]: c = list(nx.algorithms.community.modularity_max.greedy_modularity_communities(G2))

In [242]: c

Out[242]: [frozenset({514}),
           frozenset({534}),
           frozenset({551}),
           frozenset({555}),
           frozenset({559}),
           frozenset({767}),
           frozenset({793}),
           frozenset({933}),
           frozenset({942}),
           frozenset({943}),
           frozenset({964}),
           frozenset({972}),
           frozenset({975}),
           frozenset({978}),
           frozenset({1028}),
           frozenset({1029}),
           frozenset({1030}),
           frozenset({1038}),
           frozenset({1041}),
           frozenset({1049}),
           frozenset({1052}),
```

```
frozenset({1070}),
frozenset({1077}),
frozenset({1288}),
frozenset({1289}),
frozenset({1290}),
frozenset({1297}),
frozenset({1299}),
frozenset({1301}),
frozenset({1302}),
frozenset({1308}),
frozenset({1315}),
frozenset({1323}),
frozenset({1324}),
frozenset({1328}),
frozenset({1332}),
frozenset({1335}),
frozenset({1338}),
frozenset({1339}),
frozenset({1341}),
frozenset({1346}),
frozenset({1364})]
```

5.0.1 What community structure did the algorithm create?

From the variable c in above, we can see that each node in this graph forms it's own community. ### How does this relate to what you observed in steps 3 and 4? If we set $scale\_up = 1$ of graph visualization in step 3, we barely can see edges in the graph. Also from the table in step 4, the maximum betweenness of all nodes is 0.008472 and the maximum centrality of all nodes is 0.183288. So even all nodes have a high degree, they still cannot form communities with other nodes.