Medford Disaster Router

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In [1]:

```
# Function imports
import numpy as np
import pandas as pd
import networkx as nx
import osmnx as ox
import geopandas as gpd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as colors

ox.config(use_cache=True, log_console=True)
ox.__version__

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

1. Problem Statement

1) Build a NLP model identifies road closures based on in social media

2) Use Google maps to chart travel based on different times of day

3) Translate "bad traffic areas" as flaged map locations

4) Simulate a natural disaster that destroys roads

5) Reflect the affected roads into a map in red color

6) Produce a map of valid rescue roads/escape routes

7) Optimize dispatch for police and rescue

2. Data Collection/Import Medford

Basic information about an importated city. Due to my site specific knowledge, I decided to protoype this model on the city of Medford. Other city disasters will be investigated. I-93 was removed from the road network to simplify the initial analysis.

In [2]:
```
# get a graph for some city
place = {'city' : 'Medford',
         'state' : 'MA',
         'country' : 'USA'}


medford = ox.graph_from_place(place, network_type='bike')
fig, ax = ox.plot_graph(medford)
```

In [14]:
```python
# what sized area does our network cover in square meters?
medford_proj = ox.project_graph(medford)
nodes_proj = ox.graph_to_gdfs(medford_proj, edges=False)
graph_area_m = nodes_proj.unary_union.convex_hull.area
print(graph_area_m)

# show basic stats about the network
medford_stats = ox.basic_stats(medford_proj,
                               area=graph_area_m,
                               clean_intersects=True,
                               circuity_dist='euclidean')

# medford_stats = ox.extended_stats(medford_proj, ecc=True, bc=True, cc=
True)

pd.DataFrame(medford_stats).set_index("streets_per_node_counts")
```

```
24864732.339954104
```

Out[14]:

	n	m	k_avg	intersection_count	streets_per_node_avg	streets_
streets_per_node_counts						
0	3098	7856	5.071659	2662	2.854099	
436	3098	7856	5.071659	2662	2.854099	
14	3098	7856	5.071659	2662	2.854099	
2230	3098	7856	5.071659	2662	2.854099	
402	3098	7856	5.071659	2662	2.854099	
16	3098	7856	5.071659	2662	2.854099	

In [15]:
```python
# Edge and Node projection
nodes_med, edges_med = ox.graph_to_gdfs(medford, nodes=True, edges=True)
```

In [16]:
```python
nodes_med.head(2)
```

Out[16]:

	highway	osmid	ref	x	y	geometry
66478081	turning_circle	66478081	NaN	-71.100780	42.429287	POINT (-71.1007798 42.4292871)
1754021893	NaN	1754021893	NaN	-71.110187	42.426412	POINT (-71.11018660000001 42.4264119)

In [17]:
```python
nodes_med.shape
```

Out[17]:
```
(3098, 6)
```

2a. Major Roads Functions

To avoid cluttering up the notebook, all major functions have been exported into the "graph_functions.py" python file. See this file for futher information.

In [18]:
```
#Functions built for this project
# %load graph_functions.py

import graph_functions as gf
```

The "node_roader" function returns a data dictionary of the essential information from a plotted object.

In [19]:
```
medford_data = gf.node_roader(medford)
```

```
5         nodes in      MA 38;MA 60     colored         lightsteelblue
18        nodes in      MA 16;MA 38     colored         crimson
155       nodes in            MA 38     colored         steelblue
187       nodes in            MA 60     colored         mediumseagreen
65        nodes in            MA 16     colored         dimgrey
93        nodes in            MA 28     colored         sienna

major road map for region
```

In [20]:
```
medford_data.keys()
```

Out[20]:
```
dict_keys(['graph', 'edges', 'nodes', 'major_roads', 'major_intersectio
ns', 'major_map', 'color_dictionary', 'edge_color', 'node_color'])
```

In [21]:
```
edges_med, nodes_med, medford = medford_data["edges"], medford_data["nod
es"], medford_data["graph"]
```

In [22]:
```
nodes_med.major_inter.value_counts()
```

Out[22]:
```
0    2725
1     351
2       9
3       6
4       4
6       3
Name: major_inter, dtype: int64
```

In [23]:
```
#Long/Lat information
nodes_med[["x","y"]].describe()
```

Out[23]:

	x	y
count	3098.000000	3098.000000
mean	-71.104385	42.417810
std	0.017585	0.011473
min	-71.147362	42.396193
25%	-71.116528	42.408226
50%	-71.101943	42.416830
75%	-71.091419	42.426176
max	-71.073105	42.451141

In [25]:
```
nodes_med.head(2)
```

Out[25]:

	highway	osmid	ref	x	y	geometry	major
66478081	turning_circle	66478081	NaN	-71.100780	42.429287	POINT (-71.1007798 42.4292871)	minor
1754021893	NaN	1754021893	NaN	-71.110187	42.426412	POINT (-71.11018660000001 42.4264119)	minor

2b. Routing

The "random point" and "get_nearest_node" functions are designed to pair any longitude and latitude location with a node on the road network. Routing is handled by the Networkx package.

In [26]:
```
#A function to generate a random lat/long point
gf.random_point()
```

Out[26]: (-4.564236287744961, -83.12728159778895)

In [27]:
```
random_point_A = gf.random_point()
random_point_B = gf.random_point()

# get the nearest network node to each random point
orig_node = ox.get_nearest_node(medford, random_point_A)
dest_node = ox.get_nearest_node(medford, random_point_B)
```

In [28]:
```
# find the route between these nodes then plot it
route = nx.shortest_path(medford, orig_node, dest_node, weight='length')
fig, ax = ox.plot_graph_route(medford, route, node_size=0)
```

In [29]:
```
# Length of route in meters
nx.shortest_path_length(medford, orig_node, dest_node, weight='length')
```

Out[29]: 5718.696999999998

In [30]:
```
# Absolute Distance between two nodes (as the crow flies)
ox.great_circle_vec(medford.node[orig_node]['y'], medford.node[orig_node
]['x'],
                    medford.node[dest_node]['y'], medford.node[dest_node
]['x'])
```

Out[30]: 4109.394864817133

2c. Disaster Radius

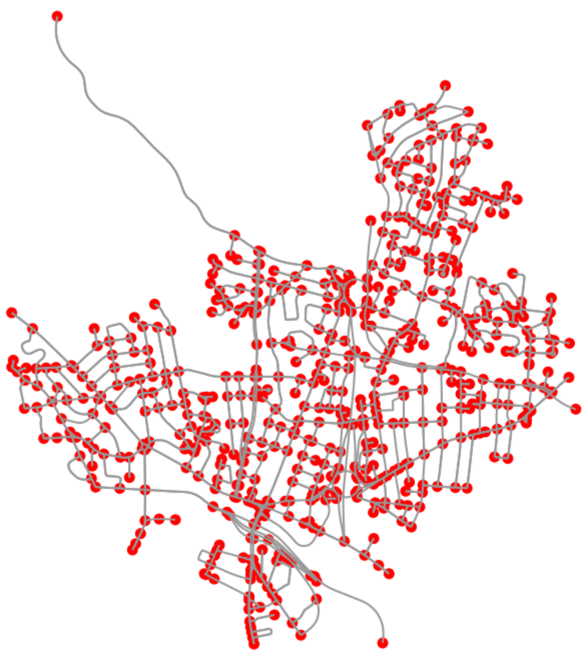
"Disaster_generator" creates a graph object around a node given a radius. This subgraph serves as the region effected by the disaster.

In [31]:
```
d_location = nodes_med[["y","x"]].sample(1).values[0]
```

In [33]:
```
print(d_location)
```

```
[ 42.4306193 -71.1129258]
```

In [32]:
```
#returns a graphs object of a disater
disaster = gf.disaster_generator(nodes_med, location_point = d_location,
radius = 2500)
```

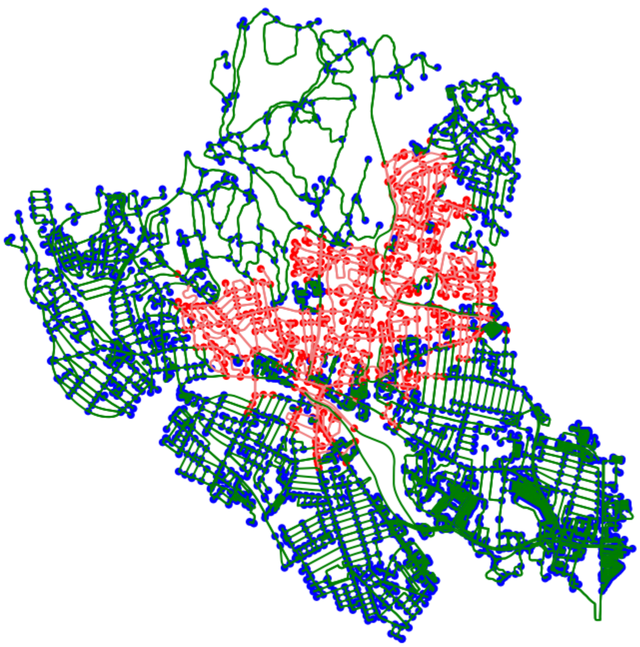


In [34]:
```
nodes_dis, edges_dis = ox.graph_to_gdfs(disaster)
```

The disaster is then reimposed onto the original city graph.

In [35]:
```
#Set Colors
ec = ['lightcoral' if i in disaster.edges() else 'green' for i in medfor
d.edges()]
nc = ['red' if i in disaster.nodes() else 'blue' for i in medford.nodes
()]

#Plot energency grid
ox.plot_graph(medford, node_size=15, node_color = nc ,edge_color=ec)
```



Out[35]:
```
(<Figure size 585.286x432 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x125a8d9e8>)
```

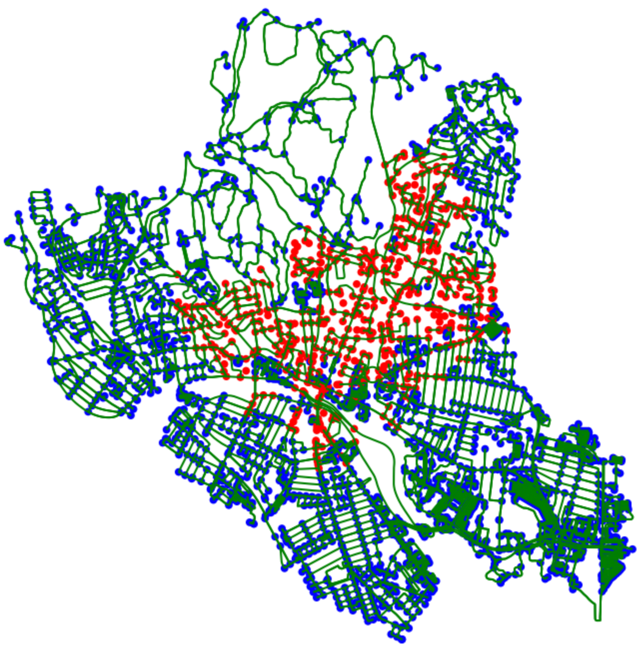
In [36]:
```
nx.degree_histogram(disaster)
```

Out[36]:
```
[0, 8, 100, 68, 92, 39, 265, 10, 26, 1]
```

The "road_kill" function destroys a given percentage of roads inside the disaster zone. These destroyed roads are removed from edges of the city network. Comparing the images above and below will demonstrate that some nodes are now completely isolated as all connecting roads are destroyed.

In [41]:
```
medford_disaster = gf.road_kill(disaster,
                                nodes_med,
                                edges_med,
                                kill_percentage = .8 )
```

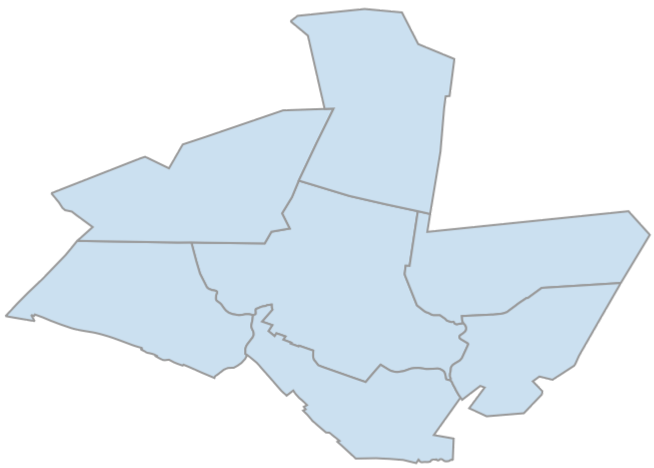
```
138320 roads remain of 149264 total roads
```



2d. City Visualizations

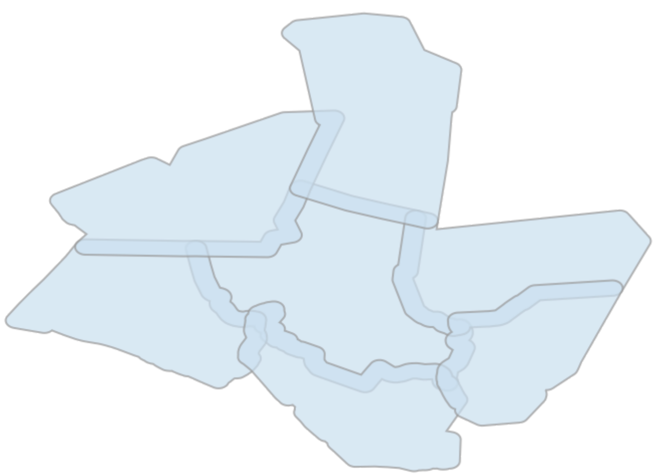
Various city road information and city information

In [ ]:
```
# get the boundary polygons for neighboring cities, save as shapefile, p
roject to UTM, and plot
place_names = ['Medford, MA, USA',
               'Arlington, MA, USA',
               'Somerville, MA, USA',
               'Malden, MA, USA',
#                'Melrose, MA, USA',
               'Winchester, MA, USA',
               'Stoneham, MA, USA',
               'Everett, MA, USA',
              ]
medford_area = ox.gdf_from_places(place_names)
fig, ax = ox.plot_shape(medford_area)
```



In [ ]:
```
# highlight one-way roads
oneway = ox.graph_from_place(place, network_type='drive')
ec = ['r' if data['oneway'] else 'b' for u, v, key, data in oneway.edges
(keys=True, data=True)]
fig, ax = ox.plot_graph(oneway, node_size=0, edge_color=ec, edge_linewid
th=1.5, edge_alpha=0.5)
```

In [ ]:
```
#Neighboor hoods buffered
neigboors_buffered = ox.gdf_from_places(place_names, gdf_name='neighboor
s', buffer_dist=250)
fig, ax = ox.plot_shape(neigboors_buffered, alpha=0.7)
```



3. Data Creation

"Random_zone_picker" creates random crosstown traffic .CSVs for google to analyze.

In [42]:
```
# DF builder of start/end nodes with long/lat and times
# Already done, commenting out to avoid clutter in notebook

router = gf.random_zone_picker(nodes_med, 10)
#router.to_csv("more_zones.csv")
```

0

In [44]:
```
router.head(3)
```

Out[44]:

	osmid_start	x_start	y_start	start_zone	osmid_end	x_end	y_end	end_zone
0	66472630	-71.116727	42.407028	0	66437756	-71.091194	42.426873	1
1	66472630	-71.116727	42.407028	0	66437756	-71.091194	42.426873	1
2	66472630	-71.116727	42.407028	0	66437756	-71.091194	42.426873	1

Police are not restricted to one city, thus, a region around Medford is mapped to potentially use as routes around the disaster. Here a 5.5 km radius is plotted around city hall.

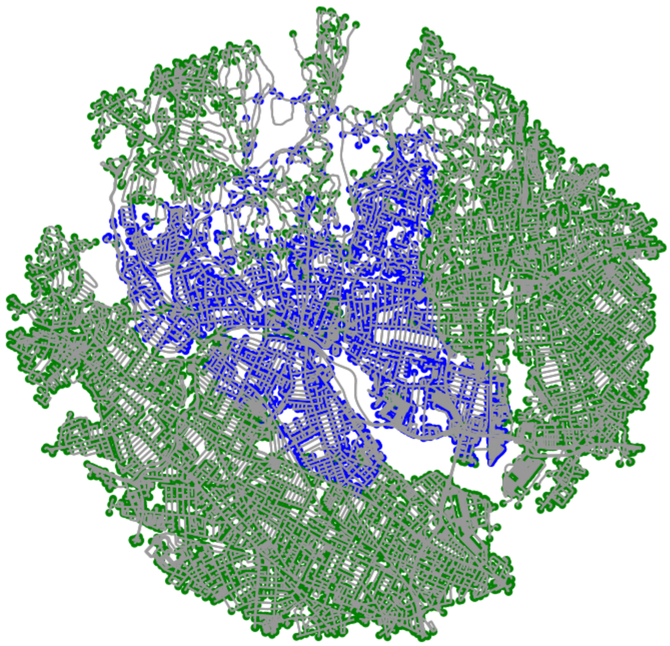
In [45]:
```
# network from address, including only nodes within 5.5km along the netw
ork from city hall
neighbor = ox.graph_from_address(address='85 George P. Hassett Drive,\
                                    Medford, MA 02155',
                                    distance=5500,
                                    distance_type='network',
                                    network_type='walk')

# you can project the network to UTM (zone calculated automatically)
neighbor_projected = ox.project_graph(neighbor)
```

In [46]:
```
# Edge and Node projection
nodes_area, edges_area = ox.graph_to_gdfs(neighbor_projected,
                                          nodes=True,
                                          edges=True)

nc = ['blue' if i in medford.nodes() else 'green' for i in neighbor.node
s()]

ox.plot_graph(neighbor,
              node_size=15,
              node_color = nc);
```



In [47]:
```
neighbor_data = gf.node_roader(neighbor)
```

```
166      nodes in        US 3;MA 2A     colored         cadetblue
10       nodes in       MA 38;MA 60     colored         darkslateblue
24       nodes in       MA 16;MA 38     colored         darkolivegreen
330      nodes in             MA 38     colored         yellowgreen
28       nodes in              MA 2     colored         mediumpurple
582      nodes in             MA 60     colored         mediumturquois
e
270      nodes in             MA 16     colored         darkseagreen
150      nodes in             MA 99     colored         darkslateblue
42       nodes in              US 3     colored         indianred
18       nodes in  US 3;MA 2A;MA 60     colored         darkslateblue
30       nodes in   US 3;MA 2;MA 16     colored         darkkhaki
22       nodes in        US 3;MA 16     colored         lightslategrey
308      nodes in             MA 2A     colored         indianred
348      nodes in             MA 28     colored         grey

major road map for region
```

In the above coloration, black nodes serve as significant intersection between major roads.

In [50]:
```
black = neighbor_data["nodes"]
black[black.color == "black"].head(2)
```

Out[50]:

	highway	osmid	ref	x	y	geometry	major	color	ma
66455370	traffic_signals	66455370	MA 16/MA 38	-71.117942	42.419096	POINT (-71.117942 42.419096)	MA 16;MA 38 MA 38 MA 16	black	
66464342	traffic_signals	66464342	NaN	-71.089860	42.424022	POINT (-71.0898596 42.4240215)	MA 60 MA 28	black	

In [51]:
```
neighbor_data.keys()
```

Out[51]:
```
dict_keys(['graph', 'edges', 'nodes', 'major_roads', 'major_intersectio
ns', 'major_map', 'color_dictionary', 'edge_color', 'node_color'])
```

In [52]:
```
nodes_area, edges_area, neighborhood = neighbor_data["nodes"], neighbor_
data["edges"], neighbor_data["graph"]
```

Major node connection vector

In [54]:
```
for i in neighbor_data['major_intersections']:
    print("Number of major nodes: ",
          len(neighbor_data['major_intersections'][i]),
         "\t with degree ",
          i,)
```

```
Number of major nodes:  0        with degree  0
Number of major nodes:  0        with degree  1
Number of major nodes:  19       with degree  2
Number of major nodes:  0        with degree  3
Number of major nodes:  1053     with degree  4
Number of major nodes:  0        with degree  5
Number of major nodes:  49       with degree  6
Number of major nodes:  0        with degree  7
Number of major nodes:  14       with degree  8
```

In [55]:
```
neighbor_data['major_intersections'].keys()
```

Out[55]:
```
dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8])
```

In [56]:
```
# find the route between these nodes then plot it
route = nx.shortest_path(neighbor, 3809869827, 65339393, weight='length'
)
fig, ax = ox.plot_graph_route(neighbor, route, node_size=0)
```

Checks to see if a neighborhood node is the city and creates a column based on data in the node geopandas dataframe

In [57]:
```
_ = gf.city_node(nodes_med,"medford",nodes_area)
```

In [58]:
```
nodes_area.head()
```

Out[58]:

	highway	osmid	ref	x	y	geometry	major	
3809869824	NaN	3809869824	NaN	-71.114121	42.379348	POINT (-71.1141215 42.3793477)	minor	white
65339393	NaN	65339393	NaN	-71.062293	42.415550	POINT (-71.0622932 42.4155504)	minor	white
3809869827	NaN	3809869827	NaN	-71.115105	42.379540	POINT (-71.11510509999999 42.3795404)	minor	white
66453510	NaN	66453510	NaN	-71.122518	42.438382	POINT (-71.122518 42.438382)	minor	white
3809869832	NaN	3809869832	NaN	-71.115190	42.379899	POINT (-71.11519029999999 42.3798988)	minor	white

4 Google Directions Import

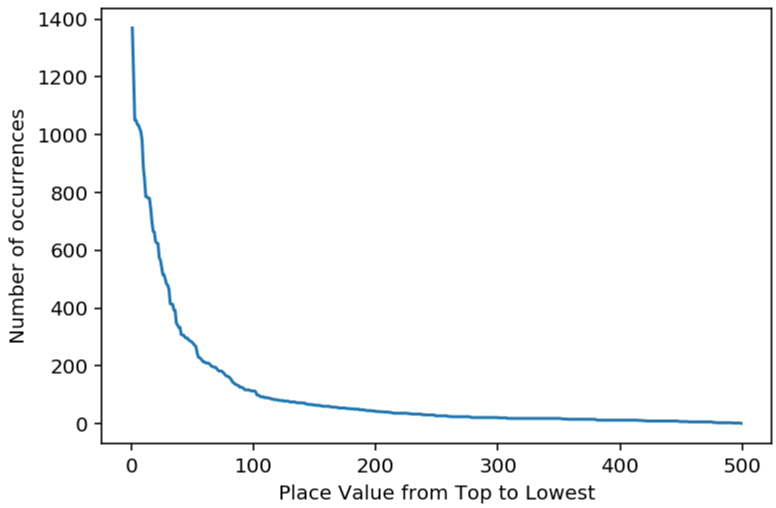
The following chart shows the approximation between the intersection use and Pareto Principle. 80% of the traffic is concentrated in 20% of the intersections.

In [59]:
```
gmap, complete_node, node_occurances = gf.directionsToDataframe("10.Goog
le_directions_api_all6k.csv")
```

```
50853 references of 499 nodes

Top 10 nodes in list

1         [(42.4191023, -71.11793759999999), 1369]
2         [(42.43623909999999, -71.1019761), 1205]
3         [(42.4175248, -71.1179305), 1050]
4         [(42.41664189999999, -71.110641), 1050]
5         [(42.4245735, -71.1062702), 1036]
6         [(42.4153957, -71.1105742), 1033]
7         [(42.4115429, -71.1217863), 1021]
8         [(42.4287603, -71.1025933), 1010]
9         [(42.4342774, -71.08368829999999), 979]
10        [(42.4058567, -71.0980563), 887]
```



4a. Google top 10 nodes

In [61]:
```
gmap.head()
```

Out[61]:

	osmid_start	lng_start	lat_start	start_zone	osmid_end	lng_end	lat_end	end_zone
0	66450694	-71.090072	42.436659	1	66449255	-71.092265	42.411050	2
1	66450694	-71.090072	42.436659	1	66449255	-71.092265	42.411050	2
2	66450694	-71.090072	42.436659	1	66449255	-71.092265	42.411050	2
3	66436104	-71.088950	42.439999	1	66445131	-71.090880	42.411045	2
4	66436104	-71.088950	42.439999	1	66445131	-71.090880	42.411045	2

In [64]:
```
google_top = gf.traffic_node(nodes_area, node_occurances)
g_list = list(google_top[google_top.traffic_importance > 887].osmid.valu
es)
```

In [65]:
```
google_top[google_top.traffic_importance > 887]
```

Out[65]:

	highway	osmid	ref	x	y	geometry	major	
66455370	traffic_signals	66455370	MA 16/MA 38	-71.117942	42.419096	POINT (-71.117942 42.419096)	MA 16;MA 38 MA 38 MA 16	
66458425	traffic_signals	66458425	NaN	-71.110596	42.416629	POINT (-71.1105965 42.4166294)	MA 38	yel
66459547	traffic_signals	66459547	NaN	-71.121782	42.411549	POINT (-71.121782 42.411549)	minor	wh
66464026	NaN	66464026	NaN	-71.117945	42.417517	POINT (-71.1179454 42.4175169)	minor	wh
65358204	NaN	65358204	NaN	-71.083640	42.434357	POINT (-71.0836398 42.4343575)	minor	wh
66424429	NaN	66424429	NaN	-71.110593	42.415511	POINT (-71.1105927 42.415511)	MA 38	yel
66426296	NaN	66426296	NaN	-71.102557	42.428794	POINT (-71.102557 42.428794)	MA 28	
66430240	NaN	66430240	NaN	-71.101967	42.436268	POINT (-71.1019671 42.4362676)	MA 28	
66444502	traffic_signals	66444502	NaN	-71.106271	42.424573	POINT (-71.10627100000001 42.4245726)	minor	wh

The following graph shows the location of the 10 most important nodes for traffic. From personal experience, this information is correct.

In [66]:
```
# Edge and Node projection
nodes_area, edges_area = ox.graph_to_gdfs(neighbor_projected,
                                          nodes=True,
                                          edges=True)

g_size = [25 if i in g_list else 0 for i in neighbor.nodes()]

ox.plot_graph(neighbor,
              node_size=g_size,
              node_color = "red", edge_alpha= .5);
```

5. Initial Monte Carlo Simulation

Rules:

1. Simulation
   A. All disasters originate in Medford with no spill over
   B. 5 patrol officers who maybe inside disaster radius
   C. 5 officers dispatched from station
   D. Police do not follow one way road rules
   E. 10 randomly selected node emergencies inside disaster radius
   F. Best route chosen for all officers
   G. Officers dispatched for on foot for unreachable emergencies (distance 10,000 listed)
   H. 10,000 simulations
   I. I-93 is taken out by the disaster
   J. Disaster radius randomly selected
2. Questions to answer
   A. Average police travel distance
   B. Most used nodes by police

In [68]:
```
import time
import pickle
from scipy.optimize import linear_sum_assignment


#Populate police station

"""
Medford Police:
100 Main St, Medford, MA 02155
42.415811 -71.110152
"""

police_node = gf.nodefinder(nodes_med,
                            lat = 42.415811,
                            lng = -71.110152)




def monte_simulator(p_e_samples, police_location, simulations, name = ""
):

    main_start = time.time()

    police_node = gf.nodefinder(nodes_med,
                            lat = police_location[0],
                            lng = police_location[1])

    police_station = [police_node] * p_e_samples

    p_e_samples *= 2


    monte_simulation = {}
    #Iteration though simulation
    for sim in range(0,simulations):

        #Initialization
        start = time.time()
        print("Starting simulation: {} at time: {}".format(sim,round(sta
rt - main_start,2)))
        monte_dis = {}

        #Generates disaster and radius
        disaster_location = nodes_med.sample(1)

        monte_dis["dis_location"] = disaster_location

        monte_dis["dis_rad"] = np.random.uniform(low = .4, high = .9) *
4000


        monte_dis["disaster"] = gf.disaster_generator(nodes_med,
                                                      location_point = d
isaster_location[["y","x"]].values[0],
```

```
                                                    radius = monte_dis
["dis_rad"],
                                                    plotter = 0)


        monte_dis["nodes_effected"] = len(monte_dis["disaster"].nodes())
        monte_dis["roads_effected"] = len(monte_dis["disaster"].edges())


        #Randomly destroys roads in disaster radius
        monte_dis["remain_per"] = np.random.uniform(low = .35, high = 1)

        monte_dis["remaining"] = gf.road_kill(monte_dis["disaster"],
                                              nodes_area, #These come fr
om the neighborhood
                                              edges_area,
                                              kill_percentage = monte_di
s["remain_per"],
                                              plotter = 0)

        #Make dictionaries for emergencies and police
        e_list = np.random.choice(list(monte_dis["disaster"].nodes()),
                                  replace=False,
                                  size = p_e_samples)

        p_list = list(nodes_med.sample(int(p_e_samples / 2)).osmid.value
s)
        p_list.extend(police_station)

        monte_dis["emergency"] = {}
        monte_dis["patrol"] = {}

        for i in range(0,p_e_samples):
            monte_dis["patrol"]["officer_{}".format(i)] = p_list[i]
            monte_dis["emergency"]["emergency_{}".format(i)] = e_list[i]

        rows = list(monte_dis["patrol"].keys())
        columns = list(monte_dis["emergency"].keys())

        #Distance Matrix
        d_matrix = pd.DataFrame(columns = columns,
                                index = rows)

        for i in range(len(rows)):
            for j in range(len(columns)):
                try:
                    path = nx.shortest_path_length(monte_dis["remaining"
],
                                                   monte_dis["patro
l"][rows[i]],
                                                   monte_dis["emerge
ncy"][columns[j]],
                                                   weight='length')
                except:
                    path = 10_000

                d_matrix.loc[rows[i], columns[j]] = path
```

```
        monte_dis["distance_matrix"] = d_matrix.astype(float)

        #Use Hungarian algorithm for linear sum assignment
        lsa = linear_sum_assignment(monte_dis["distance_matrix"].to_nump
y())
        adj_matrix = np.matrix(np.zeros((10, 10)))

        #optimized distances
        od_list = []
        for i in range(len(lsa[0])):
            od = monte_dis["distance_matrix"].iloc[lsa[0][i],lsa[1][i]]
            adj_matrix[lsa[0][i],lsa[1][i]] = od
            od_list.append(od)

        dispatch = {"officer_{}".format(lsa[0][i]):["emergency_{}".forma
t(lsa[1][i]),
                                                    od_list[i]] for i in
range(len(lsa[0]))}

        monte_dis["ad_matrix"] = adj_matrix
        monte_dis["dispatch"] = dispatch
        monte_dis["dispatch_distance"] = sum(od_list)


        monte_simulation[sim] = monte_dis

        if sim % 200 == 0:
            print("pickle dump")
            pickle.dump(monte_simulation, open( "monte_simulation_{}_{}.
p".format(name,sim), "wb" ))

        end = time.time()
        print("Ending simulation: {}. Total {} seconds for run\n".format
(sim,round(end - start,2)))

    return monte_simulation
```

Demo of five simulated disasters

In [69]:
```
monte_simulation = monte_simulator(5,[42.415811,-71.110152], 5, "demo")
```

```
Starting simulation: 0 at time: 0.05
667116 roads remain of 667836 total roads
pickle dump
Ending simulation: 0. Total 21.53 seconds for run

Starting simulation: 1 at time: 21.57
646416 roads remain of 667836 total roads
Ending simulation: 1. Total 52.21 seconds for run

Starting simulation: 2 at time: 73.78
667224 roads remain of 667836 total roads
Ending simulation: 2. Total 20.94 seconds for run

Starting simulation: 3 at time: 94.72
646164 roads remain of 667836 total roads
Ending simulation: 3. Total 35.16 seconds for run

Starting simulation: 4 at time: 129.88
664218 roads remain of 667836 total roads
Ending simulation: 4. Total 29.49 seconds for run
```

Simulations inside data dictionary

In [70]:
```
monte_simulation.keys()
```

Out[70]:
```
dict_keys([0, 1, 2, 3, 4])
```

Terms inside of each simulation

In [79]:
```
monte_simulation[0].keys()
```

Out[79]:
```
dict_keys(['dis_location', 'dis_rad', 'disaster', 'nodes_effected', 'ro
ads_effected', 'remain_per', 'remaining', 'emergency', 'patrol', 'dista
nce_matrix', 'ad_matrix', 'dispatch', 'dispatch_distance'])
```

Two sample optimized dispatches with corresponding distance in meters

In [80]:
```
monte_simulation[0]['dispatch']
```

Out[80]:
```
{'officer_0': ['emergency_5', 3165.7219999999998],
 'officer_1': ['emergency_0', 4553.591],
 'officer_2': ['emergency_6', 5421.6460000000025],
 'officer_3': ['emergency_2', 6558.164000000001],
 'officer_4': ['emergency_3', 5265.956999999999],
 'officer_5': ['emergency_9', 2448.740000000001],
 'officer_6': ['emergency_8', 3775.5390000000007],
 'officer_7': ['emergency_7', 3491.234000000001],
 'officer_8': ['emergency_4', 2368.111000000001],
 'officer_9': ['emergency_1', 2863.6080000000006]}
```

In [82]:
```
monte_simulation[2]['dispatch']
```

Out[82]:
```
{'officer_0': ['emergency_3', 2418.3430000000008],
 'officer_1': ['emergency_4', 1909.5639999999999],
 'officer_2': ['emergency_9', 10000.0],
 'officer_3': ['emergency_6', 2711.428999999999],
 'officer_4': ['emergency_0', 580.3219999999999],
 'officer_5': ['emergency_8', 3044.8880000000004],
 'officer_6': ['emergency_7', 2505.99],
 'officer_7': ['emergency_5', 3718.0879999999997],
 'officer_8': ['emergency_2', 2008.5919999999999],
 'officer_9': ['emergency_1', 3077.2379999999994]}
```

In [86]:
```
monte_simulation[2]["ad_matrix"]
```

Out[86]:
```
matrix([[    0.   ,     0.   ,     0.   ,  2418.343,     0.   ,
             0.   ,     0.   ,     0.   ,     0.   ,     0.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,  1909.564,
             0.   ,     0.   ,     0.   ,     0.   ,     0.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,     0.   ,
             0.   ,     0.   ,     0.   ,     0.   , 10000.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,     0.   ,
             0.   ,  2711.429,     0.   ,     0.   ,     0.   ],
        [  580.322,     0.   ,     0.   ,     0.   ,     0.   ,
             0.   ,     0.   ,     0.   ,     0.   ,     0.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,     0.   ,
             0.   ,     0.   ,     0.   ,  3044.888,     0.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,     0.   ,
             0.   ,     0.   ,  2505.99 ,     0.   ,     0.   ],
        [    0.   ,     0.   ,     0.   ,     0.   ,     0.   ,
          3718.088,     0.   ,     0.   ,     0.   ,     0.   ],
        [    0.   ,     0.   ,  2008.592,     0.   ,     0.   ,
             0.   ,     0.   ,     0.   ,     0.   ,     0.   ],
        [    0.   ,  3077.238,     0.   ,     0.   ,     0.   ,
             0.   ,     0.   ,     0.   ,     0.   ,     0.   ]])
```

Data frame generation

In [71]:
```
size_list = range(len(monte_simulation))
```

In [73]:
```
df = pd.concat([monte_simulation[i]["dis_location"].copy() for i in size
_list]).reset_index(drop=True)
```

In [76]:
```
extra_data = ['dis_rad', 'nodes_effected', 'roads_effected', 'remain_pe
r', 'dispatch_distance']
```

In [77]:
```
for i in range(len(monte_simulation)):
    for j in extra_data:
        df.loc[i, j] = monte_simulation[i][j]
```

In [78]:
```
df.columns
```

Out[78]:
```
Index(['highway', 'osmid', 'ref', 'x', 'y', 'geometry', 'major', 'colo
r',
       'major_inter', 'dis_rad', 'nodes_effected', 'roads_effected',
       'remain_per', 'dispatch_distance'],
      dtype='object')
```

In [84]:
```
X = df[['osmid','x', 'y','dis_rad', 'nodes_effected', 'roads_effected',
       'remain_per', 'dispatch_distance']]
```

In [85]:
```
X.head()
```

Out[85]:

	osmid	x	y	dis_rad	nodes_effected	roads_effected	remain_per
0	66457384	-71.141971	42.422531	1705.878532	395.0	1044.0	0.447029
1	1492438714	-71.084046	42.405243	3372.581750	2166.0	4908.0	0.891804
2	1479863481	-71.076628	42.411783	1904.437873	288.0	663.0	0.523666
3	66474274	-71.136638	42.429198	3004.994641	1097.0	2873.0	0.903811
4	66452598	-71.102182	42.430619	3265.576548	1299.0	3154.0	0.448429

In [ ]: