	Notebook 3  Project: "Intra-Regional Migration and Transportation in New York Metro Area"  This Notebook's Goal:
	In this notebook, we focus on our step 5 in our designed research process - to compare transit-area vs. non-transit-area data to see if transit plays an important role in forming local communities in the process of intra-regional migration. This is a new section we decided to do after midterm  In this section, we started to zoom in on the census tract level and involves lots of data comparison on the interactive maps. Therefore, this week, we only applied a part of our data (only one county and one train railroad) to test out the coding stuff. Glad this coding works out, so we wil continue building this coding to apply to all data in the following week.
	Research Step 5  In this section, we started to test out how to compare the census data in transit area vs in non transit area by using the fuction "buffer". We first apply both census tract data and transit data as the basemaps. Then we use each station as the point to draw a half mile radius circle and then make those circles to "overlay" on the census data so that we have those average nubmer touched by the circles. Finally, we figured out how to use folium to show the data and finding via different layers.
In [1]	<pre># Import all required modules  import pandas as pd import geopandas as gpd import contextily as ctx import matplotlib.pyplot as plt import plotly.express as px import plotly.graph_objects as go</pre>
In [2]:	<pre>from plotly.subplots import make_subplots import numpy as np import folium from geopandas import GeoDataFrame from shapely.geometry import Point  # This is the base census data  NYS_CensusTract_Rawdata = gpd.read_file('data5/cb_2018_36_tract_500k.shp')</pre>
In [3]: Out[3]:	# take some basic data exploration and cleaning.  NYS_CensusTract_Rawdata.head()  STATEFP COUNTYFP TRACTCE AFFGEOID GEOID NAME LSAD ALAND AWATER geometry  0 36 019 101100 1400000US36019101100 36019101100 1011 CT 583322 57750 POLYGON ((-73.46914 44.69043, -73.46972 44.693  1 36 021 000403 1400000US36031000403 36031000403 403 CT 43304008 1437337 POLYGON ((-73.72088 42.45322, -73.71799)
	1       36       021       000402       1400000US36021000402       36021000402       4.02       CT       42294908       1437327       POLYGON ((-73.72088 42.45322, -73.71799 42.470)         2       36       023       970700       1400000US36023970700       36023970700       9707       CT       2082176       0       POLYGON ((-76.20049 42.61248, -76.19596 42.612)         3       36       081       046200       1400000US36081046200       36081046200       462       CT       249611       0       POLYGON ((-73.79203 40.71107, -73.79101 40.711)         4       36       081       048100       1400000US36081048100       36081048100       481       CT       139052       0       POLYGON ((-73.88799 40.74355, -73.88621 40.743)
In [4]: In [5]: Out[5]:	NYS_CensusTract_Rawdata_trimmed = NYS_CensusTract_Rawdata[Columns_To_Keep1]           NYS_CensusTract_Rawdata_trimmed.head()           AFFGEOID         geometry           0 1400000US36019101100 POLYGON ((-73.46914 44.69043, -73.46972 44.693
75 . 29	1 1400000US36021000402 POLYGON ((-73.72088 42.45322, -73.71799 42.470) 2 1400000US36023970700 POLYGON ((-76.20049 42.61248, -76.19596 42.612) 3 1400000US36081046200 POLYGON ((-73.79203 40.71107, -73.79101 40.711) 4 1400000US36081048100 POLYGON ((-73.88799 40.74355, -73.88621 40.743)  NYS_CensusTract_Rawdata_trimmed.plot() <matplotlib.axessubplots.axessubplot 0x7f319d7b54f0="" at=""></matplotlib.axessubplots.axessubplot>
	44 - 43 - 42 -
	Tract_County1 = NYS_CensusTract_Rawdata_trimmed[NYS_CensusTract_Rawdata.COUNTYFP == '103']  Tract_County1.plot()
	<pre> cmatplotlib.axessubplots.AxesSubplot at 0x7f319d634a30&gt;  41.3 41.1 41.0 40.9 </pre>
In [9]:	# Because we are going to do buffering for each point, we want to make sure all our geo measurments are on the same CRS. #So we convert all following geodata to 2272
In [10]	<pre>Tract_County1_crs = Tract_County1.to_crs(epsg=2272)  # making sure the change is successful print(Tract_County1_crs.crs) epsg:2272  Train Station Dataframe</pre>
In [11]: In [12]:	<pre># now we are going to import the transit data as the basemap  LIRR_Railroad_Rawdata = gpd.read_file('data5/LIRR/geo_export_c4344150-8906-4247-ba0d-70c66f79a2cd.shp')  LIRR_Station_Rawdata = gpd.read_file('data5/LIRR/geo_export_cd021d1d-1a5d-46e9-bff6-446db61db8cc.shp')</pre>
Out[12]:	routename         geometry           0         Babylon         LINESTRING (-73.99309 40.75074, -73.99245 40.7           1         Babylon         LINESTRING (-73.32470 40.70060, -73.32538 40.7           2         Babylon         LINESTRING (-73.32470 40.70060, -73.32538 40.7           3         Babylon         LINESTRING (-73.32470 40.70060, -73.32538 40.7           4         Babylon         LINESTRING (-73.97736 40.68475, -73.97687 40.6
In [13]: Out[13]:	LIRR_Railroad_Rawdata.plot() <pre><matplotlib.axessubplots.axessubplot 0x7f319cfad640="" at=""></matplotlib.axessubplots.axessubplot></pre> 41.0 40.8
	40.6  -74.00 -73.75 -73.50 -73.25 -73.00 -72.75 -72.50 -72.25 -72.00  LIRR_Station_Rawdata_crs = LIRR_Station_Rawdata.to_crs(epsg=2272)  print(LIRR_Station_Rawdata_crs.crs)  epsg:2272
In [16]	LIRR_Station_Rawdata_crs.info() <class 'geopandas.geodataframe.geodataframe'=""> RangeIndex: 124 entries, 0 to 123  Data columns (total 2 columns):  # Column Non-Null Count Dtype </class>
In [18]	<pre>dtypes: geometry(1), object(1) memory usage: 2.1+ KB  LIRR_Station_Rawdata_crs['lon'] = LIRR_Station_Rawdata['geometry'].x LIRR_Station_Rawdata_crs['lat'] = LIRR_Station_Rawdata['geometry'].y  LIRR_Station_Rawdata_crs.head()</pre>
Out[18]:	stopname         geometry         Ion         lat           0         Long Island City         POINT (3019395.107 535479.309)         -73.95639         40.74128           1         Hunterspoint Avenue         POINT (3022035.576 535994.076)         -73.94679         40.74238           2         Penn Station         POINT (3008955.006 538424.062)         -73.99358         40.75058           3         Woodside         POINT (3034111.720 537779.211)         -73.90297         40.74584           4         Forest Hills         POINT (3050634.467 528924.918)         -73.84481         40.71957
In [20]	<pre># this is the critical part. we are buffer the data point of each station by half mile. # then we have a new column that contains all buffer geometry data buffer_distance = 0.5 * 5280 LIRR_Station_Rawdata_crs['geometry_buffer'] = LIRR_Station_Rawdata_crs.geometry.buffer(buffer_distance) LIRR_Station_Rawdata_crs.head()</pre>
Out[20]:	
In [21]:	LIRR_Station_Rawdata_crs.info() <class 'geopandas.geodataframe.geodataframe'=""> RangeIndex: 124 entries, 0 to 123  Data columns (total 5 columns):  # Column Non-Null Count Dtype  0 stopname 124 non-null object 1 geometry 124 non-null geometry</class>
B 25	
In [23]:	<pre>LIRR_Station_Rawdata_crs_map.info()  <class 'geopandas.geodataframe.geodataframe'=""> RangeIndex: 124 entries, 0 to 123 Data columns (total 2 columns):     # Column</class></pre>
ASSA TOSCITO	LIRR_Station_Rawdata_crs_map.columns = ['stopname', 'geometry']  LIRR_Station_Rawdata_crs_map.head()
	1 Hunterspoint Avenue POLYGON ((3024675.576 535994.076, 3024662.864) 2 Penn Station POLYGON ((3011595.006 538424.062, 3011582.293) 3 Woodside POLYGON ((3036751.720 537779.211, 3036739.008) 4 Forest Hills POLYGON ((3053274.467 528924.918, 3053261.755)  LIRR_Station_Rawidata_crs_map.plot()
Out[26]:	<pre></pre>
In [27]:	3.0 3.1 3.2 3.3 3.4 3.5 le6  LIRR_Station_Rawdata_crs_map.plot() <matplotlib.axessubplots.axessubplot 0x7f319cf34d30="" at="">  700000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 6500000 650000 650000 650000 650000 650000 650000 650000 650000 65000000 650000 650000 650000 650000 650000 650000 650000 650000 65000000 650000 650000 6500000 650000000 6500000000</matplotlib.axessubplots.axessubplot>
In [28]:	Map  # now we are trying to make some interactive maps with Folium. We are trying to add multiple layers into one map
In [29]: Out[29]:	
In [31]:	# create for Loop to map all station  for index, row in LIRR_Station_Rawdata_crs.iterrows():     folium.Marker([row.lat, row.lon], popup=row.stopname).add_to(m)  Tract_County1_crs['stopname']='No'  # using for loop to assign the new values if the census data is intersected with the created buffer geometry  for index_s, row_s in LIRR_Station_Rawdata_crs.iterrows():     for index_t, row_t in Tract_County1_crs.iterrows():         if row_t.geometry.intersects(row_s.geometry_buffer) == True:
In [33]:	Tract_County1_crs.at[index_t,'stopname'] = LIRR_Station_Rawdata_crs.at[index_s,'stopname']  Tract_County1_crs.head(50)  AFFGEOID geometry stopname 6 1400000US36103158804 POLYGON ((3271495.105 563714.033, 3271787.234 No
	7 1400000US36103159508 POLYGON ((3324563.715 560527.321, 3324551.669 No 8 1400000US36103190800 POLYGON ((3427592.295 595673.672, 3439372.827 Southampton 9 1400000US36103990100 POLYGON ((3502127.951 667800.745, 3502130.644 No 56 1400000US36103147803 POLYGON ((3256602.714 554005.289, 3257590.937 Sayville 57 1400000US36103158108 POLYGON ((3251874.981 598354.549, 3253210.684 No 58 1400000US36103158309 POLYGON ((3282586.185 596927.891, 3283758.160 No 59 1400000US36103158408 POLYGON ((3299818.880 628358.526, 3300348.502 No
In [34]: In [35]:	167 1400000US36103111001 POLYGON ((3164442.979 589916.776, 3165164.993 Huntington  168 1400000US36103111703 POLYGON ((3191405.964 594334.279, 3194046.005 Northport  235 1400000US36103112212 POLYGON ((3177983.154 567842.506, 3182559.280 No  Tract_WithinStops = Tract_County1_crs[Tract_County1_crs['stopname'] != 'No']  Tract_WithinStops.head()
Out[35]:	AFFGEOID         geometry         stopname           8 1400000US36103190800         POLYGON ((3427592.295 595673.672, 3439372.827         Southampton           56 1400000US36103147803         POLYGON ((3256602.714 554005.289, 3257590.937         Sayville           167 1400000US36103111001         POLYGON ((3164442.979 589916.776, 3165164.993         Huntington           168 1400000US36103111703         POLYGON ((3191405.964 594334.279, 3194046.005         Northport           295 1400000US36103145704         POLYGON ((3224519.302 567830.020, 3225701.112         Central Islip
50 (0.65) (0.66)	<pre>Tract_WithinStops.plot()  <matplotlib.axessubplots.axessubplot 0x7f319ac89a60="" at="">  750000 - 700000 -</matplotlib.axessubplots.axessubplot></pre>
	600000 - 550000 - 3.2 3.3 3.4 3.5 3.6 le6
In [38]:	<pre>Database  commutingCSV = pd.read_csv('data5/commuting_time.csv')  commutingCSV.columns = ['AFFGEOID', 'Name', '2014', '2018', 'Diff', 'Change']  alltract = Tract_County1.merge(commutingCSV,</pre>
0. 15	on='AFFGEOID', how='right')  alltract.info() <class 'geopandas.geodataframe.geodataframe'=""> Int64Index: 323 entries, 0 to 322 Data columns (total 7 columns): # Column Non-Null Count Dtype  0 AFFGEOID 323 non-null object</class>
	1 geometry 323 non-null geometry 2 Name 323 non-null object 3 2014 323 non-null int64 4 2018 323 non-null int64 5 Diff 323 non-null int64 6 Change 323 non-null object dtypes: geometry(1), int64(3), object(3) memory usage: 20.2+ KB
7. 1	<pre>df_merge = Tract_WithinStops.merge(commutingCSV,on='AFFGEOID',how='left')  df_merge.info()  <class 'geopandas.geodataframe.geodataframe'=""> Int64Index: 128 entries, 0 to 127  Data columns (total 8 columns):     # Column Non-Null Count Dtype  0 AFFGEOID 128 non-null object  1</class></pre>
	1 geometry 128 non-null geometry 2 stopname 128 non-null object 3 Name 128 non-null object 4 2014 128 non-null int64 5 2018 128 non-null int64 6 Diff 128 non-null int64 7 Change 128 non-null object dtypes: geometry(1), int64(3), object(4) memory usage: 9.0+ KB
	<pre>df_merge_group = df_merge.groupby('stopname').mean()  df_merge_group.info()  <class 'pandas.core.frame.dataframe'=""> Index: 40 entries, Amagansett to Yaphank Data columns (total 3 columns):     # Column Non-Null Count Dtype  0 2014 40 non-null float64</class></pre>
In [45]: In [46]:	
In [46]:	
	<pre>df_merge_group_geo = LIRR_Station_Rawdata_crs_map.merge(df_merge_group,</pre>
	stopname         geometry         2014         2018         Diff           0 Cold Spring Harbor         POLYGON ((3160237.922 576226.224, 3160225.210 372.000000 89.500000 -282.50)         372.000000 89.500000 -282.50           1 Huntington         POLYGON ((3171413.448 583109.353, 3171400.736 128.285714 96.285714 -32.00)         -32.00           2 Greenlawn         POLYGON ((3184025.225 589445.519, 3184012.512 182.500000 134.750000 -47.75)         -47.75           3 Northport         POLYGON ((3193300.912 594278.694, 3193288.199 125.750000 81.750000 -44.00)         -44.00           4 Kings Park         POLYGON ((3213193.085 596385.335, 3213180.372 173.500000 144.250000 -29.25)
In [49]:	<pre>folium.Choropleth(geo_data=alltract,</pre>
	<pre>folium.features.Choropleth at 0x7f319ac54c40&gt;  folium.Choropleth(geo_data=df_merge_group_geo,</pre>
	<pre>line_opacity=1,</pre>
	highlight_function = lambda x: {'fillColor': '#000000',
	fields=['Name','Diff'],
In [52]:	<pre>style_function = lambda x: {'fillColor': '#ffffff',</pre>
	<pre>style_function=style_function,</pre>
75 . 15	<pre>m.keep_in_front(notes)  folium.GeoJson(LIRR_Railroad_Rawdata,</pre>
- V-	+ 39 -280 -121 39 198 Monroe Somers -199 -116 -32 S1 New Haves 218 Ord
	Delevery Vernor Vernor Store Play Story Point Store Play Store Play Story Point Story Po
In [ ]	Although we are testing out this coding stuff, we think it works! Now we can see the data of transit-area census and other non-tranist area census in one map. There's a Igend on the right we can use to select the layers. Also, every time we click the census, there would be pop out windows as well. For the next step, we are going to adopt this coding to all our dataset