

Install packages required in the module

```
In [1]: import sys
#!{sys.executable} -m pip install datashader
#!{sys.executable} -m pip install pyproj
#!{sys.executable} -m pip install colorlover
#!{sys.executable} -m pip install plotly.offline.iplot()
#!{sys.executable} -m pip install shapely==1.7.0
#!{sys.executable} -m pip install plotly
#!{sys.executable} -m pip install cufflinks
```

```
In [2]: import datashader as ds
import datashader.transfer_functions as tf
import datashader.glyphs
from datashader import reductions
from datashader.core import bypixel
from datashader.utils import lnglat_to_meters as webm, export_image
from datashader.colors import colormap_select, Greys9, viridis, inferno
import copy

from pyproj import Proj, transform
import numpy as np
import pandas as pd
import urllib
import json
import datetime
import colorlover as cl

import plotly.offline as py
import plotly.graph_objs as go
from plotly import tools

from shapely.geometry import Point, Polygon, shape
# In order to get shapely, you'll need to run [pip install shapely.geometries]

from functools import partial

from IPython.display import GeoJSON

py.init_notebook_mode()
```

```
In [3]: from plotly.offline import download_plotlyjs, init_notebook_mode, plot
```

The `ny_floors_groups` object, which we will see further here, is a `pandas.series` object which does not have a `iplot` method when not linked to `plotly`. We need `cufflinks` to link `plotly` to `pandas` and add the `iplot` method.

```
In [4]: import cufflinks as cf
        cf.go_offline()
        cf.set_config_file(offline=False, world_readable=True)
```

For module 2 we'll be looking at techniques for dealing with big data. In particular binning strategies and the `datashader` library (which possibly proves we'll never need to bin large data for visualization ever again.)

To demonstrate these concepts we'll be looking at the PLUTO dataset put out by New York City's department of city planning. PLUTO contains data about every tax lot in New York City.

PLUTO data can be downloaded from [here \(https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page\)](https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page). Unzip them to the same directory as this notebook, and you should be able to read them in using this (or very similar) code. Also take note of the data dictionary, it'll come in handy for this assignment.

```
In [5]: # Code to read in v17, column names have been updated (without upper c

        #bk = pd.read_csv('PLUT017v1.1/BK2017V11.csv')
        #bx = pd.read_csv('PLUT017v1.1/BX2017V11.csv')
        #mn = pd.read_csv('PLUT017v1.1/MN2017V11.csv')
        #qn = pd.read_csv('PLUT017v1.1/QN2017V11.csv')
        #si = pd.read_csv('PLUT017v1.1/SI2017V11.csv')

        #ny = pd.concat([bk, bx, mn, qn, si], ignore_index=True)

ny = pd.read_csv('nyc_pluto_20v1_csv/pluto_20v1.csv')

# Getting rid of some outliers
ny = ny[(ny['yearbuilt'] > 1850) & (ny['yearbuilt'] < 2020) & (ny['num

/Users/priyashaji/opt/anaconda3/lib/python3.7/site-packages/IPython/c
ore/interactiveshell.py:3058: DtypeWarning:

Columns (17,18,20,22) have mixed types. Specify dtype option on impor
t or set low_memory=False.
```

I'll also do some prep for the geographic component of this data, which we'll be relying on for datashader.

You're not required to know how I'm retrieving the latitude and longitude here, but for those interested: this dataset uses a flat x-y projection (assuming for a small enough area that the world is flat for easier calculations), and this needs to be projected back to traditional latitude and longitude.

In [6]:

```
# wgs84 = Proj("+proj=longlat +ellps=GRS80 +datum=NAD83 +no_defs")
# nyli = Proj("+proj=lcc +lat_1=40.66666666666666 +lat_2=41.03333333333333")
# ny['xcoord'] = 0.3048*ny['xcoord']
# ny['ycoord'] = 0.3048*ny['ycoord']
# ny['lon'], ny['lat'] = transform(nyli, wgs84, ny['xcoord'].values, ny['ycoord'].values)

# ny = ny[(ny['lon'] < -60) & (ny['lon'] > -100) & (ny['lat'] < 60) & (ny['lat'] > 30)]

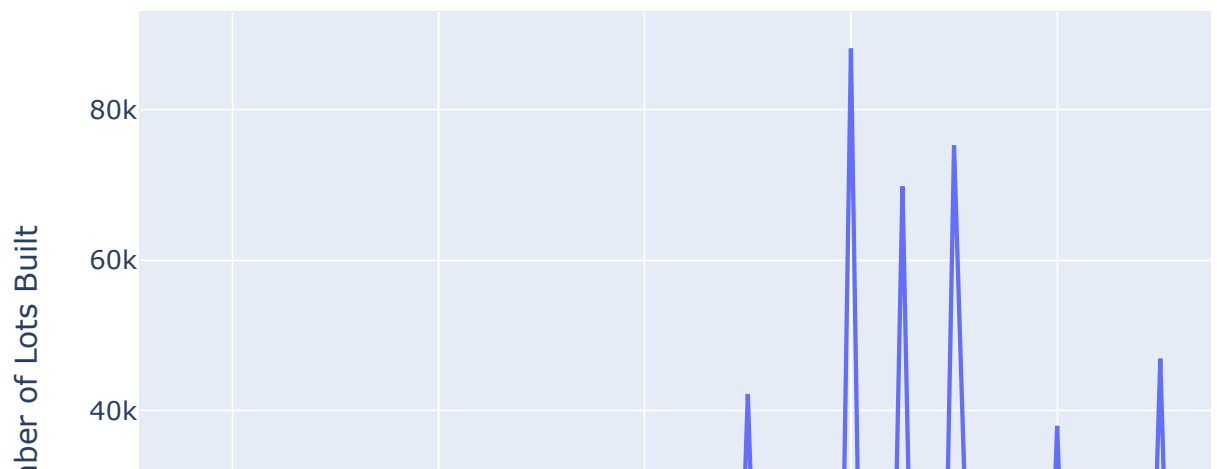
#Defining some helper functions for DataShader
background = "black"
export = partial(export_image, background = background, export_path="export.png")
cm = partial(colormap_select, reverse=(background!="black"))
```

Part 1: Binning and Aggregation

Binning is a common strategy for visualizing large datasets. Binning is inherent to a few types of visualizations, such as histograms and [2D histograms \(https://plot.ly/python/2D-Histogram/\)](https://plot.ly/python/2D-Histogram/) (also check out their close relatives: [2D density plots \(https://plot.ly/python/2d-density-plots/\)](https://plot.ly/python/2d-density-plots/) and the more general form: [heatmaps \(https://plot.ly/python/heatmaps/\)](https://plot.ly/python/heatmaps/)).

While these visualization types explicitly include binning, any type of visualization used with aggregated data can be looked at in the same way. For example, let's say we wanted to look at building construction over time. This would be best viewed as a line graph, but we can still think of our results as being binned by year:

```
In [7]: trace = go.Scatter(  
    # I'm choosing BBL here because I know it's a unique key.  
    x = ny.groupby('yearbuilt').count()['bbl'].index,  
    y = ny.groupby('yearbuilt').count()['bbl']  
)  
  
layout = go.Layout(  
    xaxis = dict(title = 'Year Built'),  
    yaxis = dict(title = 'Number of Lots Built')  
)  
  
fig = go.FigureWidget(data = [trace], layout = layout)  
iplot(fig)
```



Something looks off... You're going to have to deal with this imperfect data to answer this first question.

But first: some notes on pandas. Pandas dataframes are a different beast than R dataframes, here are some tips to help you get up to speed:

Hello all, here are some pandas tips to help you guys through this homework:

[Indexing and Selecting \(https://pandas.pydata.org/pandas-docs/stable/indexing.html\)](https://pandas.pydata.org/pandas-docs/stable/indexing.html): .loc and .iloc are the analogs for base R subsetting, or filter() in dplyr

[Group By \(https://pandas.pydata.org/pandas-docs/stable/groupby.html\)](https://pandas.pydata.org/pandas-docs/stable/groupby.html): This is the pandas analog to group_by() and the appended function the analog to summarize(). Try out a few examples of this, and display the results in Jupyter. Take note of what's happening to the indexes, you'll notice that they'll become hierarchical. I personally find this more of a burden than a help, and this sort of hierarchical indexing leads to a fundamentally different experience compared to R dataframes. Once you perform an aggregation, try running the resulting hierarchical dataframe through a [reset_index\(\) \(https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index.html\)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index.html).

[Reset_index \(https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index.html\)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index.html): I personally find the hierarchical indexes more of a burden than a help, and this sort of hierarchical indexing leads to a fundamentally different experience compared to R dataframes. reset_index() is a way of restoring a dataframe to a flatter index style. Grouping is where you'll notice it the most, but it's also useful when you filter data, and in a few other split-apply-combine workflows. With pandas indexes are more meaningful, so use this if you start getting unexpected results.

Indexes are more important in Pandas than in R. If you delve deeper into the using python for data science, you'll begin to see the benefits in many places (despite the personal gripes I highlighted above.) One place these indexes come in handy is with time series data. The pandas docs have a [huge section \(http://pandas.pydata.org/pandas-docs/stable/timeseries.html\)](http://pandas.pydata.org/pandas-docs/stable/timeseries.html) on datetime indexing. In particular, check out [resample \(https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.resample.html\)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.resample.html), which provides time series specific aggregation.

[Merging, joining, and concatenation \(https://pandas.pydata.org/pandas-docs/stable/merging.html\)](https://pandas.pydata.org/pandas-docs/stable/merging.html): There's some overlap between these different types of merges, so use this as your guide. Concat is a single function that replaces cbind and rbind in R, and the results are driven by the indexes. Read through these examples to get a feel on how these are performed, but you will have to manage your indexes when you're using these functions. Merges are fairly similar to merges in R, similarly mapping to SQL joins.

Apply: This is explained in the "group by" section linked above. These are your analogs to the plyr library in R. Take note of the lambda syntax used here, these are anonymous functions in python. Rather than predefining a custom function, you can just define it inline using lambda.

Browse through the other sections for some other specifics, in particular reshaping and categorical data (pandas' answer to factors.) Pandas can take a while to get used to, but it is a pretty strong framework that makes more advanced functions easier once you get used to it. Rolling functions for example follow logically from the apply workflow (and led to the best google results ever when I first tried to find this out and googled "pandas rolling")

Google Wes Mckinney's book "Python for Data Analysis," which is a cookbook style intro to pandas. It's an O'Reilly book that should be pretty available out there.

Question

After a few building collapses, the City of New York is going to begin investigating older buildings for safety. The city is particularly worried about buildings that were unusually tall when they were built, since best-practices for safety hadn't yet been determined. Create a graph that shows how many buildings of a certain number of floors were built in each year (note: you may want to use a log scale for the number of buildings). Find a strategy to bin buildings (It should be clear 20-29-story buildings, 30-39-story buildings, and 40-49-story buildings were first built in large numbers, but does it make sense to continue in this way as you get taller?)

create ny_floors dataframe, which has 'bbl', 'yearbuilt', 'numfloors' as columns

In [8]: *# Start your answer here, inserting more cells as you go along*

```
ny.head()

ny_floors = ny[['bbl', 'yearbuilt', 'numfloors']]
ny_floors.head()
```

Out [8]:

	bbl	yearbuilt	numfloors
0	3008340046	1931.0	3.00
1	4040420106	1910.0	2.75
2	3046790017	1920.0	2.00
3	3078310006	1920.0	2.00
4	3078310007	1920.0	2.00

```
In [9]: # Analyze maximum no. of floors in a buliding
ny.loc[:, 'numfloors'].max()
```

Out[9]: 205.0

```
In [10]: # Analyze minimum no. of floors in a buliding:
ny.loc[:, 'numfloors'].min()
```

Out[10]: 0.1

```
In [11]: # Select only columns which needs to be analyzed: bbl (as a unique id)
ny_floors = ny[['bbl', 'yearbuilt', 'numfloors']]
ny_floors.head()
```

Out[11]:

	bbl	yearbuilt	numfloors
0	3008340046	1931.0	3.00
1	4040420106	1910.0	2.75
2	3046790017	1920.0	2.00
3	3078310006	1920.0	2.00
4	3078310007	1920.0	2.00

```
In [12]: # strategy to bin buildings

floor_bins = [0,20,40,60,80,100,120]

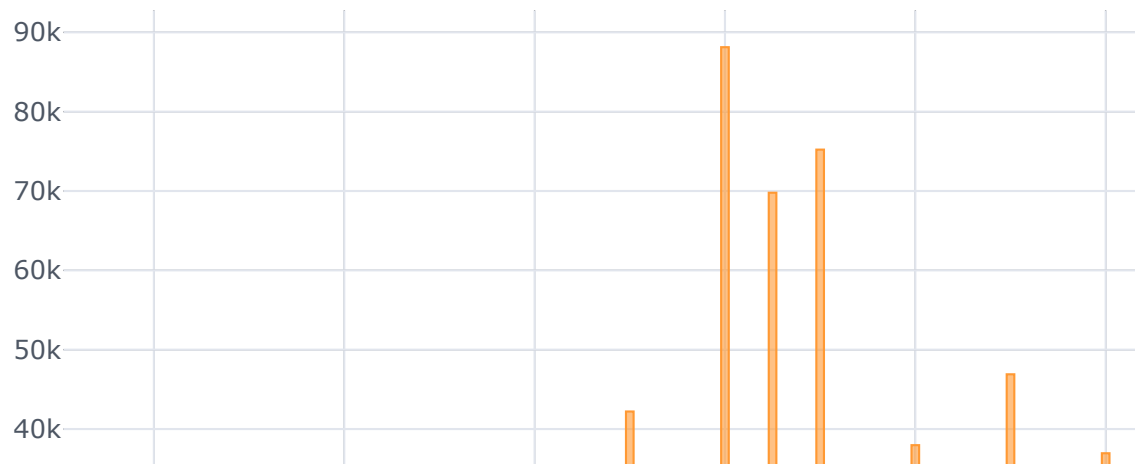
ny_floors_groups = ny_floors.groupby(['yearbuilt', pd.cut(ny_floors.numfloors, floor_bins)])
ny_floors_groups = ny_floors_groups.size().unstack()
ny_floors_groups.head()
```

Out[12]:

numfloors	(0, 20]	(20, 40]	(40, 60]	(60, 80]	(80, 100]	(100, 120]
yearbuilt						
1851.0	89.0	NaN	NaN	NaN	NaN	NaN
1852.0	209.0	NaN	NaN	NaN	NaN	NaN
1853.0	246.0	NaN	NaN	NaN	NaN	NaN
1854.0	239.0	NaN	NaN	NaN	NaN	NaN
1855.0	268.0	NaN	NaN	NaN	NaN	NaN

In [13]: *# Plot to show number of floors that were built each year*

```
ny_floors_groups.dropna(how = 'all')  
ny_floors_groups.iplot(kind='bar', barmode='overlay')
```



Part 2: Datashader

Datashader is a library from Anaconda that does away with the need for binning data. It takes in all of your datapoints, and based on the canvas and range returns a pixel-by-pixel calculations to come up with the best representation of the data. In short, this completely eliminates the need for binning your data.

As an example, lets continue with our question above and look at a 2D histogram of YearBuilt vs NumFloors:


```
In [14]: yearbins = 200
         floorbins = 200

         yearBuiltCut = pd.cut(ny['yearbuilt'], np.linspace(ny['yearbuilt'].min(), ny['yearbuilt'].max(), yearbins))
         numFloorsCut = pd.cut(ny['numfloors'], np.logspace(1, np.log(ny['numfloors'].max()), floorbins))

         xlabel = np.floor(np.linspace(ny['yearbuilt'].min(), ny['yearbuilt'].max(), yearbins))
         ylabel = np.floor(np.logspace(1, np.log(ny['numfloors'].max()), floorbins))

         fig = go.FigureWidget(
             data = [
                 go.Heatmap(z = ny.groupby([numFloorsCut, yearBuiltCut])['bbl'].count().unstack().fillna(0).values,
                             colorscale = 'Greens', x = xlabel, y = ylabel)
             ]
         )

         iplot(fig)
```

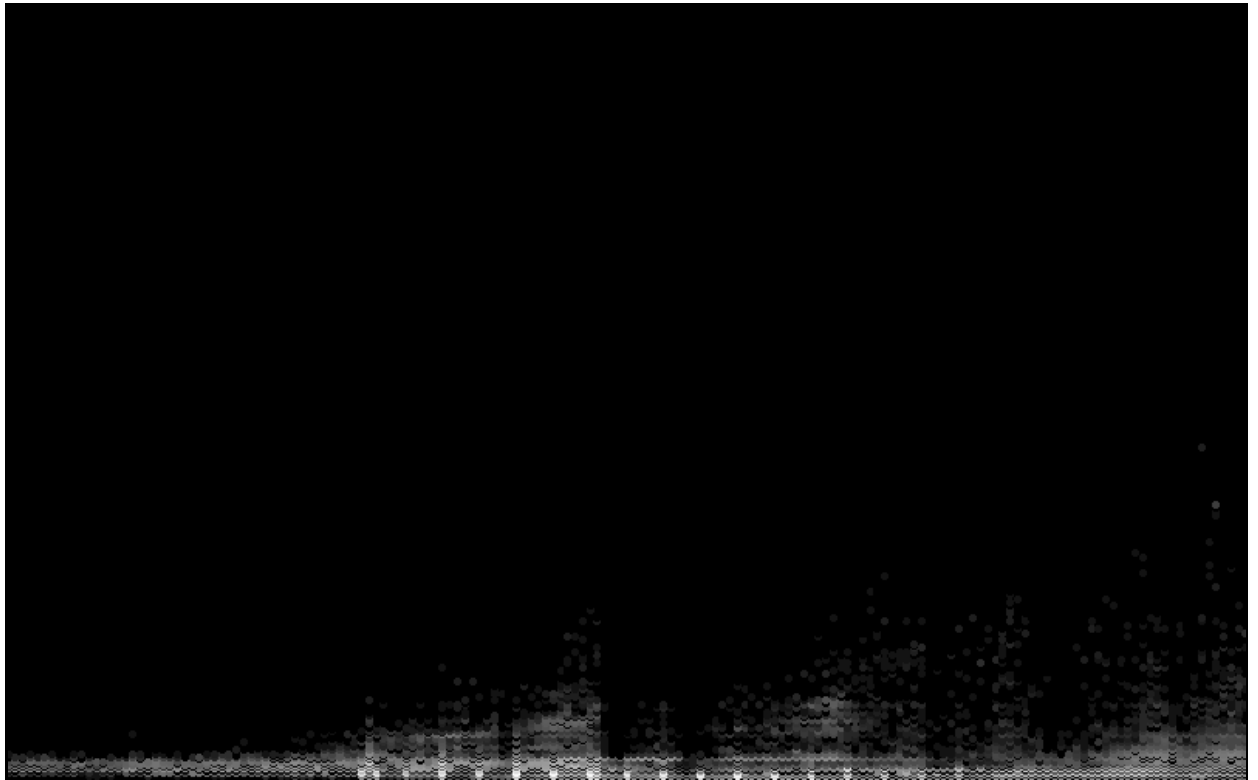


This shows us the distribution, but it's subject to some biases discussed in the Anaconda notebook [Plotting Perils \(https://anaconda.org/jbednar/plotting_pitfalls/notebook\)](https://anaconda.org/jbednar/plotting_pitfalls/notebook).

Here is what the same plot would look like in datashader:

```
In [15]: cvs = ds.Canvas(800, 500, x_range = (ny['yearbuilt'].min(), ny['yearbu
                                             y_range = (ny['numfloors'].min(), ny['
agg = cvs.points(ny, 'yearbuilt', 'numfloors')
view = tf.shade(agg, cmap = cm(Greys9), how='log')
export(tf.spread(view, px=2), 'yearvsnumfloors')
```

Out[15]:

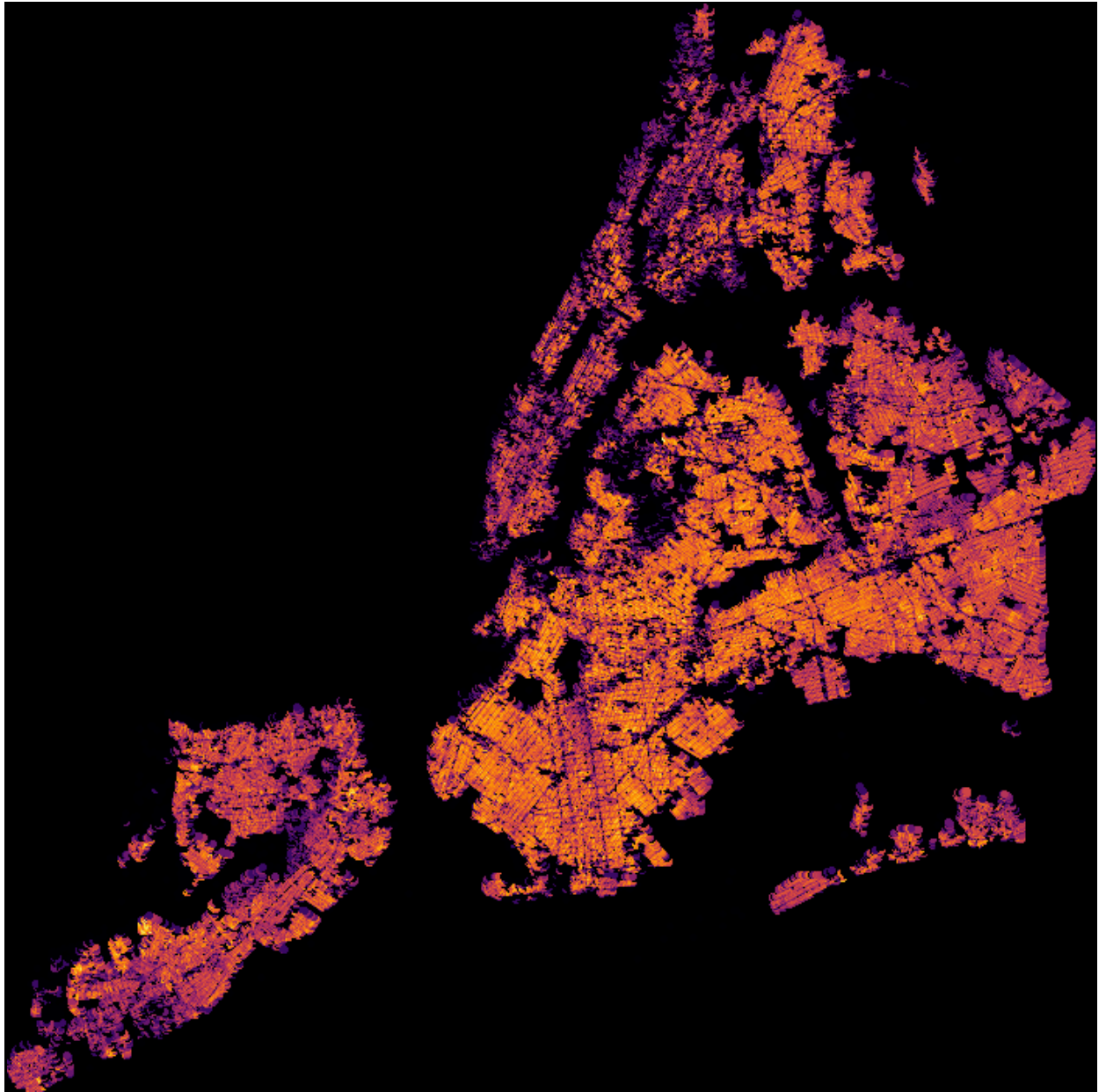


That's technically just a scatterplot, but the points are smartly placed and colored to mimic what one gets in a heatmap. Based on the pixel size, it will either display individual points, or will color the points of denser regions.

Datashader really shines when looking at geographic information. Here are the latitudes and longitudes of our dataset plotted out, giving us a map of the city colored by density of structures:

```
In [16]: NewYorkCity = (( 913164.0, 1067279.0), (120966.0, 272275.0))  
cvs = ds.Canvas(700, 700, *NewYorkCity)  
agg = cvs.points(ny, 'xcoord', 'ycoord')  
view = tf.shade(agg, cmap = cm.inferno, how='log')  
export(tf.spread(view, px=2), 'firery')
```

Out[16]:



Interestingly, since we're looking at structures, the large buildings of Manhattan show up as less dense on the map. The densest areas measured by number of lots would be single or multi family townhomes.

Unfortunately, Datashader doesn't have the best documentation. Browse through the examples from their [github repo](https://github.com/bokeh/datashader/tree/master/examples) (<https://github.com/bokeh/datashader/tree/master/examples>). I would focus on the [visualization pipeline](https://anaconda.org/jbednar/pipeline/notebook) (<https://anaconda.org/jbednar/pipeline/notebook>) and the [US Census](https://anaconda.org/jbednar/census/notebook) (<https://anaconda.org/jbednar/census/notebook>) Example for the question below. Feel free to use my samples as templates as well when you work on this problem.

Question

You work for a real estate developer and are researching underbuilt areas of the city. After looking in the [Pluto data dictionary](https://www1.nyc.gov/assets/planning/download/pdf/data-maps/open-data/pluto_datadictionary.pdf?v=17v1_1) (https://www1.nyc.gov/assets/planning/download/pdf/data-maps/open-data/pluto_datadictionary.pdf?v=17v1_1), you've discovered that all tax assessments consist of two parts: The assessment of the land and assessment of the structure. You reason that there should be a correlation between these two values: more valuable land will have more valuable structures on them (more valuable in this case refers not just to a mansion vs a bungalow, but an apartment tower vs a single family home). Deviations from the norm could represent underbuilt or overbuilt areas of the city. You also recently read a really cool blog post about [bivariate choropleth maps](http://www.joshuastevens.net/cartography/make-a-bivariate-choropleth-map/) (<http://www.joshuastevens.net/cartography/make-a-bivariate-choropleth-map/>), and think the technique could be used for this problem.

Datashader is really cool, but it's not that great at labeling your visualization. Don't worry about providing a legend, but provide a quick explanation as to which areas of the city are overbuilt, which areas are underbuilt, and which areas are built in a way that's properly correlated with their land value.

```
In [17]: # Let's analyze New York city taxes
ny_taxes = ny[['bbl', 'longitude', 'latitude', 'assessland', 'assesstot']]
ny_taxes
#ny_taxes.to_csv('ny_taxes.csv')
#ny_taxes = pd.read_csv('ny_taxes.csv')
```

Out[17]:

	bbl	longitude	latitude	assessland	assesstot
0	3008340046	-74.007347	40.637972	146250.0	350550.0
1	4040420106	-73.846003	40.786562	12240.0	78900.0
2	3046790017	-73.926923	40.653216	18120.0	34380.0
3	3078310006	-73.925958	40.623876	7680.0	24600.0
4	3078310007	-73.926030	40.623874	8160.0	29760.0
...
859167	2046560045	-73.862182	40.885331	9450.0	431100.0
859168	4086200038	-73.714035	40.733256	15120.0	40200.0
859169	3025750023	-73.952125	40.729160	20940.0	134940.0
859170	1020230046	-73.943665	40.817554	37200.0	138060.0
859171	1020590008	-73.947671	40.823816	43980.0	194400.0

811684 rows × 5 columns

```
In [18]: ny_taxes['assessland'].max()
```

Out[18]: 3211276050.0

```
In [19]: NewYorkCity = (( -74.29, -73.69), (40.49, 40.92))  
cvs = ds.Canvas(700, 700, *NewYorkCity)  
  
agg = cvs.points(ny, 'longitude', 'latitude')  
export(tf.shade(agg, cmap=['lightgreen', 'darkgreen']), 'tester')
```

Out[19]:



```
In [20]: ny_taxes_land_groups = pd.cut(ny_taxes['assessland'],
                                         np.logspace(1, np.log(ny_taxes['assessland']).max(), 10),
                                         labels=[1, 2, 3, 4, 5, 6, 7, 8, 9, 10])

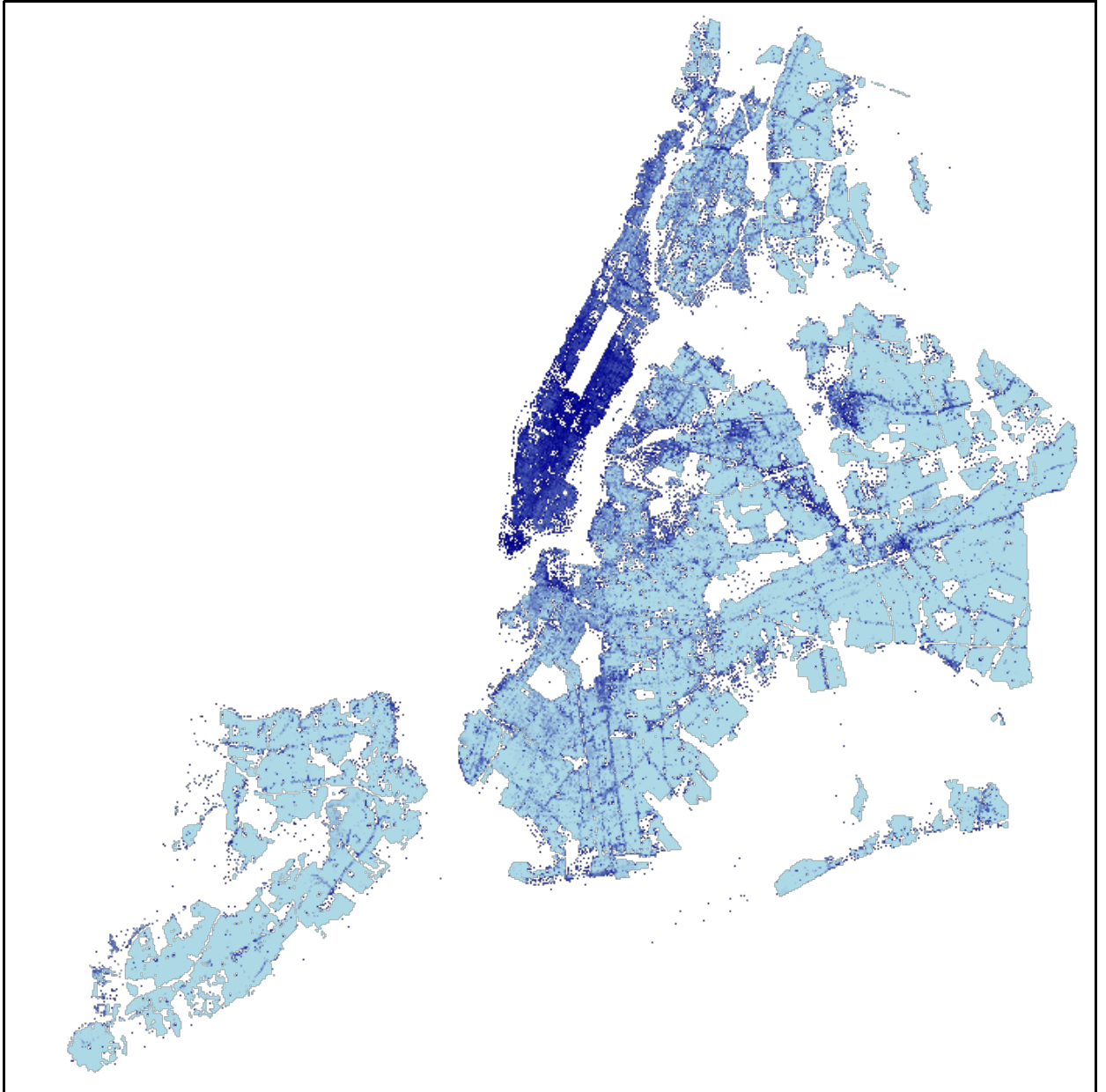
reduction = reductions.count()
glyph = ds.glyphs.Point('longitude', 'latitude')
canvas = cvs
agg = bypixel(ny_taxes, canvas, glyph, reduction)
agg
```

```
Out[20]: <xarray.DataArray (latitude: 700, longitude: 700)>
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=int32)
Coordinates:
  * longitude  (longitude) float64 -74.29 -74.29 -74.29 ... -73.69 -73.69 -73.69
  * latitude   (latitude) float64 40.49 40.49 40.49 40.49 ... 40.92 40.92 40.92
```


In [21]: *# plot for assessment land*

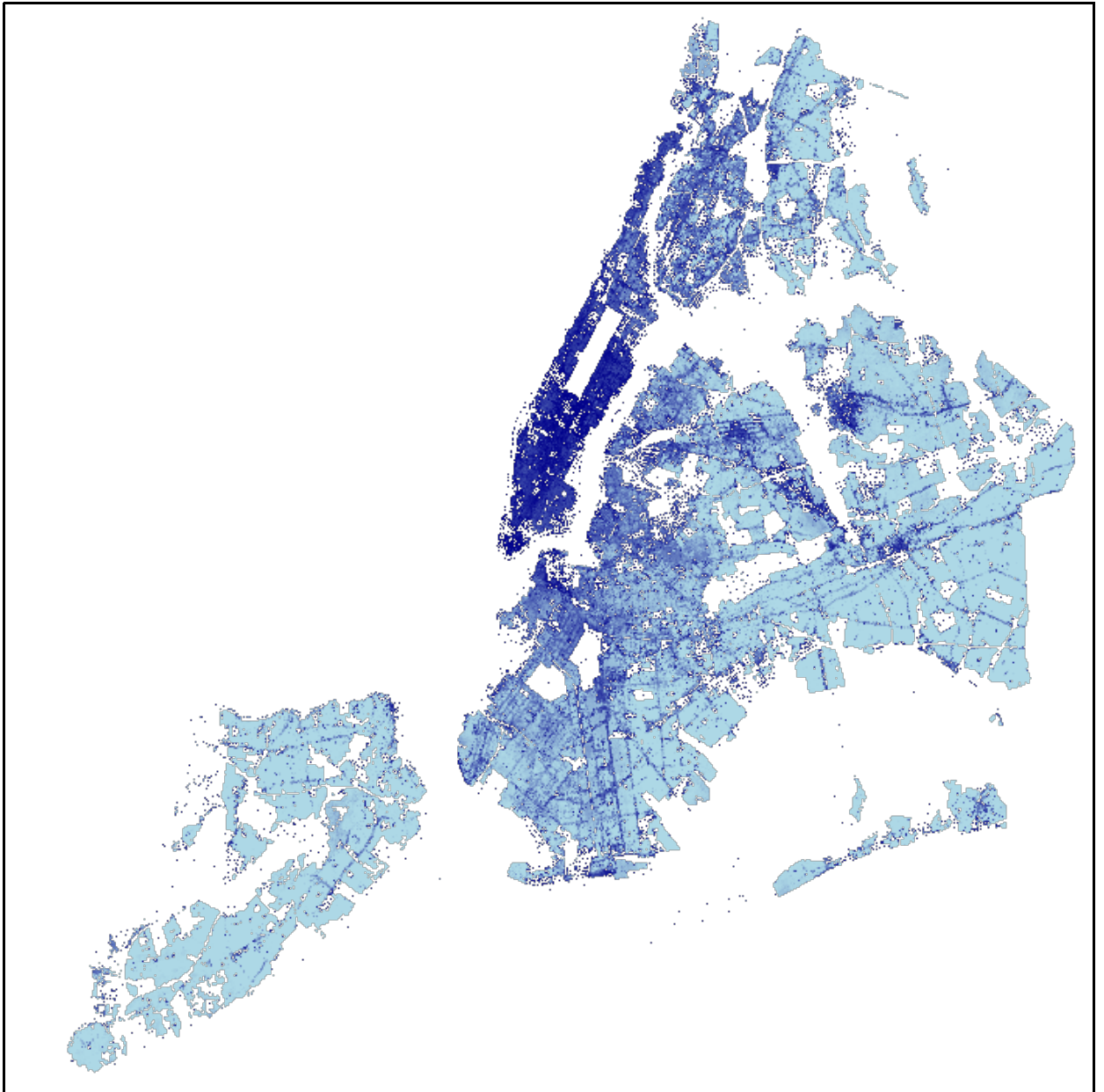
```
tf.shade(canvas.points(ny_taxes, 'longitude', 'latitude', agg=reductions.
```

Out [21]:




```
In [22]: # plot for assessment total  
tf.shade(canvas.points(ny_taxes, 'longitude', 'latitude', agg=reductions.
```

Out [22]:



In [23]: *# Creating assessproperty Variable*

```
ny_taxes['assessprop'] = ny_taxes['assesstot'] - ny_taxes['assessland']  
ny_taxes.head()
```

Out[23]:

	bbi	longitude	latitude	assessland	assesstot	assessprop
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0

```
In [24]: tf.shade(canvas.points(ny_taxes, 'longitude', 'latitude', agg=reductions.
```

Out[24]:



Now in order to analyze how many no. of bins would give an aggregate data also show distinction in the categories on the graph.

```
In [25]: # Analyzing with 10 segments
# Bin assessland into 10 segments

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assessland'])]

ny_taxes['assesslandbins'] = pd.cut(ny_taxes['assessland'],
                                   np.logspace(1, np.log(ny_taxes['assessland']).max(), 10),
                                   labels = ['one', 'two', 'three', 'four', 'five', 'six', 'seven', 'eight', 'nine'])

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assesslandbins'])]
ny_taxes.head()
```

Out[25]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two

```
In [26]: # Bin assessprop into 10 segments
ny_taxes = ny_taxes[pd.notnull(ny_taxes['assessprop'])]

ny_taxes['assesspropbins'] = pd.cut(ny_taxes['assessprop'],
                                   np.logspace(1, np.log(ny_taxes['assessprop']).max(), 10),
                                   labels = ['one', 'two', 'three', 'four', 'five', 'six', 'seven', 'eight', 'nine'])

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assesspropbins'])]
ny_taxes.head()
```

Out[26]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins	assesspropbins
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two	two
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two	two
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two	two
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two	two
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two	two

```
In [27]: # Combine categories i.e. 'assesslandbins' and 'assesspropbins'

ny_taxes['assesscat'] = ny_taxes['assesslandbins'].astype('str') + ny_taxes['assesspropbins'].astype('category')
pd.options.display.max_seq_items = 2000
ny_taxes.head()
```

Out[27]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins	assesspropbins
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two	two
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two	two
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two	two
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two	two
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two	two

```
In [28]: # These are the unique categories for 10 segments

ny_taxes.assesscat.unique()
```

Out[28]: [twotwo, twothree, threethree, threetwo, onetwo, ..., oneone, fourfour, onethree, fourthree, threeone]
Length: 12
Categories (12, object): [twotwo, twothree, threethree, threetwo, ..., fourfour, onethree, fourthree, threeone]

In [29]: *# plot the combined categories graph*

```
aggc = canvas.points(ny_taxes, 'longitude', 'latitude', ds.count_cat('tf').shade(aggc))
```

Out [29]:



Above we see that, smaller amount of bins returned too aggregated data and not able to see distinction in the categories on the graph. With 10 bins we cannot see all unique values for the combined categorisation. If variation in categories is clearer - it is difficult to set colours for specific categories if all unique values cannot be seen.

```
In [30]: # Bin AssessLand into three segments

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assessland'])]

ny_taxes['assesslandbins2'] = pd.cut(ny_taxes['assessland'],
                                     np.logspace(1, np.log(ny_taxes['assessland']).max(), 3),
                                     labels = ['low', 'medium', 'high'])

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assesslandbins2'])]
ny_taxes.head()
```

Out[30]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins	assesspropbins2
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two	low
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two	low
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two	low
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two	low
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two	low

```
In [31]: # Analyzing with three segments
# Bin assessprop into three segments
ny_taxes = ny_taxes[pd.notnull(ny_taxes['assessprop'])]

ny_taxes['assesspropbins2'] = pd.cut(ny_taxes['assessprop'],
                                     np.logspace(1, np.log(ny_taxes['assessprop']).max(), 3),
                                     labels = ['low', 'medium', 'high'])

ny_taxes = ny_taxes[pd.notnull(ny_taxes['assesspropbins2'])]
ny_taxes.head()
```

Out[31]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins	assesspropbins2
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two	low
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two	low
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two	low
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two	low
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two	low

```
In [32]: # Combine categories i.e. 'assesslandbins2' and 'assesspropbins2'

ny_taxes['assesscat2'] = ny_taxes['assesslandbins2'].astype('str') + ny
ny_taxes['assesscat2'] = ny_taxes['assesscat2'].astype('category')

ny_taxes.head()
```

Out[32]:

	bbl	longitude	latitude	assessland	assesstot	assessprop	assesslandbins	asse
0	3008340046	-74.007347	40.637972	146250.0	350550.0	204300.0	two	
1	4040420106	-73.846003	40.786562	12240.0	78900.0	66660.0	two	
2	3046790017	-73.926923	40.653216	18120.0	34380.0	16260.0	two	
3	3078310006	-73.925958	40.623876	7680.0	24600.0	16920.0	two	
4	3078310007	-73.926030	40.623874	8160.0	29760.0	21600.0	two	

```
In [33]: ## These are the unique categories with three segments

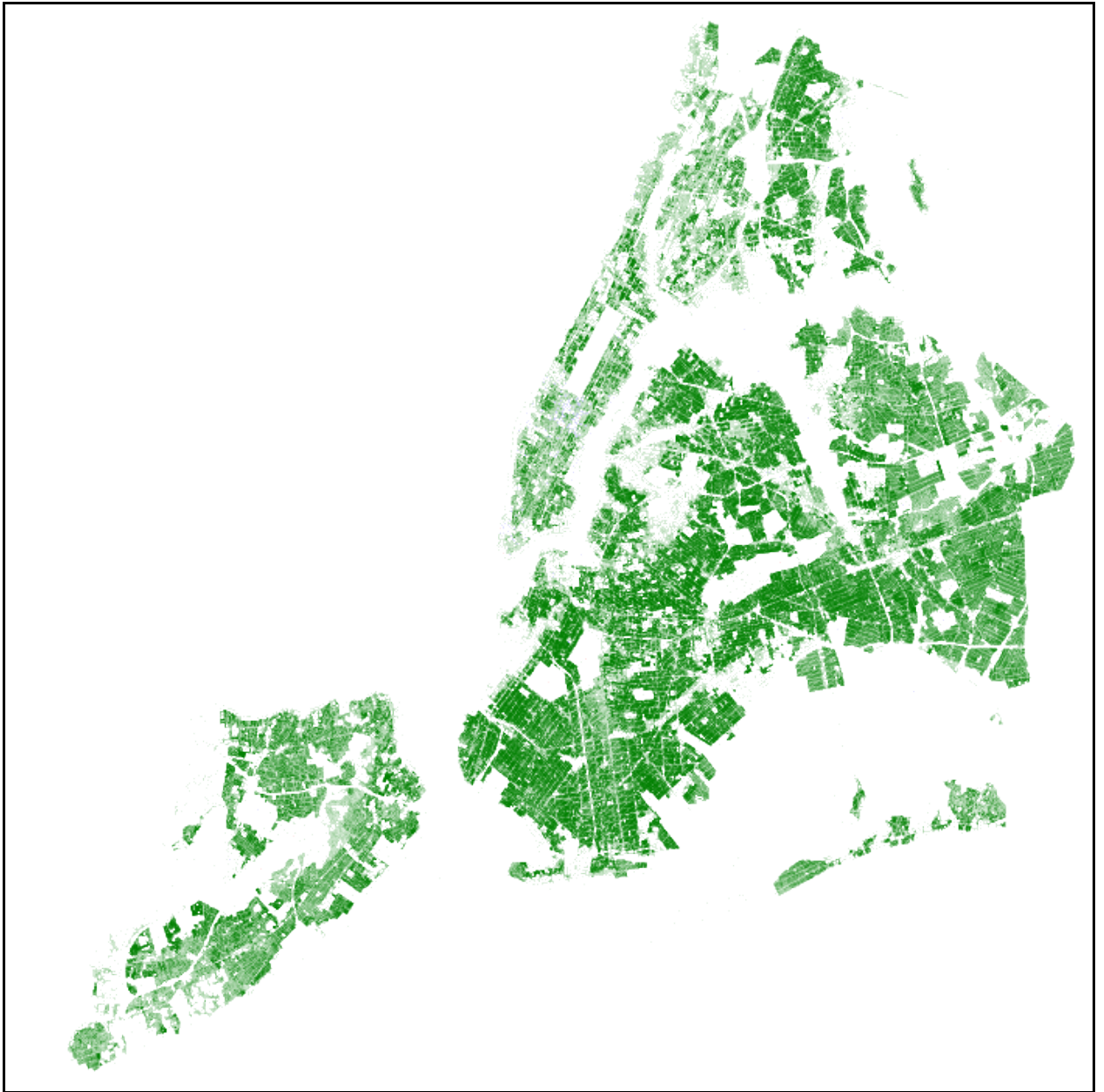
ny_taxes.assesscat2.unique()
```

Out[33]: [lowlow, lowmedium, mediummedium, mediumlow]
Categories (4, object): [lowlow, lowmedium, mediummedium, mediumlow]

In [34]: *# plot the combined categories graph*

```
aggc = canvas.points(ny_taxes, 'longitude', 'latitude', ds.count_cat('assesslandbins2', 'assesspropbins2'),  
                      colour_key = dict(lowlow='green', lowmedium='blue', mediumlow='red', mediummedium='orange'),  
                      tf.shade(aggc, color_key = colour_key))
```

Out[34]:



Therefore , the plot we see above, green shows the lowlow category of `'assesslandbins2'` and `'assesspropbins2'`. Similarly, blue shows lowmedium, red shows mediumlow and orange shows mediummedium categories.

