

21st Annual GIS/CAMA Technologies Conference Chattanooga Convention Center

GIS/CAMA • Chattanooga, TN



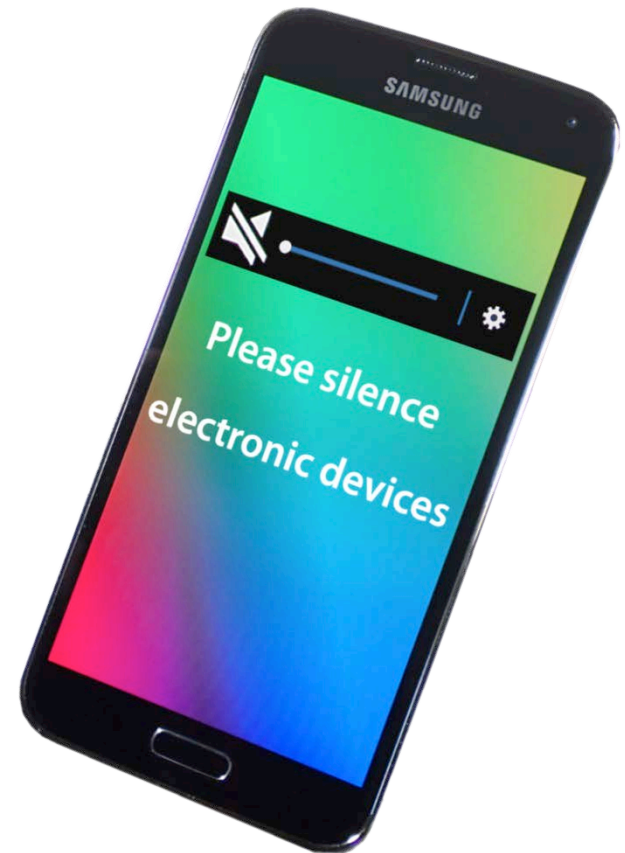
March 6-9, 2017

Continuing Education (CE) Credit

Recertification Credit forms for CE credit can be collected from the Registration Desk on Thursday.

Housekeeping

The conference proceedings will be available approximately 8 weeks after the conference.



Sub-neighborhood and baseline value study based on geographical grouping analysis for New York City

Min Zhu, Property Modeling and Research Unit, NYC DOF
Michael Cui, Property Modeling and Research Unit, NYC DOF



Study Goal:

- Seek to use statistical methods based on data(condo sales data used for this talk)
 - Guide the subdivision and grouping of existing neighborhoods
 - Produce baseline values based on location
- This is a pilot study conducted as part of a neighborhood delineation project.
- It is still an ongoing study...



About Neighborhoods

- Traditional neighborhoods?
- Existing neighborhood boundaries?
 - Market change: new emerging areas
 - Neighborhood boundary and purpose
 - New York City Released Neighborhoods
- New York City: more heterogeneity





Legend

Number of DNAinfo

1 28

We Asked You
 Nigel Chiway
 map-heres-w

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March 6-9, 2017

21st Annual GIS

Legend

Number of DNAinfo

1 49

View results base

Expand this window

Legend

Number of DNAinfo readers who included this area in their drawings

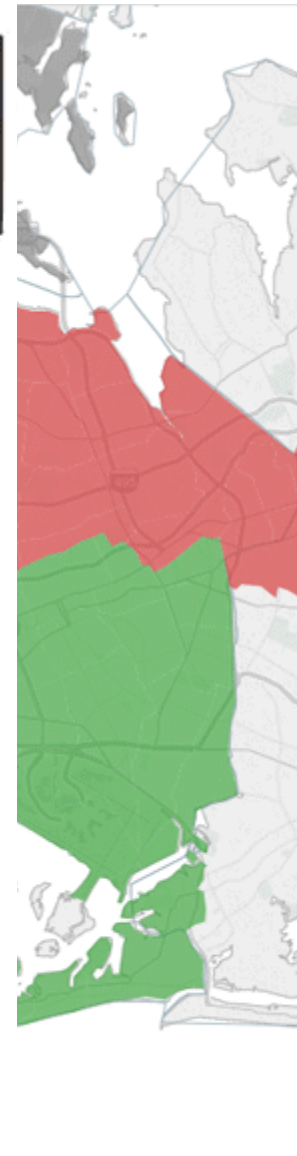
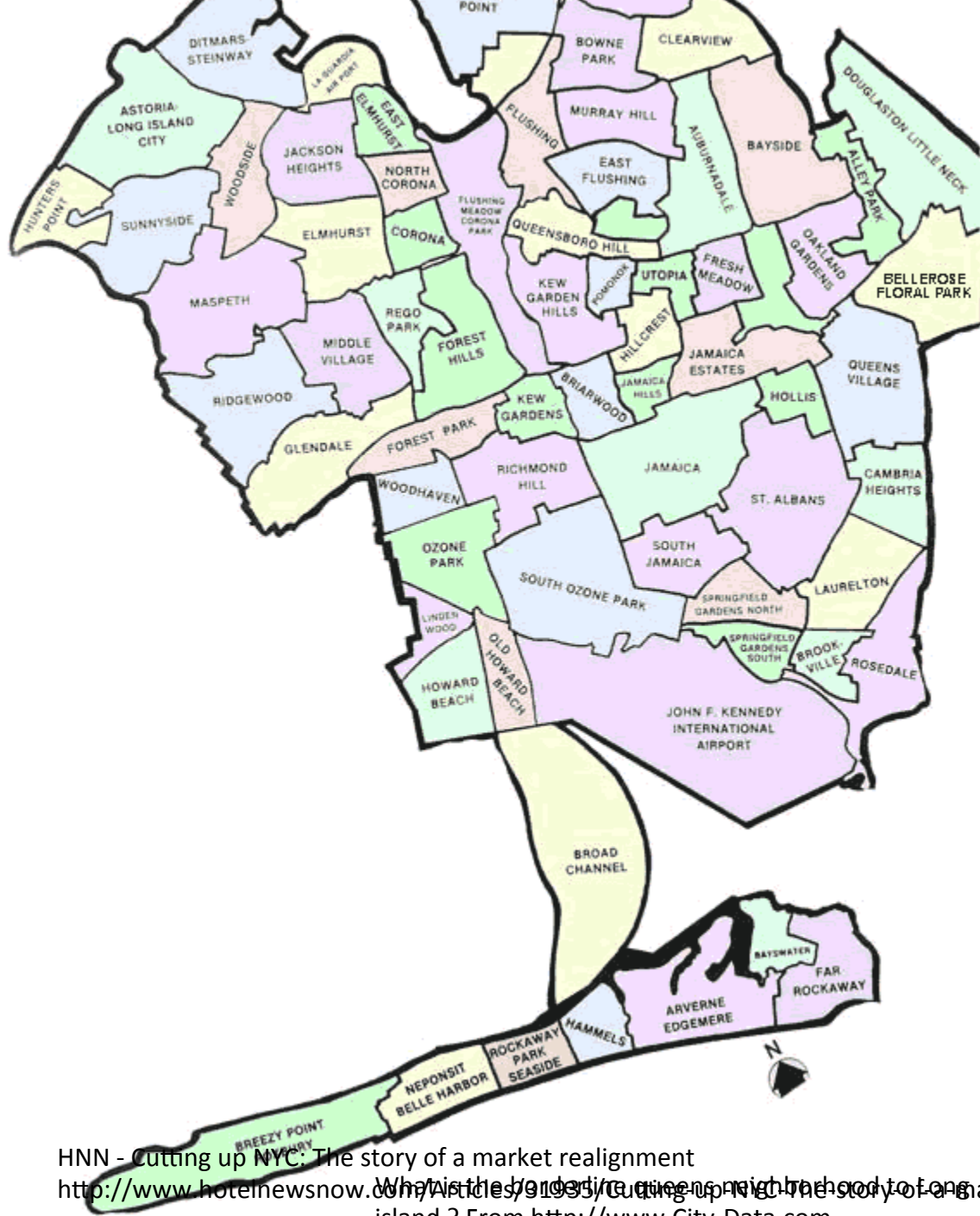
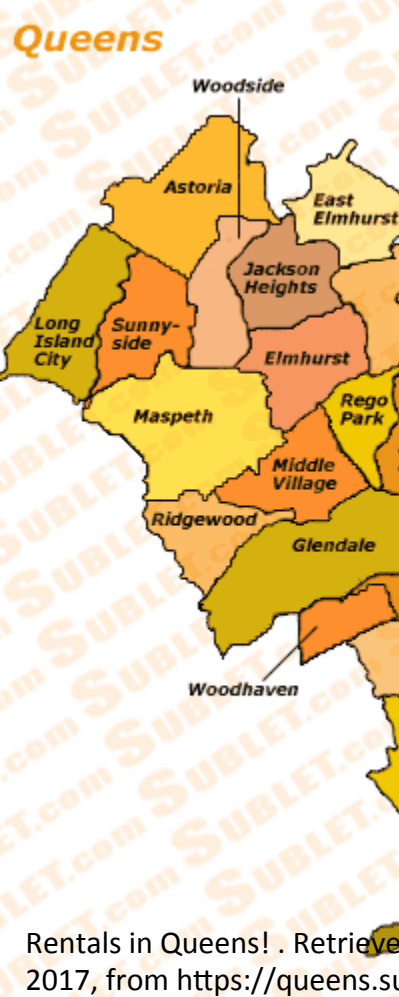
1 14 28 42 56 70 85

View results based on the number of years readers have lived in Elmhurst:

About Neighborhoods

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Rentals in Queens! . Retrieve 2017, from <https://queens.su>



21st An

HNN - Cutting up NYC: The story of a market realignment

<http://www.hotnewsnow.com/articles/2013/09/09/cutting-up-nyc-the-story-of-a-market-realignment>

What is the order of queens neighborhood to Long island ? From <http://www.City-Data.com>

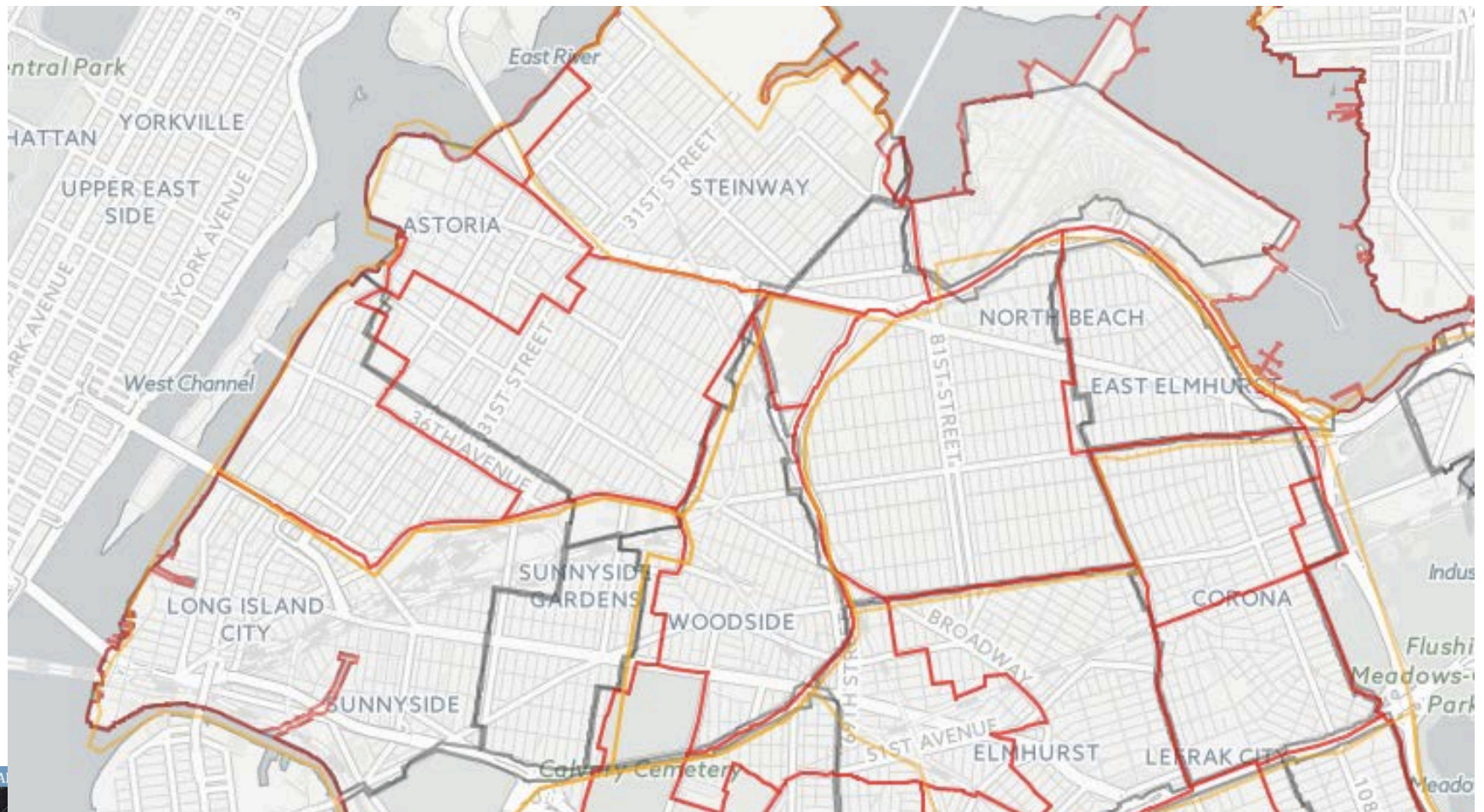
a, Tennessee

About Neighborhoods

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Overlay of different neighborhood boundaries



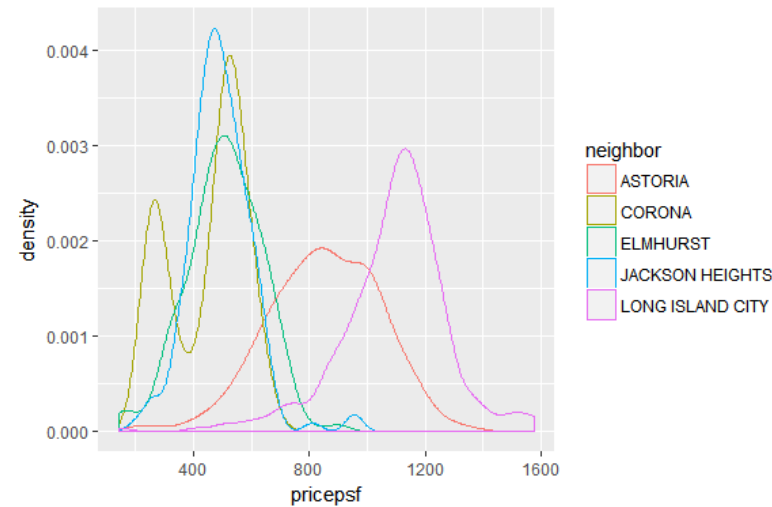
About Neighborhoods

- Traditional neighborhoods?
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- **New York City: more heterogeneity**



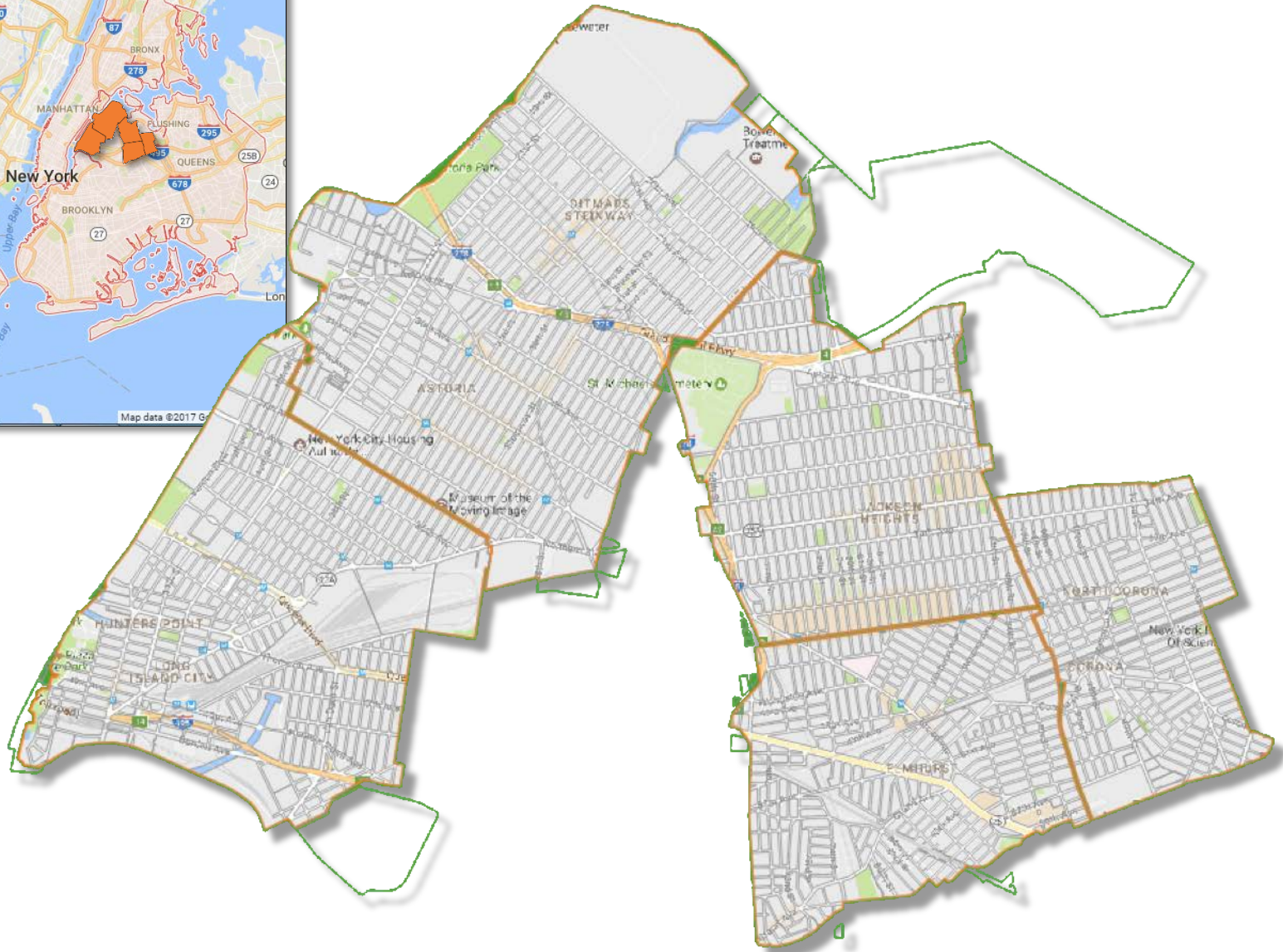
Study Area

- Study area:
 - 5 neighborhoods in Queens:
 - ASTORIA, CORONA, ELMHURST, JACKSON HEIGHTS, LONG ISLAND CITY
 - Condo Sales Price per sf (2015 -2016)



neighbor	n	Mean	Median	Q1	Q2	Q3
ASTORIA	200	\$ 850.78	\$ 853.08	\$ 729.91	\$ 853.08	\$ 993.44
CORONA	134	\$ 447.49	\$ 502.99	\$ 300.09	\$ 502.99	\$ 542.94
ELMHURST	132	\$ 507.97	\$ 511.41	\$ 435.29	\$ 511.41	\$ 600.93
JACKSON HEIGHTS	143	\$ 494.04	\$ 485.75	\$ 428.24	\$ 485.75	\$ 551.14
LONG ISLAND CITY	245	\$ 1,089.66	\$ 1,108.70	\$ 1,001.16	\$ 1,108.70	\$ 1,188.17



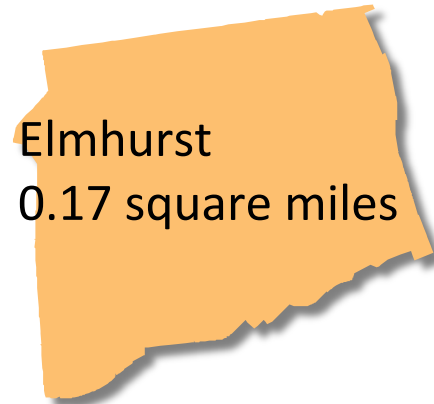
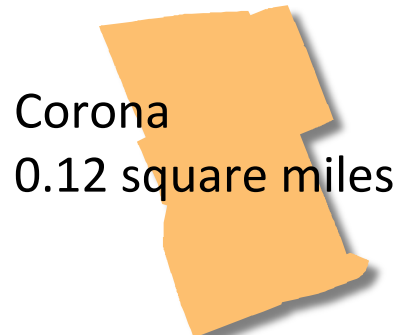


Map data ©2017 Google

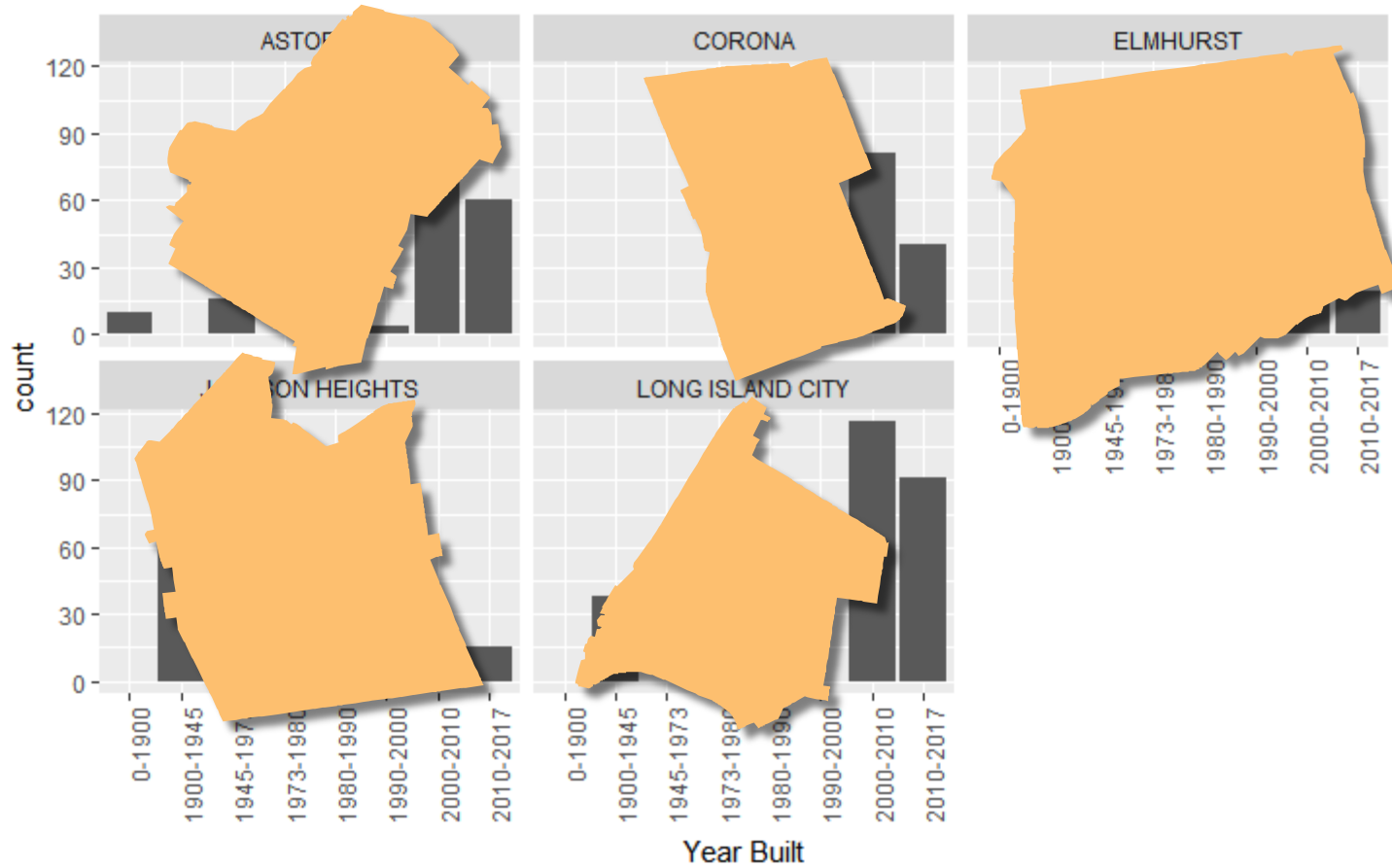
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Descriptive Data on Neighborhoods



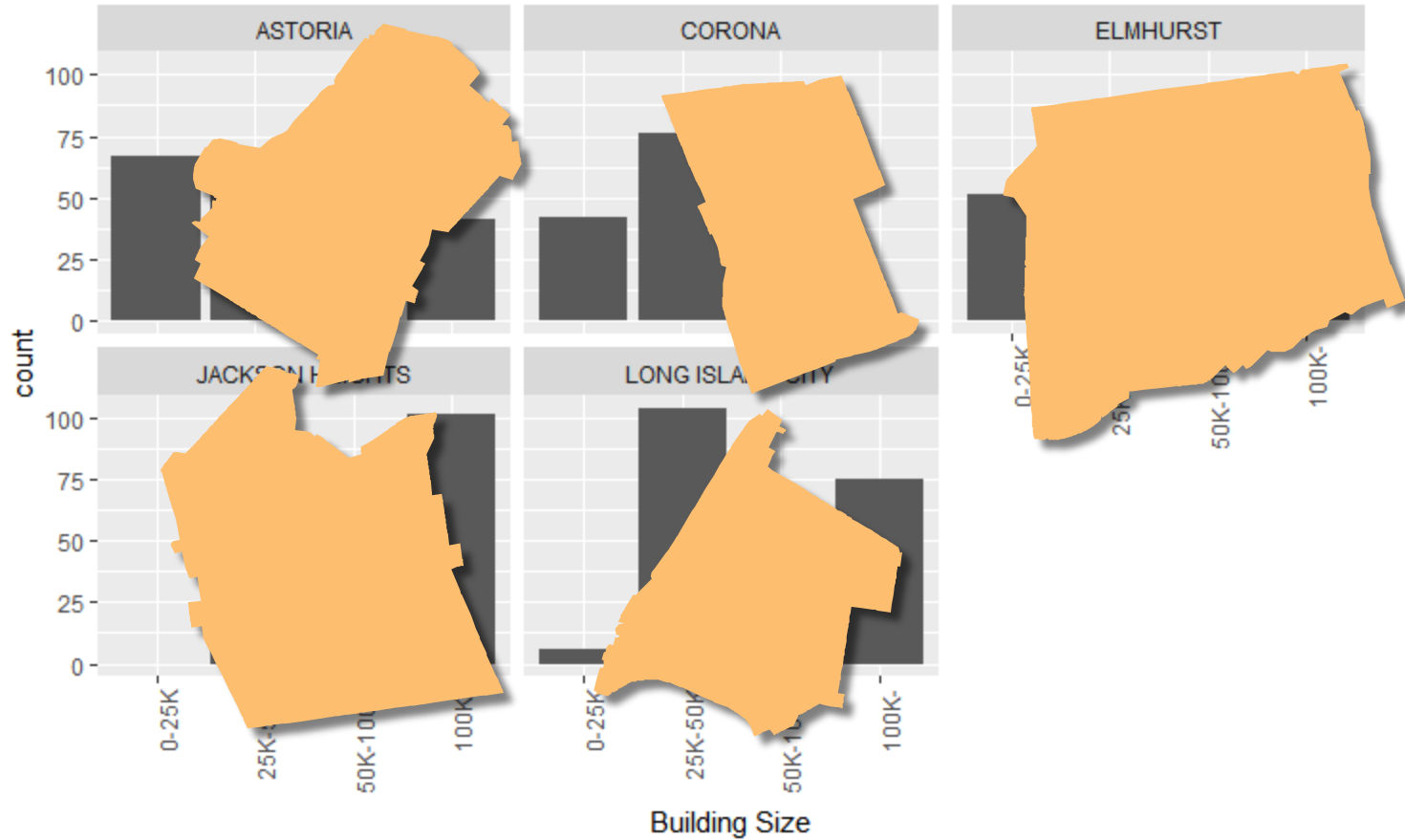
Descriptive Data on Neighborhoods



Descriptive Data on Neighborhoods



Descriptive Data on Neighborhoods



Geographical Methods:

- General discussion
 - Thin plate spline and classification
 - K nearest neighbor and classification
 - GWR and cluster analysis



Thin plate spline

- Thin plate splines (TPS) is a spline based technique for data interpolation and smoothing
- The minimization problem is:

$$\sum_{i=1}^n (y_i - f(x_i))^2 + \lambda * J_m(f)$$

- Where $J_m(f)$ is the m-th order thin plate spline penalty functional.
- The smoothing variant, uses a tuning parameter λ to control how non-rigid is allowed for the deformation



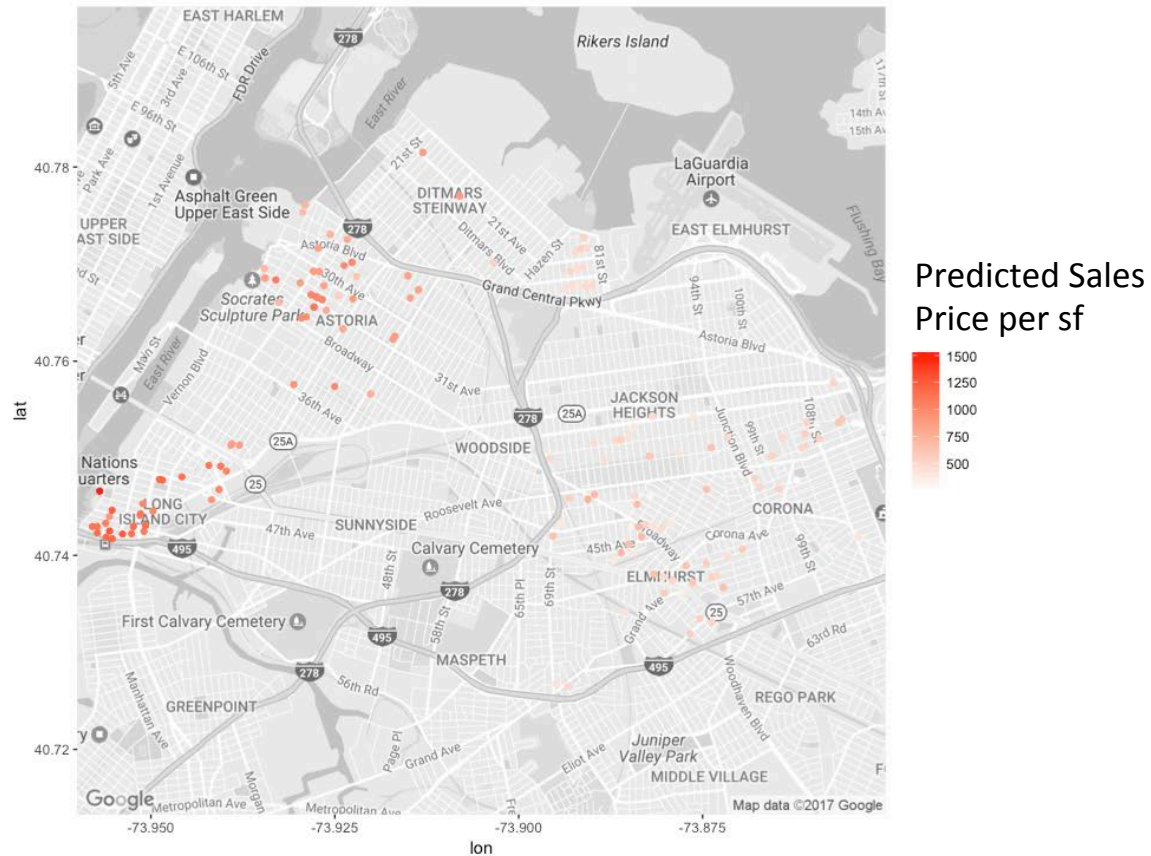
Thin plate spline

- Original Sales data: Tax Class 2



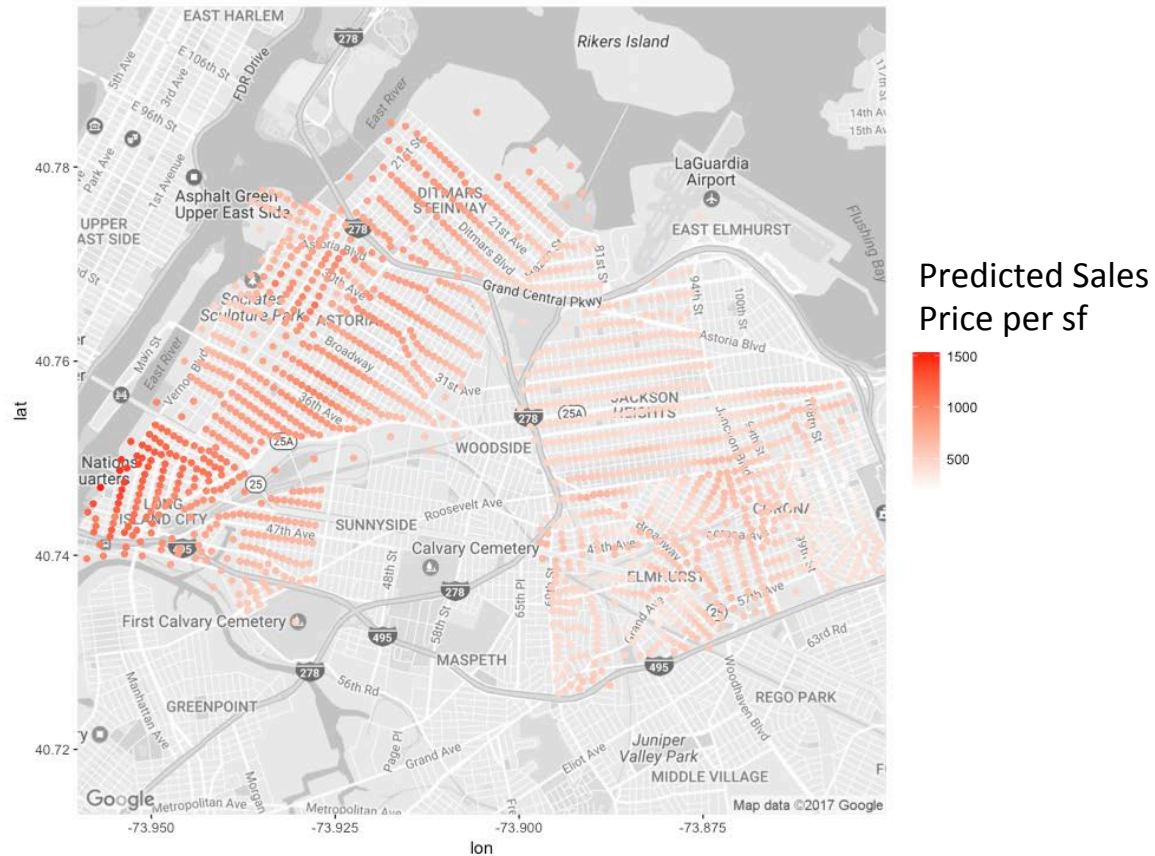
Thin plate spline

- Predictions: use optimized λ



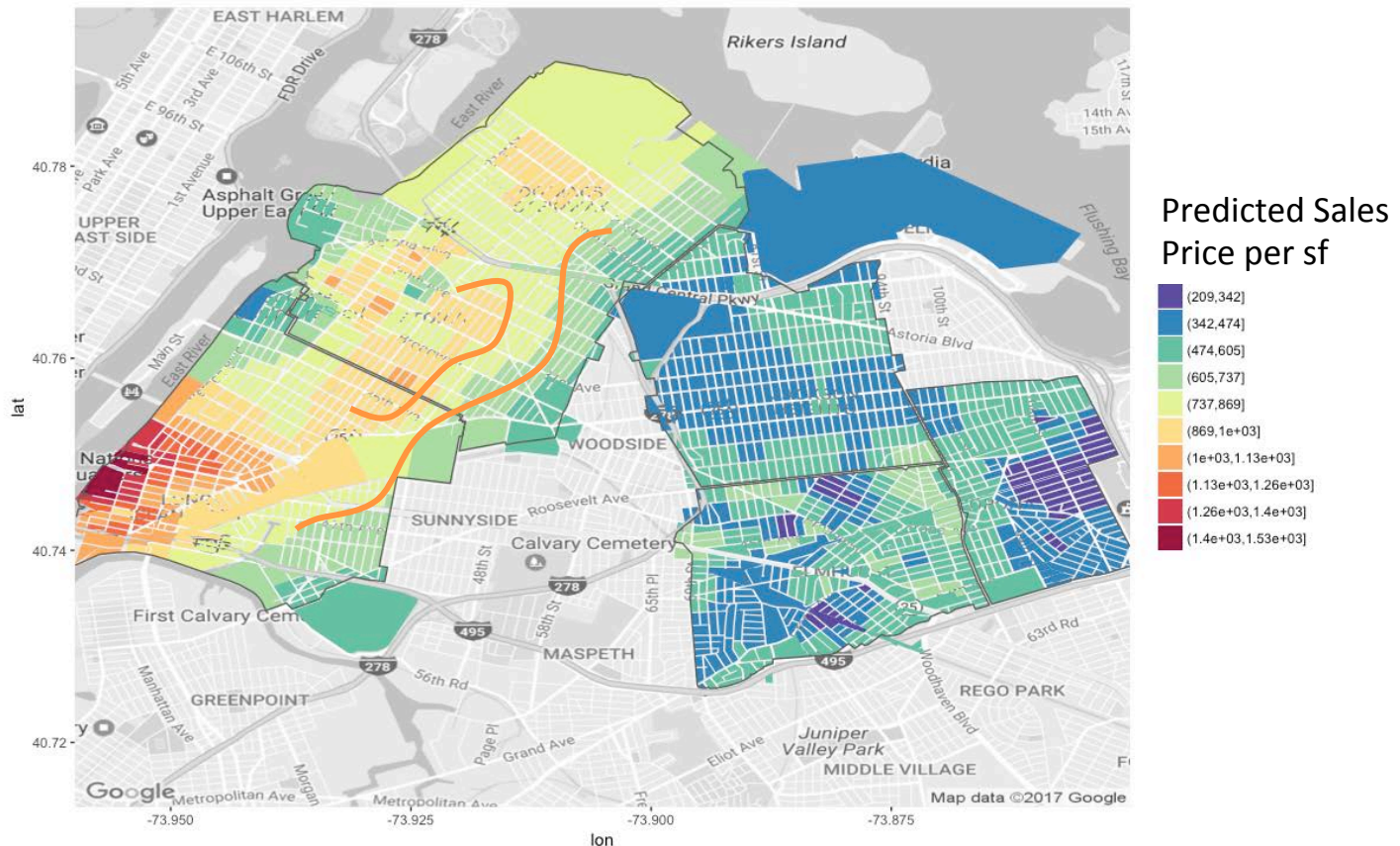
Thin plate spline

- Predictions for all blocks: use optimized λ



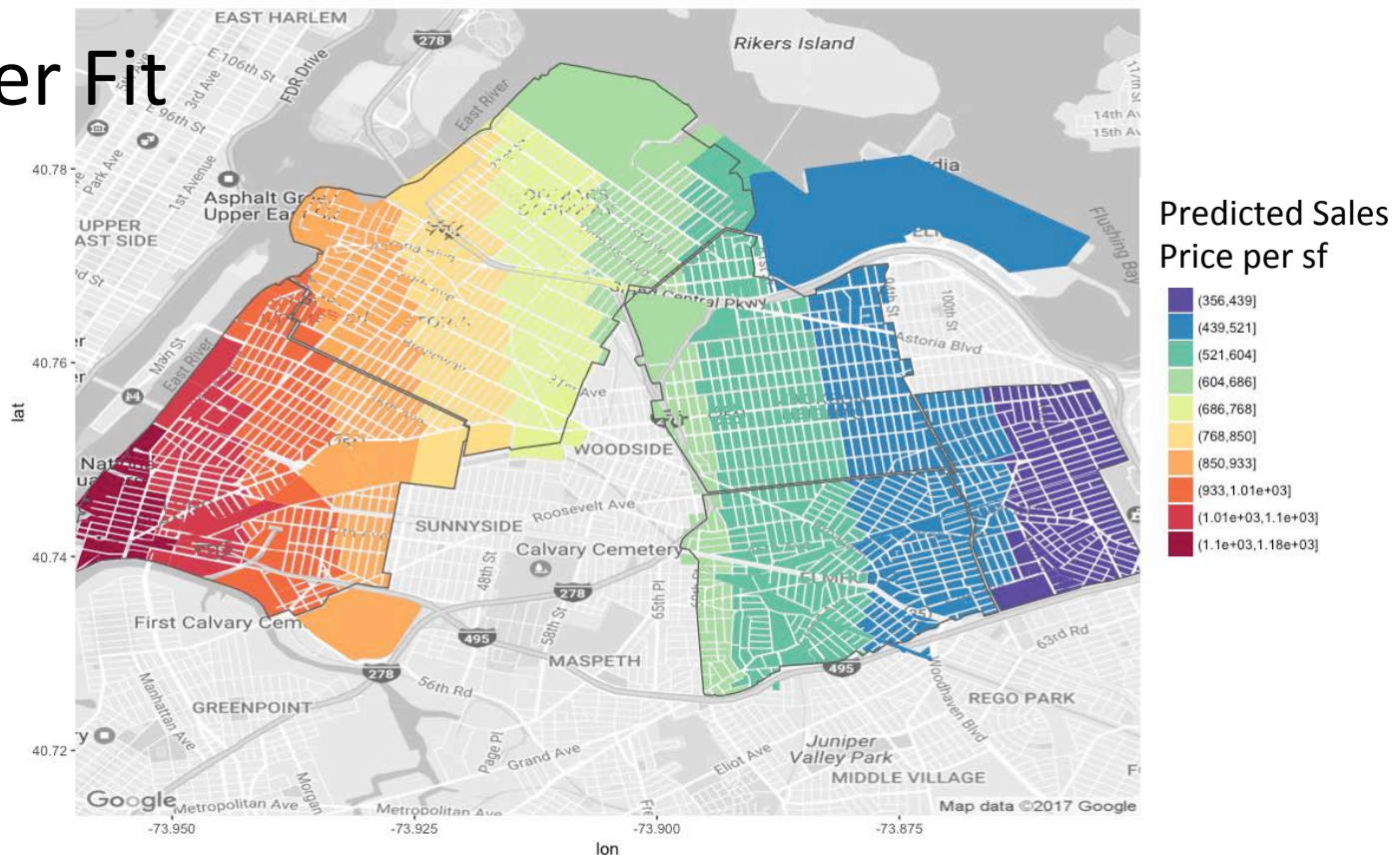
Thin plate spline

- Predictions for all blocks: use optimized λ



Thin plate spline

- Predictions for all blocks: use a larger λ
- Under Fit



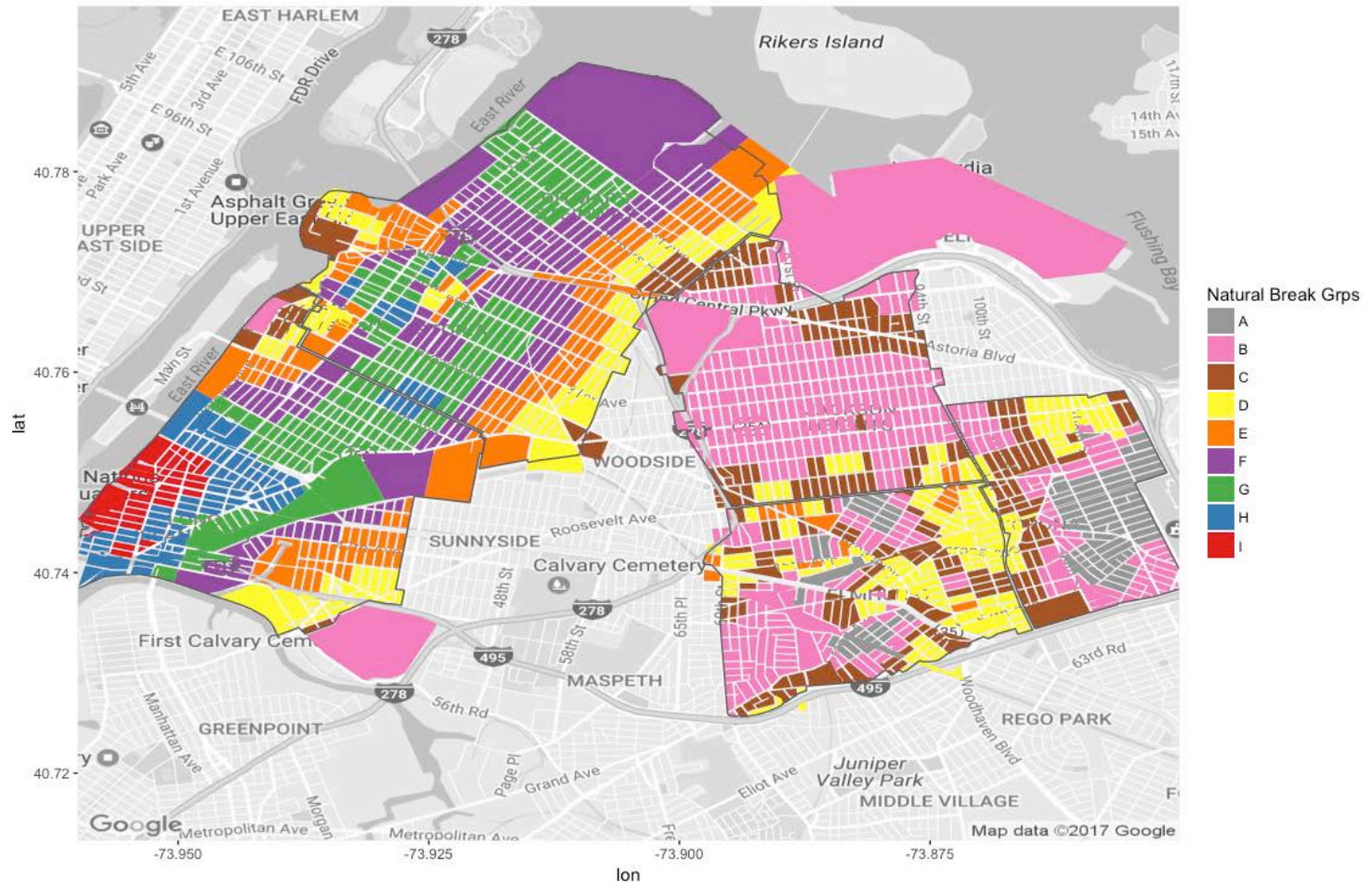
Classification: Jenks Natural Breaks

- After filling up the entire area with predicted values
- Data clustering method: Jenks Natural Breaks Classification
 - Determines the best arrangement of values into different classes
 - Divide blocks into sub-neighborhood areas
 - By reducing the variance within classes and maximizing the variance between classes



Thin plate spline

- Grouped to sub-neighborhoods: Jenks Natural Breaks



Thin plate spline

- Discussion:
 - Pros:
 - quick and straight forward,
 - use coordinates and specify lambda
 - Cons:
 - choice of lambda, can be tricky; Can over fit.
 - When data is sparse, confident level for predictions near boundary are low. May end up with interpolation values from closest point looking like contours.
 - When data variation is larger in small area, extreme peaks can form.



K nearest neighbor

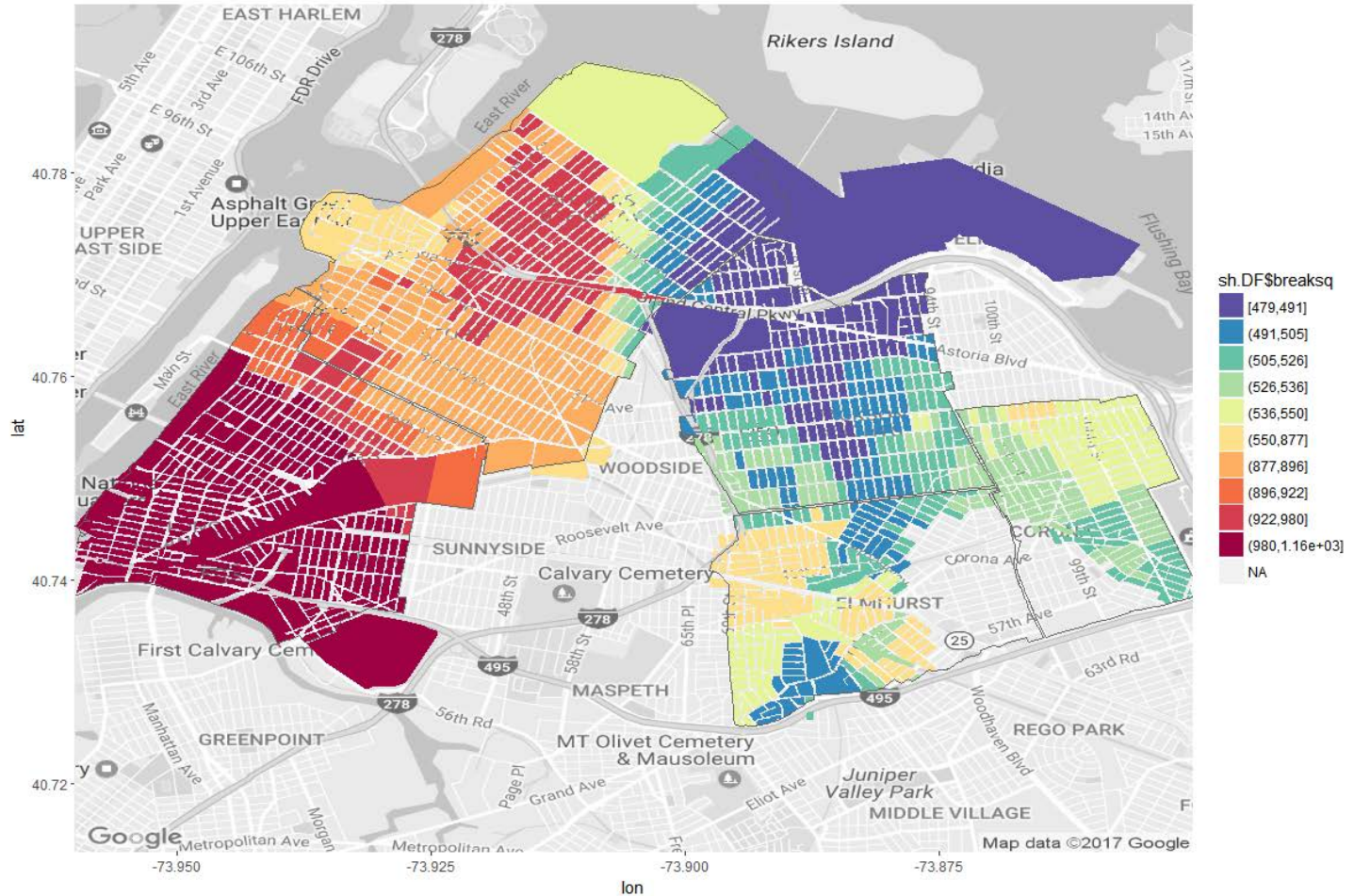
- K-nearest neighbor:
 - data interpolation and smoothing technique
 - Value of a given location determined by the k nearest neighbors around
 - Flexibility on distance
- For our purposes, we look for a subject block's value based on the median of its k nearest block values
- Classification: Jenks Natural Breaks



Sub

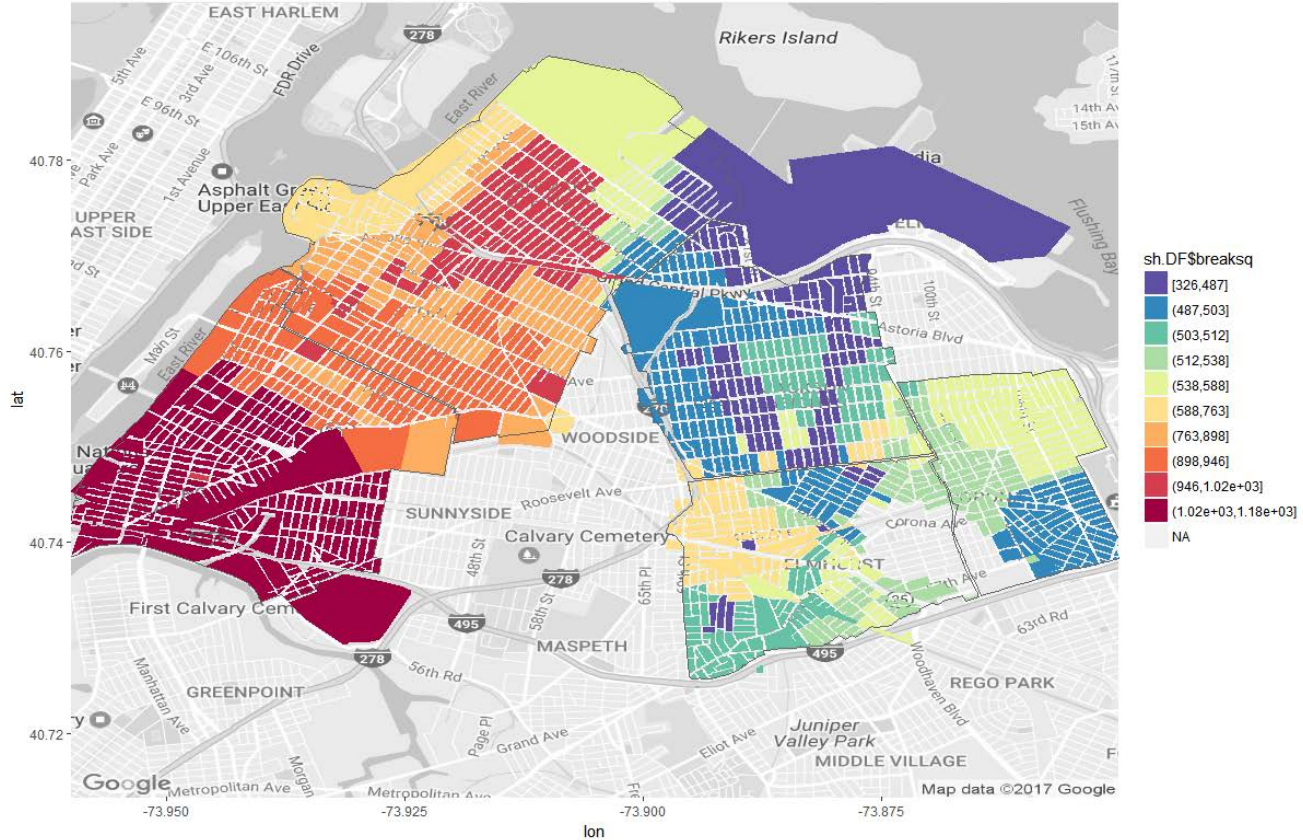
K nearest neighbor

Tc2, 10 nearest neighbor block values
Based on tc2 sales



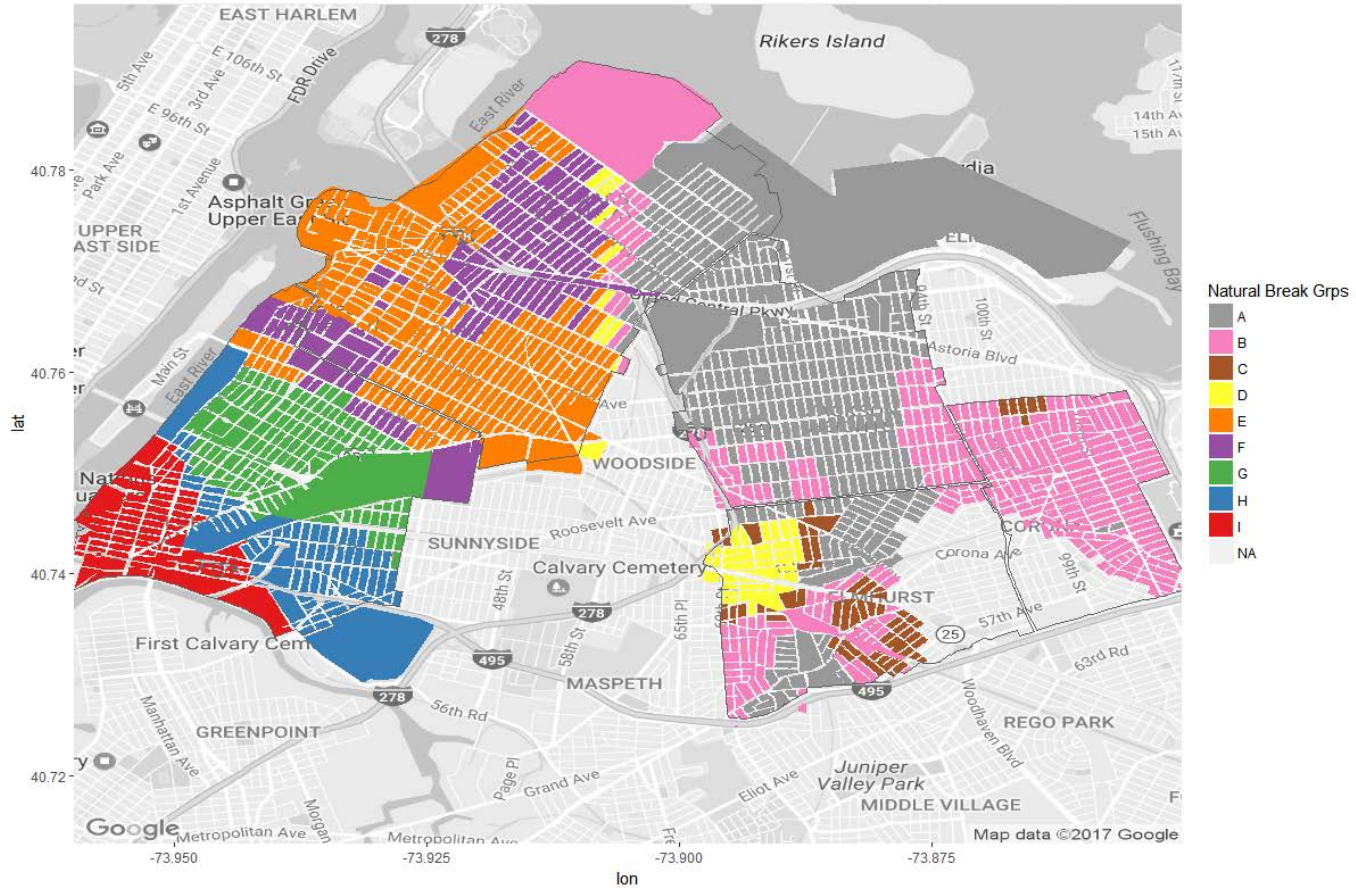
K nearest neighbor

Tc2, 5 nearest neighbor block values
Based on tc2 sales



K nearest neighbor group: Jenks Natural Break

Tc2, 10 nearest neighbor groups
Based on tc2 sales



K nearest neighbor

- Discussion

- Pros:

- Easy to interpret
 - Flexible searching distance

- Cons:

- Based on one variable: price psf
 - Small pieces of land when grouping



Geographically Weighted Regression (GWR)

- The basic form of the GW regression model is:

$$y_i = \beta_{i0} + \sum_{k=1}^M \beta_{ik} x_{ik} + \varepsilon_i$$

Dependent variable y_i

Regression coefficients β_{ik}

Residual variable ε_i

$i=1-N$ number of observations
 $J=0-M$ number of ind. variables

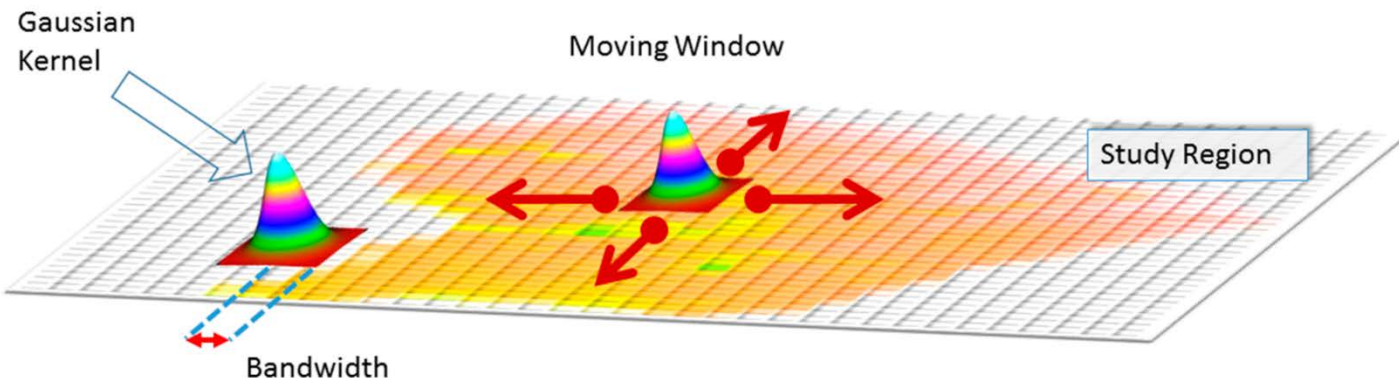
The k^{th} variable at location i

- As data are geographically weighted, nearer observations have more influence in estimating the local set of regression coefficients than observations farther away.
- Difference in local coefficients reflect the difference in sensitivity to how price respond



Geographically Weighted Regression (GWR)

- Geographically Weighted Regression scheme. Geographical weighting is achieved by a fixed Gaussian kernel function with a given bandwidth moving across the spatial domain. Bandwidth determines the rate at which the weights decay around each cell, and reflects the degree of spatial variation: if the bandwidth gets larger, the model will tend to a global regression model.



* Ceccherini, Guido; Ametztoy, Iban; Hernández, Claudia P.R.; Moreno, Cesar C. 2015. "High-Resolution Precipitation Datasets in South America and West Africa based on Satellite-Derived Rainfall, Enhanced Vegetation Index and Digital Elevation Model." *Remote Sens.* 7, no. 5: 6454-6488.

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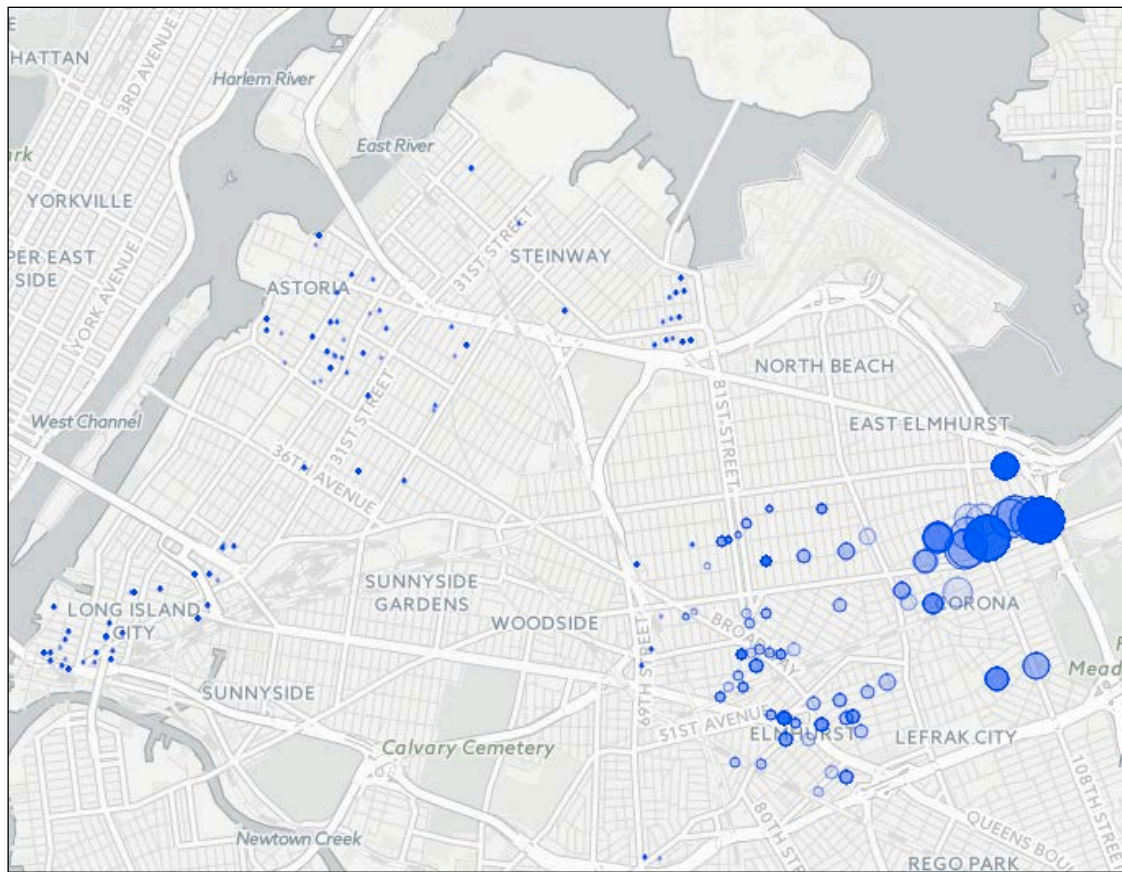
Geographically Weighted Regression (GWR)

- GWR variables
 - Predicting variables: pricepsf
 - Explaining variables:
 - Aptsize
 - Total resid unit
 - Building story
 - Year built
 - Elev/Walkup
 - Building size
 - Resratio, retraction ...
 - yearqtr
 - * Variables used in model are after transformation and scaled



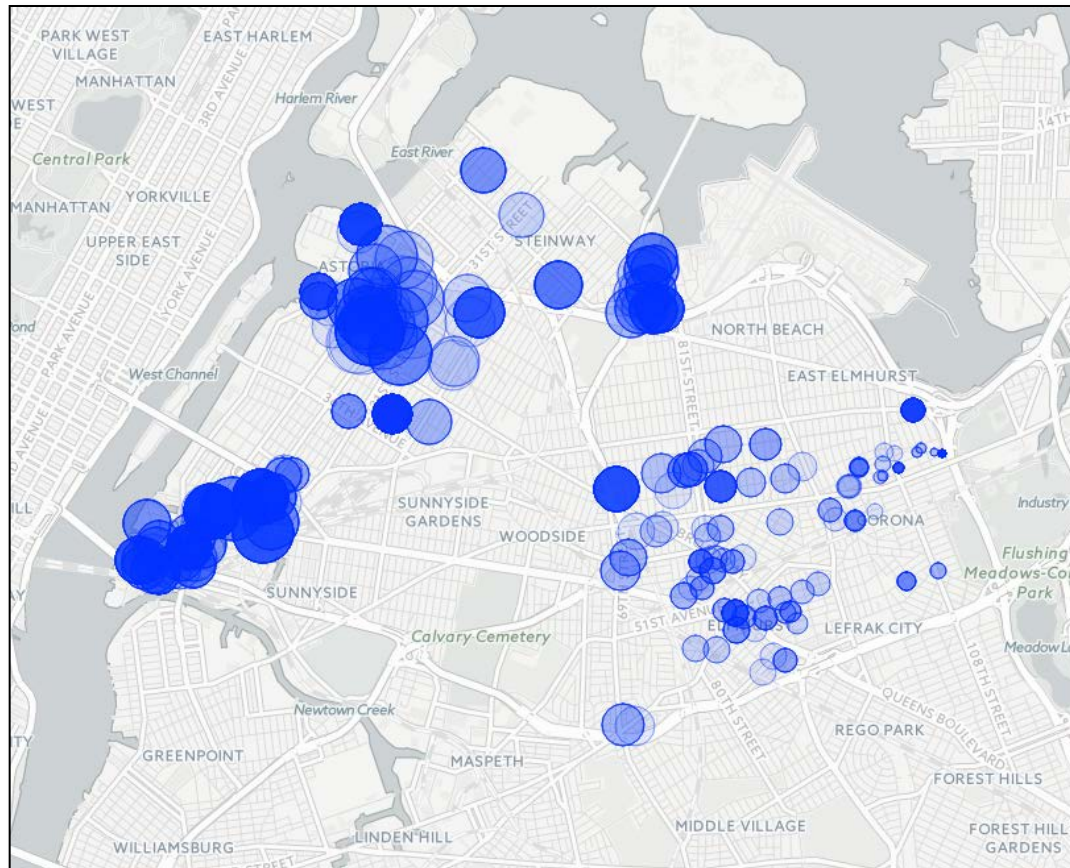
Geographically Weighted Regression (GWR)

- GWR local coefficients rendering: BLDG Story



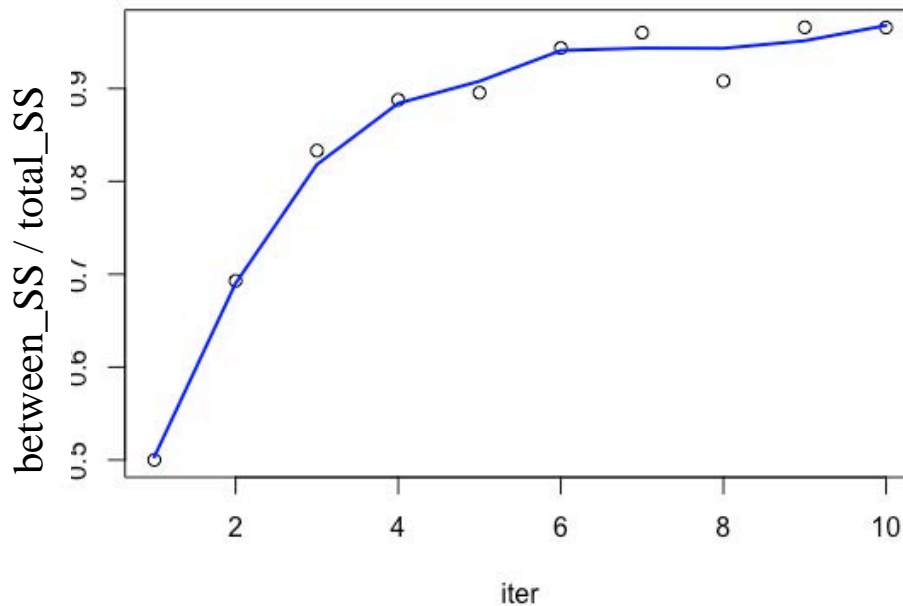
Geographically Weighted Regression (GWR)

- GWR local coefficients rendering: year built



Geographically Weighted Regression (GWR)

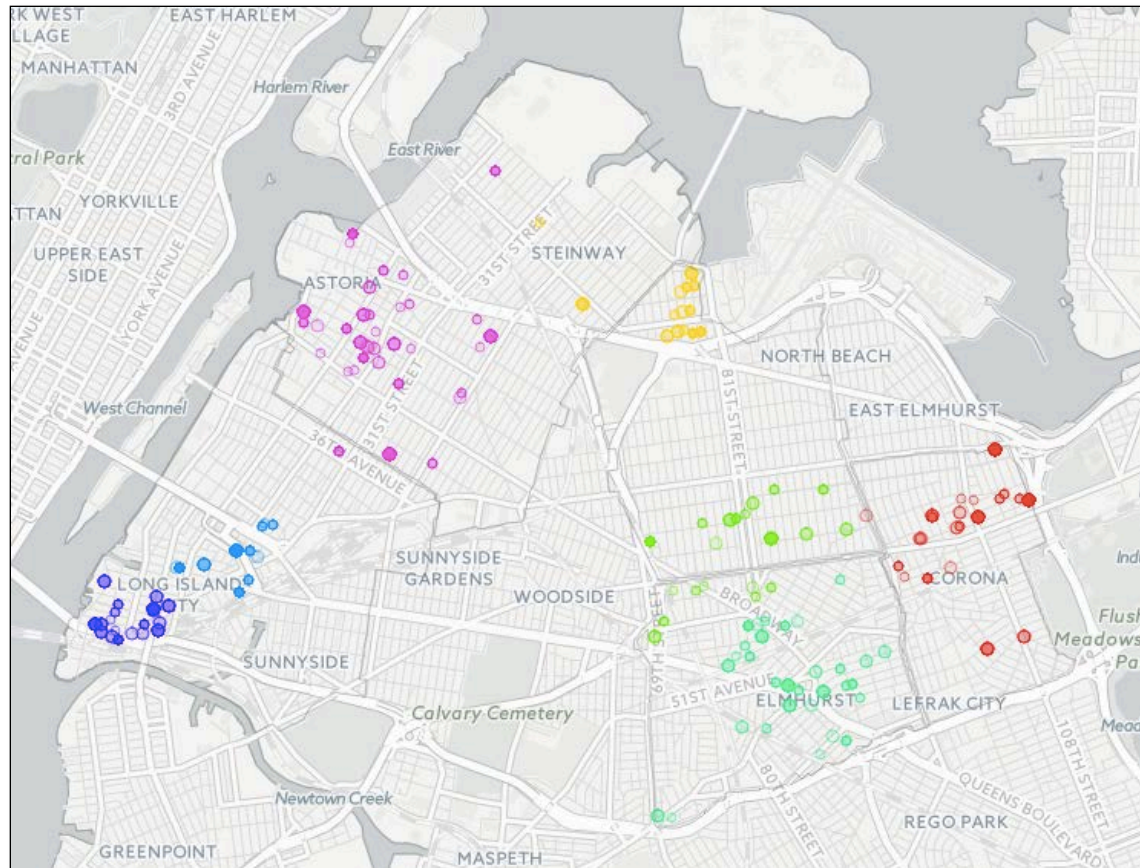
- K- means clustering
- Find optimized number of groups



Geographically Weighted Regression (GWR)

- Clustering result

[Go to Interactive map](#)



What's Next?

- Application on larger geographical area and expand sales data
- Look for systematic method to identify boundary considering the hierarchy of road system or other geo boundaries in the area
- Test in practice



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