FINDING THE FAULT LINES:

DETECTING URBAN SOCIAL BOUNDARIES USING SOCIAL DATA SCIENCE

NSF-SES
1733705

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BOUNDARIES

GOODNESS OF FIT: THE SILHOUETTE

WHOSE “GOOD” IS IT ANYWAY?

EXAMPLE: BROOKLYN

BOUNDARIES

AN EMINENTLY-GEOGRAPHICAL CONSTRUCT

GOODNESS OF FIT: THE SILHOUETTE

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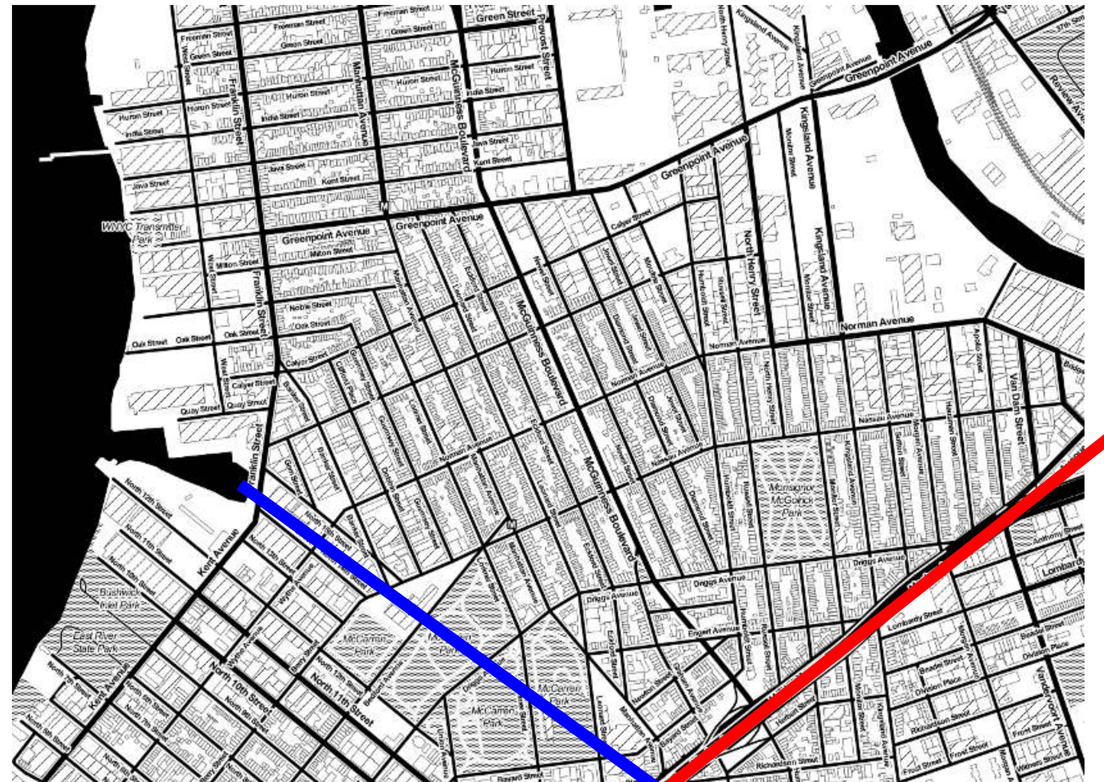
CONCEPTUALIZING BOUNDARIES

“Williamsburg becomes Greenpoint at the Bushwick Inlet”

CONCEPTUALIZING BOUNDARIES

“Williamsburg becomes Greenpoint at the Bushwick Inlet”

“Greenpoint is bordered on the southeast by the BQE”



CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS NATURALISTIC DIVISIONS OF URBAN LIFE

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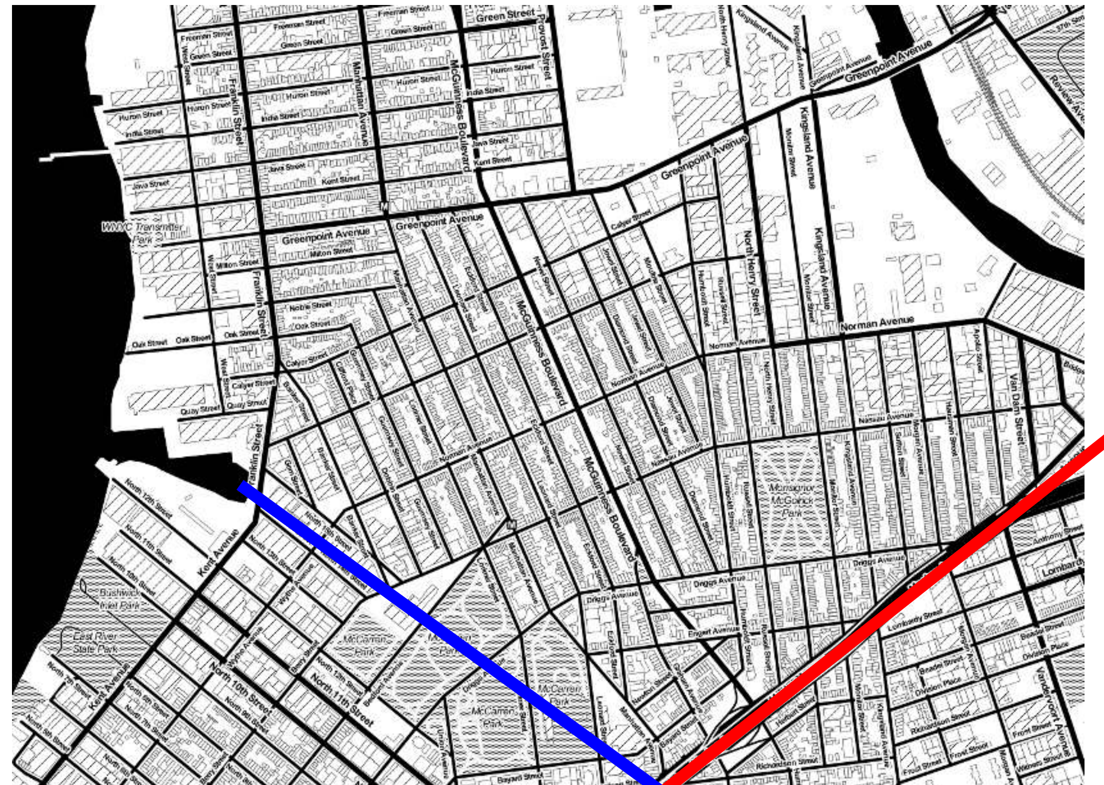
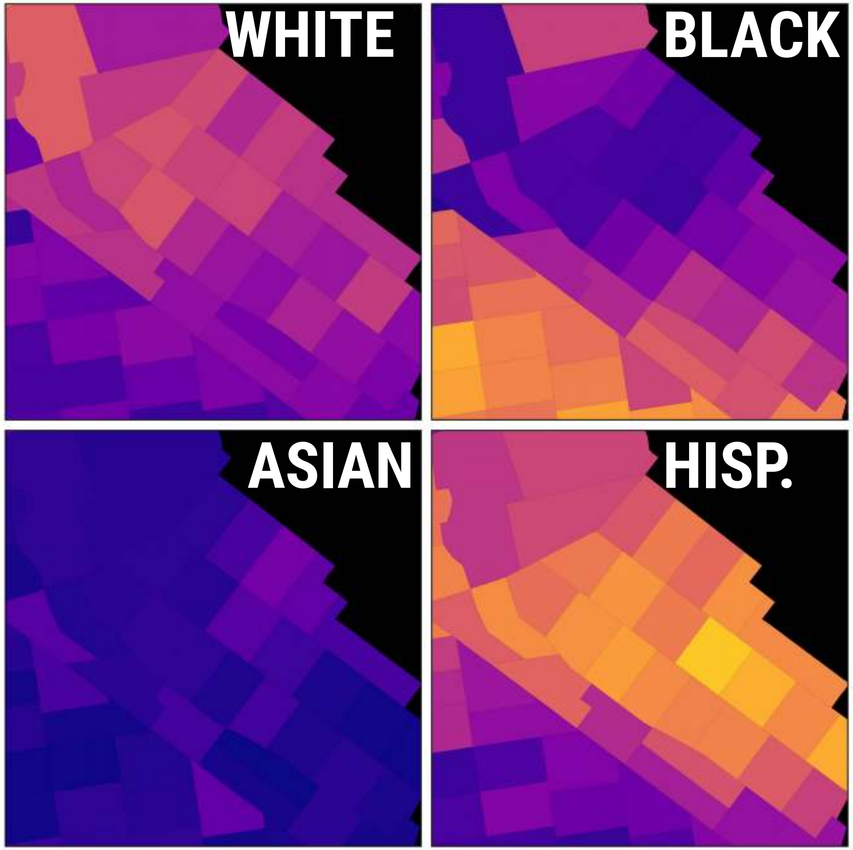


CONCEPTUALIZING BOUNDARIES

"Though an ethnic neighborhood, Bushwick's population is, for a NYC neighborhood, relatively heterogeneous"



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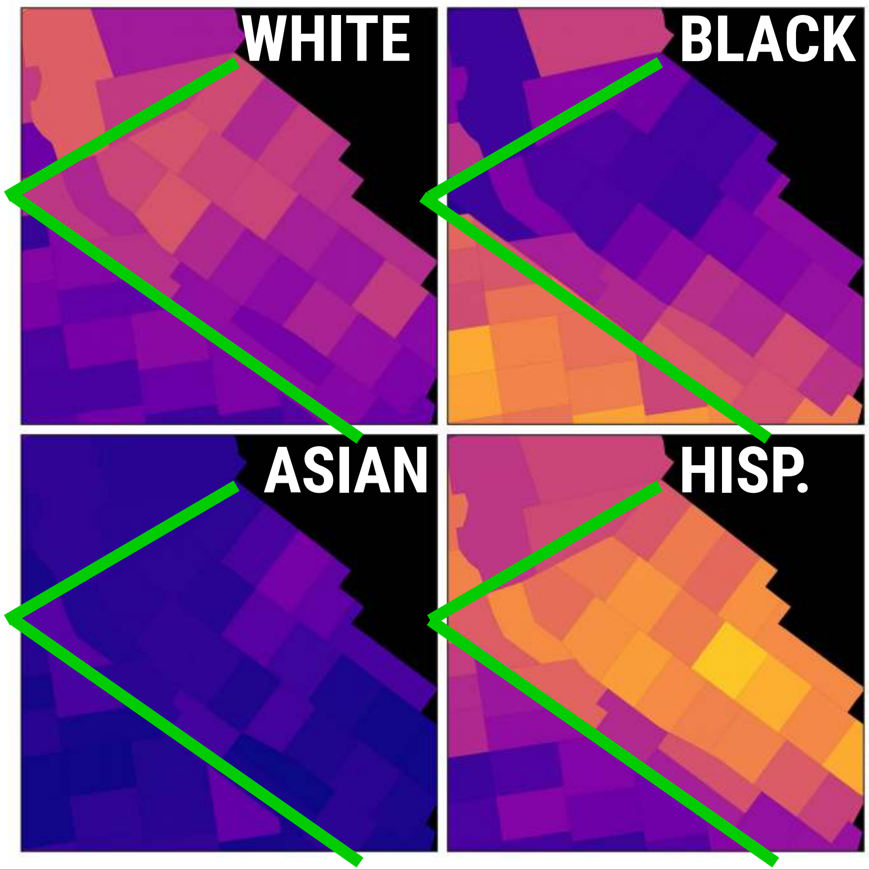

CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS SOCIALLY CONSTRUCTED DIVISIONS OF URBAN LIFE

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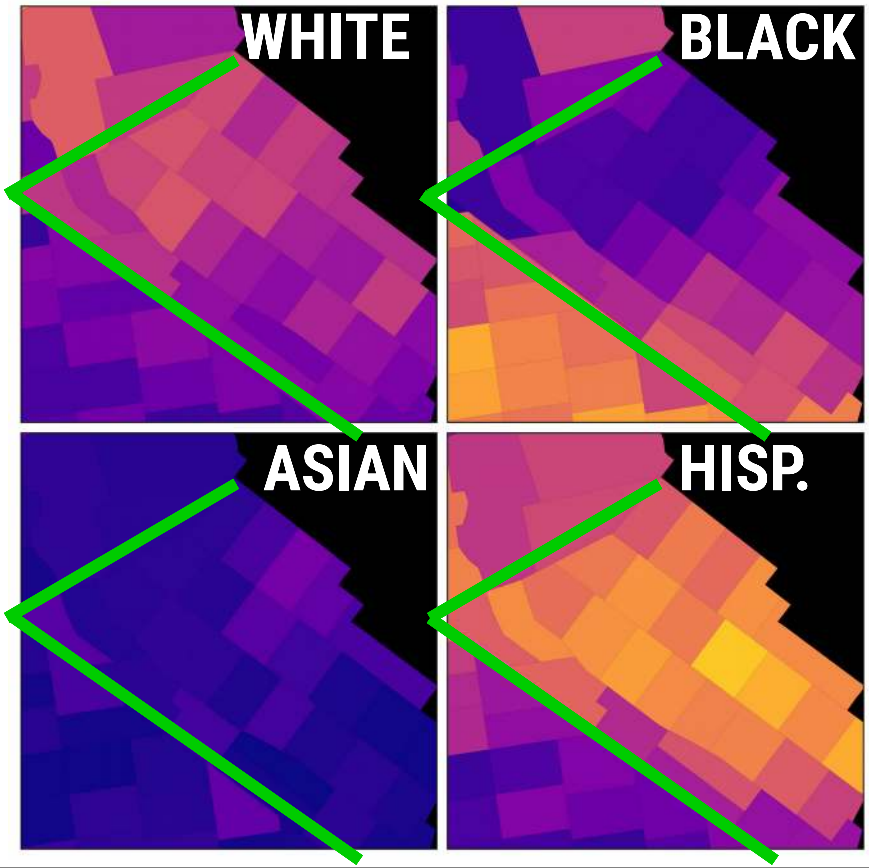

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SCHELLING (1971) Selective segregation

SUTTLES (1972) Defended communities

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GALSTER (2001) House Attribute "bundles"

HEDMAN et al. (2011) Choice geographies

HIPP & BOESSEN (2013) Access areas

LEGEWIE & SCHAEFFER (2016) Friction

KWAN (2018) Contingent social contexts

DEAN (2019) Social frontiers

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Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict[1]

Joscha Legewie
Yale University

Merlin Schaeffer
University of Cologne

"We propose the *contested boundaries hypothesis* … conflict arises at poorly-defined boundaries that separate ethnic and racial groups … because [boundaries] threaten homogeneous community life and foster ambiguities about group rank."

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Communities are neighborhoods, territories that delimit a social group.

When territory is unclear, communities come into conflict.

SPACE

PLACE

SPACE PLACE

Understanding the New Human Dynamics in Smart Spaces and Places: Toward a Splatial Framework

Shih-Lung Shaw* and Daniel Sui†

*Department of Geography, University of Tennessee
†Department of Geosciences, University of Arkansas

SPACE

PLACE

SPACE

The geographic system over which objects of study are related.

- ***Earth Surface***
- ***Road Systems***
- ***Social Networks***
- ***Economic Relations***

PLACE

Geographic entities that are constructed by distinctiveness.

- ***Regions***
- ***Neighborhoods***
- ***Home/Staying locales***
- ***Functional classifications***

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PLACE

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Geographic information science II:
less space, more places in smart cities

Stéphane Roche

Digital neighborhoods

Luc Anselin[a*] and Sarah Williams[b]

Towards the statistical analysis and visualization of places

René Westerholt et al.

SPACE

The geographic system over which objects of study are related.

- ***Earth Surface***
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PLACE

Geographic entities that are constructed by distinctiveness.

How or why do they emerge?
What are their properties?
What are their purpose?
Do they have effects on things we care about?

SPACE

The geographic system over which objects of study are related.

How do things interact?
Over what spatial systems?
In what manner?
What impact do entities have on others nearby?

PLACE

Geographic entities that are constructed by distinctiveness.

How or why do they emerge?
What are their properties?
What are their purpose?
Do they have effects on things we care about?

SPACE

The geographic system over which objects of study are related.

Boundary:

a division or discontinuity in the field of interactions.

PLACE

Geographic entities that are constructed by distinctiveness.

Boundary:

where one places becomes distinct from another.

SPACE

The geographic system over which objects of study are related.

Bounda

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PLACE

Geographic entities that are constructed by distinctiveness.

Article

B Urban Analytics and City Science

EPB: Urban Analytics and City Science
0(0) 1–19

DOI: 10.1177/2399808319875752
journals.sagepub.com/home/epb
SAGE

Geosilhouettes: Geographical measures of cluster fit

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School of Geographical Sciences, University of Bristol, UK

Elijah Knaap and Sergio Rey
Center for Geospatial Sciences, University of California Riverside, USA

BOUNDARIES

AN EMINENTLY-GEOGRAPHICAL CONSTRUCT

GOODNESS OF FIT: THE SILHOUETTE

SIMILARITY IN A COUNTERFACTUAL

WHOSE “GOOD” IS IT ANYWAY?

EXAMPLE: BROOKLYN

SILHOUETTE SCORES

Say that observation i is assigned to cluster c

SILHOUETTE SCORES

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Then, make a few friends:

$$s(i) = \frac{\min\left\{\bar{d}_k(i)\right\} - \bar{d}_c(i)}{\max\{\min\left\{\bar{d}_k(i)\right\}, \bar{d}_c(i)\}}$$

ROUSSEEUW (1987)

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AVERAGE DISSIMILARITY FROM i

TO EVERYONE ELSE IN ITS CURRENT CLUSTER c

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AVERAGE DISSIMILARITY FROM i TO EVERYONE ELSE IN SOME OTHER CLUSTER k

ROUSSEEUW (1987)

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AVERAGE DISSIMILARITY FROM i TO EVERYONE ELSE IN THE SECOND-BEST CHOICE CLUSTER

ROUSSEEUW (1987)

SILHOUETTE SCORES

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DIFFERENCE IN SIMILARITY BETWEEN CURRENT CLUSTER AND NEXT BEST FIT CLUSTER

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NORMALIZING FACTOR SO THAT $s(i)$ IS LIKE A CORRELATION COEFFICIENT

ROUSSEEUW (1987)

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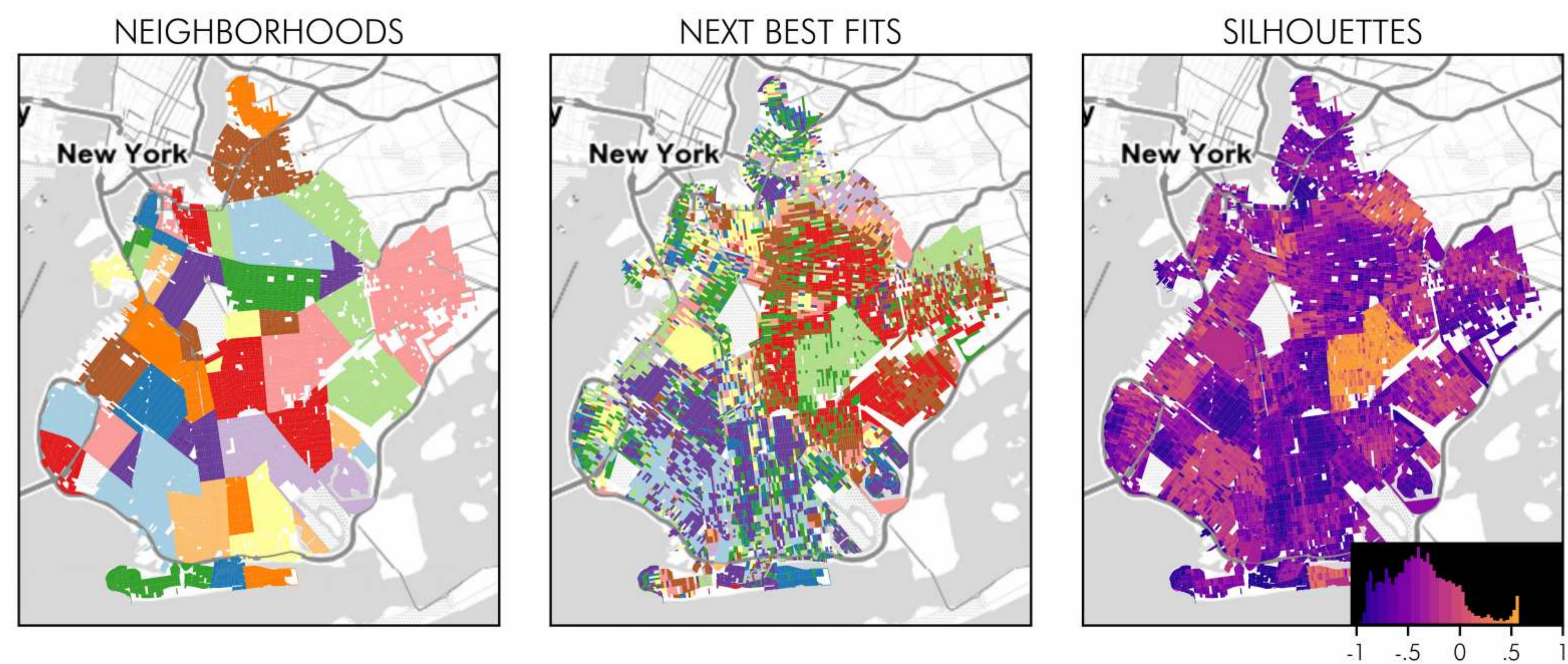
HOW MUCH MORE SIMILAR IS i TO ITS SECOND CHOICE CLUSTER THAN TO ITS CURRENT CLUSTER?

ROUSSEEUW (1987)

SILHOUETTE SCORES



ROUSSEUW (1987)

SILHOUETTE SCORES

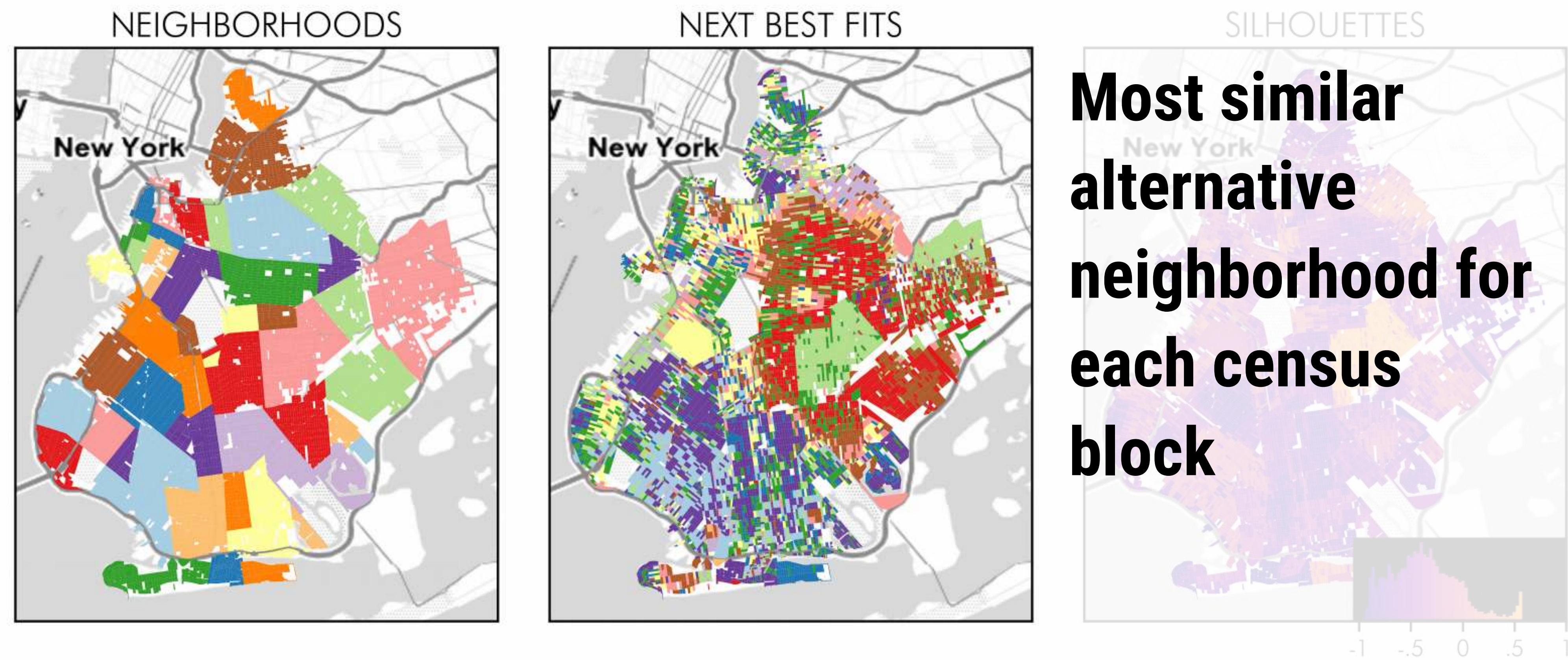
Zillow neighborhoods built from

online housing markets

official boundaries (NYCTA)

ROUSSEEUW (1987)

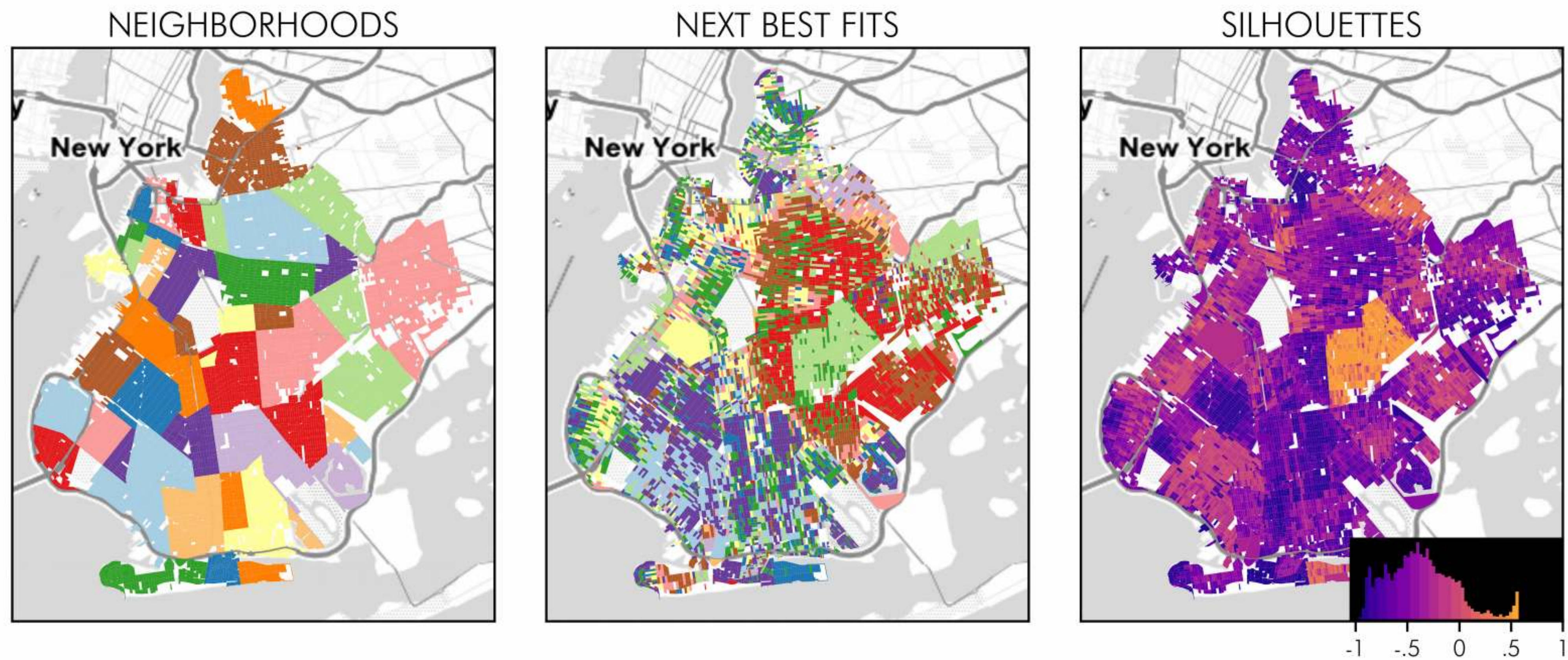
SILHOUETTE SCORES



Most similar alternative neighborhood for each census block

ROUSSEEUW (1987)

SILHOUETTE SCORES



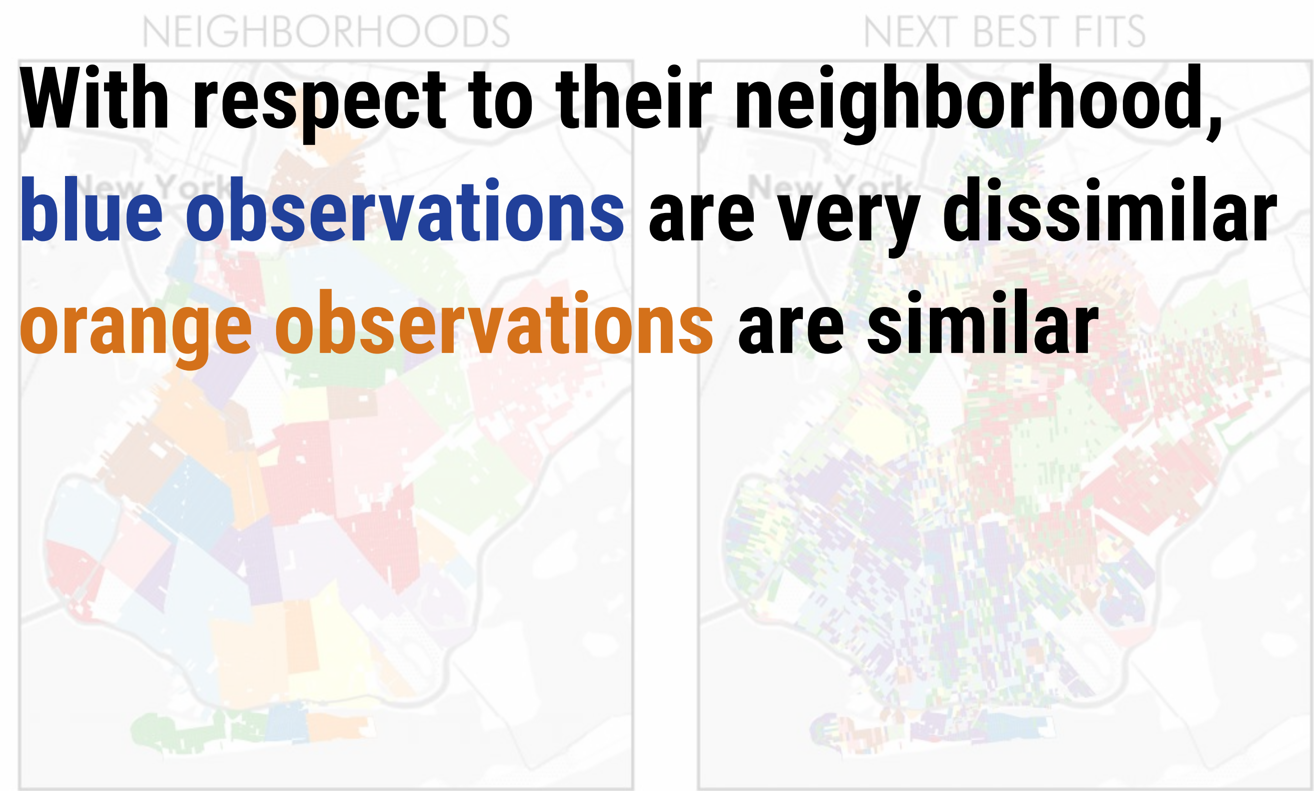
ROUSSEEUW (1987)

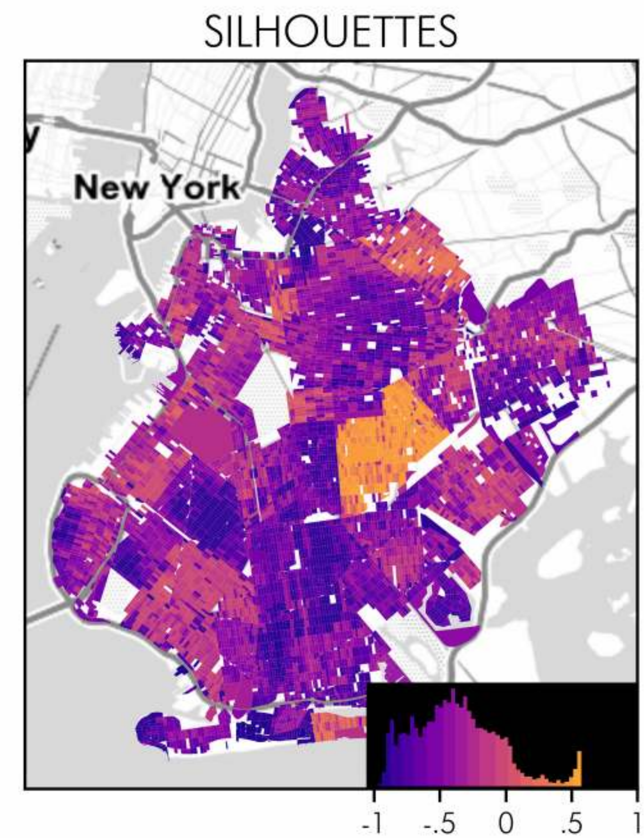
SILHOUETTE SCORES

With respect to their neighborhood,

blue observations are very dissimilar

orange observations are similar





ROUSSEEUW (1987)

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GEOSILHOUETTES: MAKING SPACE FOR BOUNDARIES

EXAMPLE: BROOKLYN

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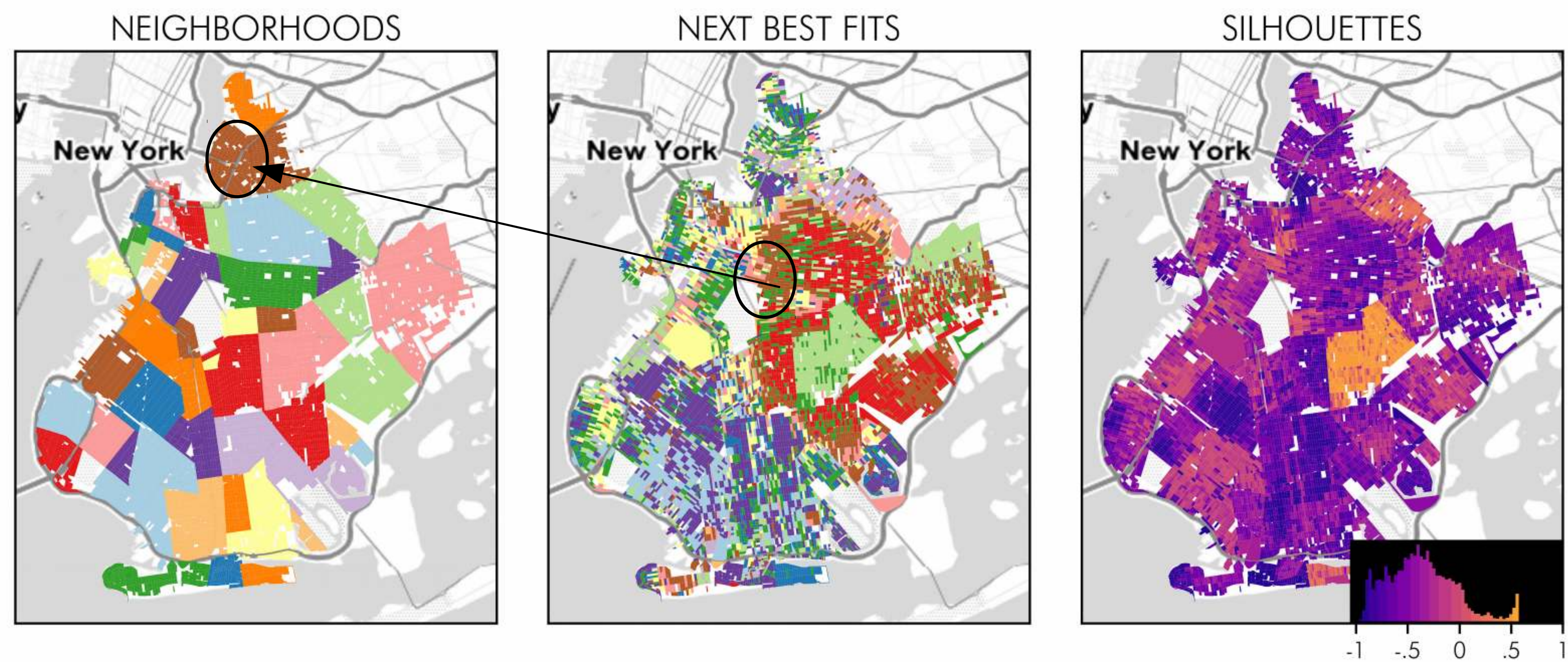
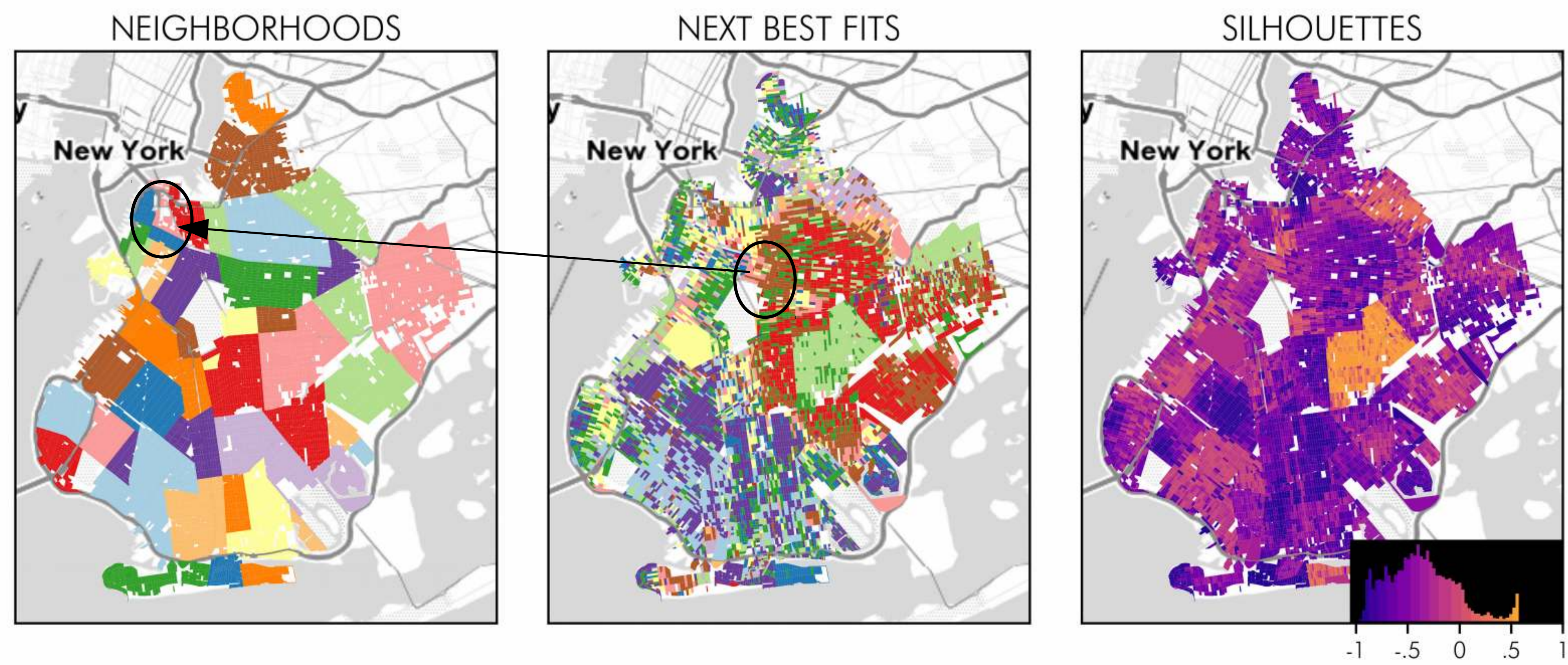


ROUSSEEUW (1987)

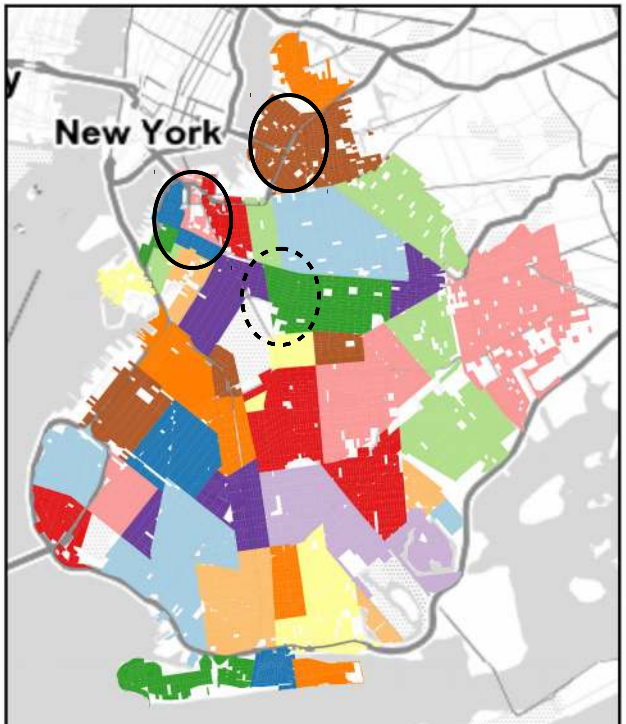
SILHOUETTE SCORES



ROUSSEEUW (1987)

SILHOUETTE SCORES

NEIGHBORHOODS



NEXT BEST FITS

SILHOUETTES

Williamsburg is (relatively) far away from south Crown Heights.

Census blocks can't really "move," so the second choice cluster isn't "real."

ROUSSEUW (1987)

PATH
SILHOUETTE

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REDEFINE d SO THAT IT INCLUDES GEOGRAPHY!

WOLF et al. (2019)

SILHOUETTE SCORES

Say that observation i is assigned to cluster c

Say that observation i is embedded in a graph G

G has an adjacency matrix, W, where

$w_{ij} = 1$ if i is connected to j, zero otherwise.

SILHOUETTE SCORES

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$$\mathbf{C}_1 = \mathbf{D} \circ \mathbf{W}$$

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C_1 **DISSIMILARITY BETWEEN ADJACENT OBSERVATIONS**

WOLF et al. (2019)

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$\mathbf{C}$ **DISSIMILARITY "COST" TO CONNECT ANY TWO OBSERVATIONS**

PATH SILHOUETTE

Say that i in G is assigned to cluster c

The PATH SILHOUETTE is:

$$s(i) = \frac{\min\left\{\bar{d}_k(i)\right\} - \bar{d}_c(i)}{\max\{\min\left\{\bar{d}_k(i)\right\}, \bar{d}_c(i)\}}$$

WHERE DISTANCES USE C

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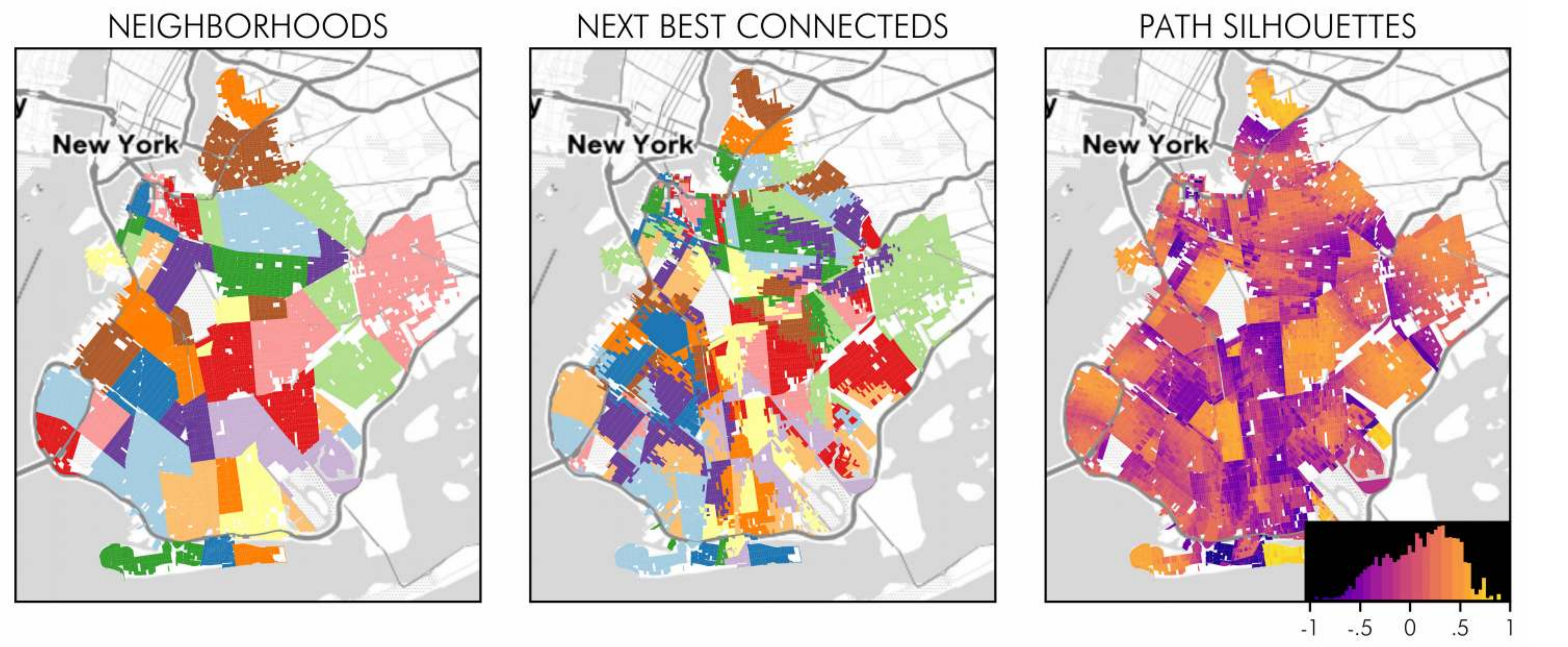
HOW MUCH MORE SIMILAR IS i TO k THAN TO c

WHEN PROXIMITY MATTERS FOR SIMILARITY?

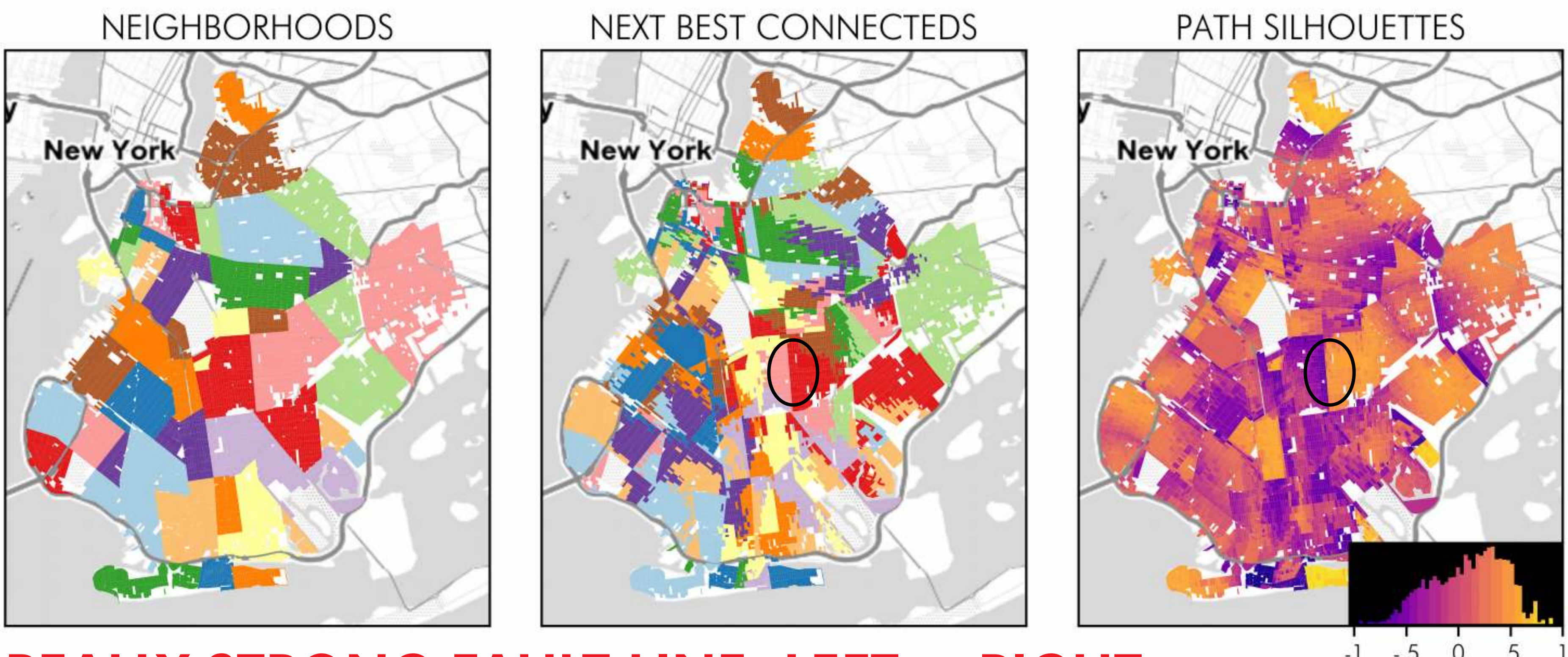
PATH SILHOUETTE



PATH : REMOTENESS x SIMILARITY

WOLF et al. (2019)

PATH SILHOUETTE

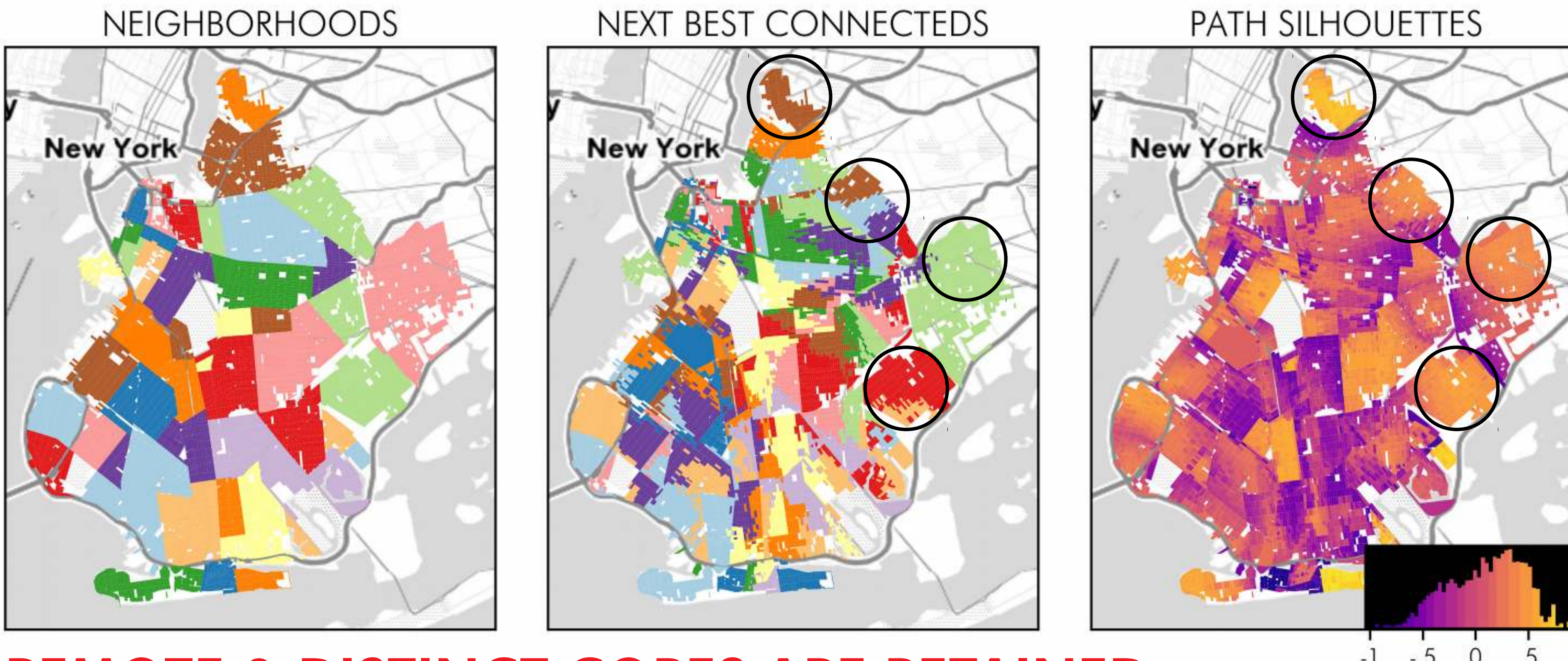


REALLY STRONG FAULT LINE: LEFT → RIGHT

PATH : REMOTENESS x SIMILARITY

WOLF et al. (2019)

PATH SILHOUETTE



REMOTE & DISTINCT CORES ARE RETAINED

PATH : REMOTENESS x SIMILARITY

WOLF et al. (2019)

PATH SILHOUETTE

Williamsburg is (relatively) far away from south Crown Heights.

BOUNDARY SILHOUETTE

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BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

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SECOND CHOICE CLUSTERS ARE ONLY FEASIBLE IF i COULD BE MOVED W/O BREAKING c OR k

BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

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A FEASIBLE SECOND CHOICE CLUSTER IS CALLED THE BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

Say that i in G is assigned to cluster c, has BLA k

The BOUNDARY SILHOUETTE is:

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WHERE k IS RESTRICTED TO BE

A FEASIBLE (i.e. local) REASSIGNMENT

BOUNDARY SILHOUETTE

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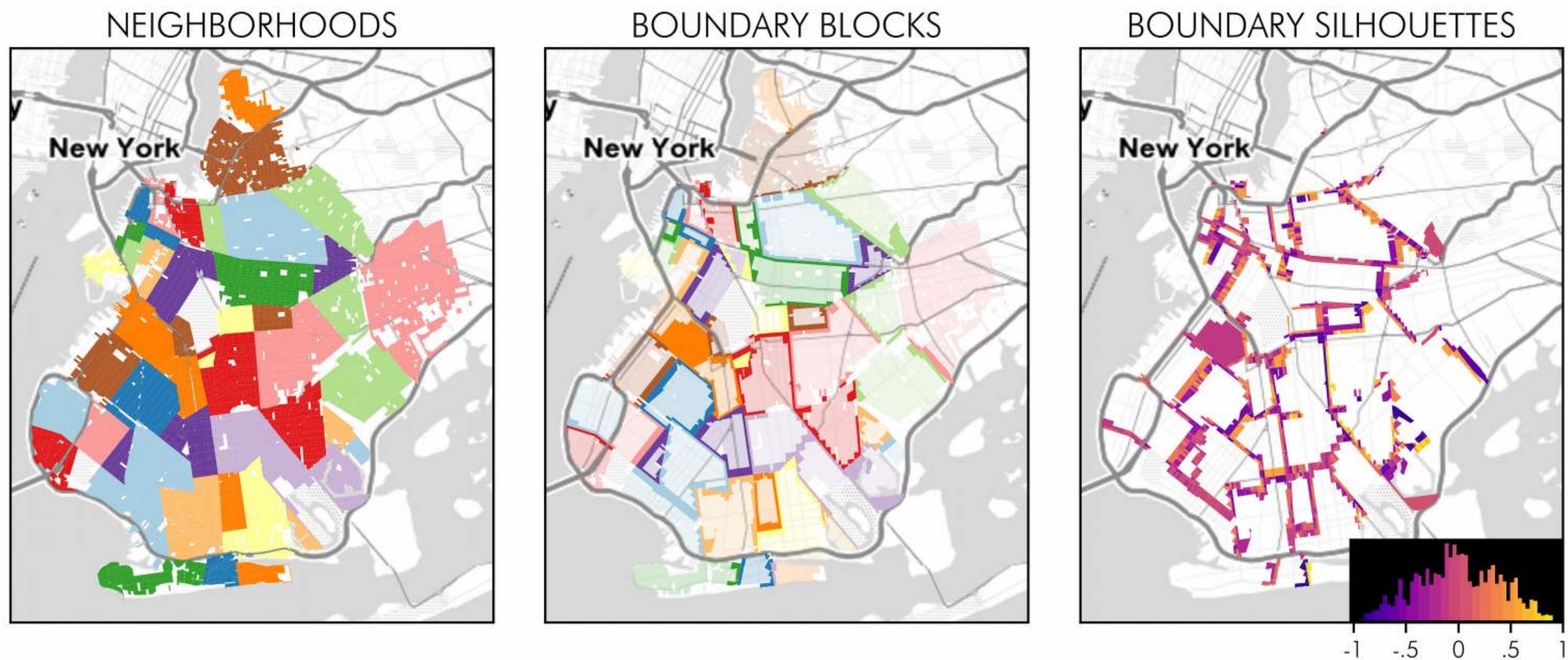
HOW MUCH MORE SIMILAR IS i TO c THAN TO THE BEST LOCAL ALTERNATIVE?

BOUNDARY SILHOUETTE

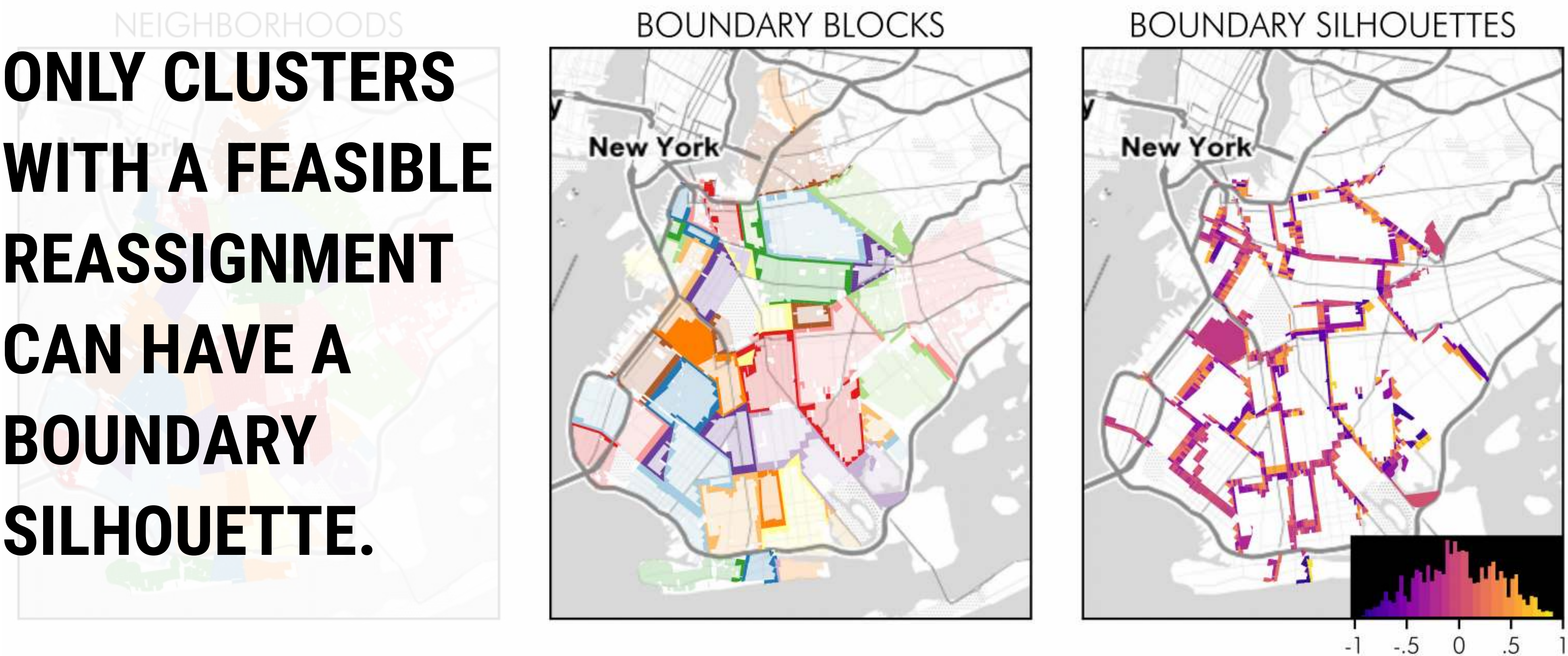


BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

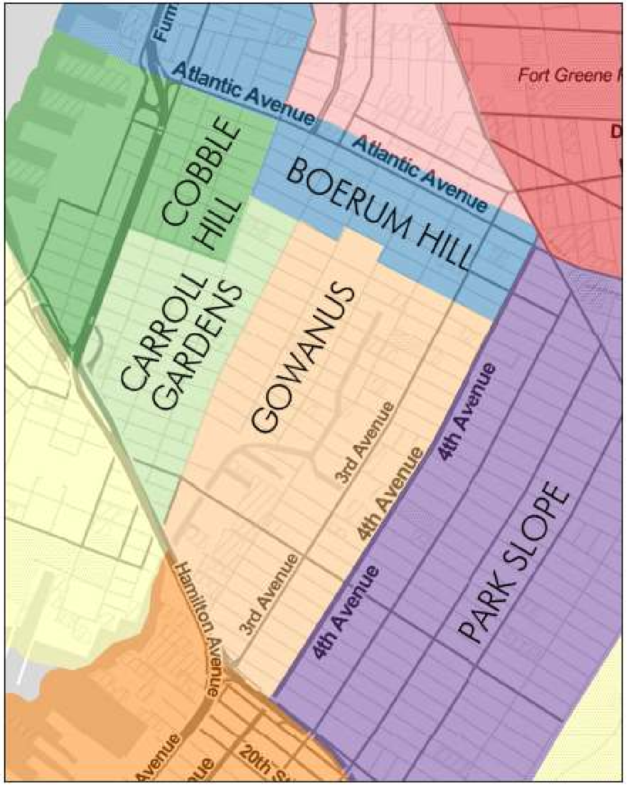
ONLY CLUSTERS WITH A FEASIBLE REASSIGNMENT CAN HAVE A BOUNDARY SILHOUETTE.



BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE



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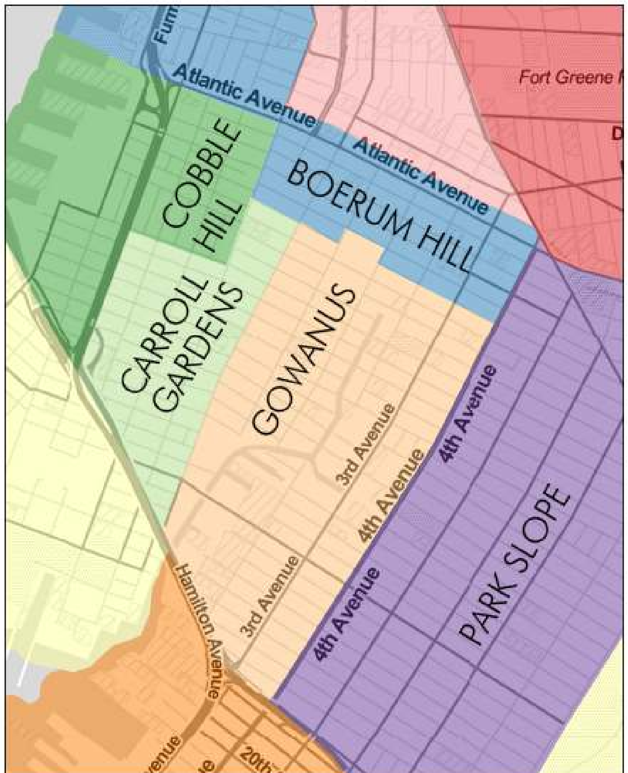
WOLF et al. (2019)

BOUNDARY SILHOUETTE



BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

neighbor focal	Boerum Hill	Cobble Hill	Carroll Gardens	Gowanus	Park Slope
Boerum Hill	0.000	-0.32	-0.358	0.274	0.122
Cobble Hill	0.627	0	-0.156	0.639	-
Carroll Gardens	0.339	0.152	0	0.710	-
Gowanus	-0.071	-0.359	-0.647	0.000	-0.168
Park Slope	0.050	-	-	0.390	0

On the Gowanus side, blocks are much more similar to those in Carroll Gardens.

WOLF et al. (2019)

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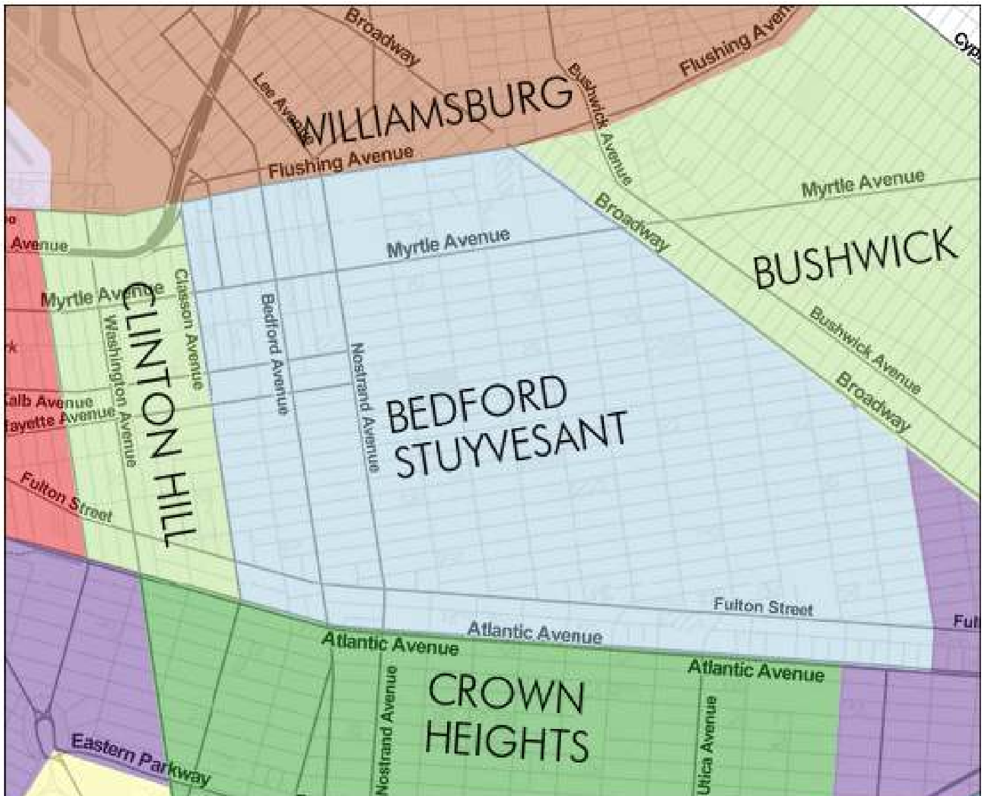
On the Carroll Gardens side, blocks are much more similar to Carroll Gardens.

The boundary is asymmetric! Gowanus border leans towards Carroll Gardens.

WOLF et al. (2019)

BOUNDARY SILHOUETTE



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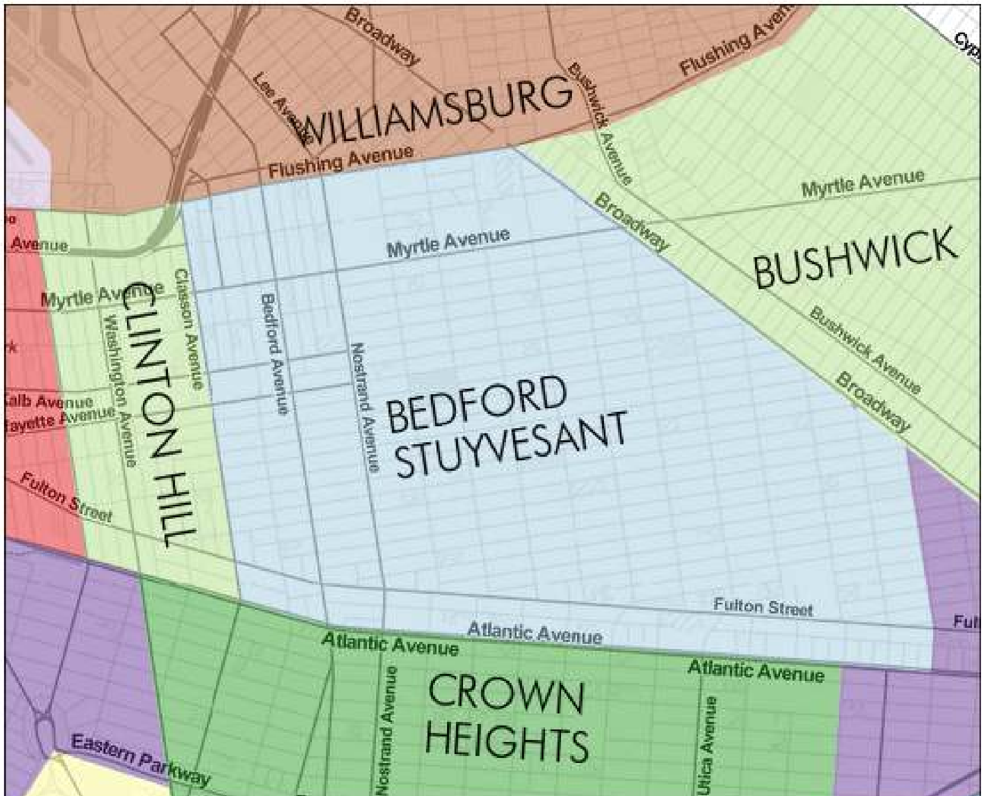

BOUNDARY: BEST LOCAL ALTERNATIVE

WOLF et al. (2019)

BOUNDARY SILHOUETTE

neighbor focal	Williamsburg	Bushwick	Bedford Stuyvesant	Clinton Hill	Crown Heights
Williamsburg	0	-0.096	0.693	0.516	-
Bushwick	0.288	0	0.482	-	-
Bedford Stuyvesant	-0.478	0.198	0.000	0.006	-0.059
Clinton Hill	-0.355	-	0.358	0	0.296
Crown Heights	-	-	0.077	-0.427	0

On the BedStuy side, blocks remain slightly more similar to blocks in BedStuy.

BOUNDARY SILHOUETTE

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WOLF et al. (2019)

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On the Bushwick side, blocks are more similar to blocks in Bushwick.

The boundary is symmetric! Not a "contested boundary"!

WOLF et al. (2019)

SILHOUETTES

Numerically robust

Multidimensional

Not “predictive” of another variate

Straightforward interpretation

SILHOUETTES

Numerically robust

Multidimensional

Not “predictive” of another variate

Straightforward interpretation

Not probabilistic (no “certainty” about strength)

Compares place boundaries, not spatial boundaries

BOUNDARIES

AN EMINENTLY-GEOGRAPHICAL CONSTRUCT

GOODNESS OF FIT: THE SILHOUETTE

SIMILARITY IN A COUNTERFACTUAL

GEOSILHOUETTES

PATH SILHOUETTE: REMOTENESS & SIMILARITY

BOUNDARY SILHOUETTE: ADJACENCY & DIRECTION

FINDING THE FAULT LINES:

DETECTING URBAN SOCIAL BOUNDARIES USING SOCIAL DATA SCIENCE

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