Geographic Data Science -Lecture VIII

Grouping Data over Space

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Today

- The need to group data
- Geodemographic analysis
- Non-spatial clustering
- Regionalization
- Examples "in the wild"

The need to group data

Everything should be made as simple as possible, but not simpler Albert Einstein

The need to group data

- The world (and its problems) are **complex** and **multidimensional**
- Univariate analysis involves focusing only one way of measure the world

The need to group data

- The world (and its problems) are complex and multidimensional
- Univariate analysis involves focusing only one way of measure the world
- Sometimes, world issues are best understood as multivariate:
 - Percentage of foreign-born Vs. What is a neighborhood?
 - Years of schooling Vs. Human development
 - Monthly income Vs. Deprivation

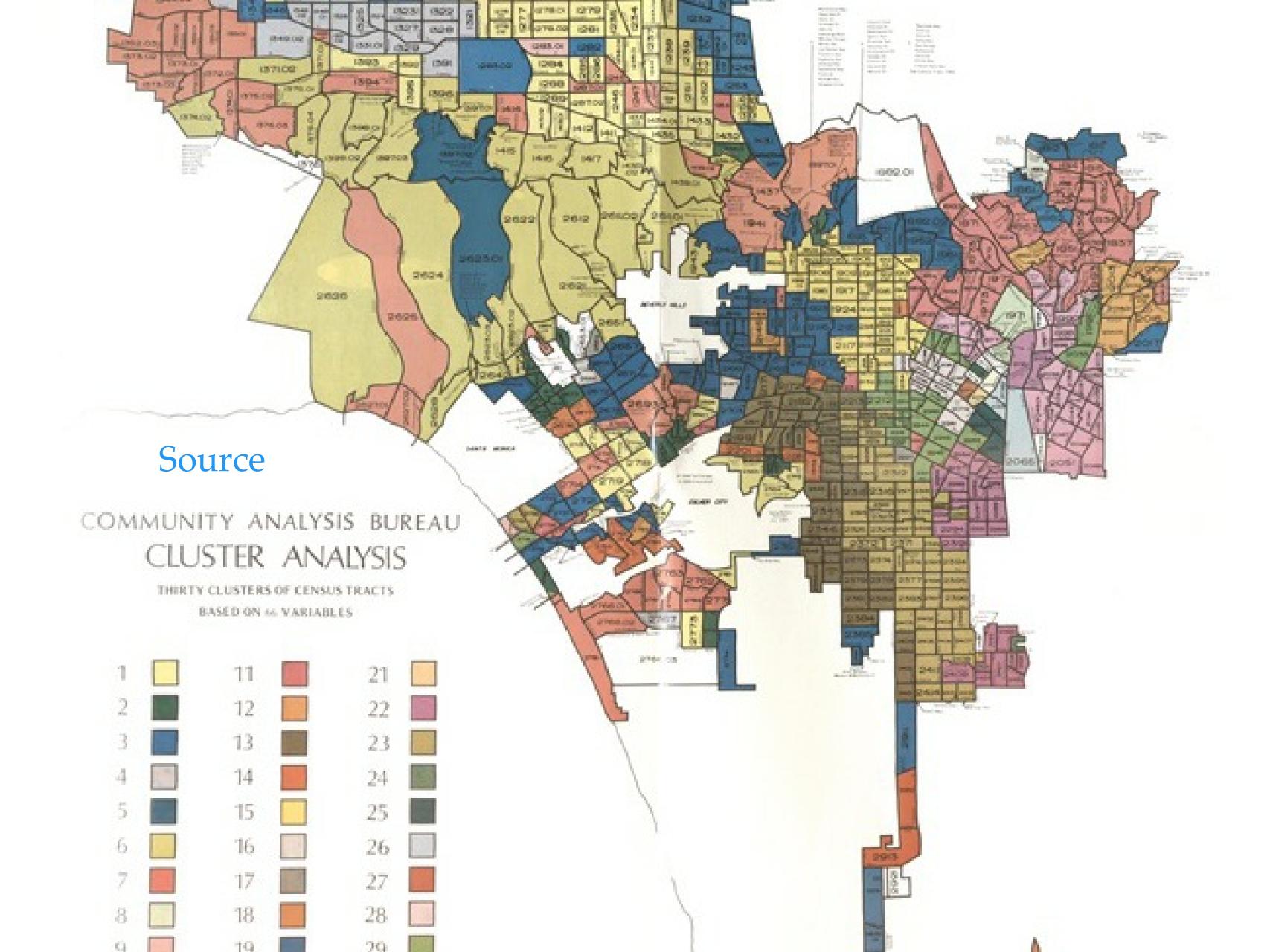
Grouping as simplifying

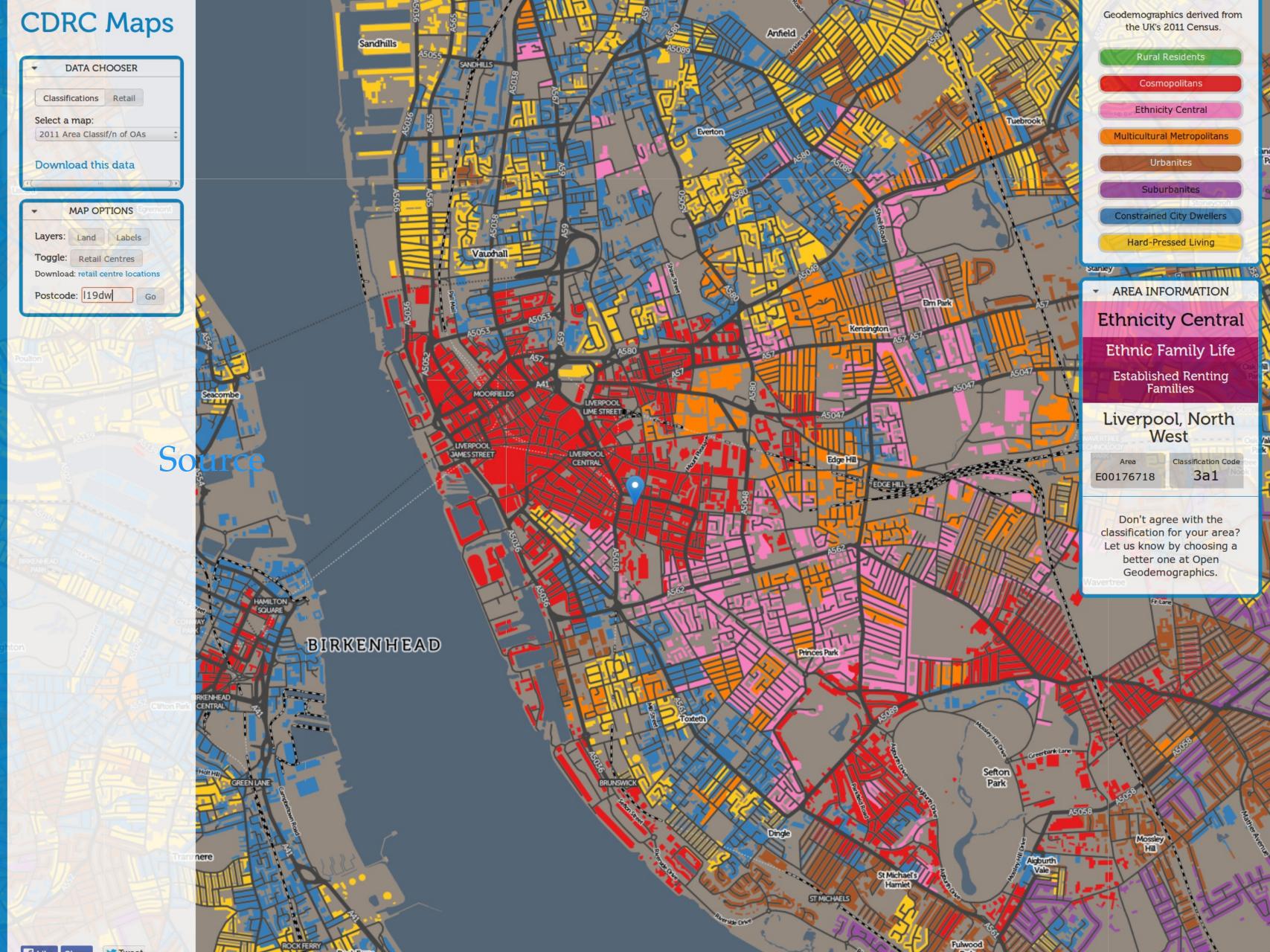
- Define a given number of categories based on many characteristics (multi-dimensional)
- Each observation in the category where it *fits best*
- Find the category where each observation fits best
- Reduce complexity, keep all the relevant information
- Produce easier-to-understand outputs

Geodemographic analysis

Geodemographic analysis

- Technique developed in 1970's attributed to Richard Webber
- **Identify similar neighborhoods** → Target urban deprivation funding
- Originated in the **Public** Sector (policy) and spread to the **Private** sector (marketing and business intelligence)





How do you segment/cluster observations over space?

- Statistical clustering
- Explicitly spatial clustering (regionalization)

Non-spatial clustering

Split a dataset into **groups** of observations that are **similar within** the group and **dissimilar between** groups, based on a series of **attributes**

Machine learning

Unsupervised

Machine learning

• The computer *learns* some of the properties of the dataset without the human specifying them

Unsupervised

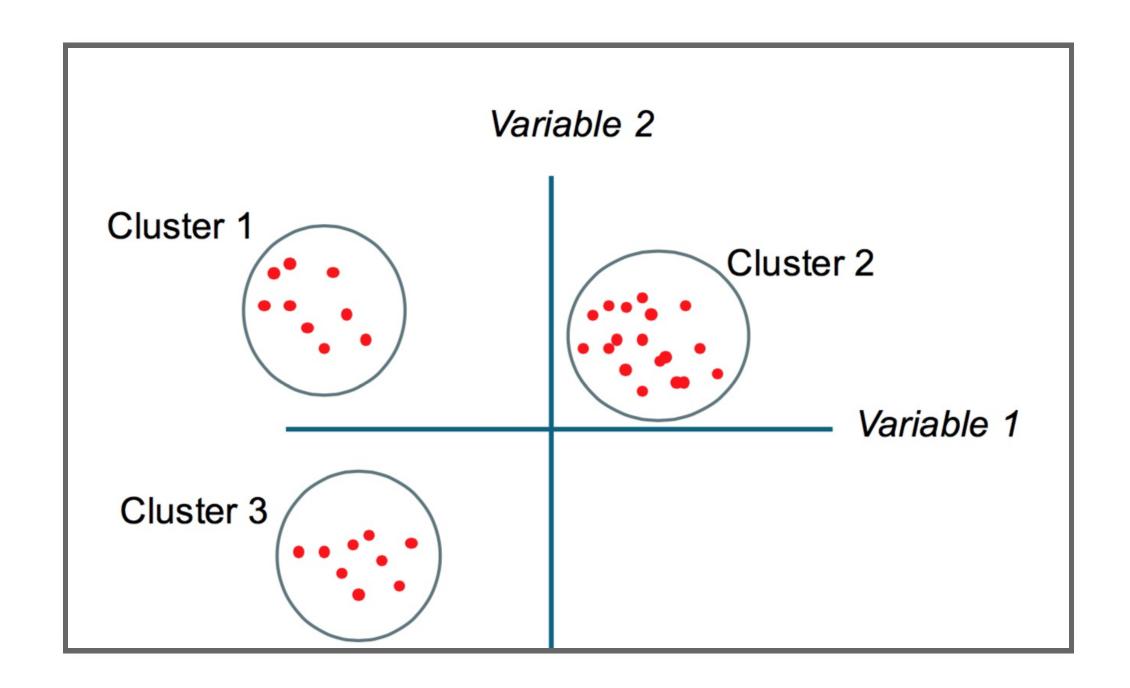
Machine learning

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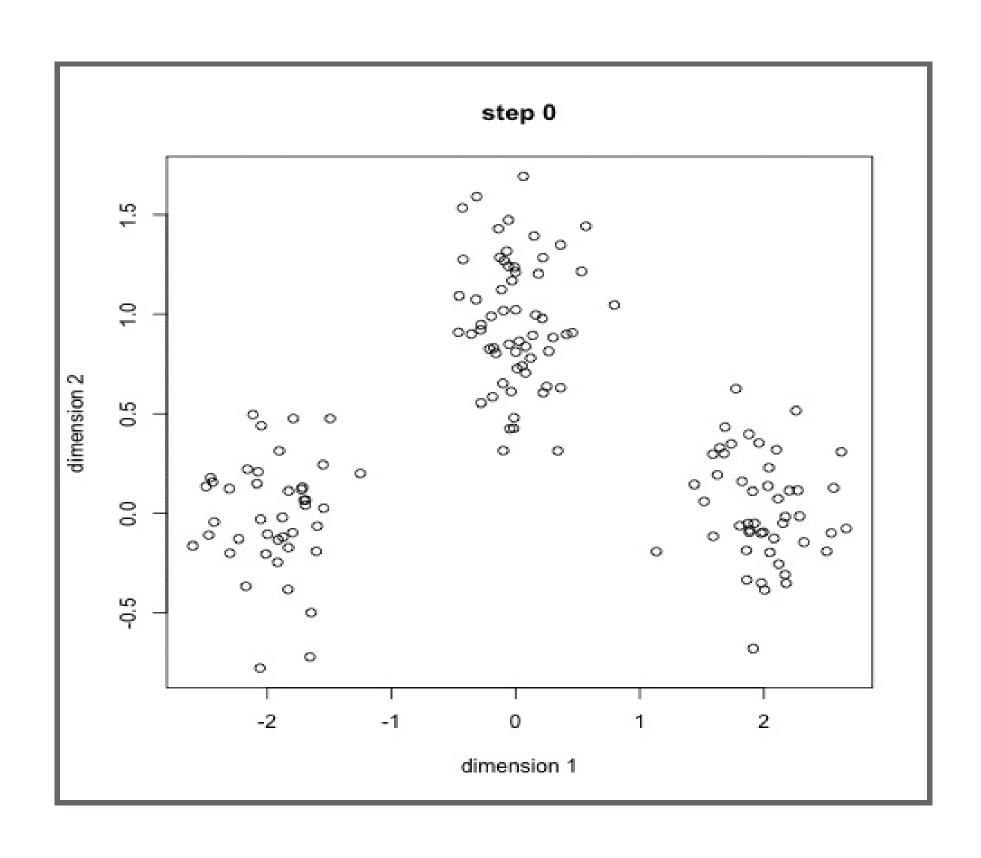
 There is no a-priori structure imposed on the classification → before the analysis, no observations is in a category

Intuition



K-means [Source]

K-means [Source]



More clustering...

- Hierarchical clustering
- Agglomerative clustering
- Spectral clustering
- Neural networks (e.g. Self-Organizing Maps)
- DBScan
- ...

Different properties, different best usecases

See interesting comparison table

Machine Learning

Spatial Machine Learning

Spatial Machine Learning

Aggregating basic spatial units (areas) into larger units (regions)

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...with the additional constraint observations need to be spatial neighbors

• All the methods aggregate geographical areas into a predefined number of regions, while optimizing a particular aggregation criterion;

• The areas within a region must be geographically connected (the spatial contiguity constraint);

• The number of regions must be smaller than or equal to the number of areas;

• Each area must be assigned to one and only one region;

• Each region must contain at least one area.

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London example w/ AirBnb

Algorithms

- Automated Zoning Procedure (AZP)
- Arisel
- Max-P

• ...

See Duque et al. (2007) for an excellent, though advanced, overview

Examples

Census geographies

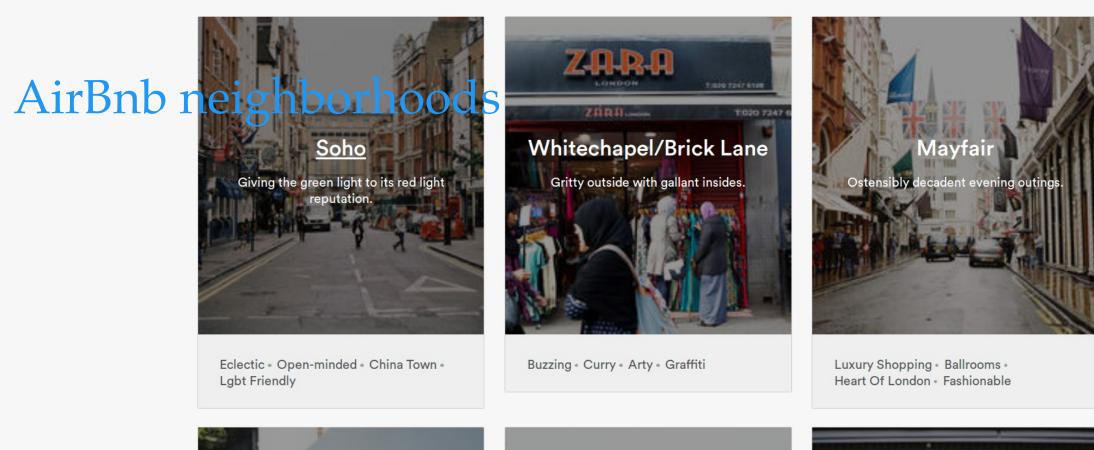
Environment and Planning A 1995, volume 27, pages 425-446

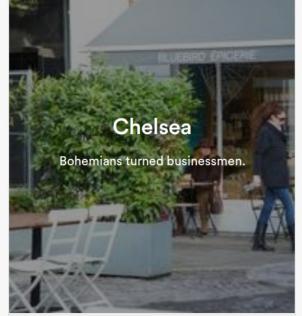
Algorithms for reengineering 1991 Census geography

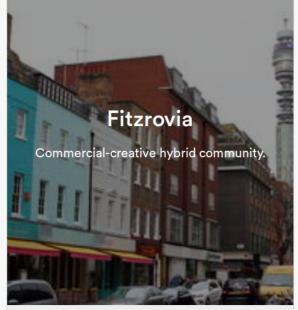
S Openshaw, L Rao¶

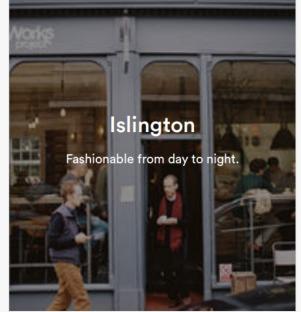
School of Geography, University of Leeds, Leeds LS2 9JT, England Received 22 April 1994; in revised form 6 October 1994

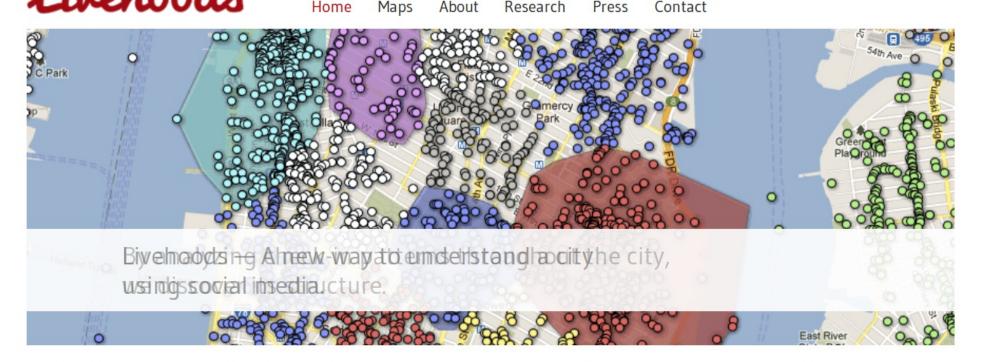
23 neighbourhoods match Dining. See all listings











Re-Imagining the City in the Age of Social Media

Livehoods offer a new way to conceptualize the dynamics, structure, and character of a city by analyzing the social media its residents generate. By looking at people's checkin patterns at places across the city, we create a mapping of the different dynamic areas that comprise it. Each Livehood tells a different story of the people and places that shape it.

> MORE

Using Machine-Learning to Study Cities

Our research hypothesis is that the character of an urban area is defined not just by the the types of places found there, but also by the people that make it part of their daily life. To explore this idea, we use data from approximately 18 million check-ins collected from the location-based social network foursquare, and apply clustering algorithms to discover the different areas of the city.

> MORE



> New York City



> San Francisco



> Pittsburgh



News and Press

Livehood at ICWSM

Our work with Livehoods won the best paper award at ICWSM in Dublin this June! Watch the video from our presentation.

Livehoods on CBC Radio

Justin was on the CBC Radio program Spark talking with host Nora Young about the Livehoods Project. Listen to the full interview.

Livehoods in the Atlantic

Livehoods appeared as the Map of the Day on the Atlantic's Cities blog. **See their post about us.**

Wired Insider

Wired's Insider blog says Livehoods is
"taking a big swing" at minining insights into
"cultural habits and how societies flow."

Read the full post.

> MORE

Recent Tweets

@tiffehr

Best map/location mashup I've seen in quite some time: http://livehoods.org/maps/nyc# (Via http://roomthily.tumblr.com)

@Werner

Livehoods is a cool CMU research project to visualize cities through the use of social media (@foursquare in this case) http://wv.ly/IJZ3We

@tomcoates

The 'Related' tab on http://livehoods.org is the best. See which neighboring places people travel too. Algorithmic divination of commuting!

@brainpicker

Forget neighborhoods, it's about Livehoods
— Carnegie Mellon maps the dynamic
character of cities through social media
http://j.mp/HzmkoN

@kellan

clearly i live on the wrong side of the bqe - http://livehoods.org/maps/nvc

Subscribe to our newsletter

Find out more about Livehoods and get updates on future developments by subscribing to our mailing list.

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Recapitulation



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