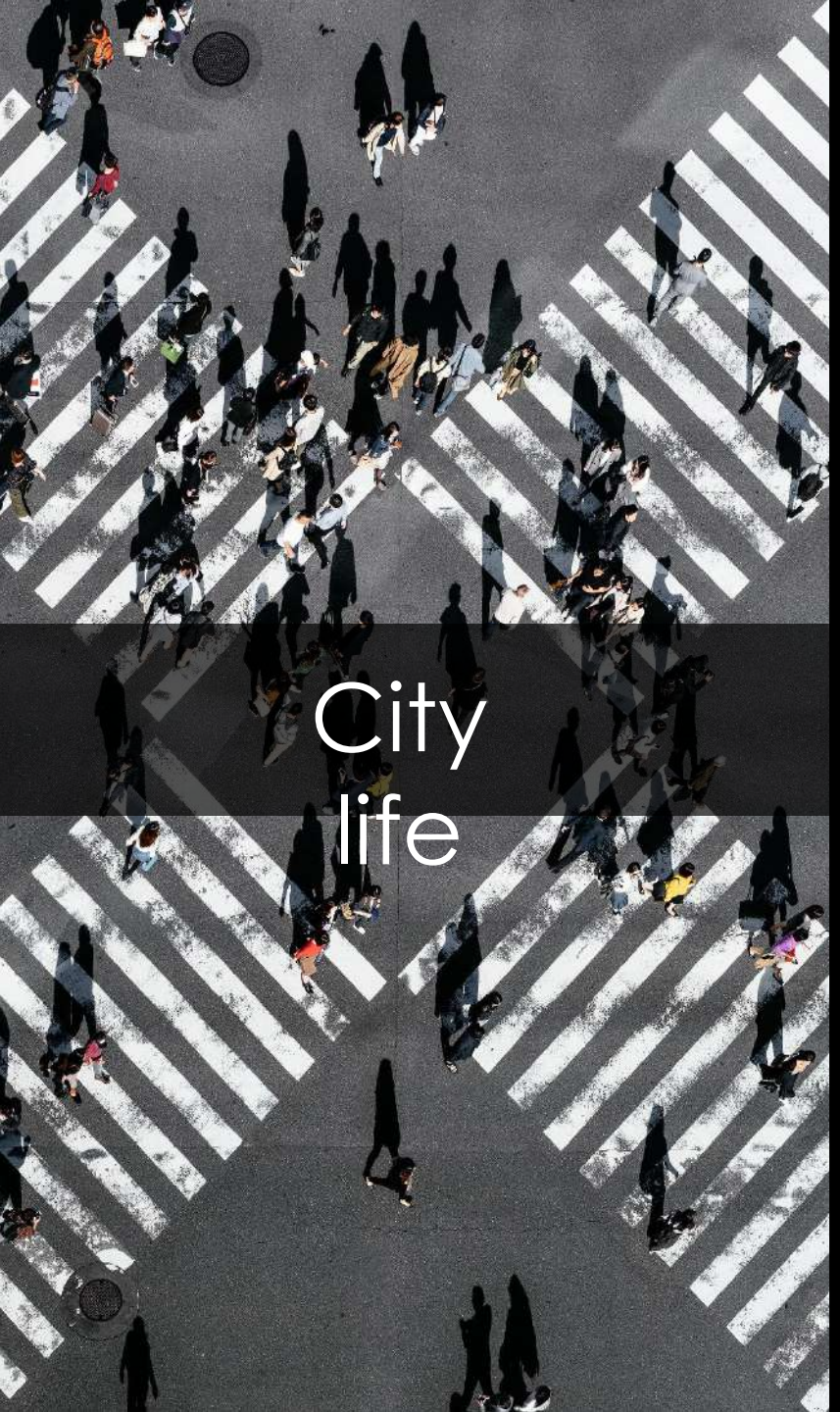
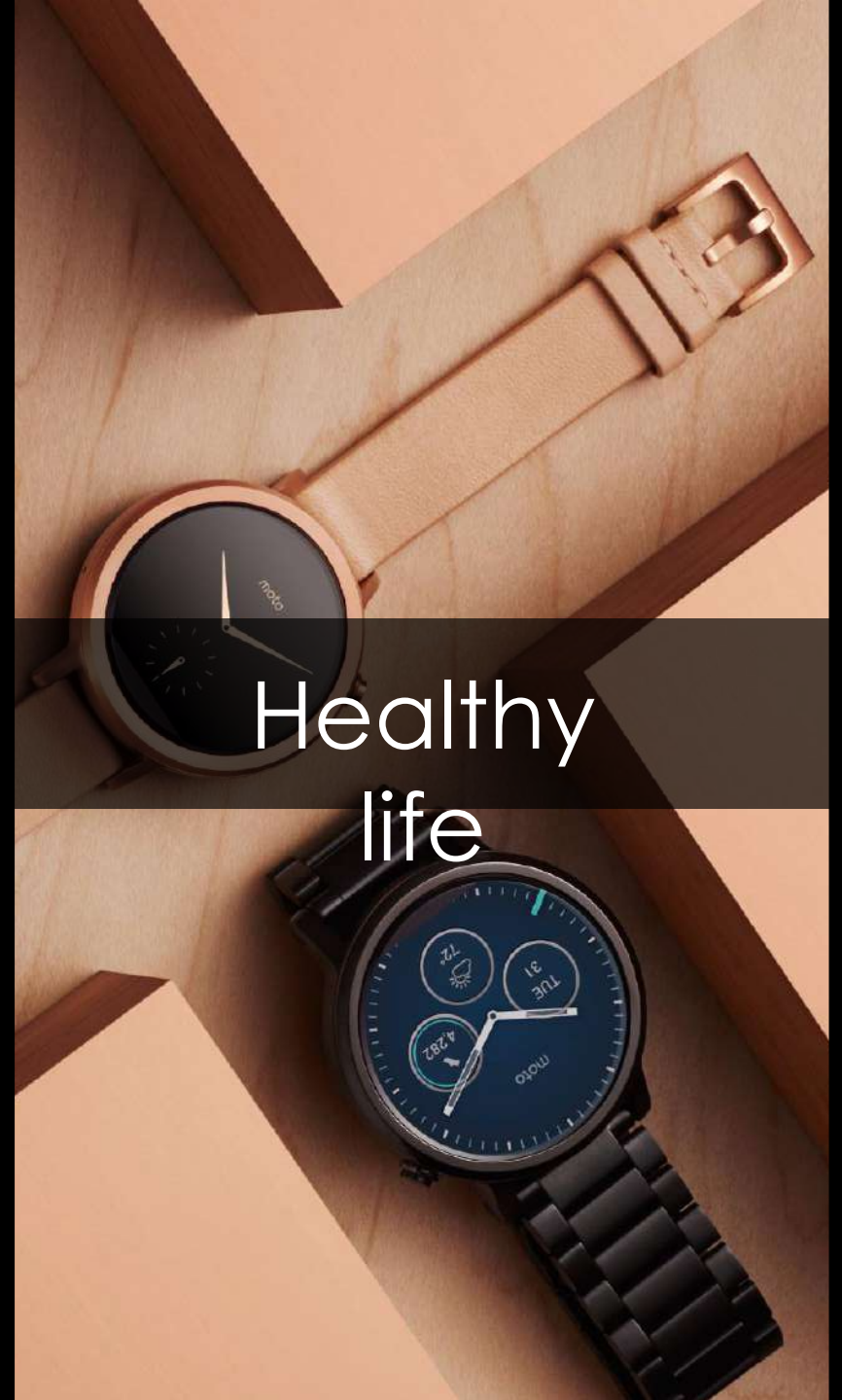

Hello!


SIGILVM·VNIVERS·AVGVSTAE·TAVRINORVM·
YAHOO!
NOKIA
Bell Labs



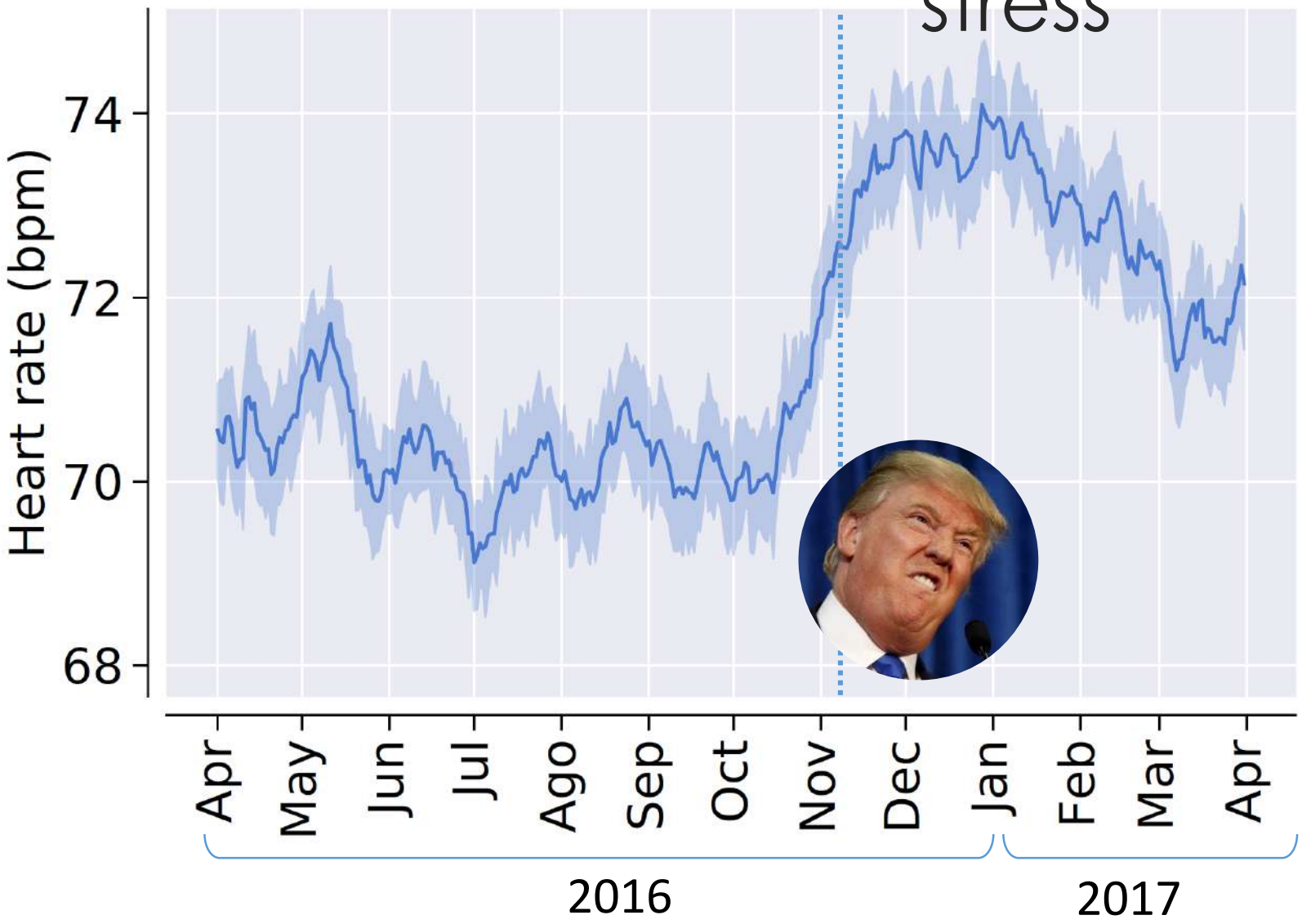
City life



Healthy life

Social life

Collective heartbeat as a proxy for stress



Coloring Social Ties

Social
Support
Power
Knowledge
Similarity
Identity

Trust
Respect
Romance
Fun
Conflict

Coloring in the Links: Capturing Social Ties as They are Perceived – CSCW 2018

Knowledge + Power

Only a fully trained Jedi Knight, with The Force as his ally, will conquer Vader and his Emperor. If you end your training now, if you choose the quick and easy path, as Vader did, you will become an agent of evil — Ben Kenobi

Status + Trust

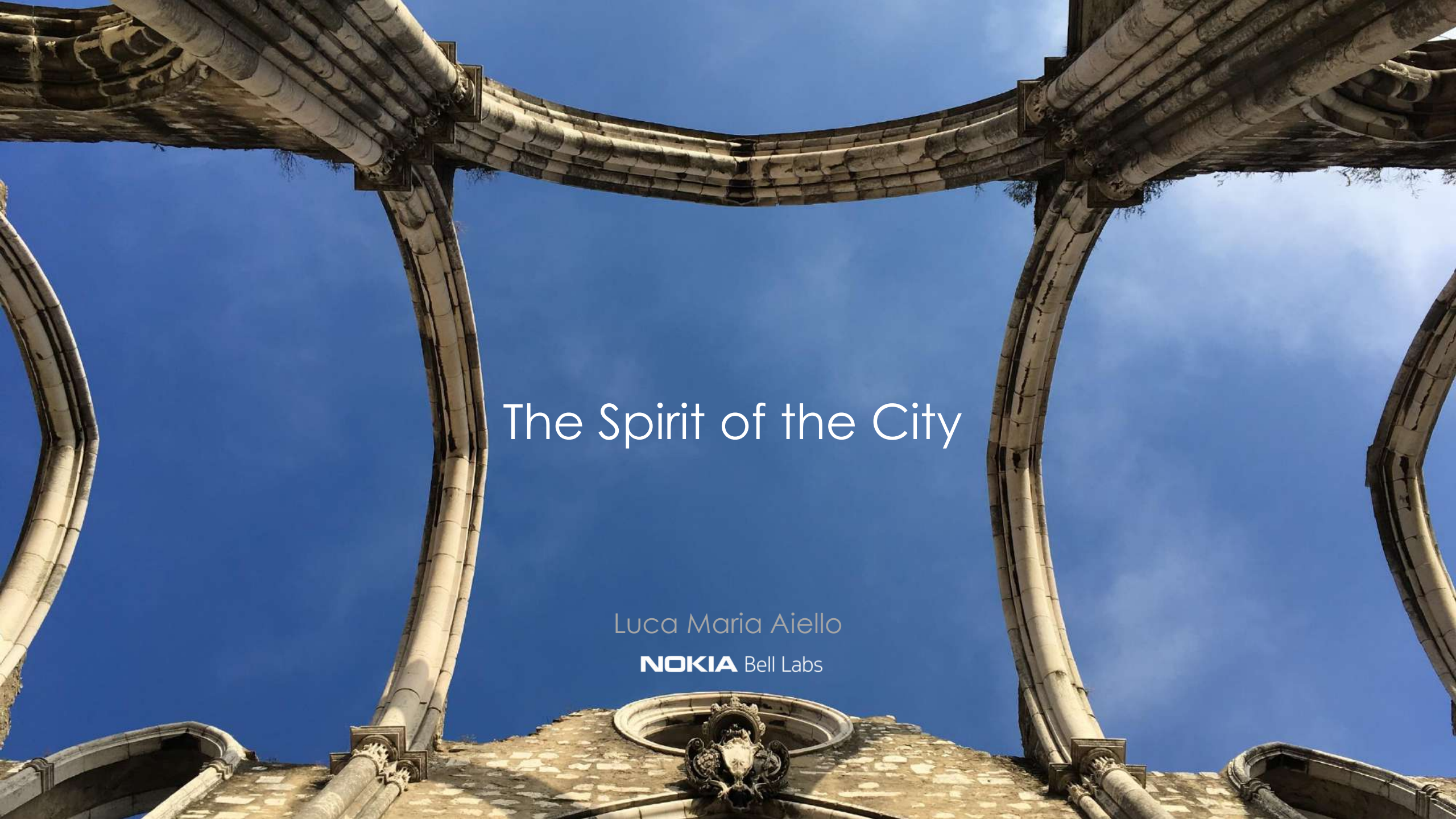
Frankie, you're a good old man, and you've been loyal to my Father for years...so I hope you can explain what you mean — Michael Corleone

Support + Knowledge

Look, Dave, I know that you're sincere and that you're trying to do a competent job, and that you're trying to be helpful, but I can assure the problem is with the AO-units, and with your test gear
— HAL 9000

Integrative Complexity

Ability to recognize and connect multiple perspectives, thus favoring conflict resolution



The Spirit of the City

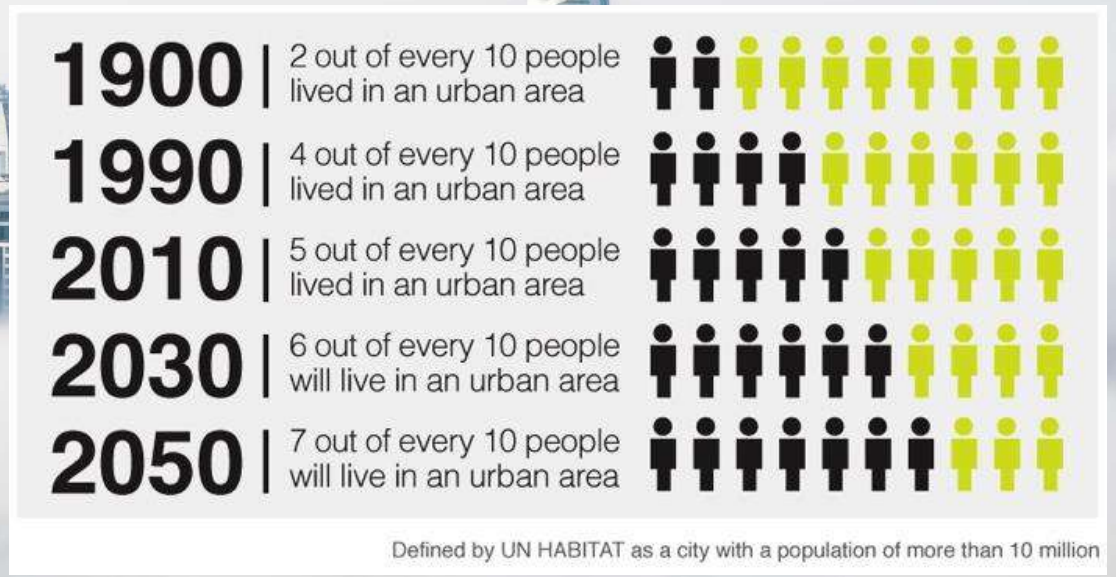
Luca Maria Aiello

NOKIA Bell Labs


Nullus Locus Sine Genio


Intangible properties

Urbanization




Smart City = Efficiency

Jane Jacobs

Stanley Milgram

Kevin Lynch

Psychological perceptions

The quest for a Good City Life

Multimedia to understand space

Part I: The Shiny

Part II: The Dirty

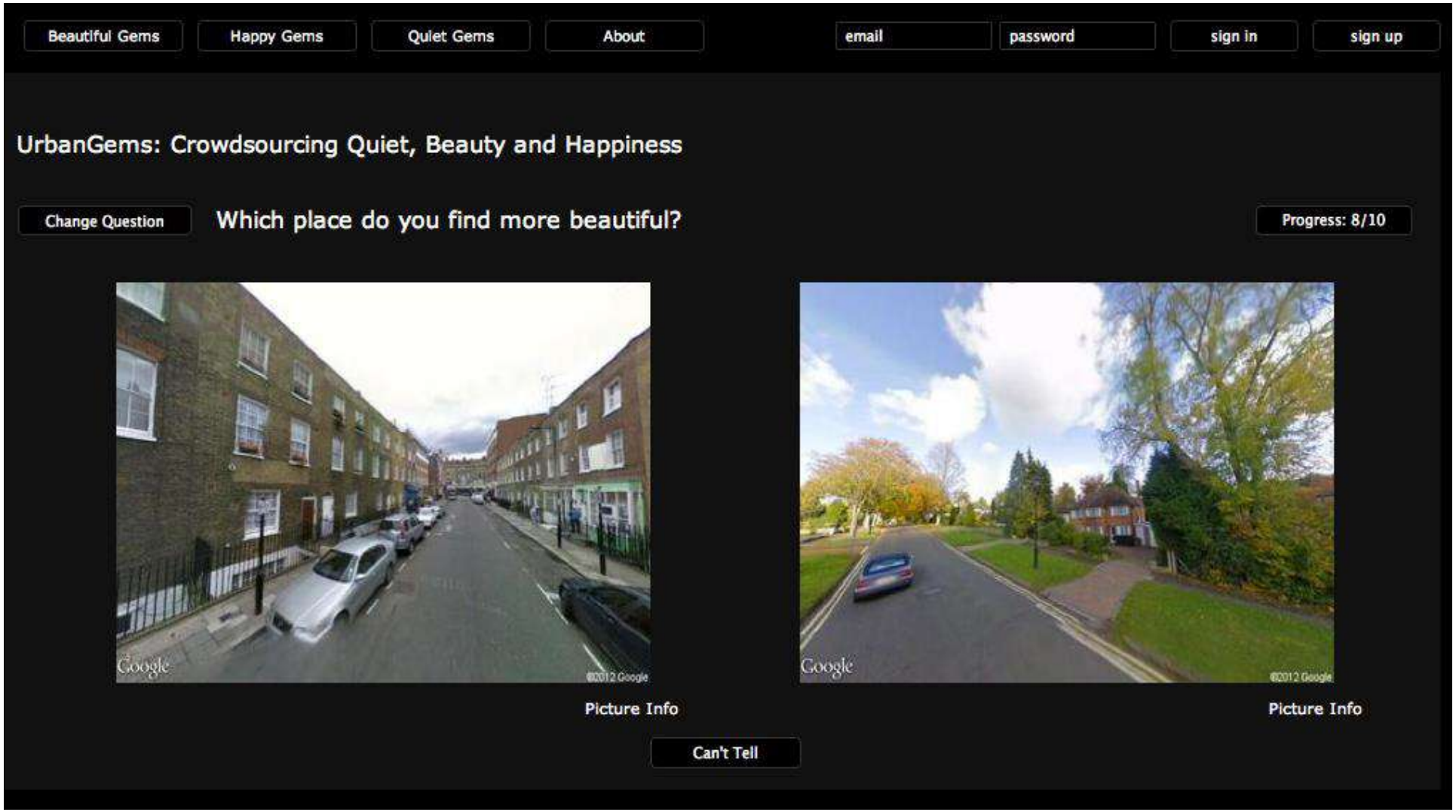

Quantifying urban beauty

Collective perception of beauty

A

B

Urbangems.org

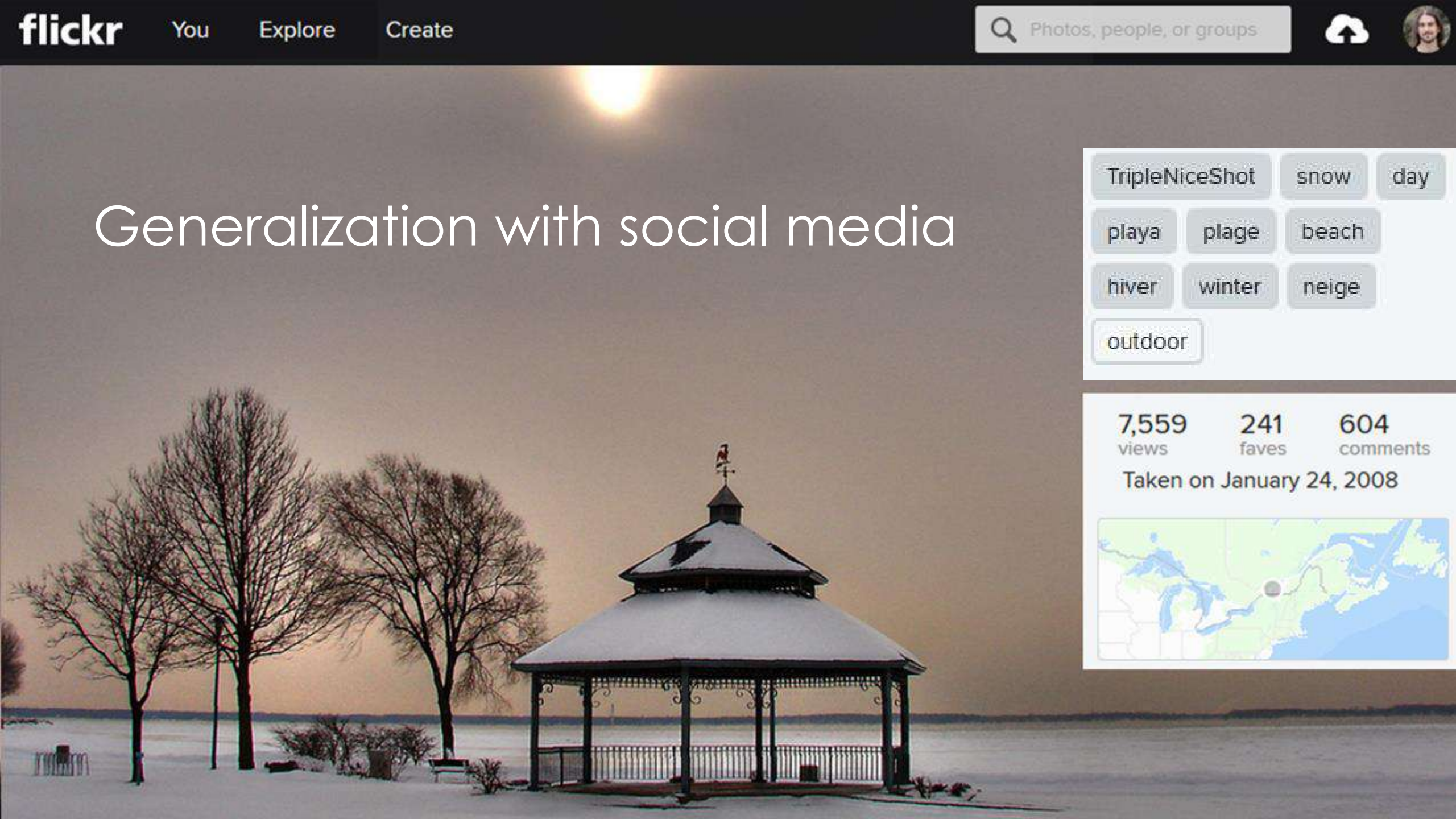


Most beautiful

trueskill.org

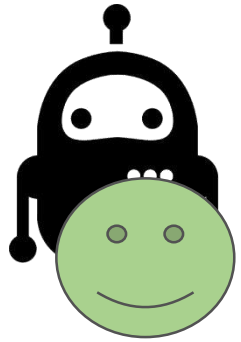
⋮

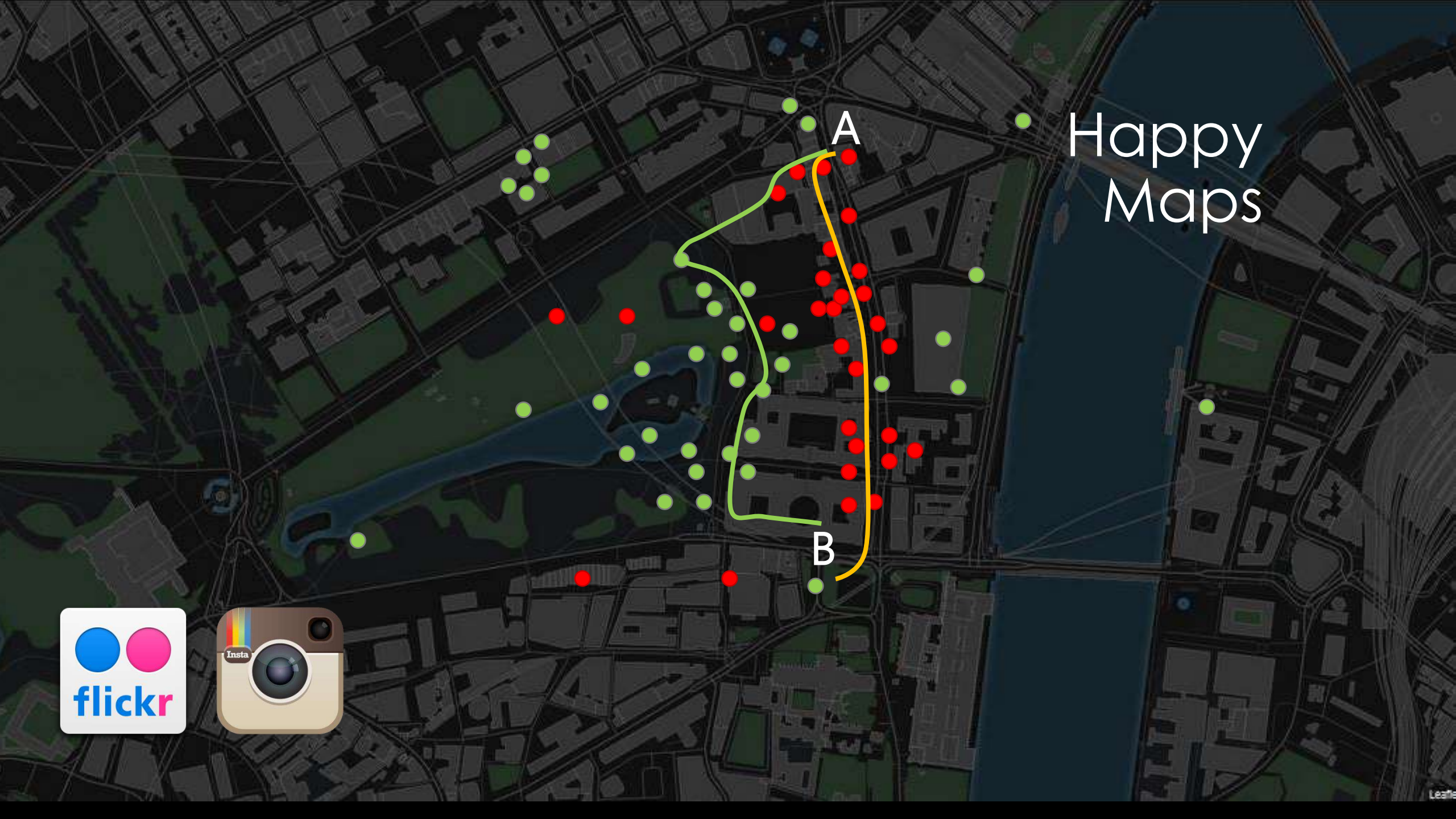
Least beautiful

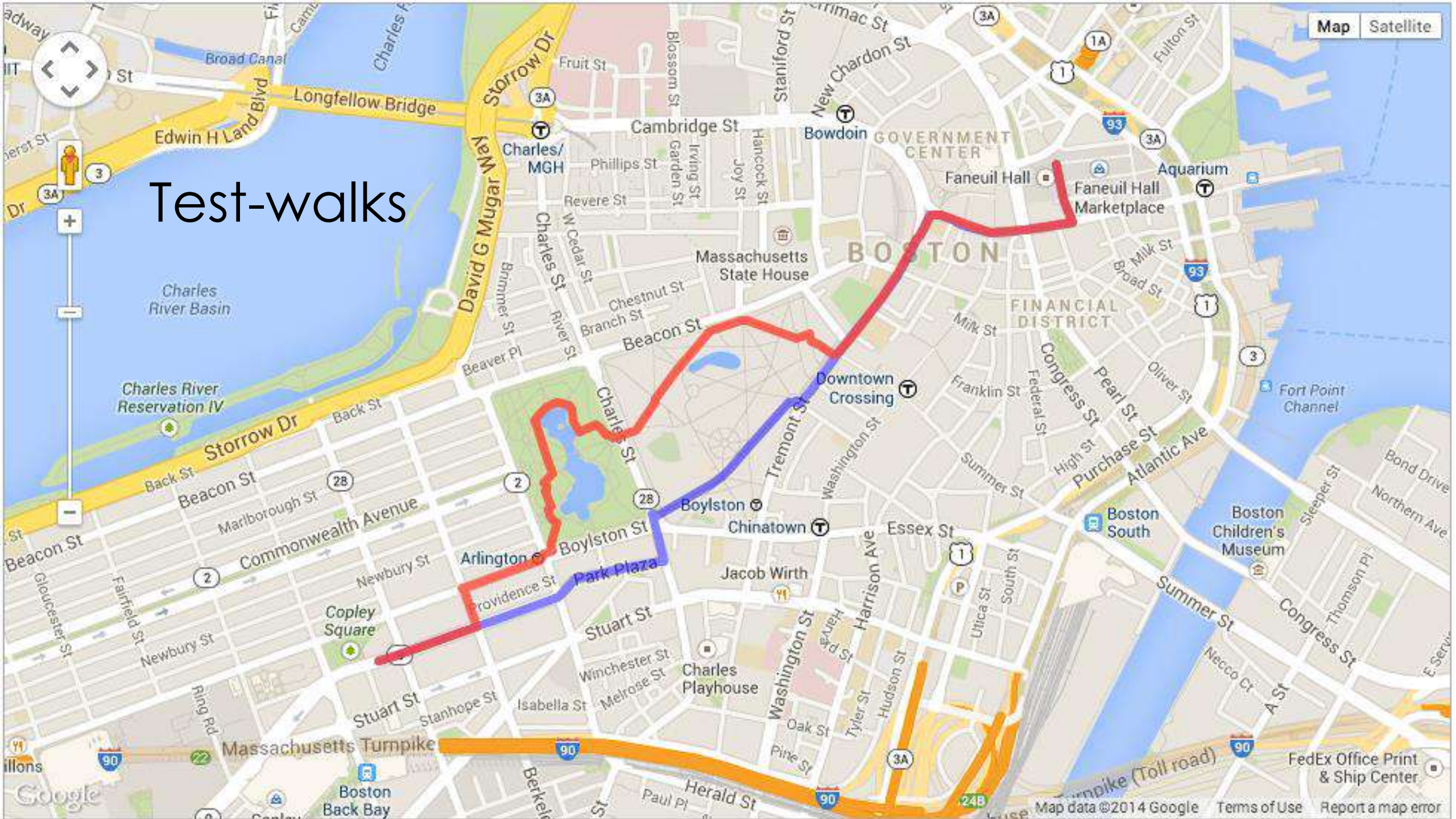

flickr
You
Explore
Create
Photos, people, or groups
Generalization with social media
TripleNiceShot
snow
day
playa
plage
beach
hiver
winter
neige
outdoor
7,559
views
241
faves
604
comments
Taken on January 24, 2008

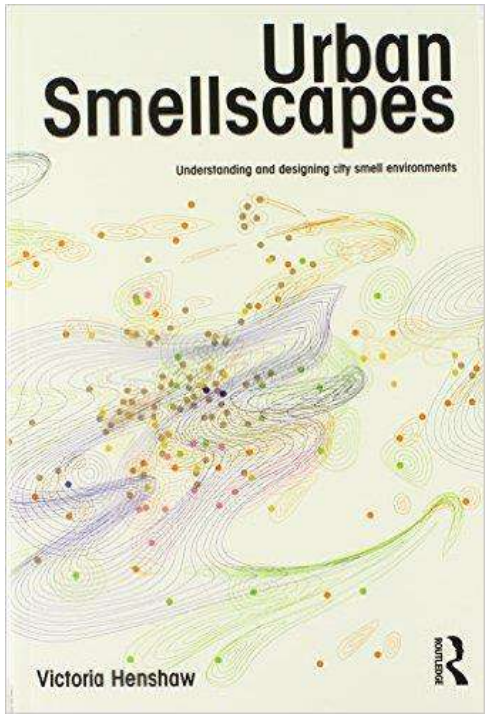
Beauty and the machine

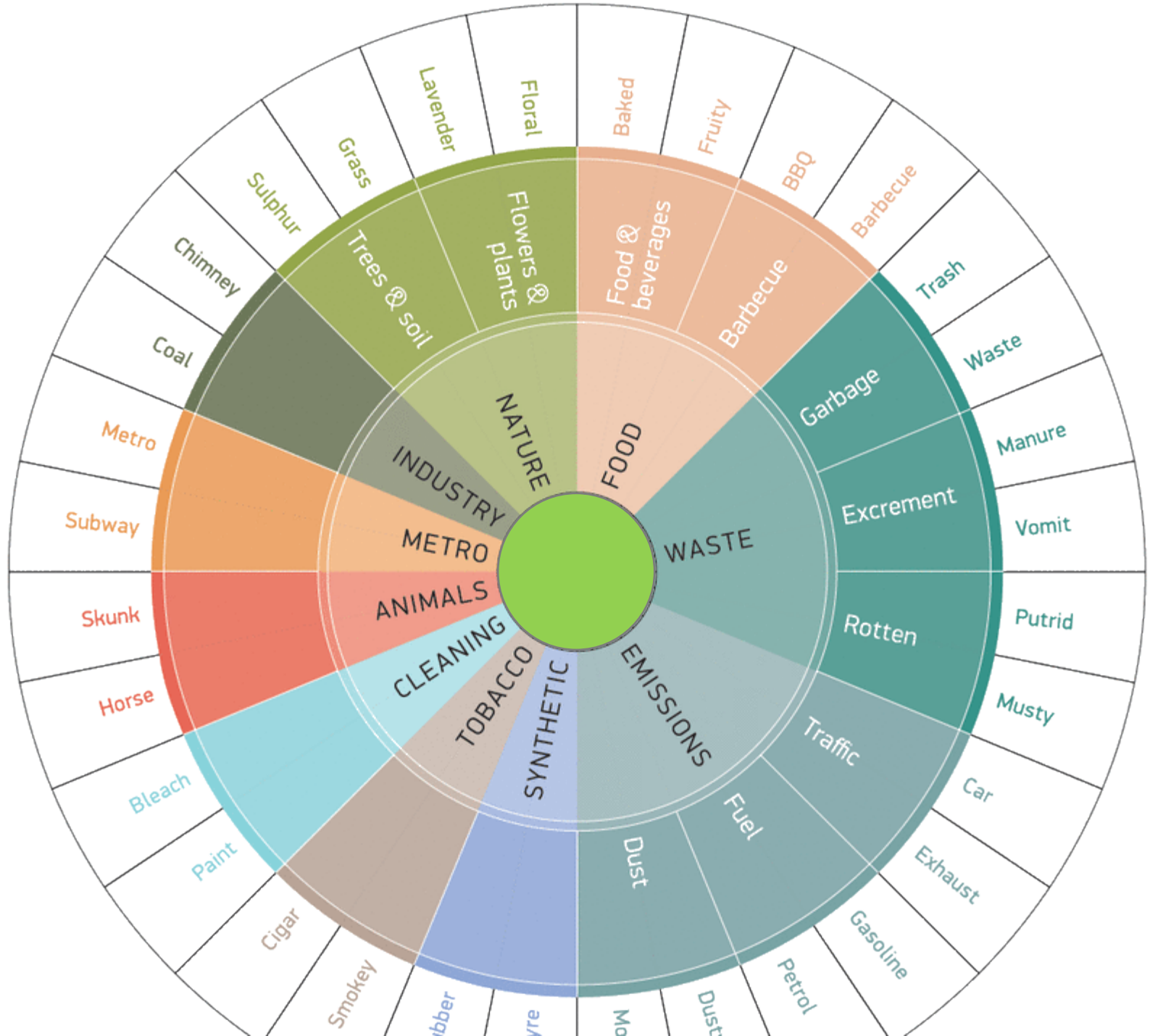
learn




A
B
Happy
Maps
flickr
Insta


Test-walks
Map
Satellite
Broad Canal
Longfellow Bridge
Edwin H Land Blvd
Storrow Dr
David G Mugar Way
Charles River Basin
Charles River Reservation IV
Fruit St
Cambridge St
Charles/ MGH
Phillips St
Revere St
Blossom St
Irving St
Garden St
Joy St
Hancock St
Staniford St
New Chardon St
Bowdoin
GOVERNMENT CENTER
Faneuil Hall
Faneuil Hall Marketplace
Aquarium
Fulton St
Massachusetts State House
BOSTON
FINANCIAL DISTRICT
Milk St
Broad St
Franklin St
Federal St
Congress St
Pearl St
Oliver St
Fort Point Channel
Downtown Crossing
Tremont St
Washington St
Summer St
High St
Purchase St
Atlantic Ave
Boston South
Boston Children's Museum
Sleeper St
Bond Drive
Northern Ave
Thomson Pl
Beacon St
Brimmer St
River St
Charles St
W Cedar St
Chestnut St
Branch St
Beaver Pl
Back St
Marlborough St
Commonwealth Avenue
Boylston
Chinatown
Boylston St
Park Plaza
Arlington
Essex St
Jacob Wirth
Harrison Ave
Utica St
South St
Newbury St
Providence St
Copley Square
Gloucester St
Fairfield St
Stuart St
Winchester St
Melrose St
Charles Playhouse
Washington St
Hayward St
Tyler St
Hudson St
Oak St
Pine St
Isabella St
Stanhope St
Ring Rd
Massachusetts Turnpike
Boston Back Bay
Herald St
Paul Pl
Berkeley St
Necco Ct
A St
Summer St
Congress St
FedEx Office Print & Ship Center
Turnpike (Toll road)
Google
Map data ©2014 Google
Terms of Use
Report a map error


Urban
Smellscapes
Understanding and designing city smell environments
Victoria Henshaw
ROUTLEDGE


NATURE
FOOD
WASTE
EMISSIONS
SYNTHETIC
TOBACCO
CLEANING
ANIMALS
METRO
INDUSTRY
Flowers & plants
Trees & soil
Food & beverages
Barbecue
Garbage
Excrement
Rotten
Traffic
Fuel
Dust
Floral
Lavender
Grass
Sulphur
Baked
Fruity
BBQ
Barbecue
Trash
Waste
Manure
Vomit
Putrid
Musty
Car
Exhaust
Gasoline
Petrol
Chimney
Coal
Metro
Subway
Skunk
Horse
Bleach
Paint
Cigar
Smokey

Enn.LI + Follow

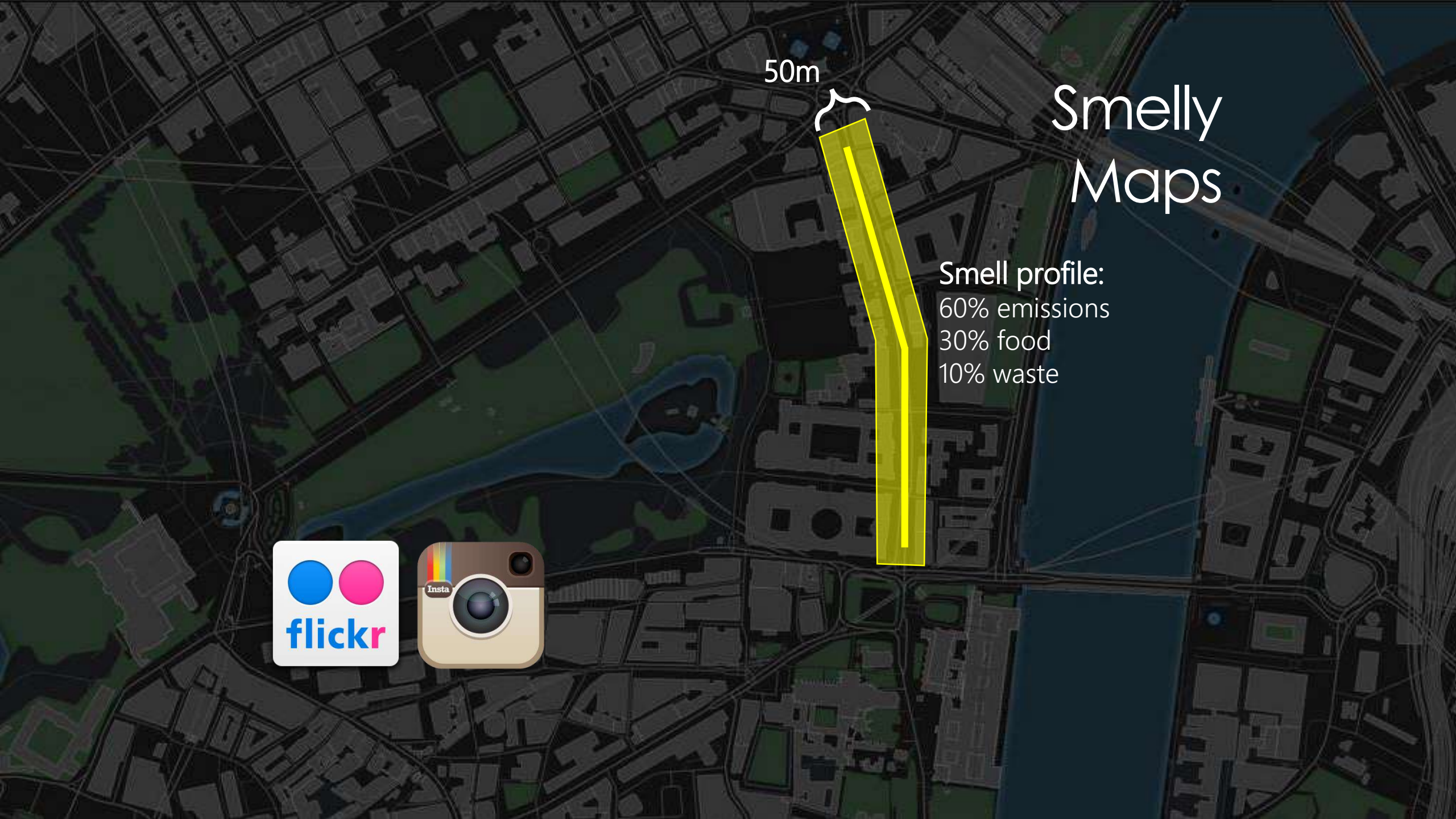
63 views 0 faves 0 comments

Varanasi street food-Aloo Chaat

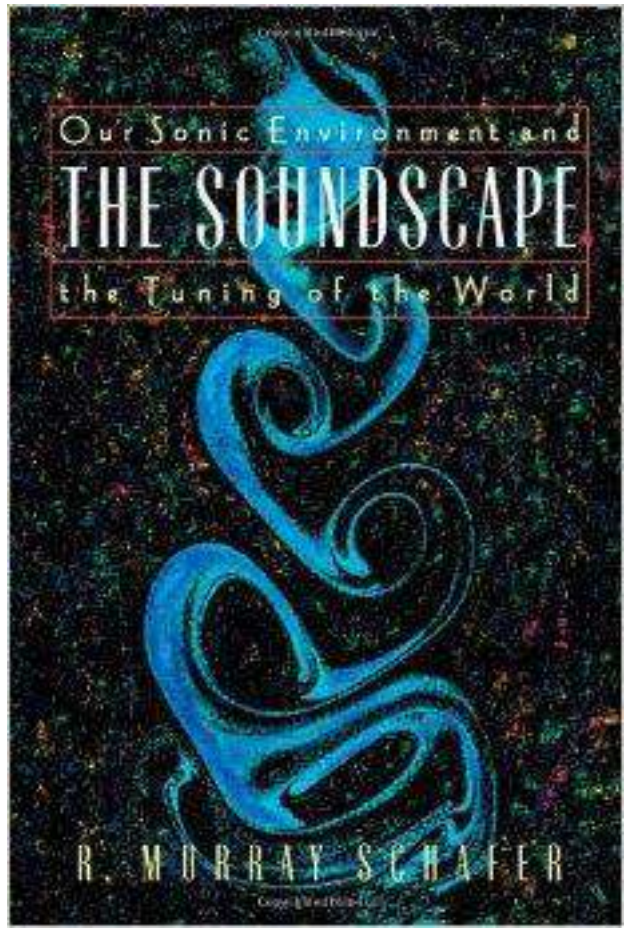
Aloo Chaat being prepared on a street stall in Varanasi

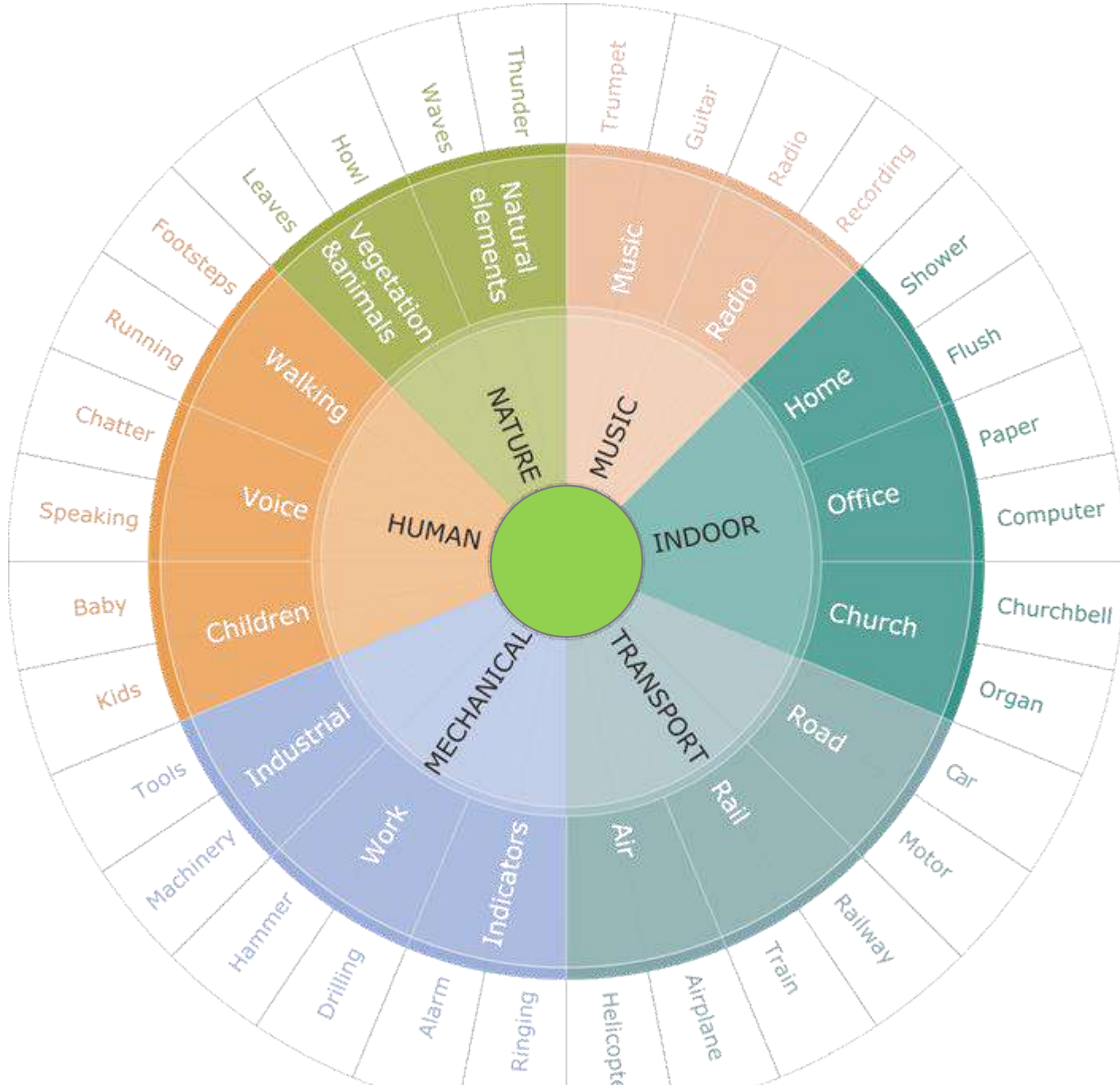
Taken on June 18, 2013

Cooking Oil | Deep Fried | Preparing Food | Market | Day | Pan | Cooking


50m
Smelly Maps
Smell profile:
60% emissions
30% food
10% waste
flickr
Insta


Takamine


Our Sonic Environment and
THE SOUNDSCAPE
the Tuning of the World
R. MURRAY SCHAFER


NATURE
MUSIC
INDOOR
TRANSPORT
MECHANICAL
HUMAN
Natural elements
Vegetation &animals
Music
Radio
Home
Office
Church
Road
Rail
Air
Industrial
Work
Indicators
Voice
Children
Walking
Thunder
Waves
Howl
Leaves
Footsteps
Trumpet
Guitar
Radio
Recording
Shower
Flush
Paper
Computer
Churchbell
Organ
Car
Motor
Railway
Train
Airplane
Ringing
Alarm
Drilling
Hammer
Machinery
Tools
Kids
Baby
Speaking
Chatter
Running

Scott Johnson + Follow

PRO

New Orleans Street Musicians ...

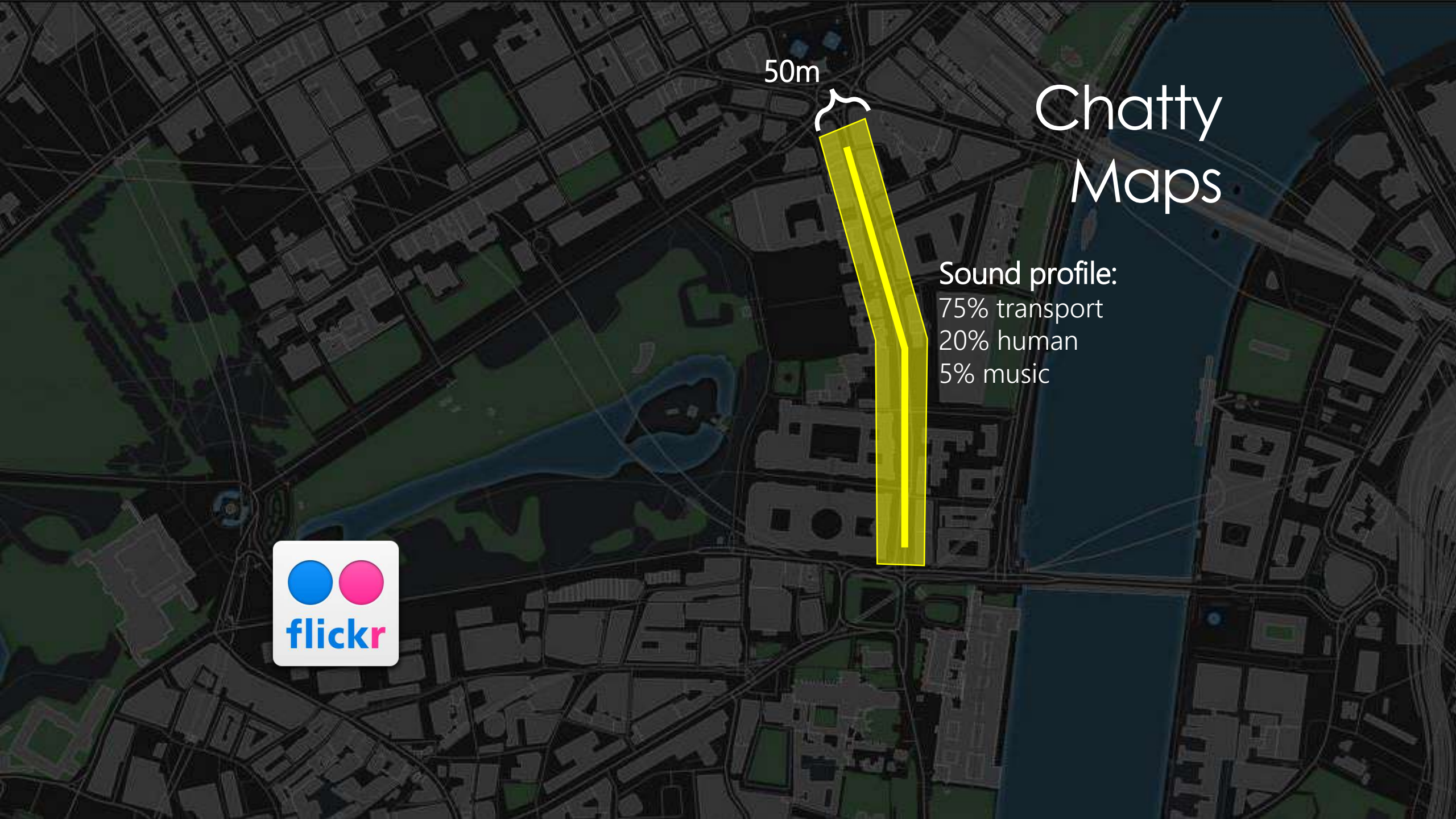
This violinist literally played with such feeling and beauty that 'gr men' were tearful in the audience.
French Quarter, New Orleans, Louisiana, USA
(Please View Full Screen ...)

musicians guitar violin music natural light Louisiana Nikon

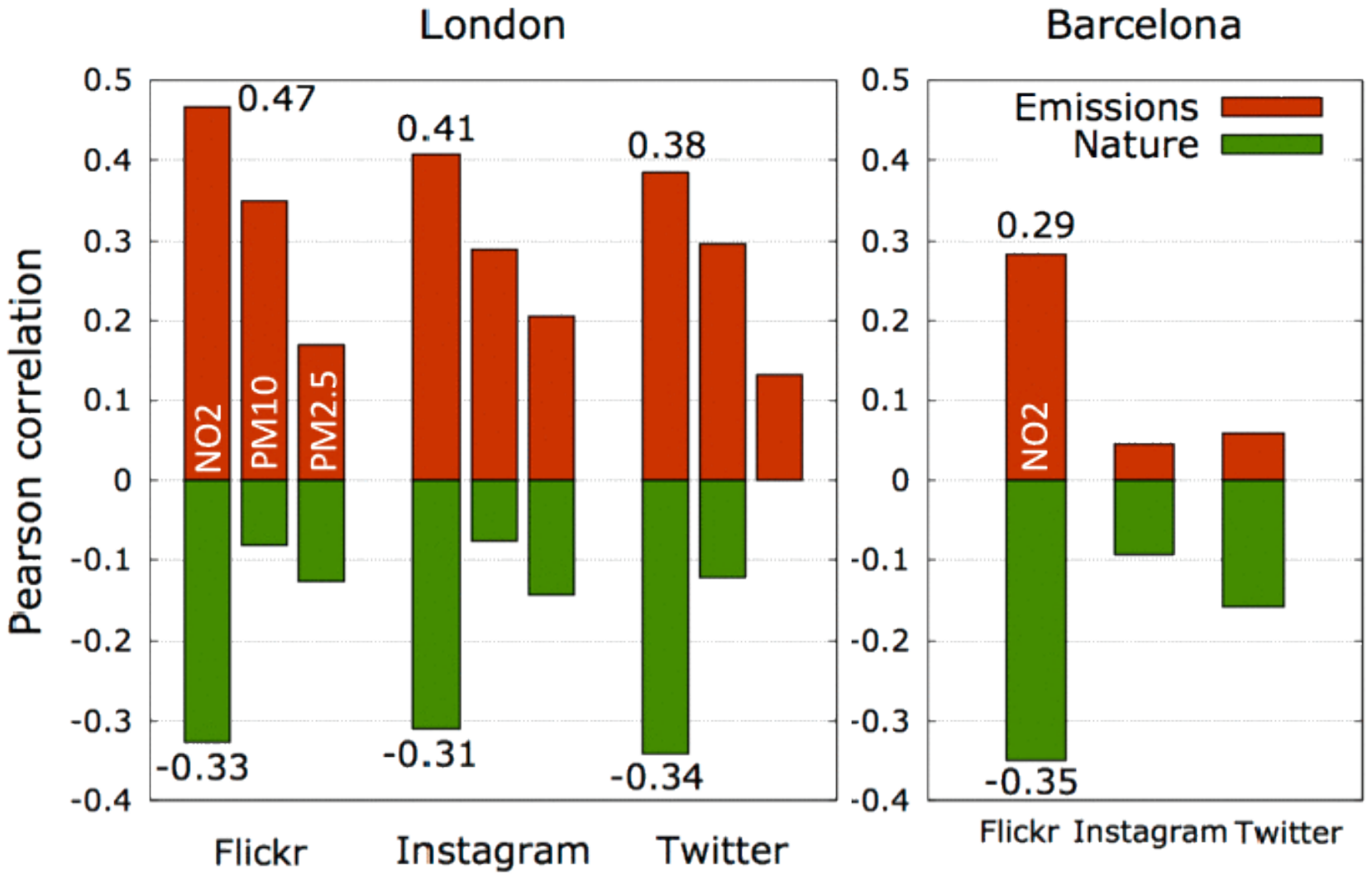
1,579 views 44 faves 13 comments

Taken on April 29, 2015

Some rights reserved


50m
Chatty Maps
Sound profile:
75% transport
20% human
5% music
flickr

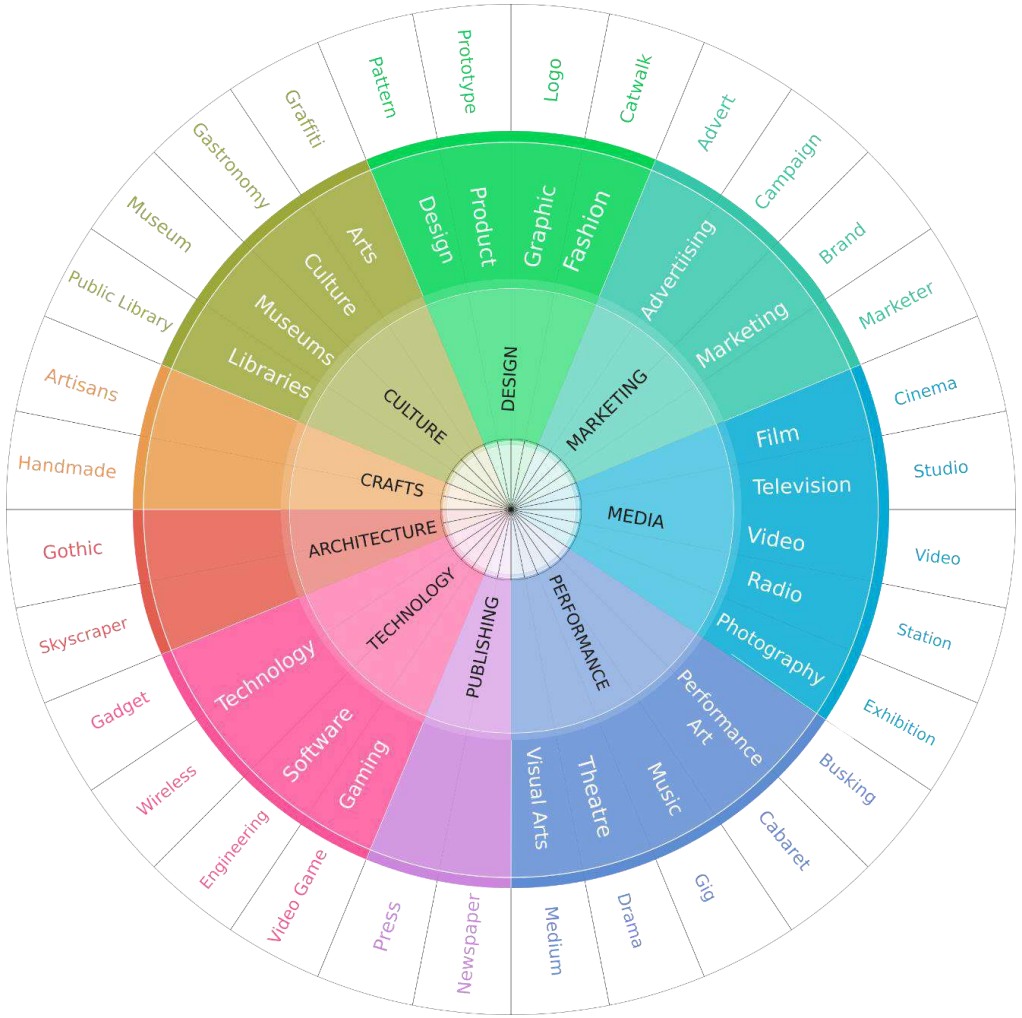
Smell and air-quality indicators

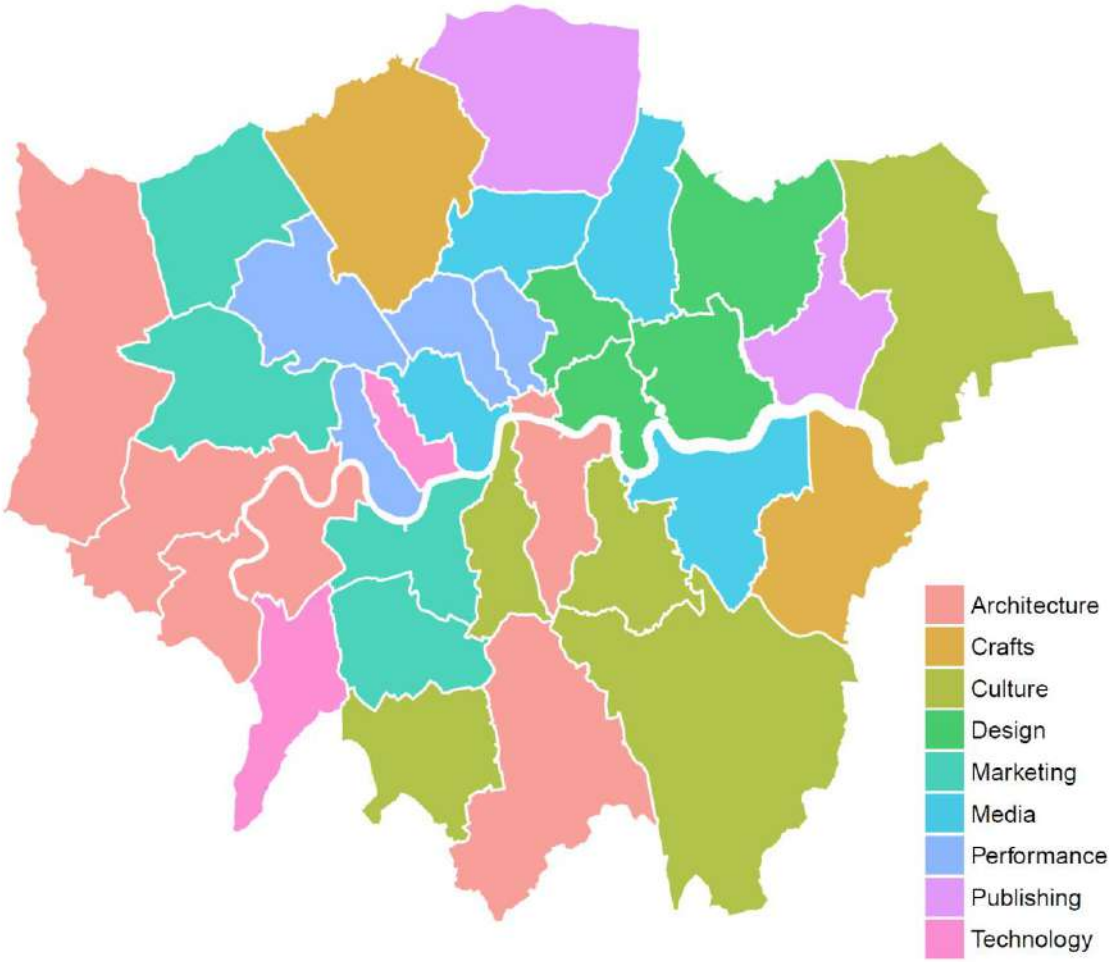


www.goodcitylife.org

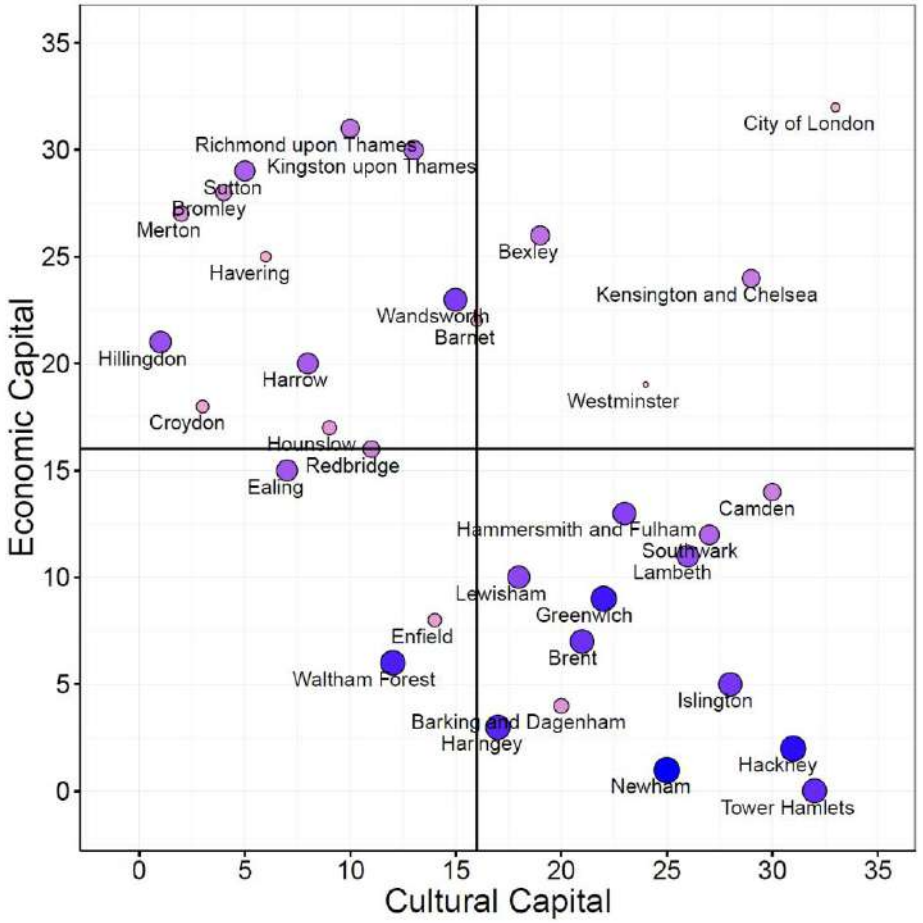

Happy
Smelly
Chatty
Emotion
Walkability
Activity
Ambiance
Culture
Food
Maps

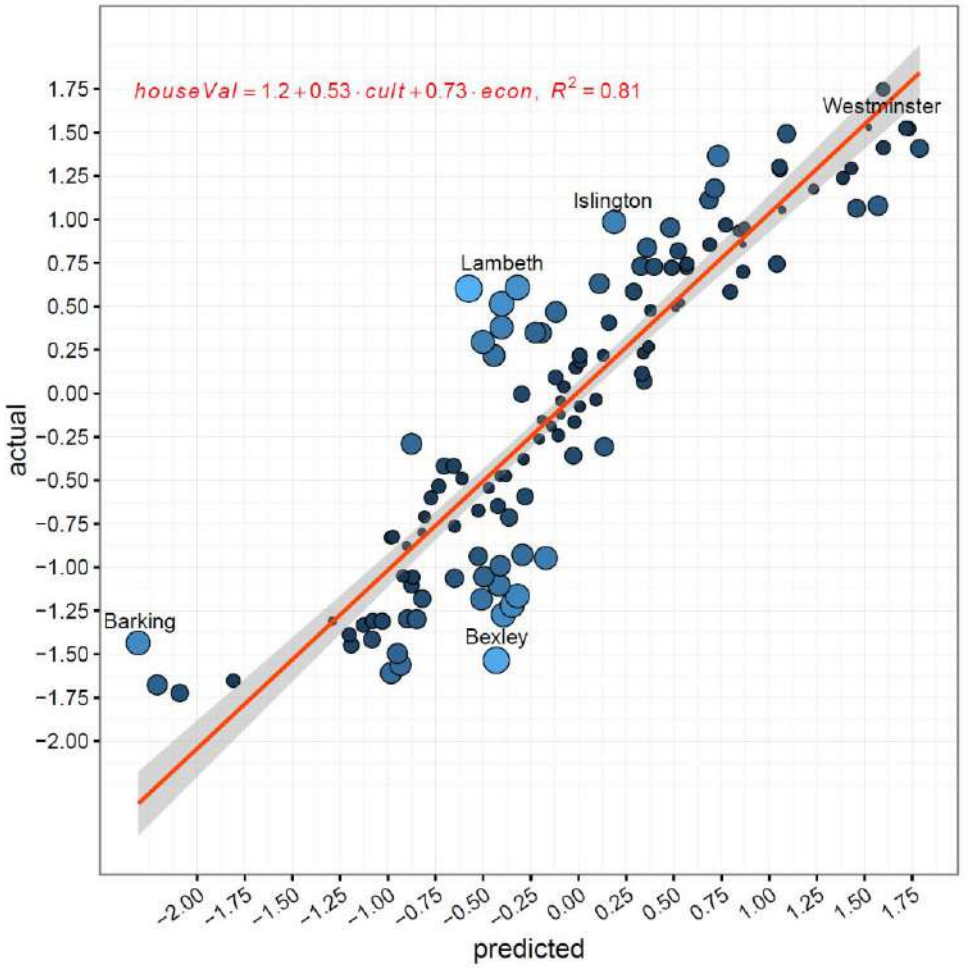
Mapping culture



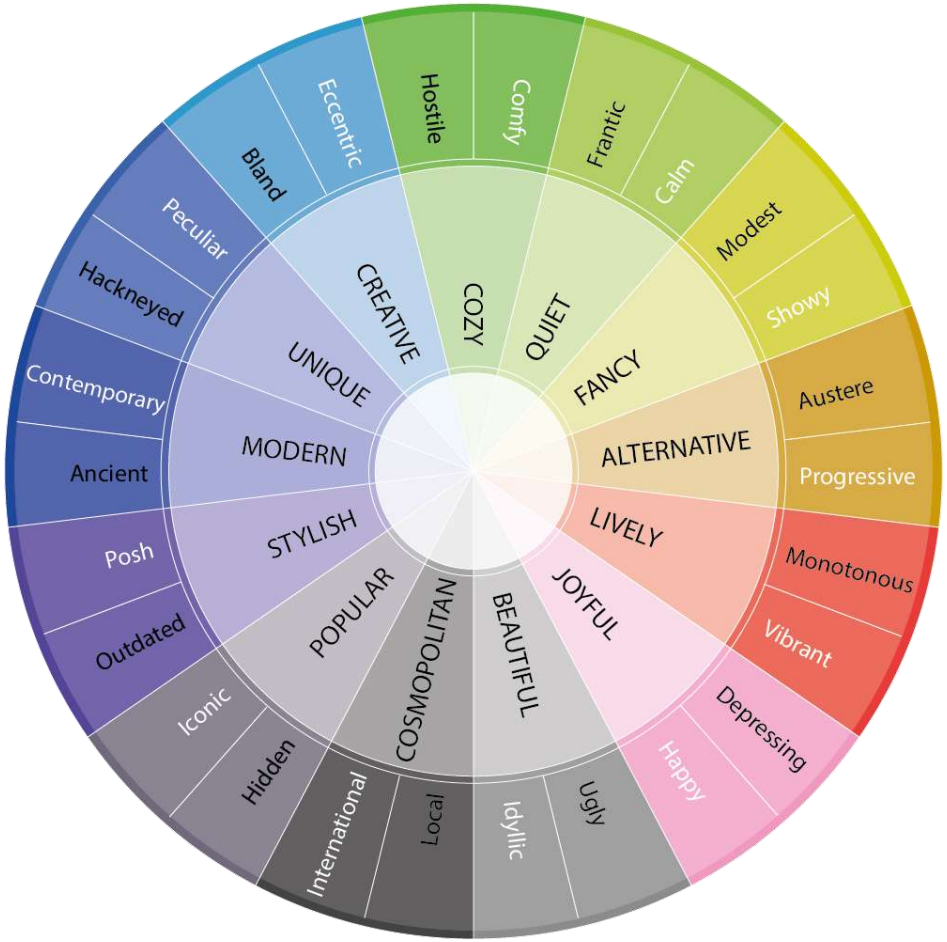


Mapping culture (Pierre Bourdieu)





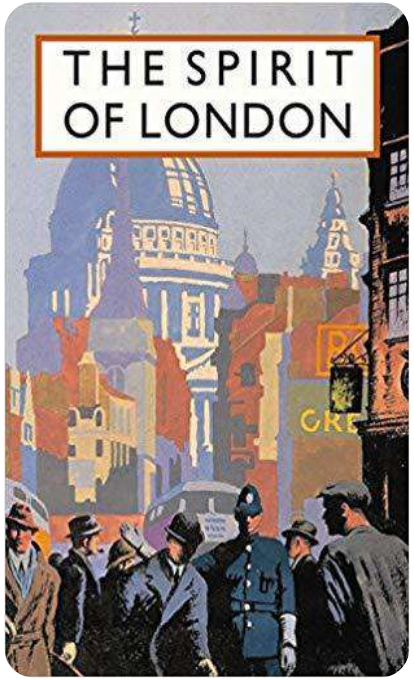
Mapping ambiance



Can the Ambiance of a Place be Determined by the User Profiles of the People Who Visit It?

Lindsay T. Graham[1], Samuel D. Gosling[2]

Department of Psychology A8000, University of Texas, Austin 78712, USA
[1] lindsaytgraham@gmail.com, [2] samg@mail.utexas.edu

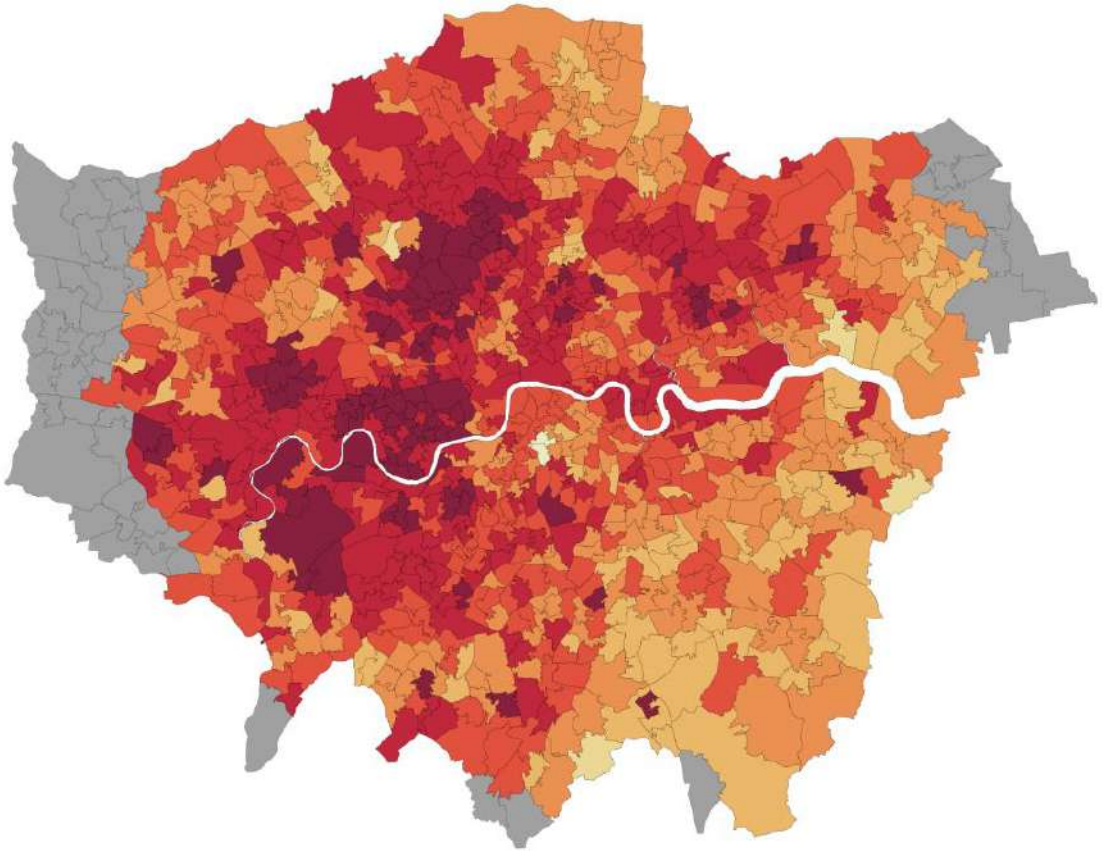


Mapping food consumption

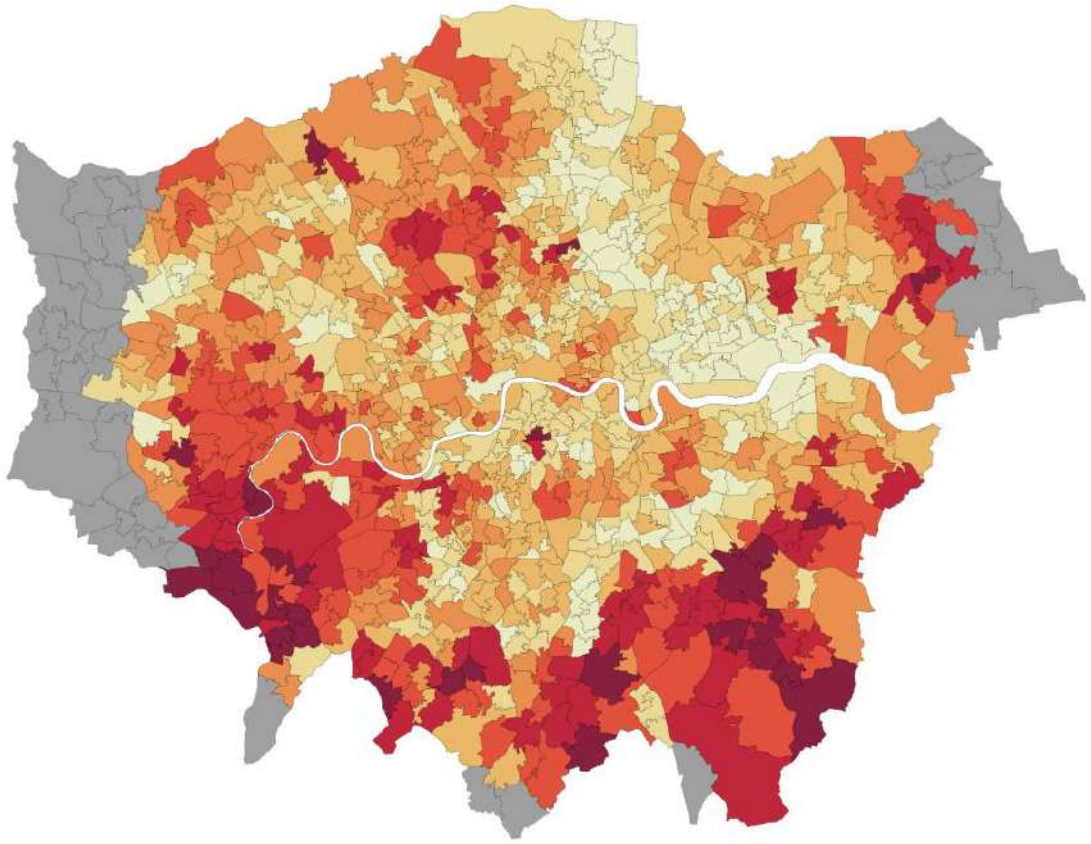
- Tesco, the largest food retailer in UK (30% of the market)
- 411 stores in greater London
- 1.6B products purchased by 1.6M customers in 2015 (zip code)
- 77k unique products
- Nutritional info and ingredients

Mapping food consumption

Fat map of London



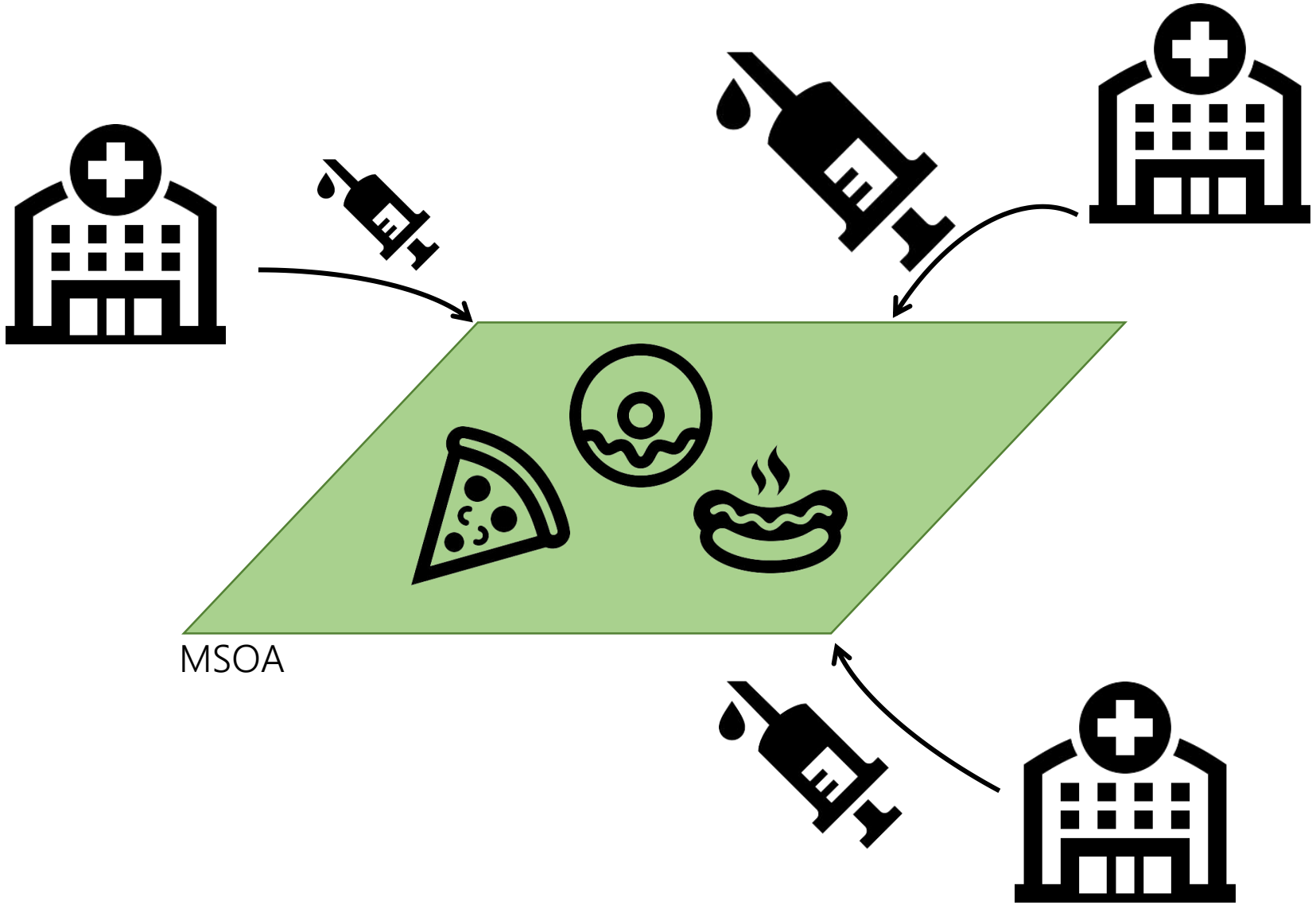
Fiber map of London



The “average” food product

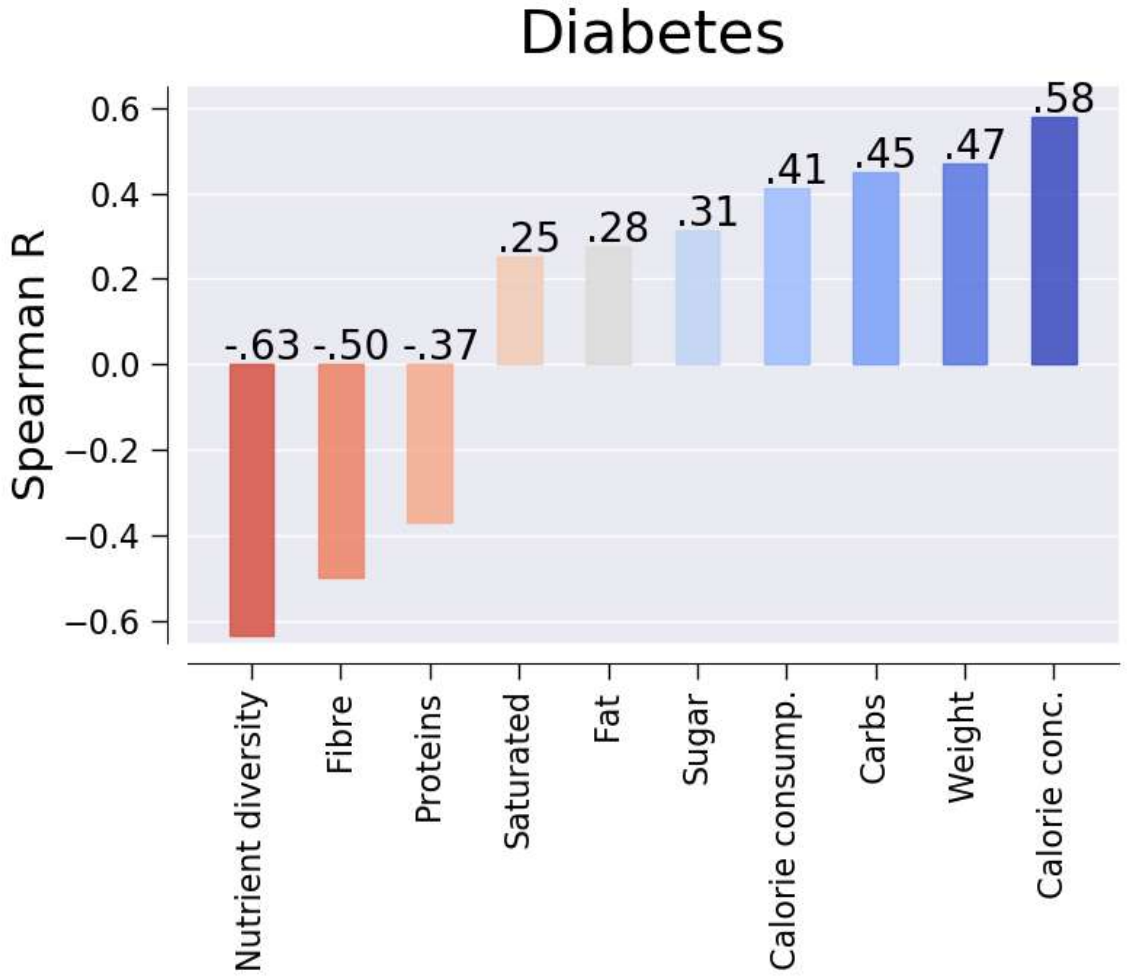
MSOA

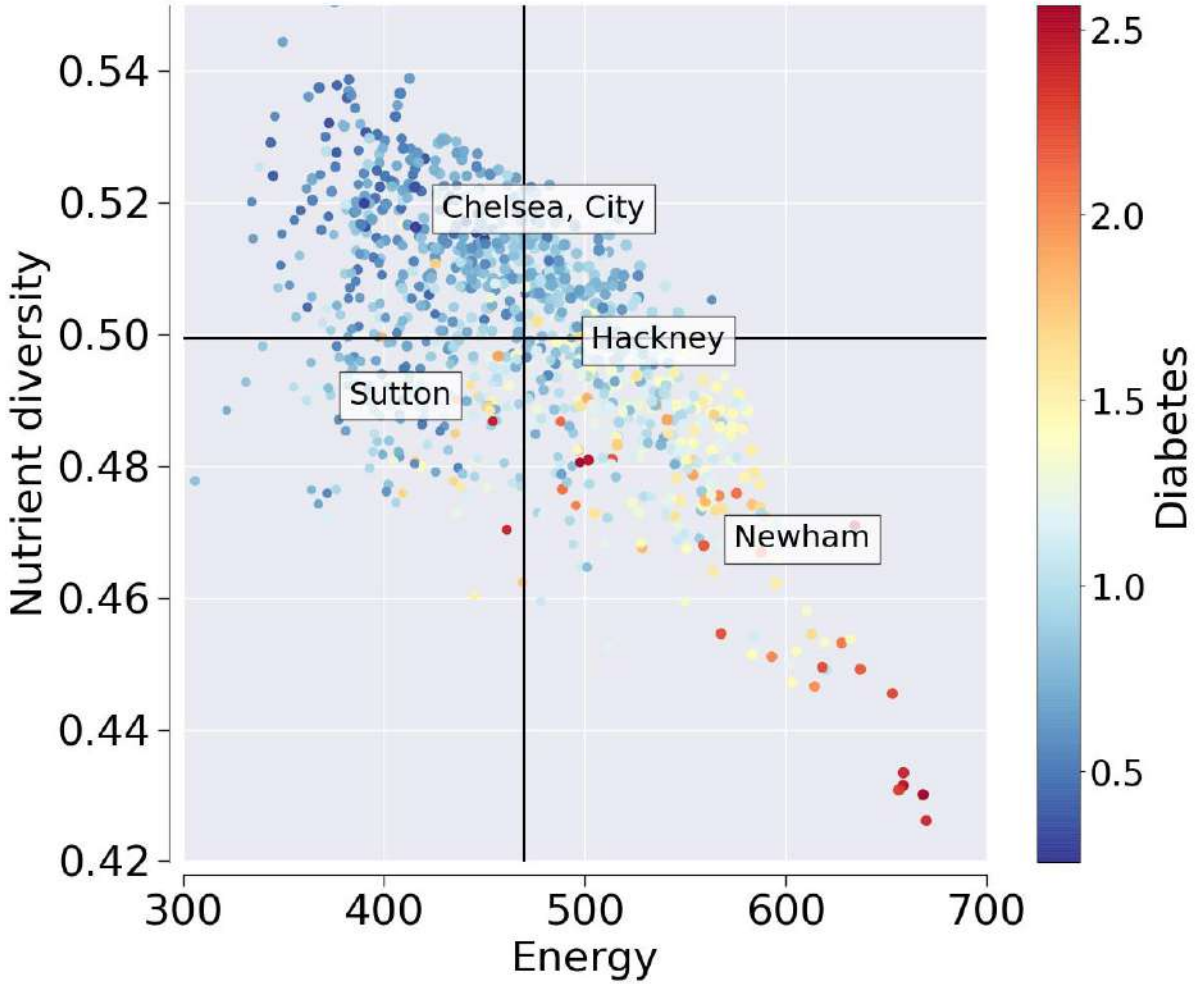
Matching food and prescriptions



https://data.gov.uk/dataset/prescribing-by-gp-practice-presentation-level

Correlation between food and health outcomes

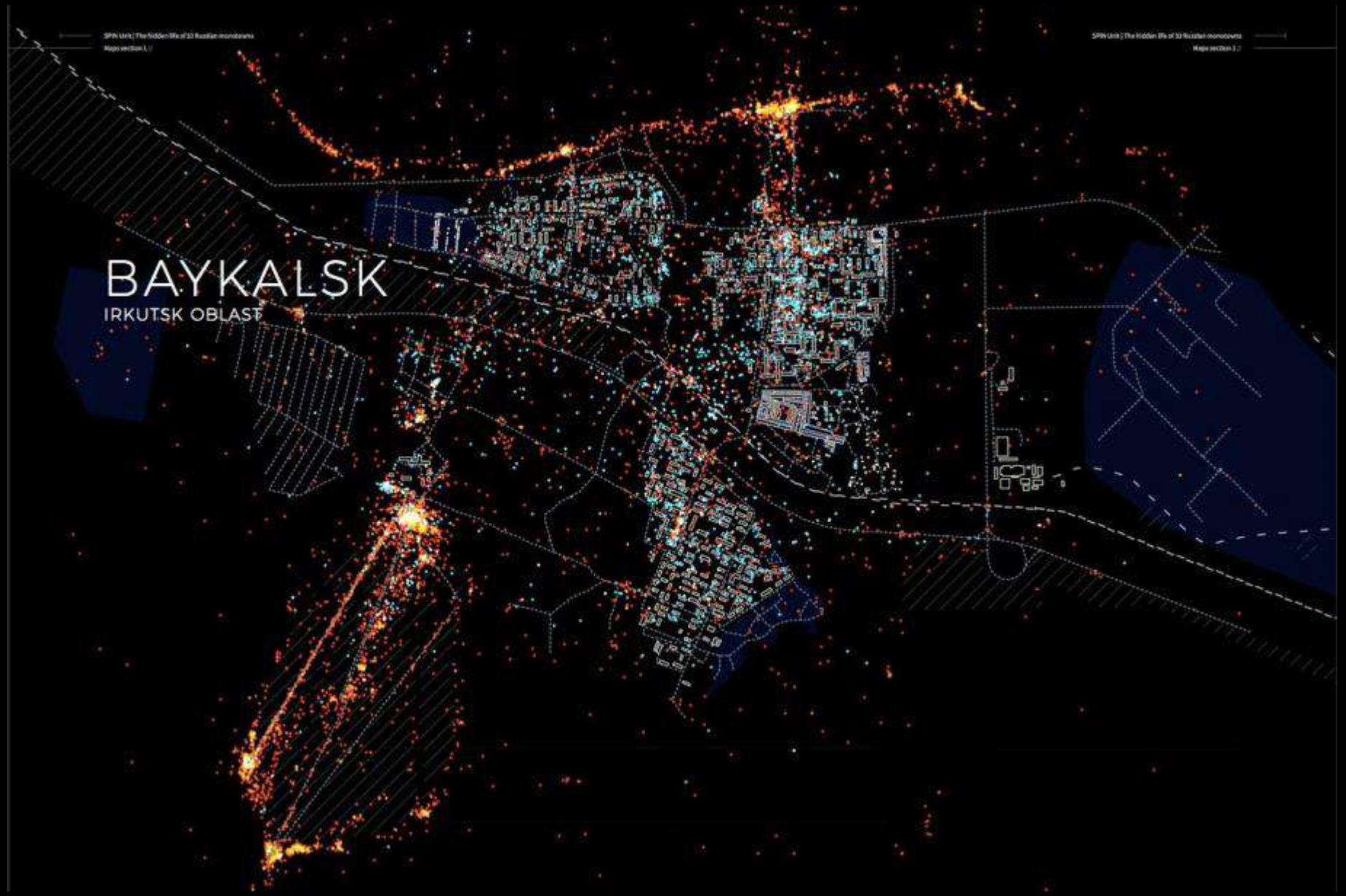




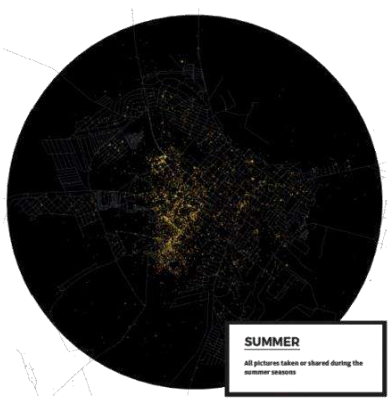

Delivering interventions

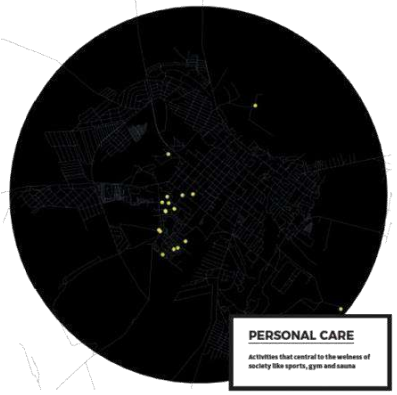
Urban design

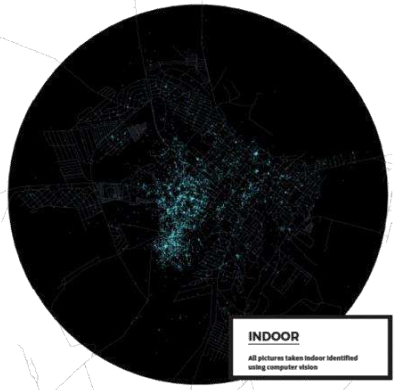
Russian Monotowns

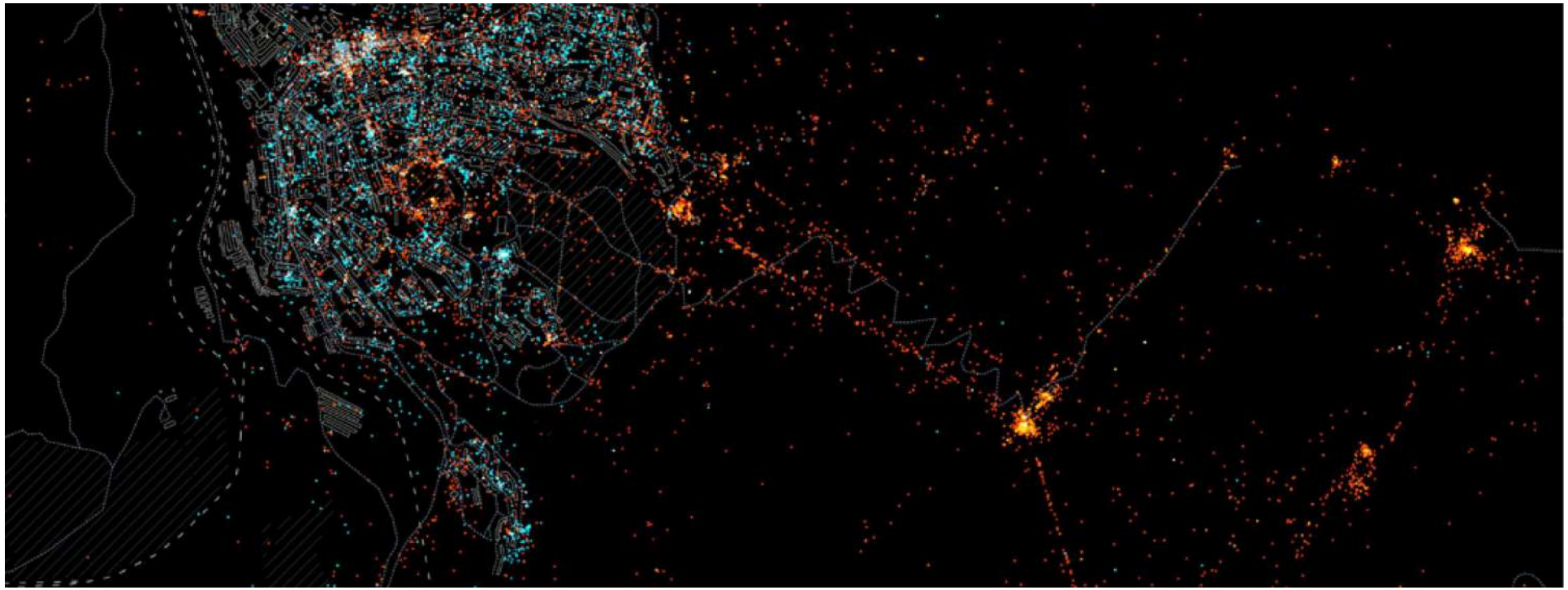

BAYKALSK
IRKUTSK OBLAST

Social media sensing → design briefs









FIFA WORLD CUP

RUSSIA 2018


Urban beautification

F A C E L I F T

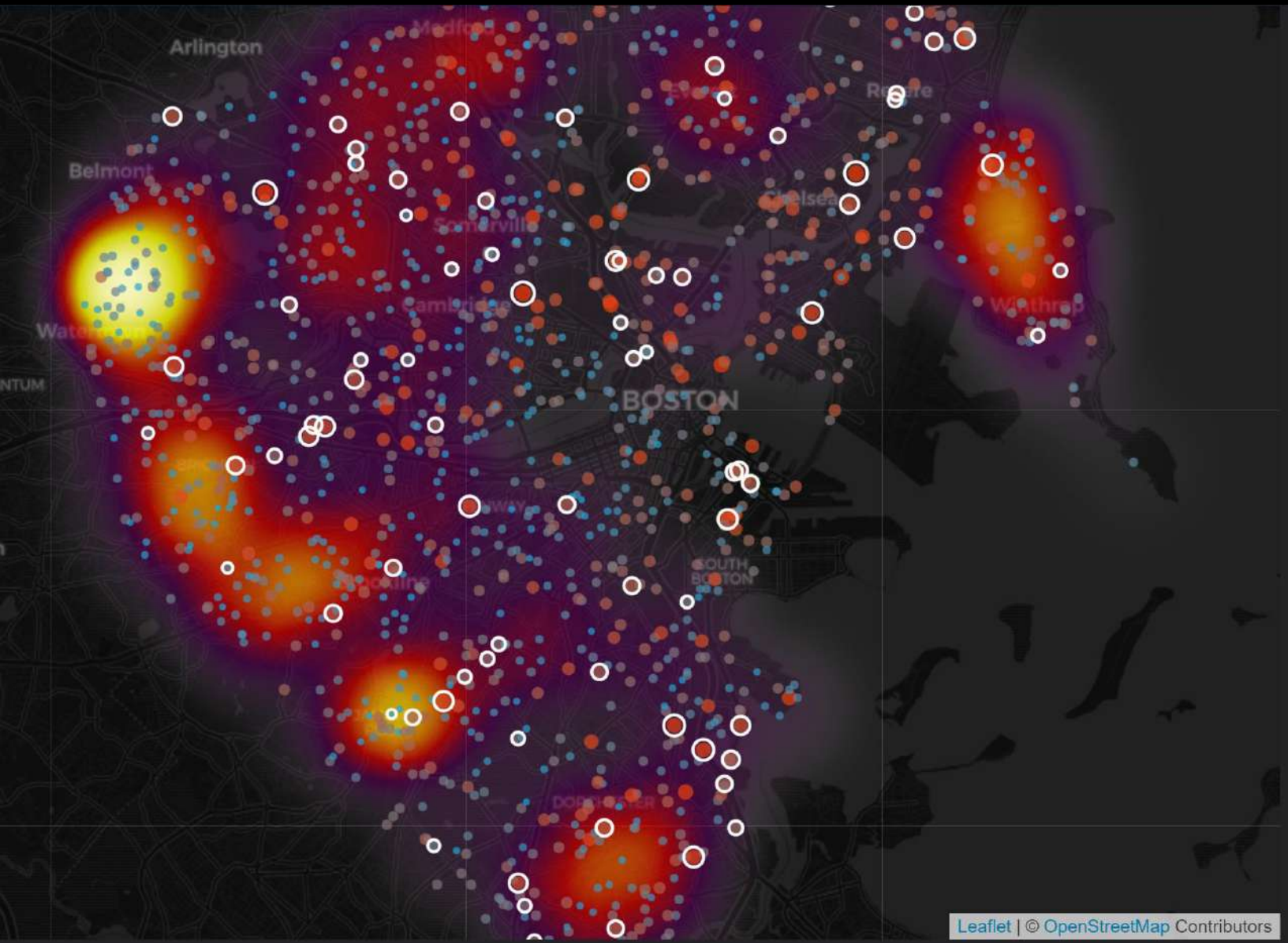
Buildings and neighbourhoods speak. They speak of egalitarianism or elitism, beauty or ugliness, acceptance or arrogance. The aim of Facelift is to celebrate egalitarianism, beauty, and acceptance by beautifying the entire world, one Google Street view at a time.

All of this is done by designing state-of-the-art technologies that make it possible to smarten a street view and read inside the Deep Learning "*black box*". With further developments of these technologies, we would be more likely to systematically understand and re-create the environments we intuitively love.

"Beauty is nothing other than the promise of happiness"
Stendhal, On Love.

Explore Boston with FACELIFT

No, first tell me more about it.



Labels are ordered by beauty, ranging from **beautiful** to **ugly**. The bigger, the more frequent.

forest_path
mansion
campsite
tree_farm
picnic_area
botanical_garden
forest_road
plaza
courtyard
driveway
inn_outdoor
coast
orchard
patio
formal_garden
apartment_building_outdoor
playground
skyscraper
yard
residential_neighborhood
hotel_outdoor
hospital
office_building
crosswalk
boardwalk
highway
alley
parking_lot
railroad_track
building_facade
cottage_garden
river
fountain
fire_escape
pond
viaduct
bayou
motel
bridge
sky
amusement_park
ski_resort
gas_station
train_station_platform
windmill
train_railway
runway
slum
construction_site
airport_terminal
harbor

currently beautiful

#513d684bfdc9f03587004309

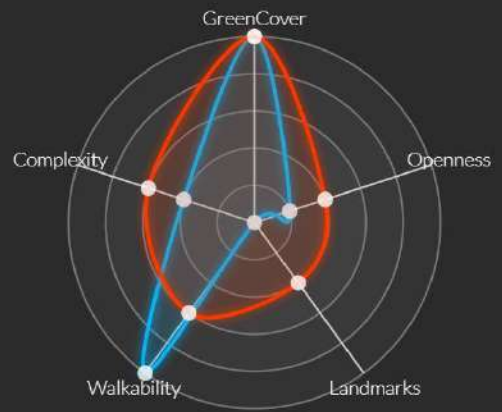
X

Original Location

Beautified Location

Urban Scences

Urban Design Metrics



Change of Urban Elements

Leaflet | © OpenStreetMap Contributors

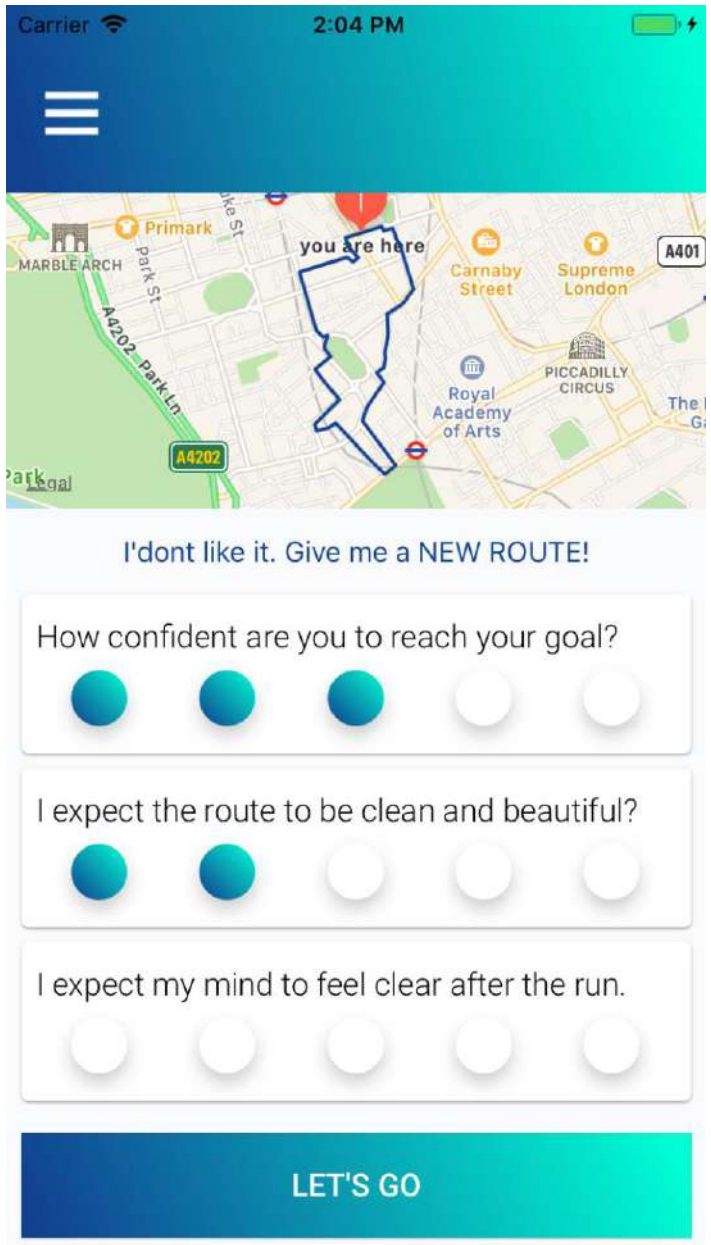
rdered by beauty, ranging from beautiful to ugly. The bigger,
equent.

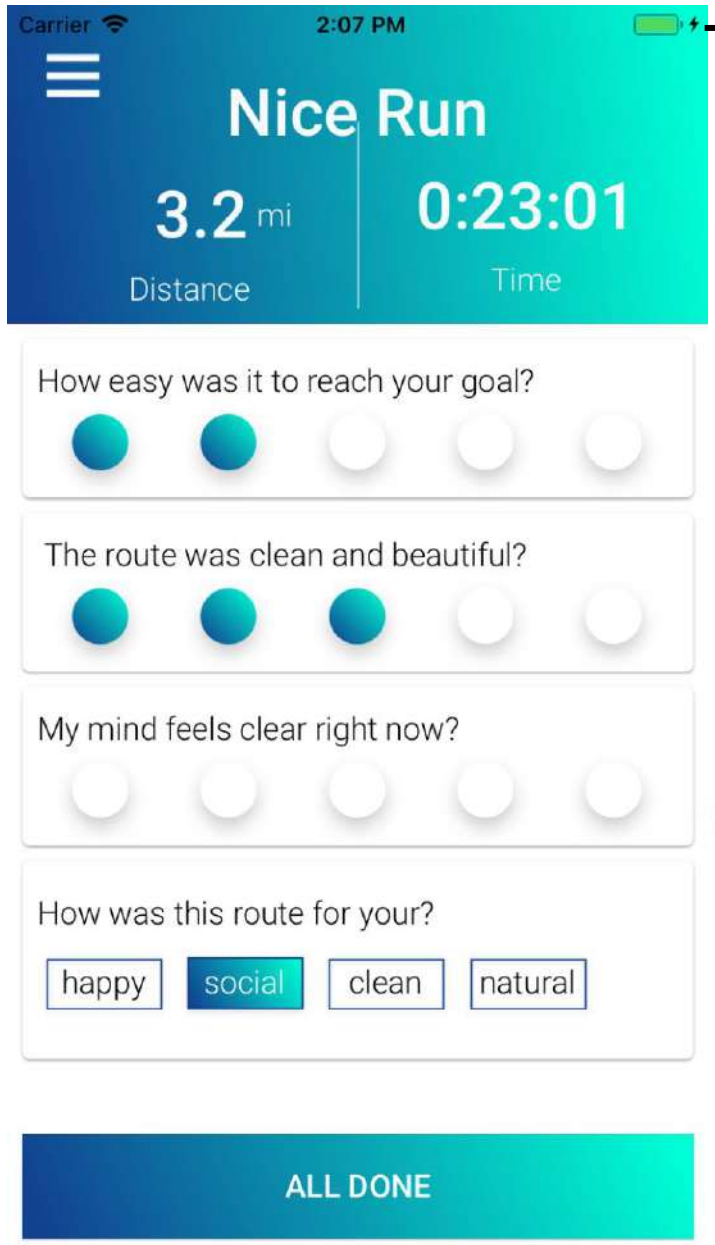
ly beautiful
currently ugly
wannabe beautiful, click to compare

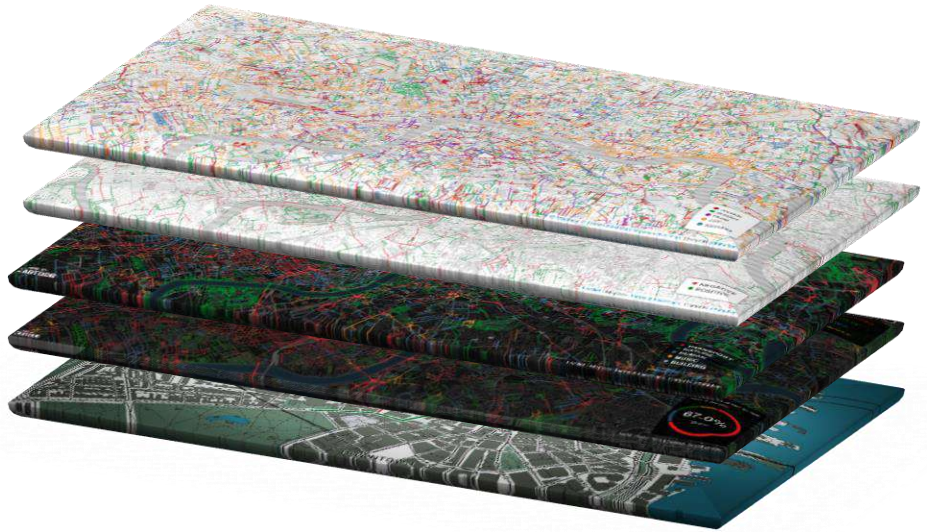

Daily habits in the city

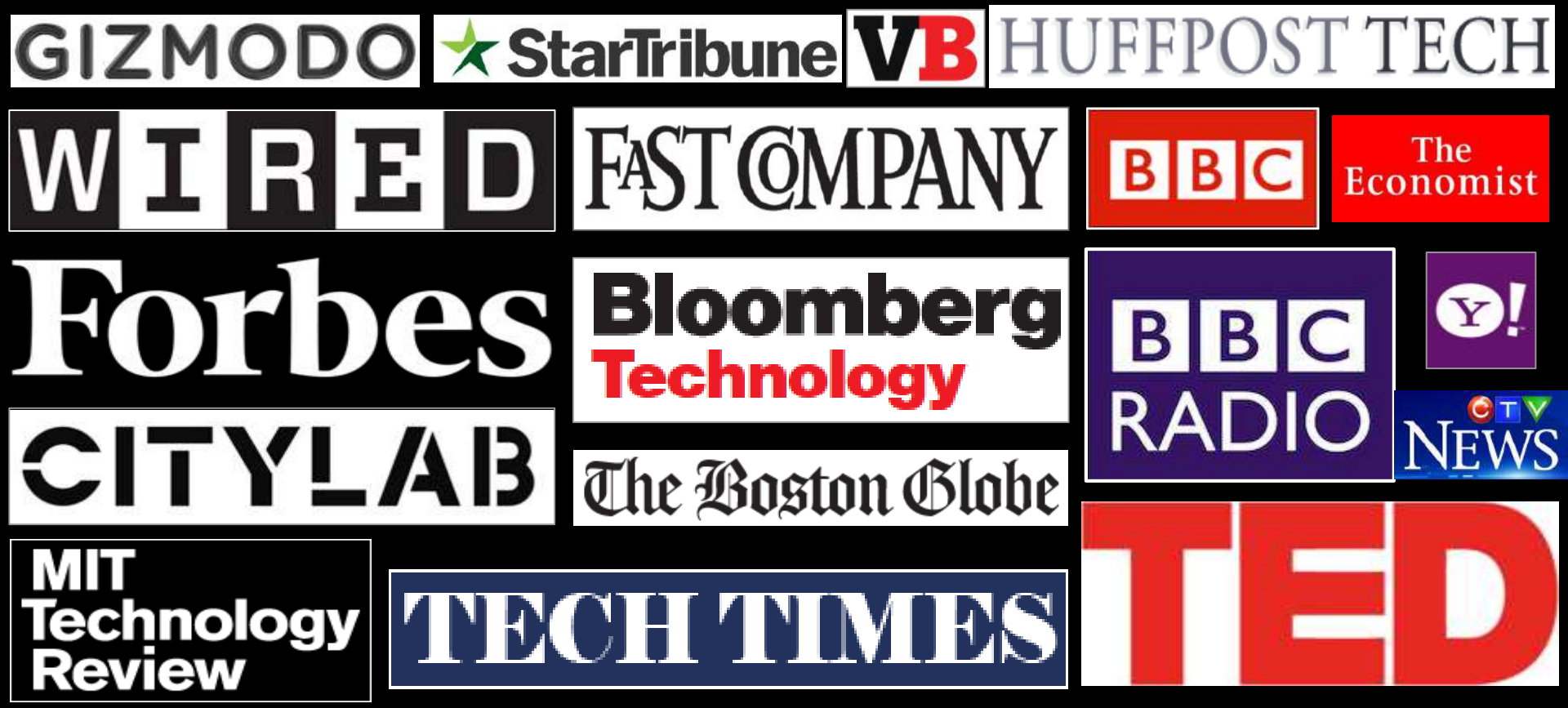
The Ultimate Running App

Soon on iOS







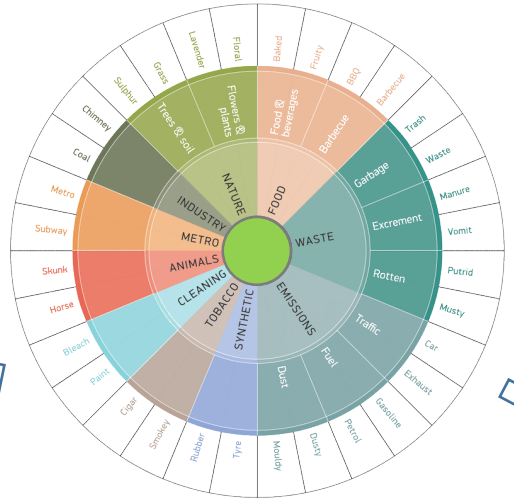

GIZMODO
StarTribune
VB
HUFFPOST TECH
WIRED
FAST COMPANY
BBC
The Economist
Forbes
Bloomberg
Technology
BBC
RADIO
Y!
CITYLAB
The Boston Globe
CTV
NEWS
MIT
Technology
Review
TECH TIMES
TED

Summary

- Efficiency is not always good
- Intangible != immeasurable
- Power of online multimedia data to describe intangible properties of space

The ~~problems~~ technical challenges

Data collection



Metadata processing

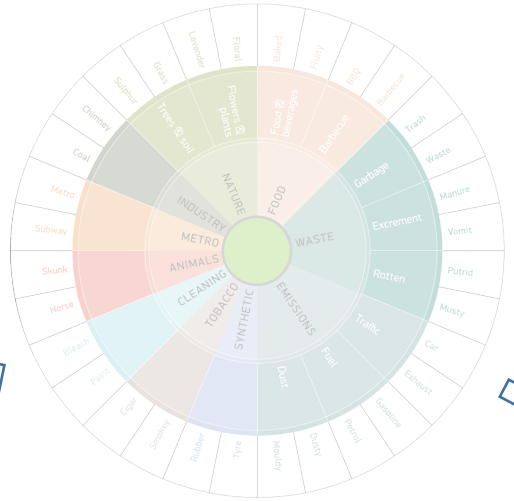
Image processing

Mapping

Visualizing

The technical challenges

Data collection



Metadata processing

Image processing

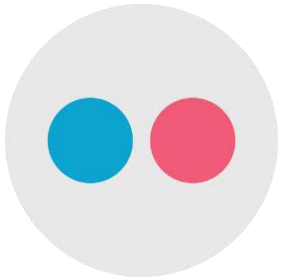
Mapping

Visualizing

The end of social media for research?

"Processing of personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, and the processing of genetic data, biometric data for the purpose of uniquely identifying a natural person, data concerning health or data concerning a natural person's sex life or sexual orientation shall be prohibited"




The "old bunch

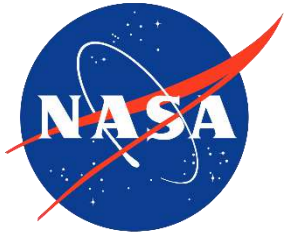
Li, Ratti
Using Google Street View for Street-Level Urban Form Analysis
Urban Morphology 2019

Fonte et al.
Using openstreetmap to create land use and land cover maps
Geospatial intelligence 2019

Garimella, Tyson
WhatsApp, Doc? A First Look at WhatsApp Public Group Data
ICWSM 2018

Sheehan et al.
Predicting Economic Development using Geolocated Wikipedia Articles
arXiv 2019

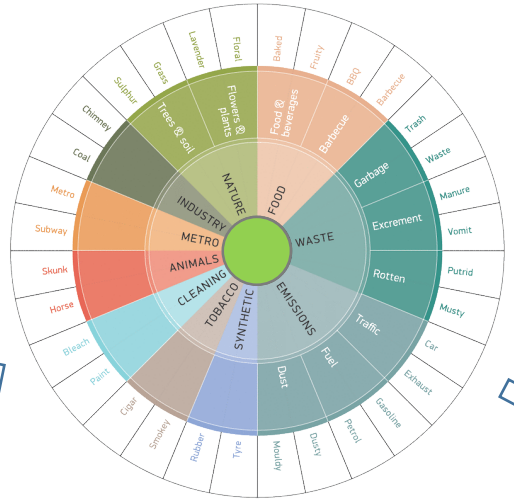
Balsamo et al.
Firsthand Opiates Abuse on Social Media
WWW 2019



Leitloff et al.
Vehicle detection in very high resolution satellite images of city areas
IEEE Trans. Geoscience 2010

The technical challenges

Data collection



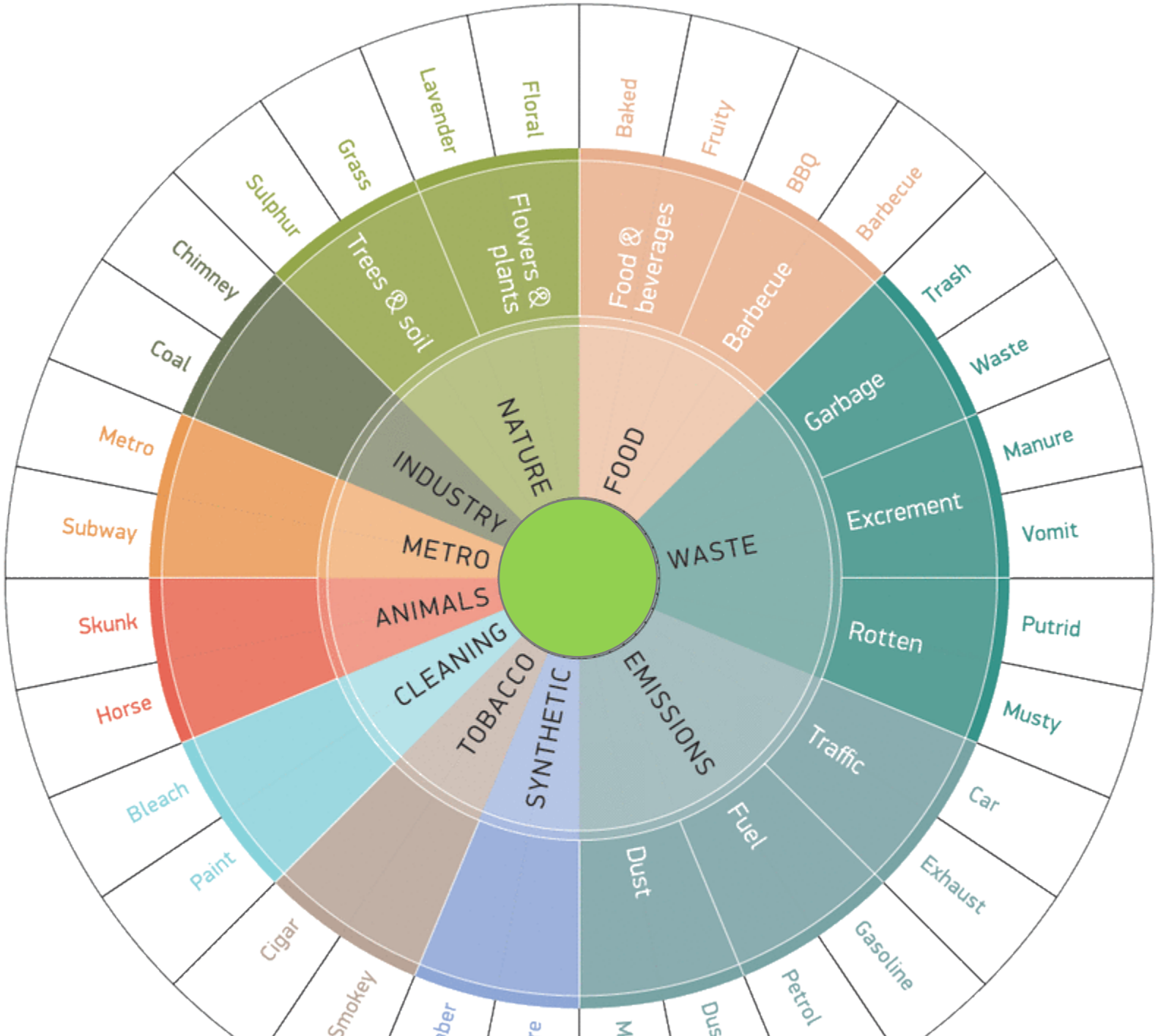
Metadata processing

Image processing

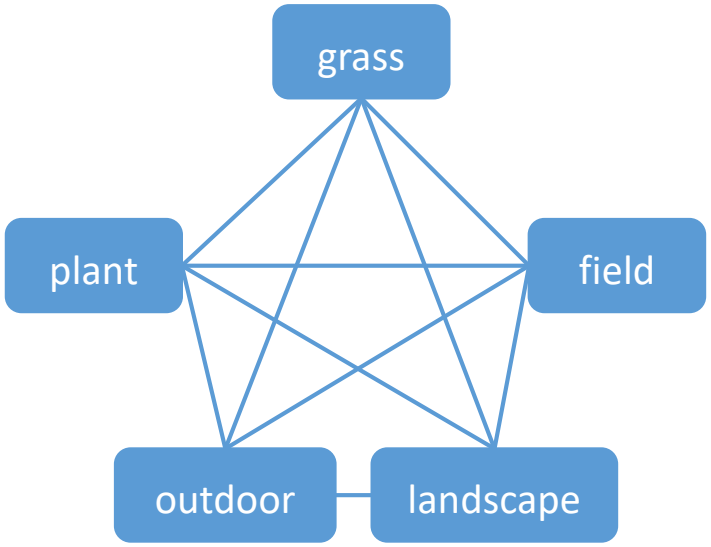
Mapping

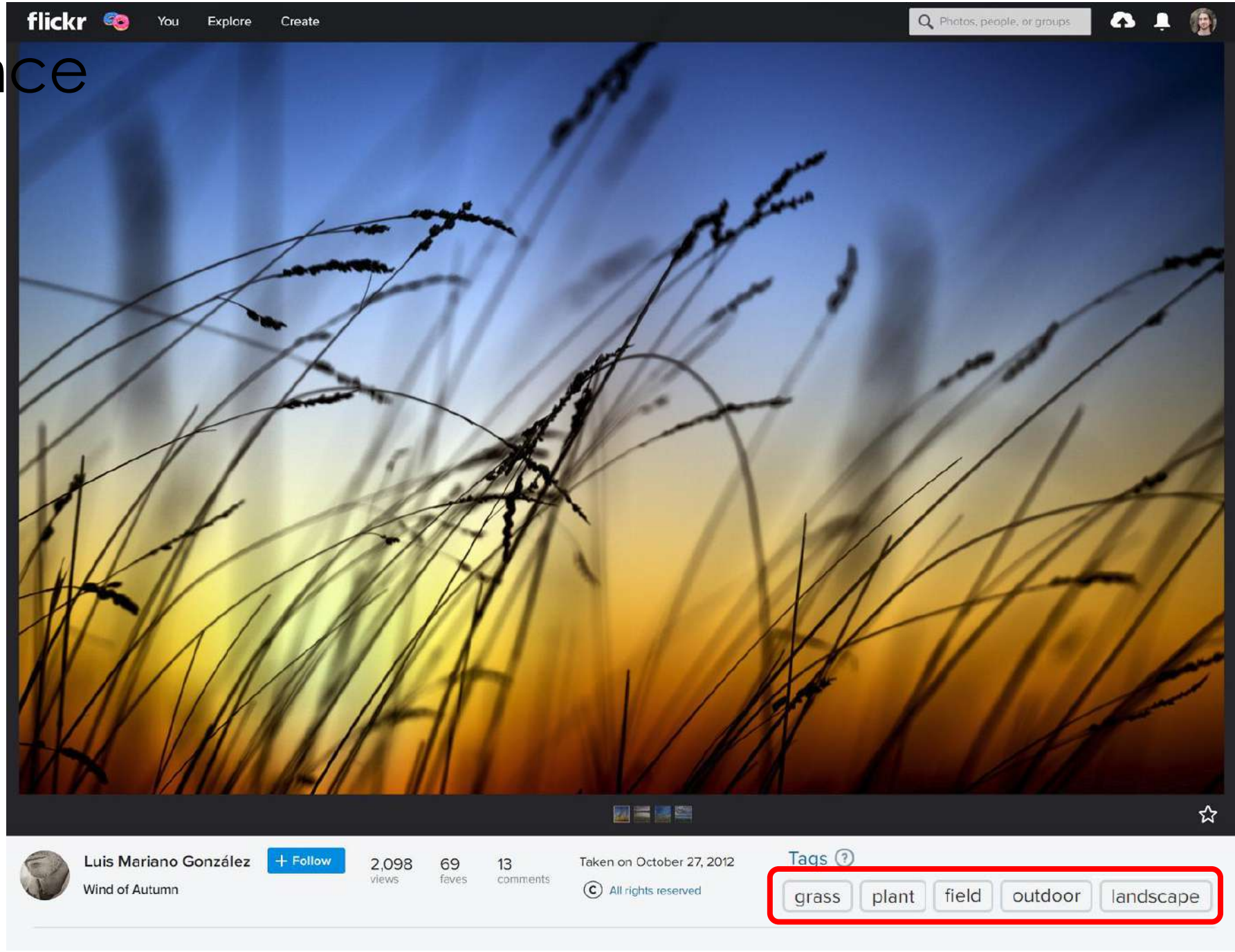
Visualizing

How do we get this?

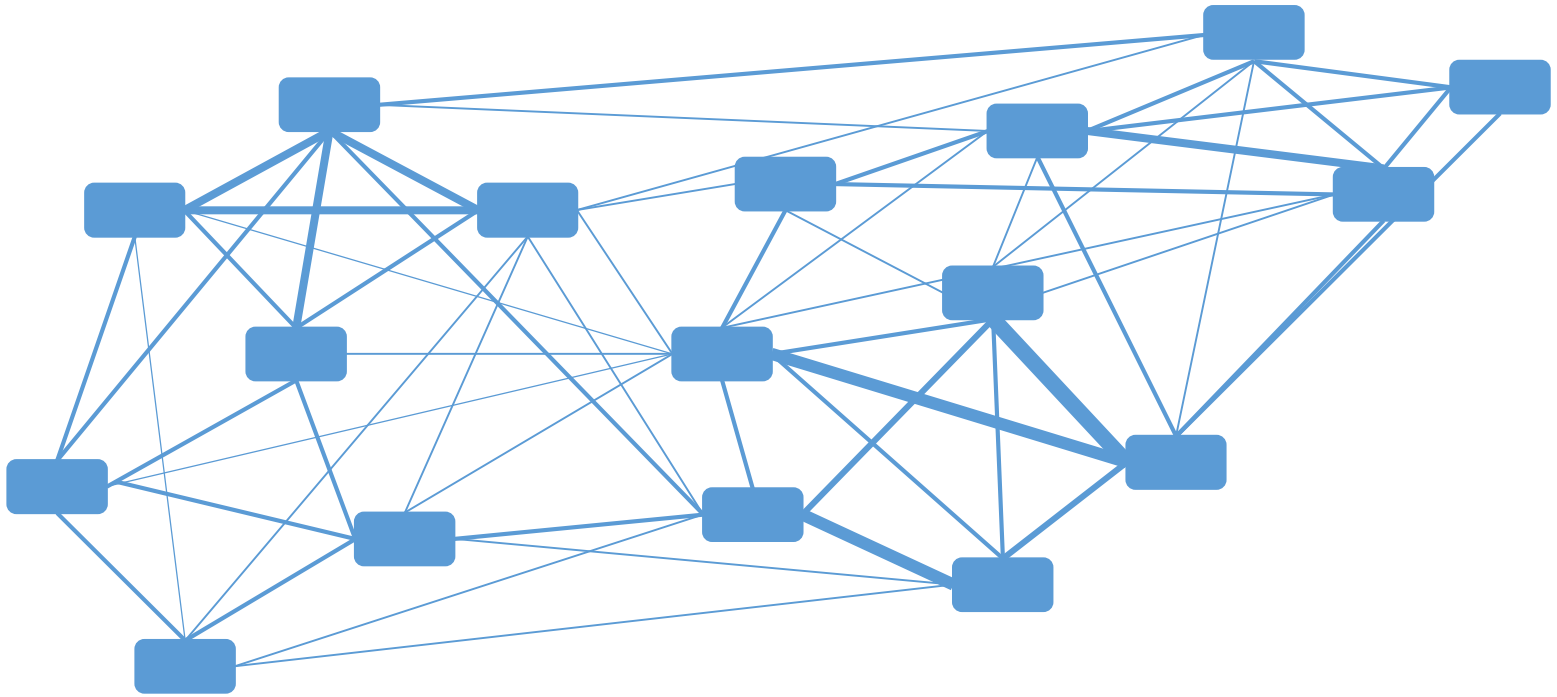


Tag co-occurrence

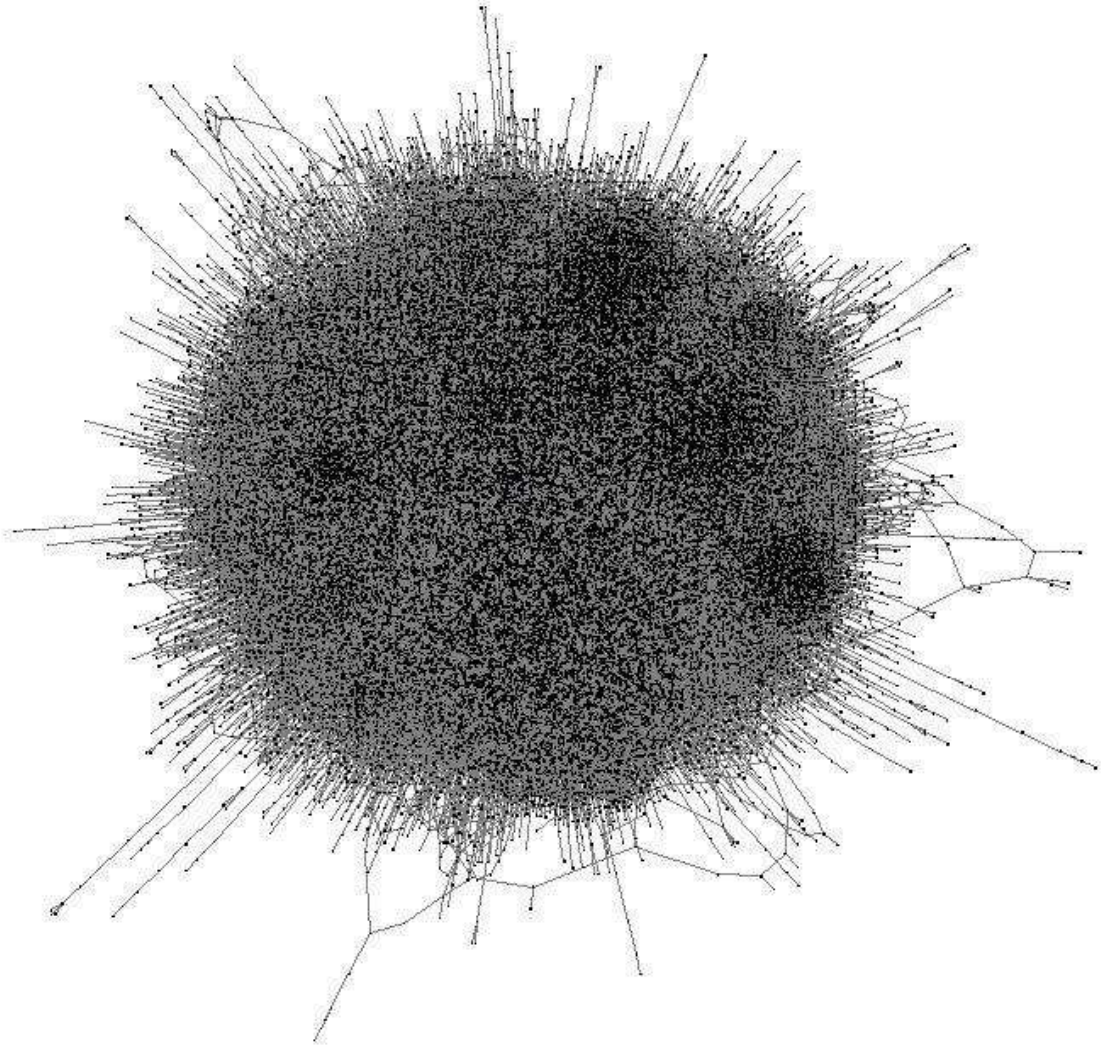




Tag co-occurrence network

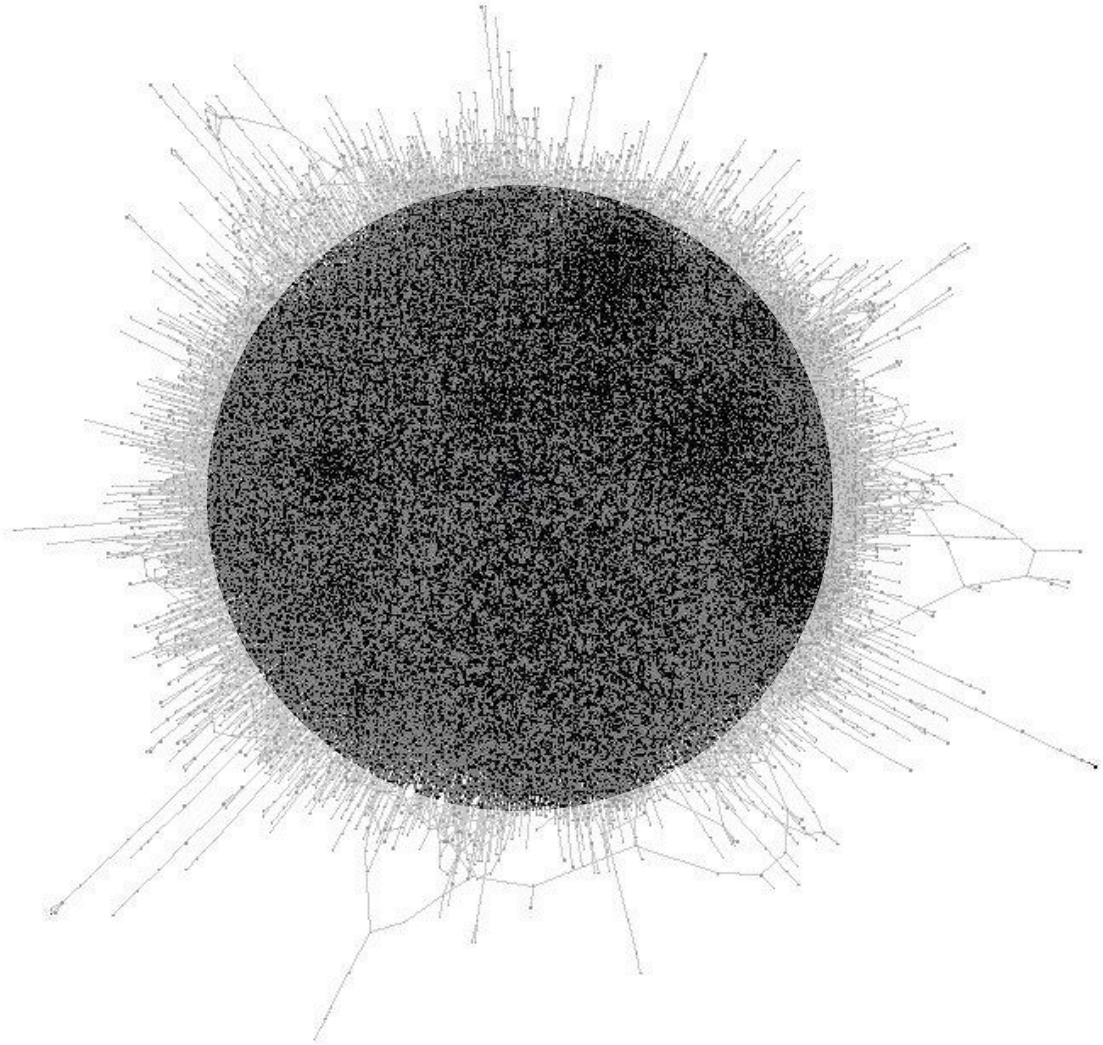


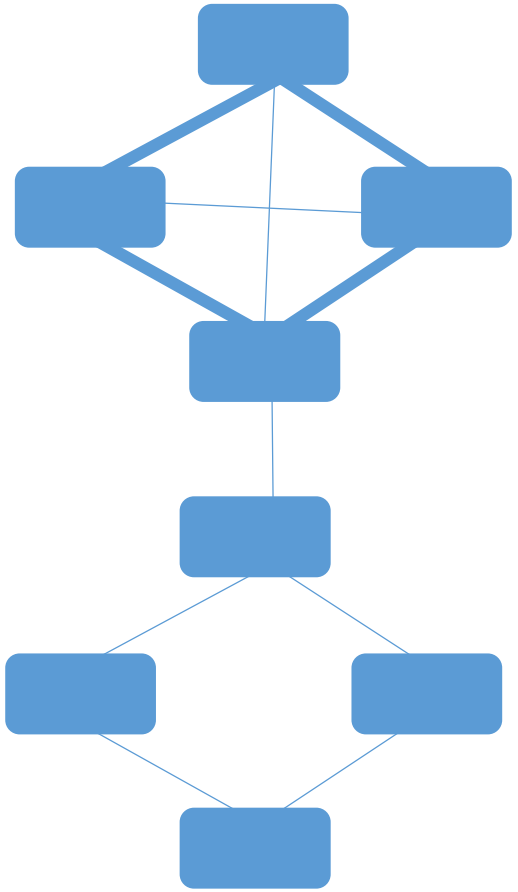
The hairball: everything is connected



Extracting structure from dense networks

Weight filtering

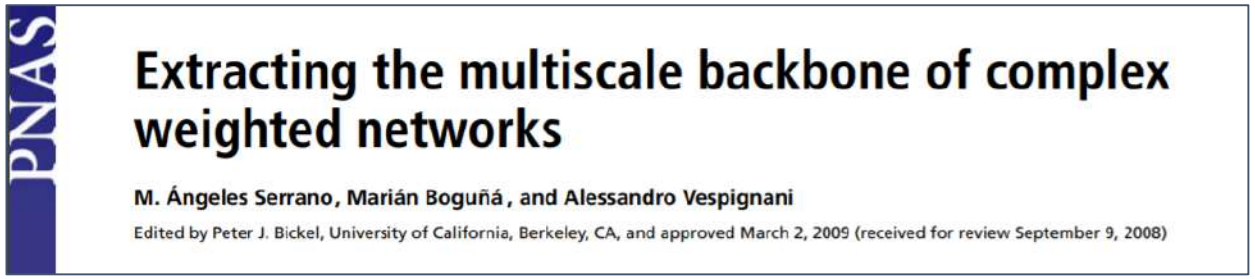




Extracting structure from dense networks

Disparity filter

- Intuition: keep only the edges that are unexpected in comparison to a null model
- Null model: hypothesize that the relative strength of outgoing edges of a given node are extracted at random from an exponential distribution
- Compute the probability that the edge weight is compatible with the weight in the null model
- If the probability is under a threshold ($p<0.01$), keep the link. Discard otherwise



“That boring slide with the formulas”

For those interested to dig into this afterwards

- Keep edges whose weights represent a significant fraction of the local strength
- Normalize the weights of edges as:
  - $p_{ij} = {}^{w_{ij}}/_{s_i}$ [w_{ij}= weight between i and j; s_i= strength of i]
- Null model: we hypothesize that the values of p_{ij} of a certain node of degree k are extracted at random from an exponential distribution
  - $\rho(x) = (k-1)(1-x)^{k-2}$
- Calculate for each edge of a given node of the probability α_{ij} that its normalized weight p_{ij} is compatible with the null hypothesis (p-value)
  - $\alpha_{ij} = 1 - (k-1)\int_0^{p_{ij}}(1-x)^{k-2}dx$
- The edge is kept if $\alpha_{ij} < \alpha$ (for both nodes i and j) – *Disparity Filter*

Noise-corrected backbone

Network Backboning with Noisy Data

Michele Coscia
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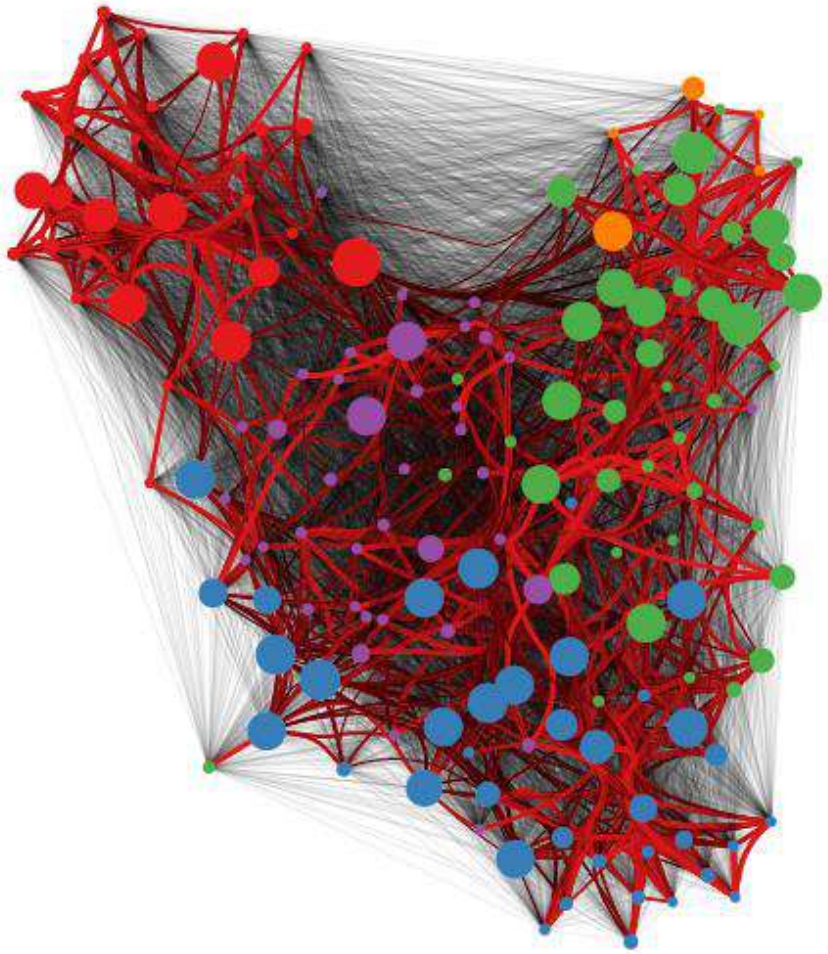
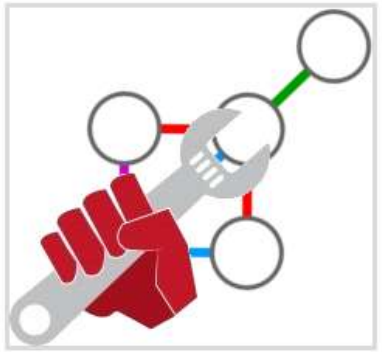
Frank M. H. Neffke
Center for International Development
Harvard University
Cambridge, MA 02138
Email: frank_neffke@hks.harvard.edu



www.michelecoscia.com

Network Backboning



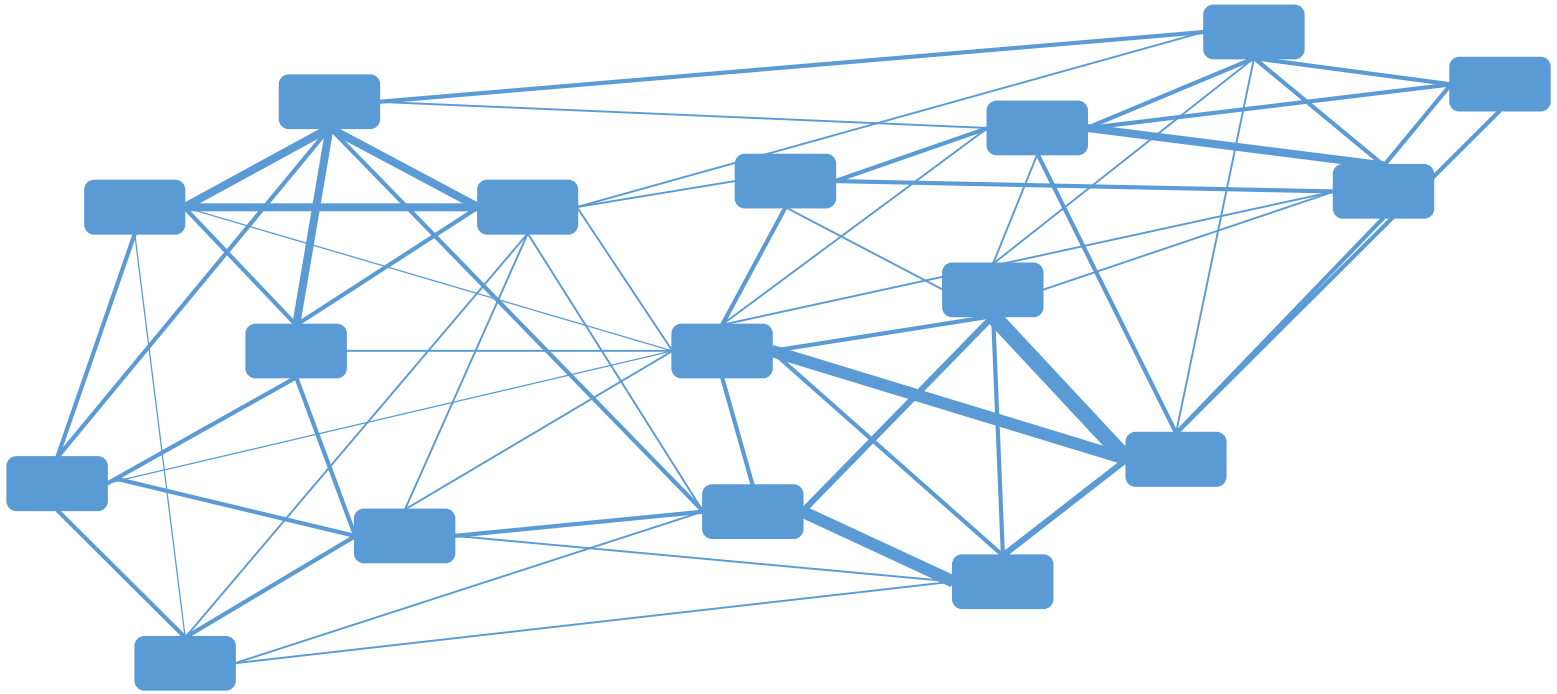
Download Backboning Code and Data

The archive contains a Python module to perform network backboning, which is the filtering of non-significant edges from a very dense and noisy network.

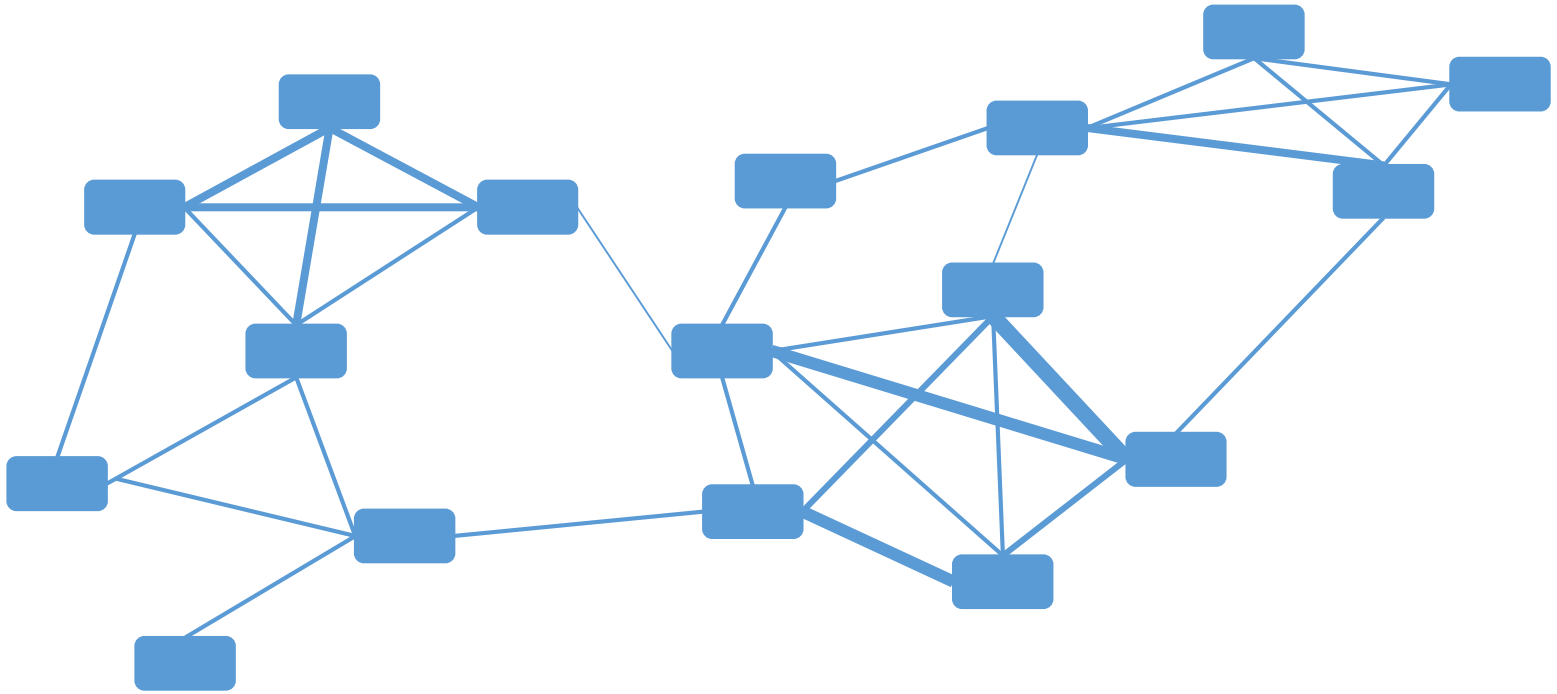
The module provides several utilities and the following methods:

- Noise Corrected: New methodology published at ICDE 2017 developed by Frank Neffke and me (please cite: Coscia & Neffke "Network Backboning with Noisy Data", ICDE 2017 — Paper, Bibtex);
- Disparity Filter: http://www.pnas.org/content/106/16/6483.full;

Backboning effect: before



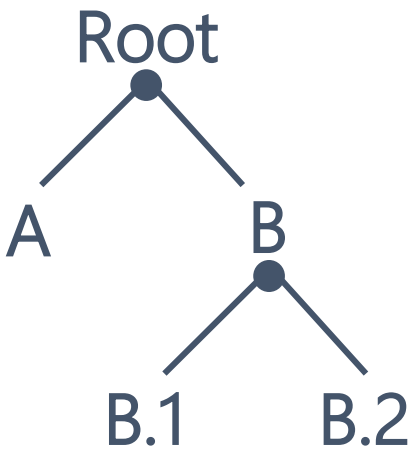
Backboning effect: after

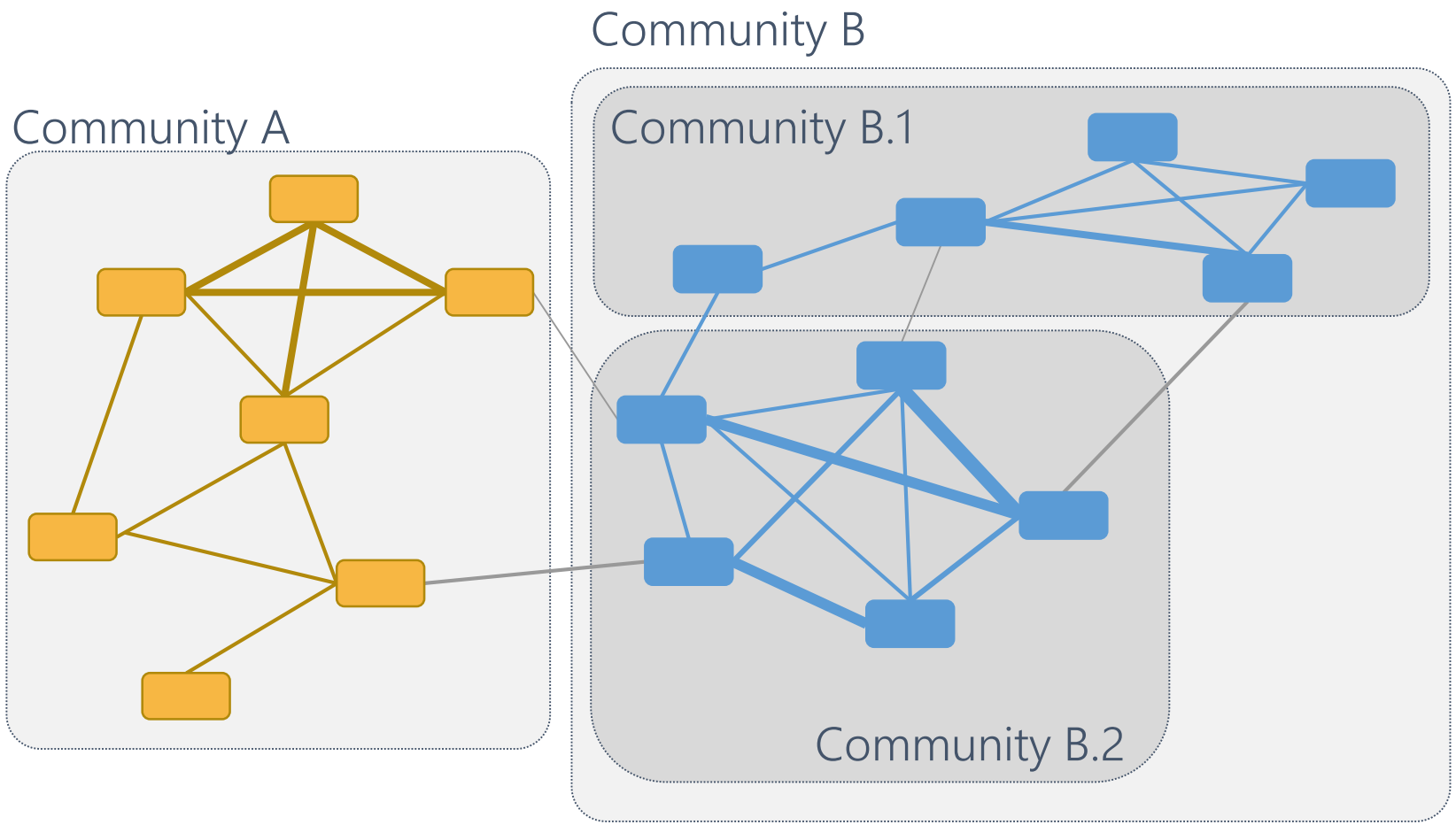


Community detection on tag co-occurrence network

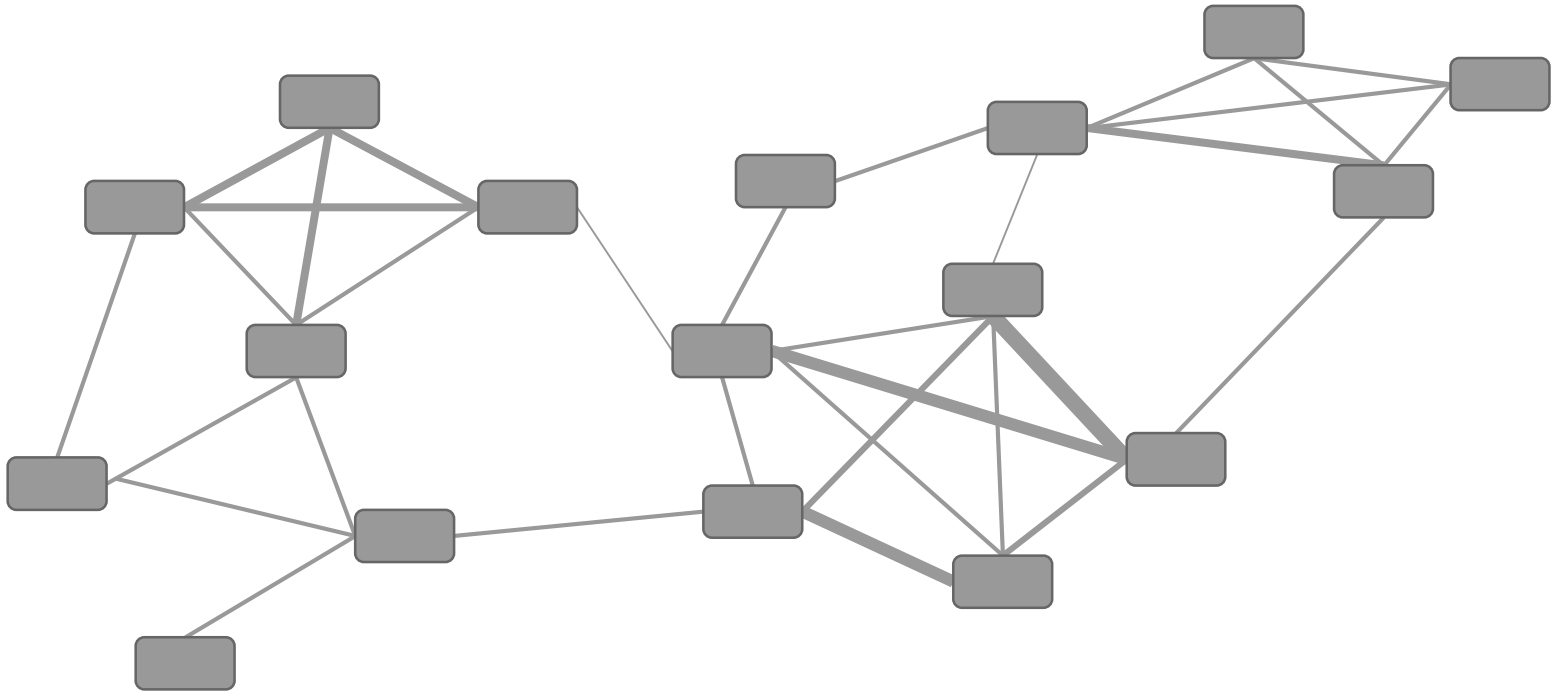
More edges inside the community than to other communities

Hierarchical arrangement of communities



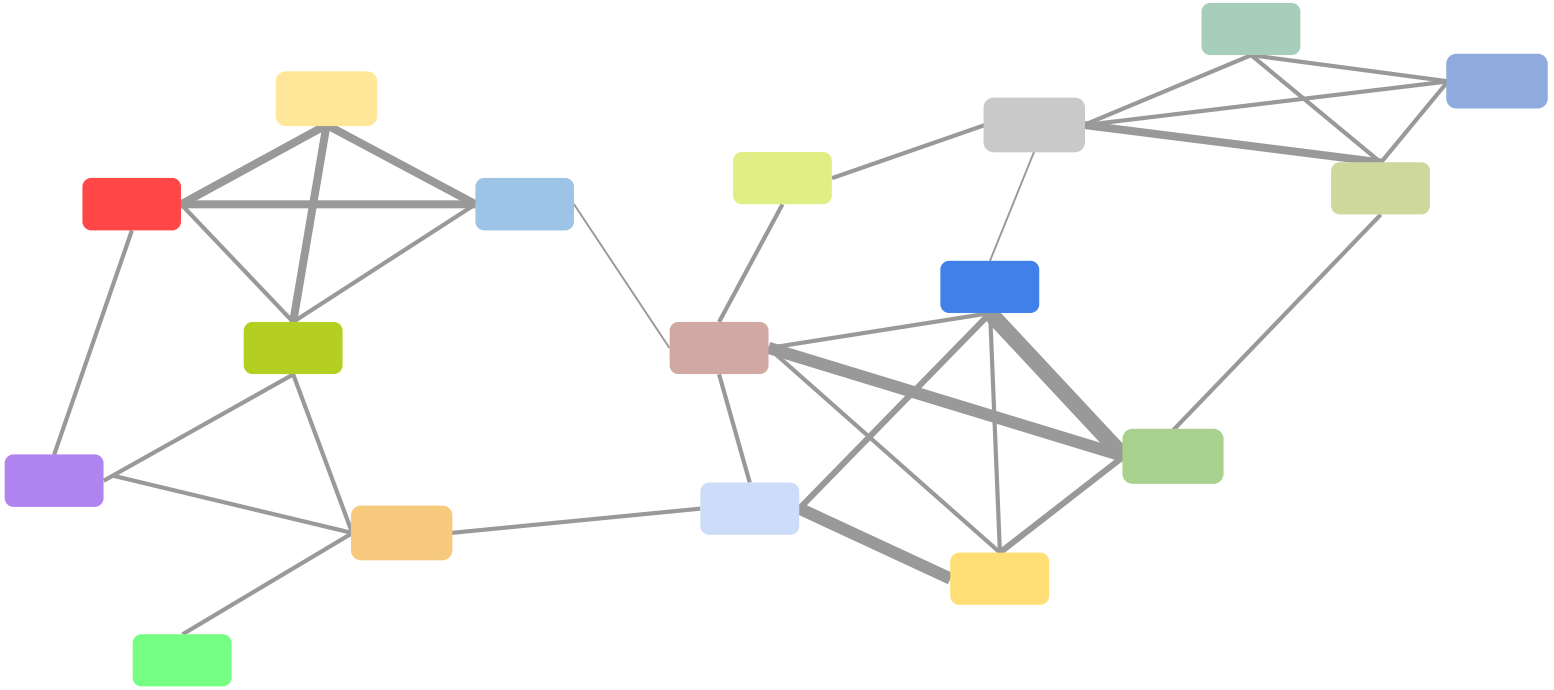


Louvain algorithm



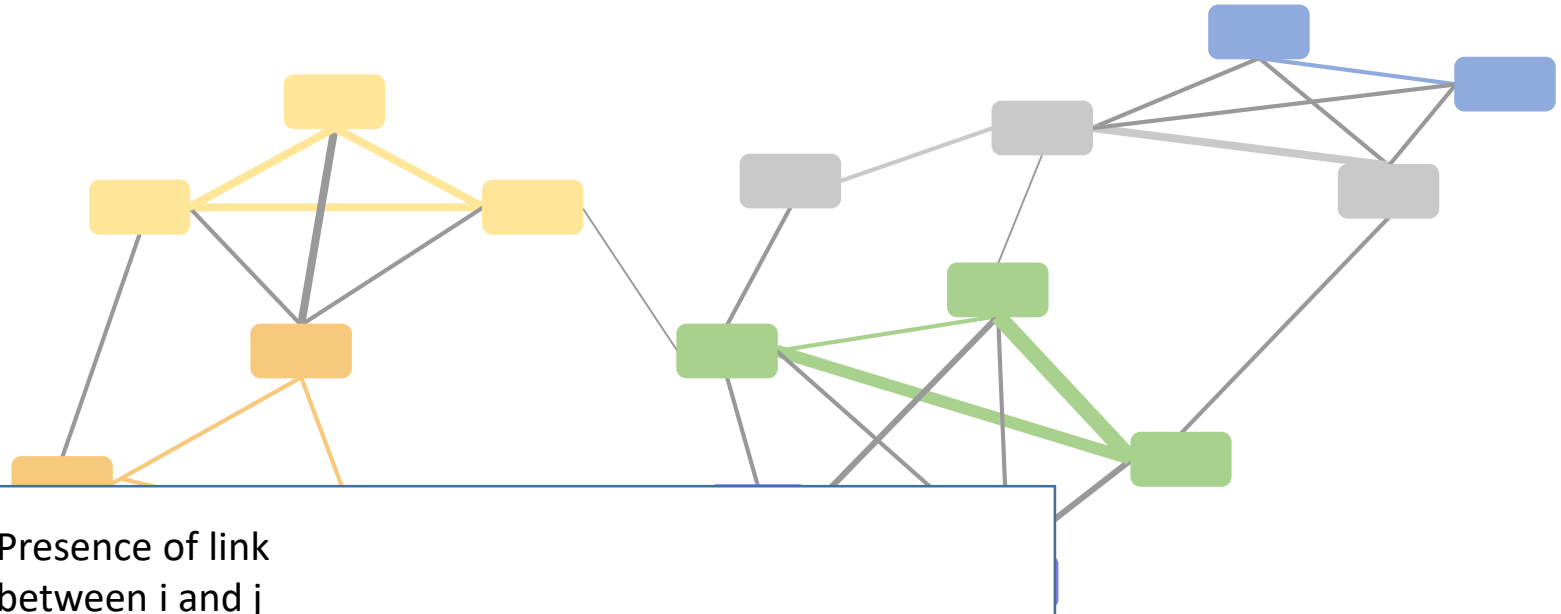
Louvain algorithm

Assign each node to a different community



Louvain algorithm

Merge communities to maximize increase of modularity



Presence of link between i and j

Presence of link between i and j expected at random

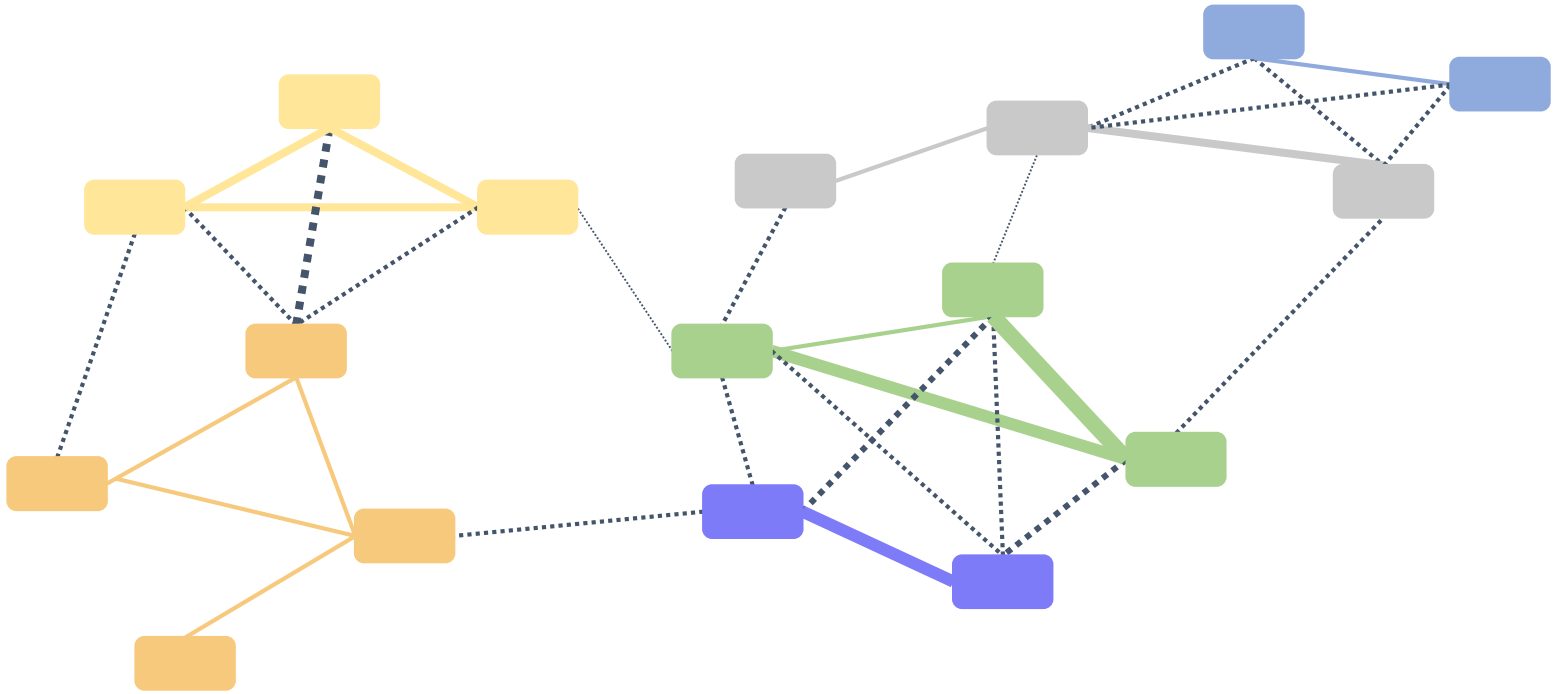
$$Q = \frac{1}{4m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i, c_j)$$

1 if the I and j are in the same community, -1 otherwise

Number of links in the network

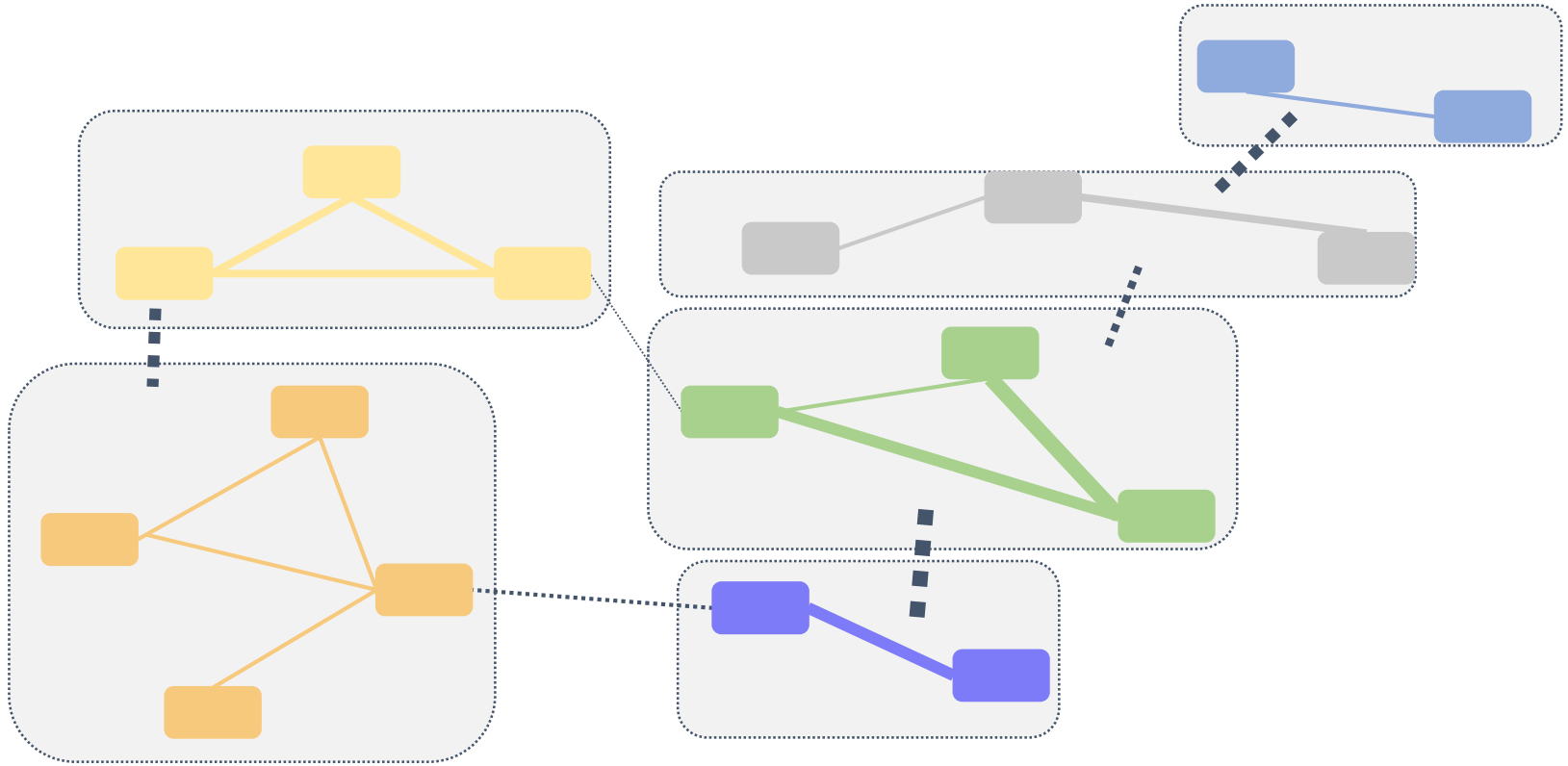
Louvain algorithm

Merge into super-nodes and aggregate edges



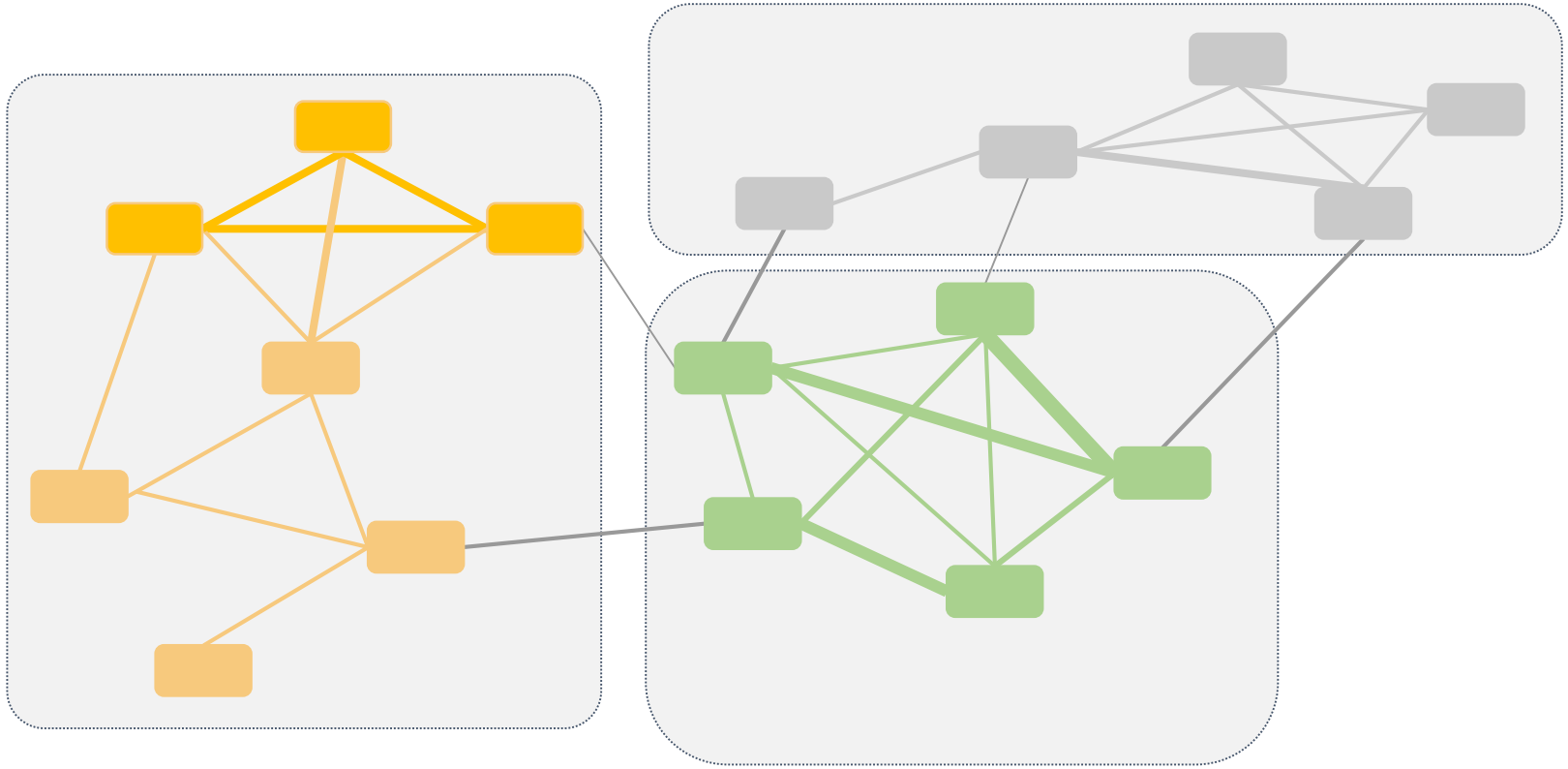
Louvain algorithm

Merge into super-nodes and aggregate edges



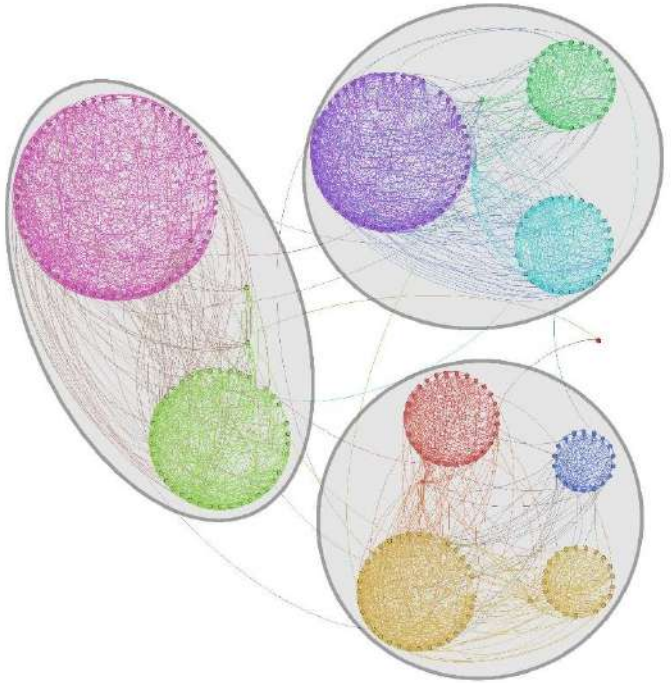
Louvain algorithm

Repeat until convergence



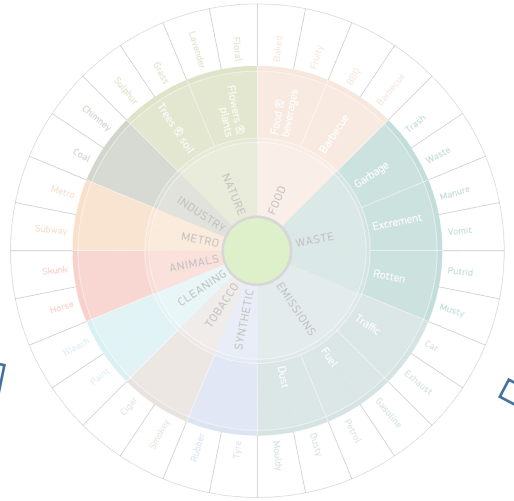
OSLOM algorithm

- Statistical significance of a cluster compared to a null configuration model
- Not based on modularity
- Communities are hierarchical and overlapping
- Code available online at www.oslom.com



The technical challenges

Data collection

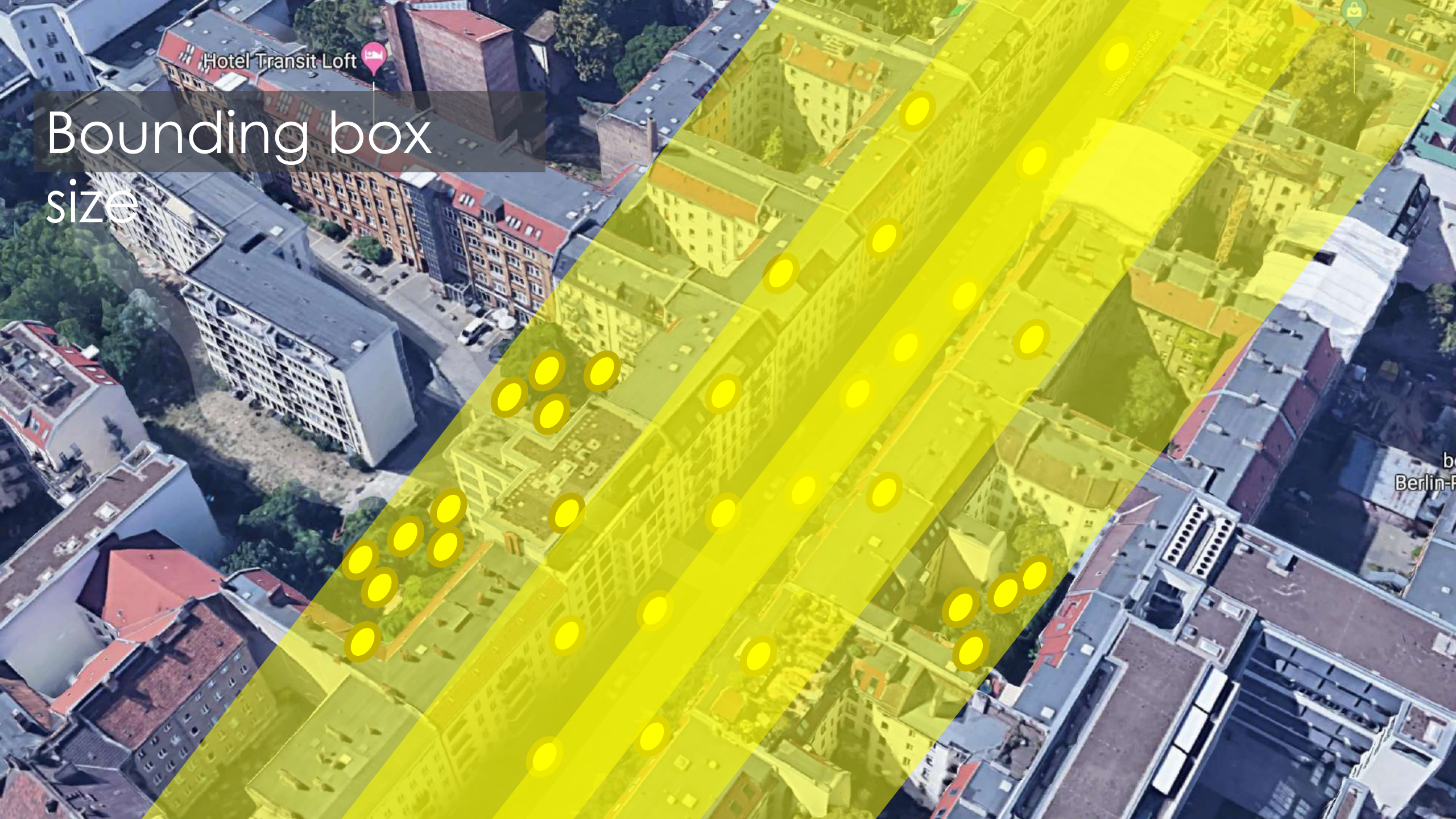


Metadata processing

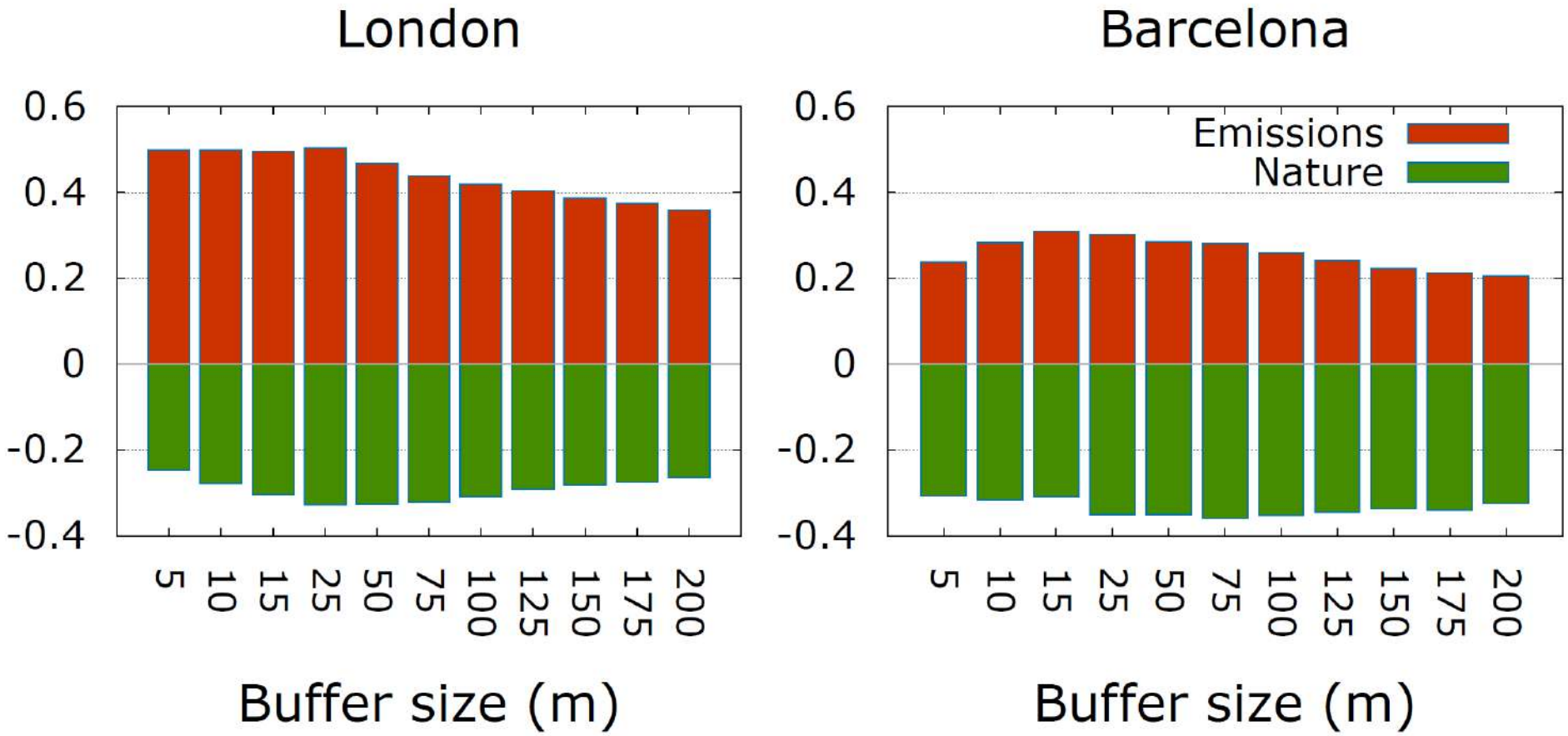
Image processing

Mapping

Visualizing


Hotel Transit Loft
Bounding box
size

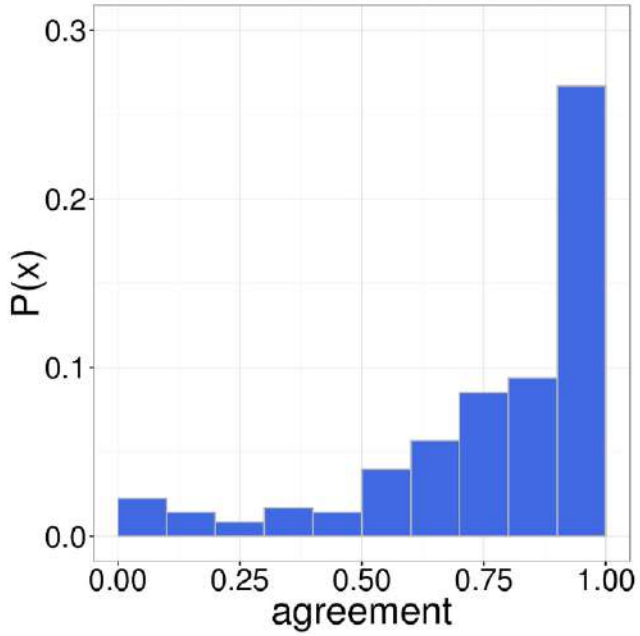
Buffer size vs. *



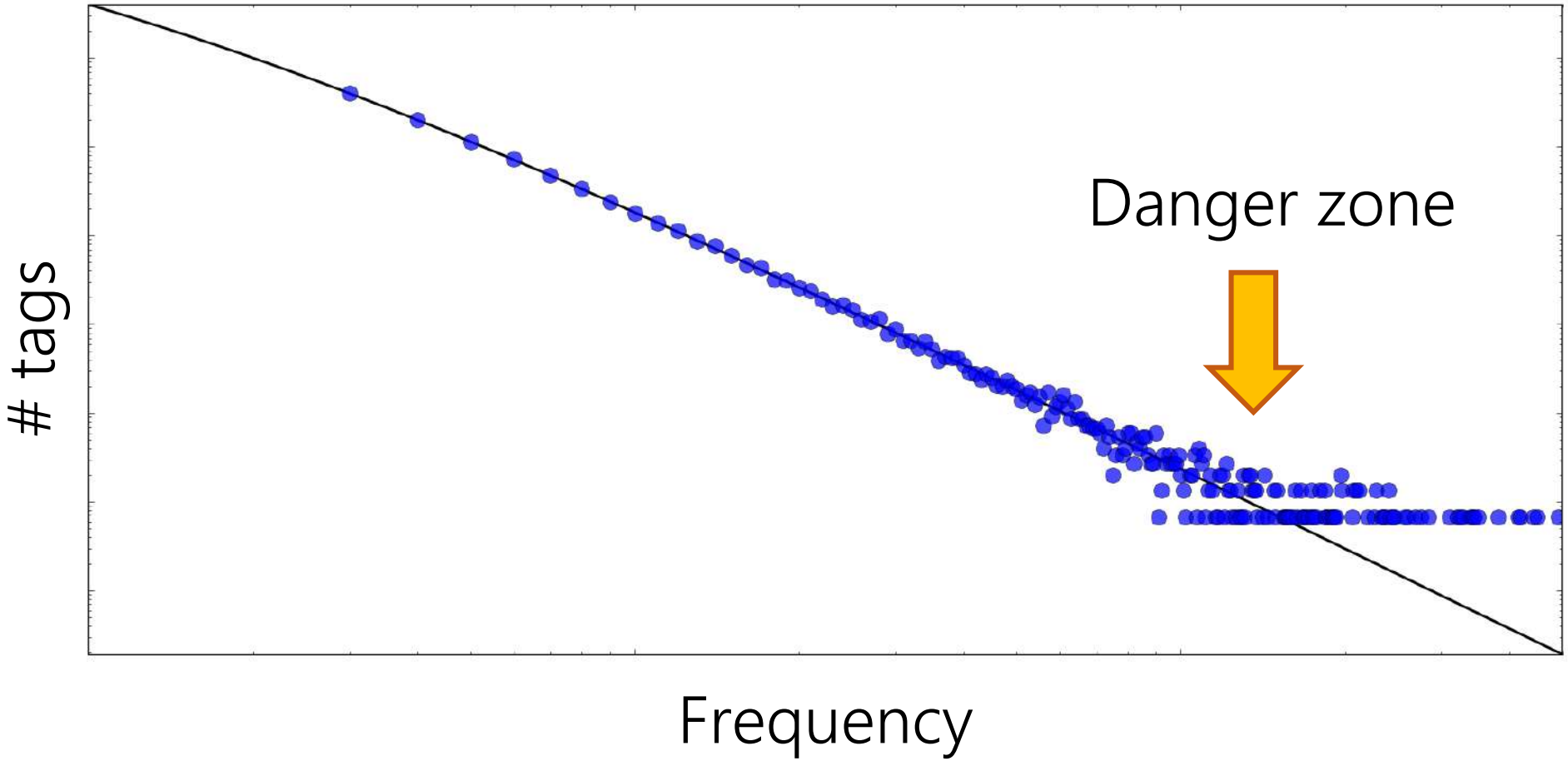
Ecological validity?

True positive

False positive



Word matching is risky…



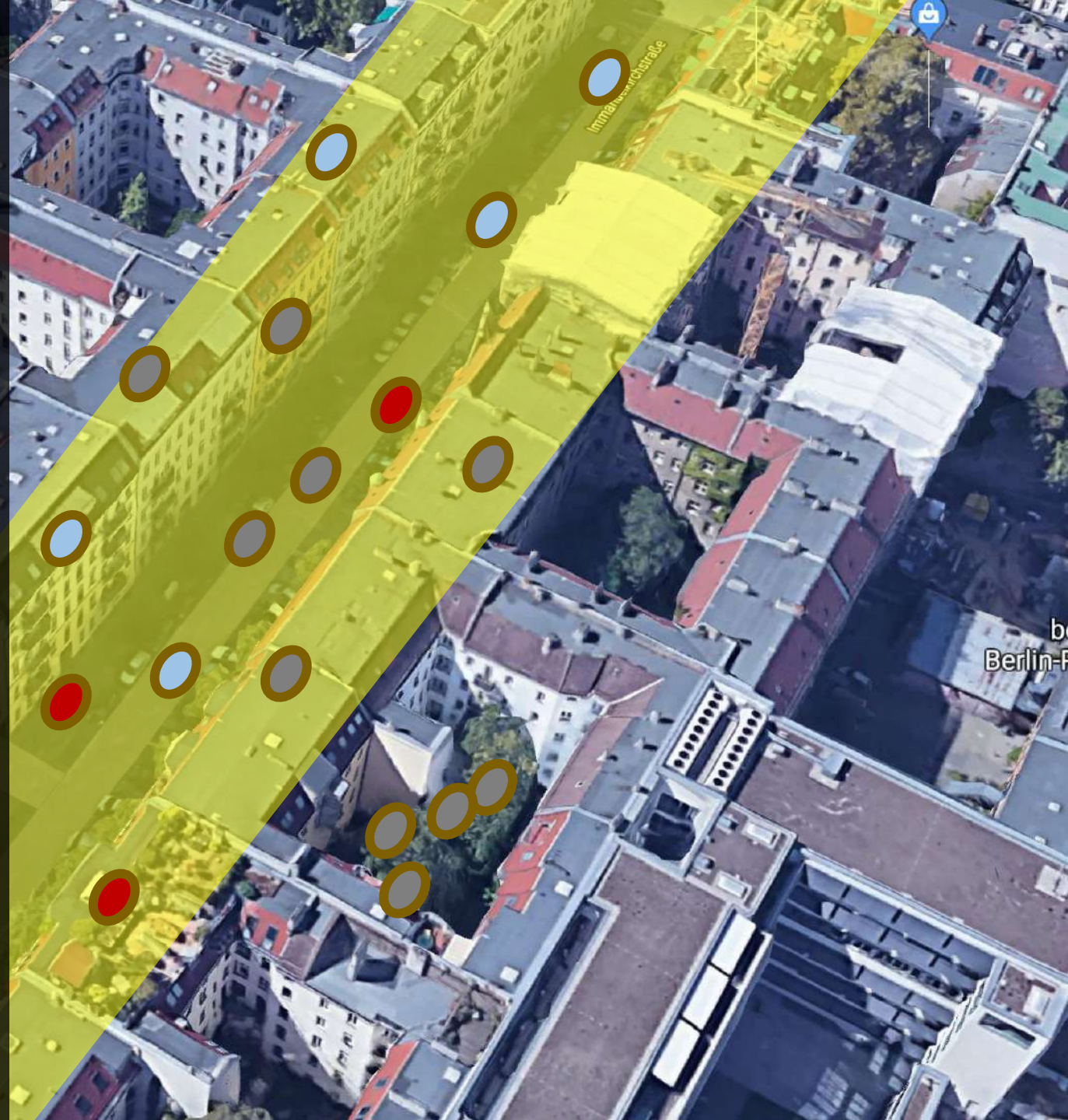
Counting

1) Raw count (#blue)
Dense areas are over-represented

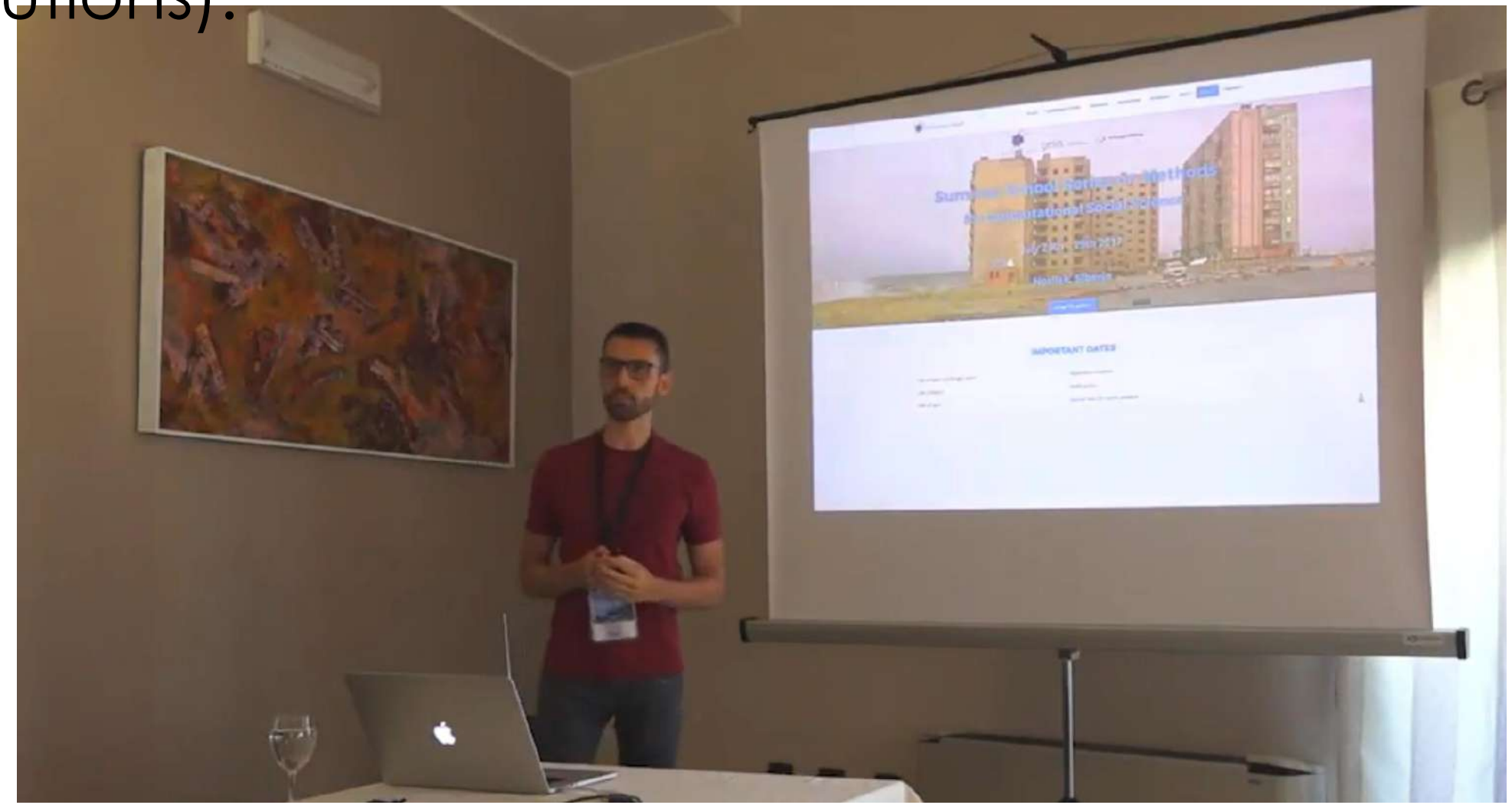
2) Global proportion (#blue/#all)
Sparse areas are over-represented
Dilution effect from other signals

3) In-group proportion
(#blue/(#red+#blue))
Sparse areas are over-represented

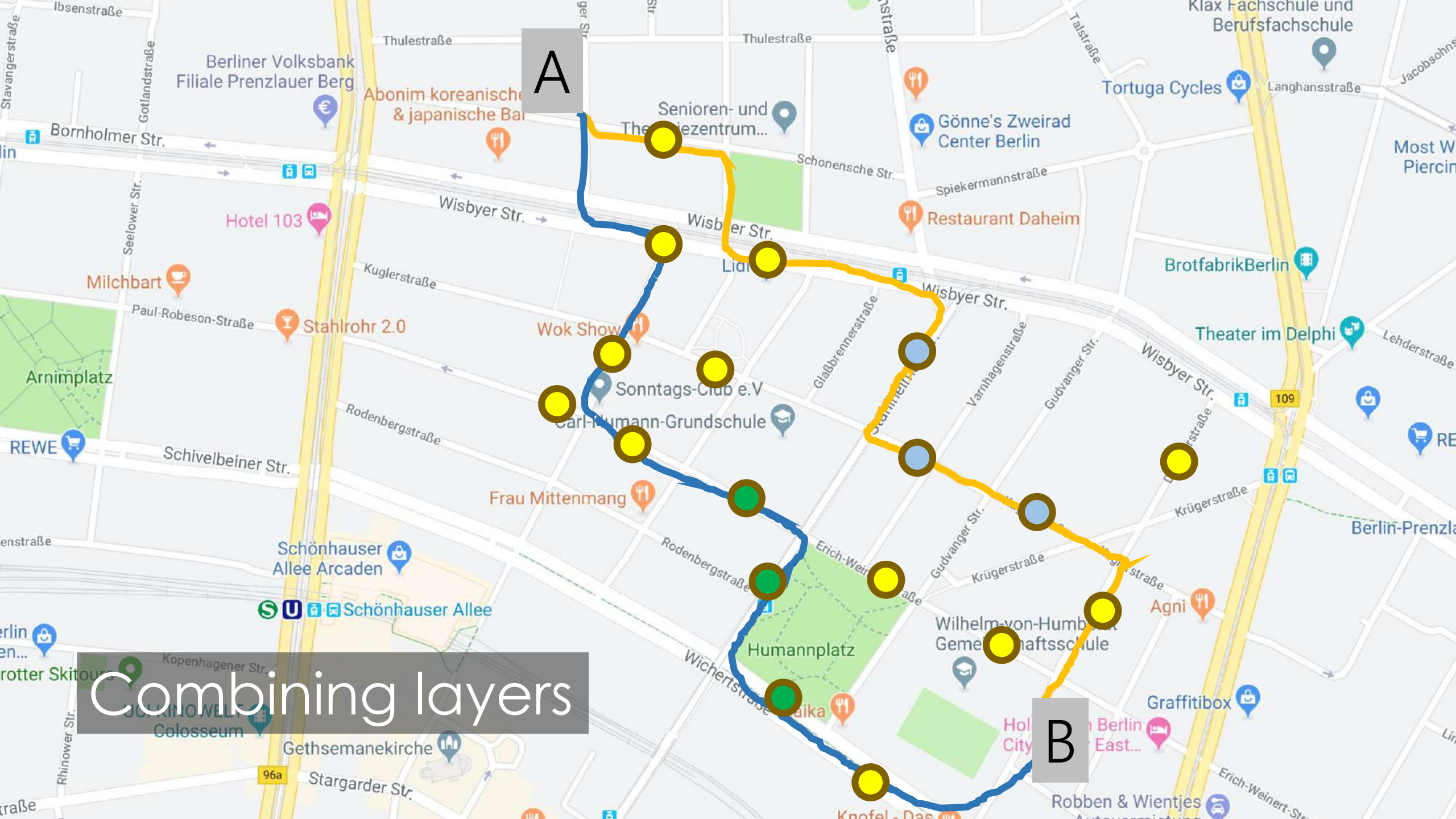
Can you think of other ways? (What about time, users…)



This and many other mapping problems (+ some solutions):



https://www.youtube.com/watch?v=UCZfkSX9FMQ


A
B
Combining layers
Thulestraße
Bornholmer Str.
Wisbyer Str.
Schonensche Str.
Spiekermannstraße
Kuglerstraße
Paul-Robeson-Straße
Rodenbergstraße
Schivelbeiner Str.
Glaßbrennerstraße
Varnhagenstraße
Gudvanger Str.
Krügerstraße
Erich-Weinert-Straße
Wichertstraße
Kopenhagener Str.
Stargarder Str.
Langhansstraße
Talstraße
Lehderstraße
Jacobsohnstraße
Seelower Str.
Gotlandstraße
Rhinower Str.
Ibsenstraße
Stavangerstraße
Arnimplatz
Humannplatz
Berliner Volksbank Filiale Prenzlauer Berg
Hotel 103
Milchbart
Stahlrohr 2.0
Wok Show
Sonntags-Club e.V
Carl-Humann-Grundschule
REWE
Frau Mittenmang
Schönhauser Allee Arcaden
Schönhauser Allee
Colosseum
Gethsemanekirche
Senioren- und
Gönne's Zweirad Center Berlin
Restaurant Daheim
Tortuga Cycles
Klax Fachschule und Berufsfachschule
BrotfabrikBerlin
Theater im Delphi
Agni
Graffitibox
Robben & Wientjes
96a
109

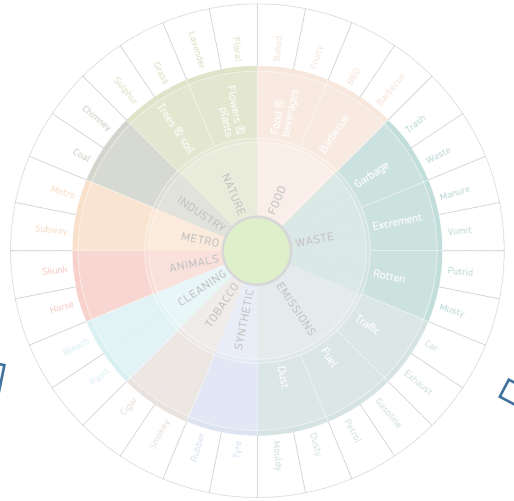
Solving the cold-start problem

Just ask people…

Dimension	Component	β_S	β_U	Proxy
Smell $\alpha_S = 1.50$ $\alpha_U = 0.40$	Nature	1.80	1.40	f^{smell}_{nature}
	Food	-0.64	-0.17	f^{smell}_{food}
	Emissions	-1.80	-1.40	$f^{emissions}_{food}$
	Chemical	-1.80	-1.40	$f^{chemical}_{food}$
	Synthetic	-1.30	-0.81	f^{smell}_{synth}
	Animals	-0.23	-0.19	$f^{smell}_{animals}$
	Odorless	1.40	0.89	—
Sound $\alpha_S = 1.20$ $\alpha_U = -0.06$	Natural	1.70	1.10	f^{sound}_{nature}
	People	0.08	0.10	f^{sound}_{people}
	Transport	-1.30	-0.68	$f^{sound}_{transport}$
	Music	0.81	0.67	f^{sound}_{music}
	Quiet	1.40	0.89	f^{sound}_{quiet}
Scenery $\alpha_S = 1.50$ $\alpha_U = 0.42$	Natural	1.90	1.50	
	River	1.80	1.40	
	Urban	0.04	0.55	$beauty$
	Beach	0.76	0.61	
	Industrial	-1.10	-0.43	
Ground $\alpha_S = 1.60$ $\alpha_U = 0.74$	Grass	0.58	0.22	OSM^{ground}_{grass}
	Pavement	0.92	1.10	$OSM^{ground}_{pavement}$
	Sand	-0.37	-0.39	OSM^{ground}_{sand}
	Park	1.60	1.30	OSM^{ground}_{park}

The technical challenges

Data collection



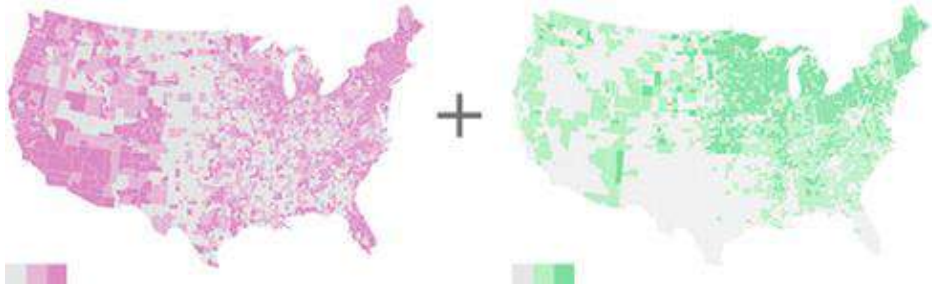
Metadata processing

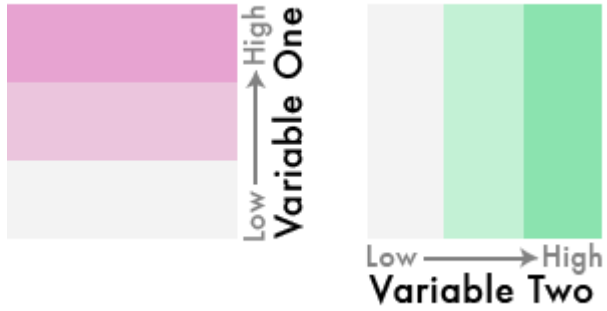
Image processing

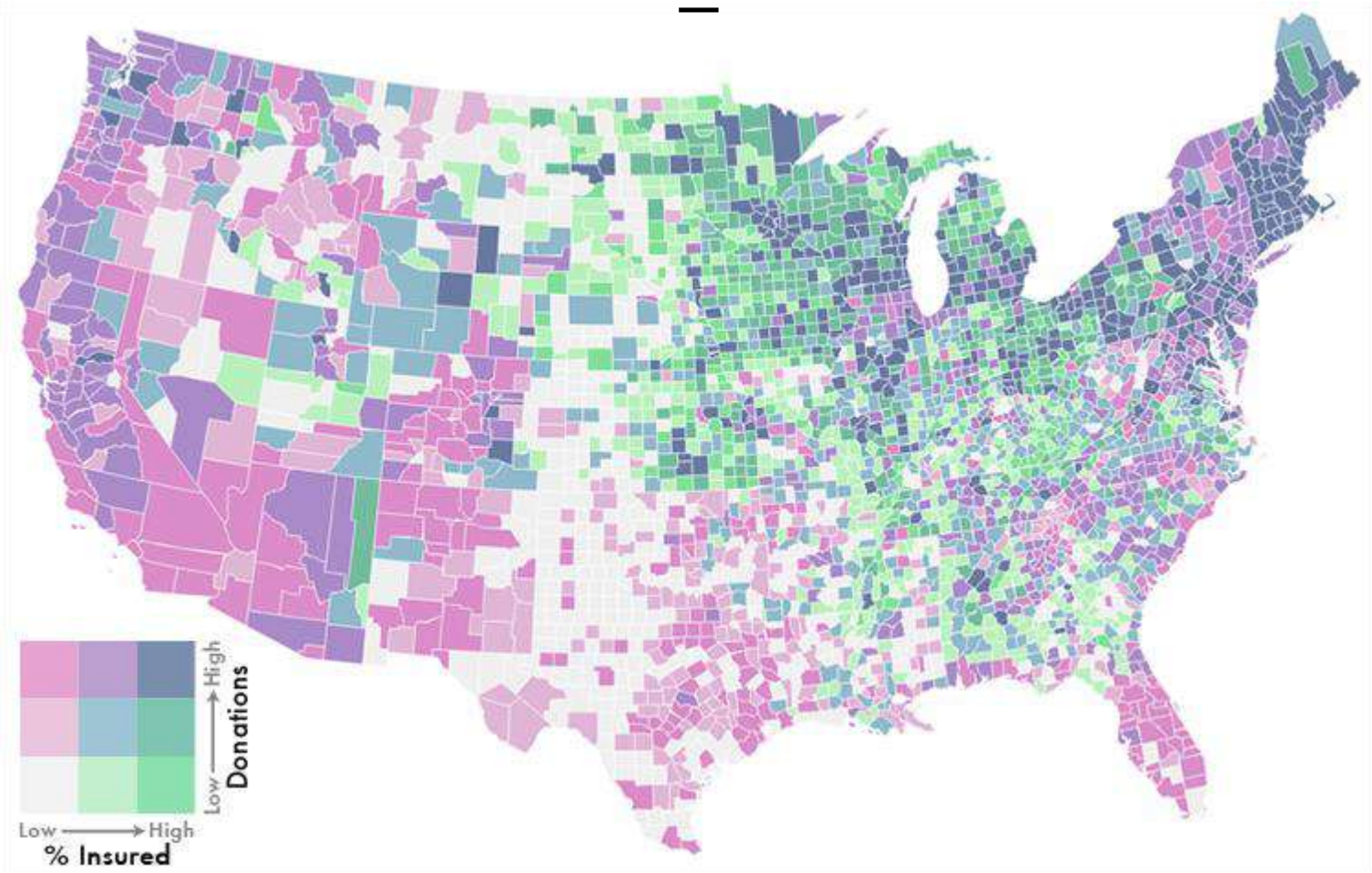
Mapping

Visualizing

Bivariate maps





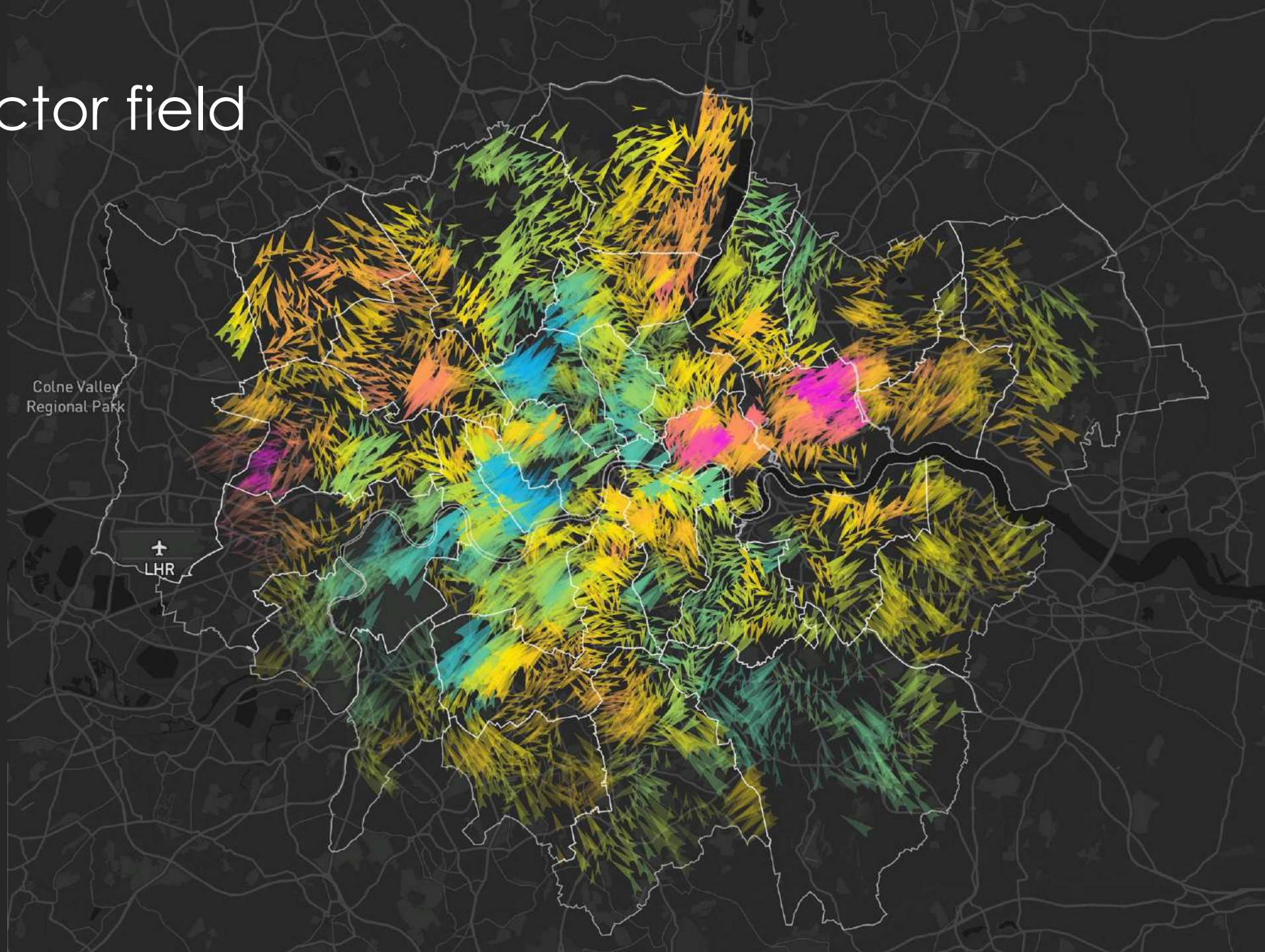


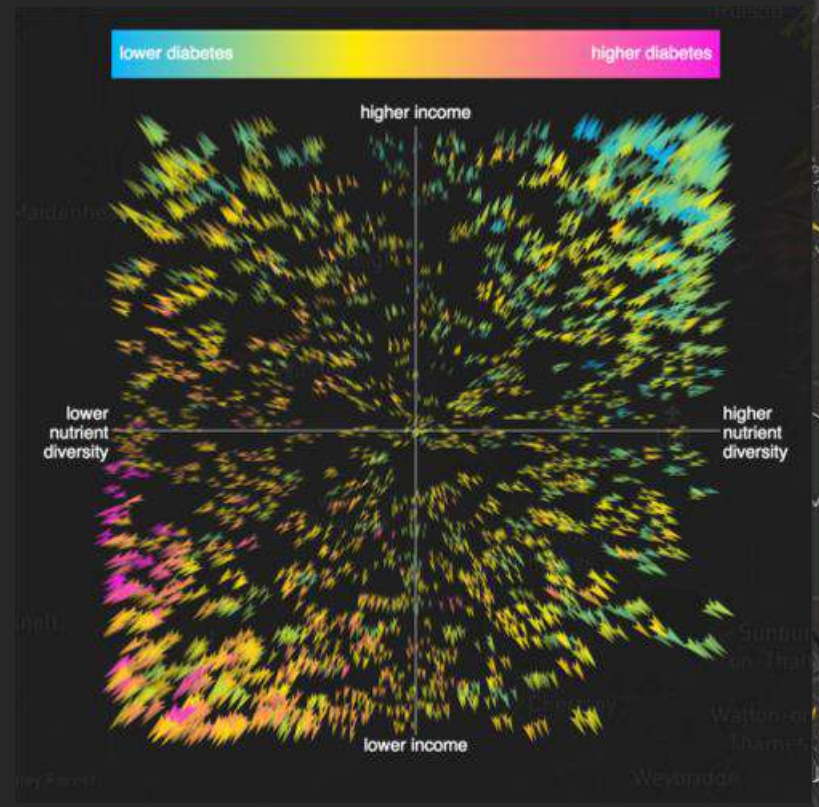
http://www.joshuastevens.net/cartography/make-a-bivariate-choropleth-map/

Multidimensional glyphs

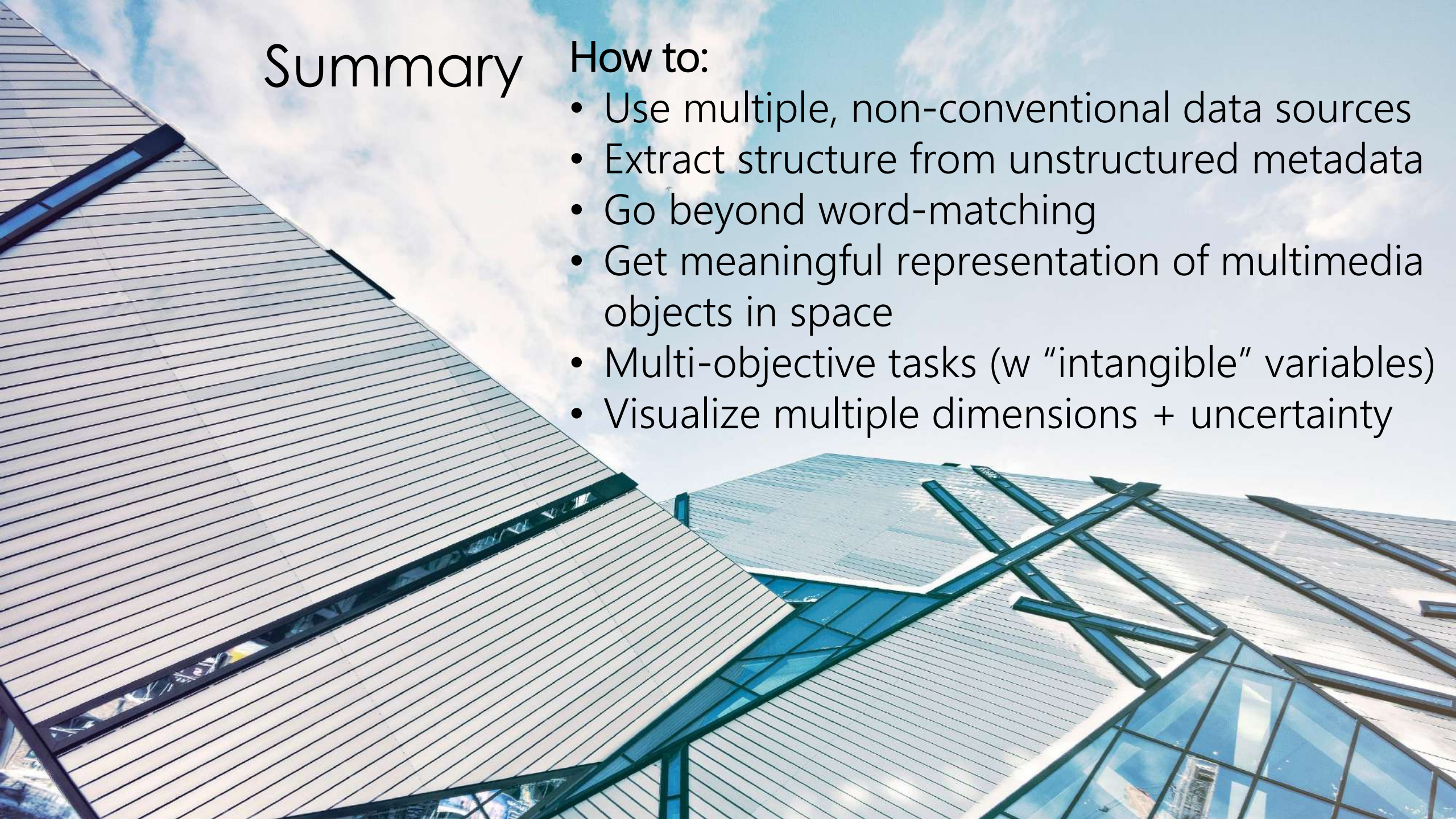
https://truth-and-beauty.net/projects/ukko

Colored vector field




lower diabetes
higher diabetes
higher income
lower income
lower nutrient diversity
higher nutrient diversity

Summary



How to:

- Use multiple, non-conventional data sources
- Extract structure from unstructured metadata
- Go beyond word-matching
- Get meaningful representation of multimedia objects in space
- Multi-objective tasks (w “intangible” variables)
- Visualize multiple dimensions + uncertainty

References

The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city – HT 2014

Smelly Maps: The Digital Life of Urban Smellscapes – ICWSM 2015

The Digital Life of Walkable Streets – WWW 2015

Chatty maps: constructing sound maps of urban areas from social media data – RSOS 2016

The New Urban Success: How Culture Pays – Frontiers Physics 2018

Mapping and Visualizing Deep-Learning Urban Beautification – IEEE Comp. Graph. Appl 2018

The Spirit of the City: Using Social Media to Capture Neighborhood Ambiance – Frontiers 2018

Large-scale and high-resolution analysis of food purchases and health outcomes – EPJ Data Science 2019

The Experience of Running – upcoming

Sagar
Joglekar

Kate
McLean

Desi
Hristova

Miriam
Redi

Lucia
Del Prete

Krisztián
Varga

Rossano
Schifanella

Daniele
Quercia

Damiano
Cerrone

Francesco
Aletta

Tobias
Kauer

Katrin
Hansel

That's all, folks!

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