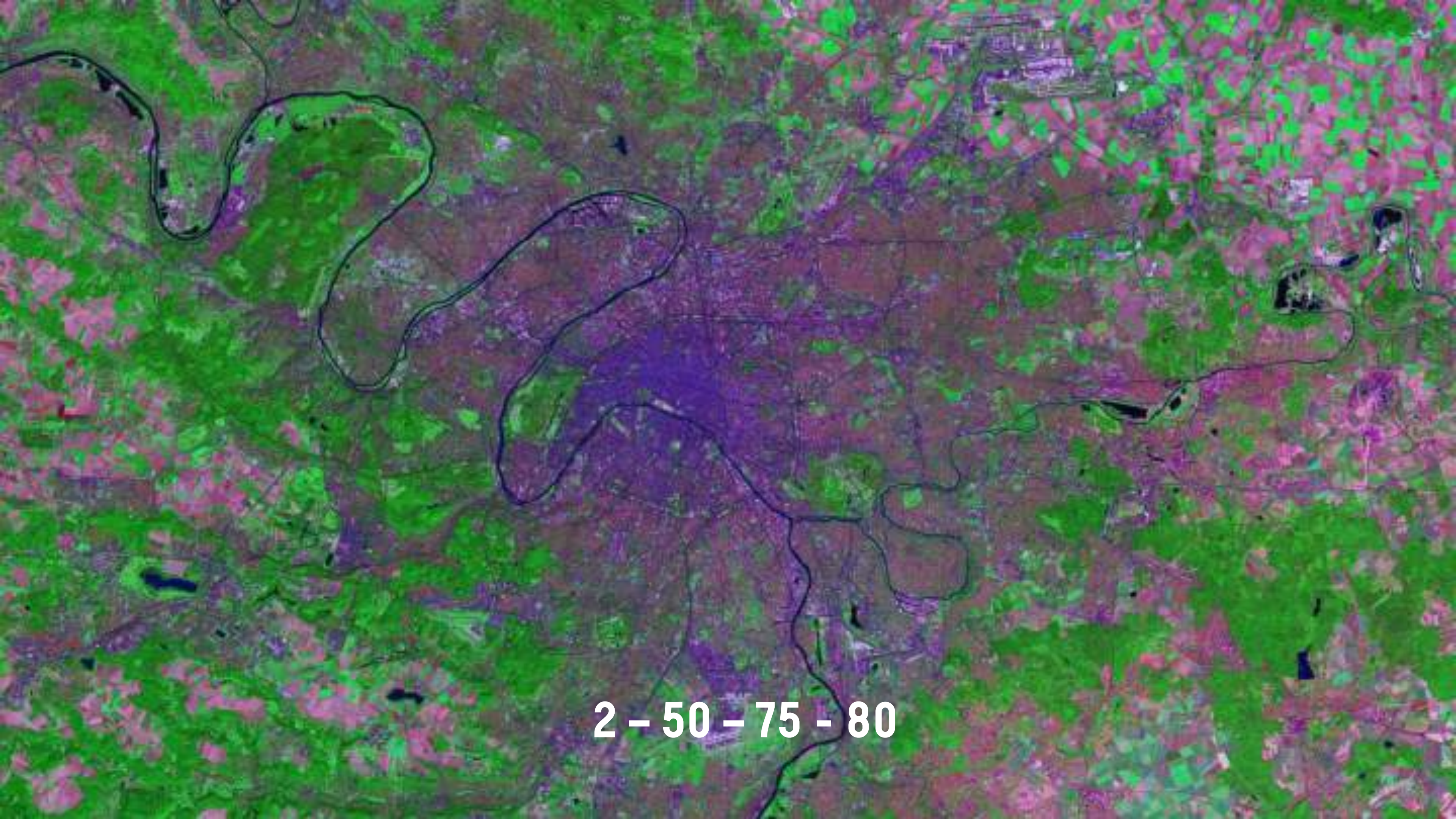
Boston, September 16th, 2020

BCC Colombian Construction Congress

SENSEABLE CITIES
JUST SOME THOUGHTS...

Carlo Ratti
Partner, Carlo Ratti Associati
Professor of the Practice of Urban Technologies, MIT


2 – 50 – 75 - 80

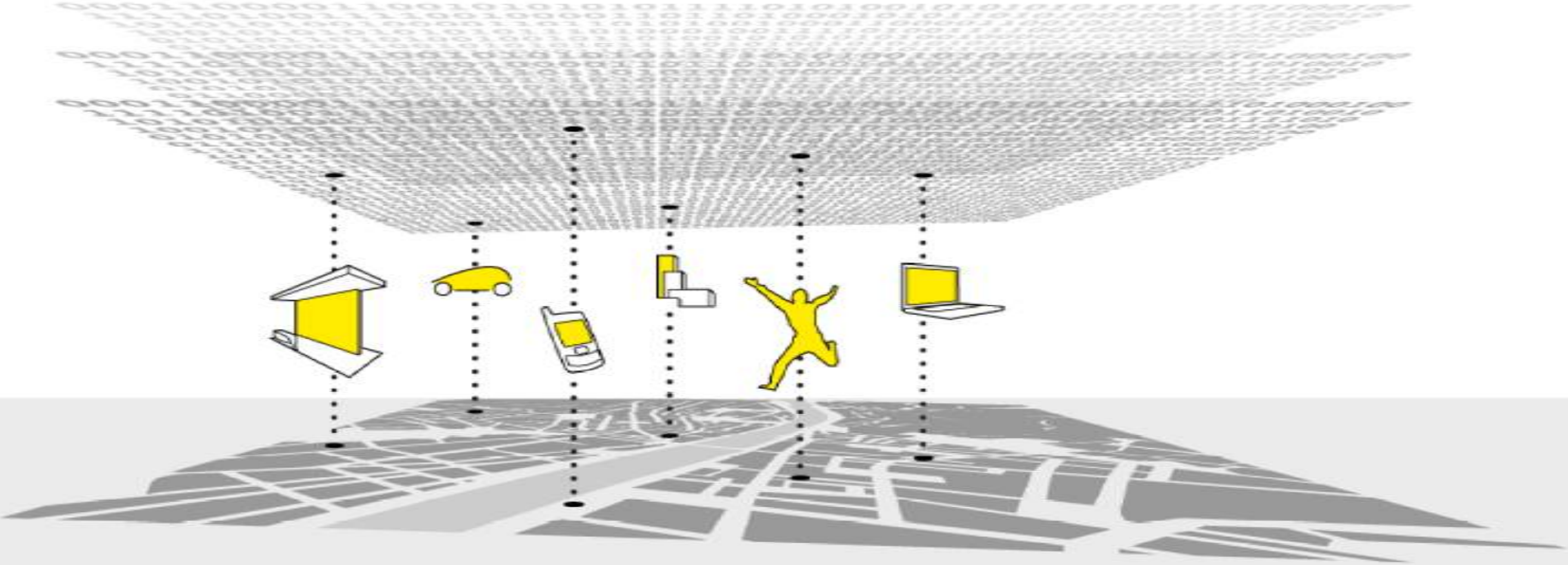

1990...

"we are headed for the death of cities"
{due to the continued growth of personal computing and distributed organizations advances}
"cities are leftover baggage from the industrial era.“

George Gilder (1995)

“in 2008, the world reaches an invisible but momentous milestone: for the first time in history more than half its human population, 3.3 billion people, will be living in urban areas. by 2030, this is expected to swell to almost 5 billion”.

United Nations Population Fund
http://www.unfpa.org/swp/2007/english/introduction.html

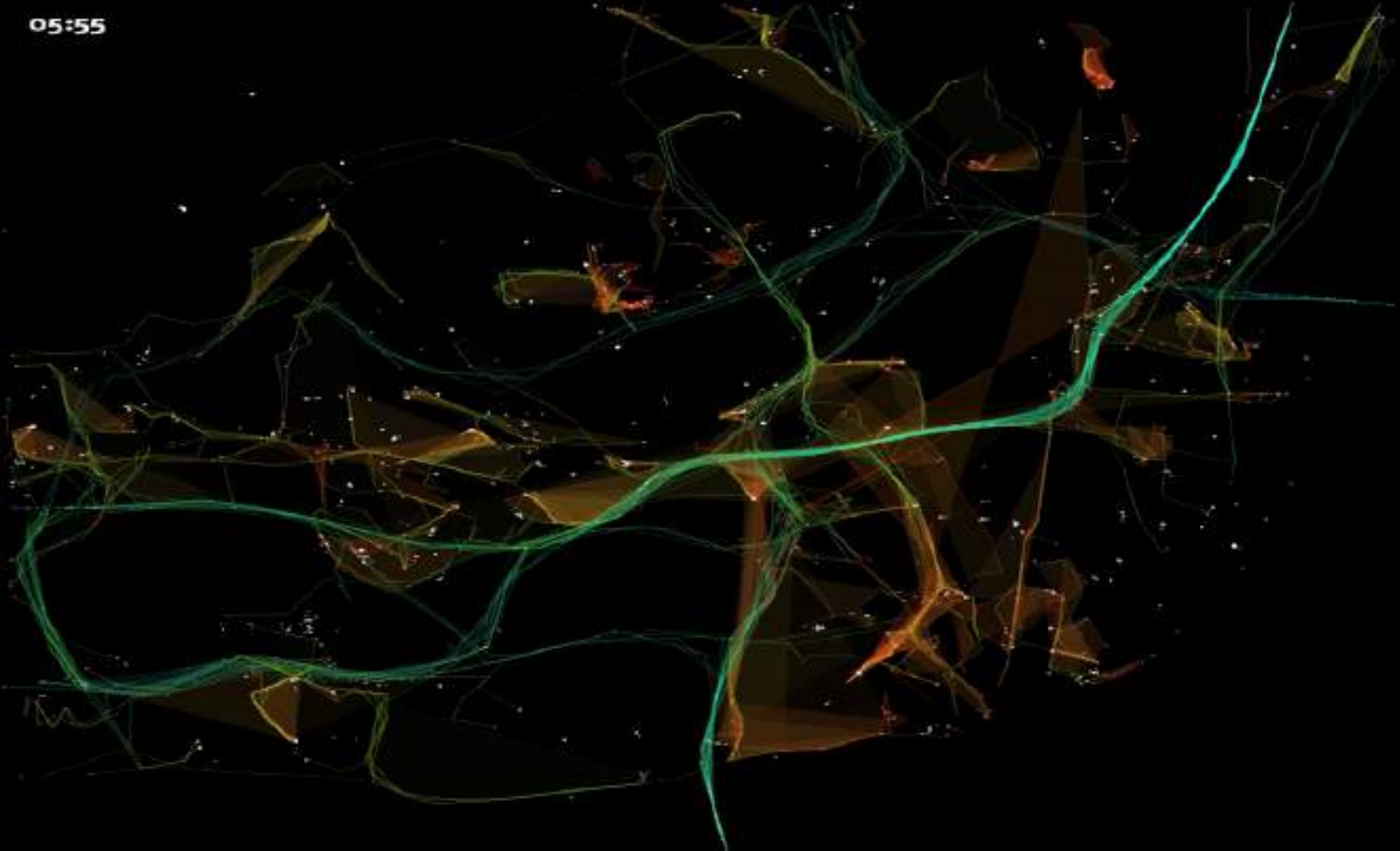



CARLO RATTI ASSOCIATI
London, UK
CARLO RATTI ASSOCIATI
Turin, Italy
SUPERPEDESTRIAN
Cambridge, MA
MAKR SHAKR
Turin, Italy
CARLO RATTI ASSOCIATI
New York, NY
MIT SENSEABLE CITY LAB
Cambridge, MA
SENSEABLE CITY LAB
Singapore

Some questions...

1. What about mobility?
2. What about office spaces?
3. What about retail?
4. ... and urban experiences?

1. What about mobility?
2. What about office spaces?
3. What about retail?
4. ... and urban experiences?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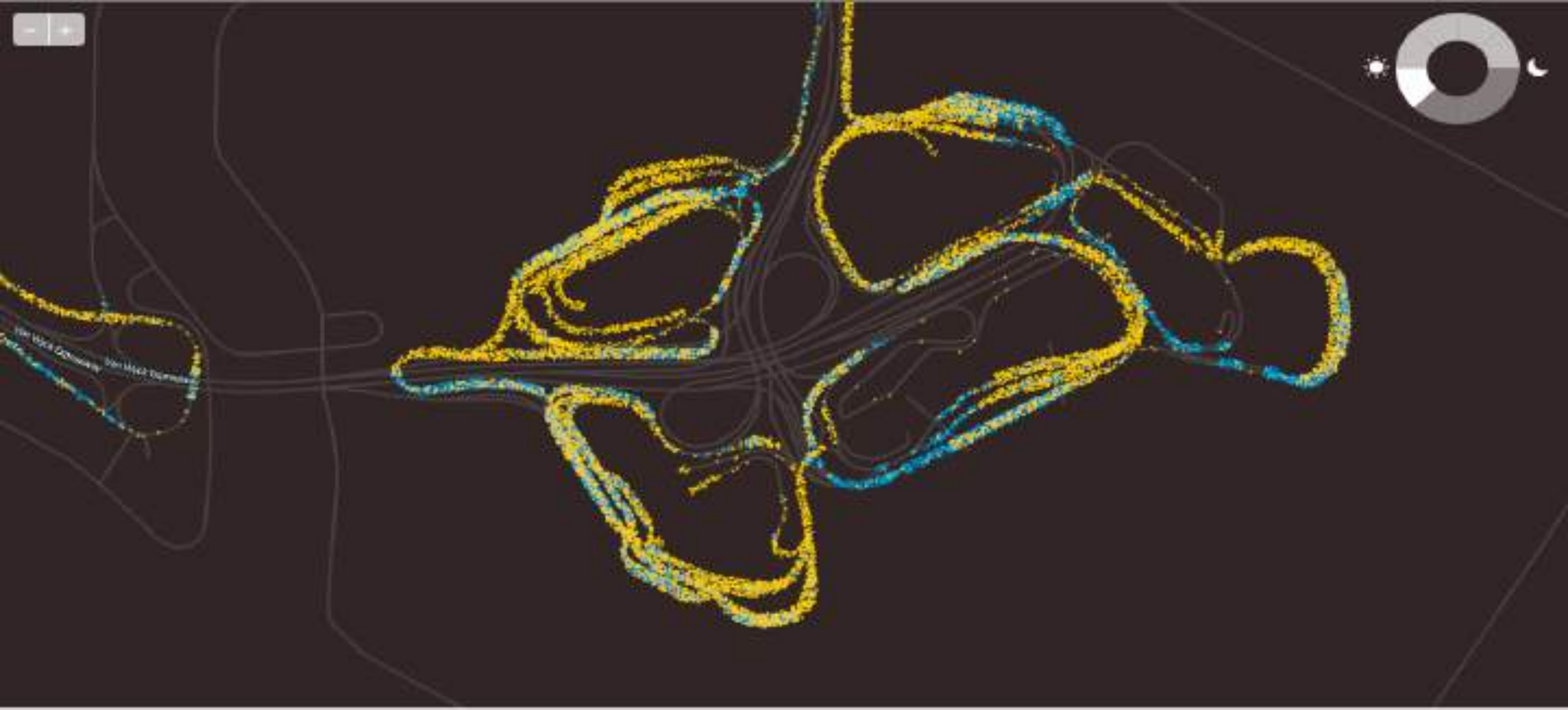


hubcab

MIT senseable city lab

HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year. Show me how it works.

Taxi Pickup

Taxi Dropoff

Learn more about the project ↓


hubcab
HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year.
Show me how it works.
Taxi Pickup
Taxi Dropoff
Learn more about the project


Sharing benefits
3,160,172 $
1,052,627 mi
445,261 kg
225k
214k
hubcab
HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year.
Show me how it works.
Taxi Pickup
West 15th Street
Total Pickups: 1069
Average duration: 12.4 min
Average distance: 3 mi
Taxi Dropoff
East 54th Street
Total Dropoffs: 3053
Average duration: 10.2 min
Average distance: 2.38 mi
Learn more about the project

Quantifying the benefits of vehicle pooling with shareability networks

Paolo Santi[a,b], Giovanni Resta[b], Michael Szell[a,1], Stanislav Sobolevsky[a], Steven H. Strogatz[c], and Carlo Ratti[a]

[a]Senseable City Laboratory, Massachusetts Institute of Technology, Cambridge, MA 02139; [b]Istituto di Informatica e Telematica del Consiglio Nazionale delle Ricerche, 56124 Pisa, Italy; and [c]Department of Mathematics, Cornell University, Ithaca, NY 14853

Edited* by Michael F. Goodchild, University of California, Santa Barbara, CA, and approved July 25, 2014 (received for review March 3, 2014)

Taxi services are a vital part of urban transportation, and a considerable contributor to traffic congestion and air pollution causing substantial adverse effects on human health. Sharing taxi trips is a possible way of reducing the negative impact of taxi services on cities, but this comes at the expense of passenger discomfort quantifiable in terms of a longer travel time. Due to computational challenges, taxi sharing has traditionally been approached on small scales, such as within airport perimeters, or with dynamical ad hoc heuristics. However, a mathematical framework for the systematic understanding of the tradeoff between collective benefits of sharing and individual passenger discomfort is lacking. Here we introduce the notion of shareability network, which allows us to model the collective benefits of sharing as a function of passenger inconvenience, and to efficiently compute optimal

At the basis of a shared taxi service is the concept of ride sharing or carpooling, a long-standing proposition for decreasing road traffic, which originated during the oil crisis in the 1970s (6). During that time, economic incentives outbalanced the psychological barriers on which successful carpooling programs depend: giving up personalized transportation and accepting strangers in the same vehicle. Surveys indicate that the two most important deterrents to potential carpoolers are the extra time requirements and the loss of privacy (7, 8). However, the lack of correlations between socio-demographic variables and carpooling propensity (8), the design of appropriate economic incentives (9), and recent practical implementations of taxi-sharing systems in New York City (http://bandwagon.io) give ample hope that many social obstacles might be overcome in newly emerging "sharing economies" (10, 11).

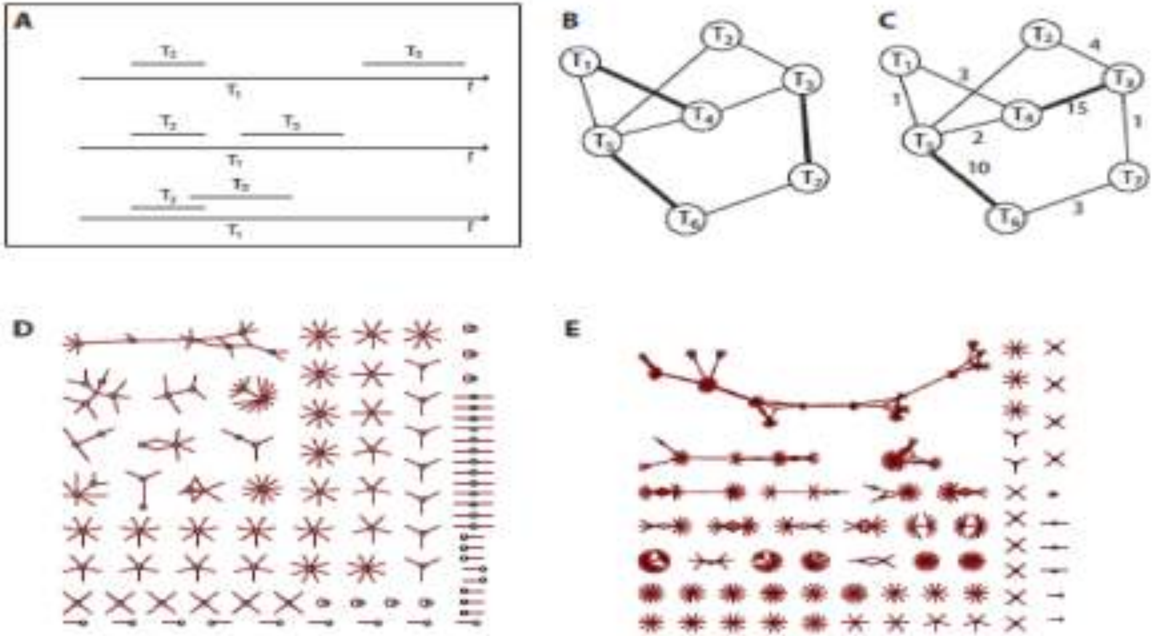
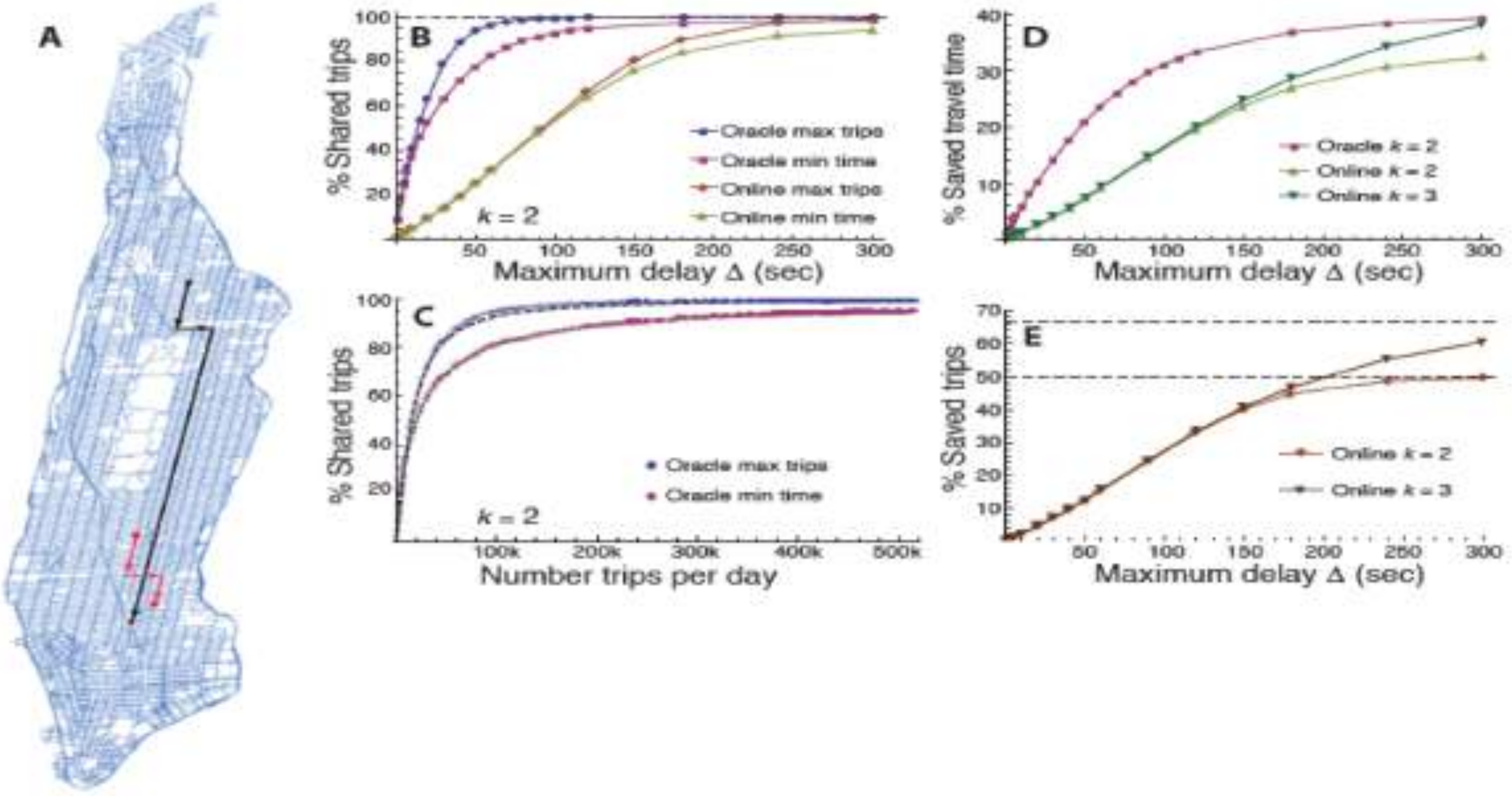


Figure 1: **Shareability networks.** **(A)** Trip sharing model and taxi capacity. Each of the three cases involves three trips T_1, T_2, and T_3 to be shared, but ordered differently in time t. The top case corresponds to a feasible sharing according to our model with $k = 2$, and the trips can be accommodated in a taxi with capacity ≥ 2. The middle case corresponds to a model with $k = 3$ since three trips are combined; notice that the three trips can be combined in a taxi with capacity two since two of the combined trips are non-overlapping. The bottom case corresponds to $k = 3$, but here a taxi capacity ≥ 3 is needed to accommodate the combined trips. **(B)** Example of maximum matching (*4*) in a simple shareability network. The links belonging to the maximum matching are displayed in bold. **(C)** Example of maximum weighted matching (*4*). **(D)** Exemplary subset of the shareability network corresponding to 100 consecutive trips for values of $\Delta = 30\,\mathrm{sec}$ and **(E)** $\Delta = 60\,\mathrm{sec}$, showing network densification effects and thus an increase of sharing opportunities with longer time-aggregation. Open links point to trips outside the considered set of trips. Isolated nodes are represented as self-loops. Node positions are not preserved across the networks.


A
B
% Shared trips
Maximum delay Δ (sec)
Oracle max trips
Oracle min time
Online max trips
Online min time
k = 2
C
% Shared trips
Number trips per day
Oracle max trips
Oracle min time
k = 2
D
% Saved travel time
Maximum delay Δ (sec)
Oracle k = 2
Online k = 2
Online k = 3
E
% Saved trips
Maximum delay Δ (sec)
Online k = 2
Online k = 3


nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
Network analysis of journeys reveals optimum size for New York taxi fleet PAGE 534
DRIVING FORCE

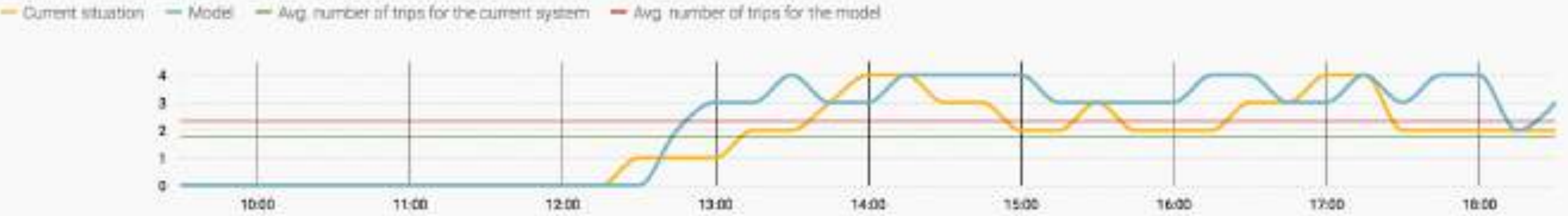
Working hour optimization

MONDAY TUESDAY WEDNESDAY THURSDAY FRIDAY SATURDAY SUNDAY

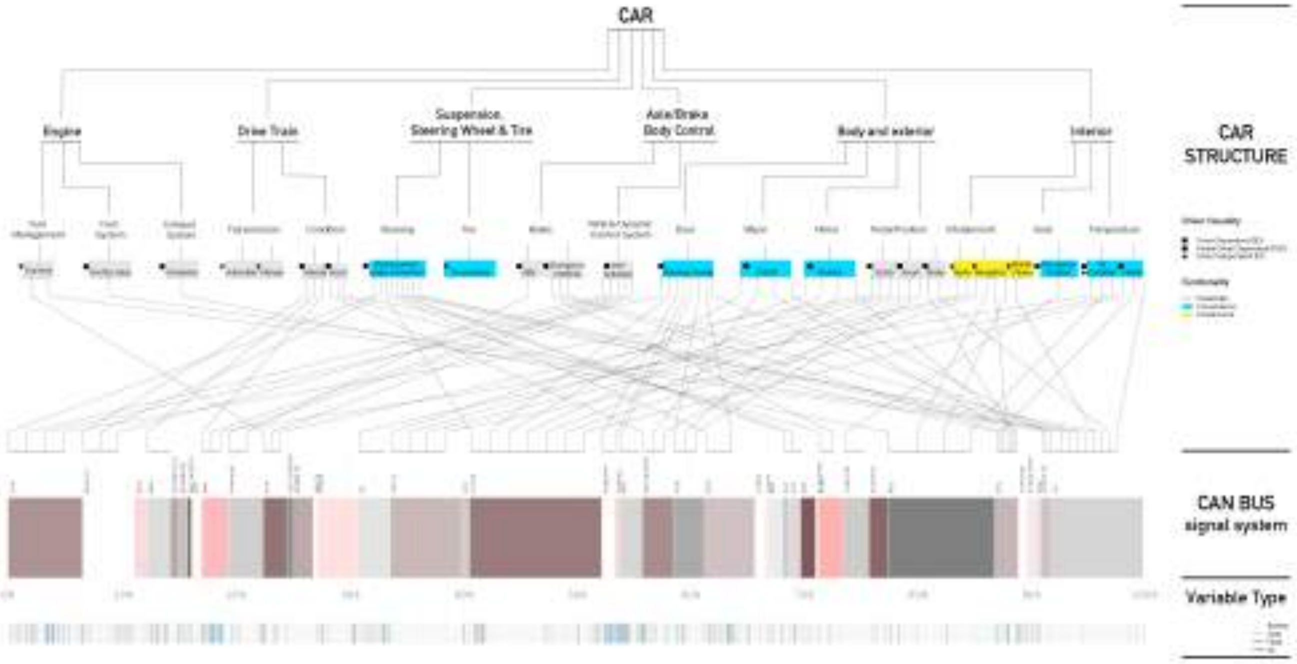
TYPES OF CAR MODES

Cumulated time with and without passenger in a typical working day

TRIPS SERVED BY HOUR AND CAR (CUMULATIVE FOR 1 HOUR)



The displayed cars represent the median number of trips for both the system and model.



CAR
Engine
Drive Train
Suspension
Steering Wheel & Tire
Axle/Brake
Body Control
Body and exterior
Interior
CAR
STRUCTURE
CAN BUS
signal system
Variable Type

The Car as an Ambient Sensing Platform

BY EMANUELE MASSARO, CHAEWON AHN, AND CARLO RATTI
MIT Senseable City Lab, Cambridge, MA 02139 USA

PAOLO SANTI
MIT Senseable City Lab Cambridge, MA 02139 USA and Istituto di Informatica e Telematica del CNR, Pisa 56124, Italy

RAINER STAHLMANN AND ANDREAS LAMPRECHT
AUDI AG, Ingolstadt D-85045, Germany

MARTIN ROEHDER AND MARKUS HUBER
Volkswagen Group of America Electronics Research Lab Belmont, MA 02139 USA

Fig. 1. **The vision of cars used as pervasive sensing platforms: CAN data are communicated to remote servers through wireless communication, possibly after onboard processing and aggregation. GPS signal is fundamental to build time- and spatially resolved databases from the multiple data streams collected by a single vehicle, as well as from data generated by different vehicles.**

In recent years, cars have evolved from purely mechanical to veritable cyber-physical systems that generate large amounts of real-time data. These data are instrumental to the proper working of the vehicle itself, but make them amenable to a multitude of other uses. For instance, GPS information has recently been used for a large number of mobility studies in the academic community [1], [2], as well as to feed traffic apps such as Google Traffic and Waze. This use of vehicle data is already having a profound impact on science, industry, economy, and society at large. Now, imagine that instead of accessing one single source of vehicle-generated data (GPS), one can access the entire wealth of data exchanged on the controller area network (CAN) bus in near real time: amounting to over 4000 signals sampled at high frequency, corresponding to a few gigabytes of data per hour. What would be the implications, opportunities, and challenges sparked by this transition?

This transition is now being made possible by the so-called connected car paradigm, which allows vehicle CAN bus data to be recorded and wirelessly transmitted to external servers for analysis. Thus, the car sensing dimension, which can be informally understood as the number of different signals that a vehicle records and makes available for data analysis, is increasing from 1 (or a few) to 4000 as above.

In the rest of the article, we discuss the groundbreaking effects this transition will have on our ability of sensing roads and the urban living environment. Guided by the preliminary

Digital Object Identifier: 10.1109/JPROC.[illegible]

INVITED PAPER

Crowdsensing Framework for Monitoring Bridge Vibrations Using Moving Smartphones

This paper discusses new services that can be delivered to urban environments through big data generated by the public's smartphones, enhancing the relationship between a city and its infrastructure.

By Thomas J. Matarazzo, Paolo Santi, Shamim N. Pakzad, Kristopher Carter, Carlo Ratti, Babak Moaveni, Chris Osgood, and Nigel Jacob

ABSTRACT | Cities are encountering extensive deficits in infrastructure service while they are experiencing rapid technological advancements and overhauls in transportation systems. Standard bridge evaluation methods rely on visual inspections, which are infrequent and subjective, ultimately affecting the structural assessments on which maintenance plans are based. The operational behavior of a bridge must be observed more regularly and over an extended period in order to sufficiently track its condition and avoid unexpected rehabilitation. Mobile sensor networks are conducive to monitoring bridges vibrations routinely, with benefits that have been demonstrated in recent structural health monitoring (SHM) research. Though smartphone accelerometers are imperfect sensors, they can contribute valuable information to SHM, especially when aggregated, e.g., via crowdsourcing. In an application on the Harvard Bridge (Boston, MA), it is shown that acceleration data collected using smartphones in moving vehicles contained consistent and significant indicators of the first three modal frequencies of the bridge. In particular, the results became more precise when information from several smartphone datasets were combined. This evidence is the first to support the hypothesis that smartphone data, collected within vehicles passing over a bridge, can be used to detect several modal frequencies of the bridge. This result defines an opportunity for local governments to make partnerships that encourage the collection of low-cost bridge vibration data, which can contribute to more effective management and informed decision-making.

KEYWORDS | Big Data; Bridge Management; Crowdsourcing; Damage Detection; Structural Health Monitoring; System Identification; Vehicular Networks; Wireless Sensor Networks; Intelligent Infrastructure

The state of U.S. infrastructure can be described as aging: about 40% of bridges are over 50 years old; in each day of 2016, Americans took 188 million trips over structurally deficient bridges [1], [2], and the backlog in bridge rehabilitation is estimated at $123 billion. For effective commerce and transit between U.S. states, federal laws require biennial bridge condition evaluations. Local governments and transportation authorities manage bridges and are responsible for a majority of the funding; they employ inspections, then form and prioritize plans based on engineering assessments and allocated budgets. Yet, modern inspection protocols are sparse in time, and often do not include sensors or other technological tools, and as a result, can miss damage indicators and/or lead to improper diagnoses.

A visual inspection is the primary condition evaluation method which, while often thorough, is subjective by nature and can be impaired by obstructive nonstructural elements or other physical restrictions [3]–[5]. Even if a compromised structural component is in clear sight of a professional bridge inspector, early signs of damage

Manuscript received [illegible]; revised [illegible]; accepted [illegible]. Date of current version [illegible]. [illegible] (Corresponding author: Thomas J. Matarazzo.)

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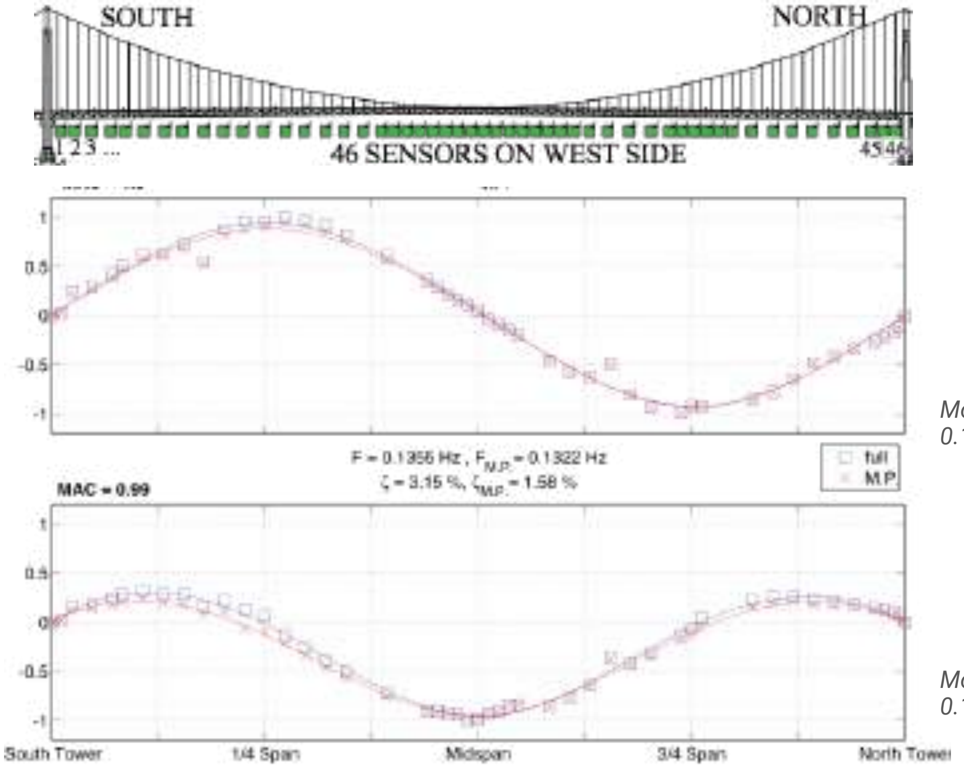
P. Santi is with MIT Senseable City Laboratory, Cambridge, MA [illegible] USA and also with Istituto di Informatica e Telematica del CNR, Pisa, Italy.
S. N. Pakzad is with Lehigh University, Bethlehem, PA [illegible] USA.
K. Carter, C. Osgood and N. Jacob are with The City of Boston, Boston, MA [illegible] USA.
B. Moaveni is with Tufts University, Medford, MA [illegible] USA.

Digital Object Identifier 10.1109/JPROC.2018.2808759



Jonathan Wiggs, Boston Globe

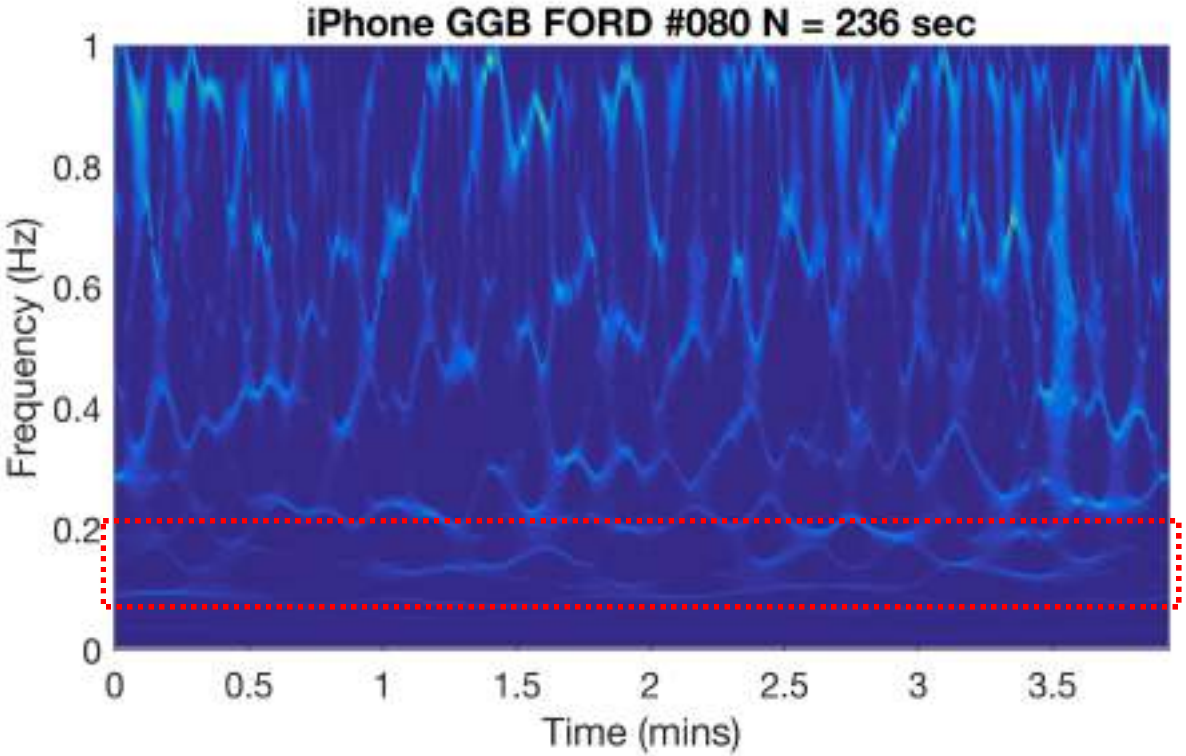

STRUCTURAL FINGERPRINT



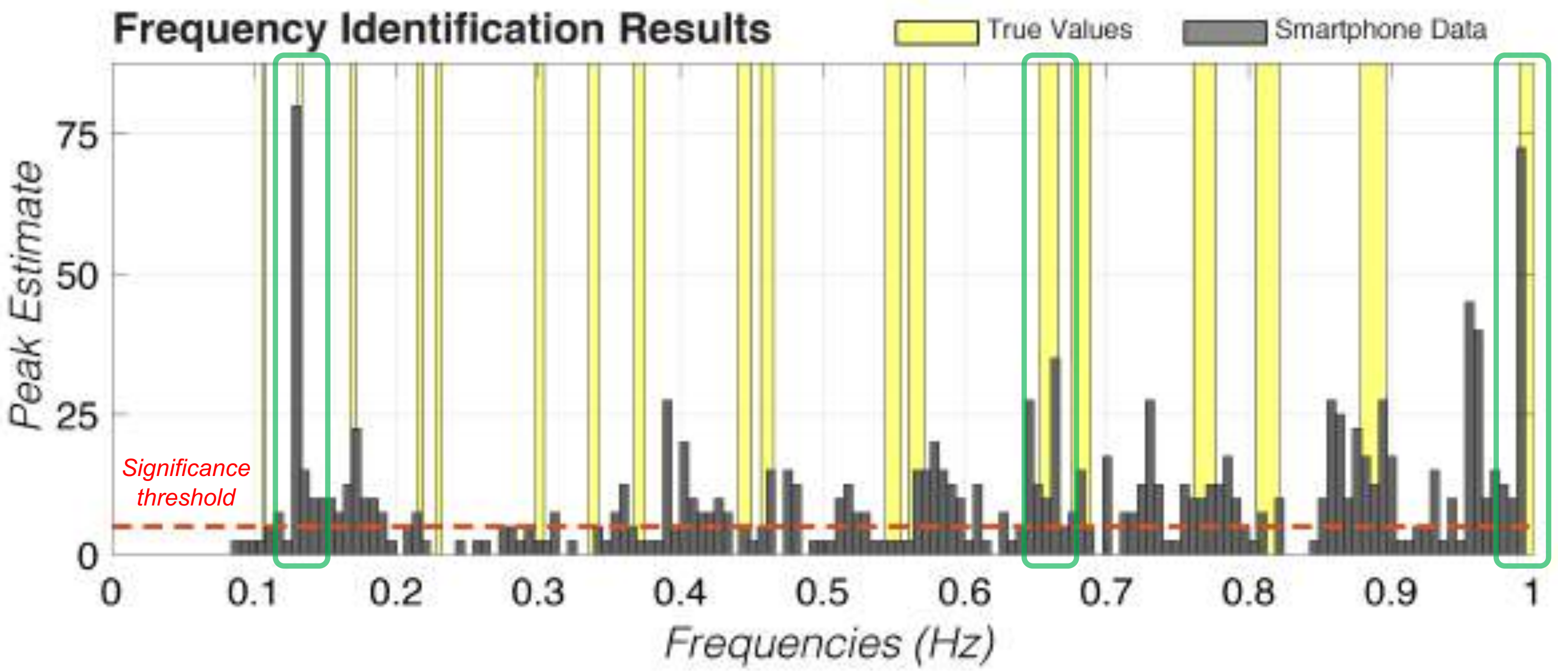
Mode 1
0.106 Hz

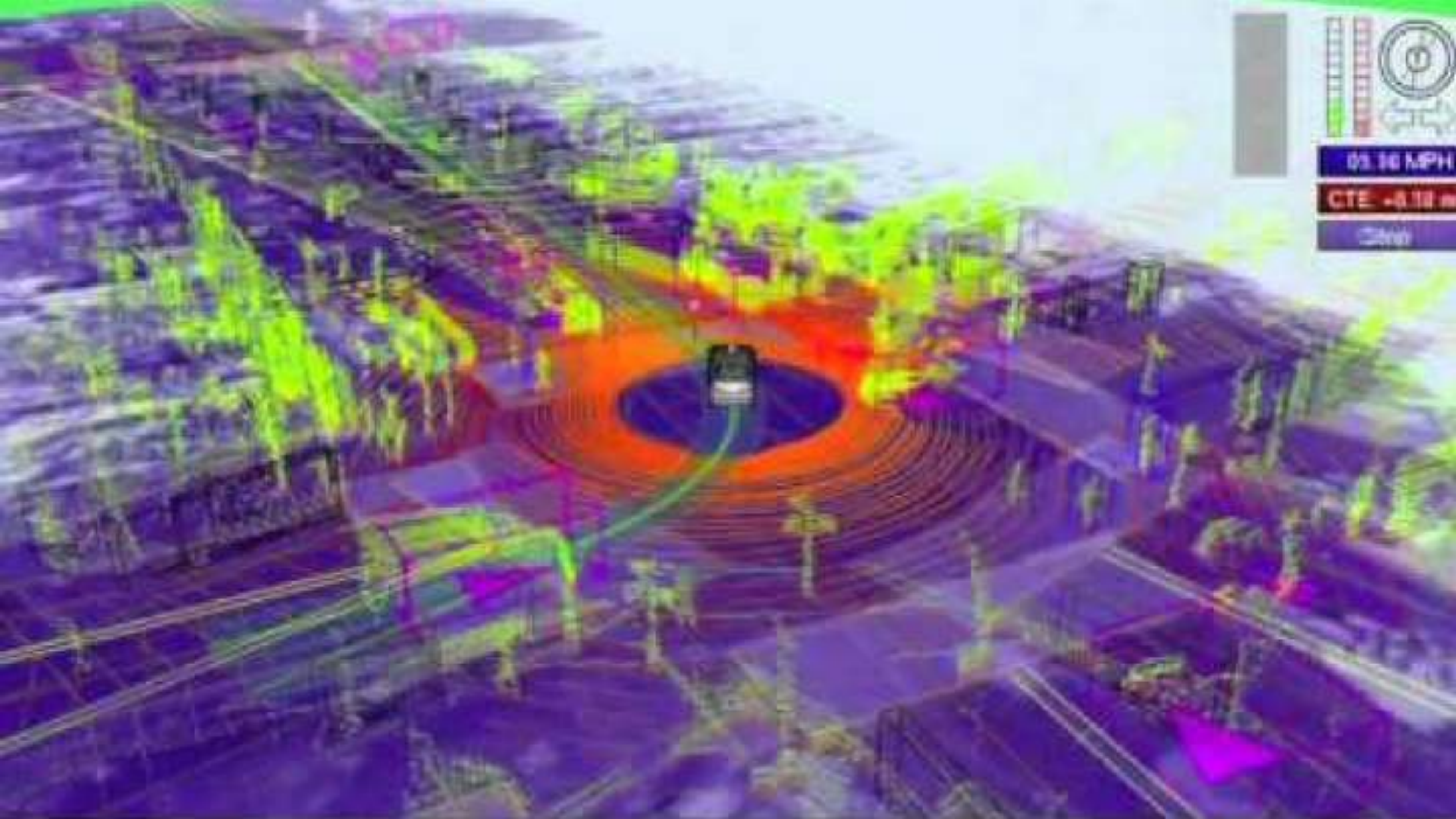
Mode 2
0.135 Hz

SPECTRAL ANALISYS



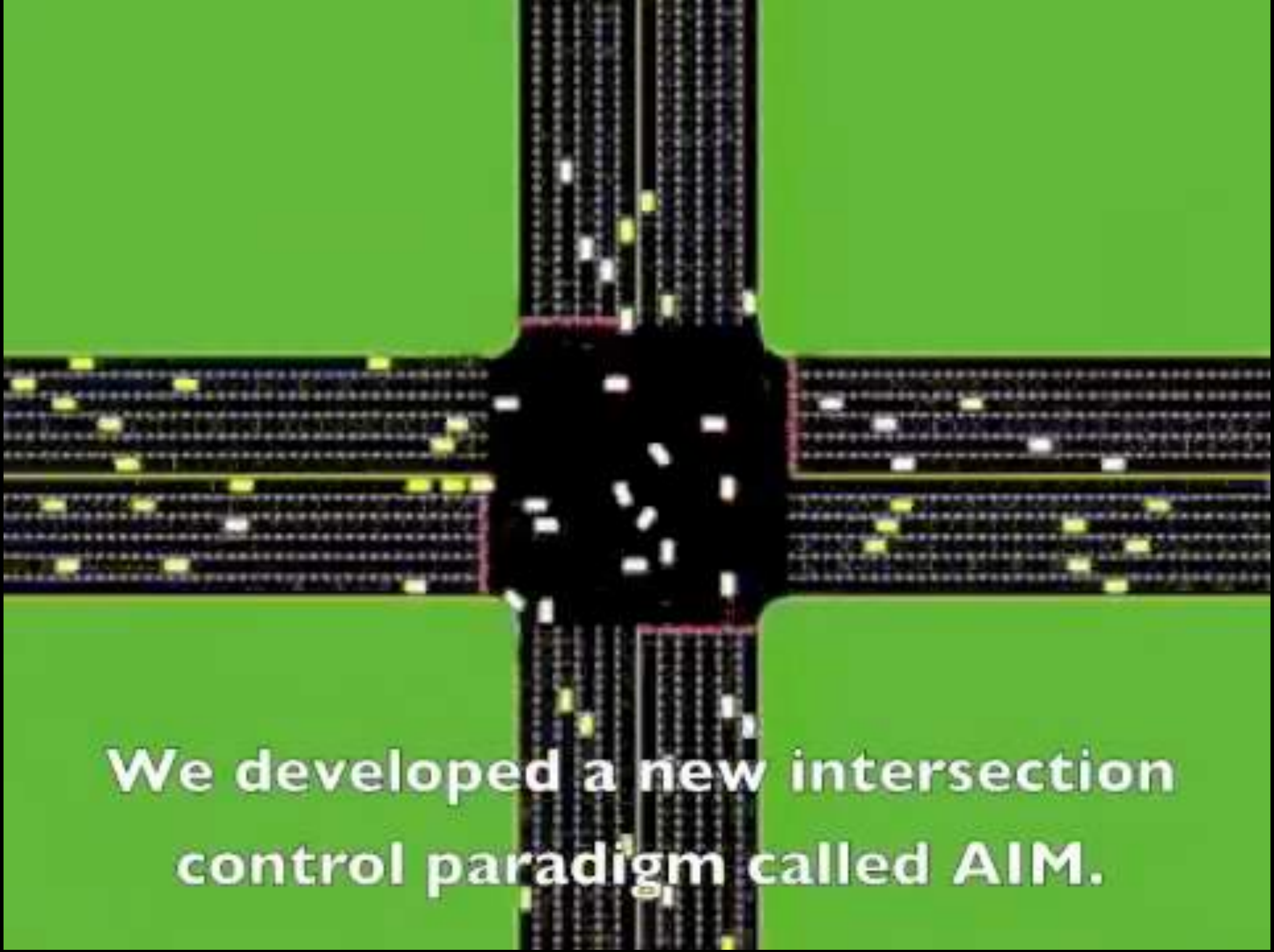
SPECTRAL ANALISYS






UBER

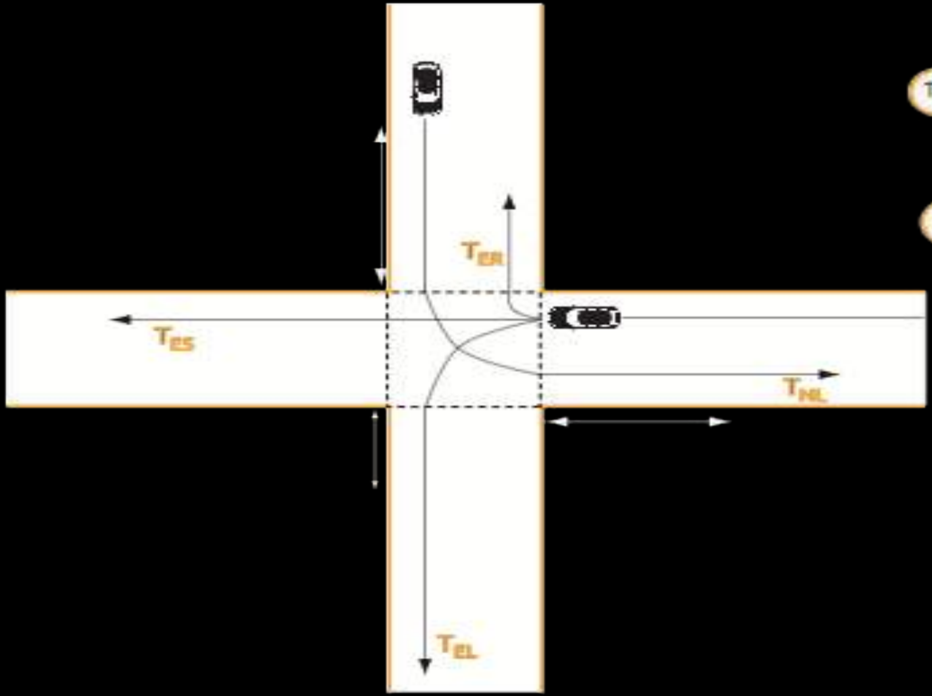

DRIVE
TO
RIGHT


We developed a new intersection
control paradigm called AIM.

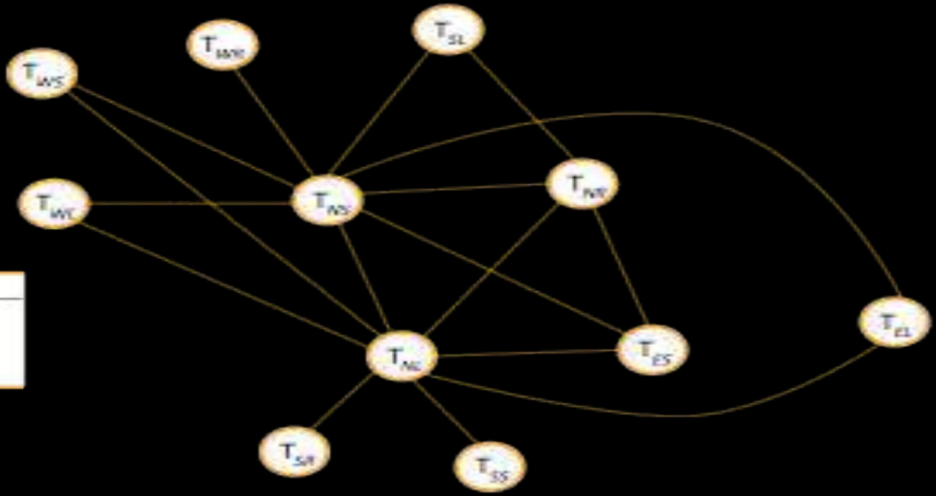
“In Milan, traffic lights are instructions.
In Rome, they are suggestions.
In Naples, they are Christmas decorations.”

Antonio Martino
Former Minister of Foreign Affairs (1994) and Minister of Defense (2001-2006)

Access to intersection based on Incompatibility Network and ….



Vehicle trajectories
(partial view)

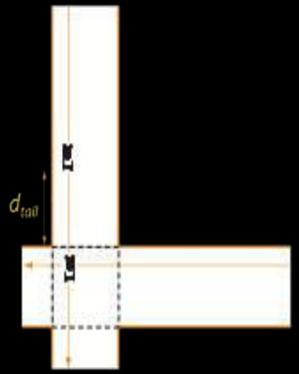


Incompatibility Network
(partial view)

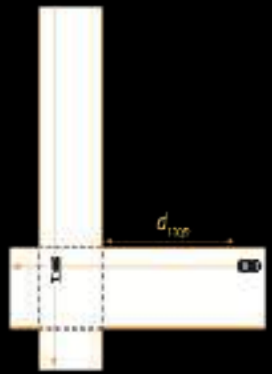
Access to intersection based on Incompatibility Network and safety constraints

Safety constraint

- based on tailgate distance (a.k.a. two seconds rule) for vehicles with compatible trajectories
- based on vehicle stopping distance for vehicles with incompatible trajectories



Typically, $d_{tail} < d_{stop}$



City Drive

Micromobility re-engineered

Superpedestrian raises $20 million for durable electric scooters

Kyle Wiggers @Kyle_L_Wiggers November 19, 2019 6:25 PM Transportation

1. What about mobility?
2. **What about office spaces?**
3. What about retail?
4. ... and urban experiences?

Harvard Business Review

WORKSPACES

If Work Is Digital, Why Do We Still Go to the Office?

by Carlo Ratti and Matthew Claudel

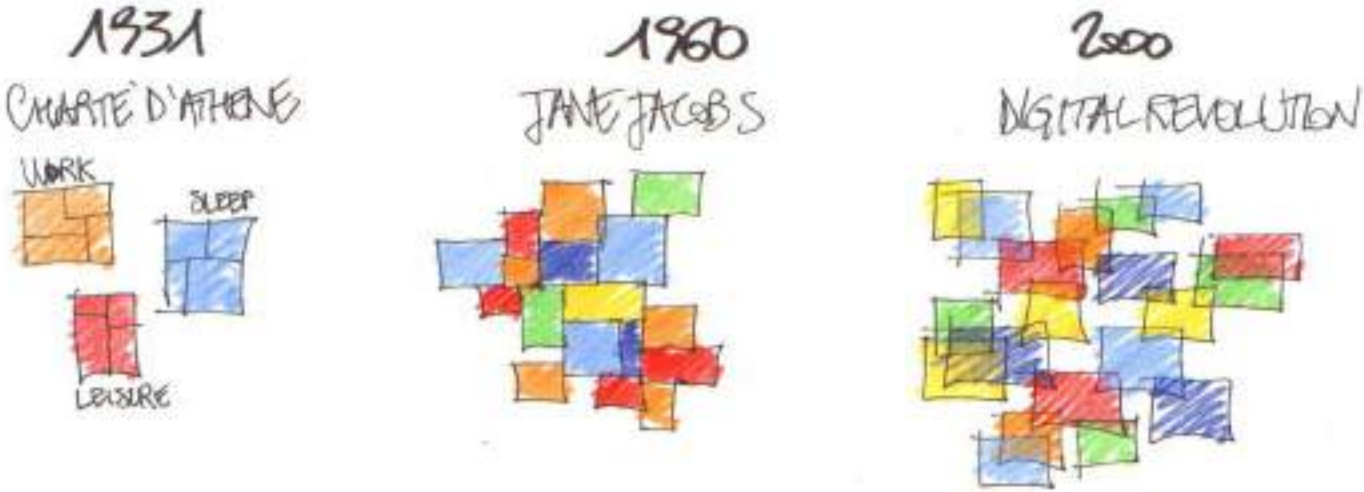
APRIL 13, 2016

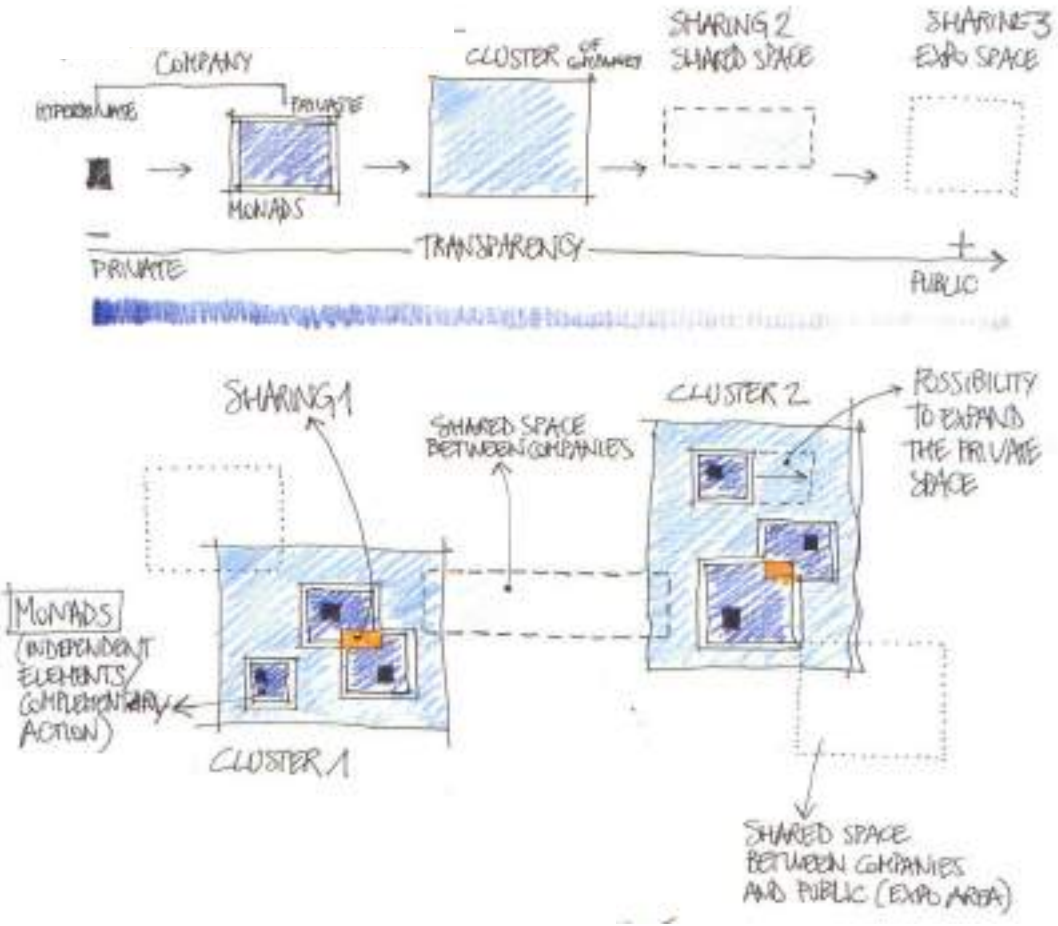
WHAT TO READ NEXT

7 Factors of Great Office Design

Le Corbusier , Charte d'Athene 1931, IV CIAM

"The four keys to urban planning are the four functions of the city: dwelling, work, recreation (use of leisure time), transportation"


1931
CHARTE D'ATHENE
WORK
SLEEP
LEISURE
1960
JANE JACOBS
2000
DIGITAL REVOLUTION


COMPANY
PRIVATE
MONADS
CLUSTER
SHARING 2
SHARED SPACE
SHARING 3
EXPO SPACE
TRANSPARENCY
PRIVATE
PUBLIC
SHARING 1
SHARED SPACE
BETWEEN COMPANIES
CLUSTER 2
POSSIBILITY
TO EXPAND
THE PRIVATE
SPACE
MONADS
(INDEPENDENT
ELEMENTS
COMPLEMENTARY
ACTION)
CLUSTER 1
SHARED SPACE
BETWEEN COMPANIES
AND PUBLIC (EXPO AREA)

Circulation

Private

Open

Composite

MIT campus
Location: Boston, MA
Area: 168 acres
People: 10,320 students and 9, 414 total employees
Buildings: over 190

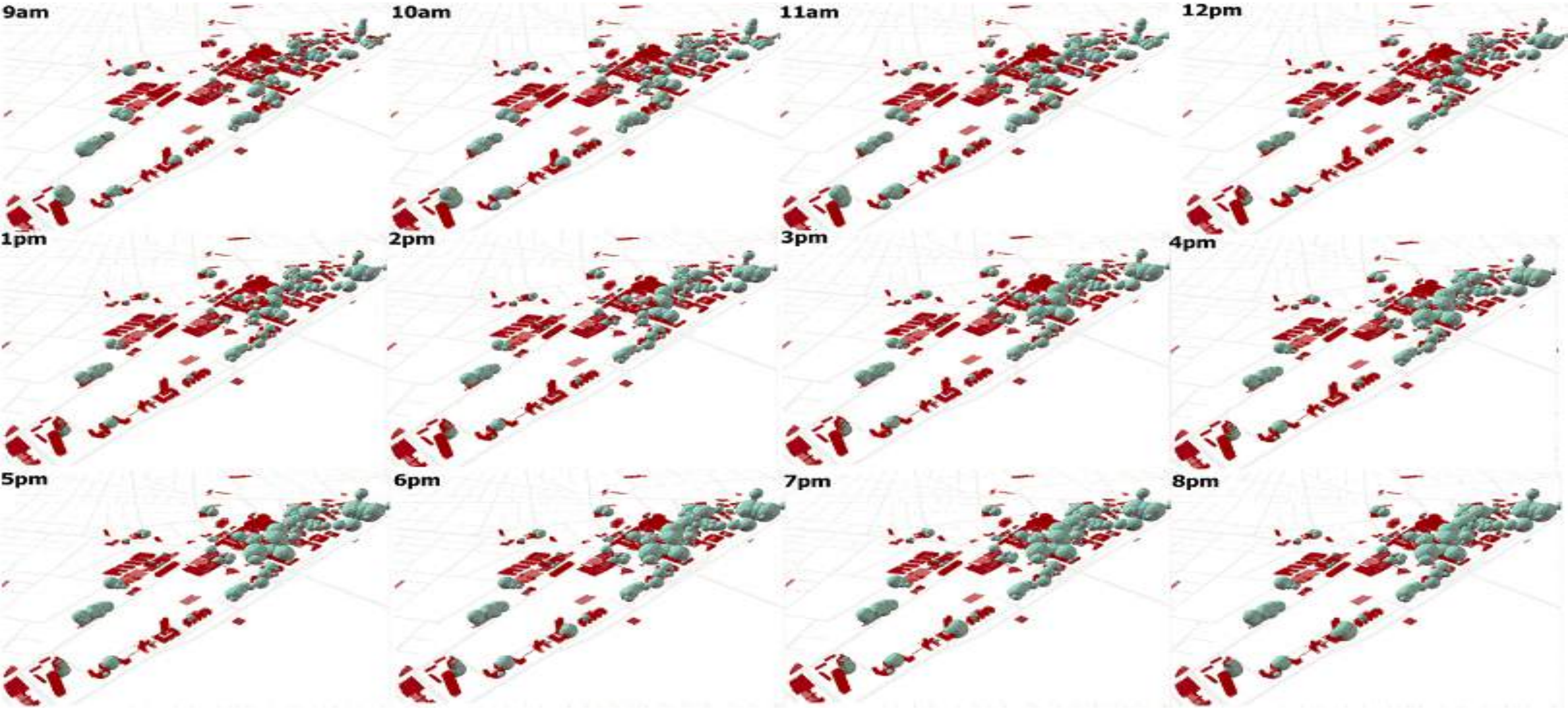
Wi Fi™

ZONE

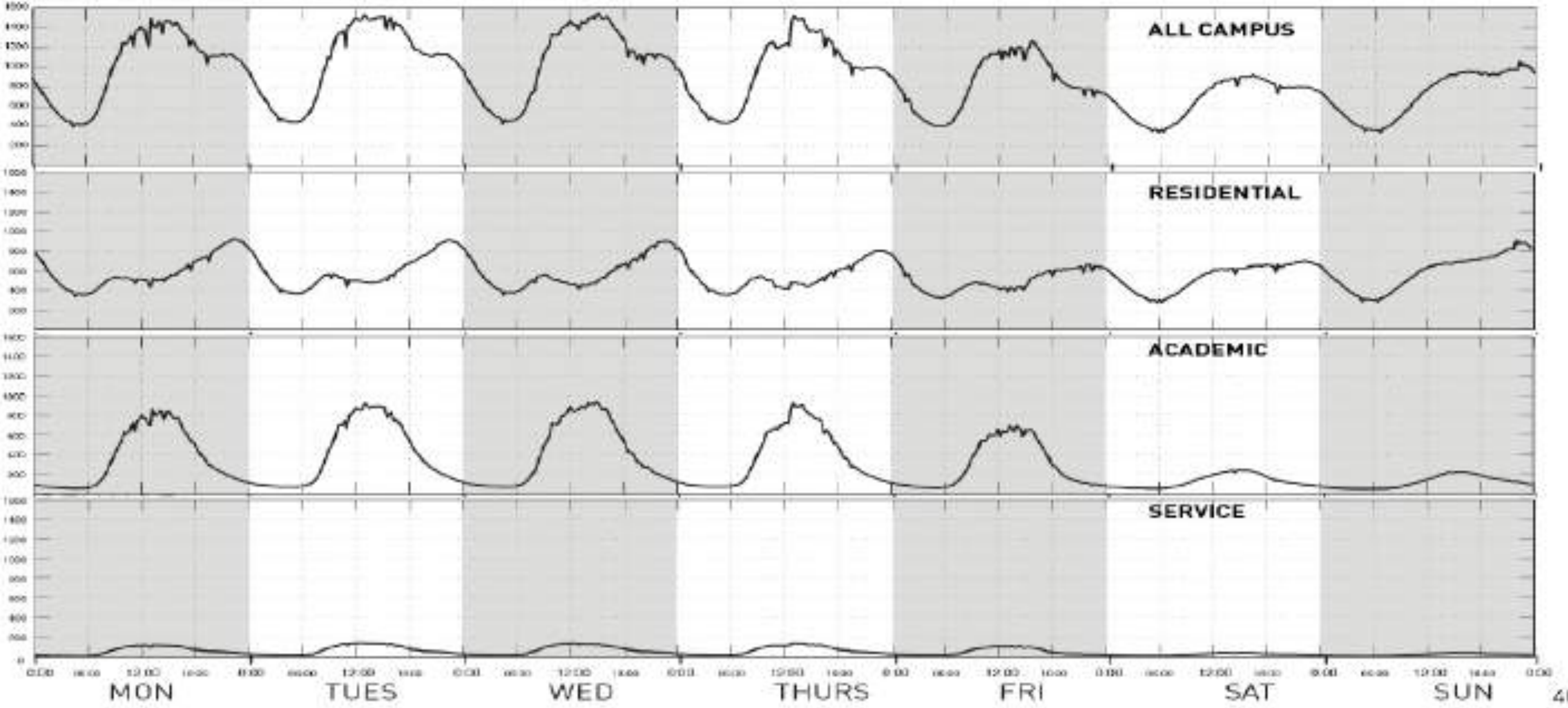
Before

After


wework

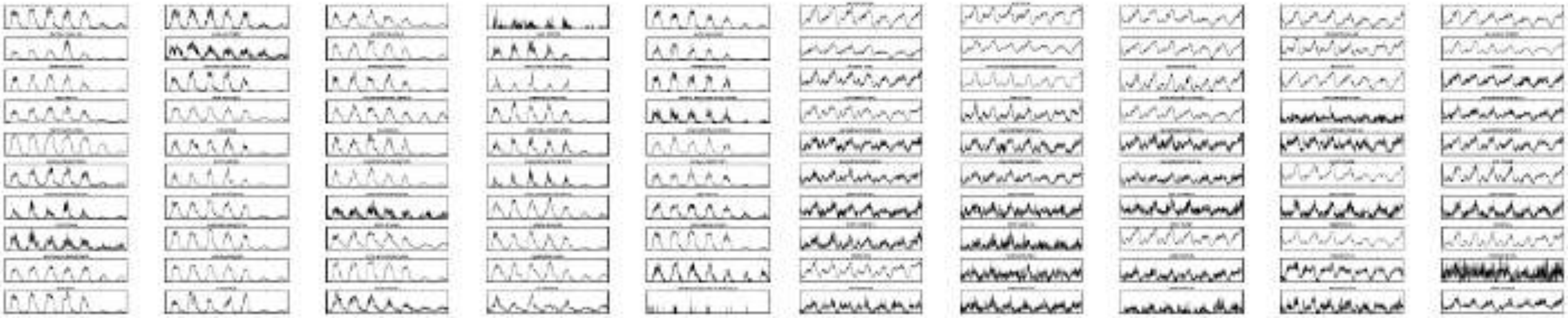

9am
10am
11am
12pm
1pm
2pm
3pm
4pm
5pm
6pm
7pm
8pm

Summary slide of the signals from the three program types discussed earlier - compared to the signature of the entire campus. The user number is the average weekly number of people connecting to the internet via WiFi.

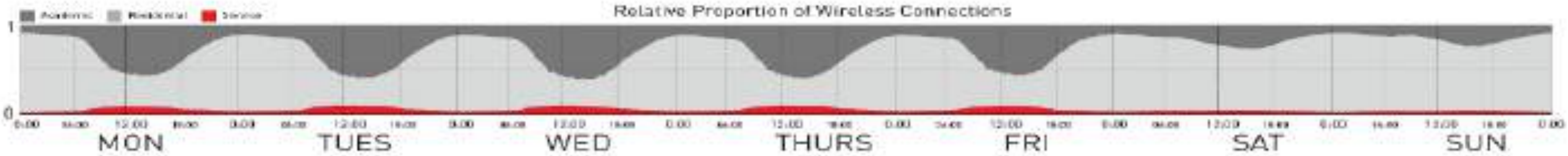


3. MIT CAMPUS

The average weekly WiFi signals from individual buildings give us a fingerprint of each building. Can these be correlated (calibrated?) to the type of people living in particular dorms? Do physicists have different WiFi usage than chemists?



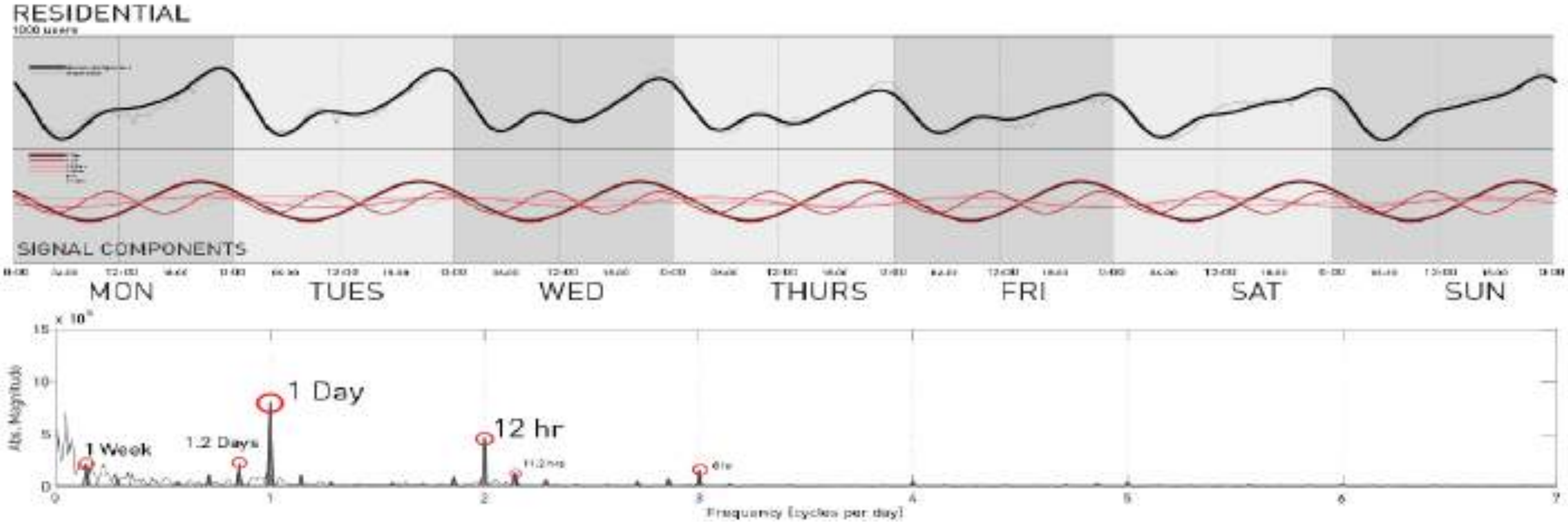
Calculating the average relative proportions of total WiFi connections among the three program types (academic/residential/service) over the course of a week revels characteristic WiFi behavior in the three program types. Although the service building WiFi use is much lower than the two other program types, in general, the service and academic buildings show a similar increase in WiFi use during normal daylight hours, while the residential use increases at night. This difference diminishes during the weekend.



3.1 MIT FFT

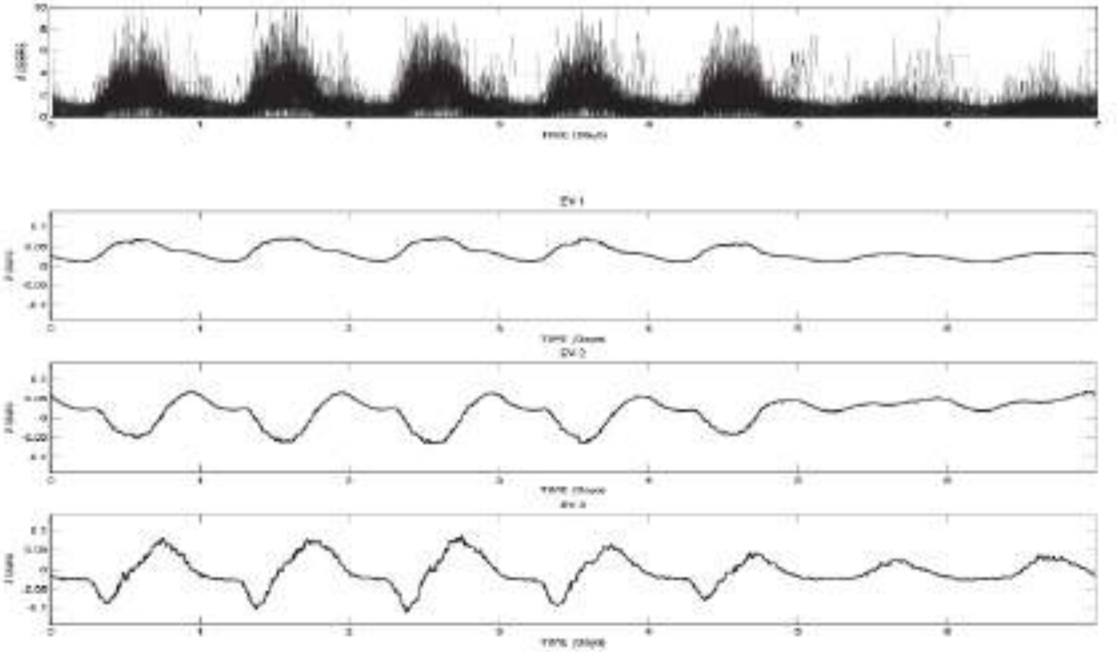
Taking an FFT of the average weekly time series allows us to separate the WiFi signatures into individual components. Shown below are the original signature, the reconstructed signature, the six frequencies used to reconstruct the synthetic time series, and the spectral graph of the original time series. The thickness and color of the individual components are a function of the magnitude of the frequency shown in the lowermost plot. The primary frequencies for residential buildings correspond to periods of 1 day, 12 hours, 1.2 days, 8 hours, and 1 week. The diurnal cycle is as expected for people who sleep at night and work during the day. The 12hr and 8hr periods correspond to daily activities such as going to class and accessing the internet in the evening. Note the largest WiFi signal comes just before midnight. Since these are mostly students in dorms, it is not surprising.

As can be seen below, the FFT technique is ideal for characterizing and extracting fundamental components of periodic behavior. Is a city periodic? I would say yes – it is governed by cycles and thus, unlike the eigenvector technique which is more interested in canonical forms (periodic or not), tends to make a ot of intuitive sense for urban analysis.



3.2 MIT EIGENVECTOR ANALYSIS AND K-MEAN CLUSTERING

The test of seeing whether WiFi antennas in Simmons Hall could be grouped according to very localized usage patterns was partially successful - there are still many uncertainties about the accuracy of the results - so it was decided to use all of the antennas on the MIT campus to determine the 14 week average signal and then calculate the eigenvectors /eigenvalues and k-mean clustering. Shown below are the results of the eigenvector analysis.



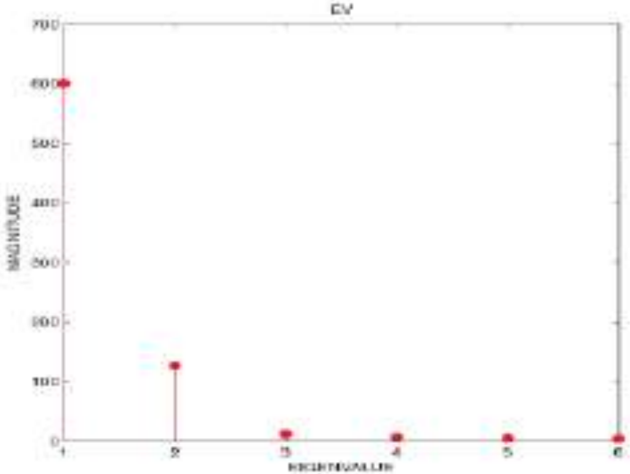
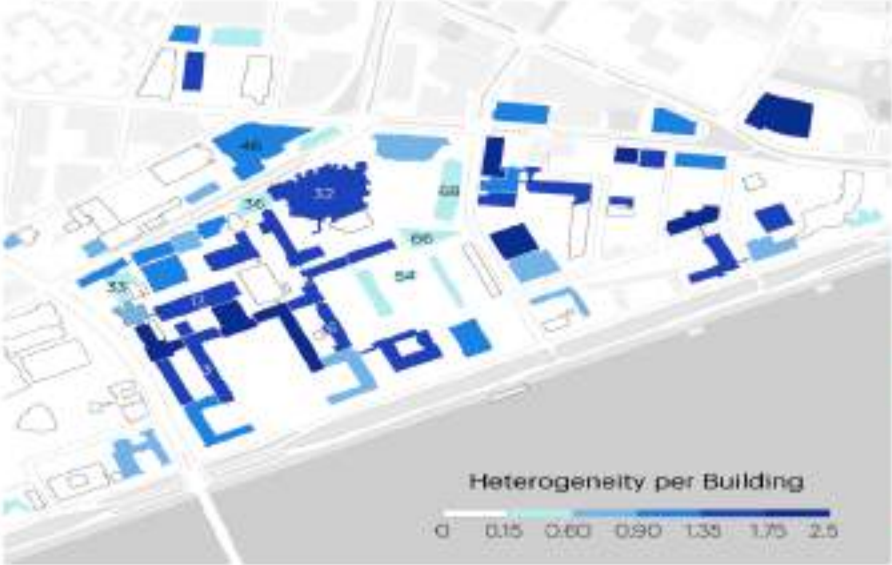


Figure 4. Patent and paper output per building between 2004 and 2014. On these choropleth maps, buildings are color coded by output volume and labeled with their name (the facility code). Colors are assigned using a Jencks algorithm with five buckets.



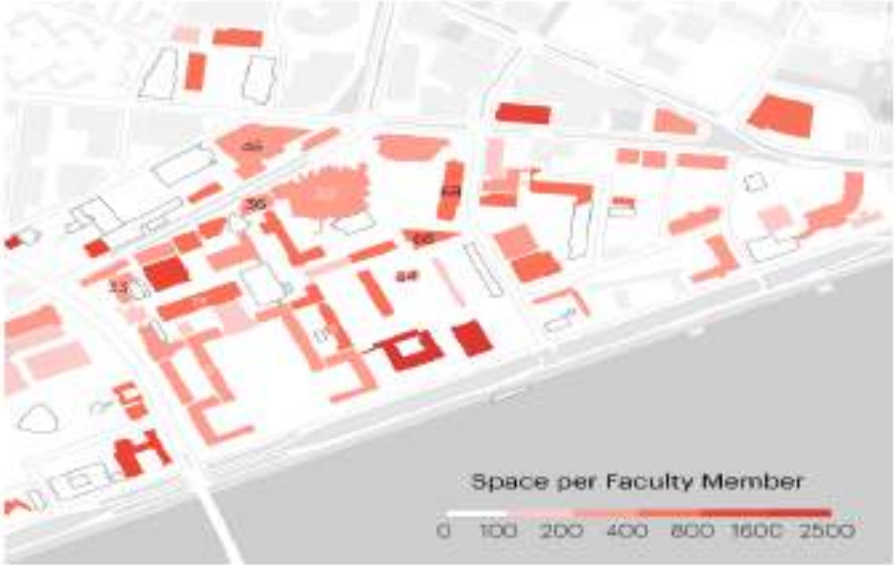
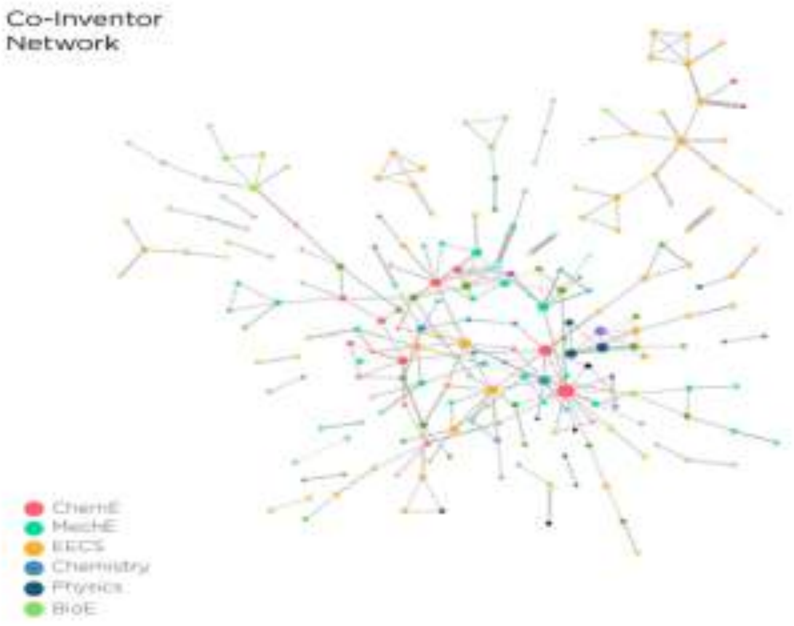
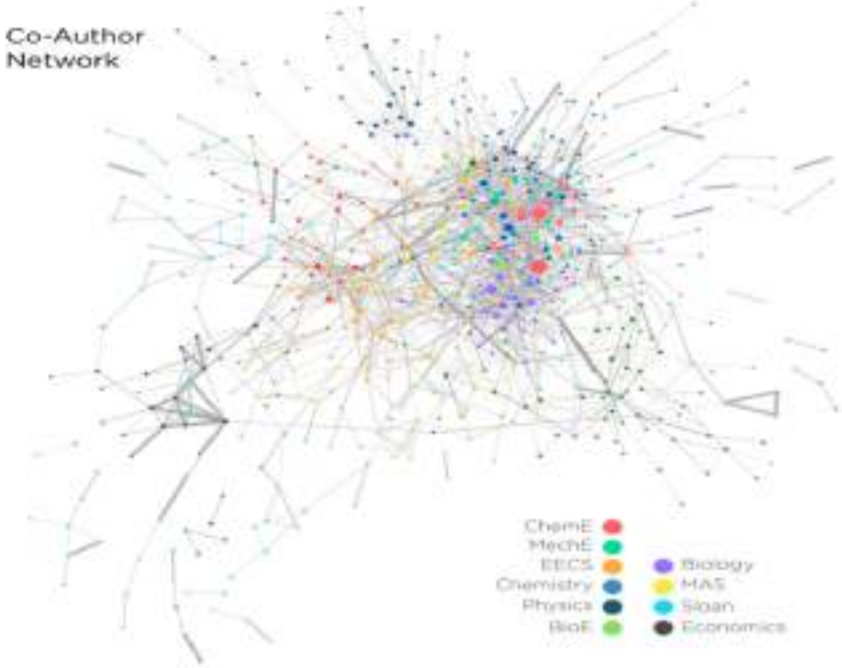


Figure 7. MIT campus buildings, coded according to heterogeneity, as calculated using the Shannon measure of information entropy. This shows variation in faculty departmental affiliations per building. Values range from 0 to 2.5, classified with a Jencks algorithm. Buildings are labeled by name (facility code).

Figure 8. MIT campus buildings, coded according the average total area of lab and office space per faculty member. There is a distribution of values from 145ft^2 to 2,065ft^2 allocated per faculty member. Buildings are labeled by name (facility code).


Co-Inventor
Network
ChemE
MechE
EECS
Chemistry
Physics
BioE


Co-Author
Network
ChemE
MechE
EECS
Chemistry
Physics
BioE
Biology
MAS
Sloan
Economics


working


passion
working
space


23°
23°
22°
22°
21°
25°


tag


States' Next Target on Sales Taxes: Sellers on Amazon


GE Chief Says 'Climate Change Is Real' in Rebuke to Trump Policy


McDonald's Upgrades Quarter Pounder, Using Fresh Beef


Years After 9/11 Chaos, U.S. to Build Wireless First-Responder Network

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At Last, a Possible Solution to Office Thermostat Wars

New technologies are giving individual office workers more control over the climate around them

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2. Film Clip: 'The Zookeeper's Wife'

3. Senate Calling 20 Witnesses for Russia Probe

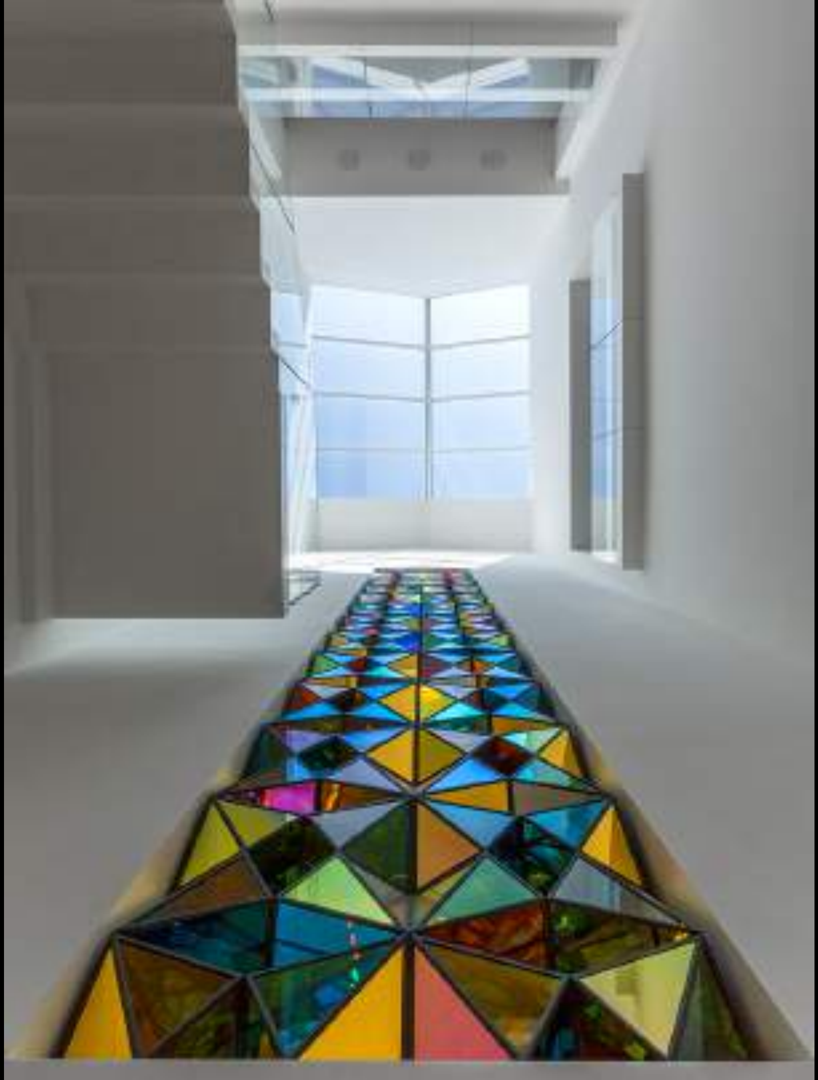
4. Opinion Journal: Border Taxes for Dummies

5. North Korean Defectors Struggle to Master Money

Most Popular Articles

1. Telecom Giants Get the OK to Mine Your Web History

Display a menu



What about covid-19?

Twitter

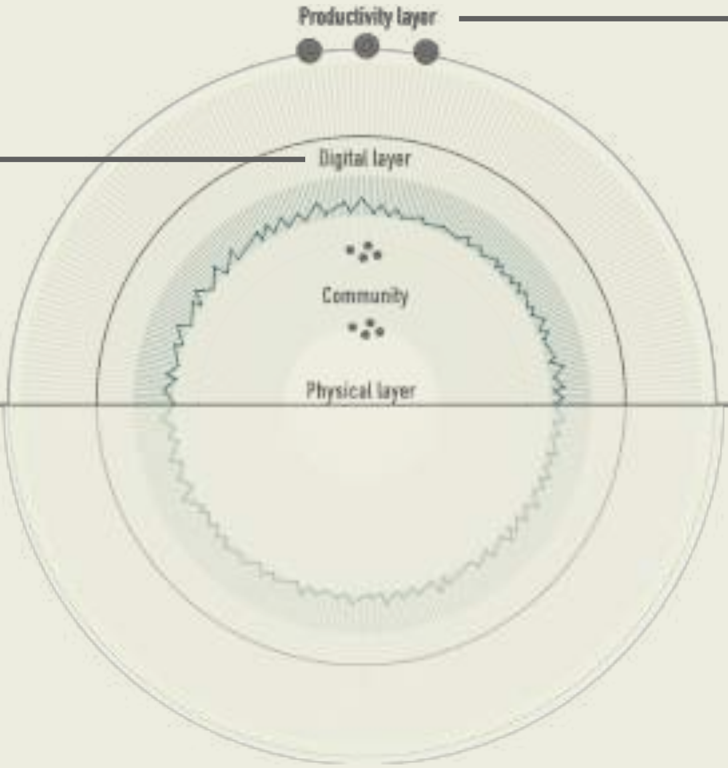
Twitter announces employees will be allowed to work from home ‘forever’

The company said those who want to return to the office won't likely do so until at least September and reopening will be ‘careful’

- Coronavirus - live US updates
- Live global updates

PRODUCTIVITY DATASET (2004-2019)
*127.664 MIT ID (articles)
* 3.670 MIT ID (books)
* 88.733 MIT ID (patents)
* 38.310 people (invention disclosure)
* 28.194 MIT ID (co-teaching, from 2010)

EMAIL DATASET (from Dec 27th, 2019)
*64 Organizational Units
* 3524 people (anonymized)



CAMPUS DATA
4 faculty, other academics, research staff (2019)
12,707 total faculty plus staff on campus
1,056 faculty members
4 schools, 31 Departments
Total students (2018) 11,574
18 student residences on campus

MIT LAYOUT ORGANIZATION
* Research units/department physical location
* 164 buildings
* 166 acres (0.67 km2)

EMAIL DATASET

3523 ANONYMIZED People's MIT email accounts (Faculty, Fellow Researchers)

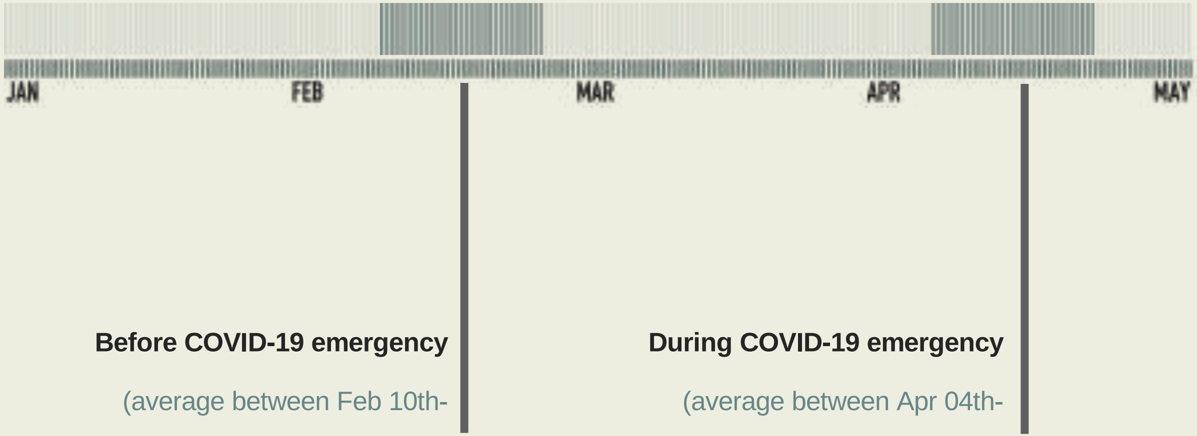
64 RESEARCH UNITS/DEPARTMENTS

5 PEOPLE OF EACH RANDOMIZED GROUP

TIME variable

We kept track of all communications related to COVID–19

TIME variable



Before COVID-19 emergency

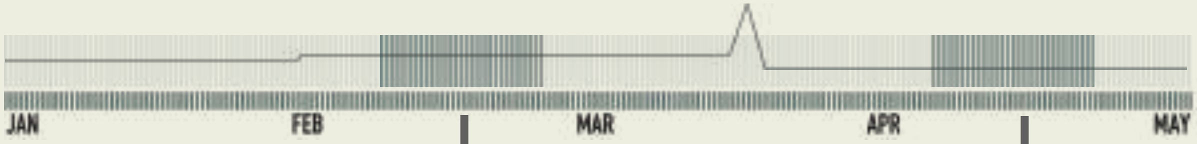
(average between Feb 10th-Feb 23th)

During COVID-19 emergency

(average between Apr 04th-Apr 19th)

TIME variable

MIT closing announce



Before COVID-19 emergency

(average between Feb 10th-Feb 23th)

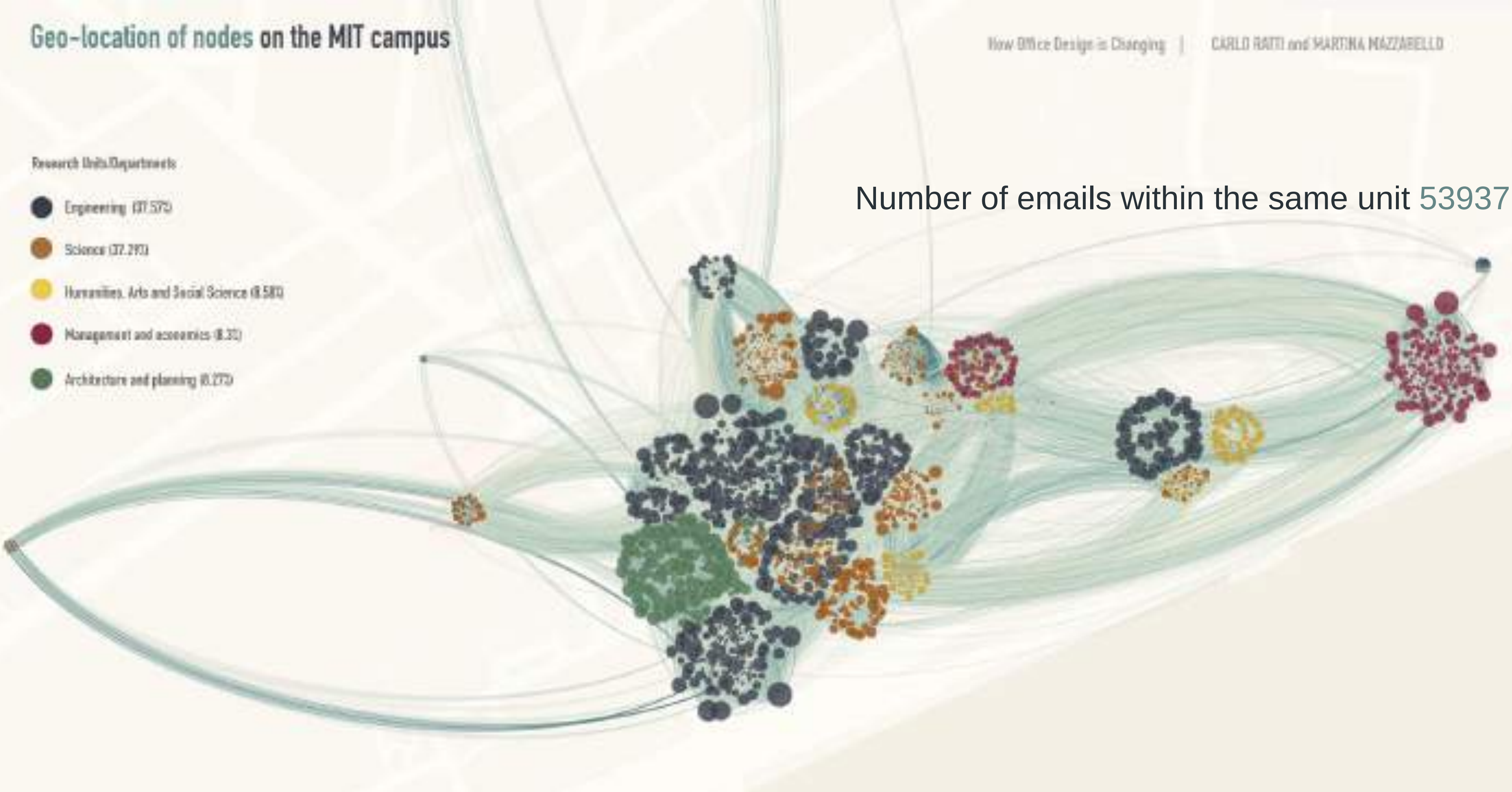
During COVID-19 emergency

(average between Apr 04th-Apr 19th)

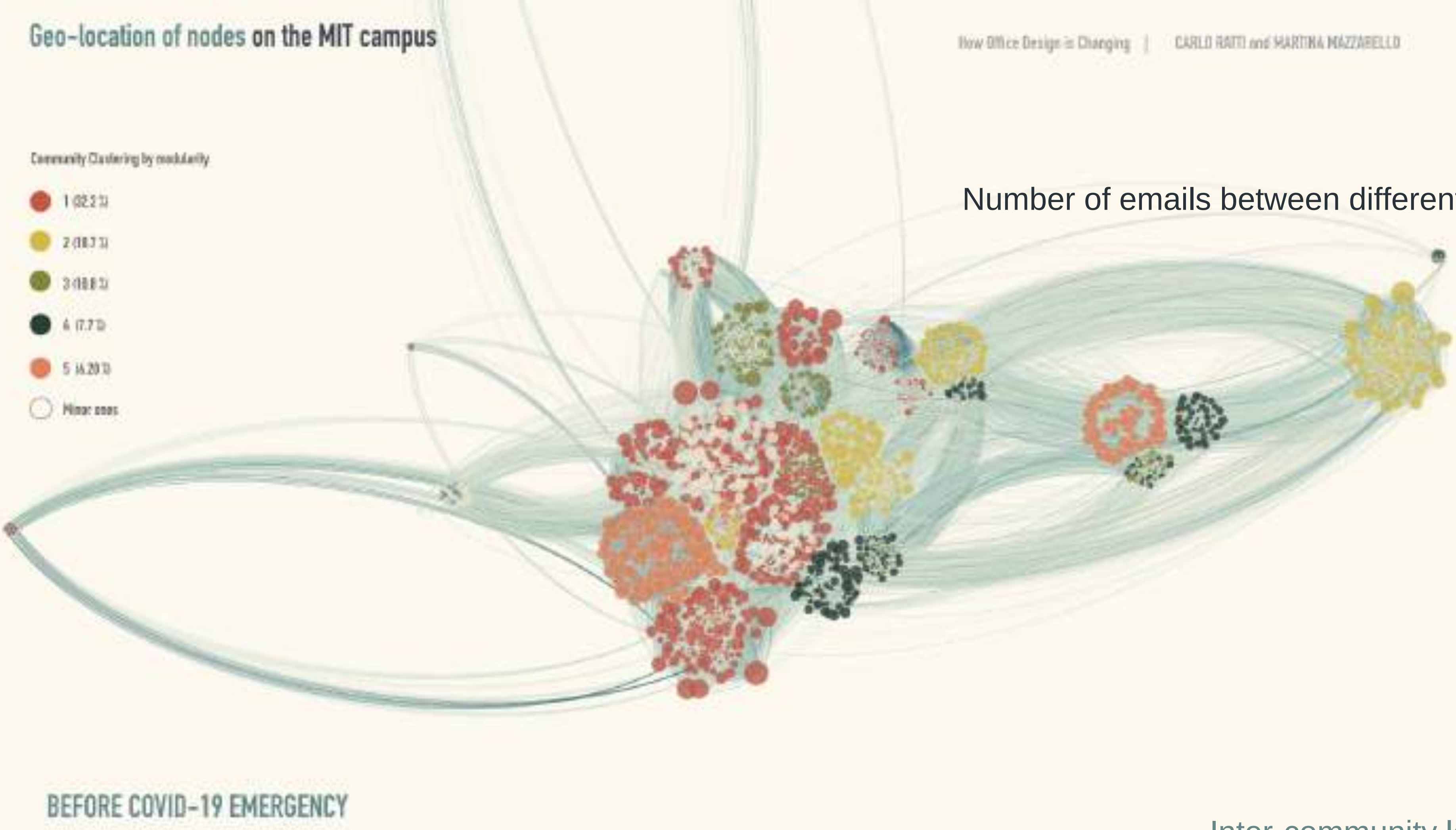
Before COVID-19 EMERGENCY

February 2020

Number of emails within the same unit 53937



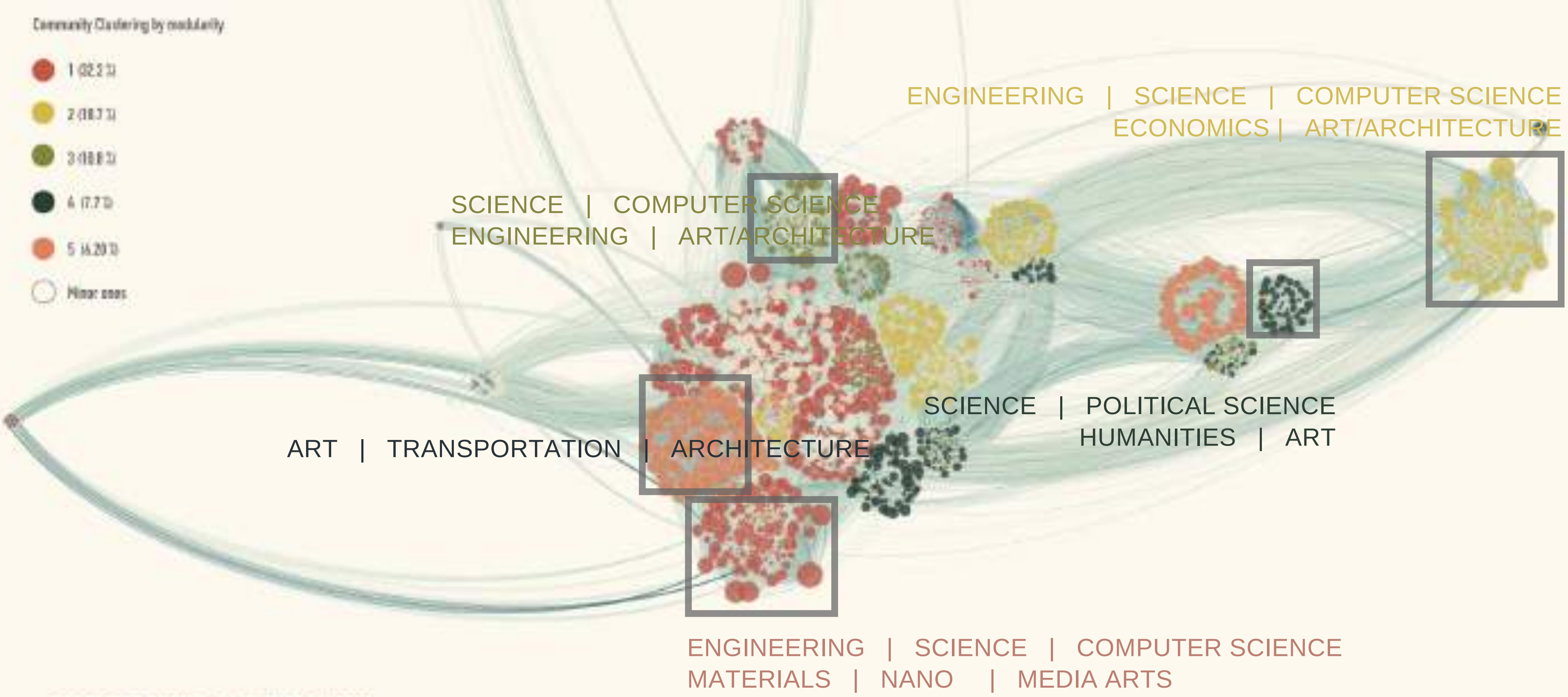
Intra-community level



Number of emails between different ur

Inter-community leve

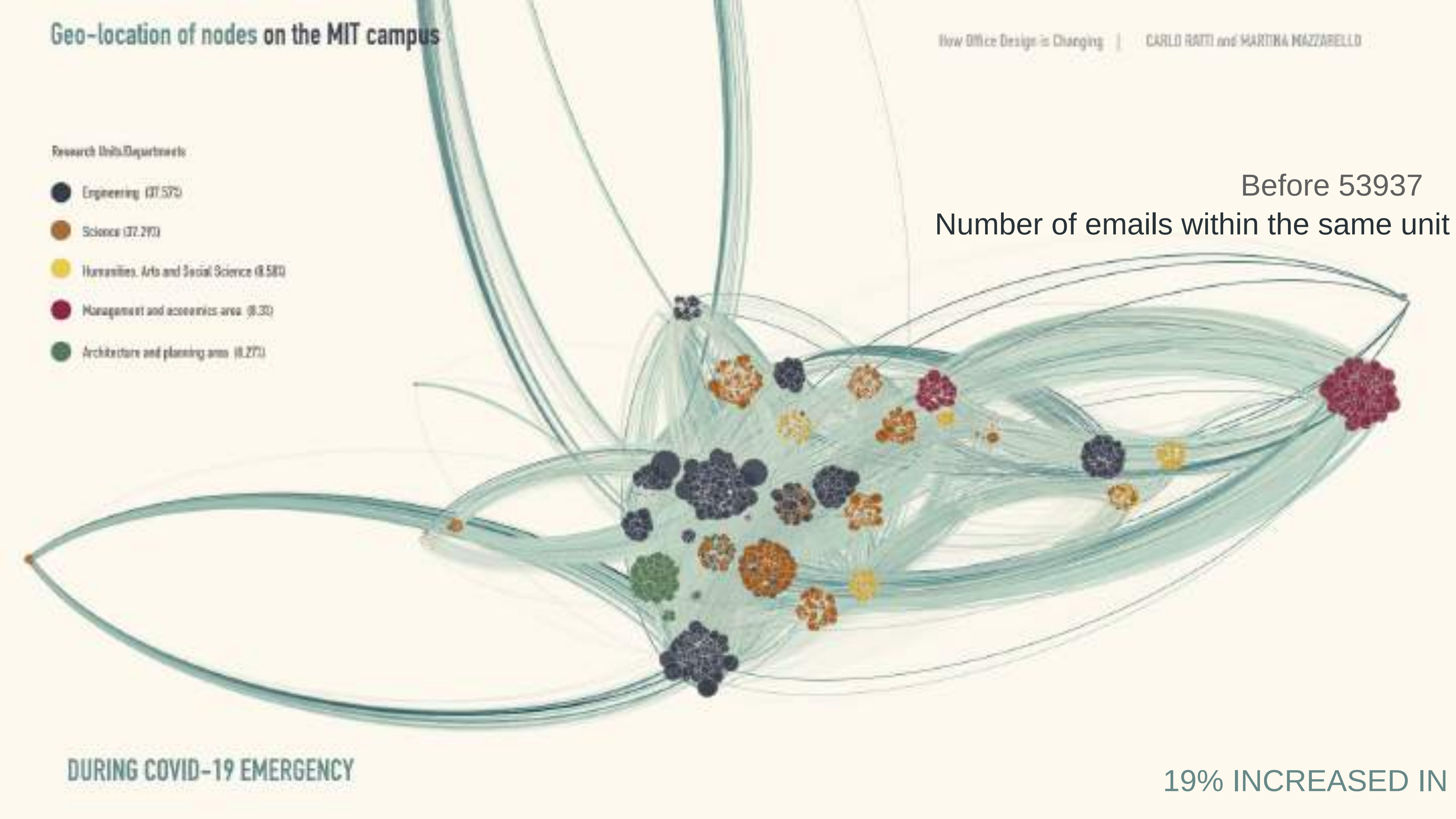
Geo-location of nodes on the MIT campus



BEFORE COVID-19 EMERGENCY

During COVID-19 EMERGENCY

April 2020



Before 53937

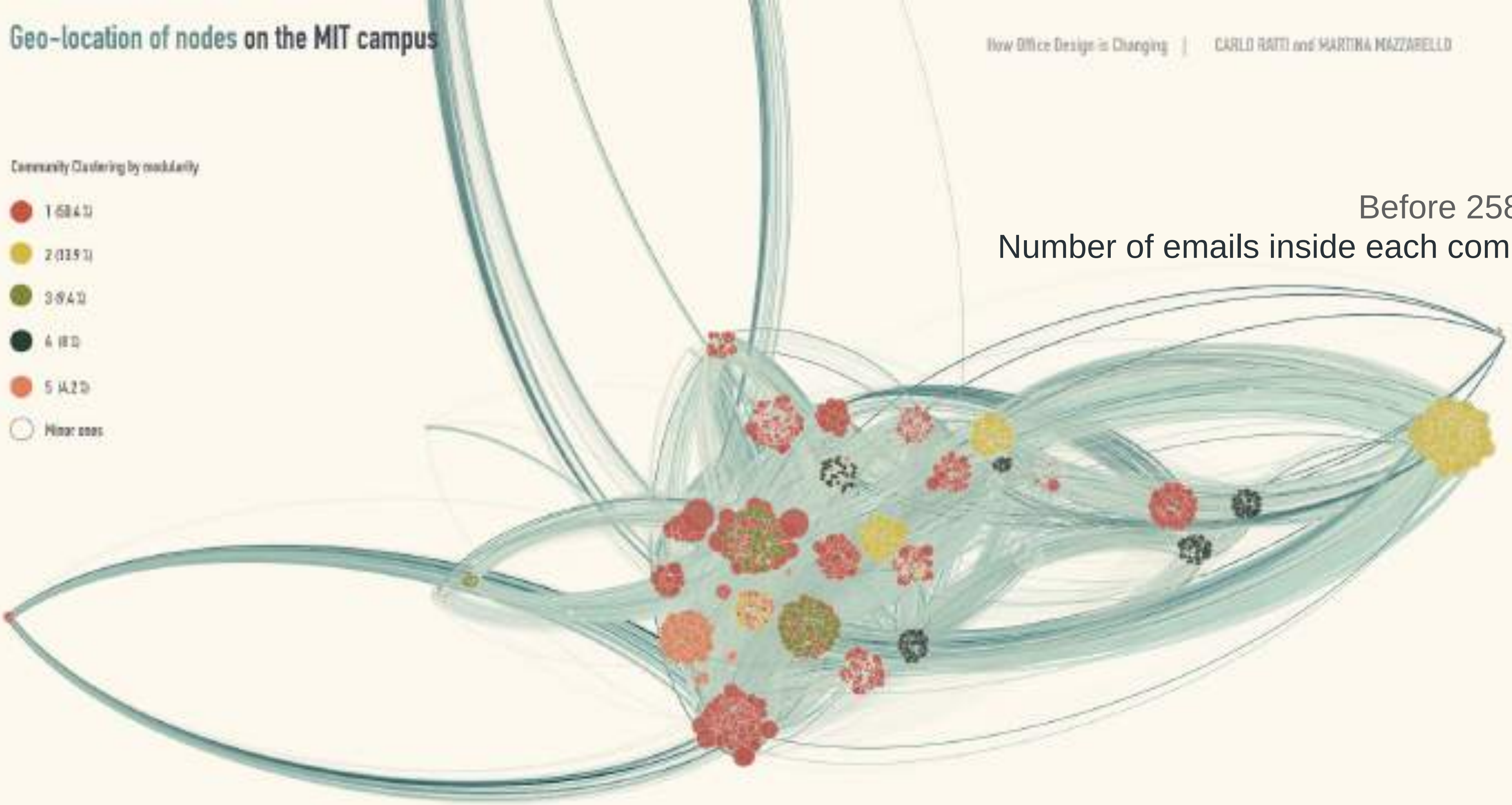
Number of emails within the same unit

19% INCREASED IN

Geo-location of nodes on the MIT campus

Before 25884

Number of emails inside each commu



DURING COVID-19 EMERGENCY

22% INCREASED IN

INCREASE at the similar level at the intra and inter-community level.

There is a stronger connection among same units in virtual communications.

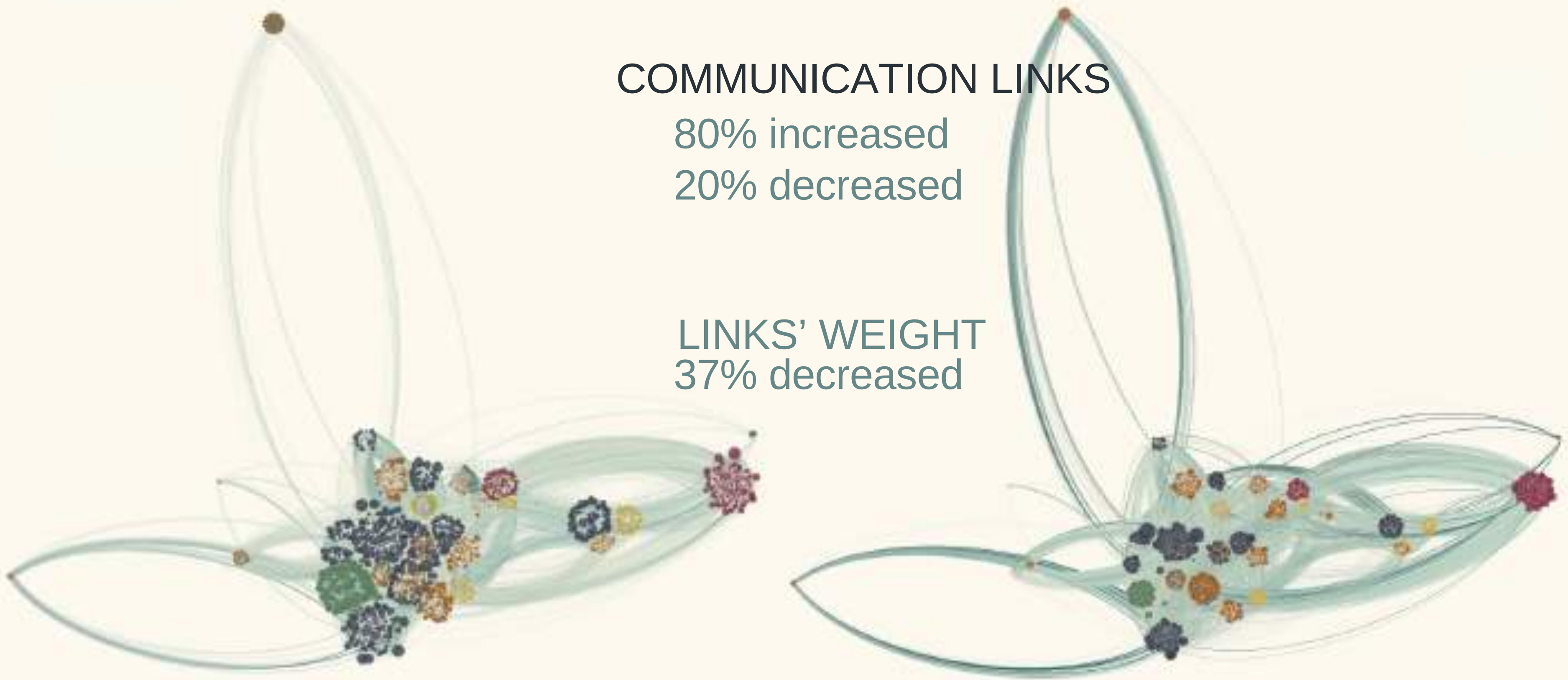
COMMUNICATION LINKS

80% increased

20% decreased

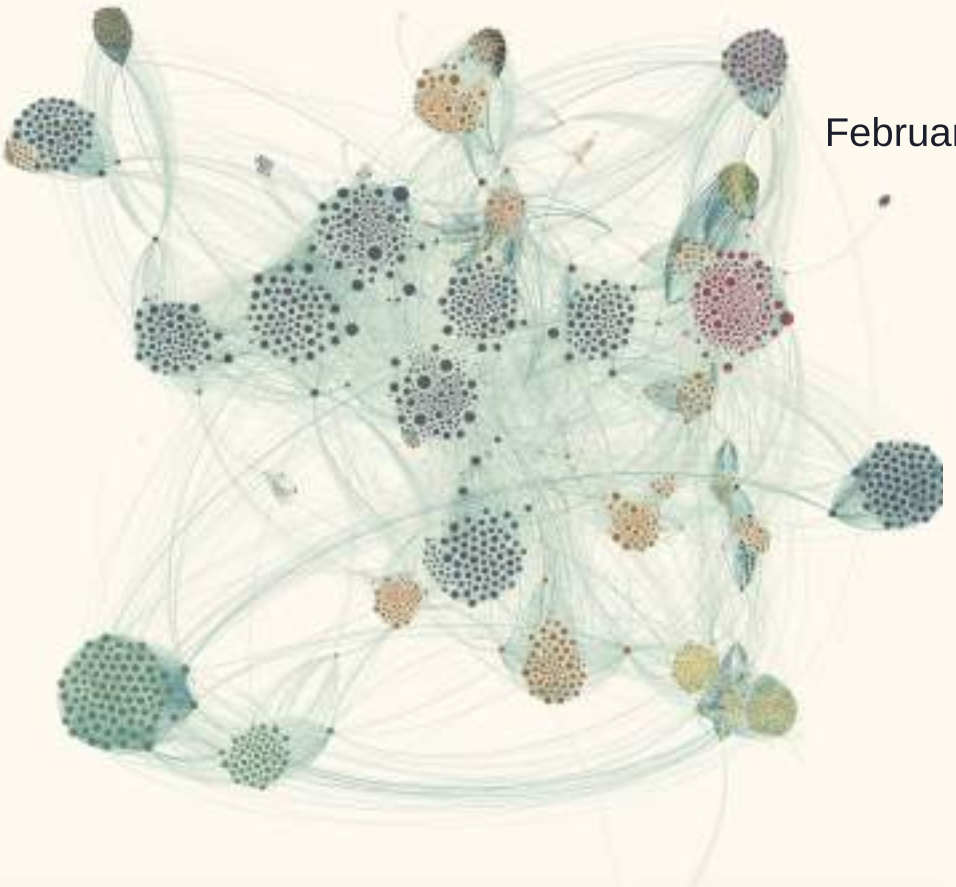
LINKS' WEIGHT

37% decreased



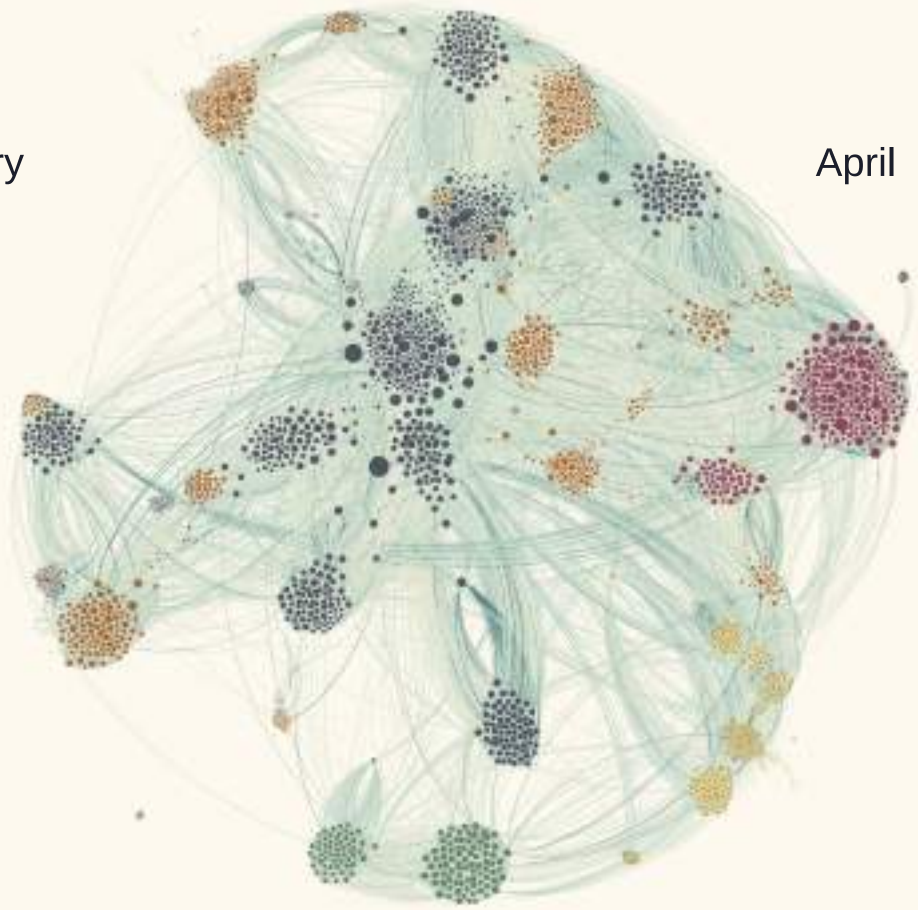
Comparison

How Office Design is Changing | CARLO RATTI and MARTI



February

BEFORE COVID-19 EMERGENCY



April

AFTER COVID-19 EME

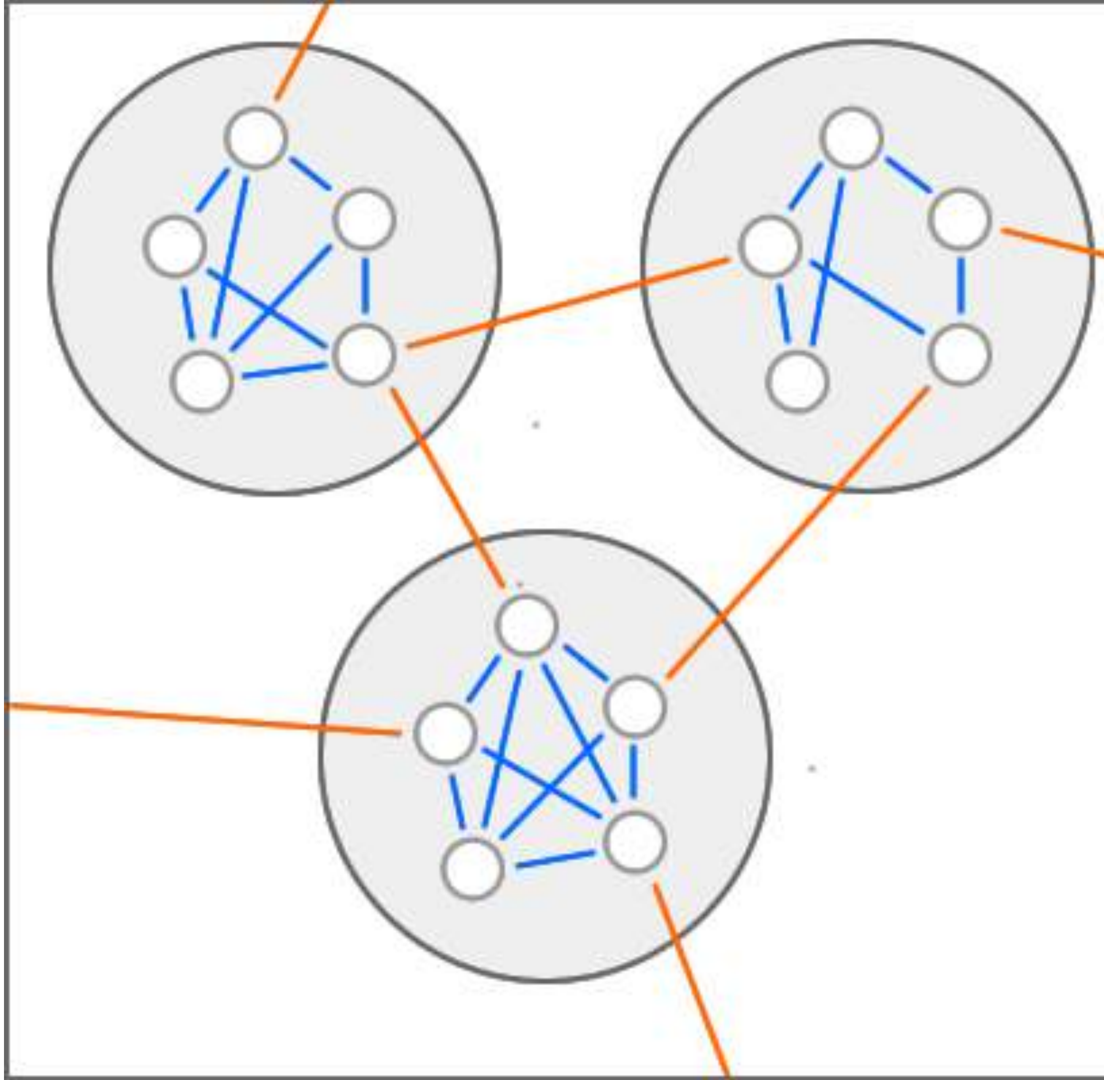
The Strength of Weak Ties[1]

Mark S. Granovetter
Johns Hopkins University

Analysis of social networks is suggested as a tool for linking micro and macro levels of sociological theory. The procedure is illustrated by elaboration of the macro implications of one aspect of small-scale interaction: the strength of dyadic ties. It is argued that the degree of overlap of two individuals' friendship networks varies directly with the strength of their tie to one another. The impact of this principle on diffusion of influence and information, mobility opportunity, and community organization is explored. Stress is laid on the cohesive power of weak ties. Most network models deal, implicitly, with strong ties, thus confining their applicability to small, well-defined groups. Emphasis on weak ties lends itself to discussion of relations *between* groups and to analysis of segments of social structure not easily defined in terms of primary groups.

A fundamental weakness of current sociological theory is that it does not relate micro-level interactions to macro-level patterns in any convincing way. Large-scale statistical, as well as qualitative, studies offer a good deal of insight into such macro phenomena as social mobility, community organization, and political structure. At the micro level, a large and increasing body of data and theory offers useful and illuminating ideas about what transpires within the confines of the small group. But how interaction in small groups aggregates to form large-scale patterns eludes us in most cases.

I will argue, in this paper, that the analysis of processes in interpersonal networks provides the most fruitful micro-macro bridge. In one way or another, it is through these networks that small-scale interaction becomes translated into large-scale patterns, and that these, in turn, feed back into small groups.



Group/Network

Group members, because of their frequent interaction, tend to think alike over time. This reduces the diversity of ideas, and in worst-case scenarios leads to "groupthink"

Weak Ties

Weak ties are relationships between members of different groups. They are utilized infrequently and therefore don't need a lot of management to stay healthy. They lead to a diversity of ideas, as they tie together disparate modes of thought.

Strong Ties

Strong ties are relationships between people who work, live, or play together. They are utilized frequently and need a lot of management to stay healthy. Over time, people with strong ties tend to think alike, as they share their ideas all the time.

Are we losing weak ties, usually relates to our physicality?

FIRST RESULTS

bridges in last two weeks of Feb (pre covid): 111.0 +- 8.85

bridges in last two weef of April (post covid): 96 +- 6

HYPOTHESIS

—> Diversity is reinforced by physicality.

—> Diversity comes with serendipitous exchange - as unexpected encounters in the physical space at MIT.

FIRST RESULTS

—> Volume exchanged at the Intra-community level is 19% increased

—> Volume exchanged at the Inter-community level almost at the similar level.


Sella


C B A
VISTA 3
Sella
Sella

@senseable_city_lab, @crassociati

@ senseablecity, @crassociati

@ senseablecity, @crassociati