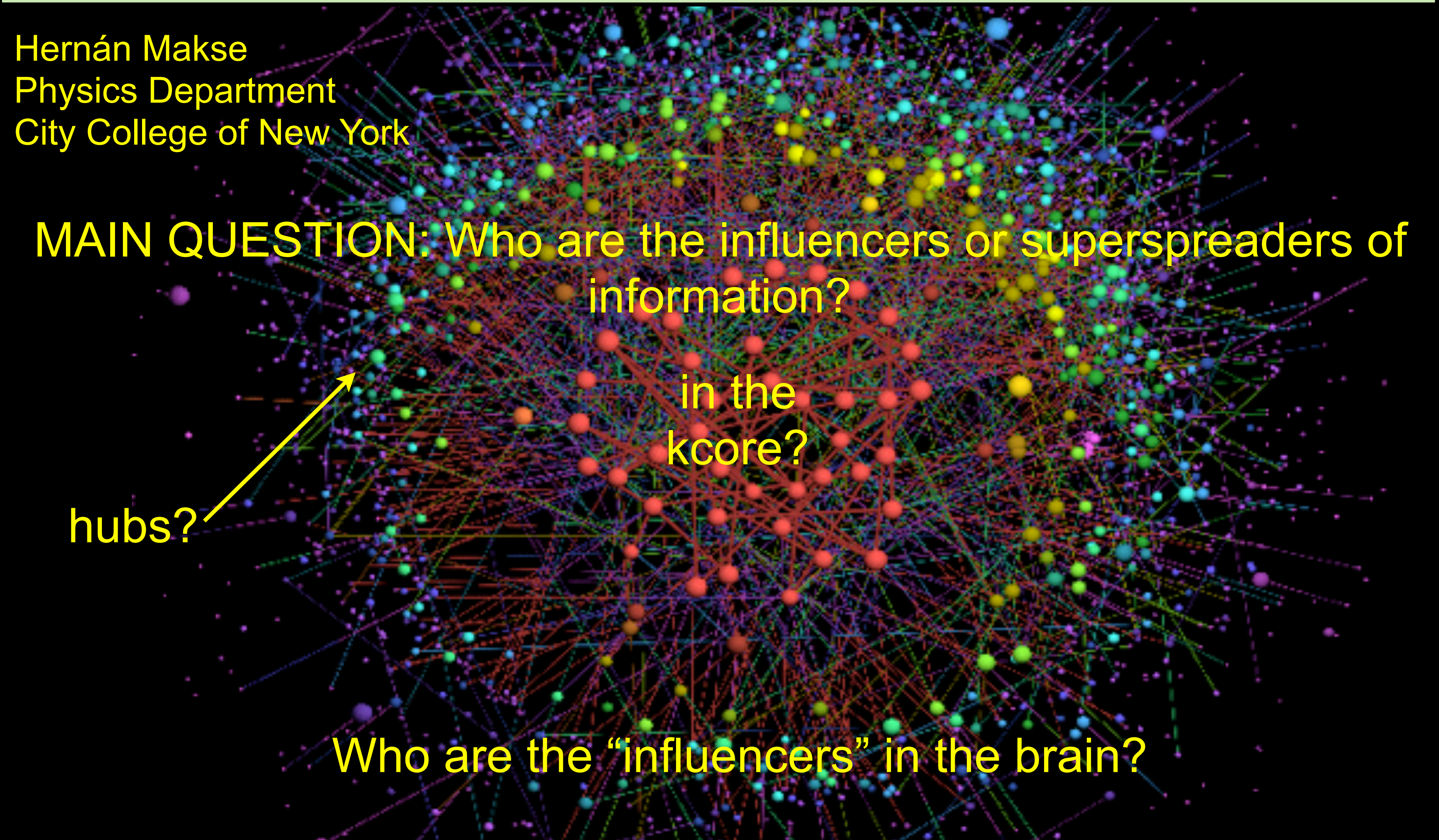
Networks, machine learning and big data: from predicting elections to understanding the brain

Hernán Makse
Physics Department
City College of New York



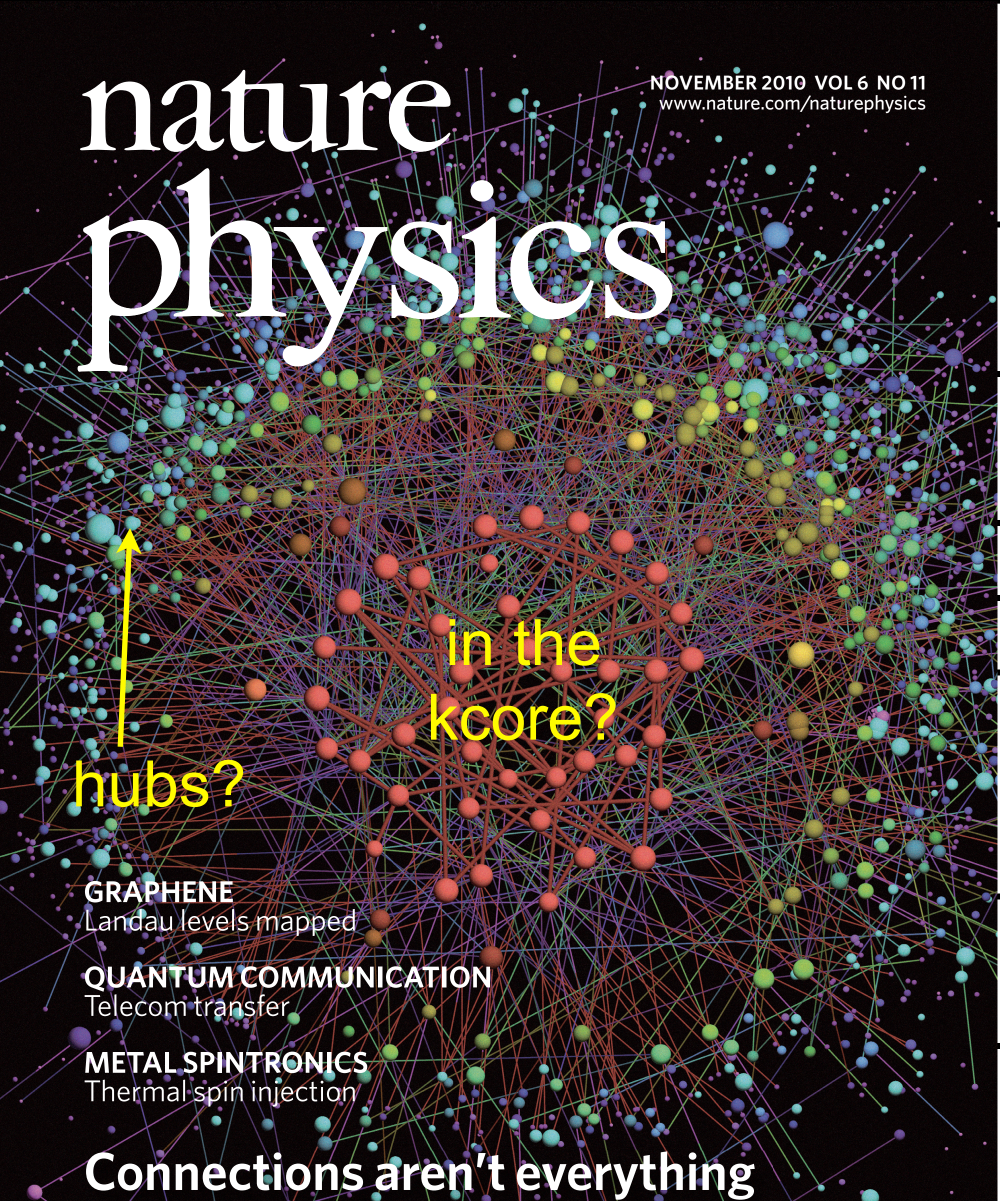
MAIN QUESTION: Who are the influencers or superspreaders of information?

in the kcore?

hubs?

Who are the “influencers” in the brain?

Longstanding Problem in Network Science



Kitsak, Gallos, Makse, Nature Phys (2010)

- Viral marketing: $$$
  Predicting trends social media
- Financial networks
  "too big to fail"
- Predict Stock markets
- Stop epidemic spreading
- Essential genes:
  gene regulation/
  protein networks
- Essential species:
  ecological networks
- Brain Networks:
  Essential nodes for integration

How to become influencer in social media? EASY

1. Funny baby faces videos

50 million hits

lindo bebito!!

How to become a New Yorker influencer? EASY

2. Funny dog faces videos

FUNNY DOG VIDEOS

50 million hits

lindos perritos!!

3. Most successful viral superspreading event in the history of humankind

Gangnam style video
by Mr Psy

as of today: 2 billion hits
(mainly teenagers)

This page refreshes every 20 minutes automagically for accuracy.

1,000,001,685

Estimate of Gangnam Style hitting 1 billion views:

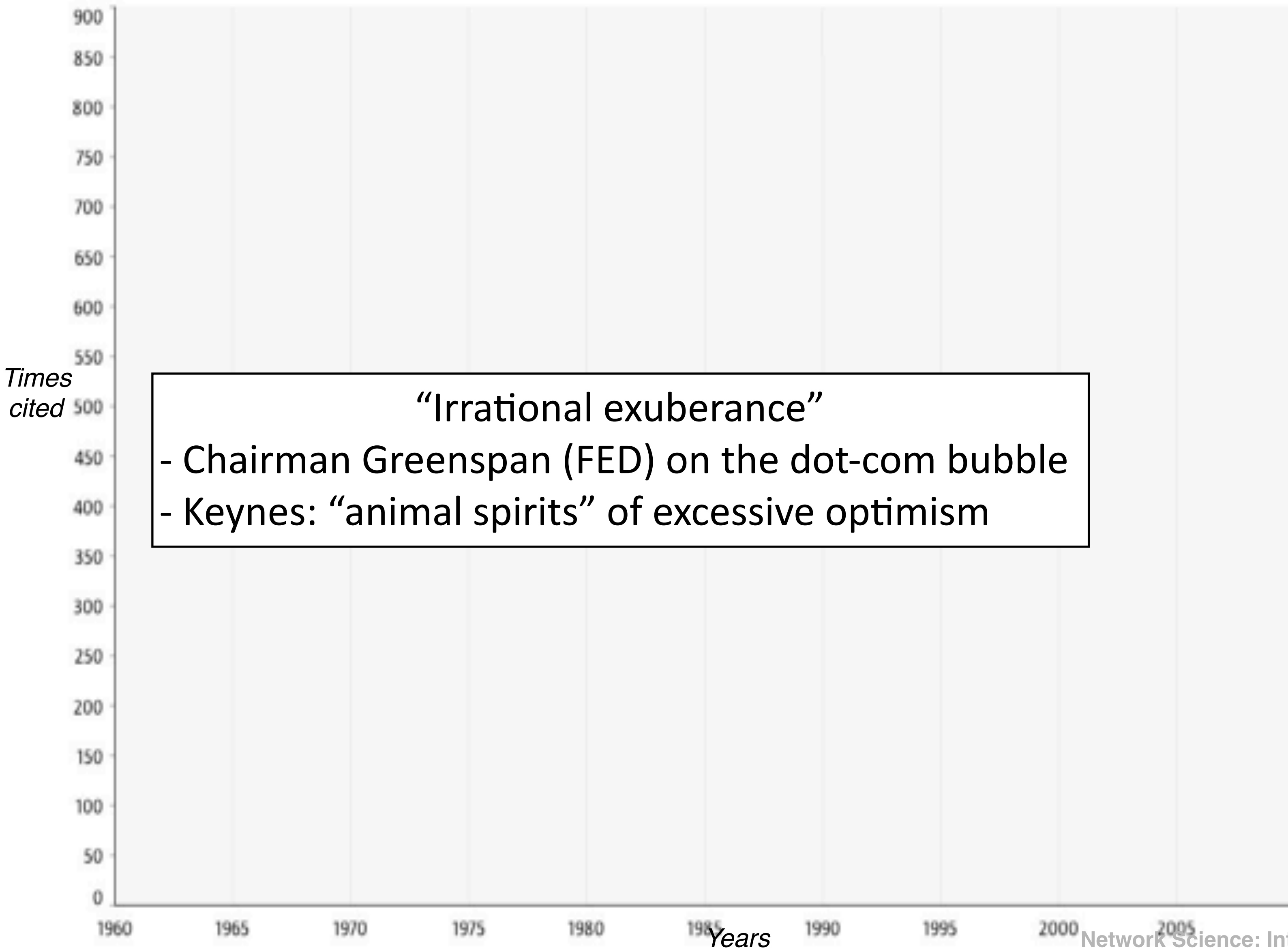
23 hours 59 minutes 44 seconds

December 21, 2012, 7:11 am PST / December 21, 2012, 10:11 am EST / December 21, 2012, 3:11 pm UTC
24 hour moving average: 105.4627 views per second

5. COMPLEX NETWORK SCIENCE: superspreading of ideas

- Analogous to herding behavior in the stock market

Courtesy of Gene Stanley



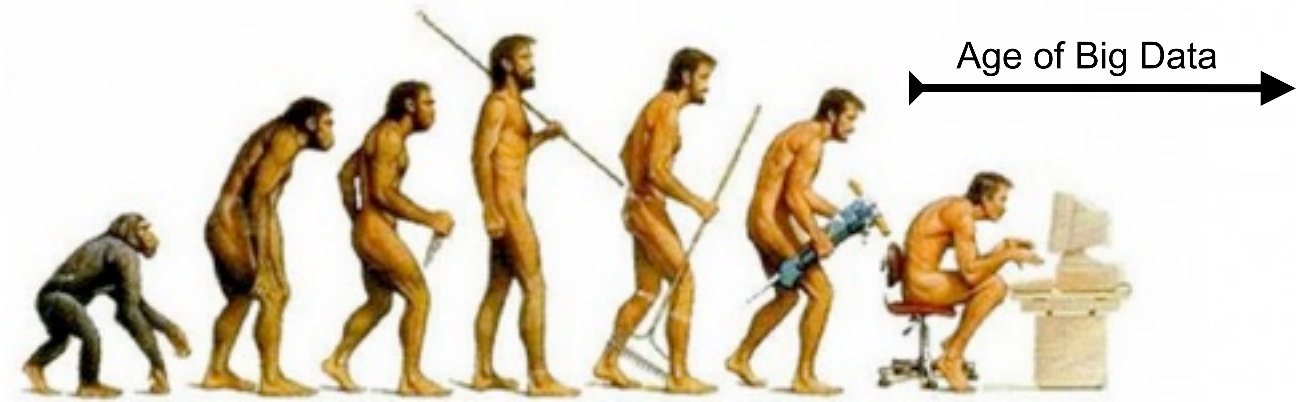
"Irrational exuberance"

- Chairman Greenspan (FED) on the dot-com bubble
- Keynes: "animal spirits" of excessive optimism

THE ANSWER:
Understanding BIG DATA

What is the Problem with Big Data?

Eric Schmidt (CEO Google): “Every two years we create as much information (5 exabytes) as we did from the dawn of civilization until 2003”



THE QUESTION ARISES:

What happened in the last two years?

Did we all get clever all of a sudden?

Most probably not

Two evidences (before Nov 2016):

Evidence #1: The USA Presidential Primary Election Debates

Evidence #2: Peter Thiel (founder PayPal)

WHY IS THAT?

THE AGE OF BIG DATA

OR

THE AGE OF BIG DATA JUNK?

The age of “fake news”:
We are drowning in information but starving for knowledge

Pipeline: Big Data - Machine Learning - Networks—-> Influencers

- Kitsak, Gallos, Makse, Nature Phys (2010)

-Morone, Makse Nature (2015)

-Bovet, Morone, Makse, arxiv.org (2017)

-Morone, Min, Roth, Makse, PNAS (2017)

-Luo, Morone, Makse, Nature Comm (2017)

INFLUENCERS

BIG DATA → MACHINE LEARNING → NETWORK

↓

INFLUENCERS ← DIMENSIONAL REDUCTION

(INFLUENCERS → BIG DATA)

THE SOLUTION: REDUCE BIG DATA TO A FEW INFLUENCERS

MINIMAL

INFLUENCERS:

the needle in the haystack

NP-hard Maximization

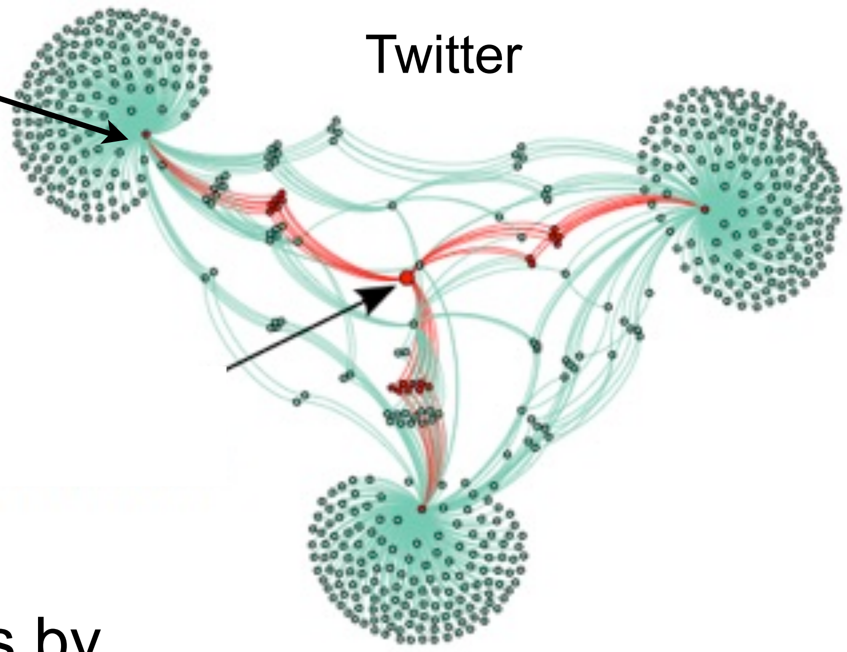
of Influence Problem:

your influence is not yours, it depends on everyone else

How Google solved this problem?

Typical approach: Brute-Force (heuristics)

Influencers = hubs (scale free theory)



Pres Obama: 55M followers

Lady Gaga: 45M followers

Very few: 1 percenters….

We want to capture influencers among the 99-percenters

Other heuristics: ranking the nodes by

PageRank (Google): the largest eigenvalue of adjacentcy matrix, betweeness, eigenvector, closeness centralities, kcore,, etc..

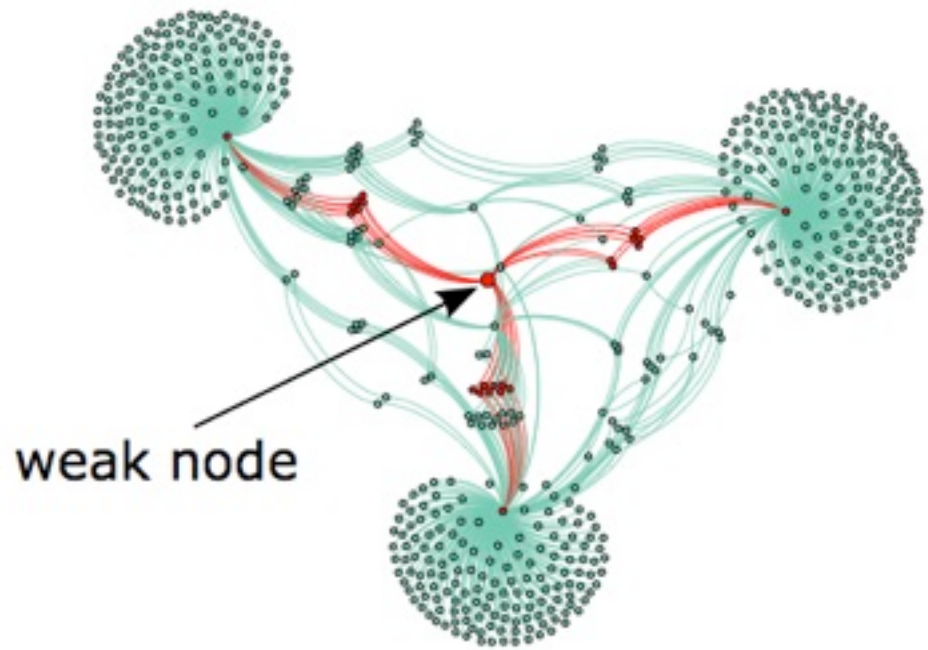
Problems: heuristics do not maximize any function of influence

Our approach

Inspired by French mime Marcel Marceau:

"Making visible the invisible"

Collective optimization theory unravels the strength of "weak nodes"

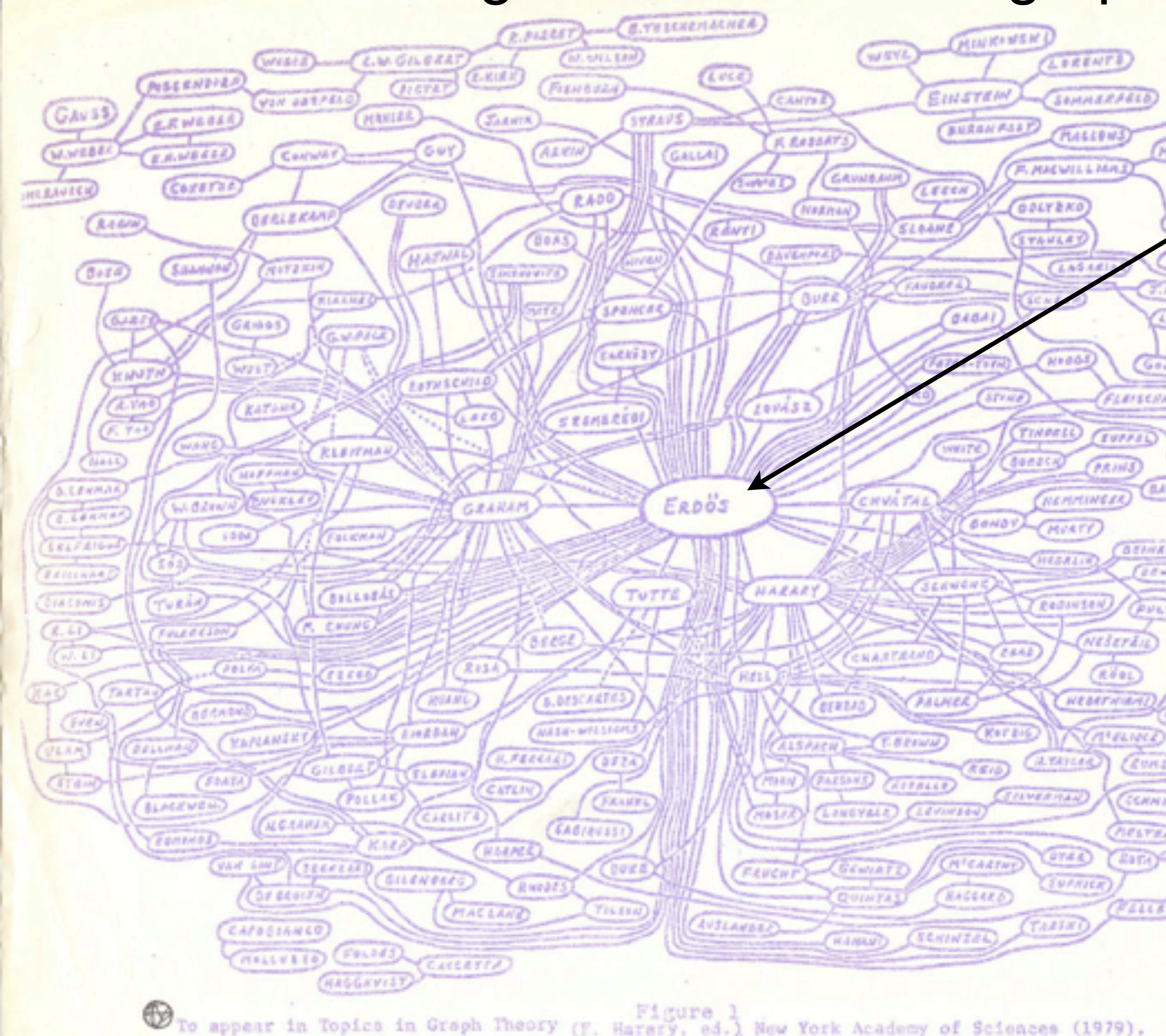


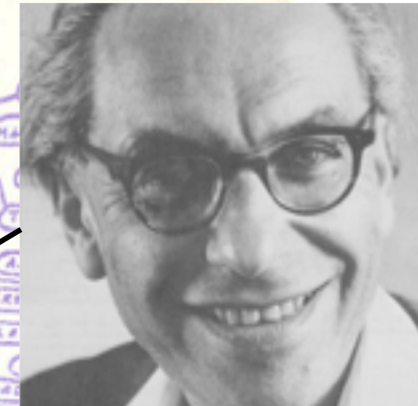
Granovetter Social Theory (1973)

"The strength of weak ties"

Pál Erdös (1913-1996) --> 1400 papers with 600 collaborators

Founding father of modern graph theory





Erdos number

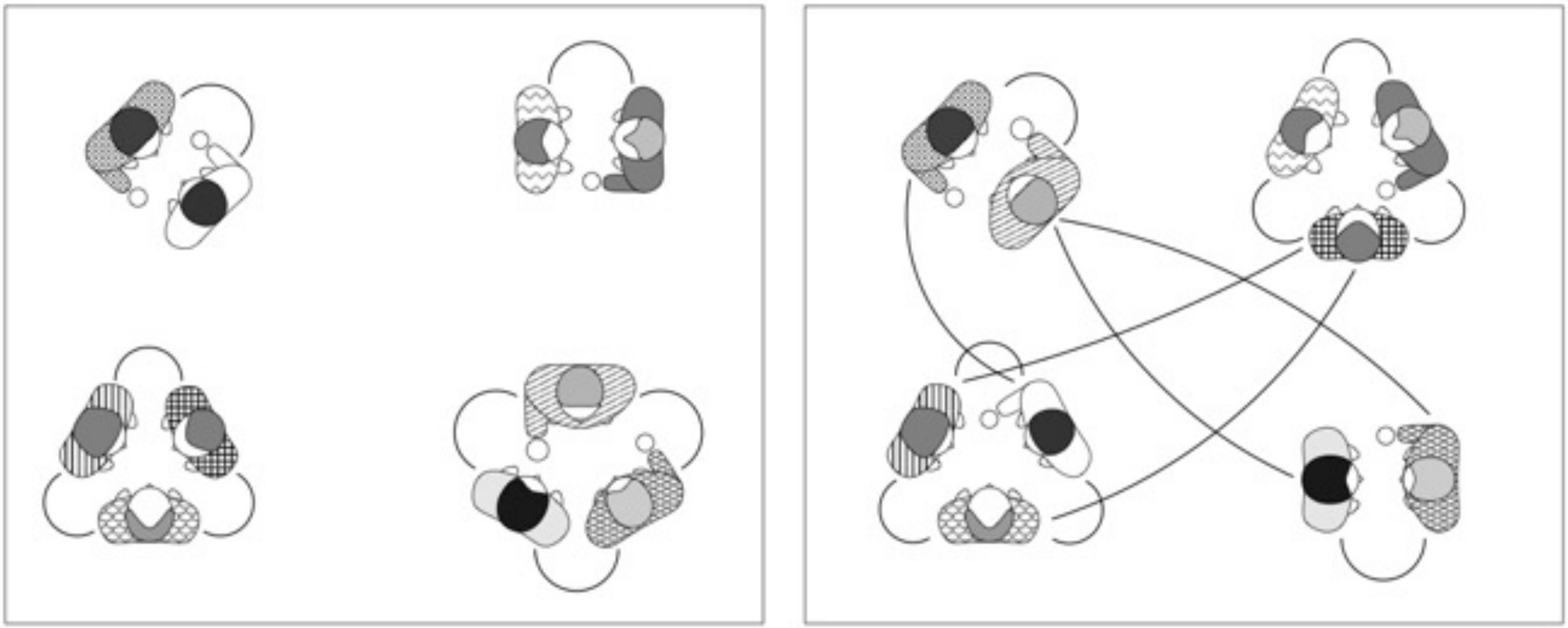
Einstein:ER=2

Nobel laureates:
ER = 1 or 2

TUTORIAL: Emergence of giant connected component

Roof Top Party in New York City with N people

k=degree



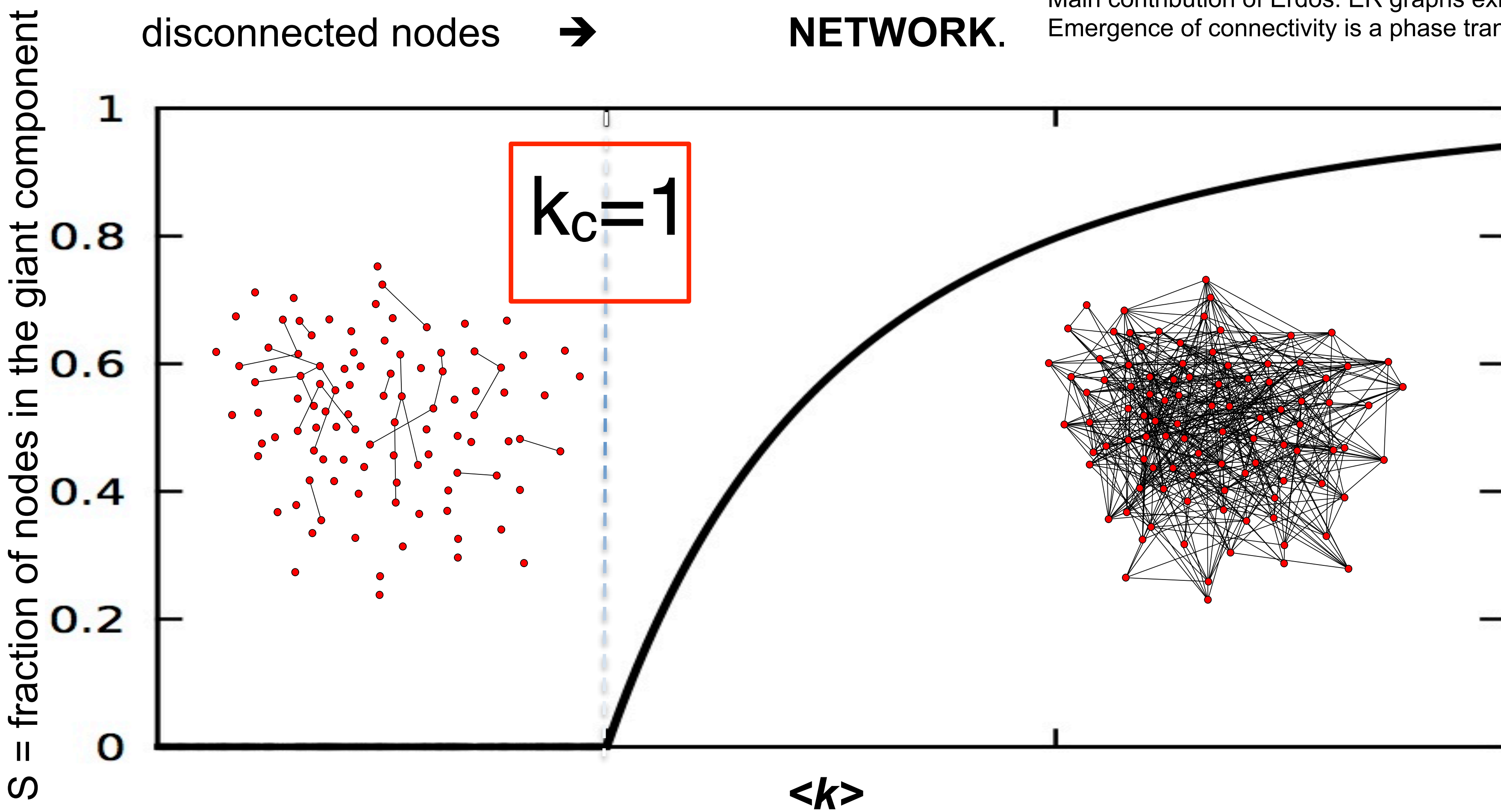
k=0 → k=2 → k=10 → k=N-1

At what time you form a connected component?

EVOLUTION OF A RANDOM NETWORK --- PERCOLATION

Main contribution of Erdos: ER graphs exhibit PT
Emergence of connectivity is a phase transition

disconnected nodes ➔ NETWORK.



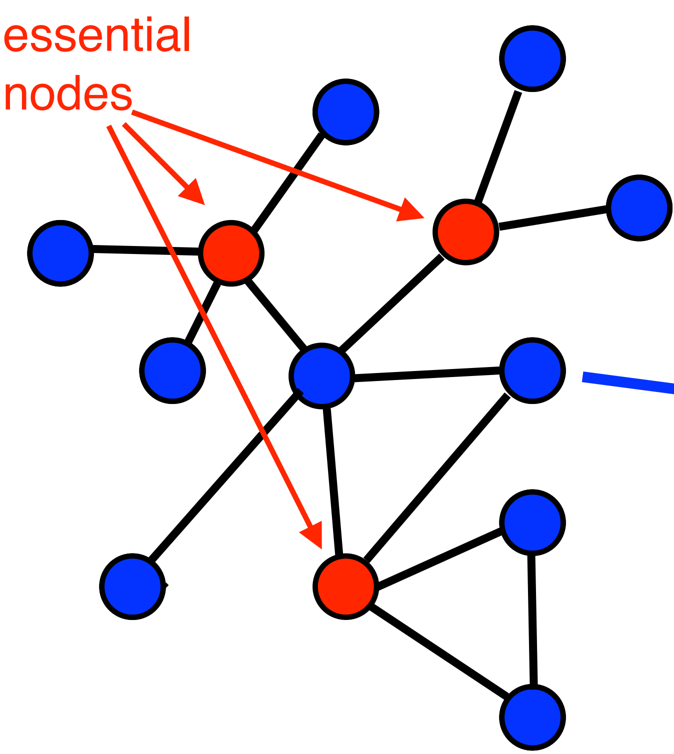
How does this transition happen?

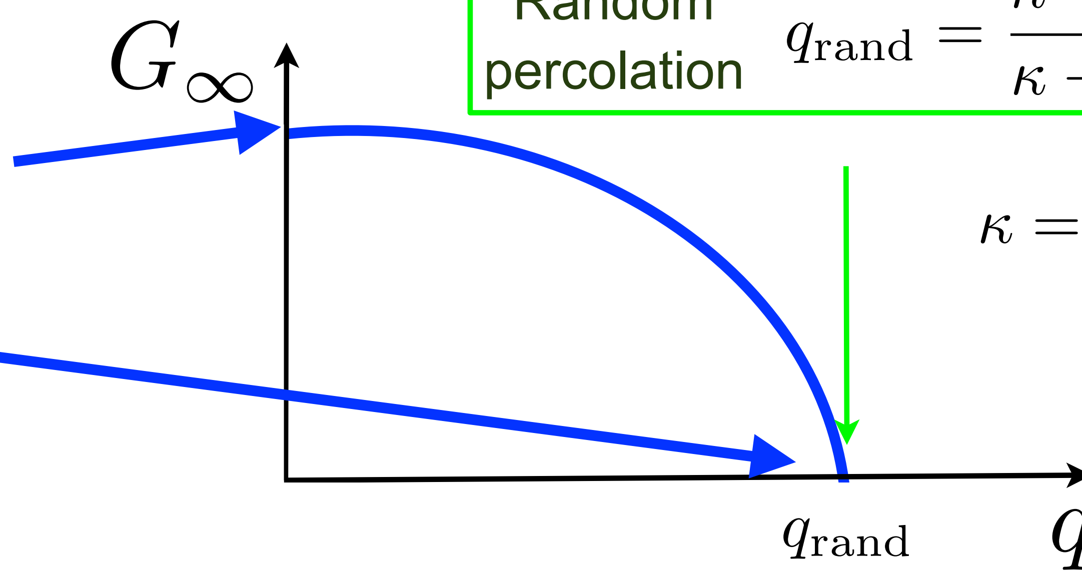
Network Science: Random Graphs 2012

Who are responsible for the emergence of the giant component?

Essential nodes are defined via graph percolation theory

Erdos-Renyi theory of percolation (ER networks, 1960)





Random percolation $q_{\rm rand} = \dfrac{\kappa - 2}{\kappa - 1}$

$$\kappa = \frac{\langle k^2 \rangle}{\langle k \rangle}$$

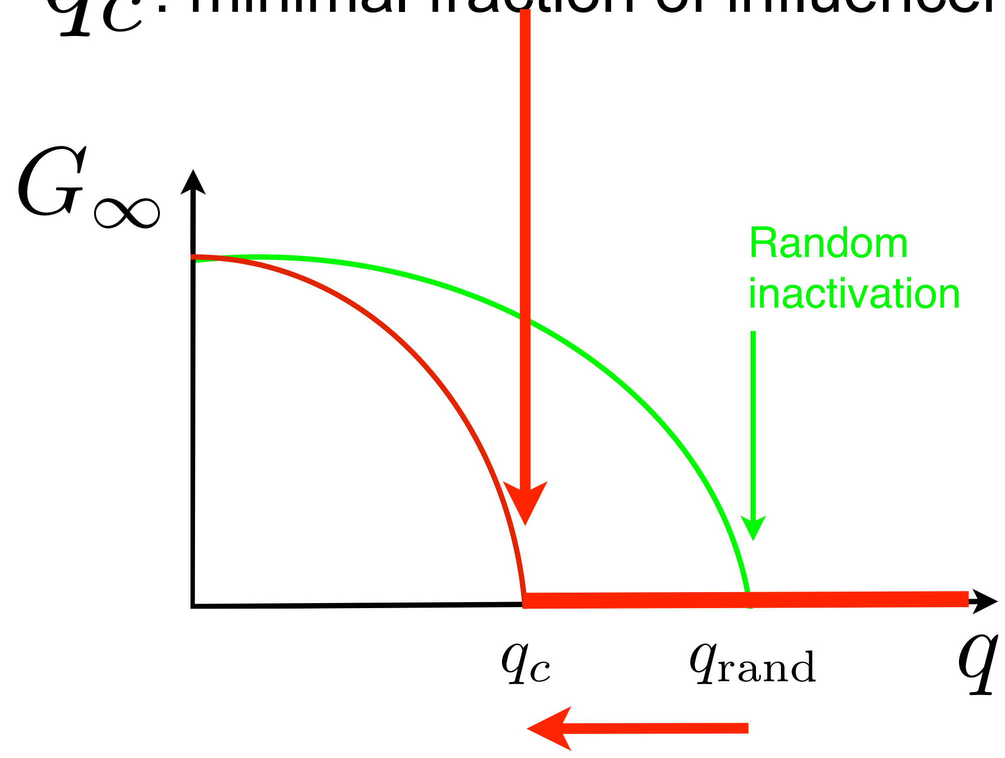
$q_{\rm rand} \approx 1$ scale-free networks

G_∞ Giant connected component versus fraction of inactivated nodes q

Influencers = Optimal Percolation

Morone, Makse, Nature (2015)

q_c : minimal fraction of influencers



Essential nodes: minimal set of nodes qc that disintegrate the giant connected component upon removal

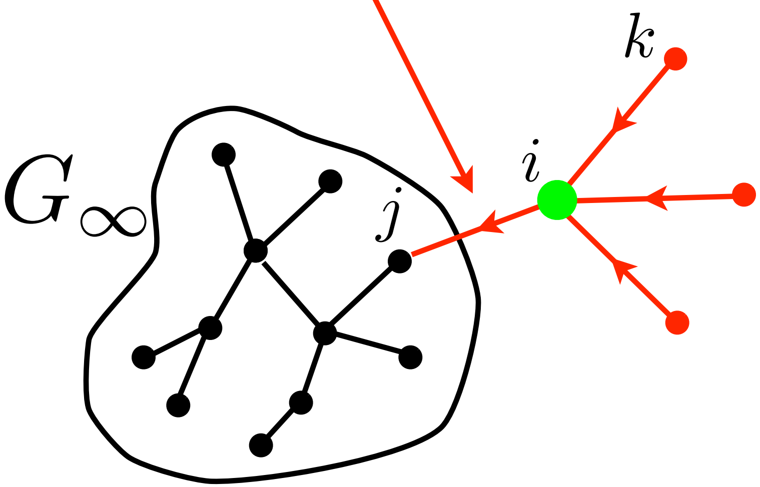
Targeted attack: Albert, Barabasi, Nature (2000)
Maximization of Influence, Kempe, Kleinberg (2003) (NP-hard, computer science, sociology)

Message passing to calculate G

approximation = local tree (no loops)

node i sends a message to node j:

membership to giant component



$n_i = 0$ node inactivation

$n_i = 1$ node active

Message passing equation in a sparse network

$$\nu_{i\to j} = n_i \left[1 - \prod_{k\in\partial i\setminus j} (1 - \nu_{k\to i}) \right]$$

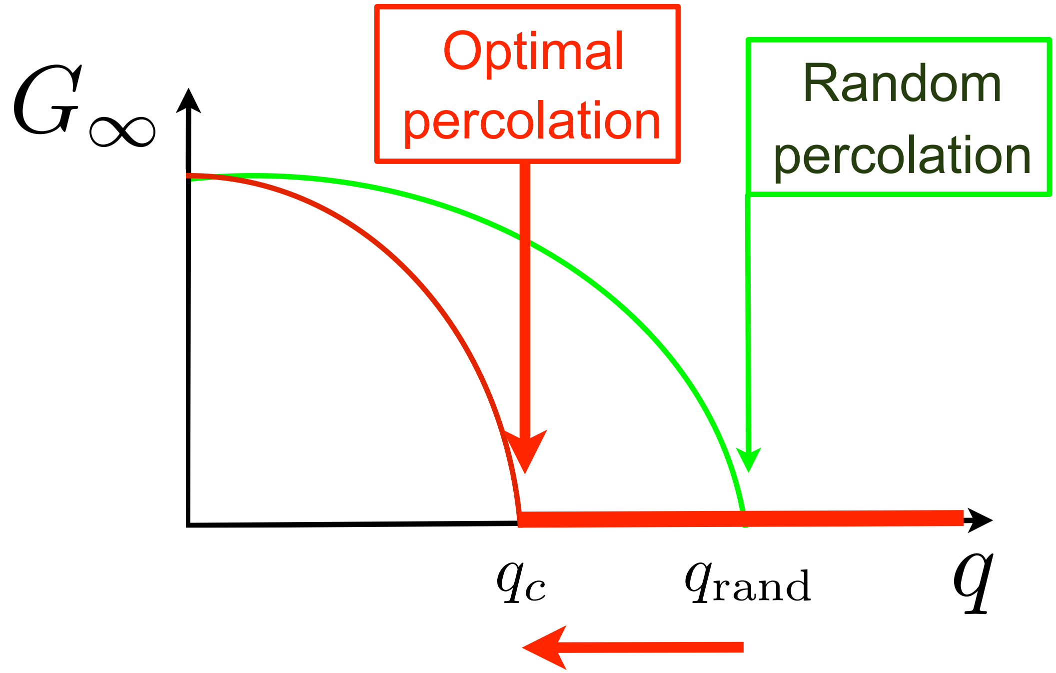
Order parameter = Prob to belong to giant component: G_∞

Optimal Percolation = minimize q_c

q_c : minimal fraction of influencers to destroy the network

NP-hard problem:

Transform the problem into a stability problem



Strategy = minimize the giant component

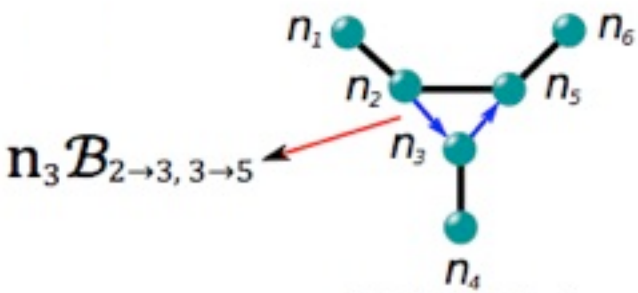
or

Minimize q_c = find the minimal influencers until the solution

$G_\infty = 0 \rightarrow \{\nu_{i\rightarrow j} = 0\}$ becomes unstable

Stability of $G_\infty = 0$ is given by largest eigenvalue of non-backtracking matrix

$$\left.\frac{\partial \nu_{i\to j}}{\partial \nu_{k\to\ell}}\right|_{\nu_{i\to j}=0} \equiv n_k \mathcal{B}_{k\to\ell, i\to j}$$



Non-Backtracking Matrix

2M x 2M matrix

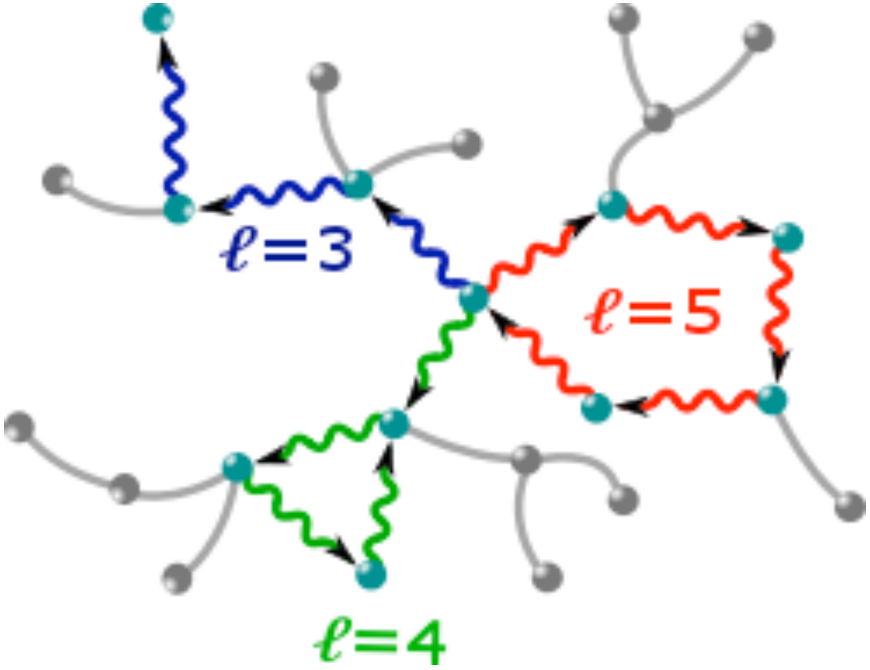
Solution is stable when the largest eigenvalue of the modified NB matrix:

$$\lambda_{\max}(\mathbf{n}, q) \leq 1$$

Finding the influencers = finding the nodes that minimizes the largest eigenvalue of the modified NB matrix:

$$\min_{\mathbf{n}} \lambda_{\max}(\mathbf{n}, \mathbf{q_c}) = \mathbf{1}$$

Essential superspreaders are the optimal non-backtracking random walkers



Non-backtracking walk of length ℓ: a walker that cannot immediately come back

- Second largest eigenvalue of NB is also optimal for community detection. Krzakala PNAS (2013), Newman PRE (2013)
- In contrast, most heuristics are based on the adjacency matrix which measures only regular random walks: PageRank largest eigenvalue A_{ij}

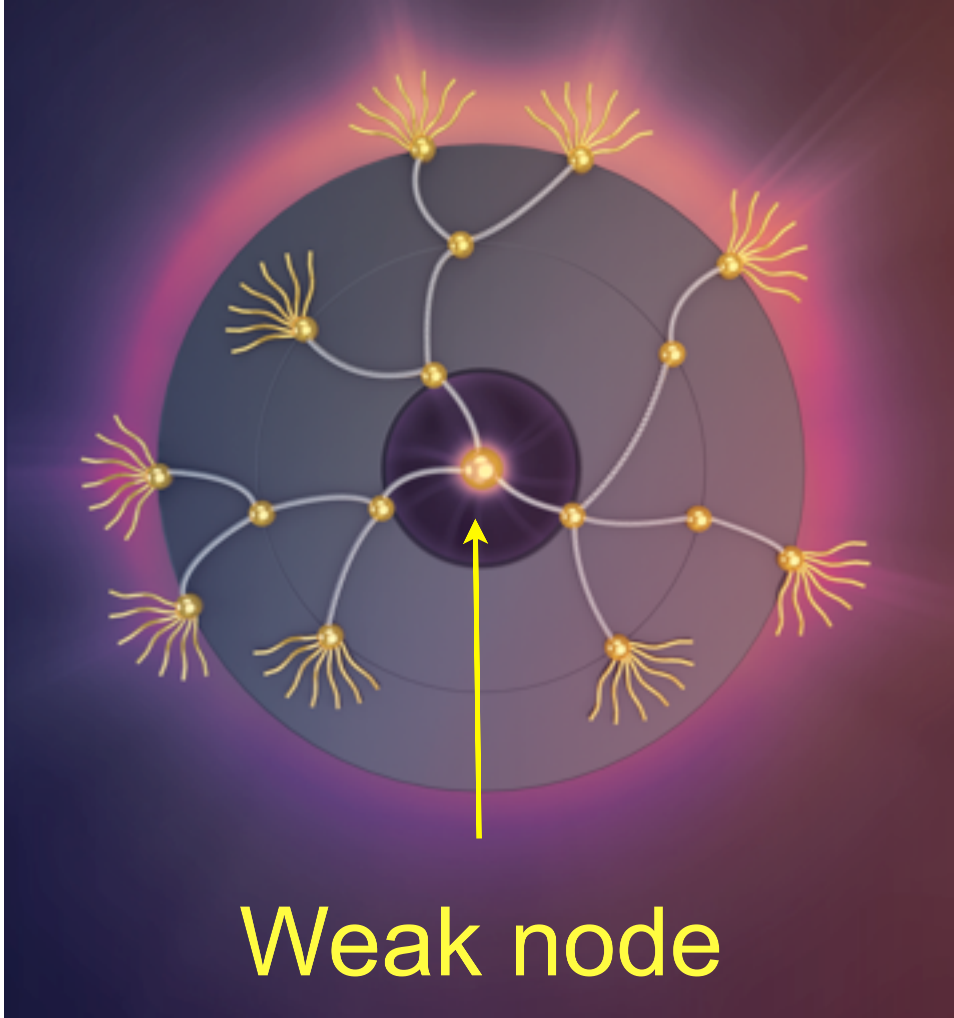
Essential nodes for integration: weak nodes and Collective Influence Algorithm: CI

$$\mathrm{CI}_\ell = (k_i - 1) \sum_{j \in \partial Ball(\ell)} (k_j - 1)$$

Optimization theory identifies a new class of influencer neglected by hub ranking and Pagerank

Weak node: a low degree node surrounded by hierarchical coronas of hubs at level ℓ

Related to Granovetter theory "Strength of weak ties" (1973) in Sociology



Next, we address the question that will doubtless arise:

Is all this mathematical gibberish of any real use?

Four applications:

1. Influencers in Twitter
2. +Machine learning in Twitter. Predicting elections: Trump vs Clinton
3. Marketing campaign from Big data mobile phone networks
4. Brain: Erasing your memories

1. Twitter Search Engine for Influencers

kcorelab.com

KCORE ANALYTICS

KCORE WHAT WE DO WHO WE ARE CASE STUDY PRESS NEWS CONTACT LOGIN

CCNY DREAM TEAM:

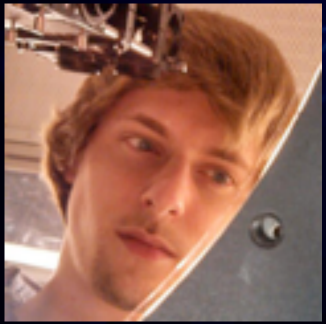
Search Engine for Influencers

Twitter Influencers

Flaviano Morone

Hernan Makse

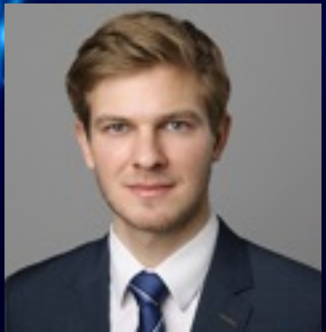
George Furbish



Andrea Morone

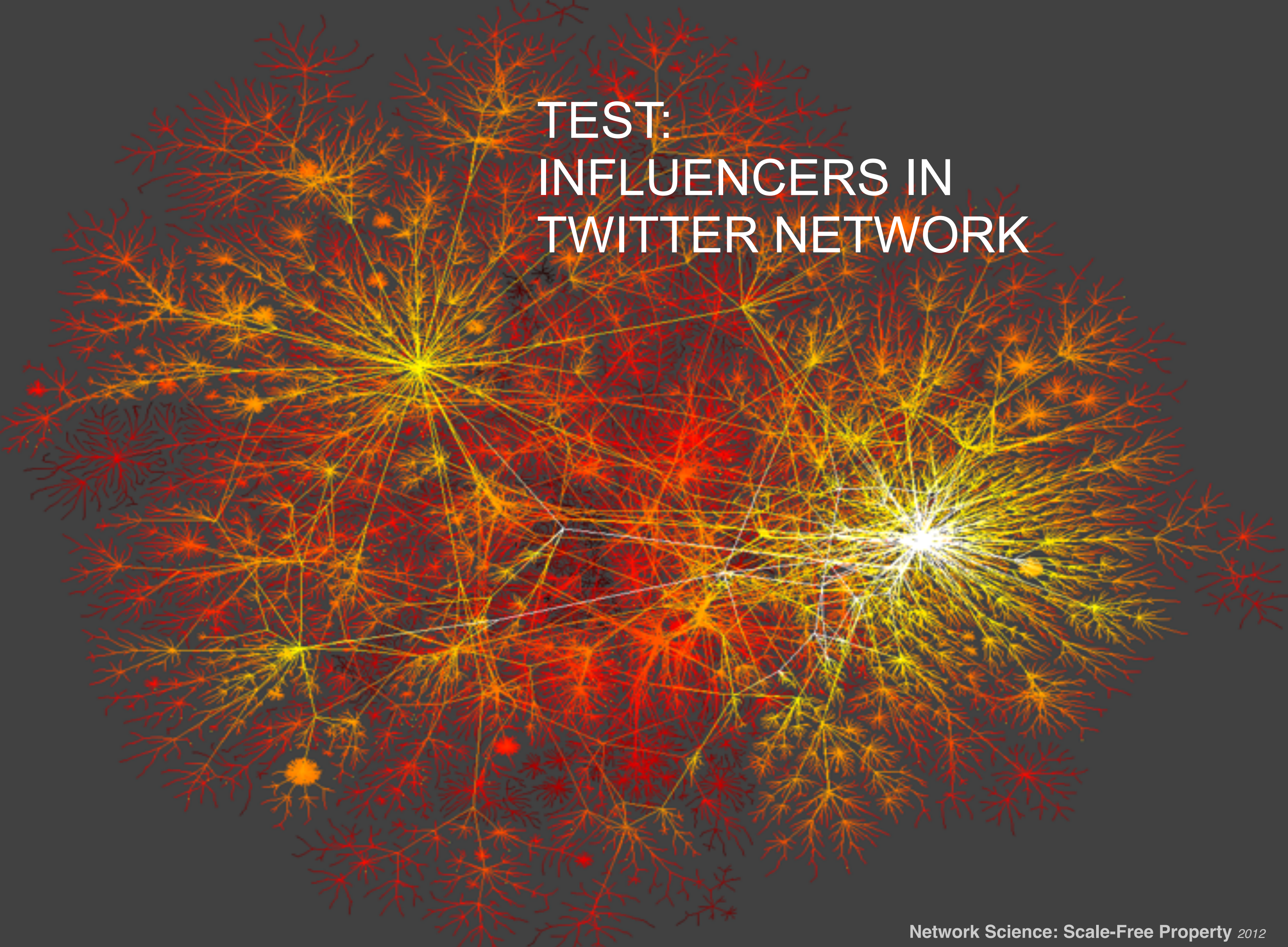
Alex Bovet

Kevin Roth

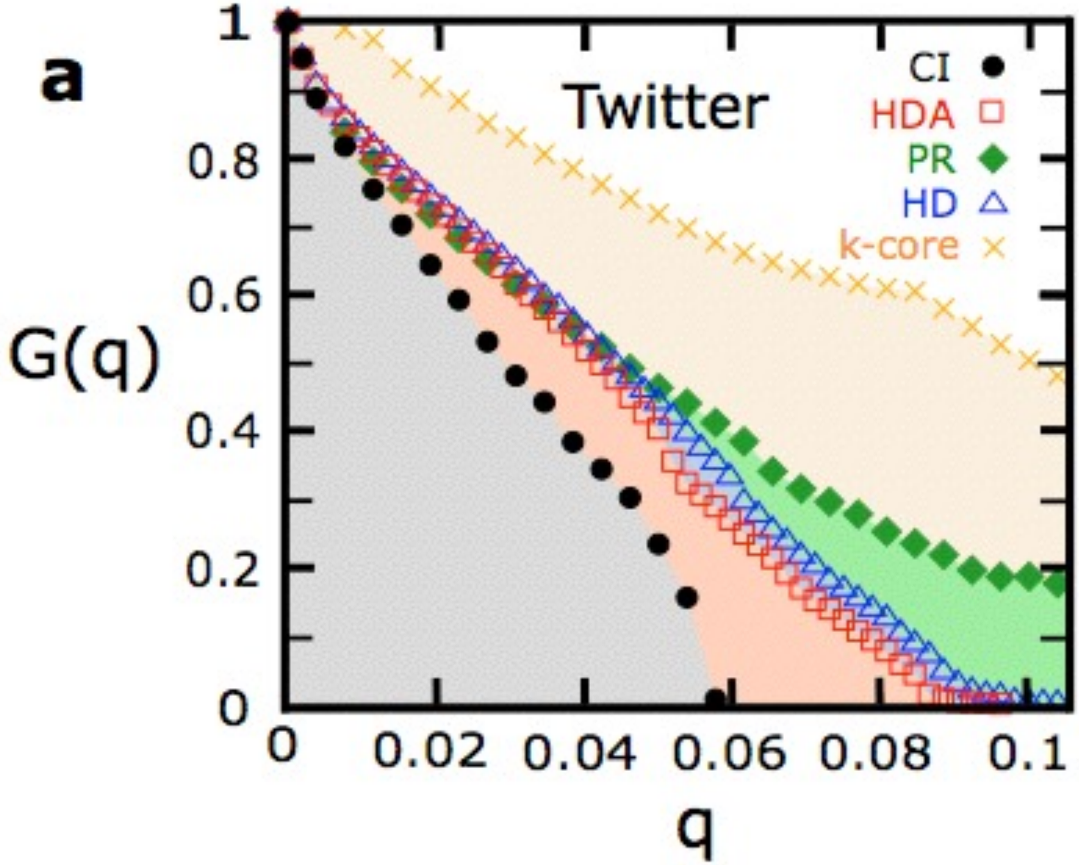


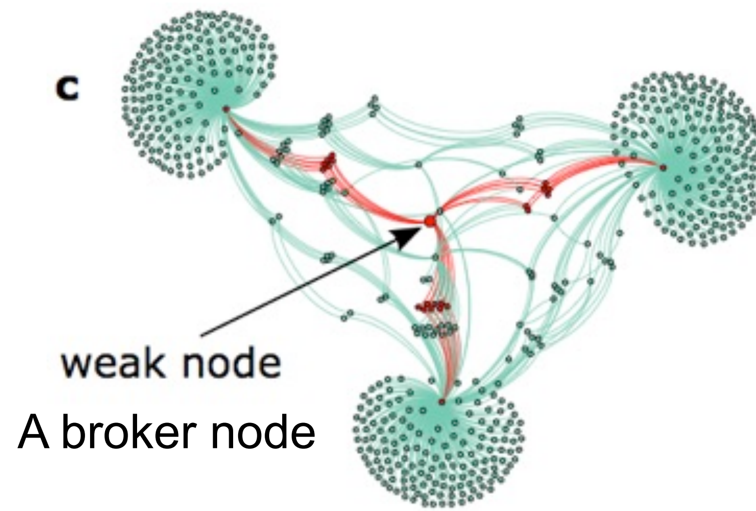
Francesca Lucini

TEST:
INFLUENCERS IN TWITTER NETWORK



Validation of CI in Big Data: Twitter





- CI identifies 40% less influencers than hubs and Google Pagerank

PREDICTIONS FROM BIG DATA

SPECIAL SECTION PREDICTION

THE PULSE OF THE PEOPLE

Can internet data outdo costly and unreliable polls in predicting election outcomes?

By **John Bohannon**

In an apartment on New York City's Upper West Side on 8 November 2016, Herman Makse and several friends cooked branzino and sipped Chablis as they watched the U.S. presidential election unfold. They hopscotched between MSNBC and Fox News while keeping an eye on *The New York Times* website on a laptop. The *Times* was streaming live updates of its "presidential election forecast." It was still early, and results from key states had not yet come in. On a chart labeled "Chance of Winning Presidency" that reflected the polling data rolling in, Hillary Clinton bounced above 80%, leaving Donald Trump mired below 20%.

Makse, a statistical physicist at City University of New York, had placed a scientific bet on the outcome. The day before, his lab group had posted a research paper to arXiv, the online preprint repository. They had feverishly revised it to make the 4 p.m. deadline and publish on Election Day. Like the gauge chart on the *Times* website, they predicted who would become president. But whereas the *Times* used data from state-by-state polling, Makse's prediction was based entirely on data gathered from Twitter in the months leading up to the election.

If Makse's group nailed the election forecast, they would have reason to brag. Polling, whether done by phone or door-to-door, is extremely labor intensive and expensive: It fuels an $18 billion industry. And it has problems. Not only have response rates fallen to single digits, leaving pollsters to rely on a thin and biased sample of people, but also an analysis last year of more than 1000 polls found evidence of widespread data fabrication (*Science*, 4 March 2016, p. 1014). By contrast, Makse's group tracked the political opinions of millions of people directly, second by second, for months—and they got those data for free.

Twitter isn't the only online data stream that scientists are funneling into predictive models of everything from elections to street protests. The largest tech companies such as Facebook and Google generate data that are free for researchers to use, though with varying degrees of inconvenience. So Makse and many other social scientists are asking: Could online data enhance polling as a forecasting tool, or even replace it?

The election night verdict: not yet. As the evening wore on, Makse's forecast based on freely harvested tweets continued to match the pricey polling data, predicting a win for Clinton with 53.5% of the vote. But both forecasts got it wrong. Before their dinner was done, Makse watched as the projections on the *Times*'s data-driven blog, The Upshot, caught up with reality. "It was funny to see how at around 8 p.m.," he says, "they switched from 20% to 90% for Trump."

The internet, it seems, can't yet reliably take the pulse of the people. But Makse and many other social scientists are convinced that it eventually will—if only they can figure out how to translate terabytes of data into human intentions.

FORECASTING WHAT PEOPLE WILL DO, and why, is the essence of social science. Considering how hard it is to divine even a single person's behavior, scaling up prediction to a community or society seems like a nonstarter. "But in some ways that is an easier problem," says Taha Yasseri, a computational social scientist at the University of Oxford Internet Institute in the United Kingdom. He offers an analogy from physics: Although the movement of a single particle looks random, "the behavior of a gas made up of millions of particles is very predictable."

The idea that society can be treated like a physics problem has deep roots. In the 1950s, science fiction author Isaac Asimov conjured up a branch of science called psychohistory. With powerful computers and gargantuan data sets, he imagined, researchers would forecast not just elections,

Both polling and an analysis of pre-election night tweets failed to flush out Trump's hidden voters.

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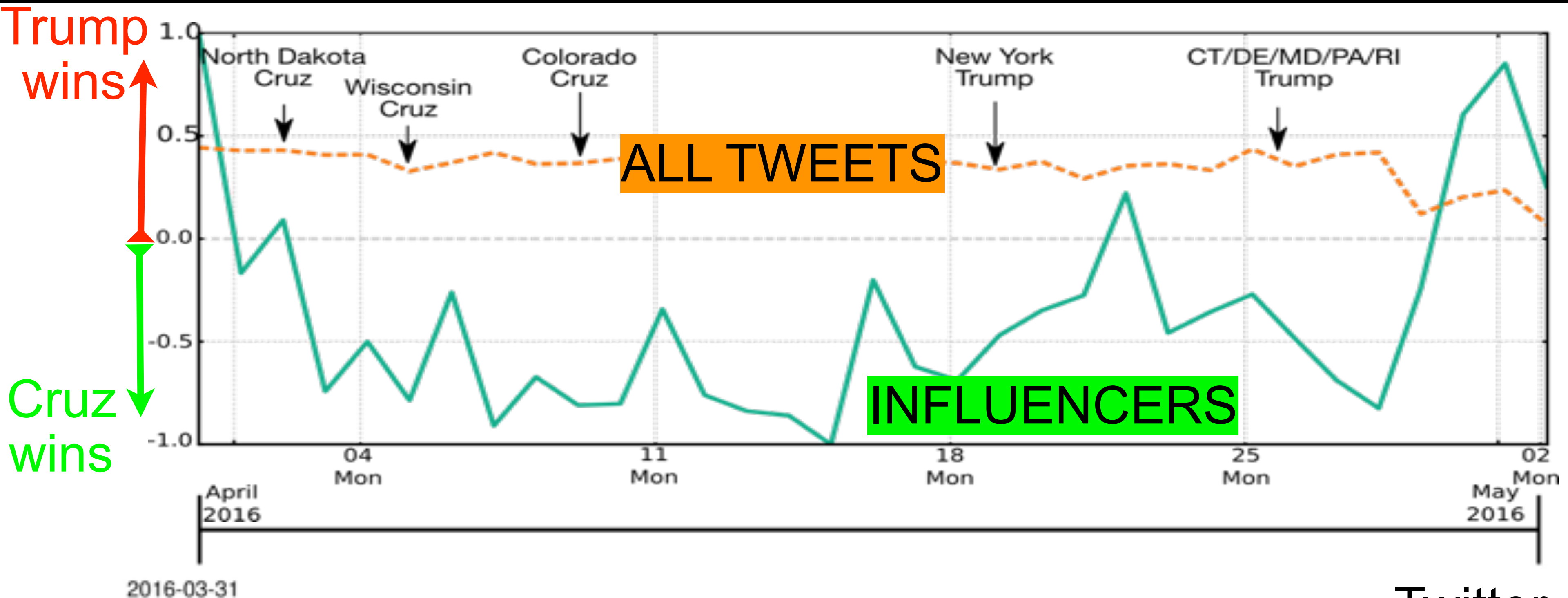
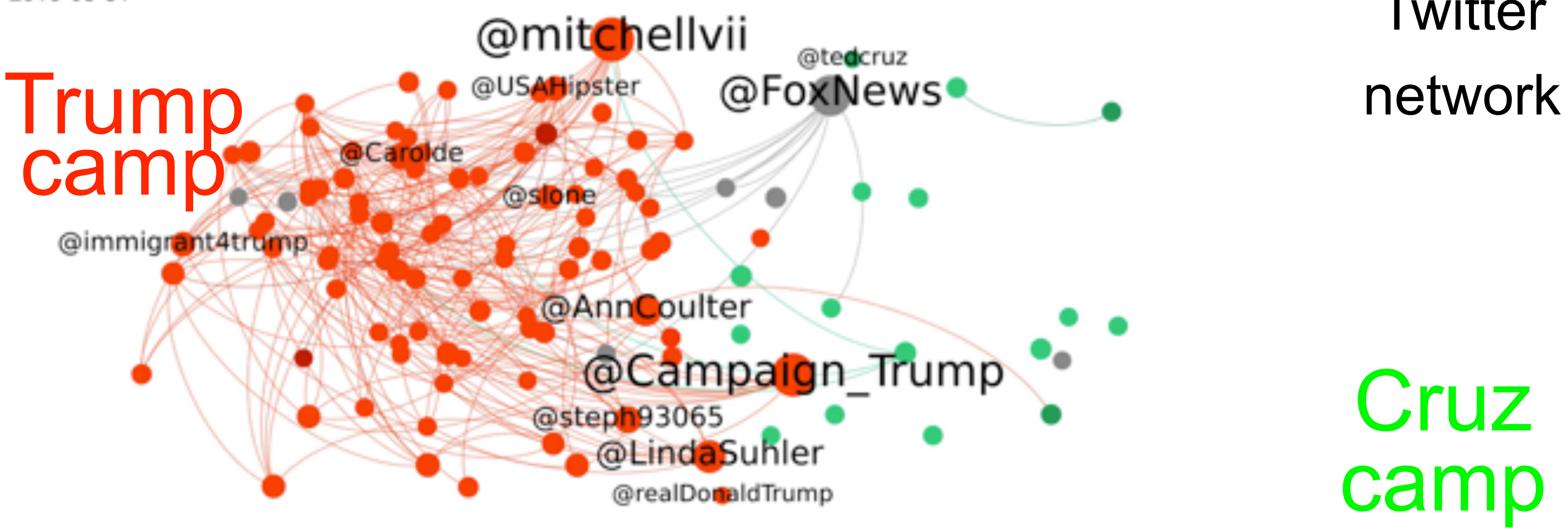
COVER A crystal ball is surrounded by a visual representation of the application of a predictive algorithm's results. Decision-makers at all levels would love to know about the future effects of current decisions. This special issue focuses on what we currently can (and cannot) predict using the emerging conjunction of machine learning, big data, and human understanding. See page 468.

1. Influencers Predict Trump Sentiment

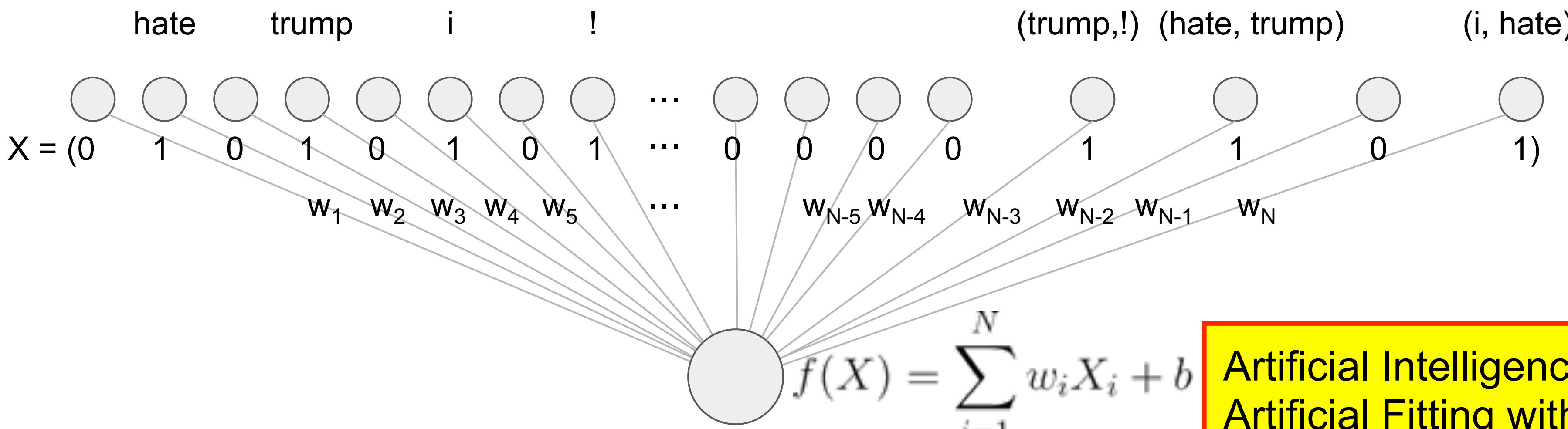




2. Add Machine Learning for Twitter opinion

How to classify a tweet:

I hate Trump!



$$f(X) = \sum_{i=1}^{N} w_i X_i + b$$

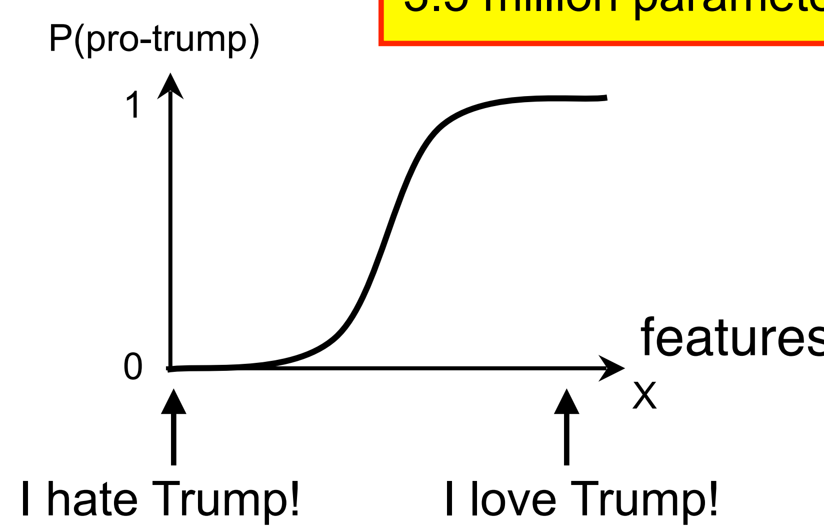
Artificial Intelligence = Artificial Fitting with 3.5 million parameters

IMPORTANT NUMBERS:

- 3.5M features = 3.5M parameters to fit
Shakespeare = 35,000 features
Whole English Language = 1M

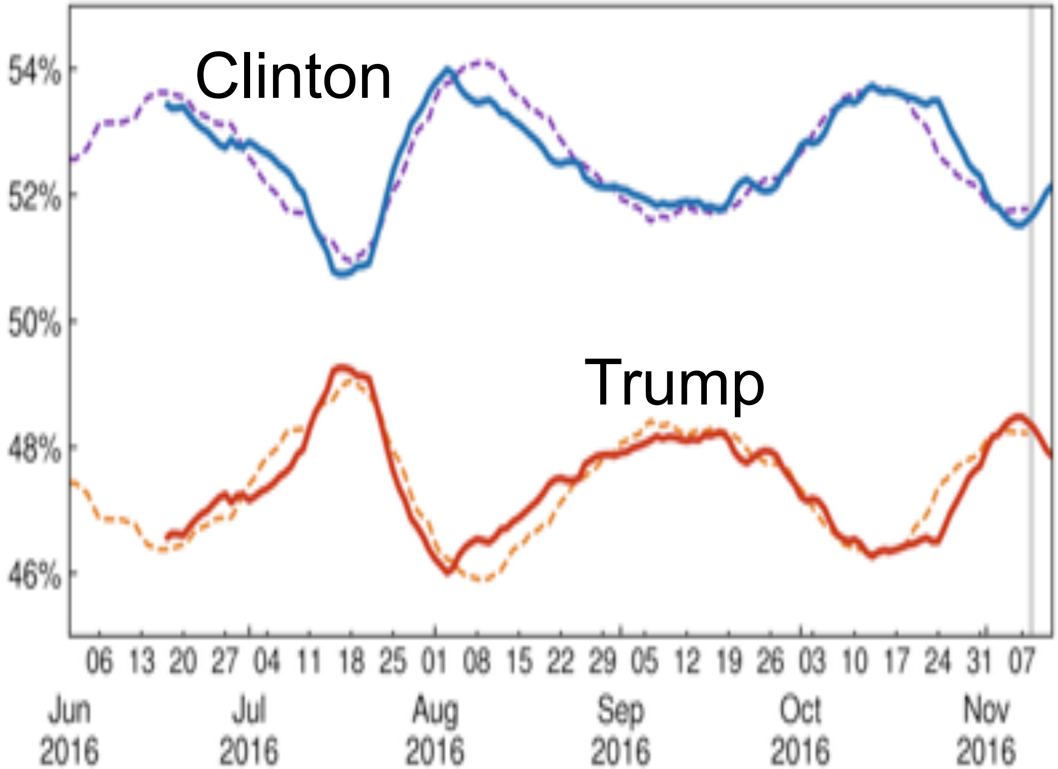
- 1M training examples (tweets)

- We infer: 100M total number of tweets



Machine Learning + Network Theory
Predict Election Trends from Twitter

Bovet, Morone, Makse (2017)



51.2%

48.8%

New York Times Polls
($19b=polling industry)

Our Twitter Analytics
($30k=graduate student)

Training set of 1 million tweets
Predicting the opinion of 100 million tweets
of 11 million people

Our Twitter Artificial Intelligence (and NYT) prediction did not go well in the Rust Belt

Electoral votes

232

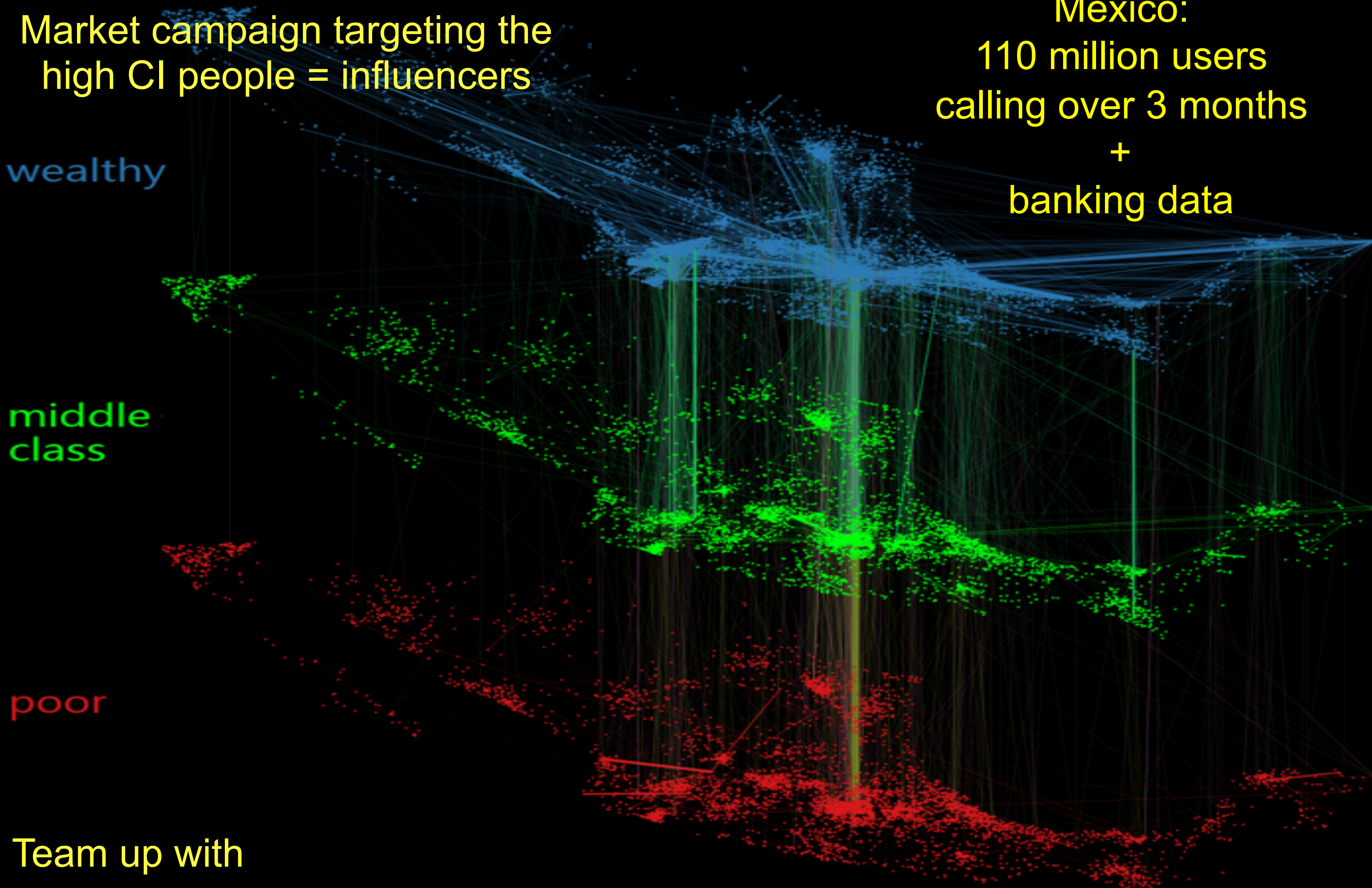
306

Grant Wood on the rural American Midwest

3. Social Network: mobile phone calls

Market campaign targeting the high CI people = influencers

Mexico:
110 million users
calling over 3 months
+
banking data

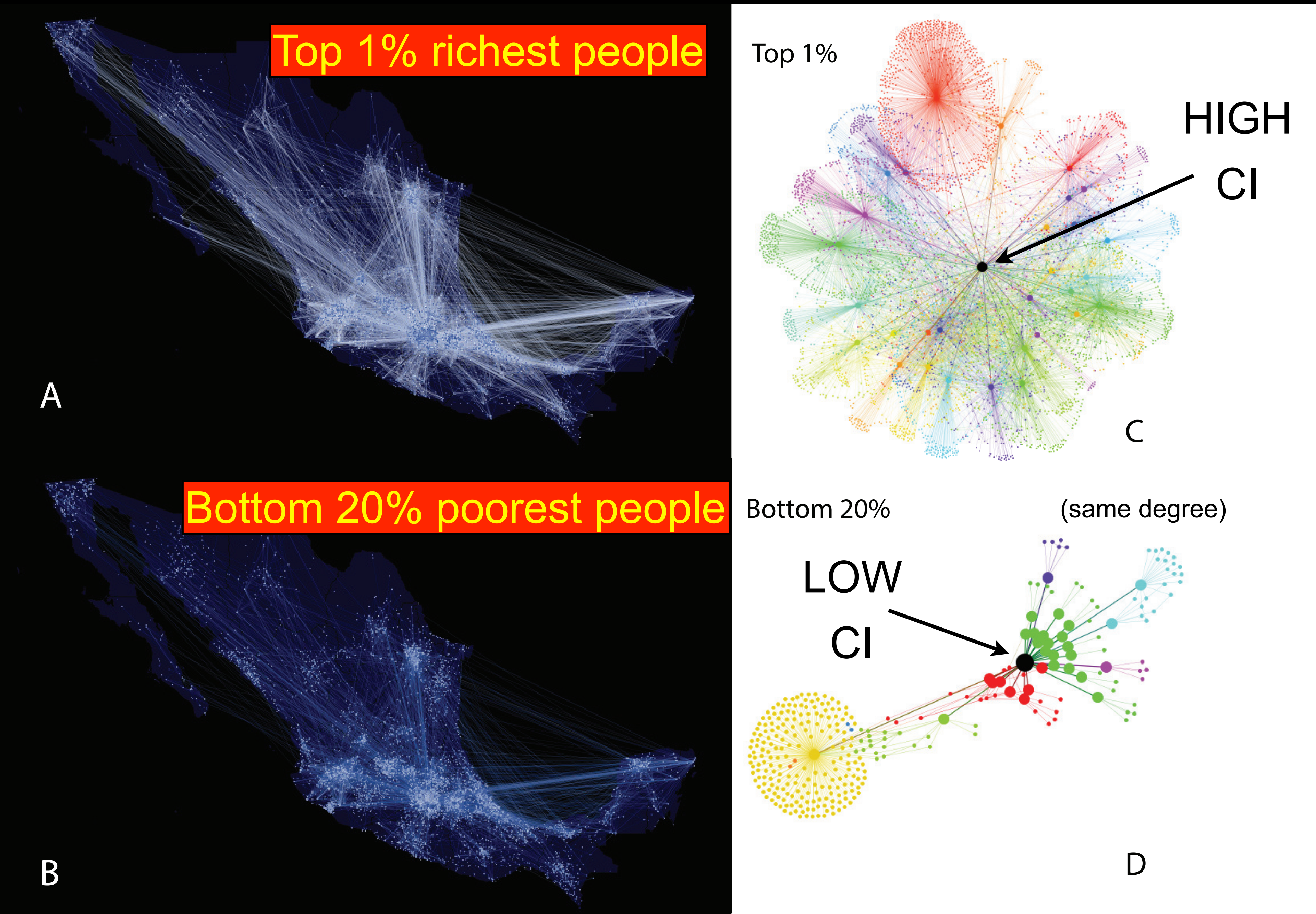


Team up with

GranData.com

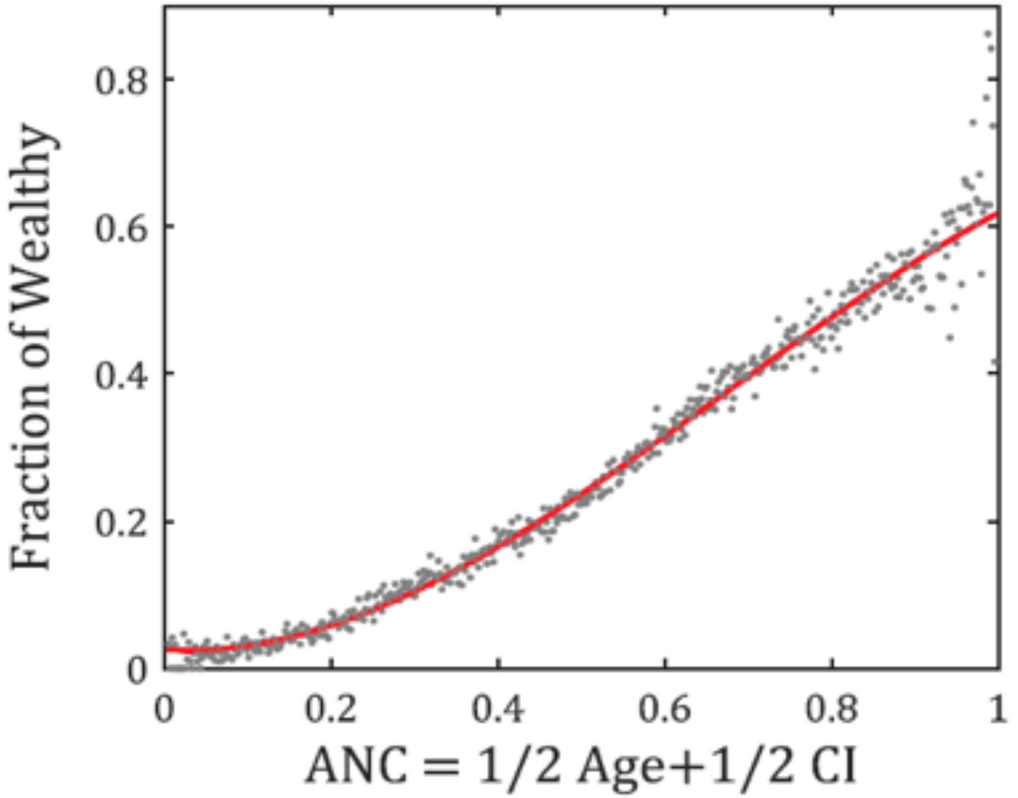
Luo, Morone, Makse, Nature Comm (2017)

Communication patterns of rich and poor



Network centrality and wealth

Collective Influence: $\mathrm{CI}(\ell)_i = (k_i - 1)\ \sum_{j \in \partial Ball(i,l)} (k_j - 1)$

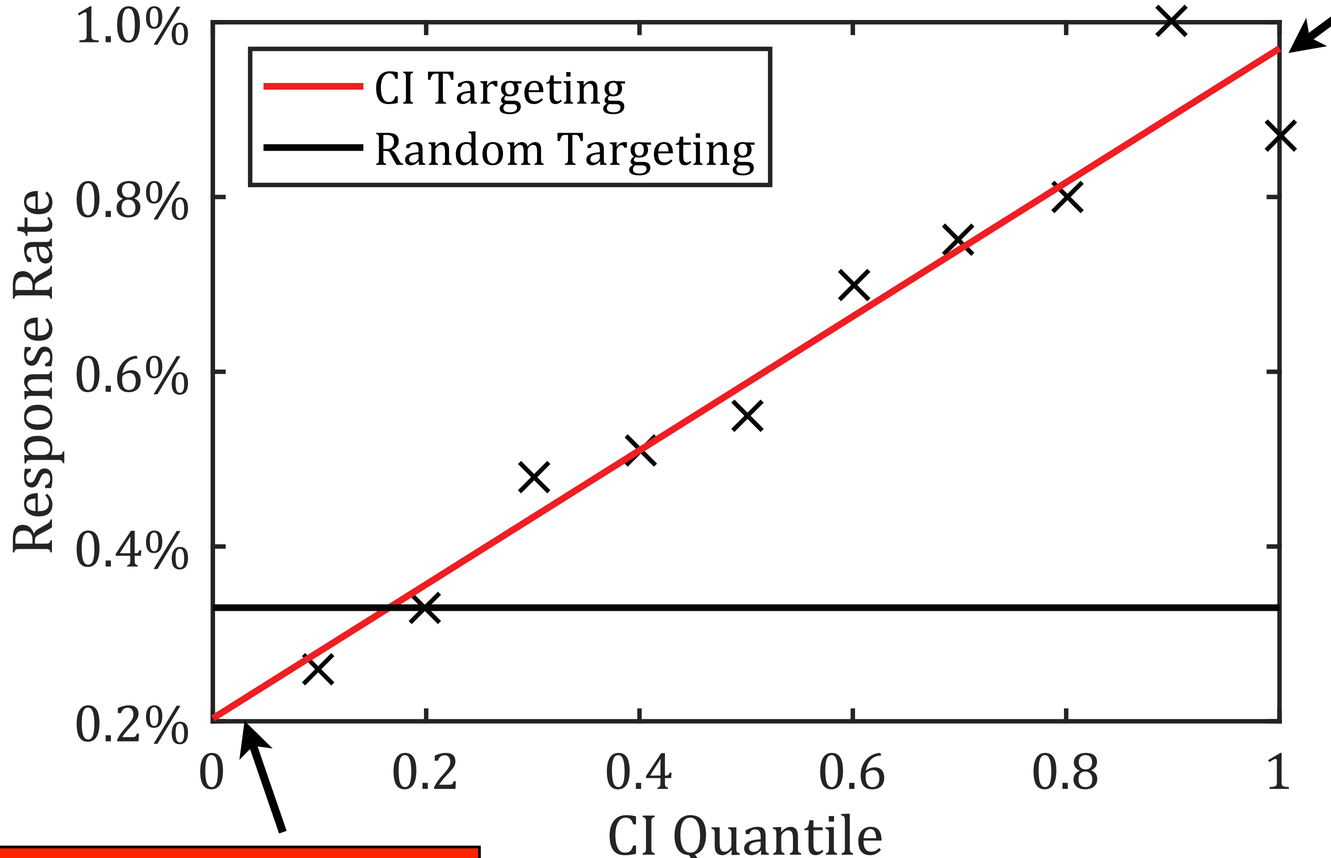


- Fraction of wealthy is strongly related to Age-Network Composite(ANC), a composite ranking of Age and CI ranking

Validation: Improve response rate in a marketing campaign by five-fold

Targeting 60,000 people according to their Collective Influence in the network of entire Mexico

High CI: wealthy people



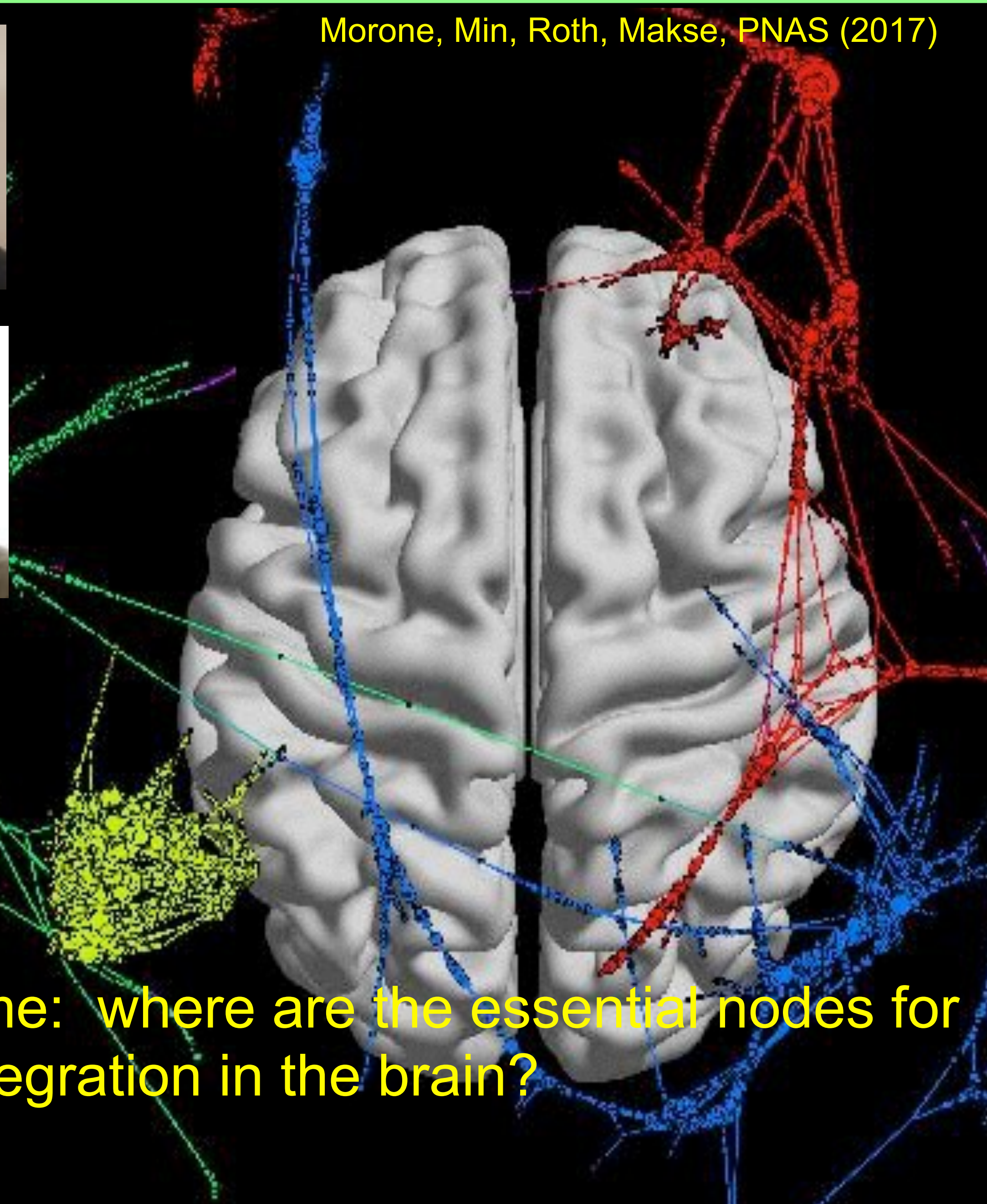
Low CI: poorest people

4. From Twitter to the Brain

Morone, Min, Roth, Makse, PNAS (2017)

- Lucas Parra
Biomedical Engineering
City College of New York
(machine learning)

-Santiago Canals
Institute of Neuroscience
Alicante, Spain
(experimental
neuroscience)



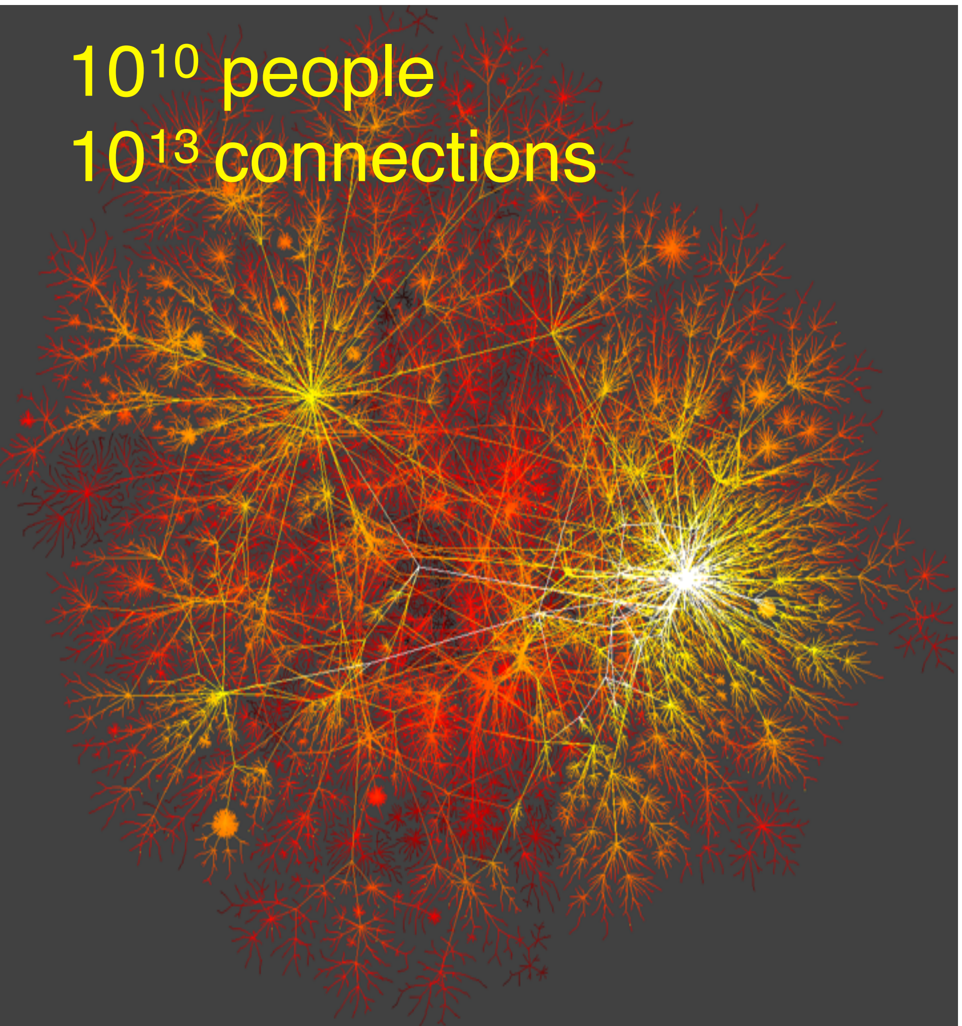
Brain Network Connectome: where are the essential nodes for global integration in the brain?

FROM TWITTER TO THE BRAIN

HUMANS:

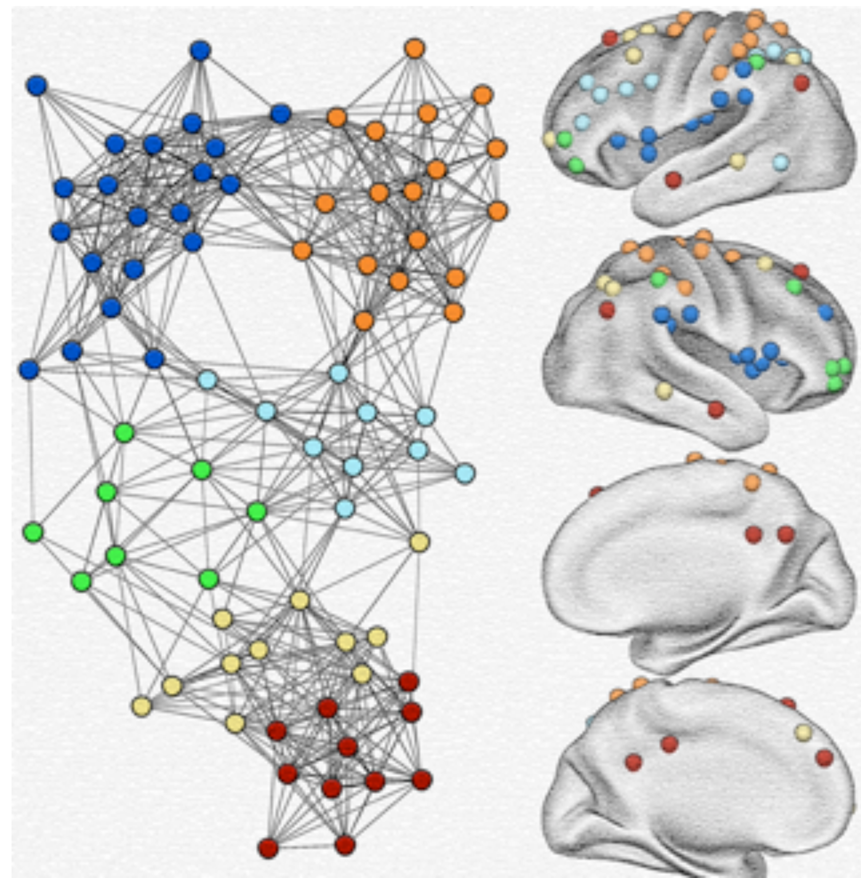
ONE NETWORK

BRAIN: NETWORK OF NETWORKS



10^{11} neurons

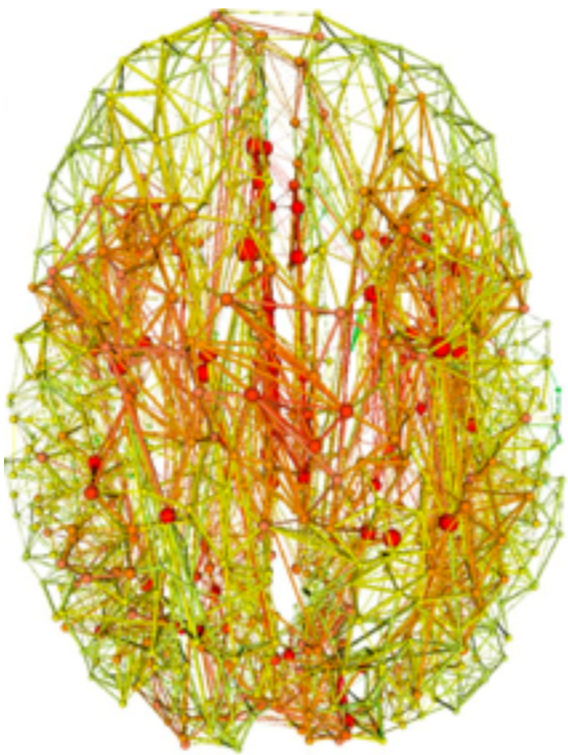
10^{15} connections

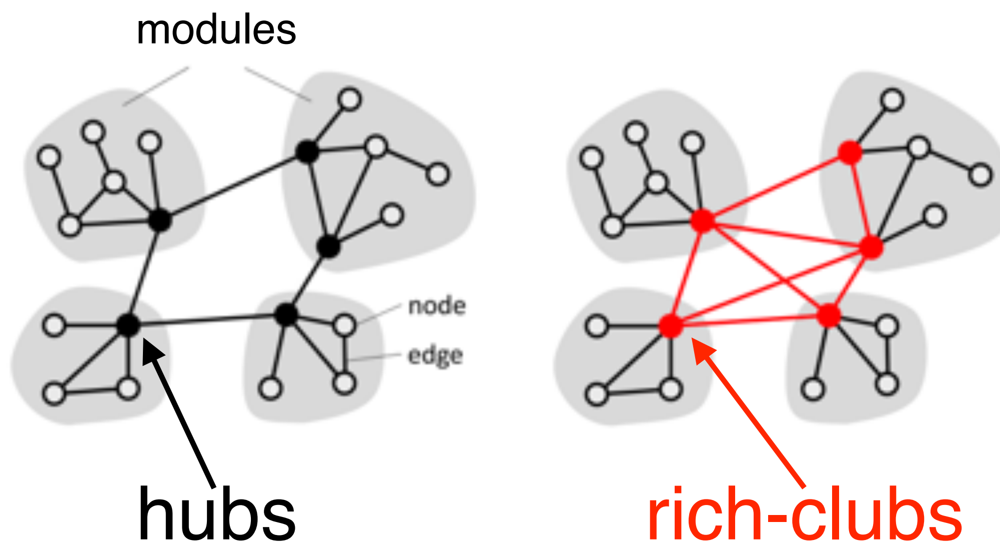


Binding problem: how the brain integrates information: influencers in the brain

Conventional hub-centric (scale-free) theory

Bullmore, Sporns, Nature Rev Neurosi (2012)





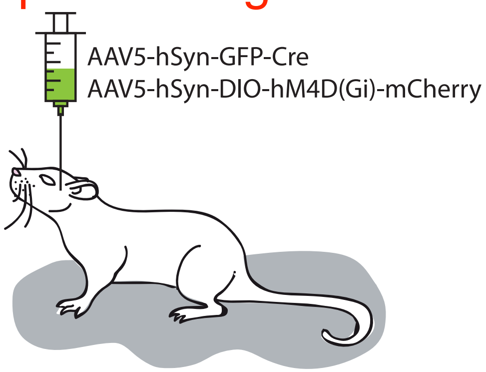
“the rich gets richer”
1%

Problems with scale-free theory:

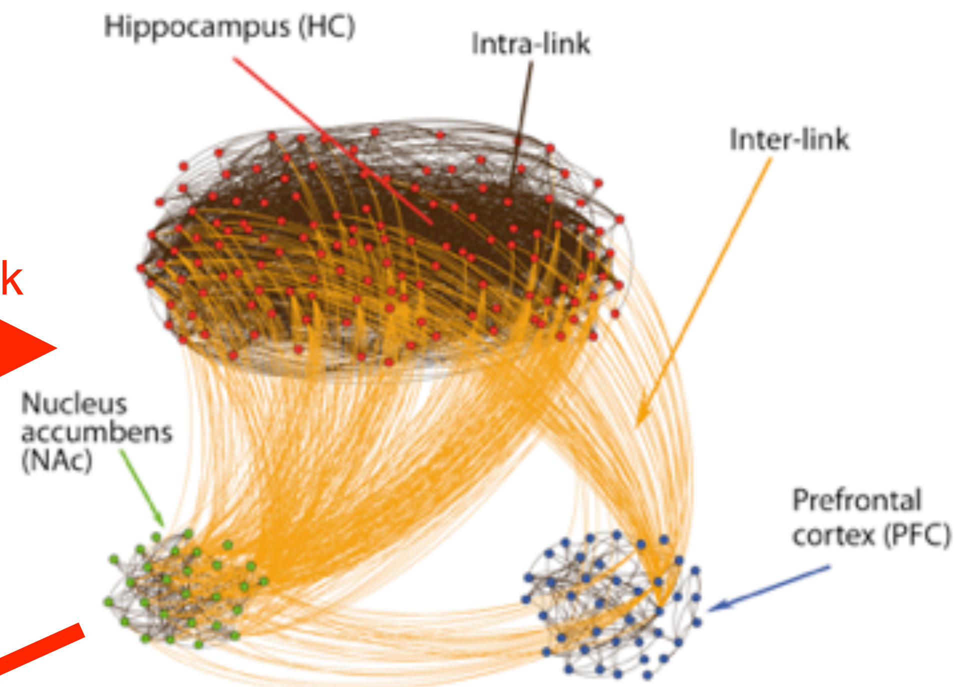
1. Not based on graph optimization theory (heuristic)
2. Doesn't guaranteed the minimal set of essential nodes

Pipeline: machine learning and network theory to predict essential nodes in rat brain

Simultaneous:
LTP + fMRI read-out
pharmacogenetics



big-data +
machine learning
to infer the network



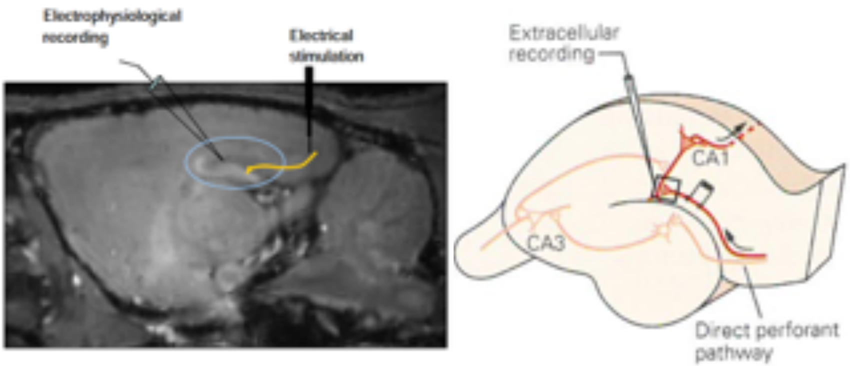
Pharmacogenetics

network theory to
predict the essential areas
in the brain

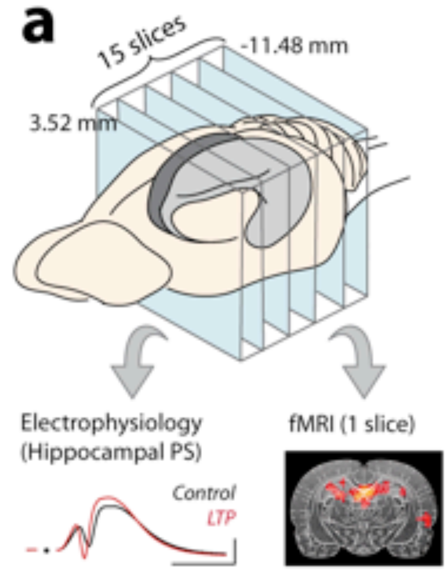
Gallos, Makse, Sigman, PNAS (2012)
Reis, Sigman, Canals, Makse, Nature Phys (2014)
Morone, Roth, Min, Stanley, Makse, PNAS (2017)

Inducing a memory network of networks in long-term potentiation in rat hippocampus

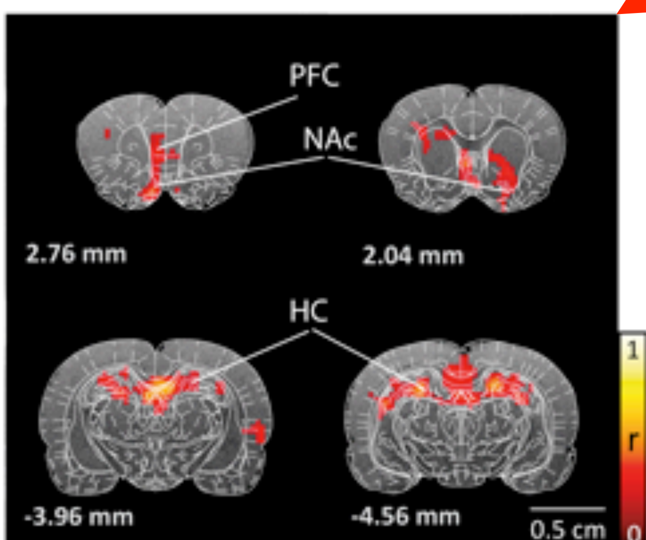
200 Hz electrical stimulation
in perforant pathway HC



Three hours later
fMRI read out



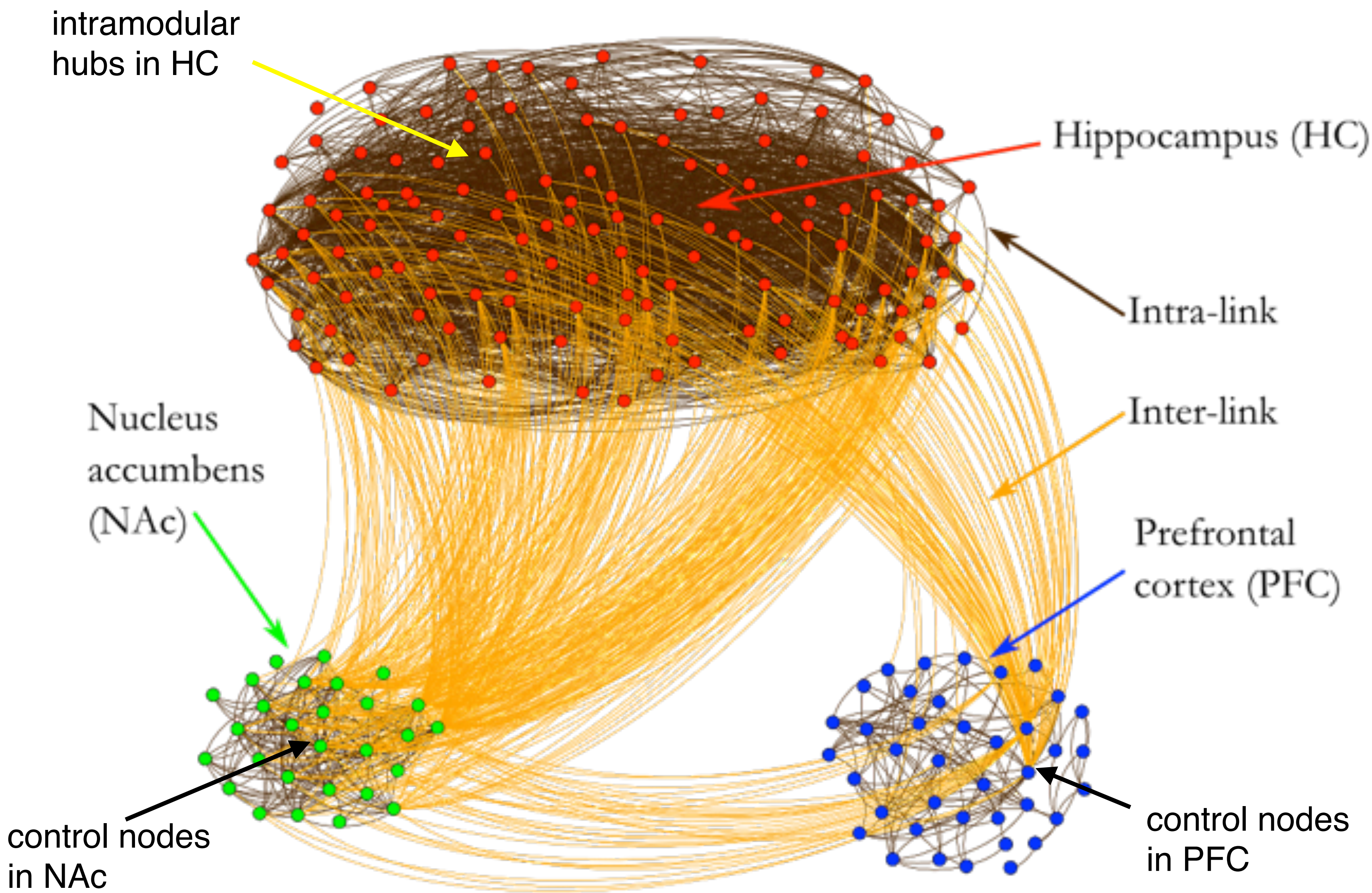
Canals, Logothetis, et al, Current Bio (2009)



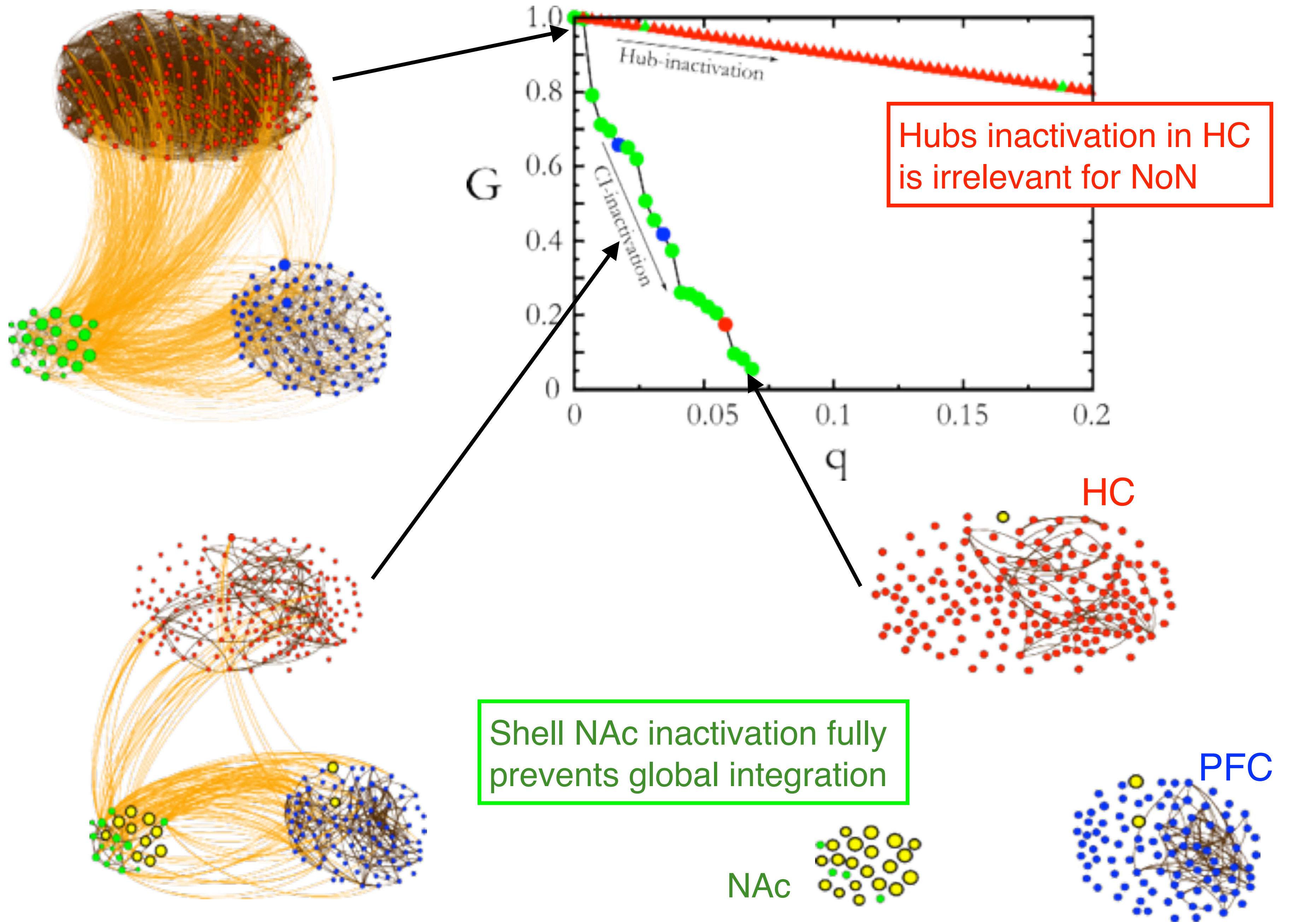
Result in global activation of three areas (mesolimbic + neocortical):

- Hippocampus: HC
- Pre-frontal cortex: PFC
- Nucleus Accumbens: NAc

Result: Sparse memory NoN



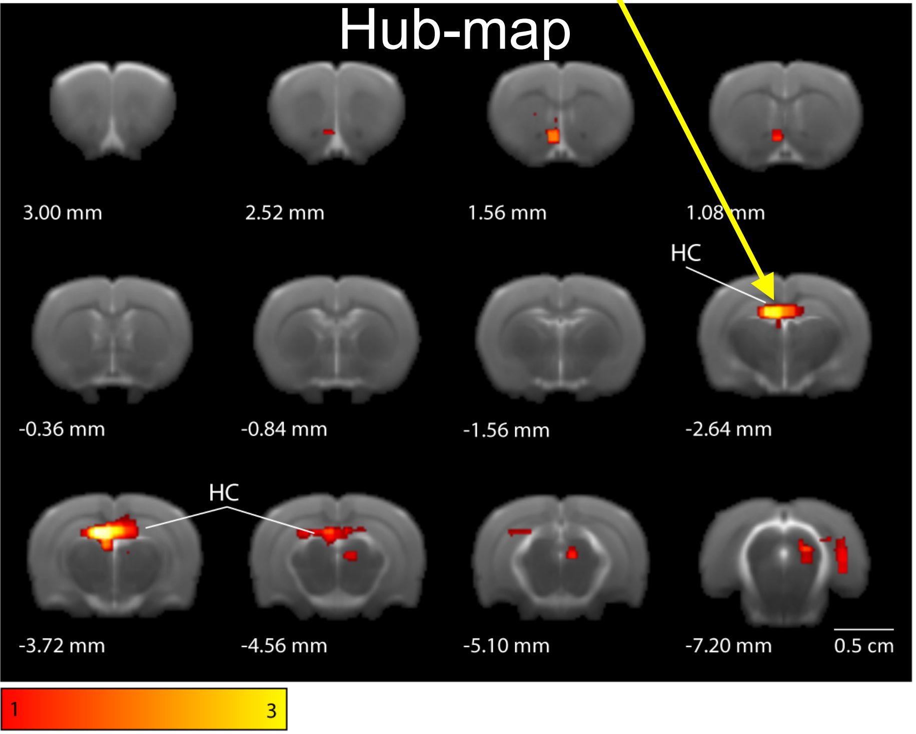
Prediction of optima percolation in NoN



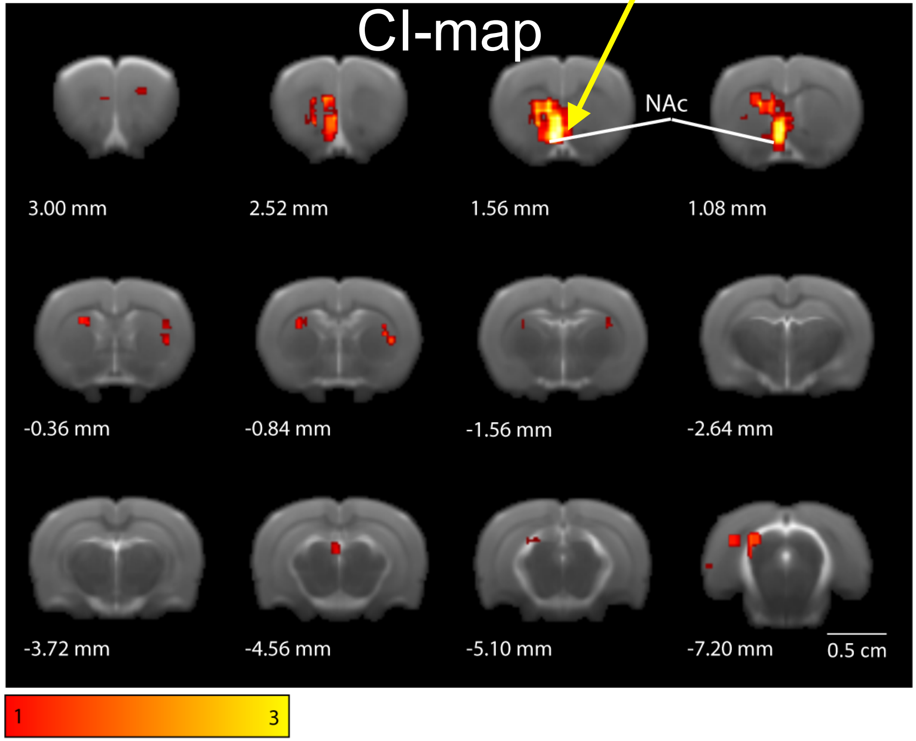
Two different predictions for essential nodes

Hub-centric theory:
Essential nodes in HC

Optimal Percolation:
Essential nodes in NAc



H

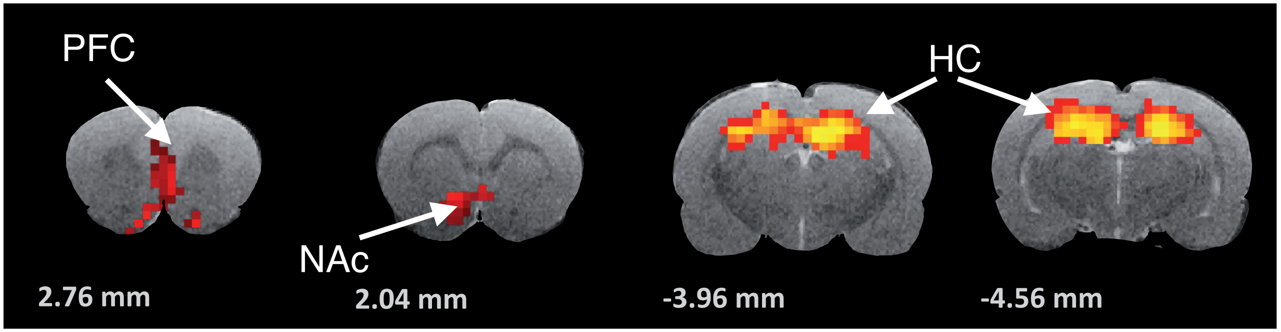


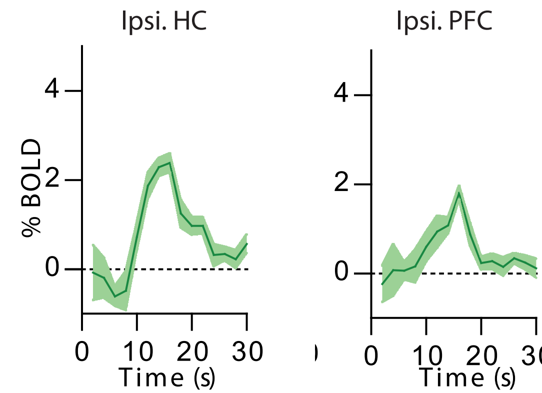
average over 6 rats

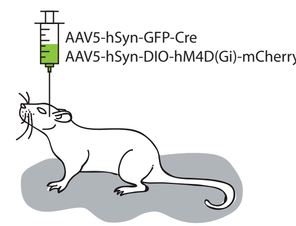
Pharmacogenetic silencing essential node in NAc shell inactivates whole memory NoN

Min, Moreno, Morone, Parra, Canals, Makse, arxiv.org (2017)

Normal LTP

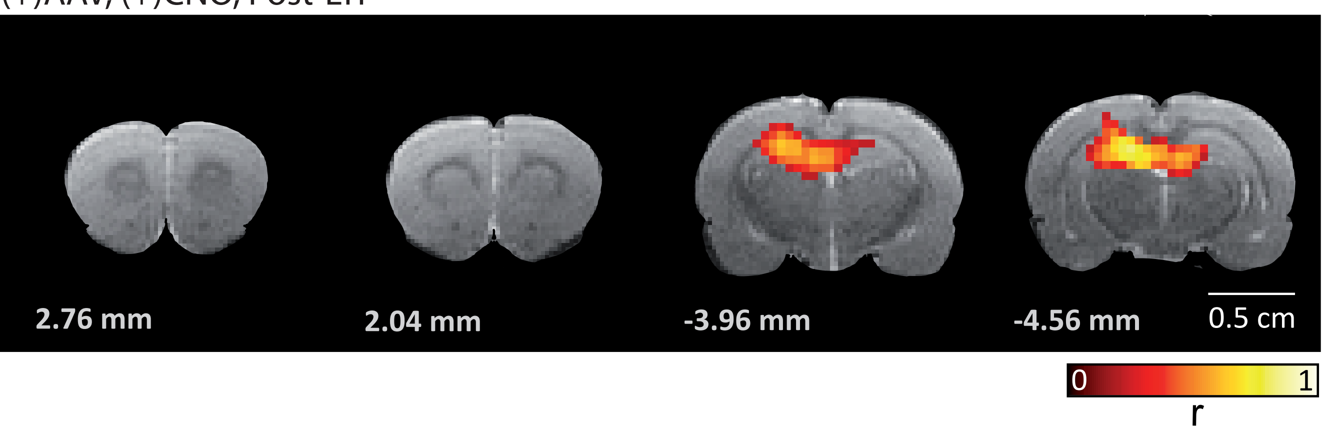


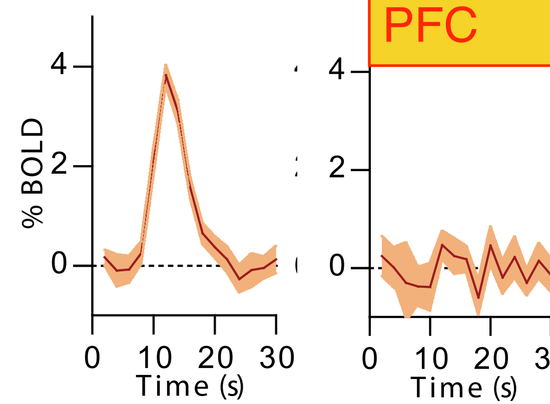




LTP + single node NAc inactivation

(+)AAV, (+)CNO, Post-LTP

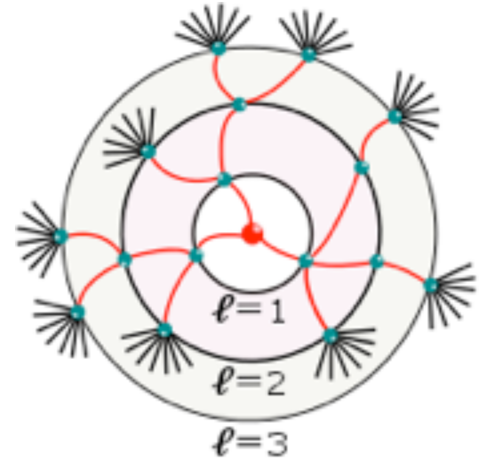




no BOLD signal in PFC

Summary

1. A new class of strategically located influencers, called weak nodes, controls the information flow in social media and the brain

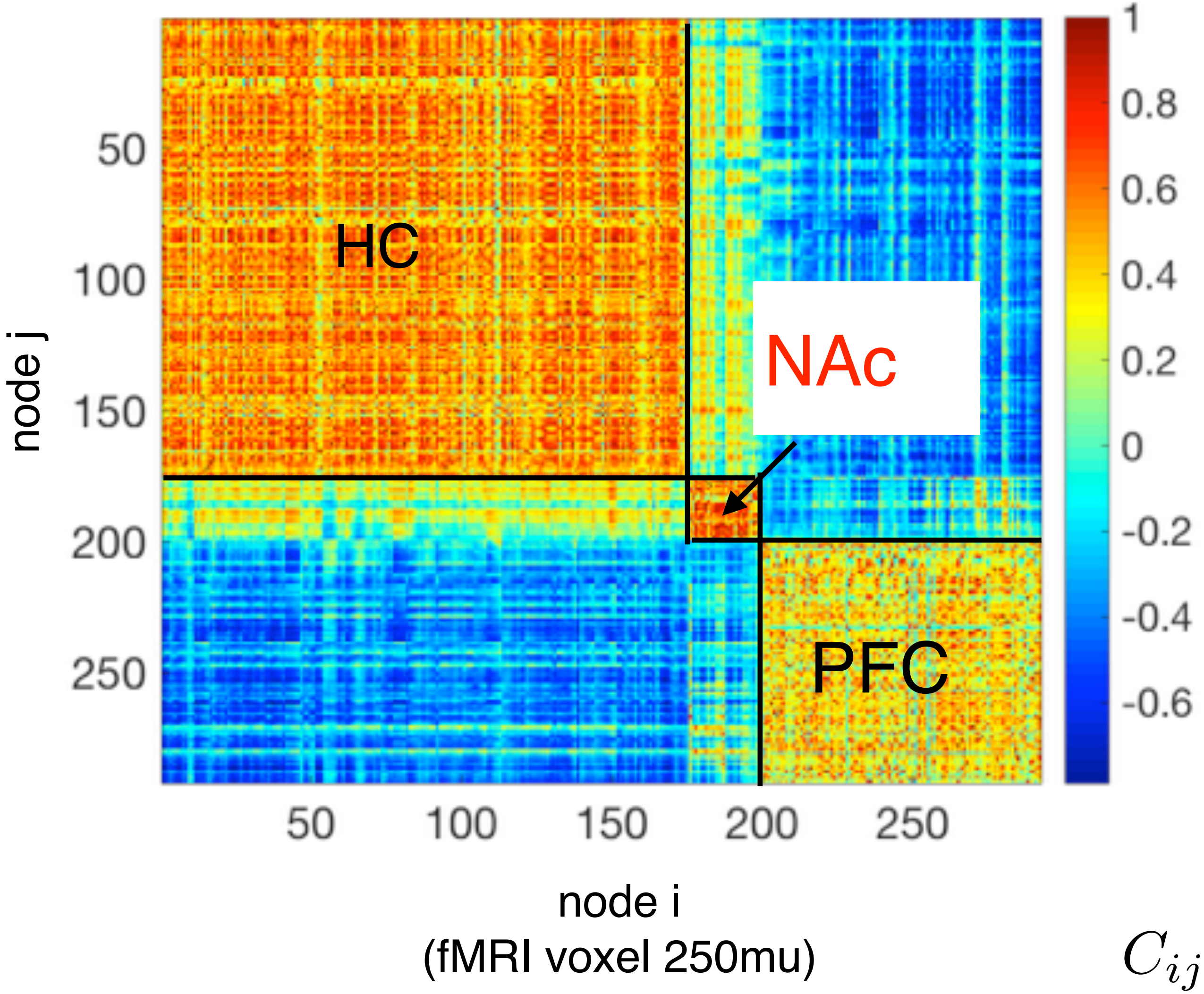


2. Implications for targeted marketing in social media and control of brain function and disease

3. Machine learning + big data + network theory might be able to realize the dreams of the digital age

Infer sparse effective network of networks

$$C_{ij}$$



Covariance matrix from BOLD signal in fMRI

$$C_{ij} = \frac{\langle x_i x_j \rangle - \langle x_i \rangle \langle x_j \rangle}{\sigma_i \sigma_j}$$

Complexity theory: basic phylosophical understanding

P. W. Anderson,
Physics Nobel laureate 1977
Structure of disordered systems

"Emergent properties", i.e., "properties not contained in the simple laws of physics, although they are a consequence of them".

COMPLEXITY SCIENCE: The realm of Matter and Life

Emergent phenomena:
Complex Systems

Sociology: human activity

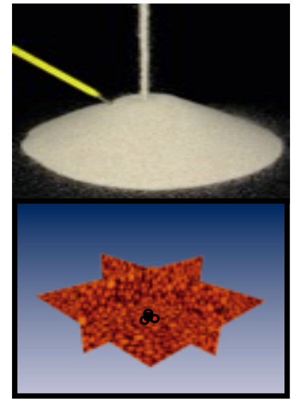
Living organisms, species

Brain → Consciousness

Cell

Biology: Macromolecules, proteins

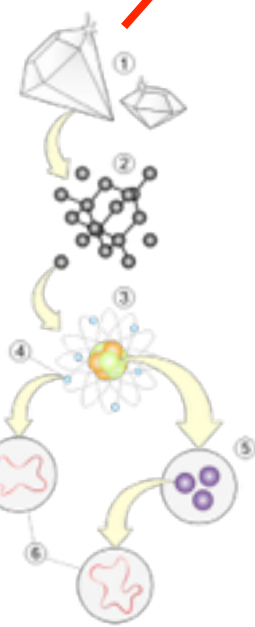
MATTER



grains of sand = mm

colloids = microns

nanoparticles = nm



Molecules = 10^{-10}m

Atoms = 10^{-11}m

Quarks - electrons = 10^{-15}m

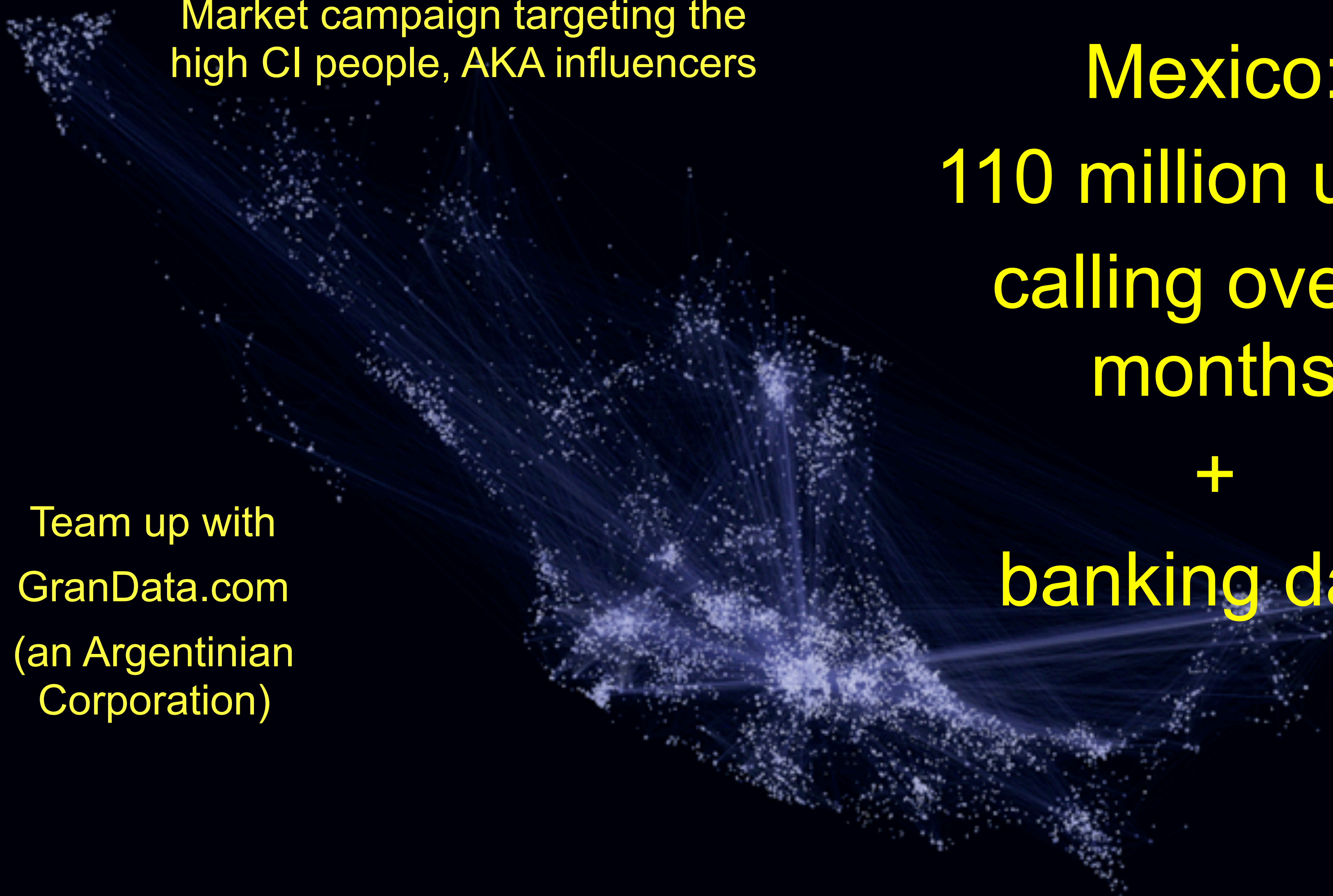
Strings = 10^{-25}m

Emergent phenomena

Reductionist approach

2. Influencers in Real Marketing Campaign using Mobile Phone Networks

Market campaign targeting the high CI people, AKA influencers



Mexico:

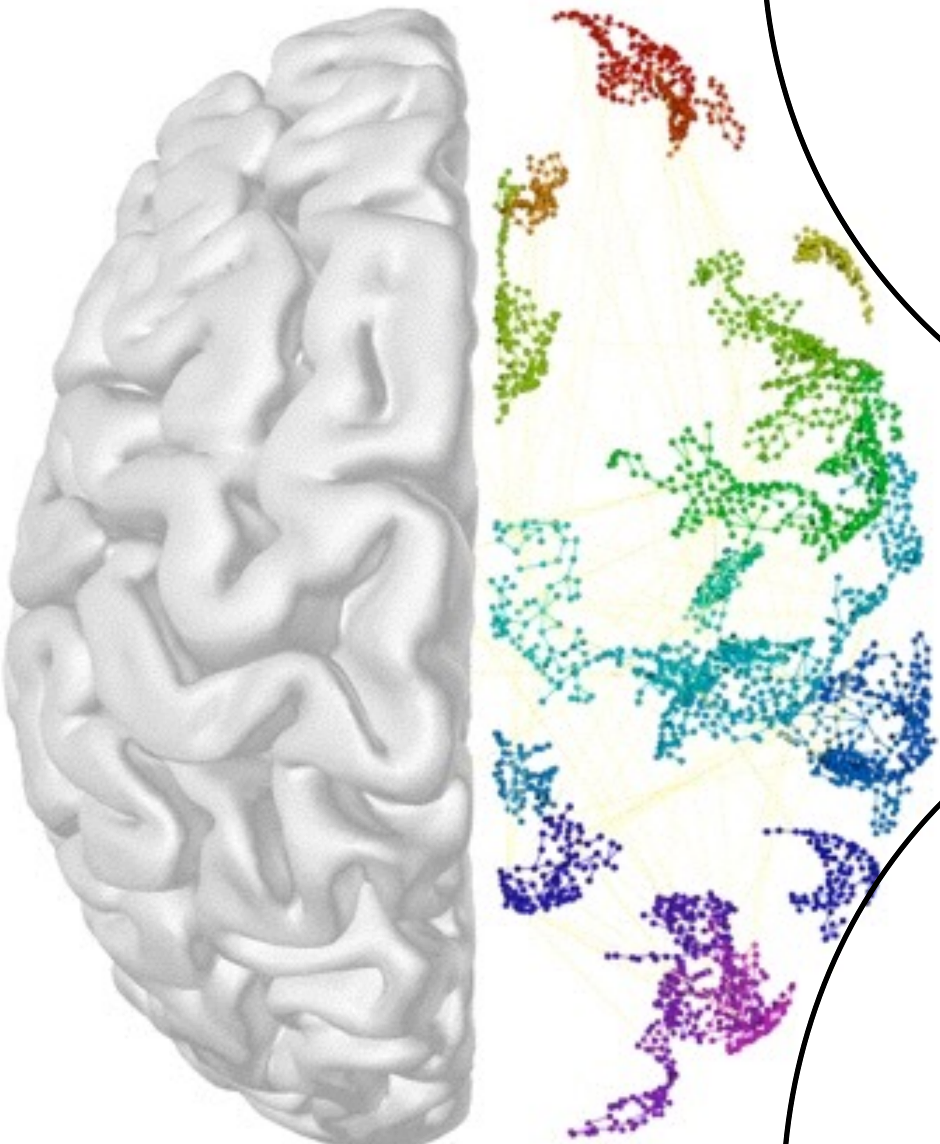
110 million users calling over 3 months

+

banking data

Team up with GranData.com (an Argentinian Corporation)

THE MAIN INFLUENCER IN A BRAIN MEMORY NETWORK



NUCLEUS ACCUMBEMS

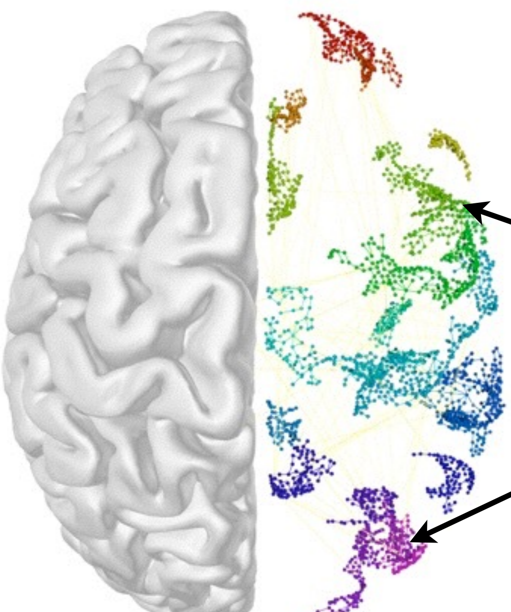
Morone, Makse

Nature 2015

4. Brain conundrum: Binding Problem

HOW THE BRAIN INTEGRATES DIFFERENT NETWORKS:
Brain modules ought to be sufficiently independent to guarantee functional specialization and sufficiently connected to bind multiple processors for efficient information transfer for, for instance, unitary perception (ie, visual areas analyze simultaneously form, color, motion, etc)

Segregation versus integration at the network level



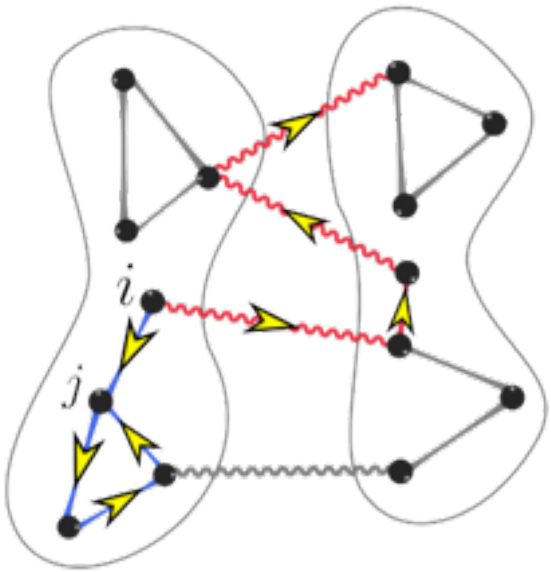
Problem of any information processing system:

Network of Networks

Gallos, Makse, Sigman, PNAS (2012)
Reis, Andrade, Sigman, Canals, Makse, Nat Phys (2014)

Influencers in a Network of Networks

Influencers are the best non-backtracking walkers walking along two types of links. Information flows via two type of messages: intra-modular and inter-modular



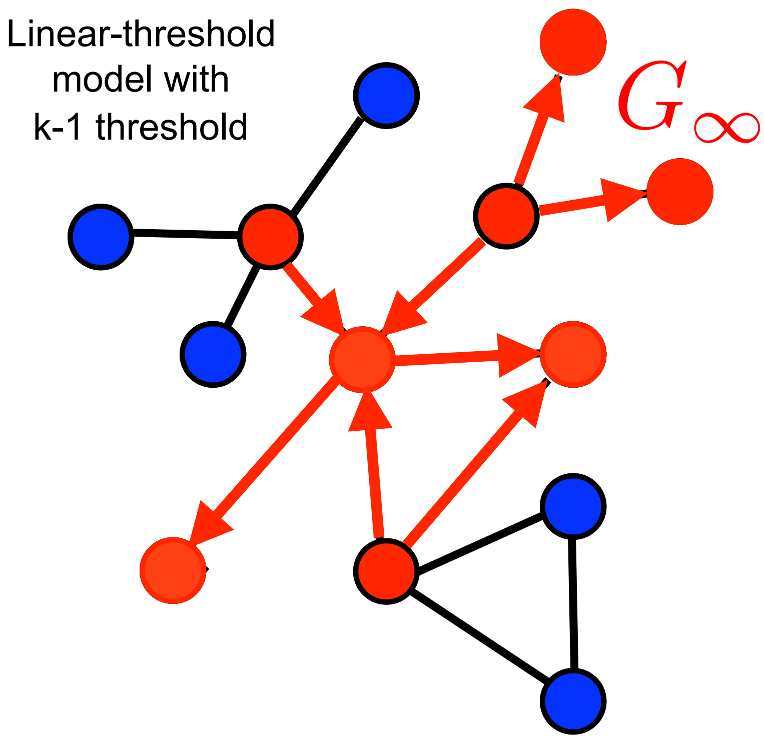
$$\mathcal{M}_{k\to\ell,i\to j}(n_i) = \left.\frac{\partial \rho_{i\to j}}{\partial \rho_{k\to\ell}}\right|_{\rho=0}$$

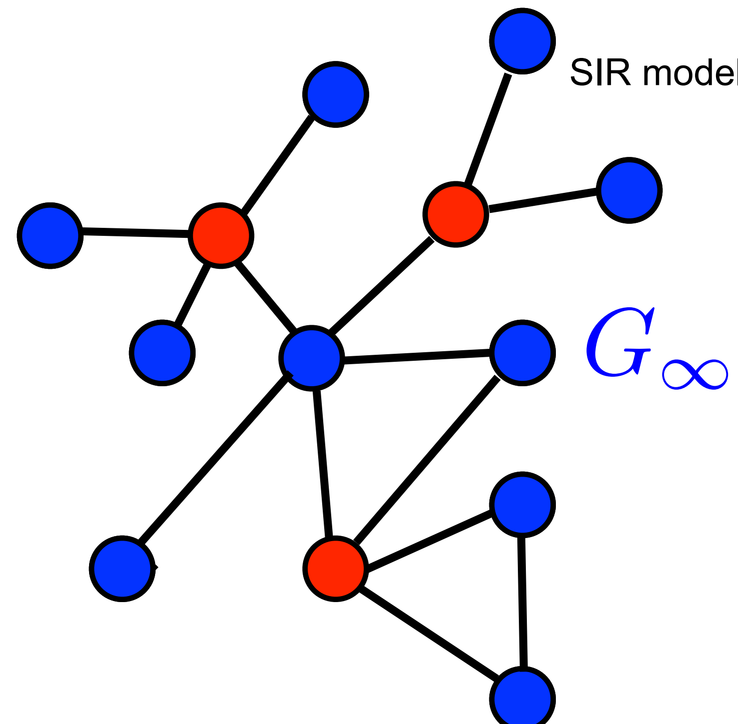
$$\hat{\mathcal{M}} \equiv \left.\begin{pmatrix} \hat{\mathcal{M}}_{\rho\rho} & \hat{\mathcal{M}}_{\rho\varphi} \\ \hat{\mathcal{M}}_{\varphi\rho} & \hat{\mathcal{M}}_{\varphi\varphi} \end{pmatrix}\right|_{G=0} \equiv \left.\begin{pmatrix} \frac{\partial\rho_{k_A\to l_A}}{\partial\rho_{i_A\to j_A}} & \frac{\partial\rho_{k_B\to l_B}}{\partial\rho_{i_A\to j_A}} & \frac{\partial\varphi_{k_A\to l_B}}{\partial\rho_{i_A\to j_A}} & \frac{\partial\varphi_{k_B\to l_A}}{\partial\rho_{i_A\to j_A}} \\ \frac{\partial\rho_{k_A\to l_A}}{\partial\rho_{i_B\to j_B}} & \frac{\partial\rho_{k_B\to l_B}}{\partial\rho_{i_B\to j_B}} & \frac{\partial\varphi_{k_A\to l_B}}{\partial\rho_{i_B\to j_B}} & \frac{\partial\varphi_{k_B\to l_A}}{\partial\rho_{i_B\to j_B}} \\ \frac{\partial\rho_{k_A\to l_A}}{\partial\varphi_{i_A\to j_B}} & \frac{\partial\rho_{k_B\to l_B}}{\partial\varphi_{i_A\to j_B}} & \frac{\partial\varphi_{k_A\to l_B}}{\partial\varphi_{i_A\to j_B}} & \frac{\partial\varphi_{k_B\to l_A}}{\partial\varphi_{i_A\to j_B}} \\ \frac{\partial\rho_{k_A\to l_A}}{\partial\varphi_{i_B\to j_A}} & \frac{\partial\rho_{k_B\to l_B}}{\partial\varphi_{i_B\to j_A}} & \frac{\partial\varphi_{k_A\to \ell_B}}{\partial\varphi_{i_B\to j_A}} & \frac{\partial\varphi_{k_B\to \ell_A}}{\partial\varphi_{i_B\to j_A}} \end{pmatrix}\right|_{G=0}$$

Optimal Percolation = Best attack = best influencers

Morone, Makse, Nature (2015)

Mapping to Optimal Percolation to find the minimal set of "influencers" to fragment the network





Best spreaders = minimize the inactive nodes = maximize giant component

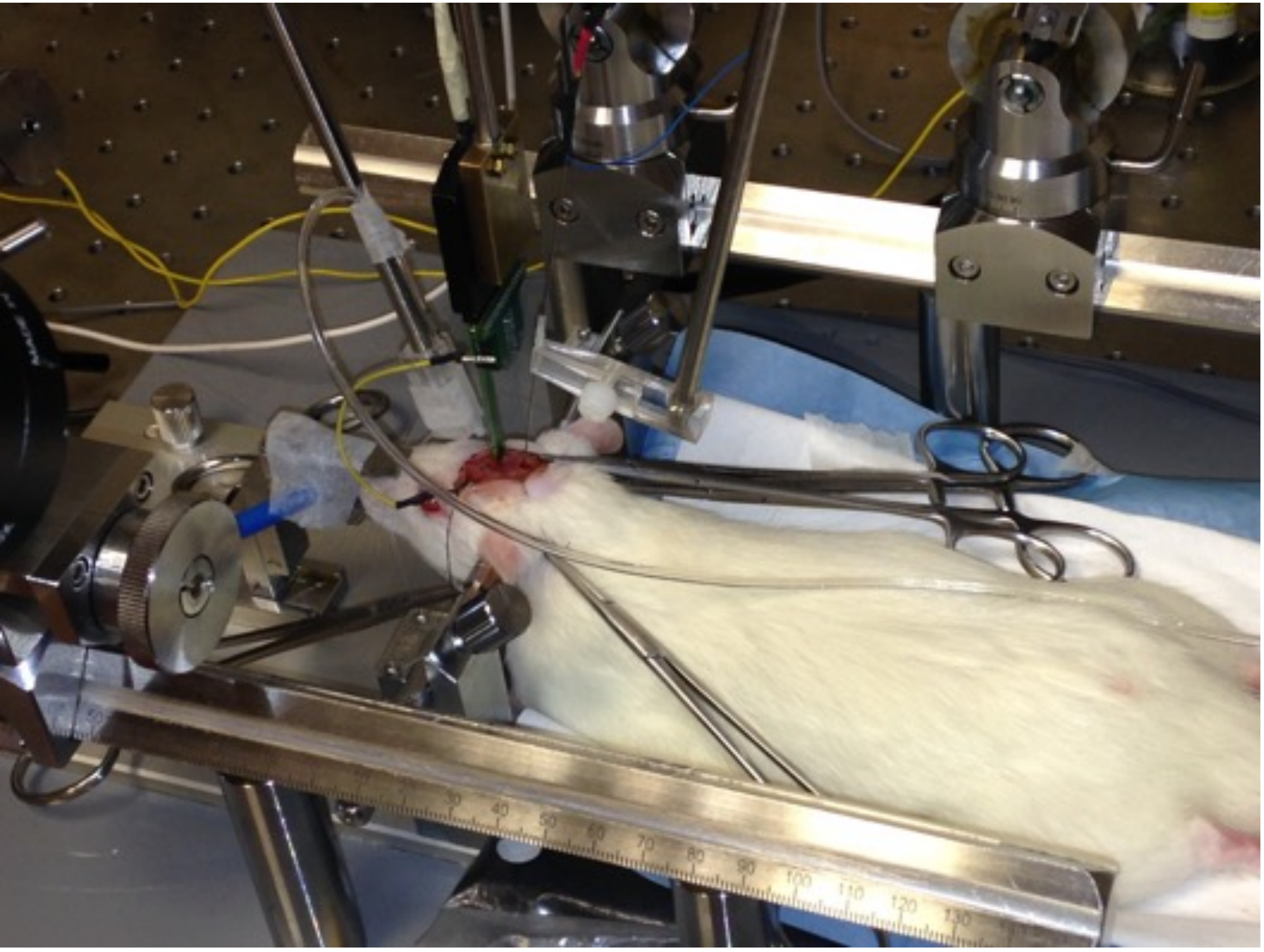
G_∞

Best attack =minimize the giant connected component

G_∞

Network Theory predicts how to inhibit the memory in a rat

SIMULTANEOUS fMRI readout + OPTOGENETICS CONTROL
to manipulate activity in essential nodes + electrical estimulation of Hippocampus in LTP



In collaboration
with Santiago Canals
Institute of
Neuroscience
Alicante - Spain

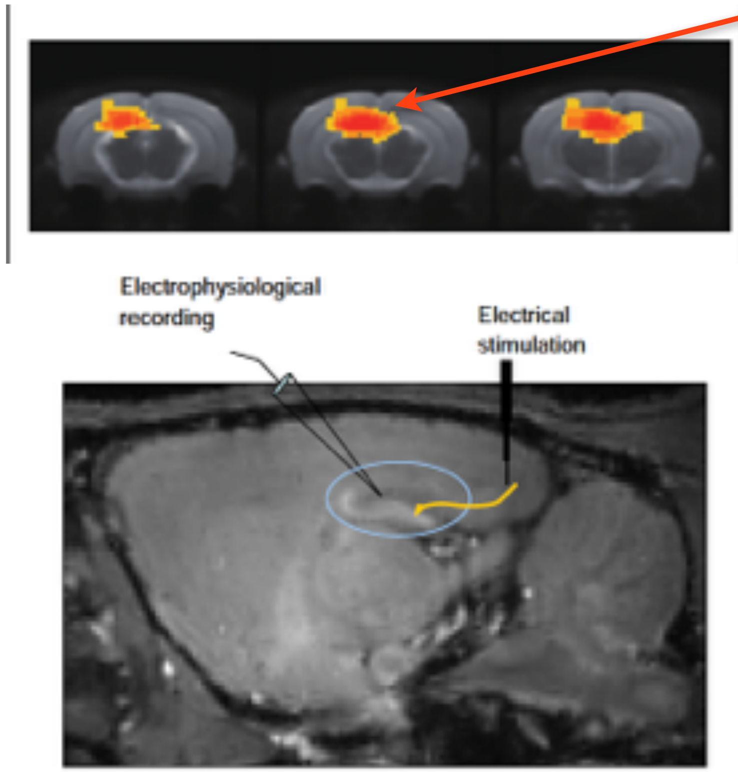
CSIC

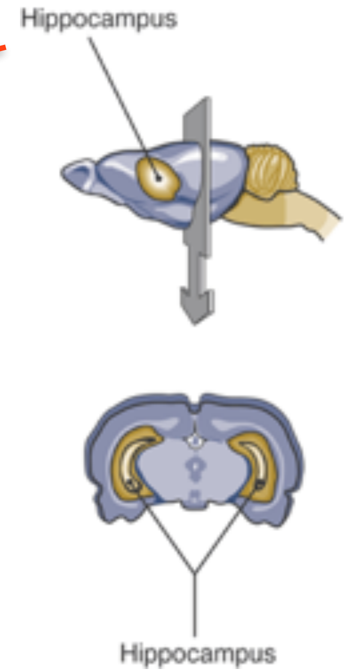
UNIVERSITAS Miguel Hernández

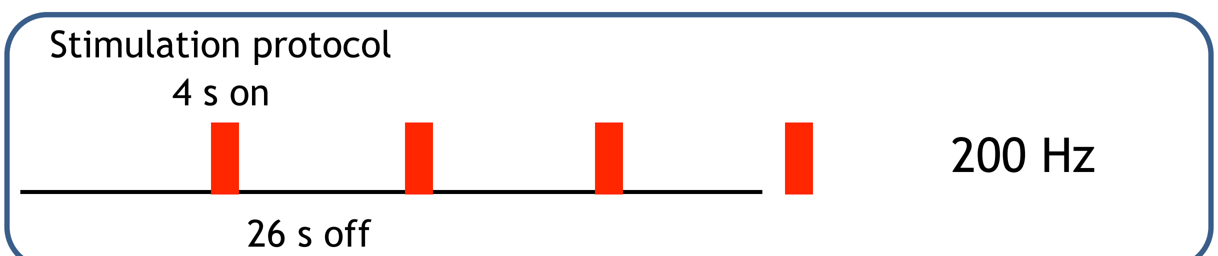
INSTITUTO DE NEUROCIENCIAS

Long-Term Potentiation (LTP) induction: High frequency electric stimulation was applied at Hippocampus

fMRI scan

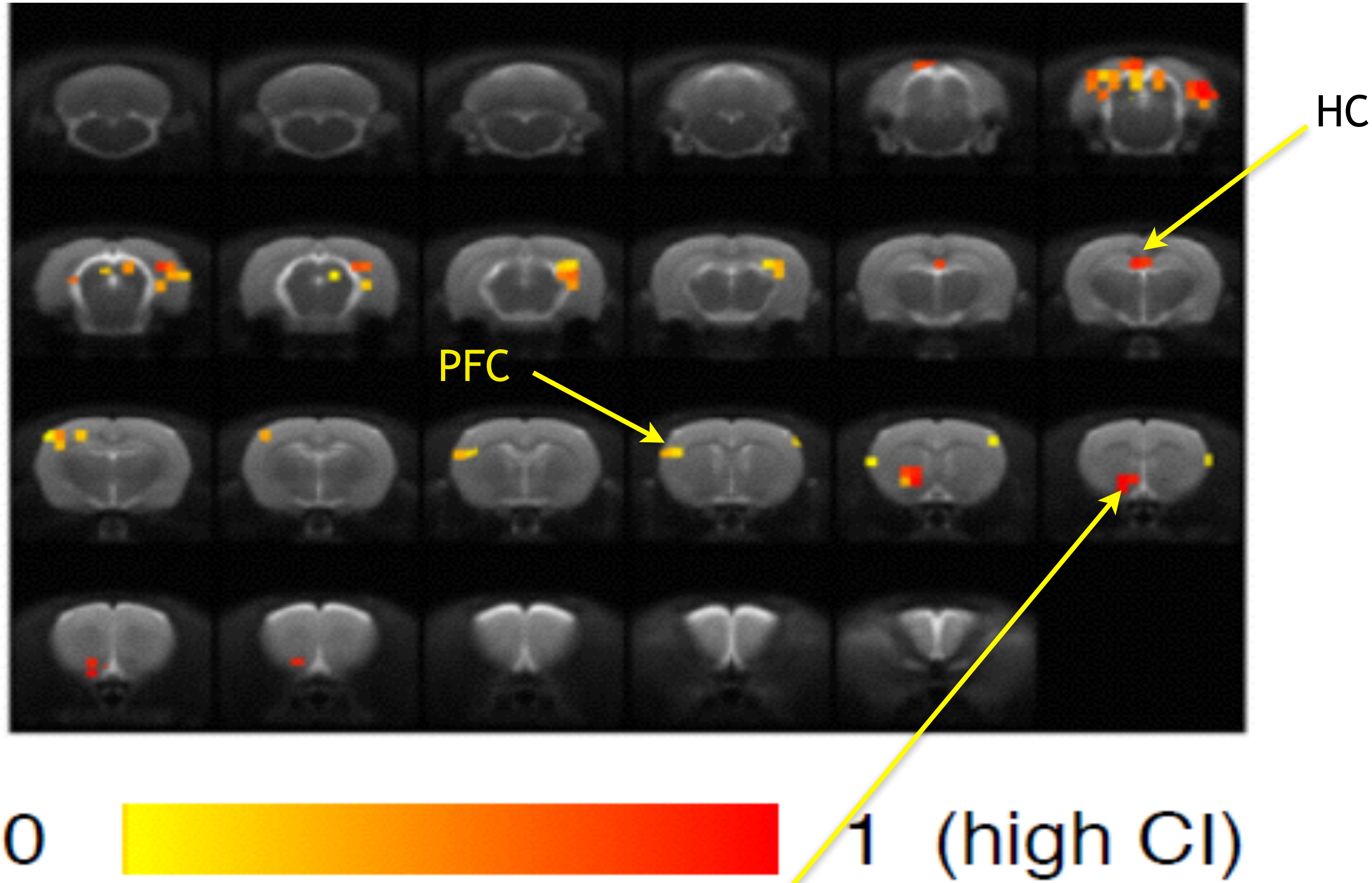






We find the Memory 3-Network of Networks: Hippocampus + Nucleus Accumbens + Prefrontal Cortex

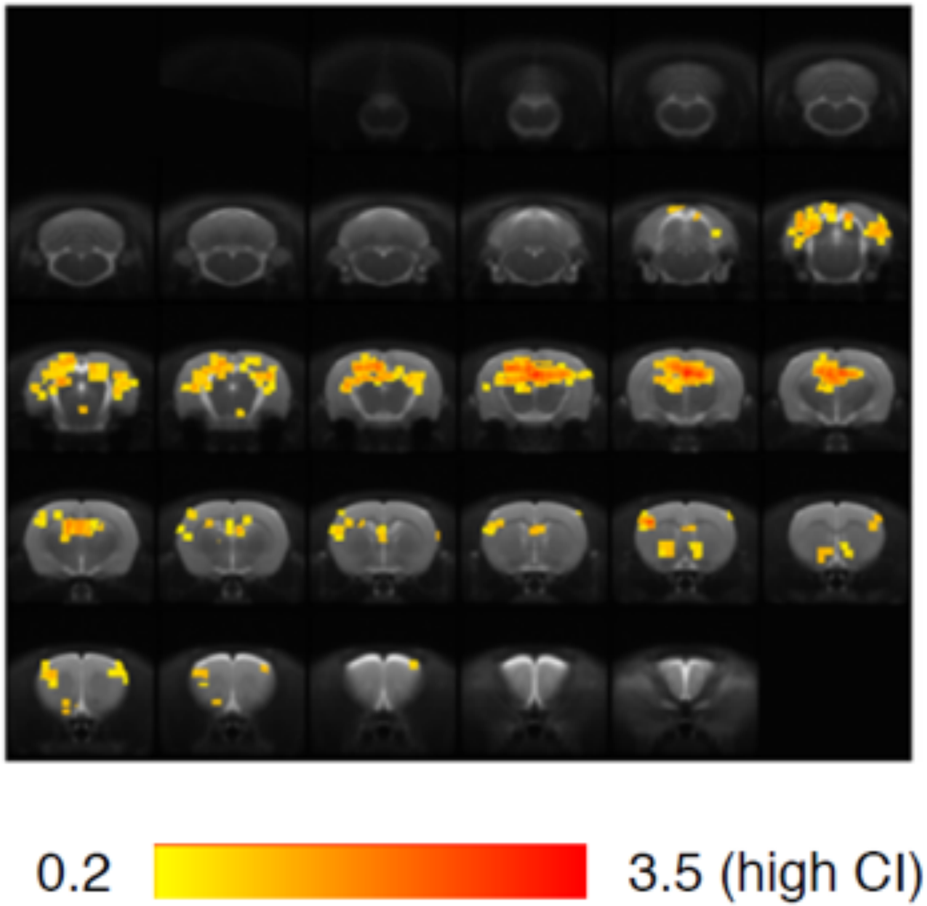
INFLUENCE MAP OF THE MEMORY NETWORK



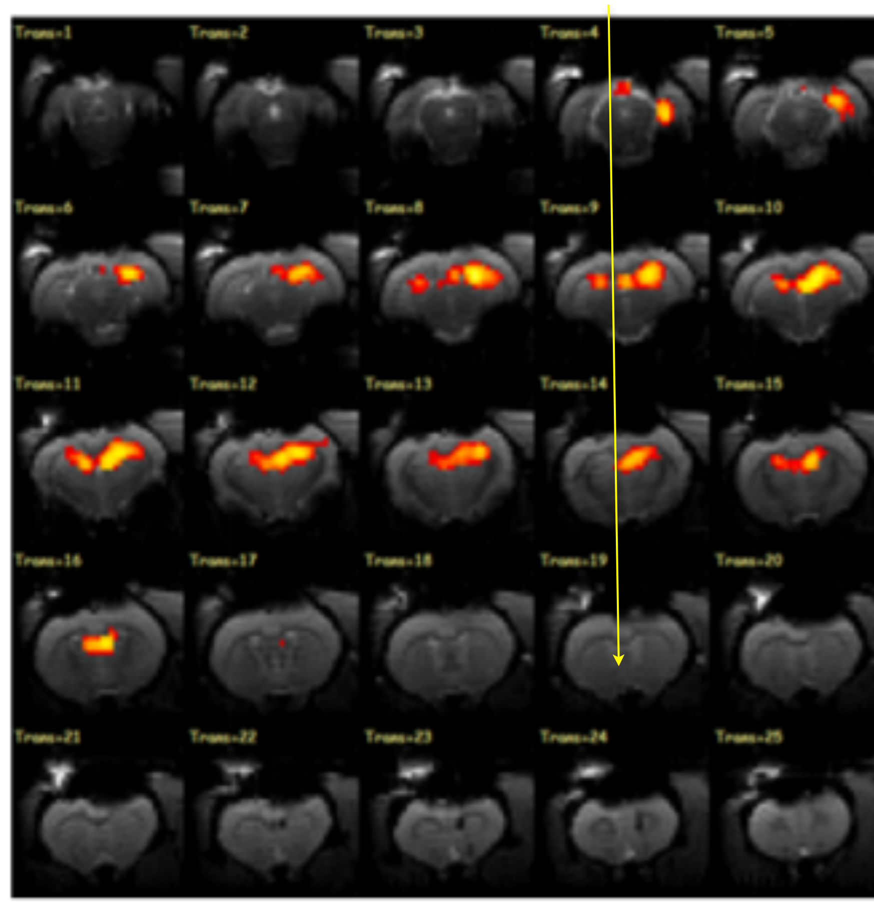
NUCLEUS ACCUMBENS IS THE MOST INFLUENTIAL AREA EVEN THOUGH IT HAS LOW CONNECTIVITY!

Inhibition of single core node in Nucleus Accumbens destroys the whole memory consolidation in the Prefrontal Cortex

ACTIVATION MAP WITHOUT KO



ACTIVATION MAP WITH KO OF ACCUMBENS



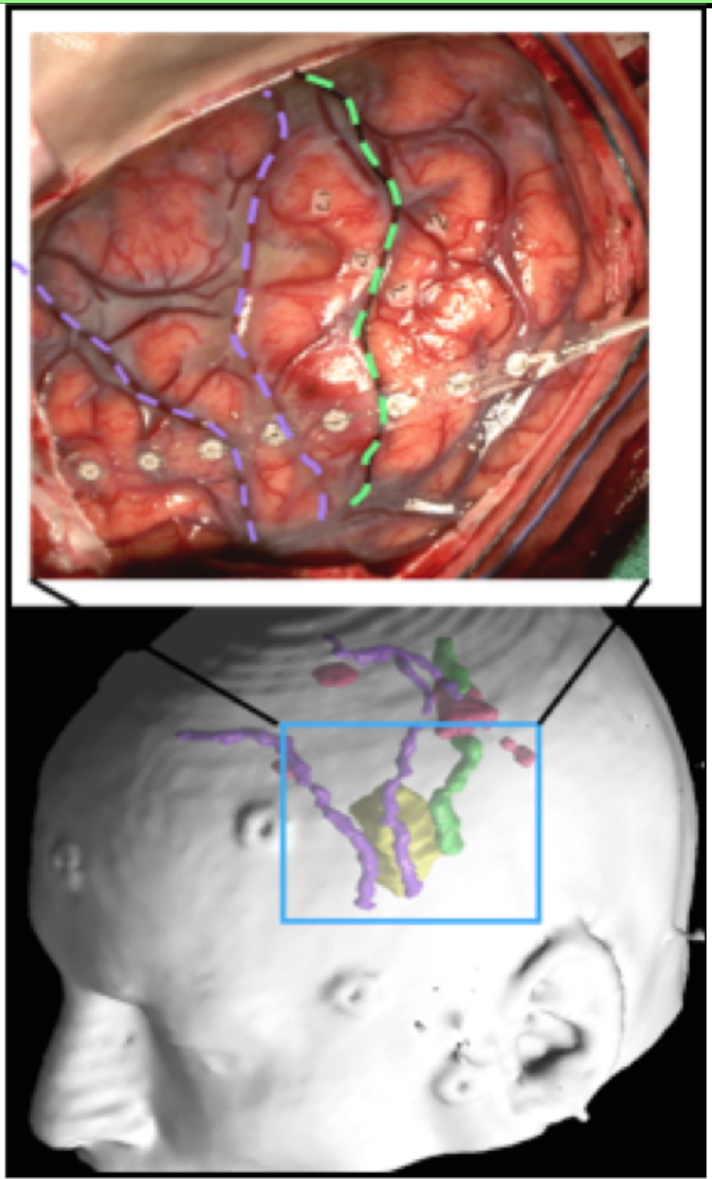
LTP does not strengthen any area when the core node in the NAc predicted by CI map is inhibited

Awake brain surgery to dissect tumor with no clear boundaries

Neurosurgeon stimulates areas
around the tumor with electrodes
to locate the essential functional areas.

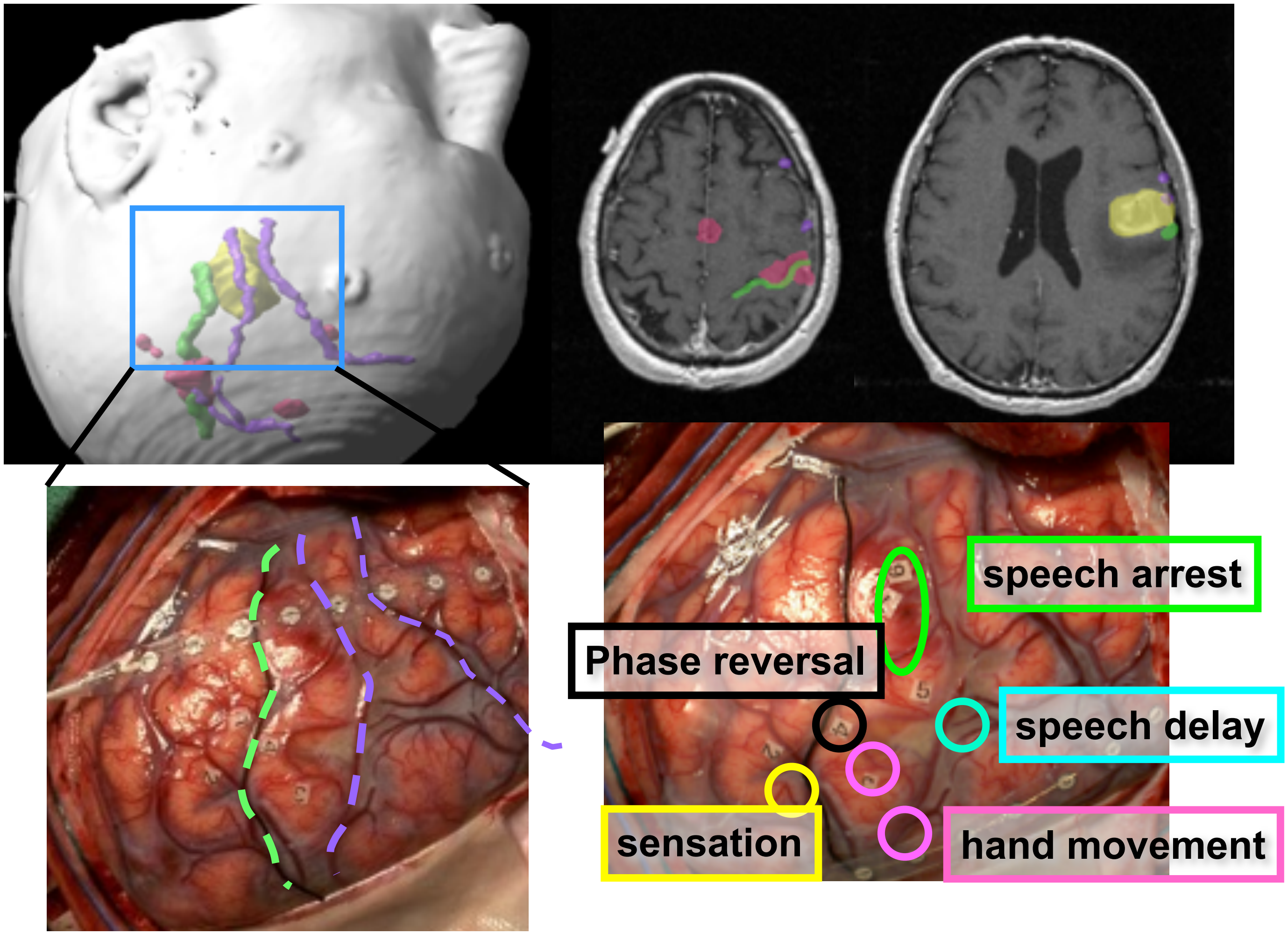
Functional areas (eg, language, motor)
are located by asking patient to talk,
move, etc. Remove as much tumor as
possible avoiding the essential areas.

GOAL: predict the essential areas of
the brain with NoN theory



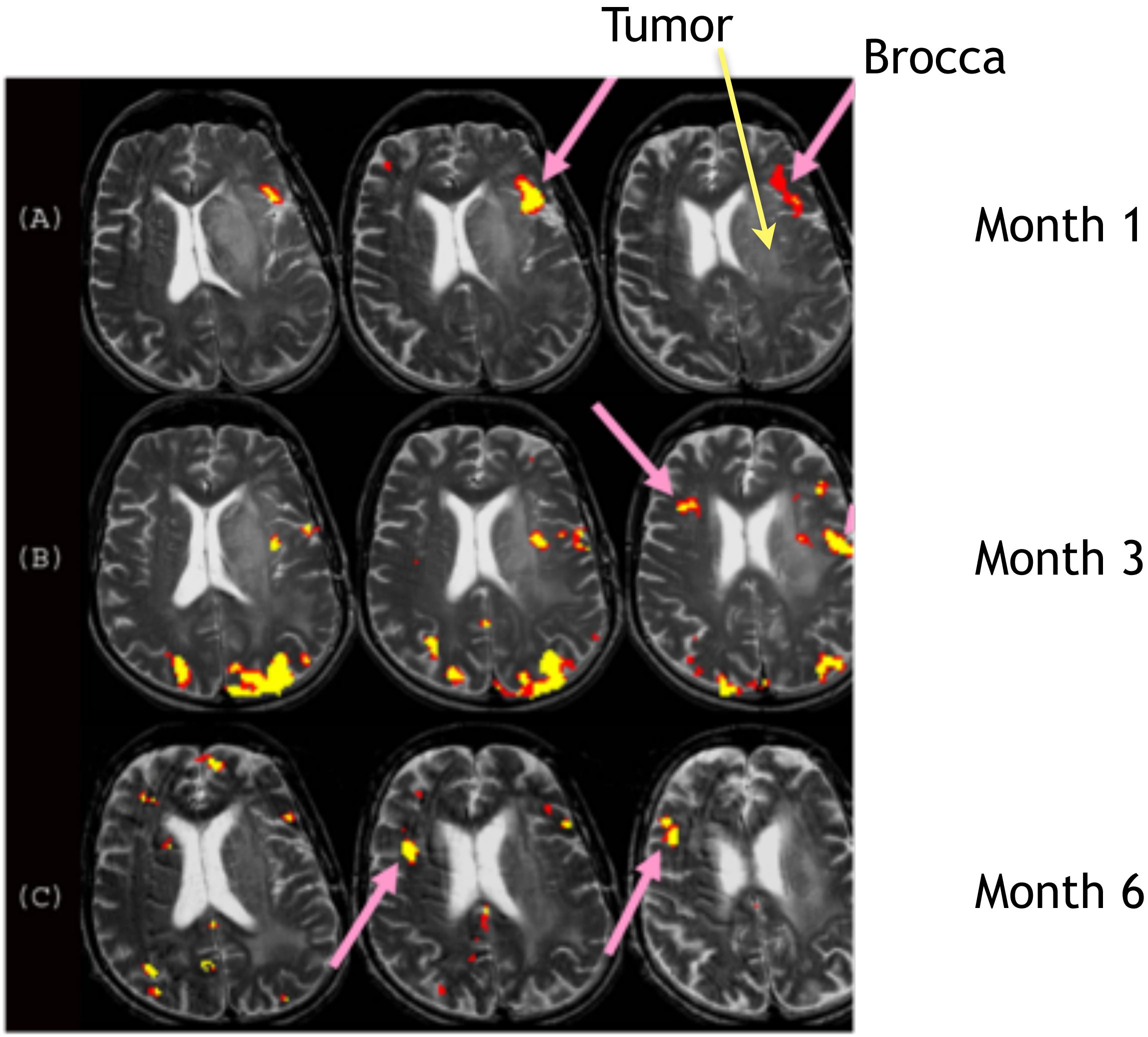
Collaboration with
Andrei Holodny, Memorial
Sloan Kettering Cancer Center

NOWADAYS: Functional areas are identified by asking patient



Functional areas are identified by asking patient to talk during awake brain surgery.

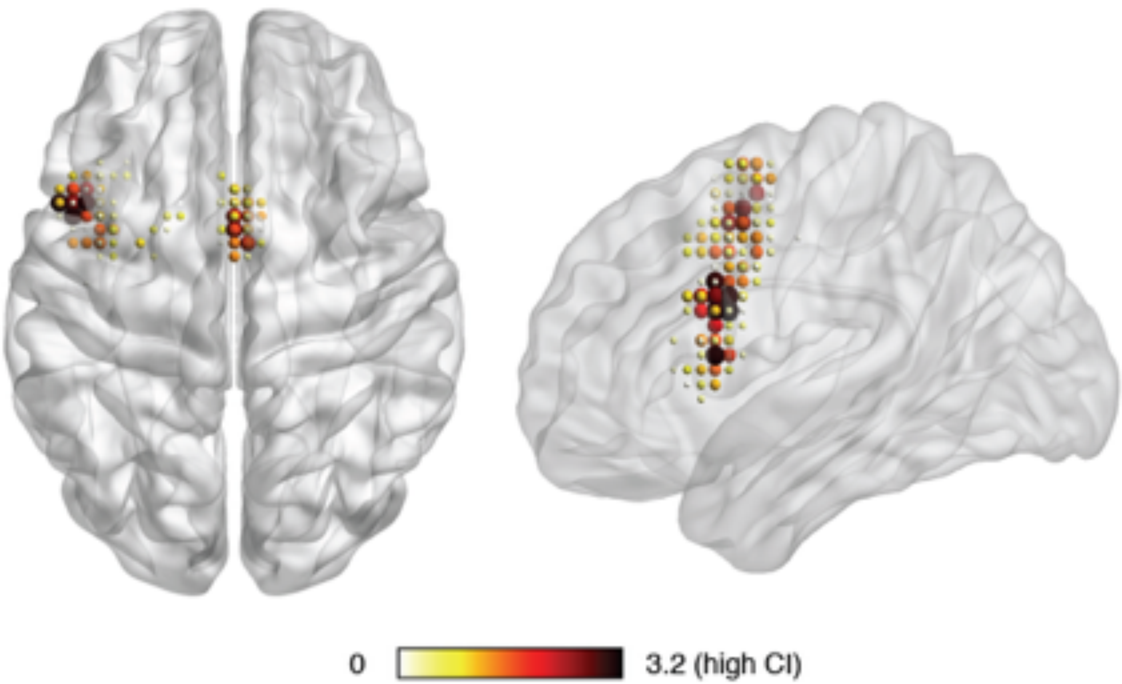
Brain reorganization of language function after tumor



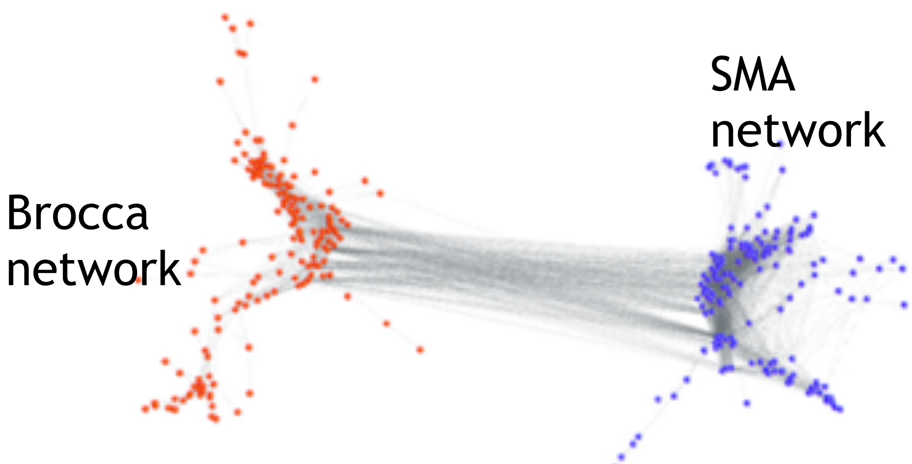
Brocca language area is reorganized!!

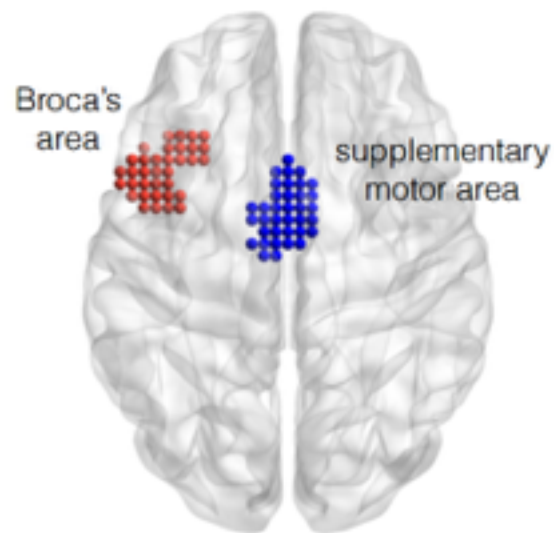
But only in half of 70 patients

Predicting the essential area in the human brain of language function may help to understand both problems (in progress)



Predicting the core nodes in language function in the brain by Network Theory





Data Analytics at the Cutting-Edge for Free!
kcore-analytics.com

KCORE ANALYTICS

KCORE WHAT WE DO WHO WE ARE CASE STUDY PRESS NEWS CONTACT LOGIN

CCNY DREAM TEAM:

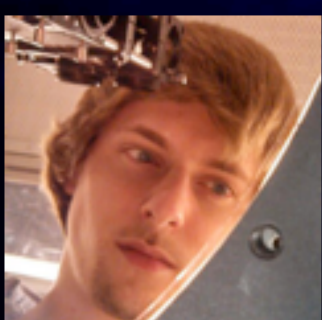
Search Engine for Influencers

Twitter Influencers

Flaviano Morone

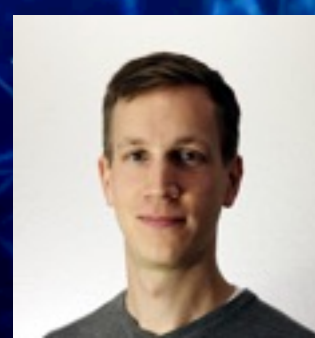
Hernan Makse

George Furbish



Andrea Morone

Alex Bovet



Kevin Roth

Francesca Lucini

Summary

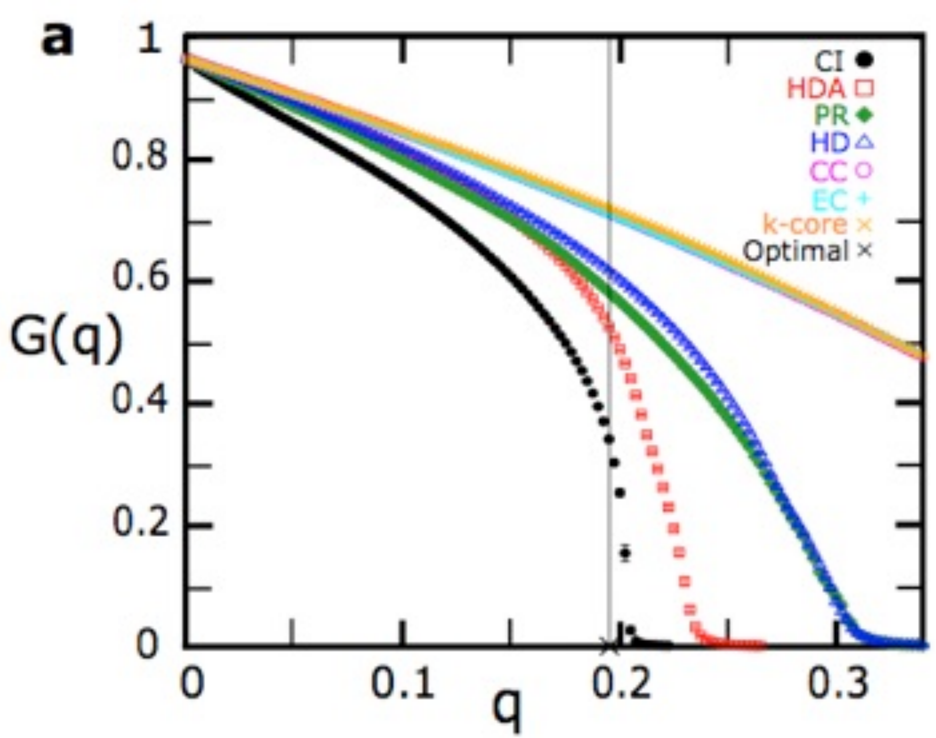
1. NETWORK THEORY allows to predict the essential areas of the brain and influencers in social networks

2. Applications to open brain surgery in collaboration with Holodny, MSKCC.

3. Test in memory consolidation in rats in collaboration with Canals, Alicante.

Test: Exact optimal solution and best approximation with CI in Erdos-Renyi network

CI outperforms heuristic centralities and approximates well the exact optimal solution

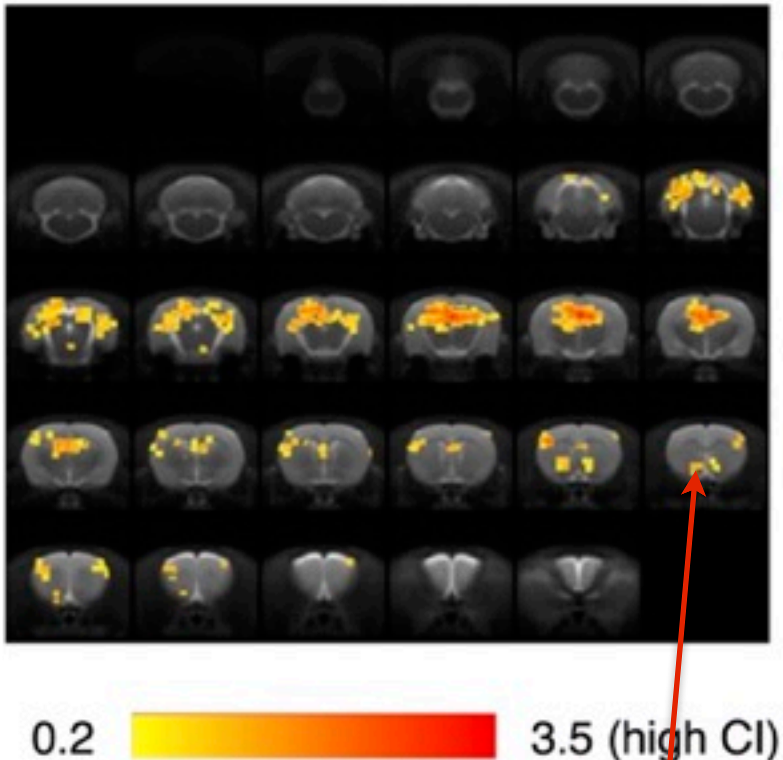


The best possible attack is to remove the loops to get a tree at q_c

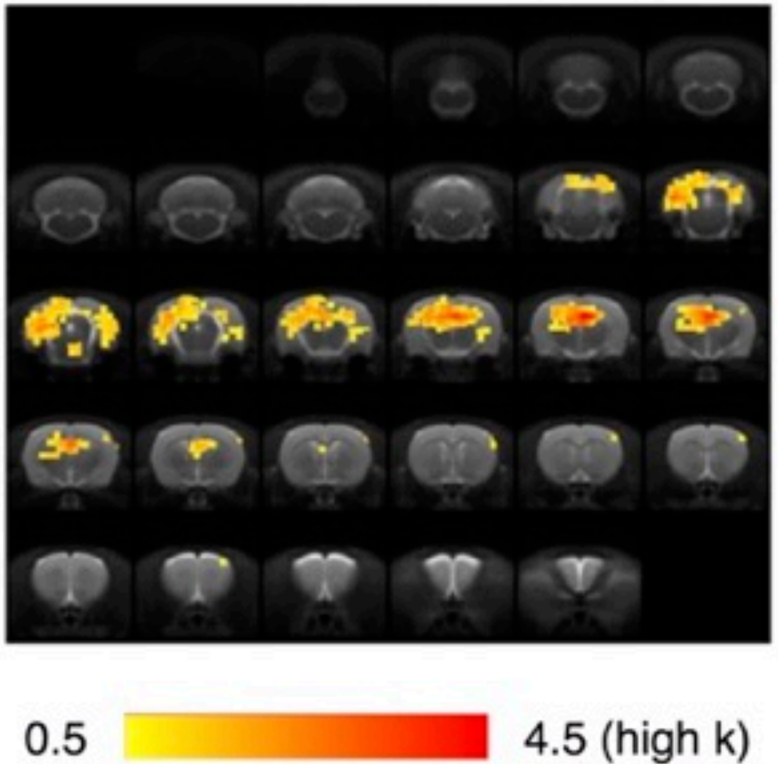
Others: hub removal (HD, high degree and adaptive HDA), PageRank, Closeness Centrality, Eigenvector Centrality, k-core, EGP

NUCLEUS ACCUMBENS IS THE MOST INFLUENTIAL AREA EVEN THOUGH IT HAS LOW CONNECTIVITY!

INFLUENCE MAP
OVER 6 RATS



HIGH CONNECTIVITY MAP



NUCLEUS ACCUMBENS

Attention involves an integration of two different influences

Corbetta, Schulman (2002)

Goal-directed by

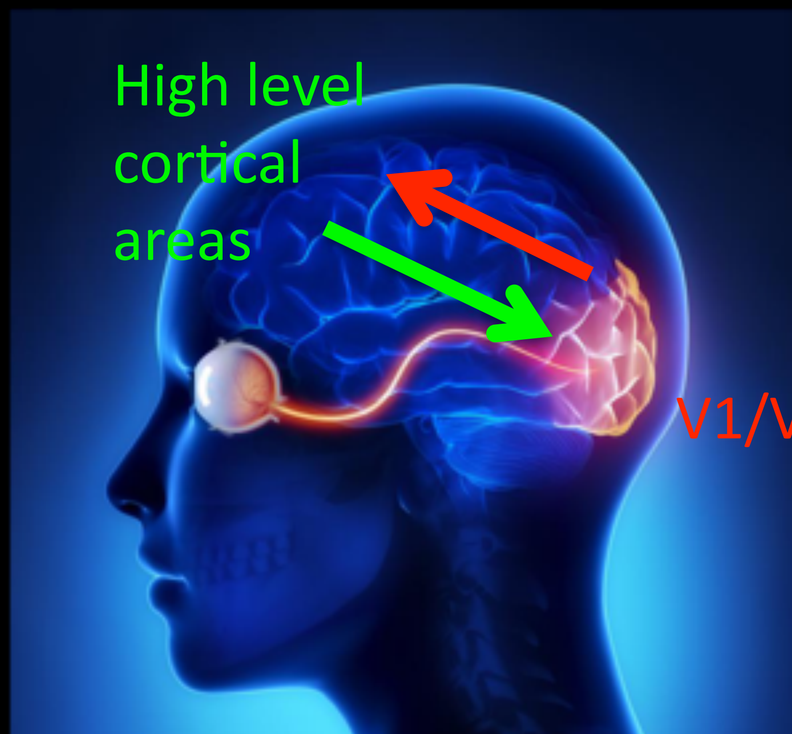
expectation, knowledge, experience

Top-Down control

Bottom-up processing

Stimulus-driven by

visual, sensory stimulation

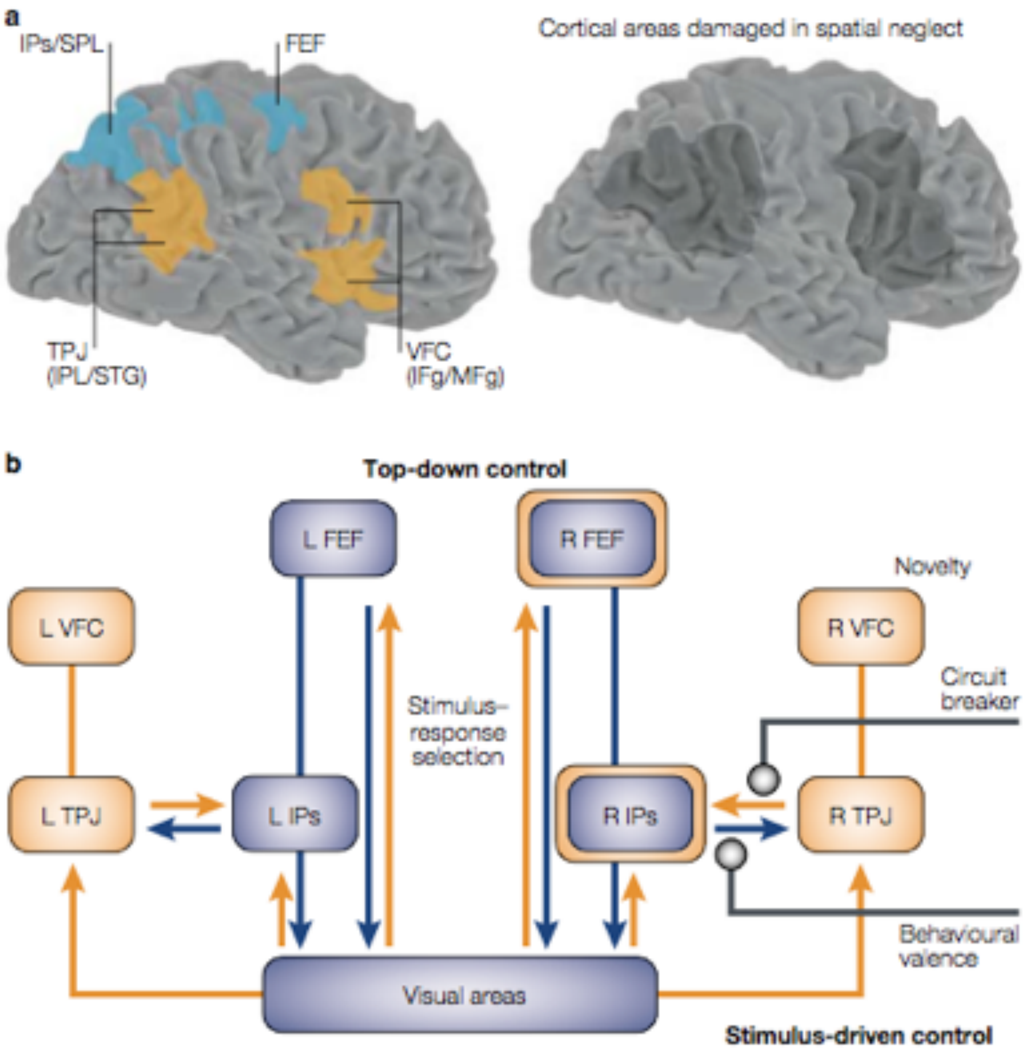


Do you see the faces or the vase?

Multistability
Gestalt

DEBATE IN NEUROSCIENCE

The binding problem: how to integrate modules in a Network of Networks (segregation vs integration)



Corbetta, Shulman '02
Tononi, Sporns, Edelman '94
Dehane, Naccache '01
Sigman, Gilbert '07
Treisman '96

Binding problem

Segregation vs integration

Selective Attention

Consciousness

A General Question in Network Science


Complexity

4. Ebola outbreak traced back to a single superspreader event

The New York Times
NYTIMES.COM

By DONALD G. McNEIL Jr.
AUGUST 28, 2014

Sierra Leone's explosion of Ebola cases in early summer appears to stem from one traditional healer's funeral at which 14 women were infected, according to scientists studying the blood of victims.

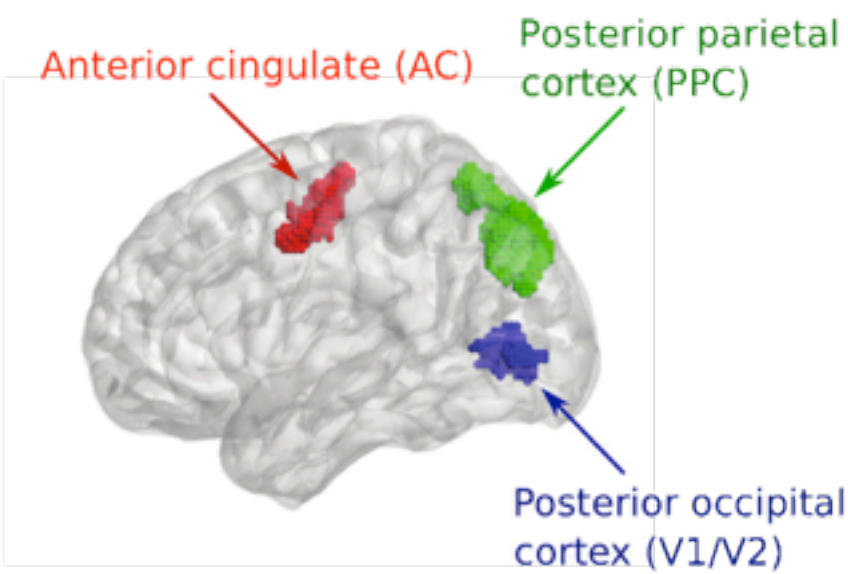
The funeral, which took place in mid-May, constitutes a "super-spreader" event comparable to one in 2003 in a Hong Kong hotel in which one doctor from China dying of SARS infected nine other guests who spread the virus throughout the city and to Vietnam and Canada.

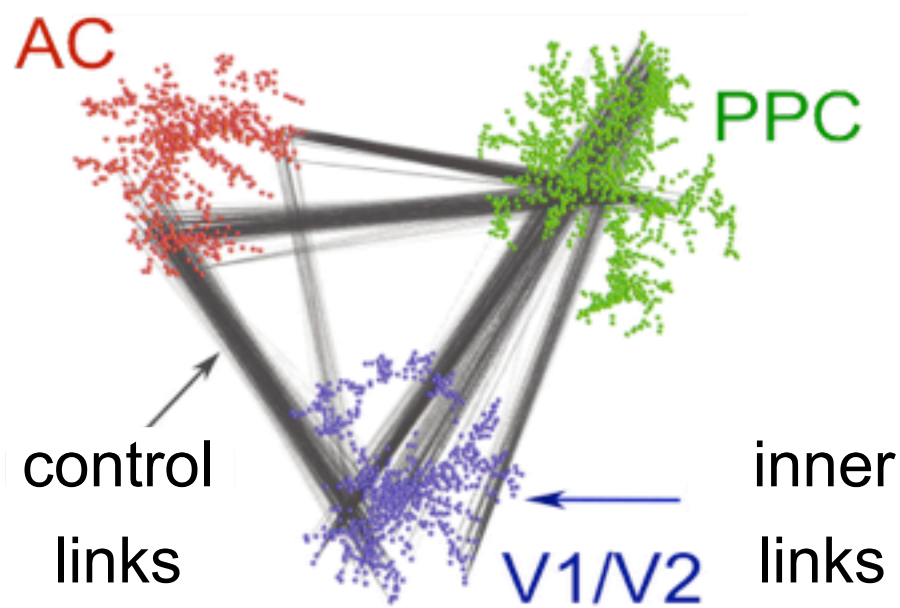
THE BRAIN IS A NETWORK OF NETWORKS

We use fMRI readouts in a dual task experiment:
visual + auditory task

Finding the essential minimal nodes in the brain

- (analogous to neural correlates of consciousness) -





Gallos, Makse, Sigman, PNAS (2012)
Reis, Andrade, Sigman, Canals, Makse, Nat Phys (2014)

HYPOTHESIS: Perception = emergence of Giant Connected Component G

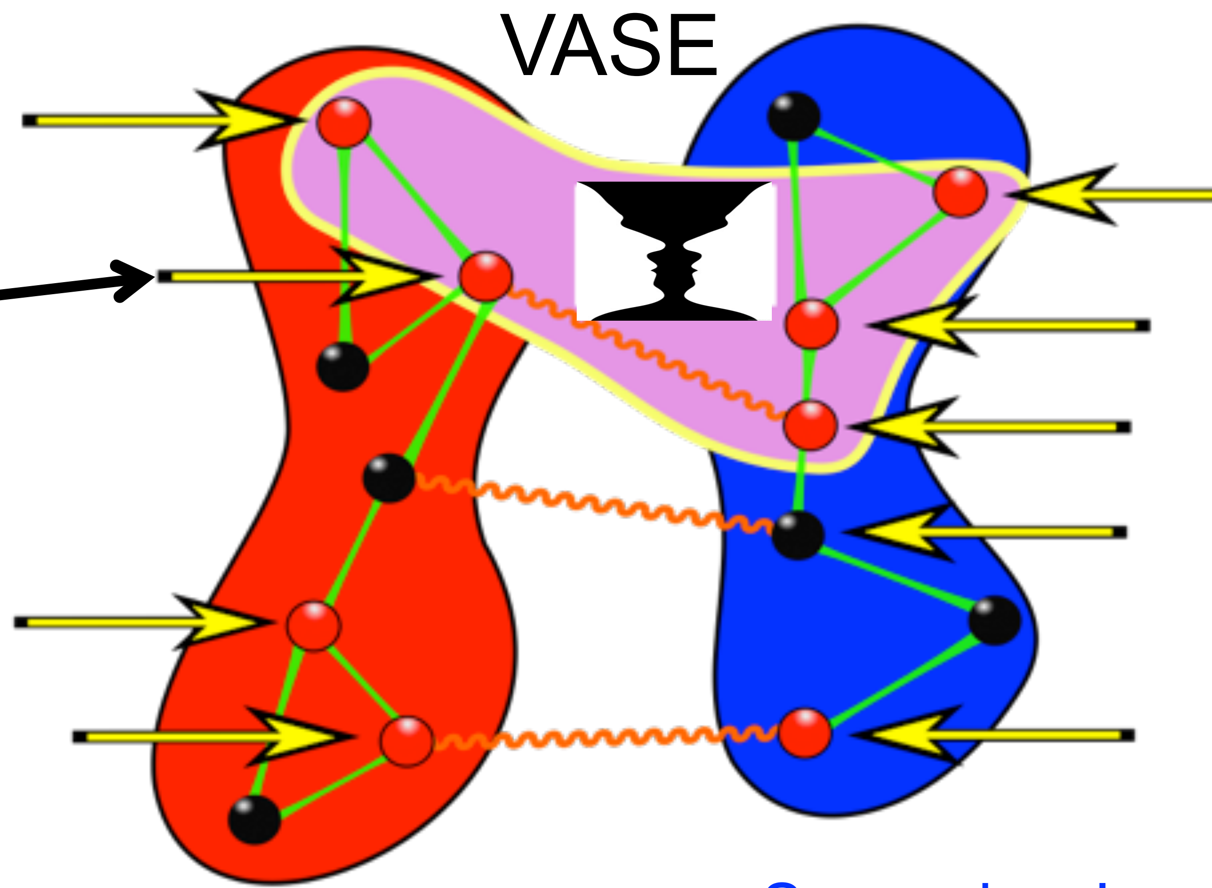
Koch and Crick

Stan Dehaene

Giant active component G

G = what you are aware of

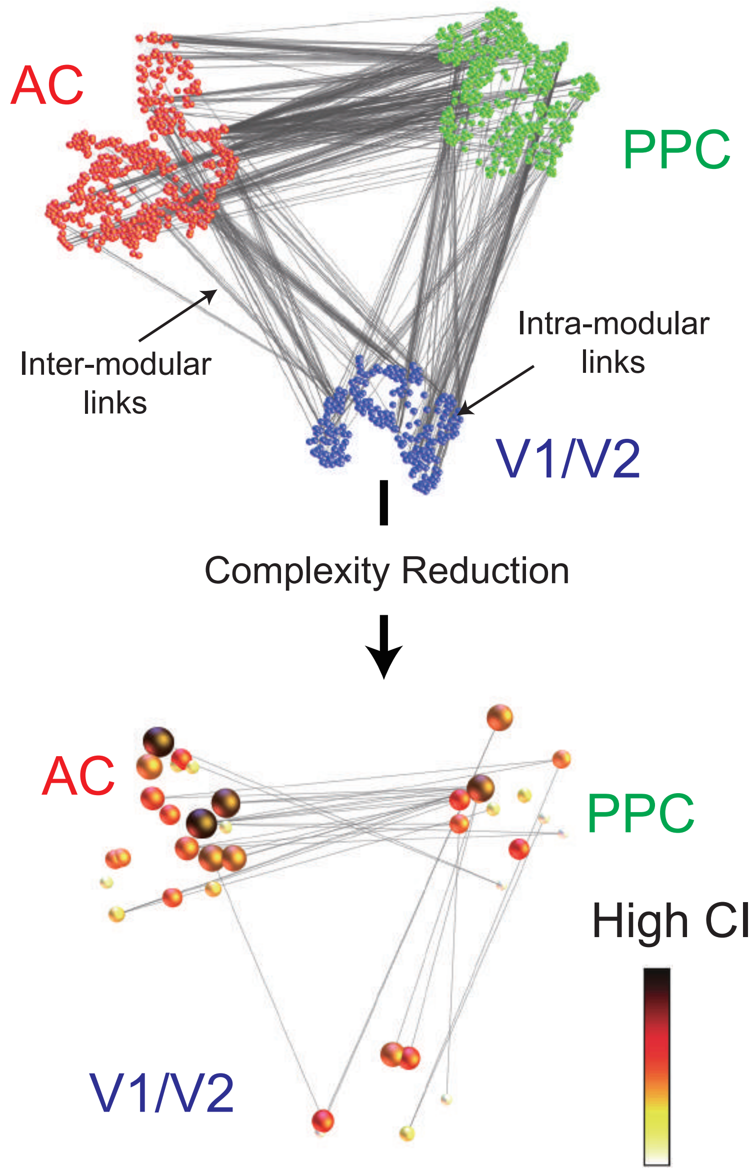
Global unitary perception

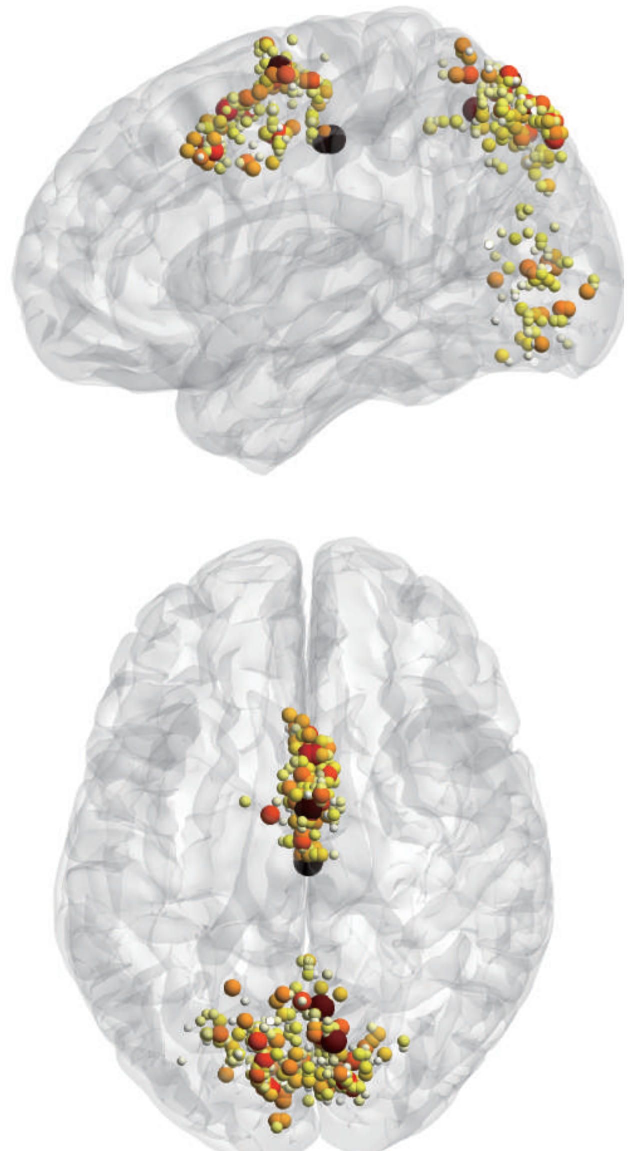


Different top-down control

Same visual input at V1/V2

Collective Influence Map of the Human Brain: reducing the brain to its essential nodes





RANDOM PERCOLATION: CREATE OR DESTROY THE NETWORK