IMT
SCUOLA
ALTI STUDI
LUCCA

ANALISI DEI DATI E ANALISI DELLE TENDENZE.
I BIG DATA

Guido Caldarelli IMT Alti Studi Lucca
www.guidocaldarelli.com
@GuidoCaldarelli

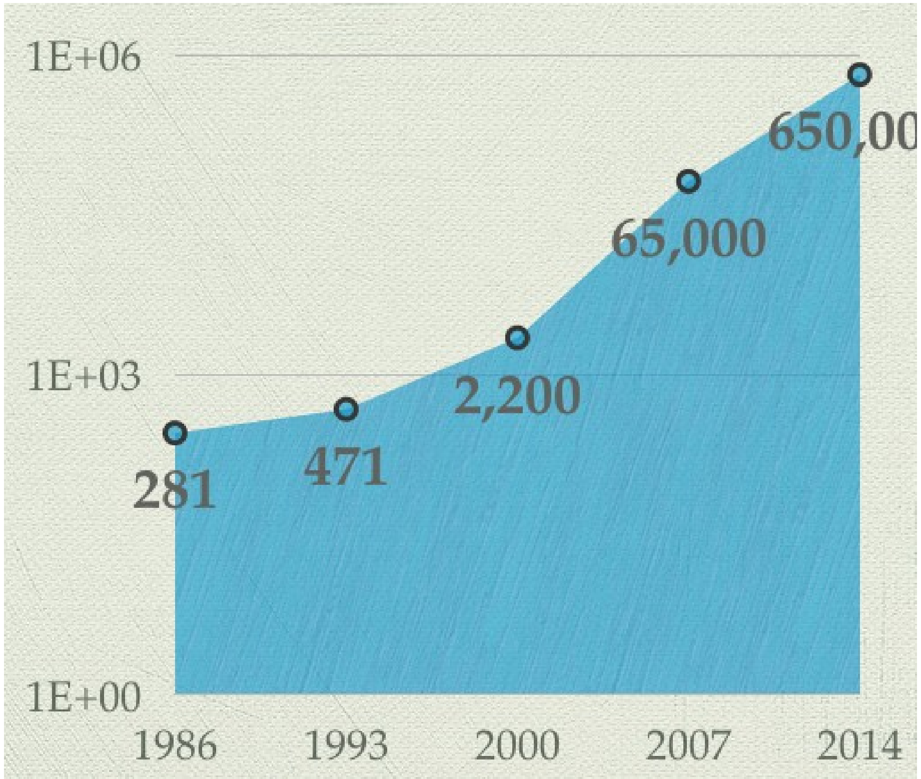
Big Data

La definizione è dinamica, visto che i computer diventano sempre più potenti e le memorie costano sempre meno.

un Petabyte=1,000,000 di Gigabyte
un Giga è circa

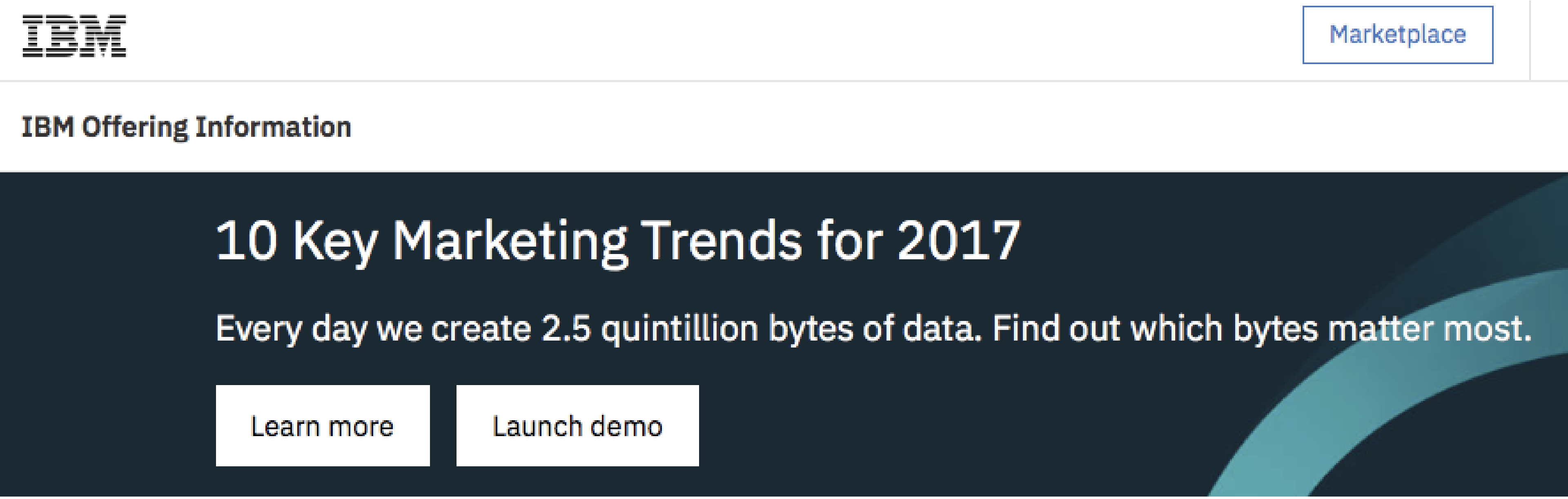
- un film compresso in mp3
- 250 canzoni
- Il traffico dati di un mese di smartphone
- 700 libri

Traffico secondo stime CISCO →



E crescono ancora

2.5 1018 byte per day = 2500 PB/day ~ 1 Million PB/year


IBM
Marketplace
Learn more
Launch demo

IBM Offering Information

10 Key Marketing Trends for 2017

Every day we create 2.5 quintillion bytes of data. Find out which bytes matter most.

Impronte digitali

SMS
@
GL Stock Images

La Connetività è la nuova impronta **"digitale"**

Google

I motori di ricerca e (parzialmente) le reti sociali sono I nuovi “Confessori”
In più
NESSUNO MENTE A GOOGLE

Certo, certo. Non bisogna arrivare a conclusioni affrettate. Teniamo conto del litigio e cerchiamo di scoprire chi urlava e perché. Rintracciamo questo padre, se non altro dobbiamo informarlo di quello che è successo. E anche il fidanzato della ragazza, capiamo quando l’ha vista per l’ultima volta. Ottavia, sappiamo dove lavora?

– Sí, per fortuna esistono i social: lí la gente mette tutto
[Gelo per I Bastardi di Pizzofalcone, M. De Giovanni]

Influenza

nature Vol 457|19 February 2009|doi:10.1038/nature07634

LETTERS

Detecting influenza epidemics using search engine query data

Jeremy Ginsberg[1], Matthew H. Mohebbi[1], Rajan S. Patel[1], Lynnette Brammer[2], Mark S. Smolinski[1] & Larry Brilliant[1]

Google
Italia
Google Search
I'm Feeling Lucky
Google.it offered in: Italiano

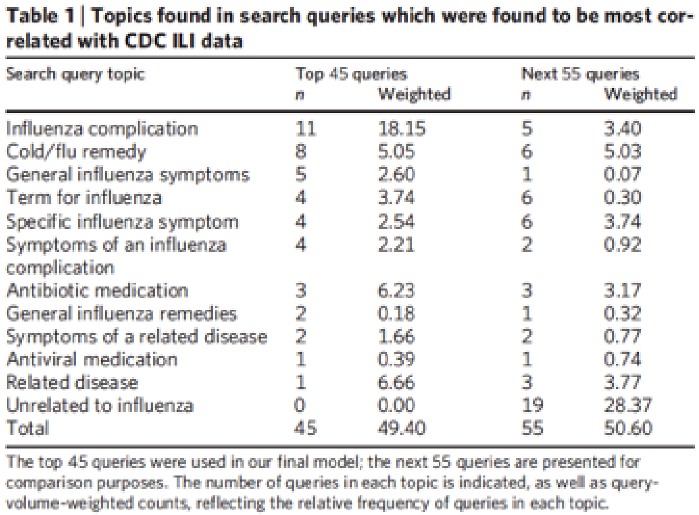


Table 1 | Topics found in search queries which were found to be most correlated with CDC ILI data

Search query topic	Top 45 queries		Next 55 queries	
	n	Weighted	*n*	Weighted
Influenza complication	11	18.15	5	3.40
Cold/flu remedy	8	5.05	6	5.03
General influenza symptoms	5	2.60	1	0.07
Term for influenza	4	3.74	6	0.30
Specific influenza symptom	4	2.54	6	3.74
Symptoms of an influenza complication	4	2.21	2	0.92
Antibiotic medication	3	6.23	3	3.17
General influenza remedies	2	0.18	1	0.32
Symptoms of a related disease	2	1.66	2	0.77
Antiviral medication	1	0.39	1	0.74
Related disease	1	6.66	3	3.77
Unrelated to influenza	0	0.00	19	28.37
Total	45	49.40	55	50.60

The top 45 queries were used in our final model; the next 55 queries are presented for comparison purposes. The number of queries in each topic is indicated, as well as query-volume-weighted counts, reflecting the relative frequency of queries in each topic.

Influenza

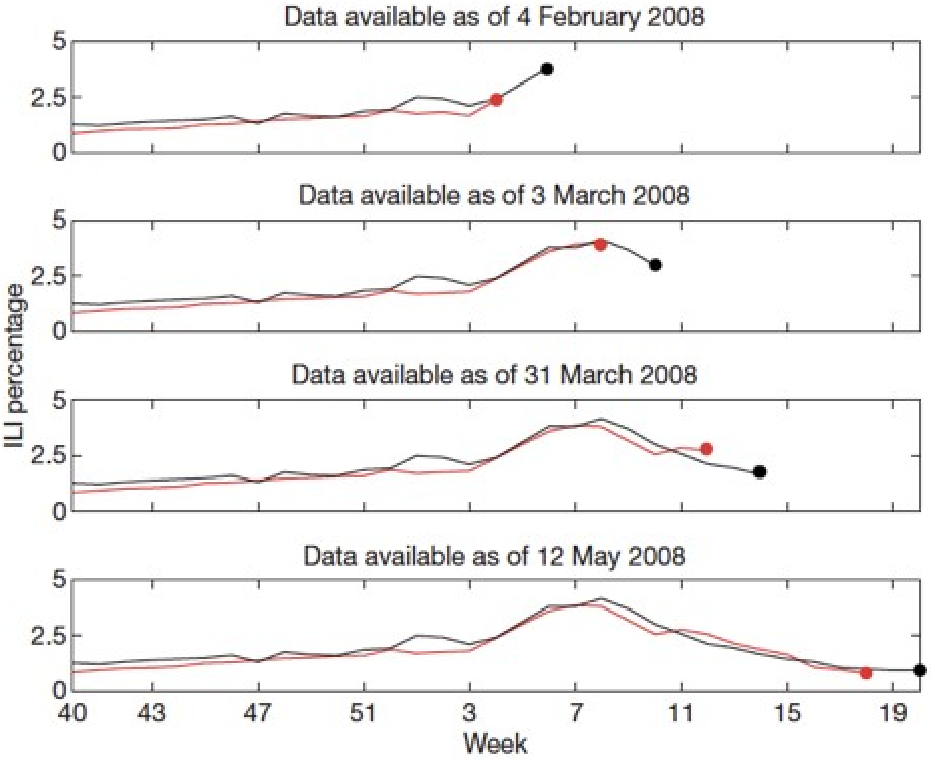
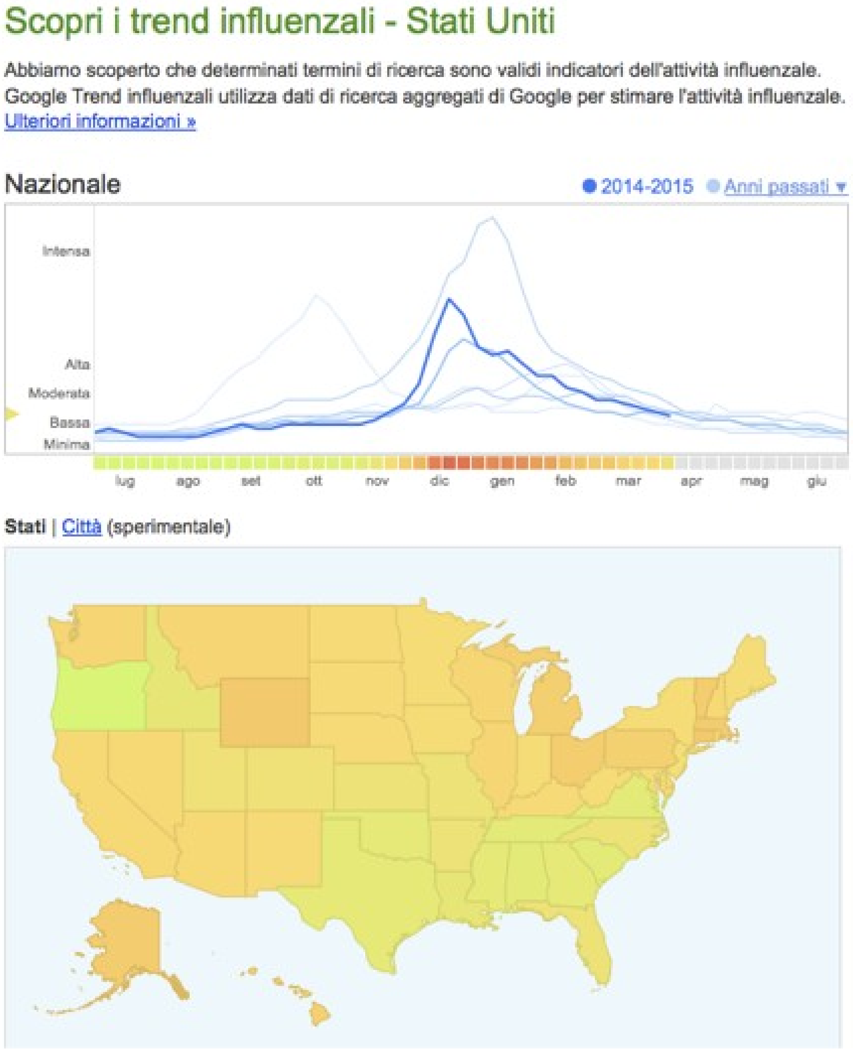


Figure 3 | ILI percentages estimated by our model (black) and provided by the CDC (red) in the mid-Atlantic region, showing data available at four points in the 2007-2008 influenza season. During week 5 we detected a sharply increasing ILI percentage in the mid-Atlantic region; similarly, on 3 March our model indicated that the peak ILI percentage had been reached during week 8, with sharp declines in weeks 9 and 10. Both results were later confirmed by CDC ILI data.



Scopri i trend influenzali - Stati Uniti

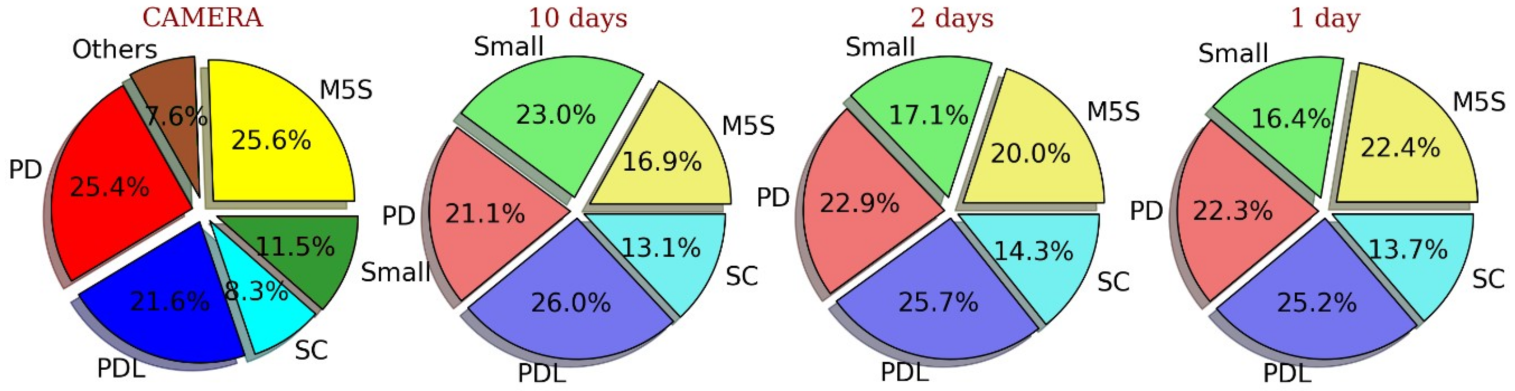
Abbiamo scoperto che determinati termini di ricerca sono validi indicatori dell'attività influenzale. Google Trend influenzali utilizza dati di ricerca aggregati di Google per stimare l'attività influenzale. Ulteriori informazioni »

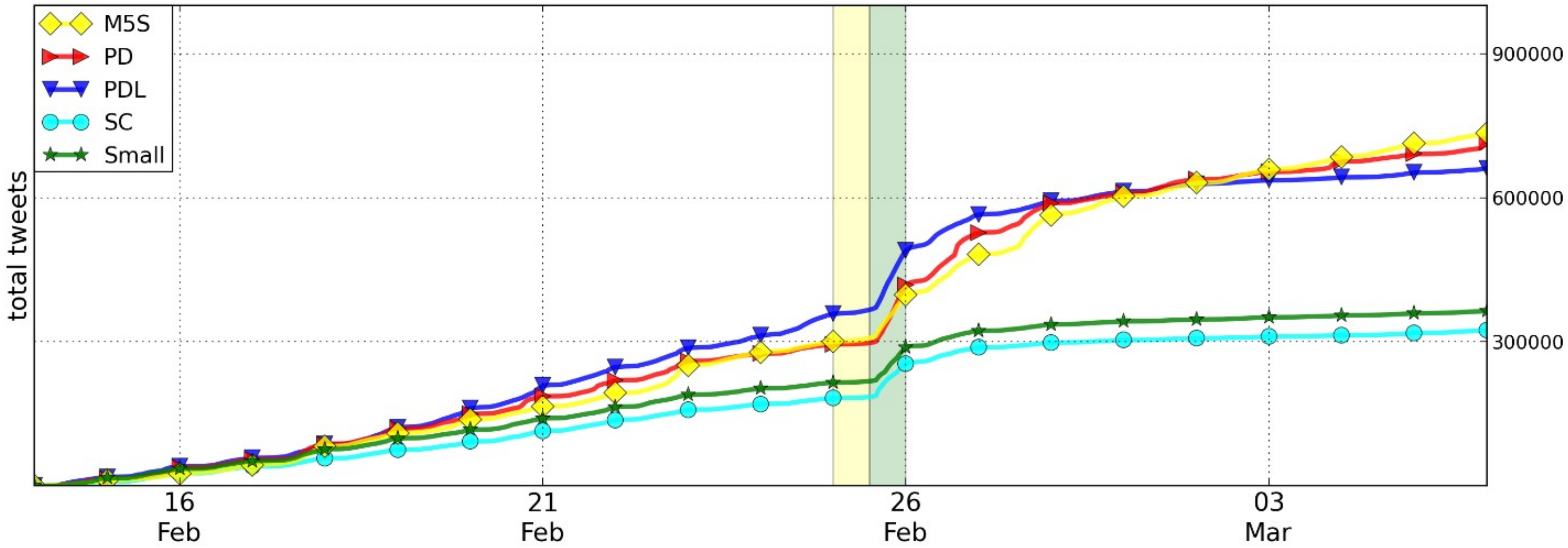
Nazionale

● 2014-2015
● Anni passati ▾
Intensa
Alta
Moderata
Bassa
Minima
lug
ago
set
ott
nov
dic
gen
feb
mar
apr
mag
giu

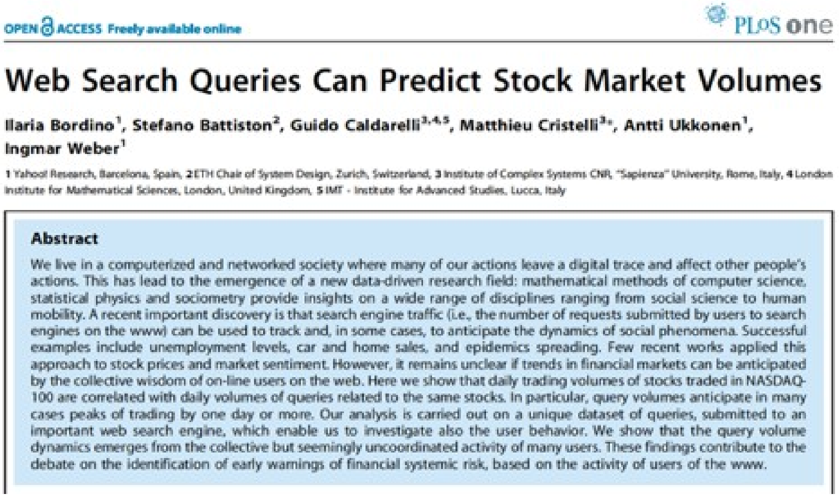
Stati | Città (sperimentale)

Twitter


CAMERA
Others
7.6%
M5S
25.6%
PD
25.4%
11.5%
Small
21.6%
8.3%
SC
PDL
10 days
Small
23.0%
M5S
16.9%
PD
21.1%
13.1%
SC
26.0%
PDL
2 days
Small
17.1%
M5S
20.0%
PD
22.9%
14.3%
SC
25.7%
PDL
1 day
Small
16.4%
M5S
22.4%
PD
22.3%
13.7%
SC
25.2%
PDL


M5S
PD
PDL
SC
Small
total tweets
900000
600000
300000
16
Feb
21
Feb
26
Feb
03
Mar

Attività



OPEN ACCESS Freely available online PLoS one

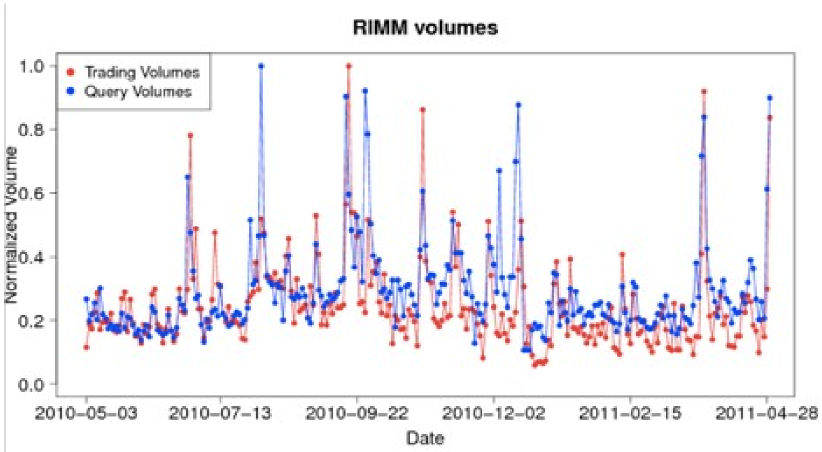
Web Search Queries Can Predict Stock Market Volumes

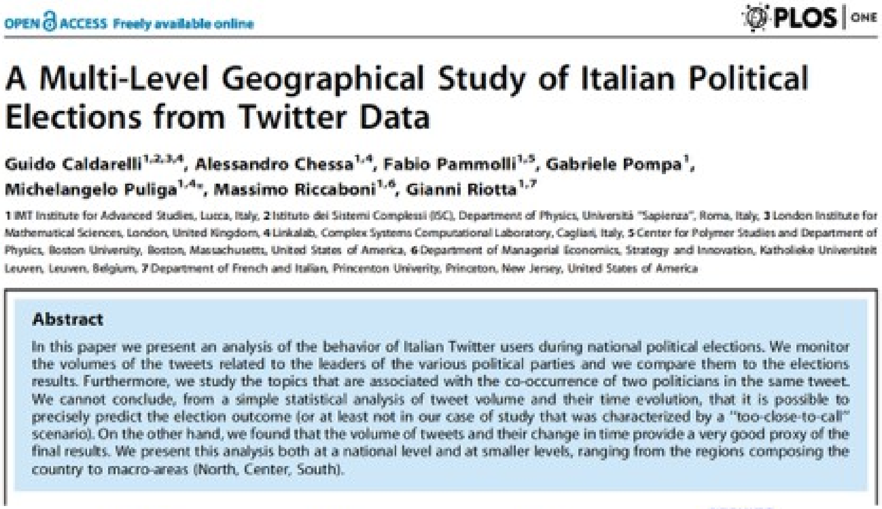
Ilaria Bordino[1], Stefano Battiston[2], Guido Caldarelli[3,4,5], Matthieu Cristelli[3]*, Antti Ukkonen[1], Ingmar Weber[1]

1 Yahoo! Research, Barcelona, Spain, 2 ETH Chair of System Design, Zurich, Switzerland, 3 Institute of Complex Systems CNR, "Sapienza" University, Rome, Italy, 4 London Institute for Mathematical Sciences, London, United Kingdom, 5 IMT - Institute for Advanced Studies, Lucca, Italy

Abstract

We live in a computerized and networked society where many of our actions leave a digital trace and affect other people's actions. This has lead to the emergence of a new data-driven research field: mathematical methods of computer science, statistical physics and sociometry provide insights on a wide range of disciplines ranging from social science to human mobility. A recent important discovery is that search engine traffic (i.e., the number of requests submitted by users to search engines on the www) can be used to track and, in some cases, to anticipate the dynamics of social phenomena. Successful examples include unemployment levels, car and home sales, and epidemics spreading. Few recent works applied this approach to stock prices and market sentiment. However, it remains unclear if trends in financial markets can be anticipated by the collective wisdom of on-line users on the web. Here we show that daily trading volumes of stocks traded in NASDAQ-100 are correlated with daily volumes of queries related to the same stocks. In particular, query volumes anticipate in many cases peaks of trading by one day or more. Our analysis is carried out on a unique dataset of queries, submitted to an important web search engine, which enable us to investigate also the user behavior. We show that the query volume dynamics emerges from the collective but seemingly uncoordinated activity of many users. These findings contribute to the debate on the identification of early warnings of financial systemic risk, based on the activity of users of the www.





OPEN ACCESS Freely available online PLOS ONE

A Multi-Level Geographical Study of Italian Political Elections from Twitter Data

Guido Caldarelli[1,2,3,4], Alessandro Chessa[1,4], Fabio Pammolli[1,5], Gabriele Pompa[1], Michelangelo Puliga[1,4]*, Massimo Riccaboni[1,6], Gianni Riotta[1,7]

1 IMT Institute for Advanced Studies, Lucca, Italy, 2 Istituto dei Sistemi Complessi (ISC), Department of Physics, Università "Sapienza", Roma, Italy, 3 London Institute for Mathematical Sciences, London, United Kingdom, 4 Linkalab, Complex Systems Computational Laboratory, Cagliari, Italy, 5 Center for Polymer Studies and Department of Physics, Boston University, Boston, Massachusetts, United States of America, 6 Department of Managerial Economics, Strategy and Innovation, Katholieke Universiteit Leuven, Leuven, Belgium, 7 Department of French and Italian, Princeton Univerity, Princeton, New Jersey, United States of America

Abstract

In this paper we present an analysis of the behavior of Italian Twitter users during national political elections. We monitor the volumes of the tweets related to the leaders of the various political parties and we compare them to the elections results. Furthermore, we study the topics that are associated with the co-occurrence of two politicians in the same tweet. We cannot conclude, from a simple statistical analysis of tweet volume and their time evolution, that it is possible to precisely predict the election outcome (or at least not in our case of study that was characterized by a "too-close-to-call" scenario). On the other hand, we found that the volume of tweets and their change in time provide a very good proxy of the final results. We present this analysis both at a national level and at smaller levels, ranging from the regions composing the country to macro-areas (North, Center, South).

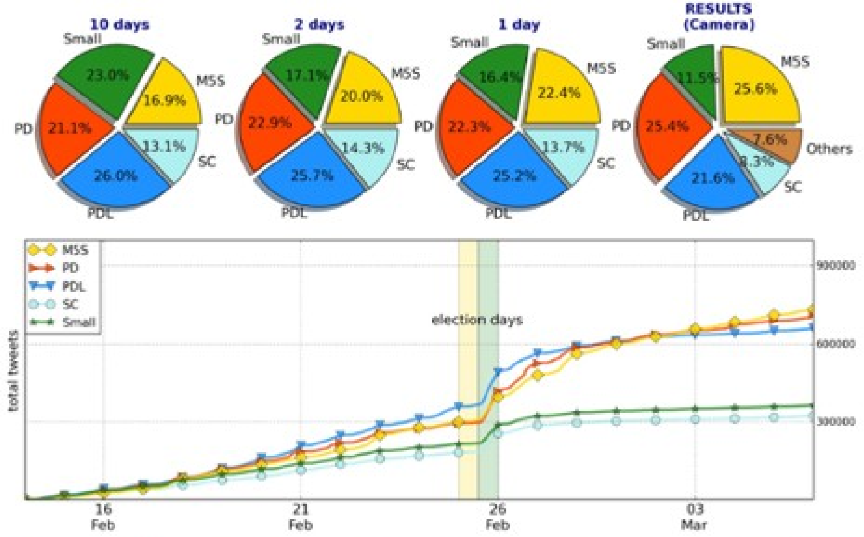
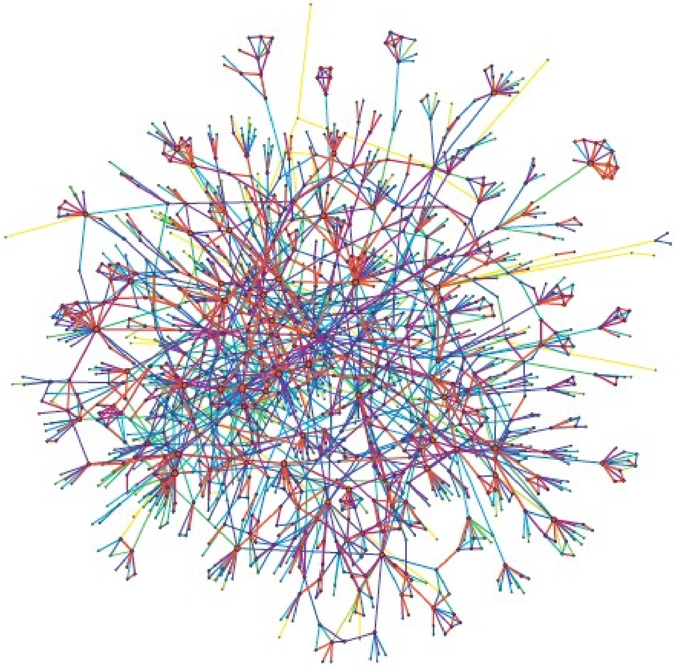


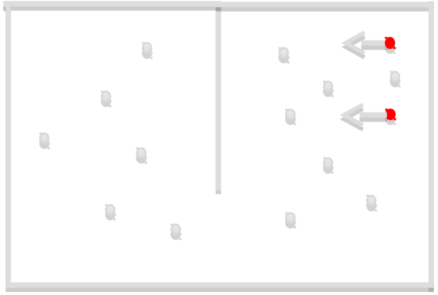
Figure 1. Results of the elections and Twitter volumes. On top: the pie-chart of the results obtained in the election by the parties. Then the forecast from the Twitter time series frozen at three different final times. Below: the cumulative number of tweets for the various parties and their daily evolution. The yellow and green vertical lines represent the election day and the day after respectively (when exit-polls are released).
doi:10.1371/journal.pone.0095809.g001

Metadati

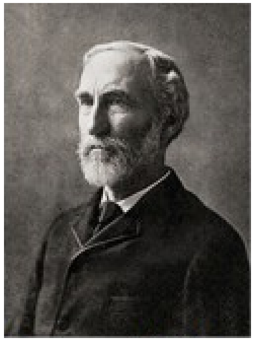
Non solo I dati sono importanti ma anche I METADATI
Ovvero le informazioni che parlano dei dati.
Non ho bisogno di intercettare una conversazione
Mi può bastare sapere che due persone si parlano in continuazione



La complessità dei dati



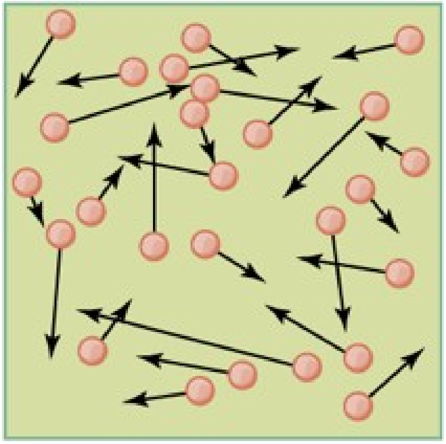
Ludwig Boltzmann

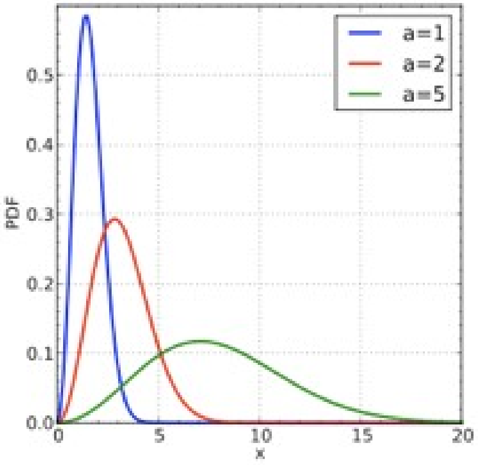


Joshua Willard Gibbs

James Clerk Maxwell

Se scambio le particelle ottengo la stessa configurazione macroscopica





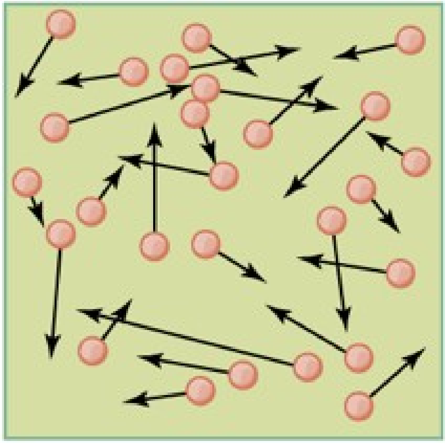
$$PV = \frac{1}{3}N m \overline{v^2}$$

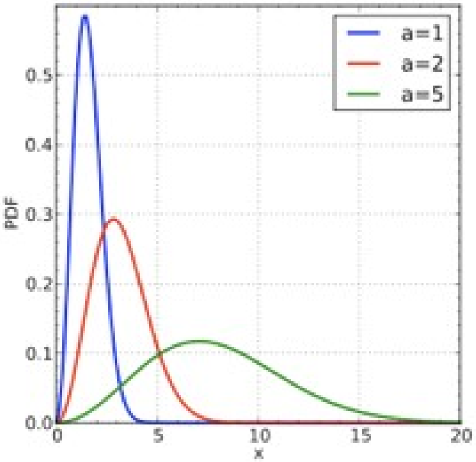
$$E = \frac{3}{2}k_B T$$

$$S = k_B \ln W$$

Il futuro

Sarà possibile fare la stessa cosa per la società?

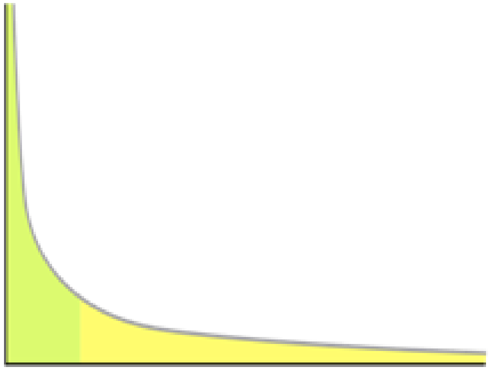




$$PV = \frac{1}{3} N m \overline{v^2}$$

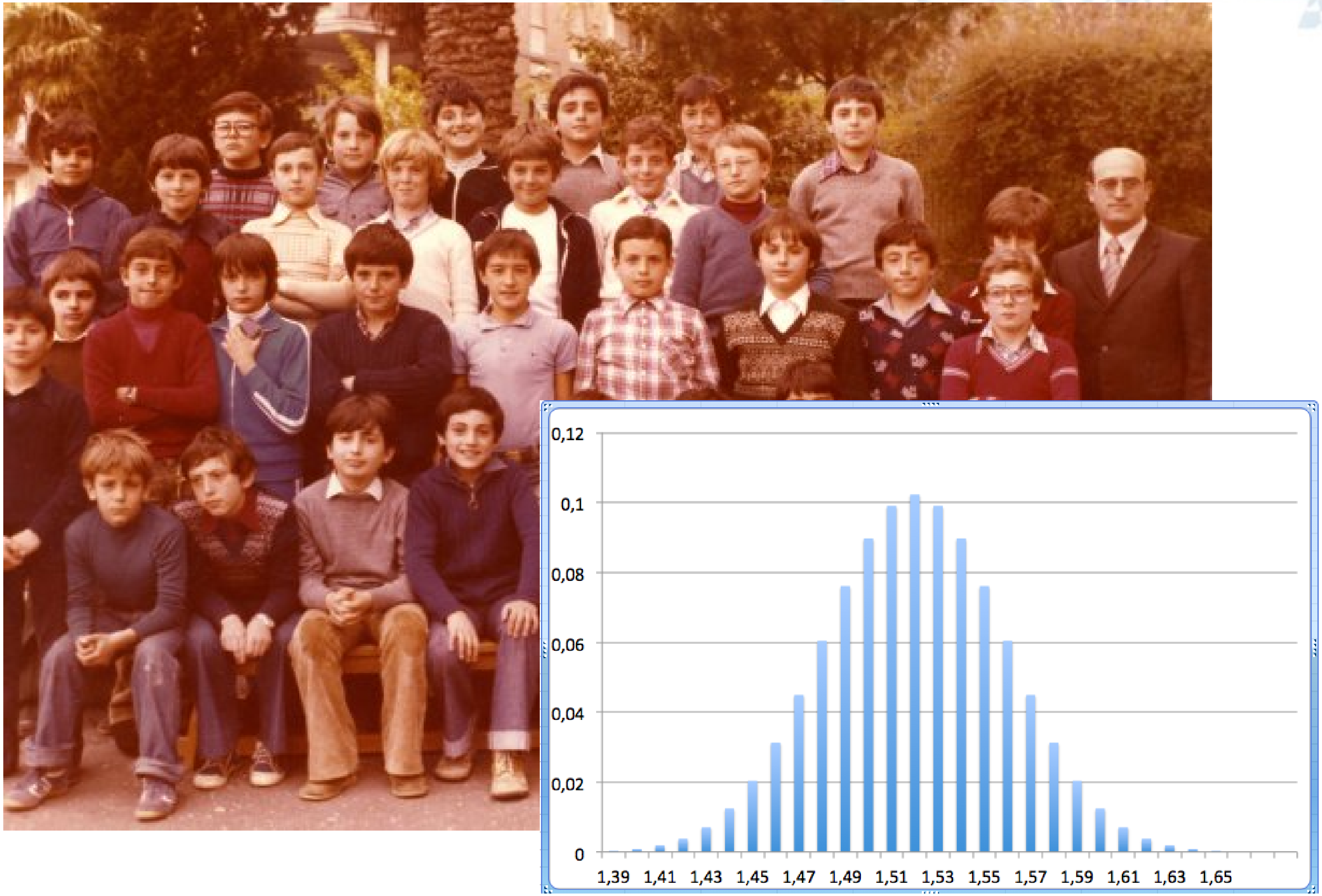
$$E = \frac{3}{2} k_B T$$

$$S = k_B \ln W$$

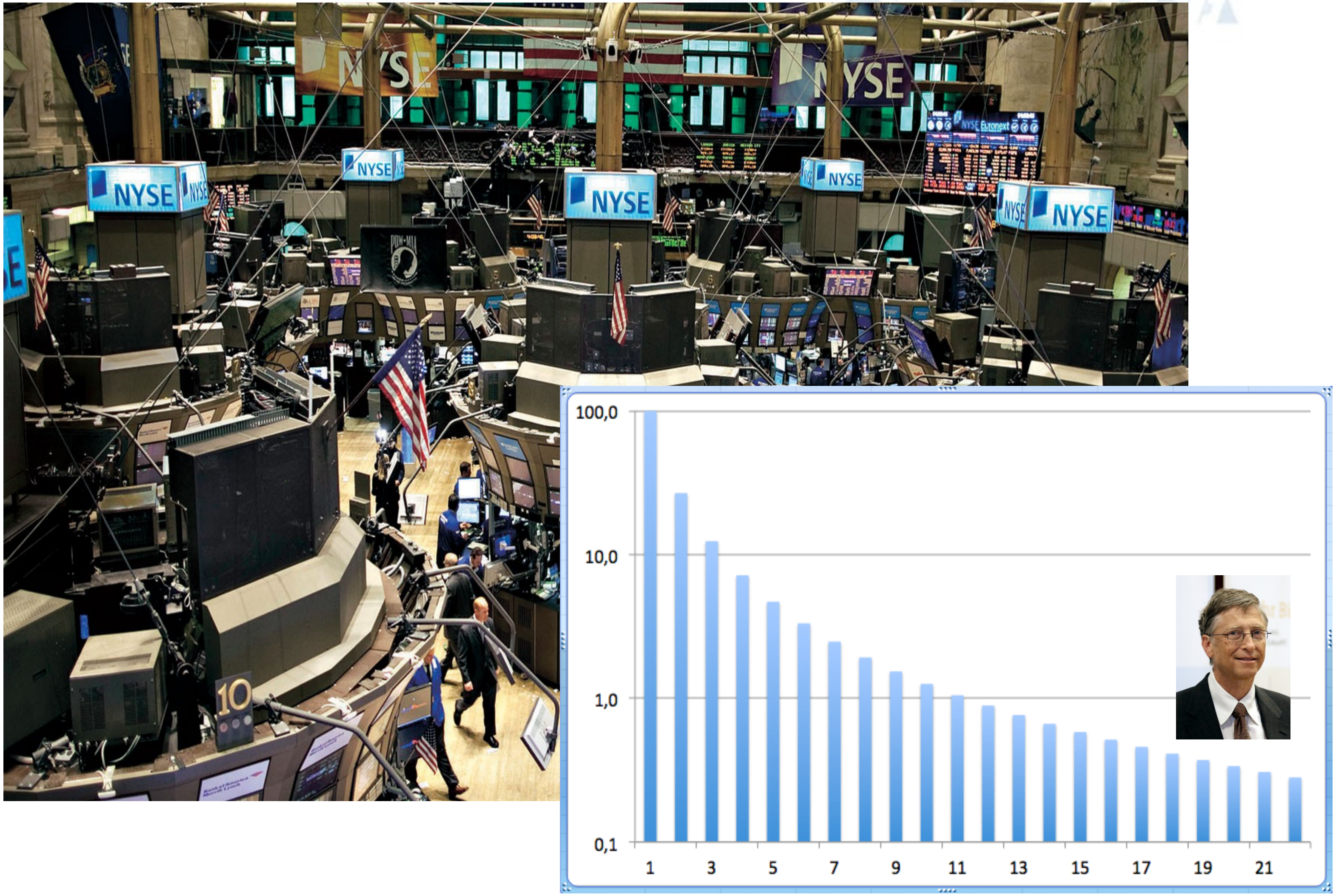


??? ???

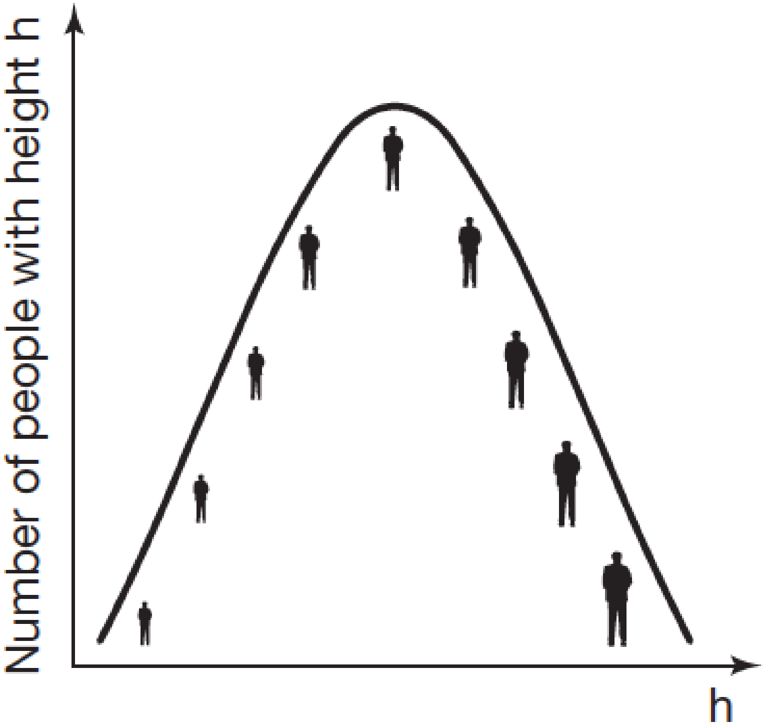
Come trattare questi dati?

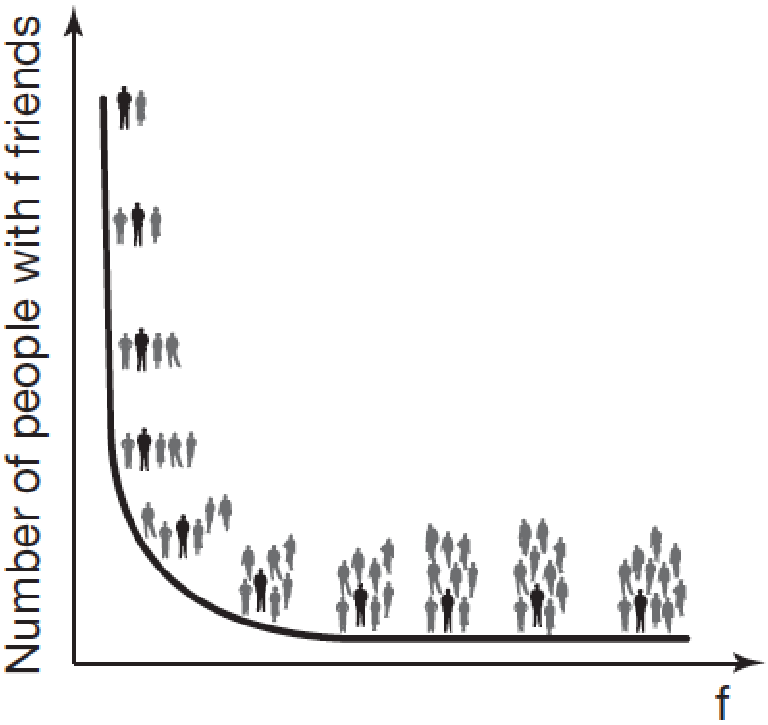


Non sono tutti uguali….



Differenti per davvero





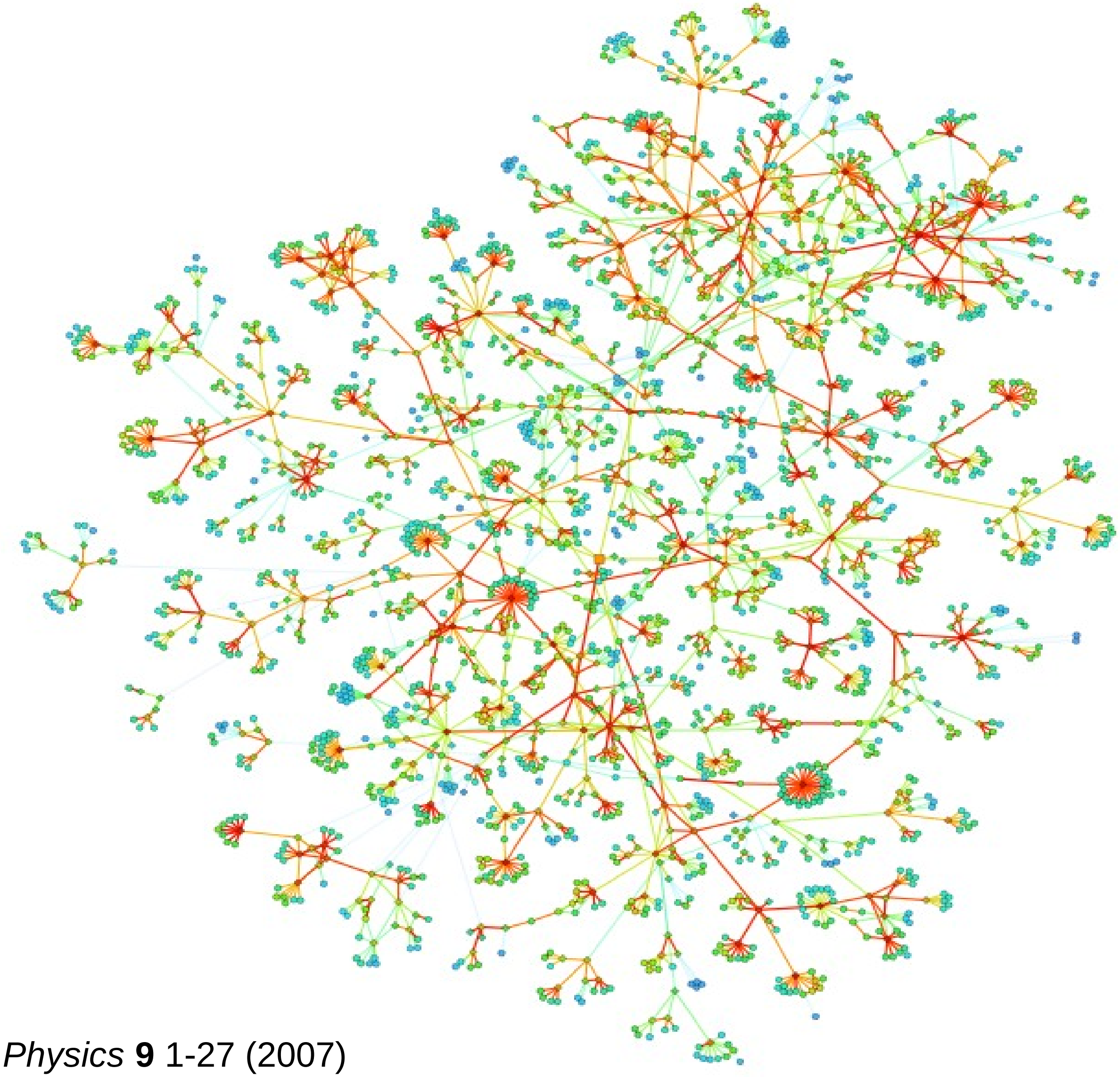
Nessuno è alto 2 mm o 20 Km

Può capitare invece che una persona abbia 1000 volte più contatti/amici/soldi di un altro

Reti di telefonate

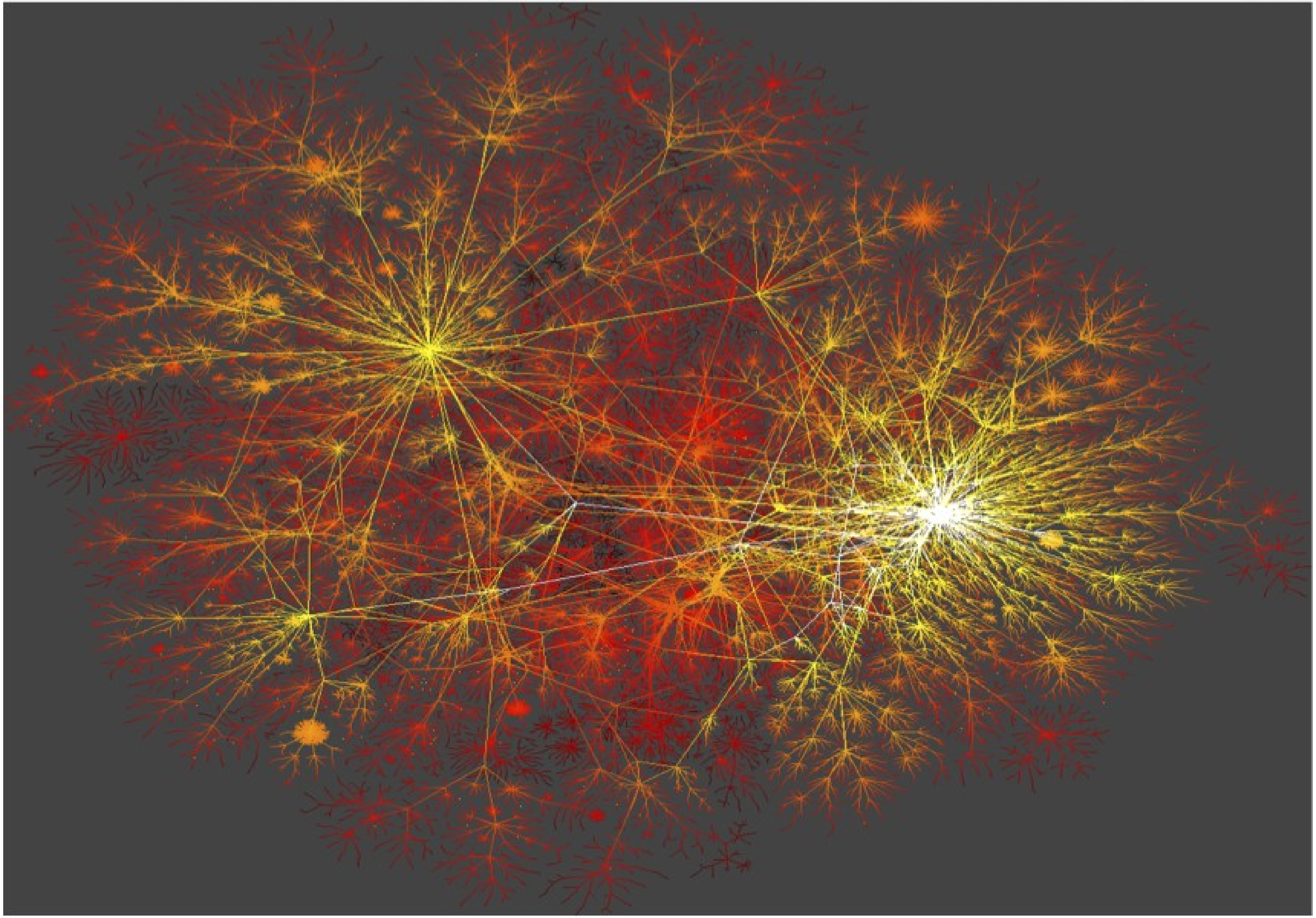
- Ogni pallina è un numero di telefono in una rete di telefonia mobile.

- Le linee di connessione sono chiamate da un numero all'altro

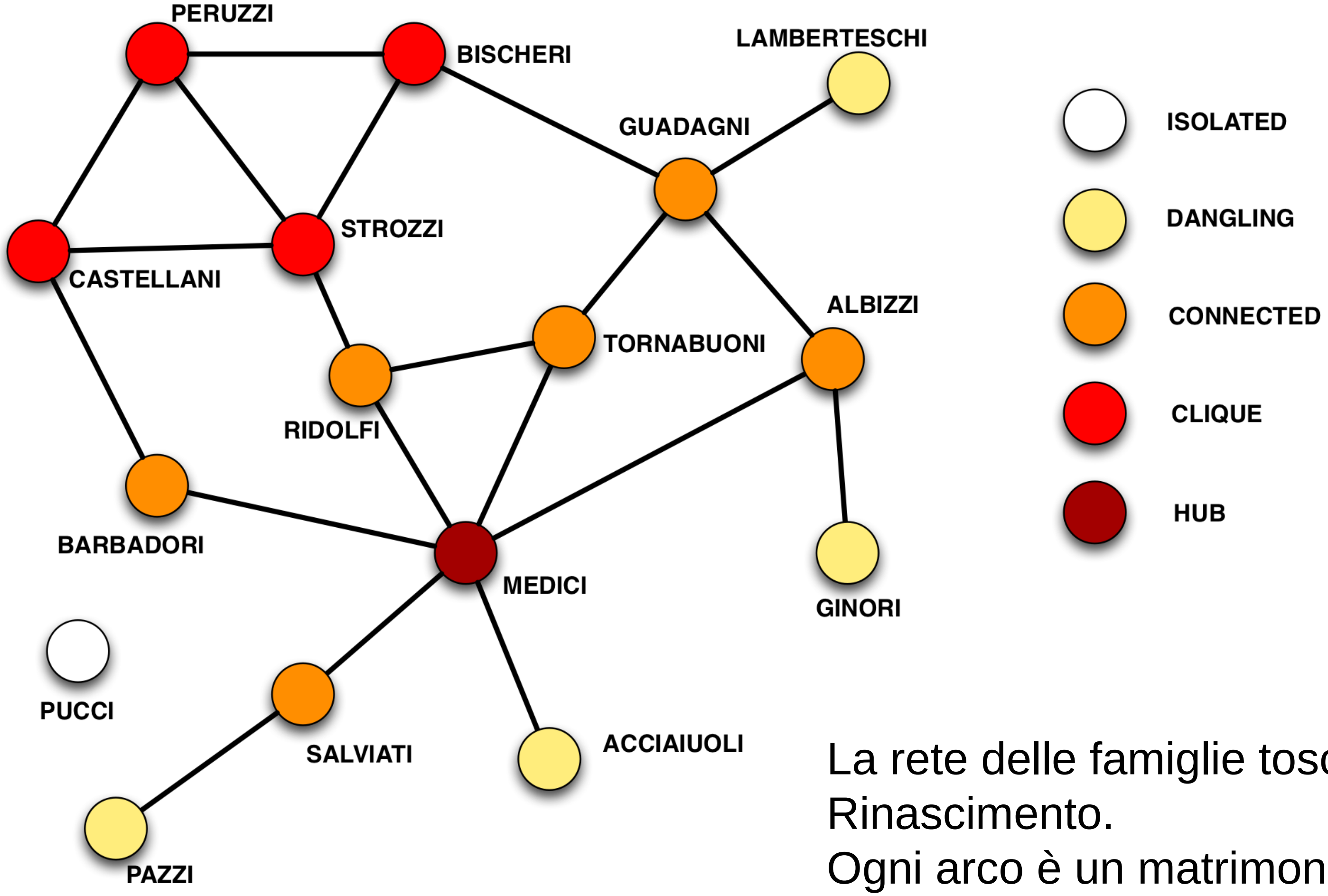


J-P Onnela et al. *New Journal of Physics* **9** 1-27 (2007)

Internet



Società


PERUZZI
BISCHERI
LAMBERTESCHI
GUADAGNI
STROZZI
CASTELLANI
ALBIZZI
TORNABUONI
RIDOLFI
BARBADORI
MEDICI
GINORI
PUCCI
SALVIATI
ACCIAIUOLI
PAZZI
ISOLATED
DANGLING
CONNECTED
CLIQUE
HUB

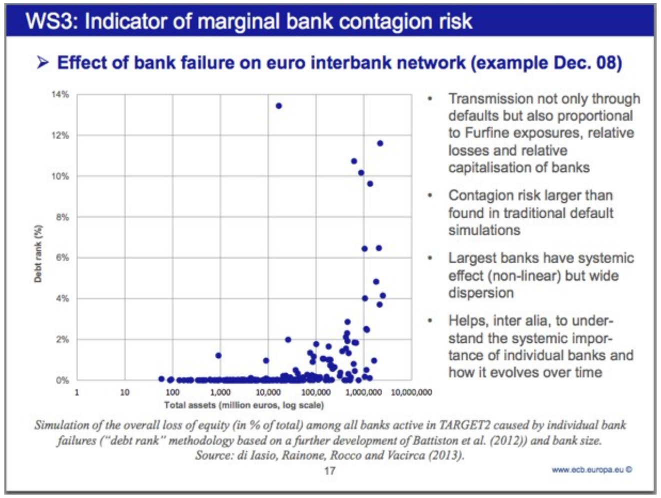
La rete delle famiglie toscane nel Rinascimento.
Ogni arco è un matrimonio

Attività

Stress test basati sulle reti

BANK OF ENGLAND

BANCO DE MÉXICO



WS3: Indicator of marginal bank contagion risk

- Effect of bank failure on euro interbank network (example Dec. 08)

- Transmission not only through defaults but also proportional to Furfine exposures, relative losses and relative capitalisation of banks
- Contagion risk larger than found in traditional default simulations
- Largest banks have systemic effect (non-linear) but wide dispersion
- Helps, inter alia, to understand the systemic importance of individual banks and how it evolves over time

Simulation of the overall loss of equity (in % of total) among all banks active in TARGET2 caused by individual bank failures ("debt rank" methodology based on a further development of Battiston et al. (2012)) and bank size. Source: di Iasio, Rainone, Rocco and Vacirca (2013).

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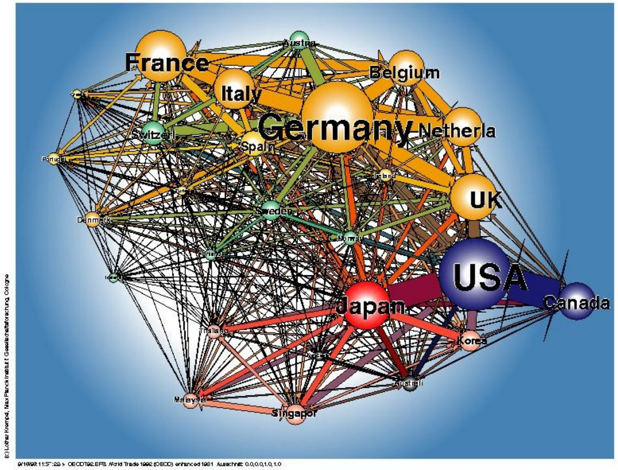
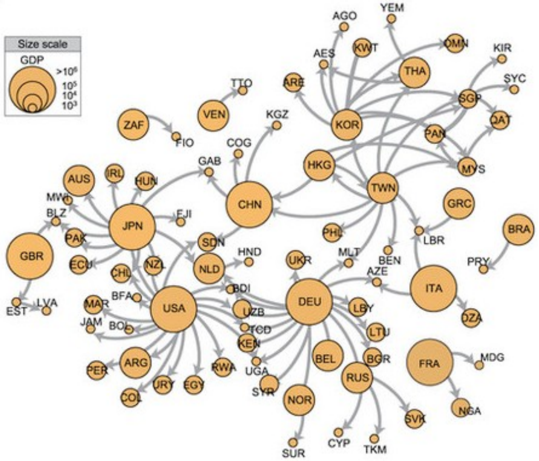
www.ecb.europa.eu ©

Studio del commercio fra le nazioni



France
Austria
Belgium
Italy
Germany
Netherla
Switzerl
Spain
Sweden
Denmark
UK
USA
Canada
Japan
Korea
Malaysia
Singapor



Size scale
GDP
>10⁶
10⁵
10⁴
10³
AGO
YEM
AES
KWT
OMN
KIR
THA
SYC
TTO
ARE
SGP
ZAF
VEN
KGZ
KOR
QAT
FIO
COG
PAN
GAB
HKG
MYS
AUS
IRL
HUN
TWN
MWI
CHN
GRC
BLZ
JPN
FJI
PAK
SDN
PHL
LBR
BRA
GBR
HND
MLT
ECU
NZL
NLD
UKR
BEN
PRY
CHL
AZE
EST
LVA
BDI
ITA
MAR
BFA
USA
DEU
JAM
BOL
UZB
LBY
TCD
LTU
DZA
KEN
PER
ARG
RWA
UGA
BEL
BGR
FRA
MDG
URY
EGY
SYR
RUS
COL
NOR
SVK
NGA
CYP
SUR
TKM

Il controllo di una rete complessa

Nell’Atlantico questa è la relazione che lega le varie specie

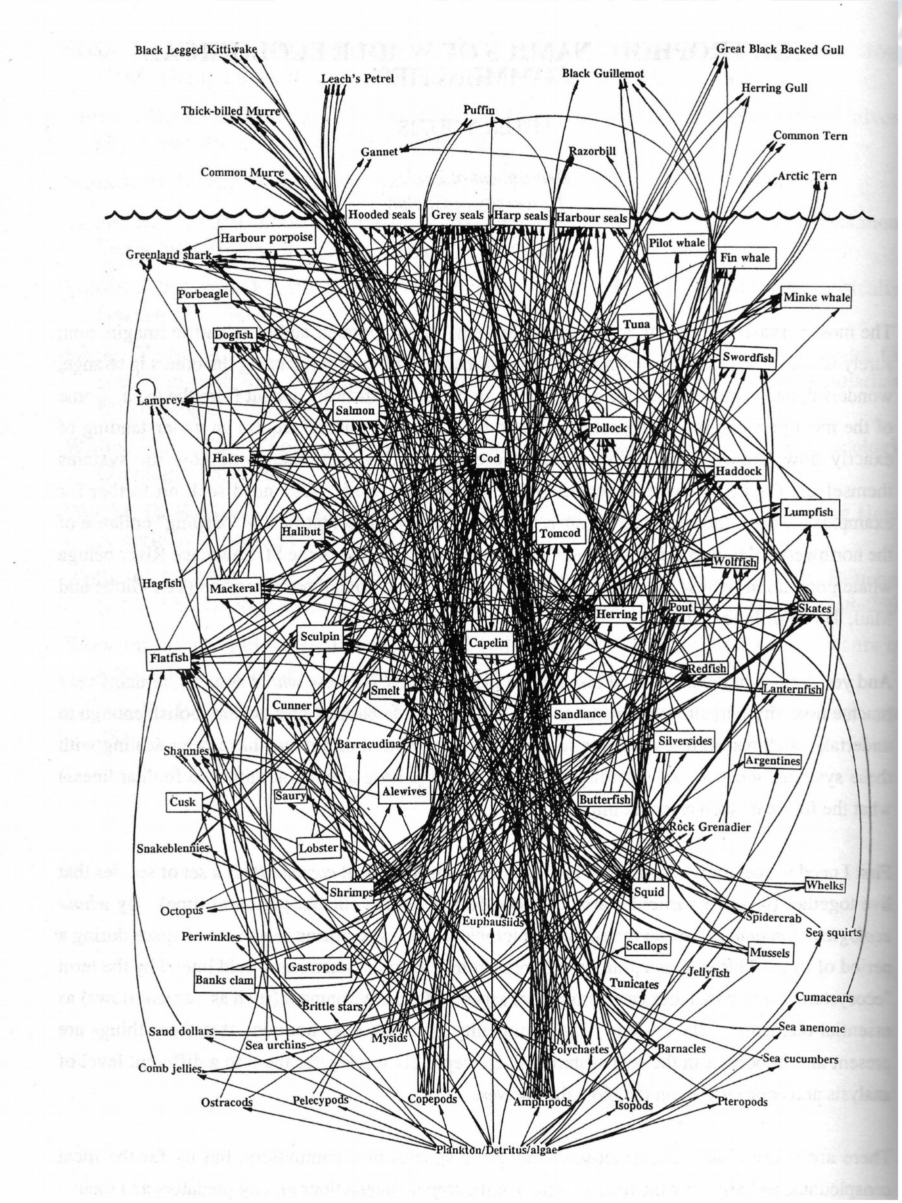
Se i merluzzi scarseggiano che posso fare?

- Cerco i loro predatori (foche)
- Uccido i loro predatori
- Ottengo più merluzzi?

NON NECESSARIAMENTE

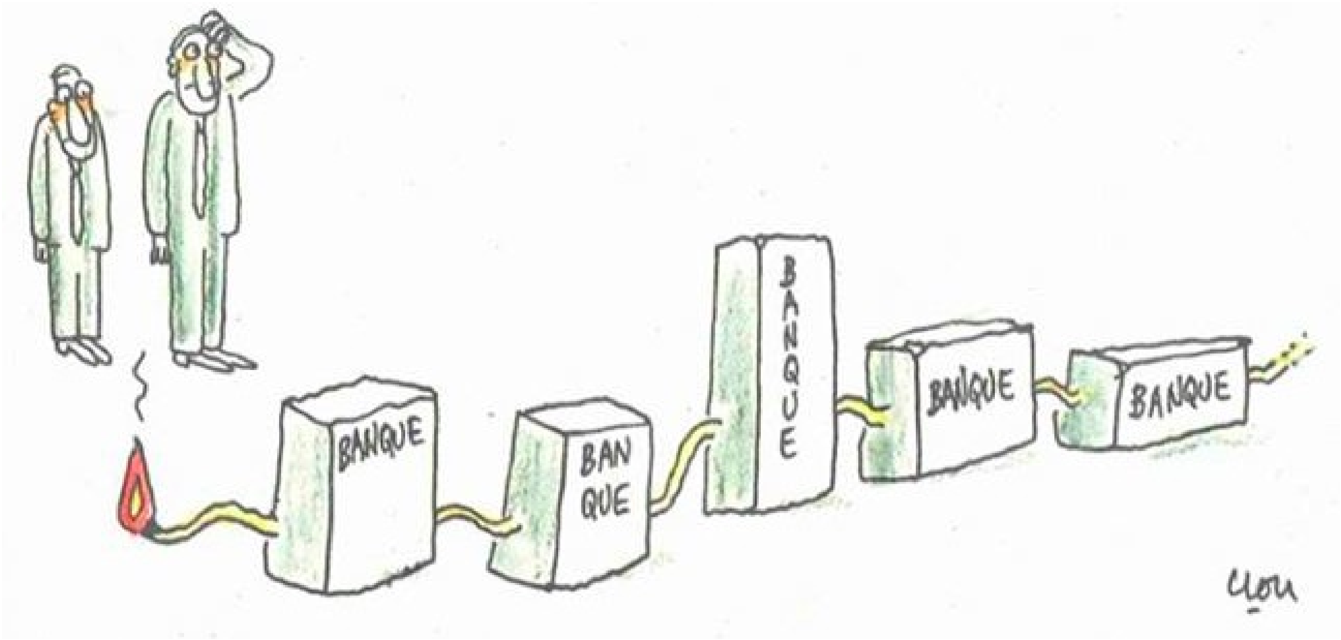
Le foche predano anche i competitori dei merluzzi

Ancora meno merluzzi di prima


Black Legged Kittiwake
Great Black Backed Gull
Black Guillemot
Leach's Petrel
Herring Gull
Thick-billed Murre
Puffin
Common Tern
Gannet
Razorbill
Common Murre
Arctic Tern
Hooded seals
Grey seals
Harp seals
Harbour seals
Harbour porpoise
Pilot whale
Greenland shark
Fin whale
Porbeagle
Minke whale
Tuna
Dogfish
Swordfish
Lamprey
Salmon
Pollock
Hakes
Cod
Haddock
Lumpfish
Halibut
Tomcod
Wolffish
Hagfish
Mackeral
Pout
Herring
Skates
Sculpin
Capelin
Flatfish
Redfish
Smelt
Lanternfish
Cunner
Sandlance
Silversides
Shannies
Barracudina
Argentines
Alewives
Saury
Cusk
Butterfish
Rock Grenadier
Snakeblennies
Lobster
Shrimps
Squid
Whelks
Octopus
Euphausiids
Spidercrab
Sea squirts
Periwinkles
Scallops
Mussels
Gastropods
Jellyfish
Banks clam
Tunicates
Cumaceans
Brittle stars
Sand dollars
Sea anemone
Mysids
Sea urchins
Polychaetes
Barnacles
Sea cucumbers
Comb jellies
Ostracods
Pelecypods
Copepods
Amphipods
Isopods
Pteropods
Plankton/Detritus/algae

Quindi?

- Una rete aristocratica è più fragile se cade il superconnettore cade tutto
- Su una rete aristocratica basta un malato per infettare tutti
- Chi è al centro è più importante
- Spesso le reti sono interconnesse fra di loro moltiplicando la fragilità


BANQUE
BAN QUE
BANQUE
BANQUE
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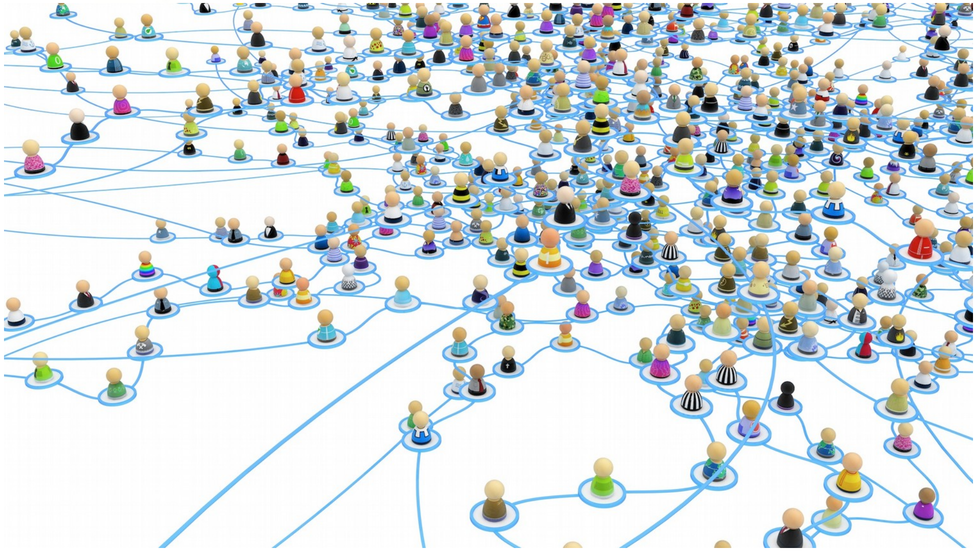
clou

La rete di connessioni

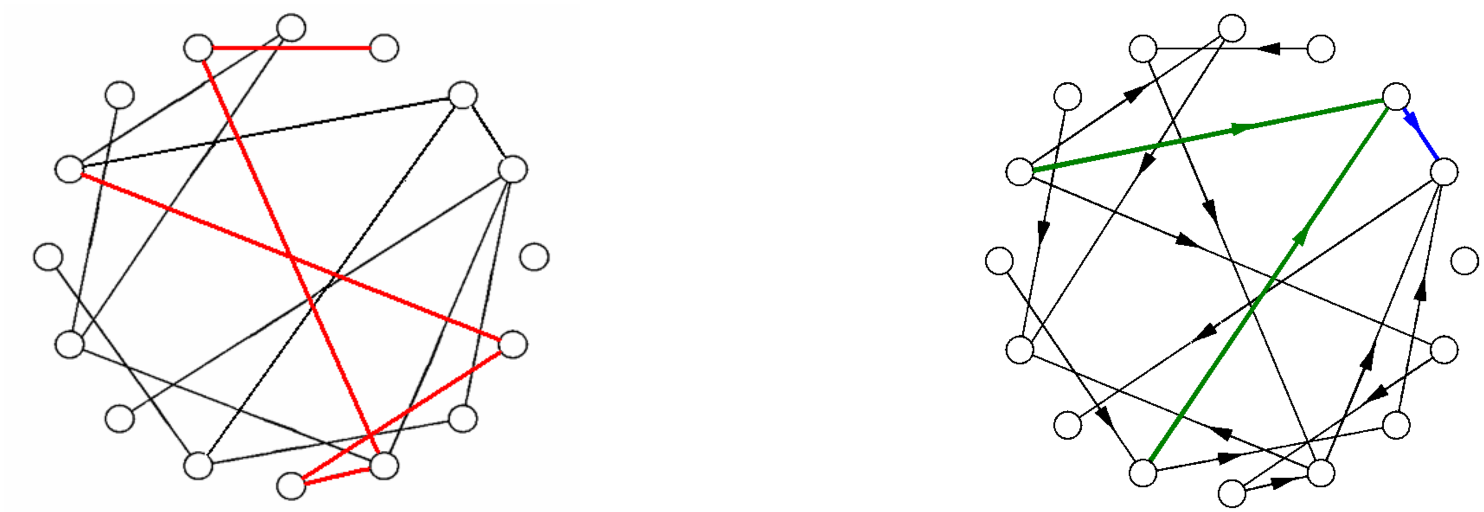


You Tube
Bē
Meetup
WEB 2.0

La teoria delle reti complesse, descrive in maniera **QUANTITATIVA** e con modelli **FALSIFICABILI,** sistemi altrimenti descritti in maniera qualitativa.

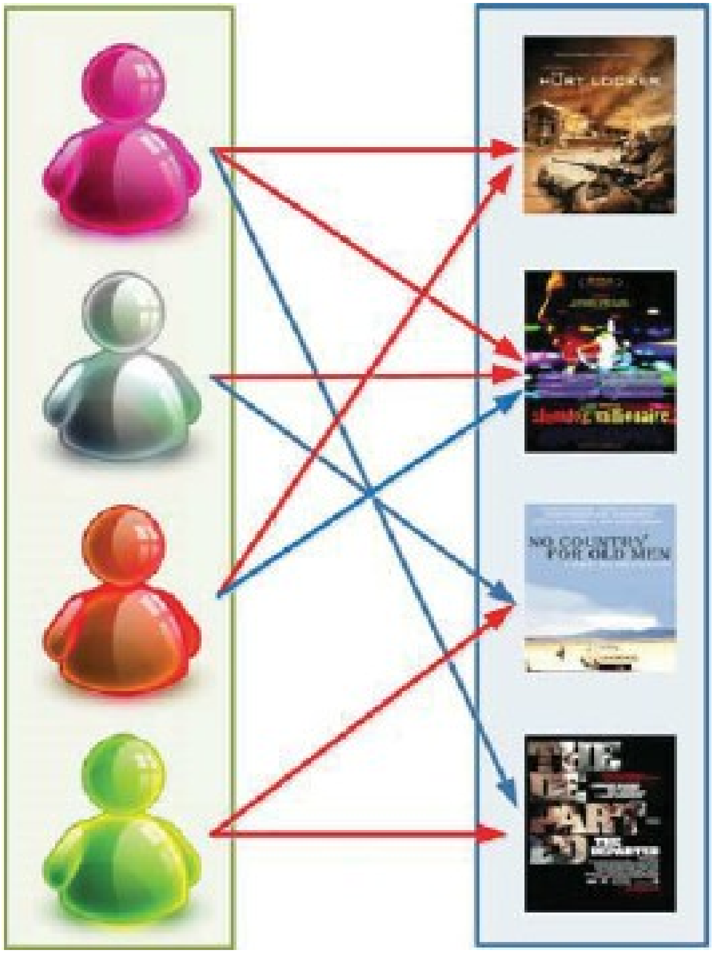
Marzo 1989 nasce
al CERN il WWW

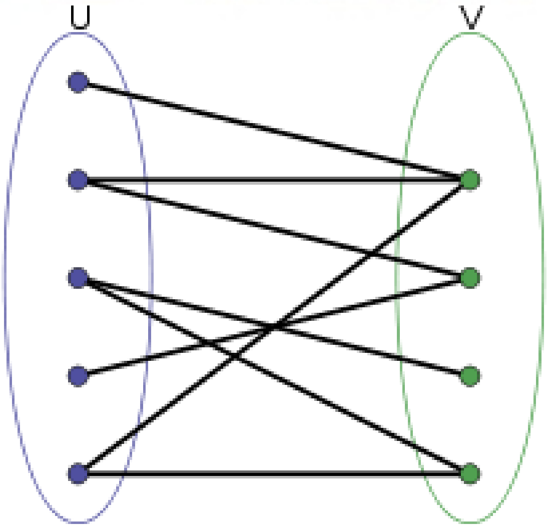
Rete

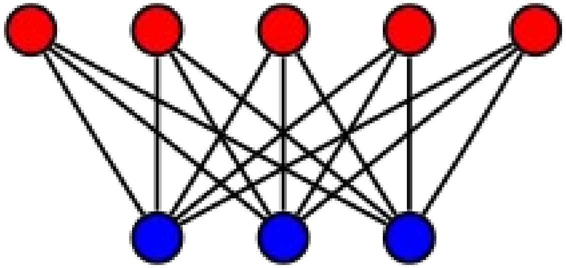


- Grado k (grado entrante k_{in} and grado uscente k_{out}) = numero di archi (orientati) per vertice
- Distanza d = numero di archi per andare da un vertice a un altro (nella regione connessa !)
- Diametro D = Massimo delle distanze (nella regione connessa !)

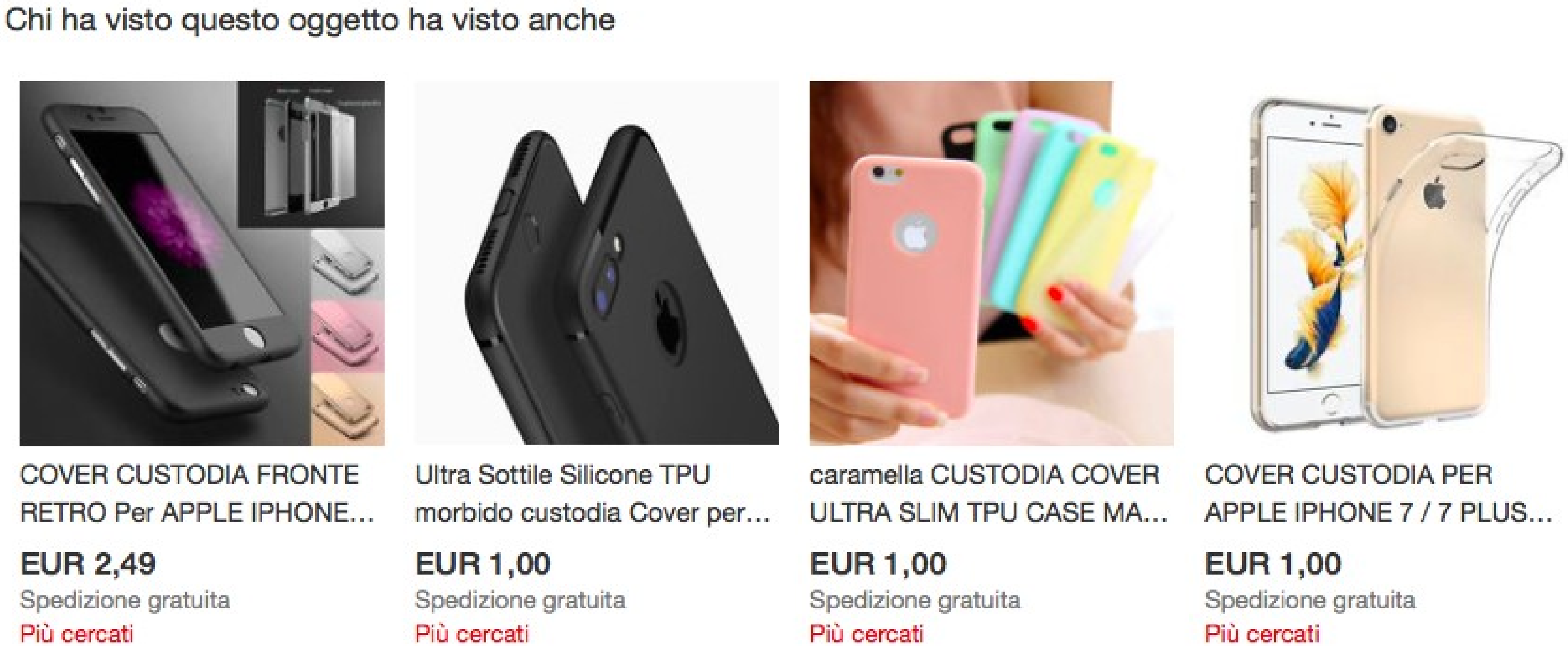
Grafi bipartiti


HURT LOCKER
slumdog millionaire
NO COUNTRY FOR OLD MEN
THE DEPARTED





Profilazione utente



Chi ha visto questo oggetto ha visto anche

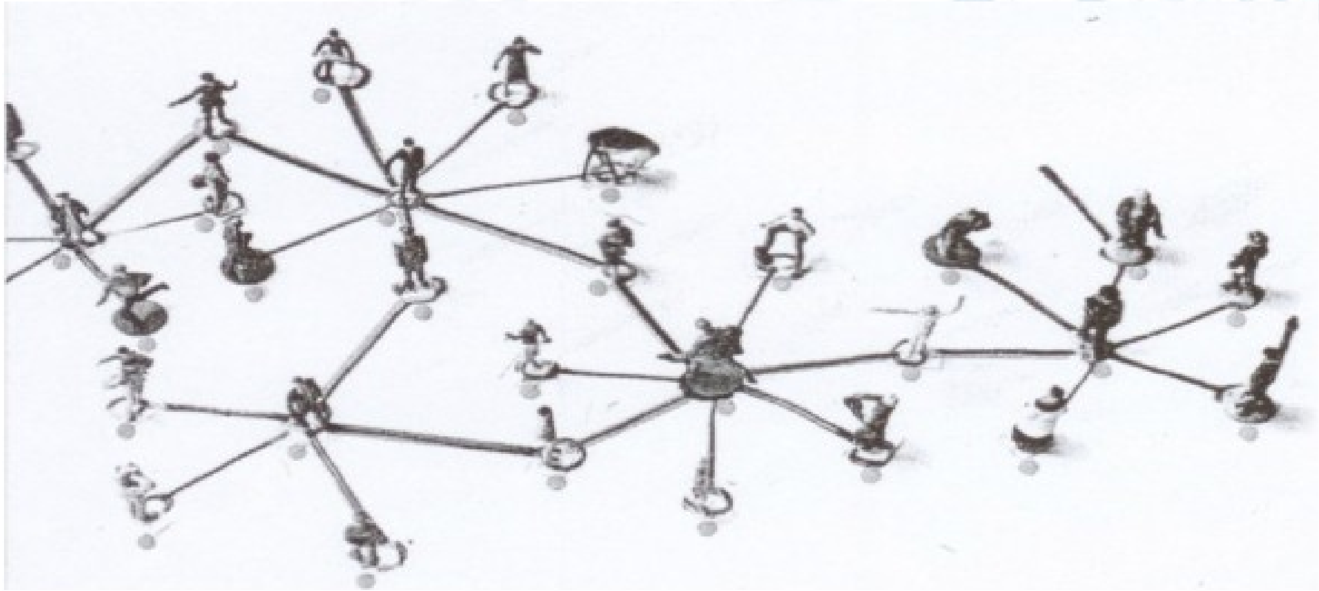
COVER CUSTODIA FRONTE RETRO Per APPLE IPHONE...
EUR 2,49
Spedizione gratuita
Più cercati

Ultra Sottile Silicone TPU morbido custodia Cover per...
EUR 1,00
Spedizione gratuita
Più cercati

caramella CUSTODIA COVER ULTRA SLIM TPU CASE MA...
EUR 1,00
Spedizione gratuita
Più cercati

COVER CUSTODIA PER APPLE IPHONE 7 / 7 PLUS...
EUR 1,00
Spedizione gratuita
Più cercati

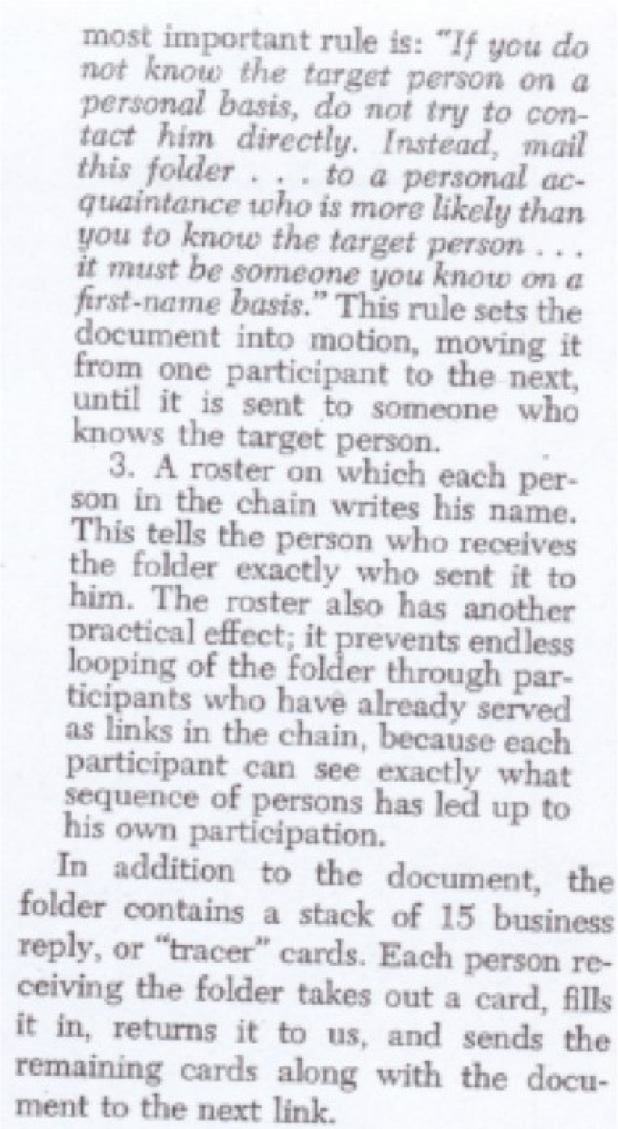
Small world



Nessuno, neanche la persona che cerchiamo è molto lontano da noi

La teoria delle reti può aiutare a trovare l’ago nel pagliaio

L'esperimento di Milgram



most important rule is: "*If you do not know the target person on a personal basis, do not try to contact him directly. Instead, mail this folder . . . to a personal acquaintance who is more likely than you to know the target person . . . it must be someone you know on a first-name basis.*" This rule sets the document into motion, moving it from one participant to the next, until it is sent to someone who knows the target person.

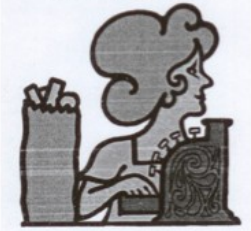
3. A roster on which each person in the chain writes his name. This tells the person who receives the folder exactly who sent it to him. The roster also has another practical effect; it prevents endless looping of the folder through participants who have already served as links in the chain, because each participant can see exactly what sequence of persons has led up to his own participation.

In addition to the document, the folder contains a stack of 15 business reply, or "tracer" cards. Each person receiving the folder takes out a card, fills it in, returns it to us, and sends the remaining cards along with the document to the next link.

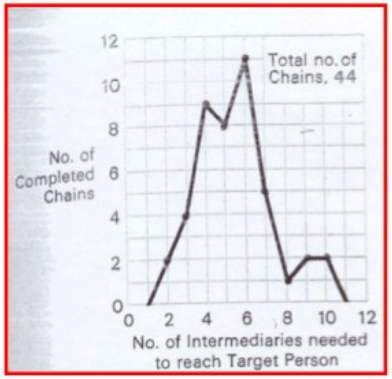
- Seleziona un obiettivo (bancario) in Boston
- Seleziona persone a caso in Omaha (Nebraska)
- Assegna a queste persone nome e indirizzo dell'obiettiv
- Se le persone di partenza conoscono l'obiettivo il gioco finisce
- Altrimenti passate l'incarico a chi credete lo possa conoscere
- MANDATEMI UNA CARTOLINA

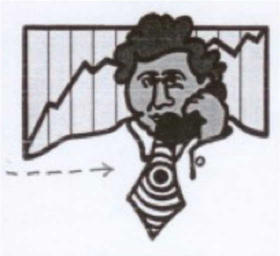
Small world

The beginning of a typical chain (#111) in the Nebraska Study.

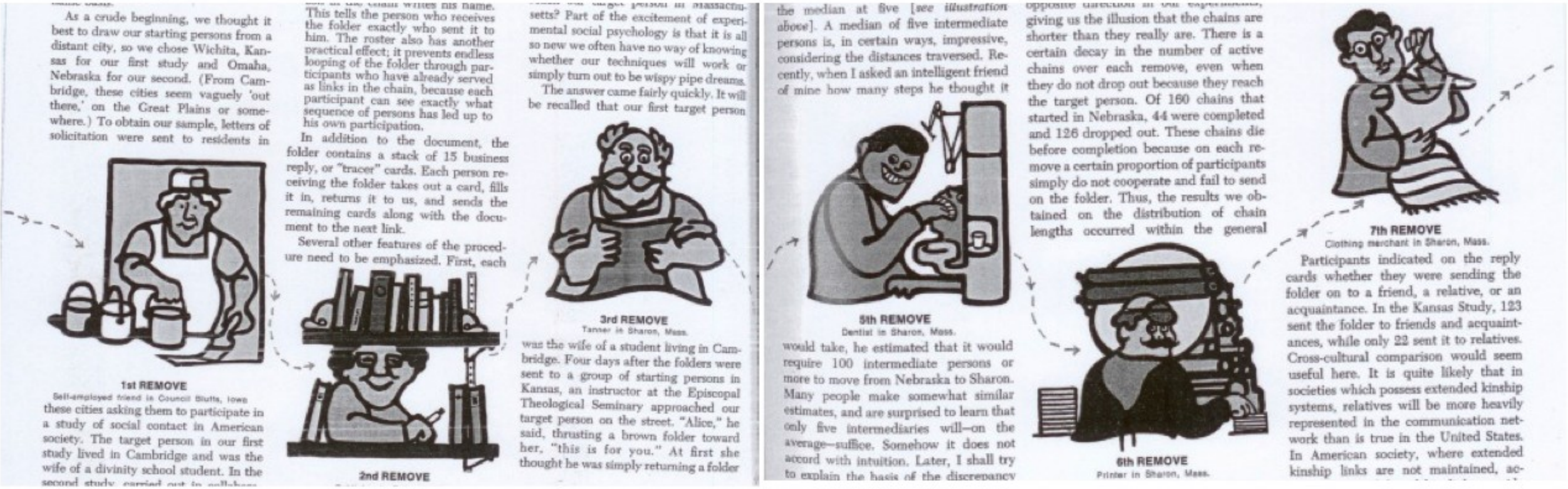


STARTING PERSON
Widowed clerk in Omaha, Nebraska





TARGET PERSON
Stock broker living in Sharon, Mass.



As a crude beginning, we thought it best to draw our starting persons from a distant city, so we chose Wichita, Kansas for our first study and Omaha, Nebraska for our second. (From Cambridge, these cities seem vaguely 'out there,' on the Great Plains or somewhere.) To obtain our sample, letters of solicitation were sent to residents in these cities asking them to participate in a study of social contact in American society. The target person in our first study lived in Cambridge and was the wife of a divinity school student. In the

1st REMOVE
Self-employed friend in Council Bluffs, Iowa

This tells the person who receives the folder exactly who sent it to him. The roster also has another practical effect; it prevents endless looping of the folder through participants who have already served as links in the chain, because each participant can see exactly what sequence of persons has led up to his own participation.

In addition to the document, the folder contains a stack of 15 business reply, or "tracer" cards. Each person receiving the folder takes out a card, fills it in, returns it to us, and sends the remaining cards along with the document to the next link.

Several other features of the procedure need to be emphasized. First, each

2nd REMOVE

setts? Part of the excitement of experimental social psychology is that it is all so new we often have no way of knowing whether our techniques will work or simply turn out to be wispy pipe dreams.

The answer came fairly quickly. It will be recalled that our first target person was the wife of a student living in Cambridge. Four days after the folders were sent to a group of starting persons in Kansas, an instructor at the Episcopal Theological Seminary approached our target person on the street. "Alice," he said, thrusting a brown folder toward her, "this is for you." At first she thought he was simply returning a folder

3rd REMOVE
Tanner in Sharon, Mass.

the median at five [*see illustration above*]. A median of five intermediate persons is, in certain ways, impressive, considering the distances traversed. Recently, when I asked an intelligent friend of mine how many steps he thought it would take, he estimated that it would require 100 intermediate persons or more to move from Nebraska to Sharon. Many people make somewhat similar estimates, and are surprised to learn that only five intermediaries will—on the average—suffice. Somehow it does not accord with intuition. Later, I shall try to explain the basis of the discrepancy

5th REMOVE
Dentist in Sharon, Mass.

giving us the illusion that the chains are shorter than they really are. There is a certain decay in the number of active chains over each remove, even when they do not drop out because they reach the target person. Of 160 chains that started in Nebraska, 44 were completed and 126 dropped out. These chains die before completion because on each remove a certain proportion of participants simply do not cooperate and fail to send on the folder. Thus, the results we obtained on the distribution of chain lengths occurred within the general

6th REMOVE
Printer in Sharon, Mass.

7th REMOVE
Clothing merchant in Sharon, Mass.

Participants indicated on the reply cards whether they were sending the folder on to a friend, a relative, or an acquaintance. In the Kansas Study, 123 sent the folder to friends and acquaintances, while only 22 sent it to relatives. Cross-cultural comparison would seem useful here. It is quite likely that in societies which possess extended kinship systems, relatives will be more heavily represented in the communication network than is true in the United States. In American society, where extended kinship links are not maintained, ac-

Come raggiungere chi vogliamo?

Secondo uno studio, l’86% delle persone che ha trovato lavoro, lo ha trovato non grazie agli amici, ma grazie ai contatti secondari o ancora meno significativi.

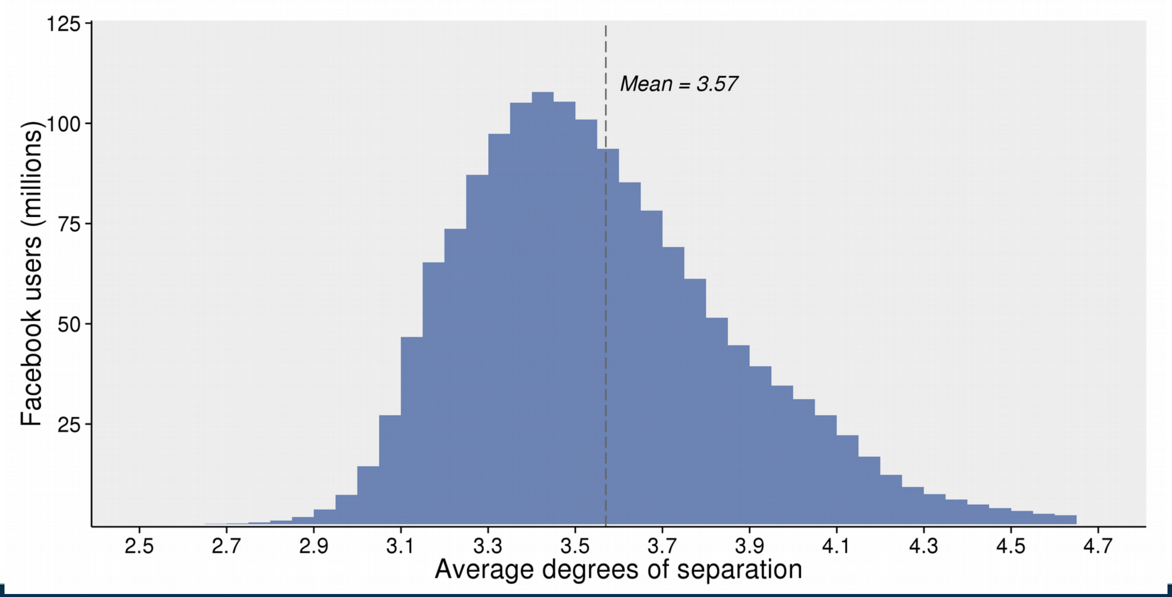
Il motivo che: alcune persone sono più interconnesse di altre e abbassano le distanze tra la domanda e l’offerta; mentre gli amici, spesso, si conoscono tra loro, dunque, non favoriscono un passaparola che vada molto in avanti

Ciao so’ Enzo, no Renzo, Enzo……

Sempre meno

In media siamo a 6 passaggi uno dall'altro

Ma in realtà molto meno

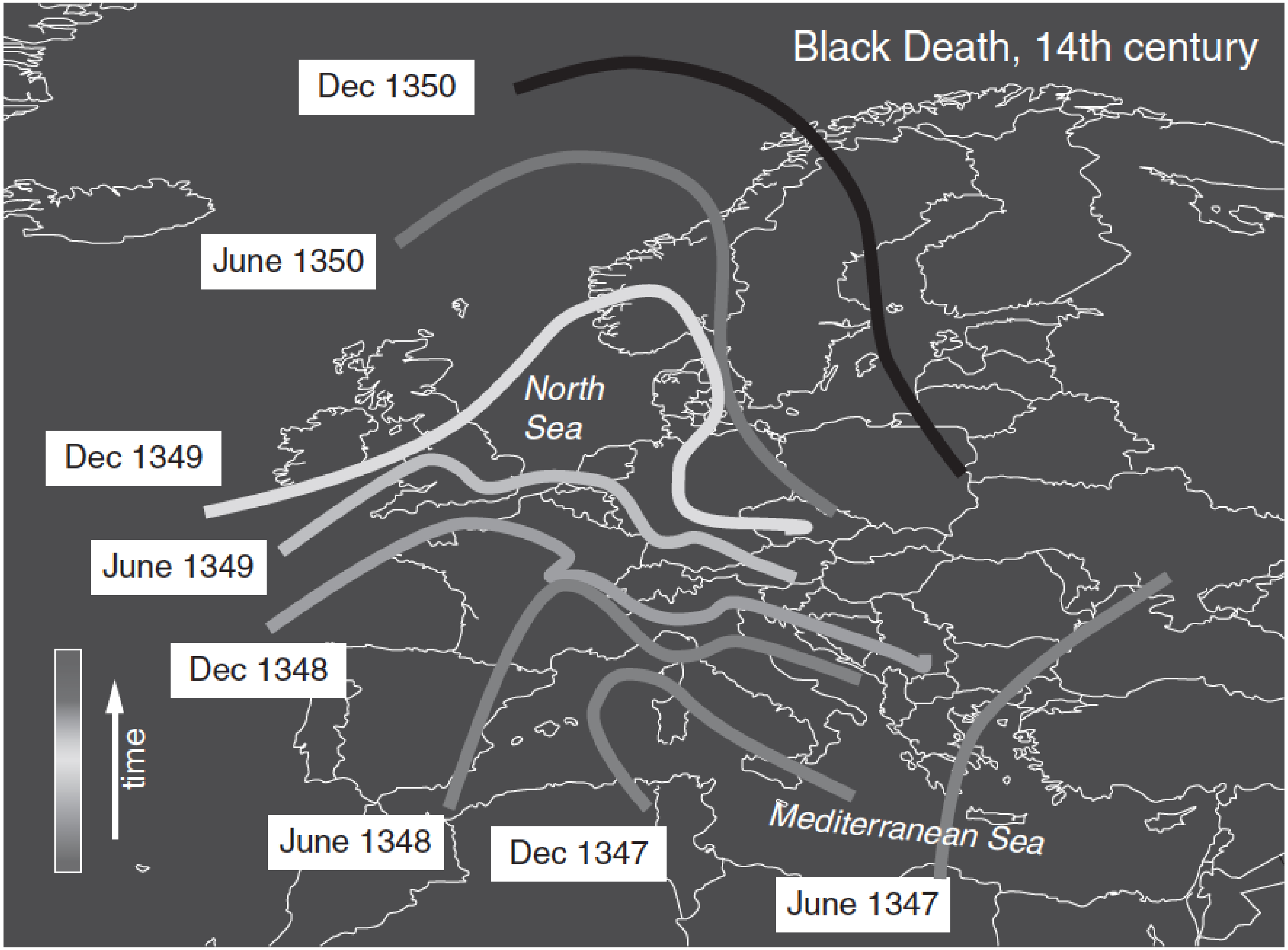


Facebook data

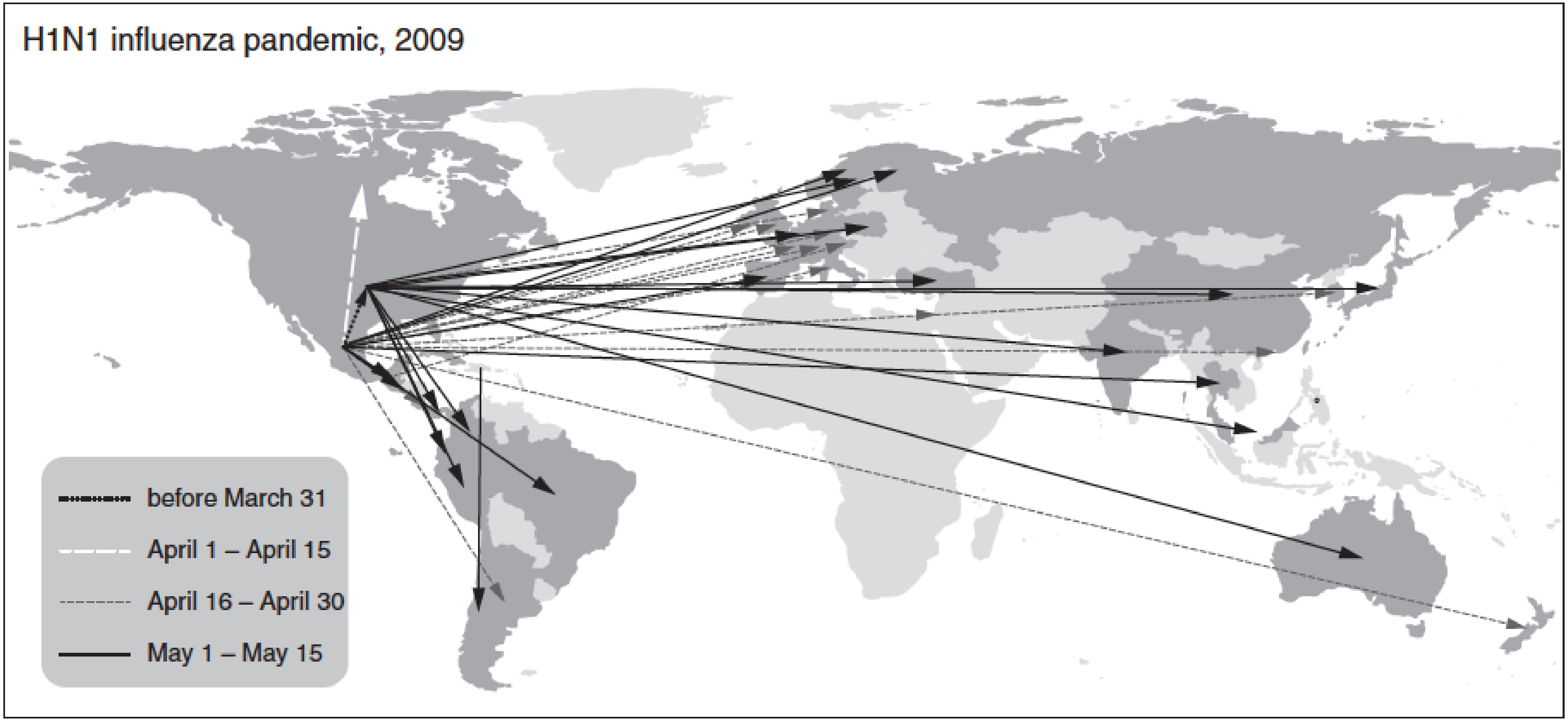
I calcoli di **Facebook** ovviamente non sono riferiti all'intera popolazione del pianeta, ma hanno comunque una certa rilevanza visto che ormai ha raggiunto **1,59** miliardi di **utenti attivi**. Utilizzando una serie di tecniche statistiche, i ricercatori di Facebook hanno creato un algoritmo che calcola la distanza media tra noi e ogni altro utente, numero che ovviamente tende a diventare minore al crescere del vostro numero di amici.

Questo significa che il numero di amici cresce esponenzialmente e che molti sono in comune

Epidemie


Black Death, 14th century
Dec 1350
June 1350
North Sea
Dec 1349
June 1349
Dec 1348
time
June 1348
Dec 1347
Mediterranean Sea
June 1347

Influenza suina

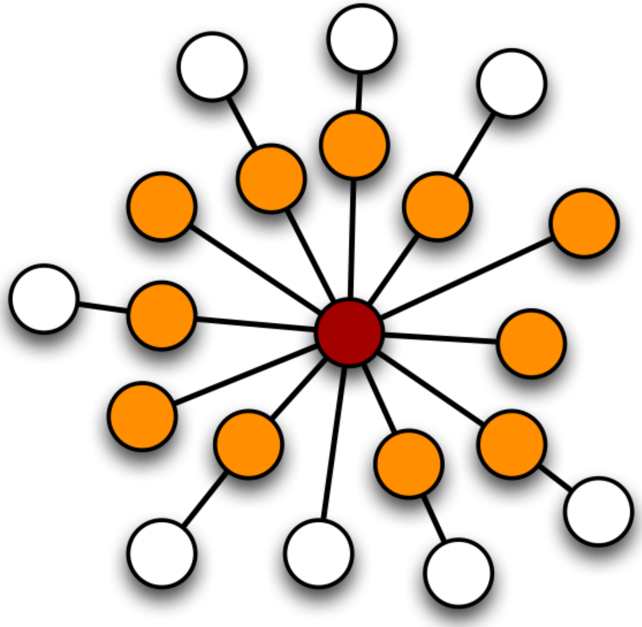

H1N1 influenza pandemic, 2009
before March 31
April 1 – April 15
April 16 – April 30
May 1 – May 15

Proprietà delle reti

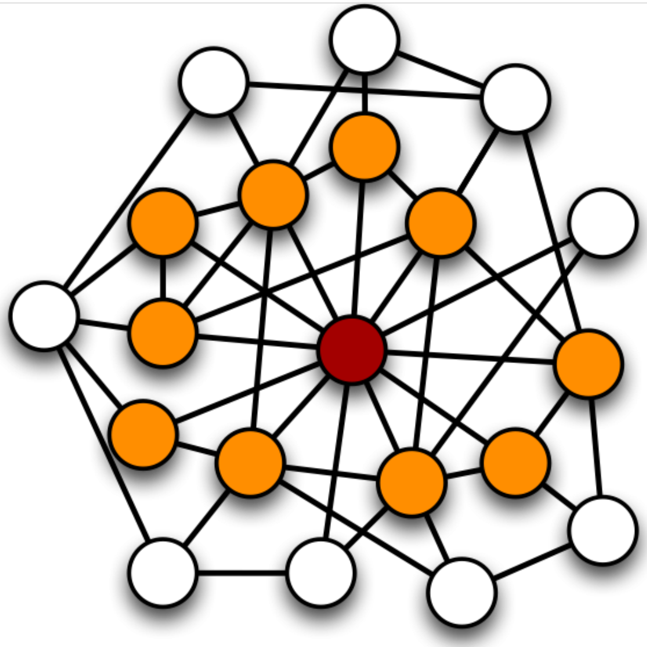
Sono aristocratiche, c`è chi ha pochi contatti e c'è chi ne ha davvero MOLTI di più

Le distanze fra le persone sono minime, in pochi passaggi si arriva a destinazione

Sono Assortative ! ☺



DISSASSORTATIVE



ASSORTATIVE

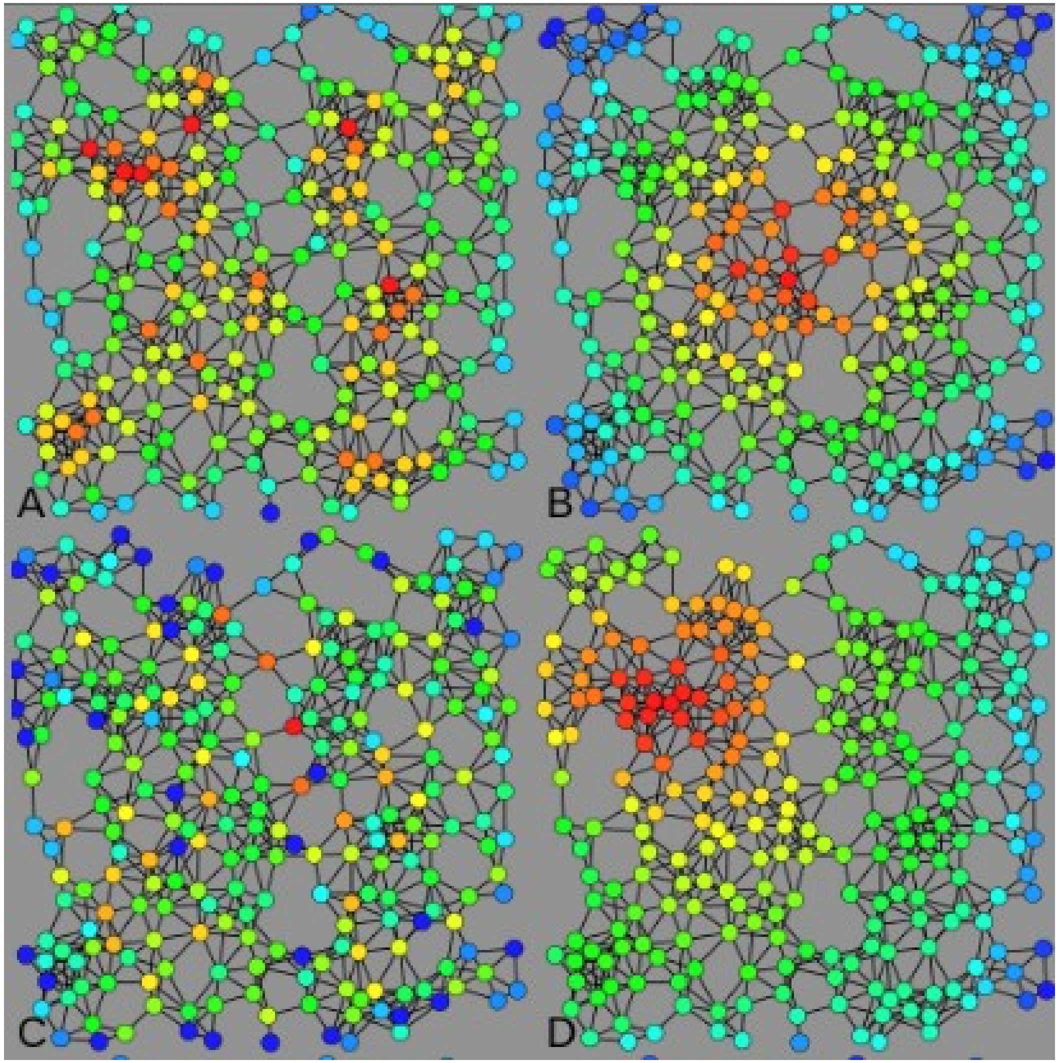
Centralità

A I vertici con il grado più alto
(Centralità di grado)

B I vertici più vicini a tutti gli altri
(Centralità di prossimità)

C I vertici con il carico maggiore
(Betweenness Centrality)

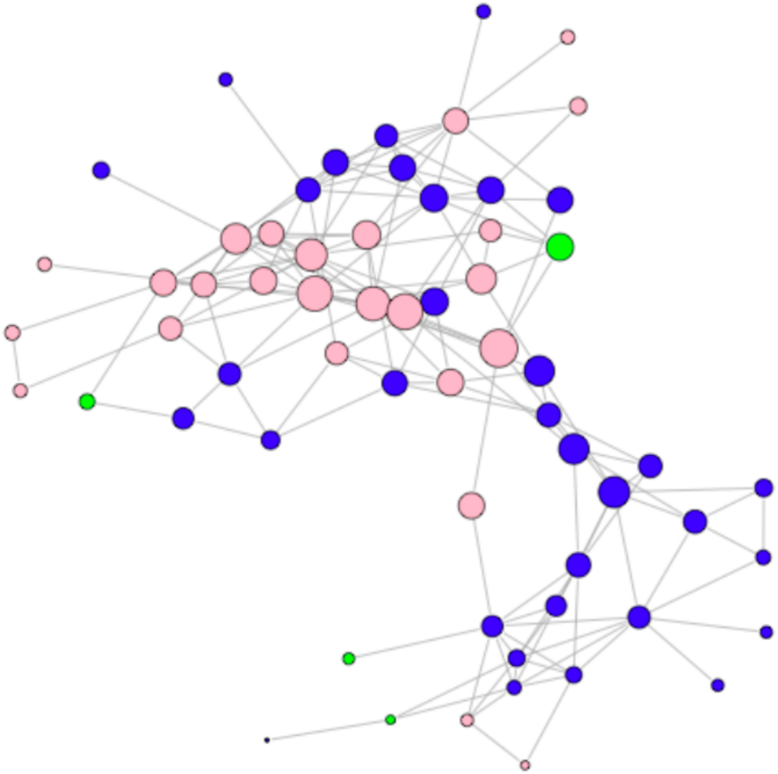
D I vertici che "più influenti"
(Centralità degli autovettori)



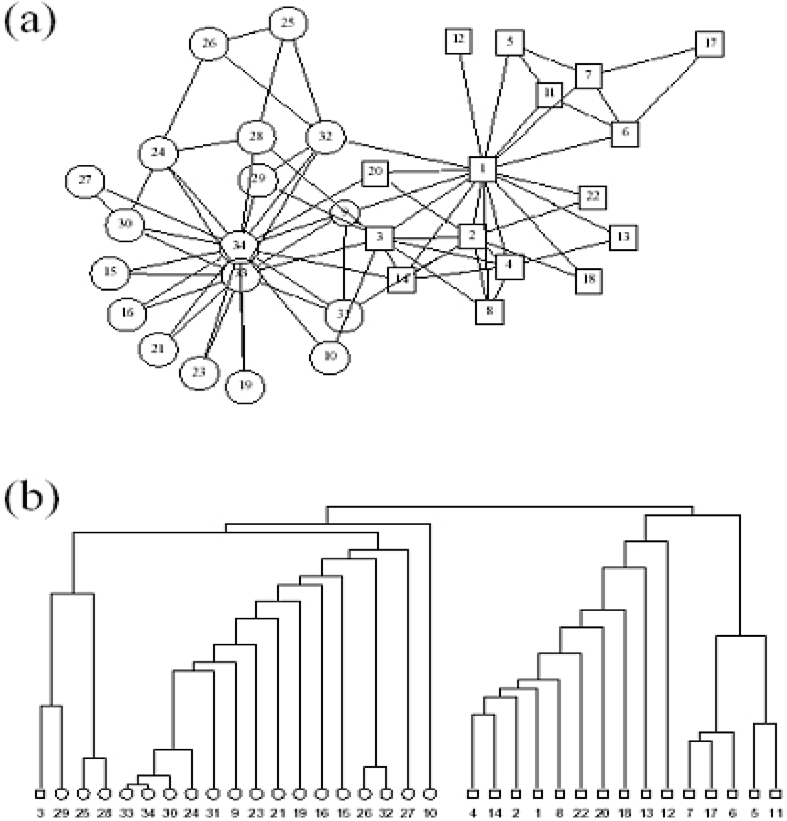
Misure di centralità

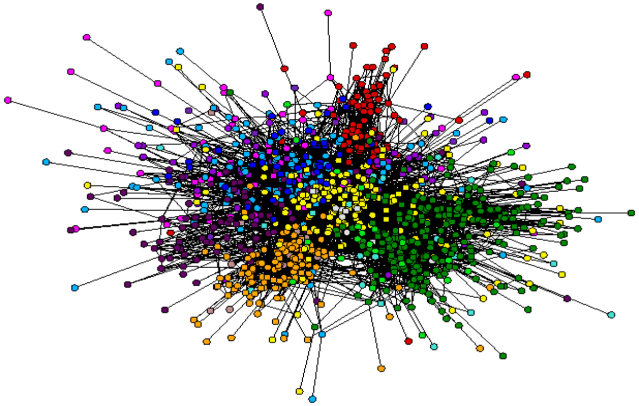
Closeness was defined by Bavelas (1950) as the reciprocal of the **farness**,[1][2] that is:

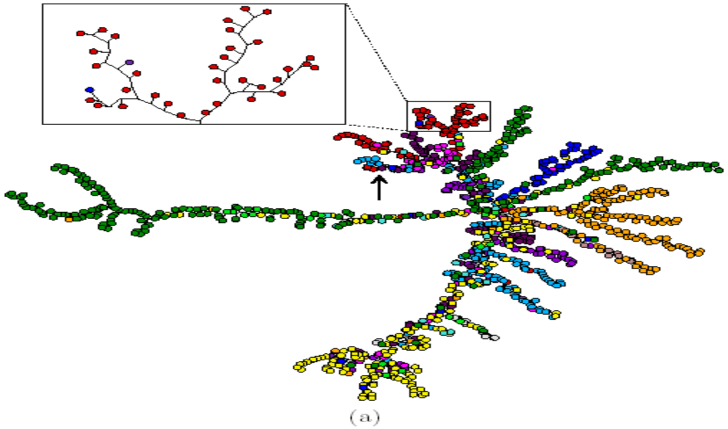
$$C(x) = \frac{1}{\sum_y d(y,x)}.$$

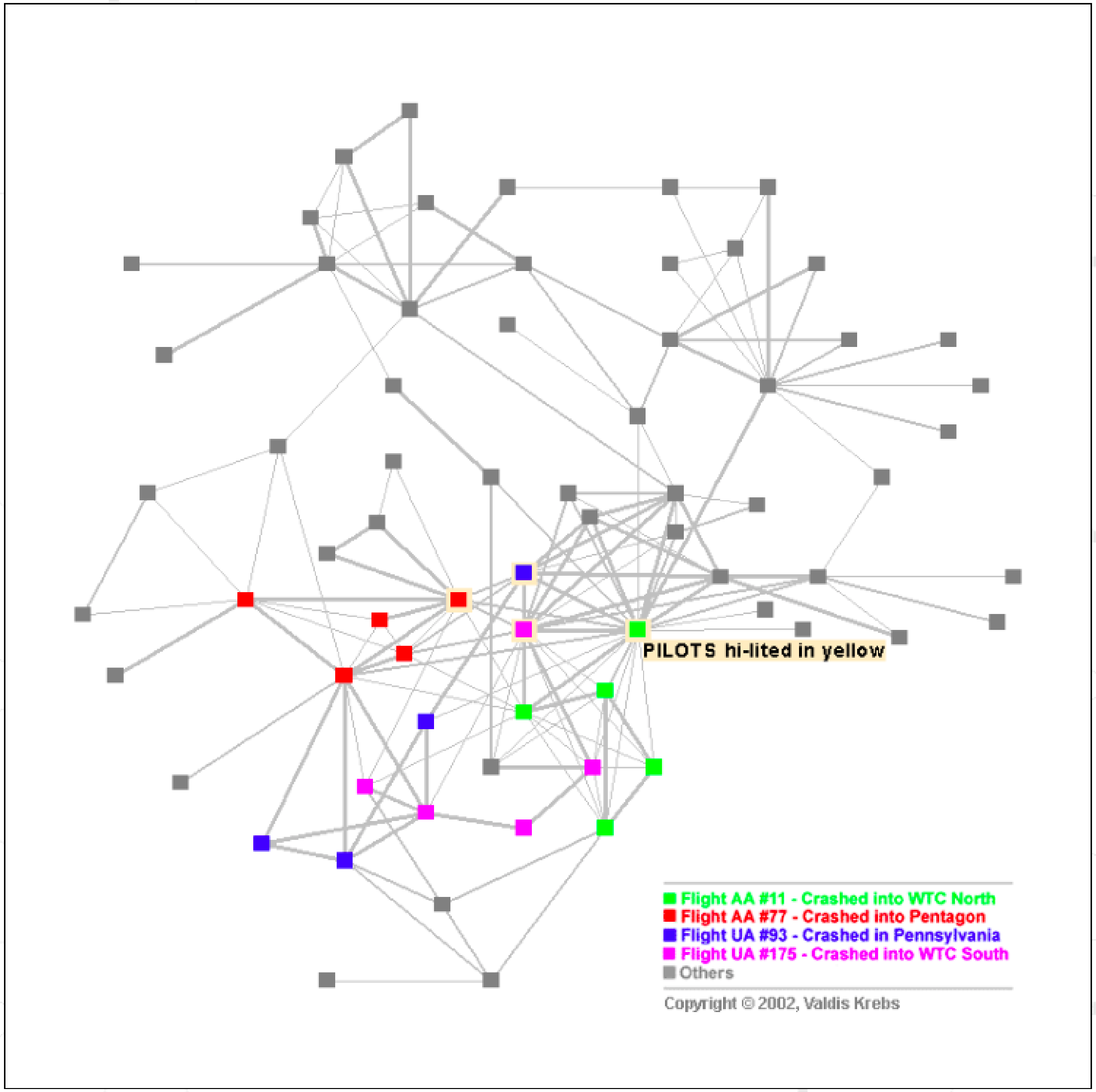


Clusterizzazione

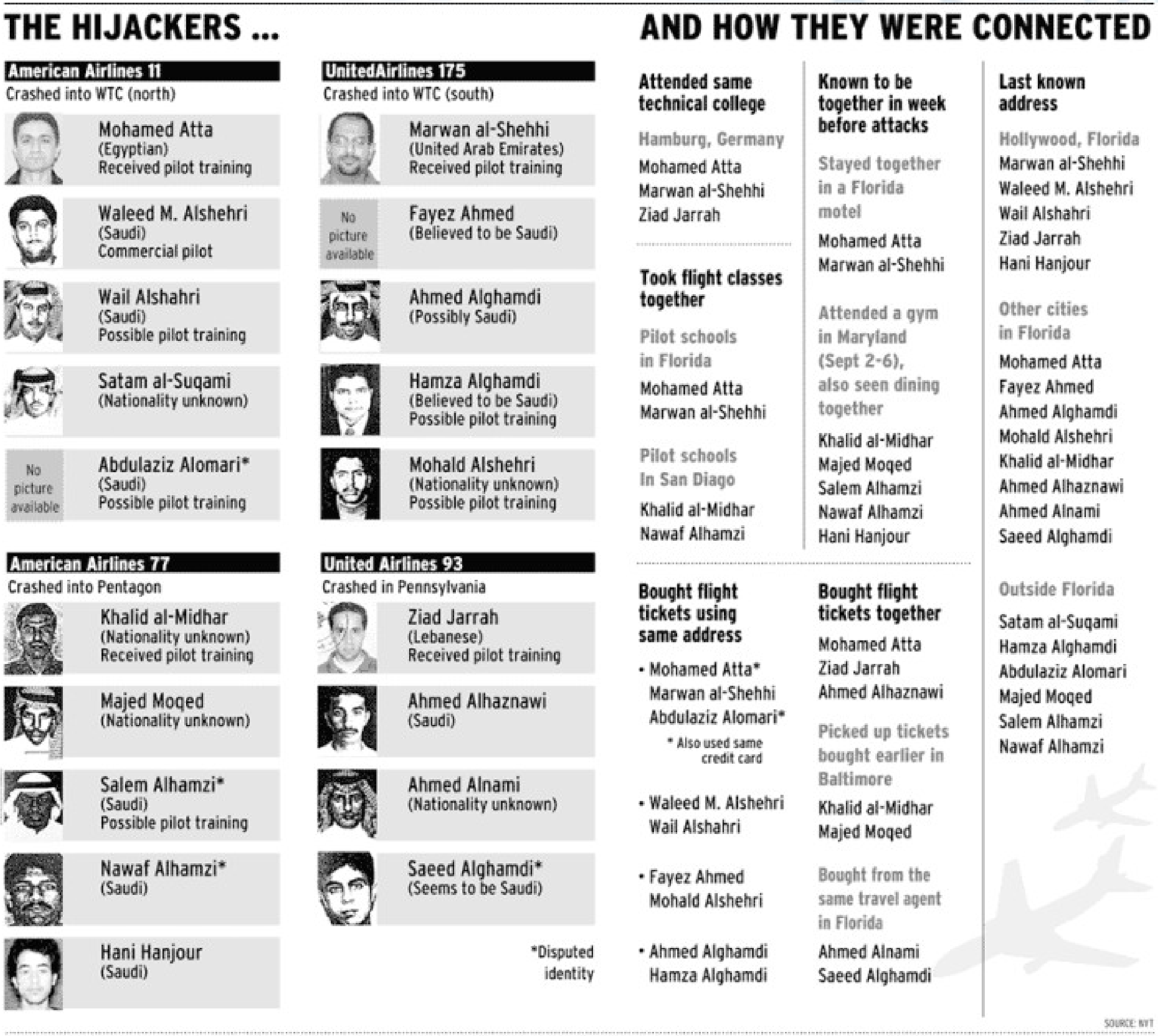

(a)
(b)
3 29 25 28 33 34 30 24 31 9 23 21 19 16 15 26 32 27 10 4 14 2 1 8 22 20 18 13 12 7 17 6 5 11






PILOTS hi-lited in yellow
🟩 Flight AA #11 - Crashed into WTC North
🟥 Flight AA #77 - Crashed into Pentagon
🟦 Flight UA #93 - Crashed in Pennsylvania
🟪 Flight UA #175 - Crashed into WTC South
⬛ Others

Copyright © 2002, Valdis Krebs



THE HIJACKERS ...

American Airlines 11

Crashed into WTC (north)

Mohamed Atta
(Egyptian)
Received pilot training

Waleed M. Alshehri
(Saudi)
Commercial pilot

Wail Alshahri
(Saudi)
Possible pilot training

Satam al-Suqami
(Nationality unknown)

No picture available

Abdulaziz Alomari*
(Saudi)
Possible pilot training

UnitedAirlines 175

Crashed into WTC (south)

Marwan al-Shehhi
(United Arab Emirates)
Received pilot training

No picture available

Fayez Ahmed
(Believed to be Saudi)

Ahmed Alghamdi
(Possibly Saudi)

Hamza Alghamdi
(Believed to be Saudi)
Possible pilot training

Mohald Alshehri
(Nationality unknown)
Possible pilot training

American Airlines 77

Crashed into Pentagon

Khalid al-Midhar
(Nationality unknown)
Received pilot training

Majed Moqed
(Nationality unknown)

Salem Alhamzi*
(Saudi)
Possible pilot training

Nawaf Alhamzi*
(Saudi)

Hani Hanjour
(Saudi)

United Airlines 93

Crashed in Pennsylvania

Ziad Jarrah
(Lebanese)
Received pilot training

Ahmed Alhaznawi
(Saudi)

Ahmed Alnami
(Nationality unknown)

Saeed Alghamdi*
(Seems to be Saudi)

*Disputed identity

AND HOW THEY WERE CONNECTED

Attended same technical college

Hamburg, Germany
Mohamed Atta
Marwan al-Shehhi
Ziad Jarrah

Took flight classes together

Pilot schools in Florida
Mohamed Atta
Marwan al-Shehhi

Pilot schools In San Diago
Khalid al-Midhar
Nawaf Alhamzi

Known to be together in week before attacks

Stayed together in a Florida motel
Mohamed Atta
Marwan al-Shehhi

Attended a gym in Maryland (Sept 2-6), also seen dining together
Khalid al-Midhar
Majed Moqed
Salem Alhamzi
Nawaf Alhamzi
Hani Hanjour

Bought flight tickets using same address

- Mohamed Atta*
  Marwan al-Shehhi
  Abdulaziz Alomari*

  * Also used same credit card

- Waleed M. Alshehri
  Wail Alshahri

- Fayez Ahmed
  Mohald Alshehri

- Ahmed Alghamdi
  Hamza Alghamdi

Bought flight tickets together

Mohamed Atta
Ziad Jarrah
Ahmed Alhaznawi

Picked up tickets bought earlier in Baltimore
Khalid al-Midhar
Majed Moqed

Bought from the same travel agent in Florida
Ahmed Alnami
Saeed Alghamdi

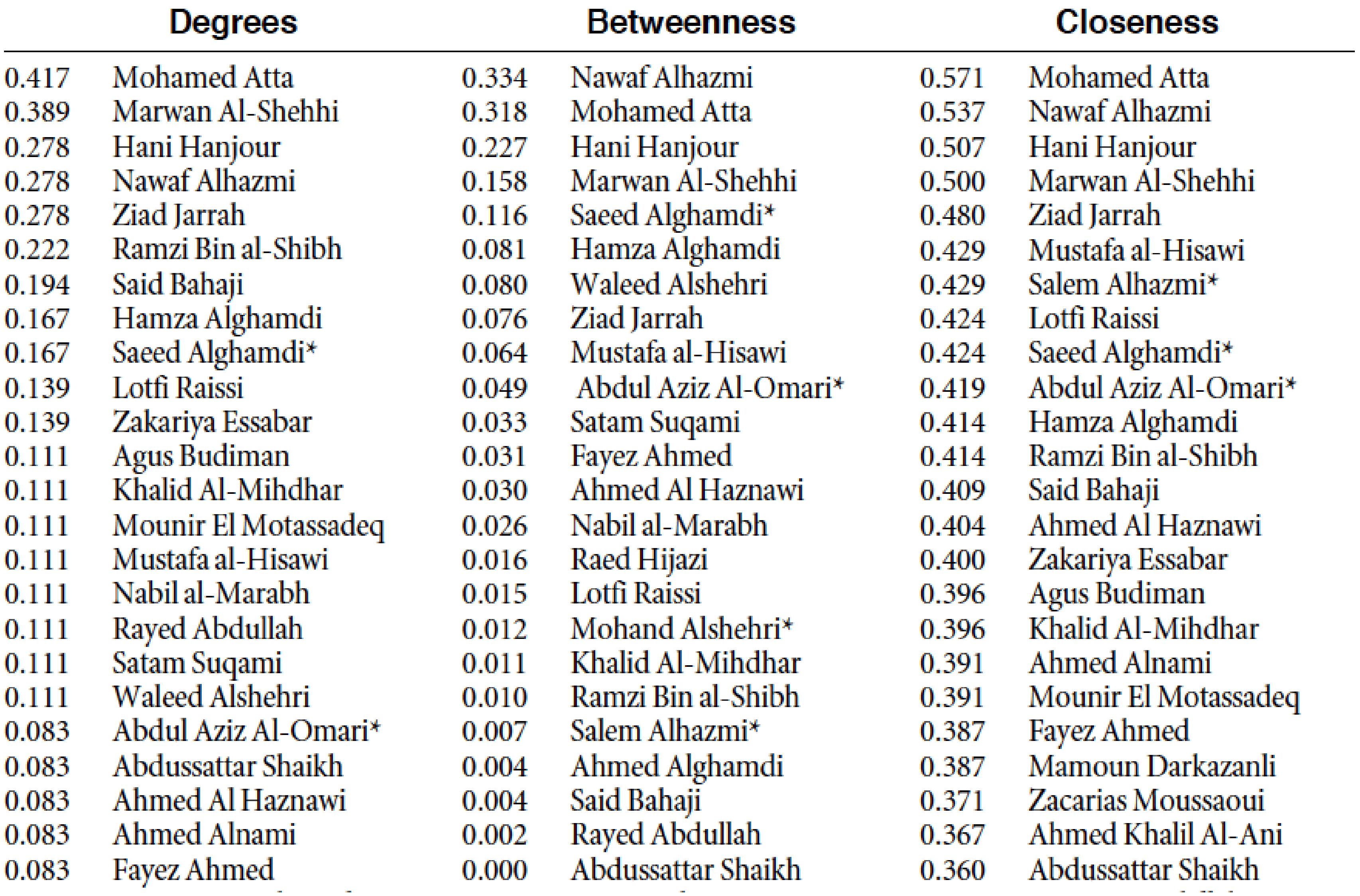
Last known address

Hollywood, Florida
Marwan al-Shehhi
Waleed M. Alshehri
Wail Alshahri
Ziad Jarrah
Hani Hanjour

Other cities in Florida
Mohamed Atta
Fayez Ahmed
Ahmed Alghamdi
Mohald Alshehri
Khalid al-Midhar
Ahmed Alhaznawi
Ahmed Alnami
Saeed Alghamdi

Outside Florida
Satam al-Suqami
Hamza Alghamdi
Abdulaziz Alomari
Majed Moqed
Salem Alhamzi
Nawaf Alhamzi

SOURCE: NYT



Degrees		Betweenness		Closeness	
0.417	Mohamed Atta	0.334	Nawaf Alhazmi	0.571	Mohamed Atta
0.389	Marwan Al-Shehhi	0.318	Mohamed Atta	0.537	Nawaf Alhazmi
0.278	Hani Hanjour	0.227	Hani Hanjour	0.507	Hani Hanjour
0.278	Nawaf Alhazmi	0.158	Marwan Al-Shehhi	0.500	Marwan Al-Shehhi
0.278	Ziad Jarrah	0.116	Saeed Alghamdi*	0.480	Ziad Jarrah
0.222	Ramzi Bin al-Shibh	0.081	Hamza Alghamdi	0.429	Mustafa al-Hisawi
0.194	Said Bahaji	0.080	Waleed Alshehri	0.429	Salem Alhazmi*
0.167	Hamza Alghamdi	0.076	Ziad Jarrah	0.424	Lotfi Raissi
0.167	Saeed Alghamdi*	0.064	Mustafa al-Hisawi	0.424	Saeed Alghamdi*
0.139	Lotfi Raissi	0.049	Abdul Aziz Al-Omari*	0.419	Abdul Aziz Al-Omari*
0.139	Zakariya Essabar	0.033	Satam Suqami	0.414	Hamza Alghamdi
0.111	Agus Budiman	0.031	Fayez Ahmed	0.414	Ramzi Bin al-Shibh
0.111	Khalid Al-Mihdhar	0.030	Ahmed Al Haznawi	0.409	Said Bahaji
0.111	Mounir El Motassadeq	0.026	Nabil al-Marabh	0.404	Ahmed Al Haznawi
0.111	Mustafa al-Hisawi	0.016	Raed Hijazi	0.400	Zakariya Essabar
0.111	Nabil al-Marabh	0.015	Lotfi Raissi	0.396	Agus Budiman
0.111	Rayed Abdullah	0.012	Mohand Alshehri*	0.396	Khalid Al-Mihdhar
0.111	Satam Suqami	0.011	Khalid Al-Mihdhar	0.391	Ahmed Alnami
0.111	Waleed Alshehri	0.010	Ramzi Bin al-Shibh	0.391	Mounir El Motassadeq
0.083	Abdul Aziz Al-Omari*	0.007	Salem Alhazmi*	0.387	Fayez Ahmed
0.083	Abdussattar Shaikh	0.004	Ahmed Alghamdi	0.387	Mamoun Darkazanli
0.083	Ahmed Al Haznawi	0.004	Said Bahaji	0.371	Zacarias Moussaoui
0.083	Ahmed Alnami	0.002	Rayed Abdullah	0.367	Ahmed Khalil Al-Ani
0.083	Fayez Ahmed	0.000	Abdussattar Shaikh	0.360	Abdussattar Shaikh

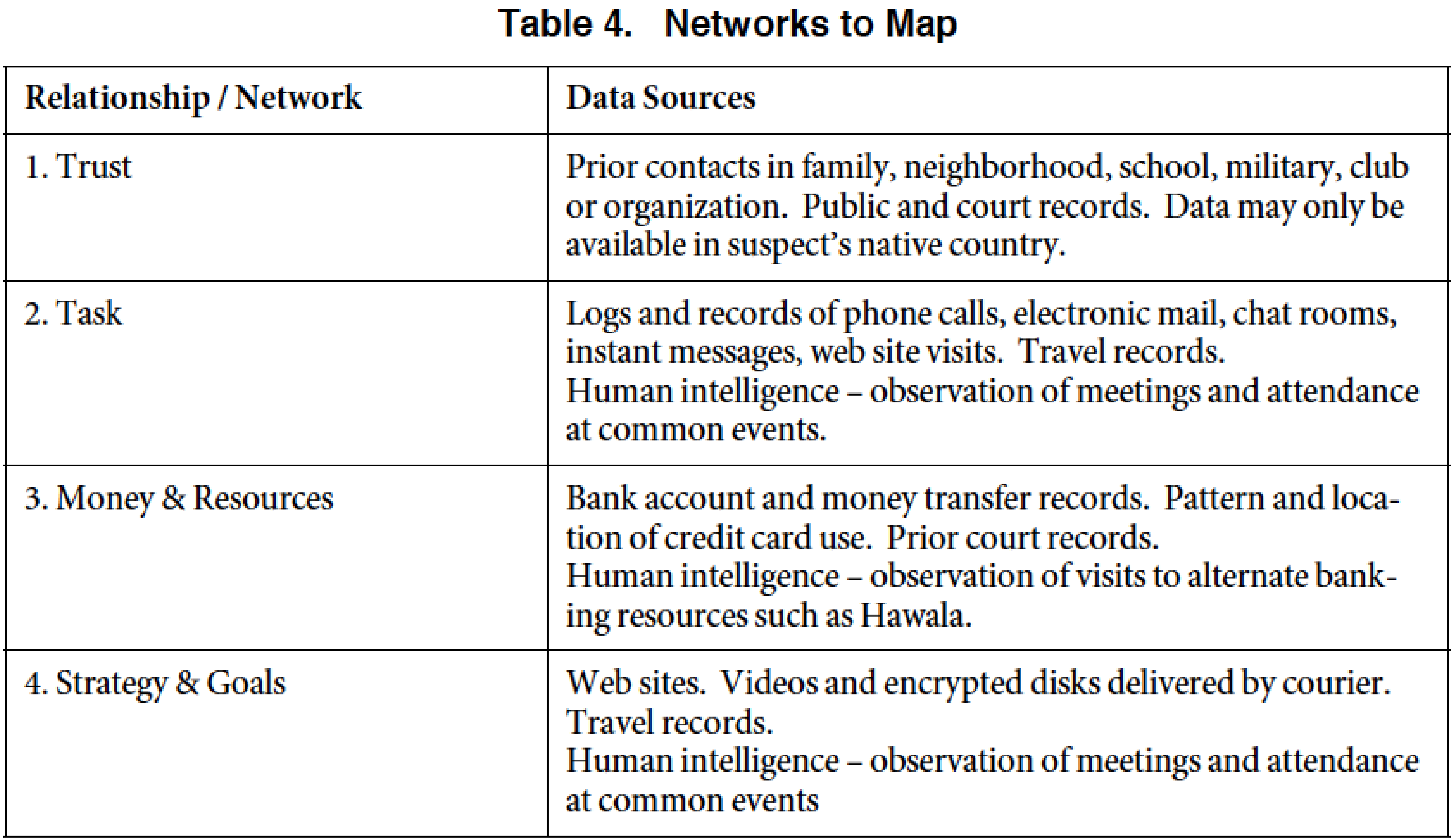
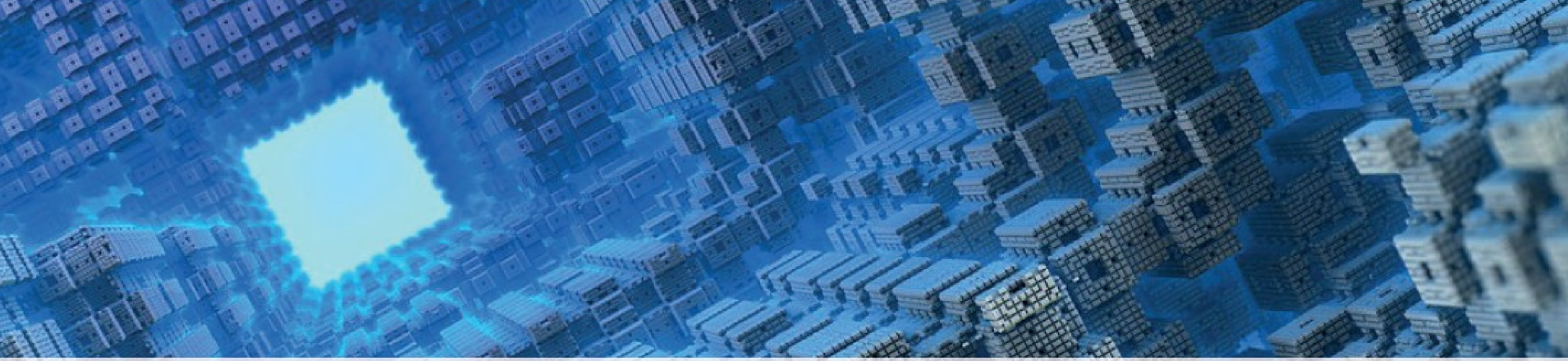


Table 4. Networks to Map

Relationship / Network	Data Sources
1. Trust	Prior contacts in family, neighborhood, school, military, club or organization. Public and court records. Data may only be available in suspect's native country.
2. Task	Logs and records of phone calls, electronic mail, chat rooms, instant messages, web site visits. Travel records. Human intelligence – observation of meetings and attendance at common events.
3. Money & Resources	Bank account and money transfer records. Pattern and location of credit card use. Prior court records. Human intelligence – observation of visits to alternate banking resources such as Hawala.
4. Strategy & Goals	Web sites. Videos and encrypted disks delivered by courier. Travel records. Human intelligence – observation of meetings and attendance at common events



15 settembre 2017

La ricerca incontra le imprese

JOTTO
Joint Technology Transfer Office
Fair

SCUOLA NORMALE SUPERIORE

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Scuola Universitaria Superiore Pisa

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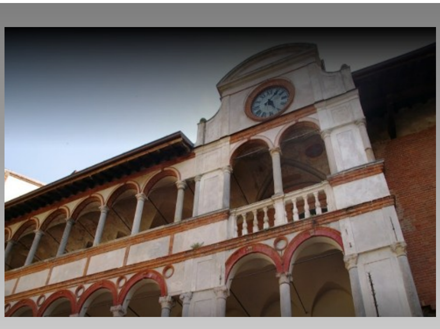
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ICT
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Spazio

Robotica e Biorobotica

Scienze Agrarie

Scienze sociali e umanistiche

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tecnologie biomediche
biotecnologie
farmaceutico
neuroscienze

Nanotecnologie
Nuovi materiali

Chimica computazionale
Beni culturali
Soft Matter

54 ricercatori

43 imprese

- **JoTTO FAIR 2019** (10 maggio 2019 @ IMT Lucca)
- Rappresentare una **best practice** di sinergia, promotrice di future iniziative complementari su più larga scala (vedasi TTO congiunto proposto dalla Regione Toscana, in fase di costituzione)
- Svolgere un ruolo importante per il TT dei nuovi **centri di competenza** regionali (Cybersecurity) e nazionali (ARTES4.0) su Impresa 4.0
- Agevolare l'implementazione delle future procedure di **valutazione della terza missione** delle Scuole e contribuire, indirettamente, al placement

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Scuola Superiore Sant’Anna
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Segreteria organizzativa JoTTO:

uvr@santannapisa.it
brevetti@sns.it
projects@imtlucca.it
terzamissione@iusspavia.it