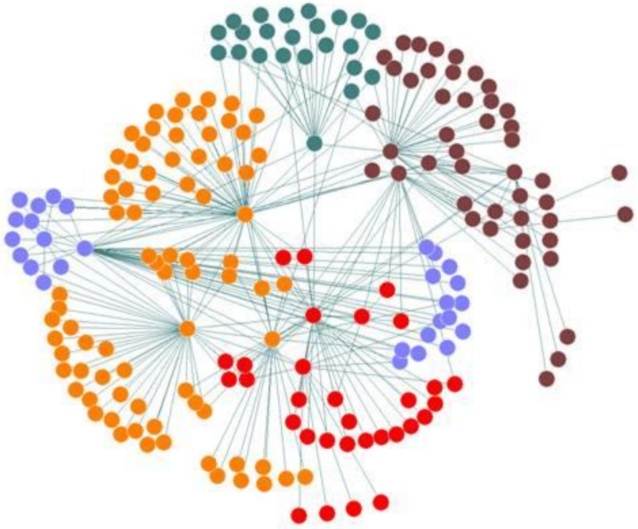
TEL AVIV UNIVERSITY

# Algorithms and Applications in Social Networks



2019/2020, Semester B

Slava Novgorodov

# Lesson #6

- Social Networks application examples:
    - Fraud
    - Crime
    - Terrorism
- Advices for in-practice social network analysis

# Fraud detection and prevention

# Motivation

- Fraud is everywhere:
  - Credit cards fraud
  - Taxes fraud
  - Fake companies fraud

- It costs our industry billions of dollars yearly

Based on: 1. GOTCHA! IMPROVING FRAUD DETECTION TECHNIQUES slides
2. Neo4j lectures about fraud detection: https://www.youtube.com/watch?v=AeNufTq1W5I

# Fraud detection

Current (non SNA) methods:

- Machine learning algorithms that gives a score to each transaction (i.e. the probability to be fraud)
    - Improvement directions:
        - Better ML algorithms
        - More labeled data
- Rules based systems, which usually works as addition to ML techniques (usually written by experts)
    - Improvement directions:
        - Automatic rules generation
        - Better sharing of rules between experts

# Example of fraud detection

| Time | Amount | Transaction Type | Location | |
|---|---|---|---|---|
| 18:02 | 107 | Online, no CCV | Online Store | FRAUD |
| 18:03 | 106 | Online, no CCV | Online Store | FRAUD |
| 18:04 | 112 | Online, with CCV | Online Store | |
| 19:08 | 114 | Online, no CCV | Online Store | FRAUD |
| 19:10 | 117 | Online, with CCV | Online Store | |
| 20:53 | 46 | Offline, without PIN | GAS Station B | FRAUD |
| 20:54 | 48 | Offline, without PIN | GAS Station B | FRAUD |
| 20:55 | 44 | Offline, without PIN | GAS Station B | FRAUD |
| 20:58 | 47 | Offline, with PIN | Supermarket | |
| 21:01 | 49 | Offline, with PIN | GAS Station A | |
| : | : | : | : | : |

**ML Score**:

0.75

0.91

0.22

0.15

0.71

…

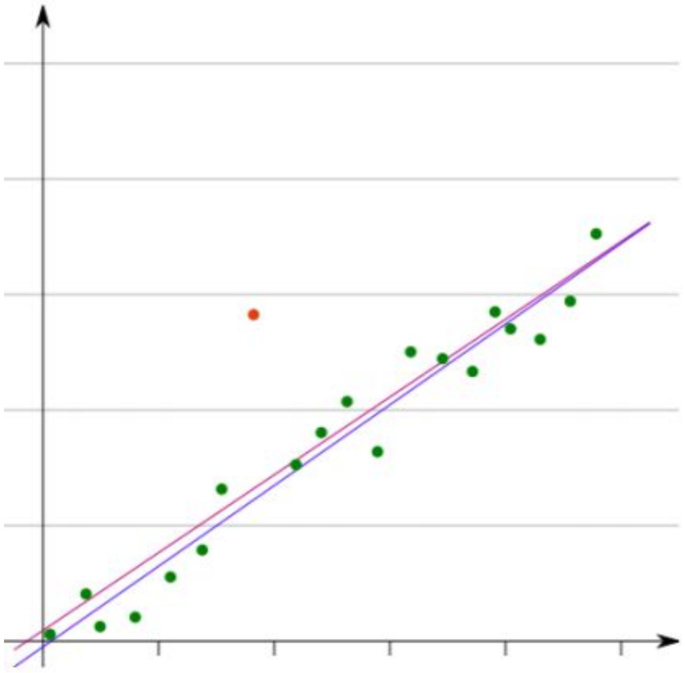
**Rules:**

1) Time ∈ [18:00, 18:05] ∧ Amt ≥ 110

2) Time ∈ [18:55, 19:00] ∧ Amt ≥ 110

# Fraud detection

- Basic method: Anomalous behavior detection
  - Outlier detection: abnormal behavior and/or characteristics in a data set might often indicate that that person perpetrates suspicious activities.

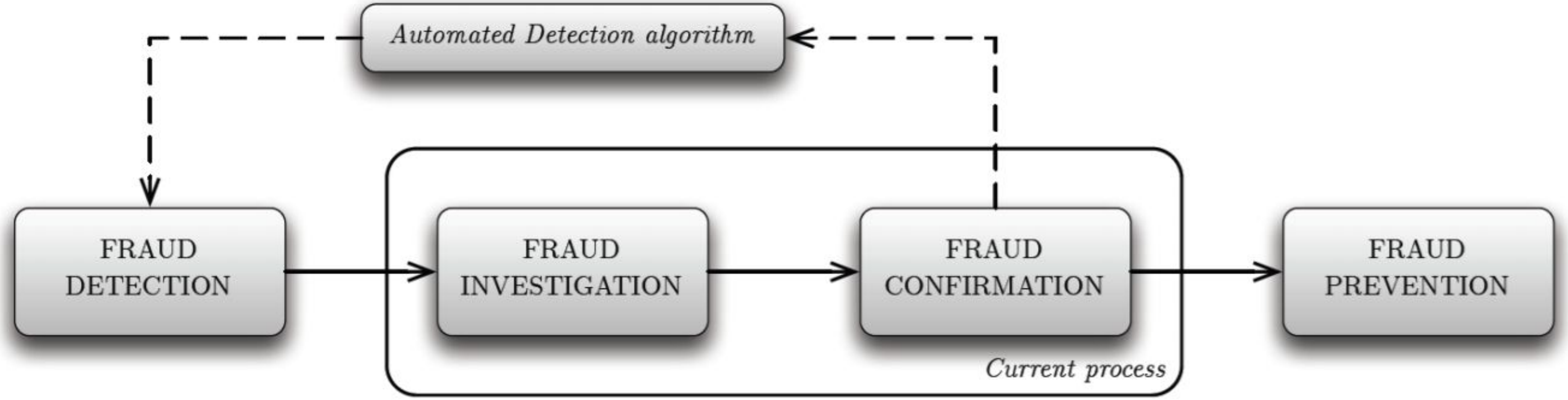


# Fraud detection

- Basic method: Anomalous behavior detection
  - Pros: Very simple method
  - Cons: A lot of false positives and false negatives

# Fraud detection

## Current workflow:



# Fraud detection

Main (not all) challenges with fraud detection:

- Unbalanced:
  - Extremely skewed class distribution
  - Big data, but only few fraudulent observations (often < 1%)
- Well-considered & Carefully organized:
  - Complex fraud structures are carefully planned
  - Outlier detection no longer sufficient: combination of patterns, preferably well-hidden
  - Relationships between fraudsters
- Imperceptibly concealed
  - Subtlety of fraud: imitating normal behavior, even in identify theft
  - Fraudsters are often first “sleeping”, pretending to be a good customer

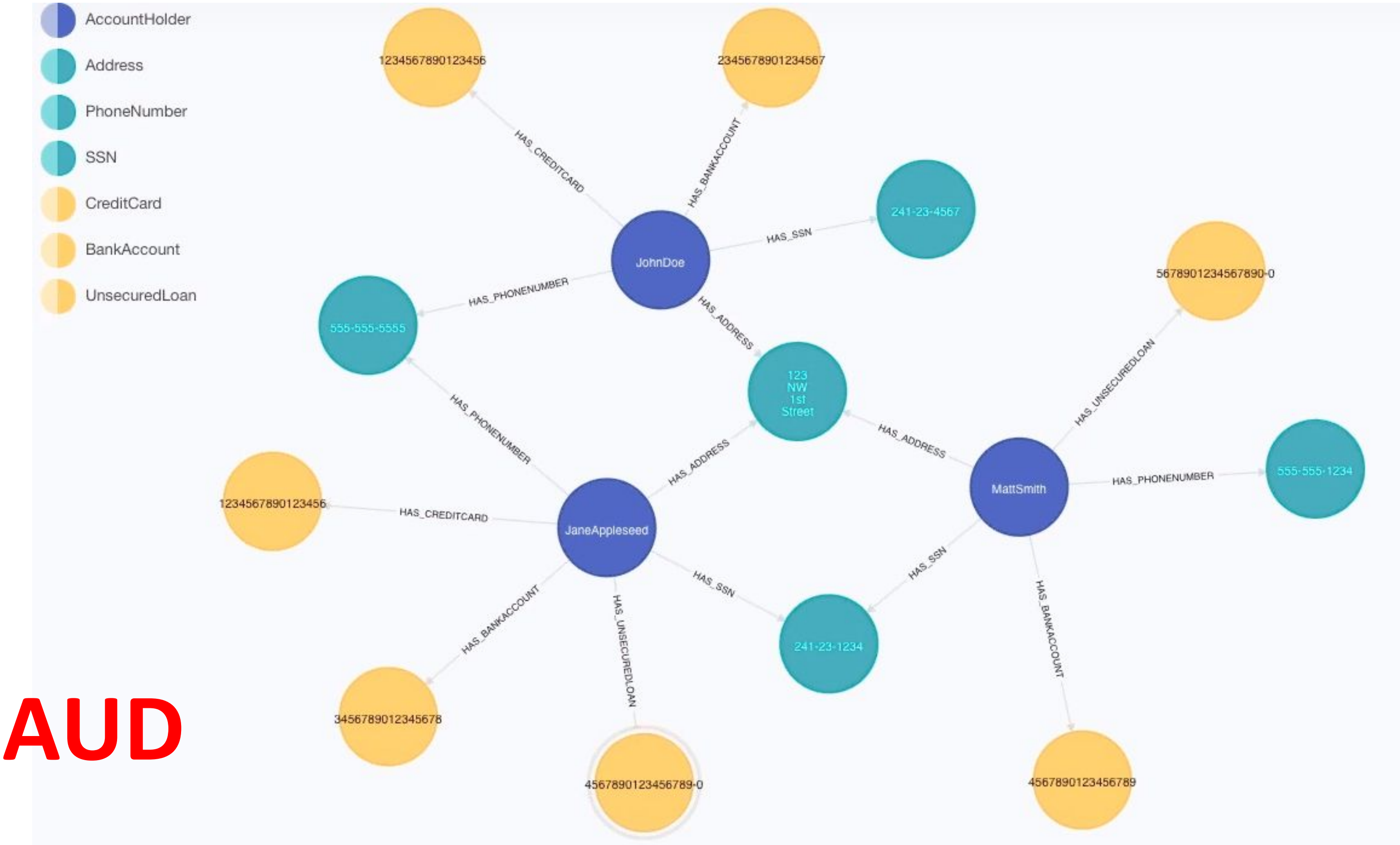
# Social Networks Analysis for Fraud Detection

Model interactions as a network:

- Nodes:
  - People (Fraudsters/Victims)
  - Banks
  - Companies
  - Resources
  - ….
- Links:
  - Credit Card transactions
  - Loans
  - "belongs to" relation, "works at" relation …
  - …

# Visualization can help!

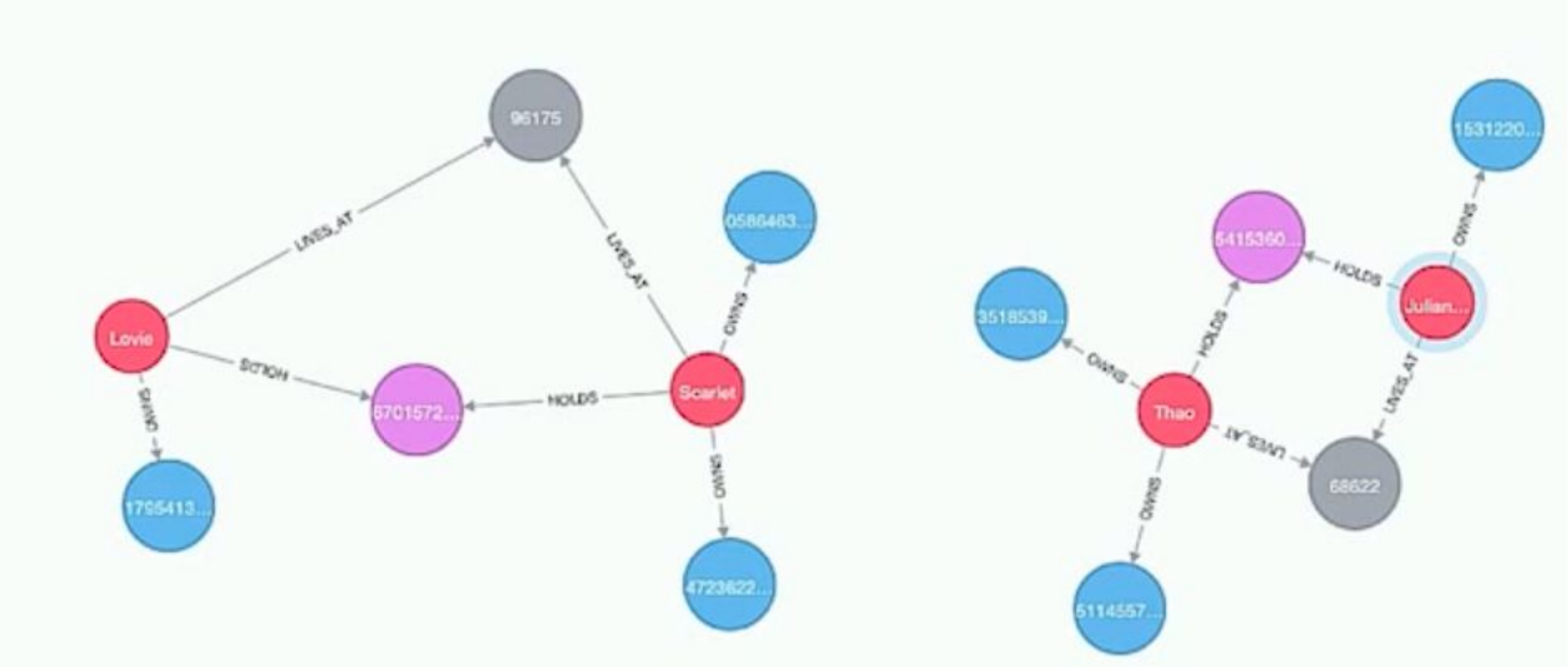
Modeling as a network can help even if you just visualize it…



FRAUD

# Visualization can help!

Modeling as a network can help even if you just visualize it…

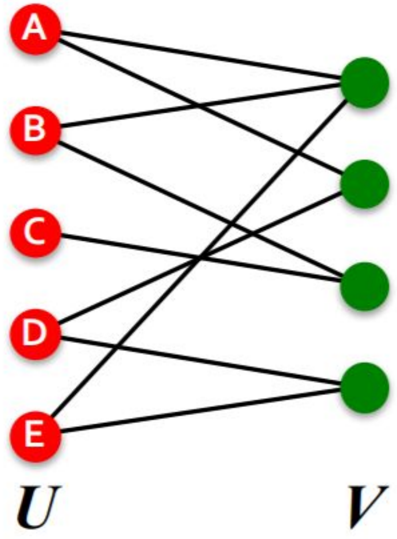


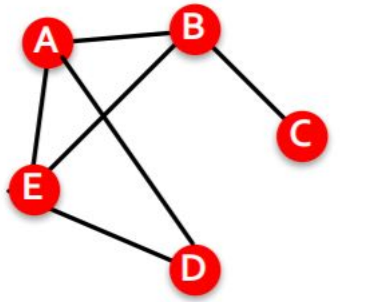
LEGITIMATE

# Bipartite graphs folding

**Folding:**

Connect every red node to other red node if they are connected to same green node





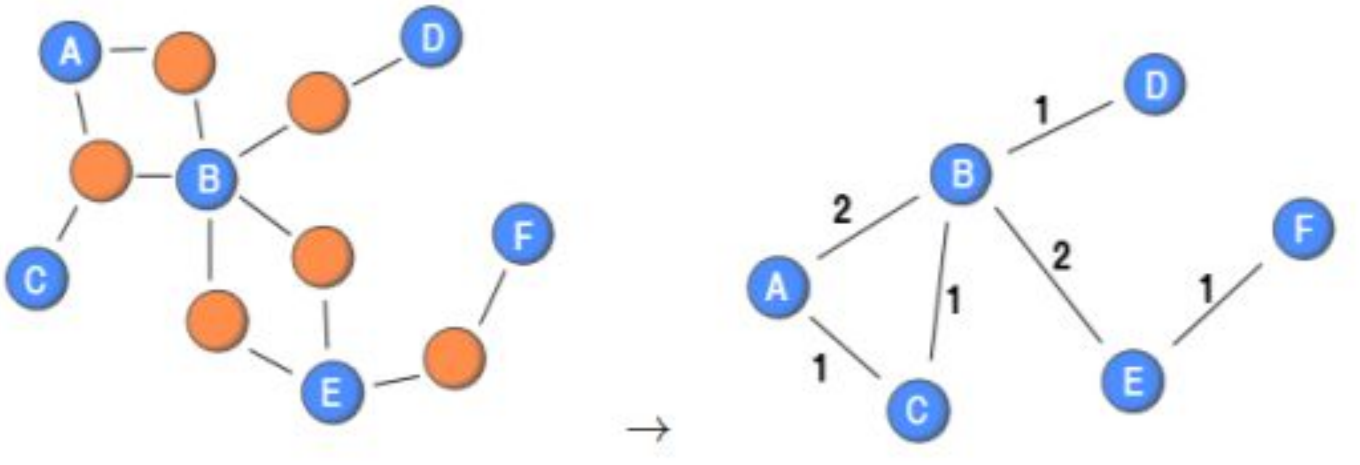
Folded version of the graph above

# Bipartite graphs weighted folding

**Folding:**

Connect every blue node to other blue node if they are connected to same orange node.

If the node already exists, add 1 to its weight

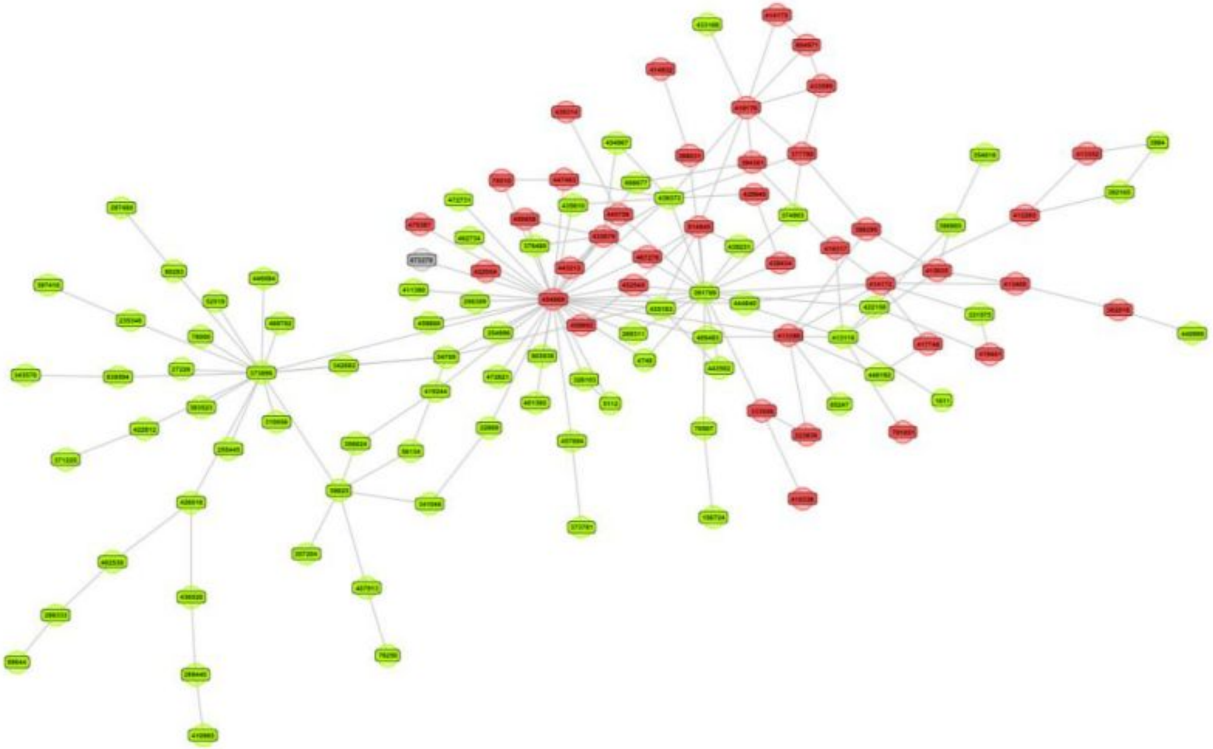


# Fraud analysis “basic scheme”

1. Take the data and represent it as a network
2. Decide of the “sides” of the bipartite network
3. Fold it
4. Detect cliques, detect communities, measure centrality…

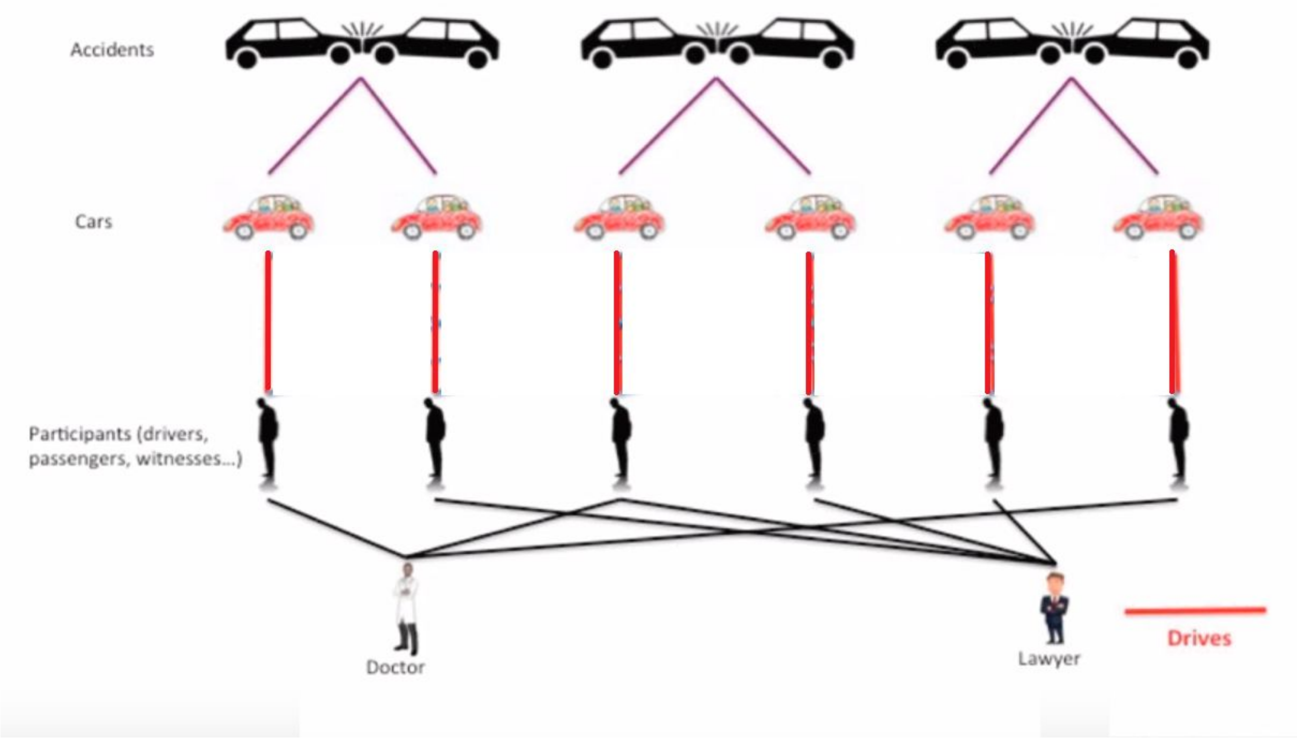
# Homophily

- People tend to associate with other whom they perceive as being similar to themselves in some way. e.g.: same city, hobbies, interests…



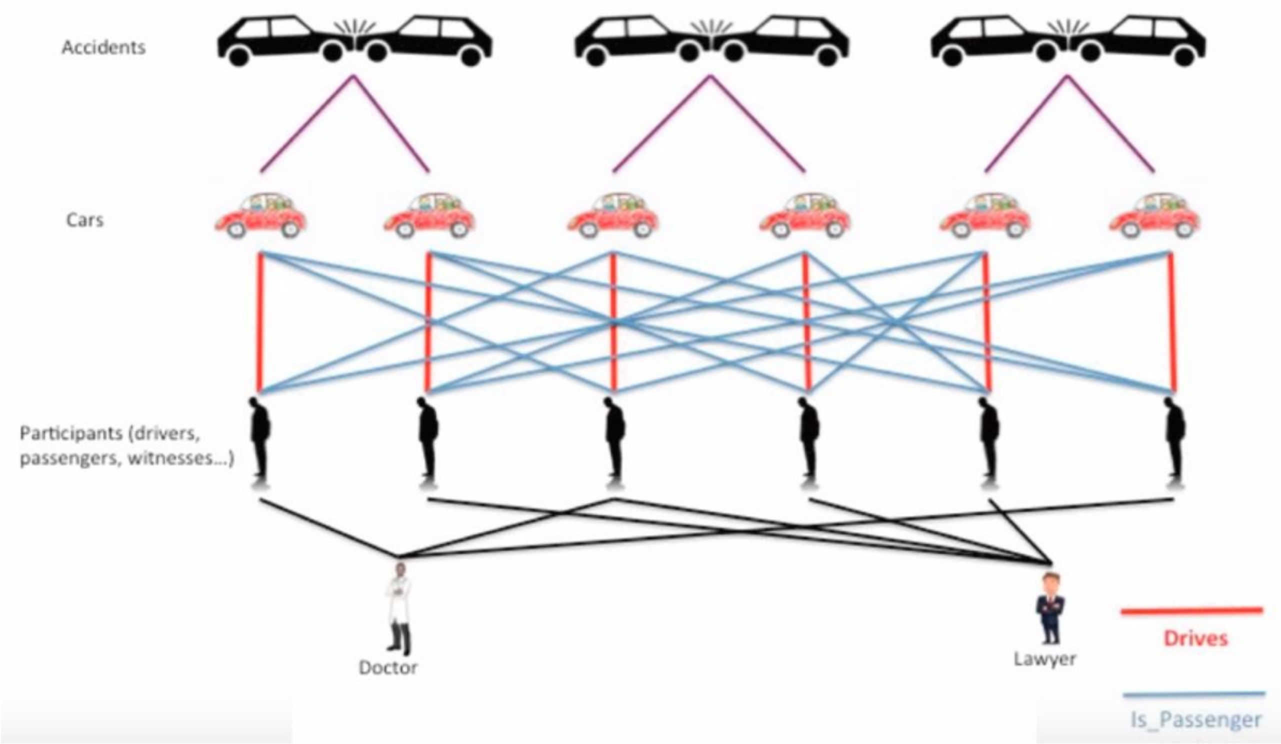
# Insurance fraud

- Combining different types of links in one network can give much more information

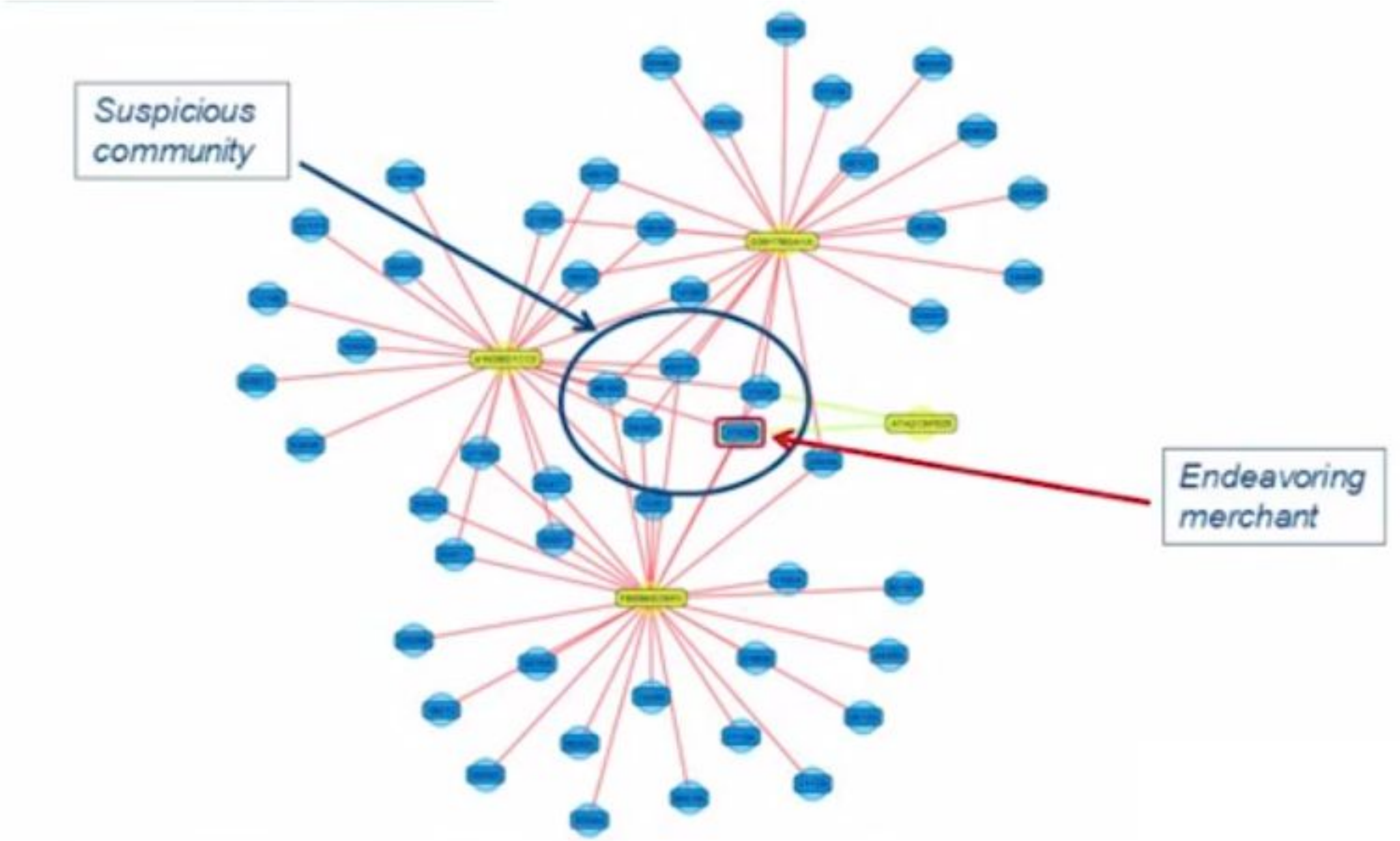


# Insurance fraud

- Combining different types of links in one network can give much more information

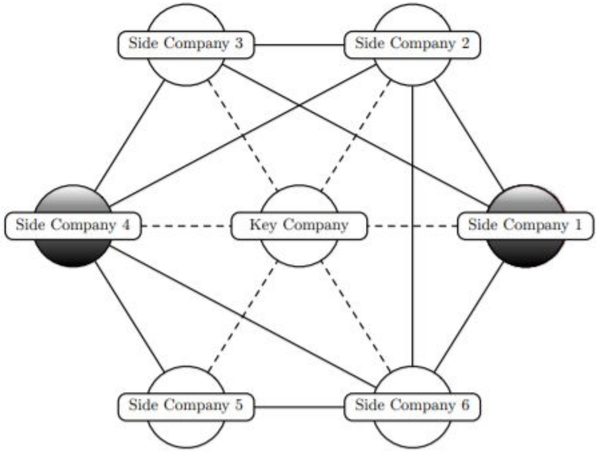


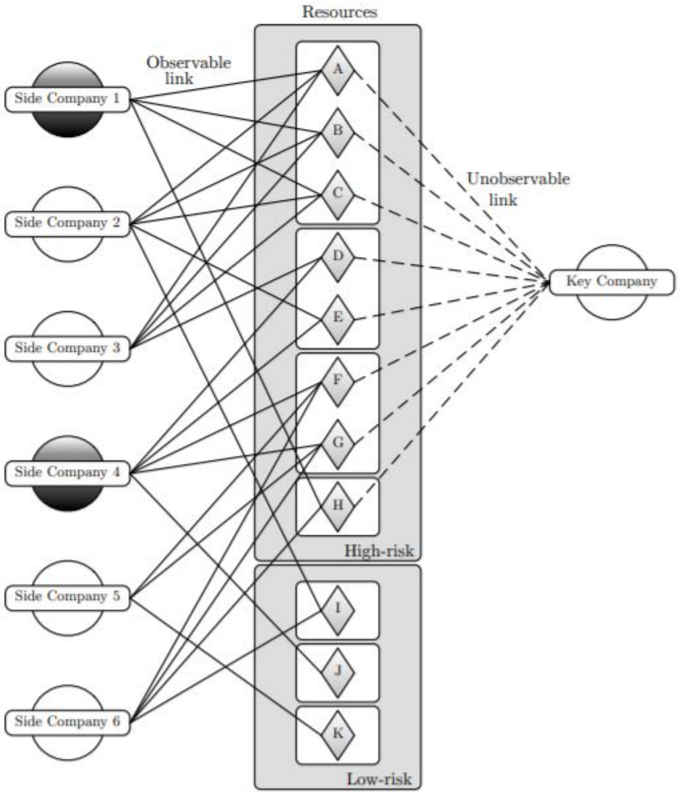
# Credit Card Fraud



Very sensitive data

# Taxes Fraud



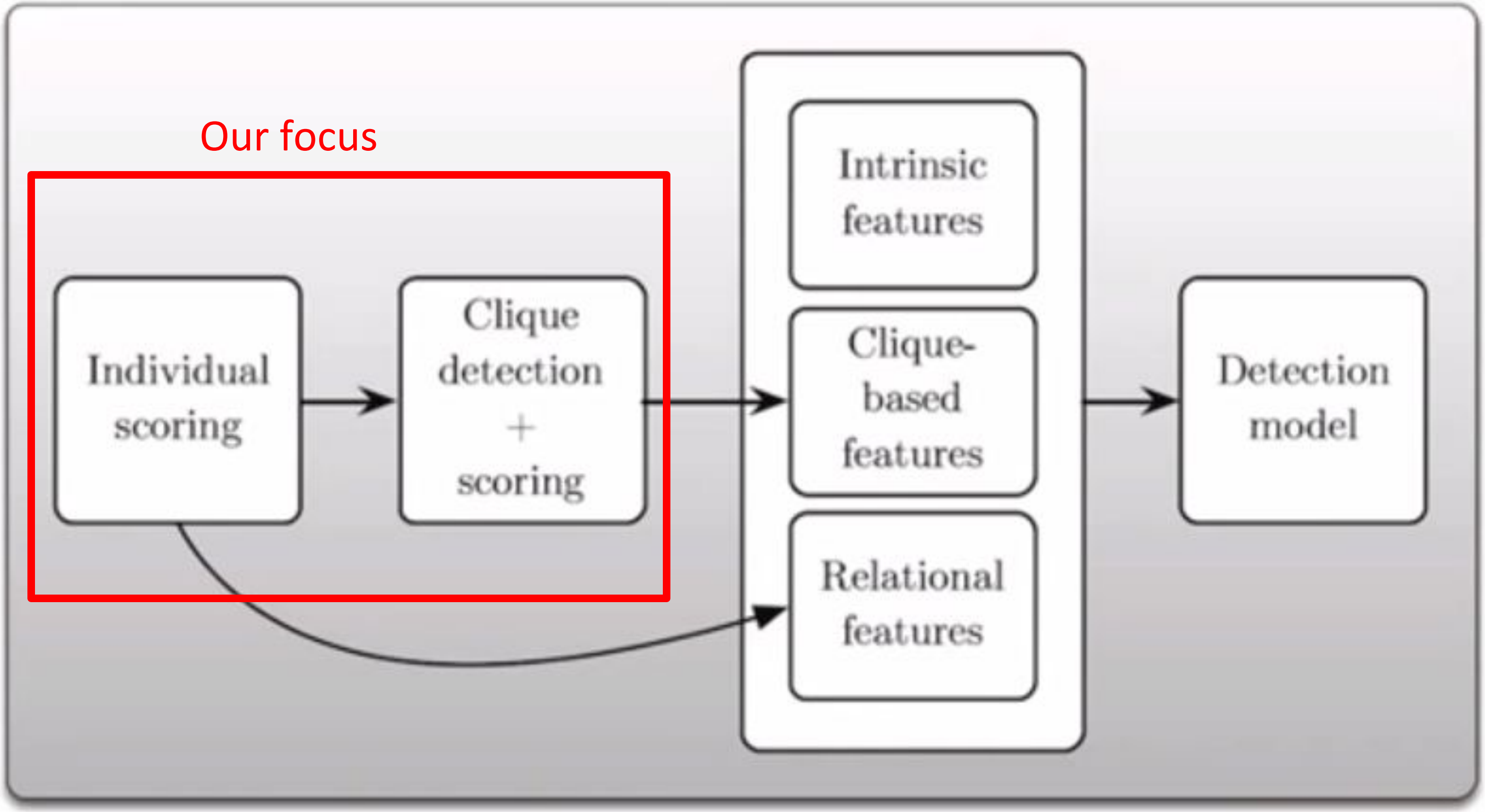


“Spider construction” fraud scheme – open a company, allocate resources, Bankrupt the company, move the resources…

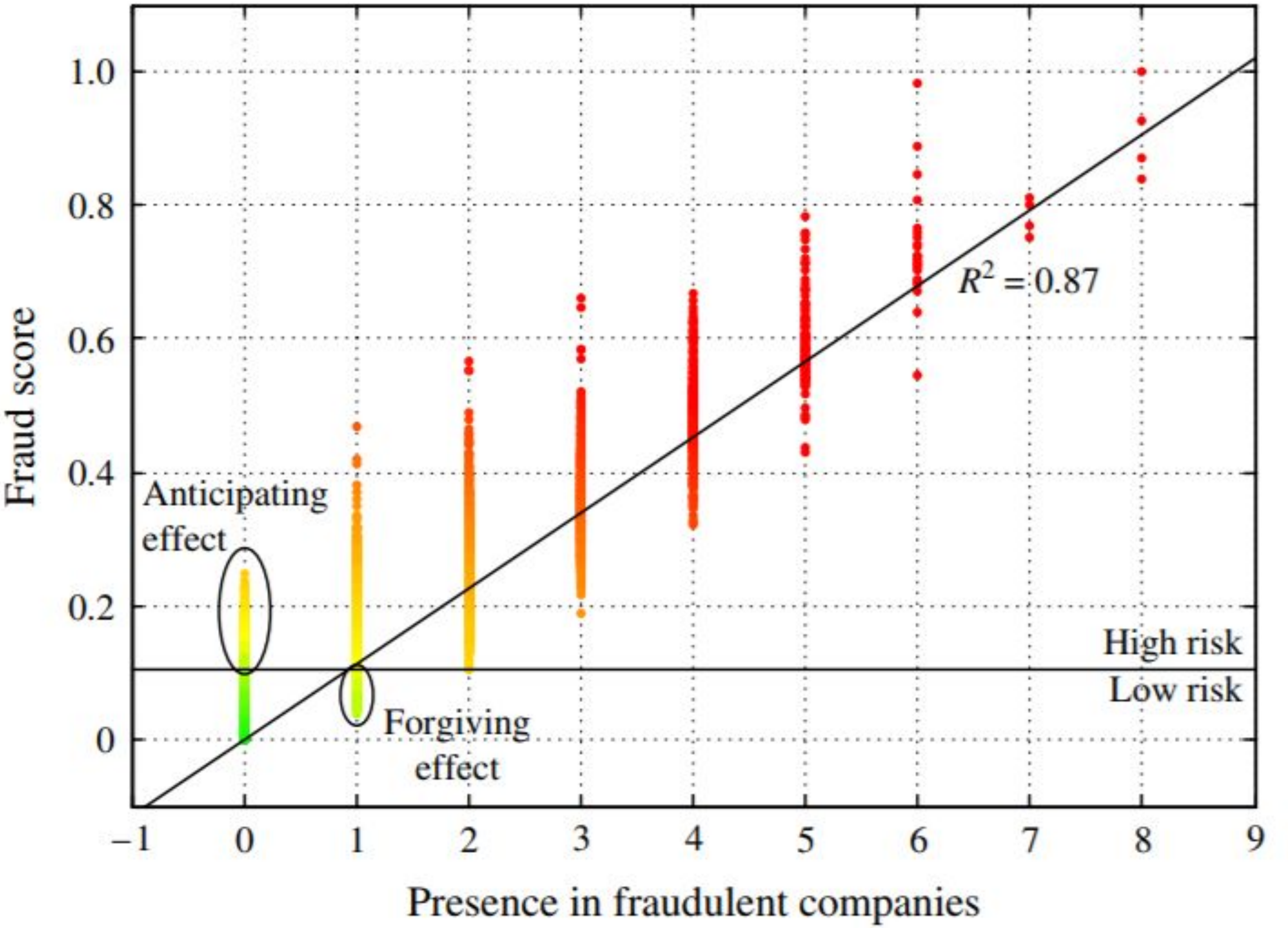
# The solution

- System called Gotcha! (Gotch'all):

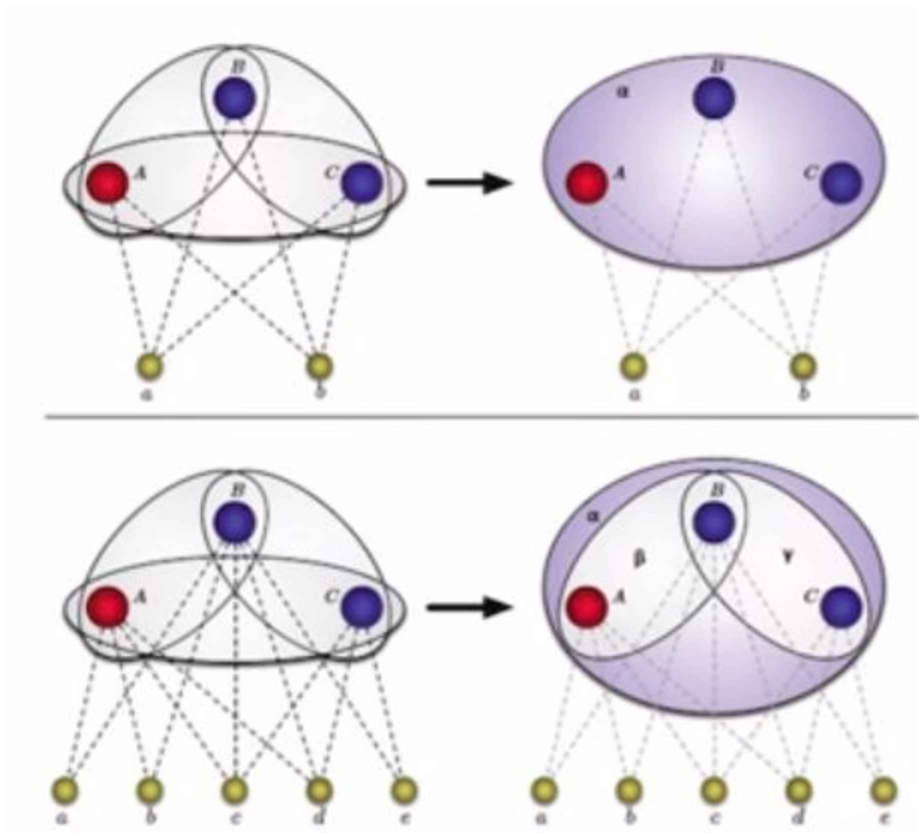
  (by Van Vlasselaer et al.)



# Individual Scoring



# Clique detection

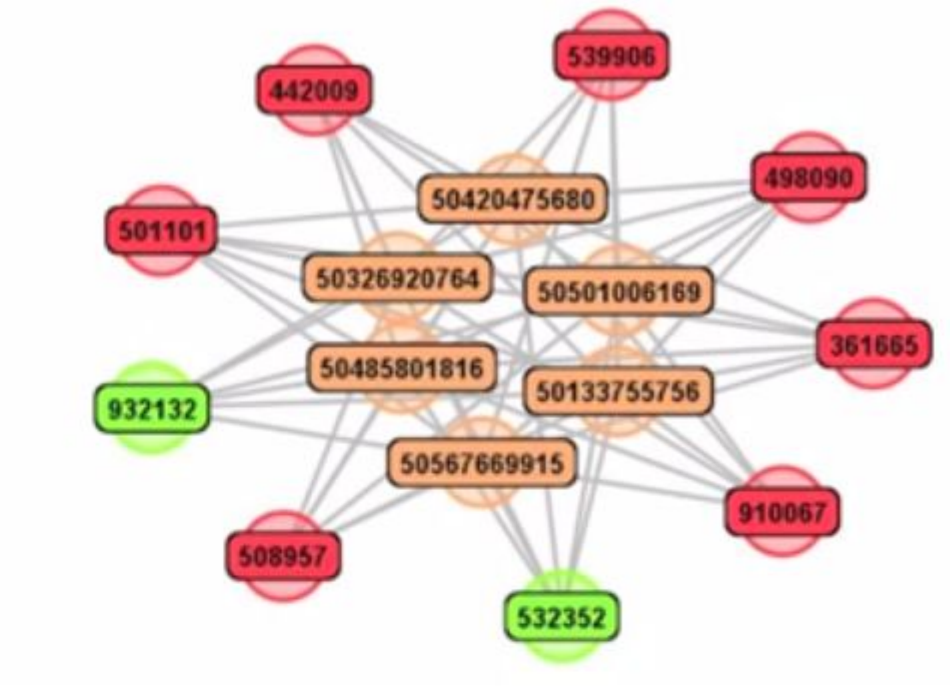


“Complete” clique

“Partial” clique

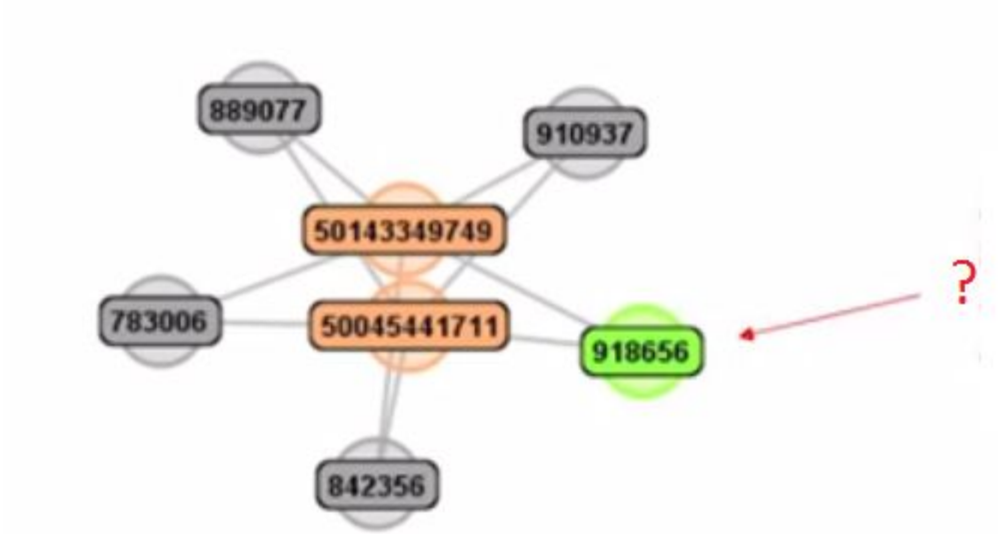
# Clique scoring

Suspiciousness of the clique: How many bankrupts? How many frauds?



# Empirical evaluation

- 5 companies, 2 resources
- 4 out of 5 companies are bankrupt
- What about the last company?



# Empirical evaluation

- 5 companies, 2 resources
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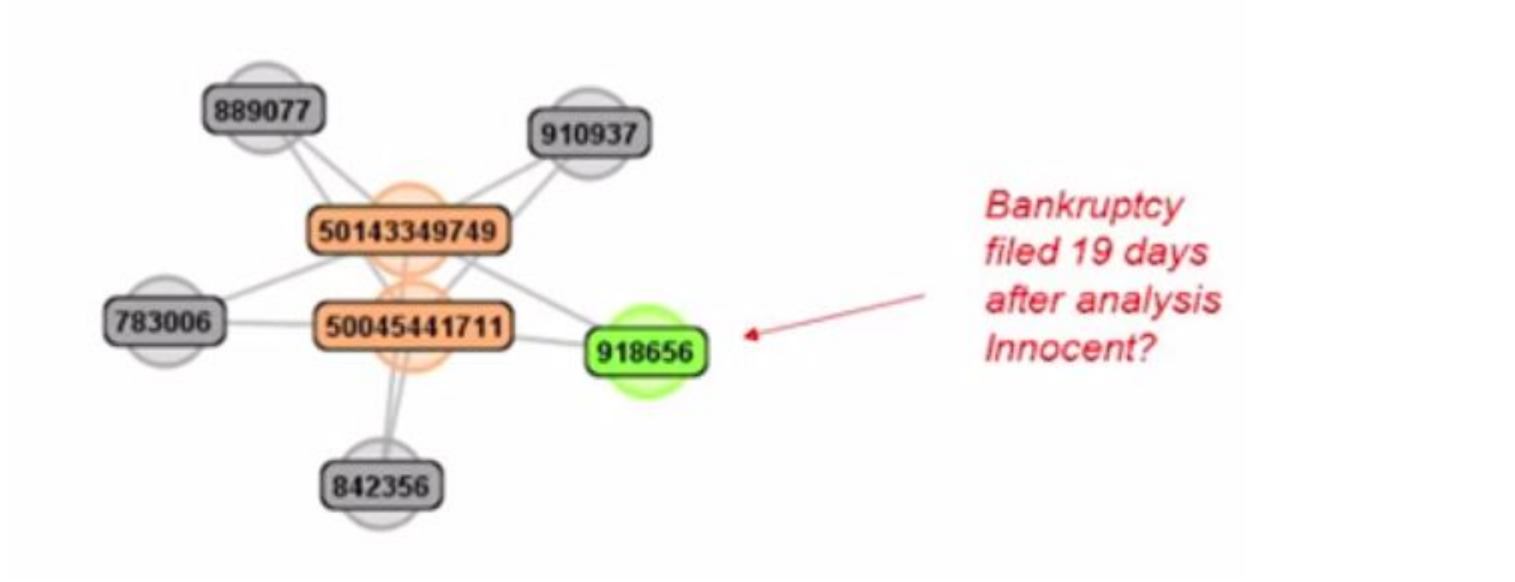


Bankruptcy filed 19 days after analysis Innocent?

# Crime detection

# Motivation

- Crime is often well organized, with individuals formed into groups/gangs, with structure and hierarchy.

- Crimes have a lot of “meta-data”, that can be better modeled as a network

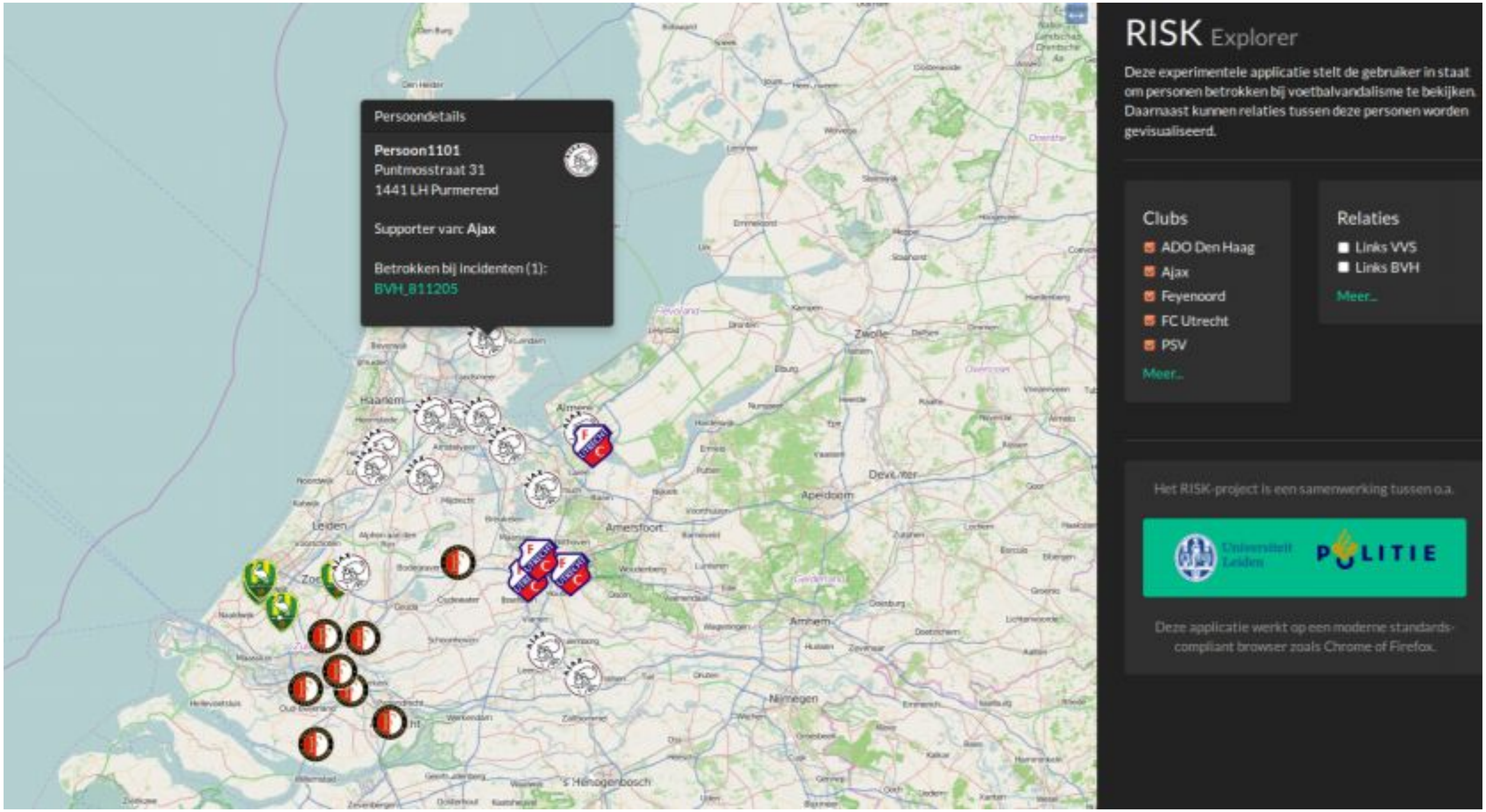
Based on: 1. http://liacs.leidenuniv.nl/~takesfw/SNACS/lecture3.pdf

# Dutch Police example

- Gain insight in social networks of soccer fans, group formation and organization
- Dataset: all entries in police systems of law violations of a particular group of people involved in soccer violence

POLITIE

# Dutch Police example



Persoondetails

**Persoon1101**
Puntmosstraat 31
1441 LH Purmerend

Supporter van: **Ajax**

Betrokken bij Incidenten (1):
BVH_811205

RISK Explorer

Deze experimentele applicatie stelt de gebruiker in staat om personen betrokken bij voetbalvandalisme te bekijken. Daarnaast kunnen relaties tussen deze personen worden gevisualiseerd.

Clubs

- ☑ ADO Den Haag
- ☑ Ajax
- ☑ Feyenoord
- ☑ FC Utrecht
- ☑ PSV

Meer...

Relaties

- ☐ Links VVS
- ☐ Links BVH

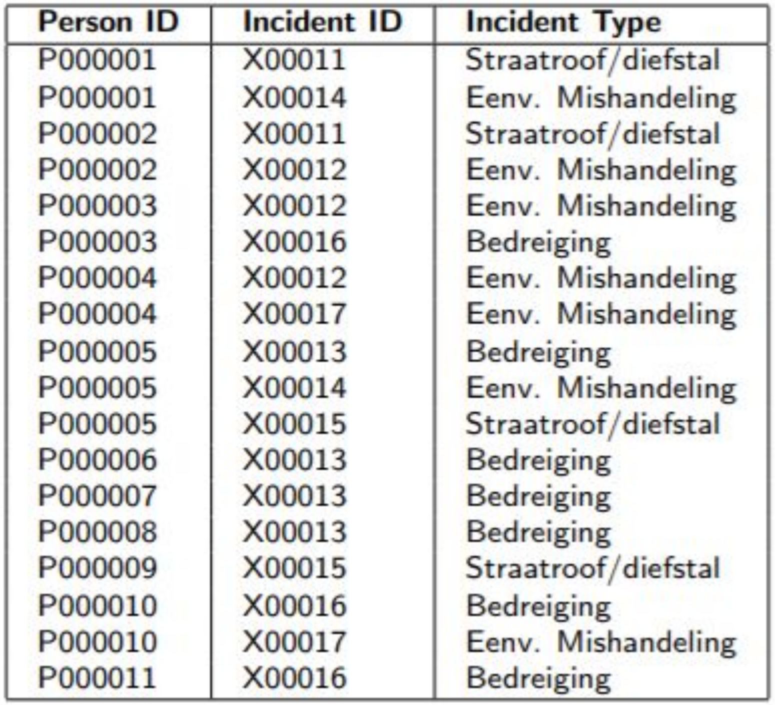
Meer...

Het RISK-project is een samenwerking tussen o.a.

Universiteit Leiden POLITIE

Deze applicatie werkt op een moderne standards-compliant browser zoals Chrome of Firefox.

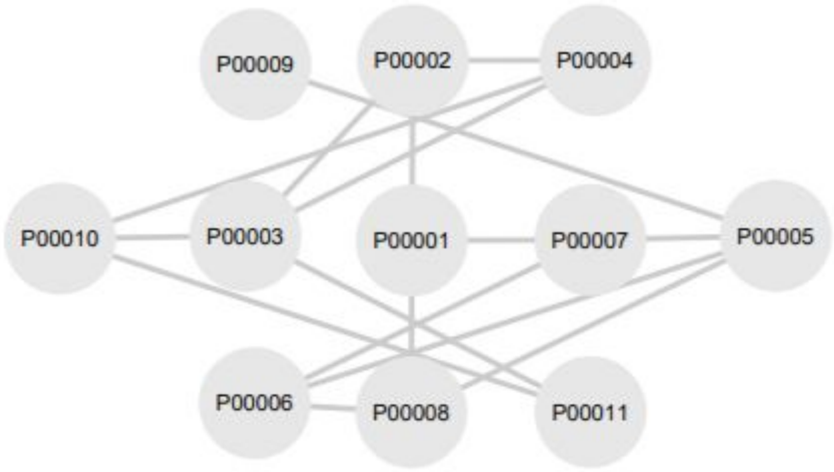
# Dutch Police example - Dataset



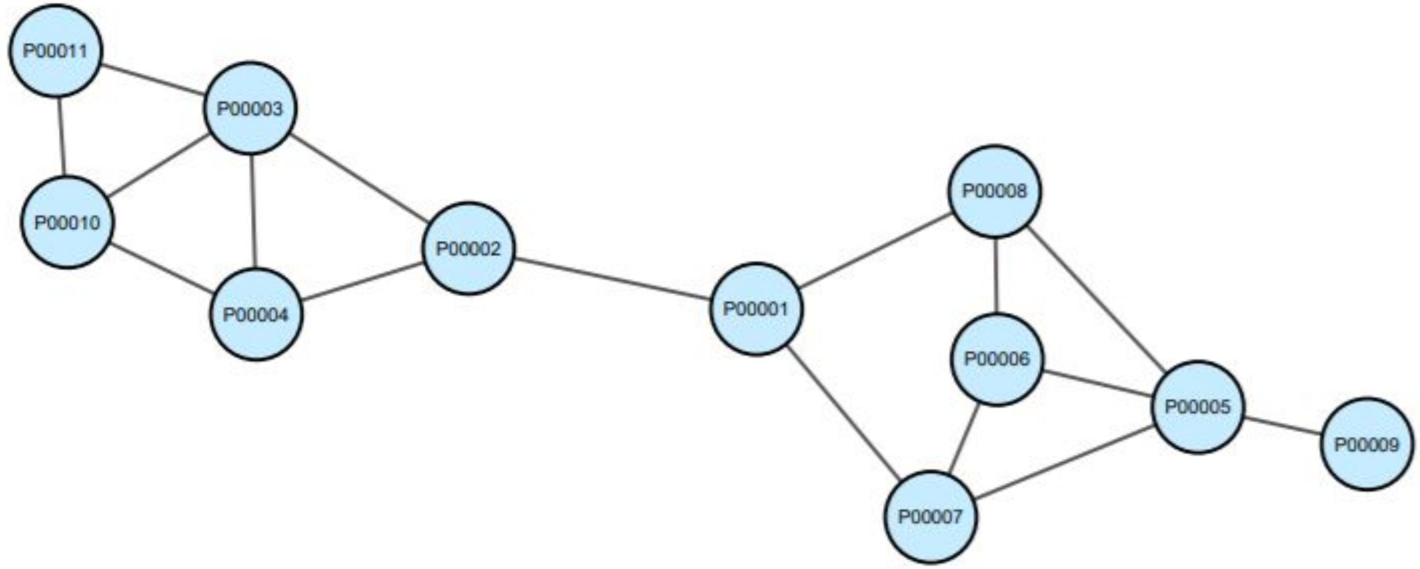
| Person ID | Incident ID | Incident Type |
|---|---|---|
| P000001 | X00011 | Straatroof/diefstal |
| P000001 | X00014 | Eenv. Mishandeling |
| P000002 | X00011 | Straatroof/diefstal |
| P000002 | X00012 | Eenv. Mishandeling |
| P000003 | X00012 | Eenv. Mishandeling |
| P000003 | X00016 | Bedreiging |
| P000004 | X00012 | Eenv. Mishandeling |
| P000004 | X00017 | Eenv. Mishandeling |
| P000005 | X00013 | Bedreiging |
| P000005 | X00014 | Eenv. Mishandeling |
| P000005 | X00015 | Straatroof/diefstal |
| P000006 | X00013 | Bedreiging |
| P000007 | X00013 | Bedreiging |
| P000008 | X00013 | Bedreiging |
| P000009 | X00015 | Straatroof/diefstal |
| P000010 | X00016 | Bedreiging |
| P000010 | X00017 | Eenv. Mishandeling |
| P000011 | X00016 | Bedreiging |

# Dutch Police example - Dataset

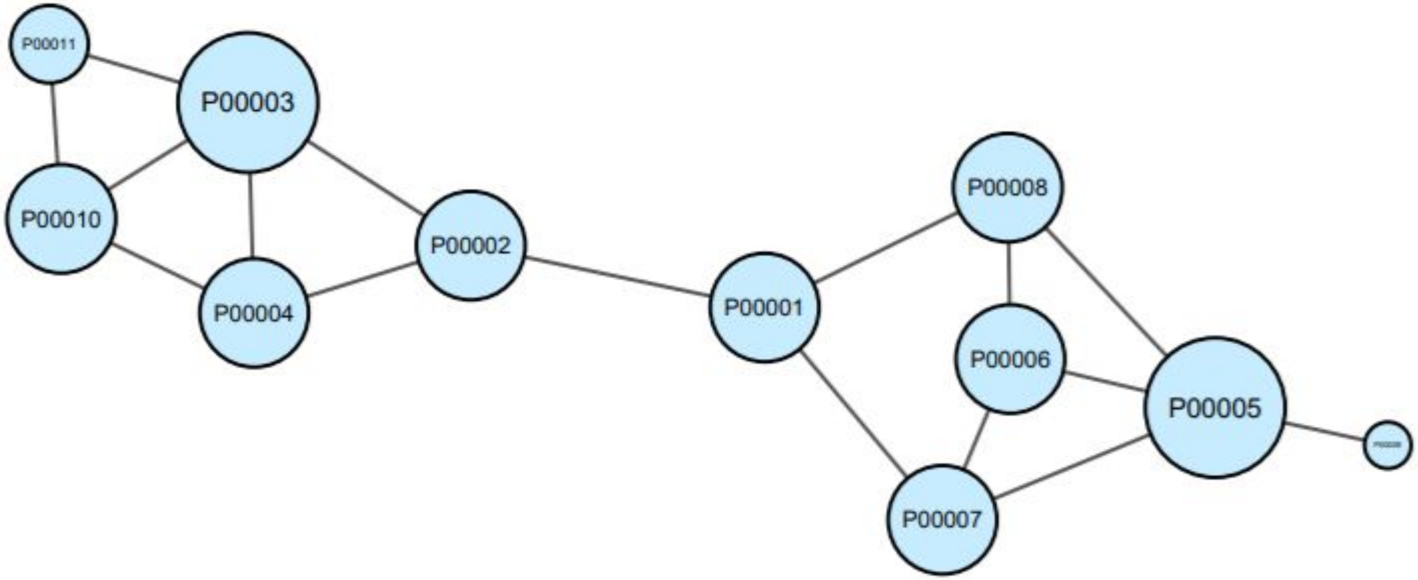
Folded bipartite graph (people and incidents):



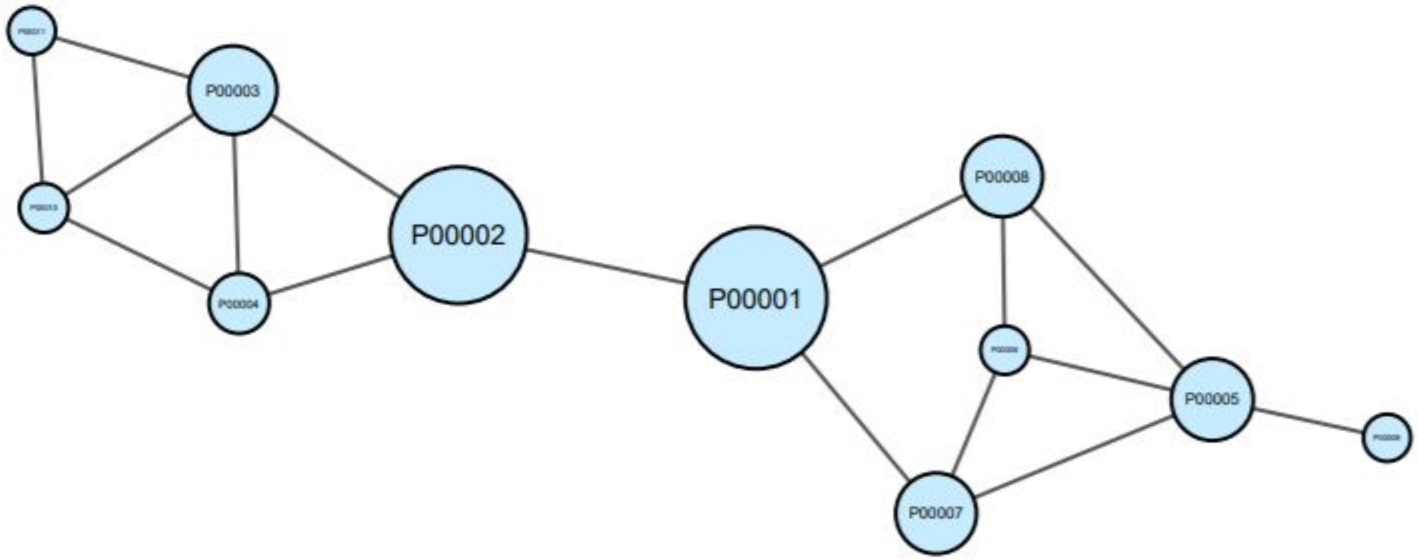
# Dutch Police example - Visualization



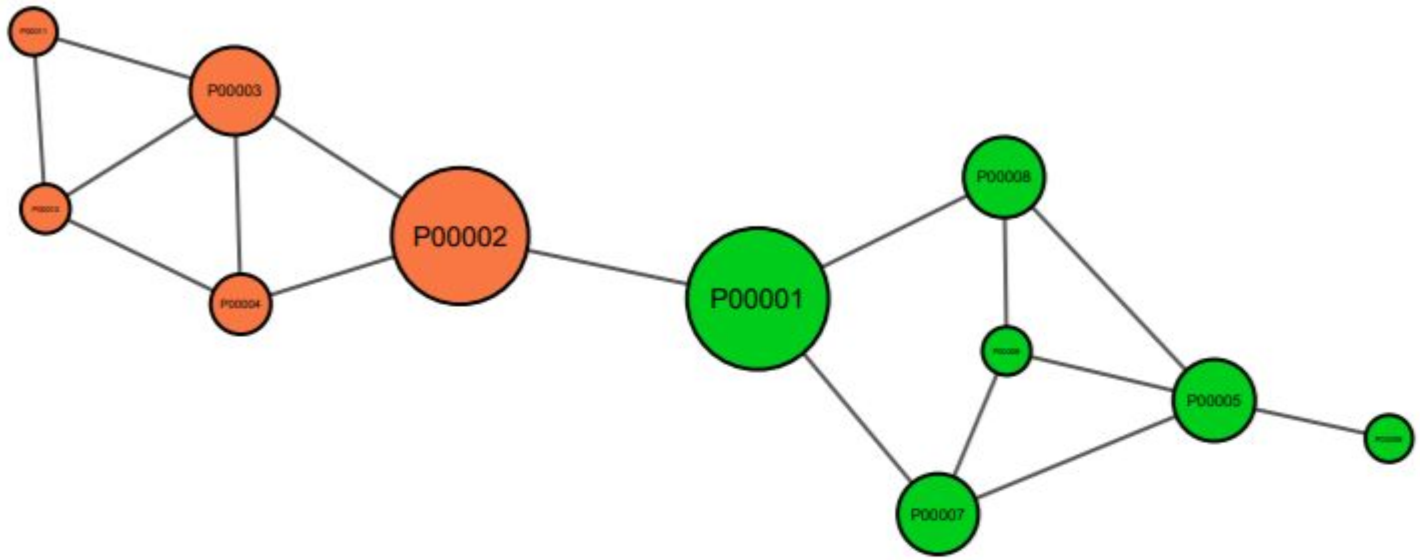
# Dutch Police example - Centrality



# Dutch Police example - Centrality

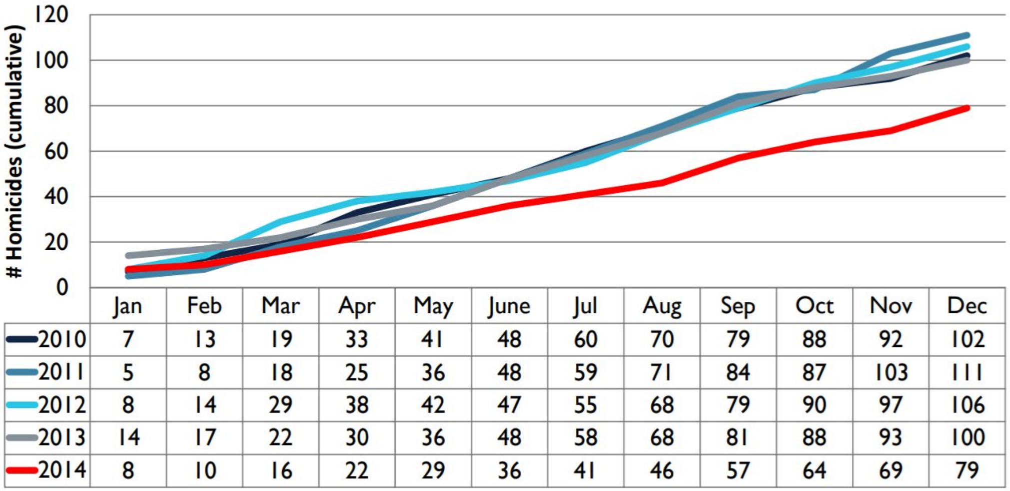


# Dutch Police example - Communities



# More examples from PD

- Kansas City crime – “Operation Clean Sweep” (2013):
  - Historically, one of the top 10 most violent cities in the US
  - Averages 106 homicides per year
  - Averages 3,484 aggravated assaults per year
- Results:



| | Jan | Feb | Mar | Apr | May | June | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2010 | 7 | 13 | 19 | 33 | 41 | 48 | 60 | 70 | 79 | 88 | 92 | 102 |
| 2011 | 5 | 8 | 18 | 25 | 36 | 48 | 59 | 71 | 84 | 87 | 103 | 111 |
| 2012 | 8 | 14 | 29 | 38 | 42 | 47 | 55 | 68 | 79 | 90 | 97 | 106 |
| 2013 | 14 | 17 | 22 | 30 | 36 | 48 | 58 | 68 | 81 | 88 | 93 | 100 |
| 2014 | 8 | 10 | 16 | 22 | 29 | 36 | 41 | 46 | 57 | 64 | 69 | 79 |

- Details: [https://www.nationalpublicsafetypartnership.org/Documents/VRN%20Social%20Network%20Analysis%20Presentation%20July%2021%202015.pdf](https://www.nationalpublicsafetypartnership.org/Documents/VRN%20Social%20Network%20Analysis%20Presentation%20July%2021%202015.pdf)

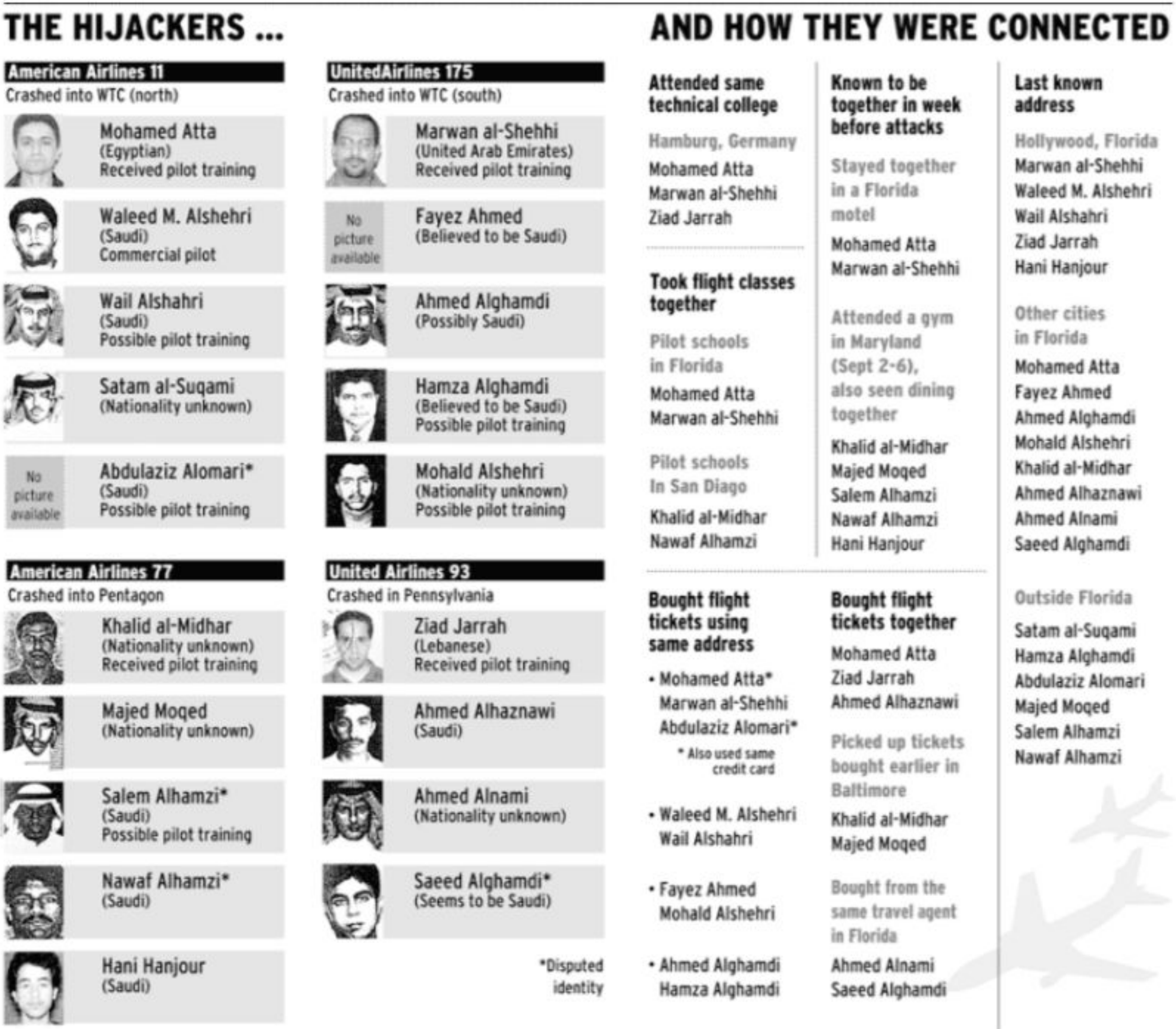
# Finding Terrorists Cells

# 9/11 Case Study

- Analyzing such networks is much easier in past, not in future. But still important for the prosecution and potentially detecting other members

- Based on Valdis E. Krebs analysis

http://insna.org/PDF/Connections/v24/2001_I-3-7.pdf



# 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

## 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)

## 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

## 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

# 9/11 Case Study

- The beginning (January 2000):

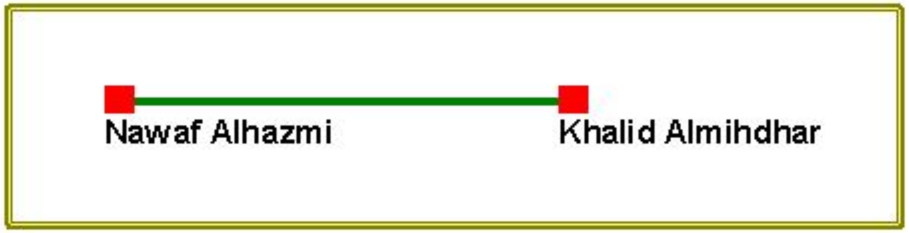
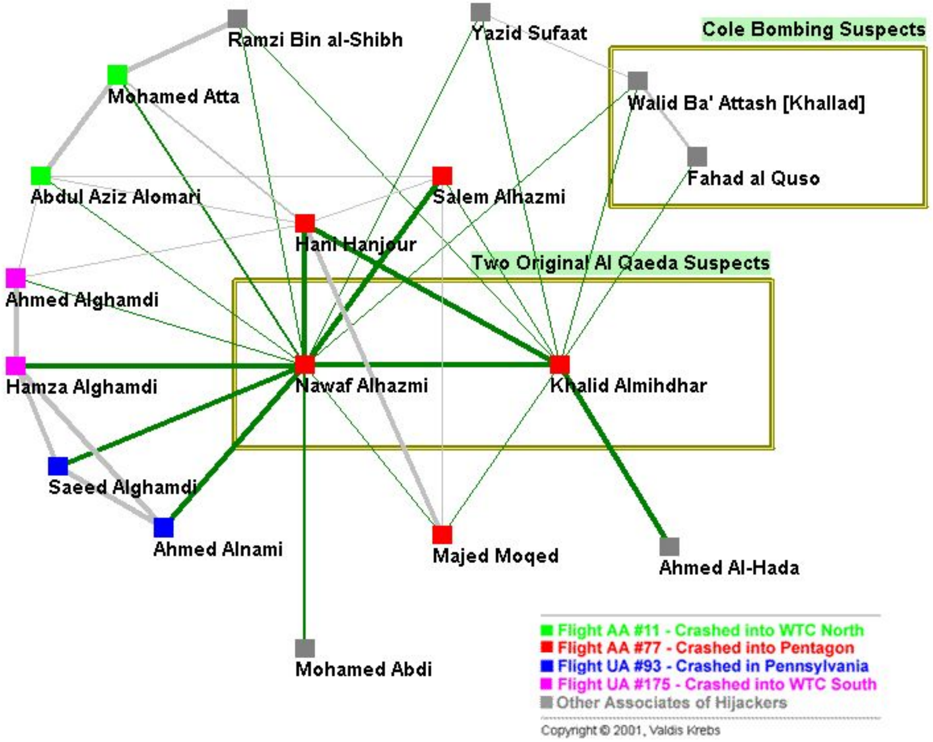


Figure 1 - Two known suspects in January 2000

# 9/11 Case Study

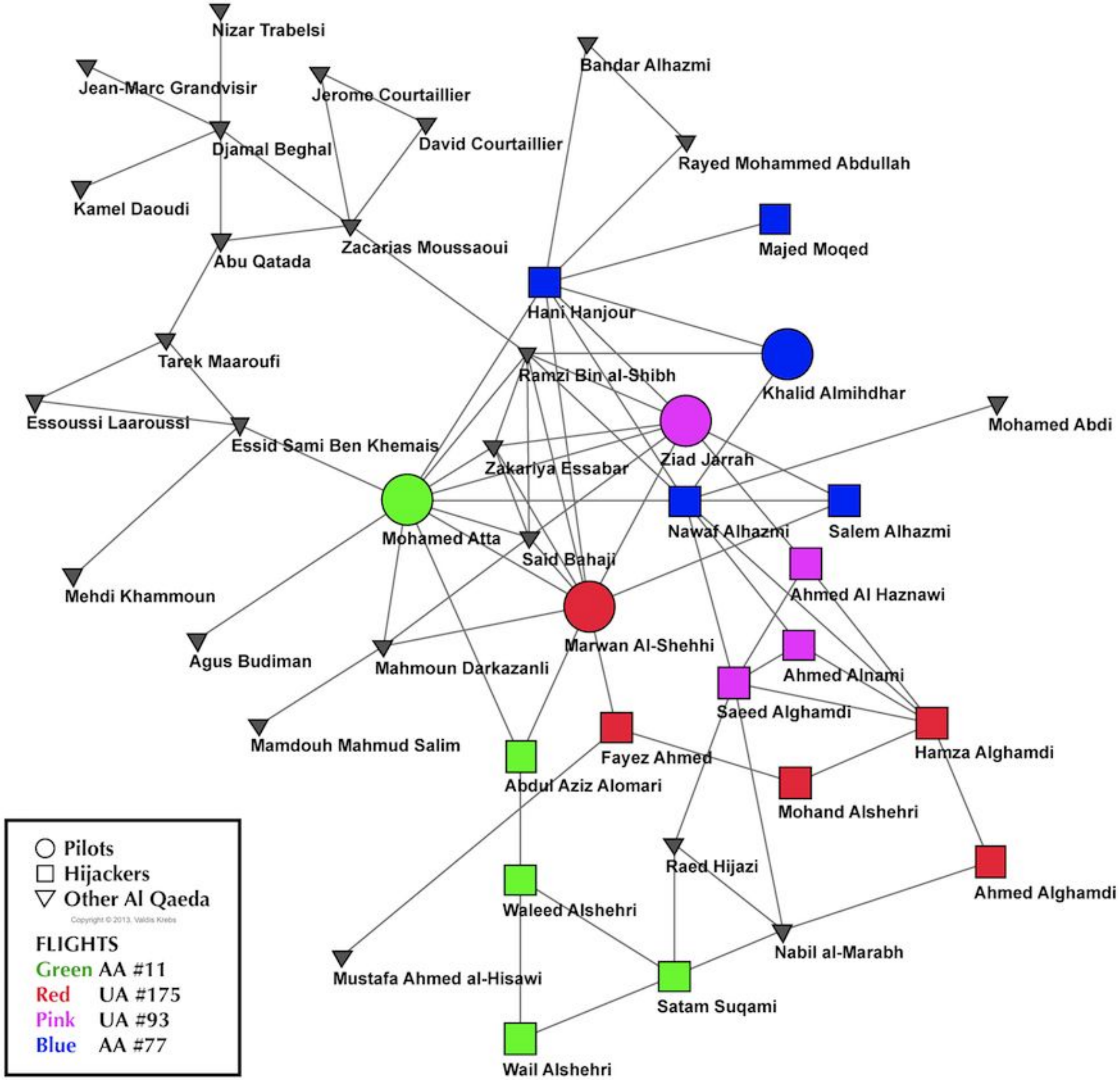
- USS Cole attack (October 2000)


Ramzi Bin al-Shibh
Yazid Sufaat
Cole Bombing Suspects
Mohamed Atta
Walid Ba' Attash [Khallad]
Fahad al Quso
Abdul Aziz Alomari
Salem Alhazmi
Hani Hanjour
Two Original Al Qaeda Suspects
Ahmed Alghamdi
Hamza Alghamdi
Nawaf Alhazmi
Khalid Almihdhar
Saeed Alghamdi
Ahmed Alnami
Majed Moqed
Ahmed Al-Hada
Mohamed Abdi
🟩 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
⬛ Other Associates of Hijackers

Copyright © 2001, Valdis Krebs

Figure 2 - All nodes within 1 step [direct link] of original suspects

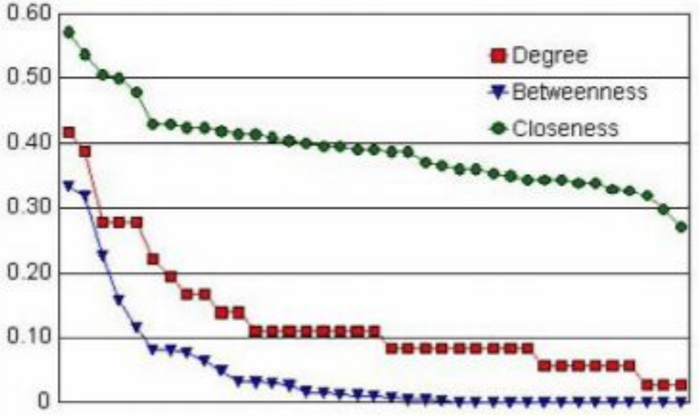
# 9/11 Case Study



# 9/11 Case Study

| | |
|---|---|
| Group Size | 37 |
| Potential Ties | 1332 |
| Actual Ties | 170 |
| Density | 13% |

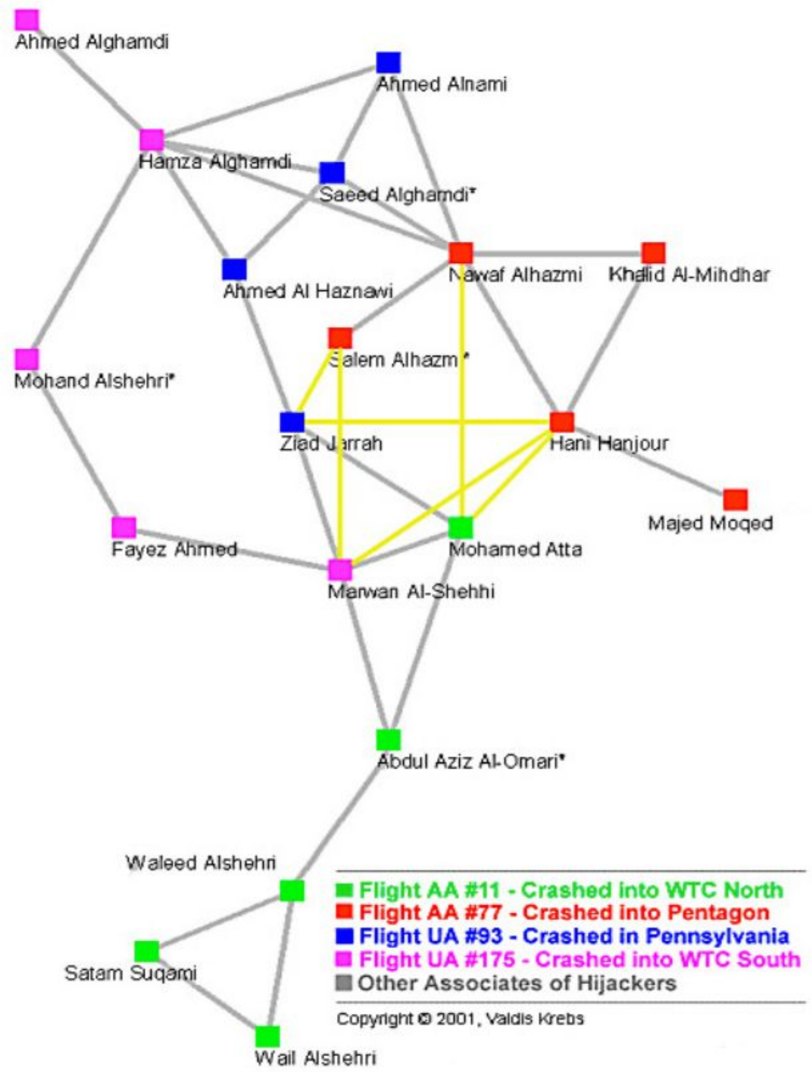
| Geodesics | |
|---|---|
| length | # |
| 1 | 170 |
| 2 | 626 |
| 3 | 982 |
| 4 | 558 |
| 5 | 136 |
| 6 | 0 |

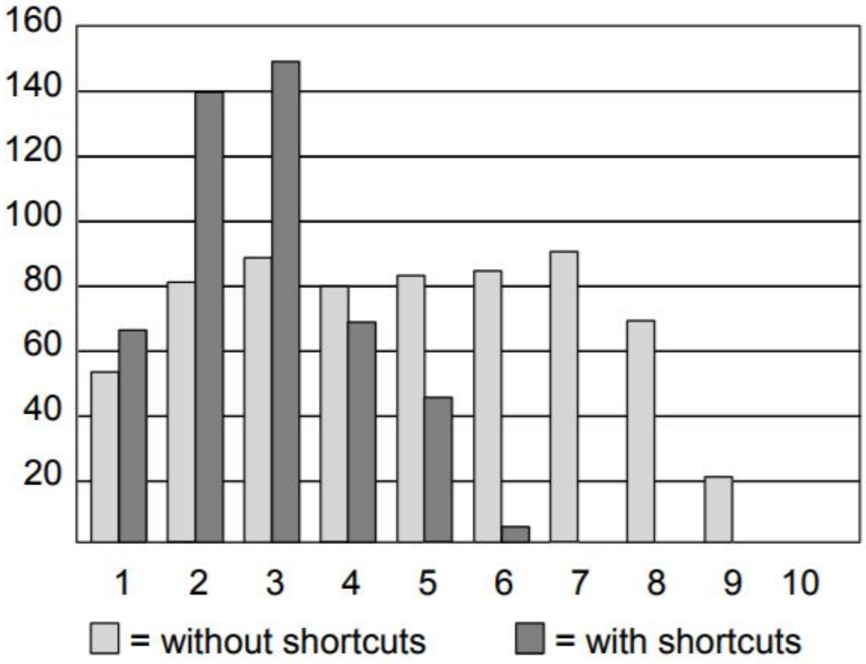


| Degrees | | Betweenness | | Closeness | |
|---|---|---|---|---|---|
| 0.417 | Mohamed Atta | 0.334 | Nawaf Alhazmi | 0.571 | Mohamed Atta |
| 0.389 | Marwan Al-Shehhi | 0.318 | Mohamed Atta | 0.537 | Nawaf Alhazmi |
| 0.278 | Hani Hanjour | 0.227 | Hani Hanjour | 0.507 | Hani Hanjour |
| 0.278 | Nawaf 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 |

# 9/11 Case Study

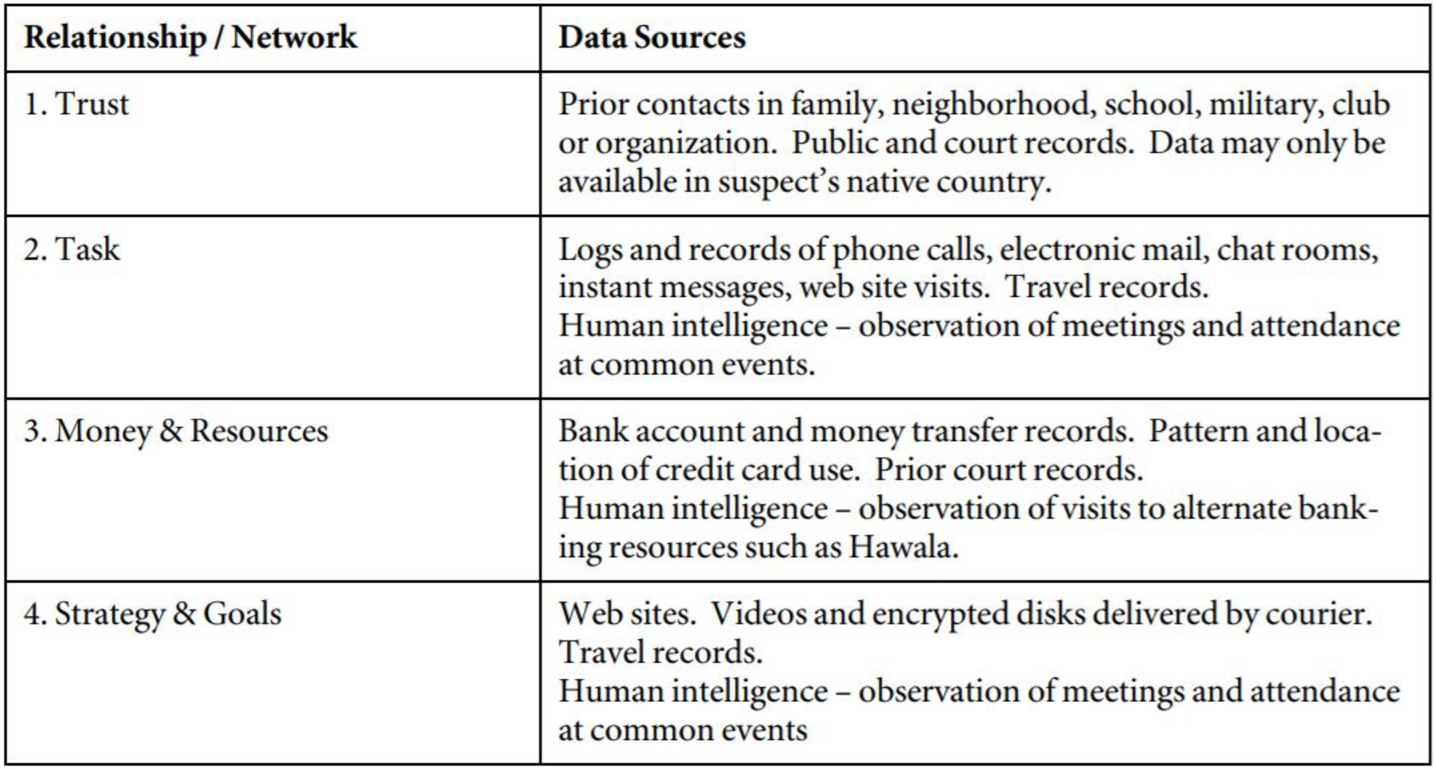
Final meetings (shortcuts) in gold





# 9/11 Case Study

## Data to build the network



| 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.<br>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.<br>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.<br>Human intelligence – observation of meetings and attendance at common events |

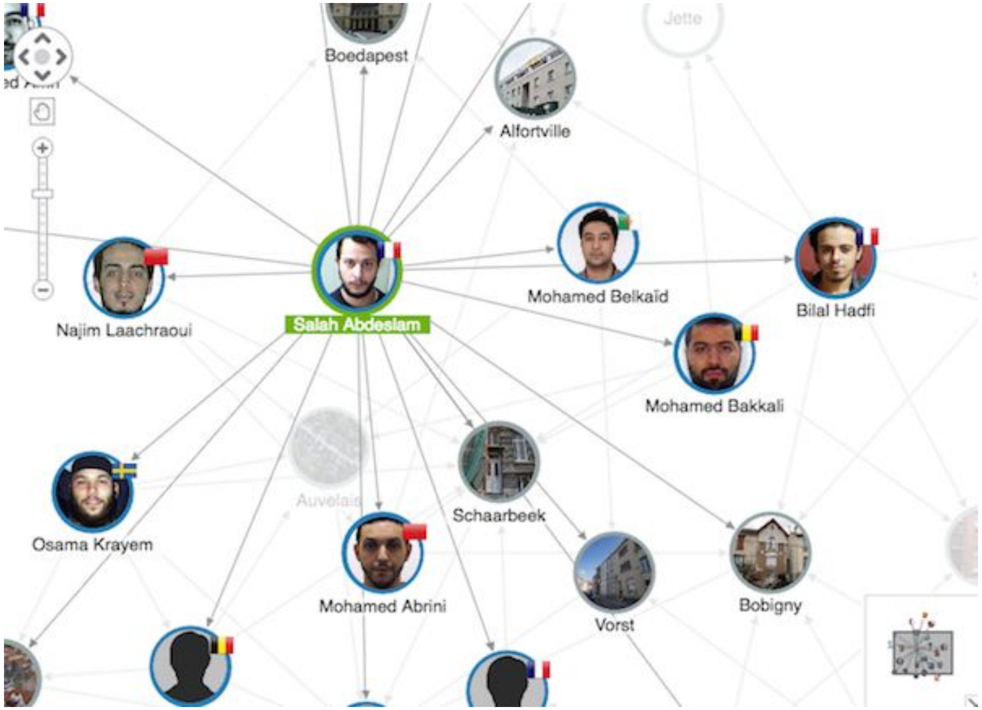
# Technologies in practice

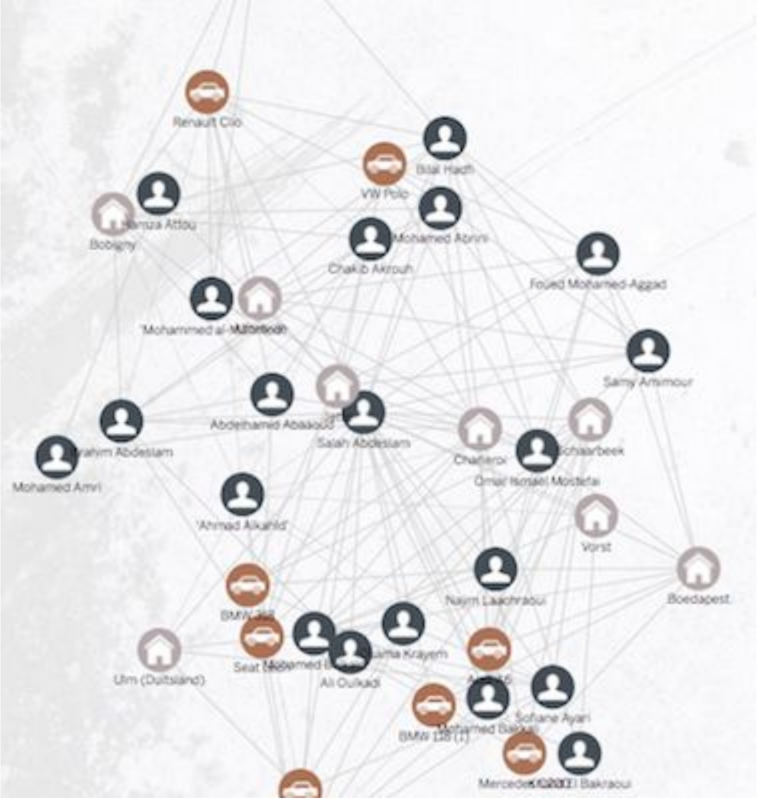
- Small networks or Initial/Partial analysis:
  - Python / NetworkX

- Huge networks
  - Graph databases, such as Neo4j
  - Distributed systems like Spark/Hadoop

# Visualization, visualization, visualization…

- Very useful in Social Network analysis, helps faster identify patters and important details





# Thank you!

## Questions?