# Hiding from Artificial Intelligence

Marcin Waniek

# Who am I?

- **June 2017**
  Defended a PhD dissertation at **MIMUW**
  Thesis: *Hiding in Social Networks*
  Main supervisor: Piotr Faliszewski
  Auxilliary supervisor: Tomasz Michalak
- **July 2017 – February 2019**
  Post-Doctoral Fellow
  at **Khalifa University**
  Supervisor: Aamena Alshamsi
- **February 2019 – September 2023**
  Post-Doctoral Associate
  at **New York University Abu Dhabi**
  Supervisor: Talal Rahwan

# Hiding from artificial intelligence

It is getting increasingly difficult to live without leaving **digital traces**…

…that can be **scrutinized by AI algorithms**.




The New York Times

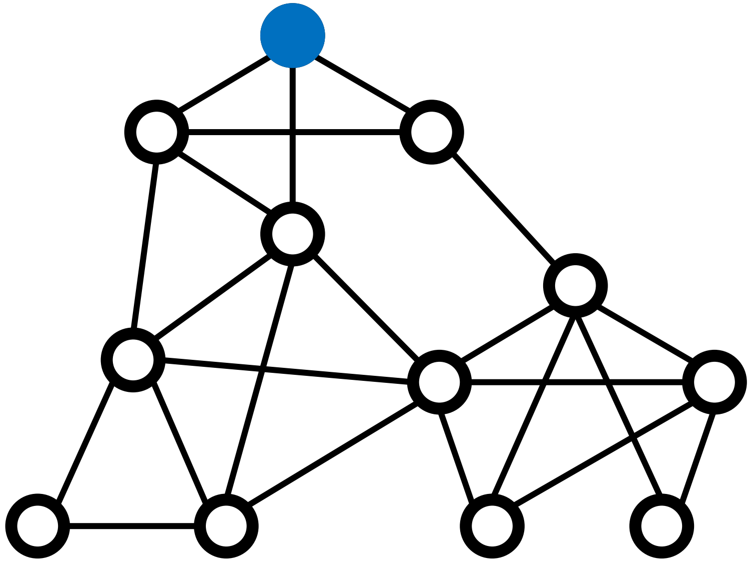
Cambridge Analytica and Facebook: The Scandal and the Fallout So Far

Revelations that digital consultants to the Trump campaign misused the data of millions of Facebook users set off a furor on both sides of the Atlantic. This is how The Times covered it.

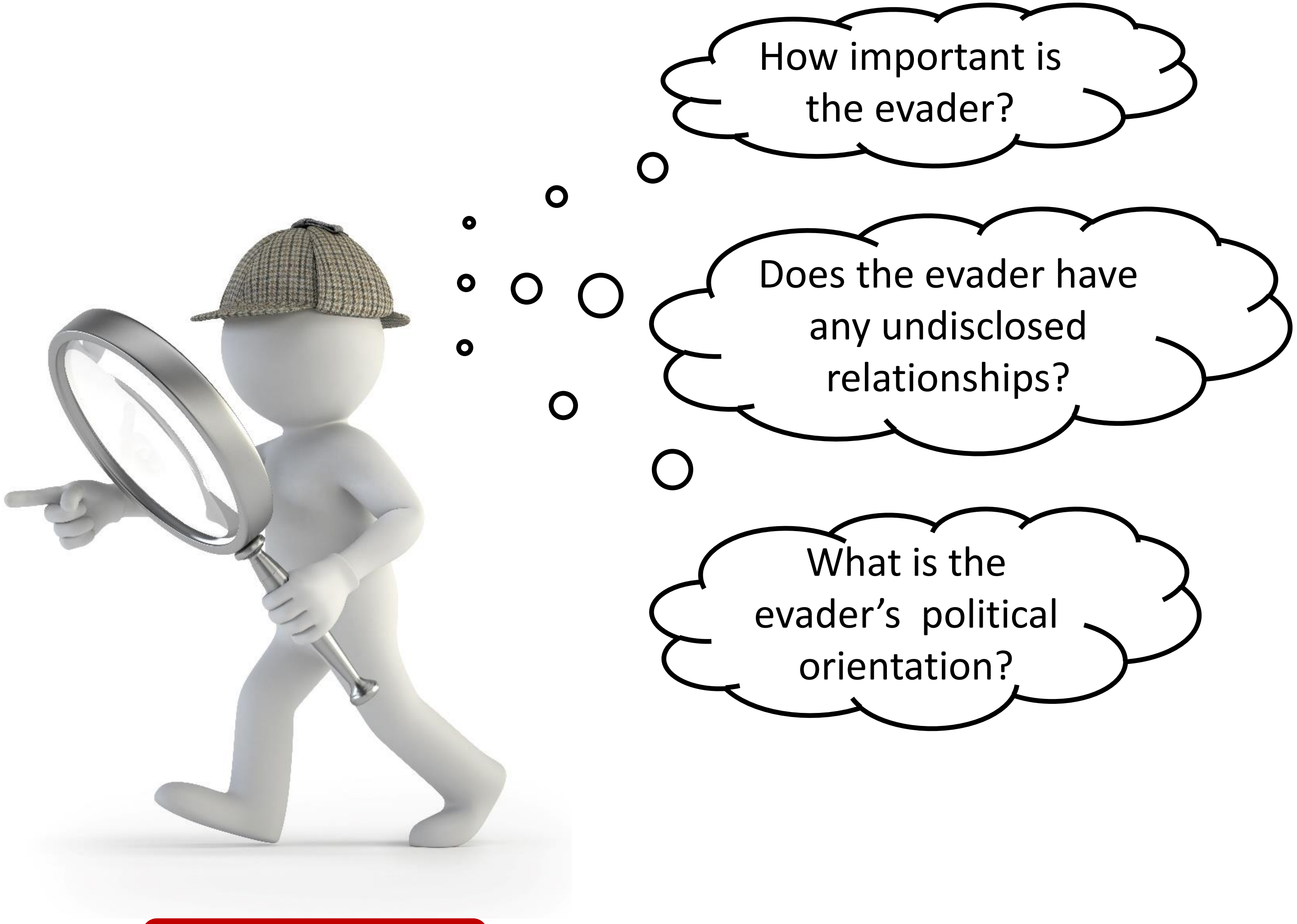
The literature assumes that the responsibility lies with a **central authority**…

…which is **prone to failure**.

# The general idea of this line of research



The evader




The seeker

# Existing literature

The evader

The seeker

# Our line of research

The evader

The seeker

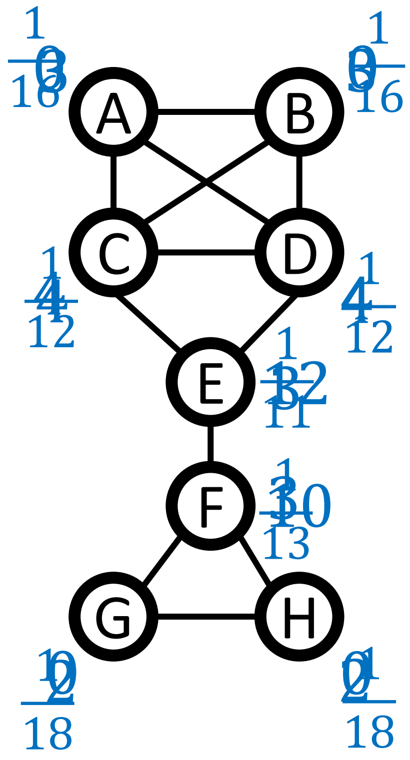
# What am I going to be talking about?

- Hiding importance from **centrality measures**
- Hiding group membership from **community detection algorithms**
- Hiding undisclosed relationships from **link prediction algorithms**
- Hiding the origin of a social diffusion from **source detection algorithms**
- Hiding opinions from **stance detection algorithms**

# Hiding from centrality measures

# Centrality

**Centrality measures** – methods of evaluating the relative importance of nodes.




- **Degree centrality** (*the most important node is the one with the greatest number of friends*)
- **Closeness centrality** (*the most important node is the one who is close to everyone else*)
- **Betweeness centrality** (*the most important node is the one who controls the flow of information*)
- **Eigenvector centrality** (*the most important node is the one with important friends*)

$$c_{degr}(v) = |N(v)|$$

$$c_{clos}(v) = \frac{1}{\sum_{w \in V} d(v,w)}$$

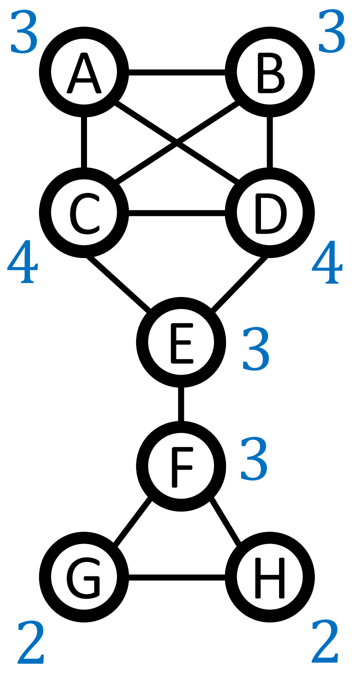
$$c_{betw}(v) = \sum_{u,w \in V} \frac{|\{p \in sp(u,w) : v \in \mathrm{p}\}|}{|sp(u,w)|}$$

$$c_{eig}(v) = x_v$$

for $Ax = \lambda^* x$

# Centrality

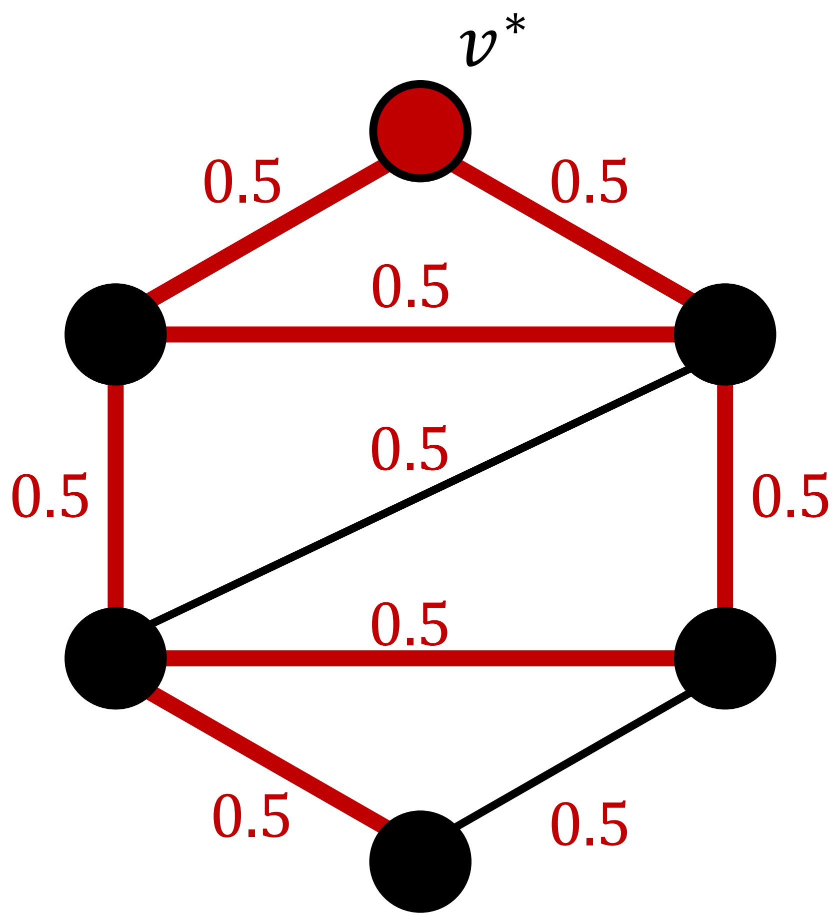
**Centrality measures** – methods of evaluating the relative importance of nodes.




| Degree | | Closeness | | | Betweenness | | |
|---|---|---|---|---|---|---|---|
| 1st | 4 | 1st | E | 1/11 | 1st | E | 12 |
| | 4 | 2nd | C | 1/12 | 2nd | F | 10 |
| 3rd | 3 | | D | 1/12 | 3rd | C | 4 |
| | 3 | 4th | F | 1/13 | | D | 4 |
| | 3 | 5th | A | 1/16 | 5th | A | 0 |
| | 3 | | B | 1/16 | | B | 0 |
| 7th | 2 | 7th | G | 1/18 | | G | 0 |
| | 2 | | H | 1/18 | | H | 0 |

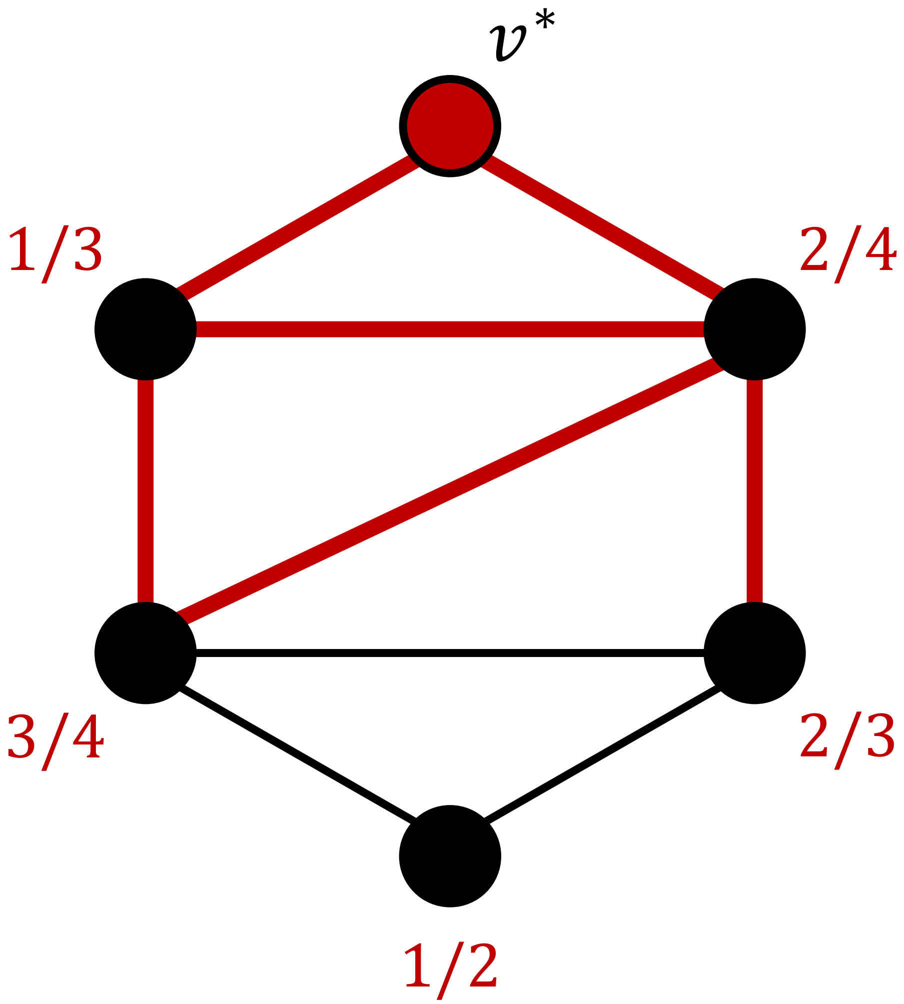
# Independent cascade influence model

- The process begins with only the **source node** being **active**.
- Every edge in the network is marked with the **probability of activation**.
- Every **newly activated node** has a **single chance** to activate each of his neighbors.
- The influence of the source node on the network is measured as the **expected number of activated nodes**.

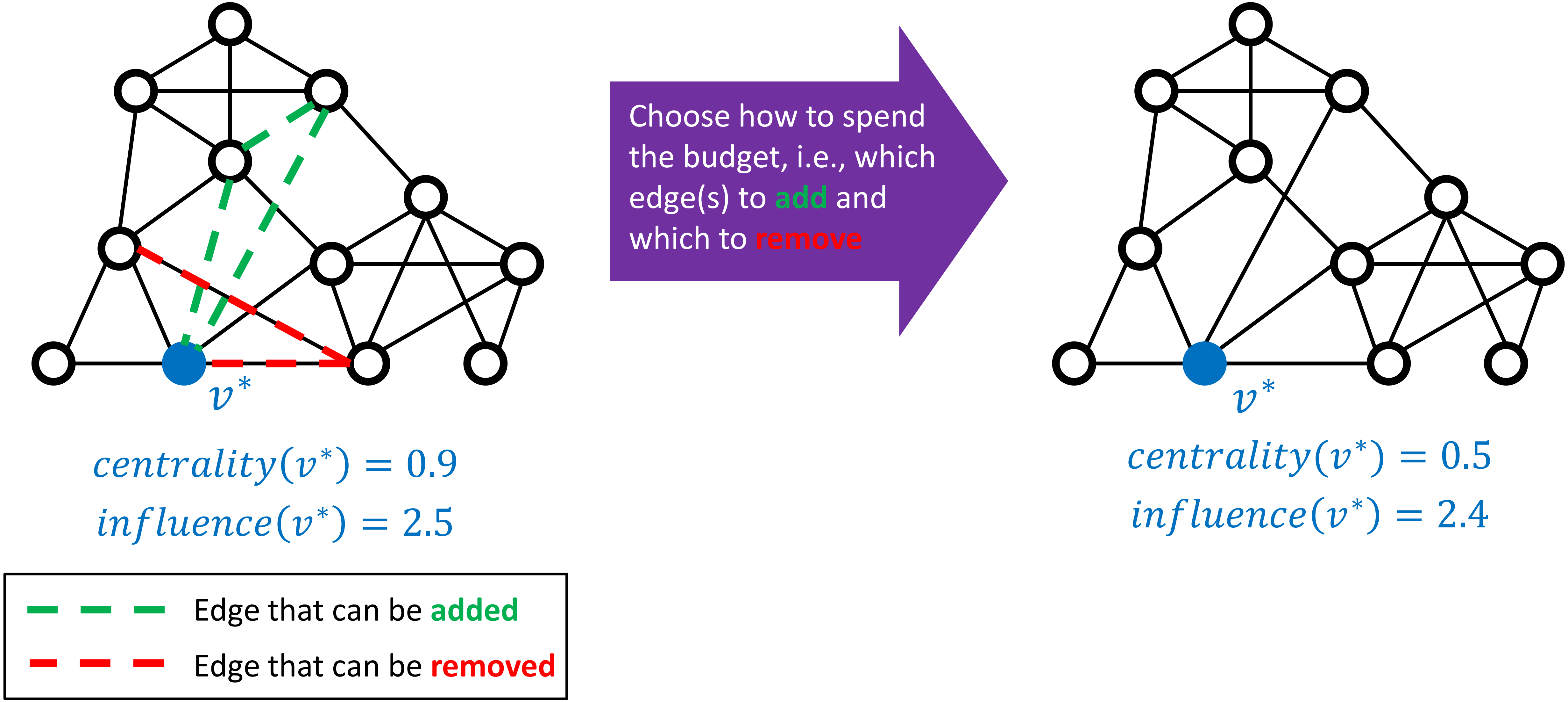


# Linear threshold influence model

- Again, the process begins with only the **source node** being **active**.
- Every other node in the network gets assigned a **threshold** from the distribution on the $[0,1]$ interval.
- A node gets activated when the **percentage of active neighbors** reaches the **threshold**.
- Again, the influence of the source node is measured as the **expected number of activated nodes**.



# Hiding from centrality measures




M Waniek, T Michalak, M Wooldridge, T Rahwan. *Hiding individuals and communities in a social network*. **Nature Human Behaviour** (2018)

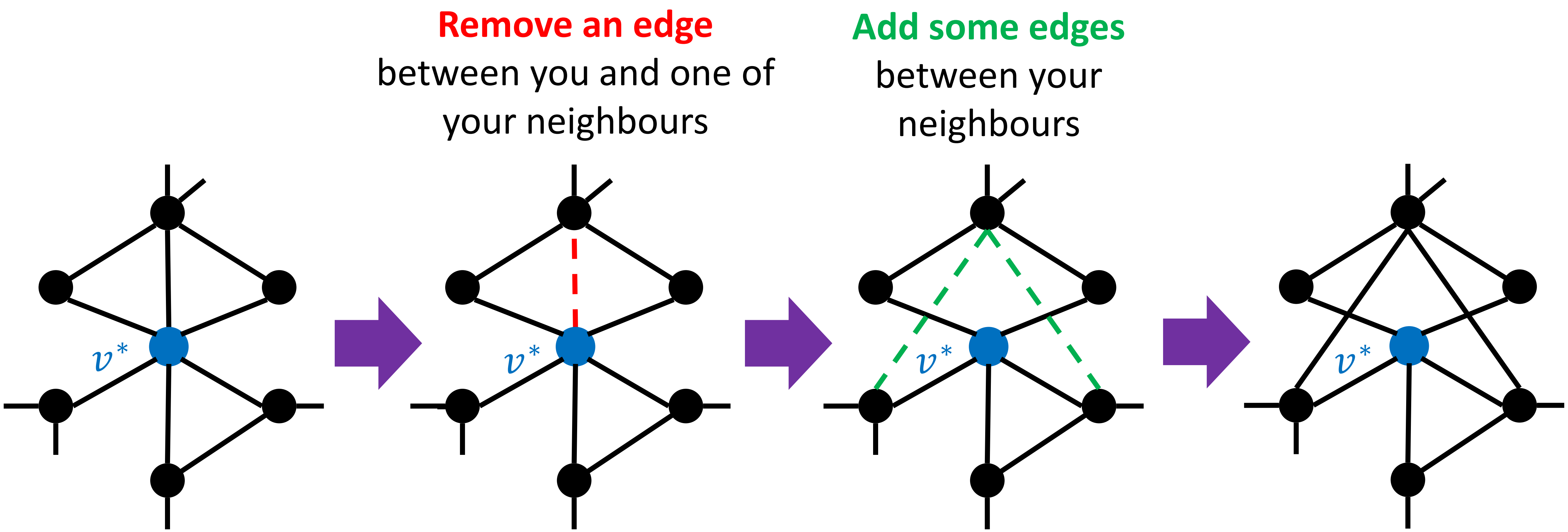
# Complexity of finding an optimal solution

| Centrality | Absolute values | Ranking |
|---|---|---|
| **Degree** | P | NP-complete |
| **Closeness** | NP-complete | NP-complete |
| **Betweenness** | NP-complete | NP-complete |

| Influence | Rebuild local | Rebuild sum |
|---|---|---|
| **Independent cascade** | NP-hard | NP-hard |
| **Linear threshold** | NP-hard | NP-hard |

M Waniek, T Michalak, M Wooldridge, T Rahwan. *Hiding individuals and communities in a social network*. **Nature Human Behaviour** (2018)
M Waniek, T Michalak, M Wooldridge, T Rahwan. *How members of covert networks conceal the identities of their leaders*. **ACM TIST** (2021)

# Our heuristic ROAM (Remove One, Add Many)



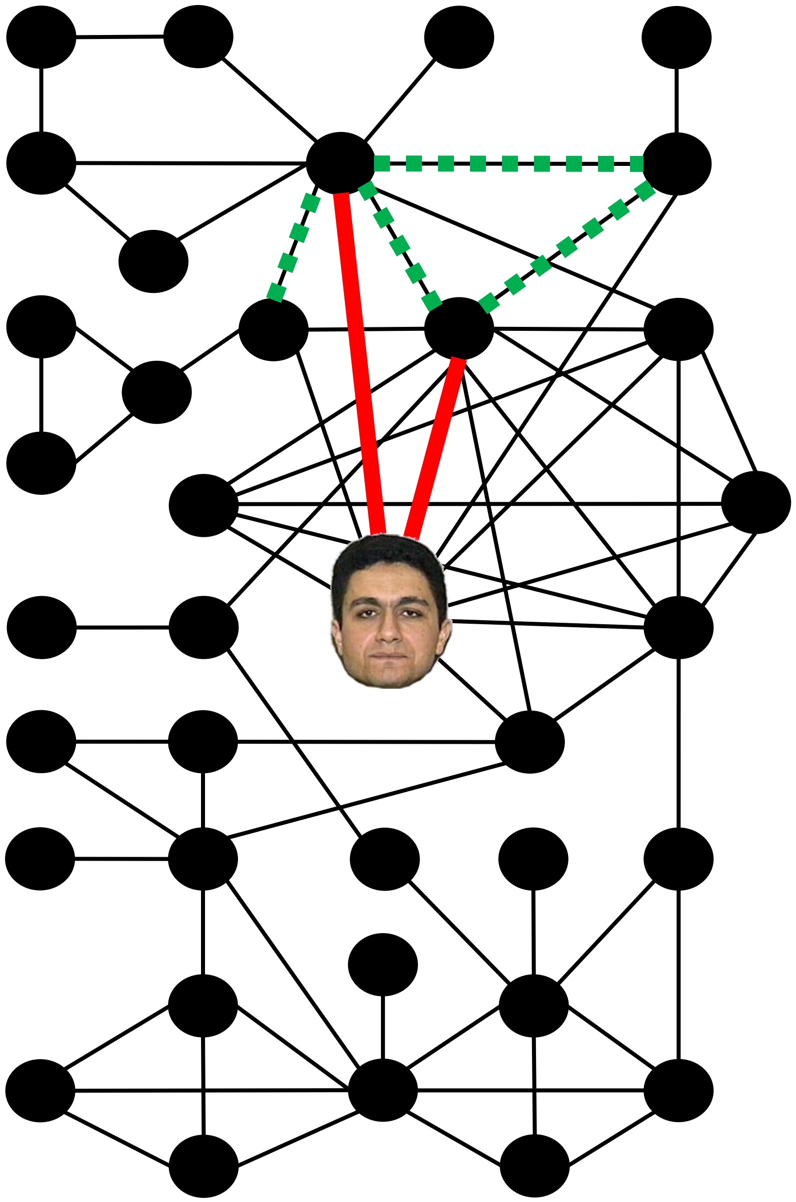

M Waniek, T Michalak, M Wooldridge, T Rahwan. *Hiding individuals and communities in a social network*. **Nature Human Behaviour** (2018)


What if criminal organizations would use such evasion techniques?

# Hiding in WTC 9/11 terrorist network

**Mohamed Atta**

**One of the ringleaders behind the attack**



**Original network**

1st in Degree centrality ranking
1st in Closeness centrality ranking
1st in Betweenness centrality ranking
**IC influence** = 2.55
**LT influence** = 6.44

**After one execution of ROAM**

**We run ROAM heuristic**

3rd in Degree centrality ranking
2nd in Closeness centrality ranking
5th in Betweenness centrality ranking
**IC influence** = 2.39
**LT influence** = 6.72

**After two executions of ROAM**

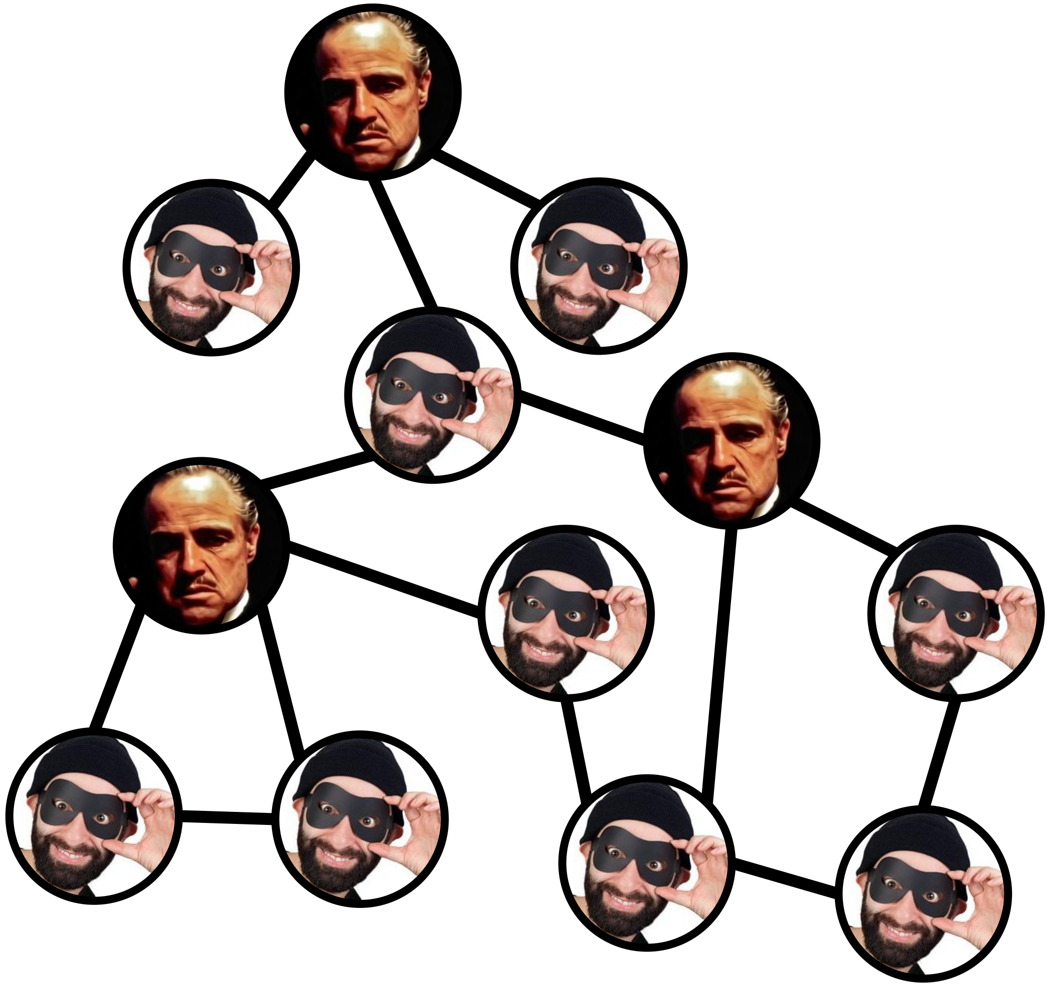
**We run ROAM heuristic one more time**

5th in Degree centrality ranking
4th in Closeness centrality ranking
11th in Betweenness centrality ranking
**IC influence** = 2.21
**LT influence** = 6.90

M Waniek, T Michalak, M Wooldridge, T Rahwan. *Hiding individuals and communities in a social network*. **Nature Human Behaviour** (2018)

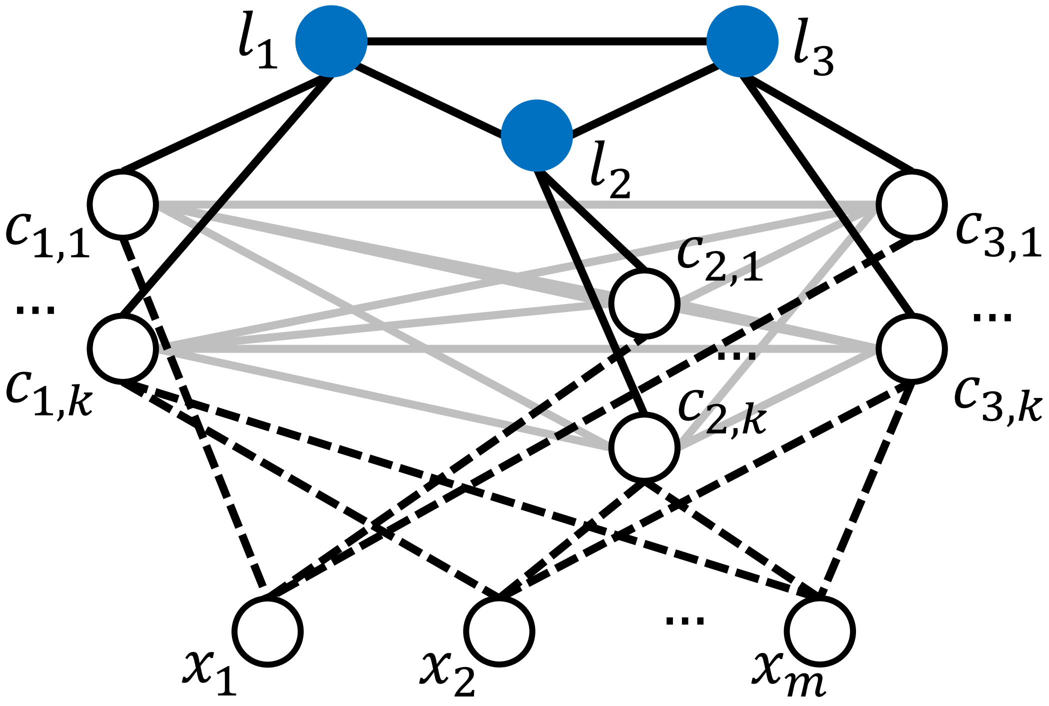
# Building a network from scratch

- What if we do not want to reshape an existing network, but rather **construct a new one from scratch**?
- Assume we have a group of **network leaders**…
- … and a group of **followers**.
- We want to connect them into a network so that:
  - there are **no leaders in top centrality ranking positions**,
  - the leaders can **effectively communicate** with the rest of the network.



M Waniek, T Michalak, M Wooldridge, T Rahwan. *How members of covert networks conceal the identities of their leaders*. **ACM TIST** (2021)

# The captains network

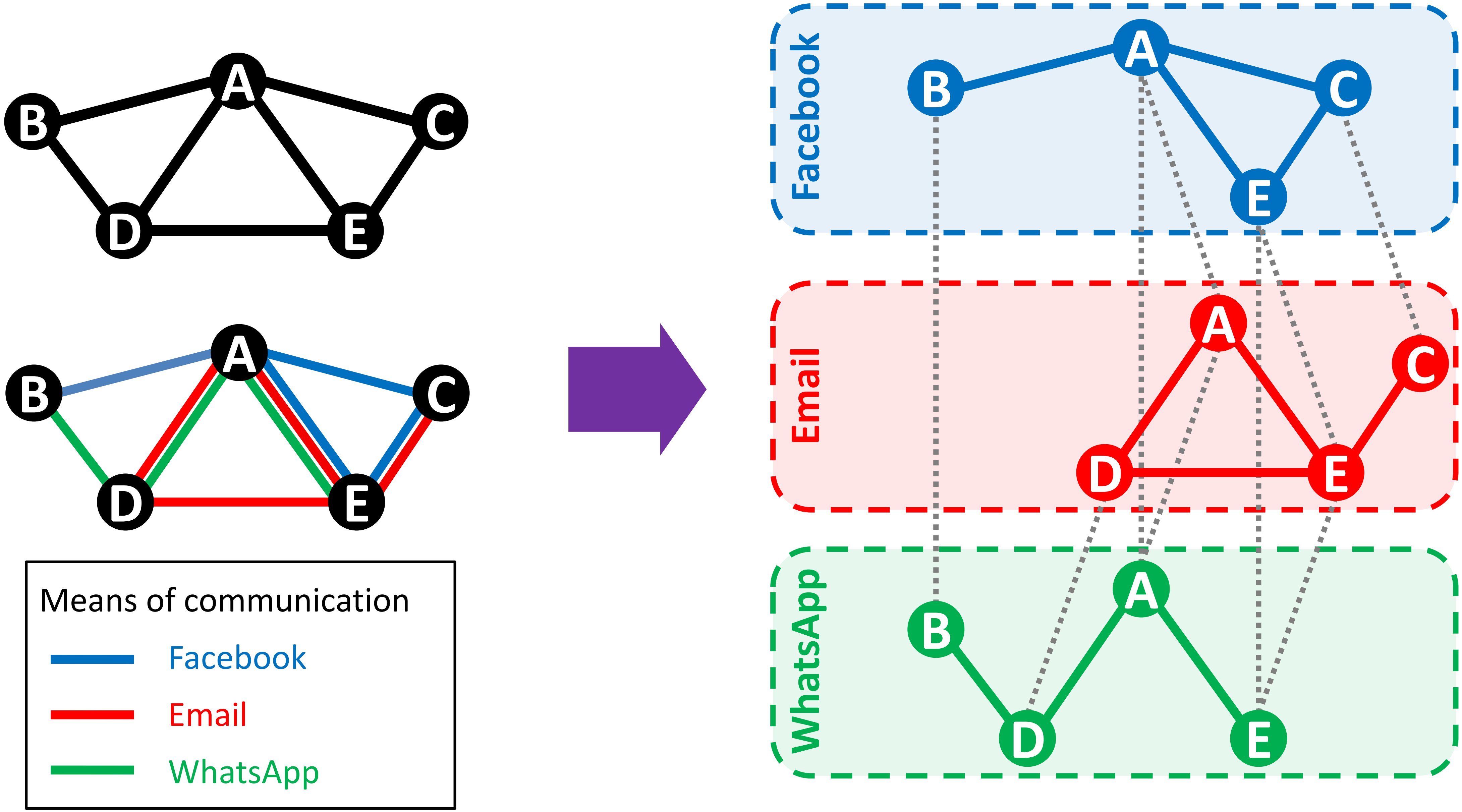



1. We start with a **group of leaders** connected into a **clique**.
2. To each leader we assign a group of **captains**.
3. We connect the captains into a **full k-partite graph**.
4. Each of the **remaining nodes** gets connected with one captain from each group.

In this network **every captain** is guaranteed to have greater degree, closeness and betweenness centrality than **any of the leaders**.

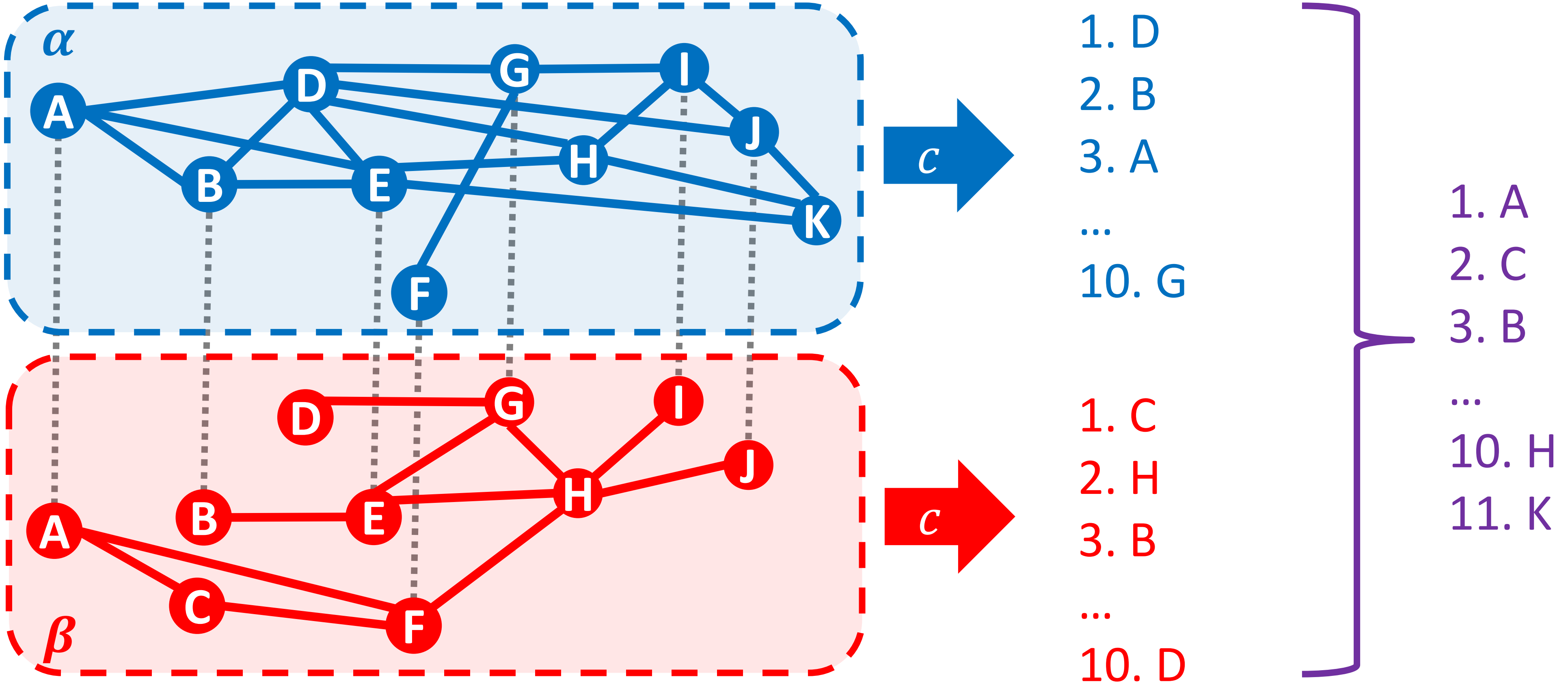
M Waniek, T Michalak, M Wooldridge, T Rahwan. *How members of covert networks conceal the identities of their leaders*. **ACM TIST** (2021)

# Multilayer networks



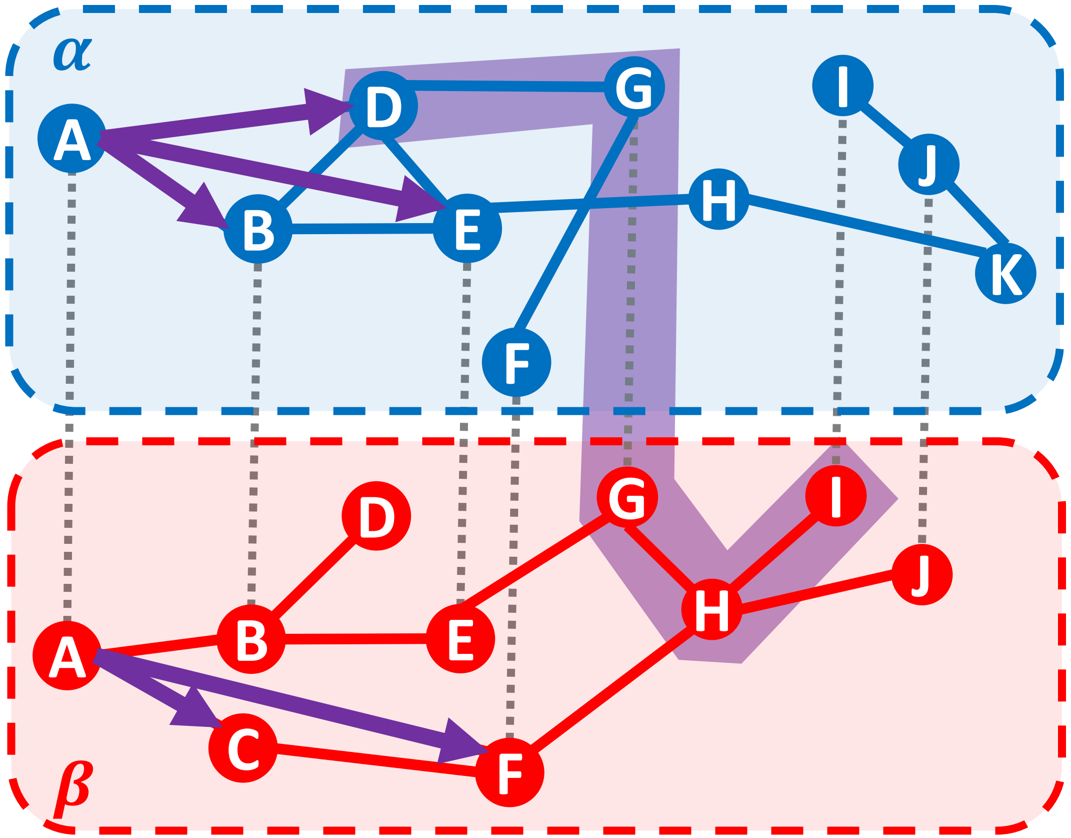
# Local centrality in multilayer networks

**Local approach** – apply standard centrality measure in each layer separately.



# Global centrality in multilayer networks

**Global approach** – treat network as a whole. Requires adjustments in centrality definitions.




$N_M(A) = \{B, C, D, E, F\}$

**Degree**

$$c_{degr}(v) = |N_M(v)|$$

where $N_M(v) = \{w \in V: (v^\alpha, w^\alpha) \in E\}$

**Closeness**

$$c_{clos}(v) = \frac{1}{\sum_{w \in V} d(v, w)}$$

where shortest paths may run between occurrences in different layers

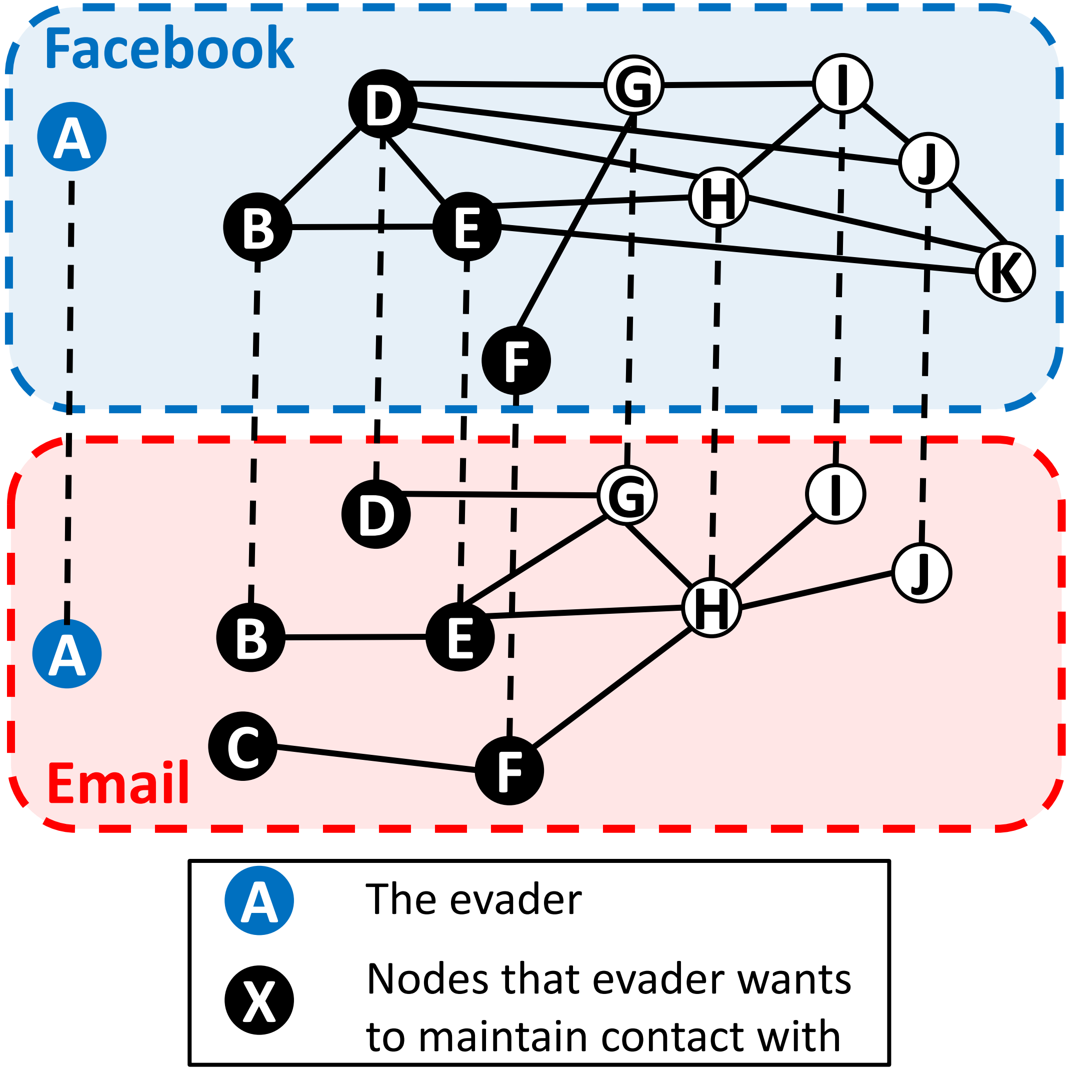
**Betweenneess**

$$c_{betw}(v) = \sum_{u,w \in V} \frac{|\{(v^\alpha, p): v^\alpha \in p, p \in \Pi(u, w)\}|}{|\Pi(u, w)|}$$

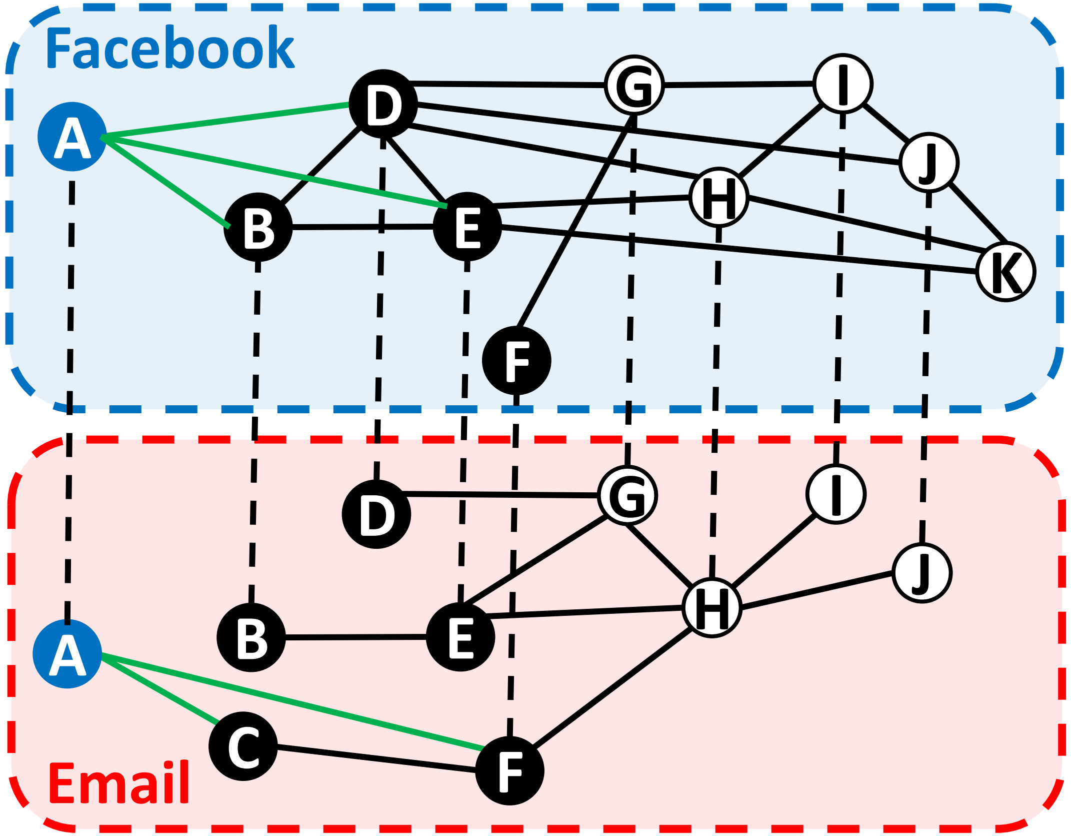
i.e., we take into consideration the number of occurrences on a shortest path

Standard version for comparison: $c_{betw}(v) = \sum_{u,w \in V} \frac{|\{p \in \Pi(u,w): v \in p\}|}{|\Pi(u,w)|}$

# Hiding in multilayer networks




Choose the layer of contact for each node



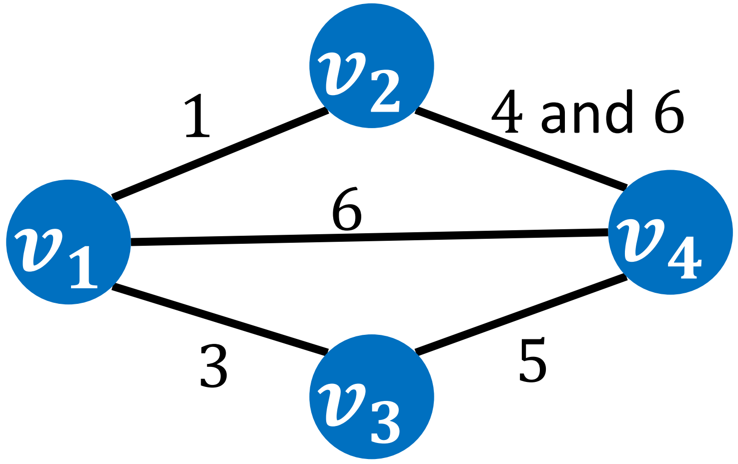

The problem is NP-complete.

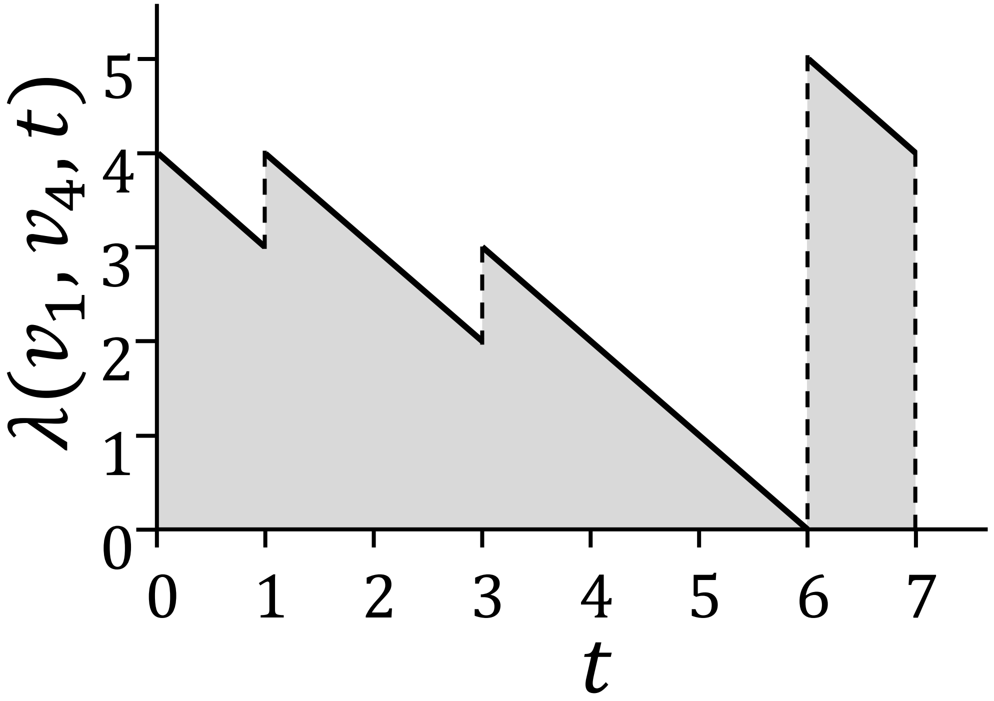
**Heuristic:** contact with densely connected group of friends in each layer.

M Waniek, T Michalak, T Rahwan. *Hiding in multilayer networks*. **AAAI** (2020)

# Temporal networks

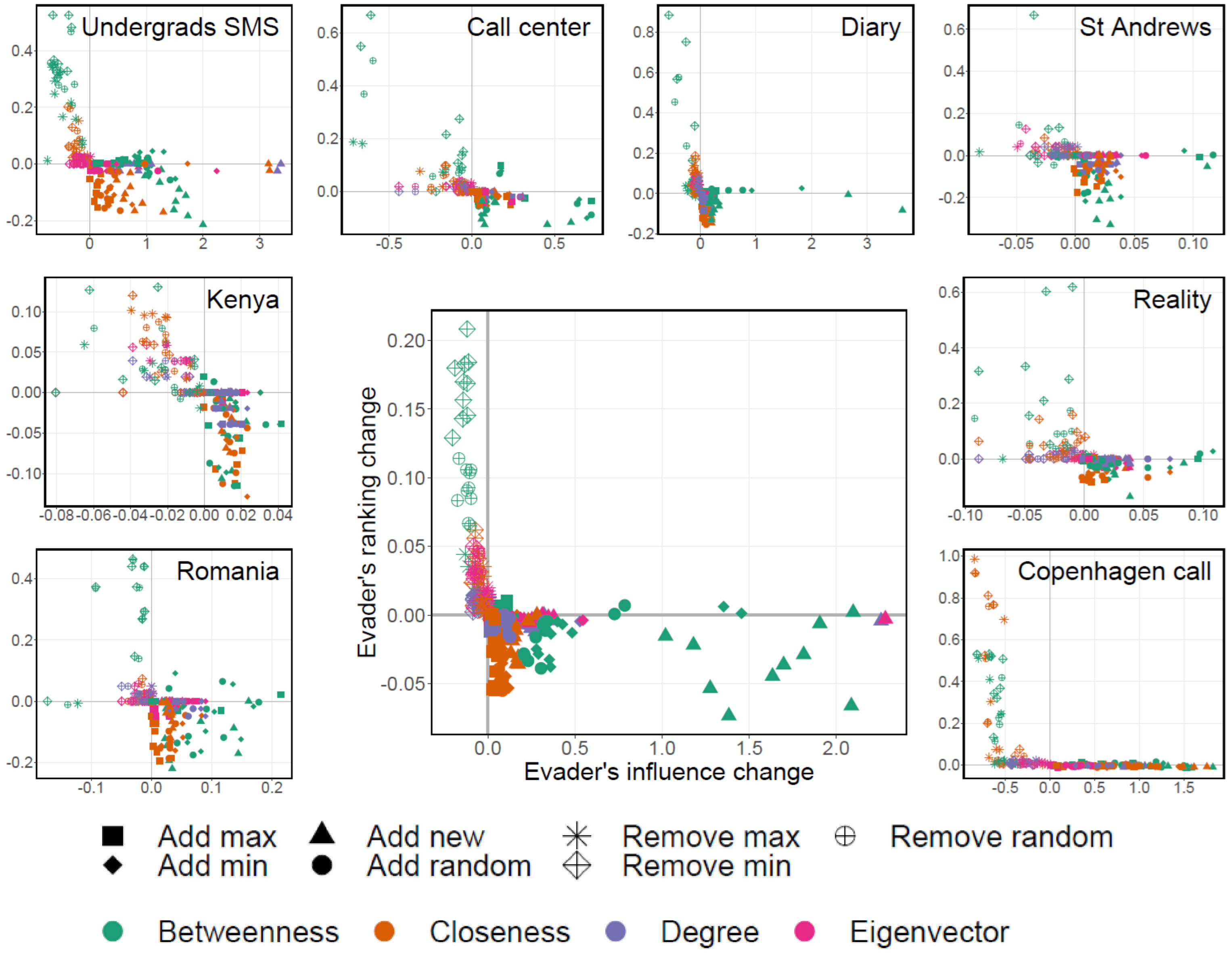
- We study hiding from centrality measures in **temporal networks**, where edges exist only at certain moments.
- A **time-respecting path** is a path where contacts occur chronologically.
- An equivalent of distance in temporal networks is **latency**.
- The **latency** between $v$ and $w$ at time $t$ is the **shortest time** it takes to reach from $v$ to $w$ starting at time $t$ along time-respecting paths.



# Hiding heuristics in temporal networks

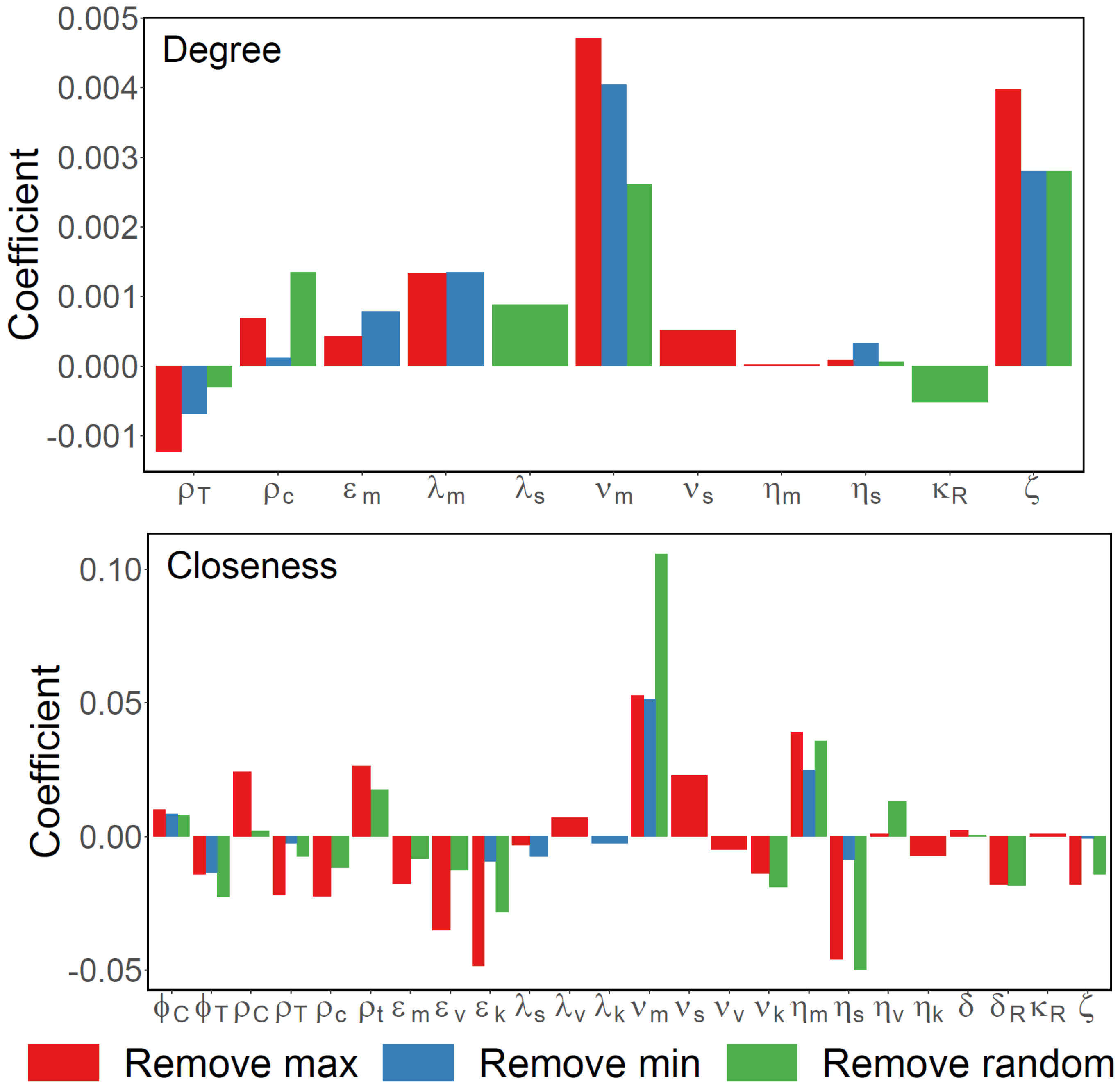
- Finding an **optimal way** to hide from temporal centralities is **NP-complete**.
- Instead, we tested a number of **heuristic solutions**.
- **Removing existing contacts** is significantly more effective in avoiding detection than adding new contacts.
- On the other hand, **adding new contacts** improves the influence.




M Waniek, P Holme, T Rahwan. *Hiding in temporal networks*. **IEEE Transactions on Network Science and Engineering** (2022)

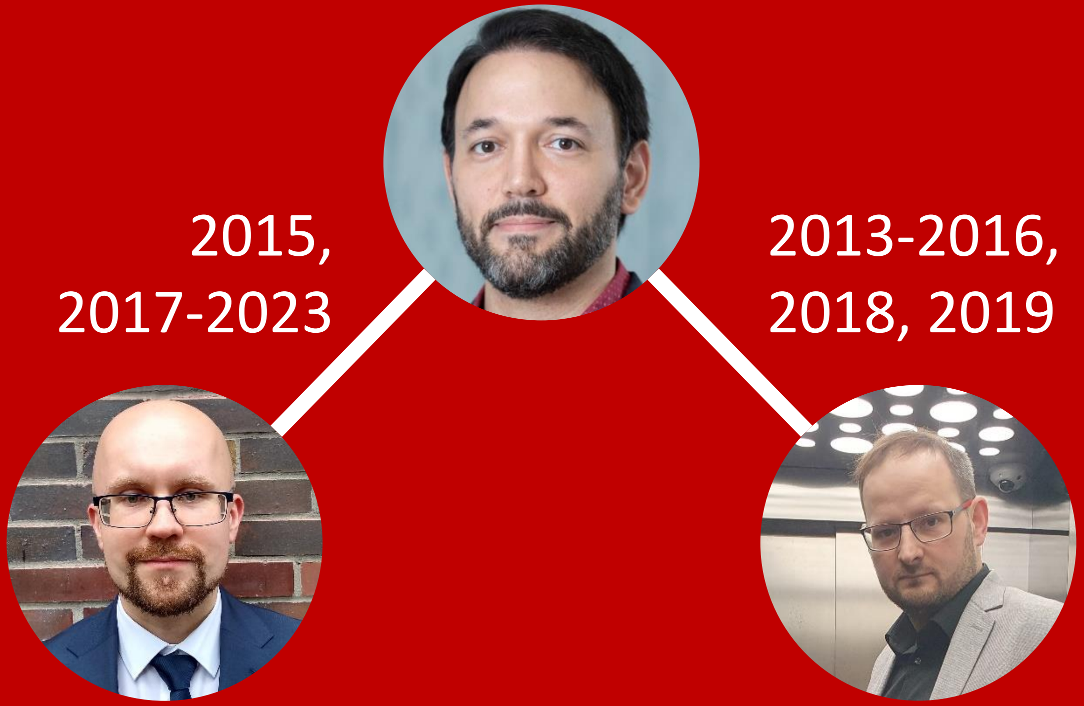
# Successful hiding in temporal networks

- Using **Lasso regression** analysis, we investigate what are **characteristics** of nodes that are **successful** in obscuring their central position.
- The **average intercontact time** $\nu_m$ has a **strong positive correlation** with the evader's ability to hide, suggesting it is beneficial for the evader to spread their contacts more uniformly over time.




<u>M Waniek</u>, P Holme, T Rahwan. *Hiding in temporal networks*. **IEEE Transactions on Network Science and Engineering** (2022)

# Project idea #1 Temporal network of scientists



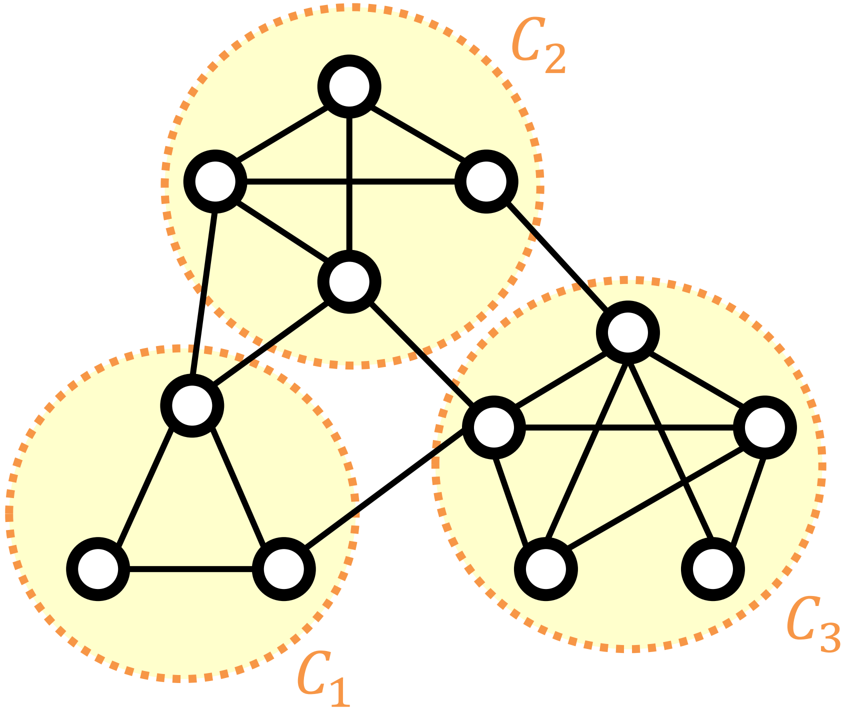

**Bedoor AlShebli**
New York University Abu Dhabi

<u>**Research question**</u>

**How important events in a scientist's career affect their centrality?**

# Hiding from community detection

# Community detection algorithms




- The term **community** is usually understood as **a group of closely cooperating individuals**.
- **Community detection algorithms** divide the set of nodes of the network into communities.
- Such division is called a **community structure**.

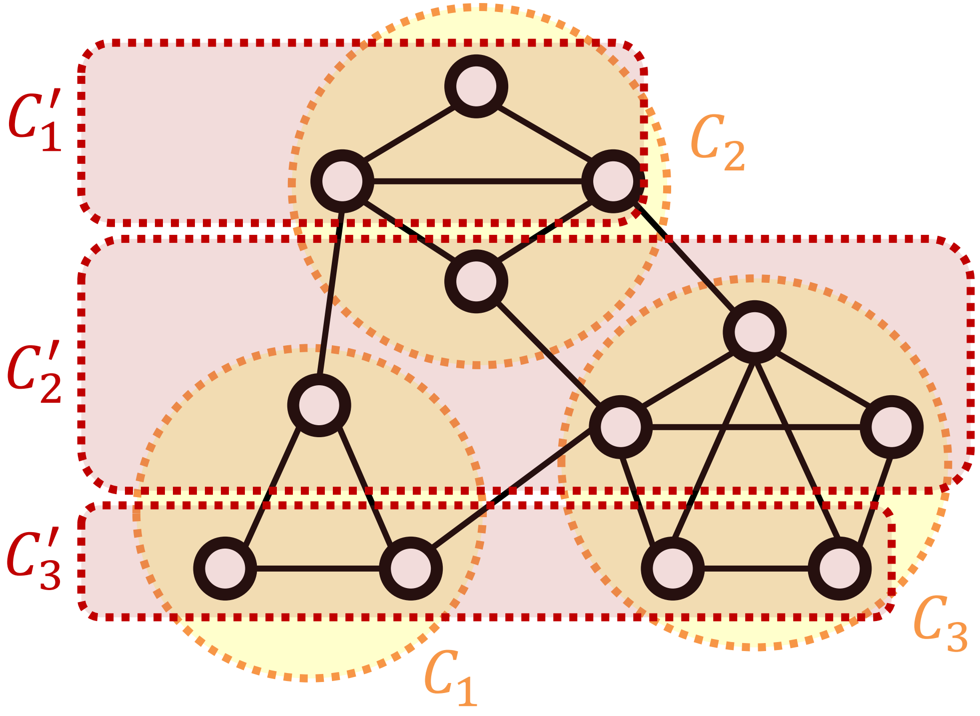
# Measuring the quality of community structure

- Intuitively, we want **more edges within** the communities **than edges between** the communities.
- A popular measure of community structure quality is **modularity**

$$Q(CS) = \sum_{C_i} \frac{|E(C_i)|}{|E|} - \left(\frac{\delta(C_i)}{2|E|}\right)^2$$

where

- $E(C_i)$ are the edges between the nodes $C_i$
- $\delta(C_i)$ is the sum of degrees of the nodes in $C_i$

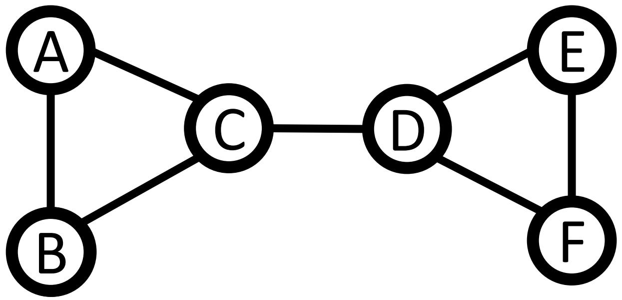


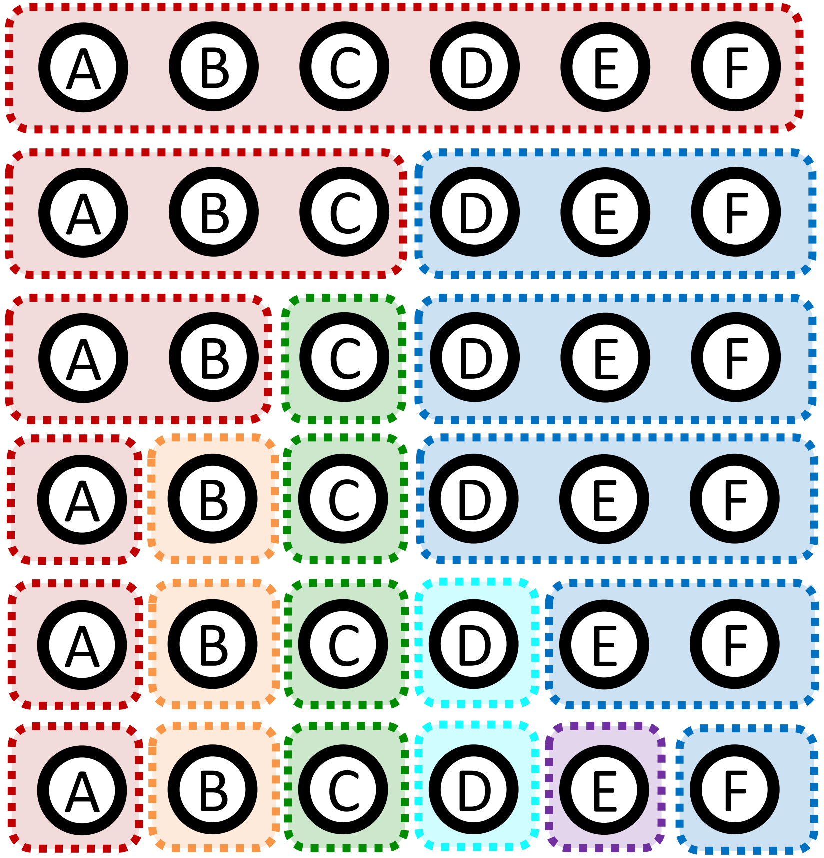

$Q(CS) = 0.42875$

$Q(CS') = 0.08625$

# Community detection algorithms

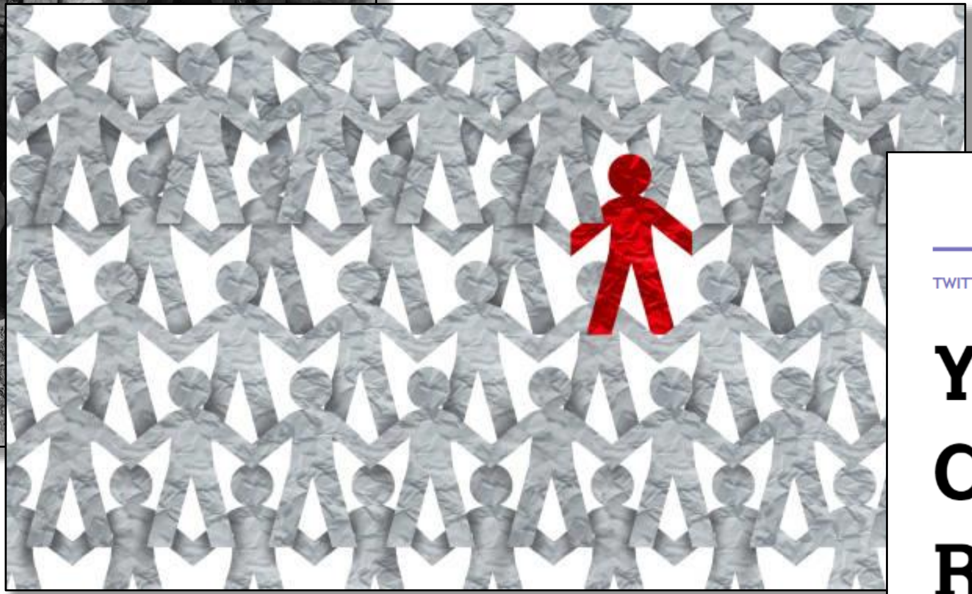
- **Betweenness** - iteratively remove edges belonging to many shortest paths
- **Greedy** - merge communities that provide greatest modularity gain
- **Walktrap** - based on a tendency of random walks to stay within the same community
- **Eigenvector** - recursively split nodes into two based on the eigenvector signs
- **Louvain** – merge locally optimal community into a single node
- **Infomap** - based on compressing a description of the probability flow
- **Spinglass** - interpreting each node as an atom in a magnet, assign community based on spin



# Hiding from community detection

Some people might prefer not to **disclose** membership of certain groups…



…e.g., **minorities** persecuted based on a **ethnic background**.

MOTHERBOARD

VICE

TWITTER | By Jordan Pearson | Sep 24 2014, 12:45am

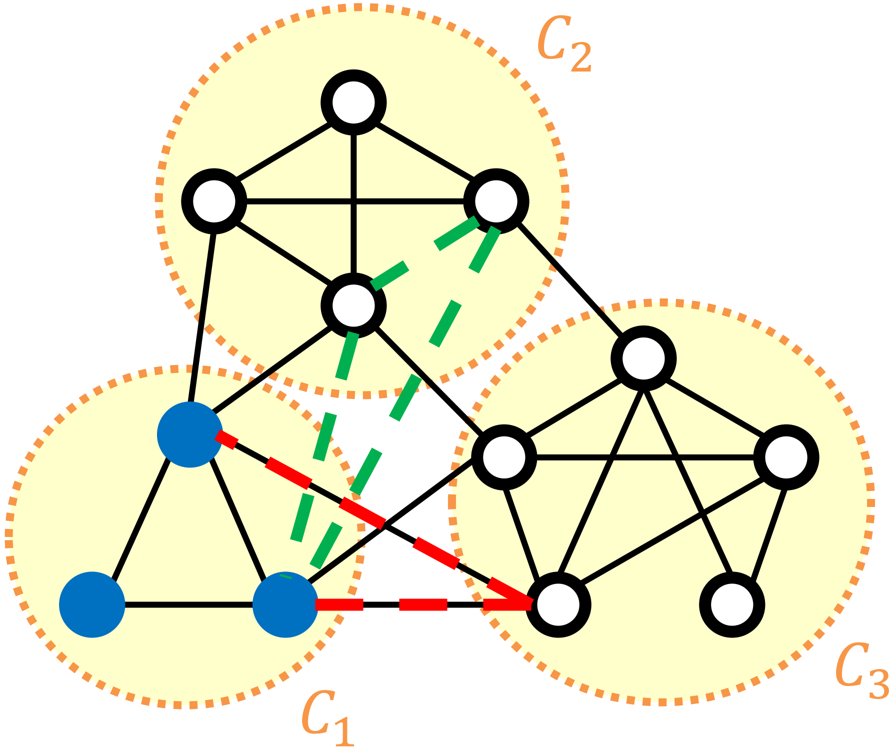
## Your Friends' Online Connections Can Reveal Your Sexual Orientation

**Facebook's "shadow profiles" were just the tip of the iceberg.**

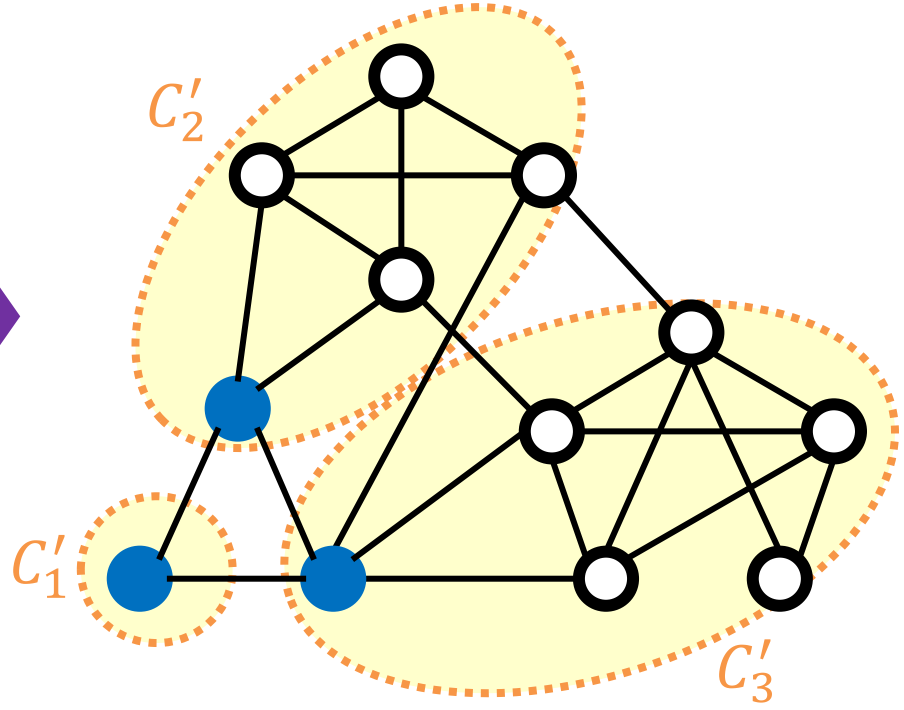
Community detection can also be used to infer other kinds of **sensitive information**.

M Waniek, T Michalak, M Wooldridge, T Rahwan. *Hiding individuals and communities in a social network*. **Nature Human Behaviour** (2018)

# Hiding from community detection




Choose how to spend the budget, i.e., which edge(s) to add and which to remove




Member of the hiding group

Edge that can be **added**

Edge that can be **removed**

**Additional requirement:**
We want to maintain communication structure of the group

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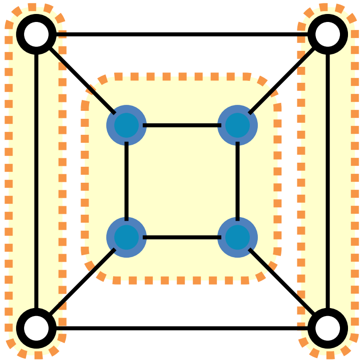
# Measure of concealment

**1) Spread out** across other communities

$$\mu_1(\boldsymbol{C^*}) = \frac{|\{C_i \in \boldsymbol{CS}: C_i \cap \boldsymbol{C^*} \neq \emptyset\}| - 1}{(|\boldsymbol{CS}| - 1)\max_{C_i}(|C_i \cap \boldsymbol{C^*}|)}$$



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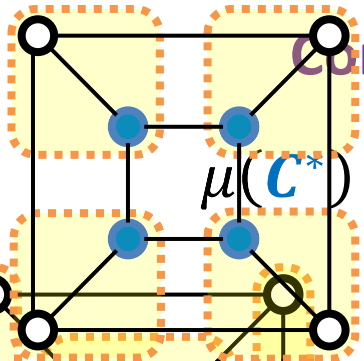
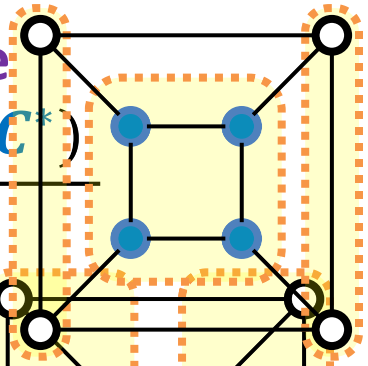


**2)** Join a larger community to **hide in the crowd**

$$\mu_2(\boldsymbol{C^*}) = \sum_{C_i \in \boldsymbol{CS}} \frac{|C_i \setminus \boldsymbol{C^*}|}{n - |\boldsymbol{C^*}|}$$



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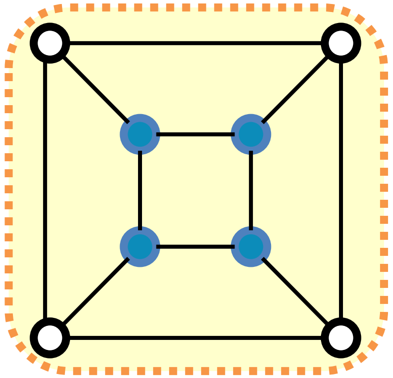

**Combined measure**

$$\mu(\boldsymbol{C^*}) = \frac{\mu_1(\boldsymbol{C^*}) + \mu_2(\boldsymbol{C^*})}{2}$$

$\mu(\boldsymbol{C^*}) = 0$ $\quad \mu(\boldsymbol{C^*}) = 0.375$ $\quad \mu(\boldsymbol{C^*}) = 1$

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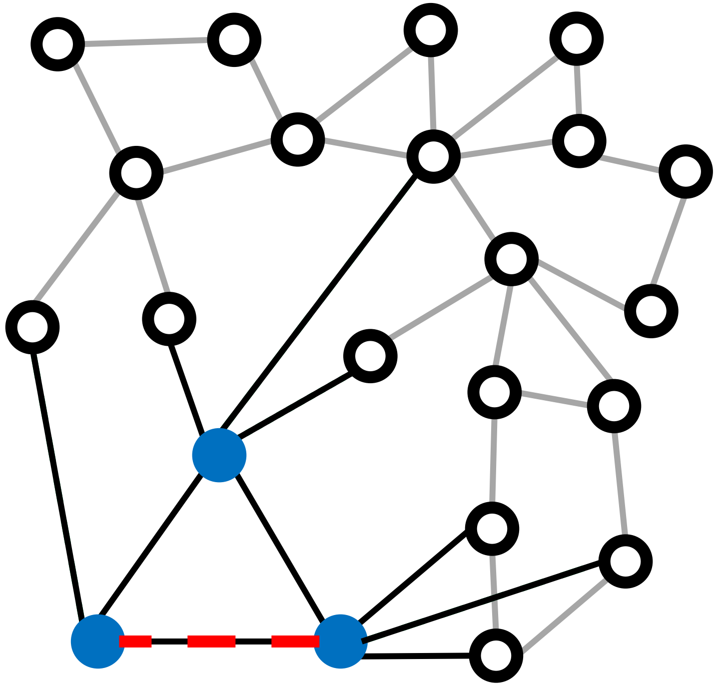
# Our heuristic DICE (Disconnect Internally, Connect Externally)



- **Every member** of the community finds one **new (randomly chosen) neighbour** from outside the community.
- The members might also **disconnect** some edges **inside** the community.

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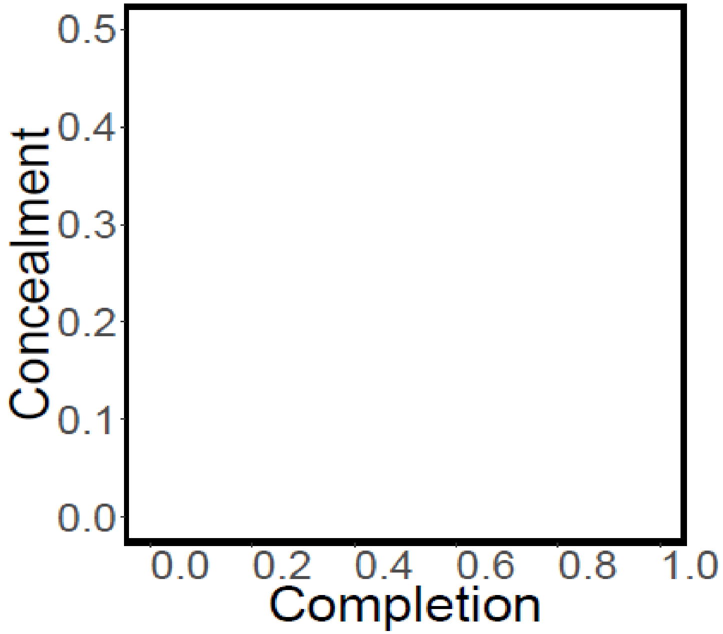
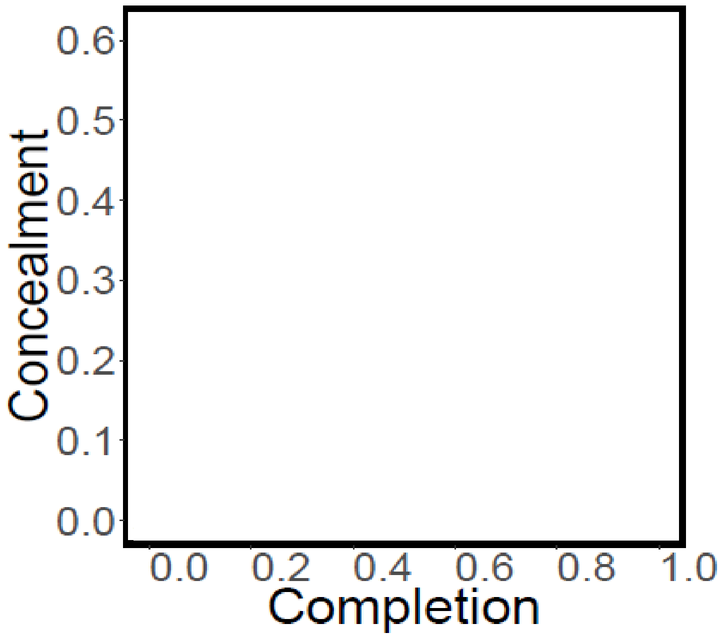
# Simulation results

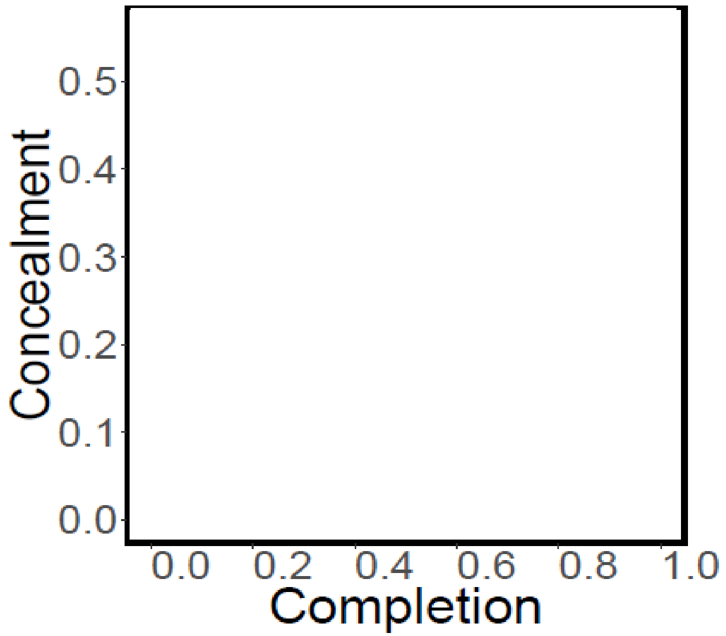
## Facebook fragment
(786 nodes, 14,027 edges)




## Madrid bombing network
(70 nodes, 96 edges)




## Scale free networks
(1000 nodes, 2994 edges)




**Community detection algorithm used by the seeker**

Betweenness, Greedy, Louvain, Walktrap, Eigenvector, Infomap, Spinglass

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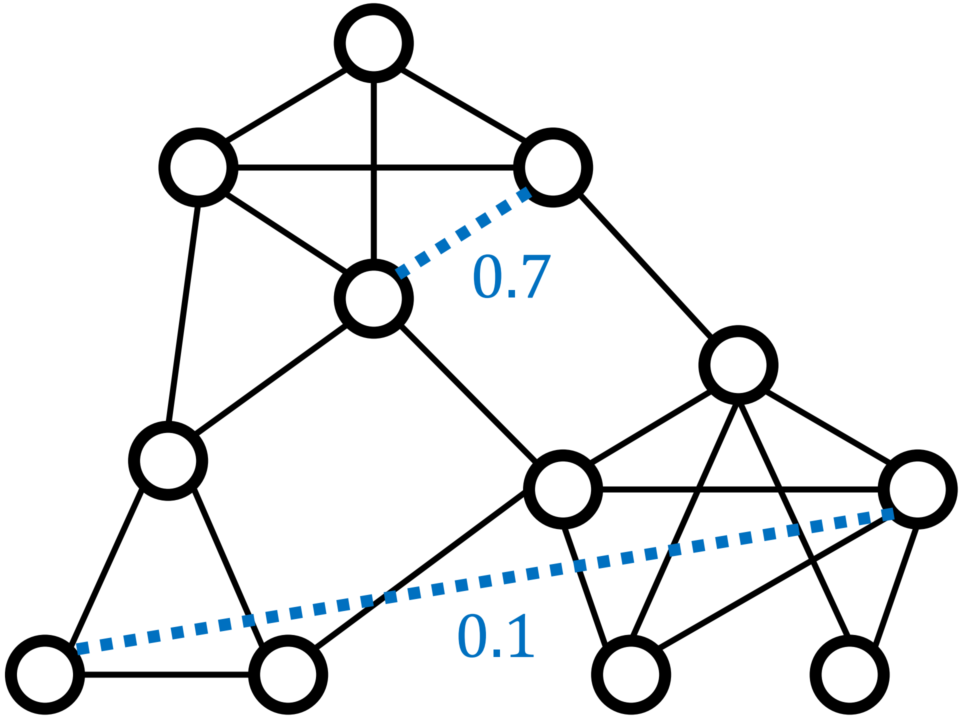
# Hiding from link prediction

# Link prediction algorithms




- **Link prediction algorithms** evaluate the likelihood of existence of a not-yet-discovered (or simply unknown) edge between a pair of nodes.
- **Similarity indices** are link prediction algorithms that assign a score to any pair of nodes that are not connected in the network.

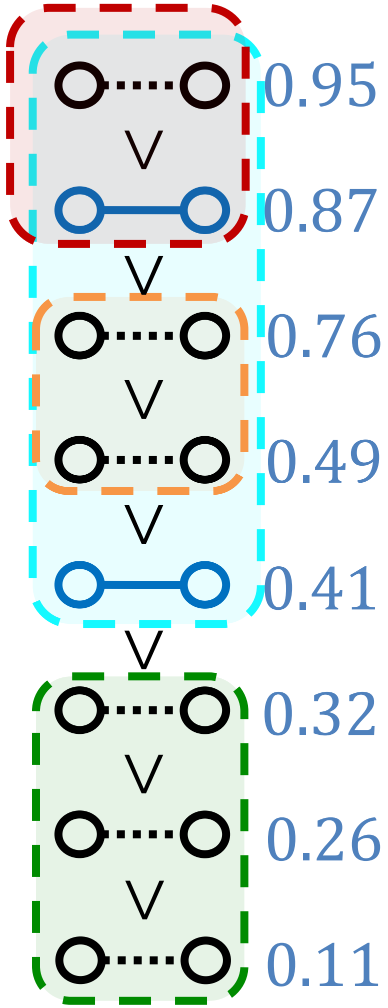
# Local similarity indices

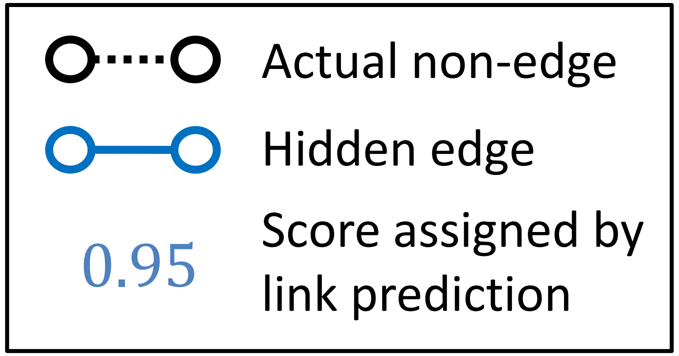
| | |
|---|---|
| **Common neighbors** | $s_{CN}(v,w) = \lvert N(v,w) \rvert$ |
| **Salton** | $s_{Sal}(v,w) = \frac{\lvert N(v,w) \rvert}{\sqrt{d(v)d(w)}}$ |
| **Jaccard** | $s_{Jac}(v,w) = \frac{\lvert N(v,w) \rvert}{\lvert N(v) \cup N(w) \rvert}$ |
| **Sorensen** | $s_{Sor}(v,w) = \frac{2\lvert N(v,w) \rvert}{d(v)+d(w)}$ |
| **Hub promoted** | $s_{HP}(v,w) = \frac{\lvert N(v,w) \rvert}{\min(d(v),d(w))}$ |
| **Hub depressed** | $s_{HD}(v,w) = \frac{\lvert N(v,w) \rvert}{\max(d(v),d(w))}$ |
| **Leicht-Holme-Newman** | $s_{LHN}(v,w) = \frac{\lvert N(v,w) \rvert}{d(v)d(w)}$ |
| **Adamic-Adar** | $s_{AA}(v,w) = \sum_{u \in N(v,w)} \frac{1}{\log(d(u))}$ |
| **Resource allocation** | $s_{RA}(v,w) = \sum_{u \in N(v,w)} \frac{1}{d(u)}$ |

All considered indices are based in some way on the **set of common neighbors**

# Measuring the quality of link prediction

- To measure the **quality of link prediction** we use two measures, AUC and AP.
- **Area under ROC curve (AUC)** - probability that similarity index assigns a greater score to a randomly chosen hidden edge than to a randomly chosen non-edge.
- **Average precision (AP)** - average precision $\left(\frac{TP}{TP+FP}\right)$ of a family of classifiers based on the ranking returned by the similarity index.




$$AUC = \frac{1}{2} * \frac{2+3}{6} + \frac{1}{2} * \frac{3}{6}$$

$$AUC = \frac{8}{12} = 0.66$$

$$AP = \left(\frac{1}{2} + \frac{2}{5}\right)/2$$

$$AP = \frac{9}{20} = 0.45$$

# Hiding from link prediction

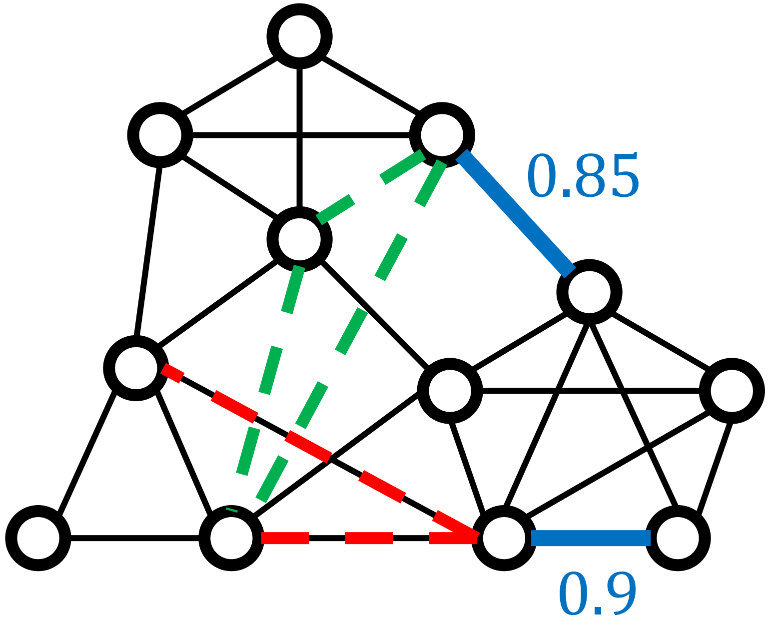
The unwarranted use of link prediction algorithms raises a lot of **privacy-related issues**.

We might prefer to **keep some of our relationships private**.

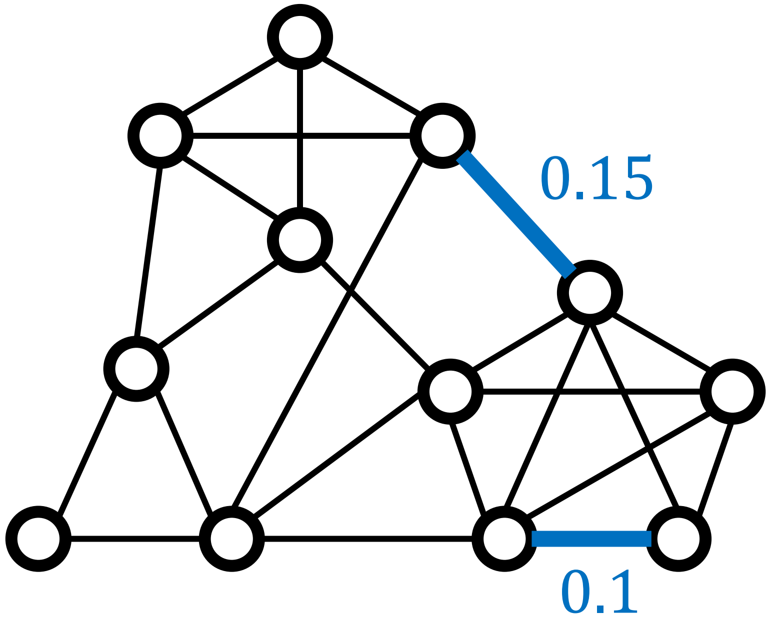

Link prediction may arrive at erroneous conclusions, associating us with **people we do not know**.

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Hiding from link prediction




Choose how to spend the budget, i.e., which edge(s) to add and which to remove




Area under ROC curve (**AUC**) = 0.8

Average precision (**AP**) = 0.7

Area under ROC curve (**AUC**) = 0.3

Average precision (**AP**) = 0.25

Edge that can be **added**

Edge that can be **removed**

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Complexity of finding an optimal solution

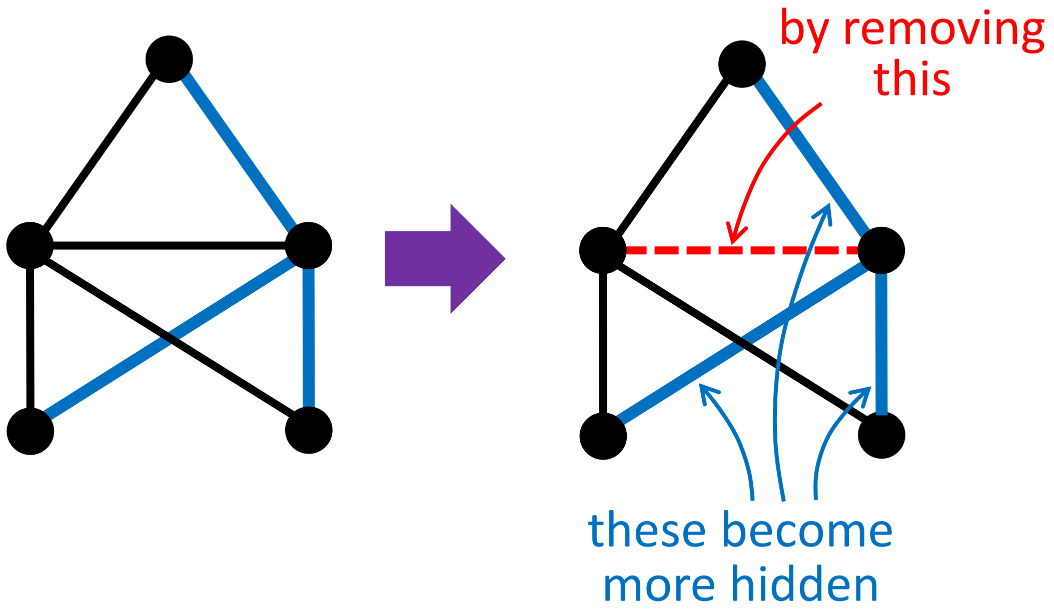
| Link prediction algorithm | Hiding complexity |
|---|---|
| Common neighbors | NP-complete |
| Salton | NP-complete |
| Jaccard | NP-complete |
| Sorensen | NP-complete |
| Hub promoted | NP-complete |
| Hub depressed | NP-complete |
| Leicht-Holme-Newman | NP-complete |
| Adamic-Adar | NP-complete |
| Resource allocation | NP-complete |

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Our heuristics

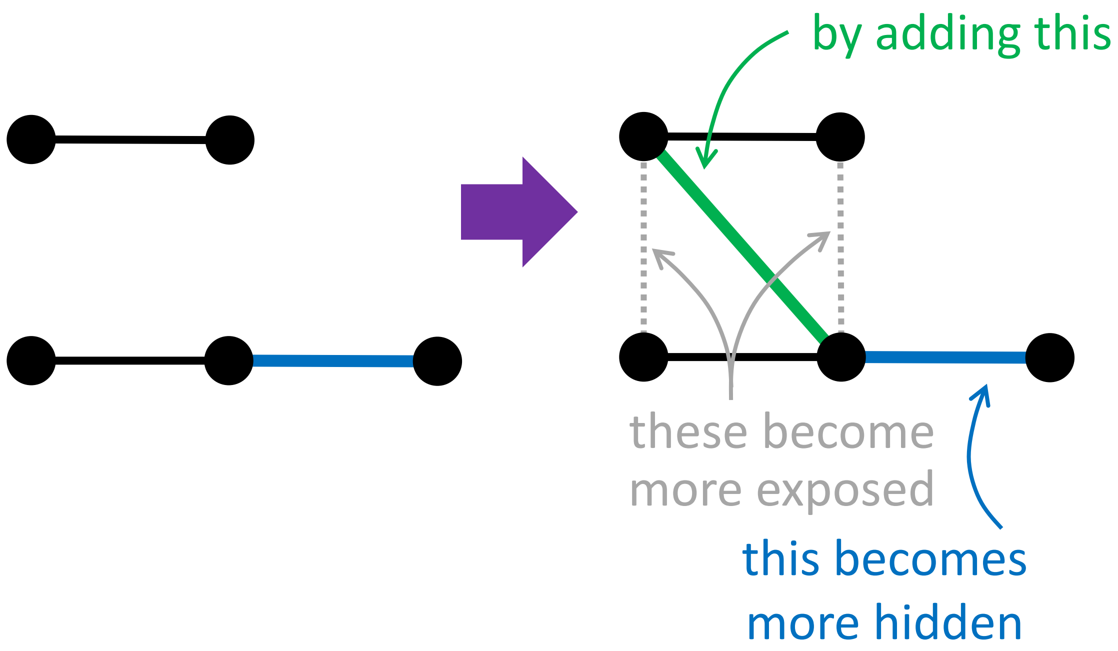
## Closed Triad Removal (CTR)

**Decreasing** scores of hidden edges by **removing** edges




## Open Triad Creation (OTC)

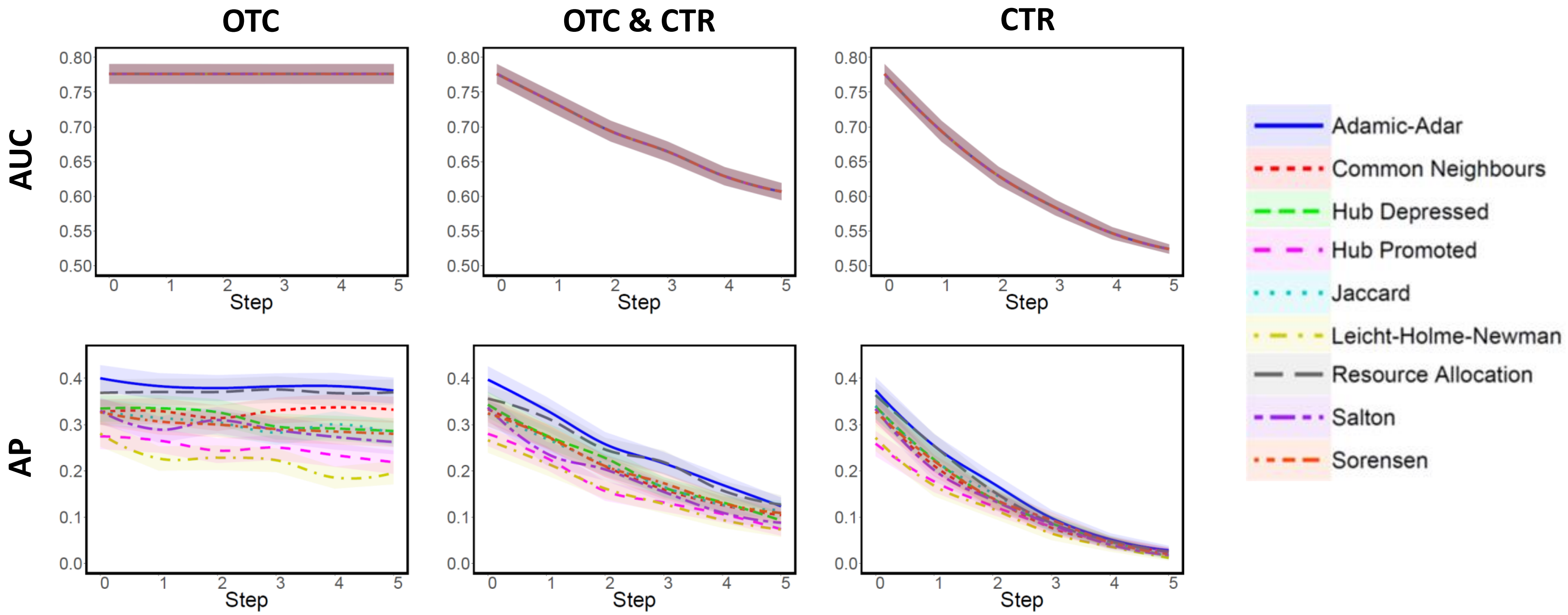
**Increasing** scores of other non-edges by **adding** edges




M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Hiding in massive real-life network

Here, we consider hiding in a **telecommunication network** of one of the major European cellular providers, consisting of 248,763 nodes and 829,725 edges.

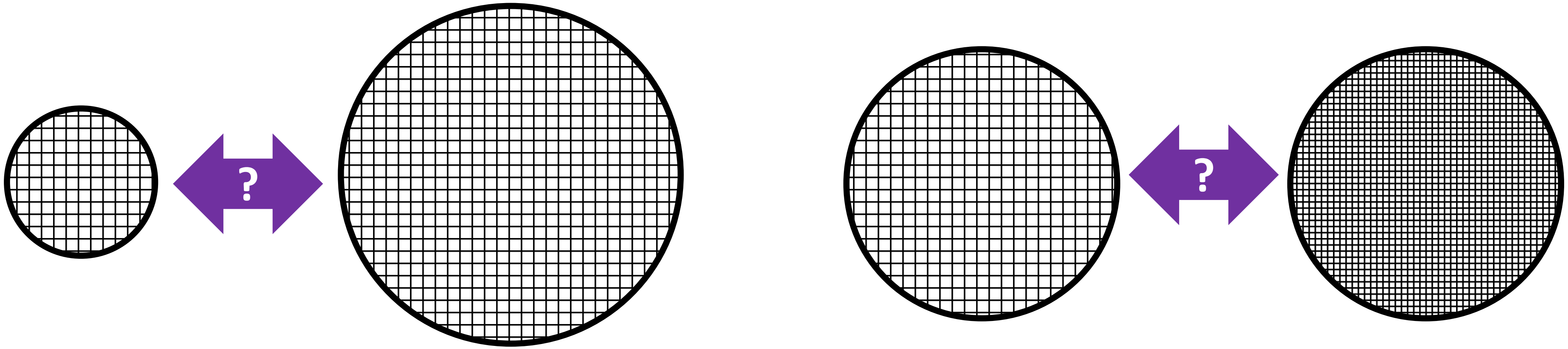



M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# The effects of size and density

Is it easier to hide your connections in **small** or **large** networks?

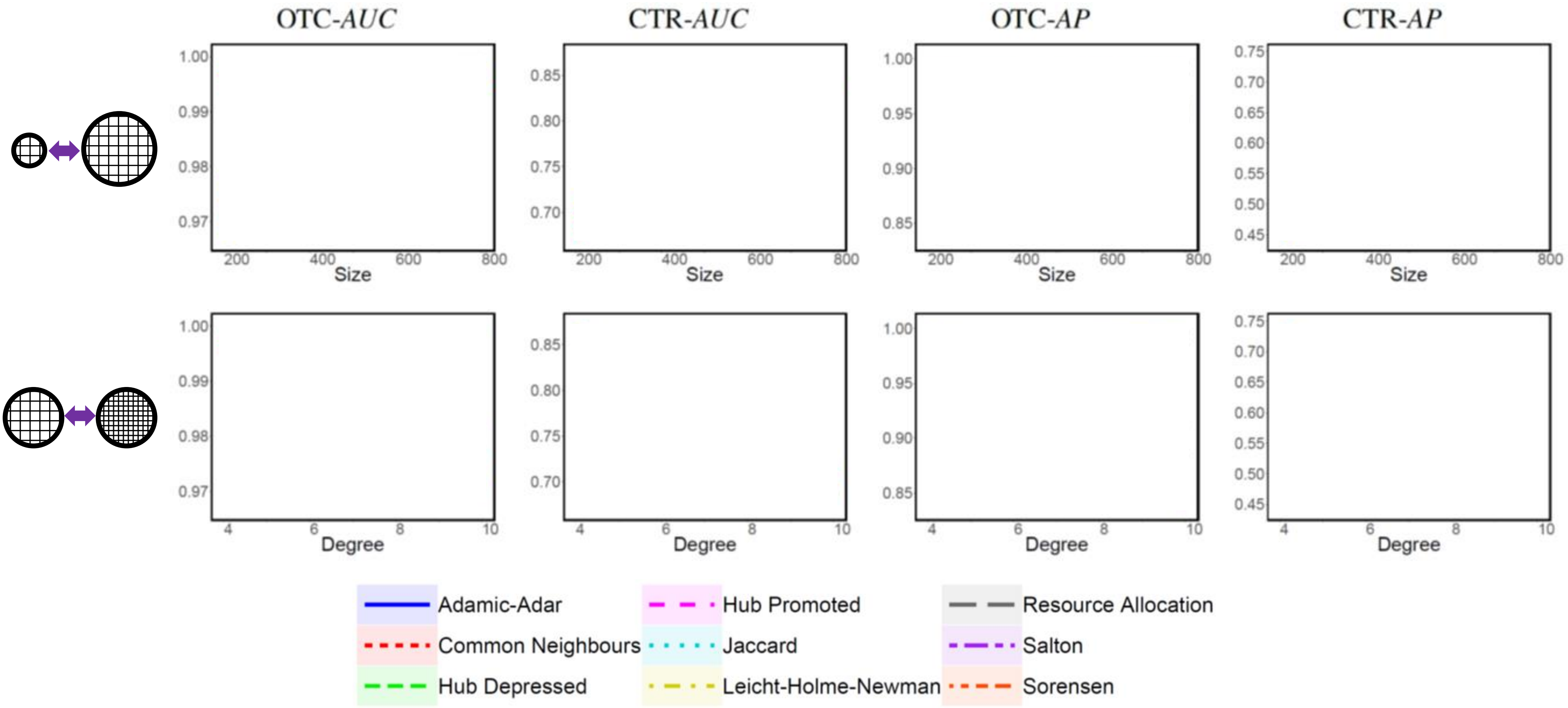
Is it easier to hide your connections in **sparse** or **dense** networks?




We perform simulations on randomly-generated networks of **varying size and density** and compare **relative value of AUC and AP** after hiding.

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# The effects of size and density




M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Random vs strategic changes

Is the hiding effectiveness actually affected by the **strategic choice** of edges to add/remove, or rather is it just a result of performing **any changes** in the network?


We perform simulations comparing the effects of **our heuristics** with the effects of **random changes** (given the same sets of edges allowed to be added/removed).

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)

# Random vs strategic hiding

## Relative change in AUC

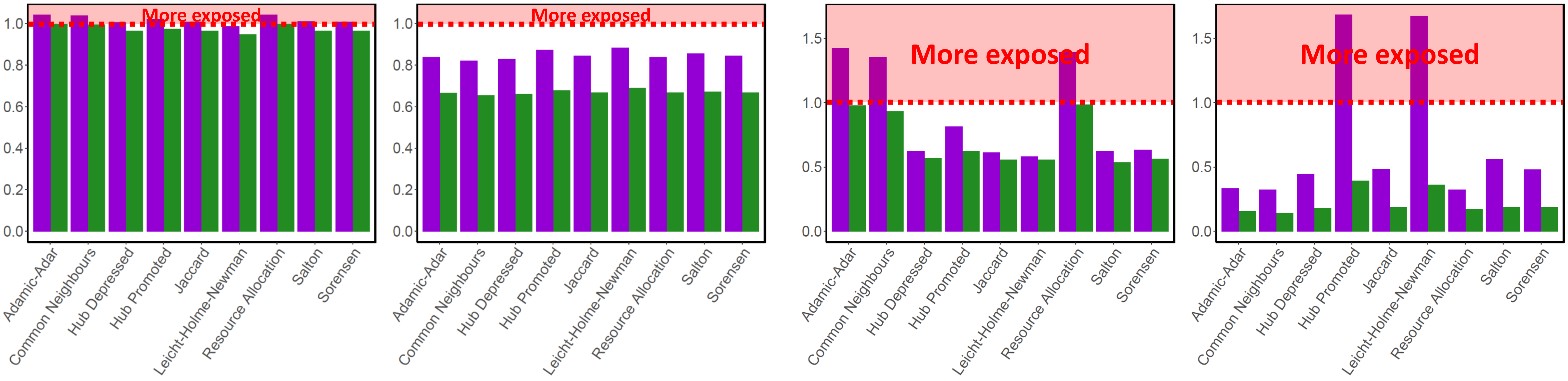
### Adding edges

### Removing edges

## Relative change in AP

### Adding edges

### Removing edges




Similarity index used by the seeker

Similarity index used by the seeker

Similarity index used by the seeker

Similarity index used by the seeker

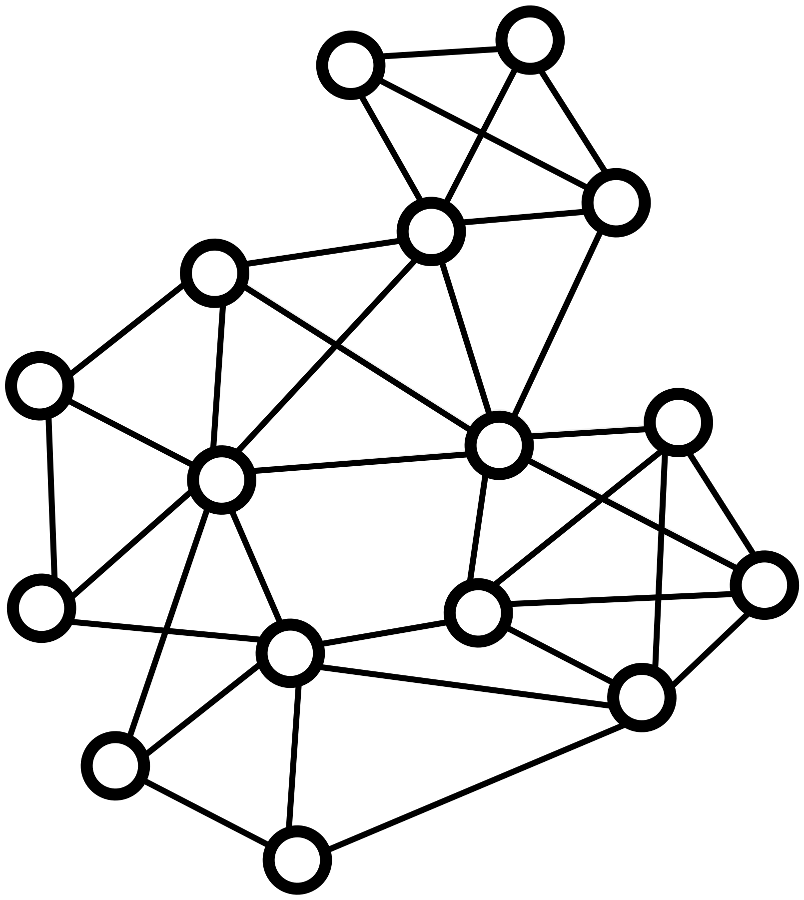
Random Strategic

M Waniek, K Zhou, Y Vorobeychik, E Moro, T Michalak, T Rahwan. *How to hide one's relationships from link prediction algorithms*. **Scientific Reports** (2019)


Hiding from
source detection

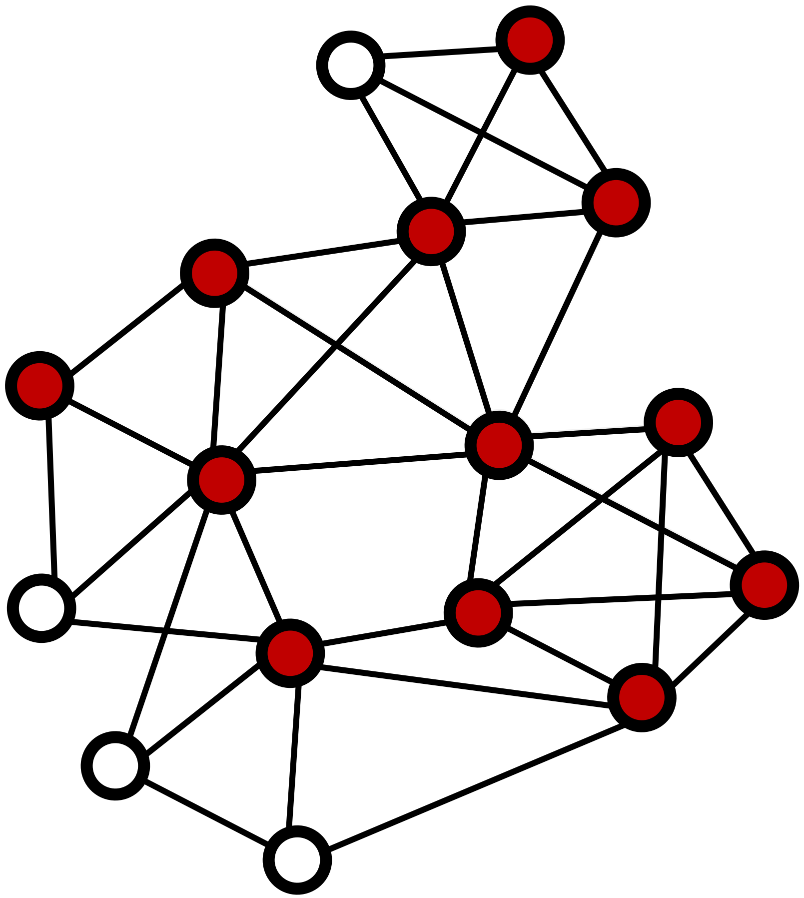
# Social diffusion

- We consider **a process spreading in a social network**, e.g., an infectious disease or a piece of information.
- The process begins with only one node, **the source**, being active.
- The process then **spreads** in the network over $T$ **rounds** according to some rules.
- In this presentation we will focus on results for the **Susceptible-Infected model**, where during each round every active nodes activates susceptible neighbors with a given probability.



# Source detection

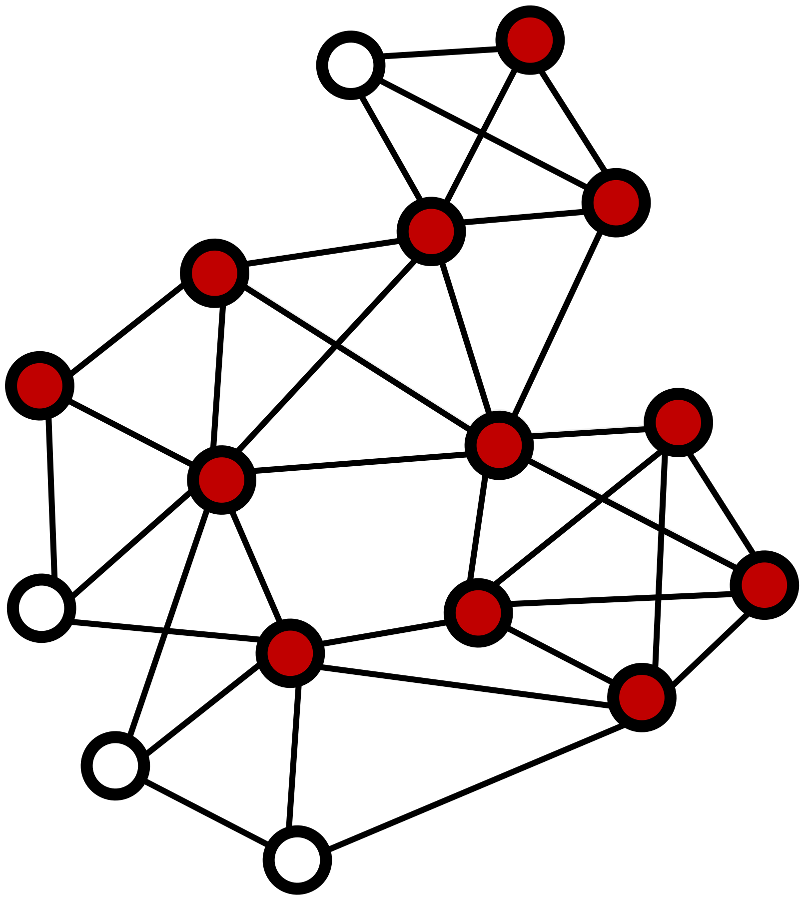
- **Source detection** is the task of inferring which node was the source based on the state of the network after the diffusion took place.
- Information available is the **structure of the network** and the **state of each node**, i.e., whether it is active or not.
- We will focus on methods that produce a **ranking of all nodes**, with the leader of the ranking being the best candidate for the source.



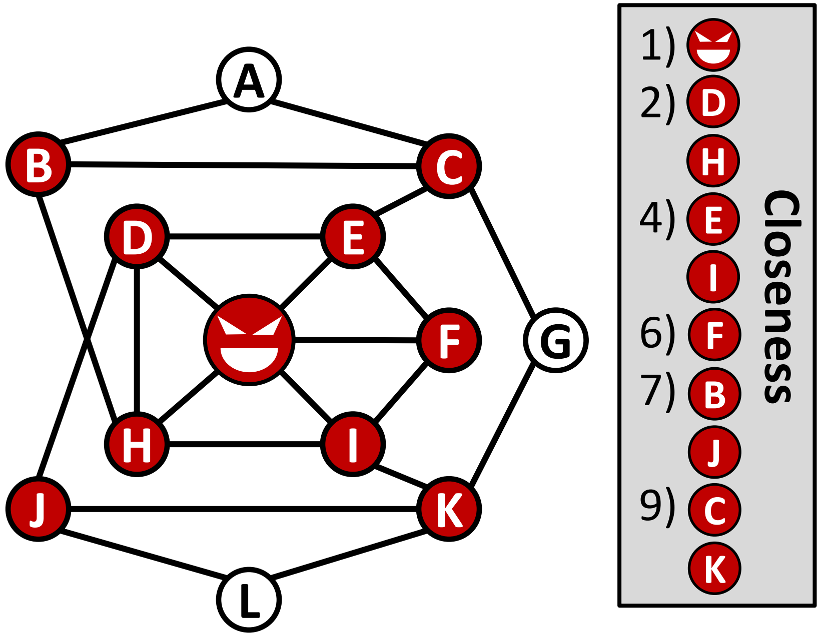
# Source detection algorithms

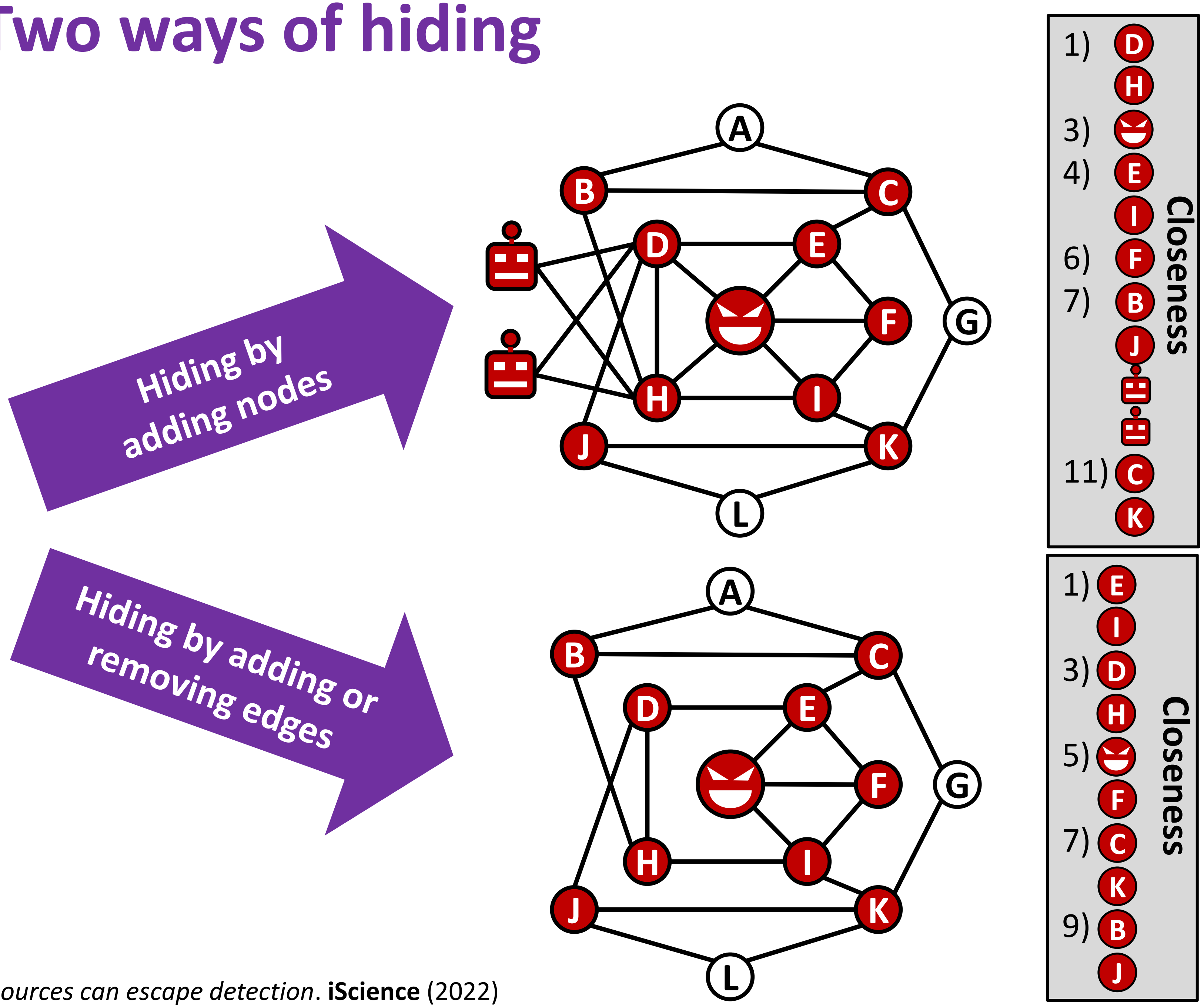
- **Random walk** – approximate the diffusion with random walks
- **Monte Carlo** – repeatedly start diffusion from each node and see how similar the outcomes are to the observed state
- **Degree**
- **Closeness**
- **Betweenness**
- **Eigenvector**
- **Rumor**

Compute **centrality** in the network induced by the infected nodes



# Two ways of hiding




Given a budget $b$, which edges to add/remove so that there are at least $\omega$ nodes above the evader in the ranking of algorithm $\sigma$?

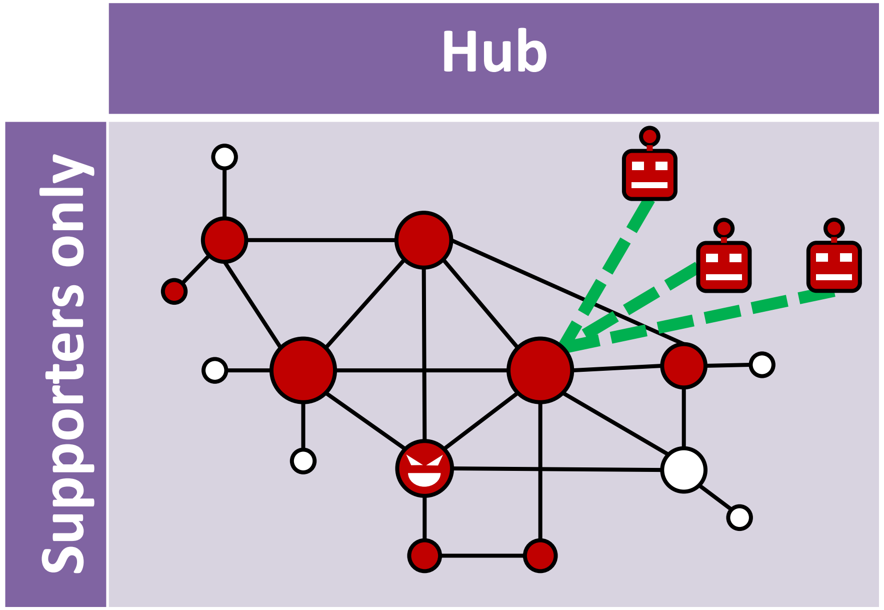
M Waniek, P Holme, M Cebrian, T Rahwan. *Social diffusion sources can escape detection*. **iScience** (2022)

# Computational complexity

| Source detection algorithm | Adding nodes | Modifying edges |
|---|---|---|
| Degree | P | NP-complete |
| Closeness | NP-complete | NP-complete |
| Betweenness | NP-complete | NP-complete |
| Rumor | NP-complete | NP-complete |
| Random walk | NP-complete | NP-complete |
| Monte Carlo | NP-complete | NP-complete |

M Waniek, P Holme, M Cebrian, T Rahwan. *Social diffusion sources can escape detection*. **iScience** (2022)

# Hiding heuristics – adding nodes

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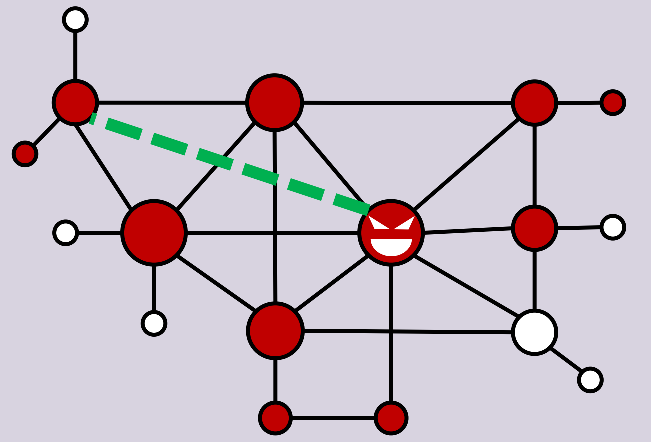
# Hiding heuristics – modifying edges

**Max degree**

**Adding edges**



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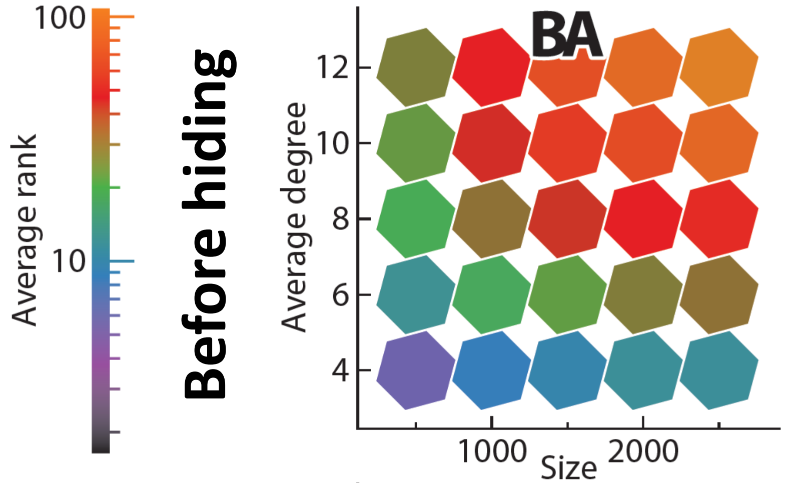
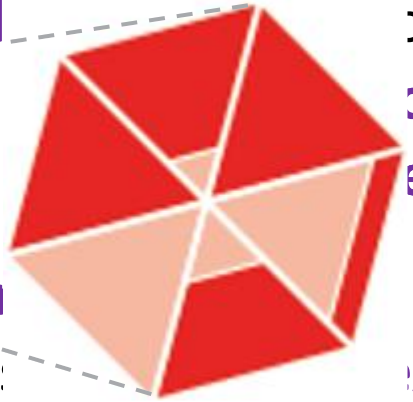
# Efficiency of hiding from Eigenvector



In **Barabasi-Al**… …orks the source is hidden by the … **…of the network**, particularly in … **…e networks**.

However, in **E…** … and **Watts-Strogatz (WS)** network… **…xposed**.

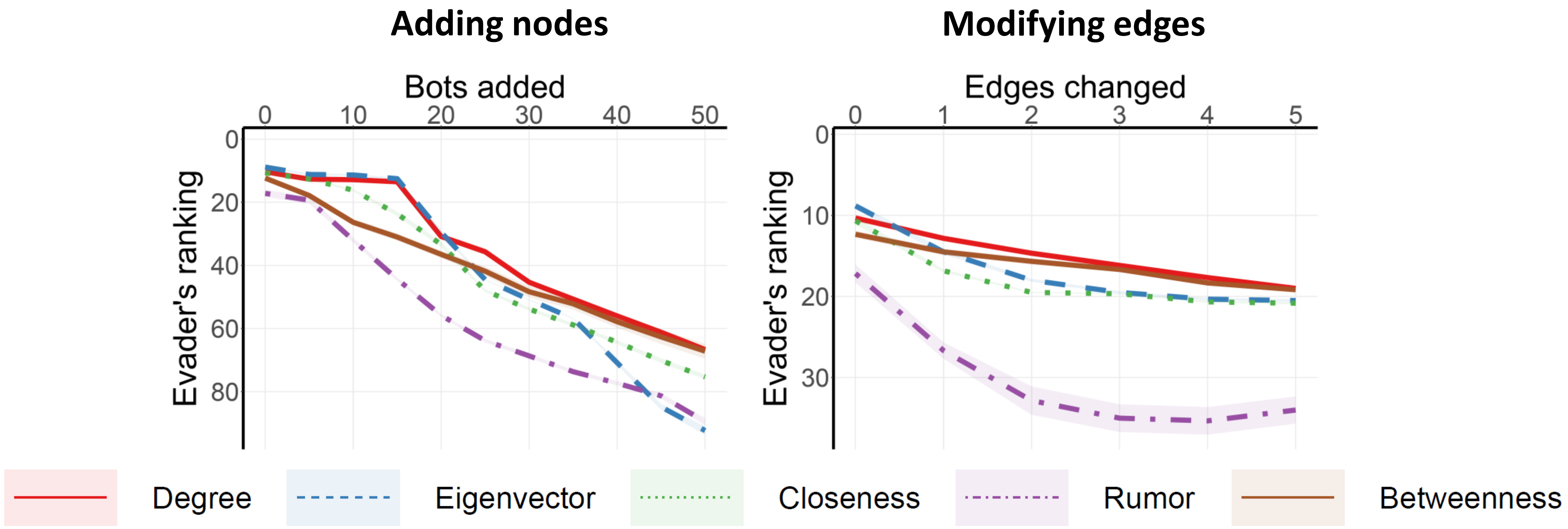
The **larger** the **highlighted triangle**, the **more effective** the heuristic.

In general, **the most effective heuristics** are those that **connect the bots into a clique**.

**Degree clique** is the **most effective** heuristic here, the **hexagon's color** corresponds to its performance.

# Hiding the source of a real cascade

We also attempt to hide the sources of **eight new Twitter hashtags** in a retweet network consisting of 241,698 nodes and 366,539 edges.

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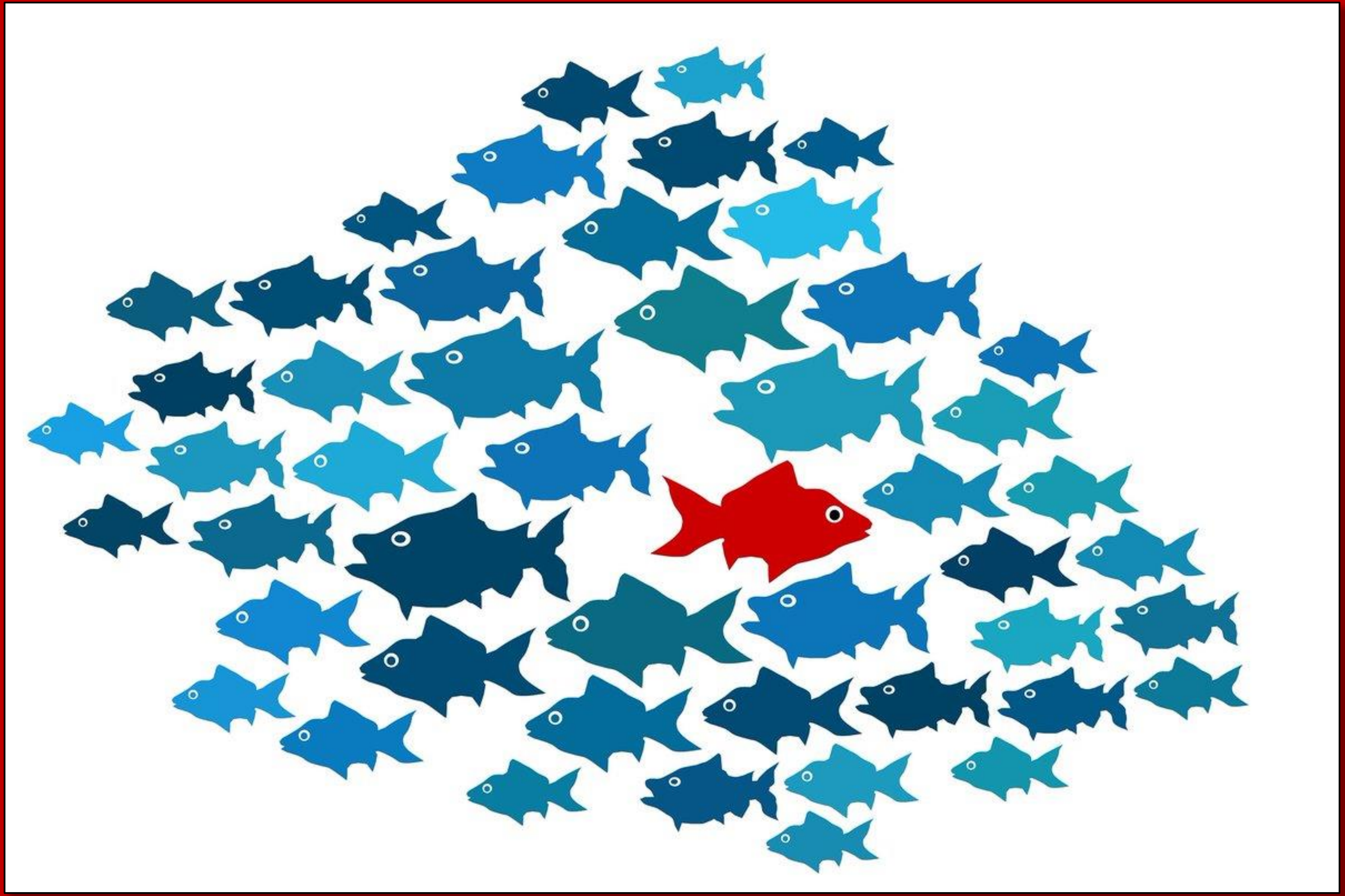
# Project idea #2 Anomaly detection for hiding



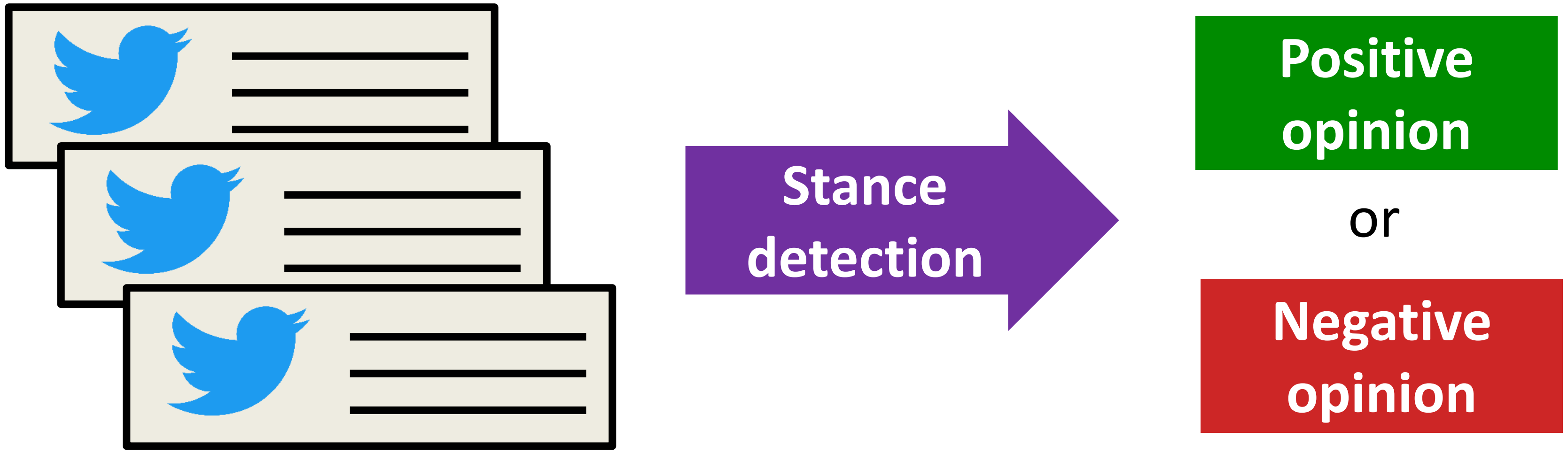
**Research question**

**Can anomaly detection algorithms be used to identify the nodes who perform strategic rewiring of the network?**

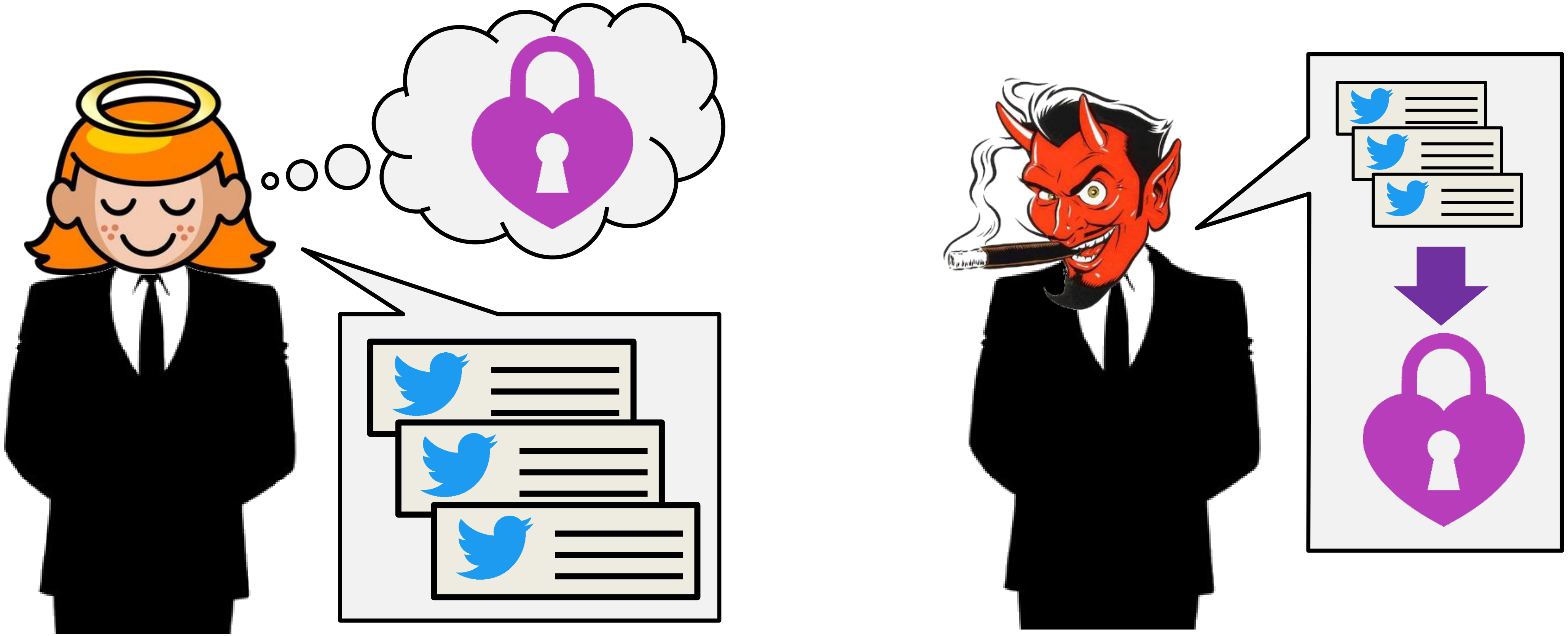
# Hiding from stance detection

# Stance detection

- **Stance detection algorithms** allow to **infer an opinion** (either positive or negative) a person holds about certain topic based on this person's **publicly available social media data** (in this study we focus our attention on **Twitter**).
- Notice that the opinion does not have to expressed directly, as the algorithms can read up on subtle clues **imperceivable to a human's eye**.



# The problem with stance detection

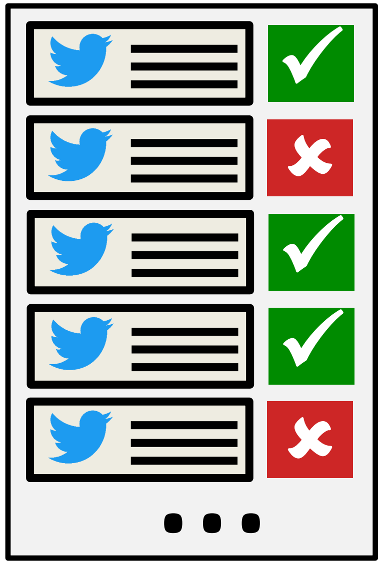


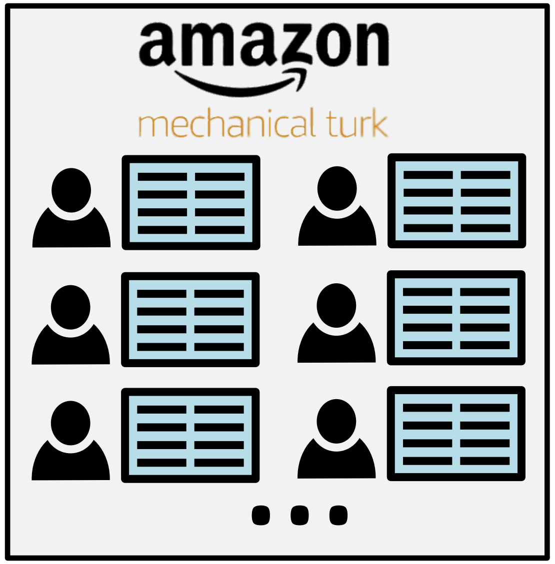
M Waniek, T Rahwan, W Magdy. *Hiding opinions from machine learning.* **PNAS Nexus** (2022)

# The datasets we use

To explore these issues, we use **two datasets**:

- To train stance detection algorithms, we used a dataset of **tweets with opinions** they indicate towards **atheism, feminism, and Hillary Clinton**.
- A **survey study** with 1,143 participants we recruited via **Amazon Mechanical Turk**, with questions based on state-of-the-art SVM classifier.



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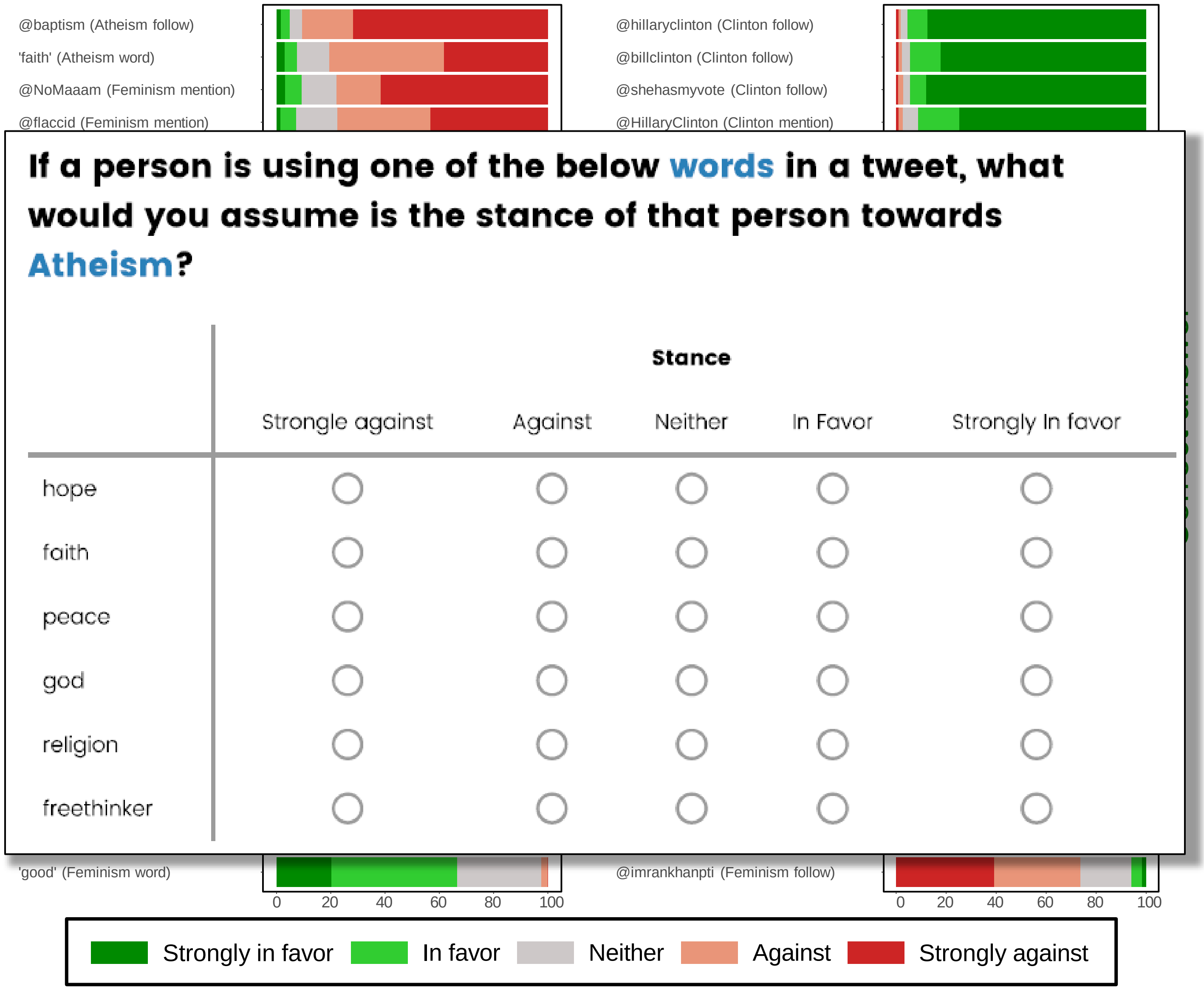
# Can people hide opinions from AI without help?

- We focused on **three types of features**: a word used in a tweet, an account followed, and an account mentioned in a tweet.
- For each of the topic and each feature type, we identify the **three features** most strongly associated with the **“against” stance**, and the three most strongly associated with the **“in favor” stance**, according to the SVM classifier.
- For each feature, we asked participants to specify **the stance that it indicates** towards the topic.

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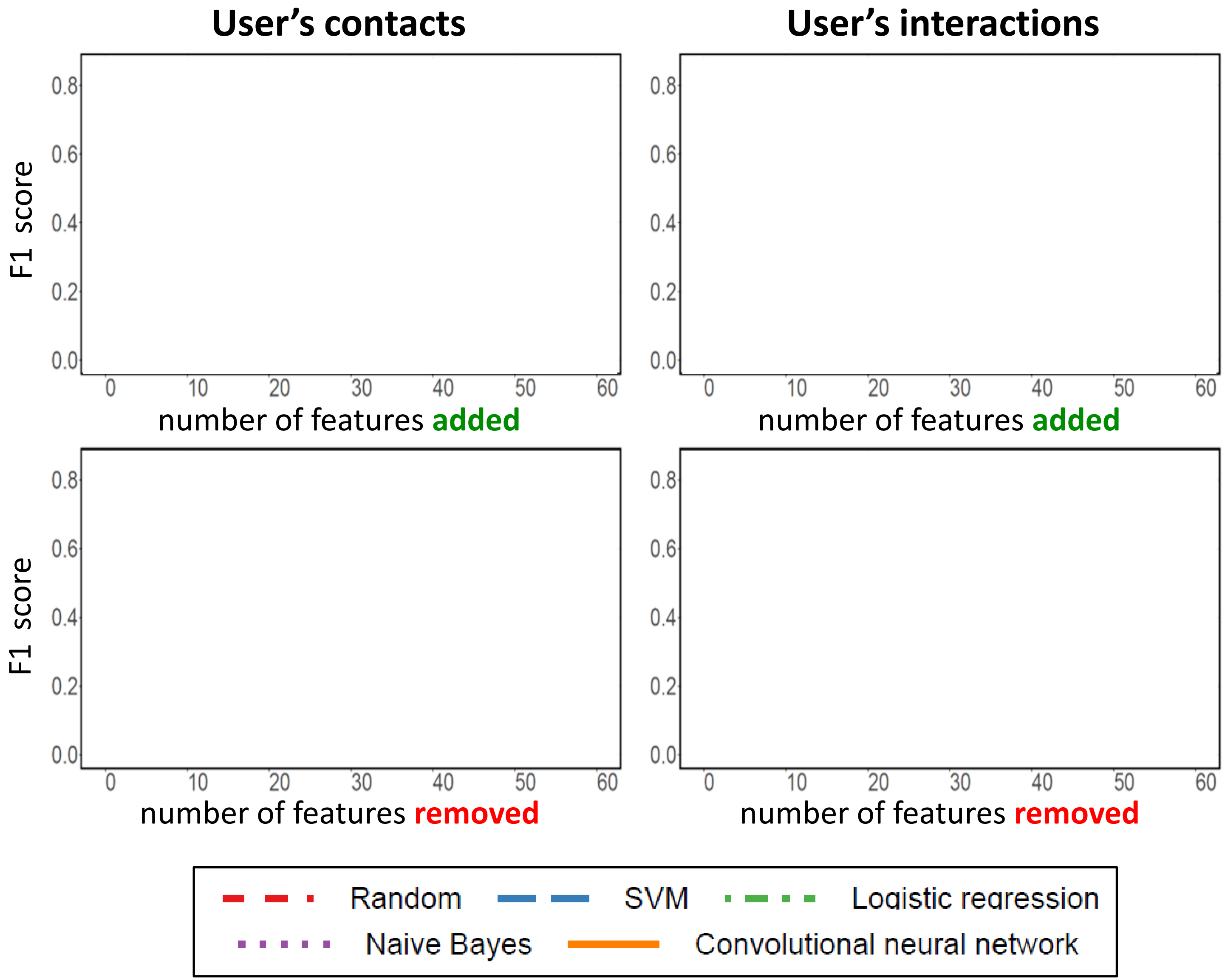
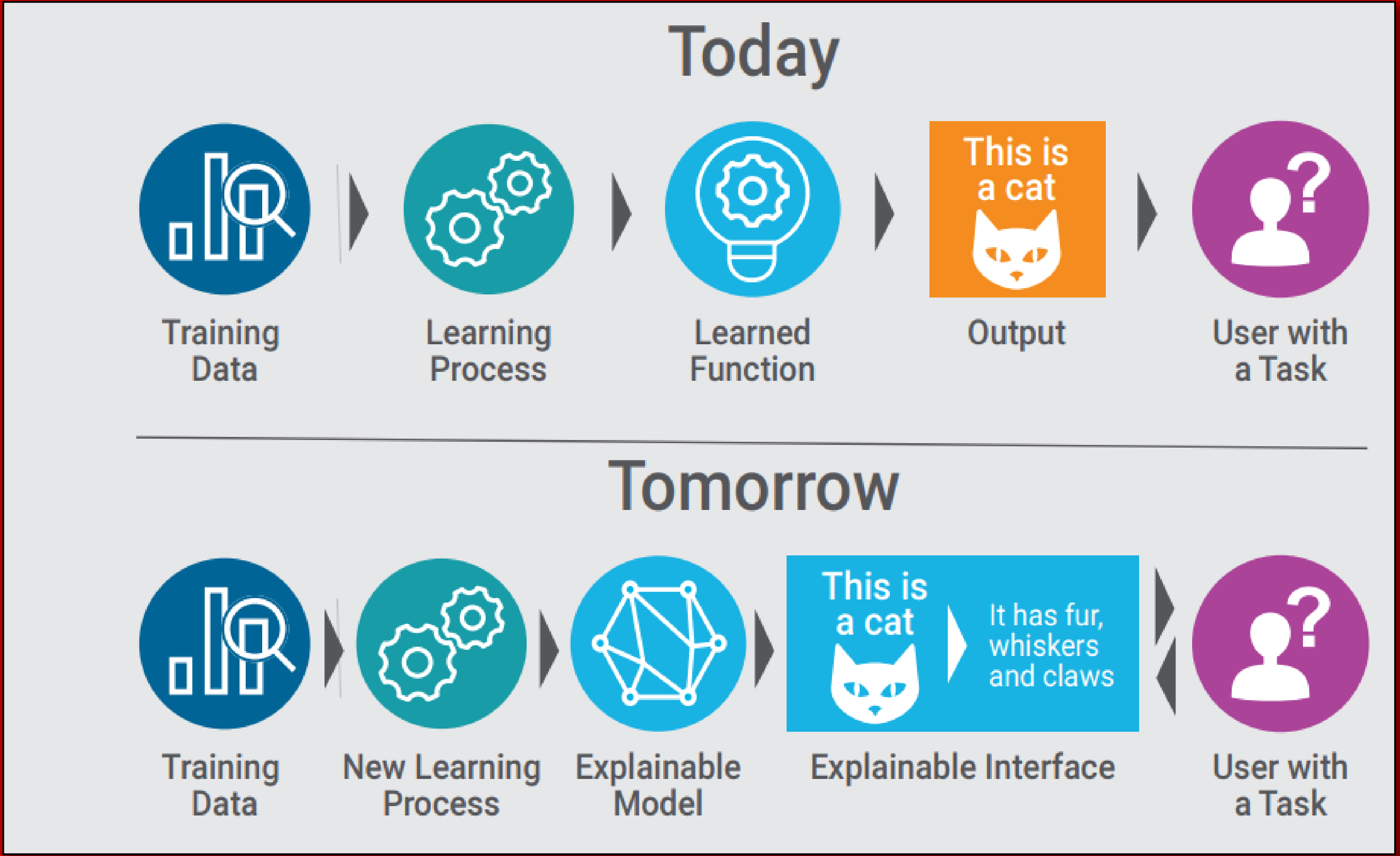
# Can algorithms help people hide their opinions from AI?

- We now try to **hide people's opinion** based on insights drawn from the SVM classifier.
- We either **remove the features** that are most indicative of the real stance, or we **add the features** that are most indicative of the opposite stance.
- We test these hiding methods against algorithms trained either on **user's contacts** (the accounts they follow) or the **user's interactions** (the accounts mentioned in their tweets).




M Waniek, T Rahwan, W Magdy. *Hiding opinions from machine learning.* **PNAS Nexus** (2022)

# Project idea #3 Hiding using XAI




**Research question**

**Can Explainable AI be used to develop more effective, personalized hiding methods?**

# Summary of proposed topics

**Idea #1 Temporal network of scientists**

**Idea #2 Anomaly detection for hiding**

**Idea #3 Hiding using XAI**