Knowing Who Knows Us

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Introduction

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Accuracy

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Implications

Example

A boy named A hears a rumor about his classmate B and thinks about telling another friends, C and D.

A doesn't realize that he has a central position in the school's social network. When he shares the rumor, it spreads very quickly and ends up hurting B deeply. Eventually, B decides to leave the school.

A feels really bad because he didn't mean for things to go that far—he just didn't know how easily information could spread through him. *He simply didn't know he was such a central player*.

Literature

- Regardless the reality, social structures also exist in the mind (Smith et al., 2020).
- Most of the literature focus on predicting the most popular subject or central in a given network (Hall *et al.*, 2010, Dahlberg, 2017, Banerjee *et al.* 2019).
- People who are able to sketch a more accurate mental map of their social network can benefit from advantages such as the acquisition of social power (Krackhardt, 1990; Kilduff & Tsai, 2003) or better outcomes (Kovářík *et al.*, 2025).
- Limited interest in how good young people are in assessing their social networks $\longrightarrow$ fundamental to their personal development (Casciaro, 1998; Freeman et al., 1988; Krackhardt, 1987).

Natural questions to make

- How do people perceive the world around them?
- Do people know the position that others occupy in the network?
- How accurate their knowledge is about **their position** in the network (Ertan et al., 2019)?
- Who has a better perception of their structural environment? Who are more accurate?
    - *Central* actors?
    - *Popular* individuals?

Preliminaries

Before talking about this paper, I'm going to take 5 or 10 minutes to talk to you about the previous one, which, as you'll see, perfectly defines why we followed this design.

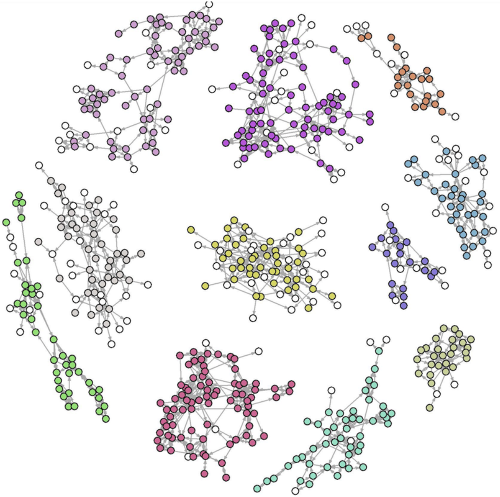
Perception of own centrality in social networks

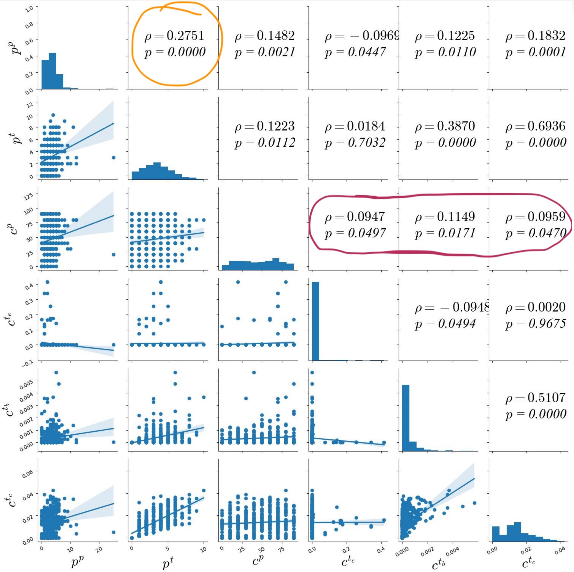
J. Kovářík, J. Ozaita, A. Sánchez & P. Brañas-Garza
PNAS, 2025

What we do?

- We gave the subjects lottery tickets to distribute among their friends (n $>$ 500 students, 11 networks) $\rightarrow$ this gives us the network.[1]
- Then we asked them to predict (with incentives) their own popularity and centrality (deciles).
  - We compare: *"True"* popularity with *"Perceived" popularity*
  - *"True" centrality* with *"Perceived" centrality*.

[1] We used this mechanism before at Piura (Peru) with 2,000 women recipients of CCT (*J. Behavioral & Experimental Finance* 2025)




ρ = 0.2751
p = 0.0000
ρ = 0.1482
p = 0.0021
ρ = −0.0969
p = 0.0447
ρ = 0.1225
p = 0.0110
ρ = 0.1832
p = 0.0001
ρ = 0.1223
p = 0.0112
ρ = 0.0184
p = 0.7032
ρ = 0.3870
p = 0.0000
ρ = 0.6936
p = 0.0000
ρ = 0.0947
p = 0.0497
ρ = 0.1149
p = 0.0171
ρ = 0.0959
p = 0.0470
ρ = −0.0948
p = 0.0494
ρ = 0.0020
p = 0.9675
ρ = 0.5107
p = 0.0000
p^p
p^t
c^p
c^{t_e}
c^{t_b}
c^{t_c}

VARIABLES	(1) Popularity	(2) Inaccuracy popularity	(3) Centrality	(4) Inaccuracy centrality
Individual positioning				
In-degree	0.262***	0.110*	1.146	-0.232***
	(0.0512)	(0.0546)	(0.844)	(0.0477)
Out-degree	0.283*	-0.00391	0.335	0.122
	(0.134)	(0.125)	(1.404)	(0.118)
Eigenvector	-1.289	-0.989	60.18**	0.390
	(1.965)	(0.928)	(25.55)	(1.748)
Betweenness	-185.8	187.0	3,033**	105.9
	(105.2)	(275.2)	(1,256)	(127.1)
Clustering coef.	-0.270	-4.089***	-24.04	-1.069
	(2.025)	(1.155)	(15.28)	(2.238)

Figure: Perception and networks measures

In short:

- $\rho(p^p, p^t) = 0.275$ ($p = 0.000$)
- $\rho(c^p, c^t) \sim 0.10$ ($p > 0.047$)

Therefore, this study suggests that subjects are quite bad at predicting their own popularity, but more importantly, that they are rather unaware of their position in the network.

Also, the more central individuals don't perform any better than the less central ones... so being central doesn't actually improve their predictions.

It really does seem true that A didn't realize how much harm he could cause to B...

One possible limitation of this study is that the *method might be too complex for the subjects*. What we're going to do in the next paper is use a much more intuitive method.

When we say the method is complex, we don't mean that people are bad at predicting their own centrality — rather, the issue lies in the prediction method itself.

Knowing Who Knows Us

Pablo Brañas

Loyola Behavioral Lab

jointly

Jaromír Kovářík, Basque Country University
Frederike Mengel, Essex University
Mónica Vasco, University of Southern California

In this paper

- We use a much simpler and more direct elicitation method. We ask each subject:
  - From the class roster, choose:
    - who your friends are
    - who you think will call you a friend
  - Then we compare this prediction to the actual links friends that person receives (one by one).

- We propose a **metric** for assessing the **accuracy** of self-perception. We study **popularity** (*in-degree*).
- We focus on **adolescents.** We are interested in adolescents because it is crucial to understand how *their social skills evolve* during this critical period of their lives — including aspects such as social integration, bullying, gossip, and more.

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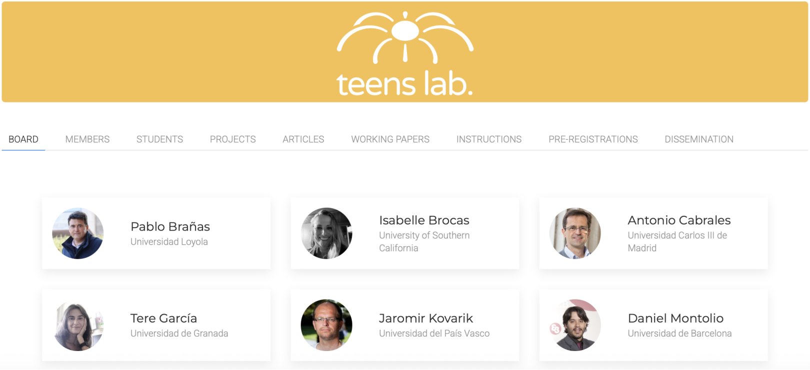

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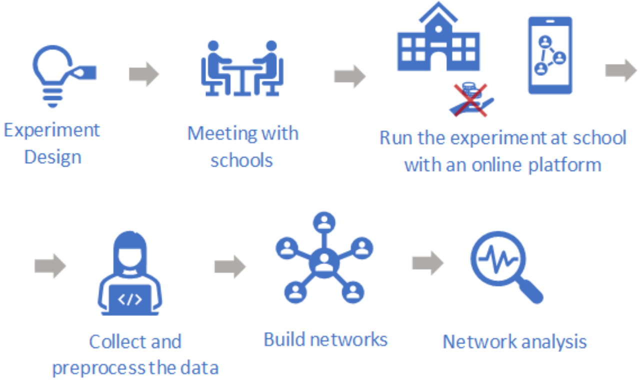
Lab-in-the-field experiment



Variables (at individual level)

- **Personal variables:** Age, Gender, Migrant origin, etc.
- **School variables:** Year (grade), score (academic marks), etc.
- **Tasks:** Eliciting risk and time preferences, Cognitive Reflection Test and Financial tasks
- **Social network variables:** Friends and predictions.

Sample

- 22 educational centers in Spain
- 117 networks
- 3,077 students
- Collected from 2021 to 2023

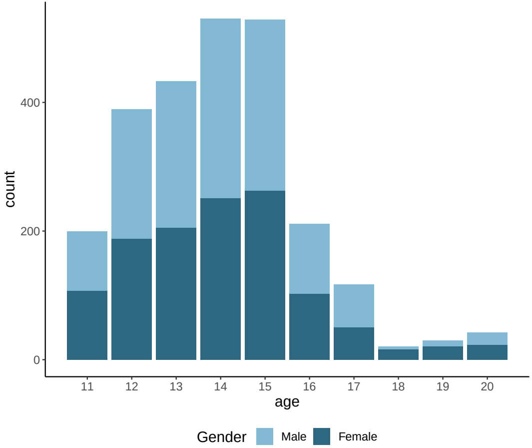


Figure: Sample distribution by age and gender

- [ ] IRENE GARCIA CRESPILLO - 1º ESO D
- [ ] MANUEL ALONSOP ALONSOM - 1º ESO D
- [ ] JAIME CAROPEP RODRÍGUEZ - 1º ESO D
- [ ] ISABEL JURADOM CARDEÑOSA - 1º ESO D
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Selection screen: Sociogram

See more

What information about networks do we have?

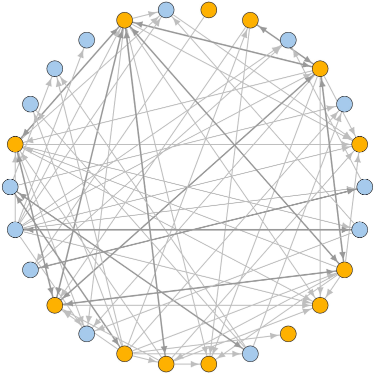
Friends	
$F_i^{out}(i)$	Peers who i mentions as friends (*outdegree*)
$F_j^{in}(i)$	Peers (j) who mention i as a friend (*indegree*)
$\hat{F}_i^{in}(i)$	Peers who i believes they (j) mention i as a friend (E[*indegree*])

Self–consistency

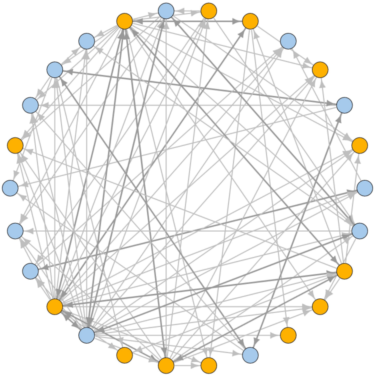
When a participant is asked to predict who will name them as a friend, several aspects of the task must be considered:

- *They have already chosen their own friends*, meaning they are familiar with the structure of the task and understand how friendship nominations work.
- *Their peers have already chosen them*, because the data are collected simultaneously. The participant knows their own outgoing choices, but not the incoming ones.

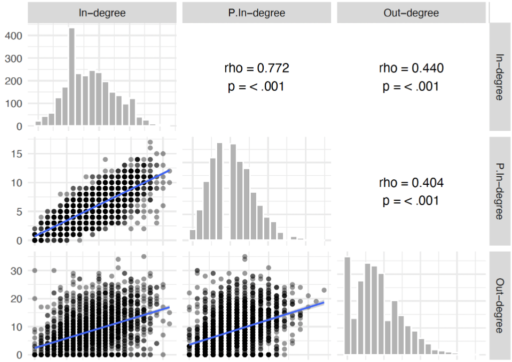
In our interpretation, we assume that the participant is trying to make an **accurate prediction** about who will nominate them. However, we do not know whether the participant cares about being **consistent** with their own choices (to be checked later!).



(a) Predicted friends



(b) Real friends



Apparently the correlation is very high, but we must keep in mind that *indegree*, E(*indegree*), and *outdegree* refer to the number (the integer count) of friends, not to the identity of those friends.

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Accuracy in friendship perception

$$\text{Accuracy}_i = \frac{\left|F_j^{in}(i) \cap \hat{F}_i^{in}(i)\right|}{\left|F_j^{in}(i) \cup \hat{F}_i^{in}(i)\right|}$$

$$0 = \text{completely inaccurate}$$
$$1 = \text{perfectly accurate}$$

Our measure of accuracy considers indegree (*exogenous*) and expected (*subjective*) indegree.

Accuracy in friendship perception

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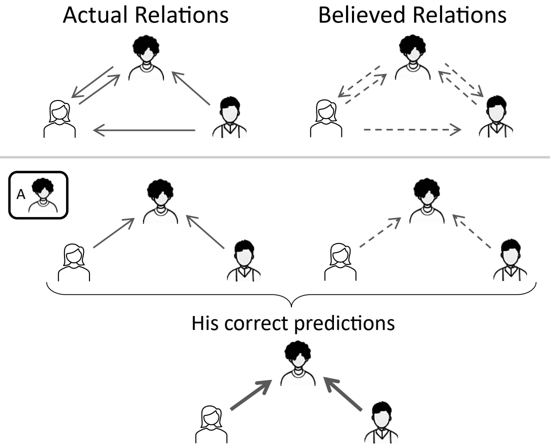
Our measure of accuracy considers indegree (*exogenous*) and expected (*subjective*) indegree.

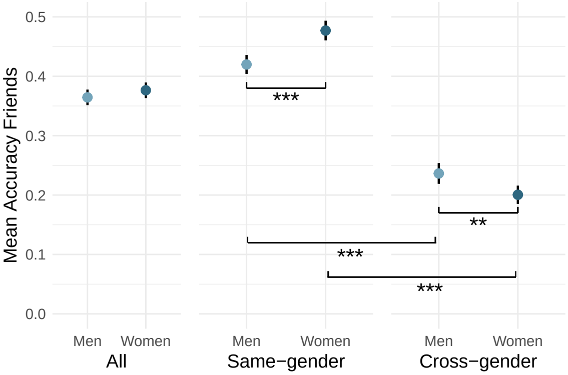
Limitations:

- Insensitive to set size: evaluates only the overlap, not how large the sets are.
- No distinction between Type I and Type II errors: false positives and false negatives are treated equally.
- Ignores unknowns: individuals outside the predicted or actual friend sets are not considered.


Actual Relations
Believed Relations
A
His correct predictions

Example

Same-gender and cross-gender relationships.



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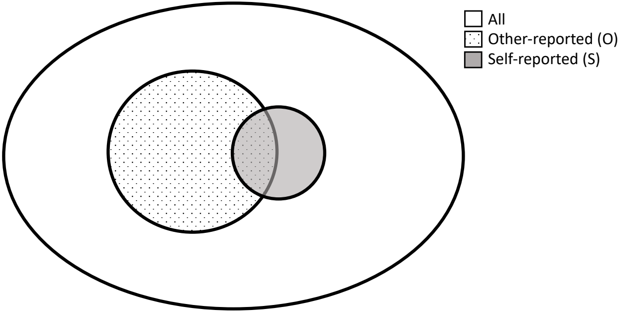
And is all of this actually relevant?

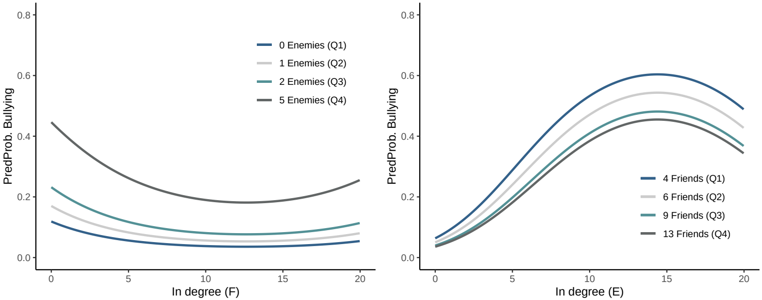
In a parallel study (with Cabrales, Kovarik, and Vasco, 2025), we found that the probability of being bullied decreases with the number of friends and increases with the number of enemies.



Victims of bullying

Some students acknowledge being bullied (2.85%), while others are identified by their peers as victims (12.75%). Only a small proportion of cases (1.52%) overlap.

We will **define a student as a victim** if they are identified as such by their peers, regardless of whether they are aware of it (or acknowledge it) or not.


0.8
0.6
0.4
0.2
0.0
PredProb. Bullying
0 Enemies (Q1)
1 Enemies (Q2)
2 Enemies (Q3)
5 Enemies (Q4)
0
5
10
15
20
In degree (F)
4 Friends (Q1)
6 Friends (Q2)
9 Friends (Q3)
13 Friends (Q4)
In degree (E)

Main results:

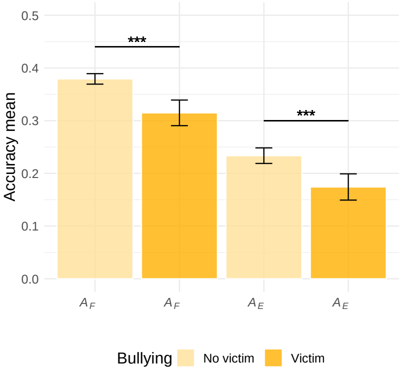
(*i*) A larger number of friends prevents teenagers from suffering bullying while a larger number of enemies exposes them to bullying.

(*ii*) The marginal impacts of both variables decline with the number of friends and enemies.

(*iii*) Omitting either the number of friends or enemies biases the estimated coefficient of the other variable upwards (in absolute value).

extra: Victims of bullying tend to be mutual friends.

If bullying is associated with having many enemies and few friends, the obvious question is *whether victims of bullying are aware that they have many enemies (and few friends)*.



In sum, knowing who is and is not your friend is important.

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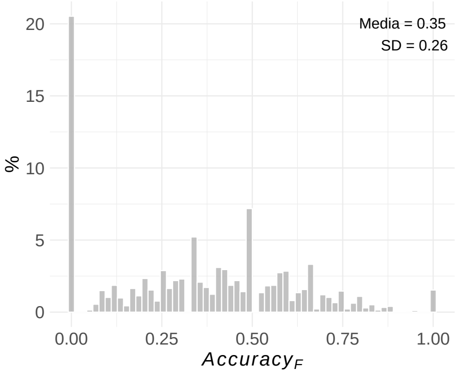
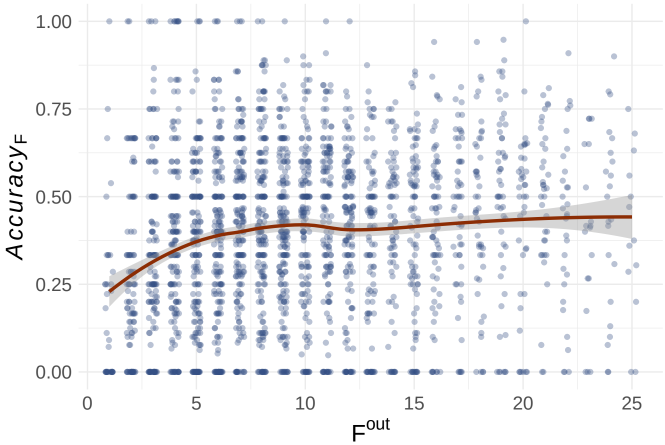


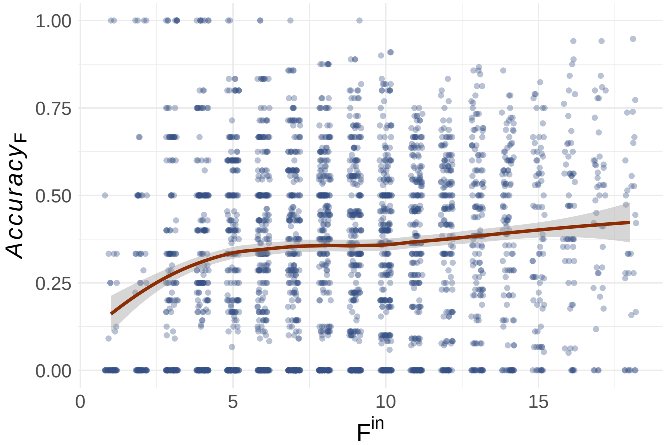
The average level of accuracy is pretty bad, $\mu = 0.35$

People tend to be **conservative** in their predictions—they usually expect fewer incoming friendship nominations ($\mu = 5.24$) than the number of friends they nominate themselves ($\mu = 8.34$). Yet their predictions remain fairly **inaccurate**.

We now test whether this reflects a **complexity** problem: children with many friends face a harder prediction task than those with few.



Accuracy does **not appear to be related** to task complexity as measured by outdegree.



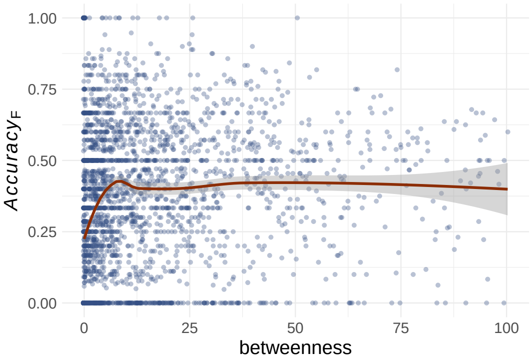
Likewise, accuracy shows **no association** with indegree.

Therefore, although the number of friends clearly increases the **complexity** of the prediction task, it does **not** seem to **affect people's accuracy**.

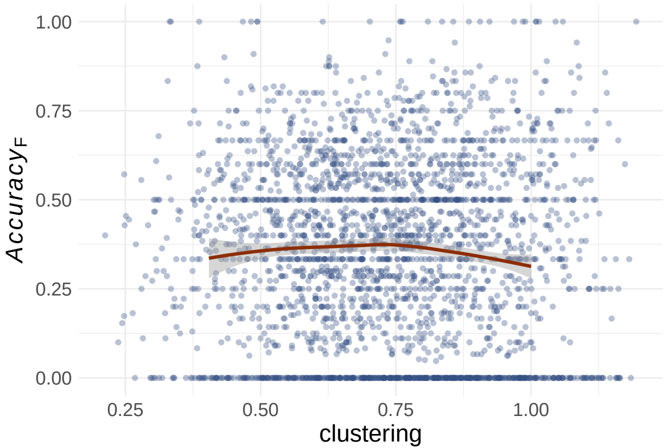
Accuracy is not explained by **complexity**.

Let's now look at centrality.

More **central** individuals should have **more information** about the social structure—and therefore should perform better.



Clearly, an individual's centrality does not explain their ability to make accurate predictions.



For completeness, we also examined clustering. The results are not particularly striking either.

More *informed* subjects do not make better predictions.

What can we conclude so far?

People are **conservative** in their predictions, they are **not very accurate**, and neither the number of friends (task **complexity**) nor their **centrality** (information available) helps explain why they perform poorly.

So now we need to rethink **how we measure predictive ability.** We need to go back to the source of the errors.

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0 = completely inaccurate
1 = perfectly accurate

Where inaccuracy comes from

Overestimation of non-existing friendships (False Positive)

$$FP_i = \left|\hat{F}_i^{in}(i) \setminus F_j^{in}(i)\right|$$

Underestimation of real friendships (False Negative)

$$FN_i = \left|F_j^{in}(i) \setminus \hat{F}_i^{in}(i)\right|$$

$$\text{Accuracy}_i = 1 - \frac{FP_i + FN_i}{\left|F_j^{in}(i) \cup \hat{F}_i^{in}(i)\right|}$$

Type 1: Overestimation

Everyone is my friend!

Children: Aidan, Mia, Lucas, Harper, Noah

Target child: **Aidan**

- Real incoming nominations: $A = \{\text{Mia}\}$
- Aidan's prediction: $B = \{\text{Mia}, \text{Lucas}, \text{Harper}\}$

Type 1 error (overestimation or False Positive):

$$B \setminus A = \{\text{Lucas}, \text{Harper}\}$$

Type 2 error: $A \setminus B = \varnothing$

Type 2: Underestimation

No one is my friend

Children: Sofia, Ethan, Lily, Mason, Chloe

Target child: **Sofia**

- Real incoming nominations: $A = \{\text{Lily}, \ \text{Chloe}\}$
- Sofia's prediction: $B = \{\text{Lily}\}$

Type 2 error (underestimation of False Negative):

$$A \setminus B = \{\text{Chloe}\}$$

Type 1 error: $B \setminus A = \varnothing$

Type 1 + Type 2: Mixed Errors

Children: Grace, Oliver, Ava, Henry, Zoe

Target child: **Grace**

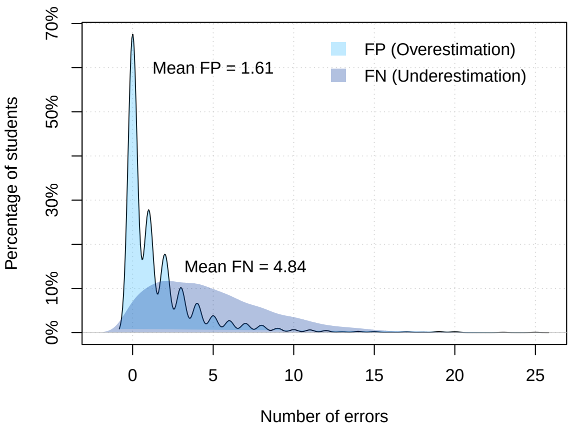
- Real incoming nominations: $A = \{\text{Oliver}, \text{Ava}\}$
- Grace's prediction: $B = \{\text{Oliver}, \text{Zoe}\}$

Type 1 error (overestimation):

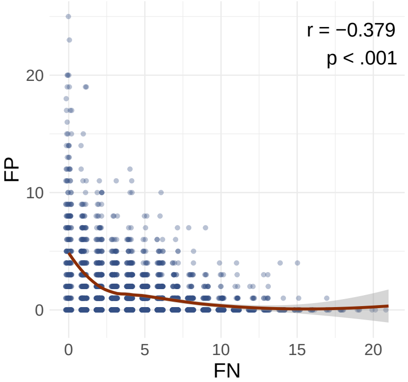
$$B \setminus A = \{\text{Zoe}\}$$

Type 2 error (underestimation):

$$A \setminus B = \{\text{Ava}\}$$

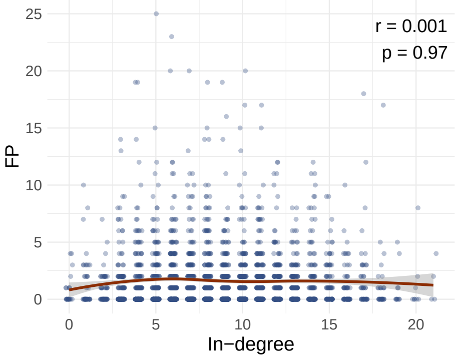


Overestimation is rare (> 60% make no mistakes), whereas **underestimation** is very common (only 1% make no errors).

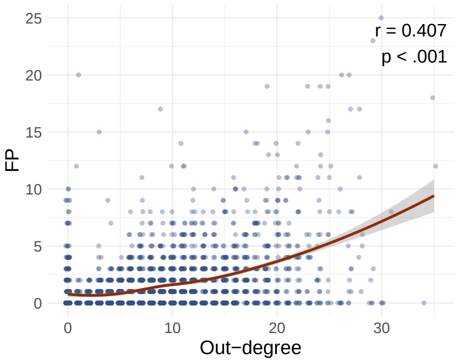


They appear to be **opposite skills**: *those who make mistakes on one side tend not to make them on the other.*

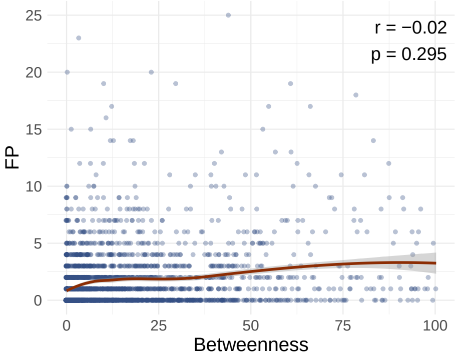
Overestimation



False positives are not related to degree-in ($p > 0.1$). Popularity doesn't make people optimistic (or likely to be overconfident).



False positives are indeed related to degree-out ($p < 0.001$). People with more friends tend to believe they have even more.

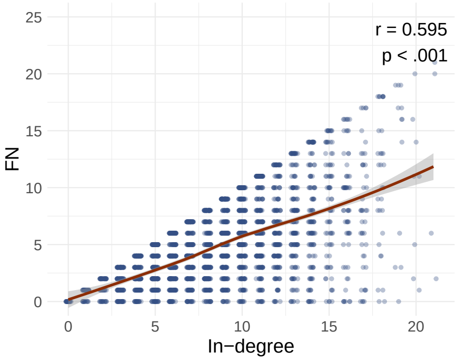


Access to more information (centrality) neither attenuates nor increases the overestimation.

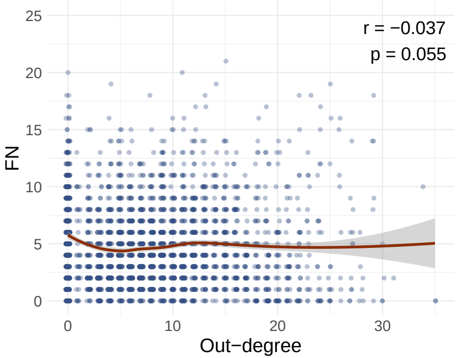
In sum, it seems that overestimation is related to out-degree and not to in-degree or centrality... which makes quite a lot of sense.

However, we must remember that overestimation is a minority phenomenon, since most people—more than 60%—do not make Type 1 errors. The real problem lies in Type 2 errors.

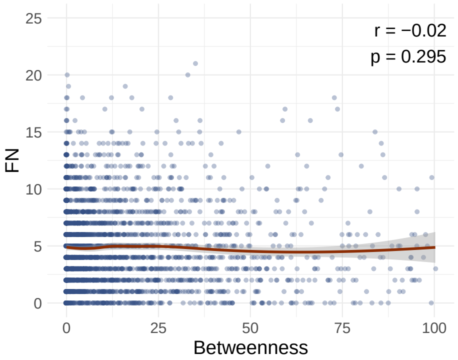
Underestimation



False negatives are strongly related ($p < 0.001$). Thus, **the most popular individuals are not aware** of their own popularity.



And individuals with higher out-degree do not commit Type 2 errors more frequently.



And once again, greater information access does not help them reduce Type 2 errors.

In sum, the most common error in friendship perception—Type 2 error—is largely explained by (lack of knowledge of) popularity and is uncorrelated with out-degree or centrality.

Therefore

What does it mean that Type 2 error is not correlated with out-degree?

It means that the inconsistency problem we previously considered does not appear to be relevant.

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... *Type 2 error is not correlated with centrality?*

having more information does not mitigate the problem at all.

Therefore

What does it mean that Type 2 error is not correlated with out-degree?

It means that the inconsistency problem we previously considered does not appear to be relevant.

... Type 2 error is not correlated with centrality?

having more information does not mitigate the problem at all.

... Type 2 error is strongly correlated with popularity?

popular people do NOT know they are popular... which brings us back to Kovarik et al. (2025), but with a much simpler device.

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Accuracy and errors

	AC	T1E: FP	T2E: FN
AC	1.000		
FP	0.113***	1.000	
FN	-0.564***	-0.359***	1.000

Accuracy is explained by false positives, but especially *by false negatives*.

And what are the false negatives associated with? With popularity.

Predicting others

Predicting who is the most central and most popular individual in a network is very common in the literature.

	T1E: FP	T2E: FN	PopPredB	PopPredB
FP	1.000			
FN	-0.359***	1.000		
PopPredB	0.014	-0.024	1.000	
CenPredB	-0.016	-0.028	0.163***	1.000

However, we observe that neither false positives nor false negatives are related to those abilities.

Conclussions

- Using an extremely simple mechanism, we observe that people do not know who their friends are. The level of accuracy is terribly low.
- They make Type 1 errors (overestimation), but above all they make Type 2 errors (underestimation).
- And these Type 2 errors are explained by the fact that individuals are unaware of their own popularity.
- Moreover, those who make Type 1 errors do not make Type 2 errors, and vice versa.
- And neither group is able to predict others' centrality or popularity.

huge thanks!!

further questions: branasgarza@gmail.com

Open call for papers

- Behavioral and experimental networks
- From childhood to adulthood
- Causal behavioral finance (coming soon)
- Null results in experiments (coming soon)