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The Face of Social Networks: Naive Observers' Accurate Assessment of Others' Social Network Positions From Faces

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Abstract

We examined whether, even at zero acquaintance, observers accurately infer others' social network positions—specifically, the number and patterning of social ties (e.g., brokerage—the extent to which a person bridges disconnected people) and the trait impressions that support this accuracy. We paired social network data ($n = 272$ professional school students), with naive observers' ($n = 301$ undergraduates) judgments of facial images of each person within the network. Results revealed that observers' judgments of targets' number of friends were predicted by the actual number of people who considered the target a friend (in-degree centrality) and that perceived brokerage was significantly predicted by targets' actual brokerage. Lens models revealed that targets' perceived attractiveness, dominance, warmth, competence, and trustworthiness supported this accuracy, with attractiveness and warmth most associated with perceptions of popularity and brokerage. Overall, we demonstrate accuracy in naive observers' judgments of social network position and the trait impressions supporting these inferences.

Keywords

social vision, social networks, face perception, social evaluation

Social networks represent complex webs of social relations. Within such networks, some individuals may have many friends, while others have few. Some individuals may connect disparate groups, while others may interact primarily within a group of densely interconnected people. While we accurately perceive such characteristics about others within our own social networks (L. C. Freeman & Webster, 1994; Parkinson et al., 2017), the accuracy and basis of our judgments about unknown others' social network positions remain unknown. Here, we investigate whether observers accurately infer social network position from faces and the trait impressions that support these inferences.

A growing body of evidence highlights the importance of understanding how we represent and perceive relationships within our social networks (Brands, 2013; Kilduff & Krackhardt, 1994; Smith et al., 2020). These studies on cognitive social structure have largely examined the accuracy with which we represent social relationships between others (L. C. Freeman & Webster, 1994; Krackhardt, 1987) and the correlates of that accuracy, such as being viewed as more powerful by peers (Krackhardt, 1990), being rated as a better performer (Yu & Kilduff, 2020), and being able to build better coalitions (Janicik & Larrick, 2005). Yet, this work has solely focused on perceivers who are already embedded within networks, leaving open the question of whether naive observers are able to assess characteristics of an individual's social network position (e.g., how many friends they have, the extent to which they "bridge" between otherwise disconnected individuals) from purely visual cues (e.g., faces).

While the idea that we can gauge a stranger's social connections simply by viewing their face is provocative, social vision and thin-slice research have long demonstrated that naive observers make keen and discerning judgments about others from minimal informational cues (Ambady & Rosenthal, 1993; Weisbuch & Ambady, 2010). Across multiple domains, perceivers accurately assess consequential outcomes associated with one's social and relational standing with others, such as electoral success (Rule & Ambady, 2010), personality traits such as extraversion (Connelly & Ones, 2010), teaching ability

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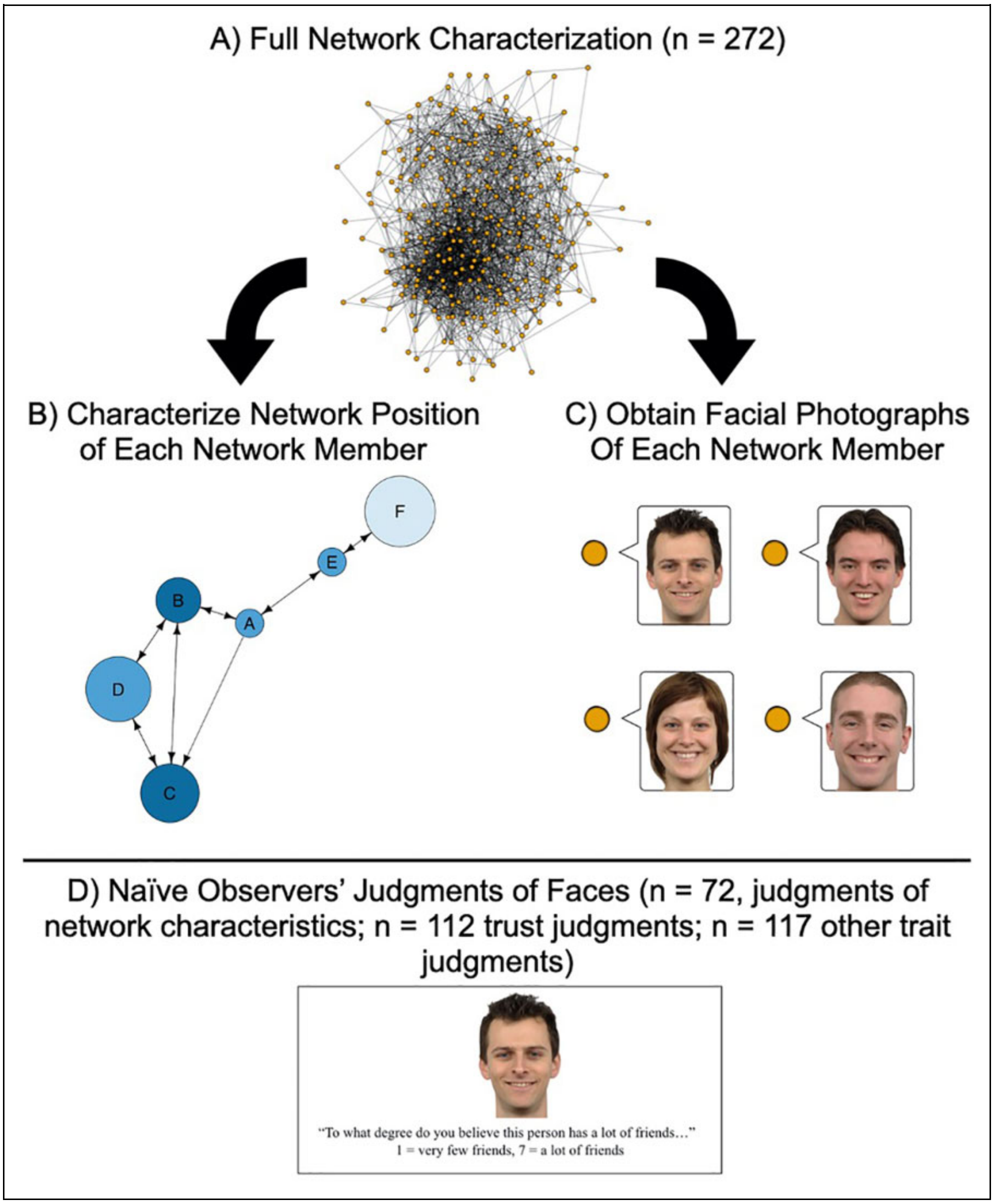

Figure 1. Schematic of study design. (A) Full network characterization: The social network comprised a cohort of first-year professional school students who completed a peer-nomination survey and submitted facial photos ($N = 272$). Nodes represent the students and lines represent mutually reported friendship ties. (B) Characterize network position of each network member: Here, we visually depict a small, example social network with the directionality of relationship ties represented by arrows. We calculated three measures of social network position for each person in the social network. First, in-degree centrality (the number of times each person was named as a friend by others) is visually depicted by darker shades representing higher in-degree centrality (e.g., node B's in-degree centrality is 3, while node F's in-degree centrality is 1). Second, we calculated out-degree centrality, or the number of friends each person named (not shown). Lastly, we calculated constraint, visually depicted by larger nodes representing higher constraint (brokerage is calculated as the inverse of constraint). (C) Obtain facial photographs of each network member: For each person within the social network, we obtained their facial photograph. The photos represented in the figure are *not* the true target photos but rather, illustrative placeholders from the Radboud Face Database (Langner et al., 2010); these are used to preserve our participants' anonymity. (D) Naive observers' judgments of faces: Samples of undergraduates, from a different institution than where the social network data were collected, rated each face on social network characteristics—network size, and in a different block (counterbalanced), brokerage ($N = 72$)—or rated each face in terms of trust ($N = 112$), or rated all faces on a subset of traits such as attractiveness, dominance, warmth, and competence ($N = 117$).

of faculty (Ambady & Rosenthal, 1993), social status (Hall & Friedman, 1999), the attained rank of military officers (Mazur et al., 1984), and even the profitability of CEOs (Rule & Ambady, 2008). Indeed, recent work finds that within small, eight-person ego-centric networks (i.e., where one person lists up to eight friends and the relationship ties connecting those eight people), a short video clip is sufficient to allow naive observers to accurately judge network size and gender composition (Mobasseri et al., 2016). Overall, this surprising accuracy in person perception reflects a ubiquitous tendency to make rapid social inferences about others in our environment.

In the present study, we use a full network analytic approach (see Figure 1) to assess whether naive observers accurately infer social network characteristics—popularity (*in-degree centrality*), self-reported network size (*out-degree centrality*), and aspects of network structure (*constraint*)—from facial images. The first two metrics provide a comparison between an individual's actual and self-perceived social connections. That is, *in-degree centrality* is a measure of how many individuals name that person as one of their friends, while *out-degree centrality* is a measure of how many people an individual marks as their friend (whether this social tie is reciprocated or not). The final metric, *constraint*, assesses the degree to which an individual is able to connect other people within the network who would not otherwise know or connect with each other (Burt, 1992). This measure offers insight into whether an individual has high or low brokerage and thus would be able to pass information or resources through the network, representing a more complex social network characteristic.

A key feature of our network data is that the network and social ties can be characterized as highly cohesive and largely closed (i.e., first-year students at a professional school in a rural location where students mainly live, eat, socialize, and work with one another). Thus, while focused on a particular target's social sphere, we likely captured many of each person's day-to-day social relationships. This approach allows us to comprehensively characterize the number and structure of social ties surrounding each target, and thus, meaningfully test whether naive observers' judgments of social network friendships and brokerage are predicted by target's real-world social network positions. Additionally, we examine common trait impressions—attractiveness, dominance, warmth, competence, and trustworthiness—to determine which traits are associated with perceived and actual network characteristics using a Brunswikian lens model (Brunswik, 1943, 1955), aligning with recent work indicating these traits predict network characteristics such as in-degree (Zhang et al., 2019). Overall, this integration of social network data and social perception research provides a novel examination into naive observers' accurate assessment of others.

Method

Facial Stimuli

Stimuli comprised 272 facial photographs (91 women) that were self-submitted by professional school students for inclusion in a class photo book. The photos were of high quality and relatively standardized (i.e., a blank White background, forward-facing, professional attire). We excluded five individuals from the stimulus set who either did not submit a photo or whose photo was nonstandard (e.g., used a color filter).

Social Network Data

All students included in the facial stimuli set previously completed a social network characterization study (see Parkinson et al., 2017) to fulfill a course requirement (99.3% response rate). The social network survey was administered approximately 4 months after students arrived on campus, thus allowing for the formation of relevant social ties. All studies were approved by the respective Institutional Review Boards.

For the social network study, participants were emailed a link to a website where they answered a question used in previous network research (see Feiler & Kleinbaum, 2015; Kovacs & Kleinbaum, 2020):

> Consider the people with whom you like to spend your free time. Since you arrived at [institution name], who are the classmates you have been with most often for informal social activities, such as going out to lunch, dinner, drinks, films, visiting one another's homes, exercising together, and so on?

All participants were presented with a class roster that consisted of the names of all students in their cohort, ameliorating the potential issue of students' biased recall of names (Brewer, 2000). Participants were given an unlimited amount of time to mark each person who fit the criteria and could indicate as many people as desired, with a minimum of two.

Social network position characteristics were computed in R using the igraph package (Csardi & Nepusz, 2006; R Core Development Team, 2014). Our full network analytic approach, in which nearly all participants in a bounded community reported their social ties, allowed us to calculate three metrics for each person in the social network: (1) *in-degree centrality* (i.e., the number of people who listed the target as a friend), (2) *out-degree centrality* (i.e., the number of people whom the target listed as a friend), and (3) *structural constraint* (i.e., the degree to which one's social ties are concentrated within a single interconnected group of people; an inverse measure of network brokerage; Burt, 1992).

Social Perception Judgments

A separate sample of undergraduate participants ($N = 72$) from a different institution provided judgments of the 272 stimuli. Given the large number of target images being rated, we aimed to recruit a minimum of 60 participants. To achieve this sample size, we collected data in lab for a prespecified period of 2 weeks, recruiting a total of 72 participants (49 women, $M_{age} = 20.84$, $SD_{age} = 4.59$). A post hoc power analysis was run in R using 5,000 simulated data sets, with parameter values derived from our models and following guidelines by Muthén and Muthén (2002). Results from this analysis determined that we had an observed power of 98.9% to detect our effect given our sample size for both participants and targets.

In counterbalanced blocks, participants provided two judgments of each photograph. In one block, participants were asked, "To what degree do you believe this person has a lot of friends, that is, many people who they spend significant amounts of time socializing or communicating with" (1 = *very few friends*, 7 = *a lot of friends*). In the other block, participants were asked, "To what degree does this person, connect, or 'broker' between people who don't socialize or communicate with each other directly" (1 = *low brokerage*, 7 = *high brokerage*). Prior to making the judgments, brokerage was defined with an infographic (see Supplemental Material). After all judgments were completed, participants provided demographic information (e.g., age, gender) and were debriefed.

For the trait ratings, we recruited two different sets of participants to rate all 272 faces on attractiveness, dominance, warmth, competence, and trustworthiness. Initially, to assess participant fatigue given the large number of judgments, we recruited one set of participants (N = 112, 83 women, M_{age} = 19.84, SD_{age} = 1.10) to rate each face on trustworthiness (1 = *definitely not trustworthy*, 9 = *definitely trustworthy*). We subsequently recruited another set of participants (N = 117, 83 women, M_{age} = 20.31, SD_{age} = 1.25) to rate each face on two randomly selected dimensions (i.e., attractiveness, dominance, warmth, and competence; 1 = *extremely not attractive, definitely not dominant, extremely cold, extremely not competent*, 7 = *extremely attractive, definitely dominant, extremely warm, extremely competent*). For this second set of participants, traits were presented in two separate blocks such that participants rated all 272 faces on one trait in one block, and then rated all 272 faces on the other dimension in another block. This procedure meant that each face, for each social dimension, was rated by at least 88 participants.[1] For all ratings, faces were presented in a random order. We combined these data with the initial ratings data (see above), to create average scores per face (see Supplemental Table S1 for intraclass correlations), for each rating and perceived social network characteristic and used these data for our lens models.

Results

Given the nesting of our data, we computed linear mixed models using residual maximum likelihood estimation in the R packages "lme4" and "lmerTest" (Bates et al., 2015; Kuznetsova et al., 2015). For these models, we included random factors for both participants and targets, with random intercepts for both factors (Judd et al., 2017); random slopes were not included due to model convergence and singularity issues.[2] All predictors were grand-mean centered prior to being included in the model. For descriptive statistics of predictors and outcomes, see Supplemental Table S4. De-identified data and analytic code are available at https://osf.io/3vxga/?view_only=48512b530c8740078edeb54fc572645e.

First, we examined whether participants' judgments of the perceived number of friends were predicted by targets' actual in-degree centrality scores (i.e., the number of people within the social network who list a given target as a friend). Results indicated that targets' in-degree centrality scores predicted participants' perceived number of friends, $B = 0.17$, $SE = 0.04$, $t(270.00) = 4.48$, $p < .001$, 95% CI [0.09, 0.24]. In contrast, we found that targets' out-degree centrality scores (i.e., the number of people whom a target lists as friends) did not predict participants' ratings of perceived number of friends, $B = 0.06$, $SE = 0.04$, $t(270.02) = 1.50$, $p = .134$, 95% CI [−0.02, 0.13]. Overall, these results suggest that observers' judgments accurately reflect targets' actual social network centrality based on the number of people who name that person as a friend but not based on the number of people whom that person lists as a friend.

Next, we tested whether participants' ratings of brokerage (i.e., the degree to which a person is judged to connect disparate people) were predicted by constraint.[3] We found that actual brokerage predicted judged brokerage, $B = 0.06$, $SE = 0.03$, $t(270.01) = 2.47$, $p = .014$, 95% CI [0.01, 0.11]. These data indicated that naive observers accurately infer, from face images, not only how many friends a stranger has but also structural characteristics of the social ties surrounding that person.

One question regarding the above results is the degree of consensus achieved across our raters. In order to quantify consensus, we calculated the interclass correlation coefficients (ICCs) using null models for the outcomes perceived number of friends and perceived brokerage. Here, ICCs indicate the percentage of variance in our dependent variable explained by target and perceiver characteristics (Kenny, 1994), with the remaining variance considered residual. We focus on target ICCs to quantify consensus or the amount of variance in our dependent variable (i.e., perceived number of friends or perceived brokerage) that is accounted for by the images being rated as opposed to the raters (i.e., perceiver ICC). We calculated target ICC and 95% CIs based on 5,000 bootstrapped samples using code available at (hehmanlab.org/toolbox). For perceived number of friends, target ICC was 0.17 (95% CI [0.14, 0.20]) and for perceived brokerage, target ICC was 0.07 (95% CI [0.05, 0.08]). For comparison, for perceived number of friends, perceiver ICC was 0.21 (95% CI [0.14, 0.20]), and for perceived brokerage, perceiver ICC was 0.18 (95% CI [0.13, 0.23]). These values align with prior work examining the influence of target versus perceiver characteristics across a variety of trait impressions (see Hehman et al., 2017), which found target ICCs to be higher for traits that have been consistently tied to particular facial features, such as trustworthiness (0.234), compared to traits that may be not as closely linked to particular facial features, such as creativity (0.062). Overall, these target ICCs provide context for the accuracy achieved by our participants, indicating some degree of consensus across raters for our dependent variables; that said, this degree of consensus was lower for perceived brokerage, likely reflecting the uncertainty associated with this judgment.

Lastly, we used lens models to descriptively assess which trait ratings of faces were associated with actual and perceived social network characteristics. Specifically, we calculated the diagnosticity of cues (i.e., which trait ratings were associated with actual social network characteristics) and the utilization validity of cues (i.e., which trait ratings were associated with perceived social network characteristics). To compute each

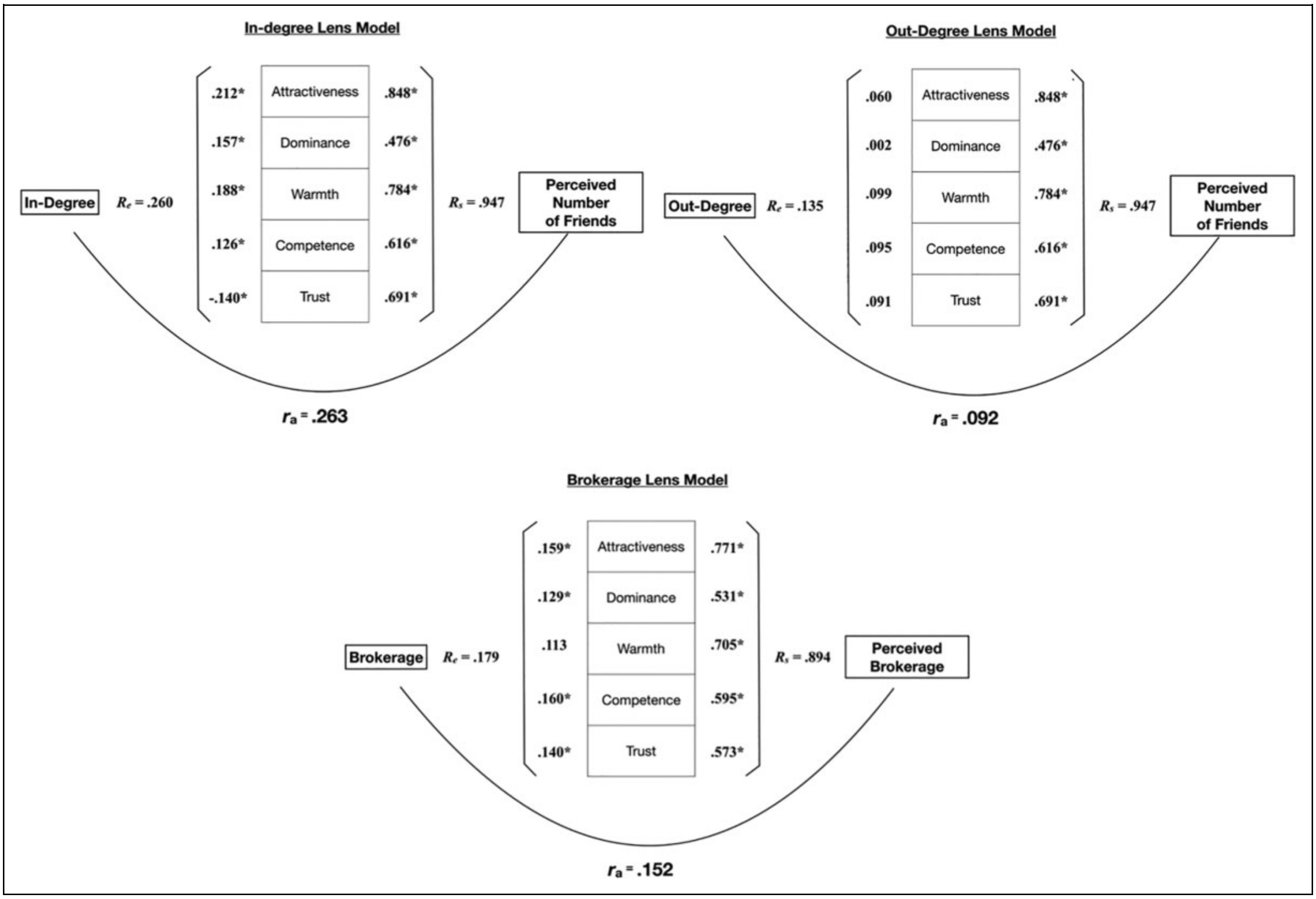

Figure 2. Lens models showing associations between social network characteristics (left) and average perceived social network characteristics (right). Values within the brackets are the zero-order correlations between the trait rating and the actual and perceived social network characteristics. *R* values next to the brackets represent the diagnosticity (left) and utilization validity (right) for the trait ratings as a whole. Overall index of achievement is noted at the bottom of each arch. See Supplemental Materials for model equation and model parameters. $^*p < .05$.

model, we calculated zero-order correlations between average scores for each trait and true and perceived social network characteristics for each face. We then used Tucker's (1964) lens equations to assess diagnosticity, utilization validity, and an overall index of achievement—that is, the degree to which trait ratings as a set were associated with accurate inferences (see also Stewart, 2001).

While results from these models are descriptive in nature, they reveal a number of insights. As shown in Figure 2, all averaged trait ratings were positively associated with perceived number of friends and perceived brokerage; trait ratings were also positively associated with actual social network characteristics, although these associations were weaker. Examining specific traits reveal that attractiveness and warmth had the strongest correlations with actual in-degree centrality, matching the pattern of correlations with perceived number of friends. This differs for brokerage: Attractiveness and *competence* had the strongest correlations with actual brokerage, yet attractiveness and *warmth* had the strongest correlations with perceived brokerage. Additionally, we did not find strong associations between trait ratings and actual out-degree centrality, aligning with the prior finding that perceptions of this characteristic were not accurate. Finally, for both in-degree centrality and brokerage, we see that as a set, trait ratings achieve relatively high utilization validity ($R_s = .947$ and .894, respectively) but relatively low diagnosticity ($R_c = .260$ and .179, respectively), which suggests that while strong associations exist between trait ratings and perceived social network characteristics (e.g., the perception that attractive individuals will have many friends), these trait ratings serve only as moderately valid cues. This is further demonstrated by the overall index of achievement (i.e., the relationship between actual and perceived social network characteristics) being rather modest for in-degree centrality ($r_a = .263$) and brokerage ($r_a = .152$).

Discussion

Using a full network approach to characterize a 272-person network, we found that naive observers made accurate judgments about others' social network positions from faces. Specifically, observers' judgments of how many friends a target has predicted targets' in-degree, but not out-degree, centrality and observers' perceived brokerage predicted targets' actual brokerage. Furthermore, lens models reveal that trait impressions were highly associated with perceived network characteristics, but were modestly associated with actual social network data, which was reflected in smaller indexes of achievement, particularly for out-degree centrality, corroborating results of perceivers' accuracy.

These findings advance our understanding of social network perception by examining the accuracy of naive observers' network judgments from visual cues and continue a tradition of "thin slice" research. While accuracy was achieved, our results do not indicate a one-to-one correspondence between naive observers' judgments and social network standing. Indeed, our results suggest a small effect, with a one-unit increase in a target's in-degree centrality/brokerage leading to a 0.17 and 0.06 increase in perceived number of friends and perceived brokerage, respectively. Interestingly, our results can be compared to the much higher fidelity found by Parkinson and colleagues (2017) who tested perceived social network characteristics for individuals who were members of the social network and thus knew the target. In addition, while estimating an effect size metric to directly compare with prior work is difficult and best practices are still unclear, especially for crossed linear mixed models with two random factors, we suggest that our findings would be lower than the correspondence between other/self and stranger's ratings for big five personality traits (e.g., meta-analytic correlations between 0.18 and 0.37, see Connelly & Ones, 2010; for comparison, our correlations between perceived and actual number of friends, and between perceived and actual brokerage, were 0.11 and 0.04, respectively). Still, given that our perceivers are complete strangers to the targets and must rely solely on visual cues for making their judgments, the fact that we found some predictive validity is noteworthy.

Additionally, two insights regarding our methods and the lens models deserve further note. First, a full network approach (compared to an ego-centric approach, see Mobasseri et al., 2016) allowed us to test our hypotheses in perceiving social connections within a relatively bounded community (e.g., a cohort of professional school students). Crucially, we were able to calculate the directionality of social relationship ties, which revealed that observers' judgments of popularity were predicted by a more actuarial measure of popularity (in-degree centrality) but not by a more ego-centric one (out-degree centrality). One possible explanation for this divergence could be that people have different thresholds for who qualifies as a friend, an intrapersonal construct that is likely less accessible to perceivers from faces and also generates greater noise for the out-degree measure. This noise, however, is reduced for in-degree centrality and brokerage, as both are derived from the collective responses from social network actors. Overall, this research highlights the value in understanding not only the present social structure but also the possibly biased or faulty cognitive representation of social relationships (Brands, 2013).

Second, our lens models reveal traits that inform naive observers' accuracy. While the lens model approach does not allow for direct testing of differences across various traits, as it is purely descriptive in nature, an inspection of correlations does reveal some insights. For brokerage, warmth was not significantly correlated with actual brokerage, however, highly correlated with perceived brokerage; competence, while correlated with both actual and perceived brokerage, had a lower correlation coefficient compared to warmth for perceived brokerage. This divergence suggests that people may use invalid cues when assessing a stranger's brokerage within a social network, possibly denoting the perception of distinct paths to social network prominence (Cheng et al., 2013).

This demonstration of naive observers' accuracy in perceiving others' social network characteristics suggests interesting future directions for both perceivers and targets of evaluation. Regarding perceivers, an intriguing set of questions emerges regarding the functionality of assessing social network characteristics from faces and the degree to which this skill could be improved. Given our lens model analysis, it may be the case that perceivers' accuracy is largely derived from integrating a set of visual cues with prior beliefs about sociality (e.g., an individual who is viewed as warm and attractive is likely to connect otherwise unknown others). This idea would fit with connectionist models of social vision (J. B. Freeman et al., 2020), whereby trait judgments are derived from a combination of visual cues and our social–conceptual knowledge (e.g., what makes someone a broker or popular). An interesting test of these questions may be the degree to which accurate perception of network characteristics is tethered to presentation and/or judgment speed. If perceiving social network characteristics is more "foundational," it may be the case that accuracy (and consensus) remains under time constraints on presentation and/or judgment time; however, if integration across multiple cues is required, accuracy (and consensus) may decrease, similar to results for traits such as intelligence (Bar et al., 2006).

In addition, as a whole, perceivers were accurate in assessing in-degree centrality and brokerage; however, there was variability in participants' accuracy. It may be the case that certain individuals are more attuned to the network characteristics of others given brief information which may confer particular advantages. Similar to work demonstrating that individuals who hold more accurate representations of status relationships being rated as better performers (Yu & Kilduff, 2020), individuals who, upon first glimpse, can more accurately identify well-connected others may be able to leverage that information to put themselves in advantageous positions within an organization. Indeed, the power advantage derived by those who accurately perceive the "political landscape" (Krackhardt, 1990) may begin even before people get to know one another.

With respect to targets, our lens model suggests particular cues (e.g., attractiveness, warmth) that might enhance one's perceived social connections, although these traits are only modestly associated with actual network position. Further, there is variation across stimuli in the extent to which the observable traits explained their network position: Not surprisingly, some people derive high (or low) network centrality from attributes of their personality which are not visually discernable to others. Still, if perceivers make inferences about social connections based on particular facial traits, these cues may serve as scaffolding by which perceivers intuit social relationships, creating self-fulfilling prophecies whereby people associate more with those who look like they have many friends. Indeed, at the group selection level, research suggests that facial cue similarity predicts group affiliation (Hehman et al., 2018). Future work should test whether ratings of targets, prior to meeting, predict the social relations that emerge within a particular network.

While our work demonstrates a novel domain for which we have accuracy in our thin-slice perception of others and advances a number of future directions, it is not without limitations. Importantly, while we assessed common trait impressions (Oosterhof & Todorov, 2008), we limited the number of rated traits due to possible participant fatigue. We believe other visually assessed traits may be predictive of each of our network characteristics (e.g., out-degree centrality is associated with narcissism, Holtzman, 2011). We were also limited to a single social network, one made up of a dense web of social ties. While this is a common network structure (Kilduff et al., 2008), other work should expand to sample other networks and domains, such as companies or other organizations (see Yu & Kilduff, 2020). Lastly, our naive observers, while typical for social perception studies, could be more representative and should extend beyond student samples.

Overall, we show that people accurately infer aspects of strangers' social network positions (specifically, in-degree centrality and brokerage) merely from viewing facial images. Furthermore, common face-based trait impressions reveal how this accuracy is achieved, with traits such as attractiveness, warmth, and competence, highly related to perceived social network position, although only modestly associated with actual social network position. These findings extend a rich tradition in person perception research, demonstrating accuracy from first impressions of faces in a relationally consequential domain—real-world social networks.

Declaration of Conflicting Interests

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. We assessed the stability of our means, that is, whether adding more participant ratings would significantly change our mean rating, using code from Hehman, Xie, et al. (2018). Results revealed a 0.5 corridor of stability was achieved with a minimum of 37–69 raters (see Supplemental Table S2 for exact values per trait). Our sample size exceeded these minimum values for all ratings.
2. We report in Supplemental Materials models with random slopes where singularity, and not model convergence issues, emerged; however, we note here that the inclusion of random slopes does not change the direction or significance of our results.
3. Constraint is an inverse measure of brokerage within a social network. For ease of interpretation, we multiplied constraint values by −1. Thus, we anticipate a positive relationship between perceived and actual brokerage.

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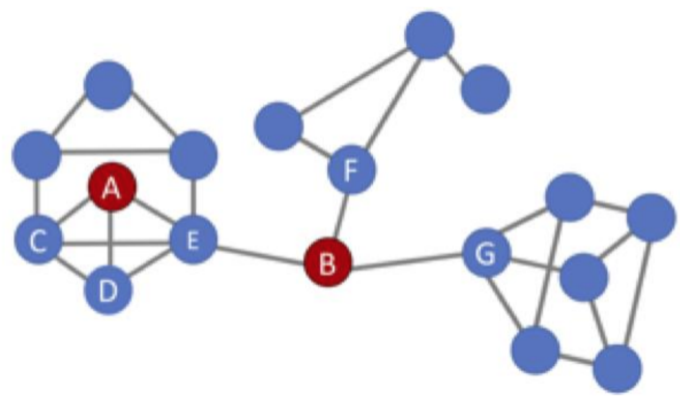
Online Supplemental Material for “The Face of Social Networks: Naïve Observers’ Accurate Assessment of Others’ Social Network Positions from Faces”

Supplemental Method

In this block, we are going to ask you about a concept called “brokerage".

Some people’s friends are all friends with one another, whereas other people participate in many distinct social circles. In other words, some people “**bridge**” or “**broker**” between people who don’t socialize or communicate with each other directly.

For example, in the social network diagram below:



- **Person A** would be considered LOW in brokerage because A's friends (C, D and E) are all friends with each other.

- In contrast, **Person B** would be considered HIGH in brokerage because B’s friends (E, F and G) do not communicate or socialize with each other directly (i.e. are not connected except through B).

Please note: Brokerage isn’t about how many friends someone has, but whether someone’s friends are friends with one another.

Please go with your best guess as to how much the person you see has friends who are all friends with each other (low brokerage) or is friends with people who do not socialize or communicate with each other directly (high brokerage).

Supplemental Figure 1. The following infographic was used to describe to participants the concept of brokerage. All participants saw this information before the brokerage question block.

Supplemental Table 1.
Intraclass Correlations and 95% Confidence Intervals (CIs) for Trait Judgments

Trait	Perceiver ICC	[95% CIs]	Target ICC	[95% CIs]
Attractiveness	0.35	[0.29, 0.42]	0.18	[0.15, 0.21]
Competence	0.37	[0.30, 0.44]	0.06	[0.05, 0.08]
Dominance	0.32	[0.26, 0.39]	0.07	[0.06, 0.08]
Trustworthiness	0.18	[0.14, 0.26]	0.13	[0.11, 0.15]
Warmth	0.18	[0.14, 0.23]	0.13	[0.11, 0.15]

	Corridor of Stability	
Trait	**+/-1.00**	**+/- 0.50**
Attractiveness	18	68
Competence	15	57
Trust	12	51
Warmth	15	59
Dominance	10	39
Num. of Friends	9	37
Brokerage	17	69

Supplemental Table 2. Values within the table indicate the estimated number of participants required to achieve a stable mean based on the corridor of stability value. As shown, our sample size was greater than all required values. We take this as evidence that our means are reliable. Within the R code, our parameter, *inarow* = 20.

Supplemental Table 3.
Parameters Used in Lens Model Equations

	Model Parameters				
Model	R_e	Rs	C	G	r_a
In-degree	0.26	0.947	0.094	0.951	0.263
Out-degree	0.135	0.947	0.059	0.57	0.092
Brokerage	0.179	0.894	0.024	0.882	0.152

Lens Model Equation (Tucker, 1964; also see Stewart, 2001):

$$r_a = GR_eR_s + C\sqrt{1 - R_s^2} \times \sqrt{1 - R_e^2}$$

Supplemental Table 4. Means and standard deviations for key variables

Variable	Mean	Standard Deviation
Social Network Characteristics		
In-Degree Centrality	30.09	13.97
Out-Degree Centrality	30.43	28.03
Constraint (Brokerage)	-0.05	0.25
Perceiver Ratings		
Perceived Number of Friends	3.91	1.51
Perceived Brokerage	3.77	1.56

Supplemental Results

We report here model results where we included random slopes, but where singularity issues (i.e., variance of the random slopes < .003), rather than model convergence issues, emerged. We note that results reported here very closely match results reported in the main manuscript. For in-degree, a model with random slopes for both target and perceiver indicated that in-degree centrality scores predicted participants' perceived number of friends, $B = 0.17$, $SE = 0.04$, $t(198.45) = 4.32$, $p < .001$, 95% CI [0.09, 0.24]. In addition, when including random slopes for only target, $B = 0.17$, $SE = 0.04$, $t(176.46) = 4.50$, $p < .001$, 95% CI [0.09, 0.24], or only perceiver, $B = 0.17$, $SE = 0.04$, $t(296.56) = 4.30$, $p < .001$, 95% CI [0.09, 0.24], results mirror findings reported above.

For out-degree, a model with random slopes for both target and perceiver indicated that out-degree centrality scores did not significantly predict participants' perceived number of friends, $B = 0.06$, $SE = 0.04$, $t(56.55) = 1.43$, $p = .159$, 95% CI [-0.02, 0.14]. In addition, when including random slopes for only target, $B = 0.06$, $SE = 0.04$, $t(53.82) = 1.45$, $p = .154$, 95% CI [-0.02, 0.14], or only perceiver, $B = 0.06$, $SE = 0.04$, $t(279.86) = 1.48$, $p = .140$, 95% CI [-0.02, 0.13], results mirror findings reported above.

For constraint, a model with random slopes for both target and perceiver and a model with random slopes on target both failed to converge. A model with random slopes for perceiver indicated that constraint predicted perceived brokerage, $B = 0.06$, $SE = 0.03$, $t(270.10) = 2.28$, $p = .023$, 95% CI [0.01, 0.12].

We examined whether participant gender interacted with our results, although we caution against a strong interpretation of these effects, given our lower number of men ($n = 19$) in the sample of perceivers. For in-degree and brokerage, there were no significant interaction effects with participant gender (ps > .520). For out-degree, there was an unexpected significant interaction between participant gender and out-degree (p = .001). Results, however, when examining men and women, revealed no significant effect of out-degree predicting perceived number of friends for men (p = .740) or women (p =.072), consistent with the non-significant result reported in the main paper.

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