Availability of demographic cues can negatively impact creativity in dynamic social networks

Raiyan Abdul Baten\(^1\), Gourab Ghoshal\(^2\), Mohammed Ehsan Hoque\(^3\)*

\(^1\) Department of Electrical and Computer Engineering, University of Rochester, NY, USA
\(^2\) Department of Physics and Astronomy, University of Rochester, NY, USA
\(^3\) Department of Computer Science, University of Rochester, NY, USA
* mehoque@cs.rochester.edu

Abstract

As the world braces itself for a pandemic-induced surge in automation and a consequent (accelerated) shift in the nature of jobs, it is essential now more than ever to understand how people’s creative performances are impacted by their interactions with peers in a social network. However, when it comes to creative ideation, it is unclear how the demographic cues of one’s peers can influence the network dynamics and the associated performance outcomes of people. In this paper, we ask: (1) Given the task of creative idea generation, how do social network connectivities adapt to people’s demographic cues? (2) How are creative outcomes influenced by such demography-informed network dynamics? We find that link formations in creativity-centric networks are primarily guided by the creative performances of one’s peers. However, in the presence of demographic information, the odds of same-gender links to persist increase by 82.03\%, after controlling for merit-based link persistence. In essence, homophily-guided link persistence takes place when demographic cues are available. We further find that the semantic similarities between socially stimulated idea-sets increase significantly in the presence of demographic cues (\(P < 10^{-4}\)), which is counter-productive for the purposes of divergent creativity. This result can partly be explained by the observation that people’s ideas tend to be more homogeneous within demographic groups than between demographic groups (\(P < 10^{-7}\)). Therefore, choosing to maintain connections based on demographic similarity can negatively impact one’s creative inspiration sources by taking away potential diversity bonuses. Our results can inform intelligent intervention possibilities towards maximizing a social system’s creative outcomes.

Keywords— Dynamic Social Networks | Creativity | Diversity | Homophily

Humans are understood to be superb social learners [1]. Rather than re-inventing solutions to complex problems, humans tend to inherit them culturally from people who have already figured the solutions out [2]. In doing so, humans are known to employ cues such as skill/competence, success, prestige, age, health and self-similarities to assess who most likely possess information useful to the learner, and form social links accordingly [3, 4, 5, 6]. An aspiring hunter-gatherer will look for expertise cues when choosing who to learn hunting skills from, a child will see who hangs out near its mother to know who to trust, so on and so forth. When it comes to creative idea generation, exposure to highly creative ideas are known to stimulate further novel ideas in people [7, 8, 9, 10, 11]. It is therefore of no surprise that humans look up to the most creative individuals among them for creative stimulation and inspiration [12]. If the connectivities among people who are striving to gen-
Figure 1: **Experimental Setup.** (A) The bipartite network structure used in the study. The ideas of the alters were pre-recorded and later shown to the egos in both study conditions. Each ego was connected to 2 alters. (B) The study protocol for each of the 5 rounds. In turn 1, the participants generated alternate use ideas on their own for a given prompt object. In turn 2, egos in the control condition were shown only the ideas of their alters, while both the ideas and the demographic information of the alters were shown to the egos in the treatment condition. The egos could add further inspired ideas to their lists. Finally, the egos rated the ideas of all the alters in the trial, and had the option to update their sets of 2 alters at the end of each round.

Creative ideas are modeled as a social network—e.g., an academic network of researchers, or a network of marketers who seek to generate creative campaign ideas—one can reasonably expect that the highly creative people will become increasingly central in the network over time due to selective link formations [13].

A paradoxical set of possibilities emerge if, in addition to the creative aptitudes of people in the network, one also considers how people’s demographic identities might impact the network dynamics in a creativity-centric social system. On the one hand, there is the notion of a *diversity bonus* that can help in creative ideation [14]. People from different demographic identities (i.e., gender or race) come with different concerns, perspectives, and life experiences. This can impact the knowledge domains they have access to, influencing the ideas they generate [15, 16, 17]. Following the previous arguments, it seems provocatively promising for humans to form links with people from different demographic identities, so as to cash in on the diversity bonuses on offer. On the other hand, literature on social network formation and growth has extensively documented *homophily*, a phenomenon where people tend to form and sustain links with peers similar to themselves (‘Birds of a feather flock together’) [18]. It can then be argued that people might forego the potentials of diversity bonuses in favor of the more comfortable similarity-based network connections. Unfortunately, it is unclear from previous work how social networks might adapt to demographic cues when faced with creative ideation tasks. This leads to our first research question.

If indeed social network connectivities are biased by demographic cues, how might that impact creative outcomes? Previous work suggests that if multiple people draw inspirations from the same/similar stimuli, then even their independently stimulated ideas can become semantically similar to each other [12]. If people form and maintain social links only with peers from particular demographic identities (i.e., homophily-guided network dynamics), then it can result in making their stimuli set uniform as the diversity bonuses will go missing. This process can, consequently, hurt the variety of ideas stimulated—leading to counter-productive outcomes in the context of divergent creativity [19]. The converse is naturally likely if instead heterophily guides the network dynamics. Exploring the effects of demographic cues on creative outcomes formulates our second research query.

The importance of understanding these dynamics can be better appreciated in the context of the future of work. Advances in AI and automation are increasingly shifting the nature of jobs from physical labor to ones that require various social-cognitive avenues of soft skills, especially creativity [20, 21, 22, 23, 24, 25]. The COVID-19 pandemic is likely to accelerate this shift in jobs [26]. Future workplaces will increasingly demand people to be creatively productive together with their peers as they tackle complex problems [27]. In doing so, people will inevitably be exposed to the demographic cues of their peers [28]. Understanding how such cues can bias the dynamics of creativity-centric social systems is a prerequisite to any informed intervention that can potentially amplify the creative outcomes of people.

Yet, studying such a creativity-centric social system poses challenges of its own. While there exists a body of literature examining the effects of diversity on creative outcomes at individual and group
levels [15, 16, 14, 29, 30], such studies typically ignore the dynamic nature of human social networks. Human networks continuously change as new ties are created all the time and existing ones fade. Groups (i.e., fully connected networks) or static network settings fail to incorporate the effects of such dynamic link formation and dissolution, as the subjects either do not have the agency to choose their own social stimulation sources, or even if they do, it is not possible to unambiguously track such ties. As a result, effects from social network phenomena such as homophily become lost from the picture. On the other hand, the body of network science literature offers the tools to study such complex systems robustly, and have previously examined the effects of dynamic social networks on cooperation [31], collective intelligence [32], and even public speaking [33]. However, this body of work falls short when it comes to the interplays among diversity, creativity and homophily in dynamic social networks, which we address in this paper.

It is challenging to identify a dataset in the wild that (1) allows for traceable links between ideas and their stimuli, (2) gives agency to the participants for choosing their own inspiration sources, (3) captures temporal evolution information of the dynamic network, and (4) offers a way of presenting the peers’ demographic information to the participants without introducing unwanted confounding effects. We thus resort to a laboratory setting, where we draw from the relevant bodies of literature and improvise the study design to explore the desired research questions. Using a modern social-media-like web interface for the interactions, we are able to address the first three challenges, while the fourth challenge is overcome by the use of avatars. We employ advanced tools for analyzing temporal networks, such as the Separable Temporal Exponential Random Graph Model, to tease out the network formation and persistence patterns therein. We also take advantage of the recently popularized natural language processing tools for computationally comparing semantic qualities of the creative ideas in our dataset.

**Experimental Setup**

We consider two core research questions in this paper: (1) When people are tasked with creative idea generation, how do network connectivities adapt to the availability of demographic cues? (2) How are creative outcomes influenced by such demography-informed network dynamics?

We run a web-based randomized control experiment with 5 rounds of creative ideation tasks (see Materials and Methods). The participants were recruited from Amazon Mechanical Turk (see SI Appendix). To ensure that everyone had uniform stimuli for creative ideation, we adopt a bipartite study design [34] that involved two kinds of roles for the participants: as alters ($N = 12$) and as egos ($N = 180$). The alters’ ideas were pre-recorded to be used as stimuli for the egos. The egos were randomly placed into either of two conditions: (1) Control ($N = 90$, diversity cues not shown) or (2) Treatment ($N = 90$, diversity cues shown). We ran two trials of the study. Each trial consisted of 6 alters, whose ideas were shown as stimuli to the egos of both the control and treatment conditions in that trial (see Materials and Methods).

To get started, each ego was randomly assigned to ‘follow’ 2 alters (out of 6 in the trial) by the researchers. In each round, the egos first generated ideas on their own (turn-1). In the control condition, the egos were then shown the ideas of the 2 alters they were following. However, in the treatment condition, the egos were additionally shown the demographic information (gender and race) of their followee alters (see Materials and Methods, and SI Appendix). This was the only difference between the two conditions. If the egos got inspired with new ideas, they could add those to their lists (turn-2). Then, the egos were shown the ideas of all 6 alters, which they rated on novelty. Finally, the egos were given the opportunity to optionally follow/unfollow alters to have an updated list of 2 followee alters each. In turn-2 of the following round, they were shown the ideas of their newly chosen alters. Figure 1 visualizes the protocol. Further quality control measures are elaborated in the Materials and Methods section.

**Results**

**Same-gender links are highly stable in the presence of demographic cues**

We employ Separable Temporal Exponential Random Graph Models [35, 36] to capture the link formation and persistence dynamics in our dataset. Two separate models are fit for each of the
control and treatment networks: (1) Formation models and (2) Persistence models. The alters were merely passive actors in the study, and the network dynamics were solely determined by the egos’ choices of their followee alters. Therefore, as exogenous features, we choose three attributes that the treatment egos were most likely to consider in making their connectivity decisions: (a) the round-wise creative performances of the alters (measured by non-redundant idea counts; see Materials and Methods), (b) gender-based homophily and (c) race-based homophily. In addition, we employ one endogenous network feature of edge-counts, to control for network density. Figure 2 summarizes the intuition, while the models and features are elaborated in the Materials and Methods section.

In the control condition, we find that the link formations are significantly guided by the non-redundant idea counts of the alters ($\beta = 0.324$, $Z$-value $= 5.47$, $P < 10^{-4}$). The positive $\beta$ naturally suggests that better performing alters are more likely to be followed by the egos. The gender and race features do not show any significant effect once the performance-based link formations are accounted for ($P > 0.05$ for both). This is intuitive, as the egos did not have any information about the alters’ gender and race, and could only see the ideas of the alters. We observe the same trend in the link persistence model as well. The stability of the links can be significantly captured with the non-redundant idea counts ($\beta = 0.421$, $Z$-value $= 6.96$, $P < 10^{-4}$), which, once again, shows an intuitively positive effect. In other words, if you are a high-performing alter, you will enjoy substantial likelihoods of gaining and retaining followers. As expected, the gender and race features do not show any significant effect ($P > 0.05$ for both).

When it comes to the treatment condition, the link formation model yet again shows only the non-redundant idea counts of the alters to be a significant predictor ($\beta = 0.197$, $Z$-value $= 3.93$, $P < 10^{-4}$), and not the demographic features ($P > 0.05$ for both). However, things get interesting in the link persistence model. We find that, in the presence of demographic cues, the persistence of the links depend significantly on both non-redundant idea counts ($\beta = 0.355$, $Z$-value $= 6.08$, $P < 10^{-4}$) and gender-based homophily ($\beta = 0.599$, $Z$-value $= 3.74$, $P < 10^{-5}$). In other words, if a link exists between participants of the same gender, its odds of persisting increases by 82.03%, after controlling for merit-based persistence. No significant effect is observed for the race feature ($P > 0.05$).

In summary, when it comes to link persistence, the availability of demographic cues in the treatment condition is observed to be associated with a significant stability in same-gender links, unlike what is seen in the control condition.

**Inter-ego semantic similarity increases when the alters’ demographic cues are known**

Typical settings in convergent thinking or collective intelligence research explore how people, under various study conditions, can get close to known correct answers in estimation tasks [37][32][38][39].
These are abilities typically tested in traditional school examinations. In such explorations, it is not worrisome if the participants’ responses become similar to each other due to their interactions, as we only care about how accurate the estimates are. In stark contrast, we focus on divergent thinking/creativity in this experiment, which leads an individual to come up with numerous and varied responses to a given prompt or situation \[19\] \[41\]. If the network processes result in making the stimulated ideas of the participants systematically similar, it hurts our purposes.

We estimate the semantic nature of the egos’ idea-sets using neural word embeddings (Word2Vec \[42\]). To compute the semantic similarities between idea-sets, we employ the cosine similarity metric \[43\] (see Materials and Methods).

Previous work suggests that following the same people, i.e., having the same stimuli, can introduce semantic similarities between the idea-sets of independently ideating followers \[12\]. Given this intuition, we consider ego-pairs in the control and treatment conditions across three sub-groups based on their number of common alters. Namely, from each round, we collect pairs of egos who share (a) 2 common alters (i.e., exactly the same stimuli), (b) 1 common alter and (c) no common alter. Then, we compute the semantic similarities between the ego-pair’s stimulated ideas in turn-2.

We adopt a $3 \times 2$ factorial design to analyze the data, with 3 levels in the number of common alters and 2 levels in the study condition factor. In doing so, we employ the Aligned Rank Transform (ART) procedure \[44\], which is a linear mixed model-based non-parametric test. We find significant main effects for both of the factors (Number of common alters: $F(2, 38376) = 101.06, P < 10^{-15}$; Study condition: $F(1, 38376) = 137.38, P < 10^{-15}$). We also find a significant interaction between the two factors ($F(2, 38376) = 19.23, P < 10^{-8}$).

Post-hoc analysis on the ART-fitted model reveals that the semantic similarity between ego-pairs increases as their number of common alters increases (0 vs 1 common alter: $t(38376) = -6.61, P < 10^{-4}$; 1 vs 2 common alter(s): $t(38376) = -9.0, P < 10^{-4}$). Further pairwise comparisons using 2-tailed tests show that in the control condition, the idea-sets of ego-pairs who have both alters in common are significantly more similar to each other than idea-sets of ego-pairs who share one or no common alter (2 vs. 1 common alter: $t(38376) = 8.57, P < 10^{-4}$; 2 vs. 0 common alter: $t(38376) = 9.26, P < 10^{-4}$). However, there is no significant difference between the idea-sets of ego-pairs with one and no common alter ($P > 0.05$). This is in agreement with previously reported results \[12\].

In the treatment condition, the inter-ego similarities increase significantly as the number of common alters increase from 0 to 1 and also from 1 to 2 (0 vs. 1 common alter: $t(38376) = -8.91, P < 10^{-4}$; 1 vs. 2 common alters: $t(38376) = -5.17, P < 10^{-4}$). These trends intuitively follow the arguments of inter-follower similarities that can stem from having common stimulation sources.
Figure 4: Homogeneity of ideas within demographic-groups. (A) shows gender-based partitioning of the alters’ ideas. Some of the ideas were submitted by both males and non-male alters, while others were submitted uniquely by either gender categories. We only consider ideas from the latter case in the similarity analysis. Pairwise comparisons of ideas within gender show a significantly higher similarity than idea-pairs between genders. (B) shows the same analysis in case of race-based partitioning of the alters’ ideas. Whiskers denote 95% C.I. ***P < 0.0001.

Notably, we observe that the inter-ego semantic similarities are significantly higher in the treatment condition compared to their control counterparts, as revealed by post-hoc analysis on the study condition factor in the ART-fitted model ($t(38376) = 11.72, P < 10^{-4}$). Further pairwise comparisons using 2-tailed tests reveal that this result holds for all of the three common-alter-based subgroups (treatment vs. control: 2 common alters: $t(38376) = 5.28, P < 10^{-4}$; 1 common alter: $t(38376) = 13.82, P < 10^{-4}$; 0 common alter: $t(38376) = 8.32, P < 10^{-4}$). In other words, in the presence of demographic cues, the egos in the treatment condition not only maintained significant stability in same-gender links, but also demonstrated a significantly higher inter-ego semantic similarity compared to the egos in the control condition. All of the $P$-values reported here have been corrected for multiple comparisons using Holm’s sequential Bonferroni procedure. Figure 5 summarizes the results.

Homophily can make one’s stimuli set less diverse

How can we explain the increased inter-ego semantic similarity in the presence of demographic cues? We attempt to test the intuition that pairs of ideas generated by alters of the same demographic group tend to be more similar to each other than those generated by alters of different demographic groups. If that is indeed the case, it will logically follow that choosing alters from only a particular demographic group, as would result from homophily-guided network dynamics, can make a follower’s stimuli idea-set uniform and similar. This can deprive the follower of any possible diversity bonuses. It can also partly explain the increase in inter-ego similarities that can stem from having similar stimuli.

To that end, we first consider the sets of ideas that were uniquely submitted by the alters of male and non-male gender identities, but not both. We create vector representations for each of the distinct ideas in the two sets (see Materials and Methods). We then consider pairs of ideas from alters of the same gender, and compute their cosine similarities. However, we only consider idea-pairs from the same round, and if an idea-pair comes uniquely from a single person, we ignore that pair. Similarly, we compute the cosine similarities between idea-pairs from alters of different genders. We find that idea-pairs within gender are indeed significantly more similar to each other than idea-pairs between gender (2-tailed test, $t(4633) = 11.66, P < 10^{-30}$).

The same story is observed along the race dimension as well. In other words, we find that idea-pairs within race are significantly more similar to each other than idea-pairs between race (2-tailed test, $t(4870) = 5.73, P < 10^{-7}$). Figure 6 summarizes the results. To substantiate the generality of these findings, we run the same statistical analysis on the entire dataset of our study and confirm similar significant trends of gender and race-based homogeneity in ideas (see SI Appendix). Thus, we confirm the intuition that drawing stimuli ideas from the same demographic groups can indeed make one’s inspiration sources uniform and similar.
Exploring how people navigate through each other’s demographic differences in the society and how that affects their personal, social and professional lives is a research avenue with far-reaching practical implications. Especially since the recent killing of George Floyd, conversations on navigating such demographic differences constructively have seen a sharp spike. Our insights join a growing body of literature that investigate how demography-driven behavior can influence human performance. We turn our focus on creativity, a soft-skill that is enjoying an accelerated demand as the world experiences a rapid shift towards automation due to the COVID-19 pandemic. We find that in a creativity-centric social network, people’s odds of maintaining same-gender links increase by 82.03%, after controlling for merit-based link persistence. Such behavior is not observed if the demographic cues are not available to people in the first place. Moreover, we find people’s ideas to be more homogeneous within demographic groups than between. Thus, homophily-guided link dynamics can reduce the diversity in people’s creative stimuli set. This reinforces that intuition that the diversity bonuses might get compromised if one systematically maintains connections based on demographic identity. We indeed find that in the presence of demographic cues, the inter-ego semantic similarity increases significantly compared to the control condition where no such cues were shown to the participants.

Diversity effects, creative stimulation and social homophily—all of these are highly complex bodies of knowledge even when studied independently, driven by their own multidimensional mechanisms. The interplays among them naturally introduce further complexities into the equations. One cannot expect to understand all the subtle nuances therein with a one-size-fits-all solution. For example, expecting diversity to magically make every team superior will not be of much help. Rather, given a particular goal, one needs to carefully contemplate whether and how the cognitive, functional or identity diversities might add a bonus to the team’s performance [14]. Creativity can take numerous forms in terms of expression, and the underlying cognitive mechanisms are elusive in their own right [45]. Homophily is a robust phenomenon in social networks, yet recent work shows that as diversity increases, people can paradoxically perceive social groups as more similar [46]. Naturally, our work does not encompass every possible combination of scenarios that can emerge in such complex systems.

Rather, we show one set of empirical evidences in support of our arguments linking the three interdisciplinary components, towards filling an important void in literature. We find evidence that demographic cues can indeed bias creativity-centric social network dynamics, which in turn can systematically influence the creative outcomes therein. As our creativity playground, we chose a text-based task in the Alternate Uses Test. Alongside the widely documented construct and predictive validities [47, 48], this test has the added benefit that it allows us to employ the modern natural language processing tools to quantify and contrast creative outcomes robustly. The use of a bipartite network structure helped us keep the egos’ stimuli sets uniform and thus track the dynamic link formation and persistence patterns in a clean manner. The use of avatars and social-media-like interaction interfaces further allowed us to overcome the natural challenges in meeting the complex experimental setup requisites.

These insights can help make informed interventions in social systems where people’s creative outcomes are sought after. For instance, consider the modern social media outlets, where people often follow the highly creative peers in their domains in hopes for getting inspirations for novel ideas. Their choices of who to follow can naturally be biased by the demographic similarity with the peers as well. Using our insights, algorithmic interventions can be made to help people diversify their creative stimulation sources. Such measures can work to guard against the issues of inter-follower semantic similarities that we uncover, towards optimizing the network-wide creative outcomes.

Our work is not without limitations. The steep costs associated with collecting the data prohibited us from obtaining an even larger dataset. Also, the study lasted for 5 rounds, which can be prohibitively short for capturing the full temporal effects in a creativity-centric social system. Longitudinal studies with closer-to-life creative challenges and larger time-spans might generate elaborate insights on our research questions, which remain part of our future work.
Materials and Methods

Divergent Creativity Task

In this experiment, we are interested in divergent creativity, which deals with a person’s ability to come up with or explore many possible solutions to a given problem [49]. We use a customized version of Guilford’s Alternate Uses Test [50], the canonical approach for quantifying divergent creative performance. In each of the 5 rounds, the participants were instructed to consider an everyday object (e.g., a brick), whose common use was stated (e.g., a brick is used for building). The participants needed to come up with alternative uses for the object: uses that are different than the given use, yet are appropriate and feasible. We choose the first 5 common objects from the Form B of Guilford’s test as the ideation objects in the 5 rounds.

Network Settings

There were two trials in the study. In the first trial, the ideas of 6 alters were used as stimuli for 72 egos each in the control and treatment conditions. In the second trial, the other 6 alters acted as the stimulation sources for 18 egos each in the two conditions. All the alters and egos were assigned their roles and conditions randomly.

Further Protocol Details

Each of turn-1 and turn-2 allowed the egos 3 minutes to submit their ideas. In turn-2, the egos in the control condition were shown only the pseudo usernames and the lists of ideas of their followee alters. The egos in the treatment condition were additionally shown the gender (male and non-male) and race (white and non-white) information using text and avatars (see SI Appendix). The avatars were used to ensure uniform visual depiction for all of the alters of the same demographic group, so as not to bias the egos by any facial, personality or other visual cues. The egos were instructed not to resubmit any of the alters’ exact ideas, and that only non-redundant ideas would contribute to their performance. They were also told that there will be a short test at the end of the study, where they will need to recall the ideas shown to them. This was to ensure that the participants paid attention to the stimuli ideas, which has been shown to positively impact ideation performances [11, 51, 52, 53].

After turn-2, the egos rated all the ideas of the 6 alters in their trial on a 5-point Likert scale (1: not novel, 5: highly novel) [54, 55]. As the egos optionally rewired their network connections to have an updated list of which alters to follow, they were required to submit the rationale behind their choices of updating/not updating links in each round. This was in place to make the egos accountable for their choices, which has been shown to raise epistemic motivation and improve systematic information processing [55, 56]. The participants were paid $10 upon the completion of the tasks, as well a bonus of $5 if they were among the top 5 performers in groups of 18.

Quantifying Creativity

Against the pool of ideas submitted by one’s peers, the number of non-redundant ideas that a participant comes up with is a widely accepted marker of his/her creativity [57, 58]. The intuition being, to be creative, an idea has to be statistically rare. First, we filtered out inappropriate submissions that did not meet the requirements of being feasible and different from the given use. Then, all the ideas submitted in a given round by all the participants were organized so that the same ideas are binned together. We followed the coding rules described by Bouchard and Hare [59] and the rules specified in the scoring key of Guilford’s Alternate Uses test, Form B, for binning the ideas.

Once all the ideas were binned, we computed the non-redundant idea counts by looking at the statistical rarity of the ideas submitted by the participants. Namely, an idea was determined to be non-redundant if it was given by at most a threshold number of participants in a given pool of ideas. For the alters, the threshold was set to 1, and the pools were set to be the round-wise idea-sets of the 6 alters in the given trial.

1Guilford’s Alternate Uses Test is Copyright @ 1960 by Sheridan Supply Co., all rights reserved in all media, and is published by Mind Garden, Inc, www.mindgarden.com.
2 research assistants independently binned similar ideas together from of all submitted ideas in the dataset. The research assistants were shown the anonymized ideas in a random order. Based on their coding, the total non-redundant idea counts of the participants in all 5 rounds were computed, which had a high agreement (Intra-class correlation coefficient $ICC(3, 2) = 0.88$, $P < 10^{-15}$, 95% C.I. = [0.83, 0.92]; Pearson’s $r = 0.83$, $P < 10^{-19}$, 95% C.I. = [0.74, 0.89]). The coding from the first research assistant was then used in the analyses.

**Separable Temporal ERGM**

In the classic framework of the Exponential Random Graph Model (ERGM), the observed network (i.e., the data collected by the researcher) is regarded as one realization out of a set of possible networks originating from an unknown stochastic process we wish to understand. The range of possible networks, and their probability of occurrence under the model, is represented by a probability distribution on the set of all possible graphs with the same number of nodes as the observed network. Against these possible networks, we can then ask whether the observed network shows strong tendencies for structural characteristics that cannot be explained by random chance alone [60]. The basic expression for the classic (static) ERGM model can be written as,

$$P(Y = y | X = x) = \left(\frac{1}{\kappa}\right) e^{\beta^T g(y, x)}$$

(1)

Here, $Y$ is the random variable for the state of the network (adjacency matrix), with a particular realization $y$. $X$ denotes the vector of exogenous attribute variables, while $x$ is the vector of observed attributes. $\beta \in \mathbb{R}^p$ is a $p \times 1$ vector of parameters. $g(y, x)$ is a $p$-dimensional vector of model statistics for the corresponding network $y$ and attribute vector $x$. $\kappa$ is a normalizing quantity which ensures that Eq. (1) is a proper probability distribution. Unfortunately, evaluating $\kappa$ exactly is non-trivial. Therefore, we need to resort to numerical methods to approximate the coefficients $\beta$.

Namely, we use Markov Chain Monte Carlo methods to simulate draws of $Y$, and from those draws we estimate the coefficients using Maximum Likelihood Estimation (MCMC-MLE method). Such estimation methods make it convenient to transform Eq. (1) to the following equivalent conditional log-odds form:

$$\log \frac{P(Y_{ij} = 1 | y_{ij}^C, X)}{P(Y_{ij} = 0 | y_{ij}^C, X)} = \beta^T \Delta_{ij}(y, x)$$

(2)

Here, $y_{ij}^C$ denotes all the observations of ties in $y$ except $y_{ij}$. $\Delta_{ij}(y, x)$ is the *change statistic*, which denotes the change in the value of the network statistic $g(y, x)$ when $y_{ij}$ changes from 1 to 0. This emphasizes the log-odds of an individual tie conditional on all other ties.

For our temporal network data, we employed an extension of the static ERGM that deals with dynamic networks in discrete time: the Separable Temporal ERGM (STERGM) [13]. In contrast to static ERGMs, here we fitted two models: one for the underlying relational *formation*, and another for the relational *persistence*. In going from a network $Y^t$ at time $t$ to a network $Y^{t+1}$ at time $t+1$, the formation and persistence of ties are assumed to occur independently of each other within each time step (hence ‘separable’), to be captured by the two models respectively. The governing equations for the formation and persistence models, analogous to Eq. (2) are then written respectively as:

$$\log \frac{P(Y_{ij,t+1} = 1 | y_{ij}^C, X, Y_{ij,t} = 0)}{P(Y_{ij,t+1} = 0 | y_{ij}^C, X, Y_{ij,t} = 0)} = \beta_f^T \Delta_{ij,f}(y, x)$$

(3)

$$\log \frac{P(Y_{ij,t+1} = 1 | y_{ij}^C, X, Y_{ij,t} = 1)}{P(Y_{ij,t+1} = 0 | y_{ij}^C, X, Y_{ij,t} = 1)} = \beta_p^T \Delta_{ij,p}(y, x)$$

(4)

Here, time indices have been added to the equations unlike before, as well as new conditionals. In the formation model in Eq. (3) the expression is conditional on the tie not existing at the previous
time step, whereas in the persistence model in Eq. 4 it is conditional on the tie existing. Figure 2 summarizes these intuitions. There are separate coefficient vectors $\beta_f$ and $\beta_p$ for the formation and persistence models respectively, as well as separate change statistics $\Delta_{ij,f}(y, x)$ and $\Delta_{ij,p}(y, x)$ for the two models. Note that in the literature, it is common to refer to the persistence model as the ‘dissolution’ model instead. However, given how Eq. 4 is set up, and given that positive coefficients in this model indicate link persistence rather than dissolution, we take the liberty to refer to the model as the persistence model.

Since our network is bipartite, we considered links to form between ‘actors’ $i$ (egos) and ‘events’ $j$ (alters). To that end, we employed one endogenous and three exogenous features. Namely, we used the number of edges as the endogenous feature, which controls for network density: $g_1(y, x) = \sum_{ij} y_{ij} = N_e$. As exogenous features, we included:

1. The alters’ creative performances (i.e., non-redundant idea counts, $x^{(score)}_j$): $g_2(y, x) = \sum_{ij} y_{ij} x^{(score)}_j$

2. Gender-based homophily between the egos and alters: $g_3(y, x) = \sum_{ij} y_{ij} \mathbb{I}\{x^{(gender)}_i = x^{(gender)}_j\}$

3. Race-based homophily between the egos and alters: $g_4(y, x) = \sum_{ij} y_{ij} \mathbb{I}\{x^{(race)}_i = x^{(race)}_j\}$

where $\mathbb{I}\{\cdot\}$ denotes the indicator function. These four features constitute the network statistic $g(y, x)$, which is then used in computing the change statistics in the Eqns. 3 and 4. Note that the fitted coefficients $\beta_f$ and $\beta_p$ are conditional log-odds ratios, so their exponentials can intuitively be interpreted as the factors by which the odds of the formation and persistence of the network ties change respectively. For our implementation, we used the tergm package available within the statnet suite in R [36].

**Semantic Similarities between Idea-sets of the Egos**

To semantically compare the idea-sets of the egos, we first removed stop words and punctuation marks to convert the idea-sets to bag-of-words documents. We represented each document by taking the Word2Vec embeddings of all of the words in the document, and computing the centroid of those embedded vectors. The centroid of a set of vectors is defined as the vector that has the minimum sum of squared distances to each of the other vectors in the set. This centroid is then used as the final document vector representation of the given idea-set [43]. Word2Vec is a popular word-embedding algorithm, which employs skip-gram with negative sampling to train 300-dimensional embeddings of words [42].

Given two idea-sets, we computed their document vectors $u$ and $v$, and estimated the similarity between the two vectors by taking their cosine similarity,

$$
cosine(u, v) = \frac{u \cdot v}{||u|| ||v||}
$$

**Computing Embeddings for Distinct Ideas of the Alters**

The same idea can be phrased differently by different people. Therefore, we made use of the manual binnings of ideas described in the Quantifying Creativity subsection, where all the different phrasings of the same idea were collected under a common bin ID. To compare the sets of ideas generated by various demographic groups, we first collected the bin IDs of ideas that were submitted uniquely by various demographic groups (i.e., male only, non-male only, white only, non-white only). Under each bin ID, all the different phrasings of the idea were collected in a bag-of-words document, with all stop-words and punctuation marks removed. Similarly as before, we took the Word2Vec embeddings of the words in this document and computed their centroid to be the final vector representation of the idea. Cosine similarity was used to compute the similarities between pairs of idea-vectors.
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