Using Ego-Clusters to Measure Network Effects at LinkedIn

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Abstract

A network effect is said to take place when a new feature not only impacts the people who receive it, but also other users of the platform, like their connections or the people who follow them. This very common phenomenon violates the fundamental assumption underpinning nearly all enterprise experimentation systems, the stable unit treatment value assumption (SUTVA). When this assumption is broken, a typical experimentation platform, which relies on Bernoulli randomization for assignment and two-sample t-test for assessment of significance, will not only fail to account for the network effect, but potentially give highly biased results.

This paper outlines a simple and scalable solution to measuring network effects, using ego-network randomization, where a cluster is comprised of an “ego” (a focal individual), and her “alters” (the individuals she is immediately connected to). Our approach aims at maintaining representativity of clusters, avoiding strong modeling assumption, and significantly increasing power compared to traditional cluster-based randomization. In particular, it does not require product-specific experiment design, or high levels of investment from engineering teams, and does not require any changes to experimentation and analysis platforms, as it only requires assigning treatment an individual level. Each user either has the feature or does not, and

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no complex manipulation of interactions between users is needed. It focuses on measuring the “one-out network effect” (i.e the effect of my immediate connection’s treatment on me), and gives reasonable estimates at a very low setup cost, allowing us to run such experiments dozens of times a year.

1 Introduction

When developing new features or new software for a large professional social network, correctly accounting for network effects is primordial. A network effect is said to take place when a new feature not only impacts the people who receive it, but also other users of the platform, like their connections or the people who follow them. This is sometimes referred to as downstream impact as well.

This very common phenomenon violates the fundamental assumption underpinning nearly all enterprise experimentation systems, the stable unit treatment value assumption (SUTVA) [5, 14, 15, 16]. When this assumption is broken, a typical experimentation platform [9, 10, 3, 24], which relies on Bernoulli randomization for assignment and two-sample t-test for assessment of significance, will not only fail to account for the network effect, but potentially give highly biased results. This bias can be illustrated as follows: if a feature given to the treatment group also has an impact on the control group, then the control group no longer represents the right counterfactual, i.e. it no longer helps estimate outcomes in a universe where the feature is not given to anybody. For example, if we give users a feature that makes them share much more content, we expect even members who do not receive the feature to be more engaged as a result of receiving more interesting content in their feed. In other words, engagement measured on the treatment group increases, but so does engagement in the control group, therefore the measured difference between the two groups underestimates the true treatment effect.

But perhaps more crucially, in some of our applications, an experimentation approach that does not address the network effect may lead to the wrong business decision. It may suggest that specific intervention has a negative impact, when its actual total impact is positive. This happens when a specific intervention reduces immediate engagement (for example, by inviting users to focus on more complex content), but increases sharing, which in
turn increases downstream engagement.

Of course, SUTVA violations are especially common in Social Network applications, where members constantly interact, which makes it likely that any treatment given to an individual would have an impact on another, and therefore require special attention in this context.

In a professional social network application, network effects are not only a “bug” (a threat to experiment validity that data scientists have to worry about), but also a “feature” (an user-driven phenomenon that product teams rely on to boost metrics). Many interventions do not count on the direct effect of being treated to increase engagement, but specifically on the network effect. For example, when one develops a new feed relevance algorithm, one not only hopes that the new ranking will increase engagement of viewers, but that the viewers themselves will share and produce more content, increasing engagement downstream, for the receivers of the newly produced content.

Typical approaches to network effects involve observational analysis, multilevel designs [8, 20], cluster-based randomization, use of natural experiments [22], and model-assisted approaches specifying models for interference [21, 2, 4, 19, 7, 17]. Observational analysis tends to be highly unreliable, because peer effects are often confounded with homophily [11, 13].

Cluster-based randomizations [23, 6, 1] partition the graph into clusters, and allocate treatment cluster by cluster, but are often infeasible when networks are highly connected: not only is it very difficult to obtain reasonably isolated clusters, but the number of clusters itself is usually low, resulting in low-powered experiments [18, 12]. For example, partitioning the LinkedIn graph into 10000 balance clusters only yields and isolation of about 20% (an individual will an average have 80% of their connections outside of their cluster), which leads to high levels of bias. On the other hand, highly customized experiments can often provide precise answers, but they are often highly specific the feature being investigated, have high engineering cost, and are difficult to generalize. Model-based approaches may be hard to generalize to a large family of products. Leveraging natural experiments can provide a low-cost and elegant approach to measuring network effects, but natural experiments are typically rare [22].

This paper outlines a simple and scalable solution to measuring network effects, using ego-network randomization, where a cluster is comprised of an “ego” (a focal individual), and her “alters” (the individuals she is immediately connected to). Our approach aims at maintaining representativity of clusters, avoiding strong modeling assumption, and significantly increasing
power compared to traditional cluster-based randomization. In particular, it does not require product-specific experiment design, or high levels of investment from engineering teams, and does not require any changes to experimentation and analysis platforms, as it only requires assigning treatment at an individual level. Each user either has the feature or does not, and no complex manipulation of interactions between users is needed. It focuses on measuring the "one-out network effect" (i.e., the effect of my immediate connection’s treatment on me), and gives reasonable estimates at a very low setup cost, allowing us to run such experiments dozens of times a year.

2 Overview of ego-network clustering

One-out network effect assumption Throughout this paper the quantity of interest is the "one-out" network effect, i.e., the effect of having all my direct peers connected to me. Call $Y_i$ the outcome of member $i$, and $I$ the set of all LinkedIn members. For simplicity, we can think of $Y_i$ as the number of sessions the users spends on our site in a week. Call $Z_i$ the treatment assignment of user $i$, where if $Z_i = 1$, the user receives a new feature and is considered treated, and if $Z_i = 0$, the user’s experience is unchanged and she is considered a control user. Call $N(i)$ the neighborhood of user $i$ in the network: Depending on the application, this may refer to all other users that $i$ is connected to, or all users that $i$ has interacted with in the past, for example. We also refer to members of $N(i)$ as $i$’s peers. In terms of potential outcomes, we assume that:

$$Y_i(Z_i, Z_{j \in N(i)} = 1) = Y_i(Z_i, Z_{j \in I} = 1)$$

Where $Y_i$ denotes the potential outcome for individual $i$, $Z_i$ denotes the individual’s own treatment status ($Z=1$ for treated, $0$ for control), and $Z_j$ denotes other individual’s treatment status. In other words, an individual’s outcome depends only on their own treatment as well as their immediate neighbor’s. This simplification allows us to partition the graph into ego-network clusters, comprised of a central individual (an ego) and their peers (the alters), and to estimate ego’s potential outcomes based on their and their alter’s assigned treatments. In the following, we simply write $Z_{j \in N(i)}$ as $Z_{-i}$.

Our procedure identifies around $\sim 200,000$ individual egos in the LinkedIn graph and assigns treatment as follows:
• For each ego, a coin is drawn:

• If the ego is assigned to "downstream treatment", all of ego’s connections are assigned the treatment variant

• If the ego is assigned to "downstream control", all of ego’s connections are assigned to the control variant

• Depending on the effect we are trying to measure, egos are either all in control, all in treatment, or split between the two

Note that putting all egos in treatment (or control) gives us the pure network effect:

$$Y_i(Z_i = 1, \ Z_{-i} = 1) - Y_i(Z_i = 1, \ Z_{-i} = 0)$$

On the other hand, assigning egos the same treatment as their alters’ gives us the total effect:

$$Y_i(Z_i = 1, \ Z_{-i} = 1) - Y_i(Z_i = 0, \ Z_{-i} = 0)$$

In many applications, isolating the network effect from the total effect is desired, especially when a product is engineered to maximize the network effect, and no direct effect is expected. An example is given in algorithm 1.

In short, this is an A/B test between:

"all of my neighbors have been treated with A" vs
"all of my neighbors have been treated with B"

The final analysis is simply a two-sample t-test (which is the core feature of nearly all experimentation systems) between egos. This allows for easy interpretation and integration into existing systems. It is worth noting that the traffic requirements are much higher than the number of egos: in order to get about 200,000 egos, we need to treat 10 million individuals.
cluster = performClustering() egoList = cluster.keys()
for memberId in egoList do
    treatment = flipCoin(probability=0.5) ;
    if treatment == true then
        assignments[memberId] = ”treated”
        for alter in cluster[memberId] do
            assignments[alter] = ”treated”
        end
    else
        assignments[memberId] = ”treated”
        for alter in cluster[memberId] do
            assignments[alter] = ”control”
        end
    end
end

Algorithm 1: assignTreatment(): Treatment Assignment Algorithm, where egos are always treated

Figure 1: High level diagram of the method
Picking the right concept of network is crucial Because of this, average degree is a major determinant of traffic requirements for any experiment. Therefore, it is crucial to pick the “right” concept of network. For example, in the context of LinkedIn, the connection graph is not always the most predictive of future interactions: it often makes more sense to, instead, use the “past feed impressions” graph or the “past messages” graph, which may have lower average degree. In our feed case, we found that feed impressions in the past 90 days were highly predictive of current impressions and interactions, and therefore use them as our concept of weights on the graph.

3 Clustering process

3.1 Definitions and Objectives

Cluster versus network For clarity, we distinguish between an ego network and an ego-cluster. We call ego network the graph that contains the ego and all of her connections. Connections present in the ego networks are called original alters. We call ego cluster the graph that results of our clustering algorithm. Connections present in the ego cluster are called cluster alters.

One cluster per node only The main constraint of our clustering application is that any node can only be part of one ego cluster. Note that in general, a node is part of many ego networks (because it has more than one connection). This implies a difference between an ego’s network and her cluster: some of her original alters will be missing from her ego cluster, because they would belong to another ego cluster and multiple membership is not allowed. In other words, for each cluster, all cluster alters are original alters, but some original alters are missing from the list of cluster alters. For each ego cluster, we call loss rate \( \alpha \) the difference between 100% and the ratio of number of alters present in the ego cluster to the number of alters present in the ego network. This measures how many of an ego’s alters were lost during the clustering.\(^1\)

\(^1\)If edge weights are used, for each ego cluster, we call weighted loss rate the difference between 100% and ratio of total edge weights present in the ego cluster to the total edge weights present in the ego network.
One treatment per node only  This choice primarily comes from a feasibility requirement: in order for our approach to be scalable and generalizable, each node can only have one treatment status. We exclude highly custom procedures where each individual can have several treatment statuses: an individual cannot be treated as a content sender and control as a content receiver and cannot be control as a viewer of content originating specific people and treated as a viewer of content from another set of people. This is because such requirements reduce the range of products and experiments the technique can be applied to, and typically induce high engineering costs that may negate the value of the experiment in the first place.

Objectives: many egos, low loss rate  Any clustering procedure is trading off two objectives:

- We want to sample a high number of ego clusters from the graph. This gives more power to A/B tests by increasing the sample size.
- At the same time, we want to minimize the average loss rate, because it produces interference, and may lead to bias.

3.2 Toy clustering procedure and validity trade-offs

In the following, we illustrate a “mock” clustering procedure (2), which is helpful to think about bias/variance trade-offs. This is not the final procedure we will present:

1. First, we randomly pick an individual among our population (LinkedIn active users)
2. Then, we collect all her peers and put them in her cluster
3. We then go back to the first step:
   - We another random ego from the population that was left over by the first step
   - We collect their peers who were not already collected by another ego in a previous step.
4. When the average loss rate of the last 20 egos we collected reach ~25%, we stop the clustering procedure.
5. We assign treatment/control status to clusters using ego-level Bernoulli randomization, as described above.

```python
alreadySelected = Set()
lossRates = List(0)
clusters = {}  # keys: egos; values: list of alters
while mean(lossRates[:-20]) < 0.25 do
    memberId = getRandomLinkedInMember()
    if memberId in alreadySelected then
        continue
    end
    alreadySelected.add(memberId)
    alters = getAllConnectedIndividuals(memberId)
    for alter in alters do
        if alter in alreadySelected then
            continue
        end
        clusters[memberId] += alter
        alreadySelected.add(alter)
    end
    egoLossRate = len(clusters[memberId]) / len(alters).toDouble
    lossRates.append(egoLossRate)
end
assignment = assignTreatment(clusters)
```

Algorithm 2: Mock clustering procedure. Note: the algorithm is written for legibility rather than for efficiency.

Thinking about the properties of this “intuitive” approach helps us outline the trade-offs any clustering algorithm has to face:

### 3.2.1 Internal Validity trade-offs of the clustering

**Loss rate increases in the number of ego networks sampled** The most intuitive effect of the above clustering algorithm is that as the procedure goes on, the egos that get picked have higher and higher losses, as their network alters were already “taken” by other egos. As can be seen in Figure 2, after drawing 100,000 egos from the LinkedIn graph, the loss rate of
additional egos reaches 30%, which is high enough to trigger interference concerns. In other words, the more clusters we produce, the more they overlap. Too much overlap may lead to bias:

\[ Y_i (70\% \text{ of peers treated}) \neq Y_i (100\% \text{ peers treated}) \]

In most of our applications, we assume that the above difference leads to an underestimate, because the expected network effect is assumed to be, in absolute value, increasing in the proportion of my peers treated.

**Almost no egos are unaffected** The proportion of egos unaffected by interference becomes even more dramatically lower over time, as can be seen in Figure [3].

In other words, it is very difficult to get a large number of clusters without dealing with significant loss rates, translating into potential interference between clusters.

### 3.2.2 External Validity trade-offs of the clustering:

**Collision rate increases in the number of ego networks sample** Beyond interference, a clustering algorithm also has to face external validity concerns in the form of ego representativity. Once individuals are sampled as an alter, they are no longer eligible to be sampled as an ego. When we try to sample an ego and realize she was already sampled as an alter, a "collision" occurs. Figure [4] shows the collision rate as a function of the progress.
Bias in ego degree distribution results  Indeed, High-degree individuals are more likely than low-degree ones to get sampled as an alter early on in the sampling process, and are therefore less likely to get sampled as an ego later on due to the above shown collisions.

This translates into a decreasing average degree of egos sampled as the
Figure 5: Original degree of drawn egos as a function of iteration number

sampling procedure progresses, as shown in Figure 5. On average, the 100,000th ego drawn has a degree about 10% lower than the first one: the egos drawn in such a way are under-representing high-degree members and over-representing low-degree members.

3.2.3 Summing up our trade-offs

To sum up, a clustering endeavor faces numerous trade-offs:

- There is a tension between the number of clusters and their overlap (internal validity)
- There is a tension between the number of clusters and representativity of egos (external validity)
- In addition, if we artificially pick low-overlap clusters, they may not be representative.

3.3 Our approach: design principles

We propose a feasible approach to these trade-offs, based on the following principles:

**A small loss rate is acceptable**  Loss rates will often lead to underestimates, and therefore makes the final t-tests more conservative. In other words, a small loss rate is acceptable, and, in most cases, may not warrant an analysis-time correction. For example, if we treat 50% of our clusters as
well as 50% of the population outside of our clusters, the effective treatment proportion of ego’s peers is symmetric in expectation. Call \( p_i \) the proportion of \( i \)’s peers that are treated, and write \( Y_i(Z_i, p_i) \) \( i \)'s outcome as a function of that proportion. Let us call \( p \) the global treatment percentage set in our experimentation platform. In most of our use cases, we use 50% treatment and 50% control, so \( p = 0.5 \). Call \( \alpha \) the average loss rate (i.e. the proportion of ego’s peers who could not be put into their cluster). For treated egos:

\[
E(p_i) = 100\% \cdot (1 - \alpha) + p\alpha
\]

For control egos:

\[
E(p_i) = 0\% \cdot (1 - \alpha) + p\alpha
\]

In other words, we would like to estimate:

\[
Y_i(Z_i = 1, p_i = 1) - Y_i(Z_i = 1, p_i = 0)
\]

but we are in fact estimating:

\[
Y_i(Z_i = 1, p_i = 1 - \alpha(1 - p)) - Y_i(Z_i = 1, p_i = \alpha p)
\]

With \( p = 1/2 \) and for small values of alpha, the difference between \( 1 \) and \( 2 \) can be expected to be small. More importantly, for many of the features we test, we can assume that the response is an increasing function of the number of peers treated:

\[
(Y_i(Z_i, p_1) < Y_i(Z_i, p_2)) \iff (p_1 < p_2)
\]

so that the \( 1 \) is always larger in absolute value than \( 2 \) our test becomes more conservative. Rather than opting for a model-based correction of (2) to try recover (1), which can introduce bias, we show an algorithm that keeps \( \alpha \) low.

**Representatvity issues come from probability of selection by the algorithm, which is a function of degree** Stratifying helps counteract that effect, by making sure egos are picked so as to be representative of the overall degree distribution of the LinkedIn graph.
The loss rate should be approximately the same for all selected egos. If an algorithm creates some clusters with systematically lower loss rate than others, then the measured effect can be biased towards a specific segment of the population. We therefore propose an algorithm that strives to equalize loss rate across all egos.

4 Proposed algorithm and validation

4.1 Algorithm

- In this algorithm, egos are picked sequentially from degree bins:
  - We first set an upper bound for loss rate.
  - We convert the graph into an adjacency list, of format \{ego, alter_1, alter_2, \ldots\}, and classify each potential ego into degree bins. The order of egos inside each bin is then shuffled.
  - An ego is first picked from the lowest-degree bin:
    * If we can pick alters and loss rate is below target, we pick just enough alters so that the ego has the target loss rate.
    * If that is not possible, another candidate ego is picked in the same bin.
  - Another one is picked from the second-lowest degree bin
  - The procedure continues iteratively it becomes impossible to draw egos from one bin without exceeding the upper bound loss rate set in the first step (usually the highest-degree bin empties first). This typically gives us between 150,000 and 200,000 egos and ensures their degree distribution is representative of the LinkedIn user base.

- Once egos are picked, we use a Map-Reduce algorithm to attach the previously unpicked alters to an ego.

- Then for each alter, we consider the list of all egos they could be attached to, and attach them to their ego with strongest edge weight, subject to an equalization condition of loss rates across all egos.
Figure 6: Loss rate distribution of three algorithms. In green: first 100K egos picked by the naive sequential algorithm. In red: egos 900K-1M picked by the naive algorithm. In blue, 100K egos picked by our optimal algorithm.

- We then assign treatment assignment using ego-level Bernoulli randomization as described above

This gives us:

- The maximum number of egos while ensuring no single egos has a loss rate higher than a preset maximum.
- A minimized loss rates across the graph by reattaching alters dynamically. Figure 6 compares the loss rate of this algorithm with the naive one. In green, it shows the first 100K egos picked by the naive sequential algorithm. In red: egos 900K-1M picked by the naive algorithm. In blue, 100K egos picked by our optimal algorithm.

4.2 Automatic Validation

We perform two distinct types of validation of the procedure:

First, we validate that the drawn egos are representative in terms of the degree distribution of the overall LinkedIn graph.

This is done with a simple t-test. Second, we also make sure that the procedure didn’t introduce bias on other variables of interest (these are various measures of engagement). The procedure does not introduce differences
between our egos and the general population, and the relevant t-tests all fail to reject the null.

Second, for each run, we validate our treatment/control assignment. For degree, as well as various measures of engagement, we produce an A/A t-test, using pre-experiment data.

As for now, we only archive this information and chose not to re-seed “bad” randomizations, so as to not invalidate p-values computed by the A/B t-test. In an extension of this paper, we present a variance-reducing nearest-neighbor treatment assignment scheme, which brings the minimum detectable effect size (with 80% power) from 1.5% to 1% on user sessions.

5 Practical considerations

Note about power and p-values While we assign treatment to both egos and alters, we only measure effects on egos, leading the effective sample size to be much smaller than the number of individuals treated (or control). In our applications, we treat several million users (egos+alters), but only analyze the egos (on the order of 200,000). This relatively small number of units results in larger p-values than users of massive online experiments, with tens of millions of members, may be used to.

As a consequence, our internal guidance for users of this tool is not expect tiny p-values. Rather, p-values under 0.1 may be considered significant, (or borderline significant) and warrant further thought. We recommend focusing on the sign and size of treatment/control differences globally rather than focus too narrowly on p-values, and encourage the users to think about both practical and statistical significance.

Importance of selecting the right concept of graph The tool asks the user what concept of graph should be used to build clusters. The recommendation is to pick the concept of graph (i.e. the definition of what constitutes an edge) to represent the channels that a users behavior might impact another, while trying to exclude as many meaningless edges as possible. For example, for many feed experiments, past feed impressions provide a good approximation of the relevant network. (Rationale: If I have never seen another member on my feed before, they are unlikely to have a downstream impact on my engagement). We discourage the use of "connections" as a concept of graph because it results in very large clusters, and only a subset
of connections are likely to be seen on a person’s feed. Having a concept of graph that is too broad reduces the number of clusters we are able to make, and eventually hurts the significance of the final results.

**Network changes and experiment duration** As in any social network, the graph changes over time. The peers selected by the clustering algorithm may no longer be relevant after a few months have gone by. For this reason, it is important never to reuse clusters (even re-randomizing treatment/control within them), but to re-run the clustering algorithm for each new experiment. Given the LinkedIn network structure, our current internal guidance is to never use a selector that is over a month old. This was one of the motivations for building a scalable self-service tool, so ”fresh” clusters can be delivered to users as quickly as possible. This also means that this approach may not be best suited for very long-running experiments (several months).

**Representativity of complement population: potential caveats when using leftover traffic to run other experiments** Our clustering algorithm, because it controls the loss rate, does not use the whole LinkedIn member population. The remainder of the population is available to use for other Bernoulli randomized experiments, with one caveat: while our approach makes sure that egos are representative of the relevant target population, it makes no such effort for alters, in order to minimize loss rate. This is a positive feature for the internal validity of egoCluster experiments themselves, but as outlined below, it may have a small impact on experiments run on leftover traffic. In general, because high degree individuals have a high likelihood of being selected as alters, the population left to parallel experiment has somewhat lower degree and lower engagement.

As can be seen in Table 1 and Figure 7, there are significant differences between the leftover population and the overall population. Some key metrics are 15-30% lower in the leftover population, and their variance is also

|                | degree   | engagement | Posting behavior |
|----------------|----------|------------|------------------|
| all data       | 100±239  | 100±124    | 100±614          |
| leftover traffic| 78±189   | 86±105     | 71±429           |

Table 1: Comparison of key variables between overall LinkedIn population and traffic left over by our clustering algorithm (used by other experiments). Values have been normalized to 100.
lower. Note that in our use cases, this has not seemed to significantly change conclusion of experiments, however. Of course, if is possible to run an orthogonal experiment, this problem disappears, and is always our recommended course of action.

6 Application and Results

Note: for all these results, A/A tests were also performed, to avoid including spurious results. Results that were significant in an A/A tests were discarded.

6.1 Trading off main effect and peer effect

The first iteration of our algorithm was tested with a small sample. We set the maximum loss rate at 20%, and only used about 80,000 egos (40,000 treatment / 40,000 control), but with a high expected network effect. We tested two potential feed recommendation algorithms:

Effect on alters. The effect of the two variants on alters was determined by a prior, Bernoulli-randomized experiment. Relative to control, treatment reduced interactions with feed content by 12% and engagement by 5%, but increased viral actions (such as comments, likes and reshares) by
16%. This was done by suggesting a different content mix, that induced less engagement by more social actions.

**Resulting network effect on egos.** All egos were assigned to control condition, so as to measure the network effect only. Egos who were assigned to “ego with treatment alters” condition had, relative to “egos with control alters”, higher engagement (+3.1%, p-value 0.03), and more scrolling (+2.9%, p-value 0.02). The total effect on sessions was 1.2%, but was borderline significant.

**Learning:** It is possible to sacrifice some direct engagement in order to induce individuals to share more. This increased sharing leads to increased downstream engagement, presumably because content that was directly recommended by peers has higher value.

### 6.2 Validating downstream optimization

In another iteration, this time leveraging the maximum sample size allowed under our loss rate criterion (180,000 egos at the time) we looked at two algorithms that recommended content that had the same probability of being reshared, but conditionally on being reshared, generated different engagement levels in peers.

**Effect on alters.** The effect of the two variants on alters was also determined by a prior, Bernoulli-randomized experiment. Relative to control, treatment generated similar levels of engagement and viral action behavior.

**Effect on egos.** Even though alters’ behavior seemed unchanged in terms of volume of viral actions, egos response to the compositional change in the content they were seeing, and increased their own viral actions by 7% (p-value 0.1). Effect on sessions was not detectable.

**Learning:** Relevance algorithms can induce downstream changes even when metrics on alters are flat, by introducing subtle compositional changes.

### 6.3 Optimizing for feedback: redistribution in the attention economy

In a more recent iteration, we looked at the effect of redistribution attention from high-profile posters (people who receive a high number of likes and comments already) to people who receive low numbers. The hypothesis was that by increasing the amount of feedback received by them, their engagement
would go up and they would be encouraged to contribute more content and feedback themselves.

**Intervention on alters:** raise the profile of egos with low feedback.

**Effect on egos:** Egos in the treatment group (whose profile was raised if they had low existing feedback and lowered if they had high existing feedback levels) were more likely to contribute new content (+0.3%, p-value 0.09) and to like existing content (+1%, p-value 0.09).

**Learning:** diverting feedback from “feedback-rich” and sending it to newer or less popular members can be worth it, as it increases their likelihood of contributing by an amount that is greater than any negative effect on individuals the feedback is diverted from.

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Figure 8: Screenshot of the UI used to request an egoClusters experiment assignment

A Reproducibility: User-facing interface: screenshot