Complex Network Analysis of North American Institutions of Higher Education on Twitter

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Abstract. North American institutions of higher education (IHEs): universities, 4- and 2-year colleges, and trade schools—are heavily present and followed on Twitter. An IHE Twitter account, on average, has 20,000 subscribers. Many of them follow more than one IHE, making it possible to construct an IHE network, based on the number of co-followers. In this paper, we explore the structure of a network of 1,435 IHEs on Twitter. We discovered significant correlations between the network attributes: various centralities and clustering coefficients—and IHEs’ attributes, such as enrollment, tuition, and religious/racial/gender affiliations. We uncovered the community structure of the network linked to homophily—such that similar followers follow similar colleges. Additionally, we analyzed the followers’ self-descriptions and identified twelve overlapping topics that can be traced to the followers’ group identities.

Keywords: complex networks, higher education, computational social science

1 Introduction

According to the National Center for Education Statistics [6], in 2018, there were 4,313 degree-granting postsecondary institutions, also known as institutions of higher education (IHEs), in the USA. This number includes public and private (both nonprofit and for-profit) universities, liberal arts colleges, community colleges, religious schools, and trade schools.

The IHEs enjoy a heavy presence on social media, in particular, on Twitter. In 2012, Linvill et al. [3] found that IHEs employ Twitter primarily as an institutional news feed to a general audience. These results were confirmed by Kimmons et al. in 2016 [2] and 2017 [14]; the authors further argue that Twitter failed to become a “vehicle for institutions to extend their reach and further demonstrate their value to society”—and a somewhat ”missed opportunity for presidents to use Twitter to connect more closely with alumni and donors” [15]. The same disconnect has been observed for IHE library accounts [11].

Despite the failed promise, the IHEs massively invest in online marketing [12] and, in reciprocity, collect impressive follower lists that include both organizations and individuals. The longer follower lists demonstrate a positive effect on IHE performance, particularly, on student recruitment [9], and may eventually
affect IHE ratings or at least correlate with them [4]. Therefore, follower lists are essential marketing instruments and should be studied comprehensively.

To the best of our knowledge, this paper is the first attempt to look at a social network of IHE Twitter accounts based on the similarities of their follower lists. We hypothesize that the exogenous parameters, such as enrollment, tuition, and religious/gender/race preferences, affect the structure of the network and positions/importance of the IHEs in it.

The rest of the paper is organized as follows: In Section 2, we describe the data set, its provenance, and structure; in Section 3, we explain the network construction; in Section 4, we go over the network analysis, and present the results; in Section 5, we take a look at the followers; in Section 6, we discuss the results. Finally, in Section 7, we conclude.

2 Data Set

Our data set consists of two subsets: social networking data from Twitter and IHE demographics from Niche [8]. We used the former to construct a network of IHEs and the latter to provide independent variables for the network analysis. Both subsets were collected in Summer 2020.

The Twitter data set describes the Twitter accounts of 1,450 IHEs from all 50 states and the District of Columbia. The majority of the accounts are the official IHE accounts, but for some IHEs, we had to rely on secondary accounts, such as those of admission offices or varsity sports teams. For each IHE, we have the following attributes (and their mean values): geographical location (including the state), the lists of followers (20,198) and friends (1,130), the numbers of favorites (“likes”; 4,656) and statuses (“posts”; 9,132), the account age in years (10.4), and whether the account is verified or not (32% accounts are verified).

With some IHEs having more than a million followers (e.g., MIT and Harvard University), we chose to restrict our lists to up to 10,000 followers per IHE. This limitation may have resulted in a slight underestimation of the connectedness of the most popular IHEs. We explain in subsection 3.1 why we believe that the underestimation is not crucial.

It is worth noting that while we have downloaded the friend lists, we do not use them in this work because they are controlled by the IHE administrations/PR offices and cannot be considered truly exogenous.

The combined list of followers consists of 347,920 users. This number does not include the “occasional” followers who subscribed to fewer than three IHEs.

The descriptive IHE data comes from Niche [8], an American company that provides demographics, rankings, report cards, and colleges’ reviews. It covers 1,435 of the IHEs that we selected for the network construction. Five more IHEs were not found on Niche and, though included in the network, were not used in further analysis.

For each IHE, we have the following attributes:

**Binary:** “Liberal Arts” college designation,
Application options: “SAT/ACT Optional,” “Common App Accepted,” or “No App Fee” (these options can be combined).

Categorical: – Type: “Private,” “Public,” “Community College,” or “Trade School”; note that all community colleges and trade schools in our data set are public; – Religious affiliation: “Christian,” “Catholic,” “Muslim” or “Jewish”; we lumped the former two together; – Online learning options: “Fully Online,” “Large Online Program,” or “Some Online Degrees”; – Gender preferences: “All-Women” or “All-Men”; – Race preferences: “Hispanic-Serving Institution” (HSI) or “Historically Black College or University” (HBCU).

Count or real-valued: Enrollment and tuition. We noticed that due to the broad range of enrollments and tuition, enrollment and tuition logarithms are better predictors. We will use log (enrollment) and log (tuition) instead of enrollment and tuition throughout the paper.

3 Network Construction

We define the network $G$ of IHEs on Twitter as $G = (N, E)$. Here, $N = \{n_i\}$ is a set of 1,450 nodes, each representing an IHE account, and $E = \{e_{ij}\}$ is a set of weighted edges.

Let $f(n)$ be a set of followers of the account $n$. As noted in Section 2, $\forall n \in N : \#f(n) \leq 10,000$. Let $f^{-1}(q) = \{n \in N | q \in f(n)\}$ be a set of all IHE accounts followed by user $q$. Note that $q$ itself may be a member of $N$: IHEs can follow each other.

The definition of an edge is derived from the concept of $G$ as a network based on co-following: two nodes $n_i$ and $n_j$ share an edge $e_{ij}$ iff they have at least one shared follower that also follows at least three IHE accounts. We denote a set of such qualified followers as $Q$:

\[ Q = \{q | \#f^{-1}(q) \geq 3\} \]

\[ \forall i, j : \exists e_{ij} \iff Q \cap f(n_i) \cap f(n_j) \neq \emptyset \]

The number of edges in $G$ is, therefore, 928,476. The network is connected (there is only one connected component) and quite dense: its density is 0.88.

Finally, let $w_{ij} > 0$ be the weight of the edge $e_{ij}$. We initially define $w_{ij}$ as the number of qualified shared followers:

\[ w_{ij} = \# (Q \cap f(n_i) \cap f(n_j)) \]

The resulting weights are large (on the order of $10^3$–$10^4$), while many network algorithms, such as community detection and visualization, expect them to be in the range $(0 \ldots 1]$. We used the algorithm proposed in [10] to normalize the weights without affecting the calculated node attributes.
3.1 A Note on Edge Weight Calculations

We mentioned in section 2 that we use only up to 10,000 followers for edge weight calculations. The truncated follower lists result in lower weights. We can estimate the difference between true and calculated weights by assuming that the shared followers are uniformly distributed in the follower lists. Let $F = \frac{\#f}{f} = 21,123$ be the mean number of followers; let $T = 10,000$; let $p \approx 0.685$ be the probability that a follower list is not longer than $T$; let $w$ be the mean edge weight; finally, let \( \bar{w}^* \) be the estimated mean edge weight. Note that if $p = 1$ then $\bar{w}^* = \bar{w}$. One can show that:

$$\frac{\bar{w}^*}{\bar{w}} \approx \left( \frac{(F - T)p + T}{F} \right)^2 \approx 1.436.$$  \hspace{1cm} (4)

Seemingly, the weights of all edges that are incident to at least one node with a truncated follower list are underestimated by $\approx 30\%$. However, we noticed that Twitter reports follower lists not uniformly but roughly in the order of prominence: the prominent followers with many followers of their own are reported first. We hope that the shared users responsible for edge formations are mostly reported among the first 10,000 followers.

4 Network Analysis

In this section, we analyze the constructed network and present the results. We looked at individual nodes’ positions in the network (monadic analysis), relations between adjacent nodes (dyadic analysis), and node clusters (community analysis).

4.1 Monadic Analysis

We used Python library networkx [17] to calculate the monadic attributes: degree, closeness, betweenness, and eigenvector centralities, and local clustering coefficient—for each node $n \in G$. All the centralities of $n$ express various aspects of $n$’s prominence in a network [16]: the number of closely similar IHEs (degree), the average similarity of $n$ to all other IHEs (closeness), the number of IHEs that are similar to each other by being similar to $n$ (betweenness), and the measure of mutual importance (eigenvector: “$n$ is important if it is similar to other important nodes). The local clustering coefficient reports if the nodes similar to $n$ are also similar to each other.

We use multiple ordinary least squares (OLS) regression to model the relationships between each of the network attributes and the following independent variables: tuition, enrollment, Twitter account age, Twitter account verified status, “No App Fee,” “Liberal Arts” designation, “SAT/ACT Optional,” “Common App Accepted,” race preferences, online learning options, type/religious affiliations, and gender preferences (see Section 2). We combined the IHE type and religious affiliations into one variable because all public schools are secular.
The number of samples in the regression is 1,348 (the intersection of the Niche set and Twitter set). Table 1 shows the independent variables that significantly ($p \leq 0.01$) explain the monadic network measures, and the regression coefficients.

**Table 1.** Variables that significantly ($p \leq 0.01$) explain the monadic network measures: betweenness, closeness, degree, eigenvector centralities, clustering coefficient, and numbers of favorites (“likes”), followers, friends, and statuses (posts). †The marked rows represent levels of the categorical variables.

| Variable     | Coef.               |
|--------------|---------------------|
|              | betw. clos. clust. degr. eigen. favorites followers friends posts |
| Liberal Arts | 0.27 0.05 0.08 0.08 -0.98 |
| Private †    | 0.29 1.40            |
| Account Age  | 0.12 0.02 0.03 0.03 0.05 |
| Tuition      | -0.21 0.02           |
| Common App   | 0.03 0.05 0.05       |
| No App Fee   | 0.05 0.09 0.09       |
| Large Online †| 0.02 0.04 0.04 -0.55 |
| Some Online †| 0.06 0.11 0.10       |
| HBCU †       | -0.04 0.07 0.07 0.63  |
| Christian †  | -0.03 -0.05 -0.05 0.66 1.30 0.52 0.48 |
| Verified     | 0.03 0.01 0.06 0.06 0.33 0.65 0.29 0.29 |

### 4.2 Dyadic Analysis

The only dyadic variable in our model is the edge weight. As a reminder, the weight of an edge is derived from the number of Twitter co-followers of the incident nodes. A stronger edge indicates a larger overlap of the followers and, presumably, a closer similarity between the IHEs, even if the nature and reason for the similarity is unclear.

We hypothesize that, because of homophily, edge weights depend on the difference between the incident node attributes. We calculate the dyadic versions of the monadic independent variables for the OLS regression modeling as follows:

**For the binary and categorical variables:** A calculated dyadic variable $y_{ij}$ equals 1 if the values of the underlying monadic variable $x$ differ, and 0, otherwise:

$$y_{ij} = \begin{cases} 0 & \text{if } x_i = x_j \\ 1 & \text{if } x_i \neq x_j \end{cases}$$

(5)

For example, if both incident nodes represent liberal art colleges, then the dyadic “Same Liberal Arts designation” variable for the edge is 0.
For the count or real-valued variables: A calculated dyadic variable $y$ equals the absolute value of the arithmetic difference of the underlying monadic $x$ variable at the incident nodes:

$$y_{ij} = |x_i - x_j|.$$  

Both clauses emphasize the difference of the monadic attributes along the incident edge. Table 2 shows the independent variables that significantly ($p \leq 0.01$) explain the edge weights, and the regression coefficients. For this analysis, we add the state in which an IHE is located to the monadic variables listed in subsection 4.1.

| Variable                          | Coef.  |
|----------------------------------|--------|
| Same state                       | 0.0169 |
| Similar enrollment               | 0.0024 |
| Similar tuition                  | 0.0022 |
| Same religious affiliation        | 0.0019 |
| Same online preferences          | 0.0010 |
| Similar account age              | 0.0008 |
| Same “Common App Accepted” option| 0.0008 |
| Same “No App Fee” option         | 0.0008 |
| Same race designation            | 0.0006 |
| Same “SAT/ACT Optional” option   | 0.0005 |
| Both verified                    | -0.0001|
| Same gender designation          | -0.0022|
| Same “Liberal Arts” designation  | -0.0026|

4.3 Community Analysis

We used the Louvain community detection algorithm [1] to partition $G$ into network communities, or clusters: tightly connected non-overlapping groups of nodes with more internal connections than external connections. We requested a resolution of 0.8 (lower than the standard 1.0) to discover smaller clusters and, as a result, partitioned $G$ into 22 disjoint clusters $C = \{c_i\}$. The Newmann modularity [7] of the partition is 0.152 on the scale $[-1/2...1]$. Each cluster contains the nodes representing the IHEs that are somewhat more similar to each other than to an IHE from another cluster. In other words, the level of homophily within a cluster is higher than between the clusters. We expect to identify the independent variables responsible for the homophily.

Table 3 shows the independent variables that significantly ($p \leq 0.01$) explain the membership in select clusters, and the regression coefficients. Note that the
Table 3. Variables that significantly ($p \leq 0.01$) explain membership in select clusters. (See Fig. 1). The marked rows represent levels of the categorical variables.

| Variable            | Coef. 1 | Coef. 2 | Coef. 3 | Coef. 4 | Coef. 5 | Coef. 6 | Coef. 7 | Coef. 8 | Coef. 9 | Coef. 10 | Coef. 11 | Coef. 12 | Coef. 13 | Coef. 14 | Coef. 15 | Coef. 16 |
|---------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Christian           | -1.75   | -3.85   |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Comm. Coll.         | 2.75    |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Common App          | -1.95   | 2.38    | 1.75    |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Enrollment          | -0.53   | 1.99    | -0.50   | -0.73   | -0.56   |         |         |         |         |         |         |         |         |         |         |         |
| HBCU                |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         | 7.29    |
| HSI                 |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         | 1.30    |
| Large Online        |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         | 3.20    |
| Liberal Arts        |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         | 2.97    |
| No App Fee          | 1.19    |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Private             |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         | -2.88   |
| SAT/ACT Opt.        | 1.44    | -0.74   |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Some Online         |         | 0.92    |         |         |         |         |         |         |         |         |         |         |         |         |         |         | -1.61   |
| Trade School        | 3.34    | -2.42   |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Tuition             | -1.85   | 1.68    | 3.14    |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| Verified            | -1.34   | -1.27   | 1.80    |         |         |         |         |         |         |         |         |         |         |         |         |         |         |

clusters 6, 9, 10, 16, and 19 do not have any significant explanatory variables, and the clusters 18, 20, 21, and 22 are single-node isolates.

As a side note, community detection can be used to visualize $G$. Large networks are usually hard to visualize, especially when their Newmann modularity is low, and the community structure is not prominent. We use the extracted partition $C$ to build a bird’s-eye view of $G$, known as an induced network $I = (C, E^I)$ (Fig. 1). An induced node in $I$ represents a cluster in $G$. An induced edge between two nodes $c_i$ and $c_j$ in $I$ exists if there exists at least one edge from any node in $c_i$ to any node in $c_j$:

$$\forall i, j : \exists e^I_{ij} \iff (\exists k, l : n_k \in c_i \land n_l \in c_j \land \exists e_{kl}).$$

Respectively, the weight of such induced edge $w^I_{ij}$ is the number of the original edges in $G$ from any node in $c_i$ to any node in $c_j$:

$$w^I_{ij} = \#\{e_{kl} \mid n_k \in c_i \land n_l \in c_j\}.$$

The name of each cluster in Fig. 1 incorporates the name of the Twitter account of the IHE with the highest enrollment in the cluster.

5 Followers’ Analysis

At the last stage of the network analysis, we shift the focus of attention from the IHEs to their followers.
We selected 14,750 top followers who follow at least 1% of the IHEs in our data set. Approximately 8% of them have an empty description or a description in a language other than English. Another 268 accounts belong to the IHEs from the original data set, and at least 326 more accounts belong to other IHEs, both domestic and international.

We constructed a semantic network of lemmatized tokens by connecting the tokens that frequently (10 or more times) occur together in the descriptions. We applied the Louvain \[1\] community detection algorithm to extract topics—the clusters of words that are frequently used together. The algorithm identified twelve topics named after the first nine most frequently used words. For each follower’s account, we selected the most closely matching topics. The names and counts for the most prominent topics are shown in Table \[4\].

Even after the manual cleanup, some of the 12,984 remaining followers’ accounts probably still belong to IHEs and associated divisions, organizations, and officials. This deficiency would explain the significance of the topics \#4 and, partially, \#2 that seem to use the endogenous terminology. The remaining topics are exogenous to the IHEs and represent higher education services, high schools, communities, career services, and individuals (“male” and “female”).
Table 4. The most prominent topics and the number of followers accounts that use them. (Since a description may contain words from more than one topic, the sum of the counts is larger than the number of followers.) †Topic #8 is technical.

| ID | Top seven topic terms                                                                 | Count |
|----|---------------------------------------------------------------------------------------|-------|
| 1  | education, service, higher, business, professional, solution, research                  | 5,039 |
| 2  | student, program, online, academic, year, helping, opportunity                         | 3,460 |
| 3  | school, high, official, twitter, news, account, follow                                 | 3,308 |
| 4  | college, community, campus, institution, mission, member, black                        | 2,870 |
| 5  | help, life, world, love, social, work, people                                         | 2,258 |
| 6  | university, career, state, new, job, find, best                                        | 1,814 |
| 7  | coach, teacher, author, husband, father, writer, book                                  | 1,125 |
| 8† | endorsement, like, link, facebook, retweets, equal, following                          | 557   |
| 9  | lover, mom, wife, mother, dog                                                          | 515   |

6 Discussion

Based on the results from Section 4, we look at each independent variable’s influence on each network and Twitter performance parameter, whenever the influence is statistically significant ($p \leq 0.01$).

It has been observed [13] that the centrality measures are often positively correlated. Indeed, in $G$’s case, we saw strong ($\geq 0.97$) correlations between the degree, eigenvector, and closeness centralities, which explains their statistically significant connection to the same independent variables (Table 1). More central nodes tend to represent:

**Some specialty IHEs:** Liberal arts colleges, HBCUs.

**Internet-savvy IHEs:** IHEs with a longer presence on Twitter, IHEs with some or many online programs.

**Bigger IHEs with simplified application options:** IHEs with no application fees (and accepting Common App—for the closeness centrality), larger IHEs.

All these IHEs blend better in their possibly non-homogeneous network neighborhoods.

The betweenness centrality—the propensity to act as a shared reference point—is positively affected by being a liberal arts college or private IHE, and longer presence on Twitter, and negatively affected by higher tuition and being a Christian IHE. On the contrary, large and Christian IHEs tend to have a larger local clustering coefficient and a more homogeneous network neighborhood.

All Twitter performance measures: the numbers of favorites, followers, friends, and posts—are positively affected by enrollment and the verified account status. The number of posts is also higher for the IHEs with a more prolonged presence on Twitter and Christian IHEs. The number of followers is also higher for private IHEs and lower for liberal arts colleges and IHEs with some online programs. The latter observation is counterintuitive and needs further exploration.
Edge weight is the only dyadic variable in $G$. Table 2 shows that the weight of an edge is explained by the differences of the adjacent nodes’ attributes. Some of the attributes promote homophily, while others inhibit it.

The strongest edges connect the IHEs located in the same state, which is probably because many local IHEs admit the bulk of the local high schools’ graduates and are followed by them and their parents. Much weaker, but still positive, contributors to the edge weight are similar enrollment and tuition, same religious affiliation, online teaching preferences, racial preferences, and application preferences, a “classical” list of characteristics that breed connections [5]. We hypothesize that prospective students and their parents follow several IHEs that match the same socio-economic profile. National, regional, and professional associations (such as the National Association for Equal Opportunity and National Association of Independent Colleges and Universities) may follow similar IHEs for the same reason.

We identified two factors that have a detrimental effect on edge weight: having the same gender designation (“All-Male,” “All-Female,” or neither) and especially the same “Liberal Arts” designation. There are 1.58% of “All-Female” IHEs (and no “All-Male”) and 11.2% Liberal Arts colleges in our data set. The IHEs of both types may be considered unique and not substitutable, thus having fewer shared followers.

In the same spirit, some network communities (clusters) of $G$ represent compact groups of IHEs with unique characteristics (Table 3). For example, cluster 1 tends to include community colleges and trade schools with no application fees, optional SAT/ACT, and lower tuition (e.g., Carl Sandburg College). Cluster 3 is a preferred locus of smaller Christian IHEs that do not accept Common App but require SAT/ACT (New Saint Andrews College). The last comprehensive example is cluster 8: smaller public, secular, expensive IHEs embracing Common App (University of Maine at Machias). IHEs with large online programs are in cluster 17 (Middle Georgia State University), Historically Black Colleges and Universities—in cluster 7 (North Carolina A&T State University), and Liberal Arts colleges—in cluster 15 (St. Olaf College).

It is worth reiterating that the membership in five clusters containing 9.1% IHEs, cannot be statistically significantly explained by any independent variable. The explanatory variables, if they exist, must be missing from our data set.

7 Conclusion

We constructed and analyzed a social network of select North American institutions of higher education (IHEs) on Twitter, using the numbers of shared followers as a measure of connectivity. We used multiple OLS regression to explain the network characteristics: centralities, clustering coefficients, and cluster membership. The regression variables include IHE size, tuition, geographic location, type, and application preferences. We discovered statistically significant connections between the independent variables and the network characteristics. In particular, we observed strong homophily among the IHEs in terms of the
number of shared followers. Finally, we analyzed the self-provided descriptions of the followers and assigned them to several classes. Our findings may help understand the college application decision-making process from the points of view of the major stakeholders: applicants, their families, high schools, and marketing and recruitment companies.

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