Mining the Web to Approximate University Rankings

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ABSTRACT
We mined a collection of data obtained from Twitter and publicly-available online academic sources to examine and rank a set of 264 U.S. universities. The examined universities were extracted from the National Collegiate Athletic Association (NCAA) Division I membership and global university ranking lists published in U.S. News & World Report, Times Higher Education, Academic Ranking of World Universities, and Money Magazine. Our Endowment, Expenditures, and Enrollment (EEE) rank factors in alumni support, athletic expenditures, and undergraduate enrollment. Our University Twitter Engagement (UTE) rank is based on the friend and extended follower network of primary and affiliated secondary Twitter accounts referenced on a university’s home page. In rank-to-rank comparisons we observed a significant, positive rank correlation (τ = 0.6018) between UTE and an aggregate reputation ranking, which indicates that UTE could be a viable proxy for ranking atypical institutions normally excluded from traditional lists. In addition, we significantly reduce the cost of data collection needed to rank each institution by using only web-based artifacts and a publicly accessible Twitter application programming interface (API).

KEYWORDS
University Ranking; Data Mining; Information Retrieval; Twitter

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ACM Reference Format:

1 INTRODUCTION
Universities and other academic institutions increasingly see their presence and visibility on the Web as central to their reputation. In this context, information content on the academic web is viewed as a reflection of the overall organization and performance of the university [1]. Academic rankings can play an important role in assessing reputation. With disparate criteria and methodologies, however, there can be a significant divergence in the rankings of a particular institution.

We consider the set of data associated with a university that is publicly available on the Web as a collection. In this work, we mine the data in this collection to compute two different metrics that can be used to approximate typical academic rankings of US universities. We mine Twitter data to compute a ranking based on the University Twitter Engagement (UTE) score. We mine other public sources of data related to endowment funds, athletic expenditures, and student enrollment to compute a ranking based on the Endowment, Expenditures, and Enrollment (EEE) score. Both of these metrics can be computed at any time and by any party, without having to wait for the release of annual university rankings or depending on subjective measures such as reputation.

University Twitter Engagement (UTE) is the total number of all affiliated users the university promotes on its home page plus the followers of any Twitter friends who indicate an affiliation with the university in their profile Uniform Resource Identifier (URI). The UTE score quantifies the potential popularity or prestige of the university without an extensive data collection effort. The Endowment, Expenditures, and Enrollment (EEE) score is computed from publicly available data on the web about alumni engagement (reflected in alumni donations and endowments), athletic engagement (reflected in athletic expenditures), and student enrollment.

We assume that (1) universities with higher undergraduate enrollment are likely to have more Twitter followers as students transition to alumni status, (2) official Twitter accounts will be featured on the university’s home page, (3) sports participation is a driver that increases awareness of the university’s brand, and (4) the data needed to compute the ranking criteria is readily available from public data on the web. Figure 1 depicts a point-in-time glimpse into the Twitter followers (675K) for Harvard University, a perennially top-ranked school, which represents an approximate 100:1 ratio to its undergraduate enrollment (6,660). On the other hand, the Twitter follower count (1,213) for Virginia Military Institute (VMI), a top-100 school, barely maintains a 1:1 ratio with its undergraduate enrollment (1,717). We would expect schools with similar enrollment to attract a similar number of Twitter followers. The large disparity between Harvard and VMI presents a first indication that some correlation may exist between rank position and Twitter followers.

The contributions of this study are as follows. We aggregate the rankings from multiple expert sources to compute an adjusted reputation rank (ARR) for each university, which allows direct comparison based on position in the list and provides a collective perspective of the individual rankings. We conduct a web-based analysis to identify and collect a mutually aligned set of primary and secondary Twitter accounts as a measure of social media engagement. We propose two easily-collected proxy measurements, UTE and EEE, that achieve comparable rankings to more complex methodologies that rely upon manual compilation. We produce a social media rich dataset containing Twitter profile data and
The notion of reputation largely serves as a feedback loop to main-
variables used and their associated weightings. Therefore, ranking
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determine best colleges based on academic excellence while the
a distinct purpose. Three of the four ranking systems we reference
direct comparisons difficult as each list may be intended to convey
ensuring stability in results over time [5].

Anchoring effect is the tendency of people to rely on a reference point in making judgments or decisions. Once a university reaches the pinnacle of any ranking system, they are anchored and often do not fall very far from their original position. As predicted by decision-making the-
in which it is better to invest in order to improve the ranking of
their institution [11]. And, as predicted by decision-making theory, Bowman and Bastelo [5] found that anchoring effects exert a substantial influence on future reputational assessments. Once a university reaches the pinnacle of any ranking system, they are anchored and often do not fall very far from their original position. Nearly always, rankings drive reputation, not the other way around. The notion of reputation largely serves as a feedback loop to maintain the status quo, establishing the credibility of the rankings and ensuring stability in results over time [5].

Figure 1: Twitter Follower Comparison

2.1 The Challenge of Ranking Universities

University rankings are subject to assumptions about the type of variables used and their associated weightings. Therefore, ranking systems reflect the conceptual framework and the modeling choices used to build them [11]. These systems can potentially give inaccurate indications to university administrators about the activities in which it is better to invest in order to improve the ranking of their institution [11]. And, as predicted by decision-making theory, Bowman and Bastelo [5] found that anchoring effects exert a substantial influence on future reputational assessments. Once a university reaches the pinnacle of any ranking system, they are anchored and often do not fall very far from their original position. Nearly always, rankings drive reputation, not the other way around. The notion of reputation largely serves as a feedback loop to maintain the status quo, establishing the credibility of the rankings and ensuring stability in results over time [5].

Heterogeneous metrics used by ranking organizations can make direct comparisons difficult as each list may be intended to convey a distinct purpose. Three of the four ranking systems we reference determine best colleges based on academic excellence while the fourth, *Money Magazine*, is focused solely on perceived value and affordability. A particular ranking list may count factors such as external funding, numbers of articles authored by faculty, library resources, and proportion of faculty with advanced degrees. This information is not always easy to obtain. Conducting surveys can be time consuming and expensive if the data must be gathered over a long period of time or requires input from a university official.

The ranking systems often assume that one set of metrics and the norms of research-based and elite universities are applicable to everyone [2]. Goglio [11] showed that the competition to improve ranks among lower ranked universities is different from the competition to do so among higher ranked universities. Grewal et al.’s [13] results showed that a top-ranked university has a 0.965 probability of appearing in the top five the next year. Ultimately, regardless of popularity, universities exhibit very little power to control their rank position; especially when the top positions are perennially dominated by the same institutions [11].

2.2 Social Media in Higher Education

Even when the ranking systems have the same goal, technical chal-
gevens can still hamper data collection; specifically, changes in page names or web domains can affect both the visibility and discover-
ability of the institution’s web presence. An organization can also use different web domains for search engines, aliases and independent domains for some of their subunits or services [1]. For example, in addition to *purdue.edu* which is the expected domain for Purdue University, we found *purduesports.com* and *purduealumni.org* as do-
domains associated with university-affiliated organizations. As noted by Aguillo [1], an adequate web presence or lack thereof may not always correlate with the prestige of the institution.

Social networking sites have proven to be an effective vehicle for organizations seeking to implement diverse branding strategies, given that such sites allow consumers to share their experiences and opinions concerning the organization’s brand in real time [14, 15]. Many organizations have rapidly adopted social networking services such as Facebook and Twitter, a move that has altered the face of customer relationship management from managing customers to collaborating with customers. While social media interactions in the higher education space are not transactional in the traditional sense, they do provide a way for institutions to continually engage with their constituents. Another form of engagement, or public involvement with a chosen organization that may fall outside of consumer interests is *affective commitment* which Kang [16] defines as a voluntary bonding between entities; perhaps similar to how a university might maintain contact with its alumni long after graduation. We will focus on engagement at a very basic or minimal level based on familiarity and cognition where one first needs to be familiar with a university’s online activity and subsequently start to follow them via social media.

A 2016 study conducted by the Pew Research Center measured social media usage in the United States. The study concluded that while Facebook continues to be the U.S.’s most popular social networking site with nearly 79% of online users using the platform, Twitter usage is holding steady at 24% and is also somewhat more popular among the highly educated [12]. Go et al.’s [10] 2016 social media benchmarking report also suggests that Twitter is perceived as the most useful application for businesses. At the organizational

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1. https://github.com/oduwsdl/University-Twitter-Engagement
We then consider which of these institutions appear among the top 351 American universities currently classified as Division I by the National Collegiate Athletic Association (NCAA). Other approaches define different types of Twitter influence, namely in-degree, retweet and mention influence [6]. Accordingly, a question arises concerning how to determine the performance of one user relative to another. The presence of homophily implies that people who are similar in some way are more likely to follow each other [3]. Measuring Twitter followers is generally considered a popular metric as having many followers can indicate a higher level of influence among interested users. This metric implies that the more followers a user has, the more impact the user has, as the user seems to be more popular [21]. Preusser [25] contends that the number of followers is an indicator of the social reputation and the number of followers will increase as the user becomes more important. Finally, Kunegis et al. [19] assert that preferential attachment indicates that people who are already followed by many people (i.e., are popular) are more likely to receive new followers.

An alternative approach for ranking Twitter users undertaken by Saito and Masuda [26] considers the number of others that a user follows, i.e., friends. They concluded the number of others that a user follows is equally important as the number of followers. In previous studies, a variety of characteristics, both personal and social, have been used to identify influencers and each study measures influence from different perspectives [4, 20, 21, 30]. Weng introduced the concept of homophily which implies that a Twitterer follows a friend because she is interested in some topics the friend is publishing, and the friend follows back because she finds they share a similar topical interest. The presence of homophily implies there are Twitter users who are highly selective when choosing friends to follow [30]. These conclusions are evidenced by super users who are followed by many, but they only follow a select group of Twitter friends (e.g., consider the friend-to-follower ratio of Harvard shown in Figure 1).

## 3 METHODOLOGY

The following section discusses how we chose the performance indicators to correspond with the entries in the expert lists, the ranking algorithm and other operational details.

### 3.1 Establishing the Selection Criteria


### Table 1: Contribution of Each Ranking List to Our Dataset

<table>
<thead>
<tr>
<th>Ranking System</th>
<th>Total Universities</th>
<th>U.S. &amp; NCAA Division 1</th>
<th>Unique Entries</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARWU</td>
<td>500</td>
<td>107</td>
<td>1</td>
</tr>
<tr>
<td>Money Magazine</td>
<td>705</td>
<td>249</td>
<td>115</td>
</tr>
<tr>
<td>THE</td>
<td>800</td>
<td>118</td>
<td>4</td>
</tr>
<tr>
<td>US News 2015</td>
<td>500</td>
<td>99</td>
<td>0</td>
</tr>
<tr>
<td>US News 2016</td>
<td>750</td>
<td>137</td>
<td>3</td>
</tr>
<tr>
<td>Any Two Lists</td>
<td>–</td>
<td>–</td>
<td>22</td>
</tr>
<tr>
<td>Any Three Lists</td>
<td>–</td>
<td>–</td>
<td>19</td>
</tr>
<tr>
<td>Any Four Lists</td>
<td>–</td>
<td>–</td>
<td>16</td>
</tr>
<tr>
<td>All Five Lists</td>
<td>–</td>
<td>–</td>
<td>84</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>264</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Table 1, we identify the overlap between the total number of universities on each list and the NCAA Division I category of interest. While Division I is not necessarily a ranking, participation in Division I athletics might be an indicator that the university garners more attention from alumni and the general public via national media exposure. For example, consider the difference in the adjusted reputation rank (Section 3.3) between Ohio State (Division I) with a rank of 56 and the smaller Case Western Reserve (Division III) with a rank of 128, which are public and private universities located within close proximity in Columbus and Cleveland. These rankings support the assertions of Standifird [27] who noted student enrollment and athletic team performance may influence the assessment of private and public universities, respectively with a slight bias towards more visible institutions in general. A review of the unique appearance of a university on one or more lists demonstrates the diversity or lack thereof between the five rankings under consideration. Only Money Magazine, with its emphasis on perceived value, includes 115 institutions not evaluated elsewhere; while more than 53% of the universities in our dataset appear on at least two of the indicated lists. This anchoring of universities among the ranking lists is consistent with previous research [5] regarding adherence to the status quo (see Section 2.1).

### 3.2 Standardizing the Rank Positions

Two of the ranking systems that contribute to our dataset bin universities alphabetically into groups after a certain threshold has been reached, resulting in tied ranking positions for those universities found lower on the list. After the first 200 individual rankings, THE places the remaining institutions ranked between 201 and 400 into bins of size 50 and then use bins of size 100 for ranks between 401 and 800. The ranking for each binned institution is the lowest
are consistently weak to moderately correlated with all other ranking lists we consider. Therefore, we exclude the *Money* rankings from our computation of ARR. The 115 schools which appeared only on the *Money* list were placed in a non-ranked position at the end of ARWU, THE, and the lists from U.S. News. A standardized ranking position was then calculated using the methodology described in Section 3.2.

### 3.4 Computing the Composite EEE Rank

We identified several candidate attributes to determine which combination of quantifiable attributes might provide a good evaluation metric for our ranking system. We empirically selected characteristics that can be calculated or retrieved from the Web: monetary value of the endowment, athletic expenditures, and undergraduate enrollment. This comprised our composite endowment, expenditures, and enrollment (EEE) ranking. We include the total expenditures for men’s and women’s sports as a measure of the institution’s commitment to promoting the university as a whole. The data sources for these values are listed below:

- **Athletic Expenditures**: [Equity in Athletics Data Analysis](http://ope.ed.gov/athletics/)
- **Undergraduate Enrollment**: [Integrated Postsecondary Education Data System (IPEDS)](https://nces.ed.gov/ipeds/)

For endowments that were attributed to a university system (e.g., University of Minnesota Foundation vs. University of Minnesota-Twin Cities), we used DBpedia to obtain the endowment value for the particular university present in the ranking lists to avoid overstating the endowment. Specific institutional data such as the founding date that could not be obtained from another already mentioned source was retrieved using web searches of DBpedia.

Due to the broad range of values, each of the enrollment, endowment, and expenditures was normalized individually across the full dataset of 264 universities to obtain the same scale, from 0 to 1, then aggregated to obtain a sequential EEE ranking of the universities. The top-10 universities as ranked by our EEE score are shown in Table 3.

Later in Section 4.3, we theorize whether the EEE score might serve as a viable proxy measure for a subset of our data, the NCAA Power Five. The NCAA Power Five Conferences include the Southeastern Conference (SEC), Atlantic Coast Conference (ACC), Big Ten, Pac-12, and Big 12. These conferences are composed of 65 flagship public and private universities who share excellent academic reputations, large endowments, and big budgets allocated for their athletic programs. These schools are representative of institutions that are playing at the highest level of NCAA competition and typically excel in two if not all three of the dimensions of enrollment, expenditures, and endowment.

### 3.5 Mining Official Twitter Accounts

One of the proposed performance indicators for our dataset is constructed around a set of primary Twitter seed accounts for each

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1 [http://wiki.dbpedia.org](http://wiki.dbpedia.org)
Table 3: Top-10 Universities Ranked by EEE

<table>
<thead>
<tr>
<th>University</th>
<th>Undergraduate Enrollment</th>
<th>Endowment, Thousands $</th>
<th>Athletic Expenditures, $</th>
<th>EEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ohio State University</td>
<td>40,452</td>
<td>3,633,887</td>
<td>136,966,818</td>
<td>1</td>
</tr>
<tr>
<td>University of Texas</td>
<td>36,072</td>
<td>3,341,835</td>
<td>152,853,239</td>
<td>2</td>
</tr>
<tr>
<td>Pennsylvania State University</td>
<td>39,077</td>
<td>3,635,730</td>
<td>117,818,050</td>
<td>3</td>
</tr>
<tr>
<td>University of Michigan</td>
<td>27,297</td>
<td>9,952,113</td>
<td>131,003,957</td>
<td>3</td>
</tr>
<tr>
<td>University of Wisconsin–Madison</td>
<td>27,867</td>
<td>2,465,051</td>
<td>122,975,876</td>
<td>5</td>
</tr>
<tr>
<td>University of Florida</td>
<td>29,577</td>
<td>1,550,000</td>
<td>130,772,416</td>
<td>6</td>
</tr>
<tr>
<td>Michigan State University</td>
<td>35,038</td>
<td>2,274,813</td>
<td>89,491,630</td>
<td>7</td>
</tr>
<tr>
<td>University of Washington</td>
<td>27,733</td>
<td>3,076,226</td>
<td>88,580,078</td>
<td>8</td>
</tr>
<tr>
<td>University of California–Los Angeles</td>
<td>29,027</td>
<td>1,864,605</td>
<td>96,912,767</td>
<td>9</td>
</tr>
<tr>
<td>Indiana University</td>
<td>31,161</td>
<td>1,974,215</td>
<td>81,161,423</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 4: Union of the Top 10 Universities According to ARR and Top 10 According to UTE, sorted by ARR. UTE score represents the total primary and secondary Twitter followers.

<table>
<thead>
<tr>
<th>University</th>
<th>ARWU Ordered</th>
<th>THE Ordered</th>
<th>USNEWS 2015 Ordered</th>
<th>USNEWS 2016 Ordered</th>
<th>Mean Reputation Score</th>
<th>Adjusted Reputation Rank</th>
<th>UTE Score</th>
<th>UTE Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harvard University</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>4,562,501</td>
<td>1</td>
</tr>
<tr>
<td>Stanford University</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2,239,440</td>
<td>2</td>
</tr>
<tr>
<td>University of California–Berkeley</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>474,901</td>
<td>19</td>
</tr>
<tr>
<td>Princeton University</td>
<td>4</td>
<td>3</td>
<td>6</td>
<td>7</td>
<td>5</td>
<td>4</td>
<td>574,758</td>
<td>15</td>
</tr>
<tr>
<td>Columbia University</td>
<td>5</td>
<td>6</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>759,574</td>
<td>7</td>
</tr>
<tr>
<td>University of California–Los Angeles</td>
<td>7</td>
<td>7</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>394,815</td>
<td>28</td>
</tr>
<tr>
<td>Yale University</td>
<td>6</td>
<td>4</td>
<td>9</td>
<td>8</td>
<td>7</td>
<td>7</td>
<td>808,461</td>
<td>4</td>
</tr>
<tr>
<td>University of Pennsylvania</td>
<td>10</td>
<td>8</td>
<td>10</td>
<td>8</td>
<td>9</td>
<td>8</td>
<td>778,805</td>
<td>5</td>
</tr>
<tr>
<td>University of Washington</td>
<td>9</td>
<td>13</td>
<td>7</td>
<td>6</td>
<td>9</td>
<td>8</td>
<td>274,674</td>
<td>44</td>
</tr>
<tr>
<td>University of Michigan</td>
<td>11</td>
<td>11</td>
<td>7</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>671,277</td>
<td>12</td>
</tr>
<tr>
<td>Cornell University</td>
<td>8</td>
<td>9</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>10</td>
<td>820,656</td>
<td>3</td>
</tr>
</tbody>
</table>

university. For the present study, the presence of Twitter friends is also needed to bootstrap the discovery of affiliated, secondary Twitter accounts. The complete process for identifying these accounts and determining the value for UTE is shown in Algorithm 1 and described here. As illustrated in Figure 2, we start with the URI for the university’s homepage obtained from the detailed institutional profile information in the ranking lists. For each URI, we navigated to the associated webpage and searched the HTML source for links to valid Twitter handles. After examining the source anchor link text, we eliminated known false positives which were longer than 15 characters (Twitter limit for a valid screen name) or included /intent, /share, /tweet, /search or /hashtag in the URI, which are directives to Twitter queries. Once the Twitter screen name was identified, the Twitter GET users/Show API was used to retrieve the URI from the profile of each user name. If the domain of the URI matched exactly or resolved to the known domain of the institution, we considered the account to be one of the university’s official, primary Twitter handles since the user had self-associated with the university via the URI reference. As an example, the user names @NBA, @DukeAnnualFund, @Duke_MBB, and @DukeU were extracted from the page source of the Duke University homepage (www.duke.edu). However, only @DukeAnnualFund and @DukeU are considered official primary accounts because their respective URLs, annualfund.duke.edu and duke.edu, are in the same domain as the university.

Ten institutions did not have a Twitter account identified on their home page as of August 2016, therefore, a primary official account could not be determined via our automated home page search. These schools included Louisville (@uofl), South Carolina (@uofsc), Missouri (@mizzou), North Carolina at Greensboro (@uncg), Ball State (@ballstate), Evansville (@evansville), Fordham (@fordhamnotes), Marist College (@marist), Portland State (@portland_state), and East Carolina (@eastcarolina). For this subset only, we used the Google Custom Search Engine8 to initiate an X-ray search using the keywords “institution” AND “twitter”. We accepted the top ranked result returned by Google, if any, as the official, primary Twitter account for the university. In the event that Google did not return a Twitter account, we manually searched using the search bar located on http://twitter.com.

8https://cse.google.com/cse/
Colleges and universities have a reputation for being decentralized, with many departments operating independently of one another, maintaining a separate social media presence. However, we observed that only 24 of the 264 universities in our dataset promoted multiple, official Twitter accounts on their homepage. For the purpose of computing our UTE score, we want to consider the contribution of all university-affiliated Twitter accounts. Therefore, for each of the identified official, primary accounts, we obtained the full list of their Twitter friends, i.e., users that they follow. Again, we used the Twitter GET users/Show API to determine which of the friends could be included as secondary official Twitter accounts based on the URI in the profile (must have the same domain as the university). These secondary accounts might include the athletic teams, faculty members, and other university organizations. Once the primary and secondary accounts were identified, we used the Twitter GET followers/IDs API to retrieve and accumulate the follower count to form the UTE score for the university.

We launched our crawler to find all of the designated Twitter followers during the time period between June 15, 2016 and August 30, 2016. In total, we collected 1,087,000 user profiles. Approximately 9% of all the user accounts we collected were protected at the profile owner’s request; allowing only their friends to view their profiles. Subsequently, we ignored these users in the computation of the UTE score because the underlying profile data is inaccessible using the Twitter API. Once we calculated the UTE score, we then ranked each university, in sequential order, based on the score, as shown in Table 4.

4 EVALUATION

In this section we evaluate our EEE and UTE rankings by computing rank-order correlation with the adjusted reputation rank (Section 3.3). We also directly compare the rankings of individual universities for the full dataset and discuss the implications for universities in the NCAA Power Five conferences.

4.1 Rank-Order Correlation

Since we know the potential for tied rankings exists in our data, we used Kendall’s Tau-b (\( \tau \)) rank-order correlation to test for statistically significant (\( p < 0.05 \)), moderate (0.40 < \( \tau \) ≤ 0.60) or strong (0.60 < \( \tau \) ≤ 0.80) correlations between the individual ranking systems and our adjusted reputation rank. Table 5 shows the respective inter-rank correlation measured in Kendall \( \tau \). With \( \tau \) values in the range of 0.3189 to 0.4191, the rankings on Money Magazine are weak to moderately correlated with all other ranking lists including our ARR. This range of \( \tau \) values confirms our intuition that the disparate ranking criteria based on value and the underlying goals of the Money Magazine system appropriately deem it an outlier among the other lists. We note a strong correlation, in the range of 0.7634 to 0.8787, between the remaining four lists which indicates that (1) the criteria traditionally used to rank universities based on academic excellence changes slowly thus resulting in minimal differentiation in the selected universities and (2) the relative ranking position of a particular university is anchored and does not vary significantly from year to year. The strong correlation of 0.8787 between subsequent lists found in the 2015 and 2016 rankings in U.S. News along with the addition of only three new entrants in 2016 (see Table 1) confirms this observation. The lack of variety between the U.S. News rankings is also consistent with the conclusions of Grewal et al. [13], noted previously in Section 2.1, which indicated the high probability of a top-ranked university retaining its rank from year to year. Our adjusted reputation rank, with \( \tau \) values in the range of 0.8285 to 0.9375, is strongly correlated with the rankings in ARWU, THE, and both years of USNEWS. Therefore, we conclude
that ARR can be used as a representative proxy for any traditional ranking system.

4.2 Composite Ranking Correlation with UTE

In order to evaluate our EEE and UTE rankings against the ARR, we again used Kendall’s Tau-b (τ) rank-order correlation to test for statistically significant (p < 0.05), moderate (0.40 < τ ≤ 0.60) or strong (0.60 < τ ≤ 0.80) correlations. Using ARR as the ranking criteria, we selected the top-50, top-100, top-141 ranked on two or more lists, and all 264 universities in our dataset. As shown in Table 6a, we found with a τ value of 0.6691, UTE is most strongly correlated with the ARR for the top-50 institutions followed closely by EEE at 0.5728. We must note the majority of the universities in the top-50 of any ranking list are usually members of the Ivy League or large schools with highly recognizable athletic programs like those in the Power Five (e.g., Ohio State, Penn State) so we might expect similarities in the metrics that comprise EEE. The observation is consistent with the strong correlation between EEE and UTE, which could explain the increase in Twitter following. Twitter engagement provides an inexpensive means for smaller schools to reach a large audience, potentially enhancing their reputations. Figure 3b also shows that there are several smaller schools (in the last EEE bin, cyan dots) that have larger Twitter followings than their academic rank (not ranked in ARR) or EEE would explain. These schools may be making a concerted effort to enhance their profile and could potentially move into the standard academic rankings in the future. This would be an interesting avenue for future study. Finally, Figure 3c shows EEE vs. UTE, which indicates that as expected, universities with more financial resources tend to have larger Twitter followings, though there are still some universities in the lower EEE bins that have significant Twitter followings.

4.3 Correlation Between the NCAA Power Five

We use the fraternity of the schools in the Power Five to more closely examine the collective ranking correlation of these conferences based on their 2016 membership. Within the complete data set, we observed that 55 out of the 65 Power Five member institutions (84.6%) were ranked within the top-100 positions based on the ARR rank. Further, we found that all 65 schools (100%) were ranked within the top-100 positions based on the EEE rank. The latter observation is consistent with the strong correlation between EEE and UTE, τ = 0.6461, shown in Table 6d, and is consistent with our intuition that large schools with ample financial resources would attract more Twitter followers. Figure 4 highlights the relationships between the Power Five and the various metrics by repeating the same charts from Figure 3 but with members of the Power Five shown in blue.

We noted several similarities which were indicative of the ten schools (15.4%) that were ranked outside of the top tier for ARR.

Table 6: Kendall’s Tau-b Correlation Between Composite Rankings and UTE Rank for Institutions on Two or More Lists

<table>
<thead>
<tr>
<th>EEE</th>
<th>UTE</th>
<th>ARR</th>
<th>EEE</th>
<th>UTE</th>
<th>ARR</th>
<th>EEE</th>
<th>UTE</th>
<th>ARR</th>
<th>EEE</th>
<th>UTE</th>
<th>ARR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EEE</td>
<td>0.5728</td>
<td>0.5310</td>
<td>0.5728</td>
<td>0.5620</td>
<td>0.5410</td>
<td>0.5728</td>
<td>0.5620</td>
<td>0.5410</td>
<td>0.5728</td>
<td>0.5620</td>
<td>0.5410</td>
</tr>
<tr>
<td>UTE</td>
<td></td>
<td>1</td>
<td>0.6691</td>
<td>UTE</td>
<td>0.5620</td>
<td>1</td>
<td>0.5960</td>
<td>1</td>
<td>0.5960</td>
<td>1</td>
<td>0.5960</td>
</tr>
<tr>
<td>ARR</td>
<td>0.5310</td>
<td>0.6691</td>
<td>0.5410</td>
<td>0.5960</td>
<td>0.5920</td>
<td>0.5388</td>
<td>0.5960</td>
<td>0.5920</td>
<td>0.5388</td>
<td>0.5960</td>
<td>0.5920</td>
</tr>
</tbody>
</table>

(a) Top 50

(b) Top 100

(c) Top 141

(d) All 264
Figure 3: Correlation of Composite Rankings (Full Dataset). Colors represent bins of the EEE rank from 1 to 264.

Figure 4: Correlation of Composite Rankings (Full Dataset). Blue dots represent member institutions in the Power Five.

Notably both Texas Christian and Mississippi State are the only schools which were not ranked on two or more of the ranking lists. Both schools also fall significantly below the mean values for the Power Five in terms of undergraduate enrollment (≈ 21,000), endowment value (≈ $2.3B), and athletic expenditures (≈ $90M), placing them at the bottom of the EEE ranking. On the other hand, Wake Forest is the smallest institution in the Power Five, but the school garners an academic reputation (ARR=45) that cannot be readily explained by its comparatively low EEE ranking (EEE=97).

We also note four schools that fall within the bottom 50% of UTE. In particular, the University of Louisville could achieve a considerable boost in UTE ranking (≈ 107,000 followers) if the Twitter account used by the athletic department (@GoCards) would reference the primary URI of the university rather than its own domain (http://gocards.com). We discovered 284 primary and secondary accounts followed by Georgia Tech, however only four of these could be considered official, because 150 of 280 secondary accounts did not include a URI in the profile bio. A similar scenario was noted for Oregon State where 271 of the 341 secondary accounts did not include a URI. While we identified 74 official accounts for the University of Pittsburgh, as was the case with Louisville, ≈ 140,000 underreported secondary Twitter accounts are associated with university sports. We discovered the Twitter followers of Wake Forest are bolstered significantly by a single celebrity professor, Melissa Harris-Perry, who in addition to her faculty position previously hosted a weekly news style program on US television. More than 80% of the Wake Forest UTE score is attributed to the verified @MHarrisPerry Twitter account which has more than 600,000 followers.

In Table 7, we provide a sampling of the diverse, though not exhaustive, list of unique university domains referenced in the profile of secondary Twitter accounts of the NCAA Power Five. The full table for all 65 universities in the Power Five is found in Appendix A of McCoy et al. [22]. Upon visual inspection of the web content of each domain, we find they are related to the university in some capacity (e.g., sports teams, clubs), but do not conform to our domain association rule. We identified 181 secondary domains associated with Purdue University. The total followers associated with the 296 Twitter accounts which referenced one of the secondary domains is 426,586. As evident by this example, the omission of followers for the secondary Twitter accounts can, in some cases, significantly lower our calculation of UTE score. For those under performing universities, in terms of Twitter followers, inclusion of more domains would elevate the UTE rank and likely present a stronger correlation of Kendall’s Tau-b (τ) than was noted in Table 5. We did not attempt to identify additional secondary domains for the entire set of 264 universities in our dataset. This exercise would be manually intensive and counter to our stated goal of automated data collection.

5 DISCUSSION AND FUTURE WORK

As noted during our own collection efforts, the quality and availability of the data chosen as performance indicators can impede the efficiency of constructing a gold standard data set. Manual correction can improve the data collection, but is expensive and is not conducive to reproducible research. We observed that institutions themselves do not maintain a complete listing of all official Twitter
Algorithm 1 Mining Official Twitter Accounts

Let \( h \leftarrow \) homepageURI
Let \( d \leftarrow \) domain(h)

function findOfficialTwitterAccounts(h, d)

let foundAccountInd \leftarrow \) false
let TwitterPrimary \leftarrow nil
let W \leftarrow ViewPageSource(H)

repeat

> Search for anchor tag with href in the Twitter format
let A \leftarrow anchorTag
let user \leftarrow TwitterRegexp(A)
if user \in TwitterAccount then
let profile \leftarrow TwitterGETusers(user)
if domain(profileURI) \subset D then

> Twitter friends are the users an account follows
let TwitterPrimary \leftarrow TwitterPrimary \union profile
let friends \leftarrow TwitterGETFriends(profile)

let TwitterPrimary \leftarrow TwitterPrimary \union friends
let foundAccountInd \leftarrow true

until W \equiv nil

if foundAccountInd then
let UTE \leftarrow 0
for i=1 \do \) length(TwitterPrimary)
let primAcct \in TwitterPrimary(i)
let profile \leftarrow TwitterGETFollowers(primAcct)
if domain(profileURI) \subset D then

let UTE \leftarrow UTE + followers

else
let searchResults \leftarrow GoogleCustomSearch(h, ”twitter”) TwitterPrimary \leftarrow searchResults(0)
let UTE \leftarrow 0
let primAcct \leftarrow TwitterPrimary(0)
let profile \leftarrow TwitterGETFollowers(primAcct)
if domain(profileURI) \subset D then

let UTE \leftarrow UTE + followers

return UTE

---

Table 7: Underreported UTE for NCAA Power Five Universities Where the URI Does Not Conform to our Domain Rules

<table>
<thead>
<tr>
<th>University</th>
<th>Homepage Domain</th>
<th>Unique Secondary Domains</th>
<th>Sampling of Secondary Domains</th>
<th>Secondary Twitter Accounts</th>
<th>Secondary UTE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arizona State University</td>
<td>asu.edu</td>
<td>92</td>
<td>thesundevils.com</td>
<td>138</td>
<td>498,097</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>asufoundation.org</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>auburntigers.com</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>auburnalabama.org</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>auburn.collegiatelink.net</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auburn University</td>
<td>auburn.edu</td>
<td>15</td>
<td>purduealumni.org</td>
<td>43</td>
<td>809,923</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>purduesports.com</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>uwbadgers.com</td>
<td>296</td>
<td>426,586</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>badgernation.com</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purdue University</td>
<td>purdue.edu</td>
<td>181</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University of Wisconsin</td>
<td>wisc.edu</td>
<td>72</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
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</tbody>
</table>

accounts as noted by the number of undiscovered and undocument accounts we extracted during a secondary search. We must also acknowledge the impact of celebrity professors and verified accounts (e.g., Melissa Harris-Perry, @MHarrisPerry). Given the small number of verified accounts among our official Twitter profiles, we contend that celebrity faculty members might be equated to the influence of Nobel Prize laureates; an indicator which is used by some ranking systems. We did not address known issues with bots and spam accounts which may over inflate the stated number of Twitter followers, the primary component of our UTE score (e.g., [7]). We also understand that our methodology constrains universities to a single official hostname which can deflate the UTE score as Twitter accounts that reference other university-owned domains are omitted. Based on our research assumptions, we observed that enrollment does not necessarily increase the Twitter followers needed to compute UTE. Universities are not taking the opportunity to advertise their Twitter accounts and are at times promoting other entities on their homepage. This observation necessitated the need to expand the follower network as we have defined. Schools with highly visible sports programs, like those in the Power Five, tend to have more Twitter followers as the public is more aware of the university’s overall brand. In general, the perceived reputation of any university is impacted less by metrics which are intrinsic to the institution, but intangibles that translate into more impressions or brand awareness by the public and constituents. This parallels the assertions in prior research [21, 25] which contends that popular entities are more likely to attract more followers (see Section 2.3). Our study is subject to a number of limitations that present opportunities for future work. Campbell’s and Goodhart’s law suggest that if UTE becomes popular, institutions may seek to artificially increase their Twitter followers in order to increase their ranking. Future work could include only the Twitter accounts of real people. In order to obtain a more complete set of official Twitter accounts, the domain associated with the account URI could be expanded to include all registered domains for the university. Additional research might also broaden the scope of our study to include both U.S. and international universities. It might also be advantageous to subject the observations made in this paper to a temporal analysis to ascertain whether the UTE rankings, at least for those in the
upper echelon, persist over time and to look for non-linear spikes in Twitter followers which may indicate artificial manipulation.

We note that universities that have large endowments, enrollments, and/or athletic budgets will be ranked higher using EEE. This is reflected in the fact that all 65 schools in the NCAA Power Five conferences are found in the top-100 EEE rank. Further analysis of the relationship between the EEE rank and UTE rank could be done to determine which factors (such as athletic engagement) affect the number of Twitter followers a university has.

The use of web metrics to compute the UTE might also provide an incentive for institutions to increase their web presence as way to further engage with constituents and the general public. Social media allows us to measure another proxy for reputation – how the universities and the public engage with one another. The universities themselves have to decide whether this kind of outreach is important and invest in it, and the public needs to be interested enough to follow them.

6 CONCLUSION

We examined and ranked a set of 264 U.S. universities extracted from the NCAA Division I membership and lists published in U.S. News & World Report, Times Higher Education, Academic Ranking of World Universities, and Money Magazine using an adjusted reputation rank (ARR) that we compared to our Endowment, Expenditures, Enrollment (EEE) and University Twitter Engagement (UTE) scores. To compute the EEE and UTE rankings, we mined available data from Twitter and other publicly-available collections of data. When compared to the ARR rank for all 264 represented universities, we noted a strong correlation with UTE (τ=0.6018) and a similar correlation with EEE (τ=0.5969). We conclude that these rankings are comparable to those presented in other academic-based ranking systems, however, we present a low-cost data acquisition methodology using only web-based artifacts. Both EEE and UTE also offer distinct advantages because (1) they can be calculated on-demand rather than relying on an annual publication and (2) they promote diversity in the ranking lists, as any university with a Twitter account can be given a UTE rank and any university with online information about enrollment, expenditures, and endowment can be given an EEE rank.

REFERENCES