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Building A Text Classifier for Analyzing Scholar’s Twitter Data

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A project submitted to the faculty of
Brigham Young University
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Doctorate of Philosophy

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Introduction

This measurement project is designed to be able to measure proportions of professional and personal uses of social media of scholars. With social media becoming a prominent tool used by scholars, there are a slew of complications that may arise that accompany the combination of personal and professional use. Understanding the proportions of use may allow us to better understand the degree to which scholars are combining or not combining their personal and professional use and may unpack a deeper understanding of online identity, personal and professional time balance, and a more quantitative understanding of the ways in which scholars use social media.

In this measurement project, I focused on interactions on Twitter because is used by many scholars (Lupton, 2014) and the platform allows for unobtrusive identification and examination of scholars’ participation on social media by using the platform’s Application Programming Interface (API). Due largely to Twitter’s popularity with academics, Twitter has been used frequently as a venue for exploring scholars’ use of social media including their use patterns, the motivations that bring them to the platform, and the challenges that they face on social media (DeGroot, Young, & VanSlette, 2015; Gettman & Cortijo, 2015; Kimmons & Veletsianos, 2016; Lemon, McPherson, & Budge, 2015; McHeyzer-Williams & McHeyzer-Williams 2016; Veletsianos & Kimmons, 2016).

It is the goal of this measurement project to create a tool that can provide a richer understanding of actual use of social media of scholars, as opposed to perceived use, as well as to develop a classification tool that will allow researchers to be able to classify large groups of data gathered from sources such as social media platforms and use this to build a deeper
understanding of the landscape which scholars are navigating as they participate on social media platforms.

**Literature Review**

Scholars’ social media practices have typically been viewed with optimism. Early studies expressed hopefulness that scholars’ use of participatory technologies would lead to a variety of improved outcomes such as enhanced connections and interactions with students, scholars, and the broader public (Burbules & Bruce, 1995; Fetterman, 1998; Greenhow, Robelia, & Hughes, 2009; Nielsen, 2012; Weller, 2011) and that the use of social media could instill a greater sense of presence and community building (Brady, Holcomb, & Smith, 2010; Naveh, Tubin, & Pliskin, 2010). These hopes have also been amplified and perpetuated by educational technology enthusiasts and vendors (Carliner & Shank, 2016; Cukier, Middleton & Bauer, 2003; Njenga & Fourie, 2010). Yet, advocacy for social media adoption is often based on beliefs rather than systematic evidence and rarely considers the day-to-day realities of social media use in academics’ lives (Kimmons, 2014; Selwyn, 2013).

Conversely, some literature reports that academics’ social media practices are complicated and appear to be rife with tensions, dilemmas, and conundrums (Jordan & Weller, 2018; Veletsianos, 2016). For instance, some scholars characterize social media use as being a time-consuming distraction and a disruptive influence on their overall productivity, often describing deliberate practices to mitigate negative outcomes that they associate with social media use (Choo, Ranney, Chan, Trueger, Walsh, Tegtmeyer, McNamara, Choi, & Carroll, 2015; Lemon, Budge, & McPherson, 2015; McHeyzer-Williams & McHeyzer-Williams, 2016). Scholars also report feeling pressure to maintain an online presence that extends beyond working hours (Ferguson, 2017) and express concerns about navigating personal-professional...
boundaries online (Lupton, 2014; Veletsianos & Kimmons, 2013). In a recent study, scholars reported more problems than benefits associated with social media use (Jordan & Weller, 2018). Understanding personal and professional balances will allow us to dive deeper into potential problems that may occur as social media use is implemented in the lives of scholars.

The existing literature reveals that scholars use social media for a number of purposes professionally (Donelan 2016). In a survey conducted by Moran, Seaman, and Tinti-Kane (2011) for example, over 90% of faculty reported using social media in classroom instruction or for their professional goals outside of the classroom. This finding would suggest that most faculty are using social media professionally to some degree. Other surveys indicate that faculty are more likely to use Twitter when they are at academic conferences as a type of backchannel for conversation surrounding presentations, speakers, and events (Donelan, 2016; Ross, Terras, Warwick, & Welsh, 2011). Therefore, one would expect that some of the professional uses of Twitter by faculty surround research dissemination and community building. Kimmons and Veletsianos (2016) found that academics’ participation in event-based hashtags on Twitter (e.g., hashtags relating to a conference or an event) exhibited spikes and slumps, thereby suggesting that Twitter participation of scholars may be motivated by a desire to participate on these platforms professionally. All of these articles collectively imply that a large percentage of academics are, or perceive themselves to be, using Twitter and other social media to some degree professionally.

**Scholarly Concerns with Time Spent on Social Media**

In a qualitative study of social media use, Kieslinger (2016) explored factors related to how frequently scholars were using social media. The author categorized scholars into heavy, targeted, and restricted users: heavy users were using social media daily, both personally and
professionally; targeted users participated on social media platforms strategically and limited their time spent online; and restricted users chose not to participate in social media related activities, and thus spent the least amount of time online of all of the types of users. These academics attributed lack of time as one of the primary reasons for the limitation of their social media use.

Scholars broadly express challenges with time burden of technology use beyond that of social media. Along with spending their time on typical scholarly activities such as writing, research, and teaching, scholars now have to consider the added burden of building and maintaining an online presence (Lowenthal, Dunlap, & Stitson, 2016). Scholars are reporting feelings of concern relative to academic workload, work-life balance, and the potential for time spent on social media to reduce scholarly productivity and impact scholars’ lives negatively (Ferguson, 2017; Lemon, McPherson, & Budge, 2015; Veletsianos & Kimmons 2013). Dowling and Wilson (2017) conducted a study of PhD candidates and how they used online tools, and found these scholars hesitant to adopt online tools beyond those necessary for basic communication and research because of productivity related concerns. They mention social media specifically as a potential distraction for these scholars as they manage the time pressures of their doctoral studies. In their report on a year spent experimenting with Twitter for scholarly professional purposes, McHeyzer-Williams and McHeyzer-Williams (2016) described using Twitter in a way that did not disrupt their regular academic work schedule. Budge, Lemon, and McPherson (2016) also provided descriptions of experiences with social media and gave examples of deliberate restrictions of Twitter use to accomodate to work schedules and retain productivity and professional boundaries.
Scholars’ difficulty to achieve and maintain work-life balance spans beyond online participation. Spurling (2015) for example, explored academia’s temporal rhythms and qualities of time in efforts to mitigate work-life tensions. Spurling found that there are efforts taken to maintain time boundaries, and that scholars feel a need to be intentional about how to divide their time between their responsibilities. Scholars are also responding to an increasingly networked workflow by fragmented their work through multitasking, which has led to reports of increased stress and lack of time for reflective thought (Menzies & Newson, 2007). In response, and in an effort to combat the culture of overwork, some have called for scholars to engage in “slow scholarship” (Berg & Seeber, 2016), which is a thoughtful, but often drawn out forms of scholarship. Black (2018) described the stories women who decided to be more intentional about slow scholarship, and their experiences, while they were found to be potentially risky, rewarded them with safe academic spaces in which they were “slowing to connect,”” and felt they were slowing down their thoughts and actions to connect more intensely to their work, institution, and community.

One, more extreme response to time concerns, especially as these relate to digital practices, has been for individuals to temporarily disengage from social media. Though a number of terms have been used to describe this phenomenon (e.g., digital sabbatical, digital detox), at its essence the action represents a withdrawal from social media for a period of time. Limited research exists on this topic, but reports found in the broader online discussion suggests that scholars may temporarily disengage for a variety of reasons such as their need to re-evaluate use, set aside more time for other professional responsibilities, and address a variety of other personal or professional concerns (Zellner, 2012). Veletsianos, Kimmons, Belikov, & Johnson (2018) studied use patterns of scholars on Twitter and found that scholars are likely taking long breaks
from social media surrounding issues of excessive workload, being new to and uncomfortable with the platform, reflecting on the health and purpose of their social media use.

**Literature on Healthy Digital Practices**

Conversations within the broader culture have raised concerns about technology use and personal well-being (Andrew-Gee, 2018; Lewis, 2017). Scholars have mentioned ‘unplugging’, undergoing a ‘digital detox’, and restricting media consumption to reduce technology-related stressors in what appears to be an effort to establish healthy digital practices (“New year, no apps?”, 2018; Sengers, 2011; Zellner, 2012). We define temporary disengagement as disengaging from social media for a specific period of time (Veletsianos, Kimmons, Belikov & Johnson, 2018) and discontinuance usage intention as ceasing to participate in an activity with the intention that the activity will never be resumed (Maier, Laumer, Weinert, & Weitzel, 2015; Turel, 2015).

For many users, social media use is a pleasurable experience that may create guilt feelings when self-perception of overuse is determined to be a threat to well-being (Turel, 2015). As a result, some users may wish to limit, pause, or discontinue the experience or habit of using social media (or a specific social media platform) when they feel that the habit has become too strong or pervasive, albeit pleasurable. Specific to scholars, Zellner (2012) discussed her habit of taking a weekly digital detox, in which she avoids the use of digital technology for 24 hours each Sunday. She reported a sense of increased productivity upon returning to her usual patterns of technology use on Monday mornings. Veletsianos, Kimmons, Belikov, & Johnson (2018) also identified that excessive workload, being new to Twitter, reflecting on social media use, and other idiosyncratic reasons may be associated with temporary disengagement.
Making decisions to mitigate potential negative outcomes of social media use by setting temporal boundaries may be challenging for scholars due to a lack of definitive evidence about how much time on technology is too much. Few guidelines exist surrounding the degree to which social media use can fit into a healthy balanced life, and the degree to which the impact of screen based devices can negatively impact scholars. Shellard (2019), a vice-chancellor, stated feeling a personal sense of addiction to social media and described conversations with students, in which they stated similar feelings. These conversations led to the organization of a week-long, campus-wide digital detox. Reflecting on the experience afterward, he wrote, “Ultimately, like all aspects of health, using social media is about balance. But it can be hard to know if you’ve got that balance right.” (para. 26).

**Methods**

First, roughly 1,000 Twitter users were identified from each of four different faculty groups: lecturer, assistant professor, associate professor, and adjunct professor. In total, we retrieved 3,996 users by querying the Twitter API with keywords for each group (e.g., “associate professor”). The Twitter API search focuses on user-provided profile descriptions and limits results returned to 1,000 users. These users’ names, usernames, biographies, and geographical location were collected. Complete available tweet histories were also extracted using the Twitter API, which permitted the extraction of up to 3,500 tweets per user along with associated metadata for each tweet (e.g., timestamp, location, number of times the tweet was retweeted). This resulted in the collection of over three million tweets, of which approximately ten thousand were randomly selected for use in the creation and evaluation of the classification tool. I thematically coded 4,693 random tweets by scholars as either personal or professional. If a tweet was not deemed to be professional, it was automatically assigned as personal to create a
simplified dichotomy. This may contribute to the loss of some professional tweets in the classification and evaluation. For example, a scholar may be tweeting at another professional contact, but the content of the tweet may seem personal in nature. It is the complicated nature of these professional relationships, as well as the interpretation of 140 character messages, that may create an over-simplification. However, the categorization of tweets as professional only if they are clearly professional creates the lack of probability for a confusion matrix that falsely classifies professional content. This means that I valued precision of professional labels over the precision of personal labels because personal use of a technology is more broadly defined, and including personal tweets in professional categorization could later confuse the understanding of what professional activities are happening online. Once these tweets were coded, they were loaded into the classification tool.

**Building of the Classification Tool**

The classification tool was built in the tool Anacondas. Within the anacondas tool, development was conducted on jupyter notebook, a web-based interactive computing notebook environment. The language used to do all coding was Python, and the pandas library was imported for use of the classification. Commonly-occurring symbols and strings such as the initiations of hyperlinks and symbols such as hashtags and mention (@) symbols were excluded from analysis to ensure they would not confuse the classifier. The technique used was text mapping classification based on previously coded Decision trees (DT), naive-bayes (NB), rule induction, neural networks (NN), K-nearest neighbors (KNN), and support vector machines (SVM) were all techniques used to further group the data so that the classification tool could be more accurate in its classification of tweets. The primary technique was naive-bayes because this is mostly commonly used in text classification to predict a class based on various attributes.
**Budget and Timeline**

The budget was completed by one primary researcher, myself, with the technical support of two secondary researchers. There were no materials needed besides the use of a computer and free software. Time for a primary researcher, and support, has been calculated in the budget table. Expenses are shown in Table 1.

Table 1

*Project Budget*

<table>
<thead>
<tr>
<th>Description of Expense</th>
<th>Cost Per Unit (/hr)</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graduate Researcher</td>
<td>$30</td>
<td>$600</td>
</tr>
<tr>
<td>Technical Support - Coding</td>
<td>$50</td>
<td>$50</td>
</tr>
<tr>
<td>Technical Support - Data Collection</td>
<td>$50</td>
<td>$100</td>
</tr>
</tbody>
</table>

The timeline of the project was for proposal, data collection, qualitative coding, programming of the classifier, evaluation of the classifier, and report of the results and process.

The timeline of the project is shown in Table 2.

Table 2

*Timeline of Project*

<table>
<thead>
<tr>
<th>Task</th>
<th>Date Completed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project proposal</td>
<td>January 2018</td>
</tr>
<tr>
<td>Data collection</td>
<td>January 2018</td>
</tr>
<tr>
<td>Qualitative coding</td>
<td>March 2018</td>
</tr>
<tr>
<td>Programming of the classifier</td>
<td>September 2018</td>
</tr>
<tr>
<td>Evaluation of the classifier</td>
<td>January 2019</td>
</tr>
<tr>
<td>Report of results</td>
<td>September 2019</td>
</tr>
</tbody>
</table>
Evaluation of the Classifier

Once the classifier was trained with human coded tweets, it was tested with a group of approximately three thousand random additional tweets that were not used to train the classifier. Initially, the accuracy was found to be approximately 86%, and this was deemed to be a promising result. However, this closely reflects the percentage breakdown between personal and professional tweets, which would mean that if the classifier were randomly assigning personal and professional as a classification, this would be the breakdown that would be expected. It was because of this that a simple evaluation based on accuracy was not found to be complex enough to evaluate the true accuracy of the model, and a more equal breakdown of personal and professional tweets was extracted as an example to test the accuracy of the classifier. From this sample, the baseline accuracy was calculated to be approximately 49%. This means that if the classifier was to randomly assign tweets to be personal or professional, it would only be right approximately 49% of the time. After pulling aside this subset of data, the accuracy was run again and found to be approximately 71%, which is 22% higher than baseline, and a significantly more accurate tool than random assignment.

The data were regrouped because of the confusion matrix that occurs when classifications are assigned. Figure 1 shows a confusion matrix that may result as predicted results are compared with actual results. Of course, the goal is to achieve a maximum number of true positives and true negatives, but unfortunately false positives and false negatives may occur. In the initial testing, approximately one third of the classifications were found to be false positive or false negative classifications. After this finding, an additional 1,500 tweets were coded and included in the sample, which brought the negative impact of the confusion matrix down to less than 25% of the results.
The accuracy and F1 of the model was found to be significant enough to be a useful classification tool, considering that there is no base value for F1 or accuracy tools, the values are significantly higher than random classification, and the complexity of the phenomena being classified play a factor in the acceptable values (Lewis, 1991). Additionally, factors that decide acceptable measures are dependent on community values (Kay, Patel, & Kientz, 2015), and accuracy and F1 values close to perfect may take several years, significant hardware updates, and identification of new features of interest (Gupta, 2010) High F1 values are only typically achieved in highly contextualized settings, whereas this is a tool that could be used with some accuracy across a variety of settings.

**Results**

In addition to the base and model accuracy, some measures of the working classifier were produced as results. In these results, I will use the terms true positive (TP), false positive (FP),
false negative (FN), and true negative (TN). These terms are being used to identify professional identifications. The recall score of the classifier was calculated with the following formula: TP/TP+FP. In this case, the recall score was 0.67, or 67%. The precision score was calculated with the following formula: TP/TP+FN. The precision score was found to be 0.72, or 72%. The F1 score was calculated using the recall and precision scores and the formula is as follows: 2*(Recall * Precision) / (Recall + Precision) and the result of this calculation was an F1 score of 69.1. This, paired with the accuracy score of approximately 71%, shows that the classifier is functioning at significantly higher levels than random assignment, especially due to the complex nature of personal and professional interactions online. I used the F1 value, because it is one of the most popular measures of evaluating text classification tools, and it evenly values precision and recall, as I do not have a reason to value one over the other (Swalin, 2018). Had I used a model, that favored the precision score, the F1 would be higher. In the limitations, I will discuss ways in which the F1 score and accuracy score bout have been improved.

Social media use was found to be 12.3% professional, indicating that scholars primarily used Twitter for personal purposes. The 15 primary returned key terms by the classifier found to be professional in the realm of scholarship were education, data, research, going, conference, writing, teaching, study, student, social, paper, ways, review, experience, and science. These terms are most commonly found in professional tweets and indicate a high likelihood of a tweet being found to be professional. The classifier used a dichotomous classification, meaning that anything that was not found to be professional was classified as personal since we could not make the assertion that it was professional. This means there were no key terms for personal use, as personal conversations vary greatly in content, language, and structure. This classification tool, in addition to being a valuable way to measure use patterns online, gave insight into topics
which faculty were discussing online. Although the term teaching was one of the top 15 primary key terms, as well as education, the bulk of the terms were related to research, publications, and scholarly interactions. Given that most of the literature surrounding social media use by faculty focuses on uses for teaching and learning, the implications of terms surrounding research, scholarly interactions, and community building can have a variety of implications for faculty and institutions alike.

**Future Uses of the Text Classification**

There are a number of ways a classifier such as this can be used. One of the implications of understanding the ways in which faculty are using social media, can be institutional action. Understanding how faculty are using social media can guide prescriptions made by universities, as prescriptions for use are not common at the institutional level despite faculty being representatives of the institution online. This may also allow institutions to create expectations of online participation, as faculty currently feel pressure to participate online from colleagues, departments, and institutions, but have no clear guidelines for type and frequency of participation (Ferguson, 2017; Lupton 2014).

This classifier can also be used to measure participation on other types of social media, to understand how faculty are participating online in a more holistic way, as opposed to just on this single platform. There would need to be accommodations made in the coding process, as scholars may participate differently on different platforms, and coding interpretations may need to be completed considering potential audience and platform differences. It can also be used to capture changes in participation over time, measuring snapshots of use, and returning after years seeing if there have been increases in personal or professional use as faculty roles and responsibilities evolve with technical advances and social change.
The classifier may even be expanded to student use. Students at universities and colleges are entering a world in which their online persona may be evaluated in conjunction with their suitability for a job (Driver, 2018). It is estimated that 70% of employers refer to an online presence in making hiring decisions, according to a Career Builder survey (Hayes 2018). With such a classifier, students would be able to input their social media activities and understand how they are achieving a balance of personal and professional activity in their social media use.

**Limitations and Future Recommendations**

There are some limitations to the classifier, and some recommendations for how to overcome these limitations that were discovered through the process.

The classifier, while significantly accurate and holding an F1 value that shows model efficiency, could be improved in quality by increasing the number of tweets that would increase the data upon which the classifier can draw on to make decisions regarding whether a tweet is personal or professional. Although the refinement of such a tool to a closer degree of accuracy is outside the scope of this measurement project, in order to make institutional decisions and prescriptions, the amount of false positives and negatives would need to be decreased so that universities can justify changing institutional expectations and policies.

The dichotomous nature of the classifier also raises some questions regarding personal and professional uses. There may be professional uses, such as a religious education professor tweeting about religious events or a political science professor tweeting about an election, that are not captured in the professional category. Although a classifier would never be able to capture these phenomena perfectly, cross referencing content with the type of field scholars represent or retraining the classifier for each domain would allow for more accurate results. This however, would mean that analyses would have to be conducted by field, as including area-of-
study-specific data into the classifier would create false positives and negatives across other areas. The qualitative nature of making these distinctions also leaves room for interpretation, as researchers coding the training of the classifier may not have full insight into the intricacies of the work of a single faculty member or the intention behind their tweets.

In understanding the balance of personal and professional use, we do not explore deeply what both personal and professional use entail beyond the collection of key terms produced by the classifier. A deeper investigation into types of personal and professional activity would provide greater insight for institutions, scholars, and students alike. There are also opportunities here for this information to be connected to a sentiment analysis, understanding whether these personal and professional interactions are largely positive or negative, and how this relates to online participation patterns. This study is also limited to Twitter use, as scholars likely participate differently on various types of social media. Expanding this study to other social media would allow us to have a more holistic view of the ways in which faculty participate on social media.

Lastly, this study is interpretive in nature, using online data to interpret faculty use patterns without understanding intentions, experiences, and outside influences that may impact the ways in which faculty have chosen to participate online. Future studies involving large-scale data interpreted by researchers and qualitative studies that ask faculty deeper questions regarding their use would be valuable. Studies answering questions such as what impacts decisions to use social media personally and professionally, how do scholars find a balance between personal and professional use, do scholars feel pressure or responsibility to participate professionally online, what benefits and drawbacks do scholars experience to online participation, and how has social media use changed over time in light of various advancements, policies, and social
changes? These are just some of the questions that can be asked to delve more deeply into understanding personal and professional balance online, as well as the influencing factors and implications that arise for faculty when participating online.

**Conclusion**

The purpose of this measurement project was to create a classification tool that could interpret data collected from the social media platform Twitter and categorize it as either personal or professional. This classifier provides this classification to create a deeper understanding of actual scholarly use of social media, as opposed to reported use, and also allows us to understand to what degree scholars are balancing their personal and professional activities online. My sample of self-identified scholars’ tweets resulted in a majority of personal tweets, however this provides insight into both personal and professional patterns. In this instance, it appears that although use is predominantly personal, key terms indicate that scholars are using social media to boost their scholarship, particularly their research and community-building. This measurement tool provides insight into use patterns amongst scholars and opens the door to asking more in-depth questions regarding motivators behind social media use decisions, as well as benefits and drawbacks of social media choices amongst scholars.
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