

INCORPORATING ARTIFICIAL INTELLIGENCE INTO THE BUSINESS COMMUNICATION CURRICULUM

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ABSTRACT

To be competitive in today's marketplace, business students need AI skills in the analysis and interpretation of social media, product reviews, and corporate communications. In particular, sentiment analysis scoring and opinion mining are two rapidly growing areas of natural language processing used to identify trends, patterns, and outliers in large data sets to make data-driven decisions. Market-leading technologies like Tableau business intelligence software and cloud-computing services, such as Microsoft's Azure Cognitive Services, can provide a viable structure for sentiment analysis. This paper proposes several pedagogical approaches for incorporating business analytics into the business communication curriculum.

Keywords: business intelligence, business communication, data visualization, sentiment analysis, textual analysis, tableau, visualization design, tabPy, python, artificial intelligence, AI, natural language processing, NLP

INTRODUCTION

Although the data-driven business world has existed for decades (Fitzgerald & O'Kane, 1999), business analytics has become a formidable tool in the 21st century workplace. Indeed, Big Data has become a critical asset in gaining operational insights into problem-solving and decision-making (Lau et al., 2012). However, the sheer volume of such data can lead to "information

paralysis," leaving company leaders overwhelmed and unsure of what actions to take. To prepare business students for the modern workforce, business communication instructors must ensure that students are versed in the methods and tools for deciphering and solving contemporary business intelligence problems.

The popularity of social media sites has created a wealth of valuable information for businesses. Consequently, sentiment analysis of social media has become a rapidly emerging part of business communication (Sánchez-Núñez et al., 2020). Historically, sentiment analysis of business communication involved manual, time-intensive classification of advertisements, marketing material, emails, memoranda, and other material (Mäntylä et al., 2018). In addition, this analysis was sometimes performed well after the fact, rendering the results outdated. However, Artificial Intelligence (AI) tools now allow the efficient interpretation of that data. Business graduates need a fundamental knowledge of these tools and the critical thinking and analytical skills to interpret Big Data to be competitive in the business world.

Because managers need to receive, correctly understand, and promptly act on data, software engineers have developed a variety of tools for collecting, organizing, interpreting, and presenting data to them. For example, researchers and programmers use programming languages such as Python and R to take vast amounts of data and perform statistical calculations to reveal insights. For non-data scientists, however, these numbers and raw statistical measurements can be challenging to interpret. Therefore, business intelligence platforms were developed that transformed arcane numbers into easily understood visualizations. Platforms such as Tableau and Microsoft's Power BI have now become mainstream in business, communicating complex information to decision-makers who are not data scientists. These platforms allow users to create interactive dashboards that display high-level representations of insights from Big Data with techniques to drill down into the underlying details.

Current business communication textbooks usually include materials on writing style, strategic approaches for various business messages, report and proposal writing, oral presentations, résumé and cover letters, and a token chapter on social media. These chapters cover the types of messages that members of organizations (and job seekers) produce, and instruct students in planning and writing those messages while considering the audiences' needs. In addition, instructors employ basic textual analysis methods to help students identify and interpret patterns in language use and to examine connotations of word usage and unintended messages in the text. However, are these current methods adequately preparing our students with all the skills they may need in business today? Has business communication pedagogy kept up with the technological advances of the 21st century? Kristen Getchell has noted that "[b]usiness communication is not defined strictly by what is produced in businesses but also by the external influences of history, time, and innovation both in commerce and in academic and intellectual spaces" (2022, p. 671). Today's external factors include AI technologies that can assist (or even replace) humans in instructing an AI writer and then reviewing (and correcting) AI-produced messages. Or—as we explore in this paper—today's business communicator may be transformed into someone who guides an AI to "read" thousands of on-line messages and then applies the results to real-time business decisions. AI technologies are not only changing the way people communicate in business; these technologies are also changing the nature of business communication itself. Our business communication pedagogy should reflect those changes as well.

This paper describes several pedagogical approaches and resources to augment the business communication curriculum and introduce business communication educators and students to AI using textual analysis in business contexts. A subjective analysis of the opinions, emotions, and

speculations of others (Quirk et al., 1985), sentiment analysis is business communication made more efficient with AI and interpretation using Python and Tableau business intelligence platforms. With the TabPy Server, Python can operate inside the Tableau data visualization application. This process allows students to develop AI skills in sentiment scoring of textual data on these platforms and to create and interpret various data visualizations that can efficiently communicate valuable and complex data to stakeholders.

LITERATURE REVIEW

As an academic discipline, AI began in the mid-1950s when Marvin Minsky and John McCarthy hosted the Dartmouth Summer Research Project on Artificial Intelligence in New Hampshire (Kaplan & Haenlein, 2019). Minsky and McCarthy, along with academicians from various fields, sought to build machines that simulated human intelligence. AI quickly gained popularity in the U.S. and abroad in the 1960s and was of primary interest in the applied sciences. However, as computer processing systems became faster and friendlier with graphical user interface (GUI), easily portable with relatively inexpensive software, and easy-to-use with high-speed internet, consumer demand beyond the applied sciences increased dramatically. By the 21st century, AI could finally process Big Data and gained entrance into the business world (Kaplan & Haenlein, 2019). It is now commonly used to analyze data, streamline job processes, and predict courses of action.

The astonishing depth and breadth of AI inquiry in the 21st century cover sixteen significant categories: "reasoning, programming, artificial life, belief revision, data mining, distributed AI, expert systems, genetic algorithms, systems, knowledge representation, machine learning, natural language understanding, neural networks, theorem proving, constraint satisfaction, and theory of computation" (Oke, 2008, p. 537). Indeed, the impact of AI on the world is significant, with applications as diverse as mitigating environmental pollution (Chan & Wang, 2013) or understanding intuition (Frantz, 2003). Kaplan and Haenlein (2019) expect AI to become part of our daily lives, much as social media and the internet are today. In addition to transforming our personal lives, it will determine how companies make decisions and communicate with their external stakeholders. AI's use in business is becoming ubiquitous.

AI Uses in Higher Education and Business Communication

Many businesses have already utilized AI to some degree, as has higher education. For example, business students may have already been exposed to AI technologies that improve business writing skills. An example of this technology is Grammarly, one of the most widely utilized writing tools using machine learning and natural language processing (NLP) to review text spelling, grammar, punctuation, and sentence structure errors (Markovsky et al., 2021). NLP is a branch of AI and uses machines programmed with rule-based modeling of language to respond to voice or text data (IBM Cloud Education, 2020). Similarly, an AI chatbot, developed by OpenAI and launched in November of 2022, mimics the grammar and structure of writing and generates frequently used phrases. Although the ramifications of ChatGPT have yet to be determined, most college students (and their professors) have already investigated its use in assignments. In the workplace, applications of similar tools include Textico, a product that can compose job position announcements and use less biased and more inclusive language (Getchell et al., 2022). In addition, AI has been used as an automated text summarization tool for corporate disclosures (Naidoo et al., 2022).

Businesses have already incorporated online artificial agents, such as avatars and chatbots, on company websites to simulate face-to-face communication and assist customers more personally (Salomonson et al., 2013). Previous researchers had investigated these face-to-face and computer-facilitated interactions only generally (Berry, 2006; Markman, 2009; Meijden & Veenman, 2005); however, Salomonson et al. (2013) compared face-to-face human interactions with digital agents to determine the differences and similarities in communication. These researchers used activity-based communication analysis (ACA) (Allwood, 2007; Allwood et al., 2010), communication and discourse analysis, and pragmatics (M. Stubbs, 1983) to understand the extent of the social interactions to improve digital exchanges and leverage e-commerce in business.

AI and machine learning (a subset of AI that uses massive amounts of data to create predictions based on that data) are also used to improve business collaboration and facilitate individual and team communication. Getchell et al. (2022) note that meeting platforms incorporate AI to observe "intensity of physical activity, proximity to colleagues [and clients], speech activity, sentiment/social listening, and electrodermal peaks to evaluate team performance" (p. 10). In addition, the authors further identify AI technologies used in business recruiting to assess candidates' pitch, tone, pace, and eye contact, among other oral delivery components. For example, HireVue is used by over 700 companies (HireVue, n.d.) to assess candidates' communication and problem-solving skills, conscientiousness, and stability. Getchell et al. (2022) predict that these technologies will continue to become more prevalent in other business contexts.

AI's impact has been observed on social media platforms such as Slack or Yammer, where management can monitor the reception of initiatives, policies, and processes introduced in an organization. Analysis of posts and messages on Facebook and Twitter can reveal the external reception of an organization's products, initiatives, and policies. In addition, customer relation management systems such as Salesforce.com or internal databases track client interactions. Similarly, product reviews on sites such as Wal-mart.com use Bazaarvoice's database system to capture the market's perception of products. These channels have recorded narratives that lend themselves to sentiment analysis that new entrants in the business workforce may be expected to monitor. The insights gained from business analytics can significantly enhance quality control and spur product innovation (E. Stubbs, 2014). Perhaps more importantly, according to Duan et al. (2020), this information can give companies a competitive advantage in, for example, analyzing a message's intent and emotion for crucial business insights or predicting trends in consumer behavior. Similarly, we can give our business communication students a competitive advantage if we can train them to understand and use tools such as AI and NLP.

This study recommends sentiment analysis as a starting point for student training in business communication. Sentiment analysis is the most common form of text classification of messages and is similar to traditional textual analysis previously used in business communication. In effect, users employ the technique to assist in the determination of the writer's underlying intention or reaction that caused the message to be sent (Mejova, 2009). Historically, the numerical scoring of such messages was conducted by manually reviewing messages and locating pre-determined keywords to represent the positive, neutral, or harmful intent. A group of reviewers would maintain the dictionary of keywords and reduce bias in the manual analysis. The process was time-consuming and cumbersome.

In AI, however, the user or the machine creates a training data set that is manually reviewed initially for accuracy. It is then automatically updated via machine learning algorithms. Sentiment analysis attempts to determine the sender's attitude, evaluations, keyword pairings, opinions, and emotions (Kudo & Matsumoto, 2004; Weibe, Wilson, Bell, & Martin, 2004) and determines

whether the underlying message is positive, neutral, or negative (Mäntylä et al., 2018; Pang et al., 2008). The message is typically scored in a range with the numerical endpoints above as the classifiers: one (1) as positive, zero (0) for neutral, and a negative one (-1) for a negative message. The neutral zone can be of varying size depending on the interpretation of the user. The analysis, in many cases, can be complicated when taking in multiple segments for analysis, but is still superior to traditional textual analysis.

In summary, AI is widely used in business and is here to stay. A 2018 survey conducted by Infosys of 1,600 world business leaders indicated that 76% of the participants believed that AI was fundamental for business success, while 64% believed that their corporation's future growth depended on AI integration. While some researchers have recently explored the role of AI as it relates specifically to business communication (Naidoo & Dulek, 2022) and preparing business students for the workforce (Getchell et al., 2022), more work needs to examine how AI fits into the current business communication curriculum. In this paper, the authors have introduced several of their proven pedagogical strategies for incorporating AI in the classroom and training students in basic AI skills for business. Sentiment analysis, focusing on the impact of the sender's attitude, evaluations, keyword pairings, opinions, and emotions on business, provides a discipline-specific point of departure for business communication instructors and business students.

USING AI IN BUSINESS COMMUNICATION

The authors' experience in teaching AI has determined that the ideal training ground for this type of skills acquisition is face-to-face in a computer lab setting over 16 weeks; students usually need more experience with these technologies, so we recommend a smaller class size of 15-25 with additional lab time, depending on the students' levels of technical competency.

Before having students use the Python and Tableau platforms for their sentiment analyses of data, we recommend that business communication instructors first accustom students to the terms and techniques used in this AI process, beginning with a definition of and introduction to sentiment analysis and the techniques used. This introduction to sentiment analysis would be particularly beneficial to students in the early stages of their business communication AI curricula. It would use cloud-based tools with no need to write code. The proliferation of these tools available in the modern workplace indicates the importance organizations are placing on the ability to have interpretation skills in the workforce. One of these tools, MAQ Software, offers a free text analytics service based on the Microsoft Azure Cognitive Services sentiment analysis and opinion mining service located at <https://textanalytics.maqsoftware.com/#/>. Users must create a free Microsoft Azure account to use the service. With this account, students may analyze an individual text or load up to fifty rows of data as a CSV file for analysis.

Following the introduction to sentiment analysis, students should then be introduced to (1) a description of algorithms used in sentiment analysis, (2) methods of data collection and (3) an overview of data visualizations available in Tableau using TabPy. Students are then encouraged to perform their own data visualization and sentiment analysis by investigating Nike's 2018 "Just Do It" Marketing Campaign or other assignments. It is also helpful to show students how to navigate the data collection process with an example of previously collected data before they perform their data collection and analysis; we use an Airline Sentiment dataset from Kaggle.com as a model (descriptions follow).

Description of Algorithms Used in Sentiment Analysis

Numerous algorithms perform sentiment analysis. However, most are related to the Natural Language Processing Toolkit (NLTK) maintained by Team NLTK and initially released in 2001. Microsoft's Text Analytics (a section of their overall Synapse Cognitive Services available on their Azure Cloud platform) has its roots in a method of analyzing social media posts called the Valence Aware Dictionary for Sentiment Reasoning (VADER). VADER is a model for determining message polarity and the intensity or strength of emotion (Prabowo & Thelwall, 2009). The developers created the NLTK for use with Python, allowing access to this algorithm by installing the NLTK package as an option in the Python installation files. Documentation for the NLTK is on the website: www.nltk.org. Microsoft's sentiment analysis extends the NLTK capabilities by introducing a neural network that learns from the analysis performed and continuously updates the training datasets from the users' data.

VADER scores the sentiment of a body of text by mapping the lexical features of its dictionary to the strength of emotions. The overall score of the text is a summation of the intensity of each word. The algorithm recognizes that words like "fantastic," "great," "joyful," or "lovely" are positive in polarity. Additionally, VADER recognizes that a phrase such as "I hate this!" has a negative polarity.

The algorithm measures a word's emotional intensity between four (the most positive) and negative four (the most negative). Zero represents a neutral position. The summation of scores of words in a sentence is then normalized to fall between one and a negative one in the same context. The normalization of the scores uses the following formula:

$$\text{Sentiment Score} = \frac{x}{\sqrt{x^2 + \alpha}}$$

where x is the sum of the sentiment scores of the words in the sentence and α is a normalization parameter set to the number of words scored in the sentence. VADER is best suited for scoring short communication (Hutto & Gilbert, 2014). Azure Cognitive Services and other cloud-based artificial intelligence platforms, such as Google's Text Analytics, are can analyze larger bodies of prose, such as emails, speeches, and press releases.

The basis for sentiment analysis on all platforms incorporates five common heuristics into their scoring system: punctuation, capitalization, degree modifiers, polarity shifters, and emoticons:

- Punctuation, the first heuristic, considers the inclusion and frequency of question marks and exclamation marks at the end of a sentence, adding or subtracting an empirical number based on whether the sentiment score is positive or negative.
- In the second heuristic, incremental values are added or subtracted from the sentiment score dependent on the amount of capitalization. So, for example, "this movie is amazing" scores lower than "this movie is AMAZING."
- The third heuristic is a degree modifier; for example, "really smart" is an increase in the intensity of the phrase; "kinda smart," is a decrease in intensity. The dictionary contains a section regulated to boosters and dampeners.
- The fourth heuristic includes polarity shifters, which include words such as "but" that change a sentence's positive section and modify the intent. For instance, in a single sentence of a restaurant review from Yelp.com --"The atmosphere was great, but the food could have been better!"-- the review sentence contains both positive and negative polarities. In this scenario, all the words before "but" have their scores diminished by fifty percent. All

the scores after "but" have increased valence to one hundred and fifty percent. Finally, the algorithm examines a tri-gram of words before a lexical feature to determine if these three words negate the intent of the sentence in combination. Figure 1 shows an example of the scoring of two phrases by VADER as it runs in a Python-only environment. The scores reflect the individual scores' negative, neutral, positive, and compound summation.

FIGURE 1
Example of VADER scoring in Python-only environment

```
# Write a Review as one continuous string (multiple sentences are ok)

review = 'The shoes I bought are amazing'

#Obtain the sid scores for your review
sid.polarity_scores(review)

OUTPUT
{'neg': 0.0, 'neu': 0.513, 'pos': 0.487, 'compound': 0.5859}

review='The mobile phone I bought was the WORST and very BAD'

#Obtain the sid scores for your review
sid.polarity_scores(review)

OUTPUT-
{'neg': 0.539, 'neu': 0.461, 'pos': 0.0, 'compound': -0.8849}
```

- Additionally, VADER will score emoticons, such as :-) as a smiling face. The inventors describe the lexicons as the "wisdom of the crowds."
- VADER developers use Amazon Turk, a crowdsourcing platform for individuals or organizations which allows users to post tasks such as taking surveys or, in the case of the NLTK, rating words and phrases. The tasks performed may be voluntary or compensated. Using this platform, the VADER developers can gain a mean score across a broad population using a particular language on the scoring words and emoticons. Using a global platform such as Amazon Turk has allowed the development team to tune the algorithm to the major languages in use around the planet. They provide a ready-made dictionary for practitioners new to the sentiment analysis process. It is independent of only English-speaking countries and is ideal for multi-national businesses. The reliability of using longitudinal self-reported data in Amazon Turk has been relatively high (Daly et al., 2015), though there has been some criticism of the platform reliability in the past. In 2013, Amazon Turk decided to stop accepting non-US-based "Turkers," individuals performing tasks on the platform, because of an increase in fraud and a decrease in the quality of results (Fort et al., 2014).

Though the scoring of messages may not agree with the users' scoring determinations in all instances, it helps construct an experiential learning environment. VADER provides a foundation for understanding the concepts of the methodology. In addition, the NLTK provides several textual analysis methods, allowing users to curate their own libraries. The same is valid

with the use of Microsoft's sentiment analysis platform. While not covered in this paper, these additional textual analysis methods would be the next logical step in furthering students' understanding of textual analysis.

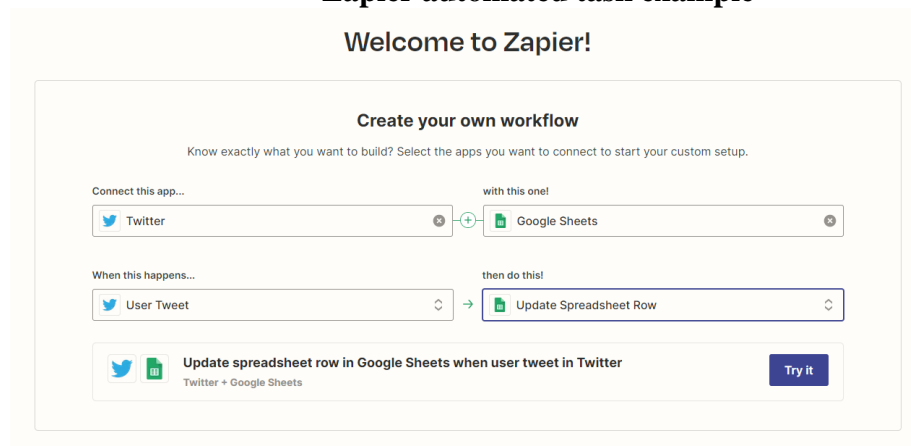
Methods of Data Collection

Creating material for a basic business communications course and more narrowly defined data visualization/visual communications curricula requires well-defined datasets. Practitioners and students alike should become well-versed in collecting data. However, they must first understand what properly curated data looks is. Two well-maintained repositories for publicly available datasets are Data.World and Kaggle.com. Both sites have curated datasets for use by the general public with additional access and features with a paid subscription. For either site, students must create a free account using their email addresses to download any datasets.

Students can accomplish manual data collection in numerous ways. An example of the most basic data collection is for students to visit their favorite e-commerce site and copy and paste product reviews into a spreadsheet. This process is labor-intensive and should only be used for short learning evaluations. For introductory Twitter analysis, using a platform that does not require students to have software coding skills is best.

Zapier.com is a web platform that allows students to create a free account and collect Twitter data effortlessly. Students can create an automated task to follow an organization, individual, or a particular hashtag, such as #lumberjacks, that will capture all the Tweets by those individuals, organizations, or hashtags (see Figure 2). Students can then write the information to an online text storage medium such as Google Drive Spreadsheets.

FIGURE 2
Zapier automated task example



An Overview of Visualizations Available in Tableau Using TabPy

Business intelligence platforms (such as Salesforce's Tableau or Microsoft's Text Analytics Playground based on the MAQ Software web portal) convert raw data into digestible graphical representations. Educators may apply for free Tableau licenses for themselves, students, and classrooms that are valid for one year. Anyone can apply for a free Microsoft Azure Cloud account and use free text analytics services. Microsoft provides its sentiment analysis services free for the first five thousand rows of information per month. The cost is \$1.00 for each additional thousand

rows. We based our choice to use Tableau upon the fact that it makes its desktop software accessible at <https://public.tableau.com> for registered users.

The request for an educator's license for Tableau is made through Tableau for Teaching at the address <https://www.tableau.com/academic/teaching>. These licenses are renewable on request. The difference between the free general use license (GUL) and the paid license is that the GUL limits data connections to text files such as comma-separated values (CSV) and Microsoft Excel. The signup process for Microsoft's Azure platform is located at <https://azure.microsoft.com/en-us/get-started/azure-portal/>.

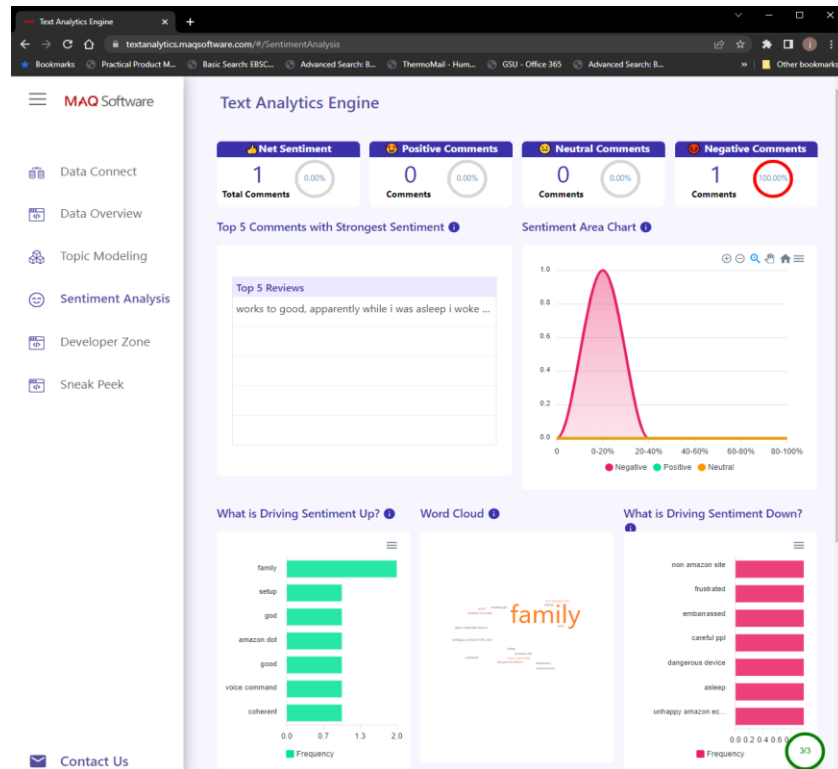
Performing real-time analyses without a deep knowledge of Python programming can be complicated and frustrating for non-technical students. Fortunately, Tableau provides an analytical extension to its desktop software called TabPy. However, users must first install a current version of Python before installing and using TabPy. The Python files and instructions are located at www.python.org. The TabPy files and instructions can be found at <https://www.tableau.com/developer/tools/python-integration-tabpy>. The optimal classroom setting is dedicated preconfigured computers maintained by information technology services to reduce the risk of students incurring installation issues. Alternatively, information technology services could maintain a configured virtual desktop environment to address these issues for online courses and performing work outside the classroom.

TabPy is a utility that allows Tableau users to create a calculated field that passes data connected to Tableau to Python. Python then performs machine learning calculations, handles external communications to cloud services, and returns Tableau results as a column of numerical data to create data-rich visualizations. For example, suppose Tableau connects to a common cloud-enabled database such as Amazon Web Services' cloud-hosted SQL MariaDB versus a file on the local hard drive. In that case, results can be instantly updated with new information. Though these visualizations can be created in Python's visualization toolset, they are static. TabPy gives Python a form of a user interface to manipulate data in real time, allowing for a deeper understanding of the data. The benefit of this approach is that a user does not need an in-depth knowledge of Python to produce results. TabPy's pre-deployed methods contain analytical methods packaged into functions that require little end-user changes for use with their particular datasets. Additionally, practitioners may create a data analysis process containing various data analytic functions that require minimal input from others and share with the community. The descriptions and use of the pre-deployed methods can be found at <https://tableau.github.io/TabPy/docs/tabpy-tools.html>.

In the example below, students were first asked to visit Amazon.com to search for Alexa-enabled devices. The students then chose a product, selected one review with the highest and the lowest star rating, copied the text in the text box shown in Figure 3, and analyzed each. The goal of the process was to see if the analytics of the text matched their perception of the review and the star rating. The figure shows that the review is negative in language from a human-readable perception. In addition, the sentiment analysis shown in Figure 4 fully concurs with the mental assessment. The user may also explore the topics and main pairings of words used to produce the sentiment and their weight in the analysis.

FIGURE 3
Input for MAQ Software Text Analytics

FIGURE 4
Example of MAQ Software Sentiment Analysis



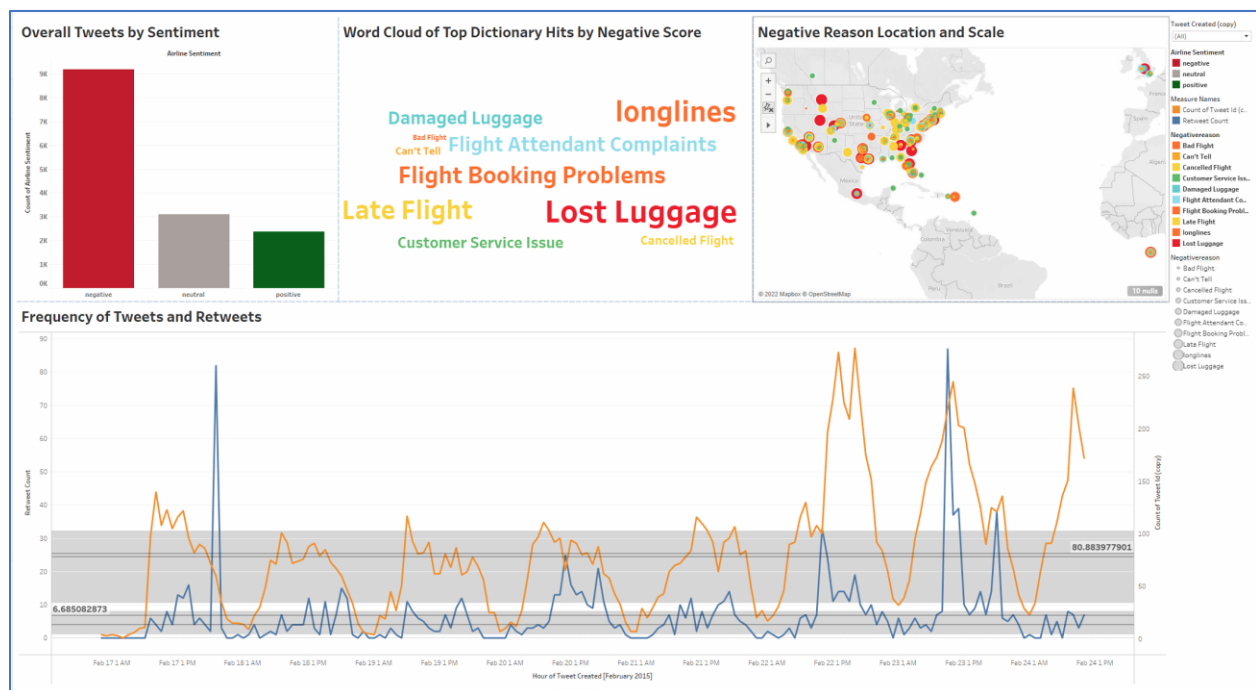
Next, to instruct students on sentiment analysis and interpretation, we begin with the Airlines Sentiment dataset from Kaggle.com. The data contains information on whether the scores were positive (1), neutral (0), or negative (-1). In addition, it contains the column of reasons for

the negative review, derived from hashtags in the original text columns for negatively scored Tweets. Also, a column containing the latitude and longitude of Tweets is present. However, due to privacy settings, not all Tweets have this information.

When considering analysis, a practitioner must determine if the coordinate labeled Data is sufficient to determine insights by region. The use of sample size determination is encouraged for inclusion in the instruction to make this determination. Also provided are the date-time stamp of the Tweets and the number of re-Tweets.

As seen in Figure 5, four worksheets were made to be combined in one dashboard representing unfiltered data. First, we SUM the Tweets and their sentiment to produce the overall sentiment of the analyzed period. In the example, students see that the proportion of negative Tweets is far more significant than neutral or positive ones.

FIGURE 5
Unfiltered data from the Virgin Airlines dataset



Next, we can determine the proportion of reasons for a negative review by constructing a word cloud from the negative reasons column. To create the word cloud, we use a Tree Map, a proportion series of boxes within an overall box container to represent the size of the measured dimension, then change the indicator type from box to text. The most prominent words are displayed as the leading reasons for negative reviews by the scaled size of the words. By adding color to the same column of data, students can see that the word cloud becomes easier to interpret. The example shows that discontent's most prominent negative reasons are lost luggage and late flights.

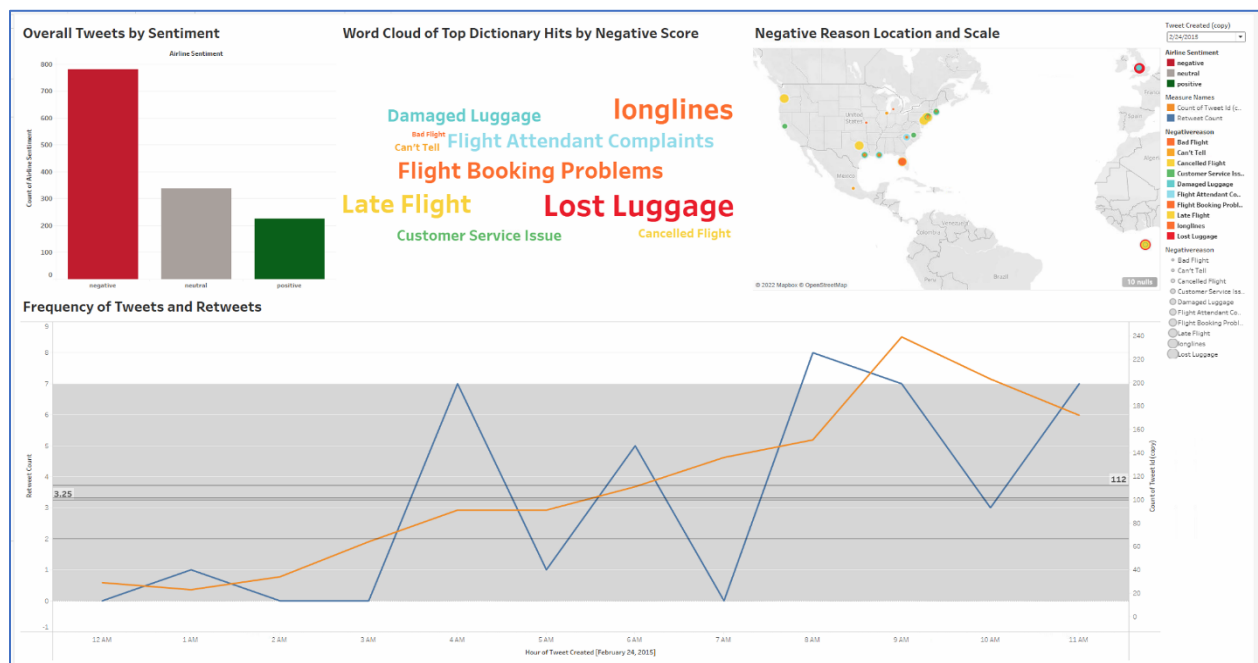
An interesting analysis point is the ability to see where a portion of the Tweets is made. (Limitations of the availability of geographical data have been previously noted.) Using the columns of data with latitude and longitude, we can create a map of the Tweet origination points. By adding color and size to the negative reason column in this worksheet, students can determine

the prominent negative reasons and their proportion in cities. This visualization also allows students to determine if the Tweets are created in areas served by the airlines.

Next, we construct a worksheet that plots the sum of Tweets and re-Tweets on a dual-axis over the analysis period. To this graph, we add the quartiles and average line to determine the average Tweets per hour and the period where most Tweets concurred during the period analyzed. The chart shows that eighty Tweets and six re-Tweets an hour occur during the six days of the complete data set. Additionally, students can see that the highest social media traffic corresponds to the end of the period analyzed, which corresponds to Sunday and Monday. These are typically heavy travel days for returning from vacation getaways and business travel.

Adding a filter to the analyzed time shown in Figure 6 allows students to observe changes to the dashboard and conclude sentiment and problematic issues during that period. In addition, this data limiting would allow hotspots and reoccurring matters to be determined. By using the technique in historical terms, airlines could find cyclical or seasonal patterns that could be addressed in overall operations planning. Airlines that use this technique in real-time could assist customers by deploying social media communications in negotiating the issues raised in the word cloud.

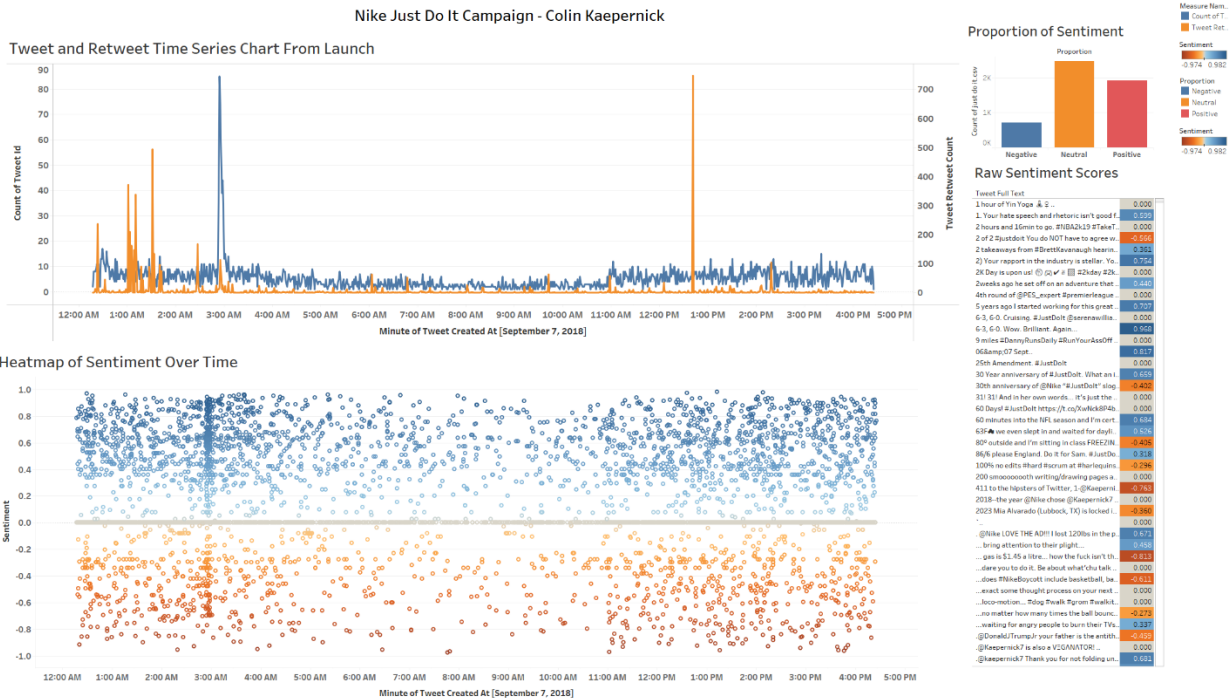
FIGURE 6
Filtered data from the Virgin Airlines dataset



Student Assignment for Data Visualization and Analysis: Nike's “Just Do It” Marketing Campaign

The data displayed in Figure 7 shows the sentiment analysis of the first 24 hours of Nike's 2018 "Just Do It" marketing campaign with Colin Kaepernick. The data set is interesting as it highlights a controversial public figure due to Mr. Kaepernick's political activism. To perform the analysis, we used the pre-deployed TabPy method for sentiment analysis that includes the VADER algorithm as its default setting. In the data, we find the column for the Tweet text, re-Tweet count, the date-time stamp, and the unique Tweet ID number.

FIGURE 7
Dashboard of Vader sentiment analysis of day one of Nike's "Just Do It" Campaign with Colin Kaepernick (2018)



Once the data connects to Tableau, students create a calculated field using the TabPy sentiment analysis method to generate the sentiment score for each review. As shown below, the calculated field created in Tableau contains a single line of Python code to simplify the ability to perform this analysis. The actual code behind the pre-deployed method is fifty-seven lines of code.

```
tabpy.query('Sentiment Analysis', _arg1)['response']
```

Next, students construct four electronic worksheets to develop the dashboard. Students create the first worksheet with the text of each Tweet and its calculated score. They accomplish this by dragging the TweetText field and the TabPy calculated field to the Rows shelf. Once the TabPy calculated field is active on the workspace, the sentiment score calculations immediately commence. The time to compute depends on the computer's power and the number of texts to evaluate. Once the computation is finished, the worksheet allows the reviewer to scroll through the list of texts and review the scores manually, if desired. The score is then color-coded for positive (1), neutral (0), or negative (-1) context. This step is accomplished by dragging the TabPy calculated field to the color marks section and then setting the color scheme. In the example in Figure 7, the color scheme was set to three steps.

The second worksheet displays the sentiment scores over time and down to the minute in granularity with gradient coloring to indicate the most positive to the most negative scores over a day. The worksheet is created by setting the Date/Time field to the Columns shelf and the TabPy calculated field to the Rows shelf. From the Show Me chart, students can select the scatter plot option. Again, students drag the TabPy calculated field to the color marks panel but allow it to use

the default gradient color scheme. The chart allows the user to observe sentiment clustering throughout the observation.

Next, the third worksheet displays the proportion of each sentiment during the period to gauge the overall reaction to the marketing campaign. Here, students construct a bar chart using the total count of Tweets and the additional calculated field to label the scores as positive, negative, or neutral. They place the TabPy calculated field on the Rows shelf and the labels calculated field on the Columns shelf. The bars will automatically color themselves with the previously selected schemes in the workbook.

Lastly, students construct a time series chart with a dual axis to show the number of Tweets and re-Tweets in the 24-hour period. They use the Date/Time field in the Columns shelf and place the Tweets and re-Tweets on the Rows shelf. Then on the bottom graph, they select a dual axis to have the two charts overlaid on each other. All worksheets are connected and arranged in a dashboard, as shown in Figure 7.

We can observe that most Tweets occur just after the campaign is launched, with a spike of re-Tweets happening simultaneously. Then the most significant re-Tweet point occurs ten hours later. Overall, the campaign maintains a neutral to positive sentiment in proportion. However, students can observe a substantial cluster of negative sentiment happening throughout the period, likely indicating opposing opinions to Kaepernick's political activism.

Other Suggested AI Pedagogical Approaches in Business Communication

In a business communication course, the pedagogical approach described in this paper could be included all or in part as a preliminary introduction to visual communication or data visualization. We suggest some additional learning activities below:

1. Data visualization is not a 21st century phenomenon. Instructors may begin their classroom discussion with Charles Joseph Minard's multivariate, space-time-story graph showing the fate of soldiers in Napoleon's Russian Campaign of 1812 (Tufte, 1983). Considered "the best statistical graph ever drawn," the graphic portrays six different data sets: geographical data (rivers, cities, battles); the French army's path to (gold) and from (black) Moscow; the number of soldiers at intervals; temperatures during the Russian winter; and the time indicated by the date and weather conditions (Tufte, 1983, p. 40). Students may find it interesting to compare Minard's 1869 graphic to Tableau's "Viz of the Day." Each weekday, Tableau selects an outstanding example of a viz (VOTD) and makes it available on the Tableau Public website at <https://public.tableau.com/app/discover/viz-of-the-day>. Students spot similarities and differences in how these visuals are constructed and learn about different ways to visualize data.
2. Students might prepare a report that analyzes and interprets the research and information in the dashboards to a targeted business audience with recommendations for improvement or product innovation. Information contained in the report could also be used as a versatile basis for a business presentation; areas such as leadership or marketing would have different objectives and utilization of the same information.
3. As the next step in curricula development, instructors might allow students to choose from a small set of publicly available data and create their dashboards using their previously acquired skills from the approach described in this paper. The process would extend the student's creative capabilities in analyzing data while producing analytical reports and dashboard introductions.

4. In a more sophisticated use of the framework, students could gather data from social media sites or portals such as Zapier.com. From the collected data, a final round of dashboard creation, analysis, and reporting should be done to demonstrate the skills acquired and refined during the course. This last assignment completes a skill required in the business where uncharacterized data must be completed and decisions made.
5. Finally, incorporating the practical use of AI technologies into the business communication curriculum provides an opportunity for instructors to engage in discussions with students about the ethical use and development of these tools and their future impact on society. Hancock, Naaman, & Levy (2020) provide an excellent discussion of these issues.

CONCLUSION

The rise of data analytics platforms, such as Python and business intelligence tools like Tableau, assist practitioners in analyzing their organizations' data. It can also provide a foundation in data analysis for current and future business students. These business analytics platforms interface through computer services and allow non-technical business users to perform critical, complex analyses with minimal training. Using business intelligence tools and data analytics platforms to create a meaningful interpretation of data is a valued skill in today's business world. With connection tools such as TabPy, the dynamic use of data becomes even easier for non-technical students and educators. In addition, Tableau and TabPy offer plenty of online support for these technologies, making it possible for educators to incorporate these tools easily into their classroom environments. These experiential, collaborative learning experiences in the curriculum can also enhance students' understanding of the communication process.

As Mancha et al. (2020) and Getchell et al. (2022) have observed, business schools have a responsibility to educate students in the business disciplines about how to use AI in the workplace. This paper's cursory literature review contains only a few AI business communication examples and applications. However, AI is developing at a rapid pace and is likely to change the ways in which we communicate in the future. These and other recent technological advances have made it necessary for educators to be more diligent in monitoring evolving practices in workplace communication to remain current in their disciplines and the curricula that business colleges offer their students. The business communication area, with its emphasis on oral and written communication, and perhaps eventually in collaboration with IT specialists, is ideally positioned to supply this training. According to Getchell et al., "AI technologies contribute to mediate, and even create oral and written communication, thus the work of AI technologies falls under [the business communication] purview" (2022, p. 26). The future of business communication necessitates additional research on AI in business contexts and emerging workplace technologies and the continued development of innovative instructional pedagogies that prepare our students for the business world.

In conclusion, incorporating business analytics into business communication courses introduces students to the fundamentals of data analysis and stimulates critical thinking skills. It also helps them understand how data collection can create business value and influence strategic and organizational change with processes, products, and services. More importantly, the knowledge of business analytic tools and visualizing and interpreting data is an important first step that prepares students for emerging genres shaped by electronic communication and digital technology and for this century's data-driven corporate culture.

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