Using Sentiment Analysis for Comparing Attitudes between Computer Professionals and Laypersons on the Topic of Artificial Intelligence

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ABSTRACT

Most research in investigating computer professionals and laypersons' attitudes toward artificial intelligence (AI) are limited to online or offline surveys. This paper analyzes computer professionals' and laypersons' attitudes toward AI by using a sentiment lexicon developed by Wilson et al. To explore whether there is a correlation between the occupation categories (computer-related versus non-computer-related occupations) and people's attitudes toward artificial intelligence, I conducted a polarity classification of over 0.6 million tweets containing references to "AI", "artificial intelligence", or both. The result did not provide evidence of a relationship between public attitudes toward AI and the occupation categories. In the end, several future directions in the data collection and the data analysis are discussed.

CCS Concepts

• Information systems→Sentiment analysis • Information systems→Information extraction • Applied computing→Sociology

Keywords

Tweets; AI; Lexicon; Polarity Classification; Public Attitudes; Scientific Knowledge; Layperson; Computer Professional

1. INTRODUCTION

With the spread of social media on mobile devices, many members of the public share almost every aspect of their lives on these platforms. Among various social media platforms, Twitter has enormous numbers of users all over the world. On average, about 500 million tweets are posted on Twitter everyday [1]. These tweets include discussions on the topic of Artificial Intelligence (AI). The development of AI technology has brought AI products into people's lives. People are keen to discuss their experience with AI products and their thoughts of how AI development might impact future lives. However, laypersons whose jobs are not in the computer field may have different attitudes than computer professionals on the topic of AI. Compared to people with non-computer-related jobs, people with computer- related jobs have more professional knowledge on computer science. Hence there could be a difference in attitudes based on the different levels of expertise.

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Scientific knowledge is important in shaping public attitudes toward science and technology [2]. Lack of understanding about science and technology may lead to a decline in public support [3], such as constraints on research funds, unfriendly regulatory policies, and low consumer interest. Researchers have intensively examined the relationship between scientific knowledge and public attitudes on scientific topics such as nanotechnology and global warming [4][5]. However, to the best of my knowledge, previous researchers have not investigated AI from this perspective. In addition, most research on attitudes toward AI used questionnaires [6][7][8] and not sentiment analysis as in my research. Given the premises that (1) scientific knowledge is a significant determinant of a person's attitude toward a particular scientific or technical area; and (2) people with computer-related jobs have more professional knowledge than laypersons, this paper explores the relationship between the occupation categories (computer-related versus non- computer-related) and attitudes toward AI.

Research based on the analysis of tweets has been conducted on various topics. For example, after scrutinizing the content and the sentiment of tweets related to the deliberation of the German federal election, Tumasjan et al. [9] found that the election result for a particular party was correlated with the number of tweets mentioning that party. In addition, Bollen et al. [10] improved stock market prediction accuracy significantly by analyzing public sentiment on the Twitter discussion of the stock market and included it in the Dow Jones Industrial Average (DJIA) predictions. Both of these studies used sentiment analysis, which is the process of extracting and quantifying opinions contained in linguistic data such as tweets. This methodology is also called opinion mining.

Typical problems in sentiment analysis include polarity classification and subjectivity classification. Polarity classification is the process of labeling the text as either positive or negative. For example, national happiness could be surveyed by measuring the polarity of texts extracted from Facebook [11]. Subjectivity classification means the process of classifying the text as subjective or objective [12]. In many situations we need to decide whether a document was subjective before doing polarity classification, because text that is a statement of fact is not subjective. The improvement of subjectivity classification can facilitate sentiment classification [13].

There are many approaches to sentiment analysis, among which sentiment lexicons and machine learning are two main categories. A list of sentiment words and phrases is called sentiment lexicon [14]. Sentiment lexicons are based on the fact that sentiment words are important indicators of sentiment expression. For example, “I feel happy today.” contains the common positive word happy, so the sentiment of this sentence is considered as positive. Linguistics Inquiry and Word Count [15] is a well-known sentiment lexicon. It divides 4500 words into 76 categories and

2 of the categories – positive emotion words and negative emotion words – are used frequently in sentiment analysis projects. Machine learning approaches usually involve building classifiers to let machines identify the sentiment-relevant features [16]. A good example is Liu et al. [17] use of 11 state-of-art labels to survey the sentiment of microblogs. Their classifier accounted for the multiple emotional states of microblogs, reaching a classification precision rate of 75.5.

To examine whether there is a correlation between the occupation categories (computer-related versus non-computer- related) and attitudes toward artificial intelligence (AI). I wrote a code to calculate the positive words ratio and negative words ratio in each tweet. I first tested whether there was a relationship between positive words ratio and two occupation categories (computer professionals verses laypersons). Then I tested whether there was a relationship between negative words ratio and two occupation categories (computer professionals verses laypersons).

2. METHODOLOGY

Python was used as the programming language for the sentiment analysis. 69,411 English-language tweets within a seven-day window in September 2018 were retrieved from the Twitter API using the Python module Tweepy. The search query used the English keywords “artificial intelligence”, “AI”, or both. Figure 1 shows the overview of my sentiment analysis algorithm.

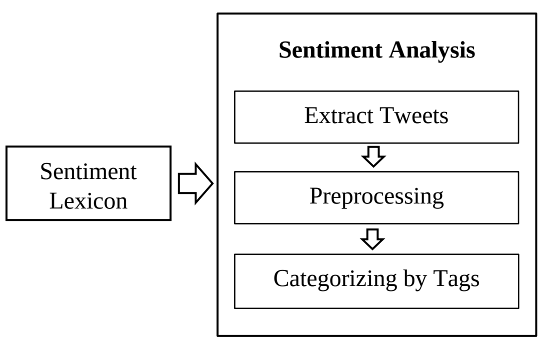

Figure 1. Algorithm Architecture

Once tweets were extracted, the text was pre-processed in order to standardize it and to ensure that only the message portion of the tweet was analyzed. First, I decoded the HTML in tweets to general text by using the Python package BeautifulSoup. Second, I erased the mentions of other usernames (e.g. @username) and URL links with the Python’s re module. Third, I decoded byte order marks and replaced them with “?”. Fourth, the punctuation of hashtag-“#” and numbers in the text were removed. Finally, extra spaces were deleted and all the letters were converted to lowercase.

Before categorizing tweets into computer professional and layperson groups, I deleted retweets, which resulted in 29,000 tweets in total. The main reason for doing so was that most retweets were news, ads, or official announcements which could not represent personal opinions.

Afterward, cleaned tweets were divided into two groups--the layperson group (tweets with owners with non-computer- related jobs) and the computer professional group (tweets with owners who take computer-related jobs)--by tagging occupation-related words in users’ bios. To find the words that describe computer-related jobs, websites such as stackoverflow.com, careerdimension.com, and careers.google.com were used as references. Then I manually compiled a list of 75 computer-tags in the layperson group came from careerdimension.com and there were 1,168 laymen tags in total. Table 1 and 2 shows some examples of the words used to tag users’ bios.

Table 1. Computer Professional Group Tags

Java developer	Web designer	deep learning
IT manager	test engineer	cloud engineer
linux	Python	...

Table 2. Layperson Group Tags

lawyer	dentist	accountant
politician	artist	HR
chef	gardener	...

I used the sentiment lexicon compiled by Wilson et al. (2005). It was used to count both the number of positive words and negative words in each tweet. The number of positive words divided by all words in a tweet was the positive words ratio. The number of negative words divided by all words in a tweet was the negative words ratio. The positive words ratio and negative words ratio of some samples were >1, which should not happen given that a total sentence word count should be greater than the number of sentiment words. The reason for this phenomenon was that after being pre-processed, some tweets had no words left. Positive words ratio and negative words ratio were dependent variables in the statistical analysis.

3. STATISTICAL TESTS

Simple linear regression was employed to test the ratio data. Two models were run. In the positive words ratio model, occupation was the independent variable and positive words ratio was the dependent variable. In the negative words ratio model, occupation was the independent variable while negative words ratio was the dependent variable.

Prior to the model fitting, outliers defined as data points more than 3 standard deviations above and below the mean of the data in the positive words ratio model were removed. Afterwards, similar outliers in the negative words ratio model were also removed.

The independent variable – occupation – was numerically coded and centered around 0. Since there were more tweets from the computer professional group (approximately 2 computer professional tweets for every layperson tweet), the computer professional group was weighted as -0.33. There were 19,376 tweets that belonged to the computer professional group. The laymen group was weighted as 0.67 with 9,037 tweets.

4. RESULTS

For the positive words ratio model, the mean of the computer professional group was 0.2550 with the standard deviation 0.1080; the mean of the layperson group was 0.2520 with standard deviation 0.1000. For the negative words ratio model, the mean of the computer professional group was 0.0850 with the standard deviation 0.0360; the mean of the layperson group was 0.0840 with the standard deviation 0.0330.

When the model of positive words was predicted, it was found that the difference of occupation was not a significant predictor (Beta = -9.126, $p>0.963$). When the model of negative words was predicted, it was again found that the difference of occupation was not a significant predictor (Beta = -3.042, $p>0.963$).

5. DISSCUSION

The positive and negative words ratio models failed to distinguish a significant difference between the two occupation groups and their attitude toward AI. Hence, the null hypothesis, that there is no relationship between occupations and attitudes about artificial intelligence, cannot be rejected.

Although the current study does not find evidence for a correlation between public attitudes toward AI and the two occupation categories (computer-related versus non-computer-relate), Peters [18] pointed out that the relationship between scientific and technological knowledge and attitudes toward science and technology was often very complex, and over time the links between disciplines vary. The survey of public attitudes toward AI was challenging because there were ambiguities on how people define the concept of AI [19]. Thus, the nature of how people think about AI might help explain the null result that I have obtained.

However, disparate methodologies can also lead to different findings. There are several possible ways to expand and refine the current study for further investigation. In terms of the dataset, some individuals' bios might contain tags belonging to both groups. For instance, some people have jobs that are unrelated to the field of computer science, yet they are interested in discussing AI or other popular computer topics, so they might have tags such as AI, computer science, and VR in their bios. Once assigned to the computer professional group due to these tags, their tweets might pollute the analysis of the sentiment in the computer professional group. It was crucial to clarify the definition of computer professionals and laypersons, in other words identifying Twitter users' occupation more precisely is crucial. To improve the occupation detection precision, a platform named about.me can be used. About.me allows users to link Twitter accounts to their LinkedIn accounts [20], so instead of relying only on the Twitter users' bio tags, the career information of Twitter users could be obtained directly.

Furthermore, there are several ways to refine the sentiment classification process. First, the present sentiment analysis assumes that if there are more positive words in a tweet then it is more positive. Based on that assumption, a dictionary compiled by Wilson et al. [21] was used to count the positive words and negative words ratio in each tweet. However, using sentiment words to evaluate a sentence's sentiment may be insufficient. It is possible that a given sentiment word may be used to express both positive and negative opinions. For instance, the word "suck" in the example "This camera sucks." indicates a negative opinion, but in the example, "This vacuum cleaner really sucks." indicates a positive opinion [16]. It is also possible that a sentence without sentiment words is opinionated [22]. For example, the sentence, "I fall for you every day." does not contain positive sentiment words such as "love" or "like", but it still expresses a positive sentiment. Also, a sentence with sentiment words may not express any sentiment, as attested by the example, "Which person looks happy?" This sentence contains the positive sentiment word "happy" but is considered neutral because it is an interrogative sentence. To fix these problems, deeper lexical properties, such as word-sense disambiguation (WSD), need to be considered [23]. WSD is a process of detecting which meaning of a word used in a sentence is the correct meaning if the word has multiple meanings. In the case mentioned above, if it can be decided which meaning of "suck" is used in each of the two sentences then the sentence's sentiment polarity can be decided. To achieve this, using a Python package that conducts sentiment classification with WSD [24] would be a good choice.

6. CONCLUSION

To discover whether there is a correlation between the occupation categories (computer-related versus non-computer- related) and attitudes toward artificial intelligence (AI), over 60,000 tweets were retrieved from Twitter API, pre- processed, and the more than 20,000 remaining tweets were analyzed by using a sentiment lexicon. After that, through two linear regression statistical tests, two results were drawn. First, it could not be rejected that there is no relationship between positive words ratio and occupation. Second, it could not be rejected that there is no relationship between negative words ratio and occupation. In the future, I will determine whether the extracted tweet expresses a personal opinion and remove those that do not. Alongside this, I will try machine learning approaches by constructing my own classifiers to improve the precision of polarity classification.

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