Dating Profile Age Analysis – a Supervised Learning Application

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Abstract

We designed an agent that uses supervised machine learning and word frequency analysis to analyze people's dating profiles. It classifies what words people in different age groups tend to use in their profiles, and can predict the age group of a dating profile's writer. We programmed our agent in Java and used TF-IDF scores and multinomial logistical regression. This technique has important potential market and research applications.

Keywords: TF-IDF, multinomial logistical regression (MLR), Natural Language Processing (NLP), word frequency analysis

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Many phone apps, dating sites like OkCupid, and social media sites like Facebook rely on user generated data to deliver customized services. This data tends to be gathered through apps, quizzes and other measures that require active user participation. However, information gleaned through self-surveys have many shortcomings. People often aren't aware of the subtleties of their behaviour, including what words they tend to use and why they use them.

Could user information be gathered in ways that didn't bear these shortcomings? One way could be through Natural Language Processing (NLP). NLP is the study of syntax, words and grammars to gather information. It has been used in a wide variety of research applications for a broad range of purposes. We will use NLP to design an App which gathers information on how people in different age groups use language to describe themselves on an online dating site. In this way, the app will glean information that users may not be consciously aware of. The app will also guess the age range of novel users, which helps us test the App and provides an entertaining way to engage users.

We've decided to use a particular kind of NLP called word frequency analysis, which gathers information based on word choice. This approach has obvious shortcomings – much of the meaning of language emerges from elements which are not included in word frequency analysis, like sentences, context, phrases, idioms and even compound words – the compound “hot dog” for example will lose all meaning if analyzed in terms of the words “hot” and "dog". When performed on large quantities of data however, word frequency analysis preserves semantic meaning a statistically significant enough portion of the time to provide useful information. Furthermore, word frequency analysis is easy for an AI system to perform accurately on huge bodies of text whereas teaching an agent more complex language structures is more difficult and error-prone. We'll look at a few examples where word frequency analysis was used successfully on a large data set.

Vongpumivitch et al. (2009) used word frequency analysis to determine how how often applied Linguistics researchers used words from the Academic Word List (AWL) in their publications. Academic language is often one of the biggest challenges facing academic teachers and learners of English as a foreign language, so this study has important pedagogical implications. They found that AWL words accounted for 11.7% of all words used in the entire Applied Linguistics Research Corpus, a data source with over 1.5 million words. This study demonstrates the scale on which word frequency analysis can be used and its potential scope in gathering broad statistical data on huge amounts of textual information.

Baruch Vilensky (1996) used word frequency analysis to determine the relative word choice distance between authors. He found that an agent using word frequency analysis alone could successfully tell whether or not two books were written by the same author. This shows how word frequency analysis can be used to gather information about writers which may not be superficially obvious.

For our “Guess your age” dating profile App, we've decided to use supervised machine learning, TF-IDF scores, and multinomial logistical regression (MLR) to carry out word frequency analysis. We'll go on to explain why we made those choices, and how we carried them out.

Method

We designed our agent to carry out supervised machine learning. This means that the agent will be trained on a data set where for each data point it is given the dependent variable (the age category) and the independent variable (the dating profile), and then will be tested on a data set where it is given the independent variable (the dating profile) and has to predict the dependent variable (the age category). We chose supervised machine learning because supervised machine learning can be done on a relatively small data sets like ours, which included approximately 1000 data points (dating profiles).

We combine two techniques for the machine learning component of our project, TF-IDF (i.e. term frequency–inverse document frequency), and multinomial logistic regression (MLR). TF-IDF scores calculate the relative frequency of each word in a document. The TF score is the frequency of each word in its particular document. This alone would not be enough – many words appear frequently simply because they're common English words, like “and”, “I”, and “in”. We're looking for words which not only appear frequently, but which appear frequently in this document relative to other documents. That's why we use IDF scores. The IDF value is the proportion of profiles a word appears in. TF and IDF scores are multiplied together to give a score for each word in each document which accurately reflects the relative frequency of that word in that document – how “significant” it is.

MLR allows us to predict the likelihood of a categorical dependent variable based on independent predictor data (generated from TF-IDF). MLR is a generalized form of logistical regression used when the dependent variable has more than two categories. MLR is what allows the agent to predict the age category of an unknown profile based on the training data it has processed.

One of the most common applications of TF-IDF is in web searches. Rahman et al. (2013) studied the usefulness of TF-IDF scores in dealing with topic drift in web searches. Topic drift is when the content of a search result drift away from the topic in its heading. They designed a webpage ranking system which uses TF-IDF to improve the relevancy of search results, demonstrating the usefulness of TF-IDF scores in pruning irrelevant data.

Nor is the utility of TF-IDF limited to written text. Smith et al. (1997) used TF-IDF to design a video search program that reduces each video to a 2 minute fragment to speed up search time. These fragments preserve relevant audio keywords while eliminating search-irrelevant information. This is accomplished using TF-IDF scores, demonstrating the power of this tool in a variety of different modalities.

Coyle et al. (2012) designed an agent that much like our agent performs word frequency analysis using TF-IDF scores and regression to analyze the effects of recreational drugs based on user testimonials that people posted on the website Erowid. Using word frequency analysis, Coyle's agent was able to accurately determine which drug was associated with each testimonial, and could identify words that were strongly associated with certain kinds of drugs, providing potential insights into those drugs' effects. This study demonstrates that the power of these tools in gathering subtle information from what people write about themselves online.

For our data set, we used 900 profiles from friendfinder.com. We copied the text of the self-description section of each person's profile (labelled "Introduction" on the site) and recorded the person's age. We divided the profiles into three age groups and designed our program around those categories. We programmed our agent in Java.

During the training phase, the agent applies TFIDF scores and Multinomial Logistical Regression to a large body of training data to determine the weight of each word relative to each age category. During the testing phase, the agent uses these values to assign the profile being tested a "score" for each category, and selects the category with the highest score. The dating profile's writer most likely falls into this age range category.

We chose the age ranges [20 – 29], [30 – 39], and [40+]. We included 300 dating profiles from each category. The techniques we used are scalable, so we could increase the number of age groups for future versions. Initially we wanted the agent to guess the participant's exact age, but if we used our current approach to do so, we'd risk over-determination. Over-determination is the risk of information loss when the categories are small and overlapping. If someone uses words that are common to a 28-year-old, they are more likely to be 29 than if they use words that are common to a 58-year-old. But if we use a categorical analysis, that information is lost. In future versions, we hope to program our agent to guess participants' exact age by programming our agent to use ordinary least squares regression, which takes a continuous dependent variable.

The use of categories also offsets the issue of how we can be sure that people are reporting their ages honestly. If we were using exact ages, it would be crucial to know that the ages were accurate, but since we're using categories, the ages can be approximate. It doesn't matter at all if people lie within a category, but if they lie across categories in a systematic way, it could influence our results. This may be taking place, since people may lie to make themselves appear to be in a particular decade. In future versions we could offset this by choosing age categories which don't correspond to decades.

Calculating TF-IDF scores

TF-IDF calculates the relative frequency of each word in each profile. The TF value equals the number of times the target word appears in that profile divided by the total number of words in that profile. The IDF value is the proportion of profiles a word appears in. The agent calculates this by dividing the total number of profiles by the number of profiles that the target word appears, and then take the tenth log of the result.

Performing MLR

To perform MLR, the agent needs to have three sets of Beta-values corresponding to each of the three age range categories. The Beta-values for a category are what we've chosen to call the representation of the linear weight of each word relative to that category – a rough estimate of how likely that word is to indicate that category.

Testing and Assignment

To determine the dating age of a profile, the agent calculates its scores for each of the age categories. The score for a profile, for each category, is the dot product of the TF-IDF values for all the words in that profile, with the Beta-value of each word for that category. This yields a number between -1 and +1 for each profile for each category. The highest scoring age category is chosen as the most likely candidate for that profile.

Evaluation

To test our agent's accuracy, we performed a 5-fold cross analysis. We divided our data of 700 profiles into 5 equal parts of 140 profiles each, all of which contained some profiles from each of the three categories. We cycled through using each 1/5th as our testing examples and training on the remaining 4/5th, or 560 profiles. Our data is displayed below.

Our agent was accurate ~54.4% of the time. Since each profile could be classified into 3 possible categories, we would expect our program to have 33.3% average accuracy by chance, with a standard error of roughly 4% (on 140 test cases). Our program's accuracy was well above the margin of error of what would be expected by chance.

Results

Our agent can tell us which words corresponded to each age group most closely. Common words in the [20 – 29] age group included “studying,” “ego,” “chill,” “creepy,” “dude” and “gay.” For the [30 – 39] age group, “therapy,” “fantasies,” “grateful,” “hollywood” and “unpredictable.” And for [40+], “financially,” “secure,” “prince,” “nonsmoker,” “worker,” “sexual” and “sincerity.” We graphed some of our more interesting results below. Positive Beta-values indicate that a word is particularly common for that age category, vice versa for negative.

Discussion

Our program combines two current streams in word frequency analysis – commercial applications which use word frequency analysis on user-generated data, and academic research which uses it to make inferences about demographics. By applying these academic techniques to an online commercial domain, we believe that our application, rudimentary though it is, opens up new avenues of study and development.

Commercial interest in word frequency analysis is booming. The Google Ngram Viewer, a program which allows users to track the frequency of words or phrases in books over time, was an early success, but by no means the last. In the summer of 2013 OpenAmplify developed an app called vs., the first entertainment app to use word frequency analysis on tweets in real time (Guess, 2013). Users select two topics and then vs. breaks down the most recent tweets on the topics to determine which is being discussed more favourably on twitter.

There's been significant interest in using word frequency analysis, among other forms of NLP, to study age demographics. Pennebaker et al. (2003)**second one** published several studies which used word frequency analysis to study demographics. They found that older individuals use more likely than younger individuals to use plural and future-tense verbs, to use positive emotion rather than language emotion words, and to use fewer self-references like “I” and “me.” Even though they didn't use word frequency analysis exclusively, Pennebaker et al. demonstrated and defended its importance as a tool for gathering important information on language use and demographics.

Schwartz et al. (2013) just published a study which used word frequency analysis on the Facebook messages of 75,000 volunteers along the lines of age, gender and personality. They found which words and compounds were common for different age groups.13 – 18 year-olds tended to use more internet slang and emoticons like “xd,” “:)” and “<3” and use words like “school” and “homework.” Common words for 19 – 22 year-olds were “school”, “fuck” and “campus.” Common words for 23- 29 year-olds were “at_work,” “beer” and “yard.” And common words for 30 – 65 year-olds were “daughter,” “fb_friends” and “country.” Schwartz et al. used an *open-vocabulary* analysis, which means that they used statistical tools to find which words were most representative of each category. This is a departure from the previously popular *a priori* analysis, where words are classified into diagnostic categories which are then applied to the textual data. We followed Schwartz et al.'s more open-ended approach as it allows for more unexpected results and is less likely to be constrained by preexisting assumptions about what different word choices mean.

Pennebaker et al. (2003)**first one** compare analyzing texts to understanding a city by driving around in a car or by flying above in a helicopter. Both confer different but equally valid views of the city. While the helicopter will likely miss details of specific streets, it can pick up information about the overall structure of the city that the car would miss. Word frequency analysis is like the helicopter. It passes over specific meanings that a straightforward reading would catch, but provides linguistic information “from a distance” that has the power to illuminate connections and insights that would otherwise remain hidden. We hope that through our project we've demonstrated the power of word frequency analysis in illuminating and disseminating demographic language trends that might otherwise remain hidden.

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Appendix

Figure 1.

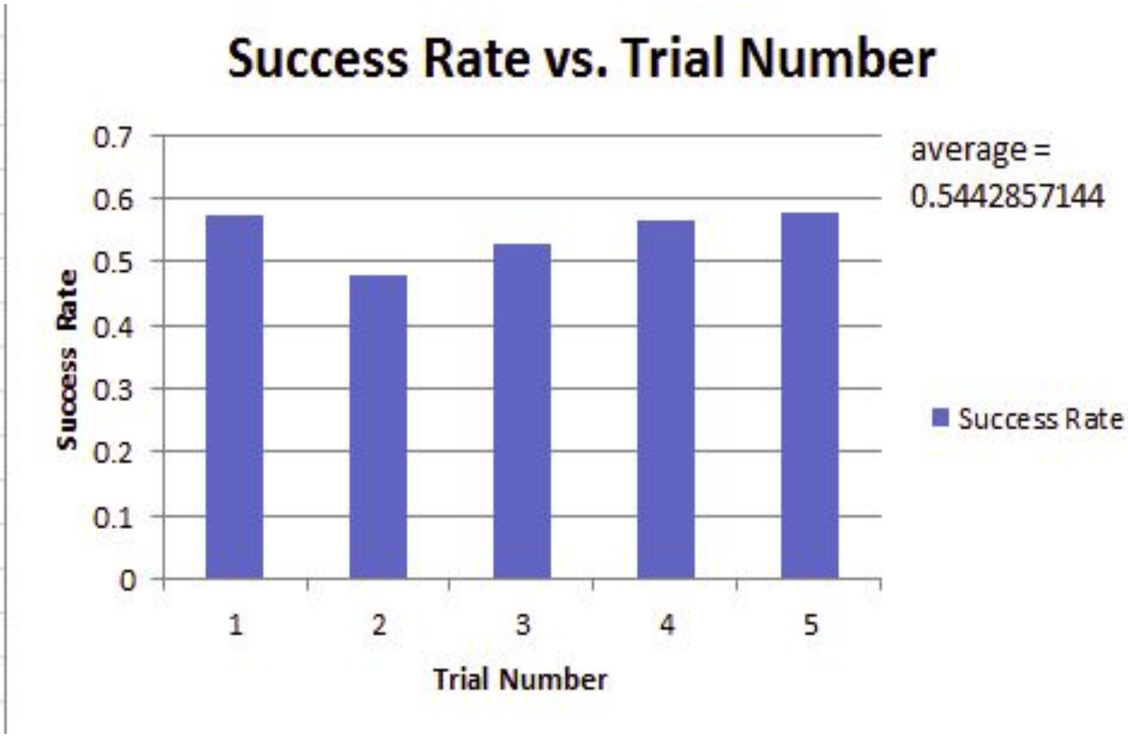
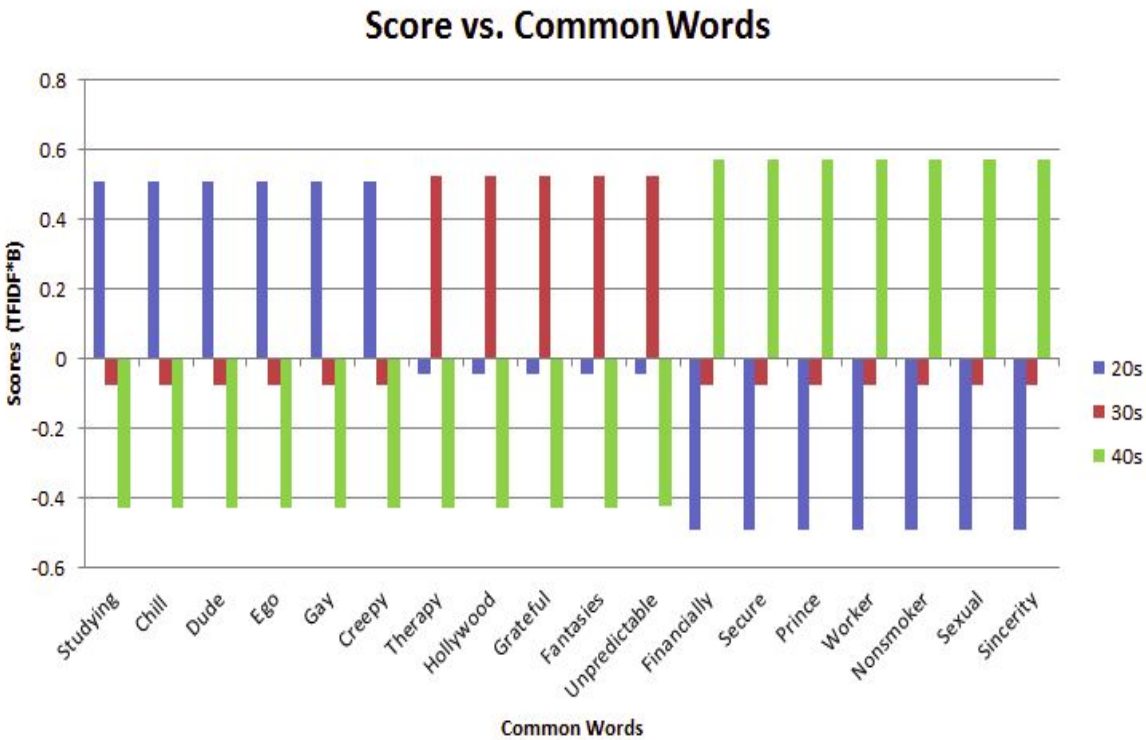


Figure 2.


Score vs. Common Words
Scores (TFIDF*B)
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Studying
Chill
Dude
Ego
Gay
Creepy
Therapy
Hollywood
Grateful
Fantasies
Unpredictable
Financially
Secure
Prince
Worker
Nonsmoker
Sexual
Sincerity
Common Words
20s
30s
40s