PREDICTING PERSONALITY TYPES FROM USER COMMENTS

An exploration of natural language processing (NLP)

Please note:
Code written can be found here:
https://github.com/abizzaar/personality-types/blob/master/preprocessing.py
Packages used include NLTK, SciKit, Pandas, re, and Seaborn.
Accuracies for all experiments referenced below can be found in the appendix at the end of the report.

Introduction

I have always been fascinated by personality types. Skeptical of its scientific validity, I have still found it to be a pretty reasonable description of the characteristics my friends and I possess. This project explores the significance of personality types in determining the use of language, particularly online comments in forums. The machine learning task is to predict personality type of a user based on comments on an online forum. The project has far-reaching implications if you consider the ever-increasing availability of user data on online forums and social media platforms. Based on a user's comments and messages, what can a platform learn about the personality of its users to better mediate discussion and provide more meaningful content?

Dataset

The dataset, titled "(MBTI) Myers-Briggs Personality Type Dataset" was found on Kaggle. It contains 8600 examples (rows) in which each row represents a specific user, containing entries of personality type (4 letters based on the MTBI type) and their 50 most recent comments on an online forum called PersonalityCafe.com. The dataset was compiled by Mitchell J, by scraping data from the website. Here is an example of the dataset:

MBTI Type	Posts
INFJ	'http://www.youtube.com/watch?v=qsXHcwe3krw|||...
ENTP	'I'm finding the lack of me in these posts ver...
INTP	'Good one _____ https://www.youtube.com/wat...
INTJ	'Dear INTP, I enjoyed our conversation the o...
ENTJ	'You're fired.|||That's another silly misconce...

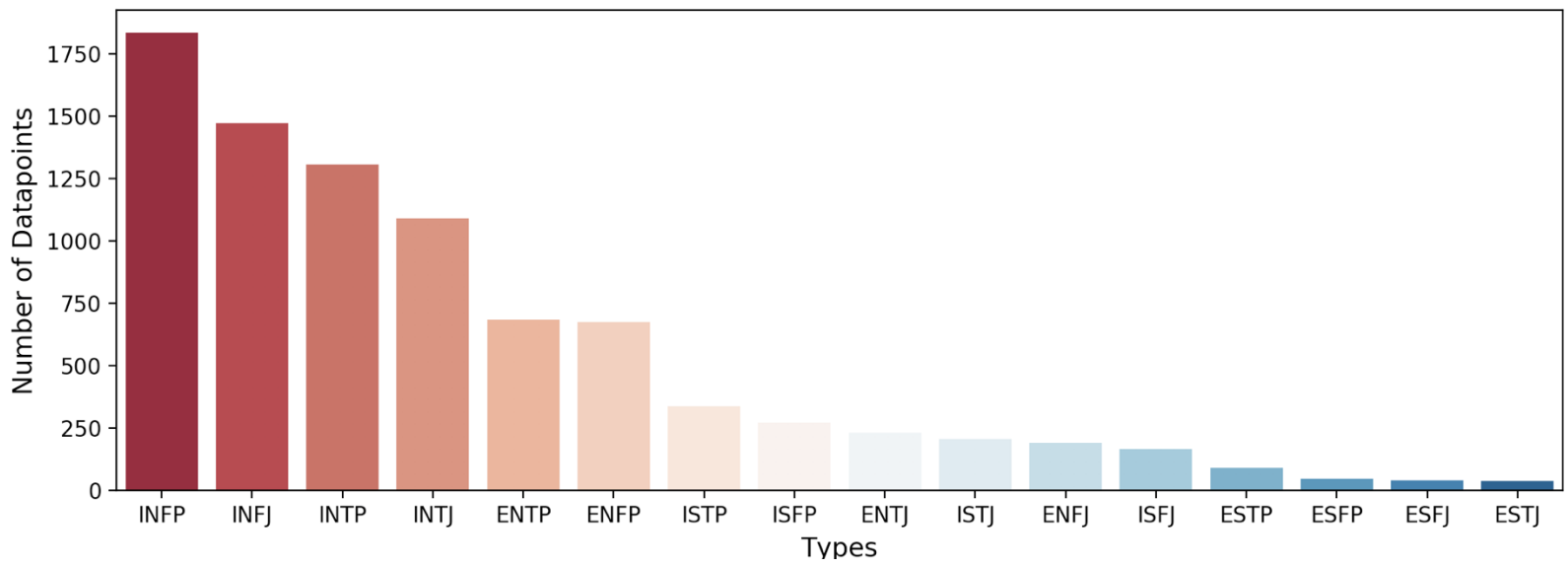
Each user comment is separated by three vertical bars "|||". The following is an example row of one user:

INTP	'Good one _____ https://www.youtube.com/watch?v=fHiGbolFFGw|||Of course, to which I say I know; that's my blessing and my curse.|||Does being absolutely positive that you and your best friend could be an amazing couple count? If so, than yes. Or it's more I could be madly in love in case I reconciled my feelings (which at...|||No, I didn't; thank you for a link!|||So-called Ti-Si loop (and it can stem from any current topic/obsession) can be deadly. It's like when you're stuck in your own thoughts, and your mind just wanders in circles...

There are 4 dichotomies in the MBTI type classification that are as follows:

Extraversion (E) – Introversion (I)	Sensing (S) – Intuition (N)	Thinking (T) – Feeling (F)	Judging (J) – Perceiving (P)

This is how the dataset was distributed with respect to the 16 distinct output classes:



Upon analyzing this distribution I noticed that the dataset was heavily skewed, with certain output classes having more examples than others. I then analyzed the distribution of each dichotomy individually, and noticed that the distribution of the third dichotomy of "Thinking (T) – Feeling (F)" and that of the fourth dichotomy of "Judging (J) – Perceiving (P)" was more evenly split than that of others. Upon testing machine learning algorithms using output class as third dichotomy and fourth dichotomy respectively, I found that accuracies were greater when considering output class as the third dichotomy. For this reason, I decided to alter my machine learning to predicting the third dichotomy of 'Thinking (T) – Feeling (F)' instead of the personality type of the user, changing the classification from multi-output to binary. This sounded like a more reasonable task to accomplish given that my dataset consisted of only 8600 examples, which isn't very large for a task involving NLP.

Preprocessing

I decided to use the bag-of-words approach to extract features from the comments of my users because, as discussed in class, it is a simple and effective technique. I decided to use bag-of-words instead of an n-gram model (such as bigrams or trigrams) because the comments in the dataset are random comments covering several different topics. Higher order n-grams would only be effective given a common thread of discussion in which we could imagine certain pairs or triplets of words holding significance.

The first phase of preprocessing was to clean the text, which involved the following steps:

- Remove all characters (special characters and numbers) except letters of the alphabet
- Make all letters lowercase
- Lemmatize the document (using NLTK's WordNetLemmatizer)
- Remove all stopwords (provided by NLTK corpus)
- Replace all urls of websites with the word "link"
- Remove all words correspoding to the 16 personality types (such as ENFP, INTP, etc.)

I chose to use lemmatization instead of stemming in my implementation. I used lemmatization instead of stemming because, after testing datasets created using stemming and lemmatizing respectively on learning algorithms, I noticed that lemmatization led to higher accuracy by ~1%. Although this difference isn't statistically significant, I chose lemmatization because it is known to return a more meaningful base form of the word.

Urls of websites were replaced the word "link" because it would become tricky to consider the different websites users mentioned. The word "link" was used so that the training algorithm could still factor in which users used urls and which didn't. For future exploration, it

could be relevant to create a separate feature for which website the user referenced in their comments.

I chose to remove all words corresponding to the 16 personality types (such as ENFP and INTP) because people are likely to talk about their own personality type on an online forum like PersonalityCafe.com. Not removing these words would be similar to giving the output class as a feature to the learner, in which case the resulting accuracy would be an exagerrated estimation of the relationship between the features and output class. Upon trying several learning algorithms with and without removing the personality types, I noticed that the results were as I had expected: the accuracy of Naïve Bayes and Logistic Regression decreased by ~4% and ~5% respectively after removing the words.

At this stage, I was curious to see which words were most frequently being used by users in the comments. To visualize this, I used the WordCloud package to generate the following image in which the size of each word corresponds to its document frequency.

Vectorization

After testing the features with both a count vectorizer and tf-idf vectorizer provided by SciKit's library, I decided to use the tf-idf vectorizer. The tf-idf vectorizer produced an almost identical accuracy to the count vectorizer for logistic regression, and produced a ~1.5% better accuracy for Naïve Bayes. Because there was not enough statistical significance to choose one vectorizer over another, I chose tf-idf because it is considered a more sophisticated and meaningful approach.

During vectorization, I changed the parameters of 'maximum features' and 'maximum document frequency' to find the optimum parameters of 1000 and 1 respectively. Changing 'maximum features' from 500 to 1000 increased accuracy by ~1% for logistic regression, while increasing it any more did not significantly increase the accuracy. When 'maximum document frequency' was reduced from 1 to 0.7 and then 0.5, the accuracy reduced by ~0.5% each time, suggesting that 1 was the optimum value for the parameter.

Machine Learning algorithms

I trained my vectorized features using ZeroR, logistic regression, naïve bayes, decision trees, and multilayer perceptrons using default training algorithms provided in the Weka software. Multilayer perceptrons did not finish training because of the large dimensionality of the feature space and the time-intensive perceptron update rule. The 10-fold cross validation accuracies of all other algorithms are noted in the appendix of this report. Logistic regression and Naïve Bayes performed the best, with accuracies far better than the accuracy of ZeroR:

Training algorithm	10-fold cross validation accuracies
ZeroR	54.11%
Logistic Regression	75.53%
Naïve Bayes	70.70%

It seems like logistic regression is the best algorithm for the task given a difference of ~5% between its accuracy and that of Naïve Bayes. I couldn't formally compare statistical significance using contigency tables and methods such as Chi-Square and Fisher's test because of the large number of features. Statistical significance will be an aspect of future research for this project. Furthermore, I did not consider precision and recall because neither the false positives nor false negatives for this task seemed particularly relevant to consider over accuracy, and the distribution of classes was evenly split.

I then performed feature selection on the dataset to find the words were the best predictors of the output class. This was the most insightful part of my project as it helped me see the correlation between words used in user comments and personality types. I used the following three approaches of feature selection: in Weka correlation based feature selection, information gain based feature selection, and learner based feature selection. I then took all the features with the highest ranks in these feature selections and analyzed the number of occurences of each of these words in the dataset, splitting based on the output class of 'Thinking (T)' and 'Feeling (F)'. I found it extremely insightful that the words we would generally associate with "thinking" and "feeling" were the ones that were the top-ranked features of each dichotomy, shown in the figure below. Once again, statistical significance of these values will be an aspect of future research for this project.

Words associated with "feeling"

Significant words (features)	Frequency of word for output class T	Frequency of word for output class F
feel	13140	25431
love	8242	17122
feeling	4133	7543
happy	2301	4702
beautiful	532	1613
really	13927	21397
heart	1064	2490
thank	5468	10116
felt	1151	2304
hope	1794	3381
sad	1300	2554
haha	3095	5528
deep	1212	2357
song	1263	2910

Words associated with "thinking"

Significant words (features)	Frequency of word for output class T	Frequency of word for output class F
information	1239	958
science	1271	889
logic	2788	1871
knowledge	1114	714
argument	1236	731

Conclusion

The words that the feature selection ranked as significant are greatly insightful to the nature of what it means to be of a "Thinking (T)" or "Feeling (F)" type. It is amazing to see that the following words, which are less explicitly related to the "feeling" dichotomy but still one of its characteristics, are predictors of the dichotomy: love, beautiful, really, heart, thank, hope, haha and song. For the "thinking" dichotomy, the results are less interesting because the difference in the frequencies for each output class are not as significant. It is not surprising that words like "feel" and "feeling" are predictors of the "feeling" type, especially because the comments in the dataset were scraped from an online forum where people talk about their personality types. This is definitely a limitation of our dataset that needs to be addressed in future

research by collecting data from other social media and discussion platforms. Furthermore, the dataset collected needs to be larger so that classification can be performed for all dichotomies.

Other topics I explored

A major area of learning for me in this project was of topic selection. In trying to choose a topic of interest and feasibility, I transitioned topics many times due to which my project proposal, status report, and final report are all on different topics.

Topic	Stage of final project	Learning
Predicting whether a sequence of dance keyframes is “good” or “bad”	Project Proposal and initial email to professor Downey.	There is no point of subjectively assigning data to art and then using machine learning on that subjective data. Data, for machine learning, needs to be “true” for any meaningful learning to happen.
Predicting “news publication” based on text of articles	Status Report	There needs to be a meaningful objective to any machine learning task– otherwise we are building technology simply for the sake of technology.
Performing “text summarization”	Conversation with professor Downey in office hours	“Text summarization” is a large unsolved problem in the world of machine learning. Additionally, any large-scale NLP tasks require extremely fast computing speeds and long training times.

Appendix

Algorithm (Weka standard)	10-fold CV accuracy	Notes
ZeroR	60.415%	Started by looking at Judging-Perceiving dichotomy, stemming instead of lemmatizing, and without having removed words of ‘personality types’ from comments.
NB	72.4957%	
LO	79.0317%	
LO	83.147%	Started looking at Thinking(T) - FEELING (F) dichotomy
DT (J48)	72.634%	
NB	68.1268%	Removed {enfp, intp} from ‘posts’
LO	74.4323%	
NB	68.1499%	Started Lemmatizing
LO	74.4438 %	
NB	69.8213 %	Changed to Tfidf Vectorizer
LO	74.5245 %	
LO	73.6023 %	Tried with max_df = 0.5. Changed back to 1.
ZeroR	54.1095 %	Changed max_features from 500 to 1000
LO	75.5274 %	
NB	70.6974 %	