MBTI TEXT CLASSIFICATION

Can we determine personality only based on written text?

CONTENT

THE GOAL

Is it possible to determine a person’s MBTI personality type through how they express themselves in written communication?

THE DATA

KAGGLE
Dataset

8600+
Observations

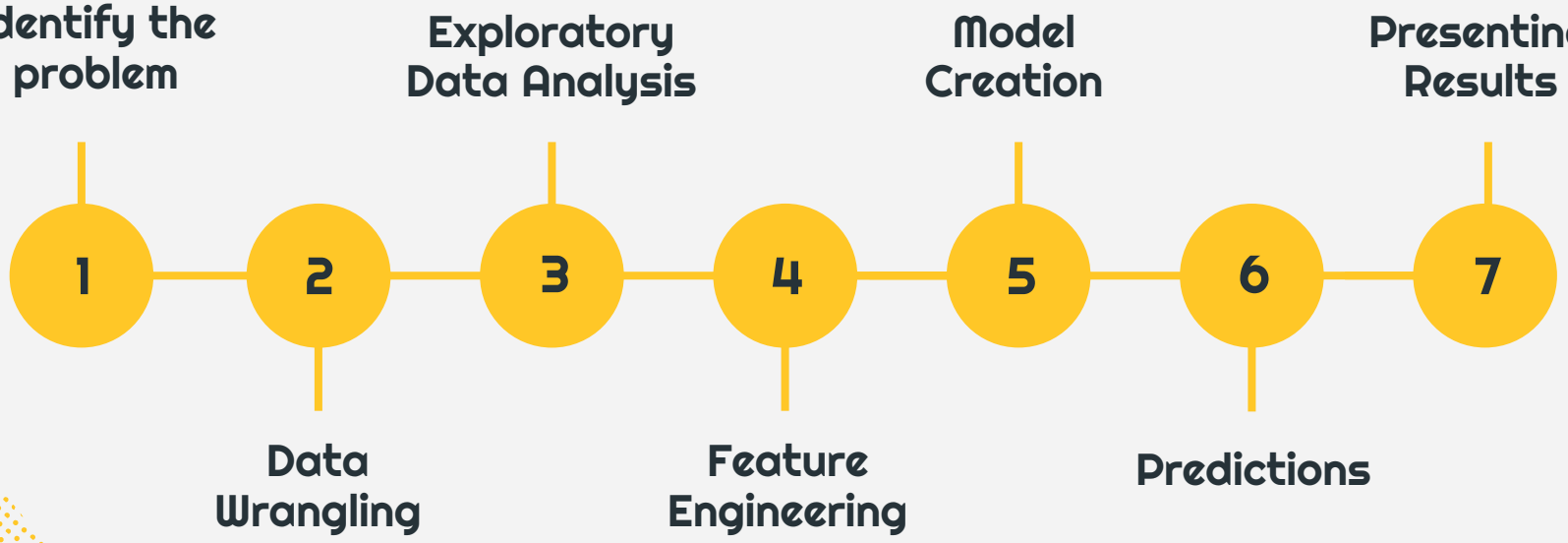
USER POSTS
Predictive Column

MBTI TYPES
Target Column

Example first rows

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

METHODOLOGY



DATA WRANGLING

The dataset contained 0 null values and did not require any correction. But we could create new features from the existing data. Here are examples:

Dichotomies & Keirsey

We extracted the individual dichotomies (I/E, N/S, T/F, J/P) and the Keirsey Temperaments (NT, NF, SP, SJ)

Text Characteristics

Average length of the words used by the person, number and type of emoticons they use, use of 1st person pronouns vs. 2nd and 3rd person...

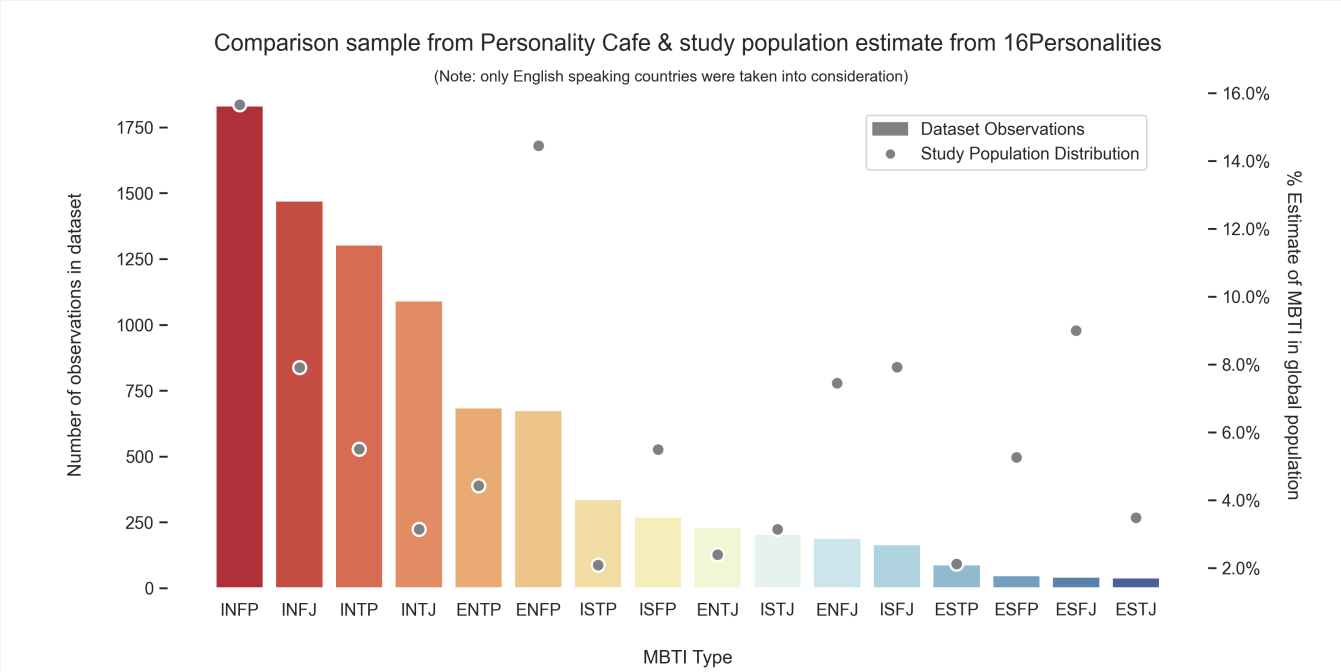
Qualitative Measures

The use of positive and negative words, readability consensus (Flesch Reading Ease score, Coleman-Liau Index), ...

Exploratory Data Analysis and Feature Engineering

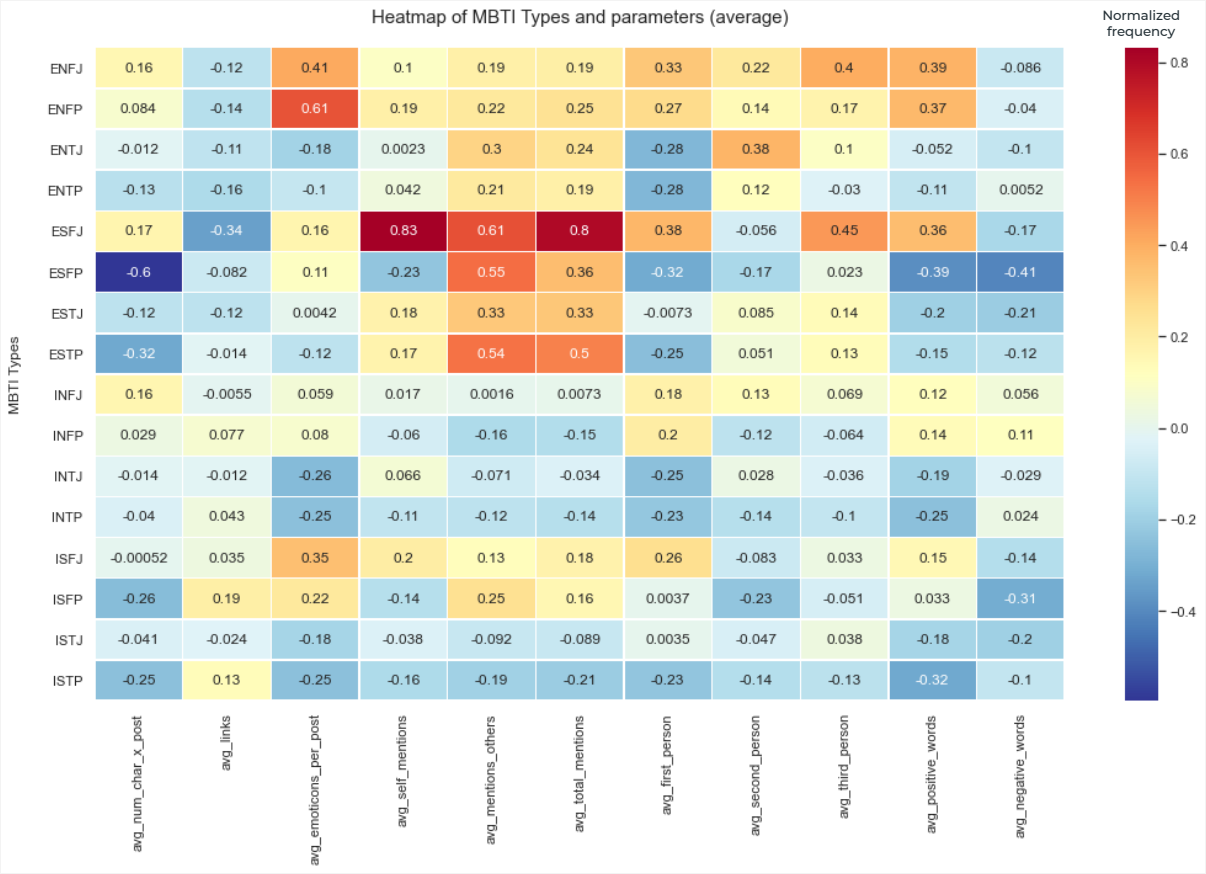
IMBALANCED DATASET

Strong imbalance towards “intuition” (N) and “introvert” (I) types. While the “sensing” (S) and “extraverts” (E) are a bit more underrepresented. Not completely representative of study population.



FEATURES and TYPES HEATMAP

We find some interesting differences amongst MBTI types when it comes to certain features.



FINDINGS

Characters x post

ESFP use less characters per post than other MBTI types while INFJs and ENFJs use slightly more characters

Emoticons

Our results confirm what one might expect that “Thinking” types use less emoticons than “Feeling” types.

Use of Pronouns

“Thinking” types use less 1st person pronouns than “Feeling” types. For 2nd and 3rd person pronouns there were no relevant differences

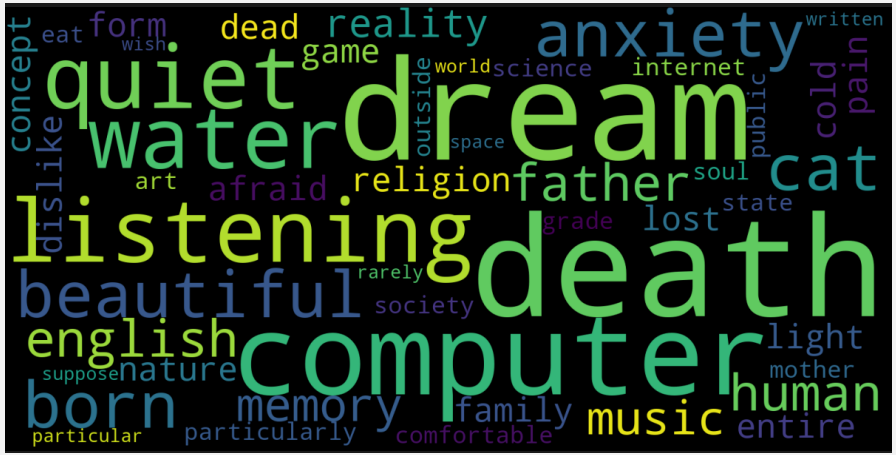
Positive-Negative

ENFJs and ESFJs use on average more positive words and INTPs, and ISTPs use less. ESFPs seem to have strong preference for both

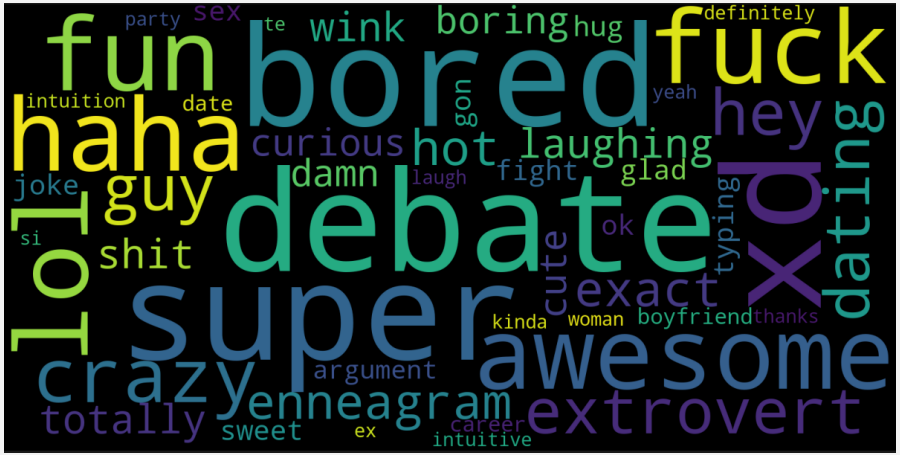
FINDINGS

CRITICAL WORDS BY DICHOTOMIES

INTROVERSION



EXTRAVERSION

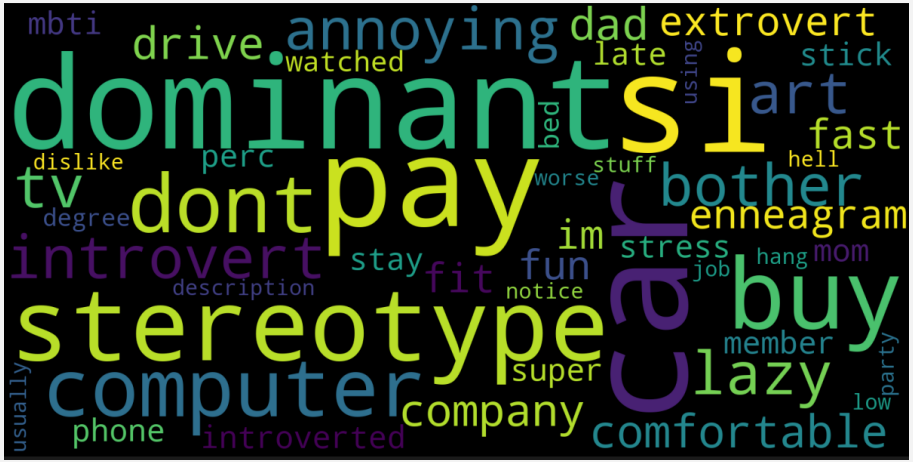


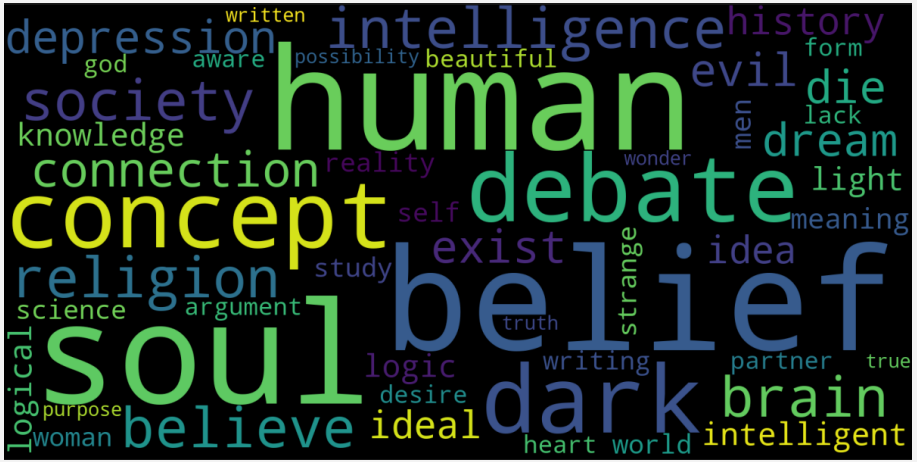
FINDINGS

CRITICAL WORDS BY DICHOTOMIES

SENSING

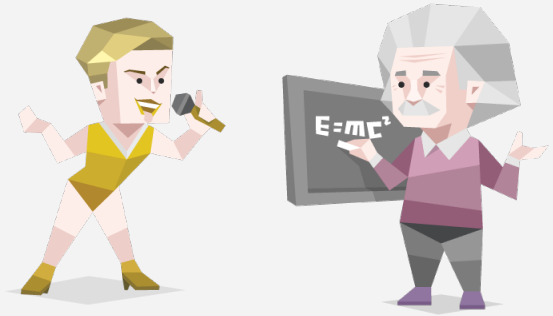
INTUITION





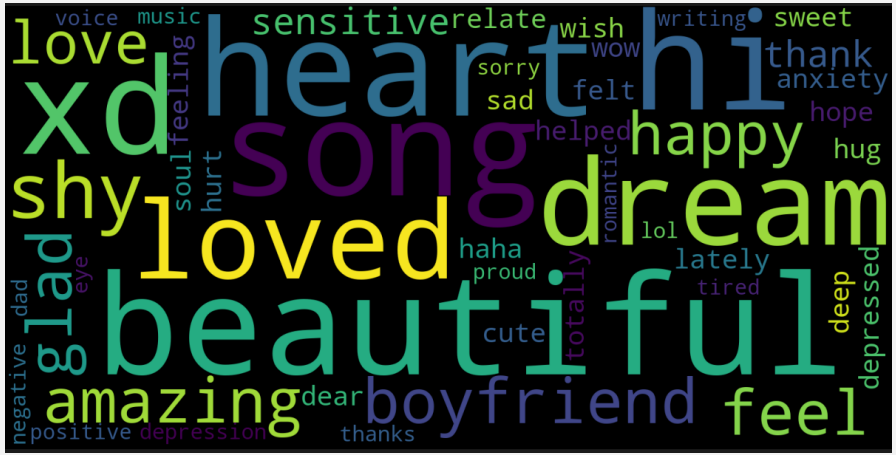
FINDINGS

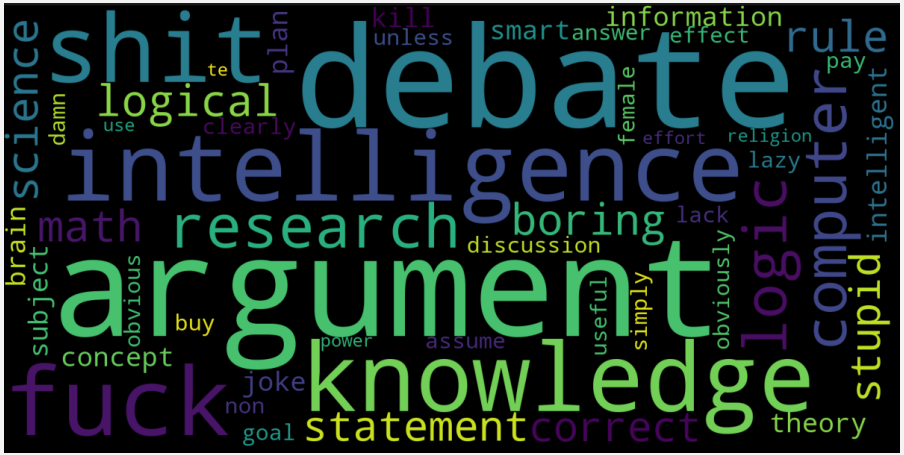
CRITICAL WORDS BY DICHOTOMIES



FEELING

THINKING



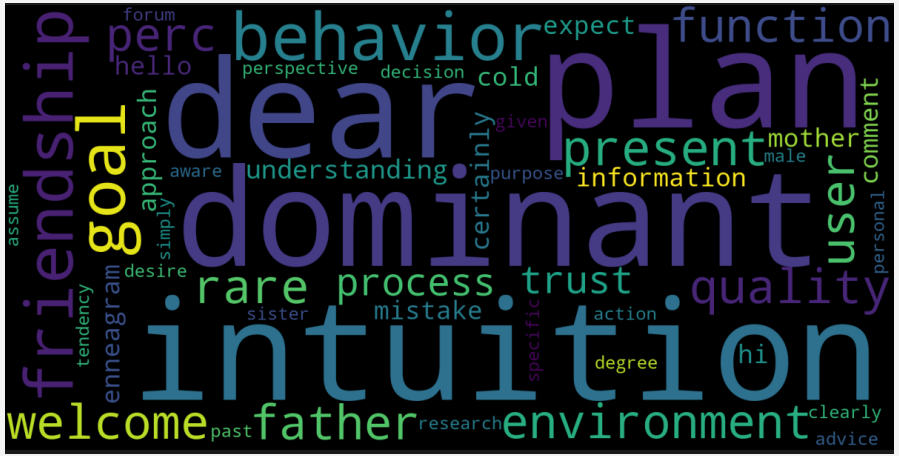


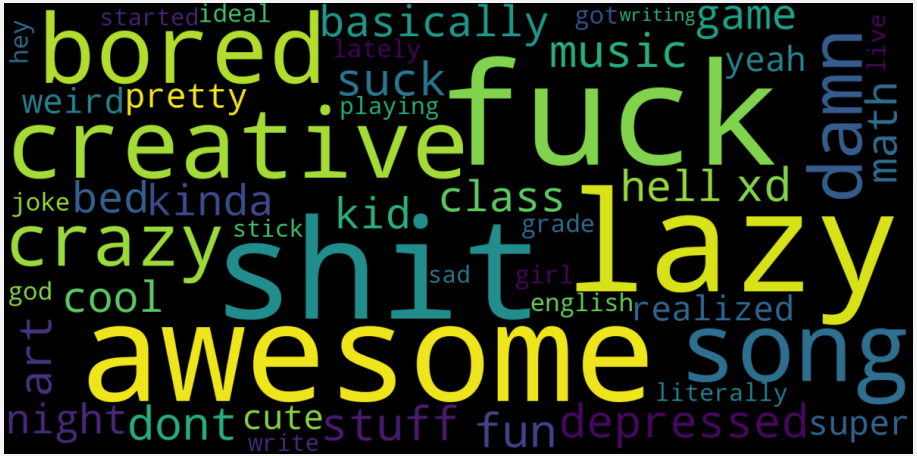
FINDINGS

CRITICAL WORDS BY DICHOTOMIES

JUDGING

PERCEIVING





Algorithms and Machine Learning

DATA & ALGOS

INPUT DATA

CountVectorizer Word Level
TF-IDF Word Level
TF-IDF N-Grams Level (2 and 3 words)
TF-IDF Character Level

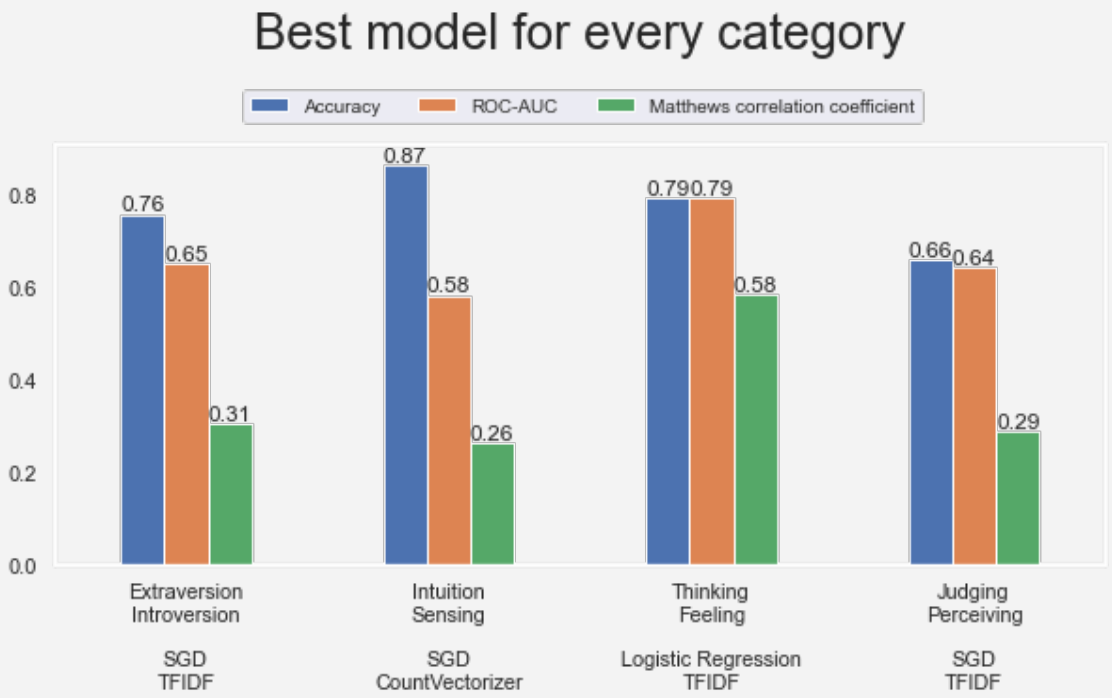
ML ALGORITHMS

- Naive-Bayes Classifier (NB)
- Logistic Regression (LR)
- Support Vector Machines (SVM)
- k-Nearest Neighbours (kNN)
- Stocastic Gradient Descent (SGD)
- Gradient Boosting (GB)
- XGBoost (XGB)
- Random Forest (RF)

BEST MODELS

The Stochastic Gradient Descent algorithm was the one that worked the best for three of the dichotomies (E/I, N/S, J/P) while Logistic Regression was the best model for T/F

The results are promising whilst not amazing. Specially good are the T/F followed by the E/I and J/P, while the accuracy of N/S was good, the ROC-AUC score shows there is room for improvement

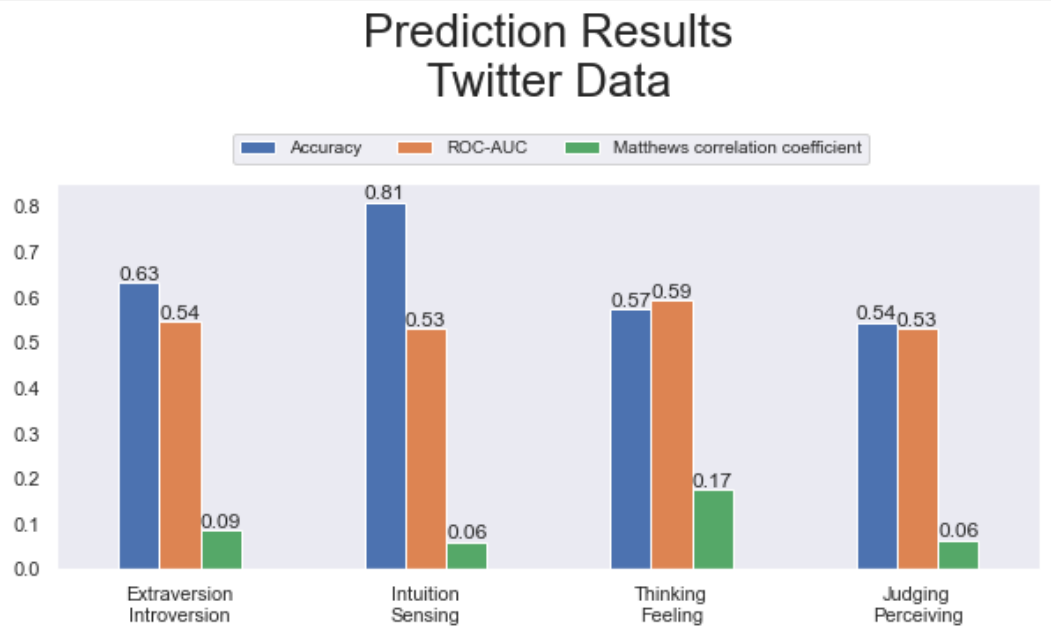


PREDICTIONS

TWITTER DATA

We tested our models on completely unseen data. We extracted 100 tweets from 1000 Twitter who had their MBTI type in their bios.

As seen in the graph on the right, the results are not very promising. This is possibly due to people using different ways to communicate in Personality Cafe (where train test data was extracted) and in Twitter (where this data was extracted from).



RECAP

In the EDA we saw there are certain differences in the way different MBTI types express themselves in written language (emoticons, average word length, use of pronouns, etc.).

With a Multinomial NB classifier we were able to extract the words that classified each dichotomy better (word clouds), the results of this analysis and the key words were most surprising.

While our best models show some promising results in the training and test data, our predictions on Twitter data were not optimal. This could be due to the origin of both datasets and how people express themselves differently in each platform where the were extracted from

CONCLUSION

Our results show that to some extent MBTI personality types can be determined through written classification.

Although there is still a long way to go to have good models that perfectly classify people into the 16 MBTI types, certain characteristics surface as statistically significantly different in how personality types express themselves in written communication.

IMPROVEMENTS & NEXT STEPS

IMPROVEMENTS

Using other features: currently we only used the original text data.

Additional data: scrape new data to train our models. Like using the Twitter data used for predictions or from Reddit's r/mbti.

Deep Learning and Transformers: we did not use these types of models but they have offered good results for NLP problems

NEXT STEPS

Web application: create a web application where people can put their Twitter screen-name or their Reddit user name and the app returns the MBTI type of the person

Cross-profiling tools comparison: do further analyses with other tools like the Big 5 and Enneagram and compare results with our MBTI dataset

THANKS

Do you have any questions?

journeydatas@gmail.com

https://github.com/DSJourney/

CREDITS: This presentation template was created by **Slidesgo,** including icons by **Flaticon**, and infographics & images by **Freepik.**