Final Project

TWITTER SENTIMENT ANALYSIS. CYBERBULLYING

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TRIGGER WARNING

It was a challenging project in a sense of exposure
to a lot of cyberbullying words.

Please consider this before reading it

EXECUTIVE SUMMARY

- As part of this project. I will analyze the sentiment of tweets posted on Twitter using natural language processing (NLP) techniques. The goal is to develop a model that could accurately classify tweets as positive, negative, or neutral based on their content.
- The project will use Python programming language and various libraries, including NLTK to scrape tweets, clean and preprocess them, and perform sentiment analysis. The dataset consisted of over 47,000 tweets related to age, religion, gender, ethnicity and other.
- The project will use machine learning algorithms such as Logistic regression, Support Vector Machines (SVM) and Random Forests to train and test the sentiment analysis model. The performance of each algorithm will be evaluated based on metrics such as accuracy, precision, recall, and F1-score.

INTRODUCTION

- Social media is used by a lot of people every day to communicate. Cyberbullying can happen on social media and it can affect anyone, anywhere, at any time.
- Cyberbullying is harder to stop than traditional bullying because people can remain anonymous online. UNICEF warned that during the COVID-19 pandemic, cyberbullying has become more common due to school closures, more screen time, and less face-to-face interaction.
- Many middle and high school students have experienced cyberbullying, and it can cause them to perform worse in school, feel sad, or even have thoughts of hurting themselves.

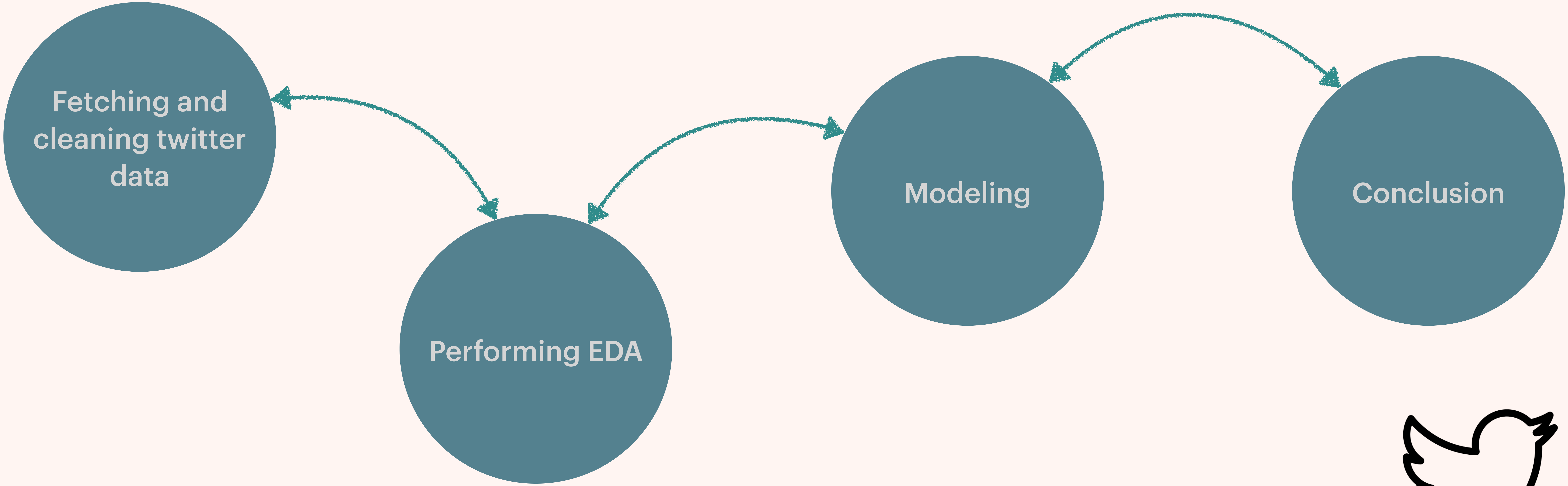
PROBLEM DEFINITION

- **Cyberbullying on Twitter poses a significant risk to users, specifically in relation to indicators such as age, ethnicity, gender, religion, and other types of cyberbullying.**
- **To better understand this issue, a sentiment analysis of a dataset of labeled tweets related to cyberbullying will be conducted to identify patterns or correlations between the sentiment of the tweets and the variables of interest.**

HYPOTESIS

- Before performing the sentiment analysis on the dataset, I predict that:
    - Tweets related to ethnicity will have a more negative sentiment than those related to other types of cyberbullying
    - Tweets related to gender will have a more negative sentiment than those related to age
    - Tweets not containing any type of cyberbullying will be more positive than those containing any type of cyberbullying

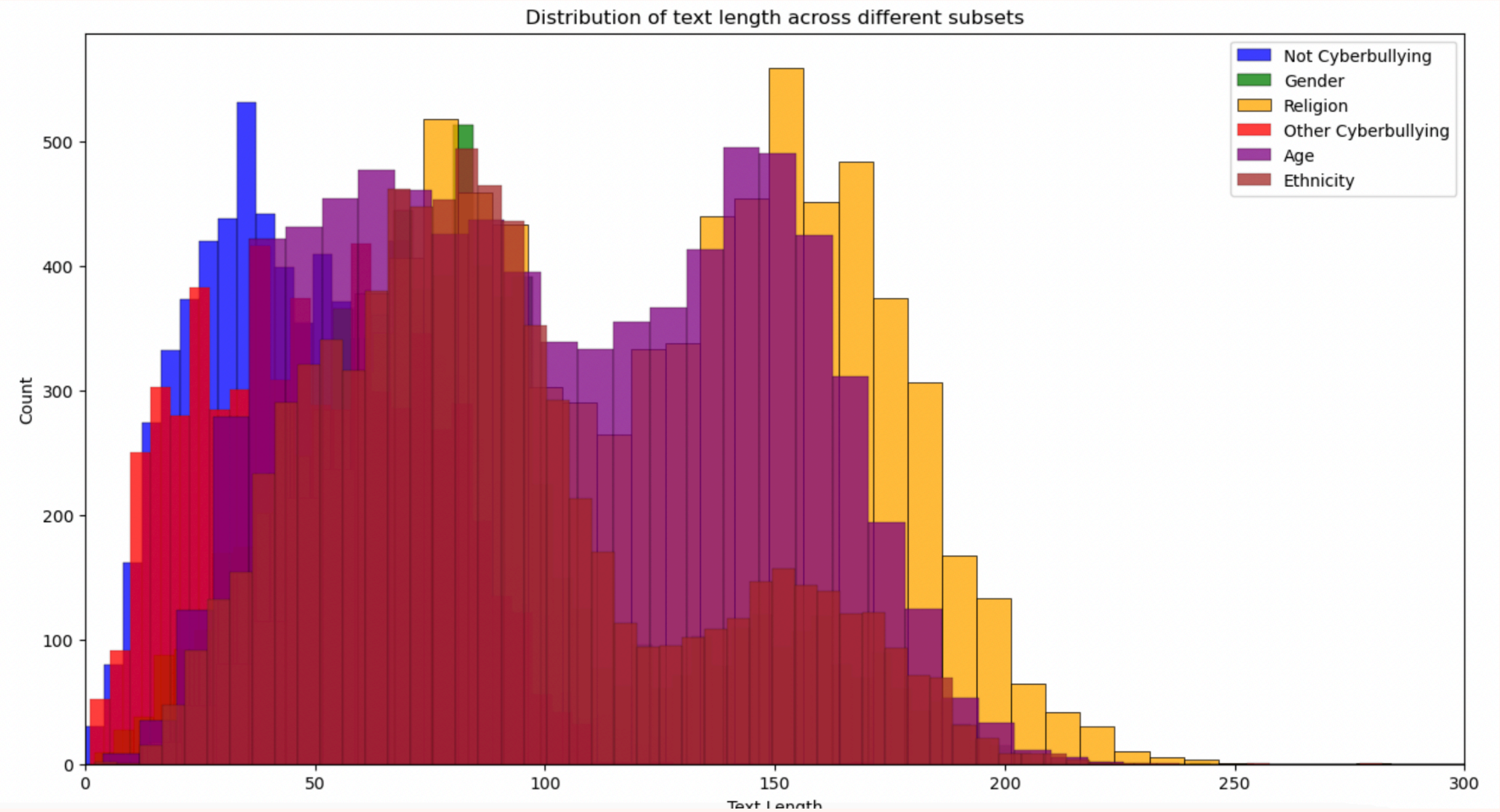
WORKFLOW


Fetching and cleaning twitter data
Performing EDA
Modeling
Conclusion

EDA

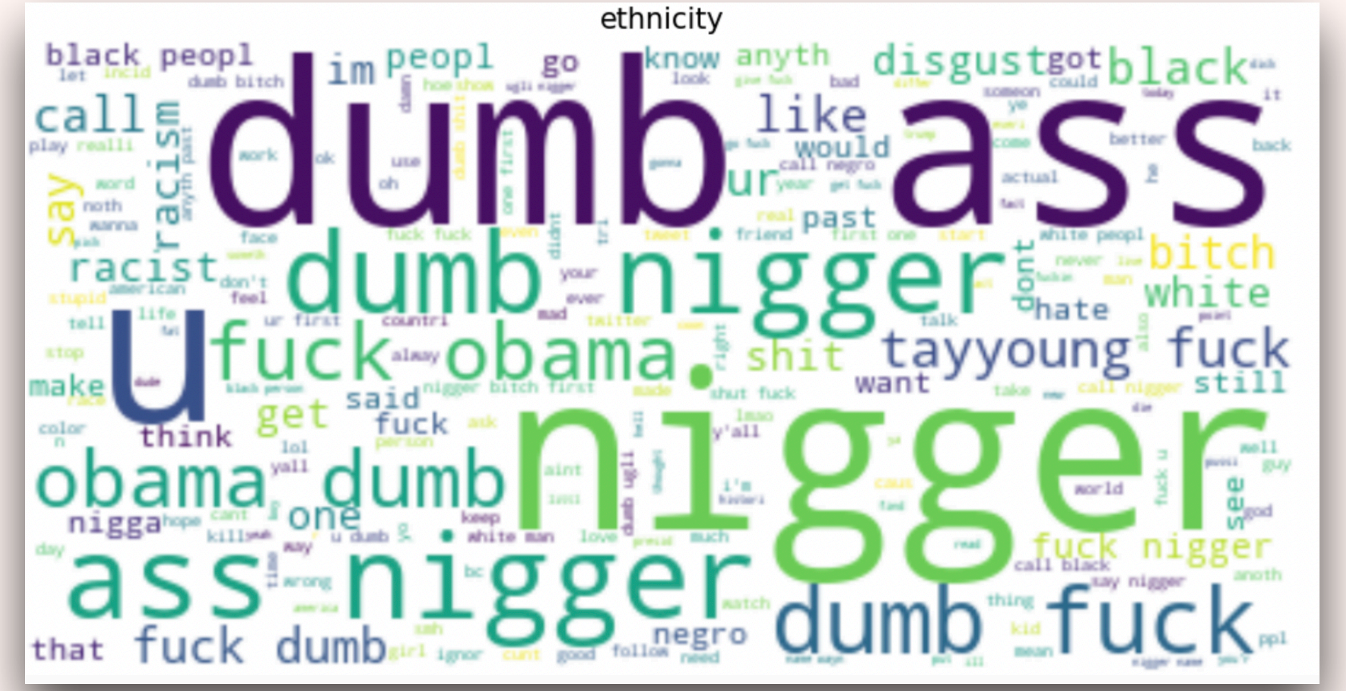
- **Histogram plot shows the distribution of text length across different subsets of the dataset, including: not cyberbullying, gender, religion, other cyberbullying, age, and ethnicity. The x-axis represents the length of the text, and the y-axis represents the frequency of occurrence.**

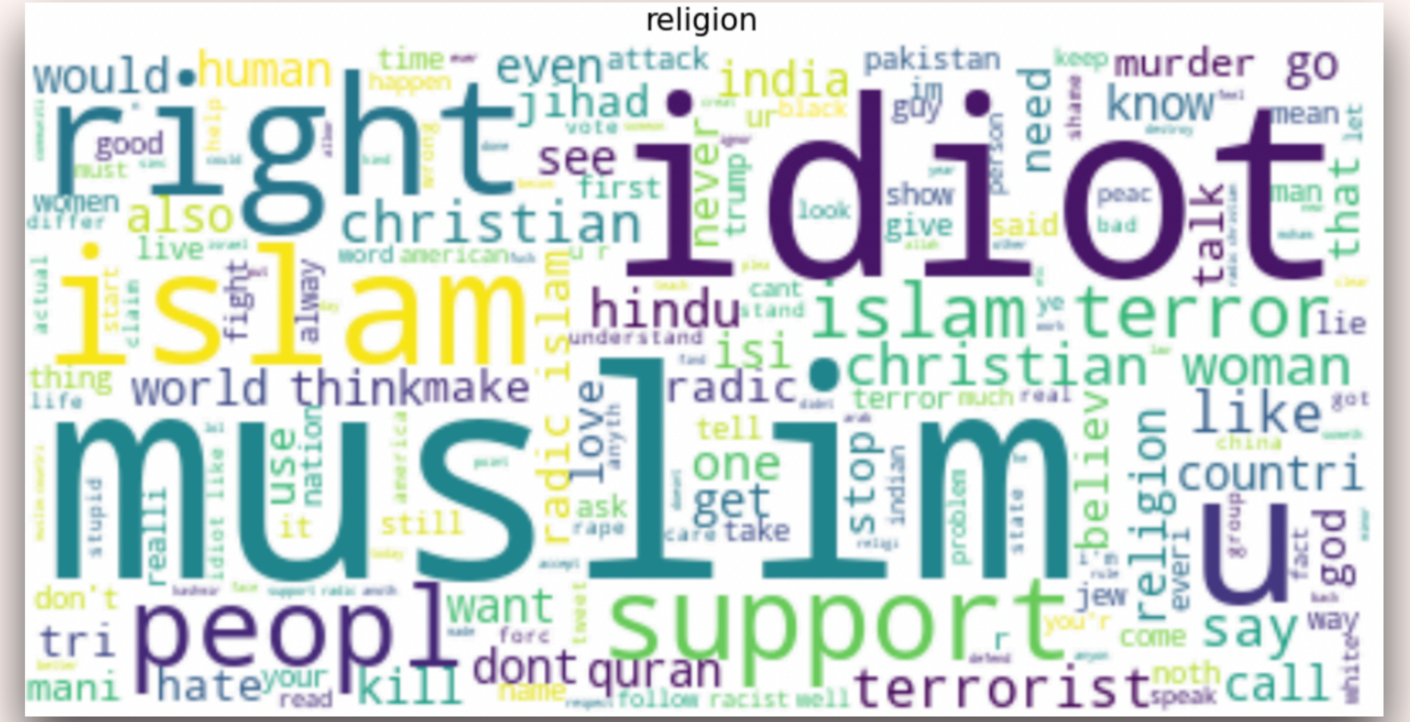
- **From the histogram we can see that religion based cyberbullying occurs the most**

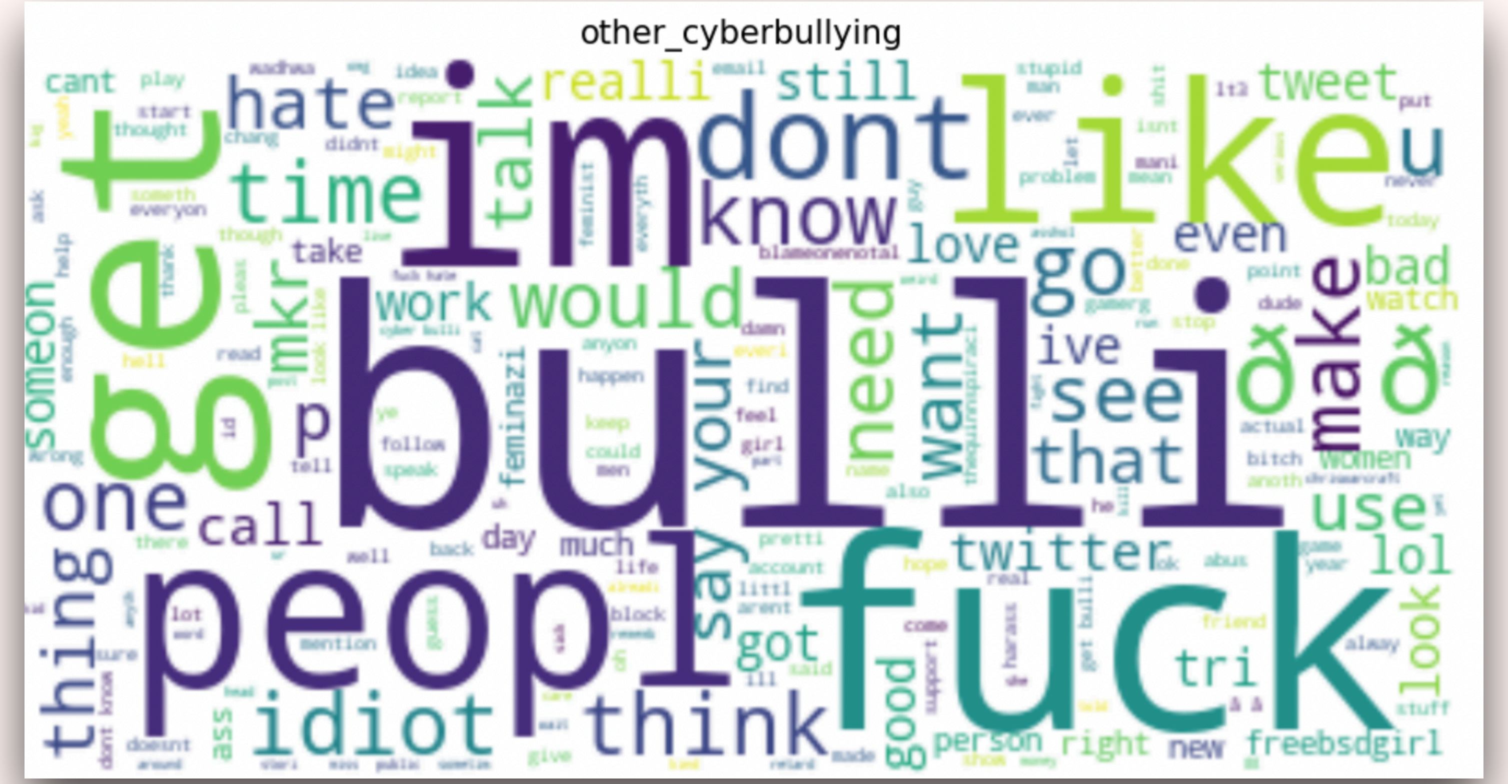


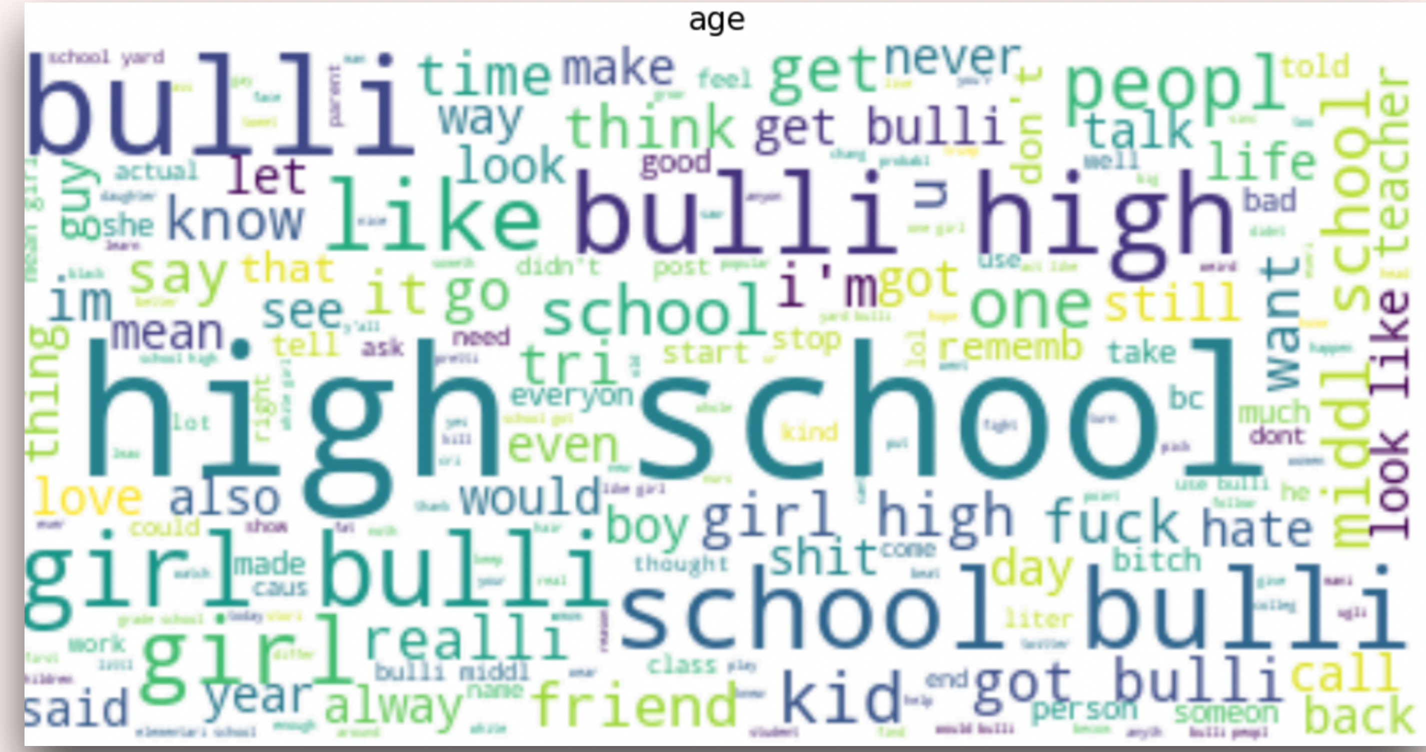
EDA

Frequency of different words across different subsets using a word cloud:



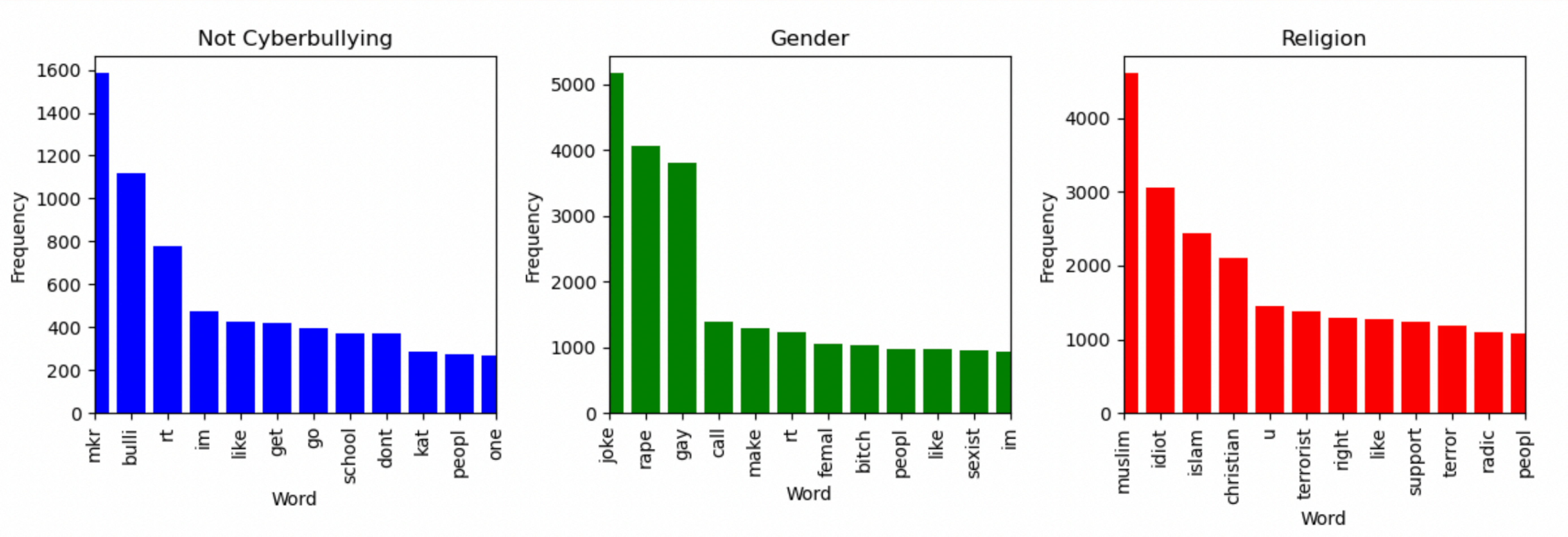


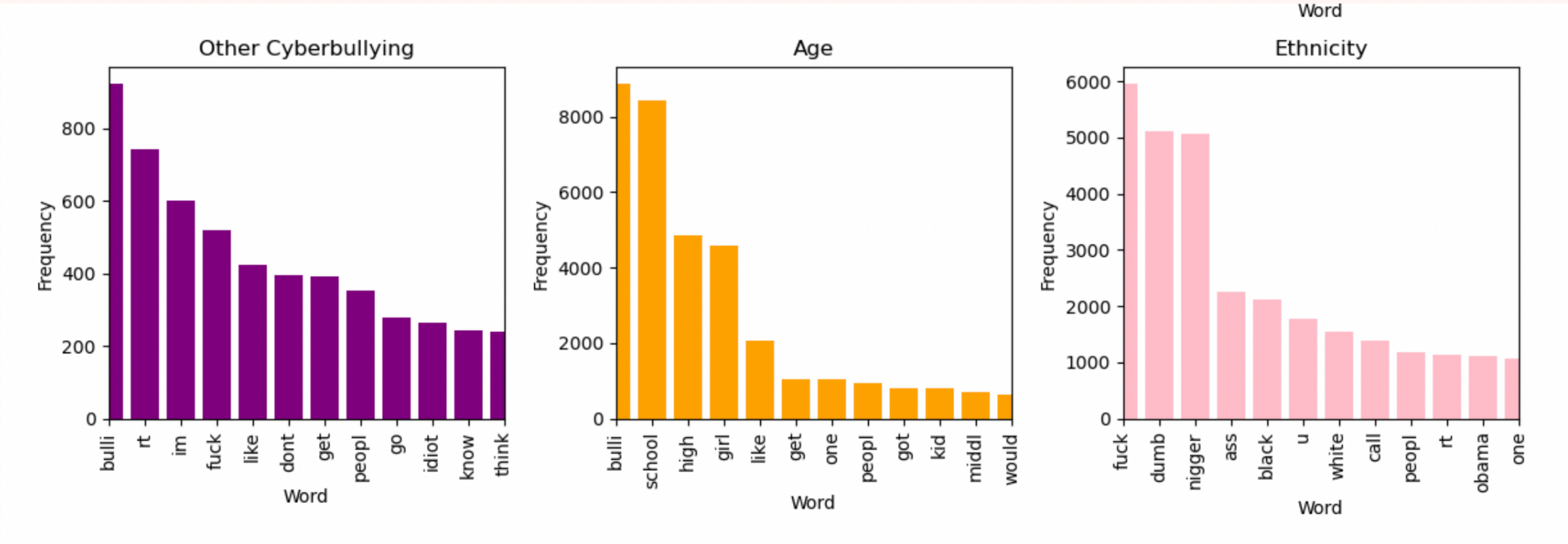




EDA

Frequency of cyberbullying words based on different subsets





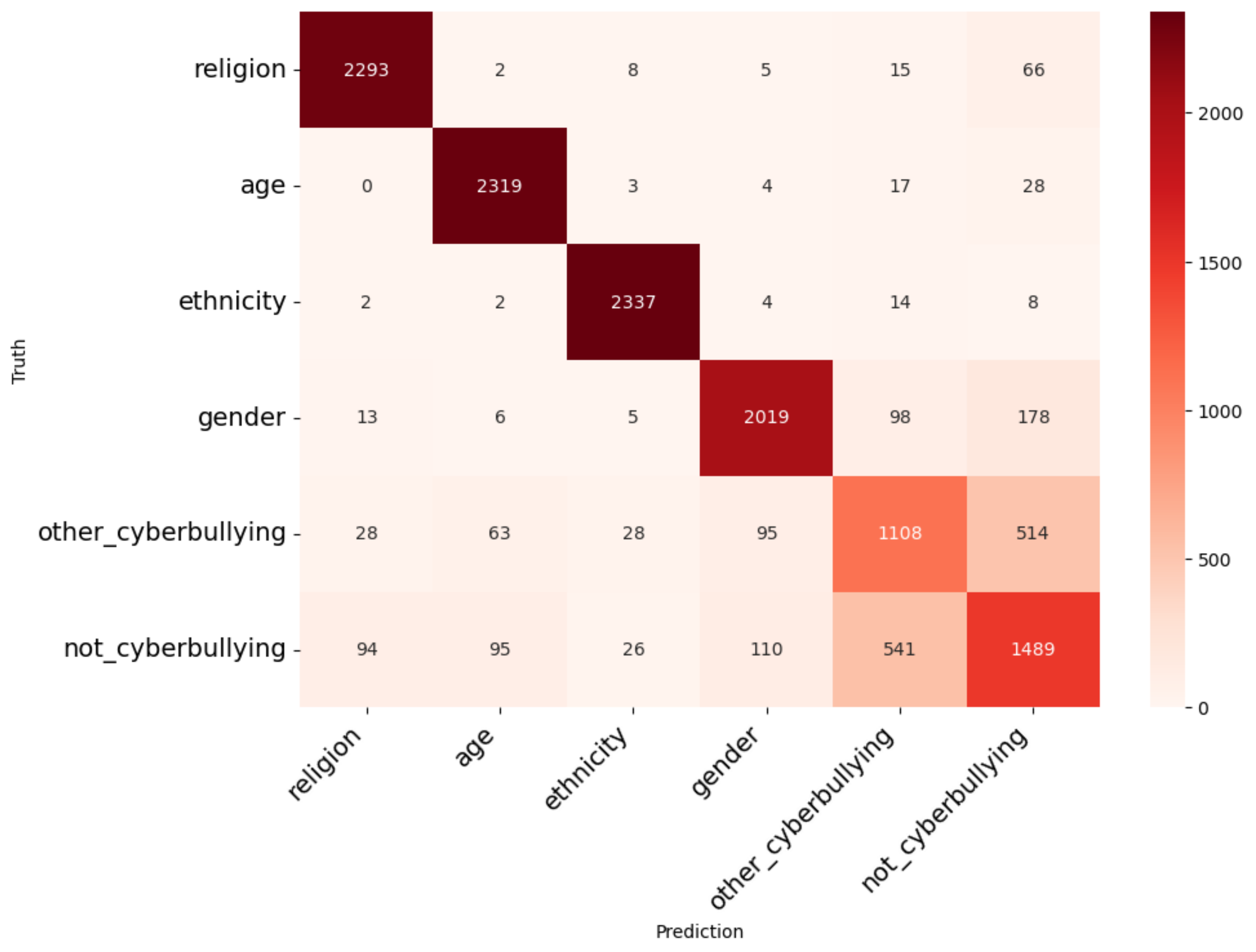
MODELING

- **Best model: Logistic regression.**
- **Looking at the precision and recall scores, we can see that the model performed well in identifying the age, ethnicity, and religion categories with precision of 93%, 97%, and 94%.**
- **However, the model had much lower precision scores in identifying other_cyberbullying and not_cyberbullying categories, which could be due to the overlap in the language used in those categories with other categories.**

Classification				
	Precision	Recall	f1-score	Support
Religion	0.94	0.96	0.95	2389
Age	0.93	0.98	0.95	2371
Ethicity	0.97	0.99	0.98	2367
Gender	0.90	0.87	0.89	2319
other_cyberbulling	0.62	0.60	0.61	1836
not_cyberbulling	0.65	0.63	0.64	2355
Accuracy			0.85	13637
Macro avg	0.84	0.84	0.84	13637
Weighted avg	0.85	0.85	0.85	13637

MODEL EVALUATION

- **The following heat map shows that there is a strong correlation in the religion, age and ethnicity categories .**
- **The correlation is lower in the gender category**
- **The lowest correlation is in the other_cyberbullying and not_cyberbullying categories.**



CONCLUSION

- The model also performed well in terms of recall scores for most categories, indicating that it was able to correctly identify a high percentage of instances belonging to each category. However, the recall score for the gender category was relatively lower, indicating that the model may have missed some instances belonging to this category.
- The f1-score was relatively high for most categories, indicating a good balance between precision and recall. However, the f1-score for other_cyberbullying and not_cyberbullying categories was lower, showcasing that the model may not have performed as well in identifying instances belonging to these categories.
- The model could be improved by finding ways to better distinguish between the language used in these categories and other categories to improve its precision and recall scores.

THANK YOU

RESOURCES

- **Kaggle:** https://www.kaggle.com/code/jayantverma9380/cyberbullying-tweet-recognition-project#Getting-data
- **Twitter:** https://twitter.com/
- **Medium.com:** https://medium.com/@nikitasilaparasetty/twitter-sentiment-analysis-for-data-science-using-python-in-2022-6d5e43f6fa6e
- **Kaggle:** https://www.kaggle.com/code/paoloripamonti/twitter-sentiment-analysis