Progress Presentation

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Project Overview

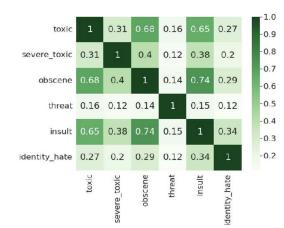
- Content Moderation Filter
 - Select a dataset of content classified as various levels of offensive
 - Train a model to classify text
 - Analyze results and performance of model
 - Study ethical implications of using such a model to classify content



https://health.clevelandclinic.org/dangers-of-social-media-for-youth

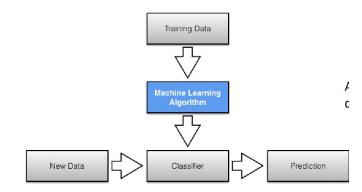
Selecting a Dataset

- Jigsaw Toxic Comment Classification Dataset
 - Purpose: Designed to classify comments as toxic or nontoxic
 - o Data Type: English text comments from Wikipedia
 - Number of Samples: 150,000
 - Labels: Multi-class classification
 - Each comment is assigned 6 binary labels: (toxic, severe toxic, obscene, threat, insult, identity hate)
- Why this dataset?
 - Well-labeled data, ideal for supervised learning
 - Real world use case
 - Diverse in types of toxicity



Plan

- Preprocess Dataset
 - Clean text (e.g. remove special characters)
 - Split data into training and test sets
 - Tokenize and convert text to numerical features
- Train Various Models
 - Classify text as toxic, not toxic, or any other label
 - Train simpler models (Logistic Regression, Random Forest)
 - Compare with more complex models (LLMs)
- Evaluate Performance
 - Use metrics such as accuracy, precision, recall, and F1-score



Ethical Considerations

Over & Under Moderation

Over-Moderation: Excessive filtering could stifle free speech, preventing open discussions on controversial but necessary topics.

Under-Moderation: If the model is too lenient, it may allow harmful content to spread unchecked.

False Positives and False Negatives

False Positives: Innocuous content being mistakenly flagged as toxic can frustrate users and limit expression.

False Negatives: Harmful content slipping through moderation could lead to harassment, misinformation, or community harm.