Detecting Cyberbullying with Natural Language Processing

Helping parents keep teens safe online

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Content Outline

1. Business Problem & Product Goals
2. Data & Methods
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5. What's Next?

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BUSINESS PROBLEM & PROJECT GOALS

Drugs/Alcohol

75.35% **of tweens and** 93.31% **of teens** engaged in conversations surrounding drugs/alcohol.

Self-Harm/Suicide

43.09% **of tweens and** 74.61% **of teens** were involved in a self-harm/suicidal situation.

Sexual Content

68.97% **of tweens and** 90.73% **of teens** encountered nudity or content of a sexual nature.

Violence

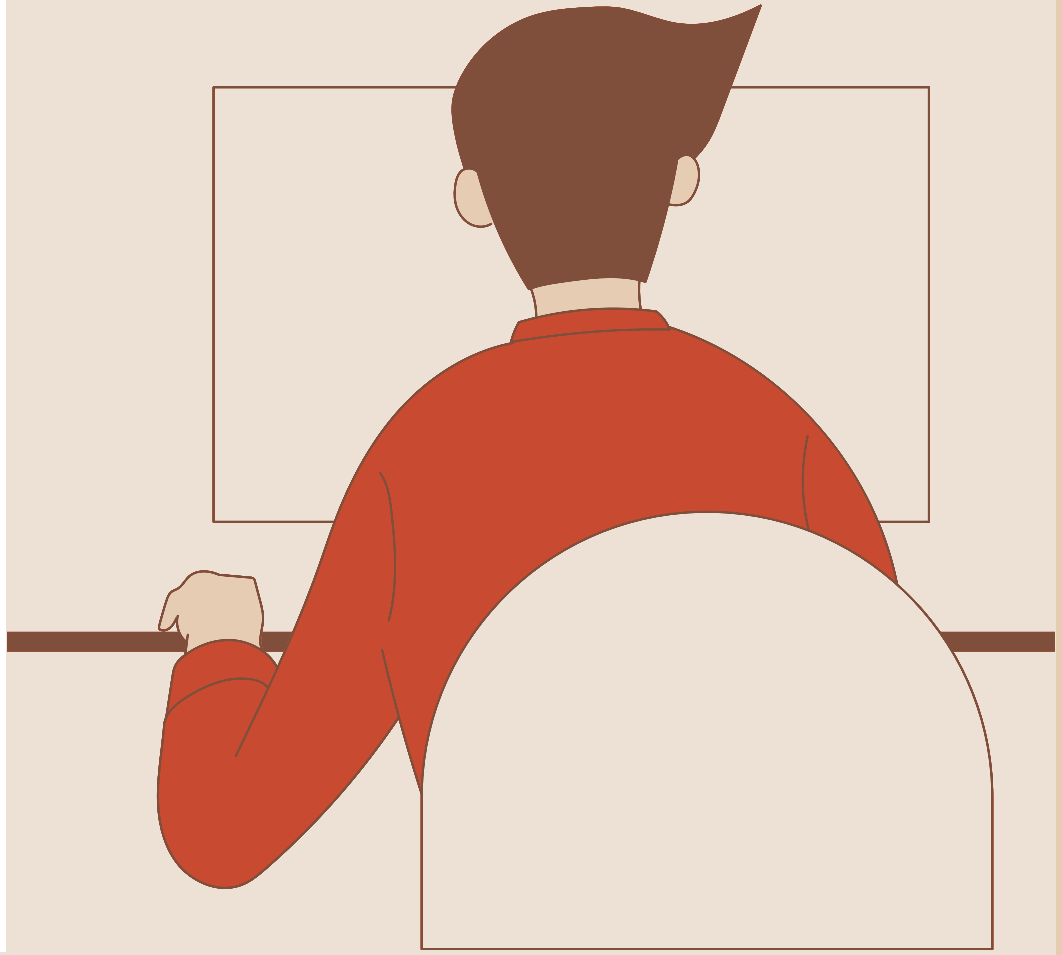
80.82% **of tweens and** 94.50% **of teens** expressed or experienced violent subject matter/thoughts.

Depression

32.11% **of tweens and** 56.40% **of teens** engaged in conversations about depression.

Bullying

72.09% **of tweens and** 85.00% **of teens** experienced bullying as a bully, victim, or witness.



Source: Bark annual survey

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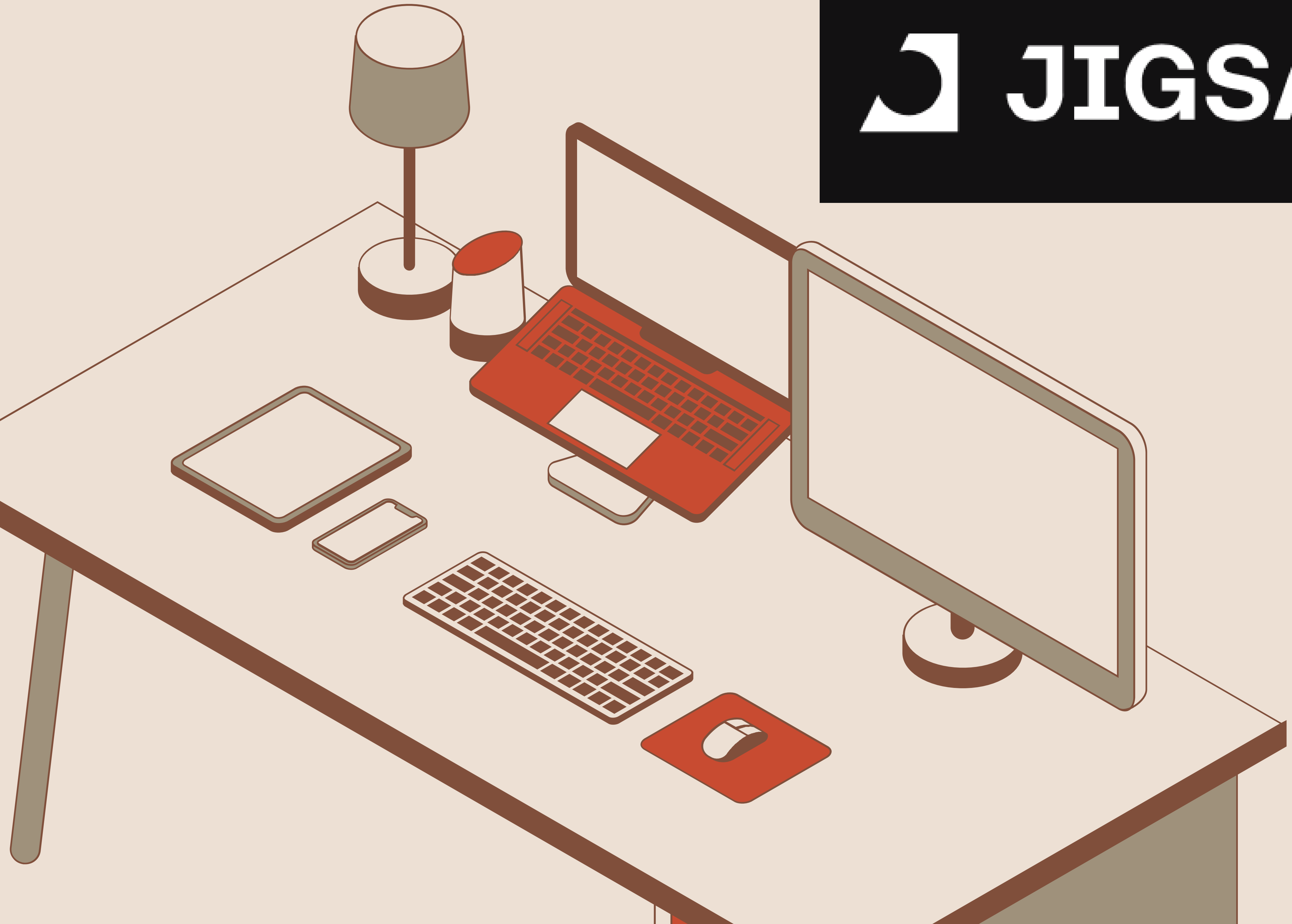
BUSINESS PROBLEM &
PROJECT GOALS

Products to help parents are limited



JIGSAW

Kindly

Kindly is the product of innovator Gitanjali Rao and UNICEF's collaboration

circle

Life360

bark

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Data

- Two million online comments
    - Collected by Civil Comments
    - Curated by Jigsaw
    - Distributed on Kaggle
- Proportion of human raters endorsing:
    - toxicity
    - severe toxicity
    - obscene content
    - threats
    - insults
    - identity attack
    - sexually explicit content

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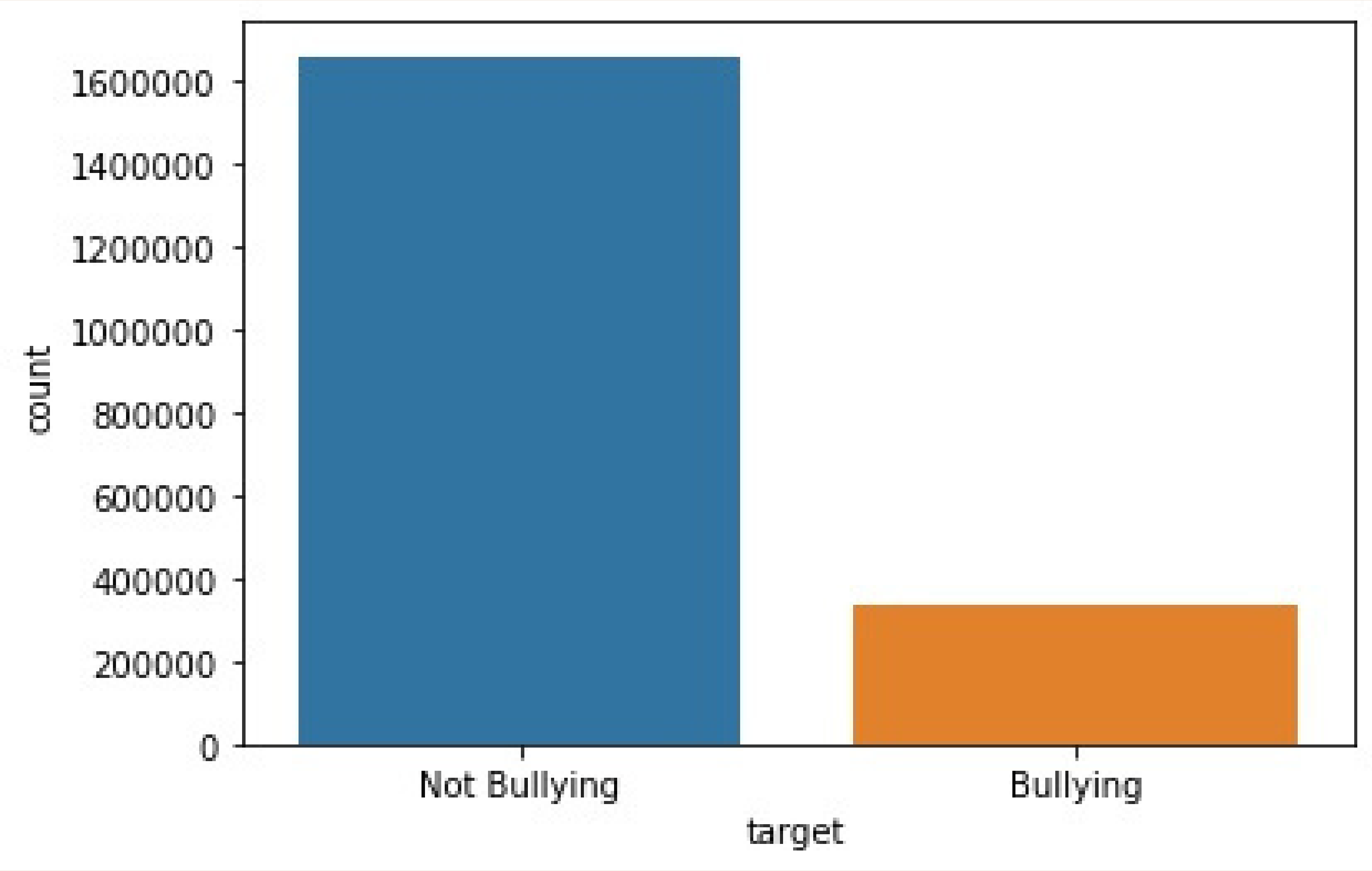
Methods

- Combined toxic subtypes into single target
- Standard "Bag of Words" preprocessing
- Undersampled "non-toxic" comments
- Naive Bayes and Logistic Regression Classifiers



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RESULTS

Toxic comments

Non-toxic comments

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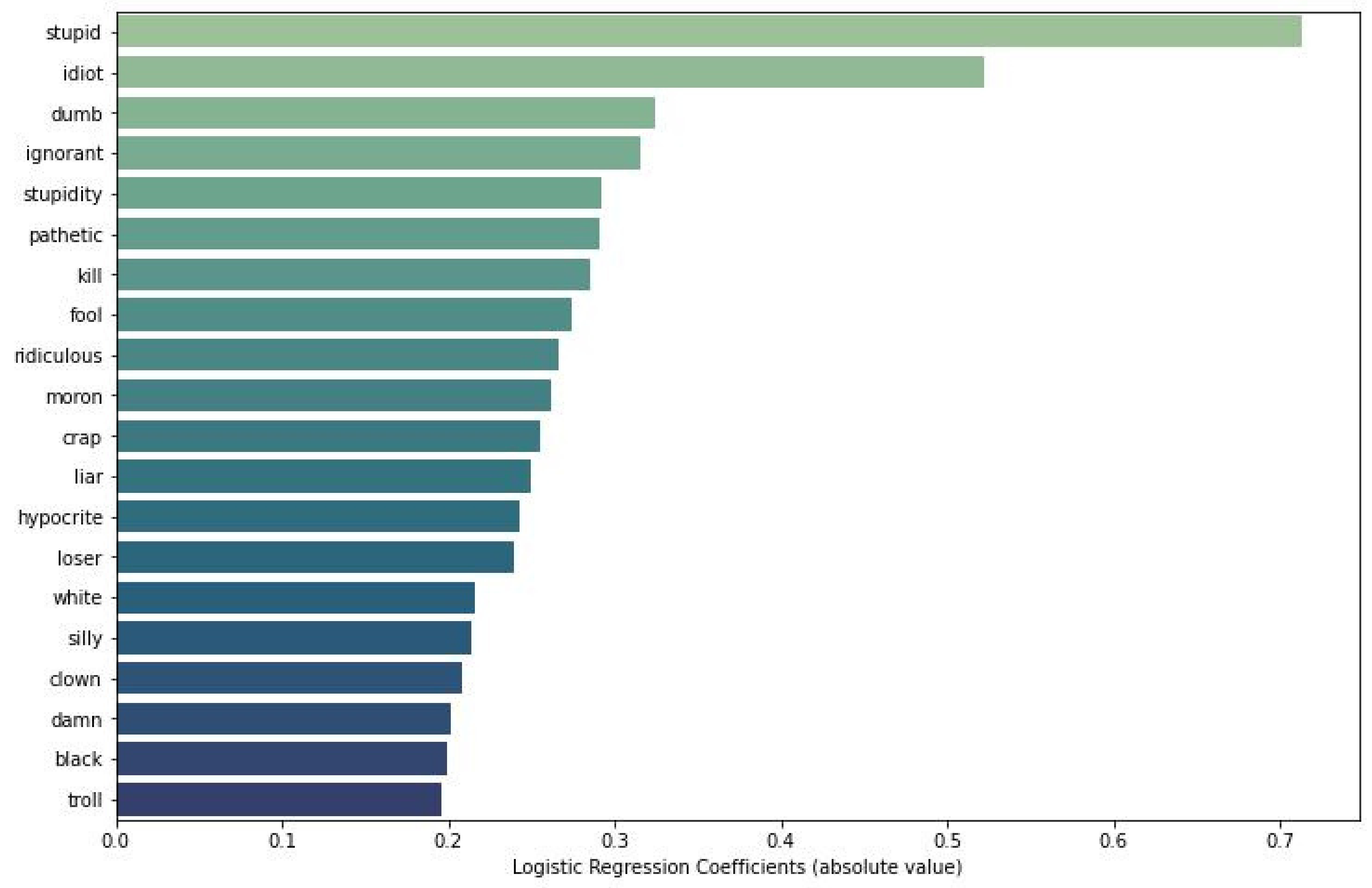
Strongest Predictors of Toxic Comments



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EXAMPLES

A comment that should be classified as 'toxic' by using some of the terms with the strongest coefficients in the logistic regression.

```
detect("You're a stupid idiot")
```

```
toxic comment
```

Another comment that, on its face, should be classified as 'non-toxic'

```
detect('You are awesome and I love you')
```

```
not a toxic comment
```

Lastly, a comment that was created to be intentionally ambiguous.

```
detect('Damn, I love you, silly')
```

```
toxic comment
```

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WHAT'S NEXT

Phase 1: Develop an API

- Connect to users' accounts
- Highlight potential toxic comments
- Provide parental alerts

Phase 2: Acquire more diverse data

- Different groups of users
- Content by app

Phase 3: Improve models

- Additional feature engineering
- Advanced models (BERT and GPT)

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Thank you for listening!

Please reach out with questions!

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