UVA DSI Capstone Project Wikimedia Foundation, Trust & Safety

Automatic Detection of Online Abuse and Prediction of Problematic Users in Wikipedia

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Unsocial Media: Tracking Twitter Abuse agai Women MPs

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1.44%

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How can we as Data Scientists do what we do best, and make these communities safer from onlir abuse

The English Wikipedia over the last few years...





Online Harassment at Wikipedia

Pew Research Centre Survey (America centric)



41% have experienced personal attacks

66% observed attacks directed towards others



47% reported a decrease in contribution and engagement levels



Problem



There is a need for a more robust process to combat harassment, one that can scale well as the Wikipedia community continues to grow in its size and diversity.

Our goal was to use machine learning to develop a model that can detect abusive content as well as predict problematic users in the community.

To that end, we leveraged a variety of data to analyse the prevalence and nature of online harassment at scale.



Data Pipeline

DATA SCIENCE IN S T I T U T F



Block User Trends in Wikipedia



- ~1.02 million unique users have been blocked in Wikipedia till Oct 2018
- 91.5% registered users
- 8.5% are anonymous users
- Increase in user bocks in 2017, 2018

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For what reasons are users getting blocked over the years?



Active status of blocked users



Blocked Users active in weeks prior to block



90% of all blocked users are most active in the week that they get blocked within their 8-week rolling window

Abuse Detection - Problem at hand

Goal

- Prediction of a toxicity score for each user comment.
- Inputs
 - > User Blocks, User Comment Text, User Activity, and Google Ex: Machina Corpus
- Challenges
 - Data Cleaning and Pre-processing
 - Ground truth labeling
 - Class imbalance



Model Building Methodology

- Corpus Aggregation + Annotation
- Feature Extraction
 - Natural Language Processing
 - Orthographical Features
- Implementing Machine Learning Algorithms
 - Classification Techniques
 - Train Test split
 - K-fold cross validation
- Model comparison
 - Using Google Ex Machina dataset to compare best performing model
- Model Tweaking



Modeling Deep Dive - Feature Extraction

- Natural Language Processing
 - Char n-gram
 - ➢ Word n-gram
 - NLTK Sentiment Analyzer
 - Latent Dirichlet Allocation
 - Word Embedding GloVe
 - Word Embedding fastText
- Orthographical Features
 - Numeric Digits
 - Capital Characters
 - Special Characters
 - Average length of characters in word



Modeling Deep Dive - ML Algorithms





Toxicity Score Evolution





User Risk Model - Early Detection of Problematic Users

• Goal

Prediction of propensity of user to be blocked in the future

• Inputs

➢ User Blocks, User Comment Text, User Activity, Toxicity Scores, and ORES Scores

Methodology

- Take into account n-1 recent scores and activity features of each user to predict the propensity for their nth comment to be abusive
- Leveraging Naïve Bayes approach with different Machine Learning Algorithms



User Risk Model - Early Detection of Problematic Users





User Risk Model - ML Algorithms





Performance of XGBoost model at different thresholds

• Optimizing for higher Recall values instead of Precision

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Threshold	Accuracy	Precision	Recall	F1	AUC
0.1	91.17%	0.81	0.94	0.87	91.97%
0.2	92.29%	0.86	0.91	0.88	91.97%
0.3	92.60%	0.88	0.89	0.89	91.60%
0.4	92.71%	0.90	0.87	0.89	91.17%
0.5 (default)	92.38%	0.91	0.84	0.88	90.29%
0.6	91.94%	0.93	0.82	0.87	89.26%
0.7	91.59%	0.94	0.79	0.86	88.44%
0.8	91.10%	0.95	0.77	0.85	87.43%
0.9	89.94%	0.96	0.72	0.82	85.30%











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