Hands-on Tutorial: Measuring Unintended Bias in Text Classification Models with Real Data

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Outline

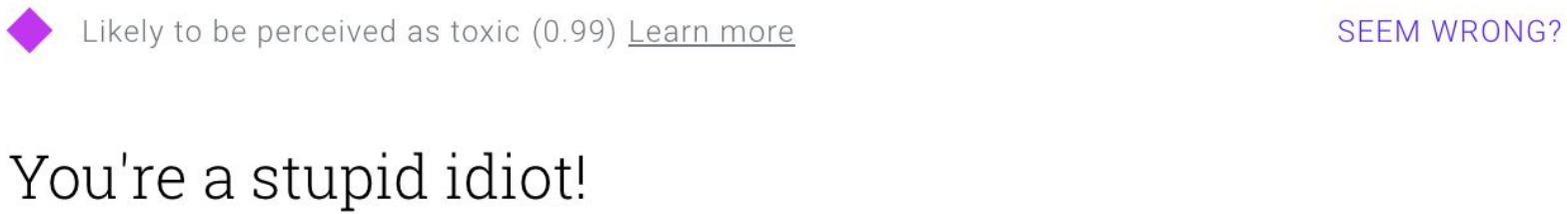
- Who we are
- The Problem
- Civil Comments Data
- Training a deep learning model
- Metrics for ML fairness
- Hands-on tutorial

Conversation-AI

ML to help improve online conversations at scale

Perspective API

ML Models to score perceived impact of a comment on a conversation



False "toxic" positives

A naively trained model will have some strong unintended biases illustrated by these false-positive examples...

Comment	Toxicity score
The Gay and Lesbian Film Festival starts today.	0.82
Being transgender is independent of sexual orientation.	0.52
A Muslim is someone who follows or practices Islam.	0.46

The Challenge

Goal: Train an ML model to detect toxicity in online comments.

Questions:

- How can we determine if there is bias in such a model?
- Where does the bias come from?
- What can we do to mitigate bias?

Civil Comments Dataset

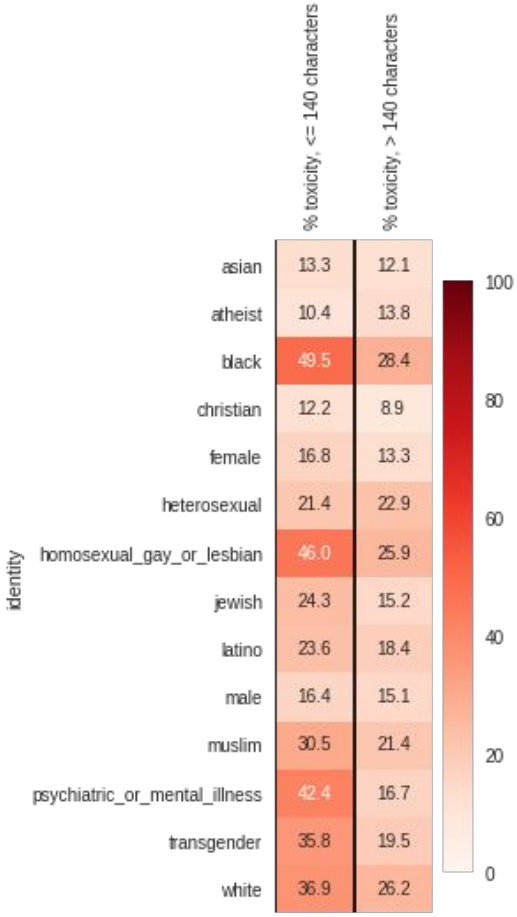
- ~2 million comments released by Civil Comments platform
- Collected via civil comments plugin on comment sections of online publications
- Annotated by Conversation AI for:
    - Toxicity, Obscenity, Sexually Explicit, Threats, Insults, Identity Based Attack
    - Subset (360k) annotated for various identity-related categories

Disclaimer: This dataset contains real comments from real users. Some of these comments may be very offensive.

Assumptions

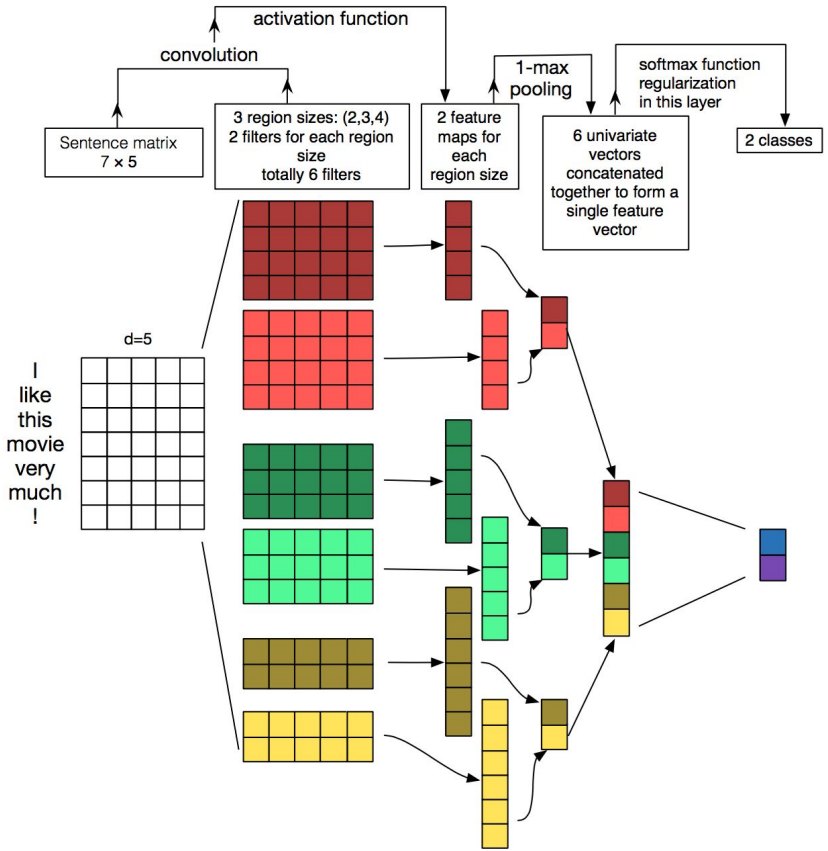
Dataset is reliable:

- Similar distribution as application
- Ignores annotator bias
- No causal analysis



Deep Learning Model

- CNN architecture
- Pretrained GloVe Embeddings
- Keras Implementation

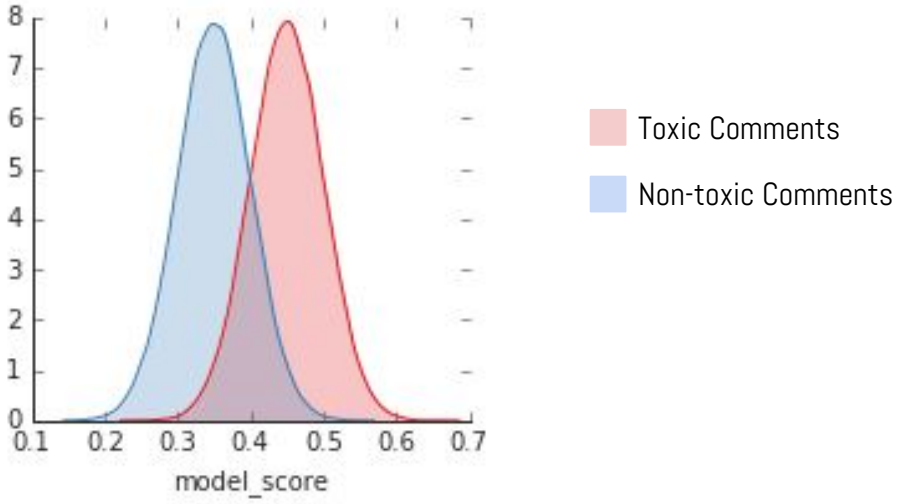


Source: Zhang, Y., & Wallace, B. (2015). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820.

Measuring Model Performance

How good is the model at distinguishing good from bad examples? (ROC-AUC)

AUC (for a given test set) = Given two randomly chosen examples, one in-class (e.g. one is toxic and the other is not), AUC is the probability that the model will give the in-class example the higher score.



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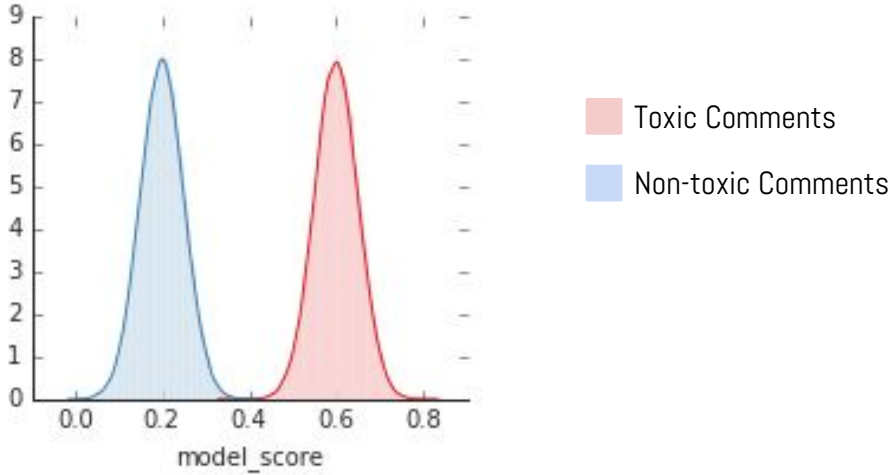
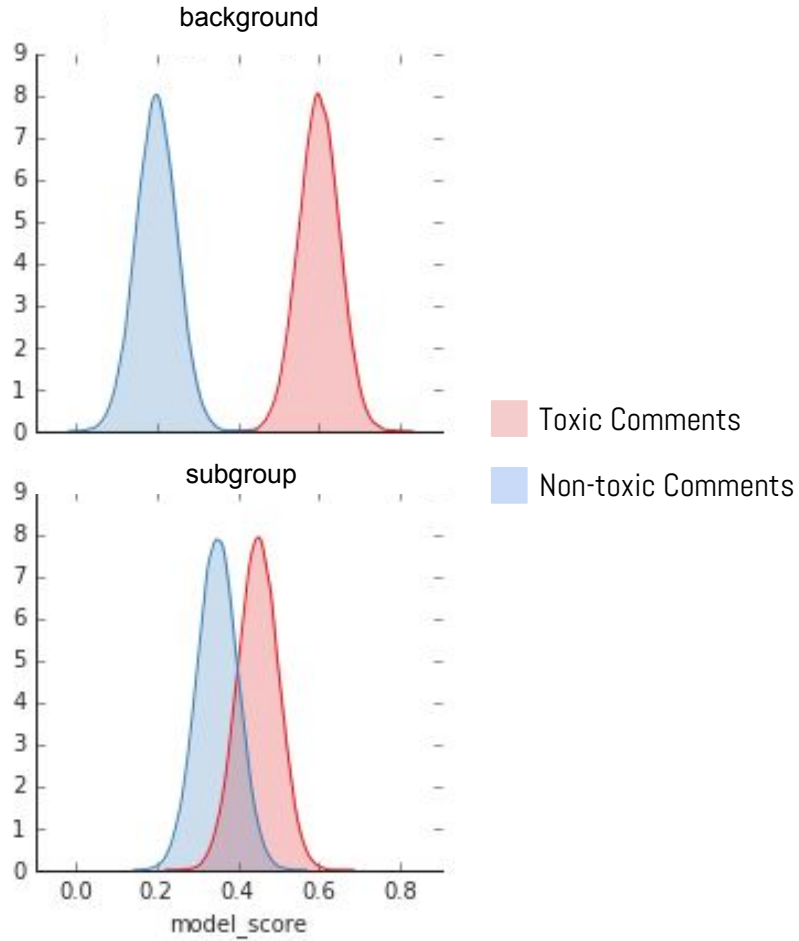


Types of Bias

Low Subgroup Performance

The model performs worse on subgroup comments than it does on comments overall.

Metric: Subgroup AUC



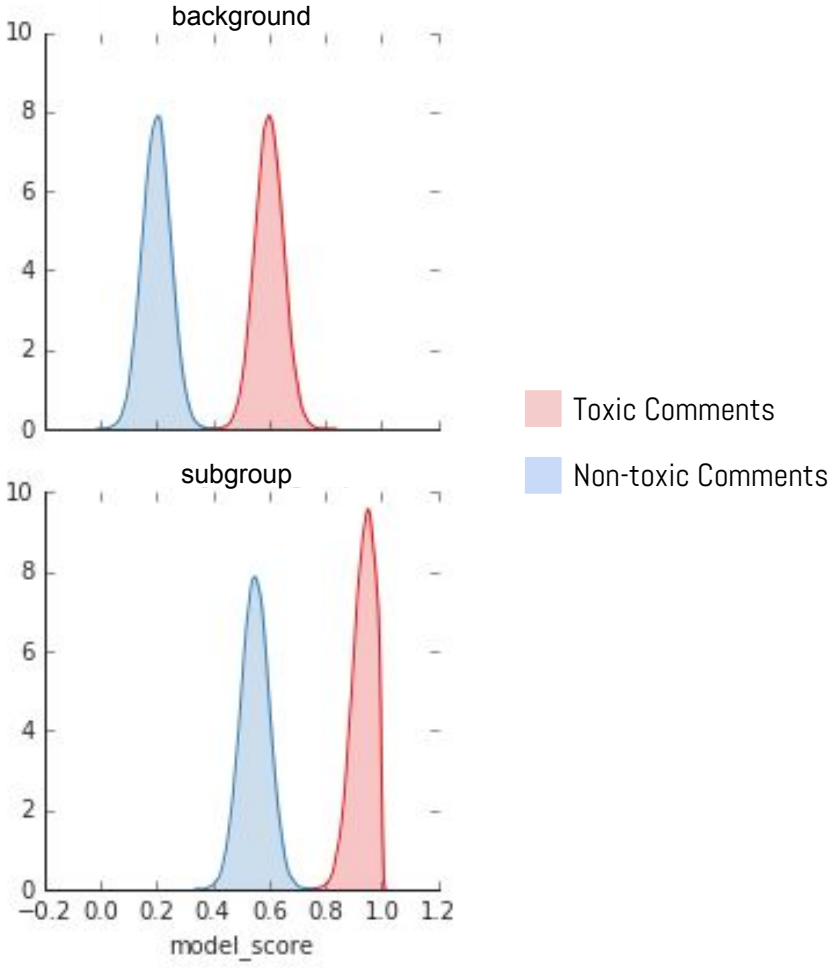
Types of Bias

Subgroup Shift (Right)

The model systematically scores comments from the subgroup higher.

Metric: BPSN AUC

(Background Positive Subgroup Negative)



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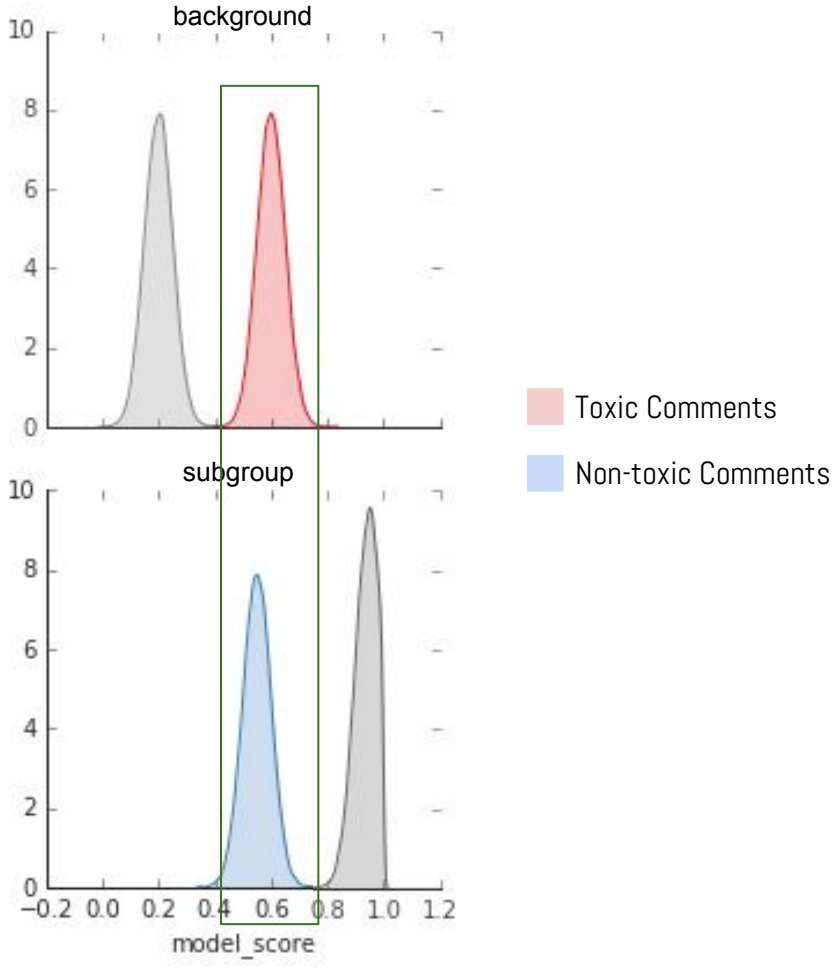

Types of Bias

Subgroup Shift (Left)

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Metric: BNSP AUC

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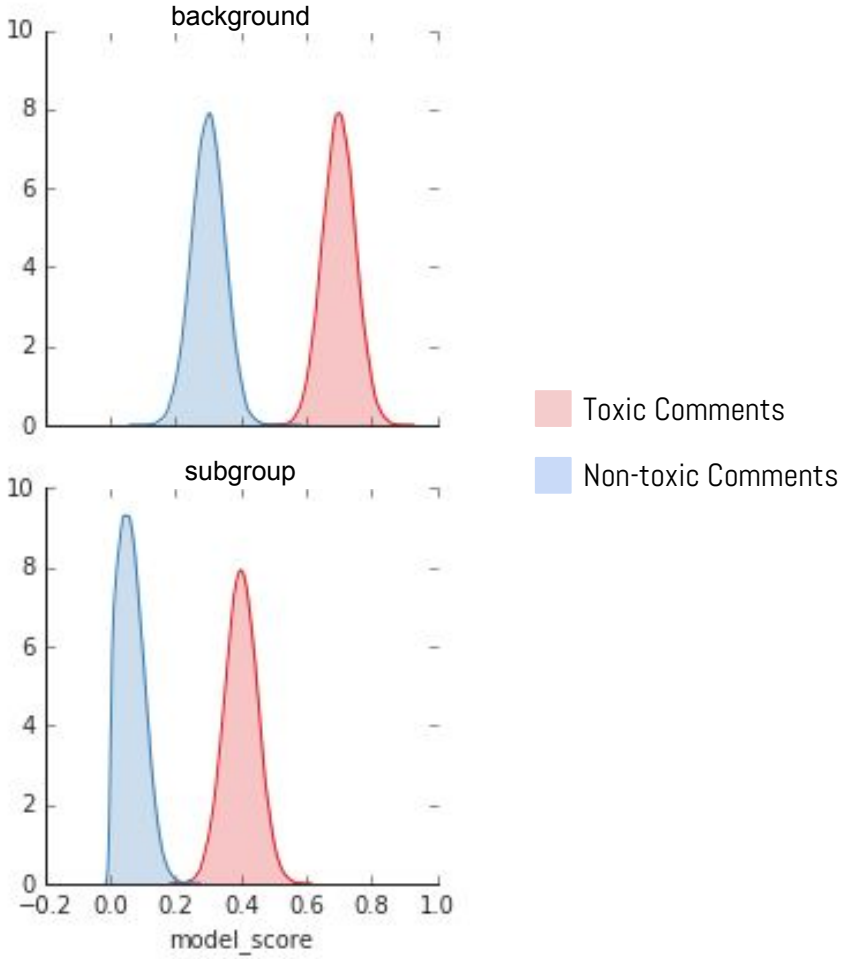

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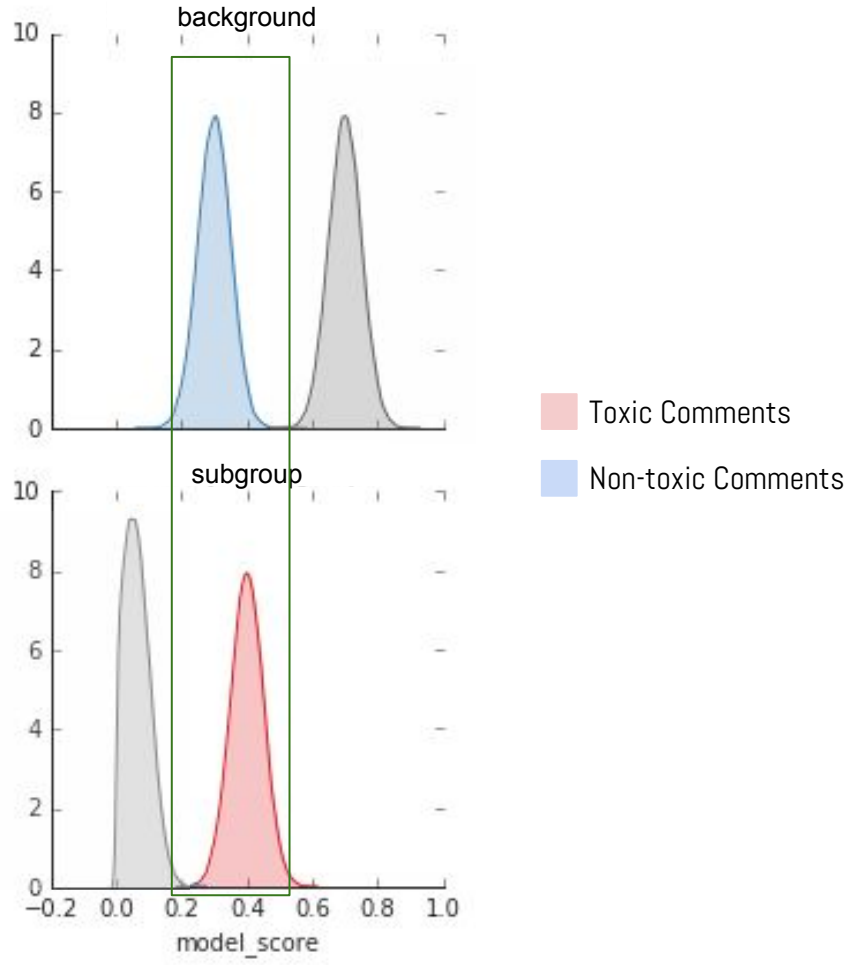

Converstion AI / Fairness Resources

- Measuring and Mitigating Unintended Bias in Text Classification
- Conversation AI Research Post
- Unintended Bias Github Repository
- Unintended Bias Blog Posts
- Google Developers Blog
- Fairness Crash Course

Tutorial

Tutorial Setup

1. Navigate to colaboratory at https://bit.ly/2UnlczF
2. Click connect in the top right corner
3. SHIFT + ↲ to run a cell

Questions