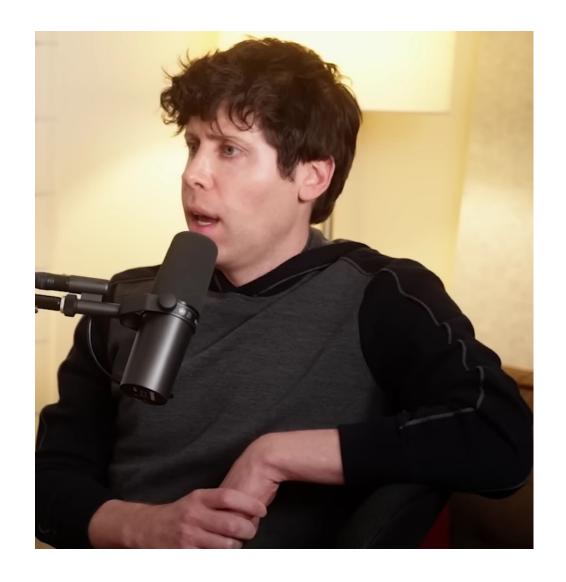


"The bias I am most nervous about is the bias of the human feedback raters"

Sam Altman March 25 2023 "The Lex Fridman Podcast"



Data Collection

Error Sources

Impact

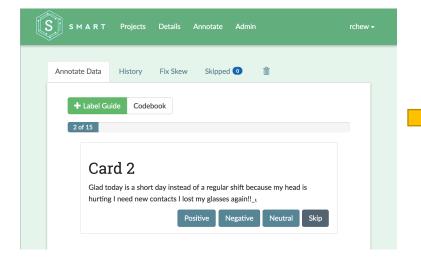
Would you say your health in general is:

- Excellent
- Very Good
- Good
- Fair
- O Poor



- Nonresponse
- Order Effects
- Interviewer Effects

Bias



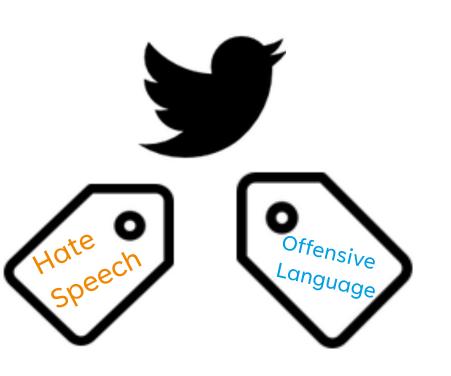
Beck et al (2022):

- Wording Effects
- Order Effects
- Annotator Effects



Prediction Error

RESEARCH DESIGN



5 annotation conditions

- Do they lead to different labels?
- Do they lead to different models?

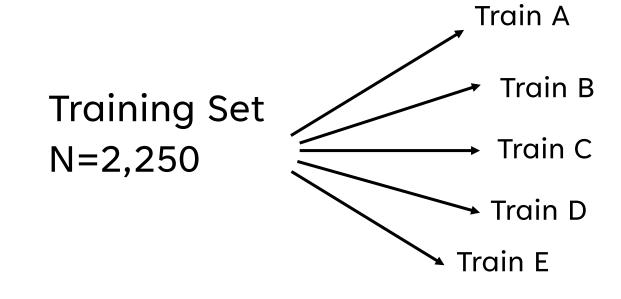
Time HS HS HS HS OL OL OL OL В Conditions HS HS OL HS OL HS OL HS HS OL OL HS HS OL OL

DATA COLLECTION

- 3000 tweets (Davidson et al 2017)
- ~900 annotators from Prolific (Nov- Dec 2022)
- 50 tweets / annotator

- 3 annotations per tweet & condition
 - →15 total annotations per tweet
- →~45k annotations

MODEL TRAINING



Test Set N=750

2 model types:

- LSTM
- BERT

2 DVs:

- Hate speech
- Offensive language

SETUP OF RESULTS

Labels

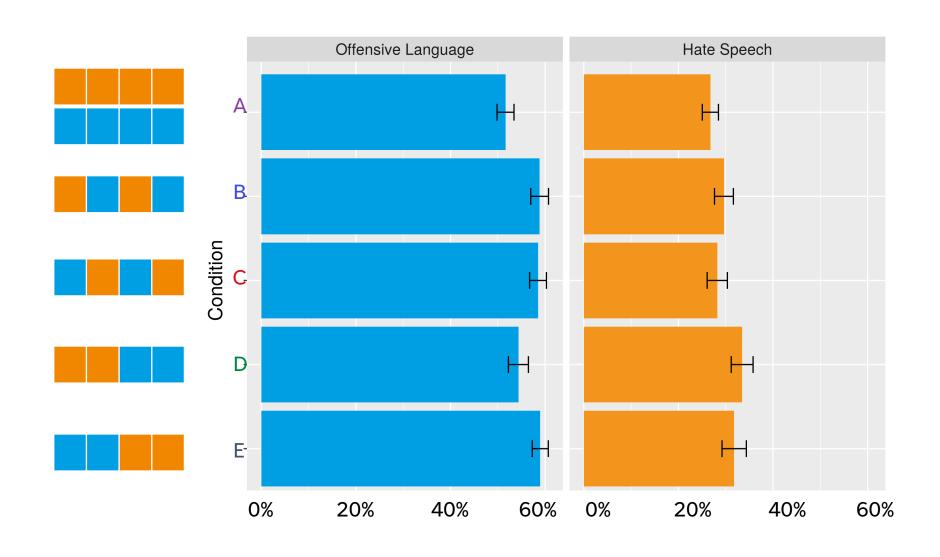
- Model Performance
 - ROC AUC
 - Learning Curves

Predictions

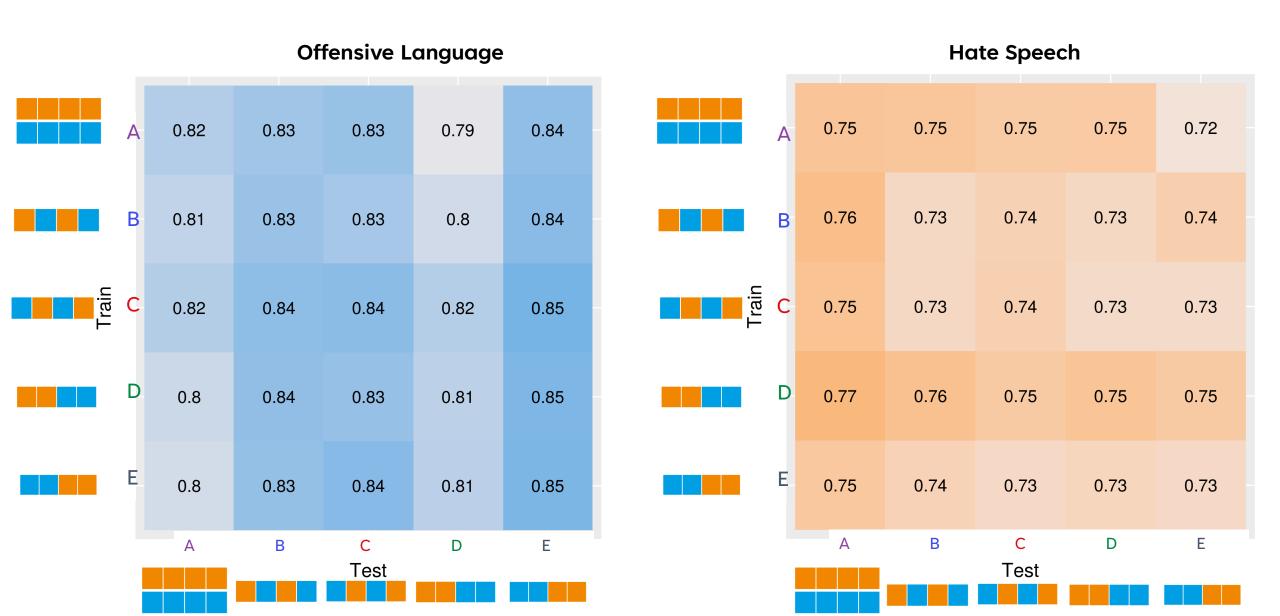
• By Condition (5)

- By Dependent Var (2)
 - Hate speech
 - Offensive language
- By model type (2)
 - LSTM
 - BERT

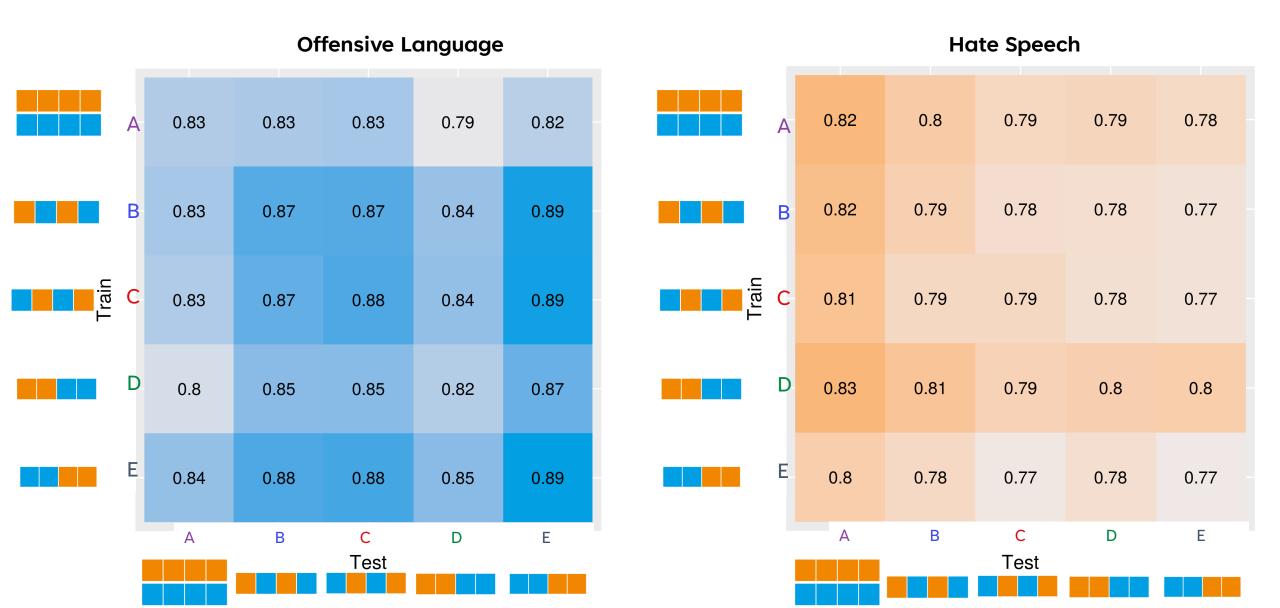
% OFFENSIVE LANGUAGE / HATE SPEECH BY CONDITION



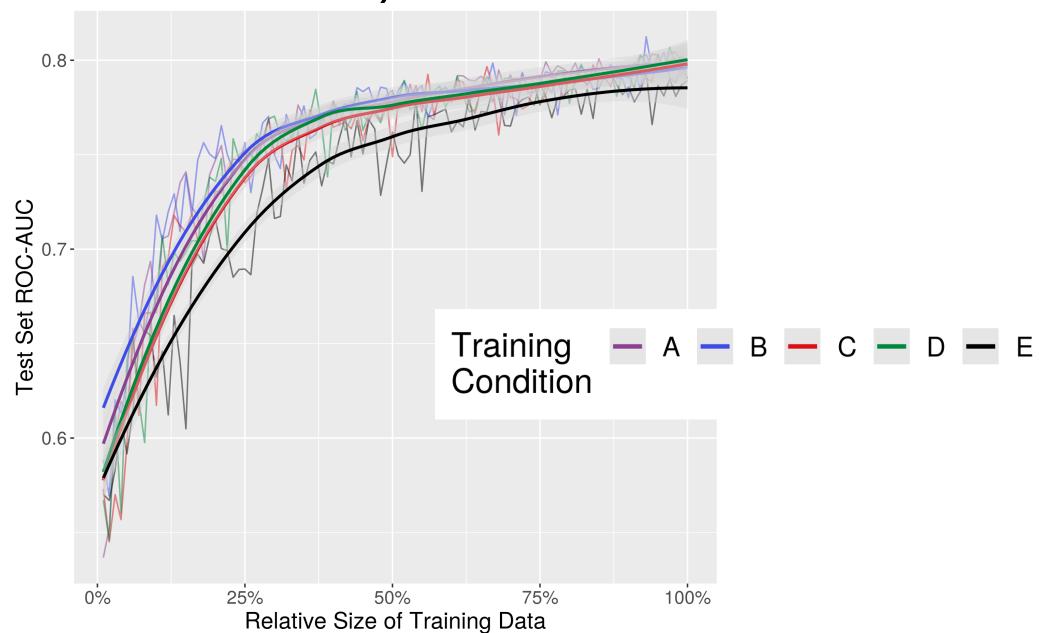
MODEL PERFORMANCE ROC-AUC: LSTM



MODEL PERFORMANCE ROC-AUC: BERT



LEARNING CURVES: BERT, HATE SPEECH



TAKEAWAYS

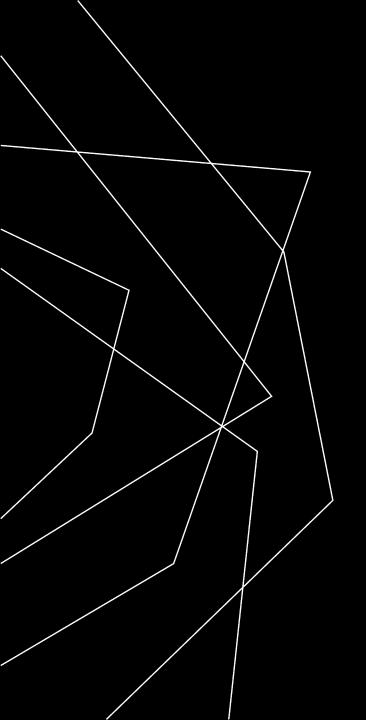
- How you collect annotations matters
 - Labels & model accuracy
- Some conditions perform better/worse as train/test data
 - More research needed to inform best practices
- Some evidence of fatigue or motivated misreporting

NEXT STEPS

Replicate with other training data (images)

Compare labels from existing annotation platforms

Vary annotators



THANK YOU

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