Toxic Comment Classification

David Braslow

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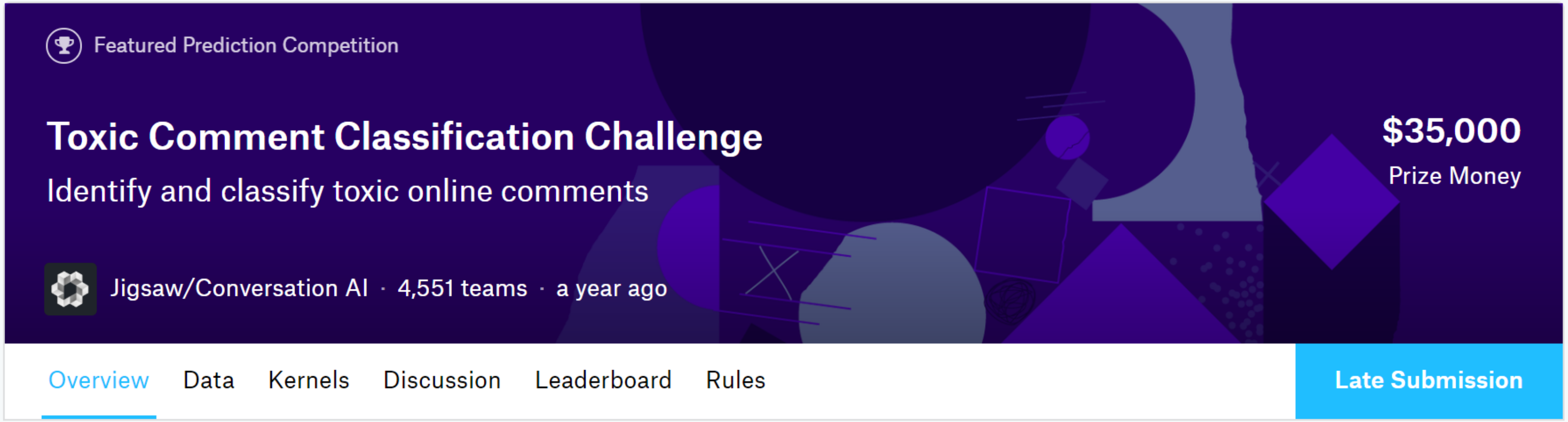
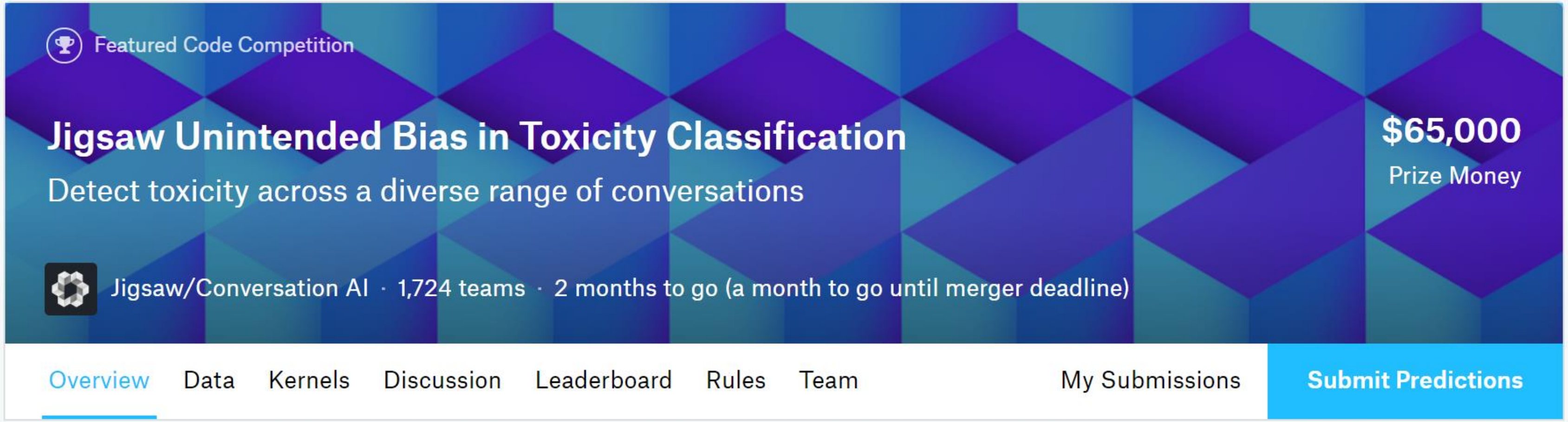
Overview

2018



Detect toxic comments

2019



Detect toxic comments — *and* minimize unintended model bias

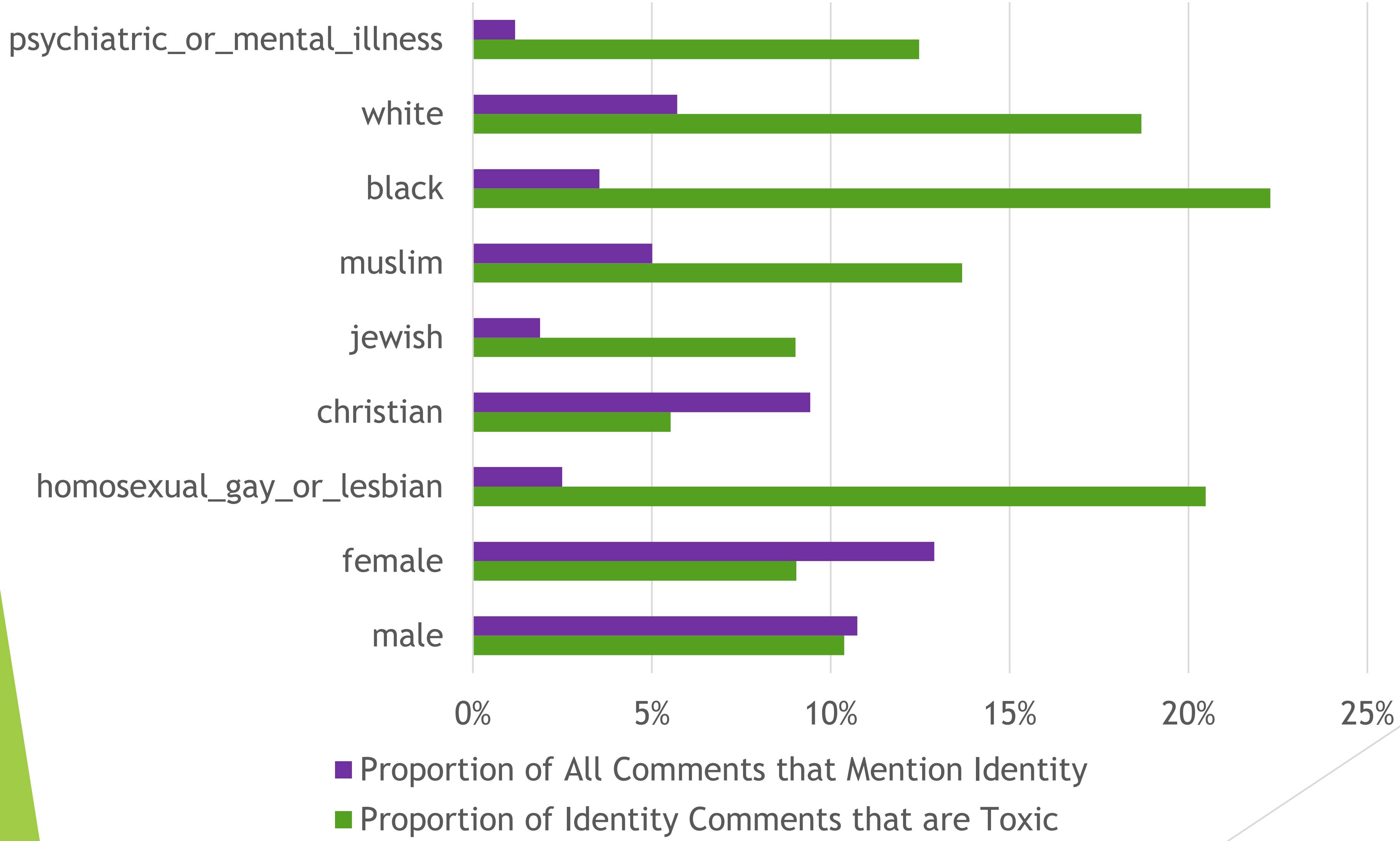
Identity Attributes

Toxicity @1

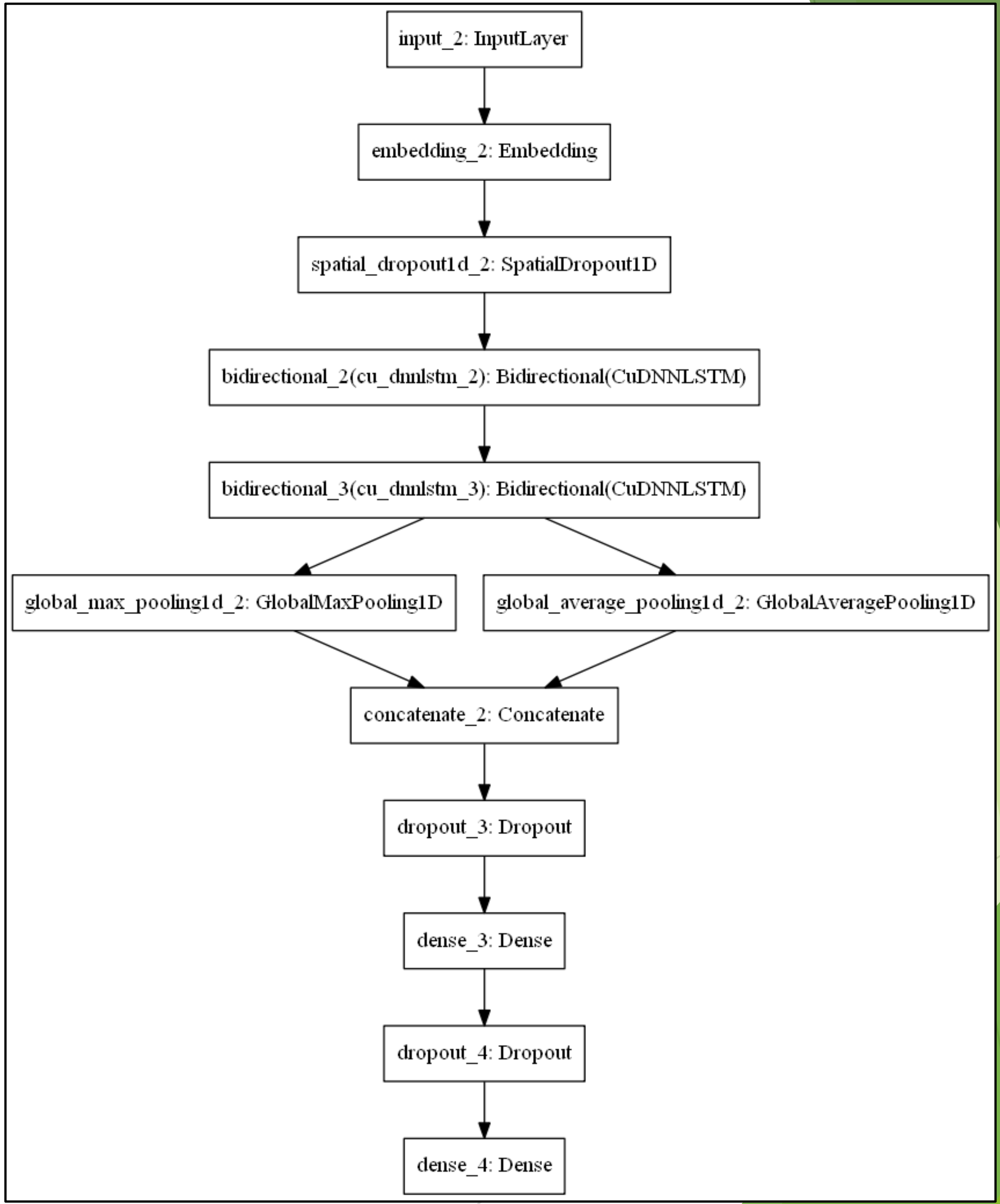
Identity groups	Subgroup AUC	BPSN AUC	BNSP AUC
lesbian	0.93	0.74	0.98
gay	0.94	0.65	0.99
queer	0.98	0.96	0.93
straight	0.99	1.00	0.87
bisexual	0.96	0.95	0.92
homosexual	0.87	0.53	0.99
heterosexual	0.96	0.94	0.92
cis	0.99	1.00	0.87
trans	0.97	0.96	0.91
nonbinary	0.99	0.99	0.90
black	0.91	0.85	0.95
white	0.91	0.88	0.94

0.5 0.6 0.7 0.8 0.9 1.0

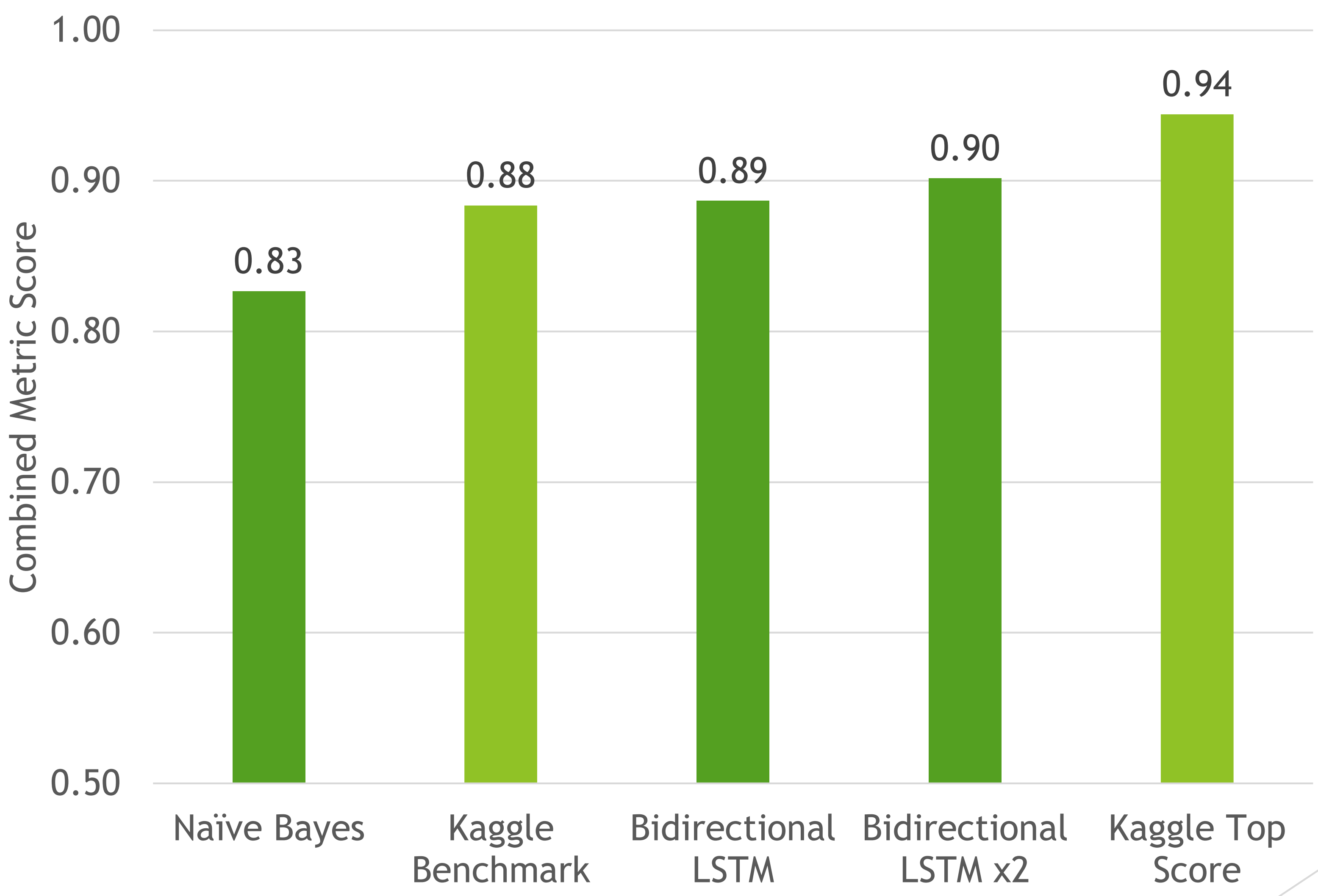
Data Exploration



Model Architecture



Results



1.00
0.90
0.80
0.70
0.60
0.50
Combined Metric Score
0.83
0.88
0.89
0.90
0.94
Naïve Bayes
Kaggle Benchmark
Bidirectional LSTM
Bidirectional LSTM x2
Kaggle Top Score

Subgroup Results

	Subgroup AUC	BPSN AUC	BNSP AUC
male	0.88	0.92	0.93
female	0.94	0.92	0.96
homosexual_gay_or_lesbian	0.84	0.78	0.98
christian	0.90	0.95	0.89
jewish	0.88	0.91	0.93
muslim	0.82	0.88	0.93
black	0.83	0.77	0.97
white	0.82	0.84	0.95
psychiatric_or_mental_illness	0.88	0.97	0.85

Conclusion

I can predict comment toxicity well using Bidirectional neural networks

This will be useful for flagging comments for removal

Race-based toxicity is particularly challenging to identify

Model improvement is possible with more computing resources