	Multi-task					Single-task				
Attention supervision	Encoded	L1	L2	Baseline 1	Baseline 2	Encoded	L1	L2	Baseline 1	Baseline 2
Gender	**0.643**	0.601	0.613	0.585	0.608	0.609	0.599	0.601	0.576	0.582
Race	**0.551**	0.505	0.503	0.483	0.505	0.354	0.323	0.330	0.168	0.307
Appearance	**0.788**	0.760	0.773	0.752	0.760	0.755	0.745	0.737	0.738	0.733
Ideology	**0.610**	0.577	0.559	0.496	0.508	0.511	0.524	0.512	0.477	0.499

Table 3: PR AUC of abuse categorization with and without attention supervision in single- and multi-task settings.

prediction loss and the attention loss:

$$L = \sum_{c \in C} \omega_c L_c + \beta L_a, \quad (7)$$

where ω_c is the weight of category c, and $\sum \omega_c = 1$. In multitasking, there is a primary category c with a higher weight ω_c than the weights $\omega_{c'}$ for the auxiliary categories c'. We report the per-category performance by taking each category as the primary category respectively. The hyperparameters were tuned on the validation data, with $\beta = 0.2$, $\omega_c = 0.7$, and $\omega_{c'} = 0.1, \forall c' \neq c$.

Experiments

As before, for our experiments on *categorizing* abusive language, we used a standard RNN model with attention as a strong baseline. Baseline 1 was trained on C, and baseline 2 was trained on C+S. A third model is an RNN model with the same idea of attention supervision (used for the classification task) but now in a multitask learning set-up described above.

We evaluated the models with 5 train-test splits, and report their average performance in Table 3. All the systems were RNNs with different attention losses in either a single-task or a multi-task setting. We report the PR AUC of each category for each system, and evaluate how supervised attention and multitask learning affect the performance. Overall, baseline 2 achieves better PR AUC than baseline 1 due to the extra sentence-level annotations. Attention supervision with encoded loss makes better use of sentence annotations than systems with other attention losses as well as the baselines without attention loss.

Comparing the models with and without attention supervision, we note that attention supervision improves categorization in both single- and multi-tasking scenarios (all are absolute gains); the highest improvement was seen in the poorly represented categories of *race* and *ideology*. For the *race* category, the supervision with encoded loss improves the PR AUC by 4.7% over baseline 2 in single tasking, and 4.6% in multitasking. As for *ideology*, the encoded attention loss yields a gain of 10.2% over baseline 2 in multitasking.

Multi-task learning improves categorization in all categories; we see an increase of 19.7% in the performance of the race category when encoded attention loss is applied, an increase of 31.5% in baseline 1, and an increase of 19.8% in baseline 2. Note that all gains reported are absolute.

The best-performing system is the combination of encoded attention loss with multi-task learning. It uses essentially the same training data as baseline 2. Compared with baseline 2 without attention supervision in single tasking, it increases the PR AUC by 6.1% in the gender category, 24.4% in race, 5.5% in appearance, and 11.1% in ideology.

Conclusion and Limitations

We have presented a new annotated dataset of abusive language from YouTube, as well as an empirical study on the use of supervised attention of neural networks to improve the detection and categorization of abusive language.

A primary limitation of our methodology is that our data comes only from feminism-related channels, which introduced bias and limits the generality of our results. Moreover, due to limitations of the annotation interface, the thread structure was not available to annotators, and they did not follow links in the comments or view the associated videos. This was intentional, so that the automatic detection would be based solely on textual information. Hence, two important directions for future work are to (a) study the performance of supervised attention on a broader class of datasets, and (b) conduct a joint analysis of text *and* the accompanying media.

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