Appendix: Categorizing Sexism and Misogyny through Neural Approaches

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1 HYPER-PARAMETER VALUES

Using experiments on a validation set, which was merged into the training set during the test runs, for each method, we choose the values of four hyper-parameters: the LSTM dimension, the attention dimension, the number CNN filters for kernel sizes 2, 3, and 4 each, and the k value in k-max-over-time pooling. The values used for all proposed methods and deep learning baselines for which we report results in our paper are provided in Tables 1, 2, 3, 4, 5, and 6. Table 3 also contains the layer sizes for the stacked autoencoder models.

The hyper-parameter values for the traditional machine learning baselines for sexism classification are as follows. For SVM, we set soft margin (C) to 1.0. For RF (Random Forest) and GBT (Gradient Boosting Trees), we use 100 estimators. For extracting character and word n-grams, the maximum number of features used, word n-gram range, and character n-gram range are set to 10000, (1,2), and (1,5) respectively. The hyper-parameter values for misogyny classification are the same as above except that the number of estimators for RF and GBT is 50.

For misogyny detection, the hyper-parameter values for the traditional ML methods are as follows. For SVM, 1 is used as the value of soft margin (C). For RF and GBT, we set the number of estimators to 100. For extracting character and word n-grams, the maximum number of features used, word n-gram range, and character n-gram range are 5000, (1,3), and (1,5) respectively.

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Table 1. Multi-label sexism classification results with the EBCE loss for deep learning methods (the sub-columns for the proposed approaches specify different configurations as to the methods through which the input is embedded and/or processed; different colors/styles represent different sentence-level concatenations)

П		Approac	h		LSTM	Attention	#CNN filters	k in k-max-
		11			dim.		of each ker-	
6	biLSTM-Attention			200	300	N.A.	N.A.	
Baselines (with ELMo)	Hierarchical-biLSTM-Attention			300	400	N.A.	N.A.	
	CNN-biLSTM-Attention				300	400	100	N.A.
	C-biLSTM				N.A.	N.A.	N.A.	N.A.
	CNN-Kim					N.A.	150	N.A.
es	biLSTM					N.A.	N.A.	N.A.
ii	BERT-biLSTM-Attention	BERT-biLSTM-Attention					N.A.	N.A.
ase	USE-biLSTM-Attention	1			300	600	N.A.	N.A.
ñ	InferSent-biLSTM-Atte	ention			100	200	N.A.	N.A.
	biL-att applied on	c-k-max applied on	c-biL-att applied on	Text Encoder				
	ELMo			tBERT	200	400	N.A.	N.A.
	ELMo, GloVe			tBERT	200	400	N.A.	N.A.
	concat(ELMo, GloVe)			tBERT	200	500	N.A.	N.A.
	Ling, ELMo, GloVe			tBERT	200	300	N.A.	N.A.
l I.	ELMo, GloVe			tBERT, USE	200	400	N.A.	N.A.
<u>s</u>	Ling, fastText, ELMo,			tBERT, USE,	200	500	N.A.	N.A.
jo	GloVe			InferSent				
eth		ELMo		tBERT	N.A.	N.A.	100	1
Proposed methods		ELMo, GloVe		tBERT, USE	N.A.	N.A.	200	1
sed			ELMo, GloVe	tBERT	200	400	150	1
bod	ELMo	ELMo		tBERT	200	500	100	1
ro	ELMo, GloVe	ELMo, GloVe		tBERT, USE	100	300	100	1
				tBERT	300	600	N.A.	N.A.
	ELMo			tBERT	300	600		N.A.
	ELMo, GloVe			tBERT	100	200		N.A.
	ELMo, GloVe			tBERT	100	200		N.A.
	ELMo, GloVe			tBERT	200	400	N.A.	N.A.
•	concat(ELMo, GloVe)			tBERT	100	100		N.A.
	concat(ELMo, GloVe)			tBERT	300	600	N.A.	N.A.
	arc	ELMo, GloVe		tBERT	300	500	100	1
.	ler		ELMo, GloVe	tBERT	100	100	100	1
11	concat(ELMo, GloVe) concat(ELMo, GloVe) Ling, ELMo, GloVe			tBERT	300	600		N.A.
	ELMo, GloVe			tBERT, USE	300	600		N.A.
	ELMo, GloVe			tBERT, <u>USE</u>	100	100		N.A.
	ELMo, GloVe			tBERT, USE	100	200		N.A.
	ELMo, GloVe	ELMo, GloVe		tBERT	300	500	100	1
	Ling, fastText, ELMo,			tBERT, USE,	200	400	N.A.	N.A.
	GloVe			InferSent				

Table 2. Multi-label sexism classification results for the proposed ensemble approach (the hierarchical architecture with one sentence-level group is used; the number of learners equals <code>max_label_subsets</code> where our automatic label subset selection method is used)

biL-att applied on	Text Encoder	Ensemble settings	LSTM	Attention	#CNN filters	k in k-max-
	dim. dim.		dim.	of each ker-	over-time	
					nel size	pooling
ELMo, GloVe	tBERT	$max_label_subsets = 2$, $label_membership = 1$	200	400	N.A.	N.A.
ELMo, GloVe, fastText,	tBERT, USE, InferSent	max_label_subsets = 2, label_membership = 1	100	100	N.A.	N.A.
Ling						
ELMo, GloVe	tBERT	max_label_subsets = 3, label_membership = 1	200	400	N.A.	N.A.
ELMo, GloVe	tBERT	max_label_subsets = 3, label_membership = 2	200	400	N.A.	N.A.
ELMo, GloVe	tBERT	8 omnipresent labels, max_label_subsets = 2,	200	400	N.A.	N.A.
		label_membership = 1				
ELMo, GloVe, fastText,	tBERT, USE, InferSent	8 omnipresent labels, max_label_subsets = 2,	200	400	N.A.	N.A.
Ling		label_membership = 1				
ELMo, GloVe	tBERT	8 omnipresent labels, max_label_subsets = 3,	200	500	N.A.	N.A.
		label_membership = 1				
ELMo, GloVe	tBERT	8 omnipresent labels, max_label_subsets = 3,	100	200	N.A.	N.A.
		label_membership = 2				
ELMo, GloVe	tBERT	all omnipresent labels, 2 learners	300	500	N.A.	N.A.
ELMo, GloVe, fastText,	tBERT, USE, InferSent	all omnipresent labels, 2 learners	200	300	N.A.	N.A.
Ling						
ELMo, GloVe	tBERT	all omnipresent labels, 3 learners	300	600	N.A.	N.A.

Table 3. Multi-label sexism classification results with the autoencoder-based method for using unlabeled data (using the hierarchical approach with biL-att on ELMo and GloVe and BERT for embedding sentences)

Encoder Settings	Layer Sizes	LSTM	Attention	#CNN filters	k in k-max-
		dim.	dim.	of each ker-	over-time
				nel size	pooling
5 stacked layers, quickly decreasing layer size	922, 819, 717, 614, 512	300	500	N.A.	N.A.
3 stacked layers, quickly decreasing layer size	922, 819, 717	200	400	N.A.	N.A.
5 stacked layers, slowly decreasing layer size	973, 922, 870, 819, 768	300	400	N.A.	N.A.
3 stacked layers, slowly decreasing layer size	973, 922, 870	100	200	N.A.	N.A.

Table 4. Multi-label sexism classification results under various settings

Multi-Label Setting	Approach	LSTM	Attention	#CNN filters	k in k-max
		dim.	dim.	of each ker-	over-time
				nel size	pooling
	biLSTM-Attention	300	600	N.A.	N.A.
Label Powerset with class imbalance correction	Hierarchical-biLSTM-Attention	200	400	N.A.	N.A.
	Best proposed method	100	100	N.A.	N.A.
	biLSTM-Attention	200	400	N.A.	N.A.
Label Powerset without class imbalance correction	Hierarchical-biLSTM-Attention	300	600	N.A.	N.A.
	Best proposed method	200	300	N.A.	N.A.
Binary Relevance	biLSTM-Attention	100	300	N.A.	N.A.
Billary Relevance	Hierarchical-biLSTM-Attention	100	300	N.A.	N.A.
	Best proposed method	100	300	N.A.	N.A.
NCE loss	biLSTM-Attention	200	500	N.A.	N.A.
INCE 1088	Hierarchical-biLSTM-Attention	200	400	N.A.	N.A.
	Best proposed method	100	200	N.A.	N.A.

Table 5. Results for misogyny detection (baselines use ELMo embeddings; proposed methods use the flat architecture)

	Approach					Attention	#CNN filters	k in k-max-
		**			dim.	dim.	of each ker-	over-time
							nel size	pooling
	CNN-Kim				N.A.	N.A.	100	N.A.
s	biLSTM			200	N.A.	N.A.	N.A.	
Baselines	biLSTM-Attention				200	400	N.A.	N.A.
eli	C-biLSTM			100	N.A.	100	N.A.	
Bas	BERT				N.A.	N.A.	N.A.	N.A.
Γ	USE				N.A.	N.A.	N.A.	N.A.
	InferSent				N.A.	N.A.	N.A.	N.A.
	biL-att applied on	c-k-max applied on	c-biL-att applied on	Text Encoder				
				tBERT	N.A.	N.A.	N.A.	N.A.
	ELMo			BERT	100	200	N.A.	N.A.
	ELMo			tBERT	100	300	N.A.	N.A.
spo	ELMo			USE	200	400	N.A.	N.A.
þ		ELMo		BERT	N.A.	N.A.	150	4
me	ELMo, GloVe			BERT	100	300	N.A.	N.A.
pa	ELMo, GloVe			BERT, USE	300	600	N.A.	N.A.
OS	concat(ELMo, GloVe)			BERT, USE	100	300	N.A.	N.A.
do.	ElMo, GloVe, Ling			BERT	100	100	N.A.	N.A.
ם	ELMO ELMO, GloVe ELMO, GloVe ELMO, GloVe concat(ELMO, GloVe) ElMO, GloVe, Ling ElMO, GloVe, Ling			BERT, USE	100	300	N.A.	N.A.
			ElMo, GloVe, fastText,		100	200	100	N.A.
			Ling					
	ElMo, GloVe, fastText,			BERT, USE, In-	100	200	N.A.	N.A.
	Ling			ferSent				
		ElMo, GloVe, fastText,		BERT, USE, In-	N.A.	N.A.	100	1
	(Ling		ferSent				
	concat(ELMo, GloVe,			BERT, USE, In-	200	400	N.A.	N.A.
	fastText, Ling)			ferSent				
		ElMo, GloVe, fastText,		BERT, USE, In-	300	600	100	1
L	Ling	Ling		ferSent				

Table 6. Results for misogyny classification (baselines use ELMo embeddings; proposed methods use the flat architecture)

		Approac	9-7 F1-F1-13 IIII			#CNN filters	k in k-max-	
		11			dim.		of each ker-	
								pooling
	CNN-Kim	CNN-Kim			N.A.	N.A.		N.A.
	biLSTM				300	N.A.		N.A.
nes	biLSTM-Attention				100	300		N.A.
elii	C-biLSTM					N.A.		N.A.
Baselines	BERT					N.A.	N.A.	N.A.
H	USE				N.A.	N.A.	N.A.	N.A.
	InferSent				N.A.	N.A.	N.A.	N.A.
	biL-att applied on	c-k-max applied on	c-biL-att applied on	Text Encoder				
	***	**	***	tBERT		N.A.	N.A.	N.A.
	ELMo			tBERT	200	500	N.A.	N.A.
		ELMo		tBERT	N.A.	N.A.	150	1
			ELMo	tBERT	100	300	100	1
	ELMo			USE	100	200	N.A.	N.A.
qs	concat(ELMo, GloVe)			tBERT	100	100	N.A.	N.A.
tho	concat(ELMo, GloVe)			USE	100	200	N.A.	N.A.
Proposed methods		ELMo, GloVe		tBERT	N.A.	N.A.	100	1
<u> </u>	ELMo, GloVe			USE	100	100	N.A.	N.A.
ose	ELMo, GloVe			tBERT	100	100	N.A.	N.A.
do			ELMo, GloVe	tBERT	100	300	100	2
Pr	ELMo, GloVe, Ling			tBERT	100	200	N.A.	N.A.
	concat(ELMo, GloVe,			tBERT	100	200	N.A.	N.A.
	Ling)							
	ELMo, GloVe			tBERT, USE	200	400		N.A.
	concat(ELMo, GloVe)			tBERT, USE	100	200	N.A.	N.A.
	ELMo	ELMo		tBERT	200	400	100	1
		ELMo, GloVe		tBERT	200	500	200	1
	ELMo, GloVe, fastText,			tBERT, USE,	200	400	N.A.	N.A.
	Ling			InferSent				
	ELMo, GloVe, fastText,			tBERT, USE,	100	200	N.A.	N.A.
	Ling			InferSent				