

Exploiting Unlabeled Data for Target-Oriented Opinion Words Extraction

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code: https://github.com/TOWESSL/TOWESSL



Reported by Xiaoke Li





The dishes are amazingly delicious but the waiter is so rude.

Given opinion target: dishes Given opinion target: waiter Corresponding opinion words: **amazingly delicious** Corresponding opinion words: **rude**

Figure 1: Example of TOWE. Words in red are opinion targets and words in blue are corresponding opinion words. TOWE extracts corresponding opinion words when given opinion targets.





Labeled data: The/O entire/O <u>dining/O experience/O</u> was/O very/B wonderful/I !/O Unlabeled data with the generated pseudo opinion target: Their <u>menu</u> is too expensive for a bubble drink .

Figure 2: Examples of labeled data and unlabeled data with the pseudo opinion target. Words with underline indicate opinion targets. The span in the labeled data beginning with *B* and followed by *I* represent the corresponding opinion words.





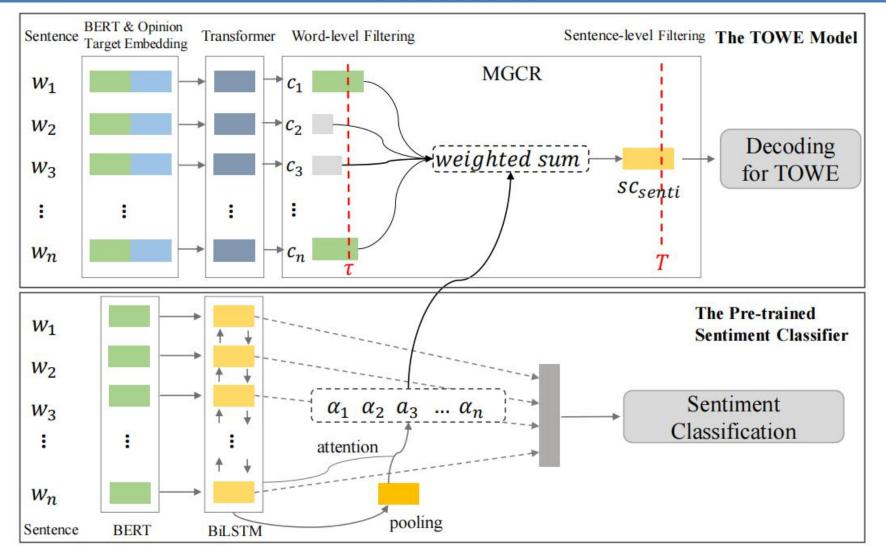
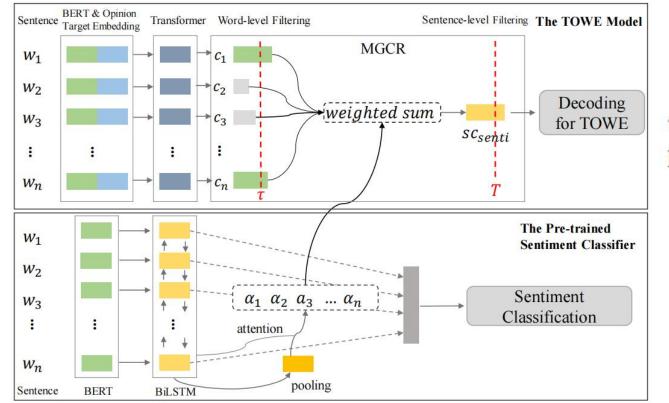


Figure 3: Overview of the architecture of multi-grained consistency regularization. For simplicity, we mark the confidence of i-th word as c_i . Note that the input sentence of the TOWE model is the same as the input sentence of the pre-trained sentiment classifier.







$$\mathbf{r}_1, \ldots, \mathbf{r}_n = \operatorname{Transformer}(\widetilde{\mathbf{h}}_1, \ldots, \widetilde{\mathbf{h}}_n).$$
 (3)

$$p_i(y|\theta; s, t) = \operatorname{softmax}(\mathbf{W}_r \mathbf{r}_i + \mathbf{b}_r), \quad (4)$$

$$\mathcal{L}_s = \frac{1}{n} \sum_{i=1}^n \mathcal{H}(y_i, p_i(y|\theta; s, t)).$$
(5)

$$\mathbf{h}_1^{pt}, \dots, \mathbf{h}_n^{pt} = \text{BERT}(w_1, \dots, w_n) \qquad (1)$$

Then the context representation \mathbf{h}_i^{pt} of the word w_i is fed to a linear layer and a softmax layer to predict the corresponding label.

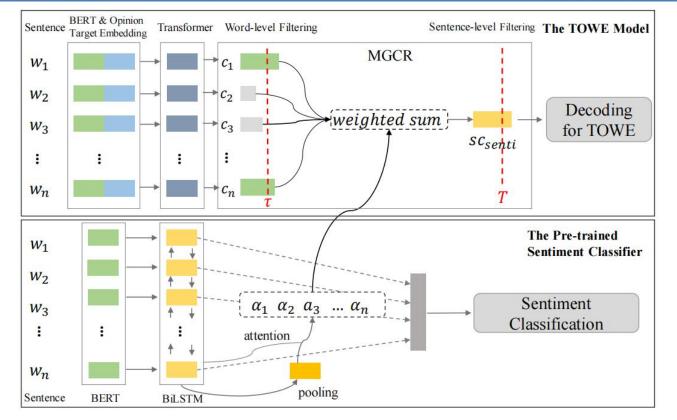
$$\frac{1}{n}\sum_{i=1}^{n}\mathcal{H}(\hat{p}_{i}(y|\theta;s^{u},t),p_{i}(y|\theta;\omega(s^{u}),t)),\quad(2)$$

where $\hat{p}_i(y|\theta; s^u, t) = \arg \max p_i(y|\theta; s^u, t)$ and $\hat{p}_i(y|\theta; s^u, t)$ denotes the predicted label of the w_i^u , the $\mathcal{H}(\cdot, \cdot)$ refers to the cross-entropy loss. In this work, we use Random Mask and Random Synonym Replacement by using WordNet (Miller, 1995) as the perturbing function ω .

$$\widetilde{\mathbf{h}}_i = [\mathbf{h}_i; \mathbf{e}_i].$$







$$sc_{avg} = \frac{1}{n} \sum_{i=1}^{n} \max(p_i(y|\theta; s^u, t)), \quad (6)$$

$$z_{avg} = \frac{1}{n} \sum_{i=1}^{n} z_i,$$

$$f(z_i, z_{avg}) = z_i \cdot \mathbf{W} \cdot z_{avg} + \mathbf{b}, \qquad (7)$$

$$\alpha_i = \frac{e^{f(z_i, z_{avg})}}{\sum_{i=1}^{n} e^{f(z_j, z_{avg})}},$$

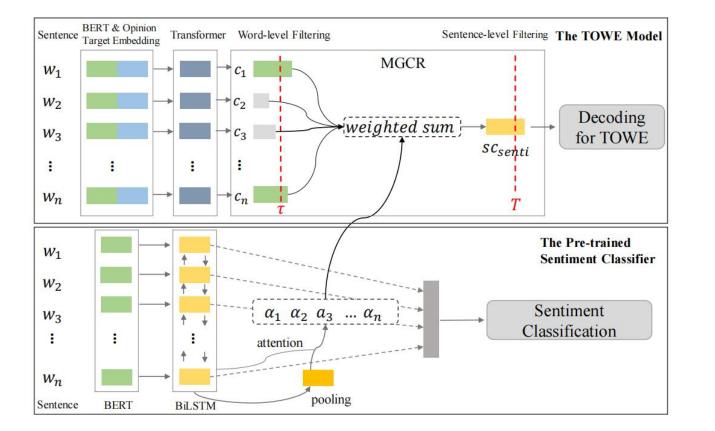
$$sc_{senti} = \sum_{i=1}^{n} \alpha_i \cdot \max(p_i(y|\theta; s^u, t)). \quad (8)$$

$$\mathbb{1}(sc_{senti} > T),\tag{9}$$

$$\mathbb{1}(\max(p_i(y|\theta; s^u, t)) > \tau).$$
(10)







$$\mathcal{L}_{c} = \mathbb{1}(sc_{senti} > T)$$

$$\cdot \{\frac{1}{n} \sum_{i=1}^{n} \mathbb{1}(\max(p_{i}(y|\theta; s^{u}, t)) > \tau)$$

$$\cdot \mathcal{H}(\hat{p}_{i}(y|\theta; s^{u}, t), p_{i}(y|\theta; \omega(s^{u}), t))\}.$$
(11)

$$\mathcal{L} = \mathcal{L}_s + \mathcal{L}_c. \tag{12}$$





Dat	tasets	#sentences	#opinion targets	
14res	Train	1,627	2,643	
	Test	500	864	
15res	Train	754	1,076	
	Test	325	436	
16res	Train	1,079	1,512	
	Test	329	457	
141ap	Train	1,158	1,634	
	Test	343	482	
Yelp	Unlabeled	100,000	9 1 75	
Amazon	Unlabeled	100,000	1	

Table 1: Statistics of TOWE datasets and unlabeled datasets. For TOWE datasets, sentence may contain multiple opinion targets. For unlabeled datasets, we randomly sampled data from Yelp for 14res, 15res, 16res datasets and Amazon for 14lap dataset. The unlabeled data is available at https://github.com/ TOWESSL/TOWESSL.

Hyperparameter	TOWE model	Sentiment Classifier
Batch size	16(96)	128
Epochs	50	-
Steps	-	3000
Learning rate (BERT)	2e-5	1e-5
Learning rate (Others)	2e-4	1e-4
Hidden dimension	512	512
Optimizer	AdamW	AdamW

Table 2: Experimental setting of the training of the TOWE model and the sentiment classifier. For the TOWE model, batch size for labeled data is 16 and 96 for unlabeled data.





Methods		14res			15res			16res			14lap	
Methods	Р	R	F1	Р	R	F1	Р	R	F1	P	R	F1
Distance-rule (Fan et al., 2019)	58.39	43.59	49.92	54.12	39.96	45.97	61.90	44.57	51.83	50.13	33.86	40.42
Dependency-rule (Fan et al., 2019)	64.57	52.72	58.04	65.49	48.88	55.98	76.03	56.19	64.62	45.09	31.57	37.14
TC-BiLSTM (Fan et al., 2019)	67.65	67.67	67.61	66.06	60.16	62.94	73.46	72.88	73.10	62.45	60.14	61.21
IOG (Fan et al., 2019)	82.85	77.38	80.02	73.24	69.63	71.35	76.06	70.71	73.25	85.25	78.51	81.69
LOTN (Wu et al., 2020b)	84.00	80.52	82.21	76.61	70.29	73.29	86.57	80.89	83.62	77.08	67.62	72.02
ONG (Veyseh et al., 2020)	83.23	81.46	82.33	76.63	81.14	78.81	87.72	84.38	86.01	73.87	77.78	75.77
Dual-MRC (Mao et al., 2021)	89.79	78.43	83.73	77.19	71.98	74.50	86.07	80.77	83.33	78.21	81.66	79.90
PER (Dai et al., 2022)	86.43	80.39	83.30	81.50	75.05	78.14	90.00	84.00	86.90	80.68	70.72	75.38
ARGCN (Jiang et al., 2021)	87.32	83.59	85.42	78.81	77.69	78.24	88.49	84.95	86.69	75.83	76.90	76.36
TSMSA (Feng et al., 2021)	-	-	86.37	-	÷π.)	81.64	0 	() , ,	89.20	-	-	82.18
MRC-MVT (Zhang et al., 2021b)	86.31	89.42	87.83	82.04	81.54	81.79	<u>90.60</u>	88.19	89.38	79.59	81.12	80.84
MGCR (ours)	88.65	89.36	89.01 [†]	84.29	83.37	83.80†	91.31	91.74	91.51 [†]	83.76	81.25	82.47 [†]

Table 3: Main results (%) including recall, precision and F1-score. The best results are in bold and second-best results are underlined. Results of all comparison methods were copied from the original papers. The marker [†] represents that MGCR outperforms other methods significantly (p < 0.01).





Mathe	ľ.	14res		[15res			16res			14lap			
Methods	Р	R	F1											
MGCR	88.65	89.36	89.01	84.29	83.37	83.80	91.31	91.74	91.51	83.76	81.25	82.47		
w/o Pre-trained Sentiment Classifier	87.69	89.03	88.35	82.79	82.89	82.77	90.67	90.60	90.63	84.18	79.19	81.05		
w/o Filtering Noisy Unlabeled Sentences	88.84	88.00	88.41	80.13	85.39	82.62	89.59	91.68	90.62	82.84	78.83	80.77		
w/o Filtering Noisy Unlabeled Words	87.29	88.12	87.70	80.10	85.33	82.66	91.02	91.30	91.16	81.99	80.19	81.07		
w/o Consistency Regularization (Labeled Data Only)	87.34	87.05	87.19	82.42	81.81	82.11	87.19	88.38	87.76	81.70	77.89	79.70		

Table 4: Ablation study results (%) when removing different components from MGCR method.



	0.5			1	0.7		0.9			
τ	Р	R	F1	Р	R	Fl	Р	R	F1	
	89.55									
0.7	89.58	87.63	88.60	87.80	88.77	88.28	88.65	89.36	89.01	
0.9	88.64	87.83	88.23	87.65	89.28	88.45	87.73	88.35	88.03	

Table 5: Results (%) of combinations of sentence-level threshold and word-level threshold on 14res. T and τ represent sentence-level threshold and word-level threshold respectively.

	0.5				0.7		0.9			
τ	Р	R	F1	Р	R	F1	Р	R	F1	
0.5	81.31	82.62	81.94	81.17	83.57	82.33	82.16	84.17	83.12	
0.7	80.13	85.39	82.62	81.84	84.04	82.92	84.29	83.37	83.80	
0.9	81.38	83.43	82.38	81.41	84.38	82.81	81.35	84.24	82.73	

Table 6: Results (%) of combinations of sentence-level threshold and word-level threshold on 15 res. T and τ represent sentence-level threshold and word-level threshold respectively.

$\setminus T$	0.5 P R F1				0.7		0.9			
τ	Р	R	F1	Р	R	F1	P	R	F1	
0.5	90.44	90.66	90.55	91.31	91.74	91.51	91.09	90.79	90.94	
0.7	90.21	90.72	90.46	89.85	91.68	90.76	90.73	90.72	90.72	
0.9	89.45	90.35	89.88	90.16	91.36	90.75	90.90	91.36	91.13	

Table 7: Results (%) of combinations of sentence-level threshold and word-level threshold on 16 res. T and τ represent the sentence-level threshold and word-level threshold respectively.

	0.5			1	0.7		0.9			
τ	P	R	F1	Р	R	F1	Р	R	F1	
0.5	83.29	79.65	81.42	84.85	78.07	81.32	84.43	77.51	80.82	
0.7	83.78	79.48	81.56	84.54	79.36	81.86	83.29	78.48	80.78	
0.9	83.29 83.78 82.43	78.83	80.77	84.21	78.82	81.36	83.76	81.25	82.47	

Table 8: Results (%) of combinations of sentence-level threshold and word-level threshold on 14lap. T and τ represent the sentence-level threshold and word-level threshold respectively.





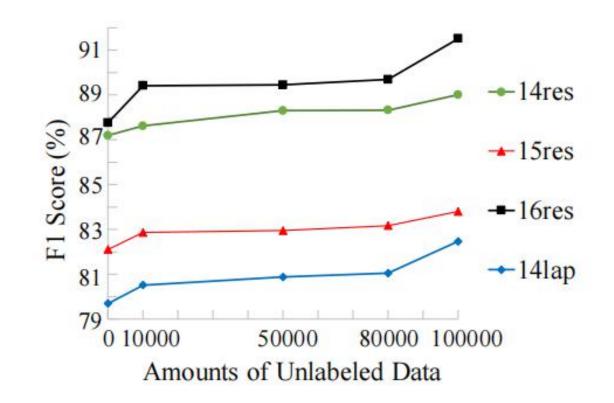


Figure 4: F1-score (%) on four TOWE datasets with varying amounts of unlabeled data.





Methods	NULL	Under-extracted	Over-extracted	Others	Total
MGCR	2	9	24	8	43
MGCR w/o Pre-trained Sentiment Classifier	3	12	29	11	54
MGCR w/o Filtering Noisy Unlabeled Sentences	5	9	29	7	55
MGCR w/o Filtering Noisy Unlabeled Words	4	14	38	11	67
MGCR w/o Consistency Regularization (Labeled Data Only)	8	11	44	15	70

Table 9: Statistics of different error types of our MGCR method and different ablation versions on the 16res dataset.



Thanks