JointCL: A Joint Contrastive Learning Framework for Zero-Shot Stance Detection

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Code： https://github.com/HITSZ-HLT/JointCL

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Reported by Zhaoze Gao

Artificial

1. Introduction
2. Approach
3. Experiments

Introduction

to generalize the stance features to the unseen targets

context-aware: Stance Contrastive Learning strategy, which effectively improves the quality of stance features by leveraging the similarity of training instances in a stance class while pushing away instances from other stance classes.

target-aware: Target-Aware Prototypical Graph Contrastive Learning.Specifically, a novel edge-oriented graph contrastive loss is deployed to make the graph structures similar for similar target-based representations, and different for dissimilar ones.

Approach

[$c_1 \cdot \cdot c_k$ h_i]

CLS

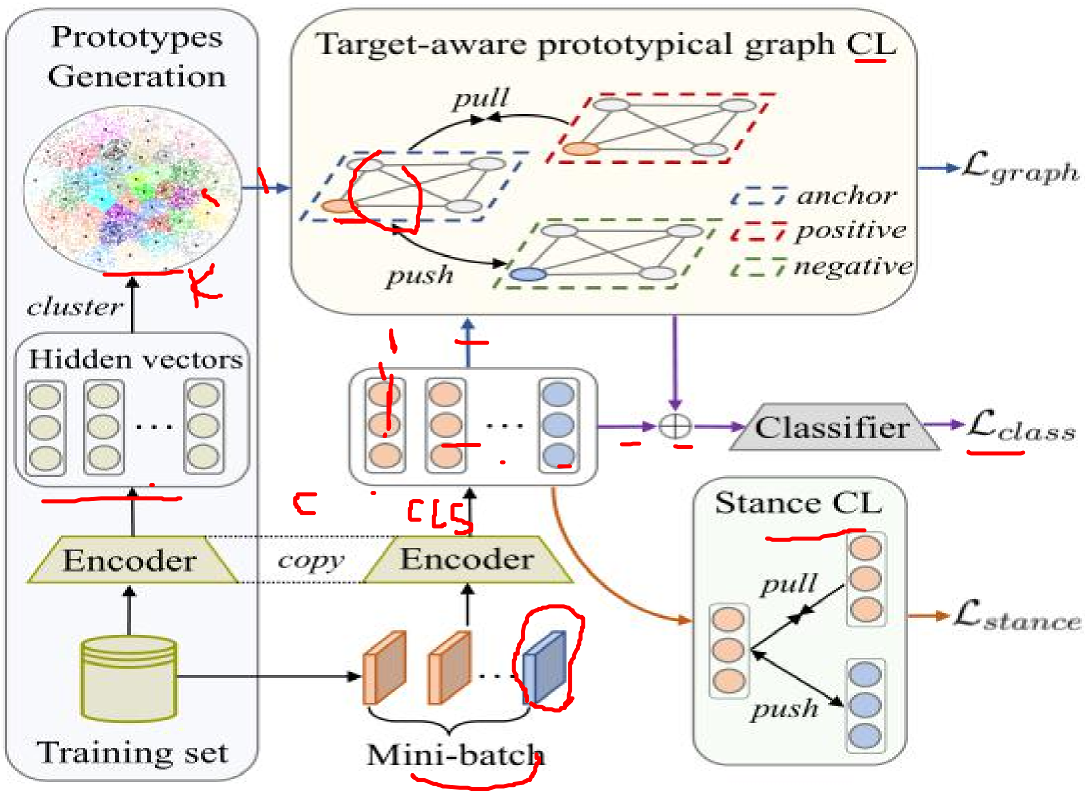
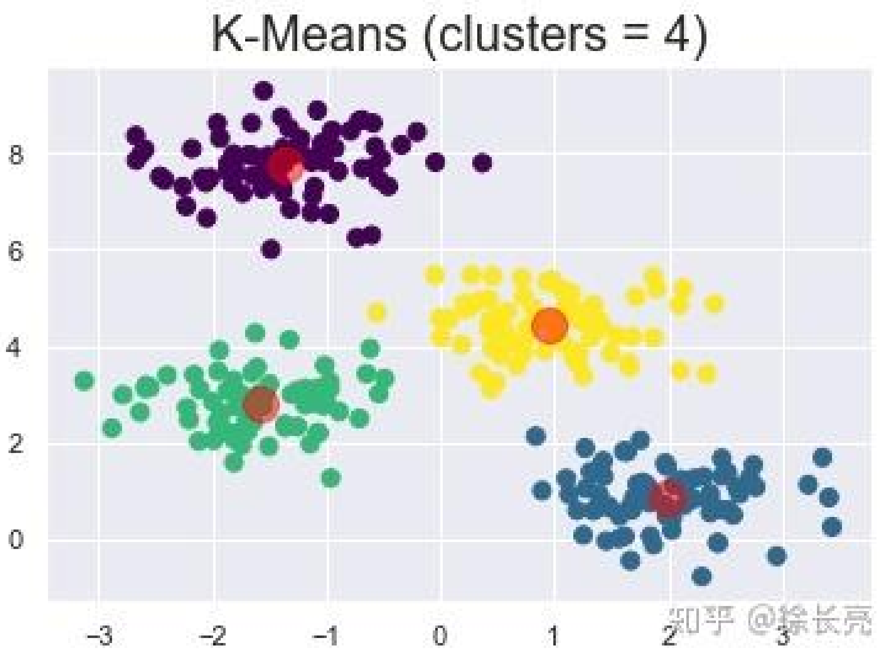
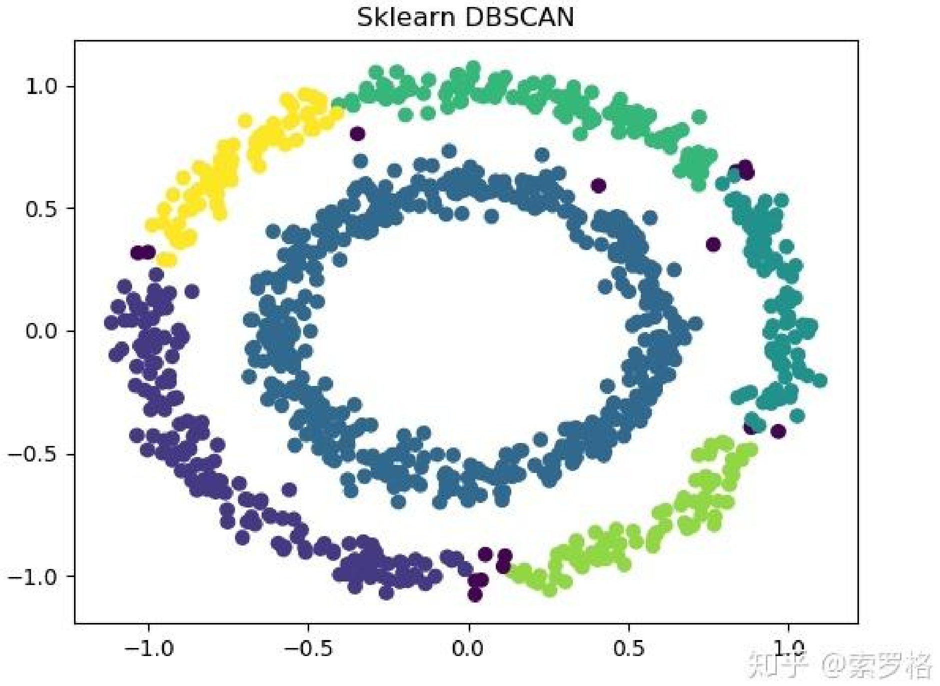


Figure 1: The architecture of our JointCL framework. $\oplus$ is vector concatenation. In the graphs, the gray ellipses denote prototypes, others denote hidden vectors. Vectors with the same color hold the same stance.

聚类


K-Means (clusters = 4)
8
6
4
2
0
−3
−2
−1
0
1
2
3
知乎 @徐长亮


Sklearn DBSCAN
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0
知乎 @索罗格

Approach

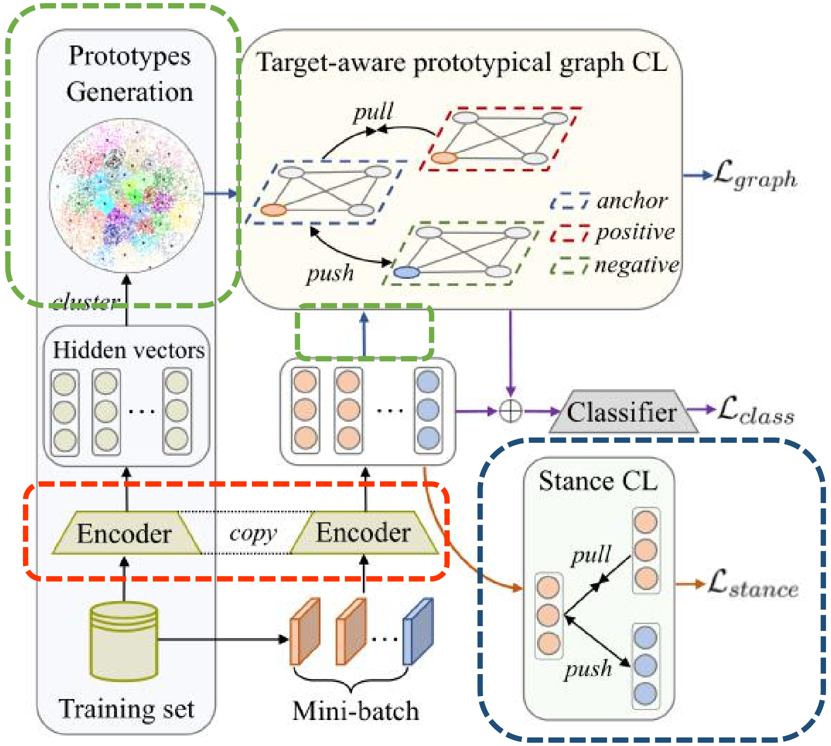


Figure 1: The architecture of our `JointCL` framework. $\oplus$ is vector concatenation. In the graphs, the gray ellipses denote prototypes, others denote hidden vectors. Vectors with the same color hold the same stance.

$$\boldsymbol{h} = \mathrm{BERT}([CLS]r[SEP]t[SEP])_{[CLS]} \quad (1) \qquad \mathcal{H} = \{\boldsymbol{h}_i\}_{i=1}^{N_s}.$$

$$\mathcal{L}_{stance} = \frac{-1}{N_b} \sum_{\boldsymbol{h}_i \in \mathcal{B}} \ell^s(\boldsymbol{h}_i) \qquad (2)$$

$$\ell^s(\boldsymbol{h}_i) = \log \frac{\sum_{j \in \mathcal{B} \setminus i} \mathbb{1}_{[y^i = y^j]} \exp(f(\boldsymbol{h}_i, \boldsymbol{h}_j)/\tau_s)}{\sum_{j \in \mathcal{B} \setminus i} \exp(f(\boldsymbol{h}_i, \boldsymbol{h}_j)/\tau_s)} \qquad (3)$$

$$\mathcal{C} = \{\boldsymbol{c}_i\}_{i=1}^{k}$$

$$\boldsymbol{X} = [\boldsymbol{c}_1, \boldsymbol{c}_2, \cdots, \boldsymbol{c}_k, \boldsymbol{h}_i]$$

$$\mathcal{G} \in \mathbb{R}^{(k+1)\times(k+1)}$$

$$\mathcal{G}_{i,j} = \mathcal{G}_{j,i} = 1.$$

Approach

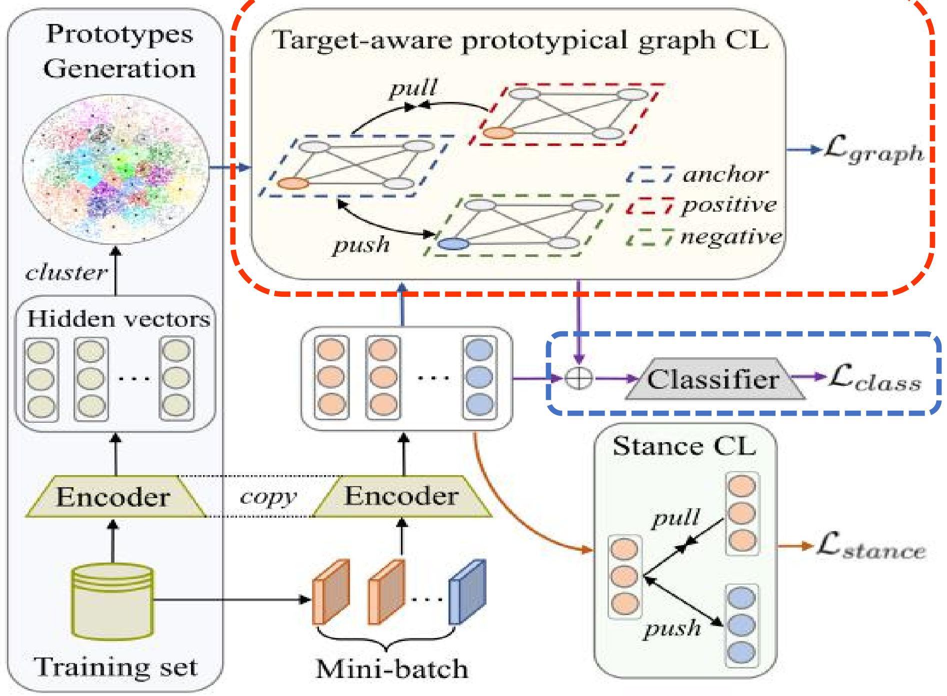


Figure 1: The architecture of our JointCL framework. $\oplus$ is vector concatenation. In the graphs, the gray ellipses denote prototypes, others denote hidden vectors. Vectors with the same color hold the same stance.

$$\boldsymbol{\alpha}_i = a(\mathrm{GAT}(\boldsymbol{X}; \mathcal{G})) \quad (4)$$

$$\boldsymbol{z}_i = f(\mathrm{GAT}(\boldsymbol{X}; \mathcal{G})) \quad (5)$$

$$\mathcal{L}_{graph} = \frac{-1}{N_b} \sum_{\boldsymbol{\alpha}_i \in \mathcal{B}} \ell^g(\boldsymbol{\alpha}_i) \quad (6)$$

$$\ell^g(\boldsymbol{\alpha}_i) = \log \frac{\sum_{j \in \mathcal{B} \setminus i} \Phi(i,j) \exp(f(\boldsymbol{\alpha}_i, \boldsymbol{\alpha}_j)/\tau_g)}{\sum_{j \in \mathcal{B} \setminus i} \exp(f(\boldsymbol{\alpha}_i, \boldsymbol{\alpha}_j)/\tau_g)} \quad (7)$$

$$\Phi(i,j) = \begin{cases} 1 & \text{if } y^i = y^j \text{ and } p^i = p^j \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

$$\boldsymbol{v}_i = \boldsymbol{h}_i \oplus \boldsymbol{z}_i \quad (9)$$

$$\hat{\boldsymbol{y}}_i = \mathrm{softmax}(\boldsymbol{W}\boldsymbol{v}_i + \boldsymbol{b}) \quad (10)$$

$$\mathcal{L}_{class} = -\sum_{i=1}^{N_b} \sum_{j=1}^{d_y} y_i^j \log \hat{y}_i^j \quad (11)$$

$$\mathcal{L} = \gamma_c \mathcal{L}_{class} + \gamma_s \mathcal{L}_{stance} + \gamma_g \mathcal{L}_{graph} + \lambda ||\Theta||^2 \quad (12)$$

Approach

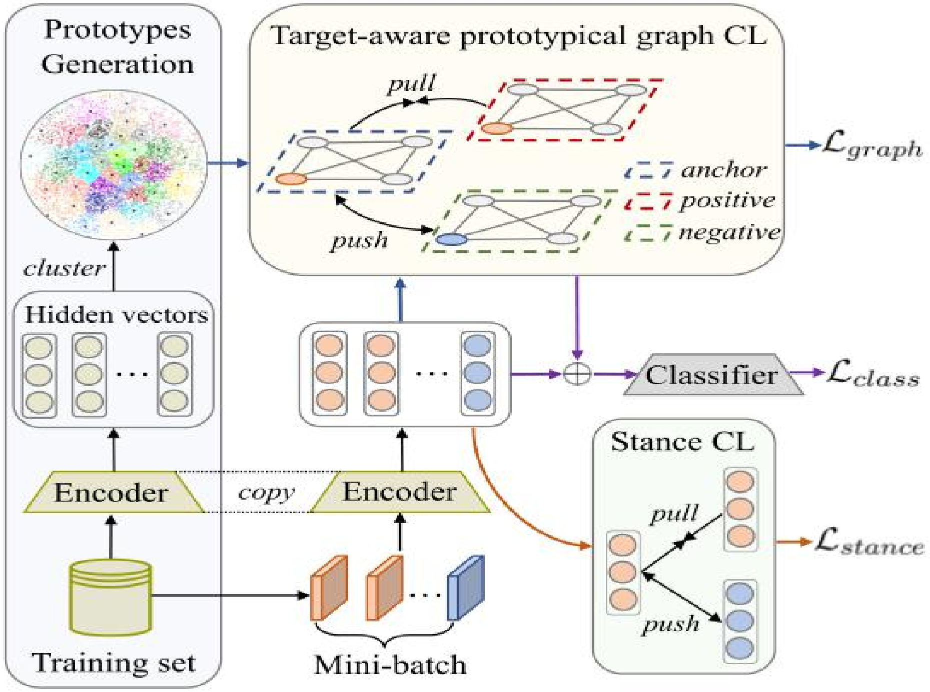


Figure 1: The architecture of our JointCL framework. $\oplus$ is vector concatenation. In the graphs, the gray ellipses denote prototypes, others denote hidden vectors. Vectors with the same color hold the same stance.

$$\mathcal{L}_{graph} = \frac{-1}{N_b} \sum_{\boldsymbol{h}_i \in \mathcal{B}} \ell^g(\boldsymbol{h}_i) \tag{13}$$

$$\ell^g(\boldsymbol{h}_i) = \log \frac{\sum_{j \in \mathcal{B} \setminus i} \mathbb{1}_{[t^i = t^j]} \exp(f(\boldsymbol{h}_i, \boldsymbol{h}_j)/\tau)}{\sum_{j \in \mathcal{B} \setminus i} \exp(f(\boldsymbol{h}_i, \boldsymbol{h}_j)/\tau)} \tag{14}$$

$$\mathcal{L}_{graph} = \frac{-1}{N_b} \sum_{\boldsymbol{z}_i \in \mathcal{B}} \ell^g(\boldsymbol{z}_i) \tag{15}$$

$$\ell^g(\boldsymbol{z}_i) = \log \frac{\sum_{j \in \mathcal{B} \setminus i} \mathbb{1}_{[p^i = p^j]} \exp(f(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{j \in \mathcal{B} \setminus i} \exp(f(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)} \tag{16}$$

Experiments

	Train	Dev	Test
# Examples	13477	2062	3006
# Unique Comments	1845	682	786
# Zero-shot Topics	4003	383	600
# Few-shot Topics	638	114	159

Table 1: Statistics of VAST dataset.

Dataset	Target	Favor	Against	Neutral	Unrelated
SEM16	DT	148	299	260	-
	HC	163	565	256	-
	FM	268	511	170	-
	LA	167	544	222	-
	A	124	464	145	-
	CC	335	26	203	-
WT-WT	CA	2469	518	5520	3115
	CE	773	253	947	554
	AC	970	1969	3098	5007
	AH	1038	1106	2804	2949

Table 2: Statistics of SEM16 and WT-WT datasets.

Experiments

Model	VAST (%) Pro	Con	Neu	All	SEM16 (%) DT	HC	FM	LA	A	CC	WT-WT (%) CA	CE	AC	AH
BiCond	44.6$^\natural$	47.4$^\natural$	34.9†	42.8$^\natural$	30.5‡	32.7‡	40.6‡	34.4‡	31.0‡	15.0‡	56.5$^\sharp$	52.5$^\sharp$	64.9$^\sharp$	63.0$^\sharp$
CrossNet	46.2$^\natural$	43.4$^\natural$	40.4†	43.4$^\natural$	35.6	38.3	41.7	38.5	39.7	22.8	59.1$^\sharp$	54.5$^\sharp$	65.1$^\sharp$	62.3$^\sharp$
SiamNet	47.5	43.3	39.6	43.5	36.9	37.5	44.3	41.6	41.2	25.6	58.3$^\sharp$	54.4$^\sharp$	68.7$^\sharp$	67.7$^\sharp$
SEKT	50.4†	44.2†	30.8†	41.8†	-	-	-	-	-	-	-	-	-	-
TPDG	53.7	49.6	52.3	51.9	47.3	50.9	53.6	46.5	48.7	32.3	66.8$^\flat$	65.6$^\flat$	74.2$^\flat$	73.1$^\flat$
TOAD	42.6	36.7	43.8	41.0	49.5‡	51.2‡	**54.1**‡	46.2‡	46.1‡	30.9‡	55.3	57.7	58.6	61.7
BERT	54.6$^\natural$	58.4$^\natural$	85.3†	66.1$^\natural$	40.1‡	49.6‡	41.9‡	44.8‡	**55.2**‡	37.3‡	56.0$^\flat$	60.5$^\flat$	67.1$^\flat$	67.3$^\flat$
TGA Net	55.4$^\natural$	58.5$^\natural$	85.8†	66.6$^\natural$	40.7	49.3	46.6	45.2	52.7	36.6	65.7	63.5	69.9	68.7
BERT-GCN	58.3†	60.6†	86.9†	68.6†	42.3	50.0	44.3	44.2	53.6	35.5	67.8	64.1	70.7	69.2
CKE-Net	61.2†	61.2†	88.0†	70.2†	-	-	-	-	-	-	-	-	-	-
JointCL (ours)	**64.9***	**63.2***	**88.9***	**72.3***	**50.5***	**54.8***	53.8	**49.5***	54.5	**39.7***	**72.4***	**70.2***	**76.0***	**75.2***

Table 3: Experimental results on three ZSSD datasets. The results with $\natural$ are retrieved from (Allaway and McKeown, 2020), $\dagger$ from (Liu et al., 2021), $\ddagger$ from (Allaway et al., 2021), $\sharp$ from (Conforti et al., 2020), and $\flat$ from (Liang et al., 2021a). Best scores are in bold. Results with $\star$ denote the significance tests of our JointCL over the baseline models at $p-$value < 0.05.

Experiments

Model	VAST (%) Pro	Con	Neu	All	SEM16 (%) DT	HC	FM	LA	A	CC	WT-WT (%) CA	CE	AC	AH
JointCL (ours)	**64.9**	**63.2**	**88.9**	**72.3**	**50.5**	**54.8**	**53.8**	**49.5**	**54.5**	**39.7**	**72.4**	**70.2**	**76.0**	**75.2**
w/o $\mathcal{L}_{stance}$	61.6	60.7	87.2	69.8	46.2	51.4	51.2	45.3	52.5	36.3	69.4	67.8	72.1	71.4
w/o $\mathcal{L}_{graph}$	62.5	62.1	87.8	70.7	48.8	52.7	51.5	48.2	53.2	38.1	70.5	68.3	74.7	73.6
w/o *graph*	60.8	62.3	87.7	70.3	46.5	50.3	49.7	45.6	52.3	37.4	69.8	68.7	73.2	71.7
w/o *cluster*	59.6	62.2	86.8	69.5	47.4	53.1	52.3	48.6	53.7	38.8	70.9	69.2	74.9	72.6
w/o *edge*	63.3	62.5	88.4	71.4	49.2	53.4	53.1	48.9	53.5	39.2	71.2	69.5	75.2	74.2

Table 4: Experimental results of ablation study.

Experiments

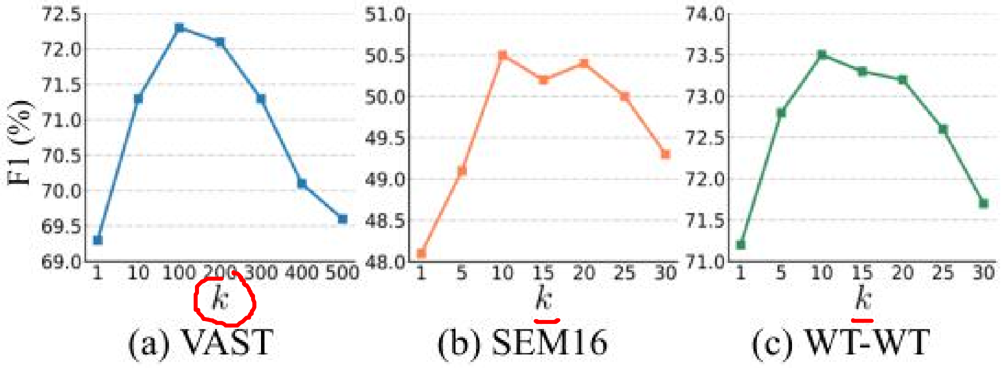


Figure 2: Experimental results of different values of k.

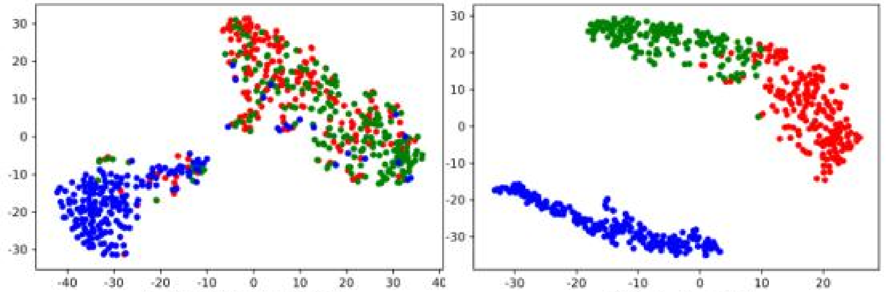
Model	Pro	Con	Neu	All
BiCond	45.4	46.3	25.9	39.2
Cross-Net	50.8	50.5	41.0	47.4
SEKT	51.0	47.9	21.5	47.4
BERT	54.4	59.7	79.6	64.6
TGA Net	58.9	59.5	80.5	66.3
BERT-GCN	62.8	63.4	83.0	69.7
CKE-Net	**64.4**	62.2	83.5	70.1
JointCL (ours)	63.2	**66.7**	**84.6**	**71.5**

Table 5: Experimental results of few-shot condition. Results of baselines are retrieved from (Liu et al., 2021).

Experiments

Model	HC→DT	DT→HC	FM→LA	LA→FM
BiCond	29.7	35.8	45.0	41.6
CrossNet	43.1	36.2	45.4	43.3
BERT	43.6	36.5	47.9	33.9
SEKT	47.7	42.0	53.6	51.3
TPDG	50.4	52.9	58.3	54.1
JointCL (ours)	**52.8**	**54.3**	**58.8**	**54.5**

Table 6: Experimental results of cross-target condition. "HC→DT" denotes training on HC and testing on DT, etc. Results of baselines are retrieved from (Liang et al., 2021a).



(a) BERT-GCN (b) JointCL

Figure 3: Visualization of intermediate embeddings. Red dots denote *Pro* examples, green dots denote *Con* examples, and blue dots denote *Neutral* examples.

Thank you！