Exploiting Sentiment and Common Sense for Zero-shot Stance Detection

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code: https://github.com/LuoXiaoHeics/StanceCS

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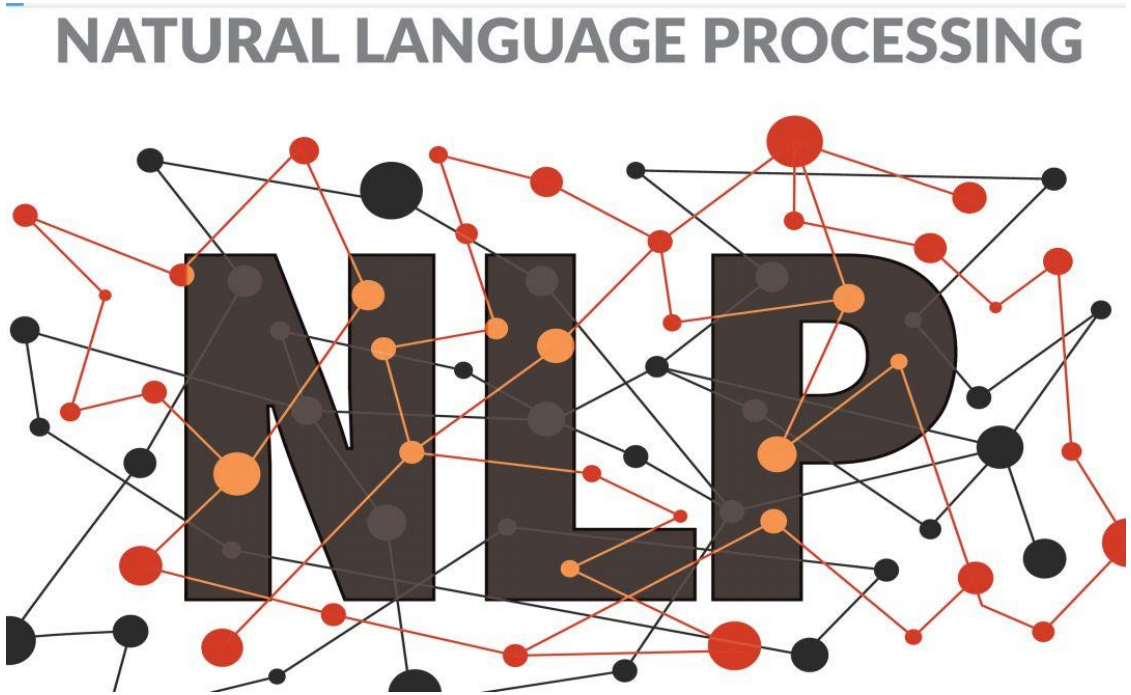

1.Introduction

2.Method

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Introduction

Example 1 Topic : Olympics **Stance :** Pro

Text : The **games** should proceed. **Athletes** have made tremendous sacrifices to qualify and be prepared. It would be cruel to deny them their chance. In the future the Games should be held in countries within the top say 15 GDP per capita.

Example 2 Topic : Nuclear power **Stance :** Pro

Text : I totally agree with this premise. As a younger person I was against **Nuclear power** (I was in college during 3 mile island) but now it seems that nuclear should be in the mix. Fission technology is better, and will continue to get better if we actively promote its development. The prospect of fusion energy also needs to be explored. If it's good enough for the sun and the stars, it's good enough for me.

Figure 1: Examples for stance detection VAST.

Since the topics can be implicit in documents, we propose the stance detection model by using sentiment and commonsense knowledge.

Method

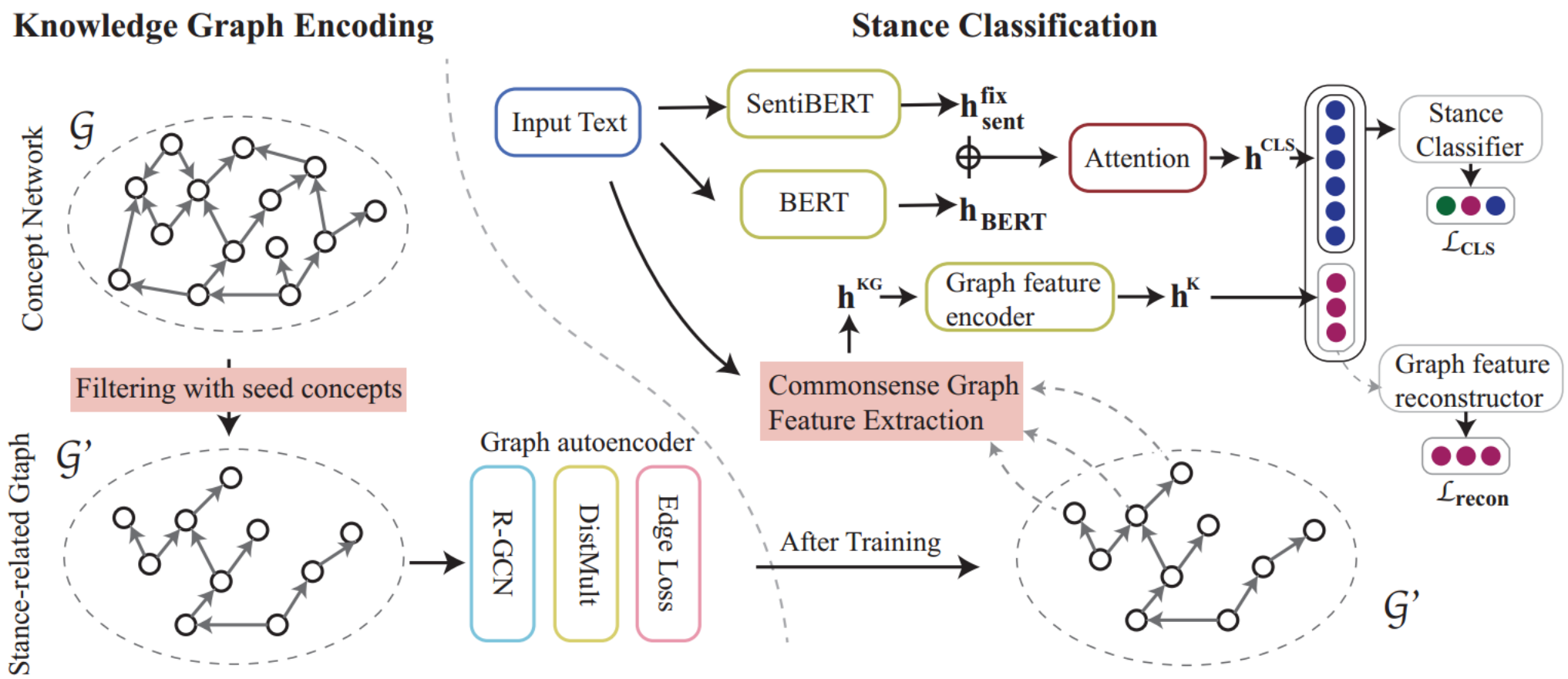
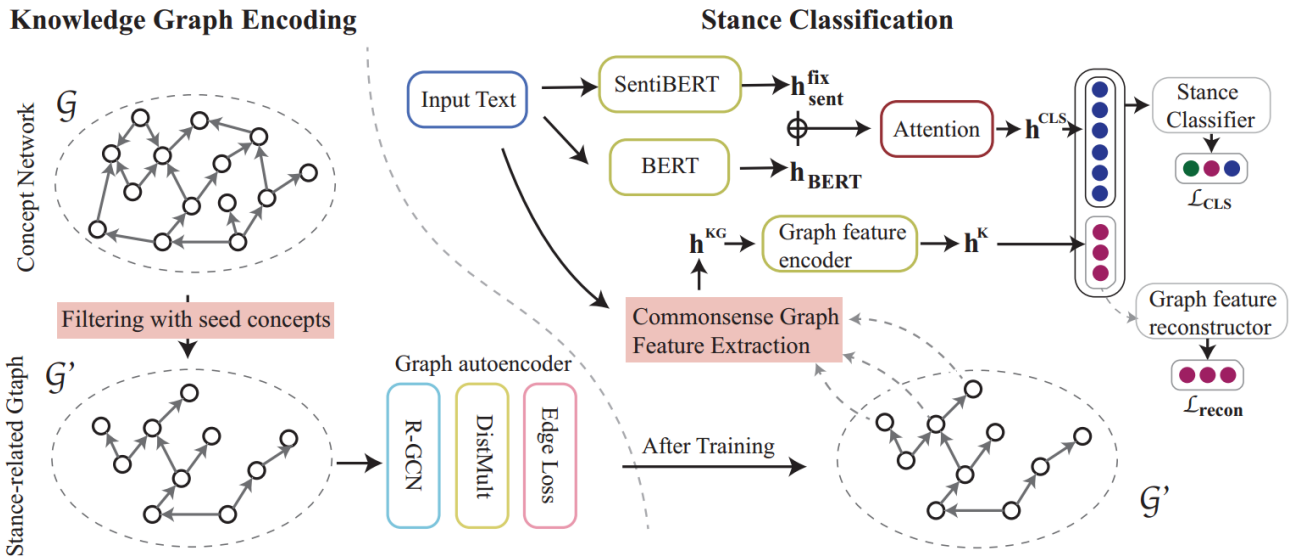


Figure 2: Framework of our proposed model, which contains two components, (1) knowledge graph encoding, (2) stance detection with sentiment and common sense.

Method



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Knowledge Graph Autoencoder

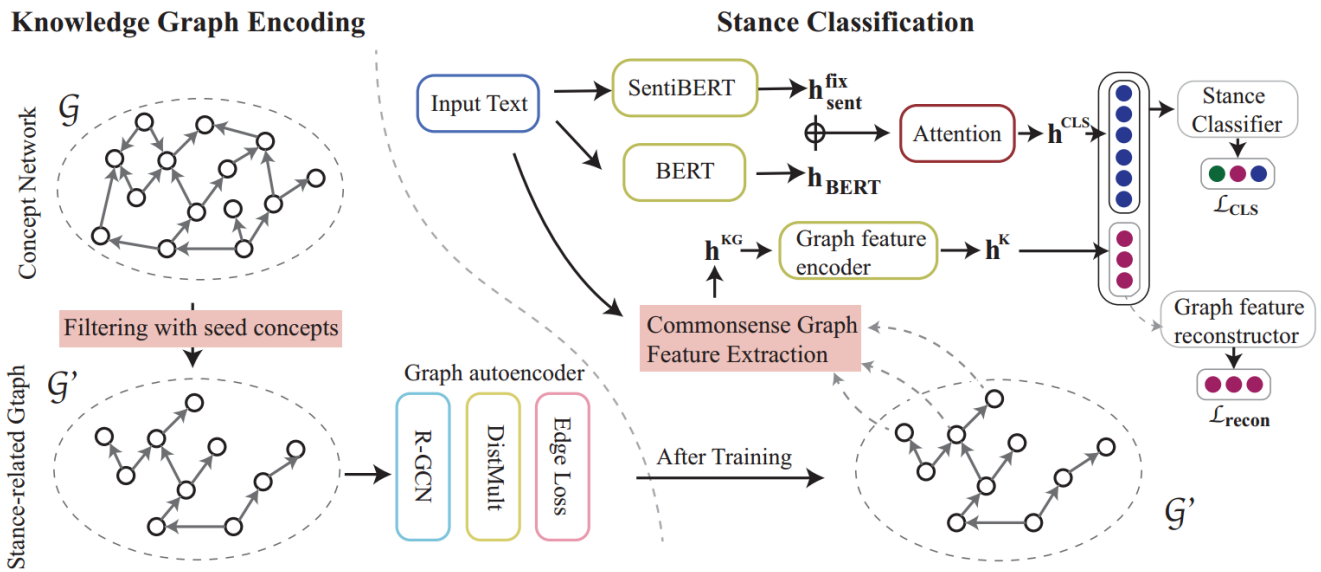
$$f(x_i, l) = \sigma(\sum_{r \in \mathcal{R}} \sum_{j \in N_i^r} \frac{1}{v_{i,r}} W_r^{(l)} x_j + W_0^{(l)} x_i),$$

$$\mathbf{h}_i = \mathbf{h}_i^{(2)} = f(\mathbf{h}_i^{(1)}, 2) \; ; \; \mathbf{h}_i^{(1)} = f(\mathbf{g}_i, 1), \quad (1)$$

$$s(v_i, r, v_j) = \sigma(\mathbf{h}_{v_i}^T R_r \mathbf{h}_{v_j}), \quad (2)$$

$$\mathcal{L}_{\mathcal{G}'} = -\frac{1}{2|\hat{\mathcal{E}}'|} \sum_{(v_i, r, v_j, u) \in \mathcal{T}} (u log\, s(v_i, r, v_j) + (1-u) log(1 - s(v_i, r, v_j))). \quad (3)$$

Method



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Stance Detection Module

$$\mathbf{h}_{sent}^{fix} = SentiBERT(x), \quad (4)$$

$$\mathbf{h}^{K} = W_k \mathbf{h}^{KG} + b_k \quad (5)$$

$$\mathbf{h}_{BERT} = BERT(x) \quad (6)$$

$$\mathbf{h}^{CLS} = CrossAttention([\mathbf{h}_{BERT}, \mathbf{h}_{sent}^{fix}])[CLS], \quad (7)$$

$$p = Softmax(W[\mathbf{h}^{CLS}, \mathbf{h}^{K}] + b), \quad (8)$$

$$\mathcal{L}_{cls} = -\frac{1}{|N|} \sum_{(x_i, y_i)} y_i log\, p(y_i), \quad (9)$$

$$\mathcal{L}_{recon} = -E_{\mathbf{h}^{KG}}(||D_{recon}(\mathbf{h}^{K}) - \mathbf{h}^{KG}||_2^2). \quad (10)$$

$$\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_{recon}. \quad (11)$$

Experiment

	#Exp	#Doc	#Zero-shot	#Few-shot
Train	13477	638	1481	4003
Dev	2062	114	682	383
Test	3066	159	786	600

Table 1: Statistics on the VAST dataset.

Experiment

Model	F1 Zero-shot				F1 Few-Shot				F1 All			
	pro	con	neu	all	pro	con	neu	all	pro	con	neu	all
BiCond	.459	.475	.349	.427	.454	.463	.259	.392	.457	.468	.306	.410
Cross-Net	.462	.434	.404	.434	.508	.505	.410	.474	.486	.471	.408	.455
SEKT	.504	.442	.308	.418	.510	.479	.215	.474	.507	.462	.263	.411
BERT-sep	.414	.506	.454	.458	.524	.539	.544	.536	.473	.522	.501	.499
BERT-joint	.546	.584	.853	.660	.543	.597	.796	.646	.545	.591	.823	.653
TGA-Net	.554	.585	.858	.666	.589	.595	.805	.663	.573	.590	.831	.665
BERT-joint-ft	.579	.603	.875	.685	.595	.621	.831	.684	.588	.614	.853	.684
TGA-Net-ft	.568	.598	.885	.684	.628	.601	.834	.687	.599	.599	.859	.686
Prior-Bin:gold	**.643**	.581	.852	.692	.632	.563	**.881**	.692	**.652**	.597	.824	.691
BERT-GCN	.583	.606	.869	.686	.628	.634	.830	.697	.606	.620	.849	.692
CKE-Net	.612	.612	.880	.702	**.644**	.622	.835	.701	.629	.617	.857	.701
Our Model												
BS	.625	.667	.870	.717	.601	.667	.828	.699	.591	.669	.858	.706
S-RGCN	.582	.669	.838	.699	.561	.623	.809	.665	.607	.657	.842	.702
B-RGCN	.594	.657	.885	.712	.568	**.678**	.851	.699	.591	.663	.865	.706
BS-RGCN(*proposed*)	.608	**.674**	**.895**	**.726**	.600	.665	.839	**.702**	.604	**.669**	**.866**	**.713**

Table 2: Overall results. The suffix "ft" means BERT is fine-tuned. BS – the combination of BERT and SentiBERT; S-RGCN – the combination of SentiBERT and the graph autoencoder; B-RGCN – the combination of BERT and the graph autoencoder; BS-RGCN – our proposed model.

Experiment

Model	Imp	mlT	mlS	Qte	Sarc
BERT-joint	.571	.590	.524	.634	.601
TGA-Net	.594	.605	.532	.661	.637
BERT-joint-ft	.617	.621	.547	.668	.673
BERT-GCN	.619	.627	.547	.668	.673
CKE-Net	**.625**	.634	.553	.695	.682
BS-RGCN	.621	**.647**	**.556**	**.701**	**.717**

Table 3: Accuracies on five challenges on the test set.

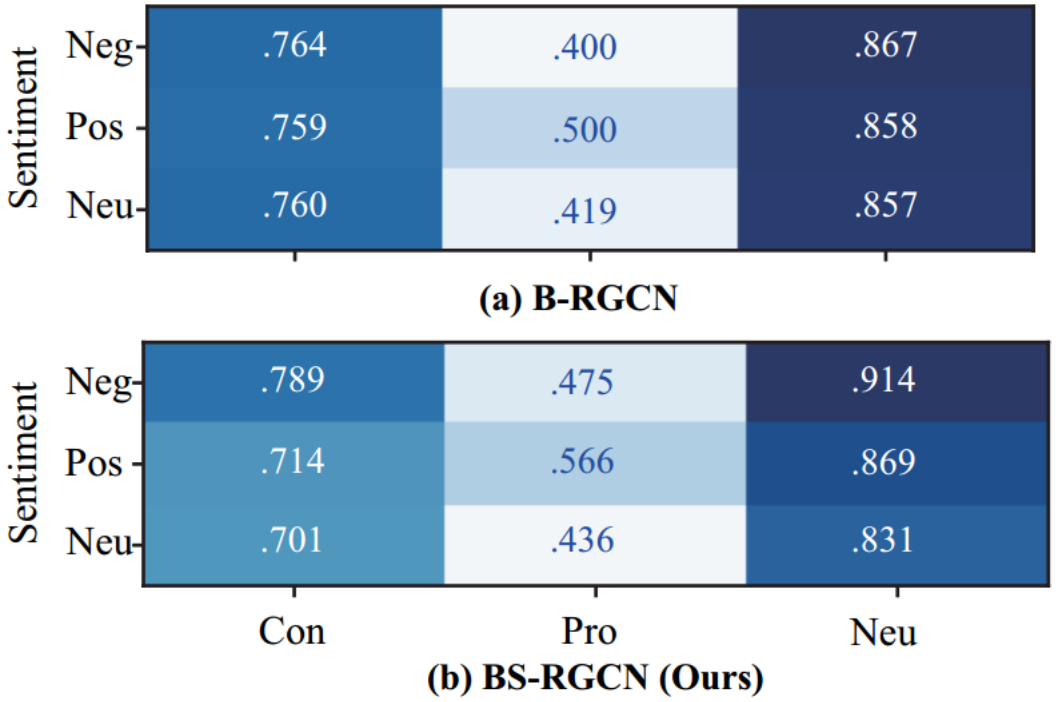

Figure 3: Accuracies of B-RGCN and BS-RGCN on all test data w.r.t different sentiment and stance pairs.

Experiment

Context	Topic	Gold Label	Output
I have lived in brazil for the last five years (and off and on over the last 27 years). I know of no one here who is even remotely excited about the Olympics. It would seem that people dont́ care. The economy is tanking and government is at a complete standstill. We have more important things on our mind right now.	Olympics	Con	Con
I can't even believe that this is a debate. Cutting the most basic **foreign language programs**? How does one appreciate that there is a world outside of America? Google translate? Suny, everyone is laughing at you and you're too smug to notice.	College	Con	Con
Good idea. I have always had a cat or two. While being inhumane, **declawing** places a cat in danger. Should my charming indoor kitty somehow escape outside, he would have no way to defend himself.	nail removal	Con	Con

Table 4: Case Study for our trained stance detection model. Case I shows the effectiveness of using sentiment information; Case II shows the importance of commonsense knowledge; Case III shows both the sentiment and commonsense knowledge help the stance detection model.

Experiment

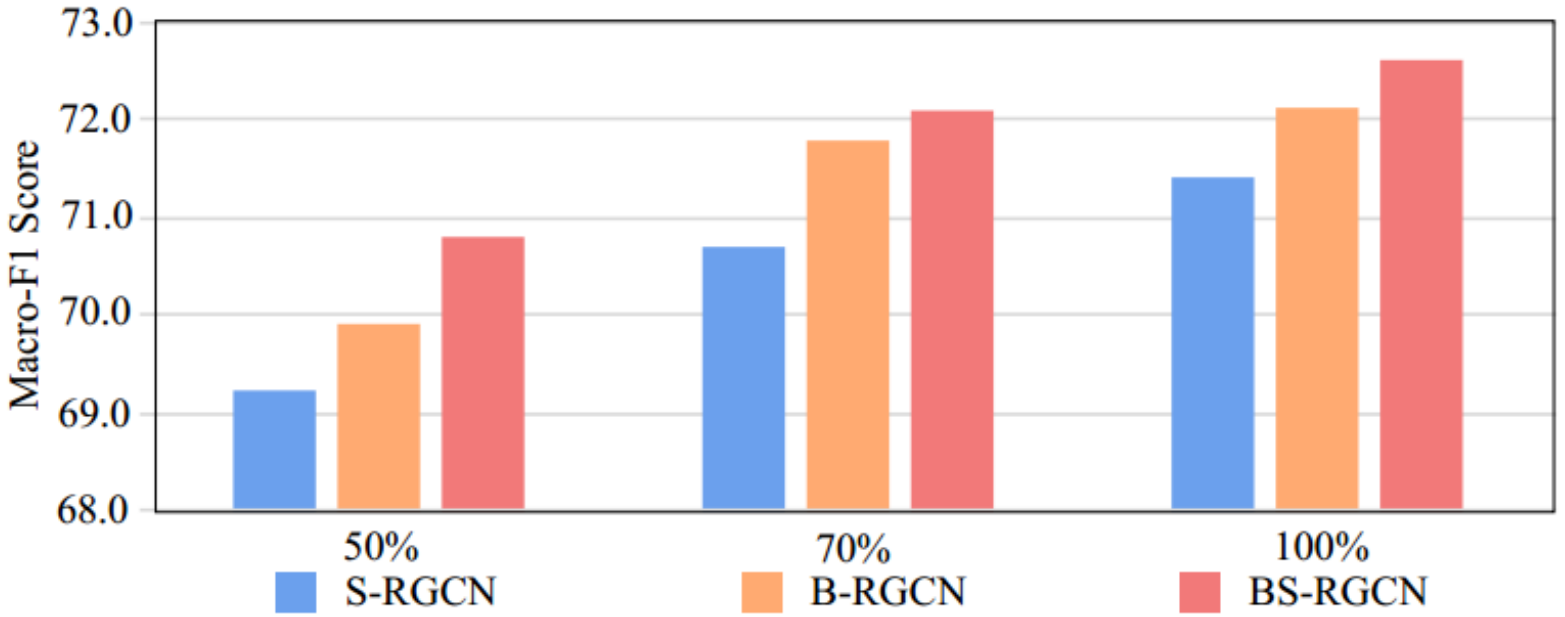

Figure 4: Macro-F1 scores of S-RGCN, B-RGCN, and BS-RGCN on zero-shot test data w.r.t different percents of commonsense knowledge for pre-training.

Thank you!