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CREATING GROWTH, ENHANCING LIVES

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GDPNet: Refining Latent Multi-View Graph for Relation Extraction

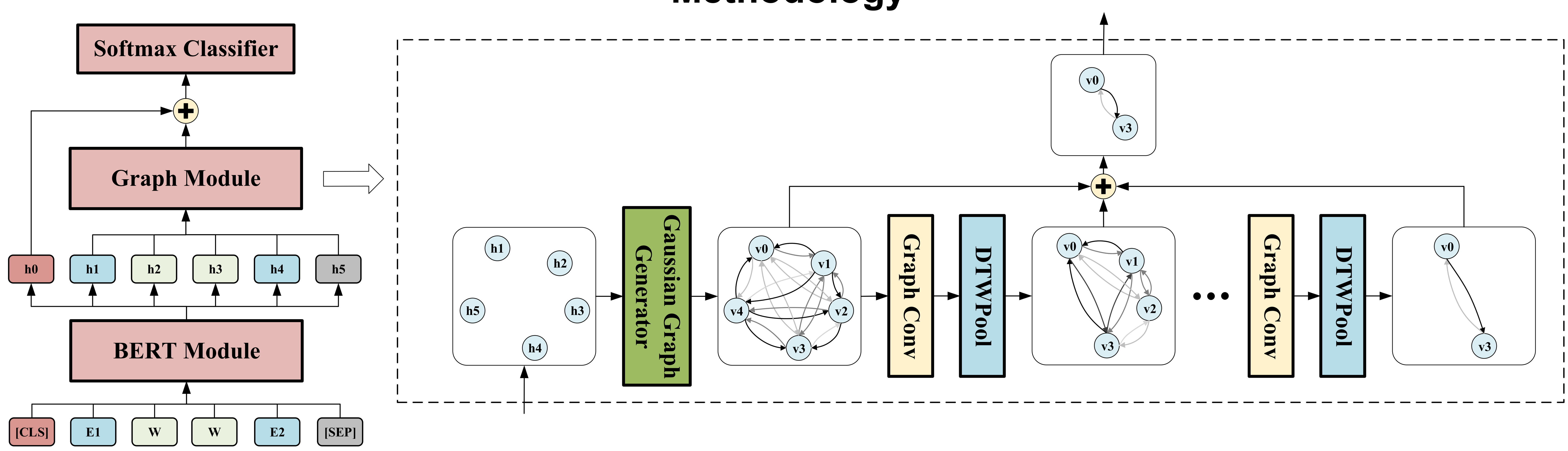
Introduction

- Given two entities and a piece of text where the two entities are mentioned, the task of relation extraction (RE) is to predict the semantic relation between the two entities. The types of semantic relations are predefined.
- When the given piece of text is long, not all words contribute to the relation prediction, but it is also challenging to identify indicative words for the prediction.
- The proposed GDPNet model constructs latent multi-view graph of tokens and refines the graph for effective RE.

Contribution

- We propose a Gaussian Graph Generator (GGG) to initialize edges for latent multi-view graph by measuring KL divergence between different Gaussian distributions of tokens.
- We propose a graph pooling method, DTWPool, to refine the latent multi-view graph learned from text sequence, with a flexible pooling ratio. To the best of our knowledge, this is the first work on multi-view graph pooling.
- We combine GGG and DTWPool to form the GDPNet, and evaluate GDPNet on two benchmark datasets for RE. Experimental results demonstrate the effectiveness of GDPNet against SoTA baselines.

Methodology



- There are three key components: BERT module, graph module, and SoftMax classifier:
  (a) BERT module encodes tokens into the corresponding feature representations.
  (b) Graph module takes in token representations from BERT and constructs a multi-view graph with a Gaussian Graph Generator (GGG).
  (c) The graph is refined through multiple interactions of graph convolution and DTWPool.
  (d) Finally, the refined latent graph is fed into a SoftMax classifier to predict relation type.

Experiments

Dialogue-level RE on DialogRE dataset.

Model	Dev		Test	
	F1(σ)	F1c(σ)	F1(σ)	F1c(σ)
CNN (Lawrence et al. 1997)	46.1(0.7)	43.7(0.5)	48.0(1.5)	45.0(1.4)
LSTM (Hochreiter and Schmidhuber 1997)	46.7(1.1)	44.2(0.8)	47.4(0.6)	44.9(0.7)
BiLSTM (Graves and Schmidhuber 2005)	48.1(1.0)	44.3(1.3)	48.6(1.0)	45.0(1.3)
BERT (Devlin et al. 2019)	60.6(1.2)	55.4(0.9)	58.5(2.0)	53.2(1.6)
BERTs (Yu et al. 2020)	63.0(1.5)	57.3(1.2)	61.2(0.9)	55.4(0.9)
GDPNet (ours)	**67.1**(1.0)	**61.5**(0.8)	**64.9**(1.1)	**60.1**(0.9)

Sentence-level RE on TACRED datasets.

Model	TACRED			TACRED-Revisit		
	Pr	Re	$F1$	Pr	Re	$F1$
LSTM (Zhang et al. 2017)	65.7	59.9	62.7	71.5*	69.7*	70.6*
PA-LSTM (Zhang et al. 2017)	65.7	64.5	65.1	74.5*	74.1*	74.3*
C-AGGCN (Guo, Zhang, and Lu 2019)	73.1	60.9	68.2	77.7*	73.4*	75.5*
LST-AGCN (Sun et al. 2020)	-	-	68.8	-	-	-
SpanBERT (Joshi et al. 2020)	70.8	70.9	**70.8**	75.7*	80.7*	78.0*
GDPNet (Our model)	72.0	69.0	70.5	79.4	81.0	**80.2**
KnowBERT (Peters et al. 2019)	71.6	71.4	**71.5**	-	-	79.3