Sparse Structure Learning via Graph Neural Networks for Inductive Document Classification

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Code:https://github.com/qkrdmsghk/TextSSL

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Artificial

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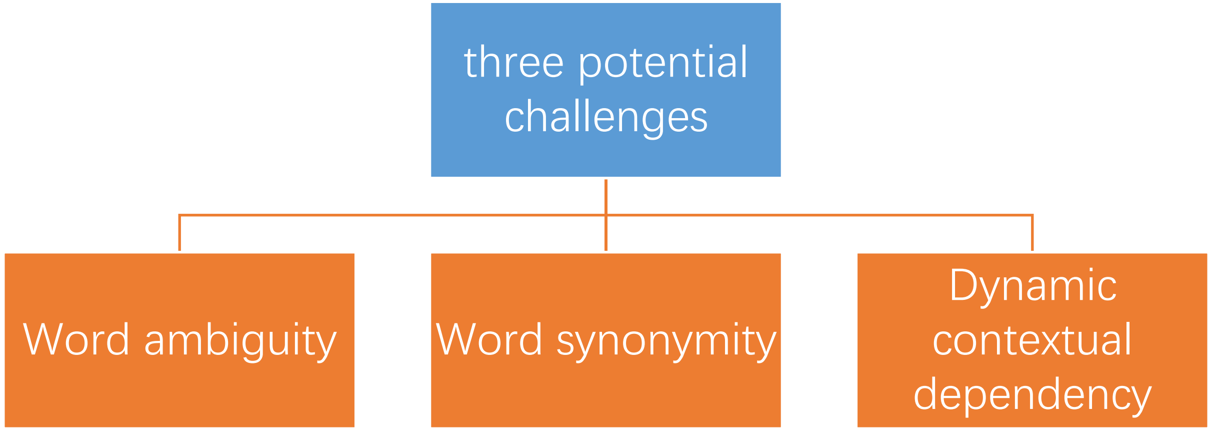
Introduction

- Document classification, a task of using algorithms to automatically classify the input document to one or multiple categories. Nevertheless, almost all graph-based methods are de-signed to construct static word co-occurrence graph for the whole document without considering sentence-level information.



- We construct a trainable individual graph consisting of sentence-level subgraphs for each document.
- We propose a sparse structure learning model via GNNs to learn an effective and efficient structure with dynamic syntactic and semantic information for each document.

Method

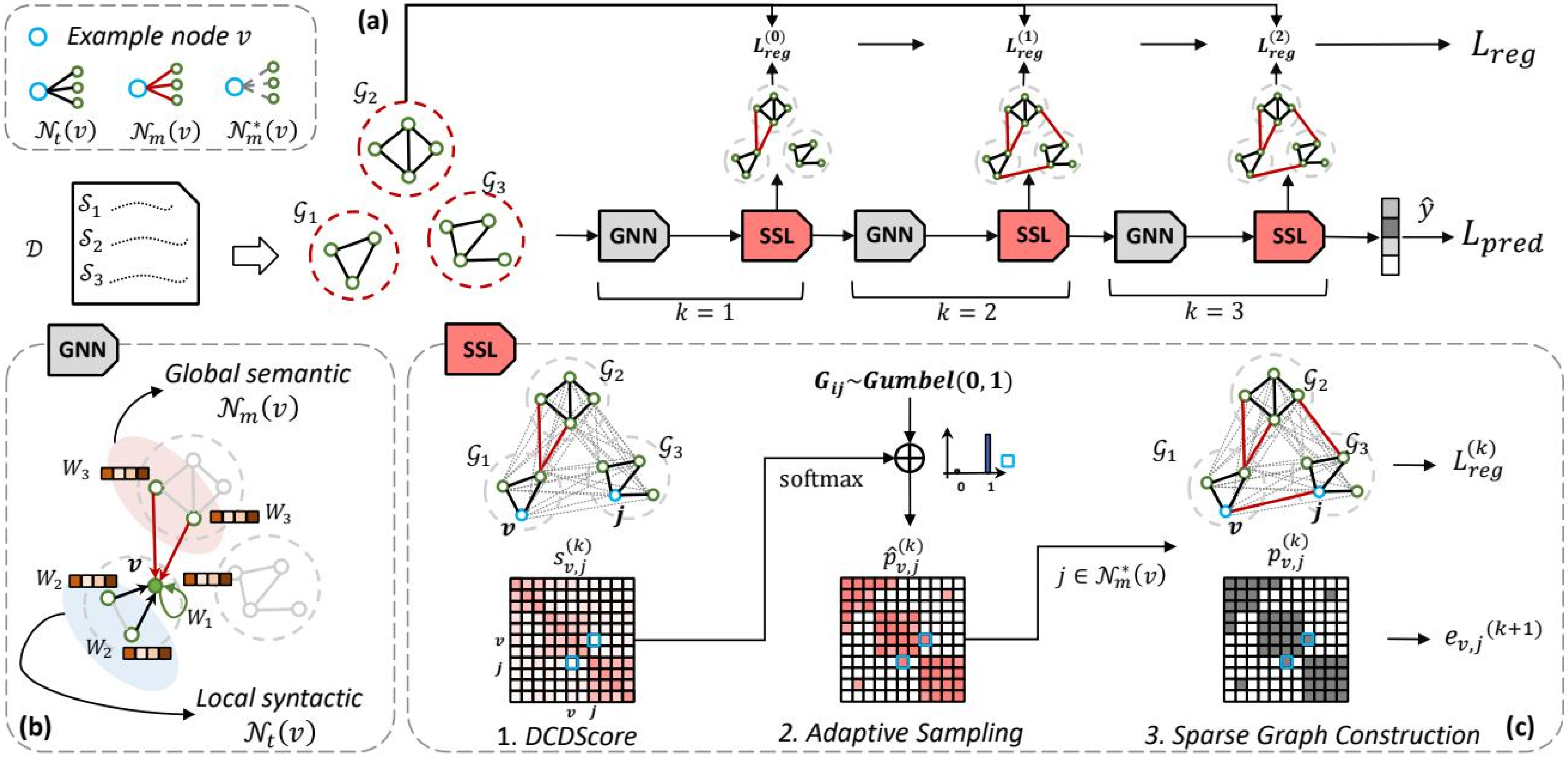
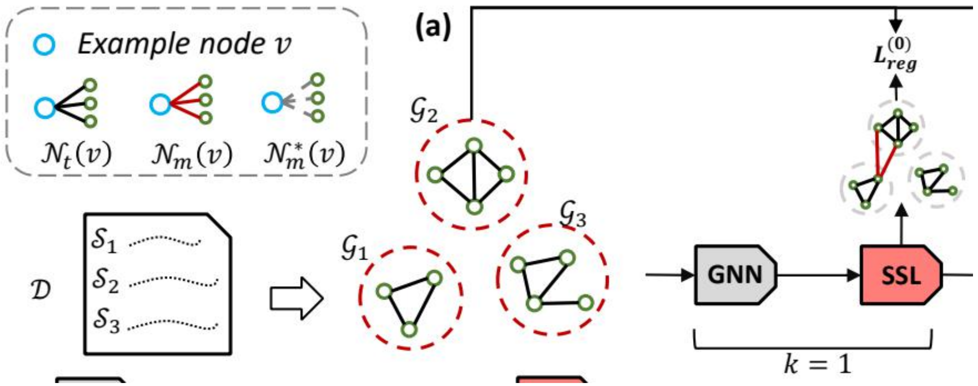
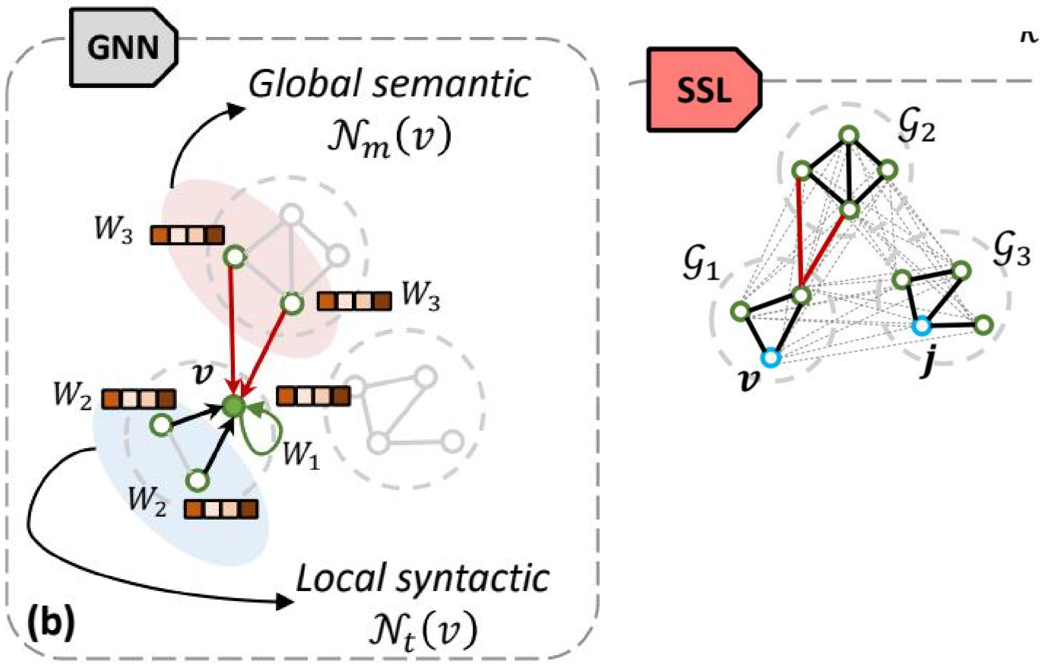


Figure 1: Overview of the proposed model. (a) Model framework. (b) GNN: Local and Global Joint Message Passing. (c) SSL: Sparse Structure Learning contains (c.1) Dynamic Contextual Dependency Score, (c.2) Adaptive Sampling for Sparse Structure, and (c.3) Reconstructing Sparse Graph.





Method

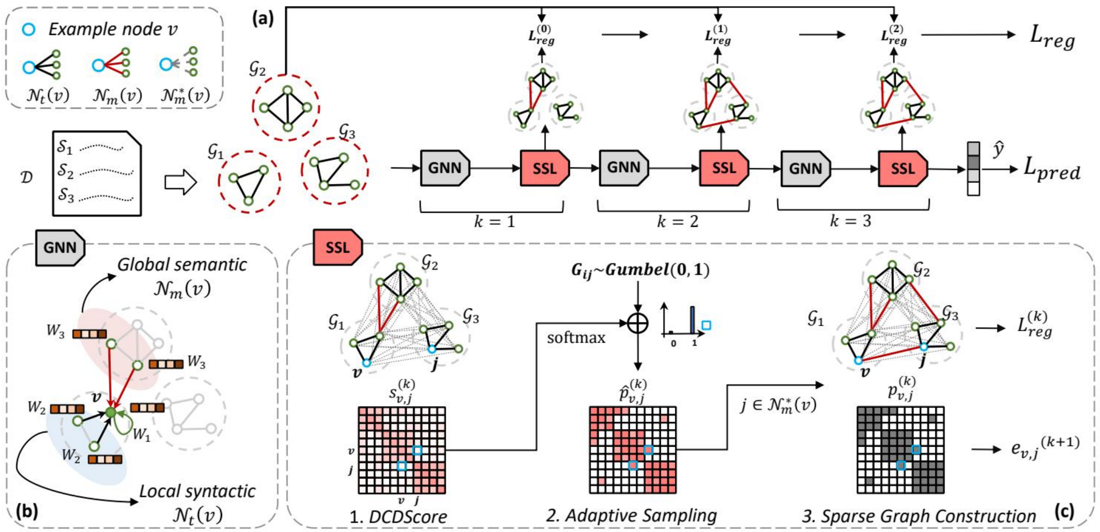
Graph Construction

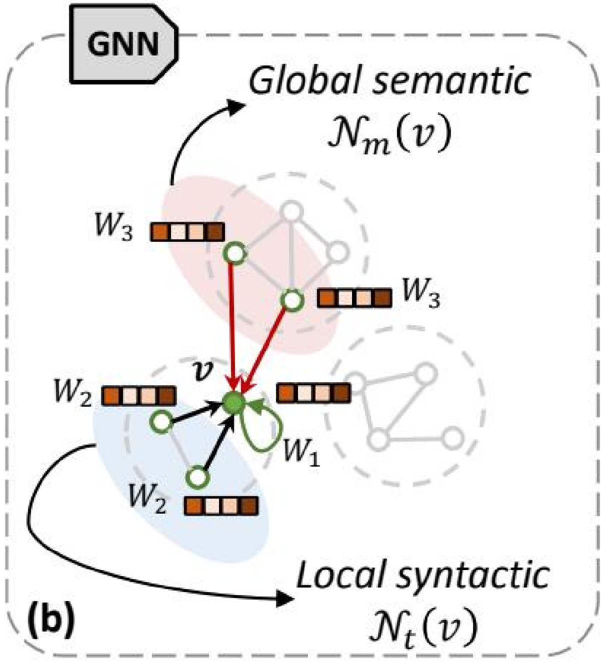
Definition 1. Sentence-level Subgraph Given a sentence $s_i \in \mathcal{S}$, a sentence-level subgraph $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$ can represent the sentence s_i as a word co-occurrence graph. The node set $\mathcal{V}_i$ contains words in sentence s_i. The edge set $\mathcal{E}_i$ contains all connections between any pair of words in $\mathcal{V}_i$

Definition 2. Local Syntactic Neighbor Given a node $v \in \mathcal{V}$ in a preliminary document graph $\tilde{\mathcal{G}}$, we define a local syntactic neighbor $u \in \mathcal{N}_t(v)$ that is adjacent to node v within sentence-level subgraphs $\mathcal{G}_\mathcal{S}$.

Definition 3. Global Semantic Neighbor Given a node $v \in \mathcal{V}$ in a preliminary document graph $\tilde{\mathcal{G}}$, we define a global semantic neighbor $z \in \mathcal{N}_m(v)$ that can have dynamic relation with node v between sentence-level subgraphs $\mathcal{G}_s$.

A document-level graph $\mathcal{G} = (\mathcal{V}, \{\mathcal{E}_t \cup \mathcal{E}_m\})$





Method

Local and Global Joint Message Passing

k-th iteration of message passing process in a GNN

$$h_v^k = \phi\left(f^{(k)}(h_v^{(k-1)}, \{h_u^{(k-1)} : u \in \mathcal{N}_v\})\right), \qquad (1)$$

obtain the entire graph's representation

$$h_G = R(\{h_v^{(K)} | v \in G\}). \qquad (2)$$

The message passing part can be reformulated as:

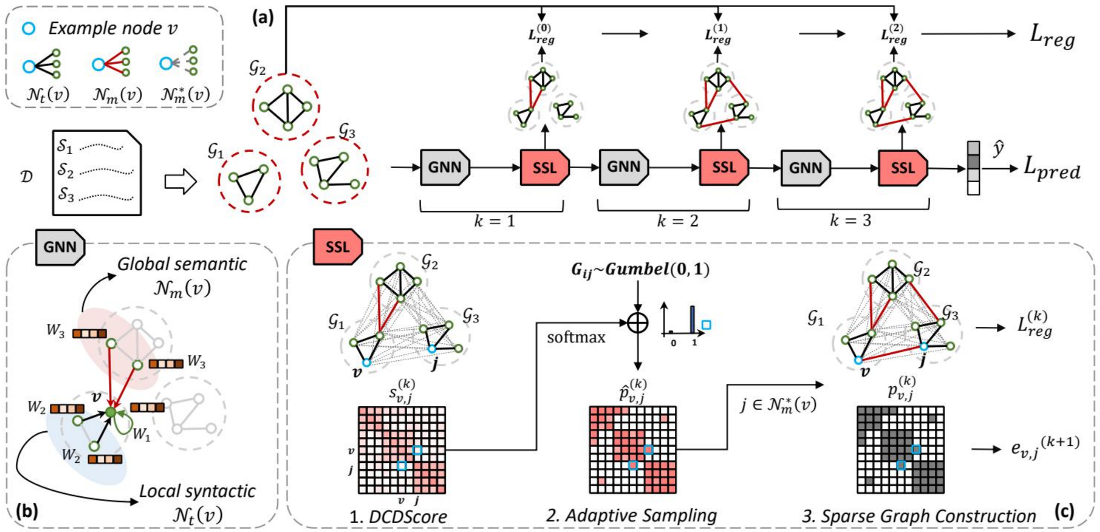
$$h_v^{(k)} = \phi\left(h_v^{(k-1)}\mathbf{W}_1^{(k)} + t_v^{(k)}\mathbf{W}_2^{(k)} + m_v^{(k)}\mathbf{W}_3^{(k)}\right), \qquad (5)$$

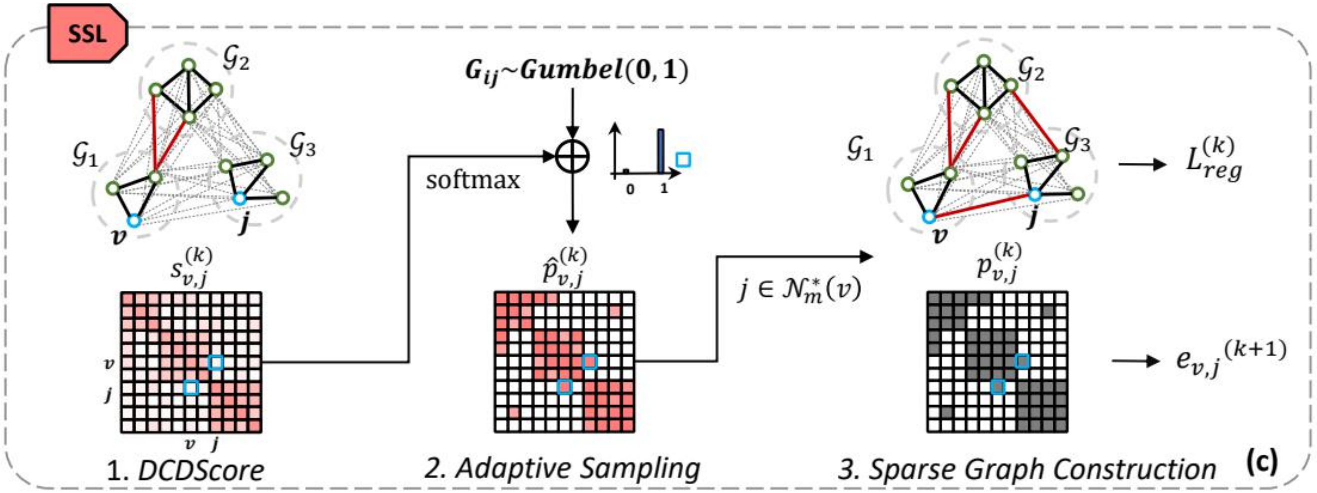
$h_v^{(k)} \in \mathbb{R}^b$ is the node representation vector and b is the number of hidden dimension. The local syntactic neighbor representations $t_v^{(k)} \in \mathbb{R}^b$ and global semantic neighbor representations $m_v^{(k)} \in \mathbb{R}^b$ can be expressed as:

$$t_v^{(k)} = \sum_{u \in \mathcal{N}_t(v) \cup \{v\}} \frac{e_{u,v}}{\sqrt{\hat{\zeta}_u \hat{\zeta}_v}} h_u^{(k-1)} \qquad (6)$$

$$m_v^{(k)} = \sum_{z \in \mathcal{N}_m(v)^{(k-1)}} \frac{e_{z,v}}{\sqrt{\hat{\zeta}_z \hat{\zeta}_v}} h_z^{(k-1)} \qquad (7)$$

$\hat{\zeta}_v = \sum_{j \in \mathcal{N}} \hat{A}_{vj}$ with self-looped adjacency matrix $\hat{A} = A + I$.





Method

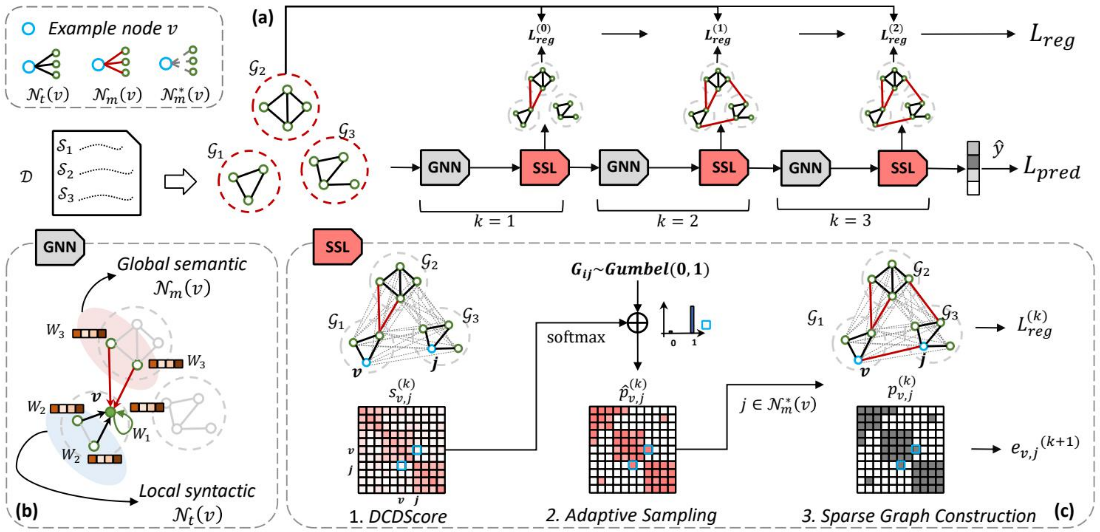
Sparse Structure Learning

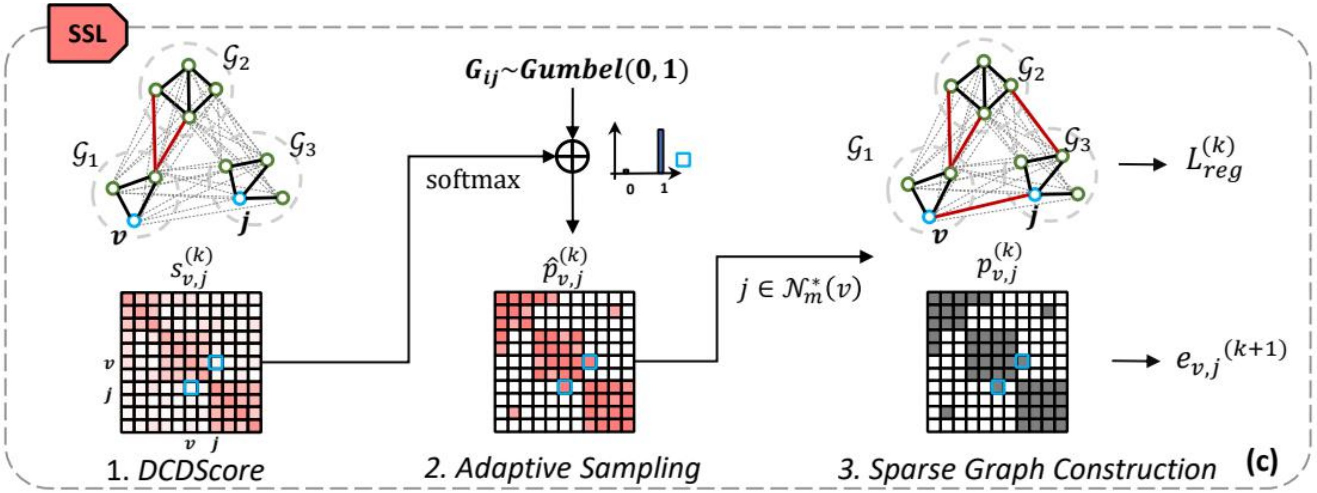
Dynamic Contextual Dependency Score Given a node $v \in \mathcal{V}$ in a complete graph $\mathcal{G}^*$, all neighbors of node v are in $\mathcal{N}^*(v)$, where we can obtain $\mathcal{N}_m^*(v) = \mathcal{N}^*(v) - \mathcal{N}(v)^{(k-1)}$ that contains all global semantic candidate neighbors of node v. We first calculate *attention coefficient score* between each neighbor $j \in \mathcal{N}^*(v)$ and node v as follows:

$$a_{v,j}^{*(k)} = \psi\left(\mathbf{a}^{(k)\top}[h_v^{(k)}\mathbf{W}^{(k)} || h_j^{(k)}\mathbf{W}^{(k)}]\right) \qquad (8)$$

where $\mathbf{W}^{(k)} \in \mathbb{R}^{b\times b}$ denotes the projection for node features $h_v \in \mathbb{R}^{1\times b}$ and $h_j \in \mathbb{R}^{n\times b}$. k denotes the current layer of our model. We adopt function ψ as LeakyReLU$(\cdot)$ activation function, and $\mathbf{a} \in \mathbb{R}^{b\times 1}$ is a learnable vector.

$$s_{v,j}^{(k)} = \frac{\exp(a_{v,j}^{*(k)})}{\sum_{u\in\mathcal{N}^*(v)}\exp(a_{v,u}^{*(k)})}. \qquad (9)$$





Method

Sparse Structure Learning

Gumbel-Softmax Distribution

Formally, let a discrete variable π has a distribution of probabilities $(\phi_1, ..., \phi_n)$ with class $C = \{c_1, ..., c_n\}$. Gumbel-max (Gumbel 1954) provides an efficient way for the categorical distribution to sample x_π with:

$$x_\pi = \operatorname{argmax}(\log \phi_i + G_i) \qquad (3)$$

Gumbel-Softmax to approximate it as follows:

$$\hat{x}_\pi = \frac{\exp((\log(\phi_i) + G_i)/\tau)}{\sum_{j=1}^{n} \exp((\log(\phi_j) + G_j)/\tau)} \qquad (4)$$

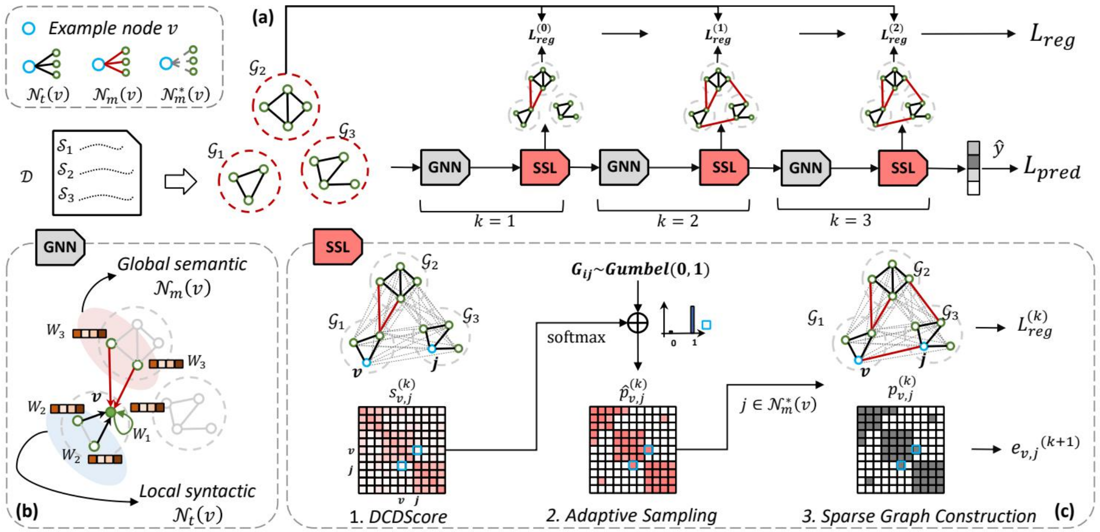
Sampling Adaptive Neighbors for Sparse Structure

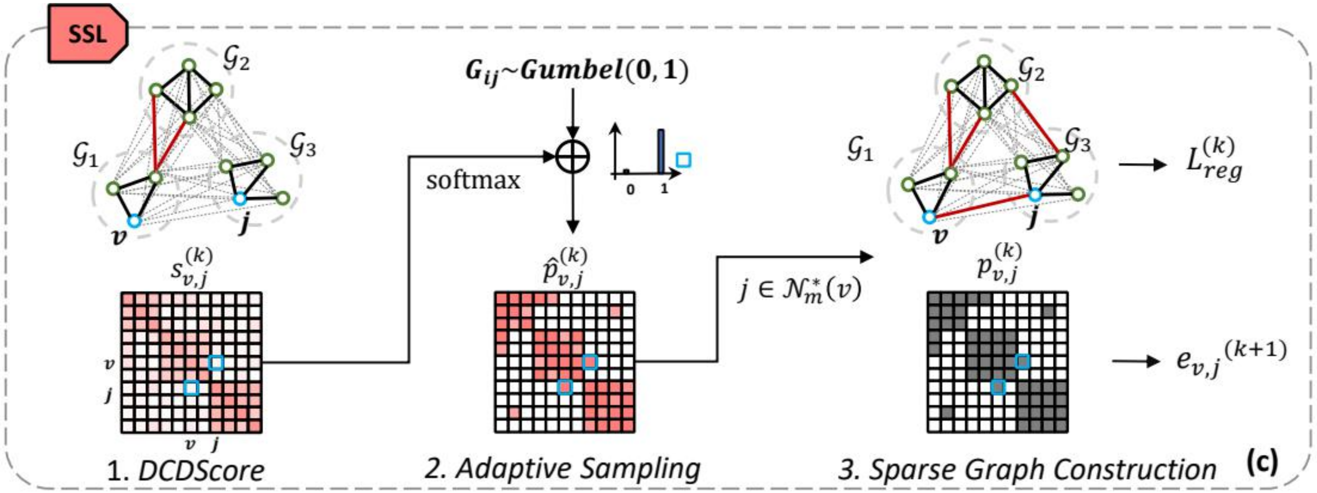
$\{\pi_1 := s_{v,j}^{(k)}, \pi_0 := 1 - s_{v,j}^{(k)}\}$ and adopt Gumbel-Softmax approach to generate differentiable probability $\hat{p}_{v,j}^{(k)}$ of selector samples $p_{v,j}^{(k)}$ as follows:

$$\hat{p}_{v,j}^{(k)} = \frac{\exp((\log \pi_1 + g_1)/\tau)}{\sum_{i \in \{0,1\}} \exp((\log \pi_i + g_i)/\tau)}, \qquad (10)$$

Method

Reconstructing Sparse Graph





document graph. Specifically, we update the global semantic neighbors $\mathcal{N}_m(v)^{(k)}$ for node v with selected candidate neighbors as follows:

$$\mathcal{N}_m(v)^{(k)} = \mathcal{N}_m(v)^{(k-1)} \cup \{j \,||\, \forall j \to p_{v,j}^{(k)} = 1\}. \quad (11)$$

where $j \in \mathcal{N}_m^*(v)$. In addition, for static local syntactic neighbors $\mathcal{N}_t(v)$, we compute the entropy to preserve consistency of the original syntactic information and prevent too much structure variation in the graph.

$$L_{reg}^{(k)} = \sum_{v\in\mathcal{V}} \sum_{j\in\mathcal{N}_t(v)} -\hat{p}_{v,j}^{(k)} \log(\hat{p}_{v,j}^{(k)}), \quad (12)$$

$$L_{pred} = l(R(h_v), y), \quad (13)$$

Experiments

Dataset	#Docs	#Training	#Test	#Classes (ρ)	#Vocab.	Avg.#Length	Avg.#Sentence	#Prop.NW
MR	10,662	7,108	3,554	2 (1.0)	18,764	20.39	1.17	30.09%
R8	7,674	5,485	2,189	8 (84.7)	7,688	65.72	4.03	2.60%
R52	9,100	6,532	2,568	52 (1666.7)	8,892	69.82	4.34	2.63%
Ohsumed	7,400	3,357	4,034	23 (62.5)	14,157	135.82	8.59	8.46%
20NG	18,846	11,314	7,532	20 (1.6)	42,757	221.26	6.06	7.40%

Table 1: Statistics of the datasets. ρ denotes class imbalance ratio (the sample size of the most frequent class divided by that of the least frequent class). The Avg.#Length and the Avg.#Sentence mean the number of words and the number of sentences in a document, respectively. The #Prop.NW denotes the proportion of new words in test.

Experiments

Categories	Baselines	MR	R8	R52	Ohsumed	20NG
Word-based	fastText	72.17±1.30	86.04±0.24	71.55±0.42	14.59±0.00	11.38±1.18
	SWEN	76.65±0.63	95.32±0.26	92.94±0.24	63.12±0.55	85.16±0.29
Sentence-based	CNN-non-static	77.75±0.72	95.71±0.52	87.59±0.48	58.44±1.06	82.15±0.52
	LSTM (pretrain)	77.33±0.89	96.09±0.19	90.48±0.86	51.10±1.50	75.43±1.72
	Bi-LSTM	77.68±0.86	96.31±0.33	90.54±0.91	49.27±1.07	73.18±1.85
Graph-based (Tr)	TextGCN	76.74±0.20	97.07±0.10	93.56±0.18	68.36±0.56	86.34±0.09
	Huang et al.	-	97.80±0.20	94.60±0.30	69.40±0.60	-
	TensorGCN	77.91±0.07	**98.04±0.08**	95.05±0.11	70.11±0.24	**87.74±0.05**
	DHTG	77.21±0.11	97.33±0.06	93.93±0.10	68.80±0.33	87.13±0.07
Graph-based (Ind)	TextING	78.93±0.65	97.34±0.25	93.73±0.47	67.95±0.52	OOM
	HyperGAT	77.36±0.22	96.82±0.21	94.15±0.18	66.39±0.65	84.65±0.31
	Our proposal	**79.74±0.19**	97.81±0.14	**95.48±0.26**	**70.59±0.38**	85.26±0.28

Table 2: Test accuracies of various models on five benchmark datasets. The mean ± standard deviation of all models are reported an average of 10 executions of each model. Graph-based (Tr) means transductive graph-based methods and Graph-based (Ind) means inductive graph-based methods.

Experiments

Graph	R8	R52	Ohsumed
WordCooc	97.20±0.29	93.82±0.15	68.08±0.32
Disjoint	97.29±0.21	94.80±0.20	69.72±0.27
Complete	97.40±0.25	94.35±0.10	67.57±0.30
Ours	97.76±0.16	95.32±0.21	70.53±0.30
Ours w/ reg	**97.81±0.14**	**95.48±0.26**	**70.59±0.38**

Table 3: Comparison with different constructions of document-level graphs. (1) WordCooc denotes word co-occurrence graph. (2) Disjoint means a disjoint union of sentence-level subgraphs. (3) Complete graph means disjoint graph with fully connected edges between sentences. (4) Ours graph is constructed by sentence-level subgraphs and learned by sparse structure learning(w/ reg means we add regularization to our model).

τ	R8	R52	Ohsumed
0.01	97.50±0.29	95.16±0.18	**70.59±0.38**
0.1	97.34±0.13	**95.48±0.26**	70.21±0.40
0.2	97.44±0.39	95.03±0.16	70.33±0.32
0.5	**97.81±0.14**	94.56±0.33	70.34±0.37
1.0	97.35±0.24	95.09±0.32	70.22±0.29

Table 4: Test accuracy with different temperatures τ for adaptive sampling.

Experiments

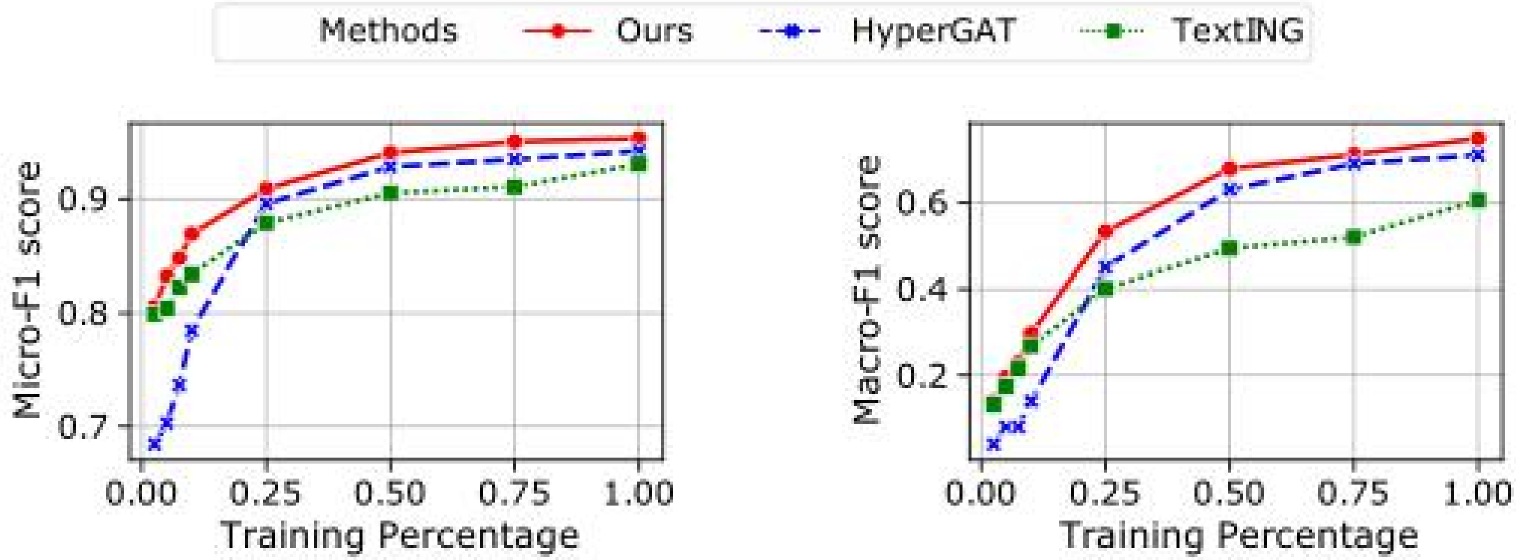


Figure 2: Micro F1 score and Macro F1 score with different percent of training data from 0.025 to 1 on R52 dataset.

Thank you!