HiTIN: Hierarchy-aware Tree Isomorphism Network for Hierarchical Text Classification

He Zhu[1*], **Chong Zhang**[1*], **Junjie Huang**[1], **Junran Wu**[1†], **Ke Xu**[1,2]
[1]State Key Lab of Software Development Environment
Beihang University, Beijing, 100191, China
[2]Zhongguancun Laboratory, Beijing, 100094, China
{roy_zh, chongzh, huangjunjie, wu_junran, kexu}@buaa.edu.cn

Abstract

Hierarchical text classification (HTC) is a challenging subtask of multi-label classification as the labels form a complex hierarchical structure. Existing dual-encoder methods in HTC achieve weak performance gains with huge memory overheads and their structure encoders heavily rely on domain knowledge. Under such observation, we tend to investigate the feasibility of a memory-friendly model with strong generalization capability that could boost the performance of HTC without prior statistics or label semantics. In this paper, we propose Hierarchy-aware Tree Isomorphism Network (HiTIN) to enhance the text representations with only syntactic information of the label hierarchy. Specifically, we convert the label hierarchy into an unweighted tree structure, termed coding tree, with the guidance of structural entropy. Then we design a structure encoder to incorporate hierarchy-aware information in the coding tree into text representations. Besides the text encoder, HiTIN only contains a few multi-layer perceptions and linear transformations, which greatly saves memory. We conduct experiments on three commonly used datasets and the results demonstrate that HiTIN could achieve better test performance and less memory consumption than state-of-the-art (SOTA) methods.

1 Introduction

Hierarchical text classification is a sub-task of text multi-label classification, which is commonly applied in scenarios such as news document classification (Lewis et al., 2004; Sandhaus, Evan, 2008), academic paper classification (Kowsari et al., 2017), and so on. Unlike traditional classification tasks, the labels of HTC have parent-child relationships forming a hierarchical structure. Due to the complex structure of label hierarchy and the imbalanced frequency of labels, HTC becomes a challenging task in natural language processing.

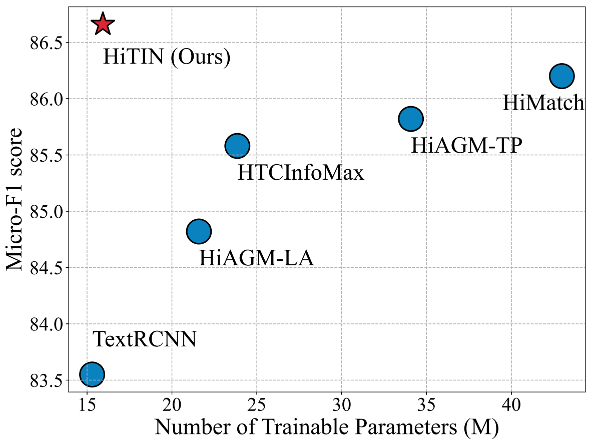


Figure 1: Micro-F1 score and the number of trainable parameters of our method and SOTAs with dual encoders on Web Of Science dataset.

Recent studies in HTC typically utilize a dual-encoder framework (Zhou et al., 2020), which consists of a text encoder for text representations and a structure encoder to inject the information of labels into text. The text encoder could be a traditional backbone for text classification, for instance, TextRCNN (Lai et al., 2015) or BERT (Devlin et al., 2019). The structure encoder is a Graph Neural Network (GNN) that treats the label hierarchy as a Directed Acyclic Graph (DAG) and propagates the information among labels. To maximize the propagation ability of the structure encoder, Zhou et al. (2020) learn textual features of labels and count the prior probabilities between parent and child labels. Based on the dual-encoder framework, researchers further complicated the model by adding complementary networks and loss functions from different aspects, such as treating HTC as a matching problem (Chen et al., 2021), introducing mutual information maximization (Deng et al., 2021). However, more complementary components result in more memory consumption, as shown in Figure 1. On

[*]Equal Contribution.
[†]Correspondence to: Junran Wu.

the other hand, their structure encoders still rely on the prior statistics (Zhou et al., 2020; Chen et al., 2021) or the representation of labels (Zhou et al., 2020; Deng et al., 2021). That is, their models require a mass of domain knowledge, which greatly reduces the generalization ability.

To this end, we intend to design a more effective structure encoder with fewer parameters for HTC. Instead of introducing domain knowledge, we try to take full advantage of the structural information embedded in label hierarchies. Inspired by Li and Pan (2016), we decode the essential structure of label hierarchies into coding trees with the guidance of structural entropy, which aims to measure the structural complexity of a graph. The coding tree is unweighted and could reflect the hierarchical organization of the original graph, which provides us with another view of the label hierarchy. To construct coding trees, we design an algorithm, termed CodIng tRee Construction Algorithm (CIRCA) by minimizing the structural entropy of label hierarchies. Based on the hierarchical structure of coding trees, we propose Hierarchical-aware Tree Isomorphism Network (HiTIN). The document representations fetched by the text encoder are fed into a structure encoder, in which we iteratively update the node embeddings of the coding tree with a few multi-layer perceptions. Finally, we produce a feature vector of the entire coding tree as the final representation of the document. Compared with SOTA methods of dual encoders on HTC tasks (Zhou et al., 2020; Chen et al., 2021; Deng et al., 2021; Wang et al., 2022a), HiTIN shows superior performance gains with less memory consumption. Overall, the contributions of our work can be summarized as follows:

- To improve the generalization capability of dual-encoder models in HTC, we decode the essential structure of label hierarchies with the guidance of structural entropy.

- We propose HiTIN, which has fewer learnable parameters and requires less domain knowledge, to fuse the structural information of label hierarchies into text representations.

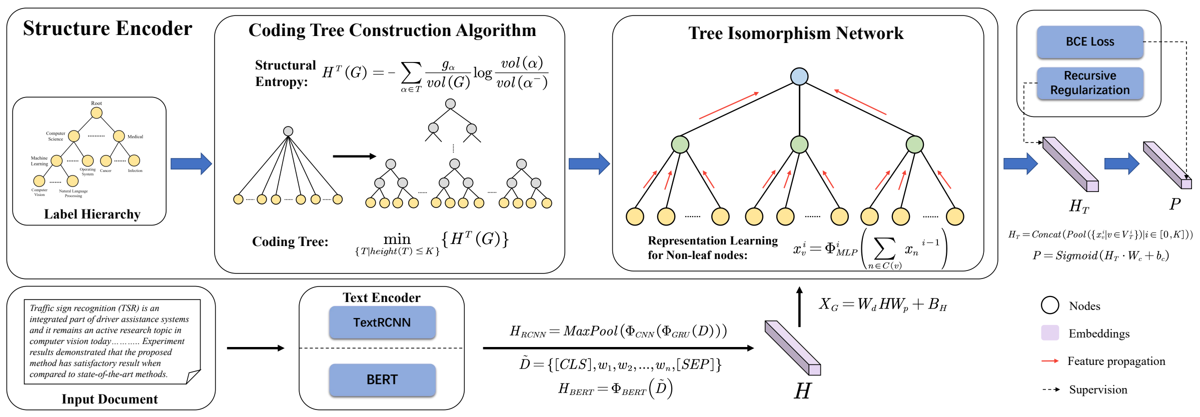
- Numerous experiments are conducted on three benchmark datasets to demonstrate the superiority of our model. For reproducibility, our code is available at https://github.com/Rooooyy/HiTIN.

2 Related Work

Hierarchical Text Classification. Existing works for HTC could be categorized into local and global approaches (Zhou et al., 2020). Local approaches build classifiers for a single label or labels at the same level in the hierarchy, while global approaches treat HTC as a flat classification task and build only one classifier for the entire taxonomy. Previous local studies mainly focus on transferring knowledge from models in the upper levels to models in the lower levels. Kowsari et al. (2017) first feed the whole corpus into the parent model and then input the documents with the same label marked by the parent model into a child model. In the next few years, researchers try different techniques to deliver knowledge from high-level models to low-level models (Shimura et al., 2018; Huang et al., 2019; Banerjee et al., 2019).

Global studies in HTC try to improve flat multi-label classification by introducing various information from the hierarchy. Gopal and Yang (2013) propose a recursive regularization function to make the parameters of adjacent categories have similar values. Peng et al. (2018) propose a regularized graph-CNN model to capture the non-consecutive semantics from texts. Besides, various deep learning techniques, such as sequence-to-sequence model (Yang et al., 2018; Rojas et al., 2020), attention mechanism (You et al., 2019), capsule network (Aly et al., 2019; Peng et al., 2021), reinforcement learning (Mao et al., 2019), and meta-learning (Wu et al., 2019) are also applied in global HTC. Recently, Zhou et al. (2020) specially design an encoder for label hierarchies which could significantly improve performance. Chen et al. (2020) learn the word and label embeddings jointly in the hyperbolic space. Chen et al. (2021) formulate the text-label relationship as a semantic matching problem. Deng et al. (2021) introduce information maximization which can model the interaction between text and label while filtering out irrelevant information. With the development of Pretrained Language Model (PLM), BERT(Devlin et al., 2019) based contrastive learning(Wang et al., 2022a), prompt tuning(Wang et al., 2022b), and other methods (Jiang et al., 2022) have brought huge performance boost to HTC.

Structural Entropy. Structural entropy (Li and Pan, 2016) is a natural extension of Shannon en-


Structure Encoder
Label Hierarchy
Root
Computer Science
Medical
Machine Learning
Operating System
Cancer
Infection
Computer Vision
Natural Language Processing
Coding Tree Construction Algorithm
Structural Entropy: $H^T(G) = -\sum_{\alpha \in T} \frac{g_\alpha}{vol(G)} \log \frac{vol(\alpha)}{vol(\alpha^-)}$
Coding Tree: $\min_{\{T \mid height(T) \le K\}} \{H^T(G)\}$
Tree Isomorphism Network
Representation Learning for Non-leaf nodes: $x_v^i = \Phi_{MLP}^i\left(\sum_{n \in C(v)} x_n^{i-1}\right)$
BCE Loss
Recursive Regularization
H_T
P
$H_T = Concat(Pool(\{x_v^i \mid v \in V_T^i\}) \mid i \in [0, K])$
$P = Sigmoid(H_T \cdot W_c + b_c)$
Input Document
Text Encoder
TextRCNN
BERT
$H_{RCNN} = MaxPool(\Phi_{CNN}(\Phi_{GRU}(D)))$
$\hat{D} = \{[CLS], w_1, w_2, \ldots, w_n, [SEP]\}$
$H_{BERT} = \Phi_{BERT}(\hat{D})$
H
$X_G = W_d H W_p + B_H$
Nodes
Embeddings
Feature propagation
Supervision

Traffic sign recognition (TSR) is an integrated part of driver assistance systems and it remains an active research topic in computer vision today………. Experiment results demonstrated that the proposed method has satisfactory result when compared to state-of-the-art methods.

Figure 2: An example of HiTIN with $K = 2$. As shown in Section 4.1, the input document is first fed into the text encoder to generate text representations. Next, the label hierarchy is transformed into a coding tree via Coding Tree Construction Algorithm proposed in Section 4.2. The text representations are mapped into the leaf nodes of the coding tree and we iteratively update the non-leaf node embeddings in Section 4.2. Finally, we produce a feature vector of the entire coding tree and calculate the classification probabilities in Section 4.3. Besides, HiTIN is supervised by binary cross-entropy loss and recursive regularization (Gopal and Yang, 2013).

tropy (Shannon, 1948) on graphs as structure entropy could measure the structural complexity of a graph. The structural entropy of a graph is defined as the average length of the codewords obtained by a random walk under a specific coding scheme. The coding scheme, termed coding tree (Li and Pan, 2016), is a tree structure that encodes and decodes the essential structure of the graph. In other words, to minimize structural entropy is to remove the noisy information from the graph. In the past few years, structural entropy has been successfully applied in network security (Li et al., 2016a), medicine (Li et al., 2016b), bioinformatics (Li et al., 2018), graph classification (Wu et al., 2022b,a), text classification (Zhang et al., 2022), and graph contrastive learning (Wu et al., 2023).

3 Problem Definition

Given a document $D = \{w_1, w_2, \ldots, w_n\}$, where w_i is a word and n denotes the document length, hierarchical text classification aims to predict a subset $\mathcal{Y}$ of the holistic label set Y. Besides, every label in Y corresponds to a unique node on a directed acyclic graph, i.e. the label hierarchy. The label hierarchy is predefined and usually simplified as a tree structure. In the groud-truth label set, a non-root label y_i always co-occurs with its parent nodes, that is, for any $y_i \in \mathcal{Y}$, the parent node of y_i is also in $\mathcal{Y}$.

4 Methodology

Following the dual-encoder scheme in HTC, the architecture of HiTIN that consists of a text encoder and a structure encoder is shown in Figure 2. The text encoder aims to capture textual information from the input document while the structure encoder could model the label correlations in the hierarchy and inject the information from labels into text representations.

4.1 Text Encoder

In HTC, text encoder generally has two choices, that is, TextRCNN encoder and BERT encoder. TextRCNN (Lai et al., 2015) is a traditional method in text classification, while BERT (Devlin et al., 2019) has shown its powerful ability in sequence feature extraction and has been widely applied in natural language processing in the past few years.

TextRCNN Encoder. The given document $D = \{w_1, w_2, \ldots, w_n\}$, which is a sequence of word embeddings, is firstly fed into a bidirectional GRU layer to extract sequential information. Then, multiple CNN blocks along with max pooling over time are adopted to capture n-gram features. Formally,

$$H_{RCNN} = MaxPool(\Phi_{CNN}(\Phi_{GRU}(D))), \quad (1)$$

where $\Phi_{CNN}(\cdot)$ and $\Phi_{GRU}(\cdot)$ respectively denote a CNN and a GRU layer, while $MaxPool(\cdot)$ denotes the max pooling over time operation. Besides, $H_{RCNN} \in \mathbb{R}^{n_C \times d_C}$, where n_C denotes the number of CNN kernels and d_C denotes the output channels of each CNN kernel.

The final representation $H \in \mathbb{R}^{n_C * d_C}$ of document D is the concatenation of H_{RCNN}. That is,

$$H = Concat(H_{RCNN}). \tag{2}$$

BERT Encoder. Recent works in HTC also utilize BERT for learning textual features (Chen et al., 2021; Wang et al., 2022a). Since there are few changes made to the vanilla BERT, we only introduce the workflow of our model and omit the details of BERT.

Given a input document $D = \{w_1, w_2, \ldots, w_n\}$, we pad the document with two specical tokens:

$$\tilde{D} = \{[CLS], w_1, w_2, \ldots, w_n, [SEP]\}, \tag{3}$$

where $[CLS]$ and $[SEP]$ respectively denote the beginning and the end of the document. After padding and truncating, document $\tilde{D}$ is fed into BERT. Then BERT generates embeddings for each token in the document:

$$H_{BERT} = \Phi_{BERT}(\tilde{D}), \tag{4}$$

where $H_{BERT} \in \mathbb{R}^{(n+2)\times d_B}$, and $\Phi_{BERT}(\cdot)$ denotes the BERT model. We adopt the CLS embedding as the representation of the entire text sequence. Thus, the final representation H of document D is:

$$H = H^0_{BERT}, H \in \mathbb{R}^{d_B}, \tag{5}$$

where d_B is the hidden dimension.

4.2 Structure Encoder

The semantic information provided by text encoder is then input into the structure encoder. Unlike previous works, we do not utilize the prior statistics or learn representations of the label hierarchy. Instead, we design a suite of methods guided by structural entropy (Li and Pan, 2016) to effectively incorporate the information of text and labels.

Structural Entropy. Inspired by Li and Pan (2016), we try to simplify the original structure of the label hierarchy by minimalizing its structural entropy. The structural entropy of a graph is defined as the average length of the codewords obtained by a random walk under a specific coding pattern named coding tree (Li and Pan, 2016). Given a graph $G = (V_G, E_G)$, the structural entropy of G on coding tree T is defined as:

$$H^T(G) = -\sum_{\alpha \in T} \frac{g_\alpha}{vol(G)} \log \frac{vol(\alpha)}{vol(\alpha^-)}, \tag{6}$$

where α is a non-root node of coding tree T which represents a subset of V_G, α^- is the parent node of α on the coding tree. g_α represents the number of edges with only one endpoint in α and the other end outside α, that is, the out degree of α. $vol(G)$ denotes the volume of graph G while $vol(\alpha)$ and $vol(\alpha^-)$ is the sum of the degree of nodes that respectively partitioned by α and α^-.

For a certain coding pattern, the height of the coding tree should be fixed. Therefore, the K-dimensional structural entropy of the graph G determined by the coding tree T with a certain height K is defined as:

$$H_K(G) = \min_{\{T|height(T)\leq K\}} H^T(G). \tag{7}$$

Coding Tree Construction Algorithm. To minimize the structural entropy of graph G, we design a CodIng tRee Construction Algorithm (CIRCA) to heuristically construct a coding tree T with a certain height no greater than K. That is, $T = CIRCA(G, K)$, where $T = (V_T, E_T)$, $V_T = (V^0_T, \ldots, V^h_T)$. To better illustrate CIRCA, we make some definitions as follows,

Definition 1 *Let $T = (V_T, E_T)$ be a coding tree for graph $G = (V_G, E_G)$, v_r be the root node of T. For any $(v_i, v_j) \in T$, if v_i is the direct child node of v_j, denote that*

$$v_i \in v_j.children;$$

and v_j is equivalent to $v_i.parent$.

Definition 2 *Following Definition 1, given any two nodes $(v_i, v_j) \in T$, in which $v_i \in v_r.children$ and $v_j \in v_r.children$.*

Define a member function $merge(v_i, v_j)$ of T. $T.merge(v_i, v_j)$ could insert a new node v_ϵ bewtween v_r and (v_i, v_j). Formally,

$$\begin{aligned} v_\epsilon.children &\leftarrow v_i; \\ v_\epsilon.children &\leftarrow v_j; \\ v_r.children &\leftarrow v_\epsilon; \\ V_T^{v_i.height+1} \leftarrow v_\epsilon; \quad E_T &\leftarrow (v_\epsilon, v_i), (v_\epsilon, v_j); \end{aligned}$$

Definition 3 *Following Definition 1, given a node v_i. Define a member function $delete(v_i)$ of T. $T.delete(v_i)$ could delete v_i from T and attach* *the child nodes of v_i to its parent node. Formally,*

$$v_i.parent.children \leftarrow v_i.children;$$
$$V_T := V_T - \{v_i\};$$
$$E_T := E_T - \{(v_i.parent, v_i)\};$$
$$E_T := E_T - \{(v_i, v) | v \in v_i.children\};$$

Definition 4 *Following Definition 1, given any two nodes(v_i, v_j), in which $v_i \in v_j.children$. Define a member function $shift(v_i, v_j)$ of T. $T.shift(v_i, v_j)$ could insert a new node v_ϵ between v_i and v_j:*

$$v_\epsilon.children \leftarrow v_i; \quad v_j.children \leftarrow v_\epsilon;$$
$$V_T^{v_i.height+1} \leftarrow v_\epsilon; \quad E_T \leftarrow \{(v_j, v_\epsilon), (v_\epsilon, v_i)\};$$

Based on the above definitions, the pseudocode of CIRCA can be found in Algorithm 1. More details about coding trees and CIRCA are shown in Appendix A.

Algorithm 1 Coding Tree Construction Algorithm

```
Input: A graph $G = (V_G, E_G)$ , a postive integer $K$
Output: Coding tree $T = (V_T, E_T)$ of the graph $G$ with height $K$
 1: $V_T^0 := V$;
    {Stage 1: Construct a full-height binary-tree}
 2: while $|v_r.children| > 2$ do
 3:     $(v_i, v_j) = argmax_{(v,v')}\{H^T(G) - H^{T.merge(v,v')}(G)\}$
 4:     $T.merge(v_i, v_j)$
 5: end while
    {Stage 2: Squeeze $T$ to height $K$}
 6: while $T.height > K$ do
 7:     $v_i = argmin_v\{H^{T.remove(v)}(G) - H^T(G)\}$
 8:     $T.remove(v_i)$
 9: end while
    {Stage 3: Erase cross-layer links}
10: for $v_i \in T$ do
11:     if $|v_i.parent.height - v_i.height| > 1$ then
12:         $T.shift(v_i, v_i.parent)$
13:     end if
14: end for
15: return $T$
```

Hierarchy-aware Tree Isomorphism Network. For representation learning, we reformulate the label hierarchy as a graph $G_L = (V_{G_L}, E_{G_L}, X_{G_L})$, where V_{G_L}, E_{G_L} respectively denotes the node set and the edge set of G_L, $V_{G_L} = Y$ while E_{G_L} is predefined in the corpus. In our work, V_{G_L} and E_{G_L} are represented by the unweighted adjacency matrix of G_L. X_{G_L} is the node embedding matrix of G_L. Instead of learning the concept of labels, we directly broadcast the text representation to the label structure. Specifically, X_G is transformed from the text representation H by duplication and projection. Formally,

$$X_G = W_d H W_p + B_H, \tag{8}$$

where $W_d \in \mathbb{R}^{|Y| \times 1}$ and $W_p \in \mathbb{R}^{d_H * d_V}$ are learnable weights for the duplication and projection. $|Y|$ is the volume of the label set. d_H and d_V respectively denote the dimension of text and node. B_H indicates the learnable bias and $B_H \in \mathbb{R}^{|Y| \times d_v}$.

Next, we simplify the structure of the label hierarchy into a coding tree with the guidance of structural entropy. Given a certain height K, the coding tree $T_L = (V_{T_L}, E_{T_L}, X_{T_L})$ of the label hierarchy could be constructed by CIRCA,

$$(V_{T_L}, E_{T_L}) = CIRCA(G_L, K), \tag{9}$$

where $V_{T_L} = \{V_{T_L}^0, V_{T_L}^1, ...V_{T_L}^K\}$ are the layer-wise node sets of coding tree T_L while $X_{T_L} = \{X_{T_L}^0, X_{T_L}^1, ..., X_{T_L}^K\}$ represents the node embeddings of $V_{T_L}^i$, $i \in [0, K]$.

The coding tree T_L encodes and decodes the essential structure of G_L, which provides multi-granularity partitions for G_L. The root node v_r is the roughest partition which represents the whole node set of G_L, so $V_{T_L}^K = \{v_r\}$. For every node v and its child nodes $\{v_1, v_2, \ldots, v_z\}$, $v_1, v_2, \ldots,$ and v_z formulate a partition of v. Moreover, the leaf nodes in T_L is an element-wise partition for G_L, that is, $V_{T_L}^0 = V_{G_L}$, $X_{T_L}^0 = X_{G_L}$.

Note that $\{V_{T_L}^i | i \in [1, K]\}$ is given by CIRCA while their node embeddings $\{X_{T_L}^i | i \in [1, K]\}$ remain empty till now. Thus, we intend to update the un-fetched node representation of coding tree T_L. Following the message passing mechanism in Graph Isomorphism Network (GIN) (Xu et al., 2019), we design Hierarchy-aware Tree Isomorphism Network (HiTIN) according to the structure of coding trees. For $x_v^i \in X_{T_L}^i$ in the i-th layer,

$$x_v^i = \Phi_{MLP}^i(\textstyle\sum_{n \in C(v)} x_n^{i-1}), \tag{10}$$

where $v \in V_T^i$, $x_v^i \in \mathbb{R}^{d_V}$ is the feature vector of node v, and $C(v)$ represents the child nodes of v

in coding tree T_L. $\Phi^i_{MLP}(\cdot)$ denotes a two-layer multi-layer perception within BatchNorm (Ioffe and Szegedy, 2015) and ReLU function. The learning stage starts from the leaf node (layer 0) and learns the representation of each node layer by layer until reaching the root node (layer K). Finally, a read-out function is applied to compute a representation of the entire coding tree T_L:

$$H_T = Concat(Pool(\{x^i_v | v \in V^i_{T_L}\}) \\ | i \in [0, K])), \quad (11)$$

where $Concat(\cdot)$ indicates the concatenation operation. $Pool(\cdot)$ in Eq. 11 can be replaced with a summation, averaging, or maximization function. $H_T \in \mathbb{R}^{d_T}$ denotes the final representation of T_L.

4.3 Classification and Loss Function

Similar to previous studies (Zhou et al., 2020; Wang et al., 2022a), we flatten the hierarchy by attaching a unique multi-label classifier. H_T is fed into a linear layer along with a sigmoid function to generate classification probability:

$$P = Sigmoid(H_T \cdot W_c + b_c), \quad (12)$$

where $W_c \in \mathbb{R}^{d_T \times |Y|}$ and $b_c \in \mathbb{R}^{|Y|}$ are weights and bias of linear layer while $|Y|$ is the volume of the label set. For multi-label classification, we adopt the Binary Cross-Entropy Loss as the classification loss:

$$L^C = -\frac{1}{|Y|} \sum_{j}^{|Y|} y_j log(p_j) + (1 - y_j) log(1 - p_j), \quad (13)$$

where y_j is the ground truth of the j-th label while p_j is the j-th element of P. Considering hierarchical classification, we use recursive regularization Gopal and Yang (2013) to constrain the weights of adjacent classes to be in the same distributions as formulated in Eq. 14:

$$L^R = \sum_{p \in Y} \sum_{q \in child(p)} \frac{1}{2} ||w_p^2 - w_q^2||, \quad (14)$$

where p is a non-leaf label in Y and q is a child of p. $w_p, w_q \in W_c$. We use a hyper-parameter λ to control the strength of recursive regularization. Thus, the final loss function can be formulated as:

$$L = L^C + \lambda \cdot L^R. \quad (15)$$

Dataset	$\|Y\|$	$Avg(y_i)$	Depth	# Train	# Dev	# Test
WOS	141	2.0	2	30,070	7,518	9,397
RCV1-v2	103	3.24	4	20,833	2,316	781,265
NYTimes	166	7.6	8	23,345	5,834	7,292

Table 1: Summary statistics of datasets.

5 Experiments

5.1 Experiment Setup

Datasets and Evaluation Metrics. We conduct experiments on three benchmark datasets in HTC. RCV1-v2 (Lewis et al., 2004) and NYT (Sandhaus, Evan, 2008) respectively consist of news articles published by Reuters, Ltd. and New York Times, while WOS (Kowsari et al., 2017) includes abstracts of academic papers from Web of Science. Each of these datasets is annotated with ground-truth labels in a given hierarchy. We split and preprocess these datasets following Zhou et al. (2020). The statistics of these datasets are shown in Table 1. The experimental results are measured with Micro-F1 and Macro-F1 (Gopal and Yang, 2013). Micro-F1 is the harmonic mean of the overall precision and recall of all the test instances, while Macro-F1 is the average F1-score of each category. Thus, Micro-F1 reflects the performance on more frequent labels, while Macro-F1 treats labels equally.

Implementation Details. The text embeddings fed into the TextRCNN encoder are initialized with GloVe (Pennington et al., 2014). The TextRCNN encoder consists of a two-layer BiGRU with hidden dimension 128 and CNN layers with kernel size=[2, 3, 4] and d_C=100. Thus, the hidden dimension of the final text representation is $d_H = r_C * d_C = 3 * 100 = 300$. The height K of the coding tree is 2 for all three datasets. The hidden dimension d_V of node embedding X_G is set to 512 for RCV1-v2 while 300 for WOS and NYTimes. $Pool(\cdot)$ in Eq. 11 is summation for all the datasets. The balance factor λ for L^R is set to 1e-6. The batch size is set to 16 for RCV1-v2 and 64 for WOS and NYTimes. The model is optimized by Adam (Kingma and Ba, 2014) with a learning rate of 1e-4.

For BERT text encoder, we use the BertModel of `bert-base-uncased` and there are some negligible changes to make it compatible with our method. $d_B = d_H = d_V = 768$. The height K of the coding tree is 2 and the $Pool(\cdot)$ in Eq. 11 is averaging. The batch size is set to 12, and the BertModel is fine-tuned by Adam (Kingma and Ba, 2014) with a learning rate of 2e-5.

Hierarchy-aware Models	WOS		RCV1-v2		NYTimes		Average	
	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
TextRCNN (Zhou et al., 2020)	83.55	76.99	81.57	59.25	70.83	56.18	78.65	64.14
HiAGM (Zhou et al., 2020)	85.82	80.28	83.96	63.35	74.97	60.83	81.58	68.15
HTCInfoMax (Deng et al., 2021)	85.58	80.05	83.51	62.71	-	-	-	-
HiMatch (Chen et al., 2021)	86.20	80.53	84.73	64.11	-	-	-	-
HiTIN	**86.66**	**81.11**	**84.81**	**64.37**	**75.13**	**61.09**	**82.20**	**68.86**

Table 2: Main Experimental Results with TextRCNN encoders. All baselines above and our method utilize GloVe embeddings (Pennington et al., 2014) to initialize documents and encode them with TextRCNN (Lai et al., 2015).

Pretrained Language Models	WOS		RCV1-v2		NYTimes		Average	
	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
BERT †	85.63	79.07	85.65	67.02	78.24	65.62	83.17	70.57
BERT+HiAGM†	86.04	80.19	85.58	67.93	78.64	66.76	83.42	71.63
BERT+HTCInfoMax†	86.30	79.97	85.53	67.09	78.75	67.31	83.53	71.46
BERT+HiMatch (Chen et al., 2021)	86.70	81.06	86.33	68.66	-	-	-	-
HGCLR (Wang et al., 2022a)	87.11	81.20	86.49	68.31	78.86	67.96	84.15	72.49
HiTIN	**87.19**	**81.57**	**86.71**	**69.95**	**79.65**	**69.31**	**84.52**	**73.61**

Table 3: Main Experimental Results with BERT encoder. All baselines above and our method adopt BERT(Devlin et al., 2019) as the text encoder. † denotes the results are reported by Wang et al. (2022a).

Baselines. We compare HiTIN with SOTAs including HiAGM(Zhou et al., 2020), HTCInfoMax (Deng et al., 2021), HiMatch (Chen et al., 2021), and HGCLR (Wang et al., 2022a). HiAGM, HTCInfoMax, and HiMatch use different fusion strategies to model text-hierarchy correlations. Specifically, HiAGM proposes a multi-label attention and a text feature propagation technique to get hierarchy-aware representations. HTCInfoMax enhances HiAGM-LA with information maximization to model the interaction between text and hierarchy. HiMatch treats HTC as a matching problem by mapping text and labels into a joint embedding space. HGCLR directly incorporates hierarchy into BERT with contrastive learning.

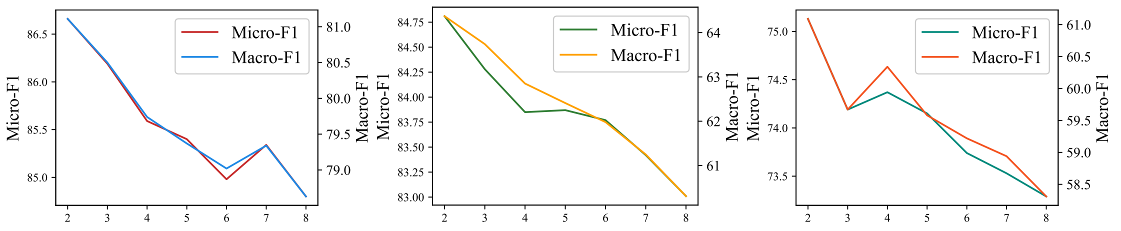
5.2 Experimental Results

The experimental results with different types of text encoders are shown in Table 2 and Table 3. HiAGM is the first method to apply the dual-encoder framework and outperforms TextRCNN on all the datasets. HTCInfoMax improves HiAGM-LA (Zhou et al., 2020) by introducing mutual information maximization but is still weaker than HiAGM-TP. HiMatch treats HTC as a matching problem and surpasses HiAGM-TP(Zhou et al., 2020) on WOS and RCV1-v2. Different from these methods, HiTIN could further extract the information in the text without counting the prior probabilities between parent and child labels or building feature vectors for labels. As shown in Table 2, when using TextRCNN as the text encoder, our model outperforms all baselines on the three datasets. Based on TextRCNN, HiTIN brings 3.55% and 4.72% improvement of Micro-F1 and Macro-F1 on average.

As for pretrained models in Table 3, our model also beats existing methods in all three datasets. Compared with vanilla BERT, our model can significantly refine the text representations by respectively achieving 1.2% and 3.1% average improvement of Micro-F1 and Macro-F1 on the three datasets. In addition, our method can achieve 3.69% improvement of Macro-F1 on NYT, which has the deepest label hierarchy in the three datasets. It demonstrates the superiority of our model on the dataset with a complex hierarchy. Compared with BERT-based HTC methods, our model observes a 1.12% average improvement of Macro-F1 against HGCLR. On RCV1-v2, the performance boost of Macro-F1 even reaches 1.64%. The improvement of Macro-F1 shows that our model could effectively capture the correlation between parent and child labels even without their prior probabilities.

Ablation Models	WOS		RCV1-v2		NYTimes	
	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
HiTIN(Random)	84.74	77.90	82.41	61.46	71.99	58.26
w/o L^R	86.48	80.48	84.14	63.12	74.93	59.95
HiTIN	**86.66**	**81.11**	**84.81**	**64.37**	**75.13**	**61.09**

Table 4: Performance when replacing or removing a component of HiTIN. HiTIN(Random) denotes the results produced by HiTIN within the random algorithm. w/o L^R stands for the parameter λ is set to 0.



(a) WOS (b) RCV1-v2 (c) NYTimes

Figure 3: Test performance of HiTIN with different height K of the coding tree on three datasets.

5.3 The Necessity of CIRCA

In this subsection, we illustrate the effectiveness of CIRCA by comparing it to a random algorithm. The random algorithm generates a coding tree of the original graph G with a certain height K just like CIRCA. First, the random algorithm also takes all nodes of graph G as leaf nodes of the tree. But different from CIRCA, for each layer, every two nodes are randomly paired and then connect to their parent node. Finally, all nodes in the $K - 1_{th}$ layer are connected to a root node. We generate coding trees with the random algorithm and then feed them into our model.

As shown in Table 4, the results demonstrate that the random algorithm leads to a negative impact which destroys the original semantic information. Thus, it is difficult for the downstream model to extract useful features. On the contrary, the coding tree constructed by CIRCA can retain the essential structure of the label hierarchy and make the learning procedure more effective. Besides, our model could achieve good performance without Eq. 14, which proves that CIRCA could retain the information of low-frequency labels while minimizing the structural entropy of label hierarchies.

5.4 The Height of Coding Tree

The height of the coding tree directly affects the performance of our model. The higher the coding tree, the more information is compressed. To investigate the impact of K, we run HiTIN with different heights K of the coding tree while keeping other settings the same. Figure 3 shows the test performance of different height coding trees on WOS, RCV1-v2, and NYTimes. As K grows, the performance of HiTIN is severely degraded. Despite the different depths of label hierarchy, the optimal heights of the coding tree for the three datasets are always 2. A probable reason is that the 2-dimensional structural entropy roughly corresponds to objects in the 2-dimensional space as the text and label are both represented with 2-D tensors. On the other hand, as K grows, more noisy information is eliminated, but more useful information is also compressed.

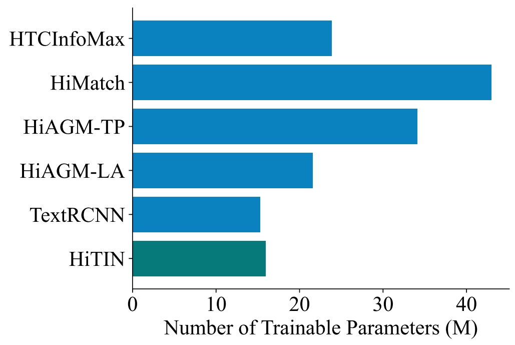


Figure 4: The number of trainable parameters of HiTIN and baseline models on WOS.

5.5 The Mermory-saving Feature of HiTIN

In this subsection, we compare the number of learnable parameters of HiTIN with that of the baselines. We set K to 2 and run these models on WOS while keeping the other hyper-parameter the same. The numbers of trainable parameters are counted by the $numel(\cdot)$ function in PyTorch (Paszke et al., 2019). As shown in Figure 4, we can observe that the parameter of our model is slightly greater than TextRCNN (Zhou et al., 2020) but significantly smaller than HiAGM (Zhou et al., 2020), HiMatch (Chen et al., 2021), and HTCInfoMax (Deng et al., 2021). One important reason is the simple and efficient architecture of HiTIN, which contains only a few MLPs and linear transformations. On the contrary, HiAGM-LA (Zhou et al., 2020) needs extra memory for label representations, HiAGM-TP uses a space-consuming method for text-to-label transformation, and both of them utilized gated network as the structure encoder, which further aggravates memory usage. HiMatch (Chen et al., 2021) and HTCInforMax (Deng et al., 2021) respectively introduce auxiliary neural networks based on HiAGM-TP and HiAGM-LA. Thus, their memory usages are even larger.

6 Conclusion

In this paper, we propose a suite of methods to address the limitations of existing approaches regarding HTC. In particular, tending to minimize structural entropy, we design CIRCA to construct coding trees for the label hierarchy. To further extract textual information, we propose HiTIN to update node embeddings of the coding tree iteratively. Experimental results demonstrate that HiTIN could enhance text representations with only structural information of the label hierarchy. Our model outperforms existing methods while greatly reducing memory increments.

Limitations

For text classification tasks, the text encoder is more important than other components. Due to the lack of label semantic information and simplified learning procedure, the robustness of text encoders directly affects the performance of our model. From Table 2 and 3, we could observe that BERT has already surpassed TextRCNN by 4.52% and 6.43% on Micro-F1 and Macro-F1. Besides, BERT beats all the TextRCNN-based methods on RCV1-v2 and NYTimes. However, when applying BERT as the text encoder, our model makes slight improvements to Micro-F1, especially on WOS. A probable reason is that BERT was pre-trained on news corpus while WOS consists of academic papers.

Acknowledgements

This research was supported by NSFC (Grant No. 61932002).

References

Rami Aly, Steffen Remus, and Chris Biemann. 2019. Hierarchical multi-label classification of text with capsule networks. In *ACL*.

Siddhartha Banerjee, Cem Akkaya, Francisco Perez-Sorrosal, and Kostas Tsioutsiouliklis. 2019. Hierarchical transfer learning for multi-label text classification. In *ACL*.

Boli Chen, Xin Huang, Lin Xiao, Zixin Cai, and Liping Jing. 2020. Hyperbolic interaction model for hierarchical multi-label classification. In *AAAI*.

Haibin Chen, Qianli Ma, Zhenxi Lin, and Jiangyue Yan. 2021. Hierarchy-aware label semantics matching network for hierarchical text classification. In *ACL*.

Zhongfen Deng, Hao Peng, Dongxiao He, Jianxin Li, and Philip S. Yu. 2021. Htcinfomax: A global model for hierarchical text classification via information maximization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021*, pages 3259–3265. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics.

Siddharth Gopal and Yiming Yang. 2013. Recursive regularization for large-scale classification with hierarchical and graphical dependencies. *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*.

Wei Huang, Enhong Chen, Qi Liu, Yuying Chen, Zai Huang, Yang Liu, Zhou Zhao, Dandan Zhang, and Shijin Wang. 2019. Hierarchical multi-label text classification: An attention-based recurrent network approach. *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*.

Sergey Ioffe and Christian Szegedy. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *Proceedings of the 32nd International Conference on Machine Learning, ICML 2015, Lille, France, 6-11 July 2015*, volume 37 of *JMLR Workshop and Conference Proceedings*, pages 448–456. JMLR.org.

Ting Jiang, Deqing Wang, Leilei Sun, Zhong-Yong Chen, Fuzhen Zhuang, and Qinghong Yang. 2022. Exploiting global and local hierarchies for hierarchical text classification.

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.

Kamran Kowsari, Donald E. Brown, Mojtaba Heidarysafa, K. Meimandi, Matthew S. Gerber, and Laura E. Barnes. 2017. Hdltex: Hierarchical deep learning for text classification. *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 364–371.

Siwei Lai, Liheng Xu, Kang Liu, and Jun Zhao. 2015. Recurrent convolutional neural networks for text classification. In *AAAI*.

David D. Lewis, Yiming Yang, Tony G. Rose, and Fan Li. 2004. Rcv1: A new benchmark collection for text categorization research. *J. Mach. Learn. Res.*, 5:361–397.

Angsheng Li, Qifu Hu, Jun Liu, and Yicheng Pan. 2016a. Resistance and security index of networks: Structural information perspective of network security. *Scientific Reports*, 6.

Angsheng Li and Yicheng Pan. 2016. Structural information and dynamical complexity of networks. *IEEE Transactions on Information Theory*, 62:3290–3339.

Angsheng Li, Xianchen Yin, and Yicheng Pan. 2016b. Three-dimensional gene map of cancer cell types: Structural entropy minimisation principle for defining tumour subtypes. *Scientific Reports*, 6.

Angsheng Li, Xianchen Yin, Bingxian Xu, Danyang Wang, Jimin Han, Yi Wei, Yun Deng, Yingluo Xiong, and Zhihua Zhang. 2018. Decoding topologically associating domains with ultra-low resolution hi-c data by graph structural entropy. *Nature Communications*, 9.

Yuning Mao, Jingjing Tian, Jiawei Han, and Xiang Ren. 2019. Hierarchical text classification with reinforced label assignment. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pages 445–455. Association for Computational Linguistics.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc.

Hao Peng, Jianxin Li, Qiran Gong, Senzhang Wang, Lifang He, Bo Li, Lihong Wang, and Philip S. Yu. 2021. Hierarchical taxonomy-aware and attentional graph capsule rcnns for large-scale multi-label text classification. *IEEE Transactions on Knowledge and Data Engineering*, 33:2505–2519.

Hao Peng, Jianxin Li, Yu He, Yaopeng Liu, Mengjiao Bao, Lihong Wang, Yangqiu Song, and Qiang Yang. 2018. Large-scale hierarchical text classification with recursively regularized deep graph-cnn. *Proceedings of the 2018 World Wide Web Conference*.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. Glove: Global vectors for word representation. In *Conference on Empirical Methods in Natural Language Processing*.

Kervy Rivas Rojas, Gina Bustamante, Arturo Oncevay, and Marco Antonio Sobrevilla Cabezudo. 2020. Efficient strategies for hierarchical text classification: External knowledge and auxiliary tasks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 2252–2257. Association for Computational Linguistics.

Sandhaus, Evan. 2008. The new york times annotated corpus.

Claude E. Shannon. 1948. A mathematical theory of communication. *Bell Syst. Tech. J.*, 27(3):379–423.

Kazuya Shimura, Jiyi Li, and Fumiyo Fukumoto. 2018. Hft-cnn: Learning hierarchical category structure for multi-label short text categorization. In *EMNLP*.

Zihan Wang, Peiyi Wang, Lianzhe Huang, Xin Sun, and Houfeng Wang. 2022a. Incorporating hierarchy into text encoder: a contrastive learning approach for hierarchical text classification. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 7109–7119. Association for Computational Linguistics.

Zihan Wang, Peiyi Wang, Tianyu Liu, Yunbo Cao, Zhifang Sui, and Houfeng Wang. 2022b. Hpt: Hierarchy-aware prompt tuning for hierarchical text classification.

Jiawei Wu, Wenhan Xiong, and William Yang Wang. 2019. Learning to learn and predict: A meta-learning approach for multi-label classification. In *EMNLP*.

Junran Wu, Xueyuan Chen, Bowen Shi, Shangzhe Li, and Ke Xu. 2023. Sega: Structural entropy guided anchor view for graph contrastive learning. In *International Conference on Machine Learning*. PMLR.

Junran Wu, Xueyuan Chen, Ke Xu, and Shangzhe Li. 2022a. Structural entropy guided graph hierarchical pooling. In *International Conference on Machine Learning*, pages 24017–24030. PMLR.

Junran Wu, Shangzhe Li, Jianhao Li, Yicheng Pan, and Keyulu Xu. 2022b. A simple yet effective method for graph classification. In *IJCAI*.

Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. 2019. How powerful are graph neural networks? In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net.

Pengcheng Yang, Xu Sun, Wei Li, Shuming Ma, Wei Wu, and Houfeng Wang. 2018. Sgm: Sequence generation model for multi-label classification. In *COLING*.

Ronghui You, Zihan Zhang, Ziye Wang, Suyang Dai, Hiroshi Mamitsuka, and Shanfeng Zhu. 2019. Attentionxml: Label tree-based attention-aware deep model for high-performance extreme multi-label text classification. In *NeurIPS*.

Chong Zhang, He Zhu, Xing Qiang Peng, Junran Wu, and Ke Xu. 2022. Hierarchical information matters: Text classification via tree based graph neural network. In *COLING*.

Jie Zhou, Chunping Ma, Dingkun Long, Guangwei Xu, Ning Ding, Haoyu Zhang, Pengjun Xie, and Gongshen Liu. 2020. Hierarchy-aware global model for hierarchical text classification. In *ACL*.

A Analysis of CIRCA

In this section, we first present the definition of coding tree following (Li and Pan, 2016). Secondly, we present the detailed flow of CIRCA, in particular, how each stage in Algorithm 1 works, and the purpose of designing these steps. Finally, we give an analysis of the temporal complexity of CIRCA.

Coding Tree. A coding tree T of graph $G = (V_G, E_G)$ is defined as a tree with the following properties:

i. For any node $v \in T$. v is associated with a nonempty subset V of V_G. Denote that $T_v = V$, in which v is called the codeword of V while V (or T_v) is termed as the marker of v.[1]

ii. The coding tree has a unique root node v_r that stands for the vertices set V_G of G. That is, $T_{v_r} = V_G$.

iii. For every node $v \in T$, if $v_1, v_2, \ldots, v_z$ are all the children of v, $\{T_{v_1}, T_{v_2}, \ldots, T_{v_z}\}$ is a partition of T_v. That is, $T_v = \cup_{i=1}^{z} T_{v_i}$.

iv. For each leaf node $v_\gamma \in T$, T_{v_γ} is a singleton. i.e. v_γ corresponds to a unique node in V_G, and for any vertex $v \in V_G$, there is only one leaf node $v_\tau \in T$ that satisfies $T_{v_\tau} = v$.

The workflow of CIRCA. In the initial state, the original graph $G = (V_G, E_G)$ is fed into CIRCA and each node in V_G is treated as the leaf node of coding tree T_L and directly linked with the root node v_r. The height of the initial coding tree is 1, which reflects the one-dimensional structure entropy of graph G. In other words, there are only two kinds of partition for V_G, one is the graph-level partition ($T_{v_r} = V_G$), and the other is the node-level partition ($T_{v_\tau} = v$). We tend to find multi-granularity partitions for G, which could be provided by the K-dimensional optimal coding tree as the coding tree with height K encodes and decodes $K + 1$ partitions in different levels for graph G.

In Stage 1, we merge the leaf nodes of the initial coding tree pair by pair until the root node v_r has only two children. Merging leaf nodes is essentially compressing structural information, which is a process of reducing the structural entropy of graph G. When selecting the node pairs to be merged, we give priority to the nodes that reduce more structural entropy of graph G after merging.

After Stage 1, the coding tree T becomes a binary tree, whose height is much greater than K and closer to $log|V_G|$ in practical applications. In Stage 2, we tend to compress the coding tree T to height K by erasing its intermediate nodes. Note that removing nodes from the highly compressed coding tree is increasing the structural entropy of graph G. Thus, we preferentially erase the nodes that cause the minimal structural entropy increase.

The result of Stage 2 might be an unbalanced tree that does not conform to the definition of coding trees. In Stage 3, we do some post-processing on the coding tree to make the leaf nodes the same height.

Complexity analysis. The time complexity of CIRCA is $O(h_{max}(|E_G|log|V_G| + |V_G|))$, where h_{max} is the maximum height of coding tree T_L during Stage 1. Since CIRCA tends to construct balanced coding trees, h_{max} is no greater than $log(|V_G|)$.

[1]For simplicity, we do not distinguish the concept of node, codeword, and marker in the body of this paper.

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
We discuss the limitations at the end of this paper.

☐ A2. Did you discuss any potential risks of your work?
Not applicable. Left blank.

☑ A3. Do the abstract and introduction summarize the paper's main claims?
The introduction is shown in Section 1.

☑ A4. Have you used AI writing assistants when working on this paper?
We utilize Grammarly's standard edition to check the spelling and grammar for the whole paper.

B ☐ Did you use or create scientific artifacts?

Not applicable. Left blank.

☐ B1. Did you cite the creators of artifacts you used?
No response.

☐ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
No response.

☐ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
No response.

☐ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
No response.

☐ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
No response.

☐ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
No response.

C ☑ Did you run computational experiments?

We conduct experiments on three benchmark datasets. The experimental results are shown in Section 5.2.

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
We report the number of parameters in Section 5.6.

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☑ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
The implementation details are shown in Section 5.1.

☑ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
The experimental results are shown in Section 5.2.

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
The implementation details are shown in Section 5.1.

D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?
Left blank.

☐ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
No response.

☐ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
No response.

☐ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
No response.

☐ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
No response.

☐ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
No response.