Hierarchical text classification (HTC) to a taxonomy is essential for various real applications but challenging since HTC models often need to process a large volume of data that are severely imbalanced and have hierarchy dependencies. Existing local and global approaches use deep learning to improve HTC by reducing the time complexity and incorporating the hierarchy dependencies. However, it is difficult to satisfy both conditions in a single HTC model. This paper proposes a hierarchy decoder (HiDEC) that uses recursive hierarchy decoding based on an encoder-decoder architecture. The key idea of the HiDEC involves decoding a context matrix into a sub-hierarchy sequence using recursive hierarchy decoding, while staying aware of hierarchical dependencies and level information. The HiDEC is a unified model that incorporates the benefits of existing approaches, thereby alleviating the aforementioned difficulties without any trade-off. In addition, it can be applied to both single- and multi-label classification with a minor modification. The superiority of the proposed model was verified on two benchmark datasets (WOS-46985 and RCV1) with an explanation of the reasons for its success.

Keywords deep learning · hierarchical text classification · encoder-decoder structure

1 Introduction

Hierarchical text classification (HTC) uses a hierarchy, such as a web taxonomy, to classify given text into single or multiple classes. It is an essential task in the real world because there is a tremendous amount of data on the web that needs to be well-organized for applications such as product navigation [1, 2], news categorization [3, 4], and question answering [5, 6].

The previous HTC methods using deep learning can be categorized into two approaches: local and global. In the local approach [8, 4, 3], a classifier for each unit is built after an entire hierarchy is broken down into a set of small units. Then, the classifiers are applied, in sequence, according to a path from a root in a top-down manner. It has the advantage of reducing the complexity of unit models but also has the disadvantage of losing the global information of the entire hierarchy owing to the difficulty of identifying the hierarchy dependencies. On the contrary, in the global approach [9, 10], a classifier for all the classes in the entire hierarchy is built, excluding the hierarchy structure through flattening. It can capture the entire hierarchy dependency because it is encoded using various models such as meta-learning [11], reinforcement learning [12], and graph neural networks [9] without an exposure bias. Unfortunately, these global approaches are not feasible when a hierarchy becomes large because the time complexity increases significantly. It is caused by the repeated use of the entire hierarchy to capture the hierarchy dependencies during training.

The ideal HTC model, one which is both effective and scalable, should incorporate the properties of local and global approaches. This paper proposes a hierarchy decoder (HiDEC) that uses recursive hierarchy decoding based on an encoder-decoder architecture. In the proposed HTC model, the encoder is implemented using a parallelizable recurrent neural network (RNN) [13], and the proposed HiDEC, a novel decoder, utilizes a self-attention mechanism similar to the decoder of the Transformer [14]. It is composed of hierarchy embeddings, level-wise masked self-attention,
text-hierarchy attention, and sub-hierarchy expansion. The purpose of the HiDEC is to recursively decode a context matrix into a sub-hierarchy sequence, similar to a parse tree, while staying aware of the hierarchical dependencies and level information. Figure 1 illustrates the conversion of three target labels of a given text into a sub-hierarchy sequence. The hierarchy dependencies and level information of three classes, including intermediate classes, are explicitly present and these dependencies and the level information are kept to a manageable size by following a parse tree notation. Therefore, although HiDEC is a unified model that incorporates the benefits of local and global approaches, thereby alleviating the aforementioned difficulties without any trade-off, based on a local approach, it takes all hierarchy dependencies with level information into account. In addition, it can deal with both single- and multi-label HTCs with a minor modification and without the loss of generality. A series of experiments using the WOS-46985 [8] and RCV1 [15] was conducted to demonstrate the superiority of the proposed model for both single- and multi-label HTCs and allowed for an in-depth analysis of the reasons underlying its success.

The contributions of this paper can be summarized as follows:

- This paper proposes a hierarchy decoder (HiDEC) with a recursive hierarchy decoding based on an encoder-decoder architecture. This decoder remains aware of the hierarchical dependencies and level information during training and inference. It is a unified model inheriting the advantages of both local and global approaches.
- The superiority of the HiDEC for single- and multi-label HTCs has been demonstrated using WOS-46985 and RCV1, respectively, and the results are utilized to reveal the role of HiDEC in HTC through in-depth analysis.

The rest of this paper is organized as follows. Section 2 presents the related works pertaining to the HTC methods. The proposed model is explained in Section 3. In Section 4, the experimental setting and results are presented. Subsequently, in Section 5, we present an in-depth analysis of the reasons underlying the success of HiDEC. Finally, we conclude the paper and propose future research directions in Section 6.

2 Related Works

Previous studies have used deep learning for text classification (TC). TextCNN [16] is a convolutional neural network (CNN) based model that was developed for sentiment classification. It is a simple adaption of the CNN in the application of TC and shows how CNNs can be applied to different information retrieval and natural language processing tasks. In [17] TextCNN was extended to deal with character-level sequences using a deeper architecture. RNN-based models with long short-term memory (LSTM) [18] and gated recurrent units (GRU) [19] were developed to exploit the ability

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2Code is available on https://github.com/SangHunIm/HiDEC
of identifying long dependencies in the input. Some authors [20, 21] have presented TC models based on an attention mechanism [22] to identify the dependency between the input of an encoder and a decoder. Recently, Transformer [14] equipped with a self-attention mechanism was proposed and became dominant since it showed remarkable improvements in all NLP tasks.

The key difference between HTC and TC is the utilization of hierarchy dependencies. Research on HTC can be categorized into two approaches: global and local approaches.

In the global approach, a single classifier for all classes is trained after flattening the entire hierarchy. There are two ways of dealing with hierarchy dependencies. First, all hierarchy dependencies can be ignored when training a model, making the problem simple and easy to process. Various methods such as sequence-to-sequence structures [23], meta-learning [11], and reinforcement learning [12] were exploited to build such a classifier. Second, all hierarchy dependencies can be incorporated into models using graph-based learning such as HiAGM [9], a capsule network [24], or HCSM [10]. However, this is not practical for large-scale hierarchies due to the huge computational cost involved.

In the local approach, a set of classifiers for small units of classes such as for-each-class [3], for-each-parent [8, 25], for-each-level [26], and for-each-sub-hierarchy [4] are trained. Owing to the decomposition of hierarchy, some local models attempt to identify the hierarchy dependencies. In [8], HDLTex was introduced as a local model that combined a deep neural network (DNN), CNN, and RNN to classify child nodes. HTrans [3] extended HDLtex with transfer learning from a parent to a child. HMCN [27] applied global optimization to the classifier of each level to solve the problem of exposure bias, whereas HR-DGCNN [4] divided the entire hierarchy into sub-hierarchies using recursive hierarchical segmentation. Unfortunately, they encountered difficulties when applying the models to a large-scale document processing. Unfortunately, they encountered difficulties when applying the models to a large-scale document processing.

Therefore, we propose HiDEC, a unified single model, which incorporates the advantages of both local and global approaches.

3 Proposed HTC Model

The HTC problem can be defined using a graph structure. A hierarchy is represented as a directed acyclic graph (DAG) $G = (V, E)$ where $V = \{v_1, v_2, \ldots, v_C\}$ is a set of C-classes in a hierarchy and $E = \{(v_i, v_j) | v_i \in V, v_j \in child(v_i)\}$ is a set of edges between a class $v_i$ and a child $v_j$ of $v_i$. $D = \{d_1, d_2, \ldots, d_K\}$ is a collection of $K$ documents. A document $d_k$ has a sub-hierarchy $G^{d_k} = (V^{d_k}, E^{d_k})$ where $V^{d_k} = L^{d_k} = \{v_i^{d_k} \in ancestor(v_j^{d_k}) | v_j^{d_k} \in L^{d_k}\}$ and $E^{d_k} = \{(v_i, v_j) | v_j \in V^{d_k}, v_i \in parent(v_j)\}$, where $L^{d_k} = \{v_1^{d_k}, v_2^{d_k}, \ldots, v_N^{d_k}\}$ is label set of document $d_k$. In other words, $G^{d_k}$ is constructed using all the classes assigned to $d_k$ and their ancestors. $G^{d_k}_{0, p} = (\{v_{root}\}, \emptyset)$ is the initial sub-hierarchy of the HiDEC where it has a root class and no edges. Based on $G^{d_k}_{0, p}$, the recursive hierarchy decoding is defined by expanding $G^{d_k}_{0, p}$ for $p$ times from $p=0$. Then, the goal of training the HiDEC is given by $G^{d_k}_{1, p} = G^{d_k}_{p}$. In Figure 2 overall architecture of the HiDEC is presented with a demonstration of recursive hierarchy decoding. The rest of this section explains the details of the proposed model.

3.1 Encoder

In the proposed model, any one of the popular encoders using deep learning can be selected because the HiDEC decodes a context matrix from an encoder into a sub-hierarchy sequence. We opted for a simple recurrent unit (SRU) [13], a parallelizable RNN that modifies the matrix-vector product as an element-wise vector product, as the baseline encoder. For simplicity, let us denote $d_k$ as $T = [w_1, w_2, \ldots, w_N]$ where $w_n$ is a one-hot vector for an index of the $n$-th token. In the beginning, a sequence of tokens was converted into word embeddings $H^0 = W^0 T \in \mathbb{R}^{N \times e}$ where $W^0$ is a weight matrix of the word embedding layer and $e$ is an embedding dimension.

Given $H^0$, the hidden state $H^l$ of $l$-th layer from bi-directional SRU can be computed using:

$$\hat{H}^l = \text{SRU}^l(H^{l-1})$$

$$\overline{H}^l = \hat{H}^l$$

$$H^l = W^l [\overline{H}^l; \hat{H}^l] + b^l$$

Where $[;]$ is a concatenation of two matrices, and $W^l$ and $b^l$ are a weight matrix and a bias, respectively.
3.2 Hierarchy Decoder (HiDEC)

3.2.1 Hierarchy Embedding Layer

To obtain the sub-hierarchy embeddings as shown in Figure 1, it is necessary to construct a sub-hierarchy sequence from a document $d_k$. It consists of two steps. First, a graph $G^{d_k} = (V^{d_k}, E^{d_k})$ of a sub-hierarchy for $d_k$ is built. Second, a sub-hierarchy sequence $S$ following a parse tree notation is generated from $G^{d_k}$. Three special tokens, "(" and ")", and "[END]", are used to properly represent the sub-hierarchy. The tokens "(" and ")" denote the start and end of a path from each class, respectively, whereas the "[END]" token indicates the end of a path from a root. For example, $S = [R (A (D (I )))) B (F ([END])) C ([END]) ]$ was constructed in Figure 1. Once again, the tokens in $S$ are represented as one-hot vectors for further processing. After processing, these tokens can be represented as $S = [s_1, s_2, \ldots, s_M]$ where $s_i = \mathbb{I}_{v_i}$ is a one-hot vector for class $v_i$ and the special tokens. Finally, the sub-hierarchy embeddings $U^0$ are constructed after explicitly incorporating level information using:

$$\tilde{U}^0 = W^S S$$

$$U^0 = \text{level\_embedding}(\tilde{U}^0)$$

3.2.2 Level-wise Masked Self-Attention

This component is responsible for capturing the hierarchy dependencies in a sub-hierarchy based on the self-attention mechanism that is used in the Transformer [14]. For computing the self-attention scores, we applied level-wise masking to retain only the ancestor-descendant dependencies from the root to the maximum level of a sub-hierarchy. The self-attention mechanism from the Transformer was exploited with a minor modification concerning level-wise masking.
Algorithm 1 Recursive Hierarchy Decoding in Inference Time

Indices: max hierarchy depth $P$, number of attentive layers $R$

Input: Context matrix from encoder $H$

Output: Predicted label set $L$

//HiDEC
1: $L = \emptyset$
2: $G_0 = (\{v_{\text{root}}\}, \emptyset)$
3: for $p = 0, \ldots, P - 1$ do
   //Sub-hierarchy embedding
   4: Convert $G_p$ to sub-hierarchy sequence $S_p$
   5: Compute $U^0$ from $S_p$ with Eq.2
   6: Generate masking matrix $M$ with Eq.6
   //Attentive layers
   7: for $r = 0, \ldots, R - 1$ do
      8: $U^{r+1} = \text{attentive\_layer}(U^r, H, M)$ with Eq.4, 5, 7, 8, 9
   9: end for
10: $U = U^R$
   //Sub-hierarchy expansion
11: for $s_i \in S_p$ do
12:   if $s_i \notin$ special token set then
13:      $v_j = s_i$
14:      for $v_j \in \text{child}(v_i)$ do
15:         $c_{ij} = U^r \cdot W^S \cdot I_{v_j}$ with Eq.10
16:      end for
17:      $p_i = F(v_i)$ with Eq.11
18:      Get $y_i$ from $p_i$ with Eq.13
19:      for $v_k \in y_i$ do
20:         $V_p = V_p \cup \{v_k\}$
21:         $E_p = E_p \cup \{(v_i, v_k)\}$
22:      end for
23:   end if
24: end for
25: $G_{p+1} = (V_p, E_p)$
26: end for
   //Label assignment
27: for $i = 0, \ldots, |V_p|$ do
28:   if $v_i \in \text{leaf}(G_P)$ then
29:      $L = L \cup \{v_i\}$
30:   else if $v_i = "$END$"$ then
31:      $L = L \cup \{parent(v_i)\}$
32:   end if
33: end for
34: return $L$

The query (Q), key (K), and value (V) of $r$-th decoder layer were computed using:

\[
Q = W^Q U^{r-1}\top \\
K = W^K U^{r-1}\top \\
V = W^V U^{r-1}\top
\]  

(4)

Then, the self-attention scores with level-wise masking were obtained using:

\[
\hat{U}^r = \text{Masked\_Attention}(Q, K, V) \\
= \text{softmax} \left(\frac{QK\top}{\sqrt{e}} + M\right) V
\]  

(5)
The masking matrix $M$ is defined as:

$$M_{ij} = \begin{cases} -1e9 & \text{if } v_i \notin \text{ancestor}(v_j) \\ 0 & \text{else} \end{cases} \quad (6)$$

We ignored the dependency between the two classes if they were not an ancestor-descendant relation by setting $M_{ij} = -1e9$. Note that the dependencies of the three special tokens with respect to other tokens, including themselves, were considered.

### 3.2.3 Text-Hierarchy Attention

In the text-hierarchy attention, we were able to compute the attention scores of classes by reflecting the importance of tokens in an input document, dynamically. A new context matrix $\bar{U}^r$ of $r$-th layer was computed by combining the context matrix $H$ from the encoder and $\dot{U}^r$ using:

$$Q = W^r_Q \dot{U}^r \top$$

$$K = W^r_K H \top$$

$$V = W^r_V H \top$$

$$\bar{U}^r = \text{Masked\_Attention}(Q, K, V) = \text{softmax} \left( \frac{QK \top}{\sqrt{d}} \right) V \quad (8)$$

Then, the output of $r$-th layer $U^r$ was obtained using a position-wise feed-forward network (FFN) using:

$$U^r = \text{FeedForward}(\bar{U}^r) \quad (9)$$

Consequently, the output of a final layer in the HiDEC was utilized in the sub-hierarchy expansion.

### 3.2.4 Sub-hierarchy Expansion

Sub-hierarchy expansion plays an important role in generating a sub-hierarchy using recursive hierarchy decoding. It results in target sub-hierarchy if the HiDEC functions as expected. For each class, classification to child nodes are performed using the contextual class matrix $U$ using:

$$c_{ij} = U_i \cdot W^S \cdot \mathbb{1}_{v_i} \quad \forall v_j \in \text{child}(v_i) \quad (10)$$

$$p_i = F(c_i) \quad (11)$$

where $c_{ij}$ is a similarity score of a child $v_j$ under a parent $v_i$, and $p_i$ is the probability of a child $v_j$ obtained using a task-specific probability function $F$ (sigmoid for single-label and softmax for multi-label). The three special tokens were excluded when selecting a parent $v_i$. We reduced the label space of HTC by focusing on the child nodes of a parent class of interest. During training, there were two different loss functions for single-label and multi-label HTC, as:

$$L_{\text{single}} = \text{CE}(p) = -\frac{1}{M_J} \sum_{i=0}^{M} \sum_{j=0}^{J} y_{ij} \log(p_{ij})$$

$$L_{\text{multi}} = \text{BCE}(p) = -\frac{1}{M_J} \sum_{i=0}^{M} \sum_{j=0}^{J} y_{ij} \log(p_{ij}) + (1 - y_{ij}) \log(1 - p_{ij}) \quad (12)$$

where CE and BCE denote cross-entropy and binary cross-entropy, respectively. $J = |\text{child}(v_i)|$ indicates the number of child nodes under a parent $v_i$. $y_{ij}$ and $p_{ij}$ denote a target label of j-th child node of $v_i$ and its output probability, respectively.

At inference time, the recursive hierarchy decoding was performed with two functions for single-label and multi-label HTC:

$$\hat{y}_i = \begin{cases} \text{argmax}(p_i) & \text{if single} \\ \text{threshold}(p_i) & \text{if multi} \end{cases} \quad (13)$$
The details of recursive hierarchy decoding are described in Algorithm 1. The number of decoding steps is the same as the maximum depth of a hierarchy. At each decoding step, all the tokens except the special ones are expanded. The decoding ends if the tokens are leaf nodes or "[END]". Finally, labels associated with "[END]" or leaf nodes are assigned to the input as predictions.

4 Experiments

4.1 Dataset

In this paper, two popular benchmark collections, RCV1-v2 [15] and Web-of-Science (WOS) [8] were chosen to evaluate the multi- and single-label HTCs, respectively. RCV1-v2 comprises 804,414 news articles divided into 781,265 and 23,149 articles for training and testing, respectively as benchmark splits. For model selection, we randomly sample 10% of the training data as validation data. Unlike RCV1-v2, WOS-46985 comprises 46,985 documents, but it is not split into training and test data. Therefore, we split it using a 8:2 ratio for training and testing. Similar to RCV1-v2, 10% of training data was used as validation data. Table 1 shows the data statistics.

| L | Depth | Avg | Train | Val | Test |
|---|---|---|---|---|---|
| RCV1 | 103 | 4 | 20,835 | 2,314 | 781,265 |
| WOS-46985 | 141 | 2 | 33,829 | 3,759 | 9,397 |

4.2 Evaluation Metrics

Standard Micro-F1 and Macro-F1 were selected as the evaluation metrics. F1 is a harmonic mean of precision and recall. Micro-F1 assigns high weights for common classes whereas Macro-F1 does so for rare classes.

4.3 Implementation Details

After text cleaning and stopword removal, the words with ten or more occurrences were chosen to retain the vocabulary. As a result, the vocabulary sizes for RCV1-v2 and WOS-46985 were 20,133 and 24,269, respectively.

For the encoder, there were two options for implementation: SRU [13] and TextRCNN [28]. The SRU-based encoder was equipped with four SRU layers, while the TextRCNN-based encoder followed the default architecture. The size of the hidden state was 300 for both. To initialize the word embedding layer in the encoders, 300-dimension word embeddings obtained using GloVe [29] were exploited while those for the OOV words were randomly initialized.

For the HiDEC, class and level embeddings with 300-dimension were initialized using a normal distribution with $\mu = 0$ and $\sigma = 300^{-0.5}$. The size of the hidden state in the attentive layer was 300. The FFN consisted of two FC layers with a 600-dimension feed-forward filter. The threshold for the multi-label HTC in recursive hierarchy decoding was set to 0.5. A dropout with a probability of 0.1 was applied to the embedding layer and behind every FFN.

For optimization, Adam optimizer [30] was utilized with $lr = 0.00005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $eps = 1 \times 10^{-8}$, and the size of the minibatch was 1024. The learning rate ($lr$) was controlled using a linear schedule with a warm-up rate of 0.1. The gradient clipping with a max gradient norm of 1.0 was performed to prevent the gradient overflow.

All models were implemented using PyTorch [31] and trained with NVIDIA A6000 * 8. The average score of the five different models were utilized as the proposed model performance where a model represents the best performing structure selected using the validation data.

4.4 Performances

Table 2 summarizes the performances of the multi-label HTC models on RCV1-v2 [15]. When comparing all the models, the global models showed relatively better performances than the local ones. The best performances were obtained by HCSM [10] and HiAGM-GCN [9], with a Micro-F1 score of 0.8580 and a Macro-F1 score of 0.6335,
Table 2: Performance comparison of multi-label HTC on RCV1-v2. The highest performances in local and global approaches are in bold and denoted with red and blue, respectively. The gains were obtained as compared to SRU+HiDEC. † indicates statistically significant difference ($p < 0.01$) from HIAGM-GCN.

| Approach     | Model            | Micro F1 | Gain | Macro F1 | Gain |
|--------------|------------------|----------|------|----------|------|
| Global       | Capsule-B [23]   | 0.7390   | -0.1053 | 0.3990   | -0.2241 |
|              | H-AGCRNN [24]    | 0.7780   | -0.0663 | 0.5130   | -0.1101 |
|              | TextRCNN [28]    | 0.8157   | -0.0306 | 0.5925   | -0.0220 |
|              | HiAGM-GCN [19]   | 0.8411   | -0.0032 | 0.6288†  | +0.0057 |
|              | HCSM [10]        |          |        | 0.8580†  | +0.0137 |
| Local        | HR-DGCNN-3 [4]   | 0.7618   | -0.0825 | 0.4334   | -0.1897 |
|              | HFT(M) [26]      | 0.8029   | -0.0414 | 0.5140   | -0.1091 |
|              | HTrans [3]       | 0.8051   | -0.0392 | 0.5849   | -0.0382 |
| Local (Proposed) | TextRCNN + HiDEC | 0.8380   | -0.0063 | 0.5328   | -0.0903 |
|              | SRU + HiDEC      |          |        | 0.8443†  | - 0.6231 |

respectively. It is an expected result because these models were trained taking the entire hierarchy structure into consideration.

The proposed model with the HiDEC as a decoder were tested as two variant models with different encoders: TextRCNN [28] and SRU [13]. The results showed that SRU+HiDEC was superior to TextRCNN+HiDEC as the best performances, 0.8443 in Micro-F1 and 0.6231 in Macro-F1, were obtained by the SRU+HiDEC.

In summary, the proposed model outperformed the local models and delivered performance comparable to the state-of-the-art (SOTA) global models (HCSM and HiAGM-GCN). The model complexities of both local and global models were high because several classifiers were used for the small units in the local models whereas the global models were trained with repeated use of the entire hierarchy. Compared to them, the proposed model with the HiDEC reduced the model complexity by using a sub-hierarchy sequence similar to a parse tree notation and incorporated the class dependencies of a sub-hierarchy using the attention mechanism. Therefore, the proposed model is a unified model inheriting the advantages of the local and global approaches although it is a local model. A detailed analysis of model complexities is presented in Subsection 5.1.

Table 3 presents the performances of the single-label HTC on WOS-46985 [8]. The same model architecture used for multi-label HTC was trained by modifying $L$ and $F$. SRU+HiDEC outperformed HDLTex [8], a SOTA model for single-label HTC. We observed the effectiveness of the proposed model on both single- and multi-label HTCs from the results on RCV1-v2 and WOS-46985.

Table 3: Model comparison on WOS-46985.

| Model   | Micro F1 of Level 1 | Overall | Overall Gain |
|---------|---------------------|---------|--------------|
|         |                     |         |              |
| HDLTex  | 0.9045              | 0.8466  | 0.7658       | -0.0403     |
| SRU+HiDEC | 0.9085            | 0.8555  | 0.8061       | -            |

5 Analysis

5.1 Model Complexities

Model complexity is a key factor that influences the practical application of an HTC since hierarchies used in practical applications are large. In Table 4, we demonstrate the superiority of the proposed model in terms of model complexity compared to that of the existing local and global models. Let us assume for this comparison that the encoders and decoders use the same architecture. The complexity of the encoders in the local models can then be set to $E$ whereas the complexity of the decoder in the other models can be set to only those involved in the final classification. Therefore,
Figure 3: Heatmaps of the attention scores in the HiDEC. (a) Sample text and decoded sub-hierarchy with assigned classes. (b) Heatmap of the level-wise masked self-attention scores from Layer 1 of the HiDEC. (c) Heatmap of the text-hierarchy attention scores from Layer 2 of the HiDEC. Attention scores under 0.3 are clipped in all the heatmaps and the similar colors indicate the same level.

Figure 4: Scatterplots of the class weight vectors after projecting to 2-dimension using PCA. The circles with the same color denote that they share the same top-level class under the root. We cannot apply PCA to the existing local models because the class weight vectors are not in the same space.
the complexity of the encoder in the local models would be $O(C' \cdot E)$ whereas the others would be $O(E)$ because the local models use a different encoder for each class whereas the other models use a single encoder for all the classes. Contrarily, in the decoders, the complexity of the global models would be $O(H \cdot C)$ whereas the others would be $O(H \cdot C')$.

In summary, in terms of encoders, the HiDEC and the global models are superior to the local models. However, the HiDEC and the local models are better than the global models when it comes to the decoders. This shows that the HiDEC utilizes the advantage of both the encoder and decoder.

| Model Complexity | Encoder | Global | HiDEC | Decoder | $\frac{C'}{C''} \gg 1$ |
|-------------------|---------|--------|-------|---------|---------------------|
|                   | Local   | Global | HiDEC |         |                     |
| $O(C' \cdot E)$   | $O(E)$  | $O(E)$ | $O(E)$ |         |                     |
| $O(H \cdot C')$   | $O(H \cdot C')$ | $O(H \cdot C')$ | $O(H \cdot C')$ |         |                     |

### 5.2 Interpretation of Attention

This subsection investigates the role of level-wise masked self-attention and text-hierarchy attention by visualizing the attention scores, as shown in Figure 5(a). In all the heatmaps, the x- and y-axes indicate the From and To, respectively. The attention scores were clipped at a threshold of 0.3. A sample text from RCV1-v2 and a corresponding sub-hierarchy are described in Figure 3(a).

The self-attention scores obtained from Head 2 of Layer 1 are visualized in Figure 3(b). In (α), the attention score between "(" and ""ECAT" is relatively high where "(" is a start of a path from ""ECAT". It shows that the special tokens "(" and ")" were appropriately associated with the corresponding classes. In (β), the dependency between child ""E21" and parent ""ECAT" were well-described since the attention scores for child nodes under parent ""ECAT" were high. In (γ), it shows the dependency between the class assignment sequence – ["(", "[END]", ")") and the class ""E21". From these three examples we can conclude that the level-wise masked self-attention effectively captures the hierarchy dependencies.

Figure 3(c) visualizes the attention scores between the input tokens and a sub-hierarchy sequence in Head 1 of Layer 2 of the decoder. Some tokens like "rating" and "moody" have high attention scores for the descendants of "CCAT" and itself, where "CCAT" denotes "CORPORATE/INDUSTRIAL". On the other hand, some tokens like "issuer", "municipal", and "investors" have high attention scores for the descendants of "ECAT" and itself, where "ECAT" denotes "ECONOMICS". It shows that the classes are associated with different tokens in different degrees.

### 5.3 Hierarchical Class Space

To investigate whether the proposed model generates good class representations reflecting the hierarchy structure, we visualized the class weight vector with projection into a 2D space using PCA, as shown in Figure 4. Each circle denotes a class and circles of the same color indicate that they belong to the same top-level class of a hierarchy. Three models, TextRCNN, HiAGM, and SRU-HiDEC, were compared. TextRCNN and HiAGM are global models, with and without a hierarchy structure, respectively. On the contrary, SRU-HiDEC is a local model with a hierarchy structure. Other local models could not be used in the comparison because the classifiers in a local model are independent. For TextRCNN and HiAGM, the class weight vectors in the last FC layer were used for projection, whereas class embeddings were used for SRU-HiDEC.

Figure 4(a) present the class space of TextRCNN. It shows that the four groups of classes are located around the origin with low separability due to the absence of a hierarchy structure. In Figure 4(b), the four groups are entirely separated and clustered around the centroid of a group. This is in line with our expectations because the HiAGM was trained with a hierarchy structure. However, the circles are spread over a large range [-100, 100]. In the case of SRU-HiDEC, as shown in Figure 4(c), the four groups seem to be clustered around the centroid of a group with high separability in a small range [-6, 8]. In other words, we can assume that SRU-HiDEC inherits the advantages of the local and global models. This piece of evidence explains the superiority of the proposed model.
5.4 Ablation Studies

Table 5: Ablation study of the HiDEC on RCV1

| Self-Attention | Level Embedding | F1 Micro | F1 Macro |
|---------------|----------------|---------|---------|
| X  X          |                | 0.8390  | 0.6055  |
| O  X          |                | 0.8409  | 0.6052  |
| X  O          |                | 0.8411  | 0.6008  |
| O  O          |                | 0.8443  | 0.6231  |

We performed ablation studies with the level-wise masked self-attention and the level embedding, as shown in Table 5. The role of the level-wise masked self-attention is to capture not only the ancestor-descendant dependencies but also the implicit level information, based on the self-attention mechanism. Similarly, the level embedding aims at providing explicit level information. In the comparison, the best performances were achieved by using the two components together, while the worst performances were obtained without them. This shows the positive effect of their combination.

It is expected that the level embeddings for classes accurately reflect level information because they have a certain level in a hierarchy. We observed that the level embeddings for the special tokens did not reflect proper level information since they were not associated with a certain level but with all classes. It was noted that the number of “[END]” generated was relatively small without the level embeddings. Fortunately, this did not affect the classification because the label assignment was done without “[END]” as shown in Algorithm 1.

6 Conclusion

In this paper, we proposed a hierarchy decoder (HiDEC) with recursive hierarchy decoding based on an encoder-decoder architecture. This decoder stays aware of the hierarchy dependencies and level information. It is a unified model of the existing local and global approaches and inherits their advantages. This model can also be applied to single- and multi-label HTCs with a minor modification.

In the experiments, we showed the superiority of the proposed model compared to the recent local and global models on the RCV1-v2 and WOS-46985 datasets. The proposed model outperformed the local models and showed competitive performances comparable to that of the global models, while maintaining reasonable model complexity.

Based on the results of the in-depth analysis, we discussed the roles of the key components through practical demonstrations as well as the reduction of model complexity.

In future, we plan to extend the proposed model to an extremely large-scale hierarchy (e.g., MeSH term indexing or product navigation) and introduce a novel training strategy combining the top-down and bottom-up manners that can effectively use a hierarchy structure.

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