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Comparison of Text Classification Algorithms based on Deep Learning

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Abstract: In the technical battlefield of text classification, extracting key features and solving the sparsity problem play a decisive role in improving the performance of classification results. Euclidean geometric models often distort the processed vectors because they are difficult to deal with complex data structures. This exploration uses hyperbolic space with huge storage potential and hierarchical structure, and proposes an innovative hyperbolic graph-based short text classification technology - L-HGAT, aiming to improve the efficiency of processing concise information. This method combines two technologies, hyperbolic geometry and attention network, to optimize the representation of text through in-depth interaction between labels and text features. The research results significantly show that L-HGAT not only has high accuracy and excellent efficiency in many benchmark data sets, but also effectively integrates label information, significantly enhancing the model's ability to capture local features. This discussion brings an innovative perspective to processing hierarchical information and demonstrates the effectiveness of hyperbolic geometry in text classification challenges.

Keywords: Text Classification, Hyperbolic Space, Graph Attention Network, Deep Learning.

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1 INTRODUCTION

In the practice of text classification, the scarcity of important information is often in contrast to its decisive role in the results [1,2]. Especially in texts with clear structures, accurately extracting key information becomes a difficult problem. The traditional Euclidean geometry model maps text features into a simple low-latitude coordinate system and uses a self-attention mechanism for learning. However, when faced with complex data structures, it often leads to numerical distortion. Compared with traditional Euclidean space, hyperbolic space has larger capacity and continuous tree structure characteristics, which makes it more suitable for describing the power law structure of documents. Therefore, this study uses a hyperbolic graph model based on A short text classification method that uses hyperbolic geometry to simulate the hierarchical structure of text and deepens the understanding of the connections between nodes through graph attention networks [3,4,5]. Furthermore, it incorporates the interaction of tags and text features to optimize the representation of text.

2 RELATED WORK

One type is a strategy based on traditional machine learning principles, and the other is a path based on deep learning technology [6]. The old routine mainly focuses on extracting features and writing formulas. In the field of deep learning, end-to-end neural networks, such as topic memory networks, long short-term memory networks and convolutional neural networks, improve semantic representation capabilities by integrating multi-layer features; models focusing on word embedding technology strive to improve The embedding effect of words in documents [7]. In text classification tasks, graph neural networks have shown powerful capabilities to deeply mine the graphical properties of text through graph convolution and graph attention networks [8,9,10,11,12,13,14,15,16]. Recently, in the field of data representation learning exploring hyperbolic geometric spaces, researchers have used sophisticated architectures such as hyperbolic hierarchical attention networks to optimize graph vector embedding and presentation of hierarchical features, thereby improving the accuracy and computing efficiency of classification tasks [17].

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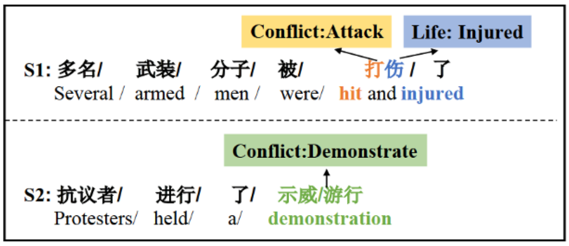

FIGURE 1. AN EXAMPLE OF WORD-TRIGGER MISMATCH PROBLEM.

FIGURE 2. AN EXAMPLE OF AMBIGUOUS SEMANTICS.

3 MODEL ESTABLISHMENT

In order to predict the label possibility of text, a new short text classification technology is studied, which relies on the hierarchical architecture of hyperbolic space and combines the powerful information processing capabilities of the attention network[18,19,20,21]. It focuses on the learning of label features and is built based on the hyperbolic graph attention network, named L-HGAT[22]. The algorithm includes three core components: exploring the expression and attribute transformation of vectors in hyperbolic space, the practical application of hyperbolic attention mechanism, and the technique of using label information to improve the text representation effect[23,24].

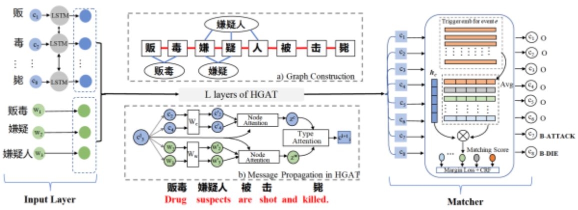

Figure 3: Illustration of our proposed architecture, which consists of an Input Layer, L layers of HGAT and a matcher module. Subfigure a) and b) show the details of graph construction and message propagation process in HGAT.

3.1 HYPERBOLIC SPACE VECTOR REPRESENTATION AND FEATURE TRANSFORMATION

This exploration focuses on vector representation and its conversion technology under the hyperbolic geometry framework, which is the core component of the L-HGAT algorithm for short text classification in the hyperbolic graph attention network [25,26,27,28,29,30]. This process is dedicated to transferring vector mapping in traditional Euclidean space to hyperbolic geometric space and performing efficient feature transformation, aiming to improve model performance [31,32,33,34,35].

Hyperbolic space vector representation:

A vector representation of a hyperbolic space that relies on mapping specific relationships between points and that space. Imagine that there is an attribute vector ti of node i located in Euclidean space, which is transformed into hyperbolic geometric space through an exponential mapping function:

$$\exp_c^m(t_i) = m \oplus_c \left(\tanh\left(\frac{\sqrt{c}t_i}{2} \right) \frac{t_i}{\sqrt{c}t_i} \right) \quad (1)$$

where m is a fixed point in hyperbolic space, usually the origin 0, and $\oplus c$ is the Möbius addition in hyperbolic space.

Feature transformation:

Once the vectors in the hyperbolic space are obtained, the next step is to perform feature transformation to enhance the model's ability to understand the features. This can be achieved through a parameterized transformation matrix M. The specific process is as follows:

$$h_i = M \otimes_c q_i \quad (2)$$

where $q_i = \exp_c^0(t_i)$ is the representation of node walk in hyperbolic space, and represents matrix multiplication in hyperbolic space.Normalizing hyperbolic vectors ensures that the vectors maintain proper length and direction in hyperbolic space:

$$\tilde{h}_i = \tanh\left(\frac{Mq_i}{\sqrt{c}q_i} \right) \frac{Mq_i}{Mq_i} \quad (3)$$

Möbius addition and multiplication: In hyperbolic space, the merging (addition) and scaling (multiplication) of vectors use Möbius operations. Möbius addition is defined as:

$$x \oplus_c y = \frac{\left(1 + 2c\langle x, y\rangle + c\|y\|^2\right)x + \left(1 - c\|x\|^2\right)y}{1 + 2c\langle x, y\rangle + c^2\|x\|^2\|y\|^2} \quad (4)$$

Möbius multiplication is used to adjust the "length" of a vector:

$$\lambda \otimes_c x = \tanh\left(\lambda \tanh^{-1}(\|x\|) \right) \frac{x}{\|x\|} \quad (5)$$

where λ is a real number representing the intensity scaled in hyperbolic space.

3.2 HYPERBOLIC ATTENTION MECHANISM

Under the hyperbolic attention mechanism, the interaction between nodes is realized through a special calculation function, which comprehensively considers the relative position of the nodes in the hyperbolic geometric space and its hierarchical structure. This mechanism relies on

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the unique properties of hyperbolic space to accurately present node attributes and their relationships while maintaining the hierarchical structure, and transform node characteristics into hyperbolic space:

$$h_i = \tanh\left(\frac{\sqrt{c}t_i}{2}\right)\frac{t_i}{\sqrt{c}t_i} \quad (6)$$

Among them, ℏ responsible is the representation of the feature vector of node walk in the hyperbolic space, falcon is the original feature vector, c is the curvature parameter of the hyperbolic space, and the attention coefficient in the hyperbolic space is calculated:

$$\alpha_{ij} = \frac{\exp\left(f\left(h_i,h_j\right)\right)}{\sum_{k\in N_i}\exp\left(f\left(h_i,h_k\right)\right)} \quad (7)$$

The function f(ℏ, ℏ j) is based on the distance or similarity measure between nodes j and j in hyperbolic space.

Similarity function:

$$f\left(h_i,h_j\right) = -\frac{2}{\sqrt{c}}\tanh^{-1}\left(\sqrt{c} - h_i \oplus_c h_j\right) \quad (8)$$

Among them, $\oplus c$ represents hyperbolic addition, which is used to calculate the hyperbolic distance between two points. The definition of hyperbolic addition:

$$h_i \oplus_c h_j = \frac{\left(1+2c\langle h_i,h_j\rangle + c\| h_j \|^2\right)h_i + \left(1-c\| h_i \|^2\right)h_j}{1+2c\langle h_i,h_j\rangle + c^2\| h_i \|^2\| h_j \|^2} \quad (9)$$

Used to calculate the sum of two node vectors in hyperbolic space and aggregate neighbor features:

$$h_i' = \sigma\left(\bigotimes_{j\in N_i}\alpha_{ij} \otimes_c h_j\right) \quad (10)$$

Here σ is a nonlinear activation function, representing scalar multiplication in hyperbolic space, used to adjust weights. The definition of hyperbolic scalar multiplication:

$$\alpha_{ij} \otimes_c h_j = \tanh\left(\alpha_{ij}\tanh^{-1}\left(h_j\right)\right)\frac{h_j}{h_j} \quad (11)$$

Used to apply attention weights to node feature vectors in hyperbolic space and update node features:

$$h_i^{\text{new}} = \bigotimes_{j\in N_i}\left(\alpha_{ij} \otimes_c h_j\right) \quad (12)$$

The feature vector of node v is updated by aggregating weight-adjusted neighbor features. Output layer calculation:

$$o_i = softmax\left(\mathbf{W}h_i^{\text{new}} + b\right) \quad (13)$$

where $\mathbf{W}$ and b are learning parameters used to transform features in hyperbolic space into predicted outputs.

3.3 Optimizing Text Representation of Label Information

In hyperbolic space, detailed annotation of text representation can greatly improve the accuracy and efficiency of classification. We will discuss how to improve the presentation of text with the help of label data. The similarity $s \quad m$ (ℏ $'$, yp) is used to measure the similarity between the optimized node representation ℏ $'$ and the label yp. The calculation of similarity is determined by the following function:

$$f_D(d) = 0.5 - \frac{\arctan(8d-20)}{\pi} \quad (14)$$

Among them, d is the distance between ℏ$'$ and yp, and fD maps the distance to the [0,1] interval to ensure that the similarity is within the appropriate range. When d is close to 0, $fD(d)$ is close to 1, indicating a high degree of similarity; as d increases, the similarity decreases, a similarity vector is constructed, and a similarity vector is created for each text, which contains the similarity between the text and each label Spend:

$$T_i = \left[sim\left(h_1',y\right), sim\left(h_2',y\right), \ldots, sim\left(h_{n_p}',y\right)\right] \quad (15)$$

This vector contains the similarity of node walk to all possible labels, which is used for subsequent classification decisions. The probabilistic prediction model uses a transformation function ϕ and a weight matrix W to process the similarity vector and generate a probability distribution:

$$P_i = \sigma\left(W\phi\left(W'T_i\right)\right) \quad (16)$$

where σ is the sigmoid function used to convert the output into probability values, and W and W' are the learned parameters. The final loss function is calculated based on the predicted probability P and the actual label, and is used to optimize parameters during the training process:

$$L_{\text{loss?}}' = -\left(\sum_{i\in L_+}\log\left(P_i\right) + \sum_{j\in L_-}\log\left(1-P_j\right)\right) \quad (17)$$

Among them, $L+$ and $L-$ represent the positive and negative class label sets respectively. This formula helps the model accurately learn to distinguish different categories from the label information.

3.4 Overall Model Framework

By integrating three core components—feature transformer, hyperbolic attention mechanism processor, and label information enhanced text presenter—the L-HGAT model can efficiently perform text classification. The whole process starts by building a graph consisting of word nodes and text nodes, and transforming the Euclidean features of the nodes into a hyperbolic space through exponential mapping to form a high-level latent representation. Subsequently, with the help of algorithm mechanism, the model accurately calculates the distance between nodes, based on which the attention weight is established. Finally, with the guidance of label information, the model enables nodes to learn deeper semantic features, and uses negative sampling technology to optimize the loss function, thereby improving computing efficiency and achieving accurate correspondence between text and labels [36,37,38]. As the number of tags increases, the model's demand for computing resources also increases accordingly [39,40,41].

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 EXPERIMENTAL DATA SETS AND EVALUATION INDICATORS

Data set	Training set	Number of training set labels	Test set	Number of test set labels	Number of words	Number of categories	Average length
20NG	15,999	9,617	6,402	36,344	52,363	20	188.07
R8	6,523	4,662	1,861	6,534	13,058	8	55.86
R52	7,735	5,552	2,183	7,558	15,294	52	59.35
Ohsumed	6,290	2,853	3,437	12,034	18,323	23	115.45
MR	9,063	6,042	3,020	15,949	25,012	2	17.33

Table 1 Dataset statistics

This study uses five generally recognized standardized data sets: 20 data sets such as 20NG, Ohsumed, Reuters' R52 and R8, and movie reviews (MR) [42]. They all have obvious organizational structures and are consistent with the hyperbolic space. consistent with the tree structure. Each of these data collections contains a variety of themes and classification tasks. For example, 20NG contains the themes of 20 news groups, and the average document length is 221.26 words; the Ohsumed database contains 7,400 texts tagged with only one topic, each The average vocabulary of the text is 23; R8 contains 8 categories, R52 has 52 categories, and the average number of words in the document is 65.72 and 69.82 respectively; the MR data set is used to classify emotions, covering 5331 positive and negative comments. The evaluation criteria of this experiment mainly look at accuracy, that is, the proportion of the number of accurately predicted samples to all samples; the division of training sets and test sets is carried out according to the method described in the literature.

Model	20NG	R8	R52	Ohsumed	MR
CNN-rand	0.6536	0.7992	0.7257	0.3729	0.6370
CNN-non-static	0.6980	0.8135	0.7446	0.4967	0.6608
LSTM	0.5584	0.7964	0.7271	0.3496	0.6376
Bi-LSTM	0.6223	0.8187	0.7699	0.4188	0.6600
fastText	0.6747	0.8171	0.7889	0.4849	0.6391
SWEM	0.7239	0.8102	0.7899	0.5366	0.6510
TextGCN	0.7339	0.8251	0.7956	0.5811	0.6520
Hyper-GAT	0.7363	0.8328	0.8074	0.5941	0.6657
L-HGAT	0.7404	0.8361	0.8068	0.6050	0.6698

Table 2 Comparison of experimental results

4.2 COMPARISON ALGORITHM

This comparison experiment focuses on this algorithm and eight other cutting-edge text classification basic models. These models are divided into three categories: within the traditional framework of deep learning, including convolutional neural networks (CNN-rand) that initialize word vectors in a random manner, and convolutional neural networks (CNN-rand) that utilize pre-trained word vectors. static), long short-term memory network (LSTM) and its bidirectional version (Bi-LSTM). In the classification of methodology, the fastText model focuses on the use of lexical context, improving data processing efficiency by combining vocabulary and its n-gram features; SWEM and simplified version of pooling technology are used to improve classification efficiency. Based on graph theory, the two methods Text-GCN and HyperGAT each show their strength. Text-GCN relies on the node characteristics of the graph convolution network, while HyperGAT uses dual vision to improve the expression learning ability of text hypergraphs.

4.3 EXPERIMENTAL ENVIRONMENT AND PARAMETER SETTINGS

The experiment was performed on a powerful server with Ubuntu 18.04 operating system, equipped with Nvidia

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RTX A4000 GPU, CUDA version 11.7, Python programming language version 3.8, and the TensorFlow 2.9.0 framework for calculations. Set experimental variables to ensure the repeatability and accuracy of experimental results, use a 50% dropout rate to prevent model overfitting, apply an eight-dimensional single-head attention mechanism to enhance the extraction of important information, and use Adam optimization at a rate of 0.02 The controller promotes rapid convergence of the model. In addition, the CNN static model, long short-term memory network (LSTM), and bidirectional long short-term memory network (Bi-LSTM) all use pre-trained word embedding technology to enhance their ability and accuracy in handling complex text classification tasks. This sophisticated experimental design provides a solid platform for evaluating and comparing various text classification algorithms.

4.4 Result analysis

Table 2 reveals that the L-HGAT model shows excellent performance in many data sets. Although it is slightly inferior to Hyper-GAT in the R52 data set, its overall strength is still strong. This highlights the powerful ability of L-HGAT to adapt to and apply to various data sets. Compared with randomly generated word embeddings, pre-trained word embeddings can significantly improve the performance of convolutional neural networks when processing long text datasets Ohsumed and 20NG. In the field of processing short texts, LSTM and its improved version have shown better performance. fastText takes advantage of the power of supervised learning and labeled data to stand out in the competition with traditional LSTM and bidirectional LSTM. SWEM improves accuracy with the help of simple pooling operations. Text GCN outperforms models using CNN and LSTM on the MR data set, proving its ability to capture long-distance word meaning interactions. Using the L-HGAT tool, hyperbolic space embedding technology and graph attention network can effectively mine the deep connections between text and tags, thereby enhancing the efficient identification of similar categories[43,44,45,46,47,48]. The hyperbolic attention principle is confirmed by implementing removal experiments, and the results show that hyperbolic attention outperforms Euclidean attention at various embedding spatial scales, especially in low-dimensional spaces. By comparing different configurations of various algorithms, the importance of label-optimized text representation was confirmed[49]. It was observed that models incorporating label information showed excellent performance in all data sets, especially in the Ohsumed data set. A comparative experiment was conducted between the hyperbolic multi-head attention network and the European multi-head attention network (L-GAT). The results show that the hyperbolic model is better at integrating multi-level features, which makes it improve the model representation ability and accuracy.

From the data in Table 1, it can be seen that the L-HGAT model outperforms other models across all five datasets, with particularly notable performance on the 20NG and Ohsumed datasets. The improvement of L-HGAT lies in its combination of hyperbolic space and attention mechanisms, significantly enhancing the model's accuracy in handling complex hierarchical data structures. In contrast, traditional LSTM and Bi-LSTM perform reasonably well in short text processing but are less effective in handling long text datasets compared to L-HGAT and Hyper-GAT. The fastText and TextGCN models also show their respective strengths on specific datasets, but overall, L-HGAT stands out in terms of accuracy.

Component	Time Complexity	Space Complexity
Node feature transformation	$O(V{\cdot}d{\cdot}d')$O(V·d·d′)	$O(V{\cdot}d{\cdot}d')$O(V·d·d′)
Attention coefficient	$O(d')$O(d′)	$O(d')$O(d′)
Node information integration	$O(V{\cdot}d'{\cdot}d'{+}E{\cdot}d')$O(V·d′·d′+E·d′)	$O(V{\cdot}d'{\cdot}d'{+}E{\cdot}d')$O(V·d′·d′+E·d′)

Table 3: L-HGAT model complexity analysis

Table 3 presents the time and space complexity analysis of the L-HGAT model[13]. The time and space complexity for node feature transformation is $O(V \cdot d \cdot d')O(V \cdot d \cdot d')$, where VV is the number of nodes, and dd and $d'd'$ represent the input and output feature dimensions, respectively. The computation of the attention coefficient has a complexity of $O(d')O(d')$, demonstrating high computational efficiency when processing large amounts of node information. The complexity for integrating node information is $O(V \cdot d' \cdot d'{+}E \cdot d')O(V \cdot d' \cdot d'{+}E \cdot d')$, ensuring that the model can effectively learn and maintain reasonable computational and storage requirements even in networks with a large number of nodes. This complexity analysis indicates that L-HGAT excels not only in accuracy but also in computational efficiency and resource utilization when handling complex hierarchical data.

4.5 Complexity Analysis

In the complexity analysis of the L-HGAT model, the time and space costs of operation are considered. The model mainly involves two types of attention mechanisms: Euclidean and hyperbolic, with the complexity of each attention mechanism varying due to its operating characteristics. The attention mechanism based on hyperbolic space has higher computational efficiency and representation ability when processing node information. First of all, the computational complexity of the L-HGAT model mainly comes from the conversion of node features and the calculation of attention coefficients. The transformation of each node feature from Euclidean space to hyperbolic space requires a nonlinear transformation, whose time complexity is $O(V{\cdot}d{\cdot}d')$, where V is the number of nodes, d and d' represent respectively Input and output feature dimensions. The calculation of the attention coefficient $aj{=}f(\hbar, \hbar j)$ involves the hyperbolic distance between two nodes, and its complexity is $O(d')$. In addition, the L-HGAT model uses graph-based learning methods, such as GAT and GCN, when integrating node information. These methods can effectively aggregate node features and learn richer node representations. The complexity of this process is $O(V{\cdot}d'{\cdot}d'{+}E{\cdot}d')$, where E represents the number of edges. This computational approach ensures that in networks with a large number of nodes, the model can learn effectively and maintain reasonable computing and storage requirements.

5 CONCLUSION

This study develops a short text classification method (L-HGAT) based on hyperbolic graph attention network, which performs well on multiple standard data sets, especially when processing complex data with hierarchical characteristics. a clear advantage. Combining hyperbolic space representation learning with the graph attention mechanism, L-HGAT not only improves accuracy, but also effectively integrates label information to optimize text representation, thereby significantly improving classification efficiency. Through comparative experiments and in-depth complexity evaluation, the effectiveness and usability of this model have been further confirmed, especially in terms of improving computational performance and enhancing expression potential. Future projects will study the application of the model on larger data sets and further refine the algorithm to cope with larger text classification challenges.

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DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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