A Study of Music Teaching Techniques Based on Deep Learning

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Abstract. In this paper, we simulate the human discovery behaviour of topic web pages in the crawling strategy, combine the topic discrimination model, the breadth traversal crawling strategy and the depth traversal crawling strategy to implement an improved topic URL crawling strategy that allows crawlers to crawl topic-related URLs in priority to improve web crawling efficiency. The experiment used Sina military news as the crawler's data object, and "Russia-Ukraine conflict" news as the crawler's topic, and analysed the crawler's running time and the proportion of topic pages by comparing with the breadth-first strategy, depth-first strategy, PageRank strategy and best-first search strategy. The experimental results show that the improved theme URL crawler strategy, which improves the calculation of the similarity of web page themes, helps the crawler to obtain URLs with better themes and improves the efficiency of the crawler, which is important for solving the problem of accessing open source web information. This paper examines the application and in-depth development of deep learning techniques for teaching music, combining computers and music teaching in an in-depth study that adds seeming models and approaches to teaching.

Keywords: deep learning · big data research · support under big data · music teaching · deep teaching

1 Introduction

Driven by the background of the information age, the entire Internet has reached an unprecedented amount of data and information and is still growing. With today's internet, the main carrier of web information is the web page, as it is easy and inexpensive to access information, and users can gather and access relevant information and resources through their browsers without installing any applications. The low threshold and explosive growth of information has made it increasingly difficult for users to access web-based information related to their target topic in the vast ocean of the Internet [1]. In some areas of applied research, a variety of topic crawling algorithms have been developed to collect, analyse, organise and extract the value of information, in order to adopt the best data collection strategy for the target topic of web information [2].

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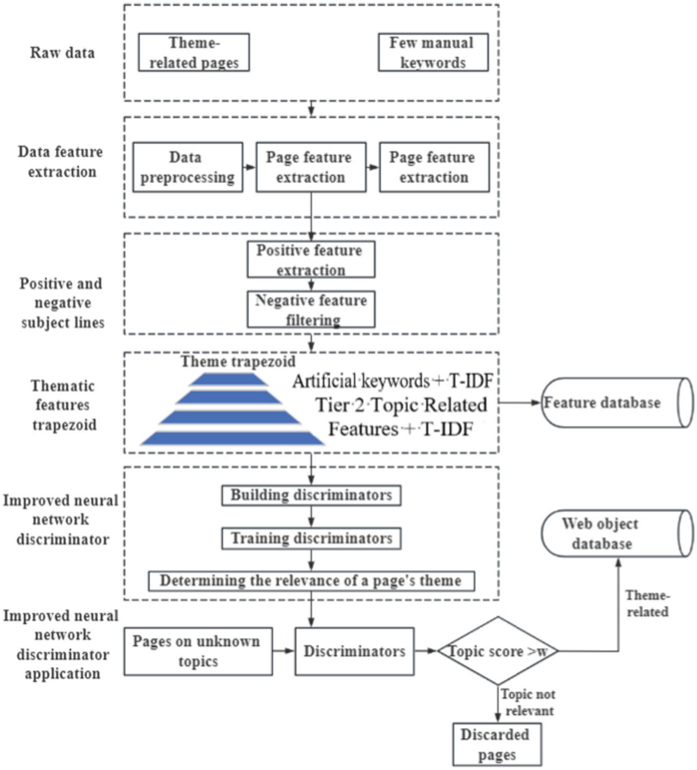

Fig. 1. Topic similarity discriminant model

2 Deep Learn Based Topic Recognition

2.1 Theme Page Identification Process

The theoretical core of topic discrimination for Chinese text is the vectorisation of already acquired topic-related web object features through a neural network-based language modelling approach [4]. Using Word2Vec's Skip-gram model and negative sampling [3].

the topic-related features in the topic pages are extracted to form a topic feature ladder, which is combined with the feature weights calculated by the improved TF-IDF as the initial input to the improved neural network discriminator. The discriminator model is trained to discriminate between topic-related and non-topic-related web pages, and ultimately the process of discriminating between topic pages is achieved [5]. The flow of the theme page discernment implementation is shown in Fig. 1.

2.2 Improved TF-IDF Based Weighting Calculation

Considering that the anchor text and tags of the web pages to be crawled have different degrees of influence on the topic feature words [6], Considering also that the use of a single label weight, which calculates the degree of thematic contribution of a feature, is prone to weight bias, a weighted accumulation of label weights is used for the calculation, and the calculation formula1 is shown below.

$$T_{wf}(k) = \frac{\sum_{i=0}^{n} m(i)}{\sum_{j=0}^{N} m(j)} \tag{1}$$

where numerator $m(i)$ denotes the weight value of the ith tag, $\sum_{i=0}^{n} m(i)$ refers to the cumulative weight of the tag where the kth key feature is located in the document, $\sum_{j=0}^{N} m(j)$ refers to the cumulative weight of all feature tags, and $T_{wf}(k)$ is the average weight of the kth feature tag in the full-text tags.

2.3 Positive Feature Extraction for Subject Pages

The computer calculates the encoded word and phrase vectors to obtain the encoded vectors [7], then finds the corresponding words and phrases from the encoding table and converts them into comprehensible text, as shown in Table 1.

However, when simple word vector encoding represents text features, it cannot effectively weigh the relationships between word vectors, cannot use context to determine the meaning of word vectors, and the encoding of data is too sparse, inefficient and prone to dimensional disasters when the volume of documents is relatively large [8].

The distributed word vector representation makes full use of the information in each dimension to reflect more meaning overall, and the concept of 'distance' between word vectors provides a basis for predicting relationships between similar thematic features, as shown in vector Table 2.

The main role of Word2Vec is to vectorize the text of web pages. There are two important models within Word2Vec: CBOW (Continuous Bag-of-Words Model), which

Table 1. Keyword vector coding table

Words and phrases	Vector coding
Crawlers	100000
Topics	000001
Depth	010000

Table 2. Keywords corresponding to distributed vector tables

Words and phrases	Figures	vectors
Page subject line 1	0	$[11, 12, 13, \cdots 1N]$ N for N dimensions
Page subject line 2	1	$[21, 12, 13, \cdots, 1N]$ N for N dimensions
...	...	...
Page subject line N	m	$[m1, m2, m3, \cdots, mN]$ m indicates the total number of dictionaries

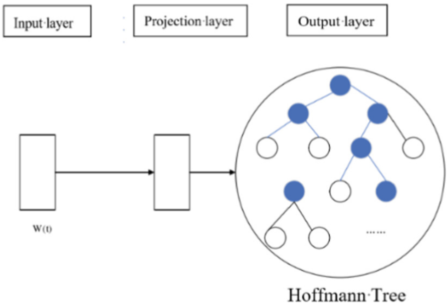

Fig. 2. Skip-gram model.

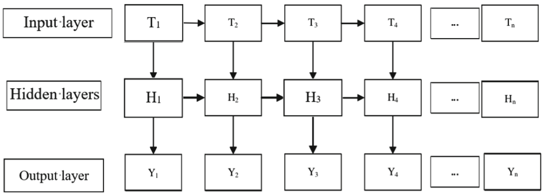

Fig. 3. Improved recurrent neural network discriminator

predicts central words from contextual feature words, and Skip-gram, which predicts contextual words from central words, whose model is shown in Fig. 2.

Skip-gram model input layer: is the word vector (one-hot encoding of words) of a specific topic word W(t) in the web page; projection layer: constructs the weight matrix between the input layer and the projection layer, also constructs the weight matrix between the projection layer and the output layer, builds a bridge between the input and output features, through training is to solve the matrix optimal weight parameters to predict the feature words in the context of the web page where the topic word is located; Output layer: [9].

With traditional recurrent neural networks, as time passes and text features are continuously input, the new input features are too far away from the earlier feature paths and tend to forget the earlier topic features [10]. As shown in Fig. 3 of the discriminator model:

The discriminator core is divided into three layers: the input layer, the hidden layer and the output layer. After the discriminator model is constructed, it needs to be trained by topic pages and non-topic related pages.

2.4 Experimental Setup

This section uses the python language for the programming experiments, as well as Google's open source Tensor flow framework as the deep learning training framework. The actual environment used is shown in Table 3. In addition, numpy, selenium, jieba and other toolkits were used to assist with the experiments.

Table 3. Experimental environment parameters

Experimental environment	Environment configuration
Operating systems	Windows11
CPU	Inter® Core (TM)i7-9750H
	CPU @ 2.6.0HG2.6.0Hz
Compilation tools	PyCharm2021.3
MONGODB	4.4.6
Compilation Language	Python3.7
REIDSE	5.0
MYSQL	5.7.26
Deep learning frameworks	Tensorflow2.0

Table 4. Html tag weighting weights parameter.

Characteristic elements	Weighted weighting parameters
HEAD	10
TITLE	6
H1	8
HREF	2
#ARTICLE	3
#KEYWORDS	5

The feature weight parameters for the tags in the html of the pages for this theme are shown in Table 4.

3 Conclusion

This chapter focuses on illustrating the improved TF-IDF algorithm for the weighted calculation of web page structure features, as well as the process of extracting a topic tree with converging features through the positive and negative sampling methods sampled by Word2Vec for web page feature extraction. The web topic similarity discriminative model is constructed, and the working principle of the web topic discriminative model is explained. Finally, we compare and analyze the experimental data of the deep learning web topic discriminative model in topic discriminations through topic recognition experiments, and finally verify the effectiveness of the deep learning discriminative model in the process of web topic discriminations.

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