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Blog text quality assessment using a 3D CNN-based statistical framework

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A B S T R A C T

Aiming at the problem that blog texts are the streaming data captured by different acquisition modality, each kind of which has its particular quality evaluation mode, this paper proposes a text quality evaluation (TQA) model based on 3D CNN correlated with blog text data. In order to achieve accurate TQA value, the model adopted a Bi-LSTM-based architecture to process video-related blog text as auxiliary part to provide additional information for our TQA architecture. First, the auxiliary part constructs feature vector for each video-related text by the model originating from Bi-LSTM and Seq2Seq. Then, the feature vector was feed to a well-trained decoder to reconstruct the original input data. Then, the feature vector complied with the blog textual data are inputted into end-to-end TQA modal based on the 3D CNN straightly. Comprehensive experimental results on the blog text/video dataset from the well-known truism website "http://www.mafengwo.cn/" have shown that the proposed model reflects the subjective quality of online texts more accurately, and has better overall blog TQA assessment performance than the other state-of-the-art non-reference methods.

1. Introduction

Blog is a major mainstream mode of Internet application with multiple advantages such as openness, interactivity, convenience and other characteristics, which are favored by many tourists. It has become one of the most potential applications in the mobile Internet era. With the rapid development of blog platform, all kinds of chaos and serious information quality problems have brought troubles to its development. Due to the lack of "gate-keepers", the fragmentation of information and the uneven level of users, the information content carried by blog can no longer meet the text quality assessment requirements of users, which is mainly reflected in the large amount of information, low effective value and difficult access. The text/video quality of blog information has become an important issue affecting the development of blog platform and the effective utilization of network information resources.

Although there is a large amount of blog data distributed on the Internet, the quality of blog data is incomplete, such as the lack of structure and standardization, which leads to the inability to analyze the results for people's decision-making. Due to the fragment and complicatedness of data like separate "islands", the difficulty of application greatly reduces the availability of blog data. The quality of blog texts directly affects and determines the usage of bog information. Therefore, it is of great significance to evaluate the quality of blog texts.

Deep learning is a kind of neural network that constructs and simulates human brain for analyzing and learning. It imitates the mechanism of human brain to interpret data, such as online shopping system, translation tool, speech recognition system and go game system [1–4]. Since the medical data is the multi-mode information that contains image, video, and text-related information. Each channel of blog data has its particular quality evaluation process. The commonly used parameters include signal-to-noise ratio, geometric correction, chromaticity, contrast, image detail, etc., which are not completely suitable for blog textual data and its corresponding text information. To solve this problem, we in this paper propose a TQA model based on

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3D CNN correlated with blog textual data. The model construct feature vector for each video-related text as input by Bi-LSTM-based autoencoder mechanism. Subsequently, the feature vector was feed to a well-trained decoder to reconstruct the original input data. The text quality evaluation is based on the similarity between the original input data and reconstructed data. The combination of each text and the feature vector extracted from the text concerned is inputted into end-to-end VQA modal by leveraging the 3D CNN straightly. The main contribution of this paper are as follows:

(1) For the quality evaluation of blog text data, a well-designed 3D CNN is proposed. It can optimally leverages volumetrically contextual information within the three-dimensional frame-based texts.

(2) In order to obtain more information, the video-related text data is extracted by an automatic encoder, and then the relevant content of video is predicted by the Seq2Seq model embedded in bidirectional long-term memory (Bi-LSTM). Finally, the extracted features from encoder part are utilized as auxiliary features for corresponding blog texts.

(3) Due to the value range of text quality evaluation model is inconsistent with that of pervasively used difference average opinion score (DMOS), we normalized the outputted values from the proposed VQA model to the range of [0,1].

2. Related work

For the related fields in this paper, the previously influential work is introduced on three topics concerned, information quality assessment, data quality and image quality assessment methods.

2.1. Information quality assessment

Maffei el al. [5] first realized the difficulty of information quality assessment in 1958. The quality of information is difficult to assess for the following reasons:

(1) Information quality standards are mainly determined by users. The subjective characteristics are hard to be automatically extracted.

(2) Information sources are usually autonomous, unorganized, and lack useful quality metadata. Some sources of information even take measures to prevent information quality assessment.

(3) Large-scale data makes it impossible to evaluate the entire information set without sampling techniques, which reduces the accuracy of the evaluation.

(4) The unorganized nature of information sources makes information vulnerable to sudden changes in content and quality, which is not conducive to information quality assessment.

For the research of information quality assessment, the early focus was mainly on data quality assessment and data quality issues. In 1979, Codd [6] proposed a mechanism for adding data labels to assess data quality, and was adopted by Wang et a. In 1993, data-based attributes were proposed and quality indicators were used to label data quality. Paradice and Fuerst [7] proposed a formula for calculating the storage error rate in 1991. These studies focus on stored data and less on user evaluation and perception of data information. In the research of data quality issues, Klein et al. [8] conducted a series of tests and found that information system users can find data errors in a specific environment. They further clarified that clear error detection targets, management instructions, training, and various incentives can improve the effectiveness of false detections. However, Dasu et al. [9] believed that some data quality dimensions, such as accuracy and completeness, are difficult to find errors or even unevaluable. Strong et al. conducted a data quality project check on three organizations, identified a general pattern of quality issues, and found that data quality issues in one category affected the quality of data in another.

With the comprehensive and in-depth understanding of information quality, the research on information quality assessment has gradually broken through the limitations of data quality. In 2000, Naumann et al. [10] developed a classification method based on evaluation-oriented information quality standards. On the basis of summarizing the classification of information quality standards by predecessors, they summarized three classification methods: semantic-oriented classification, process-oriented classification and goal-oriented classification. On this basis, the classification method of evaluation orientation is proposed, and three standards are established from the three aspects of user, information itself and information acquisition process—subjective standard, objective standard and process standard. Each type of standard has different assessment methods and techniques, including user experience, user sampling, ongoing user evaluation, data cleaning and analysis, and more. The study comprehensively summarizes all aspects of information quality assessment and establishes a mature information quality assessment standard system. YW Lee et al. [11] proposed an information quality assessment method called AIMQ to help organizations assess the quality of their information and monitor the information quality improvement process at any time.

2.2. Data quality

Maffei first realized the difficulty of data quality problems and data quality assessment. Later, with the development of computers, data quality problems have become increasingly prominent. In the research of data quality, it mainly focuses on the quality of structured data in information systems. The research mainly focuses on the definition and dimension of data quality, the solution of data quality problems, and the elimination of "data ambiguity". For data quality problems, most of these studies use technical means, data-oriented, and solve quality problems. Early research believes that data quality is the accuracy of data, and it is divided into two types: correct and wrong. It refers to the quality formed in the data production process. This view captures the essential characteristics of data quality, but it is relatively narrow. Redman [12] defined data quality at three levels—conceptual level, data value level, and formal level. Data quality at the conceptual level includes data details, view consistency, components, robustness, and flexibility. Data value hierarchy includes data accuracy, integrity, generality and consistency. The data form hierarchy includes the suitability, comprehensibility and accessibility of data. This point of view is completely based on the data in the database, with strong pertinence and operability, and relative comprehensiveness, for data quality management laid a theoretical foundation.

Because information is different from data, the focus, level, angle, and means of information quality and data quality research are different. Klein [8] believed that data quality and information quality are a multi-dimensional concept that presents different characteristics depending on the researcher's own point of view. Johannsen [13] believes that the focus of information quality in library and information services research is "quality management"; Levitin [14] believes that the use of "data quality" is primarily related to the accuracy of information products, such as databases. B Zhang [15] et al. pointed out that high-quality data is not necessarily high-quality information, and information users may still not be able to obtain valuable information. Therefore, users should first pay attention to user needs, so that information production forms a complete data producer from information user. Information manager conducts demand-based "applicability" data production quality management approach while the information sharing platform system acts as a "quality agent" for information

2.3. No-reference image quality assessment

Saad et al. [16] used the features of DCT coefficient Kurtosis and anisotropic entropy to train the SVR model. On the bases of learning based blind image quality (LBIQ), Tang et al. [17] selected the characteristics include model parameters and coincidence probability of complex pyramidal wavelet coefficient generalized Gaussian model fitting, cross-scale distribution of wavelet coefficient amplitude and phase, block PCA eigenvalue, fuzzy statistic based on two-color prior, and fuzzy kernel and noise estimation. Parameters, etc. After PCA dimensionality reduction for some high-dimensional features, the SVR regression model is trained on different features, and finally the results are weighted and combined into one quality indicator. Zhang et al. [18] utilized LOG filter to decompose the image into multiple sub-band images in different scales, and then the local binary pattern (LBP) is obtained from these sub-band images, and the normalized histogram is statistically selected as a feature to train an SVR model to predict the image quality. In addition, there are some algorithms based on the SVM + SVR model that use different image features for image quality estimation. For example, Zhang and Chandler [19,20] extracted quality-related image statistics on two scales of spatial and frequency domains. The spatial domain is the logarithmic derivative characteristic normalized by MSCN, and the frequency domain is different directional features obtained from the logarithmic Gabor filter, all of which are described by the generalized Gaussian model, with the model parameters as the classification and regression features. Liu et al. [21] adopted the statistical features including the maximum coordinates of the logarithmic histogram of the curvelet coefficient values, and the energy distributions in different directions and scales of the curved wave domain. Then based on structural risks, SVM was utilized to achieve great success in the field of machine learning. The minimization strategy is helpful to prevent the over-learning phenomenon when the sample size is small. This kind of method has achieved good results in the non-reference image quality evaluation research, but different features have important influence in estimation accuracy and computational complexity. The selection of multi-scale, multi-direction, integrated space and transform domain features are conducive to the improvement of estimation accuracy.

3. Proposed approach

Generally speaking, blog data include two kinds of information. One kind is related to image or video, which is also considered as an integration of image frames. The other kind is connected with the textual information, such as description or comment.

The architecture of the quality evaluation model for blog data splits the blog data into image/video data and text data firstly. For the text data, Bi-LSTM-based architecture extracts the key features as the input complementary of CNN-based blog TQA model.

3.1. LSTM-Based model for feature extraction of video-related text

In order to accurately extract the high-level features of the video-related text, the Seq2Seq model is upgraded to accommodate the text data. The purpose of Seq2Seq model is to translate

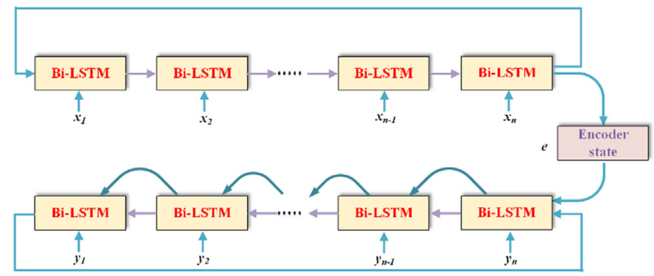

Fig. 1. The architecture of the deep model for Bi-LSTM that learn the distribution of textual information.

a language sequence into another language sequence. The whole process is to map a sequence as input to another output sequence by using RNN. However, for the time series data, RNN tends to focus on the data in the vicinity while ignoring that in the long distance. Comparatively, LSTM makes improvement to capture the information in long distance and learn the characteristics of long dependence. However, in both LSTM and RNN, predictions are made from the front to the back, so the latter data points are emphasized more than the former ones, which often leaves out information of many associated data in a long distance. Bi-LSTM is proposed to remove the defects, which conducts forward and backward LSTM training twice. Since two trainings are connected with the same output layer, and thus provide to the output layer in the input sequence of each point to complete the past and the future of context information.

Based on the Bi-LSTM model, the prediction model Bi-LSTM-S2S is proposed as shown in Fig. 1. The sequence data (x_1, x_2, ..., x_n) containing the additional features flows the encoder part of Bi-LSTM-S2S as the input data. And then it is encoded to a semantic vector e, which is input into the decoder part. The decoder adopts the output of the previous moment as the additional input of the current moment, and then realize the textual quality prediction.

Generally speaking, the preprocessed time series data first enters the encoder part as input in the Bi-LSTM structure. After a semantic vector is obtained by the encoder, the decoding part with the similar architecture interprets the semantic vector. Finally, the model infers the highest prediction probability according to the local optimal algorithm. Meanwhile, the predicted data sequence of the output is obtained by cyclically prediction operation.

We assumed the input sequence dataset as $S = \{s_i| 1 \leq i \leq m\}$, each input sequence s_i is a vector (x_1, x_2,..., x_n) in the length of n. All the Ws are weight matrices and bs are the biases. is the sigmoid function. c_t is the update vector of cell state in time t. m is the output vector in time t. g and h are the activation function of input and output of cells, respectively. is the softmax function for multi-class task. y_t is the predicted value of state in time t.

For the Bi-LSTM, if we denote the weight matrices as U, V, and W, the formulae are defined as follow.

Based the Bi-LSTM model, the formulae of the Seq2Seq version of Bi-LSTM, namely Bi-LSTM-S2S, have two parts, encoder and decoder.

From each y_t, we can obtain the predicted sequence s'_i in relation to the input sequence s_i. Then the reconstruction error between s'_i and corresponding $s_i$can be calculated by following formula.

According to the distribution of each d_i between dataset S and predicted value set S', the quality assessment value of medical record can be obtained.

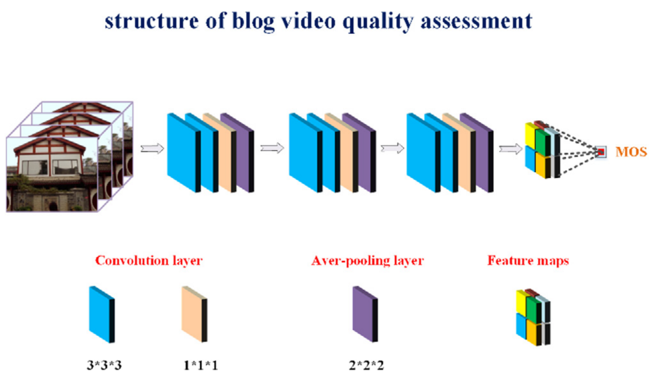

Fig. 2. The architecture of medical image quality assessment is comprised of two kinds of layers. Nine convolutional layers are utilized to extract high-level features while three average pooling layers reduce the dimension of features. Finally, the output layer predicts the quality scores of medical images as a result.

3.2. CNN-Based blog text quality assessment

The TQA model for blog video is based on 3D CNN, which consists of nine convolutional layers, three average pooling layers, and an output layer, shown as Fig. 3.

This part is comprised of three components, each of which can be represented by three convolutional layers whose kernels are with different sizes, that is, 5×5×5 and 3×3×3, associated with an average pooling layer. The first layer convolutional operations leverage the 3×3×3 kernel with padding of one. This enforces the size of the output convolutional layer the same as the input one. Meanwhile, the third convolutional layer adopts 1×1×1 kernel, which is leveraged for the dimensionality reduction task. Herein, the leaky rectifier linear unit (LReLU) [29] activation function is leveraged to build the three convolution layers. α is called leaky parameter, specifically, LReLU degenerates into ReLoU activation function when α equals to 0.

The hierarchical CNN consists of six components, as elaborated in Fig. 2. More specifically, human face, left eye, right eye, nose and mouth are fed into the neural network [27]. Each network architecture consists of four convolution layers and a maximum pooling layer, where convolution layers are used to extract deep features and maximum pooling layer is used to reduce the dimension of deep features. Then five parts are fused by a fully-connected layer. The facegrid is a binary mask that can indicate the location of different key patches of the face. In our implementation, the facegrid is 3636 size. The details of our used CNN architecture is shown in Table 1. Each key patches and face region are resized to 224.

4. Experiments and analysis

This section conducts comprehensive experiments to validate the performance of our method. We first introduce the compilation of our database based on the blog texts scratched from the website of the sina weibo in China. Afterwards, we compare our method with the comparative texts quality models.

The experiments were carried out on a Server with Intel Core i7-4720HQ CPU @ 2.60 GHz, 20GB memory, and NVidia K80 GPU.

4.1. Blog texts quality assessment datasets from MafengWo

To construct the verification dataset, we construct the data set with the blog textual data scratched from the website of the sina weibo in China. The data set consists of 5000 items, each of which includes a textual component and a video-related text component. Each item is preprocessed through integration, cleaning, the numerical characteristics of normalization, the non-numeric characteristics normalization of digital coding.

According to the subjective quality evaluation criteria, five domain experts related to the video quality evaluation use the differential mean opinion score (DMOS) to rate all 5000 texts in the data set. Besides, we collected a million-scale texts data set to validate the performance of texts from Mafengwo.

For the experiments, we randomly selected 80% of dataset for training and the other 20% for testing.

Table 1
Comparison of seven medical data quality evaluation methods on PLCC and SROCC.

Method	*SROCC*	*PLCC*
M_1	0.647	0.639
M_2	0.825	0.794
M_3	0.745	0.776
M_4	0.659	0.653
M_5	0.833	0.827
M_6	0.769	0.793
Proposed	**0.858**	**0.861**

4.2. Implementation details

First, for the record data in the training set, Bi-LSTM-s2s model was conduct to update the weights with Adam optimizer. The training of the model lasts for 1000 epochs with initial learning rate with 0.0001.

Afterwards, based on frames of each video in the training set, 3D CNN model was trained by the SGD as the optimization method. Due to the simplicity of 3D CNN model, the Adam optimization is not considered. The MBGD could achieve competent performance to the Adam with the less computation and faster convergence speed. Since the number of training set is not sufficient, the batch-size of training was set to 4 while the initial learning rate was set to 0.0001. The training iterated for 400 epochs, and the learning rate is reduced to one tenth of the original value.

4.3. Experimental results

Herein, we compare our proposed blog video quality prediction framework with a set of existing related models. More specifically, for the blog video assessment model, the following no-reference quality models are considered: three quality models proposed by Moorthy et al. [22], Mittal A et al. [23], and Saad M A et al. [16] respectively. Meanwhile, to validate the effectiveness of the aid of each video-related text, two ablation model of Bi-LSTM-s2s models, LSTM-forward and LSTM-backward, which only consider the forward and backward procedure respectively, are testified. For the sake of description, six signs of M_1 to M_6 stand for the six counterparts, Moorthy + LSTM-forward, Mittal+LSTM-forward, Saad+LSTM-forward, Moorthy+LSTM-backward, Mittal + LSTM-backward, Saad +LSTM-backward.

From experimental results of seven models on blog video set shown in Table 1, the proposed blog video quality evaluation method outperforms the other counterparts on the PLCC and SROSS measurements. The reason lies in that, in addition to effective features within 2D medical images, our method takes advantage of spatial and temporal information within the three-dimensional frame sequence within each video. Moreover, compared with the ablation models with LSTM-forward and backward, Bi-LSTM-s2s utilized bi-directional information within the corresponding text information to achieve better performance.

Fig. 3exhibits the PLCC and SROCC of different methods on blog video quality evaluation. In contrast to the traditional IQA model,

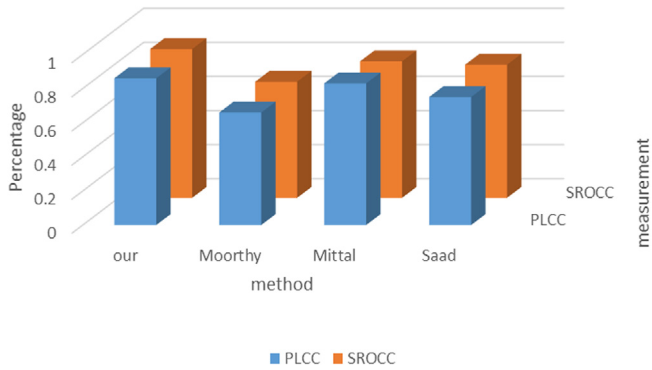

Fig. 3. The PLCC and SROCC of four methods on blog video quality evaluation.

Table 2
The TQA accuracy rates on Mafengwo dataset under different dimensions of PCA.

Dimension	Recognition rate	Standard deviation
100	0.9211	0.0021
200	0.9330	0.0015
300	0.9241	0.0017
400	0.9162	0.0020
500	0.9570	0.0018
600	0.9565	0.0012
700	0.9521	0.0005
800	0.9502	0.0011
900	0.9510	0.0012
1000	0.9511	0.0011
no-DR	0.9432	0.0012

3D CNN can extract more representative features related to the three dimensional frame sequence.

As we can see from Table 2, the TQA prediction performance by leveraging the deep representation is 93.11%. The TQA recognition rate is improved based on the dimension reduction by PCA. When the dimension is reduced to 500-D, face recognition achieves the best recognition performance 92.1%.

5. Conclusion

This paper proposes a blog text quality evaluation algorithm by leveraging the artificial intelligence, which can evaluate blog texts with the additional aid of video-related text data through the design and implement different kind of deep learning system, so as to help the blog quality control, blog operation management, promoting the level of the quality of websites. The quality evaluation model provides a new way of thinking for the application of artificial intelligence in the content management of Internet.

Experimental results based on blog texts scratched from the website of the sina weibo in China have shown that the proposed model has better overall blog text quality evaluation performance than the other mainstream non-reference IQA methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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