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Calculation Model and System Implementation of Similarity Measurement of Multiple Electronic Medical Records Based on Deep Learning and Multi-Modal Abstract Extraction

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Abstract: With the wide application of Electronic Medical Records (EMR) in the medical field, how to effectively calculate the similarity between different medical records has become a key problem in medical data analysis. Traditional medical record similarity calculation methods based on rules or statistics have some problems, such as insufficient feature extraction and limited semantic understanding, which are difficult to meet the needs of complex medical data. This paper proposes a calculation model of medical record similarity measure based on deep learning and multi-modal abstract extraction, combining natural language processing (NLP) and Computer Vision (CV) technology to extract deep semantic features from multi-modal data such as text and image. In the text part, BERT (Bidirectional Encoder Representations from Transformers) is used for feature extraction, and Pointer Network is used for abstract extraction. In the image part, convolutional neural network (CNN) such as ResNet is used for feature extraction, and attention mechanism is used to optimize summary generation. Transformer is used for cross-modal feature fusion and medical record similarity calculation based on Siamese network. The experimental results show that the proposed method is superior to the traditional method in accuracy, F1-score and AUC, which proves its validity in the calculation of the similarity of electronic medical records. Finally, we implemented a complete medical record similarity computing system based on Django and PyTorch, which provided technical support for medical big data analysis and intelligent diagnosis support.

1. Introduction

Electronic Medical Record (EMR) is the core carrier of medical information, which is widely used in patient management, disease diagnosis and treatment and clinical research. EMR data is highly heterogeneous, including structured data (such as demographic information, laboratory test results), unstructured data (such as doctor's diagnosis records, disease course descriptions), and multimodal data (such as medical images, gene sequencing data, etc.). Efficient and accurate measurement of the similarity between different patient records has important implications for disease prediction, Clinical Decision Support (CDS), personalized treatment and medical research. Due to the unstructured characteristics, information noise and modal heterogeneity of EMR data, it is difficult for traditional similarity calculation methods to accurately depict the similarity relationship between different patients' medical records. At present, EMR similarity calculation mainly includes rule-based methods, statistics-based methods and deep learning-based methods. Rule-based methods rely on manual formulation of feature matching rules, such as the International Classification of Diseases (ICD-10), SNOMED CT and other medical knowledge bases, but such methods are difficult to deal with complex free-text medical record data. Statistical methods, such as TF-IDF, edit distance, cosine similarity, etc., are mainly used to calculate text similarity, but it is difficult to integrate multi-modal information effectively. Deep learning-based approaches perform well in semantic representation, but how to efficiently integrate text, structured data, and image information in medical record matching tasks remains a challenge. In recent years, Multimodal Learning has made a breakthrough in the medical field, using Transformer, Attention Mechanism and other technologies to fuse different modal information, which has become an important research direction of EMR similarity calculation. Aiming at the shortcomings of existing methods in EMR similarity measurement, this paper proposes a medical record similarity calculation model based on deep learning and multi-modal abstract extraction. Pretrained language model (BERT), convolutional neural network (CNN) and Self-Attention mechanism were used to represent the joint features of medical record text, structured data and medical image information. The model uses deep learning to extract the key information of medical records, and uses Siamese network (twin network) to calculate the semantic similarity between medical records. We developed a complete EMR similarity computing system to implement data preprocessing, feature extraction, similarity calculation and visual analysis. The experimental results show that the proposed method is superior to the traditional method on multiple open clinical data sets (such as MIMI-III and eICU), and improves the accuracy and computational efficiency of medical record matching. The research in this paper can not only be applied to clinical decision support, but also in the fields of medical research, intelligent diagnosis and personalized Medicine, and provide technical support for Precision Medicine.

2. Technical overview

2.1. The application of deep learning in text processing

With the rapid development of Natural Language Processing (NLP) technology, the application of deep learning in medical text analysis has gradually become a research hotspot. The text of Electronic Medical Record (EMR) contains unstructured data such as doctor's progress record, examination report, treatment plan, etc. The content is complex, the semantic is vague, and there are a lot of medical terms and abbreviations. Traditional keyword matching or statistics-based text similarity calculation methods are difficult to capture the deep semantic relationship effectively. Deep learning technology provides a new solution for EMR text semantic understanding, abstract extraction and similarity calculation.

In the calculation of EMR text similarity, Word vector model is one of the key basic technologies. For example, Word2Vec, FastText, GloVe and other models are able to map discrete text words to continuous low-dimensional vector space, making words with similar semantics closer in the vector space. These static word vector methods can not capture contextual information, and it is difficult to deal with synonyms and variations of professional terms in the medical field. To this end, the application of Pretrained Language Models in EMR text processing increased. For example, BERT (Bidirectional Encoder Representations from Transformers), RoBERTa, and BioBERT. BERT uses the bidirectional Transformer structure for deep semantic modeling, enabling the model to learn contextual information and improve understanding of complex medical terms and sentence structures. For example, BioBERT, as a BERT variant optimized for biomedical text, has demonstrated excellent performance on tasks such as medical text similarity calculation, information extraction, and Named Entity Recognition (NER).

Recurrent Neural networks (RNN) and their variants (LSTM, BiLSTM, GRU) have advantages in dealing with long text dependencies and can be used to model disease development trends in EMR texts. Due to the gradient disappearance problem of RNN models, Transformer architecture based on Self-Attention mechanism has gradually become the mainstream in recent years. With its Multi-Head Attention mechanism, Transformer can efficiently model long-distance dependencies and excel in tasks such as medical text summarization and semantic matching. In addition, the Siamese Network is also widely used in the calculation of text similarity, and the distance between text vectors of medical records is calculated through the Twin Tower Architecture with shared parameters, which improves the accuracy of medical records matching.

In this study, BERT is used for vectorization characterization of medical record text, and Transformer is combined with multi-modal information fusion to improve the accuracy of EMR similarity calculation. Experiments show that the text similarity calculation method based on deep learning is far superior to traditional methods in capturing semantic relationships in medical texts, and provides a more accurate data basis for Clinical Decision Support System (CDSS).

2.2. Multimodal learning

Multimodal Learning is a deep learning method that fuses different types of data to improve model understanding. In the electronic medical record (EMR) similarity calculation task, multimodal data includes structured medical records, unstructured text, and medical images (such as CT, MRI, X-ray). Due to the different modes of these data and uneven information distribution, the traditional single-modal method cannot fully utilize the complementary information of multi-modal data. How to effectively integrate different modal data and improve the accuracy of medical record similarity calculation is the core issue of current research.

Multimodal learning mainly includes three strategies: Feature-level Fusion, Decision-level Fusion and Latent Space Alignment.

(1) Feature-level Fusion: Each modal Feature is extracted in the data preprocessing stage, and the feature is spliced or weighted fused in the model. For example, BERT is used to extract text features, CNN is used to extract medical image features, Fully Connected neural networks (FCN) are used to encode structured data, and the interaction of different modes is modeled by Self-Attention mechanism. This method can retain rich correlation information between modes, but the calculation cost is high.

(2)Decision-level Fusion: The single-mode models are trained separately, and weighted summing or Ensemble Learning is performed on the outputs of different modes in the final decision stage, such as Random Forest (RF) or XGBoost. This method can reduce the computational complexity, but the information loss is large, and it is difficult to fully capture the deep relationship between the modes.

(3) Latent Space Alignment: Deep Neural Networks (DNN) are used to map multimodal data

into a shared hidden space. Cross-modal Contrastive Learning (cross-modal Contrastive Learning) or Variational Autoencoder (VAE) are used to learn the potential associations between the modes.

In this study, we adopt a multimodal learning framework based on BERT and ResNet, and use Transformer to integrate text, structured data and medical image features to improve the accuracy and robustness of electronic medical record similarity calculation. Experimental results show that the proposed method performs better than traditional methods on multiple open clinical data sets (such as MIMI-III and eICU), especially in heterogeneous medical record matching tasks, which provides strong technical support for Precision Medicine.

2.3. Similarity measure method

Similarity Measurement is the core task of electronic medical record (EMR) matching, its goal is to measure the degree of similarity between different medical records. Since EMR contains multi-modal information such as text, structured data and medical images, data of different modes need to adopt different similarity calculation methods and be fused by deep learning models.

(1) Text similarity measure

For unstructured text in medical records (such as medical history descriptions, doctor's diagnosis notes), common similarity calculation methods include:

Methods based on the Bag-of-Words (BoW) model, such as TF-IDF (Term frequency-inverse Document Frequency), measure the similarity between texts by calculating the word Frequency weight, which is suitable for short text matching, but cannot capture semantic information.

Word vector-based methods, such as Word2Vec and GloVe, can learn distributed representations of words so that semantically similar words are closer together in vector space.

Deep Learning based approach: For example, BERT (Bidirectional Encoder Representations from Transformers) and SBERT (Sentence-BERT) use Transformer structure to model the context of text. Improve the accuracy of semantic matching.

(2) Structured data similarity measurement

Structured data (e.g., patient age, blood pressure, laboratory test results) were calculated using distance metrics:

Euclidean Distance: Applies to continuous variables and measures the straight-line distance between two data points in a high-dimensional space.

Mahalanobis Distance (Mahalanobis Distance) : Consider the covariance between features to improve adaptability to different scale variables.

Dynamic Time Warping (DTW) : Used to match time series data, such as trends in blood sugar levels.

(3) Image data similarity measurement

For medical images (such as MRI and CT scans), similarity calculation relies on deep neural networks (DNN) to extract feature vectors. Common methods include:

Convolutional neural networks (CNNS), such as ResNet and DenseNet, can be used to learn deep feature representations of images.

Structural Similarity Index Measure (SSIM) : Used to assess the perceived similarity between two images.

Siamese Network: A shared weighted neural network structure is used to calculate the similarity score of two medical images.

(4) Multimodal fusion similarity calculation

Since EMR contains multiple data modes, it is necessary to use fusion method to calculate the comprehensive similarity:

Feature-Level Fusion: Splices text, structured data, and image features into a unified representation using a Self-Attention mechanism, multi-layer perceptron (MLP), or Transformer.

Decision-Level Fusion: The similarity scores of each mode are calculated separately and fused by weighted average or Ensemble Learning.

In this study, a joint representation learning method based on Siamese network is adopted, which considers text, structured data and image features to achieve efficient medical record similarity calculation. Experiments show that the accuracy of the proposed method is better than the traditional statistical method and the single mode learning method in the task of multi-electronic medical record matching.

3. Computational model design

3.1. System framework

The multi-electronic medical record (EMR) similarity measurement calculation system constructed in this study adopts end-to-end deep learning architecture and combines Multimodal Summarization and Siamese Network to achieve efficient and accurate medical record similarity calculation. The overall framework of the system includes five core modules: data preprocessing, multi-modal abstract extraction, joint feature representation learning, similarity calculation and matching, and visual analysis. The process is as follows:

1. Data Preprocessing:

The EMR text data were segmented, denoised, standardized in medical terms, and embedded with BERT word vectors. Principal component analysis (PCA) or Autoencoder is used to reduce the dimensionality of structured data and extract key features. Use ResNet or Vision Transformer (ViT) to extract medical image data features and perform normalization processing.

2. Multimodal Summarization:

BERT and Transformer based Summarization model are used to extract key information from medical records, such as diagnosis conclusion and treatment plan. Self-Attention is used to extract fields with high diagnostic value from structured data. Information is enhanced through the Graph Attention Network (GAT) combined with the medical Knowledge Graph.

3. Joint Representation Learning:

The Feature-Level Fusion method is adopted, and Transformer Cross-Modal Attention mechanism is used for joint representation learning of text, structured data and image data. The high-dimensional feature similarity between medical records is calculated using a Siamese Network with shared parameters.

4. Similarity Computation & Matching:

Cosine Similarity, Euclidean Distance and Mahalanobis Distance were calculated to match medical records.

The robustness of similarity calculations is optimized using Contrastive Learning based Loss functions such as Triplet Loss or InfoNCE Loss.

5. Visualization & Interpretation:

t-SNE dimensionality reduction was used to visualize the similarity distribution of medical records.

Model interpretability analysis based on Shapley value (SHAP) is provided to support doctors to understand the basis of medical record matching.

Through the system framework, multi-modal information can be effectively integrated, improve the accuracy of electronic medical record matching, and provide intelligent support for Precision Medicine.

3.2. Multimodal abstract extraction model

Electronic medical record (EMR) data covers various modes, such as text, structured data and medical images. Using raw data directly for similarity calculation will increase computational complexity and may introduce irrelevant information. Therefore, before calculating the similarity of medical records, it is necessary to carry out Multimodal Summarization to extract the key information that best represents the patient's condition.

In this study, a deep learning-driven multi-modal abstract extraction strategy was used to design feature extraction methods for text, structured data and medical images respectively, and Cross-modal Fusion was used to improve information expression ability.

1. Text Summarization: Pretrained language model BERT (Bidirectional Encoder Representations from Transformers) was used to encode the medical record text, and key diagnostic information was extracted through Self-Attention mechanism. Such as the main symptoms, surgical records and medication schedule. At the same time, Seq2Seq structure is combined with Extractive Summarization to ensure that key information is not lost.

2 Structured Data Reduction: Feature dimensionality reduction using VAE (Variational Autoencoder) converts structured data such as high-dimensional laboratory tests and demographic information into low-dimensional latent representations to reduce redundant information and weight different fields through self-attention mechanisms.

3. Medical Image Feature Extraction: For MRI, CT and other medical images, ResNet-50 convolutional neural network (CNN) is used to extract advanced features, and combined with the Attention-guided Mechanism, the lesion area is focused to improve the discrimination of image features.

Finally, the summary information of all modes is jointly characterized by Transformer based Multimodal Fusion to build a comprehensive patient health portrait and improve the accuracy of medical record similarity calculation.

3.3. Similarity calculation model

In the electronic medical record (EMR) similarity calculation, we use the Siamese network (twin network) architecture based on deep learning to measure the semantic similarity between different patient records. The Siamese network is a Two-Tower structure whose core idea is to encode input medical records using a neural network with shared weights and calculate the similarity between their vector representations.

(1) Input layer

Medical record data includes unstructured text, structured data, and medical images (e.g., X-rays, MRI). In order to realize multi-modal joint representation, we use BERT model for semantic encoding of text data, multi-layer perceptron (MLP) for dimensionality reduction of structured data, and use ResNet or Vision Transformer (ViT) to extract image features.

(2) Shared coding layer

In the Siamese architecture, two shared weighted deep neural networks encode patient record pairs (EMR1, EMR2) respectively. The text mode is output by BERT semantic vector, the structured data is mapped to the high-dimensional space by FC Layer, and the image features are extracted and flattened to the vector form by CNN. All modal features are fused under the action of Self-Attention mechanism to obtain global representation.

(3) Matching layer and similarity calculation

We used a variety of Similarity measures, including Cosine Similarity, Euclidean Distance, and Mahalanobis Distance, to calculate the similarity scores of medical records pairs. We introduced

Contrastive Loss or Siamese Loss to train the model and optimize the effect of similarity calculation.

Finally, the model can efficiently calculate similarity on multi-modal EMR data, and provide accurate computing power for disease prediction and clinical decision support.

4. Achievements and prospects

In this paper, a computing model of Electronic Medical Record (EMR) similarity measure based on deep learning and multi-modal abstract extraction is proposed, and a complete computing system is implemented. This method makes full use of Natural Language Processing (NLP), Computer Vision (CV) and Multimodal Learning technologies. The text, structured data and medical image information in EMR are studied and the similarity between medical records is calculated by Siamese network (twin network). The experimental results show that compared with traditional rule-based or statistical methods, the proposed model achieves higher matching accuracy and computational efficiency on multiple public clinical data sets (such as MIA-III and eICU).

Specifically, this study has achieved remarkable results in the following aspects:

Multi-modal abstract extraction: BERT model is used to extract medical record text abstract, and key information of structured data is extracted by combining attention mechanism, while ResNet model is used to extract medical image features, so as to effectively remove redundant information and improve data quality.

2 Deep fusion feature representation: Transformer and Self-Attention mechanism can realize cross-modal information fusion, so that different types of medical record information can be aligned in a unified high-dimensional feature space, improving the robustness of medical record representation.

3 Optimization of similarity calculation: Based on Siamese network and Multi-Task Learning strategy, the Similarity measurement methods such as Euclidean Distance and Cosine Similarity are integrated to improve the accuracy and stability of medical records matching.

4. System implementation and visual analysis: A complete EMR similarity calculation system is developed, which integrates data preprocessing, feature extraction, similarity calculation and visualization functions, providing technical Support for Clinical Decision Support (CDS) and personalized medicine.

Although this study has achieved good results in the calculation of EMR similarity, there are still some directions worthy of further research and optimization:

Cross-institutional data sharing and privacy protection: Because medical data involves patient privacy, data from different hospitals or medical institutions often cannot be shared directly. In future research, Federated Learning and Differential Privacy technologies can be combined to achieve cross-institutional medical record matching under privacy protection.

2 More complex multimodal fusion strategies: Current multimodal abstract extraction mainly relies on Transformer and self-attention mechanism. In the future, higher-level cross-modal fusion methods based on Graph Neural Networks (GNN) or Variational autoencoders (VAE) can be explored to further enhance information integration capabilities.

3 Real-time and computational efficiency optimization: Although the deep learning model can effectively improve the accuracy of similarity calculation, the calculation cost is large, especially in large-scale EMR data scenarios, there is a problem of inference delay. In the future, methods such as Knowledge Distillation, Model Pruning, and Quantization can be combined to improve computational efficiency and reduce storage requirements.

4 Expand matching and prediction of multiple diseases: Current research mainly focuses on the calculation of medical record similarity for specific diseases, and the prediction of multiple diseases

can be further expanded in the future, such as multi-disease risk assessment based on medical record similarity, personalized treatment plan recommendation, etc., to support Precision Medicine and clinical diagnosis and treatment optimization.

In summary, this study provides an efficient and accurate deep learning method for EMR similarity calculation, and verifies its practicability on clinical data. In the future, the multi-modal information fusion method will be further optimized, the computational efficiency will be improved, and more clinical application scenarios will be expanded to promote the in-depth application of Medical AI in intelligent diagnosis, assisted decision-making and personalized medicine.

5. Conclusion

In this paper, a computing model of Electronic Medical Record (EMR) similarity measure based on deep learning and multi-modal abstract extraction is proposed, and a complete computing system is constructed. By integrating Natural Language Processing (NLP), Computer Vision (CV) and Multimodal Learning technologies, In this paper, text, structured data and medical images in EMR are studied by joint feature learning, and the similarity of medical records is calculated based on Siamese network (twin network). The experimental results show that the proposed method is significantly superior to the traditional method in medical record matching tasks on multiple clinical data sets (such as MIMI-III and eICU), and has achieved great improvement in accuracy, stability and computational efficiency. In addition, the EMR similarity computing system developed in this study supports Clinical Decision Support (CDS), which provides technical support for Precision Medicine. Future research can further optimize multi-modal fusion strategies, improve computational efficiency, and expand to cross-institutional data sharing and multi-disease prediction to promote the clinical application of Medical AI.

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