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Medication Recommendation System Based on Natural Language Processing for Patient Emotion Analysis

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Abstract: Natural Language Processing (NLP) is an interdisciplinary field of computer science, artificial intelligence, and linguistics that focuses on the ability of computers to understand, process, generate, and simulate human language in order to achieve the ability to have natural conversations with humans. The underlying principles of natural language processing are at multiple levels, including linguistics, computer science, and statistics. It involves the study of language structure, semantics, grammar and pragmatics, as well as the statistical analysis and modeling of large-scale corpora. In the process of concrete implementation, it is necessary to process natural language at multiple levels. Based on this, this paper combined deep learning and natural language processing technology to conduct sentiment analysis on patients' comments, so as to recommend drugs that are more suitable for patients, thus achieving accurate drug prescribing and personalized recommendation.

Keywords: Natural language processing (NLP); Artificial intelligence; Emotion analysis; Personalized recommendation; Comment analysis.

1. Introduction

The development of natural language processing dates back to the 1950s, when computer scientists began experimenting with computer programs to understand and generate natural language. Early research focused on rules and knowledge-based approaches, such as writing grammar rules and dictionaries for sentence analysis. In the 1980s, with the improvement of computing power and the emergence of a large corpus, statistical methods gradually dominated the field of natural language processing. During this period, many statistics-based machine translation, word segmentation, part-of-speech tagging and other methods appeared one after another. In the 21st century, especially in the last decade, the development of deep learning technology has greatly promoted the progress of natural language processing. Models based on deep neural networks, such as recurrent neural networks (RNN), Long and short term memory networks [1-3](LSTM), and Transformer, have greatly improved the efficiency and accuracy of natural language processing.

Internationally, technology giants such as Google, Facebook, and OpenAI have also made a series of important breakthroughs in the field of natural language processing. For example, Google's BERT model and OpenAI's GPT family of models have both achieved above-human performance on multiple natural language processing tasks. In China, natural language processing research and industrial development have also achieved fruitful results. At present, there are many domestic natural language processing research institutions and enterprises, such as the Institute of Computing Science of the Chinese Academy of Sciences, Tsinghua University, Baidu, Tencent, etc. Among them, Baidu's ERNIE, [4-6]Alibaba's BERT and other pre-trained models perform well on various Chinese natural language processing tasks. At the same time, many domestic companies have also applied natural language processing technology to intelligent customer service, search engines, recommendation systems and other scenarios.

Natural language processing (NLP) technology can process completely unstructured data, and one of the main purposes for companies to adopt NLP technology is to embed intelligent systems to optimize organizational processes, improve time efficiency, and reduce operational costs.

Regardless, there are other benefits to incorporating [7]NLP into healthcare application development. NLP can translate human language into a machine-readable form, allowing machines to derive meaning from the data provided. Healthcare is using NLP tools to control data that can be stored as voice, text, hieroglyphics, photos, and more to draw useful conclusions.

The study shows that natural language processing in healthcare is expected to increase from $1,030.2 million in 2016 to $2,650.2 million in 2021, representing a compound annual growth rate of 20.8%.

Before we discuss the use of this disruptive technology in the healthcare industry, let's understand what NLP actually means. [8]NLP is a field of artificial intelligence that aims to bridge the gap between humans and robots. With NLP capabilities, a powerful system can understand, store, process, and execute data-driven insights in human-understandable speech or text.

Natural language processing systems are becoming increasingly important and useful in healthcare application development. As a result, systems like building chatbots using NLP are also making waves in the healthcare industry. In an efficient execution state, technology can help clinicians streamline management operations by analyzing real-time data, allowing them to spend more time on patient care and improving the patient experience.

2. Related Work

2.1. Natural language processing technology (NLP)

Natural language processing (NLP) is an interdisciplinary discipline that spans multiple fields such as computer science, artificial intelligence, and linguistics. It aims to enable computers to understand, generate and process human language, and realize natural language interaction between computers and humans. With the continuous development of natural language processing technology, it will be more and more widely used in artificial intelligence, machine learning and big data. For example, in the field of artificial intelligence, natural language processing technology can help machines better understand human language and improve the interaction and semantic understanding ability of machines.[9-11] In the field of machine learning, natural language processing technology can help machines better understand and process text data, and improve the effectiveness and accuracy of machine learning. In the field of big data, natural language processing technology can help enterprises and organizations better understand and analyze large amounts of text data, helping them better understand market trends, customer needs and social hot spots.

Although natural language processing technology brings many conveniences and applications, it also faces many challenges and problems. For example, how to solve the problems of polysemy, language habits and language difficulty, how to improve the accuracy and naturalness of translation, how to solve the emotional color of language and other problems. [12]These problems need us to continue to study and explore to improve the application level and effect of natural language processing technology. It can be seen that natural language processing technology is a science and technology topic with a wide range of applications, and I will continue to talk about the cutting-edge development and application of natural language processing technology.

In recent years, the application of natural language processing technology in the field of deep learning has received extensive attention and research. Deep learning technology uses neural network model to process text data, which can learn richer language features and automatically extract hidden features from text data. This has enabled deep learning techniques to achieve many breakthrough results in the field of natural language processing.

Among them, the most representative applications are language model modeling and natural language generation. Language modeling is one of the core tasks in the field of natural language processing, which is capable of modeling text sequences to predict the probability distribution of the next word. Techniques based on language models can be used in natural language generation, machine translation, speech recognition, text classification and other tasks. At the same time, natural language generation technology has also been widely concerned and applied, such as: automatic summary, [13-16]chatbot, text generation and so on.

In addition, deep learning techniques can also be used for tasks such as syntax analysis, semantic analysis, and named entity recognition. For example, named entity recognition can automatically extract entity information such as personal name, place name and organization name from text to provide help for information extraction and data mining. Semantic analysis can help machines better understand human language and improve their understanding ability and application effect.

In addition, with the continuous development and popularization of natural language processing technology, its application scenarios are becoming more and more diversified. For example, in the medical field, natural language processing technology can help doctors better process and understand medical record data, improving the efficiency and accuracy of diagnosis and treatment. In the financial field, natural language processing technology can help financial institutions to better manage risk and information disclosure. In the field of education, natural language processing technology can help educational institutions better conduct intelligent teaching and assessment[18].

In general, natural language processing technology is a very important and cutting-edge technological development, which continues to promote the progress and development of artificial intelligence and big data. With the continuous innovation and progress of technology, it is believed that natural language processing technology will be applied and developed in more fields, bringing more convenience and change to human beings.

2.2. Natural language emotion analysis

Sentiment analysis of text in natural language processing (NLP) is an important application area, and it is often used for evaluative user feedback, such as movie reviews and post-shopping reviews. Emotion analysis is mainly based on the user's answer text data (Chinese) to conduct quantitative analysis of text emotion. The existing sentiment analysis methods are as follows: 1. [19]Emotion dictionary analysis method. 2. Machine learning analysis method. It is to cut the words of the text, remove the stop words, extract the positive keywords and negative keywords in the keywords, and calculate the emotion score.

First, the text data is cut, here the Chinese word cutting tool jieba, there are many other word cutting tools, such as snowNLP, etc., have their own advantages, but the more accurate the word cutting the more accurate the results. The second is about the generation of dictionaries, which mainly includes three dictionaries, stop word dictionary, positive emotion dictionary, negative emotion dictionary, from the dictionary of HowNet. The stop word dictionary contains conjunctions like "so" and "how" and punctuation and so on, words that don't have emotion, and when you remove these words, you're left with words that have emotion. The more data the dictionary contains, the more accurate the sentiment predictions will be.

Usually combined with the use of machine learning methods, mainly using the word vector model word2vec, the word into an array, so that by calculating the data distance between words, to measure the similarity between words, so that after the model has supervised learning of positive and negative word vectors, you can get the result. The cyclic neural network LSTM[20] is used here, and the delay performance of LSTM helps the word vector learning. The deep learning framework of tensorflow is used here.

Principle of emotion analysis algorithm

The main principles of sentiment analysis algorithms include:

1. Statistical learning method: Emotion analysis algorithm based on statistical learning method can identify emotion information in text by learning training data set. Such algorithms include naive Bayes, support vector machines, decision trees and so on.

2. Deep learning method: Emotion analysis algorithm based on deep learning method learns emotion information in text through multi-layer neural network. Such algorithms include convolutional neural network, recurrent neural network, self-attention mechanism and so on.

2.3. NLP and Healthcare

1. Speech recognition

For nearly two decades, NLP's origins in healthcare have been tied to voice recognition, a technology that allows physicians to quickly transcribe prescriptions into electronic health records (EHR).

Front-end speech recognition allows doctors to dictate prescriptions without sitting in front of a point-of-care computer, while back-end recognition corrects problems before sending transcriptions to people for verification.

Without the need for medical transcriptionists and the high costs of paying them, speech recognition is one of the most cost-effective solutions.

2. Clinical documents

The impact of NLP on speech recognition is closely related to clinical documentation due to NLP's speech-to-text dictation and structured data entry, which frees physicians from the burdensome and constrained structure of electronic health records to better care for patients.

Both Nuance and M*Modal have technology that works in tandem with speech recognition, which collects structured data and standardised terminology at the point of care for future use[21].

3. Computer Aided Coding (CAC)

The CAC collects data from procedures and treatment protocols in order to capture every possible code and optimize claims. CAC may improve the coding speed, but it does nothing to improve the accuracy of the coding.

For example, a Cleveland Clinic study showed that while CAC reduced coding time, it had poor recall and accuracy when used alone without the assistance of a qualified coder.

4. Clinical trial matching

Clinical trial matching is probably the most discussed case in the "in development" category. For example, two companies, Linguamatics Health and Clinithink, have created NLP engines to address trial matching, while two companies, IBM Watson Health and Inspirata, have invested significant resources in using NLP to aid oncology research.

In the near future, NLP appears to have the ability to make clinical trial matching a seamless and automated process.

5. Data mining research

Data mining in healthcare systems allows businesses to reduce the subjectivity of decisions while providing relevant medical knowledge. Once data mining begins, it can become a circular technique for knowledge discovery that helps all healthcare companies develop sound financial strategies to provide better patient care.

6. Ai chatbots and virtual scribes

While there is no such solution yet, there is a good chance that voice recognition applications will help humans modify clinical paperwork. Amazon's Alexa or Google Assistant would be ideal for this.

Microsoft and Google have joined forces in this regard to achieve this specific goal. Currently, chatbots built using NLP can pick up a patient's symptoms and direct them to the most appropriate treatment point.

7. Root cause analysis

Another interesting aspect of NLP is the ability of predictive analytics to provide solutions to common health problems.

Large caches of digital medical records can help identify subsets of geographic areas, ethnic groups, or other diverse demographic groups that face different types of health disparities when applying NLP. The NLP system assesses unstructured responses to determine the root cause of a patient's disease.

8. Review management and emotion analysis

NLP can also help healthcare organizations manage Internet reviews. Every day, it collects and analyzes hundreds of comments about healthcare from third-party lists, in addition to quickly assessing human emotions and the context in which those emotions are expressed[22].

Some systems can even listen to customers in comments, which can help doctors understand how consumers view their care, for example, and communicate more effectively in a language they all understand.

In conclusion, the integration of natural language processing (NLP) in healthcare brings forth a multitude of benefits across various domains. From speech recognition facilitating efficient transcription of prescriptions to clinical trial matching streamlining research processes, NLP proves to be a versatile tool for enhancing healthcare delivery. Additionally, NLP-powered applications such as chatbots and virtual scribes offer promising avenues for improving patient communication and administrative tasks. Furthermore, the ability of NLP to conduct root cause analysis and emotion analysis provides valuable insights for addressing health disparities and enhancing patient satisfaction. Overall, the utilization of NLP holds immense potential to revolutionize healthcare operations and improve patient outcomes.

3. Methodology

3.1. Emotion analysis algorithm

Emotion analysis algorithm specific operation steps:

1) Data preprocessing: The input text is cleaned, the words to stop, the partof speech tagging, the word extraction and other processing to extract meaningful features.

2) Feature extraction: The preprocessed text is converted into a vector representation for easy computer understanding and processing. This can be achieved by means of bag of words model, TF-IDF, Word2Vec and so on.

3) Model training: According to the selected algorithm principle, model training is carried out on the training data set. This can be achieved through optimization methods such as gradient descent and random gradient descent.

4) Model evaluation: Test data sets are evaluated to measure the performance and accuracy of the model. This can be assessed by metrics such as accuracy, recall rates, F1 scores, etc.

5) Model optimization: According to the model evaluation results, the model is optimized to improve the accuracy and performance. This can be achieved through hyperparameter adjustment, feature selection, model fusion and so on.

3.2. Emotion analysis mathematical model formula

1. Naive Bayes

Naive Bayes is a statistical learning method based on Bayes' theorem, which assumes that features are independent of each other. For binary classification problems, naive Bayes can be expressed as:

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} \quad (1)$$

Where P(y|x)is the probability of class y given the eigenvector x, P(x|y)is the probability of the eigenvector x given class y, P(y)is the probability of class y, and P(x)is the probability of the eigenvector x.

2. Support vector machine

A support vector machine (SVM) is a solution to the binary classification problem that separates different classes of data by finding a hyperplane that maximizes the boundary margin. The formula of support vector machine is:

f(x) = \text{sgn}(\sum*{i=1}^n |alpha*i yi *K(x*i, x) + b) (2)

Where f(x) is the output function, yi is the label of the training data, K(xi, x) is the kernel function, b is the bias term, and \alpha_i is the Lagrange multiplier.

3.3. Experimental design

This experiment uses natural language processing (NLP) technology to improve drug recommendation systems tailored to individual patient conditions. The experimental methods followed a structured methodology that included data exploration, data preprocessing, model development, conclusion and limitation assessment. In the data exploration phase, visualization and statistical techniques are used to gain insight into the characteristics of the data set. This process helps to pre-process the data and engineer the relevant features for the model. To address the limitations inherent in natural language processing, we introduce the LightGBM machine learning model. The model mitigated potential bias and improved reliability by integrating useful counting features.

In the model development phase, advanced [23-25]NLP techniques are employed, including sentiment analysis using dictionaries and n-grams, as well as deep learning algorithms. These methods allow us to extract meaningful information from text data and improve the accuracy of drug recommendations. Finally, the conclusions of the analysis are critically evaluated and any limitations or weaknesses in the approach to emotional text analysis are identified. This comprehensive approach ensures that our drug recommendation system is robust, reliable, and able to meet the diverse needs of our patients.

3.4. Exploration Data Analysis

First, you need to import training data and test data and display their sizes:

Table 1. Function of raw data set

	uniqueID	drugName	condition	review	rating	date	usefulCount
0	206461	Valsartan	Left Ventricular Dysfunction	"It has no side effect, I take it in combinati...	9	2012-05-20	27
1	95260	Guanfacine	ADHD	"My son is halfway through his fourth week of ...	8	2010-04-27	192
2	92703	Lybrel	Birth Control	"I used to take another oral contraceptive, wh...	5	2009-12-14	17
3	138000	Ortho Evra	Birth Control	"This is my first time using any form of birth...	8	2015-11-03	10
4	35696	Buprenorphine / naloxone	Opiate Dependence	"Suboxone has completely turned my life around...	9	2016-11-27	37

These are additional explanations for variables:

- drugName (categorical): name of drug
- condition (categorical): name of condition
- review (text): patient review
- rating (numerical): 10 star patient rating
- date (date): date of review entry
- usefulCount (numerical): number of users who found review useful

The structure of the data is that a patient with a unique ID purchases a drug that meets his condition and writes a review and rating for the drug he/she purchased on the date. Afterwards, if the others read that review and find it helpful, they will click usefulCount, which will add 1 for the variable[28].

3.5. Data set model training

In the data understanding phase, variables are first explored starting with the uniqueID (uniqueID). We compared the number of unique ids and the length of the training data to see if multiple reviews were written by the same patient, and the results showed that each patient corresponded to only one review, and there was no case of multiple reviews written by the same patient. Next, we analyzed the relationship between DrugName and condition, and found that there was a close correlation between drug name and condition. Among them, the unique values of drug name and condition were 3671 and 917, respectively, with an average of about 4 drugs for each condition. We further visualized the top 20 in terms of the number of drugs for each condition.

The training results are as follows:

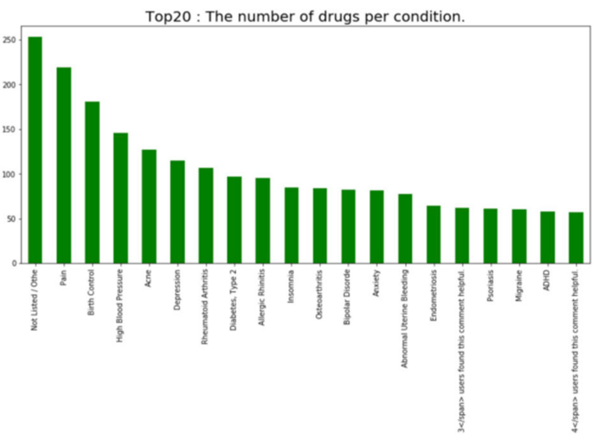

Figure 1. Training result model

Through training the model, we can see some important conclusions:

1. For the first eight conditions, the number of drugs

corresponding to each condition is about 100. This suggests that there are more drug options for these common conditions.

2. There are some exceptions in the data, for example, the condition field contains "3 users found this comment helpful.", which may be an error during the crawl. We need to remove these abnormal data during preprocessing.

3. By observing the distribution of drugs for each condition, it was found that some conditions had only one drug. For the referral system, recommendation is not feasible in this case, so we will only analyze conditions with at least two drugs.

In summary, through training the model, we can conduct an in-depth analysis of the relationship between drugs and disease conditions, and find and handle abnormal data at the same time, which provides an important reference for the establishment of the recommendation system.

3.6. Emotional text cloud word generation

Next, the next step in text analysis is to generate a word cloud. In this step, we will work on the patient's drug review, including removing HTML tags, dealing with the content of brackets that express emotion, and fixing some wrong words and characters. We will then use this pre-processed review data to generate a word cloud map to visually show the words that occur more frequently in reviews to better understand patient evaluations and experiences of drugs.

Figure 2. Generating a cloud text set

Based on the generated word cloud, we can see the words that appear more frequently in the reviews, which may reflect the patients' main concerns about the drug, their experience, and their evaluation of the drug's effectiveness. Common words may include drug names, symptom descriptions, treatment effects, etc. In addition, we can also observe some emotional words, such as "good", "bad", "satisfied", "dissatisfied", etc., which may reflect the patients' emotional tendencies towards drugs.

When looking at the distribution of usefulCount, we can notice that the difference between the minimum and maximum values is large, reaching 1291, and the standard deviation is also large, reaching 36. This is because the more drugs people search for, regardless of whether the reviews are good or bad, the more people read the reviews, making the usefulCount very high. Therefore, when creating the model, we will take into account people's accessibility by normalizing the conditions in order to more accurately assess how useful the comments are.

3.7. Experimental result

Based on the experimental results, it can be seen that a model was successfully built to recommend suitable drugs to patients. In the data exploration phase, we use visualization techniques and statistical techniques to understand the form of the data, while looking[29-31] for n-grams that best represent emotions, and the relationship between dates and ratings. In the data preprocessing stage, we preprocessed the data according to the set topic, such as deleting the case of only one drug to recommend. In the modeling process, we used a deep learning model with n-gram, and also used a machine learning model called Lightgbm to overcome the limitations of natural language processing. In addition, we utilize sentiment dictionaries for sentiment analysis to overcome the limitations of packages formed based on movie data. In addition, we normalize usefulCount with conditions to improve reliability. These steps allow us to calculate the final predicted value and recommend the appropriate drug for each case based on the order of that value.

However, we have some limitations in the project:

1. When using the sentiment dictionary for sentiment analysis, the reliability is low when the number of positive and negative words is small. For example, if the positive word is 0 and the negative word is 1, it is classified as a negative emotion. [32]Therefore, if there are fewer than 5 emotional words, we can rule out these observations.

2. In order to ensure the reliability of the predicted value, we normalized usefulCount and multiplied it by the predicted value. However, as the cumulative number of site visitors increases, usefulCount may tilt toward older reviews. Therefore, when normalizing usefulCount, we should also consider the time factor.

3. If the emotion is positive, reliability should increase in the positive direction, if it is negative, it should increase in the negative direction. However, we simply use usefulCount for reliability without taking this into account. Therefore, we should consider the symbol of usefulCount according to different emotion types, and carry out the corresponding multiplication processing.

4. Conclusion

Based on the comprehensive exploration and analysis conducted in this study, several key conclusions can be drawn regarding the integration of natural language processing (NLP) in healthcare and the development of emotion analysis algorithms:

1. Significance of NLP in Healthcare: NLP technology plays a crucial role in various aspects of healthcare, ranging from speech recognition for efficient transcription to clinical trial matching and emotion analysis for improving patient satisfaction.

2. Challenges and Opportunities[33-34]: While NLP presents immense opportunities for enhancing healthcare delivery, it also faces challenges such as low reliability in sentiment analysis with limited emotional words. However, these challenges can be addressed through careful preprocessing and model optimization techniques.

3. Methodological Approach: The methodology employed in this study involved data exploration, preprocessing, model development, and evaluation. Advanced techniques like sentiment analysis using dictionaries and n-grams, as well as machine learning models like LightGBM, were utilized to overcome limitations and improve reliability.

4. Recommendation System: The experimental results demonstrate the successful development of a drug recommendation system tailored to individual patient conditions. Through data preprocessing, modeling with deep learning and machine learning techniques, and sentiment analysis, the system effectively recommends suitable drugs based on patient reviews.

5. Limitations and Future Directions: Despite the success of the recommendation system, there are limitations related to sentiment analysis reliability and normalization of usefulCount. Future research should focus on improving reliability metrics and considering the temporal aspect in data normalization.

In conclusion, the integration of NLP in healthcare holds immense promise for revolutionizing healthcare operations and improving patient outcomes. By addressing methodological challenges and leveraging advanced techniques, NLP-powered applications like emotion analysis algorithms can significantly enhance patient satisfaction and healthcare delivery efficiency.

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In our research, we were inspired by the work of Sun et al. In particular their paper in The Journal of Industrial Engineering and Applied Sciences. [9]"The Integration of Large-Scale Language Models Into Intelligent Adjudication: Justification Rules and Implementation Pathways". By perusing their research, we gain a deeper understanding of how language models can be integrated into intelligent rulings. We would like to give special thanks to Sun et al and their team, as their work has provided us with valuable insights and implementation paths. At the same time, we would like to thank the authors of the paper, whose hard work and research results have brought new thinking and methods to the field of intelligent adjudication. We sincerely thank them for their contributions and look forward to continuing to work with them in the future to promote the development of intelligent adjudication technology.

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