

Reinforced Hybrid Graph Transformer for Medical Recommendations

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Abstract

An enormous amount of heterogeneous Textual Medical Knowledge (TMK), which is crucial to healthcare information systems, has been produced by the explosion of healthcare information. Existing efforts to incorporate and use textual medical knowledge primarily concentrate on setting up simple links and pay less attention to creating computers comprehend information accurately and rapidly. Self-diagnostic symptom checkers and clinical decision support systems have seen a significant rise in demand in recent years. Existing systems rely on knowledge bases that are either automatically generated using straightforward paired statistics or manually constructed through a time-consuming procedure. The study explored process to learn textual data, linking disease and symptoms from web-based documents. Medical concepts were scrapped and collected from different web-based sources. The research aims to generate a disease- symptom-diagnosis knowledge graph (DSDKG), with the help of web-based documents. Moreover, the knowledge graph is fed in to Graph neural network with Attention Mechanism (GAT) for learning the nodes and edges relationships. . Lastly Generative Pretrained Transformer 2 (GPT2) all enclosed in a Reinforced learning environment, is used on the trained model to generate text based recommendations.

Keywords: Disease-symptom-diagnosis knowledge graph (DSDKG), graph neural network with attention mechanism (GAT), generative pretrained transformer 2 (GPT2), reinforced learning environment

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1. Introduction

Textual medical knowledge is an integral part of the modern healthcare IT systems and is crucial for the communication of health information and decision assistance to patients and physicians. A significant amount of textual medical knowledge has evolved in recent years as a result of increasing medical book digitization, biological knowledge expansion, and the rapid development of hierarchical online healthcare providers. In view of the wide range of differing texts on medicine available, there has proved to be a difficulty in organizing and integrating relevant data before

they can be efficiently transmitted to users. Medical diagnostic reasoning is aided by automated tools, which are used by patients looking for information about their symptoms as well as doctors coping with difficult situations or trying to avoid focusing only on a few possible diagnoses. Many times, we ignore the symptoms and avoid going to a doctor, but this can lead to tremendous effect on the body as well. Even if we understand the seriousness of the symptoms such as itching in the skin, pain on left side of heart, pain in knees etc. but we don't know which specialization of doctor to visit and discuss these problems with. This research can be used for the preliminary healthcare procedure by the patients as well as doctors for initial diagnosis or treatment

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which reduces the physical examination costs as well as time for the treatment. The research aims to construct a semantic network of nodes and edges where nodes consist of labels such as diseases names, diagnosis and its corresponding symptoms. Figure 1 depicts the semantic network relationship between the nodes and edges.

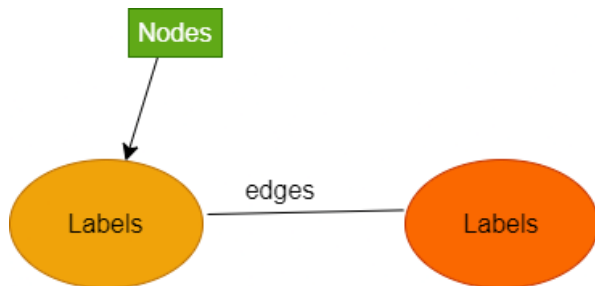


Fig 1: Semantic network of nodes and edges

Moreover, information extracted from a sentence of web collected data, we construct Subject-Verb-Object (SVO) triples also called as Head Entity, Candidate Entity and its relations for construction of our knowledge graph.

2. Related Works

There are various studies and research papers on knowledge graphs in medical domain. Recently, biomedical versions of embeddings created from language models such as Bio ELMO have been demonstrated to produce state of the art results on textual inference problems in the medical field. Somya Sharma [1]. Used BioELMo embedding model including bidirectional LSTM for Incorporating Domain Knowledge into Medical NLI using knowledge graphs. Chaveevan Pechsiri and Rapepun Piriyakul [2] used various machine learning techniques such as SVM, Naïve Bayes and Linear Logistic Regression using web-based resources and a Thai hospital web board resource for construction of Disease-Symptom knowledge graph. Natural processing techniques for text pre-processing are used by various researchers. Gyanesh Anand [3] used Natural Language based Recommender system using RegEx and UMLS parsing based entity extractor to build the knowledge graph. The EMR data give a realistic view of the patient with all his or her comorbidities, conflicting factors and distinctive features which make them individuals. An idea to learn a Health Knowledge Graph through EMR records was presented by Maya Rotmensch [4]. The model was compared to an extensive and manually Curated Knowledge Graph by Google that is also known as a Google Health Knowledge Graph (GHKG). Fang Gon a [5] built large heterogeneous graphs that were then integrated into a common low-dimension space using graph-based embedding methods. It compared the SMR (Rule-based technique, K-Most frequent method, and LEAP approach) and baselines-based medical

recommendations. Table 1 displays a comparison of various available knowledge graph-based approaches.

Ernst et al.'s [6] method for automatically creating a sizable biomedical science knowledge graph is presented. The entity thesaurus from UMLS serves as their data source, and they also used input from a range of scientific papers and postings in various health portals that couldn't be connected with health data. A strategy to successfully incorporate health data into diverse textual medical information was put out by Shi et al. [7]. In order to enhance the performance of the inference findings, they also offer a technique to remove the useless inference from the knowledge network. Using the architecture suggested by the i2b2 challenge in 2010, Goodwin et al. [8] concentrate on including the belief state of the physician for statements in the medical record. Rotmensch and others. [9] offer a method for automatically creating a graph from electronic medical record (EMR) data that maps disease to symptoms that it may cause. Over 270,000 patient visits' emergency department medical records make up their data base.

Numerous studies provide techniques for processing EMR data, such as named entity recognition (NER) [10–14], entity normalisation [15–17], relation extraction/ranking [18], and graph embedding [19,20]. However, there is presently no effective method for creating a complete medical KG from EMR data. This study intends to provide a methodical process for building the medical KG from massive EMRs. The study is carried out using a big-data platform of a 3A-class hospital in China, and the created KG has a total of 22,508 entities across 9 entity kinds. In contrast to the traditional triplet structure, we suggest a novel quadruplet structure based on the data and construct a total of 579,094 quadruplets. For each entity and connection, an embedding vector is trained using PrTransH [20]. The generated KG is used to a number of real-world applications, such as CDSS, information retrieval, and knowledge transfer using neural networks, to assess its efficacy. This essay's conclusion and a prediction for future work are presented at the end. Table 1 is a comparative study of various existing methodologies. Kumar et al. (2021) conducted [21] a comprehensive analysis of EEG signal classification on the human brain, focusing on emotion detection and brain disease analysis using Brain-Computer Interfaces (BCIs). They highlighted the potential of EEG in neurological disorder diagnosis and neurosurgery. The study reviewed papers on emotion recognition and disease prediction through EEG signals, emphasizing the evolving field of BCIs in the treatment of brain diseases. In their study, Mohanty et al. (2023) addressed [22] the challenges in implementing a sustainable digital health ecosystem in India, particularly in response to the COVID-19 pandemic. The research employed a mixed methodology, combining literature reviews and interviews with healthcare leaders. Thematic analysis revealed key challenges, and the study proposed an integrated framework using the DEMATEL technique. This research offers valuable insights for researchers, healthcare organizations, practitioners, and

stakeholders in the digital health field to enhance healthcare solutions.

3. Dataset

Data is collected from various web-based sources. The dataset is web scrapped using beautiful soup library and requests library. Initially the dataset contains 30 diseases and corresponding symptoms and diagnosis. The edges between the nodes are the relationship between the node for example let us consider two sentences. Itching and skin rash is a symptom of skin allergy. Skin allergy can be diagnosed by a dermatologist. Here the symptom nodes are itching and skin rash, disease node is skin allergy while diagnosis node is dermatologist.

4. Methodology

4.1 What is Knowledge Graph?

A knowledge graph, also known as a semantic network. Depicts the relationship between real-world entities such as objects, events, situations, or concepts. This data is typically stored in a graph database and visualized as a graph structure, giving rise to the term knowledge graph. Nodes, edges and labels are the three main components of the knowledge graph. Figure 2 is an example of disease symptom

Table 1. Comparative study of various existing methodologies

Paper	Authors	Year	Methods Used		Dataset	Strength	Limitations
Incorporating Domain Knowledge into Medical NLI using Knowledge Graphs	Soumya Sharma (IIT Kharagpur)	2019	BioELMo embedding model including bi-directional LSTM .	LSTM	MedNLI dataset	Accuracy improved that the base model.	Obtained accuracy is less. Sense of timeline is not accurate
Construction of Disease-Symptom Knowledge Graph from Web-Board Documents	Chaveevan Pechsiri and Rapepun Piriyakul	2022	machine learning techniques	SVM, Naïve Bayes and Linear Logistic regression	web-board resources, a Thai-hospital web-board resource	used the principal component analysis (PCA) to solve the high dimensional feature space	high dimensional feature problem
Knowledge Graphs in Medical Domain	Gyanesh Anand	2020	Nlp based recommender system using RegEx and UMLS Parsing Based Entity Extractor	regular expression matching algorithm and Medical named Entity tagger.	MedIndia website. Other sources were Medline, WebMD and NIH website	Developed a MedMate Web applications for recommendation	Performance metrics were not discussed.
Learning a Health Knowledge Graph from Electronic Medical Records	Maya Rotmensch*	2017	Machine Learning approach using three probabilistic models	Logistic Regression, naïve bayes classifier and Bayesian network using noisy OR gates is used as probabilistic models	electronic medical records	evaluated potential knowledge graphs in comparison to a large, manually curated Google health knowledge graph (GHKG) and medical professionals' professional judgement.	disparities between the edges present in the Google health knowledge graph and those recommended by the learnt models and deemed correct by the clinical evaluators
SMR: Medical Knowledge Graph Embedding for Safe Medicine Recommendation	Fan Gong a, Meng Wang b,c,*	2020	Embeddings	On the basis of graph-based embedding models, large heterogeneous graphs were built and embedded ³ into a common low-dimension space.	ICD ontology, MIMIC(3 RD) and DrugBank	Comparing baselines with SMR (Rule-based approach, K-Most frequent method, and LEAP method)-generated medication recommendations	Low Linking accuracy

relationship where chicken pox is subject node while high fever, skin rash, fatigue and itching are the object nodes.

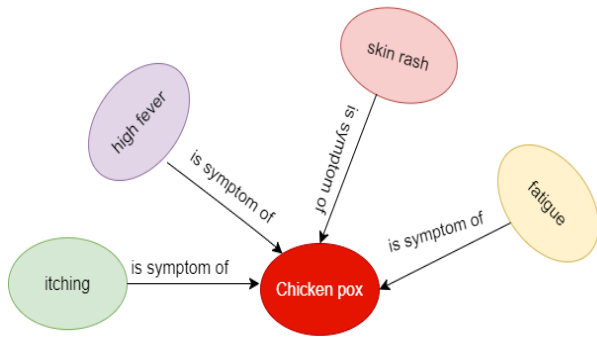


Fig 2: Disease Symptom relationship of Chicken pox

4.2 Why Knowledge Graph?

Graphs are a popular way to visually depict data relationships. A graph's purpose is to present data that is too numerous or complicated to be adequately described in text and in less space. Ayurvedic scripts about medicines and remedies have a long tradition behind them, so interpreting the data in the scripts is not easy. Thus, knowledge graph helps us to easily depict the data.

4.3 Data pre-processing

The Data is cleaned using various techniques such as tokenization, stop word removal, punctuation removal, URL removal etc. Tokenization is the processes of splitting a string or sentence into parts or tokens. Here we used sentence tokenization as well as words tokenization. Dependency parsing is an analysis of the relationships between words in a phrase to determine its grammatical structure. The result is a sentence that's broken down into multiple parts. This process presupposes the notion that each linguistic component of a phrase is connected with one another in some way. These connections are described in the Dependencies. Corpus is prepared using a dependency parser which gives us the subject, root, object, auxiliary, adjective parse words. Fig 3 shows the output of a dependency parser.

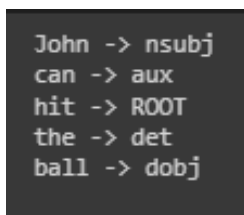


Fig 3: Dependency parsing

Moreover, we constructed SVO (triples) from the text.SVO triples are subject verb object triples. From each sentence we will construct SVO triples such that subject and object will be our nodes of the knowledge graph which will depict diseases, symptom and diagnosis whereas the Verb part in SVO triple will be the relation or edges between the nodes.

4.4 What is GAT?

Graph attention Networks is type of neural network. It is used to learn representations of the nodes and edges in the graph. The idea of attention is used by GATs to learn node and edge embeddings. A process called attention enables the model to concentrate on some elements of the incoming data while ignoring others. An attention-based weighted sum of the representations of nearby nodes and edges is learned in the context of GATs. This allows the model to learn the structural information of the graph and create node and edge embeddings that capture the relationships between entities. GATs can be used to depict the medical knowledge graph in the context of medical recommendations. The medical knowledge graph can be visualised as a graph structure, with nodes standing in for various medical concepts including diseases, symptoms, medications, physicians, and hospitals, and edges for connections between concepts like therapy, diagnosis, and referral. Each node may include text-based information related to it, such as reviews or descriptions. By modelling the medical knowledge graph as a graph structure, using GATs to learn the structural information of the graph, and creating node and edge embeddings that capture the relationships between medical entities, the medical knowledge graph can be used for medical recommendations.

4.5 What is GPT-2?

Generative Pretrained Transformer is a transformer architecture used to produce text-based recommendations in the area of healthcare. To learn the language used in the medical arena, GPT-2 can be trained on a corpus of medical data including medical articles, clinical reports, and patient reviews. Once trained, GPT-2 may produce text-based suggestions based on user input for medical entities like drugs, physicians, and hospitals. For example, if a user inputs a symptom such as “akin allergy”, GPT-2 can generate a list of possible causes of the symptom such as itching, skin rashes etc based on the medical data it has been trained on. Similarly, if a user inputs a medication name such as “paracetamol” then GPT-2 can generate information about the medication such as its uses, side effects, and dosages. Other recommendation methods, such collaborative filtering and content-based filtering, can be used in conjunction with GPT-2. While content-based filtering recommends products based on their attributes, collaborative filtering bases its recommendations on the preferences of comparable users. For the purpose of content-based filtering, GPT-2 can produce text-based descriptions of medical entities. In order to suggest similar prescriptions to consumers, GPT-2, for

instance, can produce text-based descriptions of pharmaceuticals based on their purposes, side effects, and dosages. Finally, GPT-2 is a potent language model that may be utilised to produce text-based recommendations for medical care based on user input and medical information. To increase the precision of recommendations, it can also be used in conjunction with other techniques like collaborative filtering and content-based filtering and GAT.

4.6 Model Training Flow

Figure 4 is the training flow of our research paper.

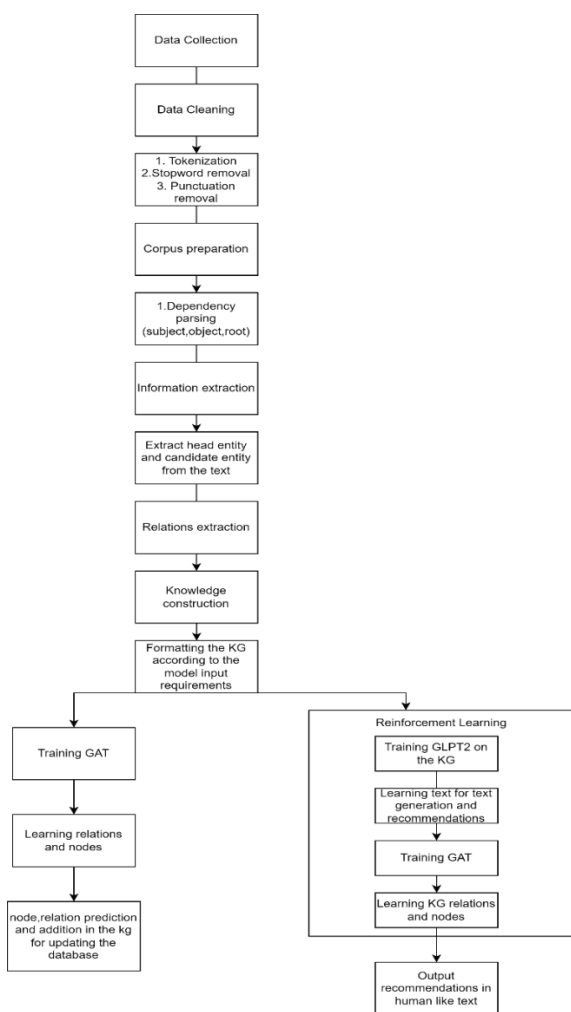
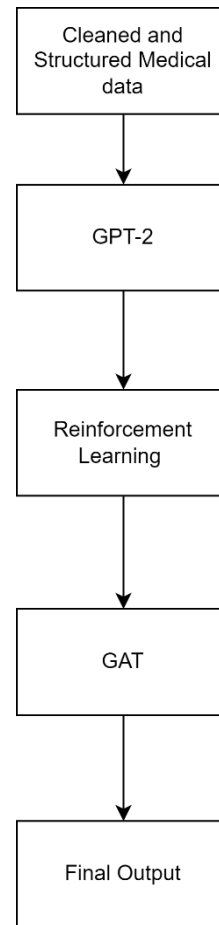


Fig 4: Training Flow of research paper

4.7 Model Architecture

We use cleaned and structured data medical data in the form of knowledge graph database. Fig 5 depicts the model architecture.



4.8 Why this architecture is used?

Reinforced hybrid graph transformer for medical recommendations is an ideal model for medical recommendations due to several reasons. First off, the model makes use of the advantages of both graph neural networks and language models to offer precise and individualised medical advice. The GPT-2 component of the model creates natural language suggestions that are customised to the patient's unique medical needs and history, while the GAT component of the model enables effective representation learning of the medical knowledge graph. Second, by utilising reinforcement learning, the model can modify its suggestions based on the patient's health outcomes, thereby increasing the recommendations' accuracy. This makes it possible for the model to continuously learn and enhance its suggestions, which increases its efficacy for long-term medical management. Furthermore, the model's hybrid architecture enables it to manage both organised and unstructured data, increasing its flexibility and adaptability to various forms of medical data. This is significant in the medical industry because it frequently requires the integration and analysis of a wide range of data sources and formats.

Additionally, the model's interpretability is improved through the application of methodologies, making it simpler for patients and medical professionals to comprehend the rationale behind the suggestions. For the advice to be trusted and accepted in a clinical setting, this is crucial. Overall, the hybrid architecture, reinforcement learning approach, and methodologies of the RH-GTMR model make it a perfect model for medical recommendations, with the potential to greatly enhance patient outcomes and quality of treatment.

5. Results and Discussion

Google health knowledge graph and physical experts can be used for evaluating the results of the model.

6. Conclusion and Future Scope

The Reinforced Hybrid Graph Transformer for Medical Recommendations (RH-GTMR) model has a bright future in the field of medical recommendation systems for additional study and advancements. To further customise the recommendations, one potential enhancement would be to add more complicated medical data into the algorithm, such as genomics data or electronic health records. To ensure compliance with the knowledge graph, this may necessitate more pre-processing of the data, but it could result in recommendations that are more precise and focused. The application of more sophisticated reinforcement learning methods, such as deep Q-learning or actor-critic approaches, to further improve the model's performance could be another area for development. The model could also gain from the incorporation of different graph neural network architectures or attention-based models to enhance the representation learning of the incoming medical data and knowledge graph. To further aid in the comprehension of the model's recommendations by patients and medical professionals, explain techniques like attention visualisation, saliency maps, or decision tree visualisation should be added.

To validate the RH-GTMR model's efficacy in various clinical contexts, larger datasets with a wider range of medical disorders could be used. In terms of future study and development in the area of medical recommendation systems, the RH-GTMR model offers a lot of promise.

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