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A Extensive Study on Deep learning Architecture on Patient Treatment Trajectory Mining

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Abstract

Patient treatment trajectory mining is current research field to access the response of the patient to new treatment data in clinical trials which is available in form high dimensional data. However processing of high dimensional trajectory data using machine learning model named markov chain model, learns the events but it is cumbersome and ambiguous on identifying the latent events and it fails to tackle long term dependencies between the clinical events. In order to tackle those challenges, deep learning model has been employed to effectively classify the patient treatment data to highlight the future outcome of the patients. In this paper, an extensive study has been carried out on deep learning architecture to predict the future outcomes on the patient treatment trajectory data. It is vital and essential task for providing detailed insight on disease progression and interventions. We demonstrate the efficacy of the model on long term dependency for disease progression modelling, intervention recommendation, and future risk prediction on treatment trajectory data. Further prediction on the irregularly distributed data has been analysed on employment of sampling, latent representatives and effective use of loss function. Moreover importance of activation function for learning representatives has been exploited for efficient future event prediction on extracted trajectory representation. Finally outline of the proposed methodology as framework to predict the prognosis of the patient has provided. Evaluation of models has been carried out on the ovarian cancer patient treatment data.

Keywords: Deep Learning, Trajectory Mining, Patient treatment trajectory, ovarian cancer

1. Introduction

Patient treatment trajectory mining is a recent emerging topic in the research on encompassing broad concept. It can be formulated as a sequence of clinical events for disease management and care[1]. The data irregularly and large volume of health information occurred in a long and continuous period as patient treatment data is highly challenging task on employment of machine learning models for understanding and predicting the future clinical events of patients. It is mostly based on the classification or clustering of events in the treatment[2]. The prediction results demonstrate the future occurrence on treatment trajectory data[3].

In order to generate effective and proactive event prediction model, deep learning architecture[4] is capable to handling those challenges of machine learning model[5] in terms of high dimensional features and size of the data[6]. Effective sampling of mutual excitations between clinical event pairs provides nontrivial knowledge about how the appearances of clinical events are correlated to each other. However an extensive study on the deep learning architecture on the patient treatment data will help us to model an efficient prediction framework towards disease progression modelling[7], intervention recommendation[8], and future risk prediction

Deep learning approach can capture the long-range dependency over data with arbitrary time intervals. Hidden layer of the model extract the latent feature vector from the affiliated data[10]. The obtained feature vector and the embedding of the event type are combined to be the input of model feature concatenation and fusion, are developed to explore an effective way to handle representative features.

The remainder of this paper is organized as follows: We discuss the review of literature in Section 2 and presents deep learning technique for trajectory mining models in Section 3. Section 4 provides objective of the work and section 5 outlines the proposed methodology. Section 5 provides conclusion of the work.

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2. Review of literatures

In this section, various existing model applied to prediction of the clinical outcomes on patient treatment trajectories by utilizing machine learning model and deep learning has been detailed as follows.

2.1. Collaborative and trajectory prediction models of medical conditions by mining patients' Social Data

In this method, Social Data-based Prediction of Incidence and Trajectory has been used to predict potential risks on medical conditions as well as its progression trajectory has been used to identify the comorbidity path of the individual patient. Correlated disease progression of the patient leading to various diseases on outcome of clinical trials has been computed efficiently[11]. This correlation established on the disease is called comorbidity relationship. The framework utilizes trajectory of patients' publicly available social media data, data has been extracted using feature extraction model and further extracted feature has been processed using PCA collaborative prediction of comorbidity incidences on computation of eigen value and eigen vector[12]. Eigen vector predict the ranked list of potential comorbidity incidences, and eigen value of the trajectory features reveal different paths of condition progression. Finally results of the framework predict future conditions with a coverage value of 48% and 75% for a top-20 and a top-100 ranked list, respectively and it is able to reveal each potential progression trajectory between any two conditions and infer the confidence of the future trajectory on any condition

Drawbacks

- Discovering the comorbidity relationships is complex and difficult due to the limited access to Electronic Health Records.
- Model limited coverage in terms of population of social data and is hard to be integrated with other datasets due to different formats.

2.2. Interpretable Patient Trajectories from Temporally Annotated Health Records

In this literature, Graph based trajectory mining has been employed to patient electronic health record to cluster or class of clinical events that occur to a patient in some time frame[13]. The paths contain the most common trajectories followed by patients has been summarised in form of different set of trajectories in a trajectory graph[14]. The graph contains events on its nodes and the edges indicate the temporal relations. In this model, uses a procedure to extract the trajectory graphs more accurately on the patient dataset on single disease. In addition, it is close to a notion of patient state which clinicians use intuitively, facilitating interpretation of particular disease along. The method can be described can be applicable for any sequences of other events.

Drawbacks of the model

- Graph based building trajectory only allow for one event at each node which potentially loses association of information of another event with particular patient.

2.3. Mining Trajectories of Laboratory Data using Multiscale Matching and Clustering

In this literature, clustering of the medical trajectory data has been analysed on multivariate time series data. In addition, multiscale matching has been carried out in clustering for mining the feature on Discriminant information. In medical trajectory data[15], it enables us to find the part-to-part correspondences between two trajectories of the same patient on disease diagnosis by taking into account the relationships between different laboratory examinations in a two dimensional plane. The resultant dissimilarity can be further used as input for clustering algorithms for finding the groups of similar cases[16]. Each trajectory is segmented and compared with other trajectories by multiscale matching, and clustered by using similarities obtained by matching technique.

Drawback of the model

- It could not find the similarities on slight chronic changes of the similar patients due to elimination of cluster adaption model
- Complication in determining the global minima

2.4. Augmentation Techniques for Sequential Clinical Data to Improve Deep Learning Prediction Techniques

In this literature, neural network based deep learning framework has been used for event prediction in the medical domain as it deals with large amount of the data and it process with advanced models. Especially it is employed to eliminate the overfitting issue and variance in the subset generated. Additionally data augmentation has demonstrated to be an effective solution to reduce over fitting, its principle is to increase the amount of training data based on the data already available[17]. Data augmentation is especially useful to reduce the problem of unbalanced data. Moreover, data augmentation can lessen the data outage of clinical data due to the strong privacy constraints concerning this kind of information[18]. This model predicts probable clinical conditions of a patient on processing of the medical data. In this model, trajectories has been generated on existing data on extraction of subsequence's of trajectories to emphasize the transition and hierarchical structure of standard diagnosis codes trajectories whose characteristics resemble those of real-world clinic.

Drawback of the model

- It can't be explored to automated prognoses on large no of missing value in high dimensional dataset and due to unstructured data.
- There often exist missing parts in medical examination data due to various human factors, for instance, because human subjects occasionally miss their annual examinations.

2.5. Deep neural networks with missing information imputation for medical examination data prediction

In this work, deep neural network (DNN) has been analysed in detail as it predict the medical examination data with missing parts also. However determining the missing information is very hard to predict the future examination data by learning model. Hence data imputation using random projection is employed to fill the missing information towards accurate prediction of medical examination data[19]. Among various types of ANNs[20], we choose simple neural network to predict the missing information as well as the future medical examination data, as they show good performance in many relevant applications. In this model the temporal trajectories of the medical examination measurements are modelled with the missed measurements is then used to predict the future measurements to be used as diagnosing the diseases of the subjects in advance.

Drawbacks of the model

- It fails determine the long dependency sequences
- Slow converge

3. Overview of Deep learning Techniques for Trajectory Mining

Personalized predictive medicine necessitates the modeling of patient illness and care processes, which inherently have long-term temporal dependencies. Healthcare observations, stored in electronic medical records are episodic and irregular in time. Deep learning reads medical records, stores previous illness history infers current illness states and predicts future medical outcomes. Deep learning methods to handle irregularly timed events by moderating the forgetting and consolidation of memory and also explicitly models medical interventions that change the course of illness and shape future medical risk. Moving up to the health state level, historical and present health states are then aggregated through multiscale temporal pooling, before passing through a neural network that estimates future outcomes. Long-term dependencies in healthcare and episodic recording and irregular timing is a effective modelling of trajectory data for the future illness and care may depend critically on historical illness and interventions for medical records vary greatly in length, are inherently episodic in nature and irregular in time. Finally Confounding interactions between disease progression and interventions has been determined. Deep learning is capable of handling complexity in data in terms of variable length and long-term dependencies.

4. Objective of the work

Research was focused on patients' trajectories based on disease management and care. The objective of this study is to mine the medical trajectory data towards diagnosis and prognosis of ovarian cancer and comorbidity. The prediction technique towards identification of the stages of the disease and patient response to the clinical trials has been computed on the trajectory data. The objective of the work on Treatment trajectory can be constructed using Dynamic Recurrent Neural Network to predict the prognostic outcome of the ovarian cancer patients on particular drug treatment on following aspects to determines the regions related to the volumetric growth or shrinkage of the metastatic tumors, and density changes related to variation of necrosis inside the solid tumors.

1. Effective feature space construction for the Classification and prediction of high dimensional medical data using missing imputation technique and LTSM model.
2. An effective Hyper parameter optimization method for RNN to reduce Complexity of sequence data processing.
3. Optimizing long short-term memory recurrent neural networks using particle Swarm Optimization to eliminate the computational error and irregularities in the data.

5. Outline of the proposed methodology

In medical trajectory mining, analysing of the large amount of data with sequence of numerical observation more accurately and finding more significant prediction of the diseases is becoming essential in current research. To enable the effective solution, a novel framework has to be established on inclusive of solutions to handle above mentioned difficulties. The framework composed of methodology is as follows

5.1. Prediction of prognostic outcome of Ovarian Cancer Patient towards Drug Treatment Trajectory using Dynamic Recurrent Neural Network

This as trajectory technique has been developed using deep learning model named as Dynamic Recurrent Neural Network to predict the prognostic outcome of the ovarian cancer patients on drug treatment. The model determines the regions related to the volumetric growth or shrinkage of the metastatic tumors, and density changes related to variation of necrosis inside the solid tumors.

5.2. Hyper Parameter optimization of Dynamic Recurrent Neural Network towards predicting comorbidity on Patient Treatment trajectory data

This trajectory techniques has been developed on optimization of the Recurrent Dynamic neural network on hyper parameter using quantum annealing to optimize the complexity of the sequence data processing of drug information's on determining the comorbidity relationship of the particular patient and increase the converge of data on estimating the global minima of the error function.

5.3. Optimizing long short-term memory recurrent neural networks using particle Swarm Optimization to predict prognostic outcome on patient treatment trajectory data

This trajectory technique has been developed using long short-term memory recurrent neural networks to store long dependency of the trajectory data. Processing of large scale data leads to computational error and irregularities in the data which can be eliminated by activating the error function with particle swarm optimization to generate the effective feature space for the prediction of the prognosis outcome.

6. Importance of Dynamic Recurrent Neural Network

Dynamic Recurrent Neural Network uses Long Short-Term Memory (LSTM) which is equipped with memory cells to store medical treatment and outcomes as experiences of patient on specified diseases. LSTM reads an input, updates the memory cell, and returns an output. Memory is maintained through a forget gate that moderates the passing of memory from one time step to another, and is updated by seeing new input at each time step. The output is determined by the memory and moderated by an output gate. LSTM models the illness and treatment trajectory and prognostic outcome of a patient encapsulated in a time-stamped sequence. The inputs to the LSTM are information extracted from treatment trajectory to specified drug on the patients. The output represents the survival rate of patient. DRNN is to embed these elements into continuous vector spaces.. Figure 1 represents the architecture of Dynamic Recurrent Neutral Network

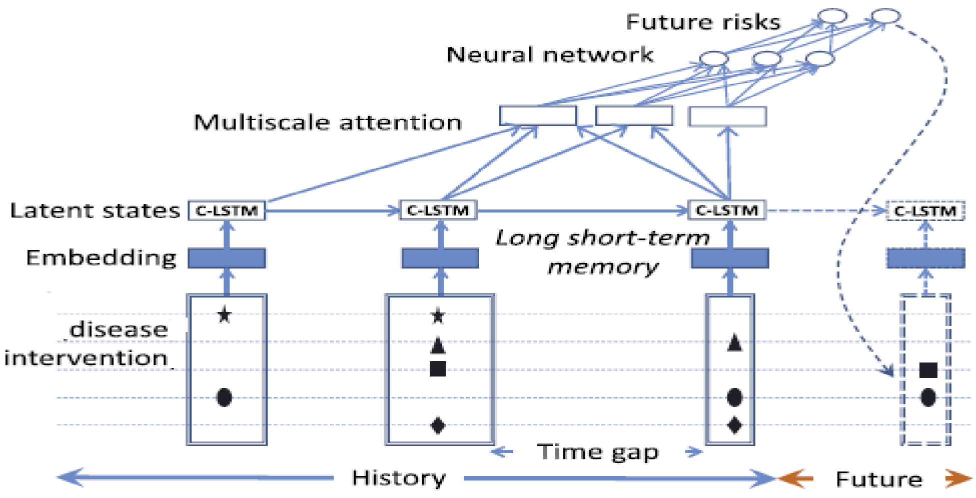

Figure 1: Prediction of Prognostic outcome of patient on Drug Treatment Trajectory

Vectors of the same type are then pooled into a single vector. Type-specific pooled vectors are then concatenated to represent a treatment to the specific disease. Output of LSTM is treatment states which are aggregated as multiscale pooling strategy for future projection

Conclusion

In this paper, an extensive study on the deep learning technique to mining trajectory on medical domain has been presented in detail. It has been analysed on layers of the architecture in different literatures on basis of extracting the time varying features and clustering it based on similarities. Especially prediction model deals on progression accurately on the underlying features. These analyses help to model a new methodology as framework for disease progression and interventions.

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