Deep EHR Literature Review - 1

https://qdata.github.io/deep2Read
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Outline

Electronic Health Record (EHR)

- EHR systems store data associated with each patient encounter, including demographic information, current and past diagnoses, laboratory tests and results, prescriptions, radiological images, clinical notes, and more.
- In part due to the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which provided $30 billion in incentives for hospitals and physician practices to adopt EHR systems.
- According to the latest report from the Office of the National Coordinator for Health Information Technology (ONC), nearly 84% of hospitals have adopted at least a Basic EHR system, a 9-fold increase since 2008.
- Additionally, office-based physician adoption of basic and certified EHRs has more than doubled, from 42% to 87%

What can we do with EHR

While primarily designed for improving healthcare efficiency from an operational standpoint, many studies have found secondary use for clinical informatics applications.

- medical concept extraction
- patient trajectory modeling
- disease inference
- clinical decision support systems

TABLE I
SEVERAL RECENT DEEP EHR PROJECTS.

Project	**Deep EHR Task**	**Ref.**
DeepPatient	Multi-outcome Prediction	Miotto [14]
Deepr	Hospital Re-admission Prediction	Nguyen [19]
DeepCare	EHR Concept Representation	Pham [20]
Doctor AI	Heart Failure Prediction	Choi [21]
Med2Vec	EHR Concept Representation	Choi [22]
eNRBM	Suicide risk stratification	Tran [23]

Deep EHR Application

TABLE III
SUMMARY OF EHR DEEP LEARNING TASKS.

Task	**Subtasks**	**Input Data**	**Models**
EHR Information Extraction	(1) Single Concept Extraction (2) Temporal Event Extraction (3) Relation Extraction (4) Abbreviation Expansion	Clinical Notes	LSTM, bi-LSTM, GRU, CNN RNN + Word Embedding AE Custom Word Embedding
EHR Representation Learning	(1) Concept Representation (2) Patient Representation	Medical Codes	RBM, Skip-gram, AE, LSTM RBM, Skip-gram, GRU, CNN, AE
Outcome Prediction	(1) Static Prediction (2) Temporal Prediction	Mixed	AE, LSTM, RBM, DBN LSTM
EHR Phenotyping	(1) New Phenotype Discovery (2) Improving Existing Definitions	Mixed	AE, LSTM, RBM, DBN LSTM
EHR De-identification	Clinical text de-identification	Clinical Notes	Bi-LSTM, RNN + Word Embedding

Outline

Single Concept Extraction

- Structured prediction models for RNN based sequence labeling in clinical text (EMNLP 2016)
- Bidirectional RNN for Medical Event Detection in Electronic Health Records (NAACL 2016)

Single Concept Extraction

Example task:
The follow-up needle biopsy results were consistent with bronchiolitis obliterans, which was likely due to the Bleomycin component of his ABVD chemo. In this sentence, the true labels are Adverse Drug Event(ADE) for bronchiolitis obliterans and Drugname for ABVD chemo.

Labels	**Annotations**	**Avg. Words / Annotations**
ADE	905	1.51
Indication	1988	2.34
Other SSD	26013	2.14
Severity	1928	1.38
Drugname	9917	1.20
Duration	562	2.17
Dosage	3284	2.14
Route	1810	1.14
Frequency	2801	2.35

Table 1: Annotation statistics for the corpus.

Single Concept Extraction

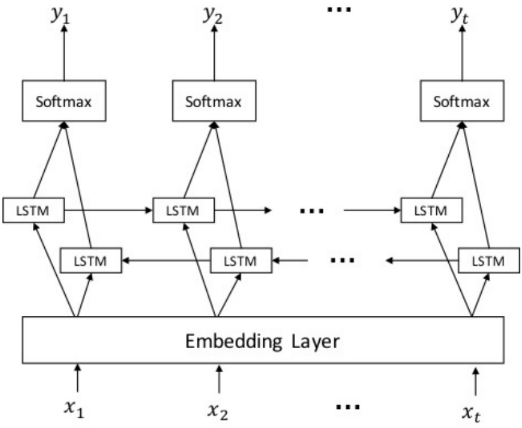

Figure 1: Sequence Labeling model for LSTM network

Temporal Event Extraction

- Brundlefly at SemEval-2016 Task 12: Recurrent Neural Networks vs. Joint Inference for Clinical Temporal Information Extraction (SemEval-2016)
- Incremental Knowledge Base Construction Using DeepDive (The VLDB Journal)

Example Task:
`http://alt.qcri.org/semeval2016/task12/`

They train three RNN models: a character-level RNN for tokenization; and two word-level RNNs for POS tagging and entity labeling.

Relation Extraction

- Clinical Relation Extraction with Deep Learning (International Journal of Hybrid Information Technology)

Example task: treatment X improves/worsens/causes condition Y, or test X reveals medical problem Y

I. Medical problems and treatment relations:

a. Treatment improves medical problem (TrIP)
b. Treatment worsens medical problem (TrWP).
c. Treatment causes medical problem (TrCP).
d. Treatment is administered for medical problem (TrAP).
e. Treatment is not administered because of medical problem (TrNAP).
f. Treatments and problems that are in the same sentence, but do not fit into one of the above defined relationships are not assigned a treatment-problem relationship.

II. Test relations and medical problems:

a. Test reveals medical problem (TeRP).
b. Test conducted to investigate medical problem (TeCP).
c. Tests and problems that are in the same sentence, but do not fit into one of the above defined relationships are not assigned a test-problem relationship.

III. Medical problem and other medical problems:

a. Medical problem indicates medical problem (PIP).

Outline

Concept Learning

- Distributed Embedding: word2vec, this part is very similar to learning word embeddings in NLP field.
- Latent Encoding: Autoencoders (AE)

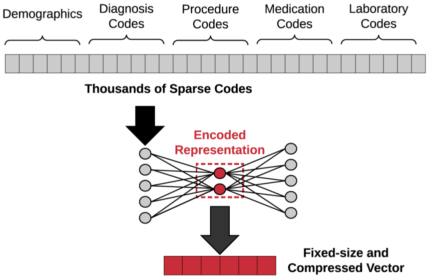

Fig. 7. Illustration of how autoencoders can be used to transform extremely sparse patient vectors into a more compact representation. Since medical codes are represented as binary categorical features, raw patient vectors can have dimensions in the thousands. Training an autoencoder on these vectors produces an encoding function to transform any given vector into it's distributed and dimensionality-reduced representation.

Patient Learning

- Med2Vec framework to derive distributed vector representations of patient sentences, i.e. ordered sequences of ICD-9, CPT, LOINC, and National Drug Codes (NDC).
- Deepr framework uses a simple word embedding layer as input to a larger CNN architecture for predicting unplanned hospital readmission.
- Miotto et al. directly generate patient vectors from raw clinical codes via stacked AEs, and show that their system achieves better generalized disease prediction performance as compared to using the raw patient features.

Patient Learning

- Choi et al. derive patient vectors by first generating concept and encounter representations via skip-gram embedding, and then using the summed encounter vectors to represent an entire patient history to predict the onset of heart failure.
- Doctor AI system utilizes sequences of (event, time) pairs occurring in each patients timeline across multiple admissions as input to a GRU network. At each time step, the weights of the hidden units are taken as the patient representation at that point in time, from which future patient statuses can be modeled and predicted.

Outline

Scalable and accurate deep learning for electronic health records (Jeff Dean @ Google Brain)

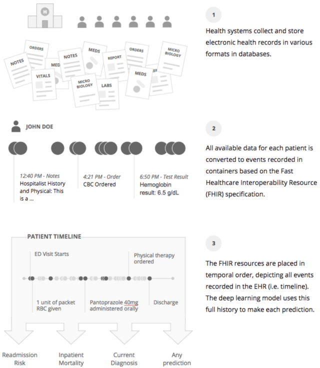

Figure 1: Data from each health system an appropriate FHIR (Fast Healthcare Interoperability Resources) resource and placed in temporal order. This conversion did not harmonize or standardize the data from each health-system other than map them to the appropriate resource. The deep learning model could use all data available prior to the point when the prediction was made. Therefore each prediction, regardless of the task, used the same data.

MIMIC-III

The latest version of MIMIC is MIMIC-III v1.4, which comprises over 58,000 hospital admissions for 38,645 adults and 7,875 neonates. The data spans June 2001 - October 2012.

Class of data	Description
Billing	Coded data recorded primarily for billing and administrative purposes. Includes Current Procedural Terminology (CPT) codes, Diagnosis-Related Group (DRG) codes, and International Classification of Diseases (ICD) codes.
Descriptive	Demographic detail, admission and discharge times, and dates of death.
Dictionary	Look-up tables for cross referencing concept identifiers (for example, International Classification of Diseases (ICD) codes) with associated labels.
Interventions	Procedures such as dialysis, imaging studies, and placement of lines.
Laboratory	Blood chemistry, hematology, urine analysis, and microbiology test results.
Medications	Administration records of intravenous medications and medication orders.
Notes	Free text notes such as provider progress notes and hospital discharge summaries.
Physiologic	Nurse-verified vital signs, approximately hourly (e.g., heart rate, blood pressure, respiratory rate).
Reports	Free text reports of electrocardiogram and imaging studies.

Table 3. Classes of data available in the MIMIC-III critical care database.