Deep EHR Literature Review - 2

https://qdata.github.io/deep2Read

Presenter: Chao Jiang

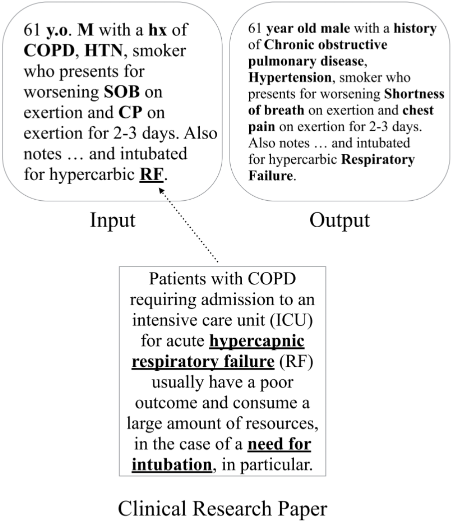
IEEE Journal of Biomedical and Health Informatics, 2017

Outline

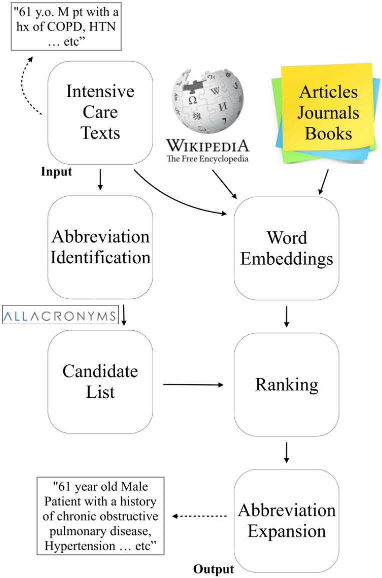
1. Single Concept Extraction - Abbreviation Expansion
2. Computational Phenotyping
   - New Phenotype Discovery
   - Improving Existing Definition
3. Discussion and Future Direction
4. MIMIC dataset

Abbreviation Expansion

Example Task:



Abbreviation Expansion

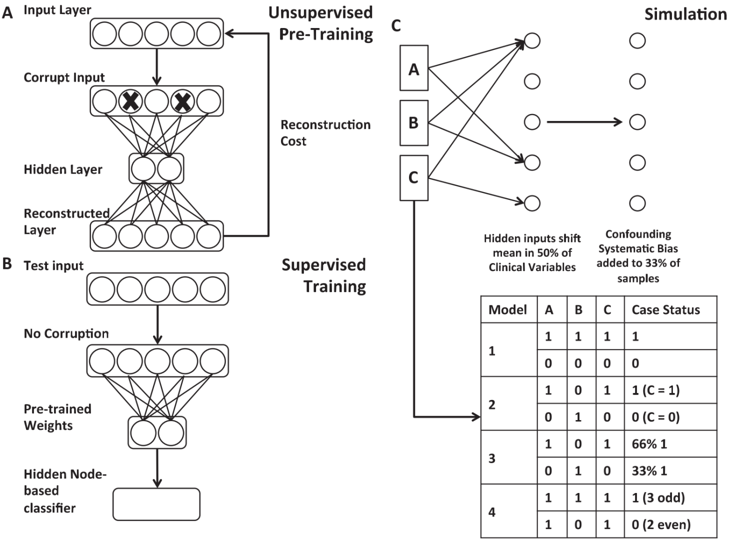


Outline

New Phenotype Discovery

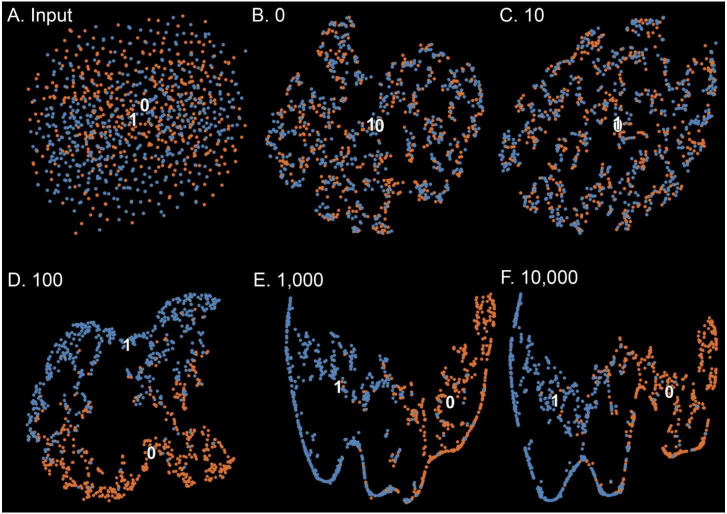
Example Task: Unsupervised Reperesentation Learning
As phenotyping is a largely unsupervised task, several recent studies have utilized AEs for discovering phenotypes from raw data, since enforcing a lower-dimensional data representation encourages discovery of latent structure.

New Phenotype Discovery



Model	A	B	C	Case Status
1	1	1	1	1
	0	0	0	0
2	1	0	1	1 (C = 1)
	0	1	0	0 (C = 0)
3	1	0	1	66% 1
	0	1	0	33% 1
4	1	1	1	1 (3 odd)
	1	0	1	0 (2 even)

New Phenotype Discovery



New Phenotype Discovery

- A drawback of prior work is that the 20,000-patient dataset was synthetically constructed under their own simulation framework.
- Miotto et. al devised a similar but more complex approach to patient representation based on AEs, using 704,587 real patient records from the Mount Sinai data warehouse. DeepPatient framework uses a combination of ICD-9 diagnoses, medications, procedures, lab tests, and conceptual topics from clinical free text as input to their AE framework.
- Cheng et al. used a CNN model which yielded superior phenotypes, classification performance over baselines. They represent patient data as a temporal matrix with time on one axis and events on the other and build a four-layer CNN model for extracting phenotypes and perform prediction.

Outline

1. Single Concept Extraction - Abbreviation Expansion
2. Computational Phenotyping
   - New Phenotype Discovery
   - Improving Existing Definition
3. Discussion and Future Direction
4. MIMIC dataset

Improving Existing Definition

This class of algorithms typically try to improve current phenotypes by using a supervised learning approach.

- Lipton et al. utilize multivariate time series consisting of 13 variables from the ICU to predict phenotypes. They frame the problem of phenotyping as a multi-label classification problem.
- Che et al. use a standard MLP architecture pre-trained with DAE and also treat the phenotyping task as a multi-label classification problem.

Discussion and Future Direction

- Tracing back the deep learning-based advances in image and natural language processing, we see a clear chrono-logical similarity to the progression of current EHR-driven deep learning research.
- Namely, a majority of studies in this survey are concerned with the idea of representation learning, i.e., how best to represent the vast amounts of raw patient data that has suddenly become available in the past decade.

Discussion and Future Direction

- Fundamental image processing research is concerned with increasingly complex and hierarchical representations of images composed of individual pixels.
- Likewise, NLP is focused on word, sentence, and document-level representations of language composed of individual words or characters.
- In a similar fashion, we are seeing the exploration of various schemes of representing patient health data from individual medical codes, demographics, and vital signs.
- The parallels are strong, and these recent studies represent a critical launching off point for future deep clinical research.

Challenge

- Data Heterogeneity: EHR patient data can arise not only in the form of free text from clinical notes and radiological reports, but also as discrete billing-centric medical codes, patient demographic information, continuous time-series of vital signs and other laboratory measurements, medication dosages of varying potency, and more.
- Irregular Measures: some studies focusd on the wealth of continuous time series data available in the form of vital signs and other timestamped measurements. The primary concern with this type of framework is the irregularity of scale - some signals are measured on an sub-hourly basis while others are on a monthly or yearly time scale.
- Clinical Text: a wealth of information but complete lack of structure. The same type of note can appear very differently depending on its author, due to various shorthand abbreviations, ordering preferences, and writing style.

Challenge

- Benchmarks: Another key Deep EHR issue that must be addressed is the lack of transparency and reproducibility of reported results. Most of the studies in this paper use their institutions own private dataset. Many studies claim state-of-the-art results, but few can be verified by external parties.
- Interpretability: Model transparency is of utmost importance to clinical applications, practitioners must be able to understand the predictions and recommendations made by deep learning systems.

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.