SEOUL AI MEETUP

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2PM - 4PM

SEOULAI.COM

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Cinyoung is a Data Engineer at Linewalks. She was a Software Engineer at ETRI. She received her Bachelors and Master degree from Sookmyung Women's University. Her interests span Data mining and modeling approaches for addressing challenges related to complex healthcare data.

MACHINE LEARNING AND ELECTRONIC HEALTH RECORDS

This talk reviews current research on applying deep learning to clinical tasks based on electronic health records (EHR). Various deep learning techniques are used in different types of clinical applications including outcome prediction, phenotyping, and de-identification. This talk focuses outcome prediction in respect to model interpretability and data heterogeneity.

서울시 서초구 서초대로78길 5, 대각빌딩 14층

Deep Learning and Electronic Health Records

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Co-organizer - Seoul AI

Overview

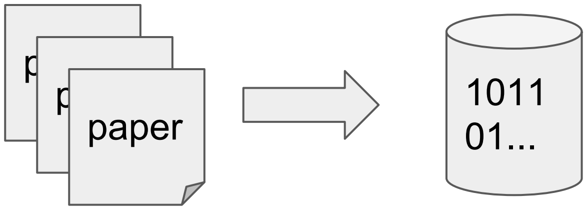
- What is EHR
- Deep EHR Learning Applications
- Open Dataset

Deep EHR: A survey of Recent Advances on Deep Learning Techniques for Electronic Health Record(EHR) Analysis, B. Shickel et al.

Electronic Health Records

- Patient Registry
- Disease Registry
- Drug Registry

- Electronic Health Record
  - A collection of health data from all clinicians involved in a patient’s care
  - more patient-centric, powerful and useful for diagnosis and treatment



80% adoption

EHR data types

- Demographics
- Encounters
- Diagnosis
- Procedures
- Physical exams
- Sensor measurements
- Laboratory test results
- Prescribed or administered medications
- Clinical notes

EHR data types

- Numerical quantities
  - body mass index, height, blood pressure
- Datetime
  - data of birth, time of admission
- Categorical value
  - ethnicity, codes from controlled vocabularies
- Natural language free-text
  - progress notes, discharge summaries
- Derived time series
  - vital sign signals during the course of the operation

Example Classification Schema

- Demographics
- Encounters
- **Diagnosis***
- **Procedures***
- Physical exams
- Sensor measurements
- **Laboratory test results***
- **Prescribed or administered medications***
- Clinical notes

Schema	**Number of Codes**	**Examples**
ICD-10 *(Diagnosis)*	68,000	- J9600: Acute respiratory failure - I509: Heart failure - I5020: Systolic heart failure
CPT *(Procedures)*	9,641	- 72146: MRI Thoracic Spine - 67810: Eyelid skin biopsy - 19301: Partial mastectomy
LOINC *(Laboratory)*	80,868	- 4024-6: Salicylate, Serum - 56478-1: Ethanol, Blood - 3414-0: Buprenorphine Screen
RxNorm *(Medications)*	116,075	- 161: Acetaminophen - 7052: Morphine - 1819: Buprenorphine

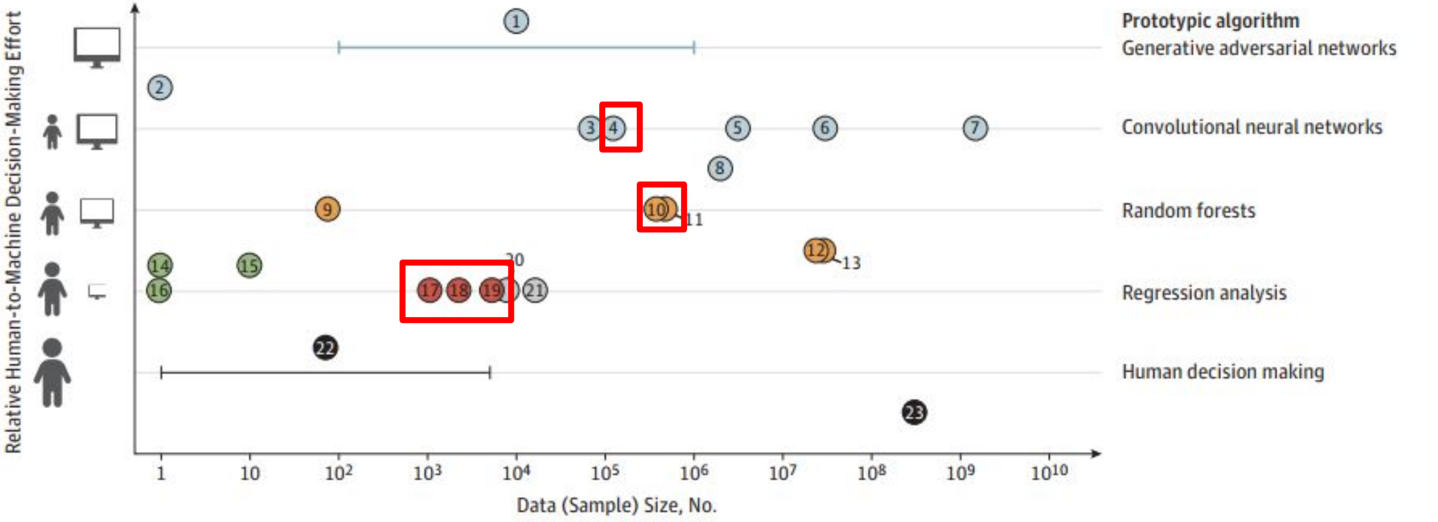
Machine Learning

hand-crafted features

vs.

Deep Learning

automatic data-oriented feature extraction



Deep learning

1. Generative adversarial networks (2014)
2. Google AlphaGo Zero (2017)
3. ATM check readers (1998)
4. Google diabetic retinopathy (2016)
5. ImageNet computer vision models (2012-2017)
6. Google AlphaGo (2015)
7. Facebook Photo Tagger (2015)
8. Prediction of 1-y all-cause mortality (2017)

Classic machine learning

9. Diffuse large B-cell lymphoma outcome prediction by gene-expression profiling (2002)
10. EHR-based CV risk prediction (2017)
11. Netflix Prize winner (2006)
12. Google Search (1998)
13. Amazon product recommendation (2003)

Expert AI systems

14. MYCIN (1975)
15. CASNET (1982)
16. DXplain (1986)

Risk calculators

17. CHA_2DS_2-VASc Score for atrial fibrillation stroke risk (2017)
18. MELD end-stage liver disease risk score (2001)
19. Framingham CV risk score (1998)

Randomized Clinical Trials

20. Celecoxib vs nonsteroidal anti-inflammatory drugs for osteoarthritis and rheumatoid arthritis (2002)
21. Use of estrogen plus progestin in healthy postmenopausal women (2002)

Other

22. Clinical wisdom
23. Mortality rate estimates from US Census (2010)

* Big Data and Machine Learning in Health Care, A. L. Beam et al

Deep EHR Learning Applications

- Representation Learning
  - Concept Representation
  - Patient Representation
  - *Input data: Medical codes*
- Outcome Prediction
  - Static Prediction
  - Temporal Prediction
  - *Input data: Medical codes + Clinical notes*

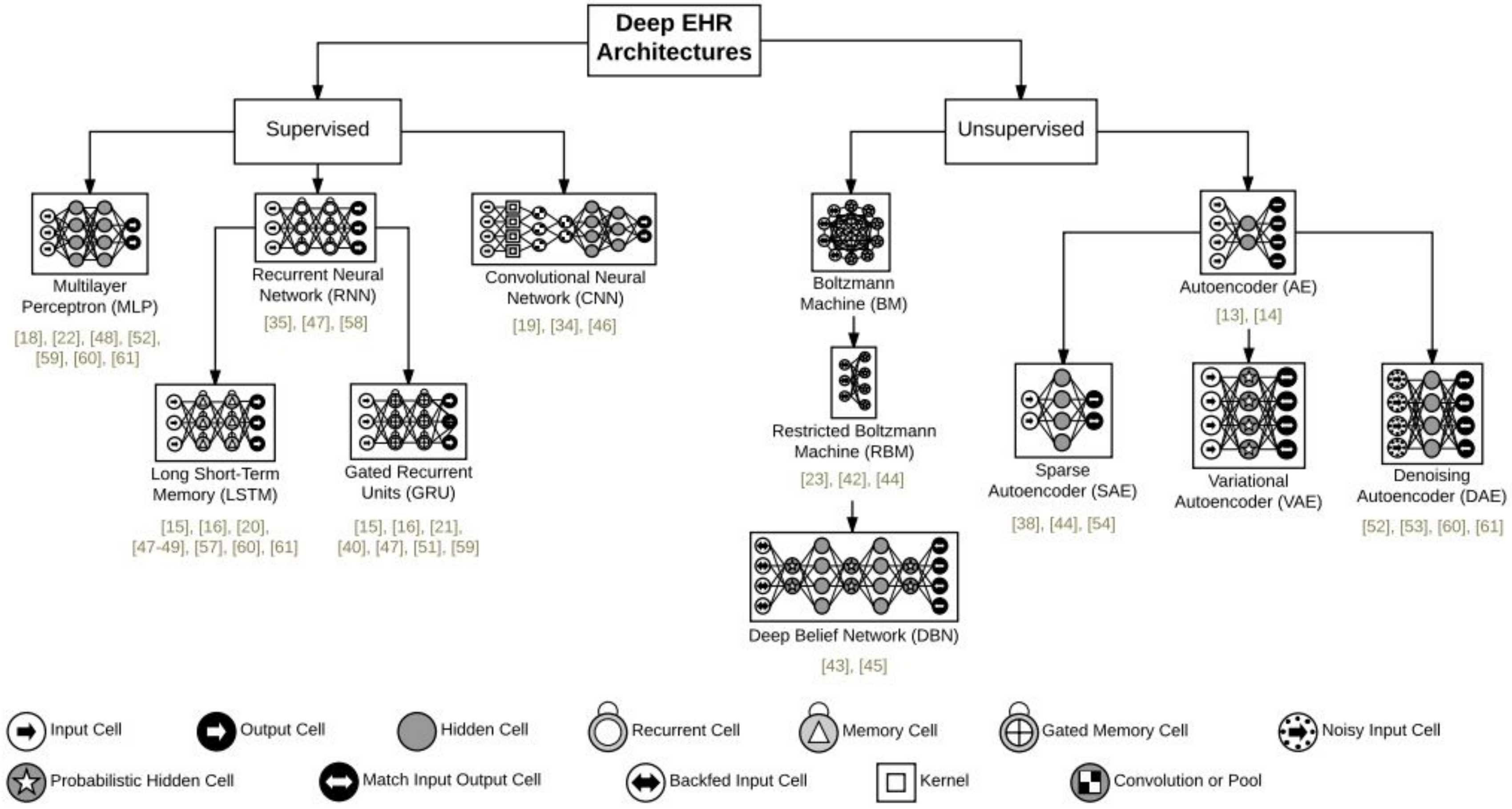


Fig. 3. The most common deep learning architectures for analyzing EHR data. Architectures differ in terms of their node types and the connection structure (e.g. fully connected versus locally connected). Below each model type is a list of selected references implementing the architecture for EHR applications. Icons based on the work of van Veen [30].

EHR Representation Learning

- Discrete medical codes
  - For administrative and billing tasks
  - Static hierarchical relationships
  - Hard to measure similarity between concepts of different types and coding schemes

Schema	Number of Codes	Examples
ICD-10 *(Diagnosis)*	68,000	- J9600: Acute respiratory failure - I509: Heart failure - I5020: Systolic heart failure
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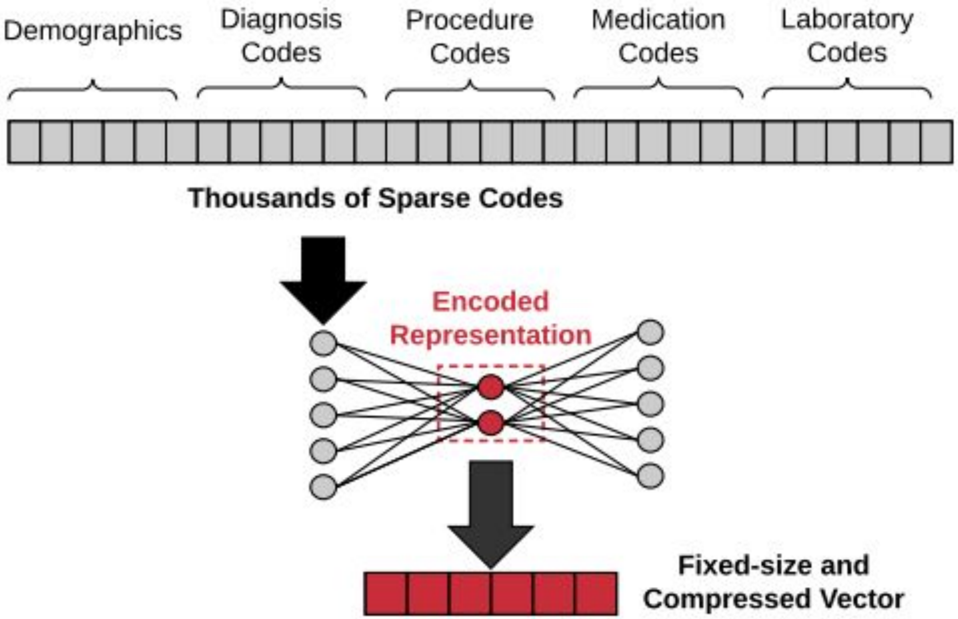
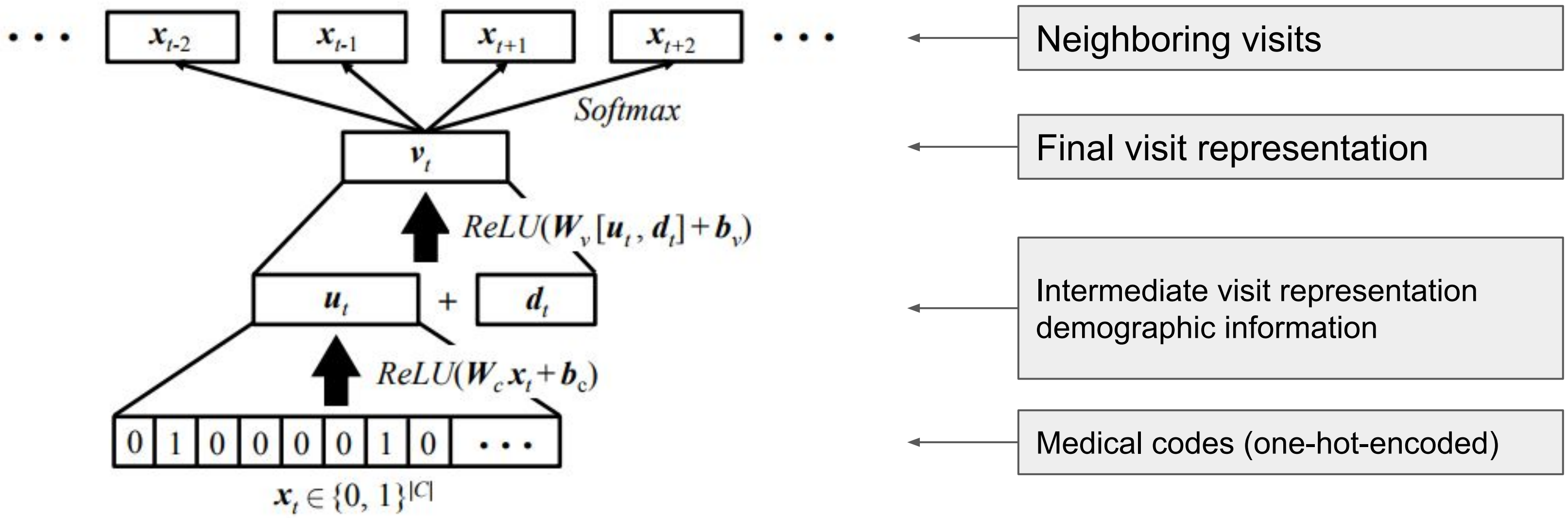
EHR Representation Learning

- Project discrete codes into vector space



EHR Representation Learning
: Concept Representation

- Med2Vec



http://www.kdd.org/kdd2016/papers/files/rpp0303-choiA.pdf

EHR Representation Learning
: Concept Representation

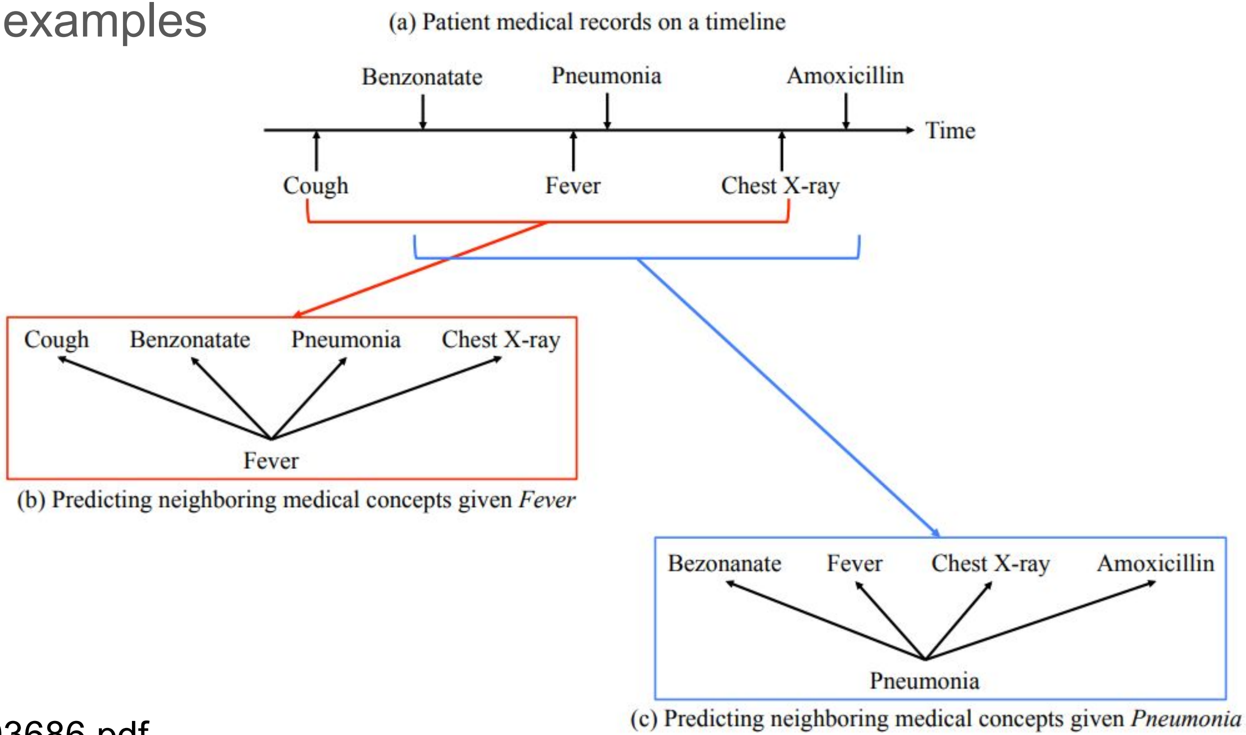
- Med2Vec examples
  - (R):medication, (P): procedure

Coordinate 112	Coordinate 152
Kidney replaced by transplant (V42.0)	X-ray, knee (P)
Hb-SS disease without crisis (282.61)	X-ray, thoracolumbar (P)
Heart replaced by transplant (V42.1)	Accidents in public building (E849.6)
RBC antibody screening (P)	Activities involving gymnastics (E005.2)
Complications of transplanted bone marrow (996.85)	Struck by objects/persons in sports (E917.0)
Sickle-cell disease (282.60)	Encounter for removal of sutures (V58.32)
Liver replaced by transplant (V42.7)	Struck by object in sports (E917.5)
Hb-SS disease with crisis (282.62)	Unspecified fracture of ankle (824.8)
Prograf PO (R)	Accidents occurring in place for recreation and sport (E849.4)
Complications of transplanted heart (996.83)	Activities involving basketball (E007.6)

http://www.kdd.org/kdd2016/papers/files/rpp0303-choiA.pdf

EHR Representation Learning
: Concept Representation

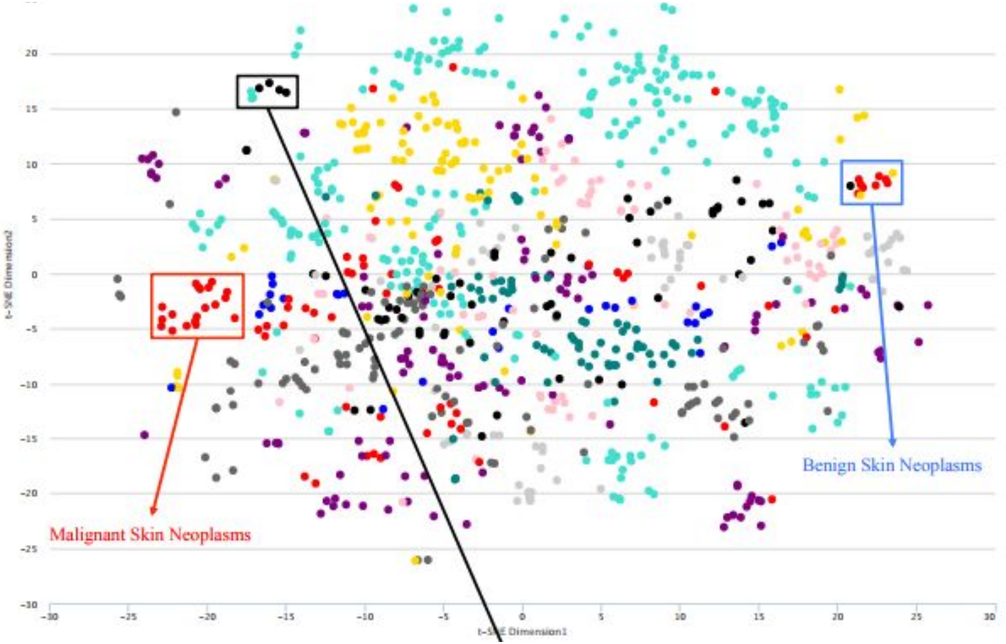
- Skip-gram training examples



https://arxiv.org/pdf/1602.03686.pdf

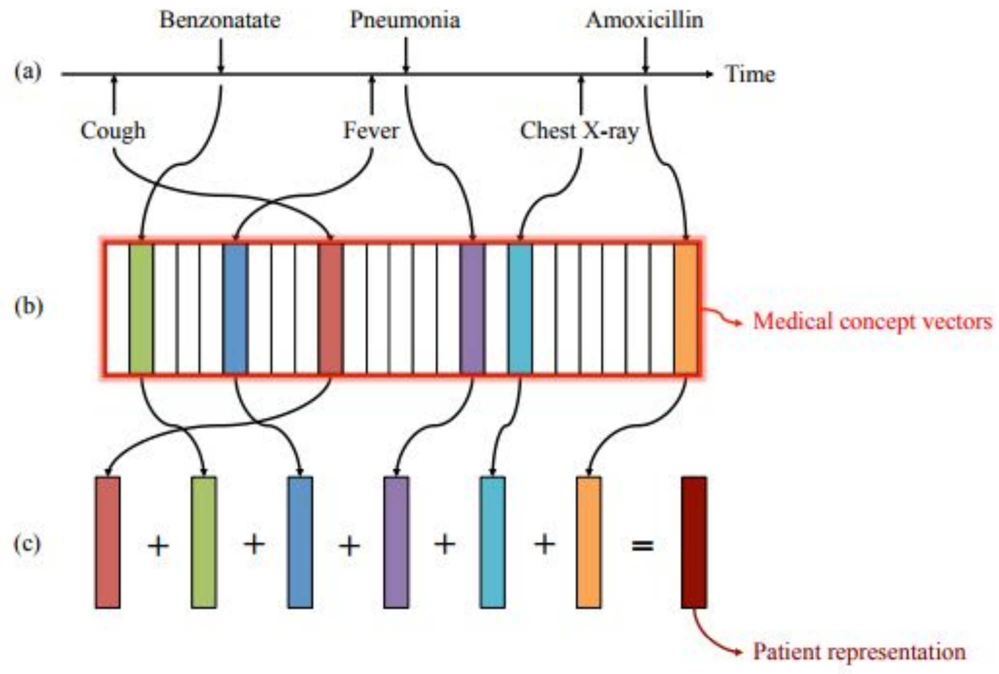
EHR Representation Learning
: Concept Representation

- Evaluation of Medical Concept Representation Learning



https://arxiv.org/pdf/1602.03686.pdf

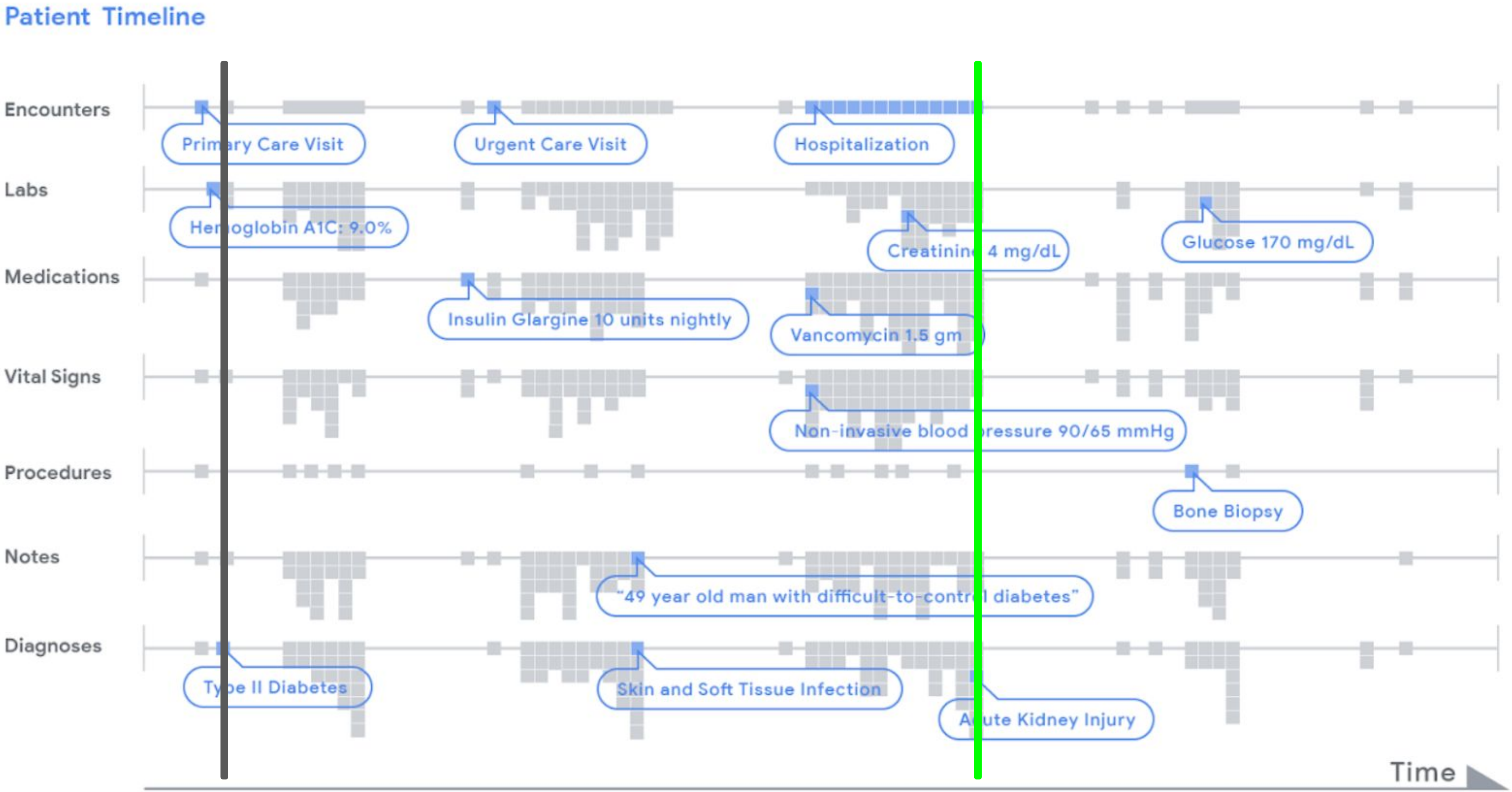
EHR Representation Learning
: Patient Representation



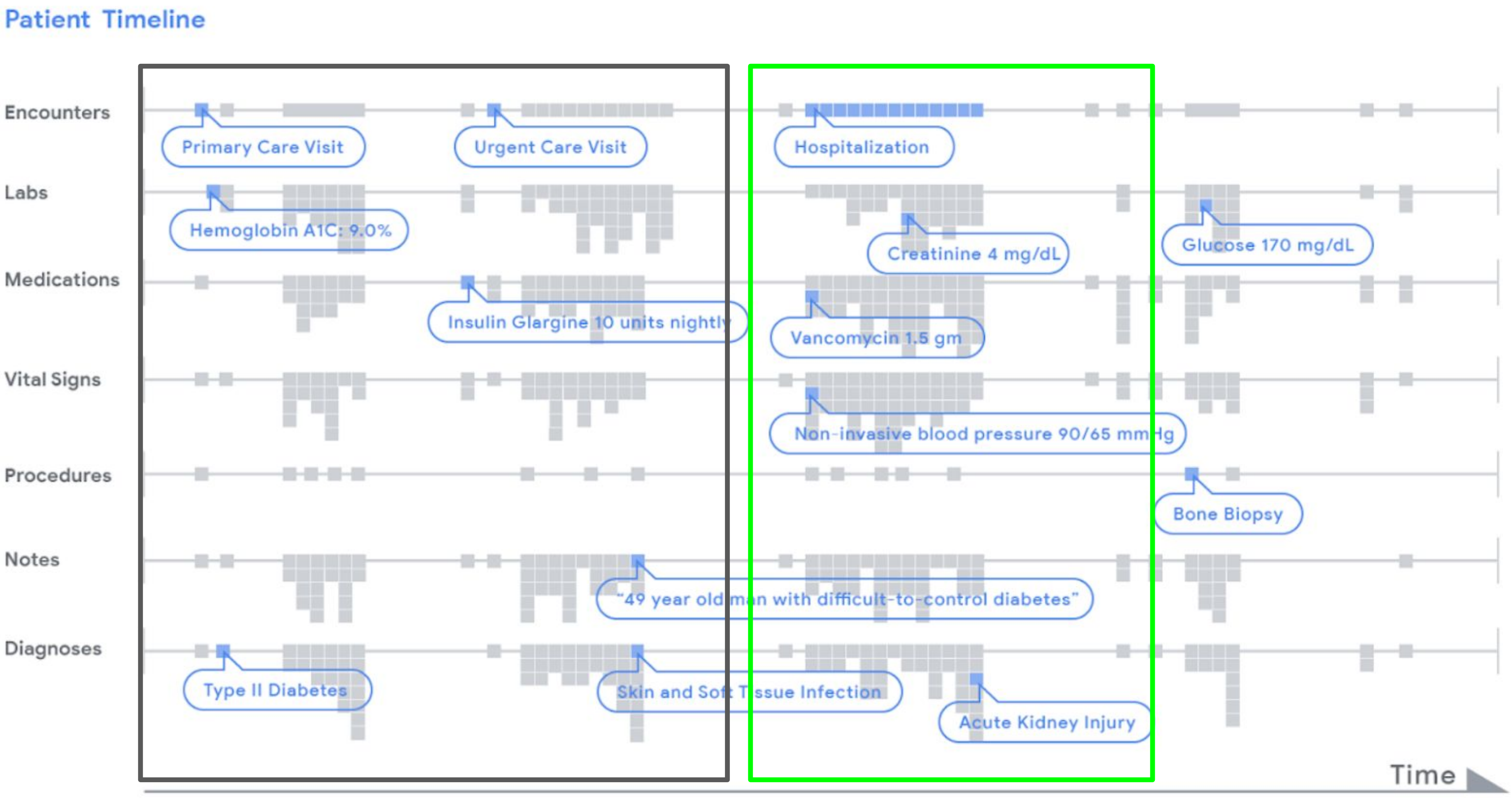
https://arxiv.org/pdf/1602.03686.pdf

Outcome Prediction

- Static(One-time) Outcome prediction
  - Heart failure prediction using data from a single encounter
- Temporal outcome prediction
  - Heart failure prediction within the next 6 months
  - Disease onset prediction using historical data from sequential encounters



https://ai.googleblog.com/2018/05/deep-learning-for-electronic-health.html



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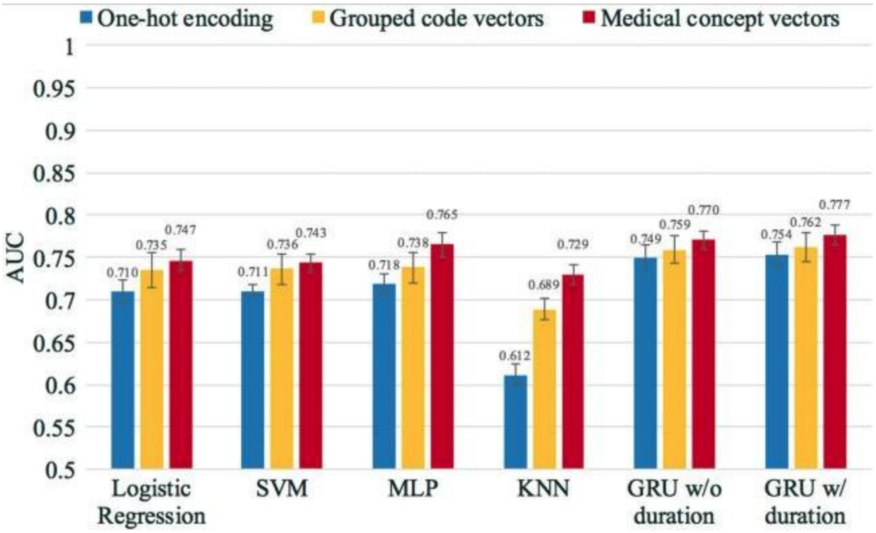
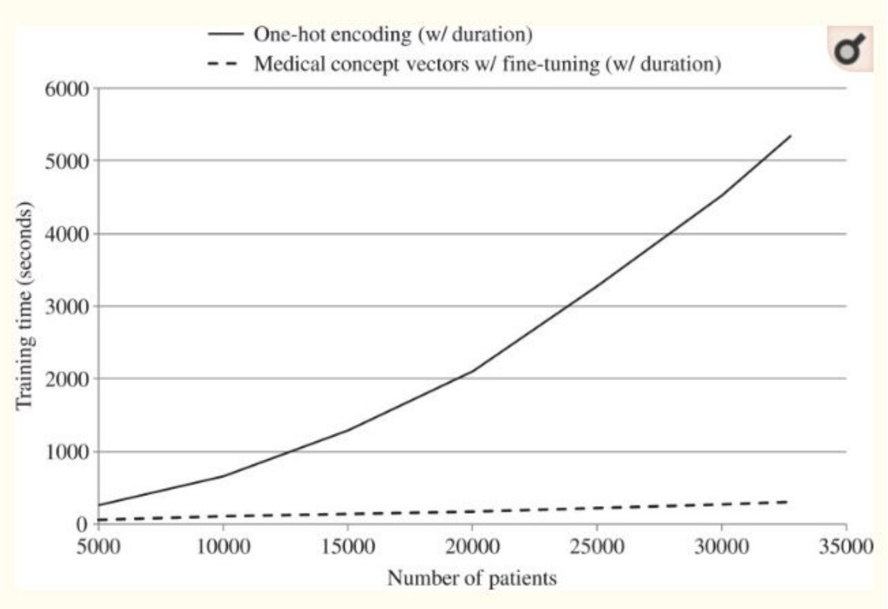
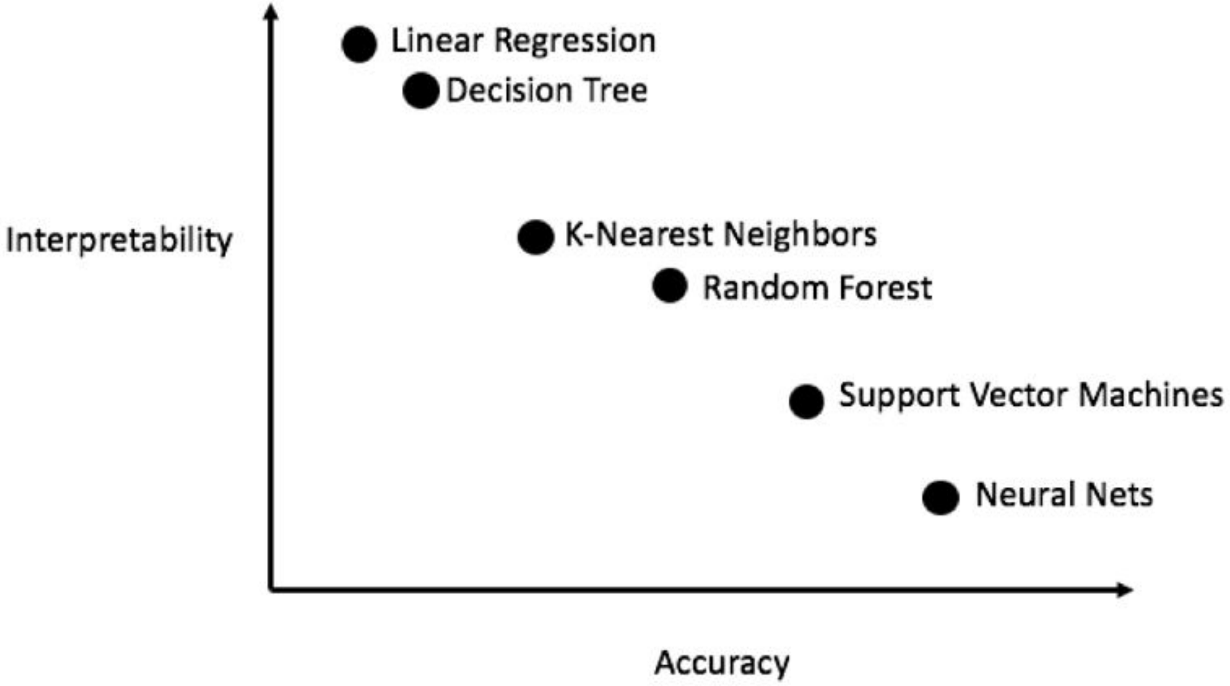
Outcome Prediction





https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5391725/

Interpretability matters

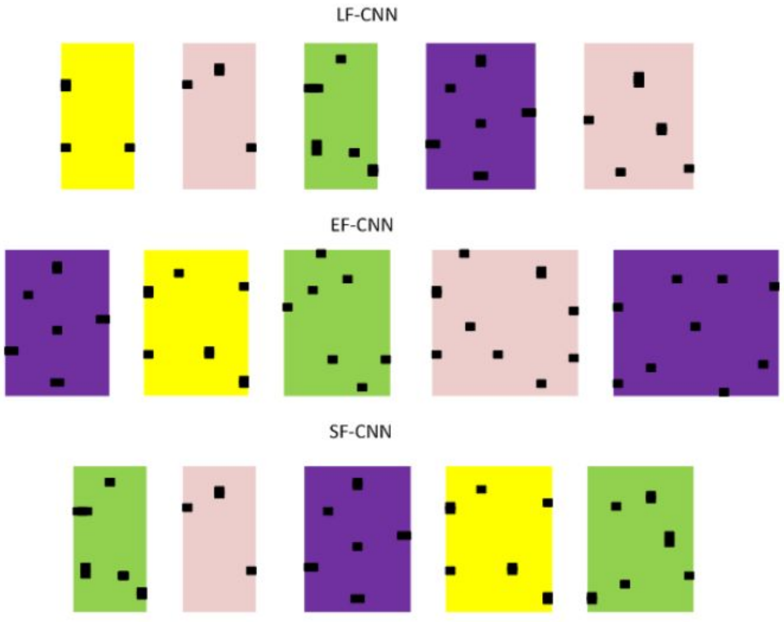


https://medium.com/ansaro-blog/interpreting-machine-learning-models-1234d735d6c9

Interpretability

- Maximum activation
- Constrains
- Qualitative Clustering

Maximum Activation for Congestive Heart Failure

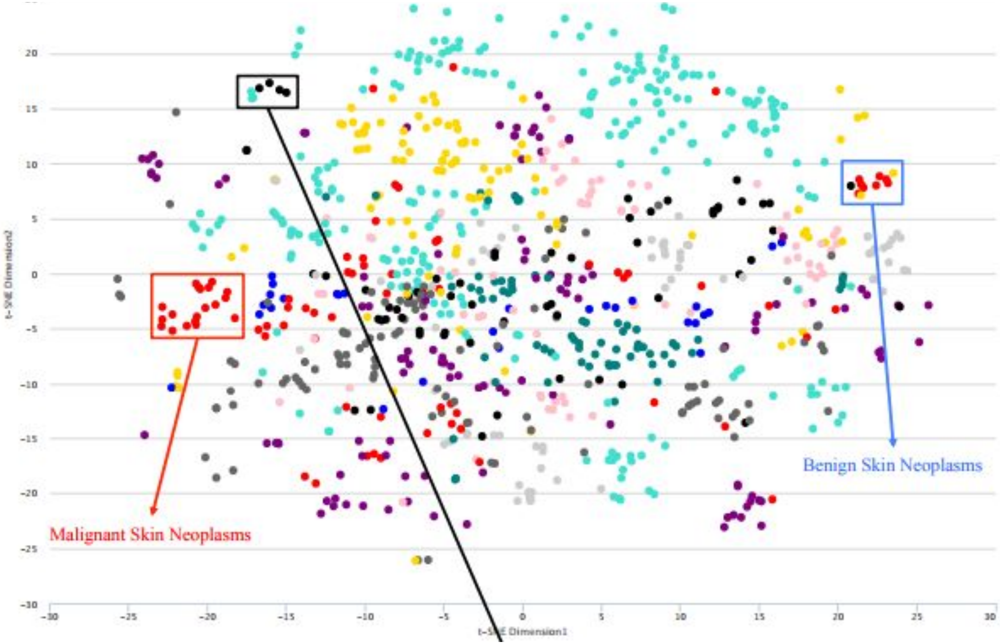


(a) CHF

https://www.mathworks.com/help/nnet/examples/visualize-activations-of-a-convolutional-neural-network.html
https://astro.temple.edu/~tua87106/sdm16.pdf

Qualitative Clustering

t-SNE, heatmap, etc.



https://arxiv.org/pdf/1602.03686.pdf

MIMIC 3.0 dataset

https://github.com/MIT-LCP/mimic-code

MIMIC Code Repository build passing DOI 10.5281/zenodo.821872 chat on gitter

This is a repository of code shared by the research community. The repository is intended to be a central hub for sharing, refining, and reusing code used for analysis of the MIMIC critical care database. To find out more about MIMIC, please see: https://mimic.physionet.org

You can read more about the code repository in the following open access paper: The MIMIC Code Repository: enabling reproducibility in critical care research.

If you use code or concepts available in this repository, we would be grateful if you would cite the above paper as follows:

> Johnson, Alistair EW, David J. Stone, Leo A. Celi, and Tom J. Pollard. "The MIMIC Code Repository: enabling reproducibility in critical care research." Journal of the American Medical Informatics Association (2017): ocx084.

You can also directly cite the repository using the above DOI from Zenodo.

https://github.com/hurcy/awesome-ehr-deeplearning

awesome

Awesome EHR-based deep learning papers

Curated list of awesome papers for electronic health records(EHR) mining, machine learning, and deep learning.

Background

We would like to provide a must-read papers in this domain.

Content

- Survey
- Data mining
- Machine learning
- Deep learning
- Visualization

Thanks!