Case Study: Electronic Health Records (EHRs)

ter.ps/389iweek6

Last week

- What are EHRs?
- Digital Health Regulation
- Data privacy and sharing
- Challenges with accessing and processing EHR data

This week

- Deep Learning in EHRs
- Challenges with understanding EHR data
- Pain tolerance between men and women
- Asthma drug for ALS

Atul Butte @atulbutte · 13h

I really believe that in 5 years, any academic medical center that ISN'T using their clinical data to improve the practice of medicine will be seen as irresponsible!

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Google AI Blog

Deep Learning for Electronic Health Records

Tuesday, May 8, 2018

Hospital Visits

- Patients wonder:
  - When will I be discharged?
  - Will I recover?
  - Will I have to come back?

- Prediction problem
  - ***Scalable*** *and* ***accurate*** *deep learning with electronic health records*
    https://www.nature.com/articles/s41746-018-0029-1

Scalable and accurate deep learning with electronic health records

- UCSF, UChicago, Stanford
- Deep learning models to make broad set of predictions with de-identified EHRs on hospitalized patients

Data

- De-identified EHR data from: UCSF (2012-2016) & UCM (2009-2016)

- Contains:
    - patient demographics, provider orders,
    - diagnoses, procedures,
    - medications, laboratory values,
    - vital signs, and flowsheet data.
    - UCM data contained free-text medical notes.

Methods

- De-identified EHR data of 216k hospitalized adult patients
- Almost **47 billion** data points

Methods

- DL models could predict with high accuracy:
  - **In-hospital mortality** (AUC 0.93-0.94)
  - **30-day unplanned readmission** (AUC 0.75-0.76)
  - **Prolonged length of stay** (AUC 0.85-0.86)
  - All of patients' **final discharge diagnoses** (AUC 0.90)
- Outperformed traditional clinical predictive models

Challenges

- Scaling is difficult
  - preprocessing, merging, customizing, cleaning
- Free-text notes from physicians → thousands of predictor variables
- Interoperability of health data from multiple sites

Challenges

- Predicting patient’s *full suite* of discharge diagnoses
  - N = 1-228 diagnoses, unknown at time of prediction
- Each diagnosis selected from **14,025** ICD-9 diagnosis codes
  - exponential # of possible diagnoses

Challenges

Many ICD-9 codes clinically similar but numerically distinct. e.g.:

011.30 “*Tuberculosis of bronchus, unspecified*”

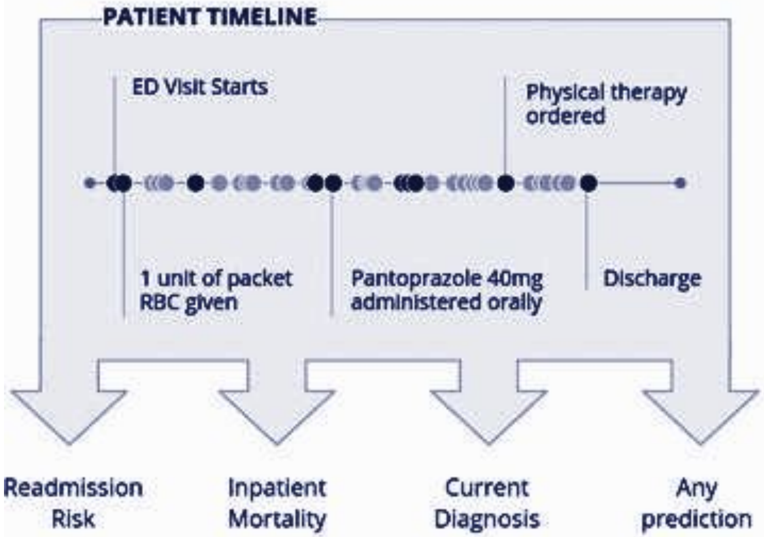
011.31 “*Tuberculosis of bronchus, bacteriological or histological examination not done*”

1

Health systems collect and store electronic health records in various formats in databases.

2

All available data for each patient is converted to events recorded in containers based on the Fast Healthcare Interoperability Resource (FHIR) specification.



3

The FHIR resources are placed in temporal order, depicting all events recorded in the EHR (i.e. timeline). The deep learning model uses this full history to make each prediction.

Machine learning predicts hypertension onset from EHR data

Prediction Algorithm

- 823.6k EHRs from Maine Health Information Exchange Network
- ML algorithm, dubbed XGBoost
- Tested on additional 680.8k EHRs
- Evaluated on sorting patients into one of 5 risk factors based on probability of developing hypertension in a year

Prediction Algorithm

- algorithm recognized
  - type 2 diabetes
  - lipid disorders
  - cardiovascular disease
  - mental illness
  - clinical utilization indicators
  - and socioeconomic determinants

as features associated with hypertension.

Prediction Algorithm

- AUC 0.87-0.91
- Social determinants strong indicators
  - community-level factors, education level, type of health insurance, dietary habits, physical activities
- Model deployed in the state of Maine

Women report feeling pain more intensely than men, says study of electronic records

2012 Pain Study

- *Journal of Pain* 2012
- “first-ever systematic use of data from electronic medical records to examine pain on this large a scale, or across such a broad range of diseases.”
- Pain intensity reported on 1-10 scales

2012 Pain Study

- search algorithm searched 72,000 patient EMR data
- more than 160,000 instances of pain scores reported
- across 250 disease categories

2012 Pain Study

- Female patients reported higher pain scores across the board
- Statistically and clinically significant
- In many cases, difference approached 1 point on the scale
    - “A pain-score improvement of one point is what clinical researchers view as indicating that a pain medication is working.”

Do women actually feel more pain than men?

- Unknown!
- Could be confounded by social factors
- Searching EMRs for **objective measurement of pain** necessary
    - Biomarker for pain

Repurposing Asthma drug for ALS using electronic medical records

Science Reports study

- > 13 years of hospital EMRs
- > 9.4 million lab tests from > 530,000 patients
- diverse genomic signatures

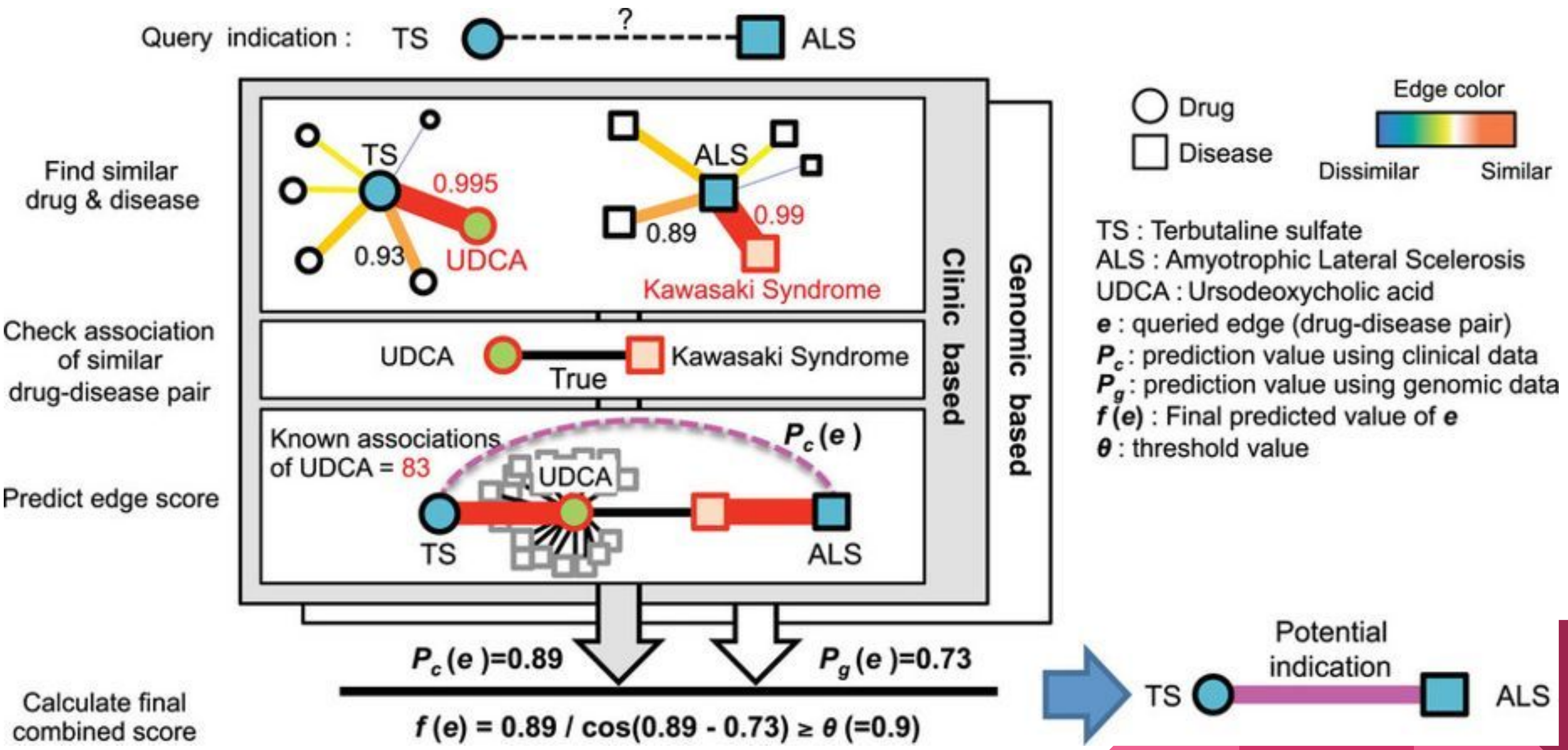
Science Reports study

- Cross validation w/ > 17,000 known drug-disease associations

- terbutaline sulfate, widely used asthma drug, is promising candidate for ALS, which has few therapeutic options

Science Reports study

- *in vivo* tests with zebrafish found that the drug prevents defects in axons and neuromuscular junction degeneration



Query indication : TS ? ALS
Drug
Disease
Edge color
Dissimilar
Similar
Find similar drug & disease
TS
0.995
UDCA
0.93
ALS
0.89
0.99
Kawasaki Syndrome
Check association of similar drug-disease pair
UDCA
True
Kawasaki Syndrome
Known associations of UDCA = 83
$P_c(e)$
UDCA
Predict edge score
TS
ALS
Clinic based
Genomic based
TS : Terbutaline sulfate
ALS : Amyotrophic Lateral Scelerosis
UDCA : Ursodeoxycholic acid
e : queried edge (drug-disease pair)
P_c : prediction value using clinical data
P_g : prediction value using genomic data
$f(e)$: Final predicted value of e
θ : threshold value
$P_c(e)=0.89$
$P_g(e)=0.73$
Calculate final combined score
$f(e) = 0.89 / \cos(0.89 - 0.73) \geq \theta\ (=0.9)$
Potential indication
TS
ALS