Reusable clinical profiles with temporal patterns for machine learning applications

Kenneth D. Roe
Johns Hopkins University
kroe6@jhu.edu

Vibhu Jawa
Johns Hopkins University
vjawa1@jhu.edu

Richard Zhu
Johns Hopkins University
zhu@jhu.edu

Brant Chee
Johns Hopkins University
Applied Physics Laboratory
Brant.Chee@jhuapl.edu

Jordan Matelsky
Johns Hopkins University
Applied Physics Laboratory
jm@jhu.edu

Matt Kinsey
Johns Hopkins University
Applied Physics Laboratory
Matt.Kinsey@jhu.edu

Jeremy Epstein
Johns Hopkins University
epstein@jhmi.edu

Xiaohan Zhang
Johns Hopkins University
xzhan161@jhmi.edu

Christopher G. Chute
Johns Hopkins University
chute@jhu.edu

Casey Overby Taylor
Johns Hopkins University
cot@jhu.edu

1 INTRODUCTION

Longitudinal electronic health records (EHR) are rich data sources that can be used to examine changes in clinical measures over time and relationships with clinical outcomes. Machine learning (ML) algorithms can be applied to *learn* patterns from EHR data to identify relationships between an individual's trajectory and clinical presentation and to make predictions. While methods do exist to analyze temporal patterns in EHR data, as evident in recent examples[2, 3], few studies use temporal patterns for ML applications[1].

2 OBJECTIVE

The primary objective of this work was to propose a novel model to generate reusable clinical profiles from EHR datasets that include temporal patterns and can be leveraged in ML applications.

3 METHODS

Our approach uses temporal abstraction to represent patterns of laboratory results (temporal patterns) and their relationship to clinical actions (procedures and drug prescriptions) and outcomes. The model to generate clinical profiles uses co-occurrence counts of temporal patterns to build a vector space. We apply this approach to create a clinical profile from de-identified EHR data from a large academic medical center. In particular, we select patients with an intensive care unit (ICU) admission due to an asthma event. We then demonstrate an application of the profile to determine what changes in laboratory tests following a procedure or medication treatment (i.e., temporal patterns), may be estimators of fatality.

4 RESULTS

We generated a clinical profile from 507 patients with no more than one ICU admission event, asthma listed as an admission reason, and with at least one asthma medication prescription recorded. Demographic measures, laboratory values, medication prescriptions, procedures, diagnoses, and one clinical outcome (death), were used to generate a clinical profile. Among this patient population, 190 died. We then demonstrate one application of the clinical profile to provide a ranked list of temporal patterns associated with event mortality. In particular, we observe changes in laboratory tests following a procedure or medication prescription (i.e., temporal patterns) that may be estimators of fatality. We provide a sorted list of temporal patterns according to their mutual information scores.

NECHS'18, April 27, 2018, Cambridge, MA
.

5 DISCUSSION AND CONCLUSION

We proposed a new model to generate clinical profiles containing temporal patterns from EHR datasets that are reusable by others and can be used with ML approaches to assess clinical outcomes. Highly scored temporal patterns we identified warrant further investigation into their therapeutic relevance. One area we have not yet explored is the use of existing biomedical evidence to understand the role of drug and disease mechanisms in clinical presentation. Ontological analyses of clinical profiles with such evidence will offer new research opportunities to discover underlying relationships between clinical presentation and drug/disease mechanisms.

ACKNOWLEDGMENTS

The work is supported by Grant No. NIH NCATS 1OT3 TR00201.

REFERENCES

[1] B A Goldstein, A M Navar, M J Pencina, and J P A Ioannidis. 2017. Opportunities and challenges in developing risk prediction models with electronic health records data: a systematic review. *J of the Am Med Info Assoc* 24, 1 (Jan. 2017), 198–208.

[2] R Miotto, L Li, B A Kidd, and J T Dudley. 2016. Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records. *Scientific Reports* 6 (May 2016), 26094.

[3] R Moskovitch, H Choi, G Hripcsak, and N P Tatonetti. 2017. Prognosis of Clinical Outcomes with Temporal Patterns and Experiences with One Class Feature Selection. In *Proc of the IEEE/ACM TCBB*, Vol. 14. IEEE Comp Society Press, 555–563.