A Deep Learning Model for Pediatric Risk Stratification

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Nationwide Children's
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Objectives

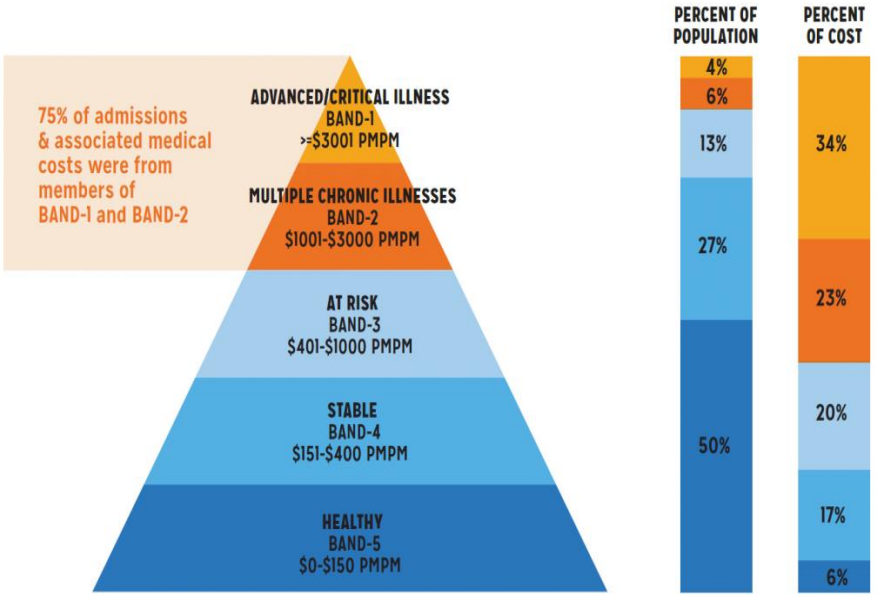
Current risk prediction models perform poorly for pediatric patients. The goal of this study is to:

- Develop a deep learning approach for pediatric patient risk prediction that can be used to improve patient risk stratification.

- Foster a collaboration between NCH data science and health policy researchers at OSU CPH to bring Machine Learning to a healthcare policy audience.

Specific Aim: Use a deep learning model to develop a predictive algorithm for future healthcare utilization from claims data and assess the predictive validity of this model on a small pediatric dataset.

Why care about risk stratification?



- Healthcare reform through value based purchasing - holding healthcare organizations accountable for population based outcomes.
- Risk stratification of patient cohorts facilitates appropriate resource allocation and planning, care coordination for high needs patients, and financial forecast.

Image credit: https://www.rxadvance.com

Challenges in Pediatric Risk Stratification

- Risk stratification of patients using predictive regression models has long been an analytic challenge because of sparse, high dimensional, and noisy data from insurance claims.

- The state-of-the-art risk stratification models rely on groupers of diagnosis codes developed in the early 2000s. These traditional grouper models were labor-intensive to develop as they rely on practitioner expertise and domain knowledge.

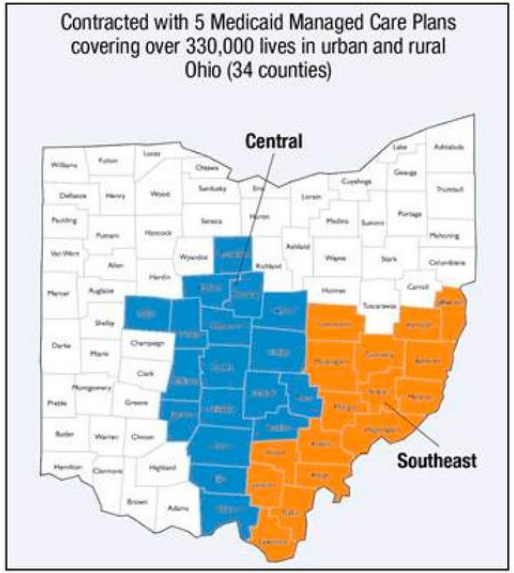
- These methodologies were developed using a standard population with an emphasis on adults, resulting in poor predictability in pediatric population.

Deep Learning for Risk Stratification

- Deep learning can handle and leverage the complex relationships in large, sparse, high-dimensional, and noisy data.
- Deep learning has made the implementation of predictive analytics easier due to an unsupervised learning approach with automatic feature engineering.
- The application of deep learning to patient-level risk prediction is a new area of exploration. Early work showed promise of deep learning in predicting a patient's future medical condition from EHR (Miotto et al.,*Sci. Rep*., 2016).
- We hypothesize that apply deep learning on a pediatric dataset can be an efficient and effective approach in performing pediatric patient risk stratification.

Methods

Study Population: Partners for Kids (PFK) is an Accountable Care Organization (ACO) affiliated with Nationwide Children's Hospital in Columbus Ohio. As one of the oldest and largest pediatric ACOs, PFK assumes full financial risk for a pediatric population of over 330,000 Medicaid-qualified children in central and southeastern Ohio.

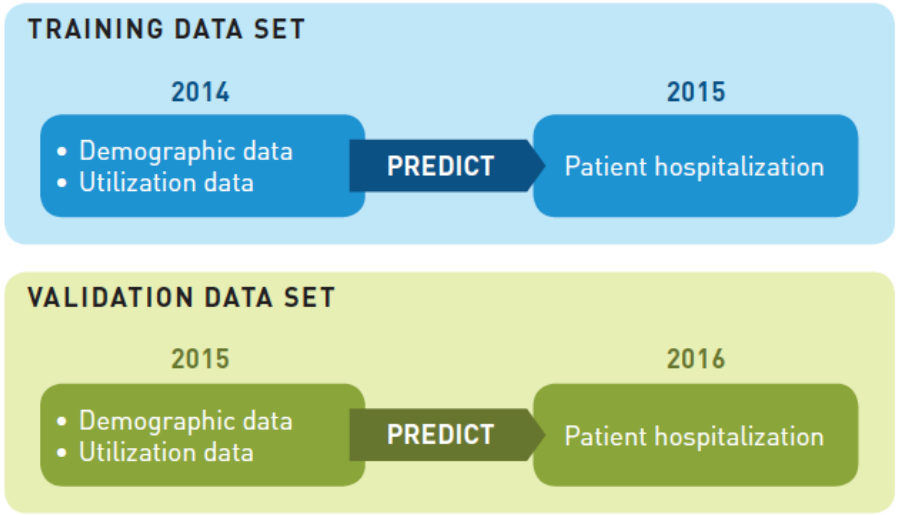


Dataset

The final dataset consisted of 112,641 unique PFK members with continuous eligibility from 2014 – 2016, balanced in gender distribution with a mean age of 8 years old.

Predictive model developed using 2014-2015 data and validated with 2015-2016 data.

FIGURE. Schematic Representation of Study Data Set

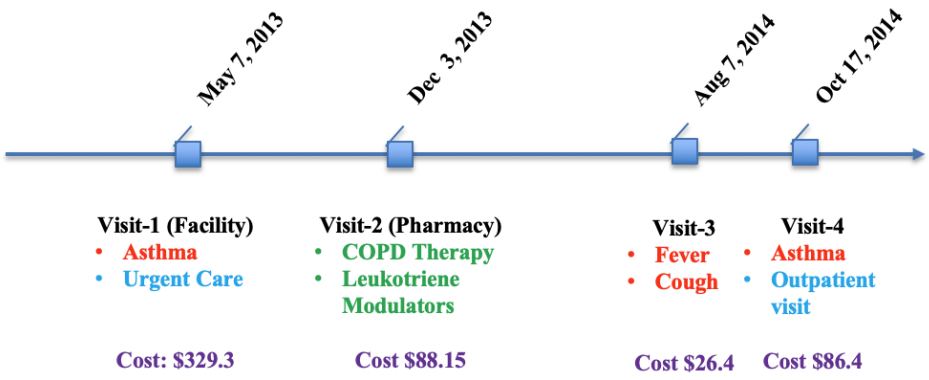


Claims Data

In claims data, a patient is represented as a sequence of medical visits. Each visit contains a set of medical events and corresponding attributes.

Data elements:

- Patient demographic data: sex, age, zip code
- Utilization data: medical codes (diagnosis, procedure, medication)
- Corresponding medical cost and service detail information (date, type, location, provider).

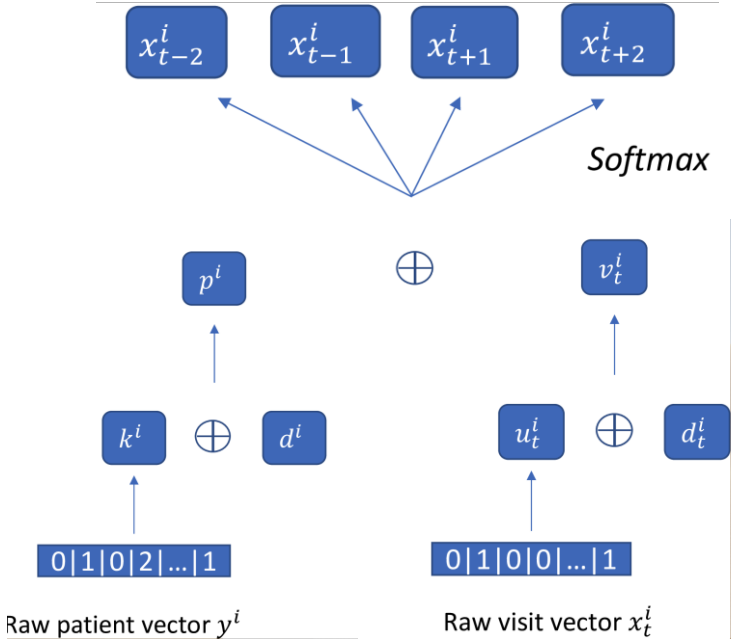


Model Architecture

The training objectives are to:

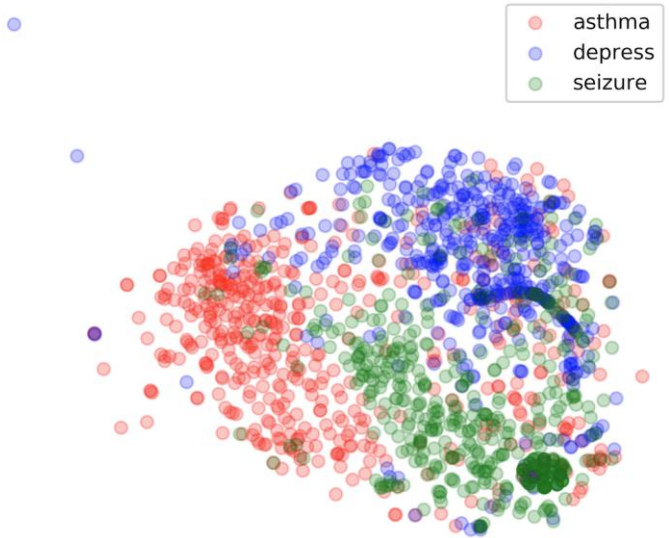
1) learn medical code representation that is good at predicting neighboring codes within the same visit.

2) learn patient representation that is good at predicting nearby visits.

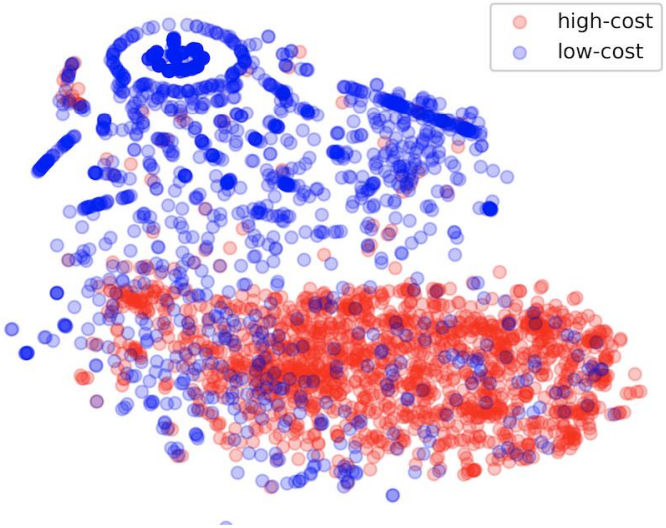


The Output: Learned Representation

Code representation



Patient representation



After obtaining the meaningful patient representation, we use it to predict patient hospitalization in the *subsequent* year.

Model Evaluation

Area under the curve (AUC) was used as the primary evaluation metric.

Model	AUC
Logistic Model with Demographic and Utilization (D/U) variables	73.1%
Clinical Classification Software (CCS) which groups related medical codes	71.1%
CCS with D/U	73.8%
DxCG Intelligence *	72.0%
Deep Learning	73.5%
Deep Learning with D/U	75.1%

**Verscend's proprietary DxCG Intelligence predictive model (Verscend, NJ) is considered to be a gold standard in risk stratification for the Medicare population.*

Financial Impact

- The deep learning model can more accurately select the high medical utilization / high cost patients by predicting risk for hospitalization.
- Small improvements in model performance can have significant practical impact.

Top 1% individual selected by: Combined actual cost (n=1126)

Deep Learning → $ 31.1 million

DxCG Intelligence → $ 26.0 million

By using the deep learning model to select the top 1% of high risk individuals for care management, the ACO could potentially influence an additional $5 million in costs compared to DxCG Intelligence.

Deep Learning for Risk Stratification

Strength:

- Unsupervised learning reduce human effort.
- Fast processing allows frequent updates to constantly improve model performance.
- Can easily train model on specific population cohort, such as pediatric population, improving predictive performance on non-standard population.

Limitation of the current study:

- Small dataset.
- Continuous eligibility across all three years may distort the underlying ACO population, sensitivity analyses are needed.

Policy Implications

Improve the ability of pediatric ACOs to do preemptive planning of financial risk.

The ability to improve future diagnostic prediction of a panel of patients may

- lead to better assessment of provider performance by taking case-mix into consideration.
- more realistic and rationalized resource planning to meet patient demand

By identifying the ‘high risk’ patients, physicians and other providers can develop future oriented preemptive care planning and provide preventative treatment intervention before more serious conditions and events take place.

References available online:

American Journal of Managed Care. 2019;25(10):e310-e315
https://www.ajmc.com

METHODS

A Deep Learning Model for Pediatric Patient Risk Stratification

En-Ju D. Lin, PhD, MPH; Jennifer L. Hefner, PhD, MPH; Xianlong Zeng, MS; Soheil Moosavinasab, MS; Thomas Huber, PhD, MS; Jennifer Klima, PhD; Chang Liu, PhD; and Simon M. Lin, MD, MBA

Thank you!

Questions?

Takeaway Points

The present study benchmarked a new deep learning methodology for patient risk stratification using clinical and financial data for a small pediatric accountable care organization (ACO) data set. The predictive validity of the deep learning model was higher than that of other popular population risk prediction modeling strategies that, unlike deep learning, require practitioner expertise and domain knowledge.

The deep learning model, although preliminary, may:

- Enable population risk stratification without the investment of human resources that other modeling techniques require
- Improve the ability of pediatric ACOs and others conducting population health management to perform predictive modeling of healthcare utilization

Model Evaluation

- Deep Learning provides small but meaningful improvements in other measures of predictive performance, such as sensitivity and positive predictive value (PPV).
- PPV is a useful measure when considered in terms of selecting members for care coordination. It reflects the proportion of members predicted to have high probability of hospitalization (and hence potential target for preemptive care management) that are actually hospitalized.

B. Additional Measures for Model Evaluation for Next-Year Hospitalization Prediction

Metrics by Risk Score Threshold	D/U Only (model 1)	CCS + D/U (model 3)	DxCG (model 6)	Deep Learning + D/U (model 5)
Sensitivity				
75th percentile (n = 28,160)	0.605	0.608	0.557	0.628
90th percentile (n = 11,264)	0.395	0.416	0.392	0.452
95th percentile (n = 5632)	0.290	0.304	0.274	0.332
99th percentile (n = 1126)	0.125	0.126	0.103	0.149
Specificity				
75th percentile (n = 28,160)	0.754	0.754	0.754	0.755
90th percentile (n = 11,264)	0.903	0.904	0.903	0.904
95th percentile (n = 5632)	0.953	0.953	0.952	0.953
99th percentile (n = 1126)	0.992	0.992	0.991	0.992
Positive predictive value				
75th percentile (n = 28,160)	0.031	0.031	0.029	0.033
90th percentile (n = 11,264)	0.052	0.053	0.051	0.059
95th percentile (n = 5632)	0.076	0.080	0.072	0.087
99th percentile (n = 1126)	0.165	0.166	0.135	0.196
Negative predictive value				
75th percentile (n = 28,160)	0.993	0.993	0.993	0.993
90th percentile (n = 11,264)	0.991	0.991	0.991	0.992
95th percentile (n = 5632)	0.990	0.990	0.989	0.990
99th percentile (n = 1126)	0.988	0.988	0.988	0.988

Financial Impact

Risk Score Threshold (percentile)	Predicted Outcome Model							
	D/U Only (model 1)		CCS + D/U (model 3)		DxCG Intelligence (model 6)		Deep Learning + D/U (model 5)	
	95th (n = 5632)	99th (n = 1126)	95th (n = 5632)	99th (n = 1126)	95th (n = 5632)	99th (n = 1126)	95th (n = 5632)	99th (n = 1126)
Average annual cost in 2016, per high-risk individual	$10,273.80	$21,947.70	$10,793.60	$25,313.20	$9981.50	$23,125.50	$10,887.50	$27,593.00
Total annual cost in 2016 for selected high-risk individuals[a]	$57,862,041.60	$24,713,110.20	$60,789,555.20	$28,502,663.20	$56,215,808.00	$26,039,313.00	$61,318,400.00	$31,069,718.00
Total annual cost difference compared with model 5 (deep learning + D/U)	–$3,456,358.40	–$6,356,607.80	–$528,844.80	–$2,567,054.80	–$5,102,592.00	–$5,030,405.00	–	–