Learning **Individual Readmission-Free Survival Distributions** using **Longitudinal Medical Events**

Thesis Seminar • Sacha Davis

July 31st 2023

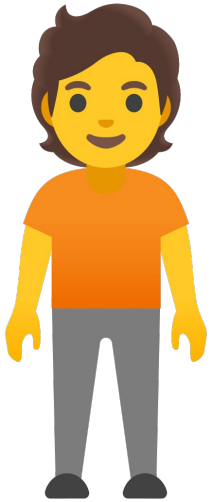


Canadian **VIGOUR** Centre
Bridging Hearts and Minds



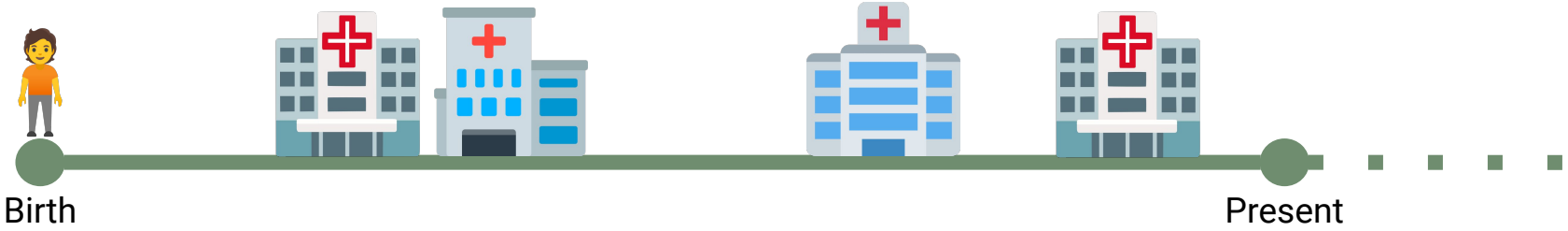
UNIVERSITY OF ALBERTA

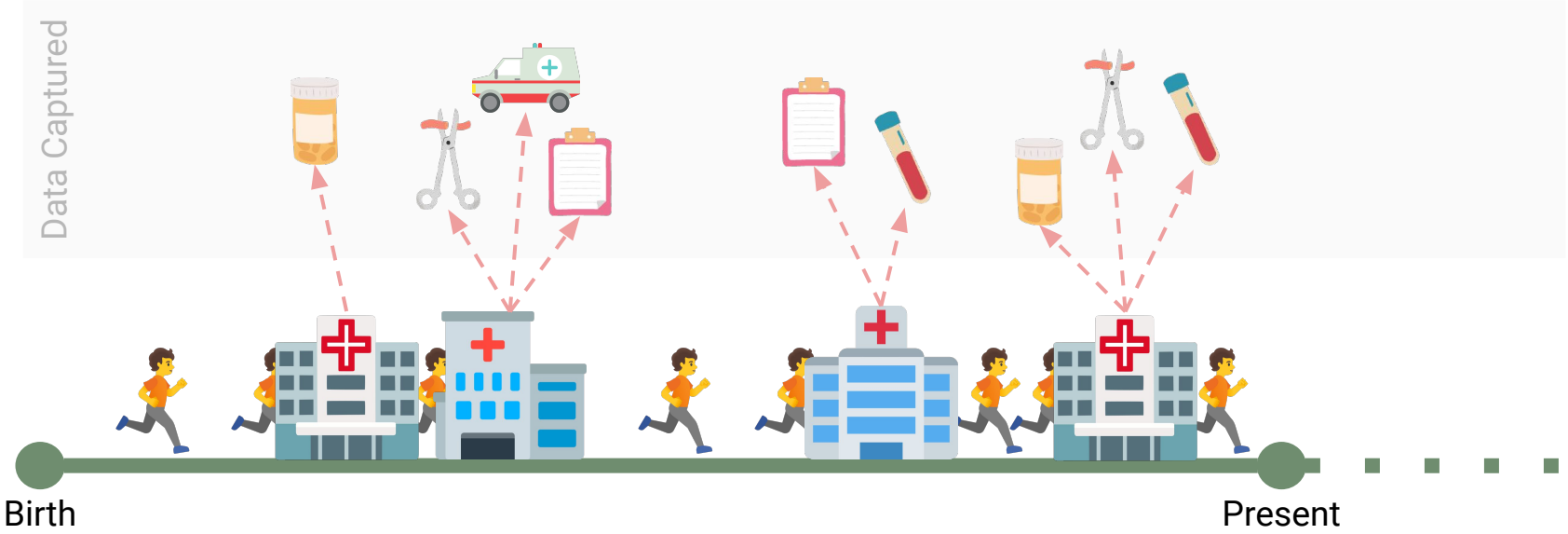


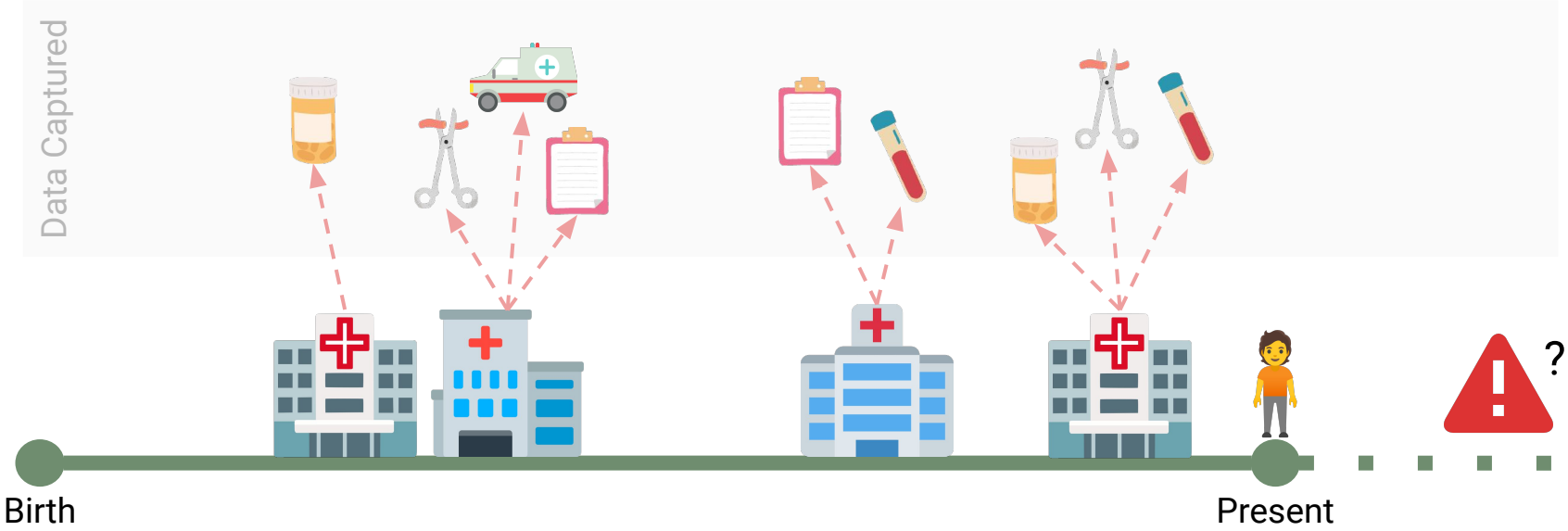


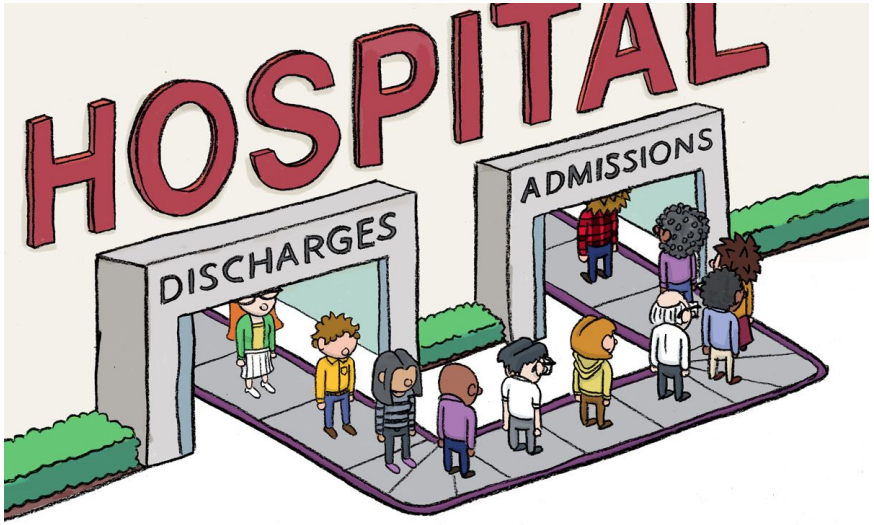
(You)

Data Captured




Data Captured
Birth
Present


Data Captured
?
Birth
Present



Hospitals face big fines for frequent readmissions

November 19, 2021 | John Russell

KEYWORDS HOSPITALS / MEDICAID / MEDICARE

Image credits: Brad Turner for IBJ

What do we have to do well?

Outline

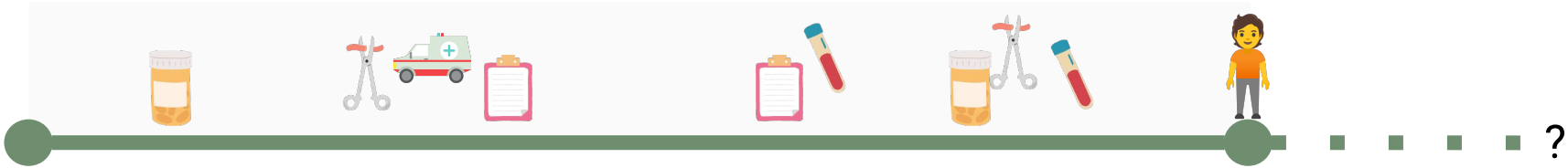
How do we represent patients from their Electronic Health Record?

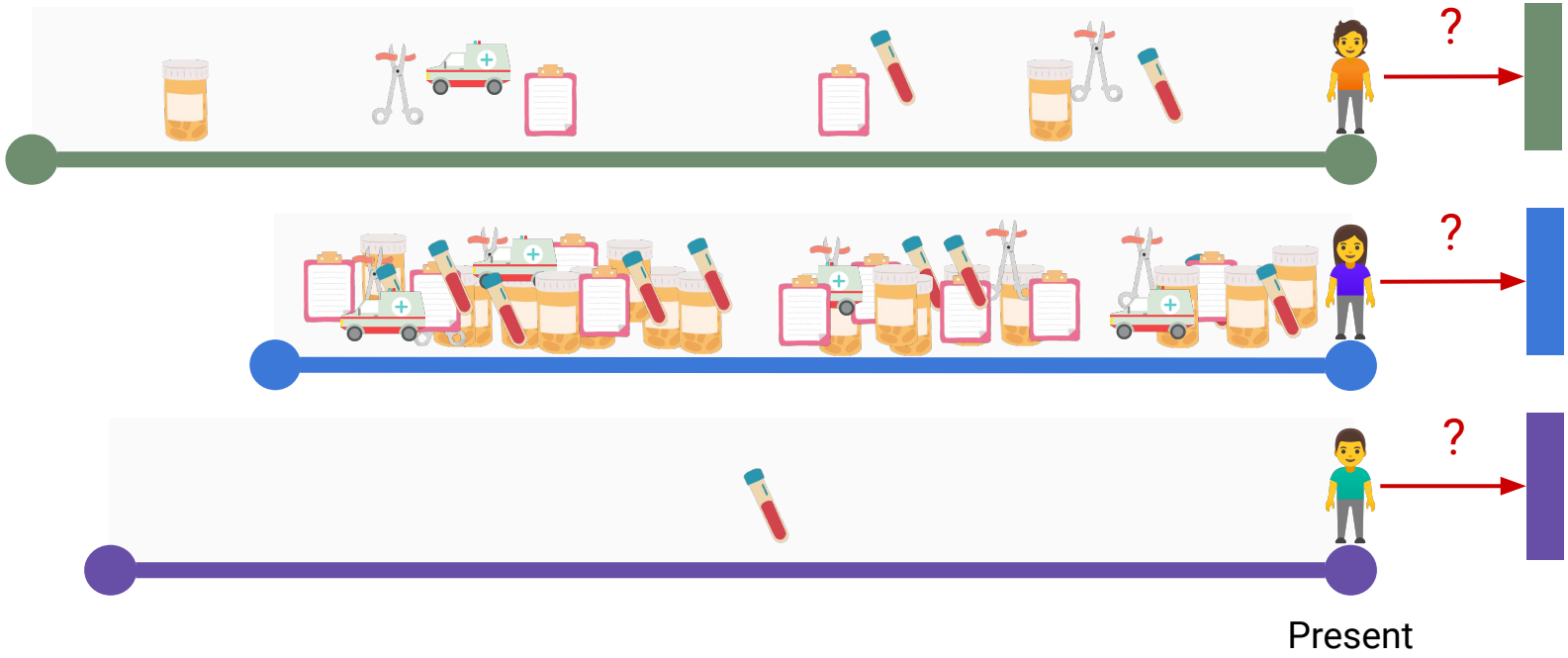
Predicting 30-day all-cause hospital readmissions using different representations

Revisiting the problem formulation

Discussion, conclusions, and future work

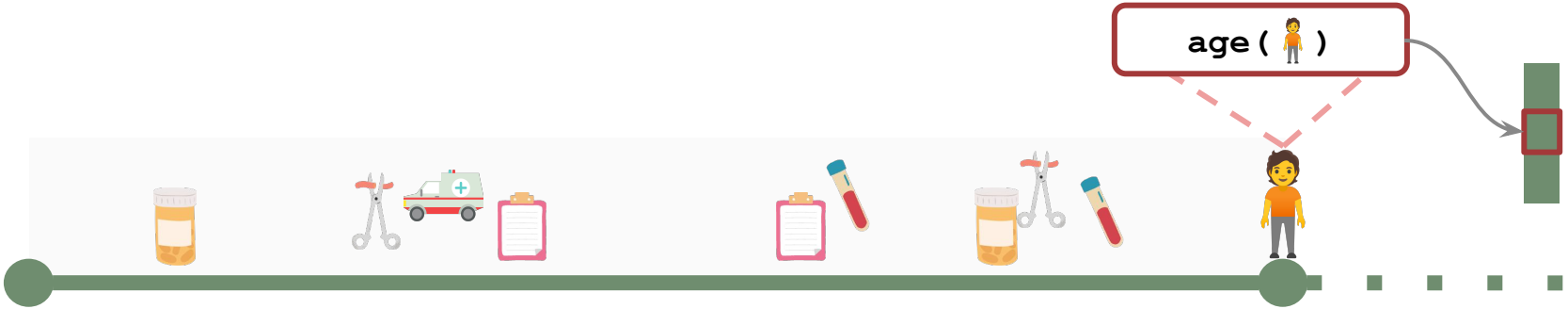
How can we represent a patient?




?
?
?
Present

Raw Features

- Can be used for ML as it is captured
- e.g., age, sex, discharge disposition, hospital admitted to



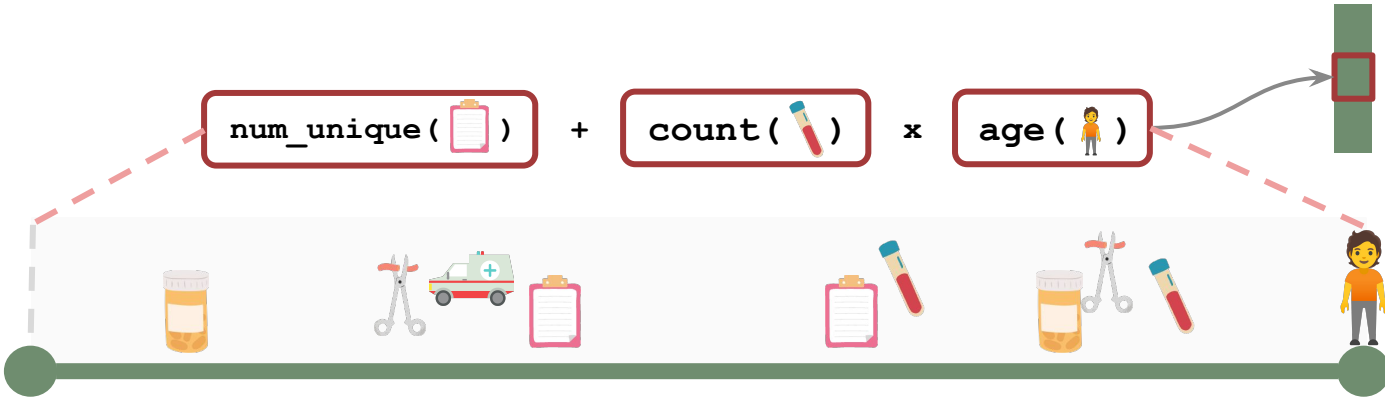
Hand-Derived Features

- Create some kind of new variable to be used for prediction
- e.g., number of emergency department visits in the last 6 months



Hand-Derived Features: Risk Scores

- Map values of raw and hand-engineered features to single scalar
- e.g., LACE index [1]

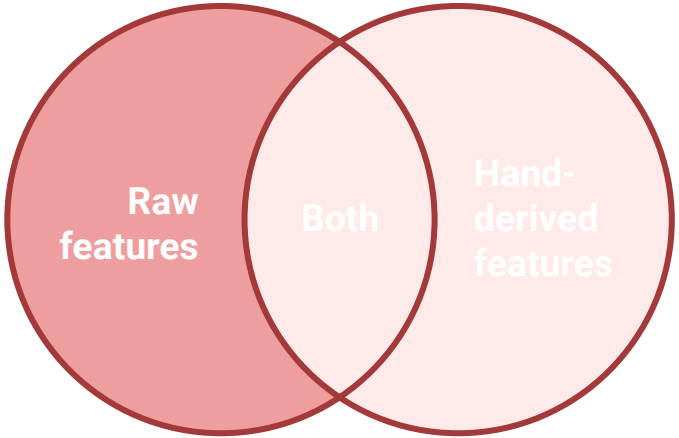


Score Component	Score
L: length of stay (days)	
1	1
2	2
3	3
4–6	4
7–13	5
≥ 14	7
A: acuity of admission	
Elective	0
Urgent/emergent	3
C: Charlson comorbidity score	
0	0
1	1
2	2
3	3
≥ 4	5
E: emergency department visits in the preceding 6 months	
0	0
1	1
2	2
3	3
≥ 4	4

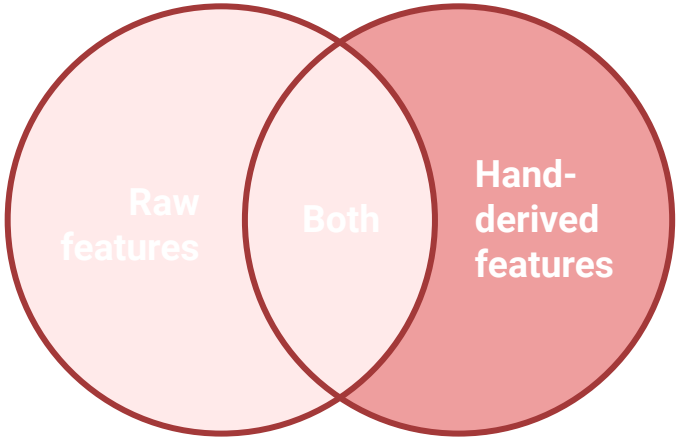
[1] van Walraven (2010)

Problems so far:

- ➔ Not many predictive ones exist
- ➔ Ignores historical information



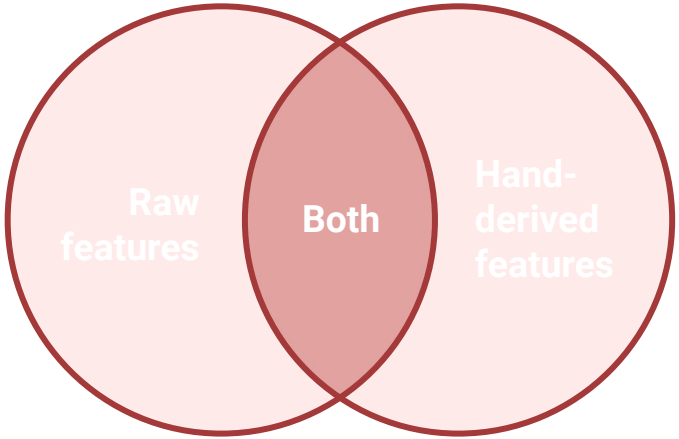
Problems so far:



- → Effort to calculate, trial and error
- → Often domain and task-specific
- → Knowledge gaps!

Problems so far:

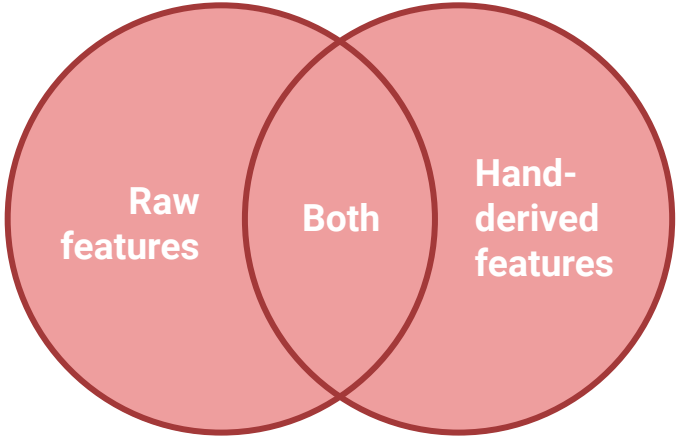
- ➔ Difficult tradeoff between granular and widely applicable
- ➔ Don’t handle time/order elegantly



Problems so far:

- ➔ Difficult tradeoff between granular and widely applicable
- ➔ Don’t handle time/order elegantly

- ➔ Not many predictive ones exist
- ➔ Ignores historical information



- ➔ Effort to calculate, trial and error
- ➔ Often domain and task-specific
- ➔ Knowledge gaps!

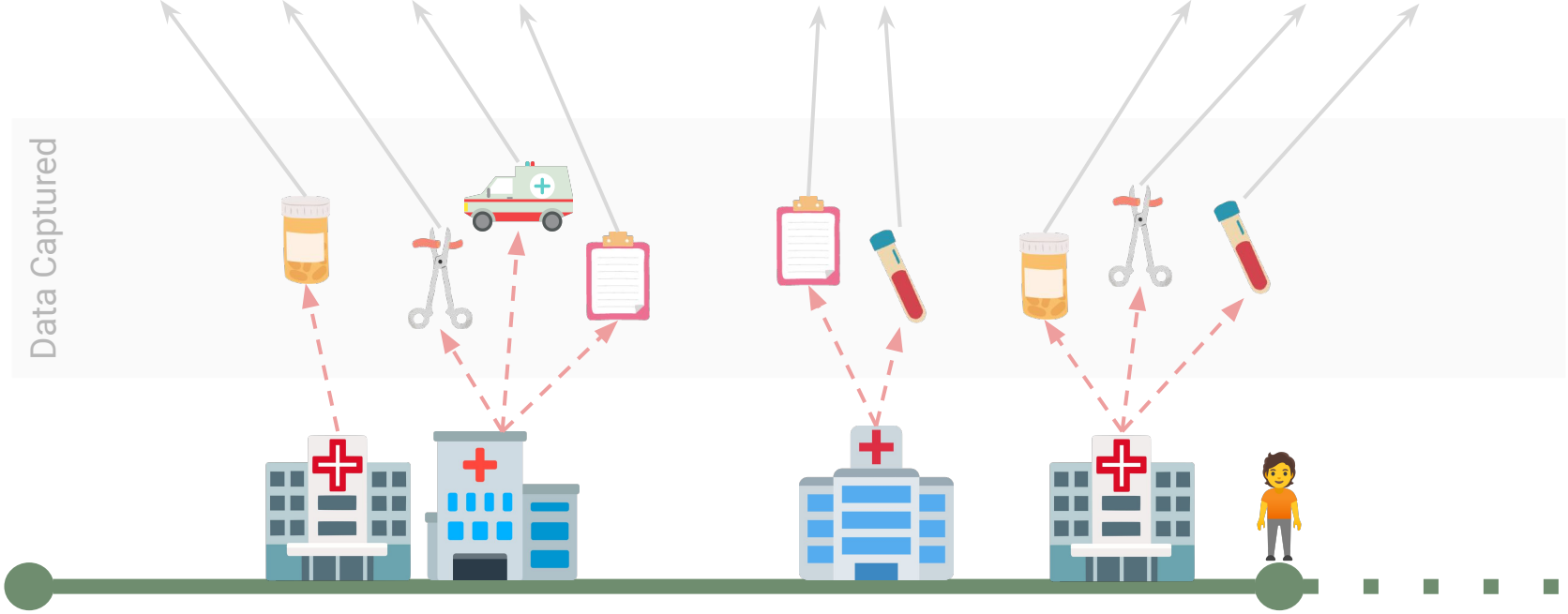
Natural Language Document



our doubts are
traitors and make
us lose the good
we oft might win
by fearing ...

our = belonging to the speaker...
doubts = a feeling of uncertainty...
are = conjugated form of be...
traitors = people who betray...
and = used to connect words...
make = form (something) by...
...

“ADM N06AA 3.SC.10 EMERG M54 05 3-6m ADM 780 03.0 04 0-1m ADM N05CF 3.SC.10 03.0 . . .”



Natural Language Document



our doubts are
traitors and make
us lose the good
we oft might win
by fearing ...

=

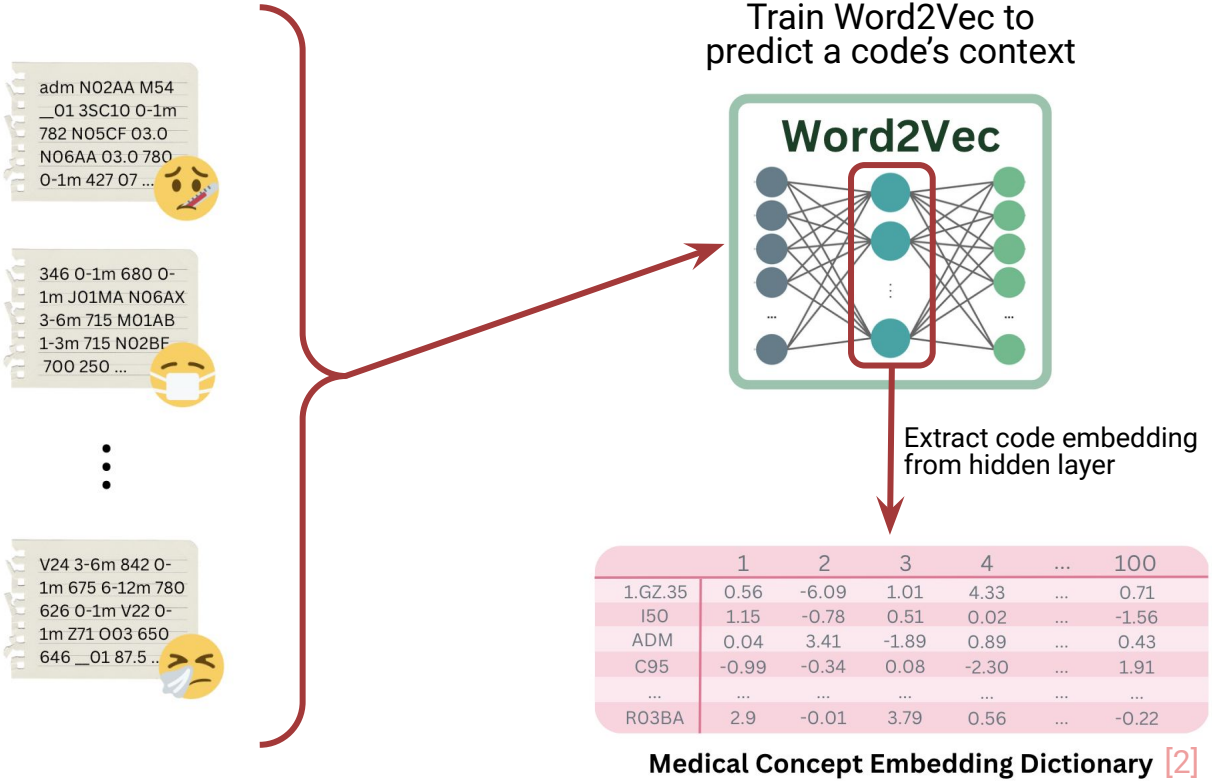
Patient History "Document"

adm M54 3SC10
N02AA _01 0-1m
782 N05CF 03.0
N06AA 03.0 780
0-1m 427 07 ...



our = belonging to the speaker...
doubts = a feeling of uncertainty...
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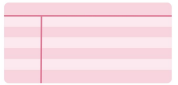
adm = admission to a hospital
M54 = dorsalgia diagnosis
3SC10 = spinal vertebrae fluoroscopy
N02AA = opium alkaloid prescription
_01 = discharged from hospital
0-1m = 7 to 30 days pass
...



	1	2	3	4	...	100
1.GZ.35	0.56	-6.09	1.01	4.33	...	0.71
I50	1.15	-0.78	0.51	0.02	...	-1.56
ADM	0.04	3.41	-1.89	0.89	...	0.43
C95	-0.99	-0.34	0.08	-2.30	...	1.91
...	...	...	...	...	...	...
R03BA	2.9	-0.01	3.79	0.56	...	-0.22

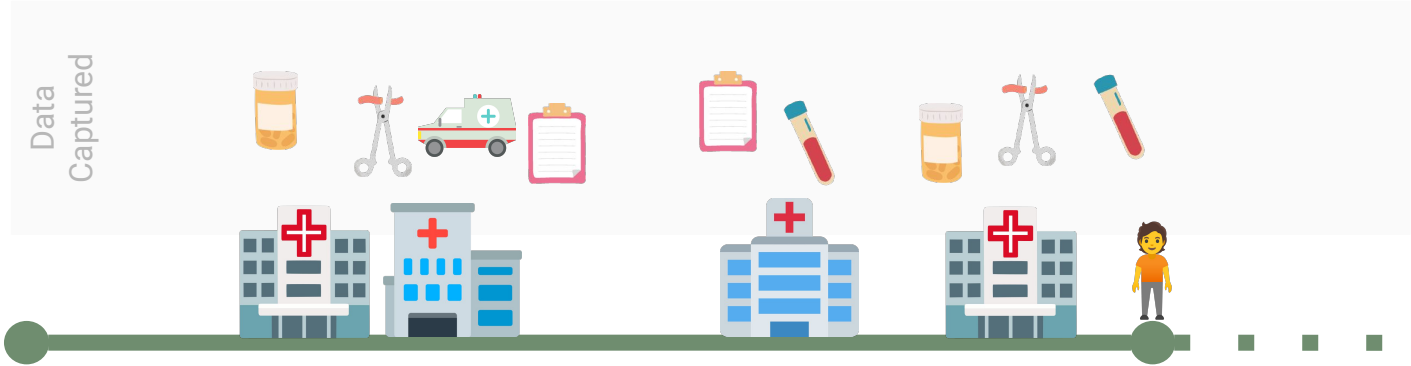
Codes that appear in similar contexts will have similar vectors.

[2] Y. Choi et al. (2016a)



$$\sum \begin{bmatrix} -0.4 \\ -1.2 \\ \vdots \\ -8.4 \end{bmatrix} \begin{bmatrix} -1.4 \\ 9.1 \\ \vdots \\ 7.4 \end{bmatrix} \begin{bmatrix} -4.1 \\ -4.0 \\ \vdots \\ -5.0 \end{bmatrix} \begin{bmatrix} 0.1 \\ 3.7 \\ \vdots \\ 8.5 \end{bmatrix} \begin{bmatrix} 5.2 \\ -1.3 \\ \vdots \\ -8.5 \end{bmatrix} \begin{bmatrix} 1.6 \\ 5.7 \\ \vdots \\ -0.3 \end{bmatrix} \begin{bmatrix} -4.1 \\ 8.6 \\ \vdots \\ 1.2 \end{bmatrix} \begin{bmatrix} -0.4 \\ -1.2 \\ \vdots \\ -8.4 \end{bmatrix} \begin{bmatrix} 3.0 \\ 2.4 \\ \vdots \\ 7.6 \end{bmatrix} \begin{bmatrix} 7.7 \\ -4.4 \\ \vdots \\ 3.9 \end{bmatrix} \begin{bmatrix} 5.1 \\ -0.5 \\ \vdots \\ 6.6 \end{bmatrix} \begin{bmatrix} -0.4 \\ -1.2 \\ \vdots \\ -8.4 \end{bmatrix} \begin{bmatrix} -1.4 \\ 9.1 \\ \vdots \\ 7.4 \end{bmatrix} \begin{bmatrix} -4.1 \\ -4.0 \\ \vdots \\ -5.0 \end{bmatrix} \begin{bmatrix} 7.7 \\ -4.4 \\ \vdots \\ 3.9 \end{bmatrix} \begin{bmatrix} 1.6 \\ 5.7 \\ \vdots \\ -0.3 \end{bmatrix} = \quad [3]$$

“ADM N06AA 3.SC.10 EMERG M54 05 3-6m ADM 780 03.0 04 0-1m ADM N05CF 3.SC.10 03.0 05”



[3] E. Choi et al. (2016b)

Features used in this project:

Status quo features:

- **Bare**: already available from Alberta Health Services



Index episode discharge disposition
Index episode length-of-stay
LACE Score
If index episode admission was emergent
Index-informed Charlson Comorbidity Score
Age at admission
Sex
Number of emergency admissions (6m)

Features used in this project:

Status quo features:

- **Bare**: already available from Alberta Health Services

- **Supplementary**: Hand-calculated from medical common knowledge and literature



Total number of procedures in index
Number of unique procedures in index
Number of unique ICD codes in index
Total number of prescription records in index
Number of unique drugs prescribed in index
Index-informed presence of hypertension
Index-informed presence of diabetes
Index-informed presence of asthma
Index-informed presence of chronic heart failure
Discharge disposition of most recent admission
Number of admissions (6m, 2y)
Total length-of-stay (6m, 2y)
Number of general practitioner visits (6m, 1y)
Number of general surgery visits (6m, 1y)
Number of internal medicine visits (6m, 1y)
Presence of a general practitioner visit (2y, 3y, 4y)
Total cost to the healthcare system (2y, 3y, 4y)
Total number of prescription records (2y)
Number of unique drugs prescribed (2y)
Number of days prescribed (2y)
Number of emergency admissions (1y)
Number of non-emergency admissions (6m, 1y)
Index-uninformed presence of hypertension
Index-uninformed presence of diabetes
Index-uninformed presence of asthma
Index-uninformed presence of chronic heart failure
Index-uninformed Charlson Comorbidity Score

Features used in this project:

Patient-Document features:

- **Agg**regated **Seq**uence: Summed embeddings from *k* most recent medical codes

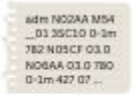


Features used in this project:

Patient-Document features:

- **Agg**regated **Seq**uence: Summed embeddings from *k* most recent medical codes

- Raw **Seq**uence: String containing whole medical biography



Seq features

“ADM N06AA 3.SC.10 EMERG M54 05 3-6m ADM 780 03.0 04 0-1m ADM N05CF 3.SC.10 03.0 05”

Do these representations work for our task?

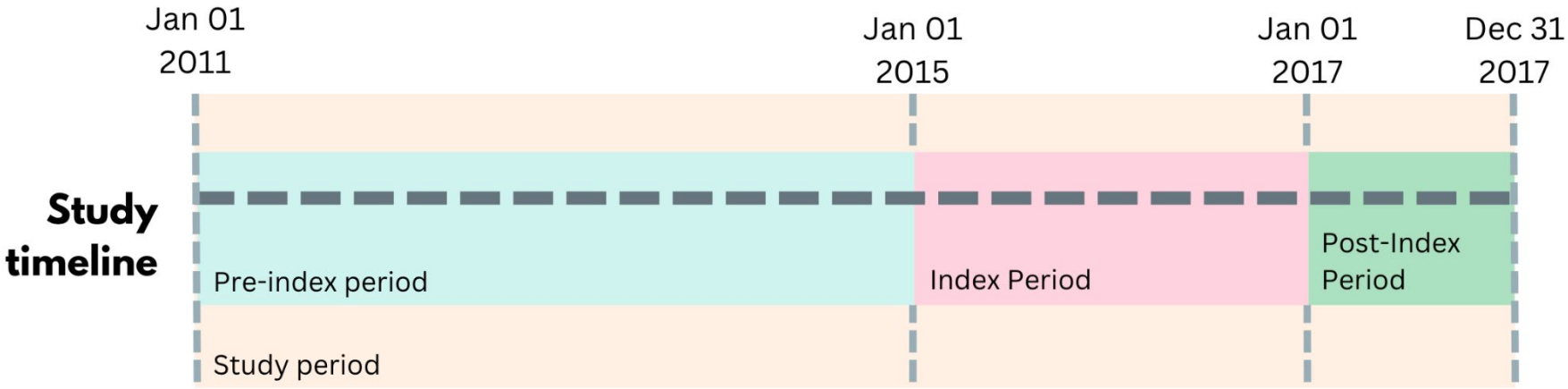
Alberta Health Services Data

DAD: In-patient hospitalizations

Claims: Insurance company billing

PIN: Prescriptions

NACRS: Outpatient ambulatory services



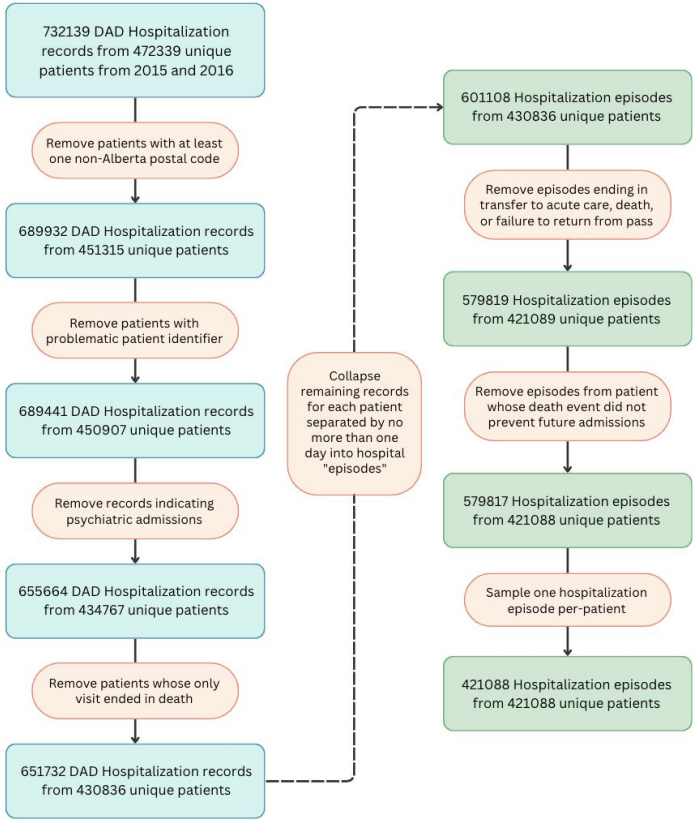
Index Admissions

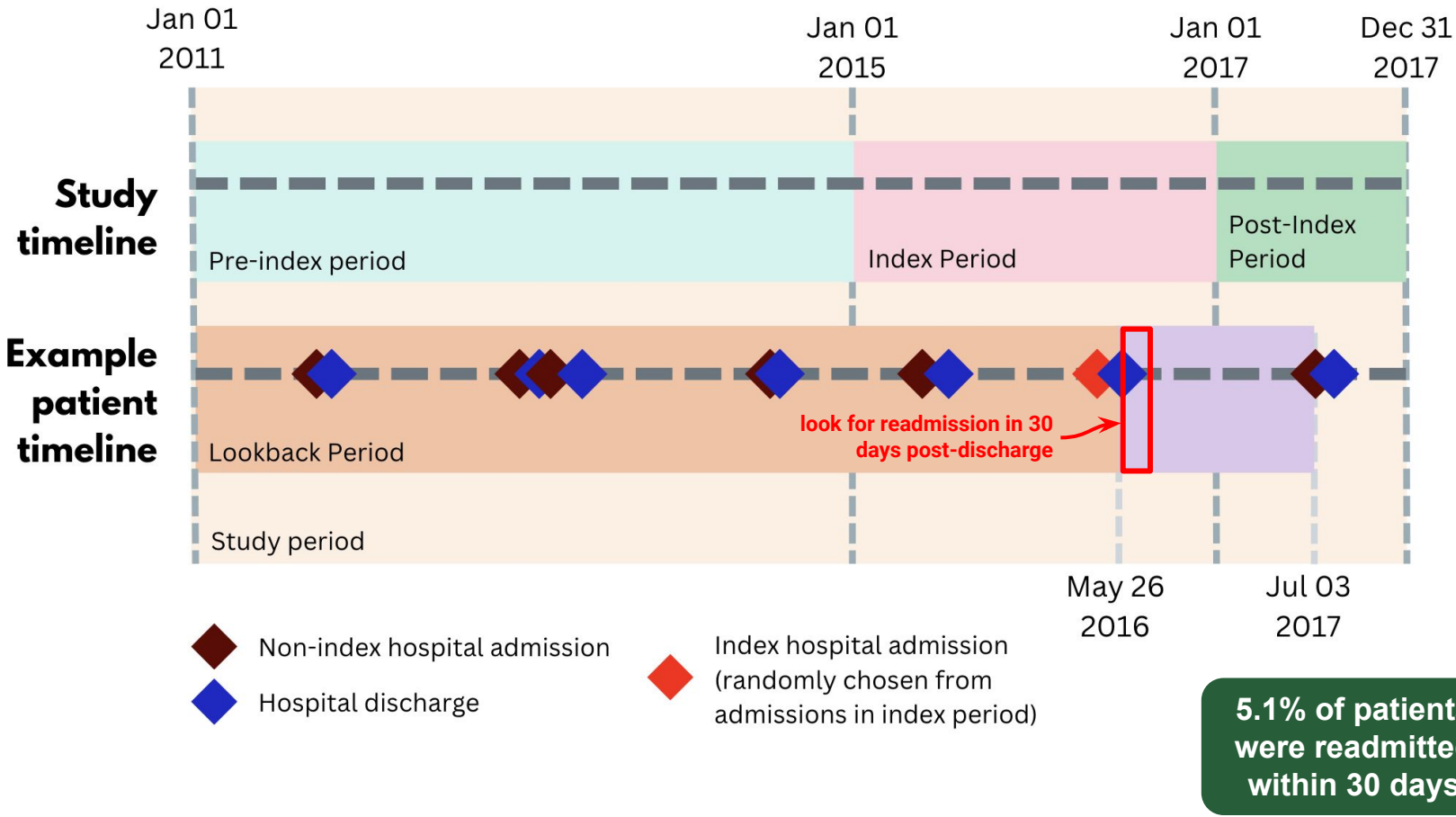
Select patients who were discharged from a hospitalization in 2015 and 2016 (index period)

…

Sample one **index hospitalization** for each patient

➔ Final dataset size: 421,088




Jan 01
2011
Jan 01
2015
Jan 01
2017
Dec 31
2017
Study timeline
Pre-index period
Index Period
Post-Index Period
Example patient timeline
look for readmission in 30 days post-discharge
Lookback Period
Study period
May 26
2016
Jul 03
2017
Non-index hospital admission
Hospital discharge
Index hospital admission (randomly chosen from admissions in index period)
5.1% of patients were readmitted within 30 days

P(30-Day Readmission) Models

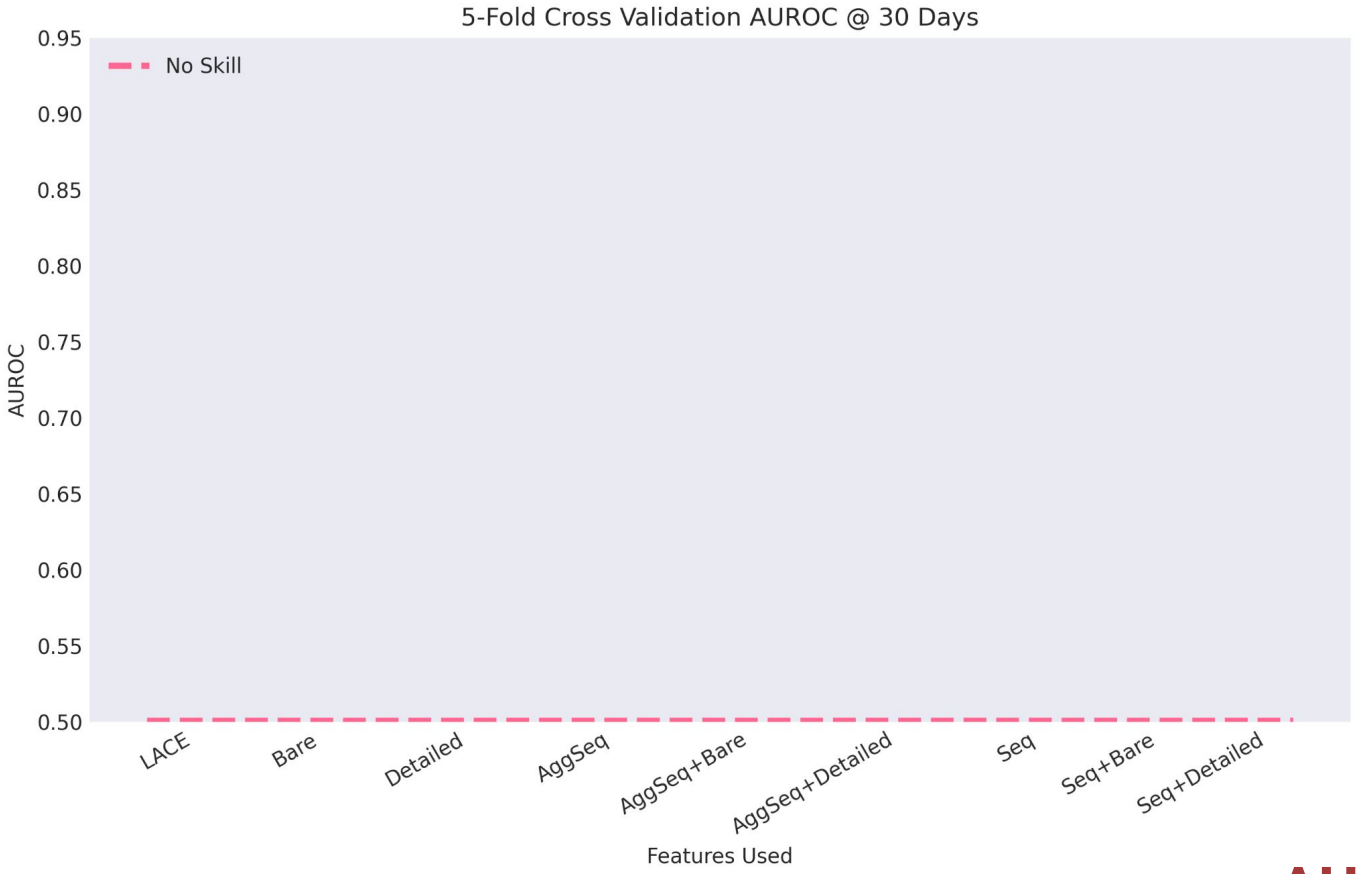


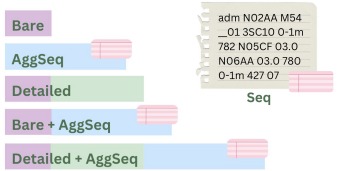
[4] E. Choi et al. (2016c)

(How are we evaluating these models?)

Group A: Readmitted in 30 days
Group B: Not readmitted in 30 days

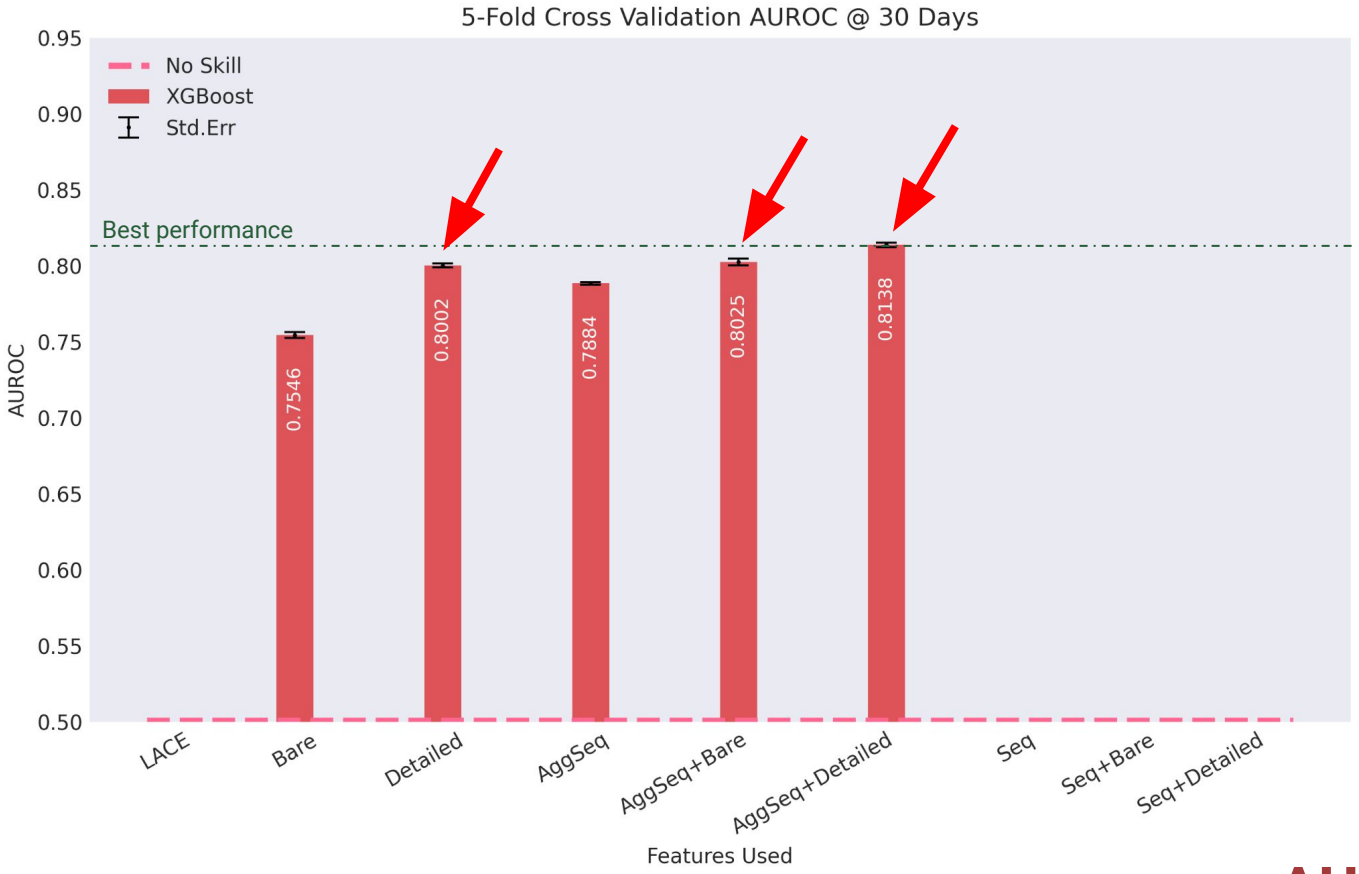
$$P_{30}(\,\mathrm{r}^{+} \mid \vec{a}\,) > P_{30}(\,\mathrm{r}^{+} \mid \vec{b}\,)$$

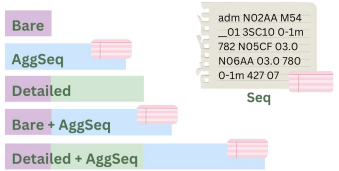




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

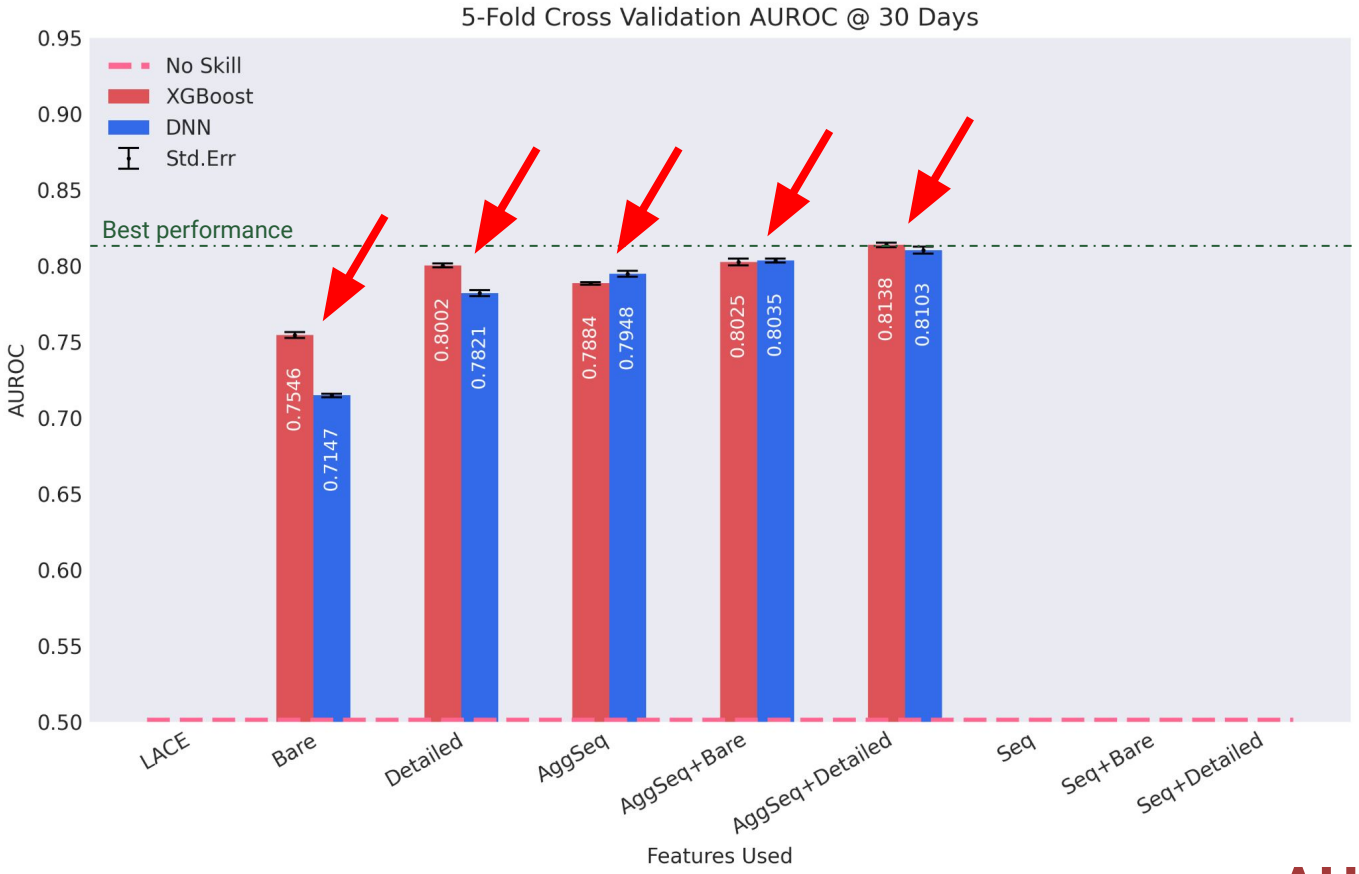
AUROC @ 30 Days

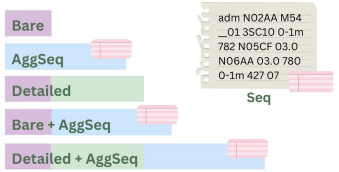




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Bare	-	✓
Detailed	-	✓

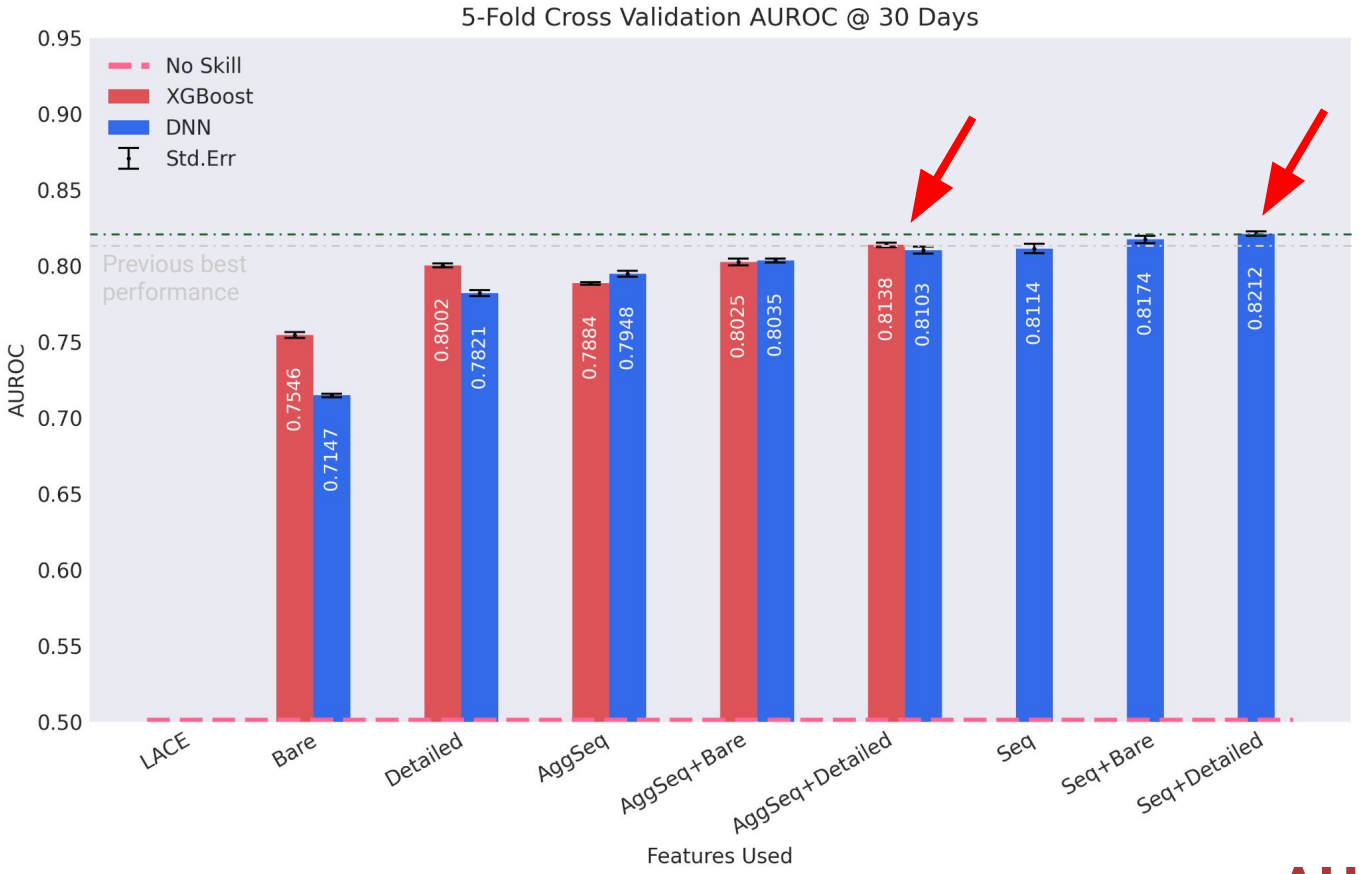
AUROC @ 30 Days

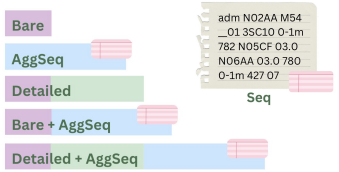




Features		
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Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

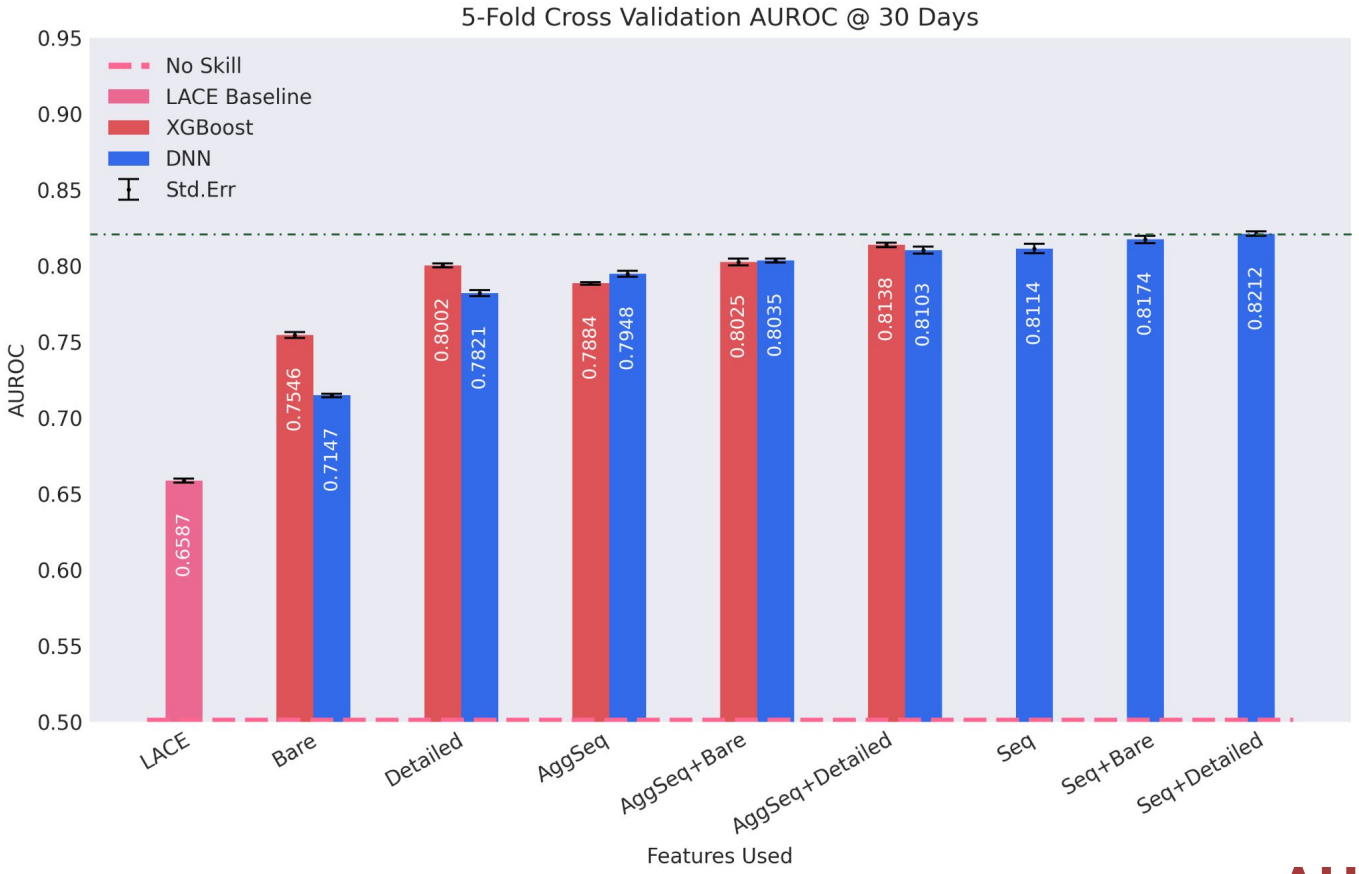
AUROC @ 30 Days

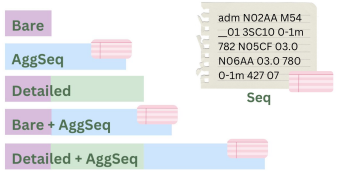




Features		
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Bare	-	-
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Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

AUROC @ 30 Days



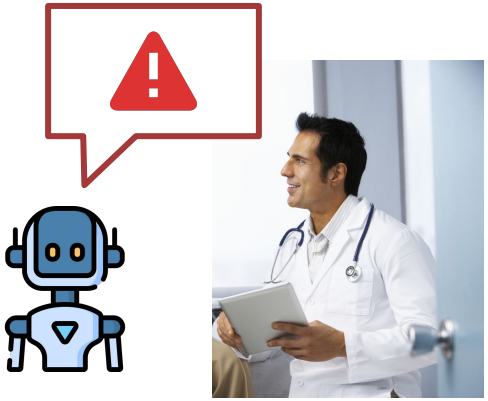


Features		
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LACE Score	-	-
Bare	-	-
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-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

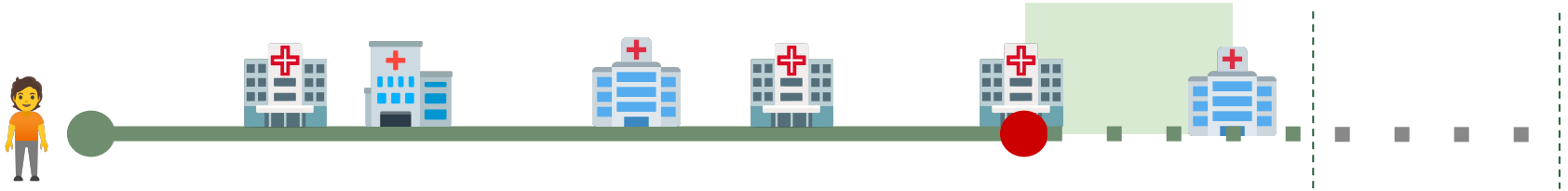
AUROC @ 30 Days

Good?

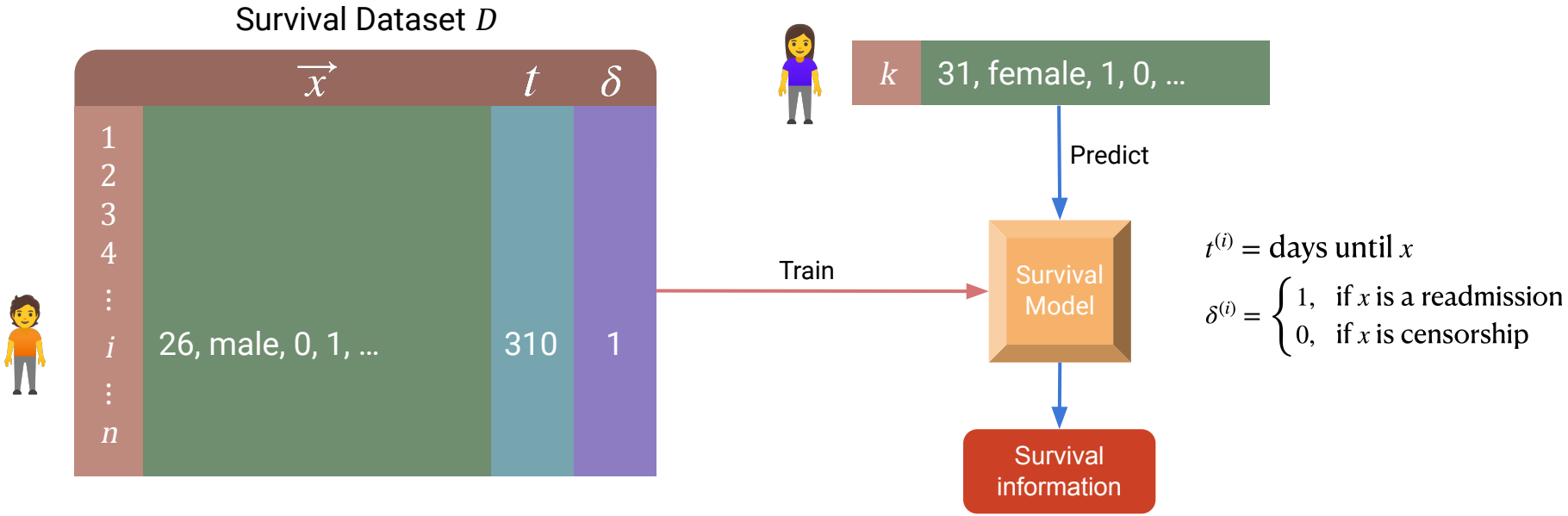
Is this interesting?
Can we do better?



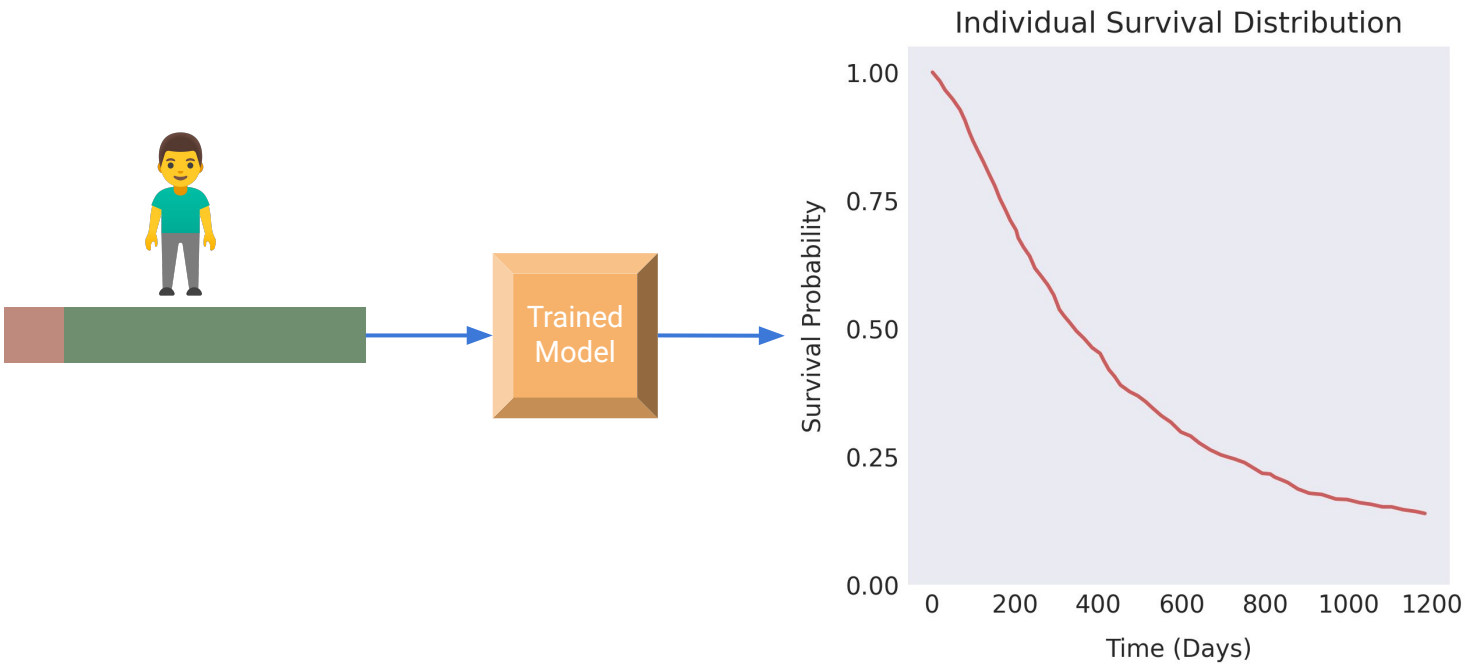
What is survival prediction?



What is survival prediction?



Individual Survival Distributions



Merits of an ISD

- Visual and intuitive
- Standalone
- **Conveys the most information**
  - can slice for more granular details (risk score, P(readmission), time-to-event)
  - can aggregate for population level information

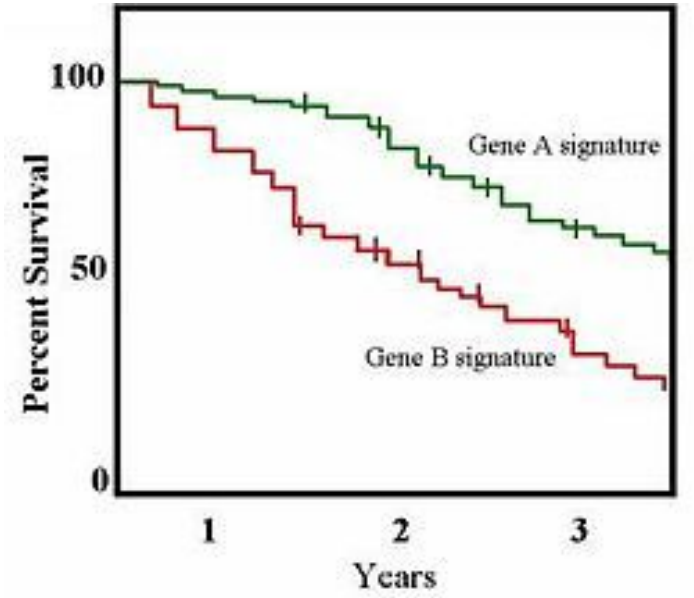


Image credits: Deanne Taylor for Wikimedia

ISD Models

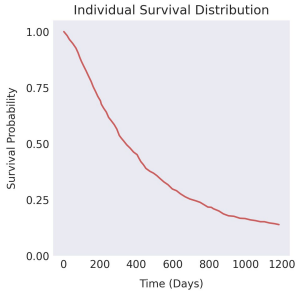
CoxPH (Lightweight) [6]:

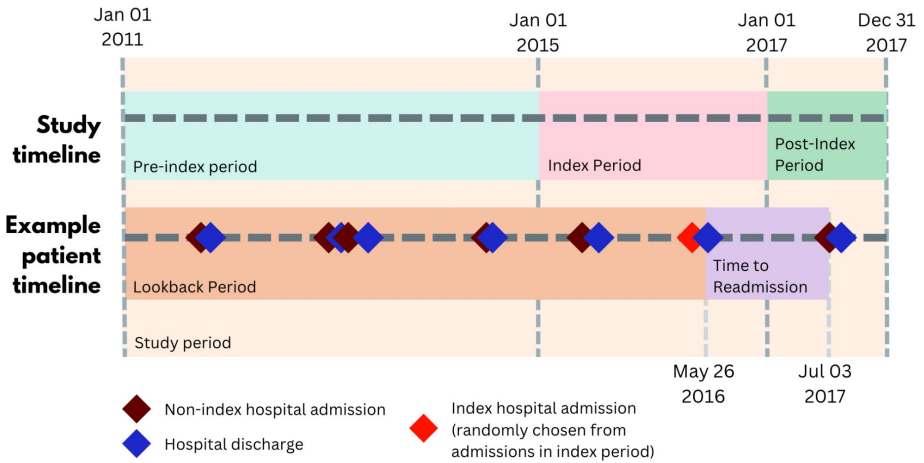
$$h_{cox}(t, \vec{x}^{(i)}) = \lambda_0(t) \exp(\vec{\theta}^{\mathsf{T}} \vec{x}^{(i)})$$

Individual risk score

$S_0(t)$

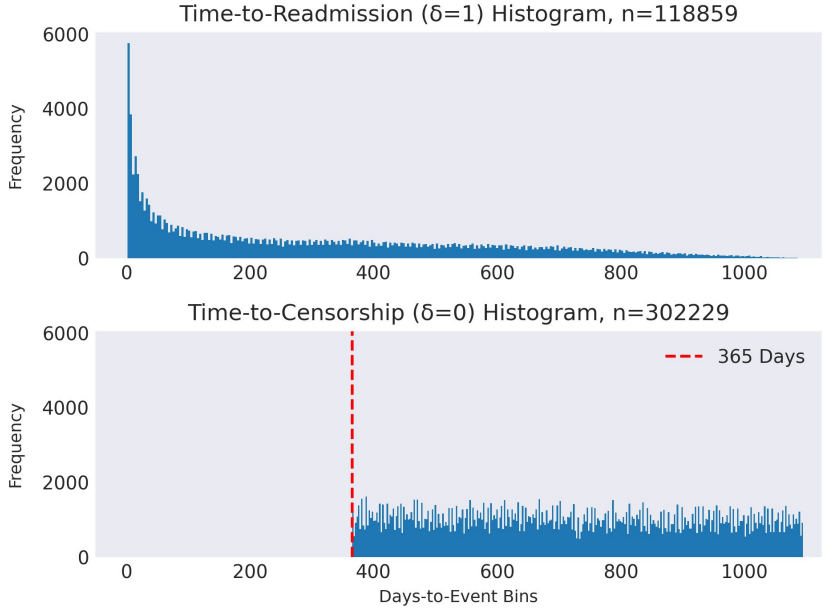
Baseline survival function (Breslow's estimator)



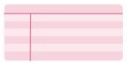


$$t^{(i)} = \text{days until } x$$

$$\delta^{(i)} = \begin{cases} 1, & \text{if } x \text{ is a readmission} \\ 0, & \text{if } x \text{ is censorship} \end{cases}$$



Average $t^{(i)}$: 603.8 ± 296.5 days
Dataset is 71.8% censored.



Medical Concept Embedding Dictionary



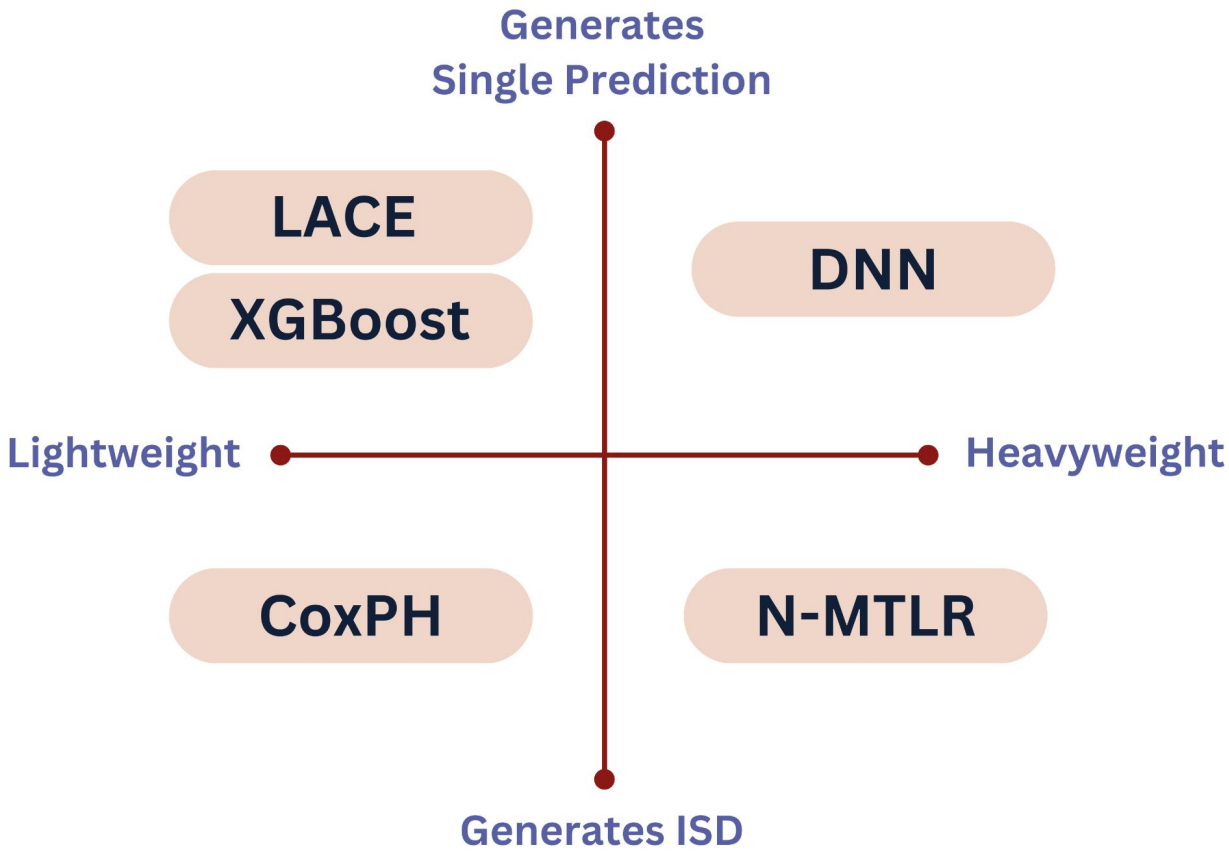
Bare Clinical Features

Supplementary Clinical Features

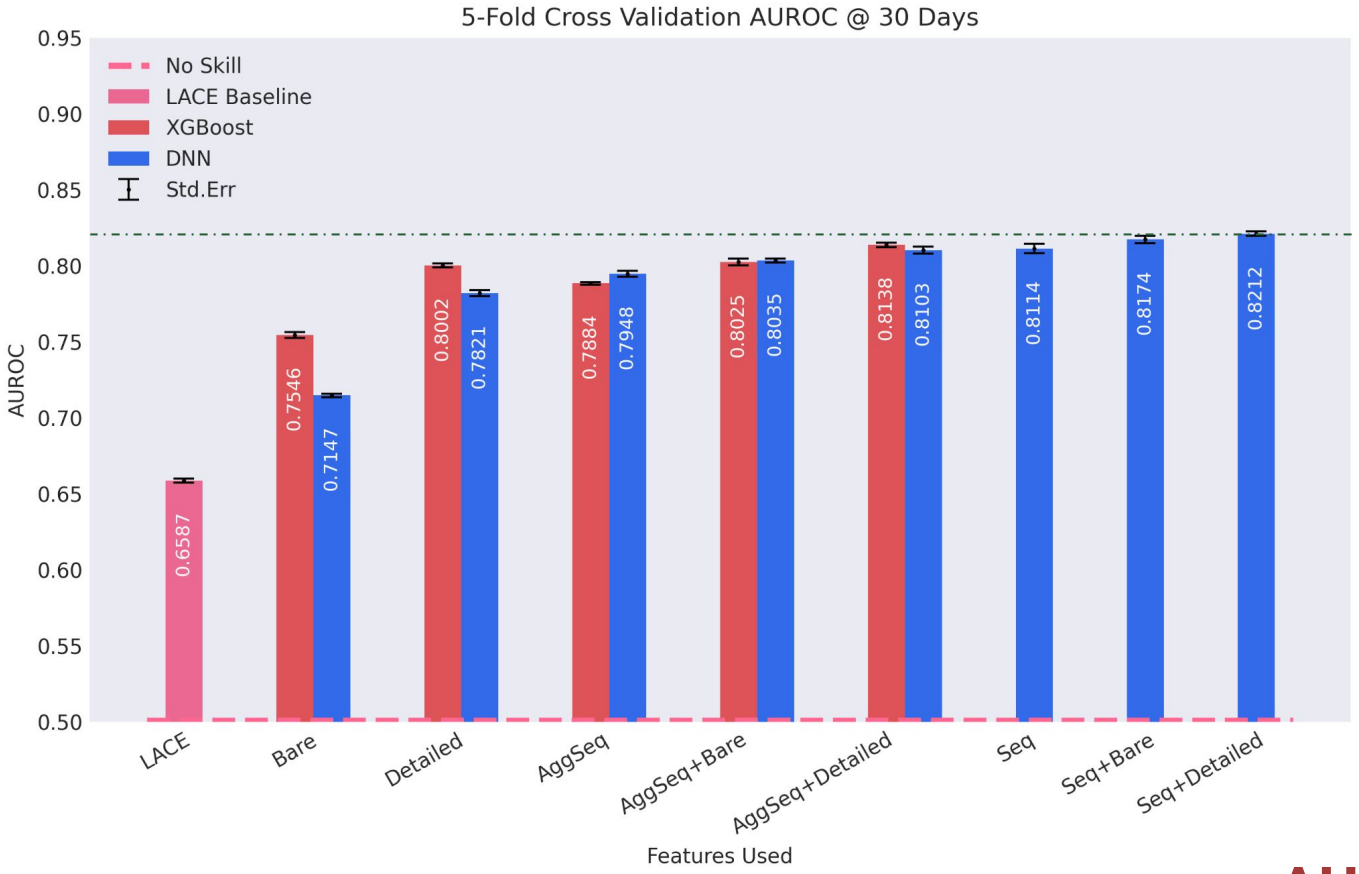
AggSeq Features

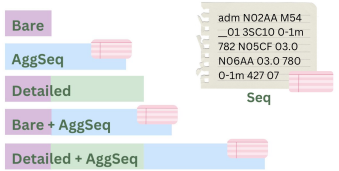


Seq features


Generates
Single Prediction
LACE
XGBoost
DNN
Lightweight
Heavyweight
CoxPH
N-MTLR
Generates ISD

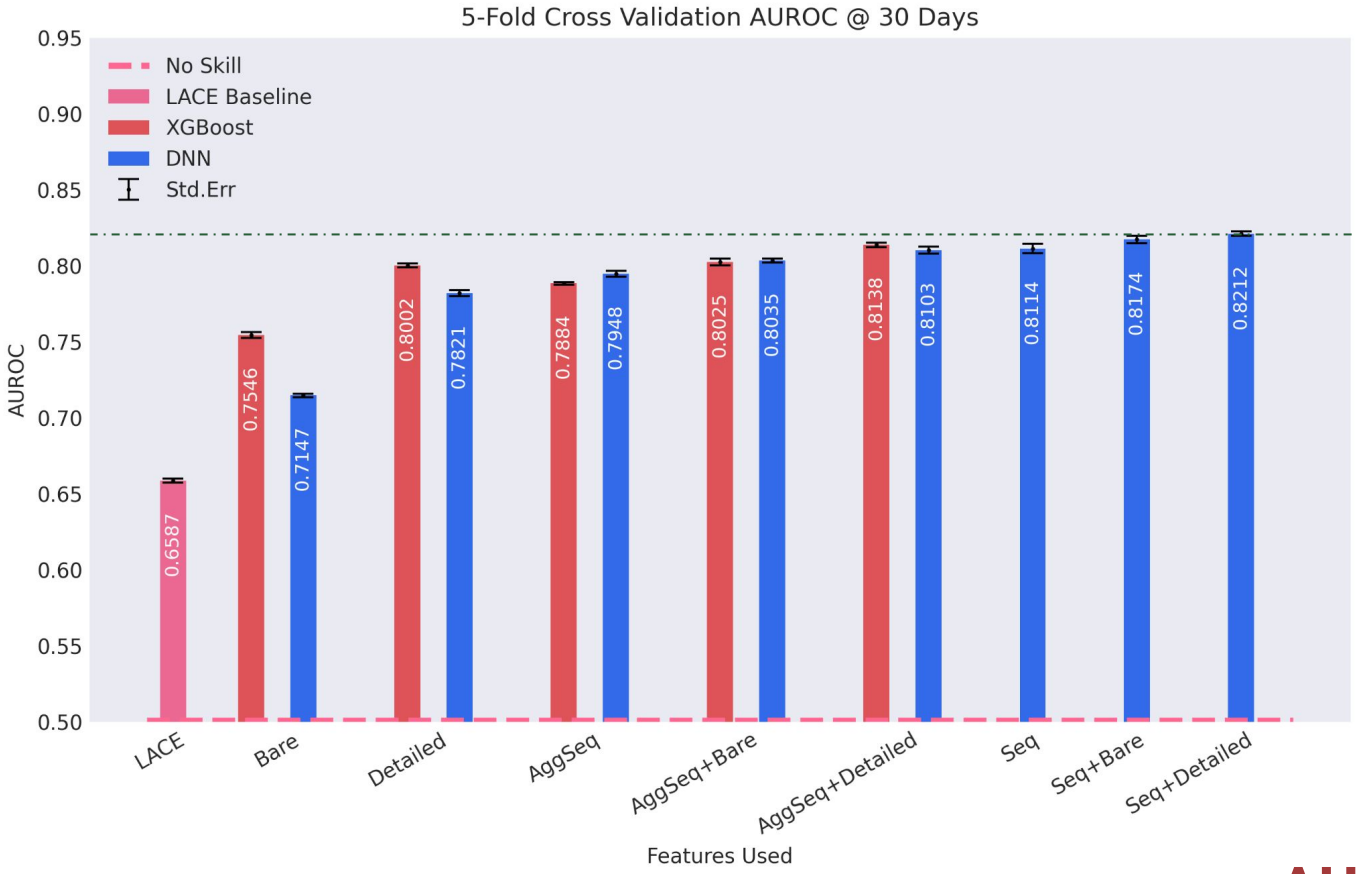
Is survival prediction worthwhile for this task?

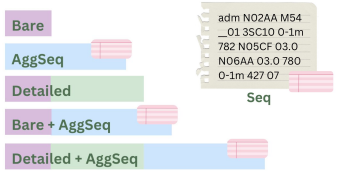




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

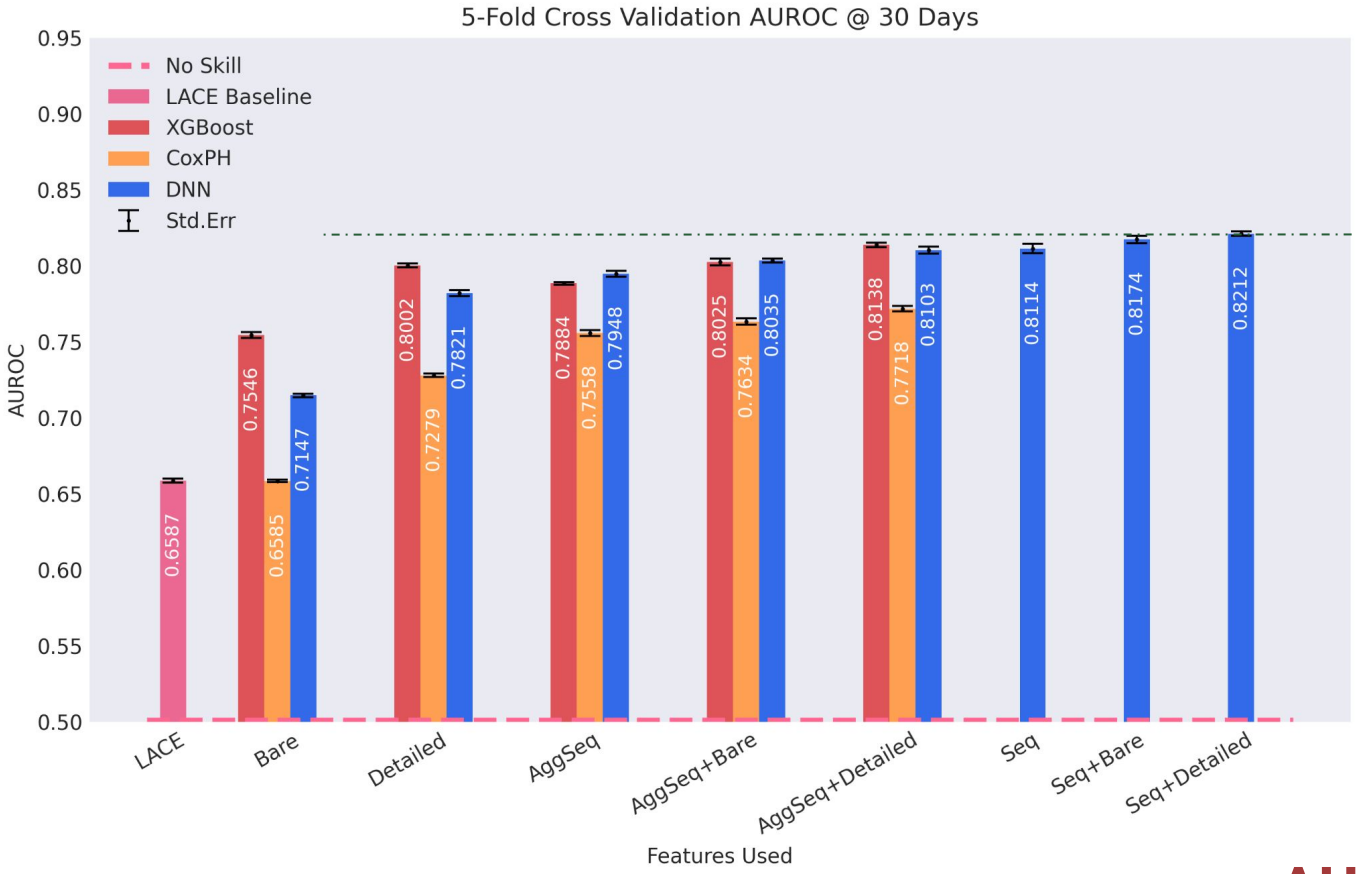
AUROC @ 30 Days

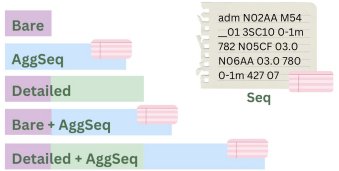




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

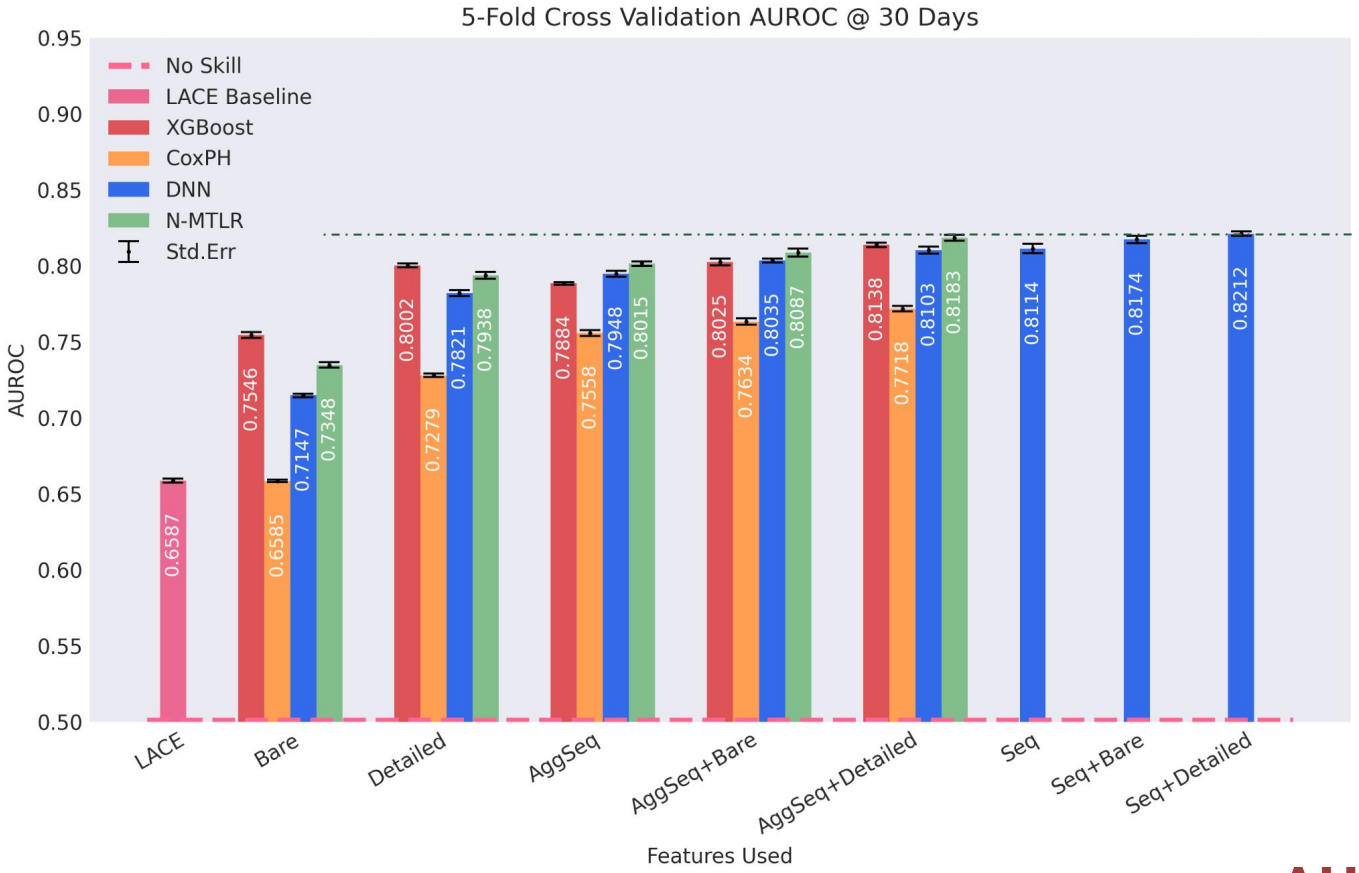
AUROC @ 30 Days

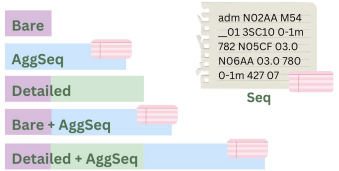




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

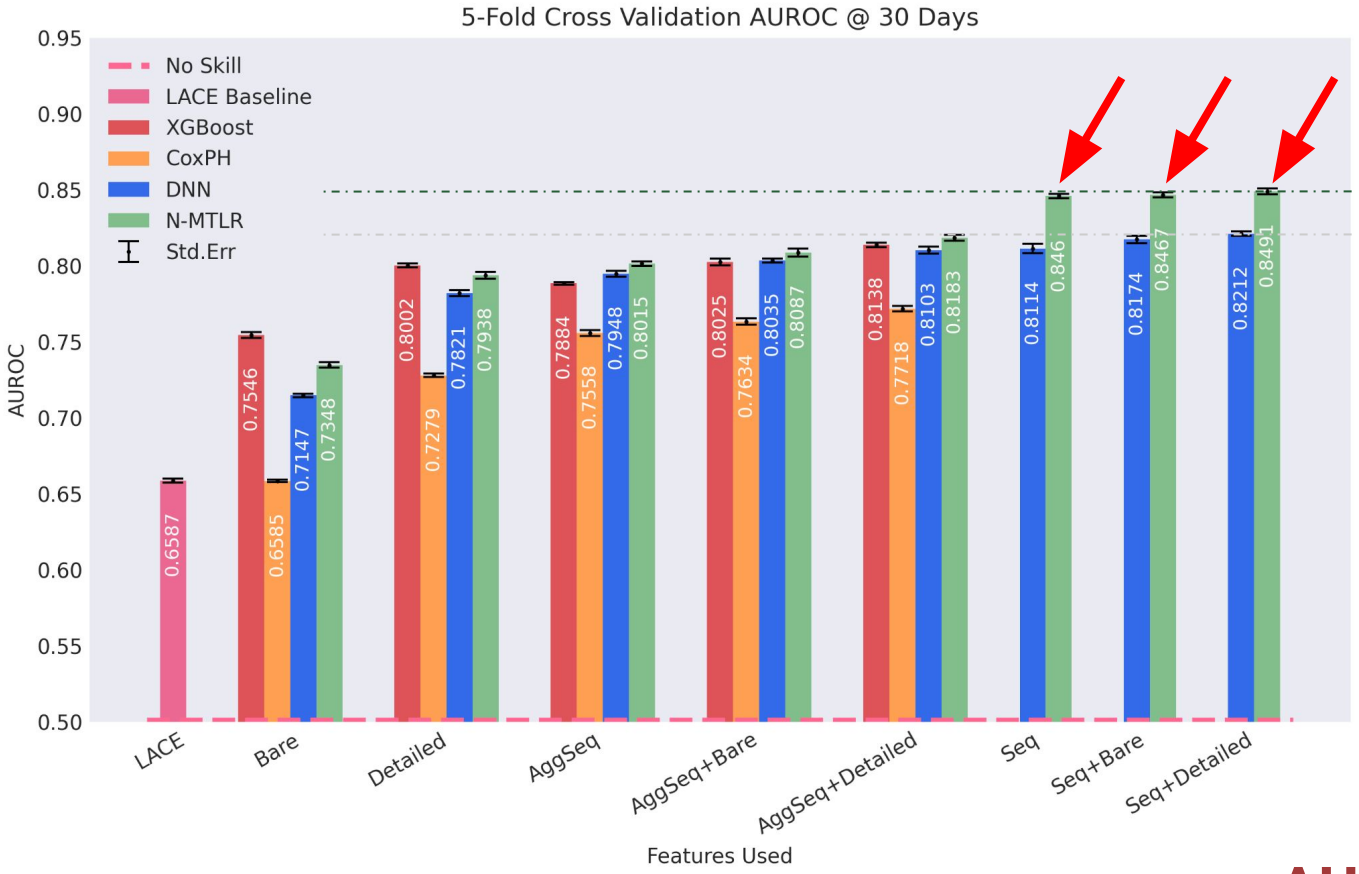
AUROC @ 30 Days

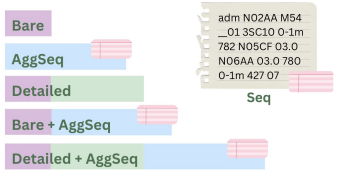




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

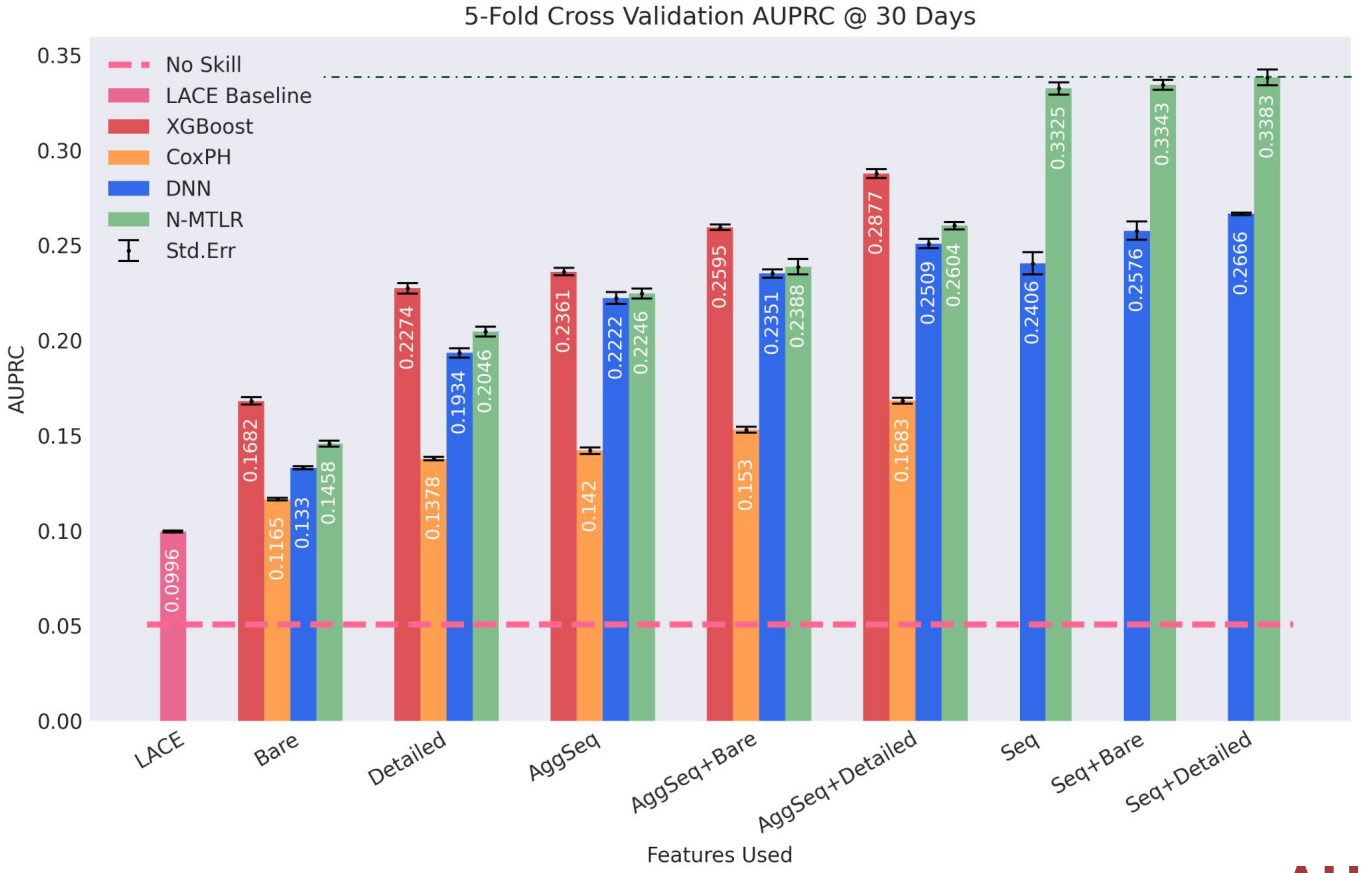
AUROC @ 30 Days

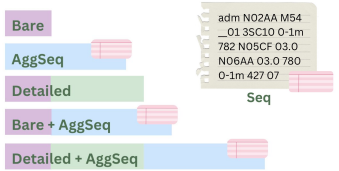




Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

AUROC @ 30 Days





Features		
Clinical Features	AggSeq Features	Seq Features
LACE Score	-	-
Bare	-	-
Detailed	-	-
-	✓	-
Bare	✓	-
Detailed	✓	-
-	-	✓
Bare	-	✓
Detailed	-	✓

AUPRC @ 30 Days

Brier @ 30 (lower is better)



Features			30-Day Brier Score±Std.Dev				
Clinical Features	AggSeq Features	Seq Features	Logistic Regression	XGBoost	CoxPH	DL	N-MTLR
LACE Score	-	-	**0.0471±0.001**	-	-	-	-
Bare	-	-	-	0.0453±0.001	0.0470±0.001	0.0463±0.001	0.0459±0.001
Detailed	-	-	-	0.0435±0.001	0.0462±0.001	**0.0423±0.001**	0.0441±0.001
-	✓	-	-	0.0436±0.001	0.0459±0.001	0.0437±0.001	0.0436±0.001
Bare	✓	-	-	0.0428±0.001	0.0456±0.001	0.0432±0.001	0.0431±0.001
Detailed	✓	-	-	**0.0419±0.001**	**0.0452±0.001**	0.0427±0.001	0.0423±0.001
-	-	✓	-	-	-	0.0431±0.001	0.0404±0.001
Bare	-	✓	-	-	-	0.0426±0.001	0.0402±0.001
Detailed	-	✓	-	-	-	0.0444±0.001	**0.0401±0.001**

Is the MCE dictionary worth it?

	DNN			N-MTLR		
	AUROC	AUPRC	Brier	AUROC	AUPRC	Brier
Trained from scratch	0.7887±0.005	0.2188±0.008	0.0440±0.001	0.8392±0.004	0.3086±0.008	0.0411±0.001
Initialized with MCE	**0.8114±0.007**	**0.2406±0.013**	**0.0431±0.001**	**0.8460±0.003**	**0.3325±0.007**	**0.0404±0.001**

Yes!

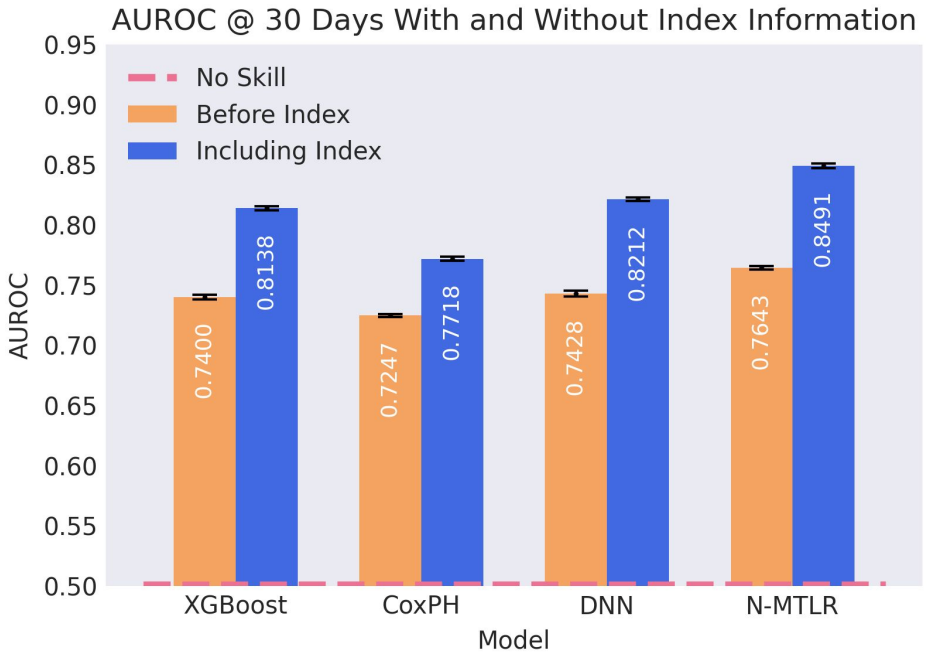
	1	2	3	4	...	100
1.GZ.35	0.56	-6.09	1.01	4.33	...	0.71
I50	1.15	-0.78	0.51	0.02	...	-1.56
ADM	0.04	3.41	-1.89	0.89	...	0.43
C95	-0.99	-0.34	0.08	-2.30	...	1.91
...	...	...	...	...	...	...
R03BA	2.9	-0.01	3.79	0.56	...	-0.22

Medical Concept Embedding Dictionary

Final task: b4idx



LACE Score using features from the index admission: AUROC @ 30 Days: **0.6587**



Final Thoughts

Discussion: Data

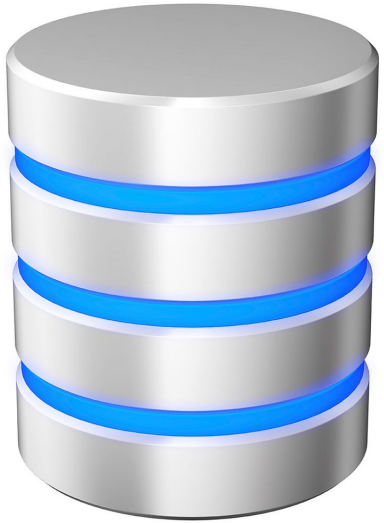




Image credits: Bruker, Alberta Health Services

Limitations

- Difficult to compare against other studies
- Data does not capture out-of-hospital deaths
- Readmissions predicted are not guaranteed to be preventable/unplanned
- Linked administrative data is less complete than other sources, and we only use medical codes

Discussion: Models & Practical Use



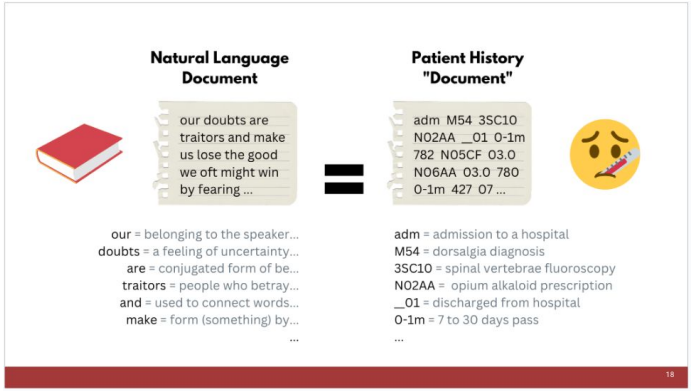
Future Work

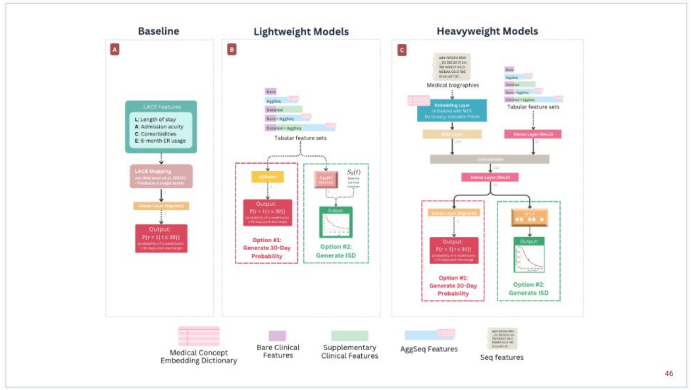
- Validating this approach with a publicly available dataset, or different domains, or with different train/test splits

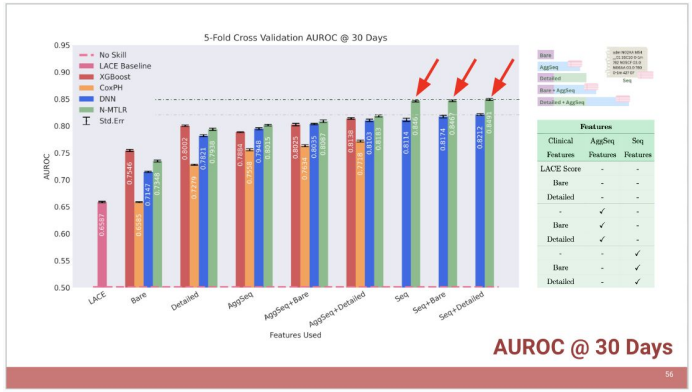
- Address most pressing data limitations:
  - Restrict to only “urgent” admissions
  - Capture deaths outside of hospital

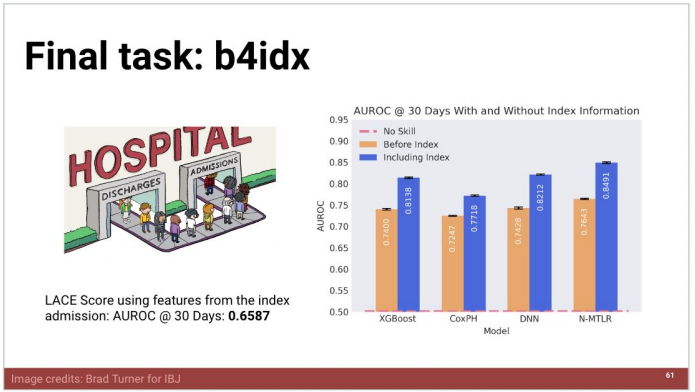
- Model tuning

- Studying how these tools could integrate with health professionals workflow


Natural Language Document
our doubts are traitors and make us lose the good we oft might win by fearing ...
Patient History "Document"
adm M54 3SC10 N02AA __01 0-1m 782 N05CF 03.0 N06AA 03.0 780 0-1m 427 07 ...
our = belonging to the speaker...
doubts = a feeling of uncertainty...
are = conjugated form of be...
traitors = people who betray...
and = used to connect words...
make = form (something) by...
...
adm = admission to a hospital
M54 = dorsalgia diagnosis
3SC10 = spinal vertebrae fluoroscopy
N02AA = opium alkaloid prescription
__01 = discharged from hospital
0-1m = 7 to 30 days pass
...
18


Baseline
Lightweight Models
Heavyweight Models
Medical Concept Embedding Dictionary
Bare Clinical Features
Supplementary Clinical Features
AggSeq Features
Seq features
46


5-Fold Cross Validation AUROC @ 30 Days
No Skill
LACE Baseline
XGBoost
CoxPH
DNN
N-MTLR
Std.Err
AUROC
Features Used
LACE
Bare
Detailed
AggSeq
AggSeq+Bare
AggSeq+Detailed
Seq
Seq+Bare
Seq+Detailed
Features
Clinical Features
AggSeq Features
Seq Features
AUROC @ 30 Days
56


Final task: b4idx
HOSPITAL
DISCHARGES
ADMISSIONS
LACE Score using features from the index admission: AUROC @ 30 Days: 0.6587
AUROC @ 30 Days With and Without Index Information
No Skill
Before Index
Including Index
AUROC
XGBoost
CoxPH
DNN
N-MTLR
Model
Image credits: Brad Turner for IBJ
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BMC-HSR Paper (2022)

SCAN ME

Thank you!

Questions?

sachamarendavis@gmail.com
sachadavis.com

Canadian VIGOUR Centre
Bridging Hearts and Minds

UNIVERSITY OF ALBERTA

amii

References

[1] Van Walraven, Carl, et al. "Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community." Cmaj 182.6 (2010): 551-557.

[2] Choi, Youngduck, Chill Yi-I. Chiu, and David Sontag. "Learning low-dimensional representations of medical concepts." AMIA Summits on Translational Science Proceedings 2016 (2016): 41.

[3] Choi, Edward, et al. "Medical concept representation learning from electronic health records and its application on heart failure prediction." arXiv preprint arXiv:1602.03686 (2016).

[4] Choi, Edward, et al. "Doctor ai: Predicting clinical events via recurrent neural networks." Machine learning for healthcare conference. PMLR, 2016.

[6] Cox, David R. "Regression models and life-tables." Journal of the Royal Statistical Society: Series B (Methodological) 34.2 (1972): 187-202.

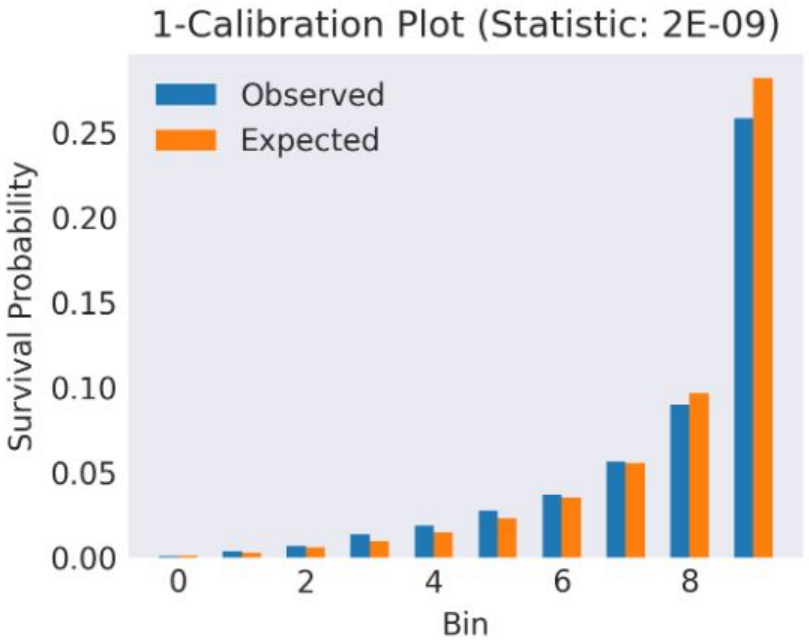
[7] Fotso, Stephane. "Deep neural networks for survival analysis based on a multi-task framework." arXiv preprint arXiv:1801.05512 (2018).

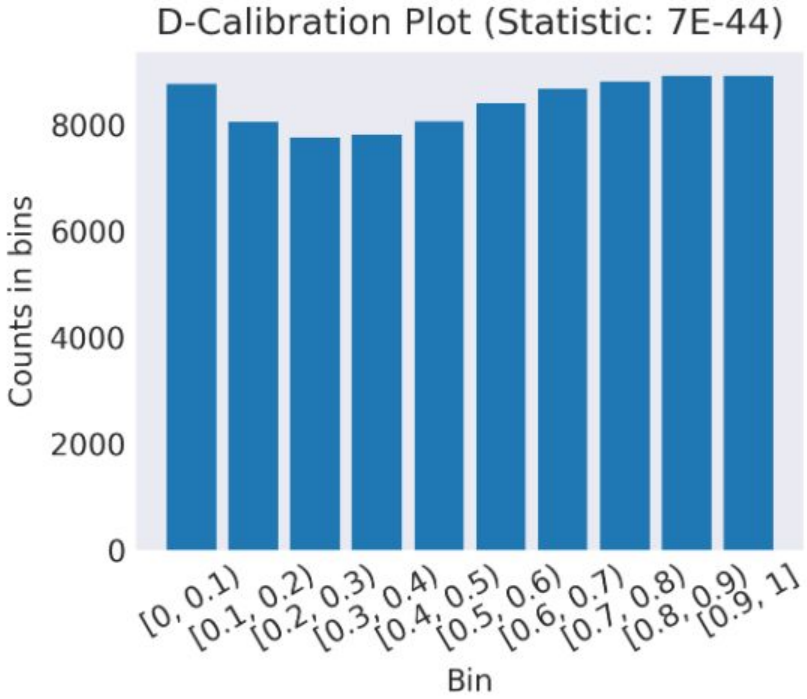
Detailed+Seq N-MTLR: Extra Statistics

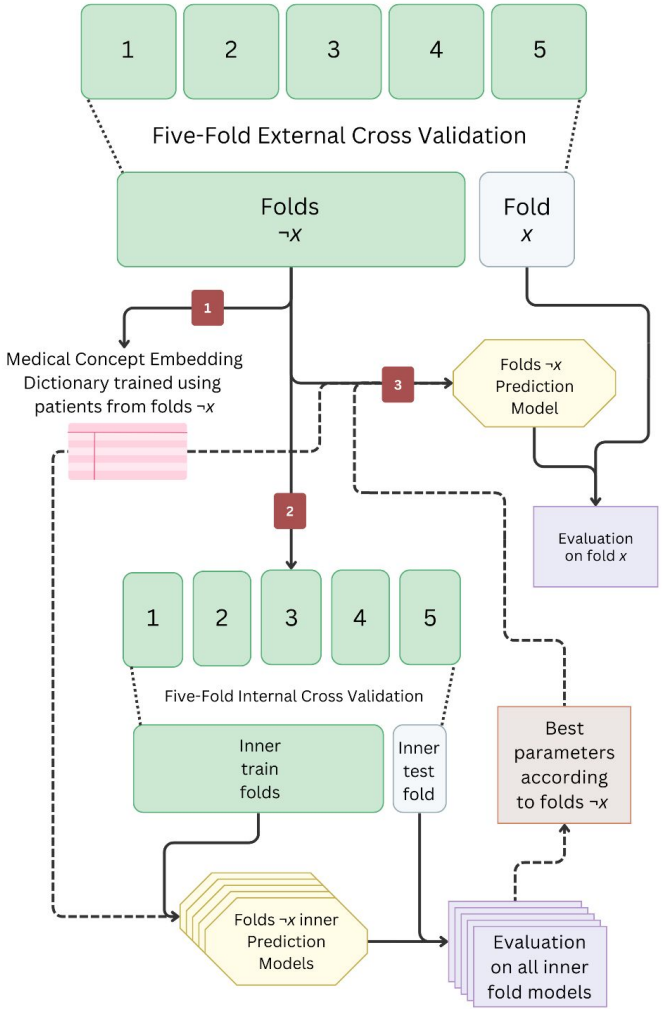
- Concordance
  - (Simplified) for any two patients A, B where A survives longer than B:
    - What are the chances that the ISD ranks them by survival time correctly?
  - **0.7533±0.004**

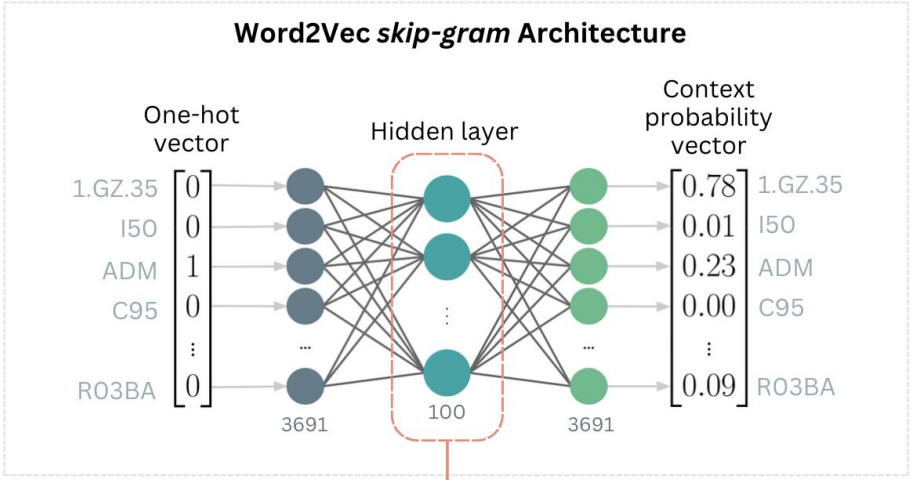
- Integrated Brier Score
  - (Simplified) what is the average brier score over all timepoints?
  - **0.1310±0.001**

- L1-Loss (with pseudo-observations)
  - (Simplified) what is the error between predicted time-to-readmission and actual time-to-readmission?
  - **1104.9±15.4 days**


1-Calibration Plot (Statistic: 2E-09)
Observed
Expected
Survival Probability
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
Bin


D-Calibration Plot (Statistic: 7E-44)
Counts in bins
8000
6000
4000
2000
0
[0, 0.1)
[0.1, 0.2)
[0.2, 0.3)
[0.3, 0.4)
[0.4, 0.5)
[0.5, 0.6)
[0.6, 0.7)
[0.7, 0.8)
[0.8, 0.9)
[0.9, 1]
Bin

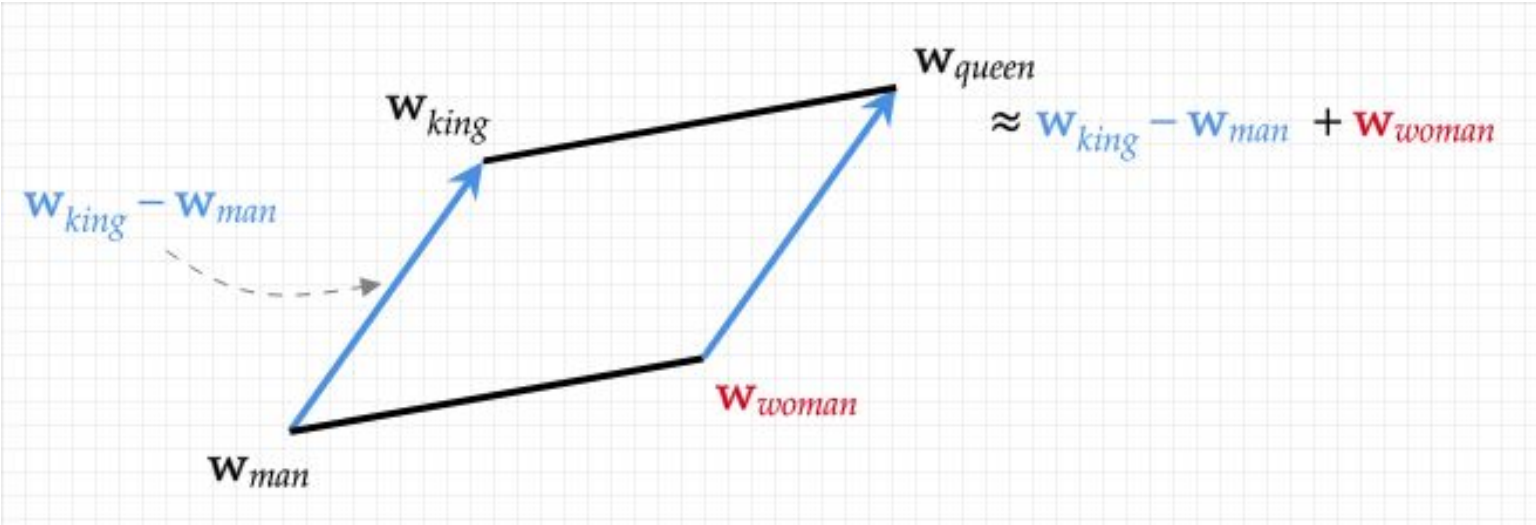

1
2
3
4
5
Five-Fold External Cross Validation
Folds
¬x
Fold
x
1
Medical Concept Embedding
Dictionary trained using
patients from folds ¬x
3
Folds ¬x
Prediction
Model
2
Evaluation
on fold x
1
2
3
4
5
Five-Fold Internal Cross Validation
Inner
train
folds
Inner
test
fold
Best
parameters
according
to folds ¬x
Folds ¬x inner
Prediction
Models
Evaluation
on all inner
fold models



Extract values at hidden layer

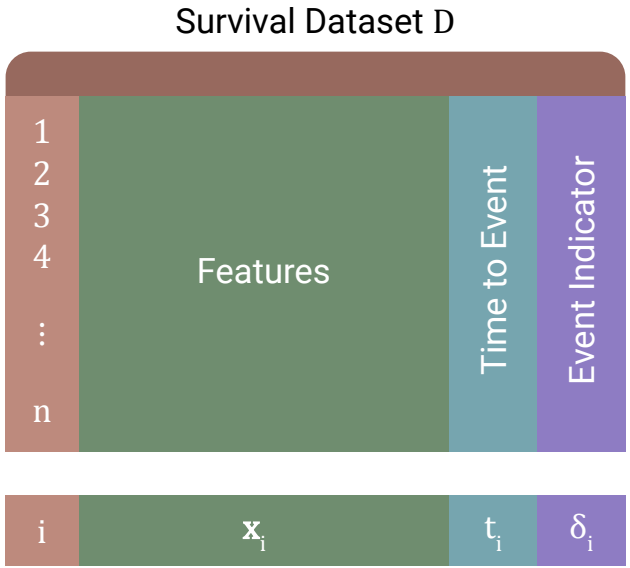
	1	2	3	4	...	100
1.GZ.35	0.56	-6.09	1.01	4.33	...	0.71
I50	1.15	-0.78	0.51	0.02	...	-1.56
ADM	0.04	3.41	-1.89	0.89	...	0.43
C95	-0.99	-0.34	0.08	-2.30	...	1.91
...	...	...	...	...	...	...
R03BA	2.9	-0.01	3.79	0.56	...	-0.22

Medical Concept Embedding Dictionary


$\mathbf{w}_{queen}$
$\approx \mathbf{w}_{king} - \mathbf{w}_{man} + \mathbf{w}_{woman}$
$\mathbf{w}_{king}$
$\mathbf{w}_{king} - \mathbf{w}_{man}$
$\mathbf{w}_{woman}$
$\mathbf{w}_{man}$

Condition Code	Condition Name	Similar Code	Cosine Similarity	Similar Code Type	Description
E11	Type 2 diabetes mellitus	E14	0.777	ICD-10	Unspecified diabetes mellitus
		N08	0.752	ICD-10	Glomerular disorders in diseases classified elsewhere
		I10	0.743	ICD-10	Essential (primary) hypertension
		E78	0.661	ICD-10	Disorders of lipoprotein metabolism and other lipidemias
		A10BX	0.612	ATC	Drugs used in diabetes: Other blood glucose lowering drugs
I10	Essential hypertension	E11	0.743	ICD-10	Type 2 diabetes mellitus
		E78	0.729	ICD-10	Disorders of lipoprotein metabolism and other lipidemias
		I25	0.63	ICD-10	Chronic ischemic heart disease
		N08	0.572	ICD-10	Glomerular disorders in diseases classified elsewhere
		Z95	0.514	ICD-10	Presence of cardiac and vascular implants and grafts
J46	Asthma	493	0.722	ICD-9	Asthma
		1.GZ.35	0.671	CCI	Inhalation pharmacotherapy
		J98	0.608	ICD-10	Other respiratory disorders
		R03AC	0.6	ATC	Selective beta-2-adrenoreceptor agonists
		R03BA	0.594	ATC	Glucocorticoids
I50	Heart Failure	428	0.863	ICD-9	Heart failure
		I42	0.805	ICD-10	Cardiomyopathy
		I25	0.706	ICD-10	Chronic ischemic heart disease
		I48	0.688	ICD-10	Atrial fibrillation and flutter
		I34	0.674	ICD-10	Nonrheumatic mitral valve disorders

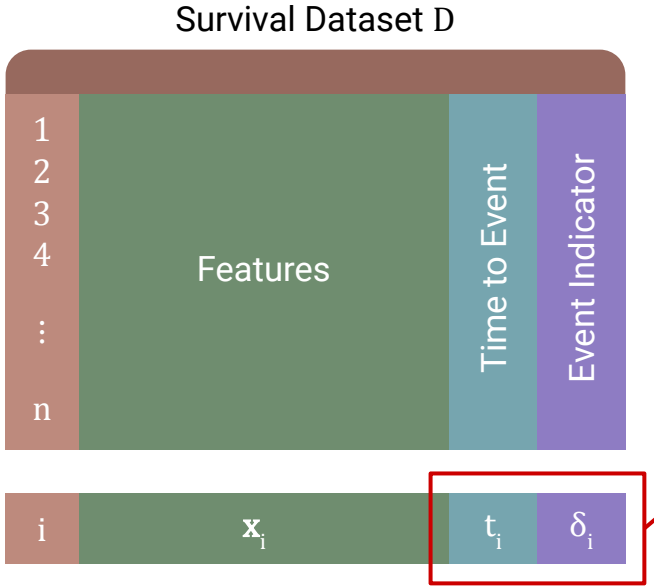
MTLR models ISDs



1. Split time into J intervals

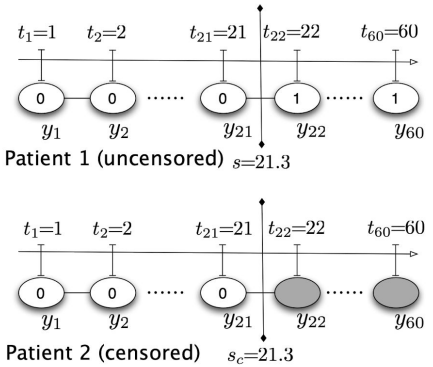


MTLR models ISDs



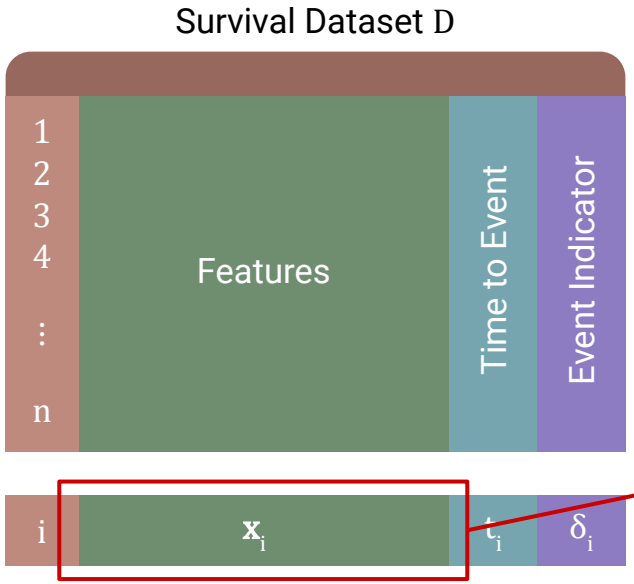
1. Split time into J intervals
2. Encode time & event indicators in $\mathbf{Y}$

$$\vec{Y} = \begin{bmatrix} y_1 = 0 \\ y_2 = 0 \\ \vdots \\ y_{s-1} = 0 \\ y_s = 1 \\ \vdots \\ y_J = 1 \end{bmatrix}$$

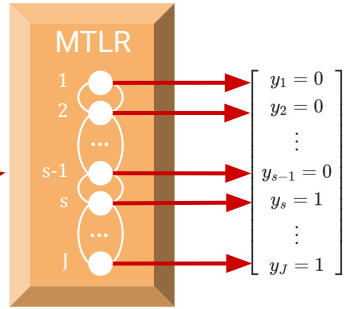




MTLR models ISDs

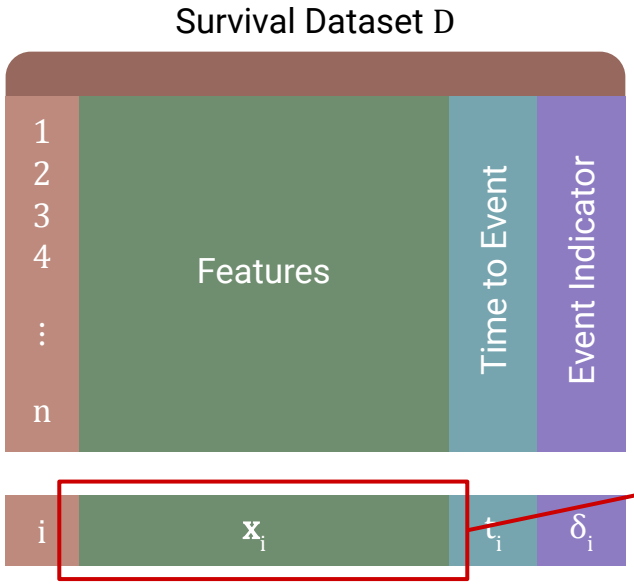


1. Split time into J intervals
2. Encode time & event indicators in $\mathbf{Y}$
3. Train J dependent logistic regression models to predict $\mathbf{Y}$

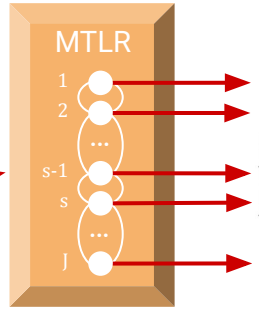


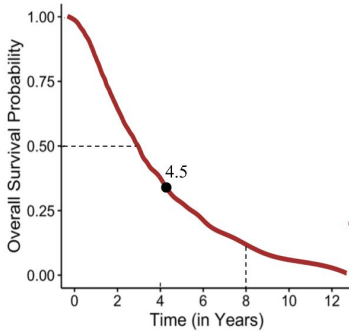


MTLR models ISDs



1. Split time into J intervals
2. Encode time & event indicators in $\mathbf{Y}$
3. Train J dependent logistic regression models to predict $\mathbf{Y}$
4. Plot!





$\tau_0 = 0$ τ_1 τ_2 τ_3 τ_{J-1} $\tau_J = \infty$

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Effective hospital readmission prediction models using machine-learned features

Sacha Davis, Jin Zhang, Ilbin Lee, Mostafa Rezaei, Russell Greiner, Finlay A. McAlister & Raj Padwal

BMC Health Services Research **22**, Article number: 1415 (2022) | Cite this article

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Abstract

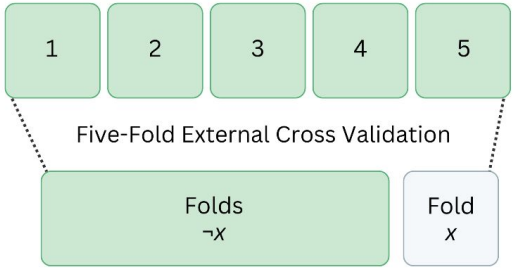
Background:

Hospital readmissions are one of the costliest challenges facing healthcare systems, but conventional models fail to predict readmissions well. Many existing models use exclusively manually-engineered features, which are labor intensive and dataset-specific. Our objective was to develop and evaluate models to predict hospital readmissions using derived features that are automatically generated from longitudinal data using machine learning techniques.

Methods:

We studied patients discharged from acute care facilities in 2015 and 2016 in Alberta, Canada, excluding those who were hospitalized to give birth or for a psychiatric condition. We used population-level linked administrative hospital data from 2011 to 2017 to train prediction models using both manually derived features and features generated automatically from observational data. The target value of interest was 30-day all-cause hospital readmissions,

SCAN ME


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Five-Fold External Cross Validation
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Fold
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