MEDS KDD 2025 Tutorial

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MEDS

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Help you to think about AI/ML over EHR data in an insightful, responsible, & empowering way.

Learning Goals

1. Understand the core concepts and design principles of the MEDS ecosystem
    a. *Apply:* Be able to transform data into the MEDS format.
    b. *Analyze:* Be able to break down a problem into different parts that can leverage different tools.
2. Understand how to build models over MEDS data
    a. *Understand:* Identify how to map data into the necessary formats for effective ML/AI
3. Identify how to participate in the MEDS community and promote reproducible research
    a. *Apply:* Use existing models via MEDS-DEV to compare to the state-of-the-art

Our Expectations of You

1. Follow the ACM KDD code of conduct
2. Be here to learn
   This will be interactive, both in terms of discussion and implementation.
   Ask questions
3. Be here to teach
   Work with those around you to share knowledge and ideas
   Share your experiences and expertise
4. Have fun!

Shared Disclaimers

Disclaimer S1: MEDS is a “data-as-interface” ecosystem. This means that, in general, rather than operating through an interface of python objects, MEDS tools operate through an interface of data in a format. This makes the ecosystem very open, enabling many ways of doing things and many tools that could be used for the same job, not just the tools we show here.

Disclaimer S2: Most MEDS tools have been designed by academic volunteers, and it is more than plausible that there are better, faster, or more efficient ways to do things. If you think you can find one -- great! Put it out there in the community, and we’ll gladly use it.

What's next?

	✓	*8:05 - 8:10*	Opening remarks
🤗	1.	*8:10 - 8:20*	What is MEDS?
	2.	*8:20 - 8:25*	Guiding Problem Setup
🤗	3.	*8:25 - 9:05*	Convert your data into MEDS
	4.	*9:05 - 9:10*	Extract a prediction task cohort with ACES
🤗	5.	*9:10 - 9:30*	Develop a predictive model 1: Tabular Baseline
♨️		*9:30 - 10:00*	Coffee Break
🤗	6.	*10:00 - 10:40*	Develop a predictive model 2: Neural Network
	7.	*10:40 - 10:45*	Participate in the open-source community
	8.	*10:45 - 11:00*	Closing Remarks

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MEDS-KDD-pres

Part 1: What is MEDS and why use it?

Driving Problem: Health AI has a Reproducibility Crisis

Table 3: Comparison of results shown from original studies ("study") and the reproduction here ("repro."). While the model used in studies varied, we grouped them as either linear (Lin) or non-linear (NonLin). We evaluated two models: a linear model (logistic regression, LR) and a non-linear model (gradient boosting, GB). The outcome was in-hospital mortality for all studies.

	Sample size		Outcome (%)			AUROC		
Cohort	Study	Repro.	Study	Repro.	Model	Study	GB	LR
Caballero Barajas and Akella (2015), W=24	11,648	11,648	-					
Caballero Barajas and Akella (2015), W=48	11,648	11,648	-					
Caballero Barajas and Akella (2015), W=72	11,648	11,648	-					
Calvert et al. (2016b)	3,054	1,985	12.84					
Calvert et al. (2016a)	9,683	18,396	10.68					
Celi et al. (2012), AKI	1,400	4,741	30.7					
Celi et al. (2012), SAH	223	350	25.6					
Che et al. (2016) (b)	4,000	4,000	13.85					
Ding et al. (2016)	4,000	4,000	13.85	14.35	NonLin	0.8177	0.8461	0.8273
Ghassemi et al. (2014), W=12	19,308	28,172	10.84	12.2	Lin	0.84	0.8846	0.8609
Ghassemi et al. (2014), W=24	19,308	23,442	10.80	12.92	Lin	0.841	0.8841	0.8651
Ghassemi et al. (2015)	10,202	21,969	-	13.51	NonLin	0.812	0.8781	0.8591
Grnarova et al. (2016)	31,244	29,572	13.82	12.49	NonLin	0.963	0.9819	0.9765
Harutyunyan et al. (2017)	42,276	45,493	-	10.54	NonLin	0.8625	0.9406	0.9286

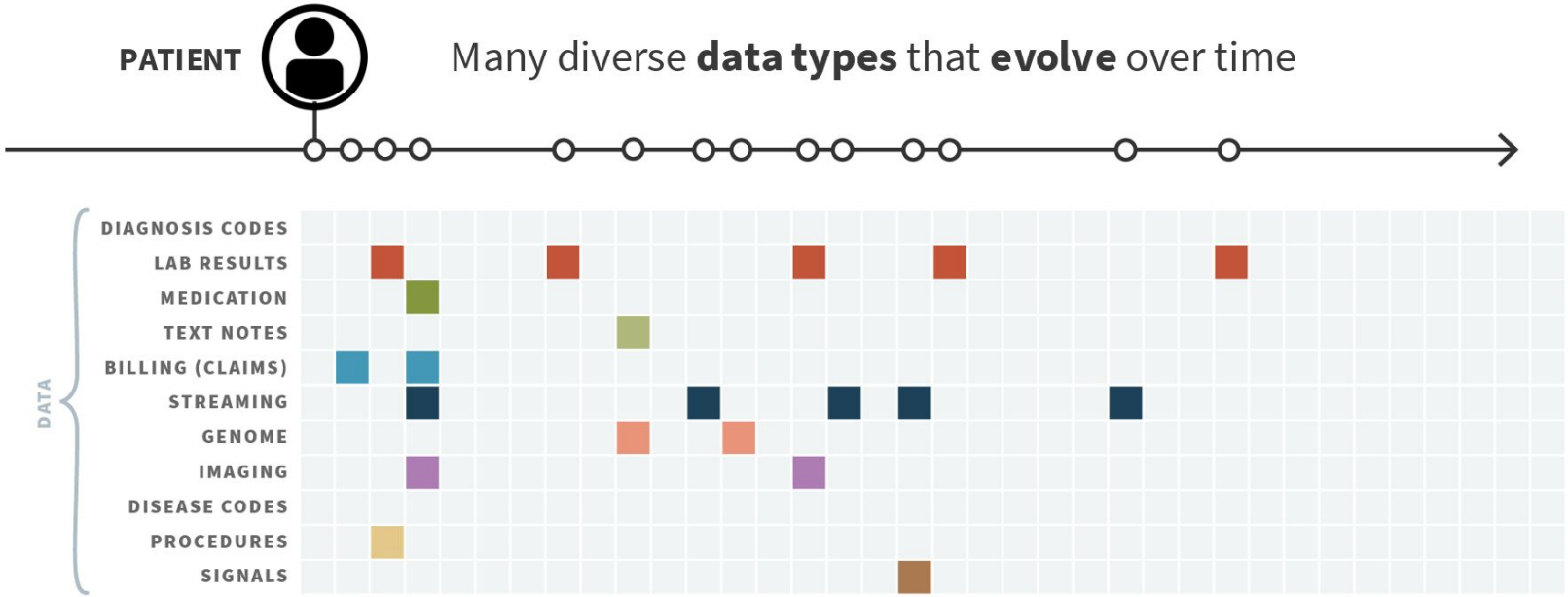
We reproduced datasets for 38 experiments corresponding to 28 published studies using MIMIC. In half of the experiments, the sample size we acquired was 25% greater or smaller than the sample size reported.

- Alistair Johnson et. al., 2017

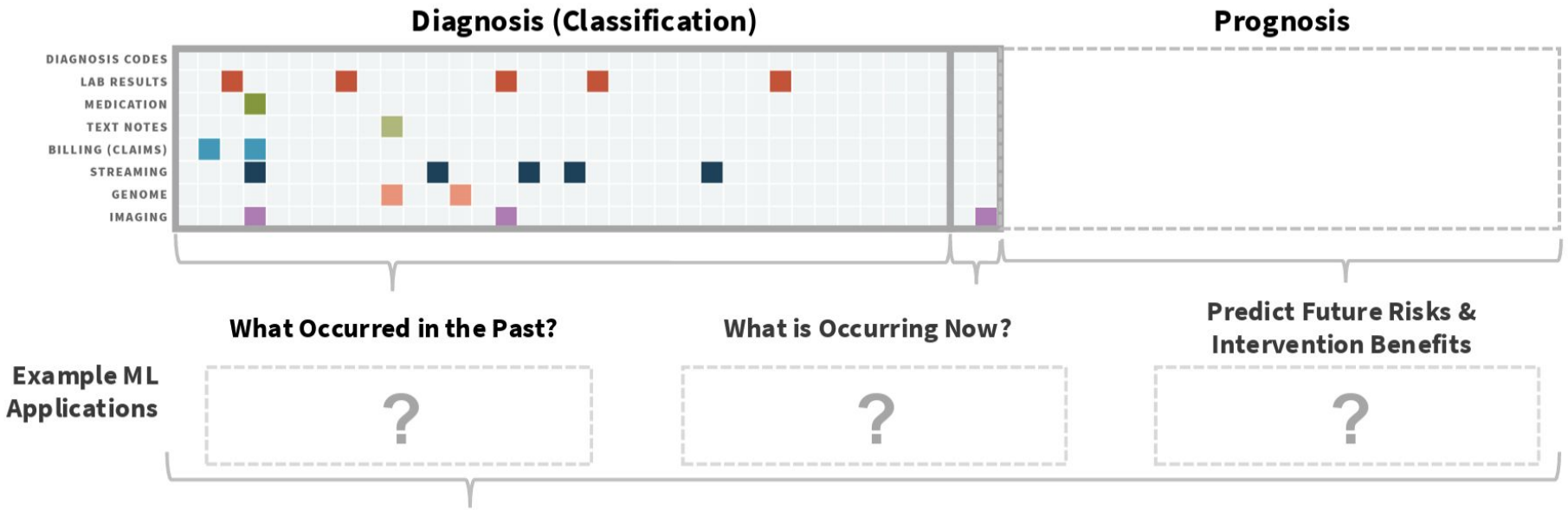
Johnson, A.E.W., Pollard, T.J. & Mark, R.G.. (2017). Reproducibility in critical care: a mortality prediction case study. *Proceedings of the 2nd Machine Learning for Healthcare Conference*, in *Proceedings of Machine Learning Research* 68:361-376 Available from https://proceedings.mlr.press/v68/johnson17a.html.

To solve this reproducibility crisis, we need a data standard designed for health AI.

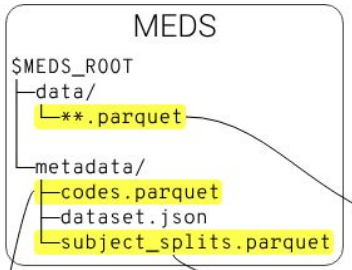
A Patient's Data can be represented as a **Timeline**



This is an opportunity to pursue many **ML applications**



MEDS



The MEDS data schema epitomizes simplicity and has only 3 required columns: `subject_id`, `time`, and `code`. It supports two optional value modalities: *`numeric`* and *`text`*.

subject_id	time	code	numeric_value	text_value
68729	*null*	RACE//WHITE	*null*	*null*
68729	*null*	SEX//M	*null*	*null*
68729	3/9/78 00:00	MEDS_BIRTH	*null*	*null*
68729	5/2/10 14:22	ED//REG	*null*	*null*
68729	5/2/10 14:34	HR//bpm	93.0	*null*
68729	5/2/10 20:00	ED//OUT	*null*	*null*
125829	*null*	SEX//F	*null*	*null*
125829	4/9/18 18:19	ADMISSION//CARDIAC	*null*	Elective

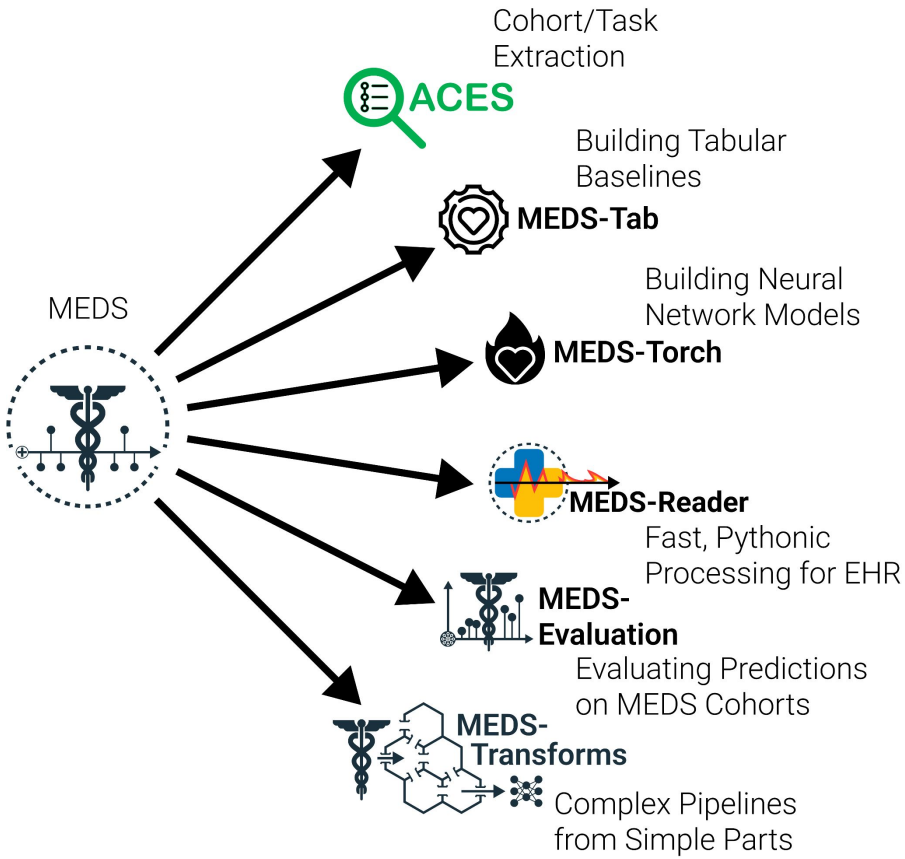
code	description	parent_codes
RACE//WHITE	The patient's race...	*null*
SEX//M	The patient's biolo...	*null*
SEX//F	The patient's biolo...	*null*
MEDS_BIRTH	*null*	*null*
MEDS_DEATH	*null*	*null*
HR//bpm	Heart rate, measu...	[LOINC/8867-4]
ED//REG	Emergency depart...	*null*
⋮	⋮	⋮

The MEDS codes schema *may* contain descriptions and links to external ontologies for elements of the `code` vocabulary.

subject_id	split
68729	train
125829	train
14392	tuning
30282	train
425678	train
⋮	⋮

The MEDS splits schema identifies which `subject_id`s are assigned to which splits.

MEDS


Cohort/Task Extraction
ACES
Building Tabular Baselines
MEDS-Tab
Building Neural Network Models
MEDS
MEDS-Torch
MEDS-Reader
Fast, Pythonic Processing for EHR
MEDS-Evaluation
Evaluating Predictions on MEDS Cohorts
MEDS-Transforms
Complex Pipelines from Simple Parts

MEDS

A

Used at more than 19 institutions

B

12 Papers

17 Datasets

10 Models

C

Up to 100x Faster

Up to 80% fewer lines of code

More than 13 tools available

Part 1 Interactive Content

Time: 5 Minutes

Learning Goals:

1. Ensure the colab notebook setting is familiar.
2. Gain familiarity with the file structure and schema contents of MEDS.

Part 2: Problem Set-up

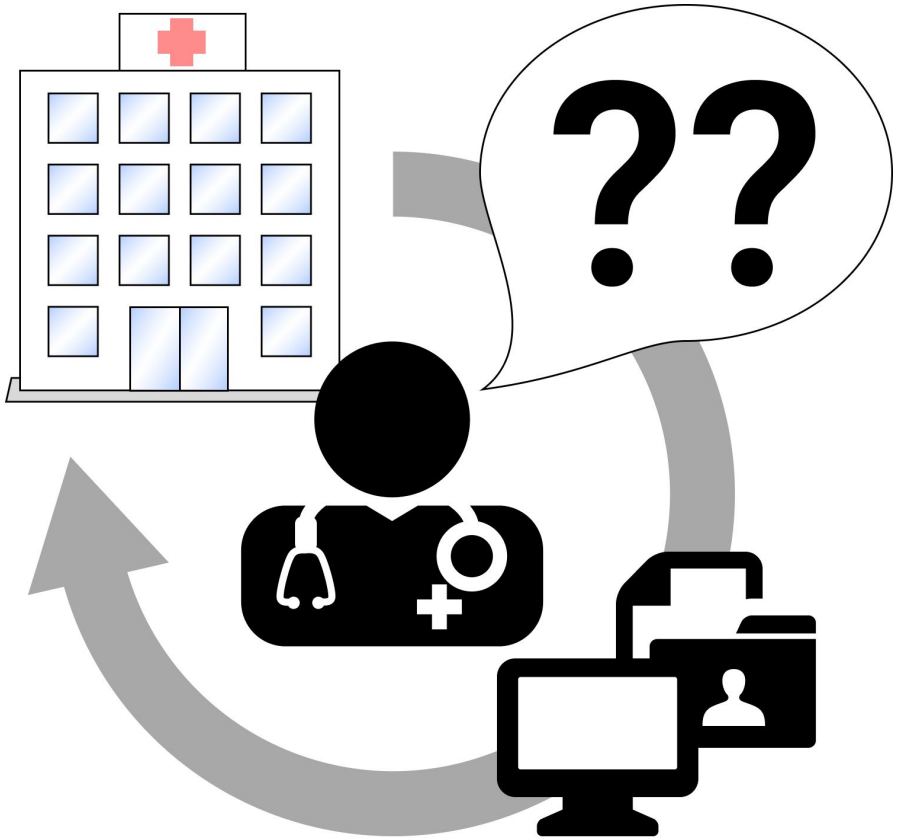
Disclaimers and Goal

This tutorial will be structured around a hypothetical problem. But...

1. The sample problem and setting were chosen for their utility in this tutorial, not for their utility as true clinical tasks!
2. This tutorial will work over *demo data only* -- you should not expect results to be individually meaningful or generalize.
3. Tools and pipelines in this tutorial are configured as they are for educational utility -- do not assume they would necessarily be appropriate in a real modeling task!

Question:

A new colleague asks you: What model should they build for their data?



This tutorial

Their data: *MIMIC-IV Demo Dataset* (https://physionet.org/content/mimic-iv-demo/2.2/)

Their problem: *Identify patients who will have a long length of stay in the ICU*

Your goal: *Help them perform this modeling task and identify the right problem framing and model to perform this prediction task, in a computational (i.e., non-deployment) setting*

What's next?

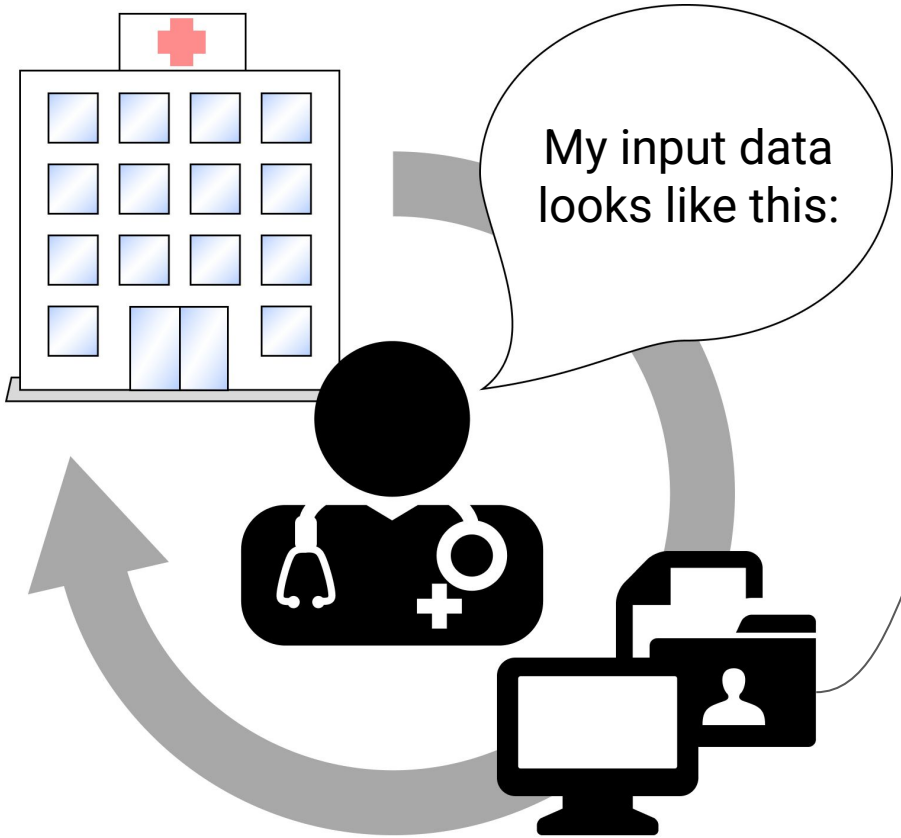
Parts:

3. Convert your data into MEDS *(Interactive)*
4. Extract a prediction task cohort with ACES *(Offline)*
5. Develop a predictive (tabular) model *(Interactive)*
6. Develop a predictive (NN) model *(Interactive)*
7. Participate in the open-source community *(Offline)*

Resources:

- All interactive sessions will leverage Google Colab notebooks. We will provide templates, and you will have to discuss and fill in cells amongst yourselves.
- All notebooks are further embedded in complete (e.g., non-interactive) form on the MEDS website: https://medical-event-data-standard.github.io/

Part 3: Convert your data into MEDS




```
$ ls $RAW_DATA_DIR

CSV  hosp/patient.csv.gz

CSV  hosp/admissions.csv.gz

CSV  icu/chartevents.csv.gz
```

Part 3 Interactive Content: Convert to MEDS

Time: 40 Minutes

Learning Goals:

1. *Identify* MEDS observations in real data.
2. *Create* a specification using MEDS-Extract that realizes those MEDS observations.

Disclaimers:

1. S1 & S2: Many ways, many tools, and all can be improved!
2. MEDS conventions are not set in stone -- if you participate in the MEDS community, you can help define new conventions for how to do things properly!

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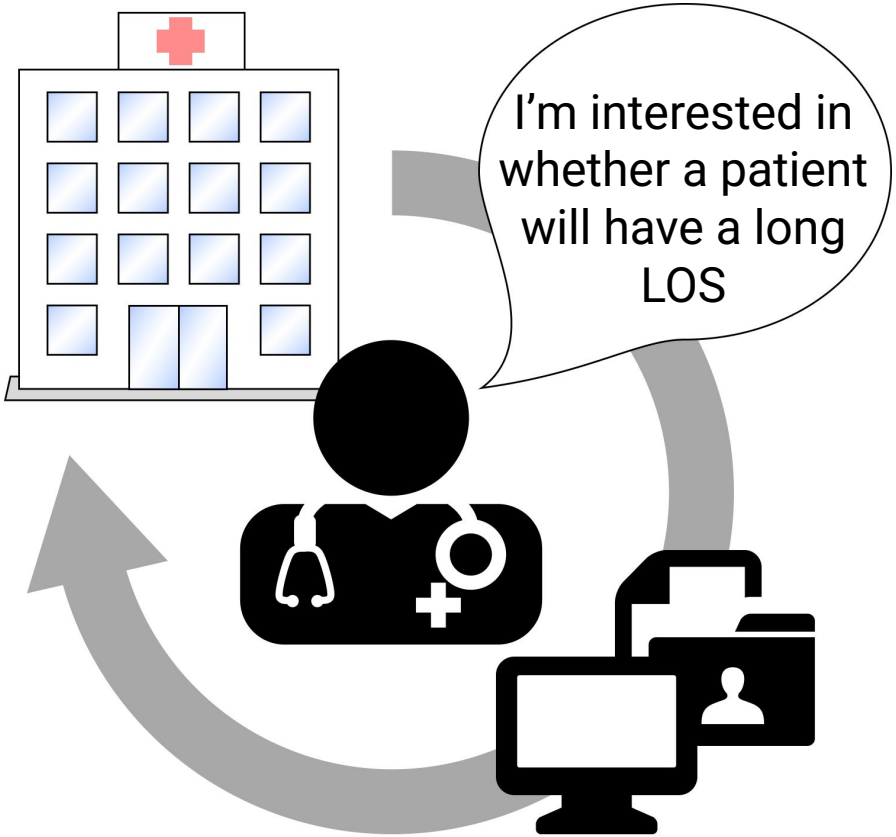
MEDS-KDD-p3

MEDS: Extract your data by asking “who”, “what”, and “when”

1. You can think about MEDS data extraction as a repeated task of asking: “To whom is this happening?”, “What is happening?”, and “When is it happening?”
2. This maps to the MEDS-Extract Specification Syntax YAML (MESSY) format: allowing you to communicate and define your extraction parameters.
3. *Bonus:* You can also extract MEDS datasets using other tools or custom pipelines -- only the MEDS output matters!
4. *Bonus:* Lots of datasets already have publicly available MEDS ETLs! Check out this link for more information:

https://tinyurl.com/MEDS-Datasets

Part 4: Identify your prediction task


I’m interested in whether a patient will have a long LOS

MEDS Label Schema

The MEDS label schema requires an index (a `subject_id`, and `prediction_time`) and permits optional labels of type including *`boolean_value`*, *`integer_value`*, *`float_value`*, and *`categorical_value`*. These labels can be predicted using any of the data of the indexed subject that occurred anytime at or before the indexed prediction time.

subject_id	prediction_time	*boolean_value*
68729	3/9/78 00:00	False
68729	5/2/10 14:22	False
68729	5/2/10 14:34	False
125829	4/9/18 18:19	True

Part 4 ***Offline, Asynchronous Content***

Time: 20 Minutes

Learning Goals:

1. *Examine*, *question*, and *refine* a stated prediction goal into a meaningful predictive cohort.
2. *Create* an ACES configuration file to extract that cohort.

Disclaimers:

1. S1 & S2: Many ways, many tools, and all can be improved!
2. This task and sample “conversation” is not necessarily representative of a real discussion with a clinician.

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MEDS-KDD-p4

ACES: Reproducible Extraction of Task Cohorts for EHRs

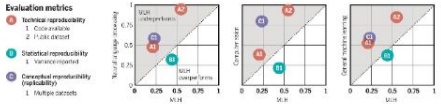
Justin Xu, Jack Gallifant, Alistair E. W. Johnson, Matthew B. A. McDermott

UNIVERSITY OF OXFORD · MIT · HARVARD MEDICAL SCHOOL

ICLR International Conference On Learning Representations

Health AI has a Reproducibility Crisis

Health AI faces a **systemic reproducibility crisis**, limiting our ability to do effective science. We need to build a health AI ecosystem to change that, and ACES builds on that foundation.



ACES Leverages Event-Stream Schemas

The MEDS data schema epitomizes simplicity and has only 4 required columns: `subject_id`, `time`, `code`, and `numeric_value`.

subject_id	time	code	numeric_value
68729	*null*	RACE//WHITE	*null*
68729	*null*	SEX//M	*null*
68729	3/9/78 00:00	MEDS_BIRTH	*null*
68729	5/2/10 14:22	ED//REG	*null*
68729	5/2/10 14:34	HR//bpm	93.0
68729	5/2/10 20:00	ED//OUT	*null*
125829	*null*	SEX//F	*null*
125829	4/9/10 18:19	ADMISSION//CARDIAC	*null*

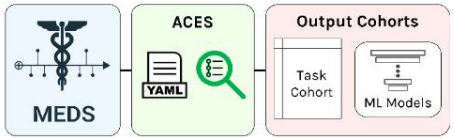
code	description	parent_codes
RACE//WHITE	The patient's race is...	*null*
SEX//M	The patient's biologic...	*null*
SEX//F	The patient's biologic...	*null*
MEDS_BIRTH	*null*	*null*
MEDS_DEATH	*null*	*null*
HR//bpm	Heart rate, measured...	[LOINC/8867-4]
ED//REG	Emergency departme...	*null*

The MEDS codes schema may contain descriptions and links to external ontologies for elements of the code vocabulary.

- Single stream of events!
- Simple and flexible to use!
- Easy transformations!

Learn More about MEDS:

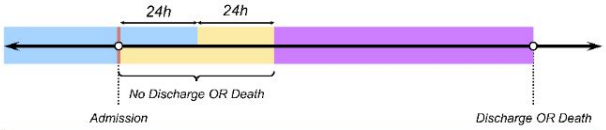
Task Extraction Made Easy!



- Transparent
- Reproducible
- Extractable on diverse datasets

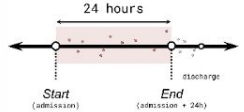
ACES Configuration Files

In-hospital Mortality: Given the first 24 hours of a patient's stay, predict whether or not they will die within this hospital admission, with a gap time of 48h.



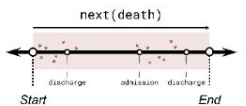

```yaml
predicates:
  admission:
    code: ADMISSION
  discharge:
    code: DISCHARGE
  death:
    code: DEATH
  discharge_or_death:
    expr: or(discharge, death)

trigger: admission

windows:
  input:
    start: NULL
    end: trigger + 24h
    start_inclusive: True
    end_inclusive: True

  gap:
    start: trigger
    end: start + 48h
    start_inclusive: False
    end_inclusive: True

  target:
    start: gap.end
    end: start -> discharge_or_death
    start_inclusive: False
    end_inclusive: True
    label: death
```

Temporal Aggregation



*Predicates are bounded by **time***

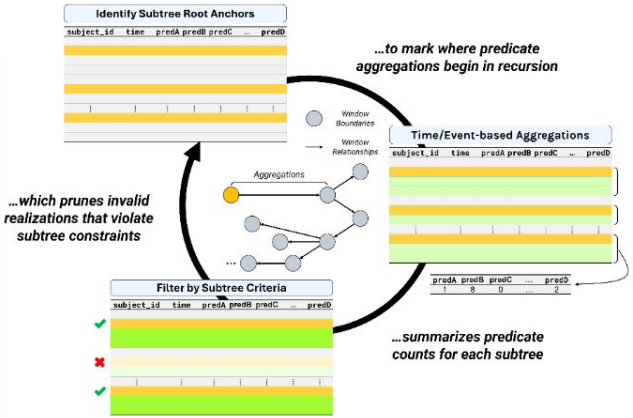
Event-based Aggregation



*Predicates are bounded by **specific events***

ACES Demo & MEDS Tutorial:

Recursive Algorithm for Extraction



How can ACES help you?

- For a variety of pre-defined tasks, check out (or contribute to) MEDS-DEV:
- For more info on how to write your own ACES configs, check out our documentation:

Acknowledgements

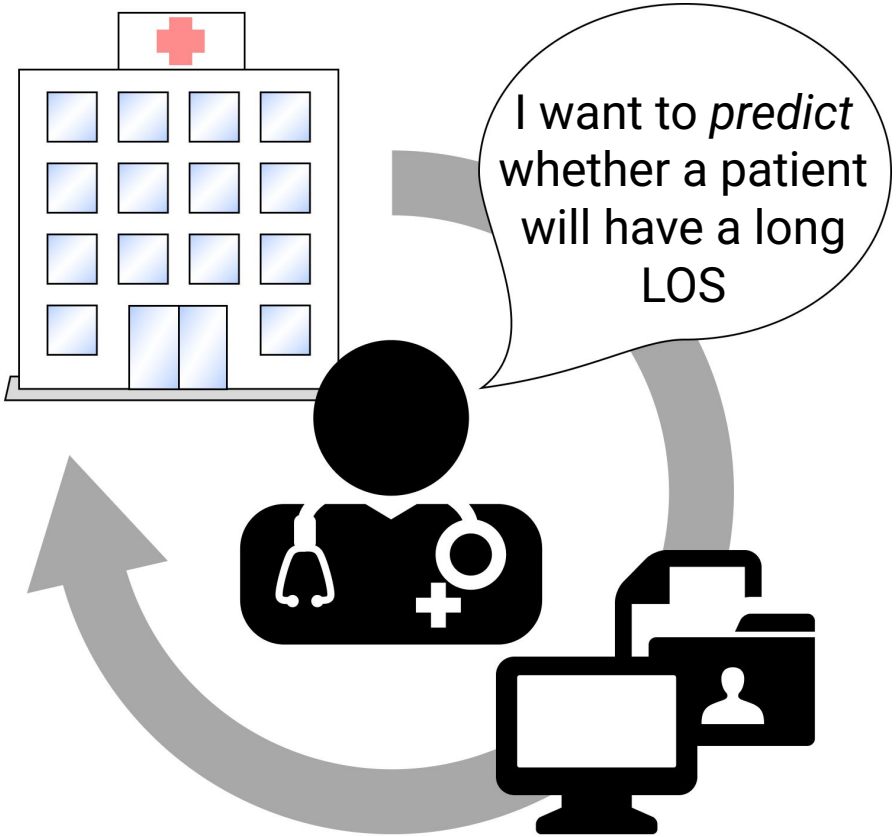
MIRAM gratefully acknowledges support from a Berkowitz Postdoctoral Fellowship at Harvard Medical School. JG is funded by the National Institutes of Health through NIH-USA RO1CA294033. JX greatly appreciates support from supervisors David Eyre (University of Oxford) and Curtis Langlotz (Stanford University). We also acknowledge valuable contributions by Tom Pollard (Massachusetts Institute of Technology) and by the broader MEDS ecosystem of contributors and users.

Final task:

Predict using the first 24 hours of data if the ICU stay will be less than 3 days long.

```yaml
predicates:
  icu_admission:
    code: { regex: "^ICU_ADMISSION//.*" }
  icu_discharge:
    code: { regex: "^ICU_DISCHARGE//.*" }
  death:
    code: { regex: "MEDS_DEATH.*" }

  # CMO predicates
  cmo_1:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "Comfort measures only"
  cmo_2:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "Comfort care (CMO, Comfort Measures)"

  # DNR predicates
  dnr_1:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "DNR / DNI"
  dnr_2:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "DNAR (Do Not Attempt Resuscitation)  [DNR]"
  dnr_3:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "DNAR (Do Not Attempt Resuscitation) [DNR] / DNI"
  dnr_4:
    code: { any: ["LAB//220001//UNK", "LAB//223758//UNK"] }
    text_value: "DNR (do not resuscitate)"

  # derived predicates
  cmo:
    expr: or(cmo_1, cmo_2)
  dnr:
    expr: or(dnr_1, dnr_2, dnr_3, dnr_4)

trigger: icu_admission

windows:
  input:
    start: null
    end: trigger + 24h
    start_inclusive: True
    end_inclusive: True
    index_timestamp: end
    has:
      cmo: (None, 0) # Exclude patients on comfort measures only
      dnr: (None, 0) # Exclude patients with DNR orders
  gap:
    start: trigger
    end: start + 30h
    start_inclusive: False
    end_inclusive: True
    has:
      cmo: (None, 0)
      dnr: (None, 0)
      icu_discharge: (None, 0)
  target:
    start: trigger
    end: start + 3d
    start_inclusive: True
    end_inclusive: True
    label: icu_discharge
    has:
      death: (None, 0)
```

Part 5: Building a model


I want to *predict* whether a patient will have a long LOS

Part 5: Tabular Baseline Interactive Content

Time: 30 Minutes *Note:* May Span Coffee Break!

Learning Goals:

1. *Explain* tabular baseline modeling needs and how MEDS supports them.
2. *Assemble* a tabular baseline model for the MEDS data *using* default MEDS tools to make a prediction.

Disclaimers:

1. S1 & S2: Many ways, many tools, and all can be improved!
2. What model will work best on your data? Nobody knows but you (eventually)

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MEDS-KDD-p5

Part 5 Takeaways:

1. Manual tabularization is not the primary goal of MEDS, but it is very tractable with sufficient data expertise.
2. Tabularization can be seen as asking “What measurements, over what windows relative to the prediction time, with what aggregation functions?”
3. Tabularization is challenging to do efficiently at large scale.

Coffee Break!

(Be back by 10:00)

Part 6: Neural Network Interactive Content

Time: 30 Minutes

Learning Goals:

1. *Explain* longitudinal neural network modeling needs and how MEDS supports them.
2. *Assemble* a neural network models *using* default MEDS tools to make a prediction.

Disclaimers:

1. S1 & S2: Many ways, many tools, and all can be improved!
2. What model will work best on your data? Nobody knows but you (eventually)

www.tinyurl.com/
MEDS-KDD-p6

Part 6 Takeaways:

1. Neural network models have very different needs than tabular models.
2. For longitudinal neural network models, you need to ask how you pad or truncate sequences, how you sample sequences during training, and how you tokenize and tensorize your data.
3. Efficiency of data loading and processing is highly important.
4. MEDS-TorchData lets you build PyTorch models over MEDS datasets out of the box.

Part 7: Leveraging and Contributing to the Community

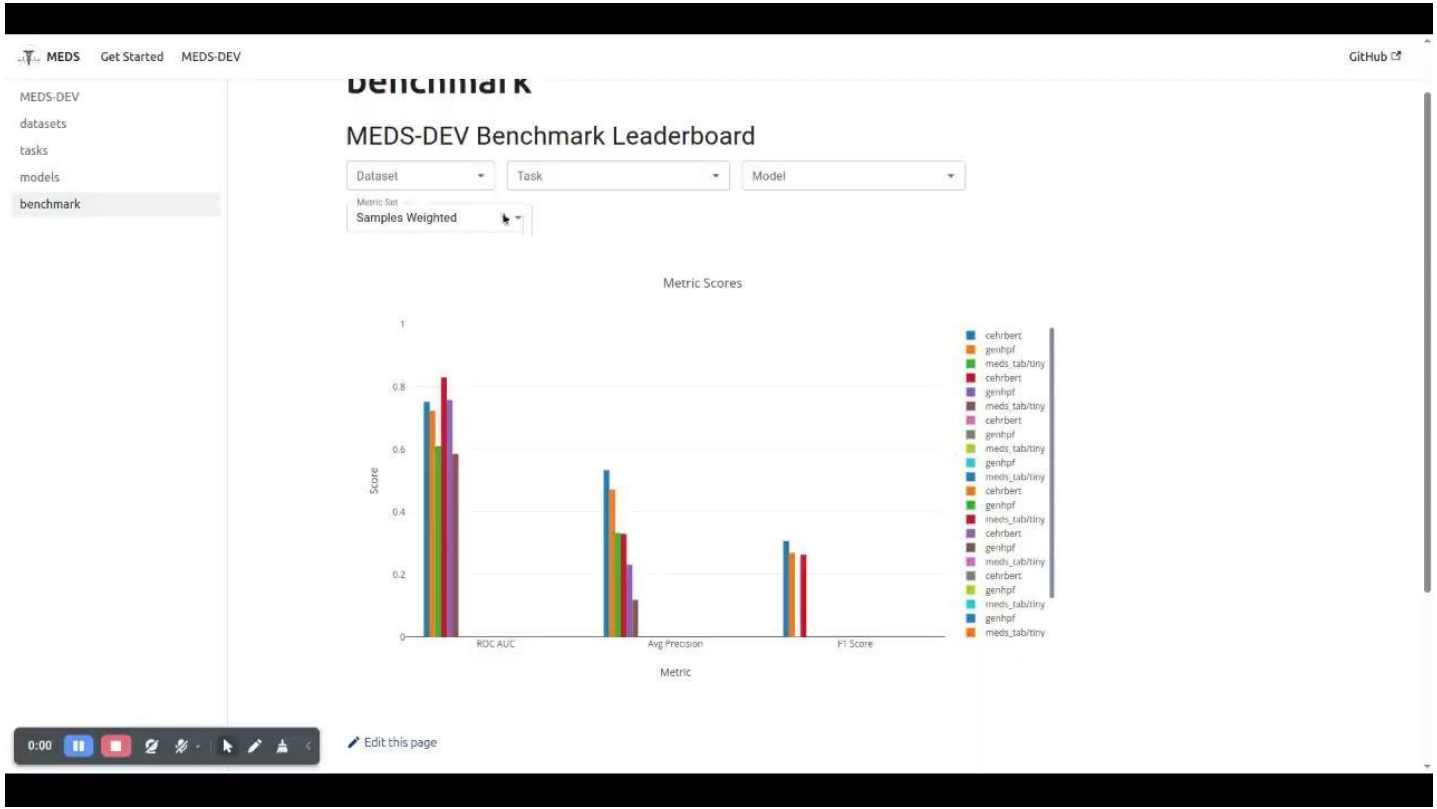
MEDS-DEV:

The MEDS Decentralized, Extensible, Validation Benchmark

If reproducibility is made trivial, we can realize all aspects of assessing a Health AI algorithm under a simple, easy to use interface

```
# Build datasets:
meds-dev-dataset dataset=$DATASET_NAME output_dir=$DATASET_DIR

# Extract tasks:
meds-dev-task task=$TASK_NAME dataset=$DATASET_NAME output_dir=$LABELS_DIR dataset_dir=$DATASET_DIR

# Train models:
# 1. Pre-train a model on unsupervised data
meds-dev-model model=$MODEL_NAME dataset_dir=$DATASET_DIR mode=train dataset_type=unsupervised
output_dir=$PRETRAINED_MODEL_DIR

# 2. Fine-tune a model on supervised data
meds-dev-model model=$MODEL_NAME dataset_dir=$DATASET_DIR labels_dir=$LABELS_DIR mode=train dataset_type=supervised
output_dir=$FINETUNED_MODEL_DIR model_initialization_dir=$PRETRAINED_MODEL_DIR

# 3. Make predictions with a model for the held-out set:
meds-dev-model model=$MODEL_NAME dataset_dir=$DATASET_DIR labels_dir=$LABELS_DIR mode=predict dataset_type=supervised
split=held_out output_dir=$PREDICTIONS_DIR model_initialization_dir=$FINETUNED_MODEL_DIR
```

Sharing Results



Conclusion

Part 1	Learn about the MEDS ecosystem	Explain why MEDS enables a collaborative, reproducible, open-source ecosystem in Health AI
Part 3	Convert new data into the MEDS format	Understand the conceptual and technical specification of MEDS-Extract
Part 4	Learn how to define prediction tasks with ACES	● Identify and decompose a task into operationalized targets ● Identify necessary predicates and criteria to define a common prediction task.
Part 5	Learn how to build baseline and neural network models using MEDS tools	● Separate tabularization and baseline model needs from NN needs. ● Leverage MEDS ecosystem tools like MEDS-Tab, MEDS Transforms, and MEDS TorchData to accelerate modeling.
Part 6	Learn how to leverage the research of the community to empower your own	

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MEDS Publications

MEDS Working Group: Bert Arnrich, Edward Choi, Jason A. Fries, Matthew B. A. McDermott, Jungwoo Oh, Tom J. Pollard, Nigam Shah, Ethan Steinberg, Michael Wornow, Robin van de Water. 2024. “Medical Event Data Standard (MEDS): Facilitating Machine Learning for Health.” In ICLR 2024 Workshop TS4H. https://openreview.net/forum?id=IsHy2ebjIG&referrer=%5BAuthor%20Console%5D(%2Fgroup%3Fid%3DICLR.cc%2F2024%2FWorkshop%2FTS4H%2FAuthors%23your-submissions).

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