Predicting Adversity in General Hospital Wards – the Cardiac Arrest Case

Zina Ibrahim and James Galloway

King's College London




King's College Hospital
NHS Foundation Trust

In-Hospital vs Out-of-hospital Cardiac Arrest

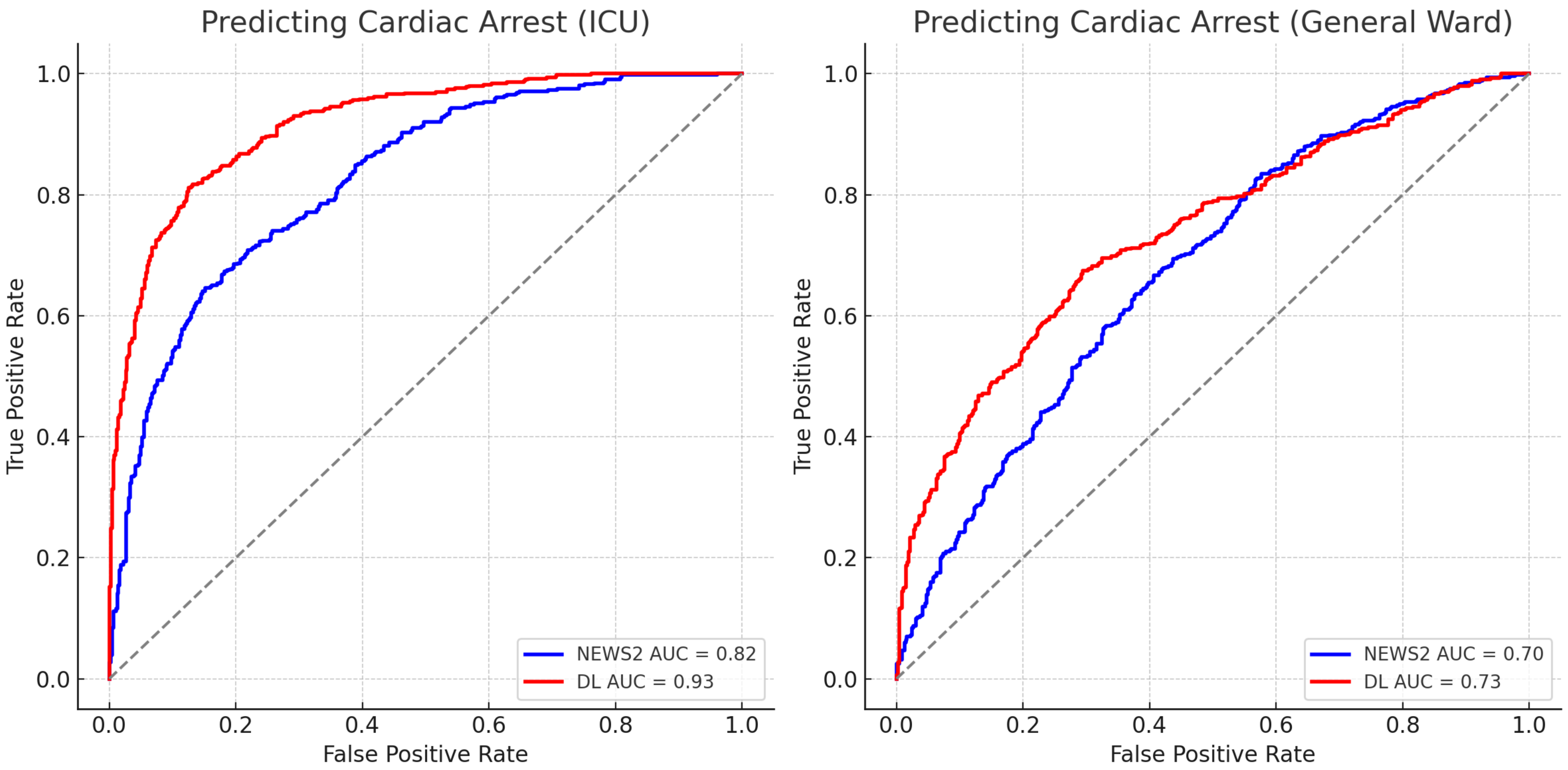
OHCA

- **Aetiology:**
  - Predominantly **cardiac in origin -** myocardial infarction, sudden arrhythmias
  - Other causes: trauma, drowning, drug overdose
  - Typically occurs suddenly and unpredictably
- **Presentation:**
  - Unmonitored (e.g., public places, homes)
  - Delayed access to emergency services

IHCA

- **Aetiology:**
  - **Non-cardiac causes are common**: respiratory failure, sepsis, electrolyte imbalances, medication reactions
  - Cardiac causes (e.g., arrhythmias, heart failure) are less frequent compared to OHCA
  - Often associated with acute decompensation of chronic illnesses
- **Presentation:**
  - Occurs in a monitored and controlled clinical setting (e.g., wards, ICUs)
  - Early signs often detected (vital signs, warning scores)
  - Immediate access to resuscitation, increasing chances of timely intervention

Predicting IHCA – ICU vs General Hospital Wards



DL for IHCA – ICU vs General Wards[1]

IHCA in ICU

- **Incidence:** 5.2% of IHCA occur in ICU
- **Early Warning:** NEWS2 AUC 0.86-0.86

Foresight

DL for IHCA Prognosis

- **Powerful:** Trained on high-throughput streams of **multimodal** data
- **High performance** on most outcomes

IHCA in Wards

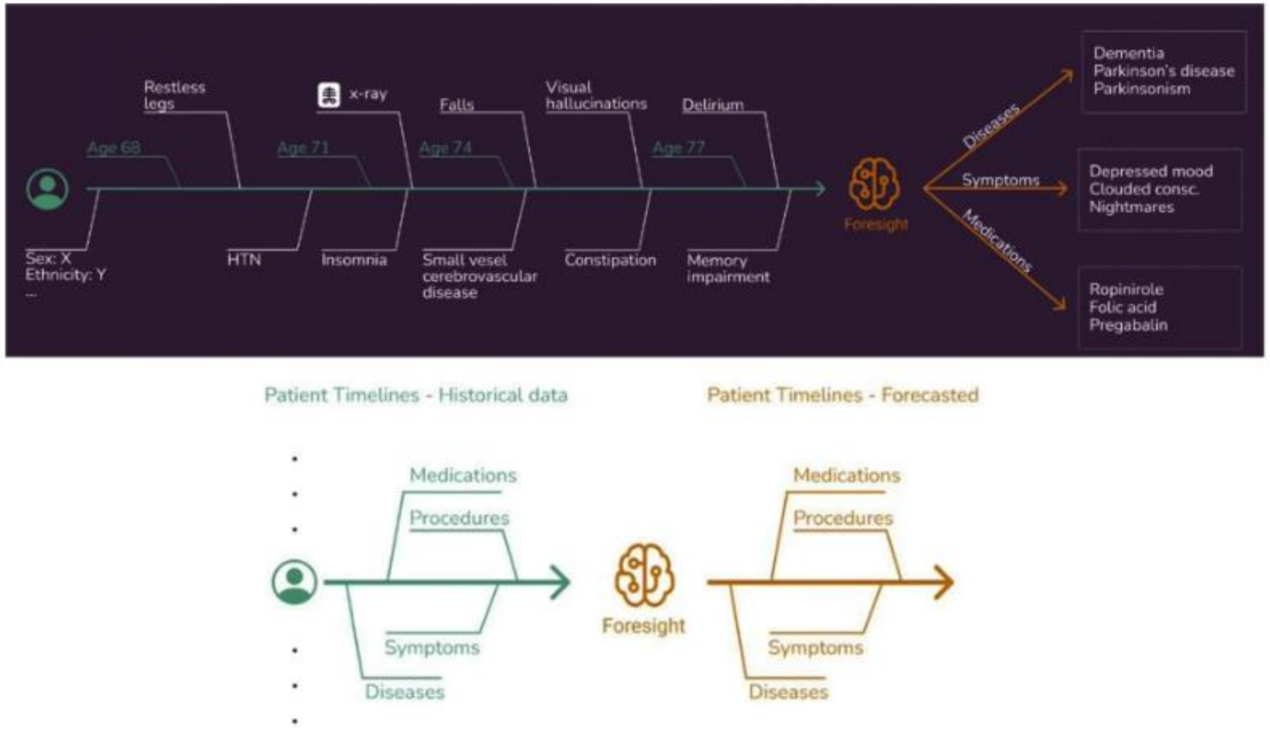
- **Incidence:** 56.6% of IHCA occur in general wards
- **Early Warning:** NEWS2 AUC 0.67-0.75
- **Outcome:** Overnight and weekend shift lead to poor outcomes (OR 1.83)

Foresight

DL for IHCA in Wards

- **Data-hungry:** Sparse ward data; DL prone to:
  - **Statistical bias:** physiological diversity reduces sample availability[2]
  - **Structural bias:** diagnostic, age[3], gender[4], race[5] & selection bias[6]

The Generative AI Phase, **Foresight**



Foresight: GPT-based Forecasting Pipeline

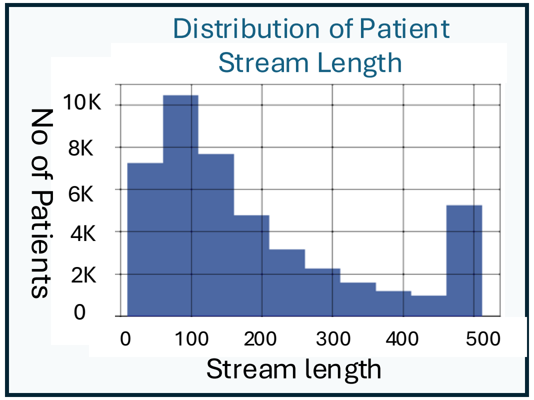
Our Project

Aim: improve Foresight’s ability to serve as a tool for early recognition of IHCA from general wards data.

Our Project

Aim: improve Foresight's ability to serve as a tool for early recognition of IHCA from general wards data.

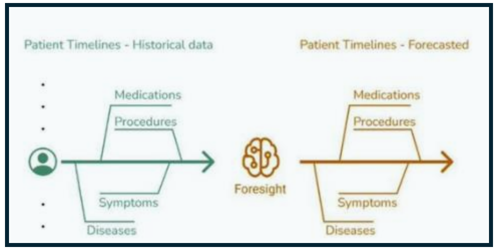
1. **Statistical bias:** Foresight is good with patients with long trails of documents. If the number of documents for a patient is low (younger patients, patients with less comorbidities, etc..), Foresight's performance plummets



Our Project

Aim: improve Foresight's ability to serve as a tool for early recognition of IHCA from general wards data.

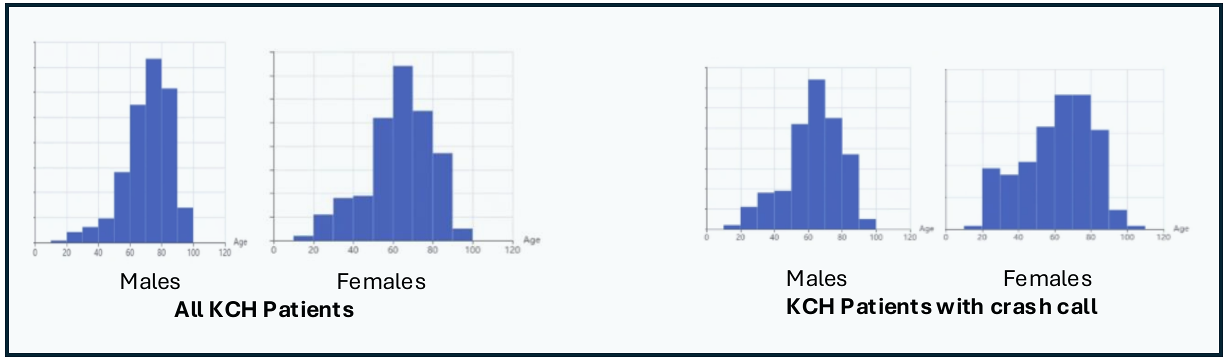
1. **Statistical bias:** Foresight is good with patients with long trails of documents. If the number of documents for a patient is low (younger patients, patients with less comorbidities, etc..), Foresight's performance plummets
2. **Model bias:** Foresight fundamentally operates with SNOMED code for Medications, Symptoms, Diseases & Procedures. No low-level numerical data – e.g. labs & vital signs.

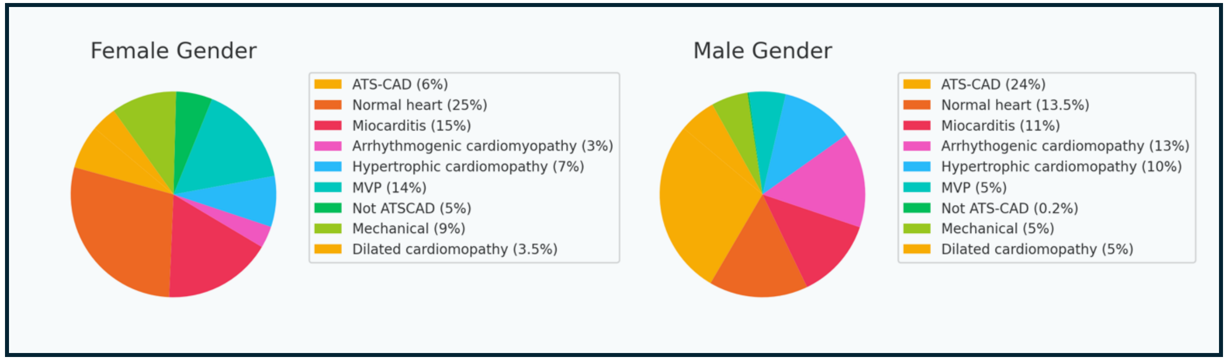


Our Project

Aim: improve Foresight's ability to serve as a tool for early recognition of IHCA from general wards data.

1. **Statistical bias:** Foresight is good with patients with long trails of documents. If the number of documents for a patient is low (younger patients, patients with less comorbidities, etc..), Foresight's performance plummets
2. **Model bias:** Foresight fundamentally operates with SNOMED code for Medications, Symptoms, Diseases & Procedures. No low-level numerical data – e.g. labs & vital signs.
3. **Structural bias:** Foresight's forecasts carry along the clinical and documentation bias within its training data





Our Project Phases

Phase 1

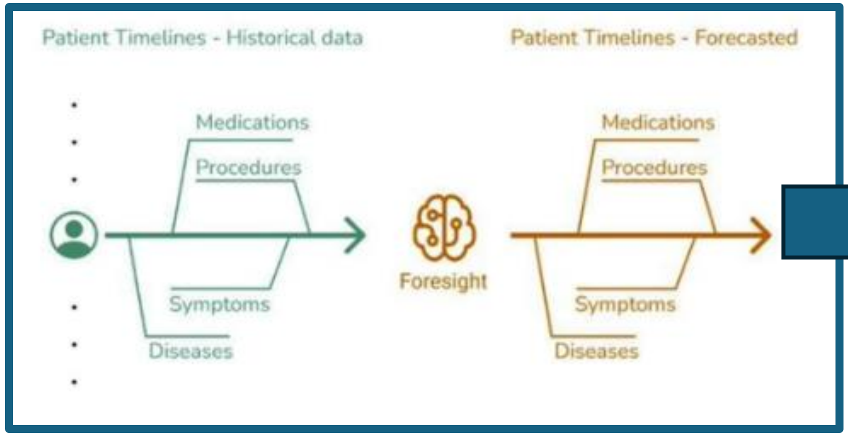
- **Model bias:** inclusion of vital signs, laboratory tests & other fine-grained patient information

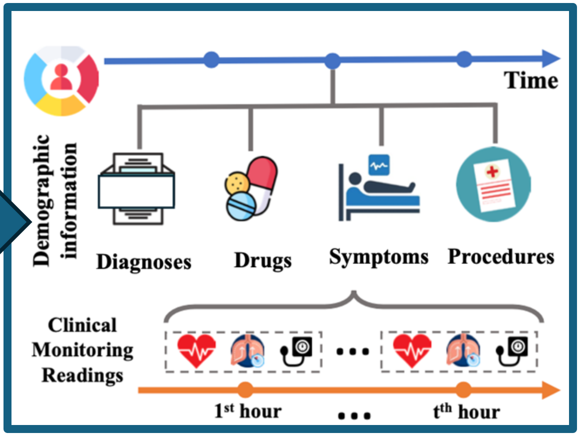
---

Phase 2

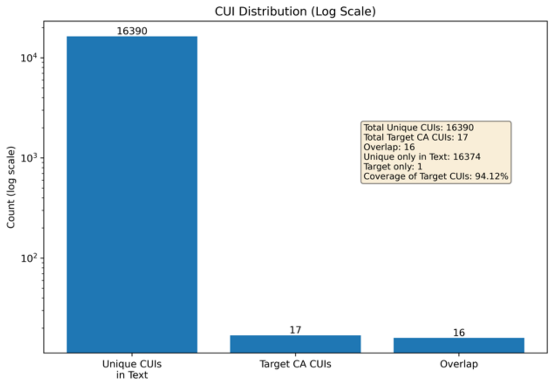
- **Statistical bias:** overcome the lack of data for some patient demographics
- **Structural bias:** overcome clinical and documentation bias within the data

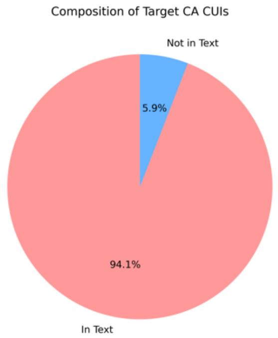
Phase 1



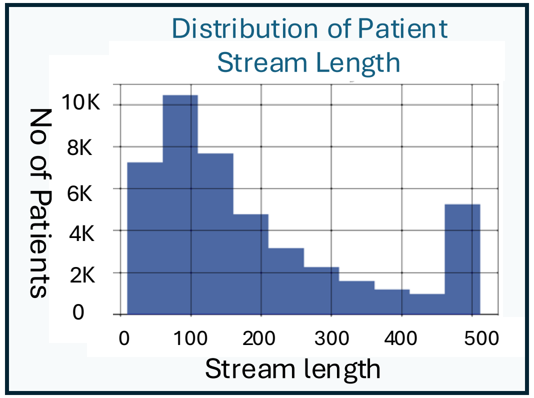


Fixing Model bias: inclusion of vital signs, laboratory tests & other fine-grained patient information





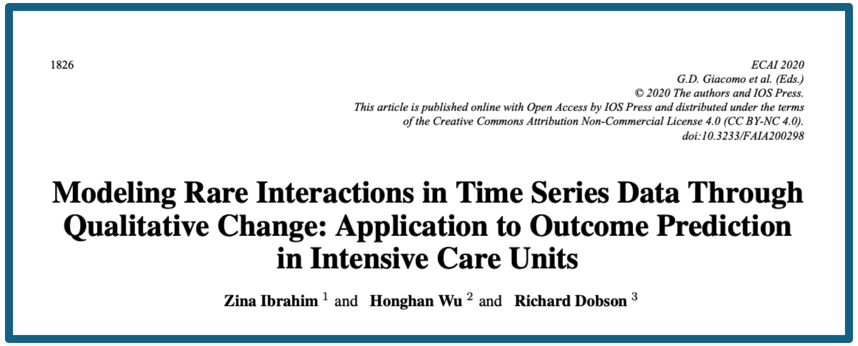
Distribution of Concept Unique Identifiers (CUIs)



Distribution of CUI Streams Per Patient with Foresight

Enriching Foresight with Measurements – the Qualitative Interaction Graph (QIG)

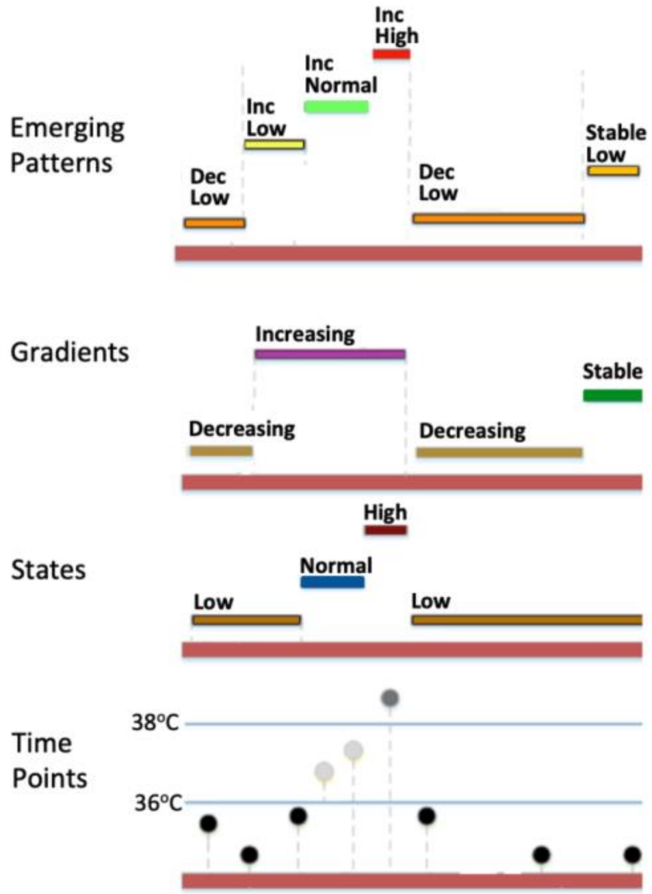
- Mine textual descriptions of vitals and lab test values for the CA cohort from the structured records
- Use the generated text as additional input to Foresight


1826

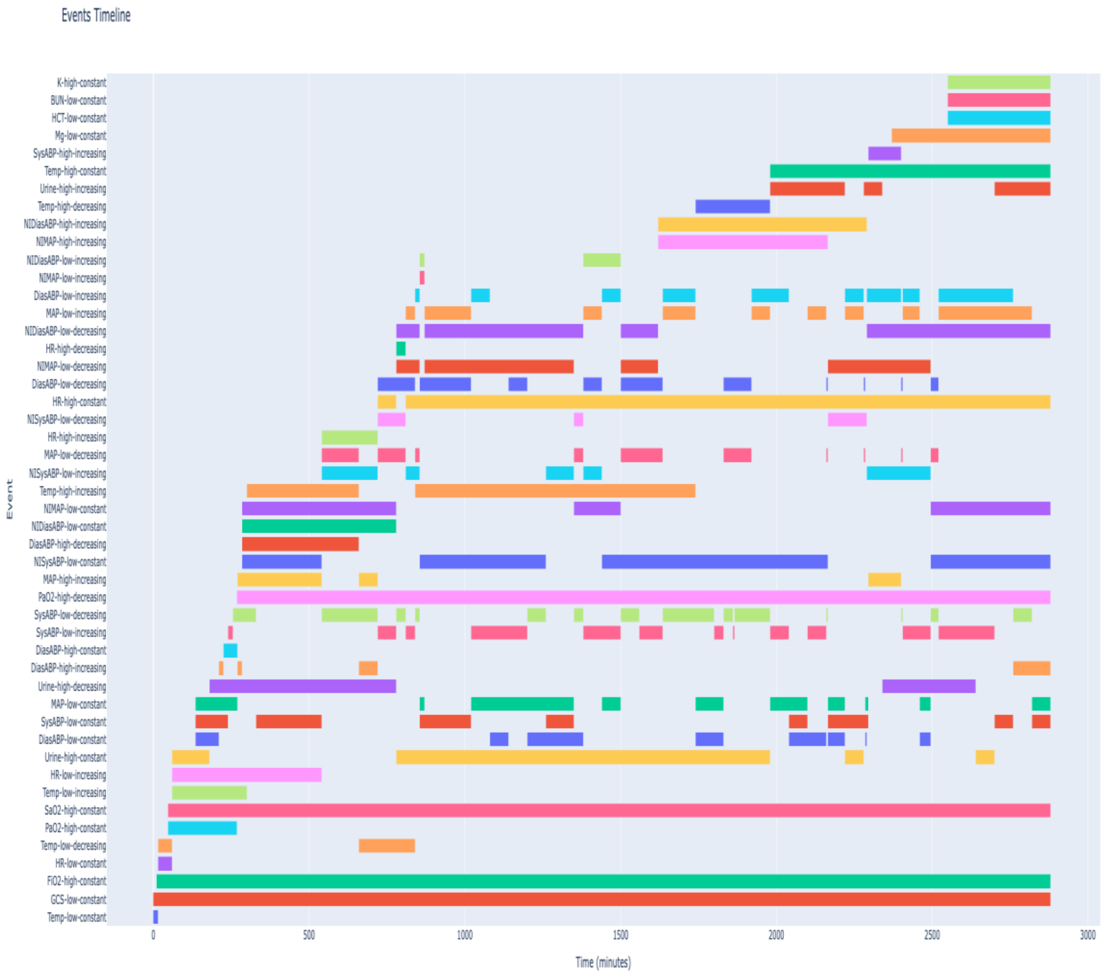
ECAI 2020
G.D. Giacomo et al. (Eds.)
© 2020 The authors and IOS Press.
This article is published online with Open Access by IOS Press and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0).
doi:10.3233/FAIA200298

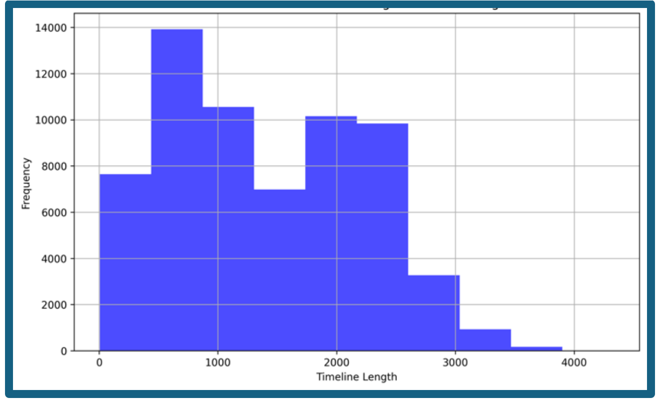
Modeling Rare Interactions in Time Series Data Through Qualitative Change: Application to Outcome Prediction in Intensive Care Units

Zina Ibrahim [1] and **Honghan Wu** [2] and **Richard Dobson** [3]



QIG for One Patient






```
First few rows of patient 3's timeline:
Total number of event states: 712
Timestamp            Event State
--------------------------------------------------------------------
2101-10-20 16:40:00     [+] CREATININE-high-constant
2101-10-20 16:40:00     [+] MAGNESIUM-high-constant
2101-10-20 16:40:00     [+] BUN-high-constant
2101-10-20 16:40:00     [+] CHLORIDE-low-constant
2101-10-20 16:40:00     [+] GLUCOSE-low-constant
2101-10-20 16:40:00     [+] POTASSIUM-high-constant
2101-10-20 18:30:00     [+] TEMP-low-constant
2101-10-20 18:45:00     [+] DBP-low-constant
2101-10-20 18:45:00     [+] SBP-low-constant
2101-10-20 18:45:00     [+] MAP-low-constant
2101-10-20 19:00:00     [-] DBP-low-constant
2101-10-20 19:00:00     [-] SBP-low-constant
2101-10-20 19:00:00     [-] MAP-low-constant
2101-10-20 19:00:00     [+] MAP-low-increasing
2101-10-20 19:00:00     [+] SBP-low-increasing
2101-10-20 19:00:00     [+] DBP-low-increasing
2101-10-20 19:12:00     [-] CREATININE-high-constant
2101-10-20 19:12:00     [-] MAP-low-increasing
2101-10-20 19:12:00     [+] LACTATE-high-constant
2101-10-20 19:12:00     [+] PO2-low-constant
```

```python
sample_event = pd.read_csv(os.path.join(patient_event_output_path, f'{sample_patient_id}.csv'))
sample_event
```

✓ 0.0s

	SUBJECT_ID	ordinal_time_start	VALUENUM	ITEMID	ordinal_time	state	gradient	ordinal_time_end	event	global_start_order	global_end_order	length
0	3	2101-10-20 16:40:00	3.2	CREATININE	0 days 00:00:00	high	constant	2101-10-20 19:12:00	CREATININE-high-constant	0	1	2.533333
1	3	2101-10-20 16:40:00	2.4	MAGNESIUM	0 days 00:00:00	high	constant	2101-10-20 19:26:00	MAGNESIUM-high-constant	0	4	2.766667
2	3	2101-10-20 16:40:00	53.0	BUN	0 days 00:00:00	high	constant	2101-10-20 19:26:00	BUN-high-constant	0	4	2.766667
3	3	2101-10-20 16:40:00	99.0	CHLORIDE	0 days 00:00:00	low	constant	2101-10-20 19:26:00	CHLORIDE-low-constant	0	4	2.766667
4	3	2101-10-20 16:40:00	91.0	GLUCOSE	0 days 00:00:00	low	constant	2101-10-20 19:26:00	GLUCOSE-low-constant	0	4	2.766667
...	...	...	...	...	...	...	...	...	...	...	...	...
351	3	2101-10-26 17:00:00	103.0	DBP	6 days 00:20:00	high	increasing	2101-10-27 17:00:00	DBP-high-increasing	171	184	24.000000
352	3	2101-10-26 17:00:00	119.0	MAP	6 days 00:20:00	high	increasing	2101-10-27 17:00:00	MAP-high-increasing	171	184	24.000000
353	3	2101-10-29 04:45:00	73.0	GLUCOSE	8 days 12:05:00	low	decreasing	2101-10-30 04:30:00	GLUCOSE-low-decreasing	172	186	23.750000
354	3	2101-10-30 04:30:00	76.0	GLUCOSE	9 days 11:50:00	low	constant	2101-10-31 04:55:00	GLUCOSE-low-constant	173	188	24.416667
355	3	2101-10-31 04:55:00	88.0	GLUCOSE	10 days 12:15:00	low	increasing	2101-11-01 04:55:00	GLUCOSE-low-increasing	174	189	24.000000

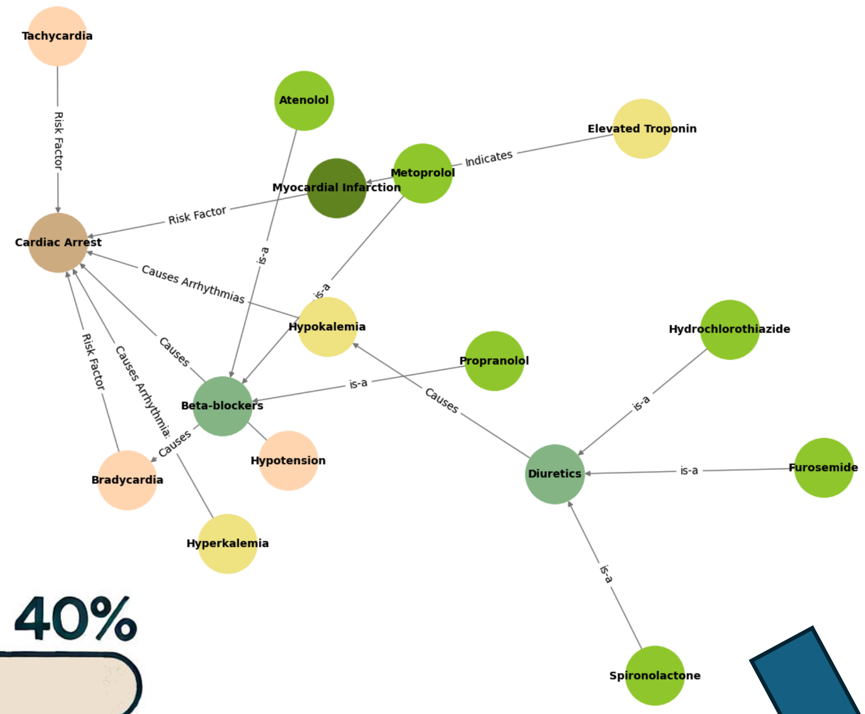
356 rows × 12 columns

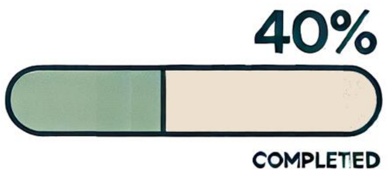
80%

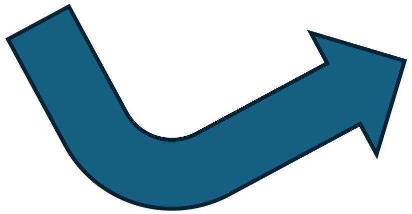
COMPLETED

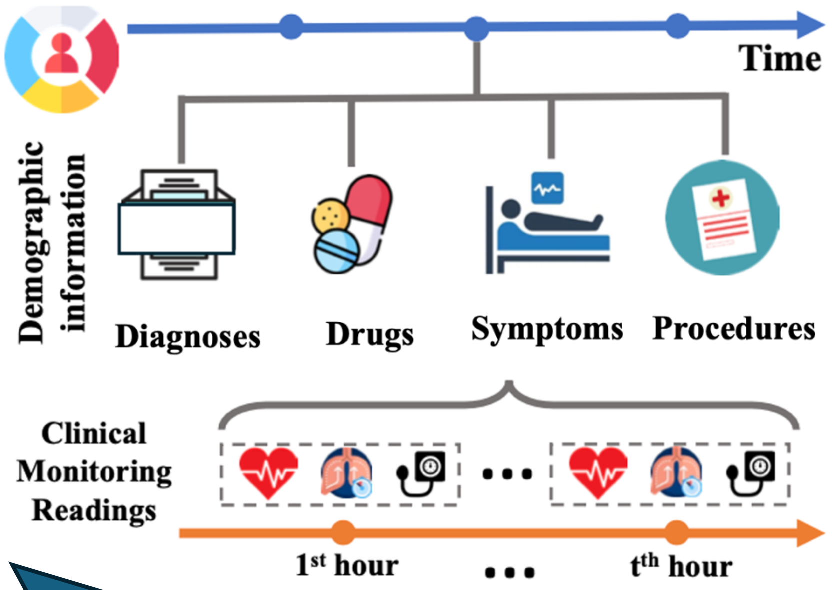
Phase 2

Strategy: use existing knowledge to **overcome sparse data** AND steer the model **away from bias**









Use graph knowledge as constraints via Transformer loss function

Thank you

1. https://www.resuscitationjournal.com/article/S0300-9572(14)00469-9/fulltext#tbl0020
2. https://www.bmj.com/content/361/bmj.k1479
3. https://pubmed.ncbi.nlm.nih.gov/20959786/#article-details
4. https://www.ahajournals.org/doi/10.1161/JAHA.117.006872
5. https://jamanetwork.com/journals/jama/fullarticle/184590
6. https://pubmed.ncbi.nlm.nih.gov/29463613/#article-details