A Novel Temporal Similarity Measure for Patients Based on Irregularly Measured Data in Electronic Health Records

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BIO-MIBLAB

Outline

- Introduction and Motivation
- Temporal Similarity Measure
- Experiment Design and Results
- Discussion and Future Work

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Background

- With increasing adoption of electronic health record (EHR) systems, millions of patients have their medical histories digitized and archived in a structured form
- The immense amount of EHR data serves as unique resources for clinical decision support (CDS)
- Finding similar patients to a target patient
  - To derive diagnostic and prognostic information for guiding the treatment of the target patient
- Personalized medicine

Motivation

- Medical history as a sequence of time-stamped events
- Inpatients are monitored based on their health status [1]
  - The choice of specific measurements
  - The order of specific measurements
  - The frequency of measurements e.g. patients are monitored more intensively when their health is deteriorating
- Most existing patient-similarity measures did not utilize all the aforementioned temporal information [2-5]

Rich information hidden in measurement patterns

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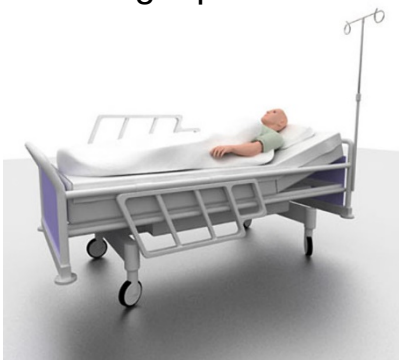
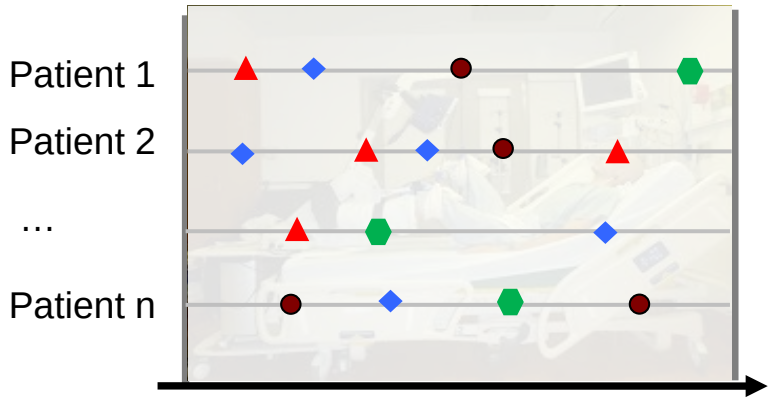
Decision Support for Case-based Reasoning

A target patient



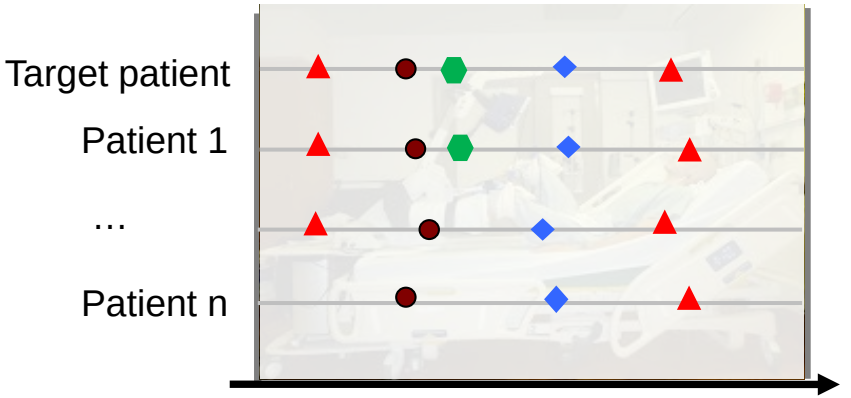
ICU database



Ranking by Temporal Similarity

Facilitate clinicians' decision making

After similarity ranking



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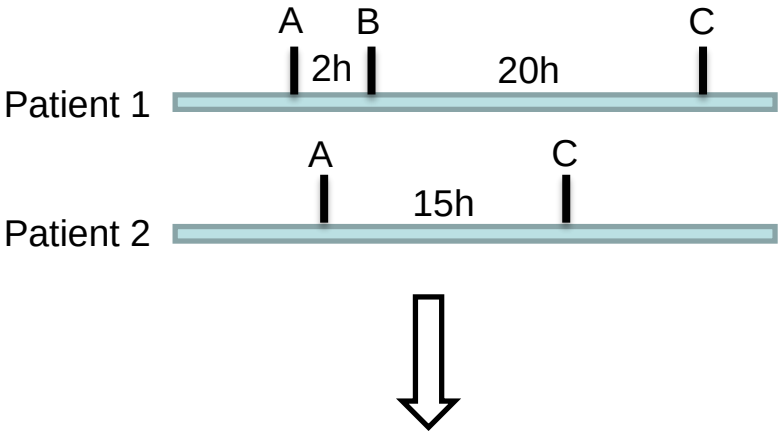
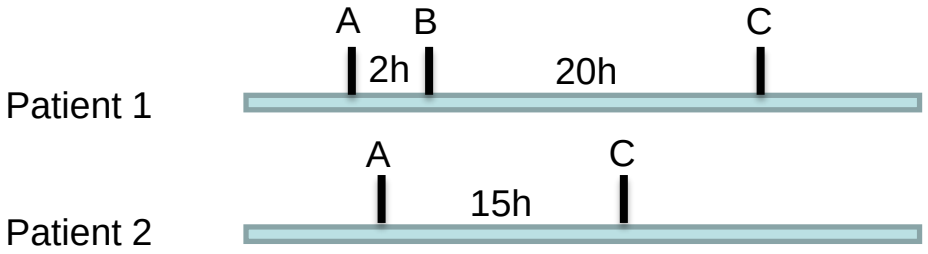
Concept

- Modification of Smith-Waterman Algorithm [7]
  - Dynamic programming
  - Determining similar regions between two strings
  - Tolerant of missing or extra events



Output:
Patient 1 = A 2h B 20h C
Patient 2 = A - - 15h C

Matrix Representation



	—	A	2h	B	20h	C
—		0	0	0	0	0
A	0	5	4	3	2	1
15h	0	4	6.75	5.75	6.75	5.75
C	0	3	3.75	4.75	5.75	11.75

	—	A	2h	B	20h	C
—	0	0	0	0	0	0
A	0	↖	←	←	←	←
15h	0	↑	↖	←	↖	←
C	0	↑	↑	↑	↑	↖

Match : +5-0.25*Δt
Mismatch: -3
Gap: -1-0.25*Δt

Output:
Patient 1 = A 2h B 20h C
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Patient Data Extraction

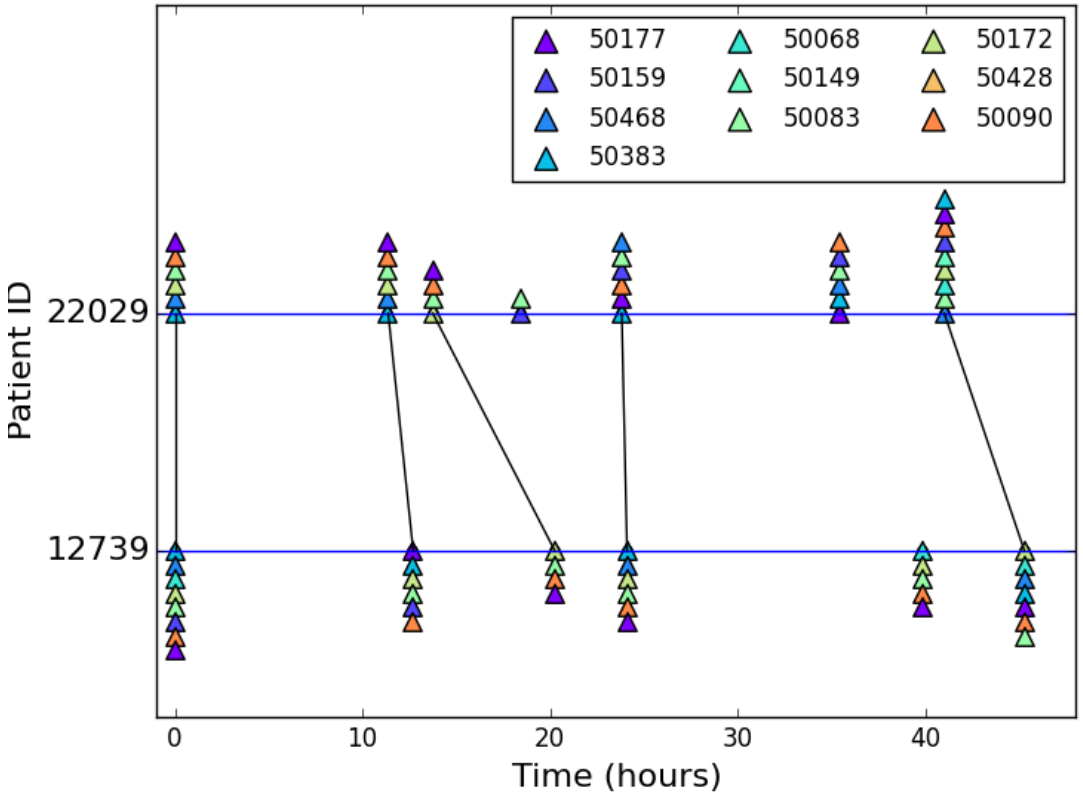
Table 1 Top 10 most frequent Laboratory Items in MIMIC-II

Laboratory Item	Identifier in MIMIC-II	# of Records		
		Total	Normal	Abnormal
Hematocrit	50,383	596,604	73,402	523,202
Potassium	50,149	561,178	494,082	67,096
Sodium	50,159	528,229	444,852	83,377
Creatinine	50,090	526,270	315,795	210,475
Platelets	50,428	526,190	338,222	187,968
Urea nitrogen	50,177	522,118	228,110	294,008
Chloride	50,083	517,904	378,534	139,370
Bicarbonate	50,172	516,225	370,295	145,930
Anion gap	50,068	507,265	474,916	32,349
Leukocytes	50,468	506,625	293,538	213,087
Total	502,177	5,308,608	3,411,746	1,896,862

Table 2 Top 10 most frequent Laboratory Items in the CHOA dataset

Laboratory Item	# of Records		
	Total	Normal	Abnormal
POC glucose	58,639	19,711	38,928
Oxygen Saturation	49,260	21,487	27,773
Arterial POC pH	49,256	21,620	27,636
Arterial POC pCO2	49,246	26,477	22,769
Arterial POC Po2	49,246	5,617	43,629
Sodium	43,603	33,872	9,731
POC ionized calcium	43,194	28,614	14,580
Potassium	42,985	28,139	14,846
Calcium	42,727	29,555	13,172
Glucose	42,629	26,712	15,917
Total	470,785	241,804	228,981

Visualization of an Alignment of Patients' History



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Predictive power of the similarity measure

- Hypothesis: Patients sharing similar lab-test trajectories in the past tend to share similar lab-test trajectories in the future

- Reasoning: Patients with higher similarity scores (by our approach) of past lab-test trajectories have higher similarity scores of future lab-test trajectories

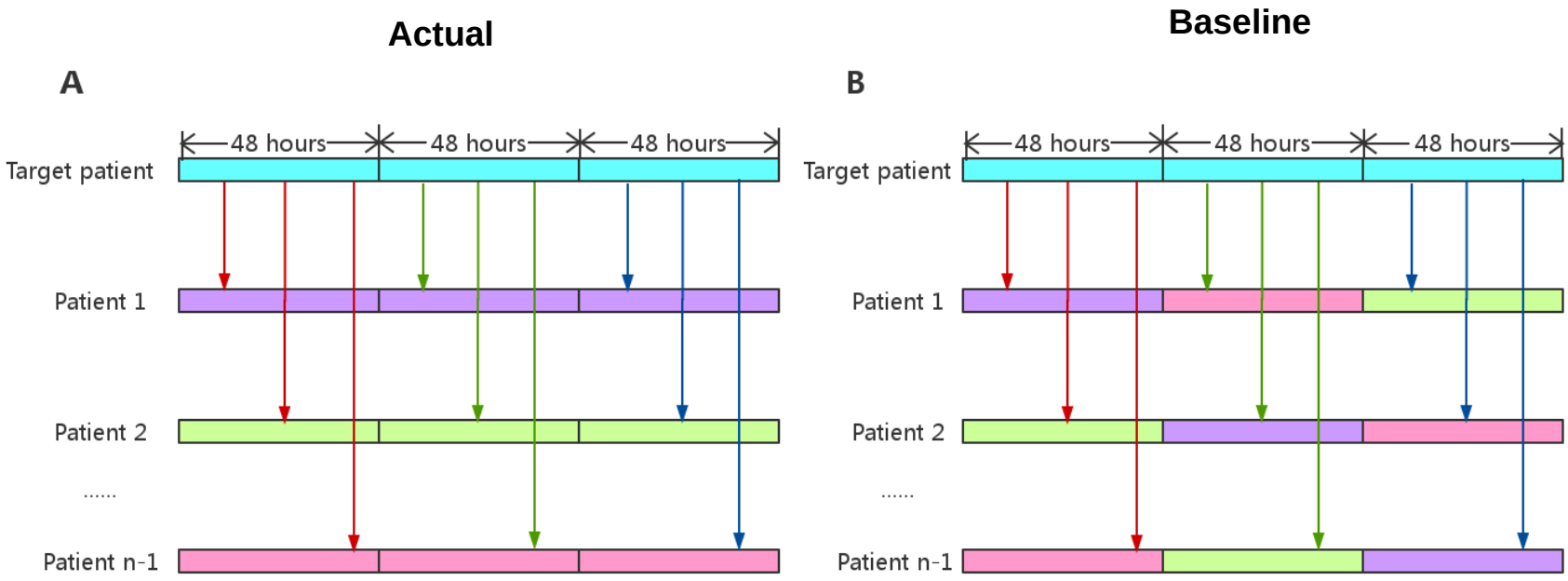
- Given a target patient, we can construct a simple linear regression models:

$$\text{SimilarityScore}_{future} = a + b \times \text{SimilarityScore}_{past}$$

Ho: $b=0$ Ha: $b \neq 0$

p-value < 0.05 ?

Proving the predictive power



SimilarityScore_second48h = a + b × SimilarityScore_first48h

SimilarityScore_third48h = c + d × SimilarityScore_first48h

SimilarityScore_second48h = a' + b' × SimilarityScore_first48h

SimilarityScore_third48h = c' + d' × SimilarityScore_first48h

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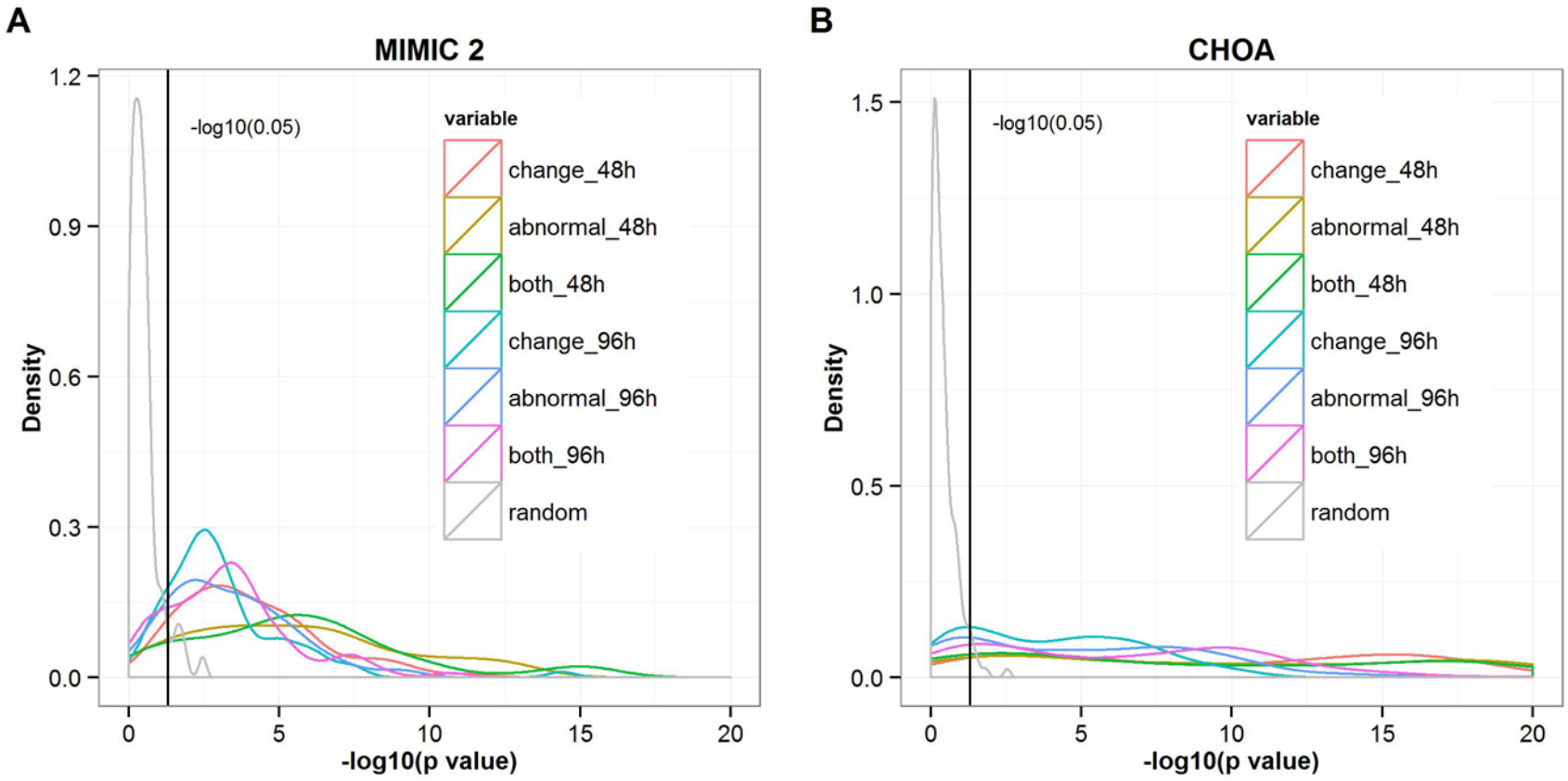
Predictive Power of Our Novel Similarity Measure



Case study: Lab testing vs 48-hr Mortality

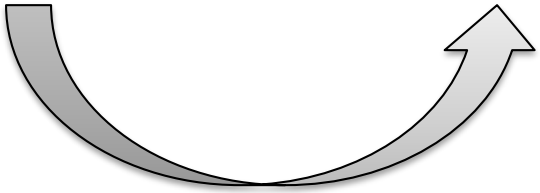
Lab tests are informative for a diagnosis of AKI

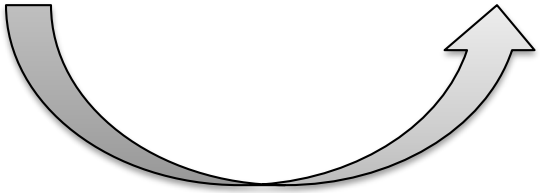
Mortality rate : 27%

A target patient diagnosed with acute kidney injury (AKI)

K most similar AKI patients to the target patients based on 48-hr-lab-test trajectories

Mortality prediction





MIMIC2 Database

Majority Voting of similar patients

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Case study: Lab testing vs 48-hr Mortality

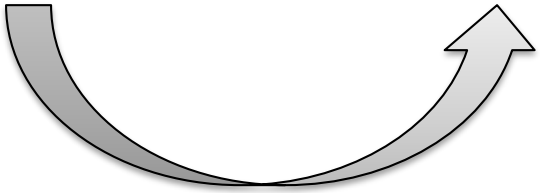
Lab tests are informative for a diagnosis of sepsis

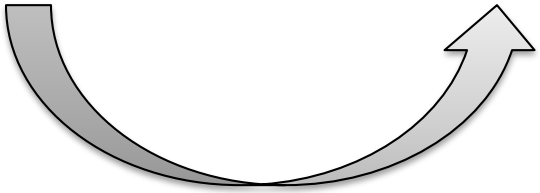
Mortality rate : 16%

A target patient diagnosed with sepsis and severe sepsis

K most similar sepsis patients to the target patients based on 48-hr-lab-test trajectories

Mortality prediction





CHOA Database

Majority Voting of similar patients

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Case study: Lab testing vs 48-hr Mortality

- Compare to two non-temporal similarity measures
  - The Jaccard Index [9] :

$$\mathrm{J}(\mathrm{A},\mathrm{B}) = \frac{|A \cap B|}{|A \cup B|}$$

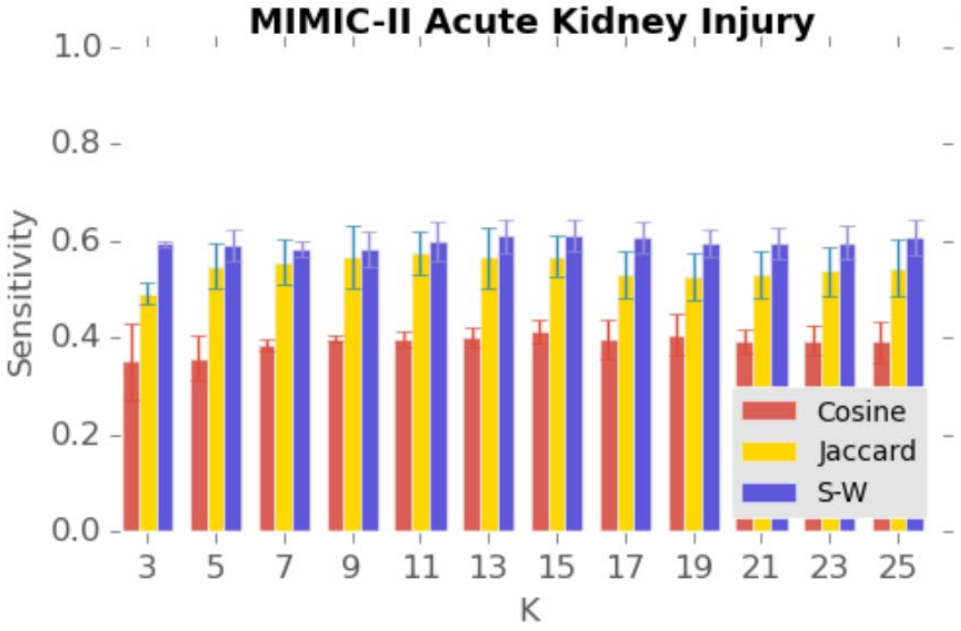
Presence or absence of specific abnormal lab-test results

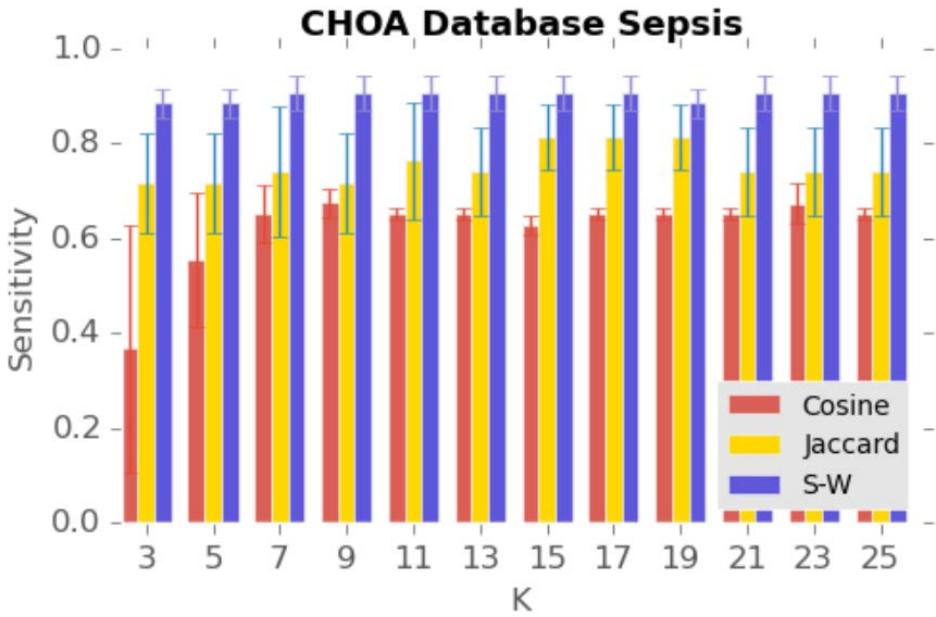
  - Cosine [10] :

$$\cos(\theta) = \frac{A \cdot B}{\|A\| \, \|B\|}$$

Number of occurrences of specific abnormal lab-test results

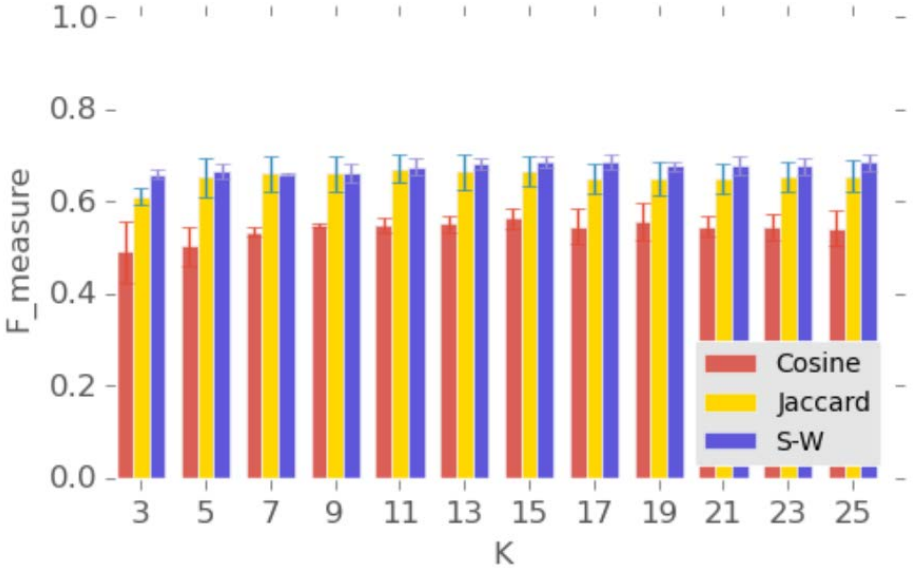
Result – Sensitivity
Varying K of KNN



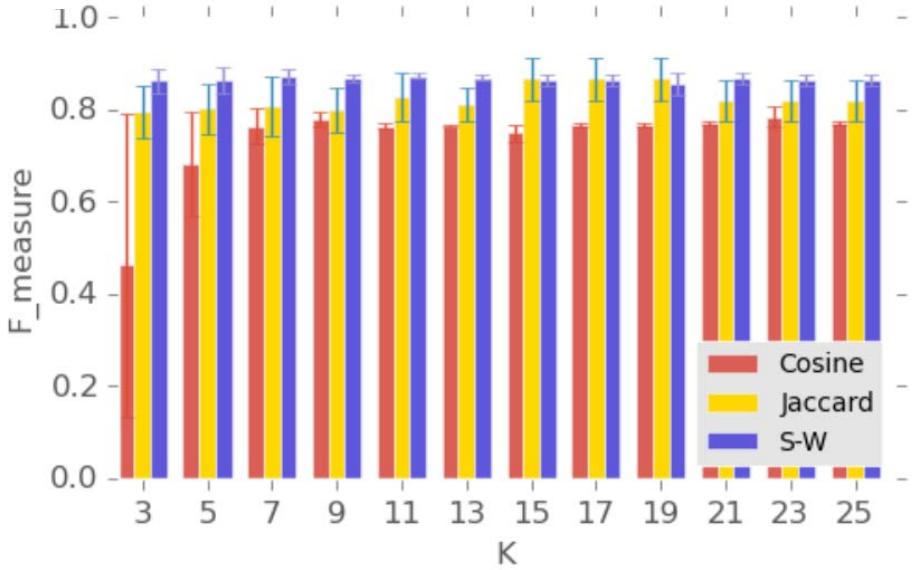


Result – F-measure
Varying K of KNN

MIMICII Acute Kidney Injury



CHOA Database Sepsis



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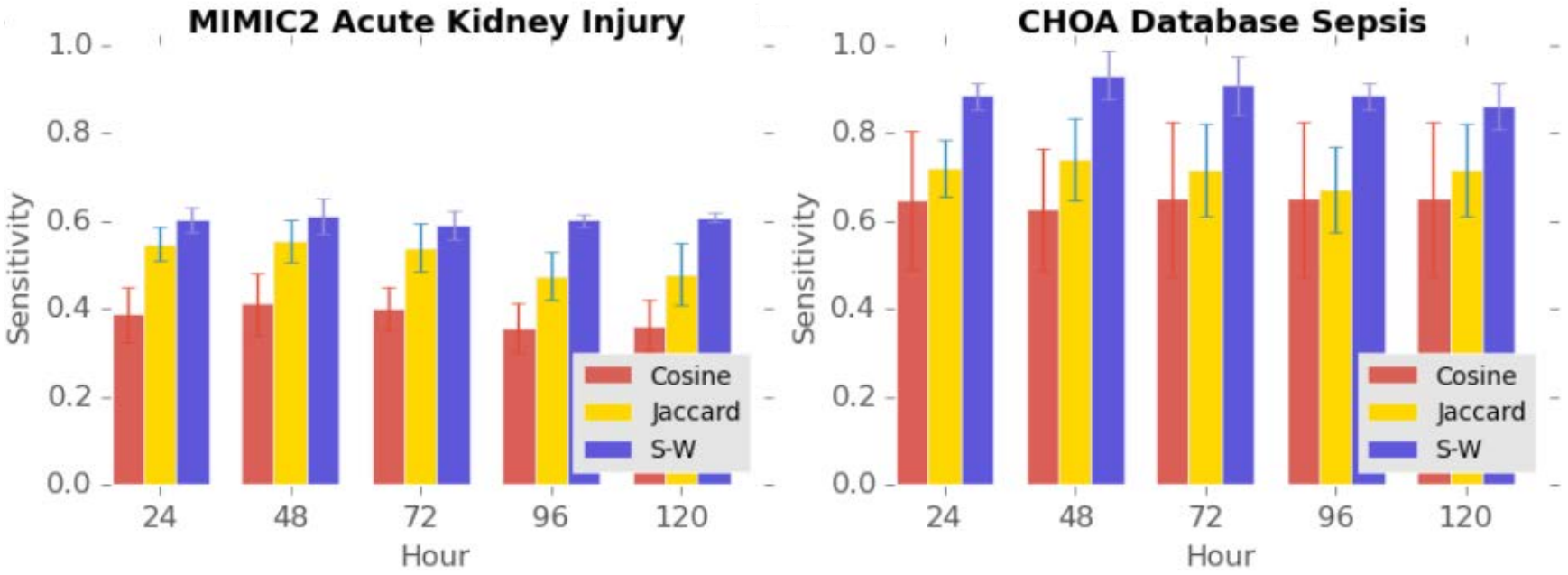
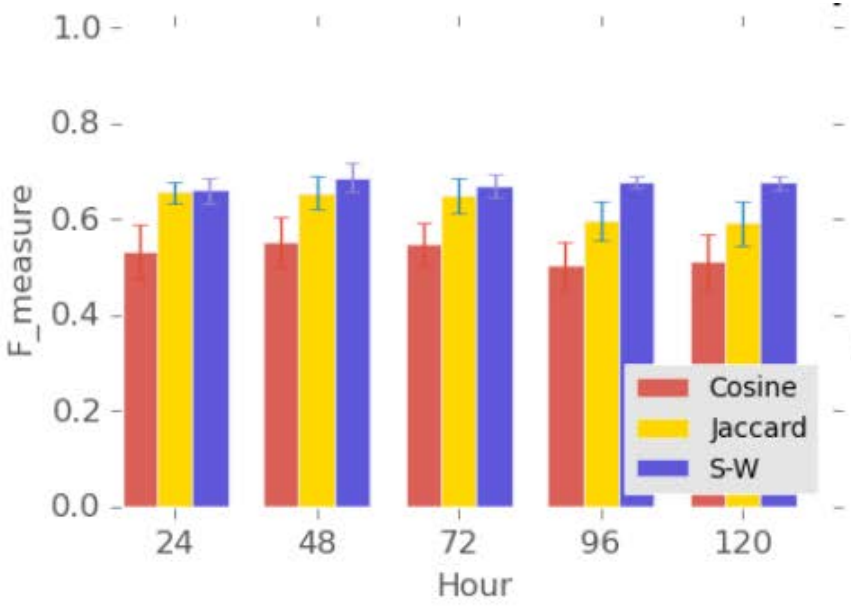
Result – Sensitivity
Varying Prediction window



Result – F-measure
Varying Prediction Window

MIMICII Acute Kidney Injury



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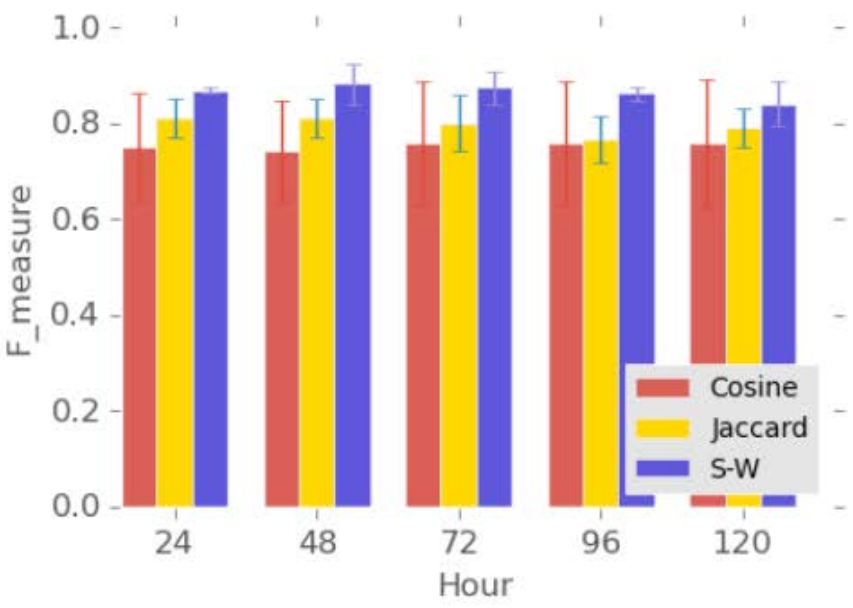

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Discussion

- Our novel similarity measure has predictive power, better than that of other non-temporal measures
- The assumption that patients are monitored more intensively when their health is deteriorating, should be experimentally validated or consulted with clinicians
- Clinical protocols may vary hospital by hospital
- Penalize a match between two time intervals according to their absolute difference
  - May hinder the application of this method to measurements spanning over multiple time scales: days for ICU care and years for outpatients

Future work

- Combine non-temporal features, i.e., demographics, with temporal features, e.g., lab tests, medication, diagnosis, I/O events
- Feature selection before similarity analysis
- Solve more real-world clinical problems

Reference

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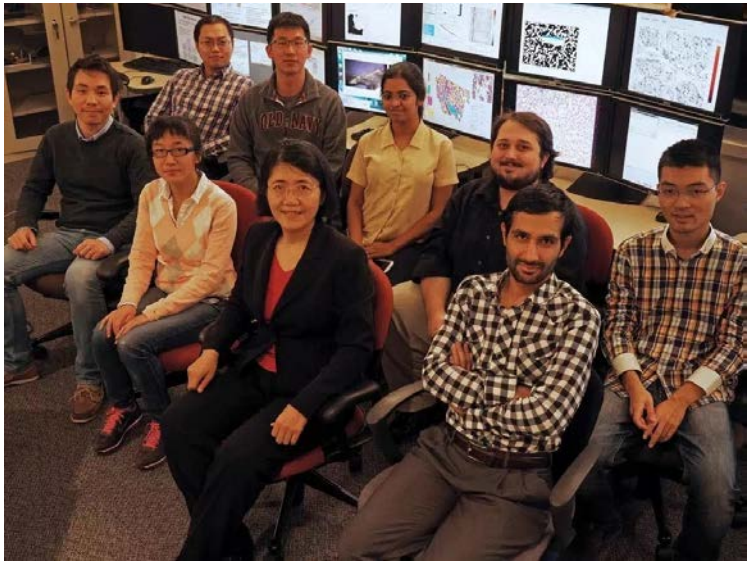
Acknowledgements



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