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

Ying Sha, Janani Venugopalan, May D. Wang
Georgia Institute of Technology
Oct. 3\textsuperscript{th}, 2016
Outline

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

• Introduction and Motivation
• Temporal Similarity Measure
• Experiment Design and Results
• Discussion and Future Work
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 \[2-5\]
Outline

• Introduction and Motivation
• **Temporal Similarity Measure**
• Experiment Design and Results
• Discussion and Future Work
Decision Support for Case-based Reasoning

A target patient

Facilitate clinicians’ decision making

ICU database

Patient 1
Patient 2
...
Patient n

Ranking by Temporal Similarity

After similarity ranking

Target patient
Patient 1
...
Patient n
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

### Patient 1

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>2h</th>
<th>B</th>
<th>20h</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>A</td>
<td>0</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>15h</td>
<td>0</td>
<td>4</td>
<td>6.75</td>
<td>5.75</td>
<td>6.75</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>3</td>
<td>3.75</td>
<td>4.75</td>
<td>5.75</td>
</tr>
</tbody>
</table>

### Patient 2

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>2h</th>
<th>B</th>
<th>20h</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>A</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-15h</td>
<td>-</td>
</tr>
<tr>
<td>15h</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

**Match:** +5 - 0.25*Δt

**Mismatch:** -3

**Gap:** -1 - 0.25*Δt

Output:

Patient 1 = A 2h B 20h C

Patient 2 = A - - 15h C
Outline

• Introduction and Motivation
• Temporal Similarity Measure
• **Experiment Design and Results**
• Discussion and Future Work
### Table 1: Top 10 most frequent Laboratory Items in MIMIC-II

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

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

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

![Graph showing patient IDs and time (hours)]
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:
  \[ \text{SimilarityScore}_{\text{future}} = a + b \times \text{SimilarityScore}_{\text{past}} \]
  \[ \text{Ho: } b = 0 \quad \text{Ha: } b \neq 0 \]
  \[ \text{p-value} < 0.05 \]
Proving the predictive power

\[
\begin{align*}
\text{SimilarityScore\_second48h} &= a + b \times \text{SimilarityScore\_first48h} \\
\text{SimilarityScore\_third48h} &= c + d \times \text{SimilarityScore\_first48h}
\end{align*}
\]
Predictive Power of Our Novel Similarity Measure

(A) MIMIC 2

(B) CHOA
Case study: Lab testing vs 48-hr Mortality

Lab tests are informative for a diagnosis of AKI

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 rate: 27%

MIMIC2 Database

Majority Voting of similar patients

Mortality prediction
Case study: Lab testing vs 48-hr Mortality

Lab tests are informative for a diagnosis of sepsis

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

Mortality rate: 16%

CHOA Database

Majority Voting of similar patients
Case study: Lab testing vs 48-hr Mortality

- Compare to two non-temporal similarity measures
  - The Jaccard Index \([9]\):
    \[
    J(A, B) = \frac{|A \cap B|}{|A \cup B|}
    \]
    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
Result – Sensitivity
Varying Prediction window

MIMIC2 Acute Kidney Injury

CHOA Database Sepsis
Result – F-measure
Varying Prediction Window

MIMICII Acute Kidney Injury
CHOA Database Sepsis
Outline

• Introduction and Motivation
• Temporal Similarity Measure
  – Concept and Visualization
• Experiment Design and Results
• Discussion and Future Work
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


Acknowledgements

Bio-MIBLab
http://www.miblab.gatech.edu/

Emory - Georgia Tech Cancer Center for Nanotechnology Excellence

Institute for People and Technology (IPaT), Georgia Tech