Machine Learning for Healthcare

From Wearables to Electronic Health Record

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Machine Learning for Healthcare

  - Predicting clinical outcomes
  - Discover risk factors associated with outcome
  - Support clinical decisions to improve outcome

- Discover the insights behind diverse data
  - Mobile Health (mHealth)
    - Continuous monitoring outside hospitals
    - Small data: mHealth studies usually have moderate population
  - Electronic Health Record (EHR)
    - In-patient data
    - Big data: large patient population
Examples: ML for Healthcare

- ML for mHealth: predict readmission of outpatients with wearables
  - Predict readmissions of heart failure patients
  - Predict complications of patients undergoing pancreatectomy
  - Develop generalizable predictive models based on “small data”

- ML for EHR: predict clinical deterioration of inpatients in general wards
  - Early warning systems: alerts for ICU transfer and death
  - Develop specific and informative alerts
Project: Predicting Readmissions with Fitbit

- Hospital readmission rate is high for heart failure patients.
  - ~25% patients readmitted within 30 days
- Predict deterioration (readmission+death) after discharge
  - Fitbit provides continuous monitoring of outpatients
  - Just-in-time intervention → better outcome and lower cost

Joint work with Thomas Bailey (Infectious Diseases), Marin Kollef (Critical Care), Dingwen Li (CSE)

Rich Features of Wearable Data

- Heart rate (HR), step count and sleep quality were collected.
  - Sampling period: 1 min (step, heart rate); 1 day (sleep)

- Statistical features:
  - First- and second-order features extracted from sliding window
  - 1\text{st} order: mean, max, min, skewness, kurtosis
  - 2\text{nd} order: energy, entropy, correlation, inertia and local homogeneity

- Detrended Fluctuation Analysis
  - Determine statistical self-affinity of time series
  - The fluctuation is then used as feature

- Sedentary behavior

![Graph showing sedentary behavior](image)

**Important Features for Deterioration Early Warning**
## Deterioration Risk Prediction

- 25 patients as samples (18 with no deterioration vs. 7 with deterioration)

### Data Flow Diagram

- **Input:** Time of discharge from hospital
- **Model:**
  - **Predict:** Will deteriorate?
  - **Output:** X days in the future

### Model Performance

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC-ROC</th>
<th>AUC-PR</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Precision</th>
<th>Accuracy</th>
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</thead>
<tbody>
<tr>
<td>NN</td>
<td>0.4002</td>
<td>0.2048</td>
<td>0.0770</td>
<td>0.9459</td>
<td>0.3333</td>
<td>0.720</td>
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<tr>
<td>KNN</td>
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<td><strong>0.6680</strong></td>
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<td><strong>0.9820</strong></td>
<td><strong>0.9130</strong></td>
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<tr>
<td>LACE</td>
<td></td>
<td></td>
<td><strong>0.7647</strong></td>
<td>0.6250</td>
<td>0.5556</td>
<td>0.7826</td>
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</tbody>
</table>

- **AUC-ROC:** area under Receiver Operating Characteristic curve
- **AUC-PR:** area under precision-recall (sensitivity) curve

**KNN achieves higher specificity and precision than LACE index.**
Predict Surgical Complications

- Patients undergoing pancreatectomy are monitored with Fitbit before surgery, during hospital stay, and 30 days post-discharge.

- Machine learning models to predict complications and readmissions.

- 54 patients enrolled (goal: 130).

Joint work with Chet Hammill (Surgery), Dingwen Li, Ruixuan Dai (CSE)
Project: Early Warning System

- Hospital inpatients are at high risk for clinical deterioration
  - Over 9% of hospitalized oncology patients deteriorate

- Predict clinical deterioration (ICU transfer and death) of patients in general wards based on clinical data in EHR

![Diagram of patient care timeline with information horizon, prediction window, and variables for prediction]

12/13/2019 Chenyang Lu
Are Accurate Alerts Enough?

- Prospective trial of real-time alerts for clinical
  - 8 general wards at Barnes-Jewish Hospital (7/2007–12/2011)

- Alerts were highly specific for clinical deterioration.
  - Patients with alerts were at nearly $5.3$ greater risk of ICU transfer and $8.9$ greater risk of death than those without alert.

- Notifying a nurse of the risk did not result in improvement in outcomes.
  - No difference in the proportion of patients who were transferred to the ICU or who died in the intervention group as compared with the control group.

- Accurate alerts does not always lead to better outcome
  - Clinicians do not know what to do with the alerts.
  - When is it going to happen? What caused the alerts?

Joint work with Thomas Bailey (Infectious Diseases), Marin Kollef (Critical Care), Yixin Chen (CSE)

Multi-Horizon Alerts

- Alerts are associated with **time horizons**
- Alerts with **multiple** horizons → more **informative**
  - Indicate different levels of urgency
  - Allow clinical decisions regarding triage, testing, and interventions.

Joint work with Marin Kollef, Patrick Lyons (Critical Care), Dingwen Li (CSE)
DeepAlerts: Deep Multi-Task Model

- Alerts at different horizons are related → multi-task learning
  - Prior knowledge regularization → exploit task relations
  - Task-specific loss balancing → avoid overfitting specific tasks

- Adult oncology inpatients from Barnes-Jewish Hospital
  - 1,939 encounters have deterioration events.

<table>
<thead>
<tr>
<th></th>
<th>AUROC</th>
<th>Sensitivity</th>
<th>Precision</th>
</tr>
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<tr>
<td>DMNN++</td>
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<td><strong>.4346(.0087)</strong></td>
</tr>
</tbody>
</table>

6-hour alerts (specificity=0.95)
- DMNN: deep multi-task neural network
- DMNN++: DMNN with prior knowledge and loss balancing
Machine Learning for Healthcare

  - Predicting clinical outcomes
  - Discover risk factors associated with outcome
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- Unleash the potential of diverse clinical data
  - Mobile Health
  - Electronic Health Record

- Synergy between AI and clinical research
  - Clinical research provides clinical insights and data
  - AI research provides rigor and powerful tools