AI for Health: A Partnership between Clinician, Patient & Data

Jenna Wiens
Morris Wellman Assistant Professor of CSE
University of Michigan, Ann Arbor
Machine Learning for Healthcare

diagnoses
medications
vitals
procedures
locations
lab results
admissions
genetics
wearables
imaging
notes

Increasing Risk
Boston Children’s Hospital, Today
The Problem:

- Physician shortage
- Physician burnout
- Medical errors

Aging baby boomers and the millions of newly insured people are expected to tax the medical profession in coming years.

Source: Association of American Medical Colleges; American Academy of Family Physicians
The Problem:

- Physician shortage
- Physician burnout
- Medical errors
The Problem:

- Physician shortage
- Physician burnout
- Medical errors

To address this sensitivity to the choice of hyperparameter, we propose the EYE penalty which is
defined as
\[
\hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \lambda \sum_{i=1}^{p} \alpha_i |\theta_i| \right\}
\]
where \(\lambda\) is a scaling factor to make EYE homogeneous and the inner set defines the level curve to fix.

Derivations of (1) and (2) are included in the Appendix. Figure 1b shows the contour plot of EYE

\[ EYE = \text{elastic net} \]

Casting our intuition mathematically yields the EYE penalty:

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i |\theta_i| \right\} \]

where \(\alpha_i\) are weights that favor 

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

We do not wish to bias the slope of level curve in the positive quadrant to approach

\[ q \]

In fact, as long as \(q\) is symmetric around both axes, we can just focus on one "corner". That is we want the "corner"

\[ \theta^* = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

where \(\alpha_i\) are weights that favor

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

\[ EYE \]

Note that since \(q\) is symmetric around both axes, we can just focus on one "corner". That is we want the "corner"

\[ \theta^* = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

where \(\alpha_i\) are weights that favor

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

\[ EYE \]

We do not wish to bias the slope of level curve in the positive quadrant to approach

\[ q \]

In fact, as long as \(q\) is symmetric around both axes, we can just focus on one "corner". That is we want the "corner"

\[ \theta^* = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

where \(\alpha_i\) are weights that favor

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

\[ EYE \]

We do not wish to bias the slope of level curve in the positive quadrant to approach

\[ q \]

In fact, as long as \(q\) is symmetric around both axes, we can just focus on one "corner". That is we want the "corner"

\[ \theta^* = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

where \(\alpha_i\) are weights that favor

\[ \hat{\theta} = \arg\min_{\theta} \left\{ \frac{1}{2} ||X\theta - y||^2 + \sum_{i=1}^{p} \alpha_i \theta_i \right\} \]

\[ EYE \]
Healthcare-associated Infections

Graft Versus Host Disease

Cystic Fibrosis

Alzheimer’s Disease

Diabetes

An Opportunity for AI
We lack an effective clinical tool for measuring patient risk.
Leverage the contents of the electronic health records (EHR) to learn accurate models for predicting *C. diff* infections (CDI)

**Our Data-Centric Approach**

Leverage the contents of the electronic health records (EHR) to learn accurate models for predicting *C. diff* infections (CDI)

Applied to UM study population: n=191,014 features: d=4,836

- AUROC=0.82 (95% 0.80-0.84)
- predicted CDI 5 days in advance

**Increasing Risk**

- [JW, JG, EH; *JMLR* 2016]
- [JO, MM, ..., JW; *ICHE* 2018]
Where do we go from here?

Collect more data
- using ambient sensing technologies

[Yeung et al., NEJM 2018]
Where do we go from here?

Key characteristics for safe and meaningful adoption

• **Accurate**
  → the model gets it **right**

• **Credible (trustworthy)**
  → **agree**, in part, with what is known

• **Robust**
  → **adapt to changes** over time & pop.

• **Actionable**
  → **how to reduce** a patient’s risk

[JW, ES; CID 2017]
We need domain expertise

- **Accurate**
  - the model gets it **right**

- **Credible (trustworthy)**
  - agree, in part, with what is known

- **Robust**
  - adapt to changes over time & pop.

- **Actionable**
  - how to reduce a patient’s risk
Incorporating domain expertise about known risk factors

\[ J(\theta, r) = \|(1 - r) \circ \theta\|_1 + \sqrt{\|(1 - r) \circ \theta\|_1^2 + \|r \circ \theta\|_2^2} \]

- favors a solution that is sparse in set of unknown & dense in known
- increased credibility and increased robustness
What can we do?
- prevent or delay (type 2)
- manage (type 1 and 2)
Lauren, PhD Student, Type I Continuous Glucose Monitor:

- Feb - Mar:
  - Avg. glucose: 144 mg/dl
  - Std. dev.: 42 mg/dl

- Mar – Apr:
  - Avg. glucose: 125 mg/dl
  - Std. dev.: 31 mg/dl
<table>
<thead>
<tr>
<th>Medication</th>
<th>Activity</th>
<th>Biological</th>
</tr>
</thead>
<tbody>
<tr>
<td>12. Medication interactions</td>
<td>17. Level of fitness/training</td>
<td>22. Recent hypoglycemia</td>
</tr>
<tr>
<td>13. Steroid administration</td>
<td>18. Time of day</td>
<td>23. During-sleep blood sugars</td>
</tr>
<tr>
<td>Environmental</td>
<td></td>
<td>25. Infusion set issues</td>
</tr>
<tr>
<td>34. Expired insulin</td>
<td></td>
<td>26. Scar tissue and lipodystrophy</td>
</tr>
<tr>
<td>35. Inaccurate BG reading</td>
<td></td>
<td>27. Intramuscular insulin delivery</td>
</tr>
<tr>
<td>36. Outside temperature</td>
<td></td>
<td>28. Allergies</td>
</tr>
<tr>
<td>37. Sunburn</td>
<td></td>
<td>29. A higher glucose level</td>
</tr>
<tr>
<td>38. Altitude</td>
<td></td>
<td>30. Periods (menstruation)</td>
</tr>
<tr>
<td>Behavioral &amp; Decision Making</td>
<td></td>
<td>31. Puberty</td>
</tr>
<tr>
<td>39. Frequency of glucose checks</td>
<td></td>
<td>32. Celiac disease</td>
</tr>
<tr>
<td>40. Default options and choices</td>
<td></td>
<td>33. Smoking</td>
</tr>
<tr>
<td>41. Decision-making biases</td>
<td></td>
<td></td>
</tr>
<tr>
<td>42. Family relationships and social pressures</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Ultimate goal - artificial pancreas

Closed loop system
• predict and deliver appropriate amount of insulin
• patient specific predictions

Requirement – generate good forecasts
[IF, RP, LA, JW; KDD 2018]

increases in blood glucose

decreases in blood glucose
AI – *augmenting* current clinical practice

**Critical need for AI for health:**

- **Reduce costs and medical errors** – clinical decision support
- **Increase global access** – mobile applications and telehealth

**Domains where ML algorithms excel**

[Images of medical images]

**Domains where humans excel**

[Image of a doctor and patient]

[AE, et al., Nature 2017]

To improve health – we need both