Learning Treatment Policies in Mobile Health

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The Dream!

“The Continually Learning Mobile Health Intervention”

• Help maintain healthy behaviors
• Help you achieve your health goals
  – Help you better trade off long term benefit with short term momentary pleasure
• The ideal mHealth intervention
  – will be there when you need it and will not intrude when you don’t need it.
  – will adjust to unanticipated life challenges
mHealth

MD2K Smoking Cessation Coach

- Wearable bands measure activity, stress, cigarette smoking, sleep quality……..
- Supportive stress-regulation interventions available on smartphone 24/7
- In which contexts should the wrist band provide supportive “cue” and smartphone activate to highlight associated support?
mHealth

HeartSteps Activity Coach

- Wearable bands measure activity, phone sensors measure busyness of calendar, location, weather, …..

- In which contexts should smartphone ping and deliver activity recommendations?
Data from wearable devices that sense and provide treatments

On each individual:

\[ O_1, A_1, Y_2, \ldots, O_t, A_t, Y_{t+1}, \ldots \]

\( O_t \): Observations at \( t^{th} \) decision time (high dimensional)

\( A_t \): Action at \( t^{th} \) decision time (treatment)

\( Y_{t+1} \): Proximal Response (aka: Reward, Cost)
Examples

1) Decision Times (Times at which a treatment can be provided.)
   1) Regular intervals in time (e.g. every 10 minutes)
   2) At user demand

HeartSteps: Approximately every 2-2.5 hours

Smoking Cessation: Every 1 minute during 10 hour day.
Examples

2) Observations, $O_t$
   1) Passively collected (via sensors)
   2) Actively collected (via self-report)

HeartSteps observations include activity recognition, location, busyness of calendar, usefulness ratings, adherence……..

MD2K smoking cessation observations include stress, smoking detection, mood,……..
Examples

3) Actions, $A_t$
   1) Treatments that can be provided at decision time
   2) Whether to provide a treatment

HeartSteps: Activity Recommendation
Smoking Cessation: Cue on wrist band
Momentary Activity Recommendation

No Message or
Examples

4) Proximal Response (reward) $Y_{t+1}$

HeartSteps: Activity (step count) over next 60 minutes.
Smoking Cessation: Stress level over next x minutes
Steps Toward Long Term Goal

1) Develop trial designs/data analytics for assessing if there are effects of the actions on the proximal response. *experimental design*

2) Develop learning algorithms for use with resulting data: assess if there are delayed effects of the actions; assess if the effects vary by context, observations; predict treatment burden. *causal inference*

3) Develop learning algorithms for using a training set to construct a “warm-start” treatment policy. *batch RL*

4) Develop online training algorithms that will result in a Personalized Continually Learning mHealth Intervention *online RL*
Micro-Randomized Trial

Randomize between actions at decision times → Each person may be randomized 100’s or 1000’s of times.

- These are sequential, “full factorial,” designs.
- Design trial to detect main effects.
Why Micro-Randomization?

• Randomization is a gold standard in providing data to assess the effect of an intervention option.

• Sequential randomizations will enhance replicability and effectiveness of treatment policy learned from data.
Micro-Randomized Trial Elements

1. Record outcomes
   – Distal (scientific/clinical goal) & Proximal Response
2. Record context (sensor & self-report data)
3. Randomize among treatment actions at decision points
4. Use data after study ends to assess treatment effects, learn warm-start treatment policy
Micro-Randomized Trial

How to justify the trial costs?

• Address a question that can be stated clearly across disciplinary boundaries and be able to provide guarantees.

• Design trial so that a variety of further interesting questions can be addressed.

First Question to Address: Do the treatment actions impact the proximal response? (aka, is there a signal?)
Micro-Randomized Trial for HeartSteps

• 42 day trial

• Whether to provide an Activity Recommendation? \( A_t \in \{0, 1\} \)

• Randomization in HeartSteps

\[ P[A_t = 1] = .4 \quad t = 1, \ldots, T \]
Micro-Randomized Trial

Time varying potentially intensive/intrusive treatment actions → potential for accumulating habituation and burden

→

Allow main effect of the treatment actions on proximal response to vary with time
Availability & the Treatment Effect

• Treatment actions can only be delivered at a decision time if an individual is available.

• The effect of treatment at a decision time is the difference in proximal response between available individuals assigned an activity recommendation and available individuals who are not assigned an activity recommendation.
Availability

• $A_t$ is only delivered if the individual is available at decision time $t$.

• Set $I_t = 1$ if the individual is available at decision time $t$, otherwise $I_t = 0$
Treatment Effect

• The Main Effect at time $j$ is

$$\beta(t) = E[Y_{t+1} | I_t = 1, A_t = 1] - E[Y_{t+1} | I_t = 1, A_t = 0]$$

• What does this main effect $\beta(t)$ mean?
Sample Size Calculation

• We calculate the number of subjects to test $H_0$: no effect of the action, i.e.,

$$H_0 : \beta(t) = 0, t = 1, 2, \ldots, T$$

• Size to detect a low dimensional, smooth alternate $H_1$.
  – Example: $H_1$: $\beta(t)$ quadratic with intercept, $\beta_0$, linear term, $\beta_1$, and quadratic term $\beta_2$ and test

$$\beta_0 = \beta_1 = \beta_2 = 0$$
Sample Size Calculation

• Our test statistic uses estimators from a “generalization” of linear regression.

• The test statistic is quadratic in the estimators of the $\beta$ terms.

• Given a specified power to detect the smooth alternative, $H_1$, a false-positive error prob., and the desired detectable signal to noise ratio, we use standard statistics to derive the sample size.
Sample Size Calculation

Alternative hypothesis is low dimensional → assessment of the effect of the activity recommendation uses contrasts of between subject responses + contrasts of within subject responses.

--The required number of subjects will be small.
<table>
<thead>
<tr>
<th>Standardized Average Main Effect over 42 Days</th>
<th>Sample Size For 70% availability or 50% availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.06 standard deviations</td>
<td>81 or 112</td>
</tr>
<tr>
<td>0.08 standard deviations</td>
<td>48 or 65</td>
</tr>
<tr>
<td>0.10 standard deviations</td>
<td>33 or 43</td>
</tr>
</tbody>
</table>
The micro-randomized trial is a sequential factorial trial with multiple factors, e.g.

Factor 1: Activity recommendation is randomized 5 times per day

Factor 2: Daily activity planning is randomized each evening
Experimental Design Challenges

Micro-randomized trials are a new type of factorial design

i. Time varying factors $\rightarrow$ time varying main effects, time-varying two-way interactions, different delayed effects

ii. Randomization that depends on an outcome of past actions

iii. Design studies specifically to detect interactions between factors.
Steps Toward Long Term Goal

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Treatment policies

- Most current treatment policies are constructed using behavioral theory, clinical experience, observational data analyses and expert opinion.

- We aim to develop algorithms for use with data in constructing treatment policies.
  -- treatment policy should be interpretable.
  -- treatment policy can act as a “warm-start” in future implementation of an online algorithm.
Stochastic Treatment Policy

Construct a parameterized policy, $\pi_\theta(a|s)$

- Ensure $\pi_\theta(a|s)$ probabilities bounded away from 0 and 1: variation in actions can help retard habituation and maintain engagement.
- Parameterized $\pi_\theta(a|s)$ can be interpreted/vetted by domain experts
Setup

1) On each of \( n \) individuals, data set contains:

\[ S_1, A_1, Y_2, \ldots, S_T, A_T, Y_{T+1} \]

-- \( S_t \) is a summary of \( O_1, A_1, Y_2, \ldots, Y_t, O_t \) that permits the Markovian property; this is a modeling assumption.

-- known randomization

\[ P[A_t = a | S_t = s] = \mu(a | s) \]

2) Optimality criterion to maximize: Average Reward resulting from use of policy \( \pi_\theta \)
Markov Decision Process

Markovian Assumptions

\[ P[S_{j+1} = s' | S_1, A_1, \ldots, S_j, A_j] = P[S_{j+1} = s' | S_j, A_j] \]

and

\[ P[Y_{j+1} = r | S_1, A_1, \ldots, S_j, A_j] = P[Y_{j+1} = r | S_j, A_j] \]

Stationarity Assumptions

\[ P[S_{j+1} = s' | S_j = s, A_j = a] = p(s' | s, a) \]

and

\[ E[Y_{j+1} | S_j = s, A_j = a] = r(s, a) \]
Optimality Criterion (to maximize)

Average Reward, $\eta_{\theta}$, for policy $\pi_{\theta}$:

$$
\eta_{\theta} = \lim_{T \to \infty} \frac{1}{T} E_{\theta} \left[ \sum_{t=0}^{T-1} Y_{t+1} \bigg| S_0 = s_0 \right]
$$

$$
= \sum_s d_{\theta}(s) \sum_a \pi_{\theta}(a|s)r(s,a)
$$

$E_{\theta}$ denotes expectation under the stationary distribution, $d_{\theta}$, associated with $\pi_{\theta}$. 

Background: Differential Value

$V_\theta$ is the Differential Value

$$V_\theta(s) = \lim_{T \to \infty} E_\theta \left[ \sum_{t=0}^{T} \left( Y_{t+1} - \eta_\theta \right) \bigg| S_0 = s \right].$$

$V_\theta(s) - V_\theta(s')$ reflects the difference in sum of centered responses accrued when starting in state $s$ as opposed to state $s'$.

($\eta_\theta$ is the average reward)
Background: Bellman Equation

Oracle Temporal Difference:

\[ \delta_t = Y_{t+1} - \eta \theta + V_\theta(S_{t+1}) - V_\theta(S_t) \]

Bellman Equation:

\[ E_\theta \left[ \delta_t \left| S_t \right. \right] = 0 \]

\( S_t, A_t, Y_{t+1}, S_{t+1} \)
Bellman’s equation implies that

\[ E \left[ \frac{\pi_\theta(A_t|S_t)}{\mu(A_t|S_t)} \left( Y_{t+1} - \eta + V(S_{t+1}) - V(S_t) \right) \left( \frac{1}{f(S_t)} \right) \right] \]

will be, for all \( t \), for any vector, \( f(.) \), of appropriately integrable functions, and expectation over data generating distribution, \( E \), equal to 0 if \( \eta = \eta_\theta \), \( V = V_\theta \)
Estimating Function

• Construct a flexible model for, $V_\theta(s)$, say $f(s)^T v_\theta$ for $f(s)$ a $p$ by 1 vector of basis functions evaluated at $s$ ($p$ is large)

• Solve

$$\mathbb{P}_n \left[ \sum_{t=1}^{T} \frac{\pi_\theta(A_t|S_t)}{\mu(A_t|S_t)} \left( Y_{t+1} - \eta + f(S_{t+1})^T v - f(S_t)^T v \right) \left( \begin{array}{c} 1 \\ f(S_t) \end{array} \right) \right] = 0 \text{ for } \hat{\eta}_\theta, \hat{v}_\theta$$

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Overview of Algorithm

• The resulting $\eta$ and $\nu$ are functions of $\theta$, denote by $\hat{\eta}_\theta$, $\hat{\nu}_\theta$
  • $\hat{\eta}_\theta$, $\hat{\nu}_\theta$ are the output of the Critic
• The Actor maximizes $\hat{\eta}_\theta$ over $\theta$ to obtain $\hat{\theta}$.
  • this will require repeated calls to the Critic
• $\hat{\theta}$ is the output of the Actor
Actor

- The objective function for the actor is given by

\[
\hat{\eta}_\theta = \mathbb{P}_n \left[ \sum_{t=1}^{T} \frac{\pi_\theta(A_t|S_t)}{\mu(A_t|S_t)} \left( Y_{t+1} + f(S_{t+1})^T \hat{\nu}_\theta - f(S_t)^T \hat{\nu}_\theta \right) \right]
\]

- We want to construct a policy, \( \pi_\theta \) that is bounded away from 0, 1.

Binary action: \( \pi_\theta(a|s) = \frac{e^{\theta^T g(s) a}}{1 + e^{\theta^T g(s)}} \)
Actor

Chance constraint on $\theta$:

$$\min_a P^* \left[ p_0 \leq \pi_\theta(a|S) \leq 1 - p_0 \right] \geq 1 - \alpha$$

given $\alpha$, $p_0$ and $P^*$, a reference distribution over states, $S$.

This constraint is nonconvex; we relax via Markov inequality.
Write

\[
\mathbb{P}_n \left[ \sum_{t=1}^{T} \frac{\pi_t(A_t|S_t)}{\mu(A_t|S_t)} \left( Y_{t+1} - \eta + f(S_{t+1})^T v - f(S_t)^T v \right) \left( \begin{array}{c} 1 \\ f(S_t) \end{array} \right) \right] \\
= \hat{A}_\theta \begin{pmatrix} \eta \\ v \end{pmatrix} - \hat{b}_\theta
\]

The critic minimizes

\[
\| \hat{A}_\theta \begin{pmatrix} \eta \\ v \end{pmatrix} - \hat{b}_\theta \|^2 + \lambda_c \|v\|^2
\]

to obtain

\[
\hat{\eta}_\theta, \ \hat{v}_\theta
\]
The actor obtains $\hat{\theta}$ by maximizing

$$\hat{\eta}_\theta = \mathbb{P}_n \left[ \sum_{t=1}^T \frac{\pi_\theta(A_t|S_t)}{\mu(A_t|S_t)} \left( Y_{t+1} + f(S_{t+1})^T \hat{v}_\theta - f(S_t)^T \hat{v}_\theta \right) \right]$$

subject to the constraint, $\theta^T \Sigma_g \theta \leq k_{max}$

$$\Sigma_g = T^{-1} \sum_{t=1}^T E^* [g(S_t)g(S_t)^T]$$
BASICS Mobile

• Smartphone-based intervention to curb heavy drinking and smoking in college students
  – 14 day study
  – Self-report 3x/day (morning, afternoon, evening)
  – Intervention 2x/day (afternoon, evening)
    • Mindfulness-based intervention \( A_t = I \) vs general health information \( A_t = 0 \)
• Question: Should a mindfulness-based intervention (vs general health info) be provided when there is an increase in need to self-regulate?
BASICS Mobile

- n subjects = 27, T decision points = 28
- Availability: To be available to receive a treatment, the student must complete self-report questions (I_t = 1). If the student is available then the student is provided a treatment with probability 2/3.
- Reward is (-)smoking rate
BASICS Mobile

- $S_t$ is 8 dimensional composed of 5 discrete and 3 continuous valued features.
- Differential value approximated by B-splines and two way products of B-splines constructed from entries in $S_t$.
- Parameterized policy:

$$\pi_\theta(1|s) = I_t \frac{e^{\theta_0 + \theta_1 g_1 + \theta_2 g_2}}{1 + e^{\theta_0 + \theta_1 g_1 + \theta_2 g_2}}$$
BASICS Mobile

- $g_1$ is indicator for an increase in self-control demands (1 if yes, 0 if no)
- $g_2$ is indicator for no burden (1 if yes, 0 if no)
- $\hat{\theta}_0 = .74$, $\hat{\theta}_1 = - .95$, $\hat{\theta}_2 = 2.26 \rightarrow$ An available student with no increase in self-control demands and who is not indicating burden is recommended treatment with probability 0.85

$$\pi_{\theta}(1|s) = It \frac{e^{\theta_0 + \theta_1 g_1 + \theta_2 g_2}}{1 + e^{\theta_0 + \theta_1 g_1 + \theta_2 g_2}}$$
Challenges

• Bandit vs Average Reward vs Discounted Reward?
  – Burden → disengagement raises the need to pay attention to future.
  – In batch setting and/or online setting?

• Any method should provide confidence intervals/permit scientists to test hypotheses.

• Computational problems…….
General Challenges

• How to reduce the amount of self-report data (How might you do this?)

• How to accommodate/utilize the vast amount of missing data, some of which will be informative…….

• Measuring burden without causing burden.

• How to best incorporate burden into learning?

• Incorporating delayed rewards
Collaborators