Micro-randomized Trials in Mobile Health

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Future of Data Science
mHealth

MD2K Smoking Cessation Coach

- Wearable chest and wrist bands measure activity, stress, cigarette smoking……..
- 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 band measures 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:

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

- \( O_t \): Context at \( t^{th} \) decision time (high dimensional)
- \( A_t \): Action at \( t^{th} \) decision time (treatment)
- \( Y_{t+1} \): Proximal Response (aka: Reward, Cost)
Data

1) Decision Times, $t$: Times at which a treatment can be pushed to user.

   1) Regular intervals in time (e.g. every 10 minutes)
   2) At user demand

HeartSteps: Approximately every 2-2.5 hours
Data

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

HeartSteps: activity recognition, location, busyness of calendar, step count, usefulness ratings, adherence…….
Treatment

3) Actions, $A_t$
   1) Type of Treatment
   2) Whether to provide a treatment

HeartSteps: Activity Recommendation
Activity Recommendation

No Message or
Data

4) Proximal Response, $Y_{t+1}$

HeartSteps: Activity (step count) over next 60 minutes.
Data Science mHealth Roadmap

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

2) Develop learning algorithms for use with resulting data to assess if there are delayed effects of the actions; assess if the effects vary by context. *causal inference*

3) Develop learning algorithms for using resulting data 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.
Micro-Randomized Trial for HeartSteps

• 42 day trial

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

• Randomization in HeartSteps

$P[A_t = 1] = 0.4 \quad t = 1, \ldots, T$
Micro-Randomized Trial

Time varying potentially intensive/intrusive treatment actions $\rightarrow$ potential for accumulating habituation and burden

$\rightarrow$

Allow 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.
Treatment Effect

- \( \mu(t) \) denotes the treatment effect at decision time \( t \).
- What does this treatment effect, \( \mu(t) \), mean???
Sample Size Calculation

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

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

• Size to detect a low dimensional, smooth alternate $H_1$.
  – Example: $H_1$: $\mu(t)$ quadratic with intercept, $\mu_0$, linear term, $\mu_1$, and quadratic term $\mu_2$ and test

  $$\mu_0 = \mu_1 = \mu_2 = 0$$
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.
Sample Size Calculation

Given a specified power to detect the smooth alternative, a false-positive error probability, and the desired detectable signal to noise ratio, we use statistics, aka “data science!” to derive the sample size.
### HeartSteps Sample Sizes

**True-positive power** = 0.80, **False-positive error** = 0.05

<table>
<thead>
<tr>
<th>Signal/Noise ratio over 42 days</th>
<th>Sample Size for 70% availability or 50% availability</th>
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</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>
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Steps Toward Long Term Goal

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General Challenges

- How to reduce the amount of self-report data (How might you do this?)
- Missing data
- Detection of outcomes using sensor data
- Predictors of latent states, predictors of outcomes (using sensor data)
- Measuring treatment fatigue without causing treatment fatigue.
- Incorporating delayed rewards
The mHealth Dream!

“Continually Learning Mobile Health Intervention”

• 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
Why Micro-Randomization?

• Randomization is the gold standard for providing data to assess the effect of a treatment action.

• Sequential randomizations will enhance replicability and effectiveness of treatment policy learned from data.