A/B Testing in Crowdsourcing & Personalizing Interventions

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NUS, School of Computing, Information Systems & Analytics, NUS-HCI Lab

[I’m originally from the Caribbean, Trinidad and Tobago]
Enhance Health Behavior Change & Learning

Mental & Physical Health

- Depression
- Smoking

Cognitive Behavior Therapy

- theMoodGym

Exercise, Nutrition & Eating

- Reflection Prompts to Explain
- Motivational Messages & Reminders to Plan

Improving Outcome of Psychosocial Treatments by Enhancing Memory, 2014

Learning Cognitive Behavior Therapy 2015
Approach: Making Experiments Collaborative, Dynamic, Personalized

Dynamic Analysis

Outcome Metric

Enhancement

Personalization

Continually add conditions

AdapComp/MOOClet

github.com/kunanit/mooclet-engine

HCI

Cognitive Science

Instructional Design

Crowdsourcing & Human Computation

Bayesian Statistics & Machine Learning

Cognitive Science 2010
J. of Exp. Psych., 2013

EDM 2015
IJAIED 2016

CHI 2016,
ACM LAS 2016

NIPS 2008, UAI 2013
ACIC 2016
Overview

• Making A/B Experiments Collaborative, Dynamic, Personalized
• Crowdsourcing explanations and using Machine Learning to choose the highest rated
• Personalizing Motivational Messages
• Future: How to apply to health behavior change?
  – Cognitive Behavior Therapy
  – Exercise
  – Eating
  – What other settings?
Enhance Health Behavior Change & Learning

Mental & Physical Health

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Exercise, Nutrition & Eating

- Improving Outcome of Psychosocial Treatments by Enhancing Memory, 2014
- Learning Cognitive Behavior Therapy 2015
x = matrix(rnorm(m*n),m,n)
What is the standard error?

Answer: [Blank]

Explanation
A z-score is defined as the number of standard deviations a specific point is away from the mean.

CHI 2016

Explain why this answer is correct.

A | B | ... | N
Continually add conditions

Analyze & Dynamically Adapt

A | B
X% | 100-X%

ACM Learning @ Scale 2016
(Nominee for best paper)

Renkl, 1997
Linda is training for a marathon, which is a race that is 26 miles long.

Her average training time for the 26 miles is 208 minutes, but the day of the marathon she was \(x\) minutes faster than her average time.

What was Linda's running speed for the marathon in miles per minute?

\[
\frac{26}{(208 - x)}
\]

Explanation

Linda's speed is the distance she ran divided by the time it took. The distance Linda ran was 26 miles. The time it took her was 208 – \(x\). Linda's speed was \(\frac{26}{(208 - x)}\)

How helpful was the above information for your learning?

Completely Unhelpful

Unhelpful

Helpful

Perfectly Helpful

0 1 2 3 4 5 6 7 8 9 10

To help you learn, explain in your own words why the answer is correct.

Explanation

C
Dynamic Experimentation: Exploration vs Exploitation

- Multi-Armed Bandit (Reinforcement Learning)
- Randomized Probability Matching (Thompson Sampling)

Action $a \in A$

Reward $R$

Policy $\pi$

Parameters $\theta$

$\epsilon_i \sim \text{Beta}(\alpha, \beta)$ (Probability of Explanation being Rated Helpful)

$R \sim \text{Bin}(10, \epsilon_i)$ (0 to 10 Rating by Student)

$P(\theta|D) \propto \prod P(r_i|a_i, x_i, \theta)P(\theta)$

Explanation
The probability is $3/7 \times 5/8$, because the number of cookies is changing.

Rating
How helpful was the above information for your learning?

0       1       2       3       4       5       6       7       8       9       10

<table>
<thead>
<tr>
<th>Exp 1</th>
<th>Exp 2</th>
<th>Exp 3</th>
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<tbody>
<tr>
<td>15%</td>
<td>65%</td>
<td>20%</td>
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</table>

(Probability of Explanation being Rated Helpful)
Multi-Armed Bandits (subset of Reinforcement Learning)

**Bandit**
- Action $a \in A$
- Reward $a \in A \rightarrow R$
- Policy $\pi : a_t, t \in [1, \ldots n]$

**Contextual Bandit**
- Action $a \in A$
- Context $c \in C$
- Reward $(c \in C) \times (a \in A) \rightarrow R$
- Policy $\pi : a_t | c_t$

MDP Markov Decision Process from RL

- State $s \in S$
- Action $a \in A$
- Reward $(s \in S) \times (a \in A) \rightarrow R$
- Transition Probabilities $T : P(s' \mid s, a)$
- Policy $\pi : a \mid s$
Model of Explanation Quality and Learner Ratings

\[ \epsilon_i \sim \text{Beta}(\alpha, \beta) \quad R \sim \text{Bin}(10, \epsilon_i) \]

(Probability of “Good” Rating) (0 to 10 Rating by Student)

\[ \epsilon_{i,t} \sim \text{Beta}(\alpha, \beta) \]

\[ R_{i,t} = 8 \]

\[ \epsilon_{i,t+1} \sim \text{Beta}(\alpha + 8, \beta + 2) \]

\[ P(\theta | D) \propto \prod P(r_i | a_i, x_i, \theta) \tilde{P}(\theta) \]

Require: \( \alpha, \beta \): hyperparameters of the beta prior
1: initialize \( n_{a,0} = n_{a,1} = i = 0 \) for all \( a \)
2: repeat
3: for \( a = 1, \ldots, K \) do
4: \[ \tilde{w}_a \sim \text{beta}(\alpha + n_{a,1}, \beta + n_{a,0}) \]
5: end for
6: \[ a_i = \arg \max_a \tilde{w}_a \]
7: Observe \( y_i \) by pulling arm \( a_i \)
8: if \( y_i = 0 \) then
9: \[ n_{a_i,0} = n_{a_i,0} + 1 \]
10: else
11: \[ n_{a_i,1} = n_{a_i,1} + 1 \]
12: end if
13: \[ i = i + 1 \]
14: until stopping criterion reached
• AXIS deployed with n=150

AXIS Policy: Probability distribution over explanations

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<td>1</td>
<td>18</td>
<td>13</td>
<td>4</td>
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<td>8</td>
<td>18</td>
<td>22</td>
<td>6</td>
<td>3</td>
<td>1</td>
<td>2</td>
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</table>
• Do AXIS explanations help learning?

Problem: x = matrix(rnorm(m*n),m,n)
What is the standard error?

Answer: 

Problem: x = matrix(rnorm(m*n),m,n)
What is the standard error?

Answer: 

AXIS Explanation

Problem: x = matrix(rnorm(m*n),m,n)
What is the standard error?

Answer: 

Filtered Explanation

Problem: x = matrix(rnorm(m*n),m,n)
What is the standard error?

Answer: 

Instructor Explanation
Impact of AXIS Explanations on Learning

Instructor reported the AXIS explanations comparable to their own.

Accuracy Increase

0% 10% 20%

Original Problems (No Explanations)  AXIS Explanations  Filtered Explanations  Instructor's Explanations

3% 12% 2% 9%
Contributions

• Crowdsourcing from self-interested contributors
• Dynamic experimentation put data into practice
Discover how to personalize email messages

Emails
Dear Sam,

Would you please take this short survey, so we can improve the course for future students?

Click here to take the survey.

Note:
- Brief Message: 
  Would you please take this short survey, so we can improve the course for future students?
- Mention Absence: 
  It has been a while since you logged into the course, so we are eager to learn about your experience. Would you please take this short survey, so we can improve the course for future students?
Optimization through Personalization

• 14.5% more responses

Personalization

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Review

• Making A/B Experiments Collaborative, Dynamic, Personalized
• Crowdsourcing explanations and using Machine Learning to choose the highest rated
• Personalizing Motivational Messages
• Future: How to apply to health behavior change?
  – Cognitive Behavior Therapy
  – Exercise
  – Eating
  – What other settings?
Enhance Health Behavior Change & Learning

Mental & Physical Health

Exercise, Nutrition & Eating

Improving Outcome of Psychosocial Treatments by Enhancing Memory, 2014

Learning Cognitive Behavior Therapy 2015

Reflection Prompts to Explain

Motivational Messages & Reminders to Plan
• Combine humans & algorithms to solve problems
• Generate actions (explanations)
• Reward signals (ratings)
• Encode expert prior knowledge
• Interpretable Machine Learning
• Interactive Machine Learning
Tool for Involving Instructors in Co-Design of Experiments

Teachers

Social-Behavioral Scientists

On-Campus Courses

Enhancement

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<th>A</th>
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Dynamic Analysis

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<th>A</th>
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<tbody>
<tr>
<td>X%</td>
<td>100-X%</td>
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CHI (2017, in prep)
Teacher Experimentation on Problems

- Go to URL tiny.cc/cdesite to use the app
Design of Learning Tips, Hints, & Explanations

Click below to add and edit different versions of feedback messages that will be shown when a student chooses this answer.

Add new version

1. Answer: 20
   Edit this Version

2. Hint: What kind of sampling does this correspond to?
   Edit this Version

3. Solution: To assign a season to each person, we sample with replacement from the set of 4 seasons. By Bose-Einstein, there are
   $(4 + 3 - 1 \text{ choose } 3) = (6 \text{ choose } 3) = 6!/(3!*3!) = (6*5*4)/6 = 20$
   possibilities.
   Edit this Version

View Ratings of Feedback Messages

- View Data and Policy Dashboard

Change Method for choosing Versions

Enter Instructor Judgments about Versions

Choose which method or Policy should be used for assigning versions of feedback messages to students.

Policy: thompson_sampling  Save
<table>
<thead>
<tr>
<th>Explanation</th>
<th>Probability</th>
<th>Mean</th>
<th>Student Rating</th>
<th>Number of Students</th>
<th>Standard Deviation of Rating</th>
<th>Standard Error of the Mean</th>
<th>Instructor Rating</th>
<th>Instructor Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantitative</td>
<td>0.23</td>
<td>7.26</td>
<td>46.00</td>
<td>1.87</td>
<td>0.28</td>
<td>7/10</td>
<td>2/5</td>
<td></td>
</tr>
<tr>
<td>Analogical</td>
<td>0.77</td>
<td>7.48</td>
<td>56.00</td>
<td>1.59</td>
<td>0.21</td>
<td>5/10</td>
<td>2/5</td>
<td></td>
</tr>
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Overview

- Motivation & Reflection
- Adaptive eXplanaation Improvement System (AXIS)
- Discovering how to personalize
- Future
Overview

- Motivation & Reflection
- Adaptive eXplanation Improvement System (AXIS)
- Discovering how to personalize
- Future
Future

• 1. Bridging Designers, Social-Behavioral Scientists, & Machine Learning
• 2. Enhancing Mental & Physical Health via Learning to Change Habits & Behavior
1. Bridging Designers, Scientists, Machine Learning

Enhancing and Personalizing Online Resources through Tools for Experimentation (under review)
Interpretable & Interactive Interfaces to ML

Designers

Social-Behavioral Scientists

Statistics & Machine Learning

Interpretable ML

Interactive ML

Designer influences exploration vs exploitation tradeoff?

Encode designer/scientist’s prior knowledge via Bayesian models?

<table>
<thead>
<tr>
<th>Probability of Version</th>
<th>Mean Student Rating</th>
<th>Number of Students</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.49</td>
<td>4.3</td>
<td>3</td>
</tr>
<tr>
<td>0.51</td>
<td>5.2</td>
<td>5</td>
</tr>
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AdapComp/MOOClet Software Requirements Specification for Experiments

**AdapComp**

Python/Django web app
github.com/kunanit/mooclet-engine

**AdapComp API Specification**

<table>
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<tr>
<th>Endpoint</th>
<th>Parameters</th>
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<tbody>
<tr>
<td>getLearnerContext</td>
<td>learner_id</td>
</tr>
<tr>
<td>getPastRewards</td>
<td>adapcomp_id</td>
</tr>
<tr>
<td>assignLearnerCondition</td>
<td>learner_id, adapcomp_id, condition</td>
</tr>
</tbody>
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ACM LAS 2017, RecSys Poster, Ongoing
MOOClet Engine: Separates Versions, Policy, Data

Learner Interface

Resource

API/ assignVersionofResource

MOOClet

Version Set

API/ modifyVersion

Policy

API/ setPolicyandParams

Learner Data Store

API/ modifyVariable

github.com/kunanit/mooclet-engine
test.mooclet.vpal.io/moocletengine/api/
Dynamic Experiments as Testbeds for Algorithms & Models

Statistics & Machine Learning

MOOClet/AdapComp

Abstraction for Reinforcement Learning

AdapComp API Specification

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<tr>
<td>getLearnerContext</td>
<td>learner_id</td>
<td>{age: 28, days_active: 2, ...}</td>
</tr>
<tr>
<td>getPastRewards</td>
<td>adapcomp_id</td>
<td>{learner_id1: reward_value, learnerid2: ...}</td>
</tr>
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<td>assignLearnerCondition</td>
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<td>{learner_id, adapcomp_id, condition}</td>
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1. Bridging Designers, Scientists, Machine Learning

Designers → A, B, ..., N → Social-Behavioral Scientists → Statistics & Machine Learning
2. Mental & Physical Health: Habit & Behavior Change

Improving Outcome of Psychosocial Treatments by Enhancing Memory, 2014

Learning Cognitive Behavior Therapy 2015

Enhancing Mental Health through Scalable Training for Peer Counselors

*CHI Computing & Mental Health Workshop, 2017*

Reflection Prompts to Explain

Motivational Messages & Reminders to Plan
**Conclusion**

- **Vision:** Perpetually Improving Systems
- **Approach:** Collaborative, Dynamic, Personalized Experimentation
- **Motivation & Reflection**
- **Adaptive eXplanation Improvement System (AXIS)**
- **Discovering how to personalize**
- **Future**
  - Bridging Designers, Social-Behavioral Scientists, & Machine Learning
  - Enhancing Mental & Physical Health via Learning to Change Habits & Behavior
Thank You!

- Juho Kim, Krzysztof Gajos, Anna Rafferty
- Harvard VPAL (Vice Provost for Advances in Learning) Research
- Tania Lombrozo & Tom Griffiths
- Candace Thille & John Mitchell
- Jascha Sohl-Dickstein, PERTS, Khan Academy
- Sam Maldonado
- Lytics Lab
Conclusion

Vision: Perpetually Improving Systems
Approach: Collaborative, Dynamic, Personalized Experimentation
Motivation & Reflection
Adaptive eXplanation Improvement System (AXIS)
Discovering how to personalize
Future
– Bridging Designers, Social-Behavioral Scientists, & Machine Learning
– Enhancing Mental & Physical Health via Learning to Change Habits & Behavior
B. Co-Creation of Experiments by Designers & Scientists

Designers + Social-Behavioral Scientists

Product Design

Instructor/Researcher Interface

On-Campus

Alternative Feedback Messages for Answer

Click below to add and edit different versions of feedback messages that will be shown when a student chooses this answer.

1. When a program’s impact is lower, the statistical power to detect an effect is reduced. So a larger sample size is needed to compensate and maintain statistical power – keep ...

2. When a program’s impact is lower, the statistical power to detect an effect is reduced. So a larger sample size is needed to compensate and maintain statistical power – keep ...

Add new version

View Ratings of Feedback Messages
Balance Practical Impact against Scientific Research

Designers | Social-Behavioral Scientists
---|---
Enhancement

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Dynamic Analysis

A | B
---|---
X% | 100-X%

Making research practical: “a valuable tool. Putting in the hands of the teacher to understand how their students learn. Not just in broad terms, but specifically in their course” “you must know plenty of general things about how students learn, whereas I know specific things about how they get calculus”

Directly helping students: “improved the experience of many of the students by giving them answers that are more helpful… the earlier ones can help improve the experience of the later students. That’s pretty neat”

<table>
<thead>
<tr>
<th>Version</th>
<th>Probability of Condition</th>
<th>Mean Student Rating</th>
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<th>Instructor Prediction of Quality</th>
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<tbody>
<tr>
<td>1. Quantitative Explanation</td>
<td>0.23</td>
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