Virtual advisors have proven useful
One size does not fit all

(a) Focused content, large-load, graphical morph
(b) General, small-load, verbal morph

Outline of presentation

• Theory
  - selecting a “morph” if we know the cognitive style
  - selecting a “morph” if the cognitive style is a latent construct
    • inferring cognitive style of visitors
    • empirically-grounded synthetic visitors

• Empirical
  - priming study (835 respondents); priors and preferences matrix
  - creating the websites (Gen-1, Gen-2); website design recommendations

• Other applications

Cognitive styles and website characteristics (details later)

Cognitive-style dimensions (2 x 2 x 2 x 2)
• leader vs. follower
• analytic/visual vs. holistic/verbal
• impulsive vs. deliberative
• (active) reader vs. (passive) listener

Website characteristics (2 x 2)
• graphical vs. verbal presentations
• small- vs. large information load
• focused vs. general content
Key Challenges

Fundamental Problems are general and application independent (morphs can be sites, products, ..)

- How do we update our beliefs about the cognitive style of each user?
- Given these beliefs, what is the optimal morph (optimal website version to use)

Our task

- 16 cognitive styles, lots of links on a page
- We have population-level information, but we know nothing about site users
- We need to update beliefs about cognitive styles after a stream of clicks,
- Once we have sufficient information, we might morph to a more optimal site

Morphing Method
Respondent enters website. Observe purchase opportunity. Visitor either purchases or not.

Update beliefs (\(\alpha_n', \beta_n'\)) about purchase probabilities using observed purchase opportunity and prior beliefs (\(\alpha_{n-1}', \beta_{n-1}'\)).

Compute new morph-assignment rule (using posterior purchase probability distributions).

Dynamic-programming loop (after each respondent)

Cognitive-style inference loop (dashed box, potentially after each click)

Assign initial morph, \(m_o\), based on prior beliefs about cognitive styles, \(r_n\).

Website visitor sees morph, \(m\), and clicks on one of \(J_k\) alternatives.

Bayesian update of cognitive style, \(r_n\), based on clickstream.

Assign morph based on current morph-assignment rule and updated cognitive-state probabilities.

Visitor goes to purchase opportunity. Visitor saw optimal morph, \(m_r^*\), based on updated beliefs about cognitive styles.

Summarizing our knowledge (assume we know cognitive style)

- We update priors on purchase probabilities, \(p_{rmn}\)
  - priors are beta distributed with parameters, \(\alpha_{rmn}\) and \(\beta_{rmn}\)
  - \(\alpha_{rmn}\) and \(\beta_{rmn}\) set with priming study (or weakly informative)
  - \(\alpha_{rmn}\) and \(\beta_{rmn}\) updated with standard beta-binomial updating

- Given \(\alpha_{rmn}'s\) and \(\beta_{rmn}'s\), we need to choose the optimal morph, \(m_r^*\)
  - exploitation: benefit immediately from highest expected probability
  - exploration: try a different morph to learn about its probability
    - in morphing discount factor is much closer to 1.0 than typical
    - 100,000 visitors per annum
    - vs. clinical trials, optimal experiments, job search, oil exploration, technology choice, and research & development

Dynamic optimization (assume we know cognitive style)

Framed as a "multi-arm bandit" as solved optimally by Gittins in 1979.

"[The bandit problem] was formulated during World War II, and efforts to solve it so sapped the energies and minds of Allied analysts that the suggestion was made that the problem be dropped over Germany, as the ultimate instrument of intellectual sabotage."

> John Whittle before the Royal Statistical Society in 1979

\[
R(\alpha_{rmn}, \beta_{rmn}, \theta) = \max \left\{ \sum_{\theta=1}^{\alpha_{rmn}} \frac{\alpha_{rmn}}{\alpha_{rmn} + \beta_{rmn}} \left[ 1 + \frac{\alpha_{rmn}}{\beta_{rmn}} \frac{\alpha_{rmn}}{\beta_{rmn}} \frac{\theta}{\theta + 1} \right] \right. \\
\left. + \frac{\beta_{rmn}}{\alpha_{rmn} + \beta_{rmn}} \frac{\alpha_{rmn}}{\beta_{rmn}} \right\}.
\]
Optimal solution with Gittins’ indices (assume we know cognitive style)

Gittins’ indices for the eight morphs.

System experiments with Morph 3 for a while before settling back to Morph 2.

Morph that was chosen.

POMDP: Cognitive styles are latent!

- We have, at best, beliefs about the cognitive-style segments
  - \( q_r \) = probability that the \( n \)th visitor belongs to segment \( r \)
  - Expected Gittins Index allows assigning observations to \( q_r \), maintaining indexability (Krishnamurthy & Michova, 1999)

- Visitors have preferences, \( \Omega \), for "click-alternative" characteristics
  - If we know characteristics and \( \Omega \), we can predict choice
  - Assume a logit model (extreme-value errors), estimate \( \Omega \)

- If we observe clicks and know \( \Omega \), we can compute \( q_r \) with Bayes Thm

\[
q_r = \frac{\prod_i \prod_j \prod_k \prod_m \prod_n q_r^m \cdot \Omega^n \cdot \Omega_j \cdot \Omega_k \cdot \Omega_m}{\sum \prod_i \prod_j \prod_k \prod_m \prod_n q_r^m \cdot \Omega^n \cdot \Omega_j \cdot \Omega_k \cdot \Omega_m}
\]

Empirically-grounded synthetic visitors (normalize profit to 1.0)

<table>
<thead>
<tr>
<th></th>
<th>Expected Reward</th>
<th>Improvement</th>
<th>Efficiency</th>
<th>Relative Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Gittins’ loop nor knowledge of cognitive styles.</td>
<td>0.3205</td>
<td>0.0%</td>
<td>60.4%</td>
<td>0.0%</td>
</tr>
<tr>
<td>No morphing: Website chosen optimally by Gittins’ loop.</td>
<td>0.3625</td>
<td>13.1%</td>
<td>91.0%</td>
<td>53.9%</td>
</tr>
<tr>
<td>Morphing: Match characteristics to cognitive style</td>
<td>0.3844</td>
<td>19.9%</td>
<td>96.5%</td>
<td>82.0%</td>
</tr>
<tr>
<td>Bayesian inference of cognitive styles (10 clicks)</td>
<td>0.3865</td>
<td>20.6%</td>
<td>97.0%</td>
<td>84.7%</td>
</tr>
<tr>
<td>Perfect information on cognitive styles. Gittins’ loop.</td>
<td>0.3879</td>
<td>21.9%</td>
<td>97.4%</td>
<td>85.3%</td>
</tr>
<tr>
<td>Perfect information on style and purchase probabilities*</td>
<td>0.3984</td>
<td>24.3%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

*Upper bounds. BT does not have perfect information on either cognitive style or purchase probabilities.
Priming study

- 835 respondents in target market
- explore one of eight morphs, chosen randomly
- pre- and post- consideration and purchase intent
- conjoint-like exercise on 2^3 design of morphs (paired comparison)
- direct measurement of cognitive-styles

- provides initial segment x morph probabilities, \( p_{rmo} \)
- provides data with which we estimated \( \Omega \)

Measures of cognitive styles

We infer posterior distribution of \( \Omega \)

- Reverse of inference process for \( q_{rb} \)

- Observe
  - click choice
  - characteristics of website and clicks
  - cognitive styles

- Infer preferences for characteristics for each cognitive-style segment

- Bayesian inference with MCMC methods (standard logit likelihoods)