Two main tasks

• Develop models of training and investigate training principles
  – In Collaboration with Purdue: IBLT models of intermixed SRC and Simon effects in ACT-R
  – In Collaboration with U of Colorado: Comparison of Instance and Strategy Models in ACT-R

• Building an integrated and easy to use instance-based decision making modeling tool
  – the tool will create a computational framework with ACT-R mechanisms relevant to the Instance-Based Learning Theory (IBLT) of decision making (Gonzalez, Lerch & Lebiere, 2003).
• Common cognitive explanation: *dual-route account* (Proctor & Vu, 2006), (direct and indirect) automatic and controlled
• BUT: These effects can be eliminated or reversed:
  – When incompatible mapping is used prior to performing the Simon task
  – When participants perform trials of an SRC (location-relevant) task with incompatible mapping intermixed with trials of the Simon (location-irrelevant).
• Thus, processes are not purely automatic
• IBLT (Gonzalez et al., 2003) may help explain how the cognitive processes in these tasks can become automatic and how the effects can be attenuated when tasks are intermixed.
People make decisions by storing and retrieving experiences in the form of “instances”:
- “SDU” triplet containing the situation (S) (cues that describe the task), the decision (D) (response made in that situation), and the utility (U) (accuracy of that response)

People move gradually from the use of explicit rules of action to implicit recognition of familiar patterns. How soon and how gradual this transition is depends on:
- Similarity of the situations confronted
- Number of instances stored
- Accuracy of the decisions made

Fixed 5 step process in every decision: Recognition, Judgment, Choice, Execution, Feedback
IBLT builds on ACT-R

The 2x2 levels of ACT-R

<table>
<thead>
<tr>
<th>Symbolic</th>
<th>SubSymbolic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Declarative Memory</strong></td>
<td><strong>Procedural Memory</strong></td>
</tr>
<tr>
<td>Chunks: declarative facts</td>
<td>Productions: If (cond) Then (action)</td>
</tr>
<tr>
<td>Activation of chunks (likelihood of retrieval)</td>
<td>Conflict Resolution (likelihood of use)</td>
</tr>
</tbody>
</table>
Activation makes chunks available to the degree that past experiences indicate that they will be useful at the particular moment.

Base-level: general past usefulness: how recently and frequently the chunk has been used in the past
Associative Activation: relevance to the goal and interference
Matching: relevance to the specific match required
Noise: stochasticity

Higher activation = fewer errors and faster retrievals
• Can IBLT explain and represent the cognitive processes involved in the SRC and Simon tasks?
• Can IBLT predict the human learning and performance obtained when Simon and SRC tasks are intermixed?
Simon and SRC paradigm

**Simon Trials**

**SRC Trials**

Cues: color, line orientation, position

Response: R or L
• Instance structure
  – Situation: Color (Red, Green, White), Orientation (Horizontal, Vertical), Position (Left, Right)
  – Decision: Left key ("z") or Right key ("/")
  – Utility: +1 (for correct decision), -1 (for incorrect decision), and 0 (unknown)

<table>
<thead>
<tr>
<th>Color</th>
<th>Orientation</th>
<th>Position</th>
<th>Decision</th>
<th>Utility</th>
<th>IBLT-State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td></td>
<td>Left</td>
<td>“Z”</td>
<td>1</td>
<td>Feedback</td>
</tr>
</tbody>
</table>

• IBLT process
  – Recognition: retrieve something similar to the stimulus on the screen
  – Judgment: Recognition failure? → random answer; or apply decision in instance retrieved
  – Choice: pick the “best” key
  – Execution: Press the key
  – Feedback: Correct? → +1, Incorrect? → -1

• All ACT-R subsymbolic parameters were left at ACT-R default values
N=32 students, 4 blocks, 80 trials Simon and 80 trials SRC (40 each compatible and incompatible mappings)

Practice: 16 trials Simon, 16 SRC (8 each for compatible and incompatible)

Tone feedback on incorrect response

Dependent Measures: Response Time, Percent Error

Measures of fit: $R^2$ (for trend) and Root Mean Squared Error (RMSE; for closeness of fits)

Model ran with the same tool as human subjects

Predictions:
- Learning effects: RT decreases with practice; Learning due to repetition
- Sequential effects:
  - Model’s RT slowest when task changes and mapping switches
  - Model’s RT fastest when task is the same and mapping repeats
Model Fits: Learning Effects, RT

\[
R^2 = 0.97 \text{ and RMSD} = 62.96 \text{ ms}
\]

\[
R^2 = 0.64 \text{ and RMSD} = 84.54 \text{ ms}
\]

\[
R^2 = 0.98 \text{ and RMSD} = 61.21 \text{ ms}
\]

\[
R^2 = 0.97 \text{ and RMSD} = 62.96 \text{ ms}
\]
Model Fits: Sequential Effects, RT

- **Simon Non-Corresponding**
  - $R^2 = 0.91$ and RMSD = 31.32 ms

- **Simon Corresponding**
  - $R^2 = 0.96$ and RMSD = 24.87 ms

- **SRC Incompatible**
  - $R^2 = 0.95$ and RMSD = 28.82 ms

- **SRC Compatible**
  - $R^2 = 0.97$ and RMSD = 15.86 ms
Model’s predictions in novel conditions of the task

- One well calibrated model can be used to predict behavior in novel conditions of the task
- Experiment 2: What is the effect of feedback in the model? What is the effect of favoring (with higher payoffs) the incompatible and non-corresponding trials
- Experiment 3: What is the effect of the base-rate of Simon and SRC trials? (e.g. Experiment 1 used 50-50):
  - SRC-biased: 80% SRC, 20% Simon
  - Simon-biased: 80% Simon, 20% SRC
  - Same proportions of Compatible/Incompatible and Corresponding/non-corresponding trials
- Predictions:
  - The higher base-rates conditions will show better performance than the lower base-rates conditions
Model predictions in Experiment 3 (RT)
Model predictions and fits (RT; Experiment 3; Simon-biased)

\[ R^2 = 0.95 \text{ and RMSD} = 37.26 \text{ ms} \]

\[ R^2 = 0.93 \text{ and RMSD} = 47.95 \text{ ms} \]

\[ R^2 = 0.94 \text{ and RMSD} = 14.50 \text{ ms} \]

\[ R^2 = 0.89 \text{ and RMSD} = 14.57 \text{ ms} \]
Model predictions and fits (RT; Experiment 3; SRC-biased)

R^2 = 1.00 and RMSD = 24.21 ms

R^2 = 0.99 and RMSD = 41.42 ms

R^2 = 0.68 and RMSD = 33.34 ms

R^2 = 0.81 and RMSD = 69.09 ms
**Sequential Effects (RT; Experiment 3; Simon-biased)**

- **Simon Non- Corresponding**
  - $R^2 = 0.82$ and RMSD = 55.97 ms

- **Simon Corresponding**
  - $R^2 = 0.89$ and RMSD = 44.50 ms

- **SRC Incompatible**
  - $R^2 = 0.85$ and RMSD = 32.25 ms

- **SRC Compatible**
  - $R^2 = 0.97$ and RMSD = 15.78 ms
Sequential Effects (RT; Experiment 3; SRC-biased)

**Simon Non-Corresponding**

$R^2 = 0.72$ and RMSD = 30.20 ms

**SRC Incompatible**

$R^2 = 0.99$ and RMSD = 65.35 ms

**SRC Compatible**

$R^2 = 0.99$ and RMSD = 89.97 ms
• IBLT model: good account for performance

• Learning effect explained by the IBLT process

• Correct instances repeated use raises activation reducing RT in sequential fits

• Task and mapping repetition decreases RT due to recency of use.

• Some future model predictions:
  ▪ Unequal compatibility (e.g. more corresponding than non-corresponding)
  ▪ Stronger differences in payoffs (e.g. pay significantly more for correctness in non-corresponding trials)
Comparison of Instance and Strategy Models in ACT-R

Gonzalez, Dutt, Healy, Young, & Bourne, 2009;
Gonzalez & Dutt, in preparation

Dynamic Decision Making Lab
www.cmu.edu/ddmlab
Social and Decision Sciences Department
Carnegie Mellon University
Compare two modeling approaches, built on the same cognitive architecture, ACT-R, in two different dynamic decision making tasks, Dynamic Stocks and Flows (DSF) and RADAR.

**Approaches:**
- SBL approach (more popular): strategies by which humans perform a task
- IBL approach (less popular): generic decision making process in production rules (Gonzalez et al., 2003)

**Compare the IBL and SBL models on:**
- (1) fit: how well each model fits human data
- (2) adaptability: how well each model is able to reproduce the way humans having learned in one scenario of the task adapt to a testing condition

**Results (for both DSF and RADAR):**
- Both SBL and IBL models have good fit to human data
- IBL model does better than SBL model on adaptability … but one can always make the SBL model adaptable!
Instance Based Learning Tool

Last year project: Gonzalez & Dutt

Dynamic Decision Making Lab
www.cmu.edu/ddmlab
Social and Decision Sciences Department
Carnegie Mellon University
In a nutshell

• Need to formalize the IBLT approach to modeling in a tool:
  – Brings the theory closer to people who want to make use of it – Share
  – Makes possible the use of theory on different, diverse tasks - Generalize
  – Makes the use and understanding of the theory easier - Understand
  – Abstracts from specifics of implementation in computer languages - Robust
  – Makes the theory interact with tasks easier – Communicate
  – Helps to make the theory more transparent - Usable

• What would the IBLT tool consist of?
  – We have already implemented the ACT-R IBL mechanisms from LISP into Visual basic
  – We have demonstrated that the implementations are comparable (Gonzalez, Dutt, & Lebiere, in preparation)
  – It will allow any one to build an IBLT-based model in ACT-R for a specific task, step by step
  – It will allow to produce model predictions – data from a model run
Instance-Based Learning Theory (IBLT)

Definition of Instance (SDU):

Please define the SDU structure in the format \{Name, Type\} by entering into the table below. Click “Continue” to move forward:
Definition of similarity function:

Please define the similarity function to be used for comparing the retrieval cue with instances stored in the memory below (remember the cues for which you will define similarity function will take part in retrieval):

\[ M = P \times \text{Abs}(\text{Cue.Amount} - \text{Memory.Amount}); \]
\[ P = -1.0; \]

- Time
- Amount
- EI
- EO
- UI
- UO
- Goal
- Utility

Do you want to use?

- Use Base Level Activation
- Use Noise

Parameter | Value
--- | ---
blt, t | 1.0, -0.5
s |
Please define what happens in judgment if recognition (retrieval) fails and succeeds (remember Memory tag addresses retrieved instance):

<table>
<thead>
<tr>
<th>Recognition</th>
<th>Judgment Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fails</td>
<td>Cue.Utility = (Cue.Amount – Cue.goal) + (Cue.EI – Cue.EO) + (Cue.EI – Memory.EI) / (Cue.Time – (Cue.Time -1));</td>
</tr>
<tr>
<td>Succeeds</td>
<td></td>
</tr>
</tbody>
</table>
Please define what happens in Choice for Decision:

<table>
<thead>
<tr>
<th>Choice</th>
<th>Choice Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>UI</td>
<td>If Cue.Utility &gt; 0 Then Cue.Utility Else 0;</td>
</tr>
<tr>
<td>UO</td>
<td></td>
</tr>
</tbody>
</table>
IBLT

Click “Simulate” to Test your Model. You can click “<Back” button to change definitions of your model later and come back to this screen to simulate model behavior once again. As you will appreciate modeling is also an iterative process 😊
Summary of Accomplishments & Next Steps

• Develop models of training and investigate training principles
  – In Collaboration with Purdue: IBLT models of intermixed SRC and Simon effects in ACT-R
  – In Collaboration with U of Colorado: Comparison of Instance and Strategy Models in ACT-R

• Building an integrated and easy to use instance-based decision making modeling tool
  – Conceptual design and building blocks

• Develop an integrated IBLT tool in Visual Basic
  – Demonstrate the use of the IBL tool in multiple tasks (Simon, SRC, RADAR, data entry)
  – Publish overall results and make tool available