A Hybrid Model of Decision-Making Under Uncertainty

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Modeling Decision Processes is Important to Engineering Systems Research

Some examples:

• **Engineering decisions**
  ▫ Problem framing – how large will you draw the box?
  ▫ Optimization: Pareto set decisions; defining parameters, constraints, variables

• **Management and Policy decisions**
  ▫ Predictions of how a population respond to a change
  ▫ Interpretation and use of model results

• **Individual choices and preference**
  ▫ Modeling product demand and market share can help determine costs, production scale, advertising campaigns, environmental impacts
  ▫ Modeling consumer product preference allows the design of more preferable products
Decision Fundamentals

All decisions share common concepts

- Collecting relevant knowledge
- Framing prospects and associated outcomes
- Assessing the likelihood of outcomes
- Valuing the prospects and outcomes
- Making a choice
- Observing the outcome
- Iteration!
Research on Decision Fundamentals

Collecting relevant knowledge
Framing prospects and associated outcomes
Assessing the likelihood of outcomes
Valuing the prospects and outcomes
Making a choice
Observing the outcome
Iteration!

Heuristics and Biases
Construction of Preferences
Choice Modeling
Reinforcement Learning
Motivational Research
Approaches to Modeling Decisions

• Observe decisions
  ▫ Fit real-world decision data to a model
  ▫ Is the model applicable to new decision situations?

• Self-explicated decisions
  ▫ Ask “Why?”
  ▫ Quantitative or qualitative analysis to form model
  ▫ Varying levels of usefulness and accuracy, depending on decision

• Experiment with decisions
  ▫ Measure choices in an experimental setting
  ▫ Estimate empirical model to predict choices
  ▫ Heuristics, biases, and construction of preference can be studied as experimental manipulations
  ▫ Subject to experimentally-induced biases, limits of knowledge provided in experiment
  ▫ Expensive and cognitively taxing
A new approach to Decision Modeling:

“First Principles” Hybrid

- Analogy: Engineering
  Physical constants can either be deduced from experiments or derived from mathematical representations (or both).
- We hypothesize that certain components of a decision can also be modeled empirically or derived from psychological representation (or a combination of the two).
Advantages of Hybrid Decision Modeling Approach in Engineering Systems

• Ability to match levels of information in user decision-making and engineering systems, as well as uncertainty in parameters
• Particular to System Dynamics: Incremental changes in systems can be balanced with decisions based on incremental information updates
• Can use both empirically-estimated and first principles representations of decisions in the same model
Case Study: Prospect Theory
Modeling decision making under risk

Consider a simple decision involving risk:

- The decision maker chooses one option from a pair of options, where each option offers its outcomes probabilistically.
- We observe repeated decisions.
- Observations summarized as a vector of binary codes 011010001... indicating the choices made by the decision maker.
- Report the proportion of times 1 is selected.
Typical Empirical Decision Models

- Observations are binary and reported as proportions
- Typical models impose a latent, unobserved construct that is continuous and a transformation maps the construct to choice probability, for example, a logit choice model
  - $Z = XB + e$ for design matrix $X$, unknown parameter vector $B$ and error vector $e$
  - $1/(1+\exp(z))$ maps $Z$ to the interval $[0,1]$
Behavioral Highlights from Decision Making Research

- Risk aversion in gains
- Risk seeking in losses
- Loss aversion

Classic decision making models under risk do not treat gains and losses separately, but behaviorally there is much evidence that people respond differently.
Gains and Losses

- $(1, $3000) > (.80, $4000)$ (80%)
  Consistent with “risk aversion”

- $(1, -$3000) < (.80, -$4000)$ (92%)
  Reversal: risk seeking in losses
The Value Function

- Risk aversion in gains implies concavity of the value function
- Risk seeking in losses implies convexity of the value function
- Loss aversion implies the value function is steeper in losses than in gains

*Figure 3.* A hypothetical value function.
Typical Functional Form:
Two piece power

\[ v(x) = \begin{cases} 
  x^\alpha & \text{if } x \geq 0 \\
  -\lambda(-x)^\beta & \text{if } x < 0 
\end{cases} \]

\[ \alpha = \text{risk aversion parameter (gains)} \quad 0.88 \]
\[ \beta = \text{risk seeking parameter (losses)} \quad 0.88 \]
\[ \lambda = \text{loss aversion} \quad 2.25 \]
Limitations in the literature

- Structure is empirically inferred from choice
- No theoretical mechanism, merely descriptive
- Learning is not typically modeled
- Feedback rarely occurs, so preference changes in response to changing environment are rarely examined
Cumulative Prospect Theory (CPT)

- Combines the value function with a risk weighting function to arrive at a reasonable predictive model of how people make decisions
- Weighting function left for future discussion
- Integration with System Dynamics is fluid because CPT hypothesizes that outcomes are evaluated as incremental gains and losses
Simple Example

The sheep experiment.
Results “Herd Mentality”

Not Dispersed

Dispersed
Assessing Value
**Framing**

**Assumption:**
Prey have perfect information

**Future Goal:**
Prey use heuristics
Prospect Theory

Loss loom larger than gains.

\[ v(x) = \begin{cases} 
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Prospect Theory

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Prospect theory acts as a dampener, perhaps working well with imperfect information and heuristics in decisions.
Next Steps

- Remove hard-coded prospect theory coefficients
- Remove perfect information from prey’s decision
- Add heuristics
- Add reinforcement learning
- What prospect theory coefficients will develop?
Looking forward

• Engineering and product choice models
  ▫ Can we predict demand for new products using only principles from psychology and current “known” product information?
  ▫ Is the level of detail enough to produce useful results?
  ▫ What will customer inputs to this process look like?

• Encouraging people to buy sustainable products
  ▫ What happens to green product sales when we increase/decrease social desirability bias?
  ▫ Can we activate certain judgment heuristics using product design to increase demand? For example, increased trust of environmental impact information provided by company, or decreased cognitive dissonance.
  ▫ Experiment with motivation for behavior change and reinforcement learning with respect to sustainable product purchase and use decisions