A cognitive principle of least effort explains many cognitive biases

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Choices ....

What’s for dinner?

Which posters to go to?

Rational choice using expected utility

An alternative view of rationality

Minimize cognitive effort while satisfying needs.

Modeling Reward for Need Satisfaction

Need new memory model to find optimal quality beliefs

A new rational choice model

Define quality beliefs on a set of outcomes \(x\). Then we can define a measure of surprise at arriving at a new quality belief \(x\) with respect to an old one \(x_0\):

\[ R(x; x_0) = \frac{1}{2} \log \frac{p\left(x_0|x\right)}{p\left(x|x_0\right)} \]

The exceptionality of a past quality belief is measured as the degree to which it is surprising with respect to the current quality belief,

\[ A(x; x_0) = |R(x; x_0)| - |R(x_0; x)| \]

evaluating the intuition that both highly surprising and highly unsurprising events are exceptional. The most exceptional a past quality belief, the more available, and hence, less costly, it will be to recall. Assuming a nominal recall cost of unity, the total cognitive cost \(T\) of populating an active memory \(M\) from all past experiences is,

\[ T = \sum_{x_0 \in M} A(x; x_0) \]

This cognitive cost \(T\) is expanded in constructing a new quality belief that allows reward collection. Thus, cognitive cost trades off against the reward predicting utility of the quality belief. The cognitive process generates the quantity this using a measure of prediction confidence,

\[ c = \frac{|R(x)|}{|R(x)| + |R(x_0)|} \]

where \(H(x)\) is a measure of information entropy.

Our decision model yields a novel principle of rational action: need satisfying cognitive cost minimization, or,

\[ \arg\min_{x_0} T(x; x_0) \]

We solve this as a combinatorial optimization problem of identifying which prior beliefs to recall into active memory. Once this subset \(M\) is identified, the agent’s new experience expectation is obtained by averaging over beliefs in this set,

\[ \bar{H} = \sum_{x_0 \in M} \frac{1}{|M|} p(x|x_0) H(x) \]

This expectation is the model’s choice preference at event instance \(t\). The effect of new reward inference from subsequent experience is combined with this expectation as,

\[ \bar{H} = \bar{H} + (1 - \bar{H}) \gamma \]

to obtain an updated quality belief, thereby completing our choice model.

Experimental results

• Sequential choice simulations replicate confirmation biases
• Replicate learned helpless behavior when the generative mechanism of reward signals is unpredictable.

Take-away messages

• Alternative information-theoretically motivated definition of rationality retrieves realistic decision model
• Testable neuroscientific implications about the nature of reward encoding and memory access - rewards are relative, memory encoding maximizes information compression
• Natural emergence of multiple families of cognitive biases with no prior common explanation.

Acknowledgements

Supported by ONR MURI N 00014-07-1-0937