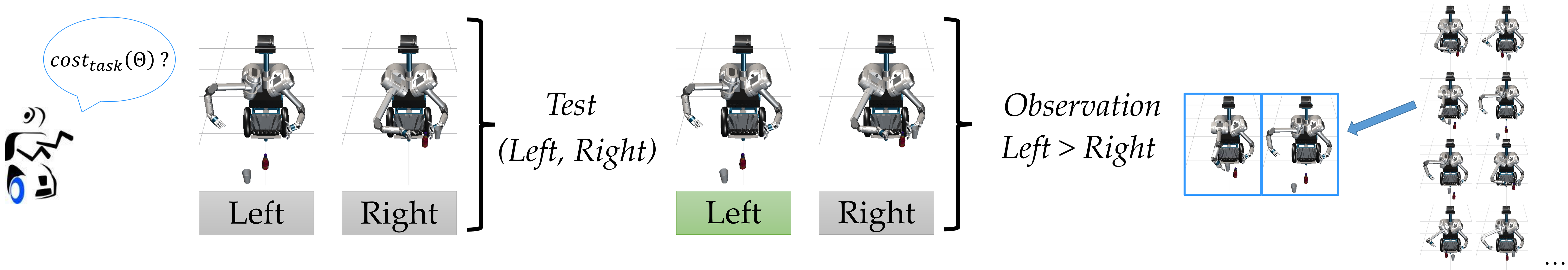
Active Comparison Based Learning Incorporating User Uncertainty and Noise

Rachel Holladay[1], Shervin Javdani[1], Anca Dragan[2], Siddhartha Srinivasa[1]

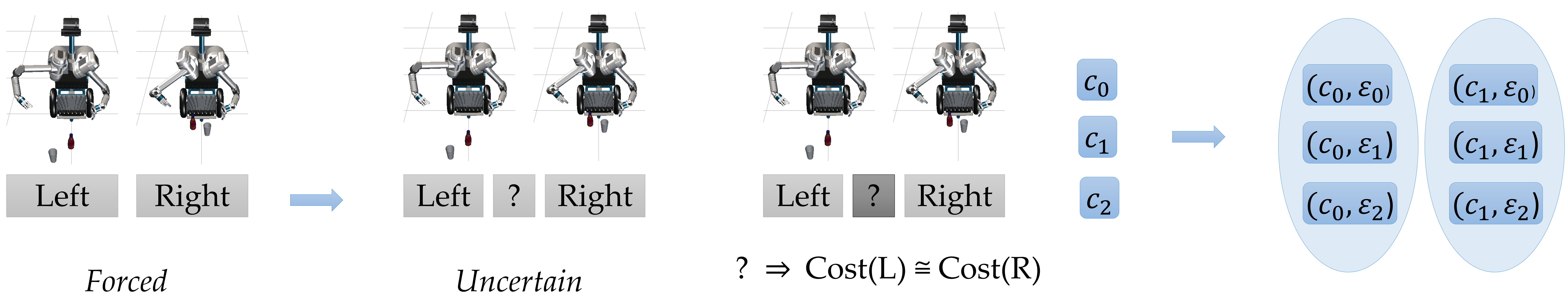
[1]Personal Robotics Lab, Carnegie Mellon University

[2]InterACT Lab, University of California Berkeley

Active Comparison Based Learning for Cost Functions



Key Insight: The user's uncertainty is informative about their cost function.



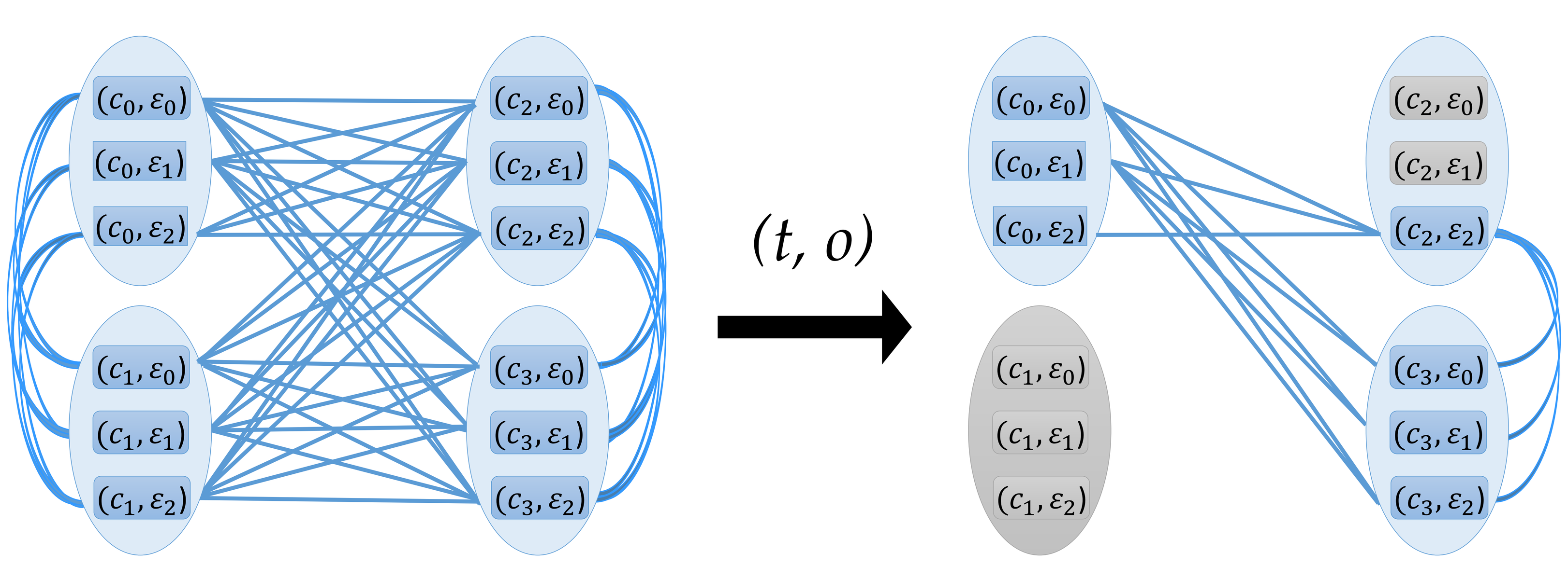
Forced Preference

Uncertain Preference

? ⇒ Cost(L) ≅ Cost(R)

| Cost(L) – Cost(R) | < ε

Comparison Learning Algorithm for Uncertain Situations (CLAUS)



Symbol Key

S : evidence

h ∈ H : hypotheses

a ∈ A : edges

o ∈ O : observations

t ∈ T: tests

$$f_{CLAUS}(S) = w(A) - w(A|S)$$

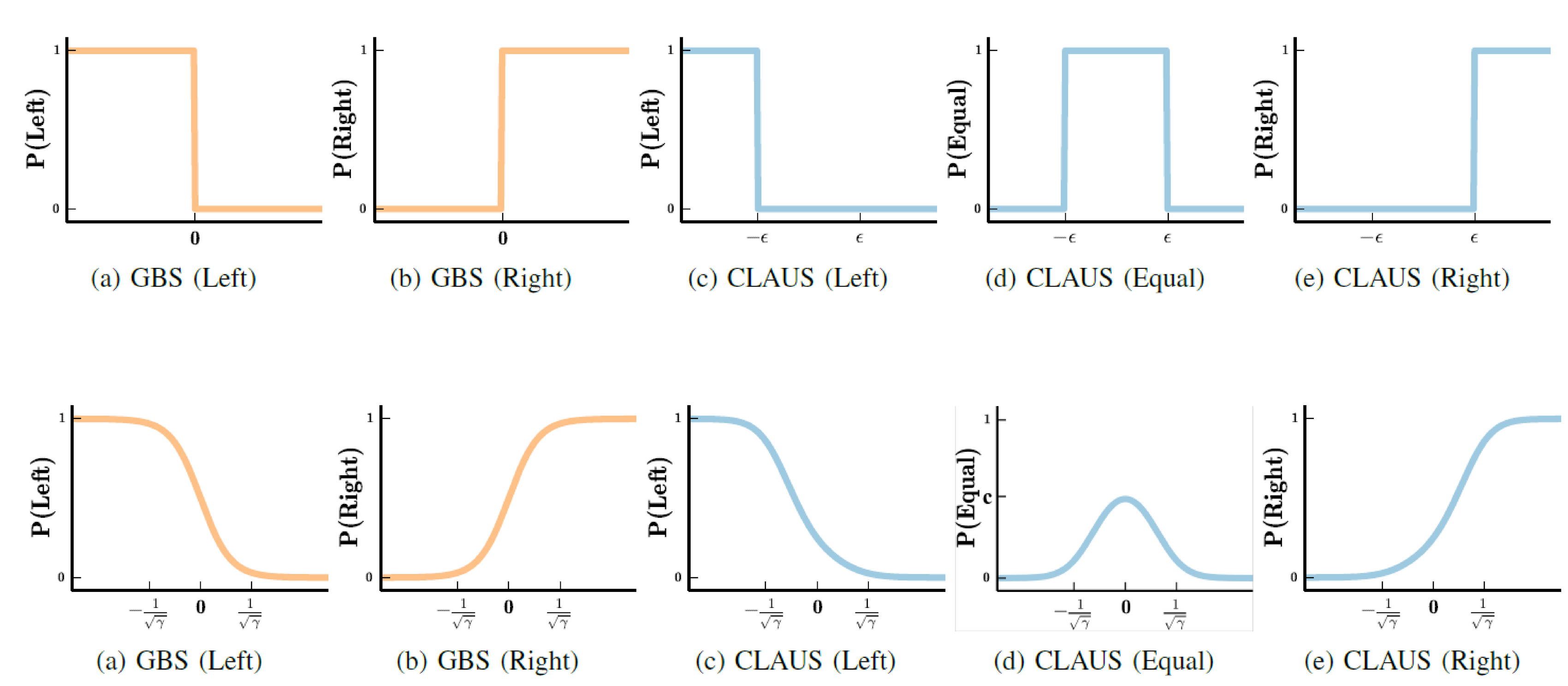
$$w(A|S) = \sum_{a \in A} w(a\,|S)$$

$$w(a\,|S) = \prod_{h \in a} w(h\,|S)$$

$$w(h\,|S) = p(S\,|h)$$

$$p(S\,|h) = \prod_{(t,o) \in S} p\big((t,o)\big|h\big)$$

Noise Model: Query-Dependent



Forced Preference

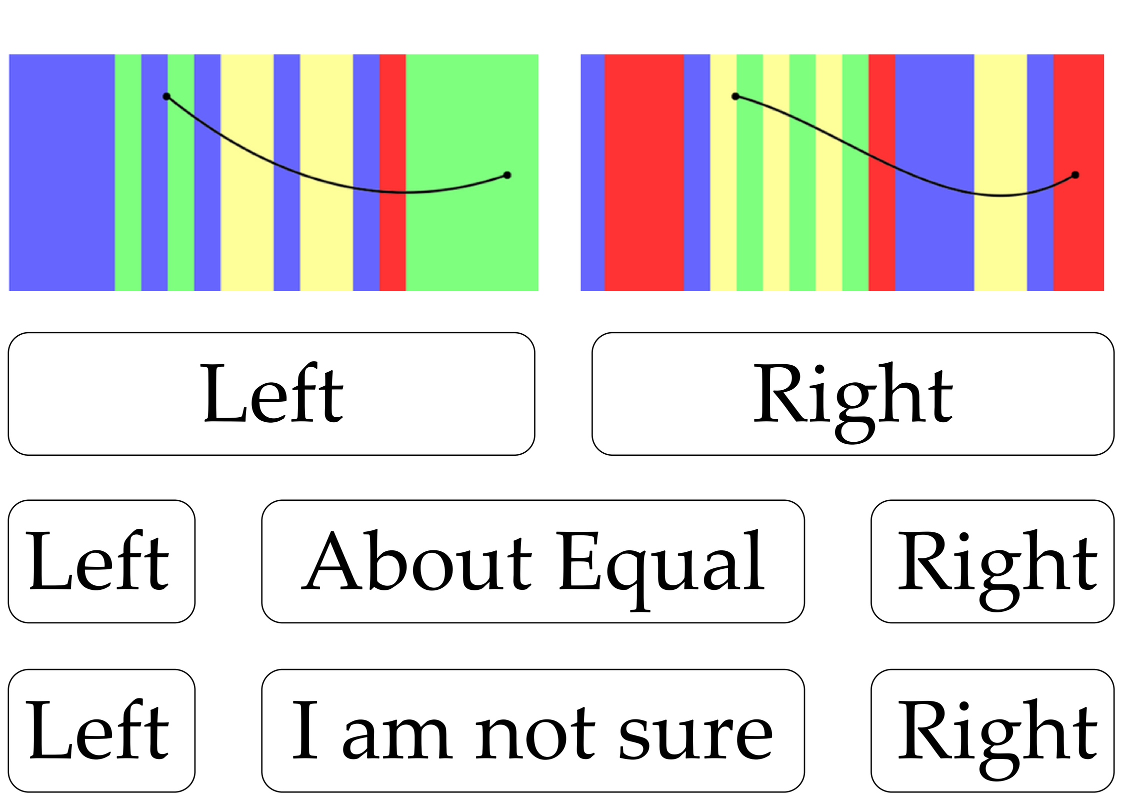
$$p\big((t, o = x)\big|h\big) \propto \exp(-\gamma c_h(x))$$

Uncertain Preference : CLAUS

$$p\big((t, o = x)\big|h\big) \propto \exp(-\gamma(c_h(x) - c_h(y)))$$

$$p\big((t, o = xy)\big|h\big) \propto \exp\left(-\frac{1}{\varepsilon_h^2}[c_h(x) - c_h(y)]^2\right) c$$

User Evaluation with a Known Cost Function



H1. The uncertainty labeling effects user's performance.

H2. Accounting for uncertainty leads to fewer queries.

H3. Accounting for uncertainty performs as accurate as forcing an answer.