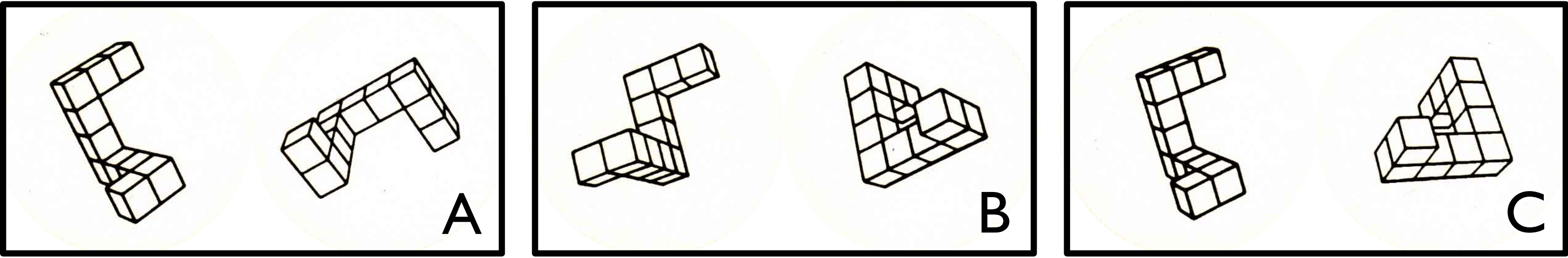


## Introduction

How should an agent make best use of its computing resources?

**Mental rotation task:** determine whether images in each pair depict the same object in multiple orientations, or different objects [1]:



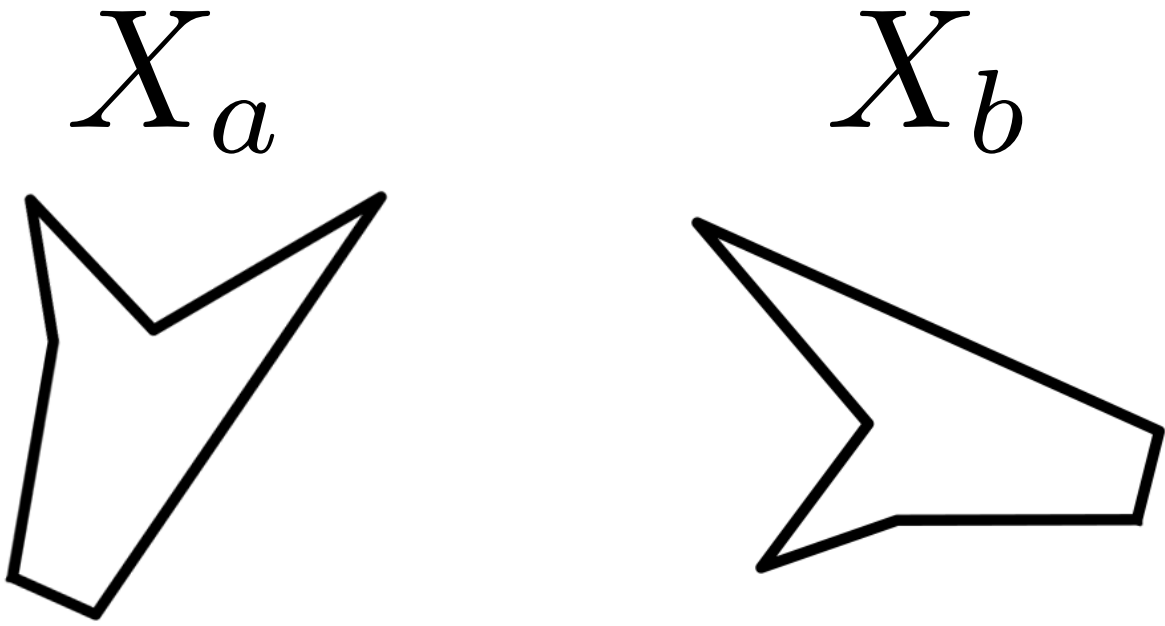
How do people determine: (1) Which direction to rotate? (2) When to stop rotating?

**Hypothesis:** estimate the probability of one shape given the other using sequential rotations (samples), using active learning to choose the direction of rotation.

## Computational-level model

### Problem:

Determine if  $X_a$  is the same as  $X_b$



**Hypotheses:**  $p(h \mid X_a, X_b) \propto p(X_a, X_b \mid h)p(h)$

$h_0$ : objects are different

$$p(X_a, X_b \mid h_0) = p(X_a)p(X_b)$$

$h_1$ : same object rotated by  $R$

$$p(X_a, X_b \mid h_1) = \int_R p(X_a)p(X_b \mid X_a, R)p(R) \, dR$$

### Decision:

The hypotheses are equally likely *a priori*, so the priors cancel. So, we compare the hypotheses via their *likelihood ratio*:

$$\ell = \frac{\int_R p(X_b \mid X_a, R)p(R) \, dR}{p(X_b)}$$

Choose  $h_0$  when  $\ell < 1$

Choose  $h_1$  when  $\ell > 1$

## Algorithmic approximation

A *mental image*  $X_R$  is generated by performing many small rotations:

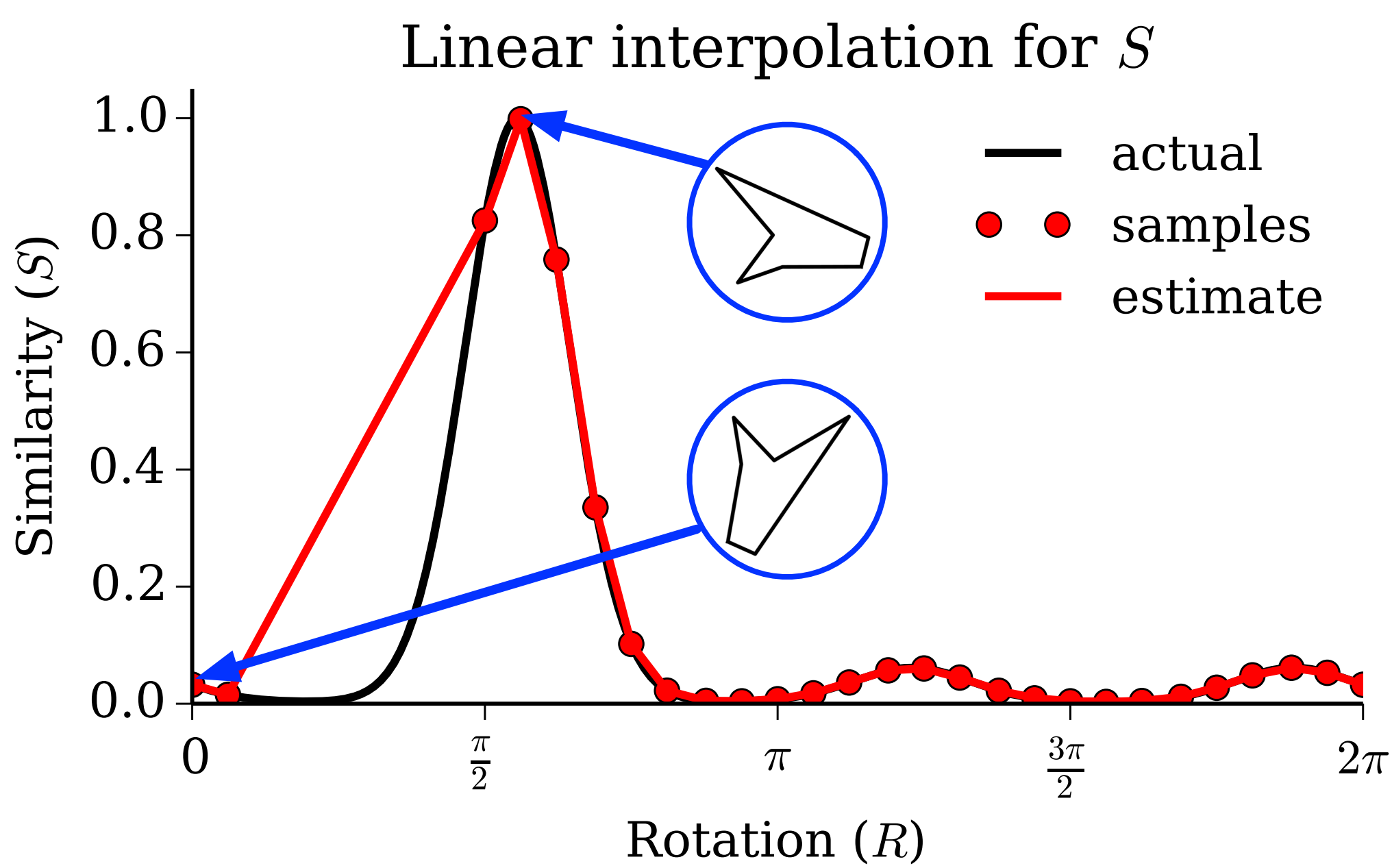
$$X_R = RX_a = \tau(X_{R-r}, r) = \tau(\tau(X_{R-2r}, r), r) = \dots = \tau^{(\frac{R}{r})}(X_a, r)$$

We can approximate the likelihood using these small rotations:

$$\begin{aligned} p(X_a, X_b \mid h_1) &= \int_R \int_X p(X_b \mid X)p(X \mid X_a, R)p(X_a)p(R) \, dX \, dR \\ &= \int_R \int_X p(X_b \mid X)\delta(\tau^{(\frac{R}{r})}(X_a, r) - X)p(X_a)p(R) \, dX \, dR \\ &= p(X_a) \int_R p(X_b \mid X_R)p(R) \, dR \approx p(X_a) \cdot Z \end{aligned}$$

where  $Z = \int_R S(X_b, X_R)p(R) \, dR$ .

**Naive:** hill-climbing until maxima is reached, linearly interpolate to approximate  $S$ , then estimate  $Z$  with the trapezoidal rule.



**Bayesian Quadrature:** one hill-climbing step, then Gaussian Process prior over  $\log S$ , then active sampling of rotations to reduce uncertainty, as in [2]:

$$\begin{aligned} \mu_Z &= \int_{\log S} \left( \int_R \exp(\log S(X_b, X_R))p(R) \, dR \right) \mathcal{N}(\log S \mid \mu_{\log S}, \Sigma_{\log S}) \, d\log S \\ &\approx \int_R \mu_S(1 + \mu_{\Delta_c})p(R) \, dR, \text{ where } \Delta_c = \mu_{\log S} - \log \mu_S \end{aligned}$$

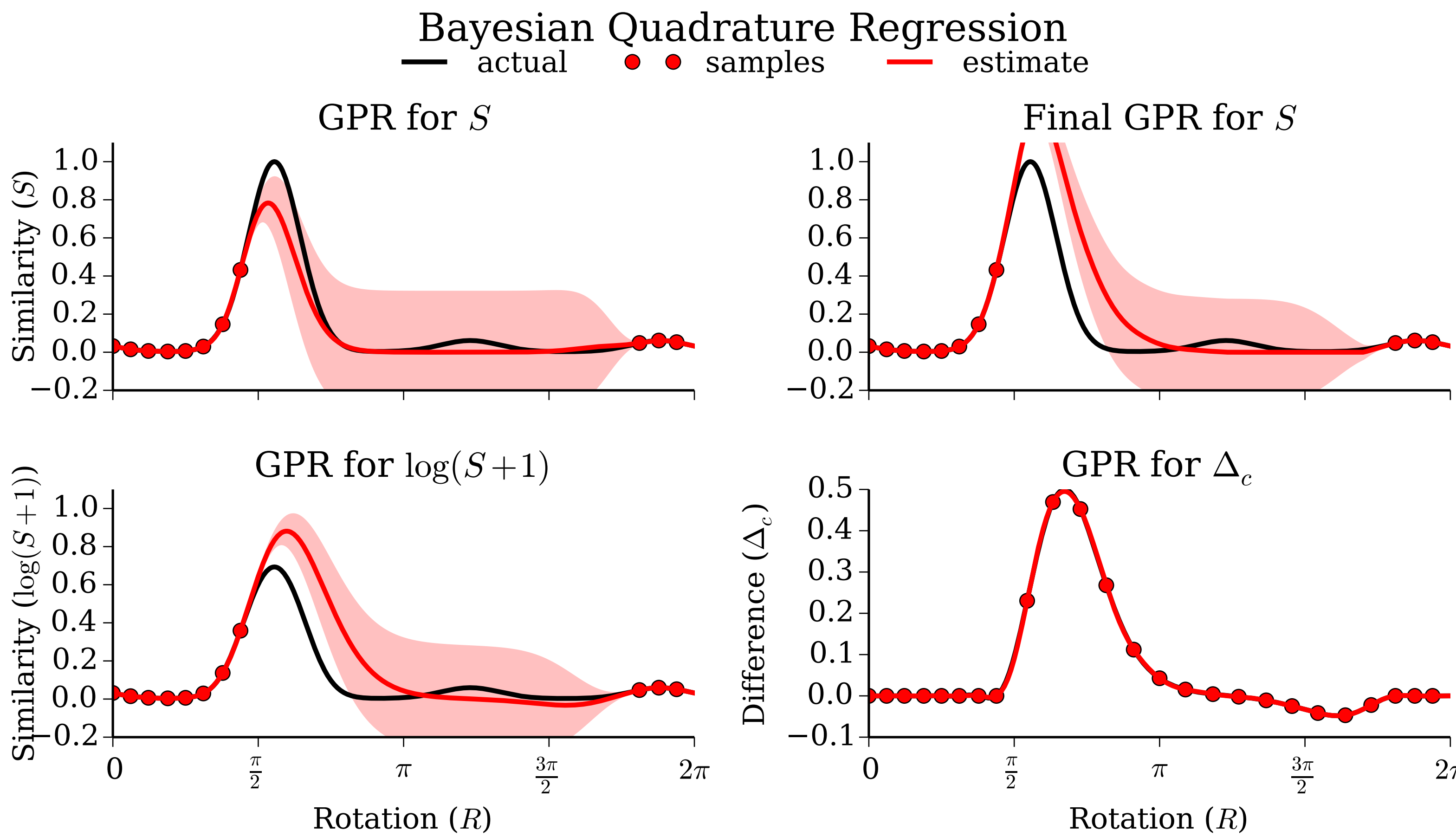
This gives us a distribution over  $\ell$ :

$$p(\ell) \approx \mathcal{N}(Z \mid \mu_Z, \sigma_Z) / p(X_b)$$

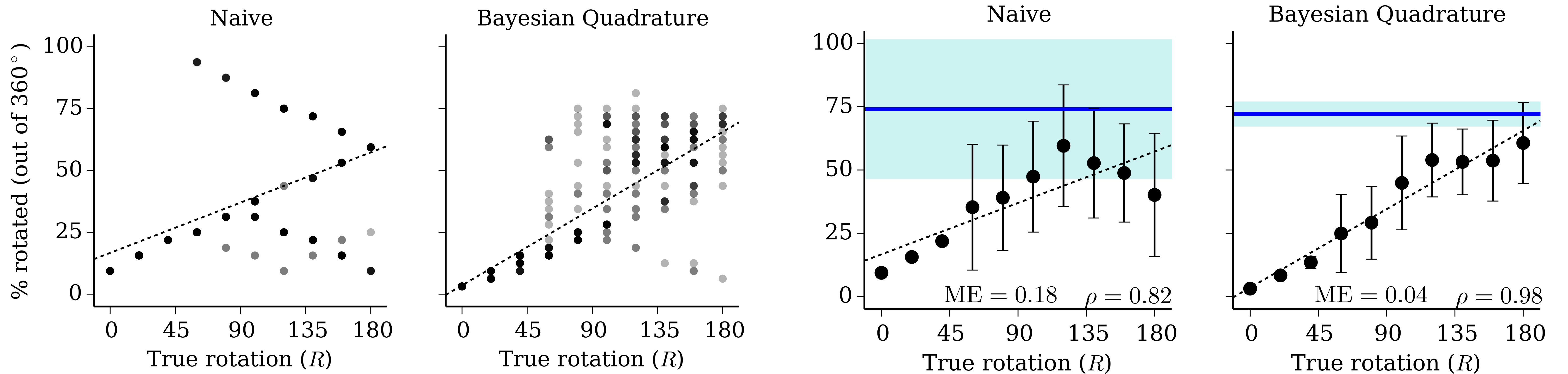
1. Choose  $h_0$  when  $p(\ell < 1) \geq 0.95$

2. Choose  $h_1$  when  $p(\ell > 1) \geq 0.95$

3. Otherwise, keep rotating



## Results



### Conclusions

Mental rotation task is nontrivial, and cannot be solved by a naive heuristic model

BQ model is qualitatively similar to classic results [1] and provides plausible answers:

- 1.Which direction? *Whichever lowers uncertainty.*
2. How long? *Until a certain threshold of confidence has been reached.*

### References

1. Shepard & Metzler (1971). Mental Rotation of Three-Dimensional Objects. *Science* 171(3972), 701-703.
2. Osborne et al (2012).Active Learning of Model Evidence Using Bayesian Quatrature. *NIPS 2012*.

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