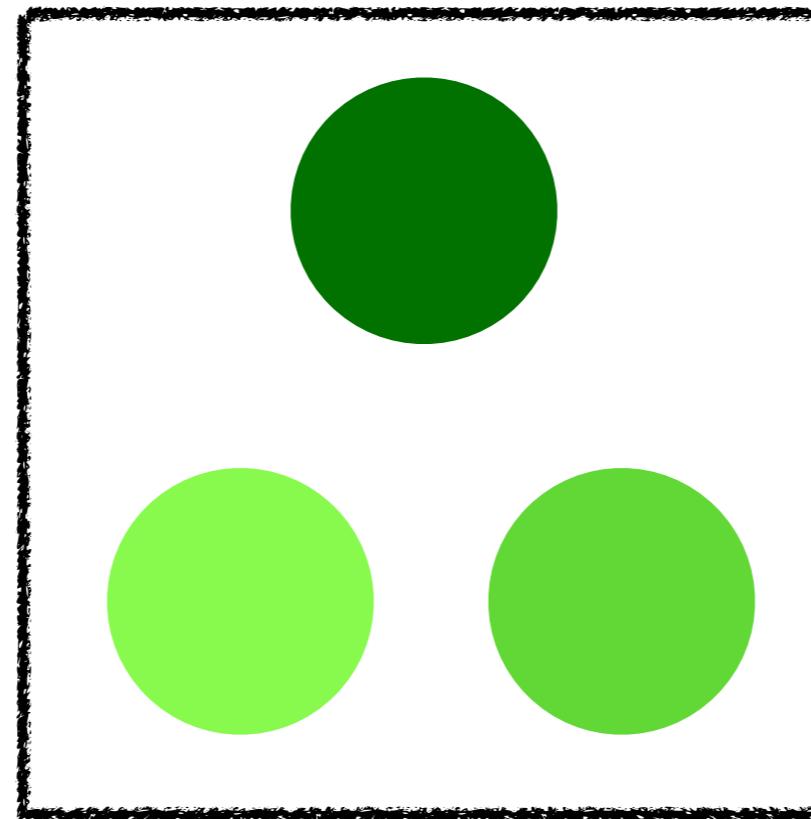


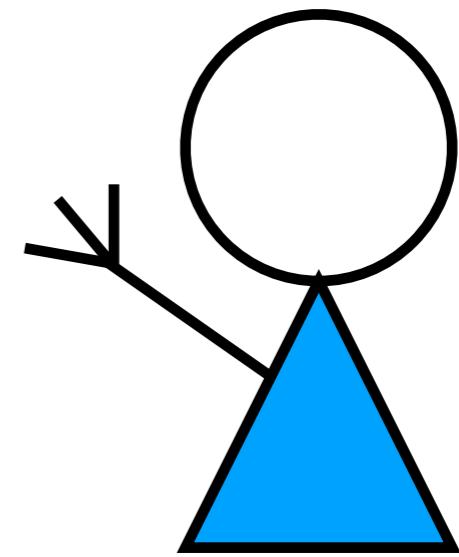
A unifying computational framework for **teaching** and **active learning**

Scott Cheng-Hsin Yang, Wai Keen Vong,
Yue Yu & Patrick Shafto

Active learning

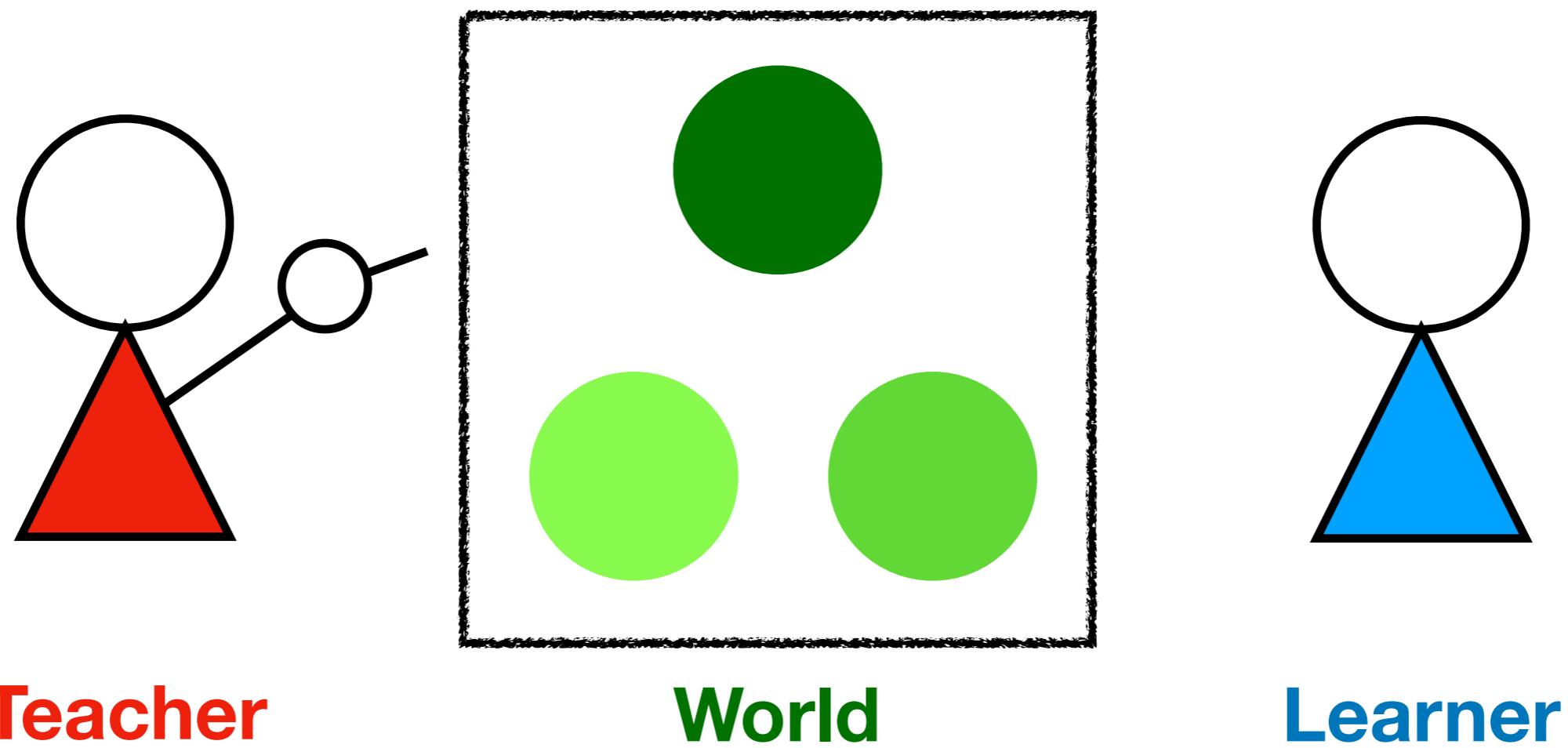


World

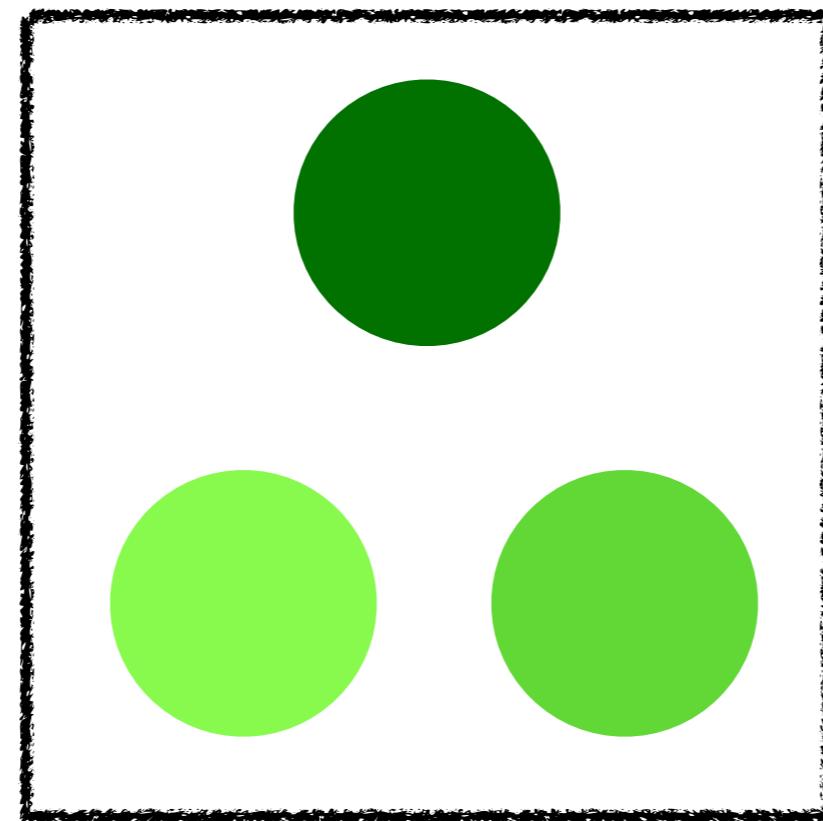


Learner

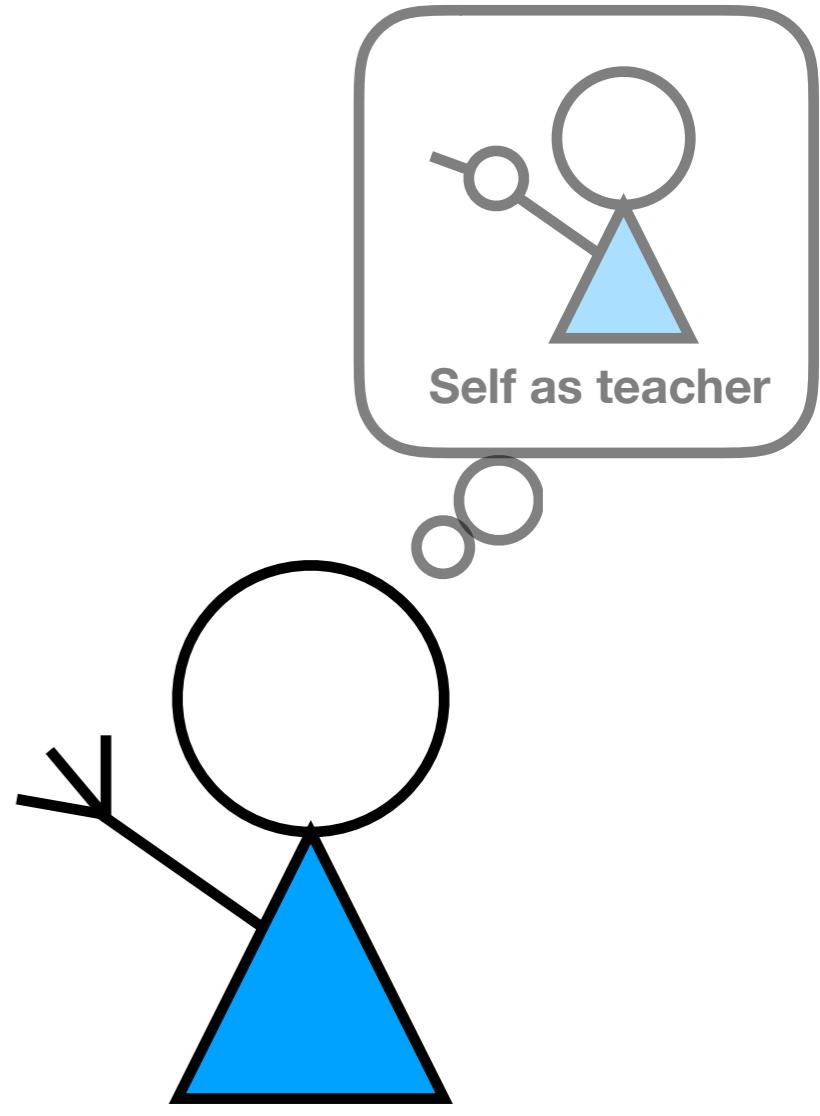
Teaching



Self-teaching

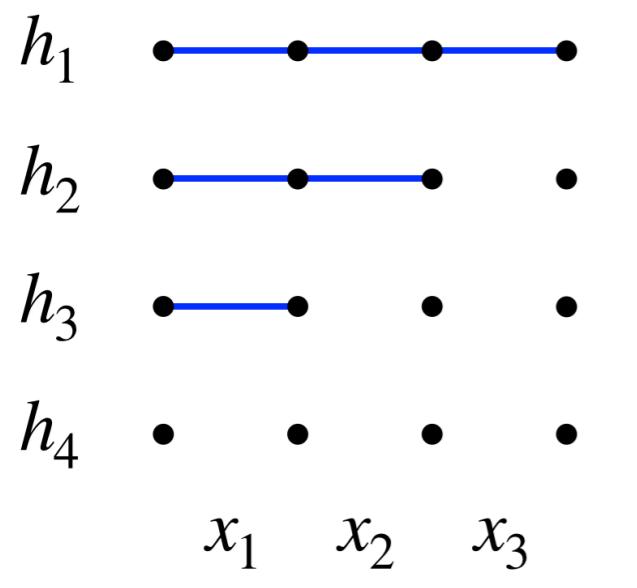


World

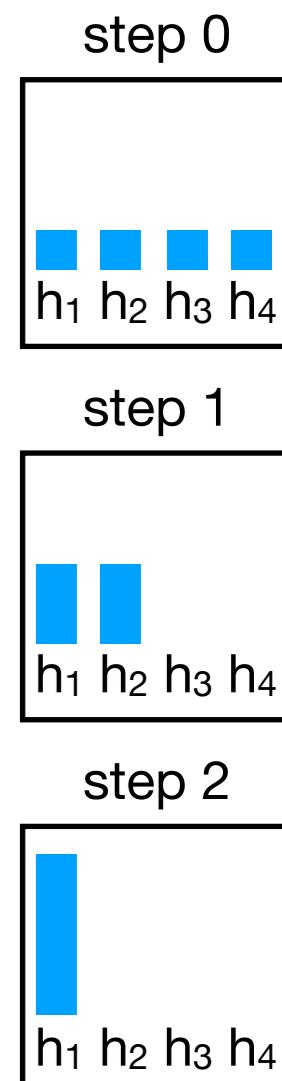
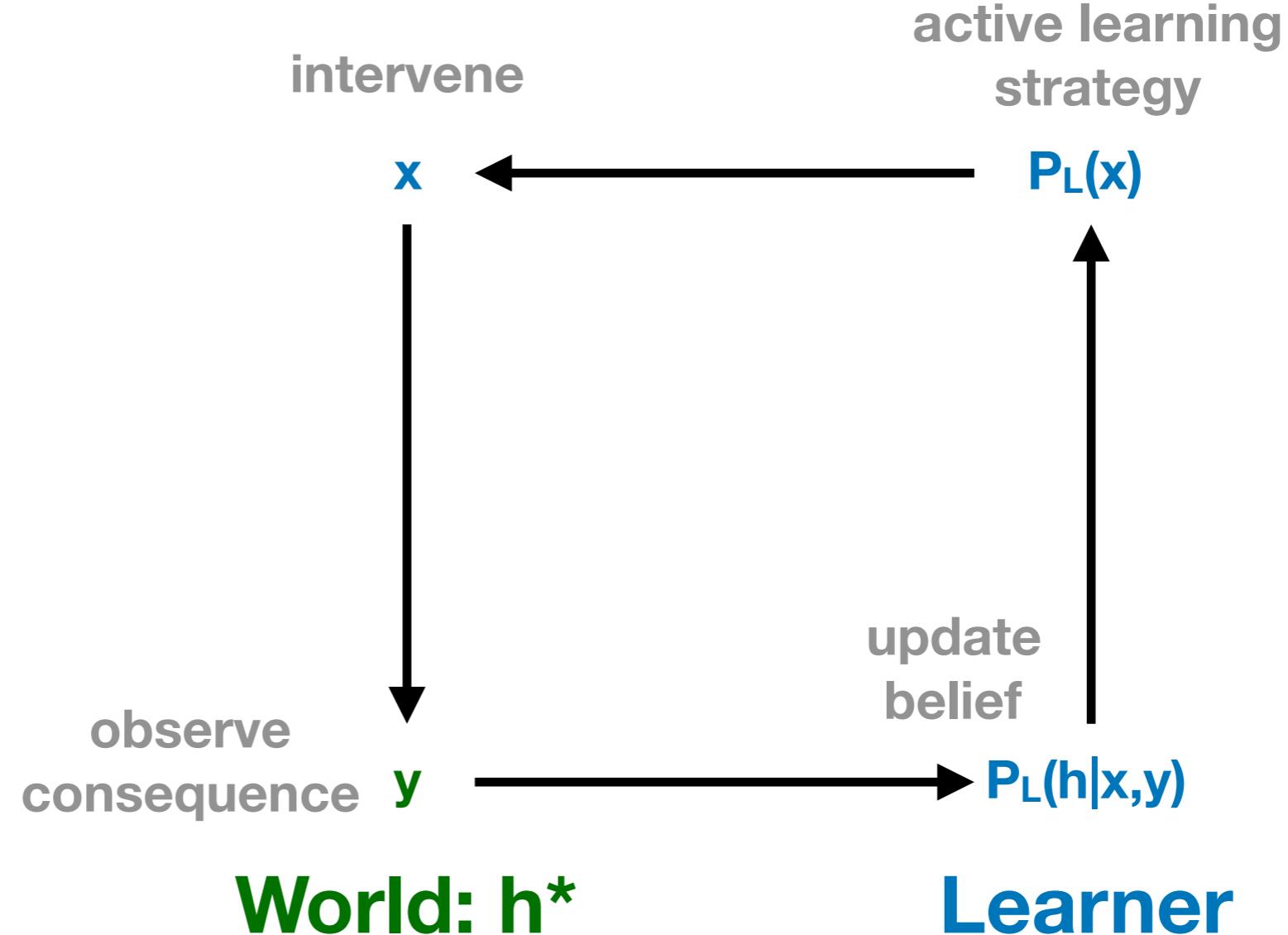


Learner

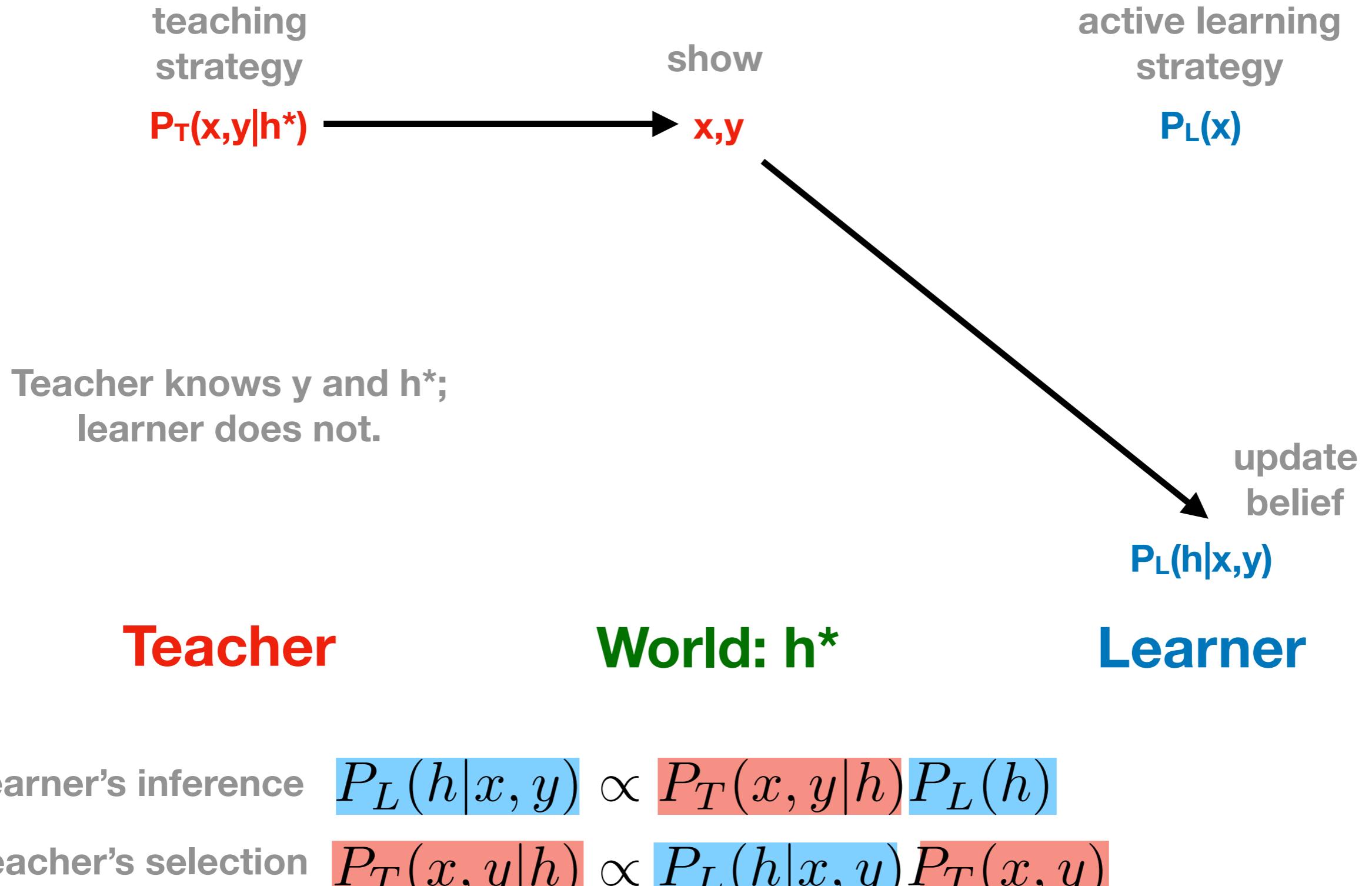




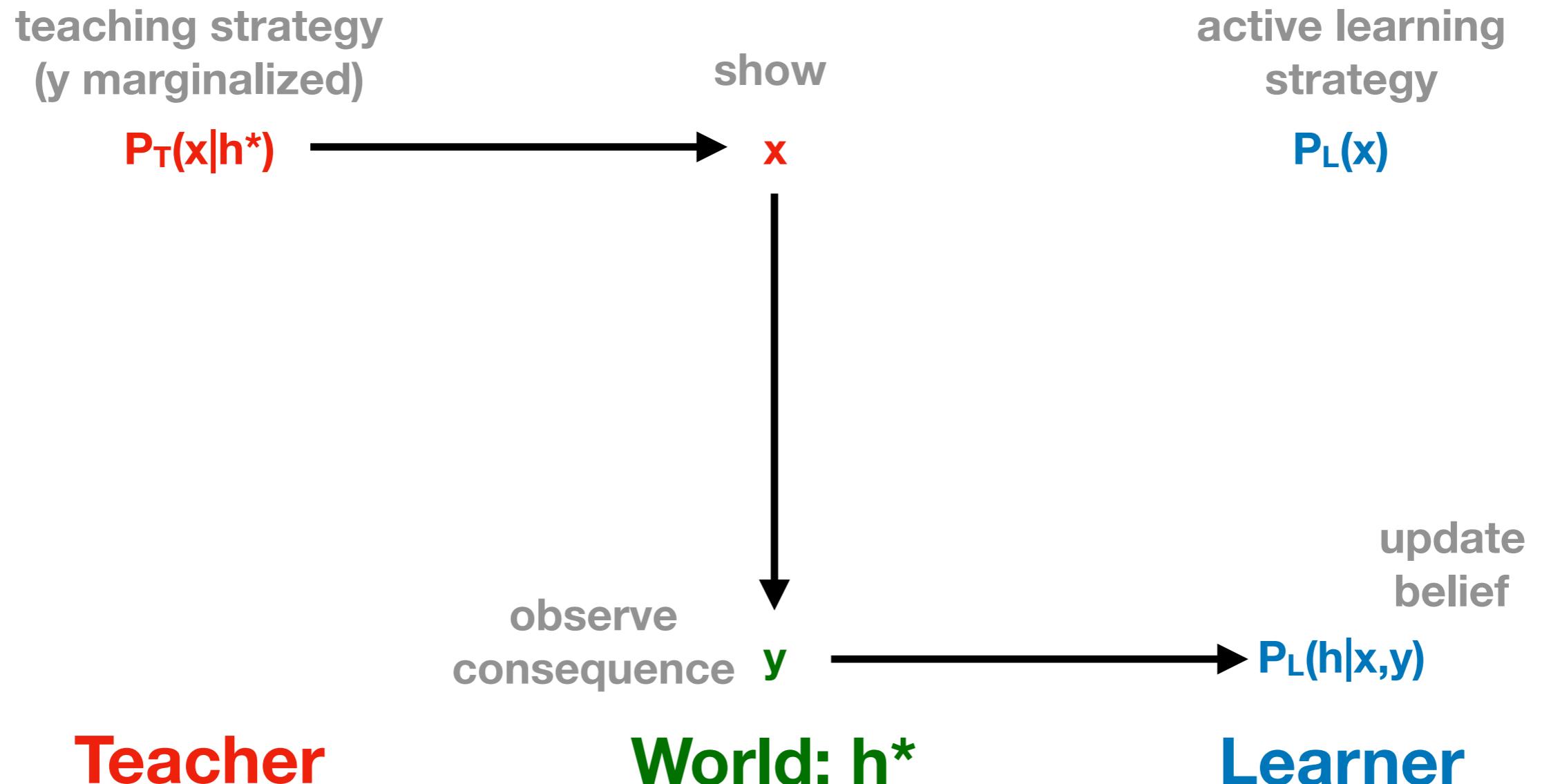
Active learning



Teaching



Teaching (marginalize out y)



learner's inference $P_L(h|x,y) \propto P(y|x,h)P_T(x|h)P_L(h)$

teacher's selection $P_T(x|h) = \sum_{y \in \mathcal{Y}} P_T(x,y|h)$

Knowledgeability (marginalize out “h”)

teaching strategy
(y marginalized)

$$P_T(x|h^*)$$

teaching strategy
(y & h* marginalized) = active learning
strategy

$$P_T(x) = P_L(x)$$

$\delta(g|h)$: truth

	h_1	h_2	h_3	h_4
g_1	1	0	0	0
g_2	0	1	0	0
g_3	0	0	1	0
g_4	0	0	0	1

Teacher

$\delta_{ST}(g|h) = P_L(h)$: truth

	h_1	h_2	h_3	h_4
g_1	1/4	1/4	1/4	1/4
g_2	1/4	1/4	1/4	1/4
g_3	1/4	1/4	1/4	1/4
g_4	1/4	1/4	1/4	1/4

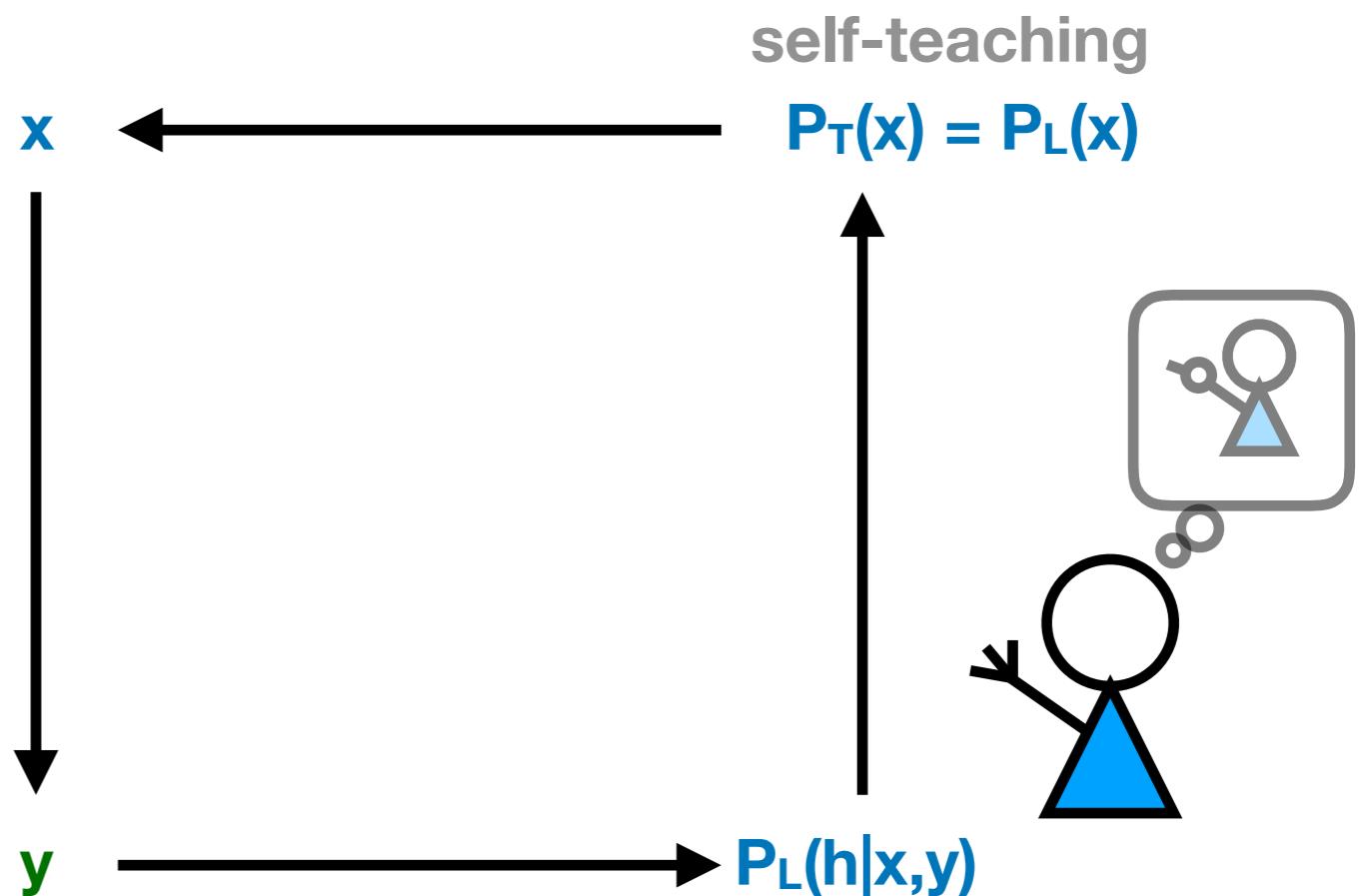
learner's belief

Learner

$$P_T(x|h) = \sum_{g \in \mathcal{H}} P_T(x|g) \delta(g|h)$$

$$P_T(x) = \sum_{g \in \mathcal{H}} P_T(x|g) P_L(g)$$

Self-teaching



World: h^*

Learner

learner's inference

$$P_L(h|x,y) = \frac{P(y|x,h) \cancel{P_T(x)} P_L(h)}{\sum_{h' \in \mathcal{H}} P(y|x,h') \cancel{P_T(x)} P_L(h')}$$

self-teacher's selection

$$P_T(x) = \sum_{g \in \mathcal{H}} P_T(x|g) P_L(g)$$

How is the Self-Teaching model different from the most common model of active learning objective – optimizing for expected information gain?

Does the Self-Teaching model capture human's active learning behavior?

Self-Teaching

$$P_T(x) = \sum_{g \in H} \sum_{y \in Y} \frac{P_L(g|x, y) P_T(x, y)}{Z(g)} P_L(g)$$

- Uses only the rules of probability
- Meta-reasons about oneself as the **teacher**
- Hypothesis testing for distinctive hypothesis

Expected information gain

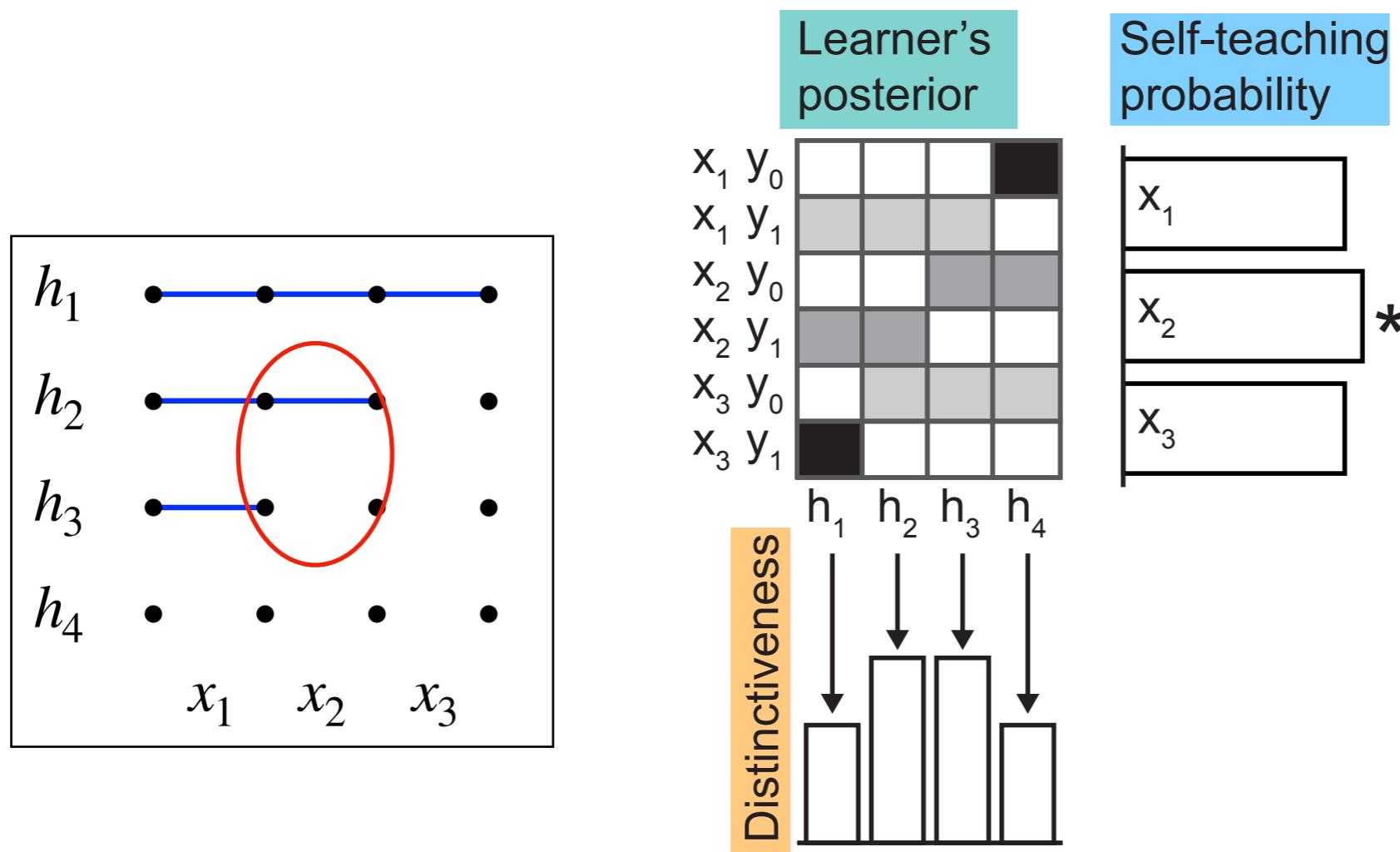
$$EIG(x) = H(h) - \sum_{y \in Y} P_L(y|x) H(h|x, y)$$

- Also uses entropy and subtraction
- Reasons about the **world**
- Overall uncertainty reduction

Self-teaching: confirming distinctive hypotheses

$$P_T(x) = \sum_{g \in \mathcal{H}} P_T(x|g)P_L(g) = \sum_{g \in \mathcal{H}} \sum_{y \in \mathcal{Y}} P_L(g|x,y)P_T(x,y)P_L(g)Z(g)^{-1}$$

$$Z(g) = \sum_{y \in \mathcal{Y}} \sum_{x \in \mathcal{X}} P_L(g|x,y)P_T(x,y)$$

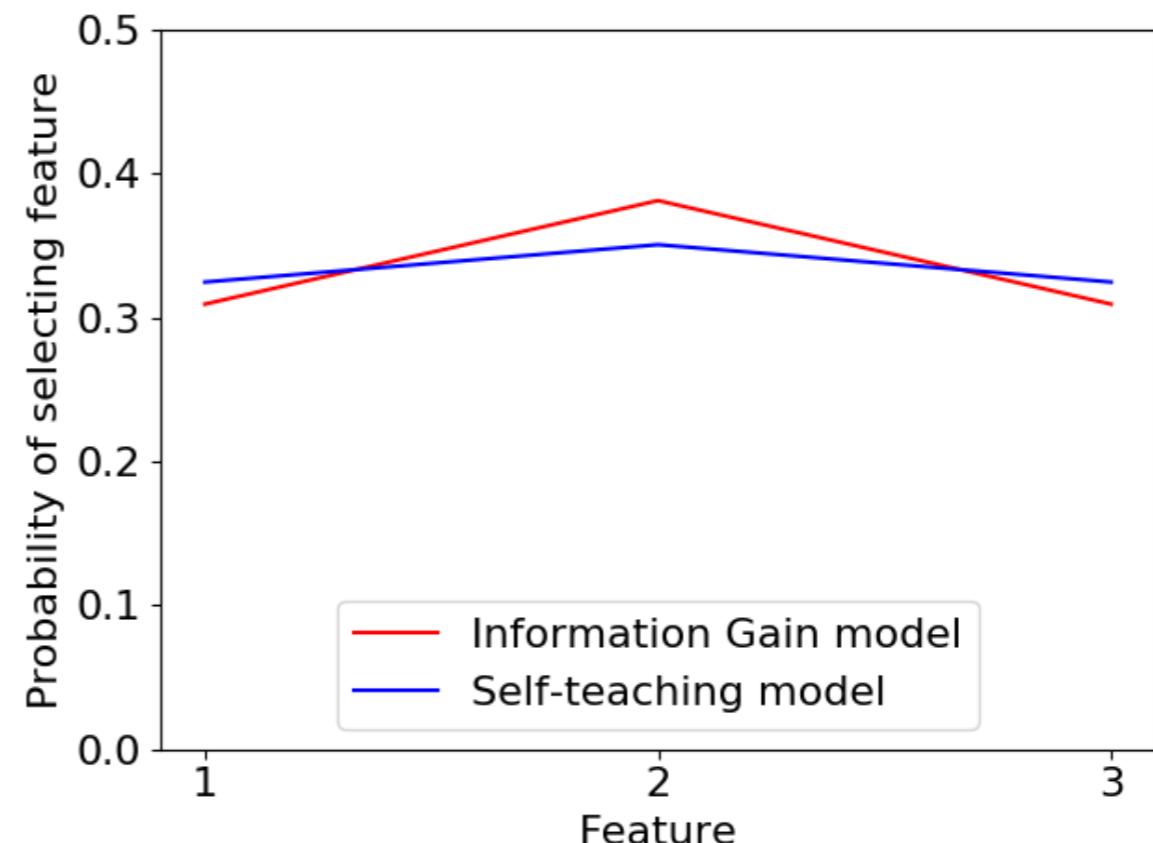
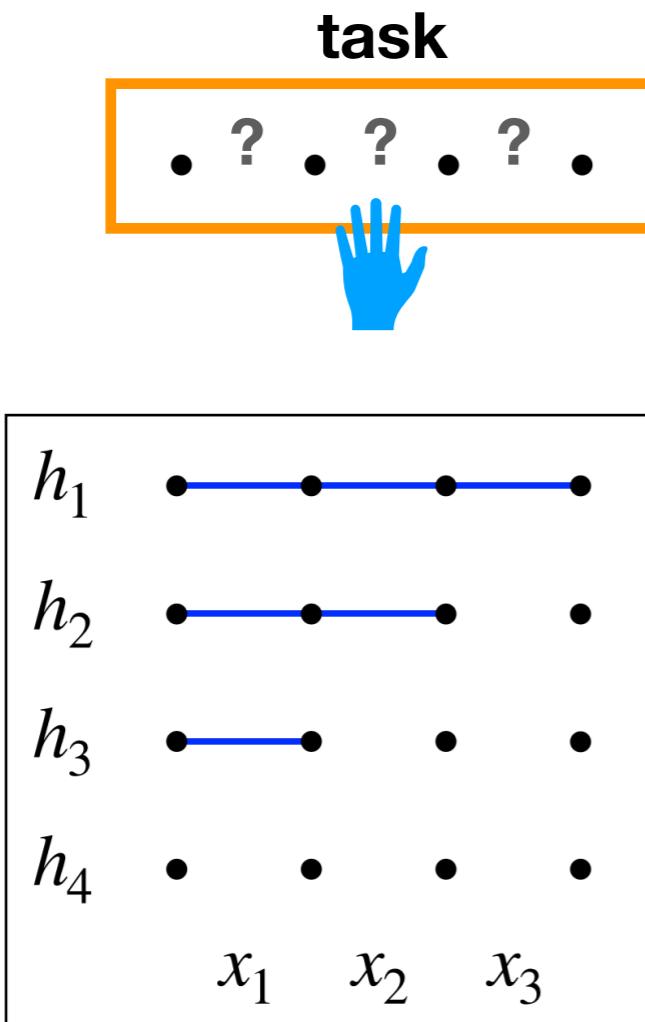


A **distinctive hypothesis** is one that is on average less likely to be inferred if all interventions and observations are equally likely to occur.

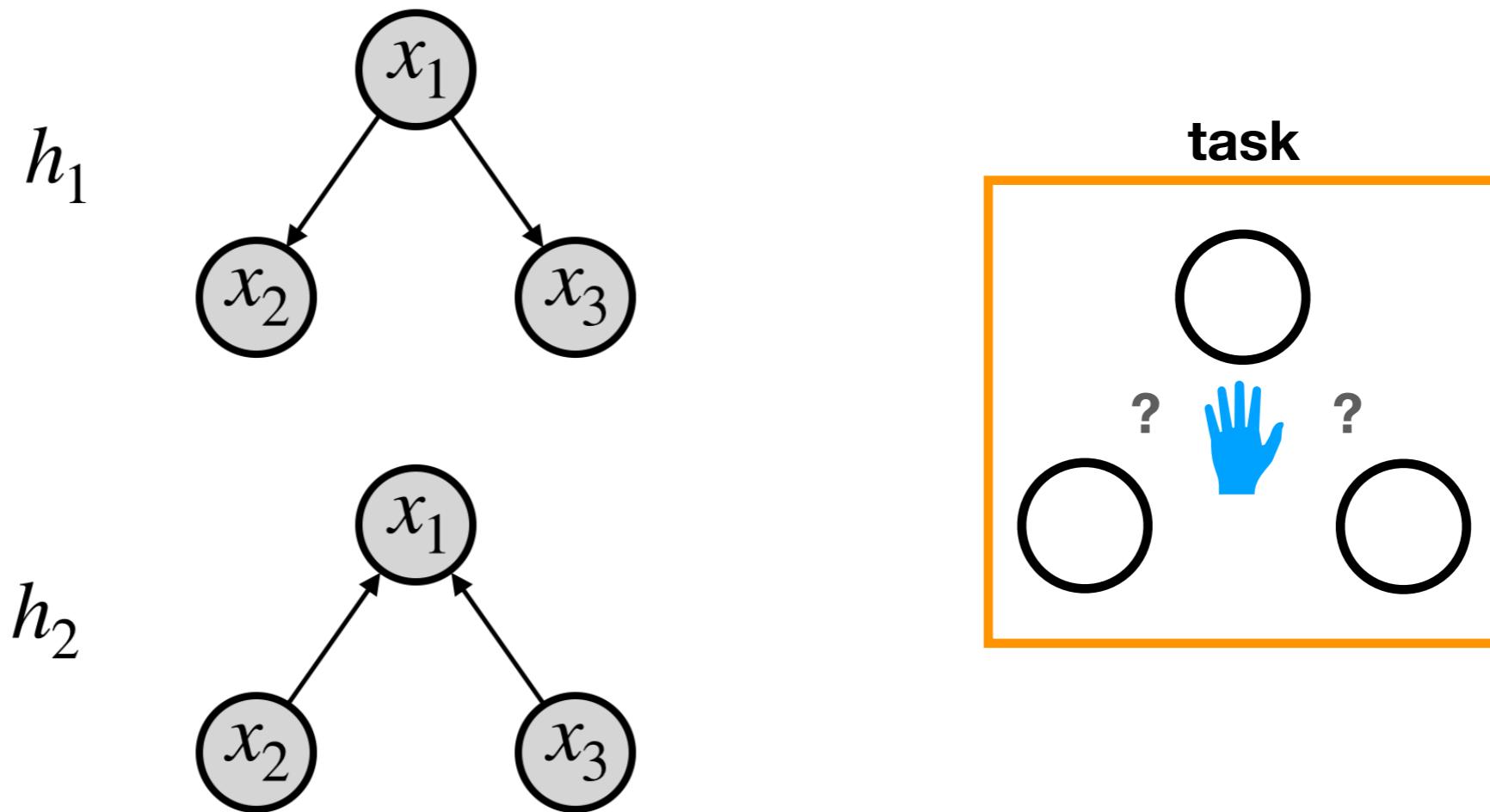
How is the Self-Teaching model different from the most common model of active learning objective – optimizing for expected information gain?

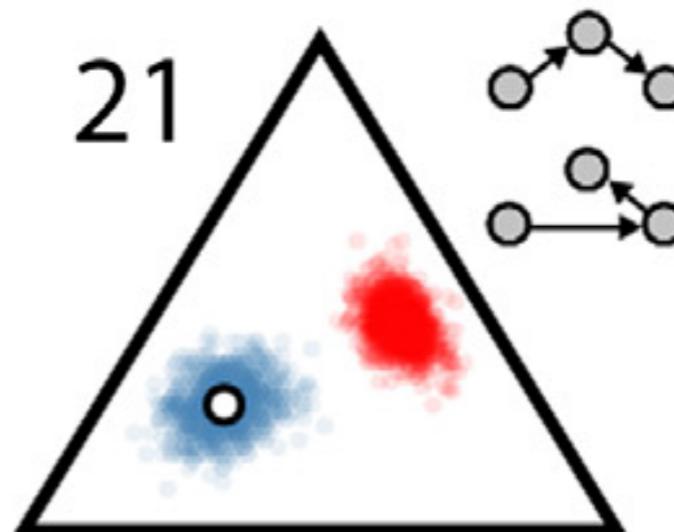
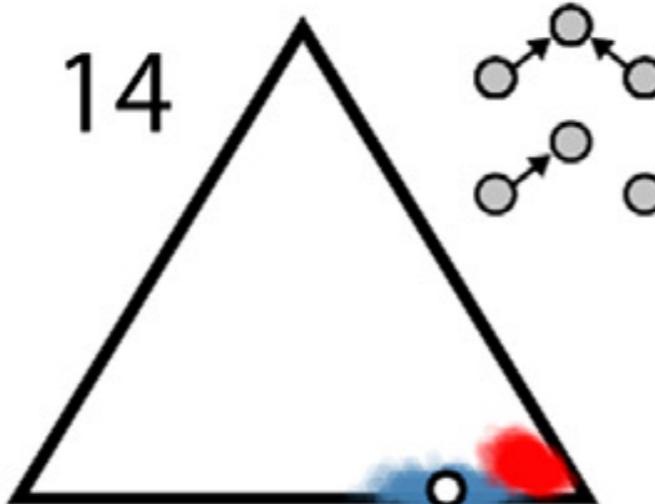
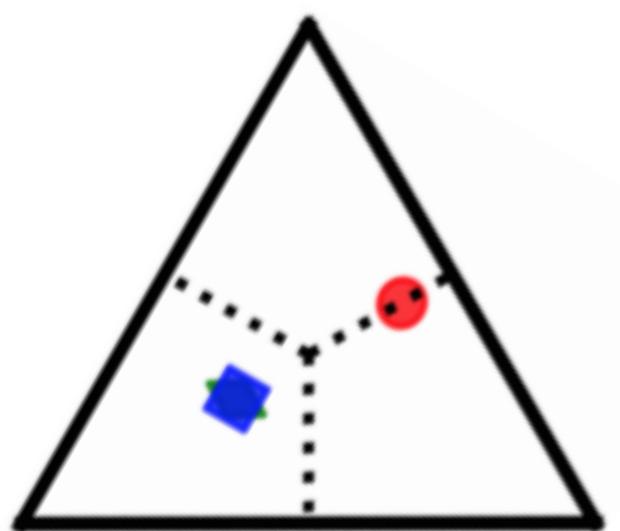
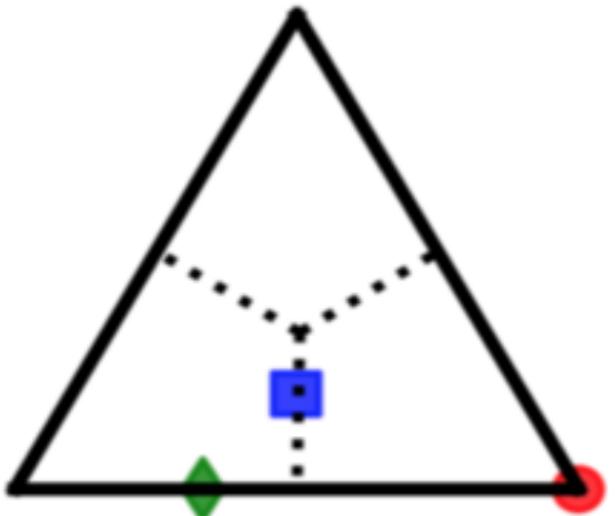
Does the Self-Teaching model capture human's active learning behavior?

Boundary game



Causal graph learning

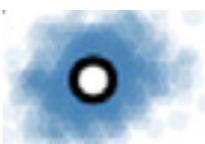




Self-Teaching model



Expected information gain



Human choices



Expected information gain

Coenen, Rehder, & Gureckis. (2015). Strategies to intervene on causal systems are adaptively selected. *Cognitive psychology*, 79, 102-133.

Conclusions

- We derived a **Self-Teaching model**, a novel form of active learning.
- It depends on only the rules of probability (may have implications for active machine learning).
- It unifies teaching and active learning under a single learning mechanism.
- It matches human's active learning behavior in many cases.

Collaborators



Wai Keen Vong



Yue Yu



Patrick Shafto

Yang, Vong, Yu & Shafto. (2019). A unifying computational framework for teaching and active learning. *Topics in Cognitive Science* 11(2): 316-337.