Learning Functional Categories with Soar-RL

Yongjia Wang
University of Michigan

Motivation

- Study the interaction between category learning and behavior adaptation
  - How category learning influence behavior adaptation
  - How behavior adaptation influence category learning
- Computational account for a prevailing cognitive phenomenon – basic level category
  - Emergent property of Soar-RL (surprisingly)

Outline

- Background
- Demonstration task
- Simulation Results and Analysis
- Nuggets and Coal

Category Learning Tasks

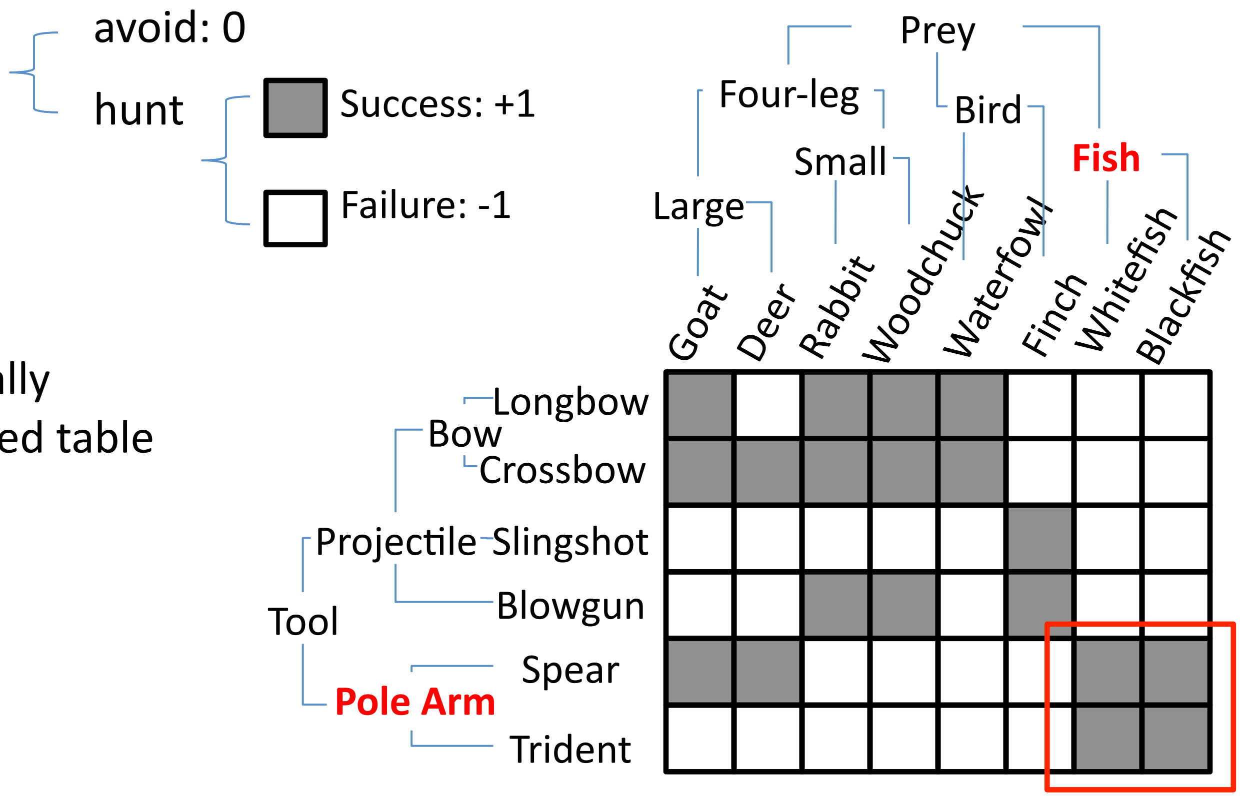
- Supervised category learning (classification)
  - Example: naïve Bayes classifier, SVM, logistic regression
  - Con: require predefined category labels
  - Pro: category labels are designed to be consistent with making action decisions
- Unsupervised category learning (clustering)
  - Example: k-means clustering, hierarchical clustering, Gaussian mixture model (soft clustering)
  - Pro: automatically generate labels
  - Con: category labels may be irrelevant to decision making

Functional Category Learning

- Combine unsupervised and supervised learning
  - Automatically generate category labels
  - Find categories that are functional (contribute to decision making)

Demonstration Task (hunting)

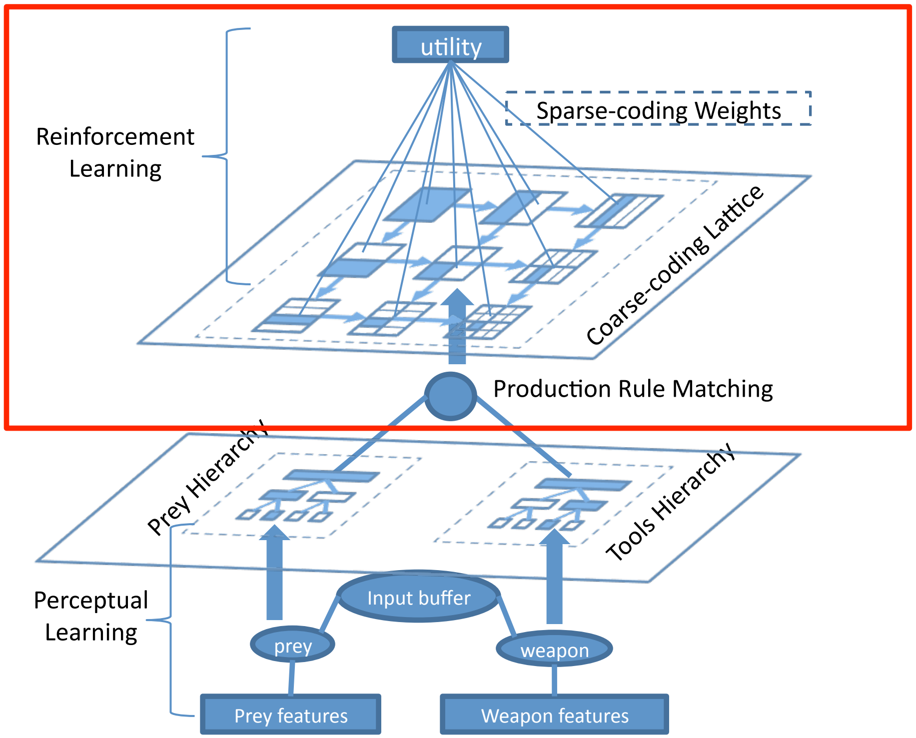
Manually designed table



Unsupervised hierarchical categorization based on innate perceptual features

Useful to generalize: learn "region-by-region" rather than "cell-by-cell"

Overall Architecture



Soar-RL Updates

Input	action	reward
Deer, Crossbow	hunt	+1

K=(k1, k2):
(Corssbow, Deer), (Bow, Deer),(Projectile Deer)
(Tool, Deer), (Crossbow, Large), (Bow, Large),
(Projectile, Large), (Tool Large) …
(Tool, Prey)

Each cell C_K corresponds to a Soar-RL rule, with an attached numeric value $w(C_K)$

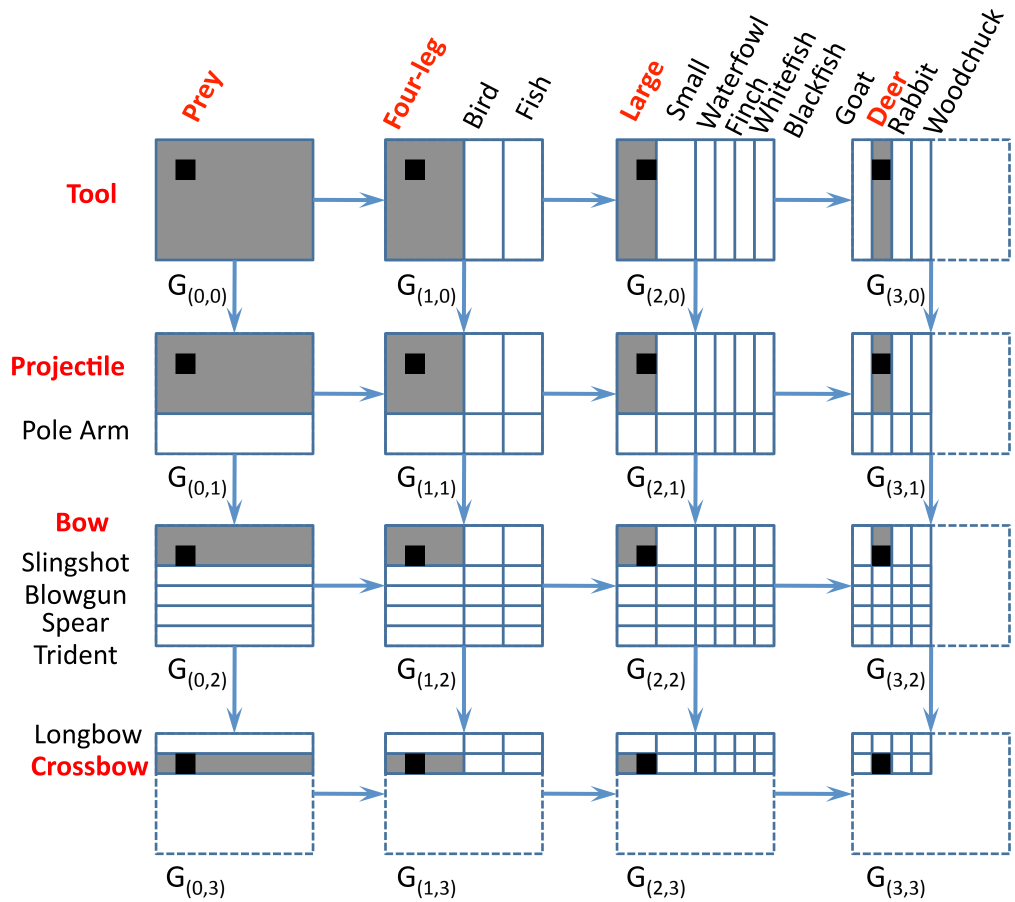
Predicted Q value:

$$y = \sum_{C_K} w(C_K) a(C_K)$$

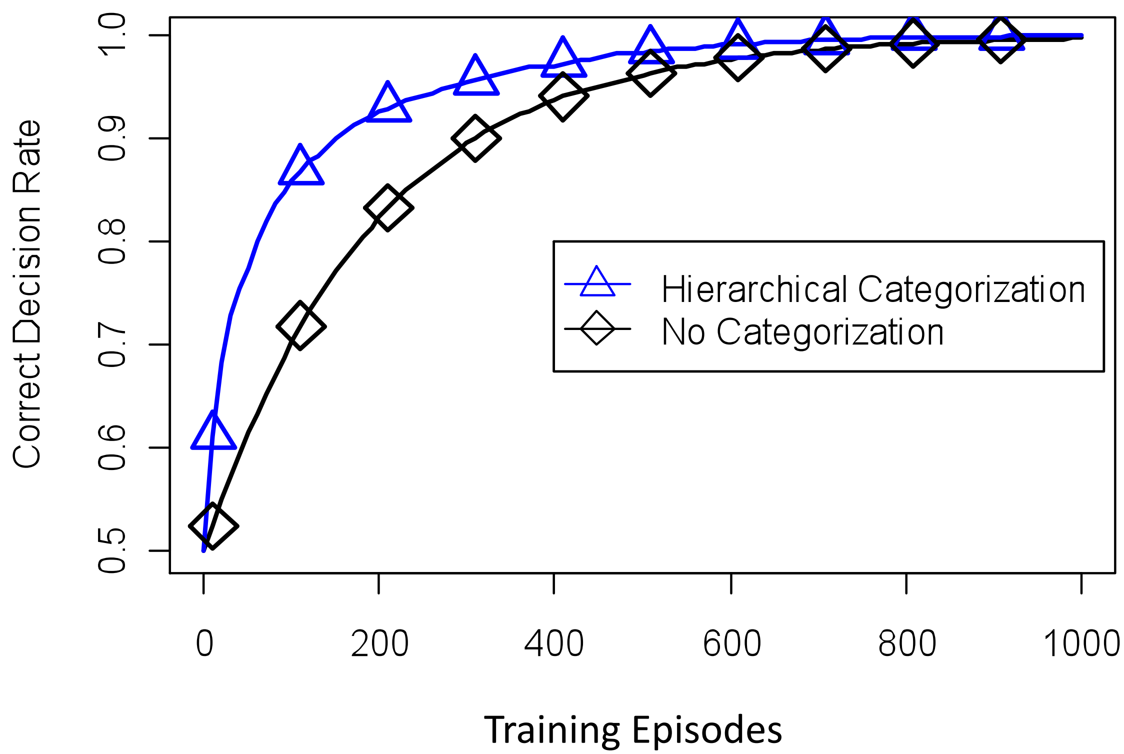
$$a(C_K) = \begin{cases} 1 \text{ if matches} \\ 0 \text{ if not matches} \end{cases}$$

Updates

$$\Delta w(C_K) = \frac{\alpha}{\sum_{C_K} a(C_K)} (t - y) a(C_K)$$



Categorization Speeds RL



Basic Level Categories

- Examples
  - Furniture, chair, rocker
  - Vehicle, car, sedan

- Definition (Rosch 1978)
  - Maximally informative categories
  - Maximize number of attributes shared within the category, and minimize number of attributes shared with other categories
  - Generally appear in the middle of an abstraction hierarchy

Basic Level Categories

- Issues with theoretical definition of basic level categories
  - Context free, at least implicit
  - Lacks of grounding to learning experience
- Our hypothesis about basic level categories
  - Related to functionality of the objects and personal experience
  - How do they help the cognitive agent?
    - Speeds RL
  - How are they learned?
    - Emerging phenomenon of the learning process
    - Basic level categories have highest overall activations

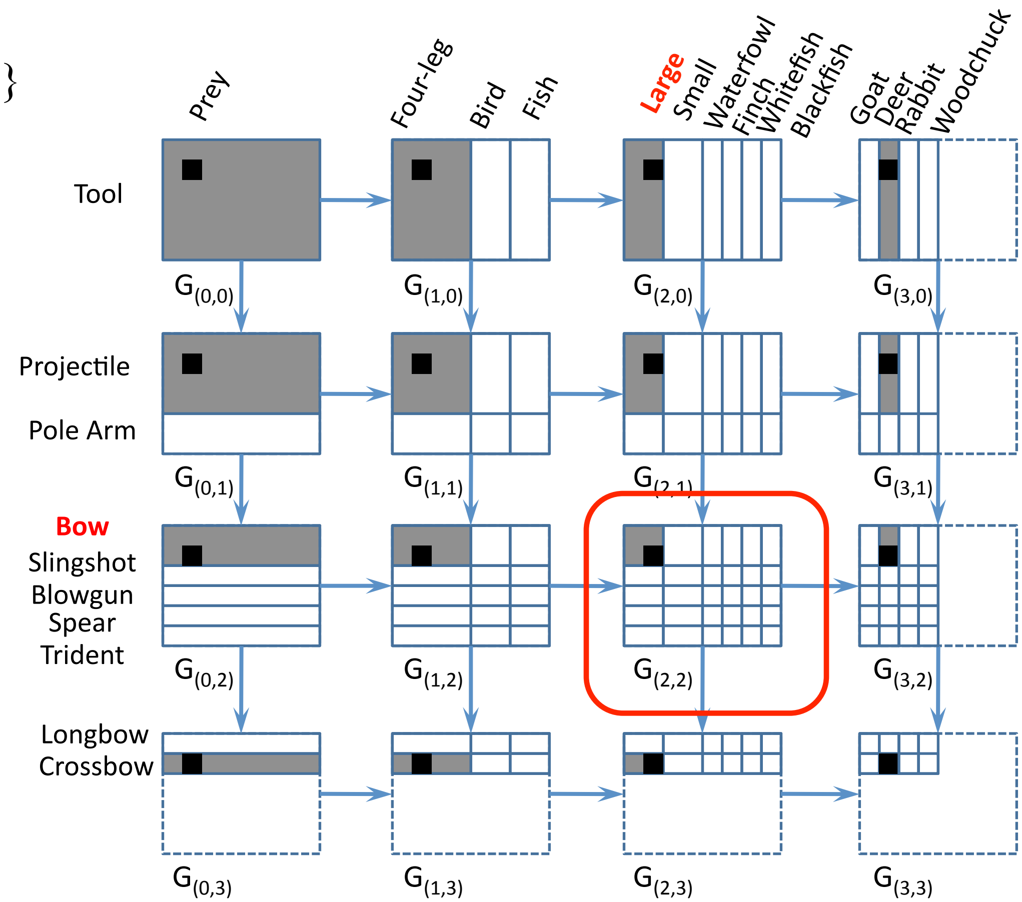
Extract Basic Level Categories from Activation Patterns

$$WinningCell = \underset{Cell}{ArgMax}\{|value(Cell, input)|\}$$

A *winning cell* balances two factors:
1. More frequent updates – favors larger cells
2. Consistent updates – favors smaller cells

Each winning cell corresponds to two ***dominating categories***, which will emerge in the middle of the hierarchies:
'Bow' and 'Large'

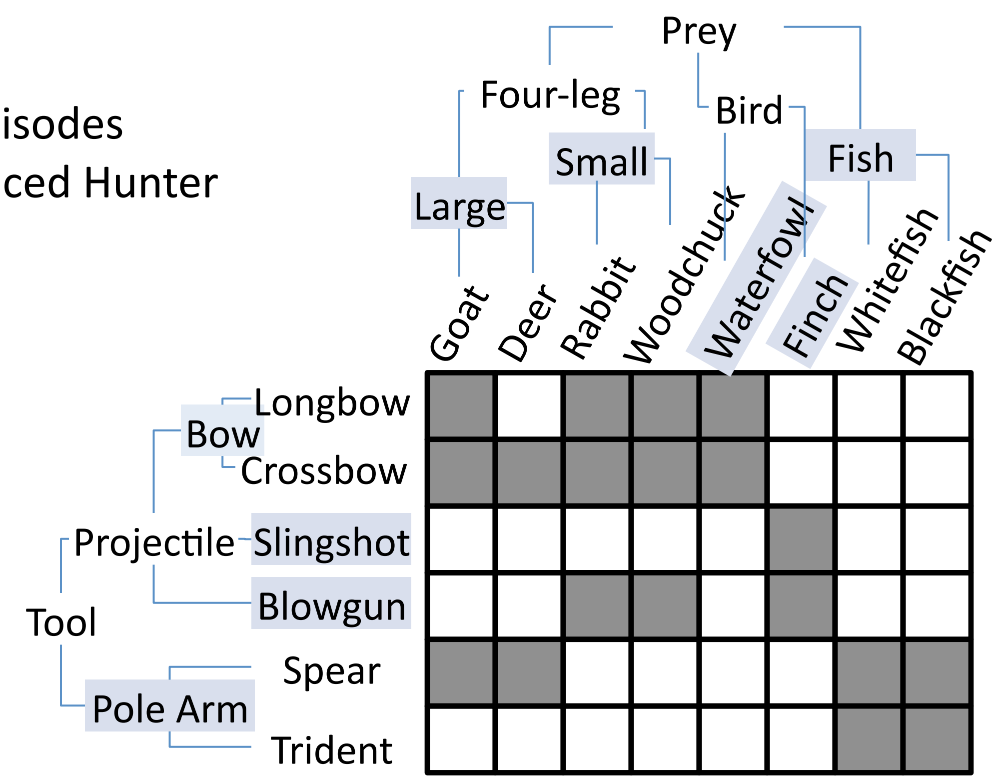
Domination rate: how often a category dominates all superordiante and subordinate categories



Basic Level Categories

Highest Domination Rates across all Inputs

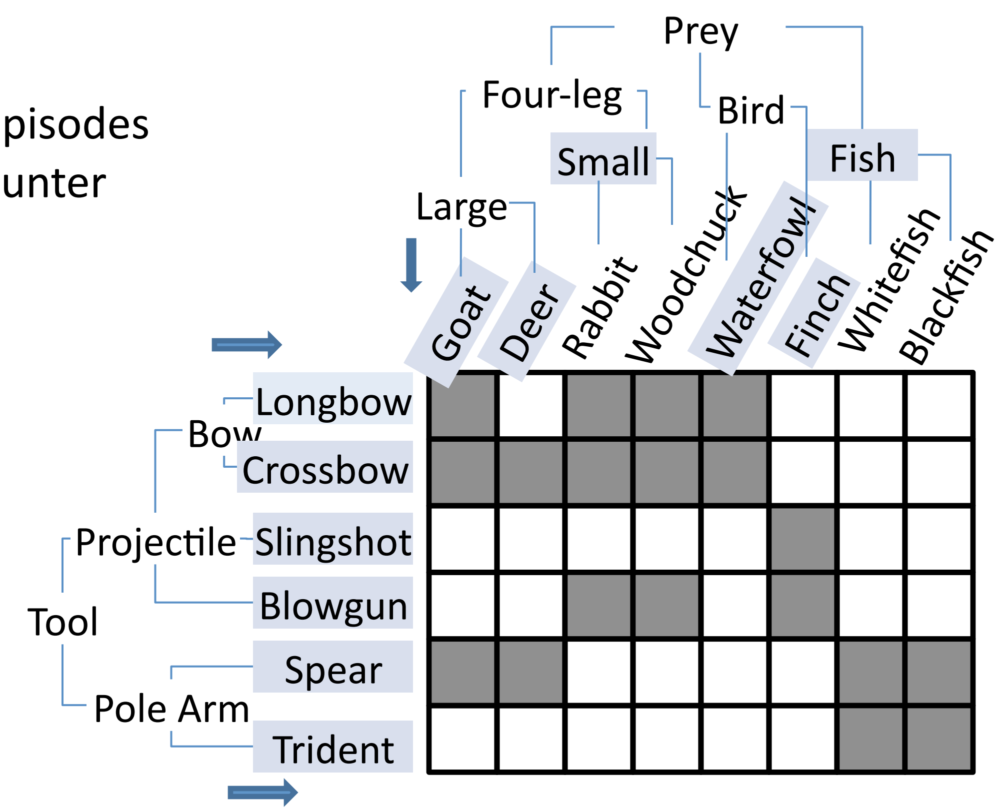
1,000 Episodes
Experienced Hunter



What will happen after more training?

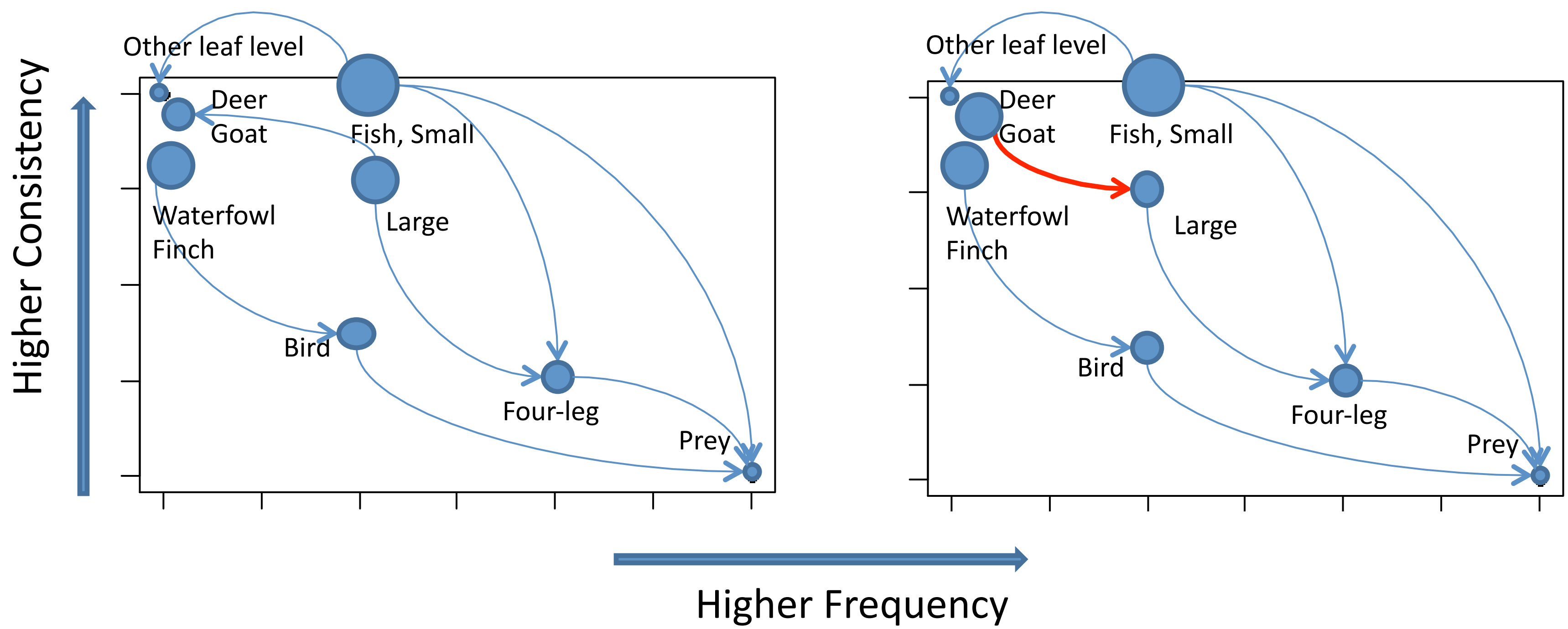
More Practice Pulls Down the Basic Level

10,000 Episodes
Expert Hunter



Frequency Consistency Tradeoff (Qualitative)

circle size represents activation of the concepts

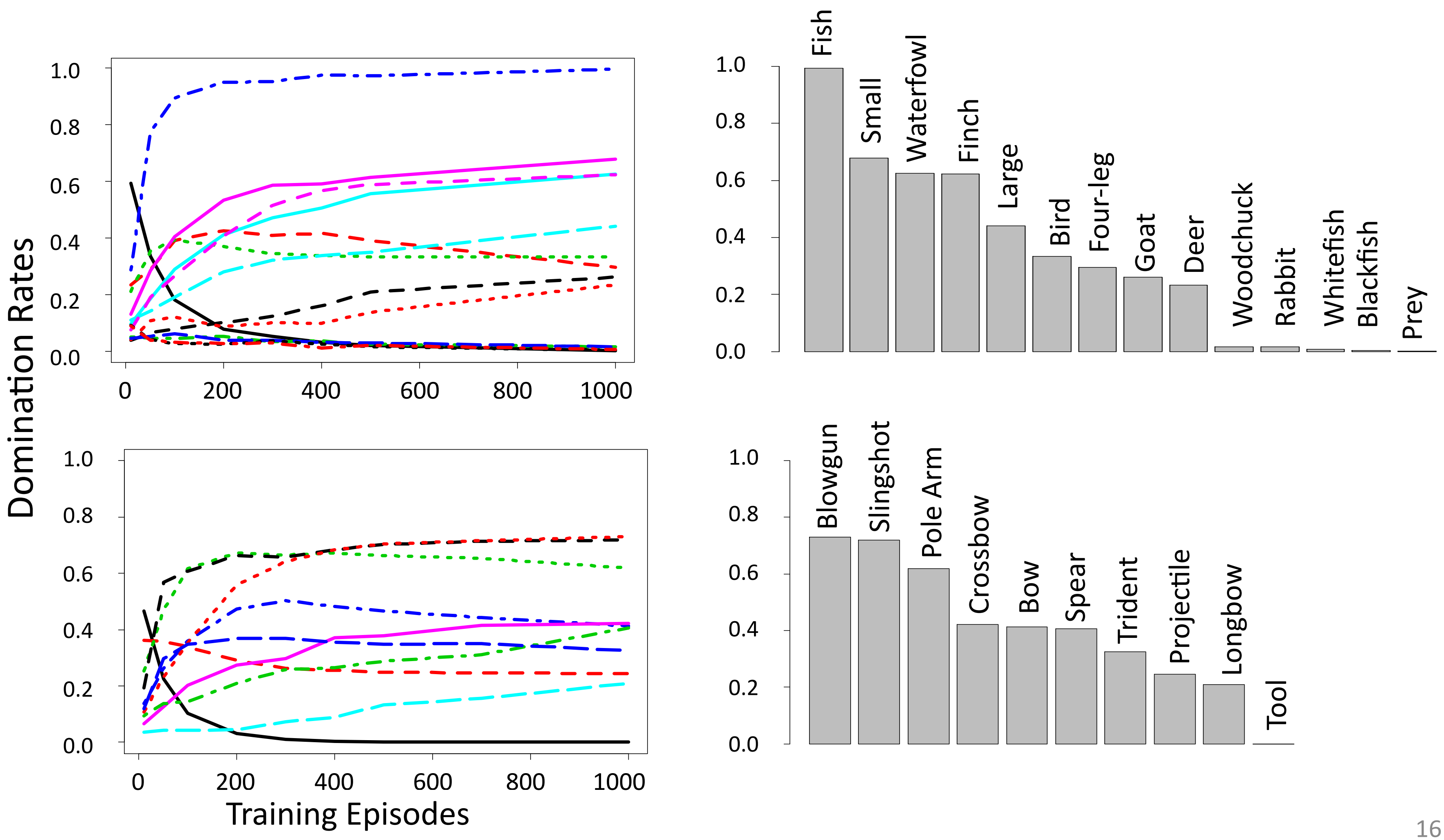


1,000 Episodes
Experienced Hunter

10,000 Episodes
Expert Hunter

Frequency bias is compensated by training experiences (saturation effect)

Dynamics of Domination Rates



Nuggets & Coal

- Nuggets
  - Analyzed the interaction between category learning and behavior adaptation
  - Provides detailed computational account for Basic Level Category
    - Dynamics of category activations
    - Consistent with theory of basic level category
  - Simultaneously learn two types of objects (prey, tool)
- Coal
  - Simple data set
  - Only one functional context (hunting)