Statistical Learning Mechanisms

Making Cognitively Plausible Models

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Outline

- Designing Informative Models
  - Cognitive Plausibility
  - How and Why
- Levels of Explanation
  - Marr's Three Level of Explanation
- Inference Modeling
  - Counting Things
  - Reinforcement Learning
  - Tolerance Principle
  - Bayesian Inference
  - Overhypothesis

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- But how?
- Theoretical, Corpus, and experimental research could help

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- But practically, making a cognitively plausible model for acquisition can still be hard despite these

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- At the end of the day, our models need to be interpretable and informative to us.

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- Implementational (how the computation is actually physically implemented via machineries/mechanisms that exist in the brain)

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Inference is the process by which a child updates their developing grammatical representations.

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A very common mechanism that is involved in inference is the ability to count things

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- Even if there are things unobserved, it is unlikely that the brain will assign zero probabilities to them
- A good/practical way to implement this is via smoothing
- Essentially, you don't start with parameters that are absolutely zero
- One way to realize this is through pseudocounts

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Initial

$$p(+wh) = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2(0.5)} = \frac{0 + 0.5}{0 + 0 + 2(0.5)} = \frac{0.5}{2(0.5)} = 0.5$$

$$p(-wh) = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2(0.5)} = \frac{0 + 0.5}{0 + 0 + 2(0.5)} = \frac{0.5}{2(0.5)} = 0.5$$

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Update

$$p(+wh) = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2 \times 0.5} = \frac{1 + 0.5}{1 + 0 + 2 \times 0.5} = \frac{1.5}{2} = 0.75$$

$$p(-wh) = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2 \times 0.5} = \frac{0 + 0.5}{1 + 0 + 2 \times 0.5} = \frac{0.5}{2} = 0.25$$

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Initial

$$p(+wh) = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2(0.5)} = \frac{0 + 0.5}{0 + 0 + 2(0.5)} = \frac{0.5}{2(0.5)} = 0.5$$

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Final

$$p(+wh) = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{+wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2 \times 0.5} = \frac{700 + 0.5}{700 + 300 + 2 \times 0.5} = \frac{700.5}{1001} = 0.6998$$

$$p(-wh) = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + 0.5 + \text{count}_{-wh} + 0.5} = \frac{\text{count}_{-wh} + 0.5}{\text{count}_{+wh} + \text{count}_{-wh} + 2 \times 0.5} = \frac{300 + 0.5}{700 + 300 + 2 \times 0.5} = \frac{300.5}{1001} = 0.3002$$

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- A datapoint is processed and options/beliefs are updated (in terms of probability) based on how well/badly this datapoint fits with the probability distribution of the options available.

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- The learning rate gamma decides how much updating is done per iteration during training.
- RL models usually have some interesting convergence behaviors

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- Exceptions need to be tolerated (to a certain extent)

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- Involves an equation that could easily be approximated as N over the natural logarithm of N

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Bayes Theorem

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)}$$

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B \mid A)\, P(A) + P(B \mid \neg A)\, P(\neg A)}$$

- Learner has a hypothesis space H

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- Given D, the goal of a child is to determine the probability of a hypothesis $h \in H$ given D, which is $P(h \mid D)$

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Bayesian Inference

$$P(h \mid D) = \frac{P(D \mid h) * P(h)}{P(D)} = \frac{P(D \mid h) * P(h)}{\sum_{h' \in H} P(D \mid h') * P(h')} \propto P(D \mid h) * P(h)$$

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One example being how it could be applied to the linguistic parameters in syntax

Suppose a child is trying to learn the head-initial rule for VPs in English (*see the penguin* rather than *the penguin see*)

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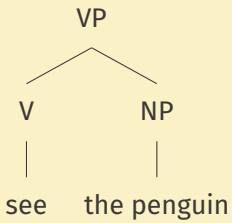
Head-initial



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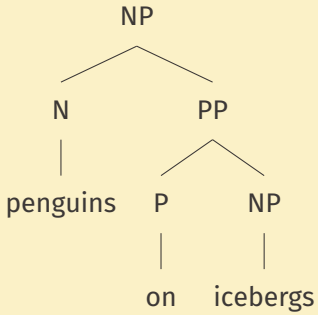

rather than

Head-final