# Model Selection through Active Learning: Do people use simple heuristics or integrative decision strategies?

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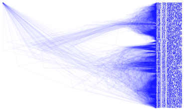
Questions in Behavioural Science

# If humans are active learners, then...

1. ...how can they learn a heuristic that is made up of building blocks on the fly when the goal is to make good decisions?


2. ...how can we use that fact to test different decision making strategies in an active learning context?



# Overview

1. **Distinguishing active versions of decision strategies**

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- How to distinguish between active versions of strategies?
- How does the used strategy depend on the environment?

# PART 1: Can heuristics emerge/grow adaptively?

- Heuristics are made of smaller building blocks
- Different combinations of blocks produce the heuritsic toolbox
- Definition of a heuristic:

  *"Ignores information to be faster and/or more accurate."*

  *"Exhibits a starting rule, a search rule, and a stopping rule."*

# PART 2: Can we distinguish different active algorithms?


- Agent has evolved to obey a certain decision algorithm
- Agent learns with the goal to apply that algorithm
- Definition of active learning:

  *"Stepwise selection of observations in order to learn faster."*

  *"Active learning leads to a banana shaped learning curve."*

# PART 2: Problem statement

## Problem

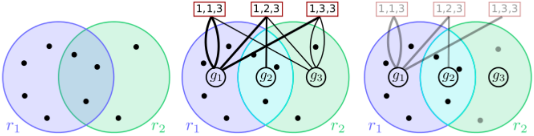
Given a number of binary cues $C_1, C_2, \ldots, C_n$ –some of which might be invalid– learn how to predict a binary outcome $y$ by selecting observations as wisely as possible.

**Current heuristics cannot deal with that, because...**

1. it is not clear how cue validities are learned
2. it is not clear how information is ignored
3. there are no active versions of them
4. active learning has never been utilized for model comparison

# PART 2: Model 1: Active TTB

- **Imagine a scenario without noise:**
  Every observation is deterministic and your only goal is, given your hypothesis space over all cue orders,
  $\mathcal{H} = \{\text{cue-order}_1, \text{cue-order}_2, \ldots, \text{cue-order}_k\}$, to select the observation $s^* = \text{argmax}\{|\mathcal{H}| - |\mathcal{H}|s|\}$
- Unfortunately, observations never come without noise
- We have to find a probabilistic version of the same algorithm



# PART 2: Model 1: Active TTB algorithm

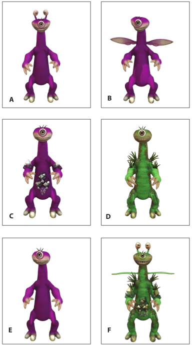
- Put a pseudo-count $\pi$ over all possible cue orders
- If a cue order makes a correct prediction, then $\pi++$
- Calculate current entropy over all cue orders $S_0 = \sum_i p_i \log p_i$
- For every possible comparison $s$ calculate $p(y = w)$ and $p(y = L)$ by $\pi$-weighted sum over all cue orders
- For every comparison $s$, calculate posterior expected entropy $\mathbb{E}[S|s] = S(y = W) \times p(y = W) + S(y = L) \times p(y = L)$
- Choose $s^* = \text{argmax}\{S_0 - \mathbb{E}[S|s]\}$, that is the observation with the highest expected information gain
- Method works well a priori

# PART 2: Model 2: Active Logistic Regression

- Given a Bayesian variant of logistic regression:
$$f(x) = \frac{1}{1+\exp(-(\beta_0+\sum_k \beta_k x_k))}$$
- Calculate the current sum of coefficients' uncertainty $S = \sum_k \mathbb{V}(\beta_k)$
- For every comparison $s$, calculate $p(y = w|s)$ and $p(y = l|s)$
- For every comparison and outcome calculate $S|s, y = w$ and $S|s, y = l$, that is the reduction of variance
- For every comparison $s$, calculate posterior expected uncertainty $\mathbb{E}[S|s] = S(y = W) \times p(y = W) + S(y = L) \times p(y = L)$
- Choose $s^* = \text{argmax}\{S_0 - \mathbb{E}[S|s]\}$, that is the observation with the highest expected uncertainty reduction
- Method works well a priori

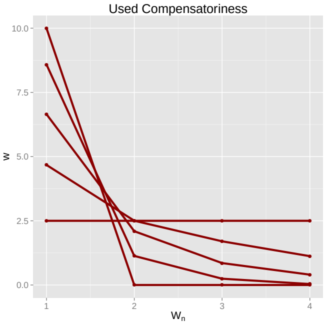
# Part 2: Alien Olympics: Design

1. Learn how well aliens perform in Olympics
2. Aliens vary on 4 different features:
   Wings, Camouflage, Diamonds, and Antennæ
3. 30 learning trials: select 2 out of 4 aliens to compete against each other ($0.5 reward)
4. 10 test trials: select 1 out of 2 aliens for your team (bonus dependent on team)
5. Environment set up with different levels of compensatoriness

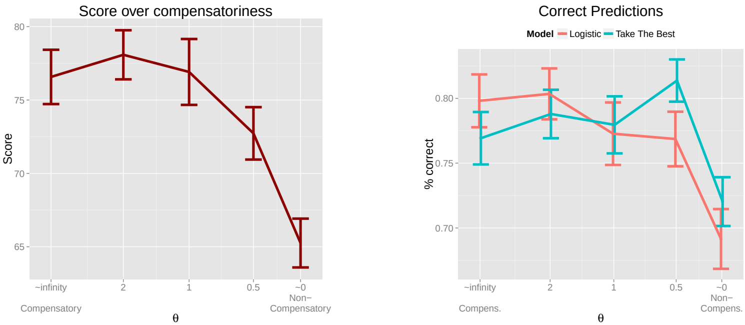


# Part 2: Alien Olympics: Results in test set

1. Underlying envrionment obeys logistic regression
2. Weights are generated by a stick-breaking process
   $\beta'_k \sim \text{Beta}(1, \theta)$
   Define $\{\beta'_k\}_{k=1}^4$ as:
   $\beta_k = \beta'_k \prod_{i=1}^{k-1}(1 - \beta'_i)$
3. Allows to trade-off different levels of compensatoriness

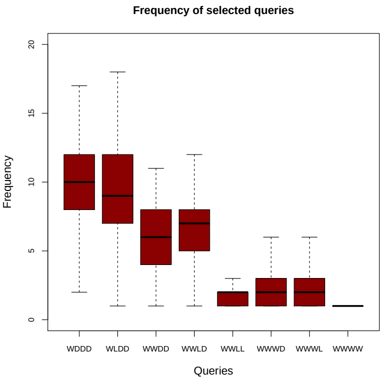


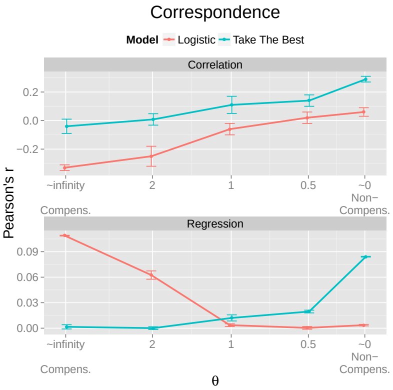
# Part 2: Alien Olympics: Results of passive part




1. Non-compensatory conditions produce lower average score
2. Hard to distinguish between models based on test set alone

# Part 2: Alien Olympics: Results of active part

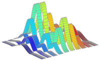



1. Participants perform simple but sensible queries
2. Can distinguish between active models:
   Only active TTB seems to match behavior well

# PART 2: Conclusion


Active learning can be used to distinguish different models


It is possible to design active versions of classic models

In a first experiment, active TTB seems to do best

Simpler follow-up, Exploitation scenarios, Non-parametrics

# Overall conclusion

**I hope to have convinced you that...**

1. ...active learning is an exciting tool to add to our methodological repertoire
2. ...it is both possible and fruitful to design active learning algorithms based on classic models
3. ...if we want to make claims about cognitive strategies, we also have to make claims about how those are acquired

**Future steps could involve...**

1. ...coming up with more active learning models
2. ...designing additional active learning algorithms
3. ...modeling both exploration and exploitation scenarios

# Thank you!

1. **Collaborators:**

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