

# Level-0 Models for Predicting Human Behaviour in Games

# Behavioural Game Theory

- Sometimes game theory recommends actions that seem counter-intuitive
- Example: “Travellers Dilemma“
- **Do people actually follow them?**

# Level-k

*"Player types are drawn from a hierarchy of smartness analogous to the levels of iterated rationalizability"*

-Stahl, D. O. (1993). Evolution of Smart<sub>n</sub> Players

# Level-k

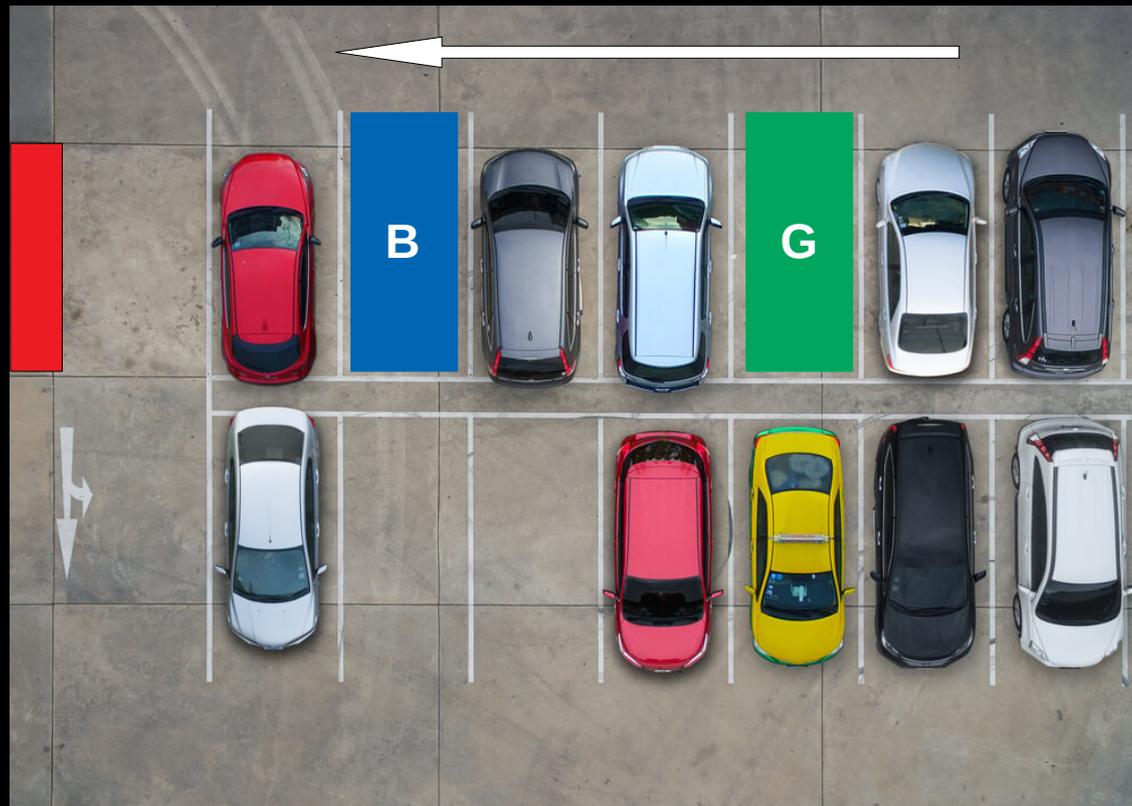


# Cognitive Hierarchy

- A Player does not necessarily fall under one of these archetypes
- Assumptions can be made about mixed populations
- E.g. 50% Level-0, 50% Level-1
  
- **Is this a model for human behaviour?**

# Quantal Cognitive Hierarchy

- Cognitive Hierarchy doesn't account for human mistakes
- Humans don't always go for the best response



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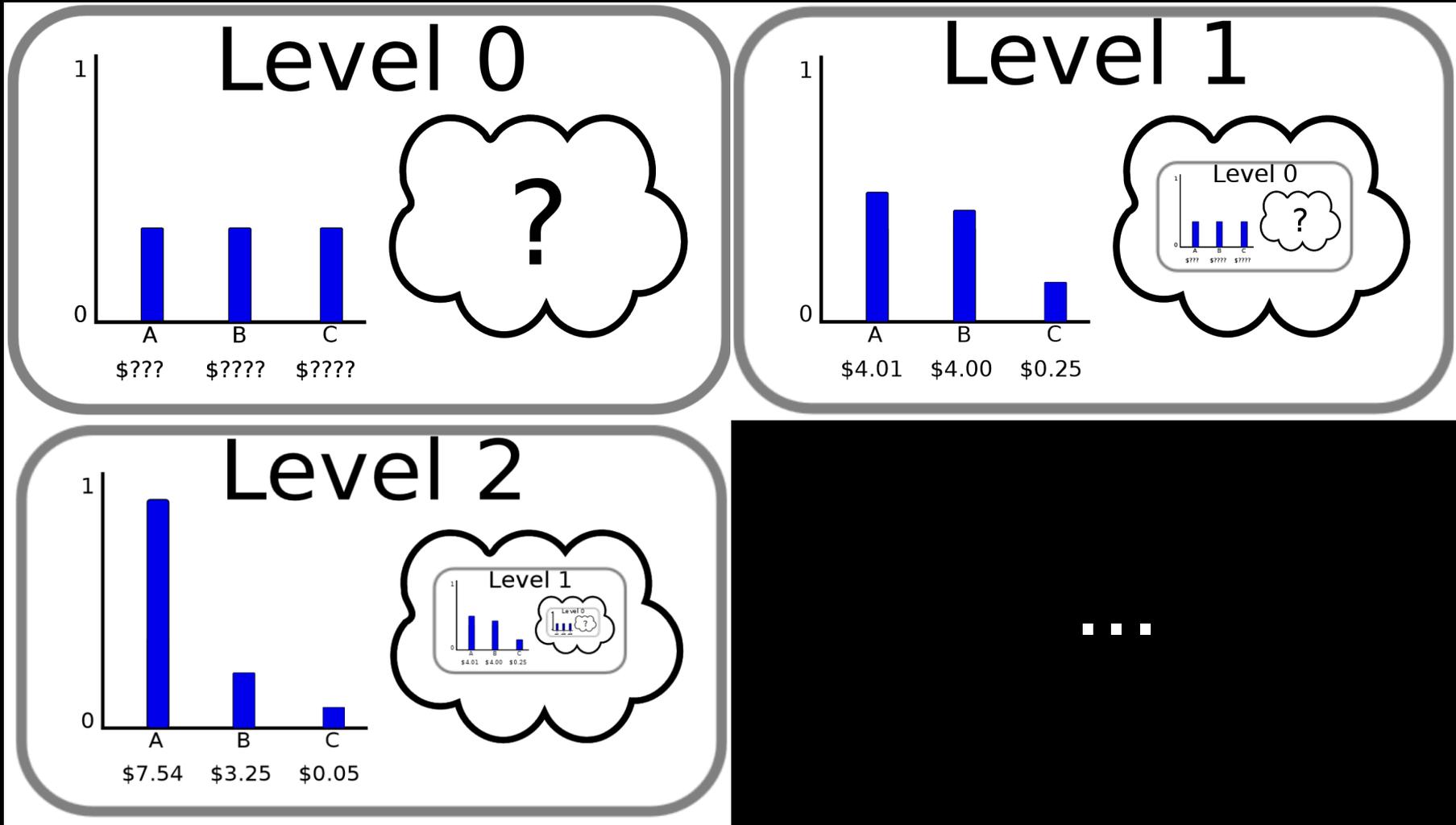
# Quantal Best Response

$\text{QBR}_i(\mathbf{s}_{-i}; \mathbf{G}, \lambda)$  always returns a single mixed strategy  $\mathbf{s}_i$

$$s_i(a_i) = \frac{\exp[\lambda * u_i(a_i, s_{-i})]}{\sum_{a'_i \in A_i} \exp[\lambda * u_i(a'_i, s_{-i})]}$$

- $u_i(a_i, s_{-i})$  = expected utility of **agent i** when playing action  $a_i$  against mixed strategy profile  $s_{-i}$
- $\lambda$  = Precision  $\rightarrow$  Agents Sensitivity to utility differences

# Iterative reasoning



# Quantal Cognitive Hierarchy

- **Poisson-QCH model:**

$$\pi_{i,0:m} = \sum_{l=0}^m \frac{\text{Poisson}(l; \tau)}{\sum_{l'=0}^m \text{Poisson}(l'; \tau)} \pi_{i,l}$$

- The truncated distribution over actions predicted for an agent of level  $0 \leq l \leq m$

# Quantal Cognitive Hierarchy

- Predicted action distribution:

$$\pi_{i,0}(a_i) = |A_i^{-1}|$$

$$\pi_{i,m}(a_i) = QBR_i(\pi_{-i,0:m-1}; \lambda)$$

- Two parameters:  $\lambda$  (precision) and  $\tau$  (mean of Poisson distribution)

# Experiment

Pick a number **from 0 to 100**, with that number representing your best guess of **two-thirds of the average** of all chosen numbers.

**For example:** Is the average of all numbers **63**, you would win by picking **42**. (No decimals or fractions)

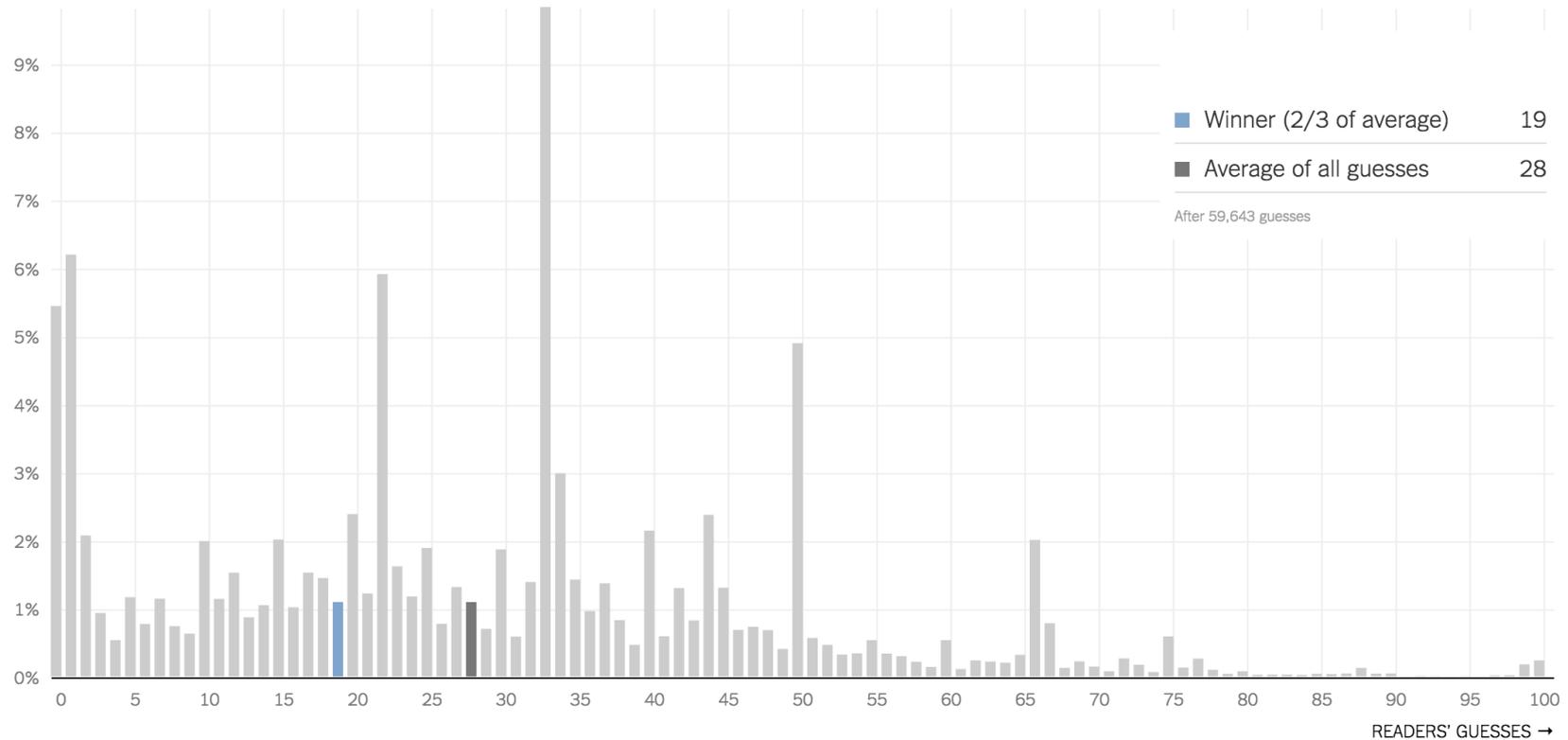
If the average is **40**, you'd win by picking **27**.

**Reason about the other people!**

# Quantal Cognitive Hierarchy

## New York Times Results (59,643 guesses)

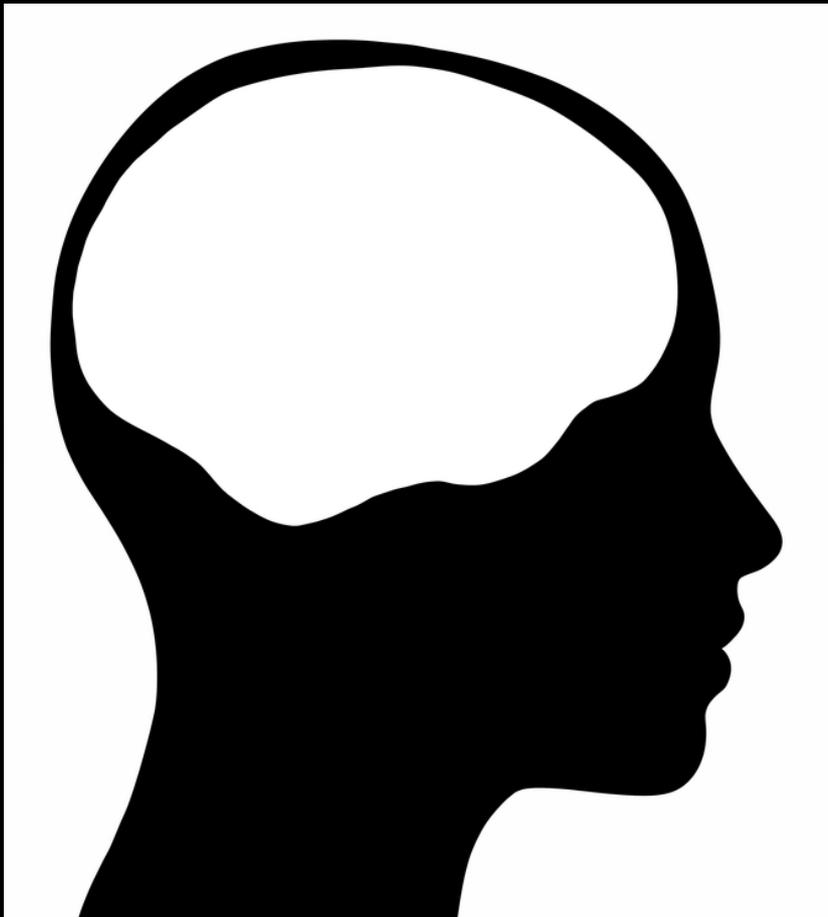
PERCENT OF READERS PICKING EACH NUMBER:



[4] [nytimes.com/interactive/2015/08/13/upshot/are-you-smarter-than-other-new-york-times-readers.html](http://nytimes.com/interactive/2015/08/13/upshot/are-you-smarter-than-other-new-york-times-readers.html)

# What's the problem with current models?

Level 0



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Level > 0



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# Level-0 Models

- I. What is non-strategic behaviour?**
- II. What are Level-0 Features?**
- III. How do we select a Model?**

# Non-strategic behaviour

- It doesn't have to be uniform!
- May take account of payoffs
- Not responding to explicit beliefs about other agents behaviour
  - Level-1 and higher = strategic
- can be computed via a finite combination of elementary agent models

# Non-strategic behaviour

## Elementary Agent Model:

An agent model for agent  $i$  is a function  $f_i(G)$  that maps from a normal-form game  $G$  to a vector of reals with dimension  $|A_i|$ .

An agent model is **elementary** if it can be computed as  $f_i(G) = h_i(\Phi(G))$ , where:

- i)  $\Phi(G)_a = \phi(u(a))$  for every action profile  $a$ ,
- ii)  $\phi(u(a)) = w^T u(a)$ .  $\phi(u(a))$  is computed by taking a linear combination of the players utilities at pure action profile  $a$  with the weights defined by a vector  $w$  in  $\mathbb{R}^n$

# Level-0 Features

- The models are driven by certain rules (“features”)
- One or more actions are recommended to greater or lesser degree
- Can be computed directly from the normal form

# Level-0 Features

1. **Maxmin payoff** – The best worst case
2. **Maxmax payoff** – The best best case
3. **Minimax regret** – The minimal maximal regret
4. **Maxmax fairness** – The “fairest” action
5. **Max symmetric** – The best response to oneself
6. **Maxmax welfare** – The best sum of utilities

We define a binary- and a real-valued version of each feature!

# Level-0 Feature combination

$F$  = set of features.  
 $w_f \in [0,1]$  with  $\sum_{f \in F} w_f \leq 1$   
 $w_0 = 1 - \sum_{f \in F} w_f$

*Weighted Linear level-0 specification*

$$\pi_{i,0}^{\text{linear},F}(a_i) = \frac{w_0 + \sum_{f \in F} w_f f(a_i)}{\sum_{a'_i \in A_i} [w_0 + \sum_{f \in F} w_f f(a'_i)]}$$

*Logit level-0 specification*

$$\pi_{i,0}^{\text{logit},F}(a_i) = \frac{\exp(w_0 + \sum_{f \in F} w_f f(a_i))}{\sum_{a'_i \in A_i} \exp(w_0 + \sum_{f \in F} w_f f(a'_i))}$$

# Level-0 Features informativeness

- Are all these features always relevant?
- Do we always get a 'good' recommendation?

**Player 2**

	A	B	C
<b>Player 1</b> X	100 20	10 67	30 40
Y	40 35	49 50	90 70
Z	40 21	42 22	41 23

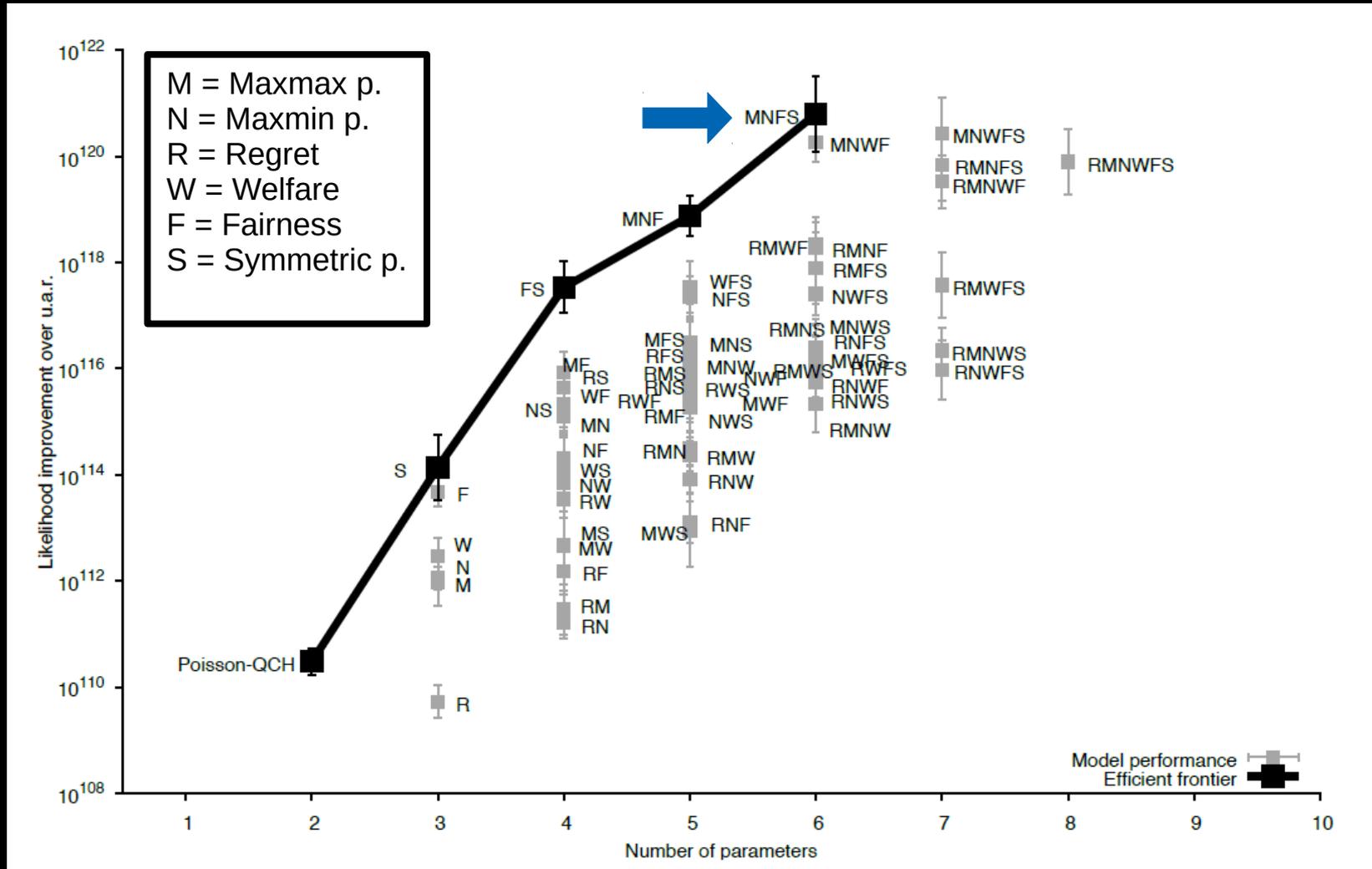
# Level-0 Features informativeness

**Player 2**

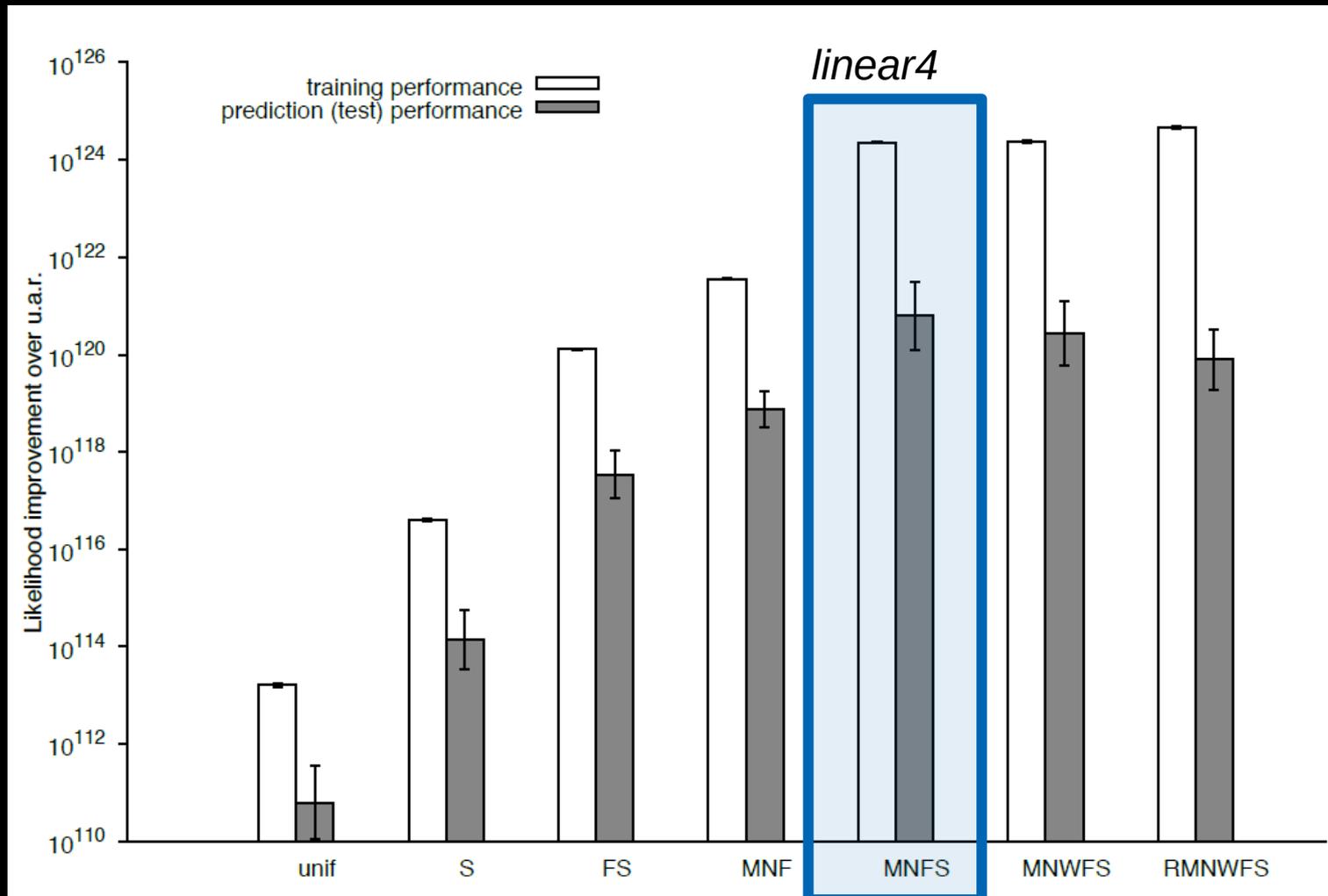
	A	B	C
<b>Player 1</b> X	100 20	10 67	30 40
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- 1) Maxmin payoff
- 2) Minimax regret

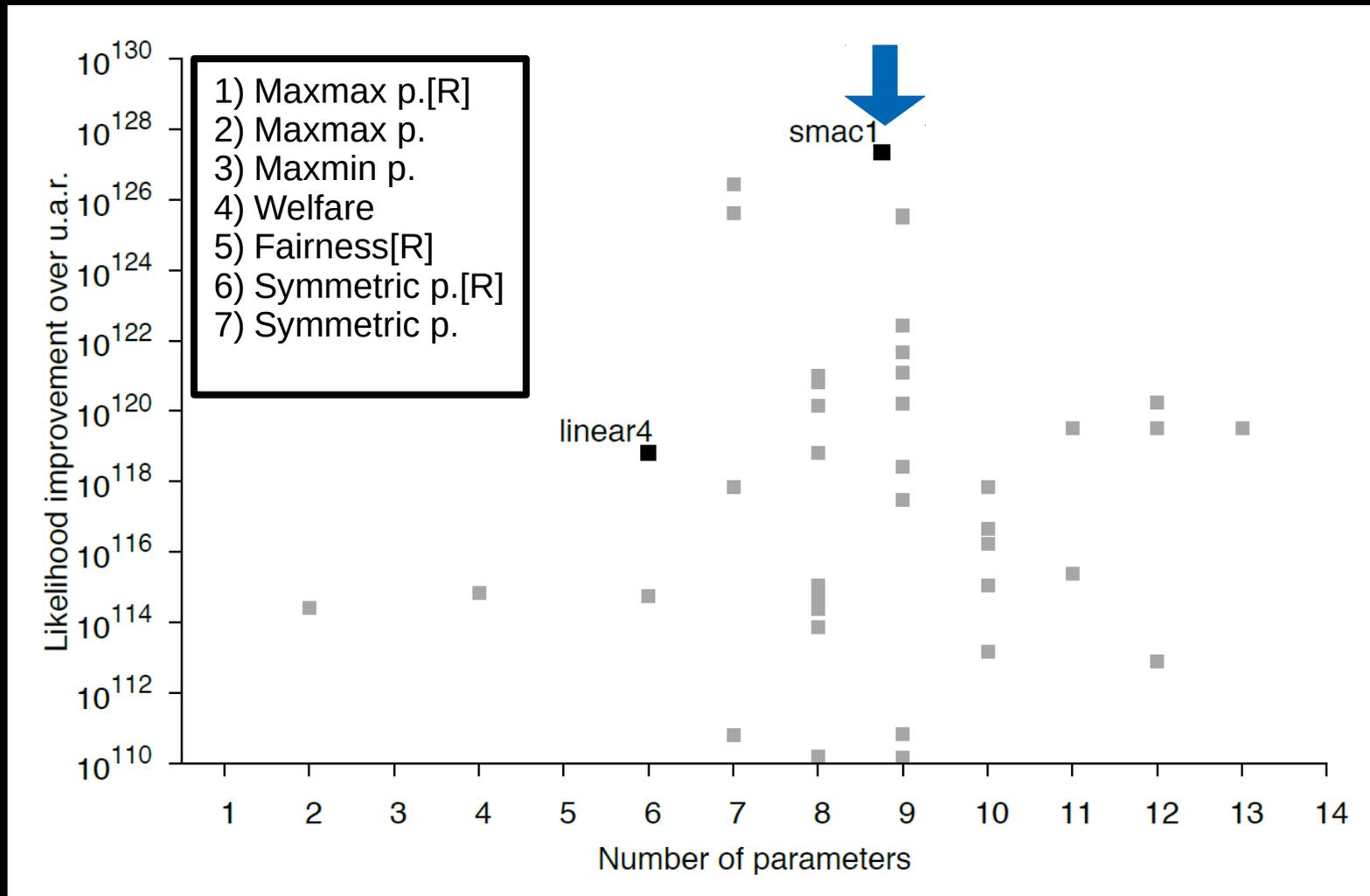
# Model selection



# Model selection

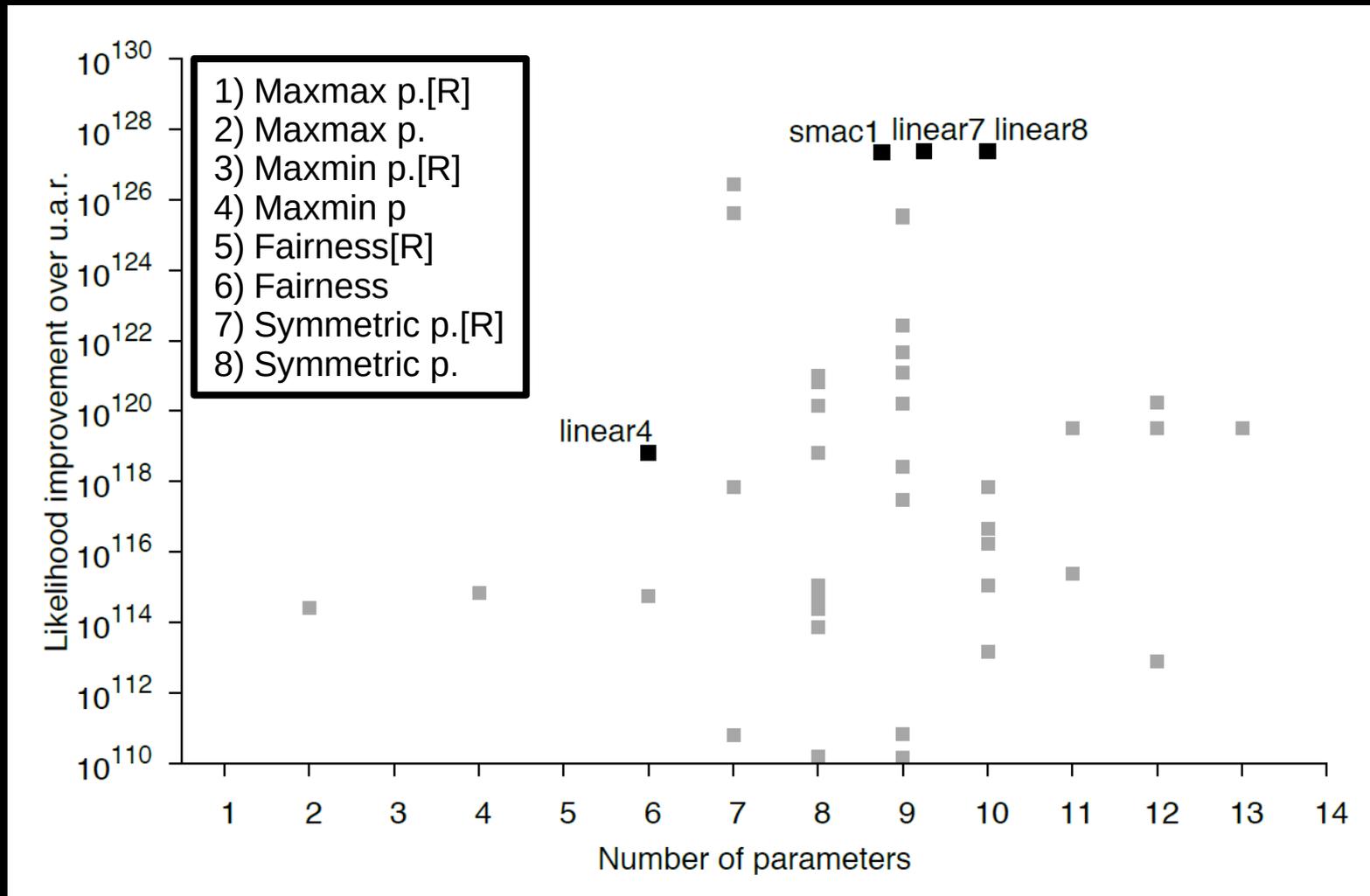


# Model selection (Bayesian optimization)



*First random training/test split*

# Model selection (Bayesian optimization)



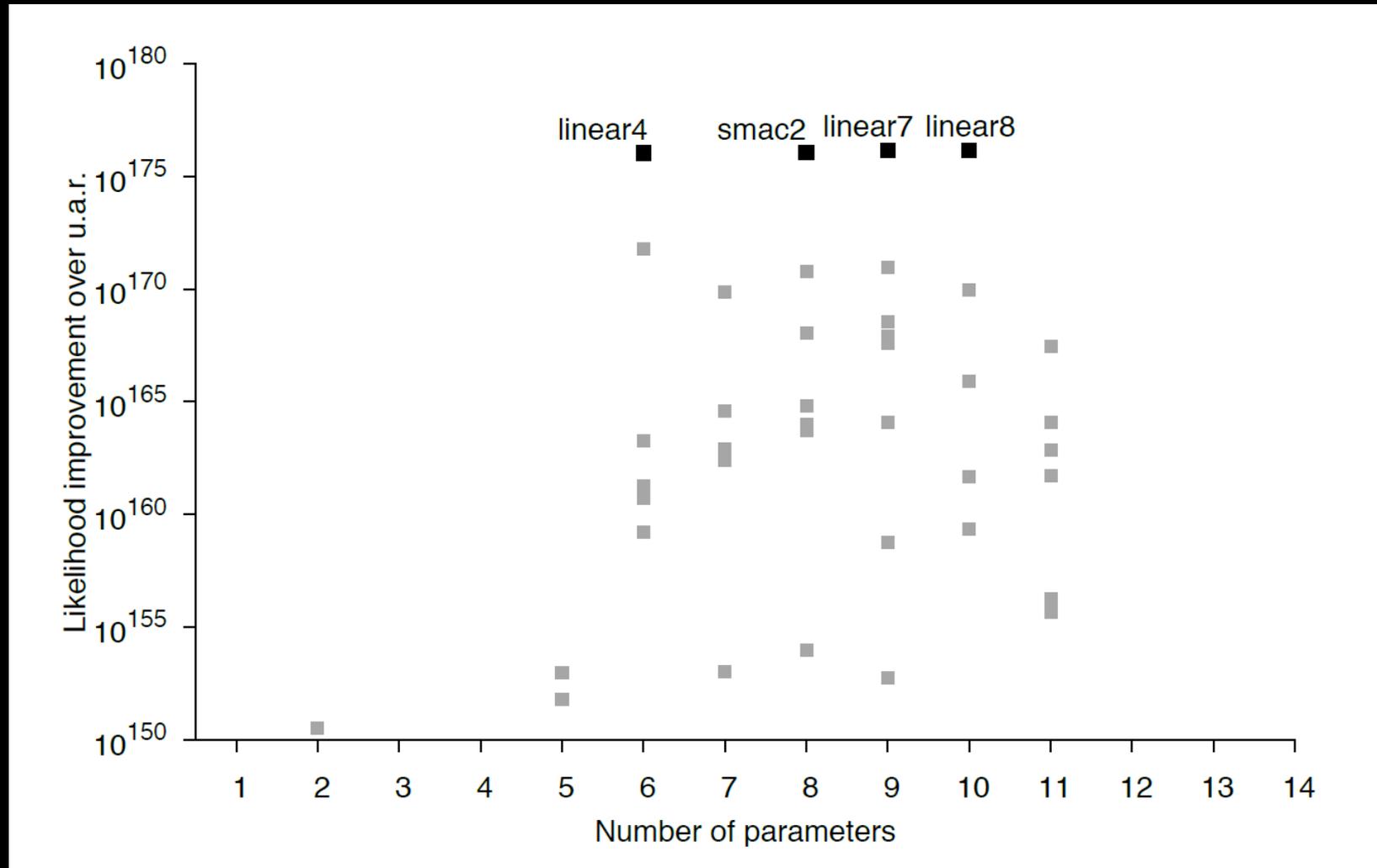
*First random training/test split*

# Model selection (Bayesian optimization)

smac1 linear7 linear8



# Model selection (Bayesian optimization)



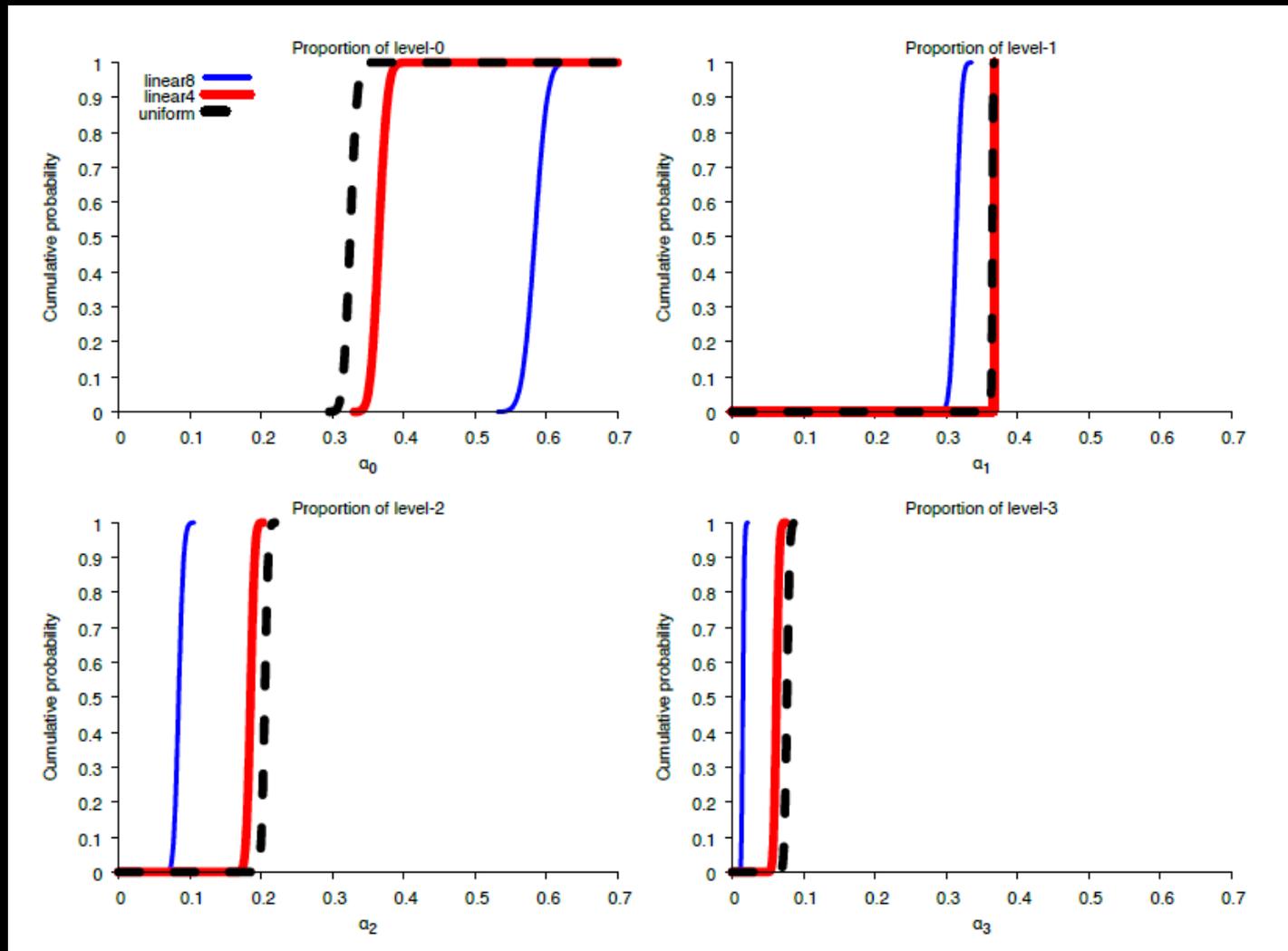
*Second random training/test split*

# Model selection (Bayesian optimization)

linear4                      smac2    linear7    linear8



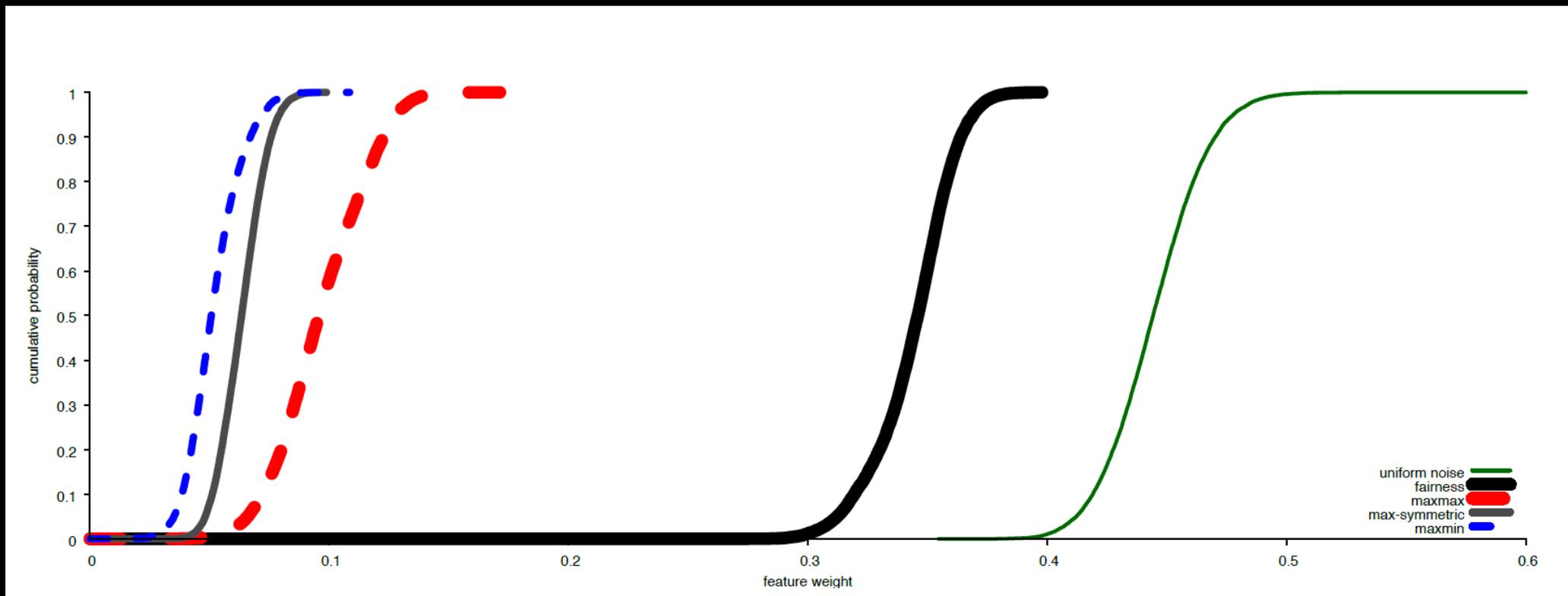
# Parameter Analysis



*Marginal cumulative posterior distributions of levels of reasoning*

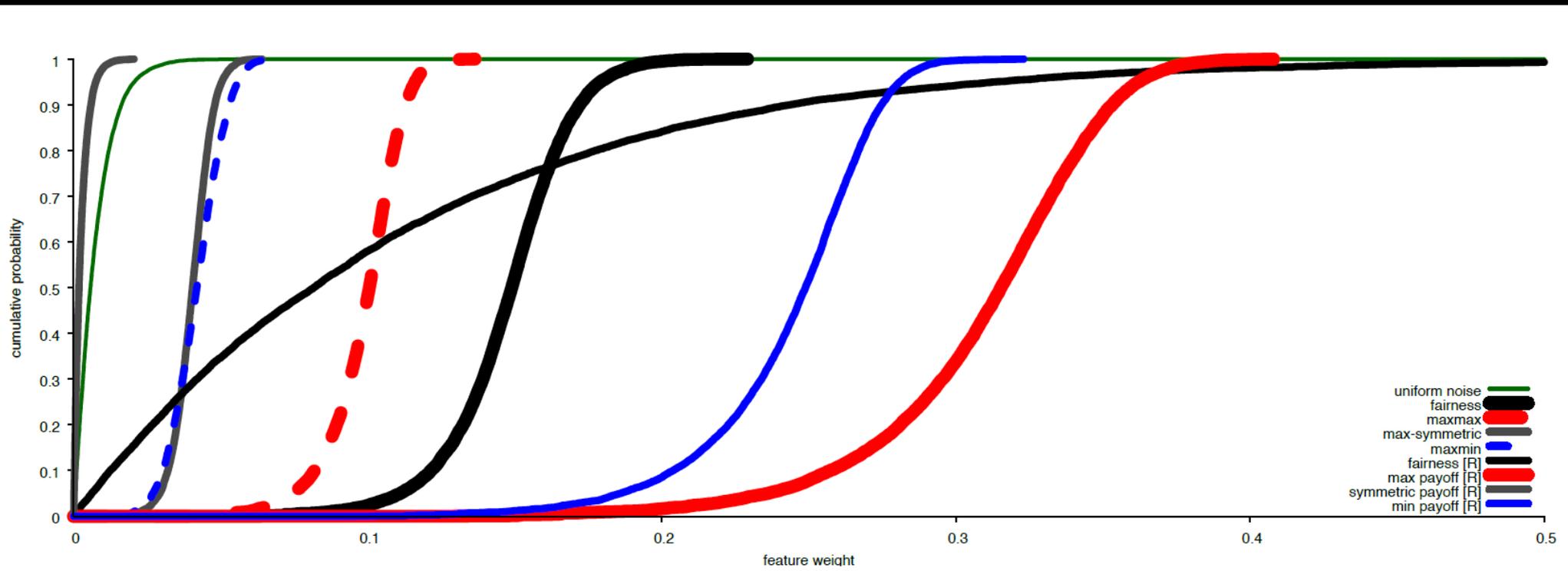
# Parameter Analysis

## Features in Linear 4

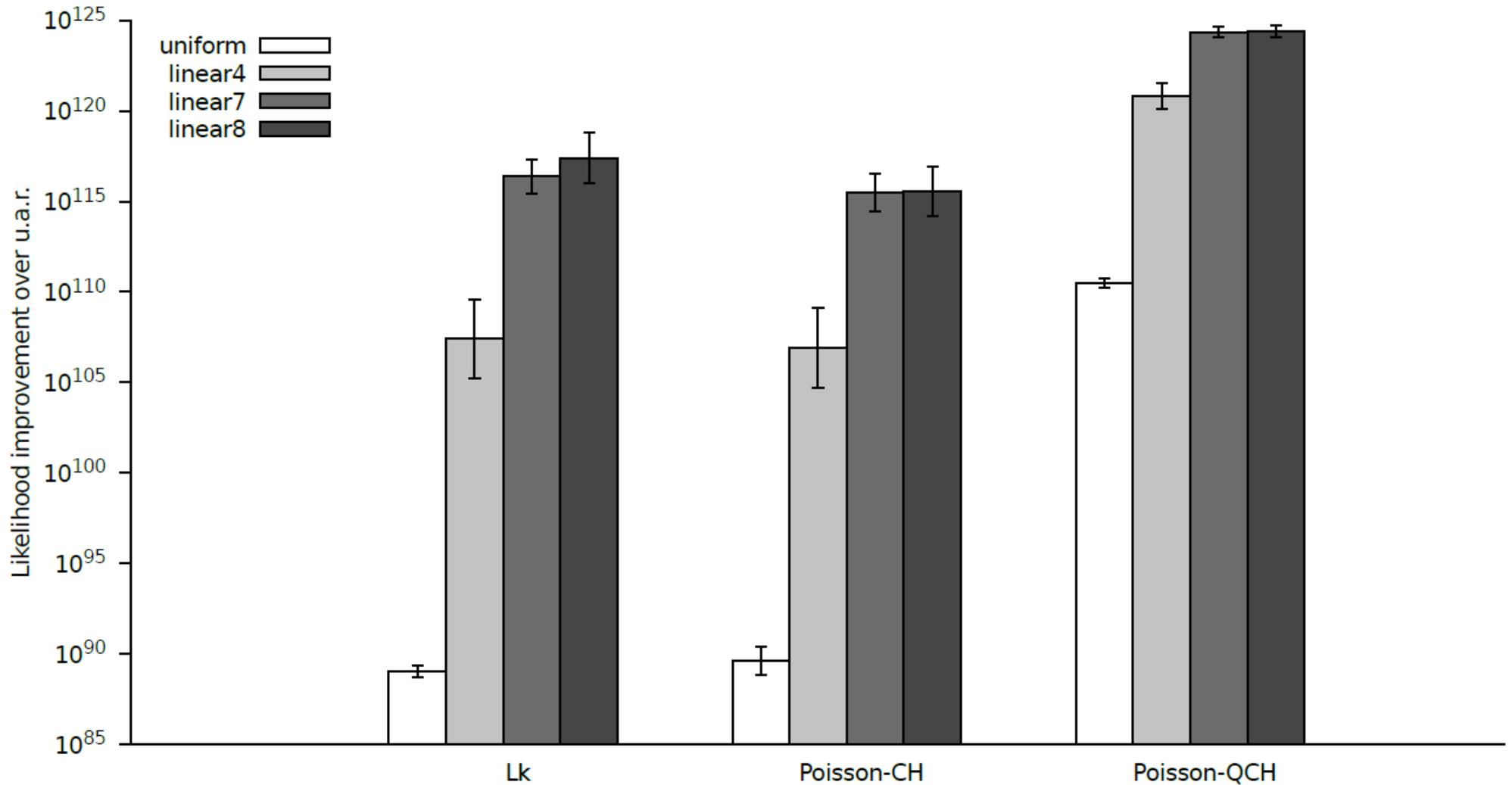


# Parameter Analysis

## Features in Linear 8



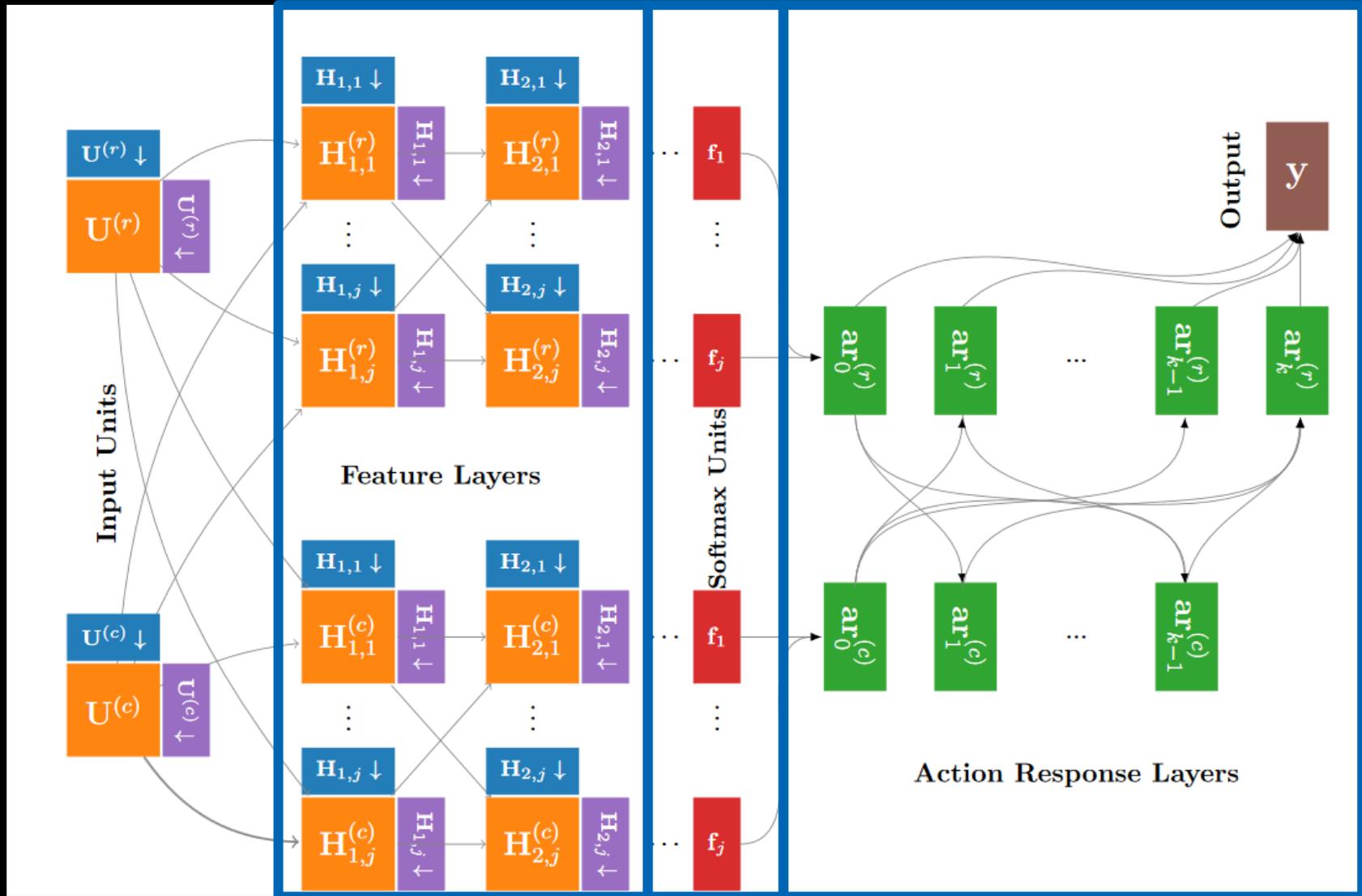
# Conclusion



# Conclusion

1. Increased performance for iterative models.
2. Dependant only on the payoff of the game.  
→ Generally applicable to any domain
3. The belief that Level-0 agents only exist in the minds of higher level agents should be questioned.
4. Non-strategic behaviour is an important aspect of human behaviour.

# Proposed Architecture



# Sources

- [1] James R. Wright and Kevin Leyton-Brown (2019): "Level-0 Models for Predicting Human Behavior in Games"
- [2] J. Hartford, J. Wright, K. Leyton-Brown (2016) - "Deep Learning for Predicting Human Strategic Behavior."
- [3] K. Leyton-Brown, J. Wright (2014), Level-0 Meta-Models for Predicting Human Behavior in Games (Slides) ([cs.ubc.ca/~kevinlb/talk.php?u=2014-Level0.pdf](http://cs.ubc.ca/~kevinlb/talk.php?u=2014-Level0.pdf))
- [4] [nytimes.com/interactive/2015/08/13/upshot/are-you-smarter-than-other-new-york-times-readers.html](http://nytimes.com/interactive/2015/08/13/upshot/are-you-smarter-than-other-new-york-times-readers.html)
- [5] [kristiannanagorcka.com/wp-content/uploads/2014/07/Depositphotos\\_12705383\\_s.jpg](http://kristiannanagorcka.com/wp-content/uploads/2014/07/Depositphotos_12705383_s.jpg)
- [6] [utmb.edu/images/librariesprovider84/default-album/strategic-planning.jpg?sfvrsn=ea098358\\_2](http://utmb.edu/images/librariesprovider84/default-album/strategic-planning.jpg?sfvrsn=ea098358_2)
- [7] [driving-tests.org/wp-content/uploads/2012/02/back-parking.jpg](http://driving-tests.org/wp-content/uploads/2012/02/back-parking.jpg)