

# Predicting Human Behavior In Games

James Wright

March 18, 2014

# Behavioral Game Theory

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- Do people actually follow them?

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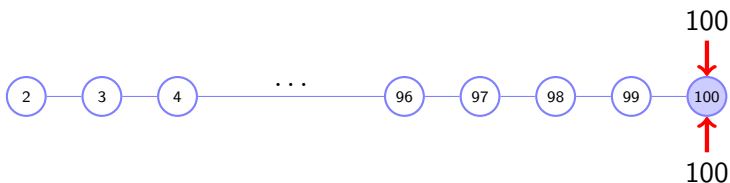
- Many of game theory's recommendations are very counter-intuitive.
- Do people actually follow them?
- **No.** A large body of experiments demonstrates otherwise.
- **Behavioral game theory:** Aims to model actual human behavior in games.

## Fun Game: Traveler's Dilemma



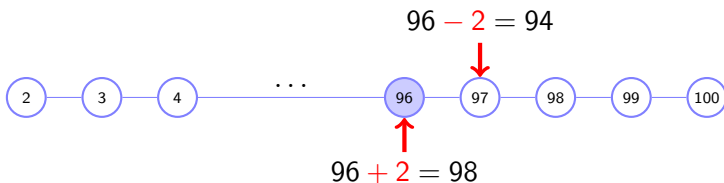
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- Give this game a try. Play any opponent only once.

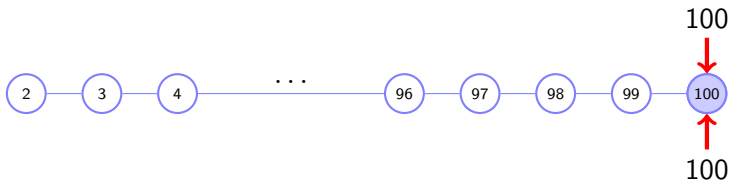
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- If they pick different numbers:
  - Lower player gets **lower** number, plus **bonus** of **30**.
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- Now play a different opponent with a larger penalty.

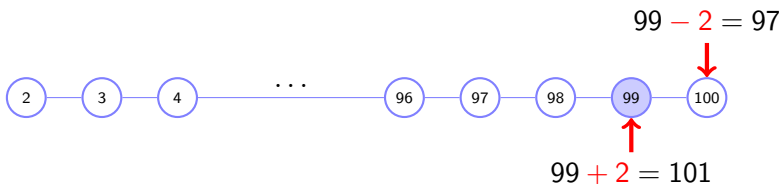


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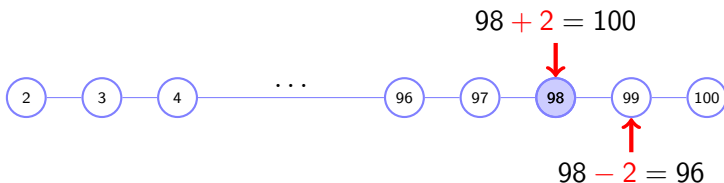
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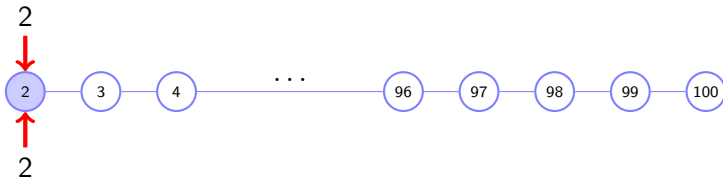
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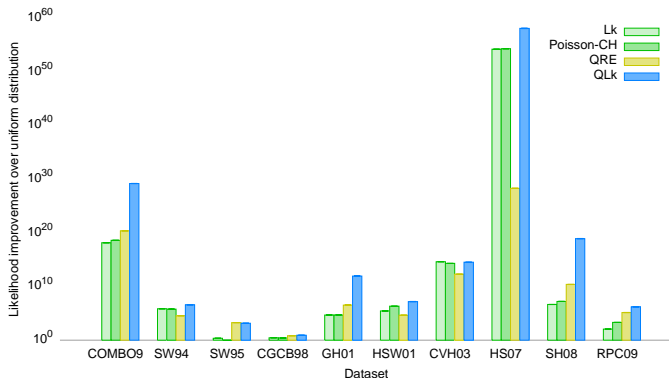
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# Comparing Behavioral Models

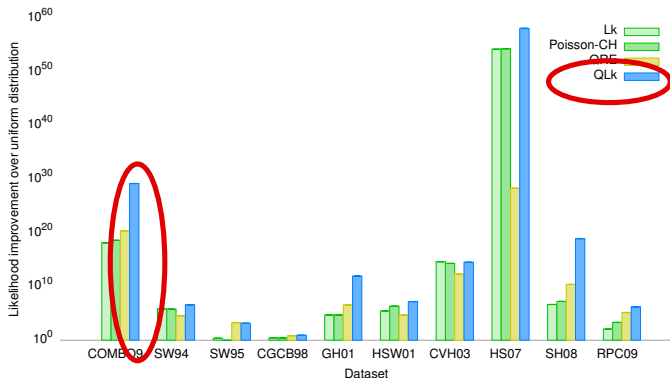
[Wright & Leyton-Brown 2010]



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# Comparing Behavioral Models

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- Many behavioral models have been proposed.
- First study to compare prediction performance of several at once.
- One model performed clearly better than the others.

## Two main ideas

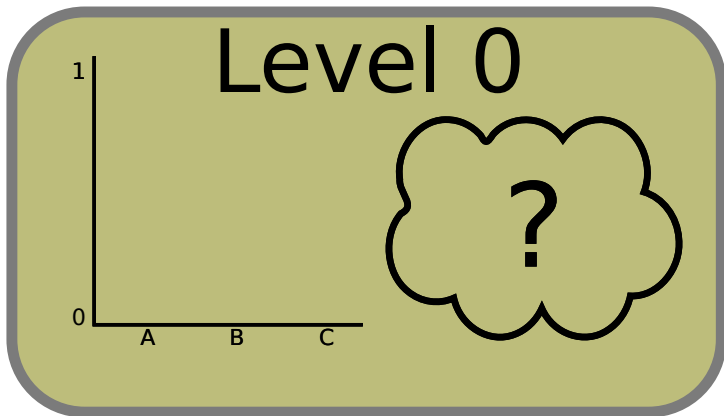
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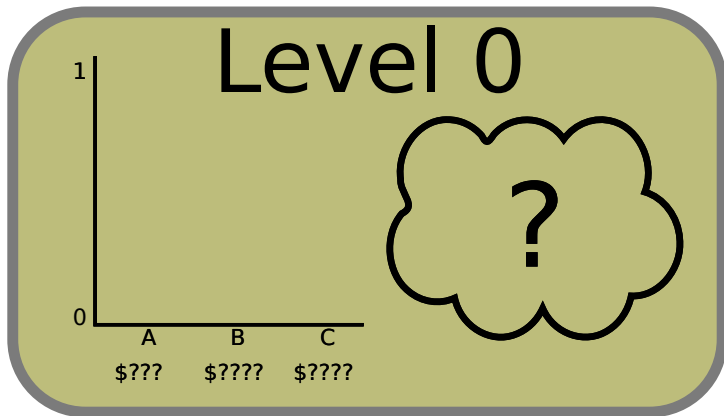
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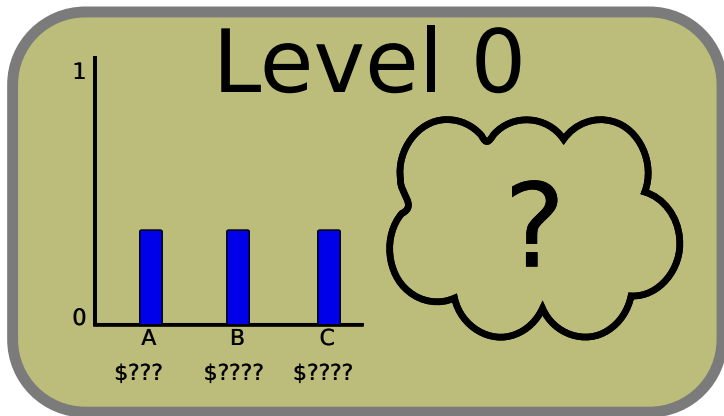
## Iterative reasoning



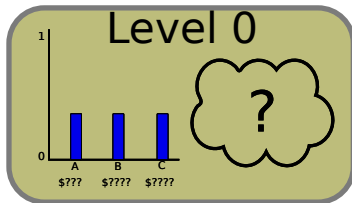
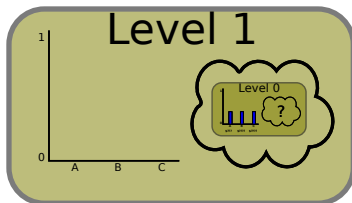
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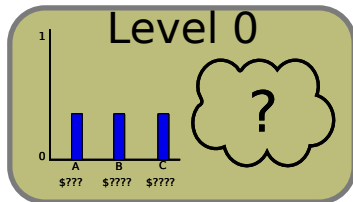
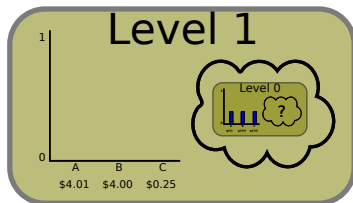
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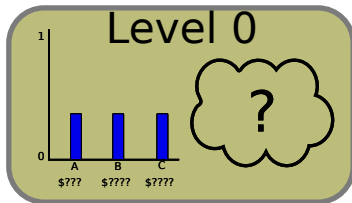
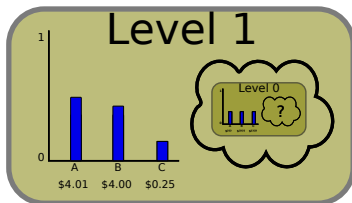
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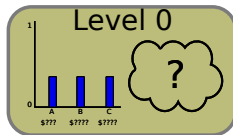
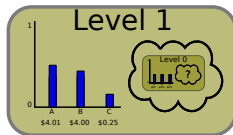
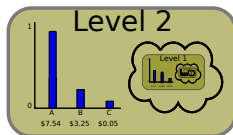
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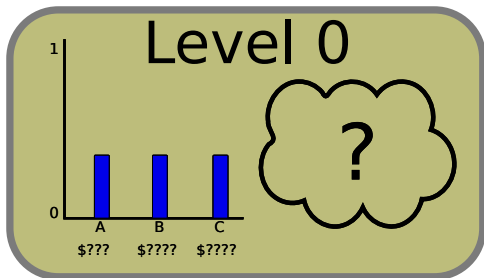
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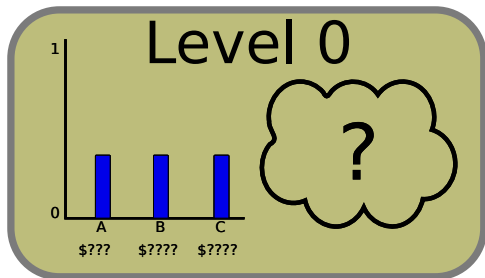
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- Level-0 agents' actions influence the behavior of **every other** level.
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- Level-0 agents' actions influence the behavior of **every other** level.
- Predictions of iterative models can change dramatically if level-0 predictions change.
- It is unlikely that anyone actually picks actions uniformly.
  - Not knowing expected value is different from knowing *nothing*.
  - Level-0 agents could use all sorts of heuristics.
- Can we do a better job of predicting level-0 actions?

# Level-0 meta-model

[Wright & Leyton-Brown, 2014 (submitted)]

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- Define a “meta-model” that predicts a **distribution** of level-0 actions.
  - Based on features of the actions that don't require beliefs about the other agents' actions.
- Use an existing iterative model (quantal cognitive hierarchy) on top of the improved level-0 prediction to make predictions.

# Features

Five binary features:

- 1 Minmin Unfairness
- 2 Maxmax payoff (“Optimistic”)
- 3 Maxmin payoff (“Pessimistic”)
- 4 Minimax regret
- 5 Efficiency (Total payoffs)

## Linear model

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Predict each action w.p. proportional to its weighted sum.

## Example

	<i>A</i>	<i>B</i>	<i>C</i>
<i>X</i>	100, 20	10, 67	30, 40
<i>Y</i>	40, 35	50, 49	90, 70
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Action X's weight:  $w_0 + w_{\max\max}$

Action Y's weight:  $w_0 + w_{\min\min} + w_{\text{total}} + w_{\text{fairness}}$

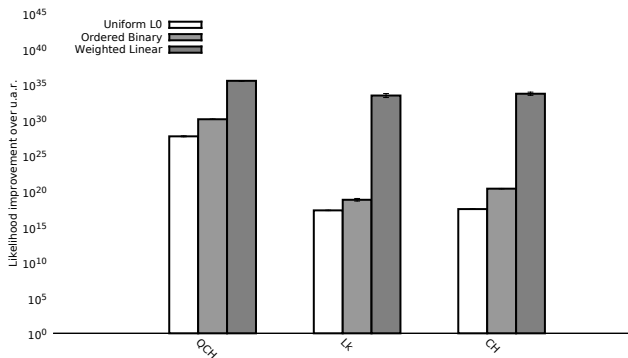
Action Z's weight:  $w_0 + w_{\min\min}$

## Data & Parameters

Name	Source	Games	$n$
SW94	[Stahl and Wilson, 1994]	10	4005
SW95	[Stahl and Wilson, 1995]	12	576
CGCB98	[Costa-Gomes et al., 1998]	18	15662
GH01	[Goeree and Holt, 2001]	10	500
CVH03	[Cooper and Van Huyck, 2003]	8	2992
HSW01	[Haruvy et al., 2001]	15	869
HS07	[Haruvy and Stahl, 2007]	20	2940
SH08	[Stahl and Haruvy, 2008]	18	1288
COMBO8	400 samples from each	111	3200

- Set parameters (weights, level frequencies, etc.) and evaluated performance using **cross validation** on combined dataset:
  - ① Divide data into 10 equal-sized random *folds*
  - ② At step  $t$ : Choose maximum-likelihood parameters for dataset minus fold  $t$  (*training folds*) and compute likelihood of fitted model on fold  $t$  (*test folds*).
- Report sum of likelihoods of test folds.

## Performance results



Three iterative models:

- ① Quantal Cognitive Hierarchy
- ② Level- $k$
- ③ Cognitive Hierarchy

Three level-0 meta-models:

- ① Uniform L0
- ② Ordered Binary
- ③ Weighted Linear



## Parameter analysis

- Maximum likelihood fits do not tell us how **important** or **identified** each feature is.

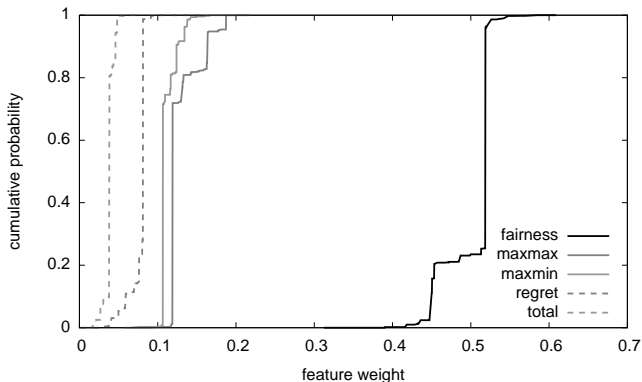
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- The models produce probabilistic predictions.
- So we can compute a posterior distribution over parameters:

$$\Pr(\dots, w_0, w_{\text{fairness}}, w_{\text{maxmax}}, \dots \mid \mathcal{D})$$

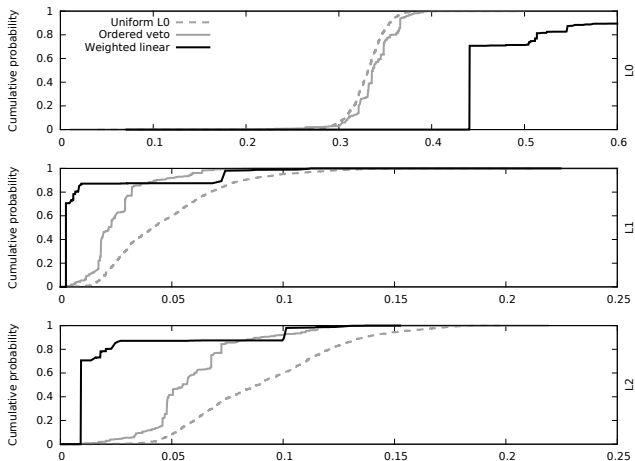
- Distribution tells us how important and/or identified parameters are.

## Parameter analysis: Weights



- Fairness is by far the highest weighted feature.
- All the features seem reasonably well identified.

## Parameter analysis: Levels



- Weighted linear  $\implies$  lower variance estimates
- $\sim$  Half the population is level-0!

# Conclusions

- Weighted linear meta-model for level-0 agents dramatically improved the performance of all three iterative models.
  - Almost erases the difference between the models themselves.
- Strong evidence for the existence of level-0 agents.
  - For any meta-model, including uniform!
  - Contrary to conventional wisdom.

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## Bibliography



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