

GameNetViz-

Jason Hartford Neil Newman CPSC547 [>]robability

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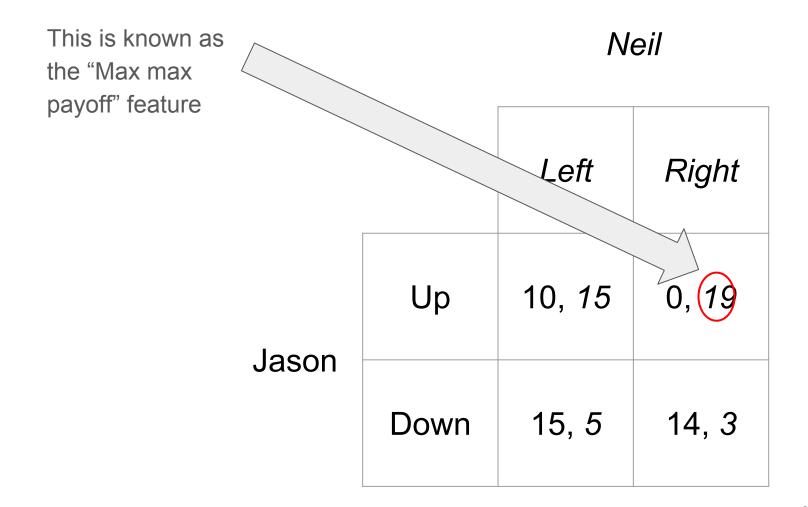
What?

Behavioural Game Theory aims to predict the behaviour of **people** as they interact **strategically**

Neil

		Left	Right
Jason	Up	10, <i>15</i>	0, 19
	Down	15, <i>5</i>	14, 3

How might you reason about this game?



Assume Neil plays right or left with some probability

Jason

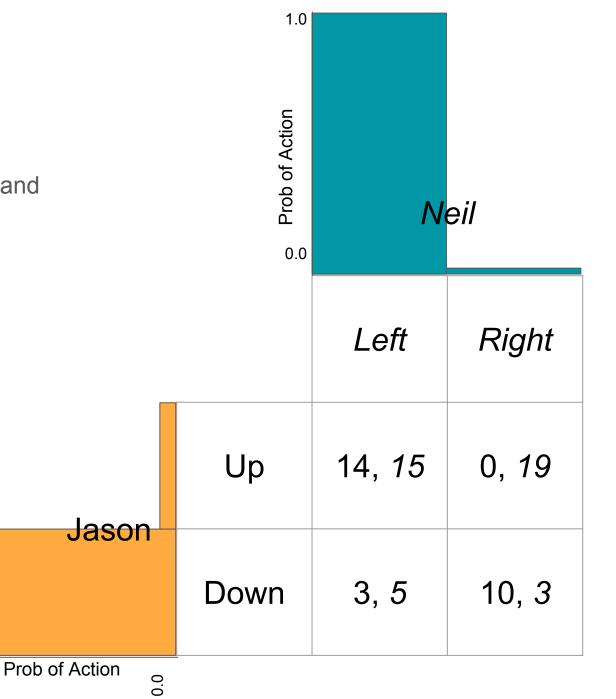
1.0		
o Prob of Action	N	eil
	Left	Right
Up	14, <i>15</i>	0, 19
Down	3, 5	10, 3

Prob of Action Respond by choosing the Neil action that make you best off, given your assumption. 0.0 Left Right 0, 19 14, 15 Up Jason Down 3, 5 10, 3 Prob of Action 1.0 0.0

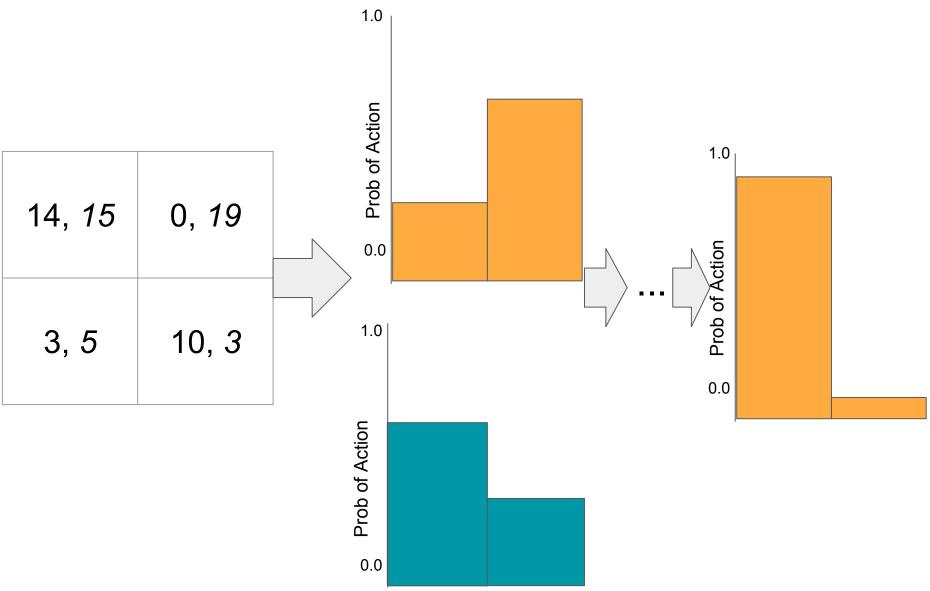
1.0

But Neil may think of that and change his action...

1.0



Abstractly...



Data

Experimental Data

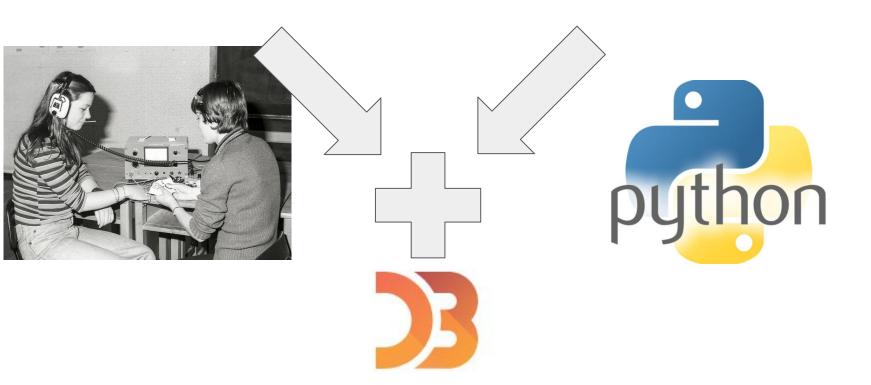
Data from 9 behavioural economics experiments on human subjects

128 unique games with 12 071 plays

Model Data

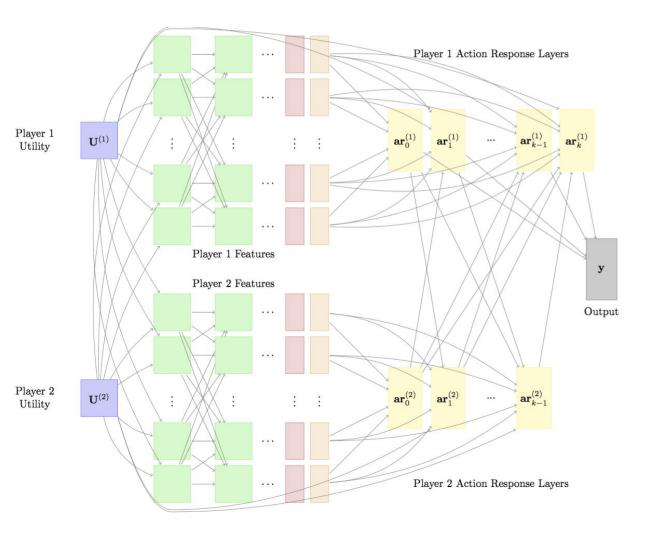
Set of numbers that parameterise the model

Output at each intermediate stage of computation.



Model...

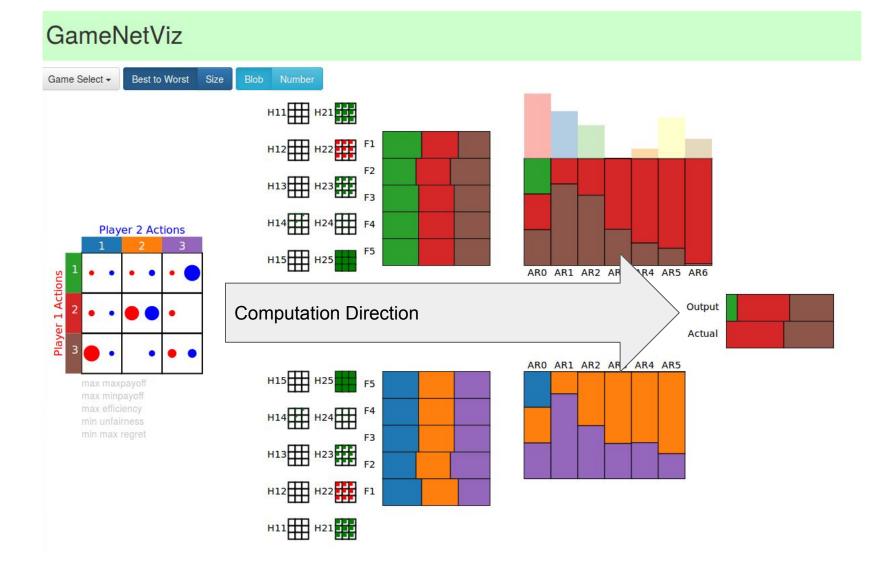
- Many parameters
- Difficult to visualise intermediate computation
- Difficult to identify design flaws / poor optimization fits



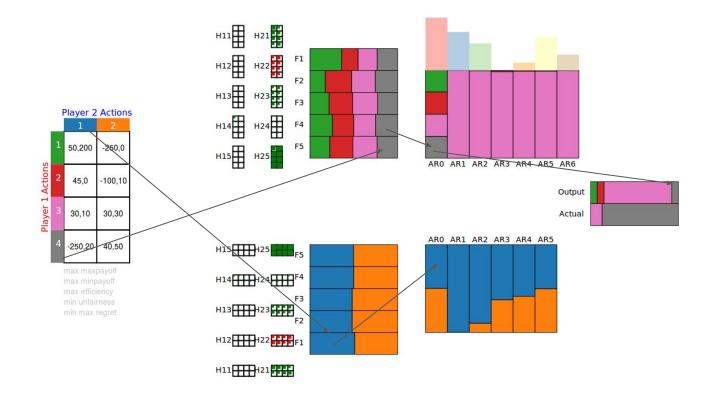
	Terminal . jasonhar@cersei:jasonhar/deep_bgt	
File Edit View Terminal Tabs Help		
	1 { 2 "hidden01_W": [
	4 -0.002310571943120875, 5 -0.09410790772179399,	
	6 0.13253334425034055, 7 -0.016074298070027485, 8 -0.09671523110057867	
	9], 10 [11 0.06438536419129069,	
	12 -0.01941429269674461, 13 0.1371778717573248, 14 -0.08205546061404798,	
	15 -0.07636868709898333 16] 17],	
	18 "hidden01_b": [19 -0.09541069363774914, 20 -0.001919040604869716,	
	21 0.24882516382545647, 22 -0.08306040589997161, 23 -0.009017137588378327	
171], 172 "pl_ar4_lam": 1.0002909618417586, 173 "p0_ar5_Wf": [174 0.6686235452809622.	24], 25 "hidden02_W": [26 [27 0.1210484563334088,	
	28 0.38546920904252585, 29 0.6985807404477473, 30 0.5297181089187918,	
178 0.04960922217853168, 179 0.09622068443648563 180 1.	31 -0.2610696947674774 32], 33 [
181	34 -0.28713039780469907, 35 0.11784195404870484, 36 0.5888558140606216,	
	37 -0.7351229103480253, 38 0.12845264210000537 39],	
	40 [41 0.08328830462922383, 42 -0.40683708605648555, 43 0.23779061868509546,	
	44 0.2711172922700234, 45 0.8817146054200034	
	46], 47 [48 0.5874260266912027,	
196 0.05858459578556083, 197 0.0 198],	49 0.6774567189948755, 50 -0.2045251133917433, 51 -0.2298122010417848,	
	52 0.2946696334723472	
game_net/experiments/vis_model/vis_model_1_par.json "game_net/experiments/vis_model/vis_model_1_par.json" [noeol] 200L, 4460C	182,1 Bot game_net/experiments/vis_model/vis_model_0_par.json	1,1 Тор

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Our Solution



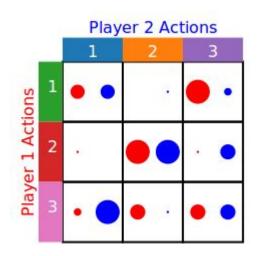
Common Colours



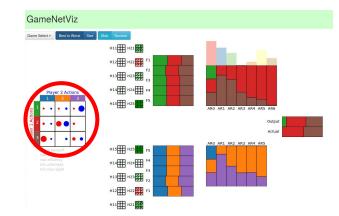
• The same colour corresponds to the same action throughout the viz

Payoff Matrix Viz

Blob	Number
DIUD	Inumber



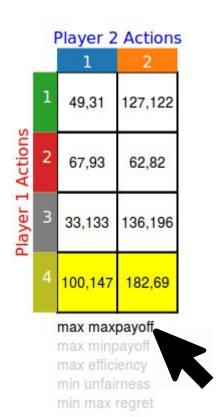
- Allows for quick summary of a game
- Very easy to spot mismatched payoffs

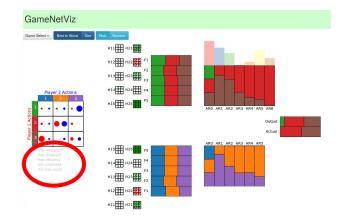


	Player 2 Actions				
		1	2	3	
ions	1	35,35	0,1	100,10	
er 1 Actions	2	1,0	100,100	1,40	
Player	3	10,100	40,1	40,40	

• Detailed information, for when subtle differences matter

Hand-crafted Features

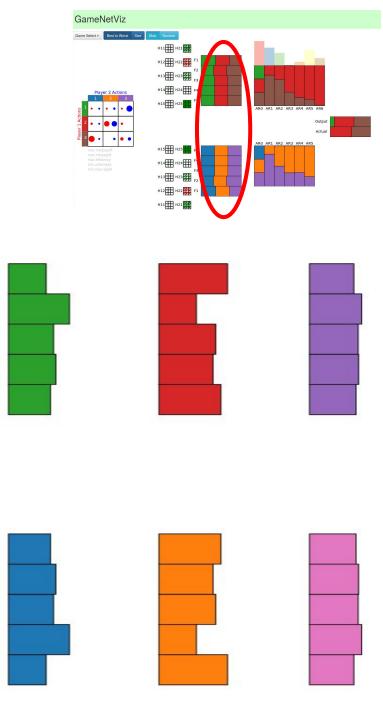


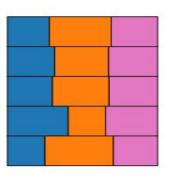


- From previous work, we know about features that players seem to like
- When hovering over a hand-crafted feature, the row(s) corresponding to that feature light up
- In this image, player 1 can achieve the highest payoff by picking action 4 (if player 2 picks action 2)
- Non-hovered features are grayed out, to avoid distraction

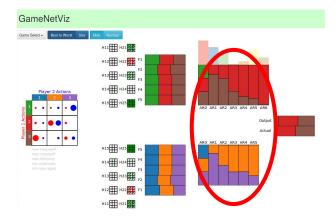
Features

- Each feature outputs a different probability distribution of playing each action
 - Clicking on the stacked bar charts splits them into grouped bar charts, so that you can compare an action's distribution across different features





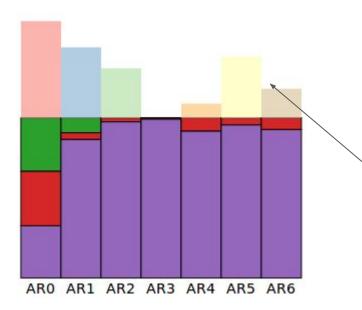
Action Response Layers Tool tip

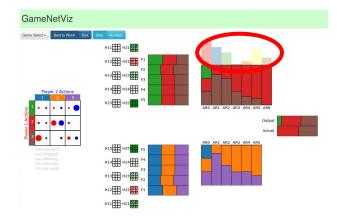


F AR	Sum	ARO	AR1
Sharpness	99.08	}	

- AR layers are weighted sums of the feature units, as well as previous AR layers
- Hovering over an AR unit produces a tool-tip showing a breakdown of how it is composed, before the non-linearity is applied.
- The sharpness parameter of the non-linearity function for that AR layer is also displayed

Level distribution

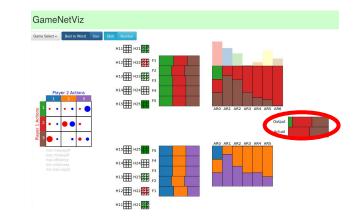


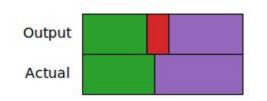


 The output is a weighted sum of all the AR units. The weight associated with each AR is encoded as a bar above the AR.

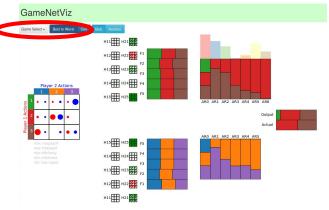
Output vs Actual Play

• Compare the model's predicted distribution of play against observed play (from experiments with human players)





Game Selector



- Games can be ordered by size, or by a derived difference between the model' s prediction and observed play
- Choosing a game from the selector will render data for that game

Game Select -	Best to Worst	Size
(2, 2)_9		
(2, 2)_19	Ū.	
(2, 3)_1		
(2, 4)_2		
(2, 4)_3		
(2, 3)_9		
(2, 2)_20		
(0.0).04		

Game Select -	Best to Worst	Size
(2, 2)_0	6	
(2, 2)_1	J	
(2, 2)_10		
(2, 2)_11		
(2, 2)_12		
(2, 2)_13		
(2, 2)_14		
10 00 1-		

DEMO

Critique & Future Work

- The blob payoff matrix encoding is invariant to scaling, so two scaled games look the same. But humans have a non-linear response to payoffs, and maybe we can find an encoding that matches this.
- Hidden layer encoding not offering any insights, could be better
- Handle larger games (e.g. 100 x 100)
- Show even more data! (Parameters, optimization)

Applause