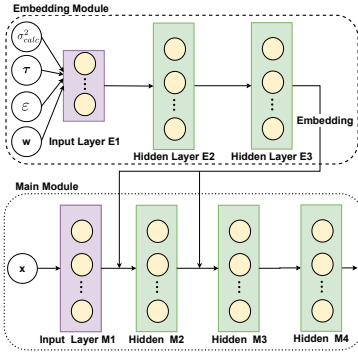


Table 1: Mean $\pm$ std. dev. for averaged NLLs on human choice data sets.

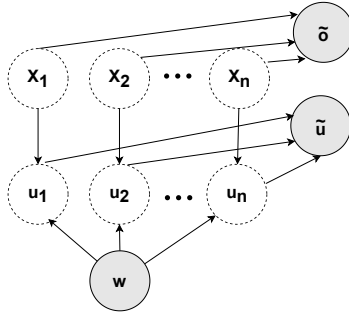
Dataset	Bradley-Terry	Bower & Balzano	LCL	CRCS (ours)	LC-CRCS (ours)
Hotels	0.944 ± 0.109	0.944 ± 0.109	0.910 ± 0.147	0.882 ± 0.104	0.882 ± 0.115
District-Smart	0.638 ± 0.015	0.637 ± 0.015	0.614 ± 0.021	0.627 ± 0.016	0.610 ± 0.020
Car-Alt	1.593 ± 0.022	1.593 ± 0.022	1.563 ± 0.041	1.573 ± 0.023	1.591 ± 0.029
Dumbalska	0.629 ± 0.259	0.629 ± 0.259	0.613 ± 0.266	0.612 ± 0.266	0.605 ± 0.273

Table 2: Mean $\pm$ std. dev. of averaged NLLs on a randomly selected held-out test set over 20 independent gradient descent runs to infer utility and choice model parameters. CRCS and LC-CRCS have non-convex likelihood functions, meaning that gradient descent is liable to get stuck in local optima. We see this here by the significantly higher standard deviation in averaged NLL achieved by various runs. In our implementation, we mitigated this by running gradient descent multiple times and selecting the best run according to a held-out portion of the training data.

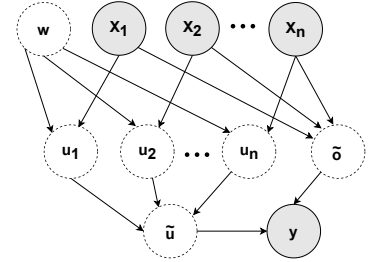
Dataset	Bradley-Terry	Bower & Balzano	LCL	CRCS (ours)	LC-CRCS (ours)
Hotels	$0.890 \pm 8 \times 10^{-6}$	$0.890 \pm 2 \times 10^{-5}$	$0.831 \pm 2 \times 10^{-5}$	0.855 ± 0.014	0.902 ± 0.063
District-Smart	$0.632 \pm 1 \times 10^{-5}$	$0.631 \pm 4 \times 10^{-6}$	$0.616 \pm 4 \times 10^{-6}$	0.628 ± 0.009	0.616 ± 0.006
Car-Alt	$1.575 \pm 3 \times 10^{-5}$	$1.575 \pm 5 \times 10^{-5}$	$1.560 \pm 5 \times 10^{-5}$	1.620 ± 0.032	1.590 ± 0.013
Dumbalska	$0.567 \pm 3 \times 10^{-6}$	$0.567 \pm 2 \times 10^{-6}$	$0.562 \pm 2 \times 10^{-6}$	0.568 ± 0.007	0.572 ± 0.007



(a) Overview of the network architecture of $\hat{q}$. $\hat{u}$ has the same architecture but takes observations $(\tilde{u}, \tilde{o})$ as input. The outputs of $\hat{q}$ are additionally transformed by a log-softmax function (not shown).



(b) The cognitive model introduced in [17] posits that humans make utility-maximizing choices (for some utility function parameters w) based only on observations $(\tilde{u}, \tilde{o})$. The options $x_1, \dots, x_n$ and their true utilities $u_1, \dots, u_n$ are not observed.



(c) An outside observer can observe each choice y made for a set of options $x_1, \dots, x_n$. From this data, the objective is to infer the utility parameter w . The observations $(\tilde{u}, \tilde{o})$ that are central to the user's choice are made in the user's head and are therefore latent.

Figure 1: (a) Visualization of the neural network architectures used and graphical models of (b) our cognitive model (see eq. (2)) and (c) the corresponding preference learning problem (see eq. (3)).

Table 3: Overview of layer sizes and training hyperparameters for $\hat{u}$ and $\hat{q}$ for the choice tasks considered in the experiments.

		embedding (3 layers)		main (4 layers)		total # params	batch	epochs	lr start/end
		layer	output dim	layer	output dim				
Risky Choice	$\hat{u}$		128,64		64	207363	1024	35000	1e-3/ 1e-5
	$\hat{q}$		128,64		64	340483	1024	50000	1e-3/ 1e-6
Hotels	$\hat{u}$		256,256,3		128	598659	8192	10000	1e-3/ 1e-3
	$\hat{q}$		256,256		128	664451	2048	50000	1e-3/ 1e-4
District-Smart	$\hat{u}$		256,256		128	784386	8192	20000	1e-2 / 1e-4
	$\hat{q}$		512,256		256	1858306	4096	60000	1e-3/ 1e-4
Car-Alt	$\hat{u}$		256,256		256	394374	8192	30000	1e-3/ 1e-3
	$\hat{q}$		256,256		256	486022	4096	100000	1e-3/ 1e-3
Dumbalska	$\hat{u}$		256,256		128	532099	4096	40000	1e-3/ 1e-4
	$\hat{q}$		128,128		128	317827	8192	25000	1e-3/ 1e-3
Crash Structure	$\hat{u}$		128,64		64	216835	1024	50000	1e-3/ 1e-6
	$\hat{q}$		128,64		64	353411	1024	35000	1e-3/ 1e-5
Water Drainage	$\hat{u}$		128,64		64	214147	1024	35000	1e-3/ 1e-5
	$\hat{q}$		128,64		64	353411	1024	50000	1e-3/ 1e-6
Retrosynthesis	$\hat{u}$		128,64		64	214147	1024	35000	1e-3/ 1e-5
	$\hat{q}$		128,64		64	353411	1024	50000	1e-3/ 1e-6