Supplementary Information for

Scaling Up Psychology via Scientific Regret Minimization

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Tables S1 to S16
References for SI reference citations

Supporting Information Text

Bayesian Feature Selection. To simulate an alternative approach towards exploratory data analysis, we conducted a form of Bayesian feature selection (1). We trained a Bayesian logistic regression model with all 'Hybrid' model features and their two- and three-way interactions. Each weight was given a prior of a Gaussian distribution with mean 0 and standard deviation 0.1. Once this model was trained, all features in which a weight of 0 was located in its 95% credible interval were removed. We then trained this new model, and repeated this procedure until all features that were fit were significant. (More computationally intensive variable selection procedures, such as marginal likelihood, were infeasible given the size of the dataset). Table S15 outlines the iterations' metrics and Table S16 reports the final features and their weights.

The resulting model from this approach performed a little better than the original 'Hybrid' model and far worse than our final choice model (and in fact worse than the model after our first iteration). It seems that for such an approach to rival ours, we would have needed to start off with a model that encapsulated at least all twenty-way interactions. Such a model would be even more intractable to conduct for Bayesian feature selection.

Methods. Due to the size of the dataset and the feature set, this model was trained through variational inference (2) rather than traditional MCMC sampling. The model was trained using a Flipout gradient estimator (3) and optimized via Adam (4). Metrics were computed by taking the MAP estimate of each weight. The model was trained using the Tensorflow Probability package (5) .

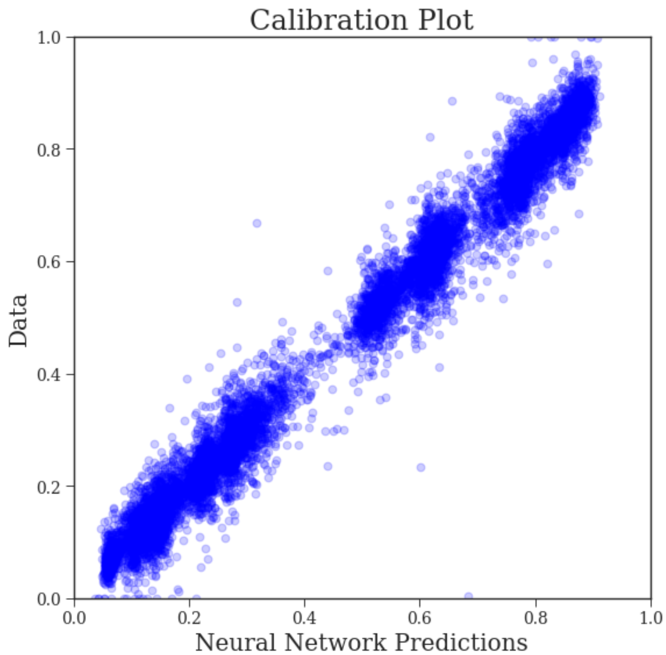


Fig. S1. A calibration plot between the neural network's predictions and the aggregate dilemmas for all dilemmas over one hundred responses. We calculated a line of best fit for all dilemmas (*i.e.* not just those with over hundred responses), weighting each dilemma by the number of participants that answered it. The line of best fit had a slope of 1.003 and an intercept of 0.001.

Table S1. Old vs. Young Dilemmas (proportions show observed or predicted proportion killing left side).

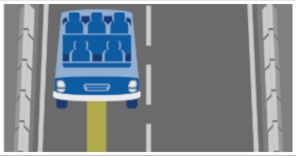
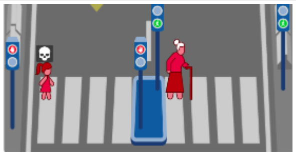
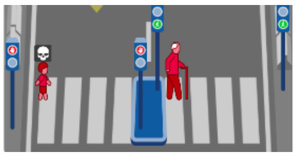
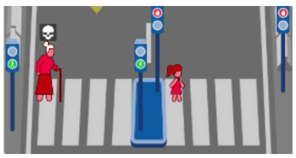
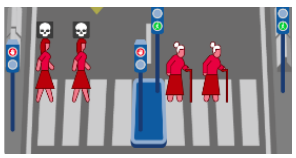
	N	Data	Choice Model	Neural Network
	11554	0.343	0.636	0.333
	11578	0.362	0.637	0.344
	7166	0.721	0.511	0.747
	5758	0.523	0.635	0.403
	5691	0.476	0.625	0.395

Table S2. Biggest Differences Between Choice Model and Data for Second Iteration

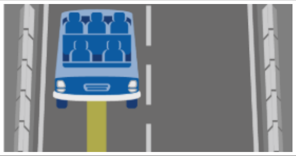
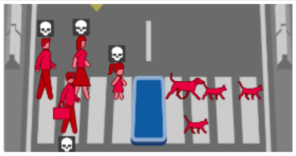
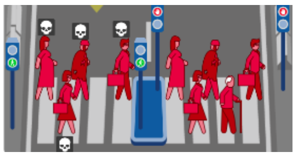
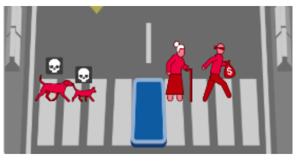
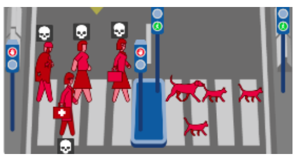
	N	Data	Choice Model	Neural Network
	649	0.994	0.164	0.168
	1124	0.000	0.600	0.442
	1113	0.288	0.791	0.680
	890	0.001	0.396	0.272
	365	0.326	0.709	0.719

Table S3. Biggest Differences Between Choice Model and Neural Network for Second Iteration

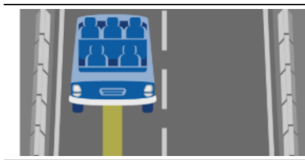
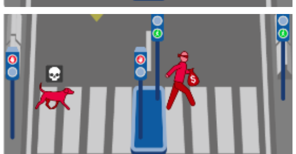
	N	Data	Choice Model	Neural Network
	130	0.600	0.869	0.537
	1471	0.434	0.712	0.394
	2898	0.436	0.714	0.420
	3879	0.520	0.786	0.509
	3377	0.224	0.508	0.231

Table S4. Biggest Differences Between Choice Model and Data for Third Iteration

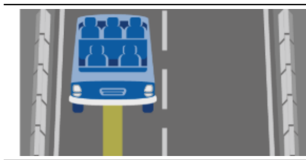
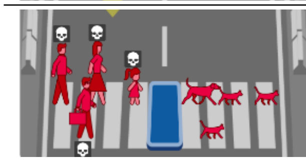
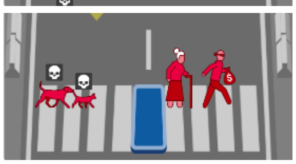
	N	Data	Choice Model	Neural Network
	649	0.994	0.155	0.168
	1124	0.000	0.605	0.442
	1113	0.288	0.806	0.680
	890	0.001	0.693	0.272
	365	0.326	0.709	0.719

Table S5. Biggest Differences Between Choice Model and Neural Network for Third Iteration

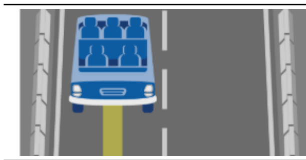
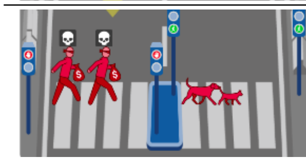
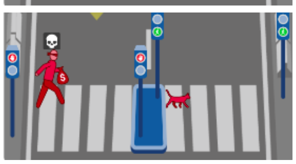
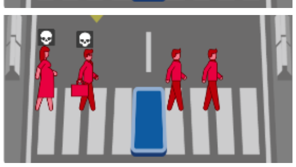
	N	Data	Choice Model	Neural Network
	162	0.599	0.835	0.567
	2606	0.558	0.765	0.499
	8235	0.340	0.637	0.373
	175	0.269	0.541	0.283
	359	0.315	0.539	0.290

Table S6. Biggest Differences Between Choice Model and Data for Fourth Iteration

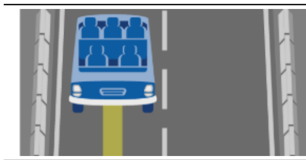
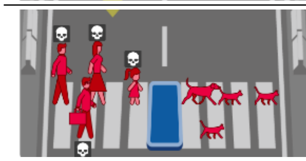
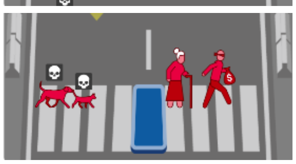
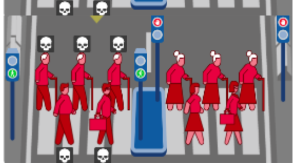
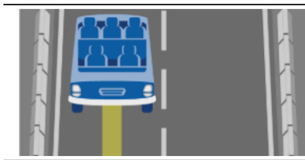
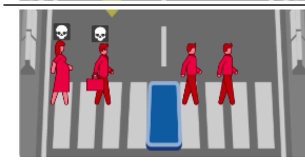
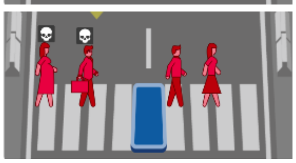
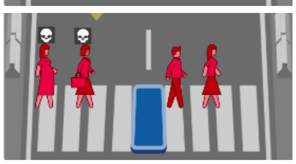
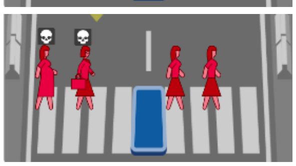
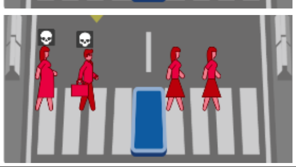
	N	Data	Choice Model	Neural Network
	649	0.994	0.147	0.168
	1124	0.000	0.517	0.442
	1113	0.288	0.763	0.680
	365	0.326	0.766	0.719
	187	0.001	0.427	0.393

Table S7. Biggest Differences Between Choice Model and Neural Network for Fourth Iteration

	N	Data	Choice Model	Neural Network
	175	0.269	0.560	0.283
	326	0.301	0.564	0.301
	359	0.315	0.552	0.290
	172	0.273	0.556	0.304
	159	0.308	0.568	0.323

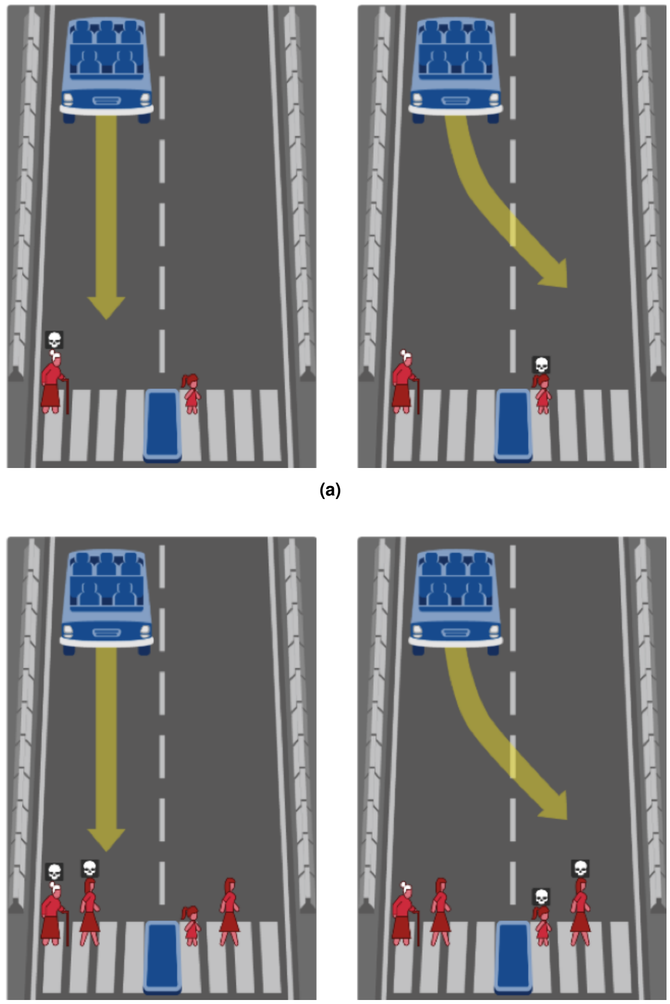
Feature	Weight
Man	0.339
Woman	0.360
Pregnant	0.502
Stroller	0.537
Old Man	0.271
Old Woman	0.264
Boy	0.452
Girl	0.466
Homeless	0.208
Large Woman	0.234
Large Man	0.165
Criminal	-0.093
Male Executive	0.351
Female Executive	0.371
Female Athlete	0.448
Male Athlete	0.407
Female Doctor	0.413
Male Doctor	0.427
Dog	0.333
Cat	0.285
Crossing Signal	1.115
Car Side	-0.427
Humans vs. Animals	1.034
Car Side on Humans	0.828
Car Side on Animals	-0.207
Legally Crossing Humans	-0.653
Illegally Crossing Humans	0.313
Car Side on Legally Crossing Humans	-0.303
Car Side on Illegally Crossing Humans	0.189
Car Side on Legally Crossing Animals	-0.124
Car Side on Illegally Crossing Animals	0.350
Criminals vs. Animals	-0.727
Car Side on Criminals	-0.427
Car Side on Animals	0.300
Legally Crossing Criminals	0.045
Illegally Crossing Criminals	0.226
Car Side on Legally Crossing Criminals	0.056
Car Side on Illegally Crossing Criminals	0.232
Car Side on Legally Crossing Animals	0.006
Car Side on Illegally Crossing Animals	0.011
Pregnant vs. Other Humans	0.338
Car Side on Pregnant	0.347
Car Side on Other Humans	0.009
Legally Crossing Pregnant	-0.109
Illegally Crossing Pregnant	-0.121
Car Side on Legally Crossing Pregnant	-0.162
Car Side on Illegally Crossing Pregnant	-0.068
Car Side on Legally Crossing Other Humans	0.053
Car Side on Illegally Crossing Other Humans	-0.053
Pregnant & Doctor vs. Other Humans	0.490
Car Side on Pregnant & Doctor	0.699
Car Side on Other Humans	0.208
Legally Crossing Pregnant & Doctor	-0.330
Illegally Crossing Pregnant & Doctor	-0.275
Car Side on Legally Crossing Pregnant & Doctor	-0.358
Car Side on Illegally Crossing Pregnant & Doctor	-0.363

Car Side on Legally Crossing Other Humans	-0.087
Car Side on Illegally Crossing Other Humans	-0.028
Executive & Doctor vs. Other Humans	0.150
Car Side on Executive & Doctor	0.056
Car Side on Other Humans	-0.094
Legally Crossing Executive & Doctor	-0.059
Illegally Crossing Executive & Doctor	-0.070
Car Side on Legally Crossing Executive & Doctor	0.002
Car Side on Illegally Crossing Executive & Doctor	-0.012
Car Side on Legally Crossing Other Humans	0.059
Car Side on Illegally Crossing Other Humans	0.061
Doctor vs. Other Humans	0.324
Car Side on Doctor	0.311
Car Side on Other Humans	-0.013
Legally Crossing Doctor	-0.146
Illegally Crossing Doctor	-0.195
Car Side on Legally Crossing Doctor	-0.177
Car Side on Illegally Crossing Doctor	-0.208
Car Side on Legally Crossing Other Humans	-0.013
Car Side on Illegally Crossing Other Humans	-0.032
Old vs. Young	-0.402
Car Side on Old	-0.680
Car Side on Young	-0.277
Legally Crossing Old	0.221
Illegally Crossing Old	0.252
Car Side on Legally Crossing Old	0.408
Car Side on Illegally Crossing Old	0.446
Car Side on Legally Crossing Young	0.194
Car Side on Illegally Crossing Young	0.187
Adult vs. Young	-0.150
Car Side on Adult	-0.457
Car Side on Young	-0.307
Legally Crossing Adult	-0.007
Illegally Crossing Adult	0.053
Car Side on Legally Crossing Adult	0.248
Car Side on Illegally Crossing Adult	0.336
Car Side on Legally Crossing Young	0.283
Car Side on Illegally Crossing Young	0.255
Old vs. Adult & Young	-0.390
Car Side on Old	-0.722
Car Side on Adult & Young	-0.332
Legally Crossing Old	0.223
Illegally Crossing Old	0.233
Car Side on Legally Crossing Old	0.441
Car Side on Illegally Crossing Old	0.500
Car Side on Legally Crossing Adult & Young	0.267
Car Side on Illegally Crossing Adult & Young	0.218
Old & Adult vs. Young	-0.207
Car Side on Old & Adult	-0.471
Car Side on Young	-0.264
Legally Crossing Old & Adult	0.099
Illegally Crossing Old & Adult	0.223
Car Side on Legally Crossing Old & Adult	0.299
Car Side on Illegally Crossing Old & Adult	0.421
Car Side on Legally Crossing Young	0.198
Car Side on Illegally Crossing Young	0.200
Old vs. Adult	-0.309
Car Side on Old	-0.714
Car Side on Adult	-0.405
Legally Crossing Old	0.295
Illegally Crossing Old	0.199

Car Side on Legally Crossing Old	0.464
Car Side on Illegally Crossing Old	0.465
Car Side on Legally Crossing Adult	0.266
Car Side on Illegally Crossing Adult	0.169
Old & Adult vs. Adult & Young	-0.663
Car Side on Old & Adult	0.145
Car Side on Adult & Young	0.808
Legally Crossing Old & Adult	0.056
Illegally Crossing Old & Adult	0.314
Car Side on Legally Crossing Old & Adult	0.026
Car Side on Illegally Crossing Old & Adult	-0.044
Car Side on Legally Crossing Adult & Young	-0.358
Car Side on Illegally Crossing Adult & Young	-0.031
All Young vs. Other Humans	0.104
Car Side on All Young	-0.055
Car Side on Other Humans	-0.159
Legally Crossing All Young	0.022
Illegally Crossing All Young	0.015
Car Side on Legally Crossing All Young	0.062
Car Side on Illegally Crossing All Young	0.041
Car Side on Legally Crossing Other Humans	0.026
Car Side on Illegally Crossing Other Humans	0.040
Male vs. Female	-0.373
Car Side on Male	-0.353
Car Side on Female	0.020
Legally Crossing Male	0.204
Illegally Crossing Male	0.159
Car Side on Legally Crossing Male	0.440
Car Side on Illegally Crossing Male	0.317
Car Side on Legally Crossing Female	0.158
Car Side on Illegally Crossing Female	0.236
Homeless vs. Other Humans	-0.320
Car Side on Homeless	-0.146
Car Side on Other Humans	0.174
Legally Crossing Homeless	0.139
Illegally Crossing Homeless	0.134
Car Side on Legally Crossing Homeless	0.196
Car Side on Illegally Crossing Homeless	0.081
Car Side on Legally Crossing Other Humans	-0.053
Car Side on Illegally Crossing Other Humans	0.057
Executives vs. Homeless	0.001
Car Side on Executives	-0.149
Car Side on Homeless	-0.150
Legally Crossing Executives	-0.029
Illegally Crossing Executives	0.024
Car Side on Legally Crossing Executives	0.214
Car Side on Illegally Crossing Executives	0.187
Car Side on Legally Crossing Homeless	0.163
Car Side on Illegally Crossing Homeless	0.243
Executives vs. Adult	0.092
Car Side on Executives	-0.125
Car Side on Adult	-0.217
Legally Crossing Executives	0.042
Illegally Crossing Executives	-0.214
Car Side on Legally Crossing Executives	0.192
Car Side on Illegally Crossing Executives	0.044
Car Side on Legally Crossing Adult	0.258
Car Side on Illegally Crossing Adult	0.150
More vs. Less	0.800
Car Side on More	0.498
Car Side on Less	-0.302

Legally Crossing More	-0.617
Illegally Crossing More	-0.375
Car Side on Legally Crossing More	-0.200
Car Side on Illegally Crossing More	0.007
Car Side on Legally Crossing Less	0.383
Car Side on Illegally Crossing Less	0.417
Fat vs. Fit	-0.293
Car Side on Fat	-0.313
Car Side on Fit	-0.021
Legally Crossing Fat	0.305
Illegally Crossing Fat	0.194
Car Side on Legally Crossing Fat	0.539
Car Side on Illegally Crossing Fat	0.360
Car Side on Legally Crossing Fit	0.166
Car Side on Illegally Crossing Fit	0.233
Fat vs. Adult	-0.392
Car Side on Fat	-0.479
Car Side on Adult	-0.086
Legally Crossing Fat	0.377
Illegally Crossing Fat	0.131
Car Side on Legally Crossing Fat	0.619
Car Side on Illegally Crossing Fat	0.366
Car Side on Legally Crossing Adult	0.235
Car Side on Illegally Crossing Adult	0.241
Adult vs. Fit	-0.071
Car Side on Adult	-0.271
Car Side on Fit	-0.200
Legally Crossing Adult	0.204
Illegally Crossing Adult	-0.063
Car Side on Legally Crossing Adult	0.462
Car Side on Illegally Crossing Adult	0.306
Car Side on Legally Crossing Fit	0.369
Car Side on Illegally Crossing Fit	0.258

Table S8. Features and Weights for Final Choice Model



(a)

(b)

Fig. S2. Two Moral Machine dilemmas that demonstrate an age gradient. Rational choice models treat these dilemmas equivalently, but the data indicated that participants do not do so when the side with children is illegally crossing.

Car Side	Signal (Human)	% Save Criminal	% Save Homeless	p-value	Prediction
Human	Legal	0.65	0.88	$p < .001$	Significant
Human	N/A	0.68	0.84	$p < .001$	Significant
Human	Illegal	0.63	0.79	$p < .001$	Significant
Dog	Legal	0.78	0.89	$p < .001$	Significant
Dog	N/A	0.71	0.90	$p < .001$	Significant
Dog	Illegal	0.69	0.83	$p < .001$	Significant

Car Side	Signal (Human)	% Save Criminal	% Save Old Man	p-value	Prediction
Human	Legal	0.65	0.87	$p < .001$	Significant
Human	N/A	0.68	0.82	$p < .001$	Significant
Human	Illegal	0.63	0.81	$p < .001$	Significant
Dog	Legal	0.78	0.87	$p = .002$	Significant
Dog	N/A	0.71	0.88	$p < .001$	Significant
Dog	Illegal	0.69	0.85	$p < .001$	Significant

Car Side	Signal (Human)	% Save Criminal	% Save Man	p-value	Prediction
Human	Legal	0.65	0.89	$p < .001$	Significant
Human	N/A	0.68	0.85	$p < .001$	Significant
Human	Illegal	0.63	0.81	$p < .001$	Significant
Dog	Legal	0.78	0.91	$p < .001$	Significant
Dog	N/A	0.71	0.89	$p < .001$	Significant
Dog	Illegal	0.69	0.83	$p < .001$	Significant

Table S9. Results from Experiment 1 comparing the percentage of participants that save criminals versus dogs and the percentage of participants that save other humans versus dogs. We used a χ^2 analysis between the proportions, where $N = 326$ and $df = 1$.

Car Side	Signal (Human)	% Save Criminal	N	% Save Homeless	N
Human	Legal	0.50	1679	0.79	1630
Human	N/A	0.44	3840	0.75	3829
Human	Illegal	0.37	2597	0.61	2526
Dog	Legal	0.56	2571	0.82	2638
Dog	N/A	0.52	3879	0.79	3955
Dog	Illegal	0.43	1551	0.65	1600

Car Side	Signal (Human)	% Save Criminal	N	% Save Old Man	N
Human	Legal	0.50	1679	0.80	1659
Human	N/A	0.44	3840	0.76	3833
Human	Illegal	0.37	2597	0.66	2538
Dog	Legal	0.56	2571	0.83	2543
Dog	N/A	0.52	3879	0.81	3825
Dog	Illegal	0.43	1551	0.69	1621

Car Side	Signal (Human)	% Save Criminal	N	% Save Man	N
Human	Legal	0.50	1679	0.81	1642
Human	N/A	0.44	3840	0.79	3889
Human	Illegal	0.37	2597	0.66	2598
Dog	Legal	0.56	2571	0.85	2597
Dog	N/A	0.52	3879	0.83	3873
Dog	Illegal	0.43	1551	0.69	1641

Table S10. Results from the Moral Machine dataset corresponding to the scenarios in Experiment 1 / Supplementary Table S9.

(a) Male

Car Side	Signal (Young)	$\%$ Save (with Adult)	$\%$ Save (without Adult)	p-value	Prediction
Young	Legal	0.83	0.77	$p = .013$	Null
Young	N/A	0.77	0.75	$p = .600$	Null
Young	Illegal	0.71	0.64	$p = .024$	Significant
Old	Legal	0.90	0.91	$p = .827$	Null
Old	N/A	0.92	0.93	$p = .538$	Null
Old	Illegal	0.81	0.75	$p = .030$	Significant

(b) Female

Car Side	Signal (Young)	$\%$ Save (with Adult)	$\%$ Save (without Adult)	p-value	Prediction
Young	Legal	0.84	0.80	$p = .094$	Null
Young	N/A	0.78	0.76	$p = .403$	Null
Young	Illegal	0.70	0.65	$p = .152$	Significant
Old	Legal	0.92	0.91	$p = .562$	Null
Old	N/A	0.92	0.89	$p = .061$	Null
Old	Illegal	0.81	0.73	$p = .001$	Significant

Table S11. Results from Experiment 2 comparing the percentage of participants that save the young side with an adult versus the percentage of participants that save the young side without the adult. We used a χ^2 analysis between the proportions, where $N = 489$ and $df = 1$.

(a) Male

Car Side	Signal (Young)	% Save (with Adult)	N	% Save (without Adult)	N
Young	Legal	0.88	3516	0.88	7124
Young	N/A	0.80	8540	0.83	17289
Young	Illegal	0.52	5745	0.64	11578
Old	Legal	0.93	5584	0.93	11428
Old	N/A	0.92	8611	0.93	17411
Old	Illegal	0.60	3487	0.72	7299

(b) Female

Car Side	Signal (Young)	% Save (with Adult)	N	% Save (without Adult)	N
Young	Legal	0.87	3589	0.89	7330
Young	N/A	0.81	8561	0.84	17193
Young	Illegal	0.53	5743	0.66	11554
Old	Legal	0.93	5680	0.94	11399
Old	N/A	0.92	8654	0.93	17306
Old	Illegal	0.61	3480	0.72	7166

Table S12. Results from the Moral Machine dataset corresponding to the scenarios in Experiment 2 / Supplementary Table S11.

(a) Male-Female Dilemmas

Car Side	Age	$\%$ Save (No Signal)	$\%$ Save (Mean)	p-value	Prediction
Male	Adult	0.14	0.25	$p < .001$	Significant
Female	Adult	0.55	0.50	$p = .224$	Null
Male	Old	0.19	0.27	$p = .012$	Significant
Female	Old	0.55	0.50	$p = .196$	Null

(b) Fat-Fit Dilemmas

Car Side	Sex	$\%$ Save (No Signal)	$\%$ Save (Mean)	p-value	Prediction
Fat	Male	0.15	0.27	$p < .001$	Significant
Fit	Male	0.44	0.46	$p = .609$	Null
Fat	Female	0.16	0.26	$p = .003$	Significant
Fit	Female	0.47	0.42	$p = .253$	Null

Table S13. Results from Experiment 3 comparing the percentage of participants that save the higher-valued individual in the no crossing signal condition versus the mean of the percentages of participants saving the higher-valued individual in the other two crossing signal conditions. We used a χ^2 analysis between the proportions, in which $N = 326$ and $df = 1$.

(a) Male-Female Dilemmas

Car Side	Age	% Save (No Signal)	N	% Save (Mean)
Male	Adult	0.19	19675	0.39
Female	Adult	0.51	19798	0.50
Male	Old	0.24	19871	0.40
Female	Old	0.57	19937	0.53

(b) Fat-Fit Dilemmas

Car Side	Age	% Save (No Signal)	N	% Save (Mean)
Fat	Male	0.18	17222	0.37
Fit	Male	0.45	17444	0.47
Fat	Female	0.20	17357	0.38
Fit	Female	0.46	17347	0.47

Table S14. Results from the Moral Machine dataset corresponding to the scenarios in Experiment 3 / Supplementary Table S13.

Table S15. Iterations of Bayesian Feature Selection

Iteration No.	No. of Features	Accuracy	AUC	AIC
1	1562	0.757	0.816	1.058
2	1251	0.757	0.816	1.053
3	678	0.758	0.818	1.046
4	519	0.758	0.819	1.041
5	372	0.758	0.819	1.041
6	289	0.759	0.819	1.041
7	250	0.759	0.819	1.041
8	235	0.759	0.819	1.041
9	227	0.759	0.819	1.041
10	220	0.758	0.819	1.041
11	212	0.758	0.819	1.041
12	207	0.757	0.819	1.041
13	185	0.759	0.819	1.041
14	181	0.758	0.819	1.040

Feature	Mean	Standard Deviation
Man	0.692	0.008
Woman	0.865	0.005
Pregnant	0.977	0.011
Stroller	1.034	0.024
Old Man	0.263	0.005
Old Woman	0.365	0.005
Boy	1.130	0.007
Girl	1.291	0.004
Homeless	0.404	0.005
Large Woman	0.677	0.003
Large Man	0.428	0.006
Male Executive	0.691	0.010
Female Executive	0.801	0.006
Female Athlete	0.961	0.005
Male Athlete	0.768	0.005
Female Doctor	0.860	0.006
Male Doctor	0.821	0.008
Dog	0.152	0.004
Crossing Signal	0.950	0.004
Car Side	-0.274	0.005
Woman * Female Doctor	-0.132	0.009
Old Man * Criminal	0.085	0.015
Old Man * Dog	-0.086	0.008
Old Woman * Boy	0.040	0.005
Old Woman * Girl	0.020	0.005
Boy * Female Doctor	0.084	0.009
Girl * Female Doctor	-0.057	0.008
Girl * Crossing Signal	-0.035	0.008
Large Woman * Male Athlete	0.061	0.009
Large Man * Dog	-0.057	0.008
Criminal * Cat	-0.052	0.008
Female Athlete * Crossing Signal	-0.049	0.006
Man * Woman * Old Man	0.025	0.004
Man * Woman * Old Woman	-0.014	0.005
Man * Woman * Large Man	-0.021	0.005
Man * Woman * Cat	0.176	0.022
Man * Stroller * Female Executive	-0.192	0.021
Man * Old Woman * Male Athlete	-0.118	0.010
Man * Boy * Crossing Signal	0.055	0.012
Man * Girl * Male Executive	-0.146	0.023
Man * Girl * Female Executive	-0.141	0.013
Man * Girl * Female Athlete	-0.206	0.017
Man * Large Man * Male Executive	-0.213	0.017
Man * Large Man * Female Doctor	-0.196	0.020
Man * Female Executive * Female Athlete	-0.121	0.023
Man * Male Athlete * Crossing Signal	-0.047	0.007
Man * Male Doctor * Dog	0.055	0.016
Man * Dog * Cat	-0.047	0.009
Woman * Pregnant * Boy	-0.181	0.026
Woman * Pregnant * Criminal	-0.220	0.056
Woman * Pregnant * Female Athlete	-0.239	0.018
Woman * Pregnant * Male Athlete	-0.293	0.029
Woman * Pregnant * Male Doctor	-0.467	0.022
Woman * Stroller * Cat	0.159	0.020
Woman * Old Man * Female Athlete	-0.210	0.015
Woman * Old Man * Male Athlete	-0.148	0.012
Woman * Old Woman * Dog	0.216	0.019
Woman * Boy * Male Athlete	-0.269	0.028
Woman * Boy * Female Doctor	-0.181	0.011

Woman * Girl * Female Doctor	-0.353	0.009
Woman * Girl * Male Doctor	-0.179	0.015
Woman * Homeless * Cat	0.134	0.012
Woman * Large Woman * Female Executive	-0.177	0.015
Woman * Large Woman * Cat	0.054	0.009
Woman * Large Man * Male Athlete	-0.034	0.004
Woman * Large Man * Female Doctor	-0.119	0.018
Woman * Criminal * Female Doctor	-0.275	0.034
Woman * Male Executive * Female Doctor	-0.189	0.016
Woman * Male Executive * Male Doctor	-0.321	0.023
Woman * Female Executive * Female Athlete	-0.254	0.015
Woman * Female Executive * Female Doctor	-0.182	0.026
Woman * Female Executive * Male Doctor	-0.271	0.015
Woman * Female Athlete * Female Doctor	-0.292	0.019
Woman * Female Athlete * Male Doctor	-0.146	0.017
Woman * Male Athlete * Female Doctor	-0.057	0.026
Pregnant * Stroller * Male Doctor	-0.265	0.051
Pregnant * Old Man * Boy	0.077	0.017
Pregnant * Old Man * Male Athlete	0.072	0.019
Pregnant * Old Man * Cat	0.078	0.024
Pregnant * Old Woman * Criminal	-0.342	0.028
Pregnant * Old Woman * Male Executive	-0.323	0.029
Pregnant * Boy * Girl	-0.251	0.028
Pregnant * Girl * Male Doctor	-0.316	0.032
Pregnant * Homeless * Male Doctor	-0.183	0.049
Pregnant * Female Doctor * Male Doctor	-0.123	0.051
Pregnant * Female Doctor * Crossing Signal	0.170	0.036
Pregnant * Dog * Cat	-0.117	0.006
Stroller * Old Woman * Boy	-0.196	0.045
Stroller * Old Woman * Girl	-0.144	0.035
Stroller * Boy * Crossing Signal	0.152	0.016
Stroller * Girl * Male Executive	-0.188	0.025
Stroller * Girl * Crossing Signal	0.289	0.039
Stroller * Homeless * Crossing Signal	-0.131	0.026
Stroller * Large Woman * Male Executive	-0.112	0.054
Stroller * Large Woman * Male Doctor	-0.135	0.035
Stroller * Female Executive * Male Athlete	-0.321	0.028
Stroller * Female Athlete * Crossing Signal	0.176	0.018
Stroller * Female Doctor * Male Doctor	-0.335	0.026
Stroller * Dog * Cat	-0.115	0.007
Stroller * Dog * Crossing Signal	0.109	0.009
Old Man * Old Woman * Boy	-0.082	0.005
Old Man * Old Woman * Girl	-0.136	0.006
Old Man * Old Woman * Female Doctor	0.074	0.008
Old Man * Old Woman * Crossing Signal	-0.047	0.006
Old Man * Boy * Crossing Signal	-0.044	0.008
Old Man * Girl * Female Doctor	-0.114	0.017
Old Man * Girl * Crossing Signal	-0.114	0.008
Old Man * Male Executive * Female Executive	-0.101	0.007
Old Man * Male Athlete * Female Doctor	-0.153	0.018
Old Man * Female Doctor * Crossing Signal	-0.090	0.014
Old Woman * Boy * Girl	0.060	0.005
Old Woman * Boy * Large Man	0.070	0.021
Old Woman * Girl * Male Executive	-0.053	0.027
Old Woman * Girl * Female Doctor	-0.174	0.018
Old Woman * Large Woman * Male Executive	-0.116	0.016
Old Woman * Large Woman * Female Executive	-0.223	0.015
Old Woman * Large Man * Criminal	0.119	0.019
Old Woman * Large Man * Male Executive	-0.109	0.019
Boy * Girl * Female Athlete	0.041	0.008
Boy * Large Woman * Female Athlete	-0.094	0.013

Boy * Large Woman * Male Athlete	-0.238	0.011
Boy * Large Woman * Crossing Signal	0.047	0.019
Boy * Large Man * Crossing Signal	0.128	0.012
Boy * Male Executive * Crossing Signal	0.130	0.013
Boy * Female Executive * Male Doctor	0.068	0.009
Boy * Female Executive * Dog	0.127	0.017
Boy * Female Executive * Crossing Signal	0.120	0.012
Boy * Female Athlete * Crossing Signal	0.178	0.015
Boy * Male Athlete * Crossing Signal	0.191	0.017
Boy * Female Doctor * Crossing Signal	0.255	0.014
Boy * Male Doctor * Crossing Signal	0.152	0.016
Boy * Dog * Cat	-0.126	0.005
Boy * Dog * Crossing Signal	0.169	0.014
Girl * Homeless * Female Doctor	-0.256	0.034
Girl * Large Woman * Large Man	0.052	0.010
Girl * Large Woman * Male Athlete	-0.174	0.014
Girl * Large Man * Cat	0.157	0.012
Girl * Criminal * Female Doctor	-0.365	0.016
Girl * Male Executive * Female Executive	0.067	0.009
Girl * Male Executive * Cat	0.073	0.023
Girl * Male Executive * Crossing Signal	0.203	0.020
Girl * Female Executive * Dog	0.211	0.014
Girl * Female Executive * Crossing Signal	0.231	0.019
Girl * Female Athlete * Crossing Signal	0.262	0.014
Girl * Male Athlete * Cat	0.072	0.014
Girl * Male Athlete * Crossing Signal	0.276	0.010
Girl * Female Doctor * Crossing Signal	0.183	0.010
Girl * Male Doctor * Crossing Signal	0.088	0.020
Girl * Dog * Cat	-0.154	0.005
Girl * Cat * Crossing Signal	0.188	0.014
Homeless * Male Executive * Crossing Signal	0.056	0.015
Homeless * Female Executive * Cat	0.116	0.024
Homeless * Cat * Crossing Signal	0.115	0.014
Large Woman * Large Man * Female Athlete	-0.030	0.005
Large Woman * Large Man * Male Athlete	-0.047	0.005
Large Woman * Female Athlete * Male Athlete	0.038	0.005
Large Woman * Male Doctor * Dog	0.070	0.027
Large Woman * Dog * Cat	-0.056	0.004
Large Man * Male Executive * Dog	0.095	0.010
Large Man * Female Doctor * Cat	0.085	0.013
Male Executive * Female Executive * Dog	0.105	0.014
Male Executive * Female Athlete * Crossing Signal	0.162	0.010
Male Executive * Male Athlete * Cat	0.148	0.014
Male Executive * Female Doctor * Cat	0.154	0.026
Male Executive * Dog * Crossing Signal	0.062	0.021
Female Executive * Female Athlete * Crossing Signal	0.255	0.015
Female Executive * Male Athlete * Male Doctor	-0.211	0.012
Female Executive * Female Doctor * Cat	0.151	0.020
Female Executive * Female Doctor * Crossing Signal	0.154	0.015
Female Executive * Male Doctor * Dog	0.096	0.018
Female Executive * Male Doctor * Crossing Signal	0.100	0.010
Female Executive * Dog * Crossing Signal	0.155	0.007
Female Athlete * Male Doctor * Cat	0.095	0.013
Female Athlete * Dog * Cat	-0.108	0.007
Female Athlete * Cat * Crossing Signal	0.165	0.009
Male Athlete * Female Doctor * Dog	0.175	0.016
Male Athlete * Female Doctor * Cat	0.123	0.018
Male Athlete * Male Doctor * Cat	0.222	0.010
Male Athlete * Dog * Crossing Signal	0.120	0.013
Female Doctor * Male Doctor * Cat	0.230	0.013
Female Doctor * Cat * Crossing Signal	0.153	0.013

Male Doctor * Cat * Crossing Signal	0.094	0.013

Table S16. Mean and Standard Deviation of Posterior Weights for Bayesian Variable Selection

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