Computational Models of Heuristics and Bias in Human Behavior

a dissertation
submitted on the twenty-fourth day of april, 2020
to the department of computer science
of the school of science and engineering of
tulane university
in partial fulfillment of the requirements
for the degree of
doctor of philosophy
by

Jaelle Scheuerman

approved:

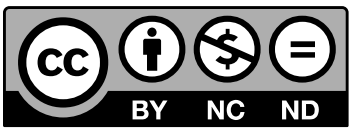
Brent Venable

Noelle Brown

Ed Golob

Nicholas Mattei

Carola Wenk



This work is protected under the following Creative Commons license:

Attribution — NonCommercial — NoDerivatives 4.0 International

☞ https://creativecommons.org/licenses/by-nc-nd/4.0/

Acknowledgments

Many people deserve acknowledgment and thanks for their support of my Ph.D. work and dissertation. First, I would like to thank my Ph.D. advisor, Dr. Brent Venable, for supporting my research and offering guidance through each of our projects. I would also like to recognize my committee members, who were each instrumental in my growth as a researcher. Dr. Edward Golob helped me to develop many interesting interdisciplinary research ideas and offered much guidance in doing good quality research. Dr. Noelle Brown introduced me to ACT-R modeling and supported me as I learned to conduct research at the Naval Research Laboratory. Dr. Nicholas Mattei gave his much of his time and guidance as we developed the heuristics in approval voting project. Dr. Carola Wenk supplied invaluable direction and advice throughout my entire Ph.D. program.

In addition to my committee, many others have supported me through the dissertation process. I am very thankful for my colleagues at the Naval Research Lab, especially Dina Acklin and Dr. Jason Harman, for presenting fresh insights and knowledge that steered the direction of my work. I also want to thank my co-authors, Max Anderson and Jesse Benzell, for their help in research and writing. Special thanks go to Blake Zaffiro, my undergraduate research assistant, who was always enthusiastic about helping out with many tasks that supported my research. Finally, my biggest thanks go out to my partner, Jeff Caradona, who has helped me through the stressful times and celebrated with me during successes. Thank you!

List of Tables

3.1 Best fitting parameters in the Simple Gaussian Model 40

3.2 Best fitting parameters in the Inhibited Goal Map Model 41

3.3 Best fitting parameters in the Reciprocal Model 41

4.1 Tested parameter values in IBL models 65

4.2 Response accuracy of each model compared to behavioral data 66

4.3 Best fitting parameters in IBL Model 1 67

4.4 Best fitting parameters in IBL Model 2 67

4.5 Tested parameter values in Hybrid models 68

4.6 Best fitting parameters in Hybrid Model 1 68

4.7 Best fitting parameters in Hybrid Model 2 69

5.1 Sample approval voting profile 77

5.2 Scenario 1a details and heuristics 85

5.3 Maximum expected utility and best voting strategies in Scenario 1a . 85

5.4 Scenario 1b details and heuristics 86

5.5 Maximum expected utility and best voting strategies in Scenario 1b . 86

5.6 Scenario 2a details and heuristics 86

5.7 Maximum expected utility and best voting strategies in Scenario 2a . 86

5.8 Scenario 2b details and heuristics 87

5.9 Maximum expected utility and best voting strategies in Scenario 2b . 87

5.10 Scenario 3 details and heuristics 87
5.11 Maximum expected utility and best voting strategies in Scenario 3 . . 88
5.12 Scenario 4 details and heuristics 88
5.13 Maximum expected utility and best voting strategies in Scenario 4 . . 88

List of Figures

2.1 Components of the ACT-R architecture 11

2.2 ACT-R's Audio Module 16

3.1 Attentional gradient examples 22

3.2 Spatial auditory attention task overview 25

3.3 Reaction times in spatial auditory attention task 26

3.4 Reaction times' relationship to attentional bias 26

3.5 Reaction times in the vigilance task 28

3.6 Constraint-based computational model schematic 30

3.7 Constraint graph example 31

3.8 Hypothesized shapes for the goal map and saliency map 32

3.9 Response times predicted by Simple Gaussian Model 39

3.10 Response times predicted by Inhibited Goal Map Model 39

3.11 Response times predicted by Reciprocal Model 40

3.12 Plot of drift diffusion parameters 42

3.13 Timeline of spatial auditory attention task in ACT-R 44

3.14 Response times of ACT-R agents using constraint model 46

3.15 Response times of ACT-R agents using drift diffusion model 49

3.16 Accuracy of ACT-R agents using drift diffusion model 50

4.1 Probabilistic learning task overview 59

4.2 Three phases of the probabilistic learning task 60
4.3 Example of an ACT-R production rule 62

5.1 Subjects' view of a scenario 84
5.2 Scenario 1a behavioral results 91
5.3 Scenario 1b behavioral results 92
5.4 Scenario 2a behavioral results 94
5.5 Scenario 2b behavioral results 95
5.6 Scenario 3 behavioral results 97
5.7 Scenario 4 behavioral results 98

Contents

Acknowledgments **ii**

List of Tables **iv**

List of Figures **vi**

1 Introduction **1**

1.1 Background 2

1.2 Contributions 4

1.2.1 Bias in a Spatial Auditory Attention Task 4

1.2.2 Confirmation Bias in Probabilistic Learning 6

1.2.3 Heuristics and Biases in Voting 8

1.3 Thesis Structure 9

2 Preliminaries **10**

2.1 ACT-R 10

2.1.1 ACT-R Components 11

2.1.2 Declarative Memory 12

2.1.3 Procedural Memory and Utility Learning 14

2.1.4 ACT-R Audio Module 15

2.2 Heuristics in Decision Making 16

3 Bias in a Spatial Auditory Attention Task **18**

3.1 Introduction . . . 19

3.2 Background . . . 21

3.2.1 Spatial Attention . . . 21

3.2.2 Computational Models of Cognition . . . 22

3.3 Behavioral Experiments . . . 25

3.3.1 Sustained Attention Task . . . 25

3.3.2 Vigilance Task . . . 27

3.4 Models of Spatial Auditory Attention . . . 28

3.4.1 Constraint Model . . . 28

3.4.2 Drift Diffusion Model . . . 34

3.5 Methods . . . 36

3.5.1 Constraint Model . . . 36

3.5.2 Drift Diffusion Model . . . 37

3.6 Results and Discussion . . . 38

3.6.1 Constraint Model . . . 38

3.6.2 Drift Diffusion Model . . . 41

3.7 Extending the ACT-R Audio Module . . . 42

3.7.1 Constraint Model Implementation in ACT-R . . . 45

3.7.2 Modeling Individual Differences and Errors . . . 46

3.8 Conclusion and Future Directions . . . 50

4 Confirmation Bias in Probabilistic Learning Tasks **52**

4.1 Introduction . . . 53

4.2 Background . . . 54

4.2.1 Instance-Based Learning . . . 55

4.2.2 Hybrid Models with Utility Learning . . . 56

4.3 Related Work . . . 56

4.3.1 Cognitive Models for Predicting Human Behavior 57
4.3.2 Cognitive Models of Learning 57
4.4 Methods 58
4.4.1 Behavioral Experiment 59
4.4.2 Model Design 61
4.5 Experimental Design and Results 64
4.5.1 Instance-based Learning Agents 64
4.5.2 Hybrid Agents 67
4.6 Discussion 69
4.7 Summary and Future Directions 71

5 Heuristics and Biases in Approval Voting **73**
5.1 Introduction 74
5.2 Preliminaries 76
5.2.1 Approval Voting 76
5.2.2 Truthfulness and Sincerity in Approval Ballots 77
5.2.3 Heuristics in Approval Voting 79
5.3 Related Work 80
5.4 Behavioral Experiment Design 83
5.4.1 Scenarios 84
5.4.2 Implementation 88
5.5 Results & Discussion 90
5.5.1 Scenarios 1a, 1b: Trivial Utilities 90
5.5.2 Scenarios 2a, 2b: Dominated Preferences 93
5.5.3 Scenario 3: Disliked Candidate 95
5.5.4 Scenario 4: Neutral Leading Candidate 98
5.5.5 General Discussion 98
5.6 Summary and Future Directions 100

6 Conclusion **102**

6.1 Published or Submitted Papers and Presentations 103

References **105**