Behavioral Learning of a Fuzzy Decision-Maker

Andrew Buck and James Keller
Computational Intelligence Research Lab – University of Missouri

Abstract

In this project, we aim to understand the behavior of a decision-making agent. In particular, we present the agent with an environment, represented as a fuzzy weighted graph, and observe the preferred routes between any two points in the graph. We assume the agent follows the principle of bounded rationality, implemented as an alpha-level OWA operator, to determine the path with the smallest perceived cost. We design an experiment to generate many such agents and environments, and to observe the preferred route between any two points. The agent parameters are then learned from the observed data using a genetic algorithm. We present our findings, in which we show a high degree of reproducibility between the original and learned agent.

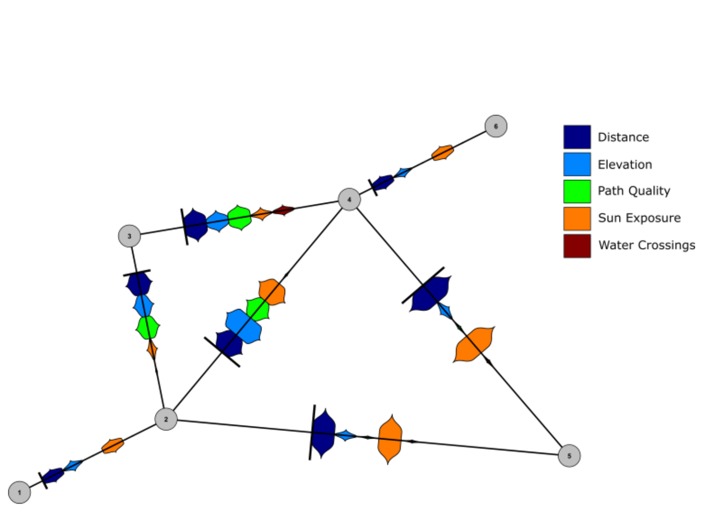
Bounded Rationality as OWA

Consider an environment with three route options as shown below. The environment can be represented as a fuzzy weighted graph and the decision process explained as a tree. Leaf nodes on the tree represent the aggregation of features along each alternate route. We define an agent model consisting of a feature weight vector $\boldsymbol{\beta}$, a vector of OWA weights $\boldsymbol{\omega}$, and an optimism parameter λ. We define the agent's cost interpretation of a fuzzy feature vector $\boldsymbol{F}$ as

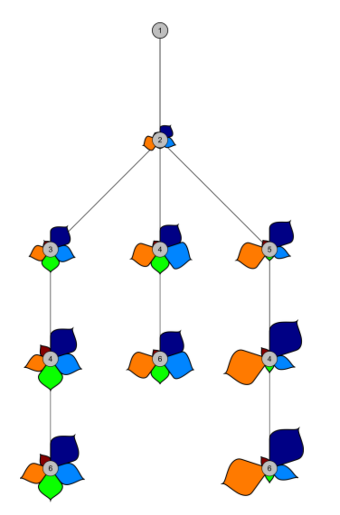
$$C = \omega_1 a_{\sigma(1)} + \cdots + \omega_N a_{\sigma(N)}, \qquad \text{where}$$
$$a_i = \beta_i f_i$$
$$\sigma: [1, N] \to [1, N] \;\; s.t. \;\; a_{\sigma(i)} \geq a_{\sigma(i+1)}$$

The λ term is used to defuzzify the agent's cost using the Liou and Wang index to get a crisp scalar used to rank alternate choices.

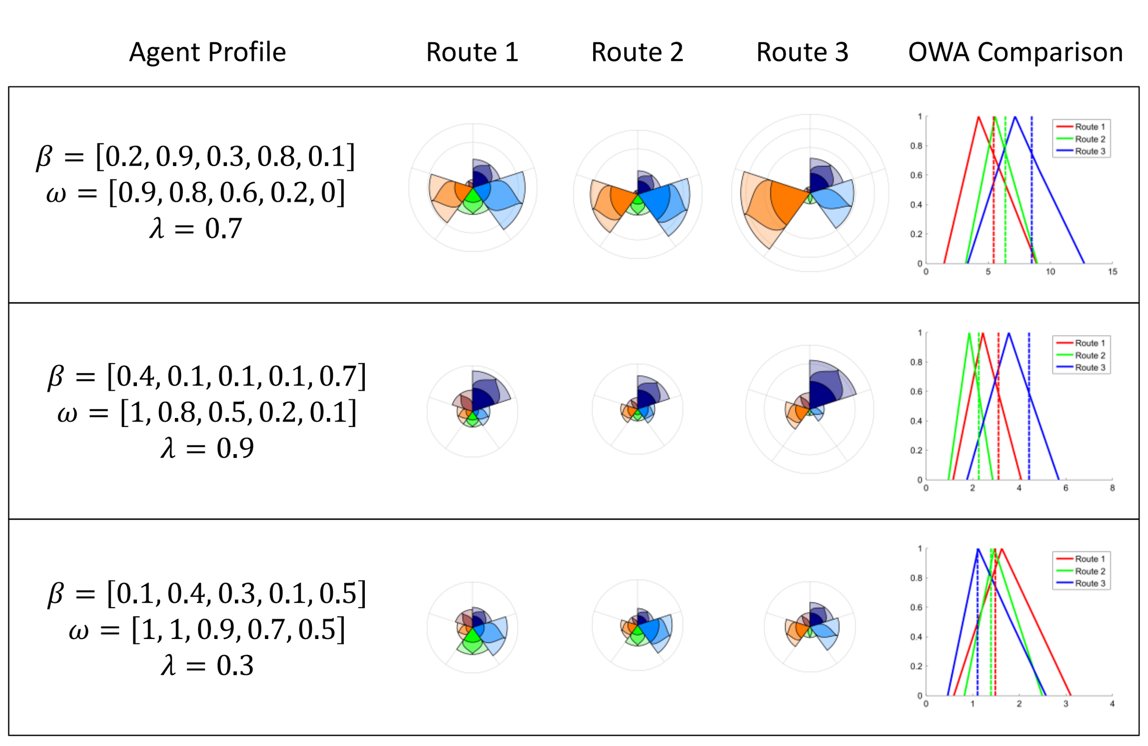
Example scene for a decision-making agent with three route choices.



Fuzzy weighted graph representation.



Decision tree representation.

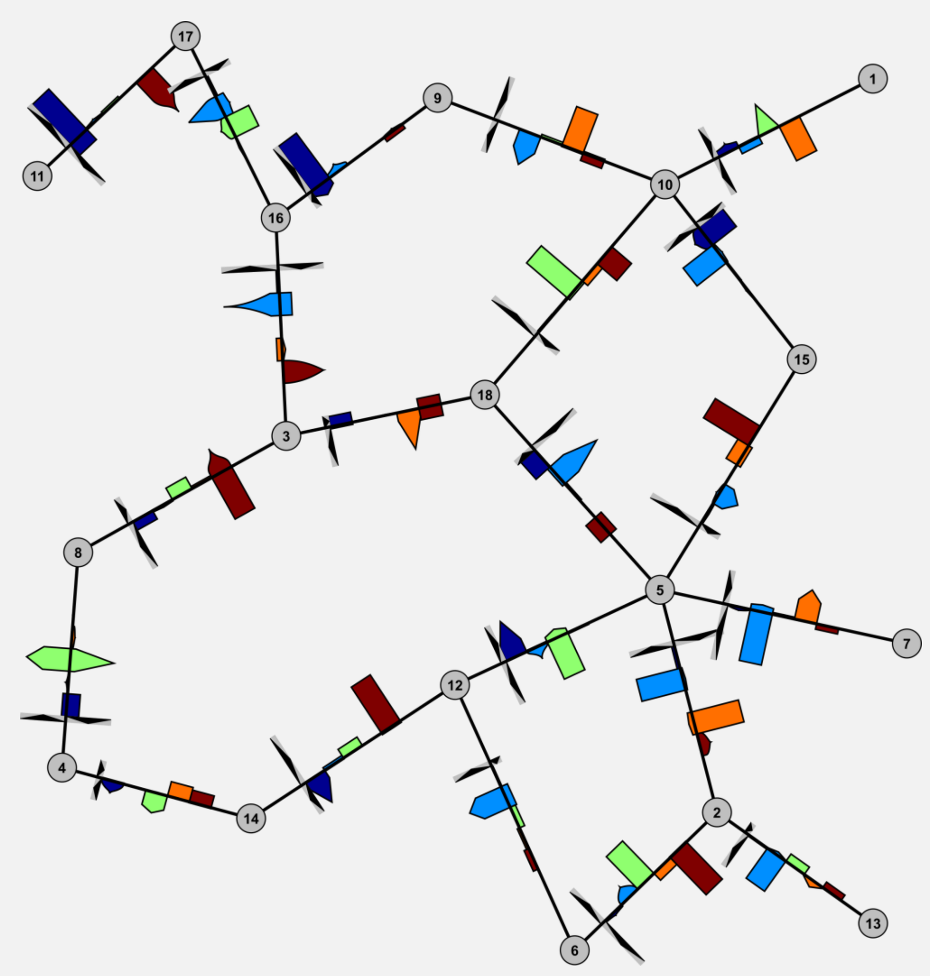


Generating a Dataset

We build a dataset consisting of many different decision scenarios for 100 randomly sampled agent parameter vectors $\boldsymbol{x} = [\beta_1, \dots, \beta_N, \omega_1, \dots, \omega_N, \lambda]$ where each $x_i \in [0, 1]$. For our experiments, we set $N = 5$. We also sort the OWA weights so that $\omega_i \geq \omega_{i+1}$. We then generate 3 random fuzzy weighted graphs for each agent and use the approach described below to create a set of decision making scenarios for planning a route between any pair of points in one of the graphs. This results in a dataset of several hundred examples.

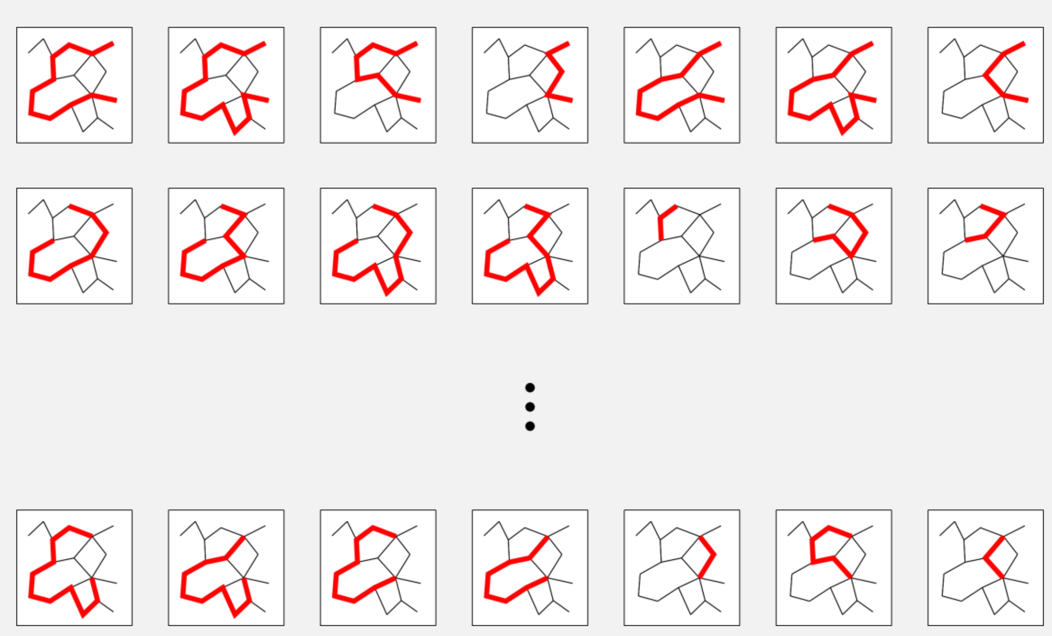
Step 1

Generate a set of random fuzzy weighted graphs representing the ground truth environment. Each edge is weighted with a vector of fuzzy numbers.



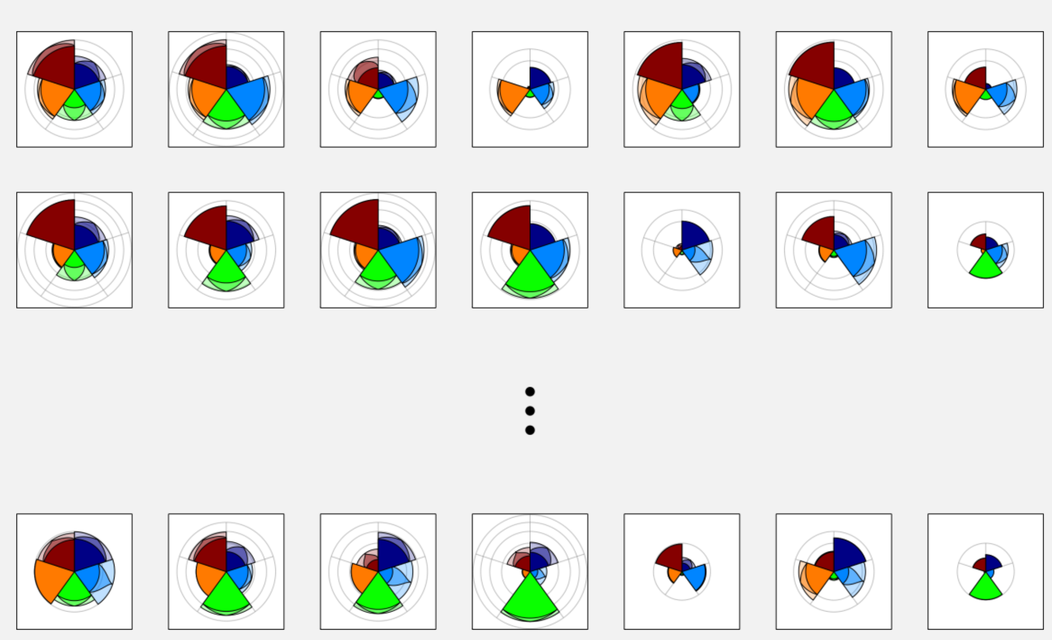
Step 2

For each pair of points in a graph, find the set of all non-looping paths between them. Each set represents the decision-making scenario of finding a route between these two points.



Step 3

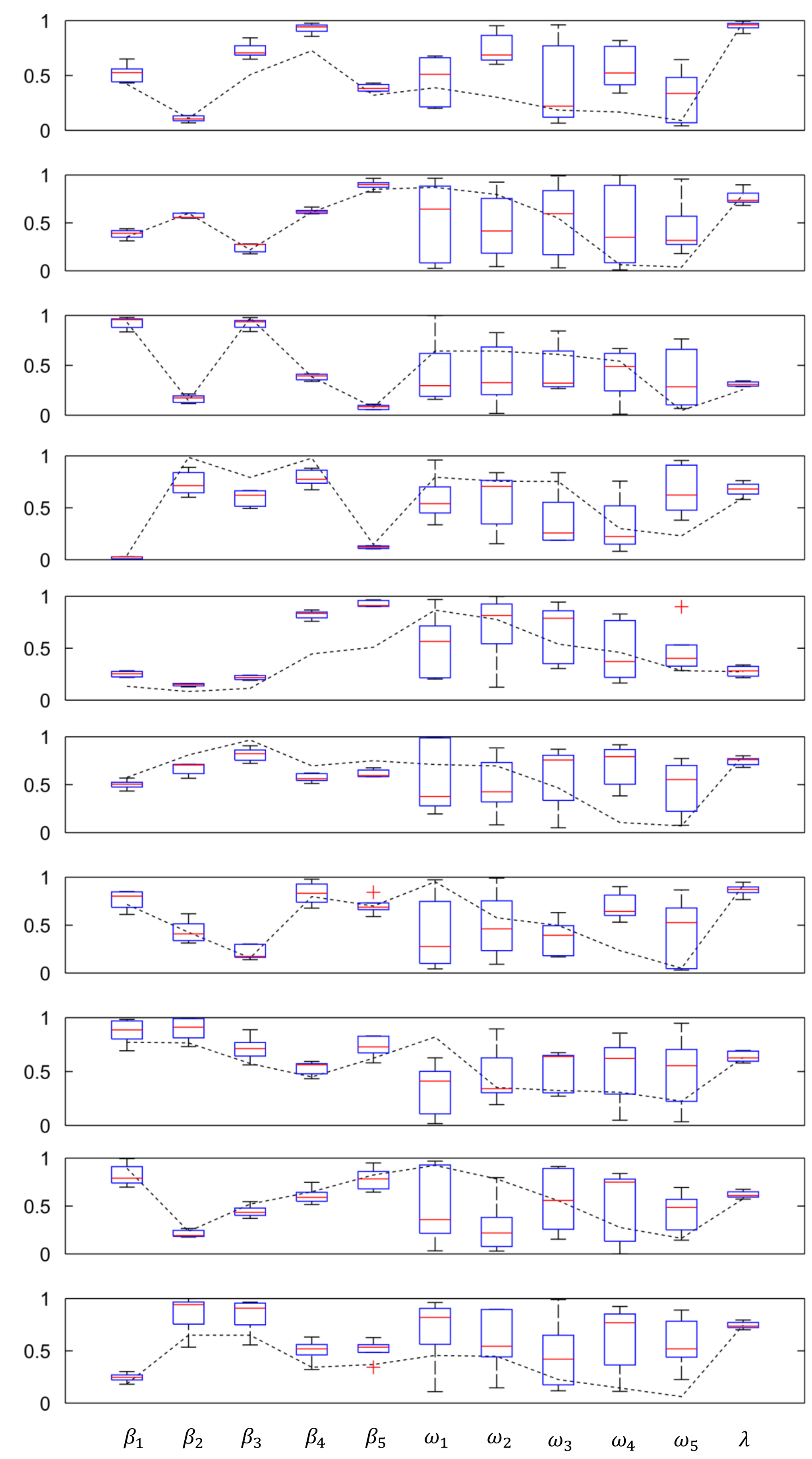
Evaluate each path according to the agent's profile. Rank the results and choose a path for each pair of points.



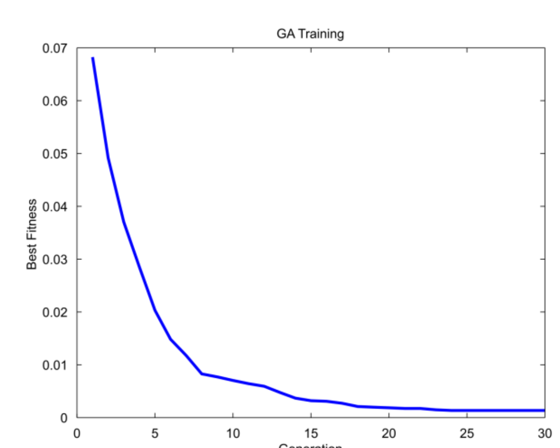
Learning the Behavior Profile

Given our randomly generated dataset, we design a genetic algorithm to learn the agent parameter vectors. For each agent in the dataset, we define a chromosome as $\boldsymbol{x} = [\beta_1, \dots, \beta_N, \omega_1, \dots, \omega_N, \lambda]$ where each $x_i \in [0, 1]$. We then define a fitness function which uses the chromosome variables to determine an OWA ranking for each of that agent's decision scenarios. The fitness is measured as the percentage of scenarios for which the incorrect choice is made.

We randomly divide the data into 5 equal sets and perform a 5-fold cross validation. We use a genetic algorithm with a population size of 200, uniform crossover rate of 0.8, Gaussian mutation rate of 0.2 and an elite size of 10. The algorithm runs until a solution is found with perfect prediction accuracy, or there are 10 stall generations with no improvement. The box plots below show the distribution of the best solutions from each set for the first 10 agents. The dotted line shows the true agent parameter values. Our algorithm was able to predict the $\boldsymbol{\beta}$ and λ values with high accuracy, however the OWA weights $\boldsymbol{\omega}$ show a wide variation.



Our algorithm achieved a prediction accuracy rate of 99.34% on the synthetic data, despite not perfectly recovering the true agent parameters. This suggests that many different models can be used to explain decision-making behavior.



References

[1] A. R. Buck and J. M. Keller, "Visualizing uncertainty with fuzzy rose diagrams," in Computational Intelligence for Engineering Solutions (CIES), 2014 IEEE Symposium on, 2014, pp. 30–36.
[2] A. R. Buck, J. M. Keller, and M. Popescu, "An alpha-level OWA implementation of bounded rationality for fuzzy route selection," in World Conference on Soft Computing, 2013.
[3] T.-S. Liou and M.-J. J. Wang, "Ranking fuzzy numbers with integral value," Fuzzy Sets Syst., vol. 50, no. 3, pp. 247–255, Sep. 1992.
[4] R. B. Urquhart, "Algorithms for computation of relative neighborhood graph," Electron. Lett., vol. 16, no. 14, pp. 556–557, 1980.