

Decisions & Learning in Computational Behavioral Game Theory

decisions in game theory

$$U_i(X) = x_i$$

Players only care about their own payoffs. This is elegant, but wrong. A host of experiments show that people don't make economic decisions this way.

ultimatum bargaining

Player 1 chooses how to split \$10. Player 2 then accepts this split (both players take their share) or rejects it (neither player gets anything). That's all.

Player 2 should accept *any* split greater than \$0, even accepting only 25¢ or 1¢. So player 1 should offer almost nothing, so as to get the most money from the game. But hundreds of experiments in different cultures, with different stakes, show that people don't behave this way. Almost always, low offers are rejected. Here, game theory doesn't predict what players do; it also doesn't offer good advice about what to do when playing with a person.

Despite some limitations in explaining economic behavior, "classical" game theory as developed by von Neumann, Nash, and others has proved an extremely powerful tool in economics. Certain obvious applications of game theory are impossible, however. Imagine a matrix game representing international trade. All the countries of the world are players, and each player's payoffs depend on the moves of all the players. To

game theory + computation

extremely simplify the possible actions, let each country simply choose one other country to focus on in improving exports. The U.S. Department of State lists 192 countries. Even if 50 of these can be neglected, the matrix for this game would have 142^{142} entries — substantially more entries than there are particles in the universe. We cannot even write down the specification of this game, much less begin to compute its Nash equilibrium. To deal with such problems, researchers in computational game theory have sought approximate solutions and have rewritten the problem to take into account the structure of interactions among players.

decisions in behavioral game theory

$$U_i(X) = x_i - \frac{\alpha}{n-1} \sum_{k \neq i} \max(x_k - x_i, 0) - \frac{\beta}{n-1} \sum_{k \neq i} \max(x_i - x_k, 0)$$

Players care about their own payoffs, they dislike others having more than them with coefficient α , and they dislike having more than others with coefficient β . This particular model (Fehr and Schmidt, 1999) is one of several behavioral theories.

I am working now with Michael Kearns and other researchers to uncover and address important questions at the intersection of computational game theory, behavioral economics, and machine learning. A new behavioral game theory is now in development, seeking to explain how people make economic decisions (as actually observed in experiments) and how they learn to reach the observed equilibria.

Many important questions remain regarding the computational aspects of the new, behavioral models: As the number of players and actions becomes large, is the computational complexity of problem similar to that of the classical game theory problem? Are the suggested learning algorithms tractable for large numbers of players or actions? I will also consider appropriate ways that graphical models can be used to encode local structure in behavioral game theory.

Camerer, Colin, Teck-Hua Ho, and Juin Kuan Chong. "Behavioral Game Theory: Thinking, Learning, and Teaching." Available online. 14 November 2001.

Fehr, Ernst and Klaus Schmidt. "A Theory of Fairness, Competition, and Cooperation." *Quarterly Journal of Economics* 114. 817-868. 1999.

learning in behavioral game theory

$$A_i^j(t) = \frac{\phi N(t-1) A_i^j(t-1) + [\delta + (1-\delta) I(s_i^j, s_i(t))] \pi_i(s_i^j, s_i(t))}{N(t-1) \phi(1-\kappa) + 1}$$

$$N(t) = N(t-1) \phi(1-\kappa) + 1$$

One model of how economic behavior changes over time is FEWA, functional experience-weighted attraction learning (Camerer, Ho, and Chong, 2001), which incorporates reinforcement and belief learning. It modifies EWA, above, replacing free parameters ϕ , δ , and κ with $\phi_i(t)$, $\delta_i(t)$, and $\kappa_i(t)$, functions of the player's experience so far.

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