CPS 590.7: Computational Microeconomics: Game Theory, Social Choice, and Mechanism Design

Instructor: Vincent Conitzer
conitzer@cs.duke.edu

https://www2.cs.duke.edu/courses/fall20/compsci590.7/

Caspar Oesterheld
Hanrui Zhang
Qingying Luo
Robert Lordi
Griffin Malm
Yikai Wu

Graduate TAs
Graduate TA (organizational)
Undergraduate TAs
Who Are We?

We are a group of Duke University faculty, postdocs, and students interested in the intersection of computer science and economics (and the social sciences more broadly) and the impact of this interplay on decisions in information technology and digital business. This includes applying techniques from computer science and optimization to economics -- for example, using computation to design market clearing mechanisms and to implement efficient allocation and pricing in them -- as well as applying techniques from economics to computer science -- for example, designing incentives for users of networked computer systems and social networks.

Contacts

For organizational questions about the seminar series:
- **Yuqian Li**
- **Catherine Moon**

For other matters, contact the relevant faculty member(s):
- **Atila Abdulkadiroglu** (Econ)
- **Vincent Conitzer** (CS)
- **Rachel Kranton** (Econ)
- **Ben Lee** (ECE)
- **Kamesh Munagala** (CS)

CS-Econ Talks
- [Upcoming Talks](http://econ.cs.duke.edu)
- [Past Talks](http://econ.cs.duke.edu)

Related Seminars
- **AI Group** (CS)
- **Algorithms Seminar** (CS)
- **Decision Sciences Seminar** (Fuqua)
- **Duke Robotics, Intelligence, and Vision (DRIV) Seminar** (CS)
- **Machine Learning**
- **Microeconomic Theory Seminars** (Econ)
M.S. Economics & Computation

The joint field of economics and computer science has emerged from two converging intellectual needs: Computer science has become increasingly important for economists working with big data to address complex questions. Students interested in learning about computational mechanism design with applications to economics are ideal candidates for this program. Students whose interest is more generally focused on data analytics across a broad range of fields may also be interested in Duke’s Master of Quantitative Management (MQM) program, offered at the Fuqua School of Business, and/or Duke’s new Master in Interdisciplinary Data Science (MIDS) program, which is accepting its first class in Fall 2018.

The MSEC program combines the strengths of the Departments of Economics and Computer Science to educate students in these important computational skills linked to economics, and to prepare them for Ph.D. studies or careers in economics, finance, government, and business. Reflecting this strong interdisciplinary relationship, Duke University ranks No. 4 for research in economics and computation, according to CSRankings.org.

This program is designed to meet the needs of students with varied levels of exposure to either field, but a strong quantitative background is recommended.
ACM Transactions on Economics and Computation (TEAC)

ACM Conference on Economics and Computation (EC)
History

John von Neumann

- Computer Science & Engineering
  - von Neumann architecture
- Economic Theory
  - game theory (minimax theorem)
- Mathematical Optimization & Operations Research
  - linear programming (duality)

1900 1950 2000
What is Economics?

• “Economics is the social science that studies the production, distribution, and consumption of goods and services.” [Wikipedia, Aug. 2020]

• Some key concepts:
  – Economic agents or players (individuals, households, firms, …)
  – Agents’ current endowments of goods, money, skills, …
  – Possible outcomes ((re)allocations of resources, tasks, …)
  – Agents’ preferences or utility functions over outcomes
  – Agents’ beliefs (over other agents’ utility functions, endowments, production possibilities, …)
  – Agents’ possible decisions/actions
  – Mechanism that maps decisions/actions to outcomes
An economic picture

$v(\text{PC}) = 200$

$v(\text{TV}) = 100$

$v(\text{Laptop}) = 400$

$v(\text{Desktop}) = 200$

$v(\text{Computer}) = 400$

$\$ 600$

$\$ 800$

$\$ 200$
After trade (a more efficient outcome)

$v(\text{ } ) = 200$

$v(\text{ } ) = 100$
$v(\text{ } ) = 400$

… but how do we get here?
Auctions?
Exchanges?
Unstructured trade?

$1100$

$v(\text{ } ) = 200$
$v(\text{ } ) = 400$

$400$

$100$
Some distinctions in economics

- **Descriptive vs. normative economics**
  - Descriptive:
    - seeks only to describe real-world economic phenomena
    - does not care if this is in any sense the “right” outcome
  - Normative:
    - studies how people “should” behave, what the “right” or “best” outcome is

- **Microeconomics vs. macroeconomics**
  - Microeconomics: analyzes decisions at the level of individual agents
    - deciding which goods to produce/consume, setting prices, …
    - “bottom-up” approach
  - Macroeconomics: analyzes “the sum” of economic activity
    - interest rates, inflation, growth, unemployment, government spending, taxation, …
    - “big picture”
What is Computer Science?

• “Computer science is the study of computation and information. Computer science deals with theory of computation, algorithms, computational problems and the design of computer systems hardware, software and applications.” [Wikipedia, Aug. 2020]

• A computational problem is given by a function f mapping inputs to outputs
  – For integer x, let f(x) = 0 if x is prime, 1 otherwise
  – For an initial allocation of resources x, let f(x) be the (re)allocation that maximizes the sum of utilities

• An algorithm is a fully specified procedure for computing f
  – E.g., sieve of Eratosthenes
  – A correct algorithm always returns the right answer
  – An efficient algorithm returns the answer fast

• Computer science is also concerned with building larger artifacts out of these building blocks (e.g., personal computers, spreadsheets, the Internet, the Web, search engines, artificial intelligence, …)
Resource allocation as a computational problem

**input**

\[ v(\text{ } ) = $400 \]

\[ v(\text{ } ) = $600 \]

\[ v(\text{ } ) = $500 \]

\[ v(\text{ } ) = $400 \]

\[ $800 \]

**output**

\[ $750 \]

\[ $450 \]

Here, gains from trade ($300) are divided evenly (not essential)
Economic mechanisms

"true" input

\[ v(\text{agent 1}) = \$400 \]
\[ v(\text{agent 2}) = \$600 \]

agents' bids

\[ v(\text{agent 1}) = \$500 \]
\[ v(\text{agent 2}) = \$501 \]

result

\[ \text{exchange mechanism (algorithm)} \]

\[ \text{Exchange mechanism designer does not have direct access to agents' private information} \]

\[ \text{Agents will selfishly respond to incentives} \]
What is game theory?

• “Game theory is the study of mathematical models of strategic interaction among rational decision-makers. It has applications in all fields of social science, as well as in logic, systems science and computer science. [...] Today, game theory applies to a wide range of behavioral relations, and is now an umbrella term for the science of logical decision making in humans, animals, and computers.”

[Wikipedia, Aug. 2020]
What is game theory…

• Game theory studies settings where multiple parties (agents) each have
  – different preferences (utility functions),
  – different actions that they can take

• Each agent’s utility (potentially) depends on all agents’ actions
  – What is optimal for one agent depends on what other agents do
    • Very circular!

• Game theory studies how agents can rationally form beliefs over what other agents will do, and (hence) how agents should act
  – Useful for acting as well as predicting behavior of others
Penalty kick example

Is this a “rational” outcome? If not, what is?
Game playing & AI

perfect information games: no uncertainty about the state of the game (e.g. tic-tac-toe, chess, Go)

imperfect information games: uncertainty about the state of the game (e.g., poker)

• Optimal play: value of each node = value of optimal child for current player (backward induction, minimax)
  
  For chess and Go, tree is too large
  
  – Use other techniques (heuristics, limited-depth search, alpha-beta, deep learning, …)

• Top computer programs better than humans in chess, not yet in Go

• Player 2 cannot distinguish nodes connected by dotted lines
  
  Backward induction fails; need more sophisticated game-theoretic techniques for optimal play

• Small poker variants can be solved optimally

• Humans still better than top computer programs at full-scale poker (at least most versions)

• Top computer (heads-up) poker players are based on techniques for game theory
Artificial intelligence masters multiplayer poker

This year, an artificial intelligence (AI) program beat some of the world’s best players in the most popular version of poker, no-limit Texas Hold ‘em. The landmark result marks the first time AI has prevailed in a multiplayer contest in which players have only imperfect information about the state of the game.

AI has been trouncing humans in games at a spectacular rate. In 2007, computer scientists developed a program guaranteed not to lose at checkers. In 2016, another team developed an AI program that defeated the best humans at Go, a board game with vastly more configurations than checkers.

Poker presents a stiffer challenge, as players cannot see their opponents’ cards and thus have limited information. In 2017, computer scientists developed an AI program unbeatable at a two-player version of Hold ‘em—in which each player forms a hand from five cards laid face up on the table and two more each holds privately.

Now, AI has bested world-class players in the full multiplayer game, as computer scientists at Carnegie Mellon University in Pittsburgh, Pennsylvania, announced in August. By playing 1 trillion games against itself, their program, Pluribus, developed a basic strategy for various kinds of situations—say, playing for an inside straight. For each specific hand, it could also think through how the cards would likely play out. In 20,000 hands with six players it outperformed 15 top-level players, as measured by average winnings per hand.
Real-world security applications

Airport security
Where should checkpoints, canine units, etc. be deployed?

Federal Air Marshals
Which flights get a FAM?

US Coast Guard
Which patrol routes should be followed?

Wildlife Protection
Where to patrol to catch poachers or find their snares?
Questions and problems in (computational) game theory

- How should we represent games (=strategic settings)?
  - Standard game-theoretic representations not always concise enough

- What does it mean to solve a game?
  - Solution concepts from game theory, e.g., Nash equilibrium

- How computationally hard is it to solve games?
  - Can we solve them approximately?

- Is there a role for (machine) learning in games?

- What types of modeling problems do we face when addressing real-world games?
  - E.g., applications in security
What is social choice?

• “Social choice theory or social choice is a theoretical framework for analysis of combining individual opinions, preferences, interests, or welfares to reach a collective decision or social welfare in some sense.” [Wikipedia, Aug. 2020]

• I.e., making decisions based on the preferences of multiple agents

• Largely, but not exclusively, focused on voting
Voting over outcomes

- Can vote over other things too
  - Where to go for dinner tonight, other joint plans, …
- Many different rules exist for selecting the winner
Combinatorial auctions

Simultaneously for sale: , , ,

\[ v(\text{server, monitor, laptop}) = $500 \]

\[ v(\text{server, monitor}) = $700 \]

\[ v(\text{laptop}) = $300 \]

used in truckload transportation, industrial procurement, radio spectrum allocation, …
Kidney exchanges allow patients with willing but incompatible live donors to swap donors.
Kidney exchange

Prescription AI
This series explores the promise of AI to personalize, democratize, and advance medicine—and the dangers of letting machines make decisions.

THE BOTPERATING TABLE

How AI changed organ donation in the US

By Corinne Purtill • September 10, 2018
Kidney exchange

- Patient 1
  - Donor 1 (Patient 1’s friend)
- Patient 2
  - Donor 2 (Patient 2’s friend)
- Patient 3
  - Donor 3 (Patient 3’s friend)
- Patient 4
  - Donor 4 (Patient 4’s friend)

Compatibilities:
Problems in computational social choice

• **Winner determination** problem
  – For some voting rules, determining the winner is NP-hard
  – In a combinatorial auction, deciding which bids win is (in general) an NP-hard problem

• **Preference elicitation** (communication) problem
  – Can be impractical to communicate all of one’s preferences (e.g., valuation for every bundle)

• **Mechanism design** problem
  – How do we get the bidders to behave so that we get good outcomes?

• **These problems** interact in nontrivial ways
  – E.g. limited computational or communication capacity can limit mechanism design options
  – … but can perhaps also be used in a positive way
What is mechanism design?

• “Mechanism design is a field in economics and game theory that takes an objectives-first approach to designing economic mechanisms or incentives, toward desired objectives, in strategic settings, where players act rationally. [...] two distinguishing features of [mechanism design] are:
  – that a game “designer” chooses the game structure rather than inheriting one
  – that the designer is interested in the game’s outcome

• [Wikipedia, Aug. 2020]
Mechanism design...

- **Mechanism** = rules of auction, exchange, ...
- A **function** that takes **reported preferences** (bids) as input, and produces **outcome** (allocation, payments to be made) as output

\[
f(\text{v(\text{[item1]})} = \$500, \text{v(\text{[item2]})} = \$400) = \text{[item1]} \text{ for } \$750, \text{[item2]} \text{ for } \$450
\]

- The **entire function** \( f \) is **one** mechanism
- E.g., the mechanism from before: find allocation that maximizes (reported) utilities, distribute (reported) gains evenly
- Other mechanisms choose different allocations, payments
Example: (single-item) auctions

- **Sealed-bid** auction: every bidder submits bid in a sealed envelope
- **First-price** sealed-bid auction: highest bid wins, pays amount of own bid
- **Second-price** sealed-bid auction: highest bid wins, pays amount of second-highest bid

<table>
<thead>
<tr>
<th>Bid</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bid 1</td>
<td>$10</td>
</tr>
<tr>
<td>Bid 2</td>
<td>$5</td>
</tr>
<tr>
<td>Bid 3</td>
<td>$1</td>
</tr>
</tbody>
</table>

- **First-price**:
  - Bid 1 wins, pays $10
- **Second-price**:
  - Bid 1 wins, pays $5
Which auction generates more revenue?

- Each bid depends on
  - bidder’s true valuation for the item (utility = valuation - payment),
  - bidder’s beliefs over what others will bid (→ game theory),
  - and... the auction mechanism used
- In a first-price auction, it does not make sense to bid your true valuation
  - Even if you win, your utility will be 0…
- In a second-price auction, (we will see later that) it always makes sense to bid your true valuation

<table>
<thead>
<tr>
<th>First Price Mechanism</th>
<th>Second Price Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bid 1: $5</td>
<td>Bid 1: $10</td>
</tr>
<tr>
<td>Bid 2: $4</td>
<td>Bid 2: $5</td>
</tr>
<tr>
<td>Bid 3: $1</td>
<td>Bid 3: $1</td>
</tr>
</tbody>
</table>

Are there other auctions that perform better? How do we know when we have found the best one?
Mechanism design...

- Mechanism = game
  - → we can use game theory to predict what will happen under a mechanism
    - if agents act strategically
- When is a mechanism “good”?
  - Should it result in outcomes that are good for the reported preferences, or for the true preferences?
  - Should agents ever end up lying about their preferences (in the game-theoretic solution)?
  - Should it always generate the best allocation?
  - Should agents ever burn money?(!?)
- Can we solve for the optimal mechanism?
Many uses of **linear programming**, **mixed integer (linear) programming** in this area

<table>
<thead>
<tr>
<th>Game theory</th>
<th>Linear programming</th>
<th>Mixed integer linear programming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominated strategies</td>
<td></td>
<td>Nash equilibrium</td>
</tr>
<tr>
<td>Minimax strategies</td>
<td></td>
<td>Optimal mixed strategies to commit to in more complex settings</td>
</tr>
<tr>
<td>Correlated equilibrium</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Optimal mixed strategies to commit to</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social choice, expressive marketplaces</td>
<td>Winner determination in auctions, exchanges, … with partially acceptable bids</td>
<td>Winner determination in: auctions, exchanges, … without partially acceptable bids; Kemeny, Slater, other voting rules; kidney exchange</td>
</tr>
<tr>
<td>Mechanism design</td>
<td>Automatically designing optimal mechanisms that use randomization</td>
<td>Automatically designing optimal mechanisms that do not use randomization</td>
</tr>
</tbody>
</table>
Which party will win the Electoral College?

Democratic 334
218
61
55
60
125

Majority

204 Republican

Biden: $60\,\text{¢} 2\,\text{¢}

Trump: $44\,\text{¢} \text{NC}

2020/8/16
1. Research and Educational Facility

PredictIt is intended and offered as an experimental research and educational facility of Victoria University of Wellington, New Zealand ("Provider" or "We"), not as an investment market or a gambling facility. PredictIt is not regulated by, nor are its operators registered with, the U.S. Commodity Futures Trading Commission (CFTC) or any other regulatory authority.

Provider has received a no-action-letter from the Division of Market Oversight of the Commodity Futures Trading Commission. Without explicitly asserting jurisdiction over Provider or any of its submarkets, this letter, dated October 29, 2014, extended no-action relief to Provider's Political and Economic Indicator Markets (the latter limited to students, faculty and staff of participating universities). The letters are available at the CFTC website as part of their Freedom of Information Act documents. Pursuant to this letter, there is "a limit of 5000 total traders in any particular contract", and "a limit on investment by any single participant in any particular contract [of] $850".

i. PredictIt is offered by Victoria University, a highly-regarded, non-profit educational institution.

ii. No political party or other organization referred to on the Website in connection with any Market has (or has had) any role in the promotion or operation of this Website or any Market.

iii. Nothing on this Website constitutes an offer or invitation to trade with any person who is under 18 years of age.

2. Terms of Use

i. These Terms of Use set out the basis on which PredictIt offers you access to, and use of, the "PredictIt" website and trading facility whose homepage is located at www.PredictIt.org (the "Website"). By accessing or connecting to the Website, you agree to abide by these Terms of Use.

ii. We can change these Terms of Use at any time and in any way we consider appropriate. Our changes will take effect as soon as we publish an updated version of these Terms of Use on the Website. It is up to you to ensure that you are familiar with the latest version of these Terms of Use.
Financial securities

- Tomorrow there must be one of ☀️ ☂️ ☂️
- Agent 1 offers $5 for a security that pays off $10 if ☂️ or ☂️
- Agent 2 offers $8 for a security that pays off $10 if ☀️ or ☂️
- Agent 3 offers $6 for a security that pays off $10 if ☀️
- Can we accept some of these at offers at no risk?
How to incentivize a weather forecaster

- Forecaster’s bonus can depend on
  - Prediction
  - Actual weather on predicted day
- Reporting true beliefs should maximize expected bonus

\[
\begin{align*}
\text{P(☀️) } &= 0.5 \\
\text{P(☁️) } &= 0.3 \\
\text{P(🌧️) } &= 0.2 \\
\text{P(⚡️) } &= 0.1 \\
\text{P(☀️) } &= 0.8 \\
\text{P(☁️) } &= 0.1 \\
\text{P(🌧️) } &= 0.1 \\
\end{align*}
\]
Peer prediction

I had a good experience with product X.

I had an OK experience with product X.

Each forecaster’s bonus depends only on how well it matches the other’s
Other kinds of private information in auctions?

my quality estimate

\[ q(\ ) = 90 \]

my need

\[ n(\ ) = 70 \]

my quality estimate

\[ q(\ ) = 80 \]

my need

\[ n(\ ) = 75 \]

How should the auctioneer use this information?
Sponsored search / ad auctions

- Choice of ads (if any) to show determined by:
  - Advertiser bid
  - Predicted likelihood of click
Deferred Acceptance algorithm

[Gale & Shapley 1962]
Learning & mechanism design

- Auctioneer may need to know distribution over private information to design optimal mechanism
  - Learn from repeated play?
  - Exploration/exploitation tradeoffs?
- Conversely: what if data for ML is generated by strategic agents?
  - Agent being classified herself
  - Data from multiple agents used to find social-welfare maximizing decision
Why should economists care about computer science?

- Finding efficient allocations of resources is a (typically hard) computational problem
  - Sometimes beyond current computational techniques
  - If so, unlikely that any market mechanism will produce the efficient allocation (even without incentives issues)
  - Market mechanisms must be designed with computational limitations in mind
  - New algorithms allow new market mechanisms
Why should economists care about computer science…

• **Agents** also face difficult computational problems in participating in the market
  – Especially acting in a game-theoretically optimal way is often **computationally hard**
  – Game-theoretic predictions **will not come true** if they cannot be computed
    • Sometimes bad (e.g., want agents to find right bundle to trade)
    • Sometimes good (e.g., do not want agents to manipulate system)
Why should computer scientists care about economics?

- Economics provides high-value computational problems
- Interesting technical twist: no direct access to true input, must incentivize agents to reveal true input
- Conversely: Computer systems are increasingly used by multiple parties with different preferences (e.g., Internet, blockchain)
- Economic techniques must be used to
  - predict what will happen in such systems,
  - design the systems so that they will work well
- Game theory is relevant for artificial intelligence
  - E.g., computer poker