Computer Science

- is the study and the science of the theoretical foundations of information and computation and their implementation and application in computer systems. [Wikipedia]

  - Building systems
  - $F(x) =$?
  - How fast can we get the answer?
  - Focus on computational and informational constricts.
Economics

- is the social science that studies the production, distribution, and consumption of goods and services. [Wikipedia]
  - Economies (systems)
  - Many self-interested agents
  - Agents’ preferences/utilities over outcomes
  - Agents’ information and beliefs
  - Agents’ decision making
  - Game-theoretic interactions of agents

The Interface

- Computer systems are increasingly being developed and used by multiple parties with different preferences
  - Predict system outcomes
  - Design systems to achieve desired outcomes
- Economic problems sometimes are (hard) computational problems
  - Resource allocation
  - Price discovery

Theories, algorithms, and systems that satisfy both economic and computational constraints.
Lots of Compelling Applications

• Internet Monetization:
  Google, Yahoo!, Microsoft are using auctions to sell ads

• Markets are used for information aggregation
  – Google, Yahoo!, Microsoft, GE, etc. have internal prediction markets

• Social network and Social Tagging:
  Facebook, MySpace, LinkedIn, Flickr, LibraryThing

This Course

• Rotating topic course
• Previous
  – Fall 2009. Assignment, Matching, and Dynamics
  – Fall 2008. Social Computing
  – Spring 2008. Computational Finance
  – Spring 2007. Computational Mechanism Design
  – Spring 2006. Multi-agent Learning and Implementation

• Seminar style
Course Goals

• Provide an introduction to an emerging, interdisciplinary literature
• Develop a level of comfort with both economic and computational thinking
• Develop general skills related to reading papers, identifying research questions
• Provide a basis for continued research.

Fall 2010

• Information, Prediction, and Collective Intelligence
• Algorithmic, game theoretic, and conceptual questions related to obtaining information, making predictions, and getting tasks done by the crowds.
• Focus on eliciting and aggregating probabilistic information, bridging from economic theory to theory of online learning.
Crowds Are Smarter...

• Who wants to be a millionaire?
  – Fifty-Fifty
    Correct 50% of the time
  – Phone-A-Friend
    Correct 65% of the time
  – Ask the Audience
    Correct 91% of the time

Crowds Are Smarter...

• Jelly-Beans-in-the-Jar Experiment
  – Professor Jack Treynor ran the experiment in his class
  – with a jar that held 850 beans
  – the group estimate was 871
  – only one of the 56 people in the class made a better guess
Are Crowds Smarter?

- No always
  - Bad committee decisions
  - Endless group meetings

- In this course, we focus on mechanisms that intend to make crowds smarter.

Structure of the Course

- Introductory lectures (5 lectures)
  - This one, information theory and Kelly criterion, and game theory
- Research Papers
  - Incentivizing experts
  - Peer prediction
  - Prediction markets
  - Online learning
  - Analysis of existing collective intelligence systems
Enrollment & Prerequisites

- Enrollment is limited to about 20 students. Complete Survey at end of class!
- Prerequisites
  - Math background is important! At least a basic course in linear algebra (such as M 21b, AM 21b, or equivalent)
  - A course on probabilities and statistics (STAT 110 or equivalent)
  - An algorithm course (CS 124, or equivalent)
  - Familiarity with the concept of rationality. An AI course or an economics/game theory course.

Advanced course in algorithms, microeconomics, game theory, or linear programming are helpful but not required.

Grading

<table>
<thead>
<tr>
<th>Component</th>
<th>Weight</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem sets</td>
<td>25%</td>
<td>2-3 homework problem sets</td>
</tr>
<tr>
<td>Participation</td>
<td>25%</td>
<td>Reading papers, submitting short summaries and questions before class, and participation in class discussion. (Note: Absent students rarely contribute to discussions.)</td>
</tr>
<tr>
<td>Presentation of one or two research papers</td>
<td>15%</td>
<td>A short survey and critique of the papers. Lead class discussion.</td>
</tr>
<tr>
<td>Project</td>
<td>35%</td>
<td>Project proposal, class presentation, and final report.</td>
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</tbody>
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Project

• **Goal:** develop a deep understanding of a specific research area and to the extend possible to work on an open research problem.
• Can be theoretical, computational, experimental, or empirical.
• Can write an exposition paper, but needs novelty!
• A list of high-level project topics will be provided. **You are encouraged to propose your own topic for approval!**
• Tentative project due dates:
  – Wednesday 11/3: project proposal due
  – Monday 12/6: brief project presentation
  – Friday 12/10: project report due

Logistics

• **TF**
  – Alice Gao

• **Office Hours**
  – Yiling: Monday 2:30 – 3:30, MD 339
  – Later will add office hours likely on Thursdays to meet with students in advance of presenting papers
  – Today, 2:30 – 3:30
  – Alice: Tue 2:30-4, MD 242

Missed course materials from the TF
Information, Prediction, and Collective Intelligence

• Motivating examples
  – Disease surveillance
  – Business forecasting
  – Multi-agent systems
  – Almost any decision making under uncertainty
  – Netflix Prize
  – DARPA Red Balloon Challenge

Examples of Course Topics

• Incentivizing experts
• Peer prediction
• Prediction Markets
• Online learning

Incentivize Experts

• Suppose I’d like to get information about tomorrow’s weather (sunny or rainy?)
• How can I ensure that an expert will tell me his/her true probability assessment of the event?

What If We Won’t Know the Outcome?

• Eg. Conditional events, subjective information
• Surveys
  – Eg. How many hours per week you spent on assignments?
    • Less than 5 hours
    • 5-10 hours
    • 10-20 hours
    • Above 20 hours

Peer Prediction and Bayesian Truth Serum
Combining information is hard!

• If we have multiple experts, how can we combine their information?
• Some impossibility results on combining probability distributions.
  – T(f1, f2, f3, ..., fn)
  – External Bayesianity
  – Independent of irrelevant alternatives
  => dictatorship

Bet = Credible Opinion

• Q: Will Obama win the Presidential election?

• Betting intermediaries
  – Las Vegas, Wall Street, Betfair, Intrade,...
Prediction Markets

• A prediction market is a futures market (betting intermediary) that is designed for information aggregation and prediction.
• Payoffs of the traded item is associated with outcomes of future events.

$\text{f}(x)$

Example: Iowa Electronic Market
A Combinatorial Betting Example

• $2^{51}$ outcomes, $2^{2^{51}}$ combinations
• Allow participants to bet on logical formulas
  – Create contracts on the fly:
    $1$ if Ohio AND Florida OR New York, $0$ otherwise
  – Specify buy price and quantity
• Computationally hard!
Learning from Expert Advice

• The algorithm maintains weights over $N$ experts

Slide Source: J.W. Vaughan

Learning from Expert Advice

• The algorithm maintains weights over $N$ experts

• At each time step $t$, the algorithm…
  • Observes the instantaneous loss $l_{i,t}$ of each expert $i$

Slide Source: J.W. Vaughan
Learning from Expert Advice

- The algorithm maintains weights over $N$ experts

\[ l_{i,t} = 0 \quad w_{1,t} \quad l_{2,t} = 1 \quad \ldots \quad l_{N,t} = 0.5 \quad w_{N,t} \]

- At each time step $t$, the algorithm…
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  - Receives its own instantaneous loss $l_{A,t} = \sum_i w_{i,t} l_{i,t}$

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  • Observes the instantaneous loss $l_{i,t}$ of each expert $i$
  • Receives its own instantaneous loss $l_{A,t} = \sum_i w_{i,t} l_{i,t}$
  • Selects new weights $w_{i,t+1}$

Slide Source: J.W. Vaughan
Learning from Expert Advice

- **Classic result:** There exist algorithms such that on any (bounded) sequence of losses,

  \[
  \text{algorithm's cumulative loss} - \text{loss of the best performing expert} < O\left(\frac{T}{\log N}\right)^{1/2}
  \]

- Holds even in a **fully adversarial** setting with **no statistical assumptions** about the sequence of losses

Slide Source: J.W. Vaughan
Learning from Expert Advice

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\[
\text{algorithm’s cumulative loss} - \text{loss of the best performing expert} < O((T \log N)^{1/2})
\]

• Holds even in a fully adversarial setting with no statistical assumptions about the sequence of losses

Algorithm is said to have “no regret” since the average regret per trial approaches 0 as \( T \) grows

Slide Source: J.W. Vaughan
For Wed. 9/8

• Submit comments on Chapter 2 (2.1 – 2.8) of Elements of Information Theory
• Reading is posted on the class schedule.
• Check course website later this week on how to submit your comments
• What is unclear? What would you like to hear about in class? What did you enjoy?

• Please hand in the survey now.