

# ORIE 6180 - Online Decision-Making and Markets

---

August 26, 2021

Semester: Fall 2021

## Essential Course Information

- *Instructor*

Sid Banerjee, 229 Rhodes Hall

[sbanerjee@cornell.edu](mailto:sbanerjee@cornell.edu)

- *Lectures*

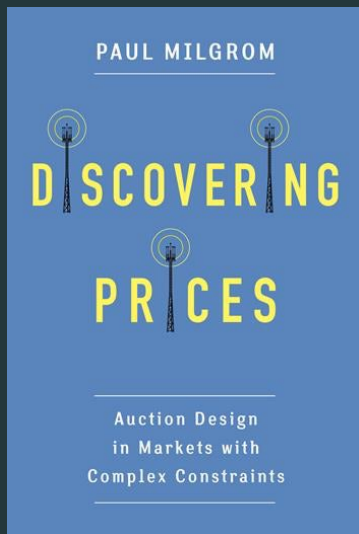
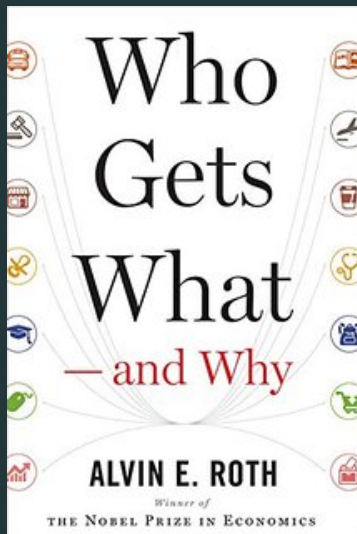
TR 9:40-10:55pm, Phillips 307

- *Website*

<http://people.orie.cornell.edu/sbanerjee/ORIE6180F21/orie6180f21.html>

# What is this course about?

online decision-making and markets



# What is this course about?

online decision-making, markets and optimization



## overture: bipartite matching

**setting:** graph  $G(V_L, V_R, E)$ , edge-weights  $w_{ij} \forall (i, j) \in E$

**aim:** pick maximum weight matching

$$\begin{aligned} - \text{OPT} &= \max \sum_{(i,j) \in E} x_{ij} w_{ij} \\ &\text{subject to} \\ &\sum_j x_{ij} = 1 \forall i \in V_L, \sum_i x_{ij} = 1 \forall i \in V_R, x_{ij} \in \{0, 1\} \end{aligned}$$

## overture: bipartite matching

**setting:** graph  $G(V_L, V_R, E)$ , edge-weights  $w_{ij} \forall (i, j) \in E$

**aim:** pick maximum weight matching

- $OPT = \max \sum_{(i,j) \in E} x_{ij} w_{ij}$   
subject to  
 $\sum_j x_{ij} = 1 \forall i \in V_L, \sum_i x_{ij} = 1 \forall i \in V_R, x_{ij} \in \{0, 1\}$
- LP relaxation gives  $OPT$  matching

## overture: bipartite matching

**setting:** graph  $G(V_L, V_R, E)$ , edge-weights  $w_{ij} \forall (i, j) \in E$

**aim:** pick maximum weight matching

- $OPT = \max \sum_{(i,j) \in E} x_{ij} w_{ij}$   
subject to  
 $\sum_j x_{ij} = 1 \forall i \in V_L, \sum_i x_{ij} = 1 \forall i \in V_R, x_{ij} \in \{0, 1\}$
- LP relaxation gives  $OPT$  matching
- greedy matching gives  $\geq OPT/2$

## overture: bipartite matching

now suppose  $V_L \equiv$  'buyers',  $V_R \equiv$  'items'; some variants we will look at:

- $V_L$  arrives dynamically, known distribution over weights  $w_{ij}$   
(MDPs, online stochastic packing)



## overture: bipartite matching

now suppose  $V_L \equiv$  'buyers',  $V_R \equiv$  'items'; some variants we will look at:

- $V_L$  arrives dynamically, known distribution over weights  $w_{ij}$   
(MDPs, online stochastic packing)
- $V_L$  arrives dynamically, unknown distribution over weights  $w_{ij}$   
(bandit problems)
- $V_L$  arrives online in arbitrary manner  
(online algorithms, competitive analysis)

## overture: bipartite matching

now suppose  $V_L \equiv$  'buyers',  $V_R \equiv$  'items'; some variants we will look at:

- $V_L$  arrives dynamically, known distribution over weights  $w_{ij}$   
(MDPs, online stochastic packing)
- $V_L$  arrives dynamically, unknown distribution over weights  $w_{ij}$   
(bandit problems)
- $V_L$  arrives online in arbitrary manner  
(online algorithms, competitive analysis)
- $V_R$  have posted prices,  $V_L$  choose favorite option  
(Walrasian prices, prophet inequalities, large-market models)
- $V_L$  are strategic buyers with private info about  $w_{ij}$   
(mechanism design)

# Course Aims

**learn** models, paradigms and tools

**explore** applications in complex systems, online marketplaces

**find** open questions, research problems

## (tentative) list of topics

from online decision-making and markets to optimization

- **Markov decision processes**: value function, HJB, LP formulations
- **non-Bayesian decision-making**: zero-sum games and minimax theorem, Yao's lemma, Blackwell approachability
- **mechanism design**: IC & IR constraints, revelation principle

## (tentative) list of topics

### from online decision-making and markets to optimization

- **Markov decision processes**: value function, HJB, LP formulations
- **non-Bayesian decision-making**: zero-sum games and minimax theorem, Yao's lemma, Blackwell approachability
- **mechanism design**: IC & IR constraints, revelation principle

### Bayesian online decision-making (MDPs)

- **exact solutions**: threshold policies, index policies
- **approximation techniques**: LP and information relaxations, coupling
- **'stochastic' bandits**: algorithms and lower bounds

## (tentative) list of topics

### from online decision-making and markets to optimization

- **Markov decision processes**: value function, HJB, LP formulations
- **non-Bayesian decision-making**: zero-sum games and minimax theorem, Yao's lemma, Blackwell approachability
- **mechanism design**: IC & IR constraints, revelation principle

### Bayesian online decision-making (MDPs)

- **exact solutions**: threshold policies, index policies
- **approximation techniques**: LP and information relaxations, coupling
- **'stochastic' bandits**: algorithms and lower bounds

### non-Bayesian online decision-making

- **no-regret learning**: multiplicative weights and FTPL, blackbox reductions
- **online algorithms**: LP approaches for competitive analysis
- **reinforcement learning**: regret bounds via optimistic algorithms

## (tentative) list of topics (contnd)

### mechanism design and markets

- **basics of mechanism design**: Myerson's lemma, impossibility theorems (bilateral trade, public goods)
- **mechanisms for complex settings**: VCG, correlated valuations
- **approximate mechanism design**

## course methods

lectures, assignments, scribing, and a project



## course methods

lectures, assignments, scribing, and a project

### caveat emptor

- large scope and number of topics:  
focus on simpler settings, intuition  
suggested reading for details, additional topics
- requires active participation  
some reading for before/after class  
scribing for lectures as well as exercise solutions

## course methods

lectures, assignments, scribing, and a project

### caveat emptor

- large scope and number of topics:  
focus on simpler settings, intuition  
suggested reading for details, additional topics
- requires active participation  
some reading for before/after class  
scribing for lectures as well as exercise solutions

prerequisites:

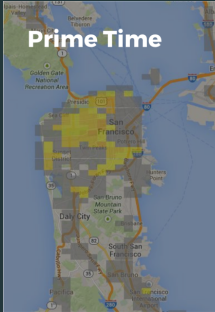
probability and stochastic processes (in particular, Markov chains, basic measure concentration): at the level of ORIE 6500

optimization: at the level of ORIE 6300

algorithms: ideally CS 6820 (at least CS 4820)

game theory, online learning: useful, but not required

# some of my favorite markets



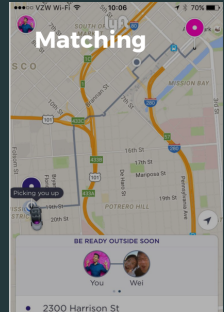
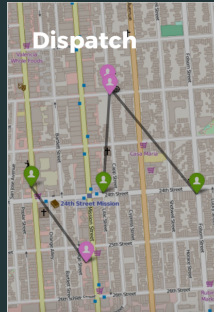
**Supply Levers**

**Easier. More Money. The Power Driver Bonus Upgrade.**

You know the Power Driver Bonus as a reliable way to earn almost all of your commission back each week - and now it's even better. With this upgrade, you can earn even more with greater flexibility. The new PDB features five extra bonuses and three additional tiers, starting with a new 30-ride benchmark.

DRIVE	GET
<b>new</b> 30 Total Rides <small>all new eligible rides</small>	<b>\$50 Bonus</b>
<b>new</b> 50 Total Rides <small>all new eligible rides</small>	<b>\$100 Bonus</b>
<b>new</b> 80 Total Rides <small>all new eligible rides</small>	<b>10% Back + \$150 Bonus</b>
<b>new</b> 100 Total Rides <small>all new eligible rides</small>	<b>20% Back + \$150 Bonus</b>
<b>new</b> 120 Total Rides <small>all new eligible rides</small>	<b>20% Back + \$200 Bonus</b>

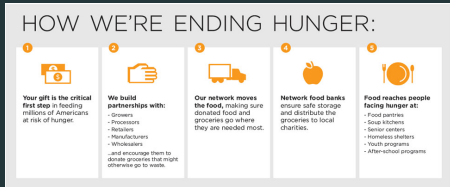
Plus, we added 19 more eligible peak hours that count toward your bonus.



<http://www.lyft.com/>

(SP'16 project) pricing and optimization in shared-vehicle systems

# some of my favorite markets



<http://www.feedingamerica.org/>

(SP'16 project) non-monetary mechanisms via artificial currencies