# Mechanism Design for Social Good

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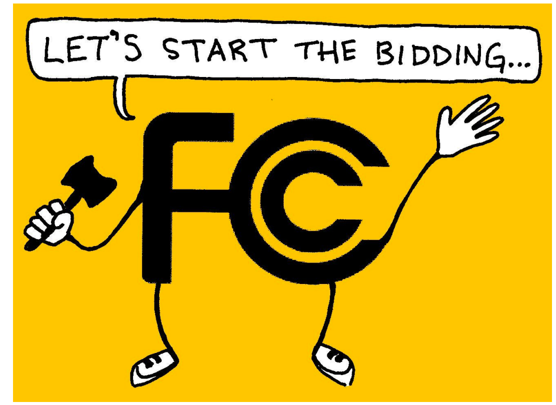
WINE TUTORIAL 2017, BANGALORE, INDIA

# Our Primary Applications

Google AdWords

bing Ads

facebook Ads

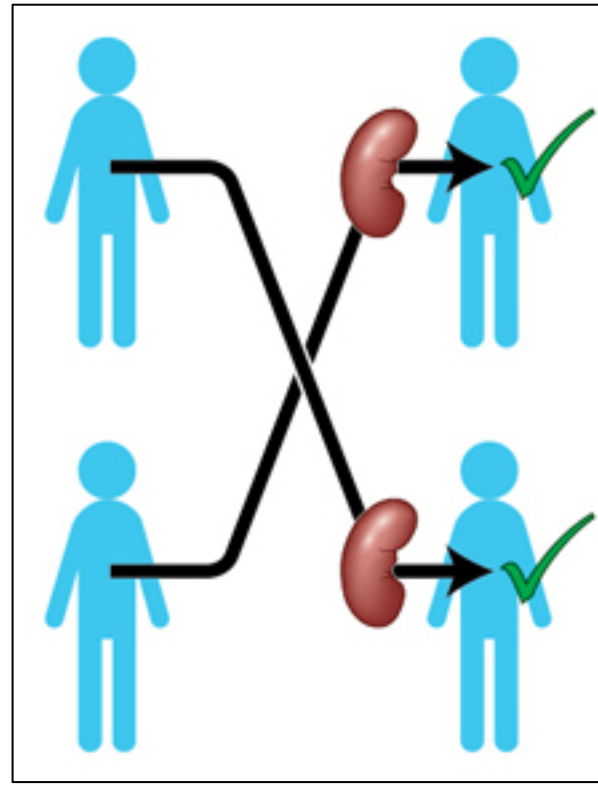



ebay™ AUCTION

# Social Good Applications

NATIONAL SchoolChoice WEEK
JANUARY 21-27, 2018

THE MATCH®
NATIONAL RESIDENT MATCHING PROGRAM®



# This Talk

Why there's so much to do here!

I. **Healthcare and Health Insurance:**
   - 3 problems, what's known in our community for solving them, and what's open

II. **Online Labor Markets and Matching Platforms:**
   - The big mechanism design question, plus other open areas

III. **Other domains:**
   - Refugee resettlement, housing, education, fairness

# Healthcare and Health Insurance

# US Health Insurance: 347 million

Employer-sponsored insurance (51%)

Government programs (40.6%)

- **Medicare** (14.7%) – elderly and disabled
  - Traditional Medicare (goverment run)
  - Medicare Advantage (private insurers)
- **Medicaid** (17.9%) – poorer people
  - Traditional Medicaid (government run)
  - Medicaid Managed Care (private insurers)
- **ACA Exchanges** (3.7%) – private insurers, govt subsidized
- **Military health insurance** (4.3%)

Uninsured (8.4%)

**Motivation:**
Competition is good

Figures from 2015

# US Health Insurance is a mess

Expensive:

- In 2015, $3.2 trillion, $9,990 per person

Many remain uninsured:

- 29 million (8.4%) despite the ACA

High variance in care quality:

- You don’t know what you’ll get or what it will cost

Patient insurance experience:

- Unexpected bills, rejected claims

Typical problems: adverse selection, moral hazard, imperfect competition, market power.

Additional caveat: Health care is considered a right.

# The Healthcare Setting

**Players:** Payers, insurers, health providers, patients

**Objectives:**

- Payer: Health of patients, low cost, choice, efficiency of market
- Insurer: Profit
- Health providers: Altruistic? Profit?
- Patients: Maximize health, minimize cost, limit risk

# What is “socially optimal”?

- Each patient is served by insurance company that maximizes his utility (value for plan – price of plan) and has choice.
- Each patient is served by the plan that can treat him in the most cost-effective way.
- Patients are only getting care they would pay for if they were spending their own money (and didn’t have a budget).
- Insurers are not engaging in “bad” risk selection.
- The government doesn’t need to inject too much money into the system.

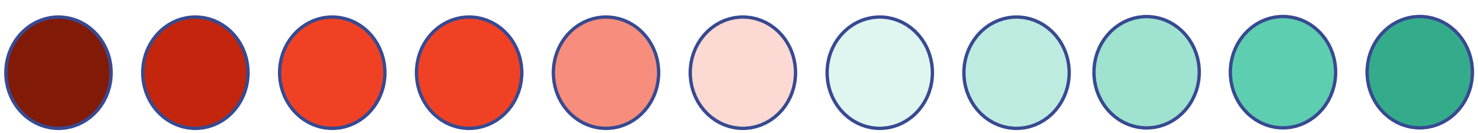
# Problem #1: Adverse Selection

High quality insurance
(expensive)

Medium quality insurance
(cheap)

Sickest

Healthiest



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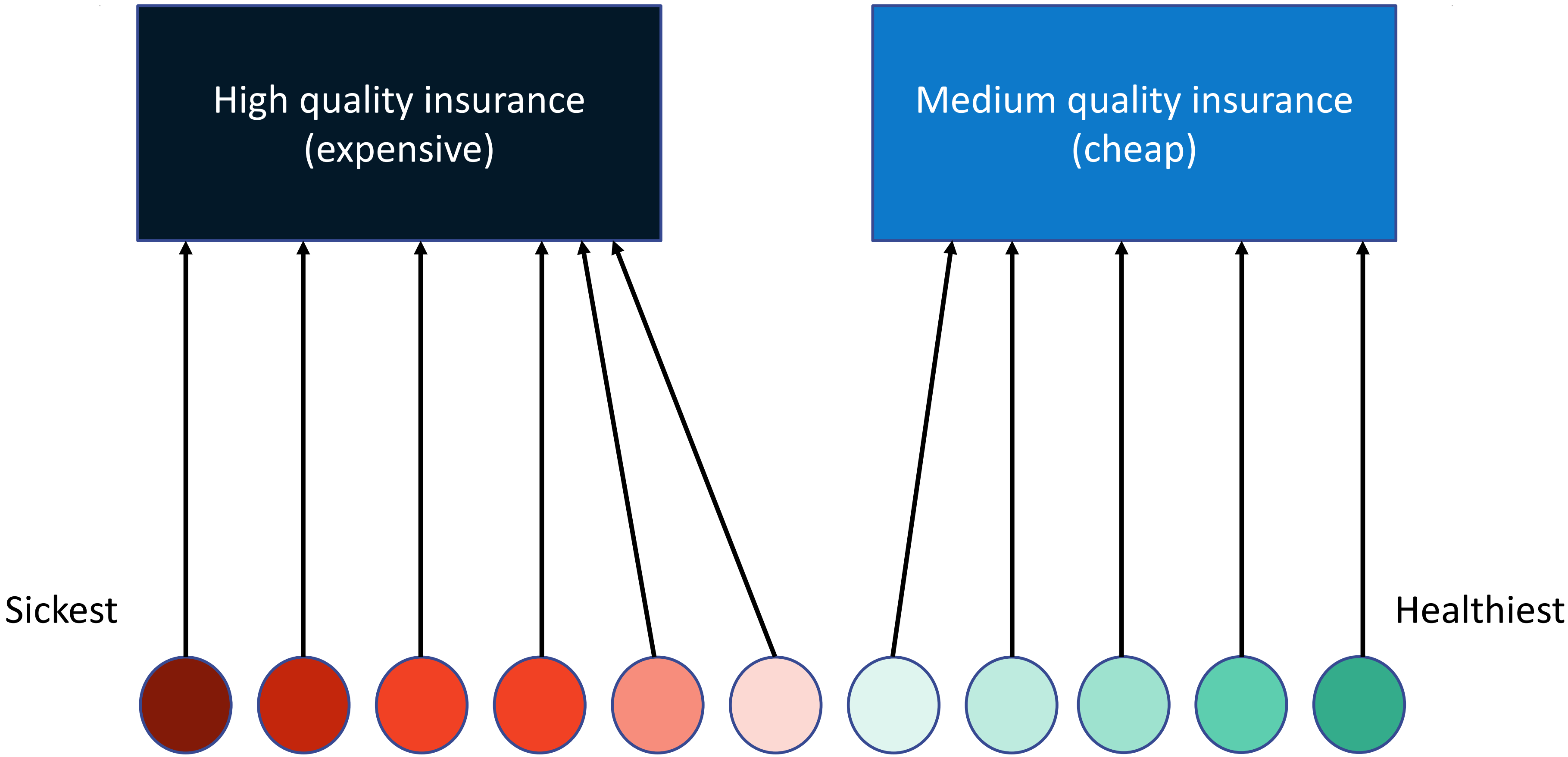

# Problem #1: Adverse Selection

Low quality insurance
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Medium quality insurance
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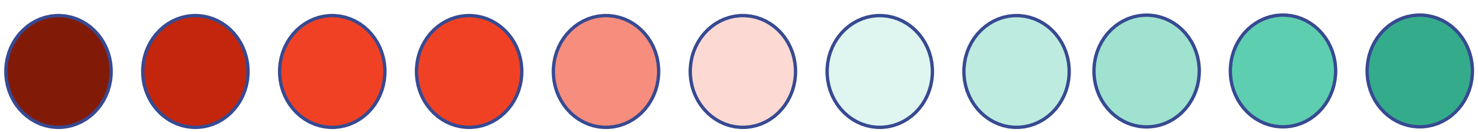
Healthiest



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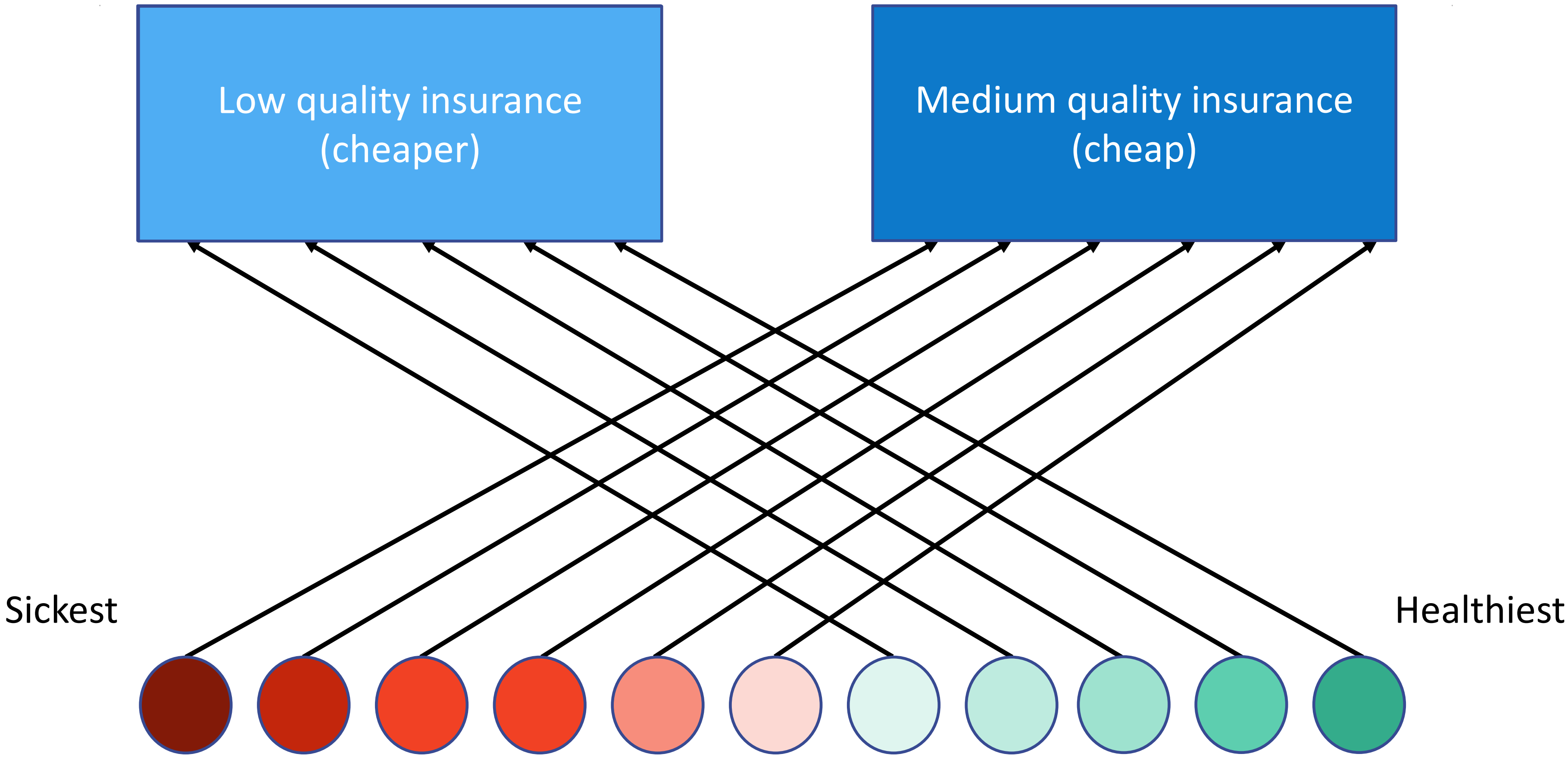

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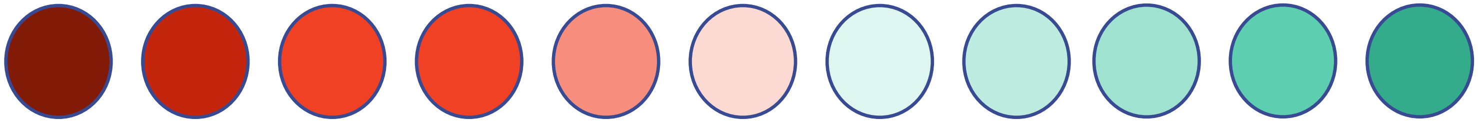
Low quality insurance (cheaper)

Lowest quality insurance (cheapest)

Sickest

Healthiest



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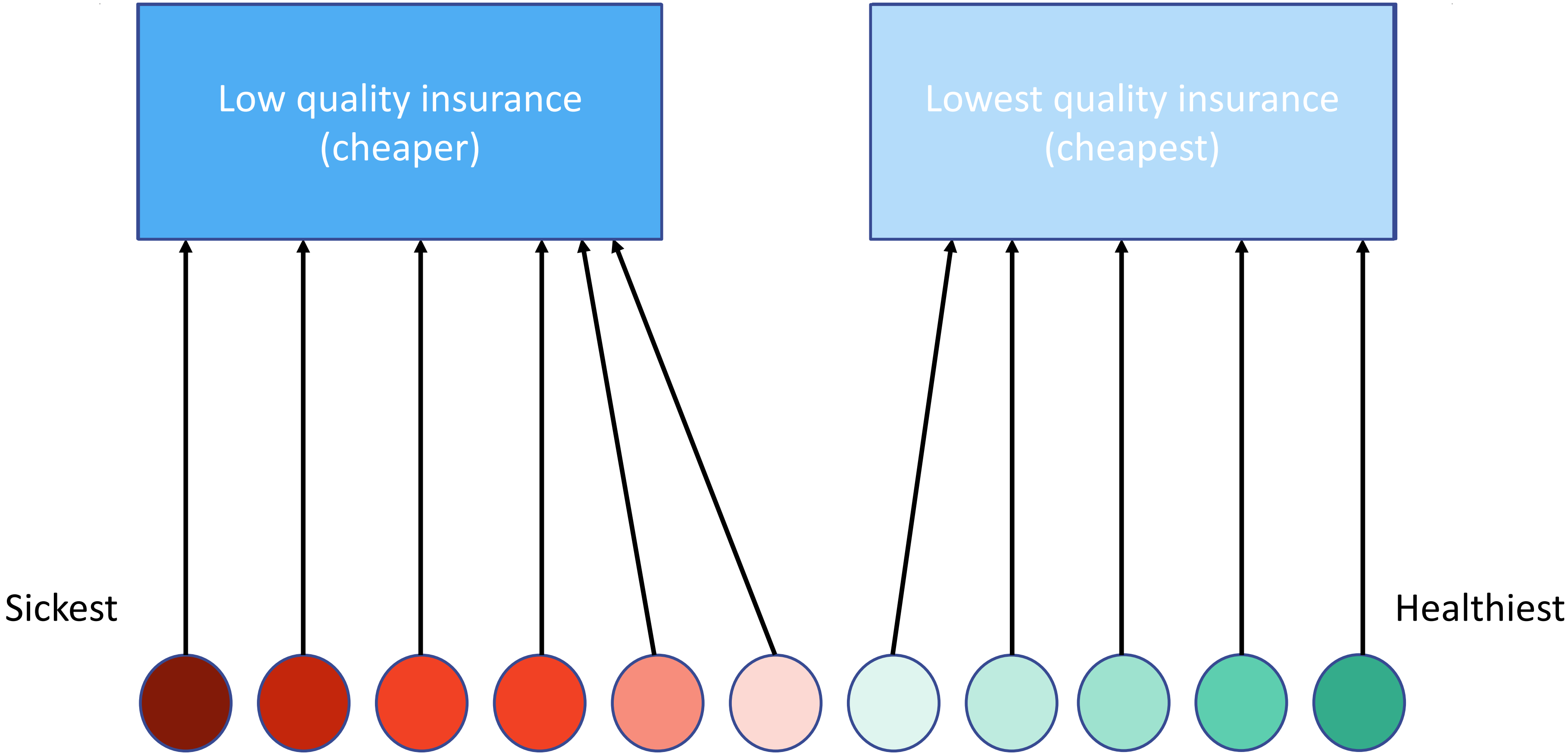
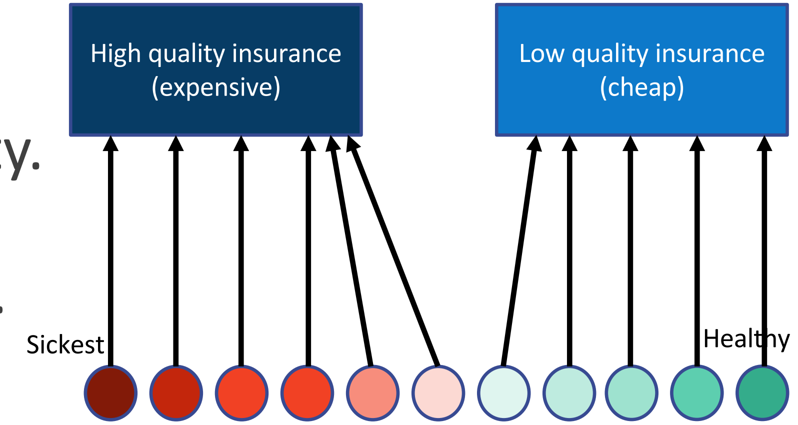


# Problem #1: Adverse Selection

[Akerlof 1970: Market for Lemons]

- Sicker patients choose high quality.
- High quality is not profitable.
- This creates a race to the bottom.



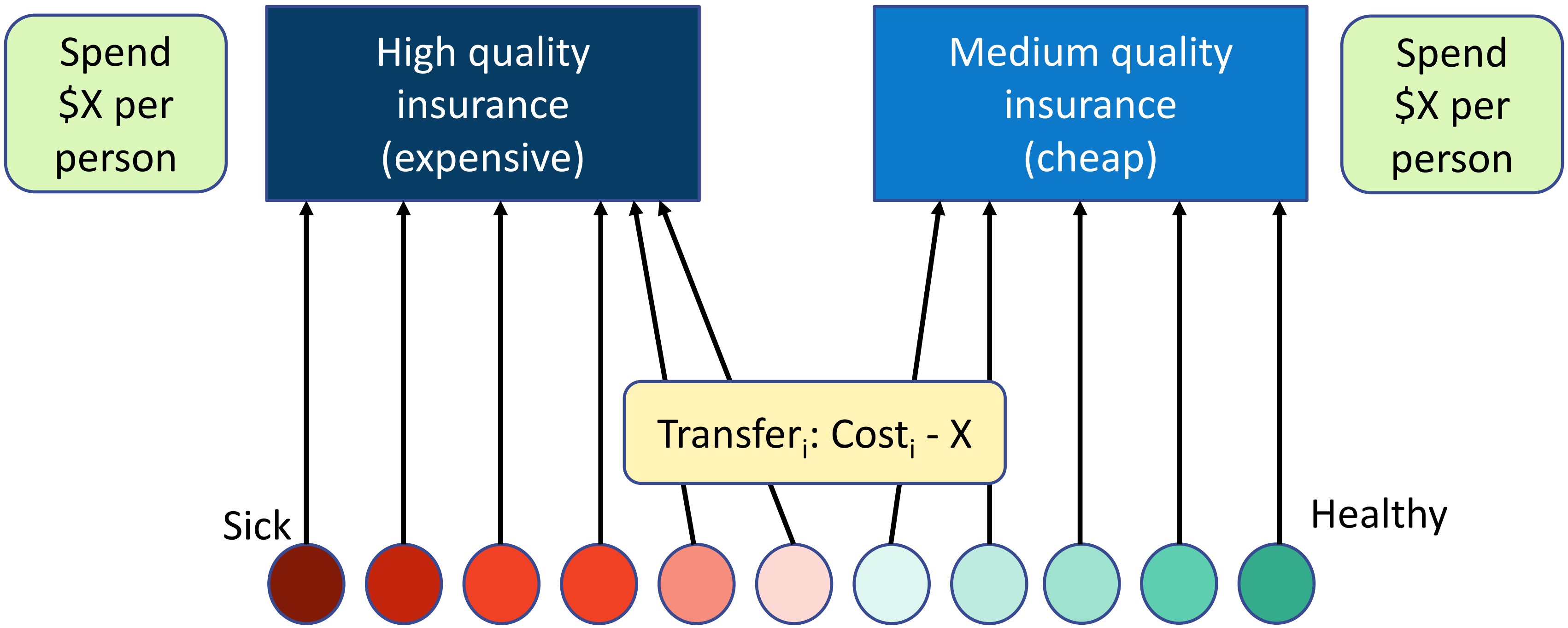

Classically, this is based on the **asymmetry of information**— buyers know their risk but **insurers don't**.

Currently, **insurers/payers actually have lots of information** about the patients, but they're not allowed to price discriminate against the sick.

How can we use this **information**?

# Solution #1: Reimbursement

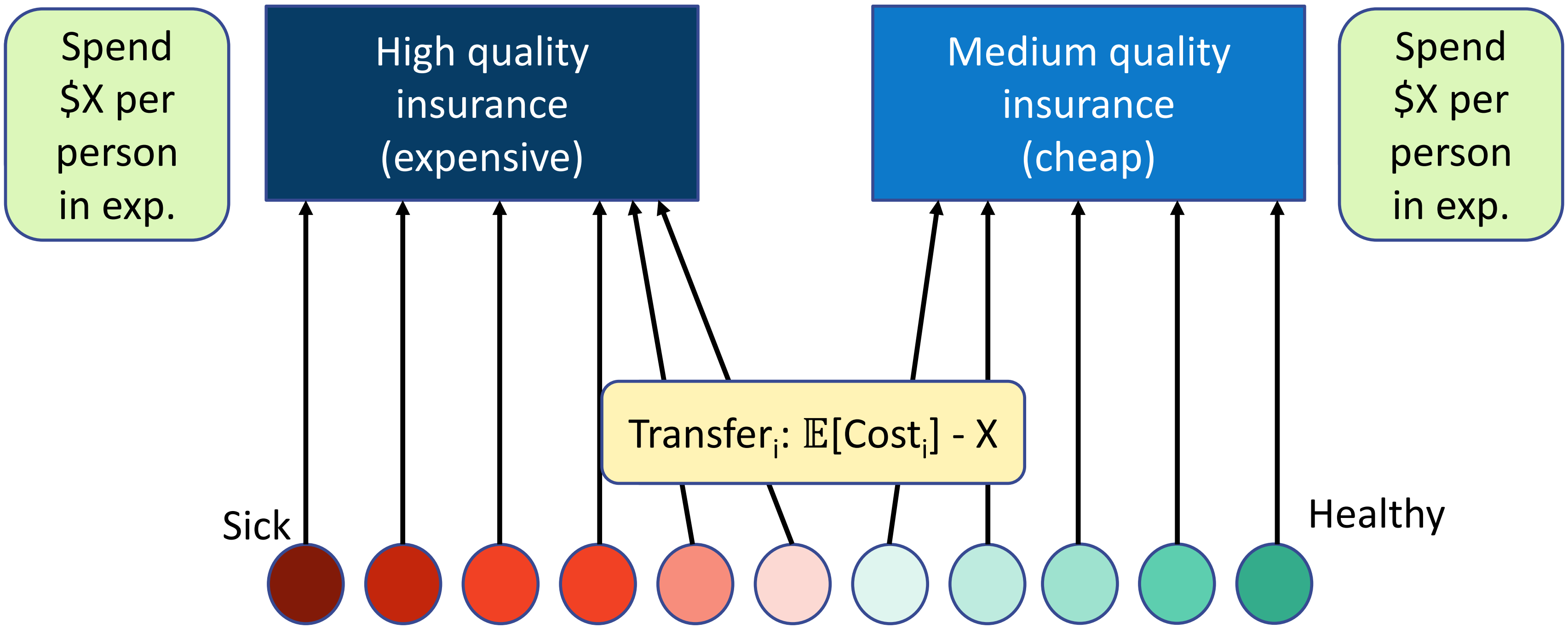
Idea: **Reimburse** anything past \$X so that all have **equal risk**.




Problem #1b: **Moral hazard**. No incentive to keep costs down.

# Solution #1b: Risk adjustment

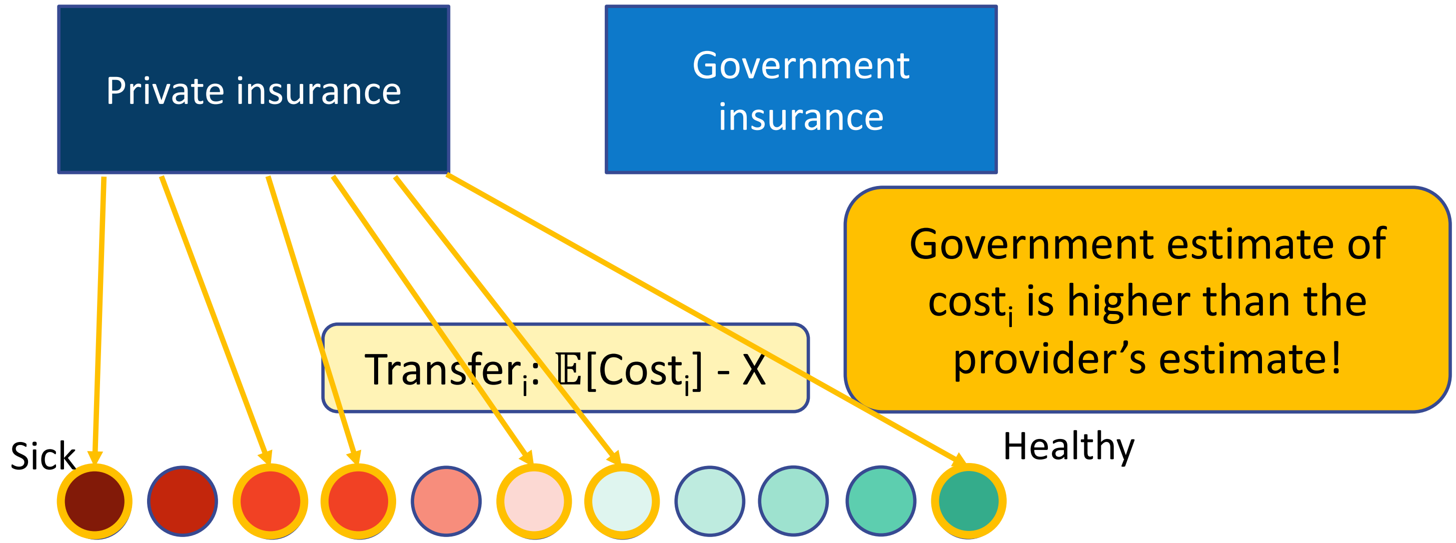
Problem #1b: **Moral hazard**. No incentive to keep costs down.




Idea: Reimburse **up front** a person's **expected costs** past $X.

# Problem #1c: Cream-skimming

Idea: Reimburse **up front** a person's **expected costs** past $X.




Problem: Government estimate ≠ insurance estimate

Insurance providers **target poorly estimated** patients to skim off the extra profits.

# Strategic Capitation Model

There are n patient types, where type i's expected health costs are drawn from $F^P_i$ when treated by provider P.

Datasets:

- **Public data**: samples from $F^G_i$ where G is the government
- **Holdout data** (government only): extra samples from $F^G_i$
- **Private data** (private provider only): extra samples from $F^G_i$ and samples from $F^P_i$ where P is private provider

**Government:** Decides what subsidies to offer to insurers who cover patients of type i (for each type i), minimizes treatment cost (maximizes efficiency)
**Private insurers:** Decide who to target, maximize profit

[Braverman Chassang 16]

# Strategic Capitation

Datasets:

- **Public data**: $F^G_i$
- **Holdout data** (only G knows): $F^G_i$
- **Private data** (only P knows): $F^G_i$ and $F^P_i$

**Government:** Decides on subsidies to offer for each type i, minimizes treatment cost (maximizes efficiency)
**Private insurers:** Decide who to target, maximize profit

Naïve Proposal: G sets $\text{subsidy}_i$ as $\mathbb{E}_{\text{public, holdout}}[\text{cost}^G_i]$

Cream-skimming example:

$\mathbb{E}_{\text{public, holdout}}[\text{cost}^G_i] = \$700$

$\mathbb{E}_{\text{public, private}}[\text{cost}^P_i] = \$650$ and $\mathbb{E}_{\text{public, private}}[\text{cost}^G_i] = \$600$

Private provider targets i even though G is efficient.

[Braverman Chassang 16]

# Strategic Capitation

**Illegitimate selection:** cream-skimming—getting profits even when not efficient because of poor estimation
**Legitimate selection:** $\mathbb{E}[\text{cost}^P{}_i] < \mathbb{E}[\text{cost}^G{}_i]$ because e.g. P is good at treating patients with diabetes.

How to incentivize legitimate but not illegitimate selection?

**Solution:** Promise to reimburse $\mathbb{E}_{\text{holdout}}[\text{cost}^G{}_i]$ but don't reveal what this is until after.

**Key idea:** Private insurers are incentivized to use all of their samples to estimate the subsidy and choose efficiently.

[Braverman Chassang 16]

# Strategic Capitation

How to incentivize legitimate but not illegitimate selection?

**Solution:** Promise to reimburse $\mathbb{E}_{holdout}[cost^G_i]$ but don't reveal what this is until after.

**Key idea:** Private insurers are incentivized to use all of their samples to estimate the subsidy and choose efficiently.

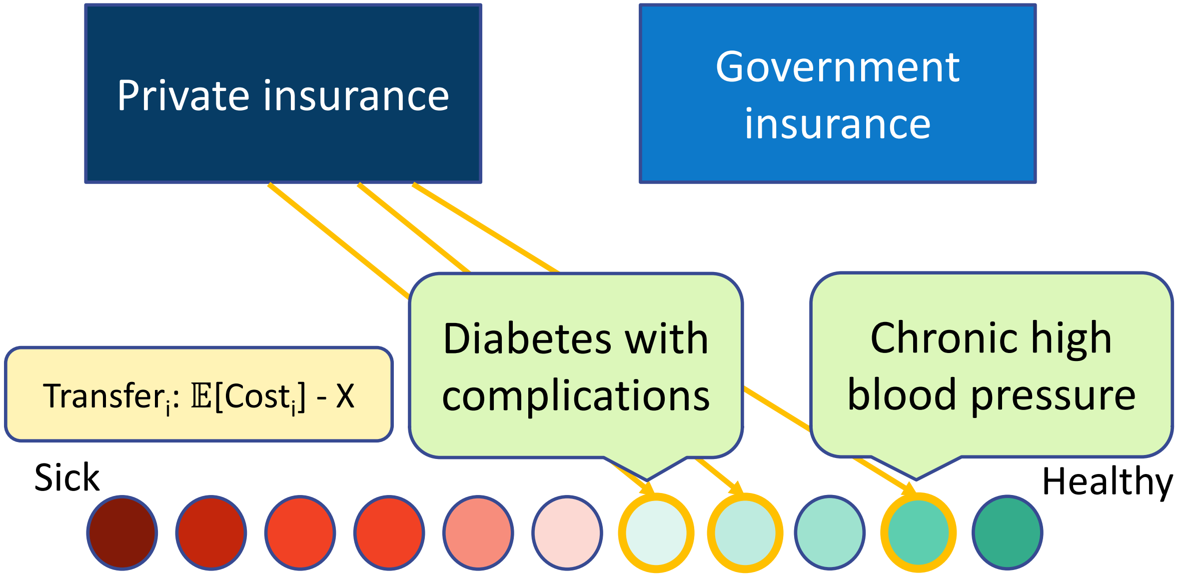
How do we know the government isn't lying about holdout?

**Solution:** Use an unbiased estimator, and penalize if it's too far from the samples in public.

[Braverman Chassang 16]

# Problem #1d: Upcoding

Type i isn't actually observable, but based on medical records
E.g. type i is diabetes, or high blood pressure.




Target **healthy patients with risky labels** to receive higher subsidies.

# Problem #1d: Upcoding

**Upcoding:** Labeling patients as sicker than they are.

Medical diagnoses aren't always objective.

If they upcode, **insurers get higher subsidies than they should**, because the risk adjustment function was trained on non-manipulated data.

As a result:

- Insurers may pressure doctors to upcode their patients.
- They may offer a discounted price to patients for certain kinds of visits that are likely to code them.

# Strategic Classification Model

- The government will classify patients as either "high risk" (and give subsidy) or "low risk".
- Each patient has a point x in a metric space (e.g. diagnoses), has a true risk classification h, and is attached to an insurer who wants the subsidy.

Game:

- The government announces risk adjustment function f.
- Point x can pay d(x,s(x)) to appear as s(x) and get classified as f(s(x)).
- Point x gets payoff 1 if f(s(x)) = "high risk", minus cost of manipulation d(x,s(x)).
- Government gets payoff $\mathbb{E}$[f(s(x)) = h(x)].

**[Hardt Megiddo Papadimitriou Wootters 16]**

# Strategic Classification Results

What is the optimal classifier f to maximize

$$\mathbb{E}[f(s(x)) = h(x)]?$$

For simple cost functions (1D metric where it's free to move down):

- A threshold function is optimal.

The paper is actually motivated by:

- Spam classification
- Admissions based on SAT scores

**[Hardt Megiddo Papadimitriou Wootters 16]**

# Recap: Adverse Selection

Adverse selection: quality isn't profitable

→ Reimburse for riskier patients

→ Moral hazard: no incentive to keep costs down

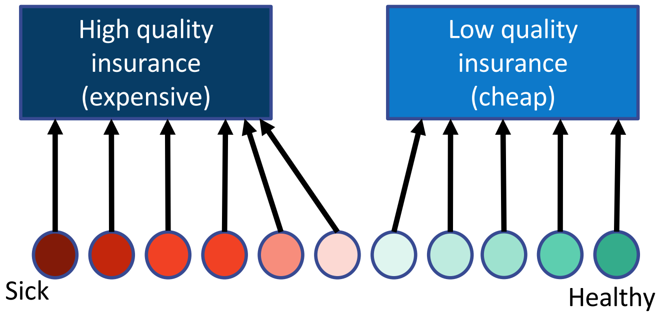
→ Risk adjustment: Reimburse expected costs up front

→ Private insurers have different data and estimates, and we need to incentive them to legitimately select

- **What's known:** Strategic capitation [BC 16]

→ Insurers may "upcode" patients, labeling them as sicker, to get higher subsidies

- **What's known:** Strategic classification [HMPW 16]



# Upcoding Open Problems

Strategic classification extensions:

- Specialize the parameters of the setting for healthcare, e.g. cost functions, priors, manipulability of features, feasible solutions
- More general metrics/classifiers
- Sample distributions should change over time
- Different benchmark: min gen. error over randomized f?
- Multi-round with updates between rounds?

ML-related problems:

- Detect upcoding
- Subjective data: throw it out? Correct for it? Balance weights with objective?
- Selection of features (accounting for manipulability)

# Cream-skimming Open Problem

**Recap:** The government announces subsidies and insurers target patients.

Many Medicaid patients do not choose an insurer.
**Idea:** Assign them to insurers in a **clever way**.

Each round, pick an unassigned patient and assign them.
Learn the government's cost for treating them.

Potential interventions:
- Charge penalty (or give bonus) if average cost for random patient is higher (or lower) than average cost for patients with same risk score.
- Provide incentives to patients to switch plans.
- Update risk score (or partition type space used for scoring).

# More Open Problems

Insurance providers do more than just cream-skim. They also dissuade sicker or under-estimated patients by dropping health providers or certain insurance services.

How can we detect/regulate/disincentivize this behavior?

Combine capitation with disincentivizing upcoding.

How can we disentangle risk adjustment from previous costs?

# Problem #2: Limited Funds

Suppose m patients all need the same procedure.

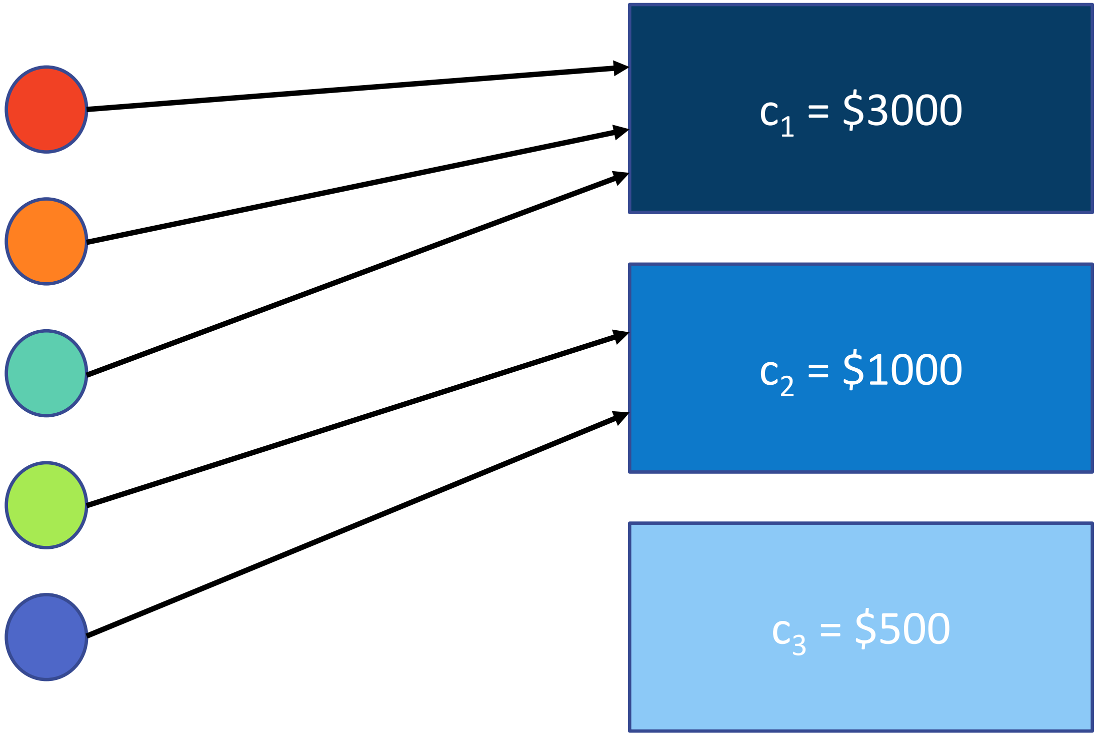
The government has promised to fully cover these procedures, but is limited to a budget B.

There are k hospitals, where hospital j has a cost $c_j$ for treatment.

Patient i gets value $v_{ij}$ for being treated at hospital j.

# Problem #2: Limited Funds

Budget = $6000.



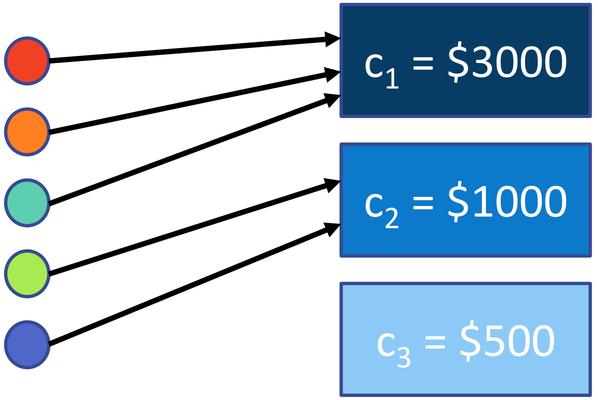

Favorite choices cost $11,000. What can we do?

# Solution: Welfare Burning

Could add copays, but sometimes this is undesirable.

Instead:
- Option 1: Just use a lottery.
- Option 2: Use wait times / waitlists / welfare burning.
  - Idea: When products are under priced, lines form.

Non-healthcare examples:
- School choice
- Subsidized housing
- Immigration



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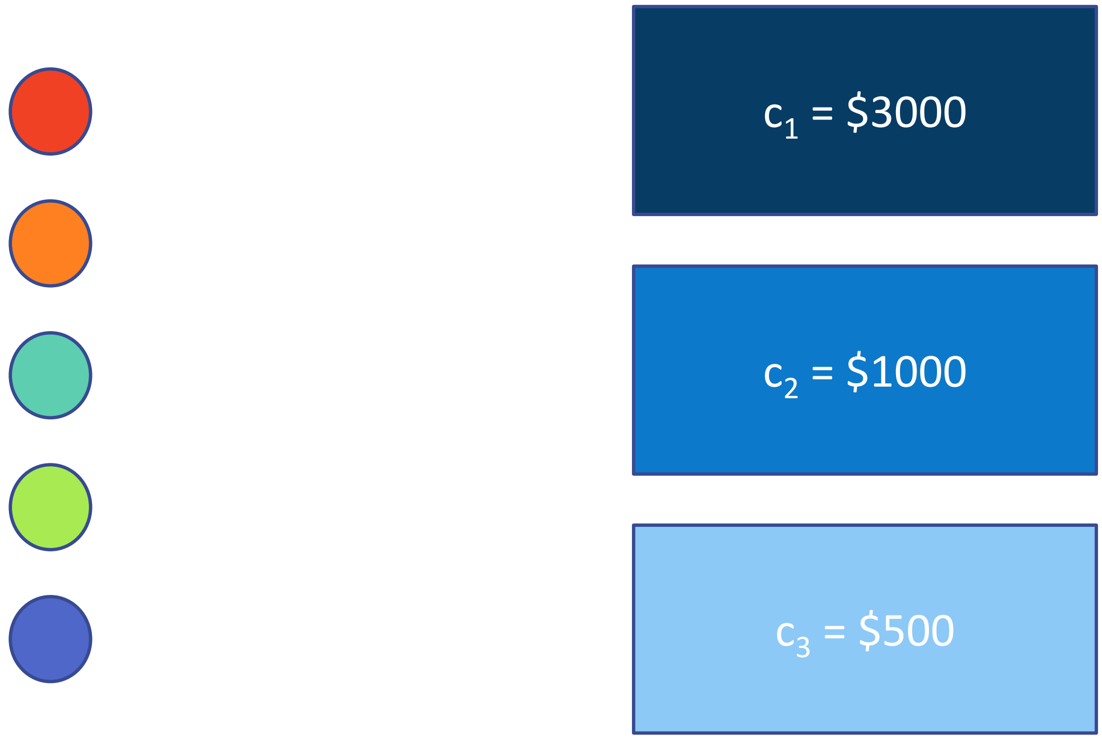

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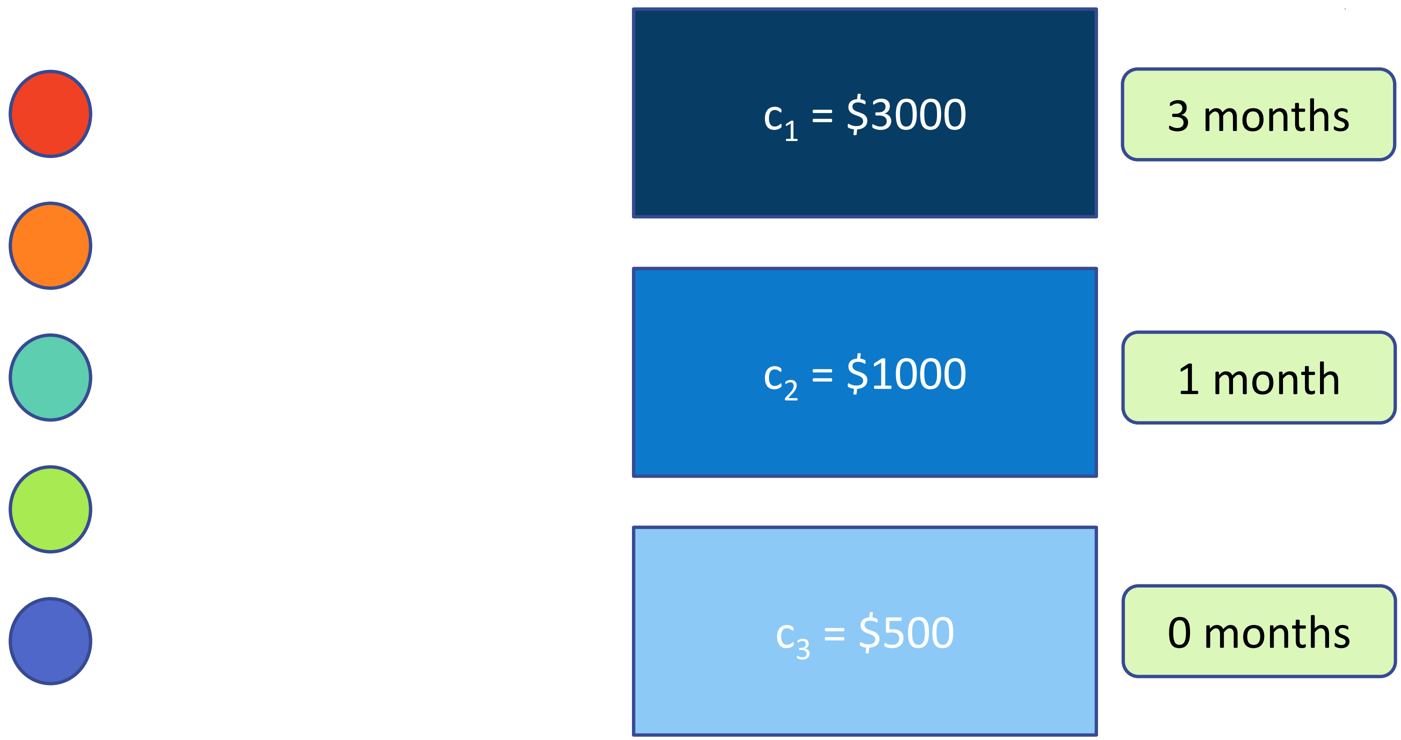

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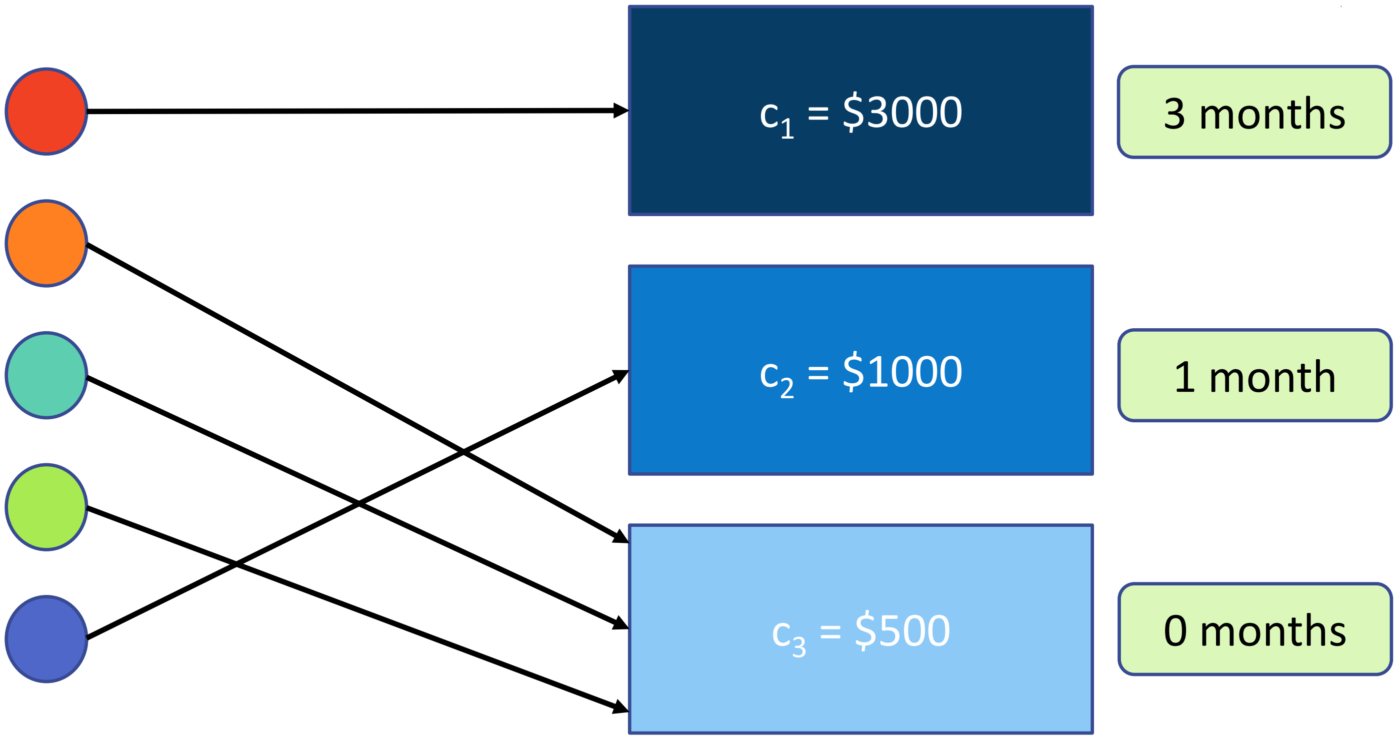



Cost = \$5500.

# Solution: Welfare Burning

maximize $\sum_i v_{i,h(i)} - w_{h(i)}$ — Utility

subject to

$v_{i,h(i)} - w_{h(i)} \geq v_{i,j} - w_j$ — IC — $\forall i, j$

$\sum_i \mathbb{1}[h(i) = j] = \lambda_j$ — Quota $\lambda_j$ for j — $\forall j$

$\sum_j \lambda_j c_j \leq B$ — Budget B

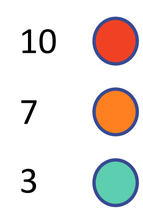
$w_j$ = waiting time for hospital j

$\lambda_j$ = quota (artificial capacity) for hospital j

$h(i)$ = allocation (assignment) of patient I

**Note:** Wait times are decided by quotas, not congestion

Budget = $6000




$c_1$ = $3000

[Braverman Chen Kannan 16]

# Solution: Welfare Burning

maximize $\sum_i v_{i,h(i)} - w_{h(i)}$ — Utility

subject to

$v_{i,h(i)} - w_{h(i)} \geq v_{i,j} - w_j$ — IC — $\forall i, j$

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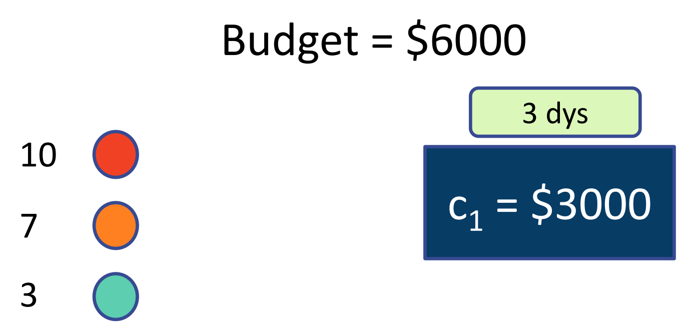


[Braverman Chen Kannan 16]

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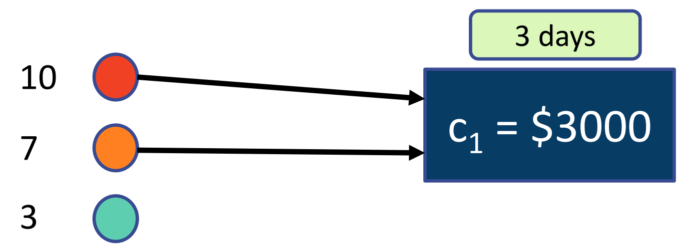



[Braverman Chen Kannan 16]

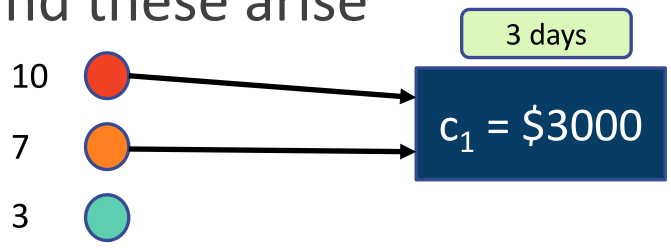
# Solution: Welfare Burning

maximize $\sum_i v_{i,h(i)} - w_{h(i)}$

subject to
$$v_{i,h(i)} - w_{h(i)} \geq v_{i,j} - w_j \quad \forall i,j$$
$$\sum_i \mathbb{1}[h(i) = j] = \lambda_j \quad \forall j$$
$$\sum_j \lambda_j c_j \leq B$$

Potential Response: It's unreasonable to dictate waiting times (or prices in a market)

However, the optimal prior-free deterministic prices given any quota vector $\vec{\lambda}$ are the VCG prices, and these arise endogenously via queue formation (think ascending auction)




[Braverman Chen Kannan 16]

# Money-Burning

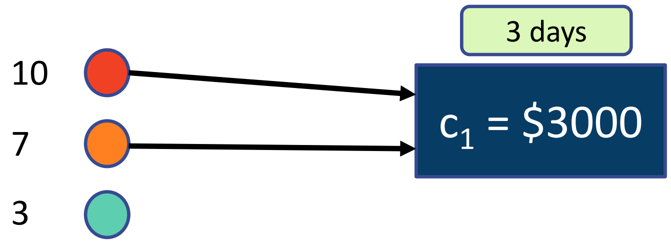
Single-parameter solved optimally **[Hartline Roughgarden 08]**

Myersonian-like theory:

- Virtual value functions: $\theta_i(v_i) = [1 - F_i(v_i)]/f_i(v_i)$
- Ironing: convexity in quantile space

Optimal utility for 1 hospital is achieved by a menu:

- wait a long time to be served with certainty
- wait a short time to be served with some probability
- don't wait

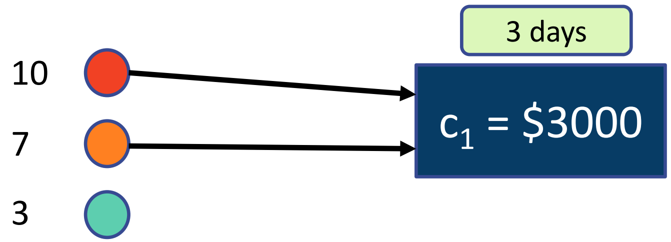


# Open Welfare-Burning Problems

- Optimal randomized mechanism given capacities
- Optimal utility given a budget
- Simple/reasonable mechanisms
- Both money (co-pays) and time with some tradeoff

Note: Patients implicitly had equal utility for wait times

- What are the alternatives?
- How can one blend time and money?
- How to incorporate other ethical preferences (e.g. priority) into such mechanisms?

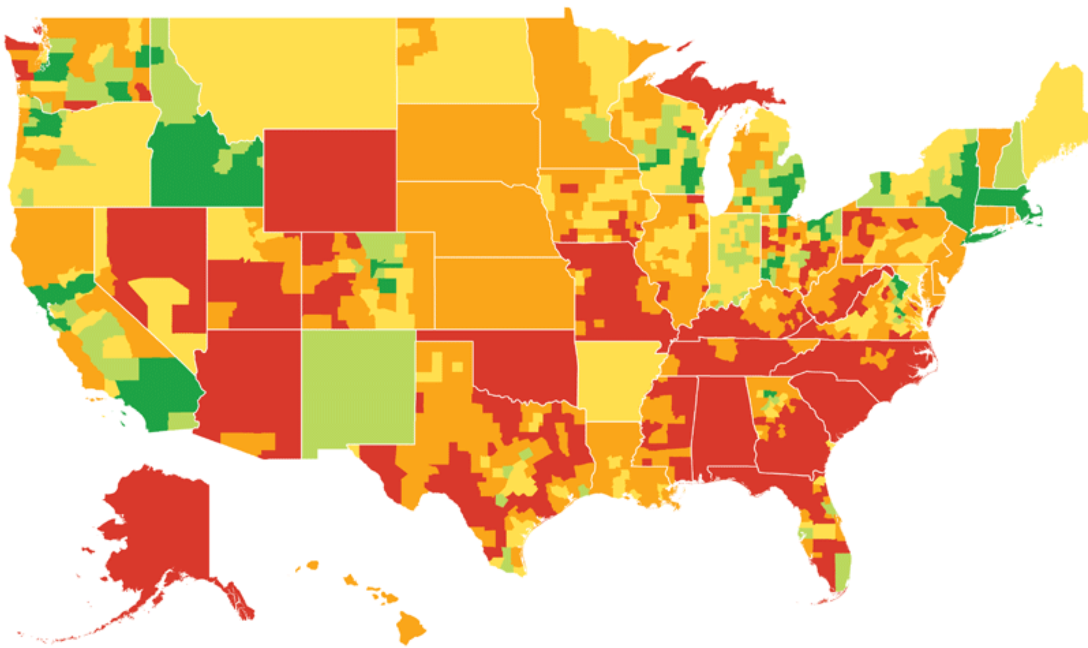


# Problem #3: Consolidation

ACA Exchanges

In 2017, consumers in nearly 70 percent of U.S. counties have only one or two insurers selling coverage on the Obamacare exchanges. Just 11 percent of counties have four or more.

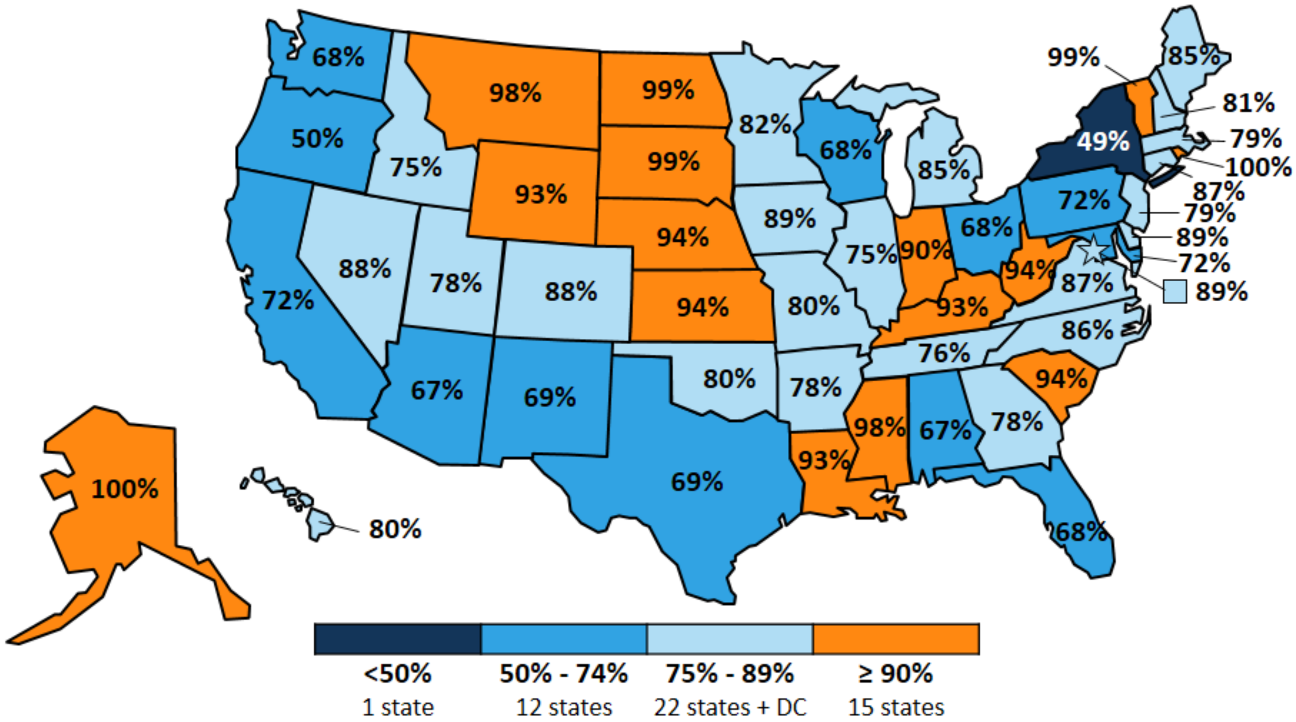
| NUMBER OF INSURERS IN COUNTY | COUNTIES | SHARE OF ALL U.S. COUNTIES |
|---|---|---|
| 1 | 1,030 | **32.8%** |
| 2 | 1,164 | **37.0%** |
| 3 | 599 | **19.1%** |
| 4 | 196 | **6.2%** |
| 5+ | 153 | **4.9%** |



# Problem #3: Consolidation

Figure 15

**Combined Market Share of the Three Firms or Affiliates with the Largest Number of Medicare Advantage Enrollees by State, 2016**




SOURCE: Authors' analysis of CMS State/County Market Penetration Files, 2016.

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# Barriers to Entry

New entrants to the insurance market must:

- Set up contracts with health providers
- Hire professionals to manage care (review claims)
- Negotiate low payment rates with health providers—very difficult for new/small insurers!

# Solution: Regulation

Can the market regulator
- limit entry
- design a procurement auction
- regulate the barriers to entry

Such that the resulting market has
- lower prices
- better welfare
- includes choice

Model from ongoing work **[Essaidi G Karlin Weinberg]**:
- For each plan j, insurer has a cost $c_j$, patient i has value $v_{ij}$, insurer submits premium $p_j$

# Other Open Problems

- Optimal MDP design: Transitions are treatments with costs, probabilistically take you to a different health state.
- How hospitals set prices: “retail” price, insurer price, government price
- Measuring quality: multi-dimensional, biased selection (sickest patients go to best doctors)
- Contract design for payment to health providers, e.g. **[Bastani Bayati Braverman Gummadi Johari 17]**
- Fee-for-service vs. pay-for-performance
- Behavioral models
- How to use auditing / second-opinions as a tool

# Healthcare experts

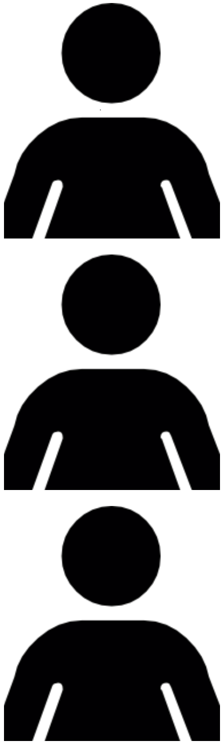
Mark Braverman,
Princeton
(theoretical CS)

Mark Shepard,
Harvard
(public policy / economics)

# Online Labor Markets

AND ONLINE MATCHING PLATFORMS

# Traditional Labor Markets

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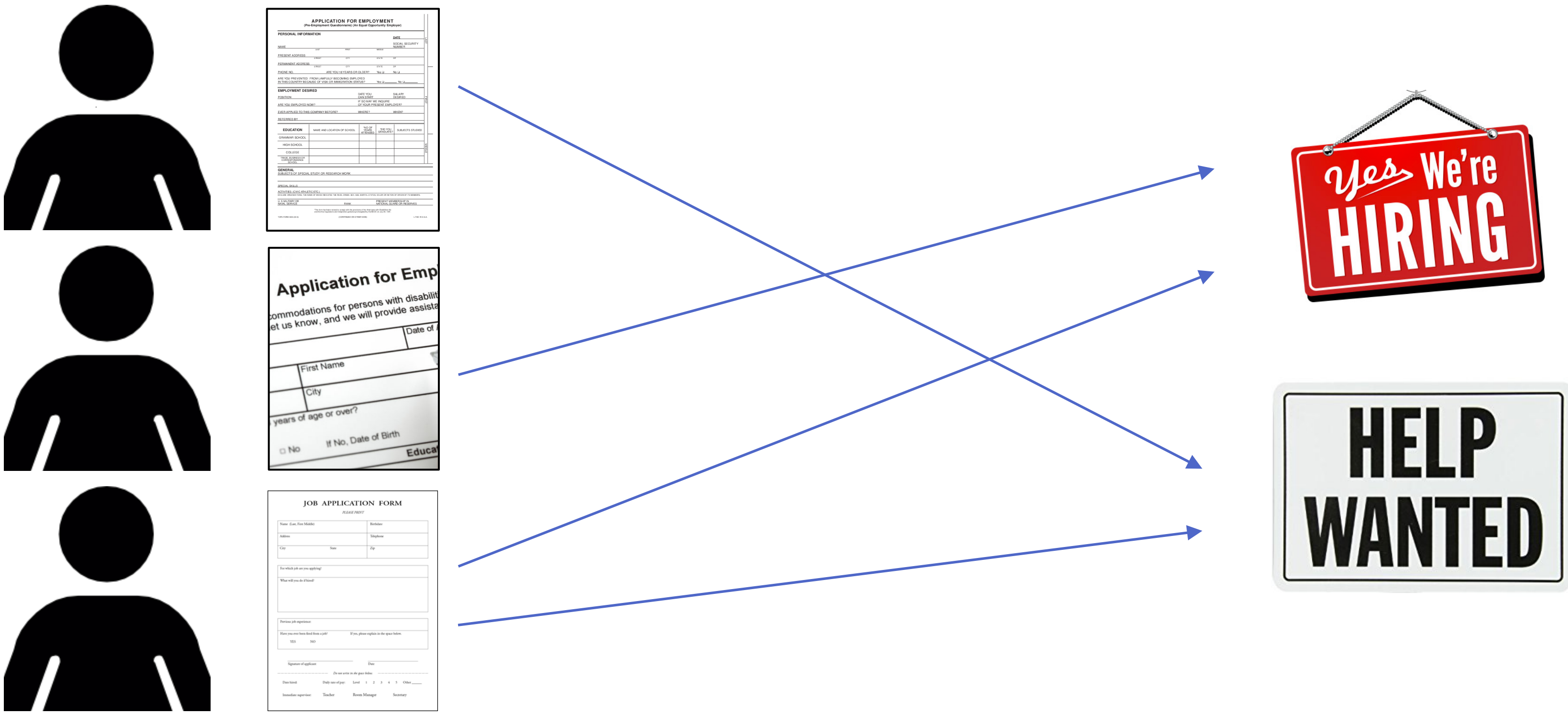

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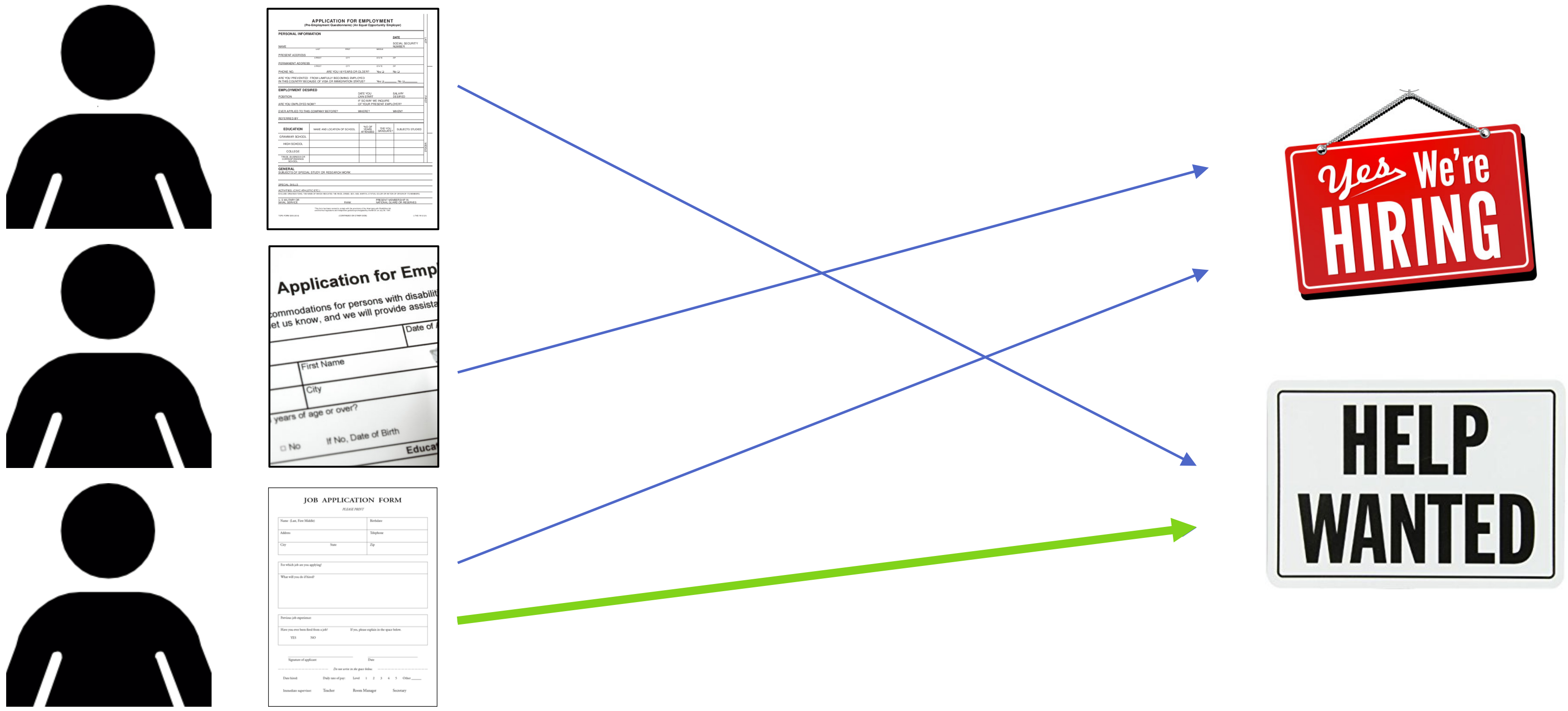
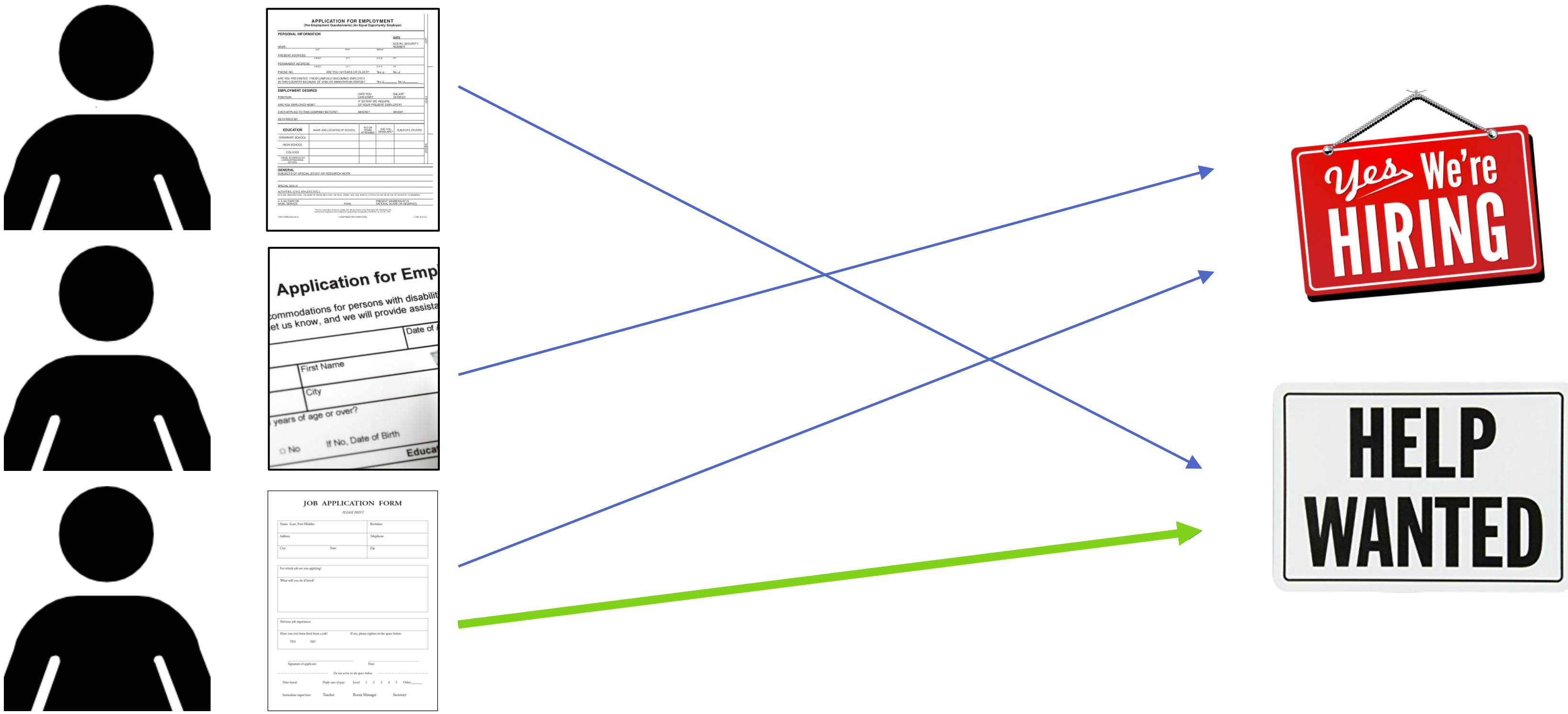


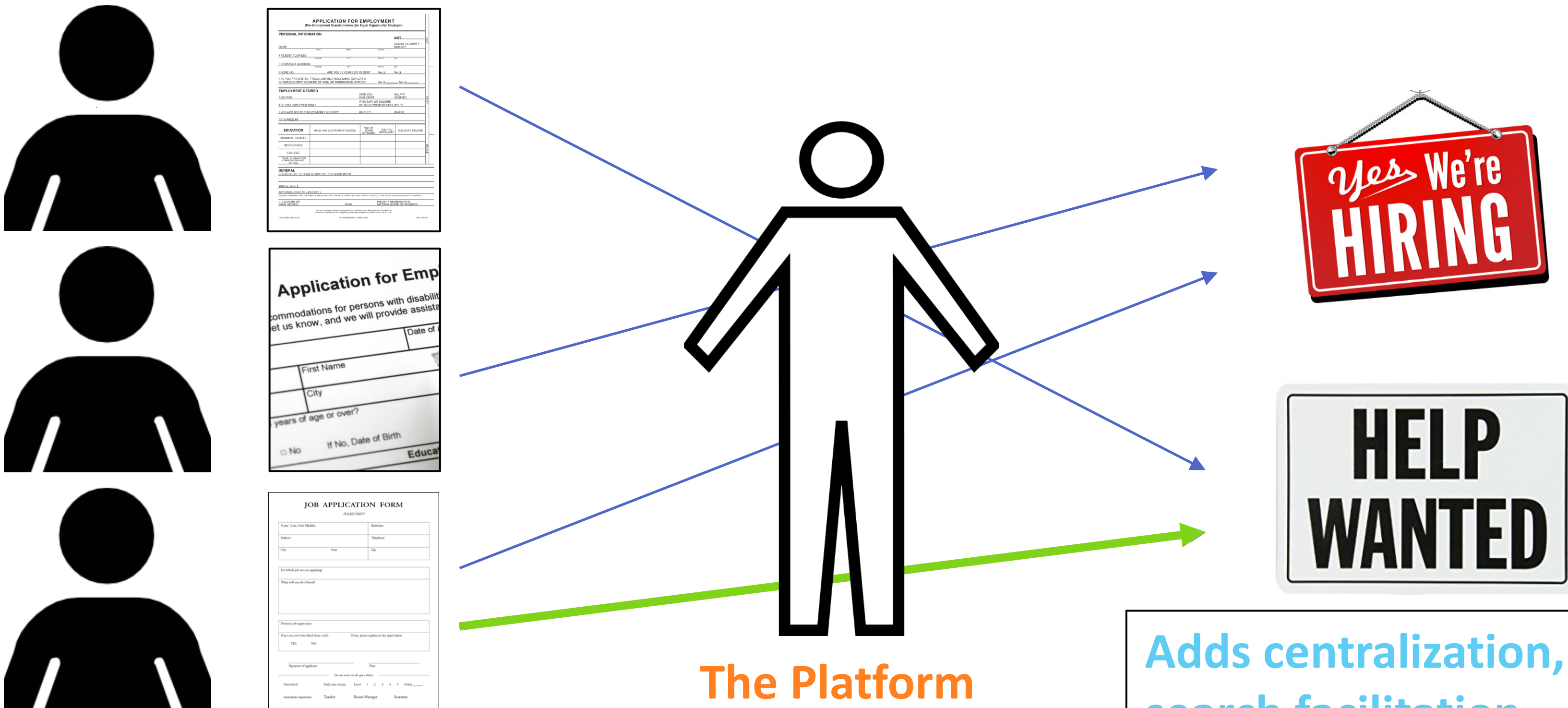
# Traditional Labor Markets




Key issues:

- Decentralization
- Lack of information—more of an experience good
- Suppliers of labor have more bargaining power and better economic circumstances

# Traditional Labor Markets




**Adds centralization, search facilitation, and trust**

Key issues:

- Decentralization
- Lack of information—more of an experience good
- Suppliers of labor have more bargaining power and better economic circumstances

# Advantages of OLMs

TLMs are poorly observed. OLMs are **well-observed**!

- Posted job, all applications, interview decisions, who is hired, at what terms, how the contract progresses

**Regulatory** power:

- Decide who can see what, enforce pricing policies

Potential to allow **economic mobility**:

- Virtual migration
- Lower barriers to entry

# Matching Platforms in General

airbnb

taskrabbit

UBER

lyft

tinder™

bumble

okcupid

coffee meets bagel

upwork™

amazon mechanical turk™
Artificial Artificial Intelligence

# Mechanical Turk

amazon mechanical turk™
Artificial Artificial Intelligence

Requesters post microtasks for pennies.

Task: Answer 10 image classification questions
Pay: $0.20

Is this a cat or a dog?

Requesters then accept/reject the work.

- Both sides are anonymous, no screening.
- Extremely concentrated group of requesters

# Upwork

Larger jobs, longer-term relationships
e.g. web design, data entry, bookkeeping

More like a traditional labor market: interviews, selection process

Job: Design my website.
Estimate: ~20 hours

Will do it for $15/hour!

How about $14?

Web design for $15/hour

Can you design my website? Estimate ~20 hours, pay $14/hour.

# Search: Who to consider?

People enter the market, and the platform dictates who they can see on the other side

Who can search?
- MTurk: requesters post and only workers search
- Uber/Lyft: no one searches

How many can they see?
- Coffee Meets Bagel: 1 per day

What's the algorithm?

Do you use a recommendation system?
- What are the effects of using one? **[Horton 16]**

# The Process

We've decided who they can see. Now the platform can answer the following questions:

- What can they evaluate about these potential matches (use to **screen**) before making a decision?
- How much **interviewing** do we allow?
- How does **proposing** work? Force auto-accepting?
- Do we inflate or subsidize the **costs** associated with parts of the process?

# The Mechanism Design Problem

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1. Search

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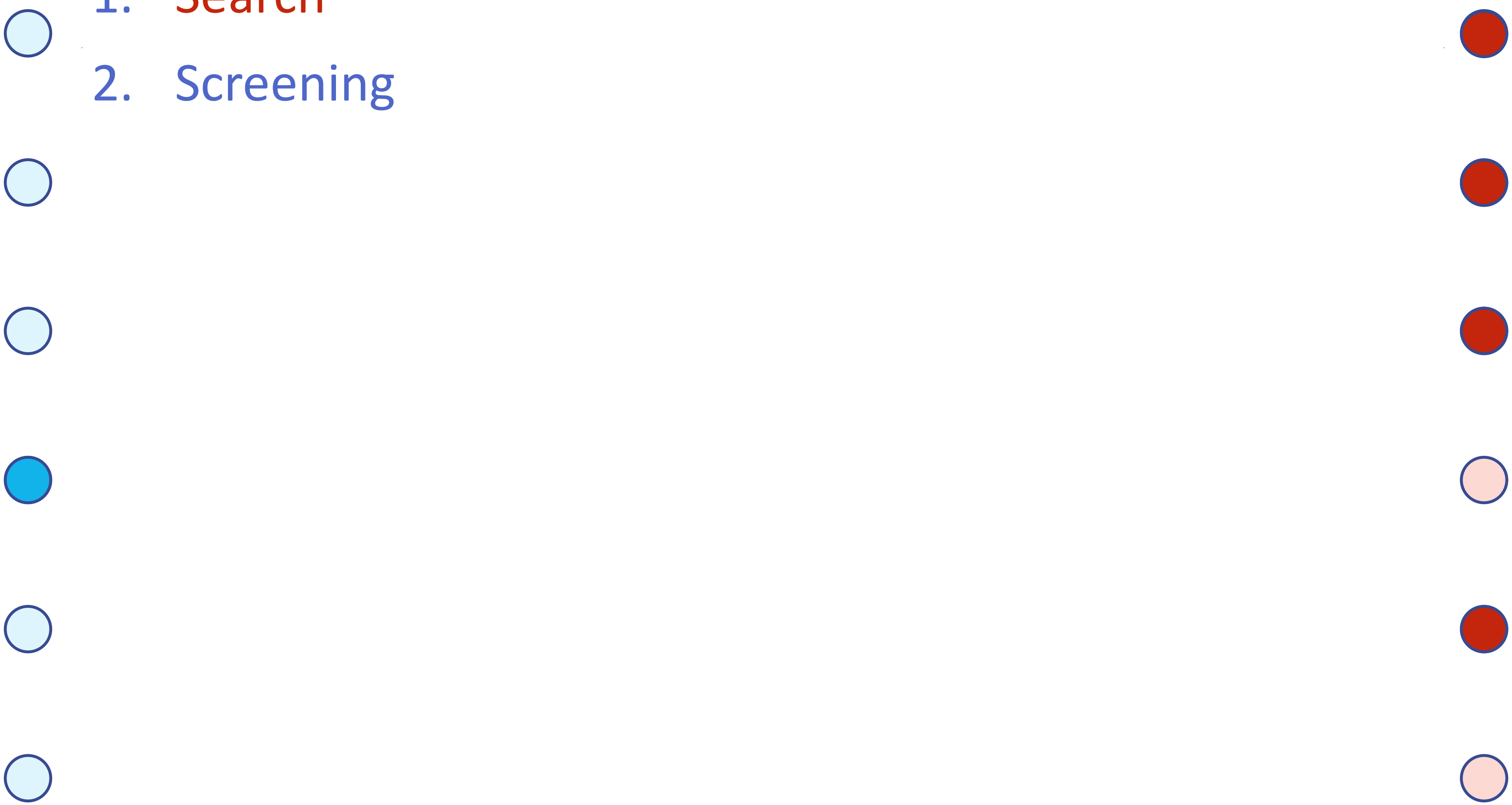
1. Search
2. Screening



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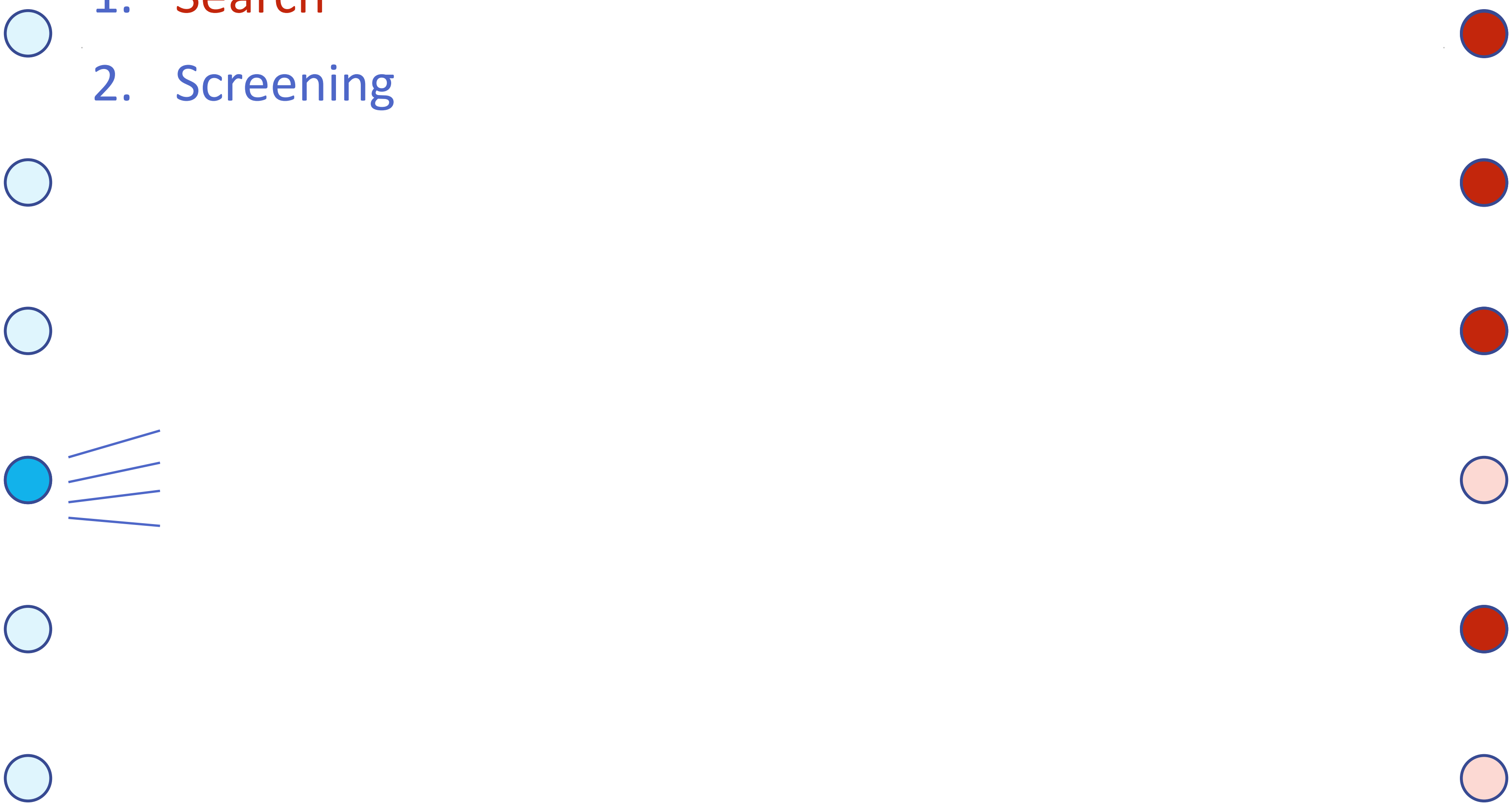

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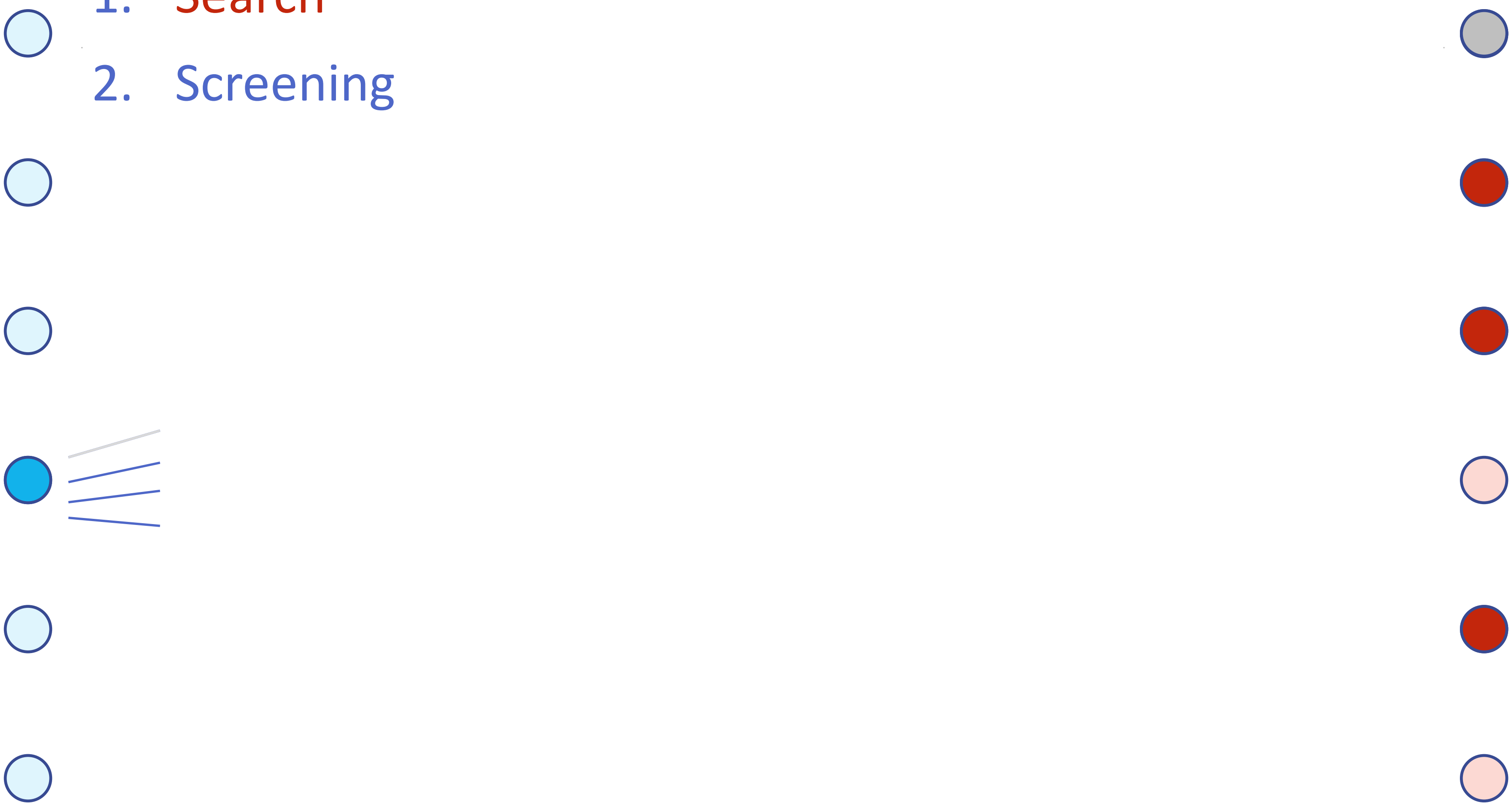

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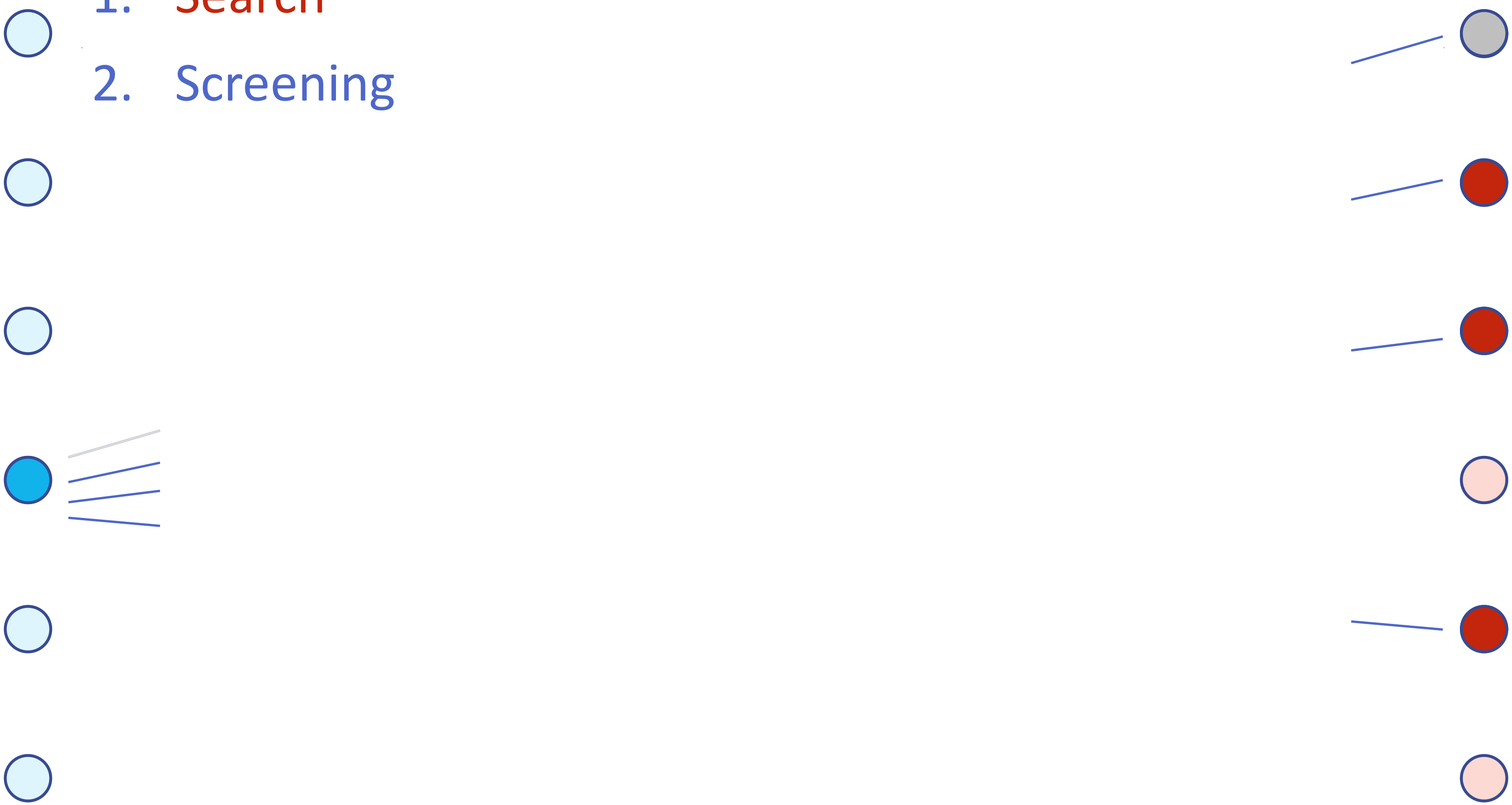

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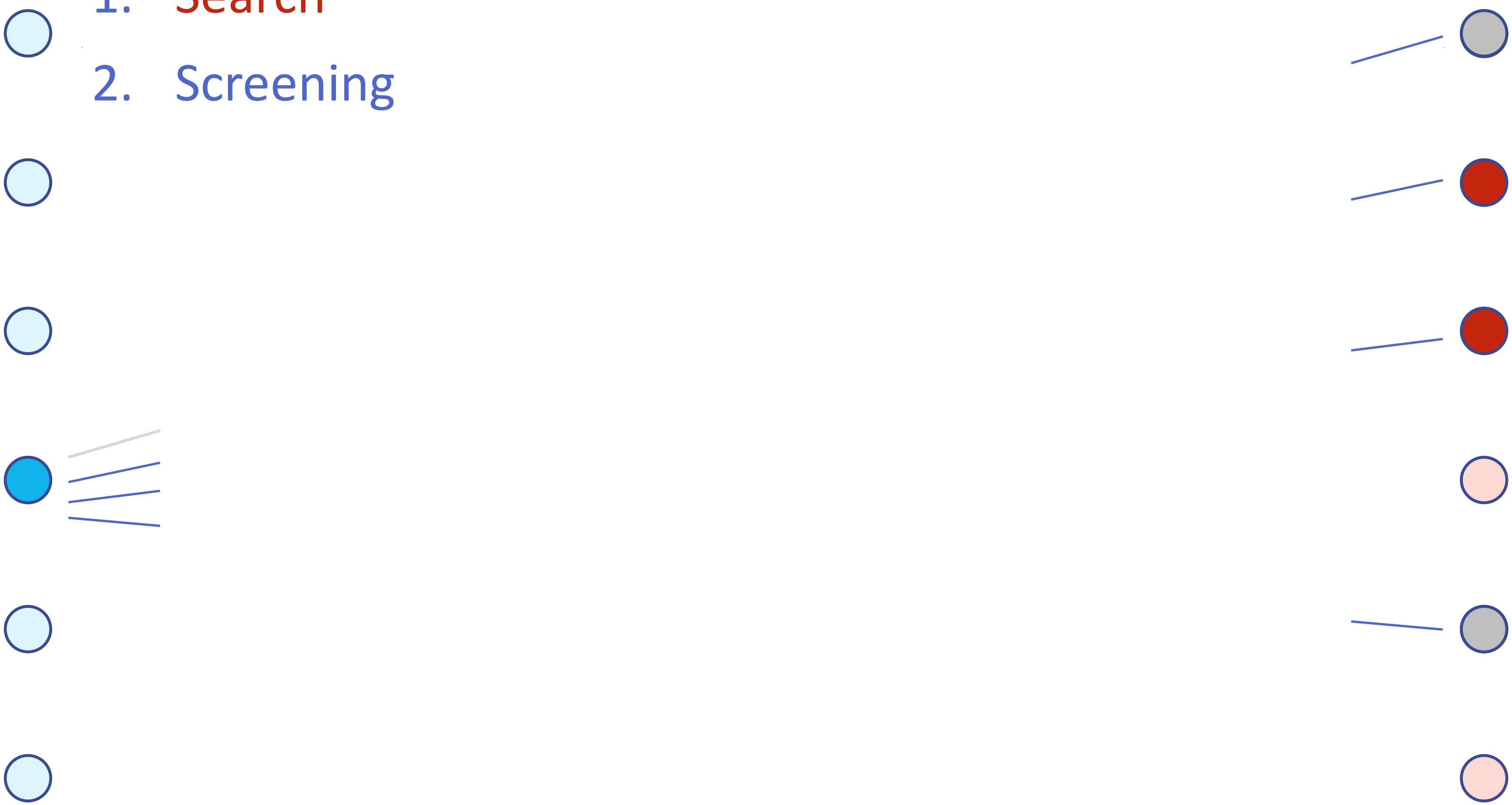

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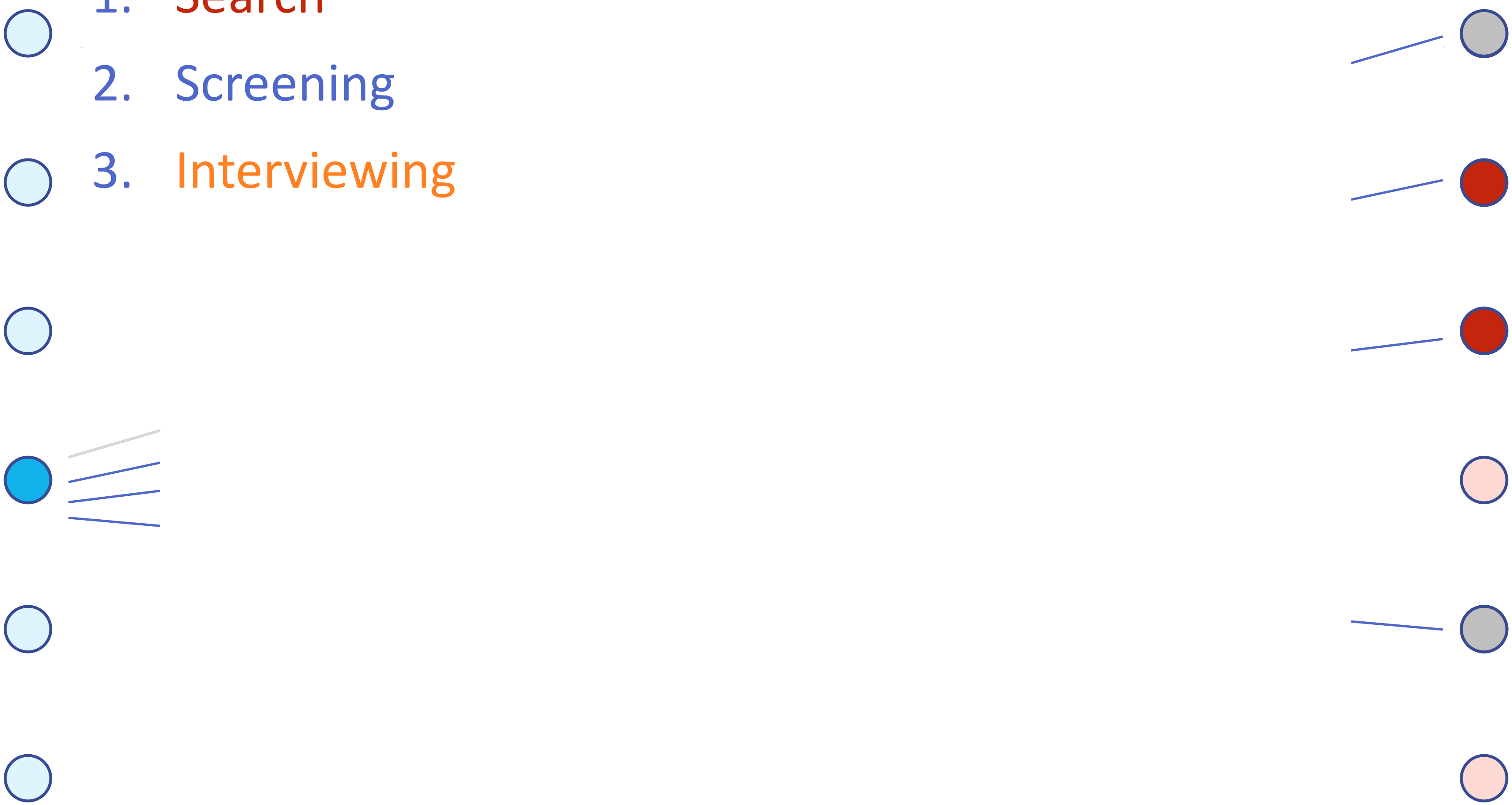

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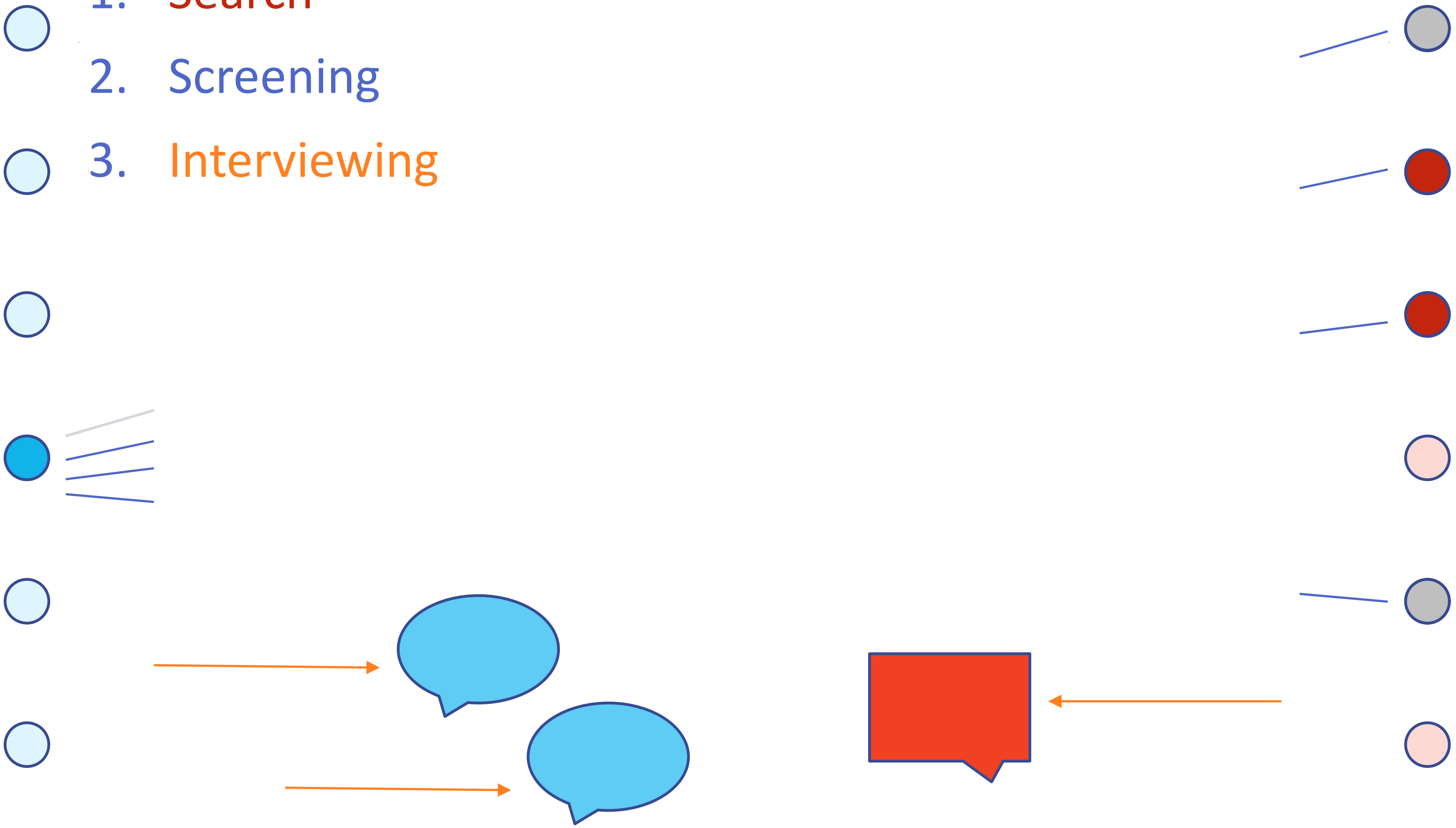

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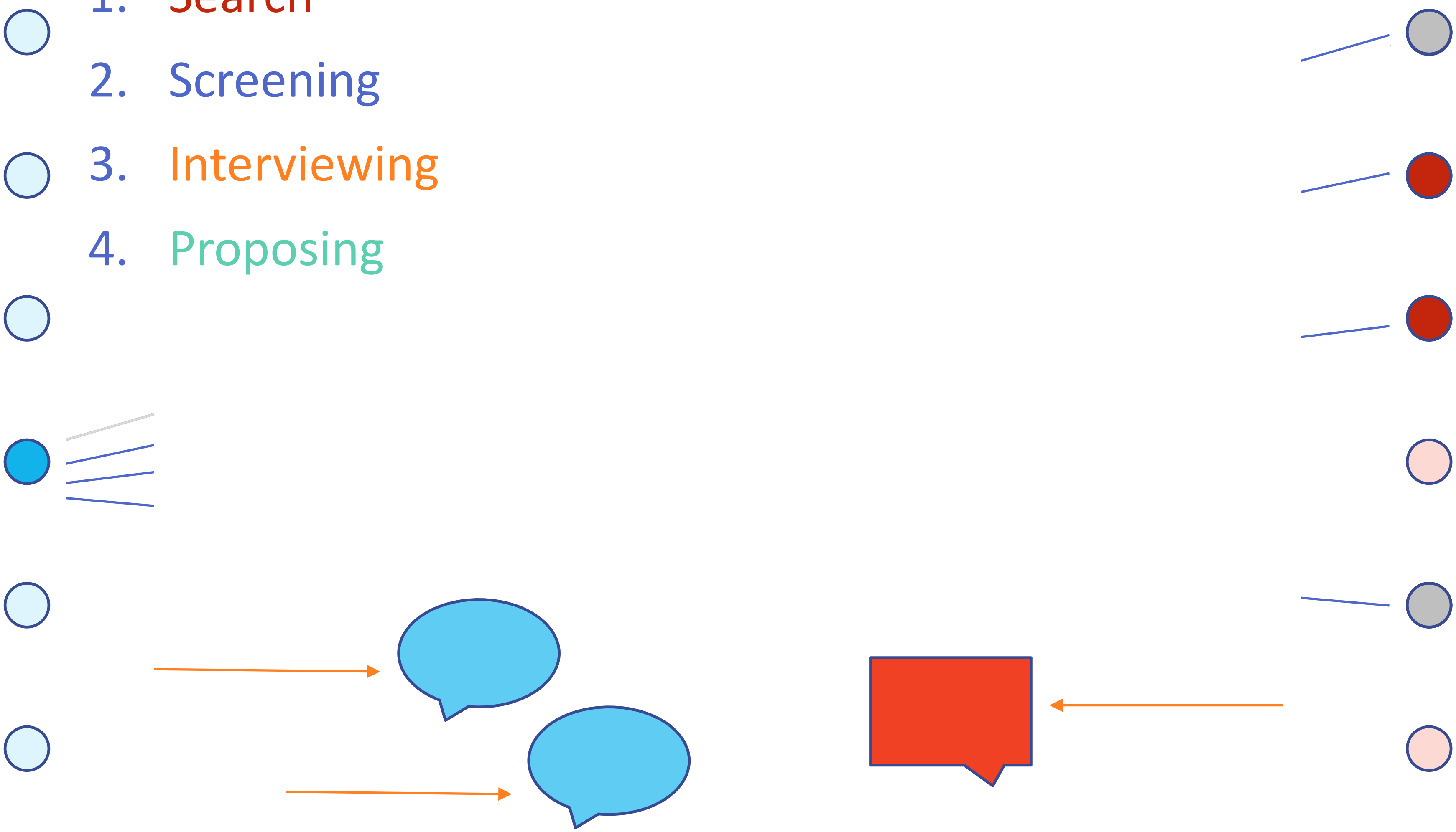

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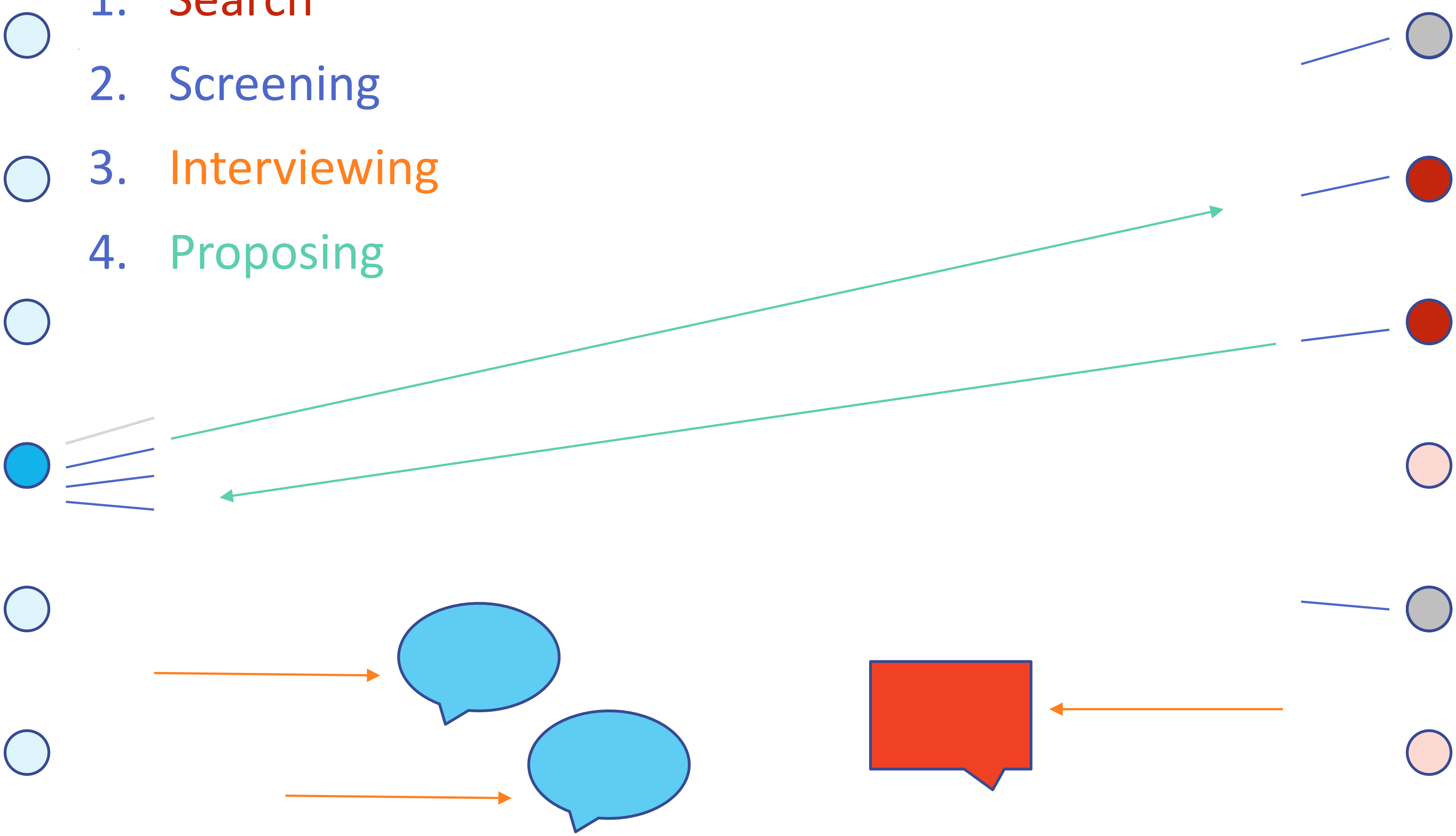

# The Mechanism Design Problem

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2. Screening
3. Interviewing
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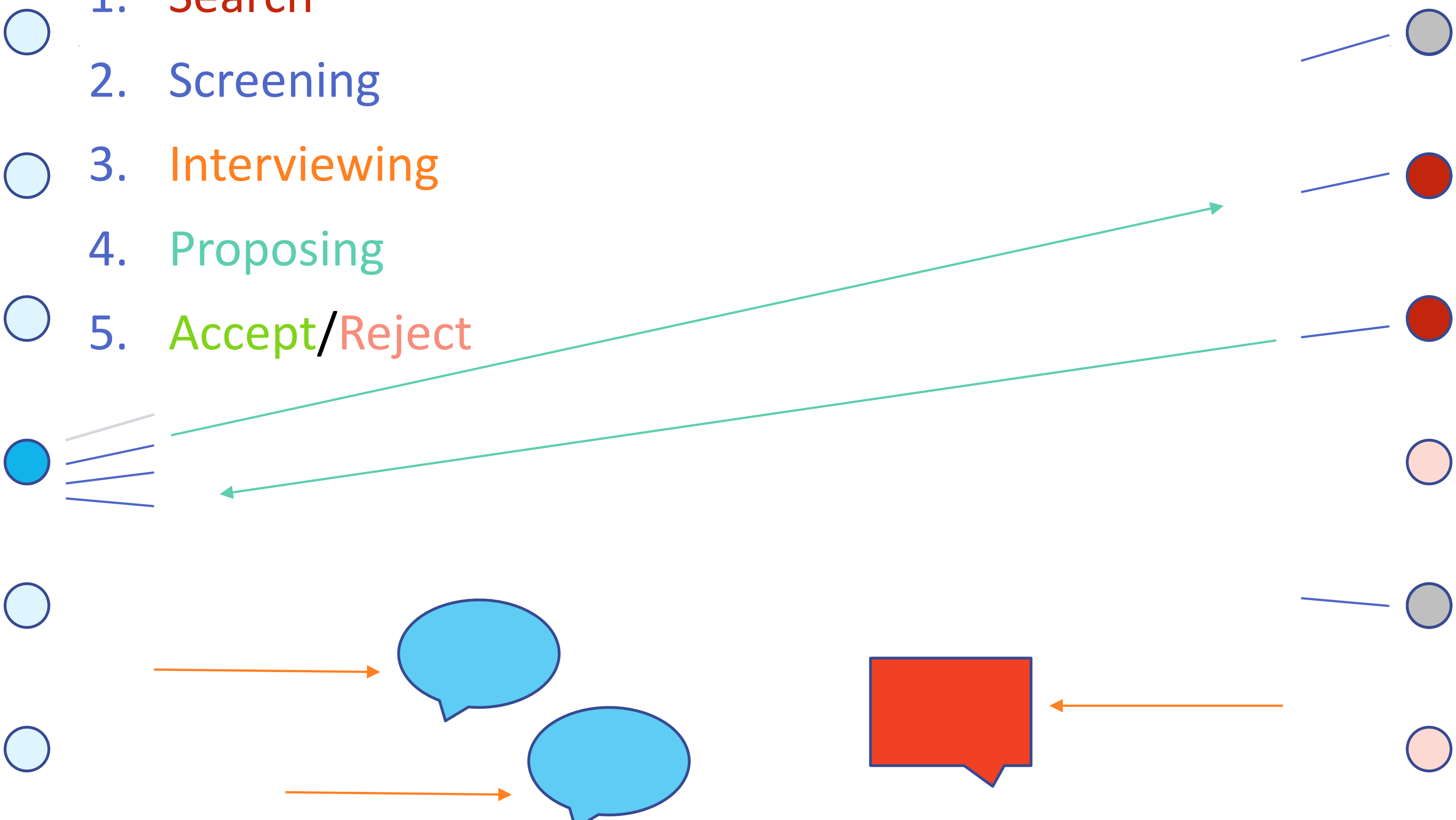
5. Accept/Reject



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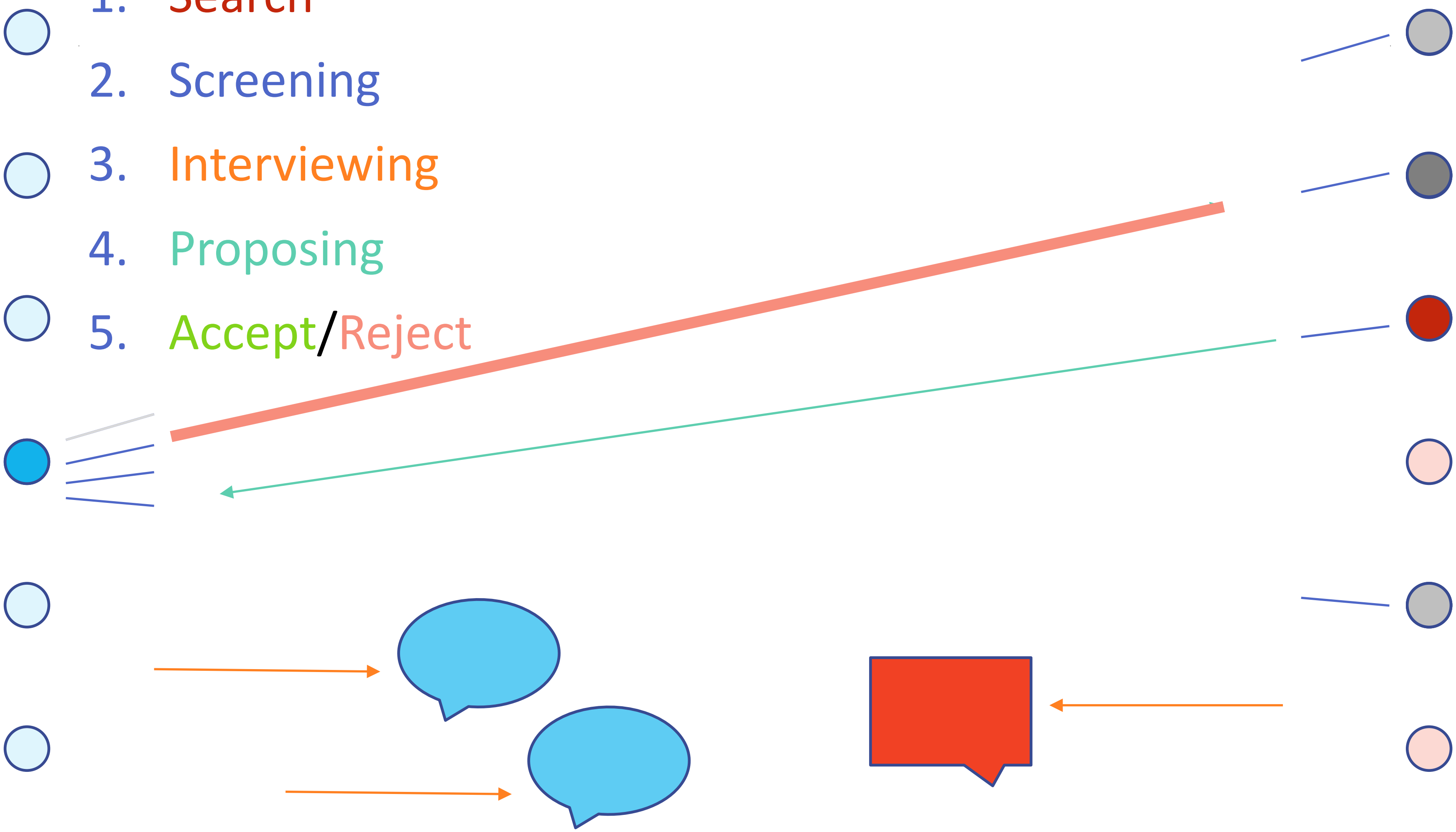

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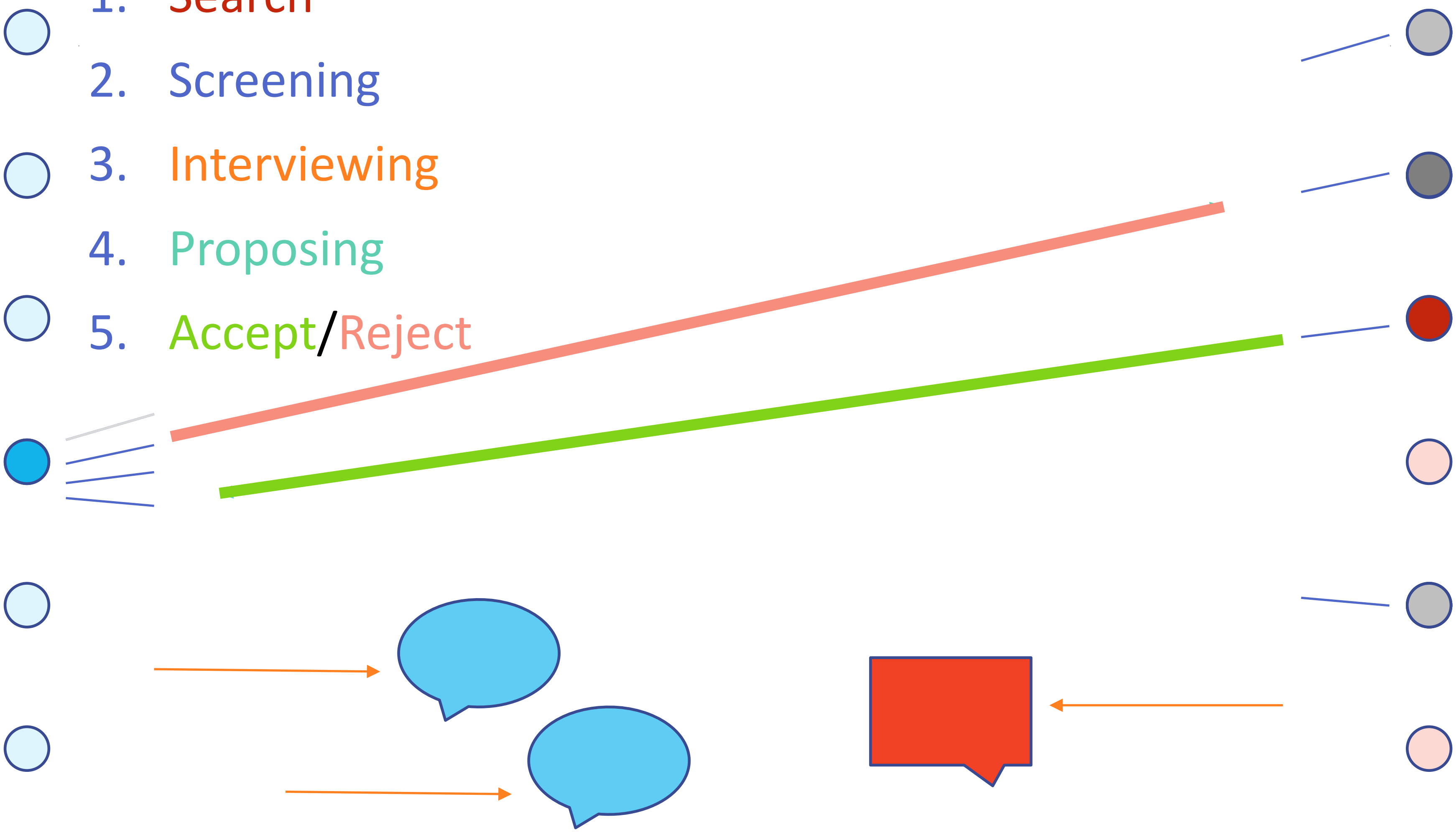

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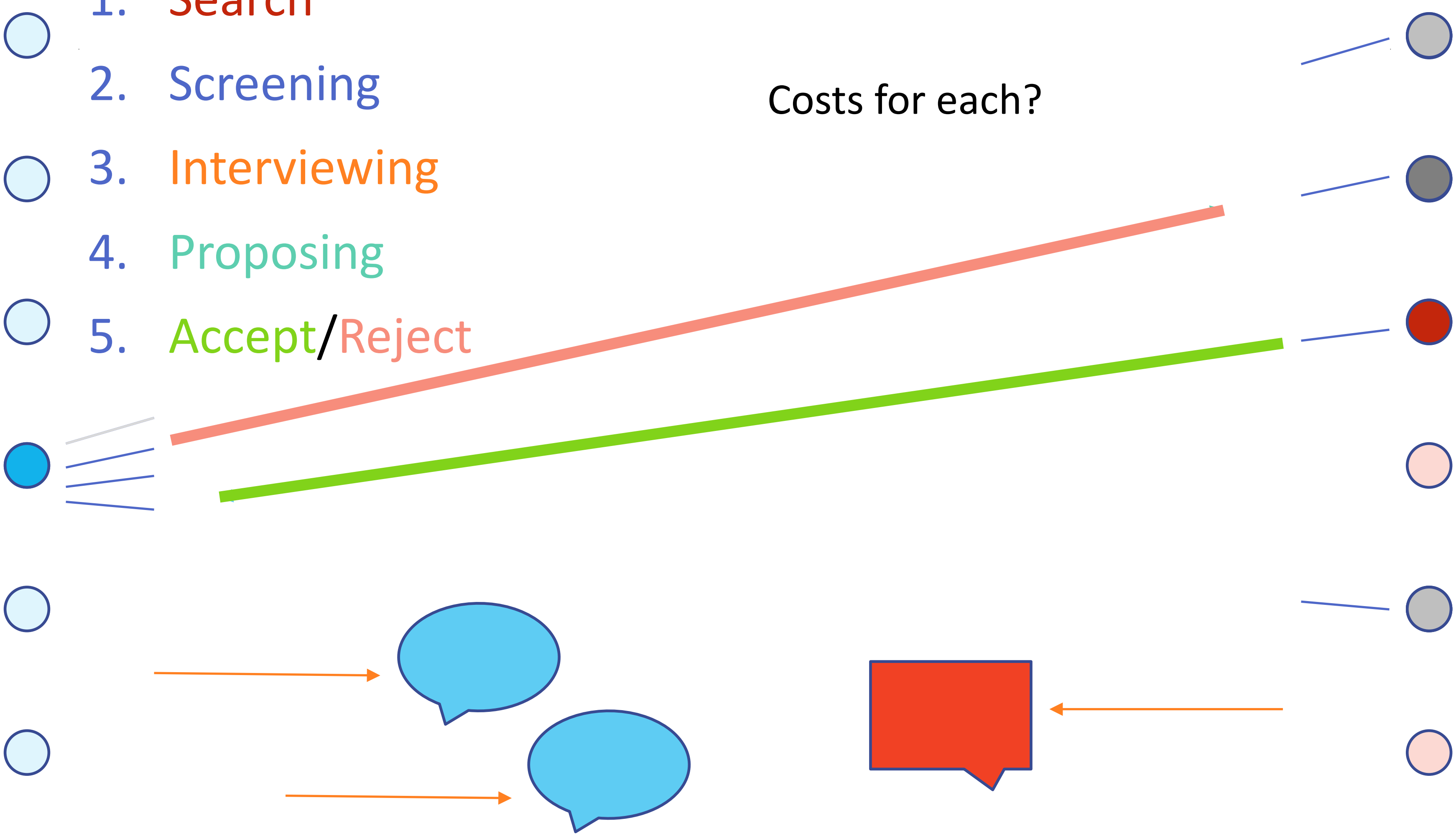
5. Accept/Reject

Costs for each?



# Examples of Mechanisms

One side searches and proposes, both screen

- Airbnb

One side search/screen/proposes, the other auto-accepts

- Airbnb instantbook
- MTurk
- Taskrabbit

Both sides search, screen, propose

- Upwork
- Dating apps

Auto match: no search/screen/proposing

- Uber/Lyft

# What's known

Facilitating Search **[Kanoria Saban 17]**:

- One side (short side) of the market proposing is more efficient for welfare, both sides screen.

Information Acquisition Costs **[Immorlica Leshno Lo Lucier 17]**:

- Iterative admission cutoffs with tentative placeholders are good for "regret-free stable matching."

Communication Requirements and Informative Signaling **[Ashlagi Braverman Kanoria Shi 17]**:

- Signaling workers with high draws and using a qualification cutoff is good for communication.

# MD Open Problems

What is optimal or approximately optimal for various objectives?

- Welfare / gains from trade—IF these things are well-defined
- Work done better (or faster)
- Feedback/Ratings
- “Would you hire this person again?”

Why would we use one choice vs. another?

Why have these current platforms evolved to pick these choices?

- Feature of the objective, the distributions, the value model?

Nice properties? (e.g. low communication, regret-free, stable)

Is there an overarching model we should be using?

# Information

**Too little** information: bad matches

- MTurk: No employer information, no work-specific info

**Lack of desired** information: statistical discrimination

- "Ban the box" leads to racial discrimination
- Hiding wage history seems to help **[Barach Horton 17]**

**Wrong** information: elicitation isn't truthful

- Price sensitivity – quality tradeoff **[Horton Johari 15]**
- Work capacity **[Horton 17]**

**Subjective** information: reputation

- Proper design? Currently right-skewed. Where does it give market power? (One-sided, e.g. MTurk and penalties)

Trust!

# Pricing

- Ex-ante wages vs. negotiating (MTurk)
  - Implement negotiations quickly at large scale?
- Hourly vs. fixed contract (Upwork)
- Minimum wage **[Horton 17]**
- Incentivizing quality (offering bonuses)
  - Prices are below equilibrium; higher pay doesn't fix quality
- Adequate compensation
  - Ensure those bearing search costs are being compensated for it

Certainly these things have been studied, but:

- At this scale?
- With this degree of uncertainty?
- Given the existing market power and information asymmetries?

# Other Directions

- Onboarding: lowering barriers to entry, bootstrapping reputations
- Upward mobility in the labor market
- Fairness: enforcing individual or group **[Hu Chen 17] [Fryer Loury 13]**
- Platform learning (when clear types exist) **[Johari Kamble Kanoria 17]**
- What's the valuation model? As a function of the (noisy) information observed?
- Competing reputation systems, third party vs. in-house?

# OLM/platform experts

John Horton, NYU (empirical labor economics)

Yash Kanoria, Columbia (AGT/OR)

Sid Suri, MSR NE (computational social science)

# Other Domains

# Refugee Resettlement

Each **community** has # slots for different resources, e.g.:

- 10 beds
- 5 school places
- 1 hospital bed
- 4 jobs

Each **family** (1) stays together and (2) has certain needs.
Has preferences over locations.

**Communities** have priorities over skills and Pr[integration].

**Question:** How to allocate?

**Idea:** Serial multi-dimensional top trading cycles.

**[Delacrétaz Kominers Teytelboym 16]**

# Refugee Resettlement

| | Preferences | Priorities | Manipulability | Computation |
|---|---|---|---|---|
| OQMP | – | – | – | NP-hard |
| MTTC | Pareto-efficient | – | Strategy-proof | Polynomial |
| Serial MTTC | Individually rational | – | Strategy-proof | Polynomial |
| Serial dictatorship | Pareto-efficient | Stable (identical priorities) | Strategy-proof | Polynomial |
| Top Choice | Family-undominated | Stable | Difficult | NP-complete |
| PFDA | Family-optimal | Quasi-stable | Only strategy-proof under low information | Polynomial |
| MRDA | – | Quasi-stable | Strategy-proof | Polynomial if housing is reducible |

**[Delacrétaz Kominers Teytelboym 16]**

# Housing

**Finding:** In factors for eviction, **a sudden shock to wealth** plays a bigger role than general wealth.

**Problem:** **[Abebe Kleinberg Weinberg]**

- As the government, you have a budget B of funds to dispense.
- Each round, each family experiences a shock in wealth.
- Below a threshold L is **eviction**.
- Above a threshold H **escapes poverty**.

How do you distribute the funds to maximize welfare?

# Education

School choice has many parameters:

1. **Menu of school options** that students are shown
2. Allowed **priorities** that schools may have over students
3. **Quotas** for places in the schools

How can we choose these parameters to optimize welfare?

Assortment Planning in School Choice **[Shi 17]**:

- Optimizing these reduces to assortment planning!
- We can use tools from revenue management.

Another direction: Funding (vouchers or no?)

# Diversity and Fairness

Each individual has a group (e.g. gender, ethnicity, …)

**Aim:** Diversity / individual fairness / group fairness
in a labor market or incoming grad class

Stages where limited # of “opportunities” are allocated

- **Develop skills**, **earn reputation**

Pay cost (according to group) to **develop skills** on their own

What policies for distributing opportunities achieve the objective? At what stage(s) are interventions most helpful?

Related: **[Hu Chen 17] [Fryer Loury 13]**

# And more!

Affirmative action in education:

- See Parag's talk tomorrow

Democracy and participatory budgeting:

- See Ariel's talk on Wednesday

# Suggestions for finding problems

1. Learn about the systems in place and the issues with them
   - Read policies in place
   - Study existing work in: economics, empirical work, public policy, sociology

2. Review related EconCS work
   - Try to draw connections between these

3. Talk to a domain expert!
   - Communicate the types of problem we're interested in and have the tools to solve
   - Start formulating interesting questions, jointly or going back and forth to ensure they're the right questions

# Credit

This talk was in part based on talks and materials of: Mark Braverman, Anna Karlin, Mark Shepard, Matt Weinberg

Most of my knowledge on this subject is due to the MD4SG research group, co-organized with Rediet Abebe.

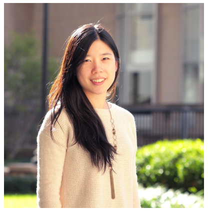
Cornell CS
Algorithms, AI, and Networks with Social Good Applications

Many resources available at www.md4sg.com.

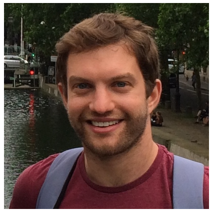
You can also find information about the members who are experts on many different domains.

On the market!

Ellora Derenoncourt
Harvard Economics
Economic Inequality



Irene Lo
Columbia OR
School Choice
+ Matching



Daniel Waldinger
MIT Economics
Housing

# Thank you!

# Precise References

- Data-Driven Incentive Alignment in Capitation Schemes [Braverman Chassang 16]
- Strategic Classification [Hardt Megiddo Papadimitriou Wootters 16]
- Optimal Provision-After-Wait in Healthcare [Braverman Chen Kannan 16]
- Optimal Mechanism Design and Money Burning [Hartline Roughgarden 08]
- Analysis of Medicare Pay-for-Performance Contracts [Bastani Bayati Braverman Gummadi Johari 17]
- The Effects of Algorithmic Labor Market Recommendations: Evidence from a Field Experiment [Horton 16]

# Precise References

- Facilitating the search for partners on matching platforms: Restricting agent actions [Kanoria Saban 17]
- Information Acquisition Costs of Matching Markets [Immorlica Leshno Lo Lucier 17]
- Communication Requirements and Informative Signaling in Matching Market [Ashlagi Braverman Kanoria Shi 17]
- How Do Employers Use Compensation History?: Evidence from a Field Experiment [Barach Horton 17]
- At What Quality and What Price? [Horton Johari 15]
- Buyer Uncertainty about Seller Capacity: Causes, Consequences, and a Partial Solution [Horton 17]
- Price Floors and Employer Preferences: Evidence from a Minimum Wage Experiment [Horton 17]

# Precise References

- Minimum Wage Experiment [Horton 17]
- Fairness at Equilibrium in the Labor Market [Hu Chen 17]
- Valuing Diversity [Fryer Loury 13]
- Matching While Learning [Johari Kamble Kanoria 17]
- Refugee Resettlement [Delacrétaz Kominers Teytelboym 16]
- Assortment Planning in School Choice [Shi 17]