Allocating Scarce Societal Resources Based on Predictions of Outcomes

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Introduction

“Resources” that are controlled by or regulated by society are scarce; often cannot rely on market mechanisms

- Shelter beds and services for homeless households
- Organs for transplantation
- Public school spaces, ...

How can we best allocate these resources to those who need them? Complex problem – we must (at least):

- Predict outcomes
- Consider preferences and incentives
- Define objectives (efficiency, equity, justice/fairness)

Today: Two case studies

- **Living donor kidney transplantation**
  - (With Zhuoshu Li, Sofia Carrillo, William Macke, Kelsey Lieberman, Chien-Ju Ho, and Jason Wellen)

- **Homelessness services**
  - (With Amanda Kube and Patrick Fowler)
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Case Study 1: Living Donor Kidney Transplantation

- About 100,000 people waiting for kidney transplants in the US (2016)
- About, 19,500 kidney transplants in recent years, \( \sim 5500 \) from living donors
- Unfortunately, willing living donors are often not medically compatible.
- One option for them is to enter a kidney exchange program
Kidney Exchange

Donors

Husband

Wife

Patients

Brother

Brother
Kidney Exchange

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[Diagram showing kidney exchange process with different relationships involving donors and patients.]
Kidney Exchange in Practice

Problems

- A raft of coordination problems
- Exchange fragmentation

Parts of the solution

- More pooling of pairs (national/international exchanges)
- Desensitization / ABO incompatible transplants
- Today: Incorporate compatible pairs into exchanges (Gentry et al., 2007)
Incorporating Compatible Pairs

Why would a compatible pair want to enter the exchange? (cf. (Anshelevich, Das, and Naamad, 2013))
Measuring Match Quality: LKDPI (Massie et al., 2016)

LKDPI Score:

9

This model calculates a risk score for a recipient of a potential live donor kidney.

Live Donor Characteristics:

- Donor age: 43
- Donor sex: male
- Recipient sex: female
- Donor eGFR: 95
- Donor SBP: 130
- Donor BMI: 24
- Donor is African-American: No
- Donor history of cigarette use: No
- Donor and recipient biologically related: Yes
- Donor and recipient are ABO incompatible: No
- Donor/Recipient Weight Ratio: 0.90 or higher
- Donor and recipient HLA-B mismatches: 1
- Donor and recipient HLA-DR mismatches: 1
From LKDPI to Graft Survival

- Expected graft survival: estimated as a function of LKDPI
  \[ 14.78e^{-0.01239LKDPI} \]
Single Center Analysis

- De-identified data from 2014 - 2016
  - All donor and recipient characteristics for calculating LKDPI

![Expected graft survival distribution](chart1)

![LK DPI distribution](chart2)

Better for deceased donor
### Heterogeneity of Match Quality

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**Takeaway:** Largely donor driven, but with some pairwise idiosyncracies
To analyze the effects of policy changes, we need a faithful simulation of the real process.

Basic simulator model:
- Generate LKDPI-related characteristics to measure expected graft survival
- Compatibility based on the simulator from Saidman et al. (2006)
## Simulator: Initial Assessment

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Including Compatible Pairs in Kidney Exchange

- Including compatible pairs to thicken the exchange with incompatible pairs
  - Increase in the number of matches for incompatible pairs (quantity)
  - Increase in the expected graft survival for compatible pairs (quality)
Batch Optimization

- Simulated population: Any size
  - Compatible & incompatible pairs
  - Expected graft survival graph

- Optimization goal
  - Sum of expected graft survivals: A-D, B-C
  - Expected number of matches: A-D, B, C-E
Batch Optimization Results

- **Increase in number of matches for incompatible pairs (quantity)**

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- **Increase in expected graft survival for compatible pairs (quality)**

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$^1$Whose assignments changed
Batch Optimization Results

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Dynamic Matching

- Compatible pairs may not be willing to wait any longer than necessary
- Also debate in the literature about the value of patience regardless (Akbarpour, S. Li, and Oveis Gharan, 2017; Ashlagi et al., 2017; Z. Li et al., 2018)
- New model: Impatient compatible pairs and a pool of patient incompatible pairs
Hybrid Static-Dynamic Matching Model
Hybrid Static-Dynamic Matching Model

Online agent (Compatible pair) $t=2$

Standby agents (Incompatible pool)

- Node 3
- Node 6
- Node 8
Hybrid Static-Dynamic Matching Model
Hybrid Static-Dynamic Matching Model

Online agent (Compatible pair)

Standby agents (Incompatible pool)
Hybrid Static-Dynamic Matching Model

Standby agents (Incompatible pool)
An Oracle for 2-Matching

\[
\begin{align*}
\text{max} & \quad \sum_{n=1}^{N} \sum_{i=0}^{I} w_{n,i} x_{n,i} \\
\text{s.t.} & \quad \sum_{i=0}^{I} x_{n,i} \leq 1, \forall n \in [T] \\
& \quad \sum_{n=1}^{N} x_{n,i} + \sum_{j=1}^{I} x_{T+i,j} \leq 1, \forall i \in [I] \\
& \quad x_{n,i} \in \{0, 1\}, \forall n \in [N], \forall i \in [I]^*
\end{align*}
\]

- w’s: weights; x’s: match variables.
- When \( i = 0 \), \( x_{n,0} \) represents a self-match of agent \( n \).
- When \( i > 0 \) and \( n \leq T \), \( x_{n,i} \) represents a match between online \( n \) and standby \( i \).
- When \( i > 0 \) and \( n > T \), \( x_{n,i} \) represents a match between standby \( j = n - T \) and standby \( i \).
Dual Formulation and the ODASSE Algorithm

\[
\begin{align*}
\min & \sum_{t=1}^{T} \alpha_t + \sum_{i=0}^{l} \beta_i \\
\text{s.t.} & \quad w_{t,i} - \alpha_t - \beta_i \leq 0, \forall t \in [T], i \in [l]^* \\
& \quad w_{t+j, i} - \beta_j - \beta_i \leq 0, \forall i \in [l], j \in [l] \\
& \quad \alpha_t, \beta_i \geq 0, \forall t \in [T], i \in [l] \\
& \quad \beta_0 = 0
\end{align*}
\]

- \( \alpha_t, \beta_i \) can be interpreted as estimated values (\textit{shadow survival estimates}) of compatible pairs and incompatible pairs respectively.

- Given optimal \( \beta_i^* \) we can derive the online assignment rule \( i^* = \arg\max_i \{ w_{t,i} - \beta_i^* \} \) (\textit{Online Dual Assignment Using Shadow Survival Estimates}).
Estimating $\beta_i^*$

- Run many simulations and get $\beta_i^*$ values
- Train a linear model on
  - Demographic information of an incompatible pair
  - Initial graph state of incompatible pairs ($\beta_i$ value when solving the dual on just the incompatible pool).
- Predicted vs. true $\beta^*$ values.
## Results

### Total expected graft survival by algorithm

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<td>72%</td>
<td>76%</td>
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<td>Expected graft survival of compatible pairs</td>
<td>9.65</td>
<td>11.13</td>
<td>11.16</td>
<td>11.39</td>
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<td>Expected graft survival of incompatible pairs</td>
<td>10.32</td>
<td>9.75</td>
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Results

![Graph showing total expected graft survival by algorithm for Greedy, ODASSE, and Oracle.](image)

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Results: Disadvantaged Populations

Overall benefits (compared with no compatibles) are disproportionately good for Type O, and proportional for High PRA patients.
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Discussion

- Quantifying benefits allows us to think about a richer mechanism that includes compatible pairs in exchanges.
- We estimate substantial benefits in terms of number of incompatible pairs matched and increase in graft survival for compatible pairs.
- Methodological directions:
  - A model with real weights for weighted matching algorithms to work on!
  - A new hybrid static-dynamic matching model.
  - Online primal-dual + learning algorithm
Case Study 2: Homelessness Services

- More than 1.4 million people used services in the US in 2016
- System struggles to keep up with demand
- Yet, limited assessment of efficacy of allocations
Improving Allocations Using Counterfactual Predictions

- **Idea:** Personalized intervention / resource allocation
- Estimate how well a household would have done if allocated to one of several different possible interventions
  - **Measure:** Probability of re-entry within two years of exit
  - **Need:** Causal / counterfactual prediction
- We use detailed demographic and assessment data from 58 different homeless agencies in a major metro area.
- Use an ensemble method called BART to estimate counterfactual probabilities of re-entry (Chipman, George, McCulloch, et al., 2010; Hill, 2011)
- Optimize allocations on a weekly basis
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Optimal Allocation

Optimization Problem

\[
\min_{x_{ij}} \sum_i \sum_j p_{ij} x_{ij}
\]

subject to

\[
\sum_j x_{ij} = 1 \quad \forall i
\]

\[
\sum_i x_{ij} \leq C_j \quad \forall j
\]

- \(x_{ij}\): whether or not household \(i\) is placed in intervention \(j\)
- \(p_{ij}\): probability of household \(i\) reentering if they are placed in intervention \(j\)
- \(C_j\): capacity of intervention \(j\)

Results

- We estimate capacities and re-allocate among interventions weekly (for 166 weeks).
- Reduces number of re-entries from 2193 households (43.04%) to 1624 in expectation (31.88%) – a 27.08% reduction!
- BART predicts 2227 re-entries out-of-sample, so empirically relatively unbiased.
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Fairness

The optimal allocation hurts as many households as it helps, it just helps **more** overall.
Who is Helped and Hurt?

▶ We use machine learning techniques to learn whether a household is likely to be helped or hurt in the new allocation.
▶ Then find the features that are most predictive and analyze them
▶ The optimal allocation seems to help households that are more in need:
  ▶ Lower monthly incomes
  ▶ Longer waits and more calls to the hotline before being placed
  ▶ More substance abuse problems
Fairness Constraints

- Allocations may be because of policy constraints
  - E.g. require prioritization of those fleeing domestic abuse
- We can require the allocation to not hurt anyone more than a small percentage in expectation
- Add a constraint

\[ \sum_{j} p_{ij} x_{ij} \leq \sum_{j} p_{ij} y_{ij} + 0.05 \forall i \]

- \( y_{ij} \) represents whether or not household \( i \) was originally placed in intervention \( j \)
“Fairer” Allocation

- Now 1904 households (37.38%) reenter the system within two years.
  - Higher than the optimized allocation without the constraint, but still a 14.66% decrease
  - Less room for improvement under constraints
Looking Forward

- **Homelessness system itself**
  - Different constraints (confidence in counterfactual?)
  - Online matching!
  - Richer sets of resources for allocation (counseling, beds, cash transfers, etc)?
  - Plan for paths through the system (shelter → transitional housing, e.g.)

- **Bigger picture:**
  - Getting the conversation started
  - How can we use data and AI in the service of efficiency, equity, and justice in society?
  - Interplay between (dynamic) optimization and prediction, combined with consideration of long-run incentives is key
  - Ethical and systemic issues must be primary
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- Bigger picture:
  - Getting the conversation started
  - How can we use data and AI in the service of efficiency, equity, and justice in society?
  - Interplay between (dynamic) optimization and prediction, combined with consideration of long-run incentives is key
  - Ethical and systemic issues must be primary