Forecasting Patient Outcomes in Kidney Exchange

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Kidney Exchange

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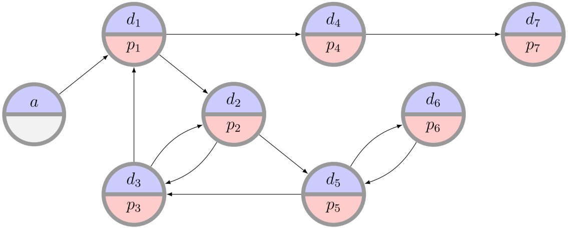

Kidney Exchange

Table 13-2: OPTN KPD Prioritization Points

If the:	Then the match will receive:
Candidate is registered for the OPTN KPD program	.07 points for each day according to Policy 13.7.G: OPTN KPD Waiting Time Reinstatement
Candidate is a 0-ABDR mismatch with the potential donor	10 points
Transplant hospital that registered both the candidate and potential donor in the OPTN KPD program is the same	75 points
Candidate and potential donor had a previous crossmatch that was one of the following:	75 points

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Waiting times and odds of match can differ dramatically depending on a pair's features.

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Ideally, prediction is fast, only requires data accessible to the exchange, and gives confidence estimates.

A Simple Approach

We propose a simple random-forest approach to infer (O, W, Q) directly from the match record.

- Predict $\Pr[O(v) = 1]$ with a RF classifier
- Estimate 95% prediction intervals $\widehat{W}_{95}$ and $\widehat{Q}_{95}$ using quantile regression forests

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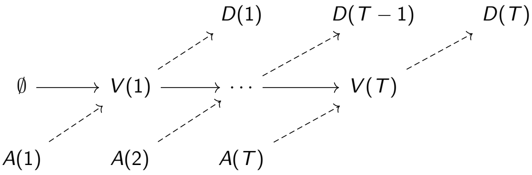
Categorical	Donor/Patient Blood Type, Donor/Patient HLA
Boolean	Donor/Patient Sex†, Donor Race, Donor Cigarette Use†
Integer	Pool Size at Entry, Donor/Patient Age, Patient CPRA
Float	Donor/Patient Weight‡, Donor eGFR‡, Donor BMI, Donor Systolic BP

Data types of features used for prediction. Features with † are independently generated. Features with ‡ are conditionally generated. All other features are from real data.

Simulation

Batch Simulation (up until time T) to obtain $\mathcal{R}_T$:



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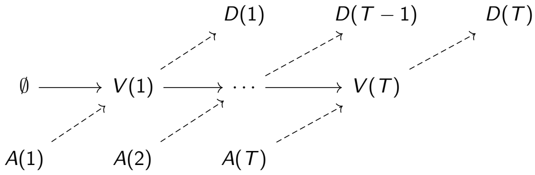
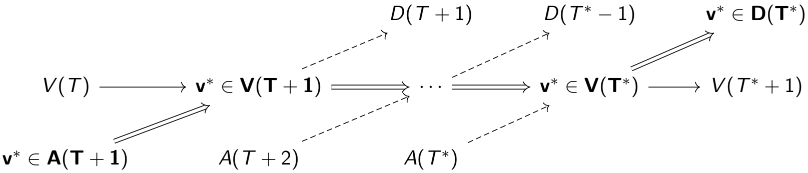


Trajectory Simulation (run τ times for S samples) to obtain the joint distribution of $(v, O(v), W(v), Q(v))$ for $v \sim f_P$:



Convergence of the Steady-State Constant

We measure the distance of the exchange to steady-state using the **steady-state constant**

$$\zeta(T) := \frac{\left|\bigcup_{t=1}^{T} D(t)\right|}{\left|\bigcup_{t=1}^{T} A(t)\right|} = \frac{\sum_{t=1}^{T} |D(t)|}{\sum_{t=1}^{T} |A(t)|} = \frac{|\mathcal{R}_T|}{|\mathcal{R}_T| + |V(T)|} \in [0, 1]$$

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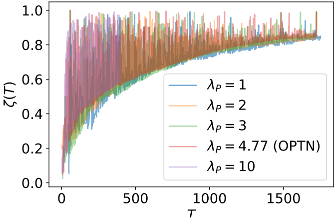
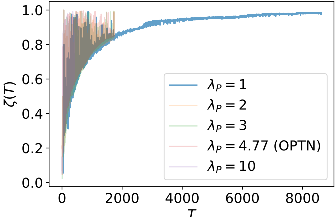
No matter the size of the exchange, the constant empirically converges to 1!





Steady-State Implies Low Shift

Theorem. *Suppose each vertex* $\boldsymbol{v}_i \in \bigcup_{t=1}^{T} A(t)$ *has features distributed as* $\mathcal{N}(\boldsymbol{\mu}, \Sigma)$ *where* Σ *is full rank. Then,*

$$\Pr[\mathcal{R}_T \text{ is } (\gamma, \delta)\text{-shifted}] \leq \underbrace{\left(\frac{e}{1-\zeta(T)}\right)^{A_T(1-\zeta(T))}}_{\text{Number of coalitions}} \overbrace{2^{\lceil \gamma d \rceil} \exp\left(-2 A_T \zeta(T) \lceil \gamma d \rceil \delta^2\right)}^{\text{Probability that a fixed coalition is shifted}}$$

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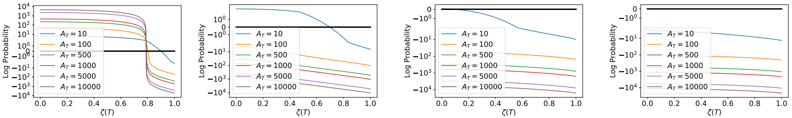


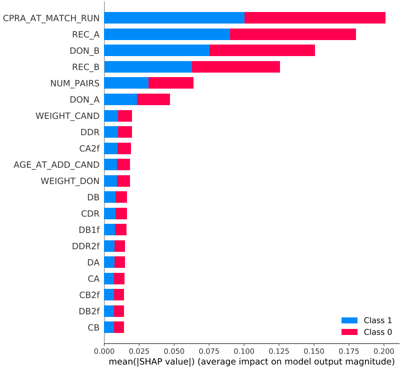
$$\gamma = \delta = 0.3, \quad d = (10, 20, 30, 40)$$

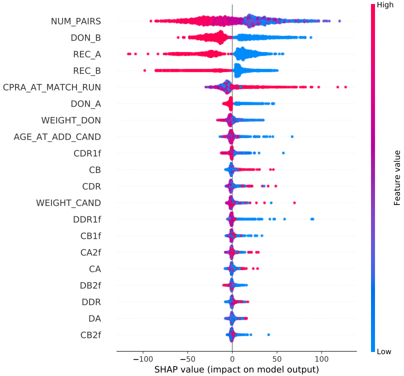
Empirical Results in Realistic Simulations

Arrival Rate	D	Federated	$\lvert\mathcal{R}_T\rvert$	ζ	$\mathrm{MAE}\left(\widehat{O}\right)$	$\mathrm{IOU}\left(\widehat{W}_{95}\right)$	$\mathrm{IOU}\left(\widehat{Q}_{95}\right)$
$\lambda_P = 1$	1500	No	56	0.397	0.258	0.451	**0.747**
$\lambda_P = 1$	4000	No	246	**0.953**	**0.191**	**0.644**	**0.761**
$\lambda_P = 1$	50000	No	4888	**0.984**	**0.130**	**0.653**	**0.632**
$\lambda_P = 2$	1500	No	157	0.477	0.221	0.336	**0.815**
$\lambda_P = 2$	4000	No	752	**0.882**	0.212	**0.620**	**0.809**
$\lambda_P = 3$	1500	No	285	0.523	**0.184**	0.386	**0.798**
$\lambda_P \approx 4.77$ (OPTN)	1500	No	593	0.509	**0.164**	**0.503**	**0.812**
$\lambda_P = 1$	1500	Yes	268	0.457	0.246*	0.232	**0.816***
$\lambda_P = 1$	4000	Yes	1224	**0.891**	**0.148***	**0.590**	**0.800***
$\lambda_P = 2$	1500	Yes	807	0.550	**0.145***	0.373*	**0.816***
$\lambda_P = 2$	4000	Yes	3773	**0.872**	**0.119***	**0.775***	**0.820***
$\lambda_P = 3$	1500	Yes	1434	0.488	**0.115***	0.421*	**0.815***
$\lambda_P \approx 4.77$ (OPTN)	1500	Yes	2652	0.537	**0.103***	0.449	**0.812**

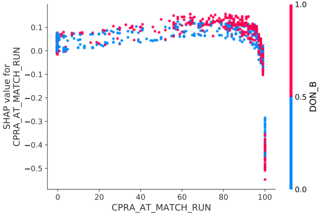
Experimental Results. We bold steady-state parameters $\zeta > 0.8$, MAE scores < 0.2, and IOU scores > 0.5. We asterisk any federated learning experiments that improve relative performance.

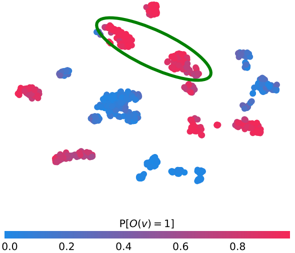
Diagnosing Mechanism Behavior with SHAP

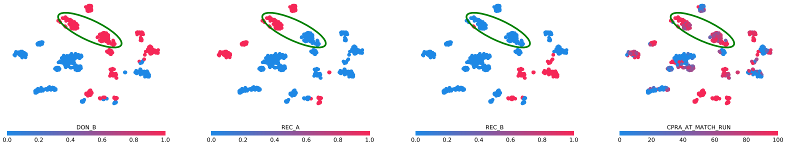




Visualizing Miscalibrations with SHAP + TSNE







Summary of Contributions

1. We proposed a random-forest approach

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3. Our approach can be used to inform policy and make kidney exchanges more fair

4. We developed a state-of-the-art simulator

Exchange Dynamics

Dynamic graph model: $V(T) = V(T-1) \cup A(T) \setminus D(T)$

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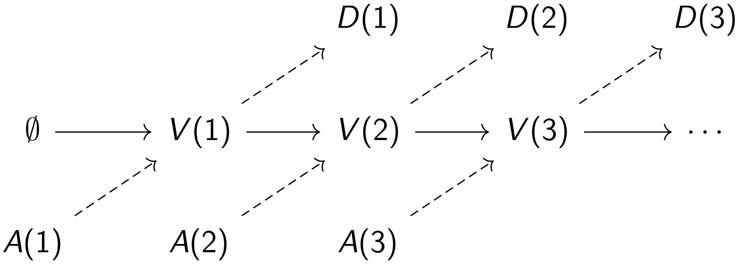

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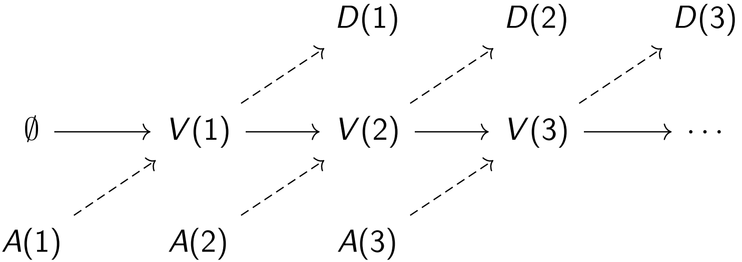
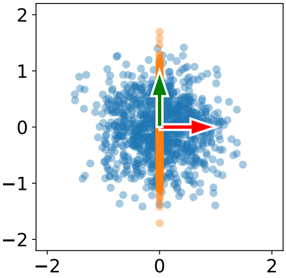


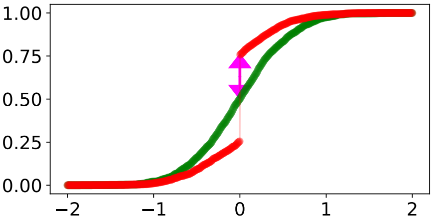
Match record:

$$\mathcal{R}_T = \left\{ (v, O(v), W(v), Q(v)) \mid v \in \bigcup_{t=1}^{T} D(t) \right\}$$

Shifted Directions

We say that a unit vector **z** is δ-shifted if the Kolmogorov distance between the one-dimensional projections of the data onto **z** is at least δ:





We say that $\mathcal{R}_T$ is (γ, δ)-shifted if at least a γ fraction of all unit directions are δ-shifted.

Distributional Shift and Steady-State Exchanges

Shift decreases as the age of the exchange increases, even controlling for the size of the dataset! But why?

D	REC_A	REC_B	DON_A	DON_B
1000	0.32	0.21	0.78	0.54
50000	0.22	0.15	0.78	0.48
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It turns out that these two phenomena are in fact related!