FutureMatch: Combining Human Value Judgments and Machine Learning to Match in Dynamic Environments

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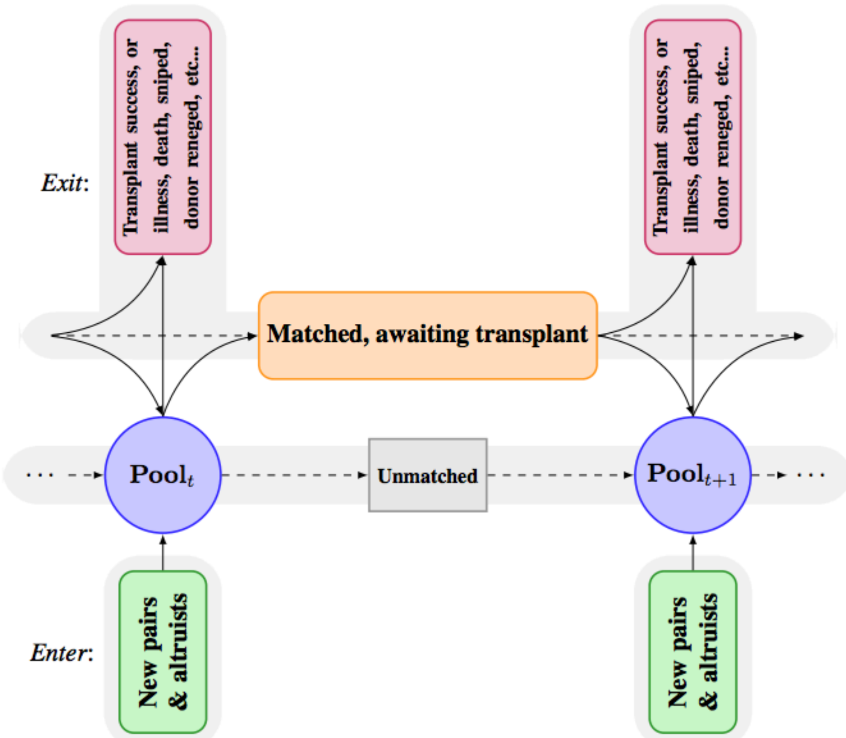
Presented by Zuxuan Wu

Motivation

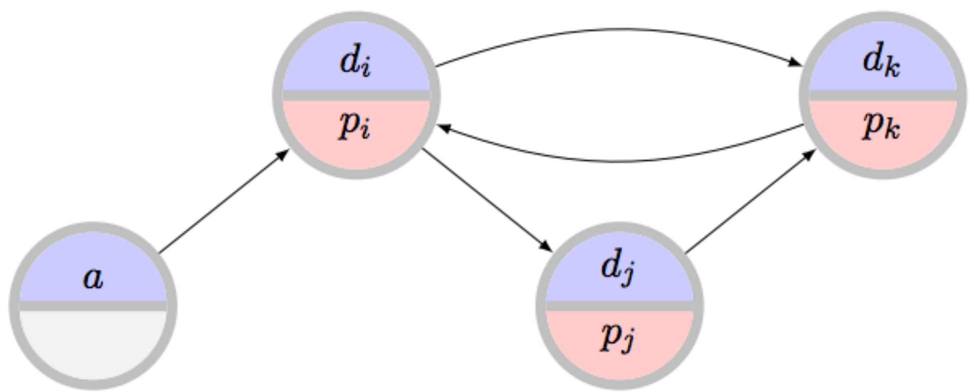


- Fielded exchanges act myopically, considering only the current pool of pairs.
- Kidney exchange is inherently dynamic.
- It's important to consider future when matching.

Contribution

- It takes as input a high-level objective decided on by experts.
- It automatically learns how to make the objective concrete.
- Utilizing historical data to learn the quality of each possible matching
- Learn the potentials of elements offline.

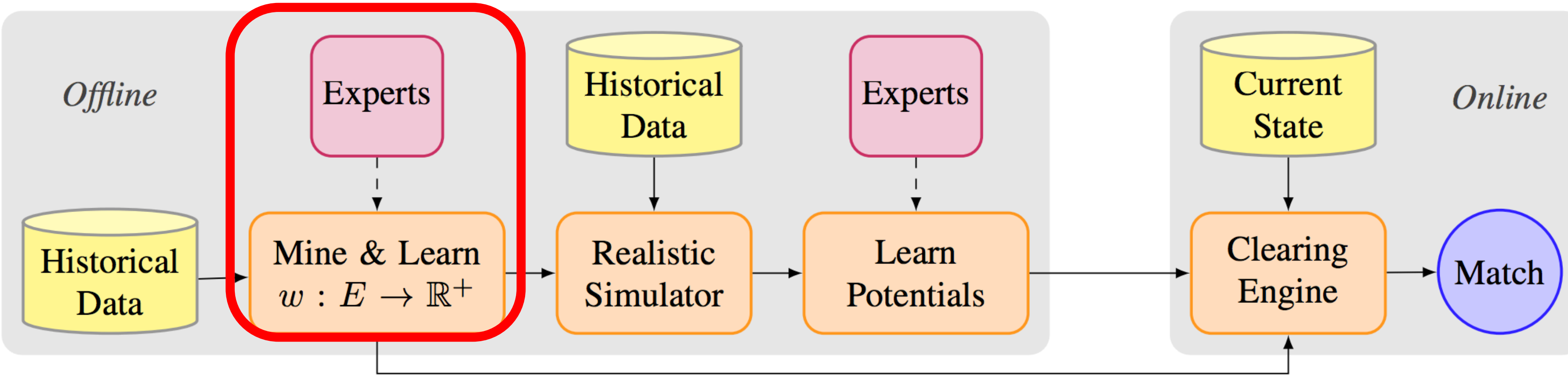
Recap: Kidney Exchange Model



- **Clearing problem**: find a matching M^* that maximizes utility function

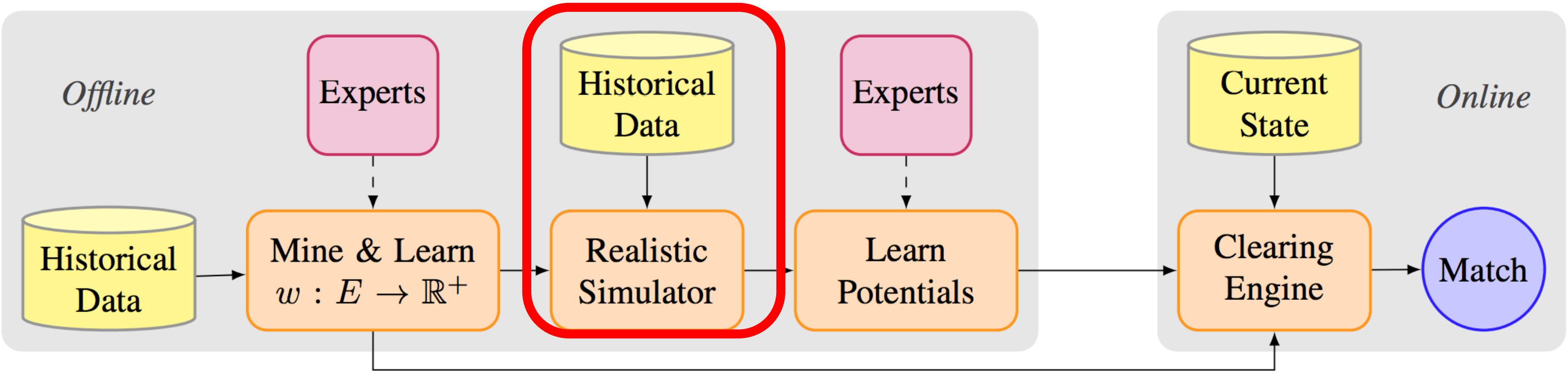
$$M^* = \underset{M \in \mathcal{M}}{\operatorname{argmax}}\, u(M)$$

Future Match Framework



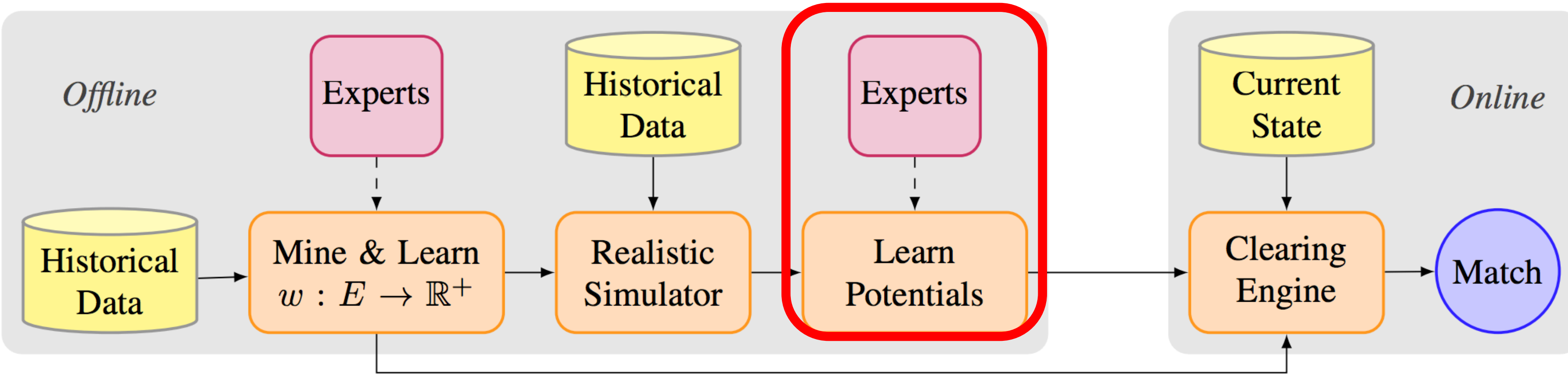
1. Overall objective is given by domain expert.
   -- e.g., maximize the number of days added
      but this is hard how to measure the utility
   -- Learning the weights!

Future Match Framework



2. A parameterized (kidney exchange) simulator to mimic distribution.

Future Match Framework



3. Learn the potential to quantify the expected utility to the exchange of that element in the future.

Encoding an Objective Function

Two different models are considered
1） deterministic: post-algorithmic failures are not quantified
2） failure-aware: are quantified

Three matching objectives:
1) MaxCard: maximize the total number of patients

2) MaxCard-Fair: maximize the total number of patients, and the “marginalized” patients are weighted more.

3) MaxLife: maximize the total time matched (deterministic) or transplanted (failure-aware) donor organs.

Encoding an Objective Function

MaxCard and MaxCard-Fair

A natural weighted fairness rule:
--adjusts edge weights by some re-weighting function.

$$\Delta^{\beta}(e) = \begin{cases} (1+\beta)w_e & \text{if } e \text{ ends in } V_P \\ w_e & \text{otherwise} \end{cases}$$

$V_P \subseteq V$ the set of preferred vertices

Pediatric or highly sensitized patients

Encoding an Objective Function

MaxLife

Learning to predict graft survival from data.

The Kidney Donor Profile Index (KDPI) score of a deceased donor kidney: the estimated quality of the donor organ being allocated to the *average* recipient.

In this paper, a *unique* quality score:
(1) donor attributes
(2) attributes of the specific potential recipient.

Encoding an Objective Function

MaxLife

75,264 living donor transplant during 1987.10 – 2013.6

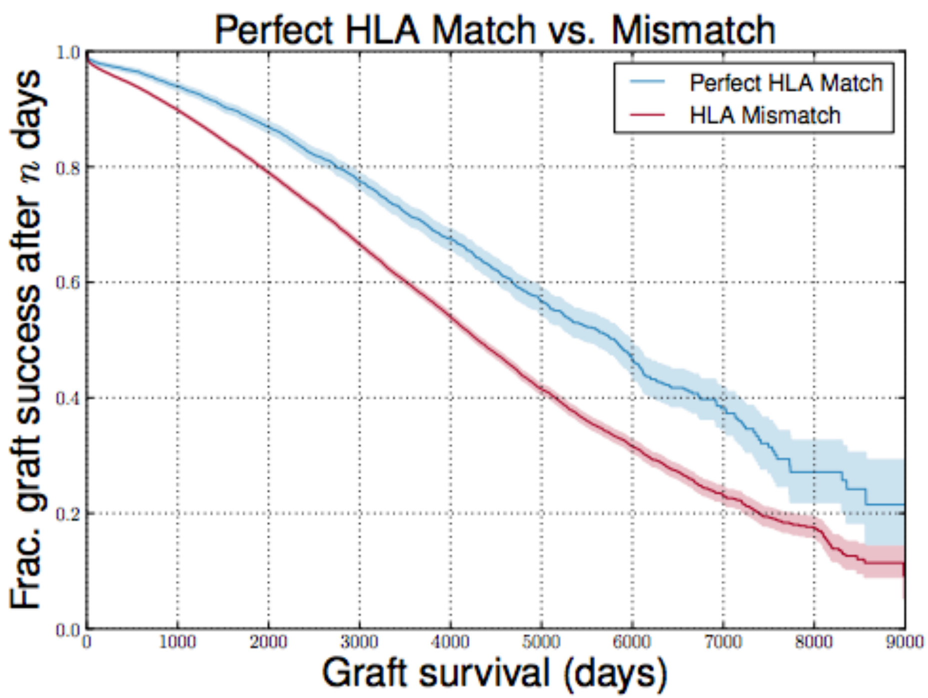
- medical characteristics of the recipient at the time of transplantation
- medical characteristics of the donor at the time of transplantation
- follow-up data regarding the health of the recipient
- follow-up data of the health of the recipient's new kidney;

Average graft lifetime is about 1912.7 days, or slightly over 5 years.

Encoding an Objective Function

MaxLife

Graft survival depends on both the donor and the recipient.



Kaplan-Meier estimator of survival functions

Encoding an Objective Function

MaxLife

Cox proportional hazards analysis for survivability.

$$H(t) = \underbrace{H_0(t)}_{\text{Baseline hazard}} \times \exp(b_1 X_1 + b_2 X_2 + \ldots + b_k X_k)$$

Features:

- recipient age,
- difference in donor and recipient's age,
- donor or recipient HLA profile HLA-A/B/DR {0, 1, 2},
- donor and recipient blood type compatibility

Encoding an Objective Function

MaxLife

Regression results:

- HLA-B mismatch did not have a significant effect (p = 0.22).
  -- Prior results on cadaveric HLA-B and HLA-DR have significant effect.

feature	$\exp(b_i)$	$\mathrm{SE}(b_i)$	z	p
recipient age	1.00753	0.0008	9.715	$< 2 \times 10^{-16}$
age diff.	1.00525	0.0007	7.766	8.10×10^{-15}
HLA-A	1.05273	0.0120	4.297	1.73×10^{-5}
HLA-DR	1.08680	0.0119	6.984	2.86×10^{-12}
ABO incomp.	1.37871	0.0748	4.295	1.74×10^{-5}

Table 1: Learned weights via Cox regression after feature pruning for statistical significance.

Each clearly has a statistically significant effect on graft survival.

Encoding an Objective Function

MaxLife

Survival probability $S_e(t)$ at time *t* for potential transplant *e*.

$$\exp\left(-H_0(t) \times \sum_i x_i^e b_i\right)$$

Weighting function:

$$E \to \mathbb{R}^+ \qquad w(e) \propto \exp\left(-\sum_i x_i^e b_i\right).$$

Higher relative weight to edges with lower risk

Learning Potentials

<u>Goal:</u>

Weight function w defined above quantifies how useful an edge is in the present myopic.

+ potentials define how useful it would be in the future

Learning Potentials

Method:

Select a set Θ of features, and assign $P_\theta \in \mathbb{R}$ usefulness.

$$\Theta_{\text{ABO}} = \underbrace{\{\text{O-O}, \text{O-A}, \ldots, \text{AB-B}, \text{AB-AB}\}}_{\text{pairs}} \cup \underbrace{\{\text{O}, \ldots, \text{AB}\}}_{\text{altruists}}$$

The weight function w learned $f_w : E \to \mathbb{R}.$ is myopic.
Consider the future value:

$$f_w(e) = w(e) \cdot (1 - P_{\theta_d} - P_{\theta_p})$$

SMAC is utilized to search the parameter space.

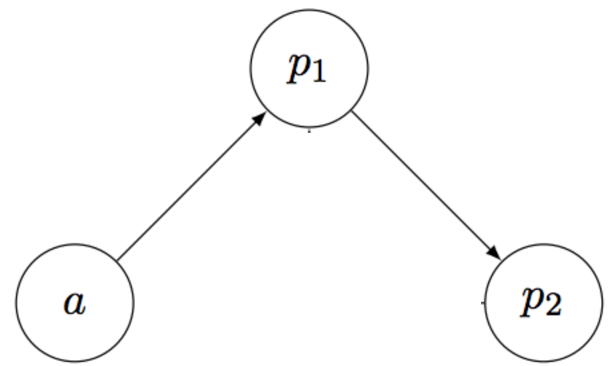
Learning Potentials

Example

$$\Theta_{\mathrm{ALT}} = \{\mathrm{ALT}, \mathrm{PAIR}\};$$

$$P_{\mathrm{ALT}} \geq P_{\mathrm{PAIR}}$$

<a, p1> and <a, p1, p2>
will have negative utility



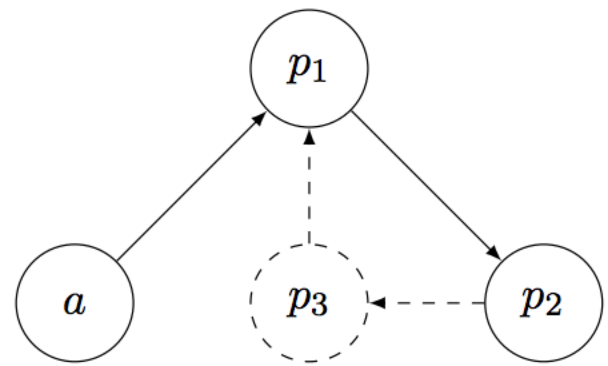
Learning Potentials

Example

$$\Theta_{\text{ALT}} = \{\text{ALT}, \text{PAIR}\};$$

$$P_{\text{ALT}} \geq P_{\text{PAIR}}$$

<a, p1, p2, p3>
will have positive utility



Experiments

Dataset: UNOS, FutureMatch vs myopic matching

Total	$\lvert V\rvert = 300$		$\lvert V\rvert = 400$		$\lvert V\rvert = 500$		$\lvert V\rvert = 600$		$\lvert V\rvert = 700$		$\lvert V\rvert = 800$		$\lvert V\rvert = 900$	
	Gain	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p
MAXCARD	+2	✓	+4	✓	+5	✓	+6	✓	+10	✓	+11	✓	+13	✓
MAXCARD-FAIR, $\beta = 1$	+1	✓	+4	✓	+6	✓	+8	✓	+9	✓	+11	✓	+12	✓
MAXCARD-FAIR, $\beta = 2$	+1		+2	✓	+3	✓	+3	✓	+5	✓	+6	✓	+10	✓
MAXCARD-FAIR, $\beta = 3$	+1		+0		+3	✓	+1		+1	✓	+3	✓	+2	
MAXCARD-FAIR, $\beta = 4$	-1		+1		+1		+1		+3	✓	+3		+2	
MAXCARD-FAIR, $\beta = 5$	+0		+0		+1		+1		+1		+2		+3	
MAXLIFE	+2	✓	+3	✓	+6	✓	+8	✓	+7	✓	+11	✓	+9	✓
Marginalized														
MAXCARD	-2	✗	-2	✗	-3	✗	-4	✗	-6	✗	-7	✗	-9	✗
MAXCARD-FAIR, $\beta = 1$	-1	✗	-1	✗	-1	✗	-2	✗	-3	✗	-3	✗	-5	✗
MAXCARD-FAIR, $\beta = 2$	+0		+0		+1	✓	+1	✓	+2	✓	+1		+1	
MAXCARD-FAIR, $\beta = 3$	+1	✓	+1	✓	+3	✓	+3	✓	+3	✓	+5	✓	+4	✓
MAXCARD-FAIR, $\beta = 4$	+1	✓	+2	✓	+3	✓	+4	✓	+4	✓	+5	✓	+5	✓
MAXCARD-FAIR, $\beta = 5$	+1	✓	+2	✓	+3	✓	+4	✓	+5	✓	+7	✓	+5	✓
MAXLIFE	-1	✗	-3	✗	-3	✗	-5	✗	-6	✗	-6	✗	-9	✗

Median gains in expected total number of transplants or marginal transplants.

Experiments

Dataset: UNOS

Total	$\|V\| = 300$		$\|V\| = 400$		$\|V\| = 500$		$\|V\| = 600$		$\|V\| = 700$		$\|V\| = 800$		$\|V\| = 900$	
	Gain	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p	*Gain*	p
MaxCard	+2	✓	+4	✓	+5	✓	+6	✓	+10	✓	+11	✓	+13	✓
MaxCard-Fair, $\beta = 1$	+1	✓	+4	✓	+6	✓	+8	✓	+9	✓	+11	✓	+12	✓
MaxCard-Fair, $\beta = 2$	+1		+2	✓	+3	✓	+3	✓	+5	✓	+6	✓	+10	✓
MaxCard-Fair, $\beta = 3$	+1		+0		+3	✓	+1		+1	✓	+3	✓	+2	
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MaxCard-Fair, $\beta = 5$	+0		+0		+1		+1		+1		+2		+3	
MaxLife	+2	✓	+3	✓	+6	✓	+8	✓	+7	✓	+11	✓	+9	✓

Marginalized														
MaxCard	-2	✗	-2	✗	-3	✗	-4	✗	-6	✗	-7	✗	-9	✗
MaxCard-Fair, $\beta = 1$	-1	✗	-1	✗	-1	✗	-2	✗	-3	✗	-3	✗	-5	✗
MaxCard-Fair, $\beta = 2$	+0		+0		+1	✓	+1	✓	+2	✓	+1		+1	
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MaxCard-Fair, $\beta = 5$	+1	✓	+2	✓	+3	✓	+4	✓	+5	✓	+7	✓	+5	✓
MaxLife	-1	✗	-3	✗	-3	✗	-5	✗	-6	✗	-6	✗	-9	✗

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	Gain	*p*	*Gain*	*p*	*Gain*	*p*	*Gain*	*p*	*Gain*	*p*	*Gain*	*p*	*Gain*	*p*
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MaxLife	+2	✓	+3	✓	+6	✓	+8	✓	+7	✓	+11	✓	+9	✓

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MaxCard-Fair, $\beta = 2$	+0		+0		+1	✓	+1	✓	+2	✓	+1		+1	
MaxCard-Fair, $\beta = 3$	+1	✓	+1	✓	+3	✓	+3	✓	+3	✓	+5	✓	+4	✓
MaxCard-Fair, $\beta = 4$	+1	✓	+2	✓	+3	✓	+4	✓	+4	✓	+5	✓	+5	✓
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MaxLife	-1	✗	-3	✗	-3	✗	-5	✗	-6	✗	-6	✗	-9	✗

Median gains in expected total number of transplants or marginal transplants.