

Extensive Games and the Sequence Form

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Overview

- Linear programming and zero-sum games
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- Extensive games
 - perfect recall and the sequence form
 - computing equilibria with the sequence form

Linear programming duality

Primal and dual linear programs

Primal LP:

$$\begin{aligned} &\text{maximize } \mathbf{c}^\top \mathbf{y} \\ &\text{subject to } \mathbf{A}\mathbf{y} \leq \mathbf{b}, \\ &\quad \mathbf{y} \geq \mathbf{0}. \end{aligned}$$

Dual LP:

$$\begin{aligned} &\text{minimize } \mathbf{x}^\top \mathbf{b} \\ &\text{subject to } \mathbf{x} \geq \mathbf{0}, \\ &\quad \mathbf{x}^\top \mathbf{A} \geq \mathbf{c}^\top. \end{aligned}$$

Primal and dual linear programs

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Weak LP duality: For any **feasible** primal \mathbf{y} , dual \mathbf{x} :

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Primal and dual linear programs

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$$(\mathbf{c}^\top)\mathbf{y} \leq (\mathbf{x}^\top \mathbf{A})\mathbf{y} = \mathbf{x}^\top(\mathbf{A}\mathbf{y}) \leq \mathbf{x}^\top(\mathbf{b})$$

Primal and dual linear programs

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Primal and dual linear programs

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Strong LP duality: If both **primal** and **dual** LP are feasible, then they have (optimal) solutions \mathbf{y} and \mathbf{x} with $\mathbf{c}^\top \mathbf{y} = \mathbf{x}^\top \mathbf{b}$.

Primal and dual linear programs

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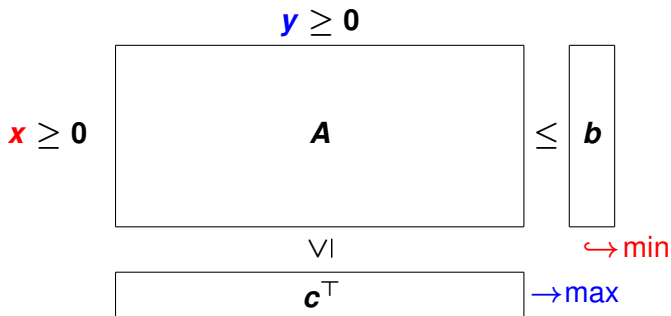
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Tucker diagram

Primal LP: maximize $\mathbf{c}^\top \mathbf{y}$ subject to $\mathbf{A}\mathbf{y} \leq \mathbf{b}$, $\mathbf{y} \geq \mathbf{0}$.

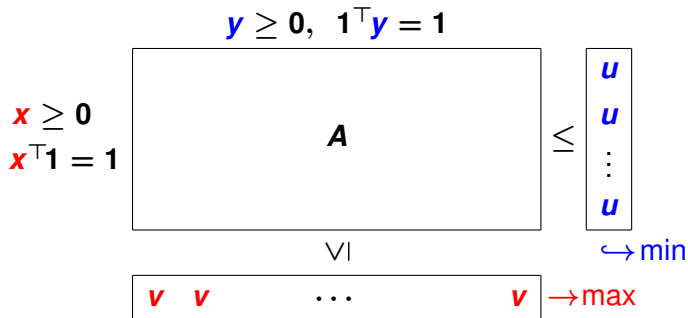
Dual LP: minimize $\mathbf{x}^\top \mathbf{b}$ subject to $\mathbf{x}^\top \mathbf{A} \geq \mathbf{c}^\top$, $\mathbf{x} \geq \mathbf{0}$.



Zero-sum game $(A, -A)$ written as general LP

Minimizer: minimize u subject to $Ay \leq \mathbf{1}u$, $y \in Y$.

Maximizer: maximize v subject to $x^T A \geq v\mathbf{1}^T$, $x \in X$.



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	$y \geq 0$		u		
$x \geq 0$	A	-1	⋮	≤	0
		-1	0		0
v	-1 ⋯ -1	0	=		-1
	∨	∥			$\hookrightarrow \min$
	0 ⋯ 0	-1			$\rightarrow \max$

Simpler LP with positive payoffs

$$\mathbf{x}^\top (\mathbf{A} + \mathbf{1}\alpha\mathbf{1}^\top) \mathbf{y} = \mathbf{x}^\top \mathbf{A} \mathbf{y} + \mathbf{x}^\top \mathbf{1} \alpha \mathbf{1}^\top \mathbf{y} = \mathbf{x}^\top \mathbf{A} \mathbf{y} + \alpha$$

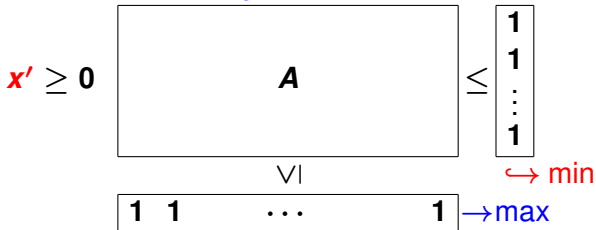
Simpler LP with positive payoffs

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\Rightarrow w.l.o.g. $\mathbf{A} > \mathbf{0}$, min-max cost $\mathbf{u} > \mathbf{0}$, max-min payoff $\mathbf{v} > \mathbf{0}$,
replace \mathbf{y} by $\mathbf{y}' = \mathbf{y} \frac{1}{\mathbf{u}}$, and \mathbf{x} by $\mathbf{x}' = \mathbf{x} \frac{1}{\mathbf{v}}$,

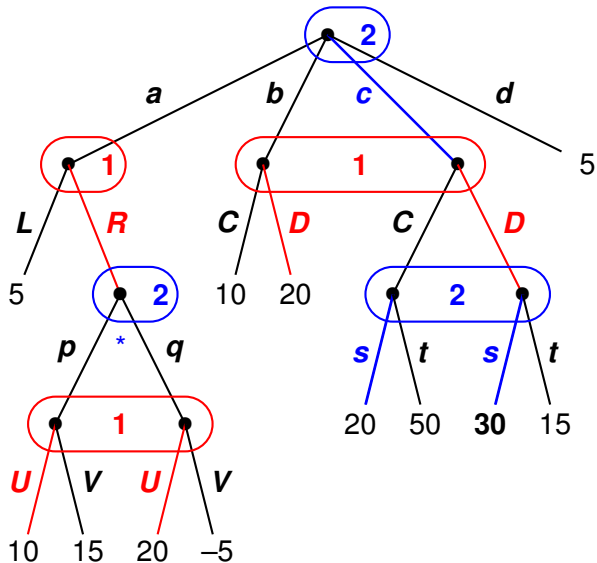
Minimizer: maximize $\mathbf{1}^\top \mathbf{y}' (= \frac{1}{\mathbf{u}})$ subject to $\mathbf{A} \mathbf{y}' \leq \mathbf{1}$,

Maximizer: minimize $\mathbf{1}^\top \mathbf{x}' (= \frac{1}{\mathbf{v}})$ subject to $\mathbf{x}'^\top \mathbf{A} \geq \mathbf{1}^\top$
 $\mathbf{y}' \geq \mathbf{0}$



Extensive Games, Sequence Form

Game tree (game in extensive form)



Strategic (or normal) form

Strategy of a player:

specifies a move for **every** information set of that player.

<i>a</i>	<i>a</i>	<i>a</i>	<i>a</i>	<i>b</i>	<i>b</i>	<i>b</i>	<i>b</i>	<i>c</i>	<i>c</i>	<i>c</i>	<i>c</i>	<i>d</i>	<i>d</i>	<i>d</i>	<i>d</i>
<i>p</i>	<i>p</i>	<i>q</i>	<i>q</i>	<i>p</i>	<i>p</i>	<i>q</i>	<i>q</i>	<i>p</i>	<i>p</i>	<i>q</i>	<i>q</i>	<i>p</i>	<i>p</i>	<i>q</i>	<i>q</i>
<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>	<i>s</i>	<i>t</i>

<i>L, U, C</i>	5	5	5	5	10	10	10	10	20	50	20	50	5	5	5	5
<i>L, V, C</i>	5	5	5	5	10	10	10	10	20	50	20	50	5	5	5	5
<i>L, U, D</i>	5	5	5	5	20	20	20	20	30	15	30	15	5	5	5	5
<i>L, V, D</i>	5	5	5	5	20	20	20	20	30	15	30	15	5	5	5	5
<i>R, U, C</i>	10	10	20	20	10	10	10	10	20	50	20	50	5	5	5	5
<i>R, U, D</i>	10	10	20	20	20	20	20	20	30	15	30	15	5	5	5	5
<i>R, V, C</i>	20	20	-5	-5	10	10	10	10	20	50	20	50	5	5	5	5
<i>R, V, D</i>	10	10	20	20	20	20	20	20	30	15	30	15	5	5	5	5

Reduced strategic form

Reduced strategy of a player:

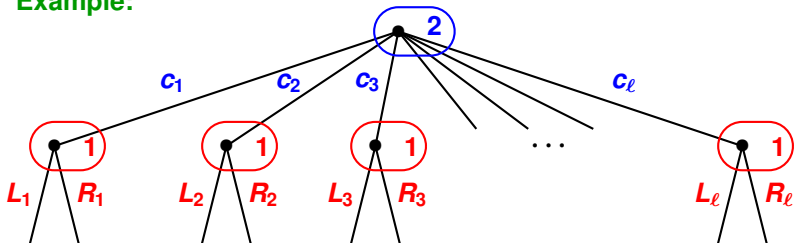
specifies a move for every information set of that player, **except** for those information sets unreachable due to an **own** earlier move (where we write * instead of a move).

	<i>a, p, *</i>	<i>a, q, *</i>	<i>b, *, *</i>	<i>c, *, s</i>	<i>c, *, t</i>	<i>d, *, *</i>
<i>L, *, C</i>	5	5	10	20	50	5
<i>L, *, D</i>	5	5	20	30	15	5
<i>R, U, C</i>	10	20	10	20	50	5
<i>R, U, D</i>	10	20	20	30	15	5
<i>R, V, C</i>	15	-5	10	20	50	5
<i>R, V, D</i>	15	-5	20	30	15	5

Exponential blowup of strategic form

number of pure strategies typically
exponential in number of information sets.

Example:



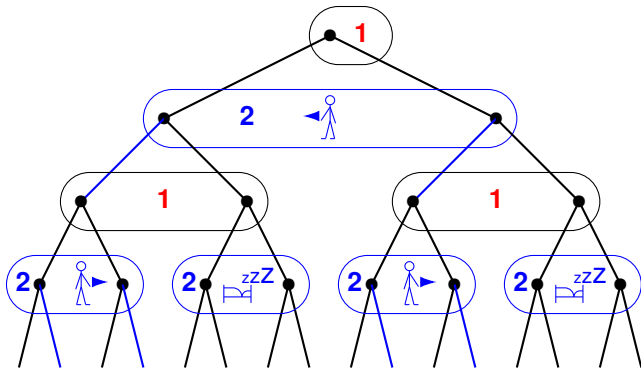
$$\begin{aligned} \text{number of information sets} &= \ell \\ \text{number of pure strategies} &= 2^\ell \end{aligned}$$

Example [Kuhn]: simplified poker game,

$$\begin{aligned} \text{number of information sets} &= \mathbf{13} \\ \text{number of pure strategies} &= \mathbf{8192} \end{aligned}$$

Exponential blowup of reduced strategic form

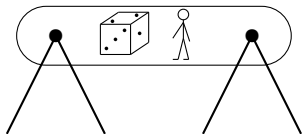
Example: Game with (1) **bounded** number of moves per node, (2) no **subgames** (otherwise simplify by solving subgames first).



This tree with n nodes: $\approx 2^{\sqrt{n}/2}$ strategies per player,
reduced strategic form still (sub-)exponential in tree size.

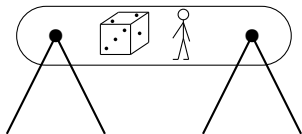
Use behavior strategies

Behavior strategy = **local** randomization



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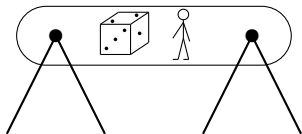


Mixed strategy too redundant, use behavior strategy instead:

- only one variable per **move**:
player 1 chooses **L** with probability X_L
player 1 chooses **R** with probability X_R . . .
player 2 chooses **a** with probability Y_a . . .
- expected payoff =
 $5 Y_a X_L + 10 Y_a X_R Y_p X_U + 15 Y_a X_R Y_p X_V + \dots$

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player 1 chooses **L** with probability X_L
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- expected payoff =
 $5 Y_a X_L + 10 Y_a X_R Y_p X_U + 15 Y_a X_R Y_p X_V + \dots$
- problem: **nonlinear**!

Variable transformation

For each **sequence** σ of moves of player 1
introduce new variable x_σ

- new variables replace products:
if $\sigma = PQRS$ then $x_\sigma = X_P X_Q X_R X_S$
- Example:

$$\begin{aligned}x_L &= X_L \\x_{RU} &= X_R X_U \\&\dots \\y_a &= Y_a \\y_{ap} &= Y_a Y_p \\&\dots\end{aligned}$$

- expected payoff = $5 x_L y_a + 10 x_{RU} y_{ap} + 15 x_{RV} y_{ap} + \dots$
is **linear** in variables of one player.

New paradigm: Sequences instead of pure strategies

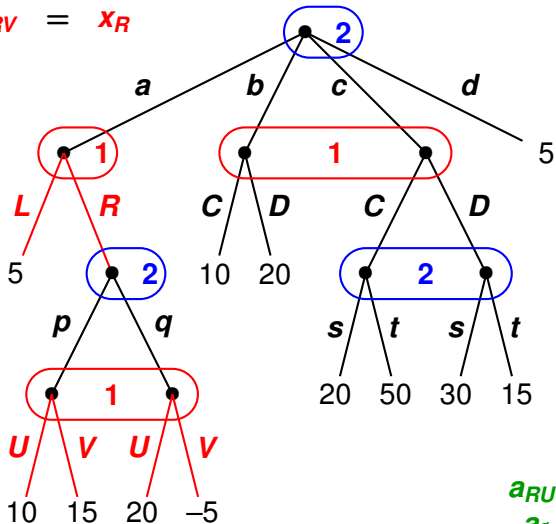
Before:

pure strategy	i
probability	x_i
mixed strategy	\mathbf{x}
characterized by	$\mathbf{1}^\top \mathbf{x} = 1$
expected payoff	$\mathbf{x}^\top \mathbf{A} \mathbf{y}$

After:

sequence	σ
realization probability	x_σ
realization plan	\mathbf{x}
characterized by	$\mathbf{E} \mathbf{x} = \mathbf{e}$
expected payoff	$\mathbf{x}^\top \mathbf{A} \mathbf{y}$

$$\begin{aligned}
 X_{\emptyset} &= 1 \\
 X_L + X_R &= X_{\emptyset} \\
 X_{RU} + X_{RV} &= X_R
 \end{aligned}$$



$$\begin{aligned}
 a_{RU,ap} &= 10 \\
 a_{\emptyset,d} &= 5 \\
 a_{RU,b} &= 0
 \end{aligned}$$

Realization plans

Realization plan $\mathbf{x} = (x_\emptyset, x_L, x_R, x_C, x_D, x_{RU}, x_{RV})$

(= vector of realization probabilities)

characterized by $\mathbf{x} \geq \mathbf{0}$ and **linear** equalities

$$x_\emptyset = 1$$

$$x_\emptyset = x_L + x_R$$

$$x_\emptyset = x_C + x_D$$

$$x_R = x_{RU} + x_{RV}$$

written as $\mathbf{E}\mathbf{x} = \mathbf{e}$ with

$$\mathbf{E} = \begin{bmatrix} 1 & & & & & & \\ -1 & 1 & 1 & & & & \\ -1 & & & 1 & 1 & & \\ & & -1 & & & 1 & 1 \end{bmatrix}, \quad \mathbf{e} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The sequence form

Payoff matrix **A**

	\emptyset	a	b	c	d	ap	aq	bs	bt
\emptyset					5				
L		5							
R									
RU						10	20		
RV						15	-5		
C			10					20	50
D			20					30	15

expected payoff $\mathbf{x}^\top \mathbf{A} \mathbf{y}$,

rows played with \mathbf{x} subject to $\mathbf{x} \geq \mathbf{0}$, $\mathbf{E} \mathbf{x} = \mathbf{e}$,

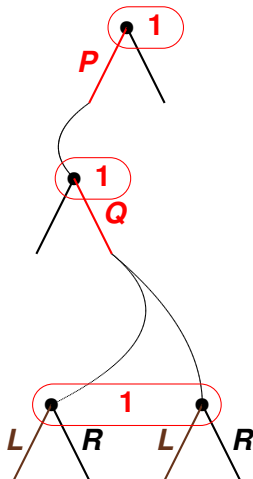
columns played with \mathbf{y} subject to $\mathbf{y} \geq \mathbf{0}$, $\mathbf{F} \mathbf{y} = \mathbf{f}$.

How to play

Given: realization plan x with $Ex = e$.

Move L is last move of **unique** sequence, say PQL , where $x_{PQL} + x_{PQR} = x_{PQ}$.

\Rightarrow behavior-probability(L) = $\frac{x_{PQL}}{x_{PQ}}$.



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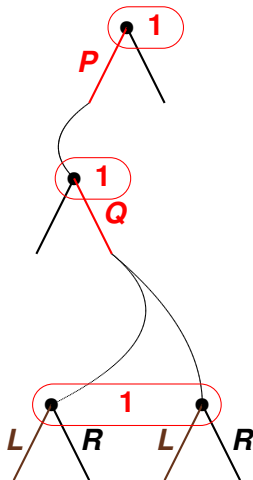
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\Rightarrow behavior-probability(L) = $\frac{x_{PQL}}{x_{PQ}}$.

Required assumption of **perfect recall**

[Kuhn 1953, Selten 1975]:

Each node in an information set is preceded by same sequence, here PQ , of the player's **own** earlier moves.



Solving the Sequence Form: Constrained Games

Constrained games

Polyhedrally constrained game:

Player 1's strategy set

$$X = \{x \in \mathbb{R}^m \mid Ex = e, x \geq 0\}$$

e.g. $E = [1 \ 1 \ \dots \ 1]$, $e = 1$: strategy **simplex**

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Player 2's strategy set

$$Y = \{y \in \mathbb{R}^n \mid Fy = f, y \geq 0\}$$

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Player 2's strategy set

$$Y = \{y \in \mathbb{R}^n \mid Fy = f, y \geq 0\}$$

payoff matrices A, B ,

expected payoffs $x^\top Ay, x^\top By$ for $(x, y) \in X \times Y$.

Best responses in a constrained game

\mathbf{x} in \mathbf{X} best response against \mathbf{y} in \mathbf{Y} : solves primal LP

$$\begin{aligned} &\text{maximize} && \mathbf{x}^\top (\mathbf{A}\mathbf{y}) \\ &\text{subject to} && \mathbf{E}\mathbf{x} = \mathbf{e} \\ &&& \mathbf{x} \geq \mathbf{0} \end{aligned}$$

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Dual LP (with same value, = best response payoff to player 1):

$$\begin{aligned} & \text{minimize} && \mathbf{e}^\top \mathbf{u} \\ & \text{subject to} && \mathbf{E}^\top \mathbf{u} \geq \mathbf{A}\mathbf{y} \end{aligned}$$

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\mathbf{x}, \mathbf{u} optimal \Leftrightarrow complementary slackness:

$$\mathbf{x}^\top (\mathbf{E}^\top \mathbf{u} - \mathbf{A}\mathbf{y}) = 0$$

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\mathbf{x}, \mathbf{u} optimal \Leftrightarrow complementary slackness:

$$\mathbf{x}^\top (\mathbf{E}^\top \mathbf{u} - \mathbf{A}\mathbf{y}) = \mathbf{0}$$

= best-response condition (only pure best responses can have positive probability)

Constrained zero-sum games

[Charnes 1953] Let $B = -A$.

For $y \in Y$, best-response payoff to player 1 = value of LP

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equals value of dual LP

$$\begin{aligned} & \text{minimize} && \mathbf{e}^\top \mathbf{u} \\ & \text{subject to} && \mathbf{E}^\top \mathbf{u} \geq \mathbf{A}y \end{aligned}$$

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which is also minimized by player 2 for $y \in Y$, i.e. as solution to

$$\begin{aligned} & \text{minimize} && \mathbf{e}^\top \mathbf{u} \\ & \text{subject to} && \mathbf{E}^\top \mathbf{u} - \mathbf{A}y \geq \mathbf{0} \\ & && \mathbf{F}y = \mathbf{f} \\ & && y \geq \mathbf{0}. \end{aligned}$$

Example

1) Best-response LP

$$\begin{aligned} \max_{\mathbf{x}} \quad & \mathbf{x}^\top (\mathbf{A}\mathbf{y}) \\ \text{subject to} \quad & \mathbf{E}\mathbf{x} = \mathbf{e} \\ & \mathbf{x} \geq \mathbf{0} \end{aligned}$$

$$\begin{array}{l} \mathbf{x}_0 \\ \mathbf{x}_L \\ \mathbf{x}_R \\ \mathbf{x}_C \\ \mathbf{x}_D \end{array} \geq \mathbf{0} \quad \left[\begin{array}{ccc|c} 1 & -1 & -1 & 0 \\ & 1 & & 2 \\ & 1 & & 2 \\ & & 1 & 1 \\ & & 1 & 0 \end{array} \right] \begin{array}{l} \\ \\ \\ \\ \downarrow \\ \text{max} \end{array}$$

$$\left[\begin{array}{ccc} 1 & 0 & 0 \end{array} \right]$$

2) dual LP

$$\begin{aligned} \min_{\mathbf{u}} \quad & \mathbf{e}^\top \mathbf{u} \\ \text{subject to} \quad & \mathbf{E}^\top \mathbf{u} \geq \mathbf{A}\mathbf{y} \end{aligned}$$

$$\begin{array}{l} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \mathbf{u}_2 \end{array} \quad \left[\begin{array}{ccc|c} 1 & -1 & -1 & 0 \\ & 1 & & 2 \\ & 1 & & 2 \\ & & 1 & 1 \\ & & 1 & 0 \end{array} \right] \geq \left[\begin{array}{c} 0 \\ 2 \\ 2 \\ 1 \\ 0 \end{array} \right]$$

$$\left[\begin{array}{ccc} 1 & 0 & 0 \end{array} \right] \rightarrow \min$$

2) dual LP

$$\begin{aligned} \min_{\mathbf{u}} \quad & \mathbf{e}^T \mathbf{u} \\ \text{subject to} \quad & \mathbf{E}^T \mathbf{u} \geq \mathbf{A} \mathbf{y} \end{aligned}$$

$$\begin{array}{ccc|c} u_0 & u_1 & u_2 & \\ \hline 1 & -1 & -1 & 0 \\ & 1 & & 2 \\ & 1 & & 2 \\ & & 1 & 1 \\ & & 1 & 0 \end{array} \geq$$

$$\boxed{1 \ 0 \ 0} \rightarrow \min$$

3) Treat \mathbf{y} as a variable:

$$\begin{aligned} \min_{\mathbf{u}, \mathbf{y}} \quad & \mathbf{e}^T \mathbf{u} \\ \text{subject to} \quad & \mathbf{E}^T \mathbf{u} \geq \mathbf{A} \mathbf{y} \\ & \mathbf{F} \mathbf{y} = \mathbf{f} \\ & \mathbf{y} \geq \mathbf{0} \end{aligned}$$

$$\begin{array}{ccc|ccc|c} u_0 & u_1 & u_2 & y_0 & y_a & y_b & y_c \geq 0 & \\ \hline 1 & -1 & -1 & & & & & \\ & 1 & & 6 & 0 & & & \\ & 1 & & 2 & 4 & & & \\ & & 1 & & & & 3 & \\ & & 1 & & & & 0 & \\ \hline & & & 1 & & & & 1 \\ & & & -1 & 1 & 1 & 1 & 0 \end{array} \geq =$$

$$\boxed{1 \ 0 \ 0} \rightarrow \min$$

Linear size instead of exponential size

Input: 2-player game tree with perfect recall.

Theorem [Romanovskii 1961], [von Stengel 1996]

A zero-sum game is solved via an LP of linear size:

$$\begin{array}{ll} \text{minimize} & \mathbf{e}^\top \mathbf{u} \\ \text{subject to} & \mathbf{E}^\top \mathbf{u} - \mathbf{A}\mathbf{y} \geq \mathbf{0} \\ & \mathbf{F}\mathbf{y} = \mathbf{f} \\ & \mathbf{y} \geq \mathbf{0}. \end{array}$$

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Theorem [Koller / Megiddo / von Stengel 1996]

A non-zero-sum game is solved via an LCP of linear size. One equilibrium is found by Lemke's algorithm.

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Theorem [Koller / Megiddo / von Stengel 1996]

A non-zero-sum game is solved via an LCP of linear size. One equilibrium is found by Lemke's algorithm.

[von Stengel / Elzen / Talman, *Econometrica* 2002]

This algorithm mimicks the **Harsanyi-Selten tracing procedure** and finds a normal-form perfect equilibrium.

(Allows variation of **starting vector** or **prior**.)

