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A SIMPLE ONLINE FAIR DIVISION PROBLEM

arXiv:1903.10361

ONLINE FAIR DIVISION PROBLEMS

- ▶ **Objects arrive sequentially and to be allocated on the spot**

allocating profitable jobs (Uber), resources in cloud computing, food in a foodbank, tasks within a firm, refugees to localities

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OUR QUESTION:

- A. optimal rules: **Welfare maximization** under the condition of **Fairness on average**
- B. **dependence** on the **information** available to the rule

COMPARING TO THE LITERATURE

Economics. Welfare implications of congestion, signalling, and strategizing on dynamic matching markets:

- ▶ **Unver (2010)** «Dynamic kidney exchange» *RevEconStud*,
- ▶ **Bloch, Cantala (2017)** «Dynamic Assignment of Objects to Queuing Agents» *AmerEconJ*
- ▶ **Akbarpour, Li, Gharan (2014)** «Dynamic Matching Market Design» *arXiv*
- ▶ **Ashlagi, Braverman, Kanoria, Shi (2017)** «Clearing matching markets efficiently: informative signals and match recommendations» *ManagementSci*
- ▶ **Ashlagi, Burq, Jaillet, Saberi (2018)** «Maximizing Efficiency in Dynamic Matching Markets» *arXiv*

AGENTS ALSO ARRIVE ONLINE AND
BRING GOODS

Computer Science. Fairness without efficiency:

- ▶ **Walsh (2011)** «Online cake cutting» *Lect.Notes in CS*
- ▶ **Aleksandrov, Aziz, Gaspers, Walsh (2015)** «Online Fair Division: Analysing a Food Bank Problem» *IJCAI*
- ▶ **Kash, Procaccia, Shah (2014)** «No Agent Left Behind: Dynamic FD of Multiple Resources» *J.Art.Intell*
- ▶ **Benade, Kazachkov, Procaccia, Psomas (2018)** «How to Make Envy Vanish Over Time» *EC-18*

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 - ▶ **PIR** are almost as efficient as **PDR**
 - ▶ **history-dependent rules** can only give a **tiny gain** compared to **PIR**
- a by -product:
first exact values of **PoF**
for **offline cake-cutting**
and **bargaining**

THE MODEL: FAIR DIVISION OF ONE RANDOM GOOD

One random good g is to be allocated to agents $i = 1, 2, \dots, n$

Vector of values $v = (v_i)_{i=1..n} \in \mathbb{R}_+^n$ has arbitrary distribution P

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A Prior-Independent rule φ does not depend* on P

*note that prior free rule «knows» the expected value of v_i

PRIOR-INDEPENDENT RULES

THE UTILITARIAN RULE

allocates g to an agent with highest \mathcal{V}_i :

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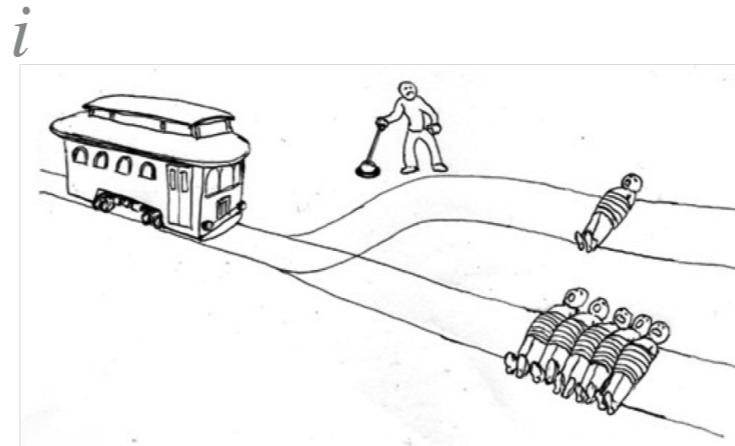
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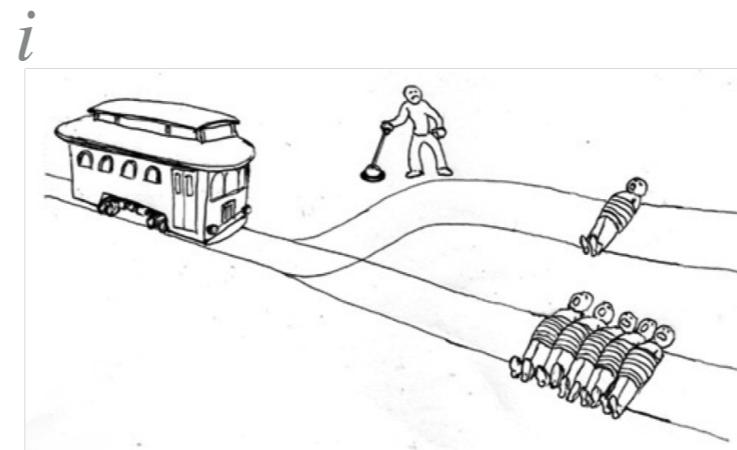
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Example:

	$p=0.99$	$p=0.01$
v_1	1	1
v_2	1.01	0.01

Agent 1 receives g with probability 0.01 and his expected value $V_1 = \mathbb{E}v_1\varphi_1(v) = 0.01 \cdot 1 = 0.01$

EXAMPLES OF RULES

FAIRNESS



FAIR SHARE GUARANTEE AKA EQUAL SPLIT LOWER BOUND

For any distribution P and any agent i

$$\mathbb{E} v_i \varphi_i(v) \geq \frac{1}{n}$$

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$$\varphi_i(v) = \frac{v_i}{\sum_{j=1}^n v_j}$$

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INTERSTOCK/ALAMY STOCK PHOTO

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Idea of the proof ($n=2$):

- want to prove $\mathbb{E}\frac{v_1^2}{v_1 + v_2} \geq \frac{1}{2}$ and know that $\mathbb{E}v_1 = \mathbb{E}v_2 = 1$
- there is a linear lower bound $\frac{v_1^2}{v_1 + v_2} \geq \frac{3}{4}v_1 - \frac{1}{4}v_2$
- take expectation from both sides.

THE MOST EFFICIENT FAIR RULE FOR TWO AGENTS

- ▶ **Ex-post welfare domination:**

$$\varphi \geqslant \psi \Leftrightarrow \forall v \quad \sum_i v_i \varphi_i(v) \geq \sum_i v_i \psi_i(v)$$

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For two agents, there exists a fair symmetric rule φ that dominates any other symmetric fair rule.

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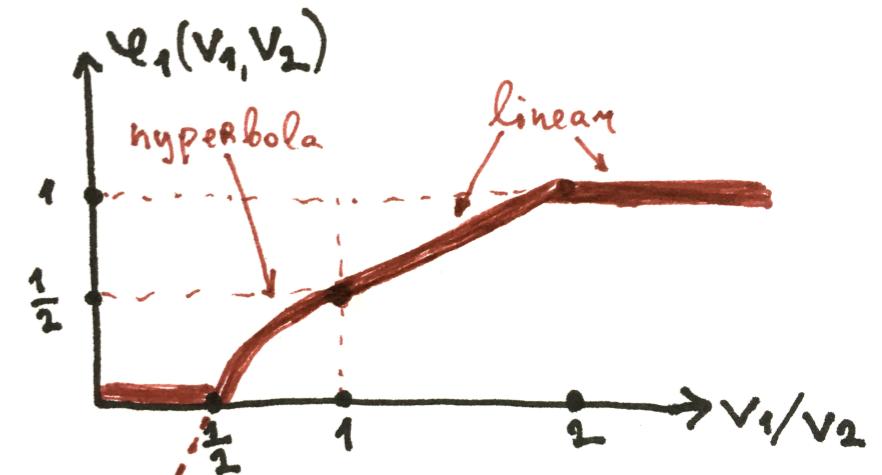
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► The Top-Heavy (TH) rule (n=2):

$$\varphi_1(v_1, v_2) = 1 - \varphi_2(v_1, v_2) = \begin{cases} 0 & \frac{v_1}{v_2} \leq \frac{1}{2} \\ 1 & \frac{v_1}{v_2} \geq 2 \\ 1 - \frac{1}{2} \frac{v_2}{v_1} & \frac{v_1}{v_2} \in [\frac{1}{2}, 1] \\ \frac{1}{2} \frac{v_1}{v_2} & \frac{v_1}{v_2} \in [1, 2] \end{cases}$$



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$$\mathbb{E}f(\xi) \geq 0 \text{ for any } \xi : \mathbb{E}\xi = 0 \iff f(x) \geq ax \text{ for some } a$$

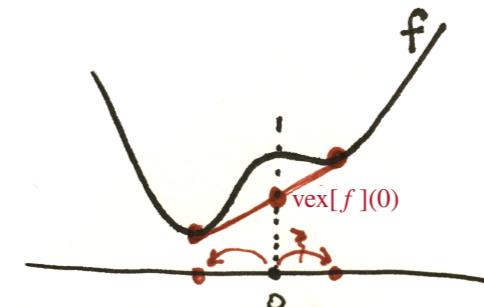
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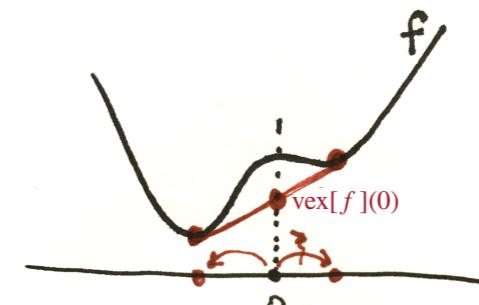
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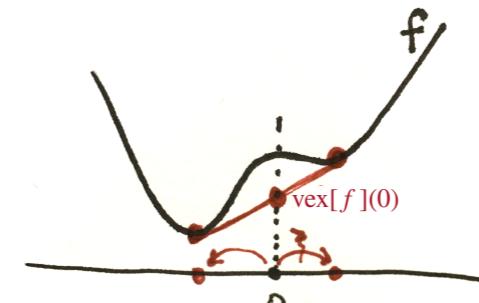
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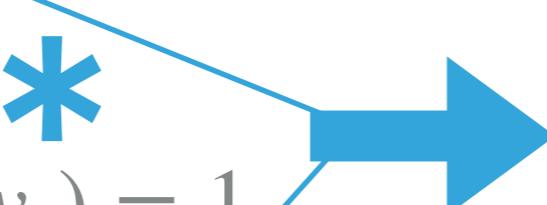
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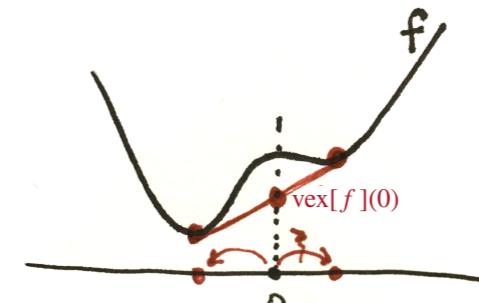
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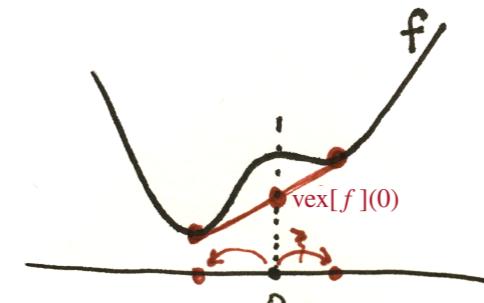
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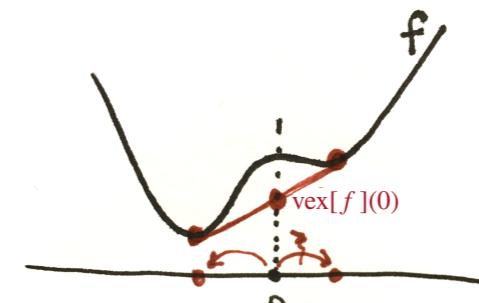
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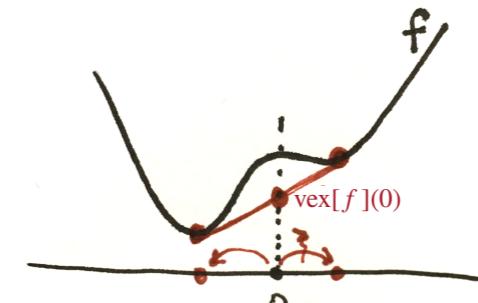
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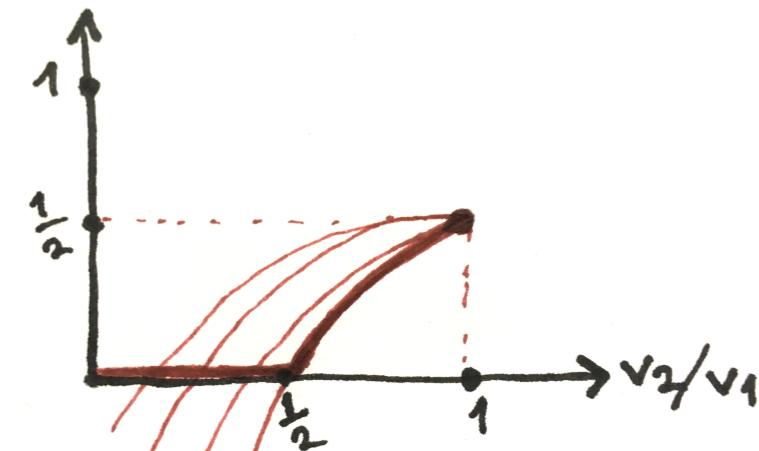
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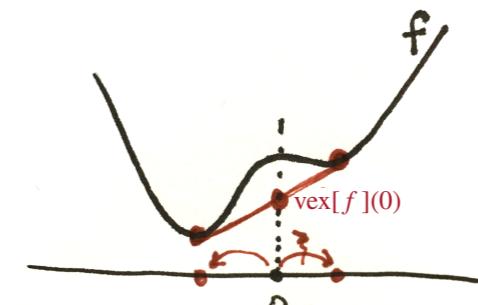
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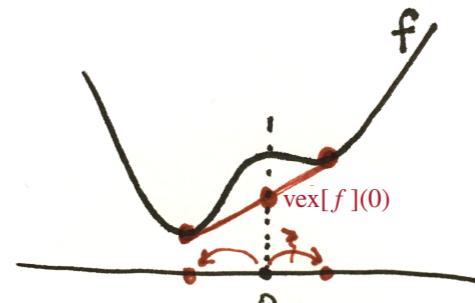
By convexity $\text{vex}[f](x) \geq \text{vex}[f](0) + ax$

COROLLARY: $\mathbb{E}v_1\varphi_1(v) \geq \frac{1}{2} \iff v_1\varphi_1(v) \geq \alpha v_1 + \beta v_2 + \gamma, \quad \alpha + \beta + \gamma \geq \frac{1}{2}$

► Symmetry

*

► $\varphi_1(v_1, v_2) + \varphi_2(v_1, v_2) = 1$



CRITERION OF FAIRNESS

$$\varphi_1(v) \geq \frac{1+\theta}{2} - \frac{\theta}{2} \frac{v_2}{v_1}, \quad \theta \in [0,1]$$

TH RULE: SELECT φ_1 AS SMALL AS POSSIBLE FOR $v_1 < v_2$

► Lower bound decreases in θ for $v_1 < v_2$

► Define $\varphi_1(v) = \left(1 - \frac{1}{2} \frac{v_2}{v_1}\right)_+$, $v_1 < v_2$

► Extend by *

BY THE CONSTRUCTION

TH gives less to the low-value agent than any other fair rule \Rightarrow domination

MORE THAN TWO AGENTS

► generalised TH rule:

$$v_i \neq \max_j v_j \Rightarrow \varphi_i(v) = \left(\frac{1}{n} + \frac{1}{(n-1)} \left(1 - \frac{\sum_j v_j}{n \cdot v_i} \right) \right)_+$$

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Remark: for bads, the dominating Bottom-Heavy rule is unique.

WORST-CASE TRADEOFF BETWEEN EFFICIENCY AND FAIRNESS

PRICE OF FAIRNESS

Bertsimas et. al (2011) The Price of Fairness.
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$$n = 2 : \quad \text{PoF} = \sqrt{2} - \frac{1}{2} = 0.914214$$

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Proof:

- ▶ $\text{PoF} = \rho[TH]$
- ▶ $\rho[TH] = \min_{v \in \mathbb{R}_+^n} \frac{\langle v, \varphi(v) \rangle}{\max_i v_i}$
- ▶ Painful computations

PRIOR-DEPENDENT RULES

NOW THE RULE KNOWS P

LINKS WITH OFFLINE PROBLEMS: CAKE-CUTTING AND BARGAINING

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► The set of feasible utilities

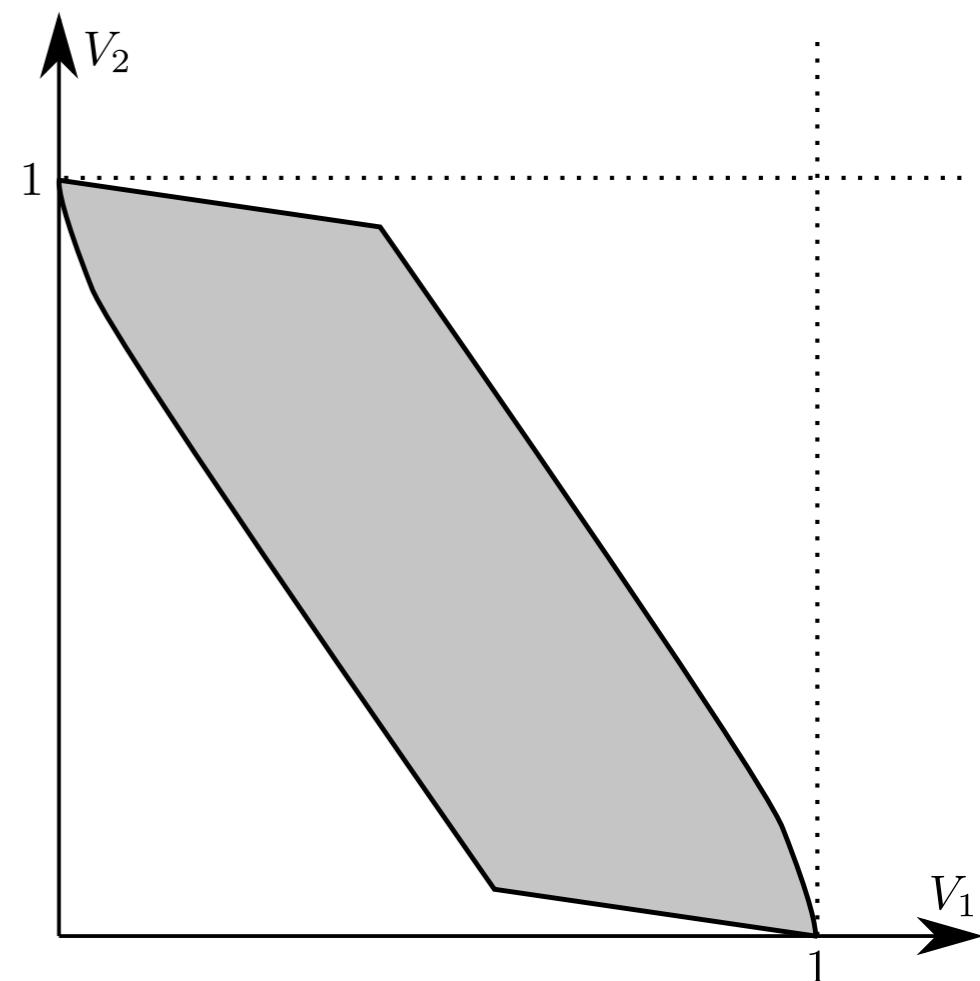
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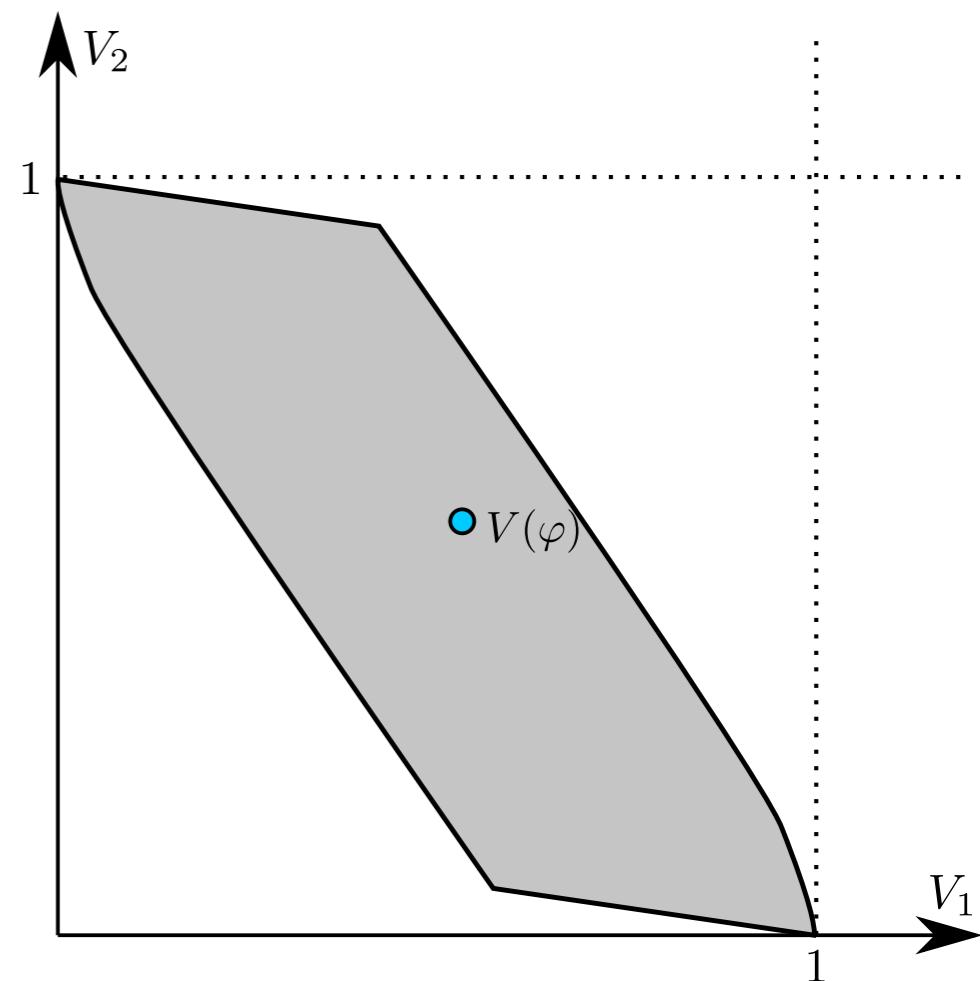
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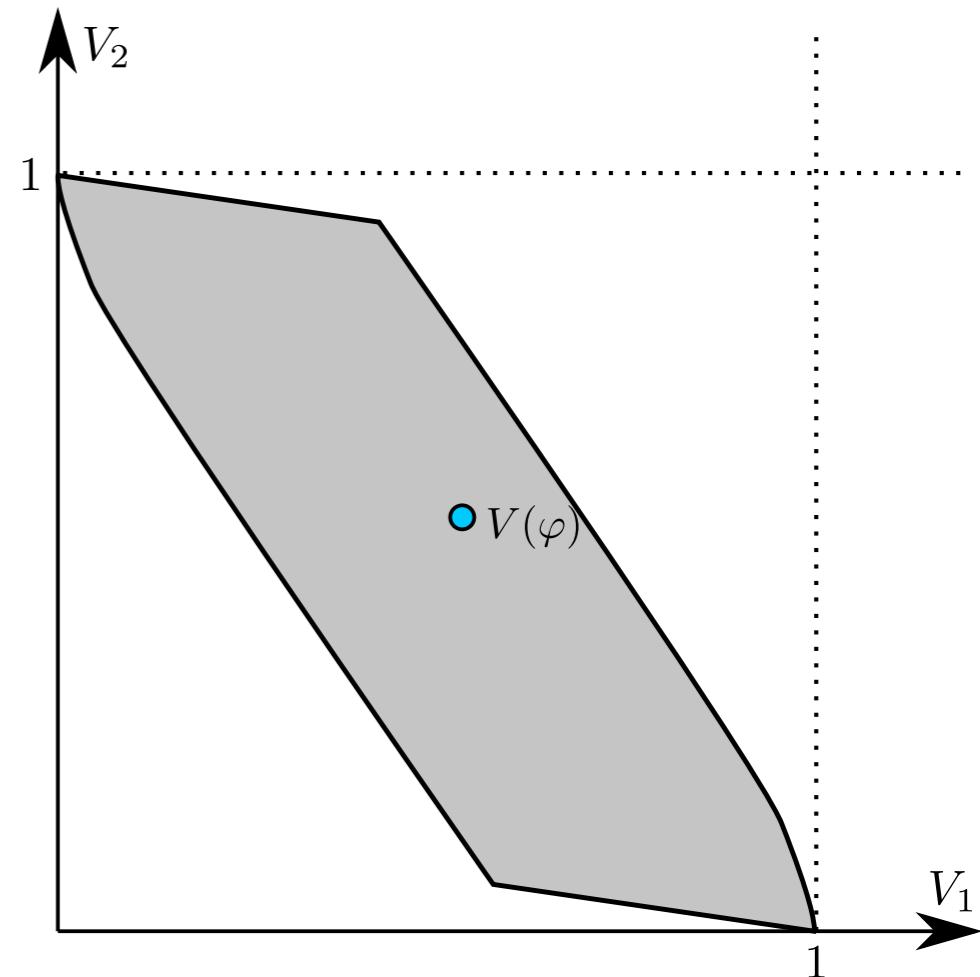
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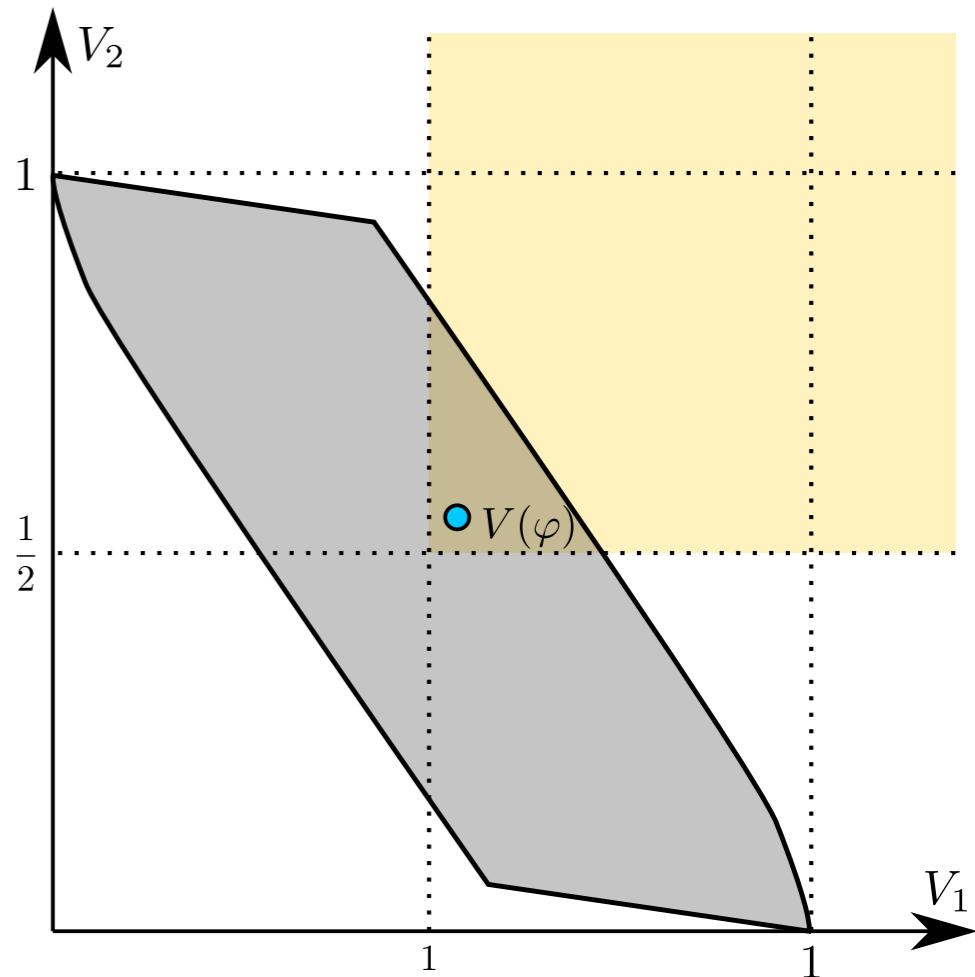
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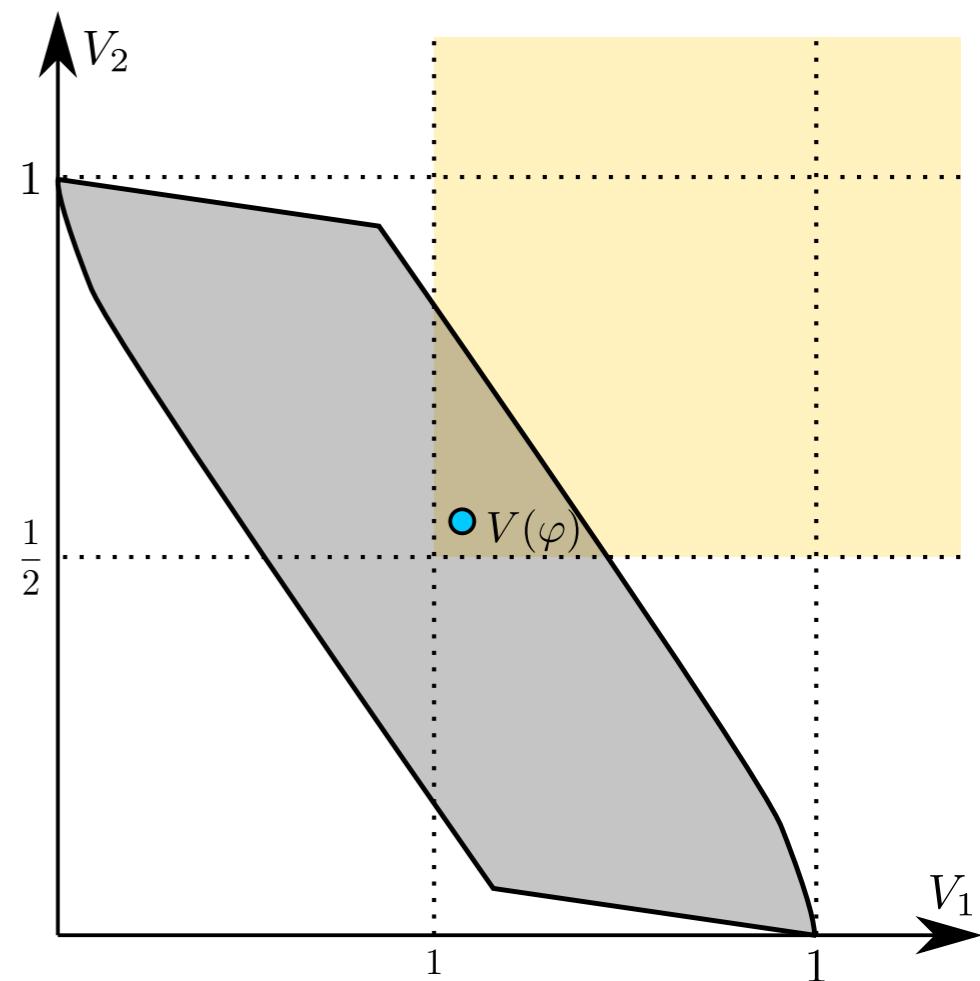
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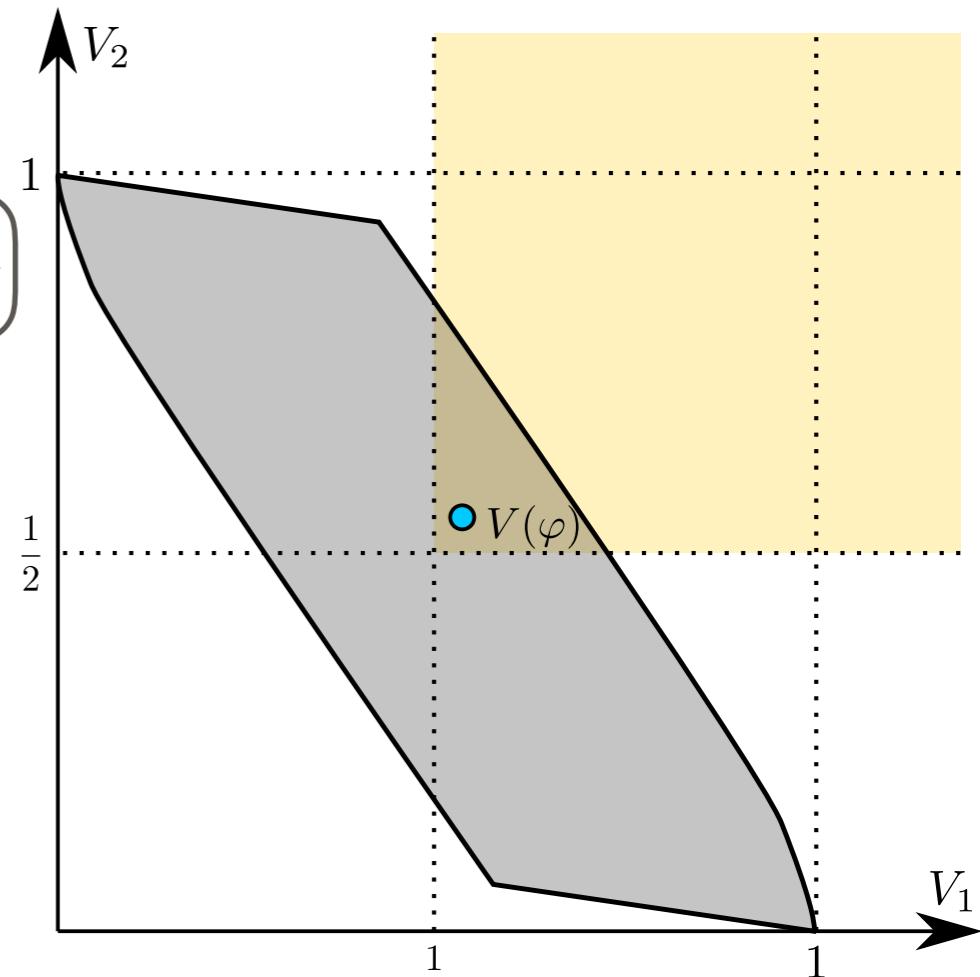
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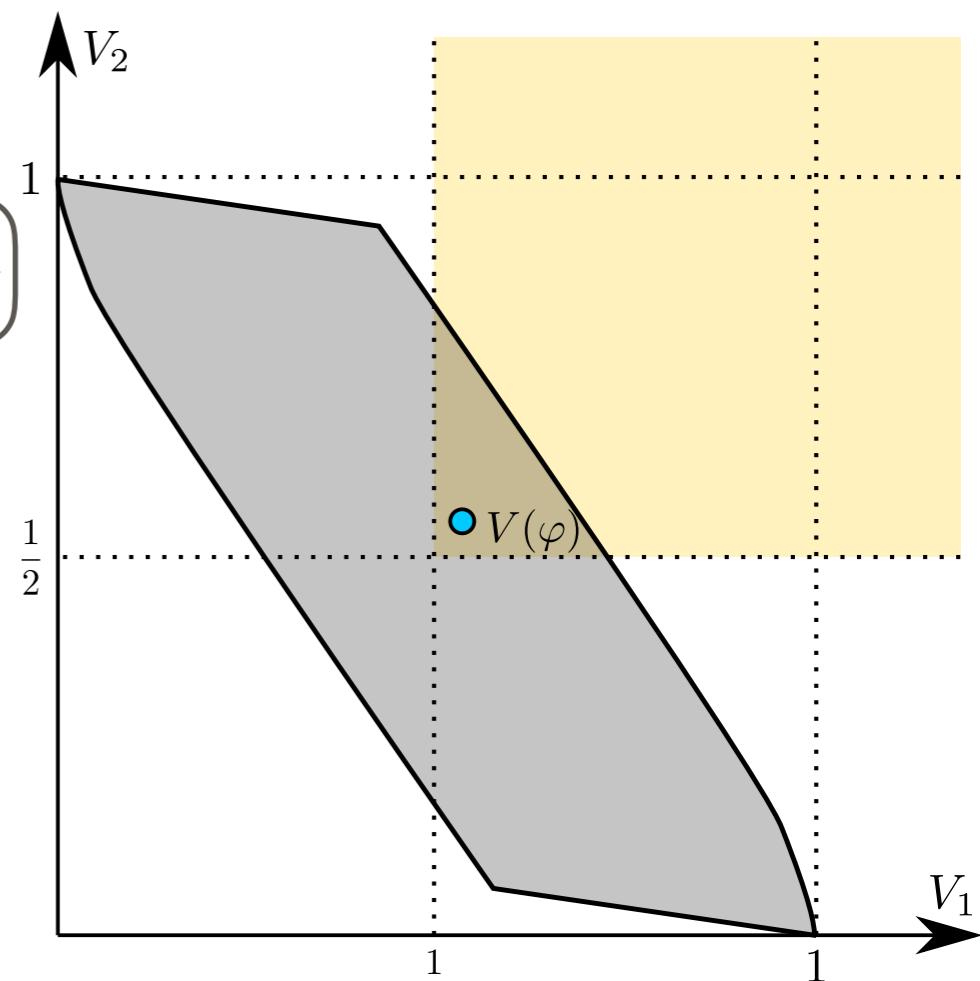
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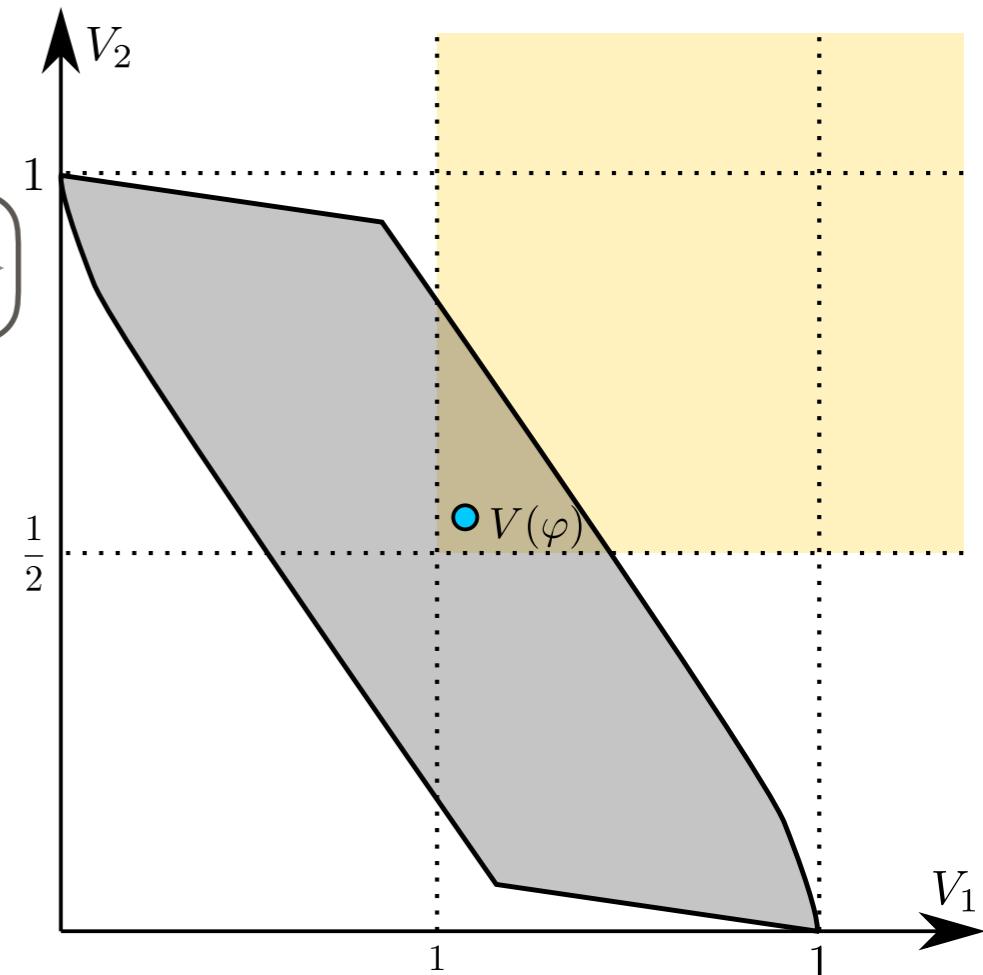
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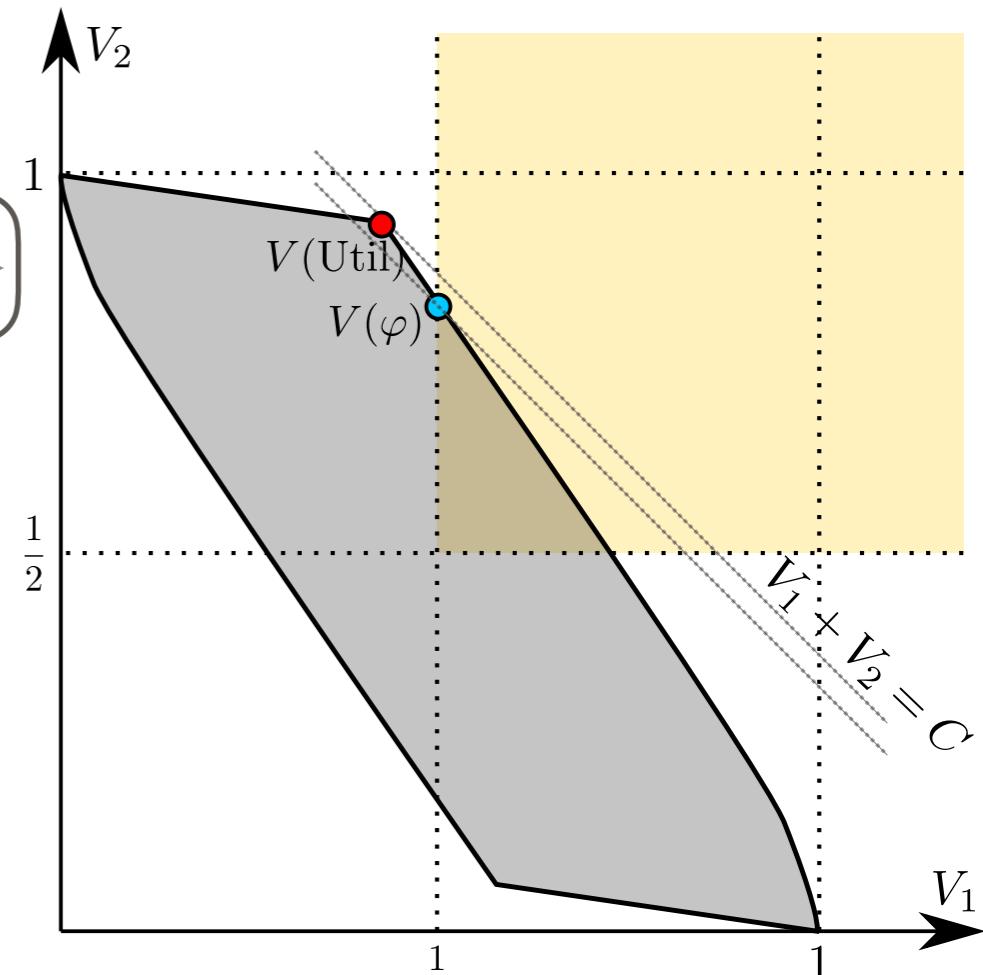
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PRICE OF FAIRNESS AND THE MOST EFFICIENT FAIR RULE

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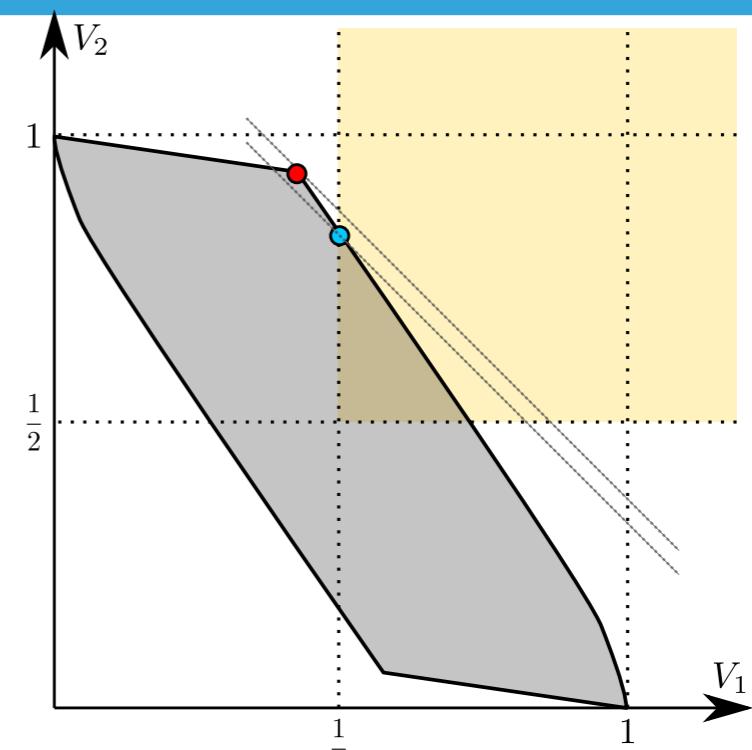
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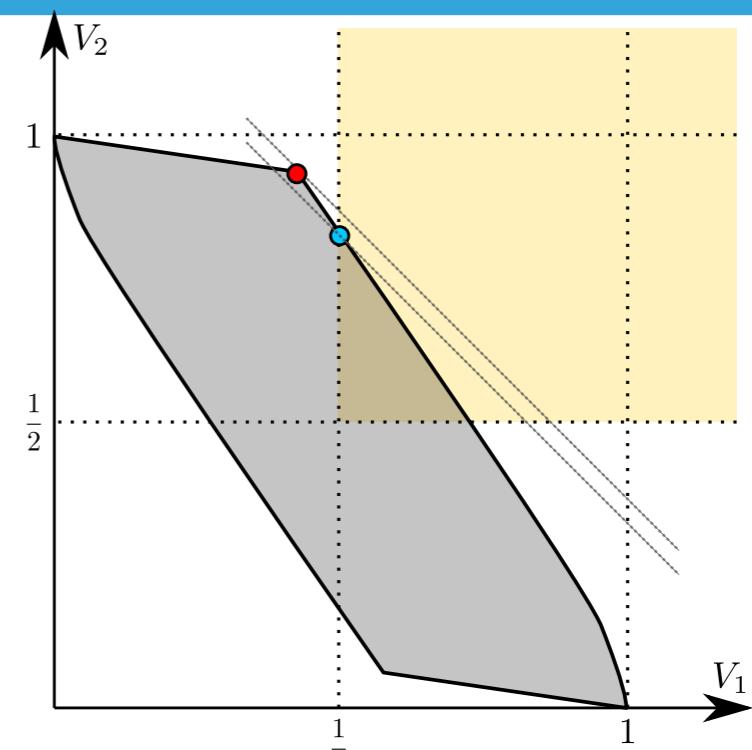
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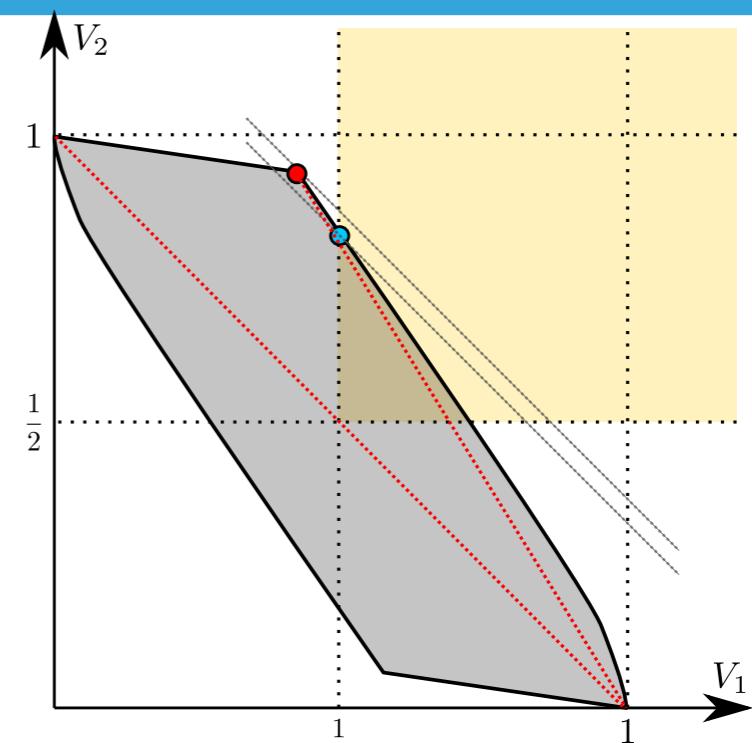
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PRICE OF FAIRNESS AND THE MOST EFFICIENT FAIR RULE

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$$\text{PoF}_{\text{PriorDep}} = \text{PoF}_{\text{Cake}} = \text{PoF}_{\text{Bargain}} =$$

$$\left\{ \begin{array}{ll} \frac{2 + \sqrt{3}}{4} = 0.933013 & n = 2 \\ \\ \min_{1 \leq m \leq n-1} \left\{ \frac{m}{n} + \frac{1}{m} \right\} - \frac{1}{n} & n \geq 3 \end{array} \right.$$

Nash rule: $\prod V_i \rightarrow \max$

Bertsimas et al. (2011)

$\rho[\text{Nash}]$: same numbers
for $n = k^2$

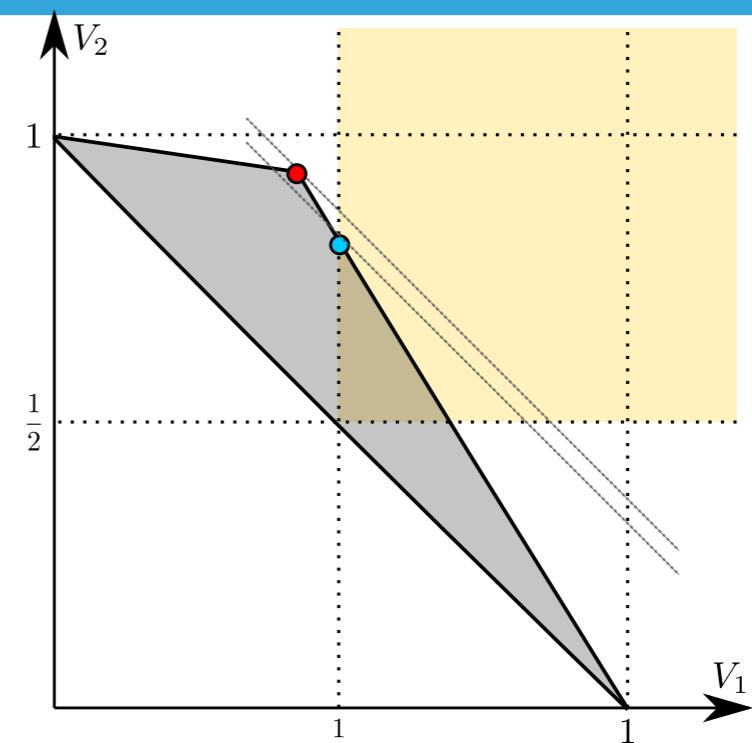
COROLLARY

Nash rule is the most
efficient among fair!

Proof of theorem:

$$\text{PoF}_{\text{Bargain}} = \inf_F \frac{\max_{V \in F \cap \left\{ V \geq \frac{1}{n} \right\}} \sum_i V_i}{\max_{V \in F} \sum_i V_i}$$

$$\inf_F = \min_{F=F(x)} , \quad F(x) = \text{conv}[x, (e_i)_{i=1}^n]$$



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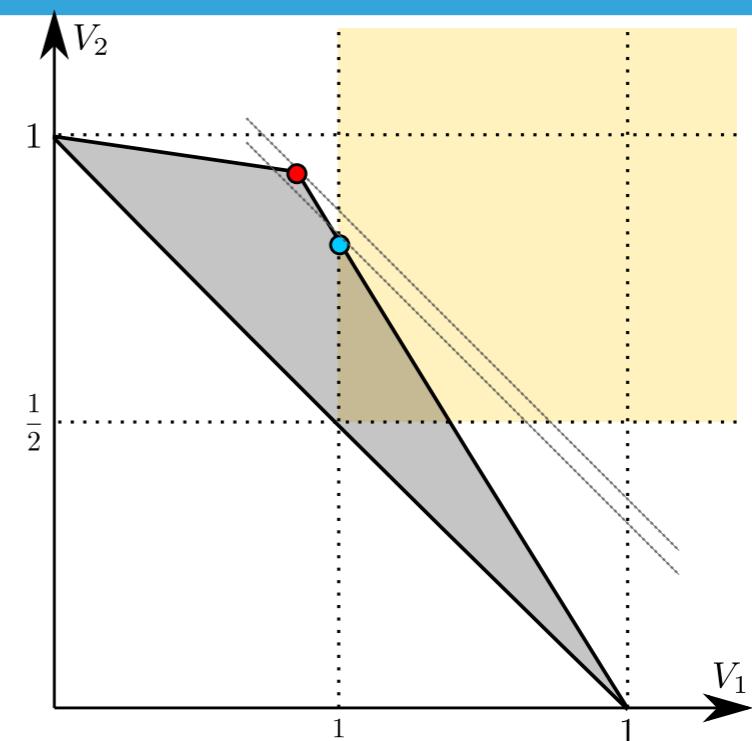
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painful finite-dimensional optimisation



SUMMARY

Prior-Independent: high worst-case efficiency without learning by prior-free mechanisms: simple and robust. Proportional rule is good, TH is the best.

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Thank you! Questions?