Private Private Information arXiv:2112.14356

Kevin He **Fedor Sandomirskiy** Omer Tamuz USC Theory Seminar, January 24 2022

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- A joint distribution \mathbb{P} over $(\omega, s_1, ..., s_n)$ defines the **private** information structure

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 - s_1 contains info about s_2 , so P2's info not fully private

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A *private* private information structure is one where the signals $(s_1, ..., s_n)$ are independent.

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 - We focus on this tension and study how informative private private signals can be

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- Privacy \simeq demographic parity w.r.t. a protected trait s_1 in fair machine learning
 - Barocas, Hardt, Narayanan. Fairness in machine learning. NeurIPS tutorial 2017

Other occurrences of private private signals

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- Worst-case information structures in robust mechanism design:
 - Bergemann, Brooks, Morris First-price auctions with general information structures:Implications for bidding and revenue Econometrica 2017
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- Feasible joint distributions of posterior beliefs
 - Arieli, Babichenko, Sandomirskiy, Tamuz Feasible joint posterior beliefs Journal of Political Economy 2021

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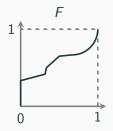
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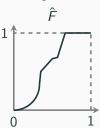
A private private structure is **Pareto optimal** if it is not dominated by another private private structure.

• Let F be a cdf of a distribution on [0,1] with mean p

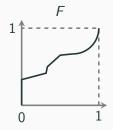
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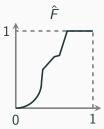
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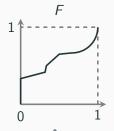
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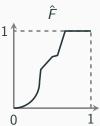




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Theorem 1

For n = 2, a private private info structure is Pareto optimal if and only if the belief distributions induced by s_1 and s_2 are conjugates.

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For any given (ω, s_1) , the optimal s_2 is unique, i.e., s_2 dominates any other s_2' independent of s_1 . Belief distributions induced by s_1 and s_2 are conjugates.

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- For ≥ 3 states ω , there may be a continuum of optimal s_2

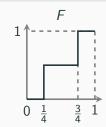
Example

- $\omega \in \{\ell, h\}$ is a job fit
- $s_1 \in \{y, n\}$ presence of a medical condition (yes/no)
- $\mathbb{P}(\omega = h) = \mathbb{P}(s_1 = y) = 1/2$
- $\mathbb{P}(\omega = h \mid s_1 = y) = \frac{3}{4}, \quad \mathbb{P}(\omega = h \mid s_1 = n) = \frac{1}{4}$
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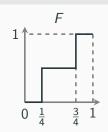


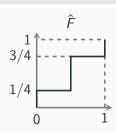
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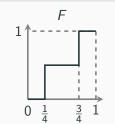


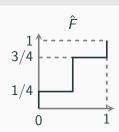


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 - A structural result: private private structures ↔ subsets of [0, 1]ⁿ
 - Results from mathematical tomography

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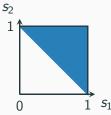
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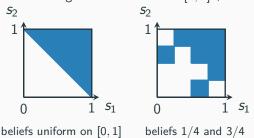
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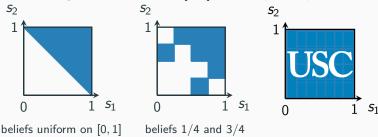


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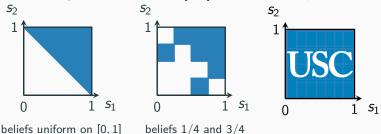
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Proposition

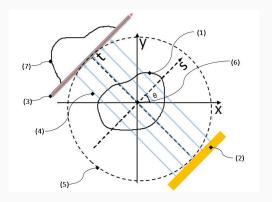
Any private private info structure is equivalent to a structure associated with some $A \subseteq [0,1]^n$

Tomography

• **Tomography** is an imaging technique that investigates the shape of an object by running x-ray through it

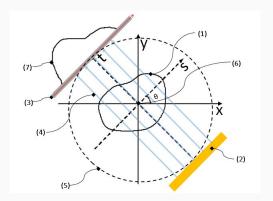
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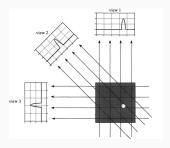
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 Produces a lower-dimensional projection of the object by looking at how much x-ray is absorbed at different points

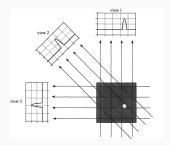
Tomography and Sets of Uniqueness

• Typically, must run x-ray from many different angles to get a good understanding of the object's geometry



Tomography and Sets of Uniqueness

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Definition

 $A \subseteq [0,1]^n$ is a **set of uniqueness** if it is determined by its n coordinate projections, i.e., for any A' such that the uniform density on A and A' has the same one-dimensional marginals, A' = A a.e. in $[0,1]^n$.

Theorem 2

For any $n \ge 2$, a private private info structure is Pareto optimal \Leftrightarrow it is equivalent to a structure associated with a set of uniqueness $A \subseteq [0,1]^n$.

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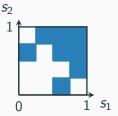
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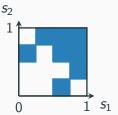


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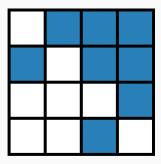
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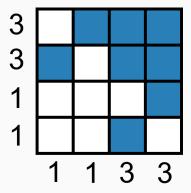
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• Hence, the blue area not a set of uniqueness. Let's check!

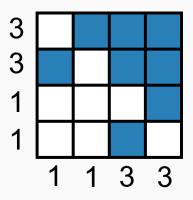
Problem for a newspaper puzzle column: is there another coloring of the 4x4 grid that preserves all column-wise and row-wise counts of colored squares?

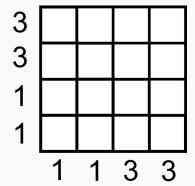


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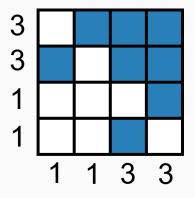


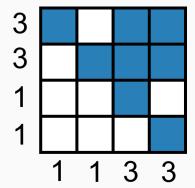
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- Use results about sets of uniqueness from tomography

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• Additive implies upward closed, equivalent if n = 2

Theorem (Fishburn, Lagarias, Reeds, and Shepp 1990)

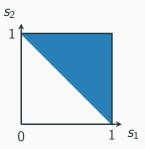
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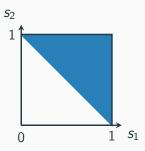
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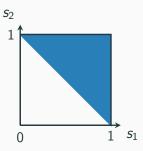


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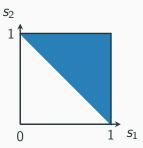
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Fishburn et al.'s theorem & our Theorem $2 \Rightarrow$

- For n = 2, characterization of Pareto optimality via conjugate distributions (Theorem 1)
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Connecting Pareto Optimality with Tomography

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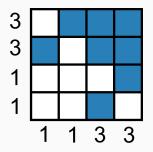
Key idea: A is not a set of uniqueness \Rightarrow the associated structure is dominated and the dominating structure can be constructed explicitly

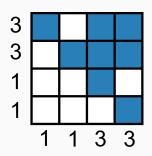
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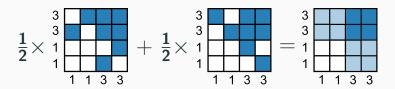
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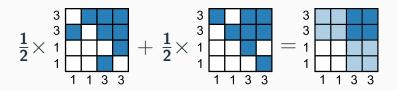
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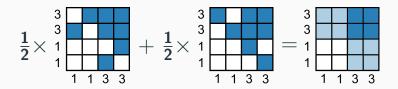




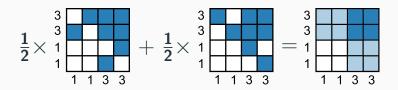




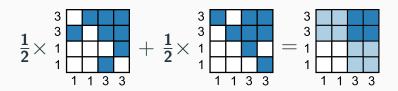
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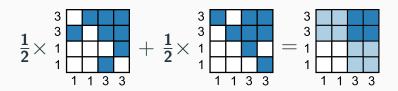
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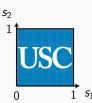


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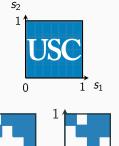
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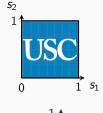
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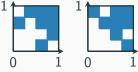






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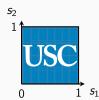


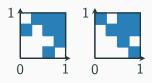


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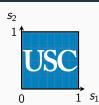


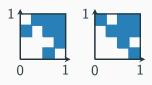
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