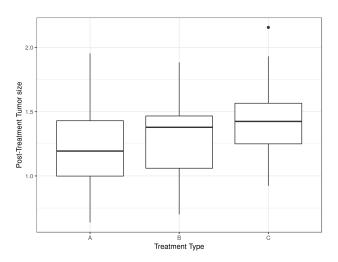
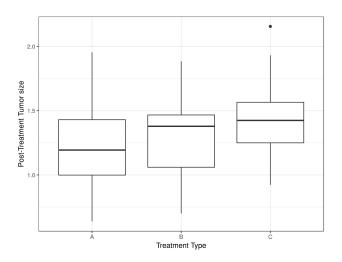
Improved Differentially Private Analysis of Variance

Marika Swanberg Ira Globus-Harris Iris Griffith Anna Ritz Andrew Bray Adam Groce









Are treatment type and post-treatment tumor size dependent?

Analysis of Variance

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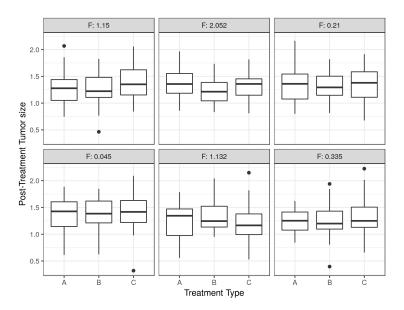
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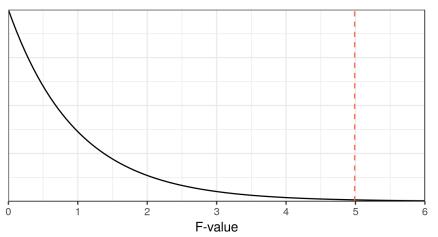
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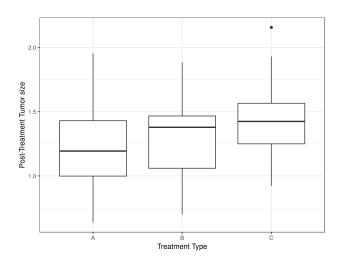
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Goal of any test statistic is achieving high power*.



What if we want to keep this data private?

Differential privacy [DMNS06]

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Definition

Two databases are **neighboring** if they differ only in the data of one individual.

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A query f is ε -differentially private if for all neighboring databases D,D' and all output sets S

$$\Pr[f(D) \in S] \le e^{\varepsilon} \Pr[f(D') \in S].$$



Properties of differential privacy [DMNS06]

Theorem (Post-processing)

If f is ε -differentially private then for any (randomized) function g, then if h(D) = g(f(D)), h is also ε -differentially private.

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Theorem (Composition)

If f is ε_1 -differentially private and g is ε_2 -differentially private then if h(D) = (g(D), f(D)), h is $(\varepsilon_1 + \varepsilon_2)$ -differentially private.

Laplace mechanism [DMNS06]

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Theorem (Laplace Mechanism)

Given any deterministic, real-valued function f on databases, define \widehat{f} as

$$\widehat{f}(D) = f(D) + Y,$$

where $Y \leftarrow \mathsf{Lap}(\Delta f/\varepsilon)$. The Laplace mechanism is ε -differentially private.

Other work on private hypothesis testing:

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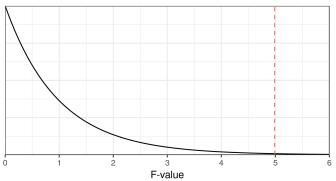
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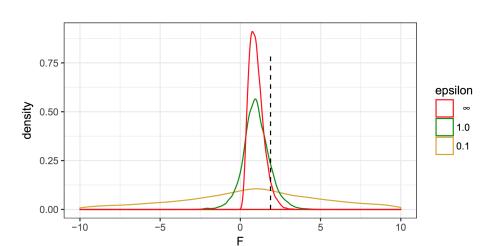
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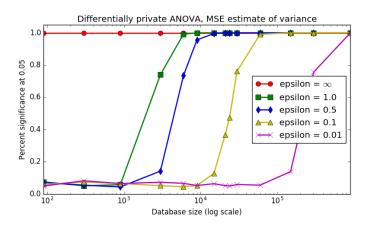
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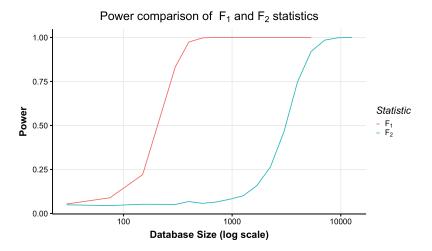
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Funding



Thank you