

Locally Minimax Optimal and Dimension-Agnostic Discrete Argmin Inference

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Joint work with



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Outline of this talk

(1) Problem Setup

(2) The Proposed Methods

(3) Theoretical Properties

(4) Empirical Results

(5) Summary

Problem Setup: Discrete Argmin Inference

- Suppose $X_1, \dots, X_{2n} \stackrel{\text{i.i.d.}}{\sim} \mathbf{P}$ in \mathbb{R}^d with mean $\mu = (\mu_1, \dots, \mu_d)^\top$ and let

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Each $r \in \Theta$ is included in $\widehat{\Theta}$ with high probability:

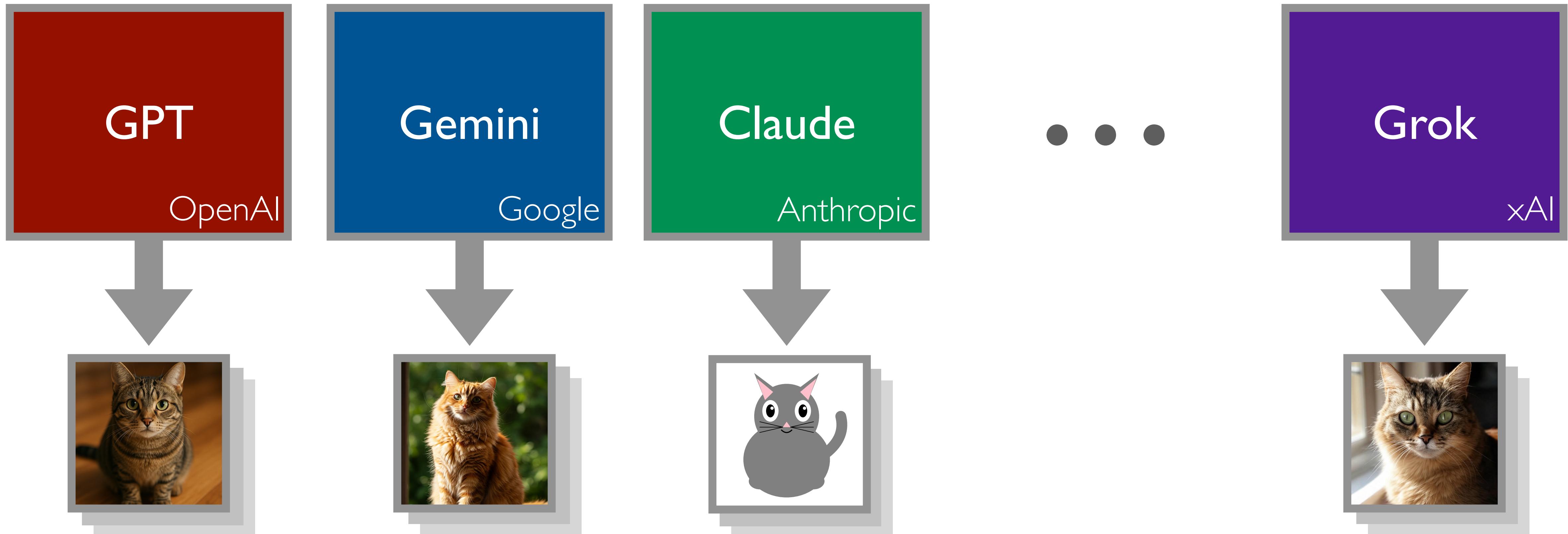
$$\inf_{\mathbf{P} \in \mathcal{P}} \inf_{r \in \Theta(\mathbf{P})} P(r \in \widehat{\Theta}) \geq 1 - \alpha$$



\mathcal{P} : class of distributions
 α : target error level

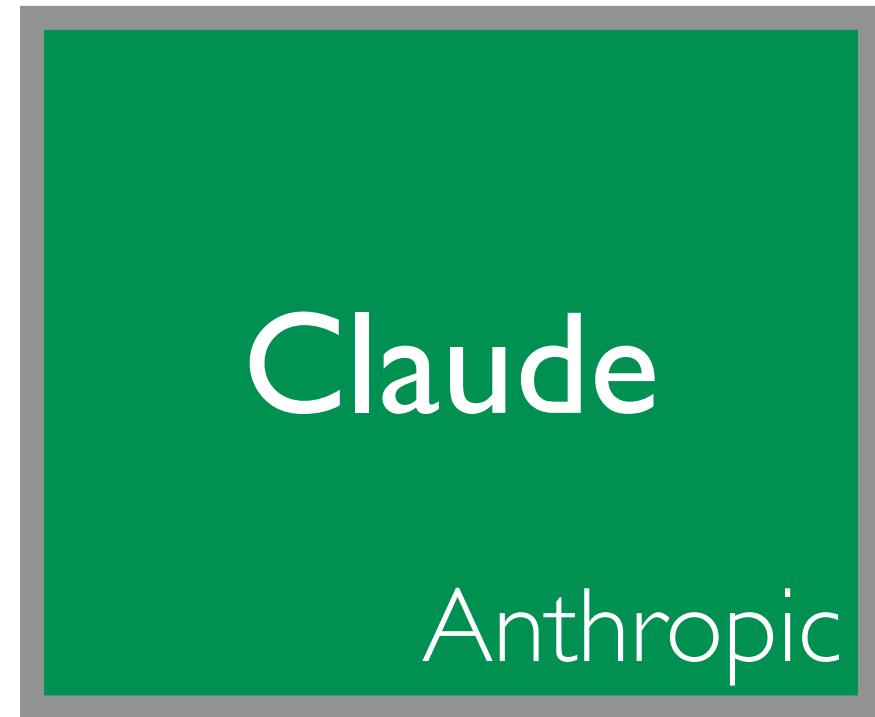
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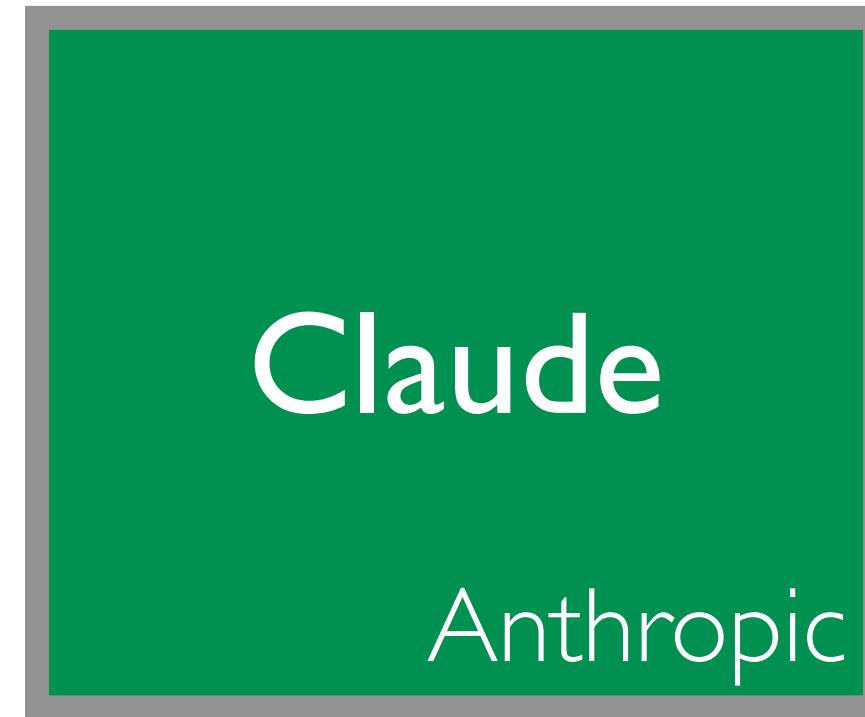
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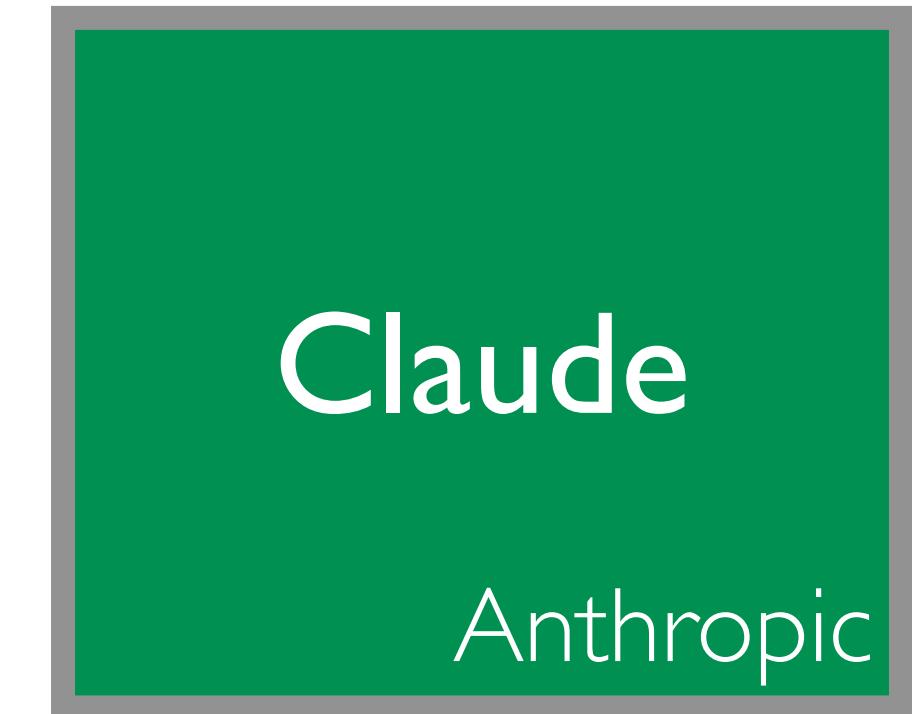
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- But **the population risk is unknown** → **the empirical risk**

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- The best model minimizes the **population risk**
- But **the population risk is unknown** → **the empirical risk**
- We must **account for statistical uncertainty** to determine which models are plausibly **optimal with statistical confidence**

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- **Zhang et al. (2024):** introduce a cross-validation + privacy approach for argmin inference
→ require careful tuning and fall short of minimax optimality

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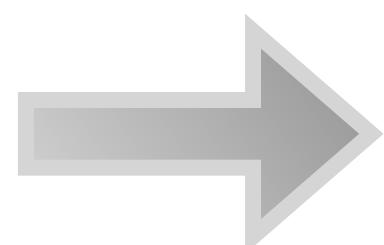
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Sample Splitting + Studentization (Kim and Ramdas, 2024)

Dimension-Agnostic Argmin Inference

Formal (Primal) Goal.

- We seek a **dimension-agnostic confidence set** $\widehat{\Theta}$ for Θ that such that

$$\liminf_{n \rightarrow \infty} \inf_{P \in \mathcal{P}} \inf_{r \in \Theta(P)} P(r \in \widehat{\Theta}) \geq 1 - \alpha, \text{ regardless of the sequence } (d_n)_{n=1}^{\infty}$$

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- We also seek a **confidence set** $\widehat{\Theta}$ for Θ such that its **expected cardinality** is small and **ideally optimal**

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$$H_0 : r \in \Theta \quad \text{versus} \quad H_1 : r \notin \Theta$$

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- We can construct a **DA confidence set** using **DA tests**



DA tests yield a DA confidence set via duality

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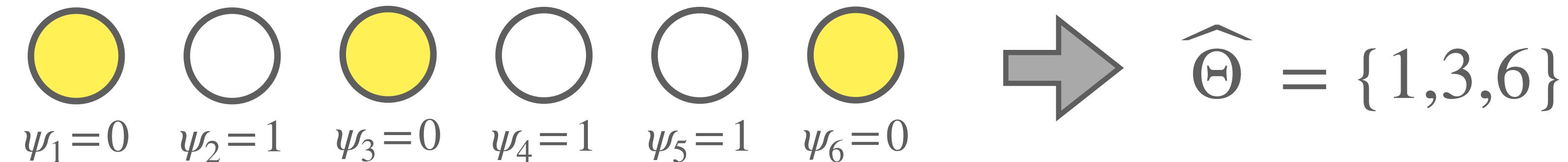
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For example,



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which results in the **DA confidence set**

$$\liminf_{n \rightarrow \infty} \inf_{P \in \mathcal{P}} \inf_{r \in \Theta(P)} P(r \in \widehat{\Theta}) \geq 1 - \alpha, \text{ regardless of the sequence } (d_n)_{n=1}^{\infty}$$

Procedures

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- Recall our (dual) goal is to test

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- Hard to calibrate $c_{1-\alpha}$ in high-dimensions

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Dimension-Agnostic Argmin Test

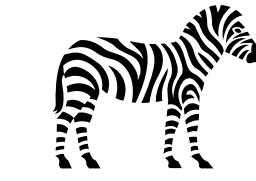
💡 Idea: use \mathcal{D}_1 to estimate s and use \mathcal{D}_2 for inference

Step I (Sample Splitting)

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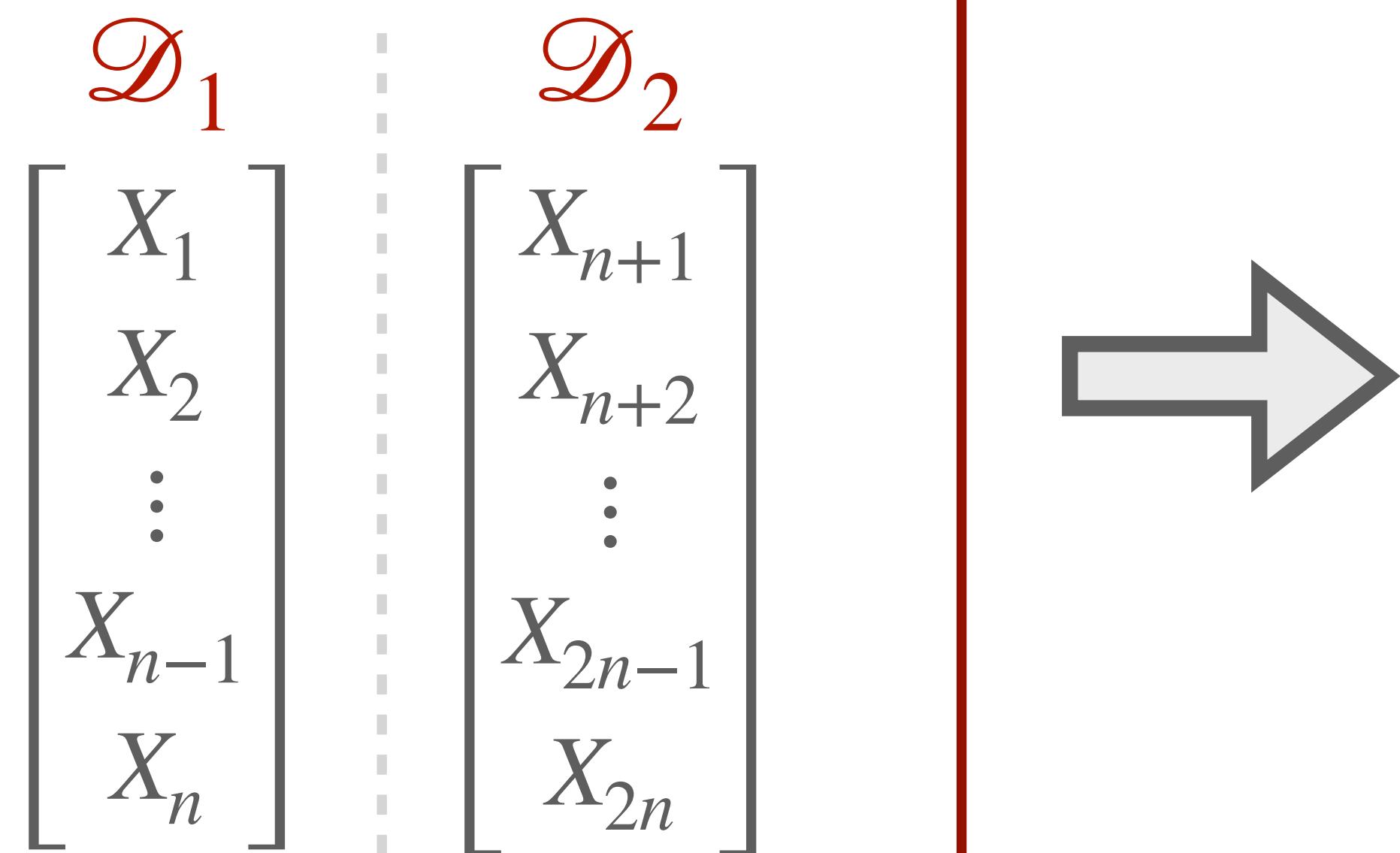


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Step II (Model Selection)

- Based on \mathcal{D}_2 , compute

I. Plug-in version

$$\hat{s} = \arg \max_{k \in [d] \setminus \{r\}} \bar{X}_{\textcolor{red}{r}}^{(2)} - \bar{X}_k^{(2)}$$

2. Noise-adjusted version

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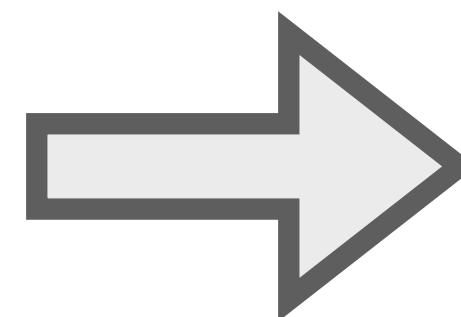
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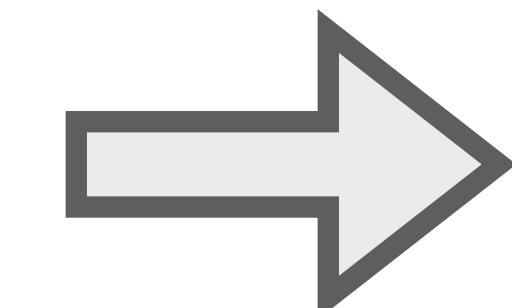
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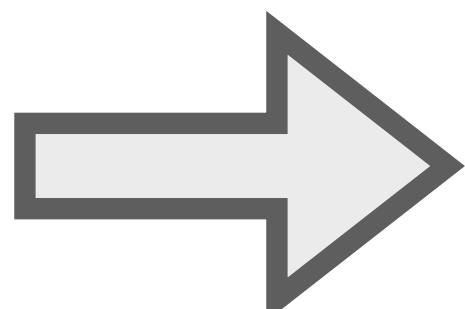
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Step III (Student's t-statistic)

- Given $\hat{s} \in [d] \setminus \{r\}$, compute a one-sided t-statistic

$$T = \frac{\bar{X}_{\color{red}r}^{(1)} - \bar{X}_{\color{blue}\hat{s}}^{(1)}}{\hat{\sigma}_{\color{red}r, \color{blue}\hat{s}}^{(1)}}$$

based on \mathcal{D}_1



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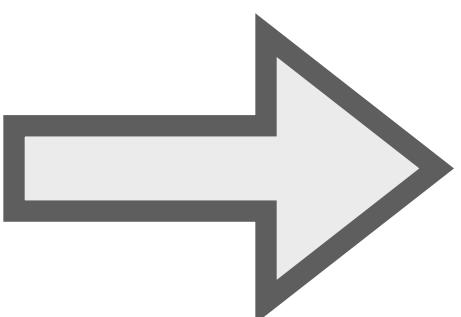
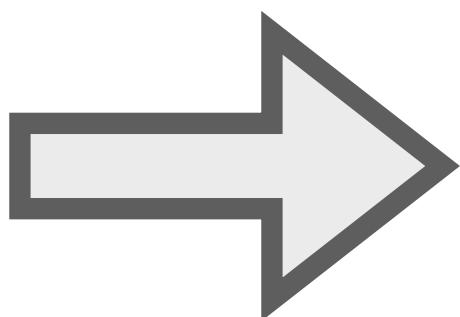
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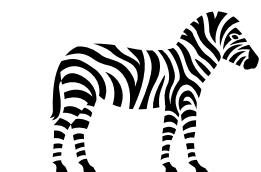
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Step IV (Decision)

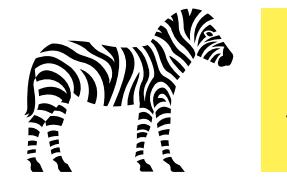
- Reject** the null if $T > z_{1-\alpha}$
- Accept** the null o.w.



$$\Phi(z_{1-\alpha}) = 1 - \alpha$$

Theoretical Properties

- ▶ I. Asymptotic Validity
- 2. Power Analysis

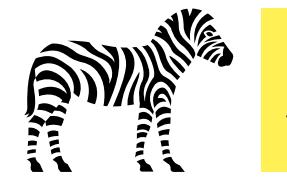


$X = (X^{(1)}, \dots, X^{(d)})$

Asymptotic Validity

Assumption (Truncated 2nd Moment Condition)

Let $W_k := (X^{(\textcolor{red}{r})} - \mu_{\textcolor{red}{r}}) - (X^{(k)} - \mu_k)$ and



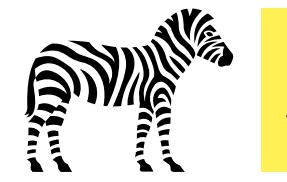
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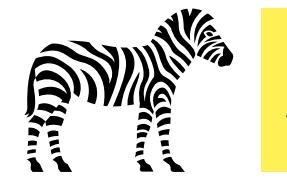
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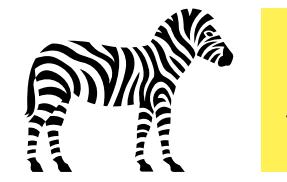
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- **Equivalent** to Lindeberg's condition (weaker than Lyapunov)



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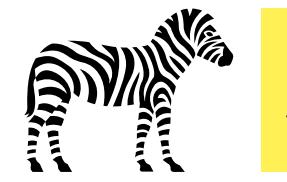
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Let $W_k := (X^{(\textcolor{red}{r})} - \mu_{\textcolor{red}{r}}) - (X^{(k)} - \mu_k)$ and

$$M_k := \sup_{P \in \mathcal{P}_{0,\textcolor{red}{r}}} \mathbb{E}_P \left[\frac{W_k^2}{\mathbb{E}_P[W_k^2]} \min \left\{ 1, \frac{|W_k|}{n^{1/2}(\mathbb{E}_P[W_k^2])^{1/2}} \right\} \right]$$

Assume that $\max_{k \in [d] \setminus \{\textcolor{red}{r}\}} M_k = o(1)$

- **Equivalent** to Lindeberg's condition (weaker than Lyapunov)
- If $X \sim N(\mu, \Sigma)$, it only requires $\text{Var}[W_k] > 0$



$X = (X^{(1)}, \dots, X^{(d)})$

Asymptotic Validity

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- **Arbitrary dependence** among the components except $X^{(\textcolor{red}{r})}$

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Theorem Kim and Ramdas (2025)

Let $\mathcal{P}_{0,r}$ be the class of null distributions with $H_0 : r \in \Theta$ that satisfy the **truncated 2nd moment condition**. Then the DA test is asymptotically valid as

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It holds for both $\left\{ \begin{array}{l} \text{I. Plug-in version} \\ \hat{s} = \arg \max_{k \in [d] \setminus \{r\}} \bar{X}_r^{(2)} - \bar{X}_k^{(2)} \\ \\ \text{2. Noise-adjusted version} \\ \hat{s} = \arg \max_{k \in [d] \setminus \{r\}} \frac{\bar{X}_r^{(2)} - \bar{X}_k^{(2)}}{\hat{\sigma}_{r,k}^{(2)} \vee \kappa} \end{array} \right\}$

Theoretical Properties

- I. Asymptotic Validity
- ▶ 2. Power Analysis

Confusion Set

- The problem **difficulty** depends the cardinality of a **confusion set** \mathbb{C}_r

$$\mathbb{C}_r := \left\{ k \in [d] \setminus \{\textcolor{red}{r}\} : \frac{\mu_{\textcolor{red}{r}} - \mu_\star}{2} \leq \mu_k - \mu_\star \leq C_n \sqrt{\frac{\log(d)}{n}} \right\}$$

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$$\mu_{\star} = \min_{i \in [d]} \mu_i$$

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\mathcal{A}

- Intuition for \mathcal{A}^c

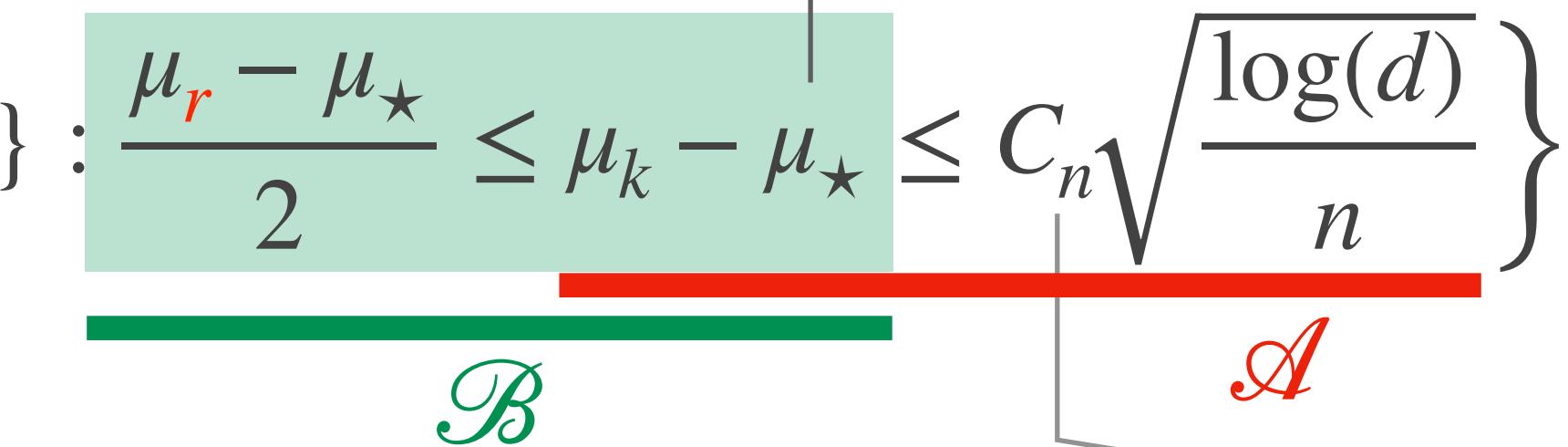
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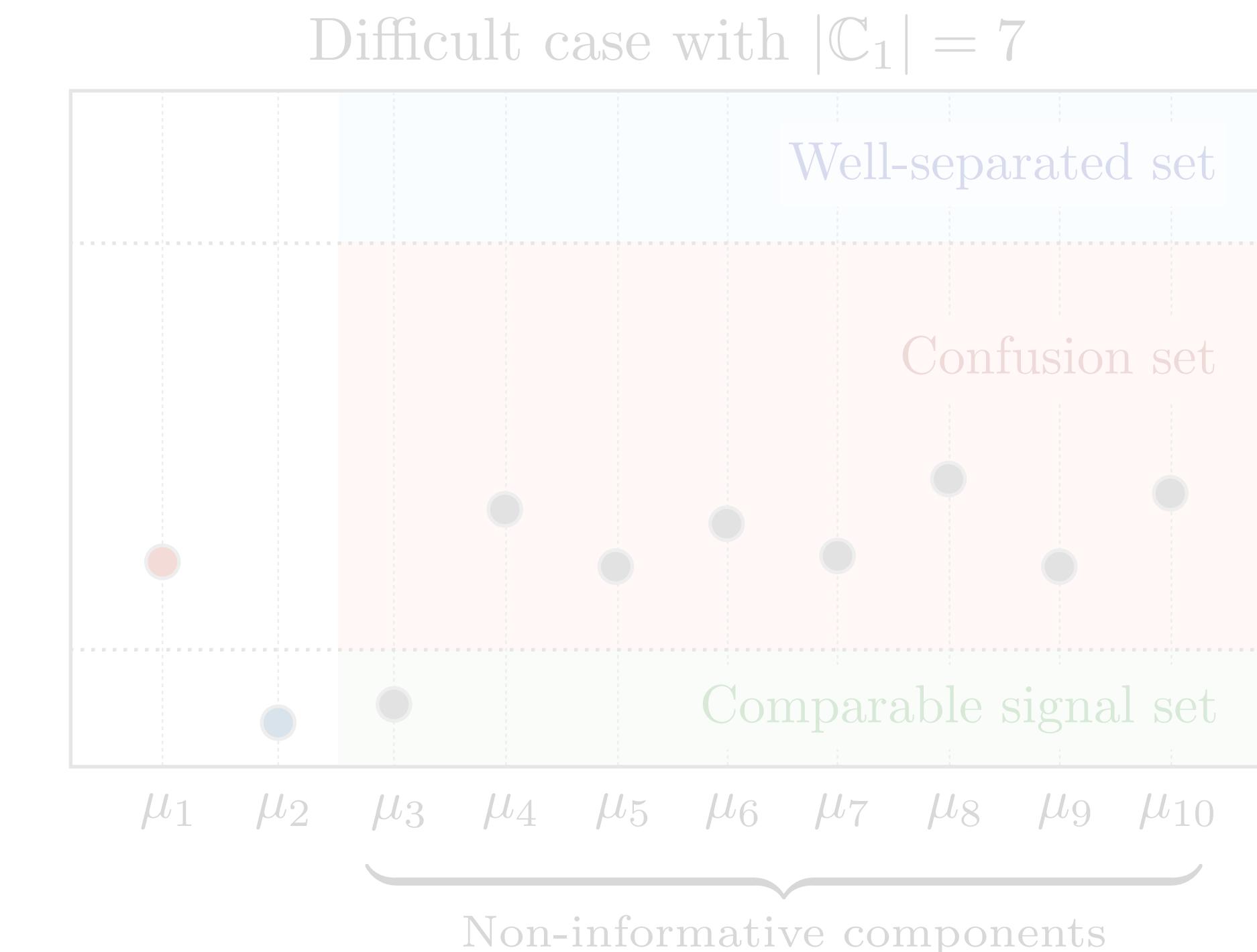
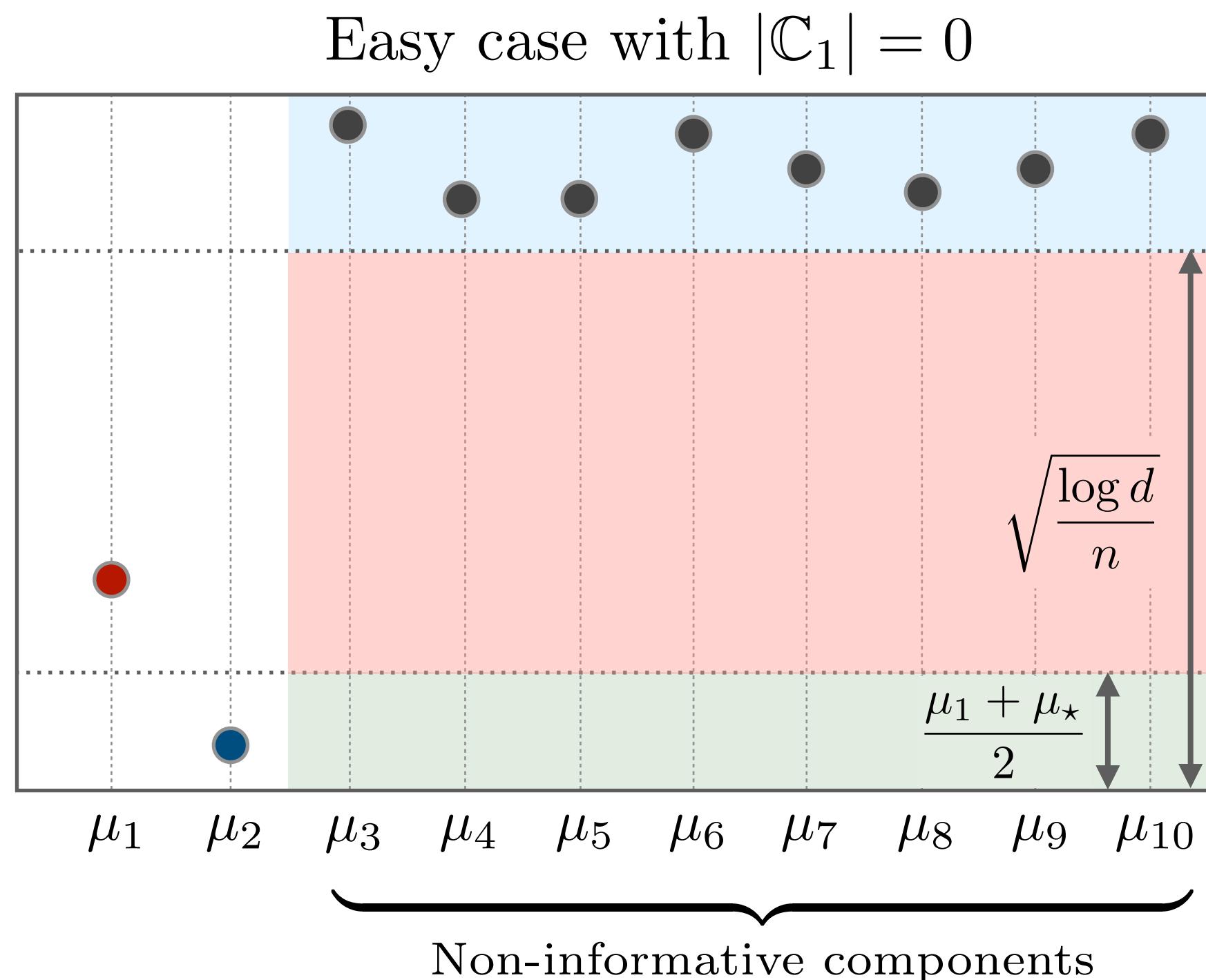
- Intuition for \mathcal{B}^c

$$\frac{\mu_r - \mu_{\star}}{2} > \mu_k - \mu_{\star} \implies \mu_r - \mu_k > \frac{\mu_r - \mu_{\star}}{2}$$

\therefore Comparable signal

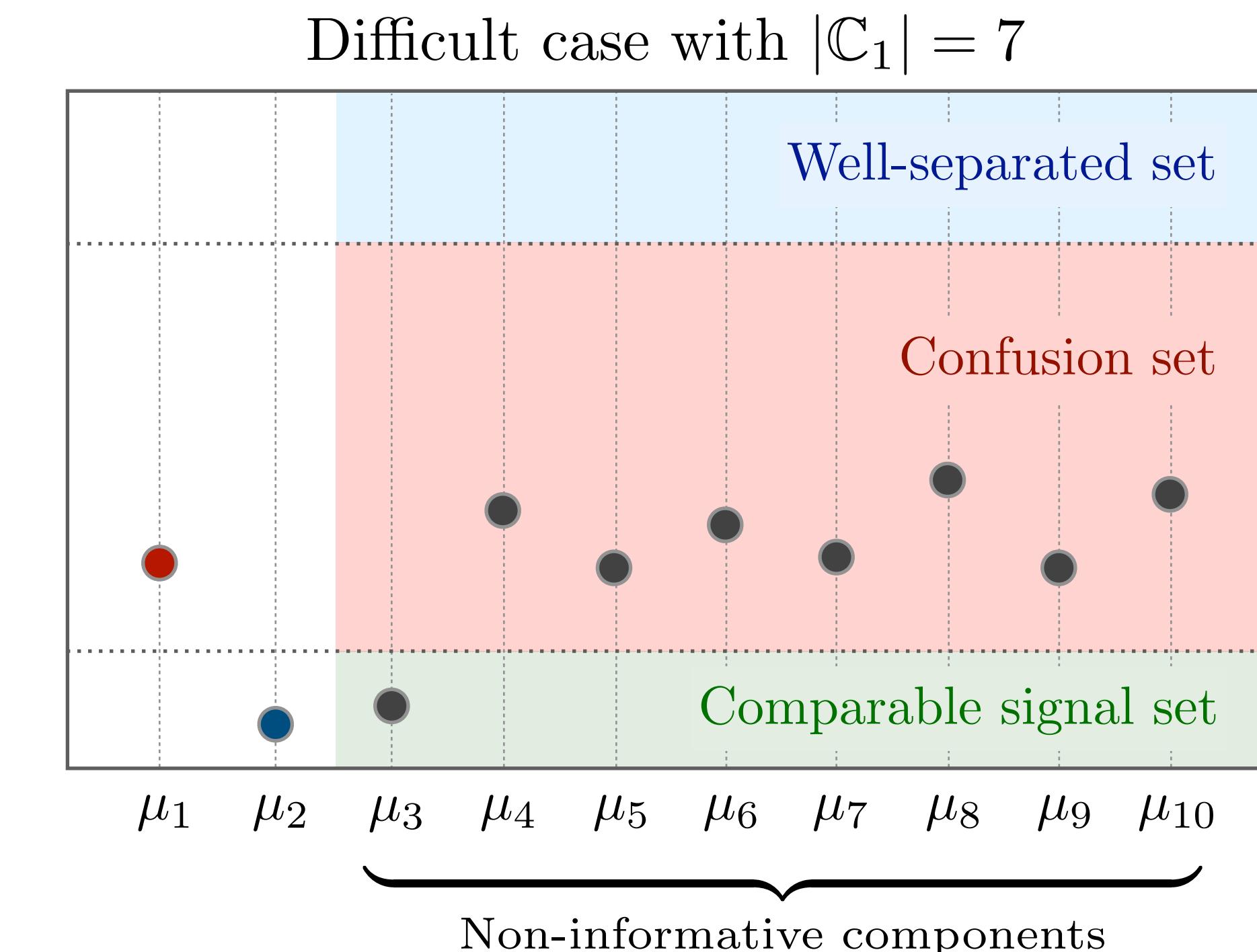
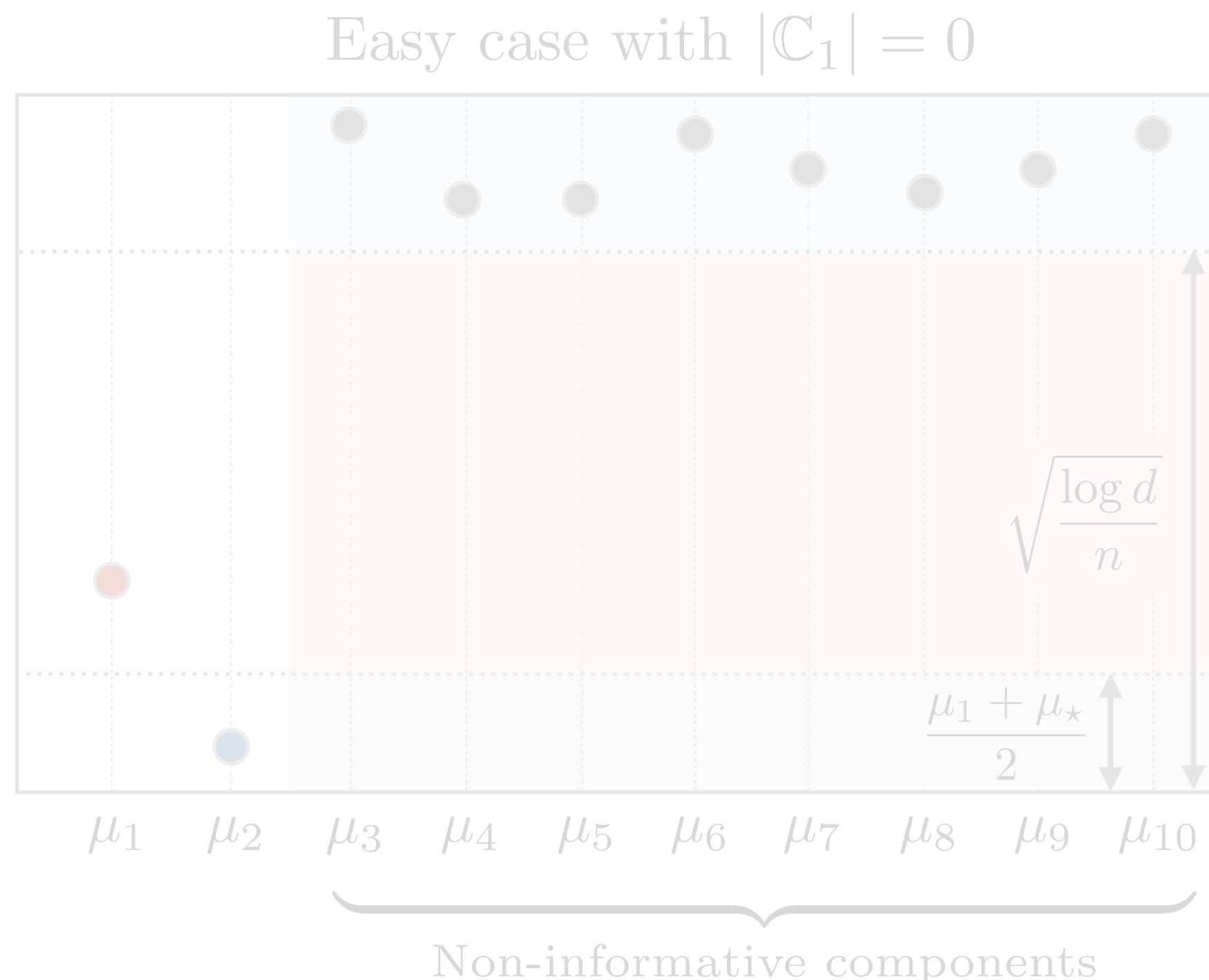
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- Set $\mu_r = \mu_1$ and $\mu_\star = \mu_2$



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$$\mathcal{P}_{1,\textcolor{red}{r}}(\varepsilon; \tau) := \left\{ P \in \mathcal{P} : \mu_{\textcolor{red}{r}} - \mu_{\star} \geq \varepsilon \text{ and } |\mathbb{C}_{\textcolor{red}{r}}| = \tau \right\}$$

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- The **critical radius** ε^{\star} is defined as

$$\varepsilon^{\star} = \varepsilon^{\star}(\tau) = \sqrt{\frac{1 \vee \log(\tau)}{n}}$$

Power Analysis

Theorem Kim and Ramdas (2025)

For any τ , suppose that $\varepsilon \gg \varepsilon^*$. Then the asymptotic uniform power of the DA test is equal to one:

$$\lim_{n \rightarrow \infty} \inf_{P \in \mathcal{P}_{1,r}(\varepsilon; \tau)} P(\psi_r = 1) = 1$$



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- The rate changes from $1/\sqrt{n}$ -rate to $\sqrt{\log(d)/n}$



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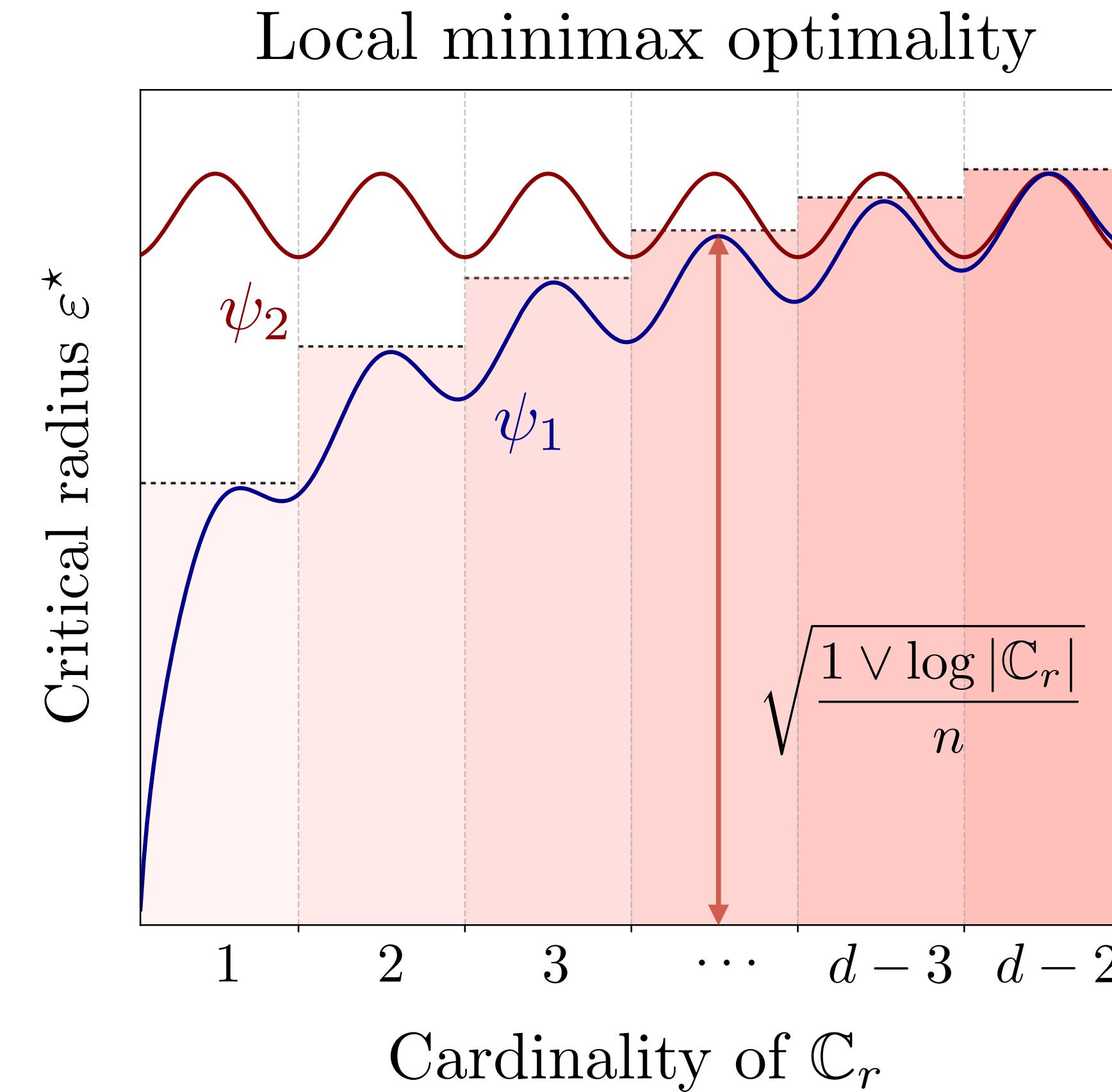
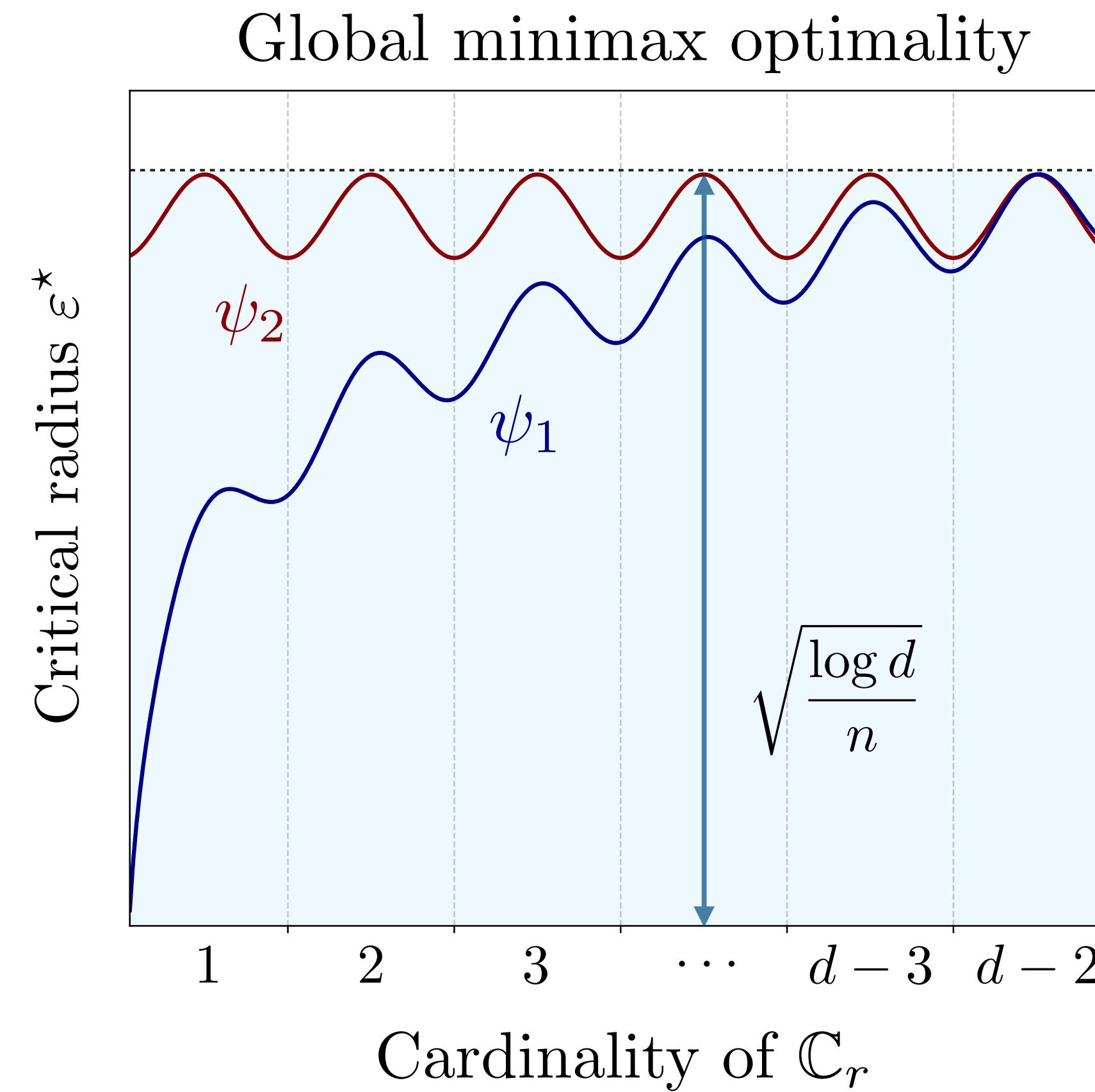
- Adaptivity to unknown $|\mathbb{C}_r|$
- The rate changes from $1/\sqrt{n}$ -rate to $\sqrt{\log(d)/n}$

Question. Can we further **improve** the **separation rate**?



$$\varepsilon^* = \sqrt{\frac{1 \vee \log(\tau)}{n}}$$

Local Minimax Optimality



Local Minimax Optimality

Theorem Kim and Ramdas (2025)

Let Ψ_α be the set of all asymptotic level- α tests over $\mathcal{P}_{0,\textcolor{red}{r}}$,

$$\Psi_{\textcolor{teal}{\alpha}} := \left\{ \psi : \limsup_{n \rightarrow \infty} \sup_{\textcolor{blue}{P} \in \mathcal{P}_{0,\textcolor{red}{r}}} \textcolor{blue}{P}(\psi = 1) \leq \alpha \right\}$$

Local Minimax Optimality

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Let Ψ_α be the set of all asymptotic level- α tests over $\mathcal{P}_{0,\textcolor{red}{r}}$,

$$\Psi_\alpha := \left\{ \psi : \limsup_{n \rightarrow \infty} \sup_{P \in \mathcal{P}_{0,\textcolor{red}{r}}} P(\psi = 1) \leq \alpha \right\}$$

If $\varepsilon \ll \varepsilon^\star$, then the **asymptotic type II error** is at least β :

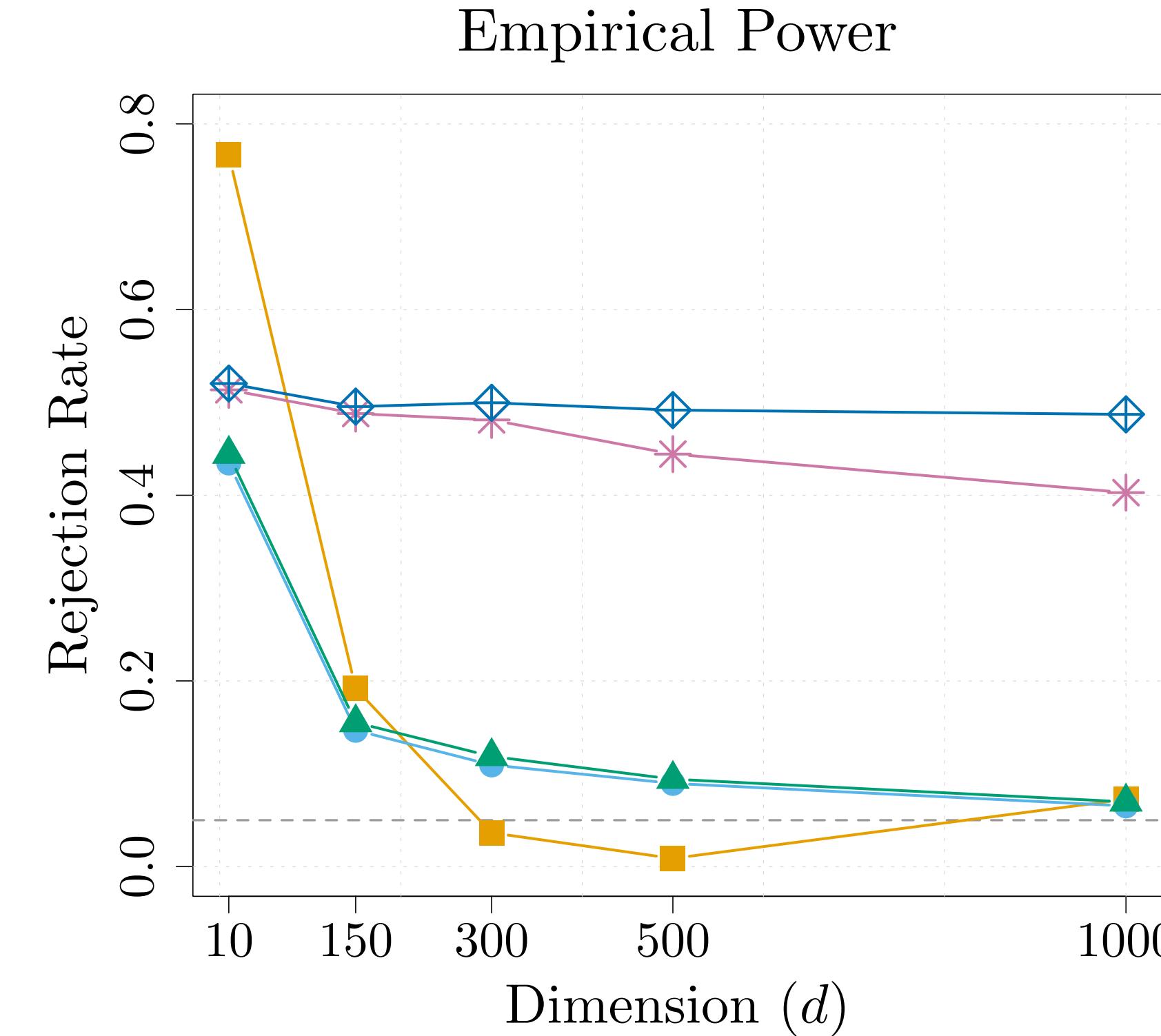
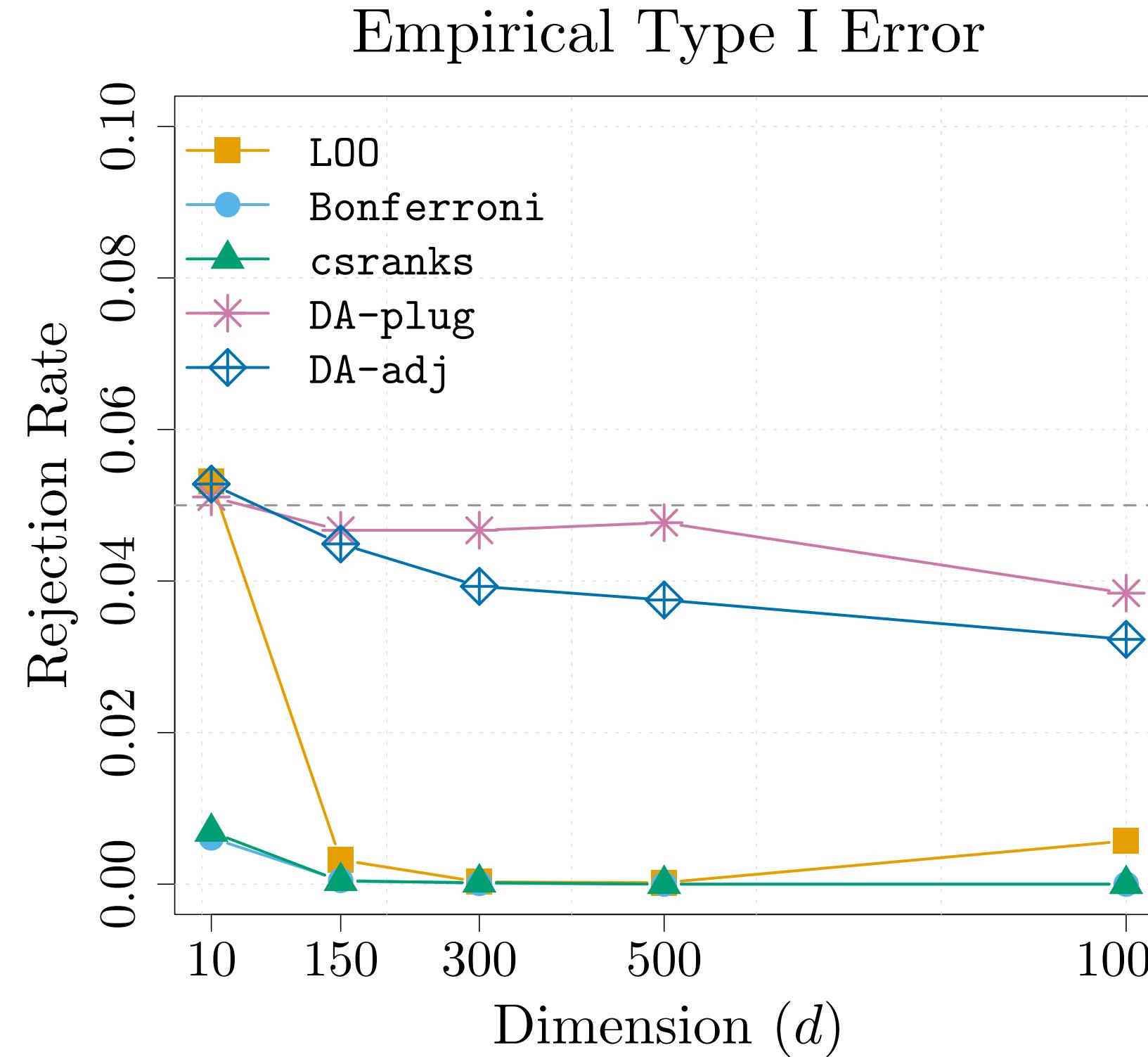
$$\liminf_{n \rightarrow \infty} \inf_{\psi \in \Psi_\alpha} \sup_{P \in \mathcal{P}_{1,\textcolor{red}{r}}(\varepsilon; \tau)} P(\psi = 0) \geq \beta$$



$$\varepsilon^\star = \sqrt{\frac{1 \vee \log(\tau)}{n}}$$

Empirical Results

Power and Validity in High-Dimensional Settings



- **L0O:** Zhang et al. (2024)
- **Bonferroni:** multiple correction
- **csranks:** Mogstad et al. (2024)
- **DA-plug:** plug-in \hat{s}
- **DA-adj:** noise-adjusted \hat{s}

• Null Setting

$$\mu = (0, 0, 1, \dots, 1)^\top$$
$$\Sigma_{11} = \Sigma_{22} = 1 \text{ & } \Sigma_{33} = \dots = \Sigma_{dd} = 20$$

• Alternative Setting

$$\mu = (0.15, 0, 1, \dots, 1)^\top$$
$$\Sigma_{11} = \Sigma_{22} = 1 \text{ & } \Sigma_{33} = \dots = \Sigma_{dd} = 20$$

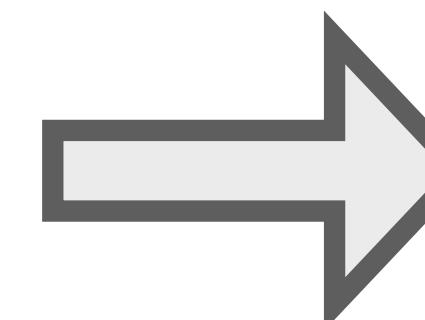
Power under Various Settings

Method	$\mu^{(a)} + \text{unequal variance}$			$\mu^{(b)} + \text{unequal variance}$			$\mu^{(c)} + \text{unequal variance}$		
	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$
L00	0.084	0.115	0.380	0.000	0.001	0.181	0.258	0.351	0.703
Bonferroni	0.171	0.130	0.055	0.166	0.103	0.030	0.017	0.006	0.003
csranks	0.184	0.381	0.962	0.162	0.363	0.961	0.019	0.041	0.223
MCS	0.004	0.002	0.004	0.000	0.000	0.000	0.140	0.156	0.166
DA-plug	0.049	0.052	0.042	0.062	0.067	0.059	0.098	0.128	0.202
DA-plug $^{ \times 10 }$	0.050	0.052	0.050	0.080	0.080	0.073	0.125	0.145	0.240
DA-adj	0.122	0.259	0.841	0.217	0.384	0.916	0.135	0.188	0.462
DA-adj $^{ \times 10 }$	0.160	0.343	0.946	0.294	0.517	0.982	0.164	0.251	0.605

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	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$
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- DA-plug: plug-in \hat{s}
- DA-adj: noise-adjusted \hat{s}
- DA-plug $^{ \times 10}$: 10 splits + average
- DA-adj $^{ \times 10}$: 10 splits + average



1. **Multiple splits** improve the power
2. **Noise-adjusted** version performs better

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DA-adj $^{ \times 10}$ achieves the **best or second-best** performance
 (with only a **small** margin)

Mean Structures

$$\mu^{(a)} = (0.1, 0, 0.1, \dots, 0.1)^\top \quad \mu^{(b)} = (0.1, 0.019, \dots, 0.99, 1)^\top$$

Power under Various Settings

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LOO performs **best** and DA-adj $^{ \times 10 }$ performs **second best**
 But LOO **does not** control the type I error rate

Mean Structure

$$\boldsymbol{\mu}^{(c)} = (0.05, 0, 0, 0, 10, \dots, 10)^\top$$

Power under Various Settings

Method	$\mu^{(a)}$ + unequal variance			$\mu^{(b)}$ + unequal variance			$\mu^{(c,0)}$ + unequal variance		
	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$	$\rho = 0$	$\rho = 0.4$	$\rho = 0.8$
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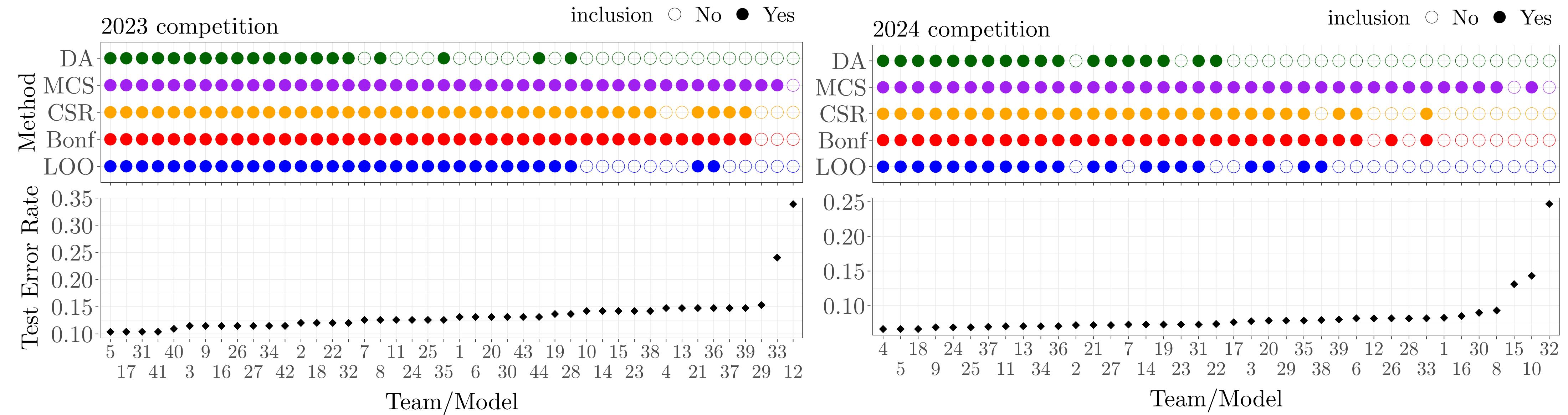
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$$\boldsymbol{\mu}^{(c)} = (0.05, 0, 0, 0, 10, \dots, 10)^\top$$

Real-World Data

- We revisit **CMU 36-462 prediction competition** analyzed by Zhang et al. (2024)
 - Spring 2023: $n = 183, p = 44$
 - Spring 2024: $n = 1246, p = 39$
- $X_{i,k} \in \{0,1\}$: correct/incorrect prediction by team k at test point i
- μ_k : the population prediction risk of team k (unknown)
- Methods to compare
 - Bonferroni correction (**Bonf**)
 - Hansen et al. (2011) (**MCS**)
 - Mogstad et al. (2024) (**CSR**)
 - Zhang et al. (2024) (**LOO**)

Real-World Data



- **Colored points** indicate the indices included in **each confidence set**
- Our method (DA-adj^{10}) produces confidence sets with **smallest cardinality**

Summary

- We have introduced a DA method for **high-dimensional argmin inference** problem based on **sample splitting** and **studentization**
- The proposed method achieves the **locally minimax separation rate** and adapts to the intrinsic difficulty of the problem characterized by the **confusion set**
- We have demonstrated its **strong empirical performance** under various settings

Thank you!



Coverage Guarantees

I. Pointwise coverage

Each $r \in \Theta$ is included in $\widehat{\Theta}$ with high probability:

$$\inf_{P \in \mathcal{P}} \inf_{r \in \Theta(P)} P(r \in \widehat{\Theta}) \geq 1 - \alpha$$

- **Less** demanding → **smaller** expected set size
- **Higher** power but **weaker** protection

2. Uniform coverage

The entire set Θ is contained in $\widehat{\Theta}$ with high probability:

$$\inf_{P \in \mathcal{P}} P(\Theta \subseteq \widehat{\Theta}) \geq 1 - \alpha$$

- **More** demanding → **larger** expected set size
- **Stronger** protection but **more** conservative



\mathcal{P} : class of distributions
 α : target error level

Future directions

- General **rank-k** inference
- Confidence sets for $\mu_{(k)}$
- **Computationally efficient** multiple splitting approach