An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Change Conclusions?

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When can I trust my data analysis?

[https://stanfordmlgroup.github.io/projects/chexnet/, https://www.ibmbigdatahub.com/blog/cyber-security-powered-ai-and-machine-learning, https://www.fairwinds.org/inside-fairwinds/fraud-protection-center/report-fraud.html]

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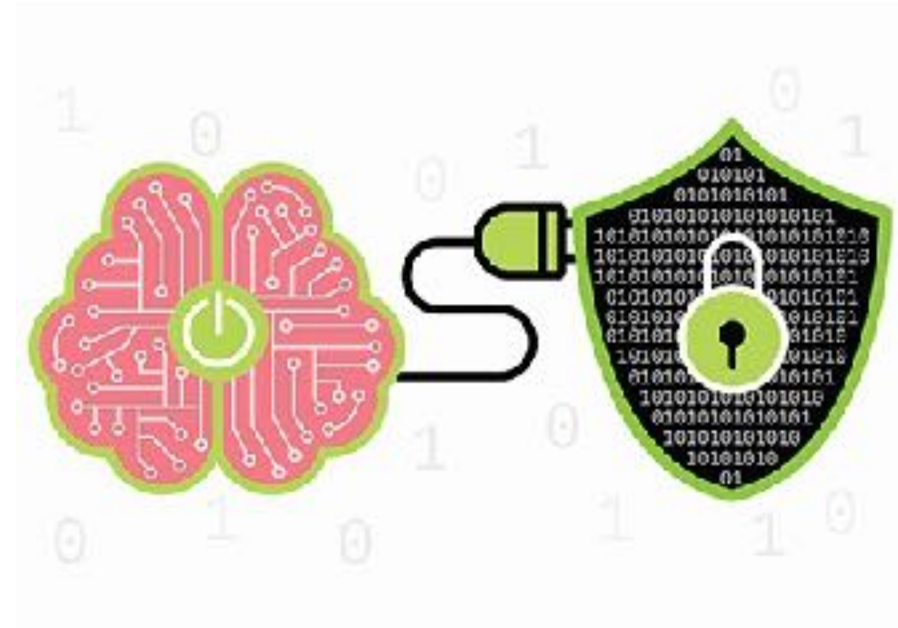

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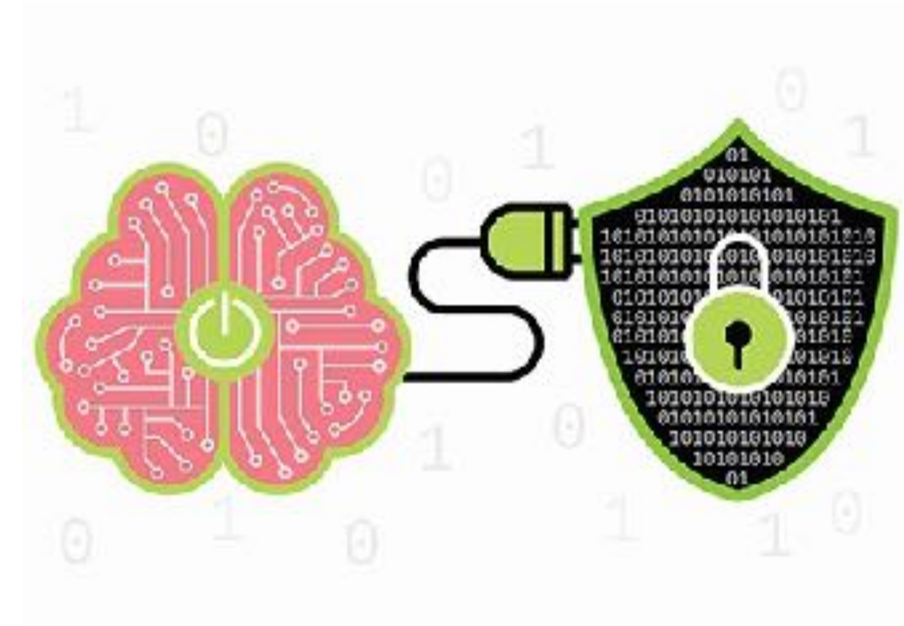

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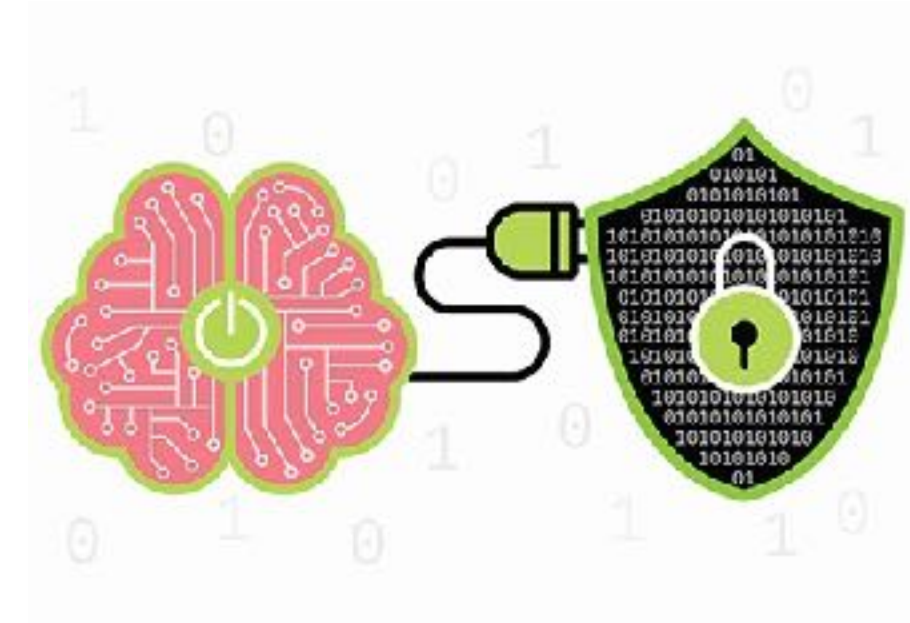

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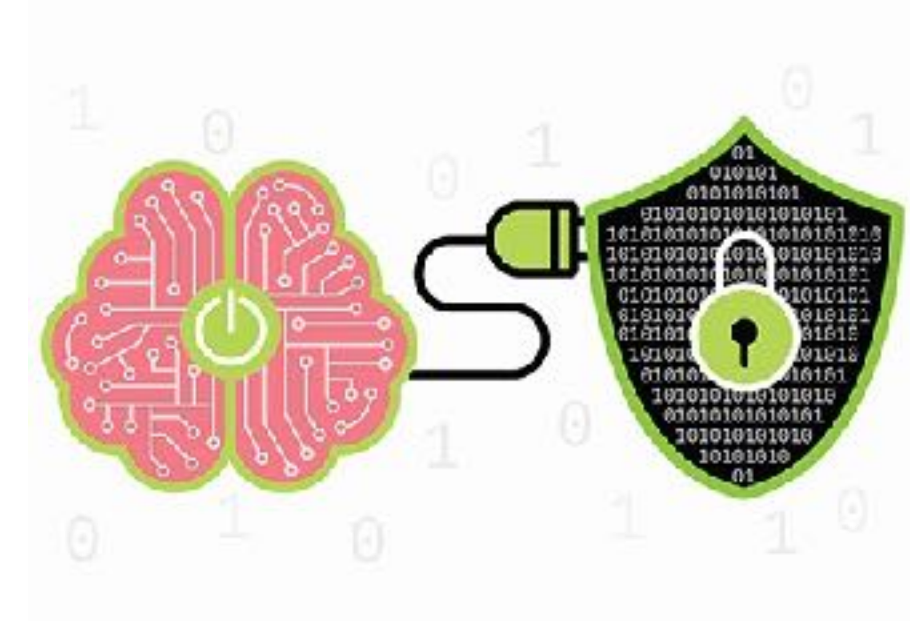

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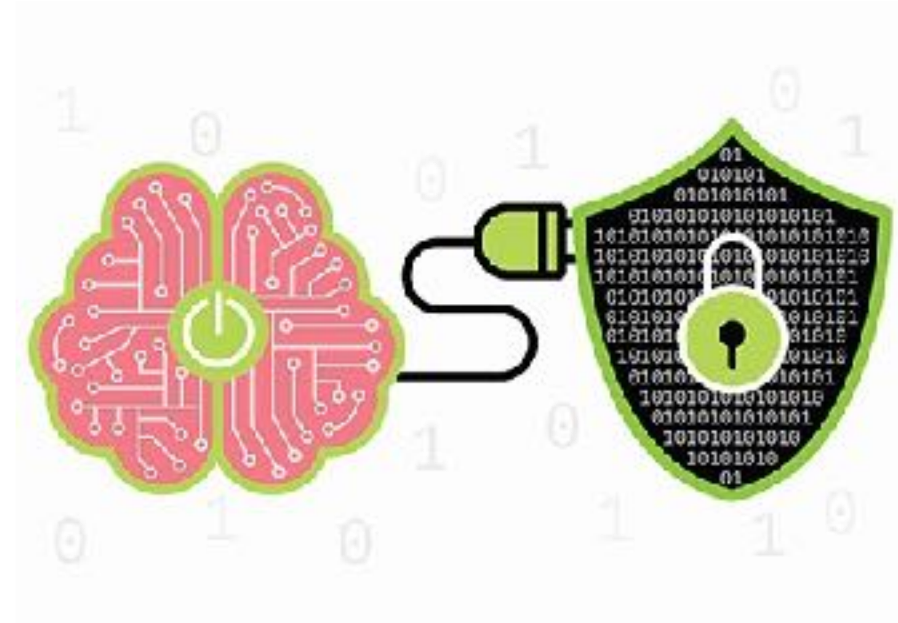

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- E.g. in a study of microcredit with ~16,500 data points, we find a single data point that drives the sign of the effect

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- Even if doesn't bother you, should be up front about it

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- Example: 16,000 data points, $\alpha = 0.001$ → >10^{53} re-runs
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- A data analysis: $\sum_{n=1}^{N} f(\theta, d_n)$

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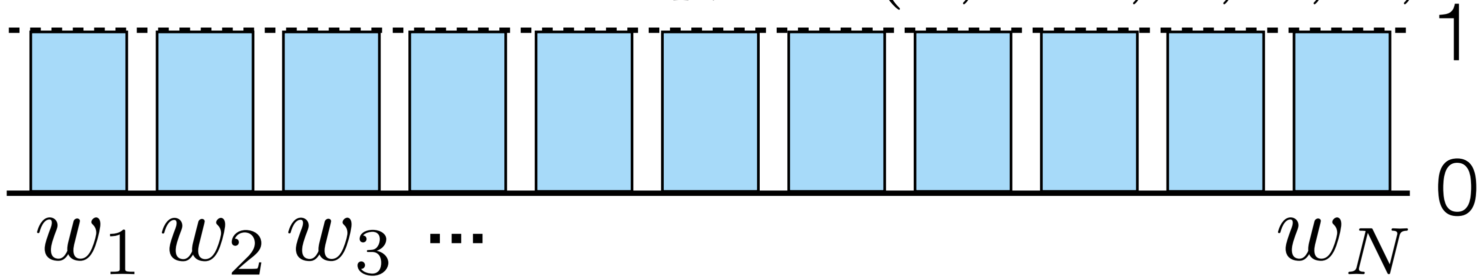

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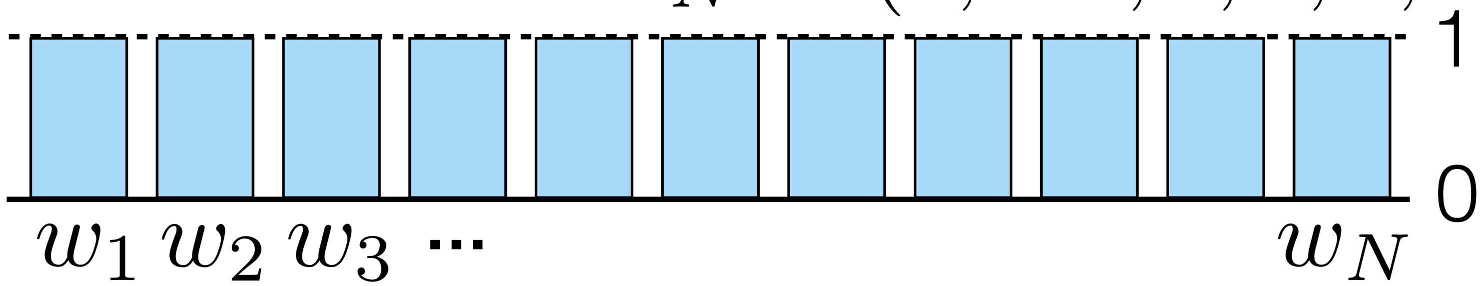

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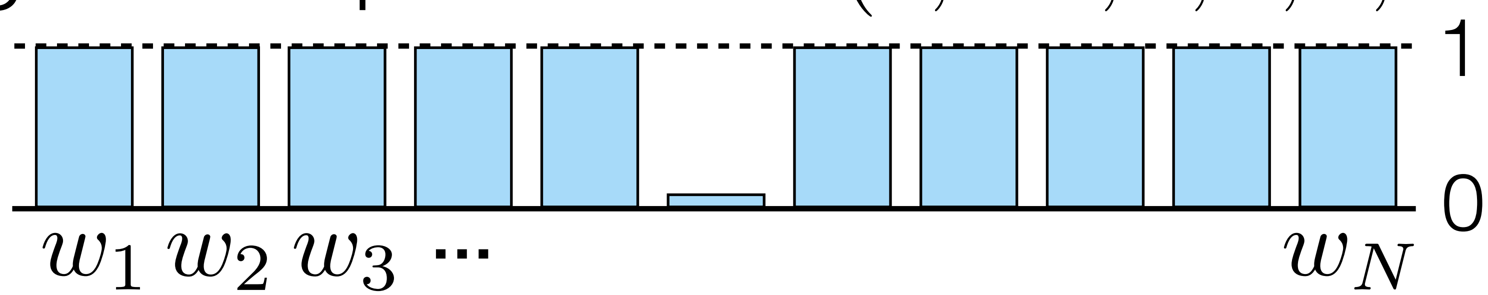

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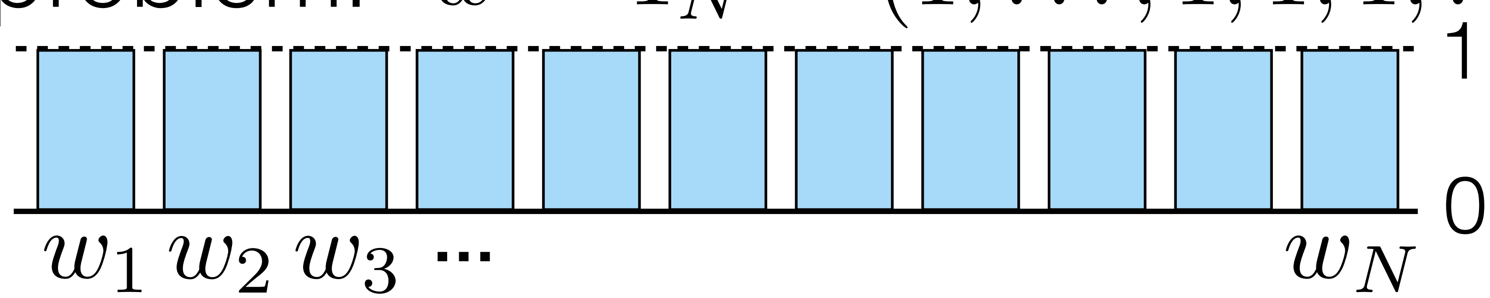

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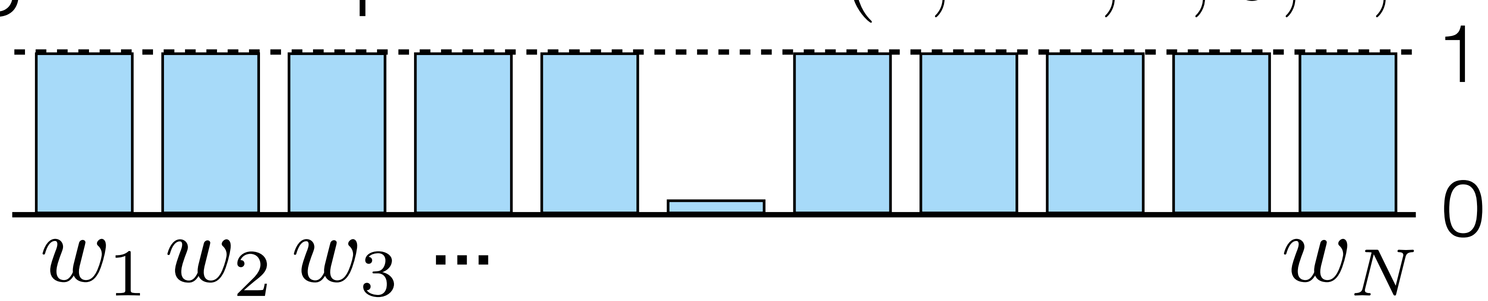

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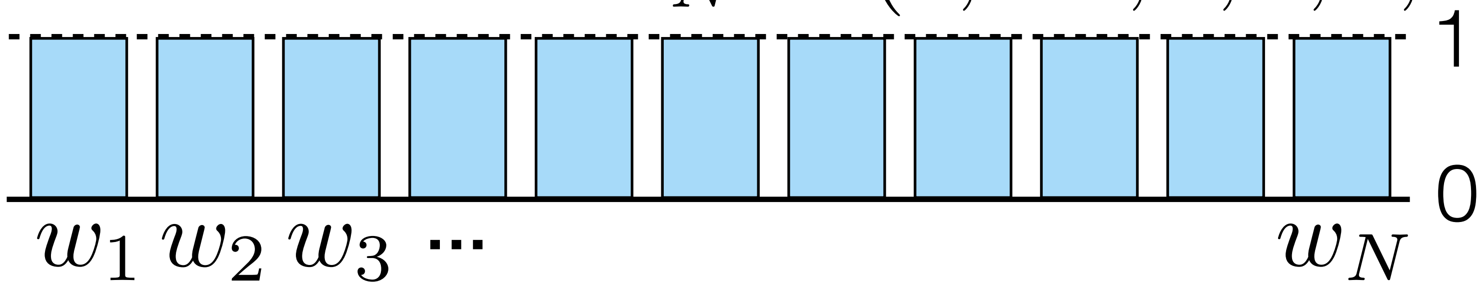

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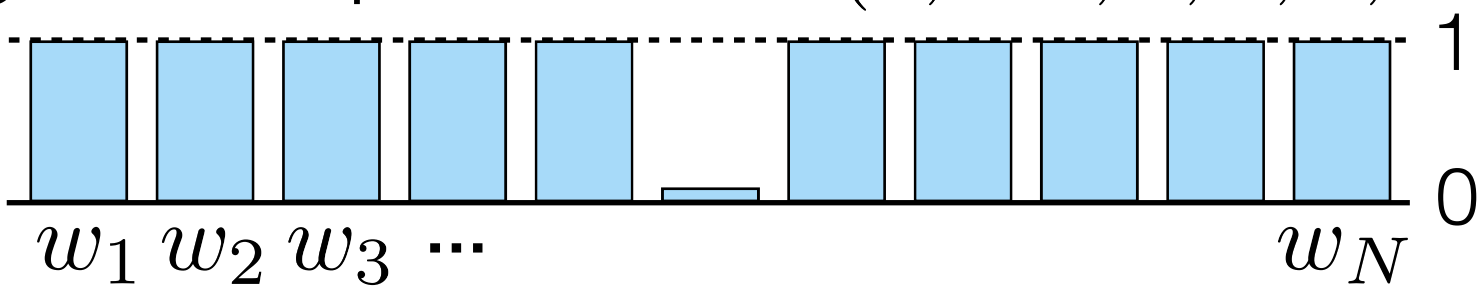

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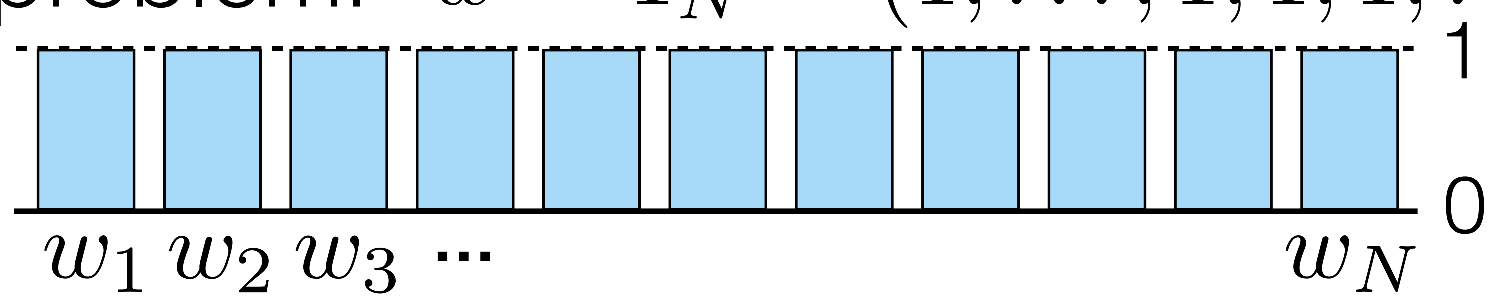

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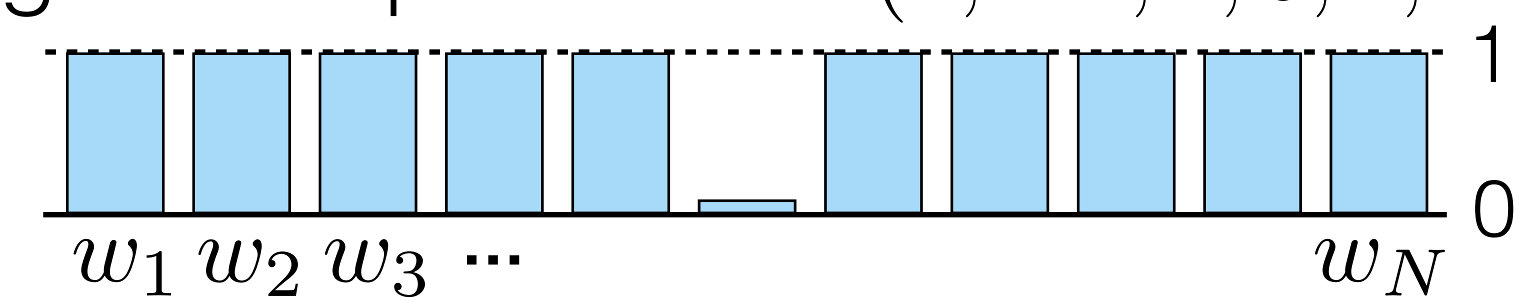

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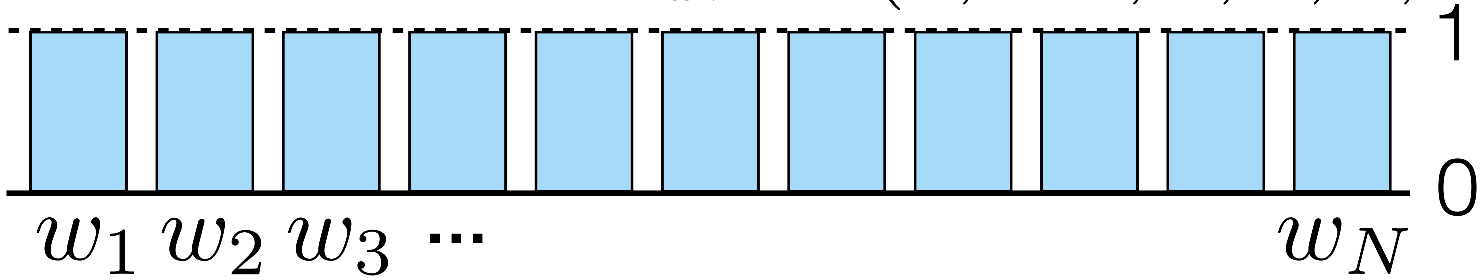

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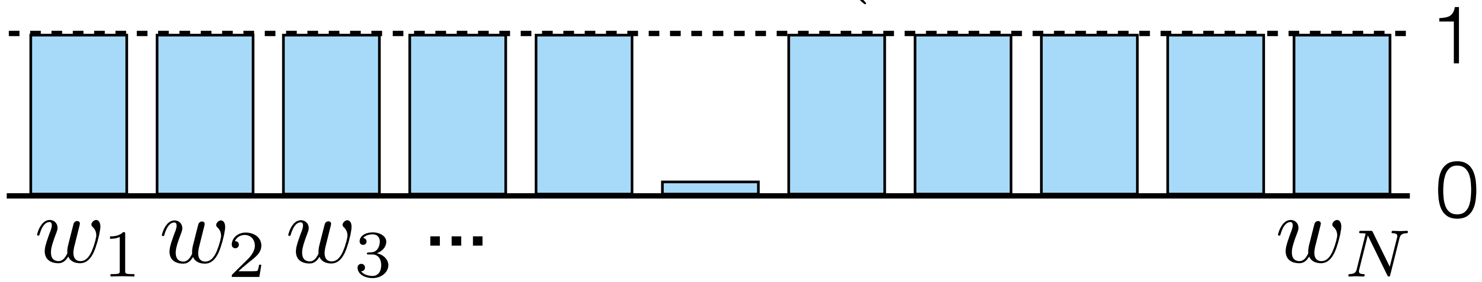

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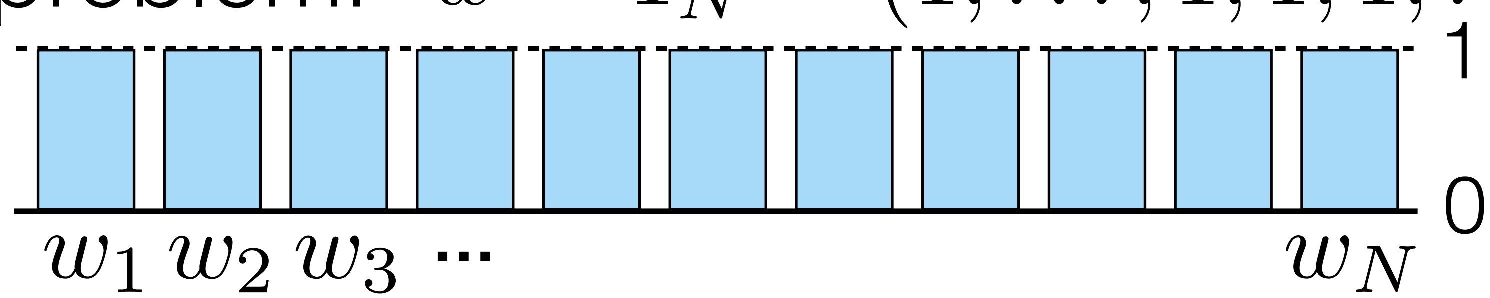

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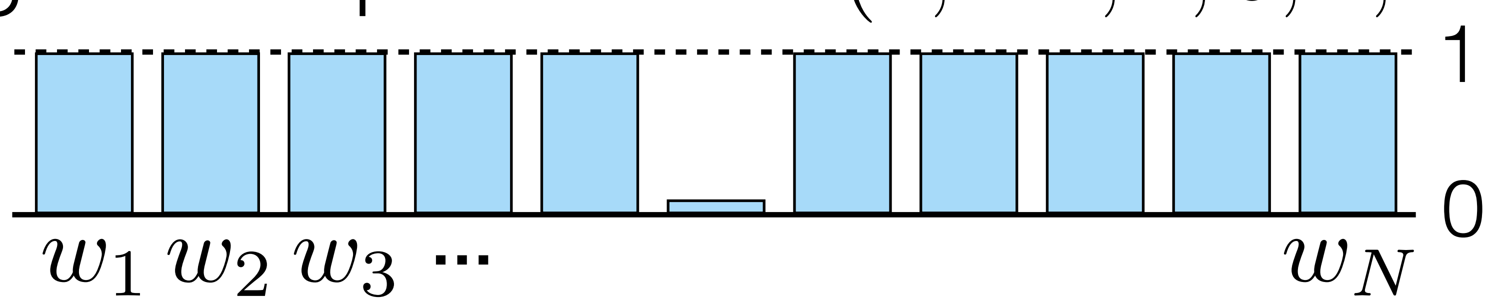

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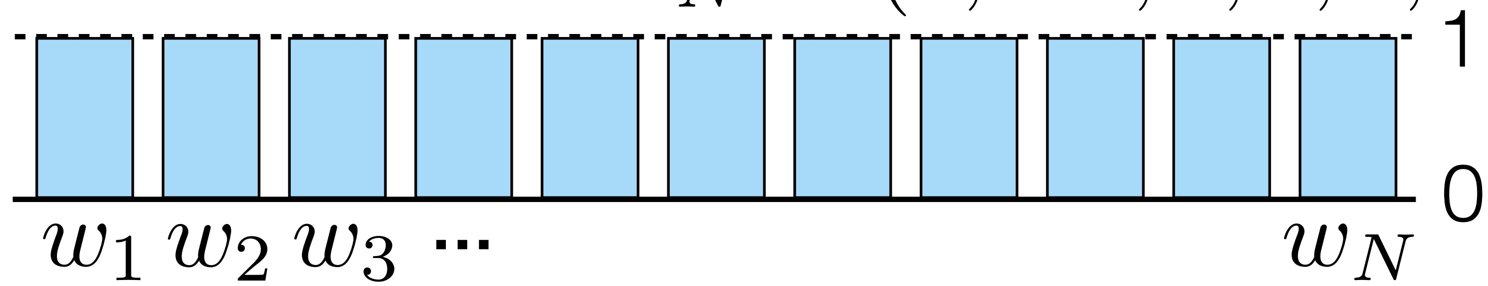

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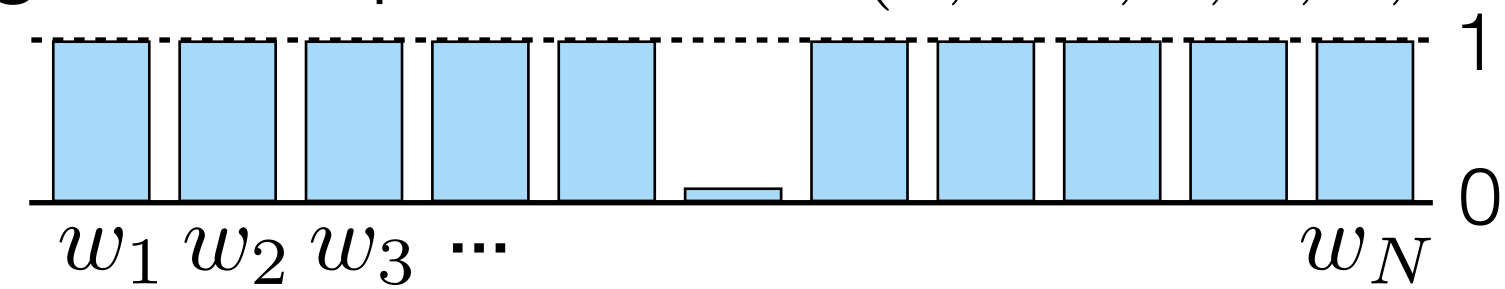

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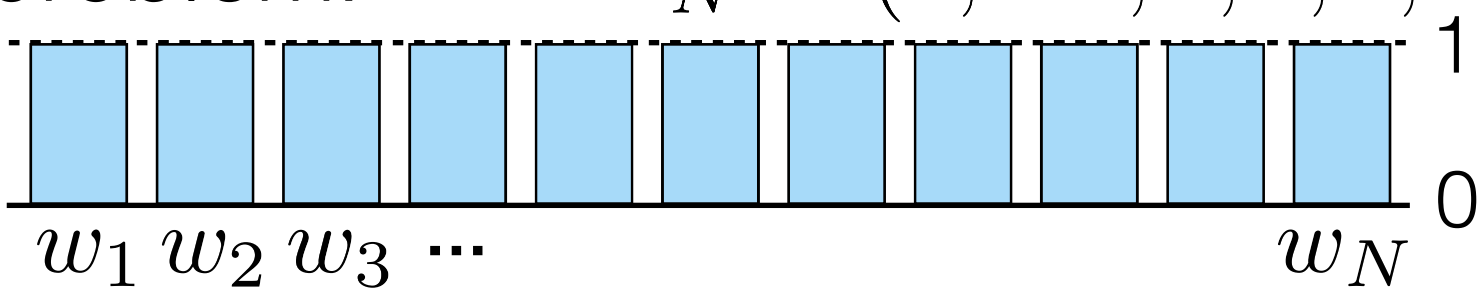

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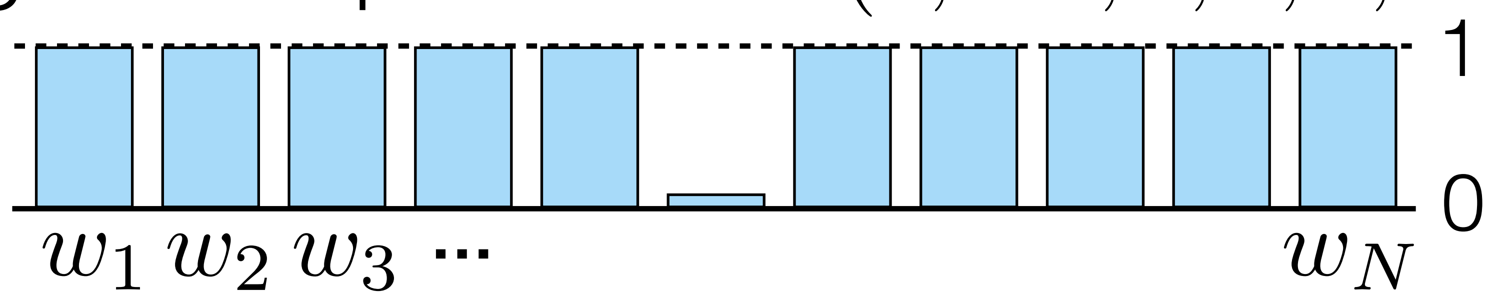

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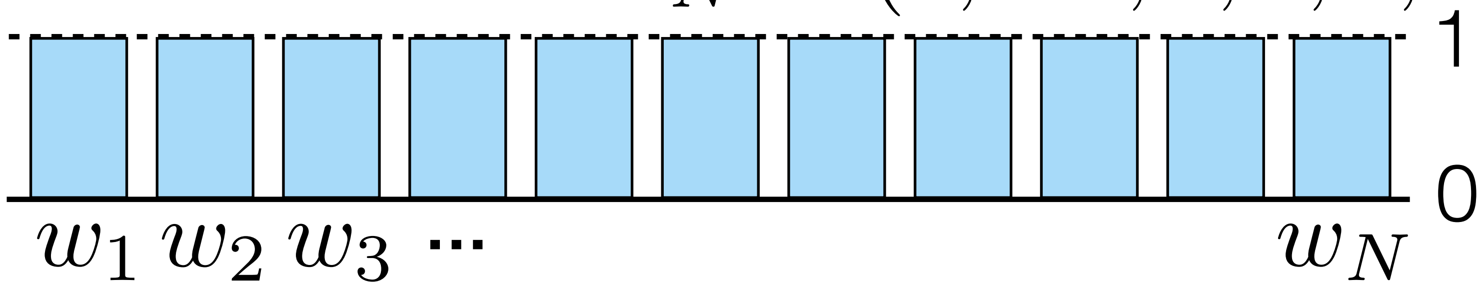

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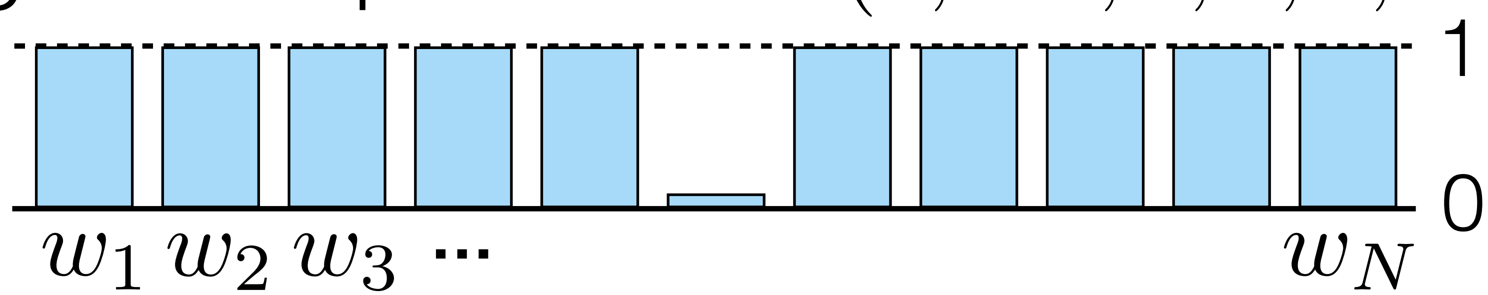

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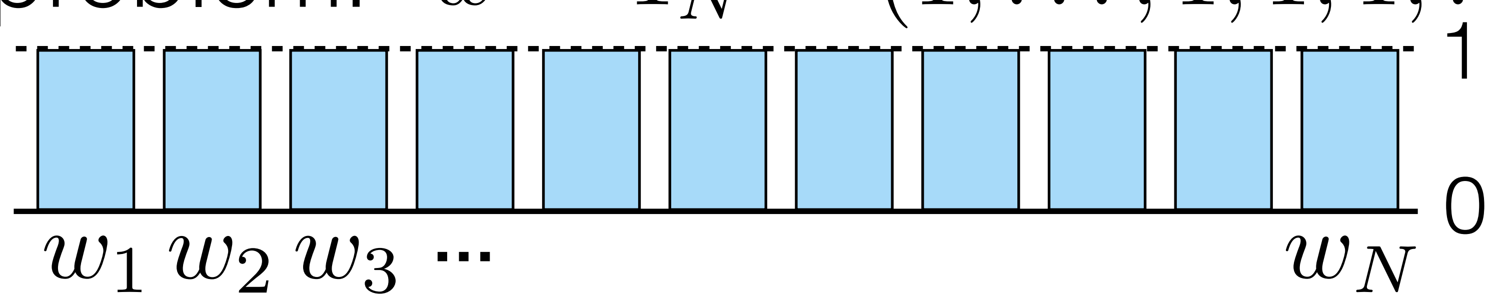

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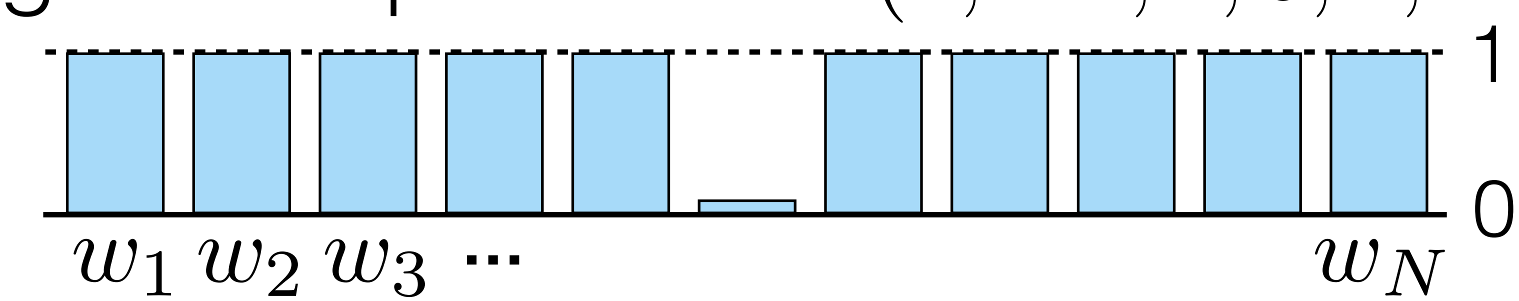

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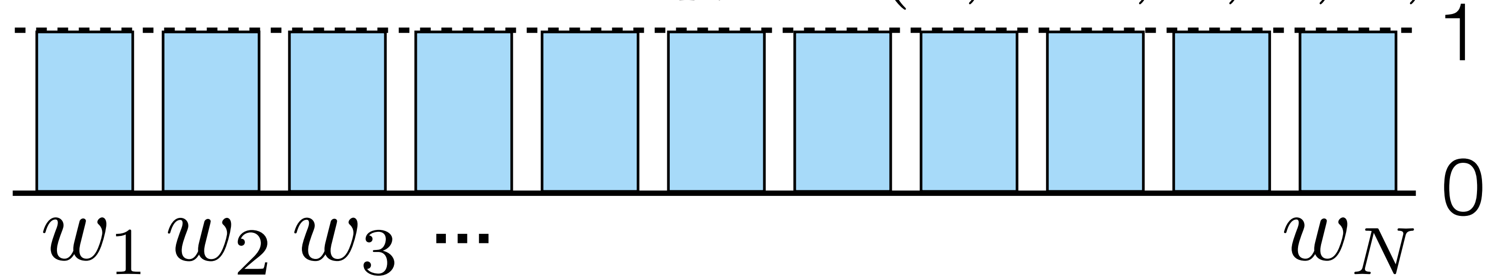

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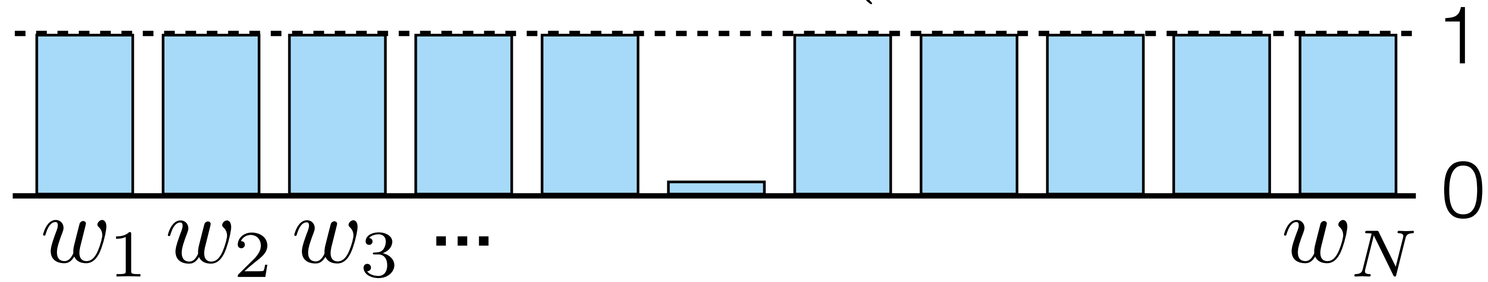

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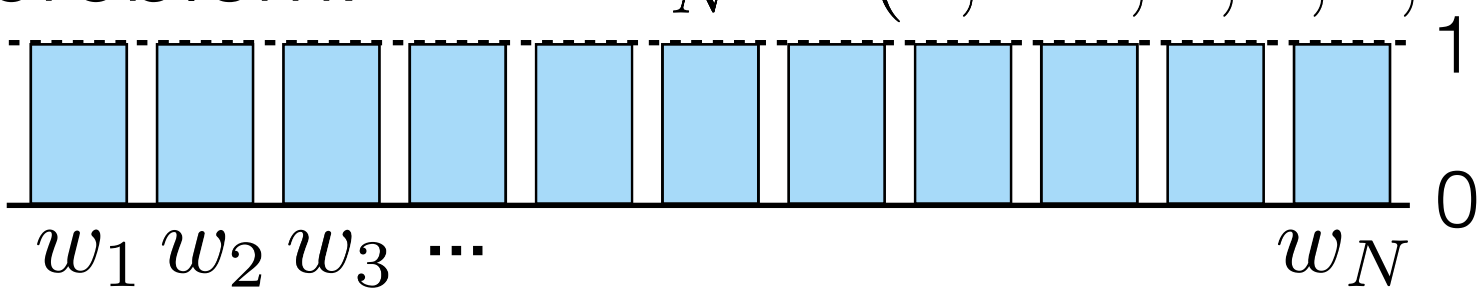

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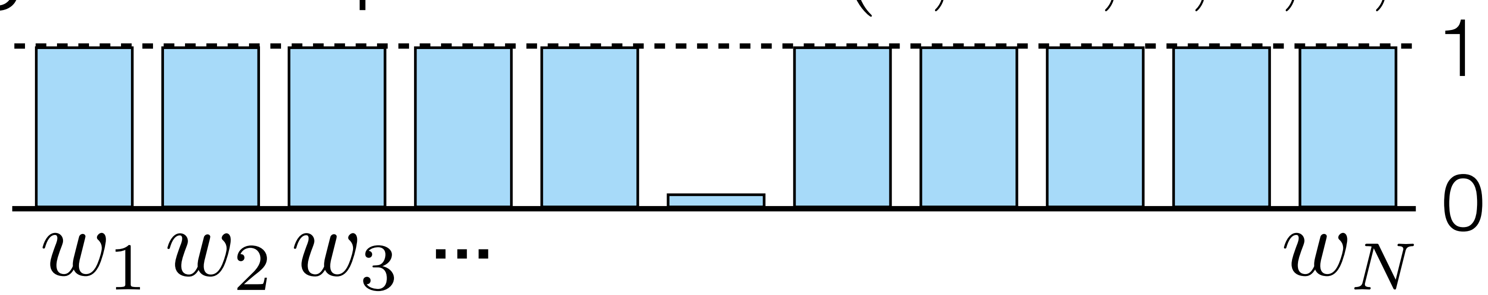

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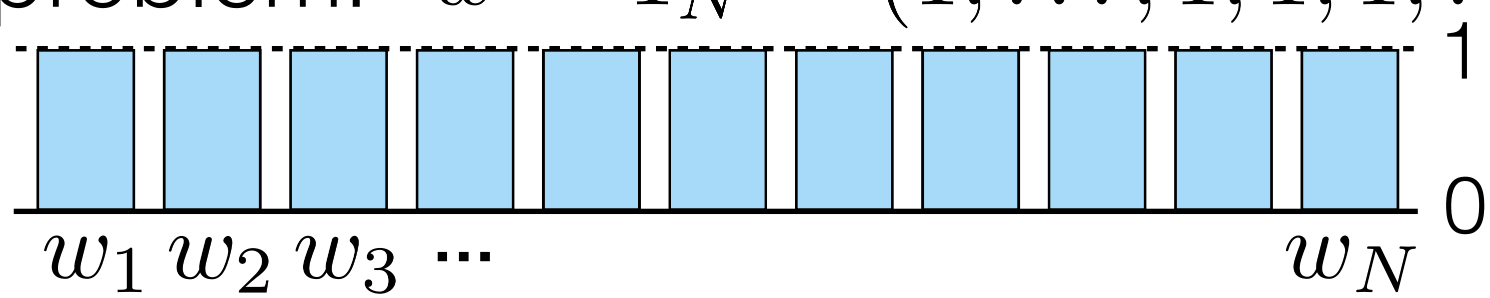

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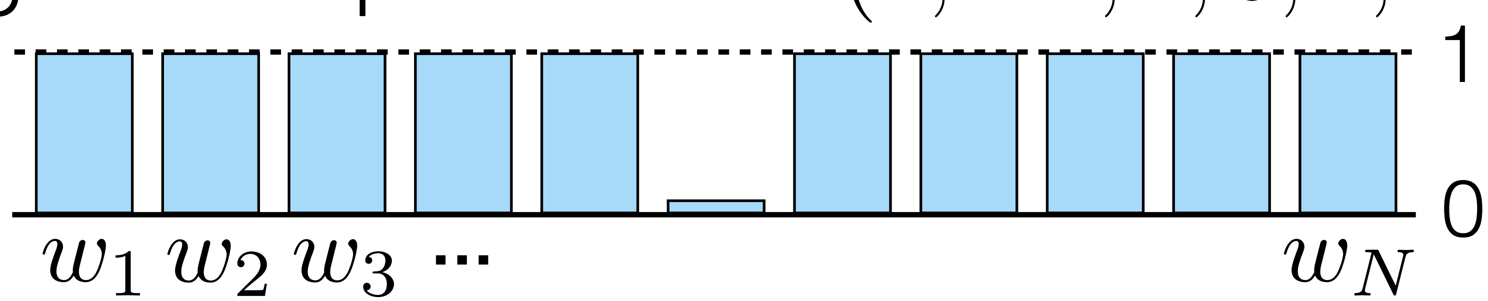

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[What about higher orders? Some very early work: Giordano, Jordan, Broderick 2019]

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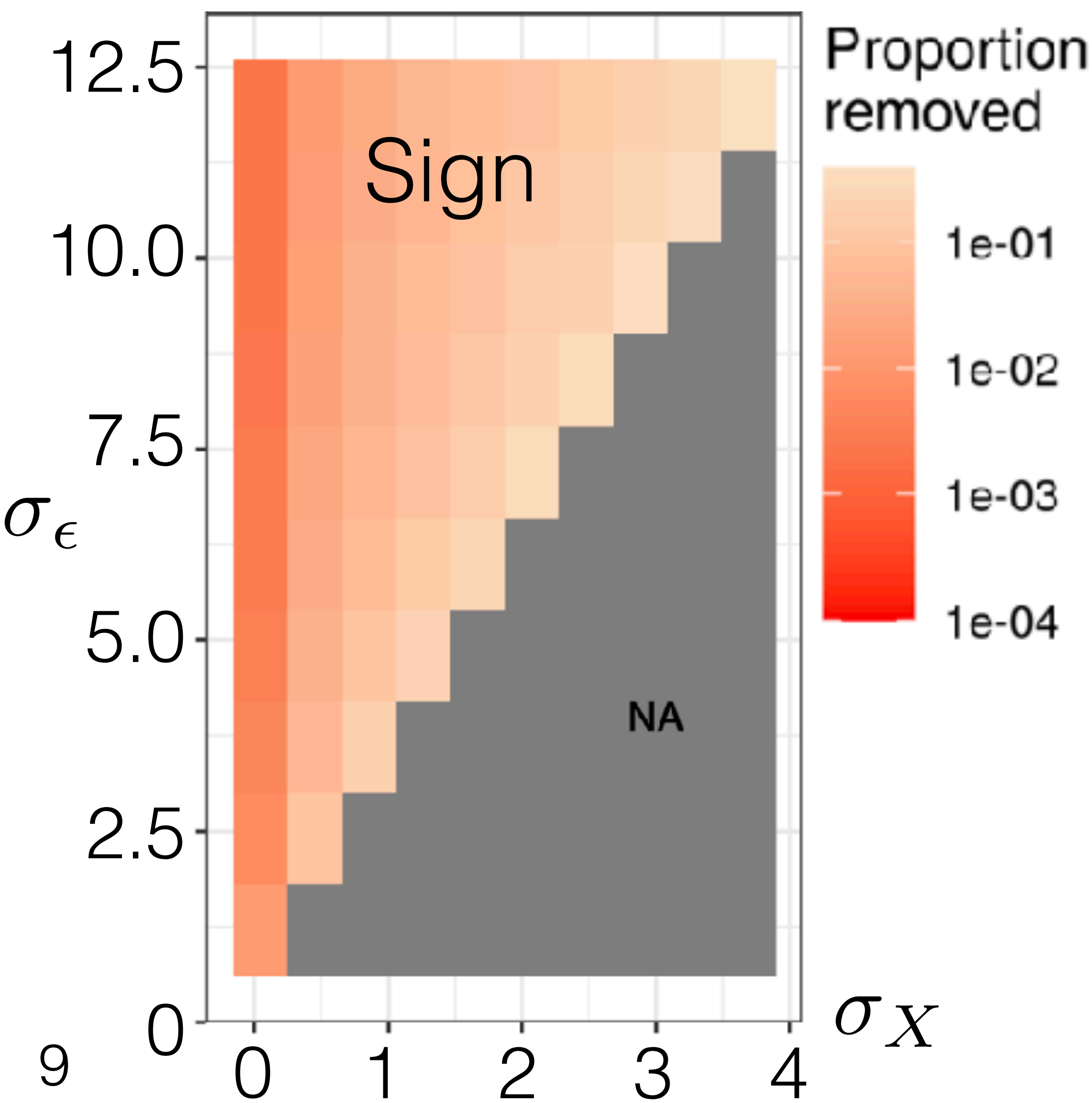

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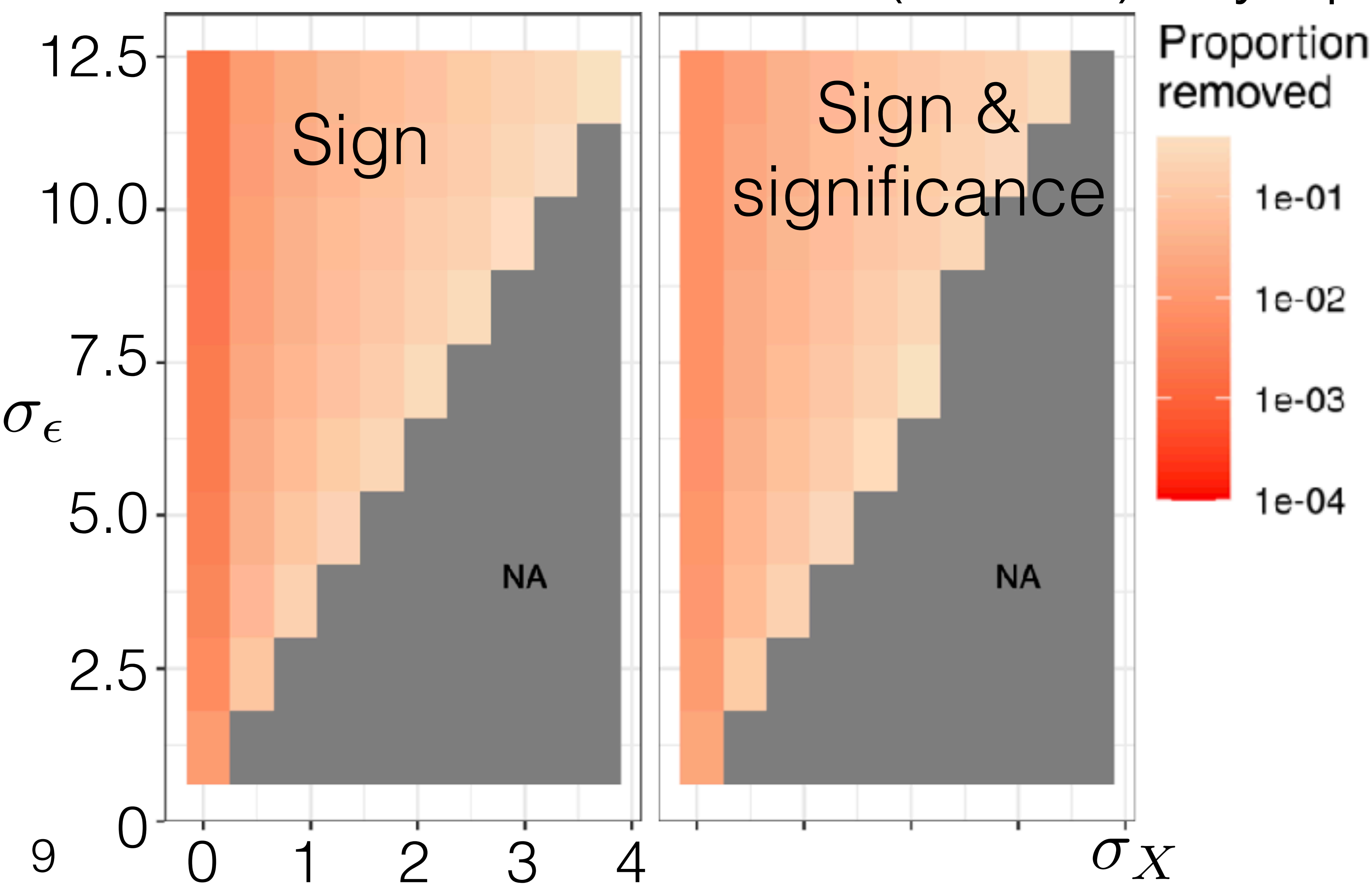

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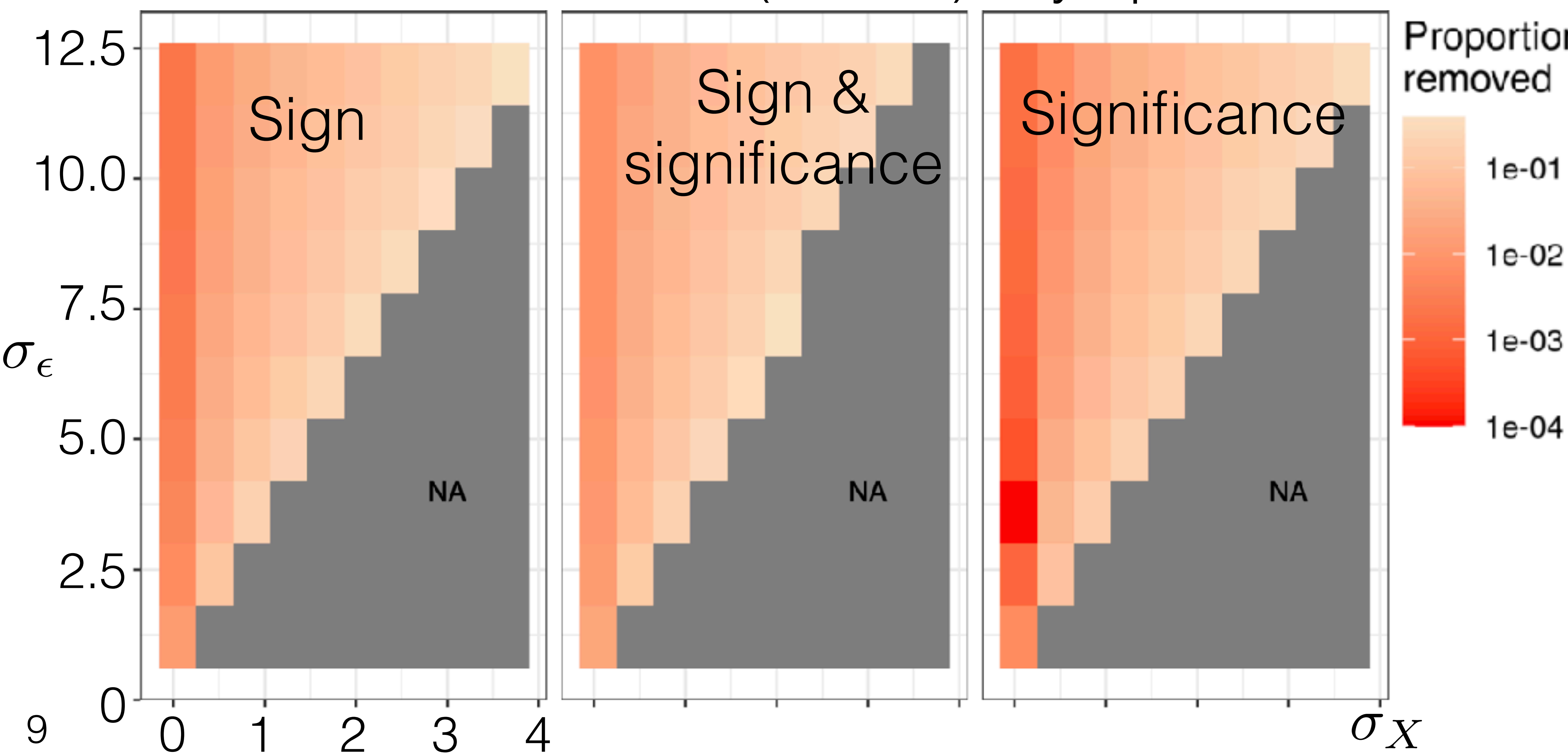

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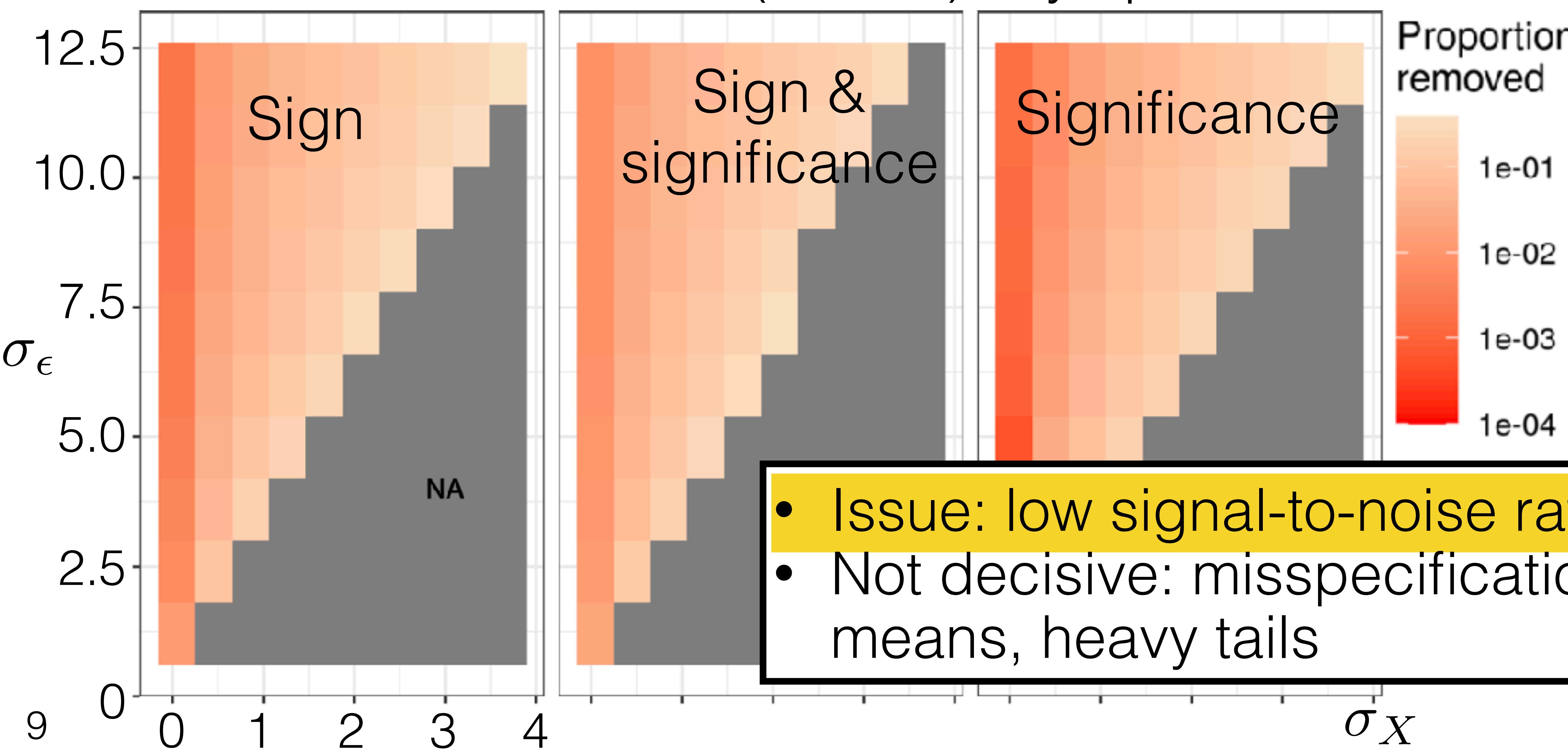


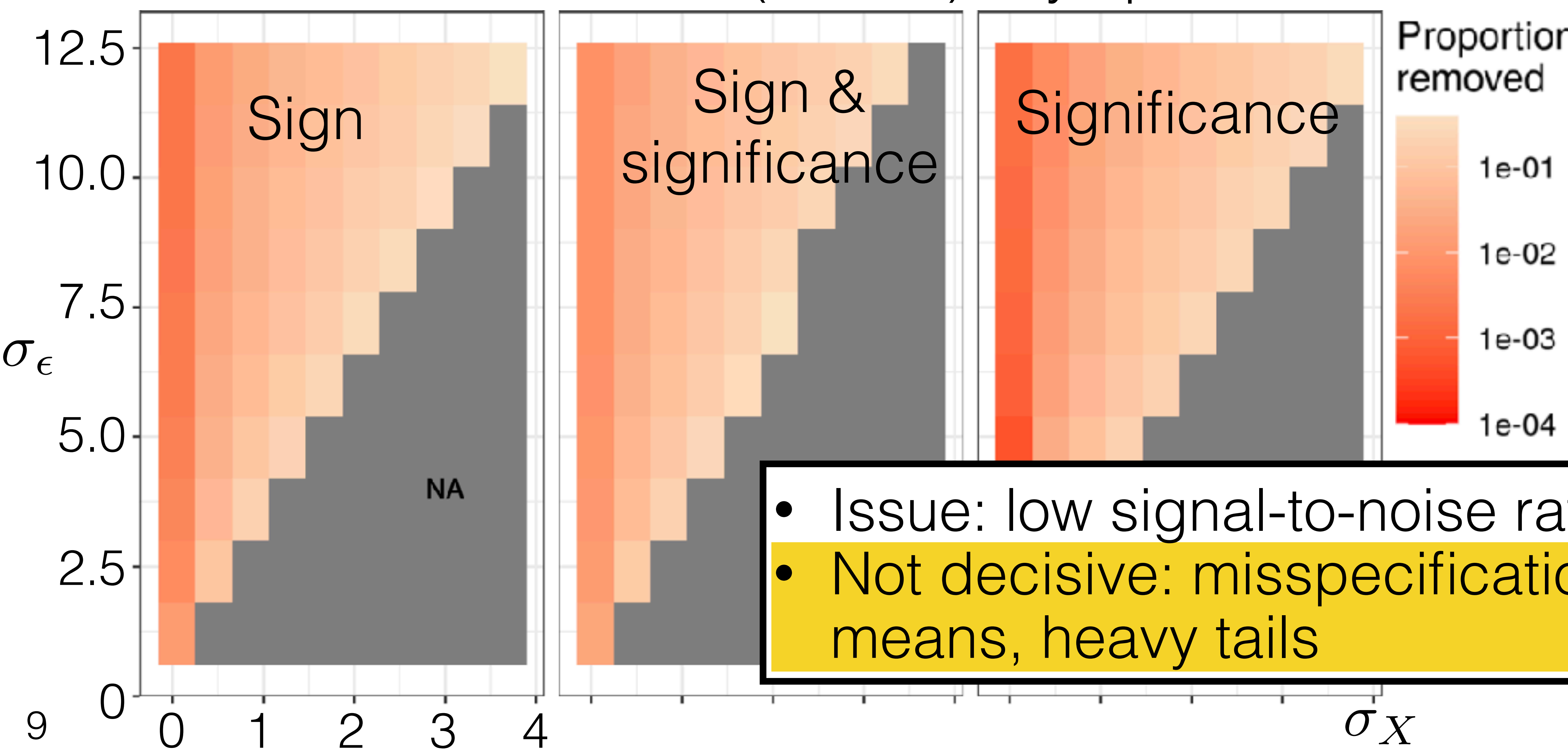
- Issue: low signal-to-noise ratio
- Not decisive: misspecification, means, heavy tails

What makes an analysis non-robust?

- Simulations from linear model with Gaussian noise

$$y_n = \theta x_n + \epsilon_n, \quad \epsilon_n \overset{iid}{\sim} \mathcal{N}(0, \sigma_\epsilon^2), \quad x_n \overset{iid}{\sim} \mathcal{N}(0, \sigma_X^2), \quad \theta = -1$$

- Can we flip sign of $\hat{\theta}$ by dropping some of 10,000 points?
- Signal = size of change of interest: $\Delta = \hat{\theta}$
- Noise = estimate of the (scaled) asymptotic std dev: $\approx \frac{\sigma_\epsilon}{\sigma_X}$



- Issue: low signal-to-noise ratio
- Not decisive: misspecification, means, heavy tails

Oregon Medicaid Study

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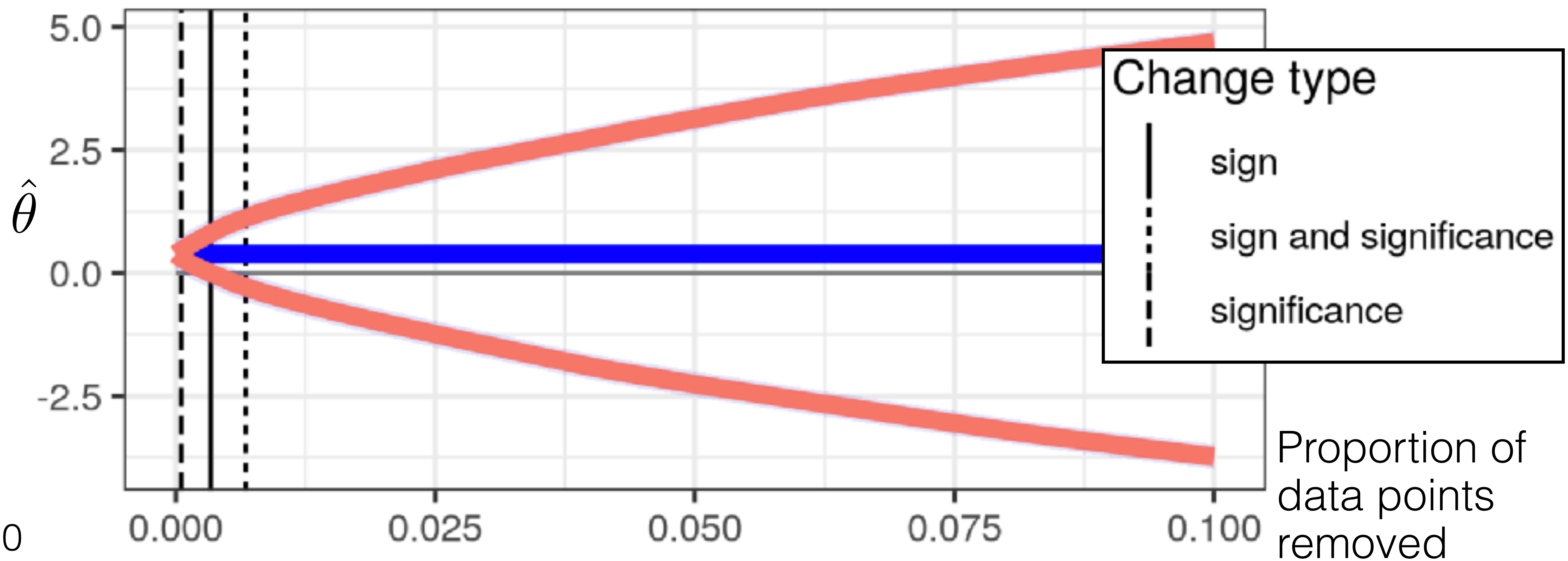

Proportion of data points removed

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  - We show: in linear regression, influence score = residual times leverage

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    - Cf. the classical "infinitesimal jackknife" [Jaeckel 1972; Clarke 1983]

Try it out!

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- **Paper**: T Broderick, R Giordano, R Meager “An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Change Conclusions?” 2020
  `https://arxiv.org/abs/2011.14999`
- **Code, readme, and examples**:
  `https://github.com/rgiordan/zaminfluence`
- Try it out on your data analysis and email us!
  `tbroderick@mit.edu, rgiordan@mit.edu, r.meager@lse.ac.uk`
- See also: “Transparency and Reproducibility in Artificial Intelligence,” *Nature Matters Arising*, 2020.
- Introduction to ML: `tamarabroderick.com/ml.html`

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See also:

- R Giordano, W Stephenson, R Liu, MI Jordan, T Broderick. A Swiss Army infinitesimal jackknife. *AISTATS* 2019.
- W Stephenson, T Broderick. Approximate Cross-Validation in High Dimensions with Guarantees. *AISTATS* 2020.
- WT Stephenson, M Udell, T Broderick. Approximate Cross-Validation with Low-Rank Data in High Dimensions. *NeurIPS* 2020.
- S Ghosh*, WT Stephenson*, TD Nguyen, SK Deshpande, T Broderick. Approximate Cross-Validation for Structured Models. *NeurIPS* 2020. (*equal)