MIT EECS
ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

MIT STATISTICS + DATA SCIENCE CENTER

CSAIL

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

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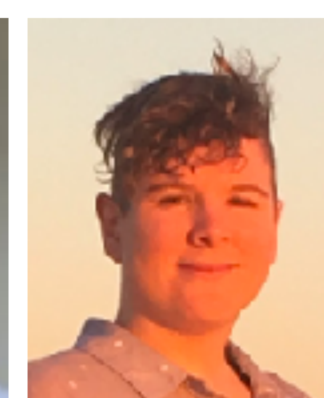
MIT

With Ryan Giordano, Rachael Meager

When can I trust my data analysis?

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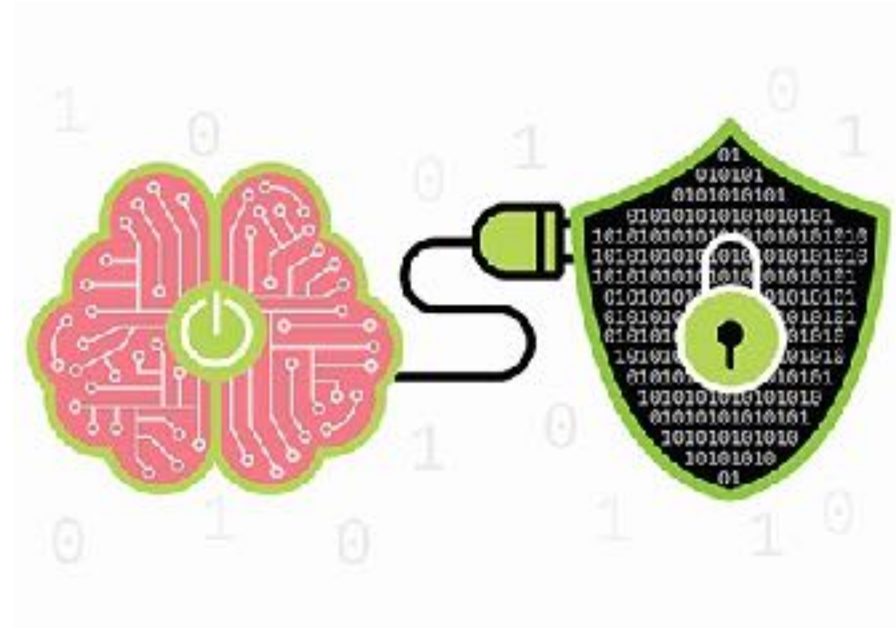

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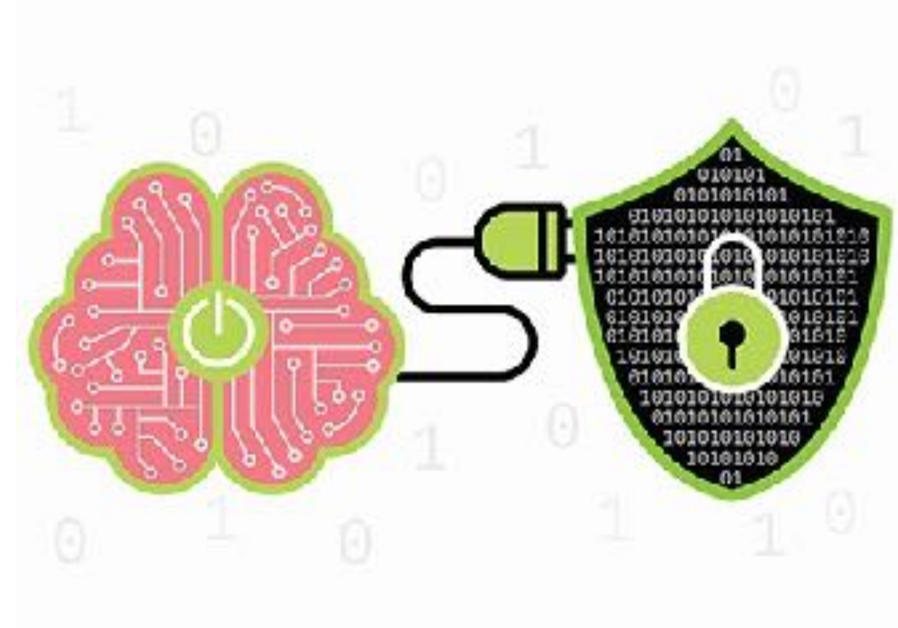

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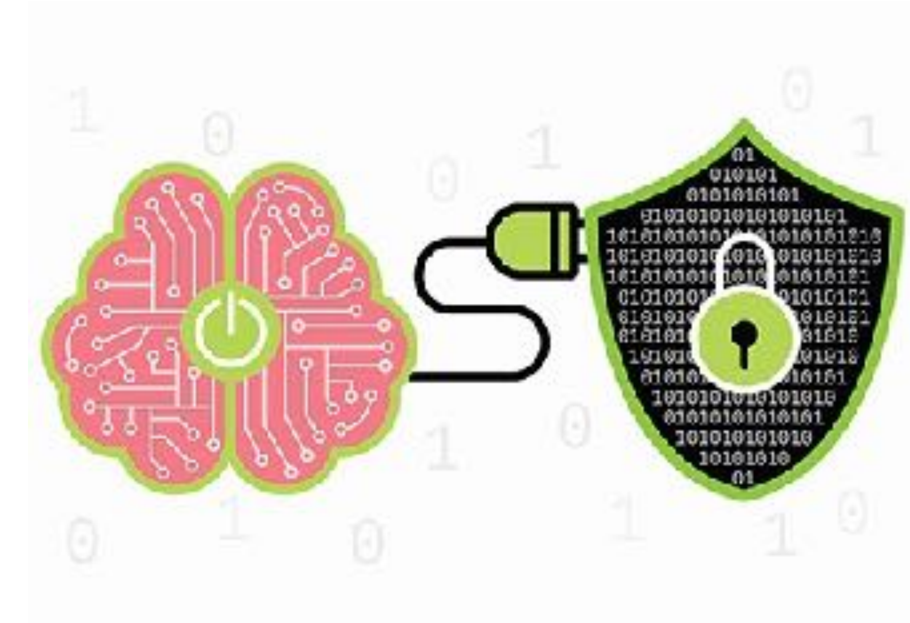

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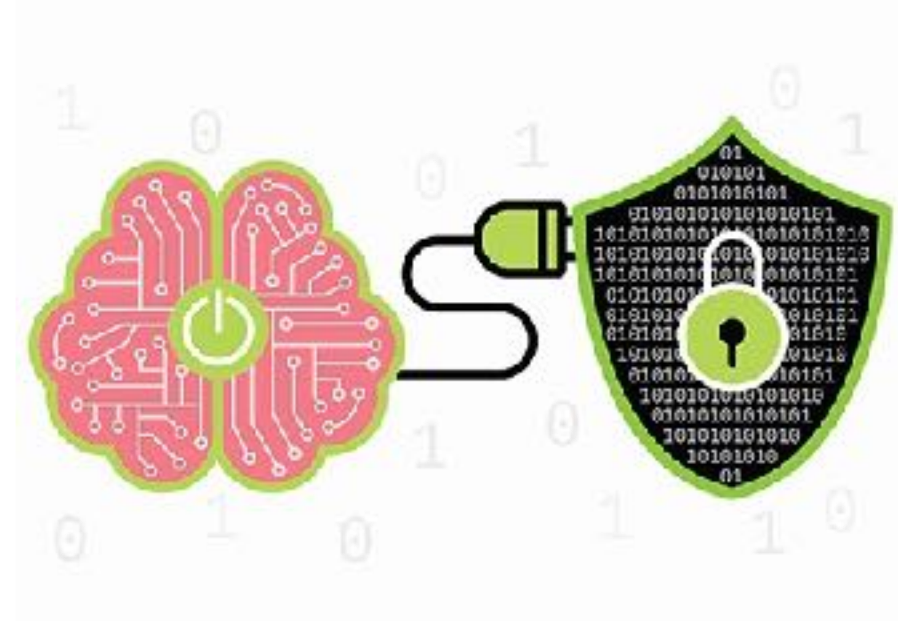

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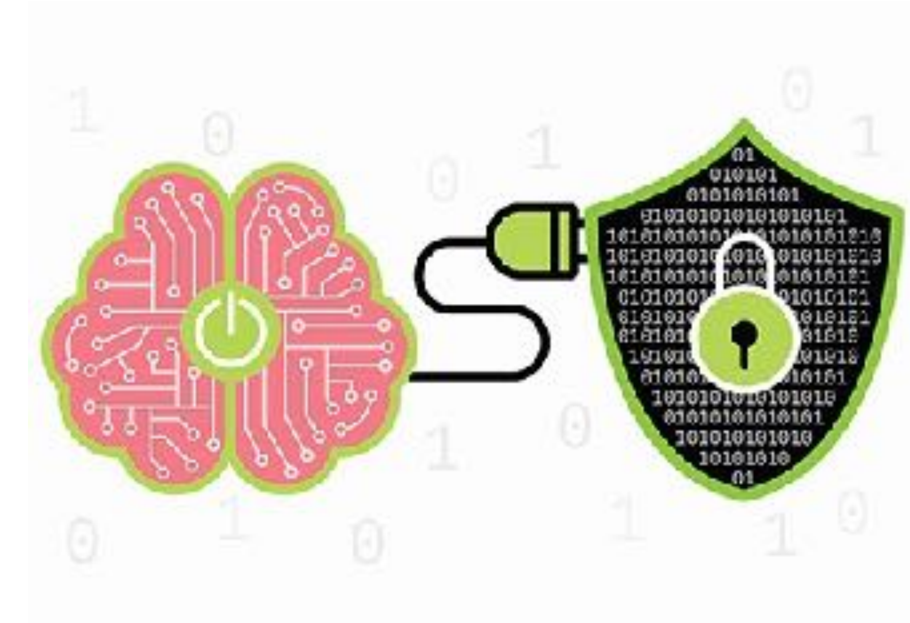


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- E.g. in a study of microcredit with ~16,500 data points, we find a single data point that drives the sign of the effect

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

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  - If analysis takes 1 second, check takes >31 years

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parameters

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loss parameters

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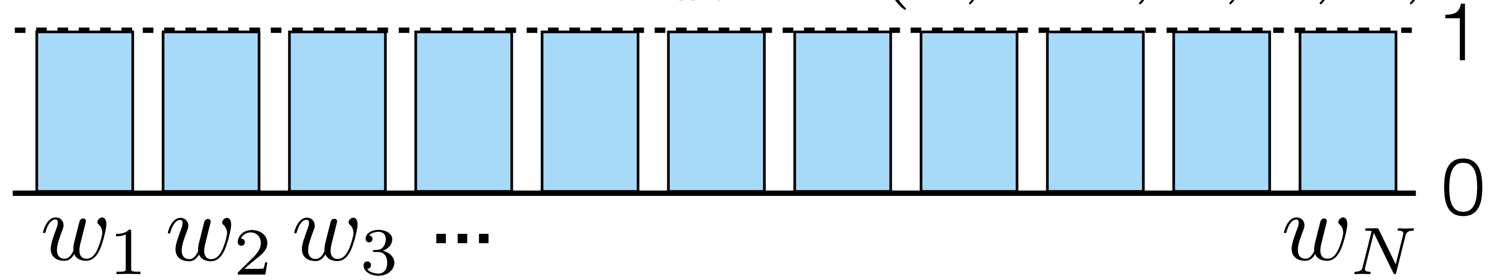

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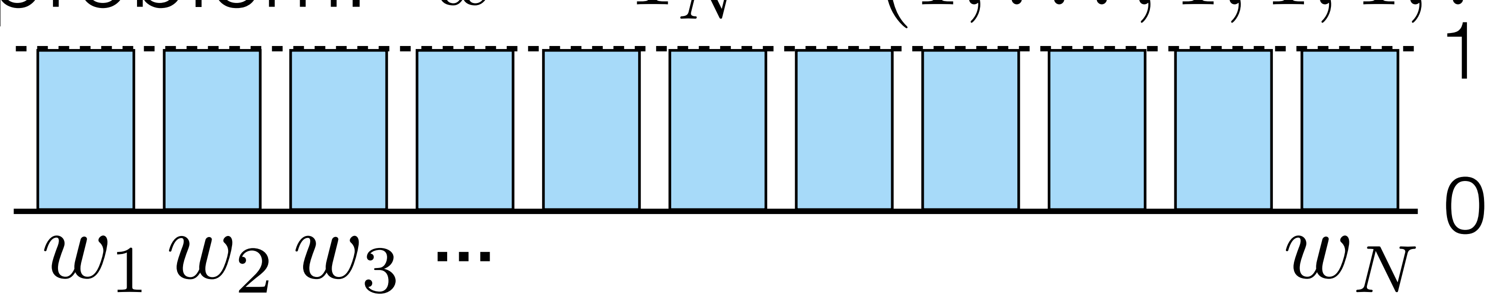

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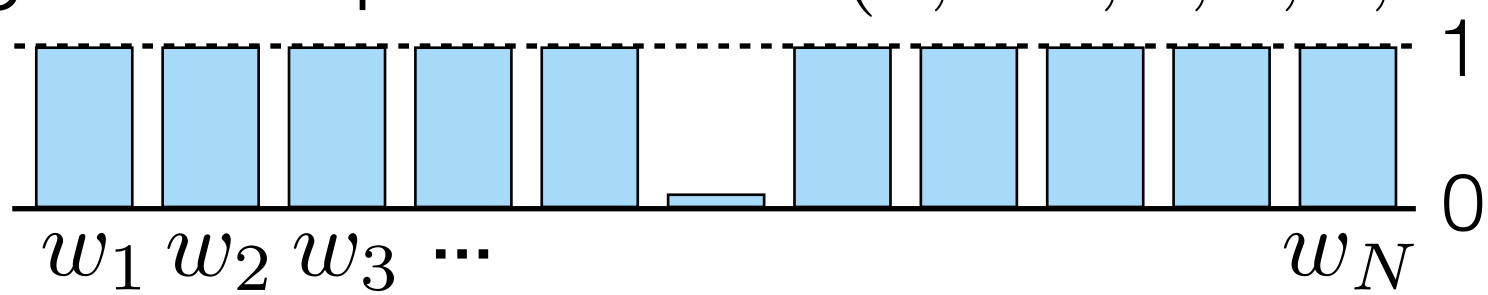

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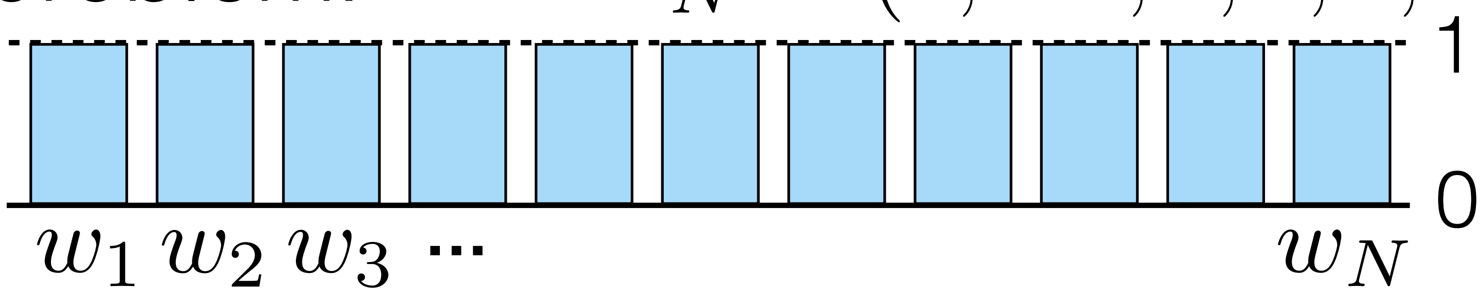

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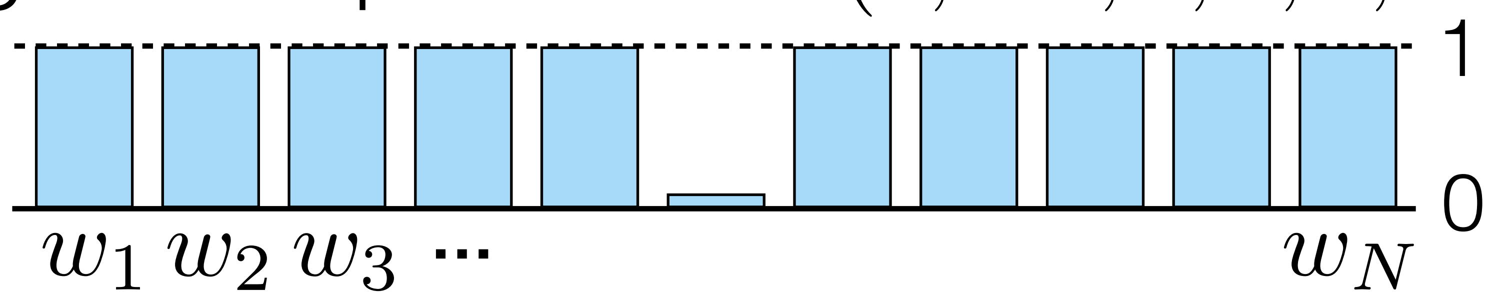

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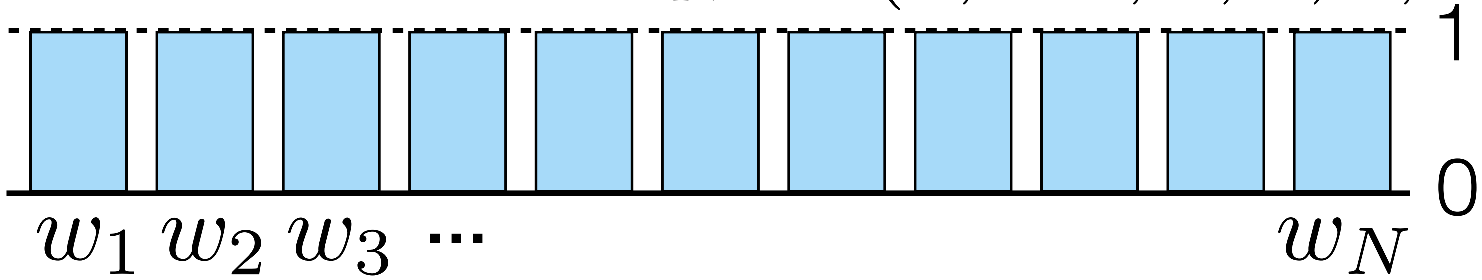

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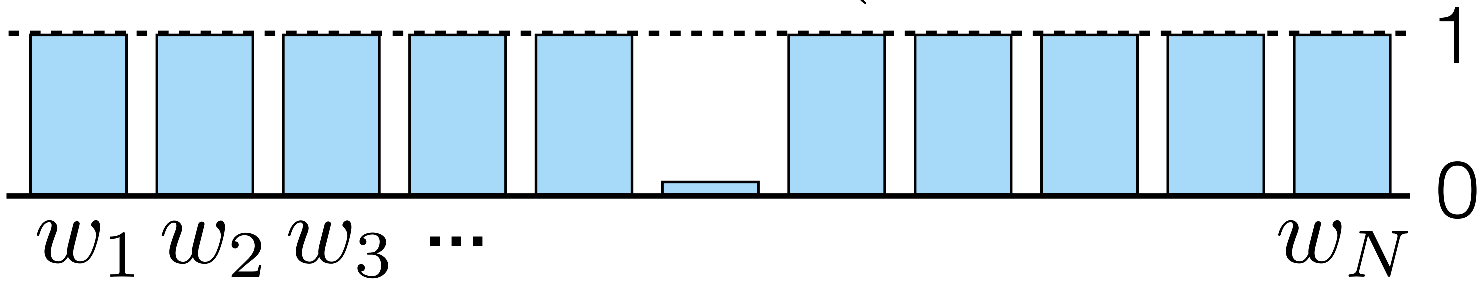

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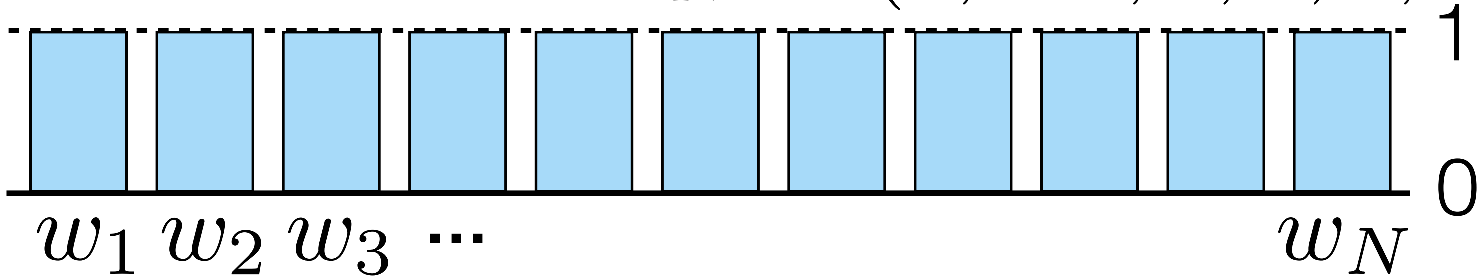

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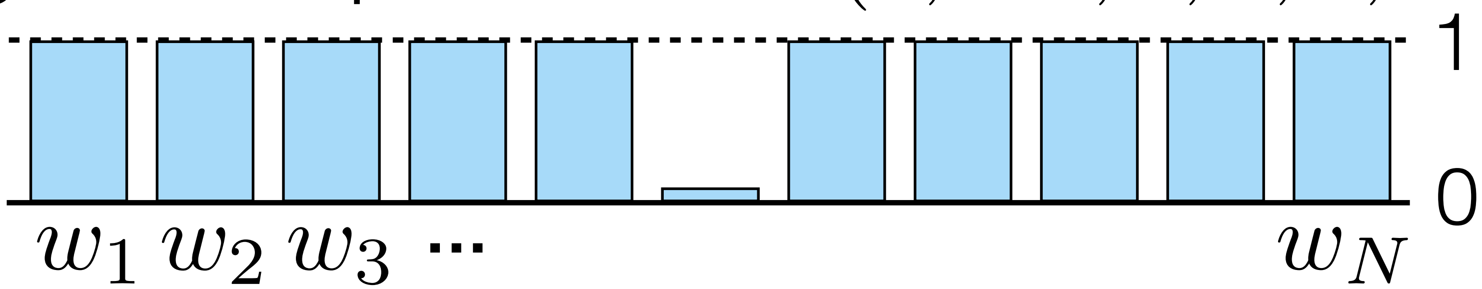

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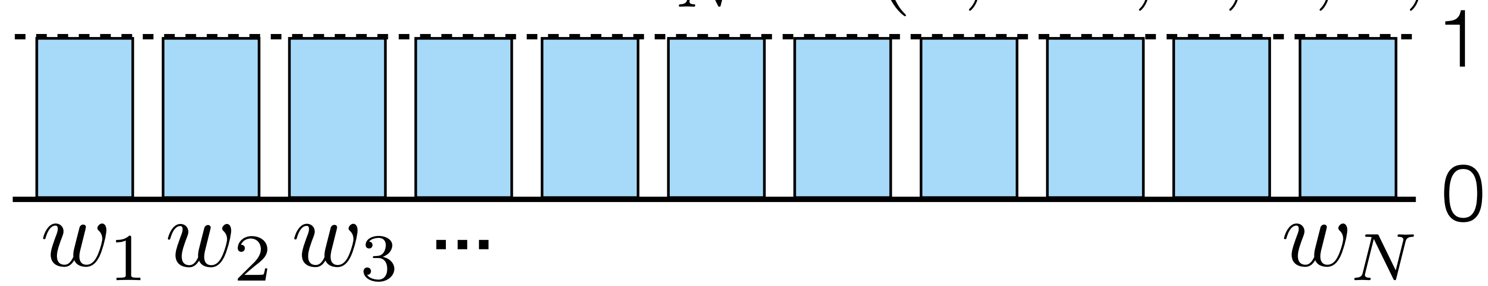

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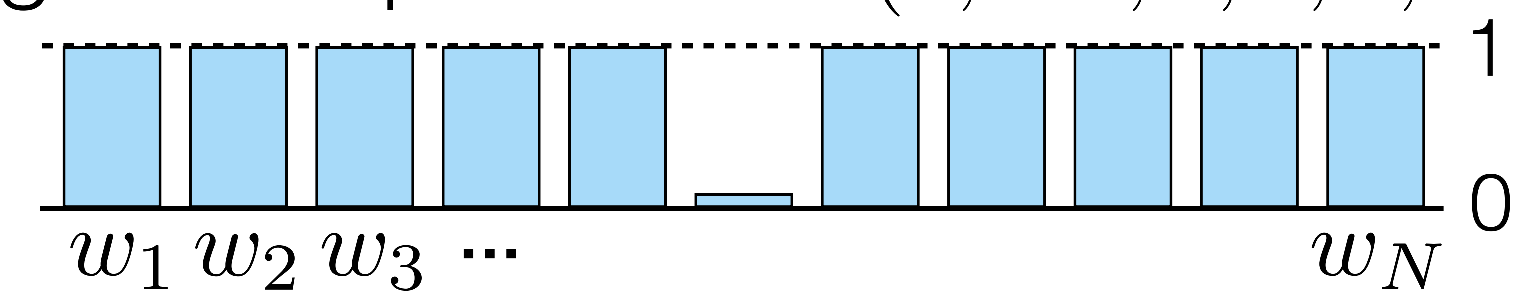

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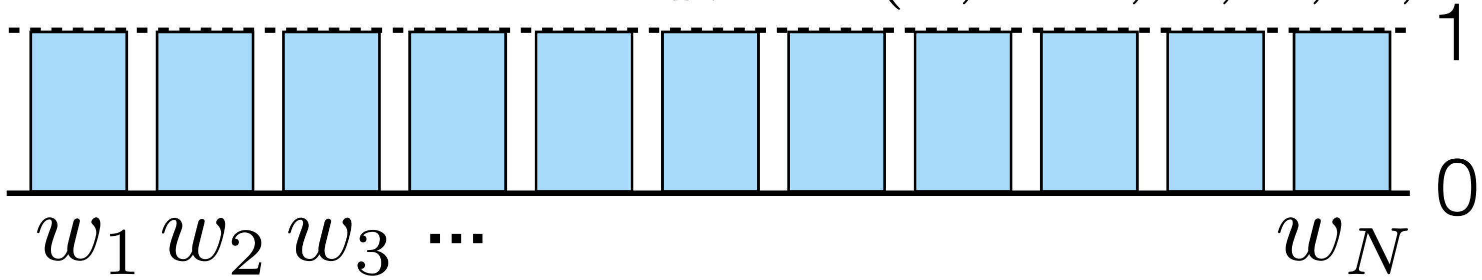

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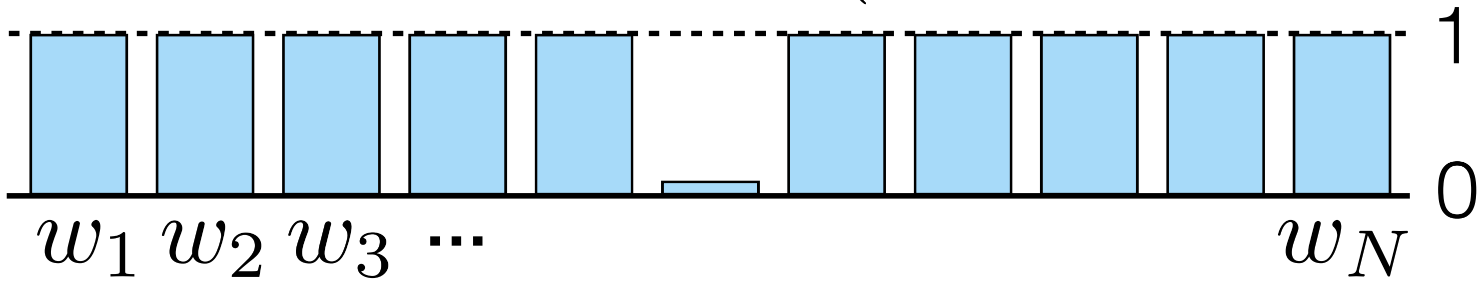

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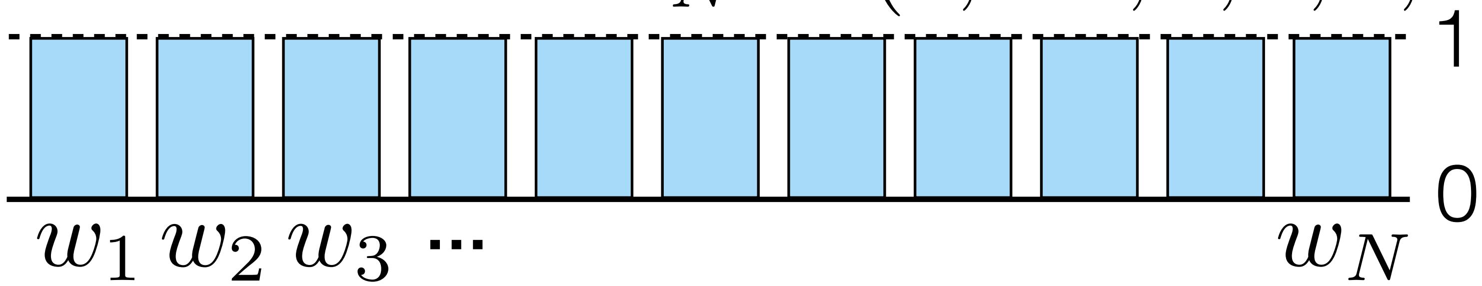

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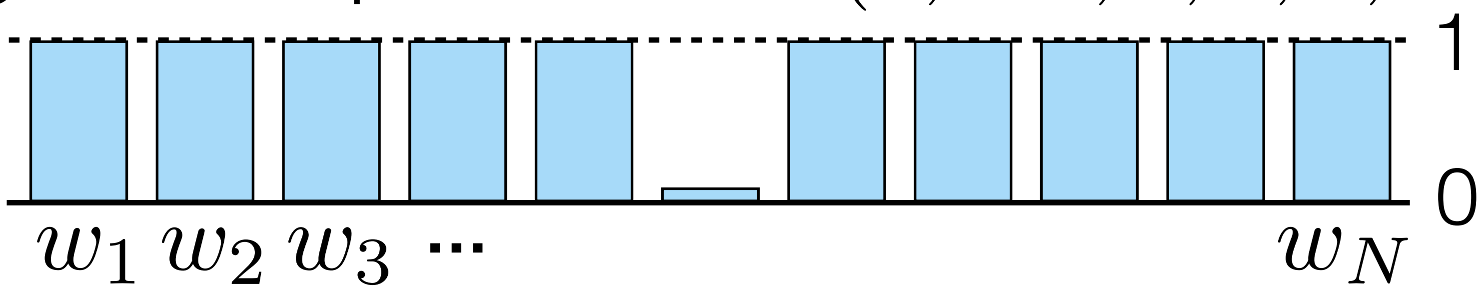

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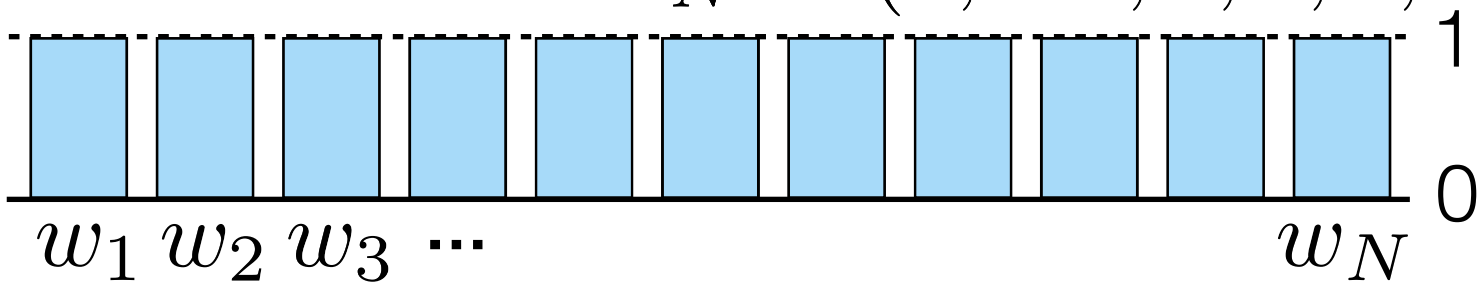

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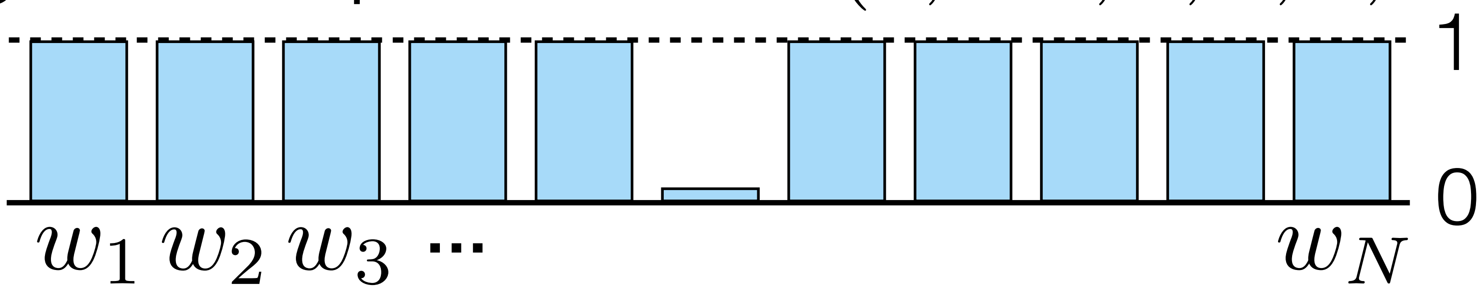

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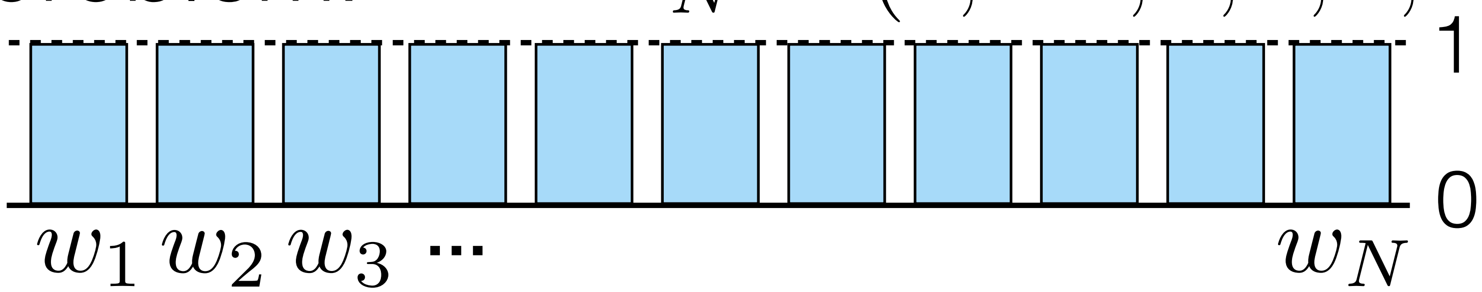

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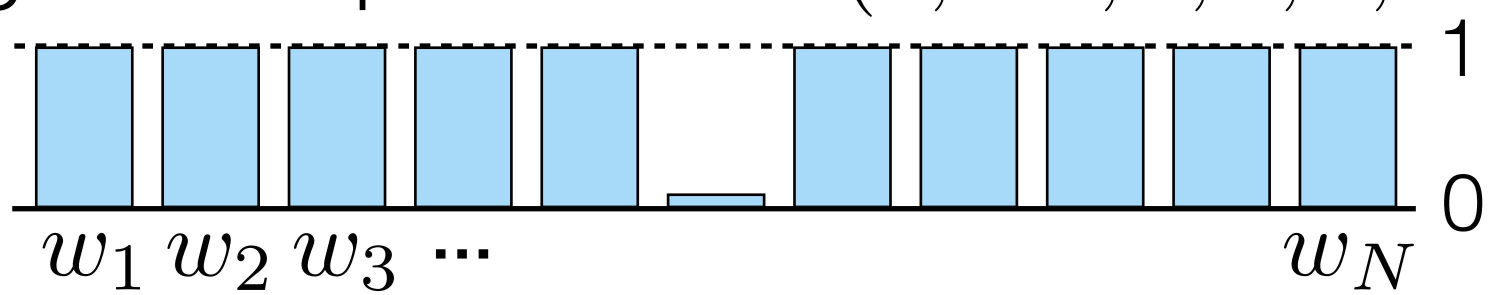

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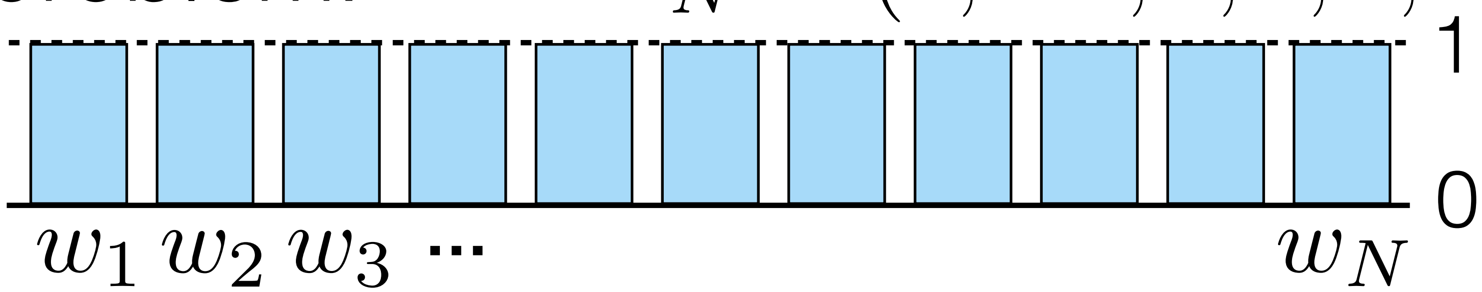

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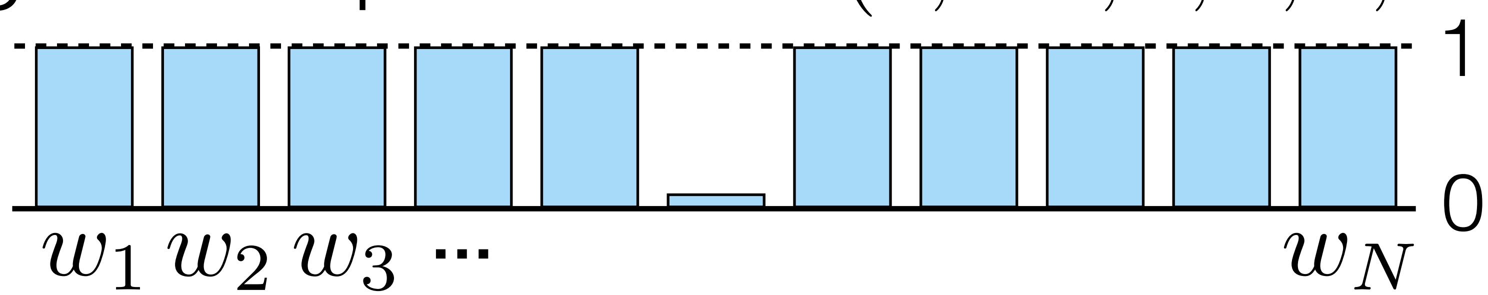

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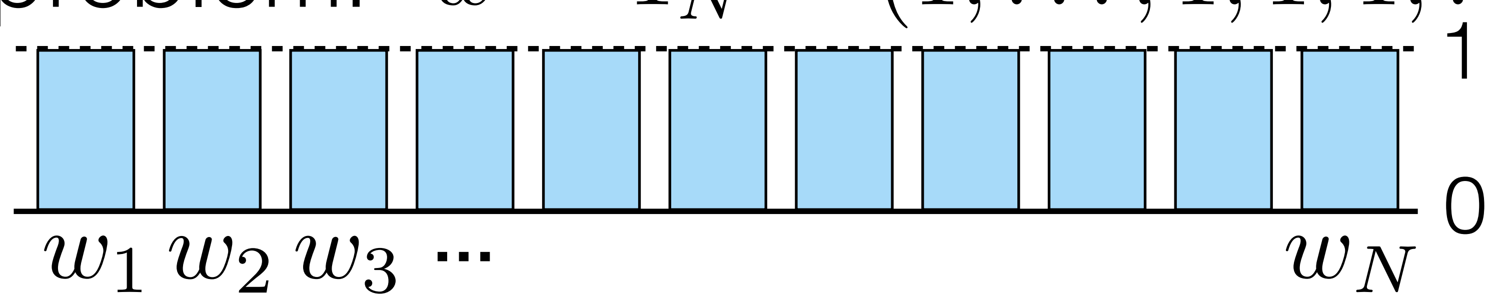

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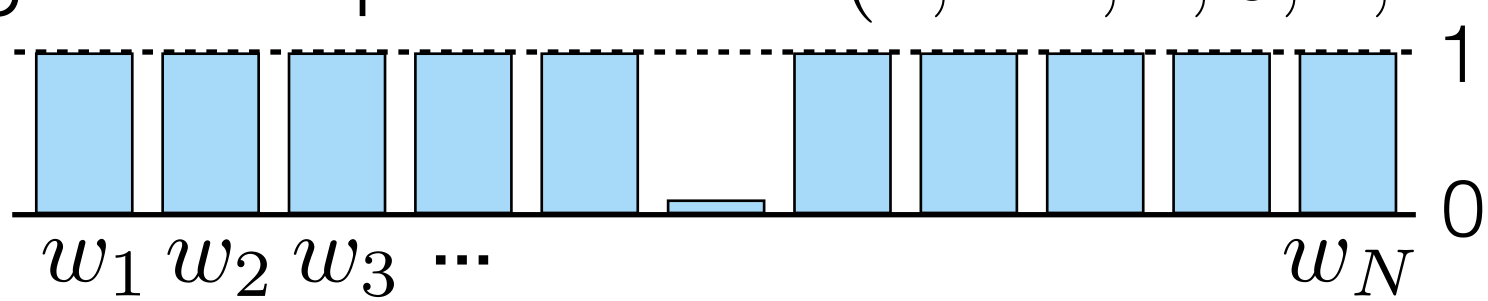

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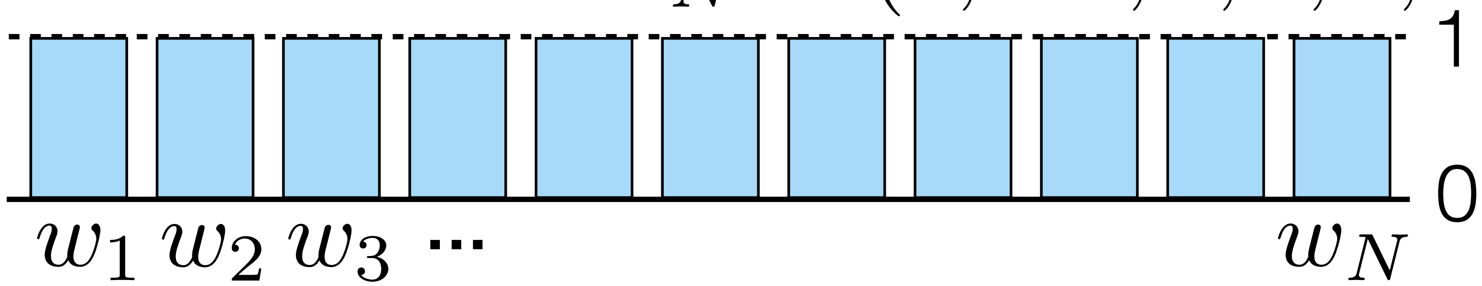

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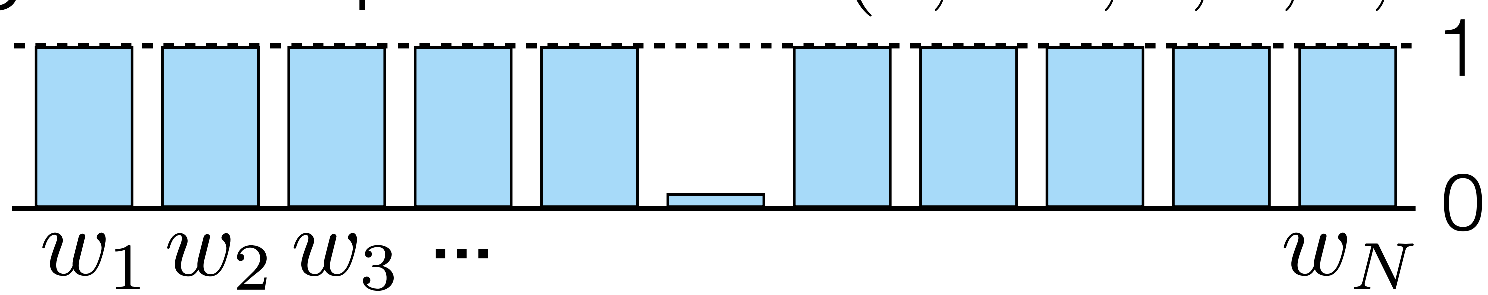

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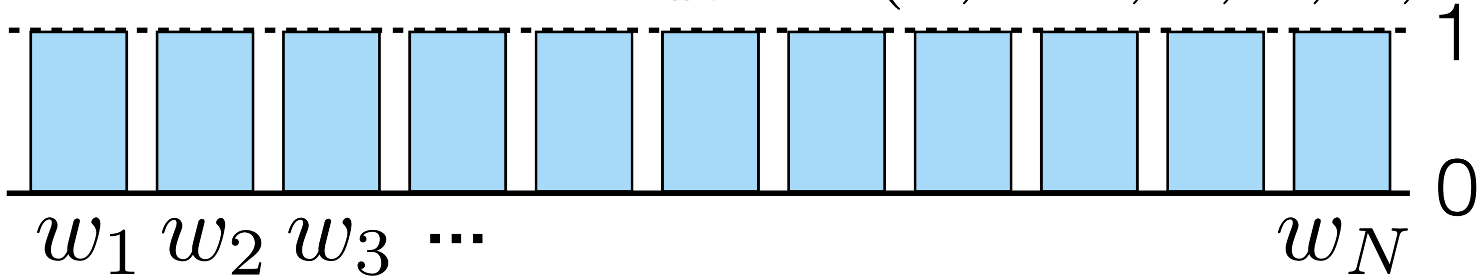

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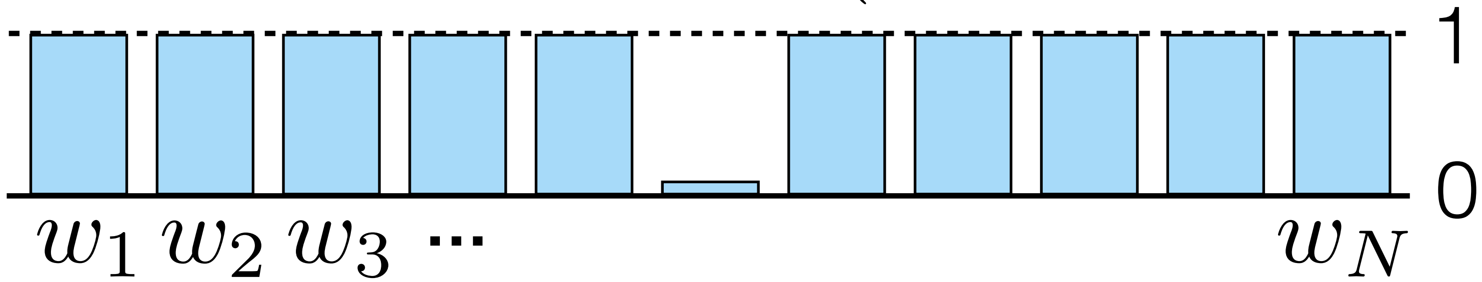

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[What about higher orders? Some very early work: Giordano, Jordan, Broderick 2019]

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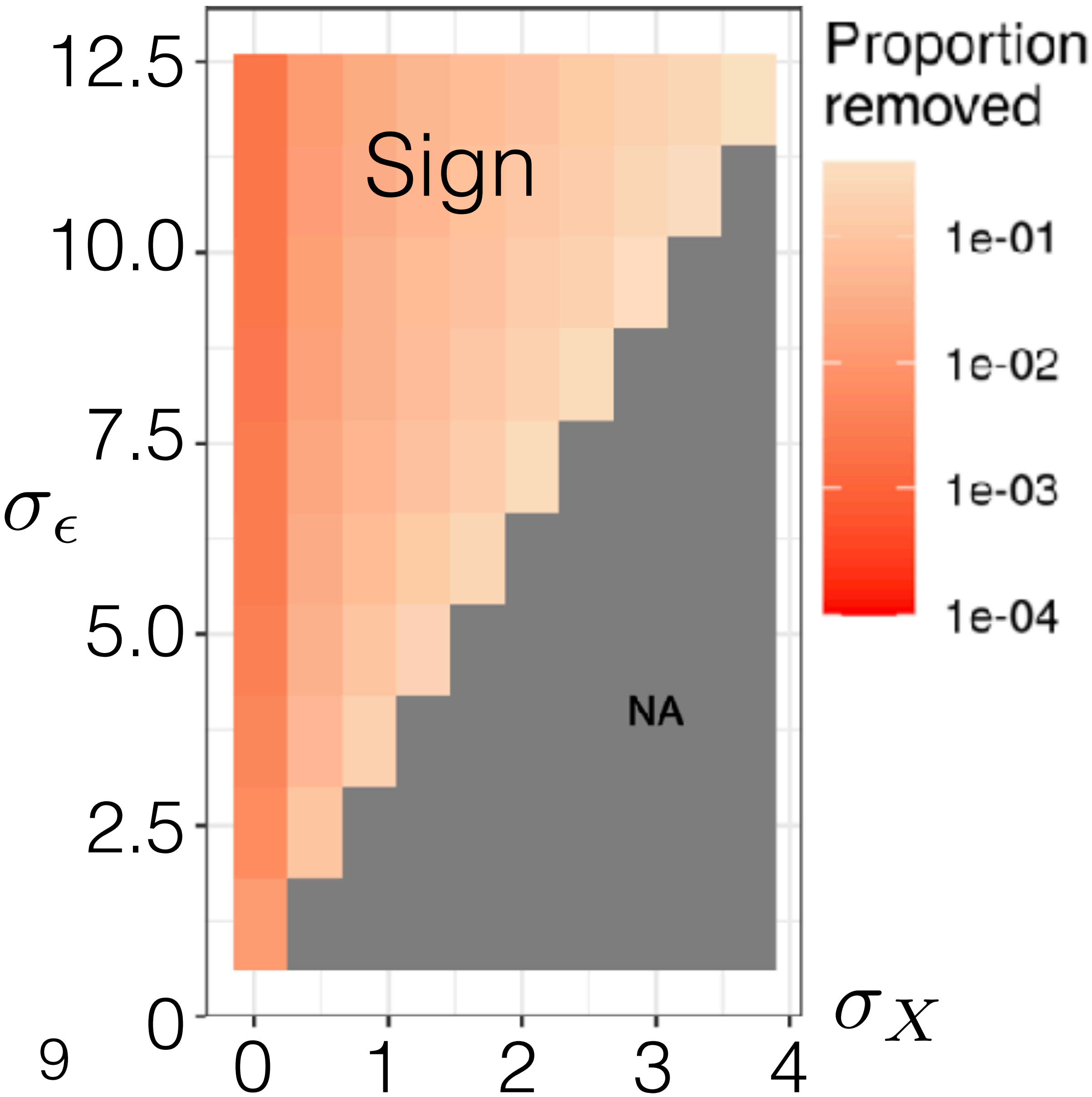

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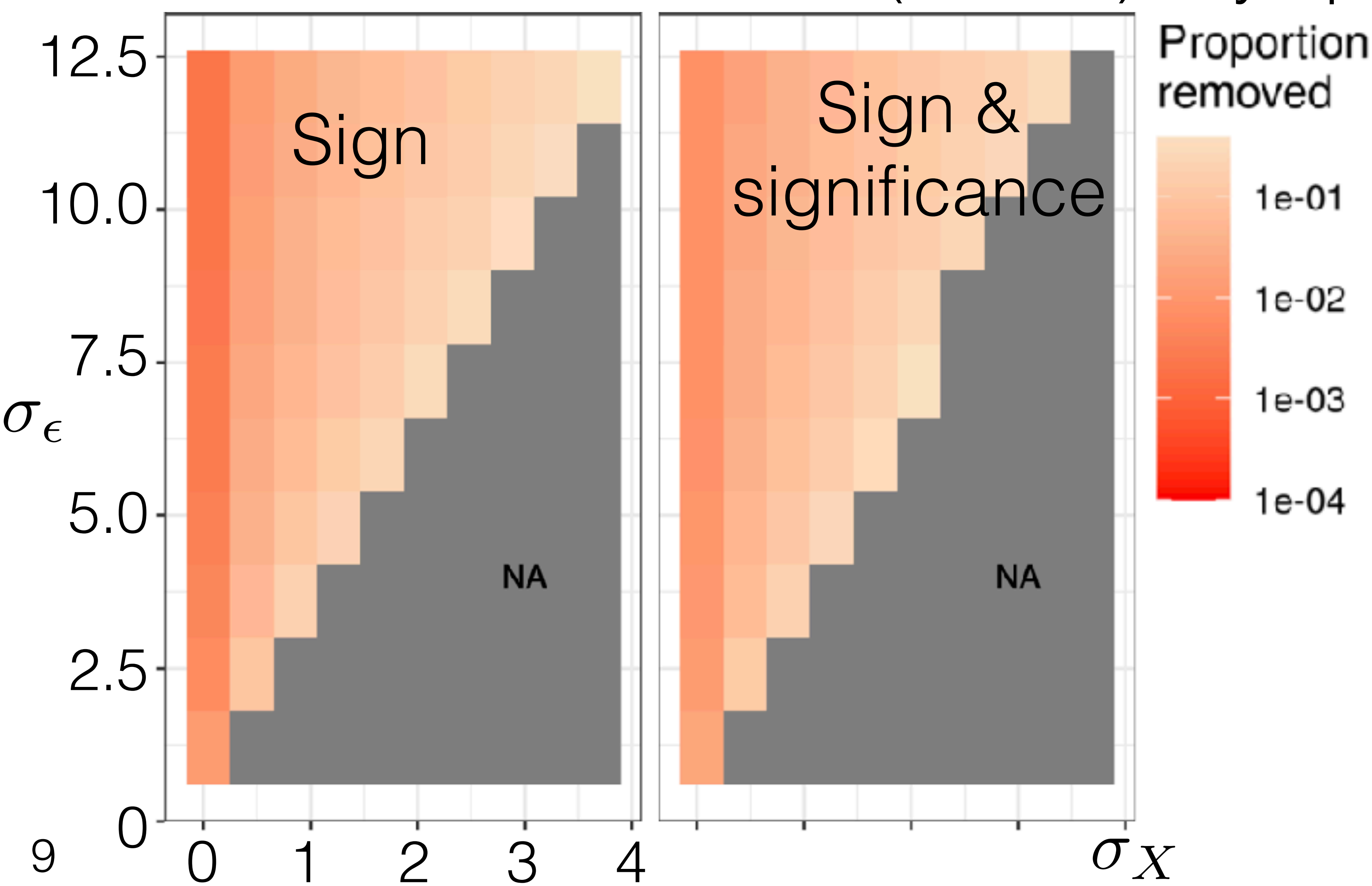

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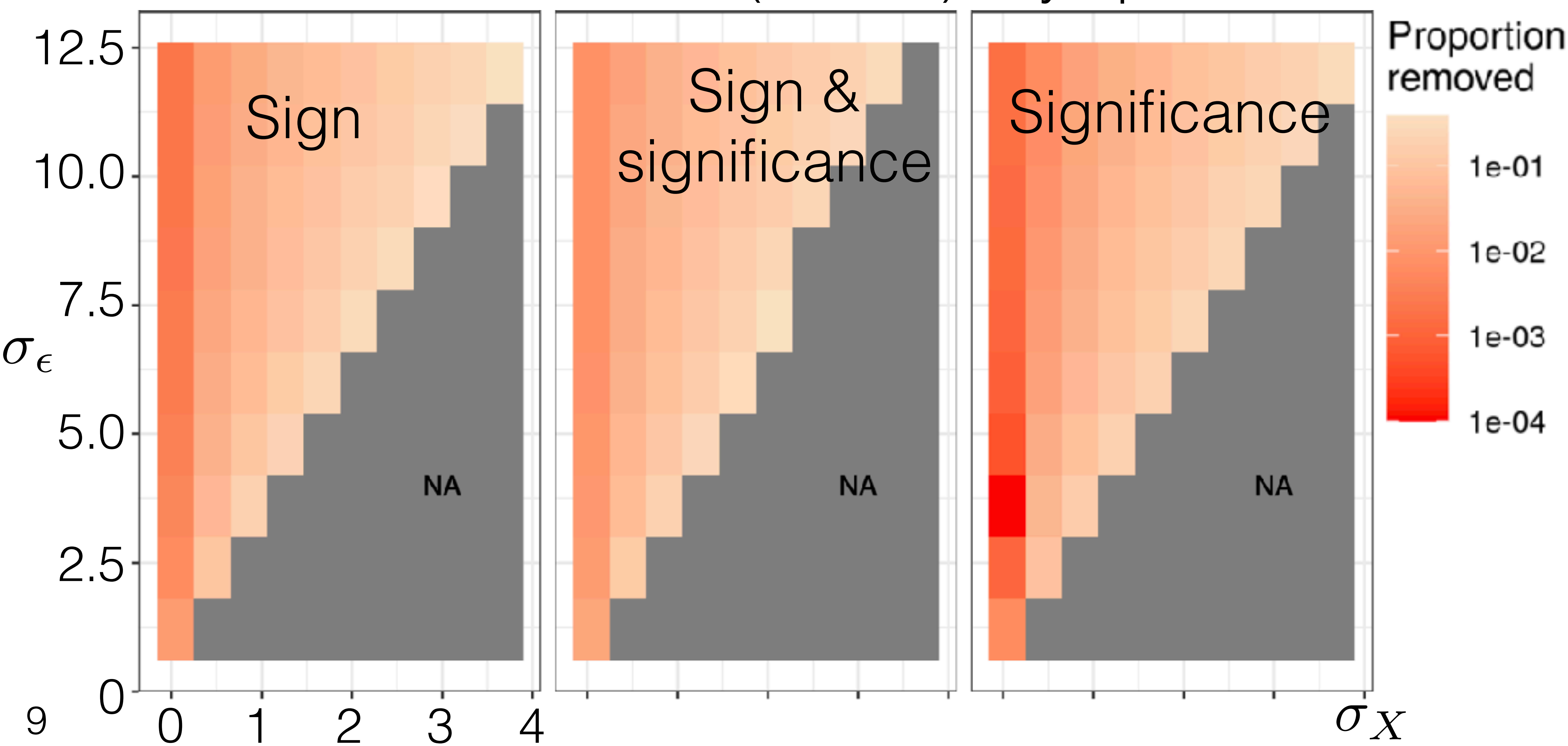

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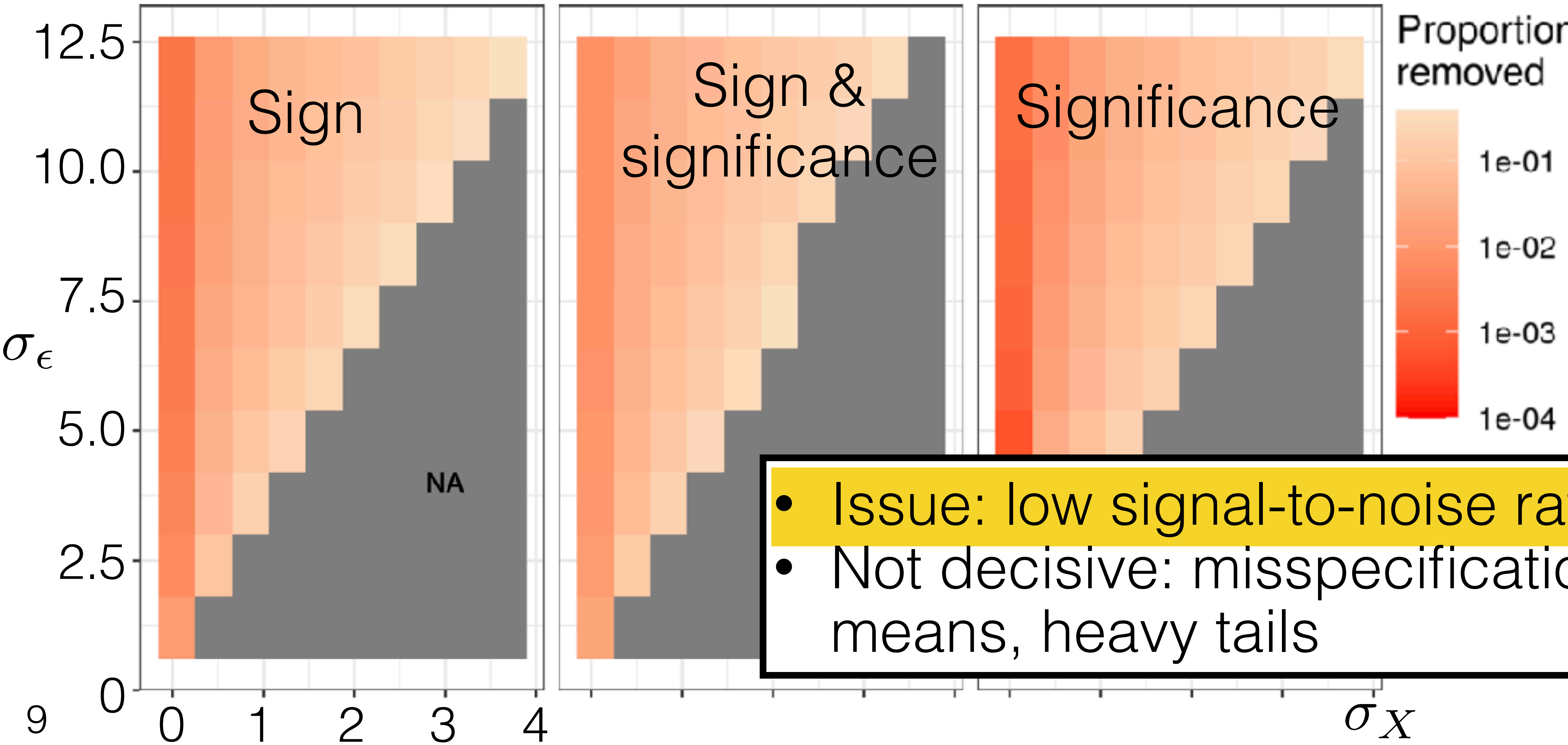


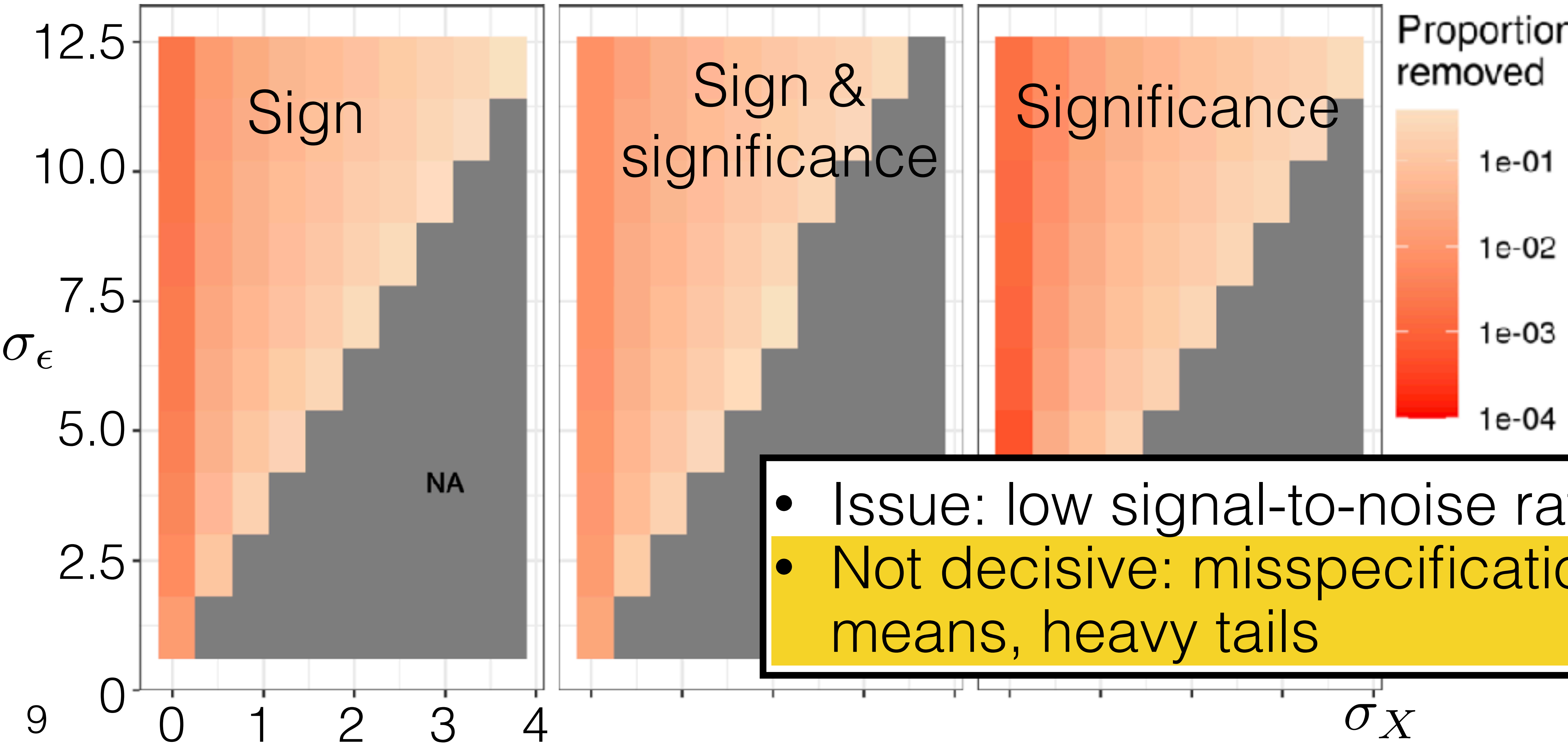
- Issue: low signal-to-noise ratio
- Not decisive: misspecification, means, heavy tails

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: $\approx \frac{\sigma_\epsilon}{\sigma_X}$



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        - But dropping 11 points (0.05%) changes significance

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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!

- We present a metric to check if there is a small fraction of data you can drop to change conclusions
- **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`
- Aside: “Transparency and Reproducibility in Artificial Intelligence,” *Nature Matters Arising*, 2020.

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- See also:
  - R Giordano, T Broderick, MI Jordan. Linear Response Methods for Accurate Covariance Estimates from Mean Field Variational Bayes. *NeurIPS* 2015.
  - R Giordano, T Broderick, MI Jordan. Covariances, Robustness, and Variational Bayes. *JMLR* 2018.
  - R Giordano, W Stephenson, R Liu, MI Jordan, T Broderick. A Swiss Army infinitesimal jackknife. *AISTATS* 2019.