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

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With Ryan Giordano, Rachael Meager

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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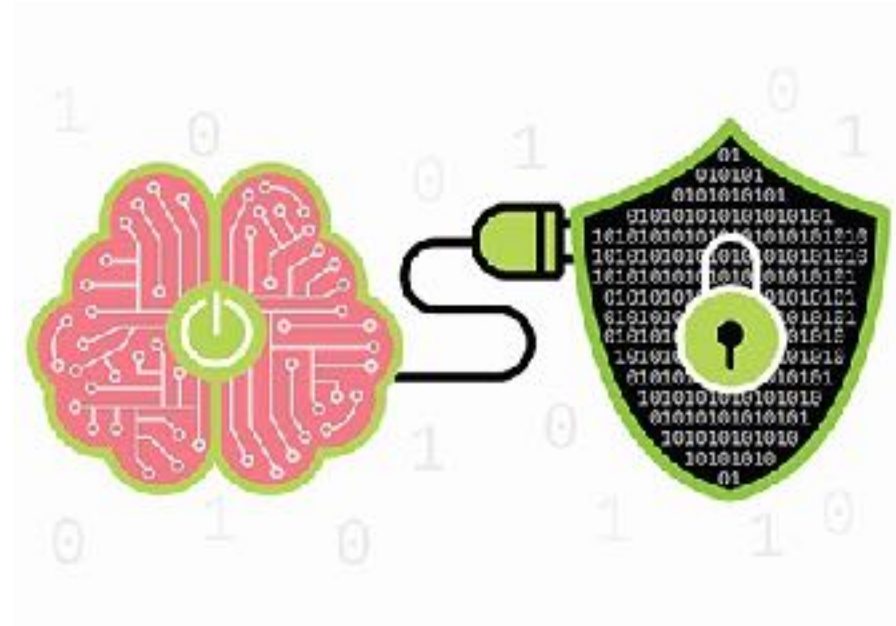


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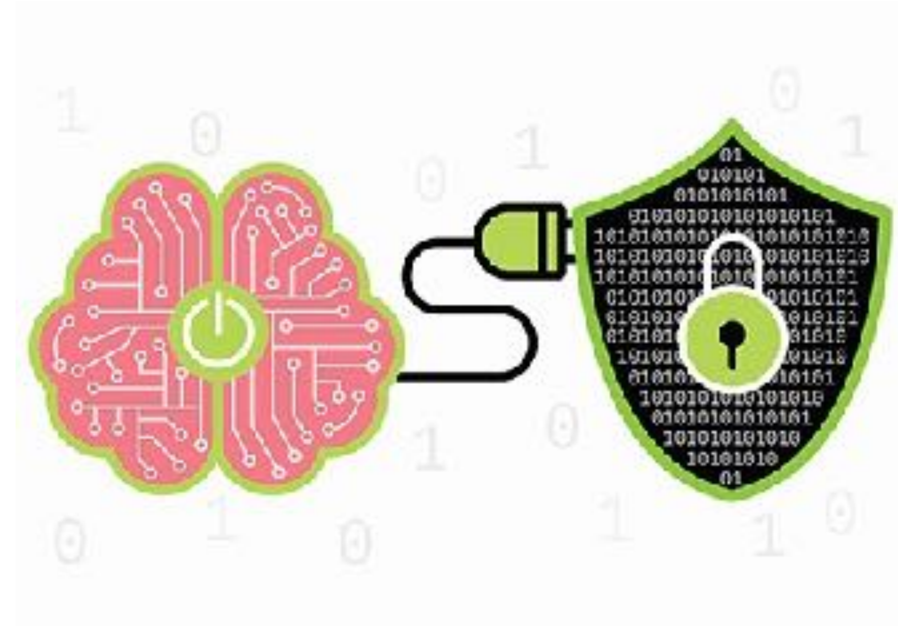

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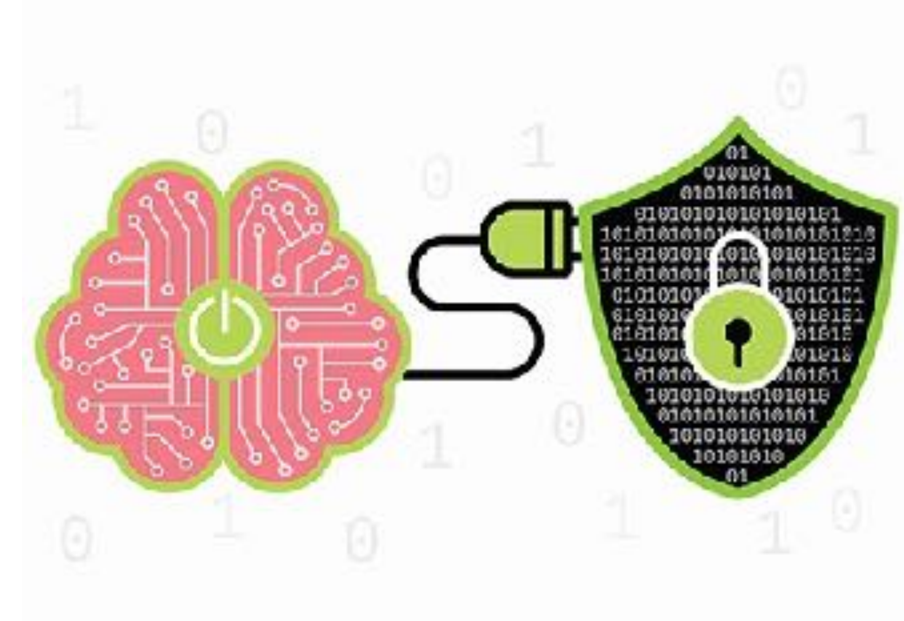

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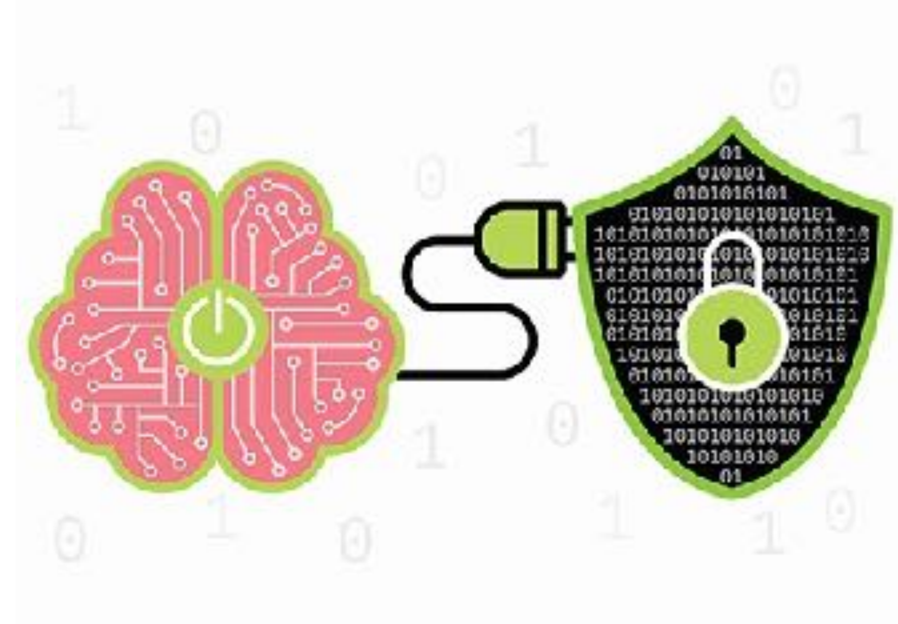

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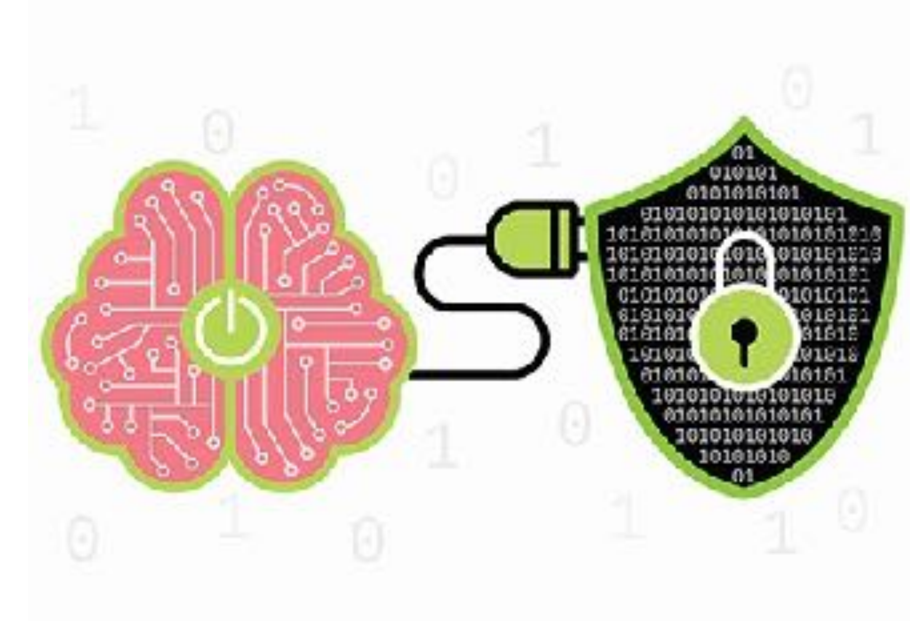

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- E.g. in a study of microcredit with ~16,500 data points, we find a single data point that drives the sign of the effect

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

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  - If analysis takes 1 second, check takes >33 years

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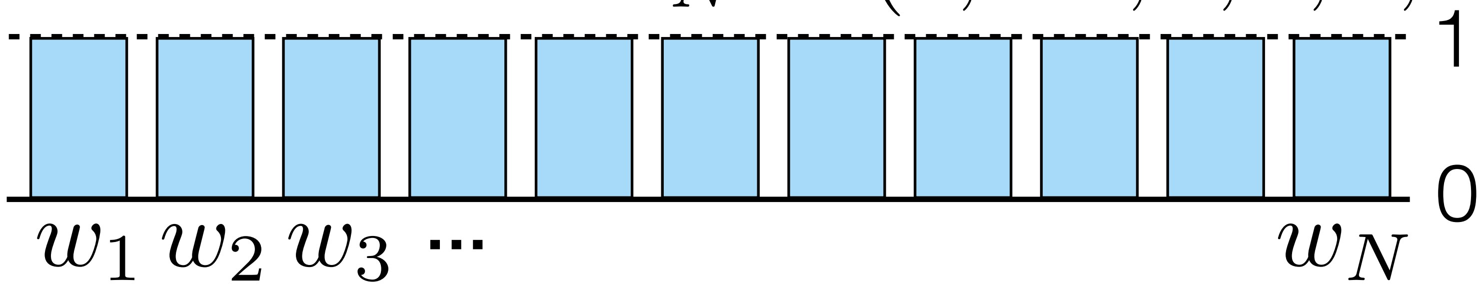

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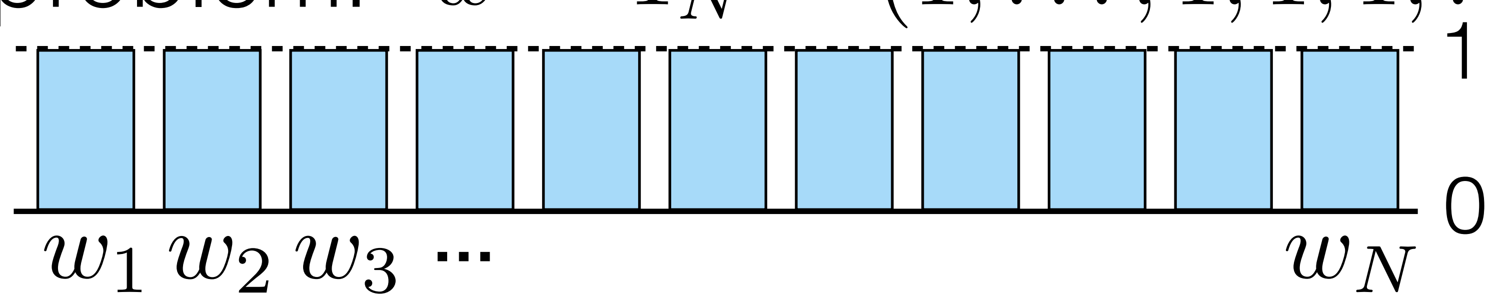
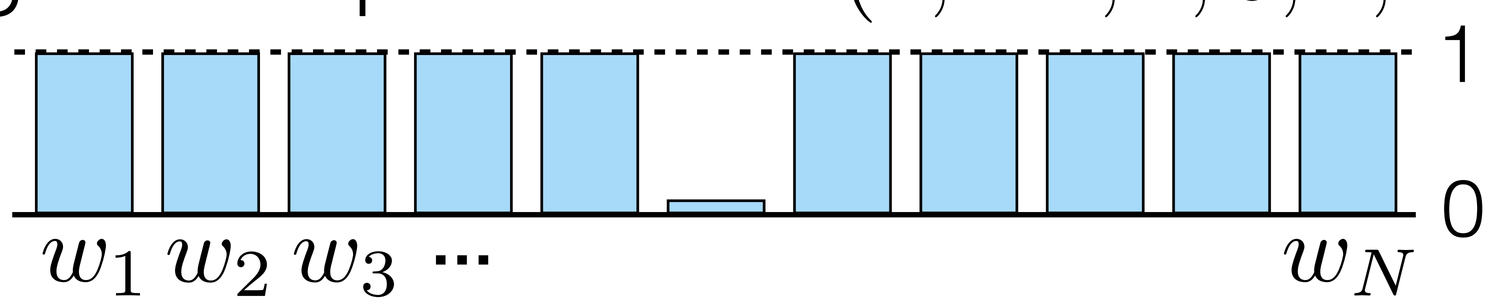


- Dropping a data point: $w = (1, \ldots, 1, 0, 1, \ldots, 1)$



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estimator

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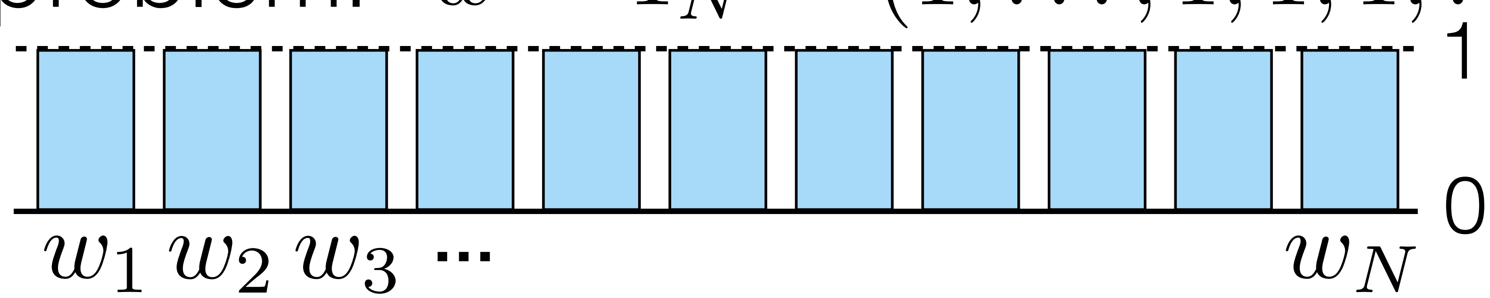

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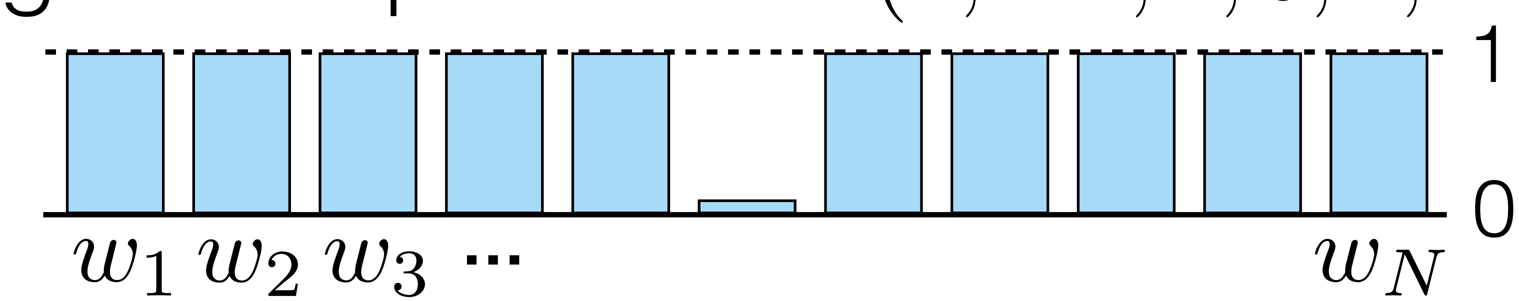

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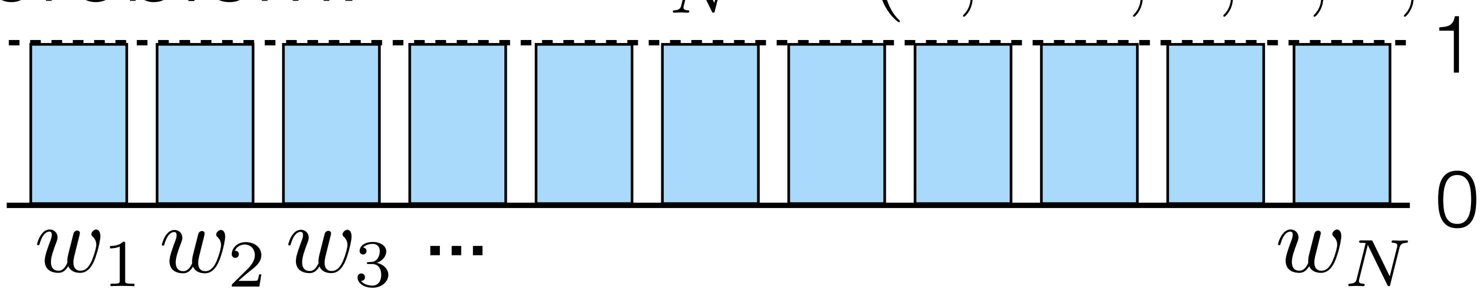

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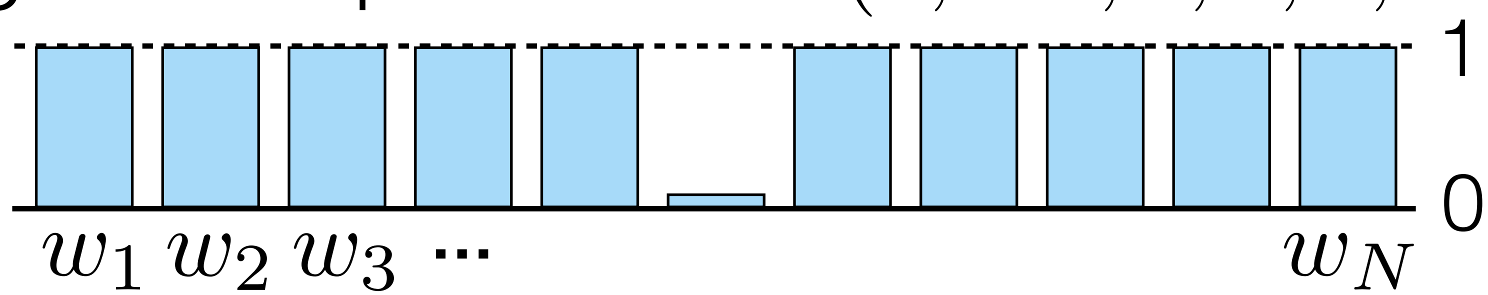

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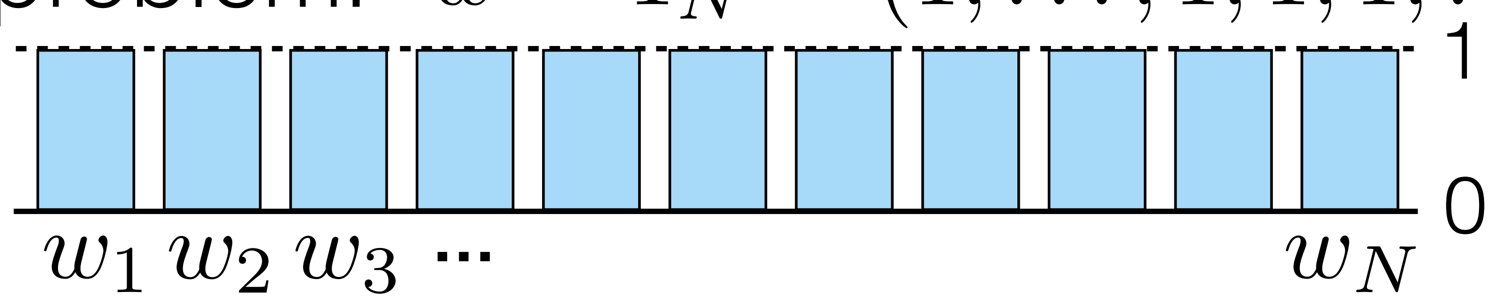

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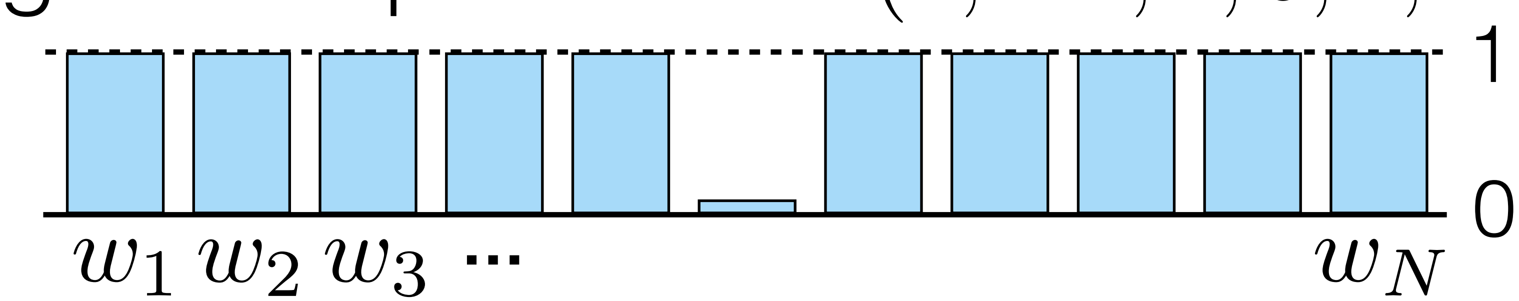

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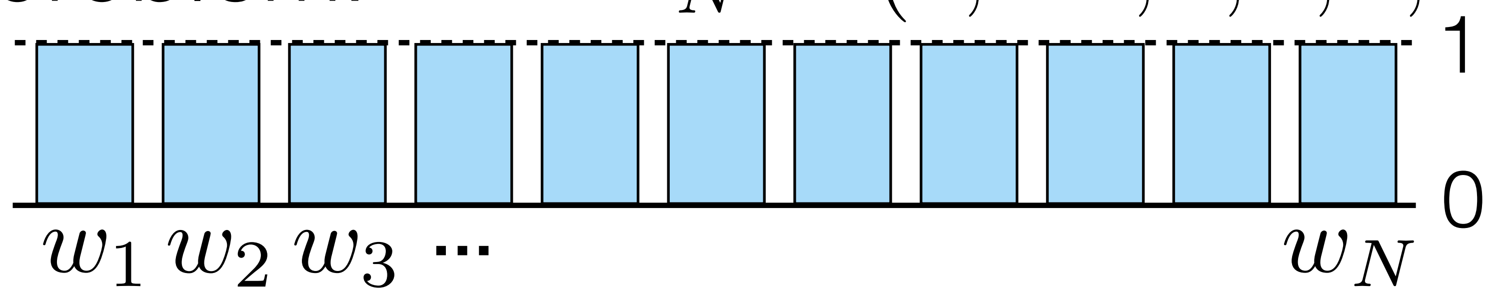

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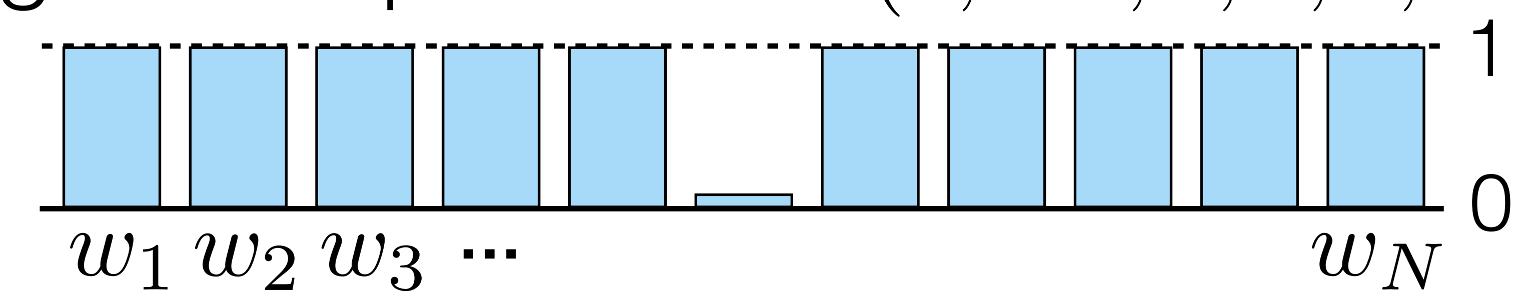

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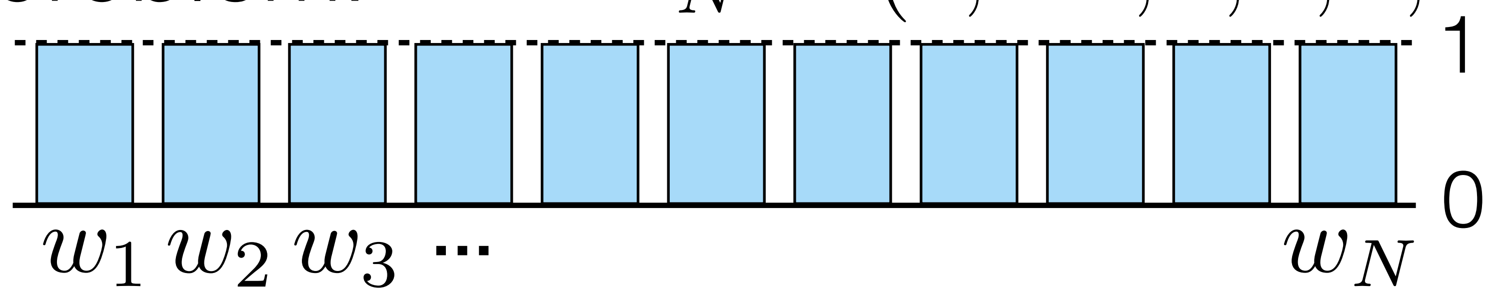

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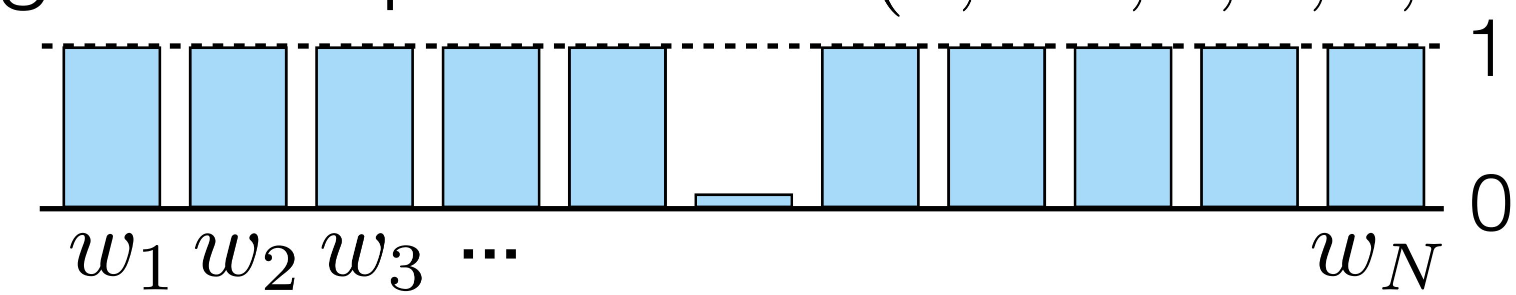

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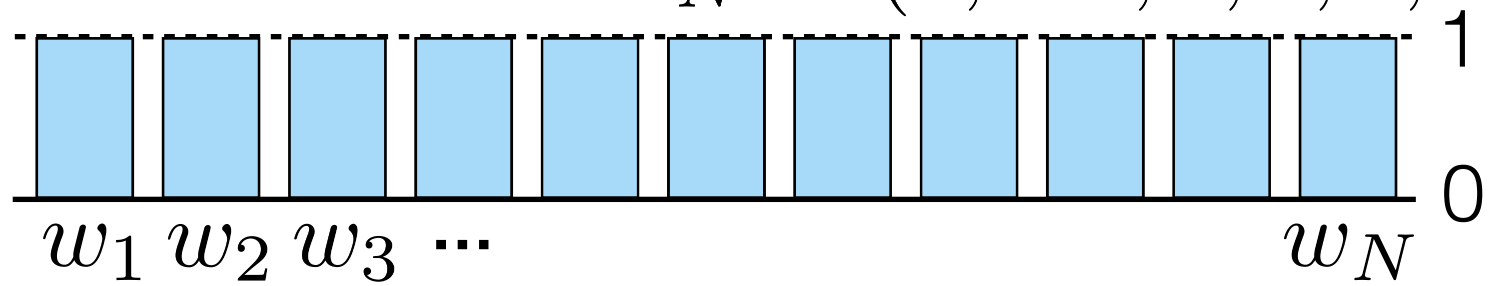

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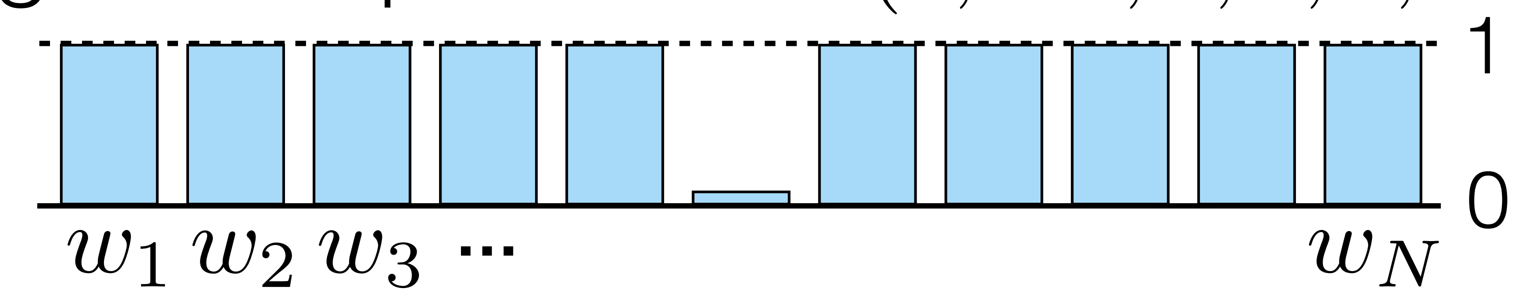

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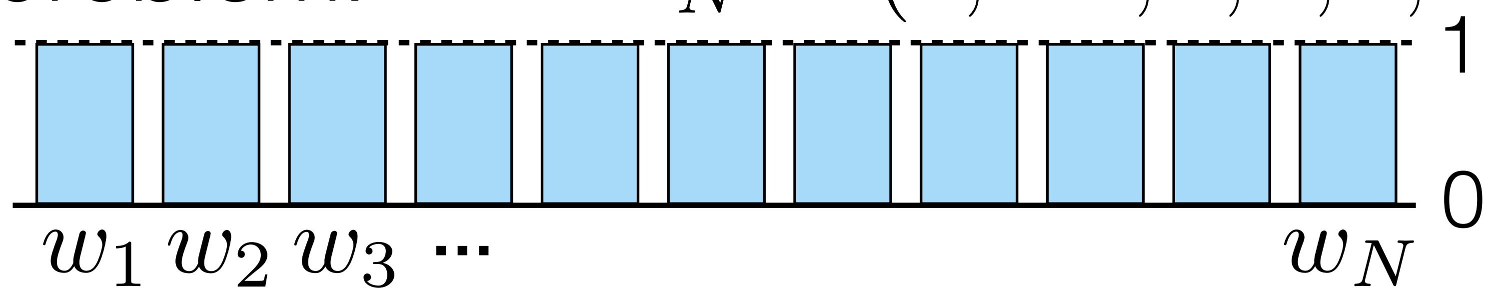

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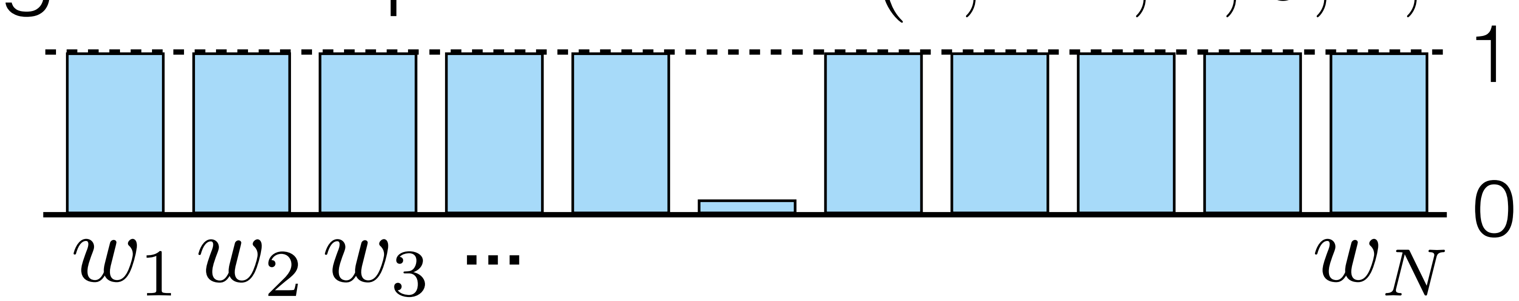

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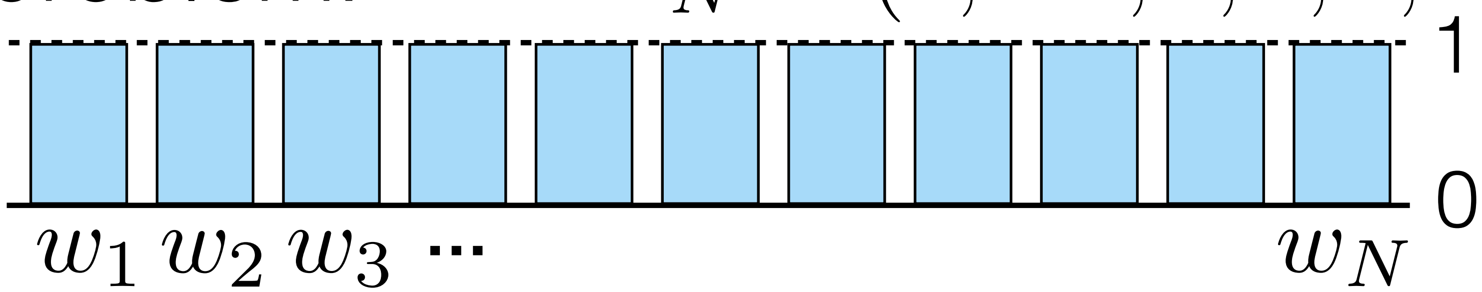

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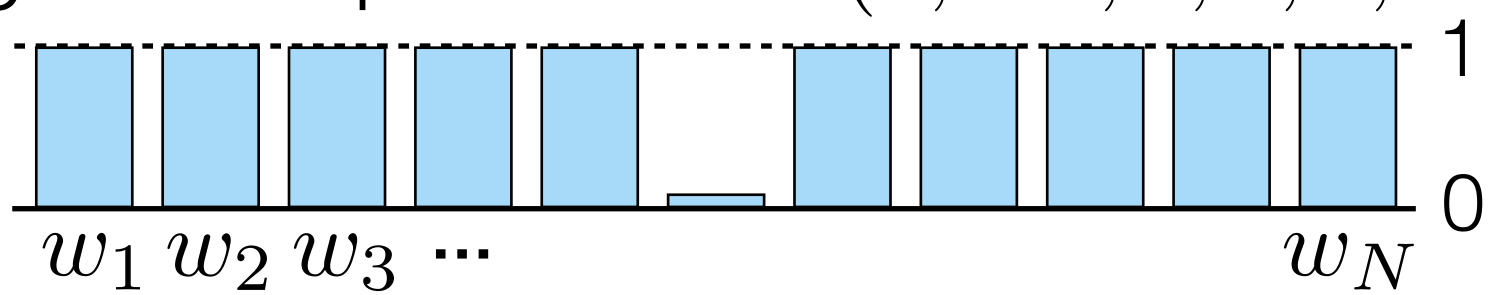

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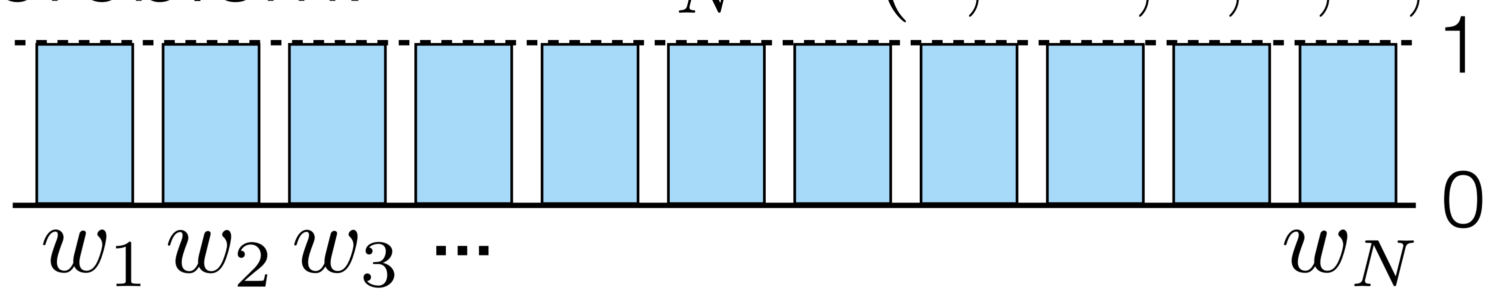

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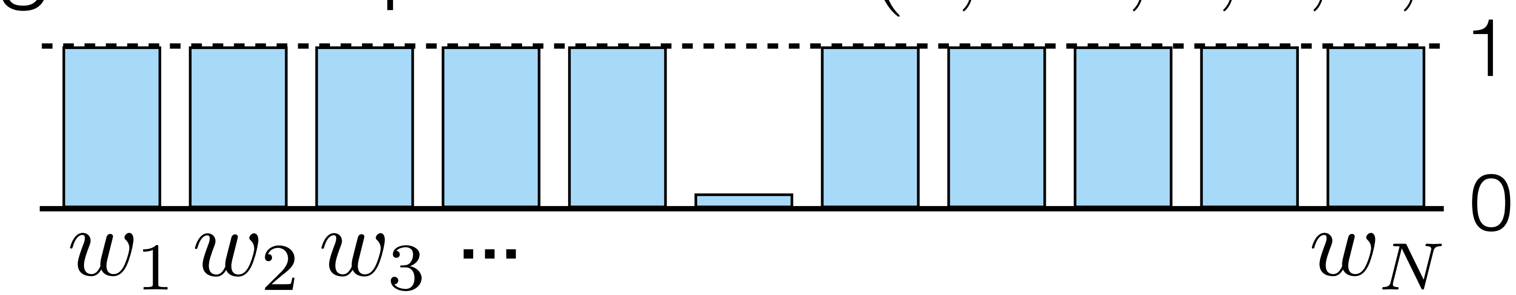

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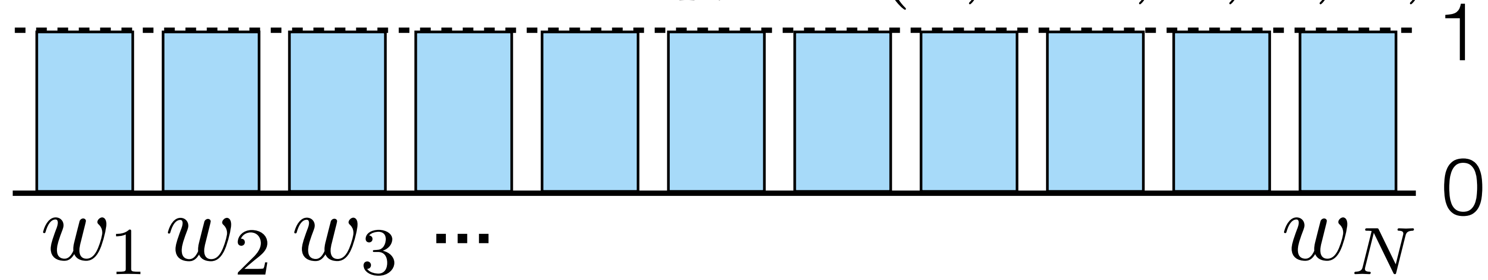

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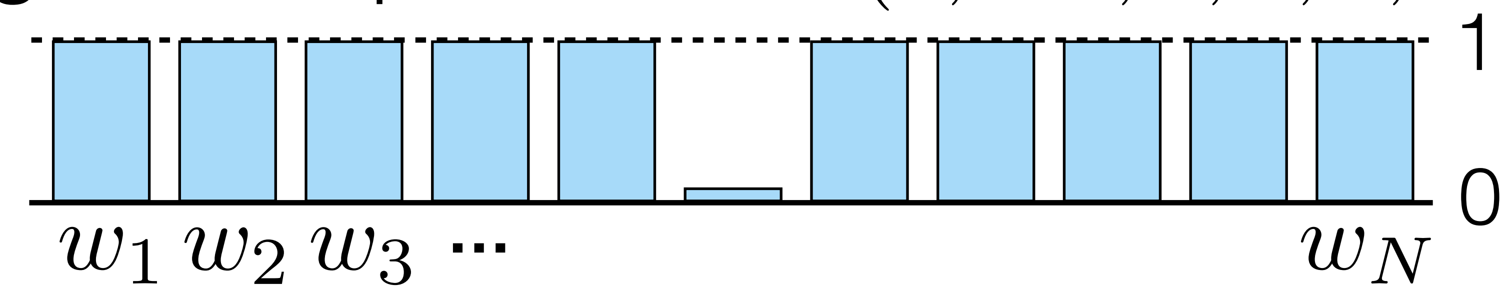

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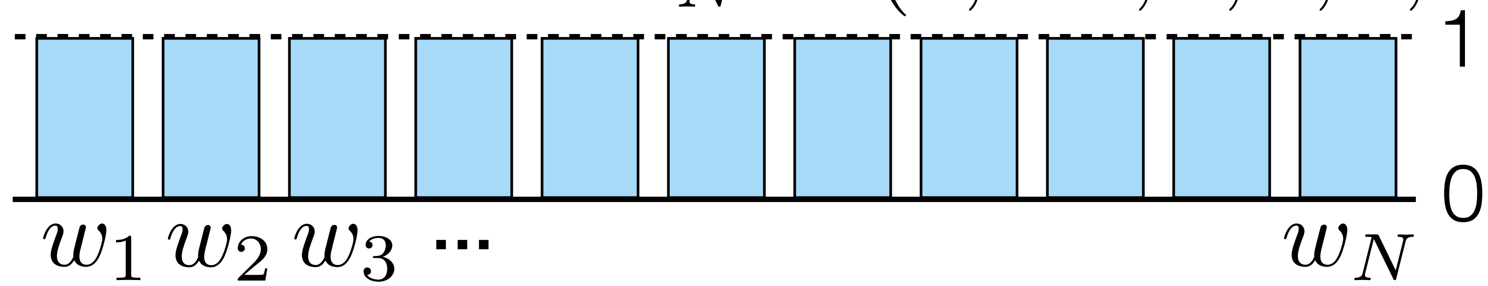

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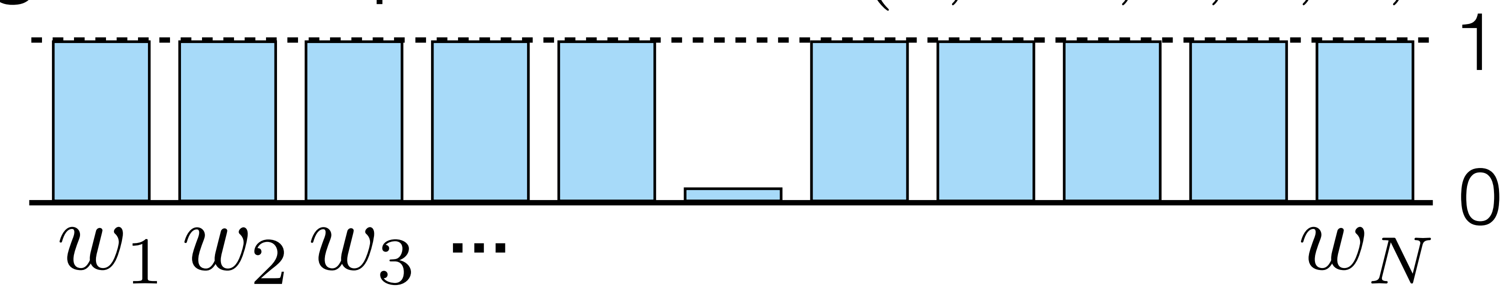

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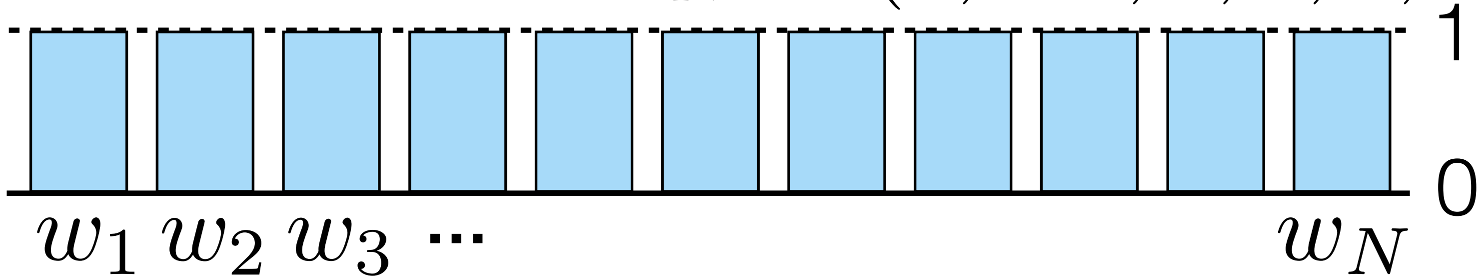

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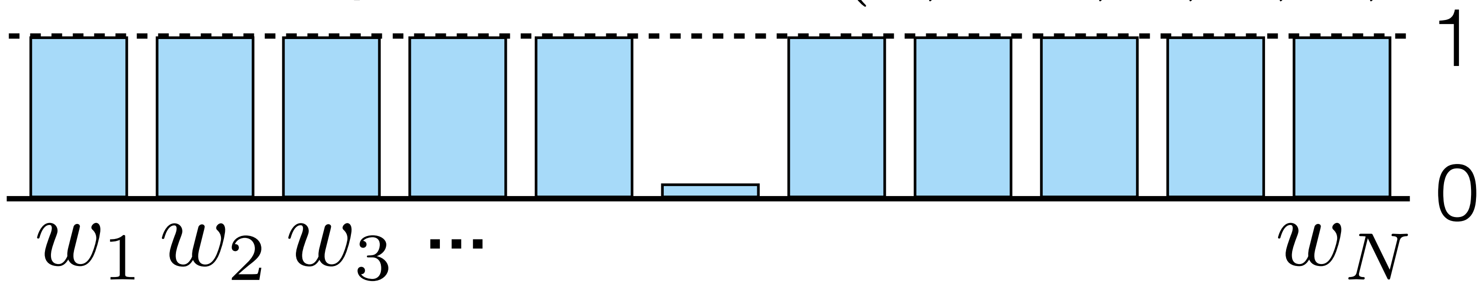

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our approximation

influence score of the *n*th data point

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  - We compute this formula with automatic differentiation (note: very different from numerical or symbolic diff)

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

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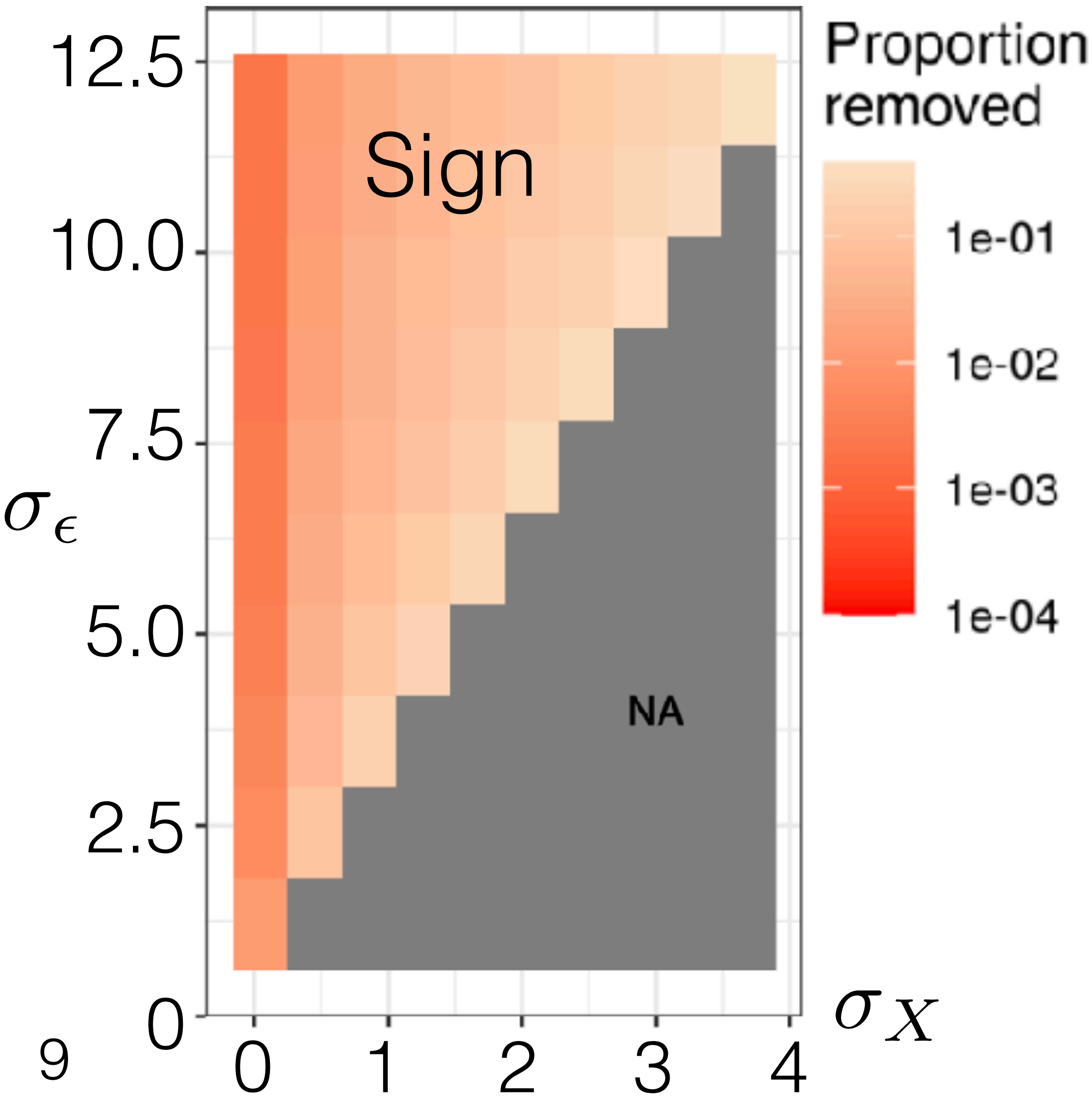

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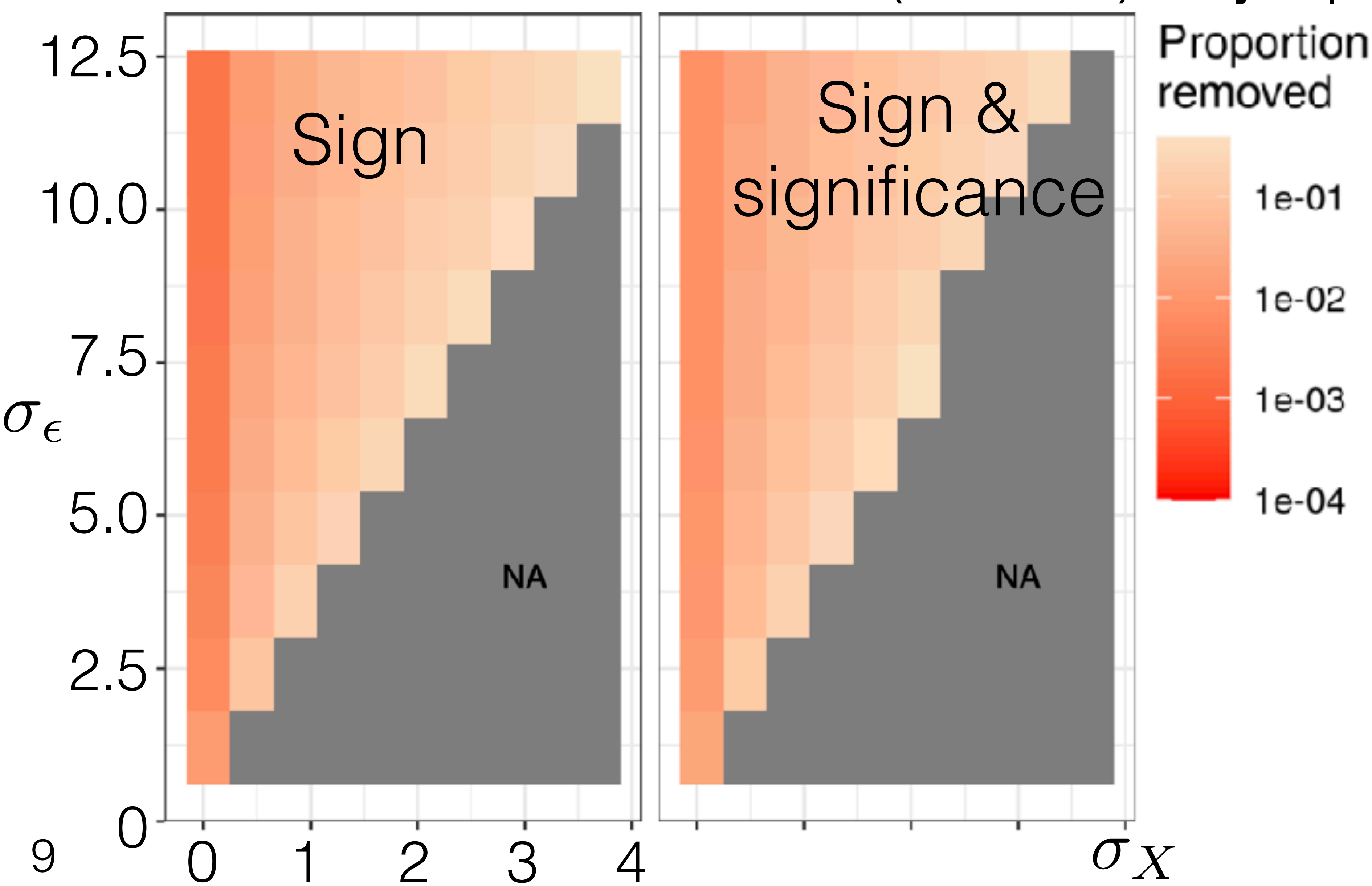

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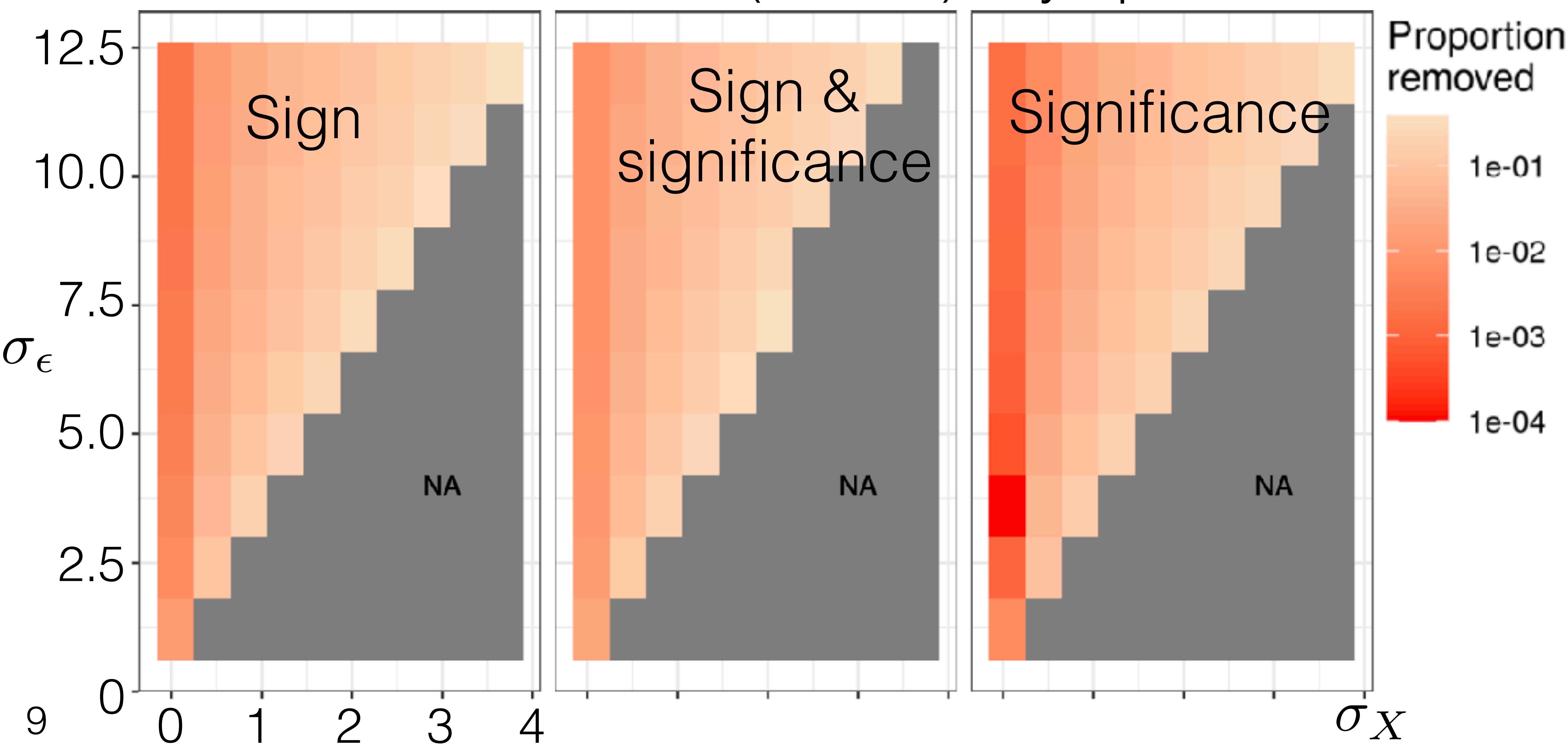

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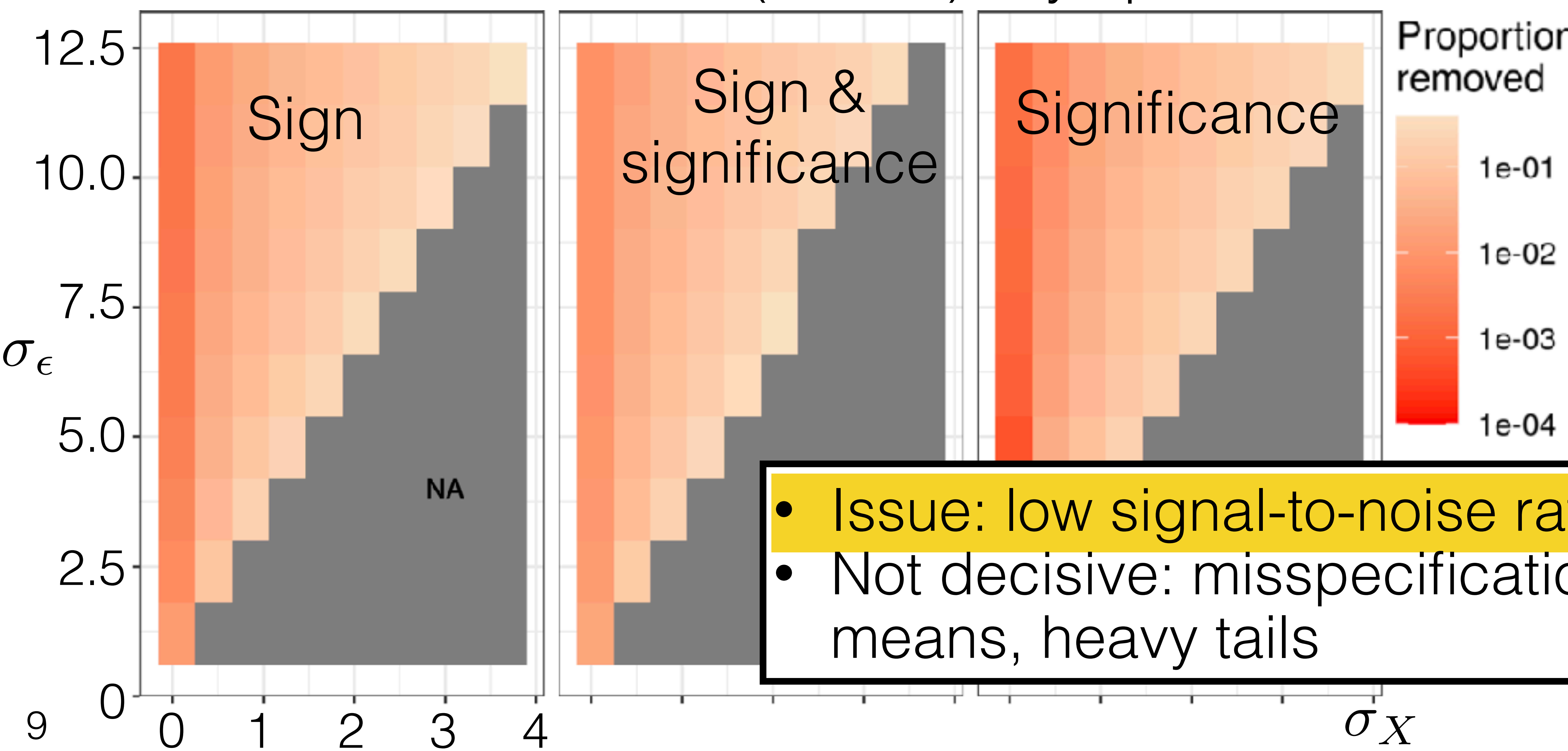

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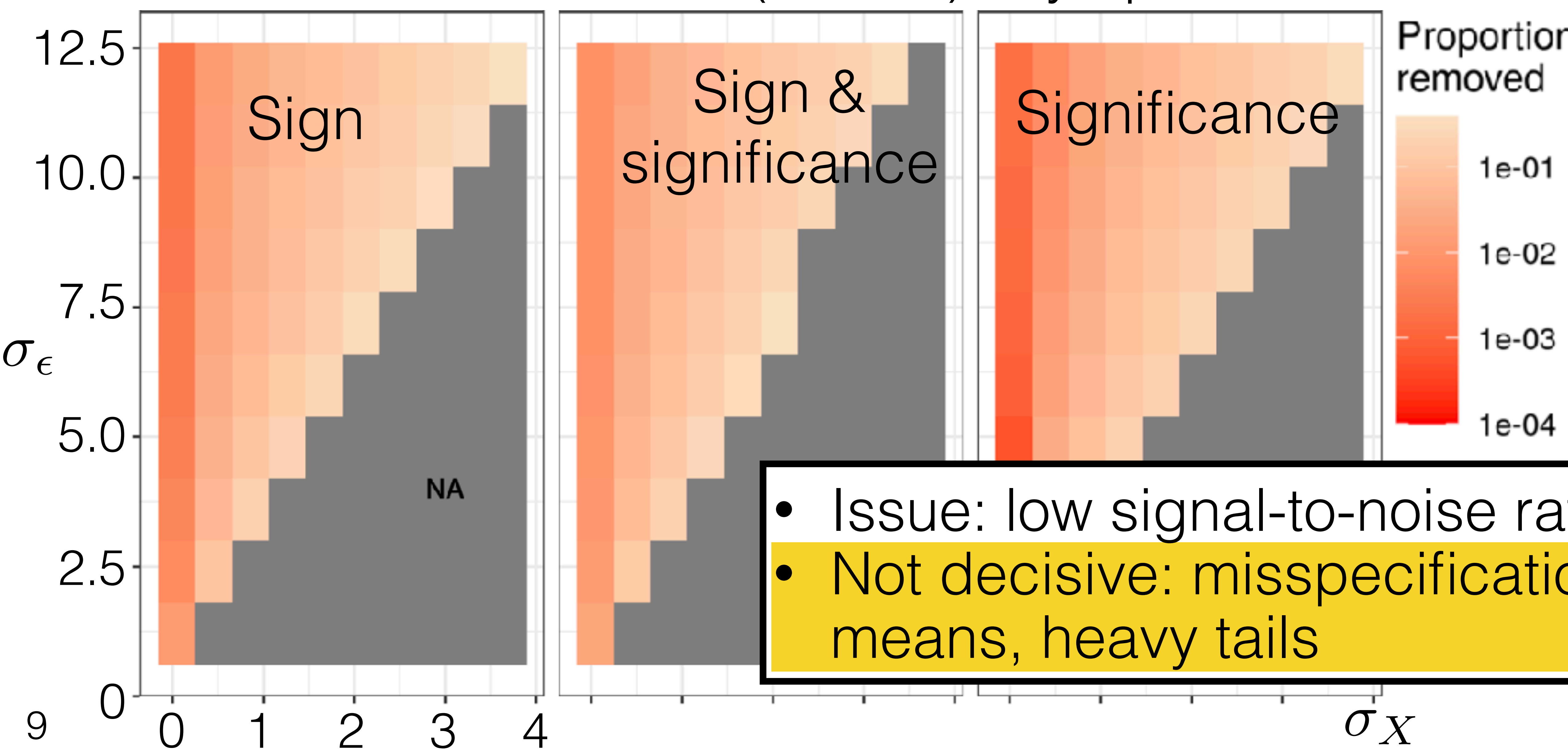

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  - We show: in linear regression, influence score = residual times leverage

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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.