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ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

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LABORATORY FOR INFORMATION & DECISION SYSTEMS
LIDS

An Automatic Finite-Data Robustness Check for Bayes and Beyond: Can Dropping a Little Data Change Conclusions?

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MIT

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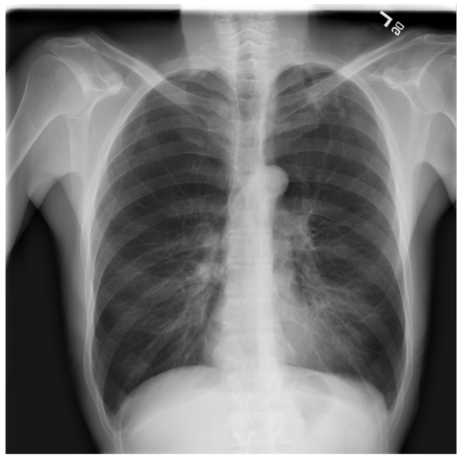

[https://stanfordmlgroup.github.io/projects/chexnet/, https://www.ibmbigdatahub.com/blog/cyber-security-powered-ai-and-machine-learning, https://www.fairwinds.org/inside-fairwinds/fraud-protection-center/report-fraud.html]

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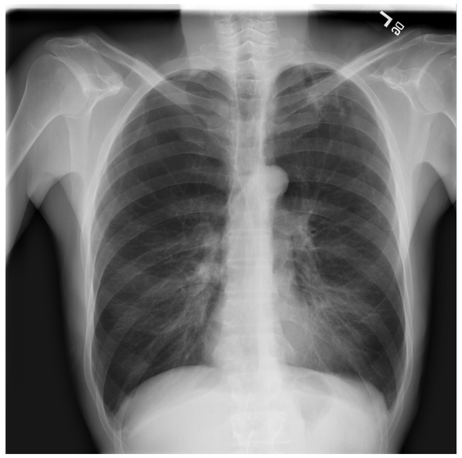

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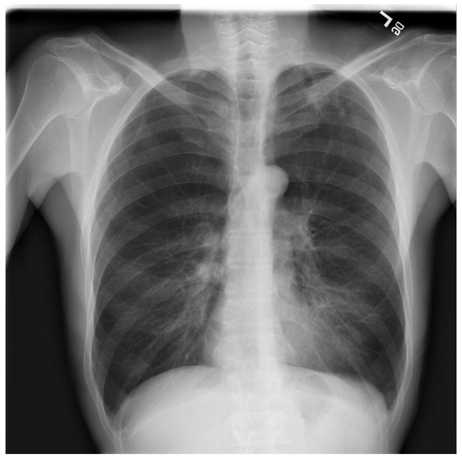

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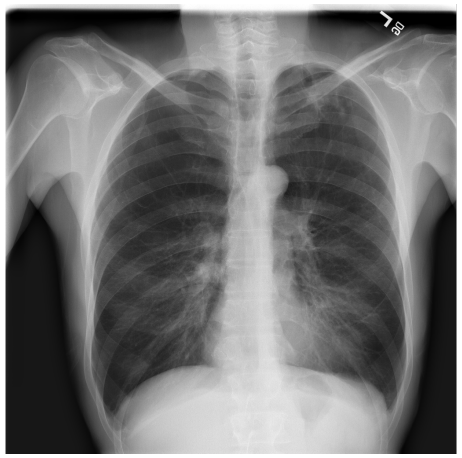

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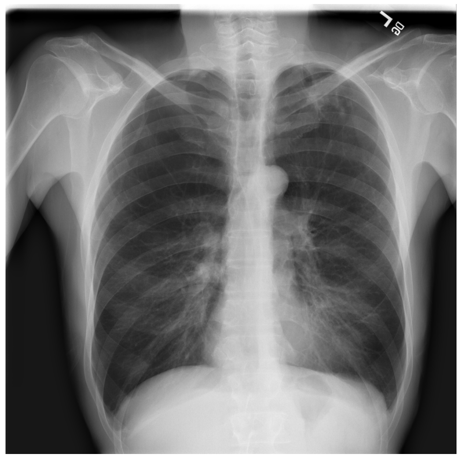

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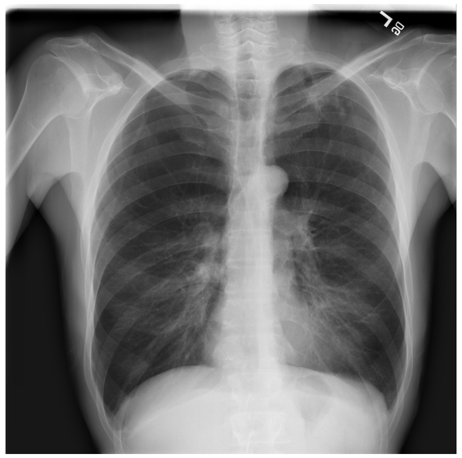

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- Even if doesn’t bother you, should be up front about it

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  - Still sensitive like the ordinary least squares analyses

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$$\underbrace{f}_{\text{loss}}(\underbrace{\theta}_{\text{parameters}}, \underbrace{d_n}_{\text{datum; e.g. } (x_n,\, y_n)})$$

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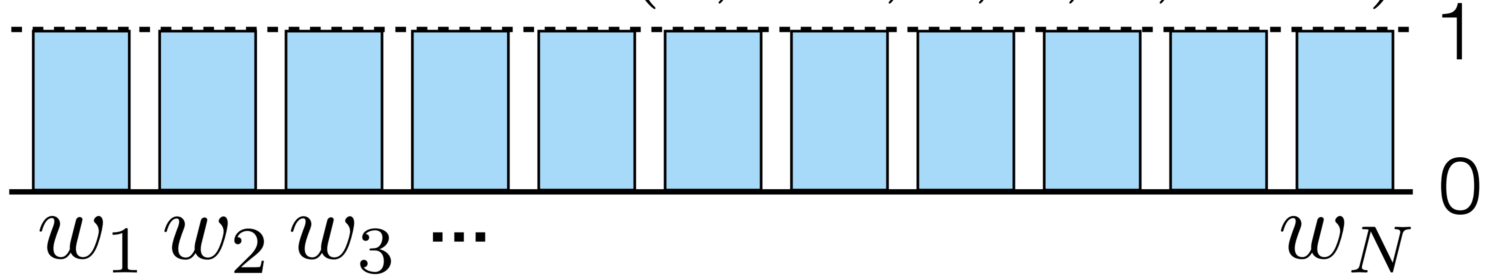

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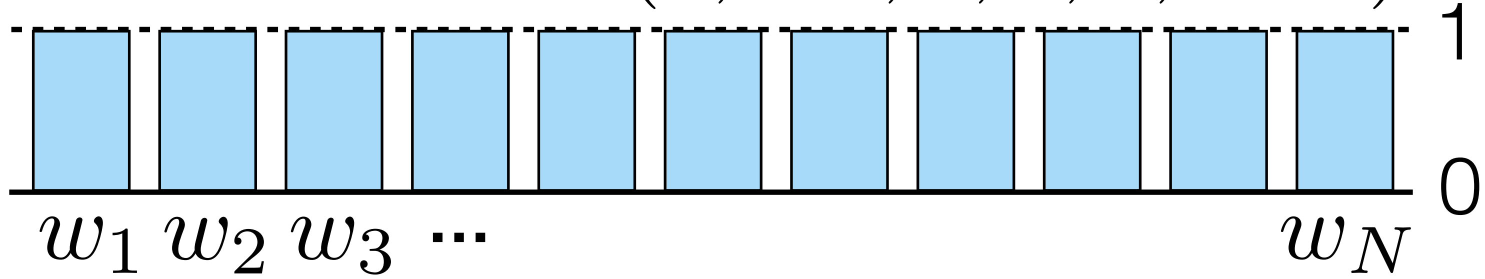

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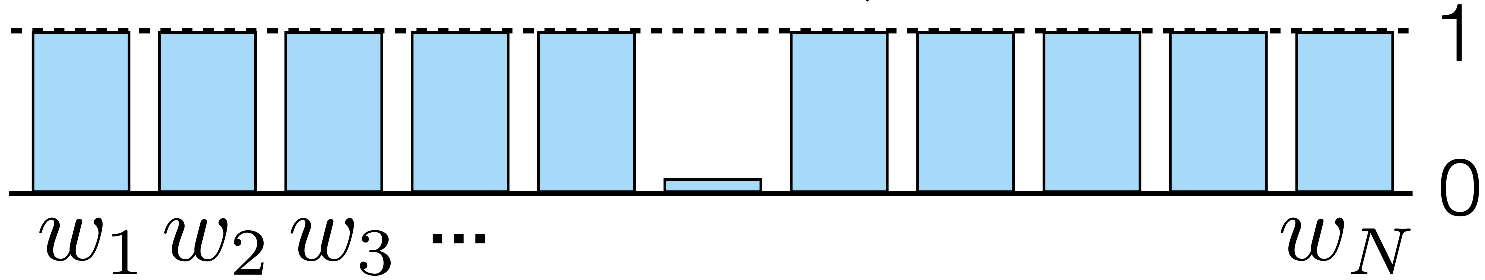

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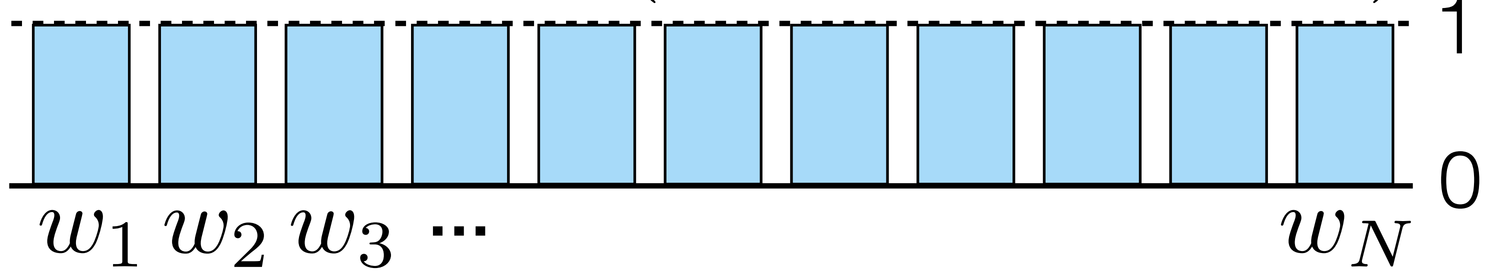

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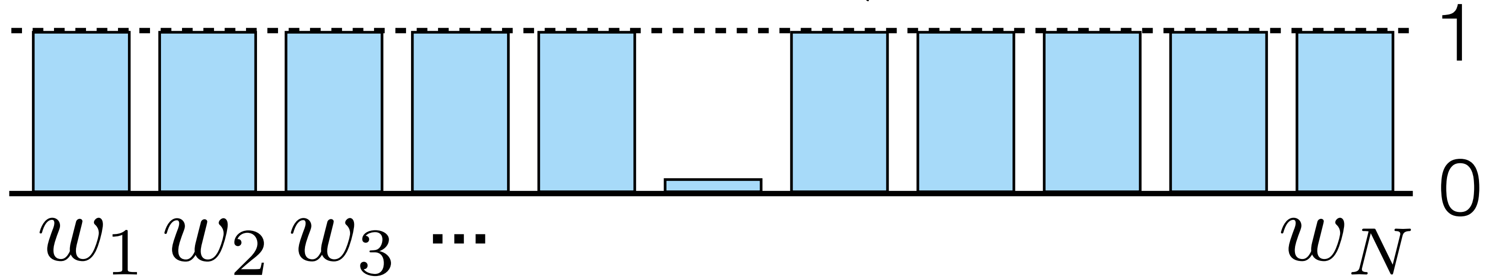

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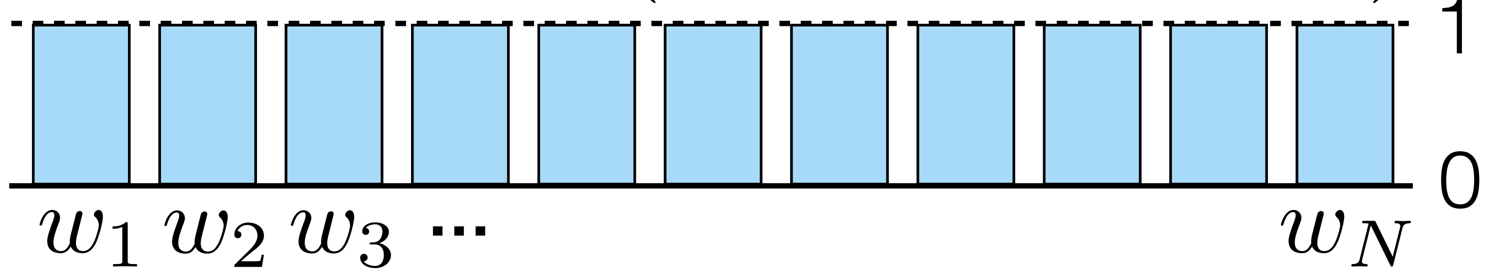

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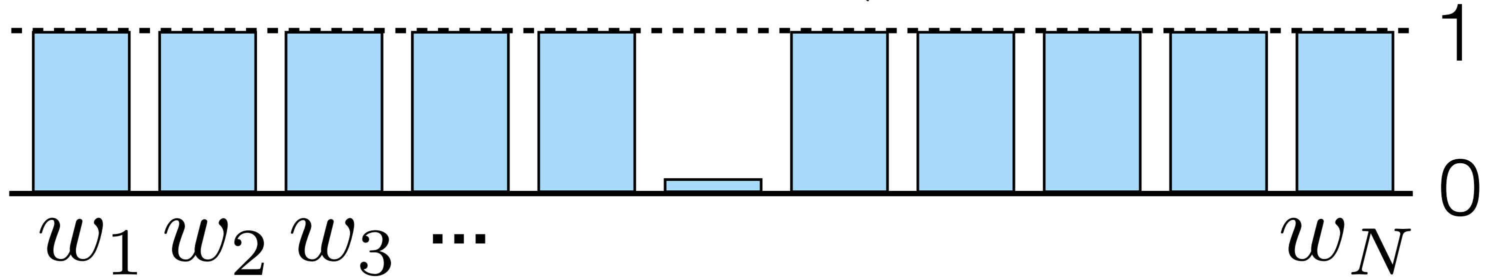

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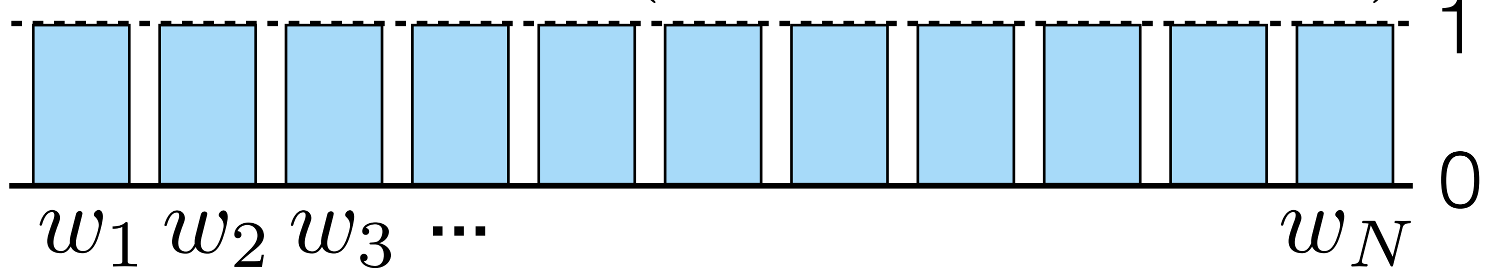

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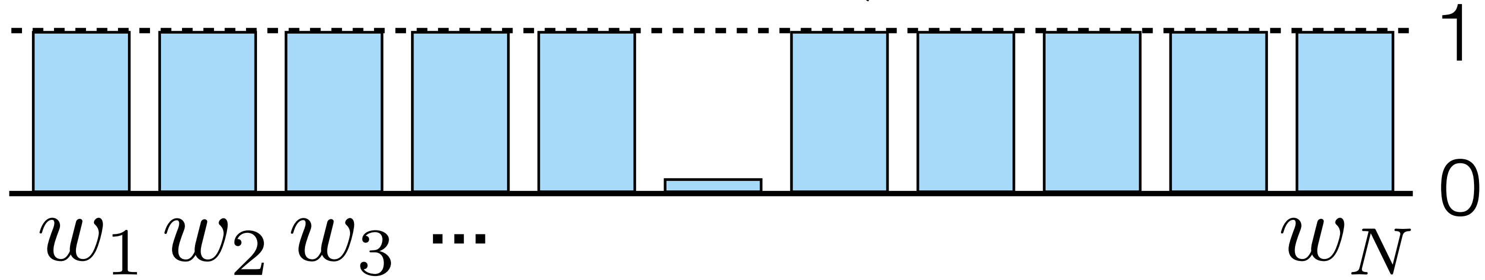

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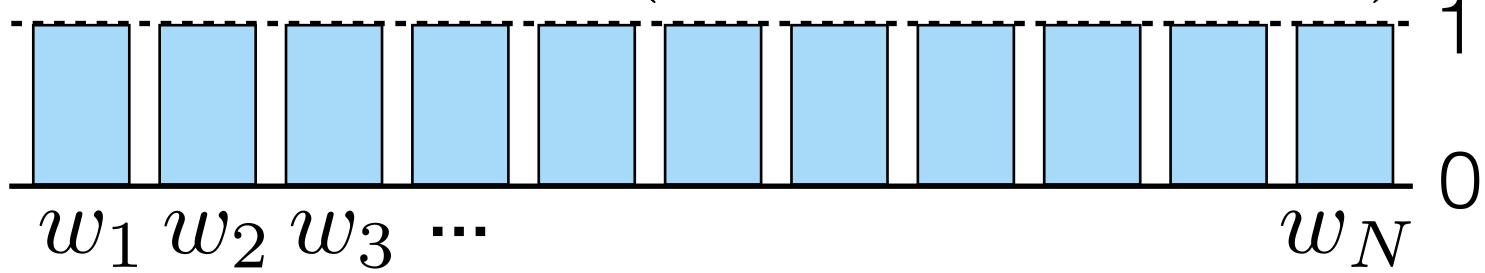

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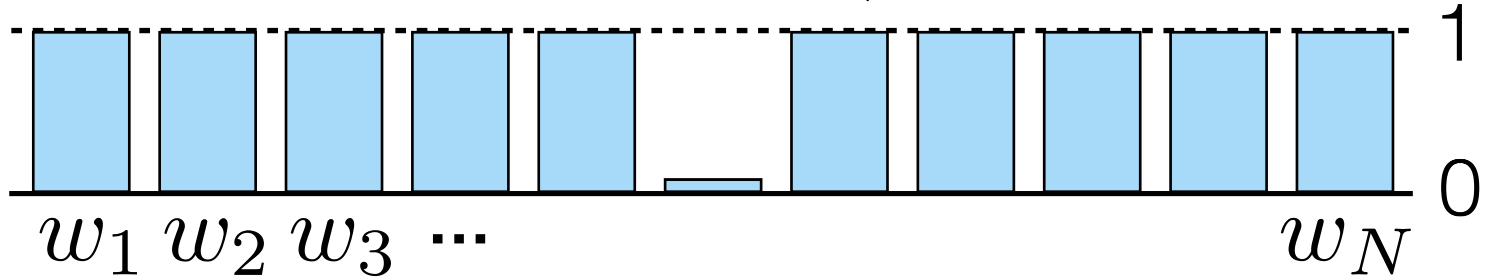

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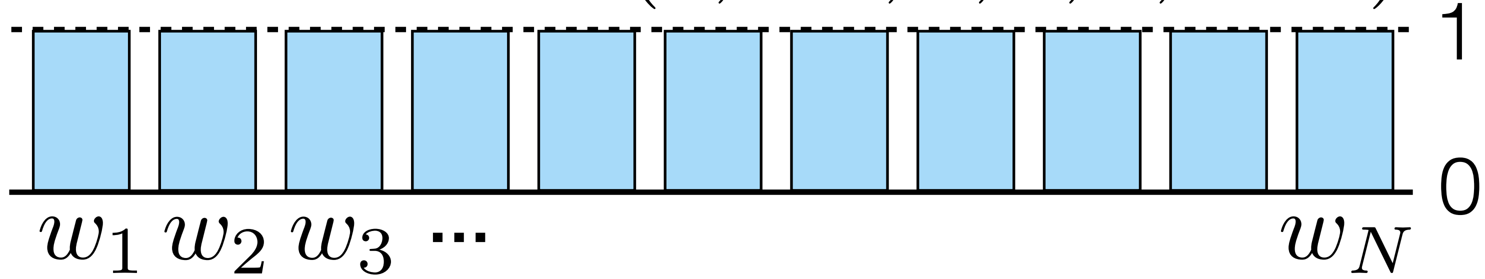

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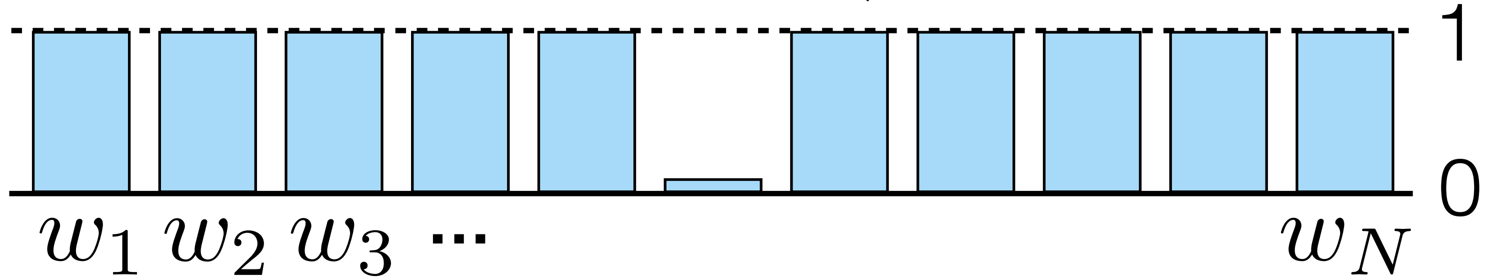

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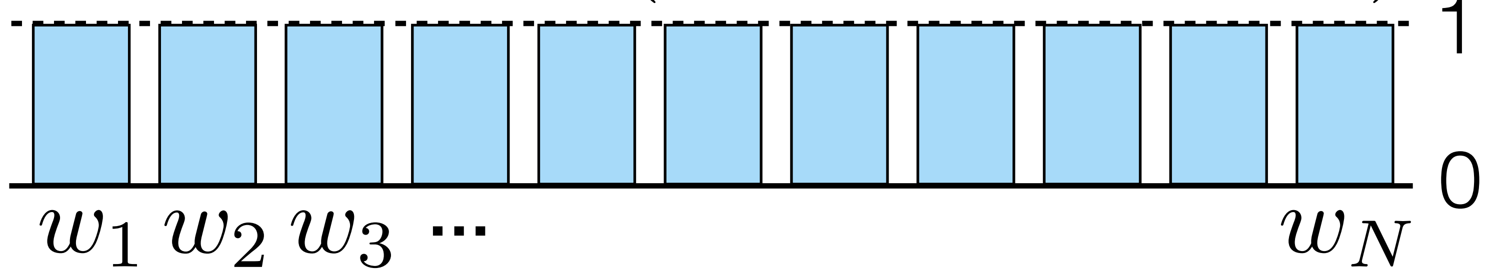

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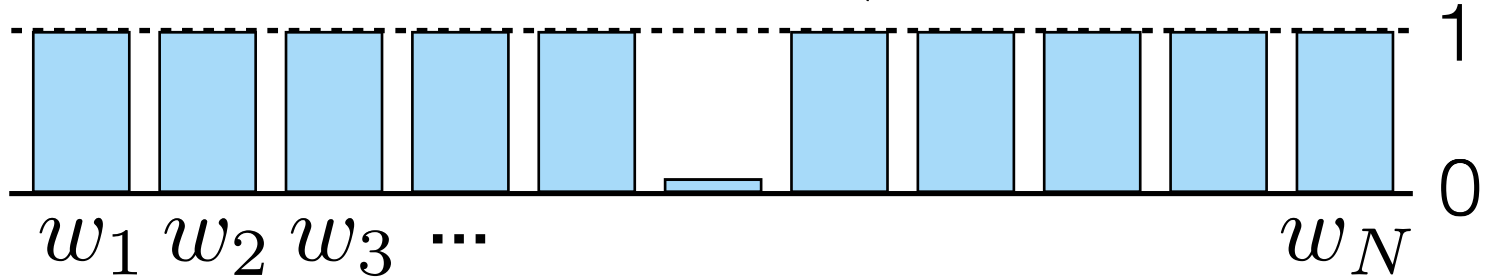

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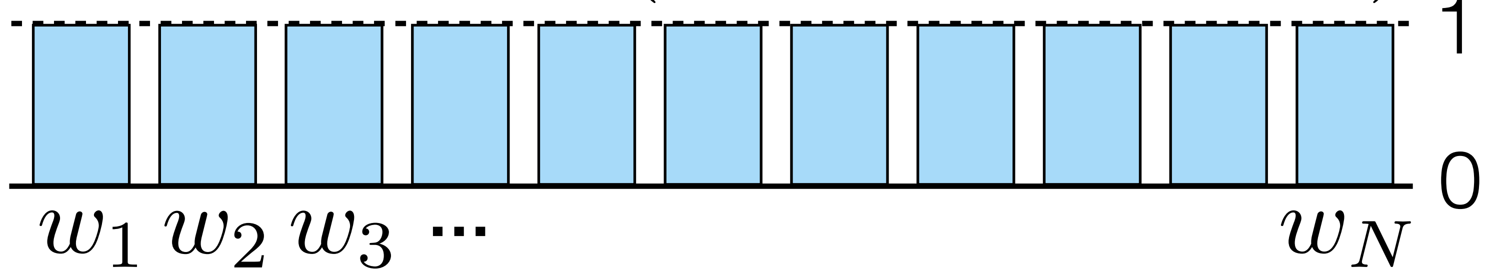

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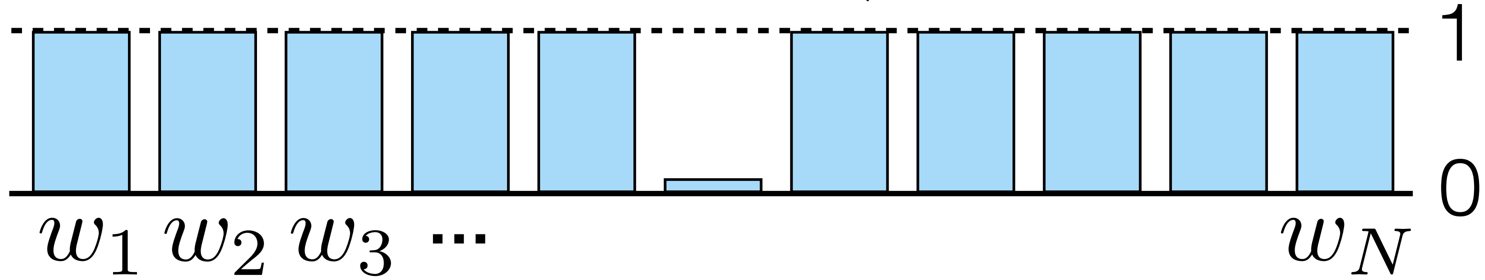

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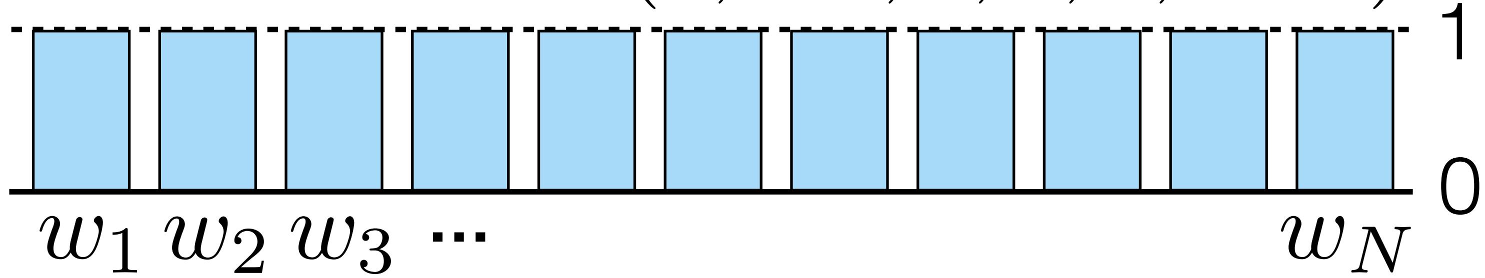

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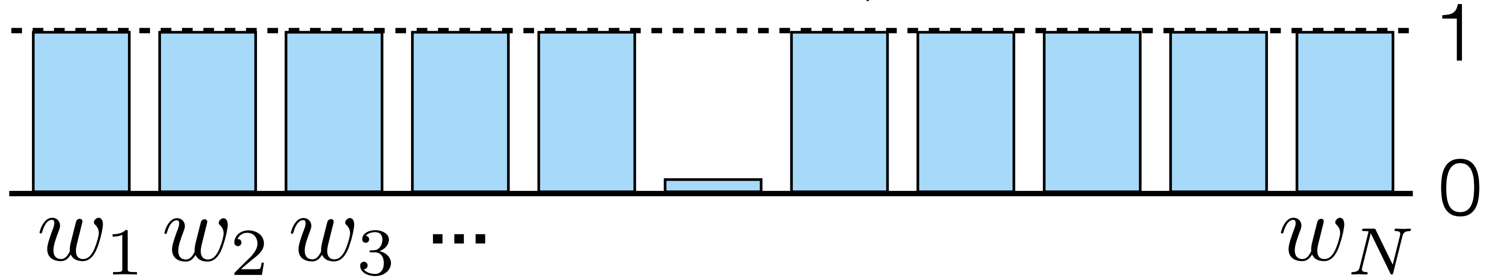

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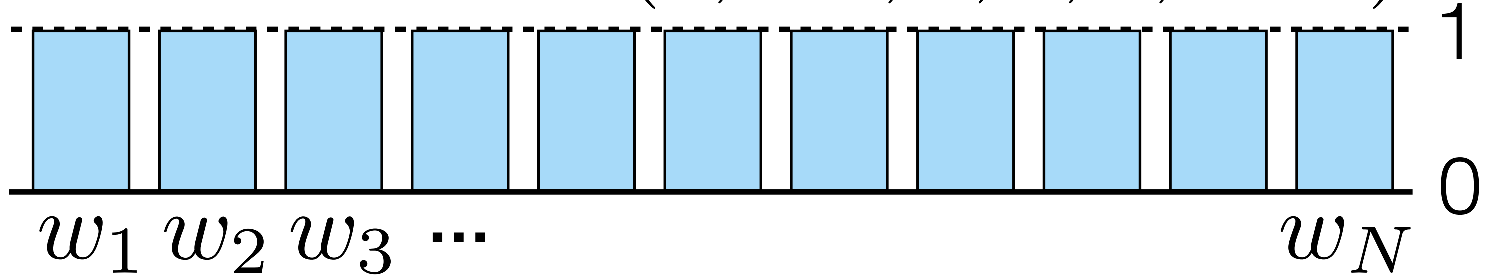

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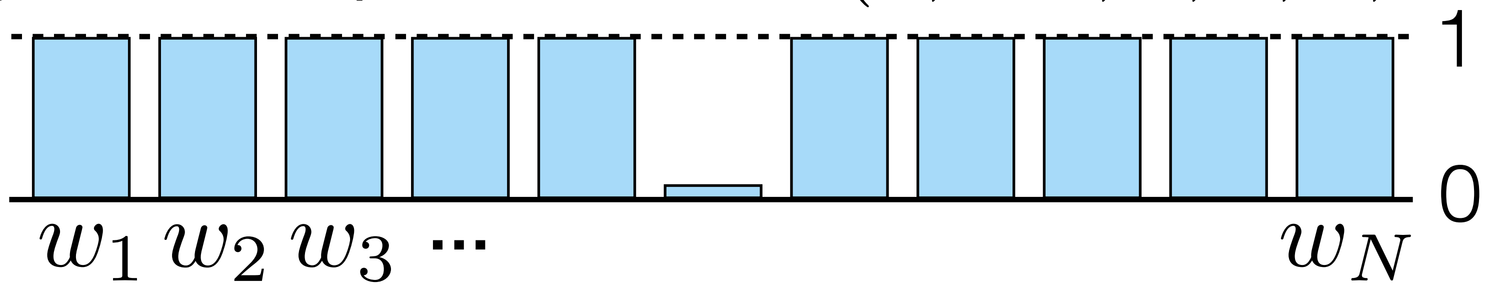

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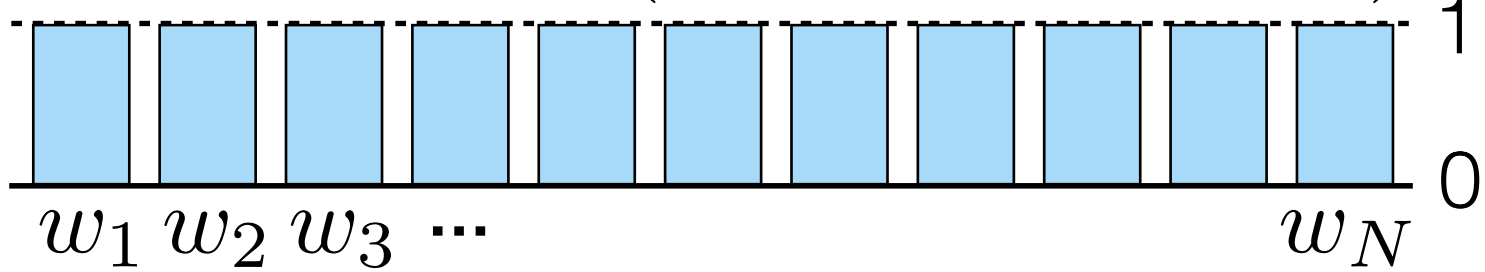

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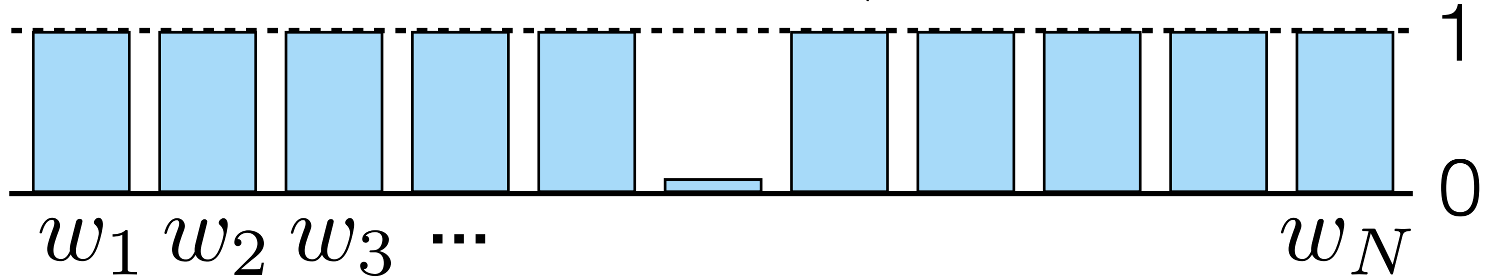

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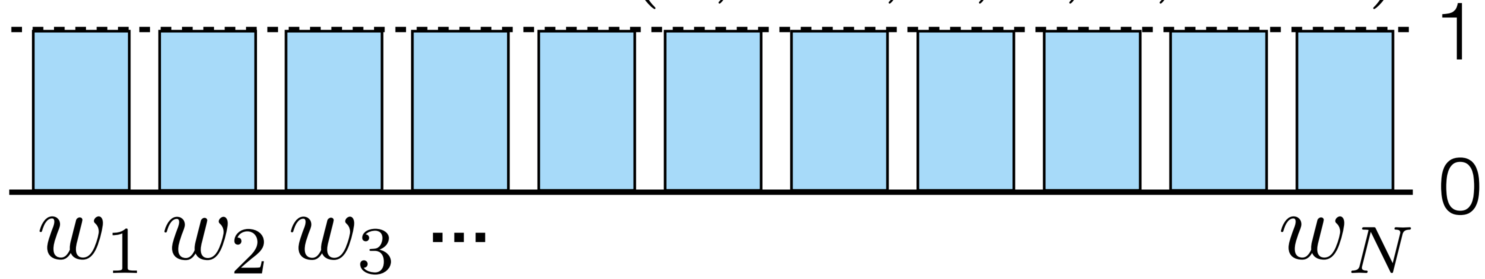

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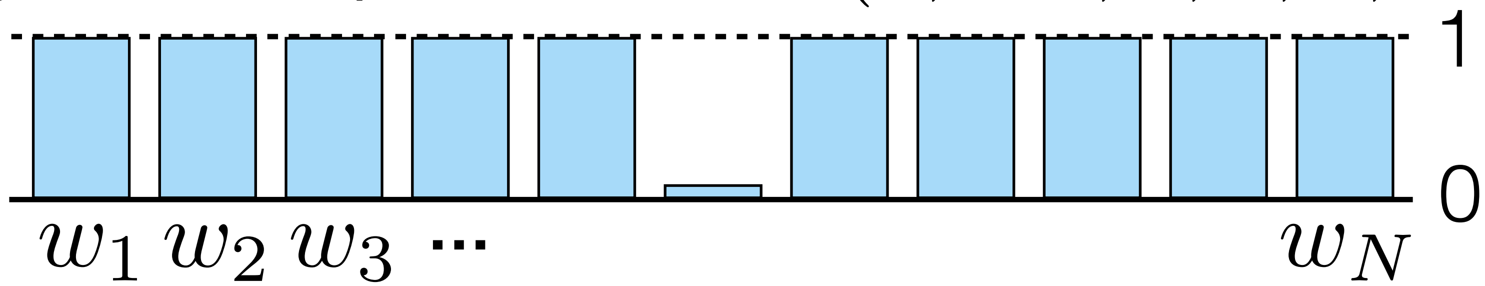

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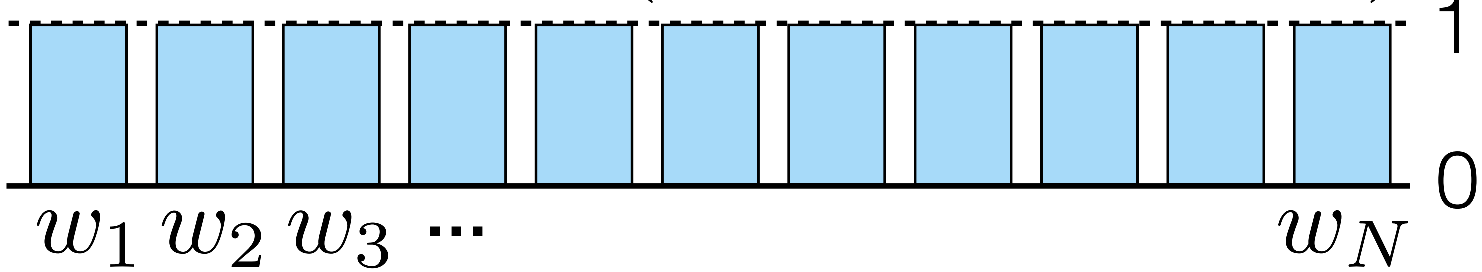

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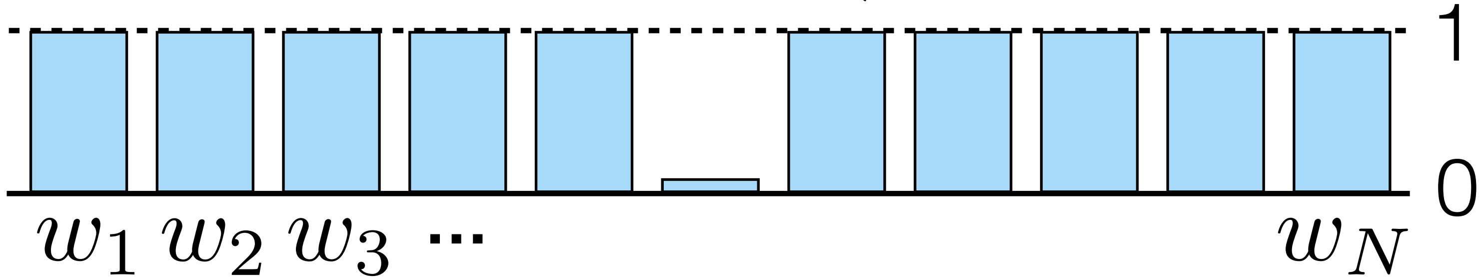

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- **It's not just heavy tails or reporting means**
  - We run Gaussian linear model simulations & find both robust/non-robust cases; **issue is signal-to-noise**

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  - rgiordan.github.io/robustness/2021/09/17/amip_p_hacking.html
- **Our check is just one part of a trustworthy workflow**:
  - Broderick, Gelman, Meager, Smith, Zheng "Toward a Taxonomy of Trust for Probabilistic Machine Learning" *ArXiv:2112.03270*

Try it out!

- We present a way to check if there is a very small fraction of data you can drop to change decisions
- **Paper**: Broderick, Giordano, Meager "An Automatic Finite-Sample Robustness Metric: When Can Dropping a Little Data Make a Big Difference?" (alphabetical)

  `arxiv.org/abs/2011.14999`
  - Paper above focused on optimization. MCMC soon!
- **Code, etc**: `github.com/rgiordan/zaminfluence`
- **Our check can flag p-hacking**:
  - michaelwiebe.com/blog/2021/01/amip
  - rgiordan.github.io/robustness/2021/09/17/amip_p_hacking.html
- **Our check is just one part of a trustworthy workflow**:
  - Broderick, Gelman, Meager, Smith, Zheng "Toward a Taxonomy of Trust for Probabilistic Machine Learning" *ArXiv:2112.03270*
- **Variational Bayes covariance correction**:
  - Giordano, Broderick, Jordan. Covariances, Robustness, and Variational Bayes, *JMLR* 2018. (Also Giordano, Broderick, Jordan, *NeurIPS* 2015.)