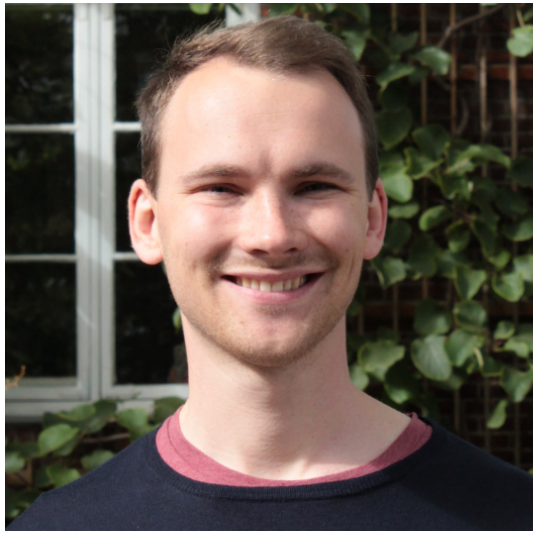
Why is My Classifier Discriminatory?



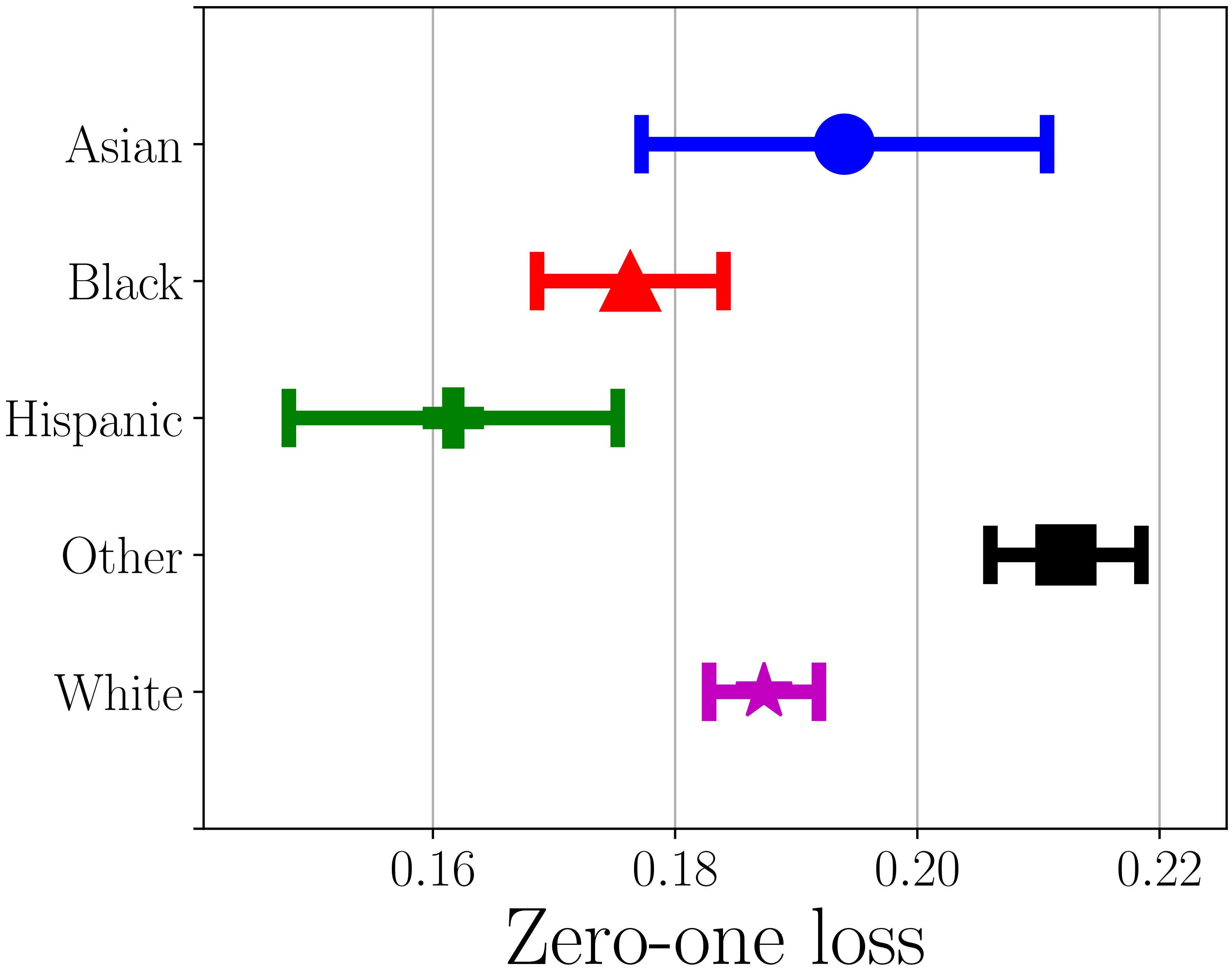
Irene Y. Chen, Fredrik D. Johansson, David Sontag

Massachusetts Institute of Technology (MIT)

NeurIPS 2018, Poster #120 Thurs 12/6 10:45am – 12:45pm @ 210 & 230

It is **surprisingly easy** to make a discriminatory algorithm.

Source: Shutterstock


Asian
Black
Hispanic
Other
White
0.16
0.18
0.20
0.22
Zero-one loss

In this paper

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2. We decompose unfairness into **bias, variance, and noise.**

3. We demonstrate methods to guide **feature augmentation** and **training data collection** to fix unfairness.

Classification fairness: many factors

Model

- Loss function constraints
  - Kamairan et al, 2010; Zafar et al, 2017
- Representation learning
  - Zemel et al, 2013
- Regularization
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Data

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Data

- Data processing
  - Haijan and Domingo-Ferrer, 2013; Feldman et al, 2015
- Cohort selection
- Sample size
- Number of features
- Group distribution

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We should examine fairness algorithms in the context of the data and model.

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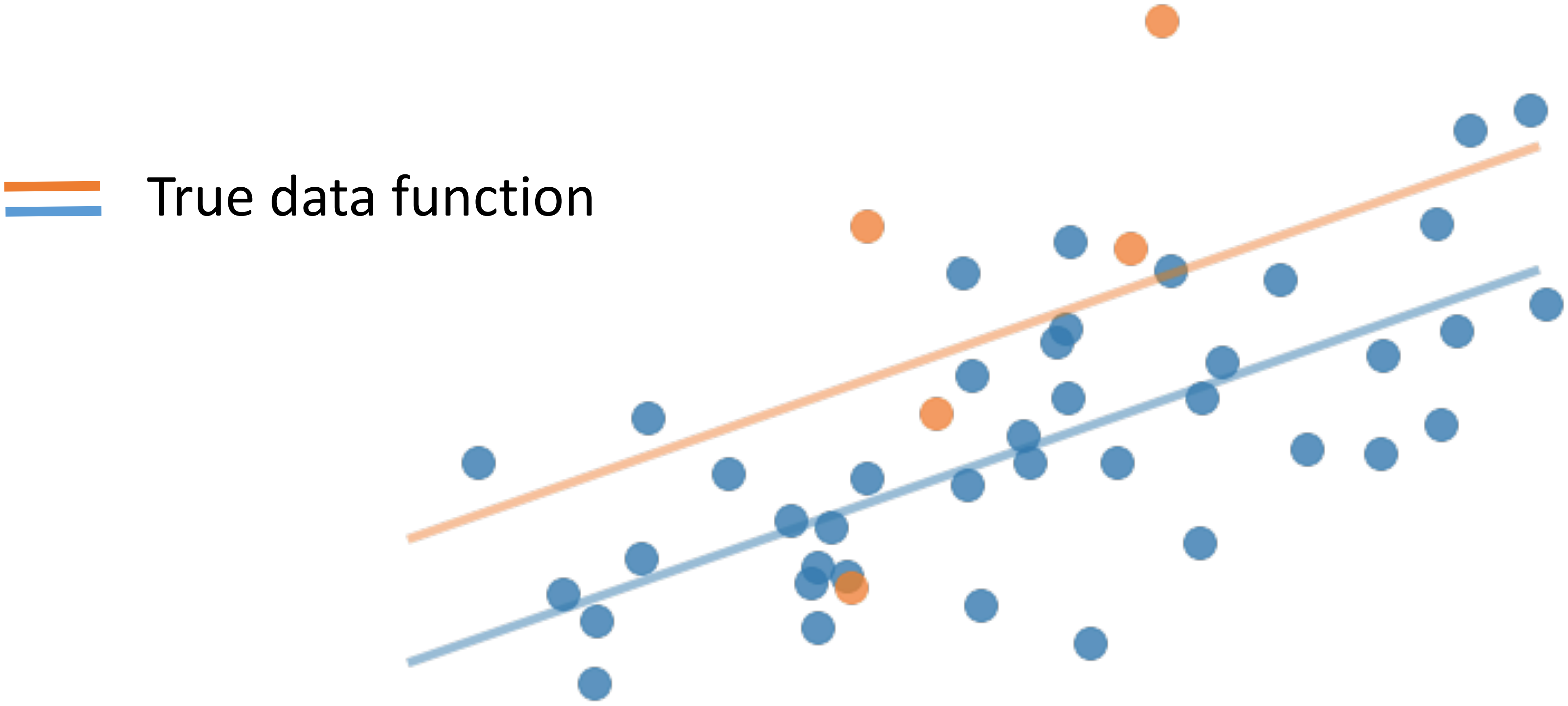

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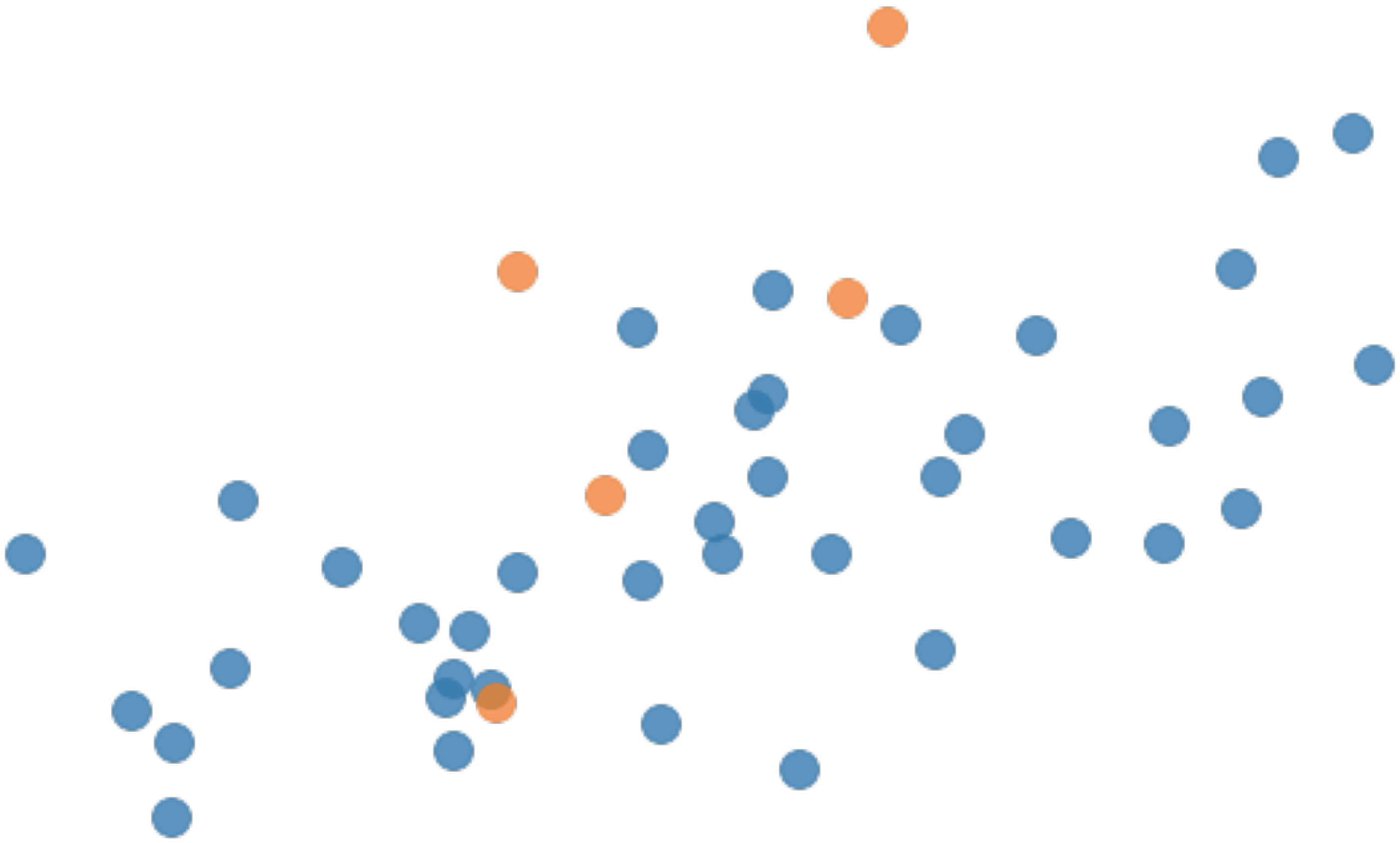

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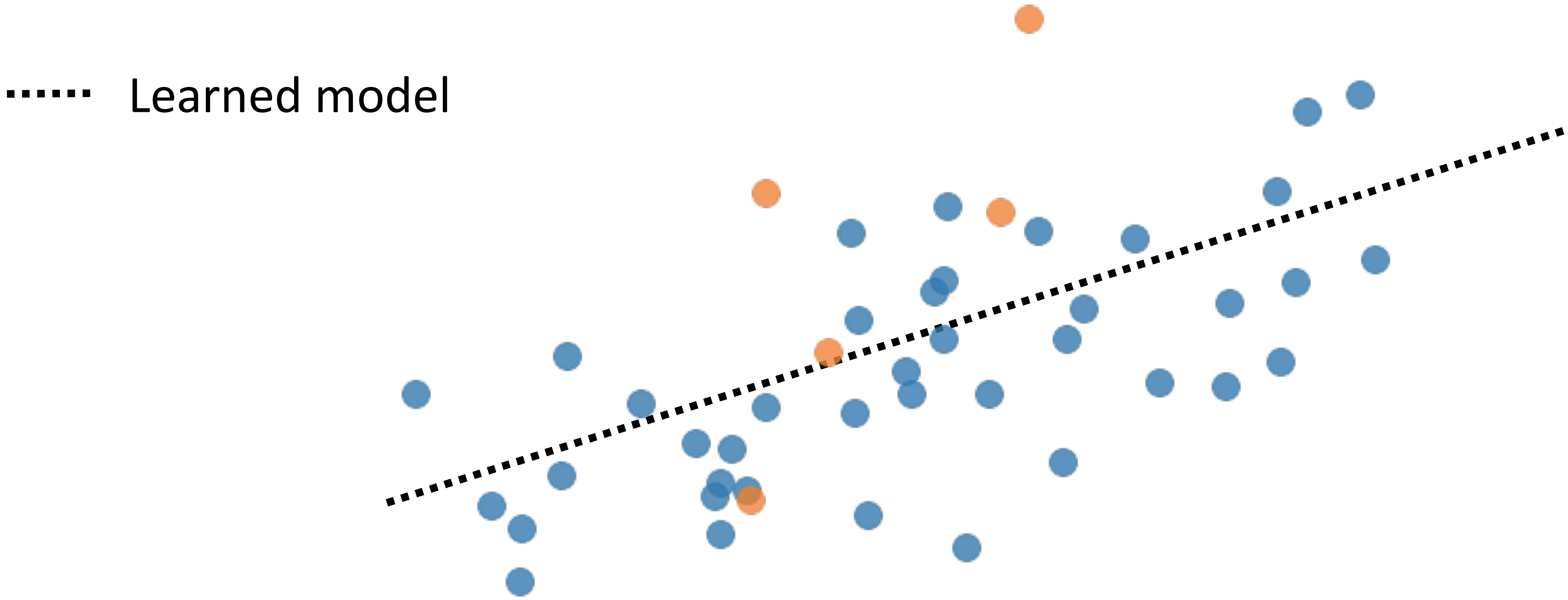

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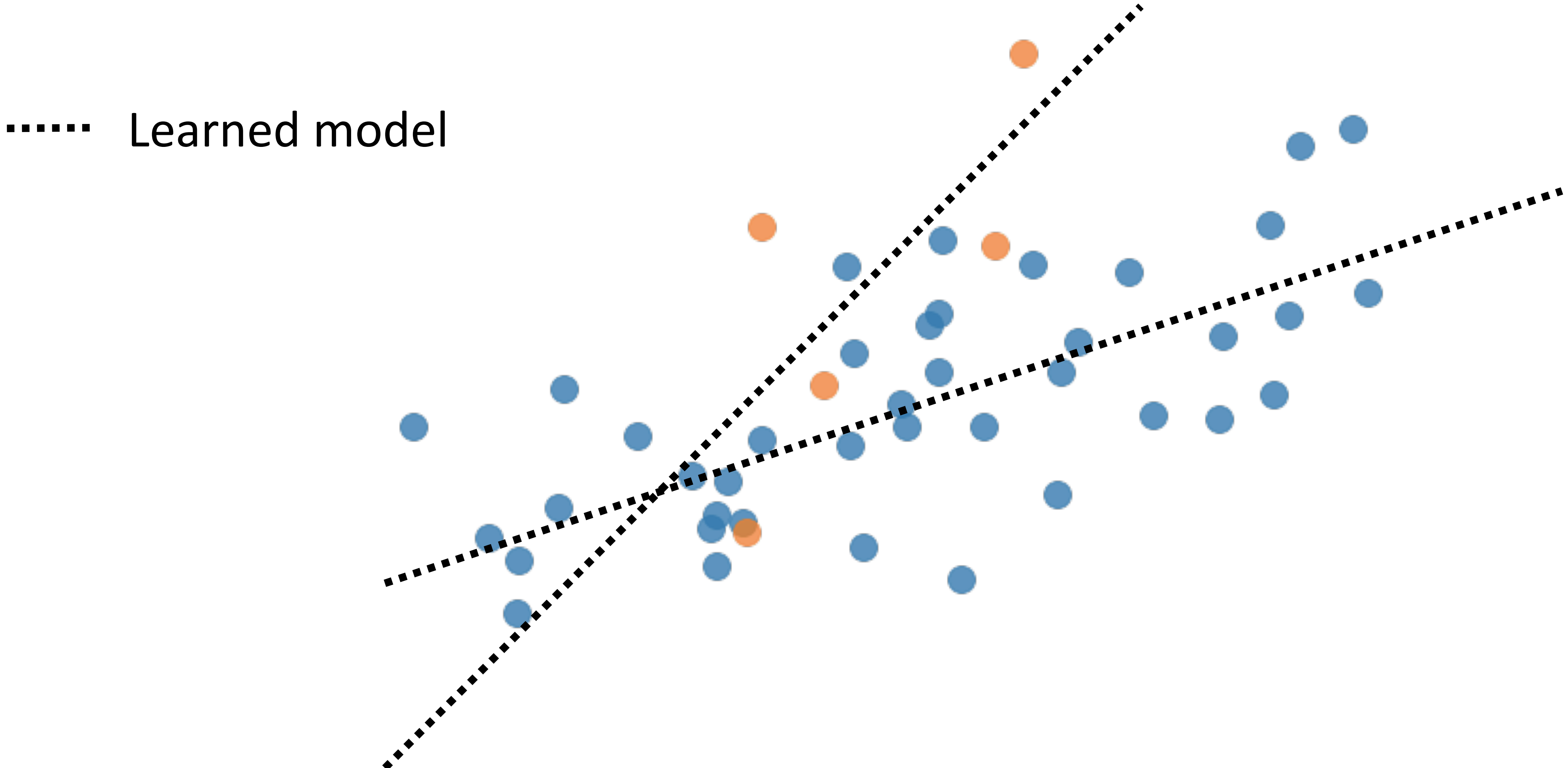

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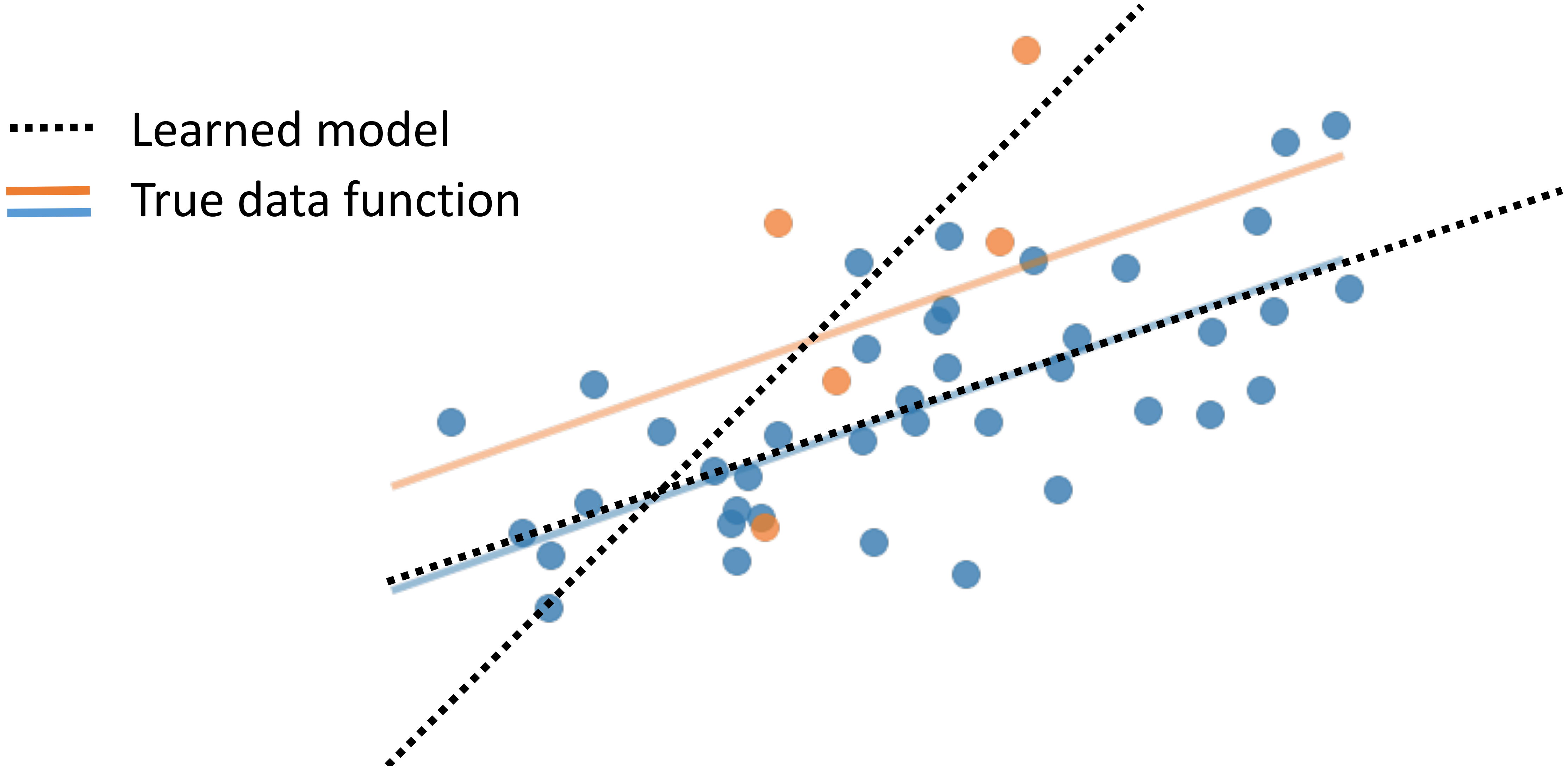

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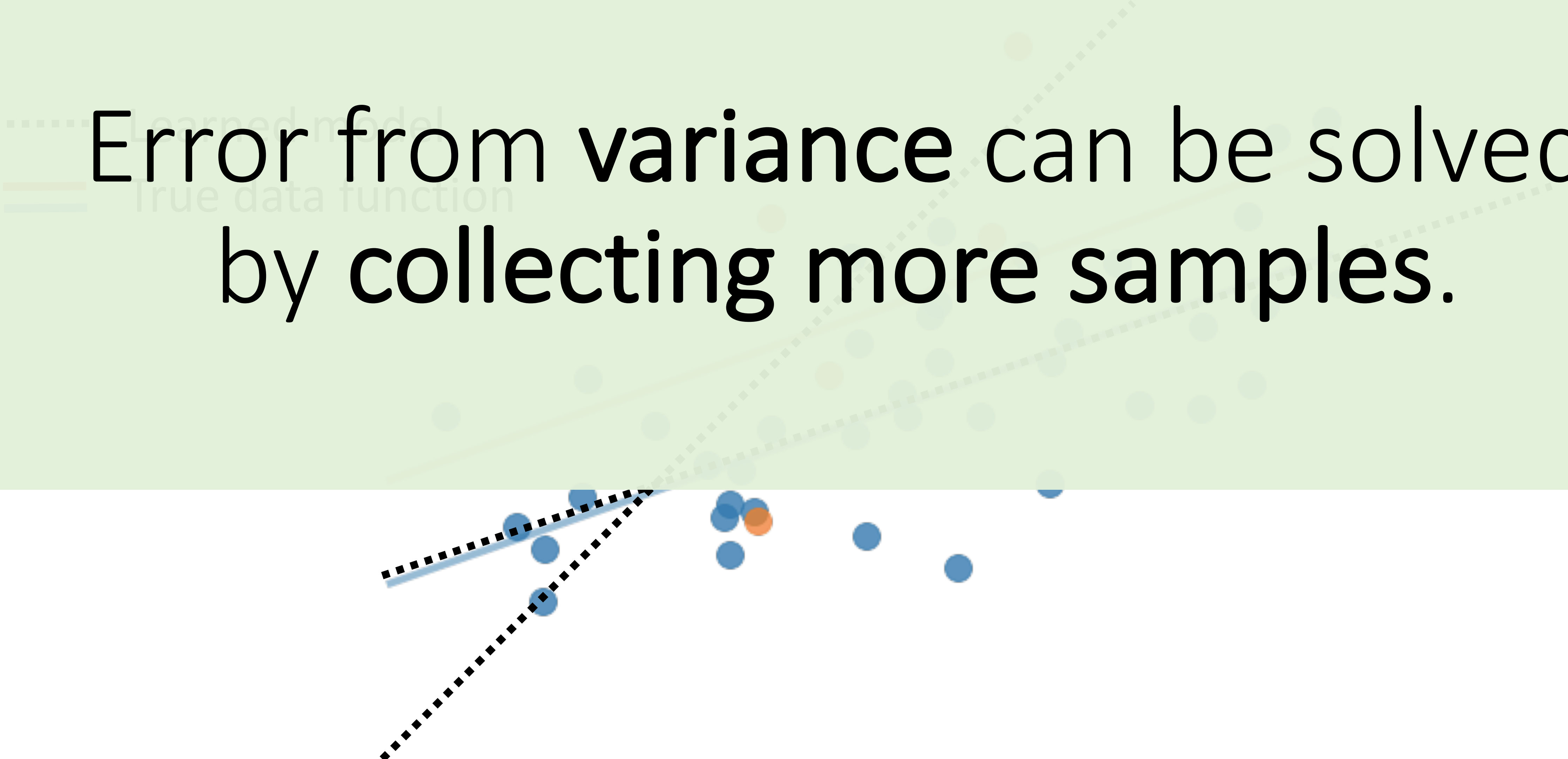

Error from **variance** can be solved by **collecting more samples.**

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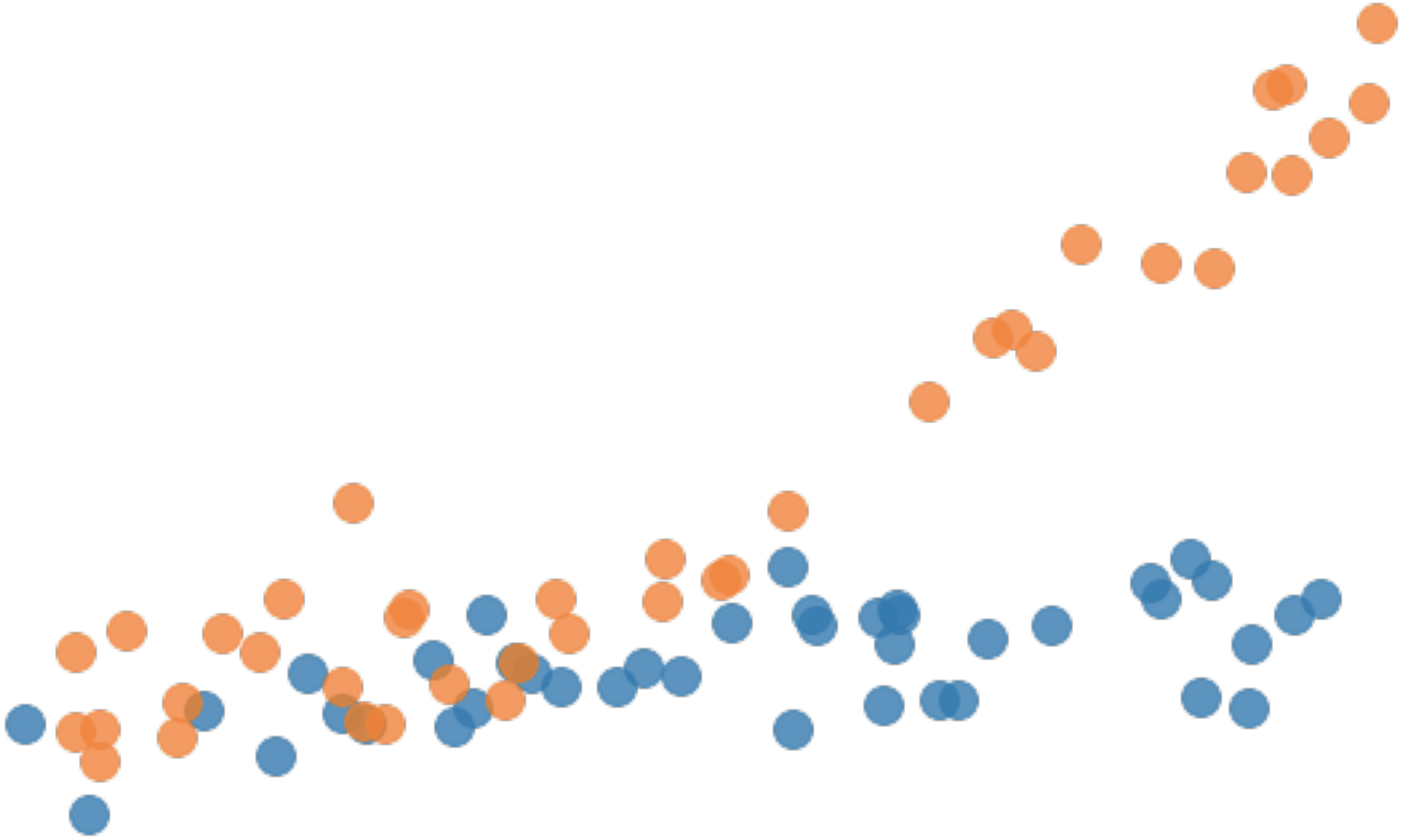

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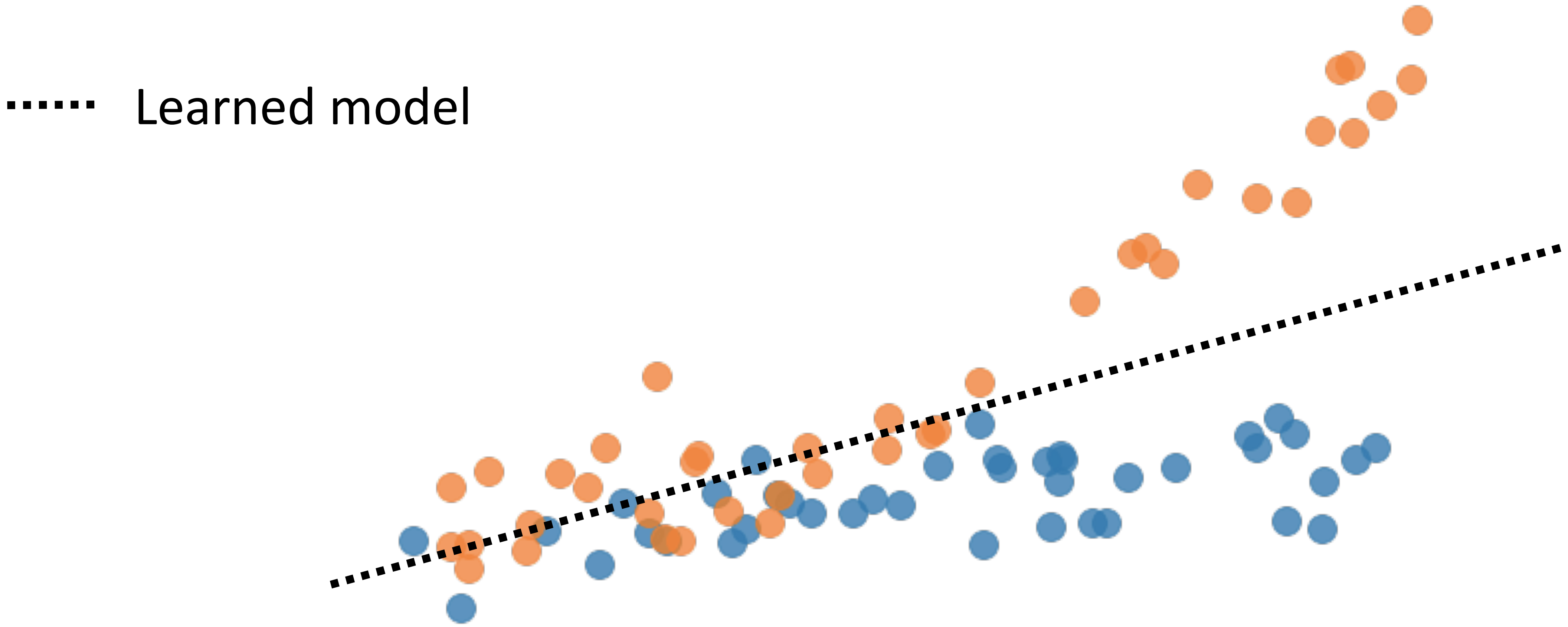

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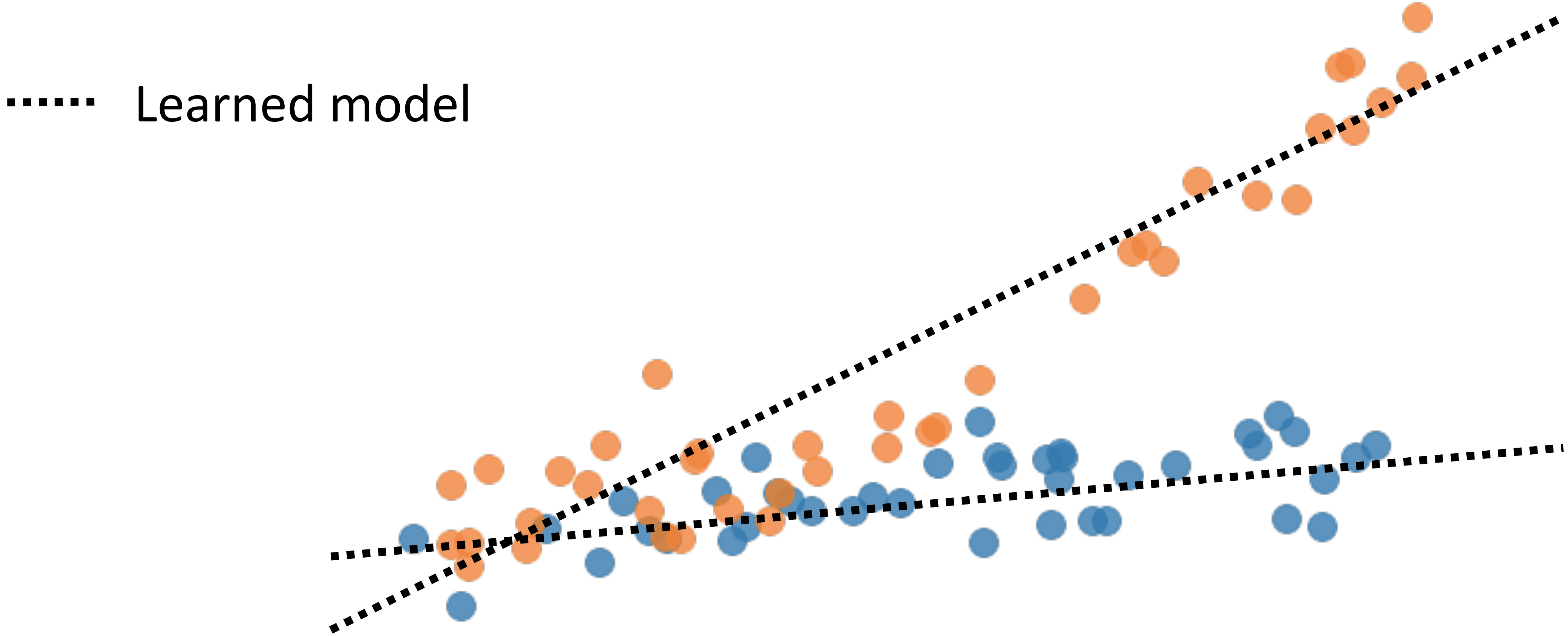

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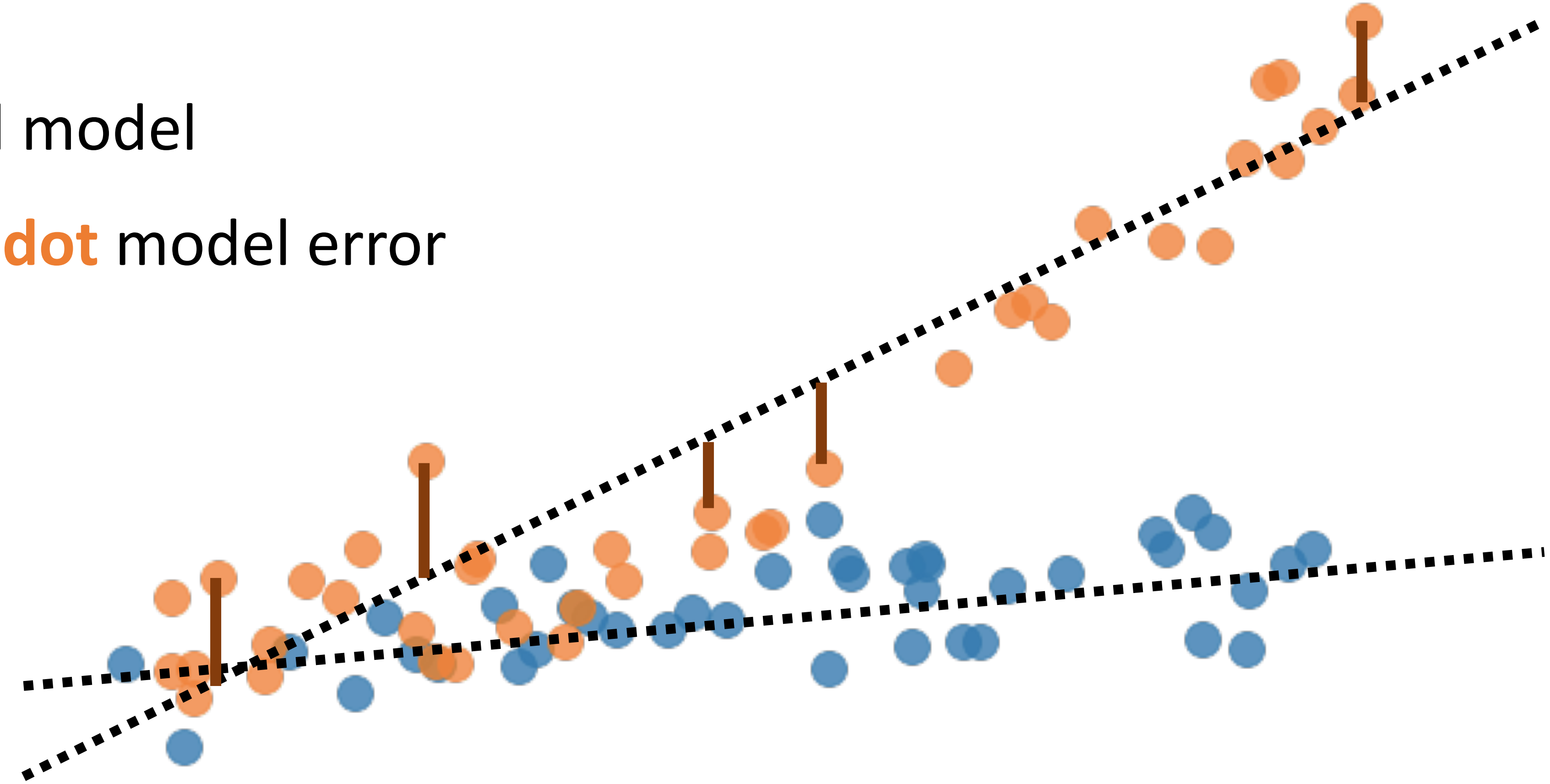
Learned model

Orange dot model error



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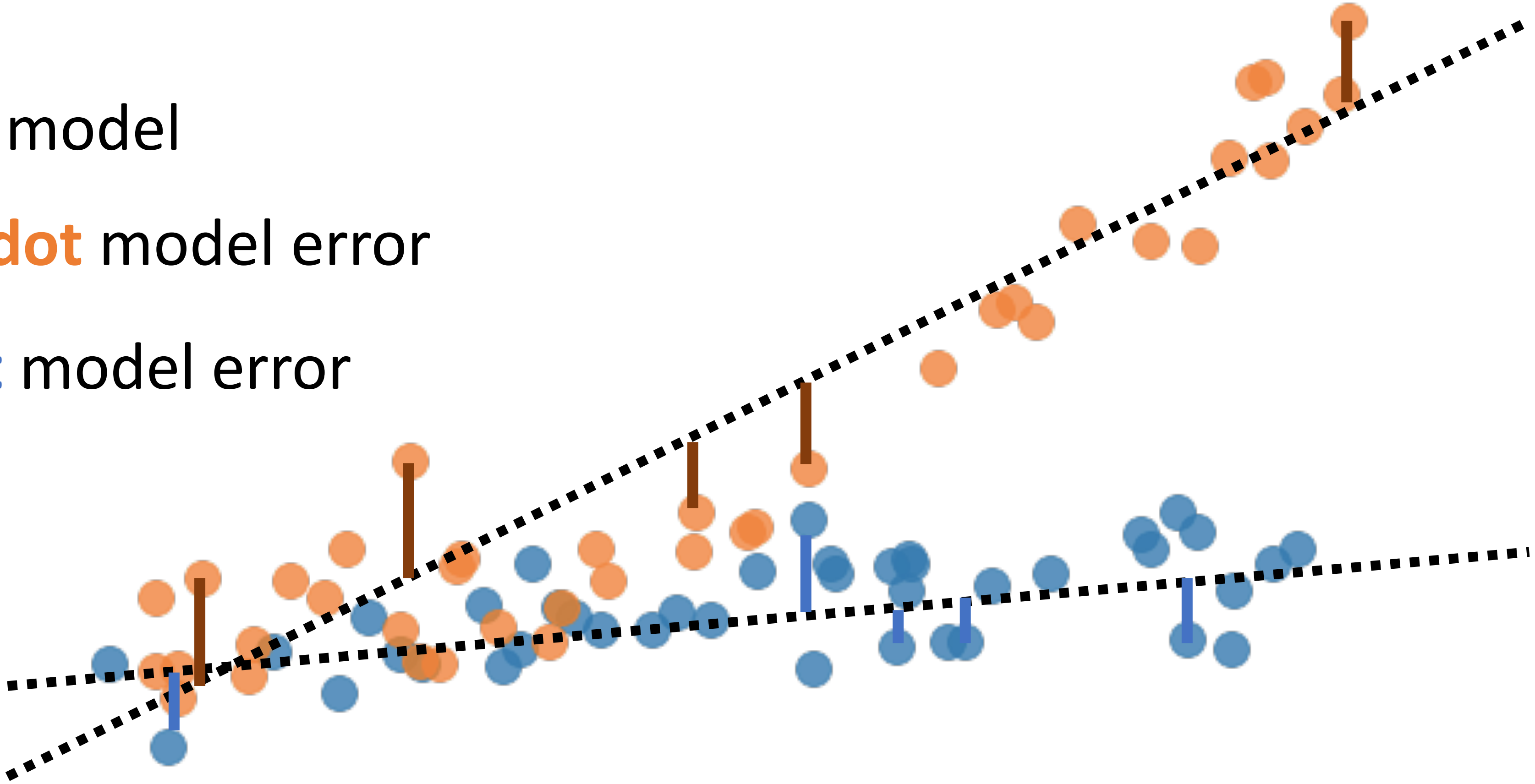
Learned model

Orange dot model error

Blue dot model error



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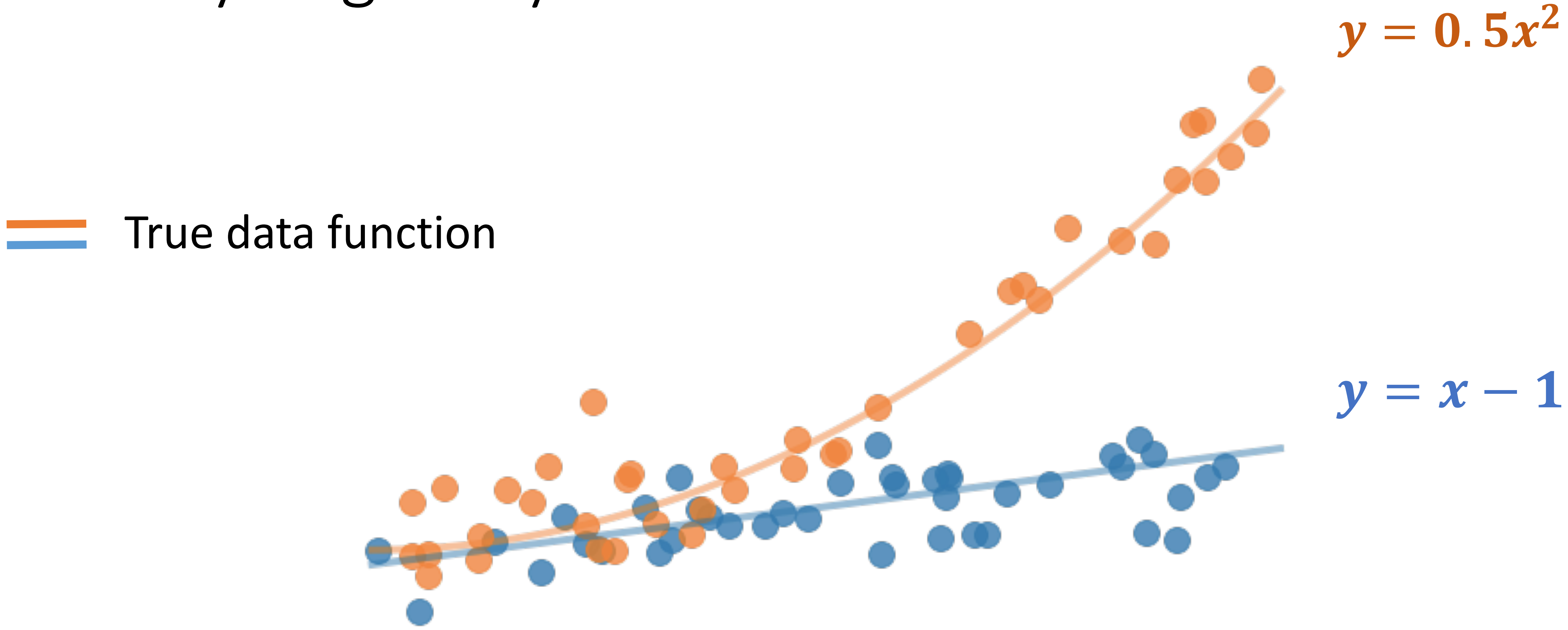

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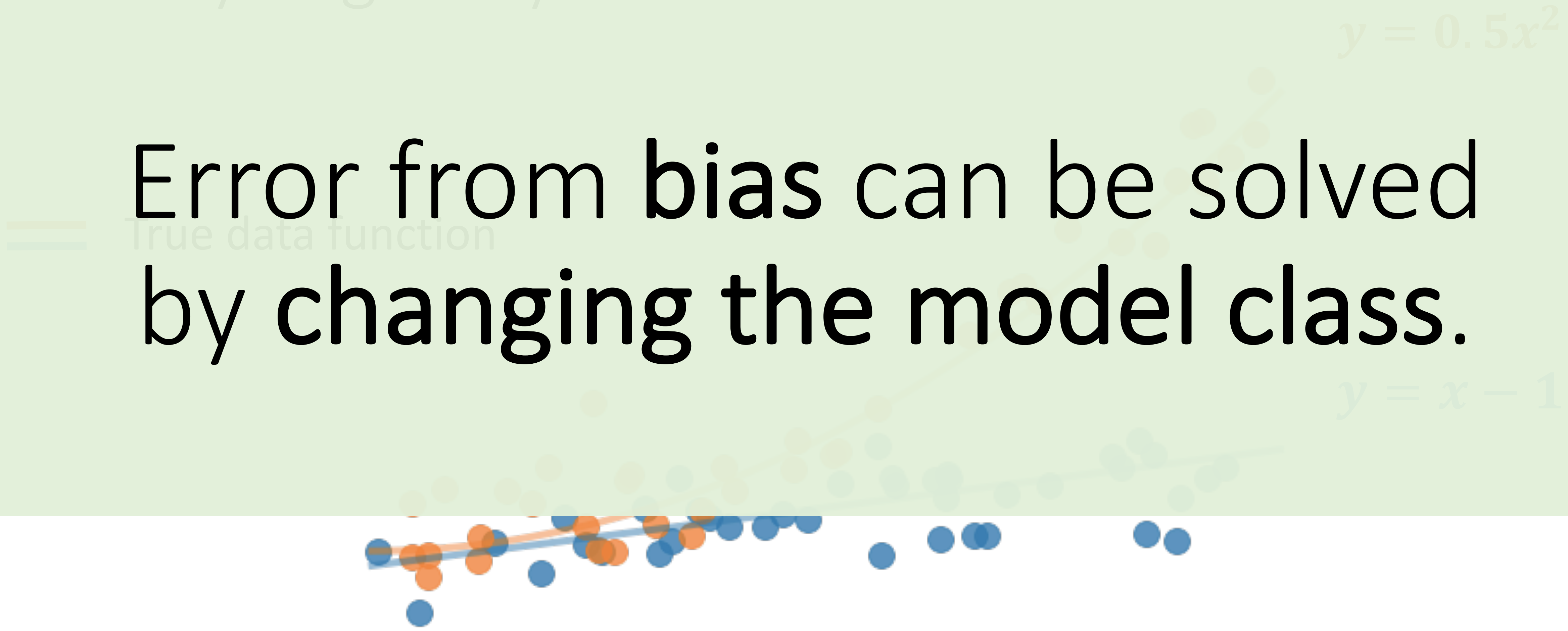

Error from **bias** can be solved by **changing the model class.**

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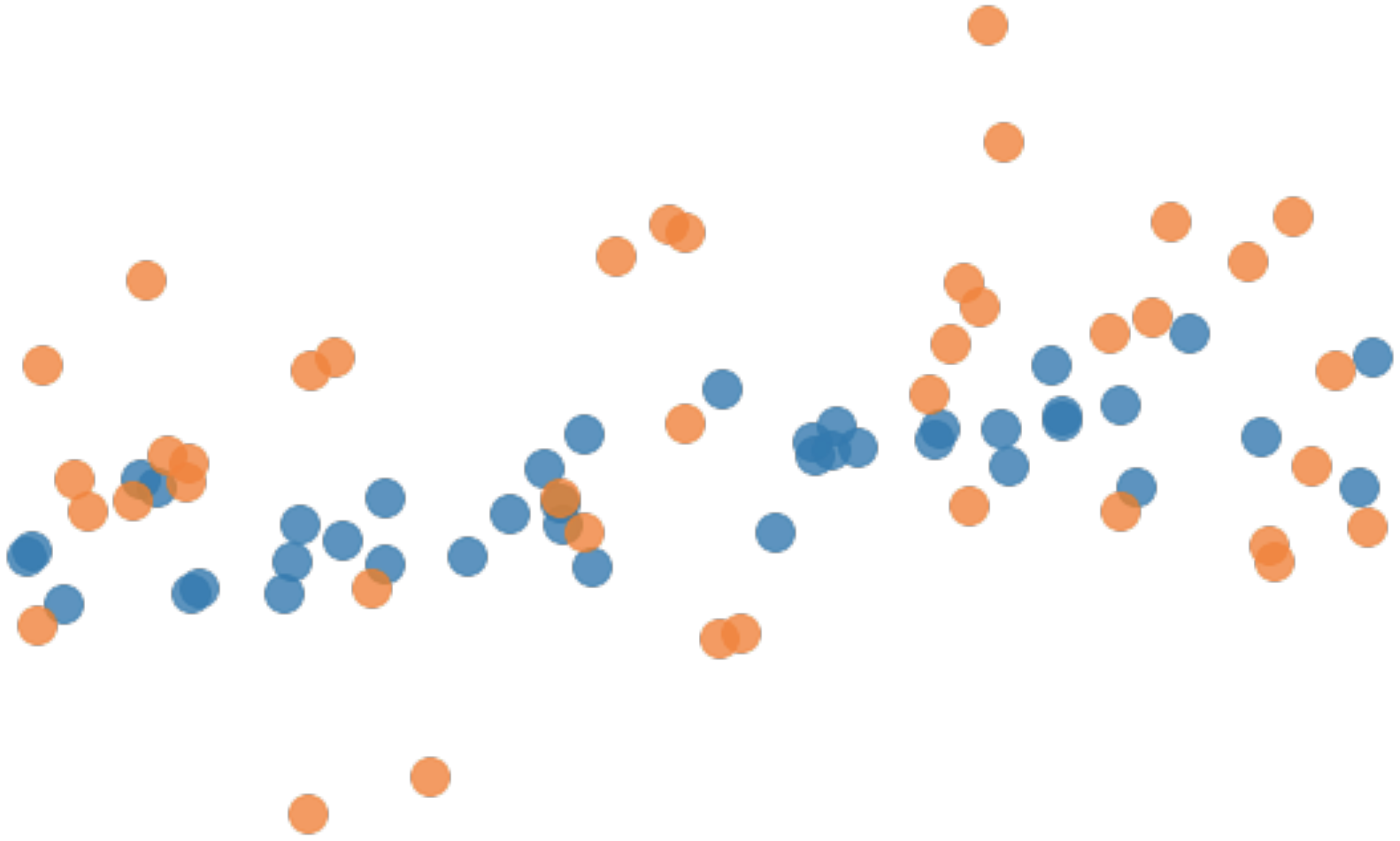

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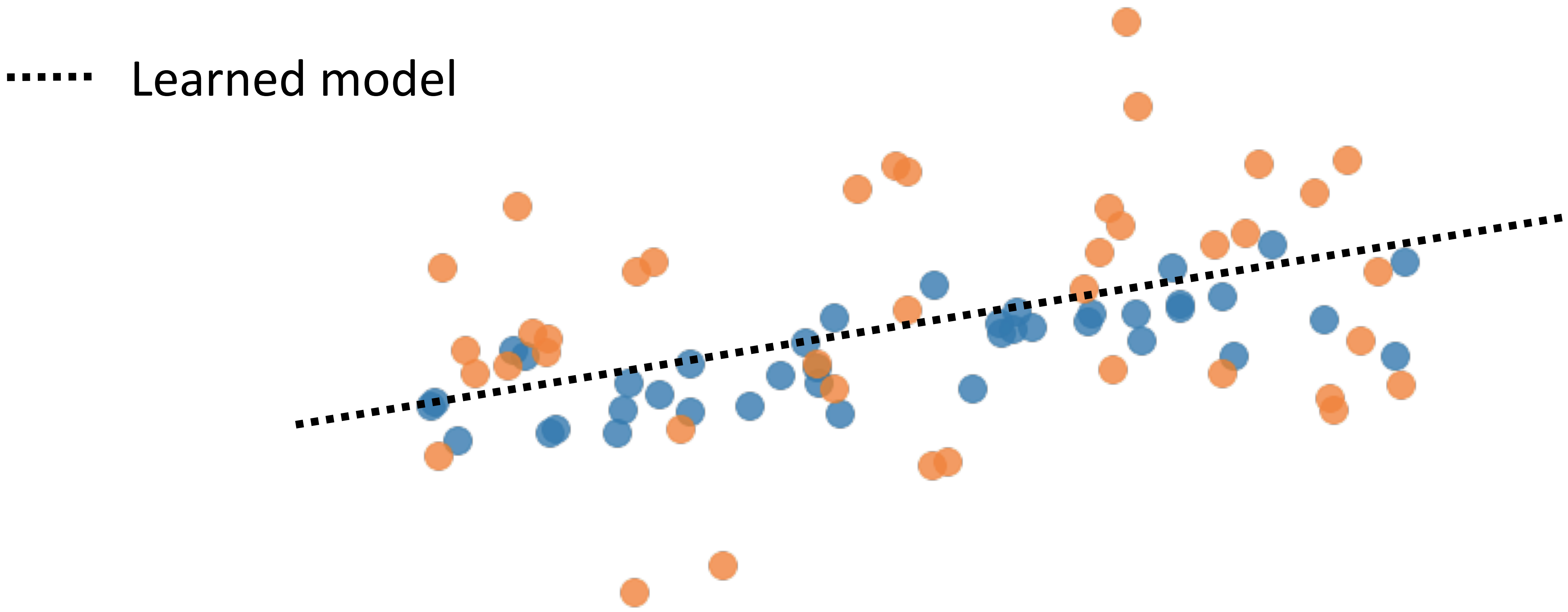

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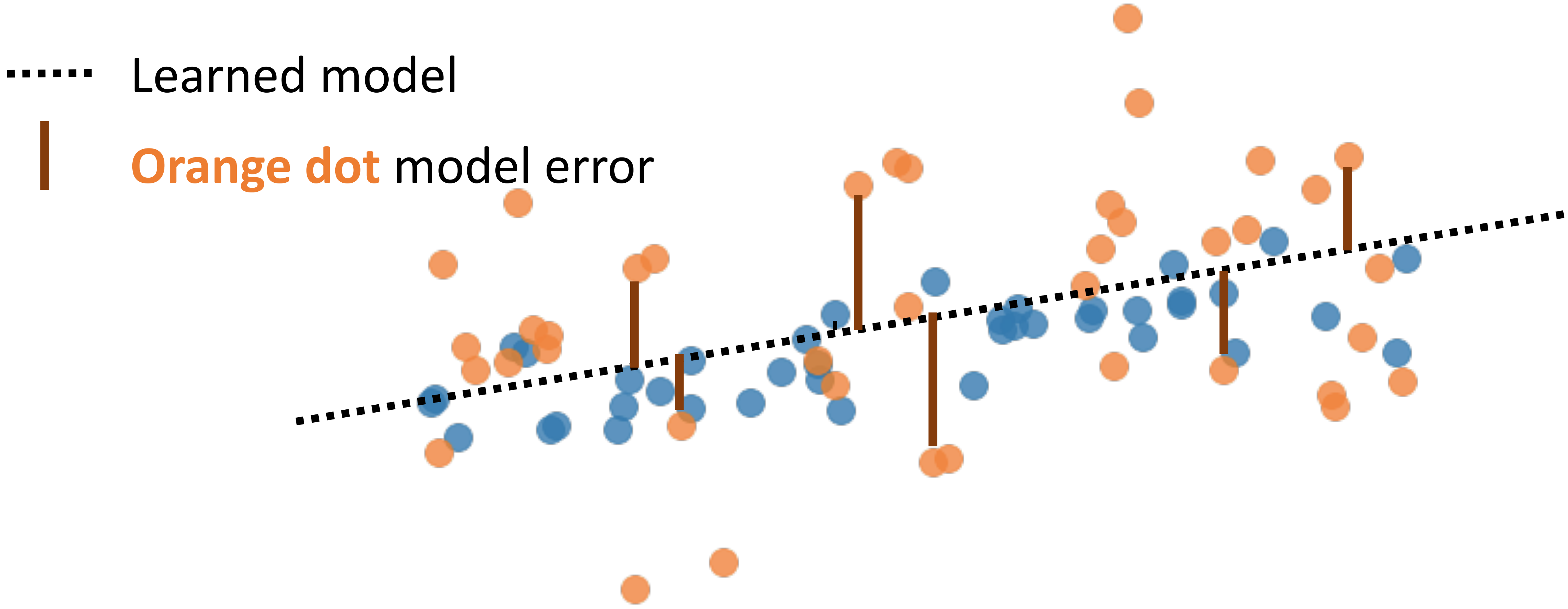

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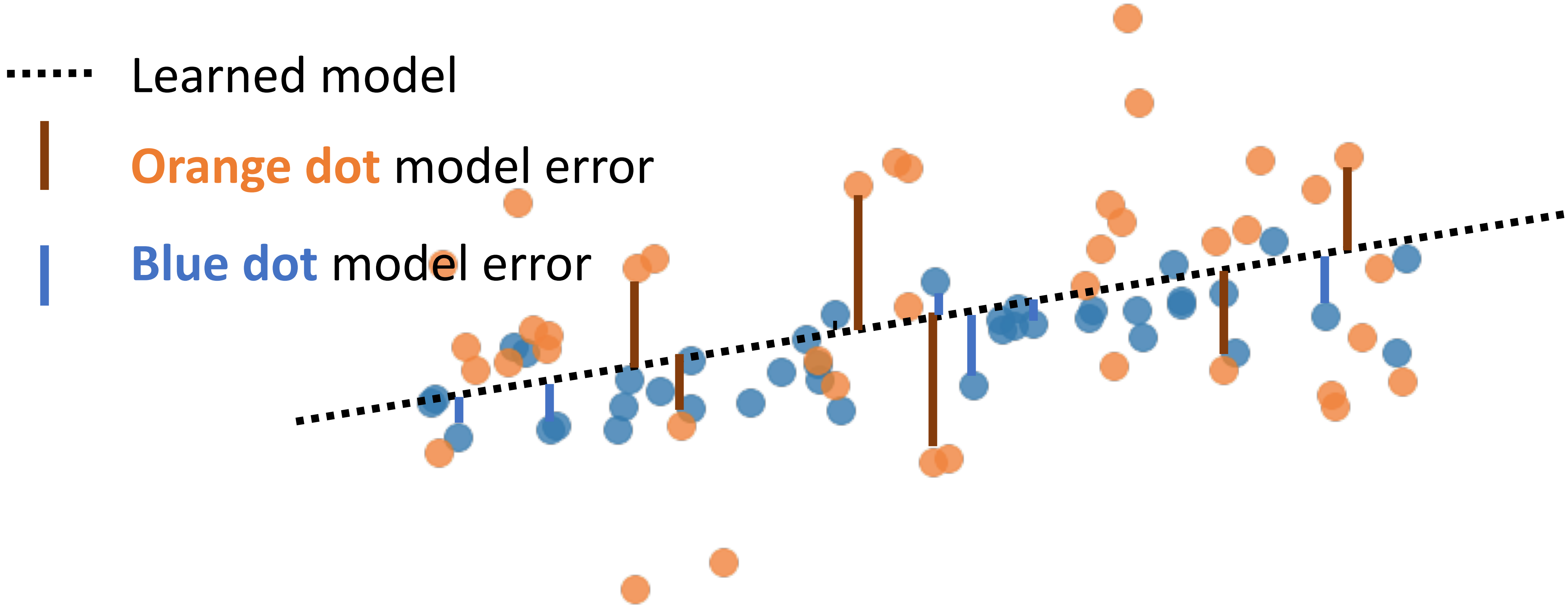

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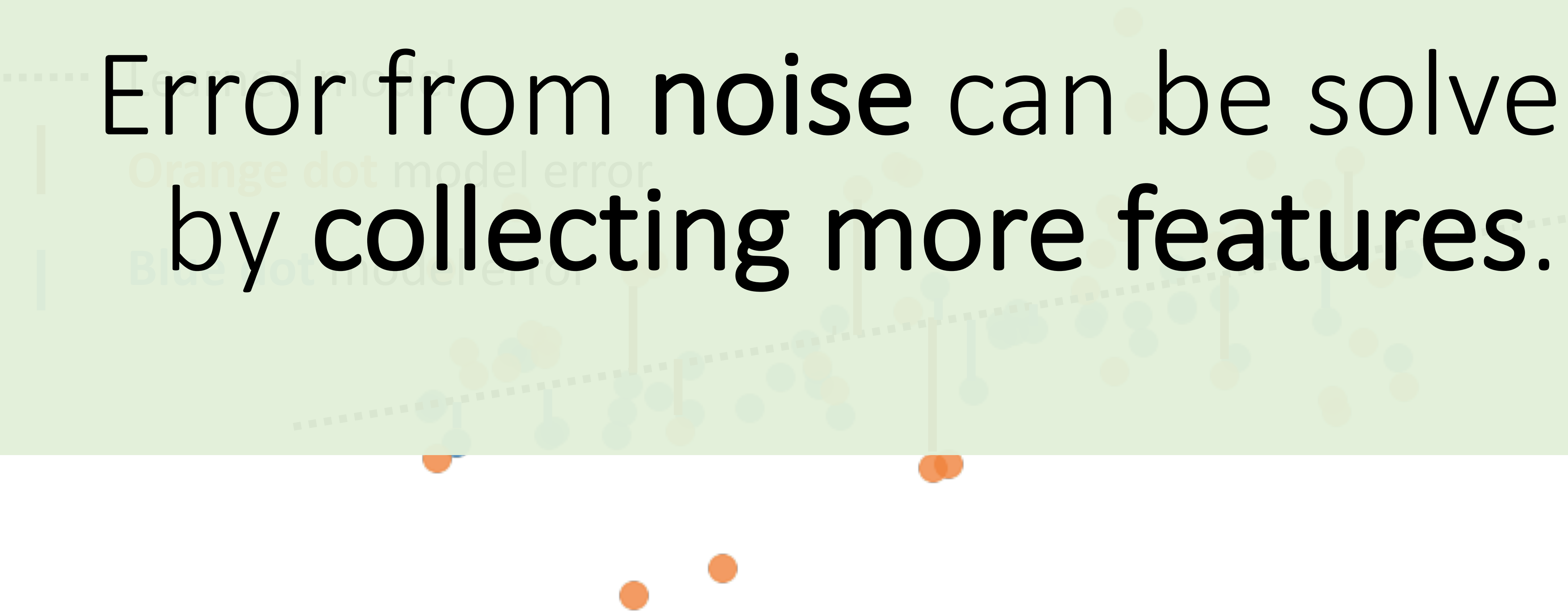

Error from **noise** can be solved by **collecting more features.**

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We define fairness in the **context of loss** like false positive rate, false negative rate, etc.

For example, zero-one loss for data D and prediction $\hat{Y}$:

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We can then formalize **unfairness as group differences.**

$$\bar{\Gamma}\left(\hat{Y}\right) := |\,\gamma_1 - \gamma_0|$$

We rely on accurate Y labels and focus on algorithmic error.

Why might my classifier be unfair?

Theorem 1: For error over group *a* given predictor $\hat{Y}$:

$$\bar{\gamma}_a(\hat{Y}) = \bar{B}_a(\hat{Y}) + \bar{V}_a(\hat{Y}) + \overline{N}_a$$

Note that $\overline{N_a}$ indicates the expectation of N_a over *X* and data *D*.

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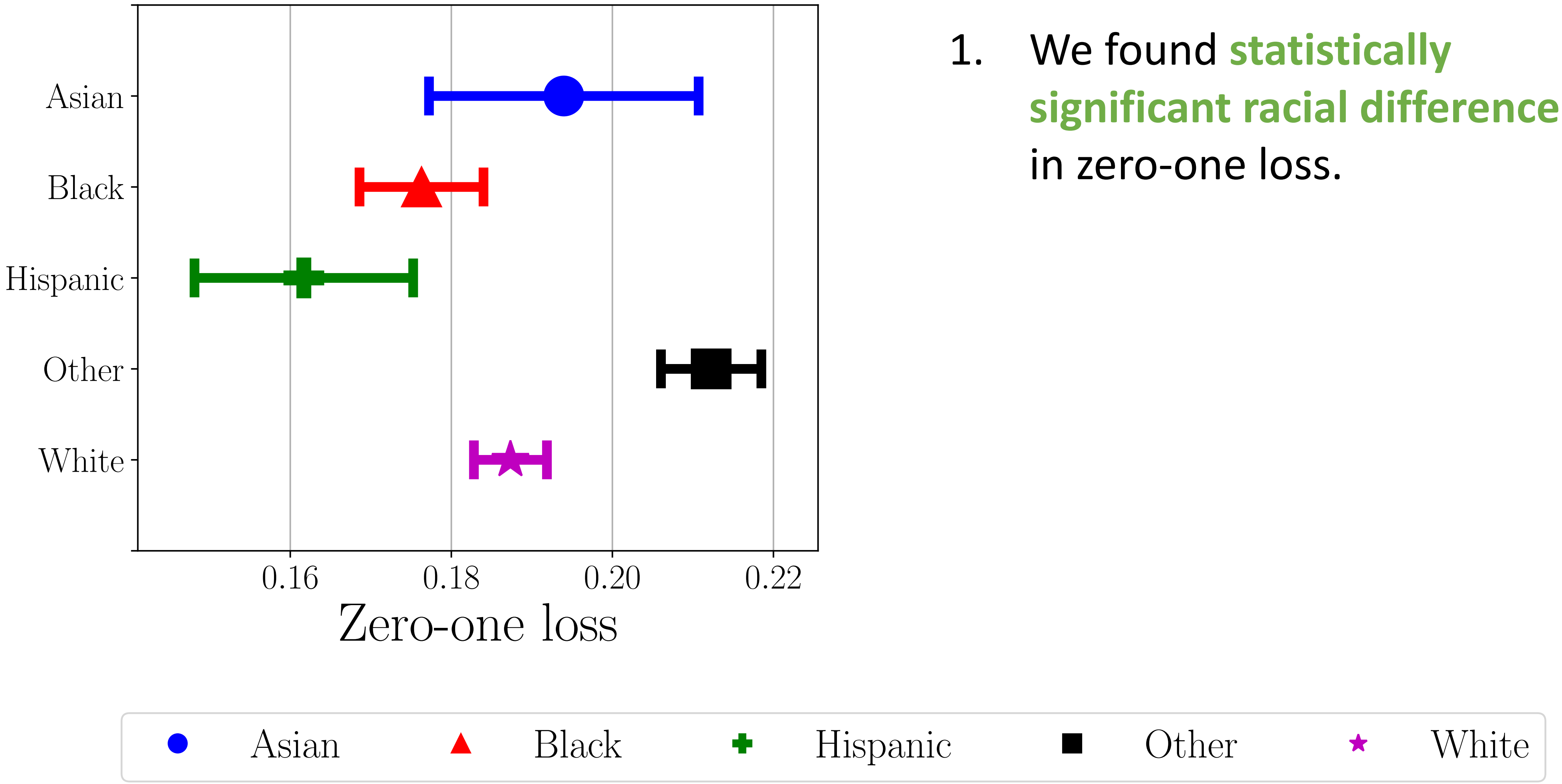
Accordingly, the expected discrimination level $\bar{\Gamma} := |\overline{\gamma_1} - \bar{\gamma}_0|$ can be decomposed into differences in bias, differences in variance, and differences in noise.

$$\bar{\Gamma} = |(\bar{B}_1 - \bar{B}_0) + (\bar{V}_1 - \bar{V}_0) + (\bar{N}_1 - \bar{N}_0)|$$

Mortality prediction from MIMIC-III clinical notes



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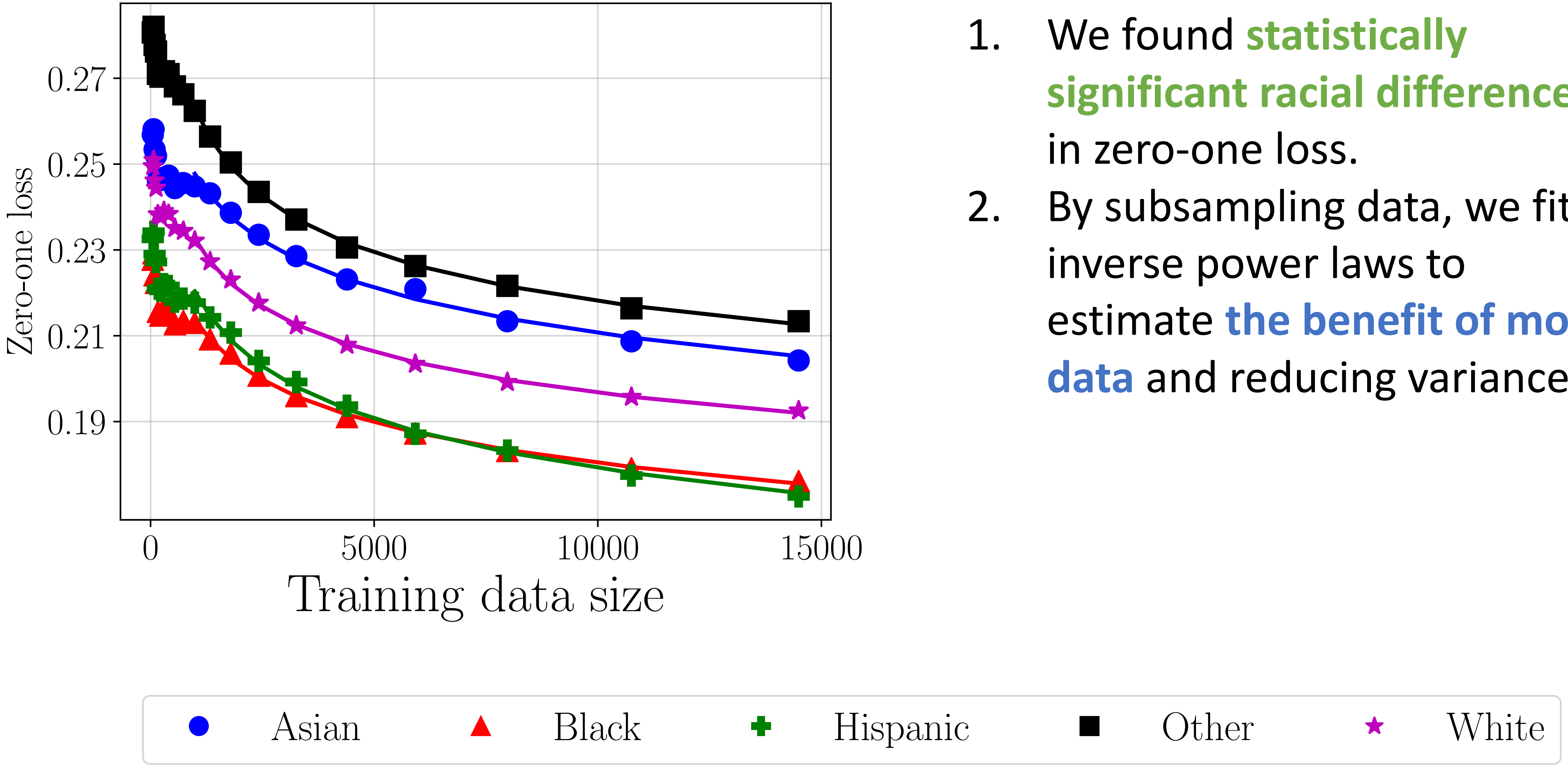

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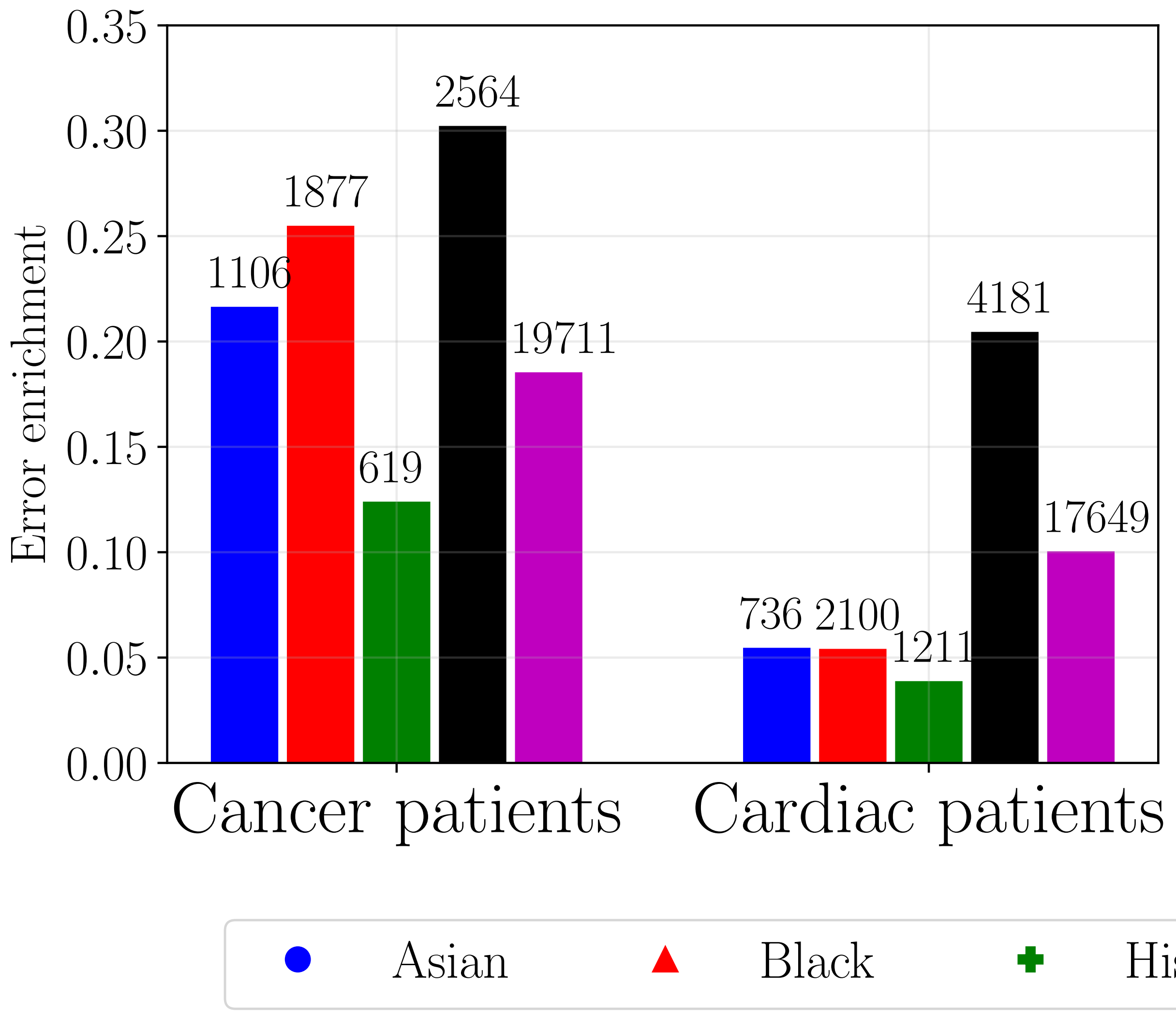

1. We found **statistically significant racial differences** in zero-one loss.
2. By subsampling data, we fit inverse power laws to estimate **the benefit of more data** and reducing variance.
3. Using topic modeling, we **identified subpopulations to gather more features** to reduce noise.

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Come to poster #120 in Room 210 & 230.