Ensembling methods

Stacking, bagging, boosting

Machine Learning and Data Mining, 2020

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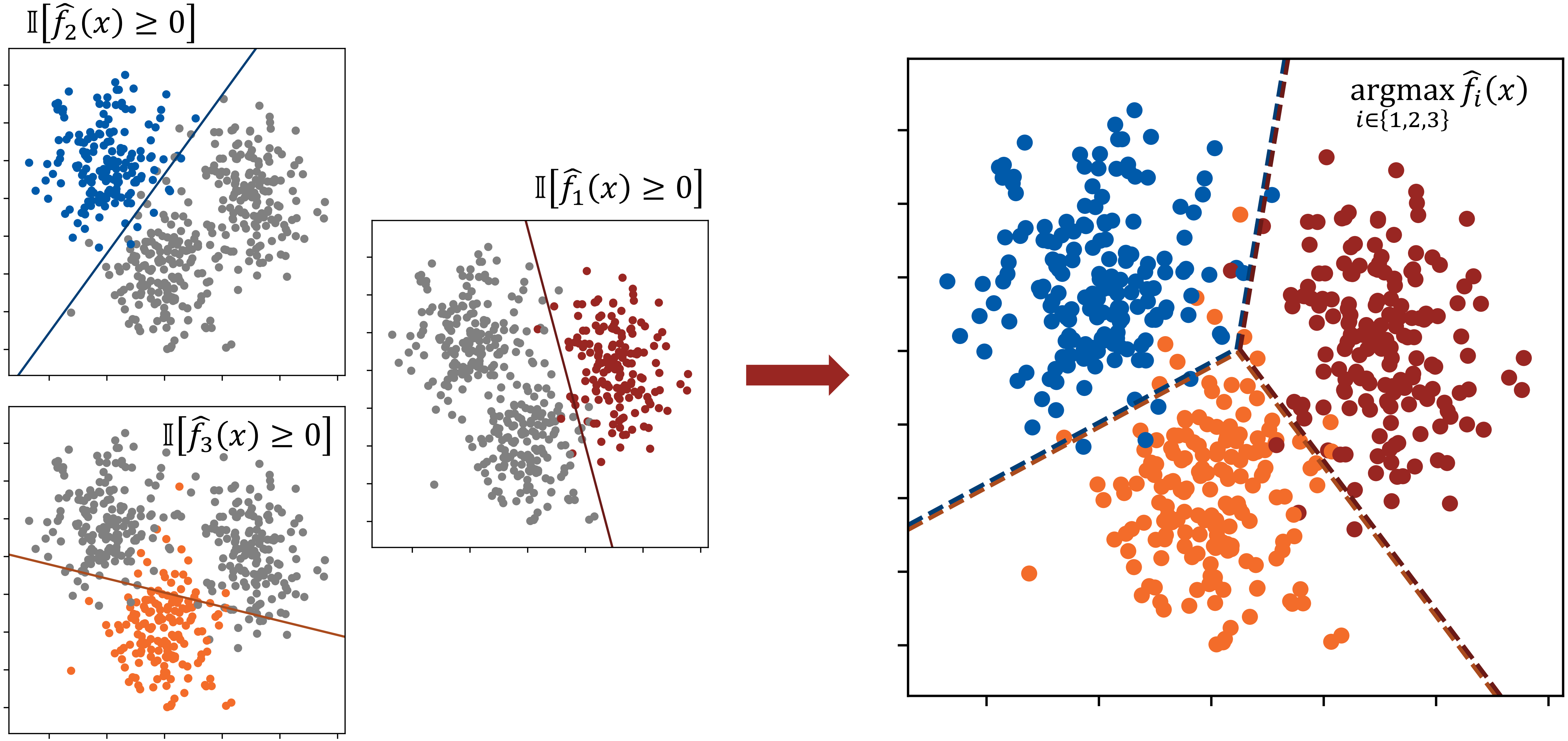
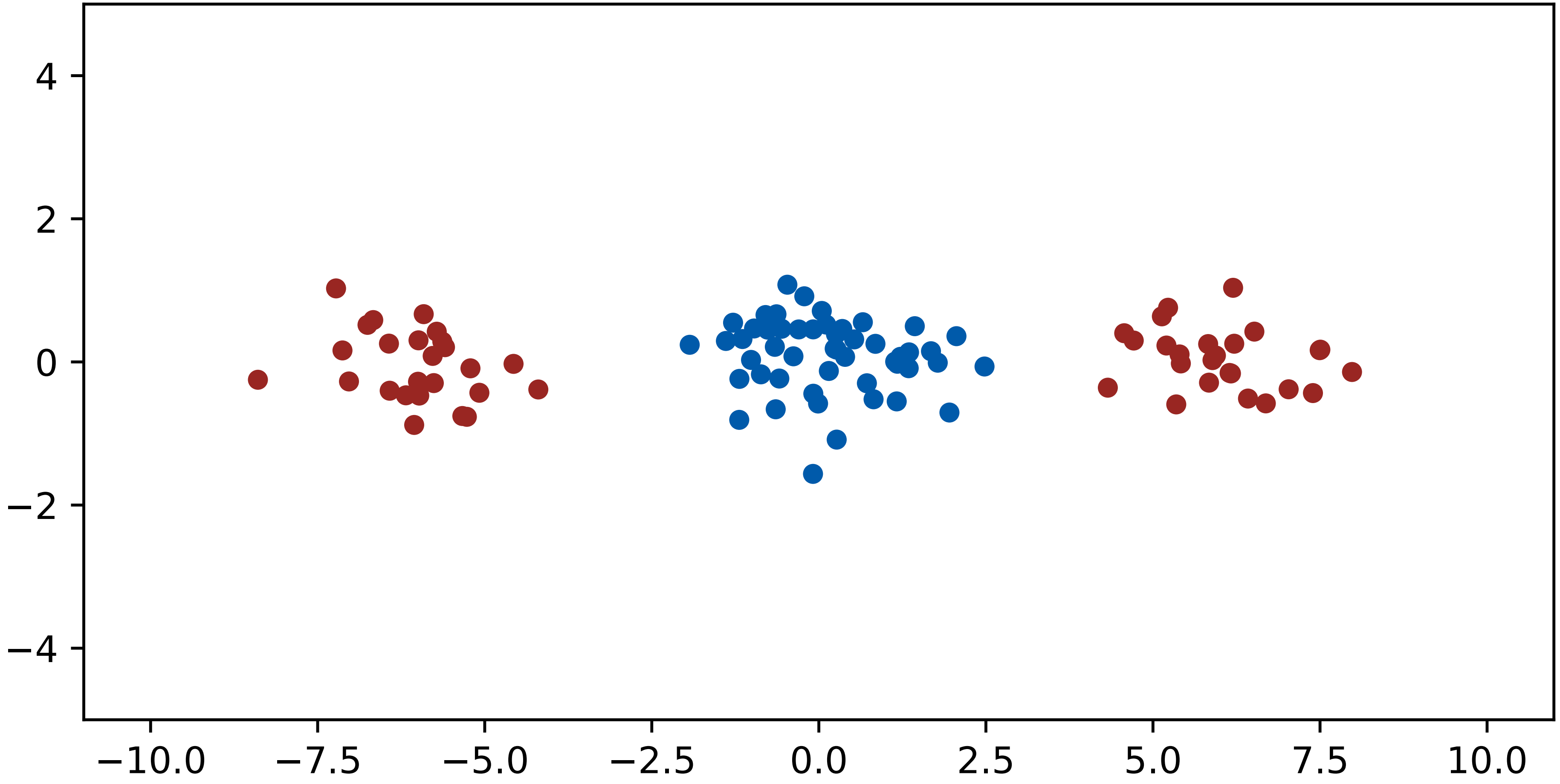
Why ensembles?

One-vs-rest classification scheme



Increasing complexity of simple underfitting models



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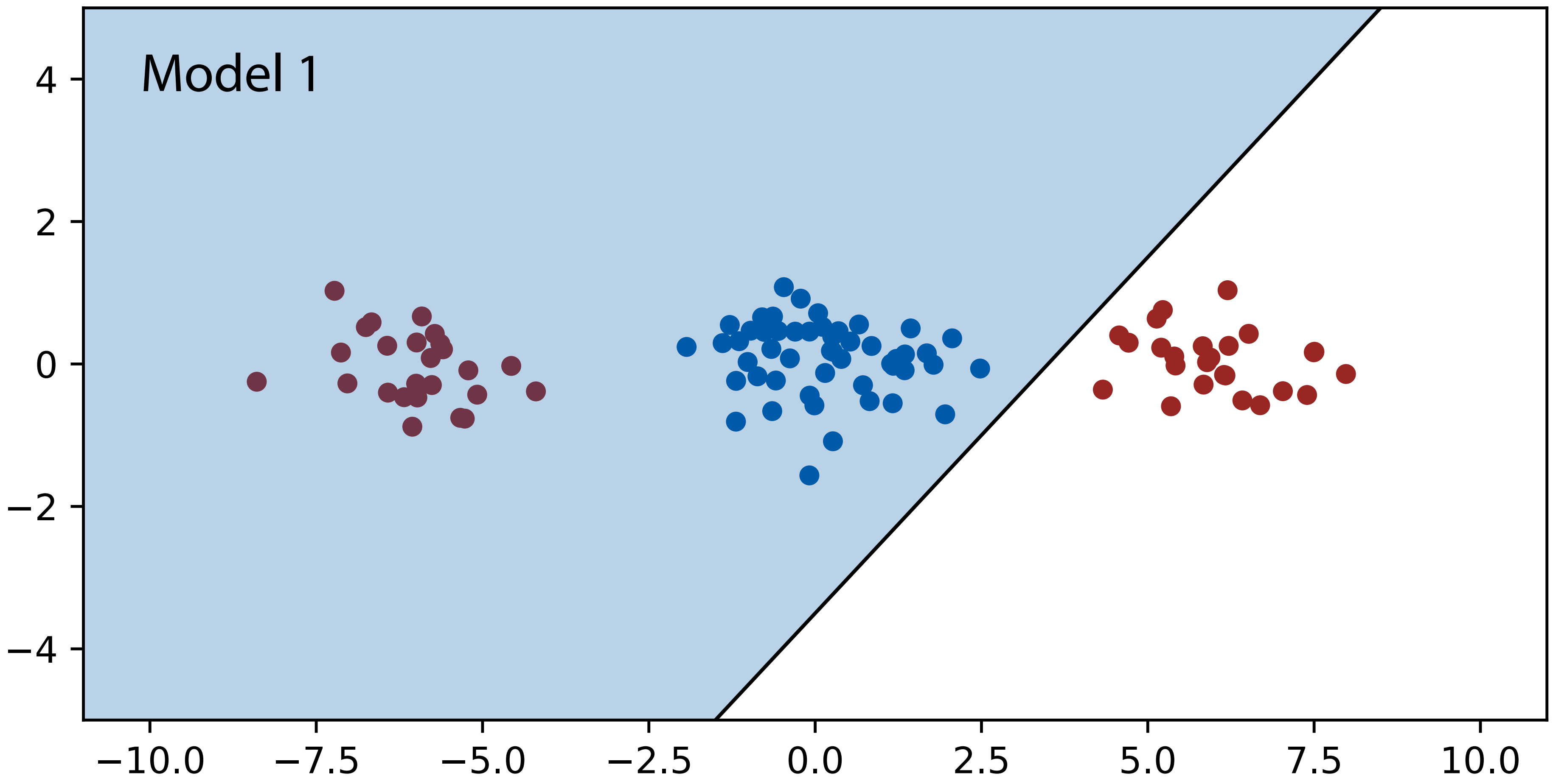

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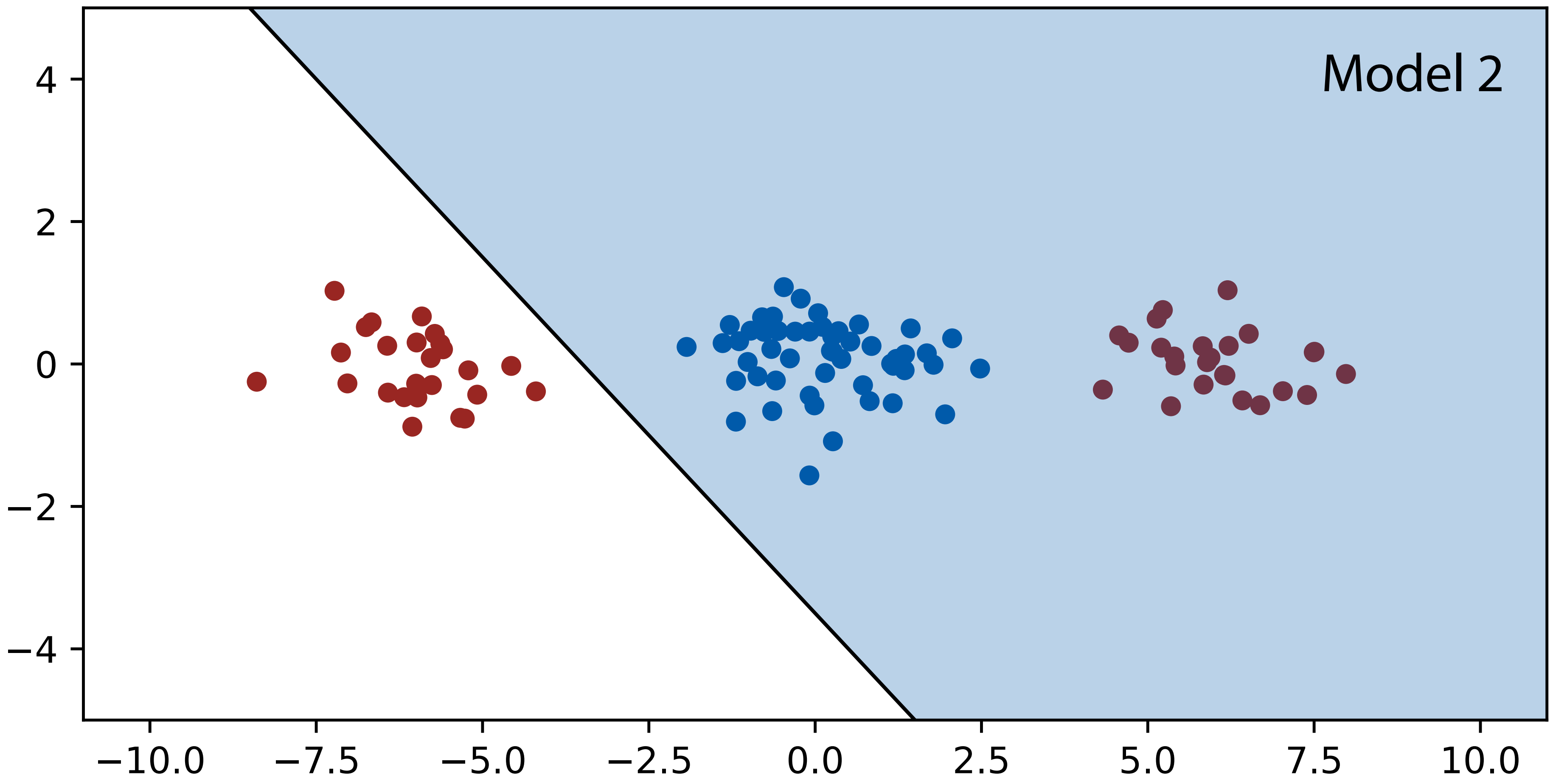

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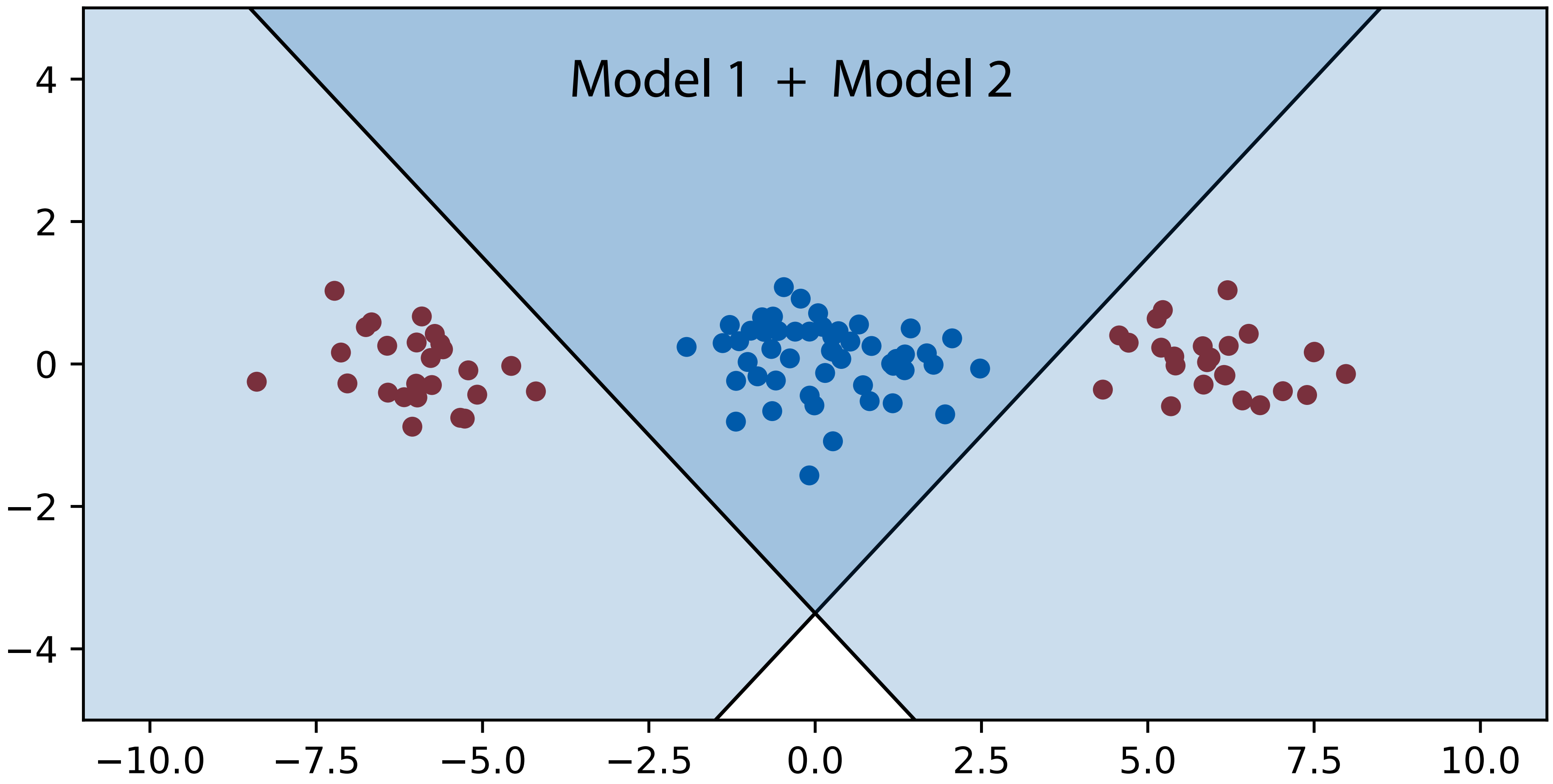
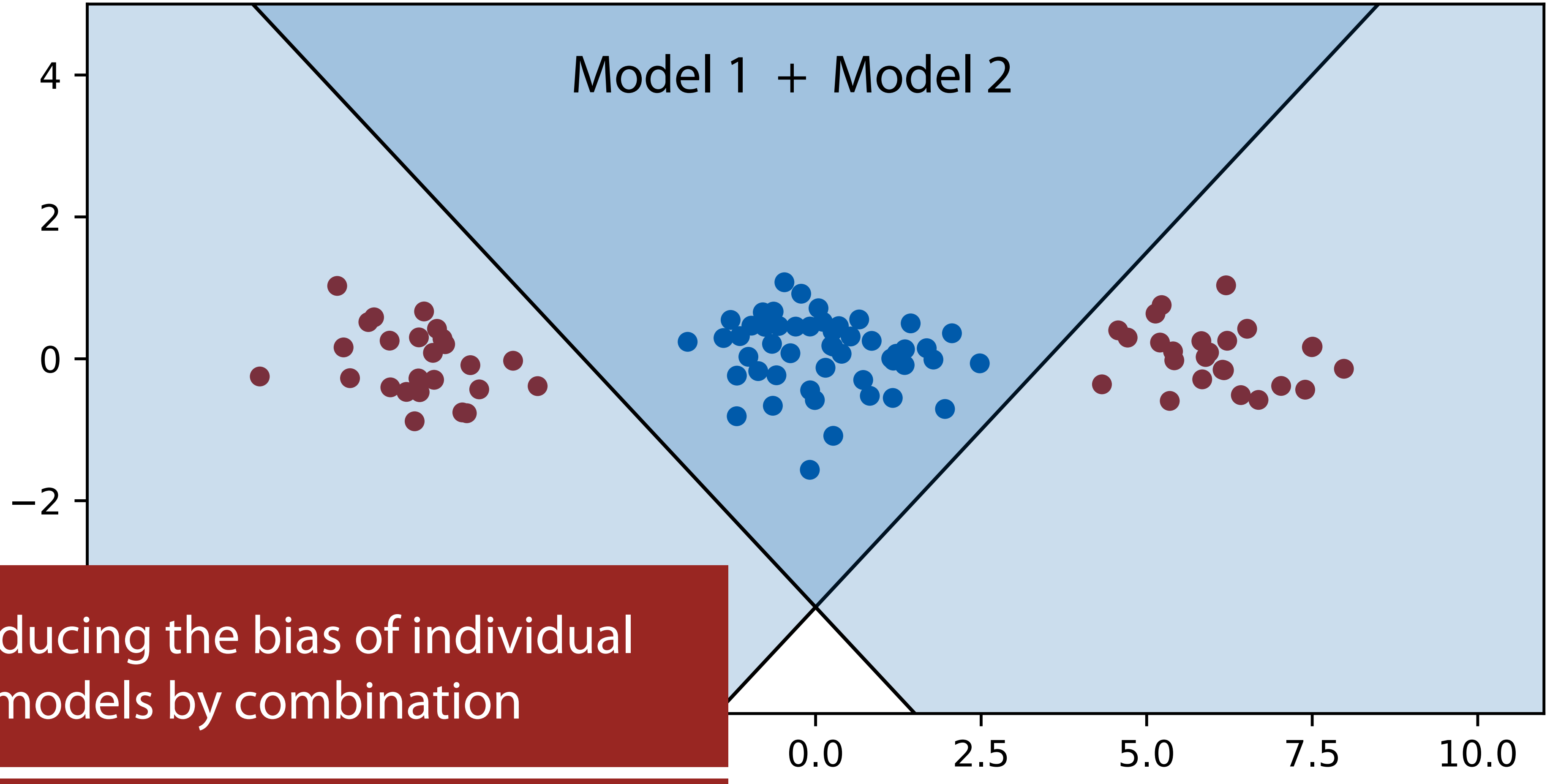


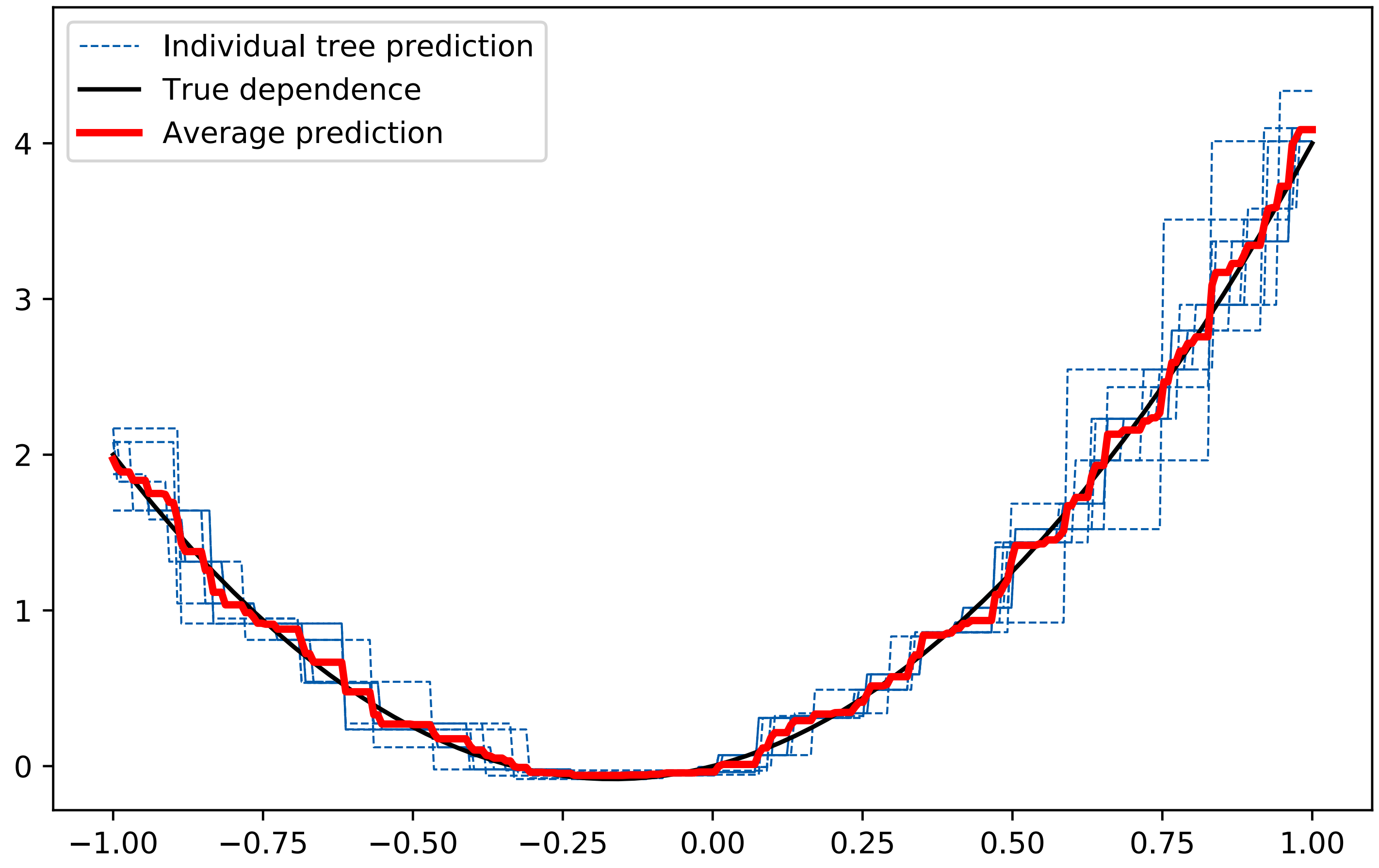
Increasing complexity of simple underfitting models



I.e. reducing the bias of individual models by combination

May increase variance

Reducing variance by averaging



- Take a set of overfitting (high-variance) models $\widehat{f_1}(x), \ldots, \widehat{f_M}(x)$
  - E.g. decision trees trained on different training sets
- For regression – average their predictions:

$$F(x) = \frac{1}{M}\sum_{i=1}^{M}\widehat{f_i}(x)$$

- For classification – majority voting

Ambiguity decomposition

Consider the following ensemble:

$$F(x) = \sum_i w_i f_i(x), \qquad w_i \geq 0, \qquad \sum_i w_i = 1$$

Then it's easy to show that:

$$\underbrace{(F(x) - y)^2}_{\textbf{Ensemble error}} = \underbrace{\sum_i w_i (f_i(x) - y)^2}_{\textbf{Base learner error}} - \underbrace{\sum_i w_i \big(f_i(x) - F(x)\big)^2}_{\textbf{Ambiguity}}$$

Disagreement reduces the error!

[Ambiguity decomposition proof]

$$F(x) = \sum_i w_i f_i(x), \qquad w_i \geq 0, \qquad \sum_i w_i = 1$$

$$(F(x) - y)^2 = \left(\sum_i w_i f_i(x) - y\right)^2 = \sum_i w_i f_i(x) \cdot F(x) - 2\sum_i w_i f_i(x) \cdot y + \sum_i w_i y^2$$

$$= \sum_i w_i [f_i(x) \cdot F(x) - 2f_i(x) \cdot y + y^2]$$

$$= \sum_i w_i \left[f_i^2(x) - 2f_i(x) \cdot y + y^2 - f_i^2(x) + 2f_i(x) \cdot F(x) - F^2(x) + F^2(x) - f_i(x) \cdot F(x)\right]$$

$$= \sum_i w_i \left[(f_i(x) - y)^2 - \left(f_i(x) - F(x)\right)^2 + F^2(x) - f_i(x) \cdot F(x)\right]$$

$$= \sum_i w_i (f_i(x) - y)^2 - \sum_i w_i \left(f_i(x) - F(x)\right)^2$$

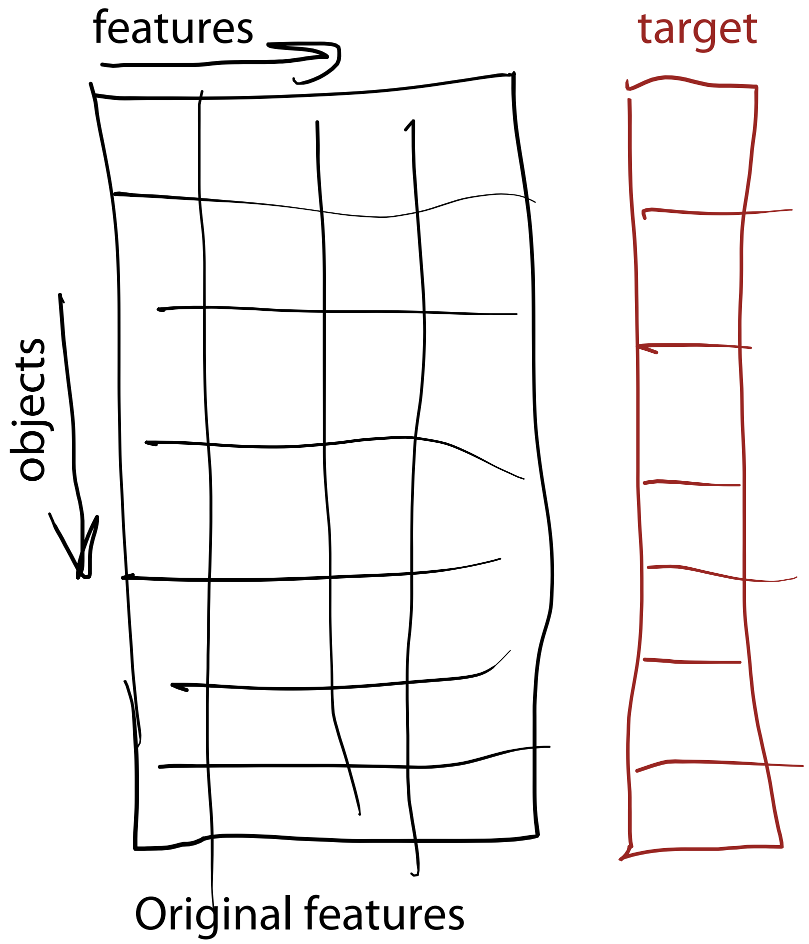
Majority voting classifier error

- Assume we have M classifiers with prediction error probability $p < \frac{1}{2}$ each
- Suppose the guesses are wrong or correct independently of each other
- Then major vote error probability $\to 0$ as $\mathrm{M} \to +\infty$.

Stacking

Stacking

- Using output of initial models as features for the aggregation model



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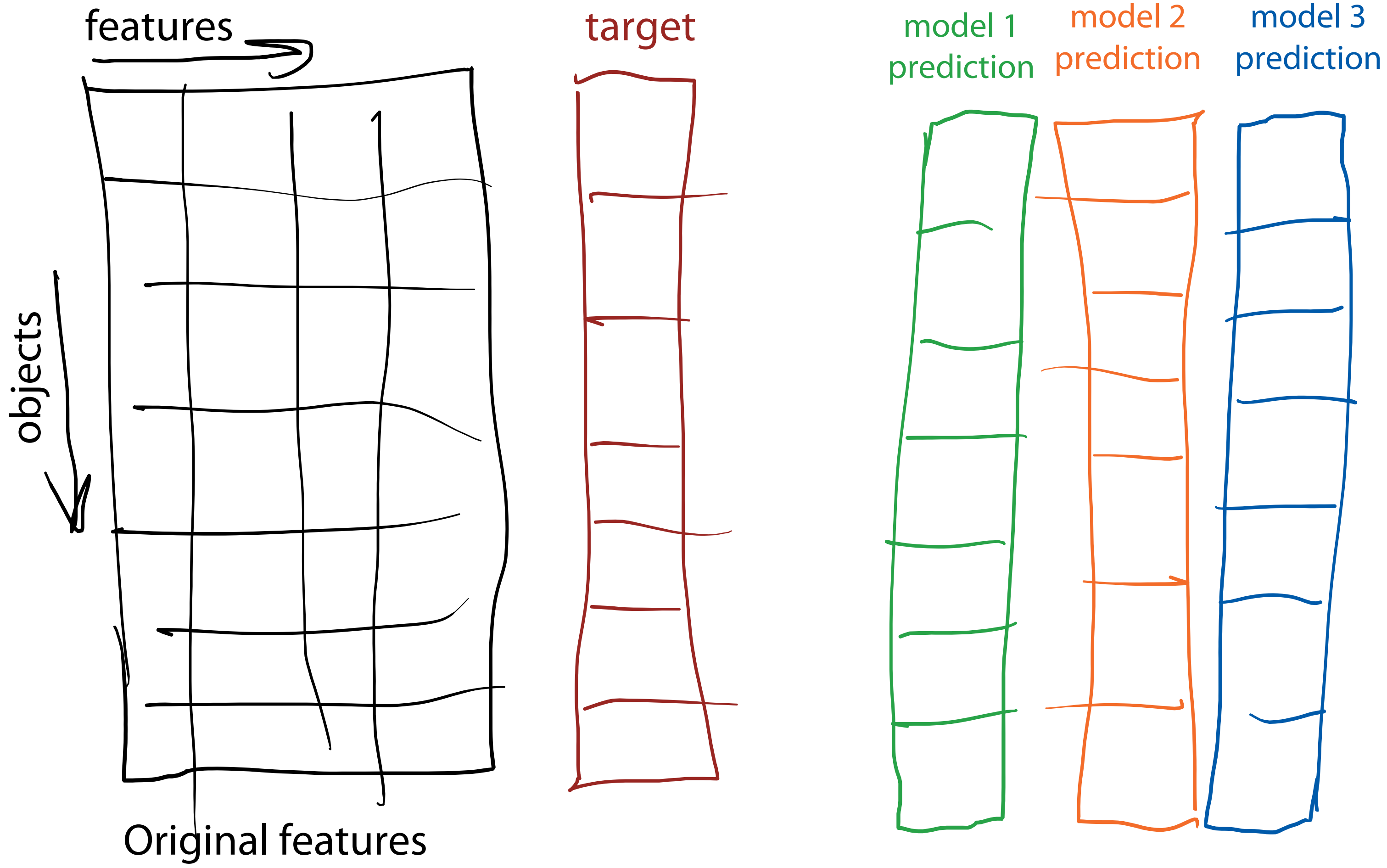

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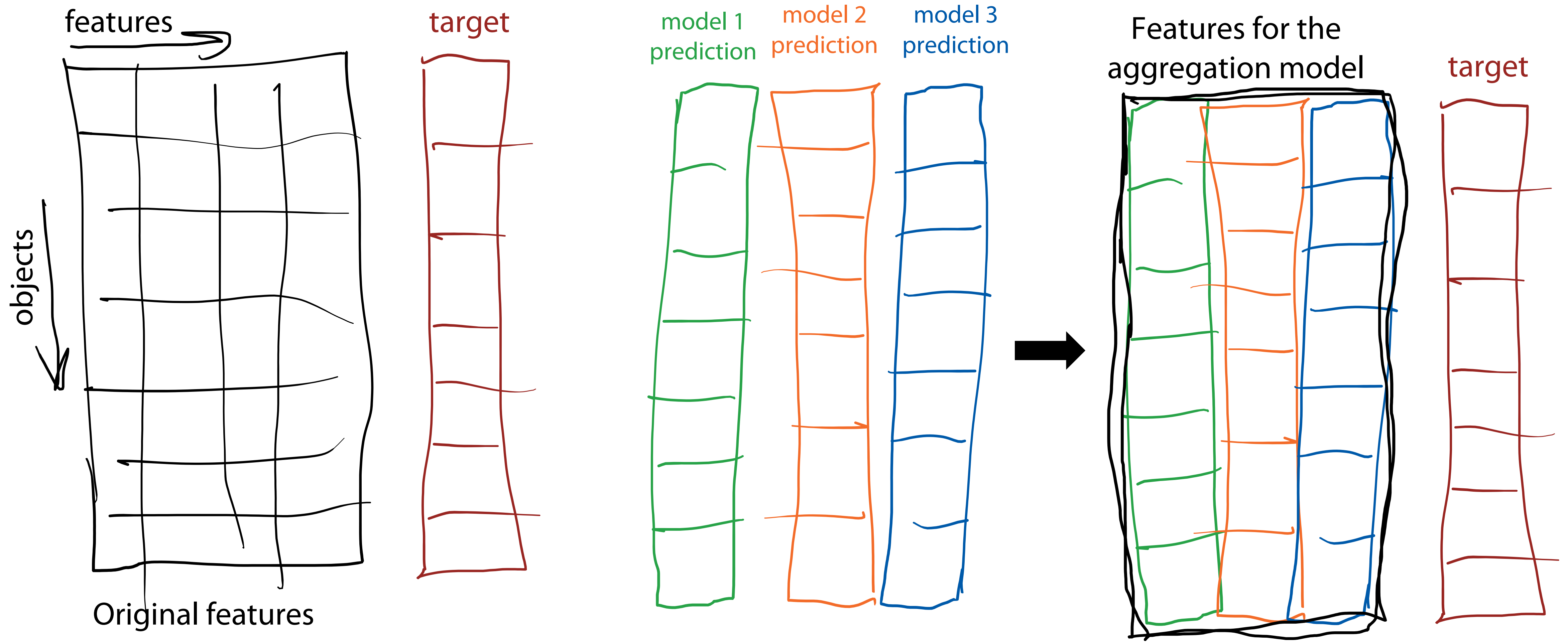

Stacking

- Using output of initial models as features for the aggregation model
- Easy to overfit if using the base models' predictions from the train data
- Solution: use cross-validated estimates

Bagging

Bagging

- Bagging = bootstrap aggregating
- Generate bootstrap samples (re-sample your data with replacement)
- Train independent base models on those samples
- Combine their predictions

- Example
  - Bagged decision trees
  - Random Forest (= bagged trees + feature subsampling)
  - Extra random trees (= Random Forest + randomized splits)

Boosting

Forward stagewise additive modeling (FSAM)

- Loss function: $L(f(x), y)$
- Base learners $\widehat{f_{\mathrm{m}}}$
- Approximate the output as:

$$F_M(x) = \widehat{f_0}(x) + \sum_{m=1}^{M} \widehat{c_m} \cdot \widehat{f_m}(x)$$

- Do so in steps:
  - Start from 0, constant or just fit $\widehat{f_0}$ to data
  - At each step solve:

$$\left(\widehat{c_m}, \widehat{f_m}\right) = \underset{c,f}{\operatorname{argmin}} \left[\sum_{n=1}^{N} L(F_{m-1}(x_n) + c \cdot f(x_n), y_n)\right]$$

AdaBoost

- AdaBoost = FSAM with exponential loss

$$L(f(x), y) = \exp[-y \cdot f(x)]$$

$$y \in \{-1, +1\},$$

  - and base learners being binary classifiers: $\widehat{f_m}(x) \in \{-1, +1\}$

- Minimization can be done analytically
  - if individual learners allow for weighted samples

AdaBoost

- Loss at step m:

$$\sum_{n=1}^{N} \exp\left[-y_n\left(F_{m-1}(x_n) + c \cdot f(x_n)\right)\right]$$

AdaBoost

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$$= \sum_{n=1}^{N} \exp[-y_n \cdot F_{m-1}(x_n)] \cdot \exp[-y_n \cdot c \cdot f(x_n)] = \sum_{n=1}^{N} w_n \cdot \exp[-y_n \cdot c \cdot f(x_n)]$$

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$$= \sum_{y_n = f(x_n)} w_n \cdot e^{-c} + \sum_{y_n \neq f(x_n)} w_n \cdot e^{c}$$

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$$= \sum_{n=1}^{N} w_n \cdot e^{-c} + \sum_{y_n \neq f(x_n)} w_n \cdot (e^{c} - e^{-c})$$

AdaBoost

- So at step m we optimize:

$$(\widehat{c_m}, \widehat{f_m}) = \underset{c,f}{\operatorname{argmin}} \left[\sum_{n=1}^{N} w_n \cdot e^{-c} + \sum_{y_n \neq f(x_n)} w_n \cdot (e^c - e^{-c}) \right]$$

$$w_n = \exp[-y_n \cdot F_{m-1}(x_n)]$$

- In other words, find $\widehat{f_m}$, s.t. $\sum_{\widehat{f_m}(x_n) \neq y_n} w_n$ is minimized
- Easy to show that for c:

$$c_m = \frac{1}{2} \ln \frac{\sum_{\widehat{f_m}(x_n) = y_i} w_n}{\sum_{\widehat{f_m}(x_n) \neq y_i} w_n}$$

AdaBoost

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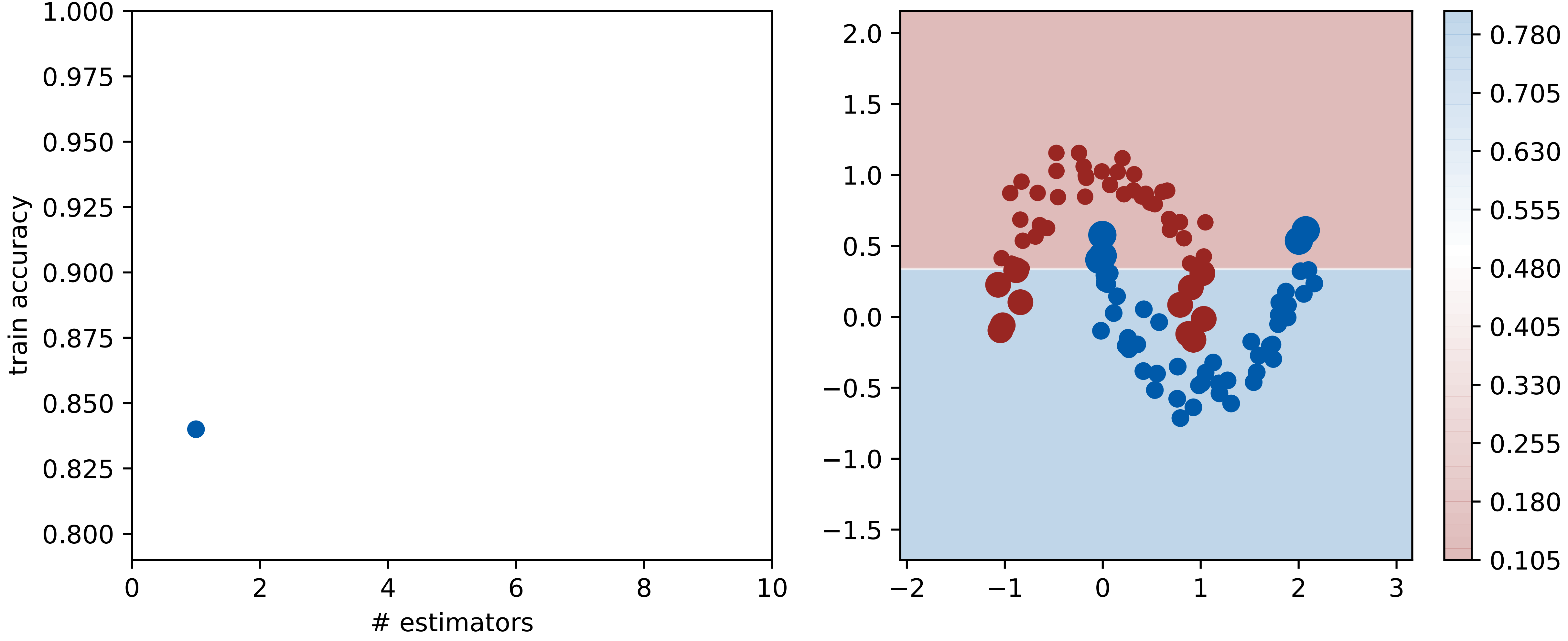
pay more attention to objects predicted wrongly

Example



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estimators
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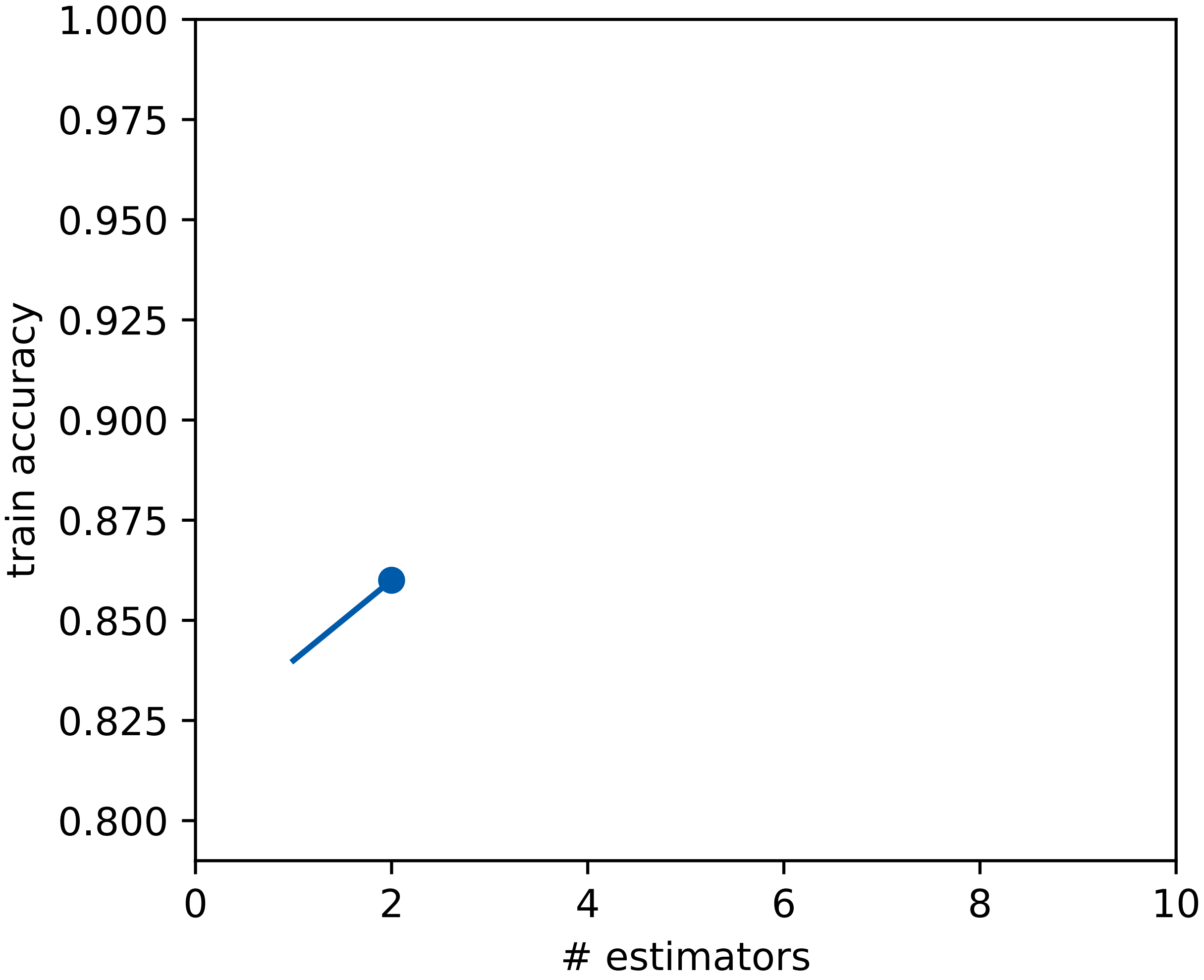
Example



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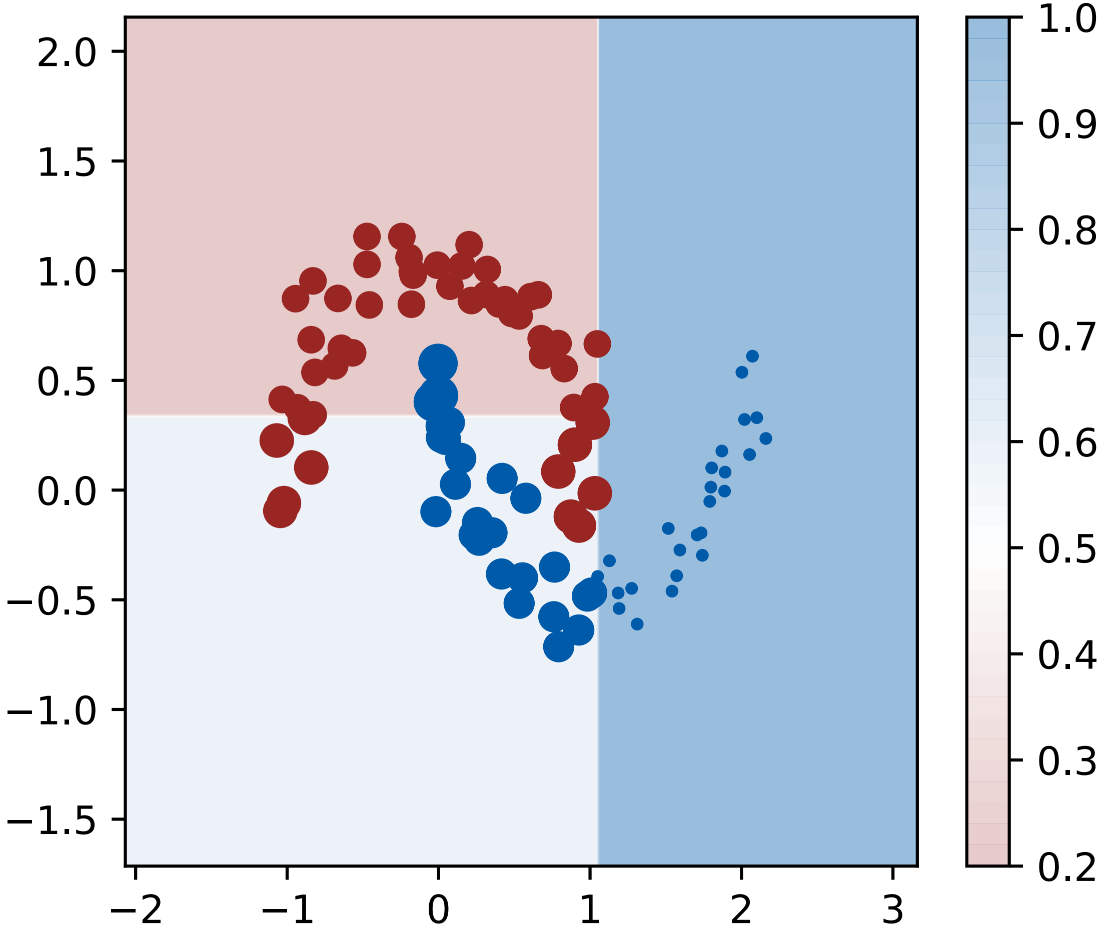

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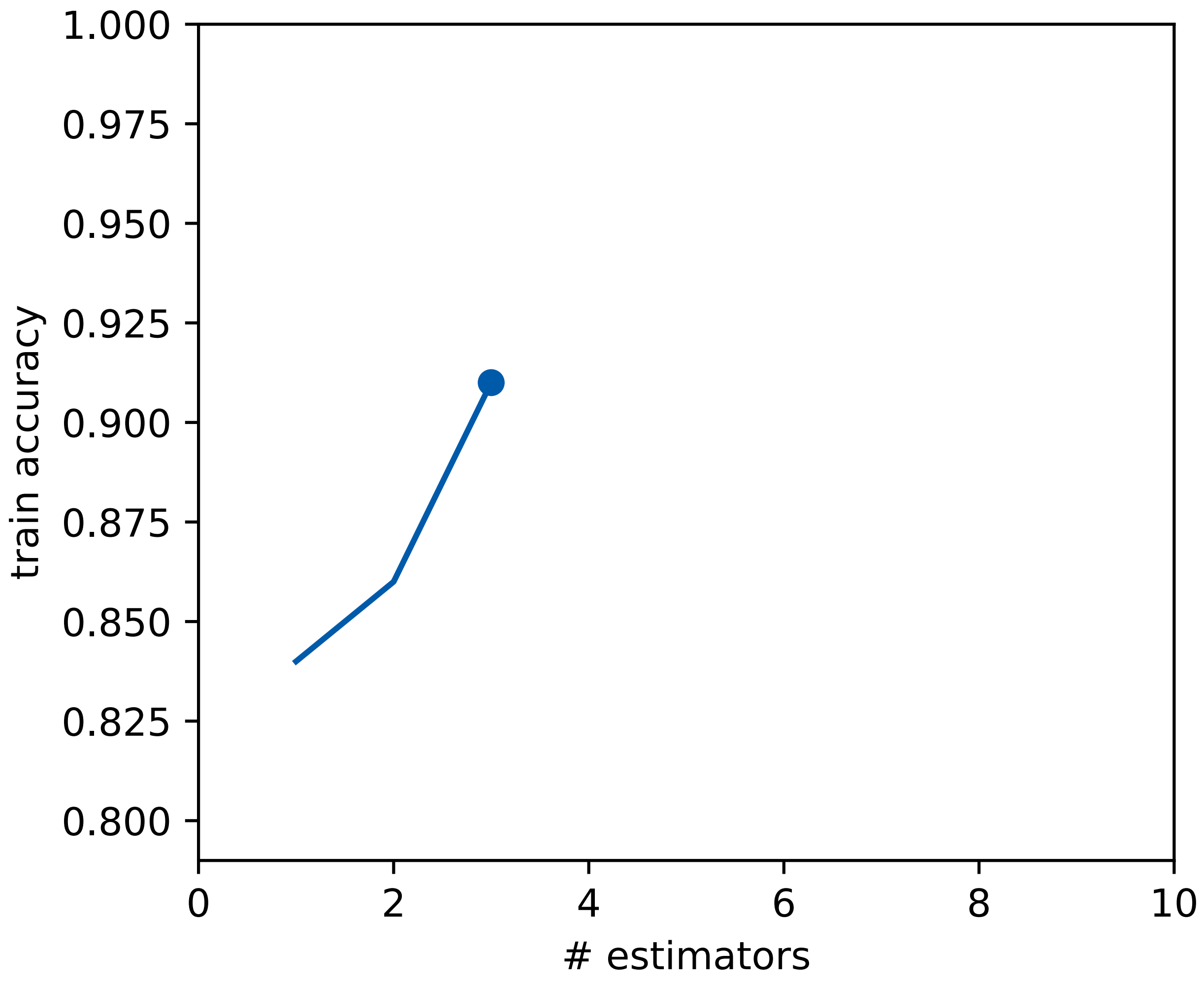

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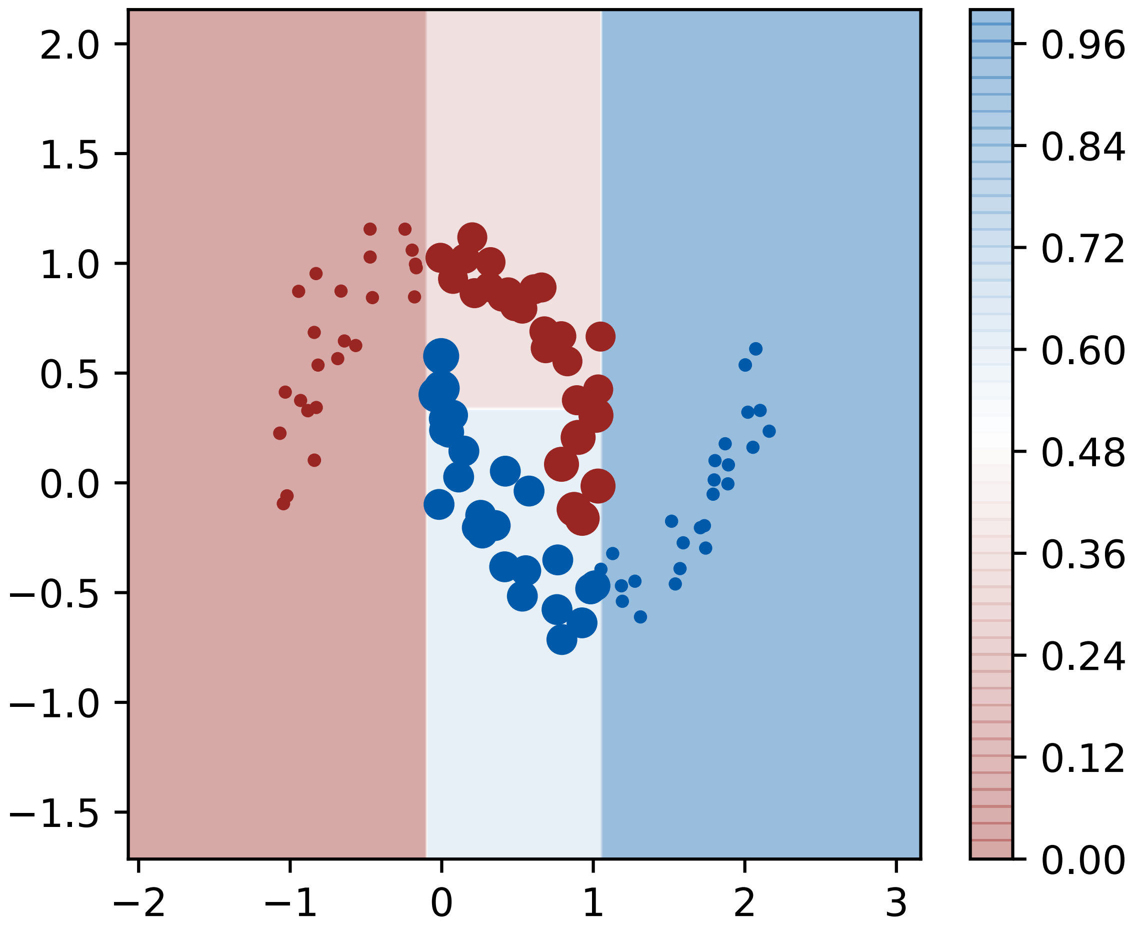

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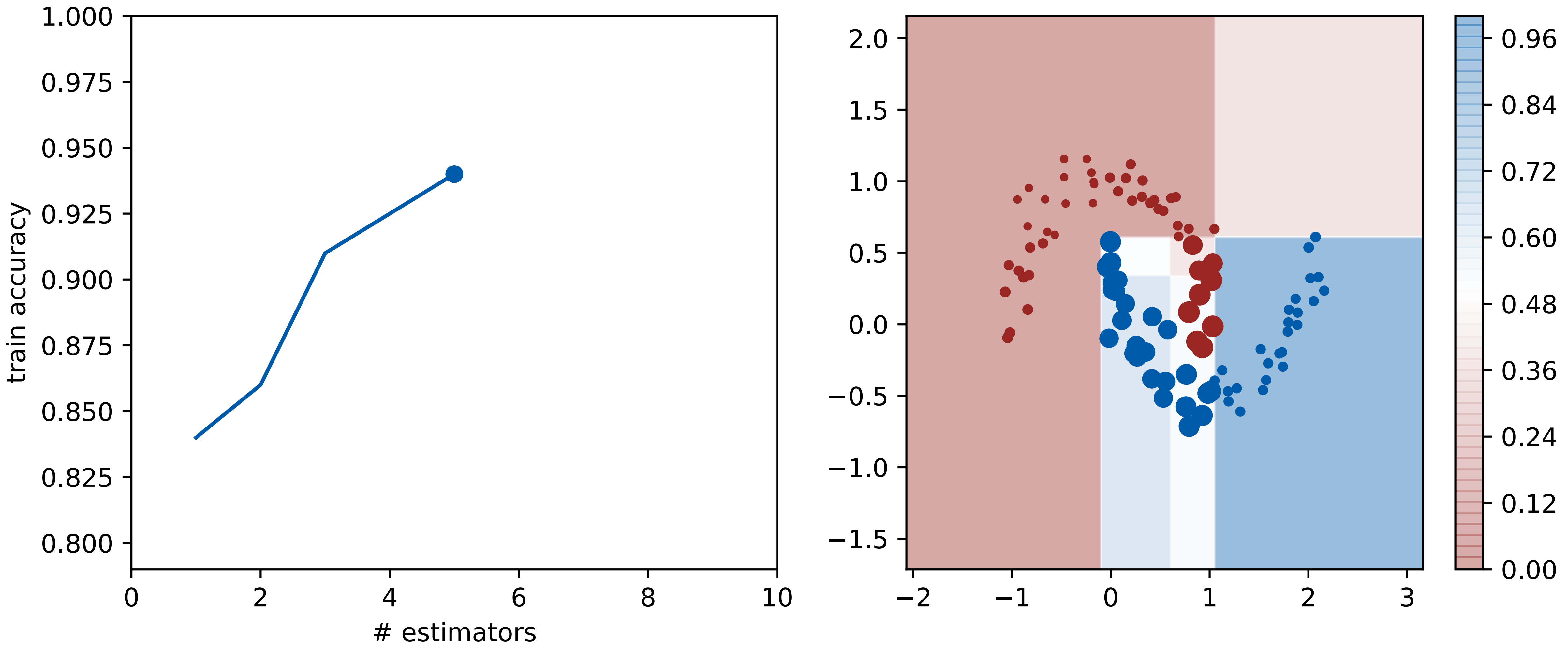

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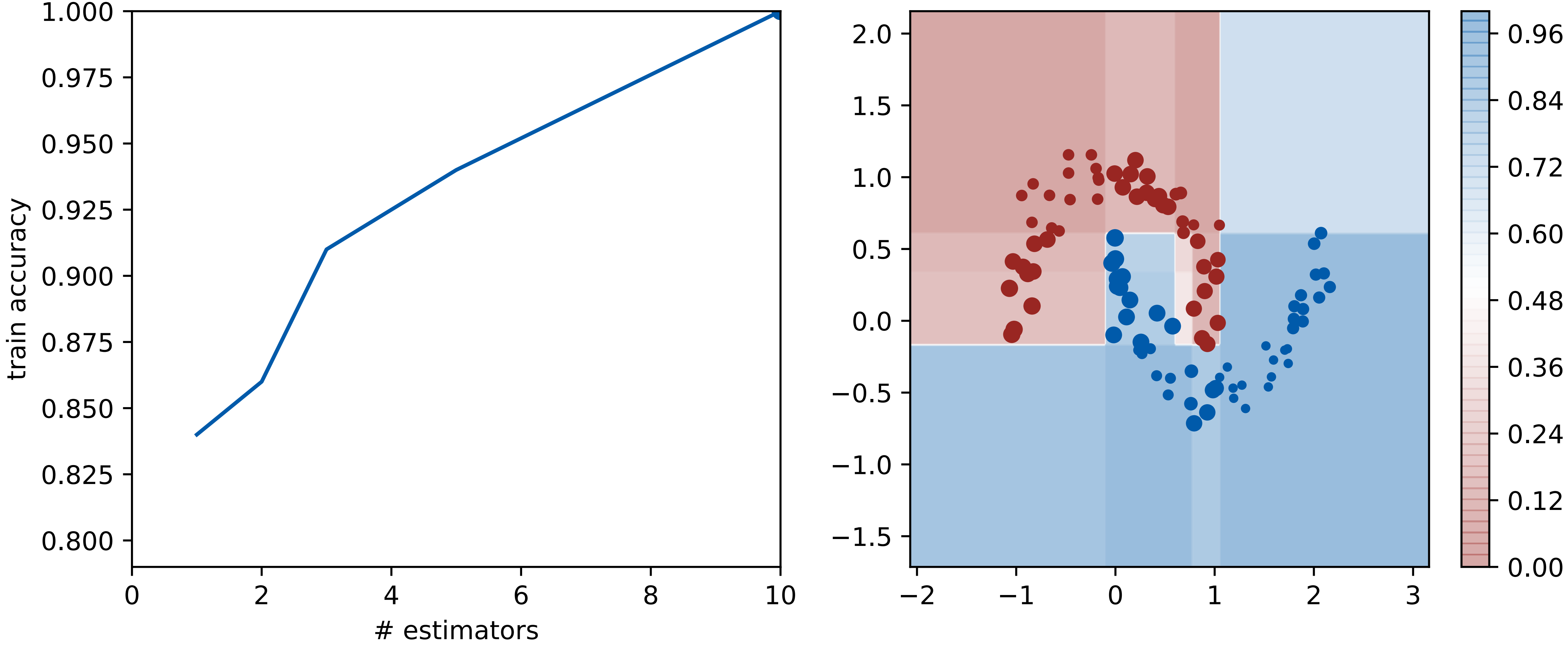
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Gradient Boosting

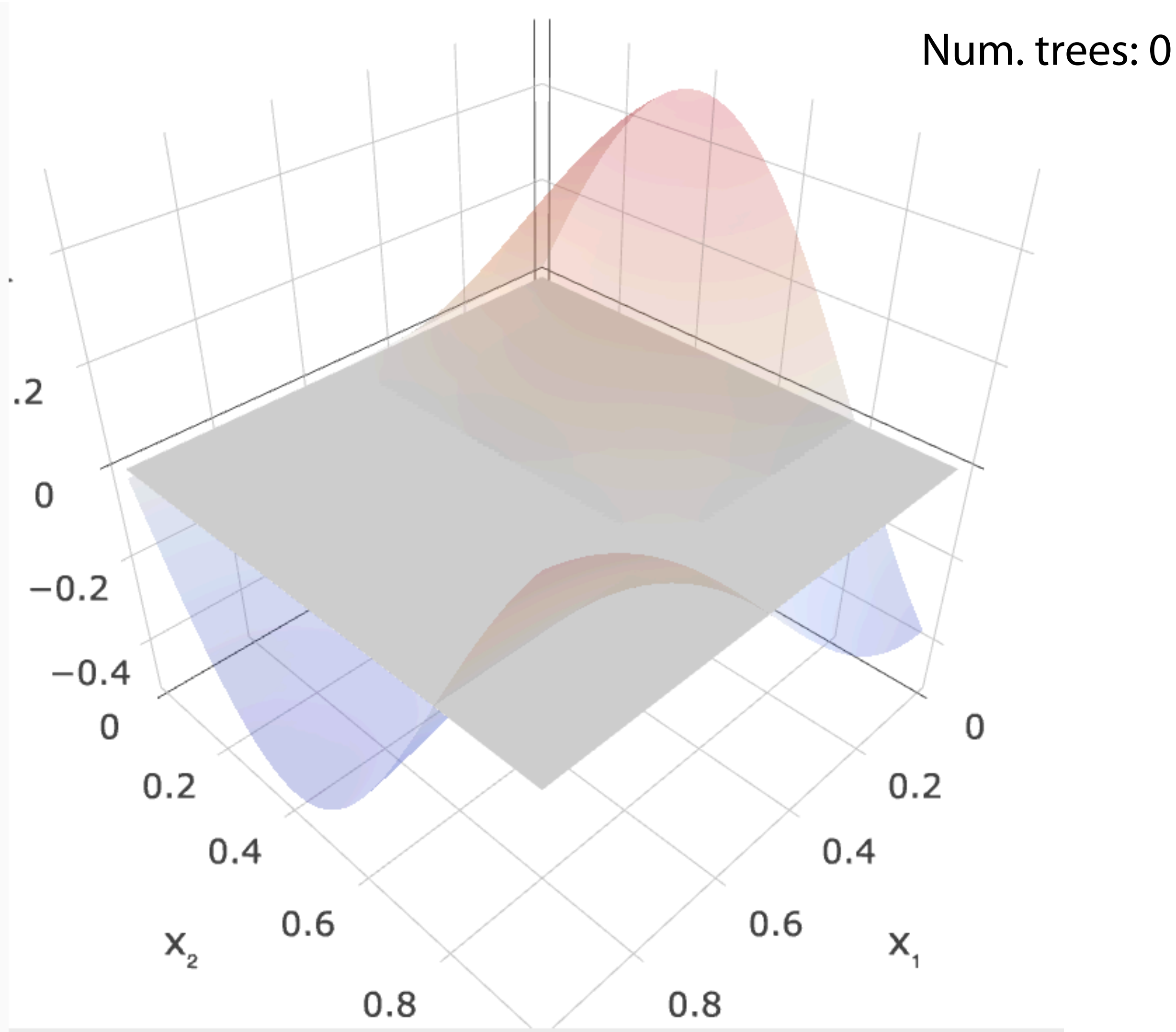
- FSAM minimization cannot be solved analytically for a general loss function
- Find approximation (linear):

$$L(F(x) + f(x), y) \approx L(F(x), y) + \frac{\partial L(F, y)}{\partial F} f(x)$$

- Gradient shows the direction of maximal increase $\Rightarrow$ fit $f(x)$ to the negative of the gradient
- Then solve for c:

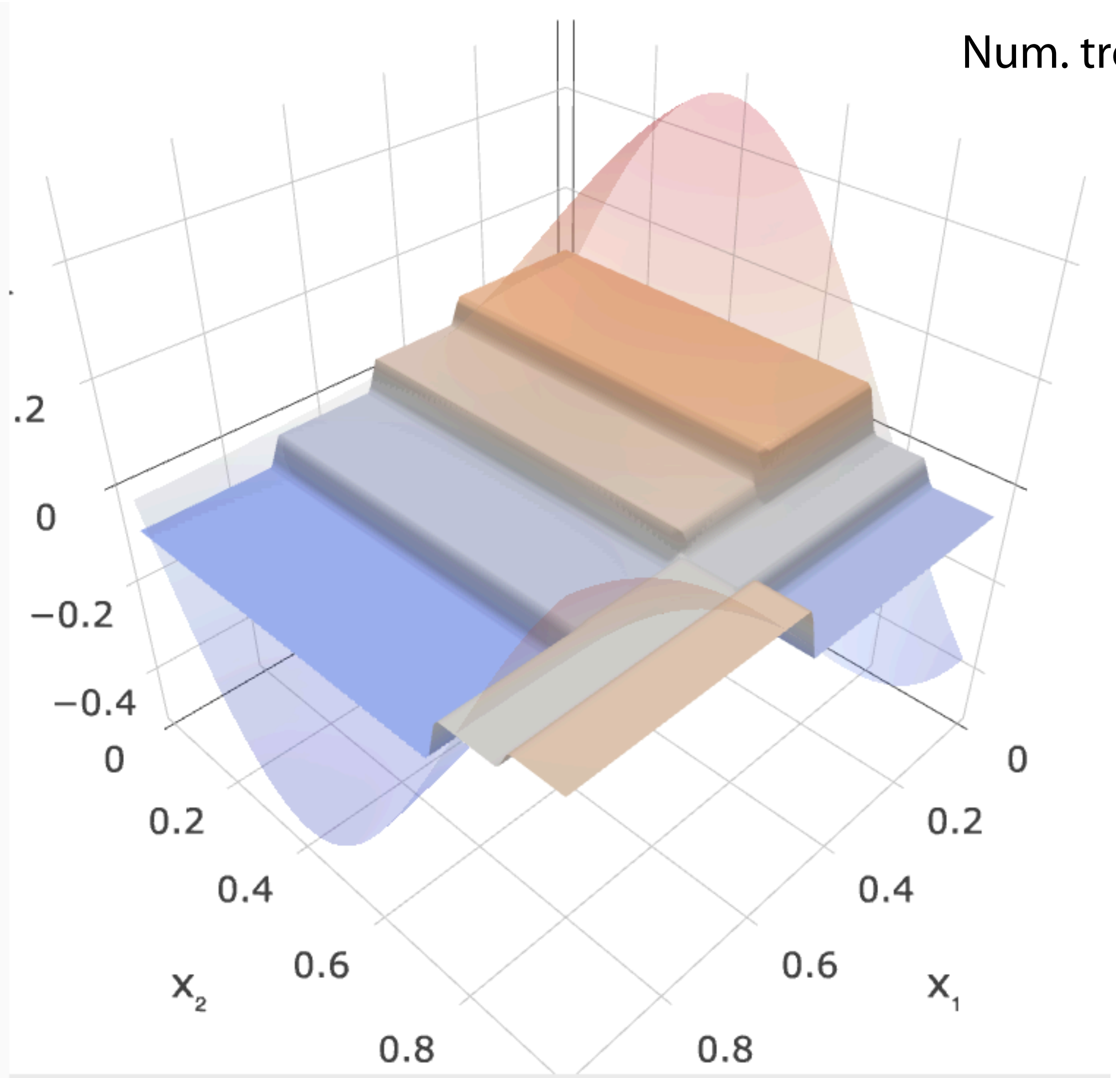
$$L(F(x) + c \cdot f(x), y) \to \min_{c}$$

Example



Nice demo: http://arogozhnikov.github.io/2016/06/24/gradient_boosting_explained.html

Example



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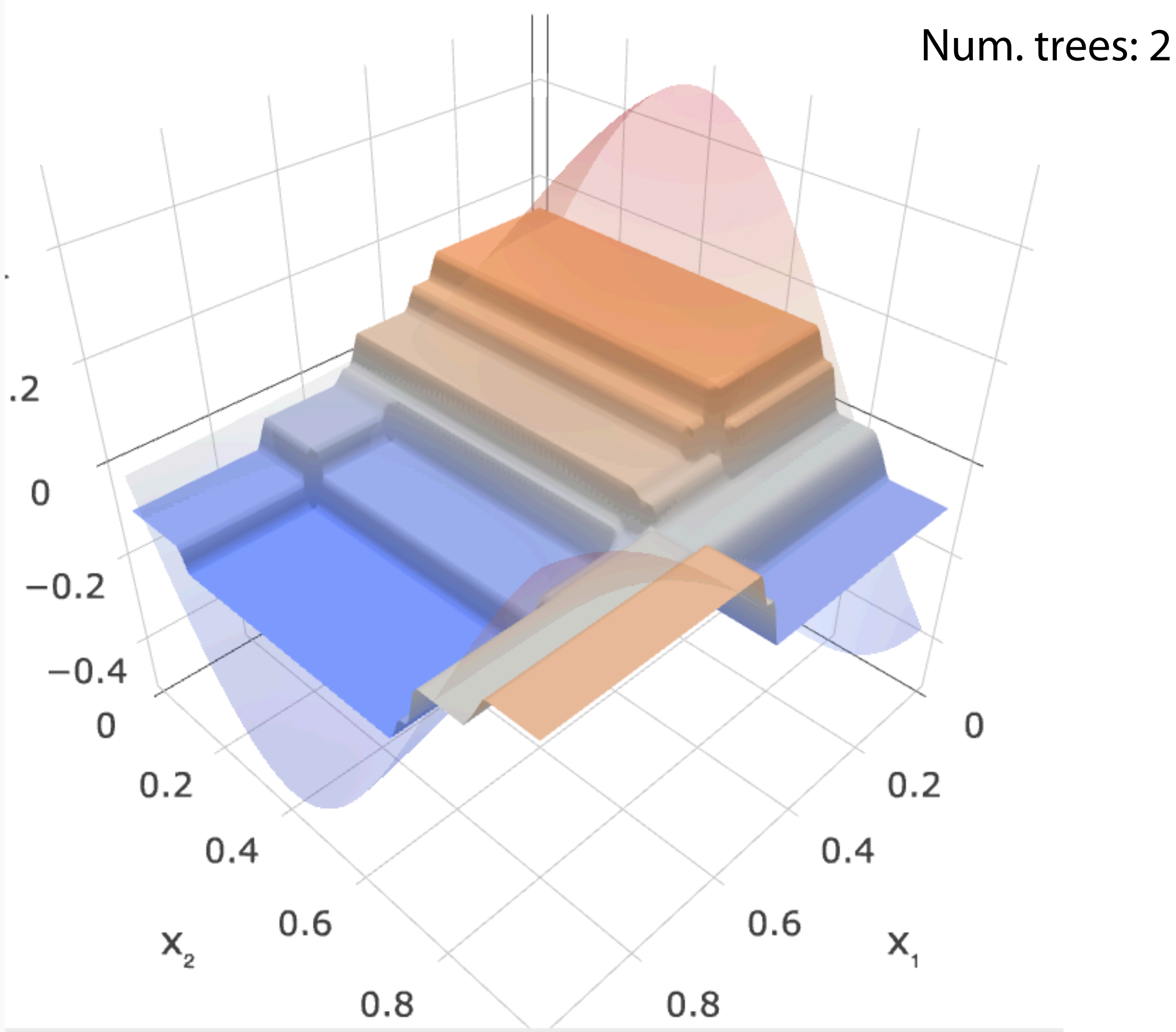

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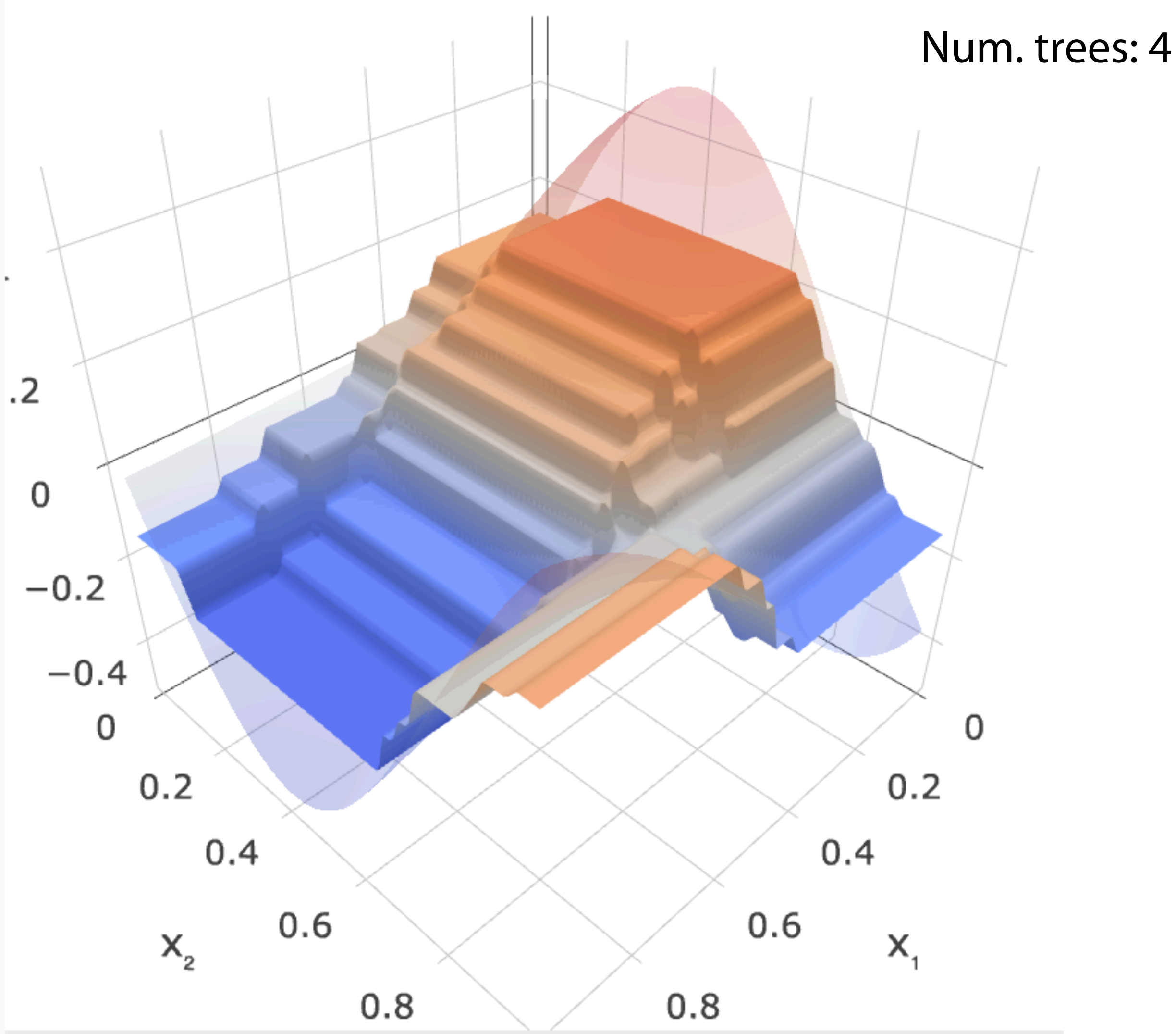

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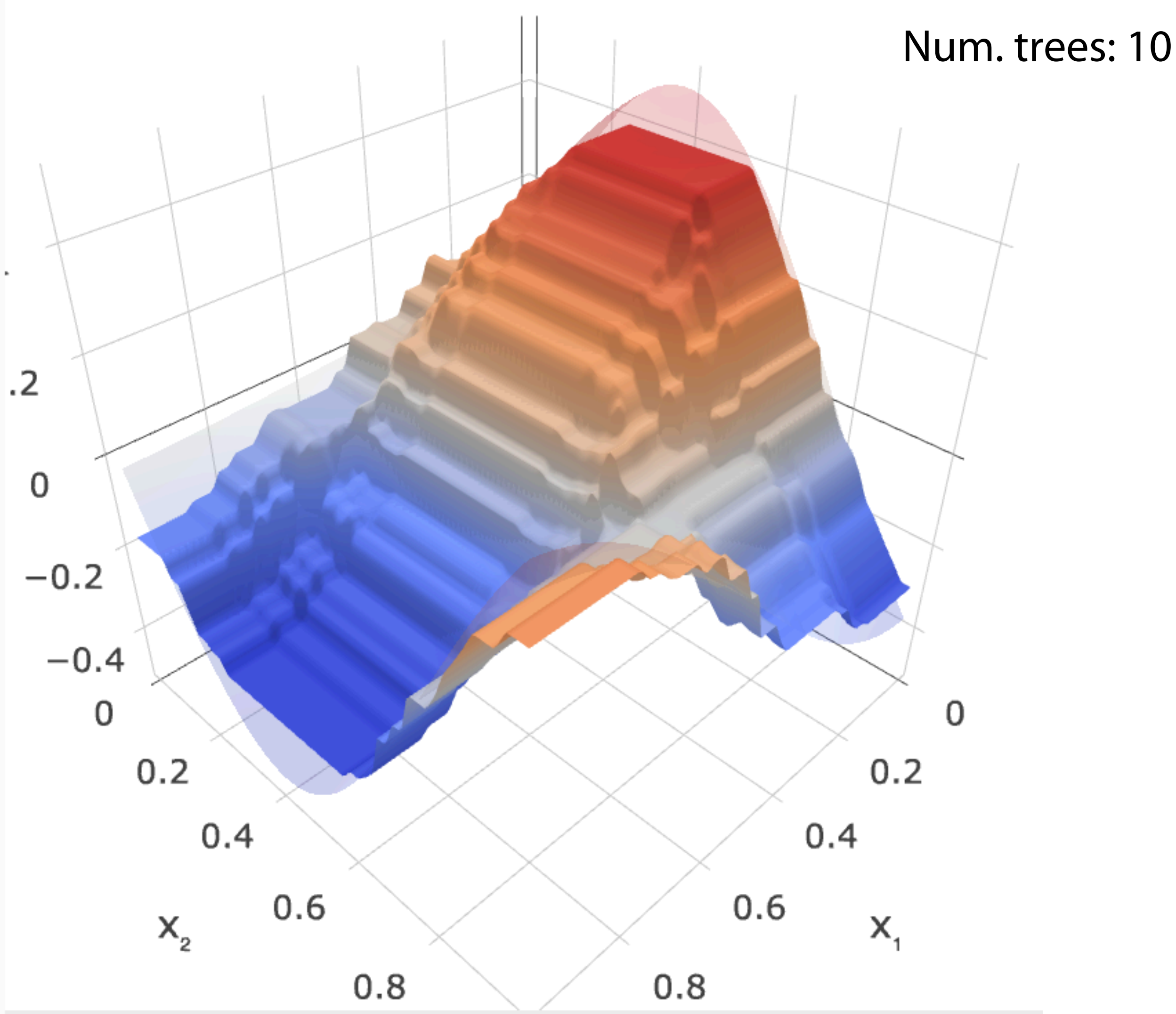

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Quadratic approximation

$$L(F(x)+f(x),y) \approx L(F(x),y) + \frac{\partial L(F,y)}{\partial F} f(x) + \frac{1}{2}\frac{\partial^2 L(F,y)}{\partial F^2}\big(f(x)\big)^2$$

$$= \underbrace{\frac{1}{2}\frac{\partial^2 L(F,y)}{\partial F^2}}_{\text{sample weights}} \left(f(x) + \underbrace{\frac{\frac{\partial L(F,y)}{\partial F}}{\frac{\partial^2 L(F,y)}{\partial F^2}}}_{\text{negative of the fitting targets}} \right)^2 + const\big(f(x)\big)$$

Summary

- Ensembling may allow to reduce variance and/or bias of the base learners
- Averaging the prediction of **independent** high-variance models reduces the variance
- With bagging, the base learners are made (quasi-) independent using bootstrapping
  - Can be done in parallel
- With boosting, the base learners are built in sequence, each next one trying to improve upon the mistakes of the previous steps
  - One of the most powerful classes of models

- Question to you: does it make sense to boost linear regression?

Thank you!

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