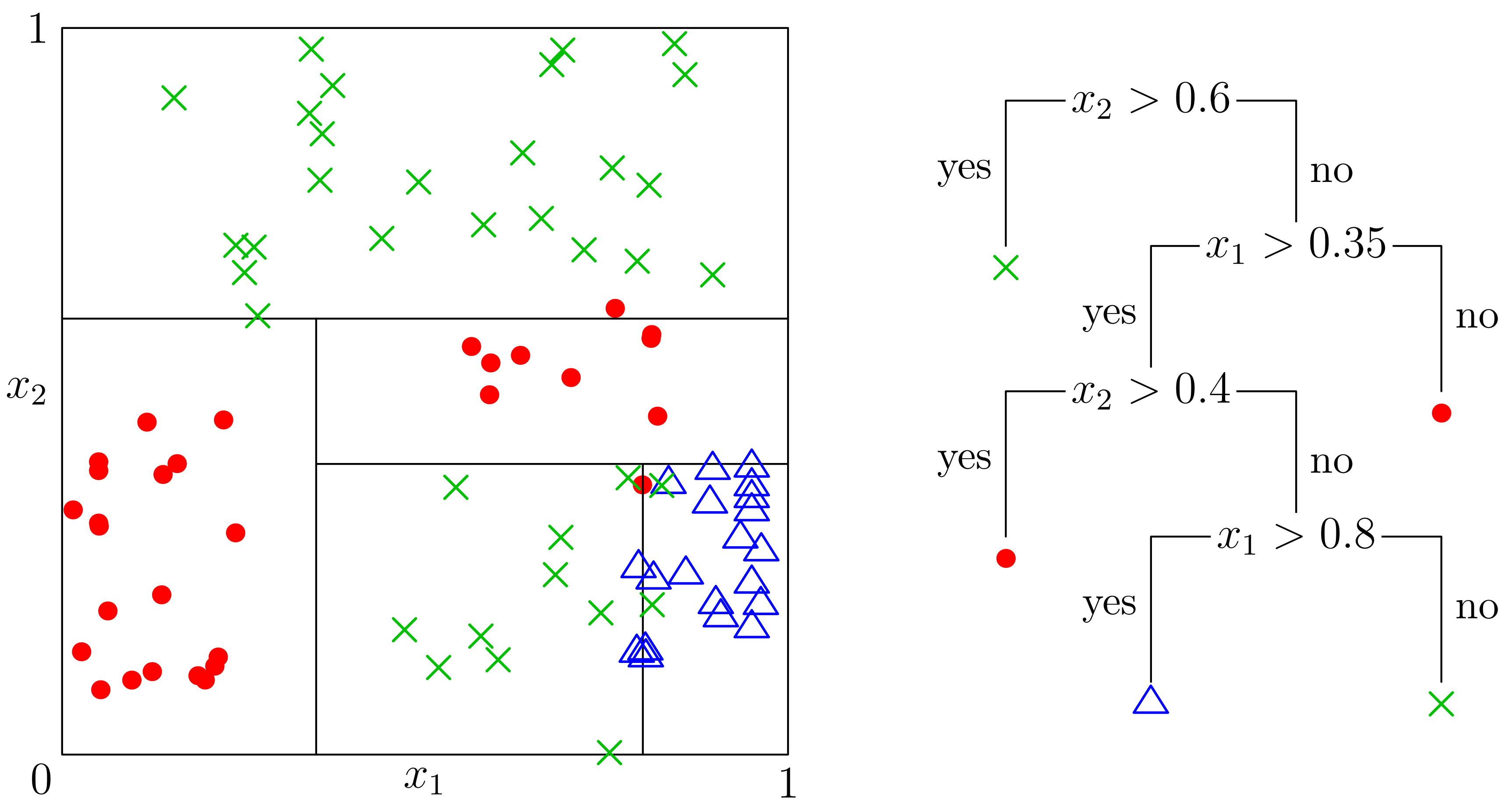
Advanced Machine Learning

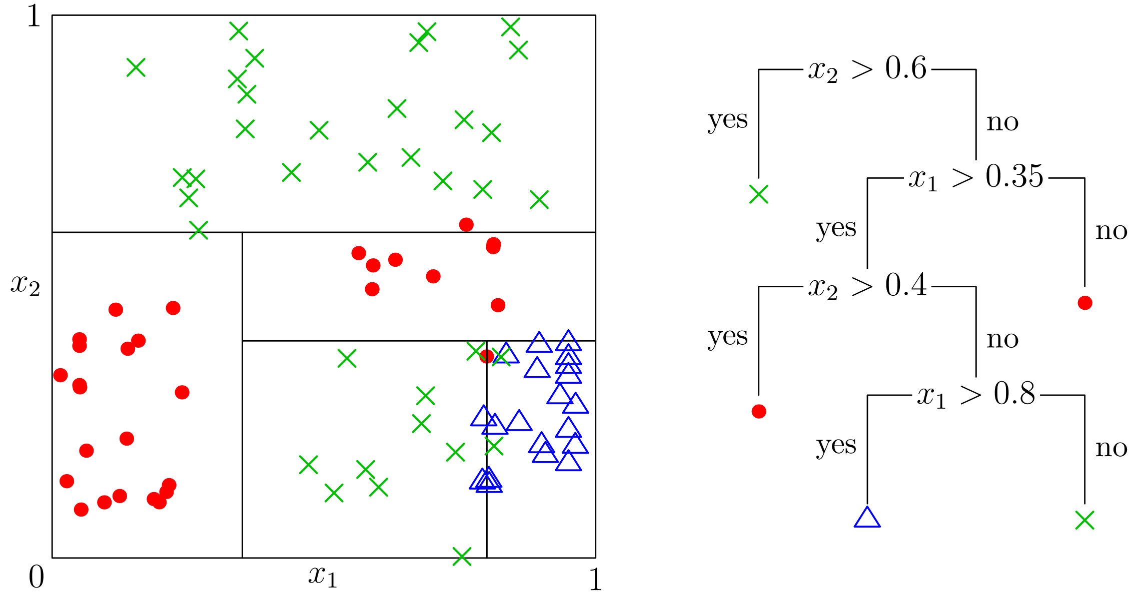
Boosting



Boosting, AdaBoost, Gradient Boosting

Outline

1. **Boosting**
2. AdaBoost
3. Gradient Boosting
4. Dropout



Boosting

- In boosting we make a **strong learner** by using a weighted sum of **weak learners**

$$C_n(\boldsymbol{x}) = \sum_{i=1}^{n} \alpha_i \hat{h}_i(\boldsymbol{x})$$

- Weak learners, $\hat{h}_i(\boldsymbol{x})$, are learning machine that do a little better than chance
- The trick is to choose the weights, α_i
- Because the weak learners do little better than chance we (miraculously) **don't** overfit

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Shallow Trees

- One of the most effective type of weak learner are very shallow trees
- Sometimes we just use one variable (the stump)
- There are different algorithms for choosing the weights
  - ⋆ adaboost
  - ⋆ gradient boosting

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  - ⋆ adaboost—a classic algorithm for binary classification
  - ⋆ gradient boosting—used for regression, trains a weak learner on the residual errors

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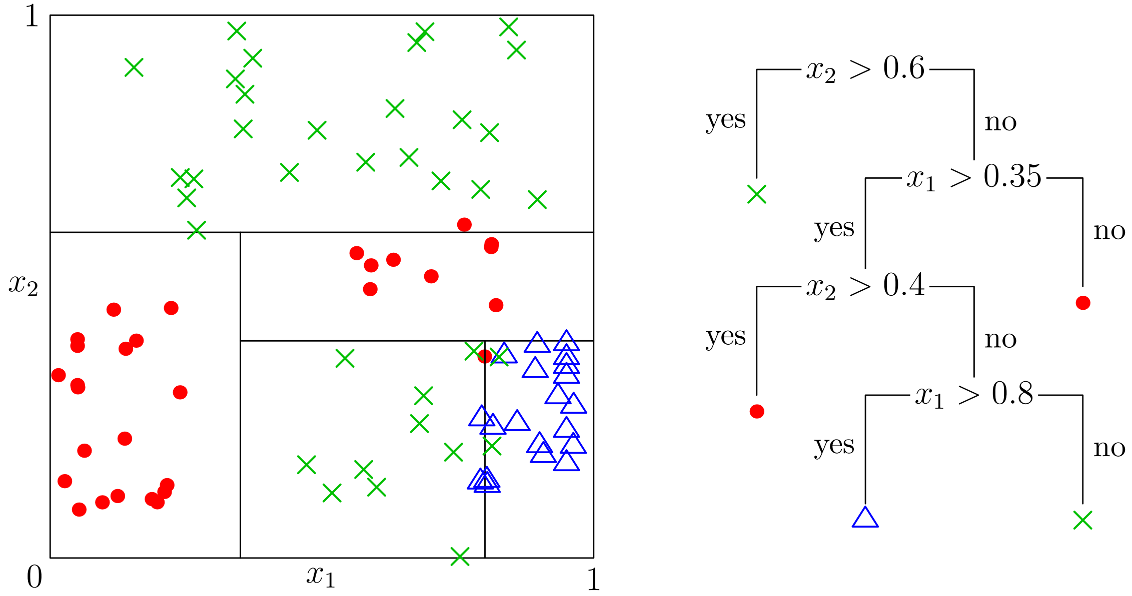

Boosting a Binary Classifier

- Suppose we have a binary classification task with data $\mathcal{D} = \{(\boldsymbol{x}^\mu, y^\mu) | \mu = 1, 2, \ldots, m\}$ with $y^\mu \in \{-1, 1\}$
- Our i^{th} weak learner provides a prediction $\hat{h}_i(\boldsymbol{x}^\mu) \in \{-1, 1\}$
- We ask, can we find a linear combination

$$C_n(\boldsymbol{x}) = \alpha_1 \hat{h}_1(\boldsymbol{x}) + \alpha_2 \hat{h}_2(\boldsymbol{x}) + \cdots + \alpha_n \hat{h}_n(\boldsymbol{x})$$

- So that $\operatorname{sgn}\big(C_n(\boldsymbol{x})\big)$ is a strong learner?

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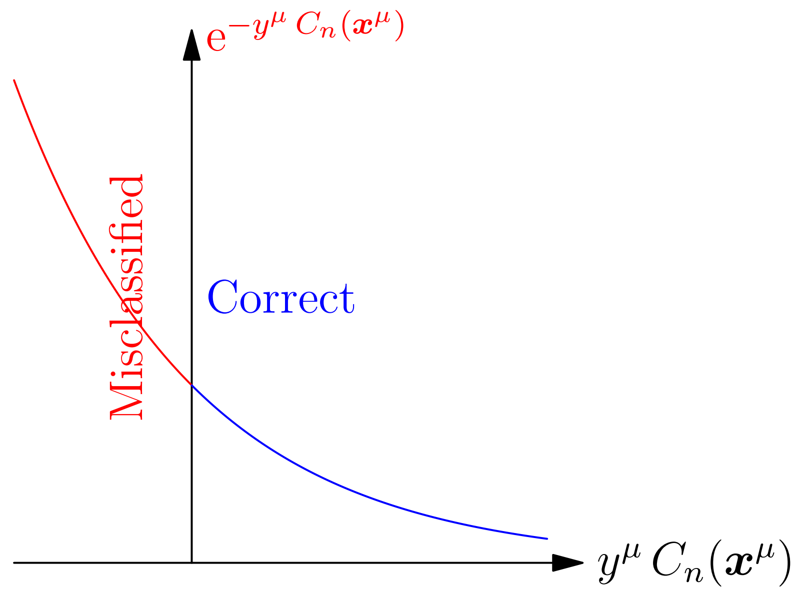
- So that $\operatorname{sgn}\big(C_n(\boldsymbol{x})\big)$ is a strong learner?
- Note we want $y^\mu C_n(\boldsymbol{x}^\mu) > 0$

AdaBoost

- AdaBoost is a classic solution to this problem
- It assigns an "loss function"

$$L_n = \sum_{\mu=1}^{m} \mathrm{e}^{-y^\mu C_n(\boldsymbol{x}^\mu)}$$



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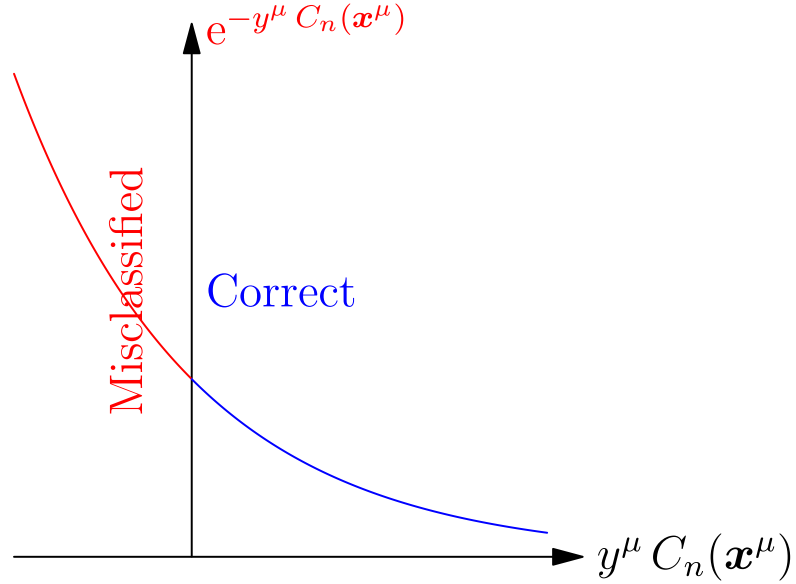

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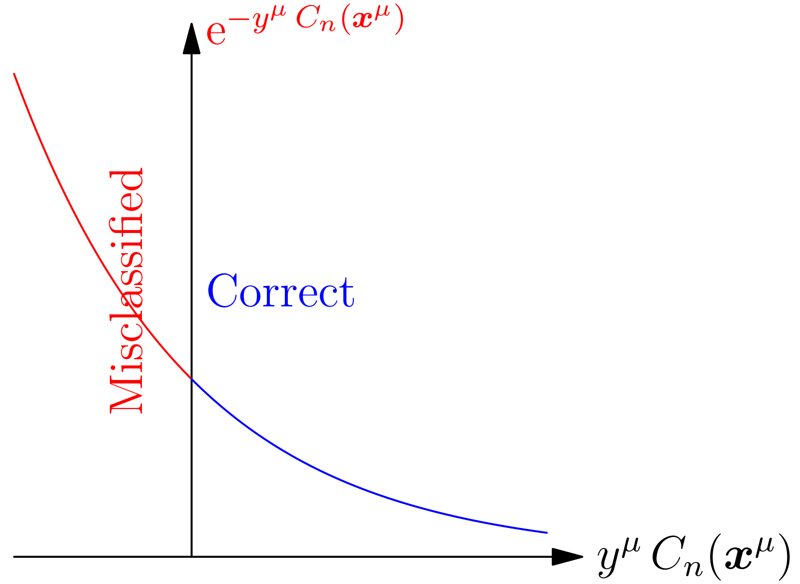

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Iterative Learning

- We build up a strong learner iteratively (greedily)

$$C_n(\boldsymbol{x}) = C_{n-1}(\boldsymbol{x}) + \alpha_n \hat{h}_n(\boldsymbol{x})$$

- Defining $w_1^\mu = 1$ and $w_n^\mu = \mathrm{e}^{-y^\mu C_{n-1}(\boldsymbol{x}^\mu)}$ then

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Choosing a Weak Classifier

- To minimise the loss

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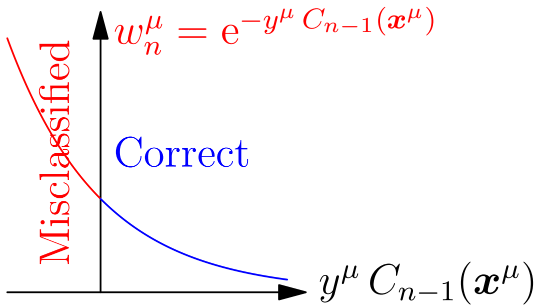

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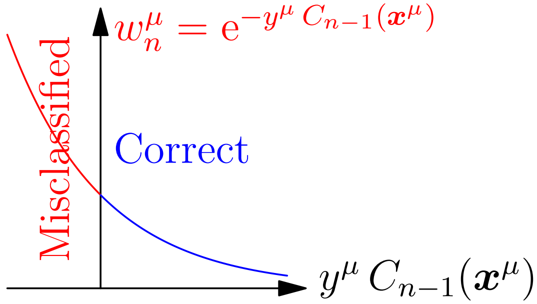

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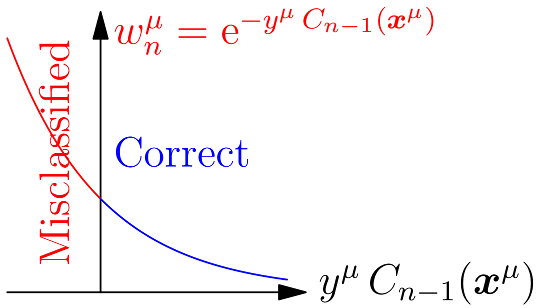

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Choosing Weights

- We now choose the weight α_n to minimise the loss $L_n(\alpha_n)$

$$\frac{\partial L_n(\alpha_n)}{\partial \alpha_n} = \mathrm{e}^{\alpha_n} \sum_{\mu : y^\mu \neq \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu - \mathrm{e}^{-\alpha_n} \sum_{\mu : y^\mu = \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu = 0$$

- That is

$$\mathrm{e}^{2\alpha_n} = \frac{\displaystyle\sum_{\mu : y^\mu = \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu}{\displaystyle\sum_{\mu : y^\mu \neq \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu} \qquad \text{or} \qquad \alpha_n = \frac{1}{2} \log \left(\frac{\displaystyle\sum_{\mu : y^\mu = \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu}{\displaystyle\sum_{\mu : y^\mu \neq \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu} \right)$$

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Algorithm

1. Start with a set of weak learners $\mathcal{W}$
2. Associate a weight, w_n^μ, with every data point $(\boldsymbol{x}^\mu, y^\mu)$, $\mu = 1, 2, \ldots, m$
3. Initially $w_1^\mu = 1$
4. Choose the weak learning, $\hat{h}_n(\boldsymbol{x}) \in \mathcal{W}$, that minimises $\displaystyle\sum_{\mu : y^\mu \neq \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu$
5. Update predictor $C_n(\boldsymbol{x}) = C_{n-1}(\boldsymbol{x}) + \alpha_n \hat{h}_n(\boldsymbol{x})$ where
$$\alpha_n = \frac{1}{2}\log\left(\frac{\sum_{\mu : y^\mu = \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu}{\sum_{\mu : y^\mu \neq \hat{h}_n(\boldsymbol{x}^\mu)} w_n^\mu}\right)$$
6. Update $w_{n+1}^\mu = w_n^\mu \mathrm{e}^{-y^\mu \alpha_n \hat{h}_n(\boldsymbol{x}^\mu)}$
7. Go to 4

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- Adaboost works well with weak learners, usually out-performing bagging
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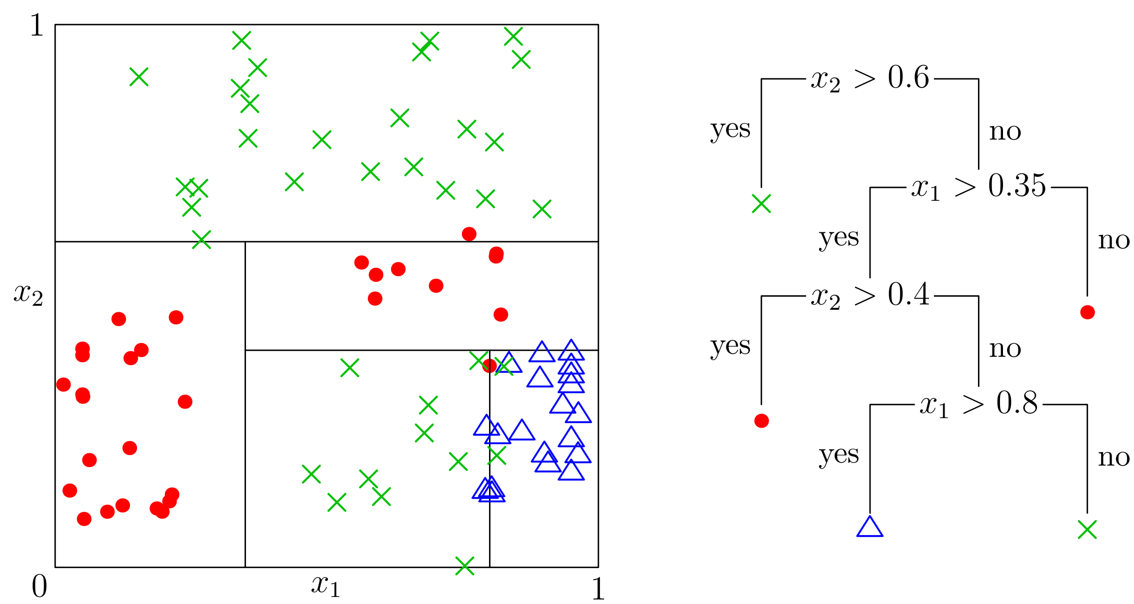

Gradient Boosting

- In gradient boosting we again build a strong learner as a linear combination of weak learners

$$C_n(\boldsymbol{x}) = C_{n-1}(\boldsymbol{x}) + \hat{h}_n(\boldsymbol{x})$$

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- At each step $\hat{h}_n(\boldsymbol{x})$ is trained to predict the **residual error**, $\Delta_{n-1} = y - C_{n-1}(\boldsymbol{x})$, (i.e. the target minus the current prediction)

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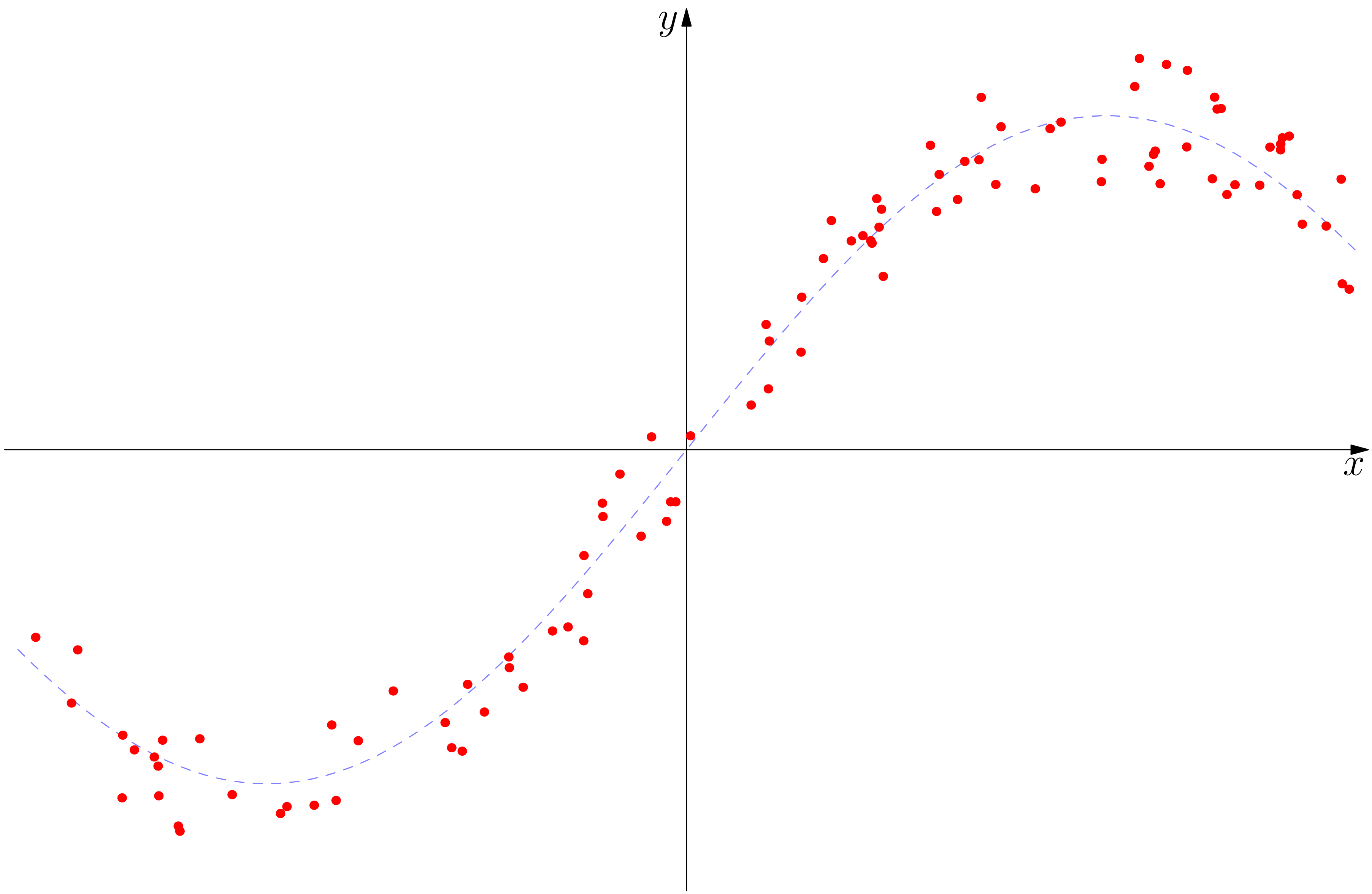

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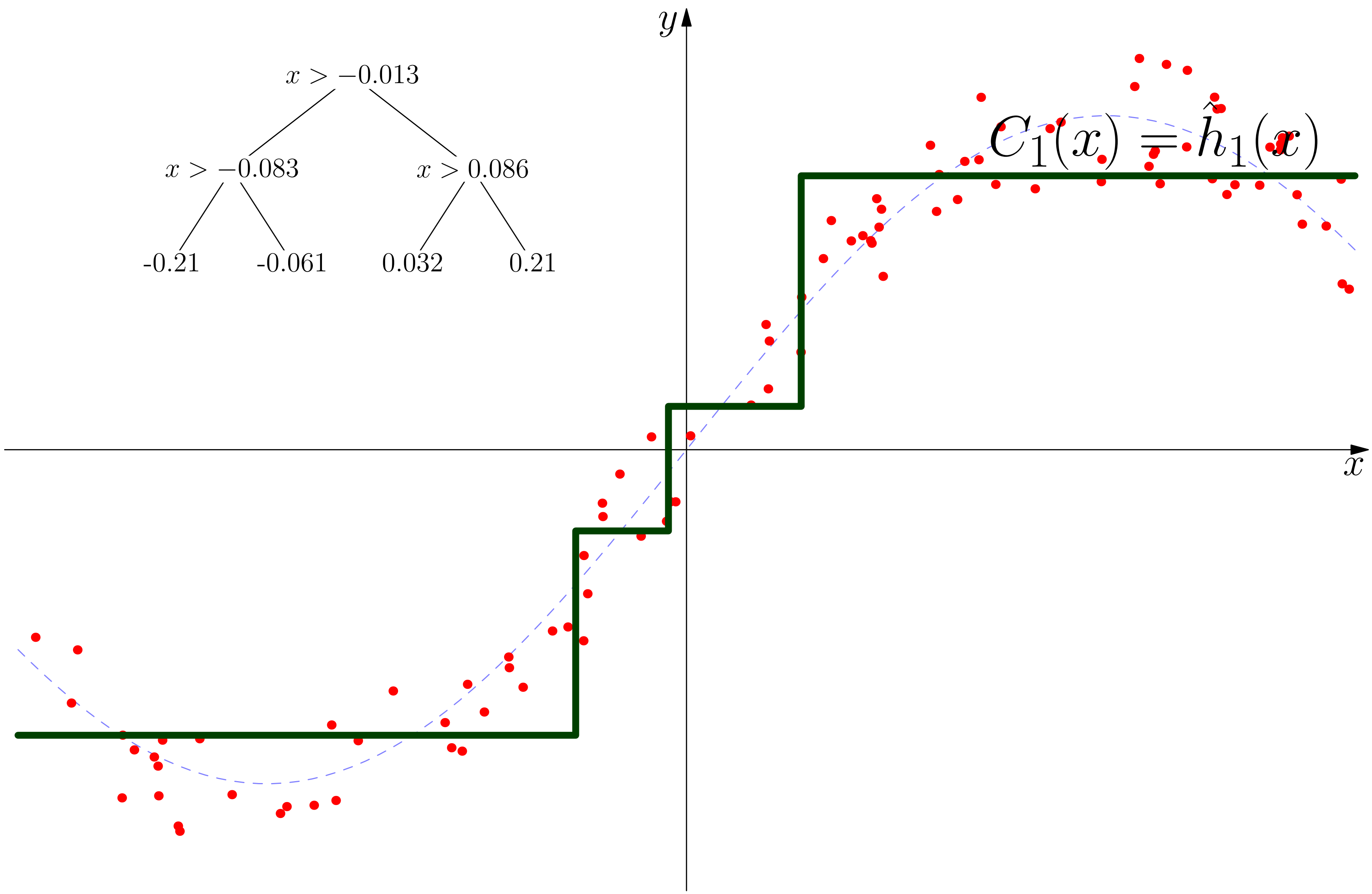

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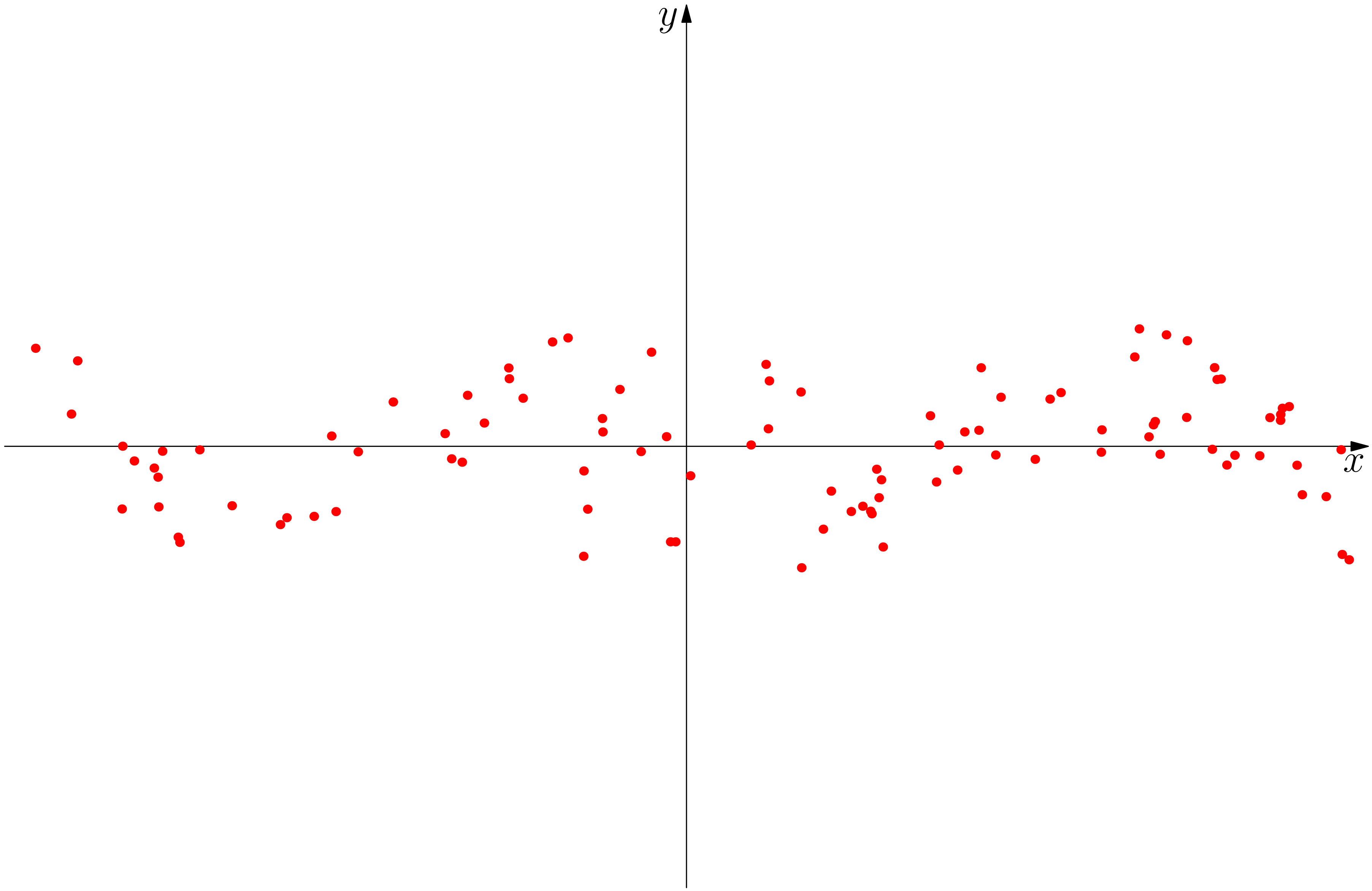

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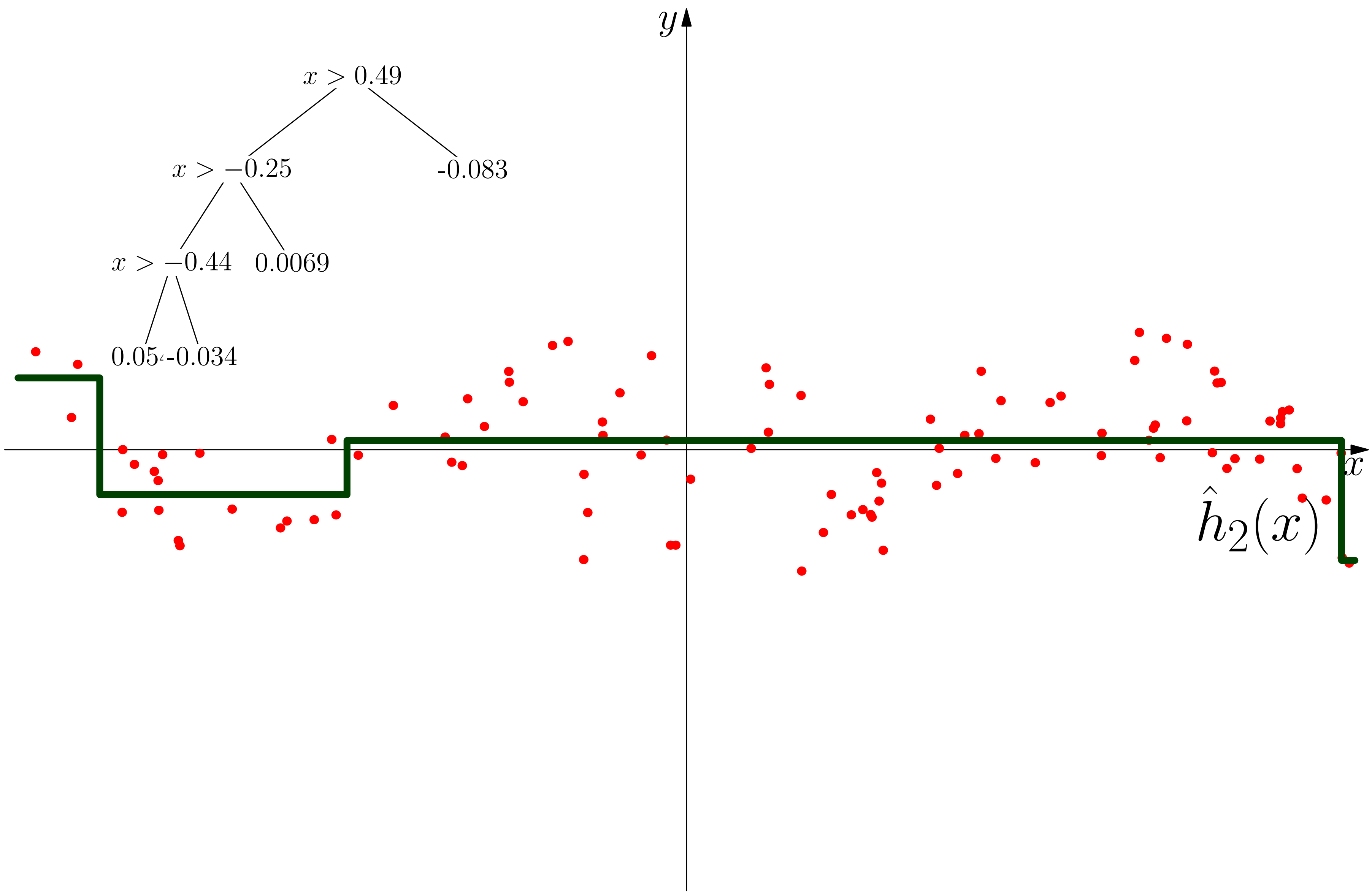

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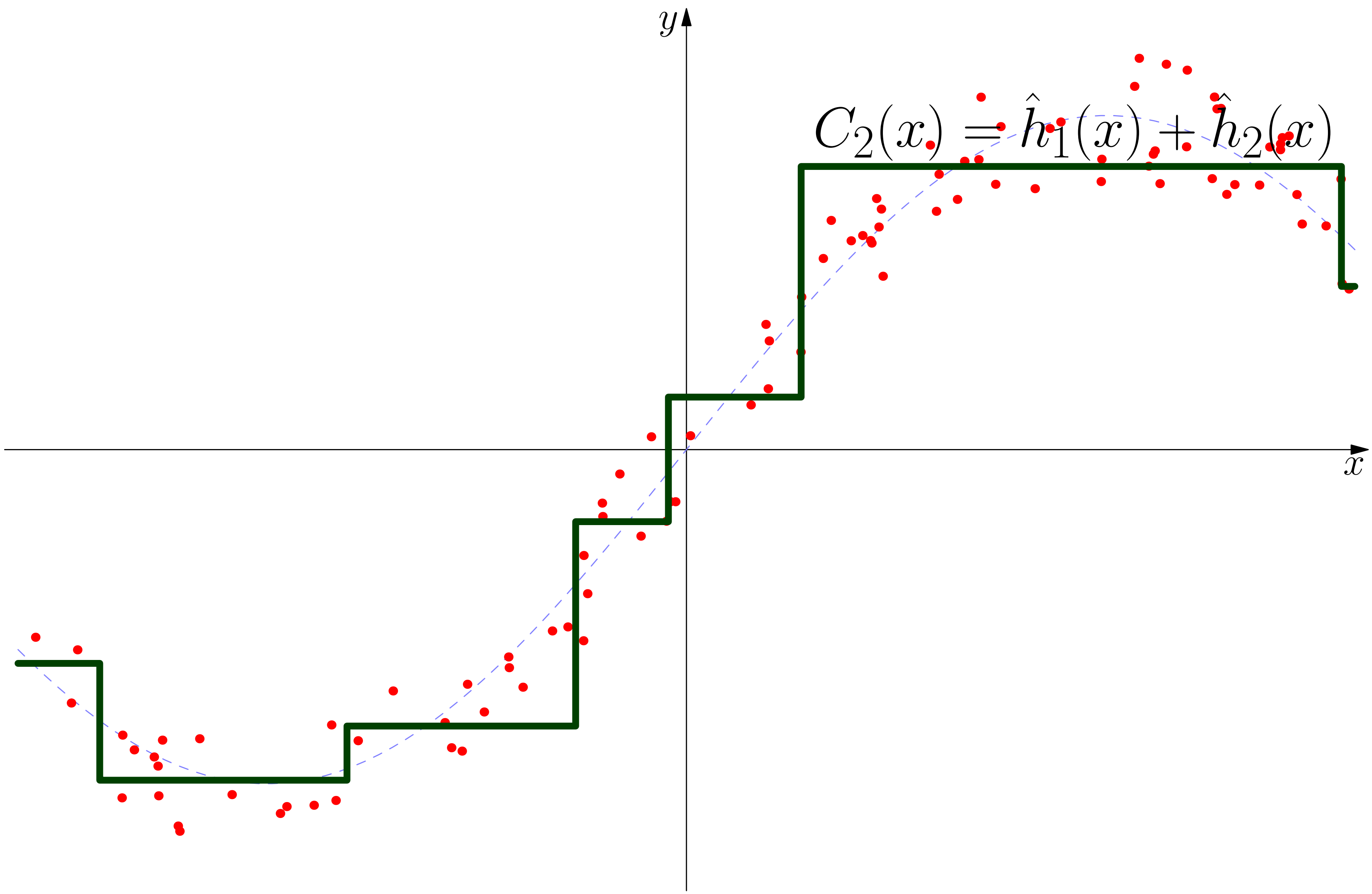

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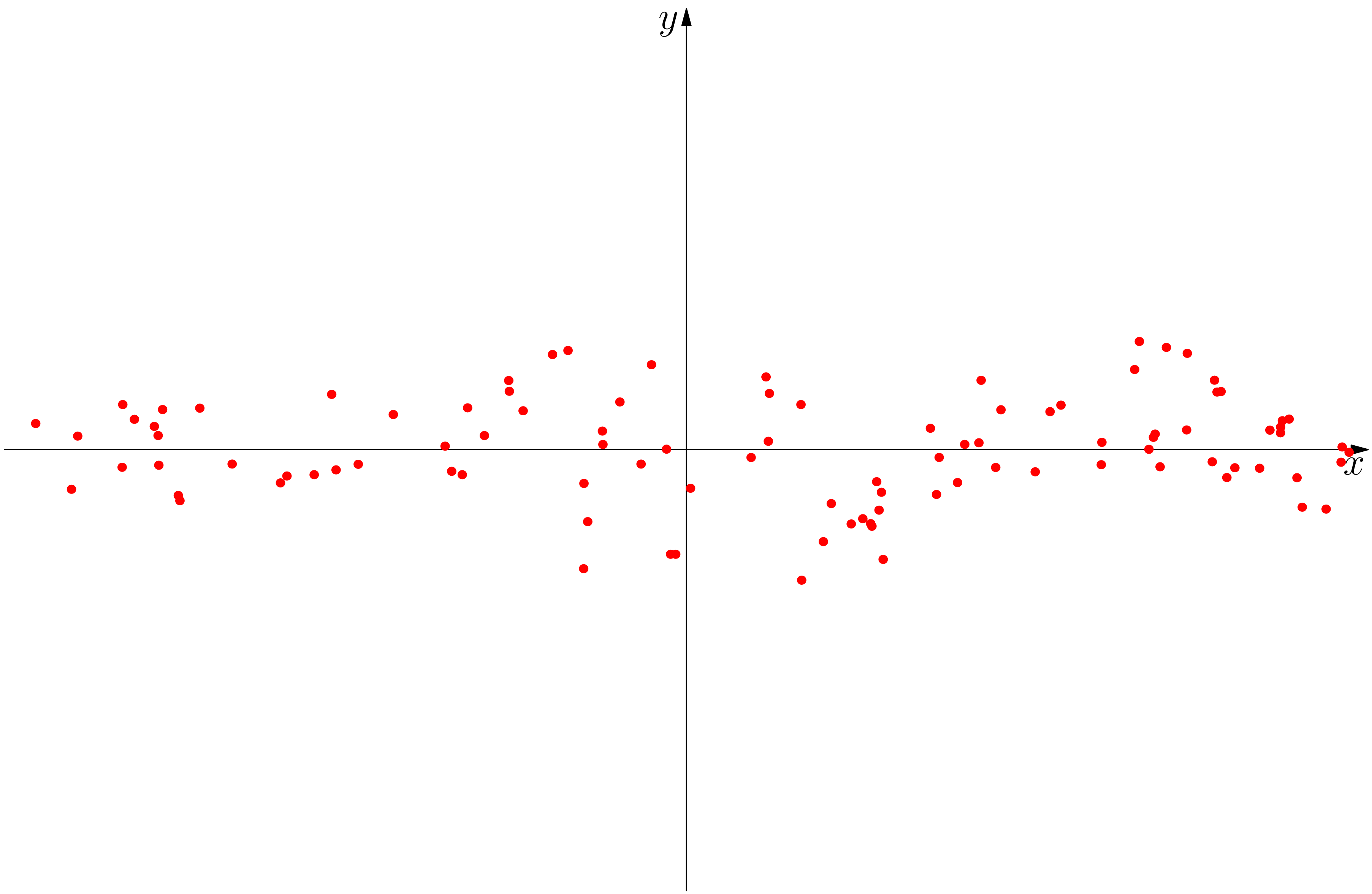

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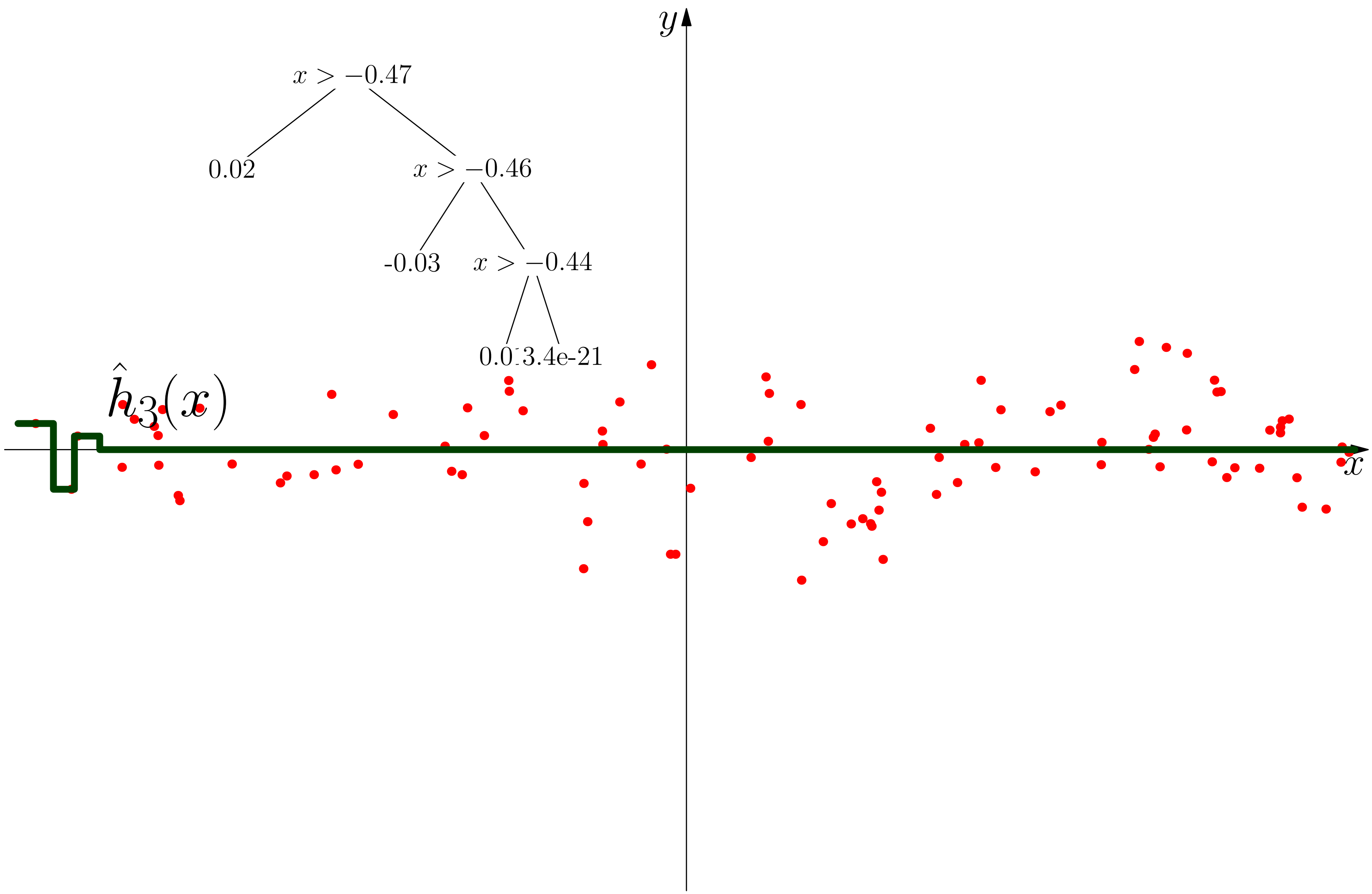

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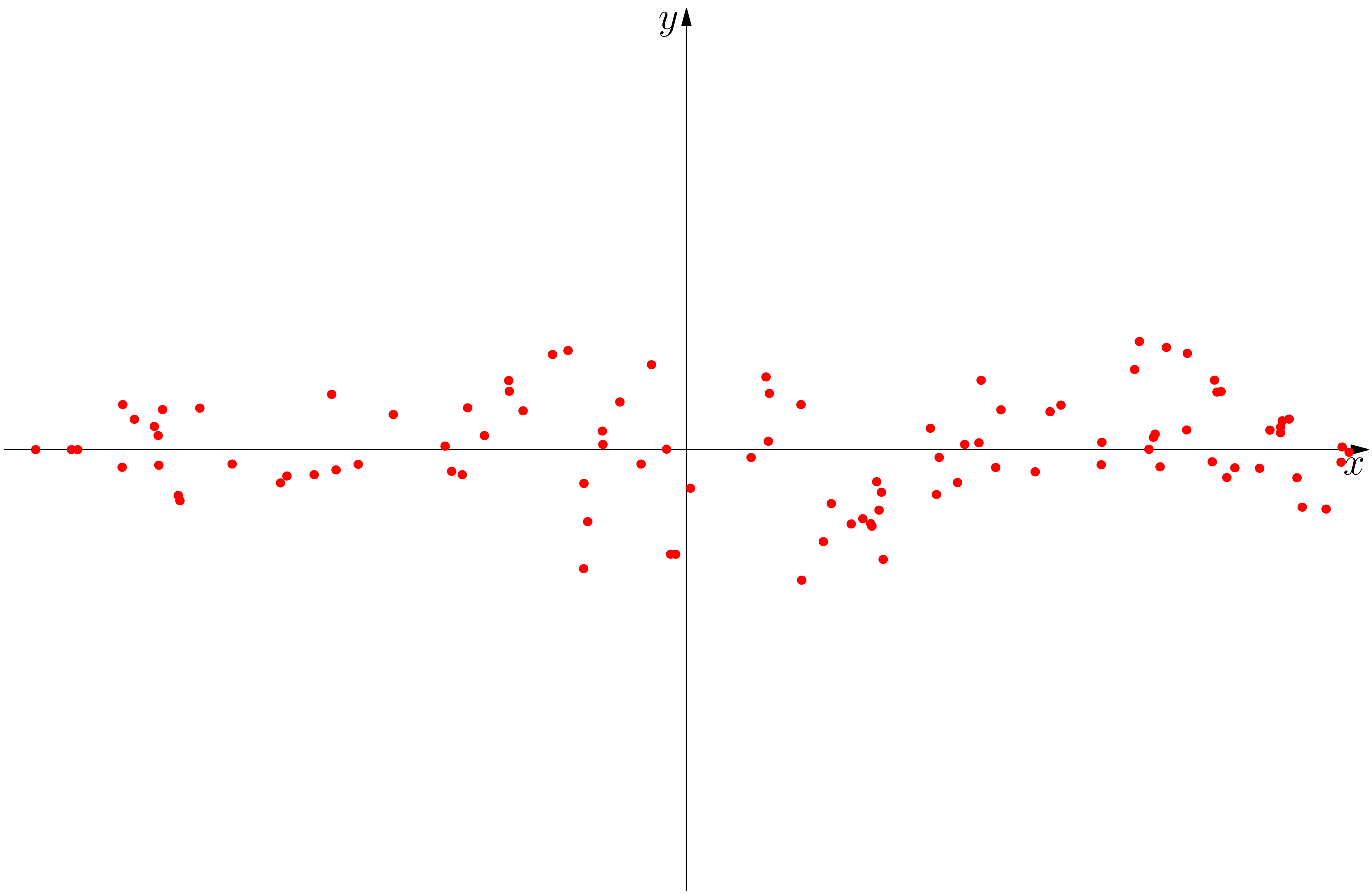

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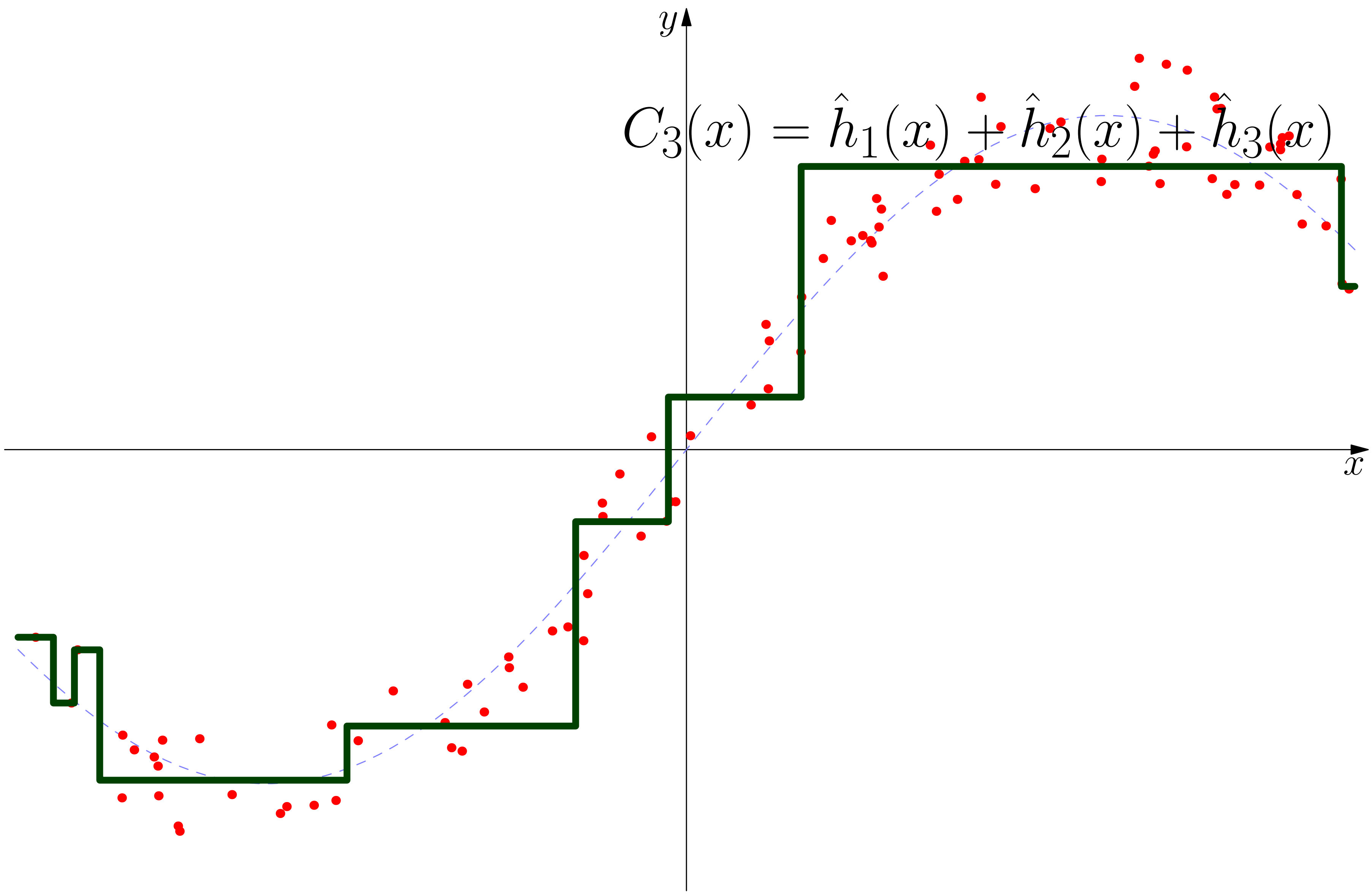

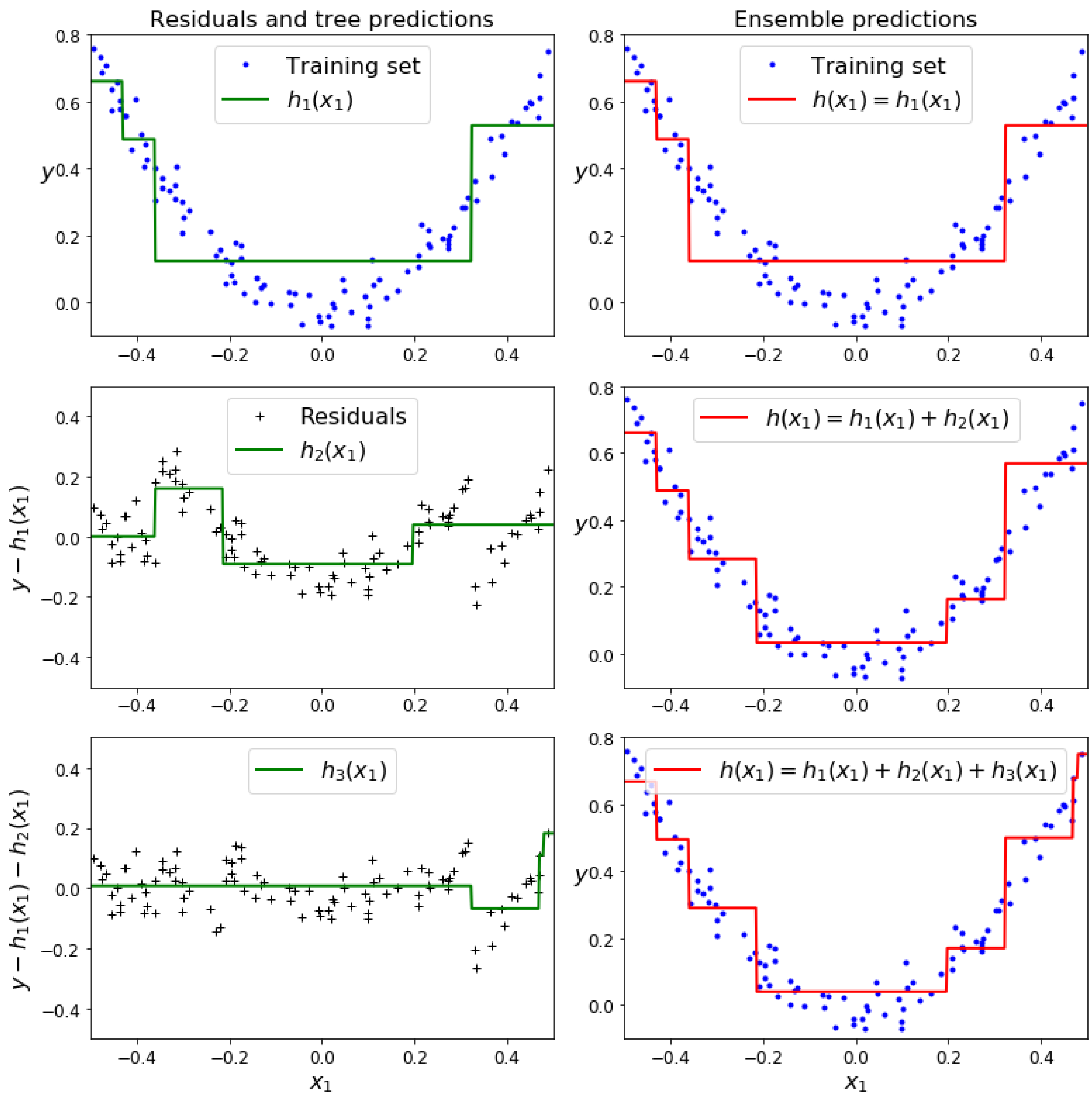

Residuals and tree predictions
Ensemble predictions
Training set
$h_1(x_1)$
$h(x_1) = h_1(x_1)$
Residuals
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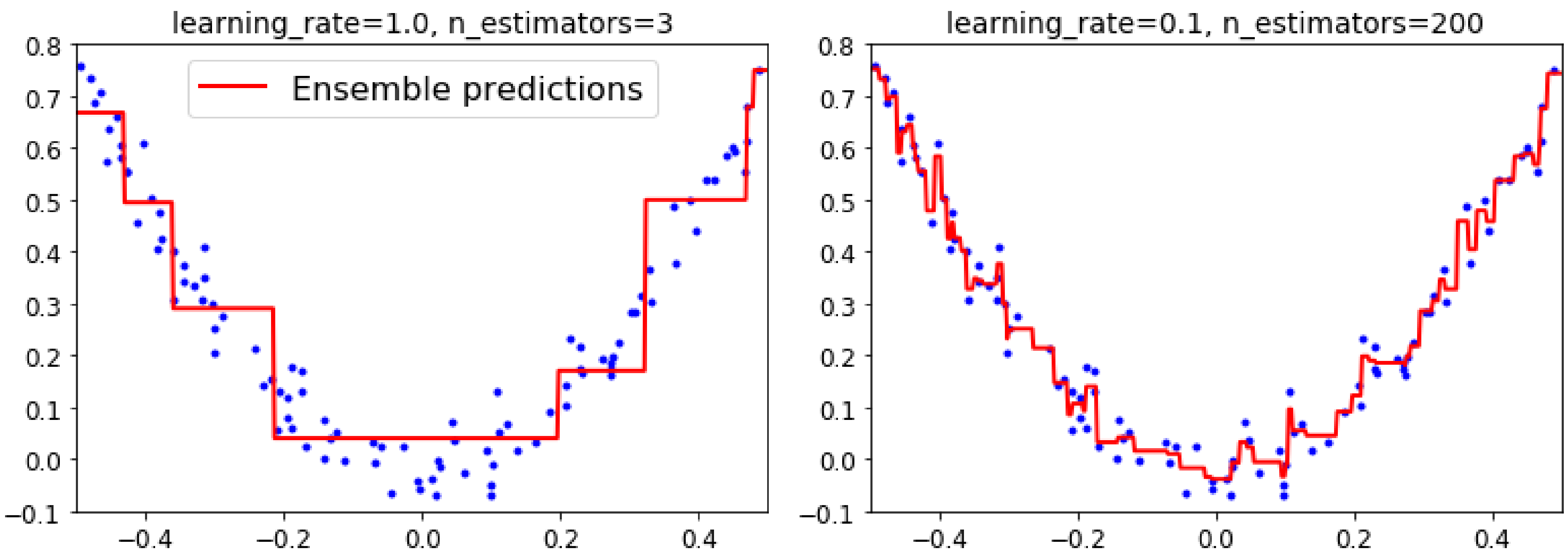
x_1

Keep On Going

- We can keep on going



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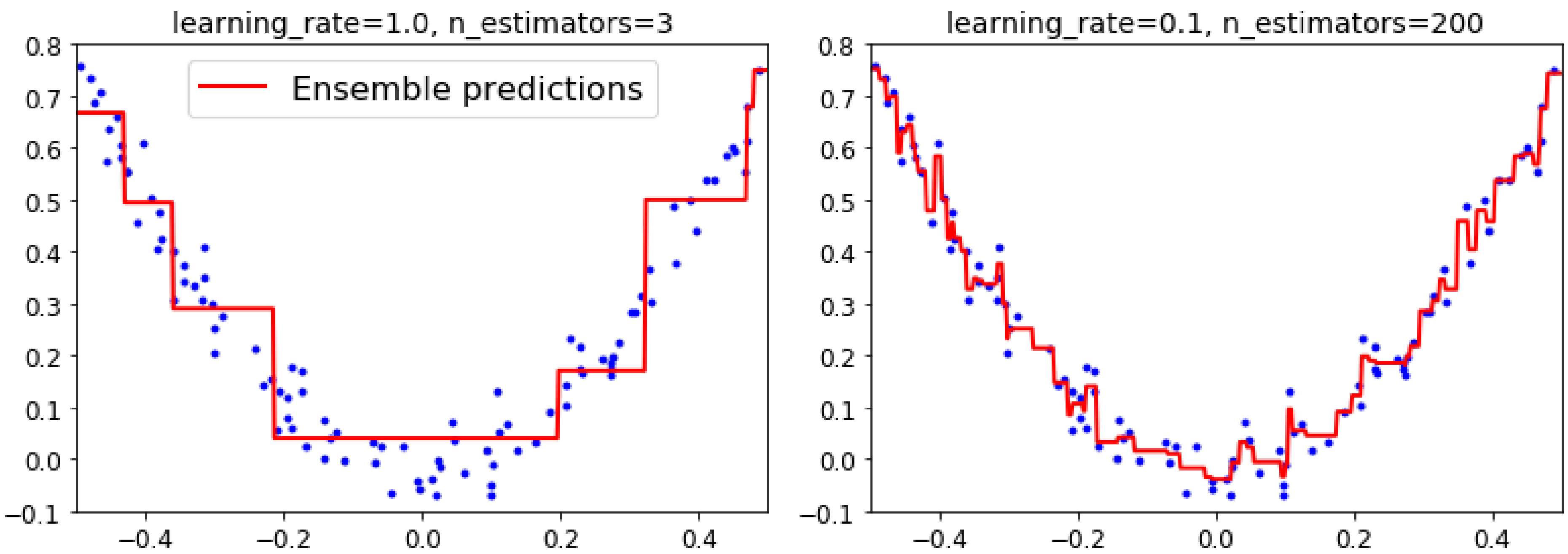
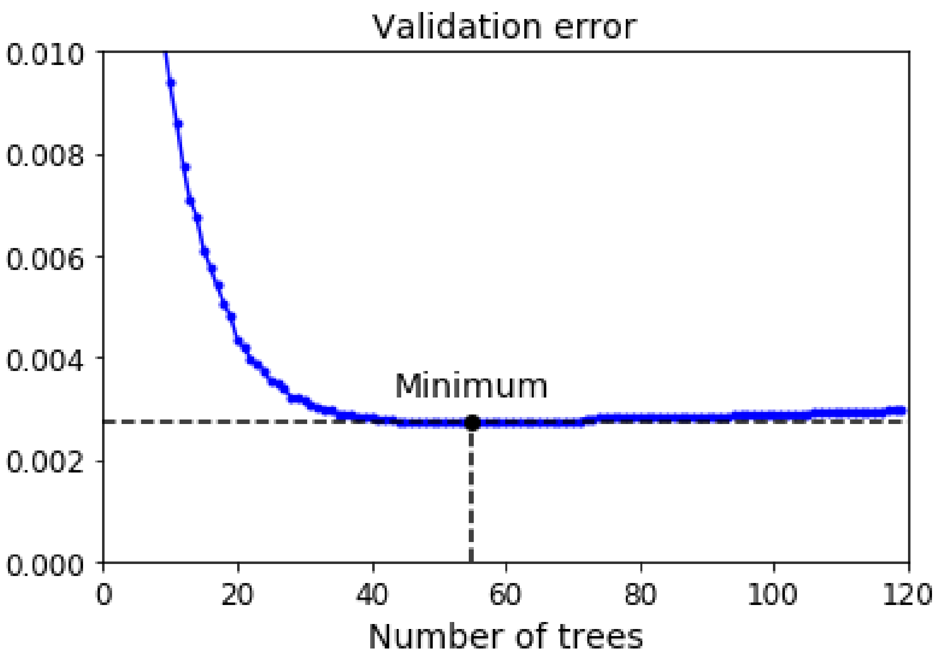
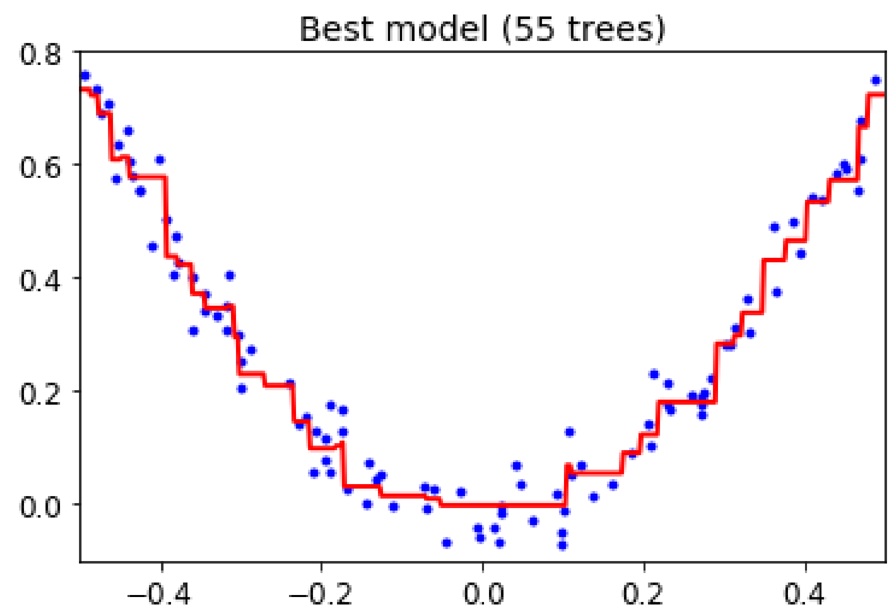


- But we will over-fit eventually

Early Stopping

- Like many algorithms we often get better results by early stopping





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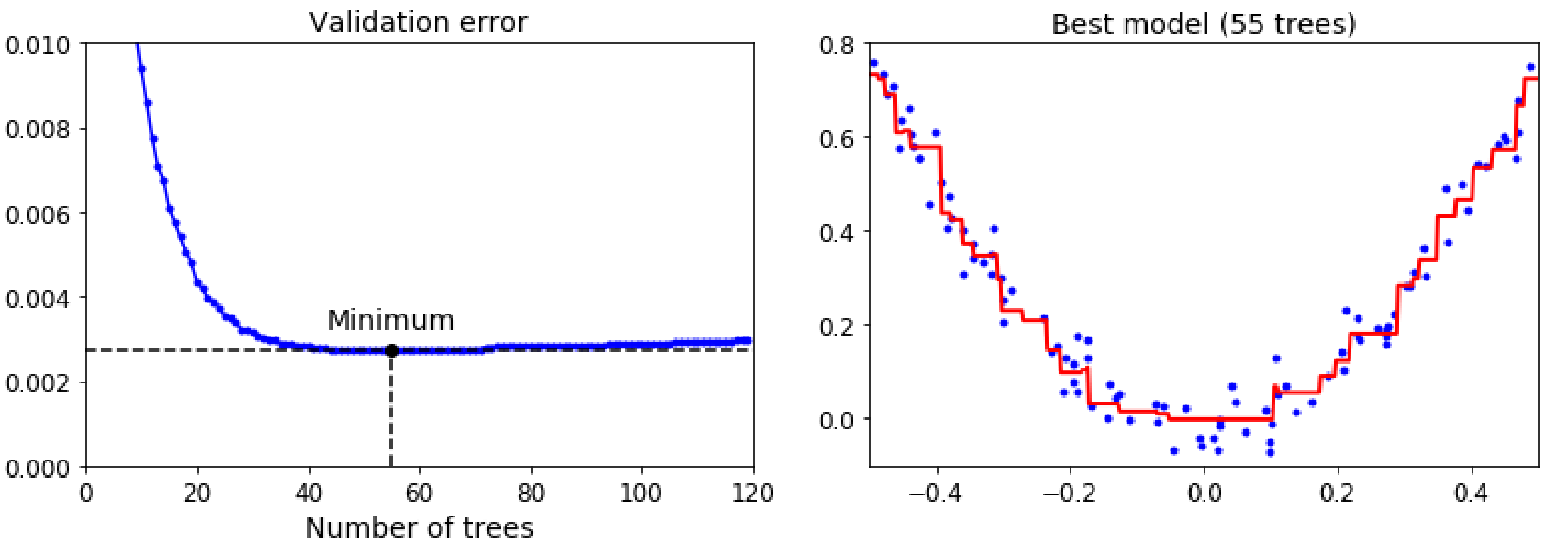

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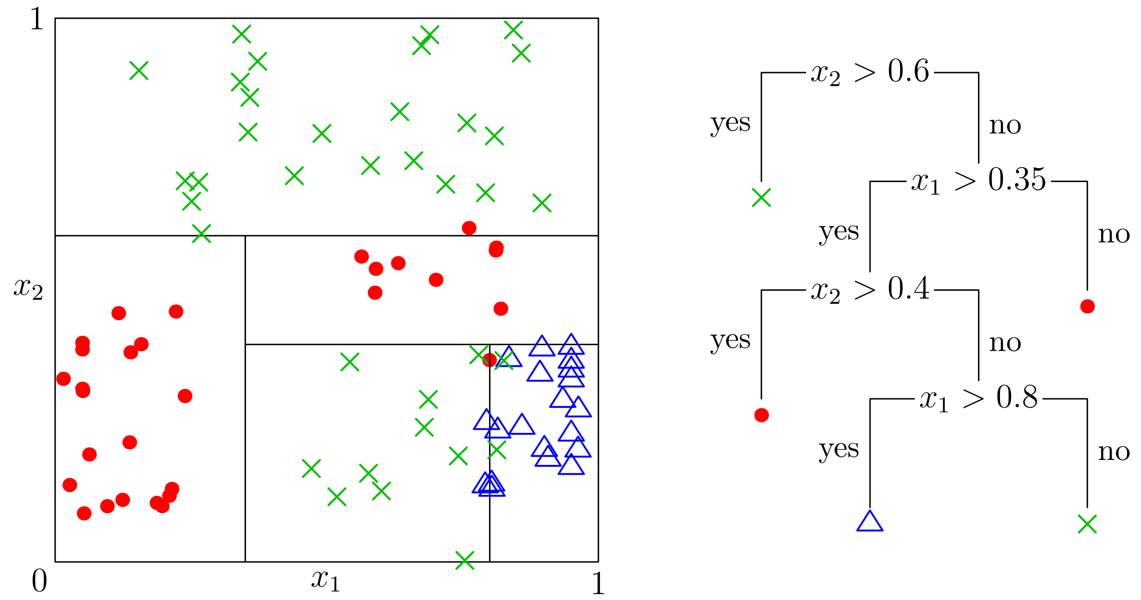

Ensembling in Deep Learning

- For most machine learning ensembling different machines usually gives a reasonable improvement in performance
- The machines should have roughly the same performance
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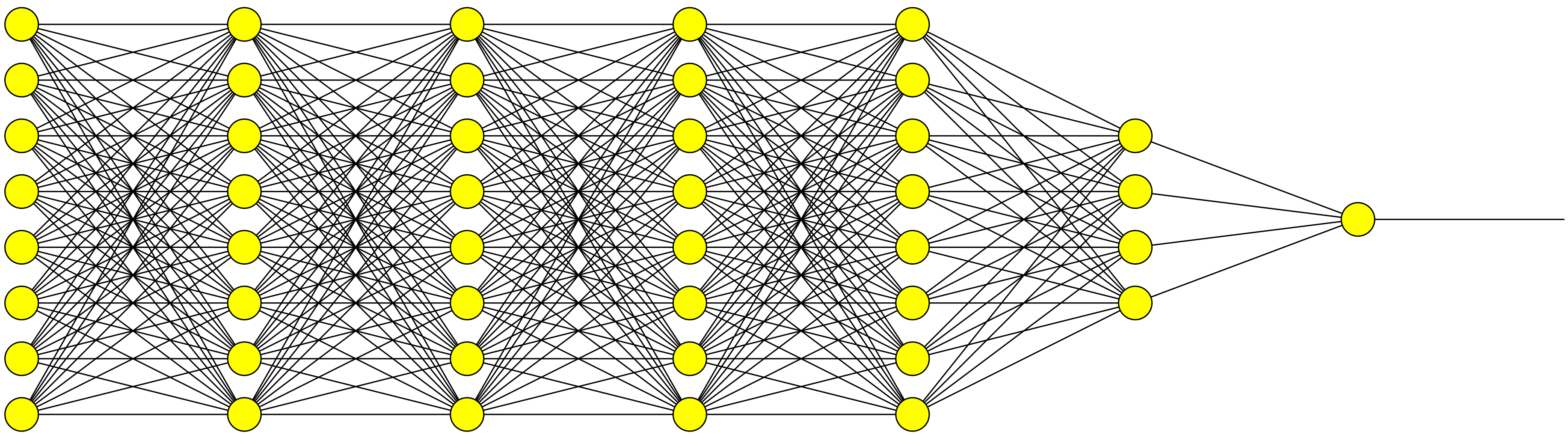

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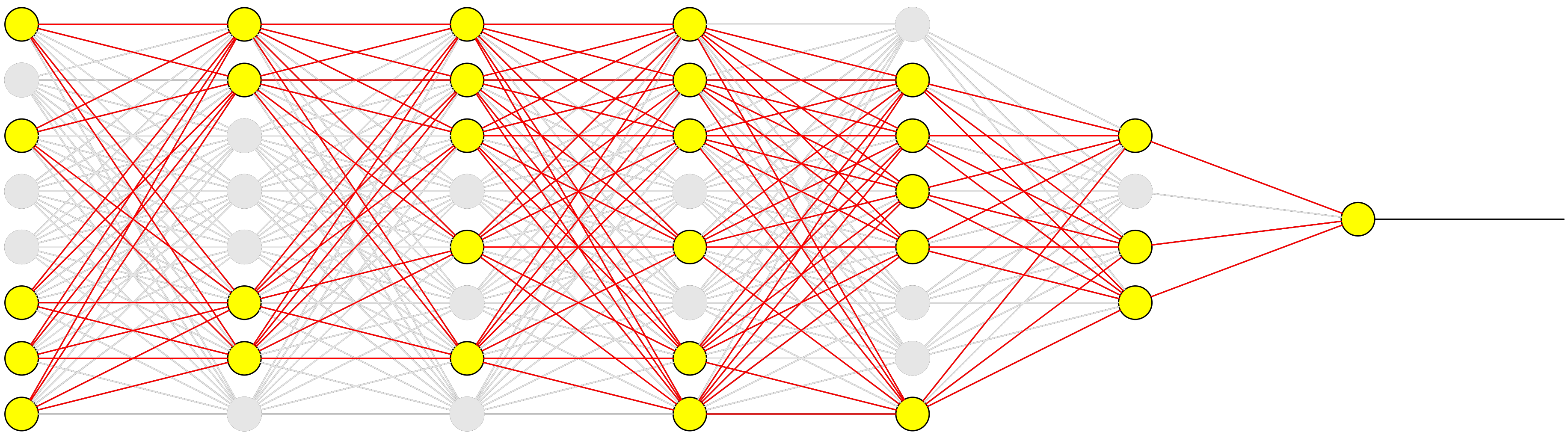

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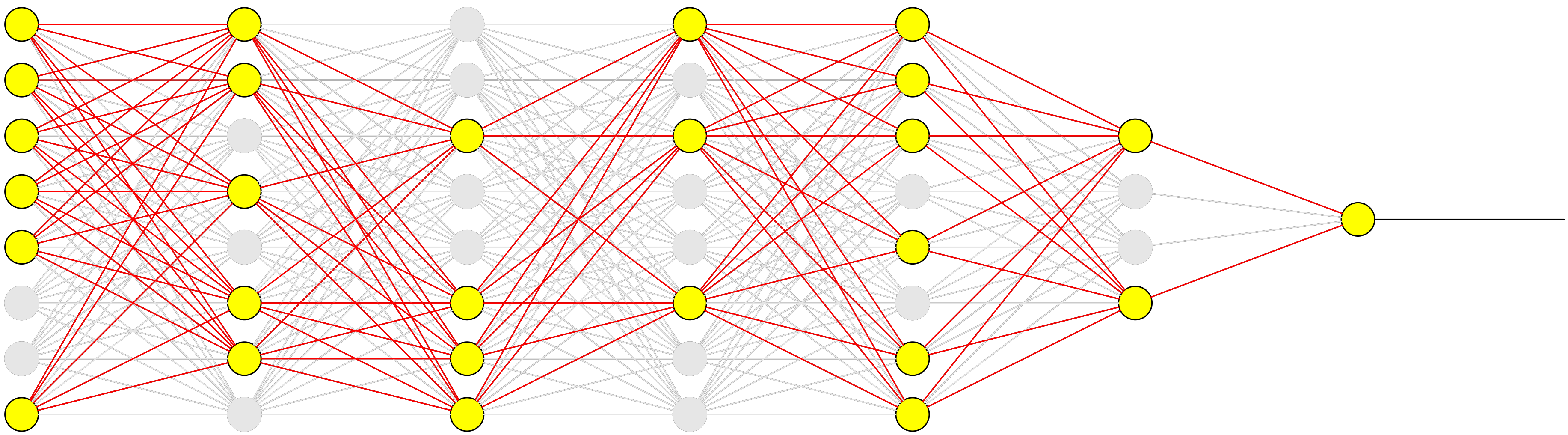

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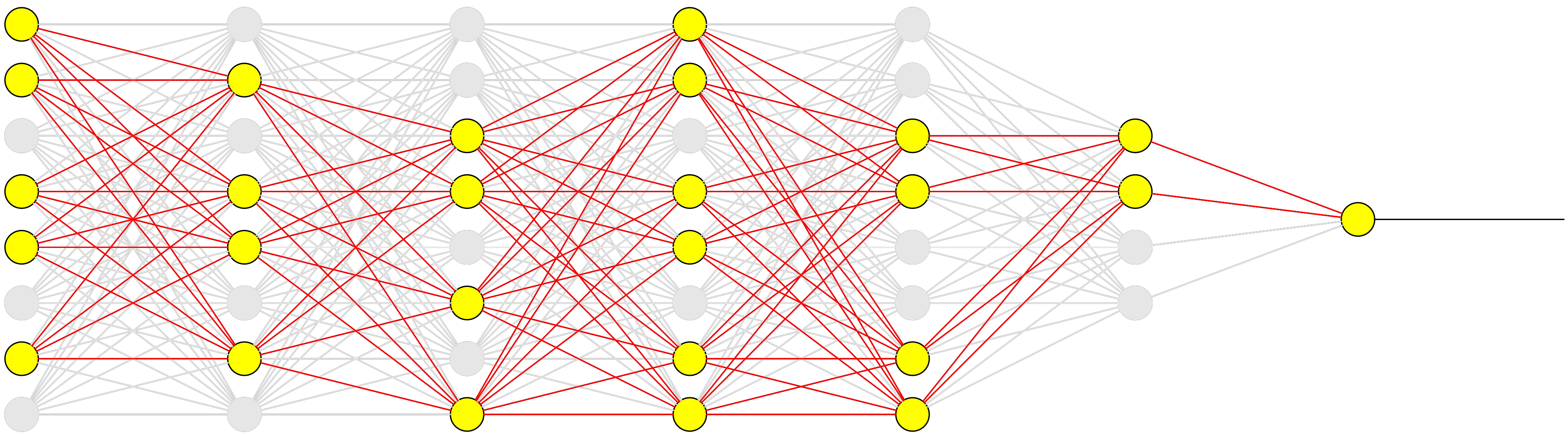

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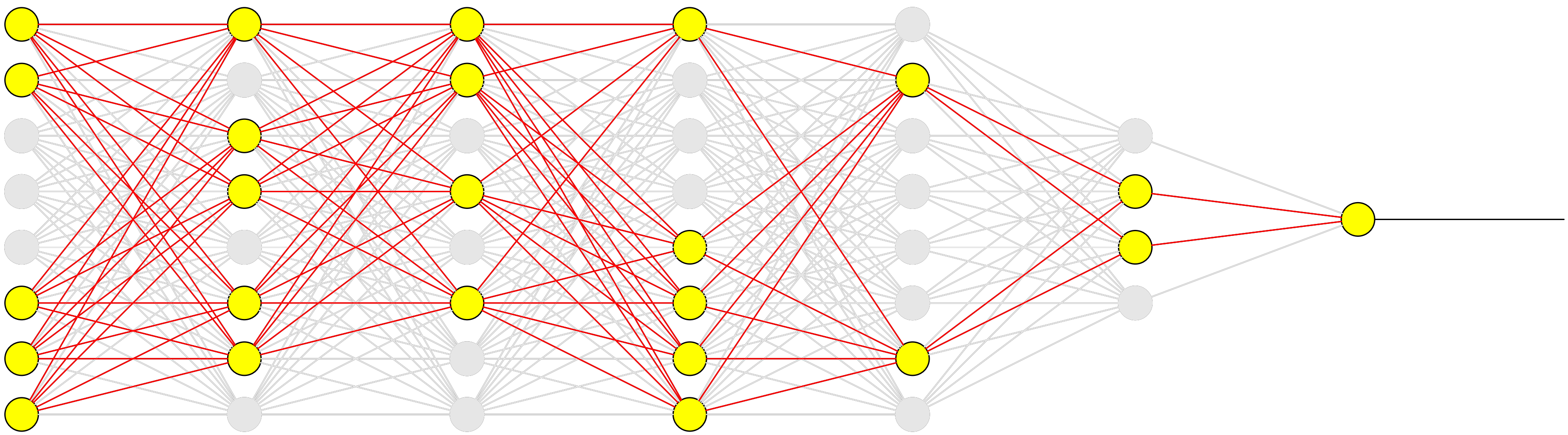

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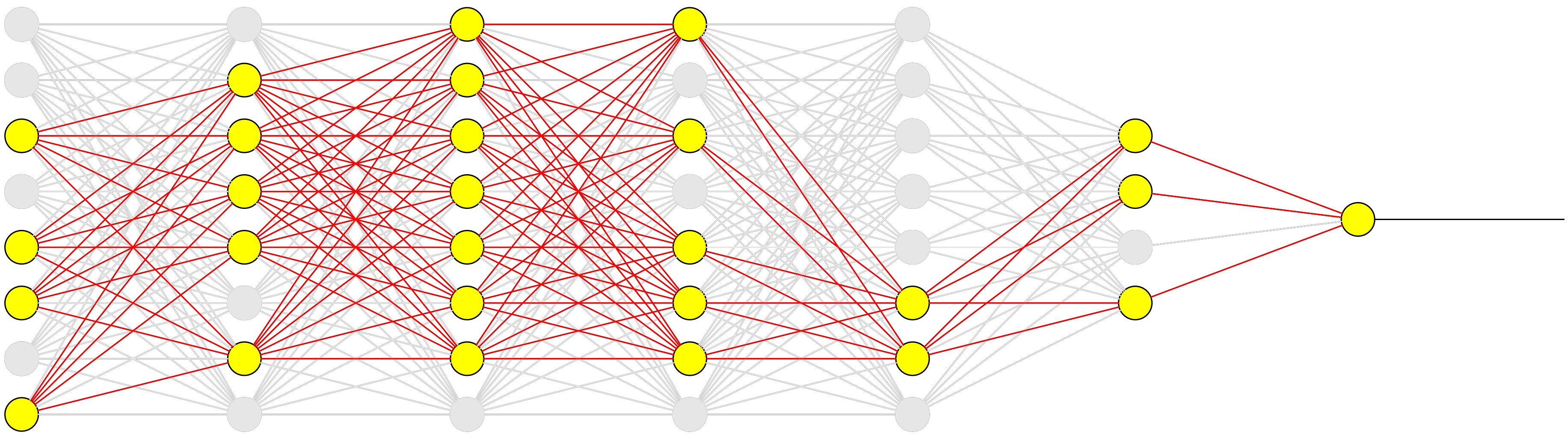

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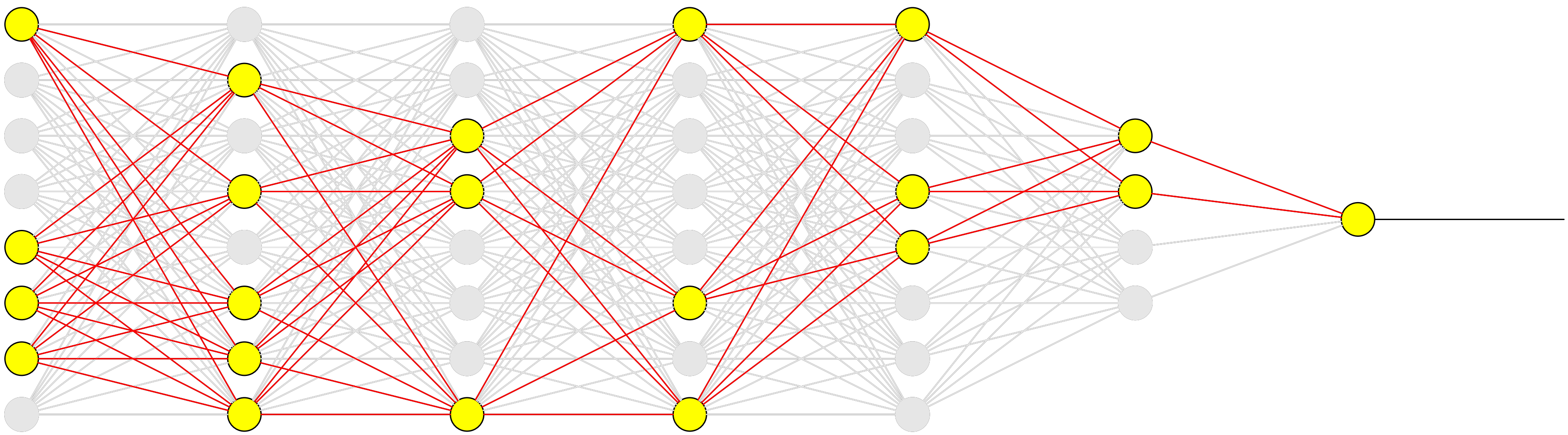

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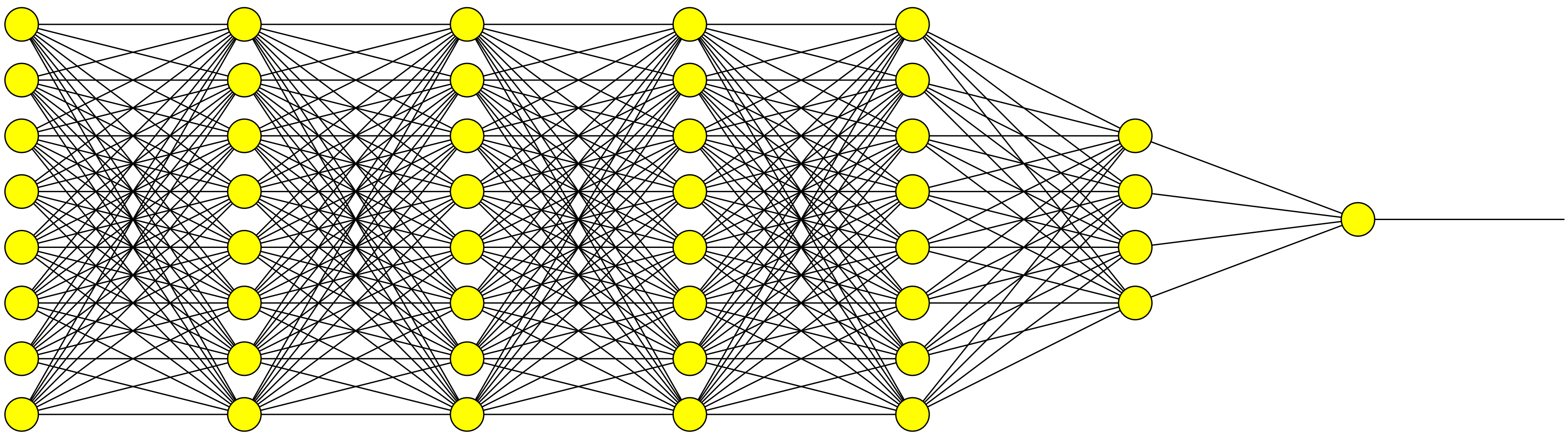

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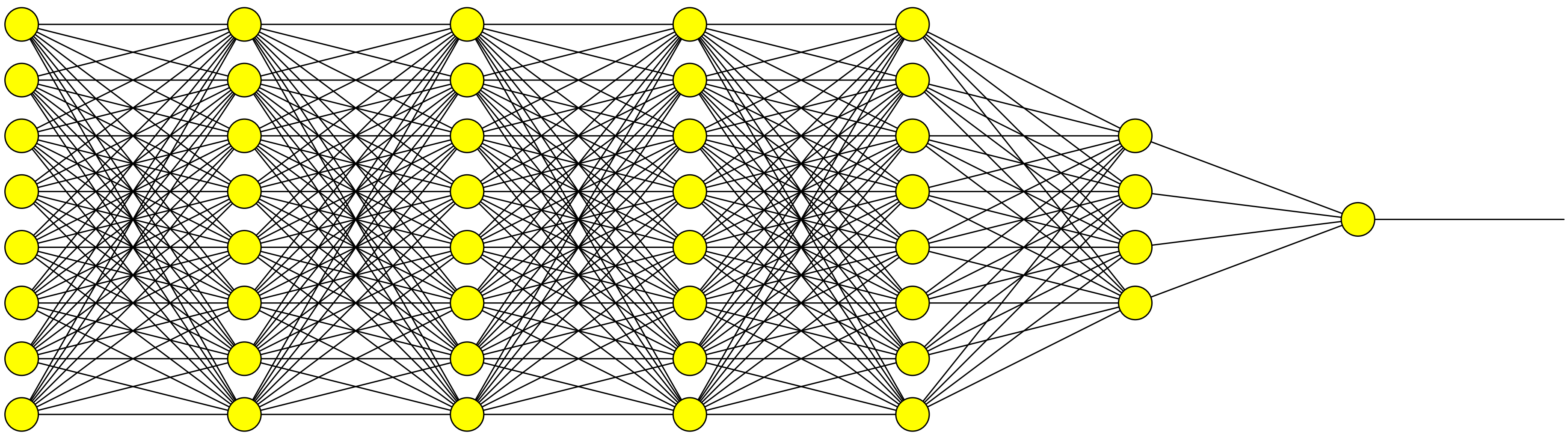

- This can be seen as ensembling lots of much simpler machines

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