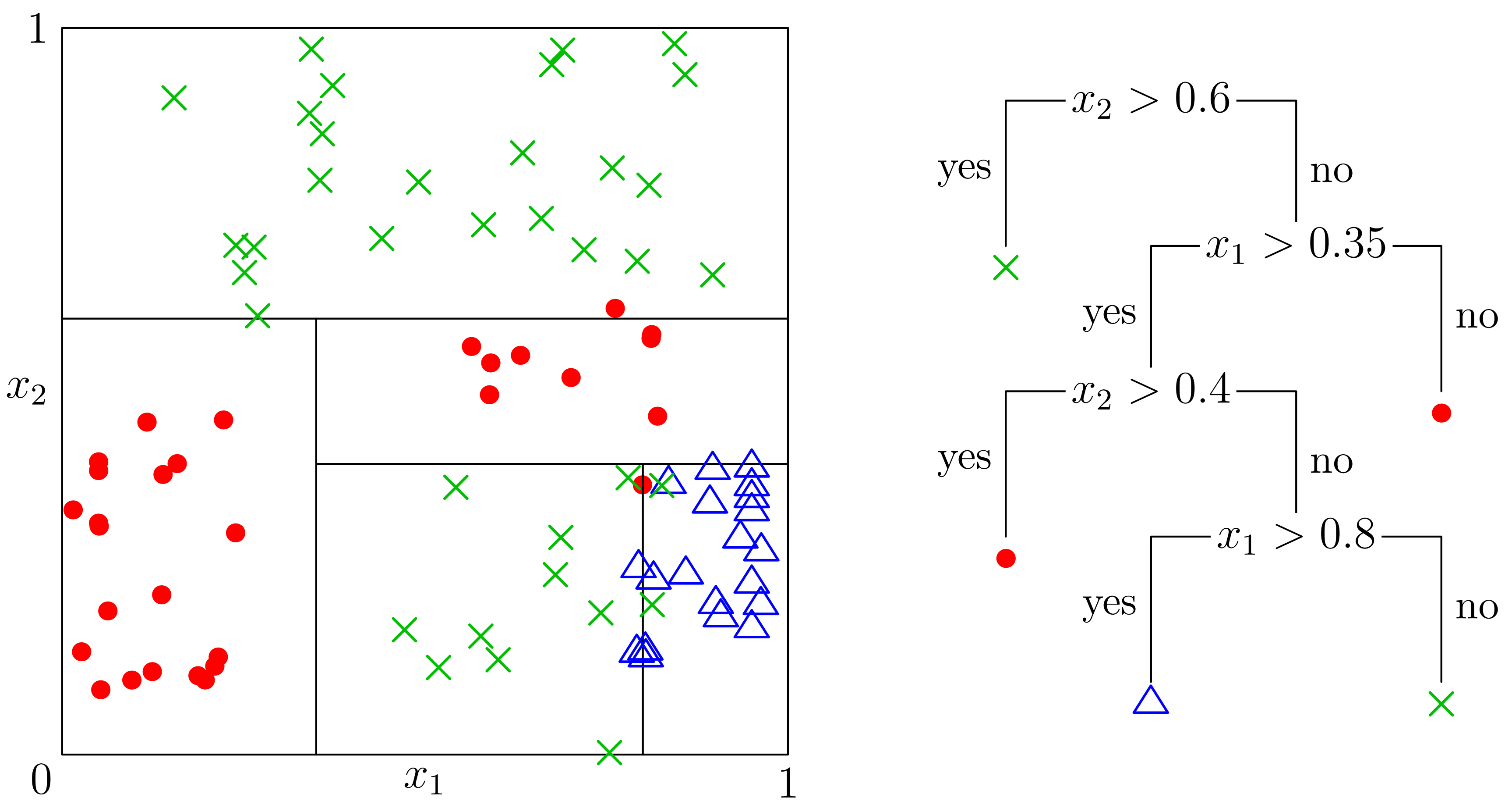
Advanced Machine Learning

Ensemble Methods

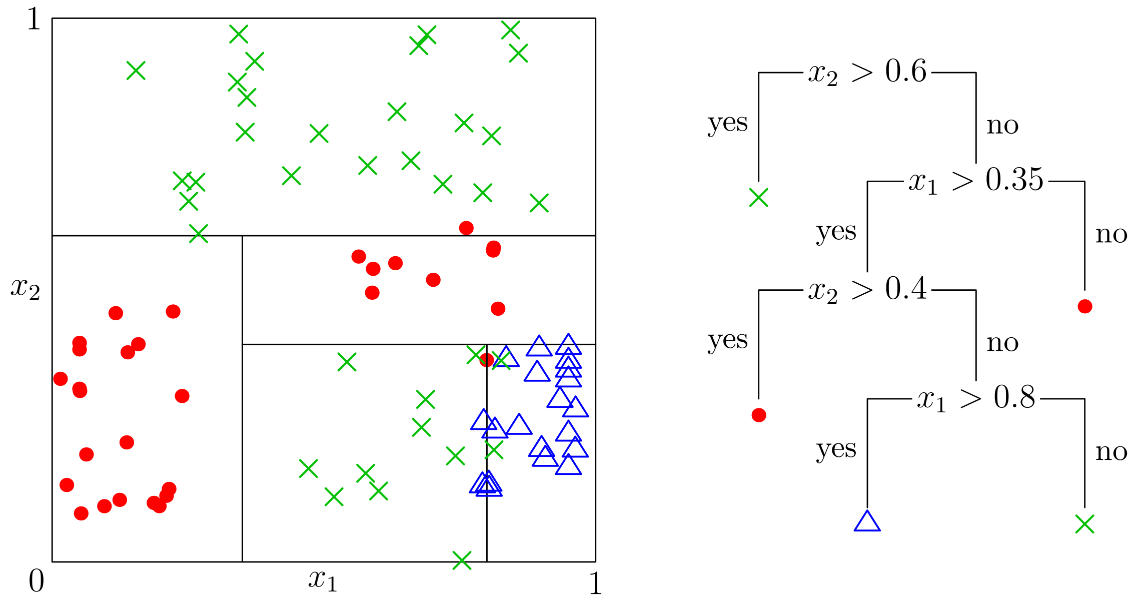


Decision Trees, Averaging, Bagging

Outline

1. **Decision Trees**

2. Bagging



Removing Variance By Averaging

- We can reduce the variance and hence improve our generalisation error by averaging over different learning machines

- There are a number of different techniques for doing this that go by the name of **ensemble methods** or **ensemble learning**

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- (nevertheless, even for deep learning taking the average response of many machines is usually done to win competitions)

Ensembling of Decision Trees

- One set of algorithms where ensembling are common place are decision trees

- These are particularly good for handling messy data
  - ⋆ categorical data
  - ⋆ mixture of data types
  - ⋆ missing data
  - ⋆ large data sets
  - ⋆ multiclass

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Decision Trees

- A decision trees builds a binary tree to partition the data, $\mathcal{D} = \{(\boldsymbol{x}_i, y_i) | i = 1, \ldots, m\}$, into the leaves of the tree
- Each decision rule depends on a single feature
- At each step the rule is chosen that maximise the "*purity*" of the leaf nodes
- Decisions can be made on numerical values or categories

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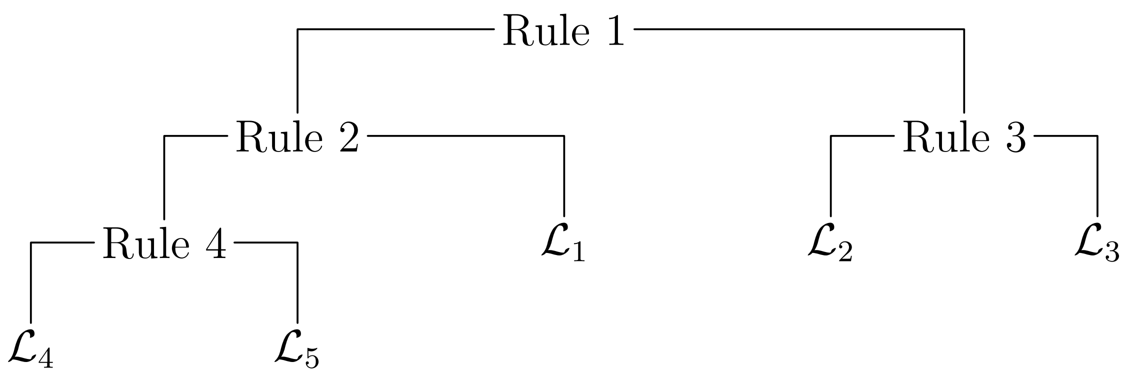
Partitioning

- Consider a classification problems with examples $(\boldsymbol{x}, y)$ belonging to some classes $y \in \mathcal{C}$

- The data is partitioned by the tree into leaves



- The proportion of data points in leaf $\mathcal{L}$ belonging to class c is

$$p_c(\mathcal{L}) = \frac{1}{|\mathcal{L}|} \sum_{(\boldsymbol{x}, y) \in \mathcal{L}} [\![y = c]\!]$$

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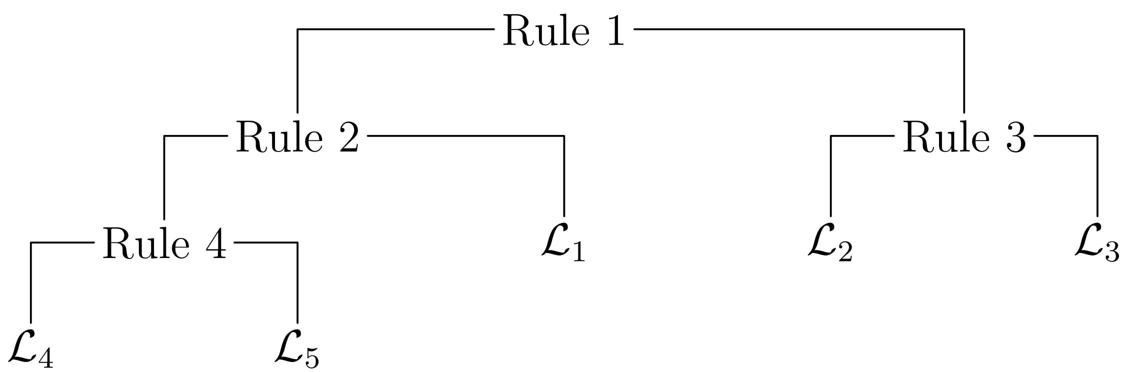

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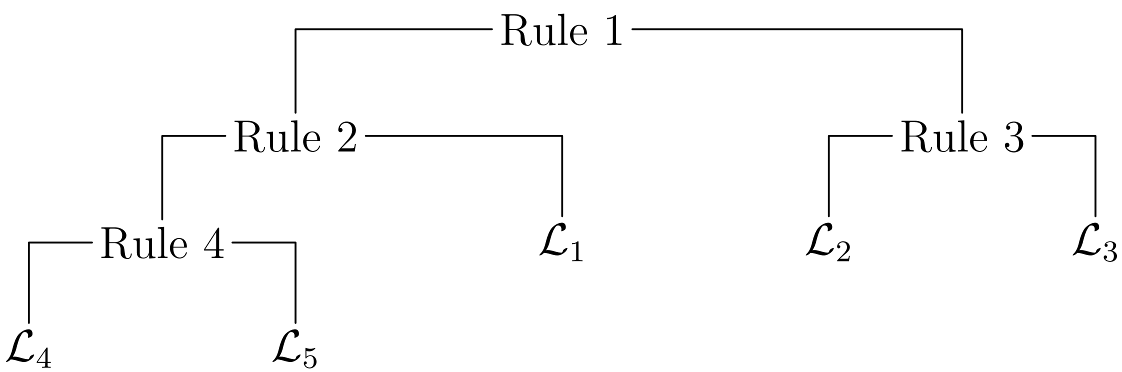

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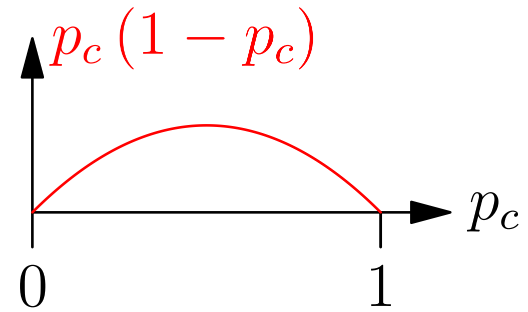
Leaf Purity

- Two different purity measures, $Q_m(\mathcal{L})$, for a leaf node $\mathcal{L}$ are commonly used
  - ⋆ **Gini index**



$$Q_m^g(\mathcal{L}) = \sum_{c \in \mathcal{C}} p_c(\mathcal{L})\,(1 - p_c(\mathcal{L}))$$

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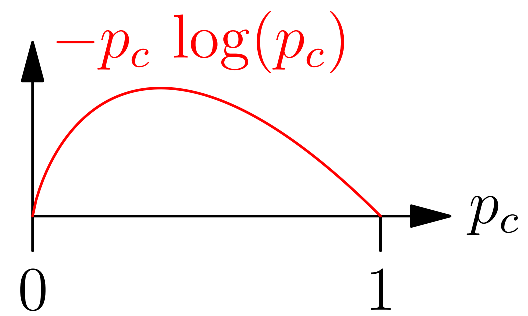

$$Q_m^e(\mathcal{L}) = -\sum_{c \in \mathcal{C}} p_c(\mathcal{L}) \log(p_c(\mathcal{L}))$$

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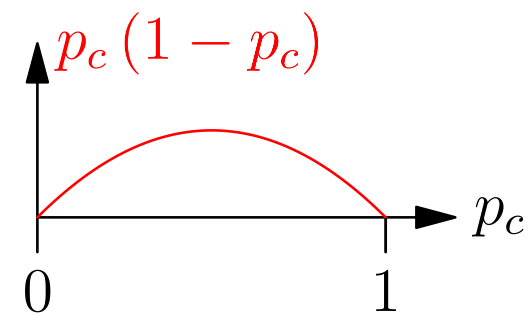

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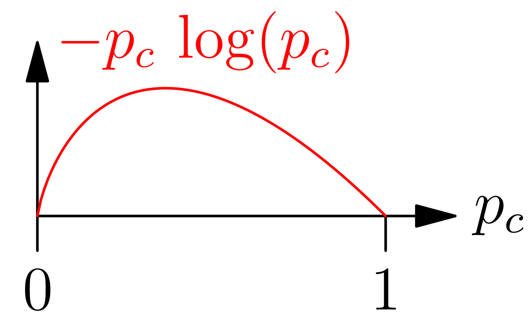

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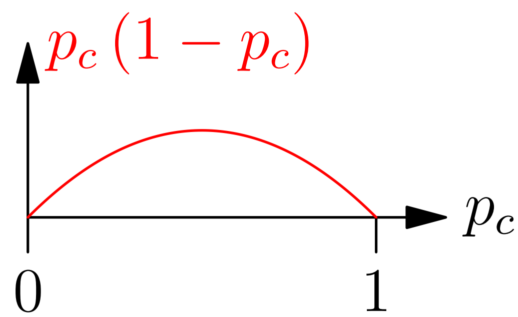

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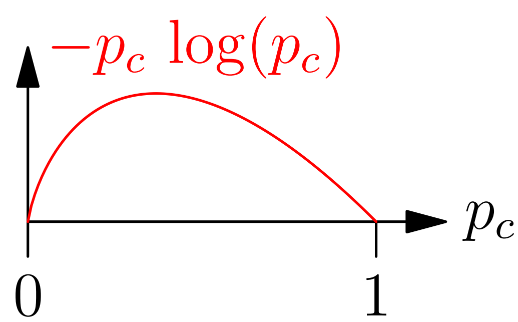
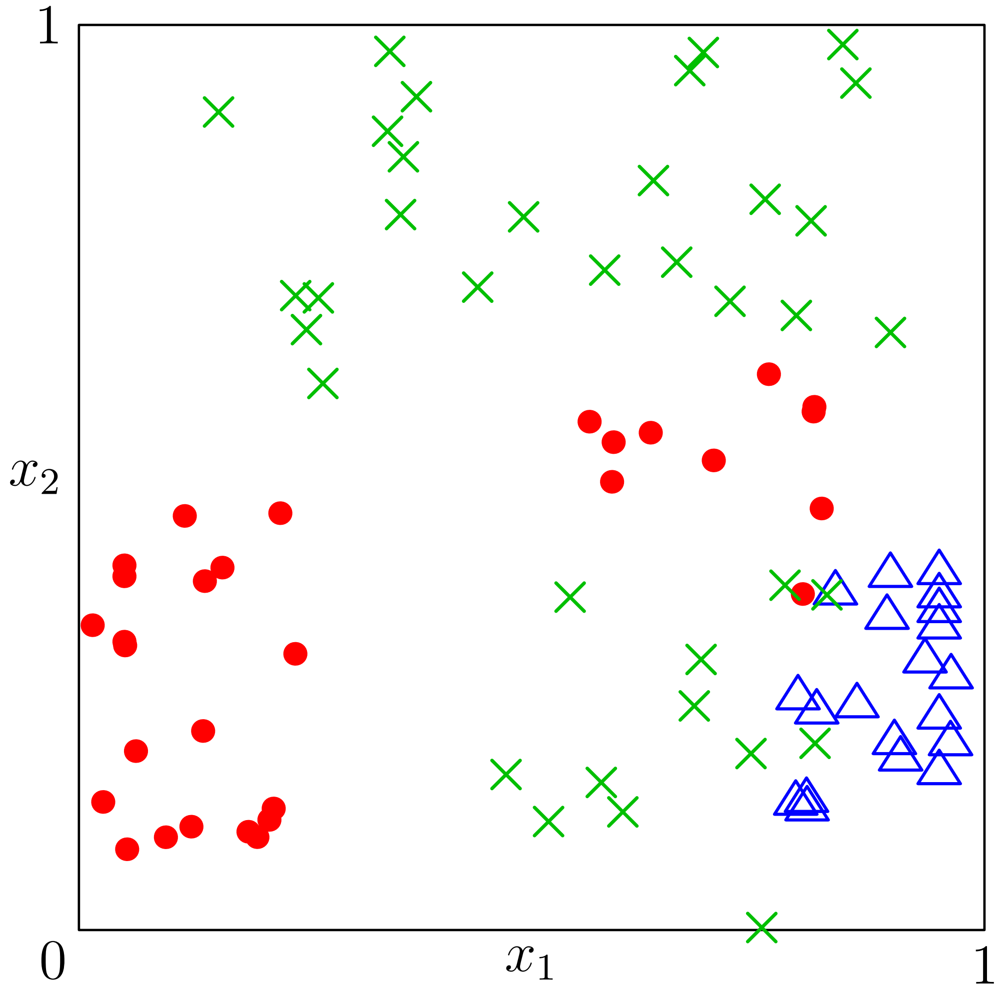


Building Decision Trees



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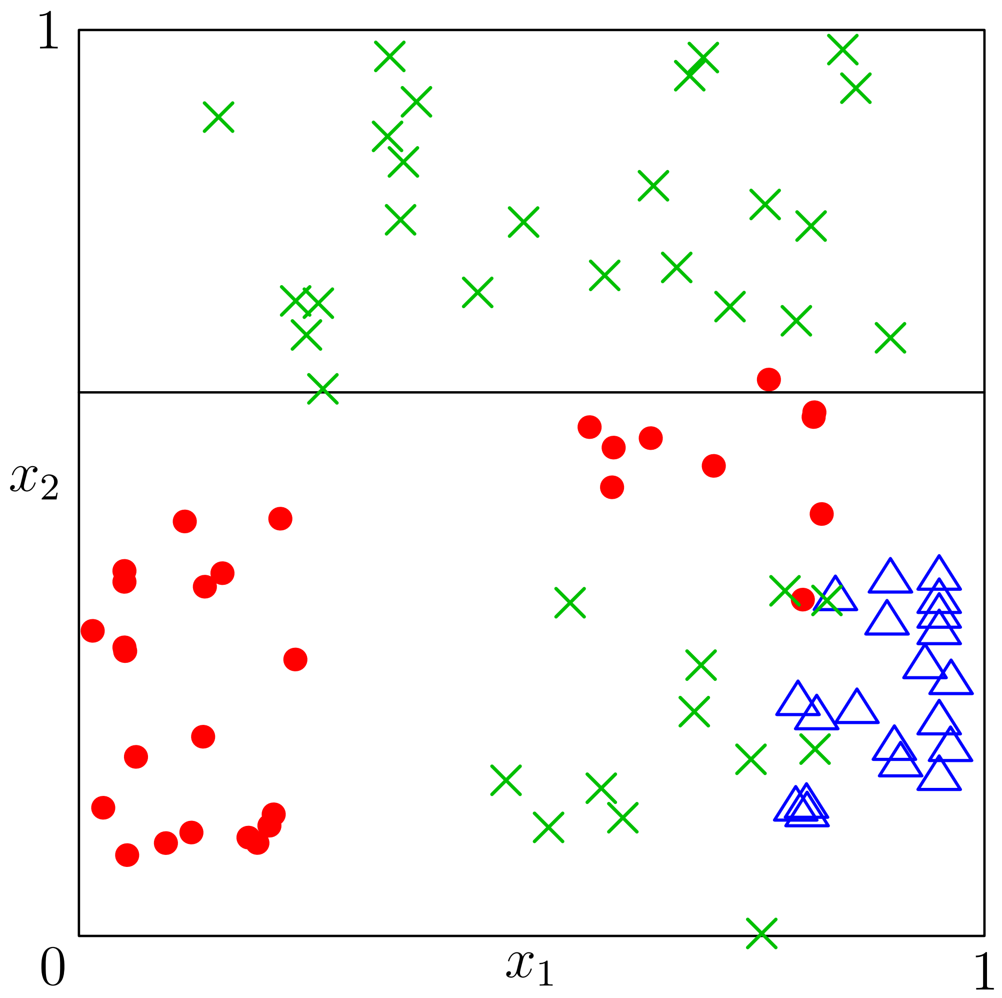

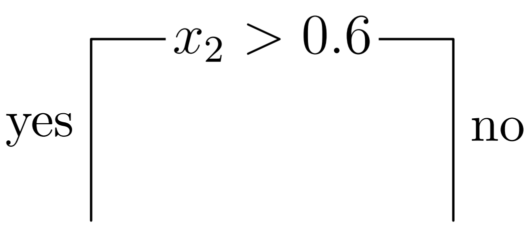

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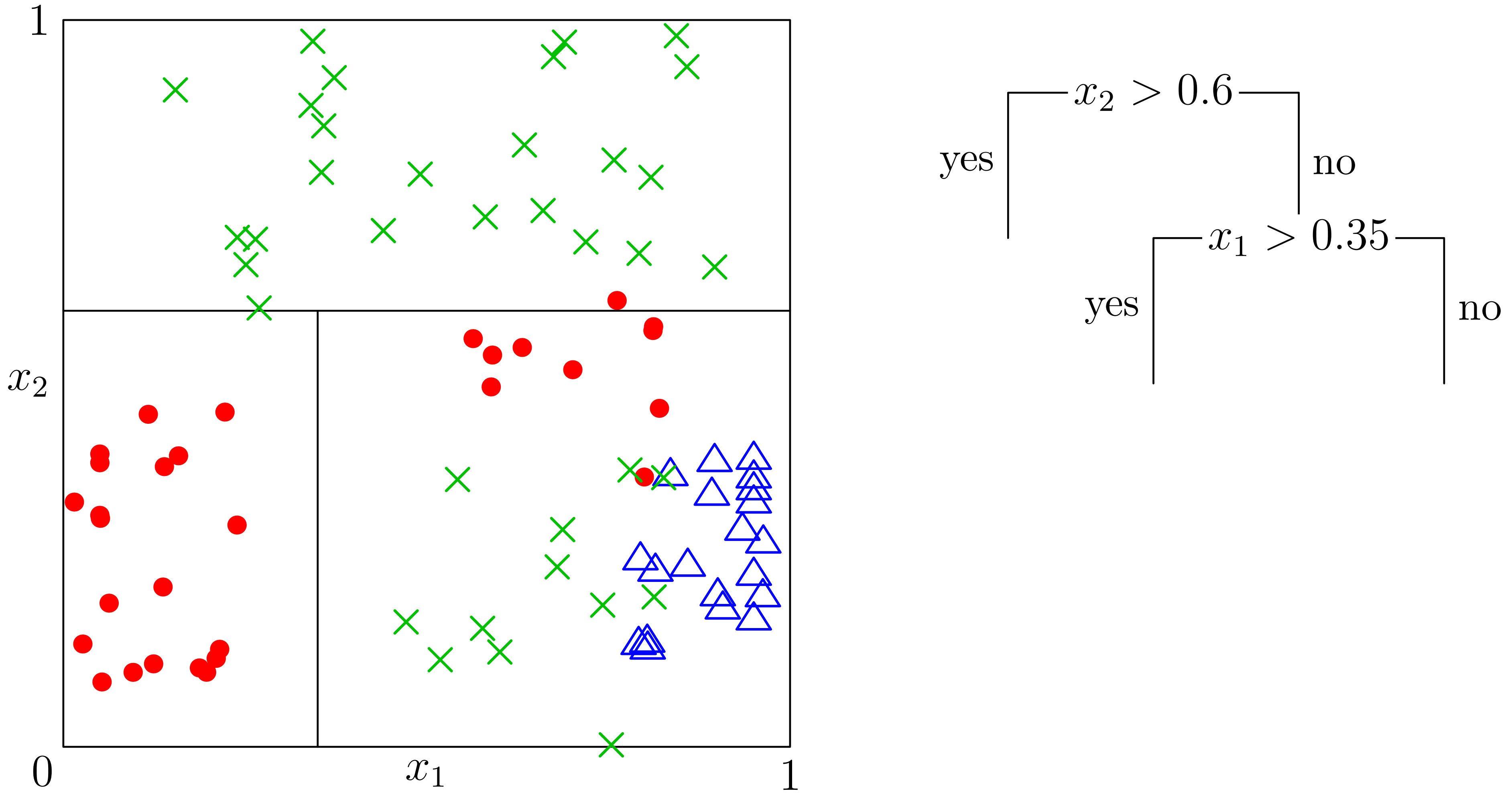

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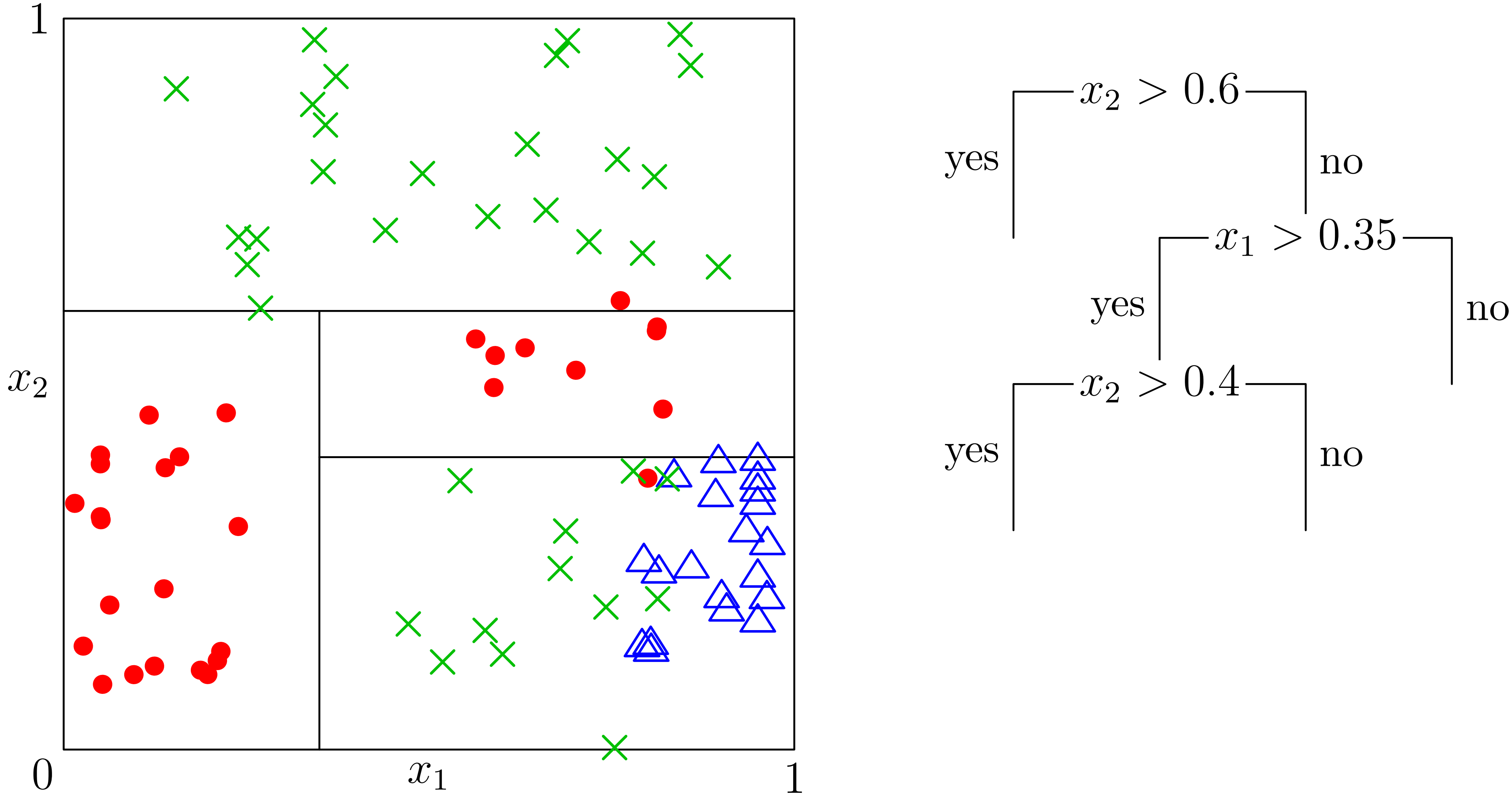

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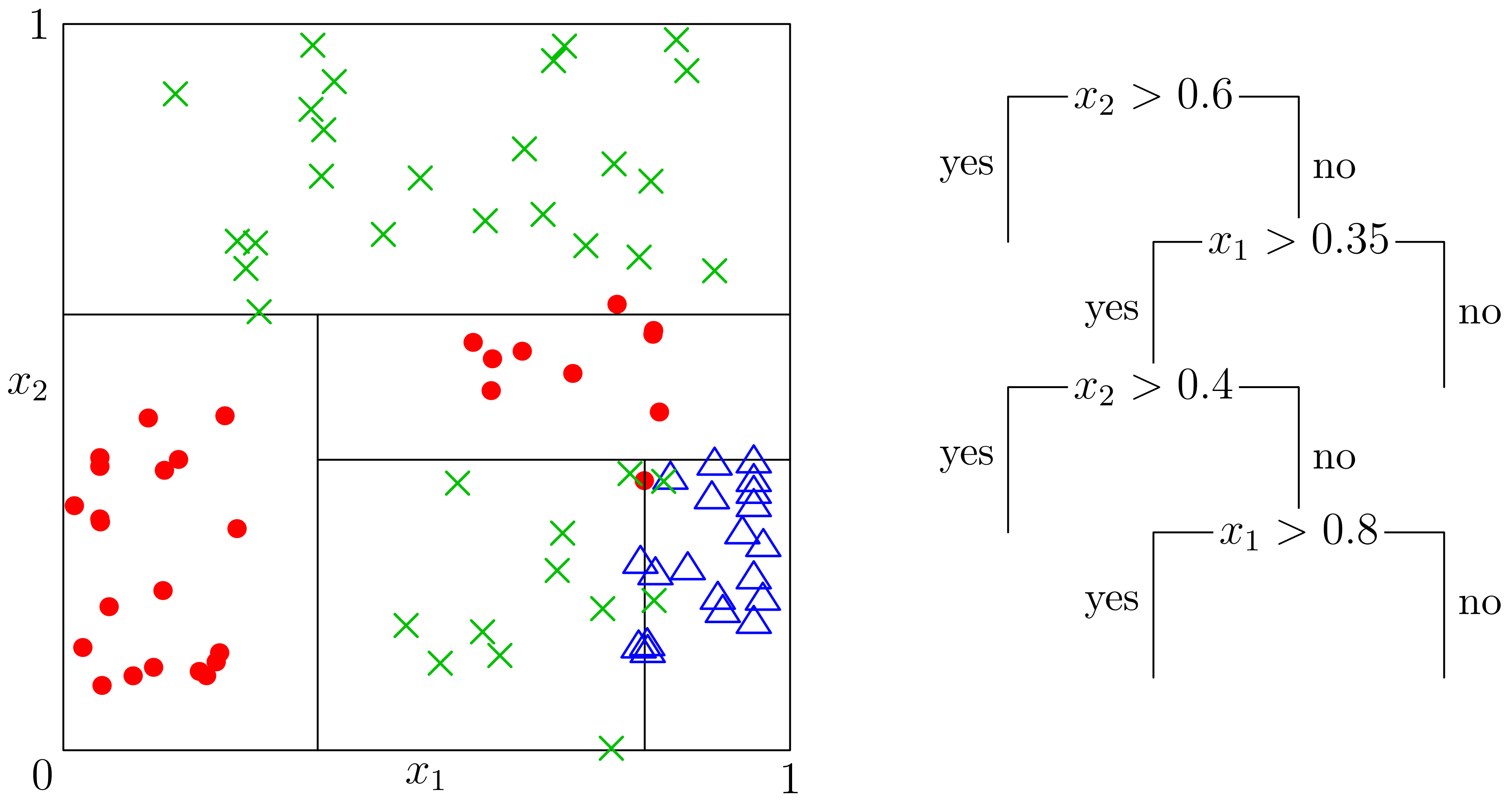

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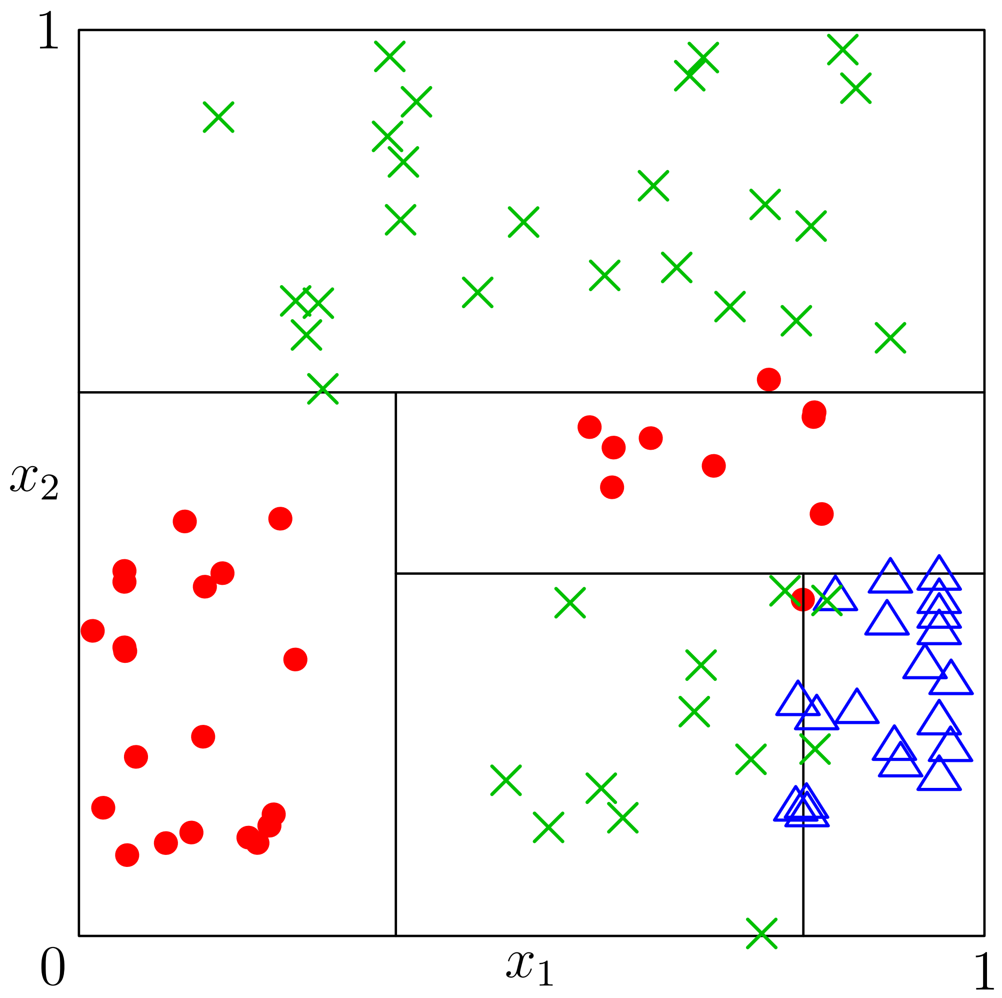

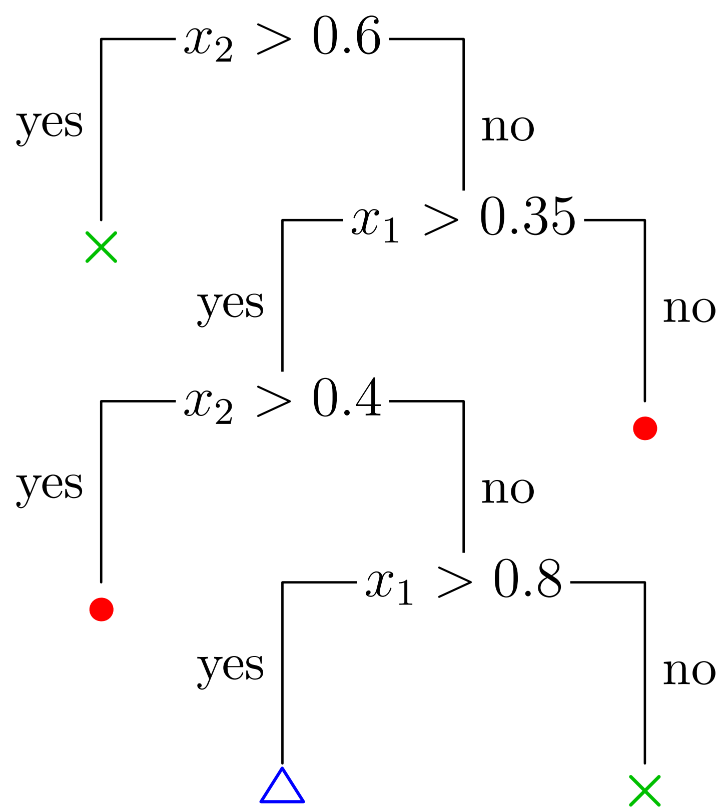

Observations

- Decision trees are very useful for exploring new data sets—the tree shows what features are most important
- Decision trees can also be used for regression problems
  - ⋆ Approximate function by a series of rules
  - ⋆ Reduce variance between data points assigned to leaf nodes
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Outline

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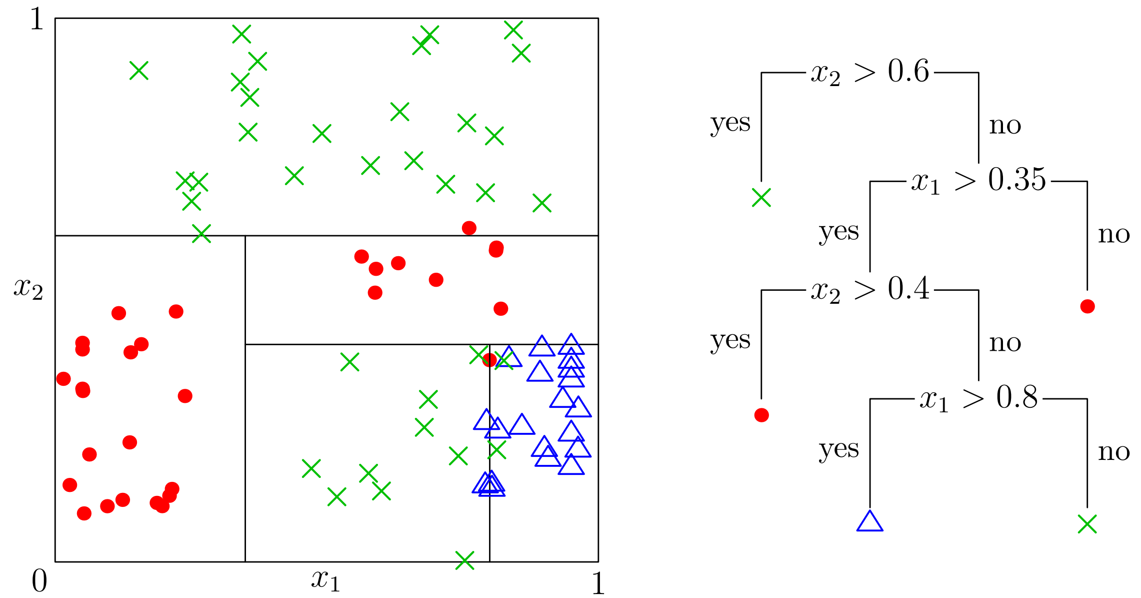
2. **Bagging**



Error In The Means

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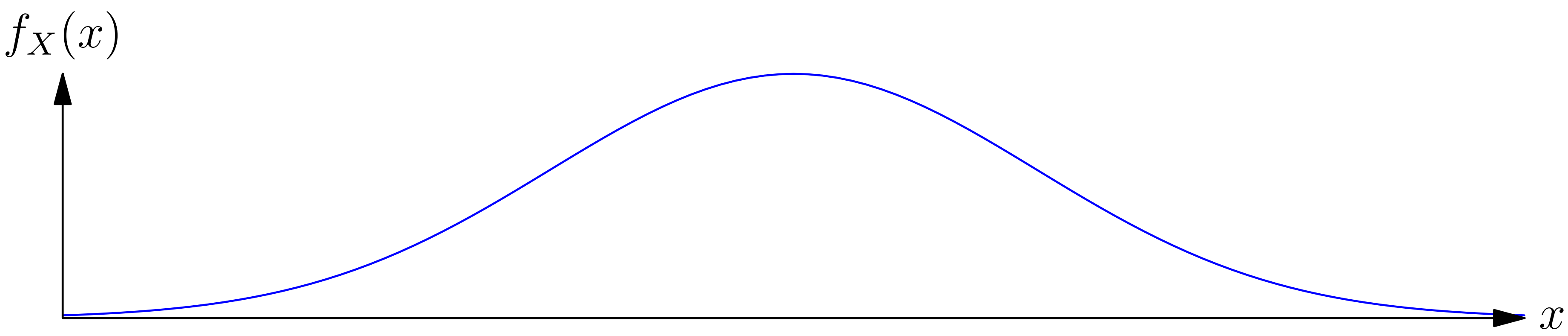

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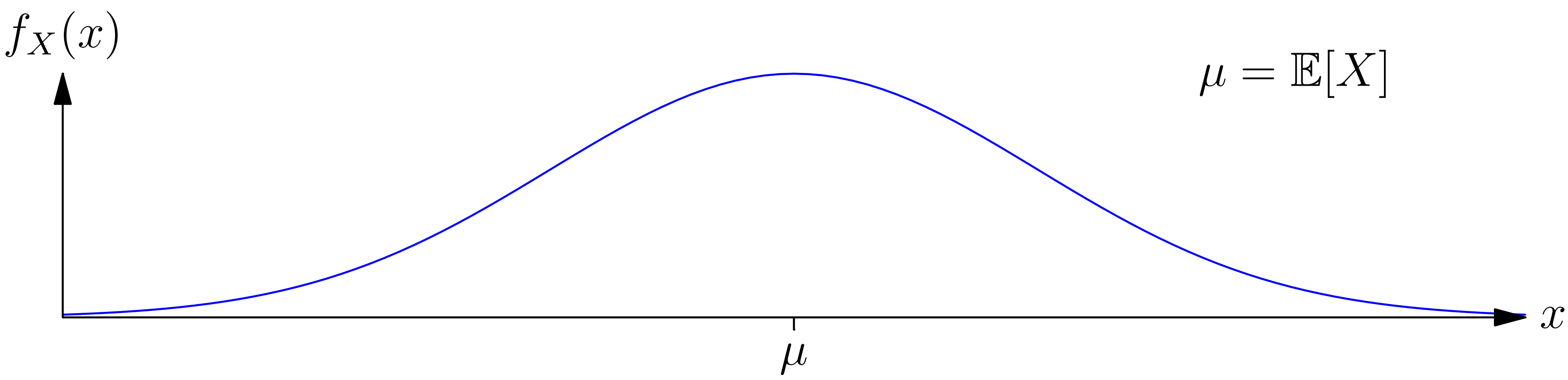

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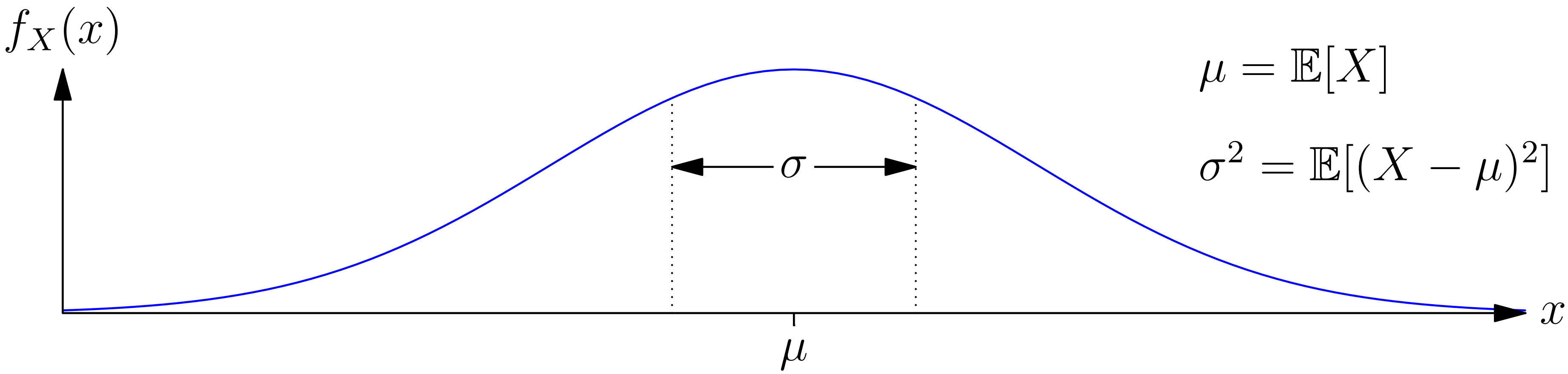

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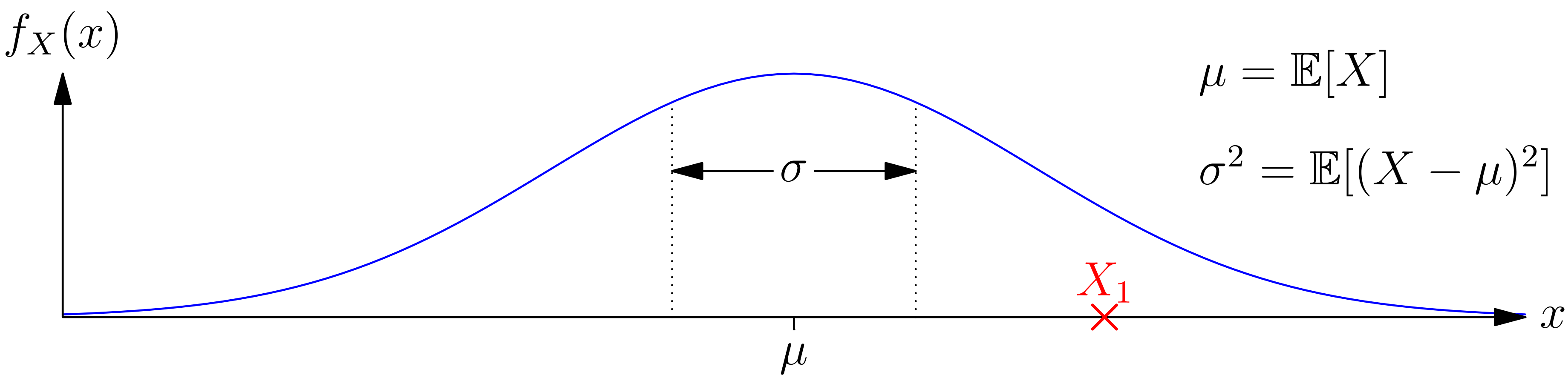

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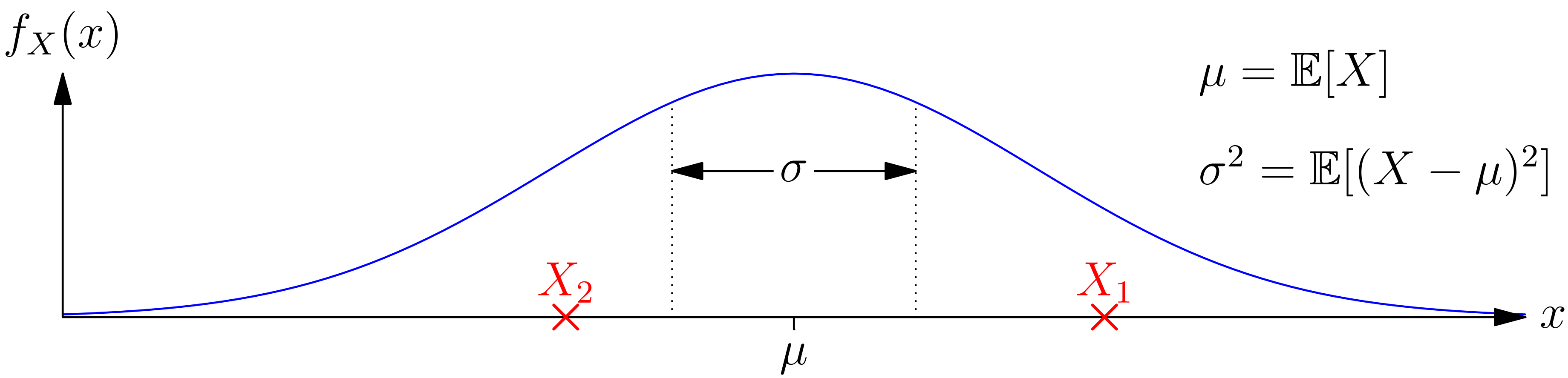

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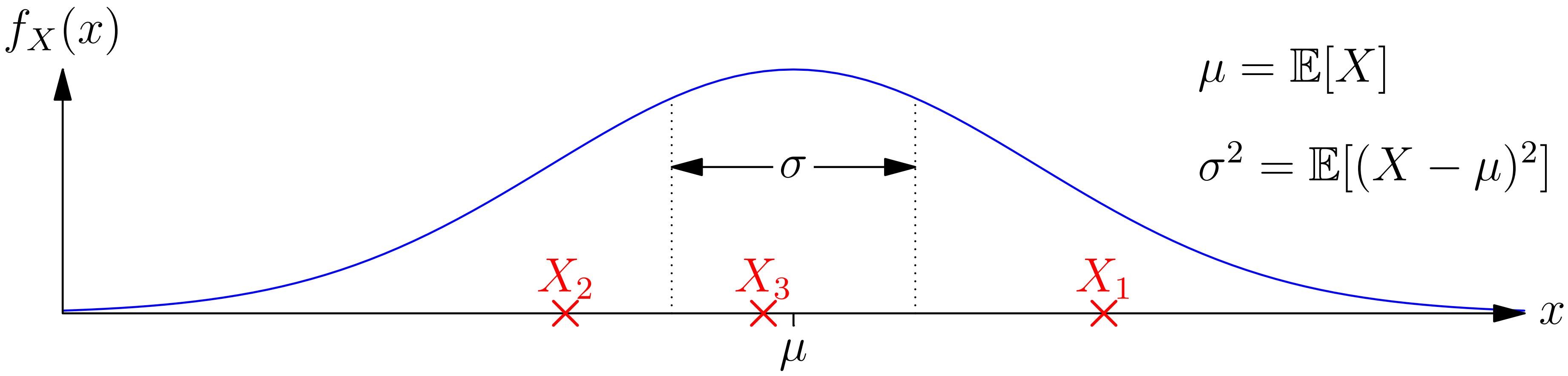

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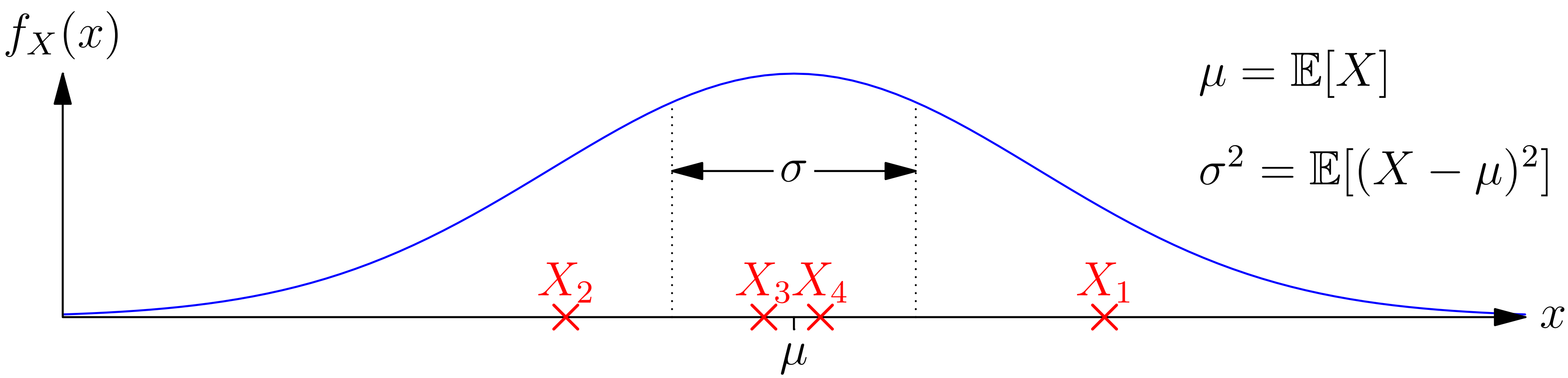

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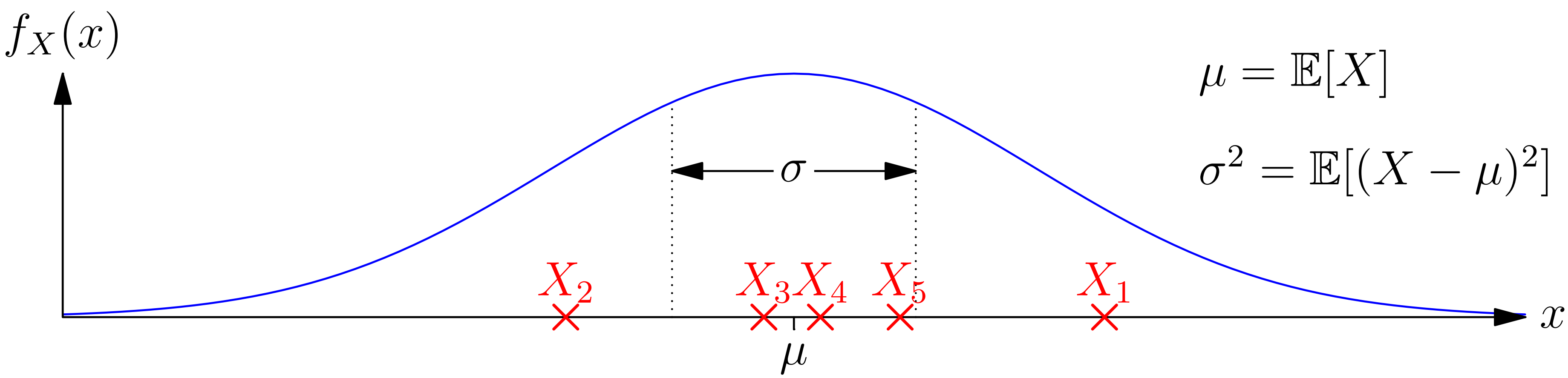

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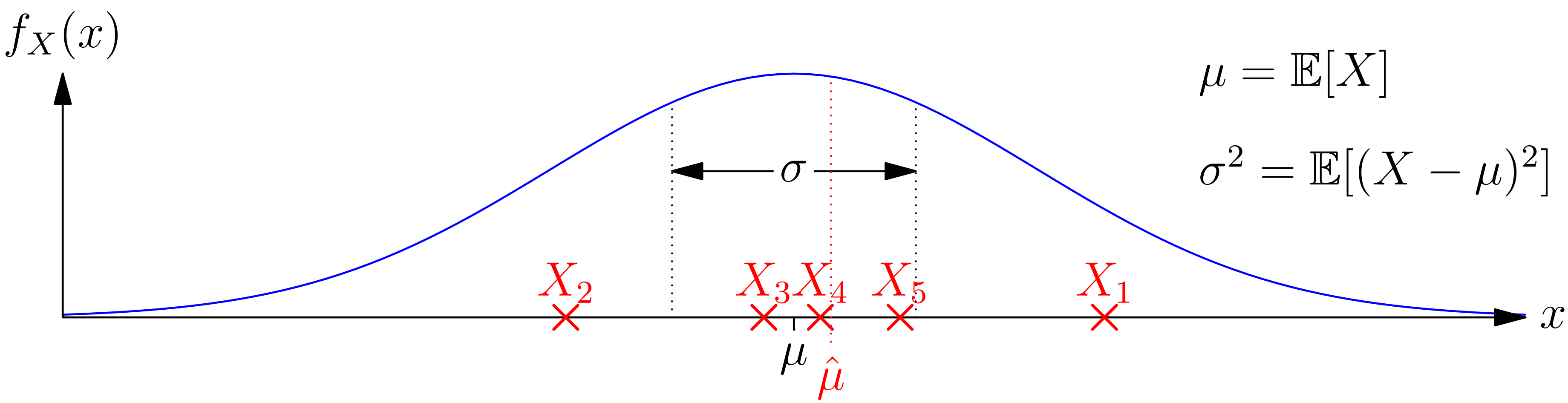

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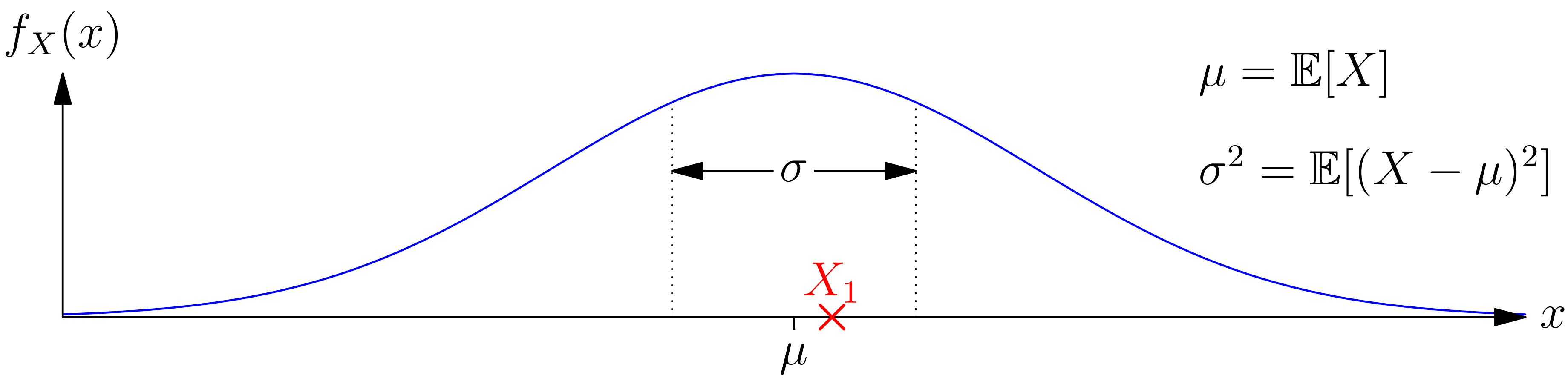

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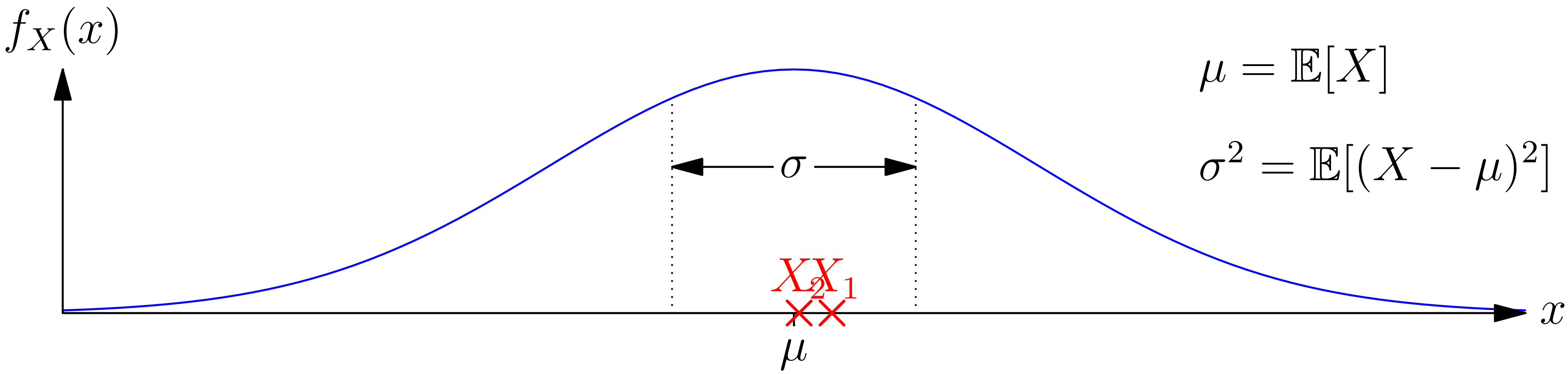

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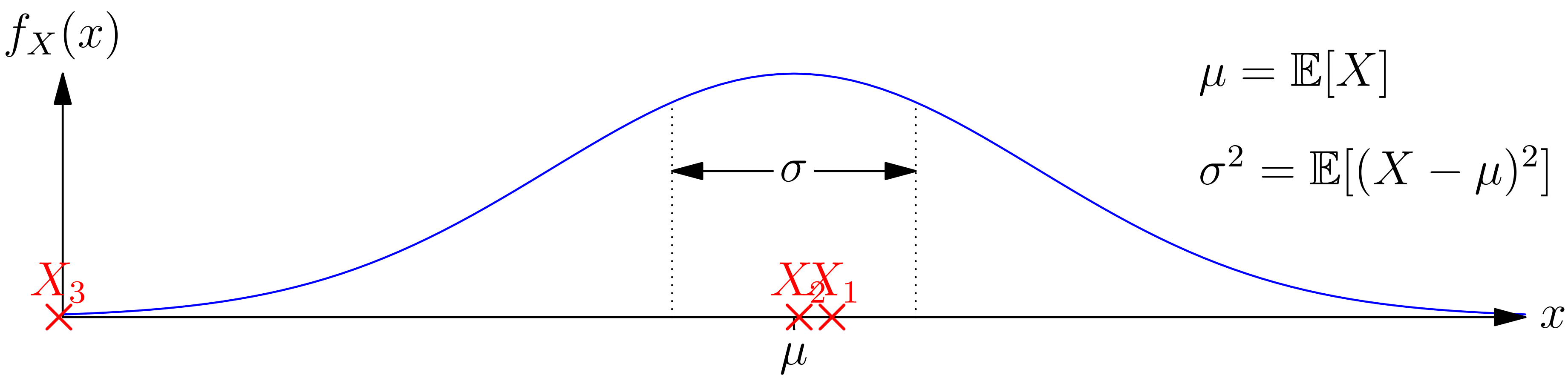

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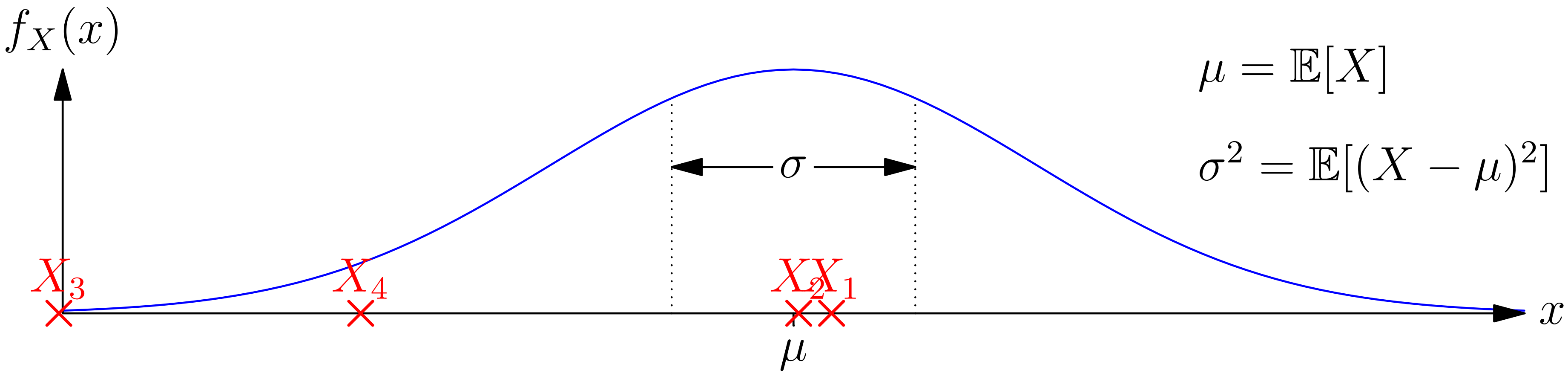

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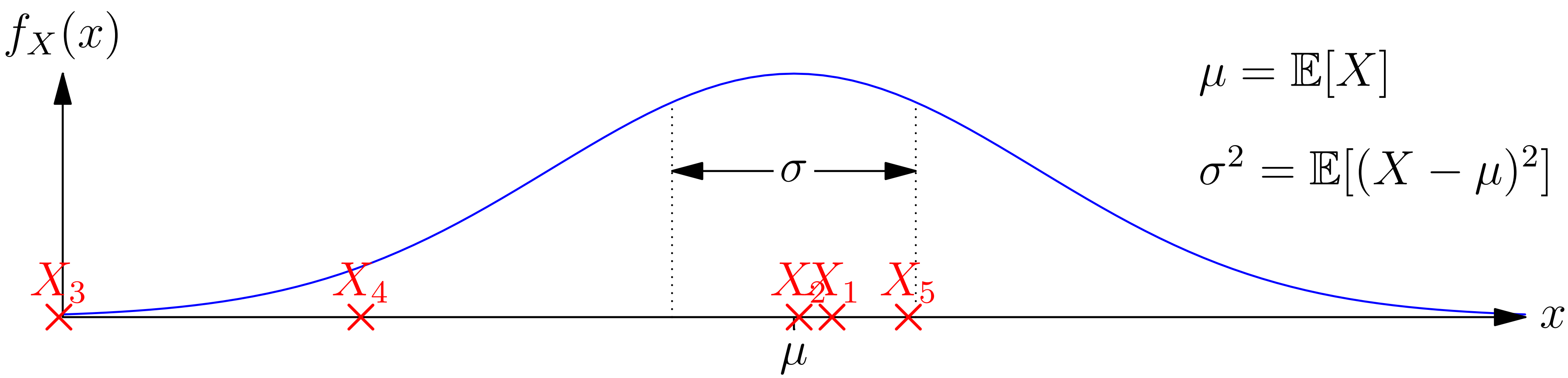

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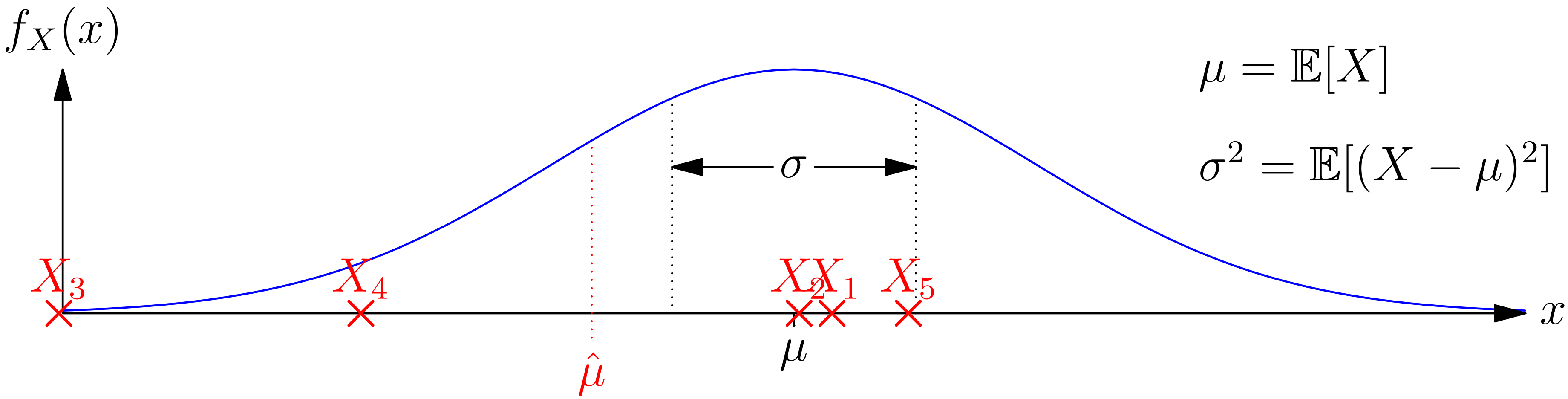

Mean and Variance

- The expected value of the mean, $\hat{\mu}_n$, of n random **independent** variables, X_i, is the expected value $\mu = \mathbb{E}[X_i]$

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- To reduce the variance in a learning machine (such as a decision tree) we can average over many machines
- To average many machines they must learn something different
- We only have one data set, but we can resample from the data set to make them look a bit different—this is known a **bootstrapping**

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Performance of Bagging

- For classification we get our different machines to vote
- For regression we can average the prediction of different machines
- Bagging improves the performance of decision trees
- However, we can usually do better using Boosting
- This is because our decision trees are correlated

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Variance of Positive Correlated Variables

- If we calculate the variance of the mean of positively correlated variables with correlation ρ we find

$$\frac{1}{n^2}\mathbb{E}\left[\left(\sum_{i=1}^{n} X_i - \mu\right)^2\right] = \rho\sigma^2 + \frac{1-\rho}{n}\sigma^2$$

$(\rho = \mathbb{E}[(X_i - \mu)(X_j - \mu)]/\sigma^2)$

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- If we want to do well we need our learning machines to be unbiased and decorrelated

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Random Forest

- In random forests we average much less correlated trees
- To do this for each tree we choose a subset of $p' \ll p$ of the features on which to split the tree
- Typically p' can range from 1 to $\sqrt{p}$
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- By averaging over a huge number of trees (order of 1000) we typically get good results
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Lessons

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- They work by averaging over different machines, trying to reduce their variance
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