

# Machine Learning for econometrics

Flexible models for tabular data

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A lot of today's content is taken from the excellent sklearn mooc (Estève et al., 2022)

# Reminder from previous session

- Statistical learning 101: bias-variance trade-off
- Regularization for linear models: Lasso, Ridge, Elastic Net
- Transformation of variables: polynomial regression
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# Reminder from previous session

- Statistical learning 101: bias-variance trade-off
- Regularization for linear models: Lasso, Ridge, Elastic Net
- Transformation of variables: polynomial regression
- 🤔 But... How to select the best model? the best hyper-parameters?

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2. Flexible models: Tree, random forests and boosting
3. A word on other families of models

# Model evaluation and selection with cross-validation

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# A closer look at model evaluation: Wage example

## Example with the Wage dataset

- Raw dataset: (N=534, p=11)

EDUCATION	SOUTH	SEX	EXPERIENCE	UNION	WAGE	AGE	RACE	OCCUPATION	SECTOR	MARR
8	no	female	21	not_member	5.10	35	Hispanic	Other	Manufacturing	Married
9	no	female	42	not_member	4.95	57	White	Other	Manufacturing	Married
12	no	male	1	not_member	6.67	19	White	Other	Manufacturing	Unmarried
12	no	male	4	not_member	4.00	22	White	Other	Other	Unmarried
12	no	male	17	not_member	7.50	35	White	Other	Other	Married

- 

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# A closer look at model evaluation: Wage example

## Example with the Wage dataset

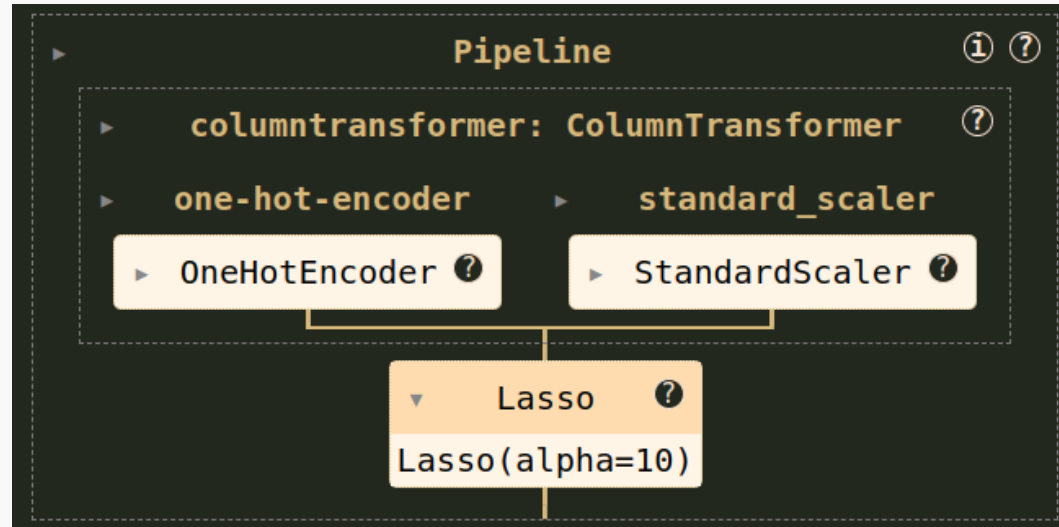
- Raw dataset: (N=534, p=11)
- Transformation: encoding categorical data, scaling numerical data: (N=534, p=23)

one-hot- encoder__SOUTH_no	one-hot- encoder__SOUTH_yes	one-hot- encoder__SEX_female	one-hot- encoder__SEX_male	one-hot- encoder__UNION_member	one-hot- encoder__UNION_not
1.0	0.0	1.0	0.0	0.0	0.0
1.0	0.0	1.0	0.0	0.0	0.0
1.0	0.0	0.0	1.0	0.0	0.0
1.0	0.0	0.0	1.0	0.0	0.0
1.0	0.0	0.0	1.0	0.0	0.0

# A closer look at model evaluation: Wage example

## Example with the Wage dataset

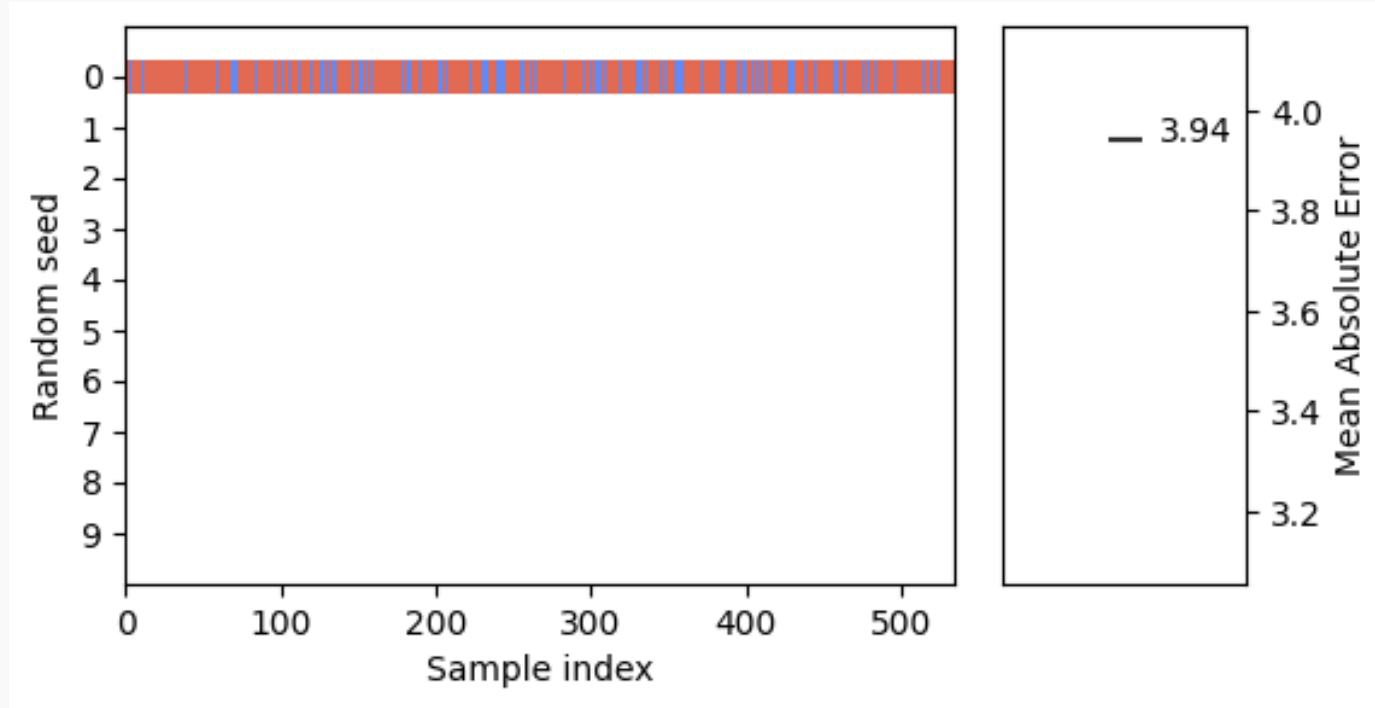
- Raw dataset: (N=534, p=11)
- Transformation: encoding categorical data, scaling numerical data: (N=534, p=23)
- Regressor: Lasso with regularization parameter ( $\alpha = 10$ )





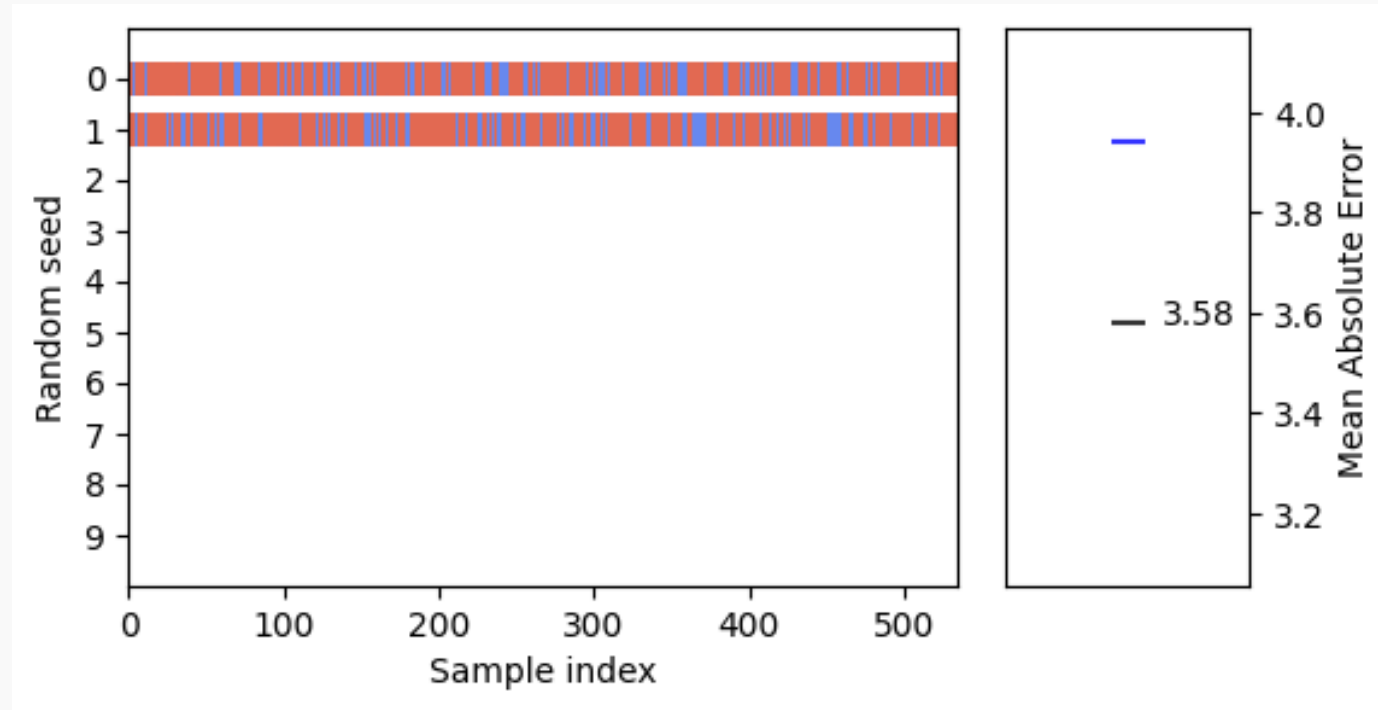
# Repeated train/test splits

**Splitting once: In red, the training set, in blue, the test set**



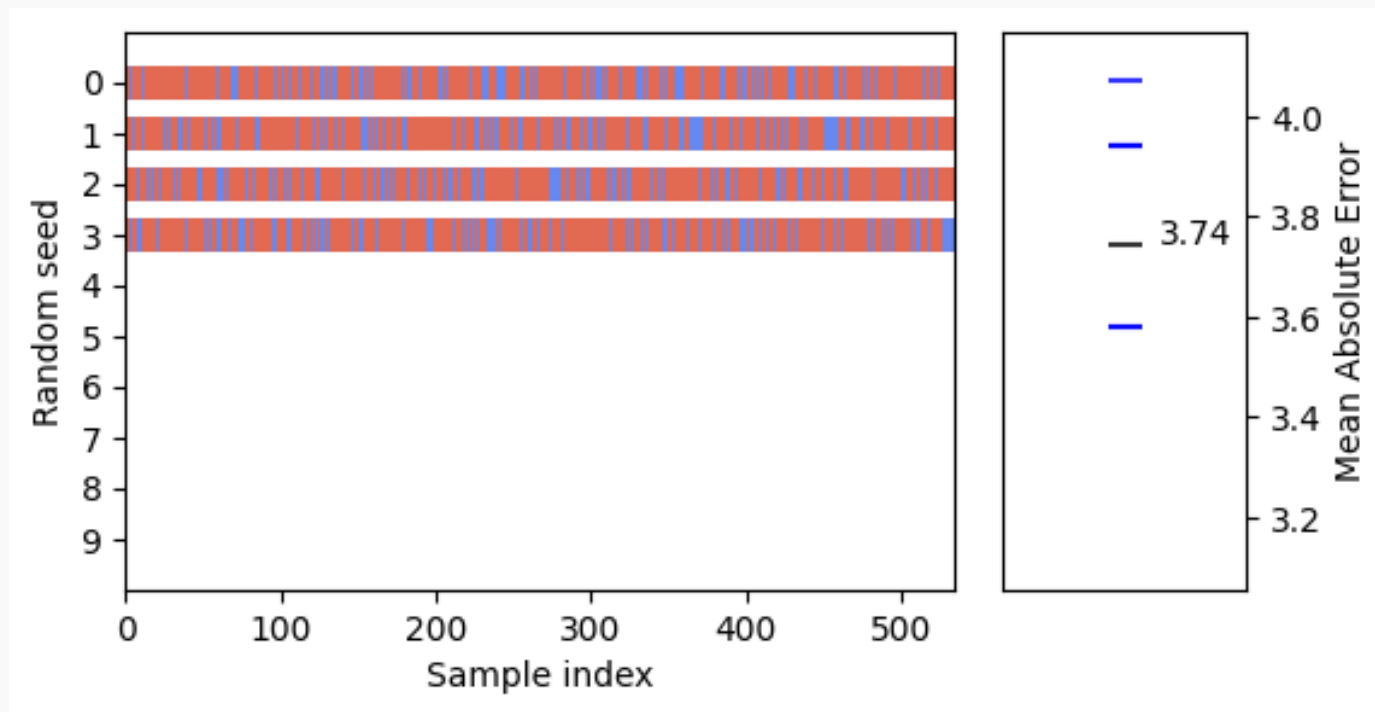
# Repeated train/test splits

But we could have chosen another split ! Yielding a different MAE



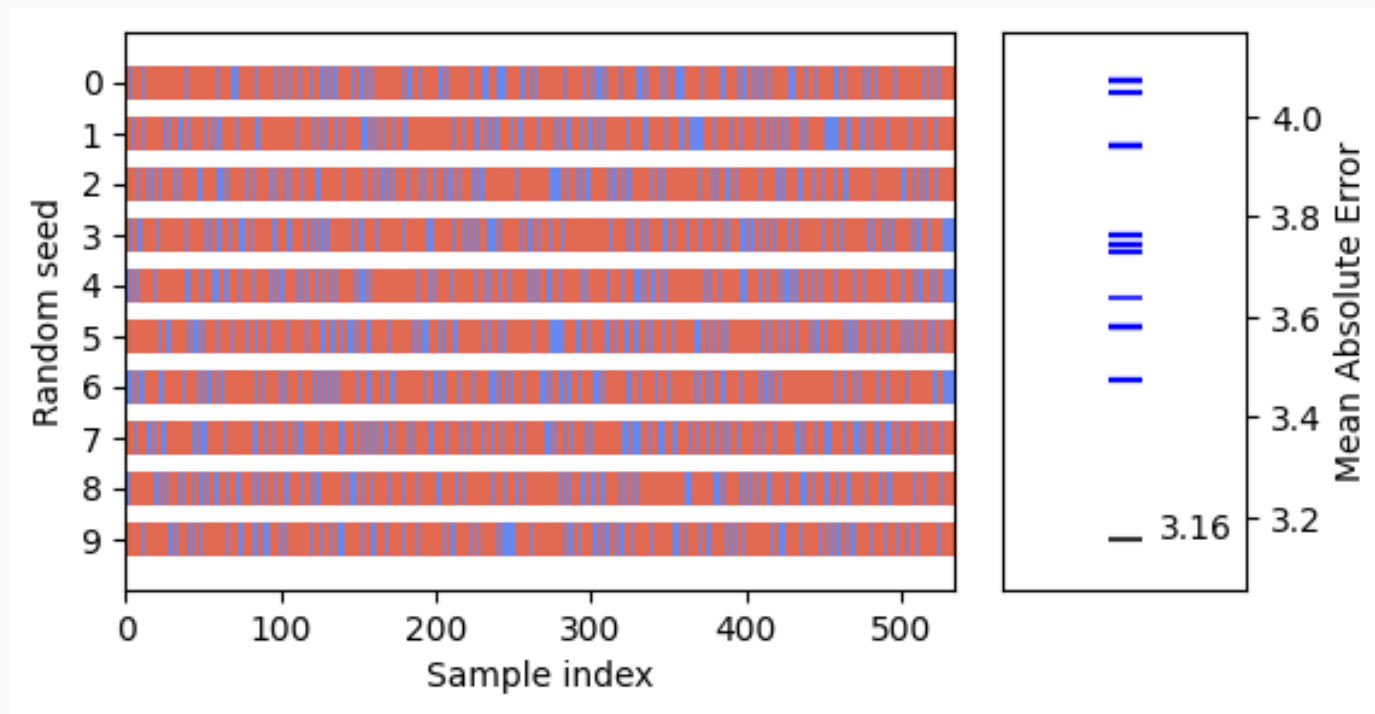
# Repeated train/test splits

And another split...



# Repeated train/test splits

## Splitting ten times



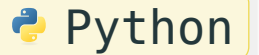
🎉 **Distribution of MAE:  $3.71 \pm 0.26$**

# Repeated train/test splits = Cross-validation

## Cross-validation

- In sklearn, it can be instantiated with `cross_validate`.

```
1 from sklearn.model_selection import cross_validate
2 from sklearn.model_selection import ShuffleSplit
3
4 cv = ShuffleSplit(n_splits=40, test_size=0.3, random_state=0)
5 cv_results = cross_validate(
6     regressor, data, target, cv=cv, scoring="neg_mean_absolute_error"
7 )
```

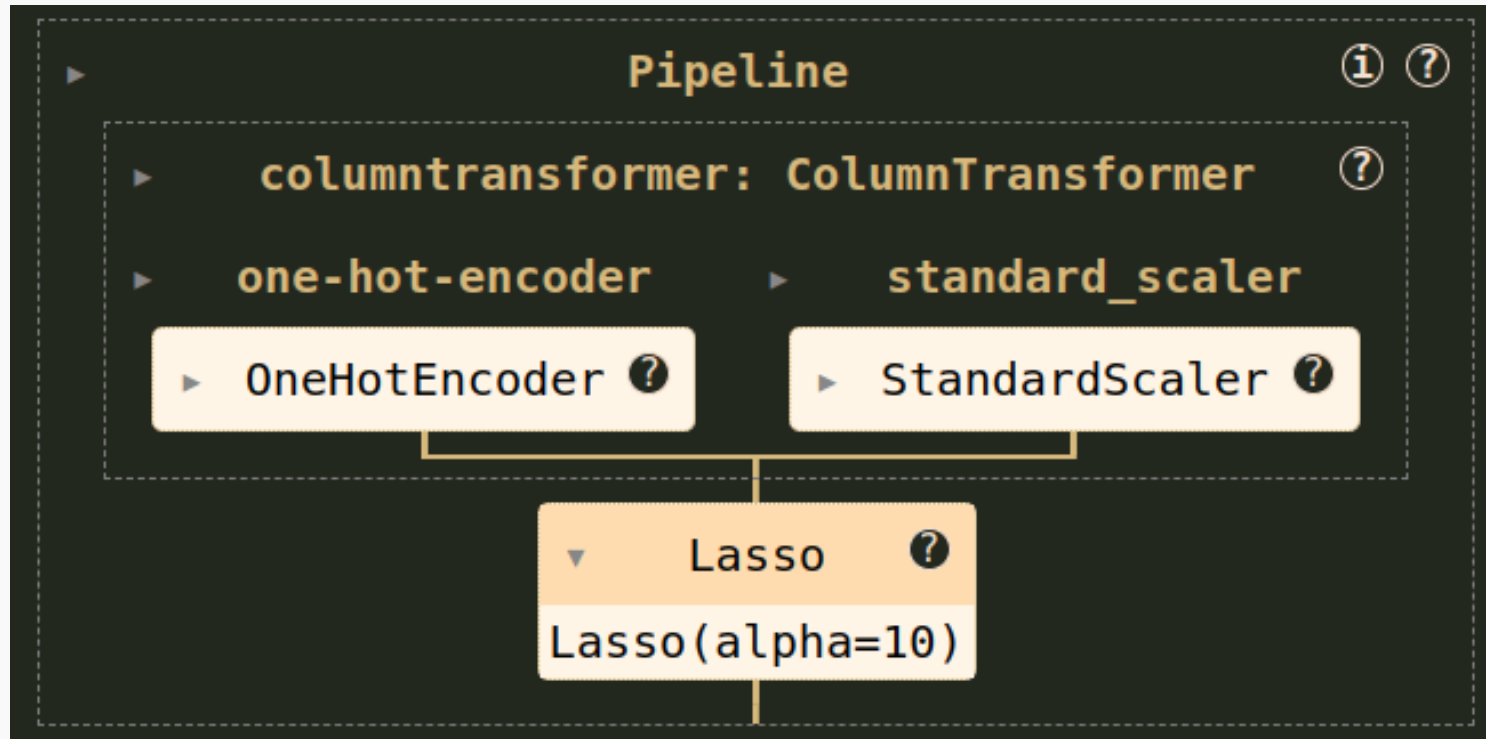


## Cross-validation

- In sklearn, it can be instantiated with `cross_validate`.
- 😊 Robustly estimate generalization performance
- 😄 Estimate variability of the performance: similar to bootstrapping (but different).
- 🚀 Let's use it to select the best models among several candidates!

# Cross-validation for model selection: choose best $\alpha$ for lasso


- Wage pipeline



# Cross-validation for model selection: choose best $\alpha$ for lasso

- Wage pipeline
- Random search over a distribution of  $\alpha$  values

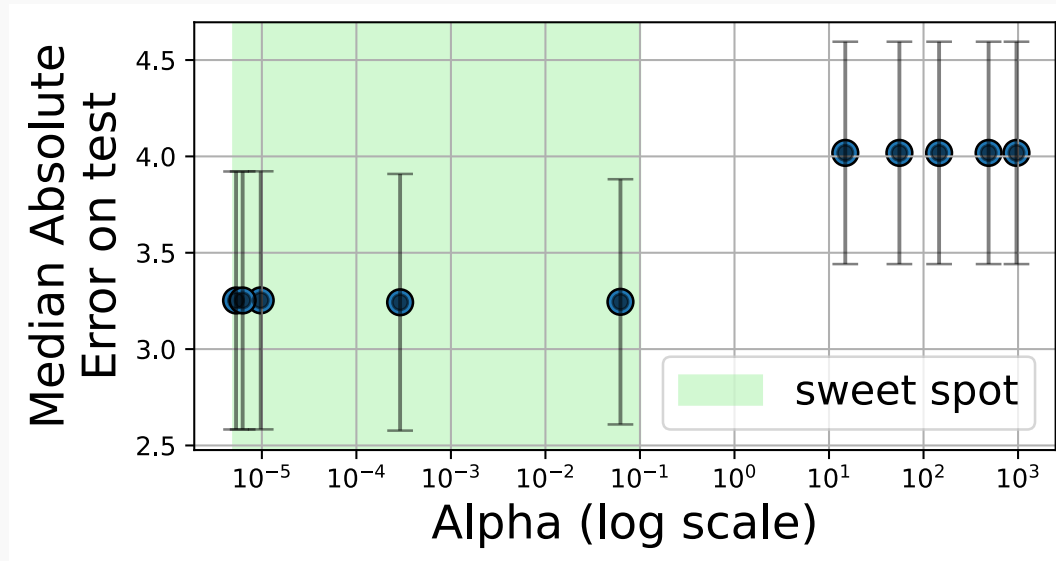
```
1 param_distributions = {"lasso__alpha": loguniform(1e-6, 1e3)}
2 model_random_search = RandomizedSearchCV(
3     pipeline,
4     param_distributions=param_distributions,
5     n_iter=10, # number of hyper-parameters sampled
6     cv=5, # number of folds for the cross-validation
7     scoring="neg_mean_absolute_error", # score to optimize
8 )
9 model_random_search.fit(X, y)
```

 Python



# Cross-validation for model selection: choose best $\alpha$ for lasso

- Wage pipeline
- Random search over a distribution of  $\alpha$  values
- Identify the best  $\alpha$  value(s)



# What final model to use for new prediction?

- Either refit on full data the model with the best hyper-parameters on the full data: often used in practice.
- Or use the aggregation of outputs from the cross-validation of the best model:

$$\hat{y} = \frac{1}{K} \sum_{k=1}^K \hat{y}_k$$

where  $\hat{y}_k$  is the prediction of the model trained on the  $k$ -th fold.

- Proof that cross-validation selects the best model asymptotically among a family of models (averaging on the folds): (Lecué & Mitchell, 2012)

# Naive cross-validation to select AND estimate the best performances

TODO

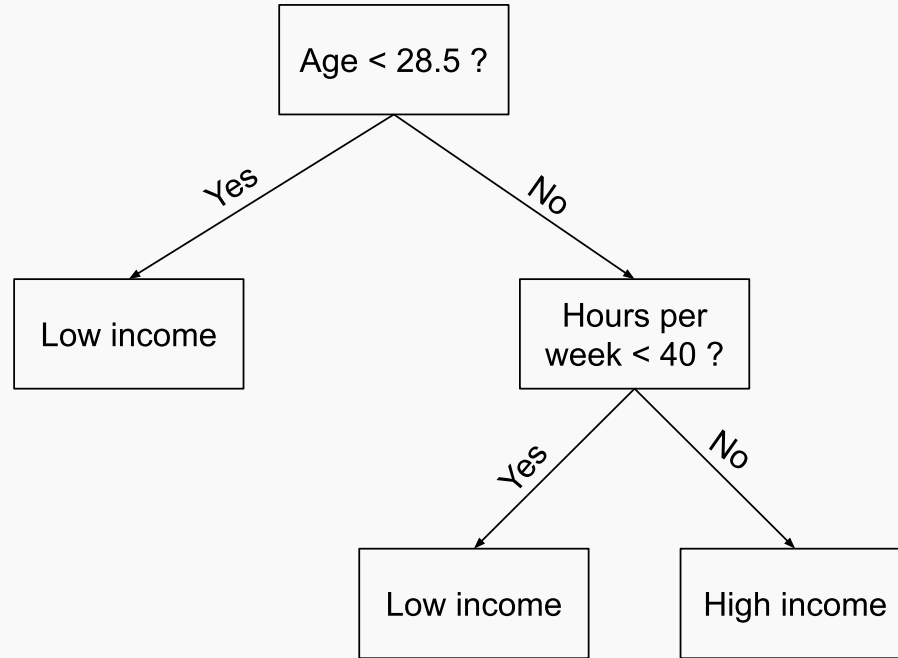
# Nested cross-validation to select the best model

TODO

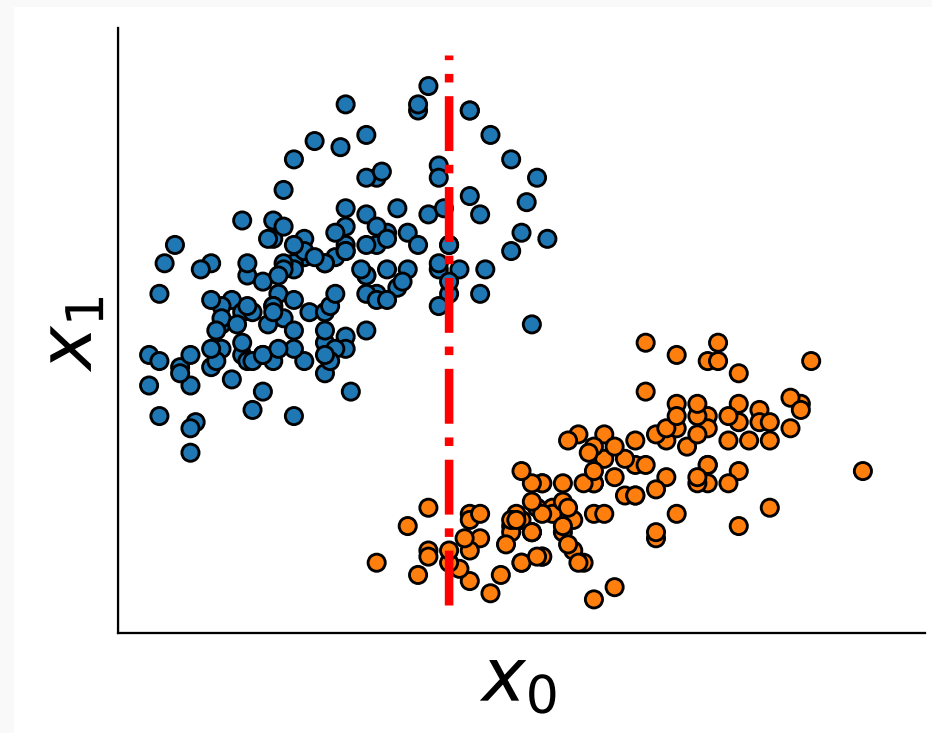
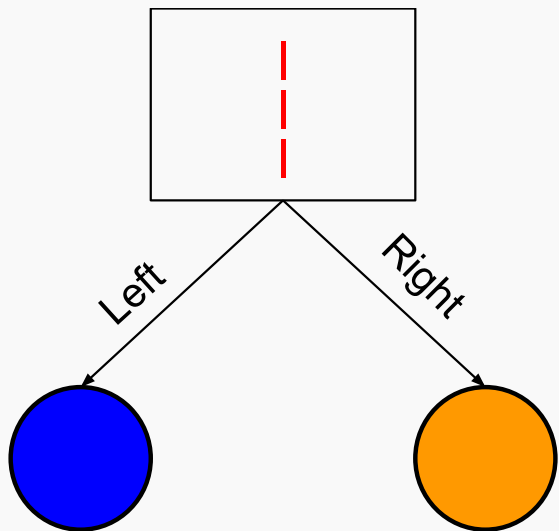
# Flexible models: Tree, random forests and boosting

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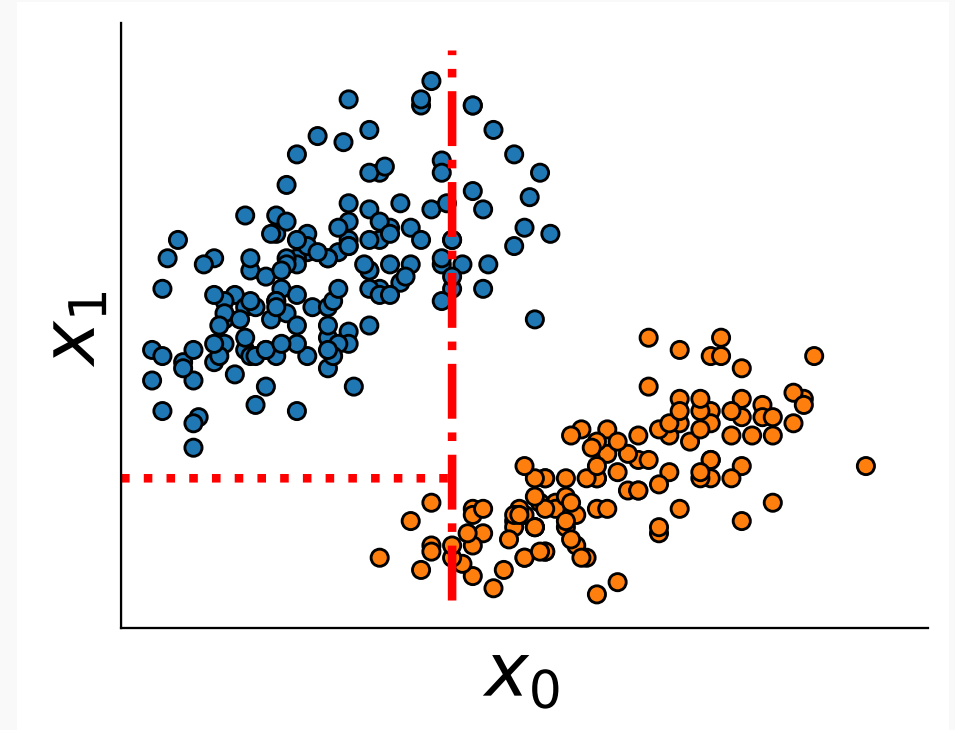
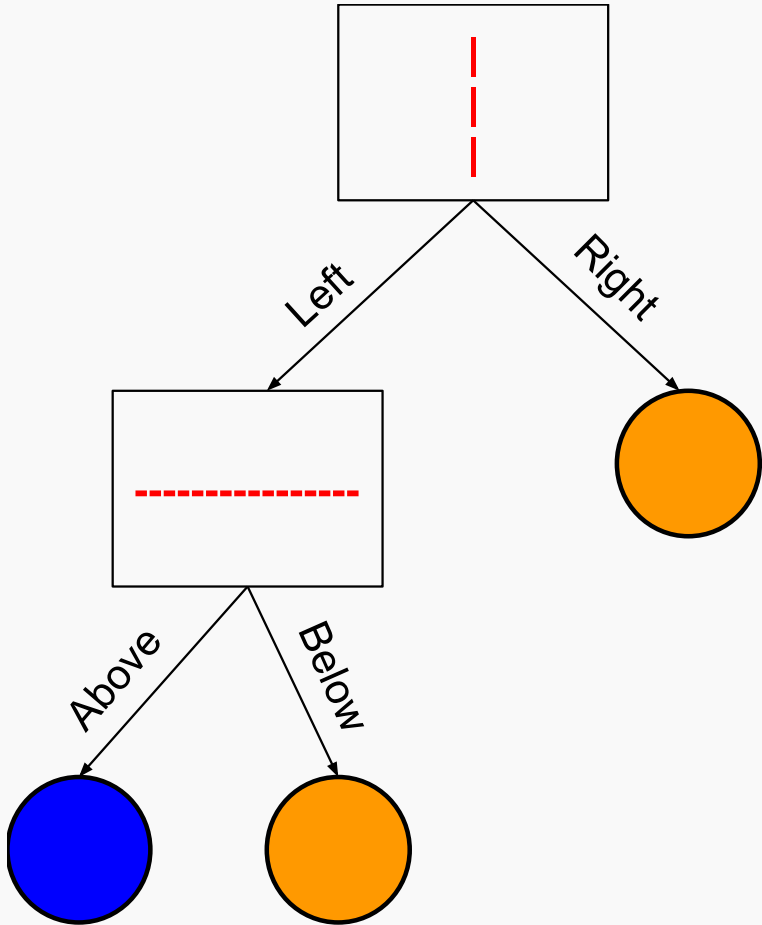
# What is a decision tree? An example.



# Growing a classification tree

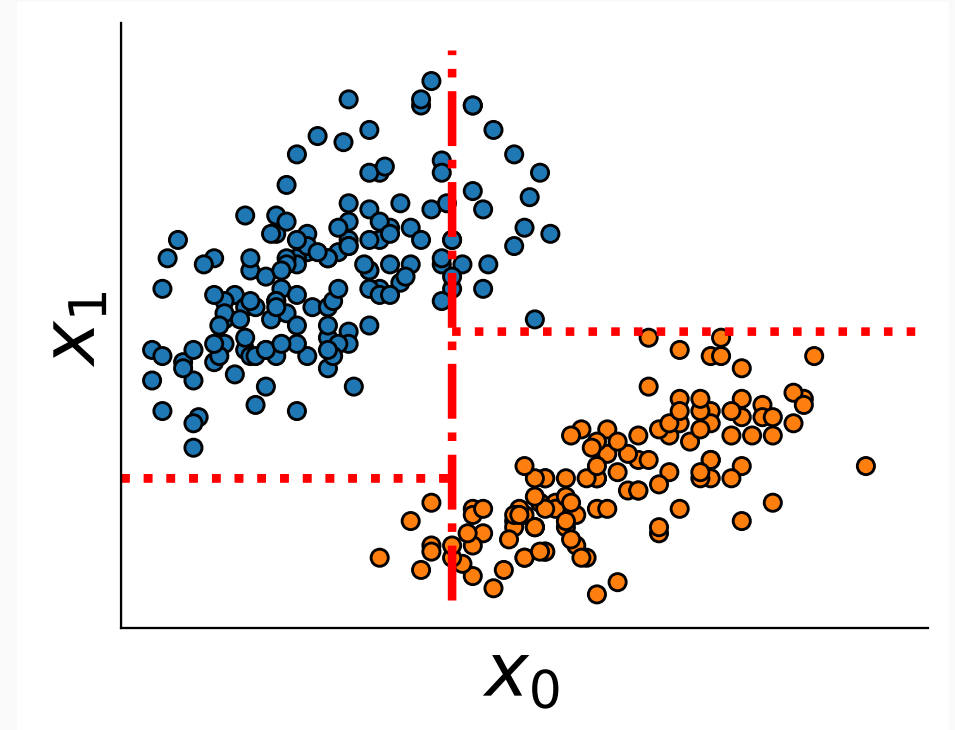
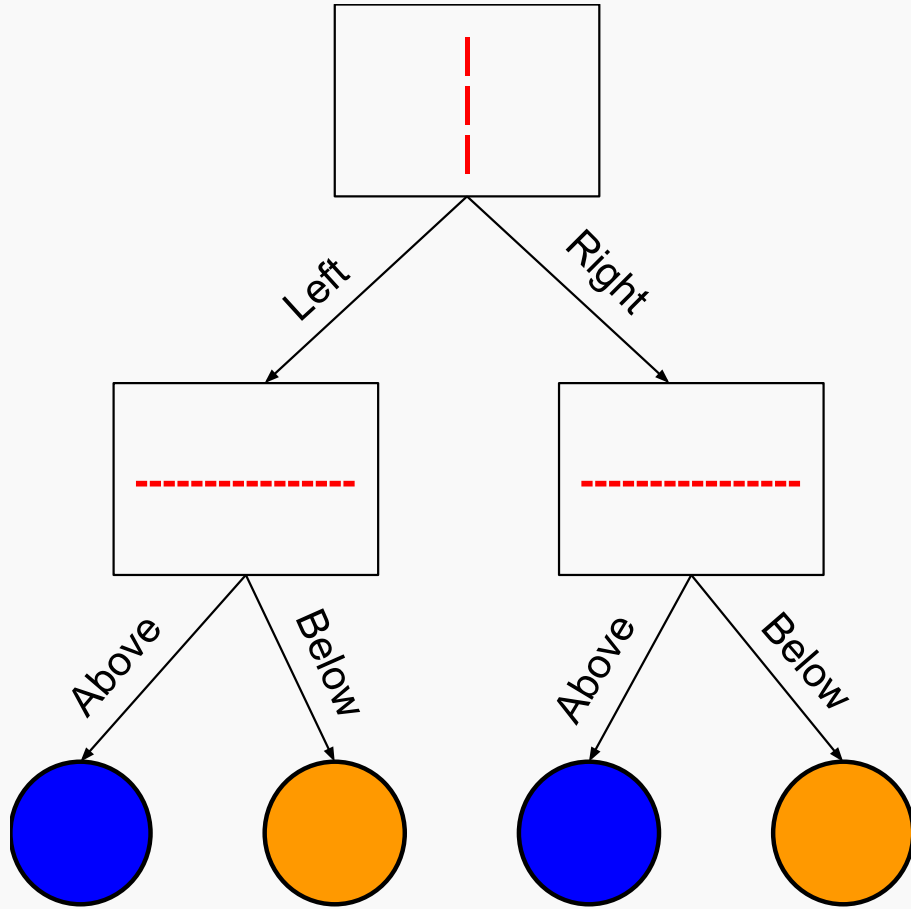


# Growing a classification tree

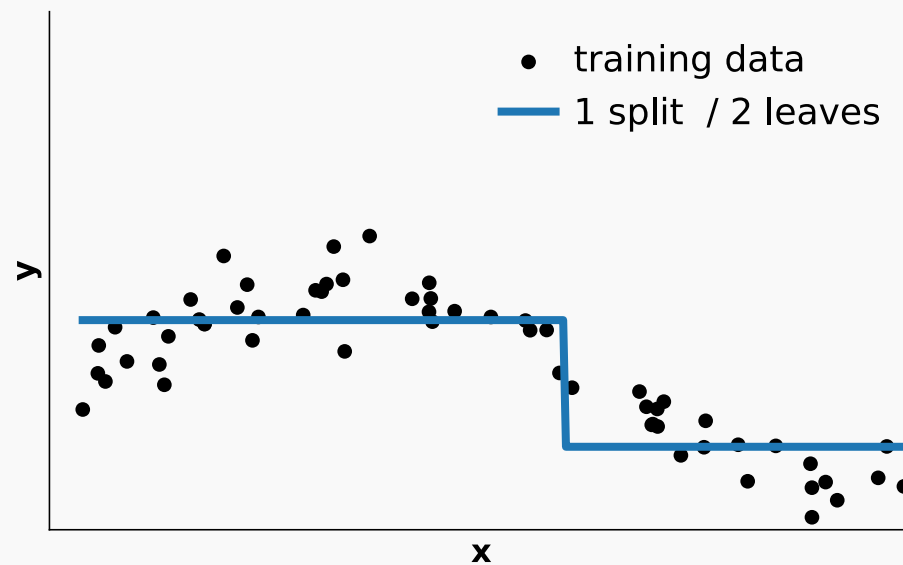
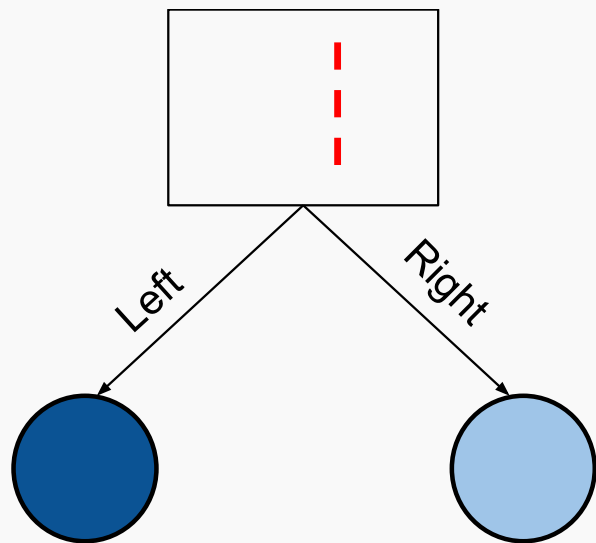




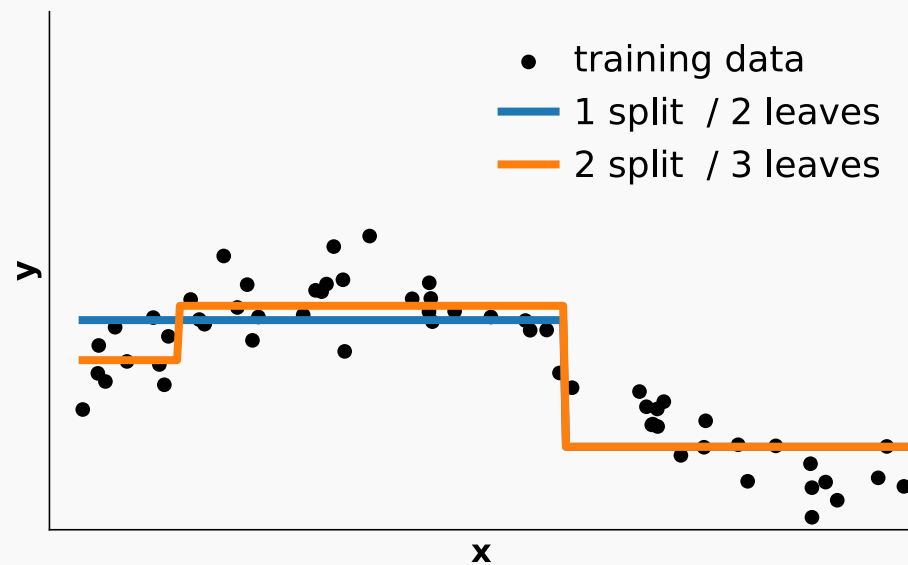
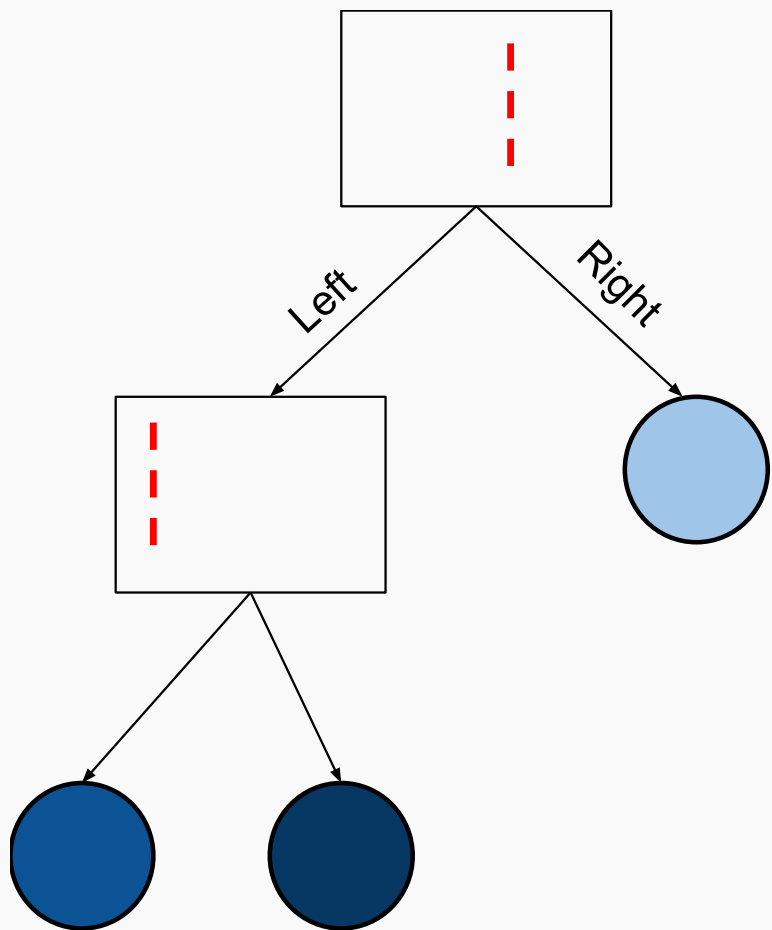
# Growing a classification tree



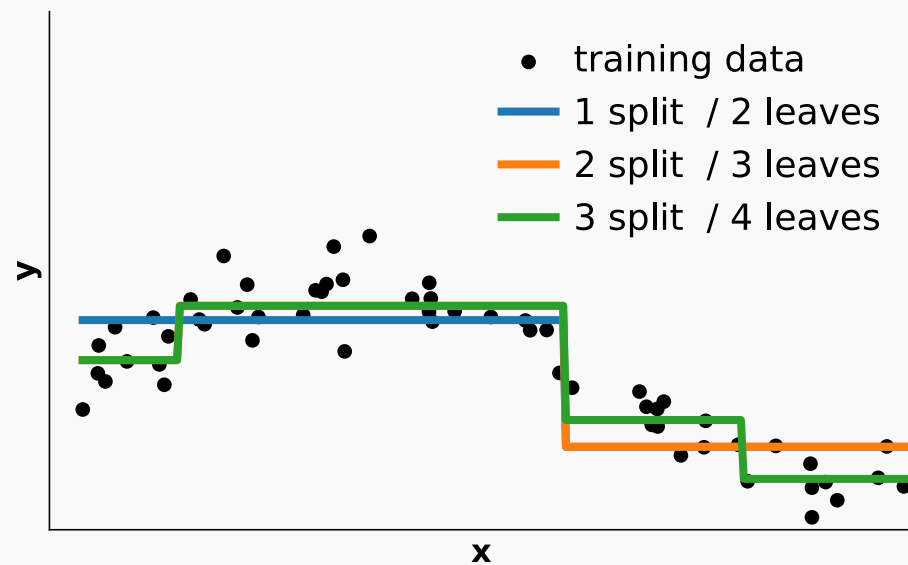
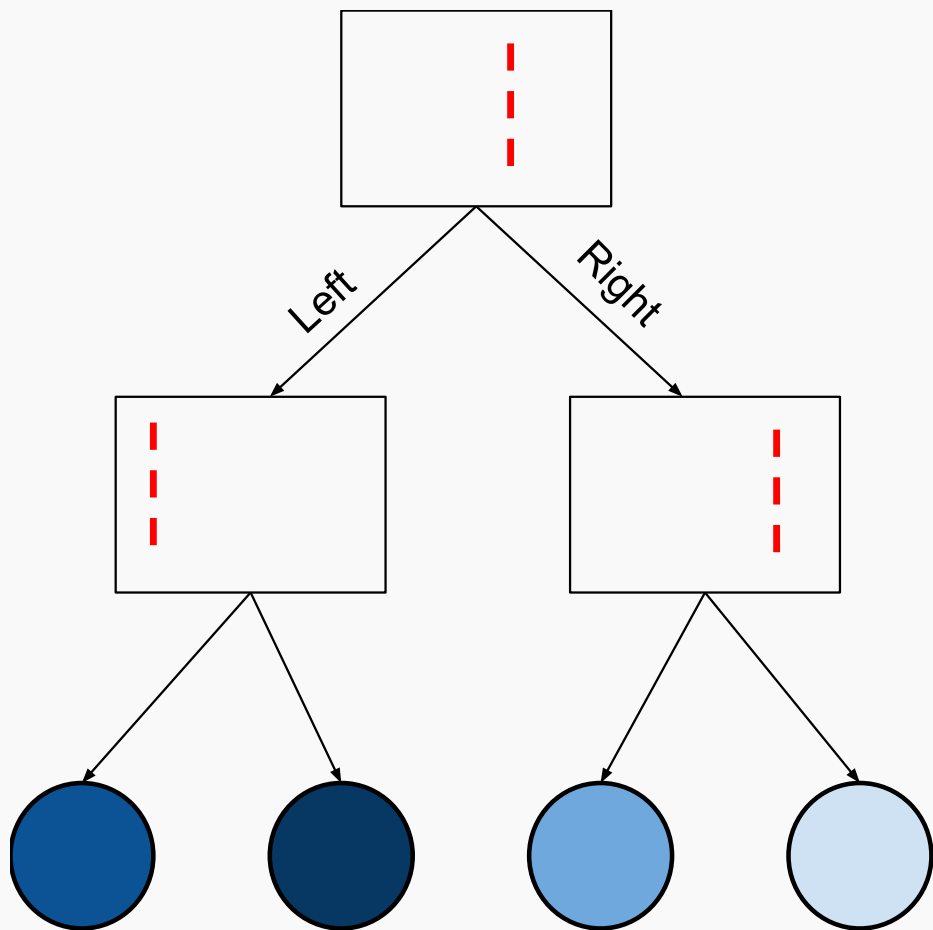
# Growing a regression tree



# Growing a regression tree



# Growing a regression tree



# How the best split is chosen?

## The best split minimizes an impurity criteria

- for the next left and right nodes
- over all features
- and all possible splits

## Formally

Let the data at node  $m$  be  $Q_m$  with  $n_m$  samples. For a candidate split on feature  $j$  and threshold  $t_m$   $\theta = (j, t_m)$ , the split yields:

$$Q_m^{\text{left}}(\theta) = \{(x, y) | x_j \leq t_m\} \text{ and } Q_m^{\text{right}}(\theta) = Q_m \setminus Q_m^{\text{left}}(\theta)$$

Then  $\theta$  is chosen to minimize the impurity criteria averaged over the two children nodes:

$$\theta^* = \operatorname{argmin}_{j, t_m} \left[ \frac{n_m^{\text{left}}}{n_m} H(Q_m^{\text{left}}(\theta)) + \frac{n_m^{\text{right}}}{n_m} H(Q_m^{\text{right}}(\theta)) \right] \text{ with } H \text{ the impurity criteria.}$$

# Impurity criteria

## For classification

### Gini impurity

$$H(Q_m) = \sum_k p_{mk}(1 - p_{mk}) \text{ with } p_{mk} = \frac{1}{n_m} \sum_{y \in Q_m} I(y = k)$$

### Cross-entropy

$$H(Q_m) = - \sum_{k \in K} p_{mk} \log(p_{mk})$$

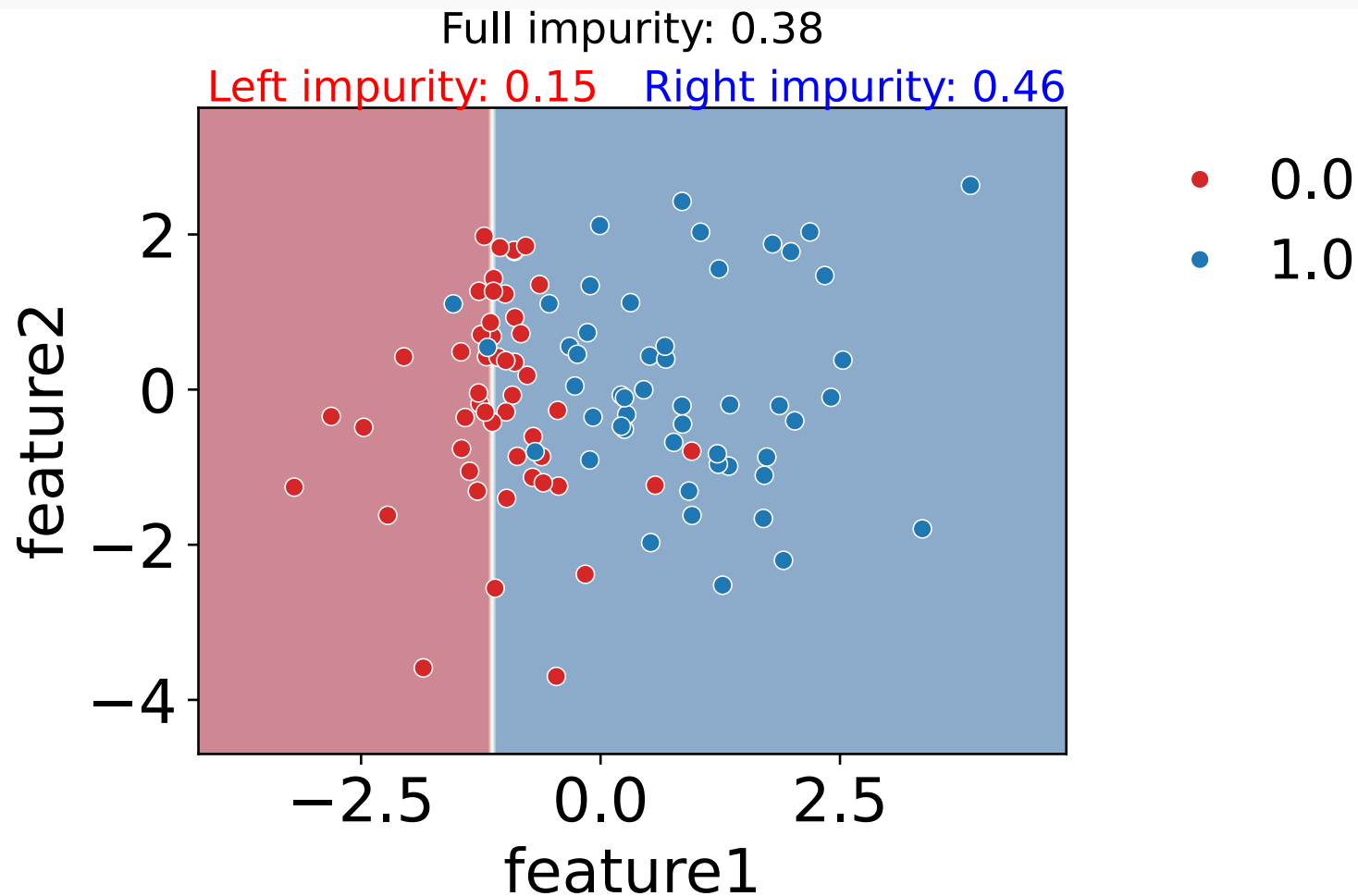
## For regression

### Mean squared error

$$H(Q_m) = \frac{1}{n_m} \sum_{y \in Q_m} (y - \overline{y_m})^2 \text{ where } \overline{y_m} = \frac{1}{n_m} \sum_{y \in Q_m} y$$

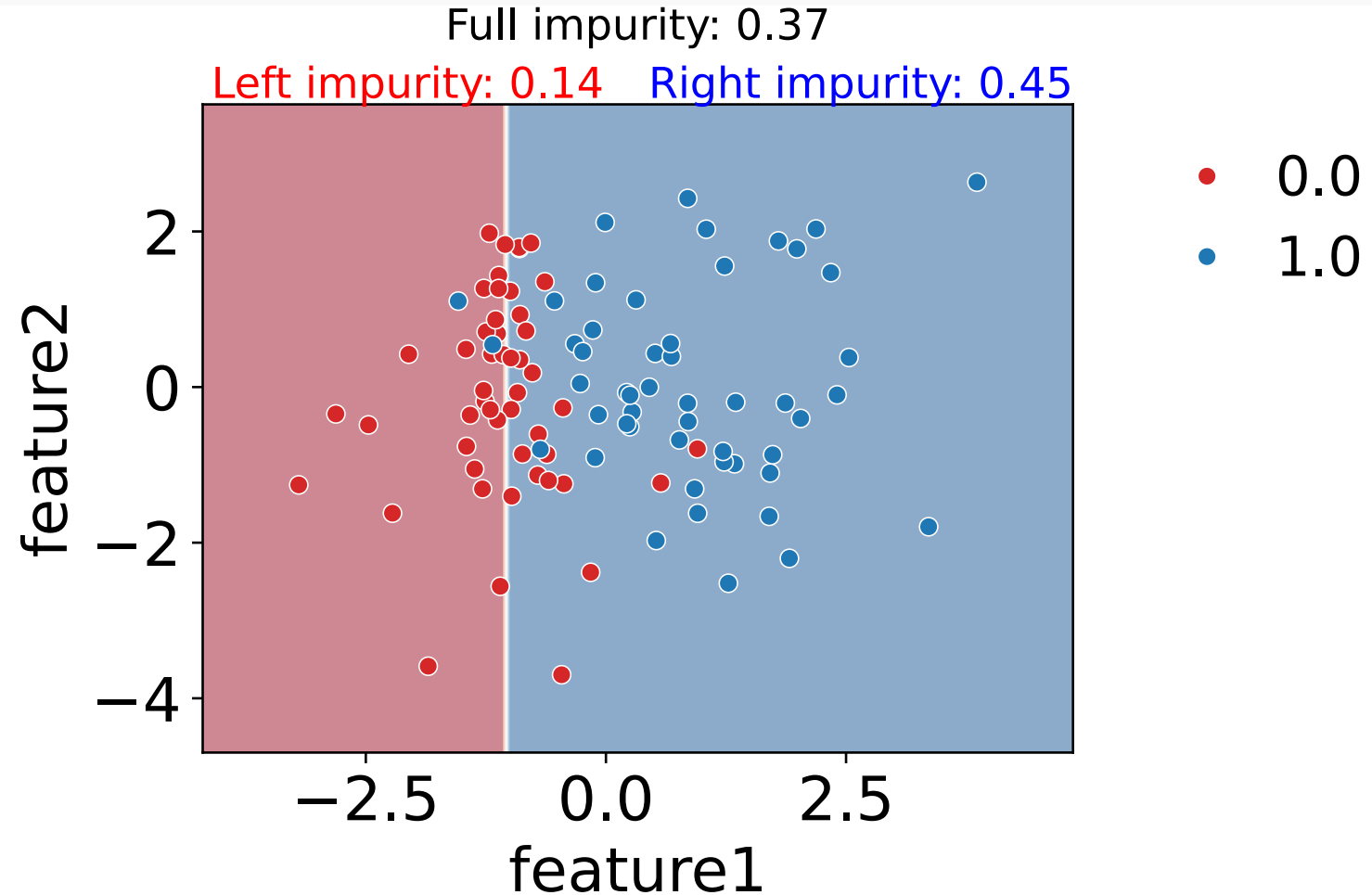
# Chose the best split: example

Random split



# Chose the best split: example

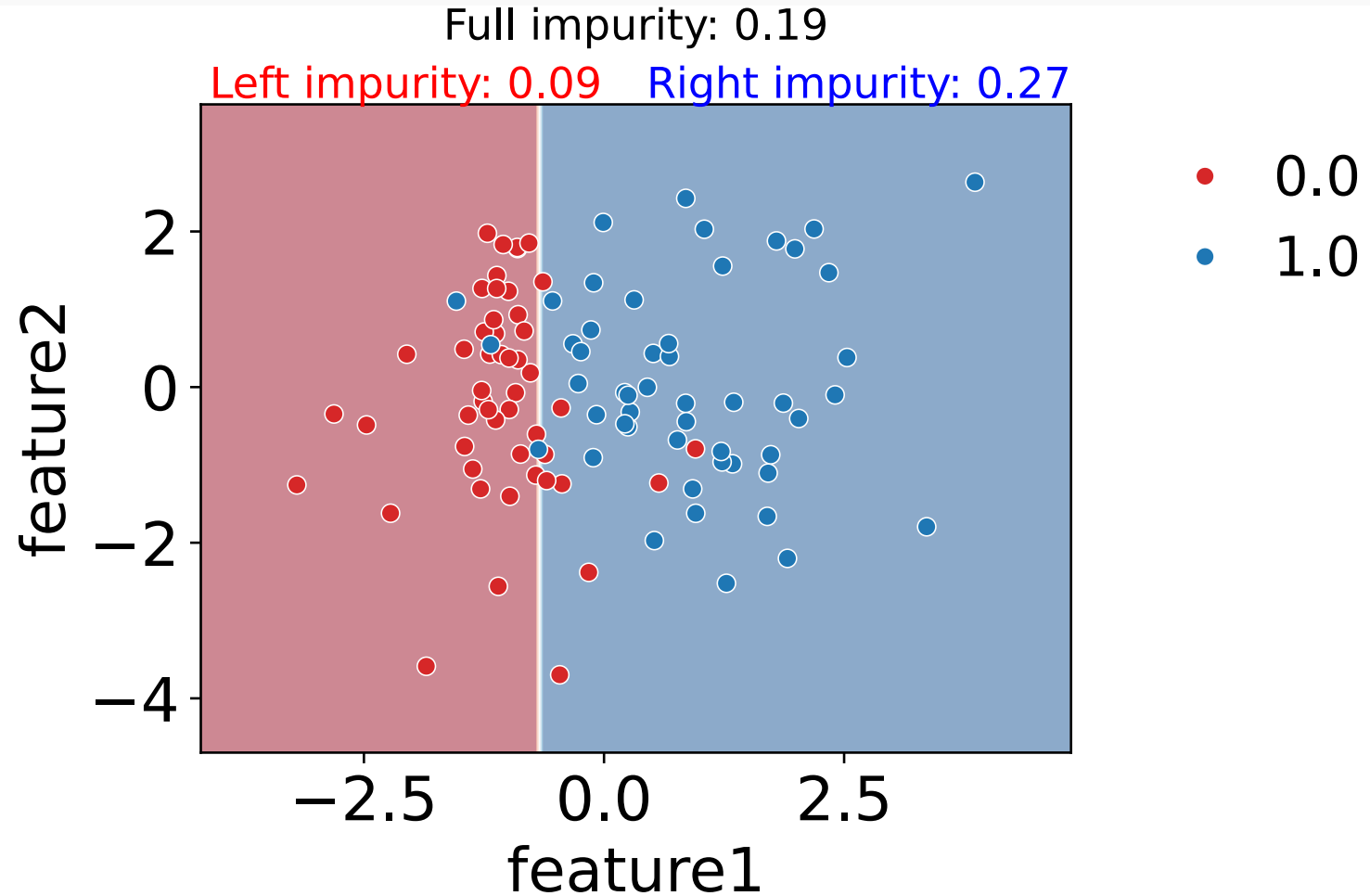
Moving the split to the right from one point





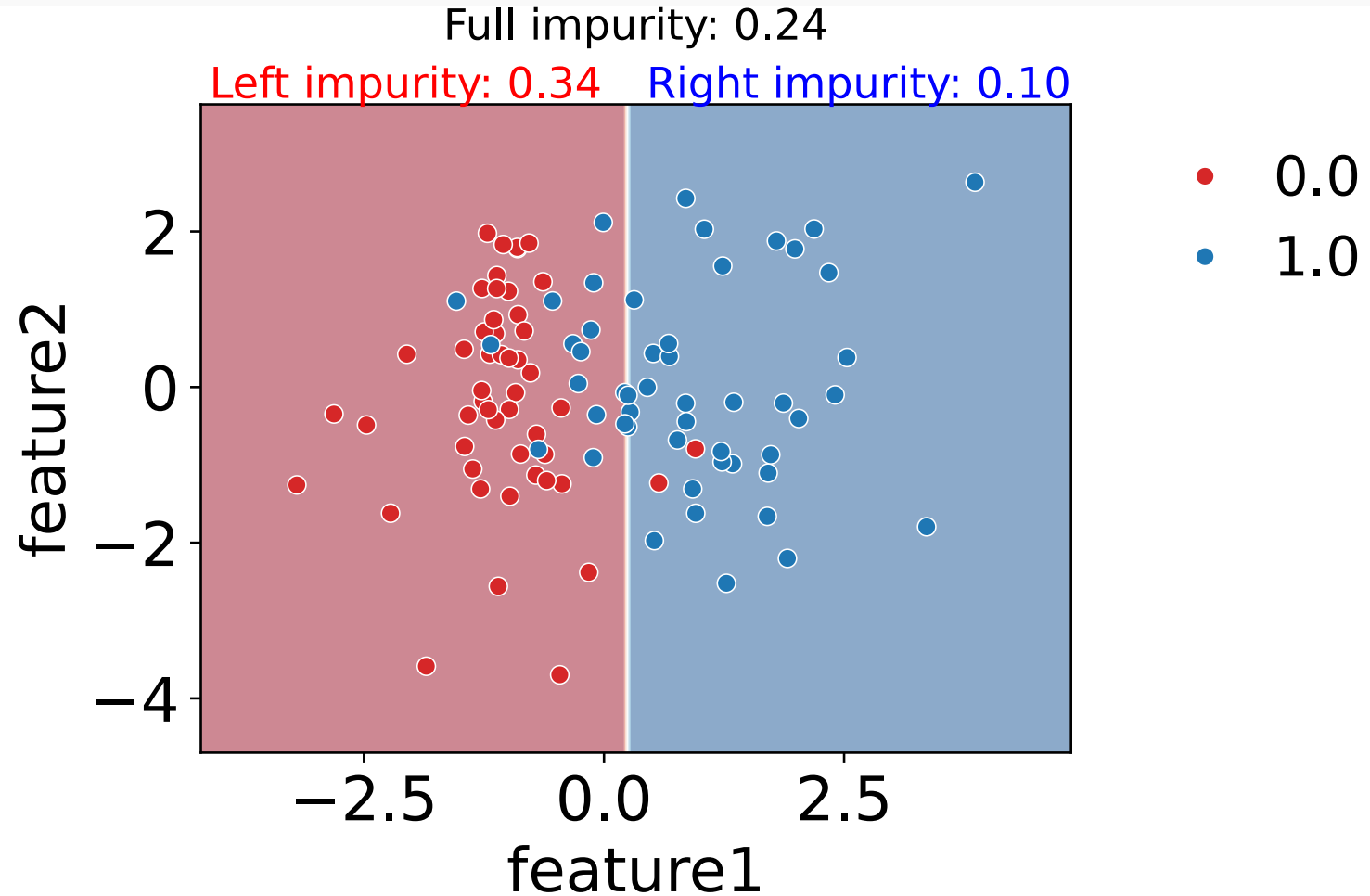
# Chose the best split: example

Moving the split to  
the right from 10  
points



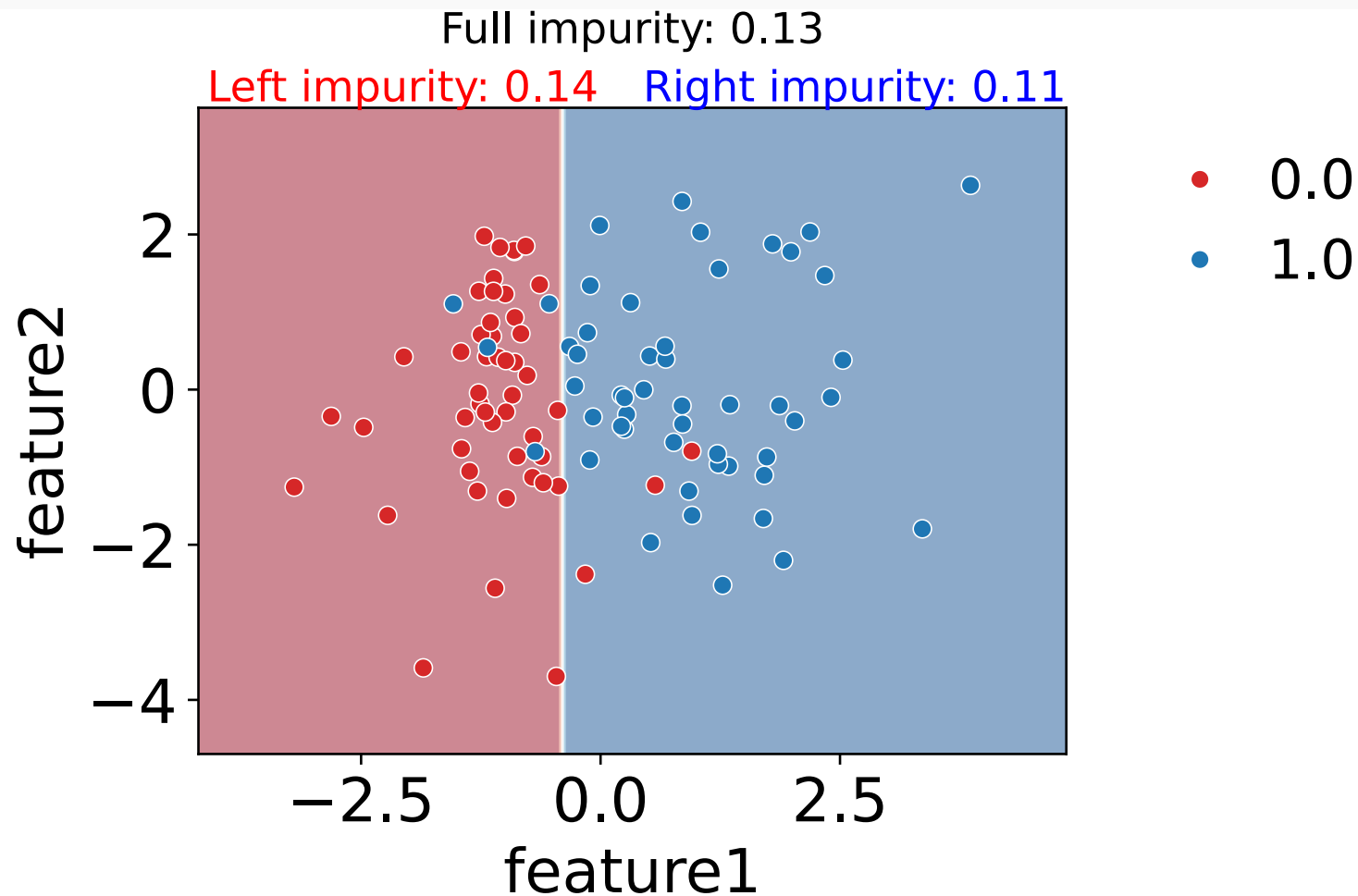
# Chose the best split: example

Moving the split to  
the right from 20  
points

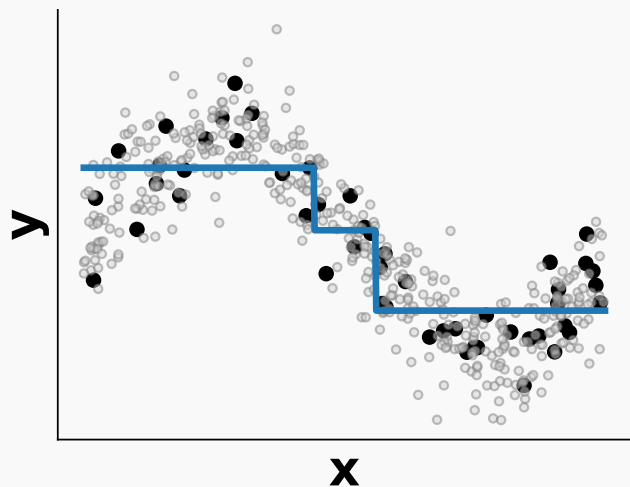


# Chose the best split: example

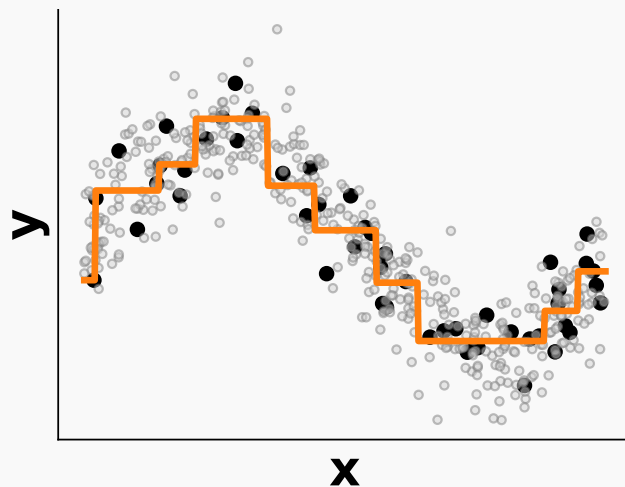
Best split



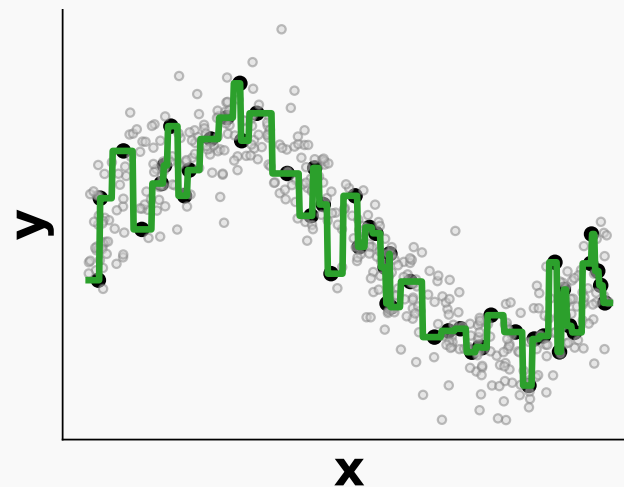
# Tree depth and overfitting



Underfitting  
max depth or  
max\_leaf\_nodes  
too small



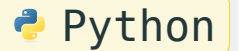
Best trade-off



Overfitting  
max depth or  
max\_leaf\_nodes  
too large

# Main hyper-parameters of tree models

```
1 DecisionTreeRegressor(  
2     criterion="squared error",  
3     max_depth=None, # Tree depth (assume symmetric trees)  
4     min_samples_split=2, # Tree depth (allowing asymmetric trees)  
5     min_samples_leaf=1, # Tree depth (allowing asymmetric trees)  
6     max_leaf_nodes=None, # Tree depth (allowing asymmetric trees)  
7     min_impurity_decrease=0.0, # Tree depth (allowing asymmetric trees)  
8 )
```



## Pros

- Easy to interpret
- Handle mixed types of data: numerical, categorical and missing data
- Handle interactions
- Fast to fit

## Cons

- Prone to overfitting
- Unstable: small changes in the data can lead to very different trees
- Mostly useful as a building block for ensemble models: random forests and boosting trees

## **Bagging: Bootstrap AGGREGatING**

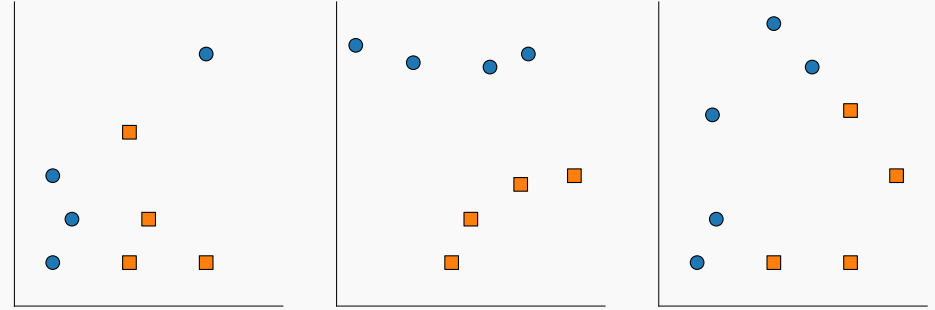
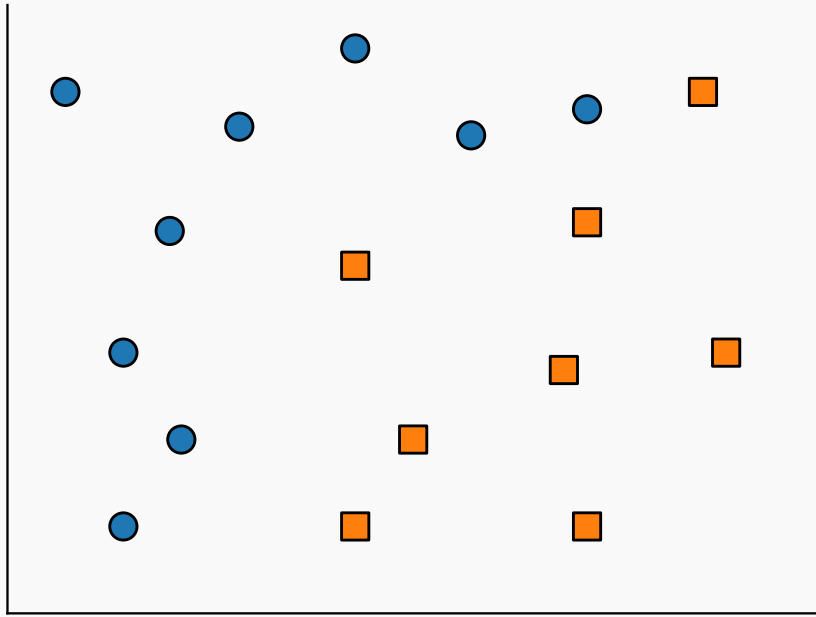
Bootstrap resampling (random sampling with replacement) proposed by (Breiman, 1996)

Built upon Bootstrap, introduced by (Efron, 1992) to estimate the variance of an estimator.

Bagging is used in machine learning to reduce the variance of a model prone to overfitting

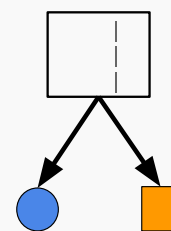
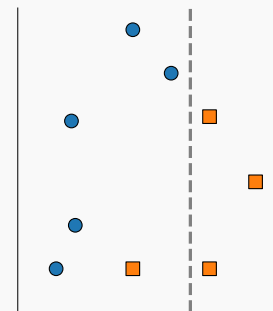
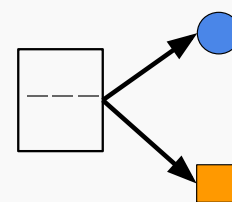
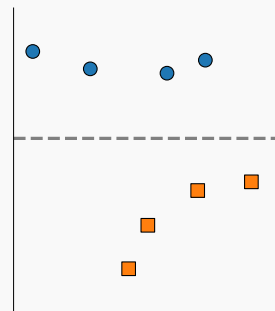
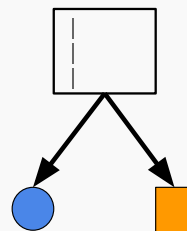
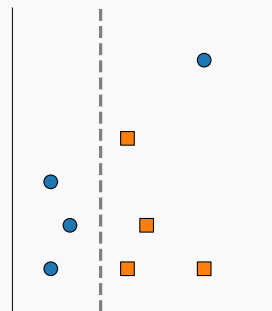
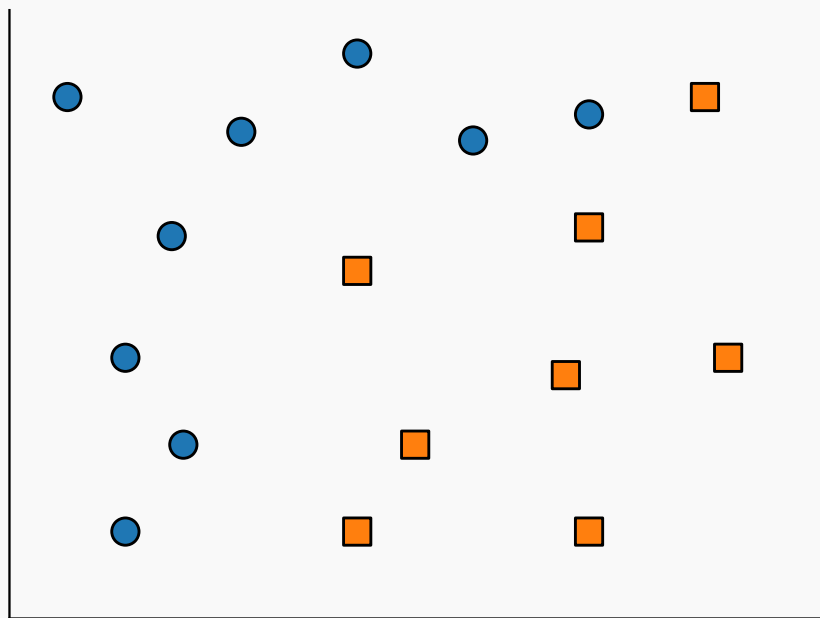
Can be used with any model

# Random forests: Bagging with classification trees

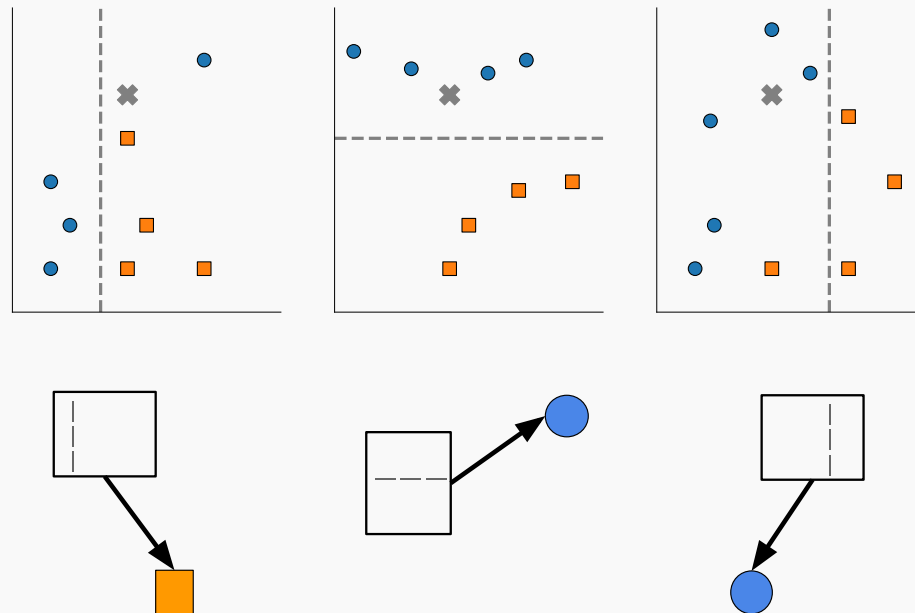
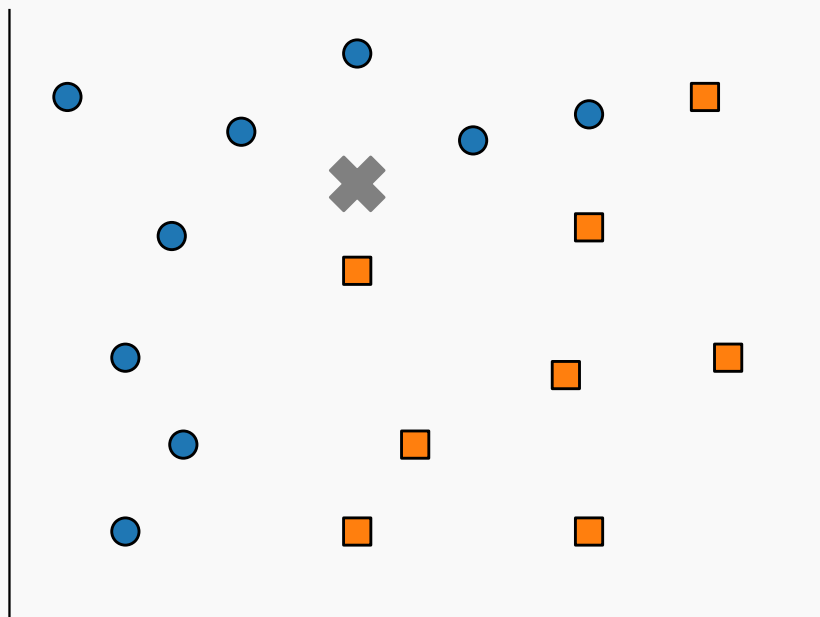




# Random forests: Bagging with classification trees

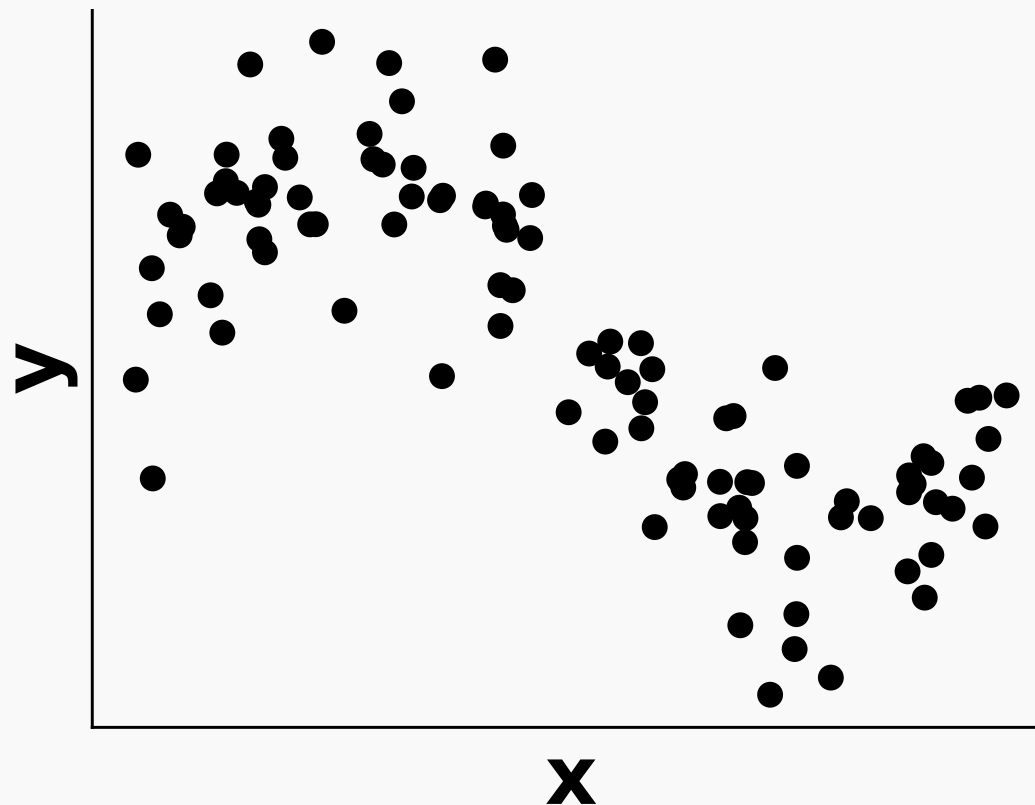


# Random forests: Bagging with classification trees

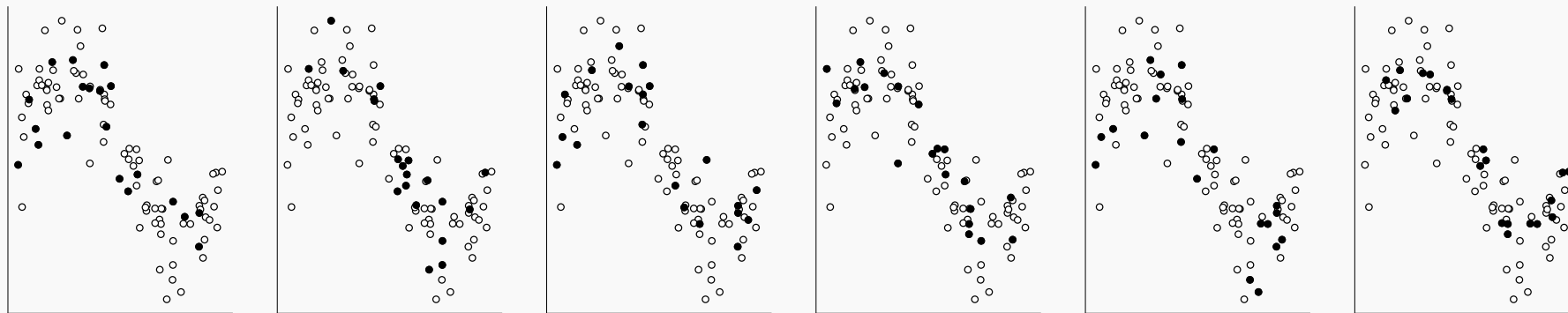


VOTE (  ,  ,  ) = 

# Random forests: Bagging with regression trees

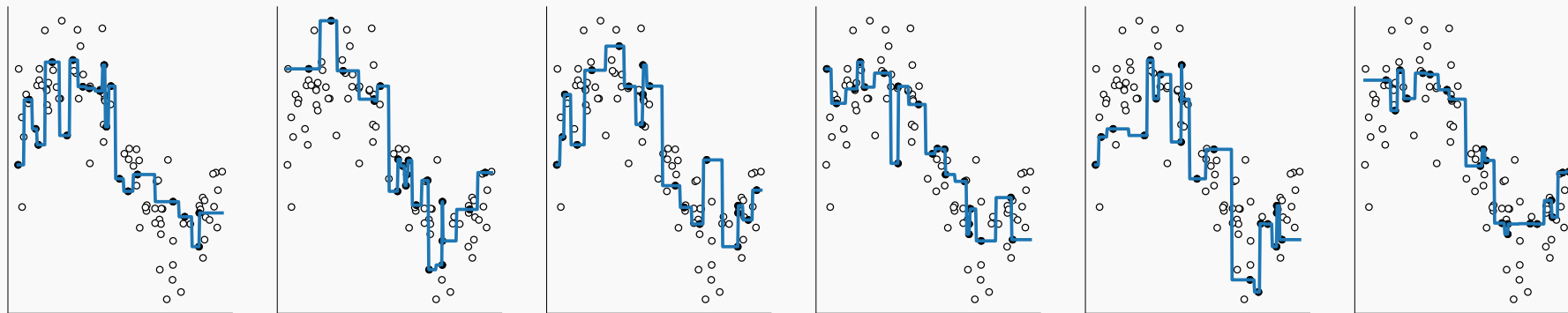


# Random forests: Bagging with regression trees



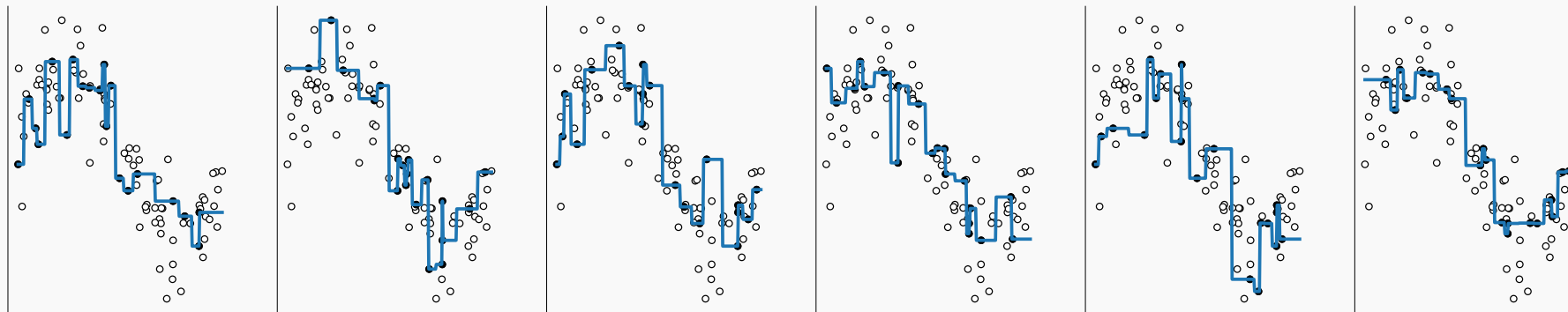
- Select multiple subsets of the data

# Random forests: Bagging with regression trees

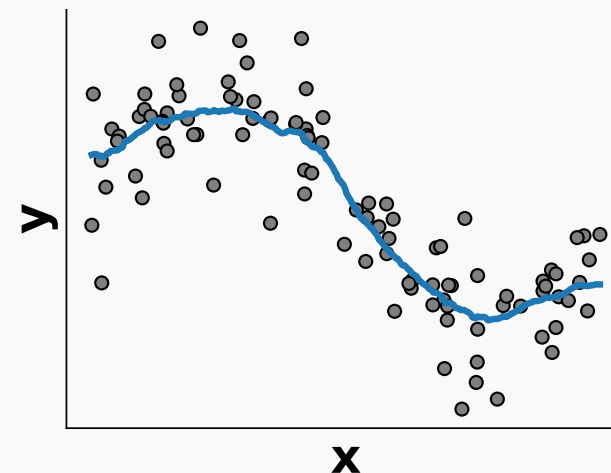


- Select multiple subsets of the data
- Fit one model on each

# Random forests: Bagging with regression trees




- Select multiple subsets of the data
- Fit one model on each
- Average the predictions



# Main hyper-parameters of random forests

```
1  sklearn.ensemble.RandomForestRegressor(  
2      n_estimators=100, # Number of trees to fit (sample randomization): not useful to  
   tune in practice  
3      criterion='squared_error',  
4      max_depth=None, # tree regularization  
5      min_samples_split=2, # tree regularization  
6      min_samples_leaf=1, # tree regularization  
7      min_impurity_decrease=0.0, # tree regularization  
8      n_jobs=None, # Number of jobs to run in parallel  
9      random_state=None, # Seed for randomization  
10     max_features=1.0, # Number/ratio of features at each split (feature randomization)  
11     max_samples = None # Number of sample to draw (with replacement) for each tree  
12 )
```

 Python

# Random Forests are bagged randomized decision trees

## Random forests

- For each tree a random subset of samples are selected
- At each split a random subset of features are selected (more randomization)
- The best split is taken among the restricted subset
- Feature randomization decorrelates the prediction errors
- Uncorrelated errors make bagging work better

## Take away

- Bagging and random forests fit trees independently
- Each deep tree overfits individually
- Averaging the tree predictions reduces overfitting



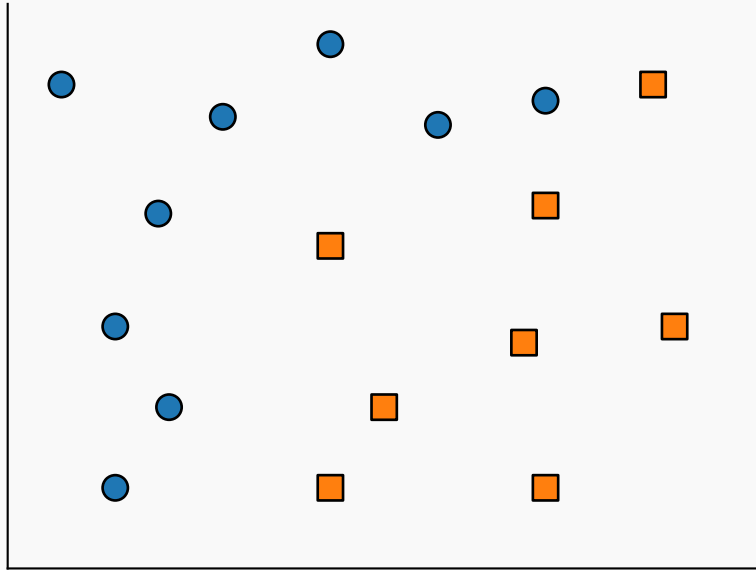
## **Boosting use multiple iterative models**

- Use of simple underfitting models: eg. shallow trees
- Each model corrects the errors of the previous one

## **Two examples of boosting**

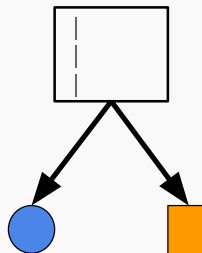
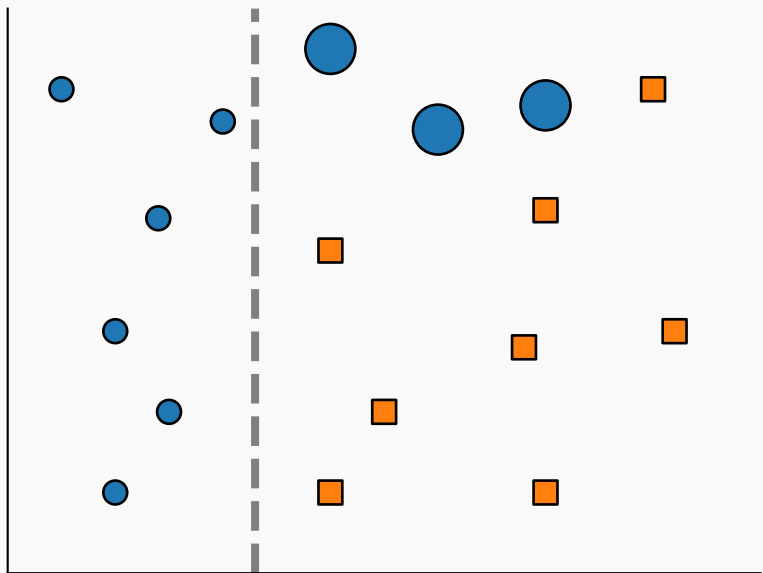
- Adaptive boosting (AdaBoost): reweight mispredicted samples at each step (Friedman et al., 2000)
- Gradient boosting: predict the negative errors of previous models at each step (Friedman, 2001)

# Boosting: Adaptive boosting, classification example

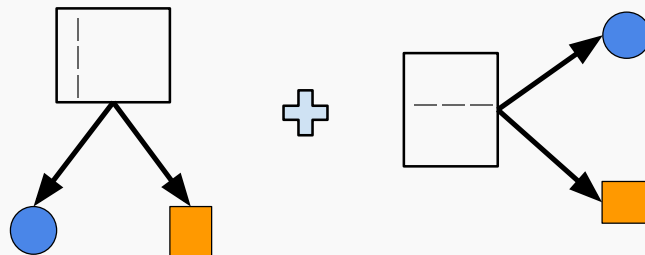
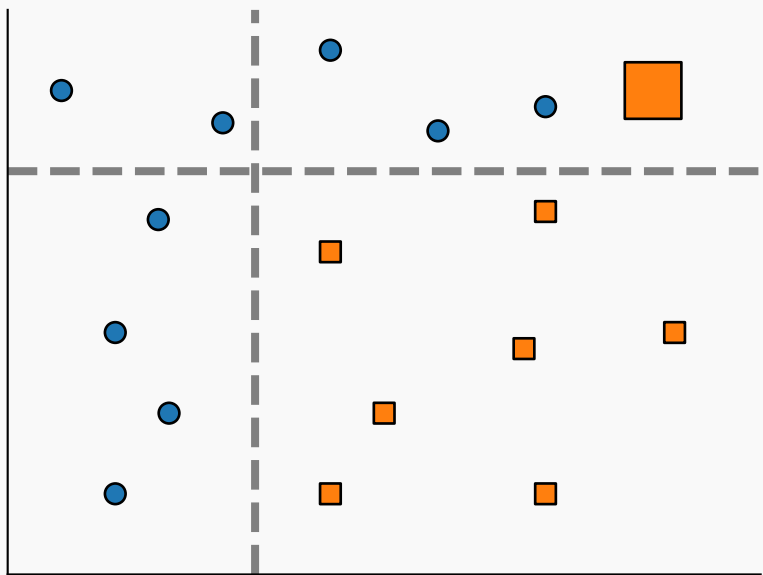


# Boosting: Adaptive boosting, classification example

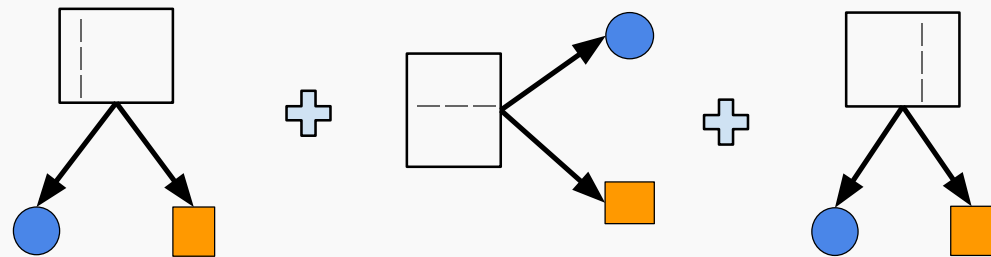
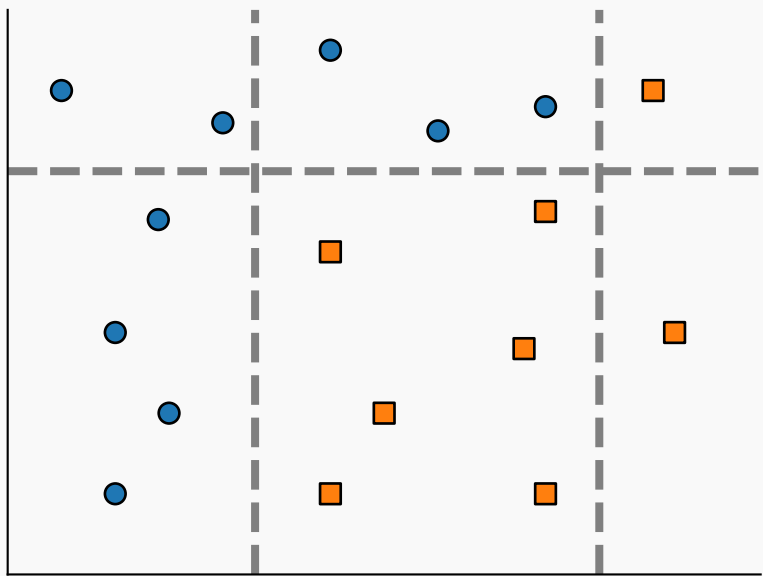
**First prediction:**



# Boosting: Adaptive boosting, classification example



# Boosting: Adaptive boosting, classification example



**At each step, AdaBoost weights mispredicted samples**

# Adaboost for classification: choice of the weight

## Algorithm for Adaboost

- Initialize the observation weights  $w_i = \frac{1}{N}, i = 1..N$
- For  $m = 1$  to  $M$  :
  - Fit a classifier  $F_m(x)$  to the training data using weights  $w_i$
  - Compute  $\text{err}_m = \frac{\sum_{i=1}^N w_i \mathbb{1}[y_i \neq F_m(x_i)]}{\sum_{i=1}^N w_i}$
  - Compute  $\alpha_m = \log\left(\frac{1-\text{err}_m}{\text{err}_m}\right)$
  - Set  $w_i \rightarrow w_i \exp[\alpha_m \mathbb{1}[y_i \neq F_m(x_i)]], i = 1..N$
- Output  $F(x) = \text{sign}\left(\sum_{i=1}^M \alpha_m G_m(x)\right)$



See (Murphy, 2022) for the motivation.

# Adaboost: Take-away

- Sequentially fit weak learners (eg. shallow trees)
- Each new learner corrects the errors of the previous one thanks to sample weights
- The final model is a weighted sum of the weak learners
- The weights are learned by the algorithm to given more importance to errors
- Any weak learner can be used

# Adaboost: Take-away

- Sequentially fit weak learners (eg. shallow trees)
- Each new learner corrects the errors of the previous one thanks to sample weights
- The final model is a weighted sum of the weak learners
- The weights are learned by the algorithm to give more importance to errors
- Any weak learner can be used

**Adaboost is tailored to a specific loss function (exponential loss)**



Can we exploit the boosting idea for any loss function?



# Gradient boosting: how to choose the iterative learners?

## Boosting formulation

$F_{m(x)} = F_{m-1}(x) + h_{m(x)}$  with  $F_{m-1}$  the previous estimator,  $h_m$ , new weak learner.

## Minimization problem

$$h_m = \operatorname{argmin}_h (L_m) = \operatorname{argmin}_h \sum_{i=1}^n l(y_i, F_{m-1}(x_i) + h(x_i))$$

Rewrite inside the sum:

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### Taylor expansion

For  $l(\cdot)$  differentiable:  $l(y + h) \approx l(y) + h \frac{\partial l}{\partial y}(y)$

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Finally:  $h_m = \operatorname{argmin}_h \sum_{i=1}^n h(x_i) g_i \rightarrow$  kind of an inner product  $\langle g, h \rangle$

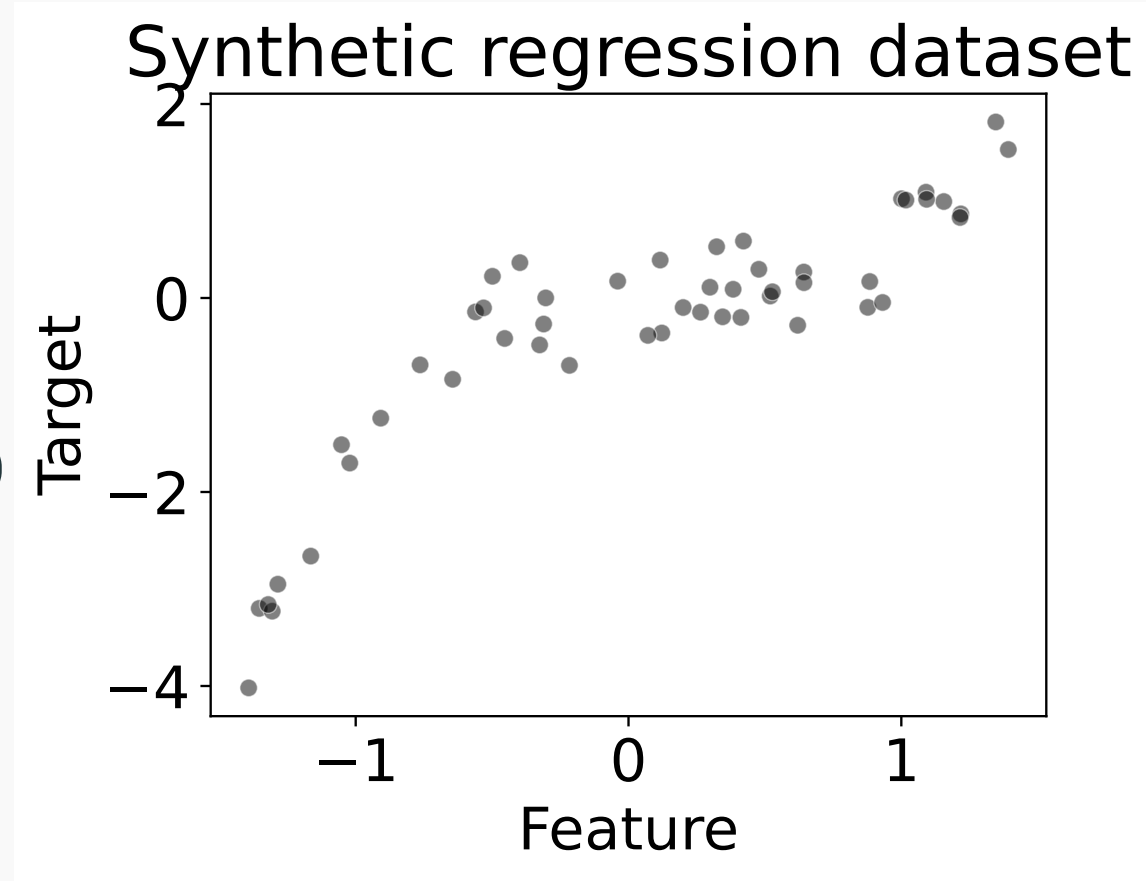
So  $h_{m(x_i)}$  should be proportional to  $-g_i$ , so **fit  $h_m$  to the negative gradient.**

# Boosting: Gradient boosting, regression example

## Regression

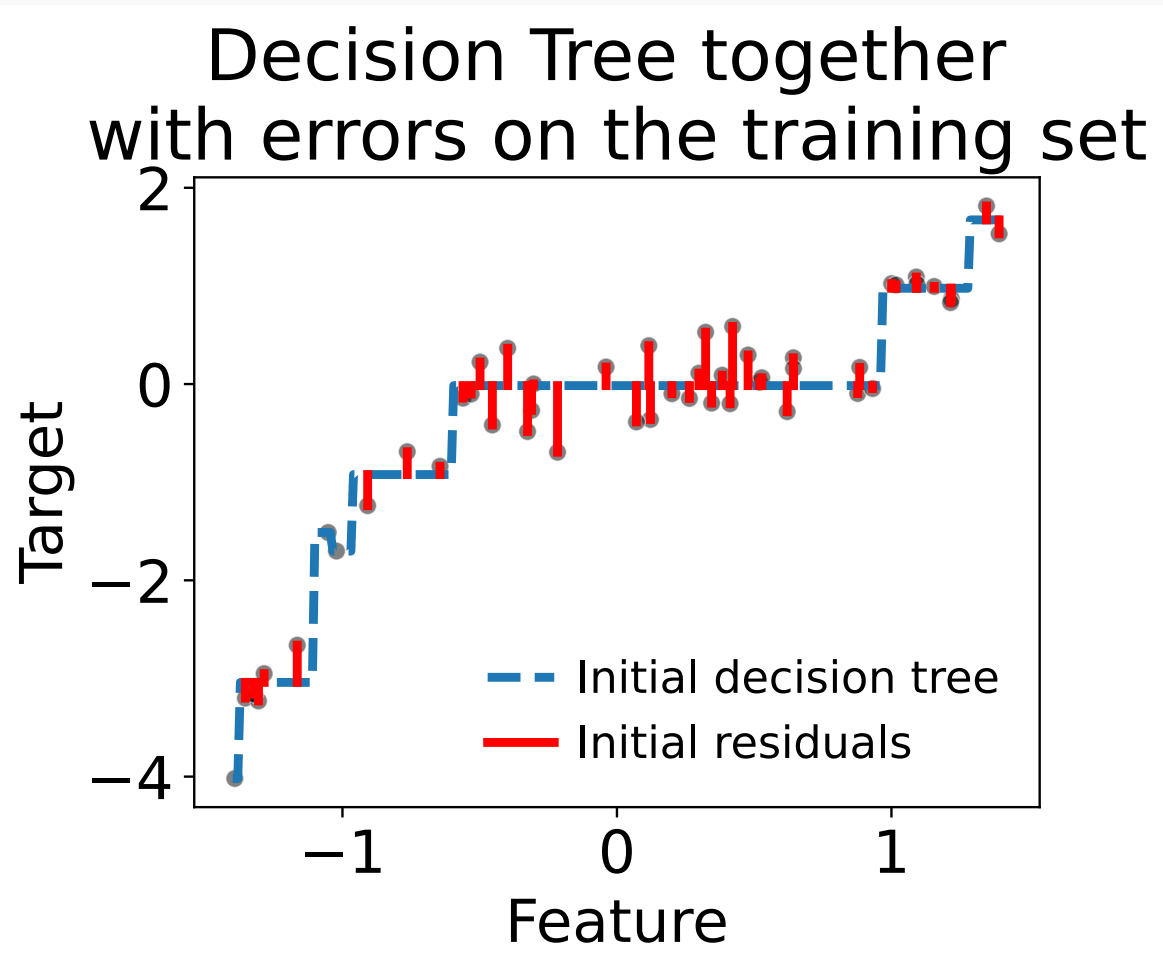
- The loss is:  $l(y, F(x)) = (y - F(x))^2$
- The gradient is:  $g_i = -2(y_i - F_{m-1}(x_i))$

💡 The new trees should fit the residuals



# Boosting: Gradient boosting, regression example

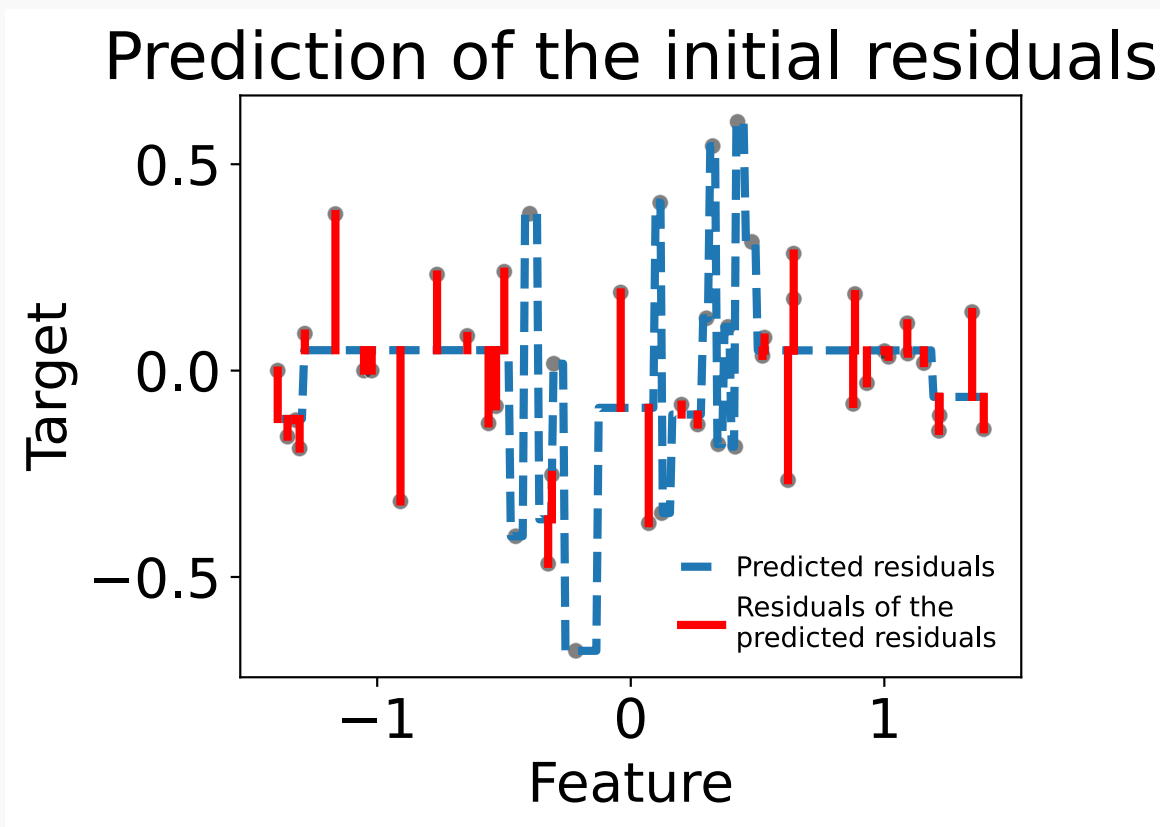
Fit a shallow tree  
(depth=3)



# Boosting: Gradient boosting, regression example

## Fit a second tree to the residuals

- This tree performs poorly on some samples.

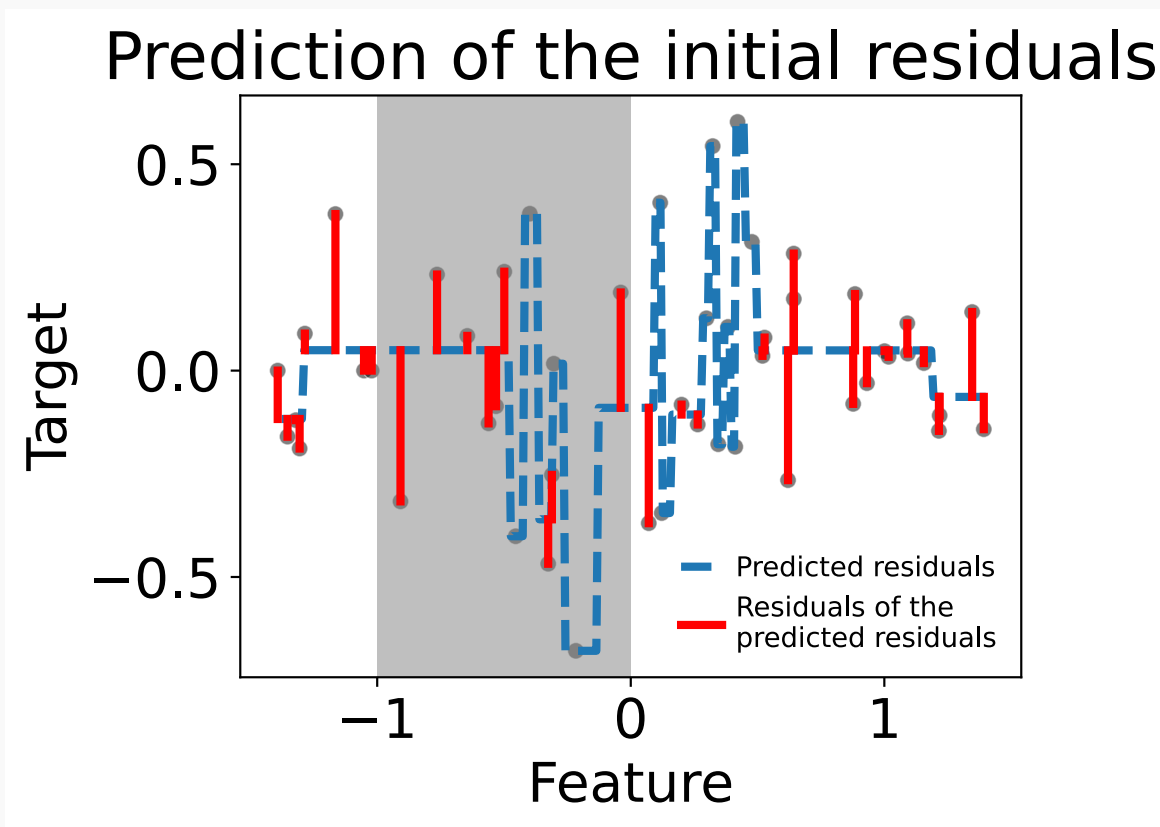




# Boosting: Gradient boosting, regression example

## Fit a second tree to the residuals

- This tree performs well on some residuals.
- Let's zoom on one of those.



# Boosting: Gradient boosting, regression example

## Focus on a sample

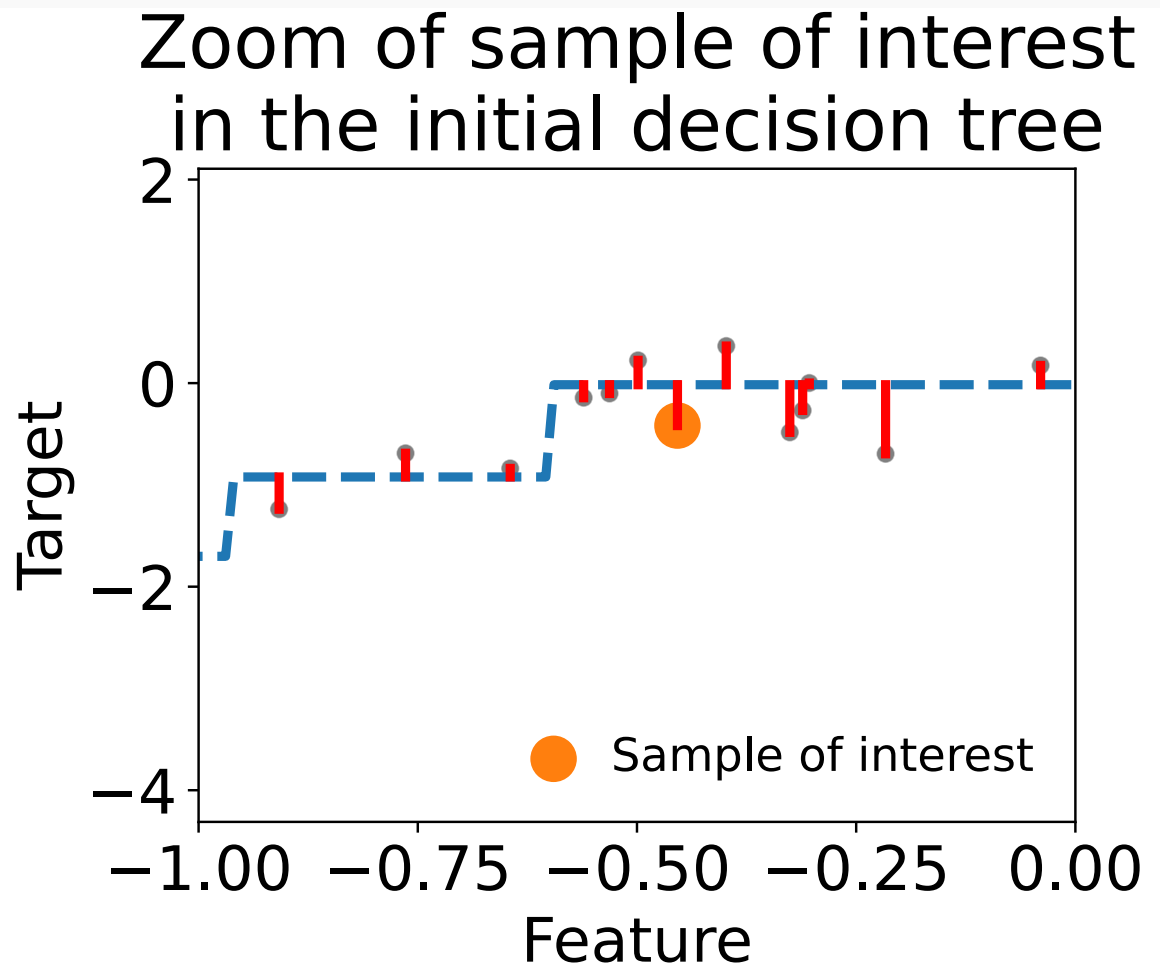
$$(x_i, y_i) = (-0.454, -0.417)$$

## First tree prediction

$$\text{Prediction: } f_1(x_i) = -0.016$$

Residuals:

$$y_i - f_1(x_i) = -0.401$$



# Boosting: Gradient boosting, regression example

## Focus on a sample

$$(x_i, y_i) = (-0.454, -0.417)$$

## First tree prediction

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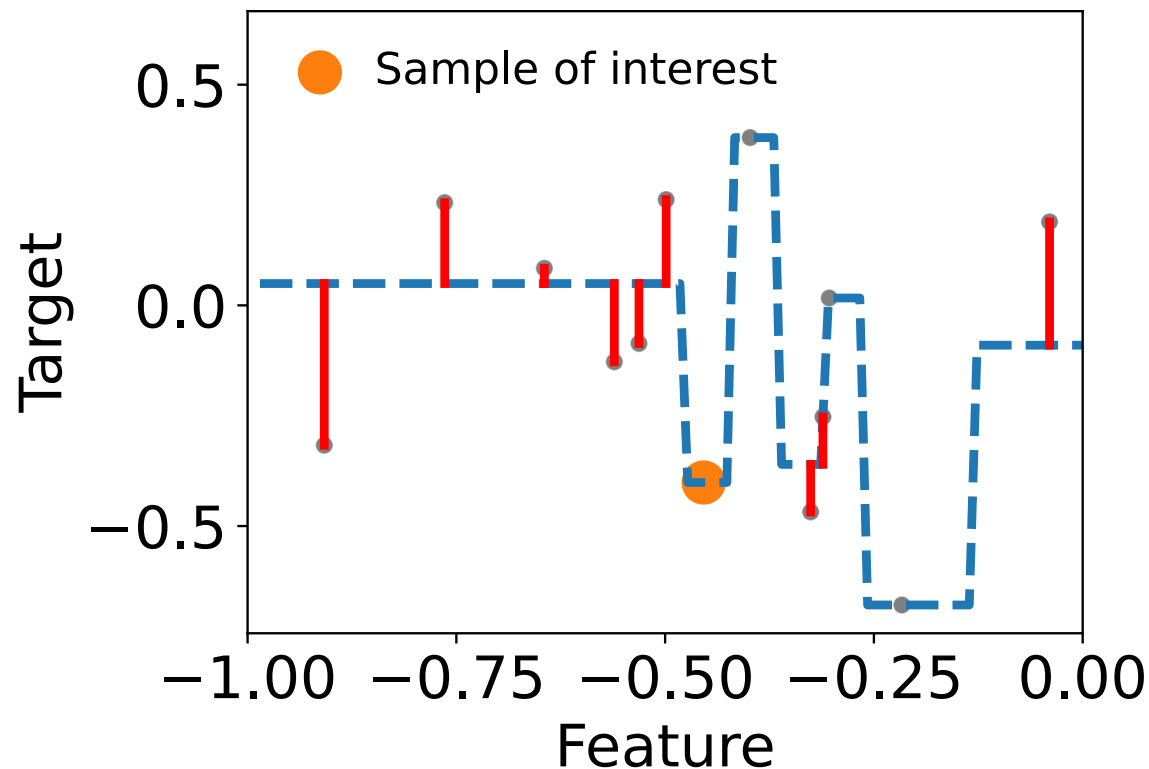
## Second tree prediction

$$\text{Prediction: } f_2(x_i) = -0.401$$

Residuals:

$$y_i - f_1(x_i) - f_2(x_i) = 0$$

## Zoom of sample of interest in the initial residuals



# Faster gradient boosting with binned features

## Gradient boosting is slow when $N > 10,000$

Fitting each tree is quite slow:  $O(pN \log(N))$  operations

## HistGradientBoosting

- Discretize numerical features into 256 bins: less costly for tree splitting
- Multi core implementation
- Much much faster

# Take away for ensemble models

Bagging (eg. Random forests)	Boosting
Fit trees independently	Fit trees sequentially
Each deep tree overfits	Each shallow tree underfits
Averaging the tree predictions reduces overfitting	Sequentially adding trees reduces underfitting

A word on other families of models

# Other well known families of models

**Generalized linear models**

**Kernel methods: Support vector machines, Gaussian processes**

**Deep neural networks**

# Why not use deep learning everywhere?

- Success of deep learning (aka deep neural networks) in image, speech recognition and text
- 🤔 Why not so used in econometrics?



# Why not use deep learning everywhere?

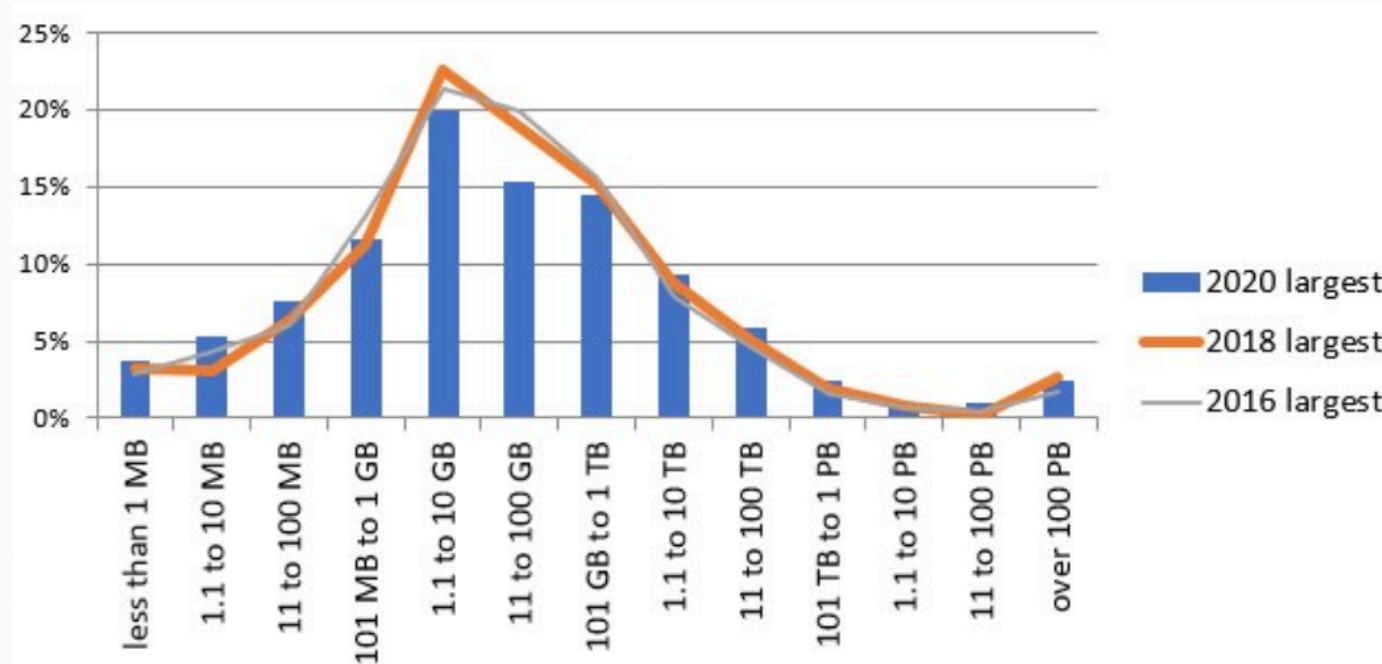
- Success of deep learning (aka deep neural networks) in image, speech recognition and text
- 🤔 Why not so used in econometrics?

**Deep learning needs a lot of data (typically  $N \approx 1$  million)**

**Do we have this much data in econometrics?**

# Answer 1: Limited data settings

- Typically in economics (but also everywhere), we have a limited number of observations

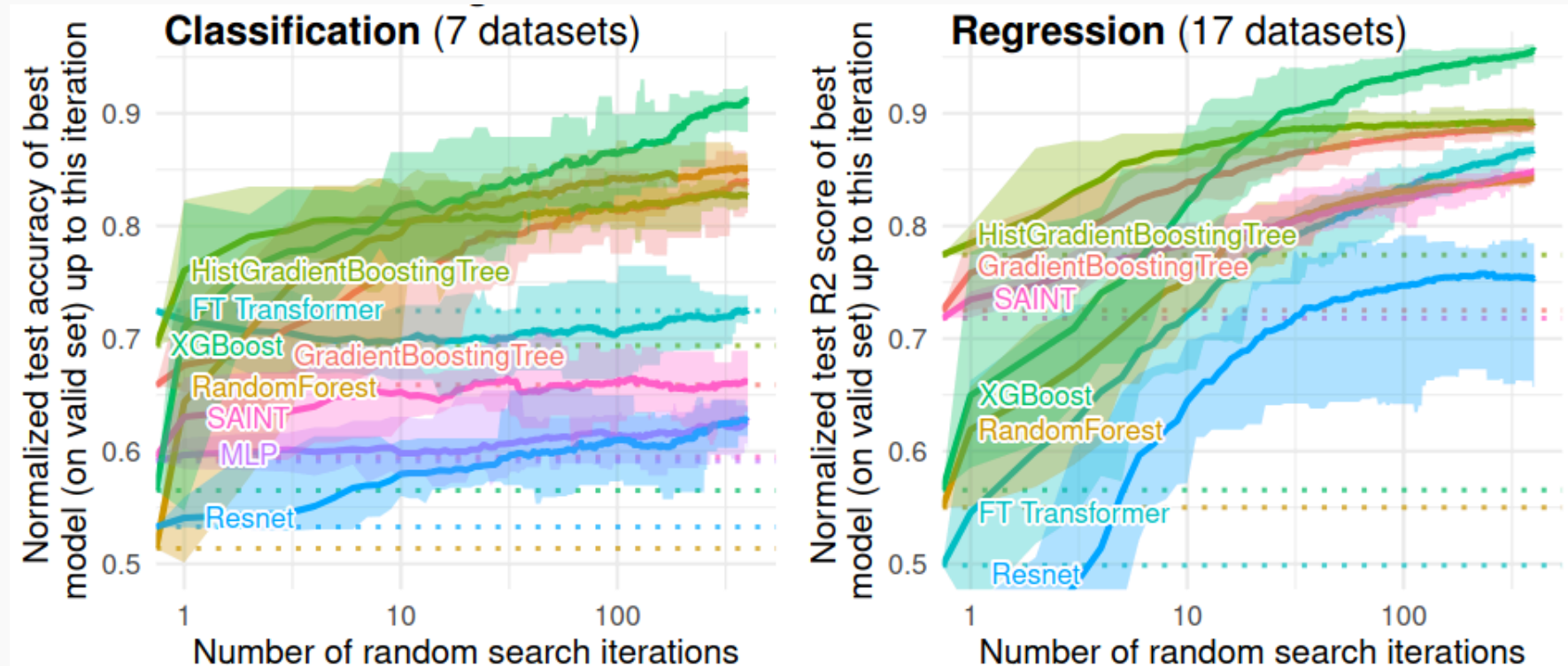


Typical dataset are mid-sized. This does not change with time.<sup>1</sup>

<sup>1</sup><https://www.kdnuggets.com/2020/07/poll-largest-dataset-analyzed-results.html>

## Answer 2: Deep learning underperforms on data tables

Tree-based methods outperform tailored deep learning architectures (Grinsztajn et al., 2022)



## **Recent work showing that tree-based models can be outperformed**

- Skrub python library: data-wrangling and encoding (same people than sklearn)
- (Kim et al., 2024): CARTE: pretraining and transfer for tabular learning
- (Grinsztajn et al., 2023) : Vectorizing string entries for data processing on tables: when are larger language models better?

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