

# Generalization Error

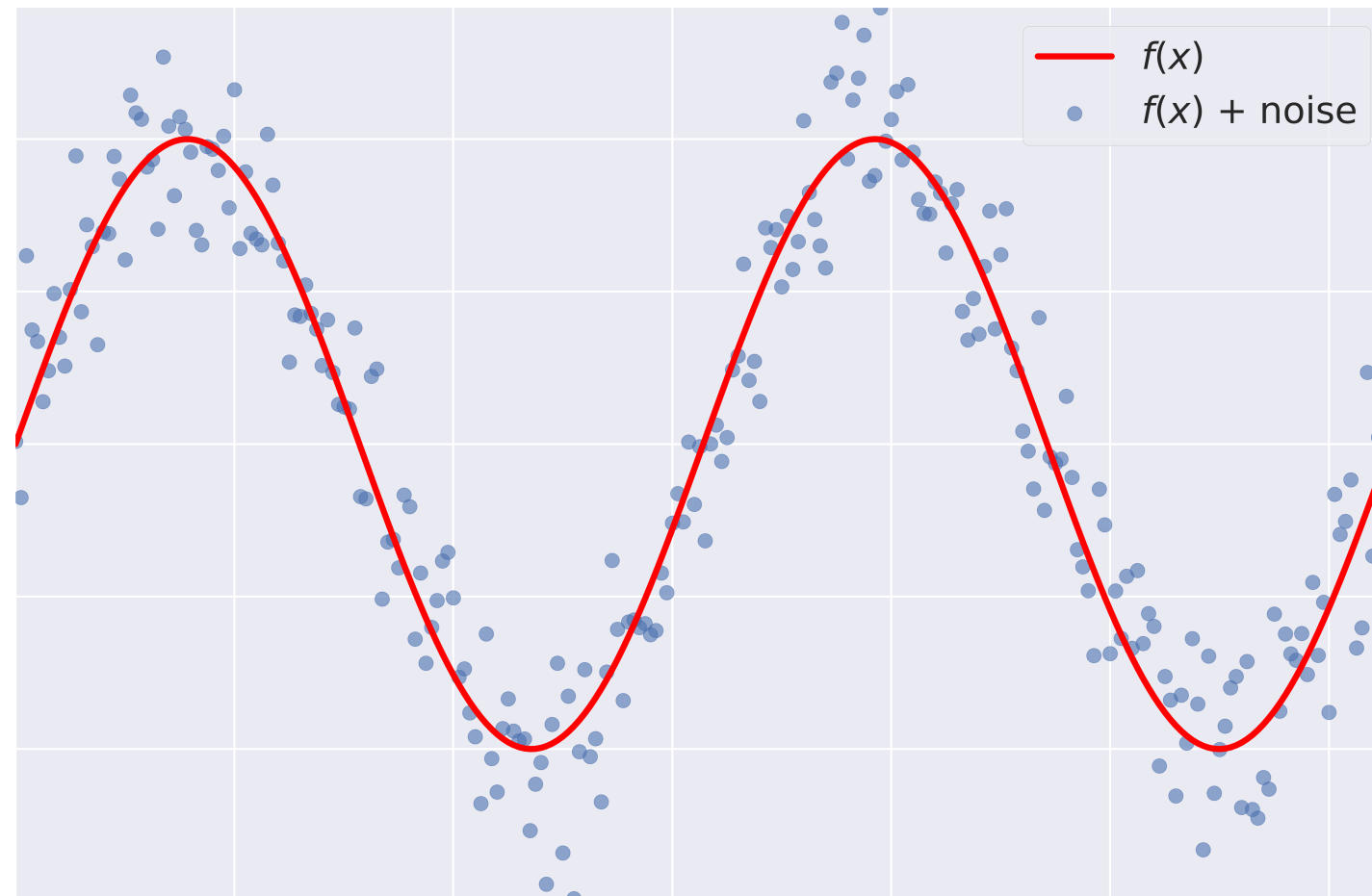
MACHINE LEARNING WITH TREE-BASED MODELS IN PYTHON



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# Supervised Learning - Under the Hood

- Supervised Learning:  $y = f(x)$ ,  $f$  is unknown.



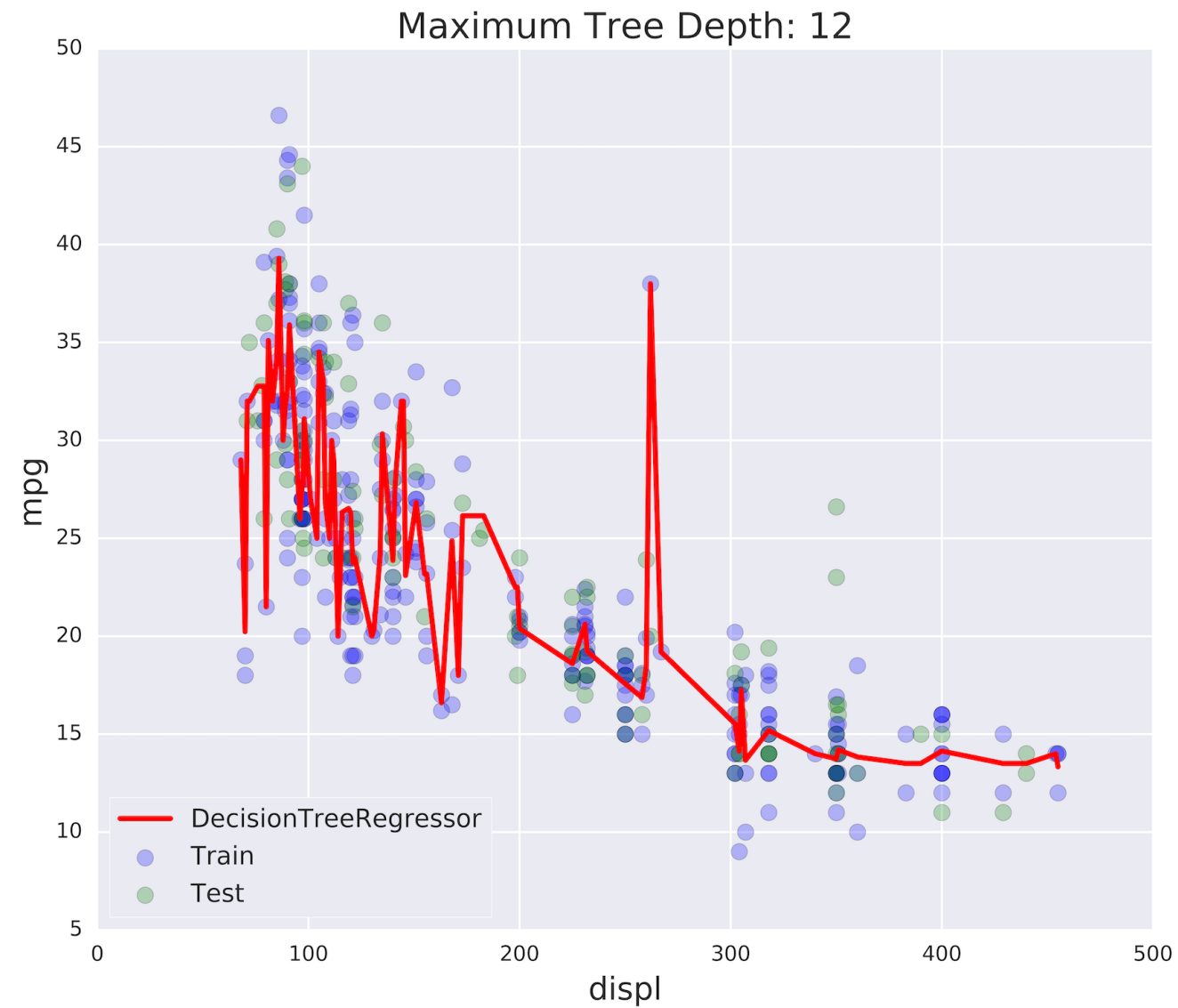
# Goals of Supervised Learning

- Find a model  $\hat{f}$  that best approximates  $f$ :  $\hat{f} \approx f$
- $\hat{f}$  can be Logistic Regression, Decision Tree, Neural Network ...
- Discard noise as much as possible.
- **End goal:**  $\hat{f}$  should achieve a low predictive error on unseen datasets.

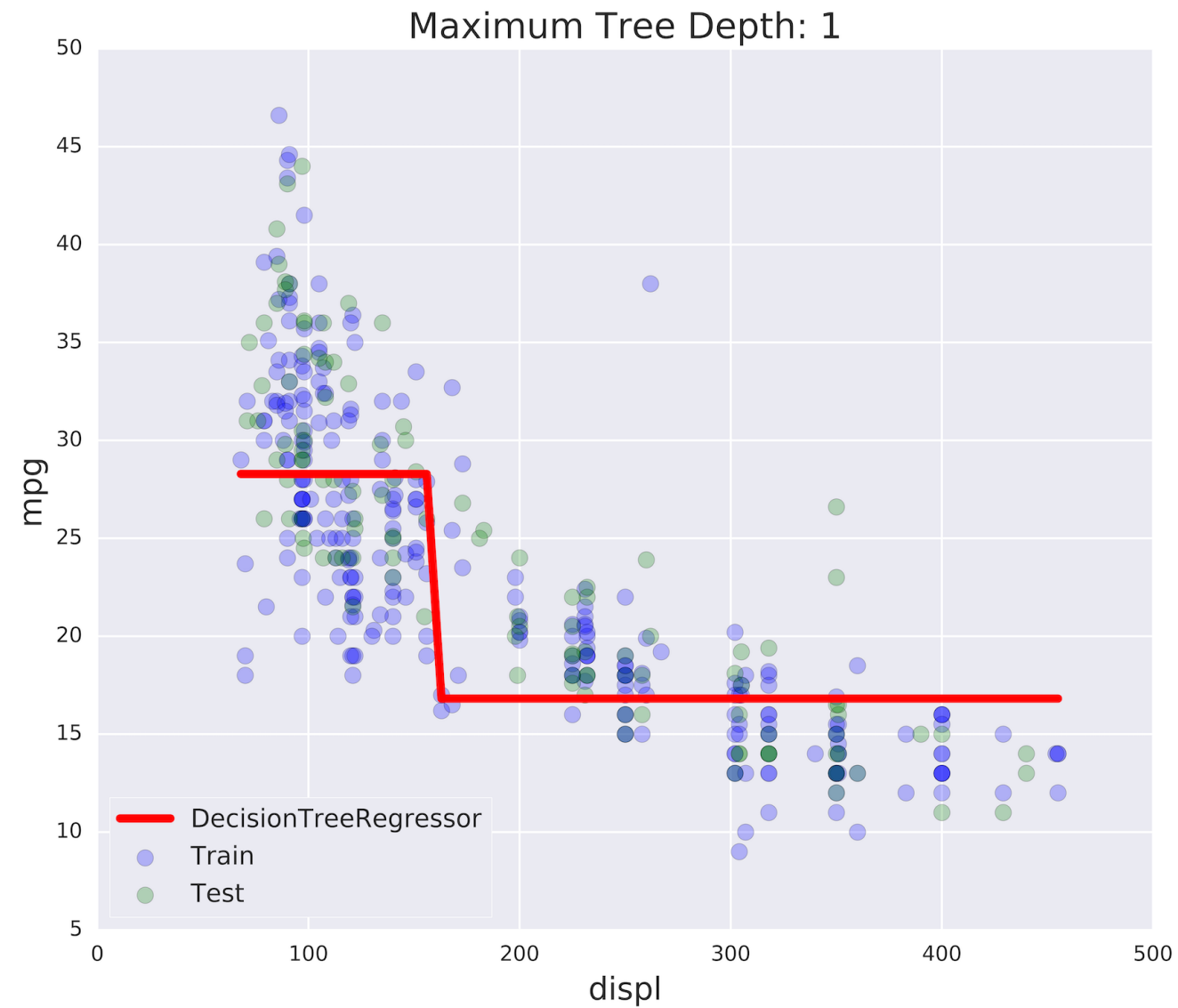
# Difficulties in Approximating $f$

- **Overfitting:**  $\hat{f}(x)$  fits the training set noise.
- **Underfitting:**  $\hat{f}$  is not flexible enough to approximate  $f$ .

# Overfitting



# Underfitting

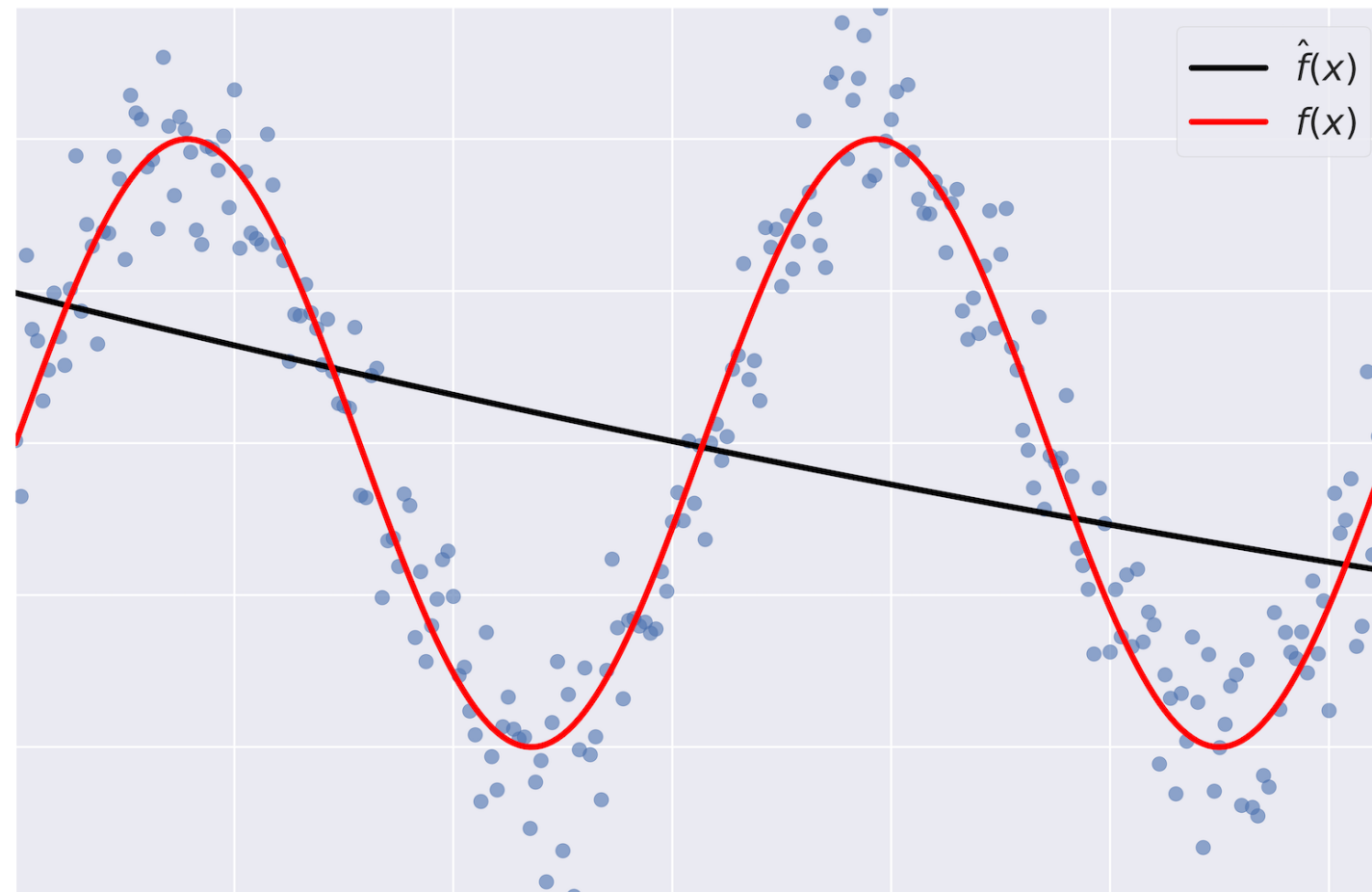


# Generalization Error

- **Generalization Error of  $\hat{f}$ :** Does  $\hat{f}$  generalize well on unseen data?
- It can be decomposed as follows: Generalization Error of  $\hat{f} = bias^2 + variance + \text{irreducible error}$

# Bias

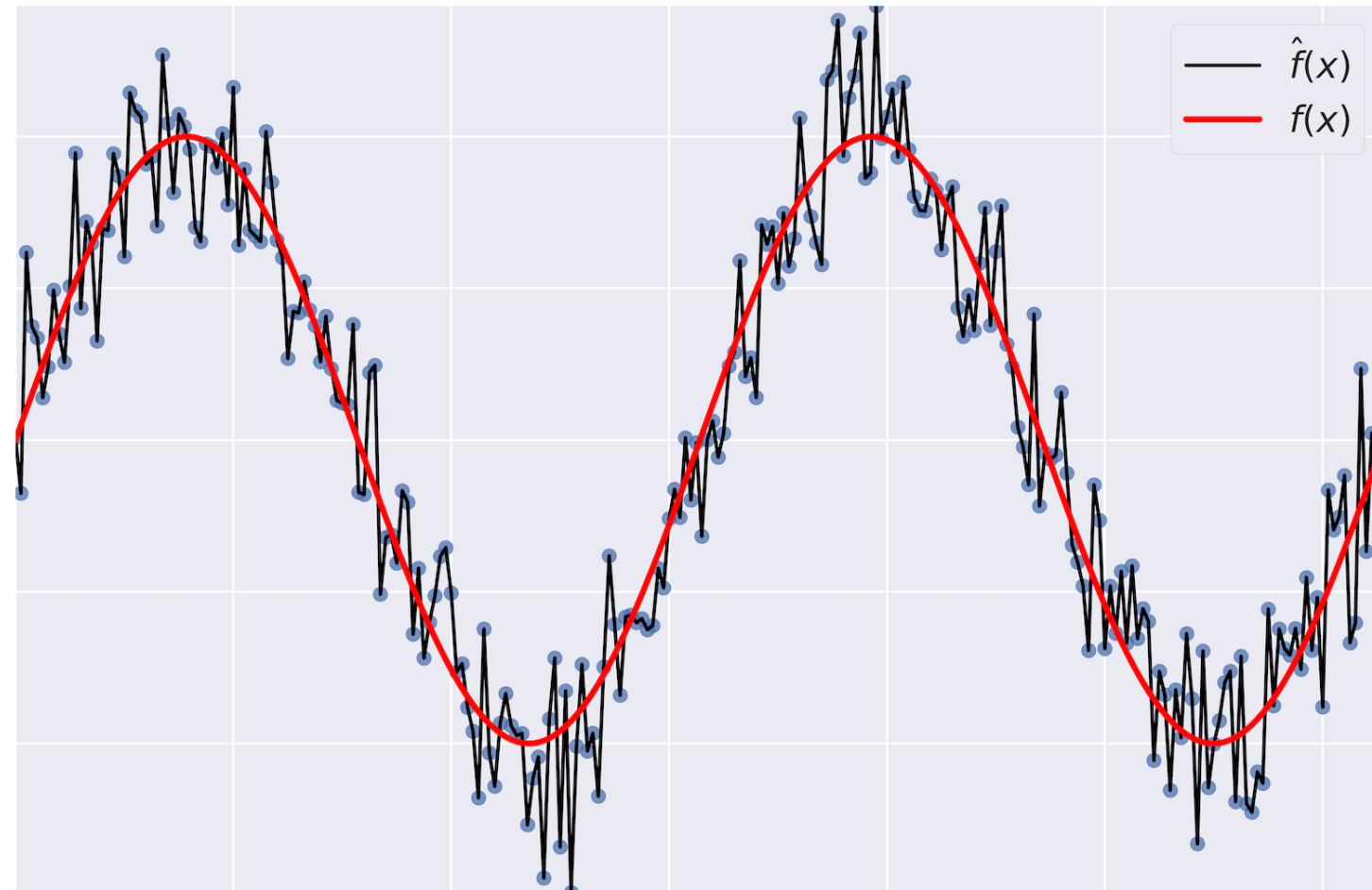
- **Bias:** error term that tells you, on average, how much  $\hat{f} \neq f$ .





# Variance

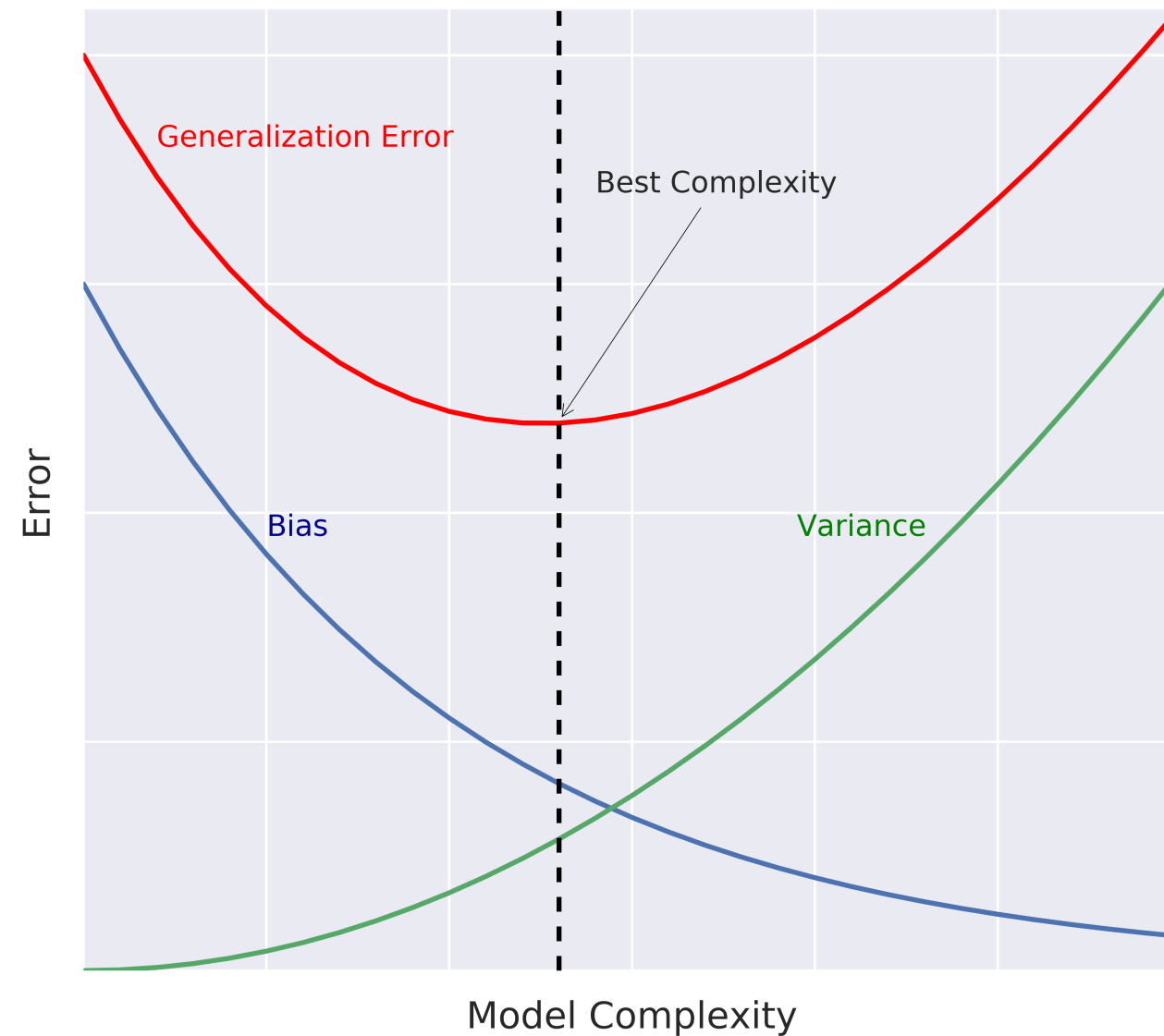
- **Variance:** tells you how much  $\hat{f}$  is inconsistent over different training sets.



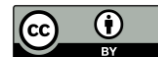
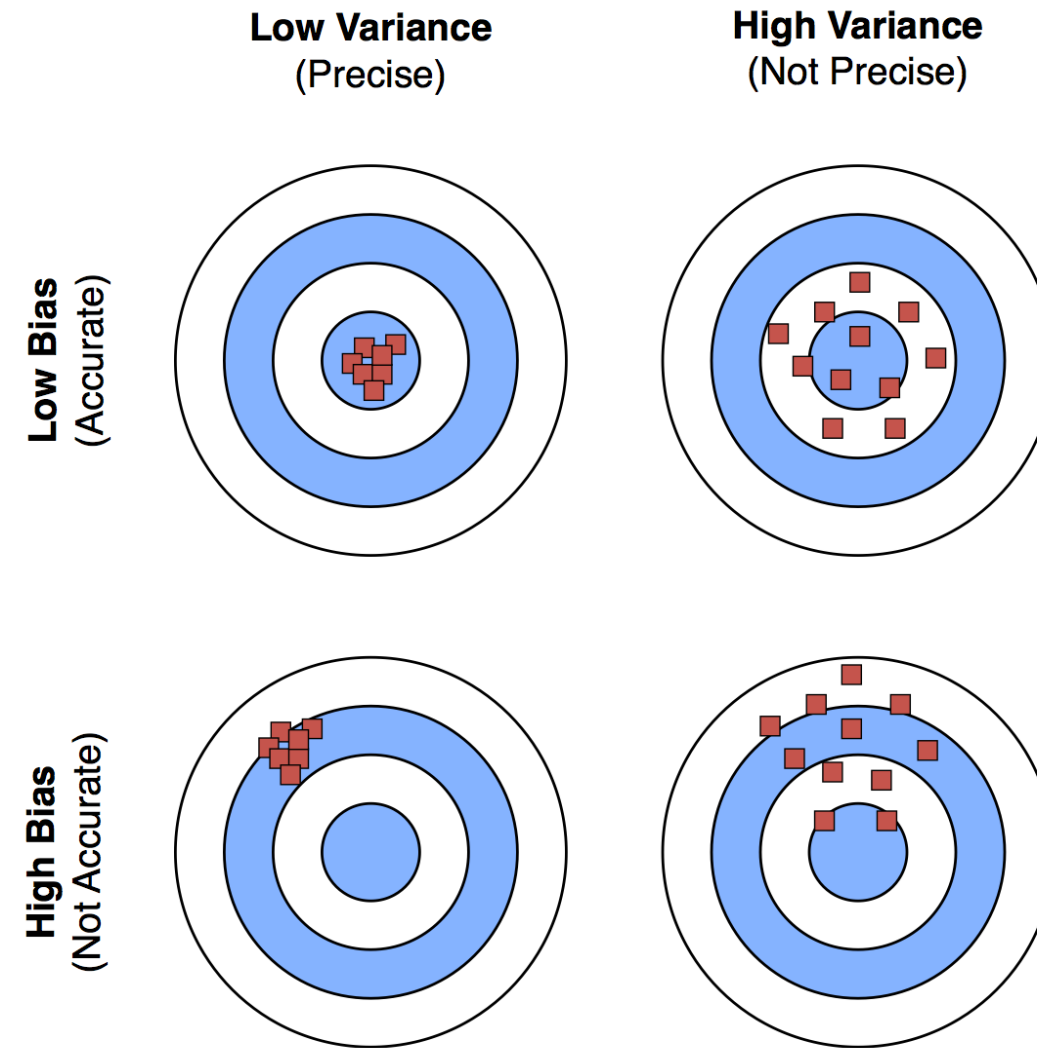
# Model Complexity

- **Model Complexity:** sets the flexibility of  $\hat{f}$ .
- Example: Maximum tree depth, Minimum samples per leaf, ...

# Bias-Variance Tradeoff



# Bias-Variance Tradeoff: A Visual Explanation



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# Let's practice!

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# Diagnosing Bias and Variance Problems

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# Estimating the Generalization Error

- How do we estimate the generalization error of a model?
- Cannot be done directly because:
  - $f$  is unknown,
  - usually you only have one dataset,
  - noise is unpredictable.

# Estimating the Generalization Error

Solution:

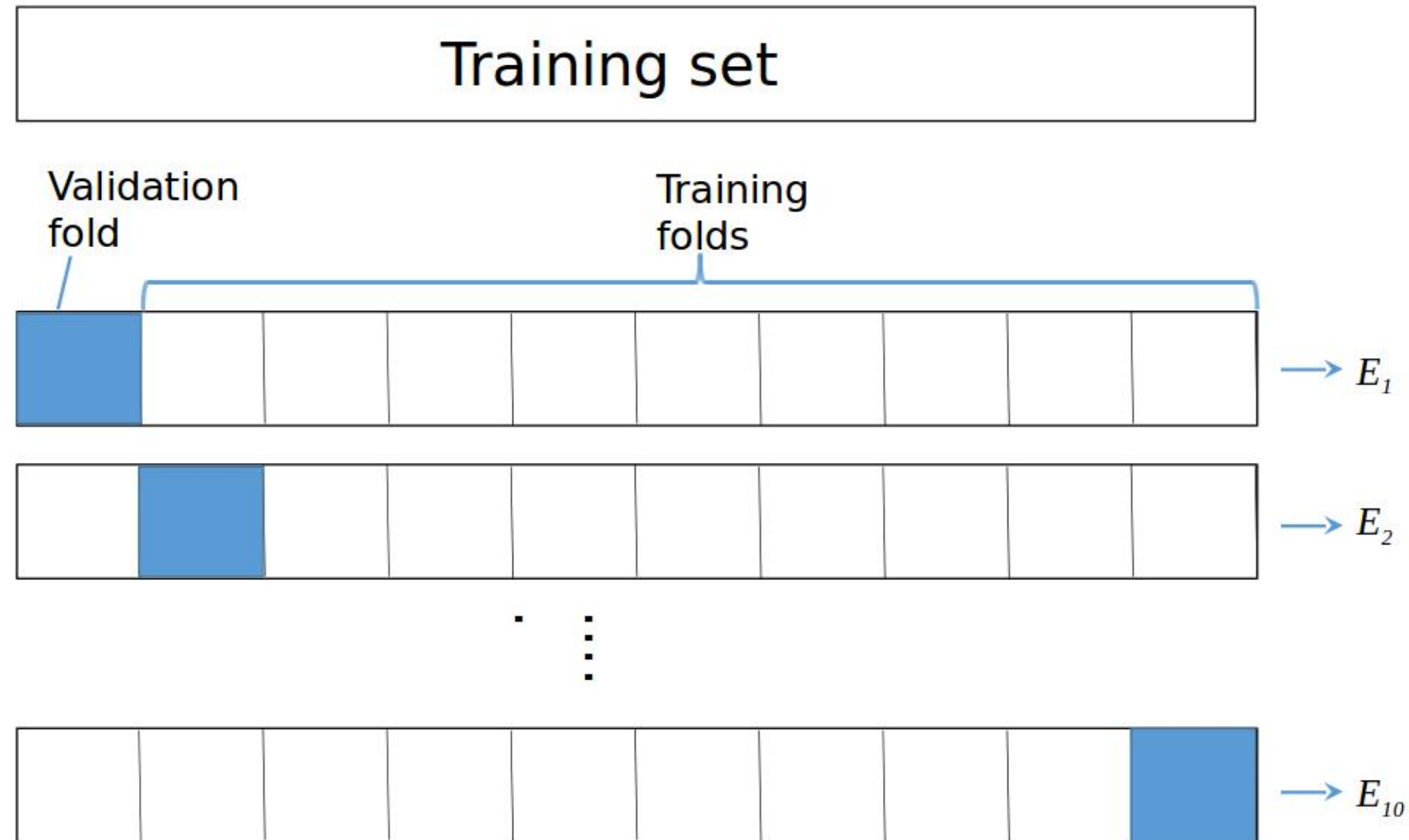
- split the data to training and test sets,
- fit  $\hat{f}$  to the training set,
- evaluate the error of  $\hat{f}$  on the **unseen** test set.
- generalization error of  $\hat{f} \approx$  test set error of  $\hat{f}$ .



# Better Model Evaluation with Cross-Validation

- Test set should not be touched until we are confident about  $\hat{f}$ 's performance.
- Evaluating  $\hat{f}$  on training set: biased estimate,  $\hat{f}$  has already seen all training points.
- Solution  $\rightarrow$  Cross-Validation (CV):
  - K-Fold CV,
  - Hold-Out CV.

# K-Fold CV



# K-Fold CV

$$CV \text{ error} = \frac{E_1 + \dots + E_{10}}{10}$$

# Diagnose Variance Problems

- If  $\hat{f}$  suffers from **high variance**: CV error of  $\hat{f}$  > training set error of  $\hat{f}$ .
- $\hat{f}$  is said to overfit the training set. To remedy overfitting:
  - decrease model complexity,
  - for ex: decrease max depth, increase min samples per leaf, ...
  - gather more data, ..

# Diagnose Bias Problems

- if  $\hat{f}$  suffers from high bias: CV error of  $\hat{f} \approx$  training set error of  $\hat{f} \gg$  desired error.
- $\hat{f}$  is said to underfit the training set. To remedy underfitting:
  - increase model complexity
  - for ex: increase max depth, decrease min samples per leaf, ...
  - gather more relevant features

# K-Fold CV in sklearn on the Auto Dataset

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error as MSE
from sklearn.model_selection import cross_val_score
# Set seed for reproducibility
SEED = 123
# Split data into 70% train and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3,
                                                    random_state=SEED)
# Instantiate decision tree regressor and assign it to 'dt'
dt = DecisionTreeRegressor(max_depth=4,
                           min_samples_leaf=0.14,
                           random_state=SEED)
```

# K-Fold CV in sklearn on the Auto Dataset

```
# Evaluate the list of MSE obtained by 10-fold CV
# Set n_jobs to -1 in order to exploit all CPU cores in computation
MSE_CV = - cross_val_score(dt, X_train, y_train, cv= 10,
                           scoring='neg_mean_squared_error',
                           n_jobs = -1)

# Fit 'dt' to the training set
dt.fit(X_train, y_train)

# Predict the labels of training set
y_predict_train = dt.predict(X_train)

# Predict the labels of test set
y_predict_test = dt.predict(X_test)
```

```
# CV MSE
print('CV MSE: {:.2f}'.format(MSE_CV.mean()))
```

CV MSE: 20.51

```
# Training set MSE
print('Train MSE: {:.2f}'.format(MSE(y_train, y_predict_train)))
```

Train MSE: 15.30

```
# Test set MSE
print('Test MSE: {:.2f}'.format(MSE(y_test, y_predict_test)))
```

Test MSE: 20.92

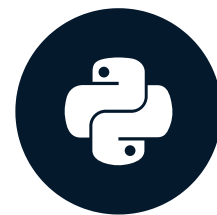


# Let's practice!

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# Ensemble Learning

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# Advantages of CARTs

- Simple to understand.
- Simple to interpret.
- Easy to use.
- Flexibility: ability to describe non-linear dependencies.
- Preprocessing: no need to standardize or normalize features, ...

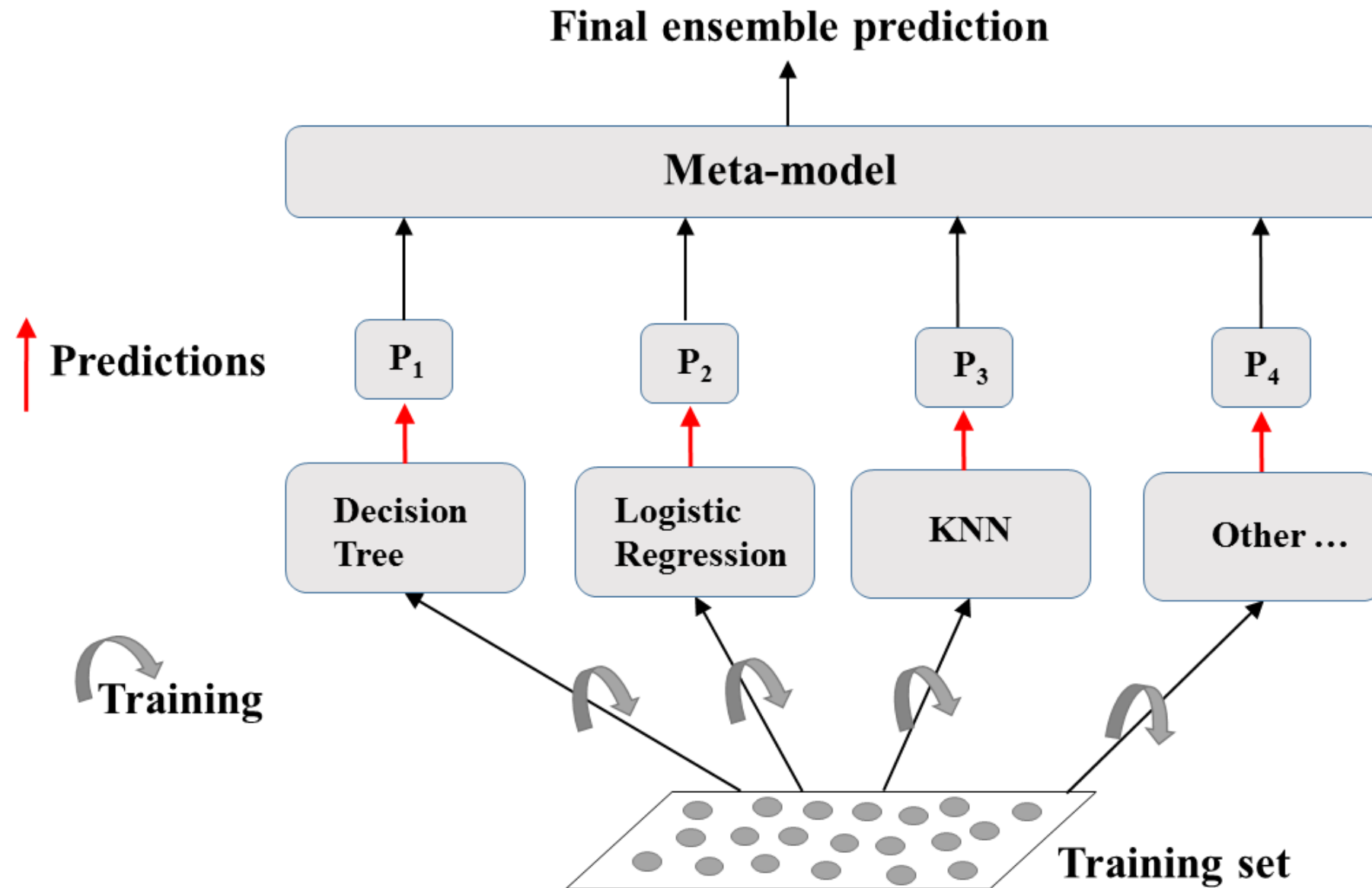
# Limitations of CARTs

- Classification: can only produce orthogonal decision boundaries.
- Sensitive to small variations in the training set.
- High variance: unconstrained CARTs may overfit the training set.
- Solution: ensemble learning.

# Ensemble Learning

- Train different models on the same dataset.
- Let each model make its predictions.
- Meta-model: aggregates predictions of individual models.
- Final prediction: more robust and less prone to errors.
- Best results: models are skillful in different ways.

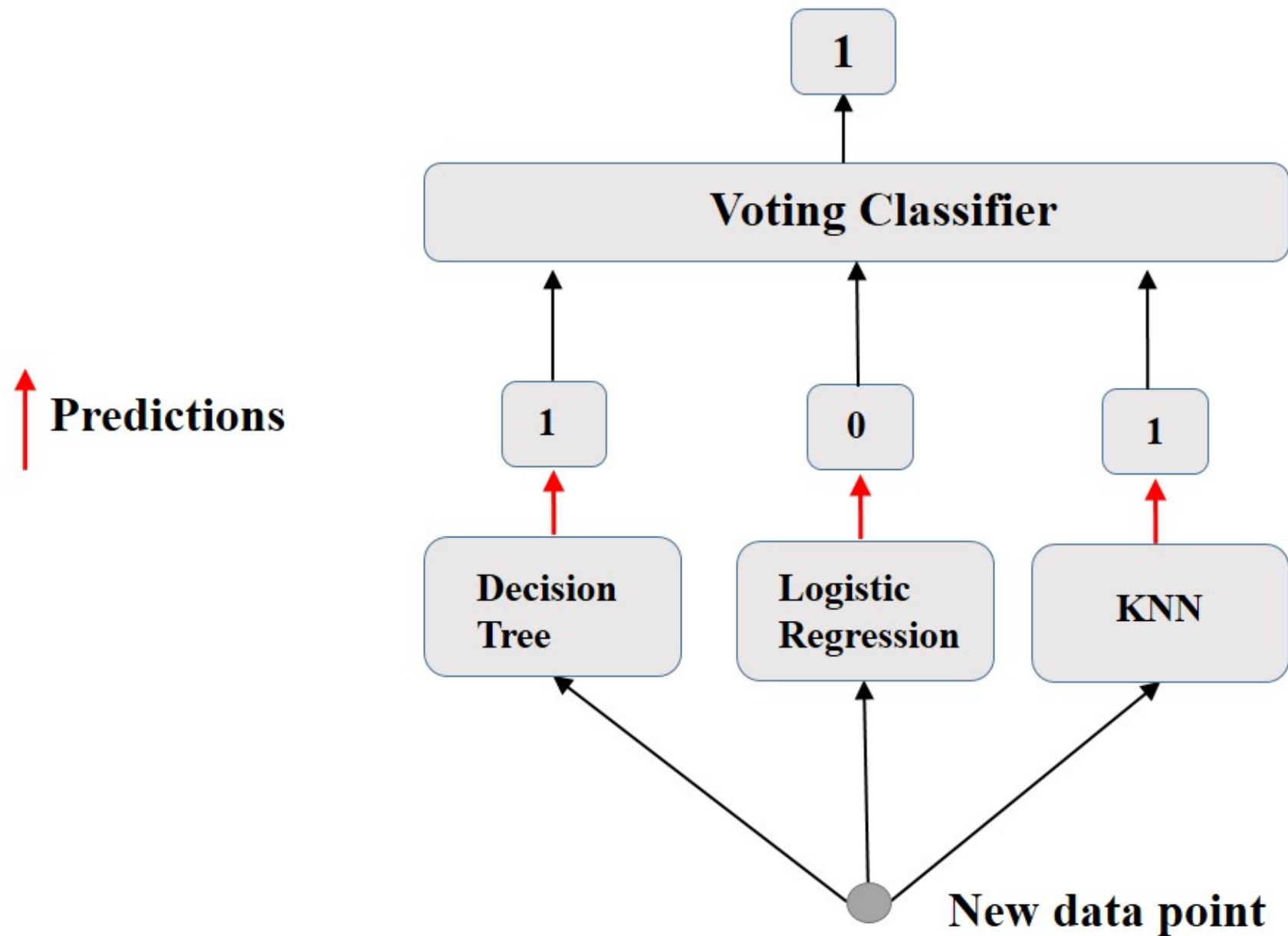
# Ensemble Learning: A Visual Explanation



# Ensemble Learning in Practice: Voting Classifier

- Binary classification task.
- $N$  classifiers make predictions:  $P_1, P_2, \dots, P_N$  with  $P_i = 0$  or  $1$ .
- Meta-model prediction: hard voting.

# Hard Voting





# Voting Classifier in sklearn (Breast-Cancer dataset)

```
# Import functions to compute accuracy and split data
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

# Import models, including VotingClassifier meta-model
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.ensemble import VotingClassifier

# Set seed for reproducibility
SEED = 1
```

# Voting Classifier in sklearn (Breast-Cancer dataset)

```
# Split data into 70% train and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size= 0.3,
                                                    random_state= SEED)

# Instantiate individual classifiers
lr = LogisticRegression(random_state=SEED)
knn = KNN()
dt = DecisionTreeClassifier(random_state=SEED)

# Define a list called classifier that contains the tuples (classifier_name, classifier)
classifiers = [('Logistic Regression', lr),
               ('K Nearest Neighbours', knn),
               ('Classification Tree', dt)]
```

```
# Iterate over the defined list of tuples containing the classifiers
for clf_name, clf in classifiers:
    #fit clf to the training set
    clf.fit(X_train, y_train)

    # Predict the labels of the test set
    y_pred = clf.predict(X_test)

    # Evaluate the accuracy of clf on the test set
    print('{:s} : {:.3f}'.format(clf_name, accuracy_score(y_test, y_pred)))
```

```
Logistic Regression: 0.947
K Nearest Neighbours: 0.930
Classification Tree: 0.930
```

# Voting Classifier in sklearn (Breast-Cancer dataset)

```
# Instantiate a VotingClassifier 'vc'
vc = VotingClassifier(estimators=classifiers)

# Fit 'vc' to the training set and predict test set labels
vc.fit(X_train, y_train)
y_pred = vc.predict(X_test)

# Evaluate the test-set accuracy of 'vc'
print('Voting Classifier: {:.3f}'.format(accuracy_score(y_test, y_pred)))
```

```
Voting Classifier: 0.953
```

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