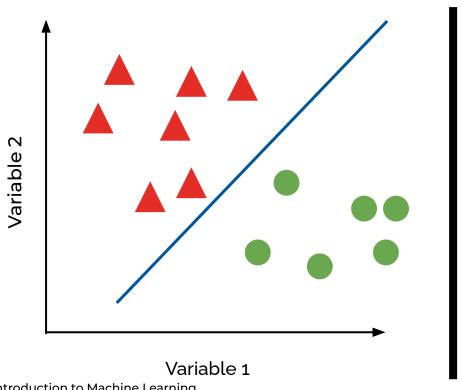
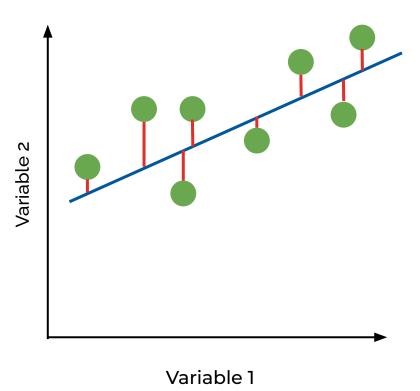


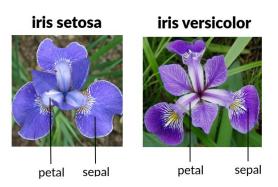
Tasks Classification and regression

Classification and regression





Example of classification



iris virginica



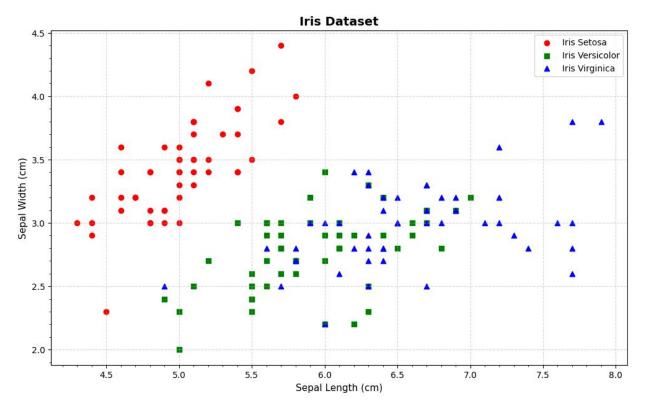
- Three different species.
- Described with the characteristics of its sepals and petals.
 - Sepal width
 - Sepal length
 - Petals width
 - Petals length
- 150 examples, 50 per species.
- Task: find a model that predicts the specy given the four characteristics.

Example of classification

```
from sklearn import datasets
# Load the Iris dataset
iris = datasets.load iris()
X = iris.data[:, :2]
y = iris.target
```

5

Example of classification

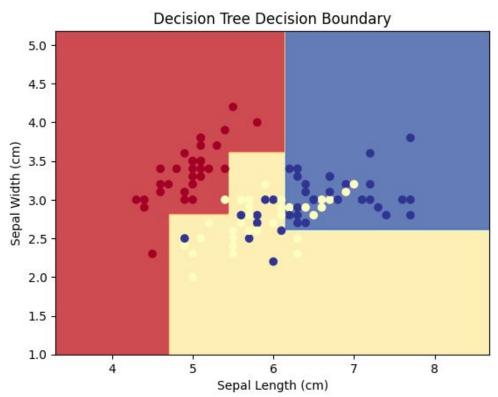


```
-\Box \times
# Split the dataset into training and testing sets
X train, X test, y train, y test = train test split(X, y,
 test size=0.3, random state=42)
# Standardize the features (optional but recommended)
 scaler = StandardScaler()
X train = scaler.fit transform(X train)
X test = scaler.transform(X test)
```

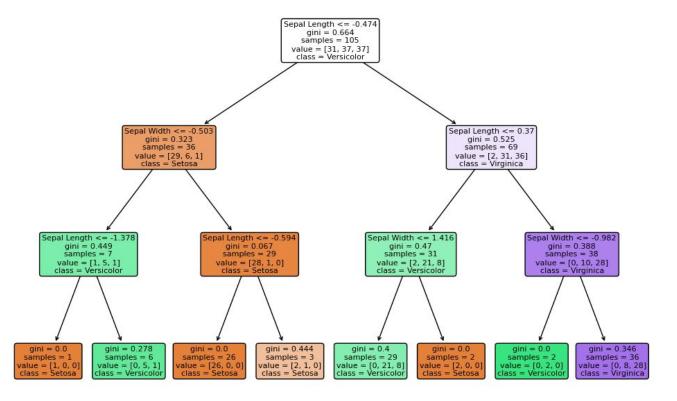
7

```
-\Box x
# Train and visualize a Decision Tree classifier
dtree = DecisionTreeClassifier (max depth=3)
dtree.fit(X train, y train)
accuracy dtree = dtree.score(X test, y test)
print(f"Decision Tree Accuracy: {accuracy dtree:.2f}")
# Decision Tree Accuracy: 0.76
```

8



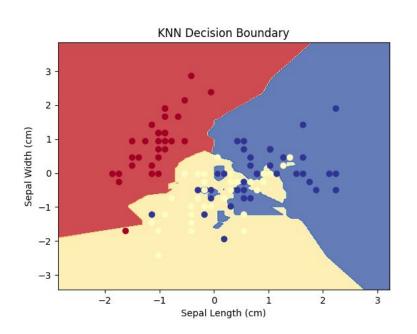
```
-\Box x
 from sklearn.tree import plot tree
 plt.figure(figsize=(12, 8)) # Set the figure size
 plot tree (dtree, filled=True, feature names=['Sepal Length', 'Sepal
 Width'], class names=['Setosa', 'Versicolor', 'Virginica'],
 rounded=True, fontsize=8)
 plt.title('Decision Tree Visualization')
 plt.show()
```

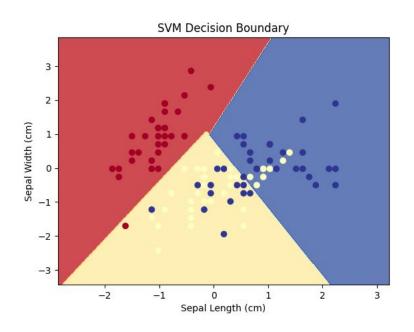


```
-\Box \times
from sklearn.tree import export text
# Extract and display the rules
tree rules = export text(dtree,
feature names=iris.feature names[:2])
print ("Decision Tree Rules:\n", tree rules)
```

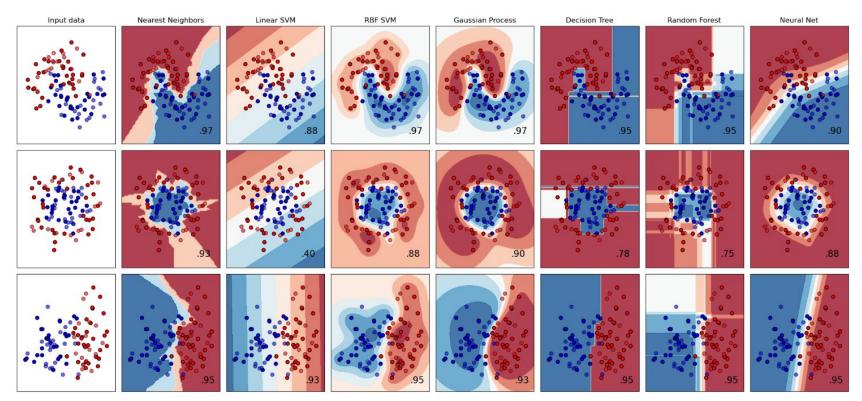
```
-\Box \times
  Decision Tree Rules:
   |--- sepal length (cm) <= 5.45
  | |--- sepal width (cm) <= 2.80
       |--- sepal length (cm) <= 4.70
  | | |--- sepal length (cm) > 4.70
  | |--- sepal width (cm) > 2.80
     | |--- sepal length (cm) <= 5.35
       |--- sepal length (cm) > 5.35
  |--- sepal length (cm) > 5.45
     |--- sepal length (cm) <= 6.15
     | |--- sepal width (cm) <= 3.60
       |--- sepal width (cm) > 3.60
     |--- sepal length (cm) > 6.15
     | |--- sepal width (cm) <= 2.60
        |--- sepal width (cm) > 2.60
```

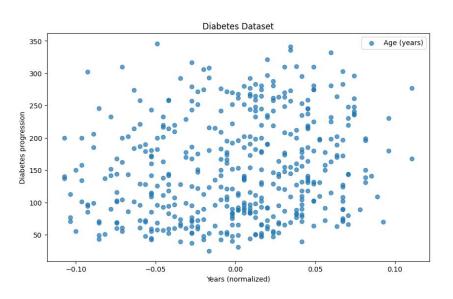
```
-\Box x
 # Define new samples with feature values
 new samples = np.array([[5.1, 3.5], # Sample 1])
                        [6.2, 2.9], # Sample 2
                        [7.3, 2.8]) # Sample 3
 # Predict the class labels for the new samples
 predicted classes = dtree.predict(new samples)
 print("predicted classes")
```



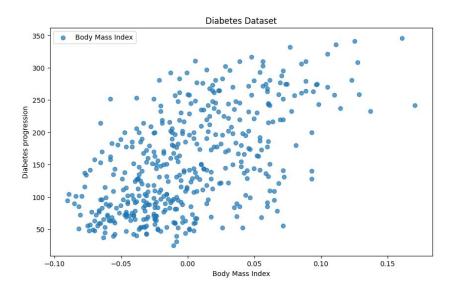


https://colab.research.google.com/drive/1Kx0okD6FHC5O74 bblgC96h47DPH6Nson?usp=sharing





- Diabetes progression
- 10 features.
 - age age in years
 - sex
 - bmi body mass index
 - bp average blood pressure
 - s1 tc, total serum cholesterol
 - s2 ldl, low-density lipoproteins
 - s3 hdl, high-density lipoproteins
 - s4 tch, total cholesterol / HDL
 - s5 ltg, possibly log of serum triglycerides level
 - s6 glu, blood sugar level
- 442 examples
- Task: find a model that predicts diabetes progression.

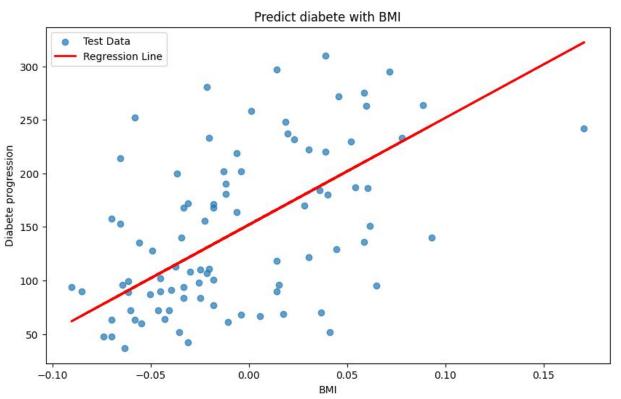


- Diabetes progression
- 10 features.
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 - s1 tc, total serum cholesterol
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 - s3 hdl, high-density lipoproteins
 - s4 tch, total cholesterol / HDL
 - s5 ltg, possibly log of serum triglycerides level
 - s6 glu, blood sugar level
- 442 examples
- Task: find a model that predicts diabetes progression.

```
-\Box \times
from sklearn.datasets import load diabetes
# Load the diabetes dataset
diabetes = load diabetes()
X = diabetes['data']
y = diabetes['target']
```

```
-\Box \times
 X \text{ selected} = X[:, 2]
 X train, X test, y train, y test = train test split(X selected, y,
 test size=0.2, random state=42)
 regression model = LinearRegression()
 regression model.fit(X train.reshape(-1, 1), y train)
```

```
-\Box \times
 # Make predictions on the test set
 y pred = regression model.predict(X test.reshape(-1, 1))
 mse = mean squared error(y test, y pred)
 r2 = r2 \ score(y \ test, y \ pred)
 print(f"Mean Squared Error (MSE): {mse:.2f}")
 print(f"R-squared (R2): {r2:.2f}")
 # Mean Squared Error (MSE): 4061.83
 # R-squared (R2): 0.23
```



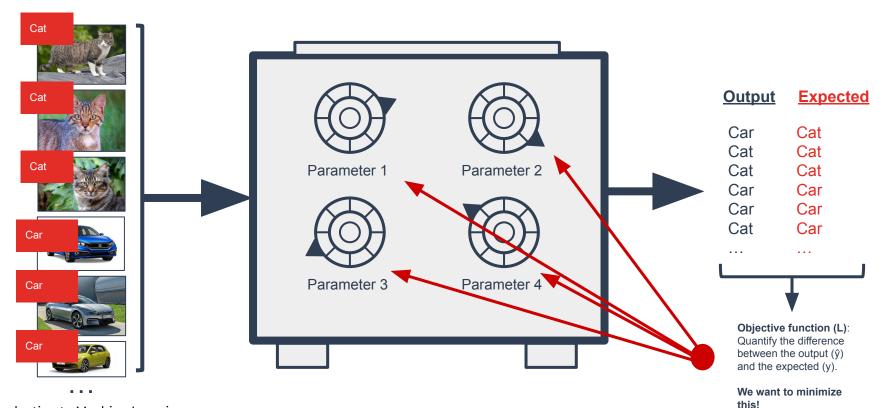
```
-\Box x
 new data point = np.array([0.05]) # Adjust the feature value as needed
 predicted value = regression model.predict(new data point.reshape(-1, 1))
 print(f"Predicted Value for New Data Point: {predicted value[0]:.2f}")
 # Predicted Value for New Data Point: 201.93
```

https://colab.research.google.com/drive/1i2To3ijnBU6uDnOgefWxsUjips0DWbF3?usp=sharing

Models

Parametric and non-parametric models

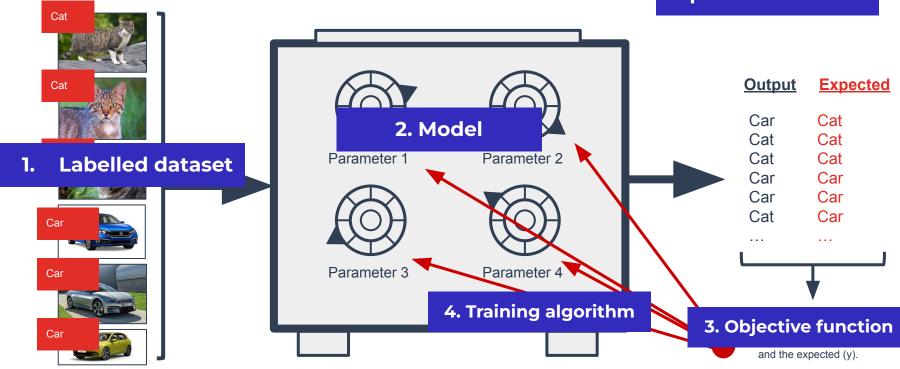
Parametric models



Parametric models

Introduction to Machine Learning

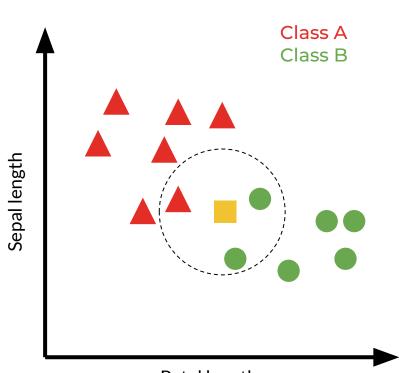
5. How to we know that our model performs well?



We want to minimize this!

28

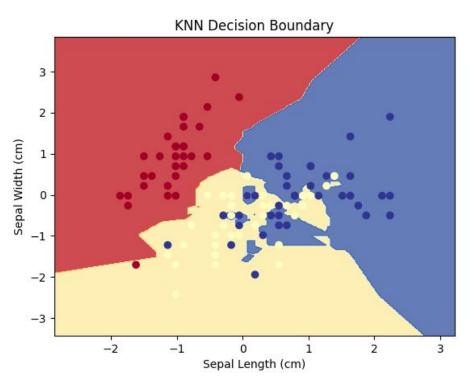
Non-parametric methods



- Try to make assumptions about the data given the patterns observed from similar instances.
- Example: K-nearest neighbor (KNN)
 - Looks for similar training patterns for new instances.
 - Assumption: the most similar are most likely to have a similar result.
- What is similarity (features)?
 Distances: Euclidean, Manhattan.

Solving the IRIS with KNN

```
-\Box \times
# Create a KNN classifier
k = 5 # Number of neighbors
clf = KNeighborsClassifier(n neighbors=k)
clf.fit(X train, y train)
y pred = clf.predict(X test)
accuracy = accuracy score(y test, y pred)
print(f'Accuracy on Test Set: {accuracy:.2f}')
# KNN Accuracy: 0.8
```



Learning methods

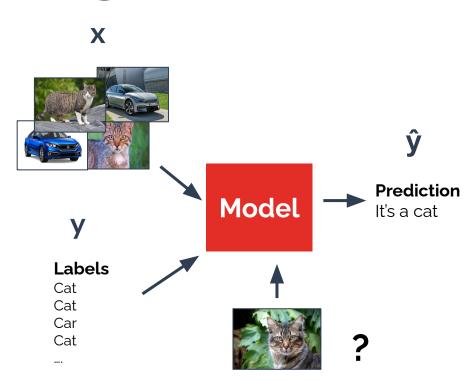
Supervised, unsupervised, self-supervised, reinforcement learning

32

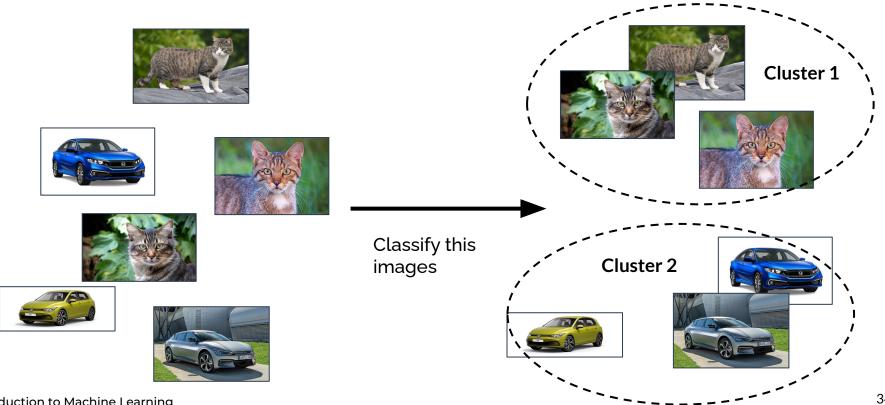
Supervised Learning

Learn a function that maps an input to an output based on examples of input-output pairs.

- Pairs of inputs (usually vectors) to and output value (target signal).
- Generalization error: we want to predict correctly on unseen examples!
- Problem: in a lot of cases you need humans to label the data!



Unsupervised Learning



Unsupervised Learning

Learn the underlying patterns (as probability densities or extracted features) from untagged data.

- We have only inputs (x) and no target signal (ŷ).
- Try to mimic that data and uses the error to correct itself.
- Try to represent the data in a simpler way and compare to reconstructed signal to the original.
- Group examples by similarity.

















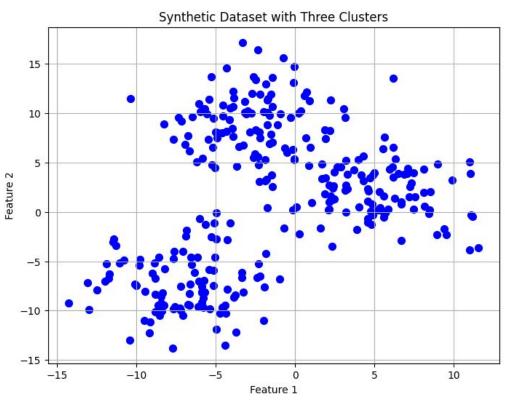


Cluster 2

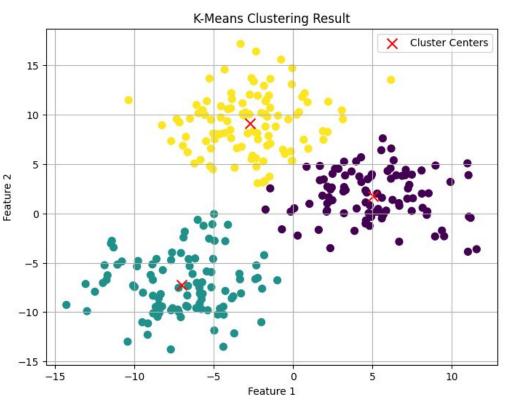
35

Example of unsupervised learning

```
-\Box x
from sklearn.datasets import make blobs
  Create a synthetic dataset with three clusters
X, y = make blobs(
    n samples=300,
    centers=3,
    random state=42,
    cluster std=3
```



```
-\Box \times
from sklearn.cluster import KMeans
# Apply K-Means clustering
kmeans = KMeans(n clusters=3, random state=42)
kmeans.fit(X)
# Get cluster assignments and cluster centers
cluster labels = kmeans.labels
cluster centers = kmeans.cluster centers
```



https://colab.research.google.com/drive/15y1WjGUoDW03_d TrU-aWLWx9JZ03ClmN?usp=sharing

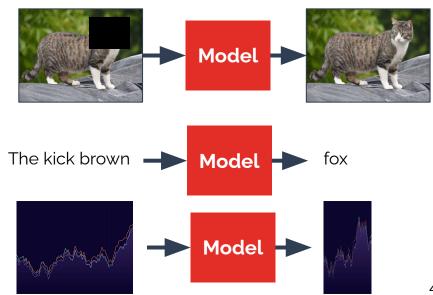
Introduction to Machine Learning

40

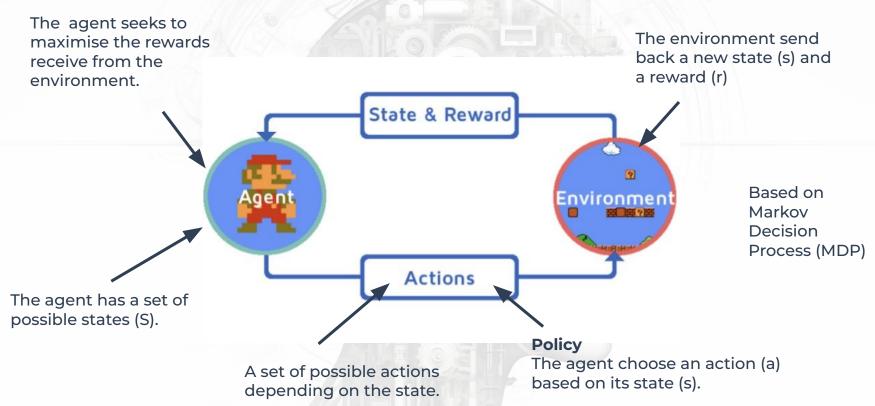
Self-supervised Learning

Key idea: the model trains itself to learn one part of the input from another part of the input.

- Intermediate between supervised and unsupervised learning.
- Pseudo-labels: labels extracted from the data.
- Use the trained model on a related task.
- Linked to the brain: predictive coding.



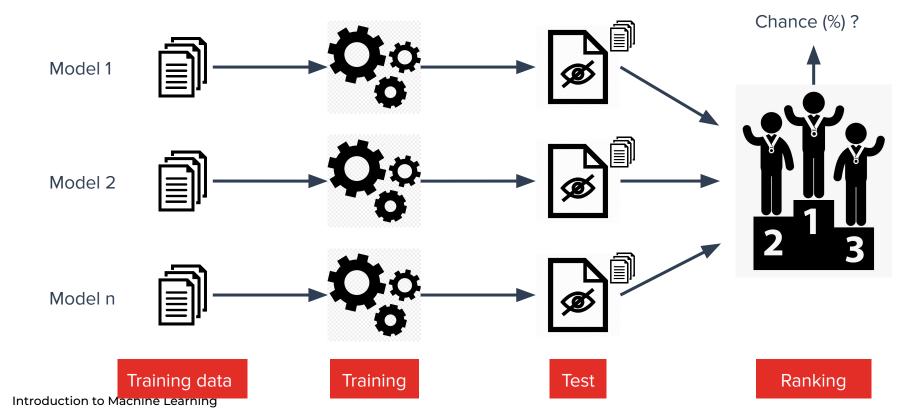
Reinforcement Learning



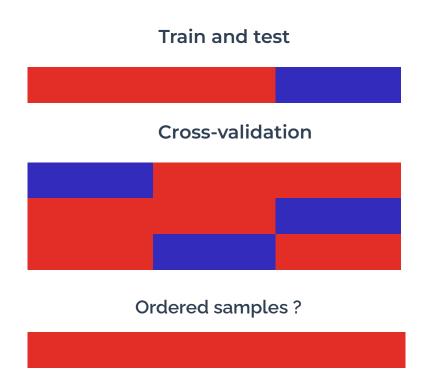
Methodology and applications

Model validation and selection

How select the best model?



Methodology is the key



- What's the definition of a good model?
- There is a lot of ways to measure the performance of a model.
- Performance (right predictions)
- Efficiency (fast predictions)
- Ethical (fair predictions)
- Economical balance (cost of false predictions)
- What data to choose to test the model? How much?
- Dependencies in training and test samples (shuffle first?).

45

Cross validation

```
-\Box x
from sklearn.model selection import cross val score
# Perform k-fold cross-validation (e.g., 5-fold)
num folds = 5
scores = cross val score(
    regression model,
    X, y,
    cv=num folds,
    scoring='neg mean squared error'
```

Cross validation

```
-\Box \times
# Initialize the models
model lr = LogisticRegression (max iter=1000)
model svm = SVC()
# Perform 5-fold cross-validation for each model
cv scores lr = cross val score (model lr, X, y, cv=5)
cv scores svm = cross val score (model svm, X, y, cv=5)
# Logistic Regression CV Scores: [0.96 1. 0.93 0.96 1.0]
```

Cross validation

```
-\Box \times
# Perform a paired t-test to compare the models' performance
t stat, p value = ttest rel(cv scores lr, cv scores svm)
 # t-statistic: 0.53
 # p-value: 0.6213
# There is 62% of chance that the difference between SVM and
logistic regression is due to randomness, that's a lot !
```

https://colab.research.google.com/drive/1cE7ZxqmMqBZqoH gTqjYcWsi5ALqeH1zl?usp=sharing