



K-means

- In its simplest form, the algorithm `k` considers nearest neighbor only one nearest neighbor - the point of the training set, the closest located to the point for which we want to get a forecast. The prediction is the answer already known for the given training point set.
- `mglearn.plots.plot_knn_classification(n_neighbors=1)`

K-means

- Here we have added three new data points, shown as stars. For each, we marked the nearest point of the training set. The prediction that the one nearest neighbor algorithm gives is –the label of this point (shown by the color of the marker). Instead of taking into account only one nearest neighbor, we can consider an arbitrary number (k) neighbors. Hence and the name of the algorithm k nearest neighbors. When we consider more than one neighbor, to assign a label is used vote (voting). This means that for each point of the test set, we count the number of neighbors belonging to class 0, and number of class 1 neighbors. We then assign test set point most frequently occurring class: other In other words, we choose the class with the majority among k nearest neighbors.

K-means

- In[11]:
- `mglearn.plots.plot_knn_classification(n_neighbors=3)`
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K-means and scikit learn

- Now let's see how the algorithm can be applied to nearest neighbors using scikit-learn. First, we will share our data on the training and test sets to evaluate generalizing ability of the model,
- `from sklearn.model_selection import train_test_split`
- `X, y = mglearn.datasets.make_forge()`
- `X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)`
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K-means and scikit learn

- Next, we import and create an instance object of the class by setting parameters, for example, the number of neighbors that we will use for classification. In this case, we set it to 3:
- `from sklearn.neighbors import KNeighborsClassifier`
- `clf = KNeighborsClassifier(n_neighbors=3)`

K-means and sklearn

- We then fit the classifier using the training set. For `KNeighborsClassifier` which means remembering a set of data, such as `X_train` and `y_train`. Thus, we can calculate the neighbors during the prediction:
- `clf.fit(X_train, y_train)`

Predict

- To get the predictions for the test data, we call the method `predict`. For each point of the test set, it calculates its closest neighbors in the training set and finds among them the most frequent occurring class:
- ```
print("Прогнозы на тестовом наборе: {}".format(clf.predict(X_test)))
```
- 
- Out[15]:
- Прогнозы на тестовом наборе: [1 0 1 0 1 0 0]
-



# Score

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- In[16]:
- `print("Правильность на тестовом наборе: {:.2f}".format(clf.score(X_test, y_test)))`
- 
- Out[16]:
- `Правильность на тестовом наборе: 0.86`
-

# Boundaries

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- Also, for two-dimensional datasets, we can show predictions for all possible test set points by placing in  $x$   $y$  plane. We will set the color of the plane according to the class which will be assigned to a point in this area. This will allow us to form decision boundary (decision boundary), which splits the plane into two regions: the region where the algorithm assigns class 0, and the region where the algorithm assigns class 1. The code below renders the borders decision making for one, three and nine neighbors

# Boundaries

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- In[17]:
- `fig, axes = plt.subplots(1, 3, figsize=(10, 3))`
- 
- `for n_neighbors, ax in zip([1, 3, 9], axes):`
- `# создаем объект-классификатор и подгоняем в одной строке`
- `clf = KNeighborsClassifier(n_neighbors=n_neighbors).fit(X, y)`
- `mglearn.plots.plot_2d_separator(clf, X, fill=True, eps=0.5, ax=ax, alpha=.4)`
- `mglearn.discrete_scatter(X[:, 0], X[:, 1], y, ax=ax)`
- `ax.set_title("количество соседей: {}".format(n_neighbors))`
- `ax.set_xlabel("признак 0")`
- `ax.set_ylabel("признак 1")`
- `axes[0].legend(loc=3)`

# KNeighborsRegressor

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- With regard to our one-dimensional data array, we can see predictions for all possible feature values (Figure 2.10). To do this, we create a test dataset and visualize received forecast lines:

# Code

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- `fig, axes = plt.subplots(1, 3, figsize=(15, 4))`
- `# создаем 1000 точек данных, равномерно распределенных между -3 и 3`
- `line = np.linspace(-3, 3, 1000).reshape(-1, 1)`
- `for n_neighbors, ax in zip([1, 3, 9], axes):`
- `# получаем прогнозы, используя 1, 3, и 9 соседей`
- `reg = KNeighborsRegressor(n_neighbors=n_neighbors)`
- `reg.fit(X_train, y_train)`
- `ax.plot(line, reg.predict(line))`
- `ax.plot(X_train, y_train, '^', c=mglearn.cm2(0), markersize=8)`
- `ax.plot(X_test, y_test, 'v', c=mglearn.cm2(1), markersize=8)`

# Code

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- `ax.set_title(`
- `"{} neighbor(s)\n train score: {:.2f} test score: {:.2f}".format(`
- `n_neighbors, reg.score(X_train, y_train),`
- `reg.score(X_test, y_test)))`
- `ax.set_xlabel("Признак")`
- `ax.set_ylabel("Целевая переменная")`
- `axes[0].legend(["Прогнозы модели", "Обучающие данные/ответы",`
- `"Тестовые данные/ответы"], loc="best")`

# Advantages and disadvantages

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- Basically, there are two important parameters in the KNeighbors classifier: the number of neighbors and a measure of the distance between data points. On the practice, the use of a small number of neighbors (for example, 3-5) is often works well, but you can of course customize this one yourself parameter. The question of choosing the correct measure of distance, is outside the scope of this book. The default is Euclidean distance that works well in many situations. One of the advantages of the nearest neighbor method is that this model is very easy to interpret and, as a rule, this method gives acceptable quality without the need for a large number of settings.

# Advantages and disadvantages

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- Typically, building a model nearest neighbors happens very fast, but when your training set is very large (in terms of the number of features or number of observations) obtaining forecasts may take some time. When using the nearest neighbors algorithm, it is important to perform data preprocessing (see chapter 3). This method does not work so well when it comes to datasets with a large number of signs (hundreds or more), and especially bad works in a situation where the vast majority of features are zero in parts of the observations (the so-called sparse datasets or sparse datasets).



# Decision trees

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- Building a decision tree means building a sequence of rules "if ... then ...", which leads us to the true answer in the shortest possible way. In machine learning, these rules are called tests (tests). Do not confuse them with the test set, which we use to test the generalizing ability of our model. As a rule, data is presented not only in the form of binary yes/no signs, as in the example with animals, but also in the form of continuous features, as in the two-dimensional dataset shown in Fig. 2.23. Tests that are used for continuous data are of the form "Sign  $i$  more value  $a$ ?"

# Decision trees

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- `mglearn.plots.plot_tree_progressive()`

# Decision trees

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- The recursive partitioning of the data is repeated until all points data in each split area (each leaf of the decision tree) is not will belong to the same value of the target variable (class or quantitative value). The leaf of the tree that contains data points referring to the same target value variable is called clean (pure). The final partition for our data set is shown in fig.

# Pruning

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Let's take a closer look at how preflight works. clipping on the example of the Breast Cancer dataset. As always, we import the dataset and split it into training and test parts. We then build the model using the default settings for building a complete tree (we grow a tree until all the leaves will not become clean). Fix `random_state` for reproducibility of results:

# Pruning

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- In[58]:
- `from sklearn.tree import DecisionTreeClassifier`
- 
- `cancer = load_breast_cancer()`
- `X_train, X_test, y_train, y_test = train_test_split(  
cancer.data, cancer.target, stratify=cancer.target, random_state=42)`
- `tree = DecisionTreeClassifier(random_state=0)`
- `tree.fit(X_train, y_train)`
- `print("Правильность на обучающем наборе: {:.3f}".format(tree.score(X_train, y_train)))`
- `print("Правильность на тестовом наборе: {:.3f}".format(tree.score(X_test, y_test)))`
- 
- Out[58]:
- `Правильность на обучающем наборе: 1.000`

`Правильность на тестовом наборе: 0.937`

# Pruning

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- If you do not limit the depth, the tree can be arbitrarily deep and complex. Therefore, unpruned trees are prone to overfitting and do not generalize well to new data. Now let's apply a pre-pruning to the tree that will stop the process of building a tree before we perfectly fit the model to training data. One option is to stop the process of building a tree when a certain depth is reached. We are here setting `max_depth=4`, that is, you can set only four sequential questions (see Figures 2.24 and 2.26). Depth limiting a tree reduces overfitting. This leads to lower correctness on the training set, but improves correctness on the test set:

# Pruning

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- In[59]:
- `tree = DecisionTreeClassifier(max_depth=4, random_state=0)`
- `tree.fit(X_train, y_train)`
- 
- `print("Правильность на обучающем наборе: {:.3f}".format(tree.score(X_train, y_train)))`
- `print("Правильность на тестовом наборе: {:.3f}".format(tree.score(X_test, y_test)))`
- 
- Out[59]:
- Правильность на обучающем наборе: 0.988
- Правильность на тестовом наборе: 0.951
-

# Visualization

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- `from sklearn.tree import export_graphviz`
- `export_graphviz(tree, out_file="tree.dot", class_names=["malignant", "benign"],`
- `feature_names=cancer.feature_names, impurity=False,`
- `filled=True)`



# Visualization

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- `import graphviz`
- 
- `with open("tree.dot") as f:`
- `dot_graph = f.read()`
- `graphviz.Source(dot_graph)`

# Visualization

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- `import numpy as np`
- `import matplotlib.pyplot as plt`
- `import pandas as pd`
- `import mglearn`
- `%matplotlib inline`
- `from sklearn.model_selection import train_test_split`
- `from sklearn.datasets import load_breast_cancer`

# Visualization

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- `from sklearn import tree`
- `from sklearn.tree import export_graphviz`
- `cancer = load_breast_cancer()`
- `X_train, X_test, y_train, y_test = train_test_split(  
 cancer.data, cancer.target, stratify=cancer.target, random_state=42)`
- `clf = tree.DecisionTreeClassifier(max_depth=4, random_state=0)`
- `clf = clf.fit(X_train, y_train)`
- 
- `import pydotplus`
- `dot_data = tree.export_graphviz(clf, out_file=None)`

# Ensembles

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- Ensembles (ensembles) are methods that combine a set of machine learning models to end up with a more powerful model. There are many machine learning models that belong to this category, but there are two ensemble models that proven to be effective on a wide variety of datasets for classification and regression problems, both use decision trees in as building blocks: a random forest of decision trees and gradient boosting decision trees.

# Random Forest

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- As we have just noted, the main disadvantage of decision trees is their tendency to overlearn. Random forest is one of the ways to solve this problem. Essentially, a random forest is a set of decision trees, where each tree is slightly different from the others. The idea of a random forest is that each tree can be pretty good at predicting, but likely overfitting to the training data. If we build many trees that work well and overfit to varying degrees, we can reduce overfitting by averaging their results. Reduction of overfitting while preserving the predictive power of trees can be illustrated using rigorous mathematics.

# Random forest

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- `from sklearn.ensemble import RandomForestClassifier`
- `from sklearn.datasets import make_moons`
- 
- `X, y = make_moons(n_samples=100, noise=0.25, random_state=3)`
- `X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,`
- `random_state=42)`
- 
- `forest = RandomForestClassifier(n_estimators=5, random_state=2)`
- `forest.fit(X_train, y_train)`
-

# Random forest

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- `fig, axes = plt.subplots(2, 3, figsize=(20, 10))`
- `for i, (ax, tree) in enumerate(zip(axes.ravel(), forest.estimators_)):`
- `ax.set_title("Дерево {}".format(i))`
- `mglearn.plots.plot_tree_partition(X_train, y_train, tree, ax=ax)`
- 
- `mglearn.plots.plot_2d_separator(forest, X_train, fill=True, ax=axes[-1, -1],`
- `alpha=.4)`
- `axes[-1, -1].set_title("Случайный лес")`
- `mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)`
-

# Breast Cancer:

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- `X_train, X_test, y_train, y_test = train_test_split(`
- `cancer.data, cancer.target, random_state=0)`
- `forest = RandomForestClassifier(n_estimators=100, random_state=0)`
- `forest.fit(X_train, y_train)`
- 
- `print("Правильность на обучающем наборе: {:.3f}".format(forest.score(X_train, y_train)))`



# Breast Cancer:

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- `def plot_feature_importances_cancer(model):`
- `n_features = cancer.data.shape[1]`
- `plt.barh(range(n_features), model.feature_importances_, align='center')`
- `plt.yticks(np.arange(n_features), cancer.feature_names)`
- `plt.xlabel("Важность признака")`
- `plt.ylabel("Признак")`
- `plot_feature_importances_cancer(forest)`
-

# Gradient Boosting

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- The basic idea of gradient boosting is to combine a set of simple models (in this context known as weak learners or weak students), small trees with shallow depths. Each tree can only give good predictions for a part of the data and thus for iterative quality improvement more and more trees are being added. Gradient tree boosting often ranks first in competitions in machine learning, and is also widely used in commercial areas. Unlike random forest, it is usually slightly more sensitive to parameter settings, however, correctly set parameters can give a higher value of correctness.

# Gradient Boosting

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- `from sklearn.ensemble import GradientBoostingClassifier`
- 
- `X_train, X_test, y_train, y_test = train_test_split(`
- `cancer.data, cancer.target, random_state=0)`
- 
- `gbrt = GradientBoostingClassifier(random_state=0)`
- `gbrt.fit(X_train, y_train)`
- 
- `print("Правильность на обучающем наборе: {:.3f}".format(gbrt.score(X_train, y_train)))`
- `print("Правильность на тестовом наборе: {:.3f}".format(gbrt.score(X_test, y_test)))`
-

# Gradient Boosting

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- `gbrt = GradientBoostingClassifier(random_state=0, max_depth=1)`
- `gbrt.fit(X_train, y_train)`
- 
- `print("Правильность на обучающем наборе: {:.3f}".format(gbrt.score(X_train, y_train)))`
- `print("Правильность на тестовом наборе: {:.3f}".format(gbrt.score(X_test, y_test)))`
- 
- Out[73]:
- Правильность на обучающем наборе: 0.991
- Правильность на тестовом наборе: 0.972
- 
- In[74]:
- `gbrt = GradientBoostingClassifier(random_state=0, learning_rate=0.01)`
- `gbrt.fit(X_train, y_train)`
- 
- `print("Правильность на обучающем наборе: {:.3f}".format(gbrt.score(X_train, y_train)))`
- `print("Правильность на тестовом наборе: {:.3f}".format(gbrt.score(X_test, y_test)))`

# Visualization

---

- `gbrt = GradientBoostingClassifier(random_state=0, max_depth=1)`
- `gbrt.fit(X_train, y_train)`
- 
- `def plot_feature_importances_cancer(model):`
- `n_features = cancer.data.shape[1]`
- `plt.barh(range(n_features), model.feature_importances_, align='center')`
- `plt.yticks(np.arange(n_features), cancer.feature_names)`
- `plt.xlabel("Важность признака")`
- `plt.ylabel("Признак")`
- `plot_feature_importances_cancer(gbrt)`