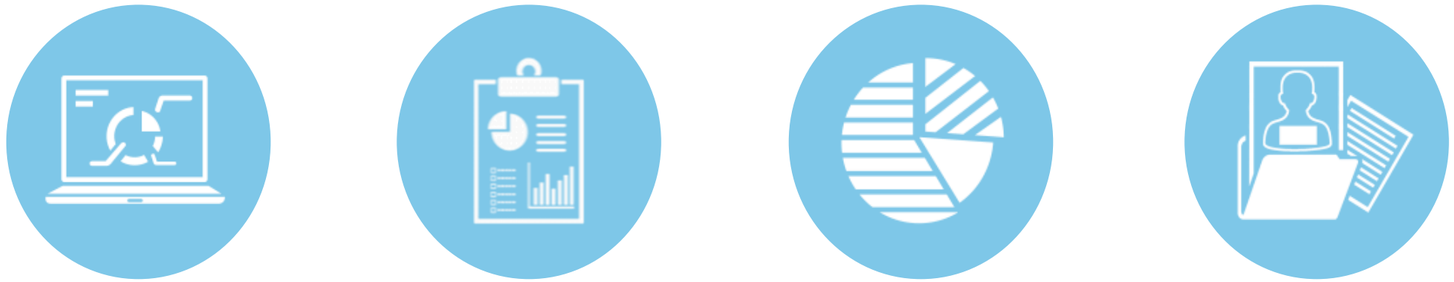
Machine Learning

Lesson 6—Classification



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Learning Objectives

- Define Classification and list its algorithms
- Describe Logistic Regression and Sigmoid Probability
- Explain K-Nearest Neighbors and KNN classification
- Understand Support Vector Machines, Polynomial Kernel, and Kernel Trick
- Analyze Kernel Support Vector Machines with an example
- Implement Naïve Bayes Classifier
- Demonstrate Decision Tree Classifier
- Describe Random Forest Classifier

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Classification

Topic 1: Classification and Its Algorithms

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Classification: Meaning

- Classification is a type of supervised learning.
- It specifies the class to which data elements belong to.
- It is best used when the output has finite and discreet values.
- It predicts a class for an input variable.
- There are 2 types of classification, binomial and multi-class.

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Classification: Use Cases

To find whether an email received is a spam or ham

To identify customer segments

To find if a bank loan is granted

To identify if a kid will pass or fail in an examination

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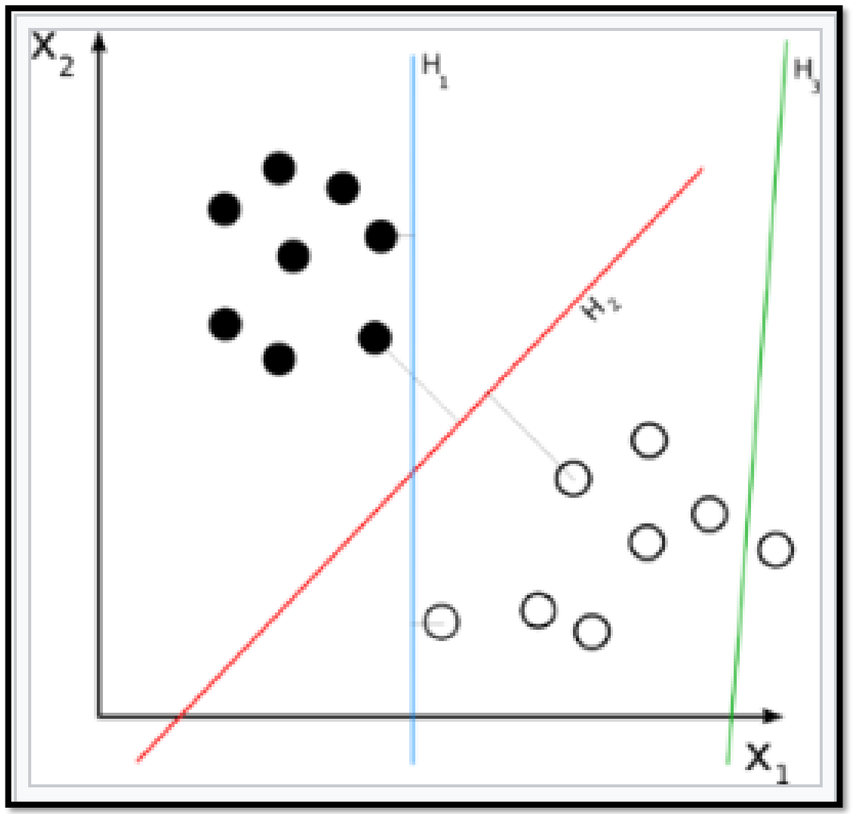
Classification: Example

Social media sentiment analysis has two potential outcomes, positive or negative, as displayed by the chart given below.



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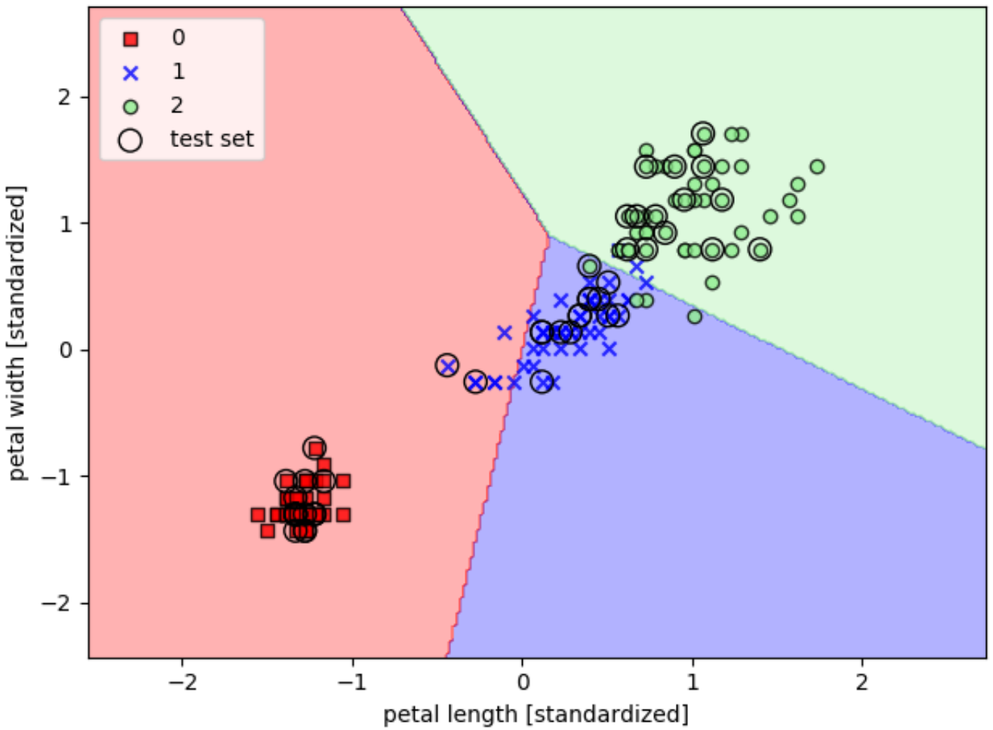
Classification: Example



- This chart shows classification of the Iris flower dataset into its three sub-species indicated by codes 0, 1, and 2.
- The test set dots represent assignment of new test data points to one class or the other based on the trained classifier model.

Source: "Python Machine Learning" by Sebastian Raschka

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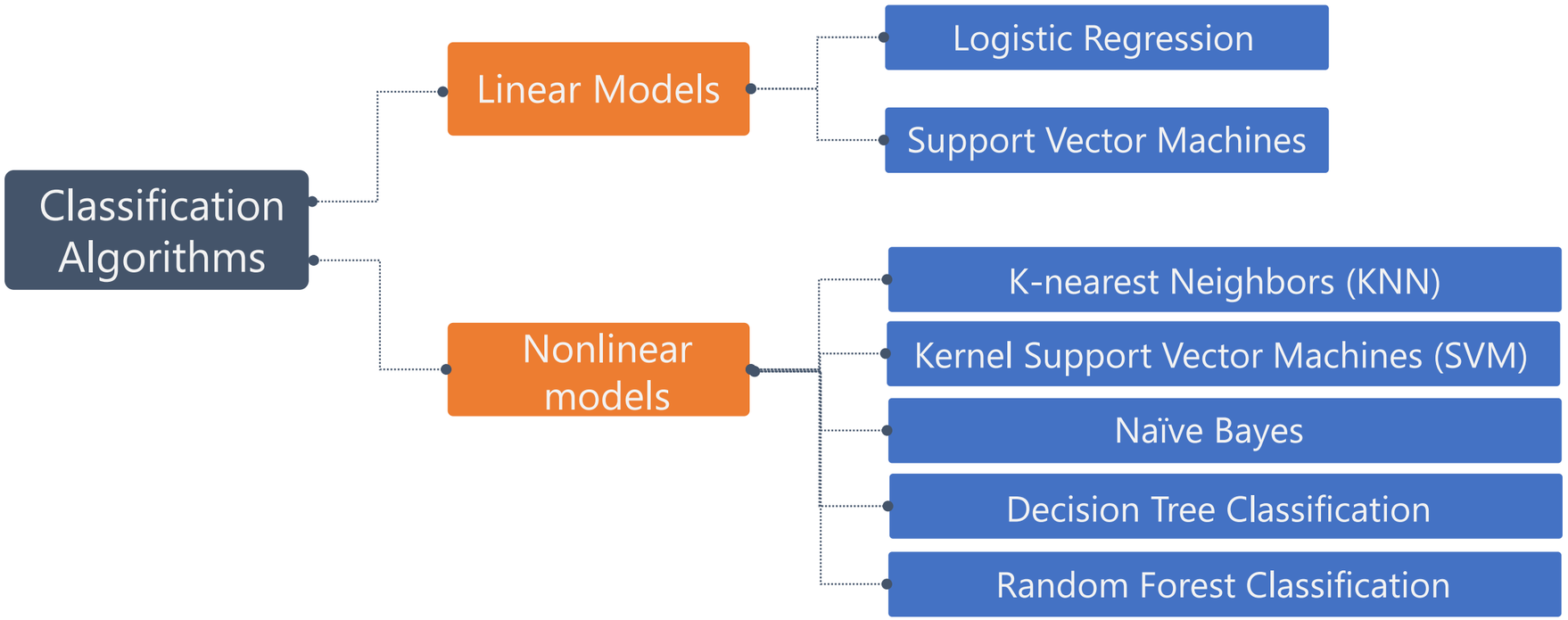
Types of Classification Algorithms



You will study each of these algorithms in this lesson.

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Classification

Topic 2: Logistic Regression

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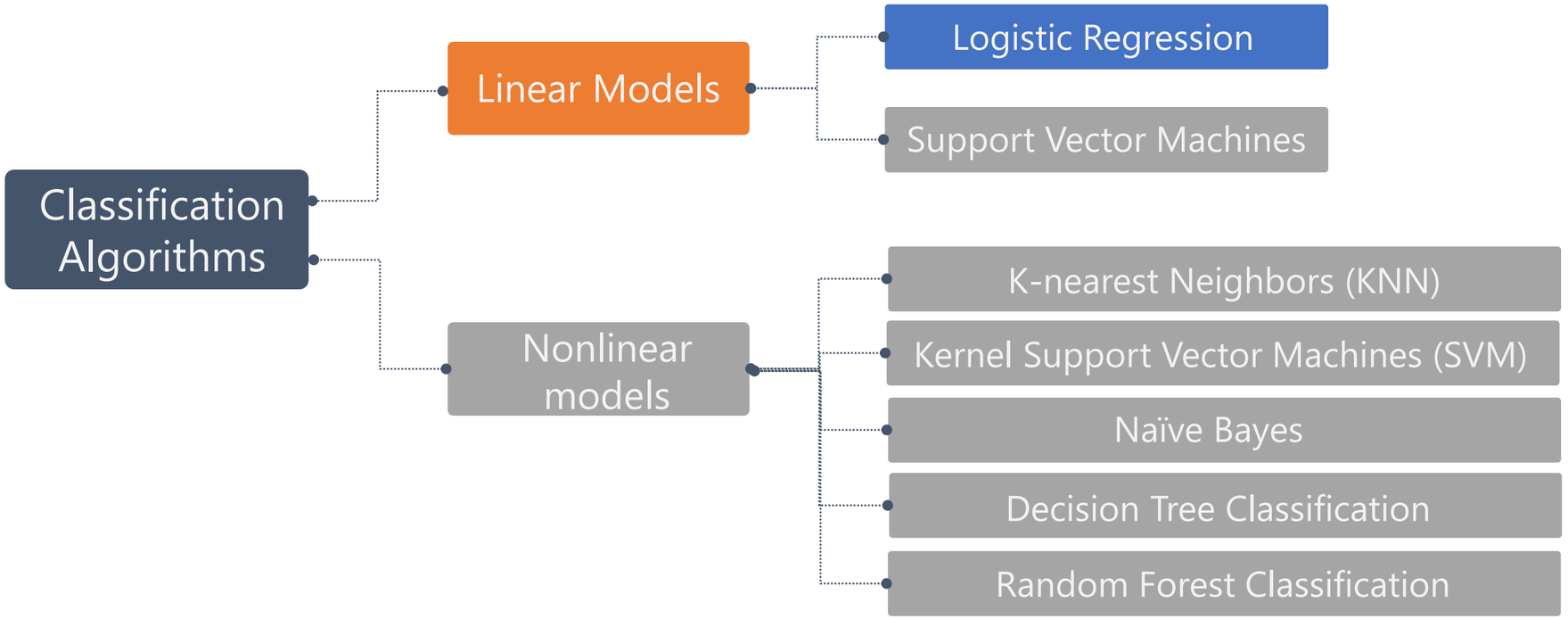
Logistic Regression



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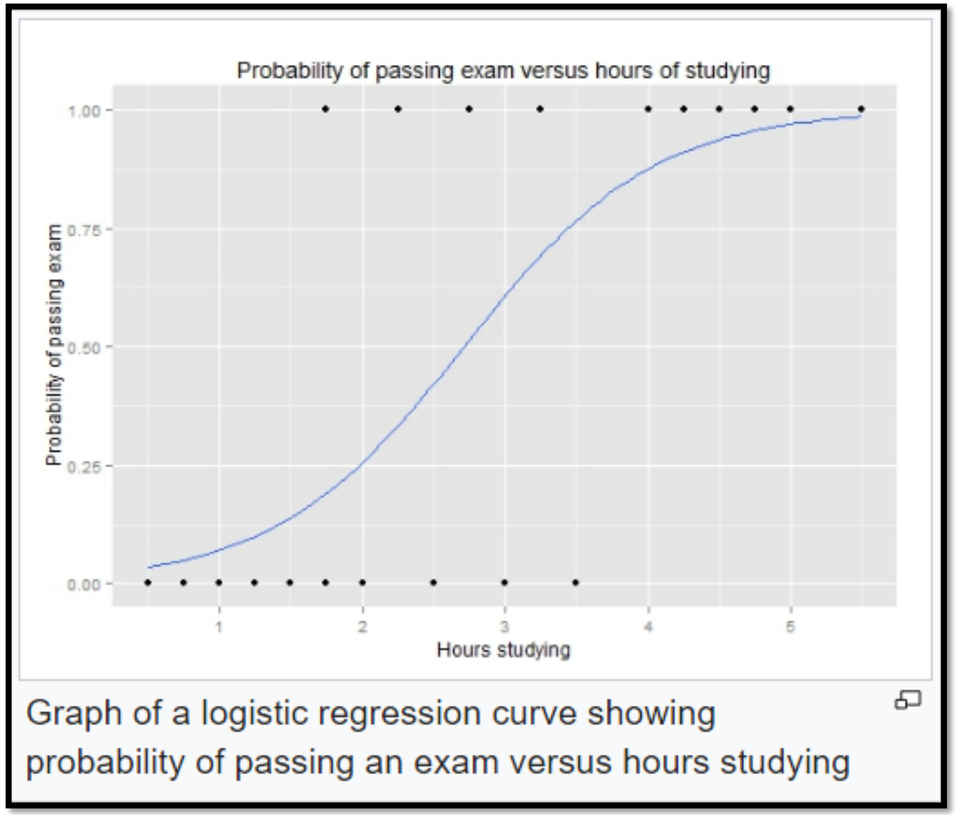
Logistic Regression: Meaning



Graph of a logistic regression curve showing probability of passing an exam versus hours studying

- This refers to a regression model that is used for classification.
- This method is widely used for binary classification problems. It can also be extended to multi-class classification problems.
- Here, the dependent variable is categorical: $y \in \{0, 1\}$
- A binary dependent variable can have only two values, like 0 or 1, win or lose, pass or fail, healthy or sick, etc.

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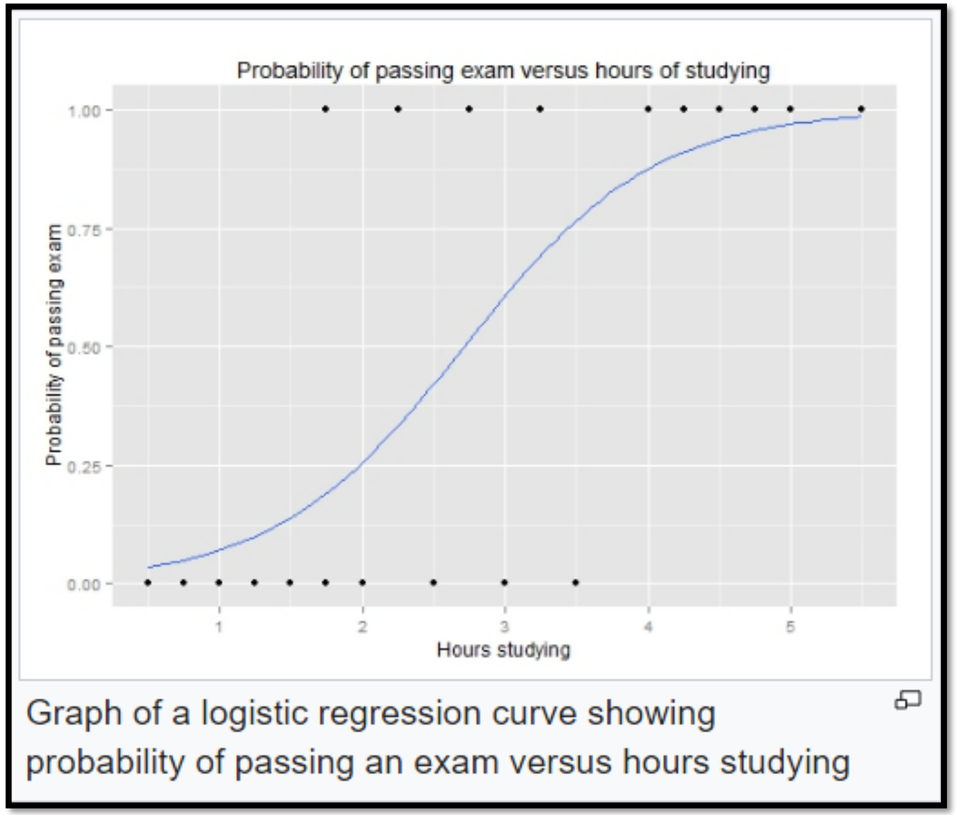
Logistic Regression: Meaning



Graph of a logistic regression curve showing probability of passing an exam versus hours studying

- In this case, you model the probability distribution of output y as 1 or 0. This is called as sigmoid probability (σ).
- If $\sigma(\theta Tx) > 0.5$, set $y = 1$, else set $y = 0$.
- Unlike Linear Regression (and its Normal Equation solution), there is no closed form solution for finding optimal weights of Logistic Regression. Instead, you must solve this with maximum likelihood estimation (a probability model to detect maximum likelihood of something happening).
- It can be used to calculate the probability of a given outcome in a binary model, like probability of being classified as sick or passing an exam.

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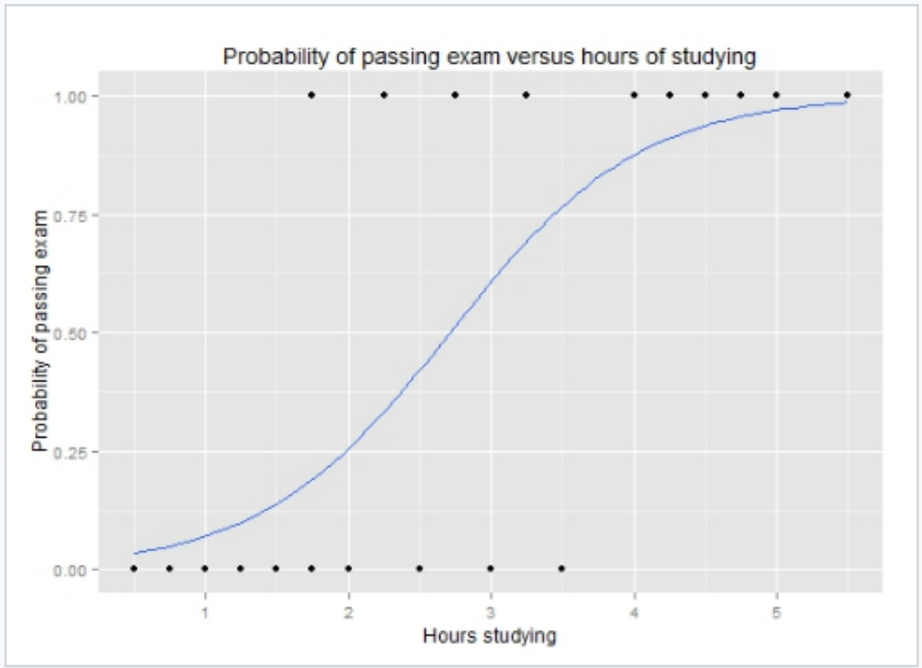
Logistic Regression: Meaning



Graph of a logistic regression curve showing probability of passing an exam versus hours studying

$$P(y = 1 \mid x; \theta) = h_\theta(x) = \sigma(\boldsymbol{\theta}^\top \boldsymbol{x})$$
$$P(y = 0 \mid x; \theta) = 1 - h_\theta(x)$$

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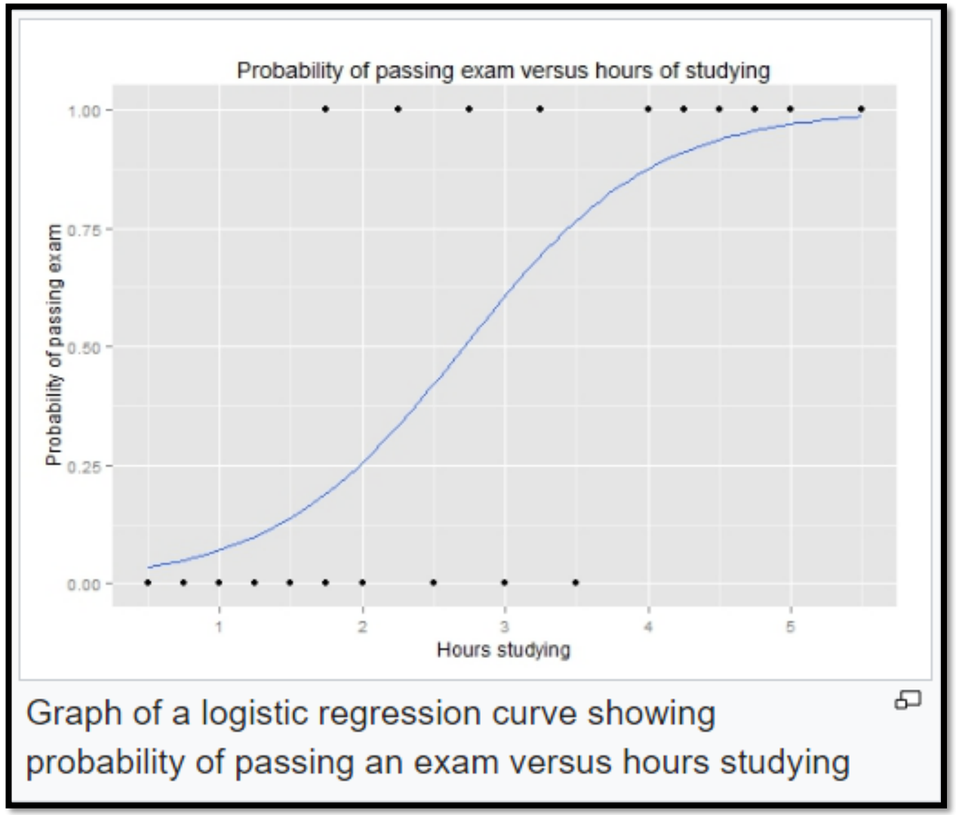
Sigmoid Probability



Graph of a logistic regression curve showing probability of passing an exam versus hours studying

- The probability in the logistic regression is often represented by the Sigmoid function (also called the logistic function or the S-curve):

$$S(t) = \frac{1}{1 + e^{-t}}$$

- In this equation, t represents data values * number of hours studied and S(t) represents the probability of passing the exam.

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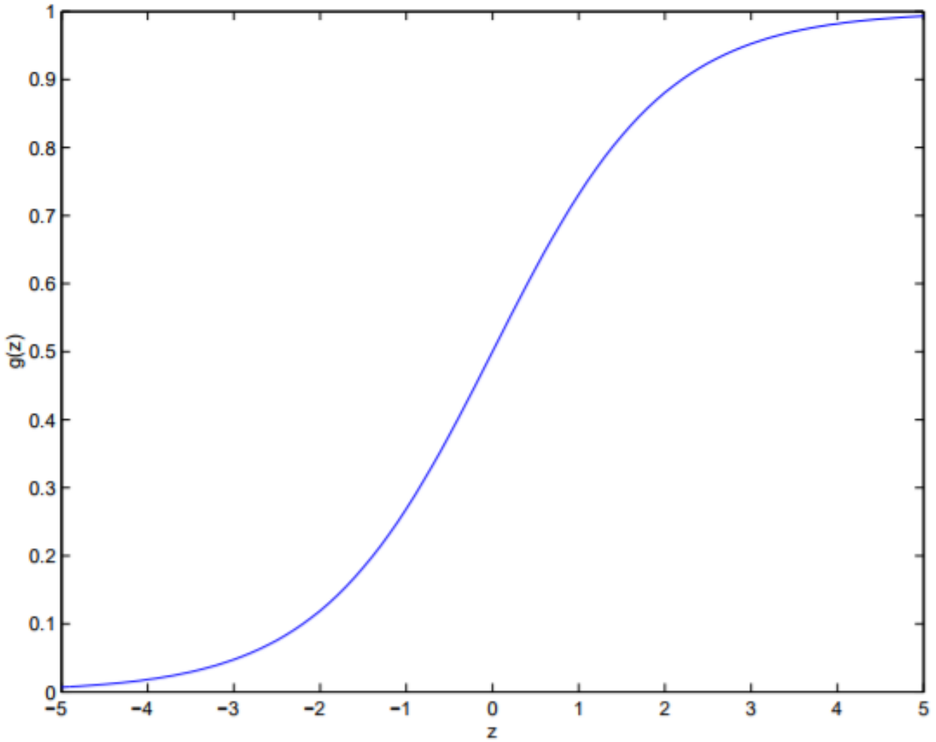
Sigmoid Probability



- Assume sigmoid function:

$$h_\theta(x) = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

- g(z) tends toward 1 as z -> ∞, and g(z) tends toward 0 as z -> - ∞

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Demo

Logistic Regression

Classify the IRIS flower dataset using Logistic Regression Scikit.

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Classification

Topic 3: K-nearest Neighbors

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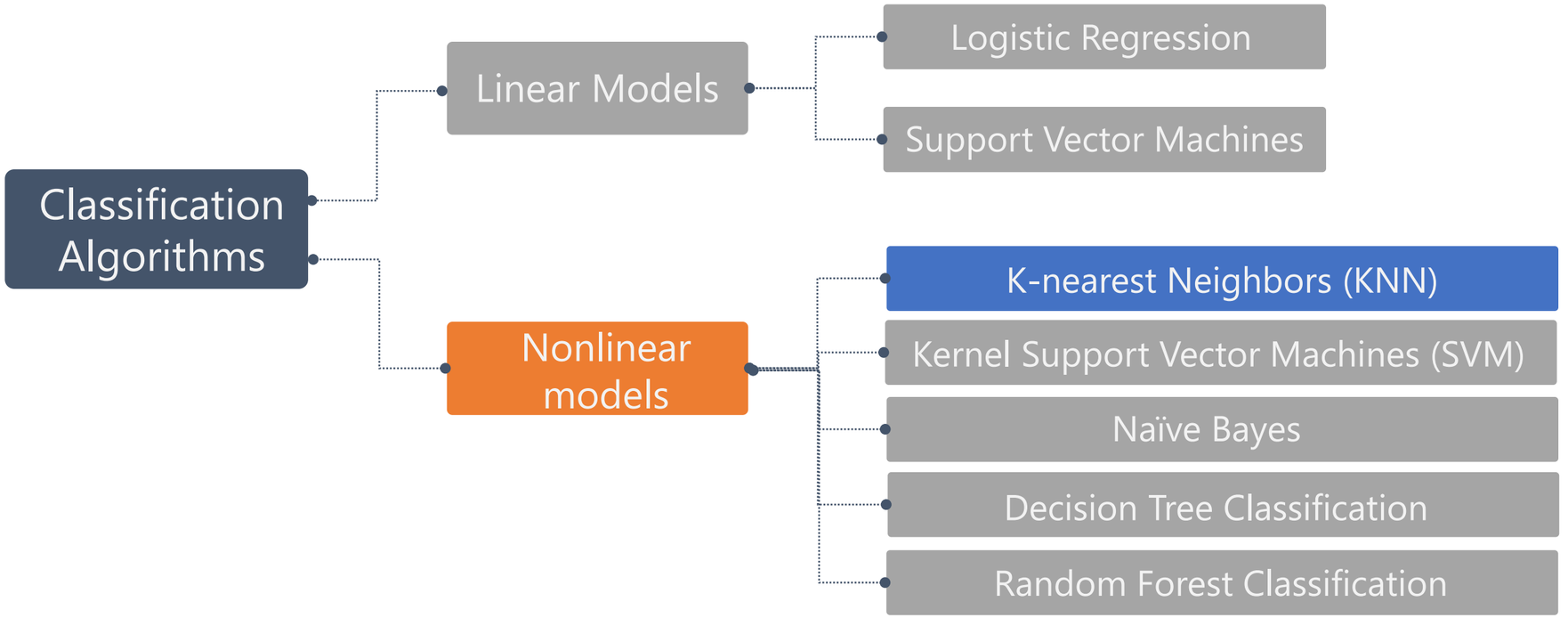
K-nearest Neighbors (KNN)



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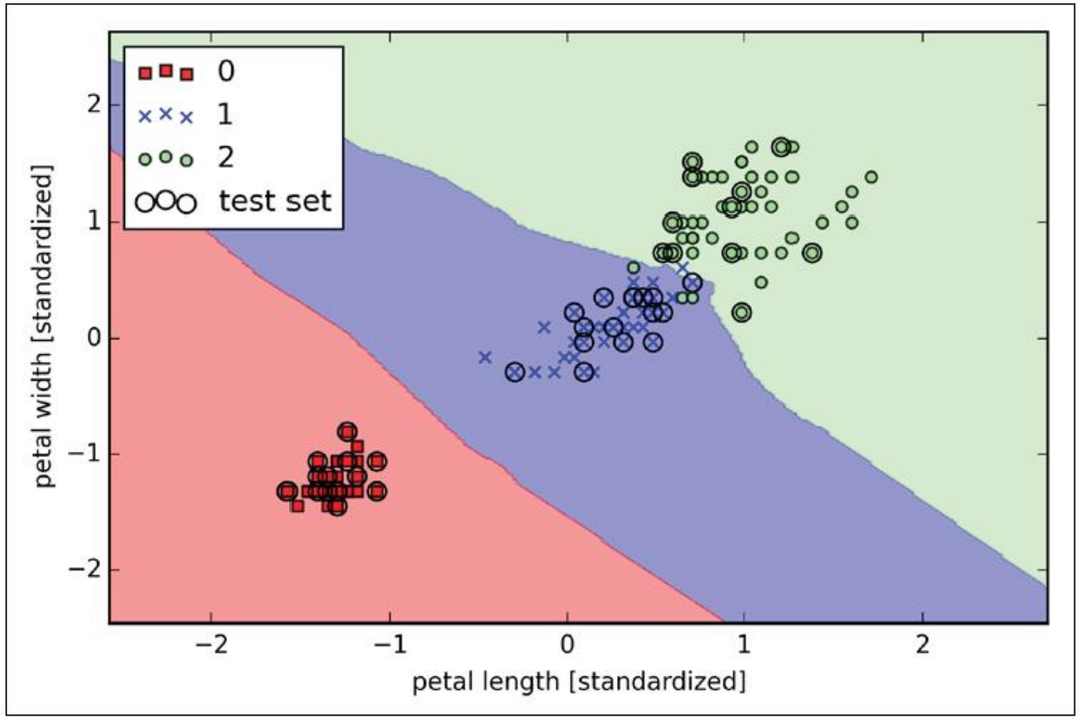
K-nearest Neighbors (KNN)



- K-nearest Neighbors algorithm is used to assign a data point to clusters based on similarity measurement.
- It uses supervised method for classification.

Source: "Python Machine Learning" by Sebastian Raschka

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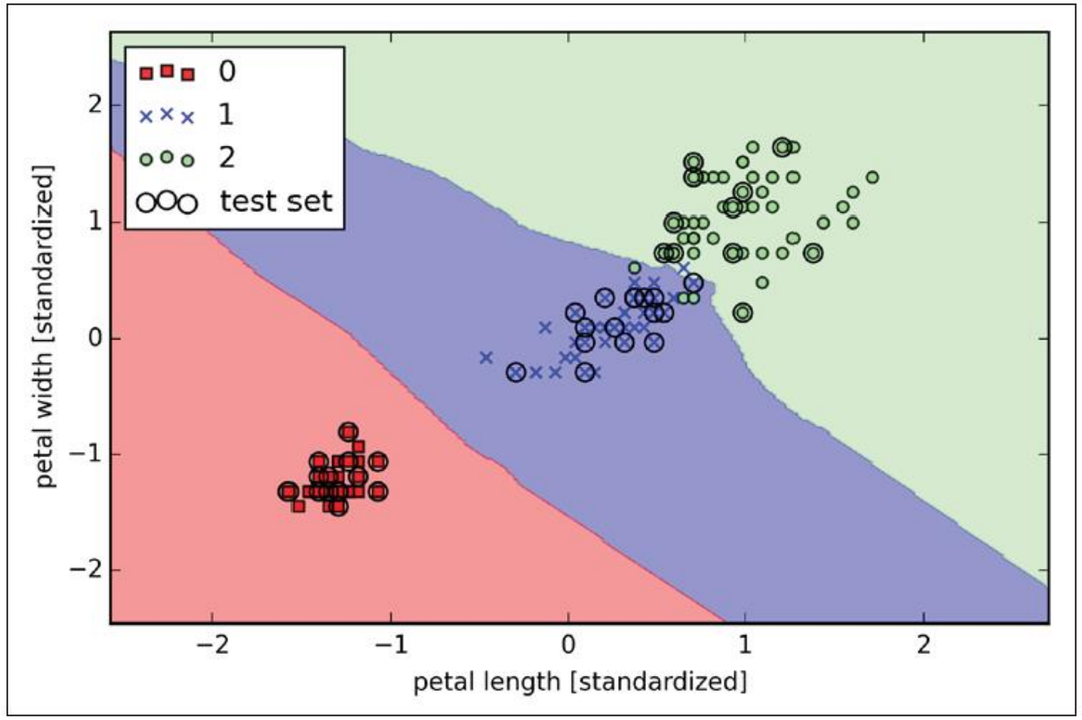
K-Nearest Neighbors Algorithm



The steps to write a KNN algorithm are as given below:

- Choose the number of k and a distance metric.
- (k = 5 is common)
- Find k-nearest neighbors of the sample that you want to classify.
- Assign the class label by majority vote.

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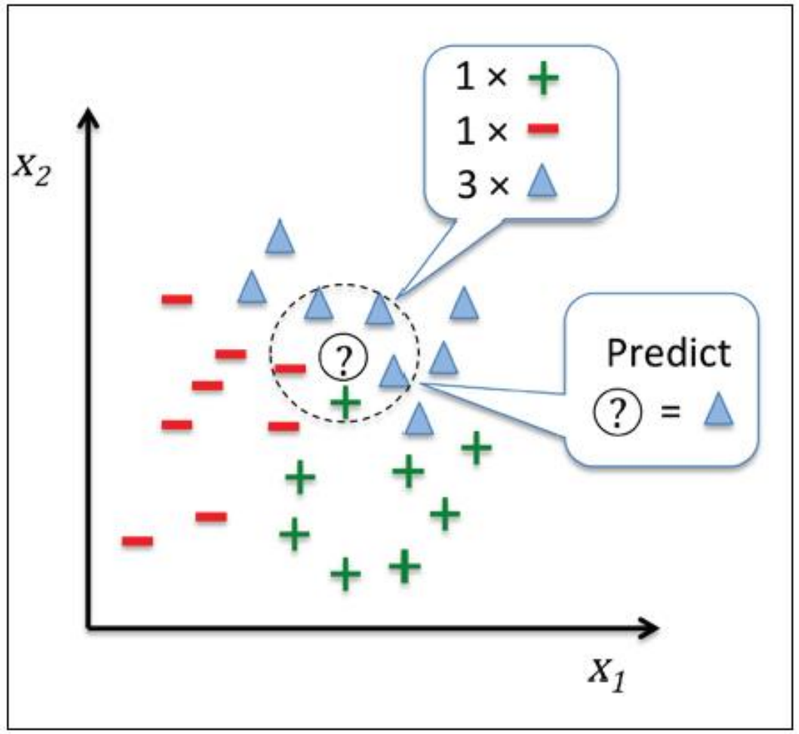
KNN Classification



- A new input point is classified in the category such that it has the most number of neighbors from that category.

For example:

- Classify a patient as high risk or low risk.
- Mark email as spam or ham.

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Demo

KNN Classification

Predict whether consumers will buy houses or not, given their age and salary. (Use KNN)

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Classification

Topic 4: Support Vector Machines

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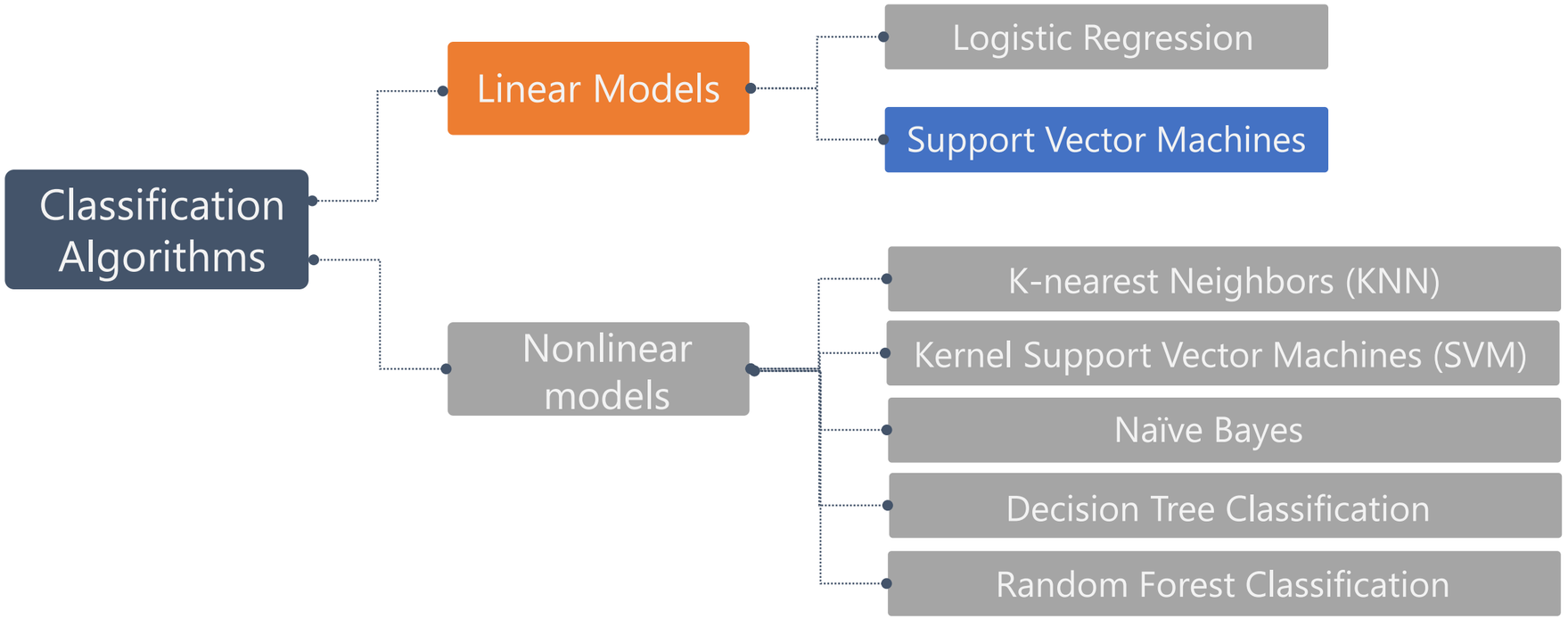
Support Vector Machines (SVM)



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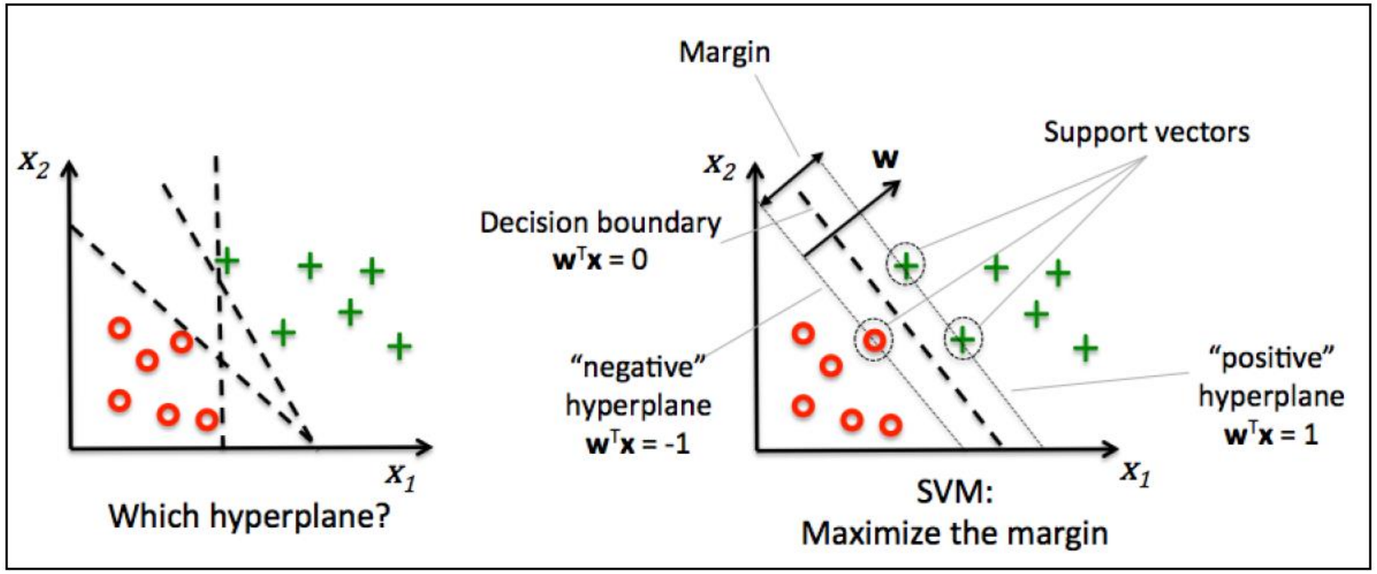
Support Vector Machines (SVM)



- SVMs are classification algorithms used to assign data to various classes.
- They involve detecting hyperplanes which segregate data into classes.
- SVMs are very versatile and are also capable of performing linear or nonlinear classification, regression, and outlier detection.

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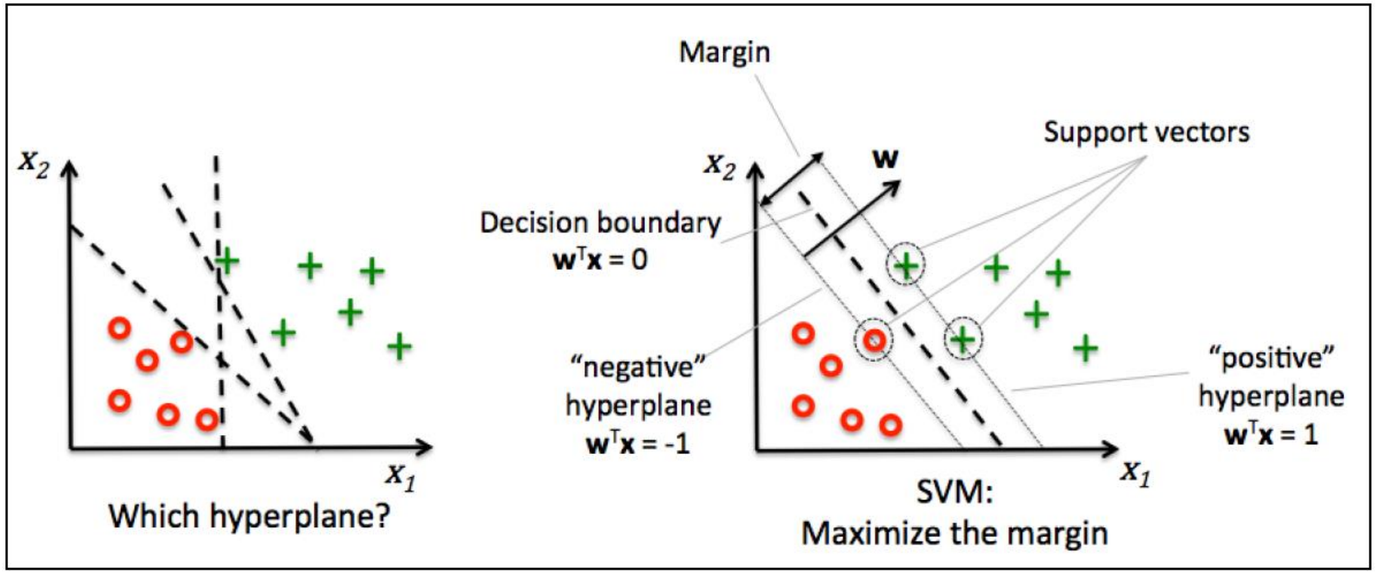
Support Vector Machines (SVM)



- Once ideal hyperplanes are discovered, new data points can be easily classified.
- The optimization objective is to find "maximum margin hyperplane" that is farthest from the closest points in the two classes (these points are called support vectors).

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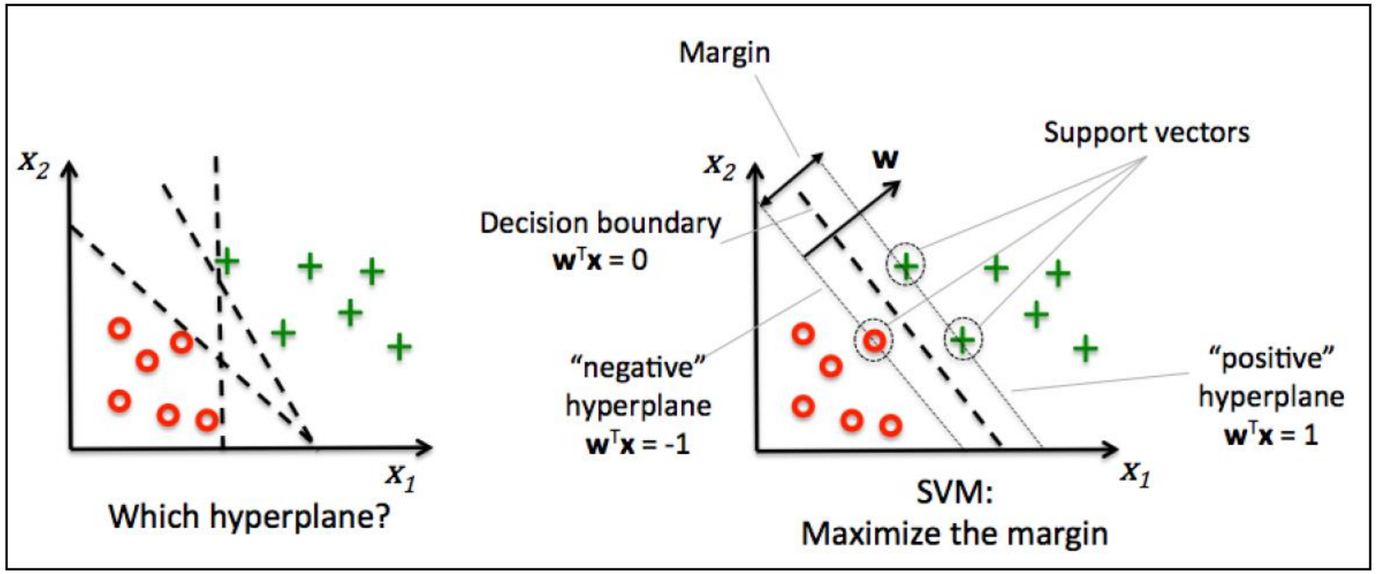
Support Vector Machines (SVM)



- In the given figure, the middle line represents the hyperplane.

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Demo

SVM Classification

Predict whether consumers will buy houses or not, given their age and salary.

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SVM: Example

- Hyperplanes with larger margins have lower generalization error.
- The positive and negative hyperplanes are represented by:

$$w_0 + \boldsymbol{w}^T \boldsymbol{x}_{pos} = 1$$
$$w_0 + \boldsymbol{w}^T \boldsymbol{x}_{neg} = -1$$

Classification of any new input sample x_{test} :

- If $w_0 + w^T x_{test} > 1$, the sample x_{test} is said to be in the class toward the right of the positive hyperplane.
- If w0 + wTxtest < -1, the sample x_{test} is said to be in the class toward the left of the negative hyperplane.

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SVM: Example

- When you subtract the two equations, you get:

$$\boldsymbol{w}^T\left(\boldsymbol{x}_{pos}-\boldsymbol{x}_{neg}\right)=2$$

- Length of vector w is (L2 norm length):

$$\|\boldsymbol{w}\|=\sqrt{\sum_{j=1}^{m} w_j^2}$$

- You normalize with the length of w to arrive at:

$$\frac{\boldsymbol{w}^T\left(\boldsymbol{x}_{pos}-\boldsymbol{x}_{neg}\right)}{\|\boldsymbol{w}\|}=\frac{2}{\|\boldsymbol{w}\|}$$

Equation SVM-1

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SVM: Hard Margin Classification

- The left side of equation SVM-1 given above can be interpreted as the distance between the positive (+ve) and negative (-ve) hyperplanes; in other words, it is the margin that can be maximized.

- Hence the objective of function is to maximize $\frac{2}{\|\boldsymbol{w}\|}$ with the constraint that the samples are classified correctly, which is represented as :

$$w_0 + \boldsymbol{w}^T \boldsymbol{x}^{(i)} \geq 1 \; if \; y^{(i)} = 1$$
$$w_0 + \boldsymbol{w}^T \boldsymbol{x}^{(i)} < -1 \; if \; y^{(i)} = -1$$

- This means that you are minimizing ||w||.

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SVM: Hard Margin Classification

- This also means that all positive samples are on one side of the positive hyperplane and all negative samples are on the other side of the negative hyperplane. This can be written concisely as:

$$y^{(i)}\left(w_0 + \boldsymbol{w}^T \boldsymbol{x}^{(i)}\right) \geq 1 \ \forall_i$$

- Minimizing ||w|| is the same as minimizing $\frac{1}{2}\|\boldsymbol{w}\|^2$ This figure is better as it is differentiable even at w = 0.

- The approach listed above is called “hard margin linear SVM classifier.”

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SVM: Soft Margin Classification

To allow for linear constraints to be relaxed for nonlinearly separable data, a slack variable ξ is introduced. $\xi^{(i)}$ measures how much i^{th} instance is allowed to violate the margin.

The slack variable is simply added to the linear constraints.

$$\boldsymbol{w}^T \boldsymbol{x}^{(i)} \geq 1 \; if \; \; y^{(i)} = 1 - \xi^{(i)}$$
$$\boldsymbol{w}^T \boldsymbol{x}^{(i)} < -1 \; if \; \; y^{(i)} = 1 + \xi^{(i)}$$

Subject to above constraints, the new objective to be minimized becomes:

$$\frac{1}{2}\|\boldsymbol{w}\|^2 + C\left(\sum_i \xi^{(i)}\right)$$

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SVM: Soft Margin Classification

- You have two conflicting objectives now—minimizing slack variable to reduce margin violations and minimizing to $\frac{1}{2}\|\boldsymbol{w}\|^2$ ase the margin.

- The hyperparameter C allows us to define this trade-off.

- Large values of C correspond to larger error penalties (so smaller margins), whereas smaller values of C allow for higher misclassification errors and larger margins.

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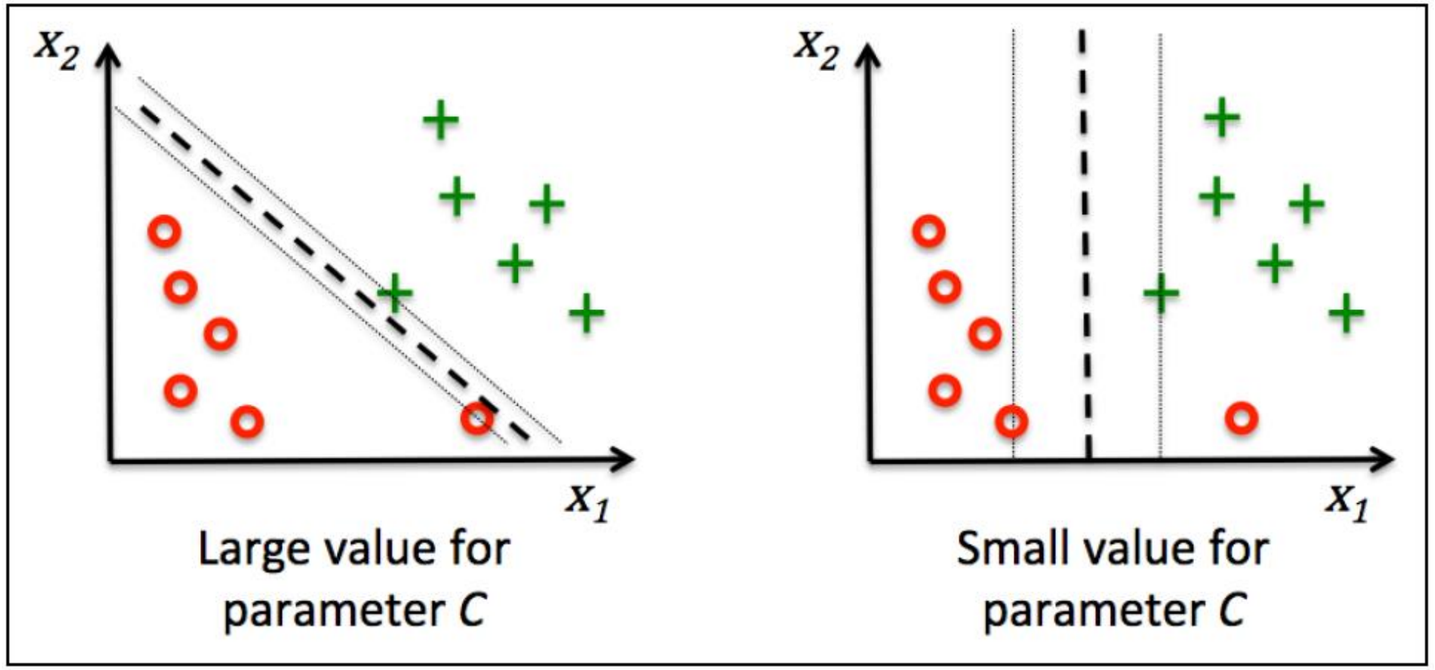
SVM: Regularization

The concept of C is reverse of regularization. Higher C means lower regularization, which increases bias and lowers the variance (causing overfitting).



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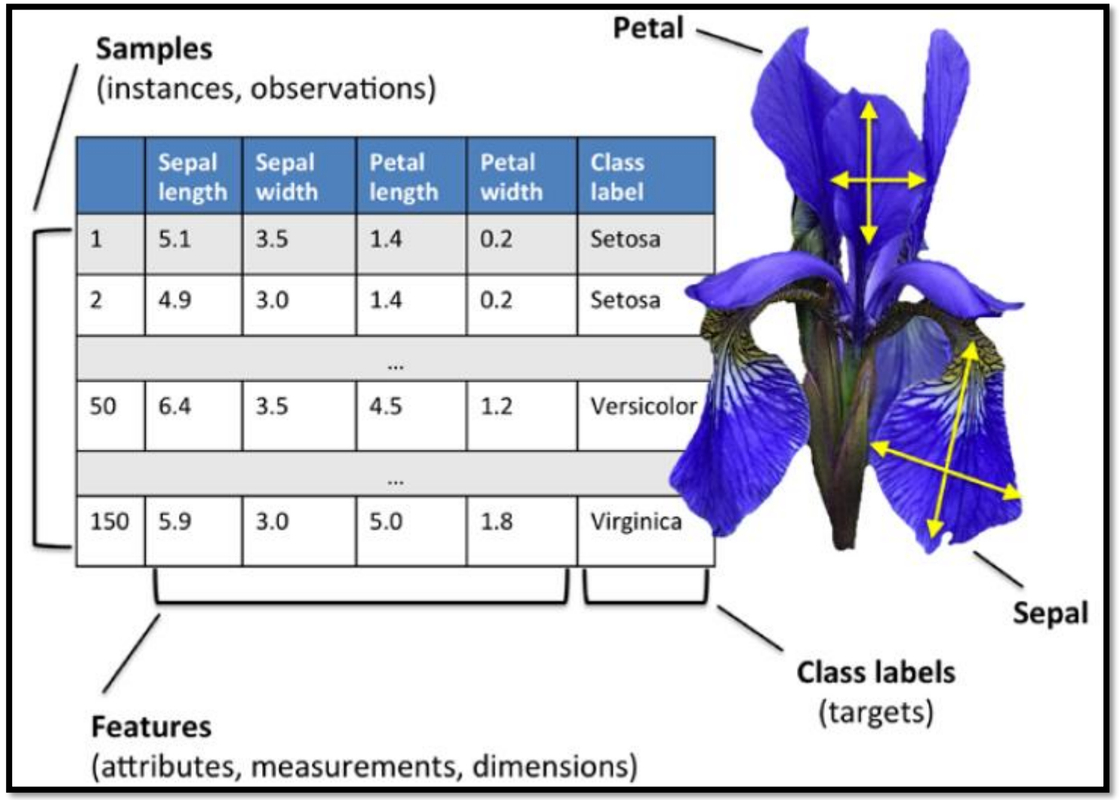
IRIS Data Set



	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

- The Iris dataset contains measurements of 150 iris flowers from three different species: Setosa, Versicolor, and Viriginica.
- Each row represents one sample.
- Flower measurements in centimeters are stored as columns. These are called features.

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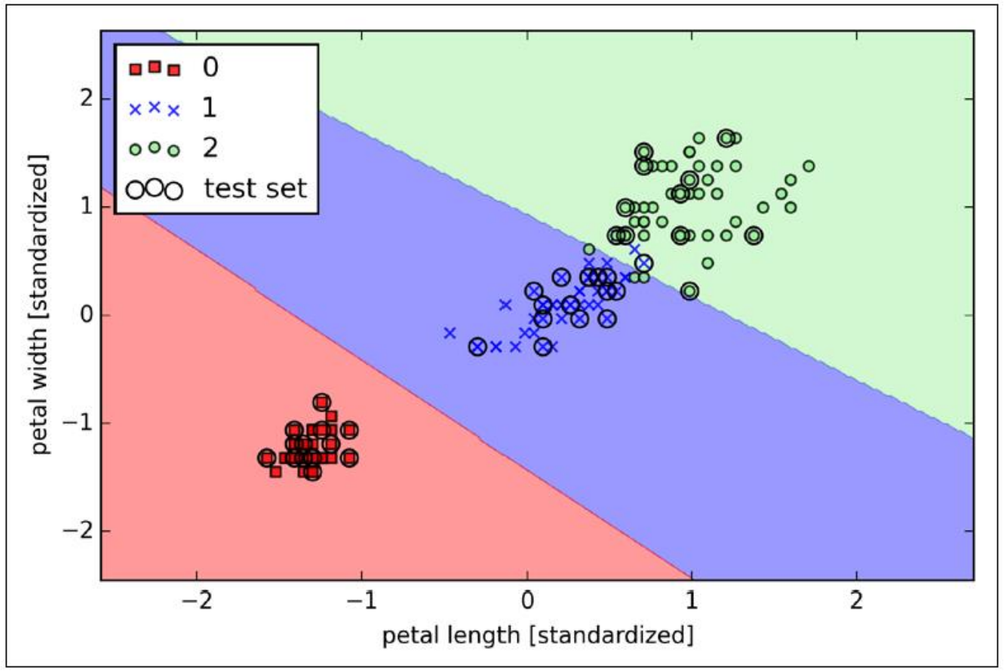
IRIS Data Set: SVM

Let's train an SVM model using scikit-learn for the Iris dataset:




```
>>> from sklearn.svm import SVC
   >>> svm = SVC(kernel='linear', C=1.0, random_state=0)
>>> svm.fit(X_train_std, y_train)
>>> plot_decision_regions(X_combined_std,
...                       y_combined, classifier=svm,
...                       test_idx=range(105,150))
>>> plt.xlabel('petal length [standardized]')
>>> plt.ylabel('petal width [standardized]')
>>> plt.legend(loc='upper left')
>>> plt.show()
```

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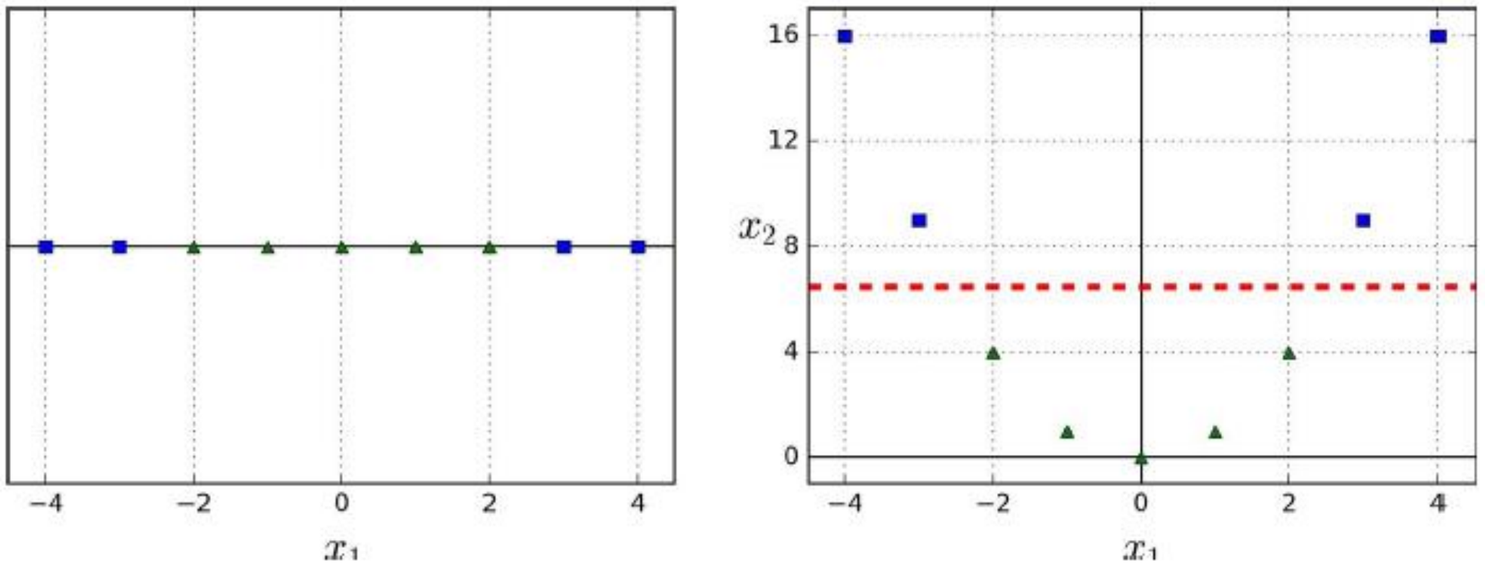
Nonlinear SVM Classification



- There are two ways to solve nonlinear SVMs, either by adding polynomial features or by adding similarity features.
- Polynomial features can be added to datasets; in some cases, this can create linearly separable dataset.

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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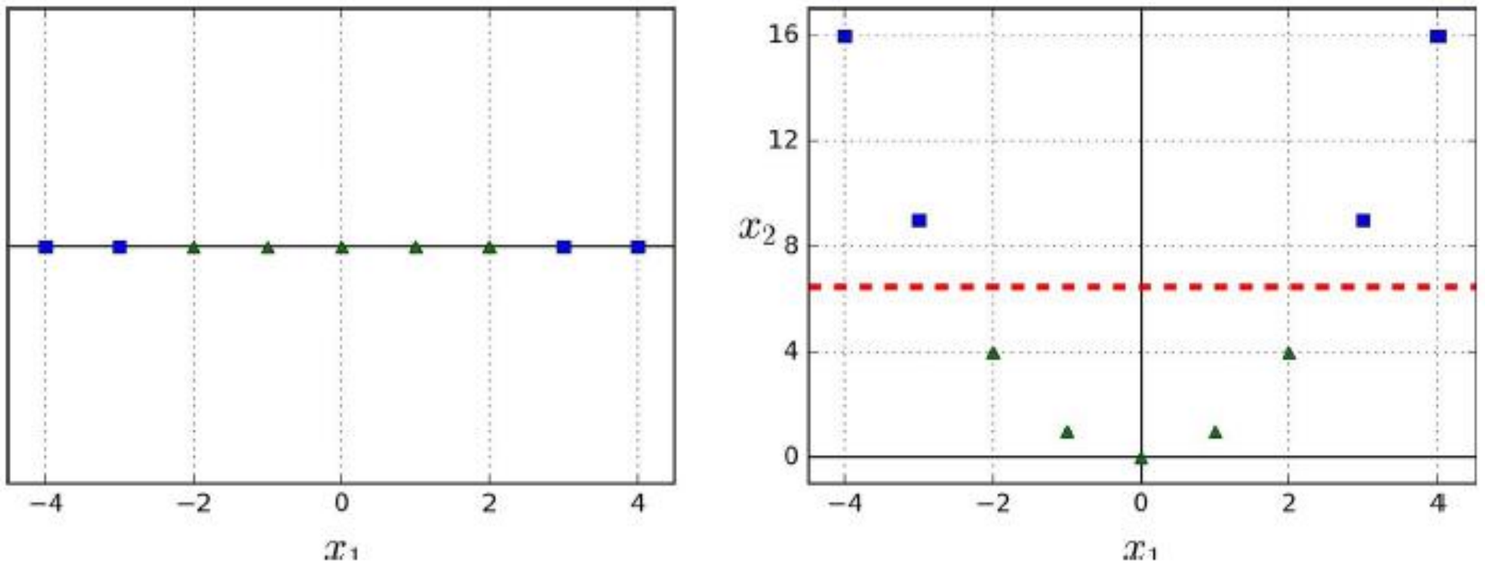
Nonlinear SVM Classification



- In the figure on the left, there is only 1 feature x1.
- This dataset is not linearly separable.
- If you add x2 = (x1)2 (figure on the right), the data becomes linearly separable.

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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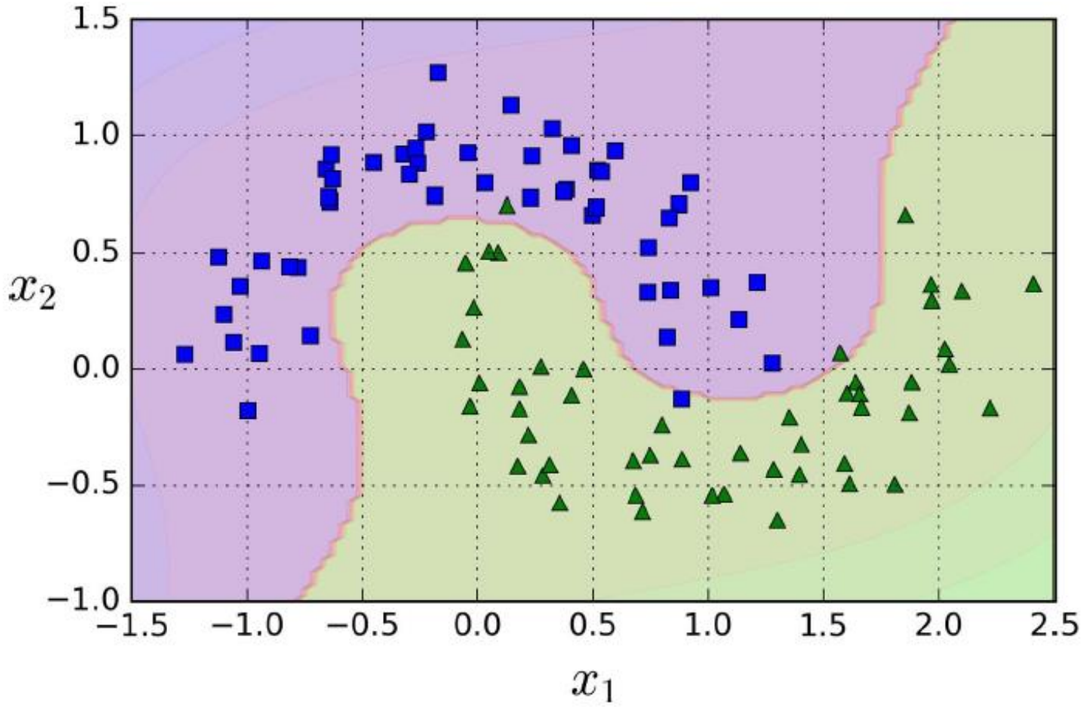
Polynomial Kernel

In scikit-learn, one can use a Pipeline class for creating polynomial features.

Classification results for the Moons dataset are shown in the figure.




```
from sklearn.datasets import make_moons
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures

polynomial_svm_clf = Pipeline((
        ("poly_features", PolynomialFeatures(degree=3)),
        ("scaler", StandardScaler()),
        ("svm_clf", LinearSVC(C=10, loss="hinge"))
    ))

polynomial_svm_clf.fit(X, y)
```

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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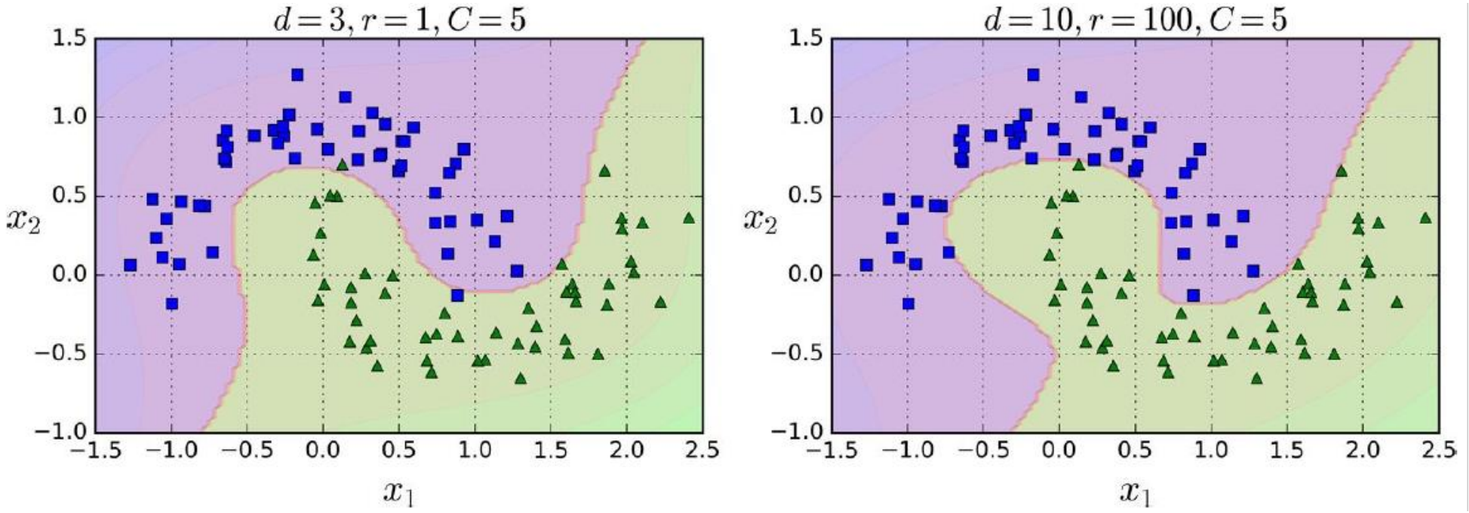
Polynomial Kernel with Kernel Trick



- For large dimensional datasets, adding too many polynomial features can slow down the model.
- You can apply a kernel trick with the effect of polynomial features without actually adding them.

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Polynomial Kernel with Kernel Trick

- The code shown (SVC class) below trains an SVM classifier using a 3rd degree polynomial kernel but with a kernel trick.

```
from sklearn.svm import SVC
poly_kernel_svm_clf = Pipeline((
        ("scaler", StandardScaler()),
        ("svm_clf", SVC(kernel="poly", degree=3, coef0=1, C=5))
    ))
poly_kernel_svm_clf.fit(X, y)
```

- The hyperparameter coefθ controls the influence of high-degree polynomials.

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Classification

Topic 5: Kernel Support Vector Machines

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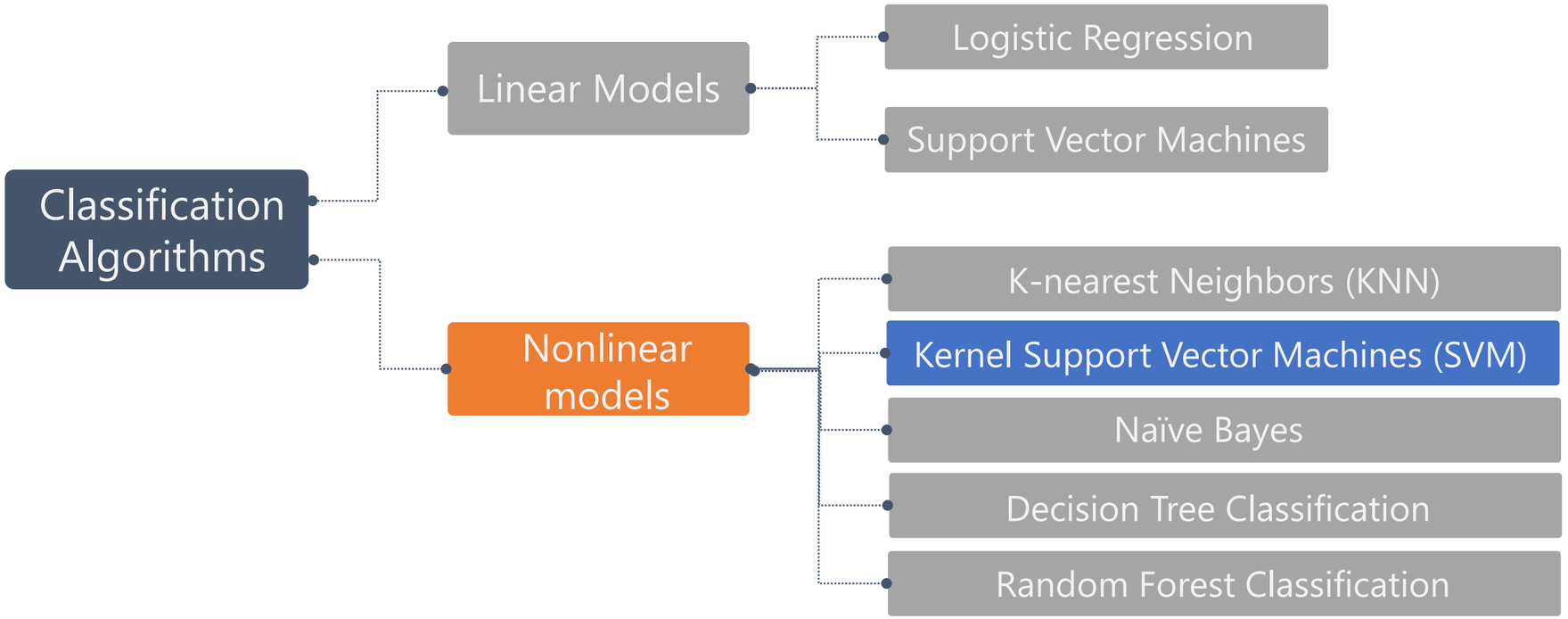
Kernel SVM



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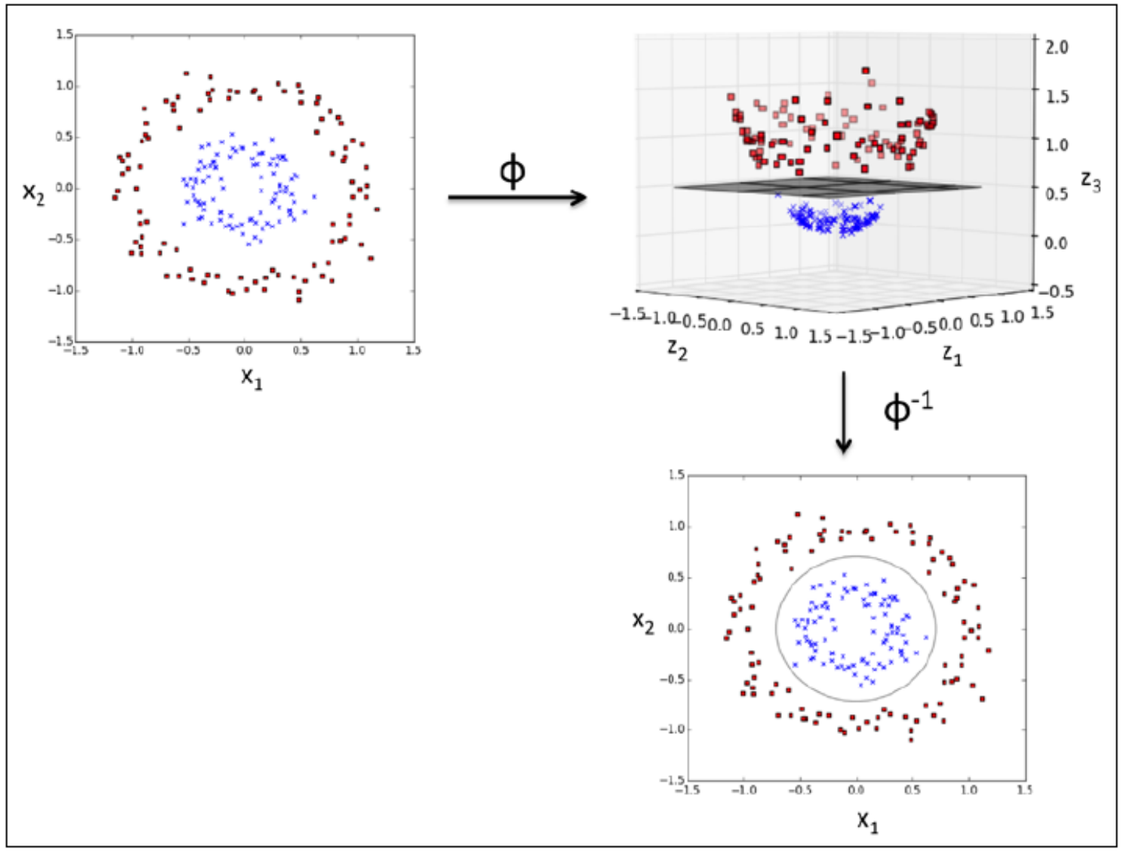
Kernel SVM



- Kernel SVMs are used for classification of nonlinear data.

- In the chart, nonlinear data is projected into a higher dimensional space via a mapping function $\phi(\cdot)$ where it becomes linearly separable.

Source Credit : "Python Machine Learning" by Sebastian Raschka

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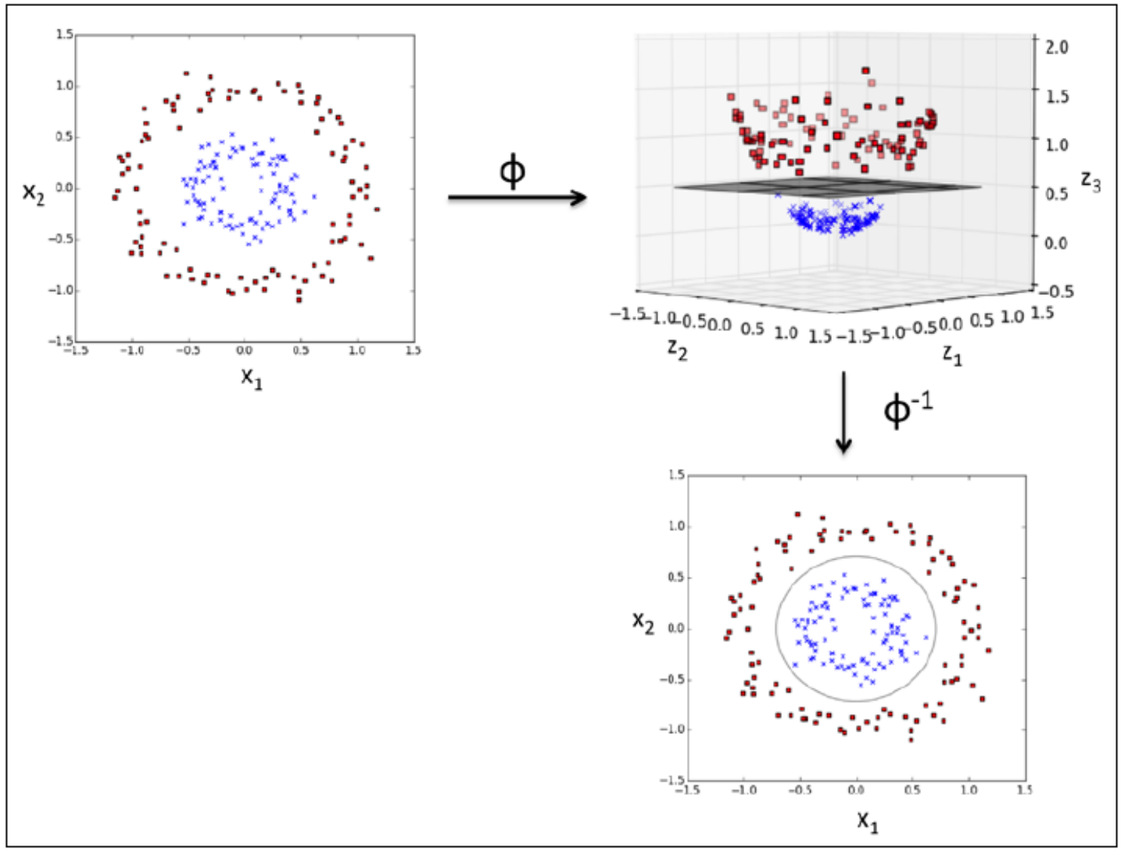
Kernel SVM



- In the higher dimension, a linear separating hyperplane can be derived and used for classification.

$$\phi(x_1, x_2) = (z_1, z_2, z_3) = (x_1, x_2, x_1^2 + x_2^2)$$

- A reverse projection of the higher dimension back to original feature space takes it back to nonlinear shape.

Source Credit : "Python Machine Learning" by Sebastian Raschka

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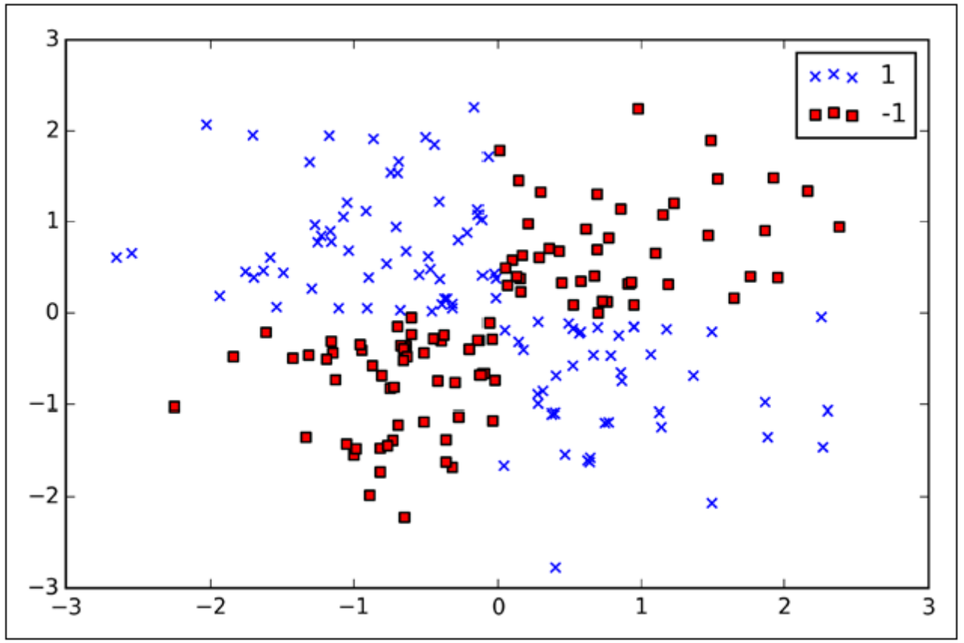
Kernel SVM



- As mentioned previously, SVMs can be kernelized to solve nonlinear classification problems.

- You can create sample dataset for XOR gate (nonlinear problem) from NumPy. 100 samples will be assigned the class sample 1, and 100 samples will be assigned the class label -1.

Source Credit : "Python Machine Learning" by Sebastian Raschka

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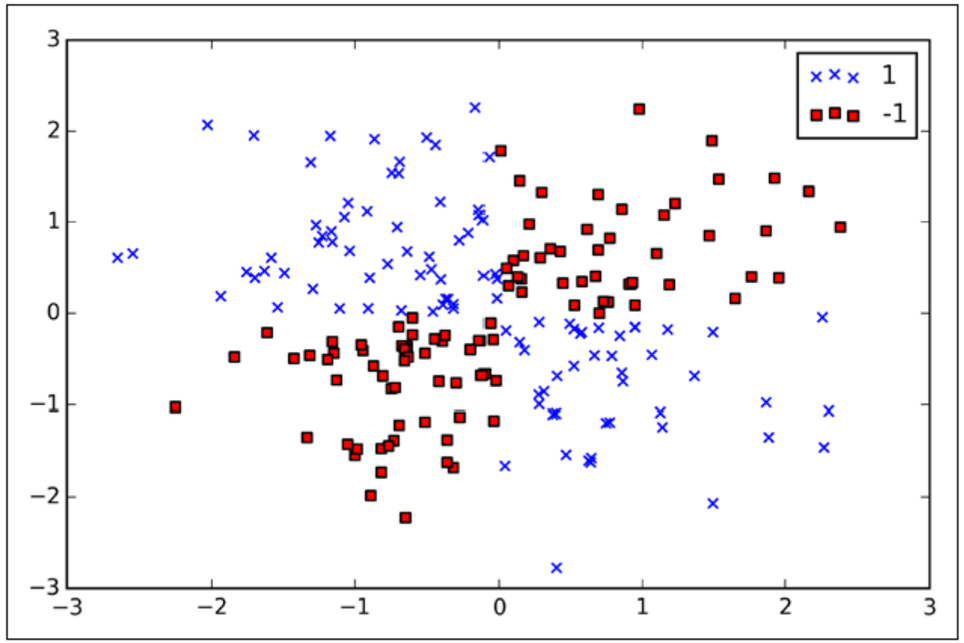
Kernel SVM

As you can see, this data is not linearly separable.




```
>>> np.random.seed(0)
>>> X_xor = np.random.randn(200, 2)
>>> y_xor = np.logical_xor(X_xor[:, 0] > 0, X_xor[:, 1] > 0)
>>> y_xor = np.where(y_xor, 1, -1)

>>> plt.scatter(X_xor[y_xor==1, 0], X_xor[y_xor==1, 1],
...             c='b', marker='x', label='1')
>>> plt.scatter(X_xor[y_xor==-1, 0], X_xor[y_xor==-1, 1],
...             c='r', marker='s', label='-1')
>>> plt.ylim(-3.0)
>>> plt.legend()
>>> plt.show()
```

Source Credit : "Python Machine Learning" by Sebastian Raschka

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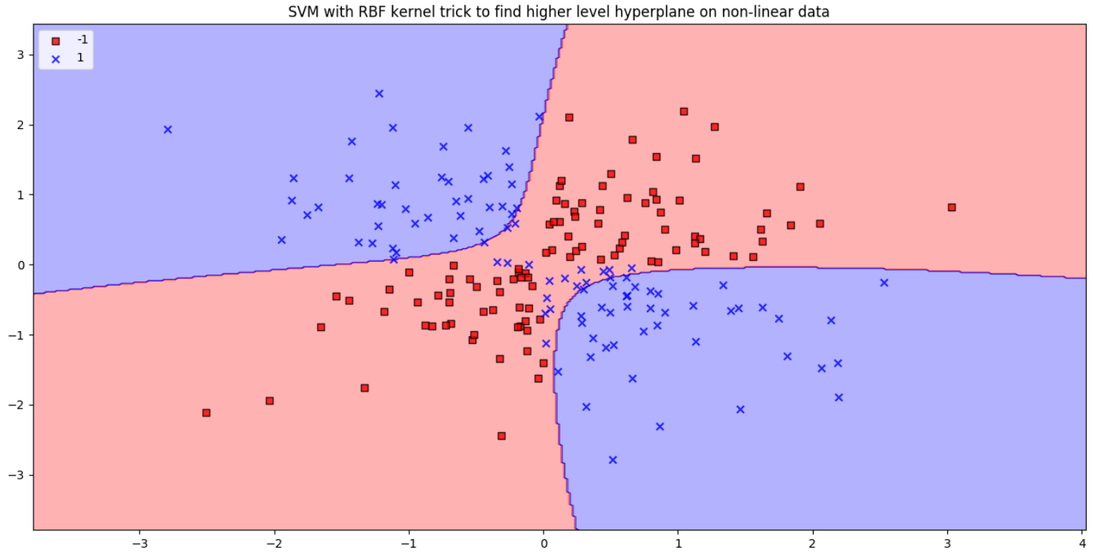
Kernel SVM

You now use the kernel trick to classify XOR data set created earlier.




```
>>> svm = SVC(kernel='rbf', random_state=0, gamma=0.10, C=10.0)
>>> svm.fit(X_xor, y_xor)
>>> plot_decision_regions(X_xor, y_xor, classifier=svm)
>>> plt.legend(loc='upper left')
>>> plt.show()
```

Source Credit : "Python Machine Learning" by Sebastian Raschka

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Demo

SVM Classification

Classify IRIS dataset using SVM; demonstrate how Kernel SVMs can help classify non-linear data.

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Classification

Topic 6: Naïve Bayes

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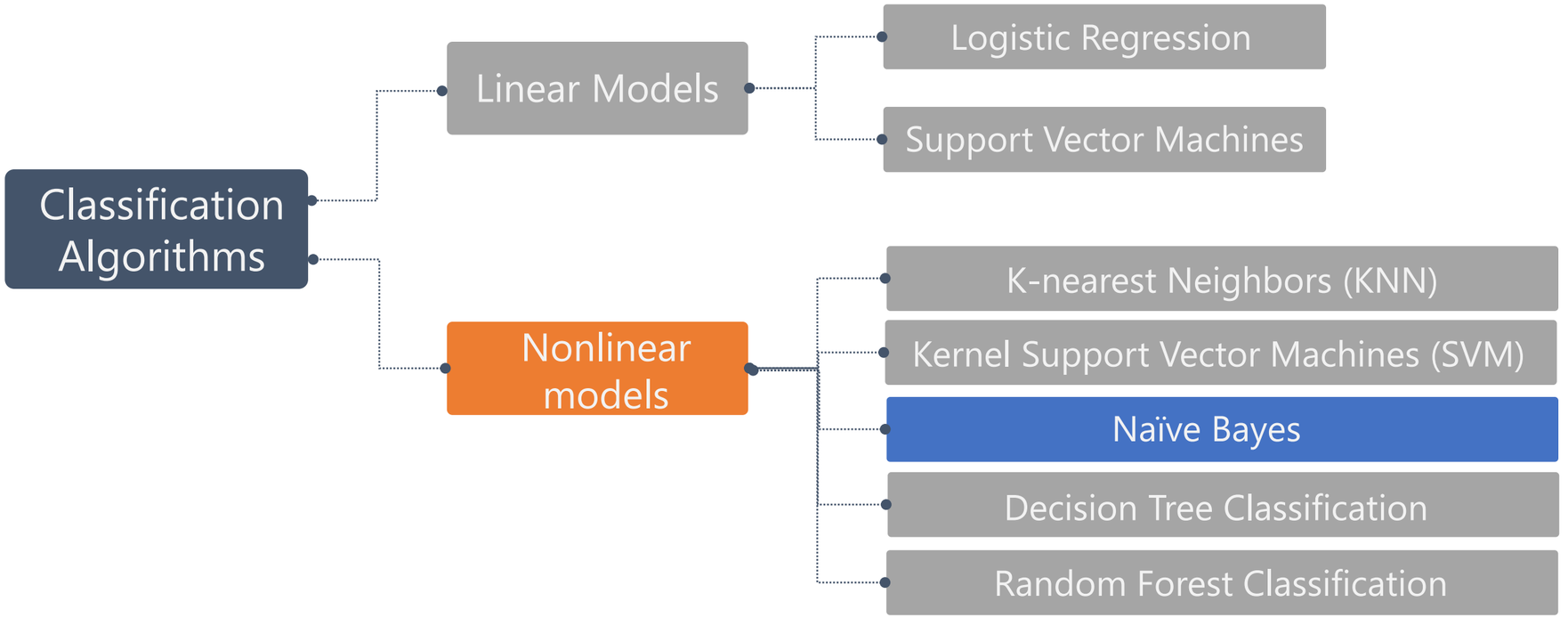
Naïve Bayes



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Naïve Bayes Classifier

- According to Bayes model, the conditional probability P(Y|X) can be calculated as:

$$P(Y|X) = P(X|Y)P(Y) / P(X)$$

- This means you have to estimate a very large number of P(X|Y) probabilities for a relatively small vector space X.
- For example, for a Boolean Y and 30 possible Boolean attributes in the X vector, you will have to estimate 3 billion probabilities P(X|Y).
- To make it practical, a Naïve Bayes classifier is used, which assumes conditional independence of P(X) to each other, with a given value of Y.
- This reduces the number of probability estimates to 2*30=60 in the above example.

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Naïve Bayes Classifier for SMS Spam Detection

Consider a labelled SMS database having 5574 messages. It has messages as given below:

spam	FreeMsg Hey there darling it's been 3 week's now and no word back! I'd like some fun you up for it still? Tb ok! XxX std chgs to send, Â£1.50 to rcv
ham	Even my brother is not like to speak with me. They treat me like untouchable.
ham	As per your request 'Melle (Oru Minnaminunginte Nurungu Vettam)' has been set as your callertune for all Callers. Press *9 to copy your friends Callertune.
spam	WINNER!! As a valued network customer you have been selected to receivea Â£900 prize reward! To claim call 09061701461. Claim code KL341. Valid 12 hours only.

Each message is marked as spam or ham in the data set.

Let’s train a model with Naïve Bayes algorithm to detect spam from ham.

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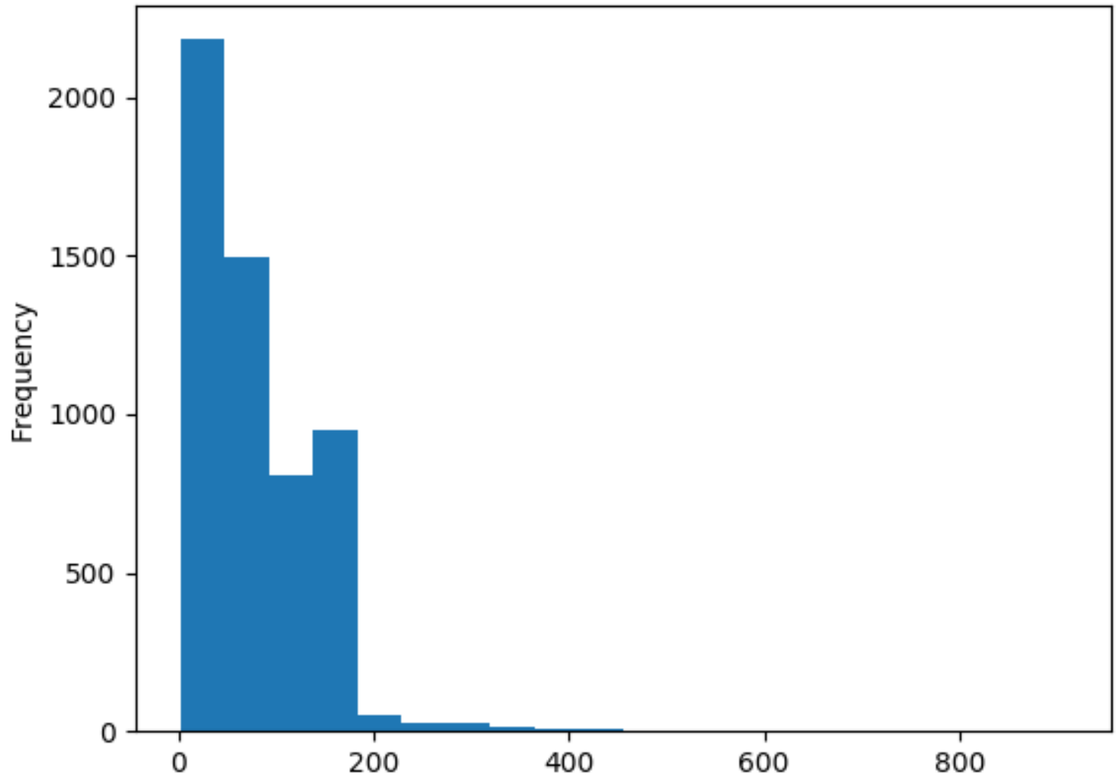
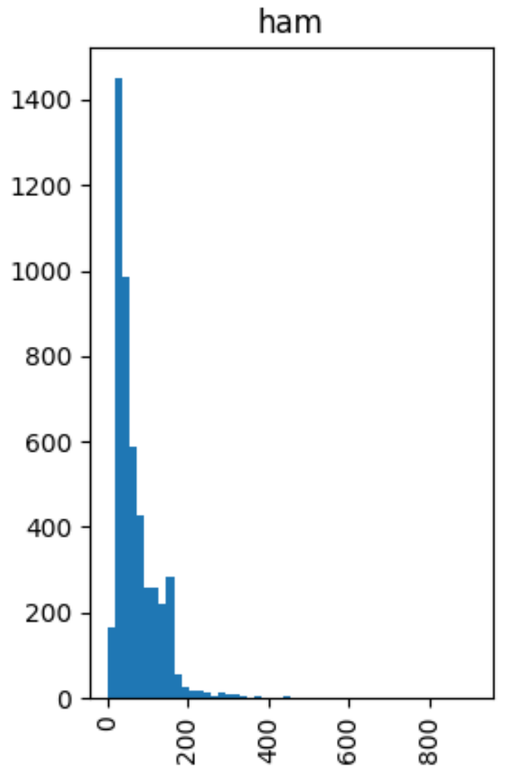
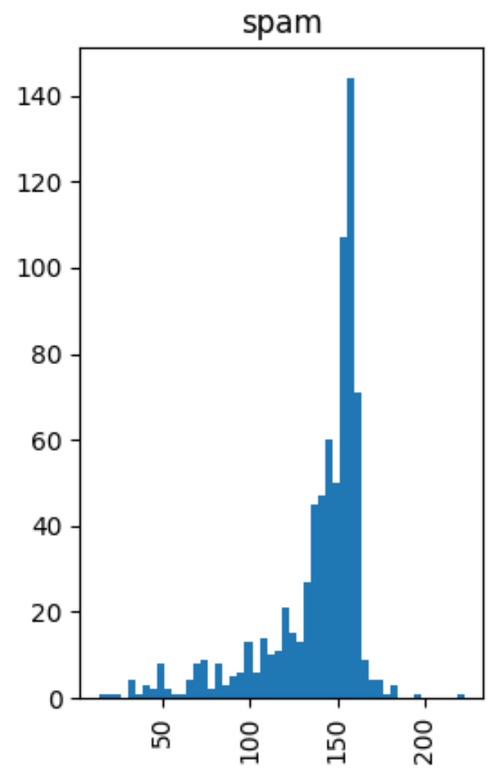
Naïve Bayes Classifier for SMS Spam Detection

The message lengths and their frequency (in the training data set) are as shown below:







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Naïve Bayes Classifier for SMS Spam Detection

Analyze the logic you use to train an algorithm to detect spam:

- Split each message into individual words/tokens (bag of words).
- Lemmatize the data (each word takes its base form, like “walking” or “walked” is replaced with “walk”).
- Convert data to vectors using scikit-learn module CountVectorizer.
- Run TFIDF to remove common words like “is,” “are,” “and.”
- Now apply scikit-learn module for Naïve Bayes MultinomialNB to get the Spam Detector.
- This spam detector can then be used to classify a random new message as spam or ham.

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Demo

Spam Detection in SMS

Train a classifier to detect SMS spam

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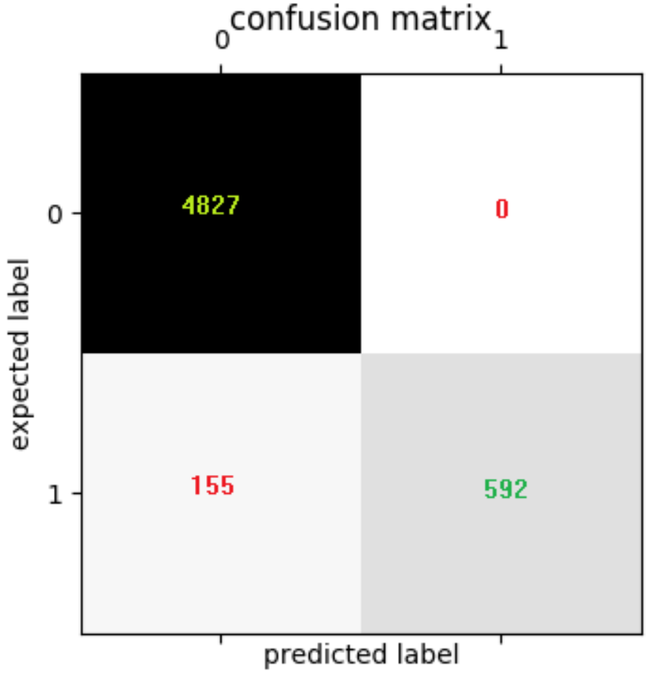
Naïve Bayes Classifier for SMS Spam Detection

- Next, the accuracy of the spam detector is checked using the Confusion Matrix.
- For the SMS spam example above, the confusion matrix is shown on the right.

Accuracy Rate = Correct / Total = (4827 + 592)/5574 = 97.21%

Error Rate = Wrong / Total = (155 + 0)/5574 = 2.78%

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)



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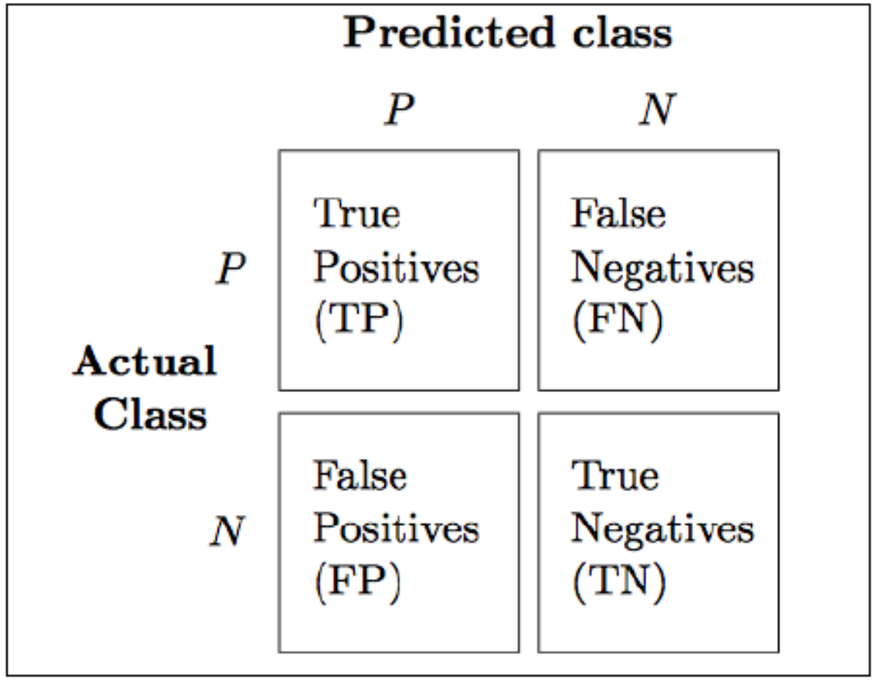
Naïve Bayes Classifier for SMS Spam Detection

Although confusion Matrix is useful, some more precise metrics are provided by Precision and Recall.



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Naïve Bayes Classifier for SMS Spam Detection

- Precision refers to the accuracy of positive predictions.

$$\text{precision} = \frac{TP}{TP + FP}$$

- Recall refers to the ratio of positive instances that are correctly detected by the classifier (also known as True positive rate or TPR).

$$\text{recall} = \frac{TP}{TP + FN}$$

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

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Precision/Recall Trade-off

To detect age-appropriate videos for kids, you need high precision (low recall) to ensure that only safe videos make the cut (even though a few safe videos may be left out).

High recall is needed (low precision is acceptable) in store surveillance to catch shoplifters; a few false alarms are acceptable, but all shoplifters must be caught.

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Classification

Topic 7: Decision Tree Classifier

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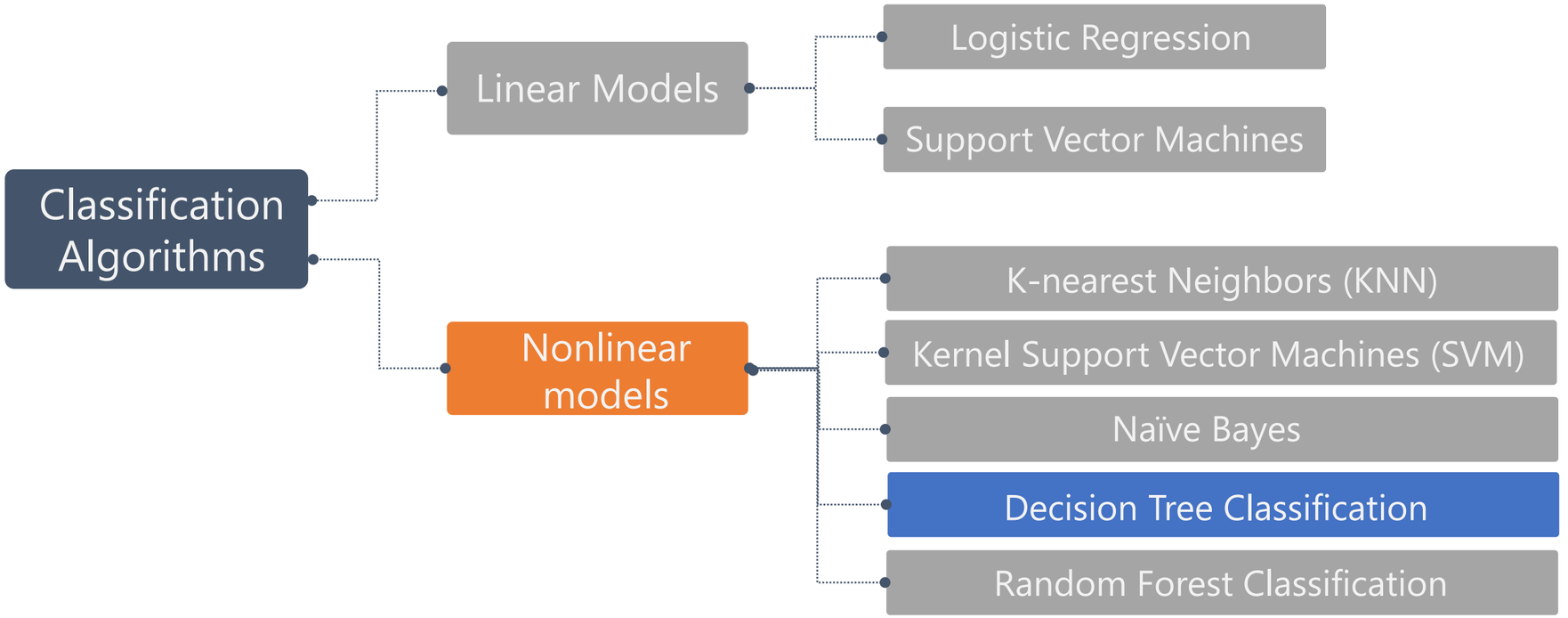
Decision Tree Classifier



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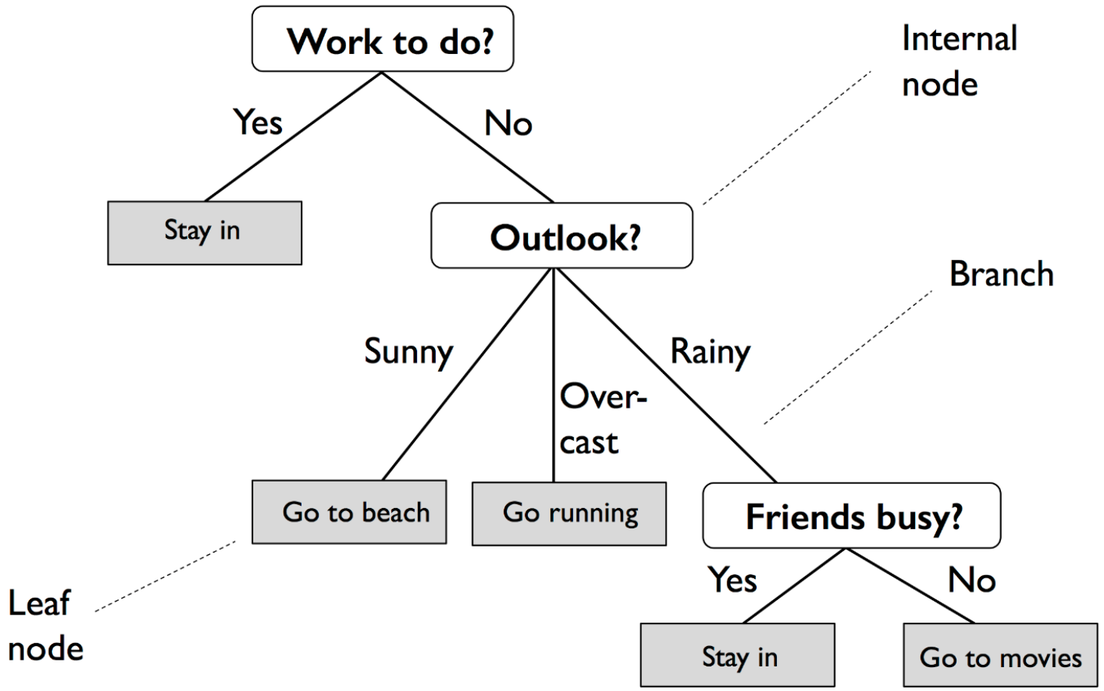
Decision Tree Classifier



- Decision Trees (DT) can be used both for classification and regression.
- The advantage of decision trees is that they require very little data preparation.
- They do not require feature scaling or centering at all.
- They are also the fundamental components of Random Forests, one of the most powerful ML algorithms.

Source: "Python Machine Learning" by Sebastian Raschka

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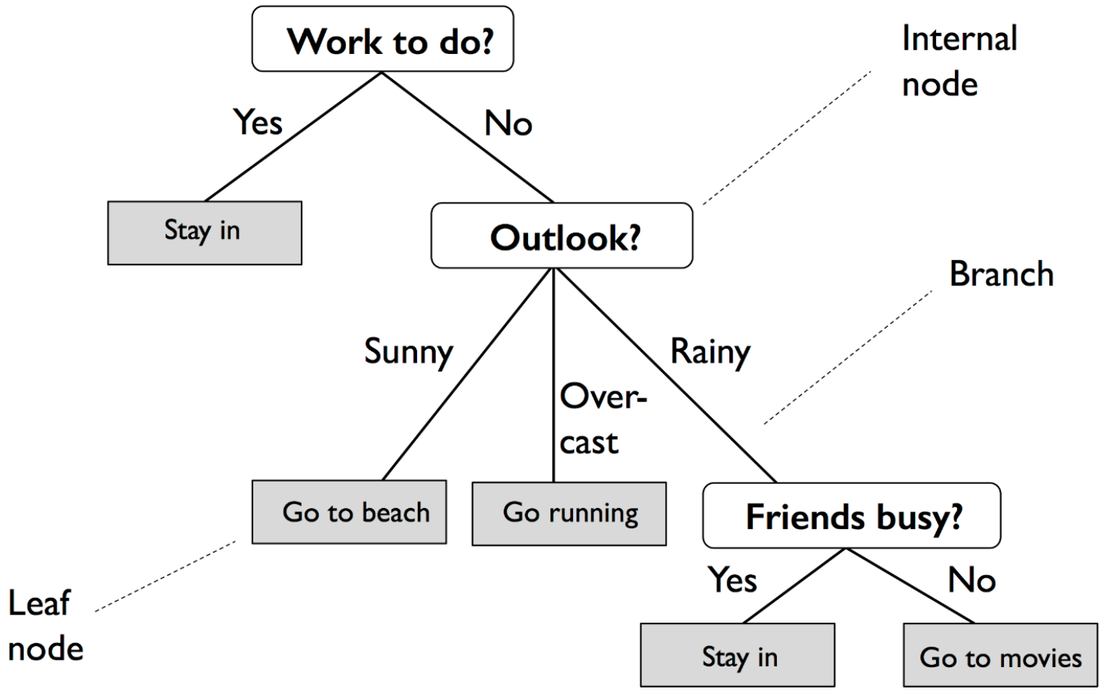
Decision Tree Classifier



- Unlike Random Forests and Neural Networks (which do black-box modelling), Decision Trees are white box models, which means that inner workings of these models are clearly understood.
- In case of classification, the data is segregated based on a series of questions.
- Any new data point is assigned to the selected leaf node.

Source: "Python Machine Learning" by Sebastian Raschka

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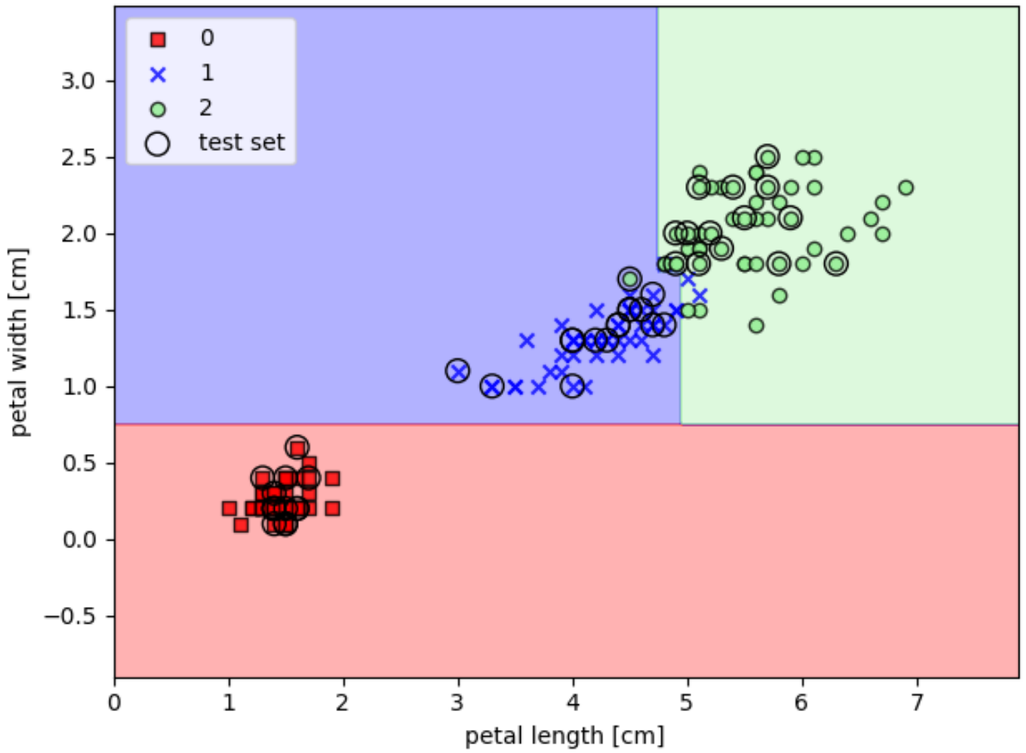
Decision Tree Classifier



- Start at the tree root and split the data on the feature using the decision algorithm, resulting in the largest information gain (IG).
- This splitting procedure is then repeated in an iterative process at each child node until the leaves are pure.
- This means that the samples at each node belong to the same class.

Source: "Python Machine Learning" by Sebastian Raschka

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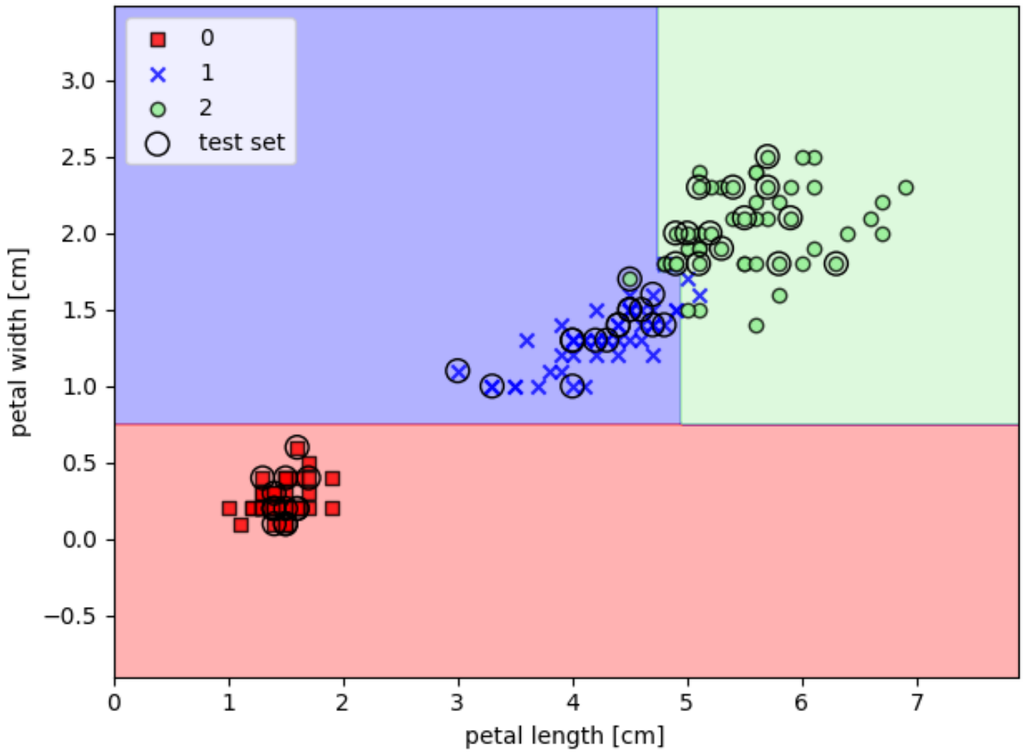
Decision Tree Classifier



- In practice, you can set a limit on the depth of the tree to prevent overfitting.
- The purity is compromised here as the final leaves may still have some impurity.
- The figure shows the classification of Iris dataset.

Source: "Python Machine Learning" by Sebastian Raschka

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Demo

Decision Trees Classification

Classify IRIS flower dataset using Decision Trees

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IRIS Decision Tree

Let's build a Decision Tree using scikit-learn for the Iris flower dataset and also visualize it using export_graphviz API.

```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier

iris = load_iris()
X = iris.data[:, 2:] # petal length and width
y = iris.target

tree_clf = DecisionTreeClassifier(max_depth=2)
tree_clf.fit(X, y)
```

```
from sklearn.tree import export_graphviz

export_graphviz(
        tree_clf,
        out_file=image_path("iris_tree.dot"),
        feature_names=iris.feature_names[2:],
        class_names=iris.target_names,
        rounded=True,
        filled=True
    )
```

The output of export_graphviz can be converted into png format:

```
$ dot -Tpng iris_tree.dot -o iris_tree.png
```

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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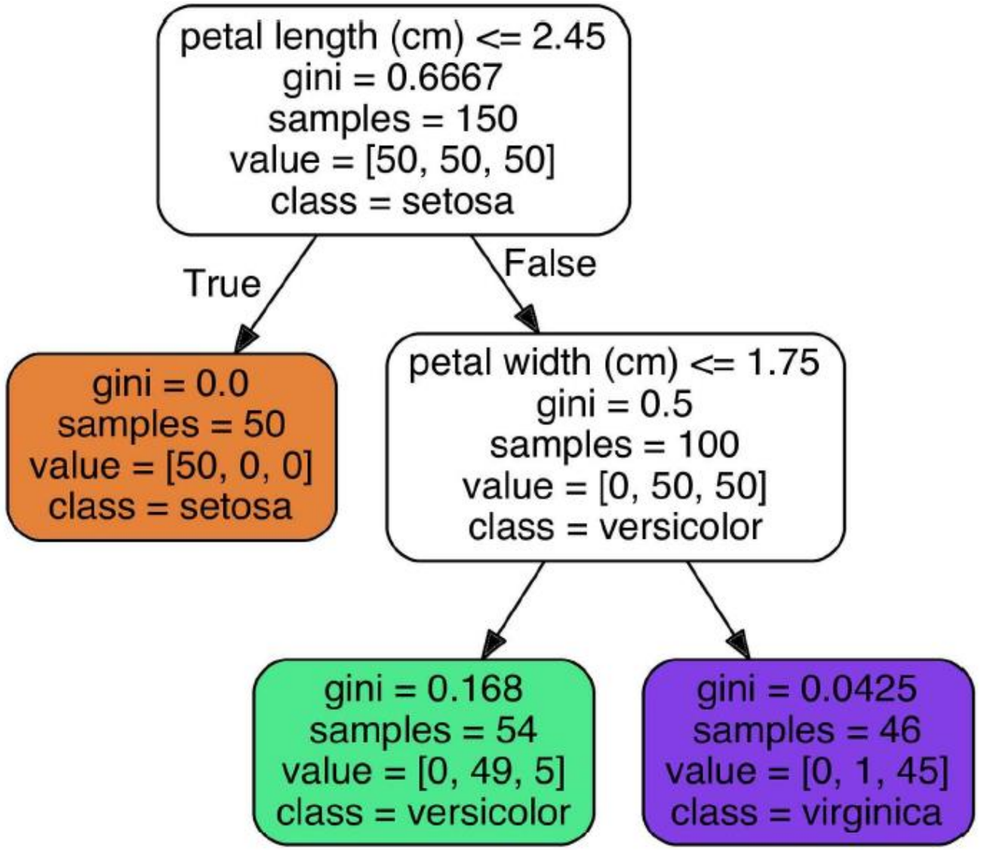
IRIS Decision Tree



- Sample attribute stands for the number of training instances the node applies to.
- Value attribute stands for the number of training instances of each class the node applies to.
- Gini impurity measures the node's impurity. A node is "pure" (gini=0) if all training instances it applies to belong to the same class.

$$G_i = 1 - \sum_{k=1}^{n} {p_{i,k}}^2$$

- For example, for versicolor (green color node), the gini is 1-(0/54)2-(49/54)2-(5/54)2 ≈ 0.168

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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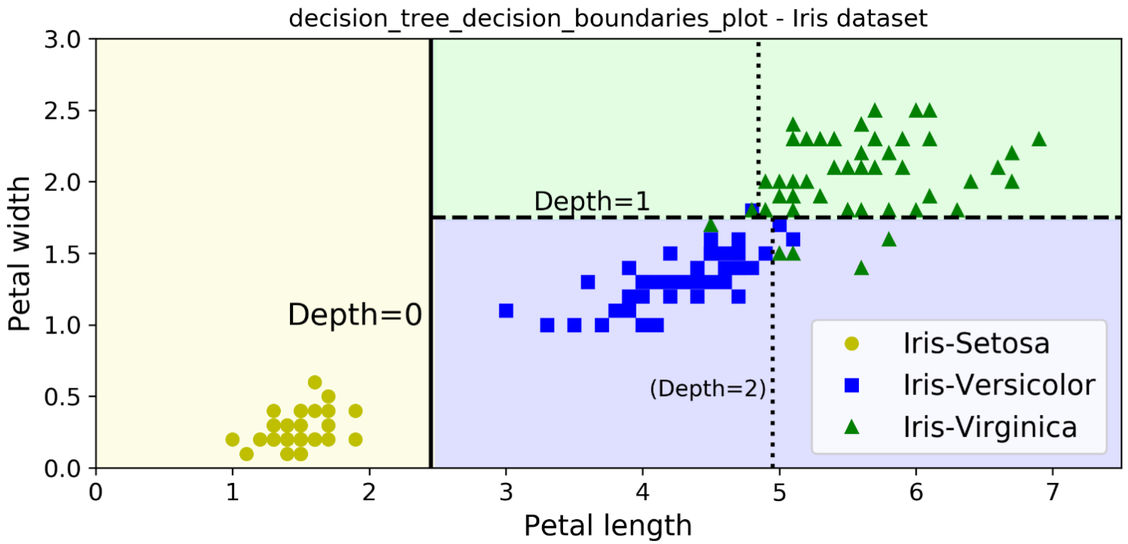
Decision Boundaries



- For first node (depth 0), the solid line splits the data (Iris-Setosa on left). Gini is 0 for Setosa node, so no further split is possible. The second node (depth 1) splits the data into Versicolor and Virginica.
- If max_depth were set as 3, a third split would happen (vertical dotted line).
- For a sample with petal length 5 cm and petal width 1.5 cm, the tree traverses to depth 2 left node, so the probability predictions for this sample are 0% for Iris-Setosa (0/54), 90.7% for Iris-Versicolor (49/54), and 9.3% for Iris-Virginica (5/54).

Source: "Hands-on Machine Learning with Scikit-Learn and TensorFlow " by Aurelien Geron

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CART Training Algorithm

Scikit-learn uses Classification and Regression Trees (CART) algorithm to train Decision Trees.

CART algorithm:

Split the data into two subsets using a single feature k and threshold tk (example, petal length < "2.45 cm"). This is done recursively for each node.

k and t_k are chosen such that they produce the purest subsets (weighted by their size). The objective is to minimize the cost function as given below:

$$J(k, t_k) = \frac{m_{\text{left}}}{m} G_{\text{left}} + \frac{m_{\text{right}}}{m} G_{\text{right}}$$

$$\text{where} \begin{cases} G_{\text{left/right}} \text{ measures the impurity of the left/right subset,} \\ m_{\text{left/right}} \text{ is the number of instances in the left/right subset} \end{cases}$$

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CART Training Algorithm

The algorithm stops executing if one of the following situations occurs:

- max_depth is reached
- No further splits are found for each node
- Other hyperparameters may be used to stop the tree:
  - min_samples_split
  - min_samples_leaf
  - min_weight_fraction_leaf
  - max_leaf_nodes

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Gini Impurity or Entropy

- Entropy is one more measure of impurity and can be used in place of Gini.

$$H_i = -\sum_{\substack{k=1 \\ p_{i,k} \neq 0}}^{n} p_{i,k} \log\left(p_{i,k}\right)$$

- It is a degree of uncertainty, and Information Gain is the reduction that occurs in entropy as one traverses down the tree.
- Entropy is zero for a DT node when the node contains instances of only one class.
- Entropy for depth 2 left node in the example given above is:

$$-\frac{49}{54} \log\left(\frac{49}{54}\right) - \frac{5}{54} \log\left(\frac{5}{54}\right)$$

- Gini and Entropy both lead to similar trees.

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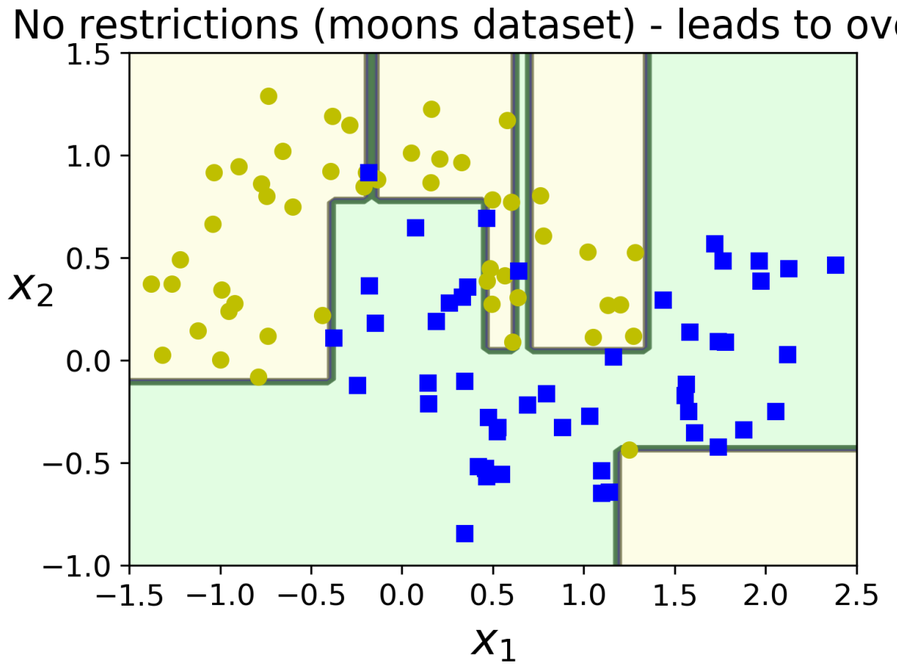
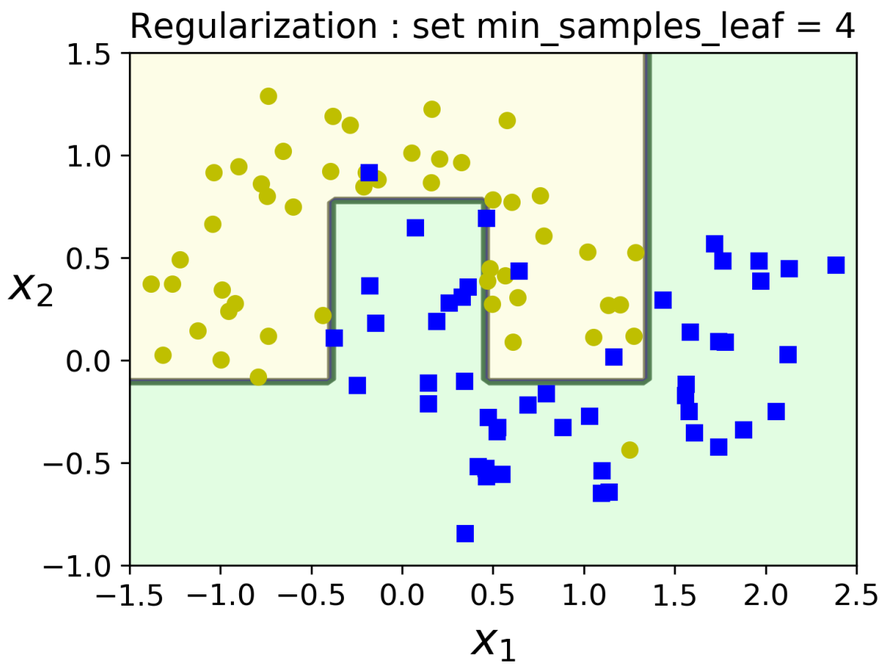
DT: Regularization

- The following figure shows two decision trees on the moons dataset.





- The decision tree on the right is restricted by min_samples_leaf = 4.
- The model on the left is overfitting, while the model on the right generalizes better.

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Demo

Decision Trees Classification and KNN

Classify the IRIS flower dataset using various classification algorithms

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Classification

Topic 8: Random Forest Classifier

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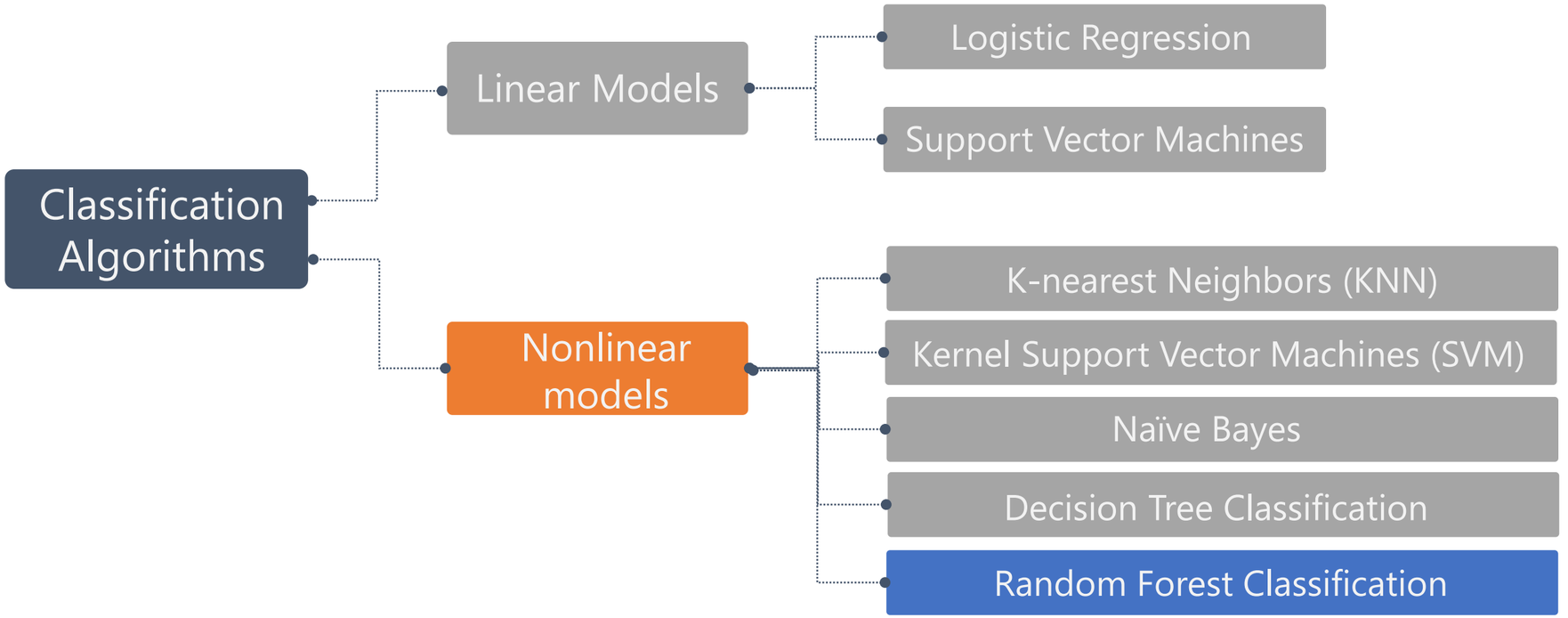
Random Forest Classifier



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Random Forest Classifier

- A random forest can be considered an ensemble of decision trees (Ensemble learning).

Random Forest algorithm:

- Draw a random bootstrap sample of size *n* (randomly choose *n* samples from the training set).
- Grow a decision tree from the bootstrap sample. At each node, randomly select *d* features.
- Split the node using the feature that provides best split according to objective function, for instance by maximizing the information gain.
- Repeat the steps 1 to 2 *k* times. (*k* is the number of trees you want to create, using a subset of samples)
- Aggregate the prediction by each tree for a new data point to assign the class label by majority vote (pick the group selected by most number of trees and assign new data point to that group).

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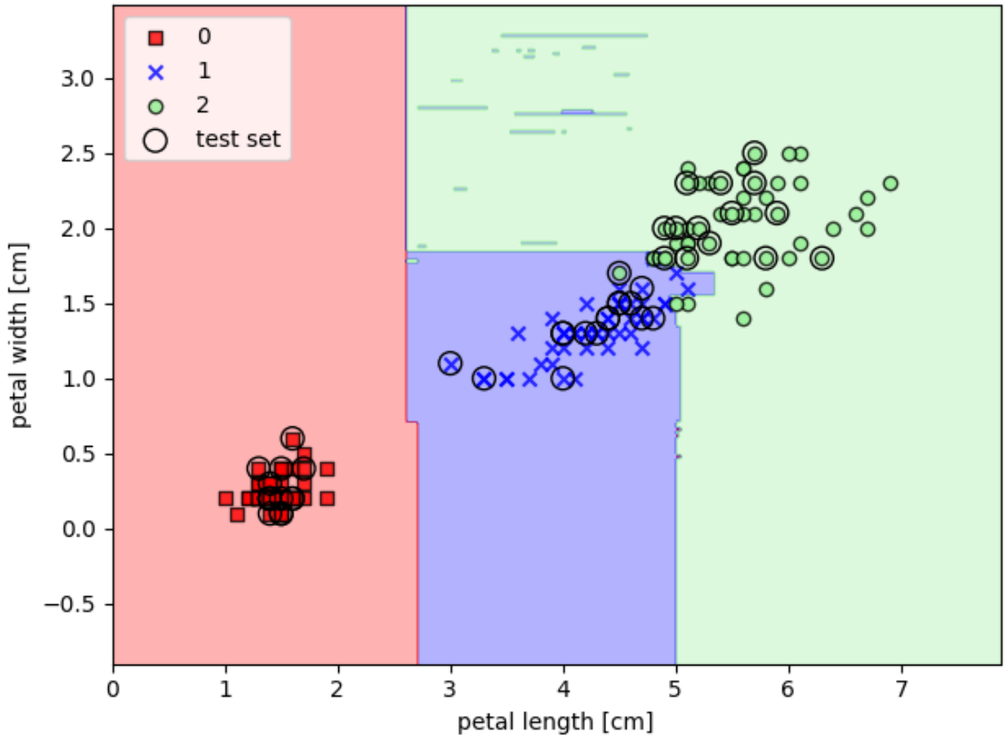
Random Forest Classifier



- Random Forests are opaque, which means it is difficult to visualize their inner workings.
- However, the advantages outweigh their limitations since you do not have to worry about hyperparameters except k, which stands for the number of decision trees to be created from a subset of samples.

Source: "Python Machine Learning" by Sebastian Raschka

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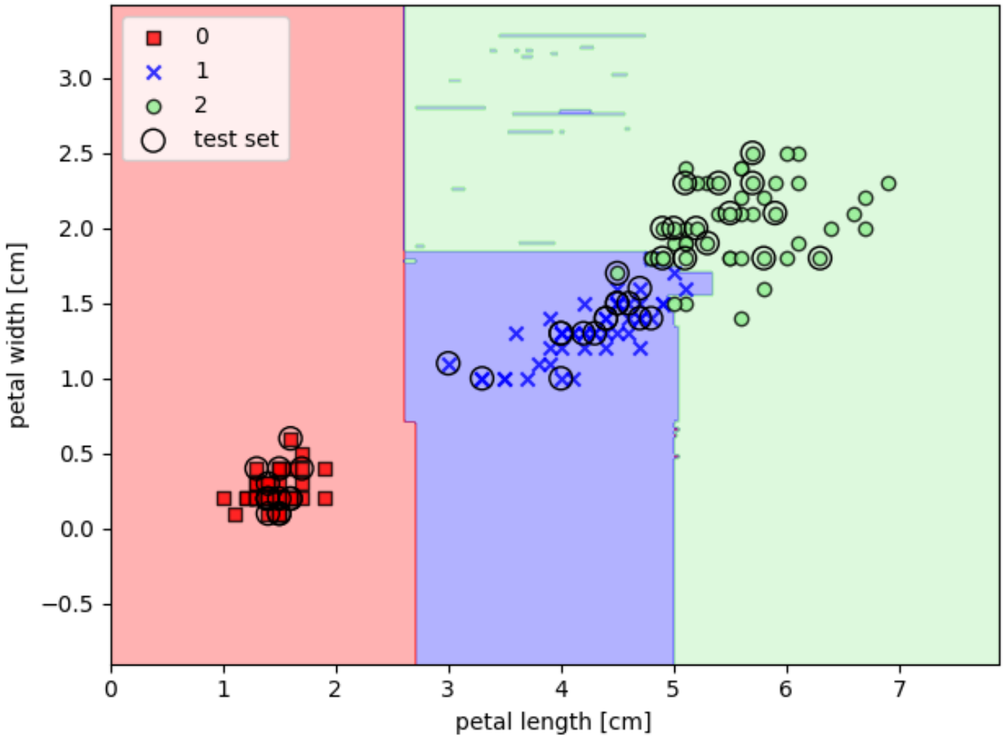
Random Forest Classifier



- RF is quite robust to noise from the individual decision trees. Hence, you need not prune individual decision trees.

- The larger the number of decision trees, the more accurate the Random Forest prediction is. (This however comes with higher computation cost).

Source: "Python Machine Learning" by Sebastian Raschka

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Key Takeaways

- Classification algorithms are supervised learning methods to split data into classes. They can work on Linear Data as well as Nonlinear Data.
- Logistic Regression can classify data based on weighted parameters and sigmoid conversion to calculate probability of classes. K-nearest Neighbors (KNN) algorithm uses similar features to classify data.
- Support Vector Machines (SVMs) classify data by detecting the maximum margin hyperplane between data classes.
- Naïve Bayes, a simplified Bayes Model, can help classify data using conditional probability models.
- Decision Trees are powerful classifiers and use tree splitting logic until pure or somewhat pure leaf node classes are attained.
- Random Forests apply Ensemble Learning to Decision Trees for more accurate classification predictions.

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Quiz

QUIZ

1

How can you ensure the effectiveness of SVM?

a. Selection of Kernel

b. Kernel parameters

c. Soft Margin parameter C

d. All of the above

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QUIZ

1

How can you ensure the effectiveness of SVM?

a. Selection of Kernel

b. Kernel parameters

c. Soft Margin parameter C

d. All of the above

The correct answer is **d.**

The SVM effectiveness depends upon how you choose the basic three requirements in such a way that it maximizes your efficiency, reduces error, and overfitting.

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QUIZ

2

How can SVMs handle classification of non-linear data?

a. Standardization of data

b. Kernel Trick

c. Gradient Descent

d. Regression

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QUIZ

2

How can SVM handle classification of non-linear data?

a. Standardization of data

b. Kernel Trick

c. Gradient Descent

d. Regression

The correct answer is **b.**

SVM handles classification of non-linear data using kernel trick.

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Hands-on Assignments

Demo File	Assignment	What it demonstrates?
DecisionTreesandKNN.py	Typically nearest_neighbours for testing class in KNN is value 5. Modify the code to change the value of nearest_neighbours to 2 and 20 and note the observations.	Predict if the consumers will buy houses, given their age and salary.
ClassificationSVM.py	Modify the kernel trick from RBF to linear to see the type of classifier that is produced, for the XOR data in this program. Interpret the data.	Classify IRIS dataset using SVM and demonstrate how Kernel SVMs can help classify non-linear data.
	For the Iris dataset, add new code at the end of this program to produce classification for RBF kernel trick with gamma = 1.0. Explain the output.	Modify the code and check the output.

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Hands-on Assignments

Demo File	Assignment	What it demonstrates?
DecisionTreesandKNN.py	Run decision tree on the IRIS dataset with max depths of 3 and 4, and show the tree output.	Classify IRIS flower dataset using Decision Trees.
	Predict and print class probability for Iris flower instance with petal_len 1 cm and petal_width 0.5 cm.	Modify the code and check the output.
LogisticRegressionScikitLearn.py	Add Logistic Regression classification to the program and compare classification output to previous algorithms?	Modify the code and check the output.

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This concludes “Classification.”

The next lesson is “Regression.”

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