# Supervised learning-SVM

Machine Learning

M2-SID

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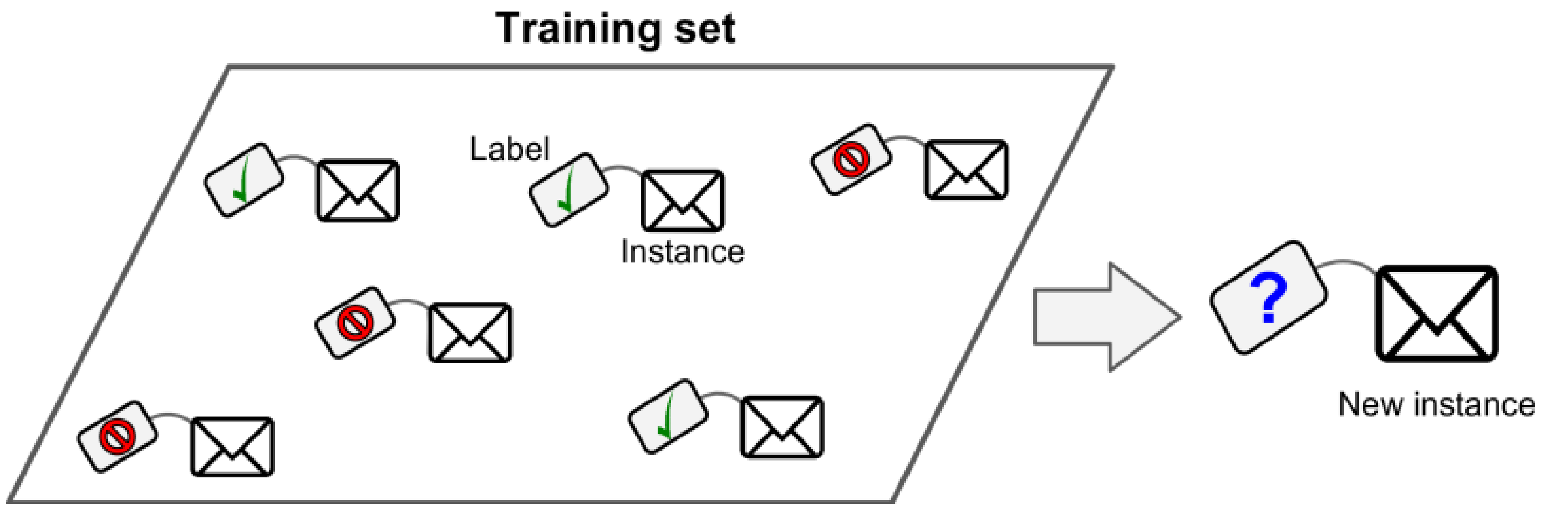
## Supervised Learning

- In supervised learning, the training data you feed to the algorithm includes the desired solutions, called labels.
- Classification : Ex. Spam filter, it is trained with many example emails along with their class (spam or ham), and it must learn how to classify new emails

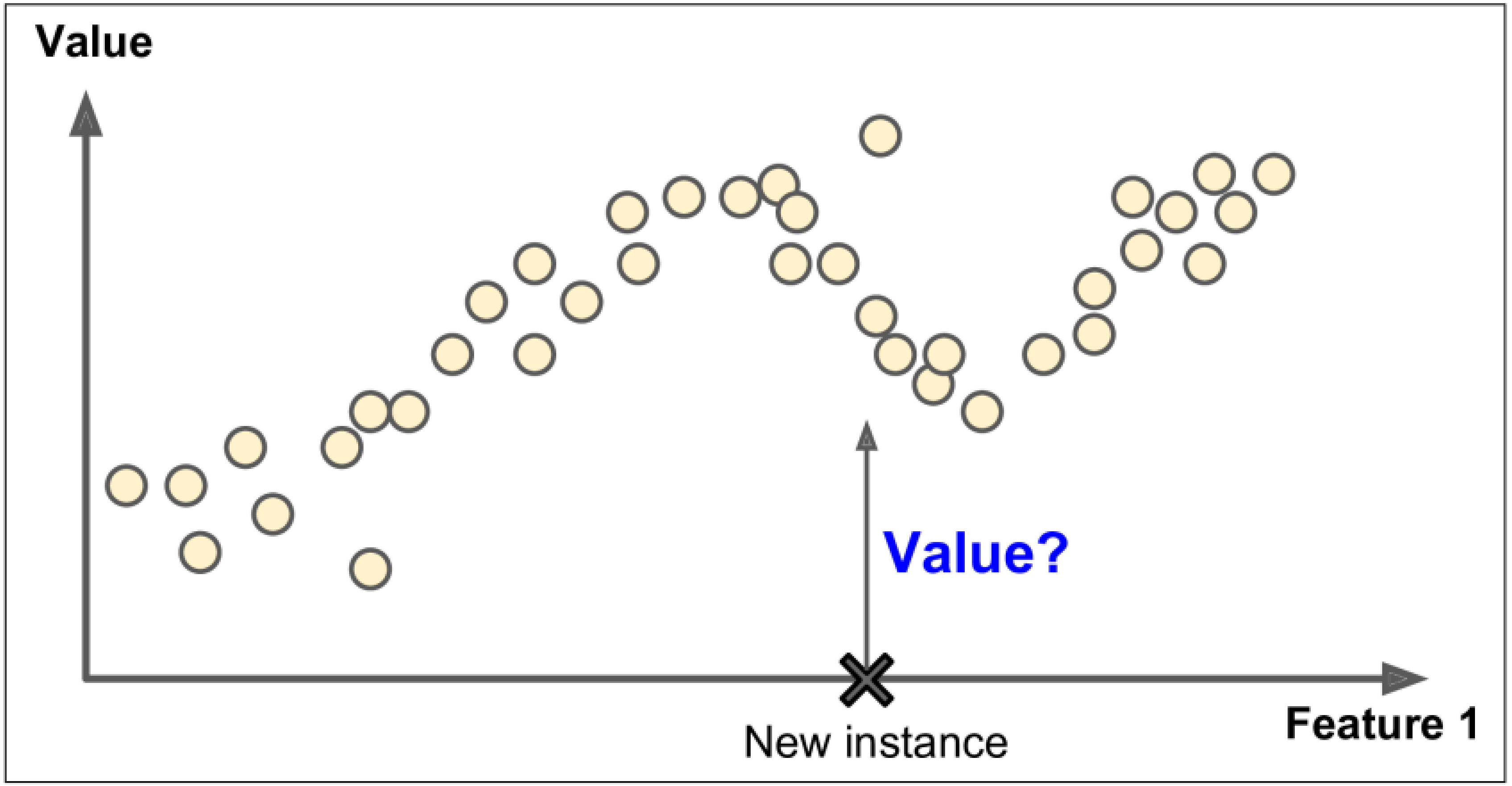


## Supervised learning STEPS

1. We are going to split our data set in :
   - Trainning data set
   - Test data set
   - Validation data set
2. We are going to train our algorithm with the training data set
   - The algorithm will learn from the training data
3. We are going to test our algorithm with the test data
   - Model performance measures on test and validation datasets
4. We ensure that our algorithm generalizes well to other data set never seen before.

## Supervised Learning

- Regression: To predict a target numeric value, such as the price of a car, given a set of features



## Most important Supervised Learning algorithms

- Support Vector Machines (SVMs)
- Linear Regression
- Logistic Regression
- k-Nearest Neighbors
- Decision Trees and Random Forests
- Neural network

## Linear Regression

- A linear model makes a prediction by simply computing a weighted sum of the input features, plus a constant called the bias term (also called the intercept term)

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}) = \boldsymbol{\theta} \cdot \mathbf{x}$$

- $\boldsymbol{\theta}$ is the model's *parameter vector*, containing the bias term $\theta_0$ and the feature weights $\theta_1$ to $\theta_n$.
- $\mathbf{x}$ is the instance's *feature vector*, containing $x_0$ to $x_n$, with $x_0$ always equal to 1.
- $\boldsymbol{\theta} \cdot \mathbf{x}$ is the dot product of the vectors $\boldsymbol{\theta}$ and $\mathbf{x}$, which is of course equal to $\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$.
- $h_{\boldsymbol{\theta}}$ is the hypothesis function, using the model parameters $\boldsymbol{\theta}$.

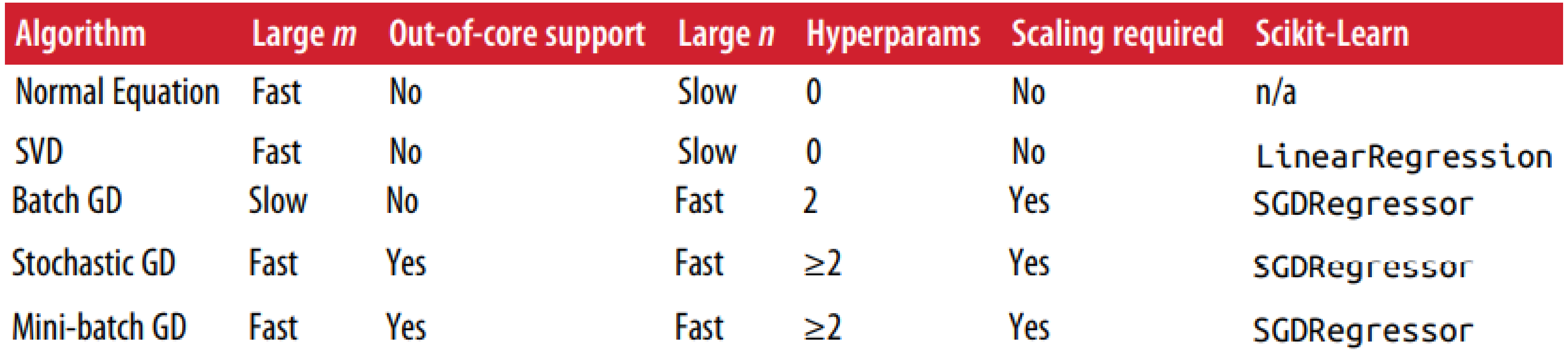
## Perfomance Linear regression

- Root Mean Square Error (RMSE)

- To train a Linear Regression model, you need to find the value of θ that minimizes the RMSE. In practice, it is simpler to minimize the Mean Square Error (MSE) than the RMSE, and it leads to the same result.

$$\mathrm{MSE}(\mathbf{X}, h_{\boldsymbol{\theta}}) = \frac{1}{m}\sum_{i=1}^{m}\left(\boldsymbol{\theta}^T\mathbf{x}^{(i)} - y^{(i)}\right)^2$$

# Optimisation algorithms for Linear Regression



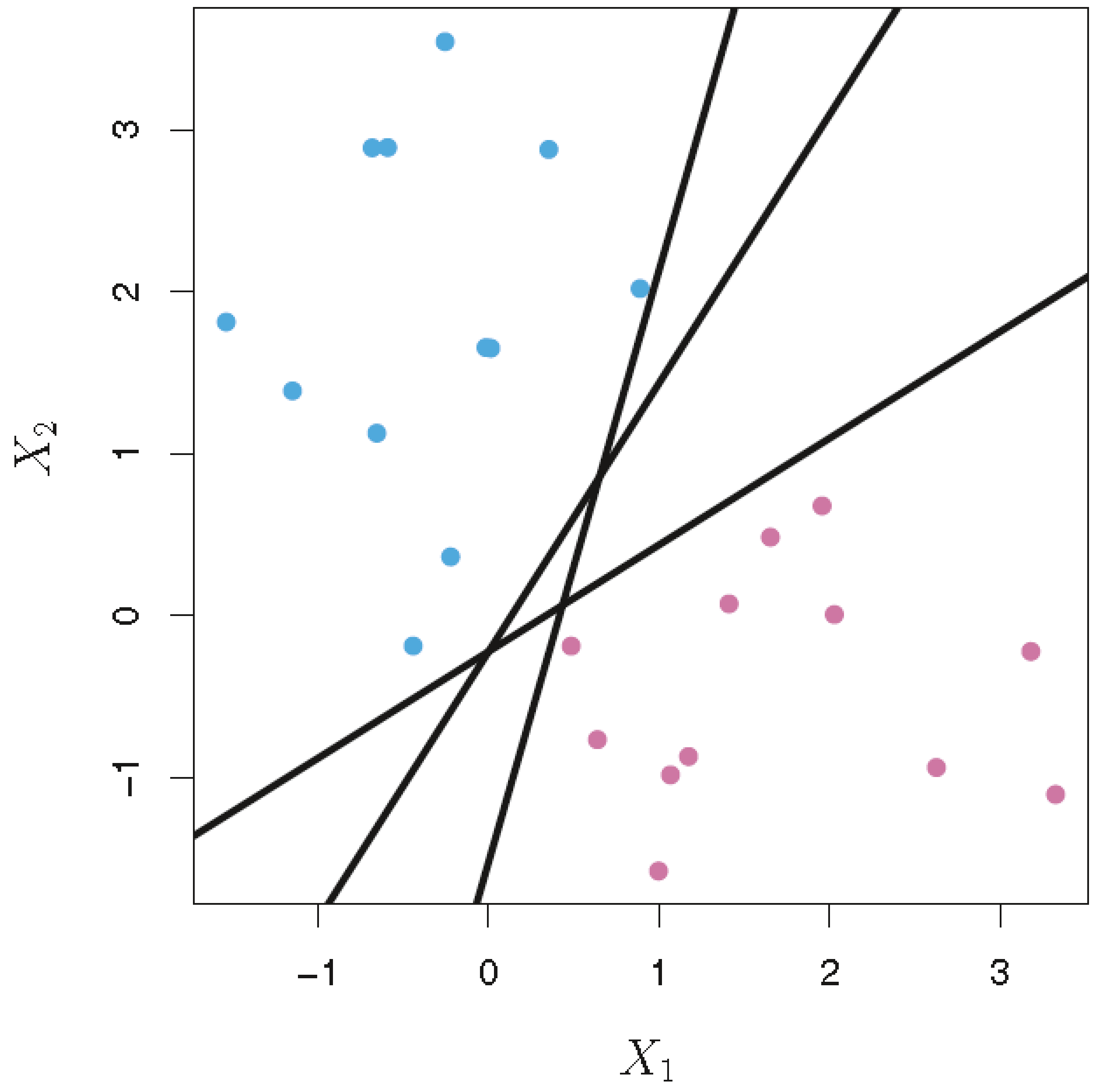
| Algorithm | Large *m* | Out-of-core support | Large *n* | Hyperparams | Scaling required | Scikit-Learn |
|---|---|---|---|---|---|---|
| Normal Equation | Fast | No | Slow | 0 | No | n/a |
| SVD | Fast | No | Slow | 0 | No | `LinearRegression` |
| Batch GD | Slow | No | Fast | 2 | Yes | `SGDRegressor` |
| Stochastic GD | Fast | Yes | Fast | ≥2 | Yes | `SGDRegressor` |
| Mini-batch GD | Fast | Yes | Fast | ≥2 | Yes | `SGDRegressor` |

## Support Vector Machines

- A Support Vector Machine (SVM) is a versatile Machine Learning model, capable of performing linear or nonlinear classification, regression, and even outlier detection.
- SVMs are particularly well suited for classification of complex but small or medium-sized datasets.

# SVM

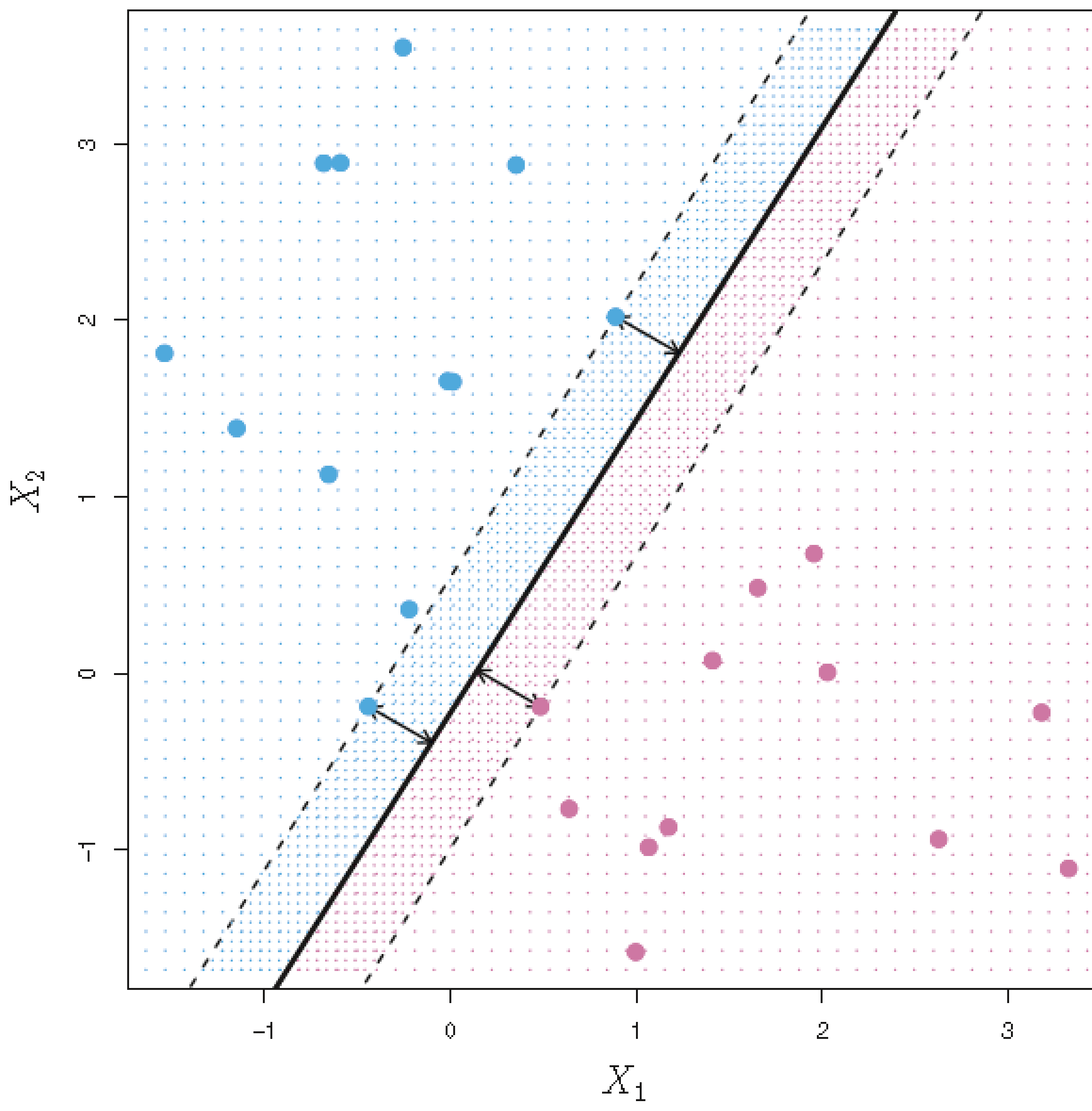
- Support vector classification aims to classify data points into various target classes. If the classes in our training data can be separated by a line or some boundary, then we can just classify the data depending on what side of this decision boundary the data lies on.
- In the following 2-d example, we can separate the data with any of the three lines, and then just assign classes based on whether the observation lies above or below the line. The data are 2-dimensional vectors specified by the features X1 and X2 with class labels as either y =1 (blue) or y = 0 (red).



# Training a SVM

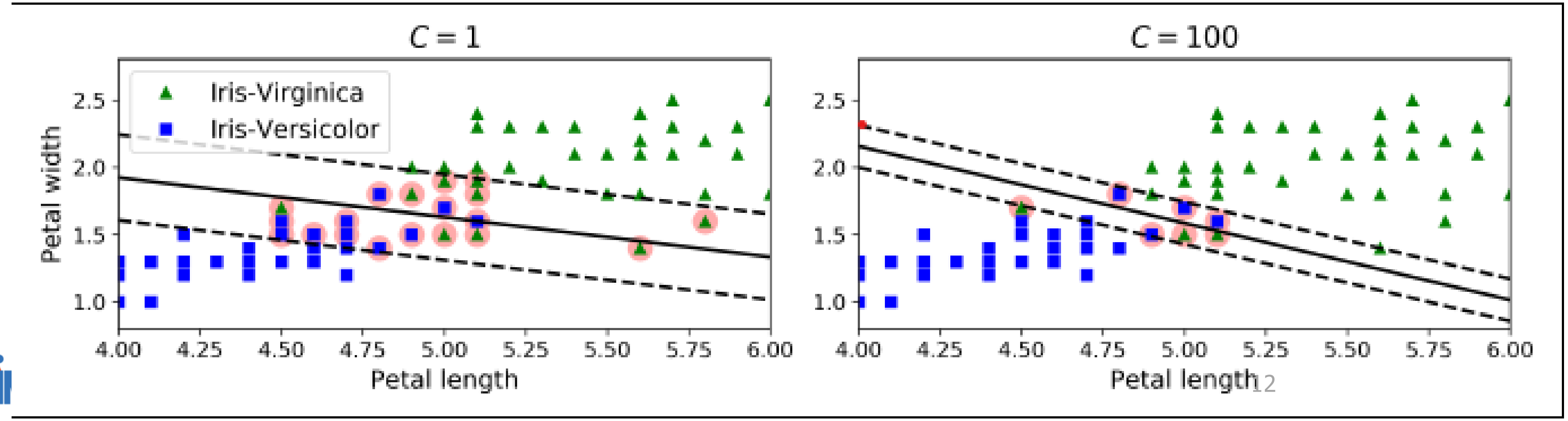
Training a linear support vector classifier is an optimization problem.

- We **maximize the *margin* :** the distance separating the closest pair of data points belonging to opposite classes.
- These points **are called the support vectors**, because they are the data observations that "support", or determine, the decision boundary.
- To train a support vector classifier, we find the ***maximal margin hyperplane*, or *optimal separating hyperplane***, which optimally separates the two classes in order to generalize to new data and make accurate classification predictions.



# SVM Soft Margin Classification

- **Hard margin classification :** we strictly impose that all instances be off the street and on the right side.
  - Works only if data is learnly separable
  - Very sensitive to outliers
- **Soft margin classification:** The objective is to find a good balance between keeping the street as large as possible and limiting the *margin violations .*
- Margin width stablished with the C parameter : a smaller C value leads to a wider street but more margin violations



## SVM

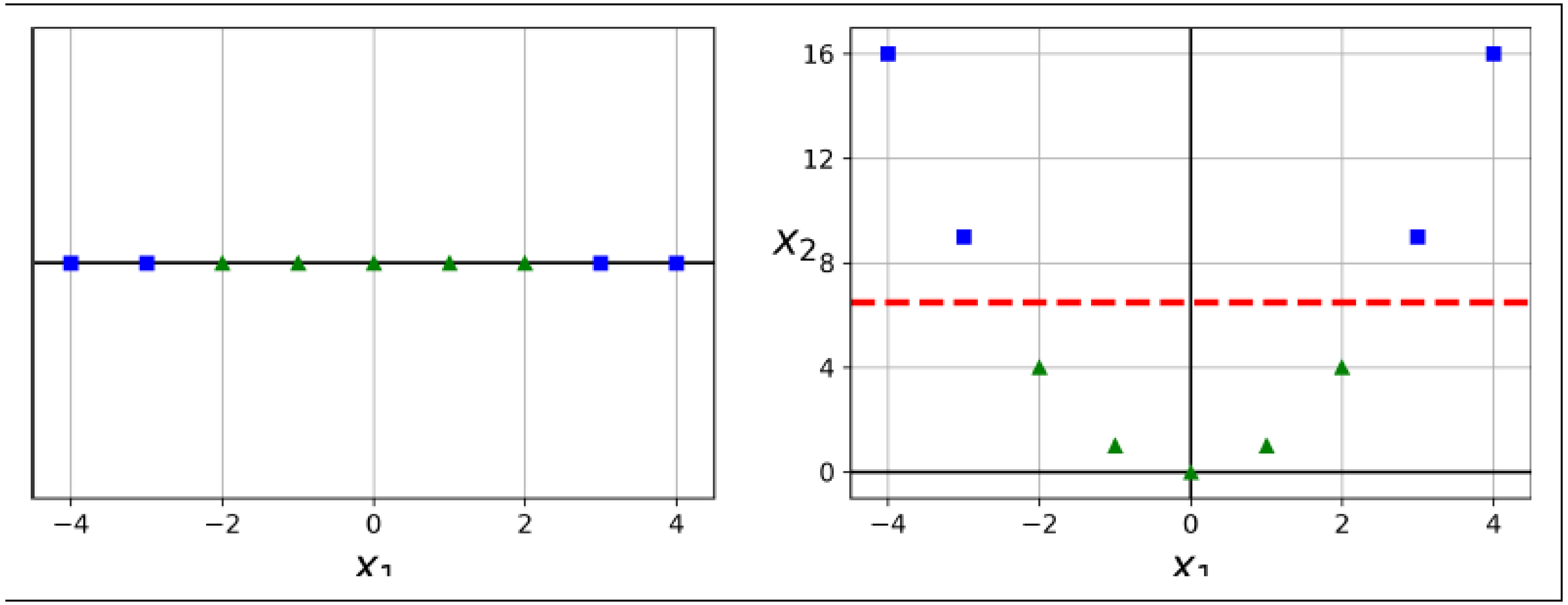
- SVM is sensitive to features scales so it is recommended to scale the data before trainning the model.

- The LinearSVC class regularizes the bias term, so you should center

the training set first by subtracting its mean. This is automatic if you scale the data using the StandardScaler

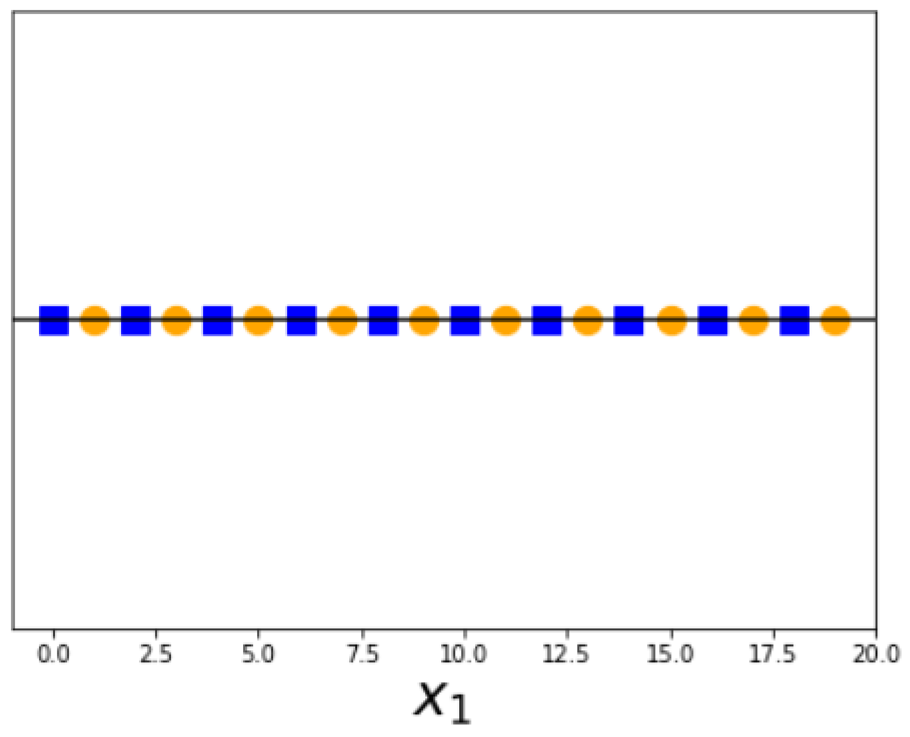
# Nonlinear SVM Classification

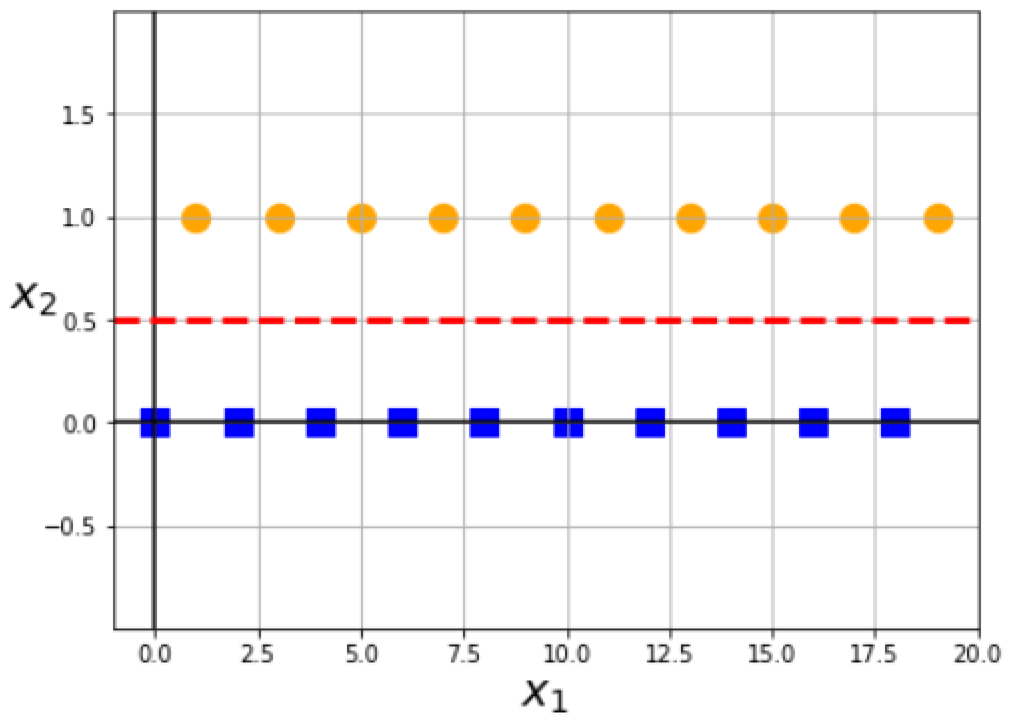
- Although linear SVM classifiers are efficient and work surprisingly well in many cases, many datasets are not even close to being linearly separable.
- One approach to handling nonlinear datasets is to add more features, such as polynomial features



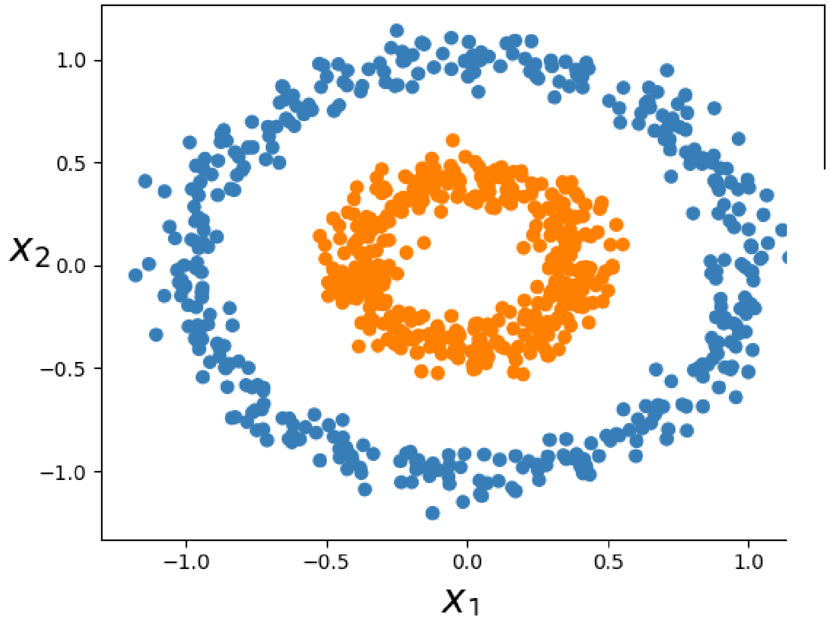
# Data transformations in non linearly separable data

- Transformation $\phi(x) = x \bmod 2$



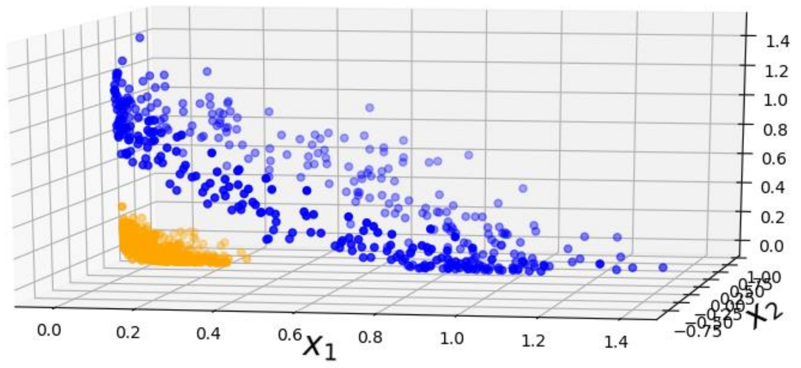


# Data transformations in non linearly separable data



*Equation 5-8. Second-degree polynomial mapping*

$$\phi(\mathbf{x}) = \phi\left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}\right) = \begin{pmatrix} {x_1}^2 \\ \sqrt{2}\, x_1 x_2 \end{pmatrix}$$



## SVM Polynomial Kernel

- Adding polynomial features is simple to implement and can work great with all sorts of Machine Learning algorithms (not just SVMs).

  A low polynomial degree  cannot deal with very complex datasets,

  A high polynomial degree  creates a huge number of features, making the model too slow.

## The kernel Trick

- Kernel methods represent the data only through a set of pairwise similarity comparisons between the original data observations **x** (with the original coordinates in the lower dimensional space), instead of explicitly applying the transformations $\phi(\mathbf{x})$ and representing the data by these transformed coordinates in the higher dimensional feature space.
- They make  possible to obtain a similar result as if many features have been added, without actually having to add them.

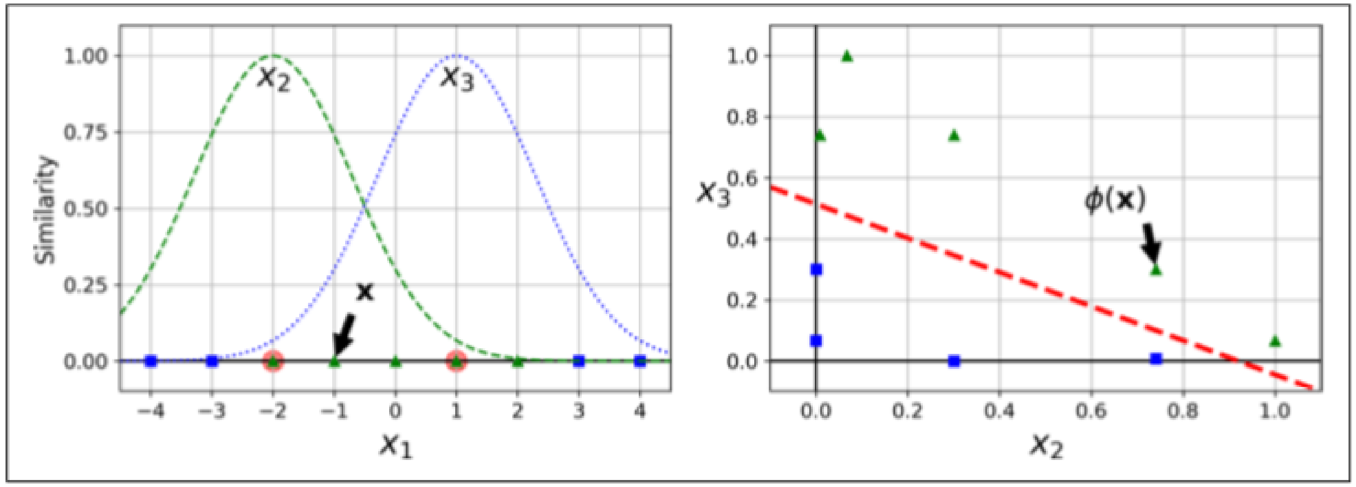
## SVM Polynomial Kernel

Hyperparameters :

- Polynomial degree
- C
- The hyperparameter coef0 controls how much the model is influenced by high-degree polynomials versus low-degree polynomials

## Adding similarity features : RBF Kernel

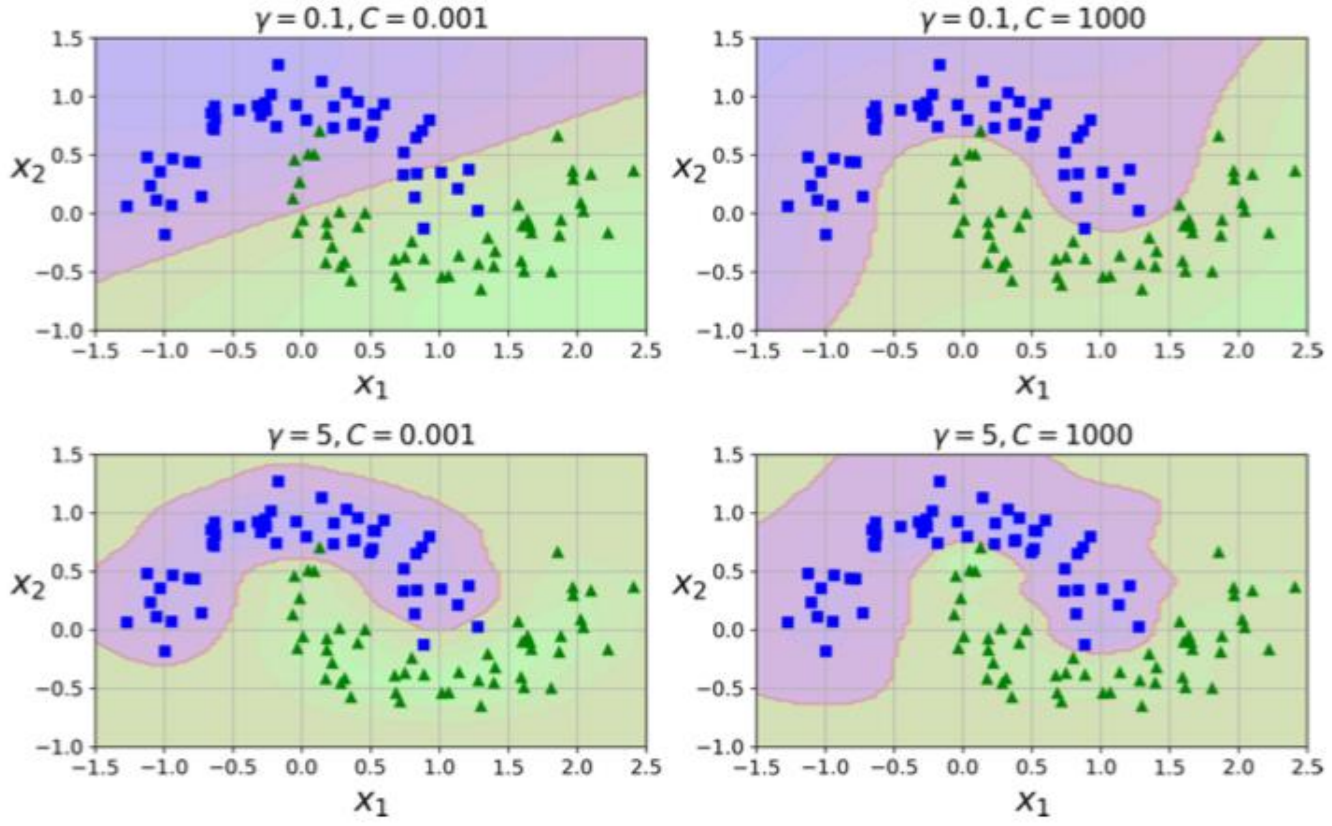
- Add features computed using a *similarity function* that measures how much each instance resembles a particular *landmark*.
- Similarity function : Gaussian *Radial Basis Function* (*RBF*)
  - bell-shaped function varying from 0 (very far away from the landmark) to 1 (at the landmark).



## RBF: Hyperparameter tunning

Hyperparameters : ***γ and C***

- Increasing ***γ*** makes the bell-shape curve narrower, and as a result each instance's range of influence is smaller. Result = Irregular decision boundary.
- A small ***γ*** value makes the bell-shaped curve wider, so instances have a larger range of influence. Result : smoother decision boundary.
- ***γ*** acts like a regularization hyperparameter:
  - if model is overfitting reduce it,
  - If it is underfitting, increase it.



## Which kernel do I choose ?

- Rule of thumb :
  - Always try the linear kernel first, especially if the training set is very large or if it has plenty of features.
  - If the training set is not too large, you should try the Gaussian RBF kernel as well; it works well in most cases.
- Experiment with other kernels using cross-validation and grid search.