Lecture 4: SVM, PCA

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Outline

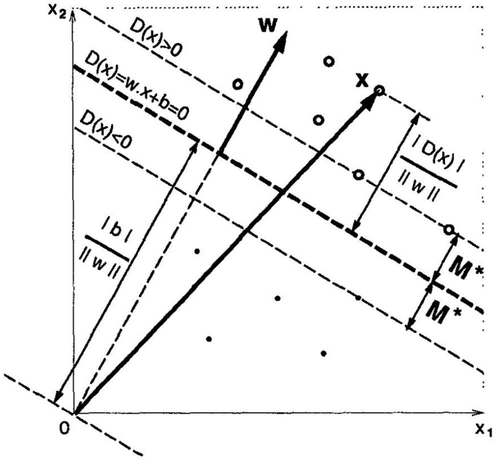
1. Support Vector Machine (SVM)
2. Dimensionality reduction and PCA
3. Validation strategies
4. Multiclass classification strategies

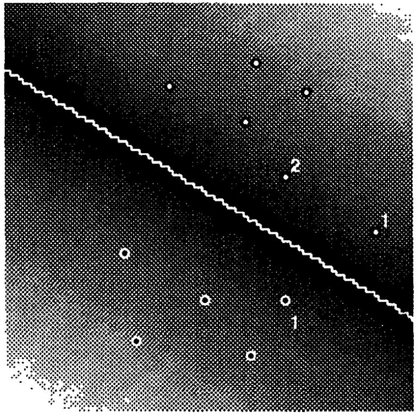
Support Vector Machines

Support Vector Machine

1. History
2. Motivation
3. Solution for separable design
4. Inseparable design, soft margin
5. Kernels
    a. Kernel definition (Hilbert spaces, inner product, positive semidefiniteness)
    b. Kernels properties (addition, infinite sums)
    c. Types of kernels (poly, exponential, gaussian)
6. Current state

History



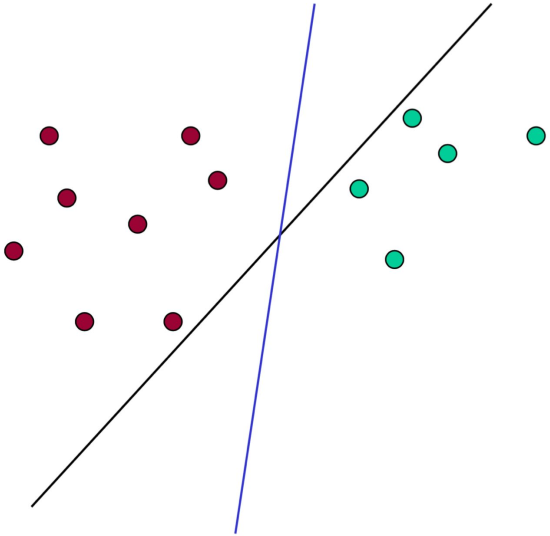


1963: SVM introduced by Soviet mathematicians Vladimir Vapnik and Alexey Chervonenkis

1992: kernel trick (Vapnik, Boser, Guyon)

1995: soft margin (Vapnik, Cortes)

Motivation



Linear separable case

Many separating hyperplanes exist

Maximize width

Margin

$$y \in \{1, -1\}$$

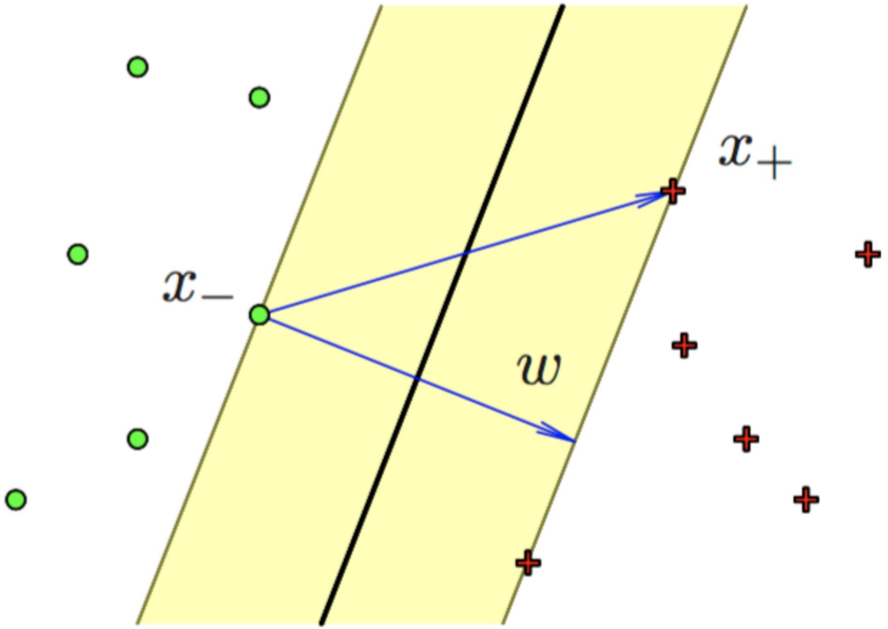
$$y_i = 1 : w^T x_i - c > 0$$

$$y_i = -1 : w^T x_i - c < 0$$

$$c_+(w) = \min_{y_i=1}(w^T x_i)$$

$$c_-(w) = \max_{y_i=-1}(w^T x_i)$$

$$\rho(w) = \frac{c_+(w) - c_-(w)}{2}$$



Theorem

$$\boxed{\rho\left(\frac{w_0}{||w_0||}\right) = \frac{1}{||w_0||}}$$

Optimization problem

$$y_i = 1 : w^T x_i - c > 0$$
$$y_i = -1 : w^T x_i - c < 0$$
$$M_i = y_i \cdot (w^T x_i - c)$$

$$\rho(w) = \frac{1}{||w||} \to \max_{w,c}$$
$$s.t.\ y_i(w^T x_i - c) \geq 1$$

Convex problem!

$$L(w, c, \alpha) = \frac{1}{2} w^T w - \sum_i \alpha_i (y_i(w^T x_i - c) - 1)$$

Some of them are zeros

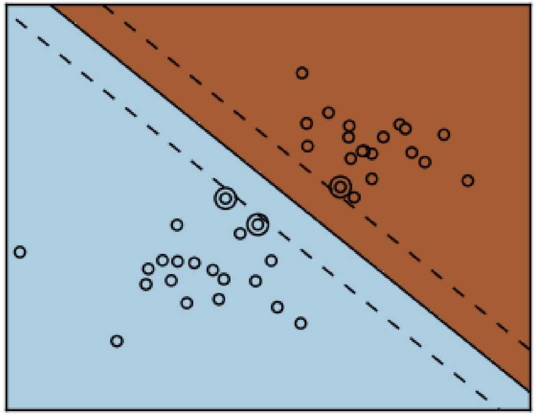
Inseparable case

Let our model mistake, but penalize that mistakes

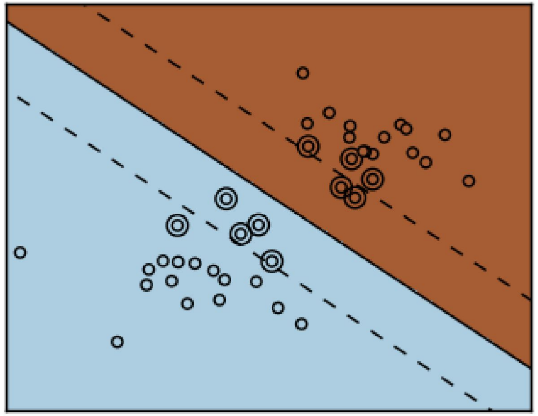
Implemented via margin slack variables

$$\begin{cases} \frac{1}{2}\langle w, w\rangle + C\sum_{i=1}^{\ell}\xi_i \to \min\limits_{w, w_0, \xi}; \\ y_i\big(\langle w, x_i\rangle - w_0\big) \geqslant 1 - \xi_i, \quad i = 1, \dots, \ell; \\ \xi_i \geqslant 0, \quad i = 1, \dots, \ell. \end{cases}$$

Big C



Small C

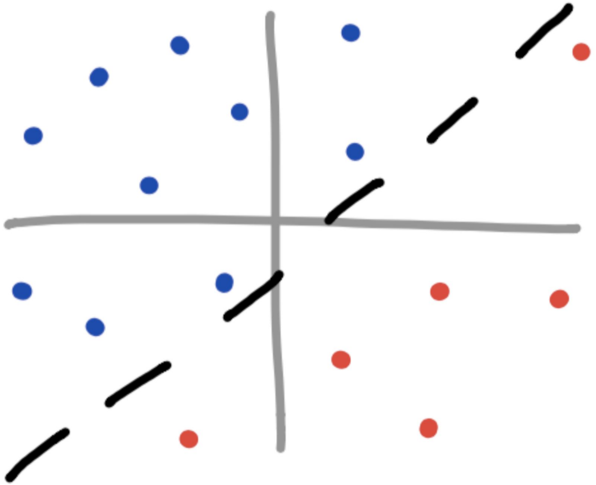


Kernel trick

$$\begin{matrix} x \mapsto \phi(x) \\ w \mapsto \phi(w) \end{matrix} \implies < w, x > \mapsto < \phi(w), \phi(x) >$$

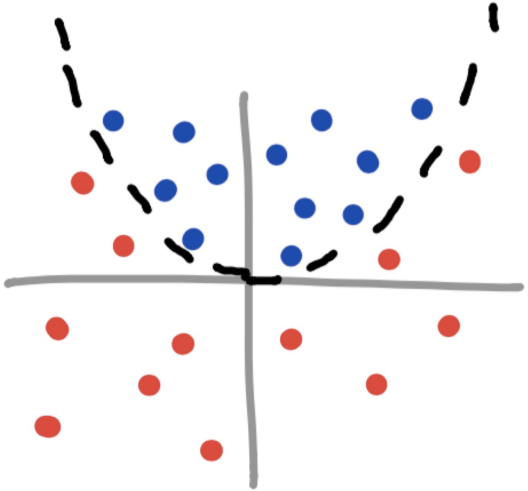
$$K(w, x) = < \phi(w), \phi(x) >$$

Kernel types



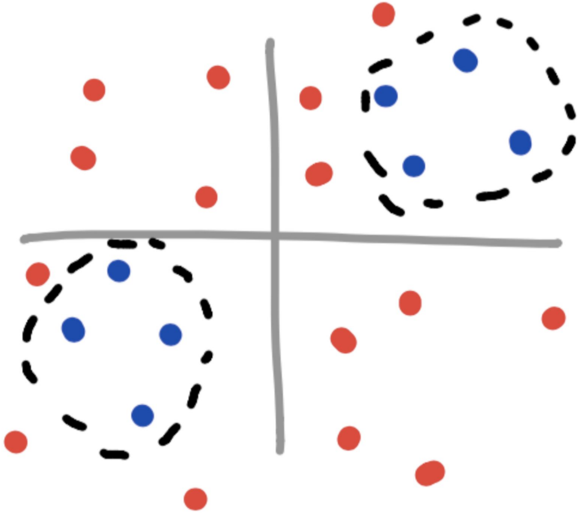
$$K(w,x) = \langle w, x \rangle$$

Linear



$$K(w,x) = (\gamma \langle w, x \rangle + r)^d$$

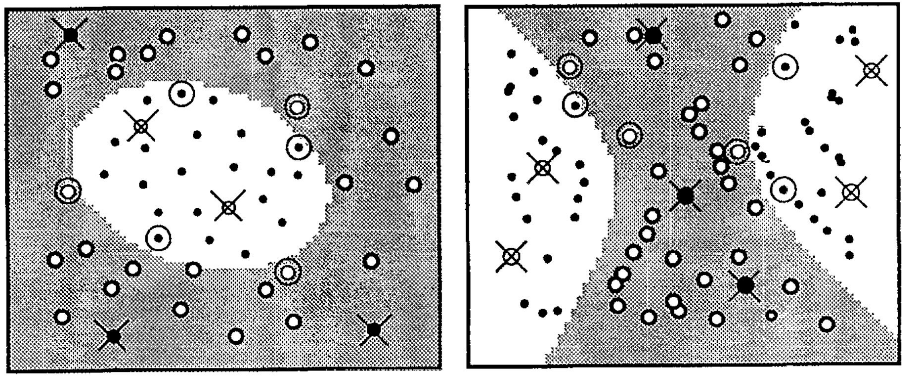
Polynomial



$$K(w,x) = e^{-\gamma \|w-x\|^2}$$

Gaussian radial basis function

Current state



Principal Component Analysis

Principal Component Analysis

$$x_1, \ldots, x_n \to g_1, \ldots, g_k, k \leq n$$

$$U : UU^T = I, G = XU, X = GU^T$$

$$\hat{X} = GU^T \approx X$$

$$||GU^T - X|| \to \min_{G,U} \; s.t. \; rank(G) \leq k$$

Singular value decomposition

$$||GU^T - X|| \to \min_{G,U} \ \ s.t. \ rank(G) \le k$$

$$X = V\Sigma U^T : ||GU^T - V\Sigma U^T||_2 = ||G - V\Sigma||_2$$

$$G = V\Sigma' : ||V\Sigma' - V\Sigma||_2 = ||\Sigma' - \Sigma||_2$$

$$||A||_2 = \sigma_{max}(A) : ||\Sigma' - \Sigma||_2 = \sigma_k(\Sigma) = \sigma_k(X)$$

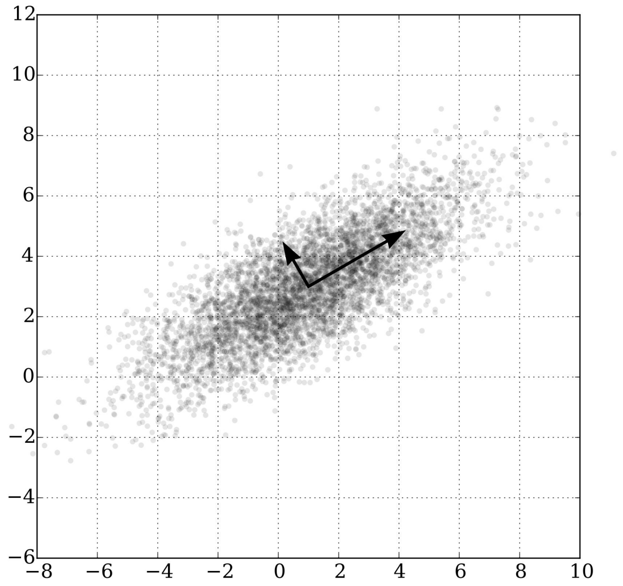
Eckart–Young–Mirsky theorem

Another approach

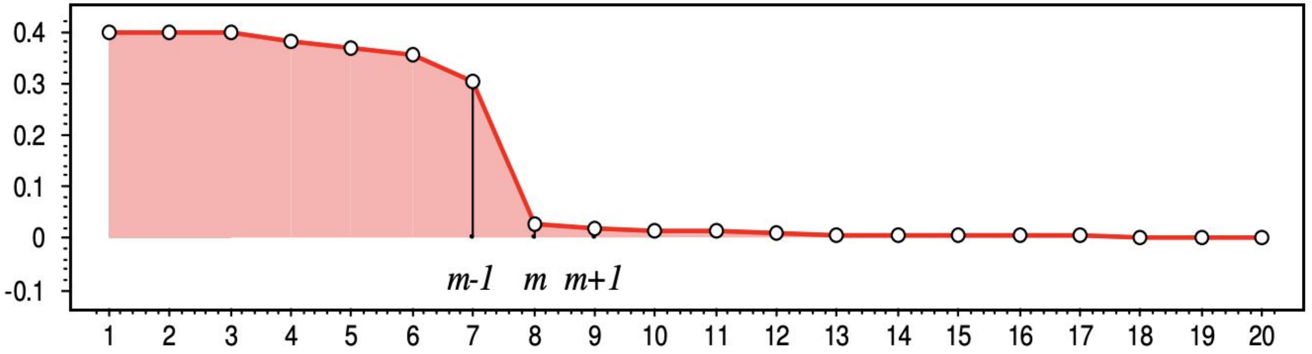
Residual variance maximization

Take new basis vectors greedy

Same result for G and U



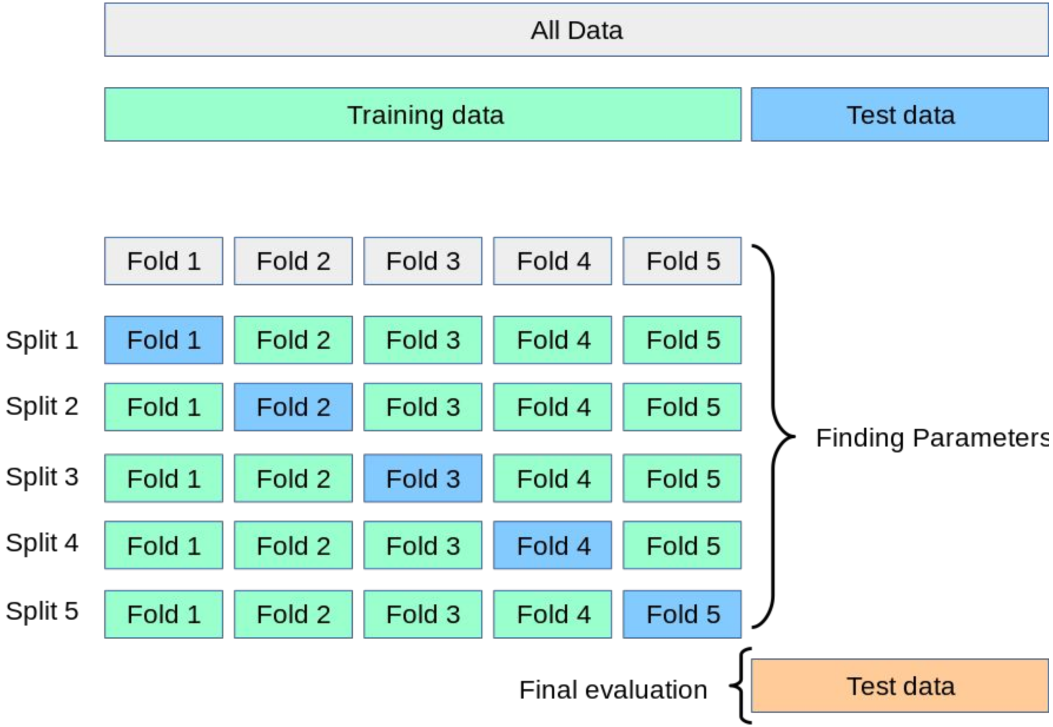
Dimensionality reduction



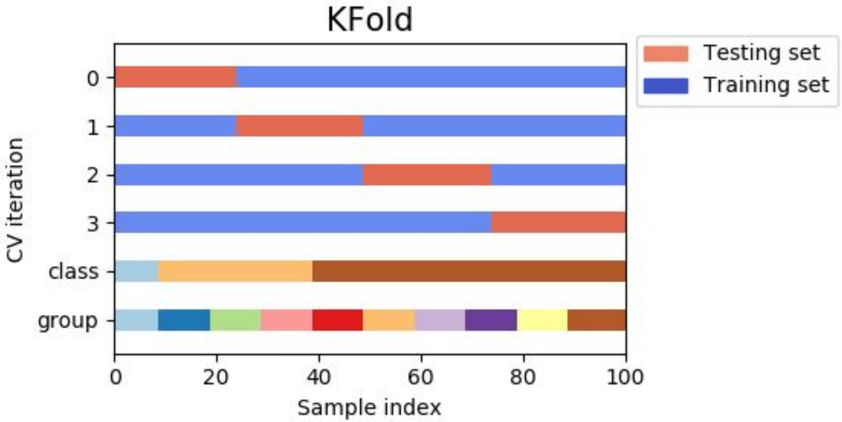
Get rid of low-variance components

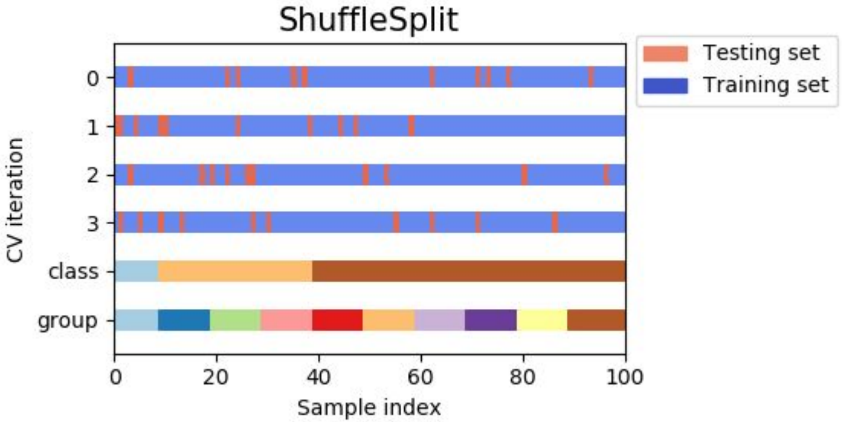
Validation strategies

Validation strategies



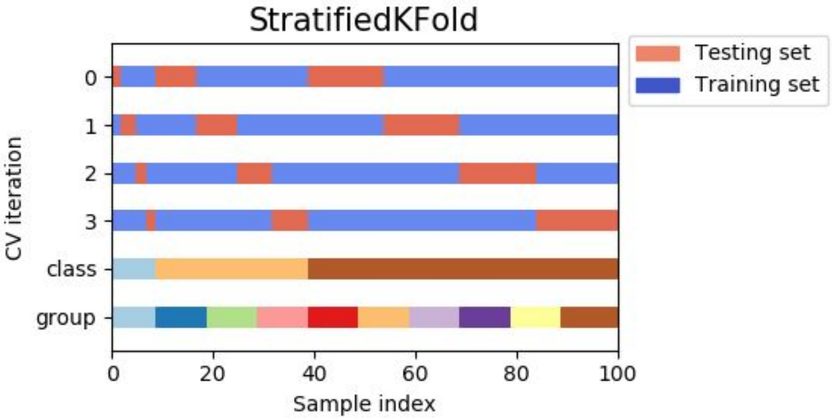
Validation strategies

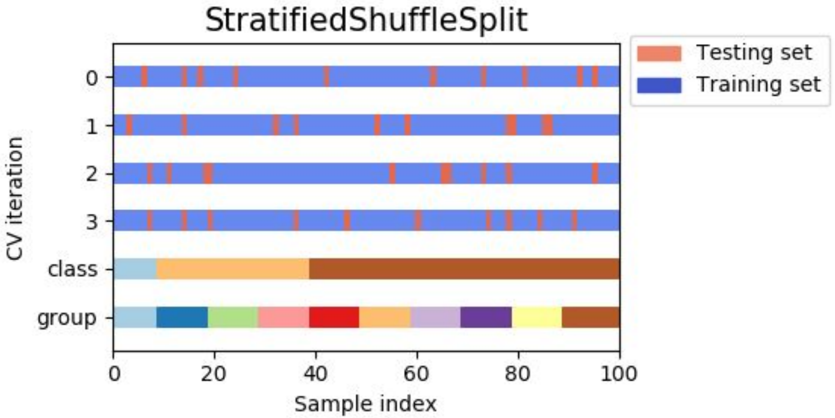




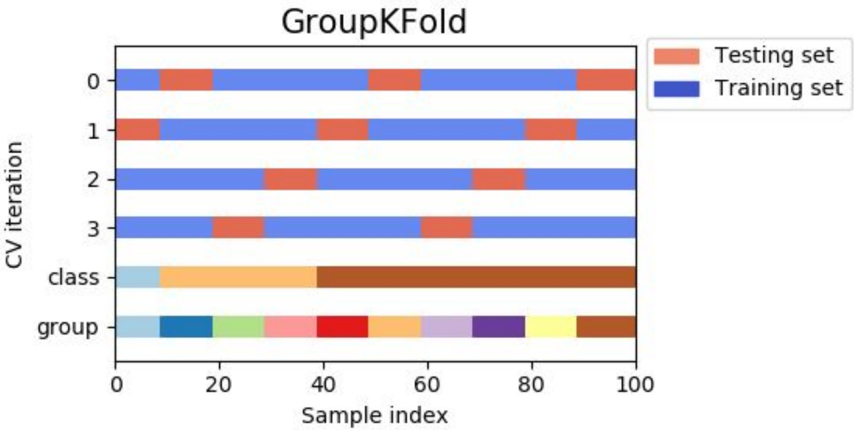
Special case: Leave One Out (LOO) - good for tiny datasets

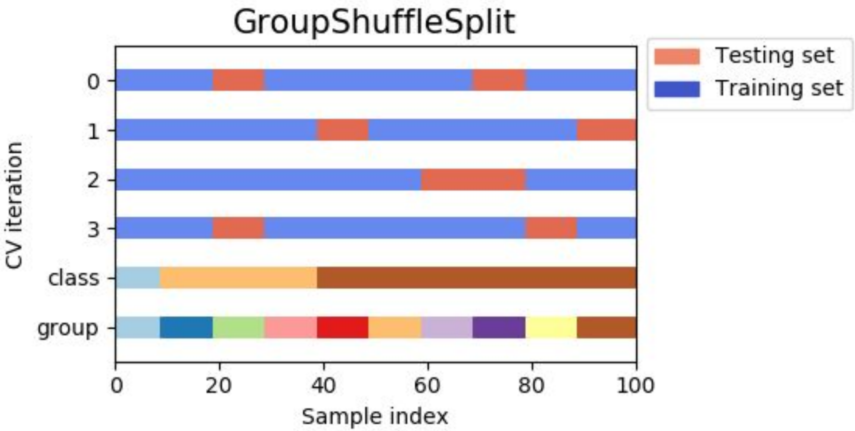
Validation strategies



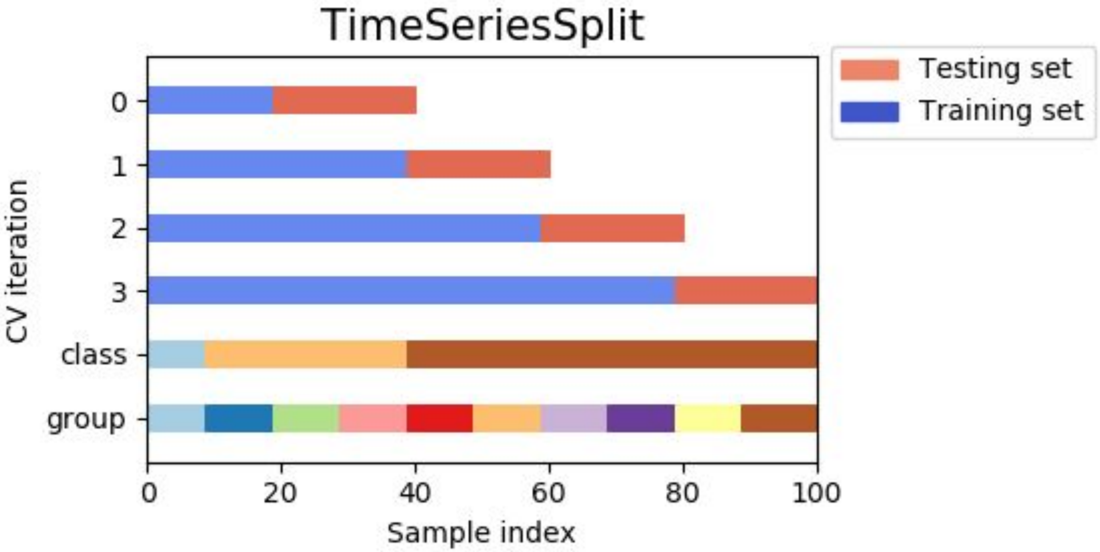


Validation strategies





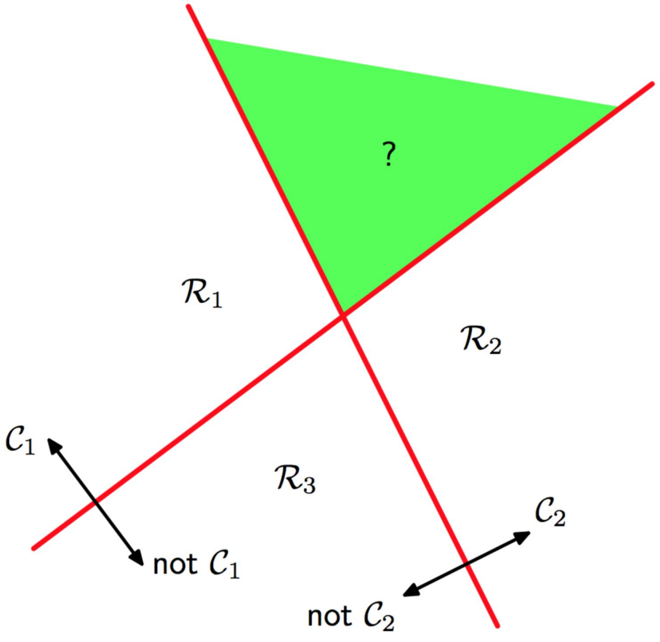
Special case: timeseries



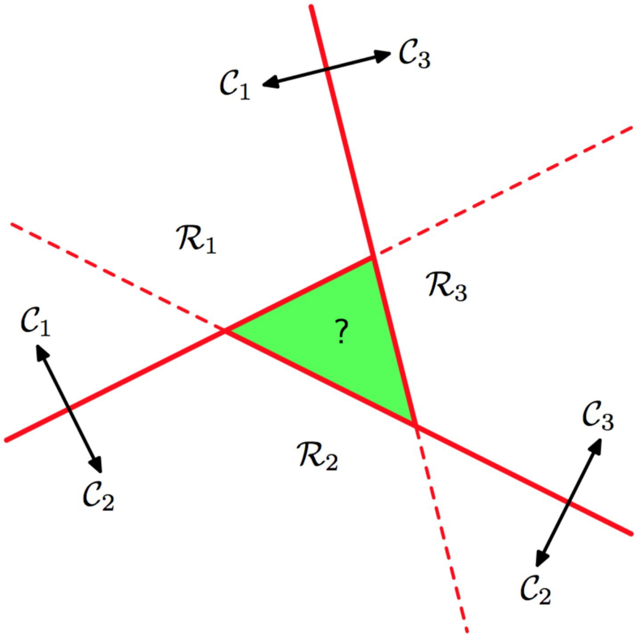
Never use train_test_split in this case!!!

Multiclass classification

Multiclass strategies



One vs Rest



One vs One

Thanks for attention!