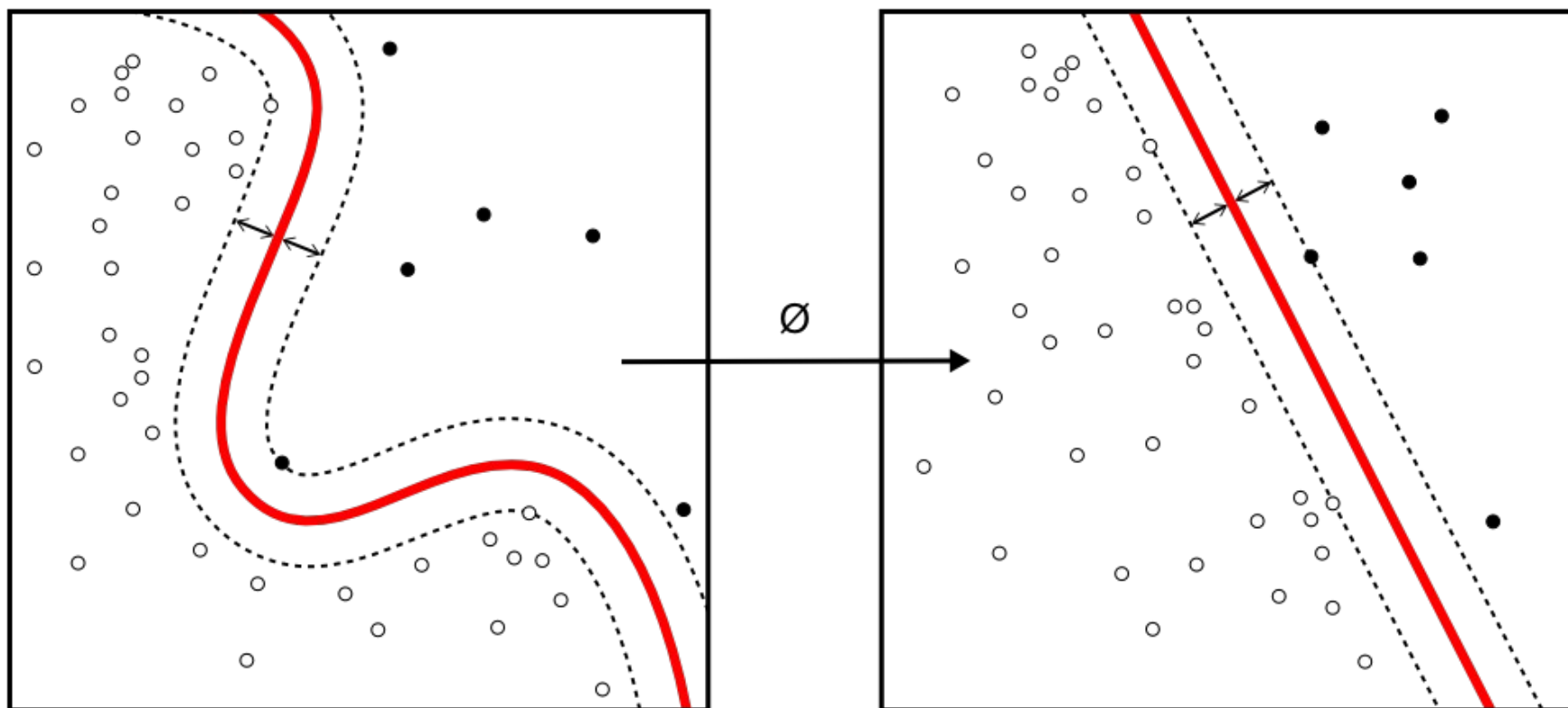
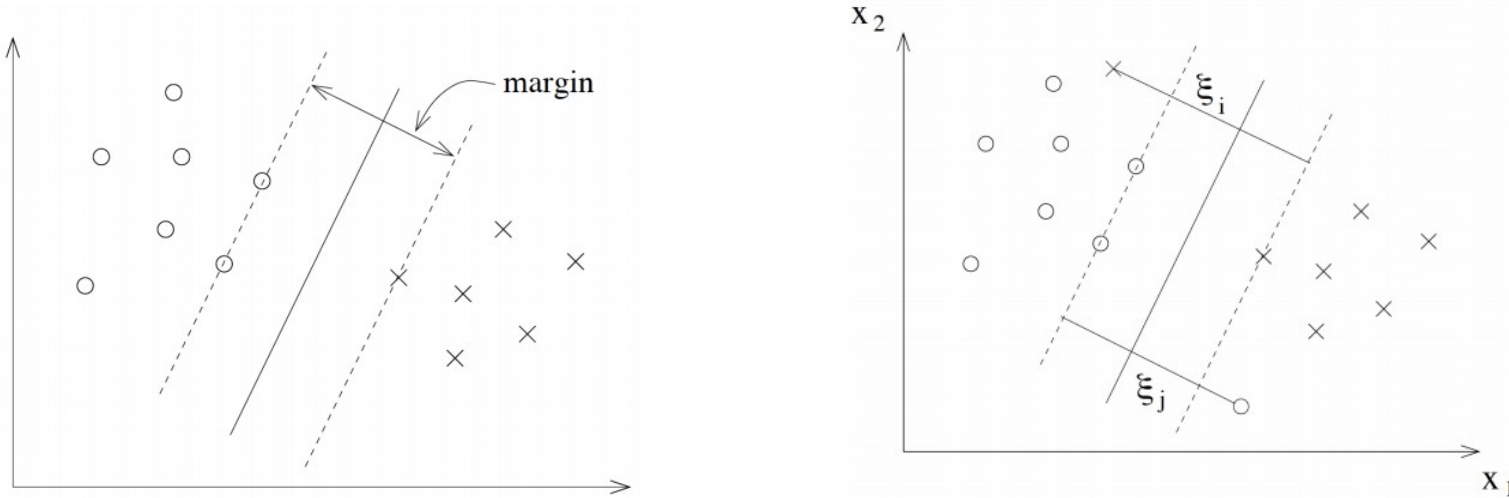


SVM



Hyperparameter C



- In this general case, the problem of SVM can be stated as:

- Find the hyperplane (w, b) that minimizes

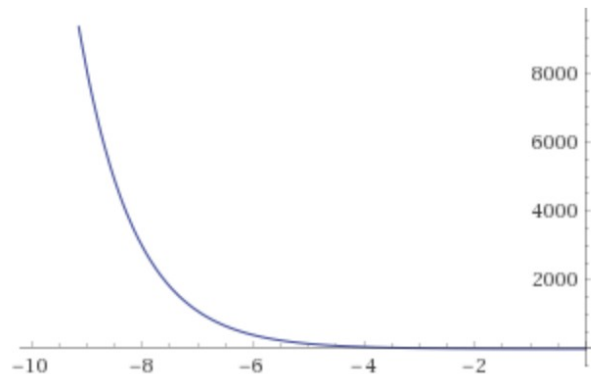
$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i$$

- Under the condition that, for $1 \leq i \leq N$:

$$y_i(w' x_i + b) \geq 1 - \xi_i$$

rbf Kernel & gamma

$$w'x + b = \sum_{i=1}^n w_i x_i + b = 0 \quad \Rightarrow \quad w\varphi(x) + b = \left(\sum_{i=1}^N \alpha_i y_i \varphi(x_i) \right) \varphi(x) + b$$
$$= \sum_{i=1}^N \alpha_i y_i \langle \varphi(x_i), \varphi(x) \rangle + b$$
$$= \sum_{i=1}^N \alpha_i y_i \kappa(x_i, x) + b$$



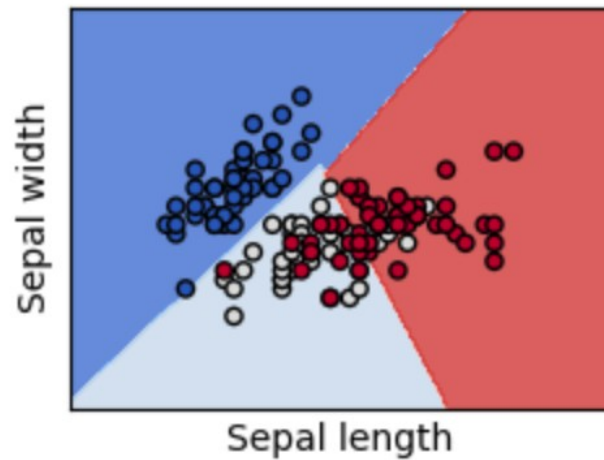
$\kappa(x, y) = \langle x, y \rangle$ linear kernel

$\kappa(x, y) = (\gamma \langle x, y \rangle + r)^d, \gamma > 0$ polynomial kernel

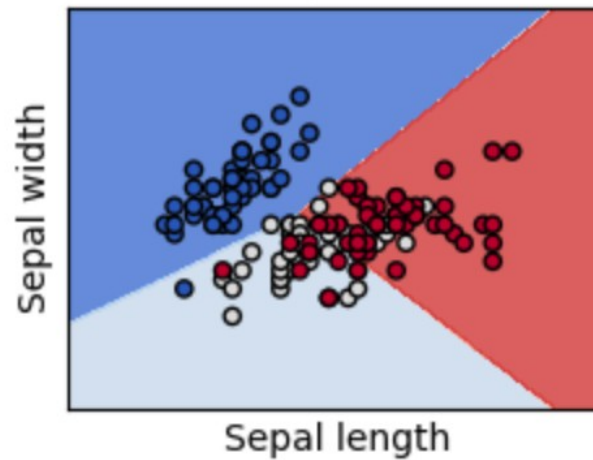
$\kappa(x, y) = \exp(-\gamma \|x - y\|^2), \gamma > 0$ RBF (Gaussian) kernel

$\kappa(x, y) = \tanh(\gamma \langle x, y \rangle + r)$ sigmoid kernel

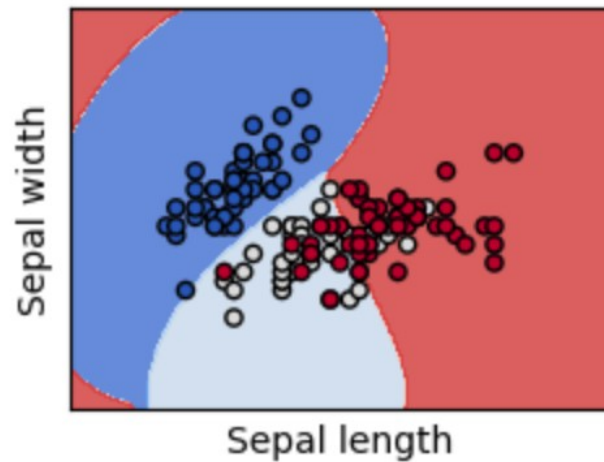
SVC with linear kernel



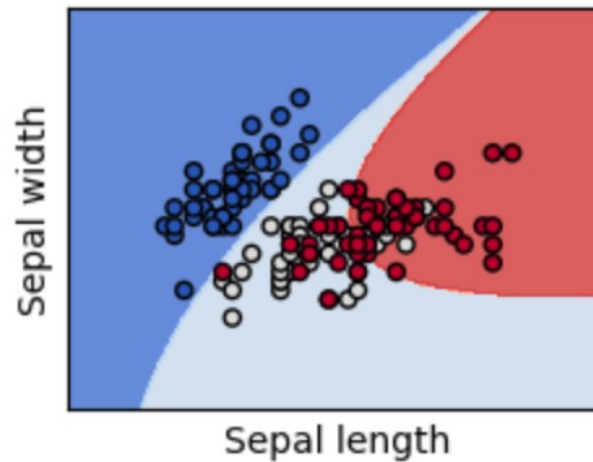
LinearSVC (linear kernel)



SVC with RBF kernel



SVC with polynomial (degree 3) kernel



Setup

```
1  import numpy as np
2  from sklearn.svm import SVC
3
4  train = np.genfromtxt('../data/MNIST/train_med.csv', delimiter=',')
5  test = np.genfromtxt('../data/MNIST/test.csv', delimiter=',')
6
7  y = train[:, 0]
8  X = train[:, 1:] / 255.
9
10 y_test = test[:, 0]
11 X_test = test[:, 1:] / 255.
```

Calculation

```
13 accuracies = np.zeros((6, 6))
14
15 for i in range(0, 6):
16     for j in range(0, 6):
17         svm = SVC(verbose=False, kernel='rbf',
18                   cache_size=4000, gamma=2**(j-5), C=10**(i+5))
19         svm.fit(X, y)
20         pred = svm.predict(X_test)
21         accuracies[i,j] = ((y_test == pred).sum() + 0.0) / len(pred)
22         print ('Gamma={0}, C={1}, Acc={2}'
23               .format(2**(j-5), 10**(i+5), accuracies[i,j]))
24
25 print accuracies
```

Results

	C	Gamma	Score	Time
1	1000000.0	0.03125	0.981745	-31.6
2	1000000.0	0.03125	0.985336	-31.7
3	1000000.0	0.03125	0.982500	-31.7
4	1000000.0	0.03125	0.985090	-31.8
5	1000000.0	0.03125	0.984328	-32.2
6	1000000.0	0.0625	0.979753	-75.6
7	1000000.0	0.0625	0.978250	-76.0
8	1000000.0	0.0625	0.980841	-76.3
9	1000000.0	0.0625	0.976494	-74.4
10	1000000.0	0.0625	0.980077	-75.2
11	1000000.0	0.125	0.892795	-188.8
12	1000000.0	0.125	0.879853	-188.8
13	1000000.0	0.125	0.888000	-189.3
14	1000000.0	0.03125	0.985090	-30.3
15	1000000.0	0.125	0.883721	-188.2
16	1000000.0	0.125	0.900717	-189.0
17	1000000.0	0.125	0.900717	-189.0

