Class 9 – Support Vector Machines (SVM)

Regression

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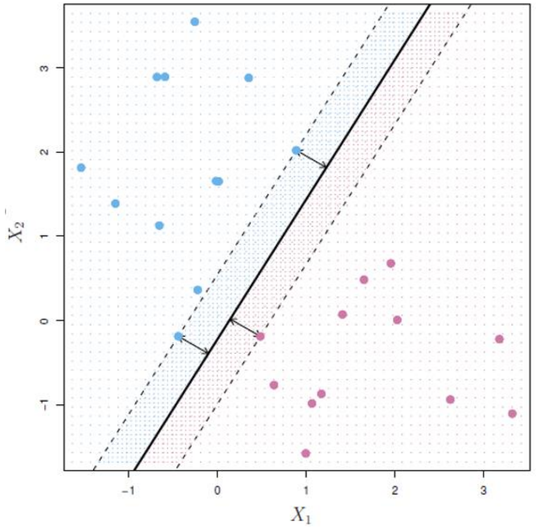
Support Vector Classification (SVC)

$$\underset{\beta_0,\beta_1,\ldots,\beta_p,\epsilon_1,\ldots,\epsilon_n,M}{\text{maximize}} \quad M$$

$$\text{subject to} \quad \sum_{j=1}^{p} \beta_j^2 = 1,$$

$$y_i(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip}) \geq M(1 - \epsilon_i)$$

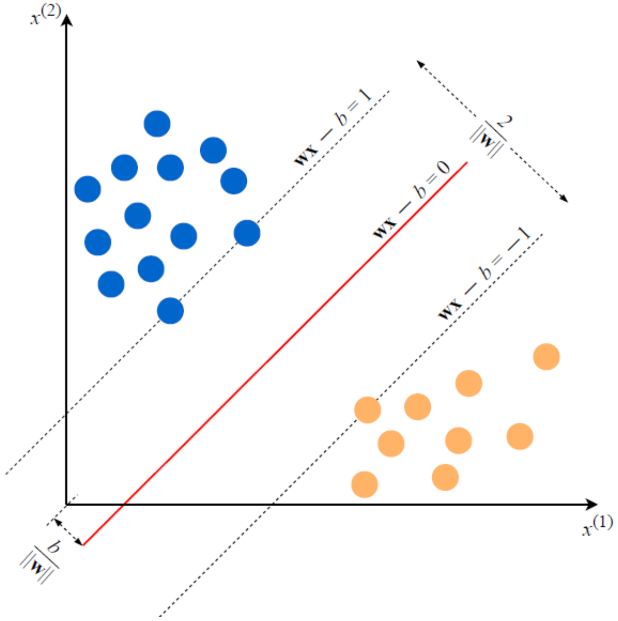
$$\epsilon_i \geq 0, \quad \sum_{i=1}^{n} \epsilon_i \leq C,$$



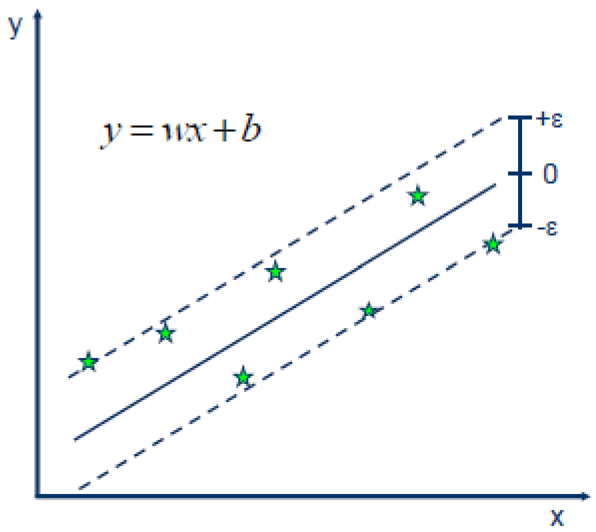
$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,$$

$$\zeta_i \geq 0, i = 1, \ldots, n$$



Support Vector Regression (SVR)

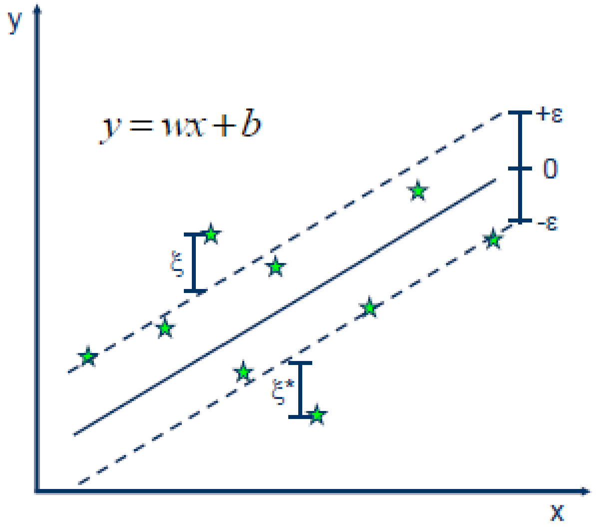


- Minimize:

$$\min \frac{1}{2}\|w\|^2$$

- Constraints:

$$y_i - wx_i - b \le \varepsilon$$
$$wx_i + b - y_i \le \varepsilon$$

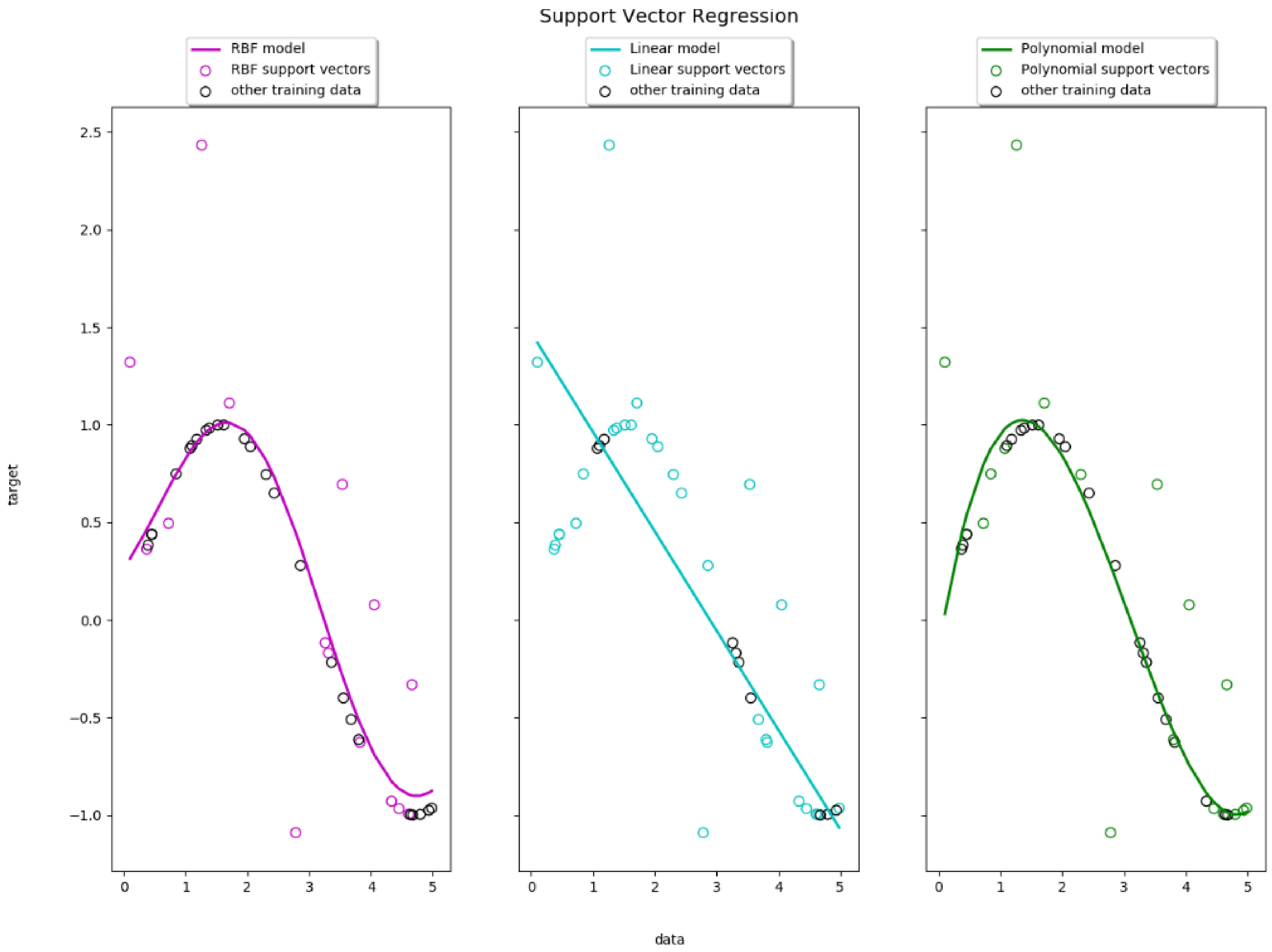


- Minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right)$$

- Constraints:

$$y_i - wx_i - b \le \varepsilon + \xi_i$$
$$wx_i + b - y_i \le \varepsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \ge 0$$



Support Vector Regression
RBF model
RBF support vectors
other training data
Linear model
Linear support vectors
other training data
Polynomial model
Polynomial support vectors
other training data
target
data
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5

SVR in Python

- Find the SVR Sklearn documentation here
- Blackbox version of SVR in python:

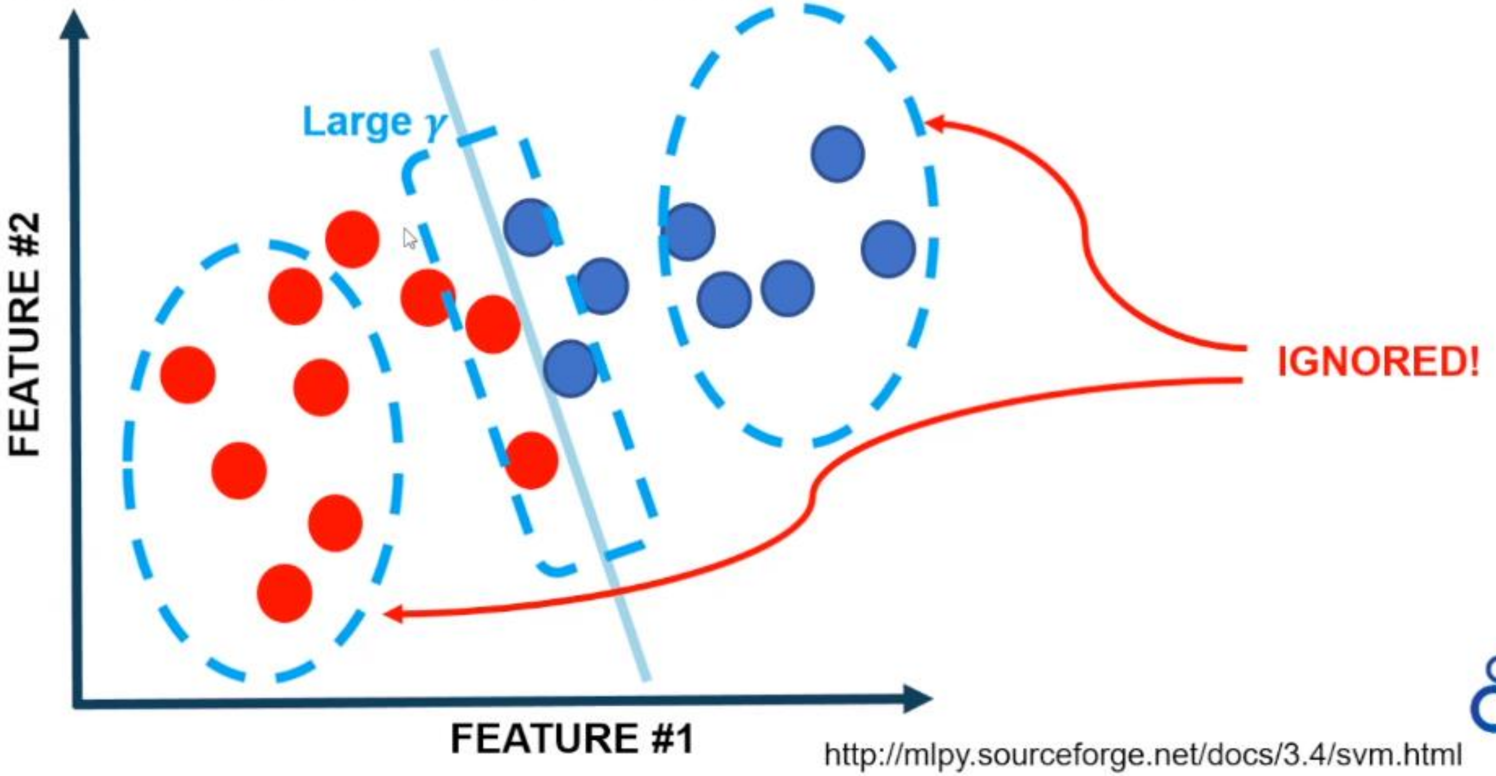
```
from sklearn import svm
X = [[0, 0], [2, 2]]
y = [0.5, 2.5]
clf = svm.SVR()
clf.fit(X, y)



clf.predict([[1, 1]])
```

```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
    gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
    tol=0.001, verbose=False)
>>> clf.predict([[1, 1]])
array([1.5])
```

SVM PARAMETERS OPTIMIZATION

Gamma parameter: controls how far the influence of a single training set reaches

- **Large gamma:** close reach (closer data points have high weight)
- **Small gamma:** far reach (more generalized solution)

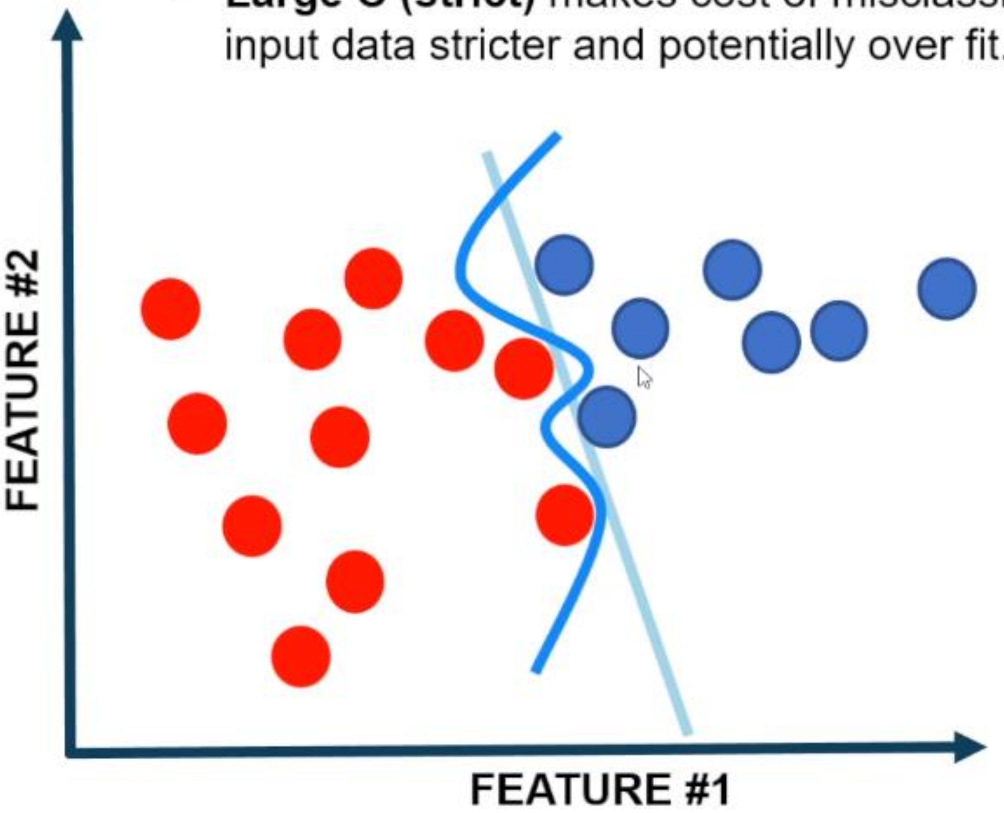


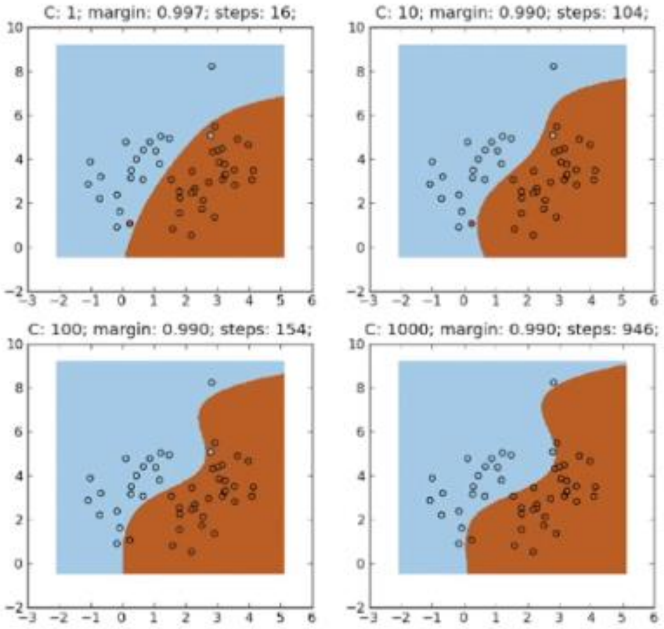
http://mlpy.sourceforge.net/docs/3.4/svm.html

SVM PARAMETERS OPTIMIZATION

C parameter: Controls trade-off between classifying training points correctly and having a smooth decision boundary

- **Small C (loose)** makes cost (penalty) of misclassification low (soft margin)
- **Large C (strict)** makes cost of misclassification high (hard margin), forcing the model to explain input data stricter and potentially over fit.





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