

## Assignment 3 (alireza Mohammadshafie) Machine Learning ¶

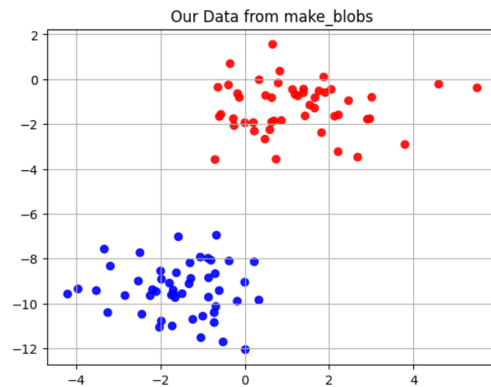
### Import libraries

```
[77]: from sklearn.datasets import make_blobs
import matplotlib.pyplot as plt
import numpy as np
```

### Generate data

```
[78]: X, y = make_blobs(n_samples=100, centers=2, random_state=2, cluster_std=1.1)
# Convert labels from {0,1} to {-1, 1} for SVM convention
y = np.where(y == 0, -1, 1)

plt.scatter(X[:,0], X[:,1], c=y, cmap='bwr', alpha=0.9)
plt.title("Our Data from make_blobs")
plt.grid()
plt.show()
```



### svm

```
[79]: class SimpleLinearSVM:
def __init__(self, lr=1e-3, n_iters=1000):
self.lr = lr
self.n_iters = n_iters

def fit(self, X, y):
n_samples, n_features = X.shape
self.w = np.zeros(n_features)
self.b = 0

for _ in range(self.n_iters):
for idx, x_i in enumerate(X):
if y[idx] * (np.dot(x_i, self.w) + self.b) < 1:
self.w += self.lr * y[idx] * x_i
self.b += self.lr * y[idx]

return self

def decision_function(self, X):
return np.dot(X, self.w) + self.b

def predict(self, X):
return np.sign(self.decision_function(X))
```

### fitting svm and plot it

```
[80]: svm = SimpleLinearSVM(lr=0.01, n_iters=1000)
svm.fit(X, y)

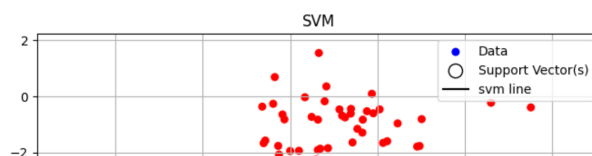
decision_values = y * svm.decision_function(X)
support_vec_idx = np.where(np.abs(decision_values - 1) < 1e-2)[0]

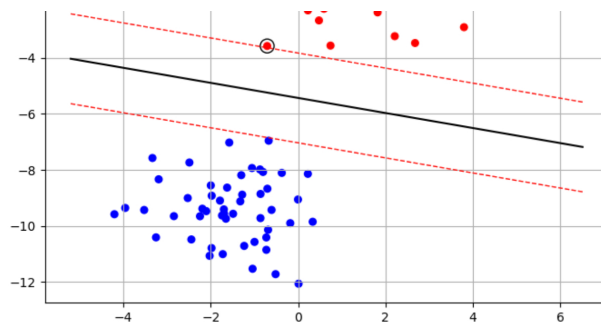
plt.figure(figsize=(8,6))
plt.scatter(X[:,0], X[:,1], c=y, cmap='bwr', s=30, label='Data')
plt.scatter(X[support_vec_idx,0], X[support_vec_idx,1],
s=120, facecolors='none', edgecolors='k', label='Support Vector(s)')

w, b = svm.w, svm.b
xplot = np.linspace(X[:,0].min()-1, X[:,0].max()+1, 100)
yplot = -(w[0]*xplot + b)/w[1]
plt.plot(xplot, yplot, 'k-', label='svm line')

margin = 1.0 / np.linalg.norm(w)
plt.plot(xplot, yplot + margin, 'r--', lw=1)
plt.plot(xplot, yplot - margin, 'r--', lw=1)

plt.title("SVM")
plt.legend()
plt.grid()
plt.show()
```





## Remove the support vector closest to the margin

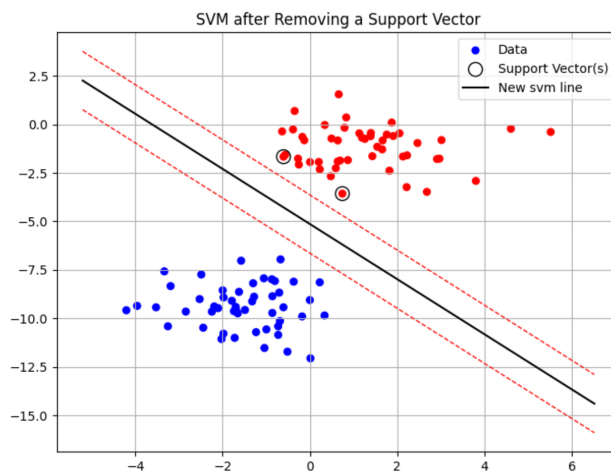
```
[81]: remove_idx = support_vec_idx[0]
X_new = np.delete(X, remove_idx, axis=0)
y_new = np.delete(y, remove_idx)

svm2 = SimpleLinearSVM(lr=0.01, n_iters=1000)
svm2.fit(X_new, y_new)
decision_values2 = y_new * svm2.decision_function(X_new)
support_vec_idx2 = np.where(np.abs(decision_values2 - 1) < 1e-2)[0]

plt.figure(figsize=(8,6))
plt.scatter(X_new[:,0], X_new[:,1], c=y_new, cmap='bwr', s=30, label='Data')
plt.scatter(X_new[support_vec_idx2,0], X_new[support_vec_idx2,1],
            s=120, facecolors='none', edgecolors='k', label='Support Vector(s)')
w2, b2 = svm2.w, svm2.b
yplot2 = -(w2[0]*xplot + b2)/w2[1]
margin2 = 1.0 / np.linalg.norm(w2)

plt.plot(xplot, yplot2, 'k-', label='New svm line')
plt.plot(xplot, yplot2 + margin2, 'r--', lw=1)
plt.plot(xplot, yplot2 - margin2, 'r--', lw=1)

plt.title("SVM after Removing a Support Vector")
plt.legend()
plt.grid()
plt.show()
```



When we remove the closest support vector and retrain the SVM, the decision boundary and margin both change. That shows that the SVM mainly depends on those support vectors for figuring out where to put the hyperplane. If we remove one, especially the closest one, the whole separator can shift, which means support vectors are really important for how SVM works.

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