

First we must import library's and data:

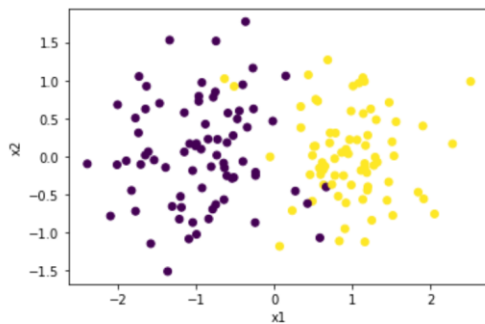
```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
```

```
1 train = pd.read_csv('train.csv')
2 test = pd.read_csv('test.csv')
3 display(train.head())
```

	x1	x2	target
0	0.525642	0.133813	1.0
1	1.009394	0.925323	1.0
2	0.776517	-0.252655	1.0
3	-0.245693	-0.872614	0.0
4	-1.540663	-0.048947	0.0

Data's plot is like this:

```
1 plt.scatter(train.x1,train.x2,c=train.target)
2 plt.xlabel('x1')
3 plt.ylabel('x2')
4 pass
```



Since we can see from diagram, they are not linearly separable so the algorithms never converge. We must set a iteration limit for it.

For perceptron algorithms to work, we must change the labels from 0 to -1:

```
1 X_train = train[['x1','x2']]
2 y_train = train['target'].apply(lambda x: -1 if x==0 else x)
3 X_test = test[['x1','x2']]
4 y_test = test['target'].apply(lambda x: -1 if x==0 else x)
5 y_train
```

```
0    1.0
1    1.0
2    1.0
3   -1.0
4   -1.0
...
145  1.0
146 -1.0
147 -1.0
148 -1.0
149 -1.0
Name: target, Length: 150, dtype: float64
```

Now our main class:

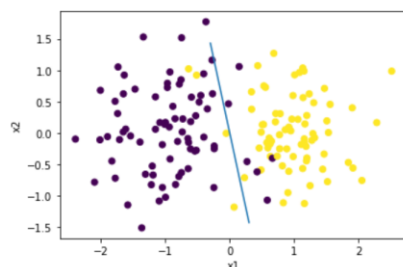
```
1 class Perceptron:
2     def __init__(self, iteration=100, alpha=0.01):
3         self.iteration = iteration
4         self.alpha = alpha
5
6     def fit(self, X, y):
7         self.weights = np.zeros(X.shape[1])
8         self.bias = 0
9         self.X = X
10        self.y = y
11        self.best_accuracy = 0
12        i, accuracy = 0, 0
13        while accuracy < 1 and i < self.iteration:
14            accuracy = 0
15            for x, label in zip(X, y):
16                if label * self.predict(x) <= 0:
17                    self.weights += self.alpha * label * x
18                    self.bias += self.alpha * label
19                else:
20                    accuracy += 1
21            accuracy = accuracy / len(X)
22            if accuracy > self.best_accuracy:
23                self.best_weights = self.weights.copy()
24                self.best_bias = self.bias
25                self.best_accuracy = accuracy
26            i += 1
27        self.weights = self.best_weights
28        self.bias = self.best_bias
29
30    def predict(self, x):
31        return np.sign(x @ self.weights + self.bias)
32
33    def test_accuracy(self, X=None, y=None):
34        if X is None:
35            X = self.X
36            y = self.y
37        return f'{round(sum(model.predict(X)*y)*100/len(X),1)}%'
38
39    def draw(self, x):
40        if len(self.weights) == 2:
41            y = (self.weights[0]*x+self.bias)/self.weights[1]
42            plt.plot(x, y)
43        else:
44            print("can't draw 3D shapes!")
```

The pocket algorithm maintains two sets of weights and biases during training: the current set and the best set. The current set is updated based on the prediction error as in a simple perceptron, but the best set is only updated if the new set leads to higher accuracy on the training data. This allows the pocket algorithm to capture the most accurate set of weights and biases encountered during training, reducing the risk of overfitting.

I also write 2 helping function test_accuracy that give accuracy of model for any given data and draw that draw the model separator line.

```
1 model = Perceptron()
2 model.fit(X_train.to_numpy(), y_train)
3 print(f'weights: ', model.weights, ', Bias: ', model.bias)
4 print('train accuracy: ', model.test_accuracy())
5 model.draw(np.array([-0.3, 0.3]))
6 plt.scatter(train.x1, train.x2, c=train.target)
7 plt.xlabel('x1')
8 plt.ylabel('x2')
9 pass
```

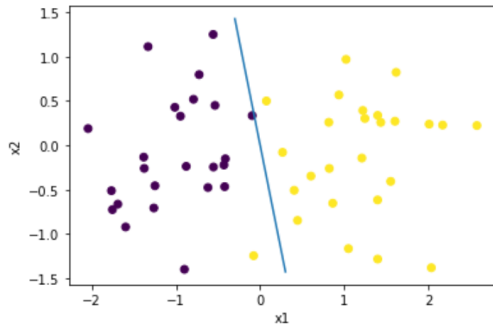
```
weights: [ 0.02244959 -0.00471331], Bias: 0.0
train accuracy: 90.7%
```



The result is interesting since our accuracy is 90.7% in just 100 iterations and the line is meaningful.

```
1 print('test accuracy:',model.test_accuracy(X_test,y_test))
2 model.draw(np.array([-0.3,0.3]))
3 plt.scatter(test.x1,test.x2,c=test.target)
4 plt.xlabel('x1')
5 plt.ylabel('x2')
6 pass
```

test accuracy: 96.0%



Also for test set we have just one missing point and the model works very well with 96% accuracy.