05Classification

March 20, 2019

1 1. 身麼是分類問題

1.1 (1). 二元分類

- 誰會買電腦?

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
30…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

- 問題對中的兩個問題是否問的是同一件事情?

id	qid1	qid2	question1	question2	is_duplicate
0	1	2	What is the step by step guide to invest in share market in india?	What is the step by step guide to invest in share market?	0
1	3	4	What is the story of Kohinoor (Koh-i-Noor) Diamond?	What would happen if the Indian government stole the Kohinoor (Koh-i-Noor) diamond back?	0
2	5	6	How can I increase the speed of my internet connection while using a VPN?	How can Internet speed be increased by hacking through DNS?	0
3	7	8	Why am I mentally very lonely? How can I solve it?	Find the remainder when [math]23^{24}[/math] is divided by 24,23?	0

id	qid1	qid2	question1	question2	is_duplicate
4	9	10	Which one dissolve in water quikly sugar, salt, methane and carbon di oxide?	Which fish would survive in salt water?	0
5	11	12	Astrology: I am a Capricorn Sun Cap moon and cap rising...what does that say about me?	I'm a triple Capricorn (Sun, Moon and ascendant in Capricorn) What does this say about me?	1

- 分類出是貓的圖片

1.2 (1). 多元分類

- 新聞分類
- 電影分類

2 2. 演算法們

1. K Nearest Neighbor (KNN)
2. Naïve Bayes (貝氏分類器)
3. Logistic Regression (羅吉斯回歸)
4. Decision Tree (決策樹)

3 IMPORT

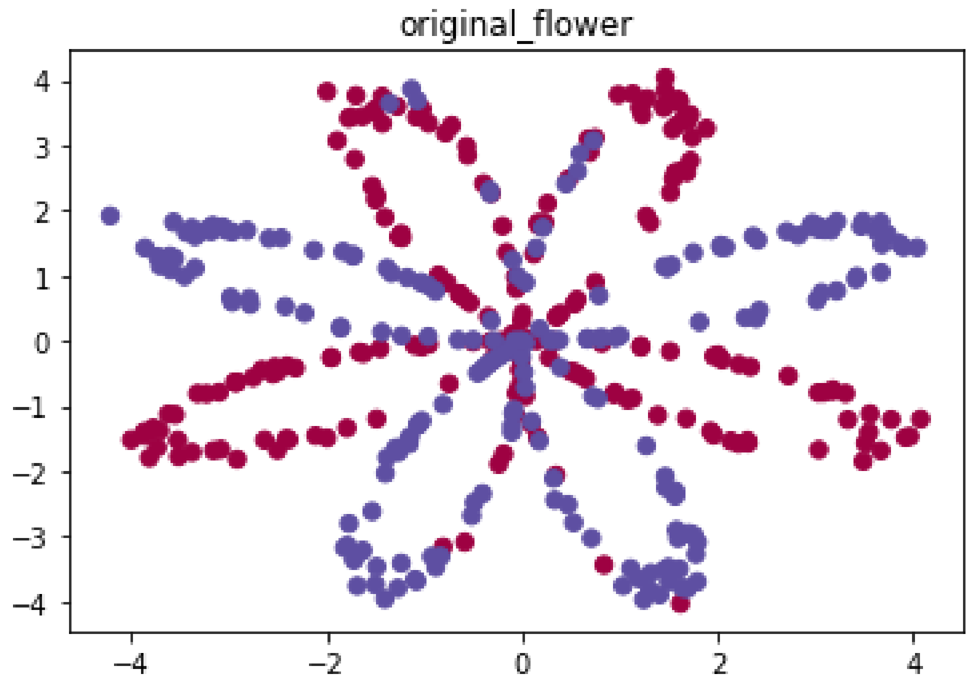
```
In [1]: import math
        import pandas as pd
        import os
        from sklearn import datasets
        iris = datasets.load_iris()
```

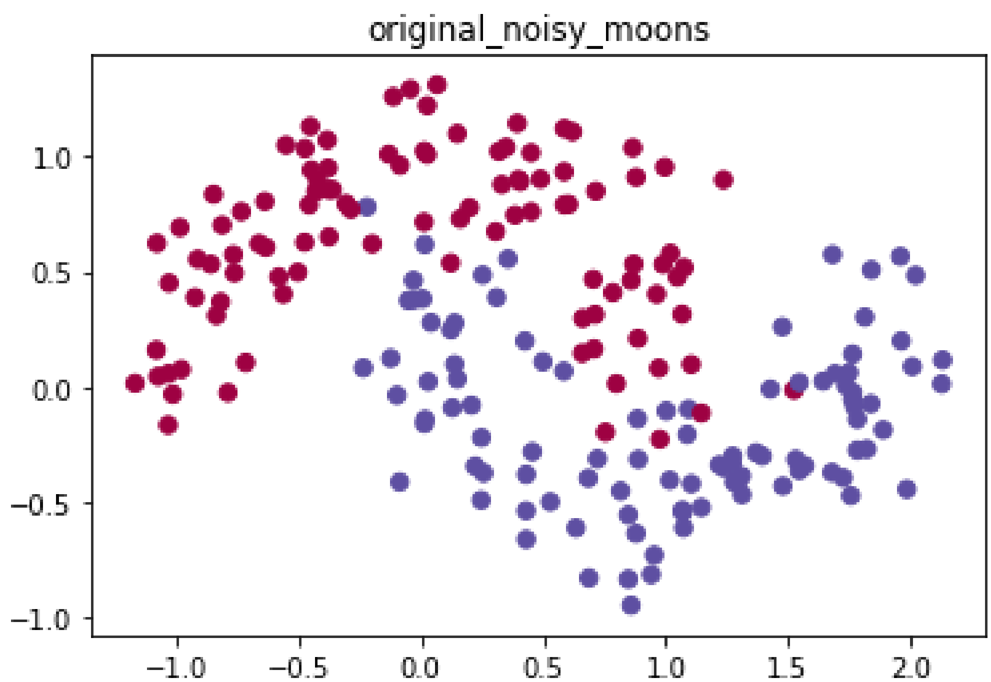
catImgs

```
import numpy as np
from pprint import pprint
from collections import Counter

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.decomposition import PCA

from planar_utils import plot_decision_boundary, sigmoid, load_planar_dataset, load_ext
```

4 DATA

```
In [2]: # First Dataset
        datas = []
        X, Y = load_planar_dataset()
        name = 'flower'
        X = X.T
        Y = Y[0]
        datas.append((name, X, Y))

        # Second Dataset
        noisy_circles, noisy_moons, blobs, gaussian_quantiles, no_structure = load_extra_datase
        datas.append(("noisy_moons", noisy_moons[0], noisy_moons[1]))

        # Visualize
        for name, X, Y in datas:
            plt.scatter(X[:, 0], X[:, 1], c=Y , s=40, cmap=plt.cm.Spectral);
            plt.title(name+'_original')
            plt.title('original_' + name)
            plt.show()
```



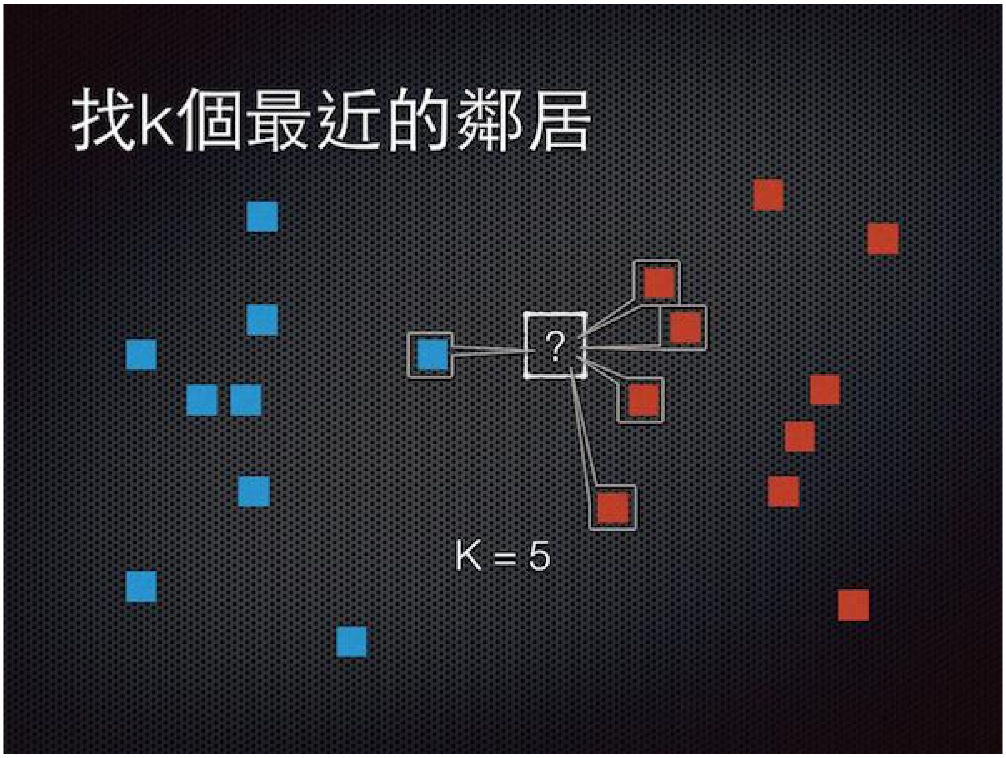



```
In [3]: X_iris = iris.data
        Y_iris_true = iris.target
```

```python
df = pd.DataFrame(iris.data)
folwer_type = {
    0:iris.target_names[0],
    1:iris.target_names[1],
    2:iris.target_names[2],
}
df.columns = iris.feature_names


df['type'] = [folwer_type.get(i) for i in iris.target]
df1 = df[df['type'] == list(folwer_type.values())[0]][:5].copy()
df2 = df[df['type'] == list(folwer_type.values())[1]][:5].copy()
df3 = df[df['type'] == list(folwer_type.values())[2]][:5].copy()
pd.concat([df1, df2, df3])
```

Out[3]:

```
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                  5.1               3.5                1.4               0.2
1                  4.9               3.0                1.4               0.2
2                  4.7               3.2                1.3               0.2
3                  4.6               3.1                1.5               0.2
4                  5.0               3.6                1.4               0.2
50                 7.0               3.2                4.7               1.4
51                 6.4               3.2                4.5               1.5
52                 6.9               3.1                4.9               1.5
53                 5.5               2.3                4.0               1.3
54                 6.5               2.8                4.6               1.5
100                6.3               3.3                6.0               2.5
101                5.8               2.7                5.1               1.9
102                7.1               3.0                5.9               2.1
103                6.3               2.9                5.6               1.8
104                6.5               3.0                5.8               2.2

           type
0        setosa
1        setosa
2        setosa
3        setosa
4        setosa
50   versicolor
51   versicolor
52   versicolor
53   versicolor
54   versicolor
100   virginica
101   virginica
102   virginica
103   virginica
```



KNN

```
104    virginica
```

5 演算法介紹

6 1. KNN

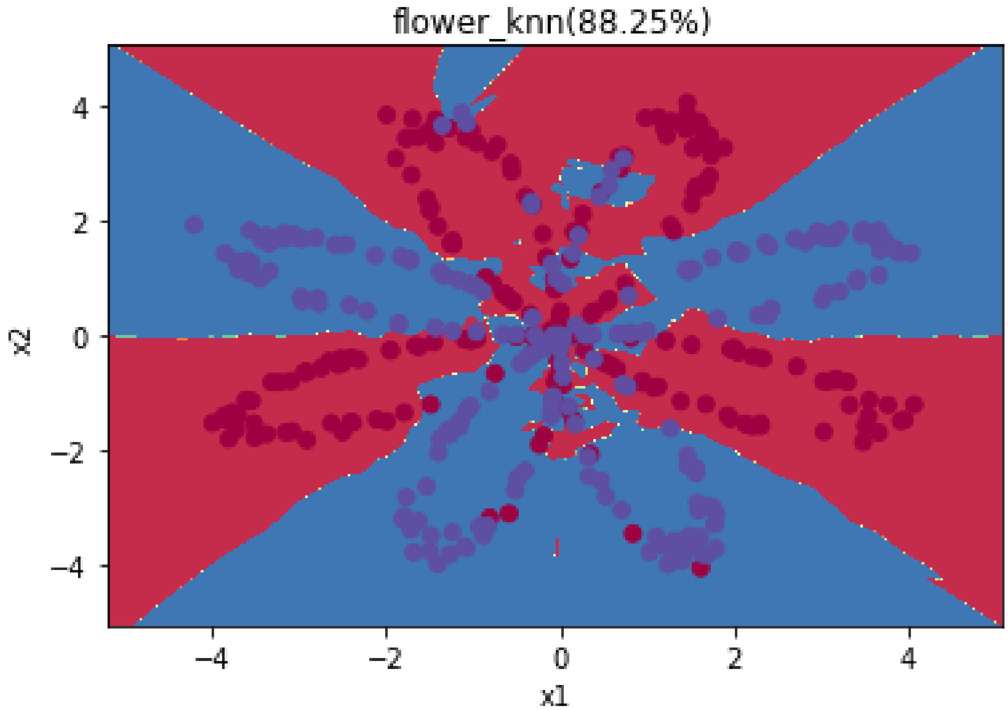
6.1 (1). 理論

6.2 (2).KNN 的使用

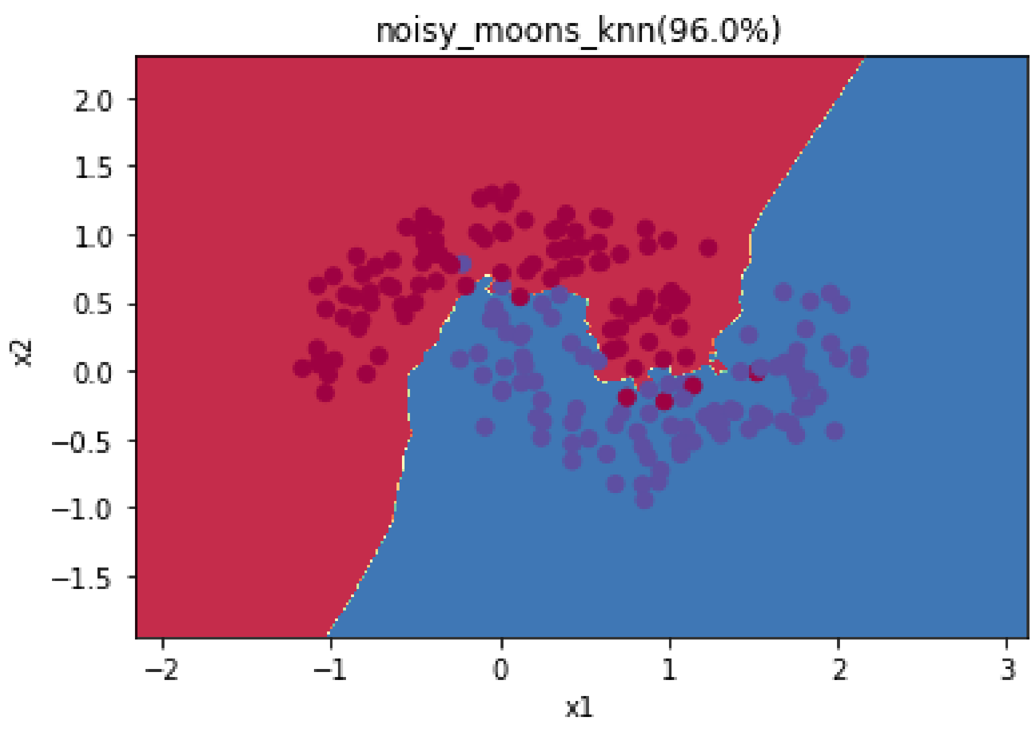
```
In [4]: from sklearn.neighbors import KNeighborsClassifier
```

```
In [5]: for name, X, Y in datas:
            clf = KNeighborsClassifier(n_neighbors=5)  ## 設定用最近的 3 個鄰居投票
            clf.fit(X, Y)  ## 訓練模型
            y_pred = clf.predict(X)  ## 預測模型
            print('Accuracy', str((Y == y_pred).sum()/ X.shape[0]*100)+"%")  ## 計算精準度

            plot_decision_boundary(lambda x: clf.predict(x), X.T, Y)  ## 視覺化分類器的分類結果
            plt.title(name+'_knn(' + str((Y == y_pred).sum()/ X.shape[0]*100)+"%)")
            plt.show()
```

```
Accuracy 88.25%
```




```
Accuracy 96.0%
```



6.3 (3). KNN 的練習

In [6]:
```python
# 請使用 KNeighborsClassifier(n=5) 來訓練 iris dataset(X_iris, Y_iris_true)
#=============your works starts===============#
knn =
Y_iris_predict =
#==============your works ends================#

print(Y_iris_predict)
print(Counter(Y_iris_predict))
# [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#  0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1
#  1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 1 2 2 2 2
#  2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
#  2 2]
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1
 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 1 2 2 2 2
 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Counter({2: 51, 0: 50, 1: 49})
```

In [7]:
```python
# 請使用 Y_iris_true 與 Y_iris_predict 計算 accuracy
#=============your works starts===============#
accuracy =
#==============your works ends================#

print("accuracy", accuracy)
# accuracy 0.9666666666666667
```

```
accuracy 0.9666666666666667
```

In [8]:
```python
# 找出分類錯誤的 row_idx
#=============your works starts===============#
faulse_idxs =
#==============your works ends================#


faulse_idxs
```

Out[8]:
```
array([ 70,  72,  83, 106, 119], dtype=int64)
```

In [9]:
```python
# indeices = [num for num, value in enumerate(iris.target != y_pred) if value == True]
folwer_type = {
```

```
        0:iris.target_names[0],
        1:iris.target_names[1],
        2:iris.target_names[2],
    }
    df = pd.DataFrame(iris.data)
    df.columns = iris.feature_names
    df['type_name'] = [folwer_type.get(i) for i in iris.target]
    df['type'] = iris.target
    df['yhat'] = Y_iris_predict

    print("分類錯誤的 row: ")
    df.loc[faulse_idxs]
```

```
分類錯誤的 row:
```

```
Out[9]:      sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
        70                 5.9               3.2                4.8               1.8
        72                 6.3               2.5                4.9               1.5
        83                 6.0               2.7                5.1               1.6
        106                4.9               2.5                4.5               1.7
        119                6.0               2.2                5.0               1.5

              type_name  type  yhat
        70   versicolor     1     2
        72   versicolor     1     2
        83   versicolor     1     2
        106   virginica     2     1
        119   virginica     2     1
```

7 2. Naïve Bayes (貝氏分類器)

7.1 (1). 理論

- 貝式定理:
  - $P(C|X) = P(X|C)P(C)/P(X)$：在 X 條件下 C 發生的機率
  - $P(C)$：C 發生的機率
  - $P(C|X)$：在 X 條件下 C 發生的機率
- 解釋:
  - 10 人，3 人喜歡看書，5 人是女生，是女生且喜歡看書者 2 人，請問假設已知甲為女生，她喜歡看書的機率是多少?
  -
  -
  -
  -

-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
- P(女 | 喜歡看書)=P(喜歡看書 | 女)*P(女)/P(喜歡看書)
- $\frac{woman\&lovereading}{lovereading} = \frac{woman\&lovereading}{woman} \times \frac{woman}{all} \times \frac{all}{lovereading}$
- P(喜歡看書 | 女) = P({女}∩{喜歡看書})/P(女) = 2/5
- (2/5) * (5/10) / (3/10)

* 資料

In [10]:
```
print("請預測每個天氣狀況網球賽會不會開打:")
df = pd.read_csv(os.path.join("dataset", "playTennis.csv"))
df
```

請預測每個天氣狀況網球賽會不會開打:

Out[10]:

	Outlook	Temperature	Humidity	Windy	play tennis
0	sunny	hot	high	False	N
1	sunny	hot	high	True	N
2	overcast	hot	high	False	P
3	rain	mild	high	False	P
4	rain	cool	normal	False	P
5	rain	cool	normal	True	N
6	overcast	cool	normal	True	P
7	sunny	mild	high	False	N
8	sunny	cool	normal	False	P
9	rain	mild	normal	False	P
10	sunny	mild	normal	True	P
11	overcast	mild	high	True	P
12	overcast	hot	normal	False	P
13	rain	mild	high	True	N

被式分類器便是將特定條件底下 (X=rain, hot, high, false)，球賽開打的機率 $P(p|X)$ 與球賽沒有開打的機率 $P(n|X)$ 進行比較，根據貝是定理:

$$P(p|X) = P(X|p)P(p)/P(X)$$

$$P(n|X) = P(X|n)P(n)/P(X)$$

因為是比較，分母可以忽略，因此請算出 $P(X|p)P(p)$ 以及 $P(X|n)P(n)$，並進行比較:

```
In [11]: # 使用 df 請計算出:
         # 1. 球賽開打的機率: P(Postive)
         # 2. 球賽沒有開打的機率: P(Negative)
         # 3. 如果球賽開打，是晴天的機率: P(Sunny|Postive)
         # 4. 如果球賽沒有開打，是晴天的機率: P(Sunny|Negative)
         possibilities = {}
         #=============your works starts===============#
         possibilities["P(Postive)"] =
         possibilities["P(Negative)"] =
         possibilities["P(Sunny|Postive)"] =
         possibilities["P(Sunny|Negative)"] =
         #==============your works ends================#


         pprint(possibilities)
         # {'P(Negative)': 0.35714285714285715,
         #  'P(Postive)': 0.6428571428571429,
         #  'P(Sunny|Negative)': 0.6,
         #  'P(Sunny|Postive)': 0.2222222222222222}
```

```
{'P(Negative)': 0.35714285714285715,
 'P(Postive)': 0.6428571428571429,
 'P(Sunny|Negative)': 0.6,
 'P(Sunny|Postive)': 0.2222222222222222}


  # Remove the CWD from sys.path while we load stuff.
  # This is added back by InteractiveShellApp.init_path()
```

可以整理成 =>

Outlook			Tempreature			Humidity			Windy		
	Condition P	Condition N		Condition P	Condition N		Condition P	Condition N		Condition P	Condition N
sunny	2/9	3/5	hot	2/9	2/5	high	3/9	4/5	true	3/9	3/5
overcast	4/9	0	mild	4/9	2/5	normal	6/9	1/5	false	6/9	2/5
rain	3/9	2/5	cool	3/9	1/5						

$$P(X|p)P(p) = P(rain, hot, high, false|p)P(p)$$

$$\approx P(rain|p)P(hot|p)P(high|p)P(false|p)P(p)$$

$$= 3/92/93/96/99/14 = 0.010582$$

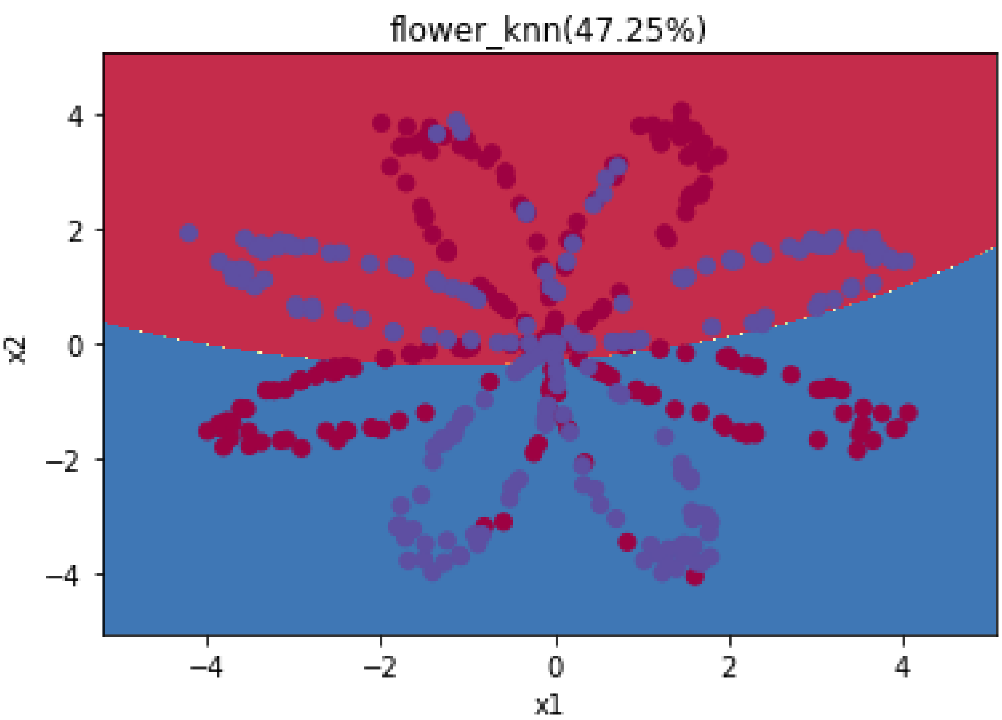
$$
\begin{aligned}
P(X|n)P(n) &= P(rain, hot, high, false|n)P(n) \\
&\approx P(rain|n)P(hot|n)P(high|n)P(false|n)P(n) \\
&= 2/52/54/52/55/14 = 0.018286
\end{aligned}
$$

7.2 (2). 貝氏分類器的使用

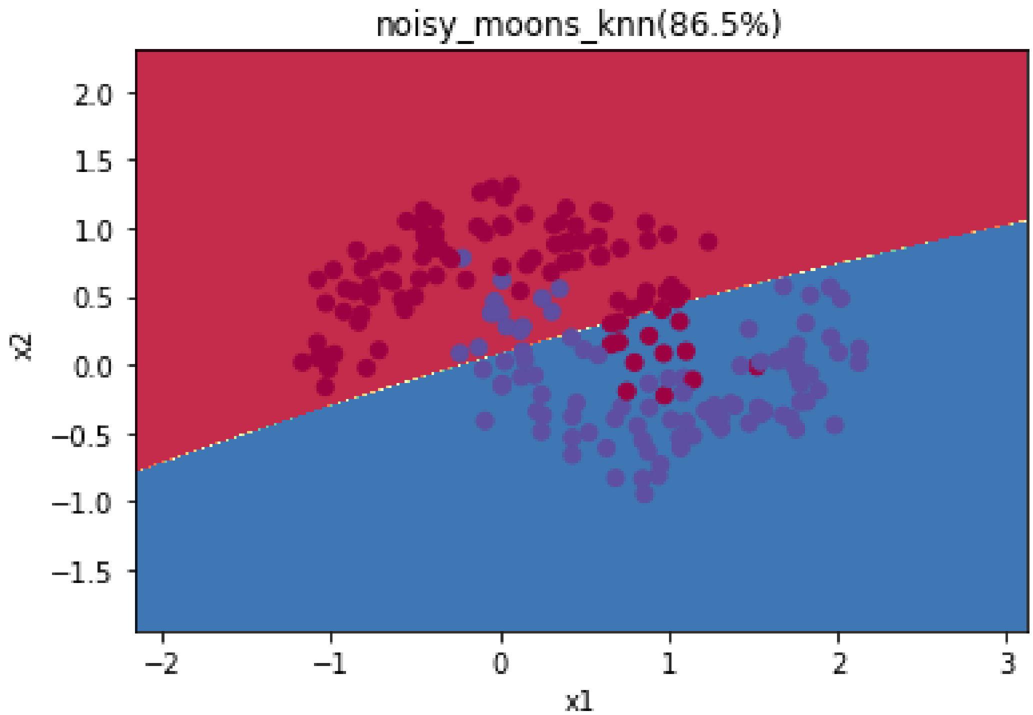
In [12]:
```
from sklearn.naive_bayes import GaussianNB
```

In [13]:
```
for name, X, Y in datas:
    gnb = GaussianNB()
    gnb.fit(X, Y)   ## 訓練模型
    y_pred = gnb.predict(X)   ## 預測模型
    print('Accuracy',  str((Y == y_pred).sum()/ X.shape[0]*100)+"%")   ## 計算精準度

    plot_decision_boundary(lambda x: gnb.predict(x), X.T, Y)   ## 視覺化分類器的分類結果
    plt.title(name+'_knn(' + str((Y == y_pred).sum()/ X.shape[0]*100)+"%)")
    plt.show()
```

```
Accuracy 47.25%
```




```
Accuracy 86.5%
```



7.3 (3). 貝氏分類器的練習

In [14]:
```
# 請使用 GaussianNB() 來訓練 iris dataset
#=============your works starts===============#
gnb =
Y_iris_predict =
#==============your works ends================#

print(Y_iris_predict)
print(Counter(Y_iris_predict))
# [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#  0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1
#  1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 1 2 2 2 2
#  2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
#  2 2]

# Counter({0: 50, 1: 50, 2: 50})
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1
 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 1 2 2 2 2
 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

```
Counter({0: 50, 1: 50, 2: 50})
```

```
In [15]: accuracy = np.sum(Y_iris_true == Y_iris_predict)/len(Y_iris_predict)
         print("accuracy", accuracy)
```

```
accuracy 0.96
```

```
In [16]: faulse_idxs = np.where(Y_iris_true != Y_iris_predict)[0]
         folwer_type = {
             0:iris.target_names[0],
             1:iris.target_names[1],
             2:iris.target_names[2],
         }
         df = pd.DataFrame(iris.data)
         df.columns = iris.feature_names
         df['type_name'] = [folwer_type.get(i) for i in iris.target]
         df['type'] = iris.target
         df['yhat'] = Y_iris_predict

         print("分類錯誤的 row: ")
         df.loc[faulse_idxs]
```

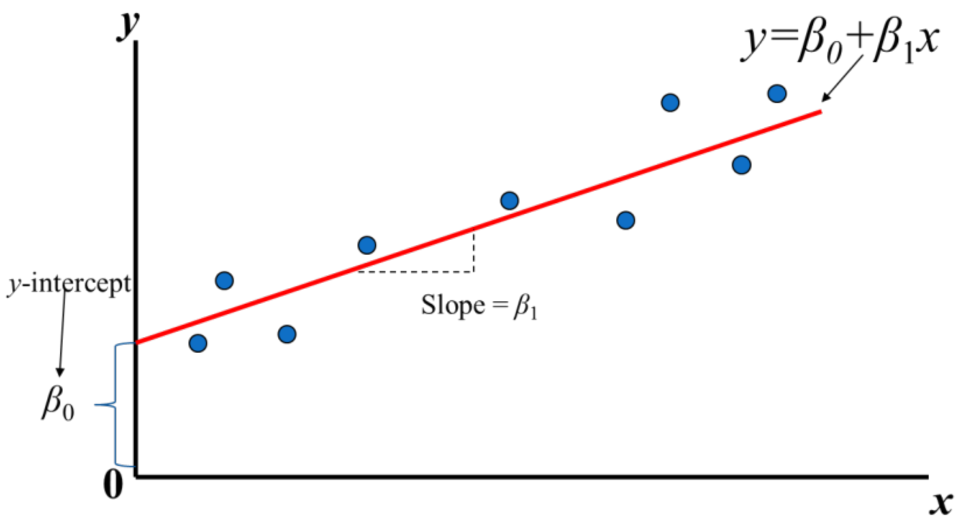
```
分類錯誤的 row:
```

```
Out[16]:      sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
         52                 6.9               3.1                4.9               1.5
         70                 5.9               3.2                4.8               1.8
         77                 6.7               3.0                5.0               1.7
         106                4.9               2.5                4.5               1.7
         119                6.0               2.2                5.0               1.5
         133                6.3               2.8                5.1               1.5

                type_name  type  yhat
         52    versicolor     1     2
         70    versicolor     1     2
         77    versicolor     1     2
         106    virginica     2     1
         119    virginica     2     1
         133    virginica     2     1
```

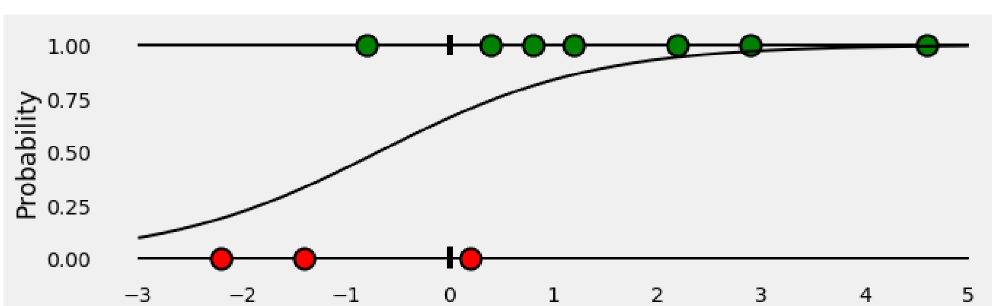
8 3. logistic regression (羅吉斯回歸)

8.1 (1). 理論

- general regression: $\hat{y} = \alpha x_1 + \beta x_2 + \gamma x_3 + bias$



regression



logistic_reg

- logistic regression: $\hat{y} = sigmoid(\alpha x_1 + \beta x_2 + \gamma x_3 + bias)$
- minimize $logloss = -(ylog(\hat{y}) + (1-y)log(1-\hat{y}))$
- 如何理解 logloss
  1. prob
  $$h_k(x) = \begin{cases} P(y=1|x) = \hat{y} & \text{if } \ y=1 \\ P(y=0|x) = 1-\hat{y} & \text{if } \ y=0 \end{cases}$$
  2. target
  $$h_k(x) = \begin{cases} \max \hat{y} & \text{if } \ y=1 \\ \max 1-\hat{y} & \text{if } \ y=0 \end{cases}$$
  3. logloss:
  $$logloss = -(ylog(\hat{y}) + (1-y)log(1-\hat{y})) \min logloss$$
  4. 詳細推倒過程

```
In [17]: from sklearn.metrics import log_loss
         import numpy as np
         print(log_loss([0, 0, 1], [0.0001, 0.0001, 0.9999]))
         print(log_loss([0, 0, 1], [0.9999, 0.9999, 0.0001]))

         def logloss(y, yhat):
             return -(y)*np.log(yhat)-(1-y)*np.log(1-yhat)
         print(logloss(1, 0.9999))
         print(logloss(1, 0.0001))
```

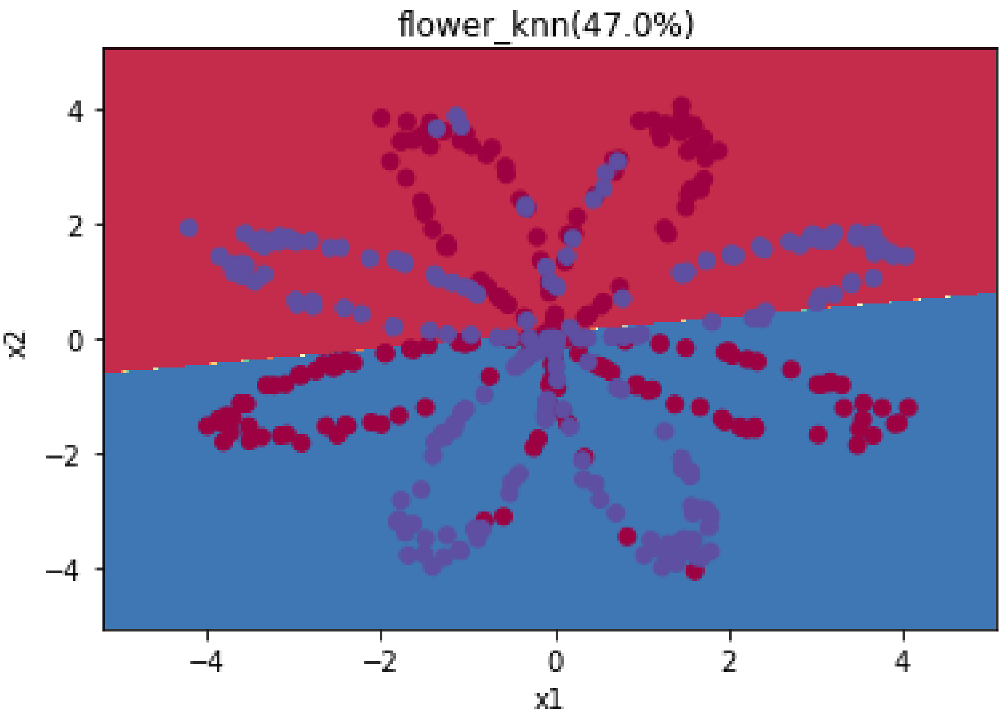
```
0.00010000500033334734
9.210340371976256
0.00010000500033334732
9.210340371976182
```

8.2 (2). 羅吉斯回歸的使用

```
In [18]: from sklearn.linear_model import LogisticRegressionCV

In [19]: for name, X, Y in datas:
             lgr = LogisticRegressionCV()
             lgr.fit(X, Y)   ## 訓練模型
             y_pred = lgr.predict(X)   ## 預測模型
             print('Accuracy',  str((Y == y_pred).sum()/ X.shape[0]*100)+"%")   ## 計算精準度

             plot_decision_boundary(lambda x: lgr.predict(x), X.T, Y)   ## 視覺化分類器的分類結果
             plt.title(name+'_knn(' + str((Y == y_pred).sum()/ X.shape[0]*100)+"%)")
             plt.show()
```

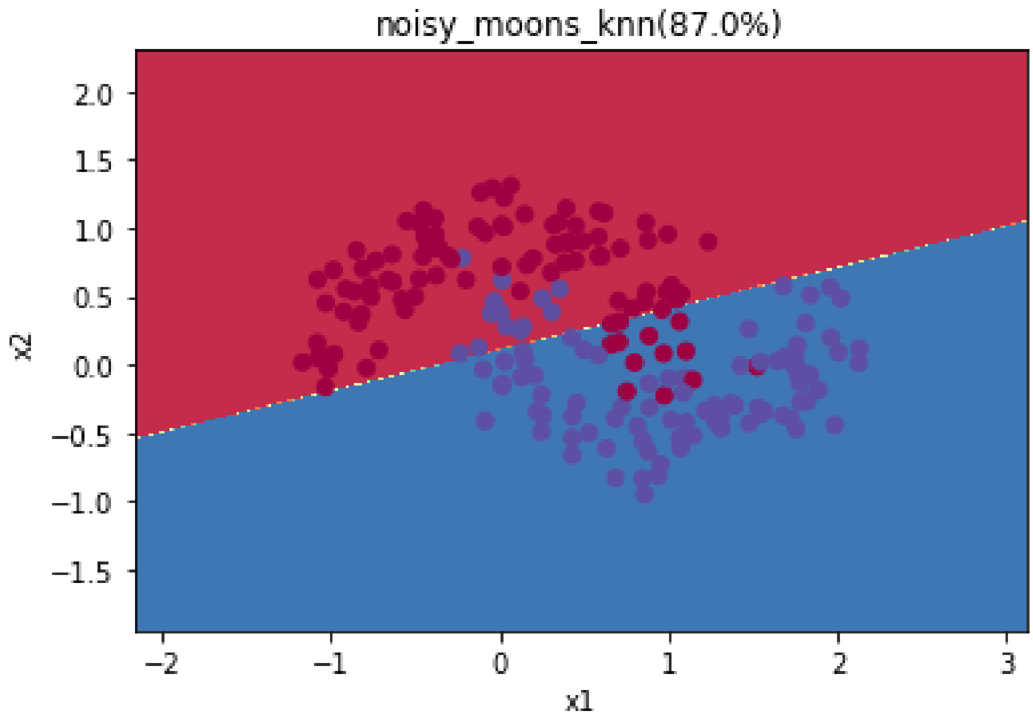
```
Accuracy 47.0%
```

```
  warnings.warn(CV_WARNING, FutureWarning)
```




```
  warnings.warn(CV_WARNING, FutureWarning)
```

```
Accuracy 87.0%
```



8.3 (3). 羅吉斯回歸分類器的練習

In [20]:
```
# 請使用 LogisticRegressionCV() 來訓練 iris dataset
#=============your works starts===============#
lgr =
Y_iris_predict =
#==============your works ends================#

print(Y_iris_predict)
print(Counter(Y_iris_predict))
# [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#  0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1
#  1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
#  2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
#  2 2]
# Counter({2: 51, 0: 50, 1: 49})
```

```
  "this warning.", FutureWarning)
  warnings.warn(CV_WARNING, FutureWarning)


[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1
 1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
```

```
 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Counter({2: 51, 0: 50, 1: 49})
```

In [21]:
```python
accuracy = np.sum(Y_iris_true == Y_iris_predict)/len(Y_iris_predict)
print("accuracy", accuracy)
```

```
accuracy 0.9666666666666667
```

In [22]:
```python
faulse_idxs = np.where(Y_iris_true != Y_iris_predict)[0]
folwer_type = {
    0:iris.target_names[0],
    1:iris.target_names[1],
    2:iris.target_names[2],
}
df = pd.DataFrame(iris.data)
df.columns = iris.feature_names
df['type_name'] = [folwer_type.get(i) for i in iris.target]
df['type'] = iris.target
df['yhat'] = Y_iris_predict

print("分類錯誤的 row: ")
df.loc[faulse_idxs]
```

分類錯誤的 row:

Out[22]:

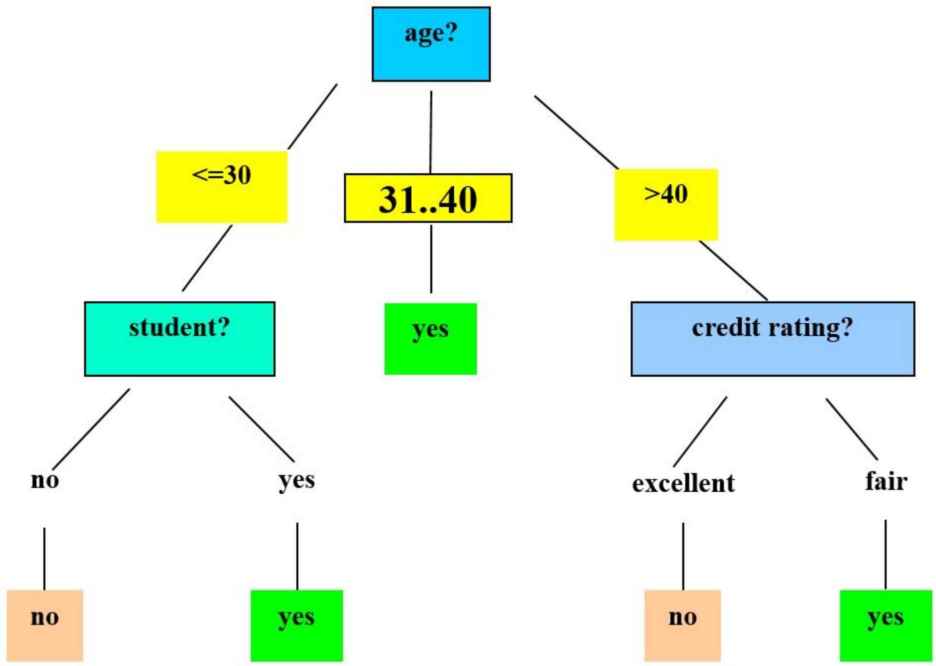
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	\
70	5.9	3.2	4.8	1.8	
77	6.7	3.0	5.0	1.7	
83	6.0	2.7	5.1	1.6	
119	6.0	2.2	5.0	1.5	
133	6.3	2.8	5.1	1.5	

	type_name	type	yhat
70	versicolor	1	2
77	versicolor	1	2
83	versicolor	1	2
119	virginica	2	1
133	virginica	2	1

9 4. Decision Tree (決策樹)

9.1 (1). 解釋

以以下資料為例，決策樹便是將下表



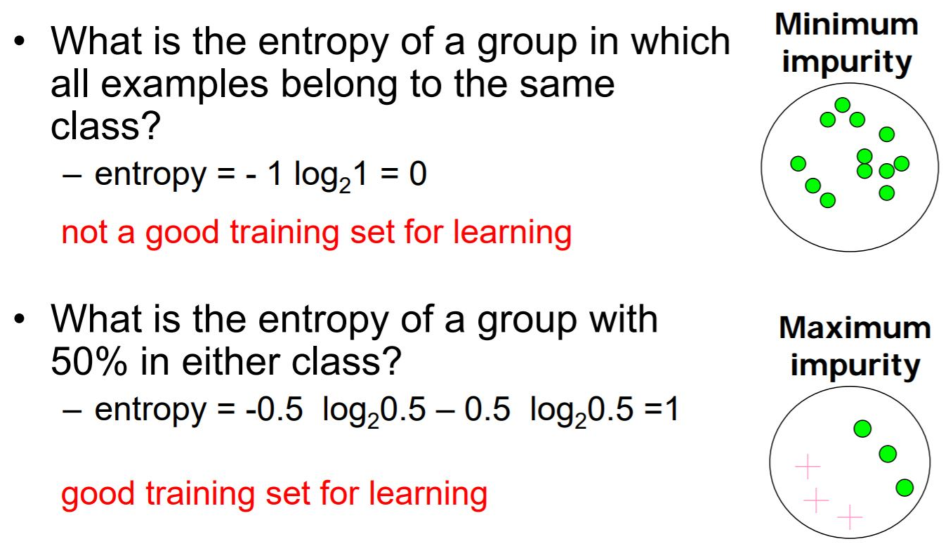
decisionTree.JPG

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

轉換成...

9.2 (2). 我們應該先將哪一個特徵值拿來分類

- 分類之後能提供較多資訊量者
- 如何量化資訊量的多寡? Entropy(熵)



entropy

- 包含 {m1, m2, ... ,mn} 的 M 訊息的 Entropy(熵) 計算如下

$$(M) = -\sum_{i=1}^{n} p(m_i) log_2 p(m_i)$$

$p(m_i)$ 指的是 m_i 在 M 裡面出現的機率 - 舉例來說

- 因此，Information Gain(資訊增量) 可以被定義如下:

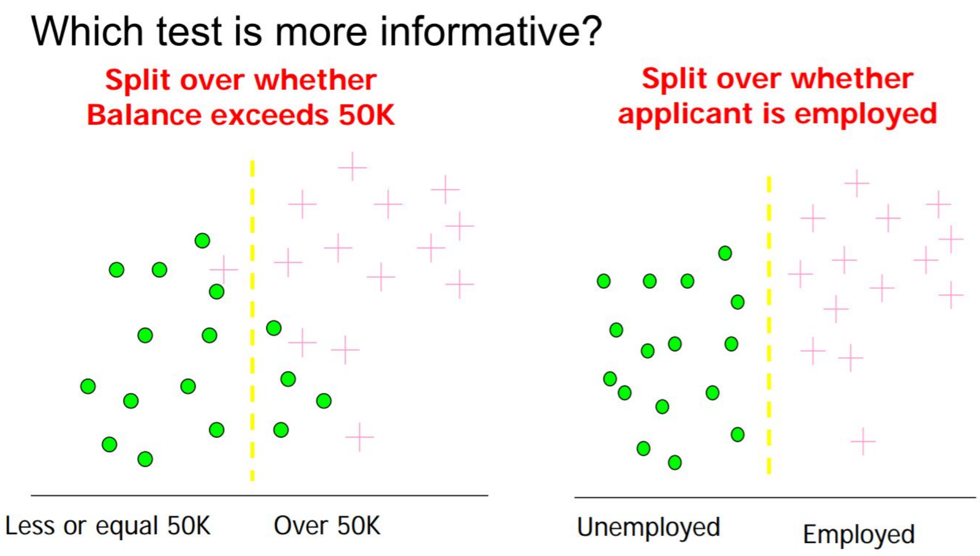
$$Inpurity_{original} = -\frac{p}{p+n} log_2(\frac{p}{p+n}) - \frac{n}{p+n} log_2(\frac{n}{p+n})$$

$$Inpurity_{split\_by\_feature} = \sum_{i=1}^{v} -\frac{p_i+n_i}{p+n} I(p_i, n_i)$$

$$InformationGain = Inpurity_{original} - Inpurity_{split\_by\_feature}$$

```
In [23]: from sklearn.metrics import log_loss
         import numpy as np
         print(log_loss([0, 0, 1], [0.0001, 0.0001, 0.9999]))
         print(log_loss([0, 0, 1], [0.9999, 0.9999, 0.0001]))

         def logloss(y, yhat):
             return -(y)*np.log(yhat)-(1-y)*np.log(1-yhat)
         print(logloss(1, 0.9999))
         print(logloss(1, 0.0001))
```

```
0.00010000500033334734
9.210340371976256
0.00010000500033334732
9.210340371976182
```



informationGain

```
In [24]: def entropy(p, n):
             # 請定義出 entropy 的 function，注意若出現 0 乘上無限大也等於 0。
             #=============your works starts===============#
             p_pn =
             n_pn =
             lpp =
             lpn =
             entropy =
             #==============your works ends================#
             return entropy

         print(entropy(0.5, 0.5))
         print(entropy(1, 0))

         # print(entropy(0.5, 0.5)*2)
         # print(entropy(0.4, 0.5) + entropy(0.6, 0.5))

         # 1.0
         # 0.0
```

```
1.0
0.0
```

```
In [25]: df = pd.read_csv(os.path.join("dataset", "buy_computers"))
         print(df.columns)
         df
```

```
Index(['age', 'income', 'student', 'credit_rating', 'buys_computer'], dtype='object')
```

Out[25]:

	age	income	student	credit_rating	buys_computer
0	<=30	high	no	fair	no
1	<=30	high	no	excellent	no
2	30…40	high	no	fair	yes
3	>40	medium	no	fair	yes
4	>40	low	yes	fair	yes
5	>40	low	yes	excellent	no
6	30…40	low	yes	excellent	yes
7	<=30	medium	no	fair	no
8	<=30	low	yes	fair	yes
9	>40	medium	yes	fair	yes
10	<=30	medium	yes	excellent	yes
11	30…40	medium	no	excellent	yes
12	30…40	high	yes	fair	yes
13	>40	medium	no	excellent	no

In [26]:
```
col_candidates = ['age', 'income', 'student', 'credit_rating']

dict_search_1st = {}
for col in col_candidates:
    # 請計算出以個欄位進行 groupby 的後每個類別的個數，並將其轉換為 dict 型別
    #=============your works starts===============#
    dict_search_1st[col] =
    #==============your works ends================#


pprint(dict_search_1st)
# {'age': {'30…40': 4, '<=30': 5, '>40': 5},
#  'buys_computer': {'no': 5, 'yes': 9},
#  'credit_rating': {'excellent': 6, 'fair': 8},
#  'income': {'high': 4, 'low': 4, 'medium': 6},
#  'student': {'no': 7, 'yes': 7}}
```

```
{'age': {'30…40': 4, '<=30': 5, '>40': 5},
 'credit_rating': {'excellent': 6, 'fair': 8},
 'income': {'high': 4, 'low': 4, 'medium': 6},
 'student': {'no': 7, 'yes': 7}}
```

In [27]:
```
dict_search_2nd = {}
for col in ['age', 'income', 'student', 'credit_rating']:
    # 請計算出以個「欄位 +buys_computer」進行 groupby 的後每個類別的個數，並將其轉換為 d
    #=============your works starts===============#
    dict_search_2nd[col] =
    #==============your works ends================#


pprint(dict_search_2nd)
```

```
# {'age': {('30...40', 'yes'): 4,
#          ('<=30', 'no'): 3,
#          ('<=30', 'yes'): 2,
#          ('>40', 'no'): 2,
#          ('>40', 'yes'): 3},
#  'credit_rating': {('excellent', 'no'): 3,
#                    ('excellent', 'yes'): 3,
#                    ('fair', 'no'): 2,
#                    ('fair', 'yes'): 6},
#  'income': {('high', 'no'): 2,
#             ('high', 'yes'): 2,
#             ('low', 'no'): 1,
#             ('low', 'yes'): 3,
#             ('medium', 'no'): 2,
#             ('medium', 'yes'): 4},
#  'student': {('no', 'no'): 4,
#              ('no', 'yes'): 3,
#              ('yes', 'no'): 1,
#              ('yes', 'yes'): 6}}
```

```
{'age': {('30...40', 'yes'): 4,
         ('<=30', 'no'): 3,
         ('<=30', 'yes'): 2,
         ('>40', 'no'): 2,
         ('>40', 'yes'): 3},
 'credit_rating': {('excellent', 'no'): 3,
                   ('excellent', 'yes'): 3,
                   ('fair', 'no'): 2,
                   ('fair', 'yes'): 6},
 'income': {('high', 'no'): 2,
            ('high', 'yes'): 2,
            ('low', 'no'): 1,
            ('low', 'yes'): 3,
            ('medium', 'no'): 2,
            ('medium', 'yes'): 4},
 'student': {('no', 'no'): 4,
             ('no', 'yes'): 3,
             ('yes', 'no'): 1,
             ('yes', 'yes'): 6}}
```

we can sort it out like this

age	count	p_count	n_count
<=30	5	2	3
30...40	4	4	0
>40	5	3	2

In [28]:
```python
col = 'buys_computer'

# 請計算原始的 entropy
#=============your works starts===============#
dict_gb_bc =
entropy_ori =
#==============your works ends================#

print(entropy_ori)
# 0.9402859586706311
```

```
0.9402859586706311
```

In [29]:
```python
weighted_impurity_mapping = {}
#!=============your works starts===============!#









#!==============your works ends================!#

weighted_impurity_mapping
# {'age': 0.6935361388961919,
#  'income': 0.9110633930116764,
#  'student': 0.7884504573082894,
#  'credit_rating': 0.8921589282623617}
```

Out[29]:
```
{'age': 0.6935361388961919,
 'income': 0.9110633930116763,
 'student': 0.7884504573082894,
 'credit_rating': 0.8921589282623617}
```

In [30]:
```python
# def cal_entropy_2nd(dict_search_2nd_target, col):
#     # 計算用「特定欄位 +buys_computer」(e.g. age+buys_computer) 分類後，
#     # 第一順位欄位為特定值 (e.g. "30...40") 時的 entropy
#     #=============your works starts===============#
#     entropy_out =
#     #==============your works ends================#
#     return entropy_out

# entropy_dict = {}
# for col in col_candidates:
#     # 計算用特定欄位進行分類後的 entropy(要考量資料的 count 作為 weight)
```

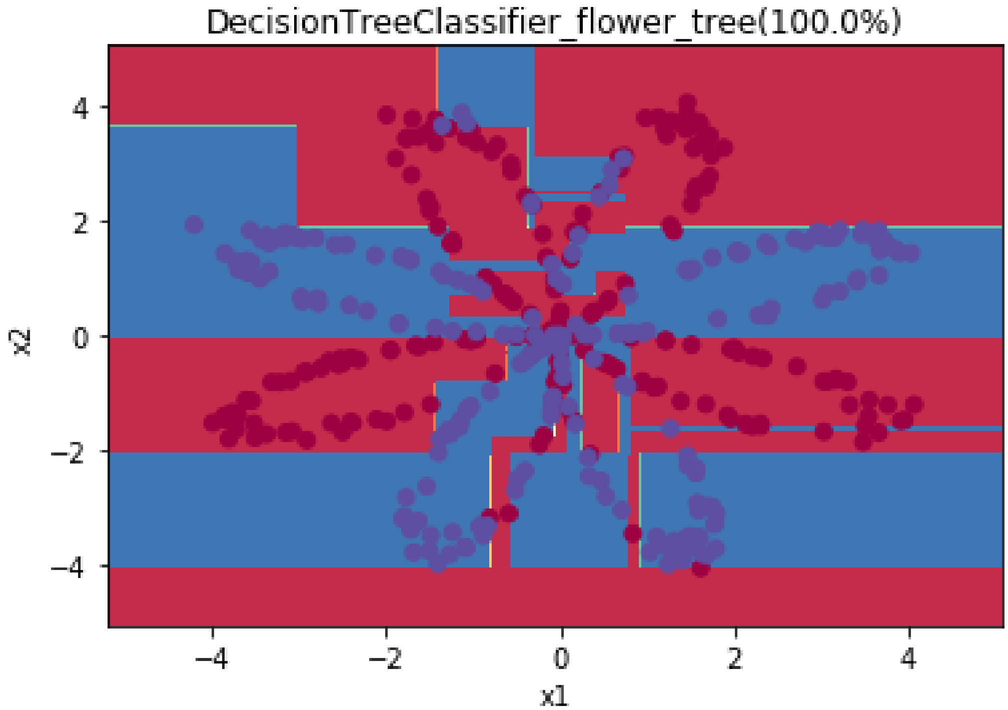
```
#     # 並計算 information gain
#     #=============your works starts===============#
#     entropy_for_each_category =
#     weights_for_each_category =
#     entropy_classfied =
#     inf_gain =
#     #==============your works ends================#
#     print(col, inf_gain)
```

9.3 (3). 決策樹的使用

In [31]:
```
from sklearn.tree import DecisionTreeClassifier  ## decision tree
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from xgboost import XGBClassifier
```

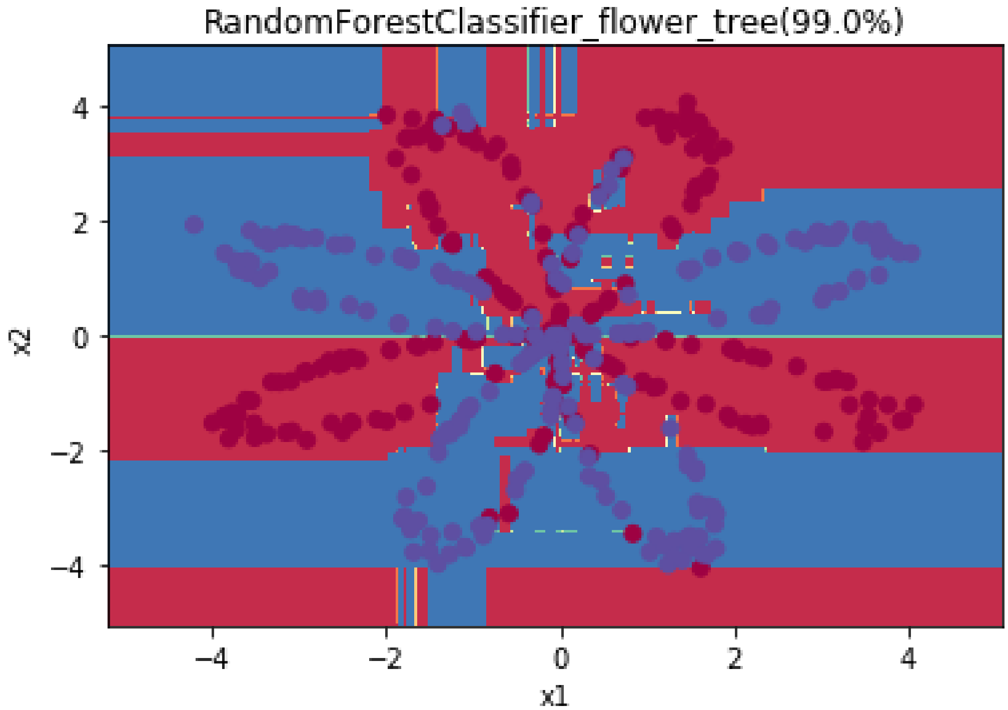
In [32]:
```
clfs={
"DecisionTreeClassifier":DecisionTreeClassifier,
"RandomForestClassifier":RandomForestClassifier,
"AdaBoostClassifier":AdaBoostClassifier,
"XGBClassifier":XGBClassifier
}
for name, X, Y in datas:
    for clf_name, clf in clfs.items():
        clf = clf()
        clf.fit(X, Y)

        y_pred = clf.predict(X)
        print('Accuracy',  str((Y == y_pred).sum()/ X.shape[0]*100)+"%")
        plot_decision_boundary(lambda x: clf.predict(x), X.T, Y)
        plt.title(clf_name + "_" + name +'_tree(' + str((Y == y_pred).sum()/ X.shape[
        plt.show()
```

```
Accuracy 100.0%
```

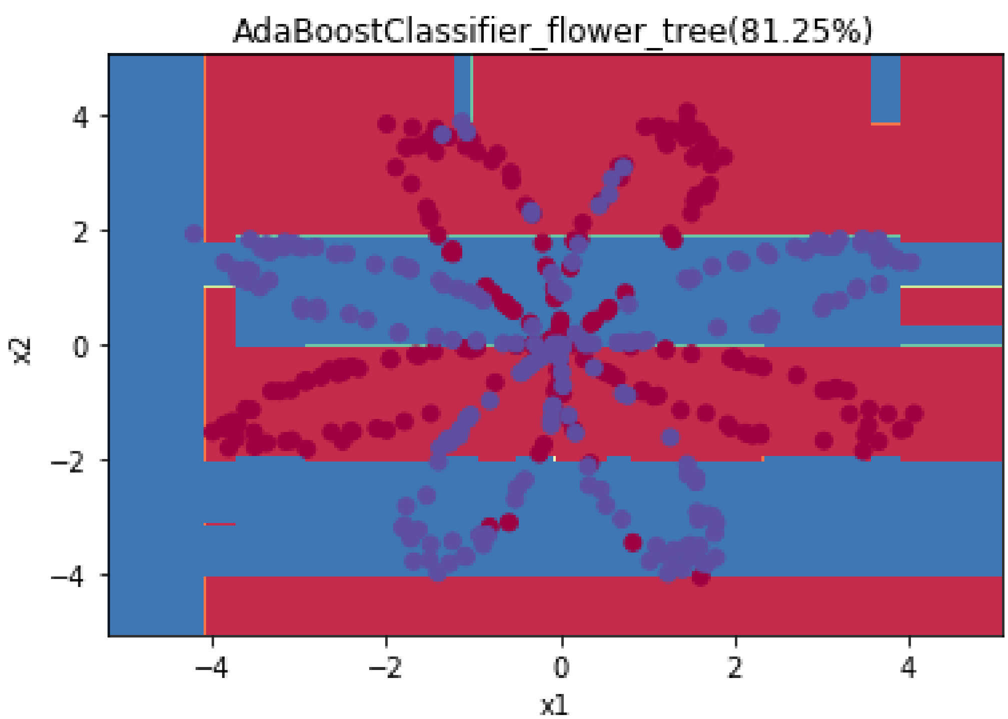



```
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

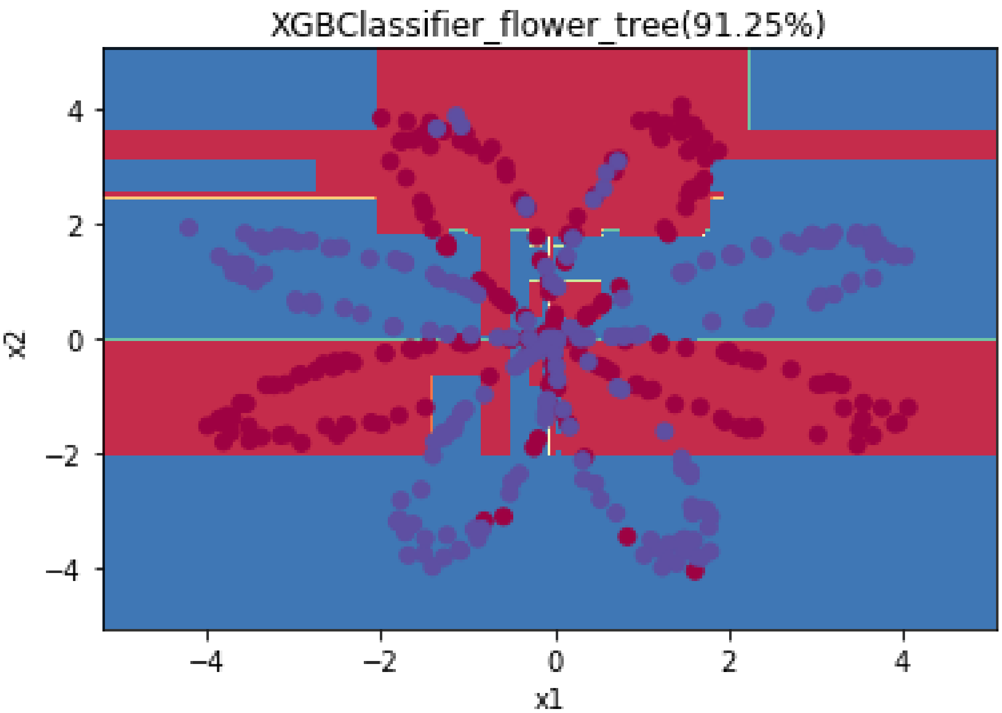
```
Accuracy 99.0%
```



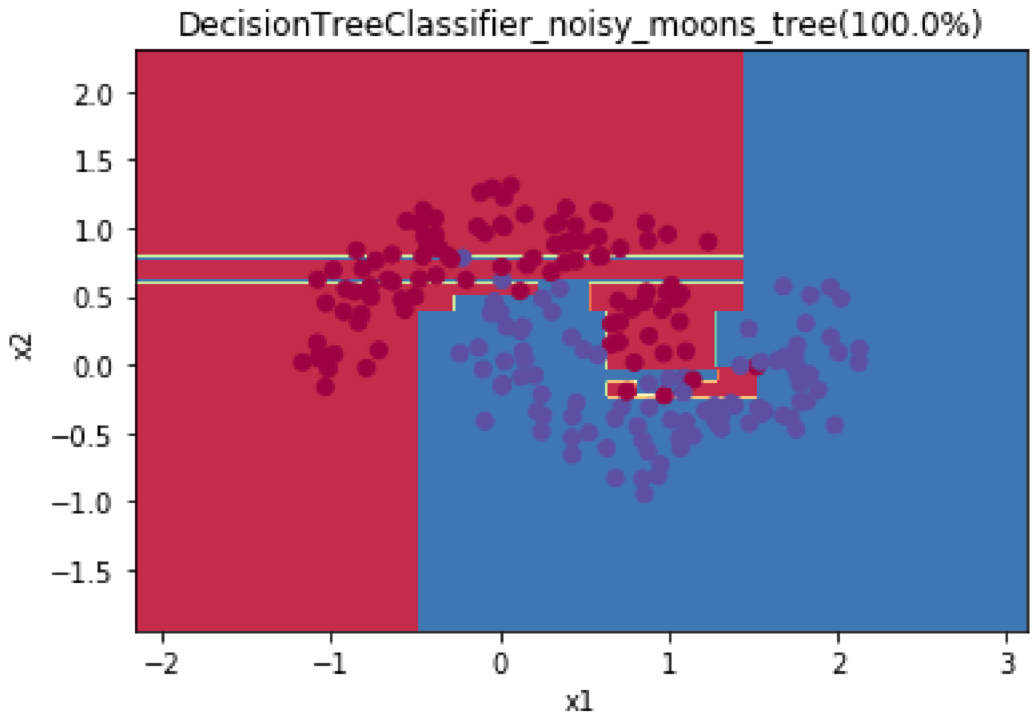
Accuracy 81.25%



```
Accuracy 91.25%
```

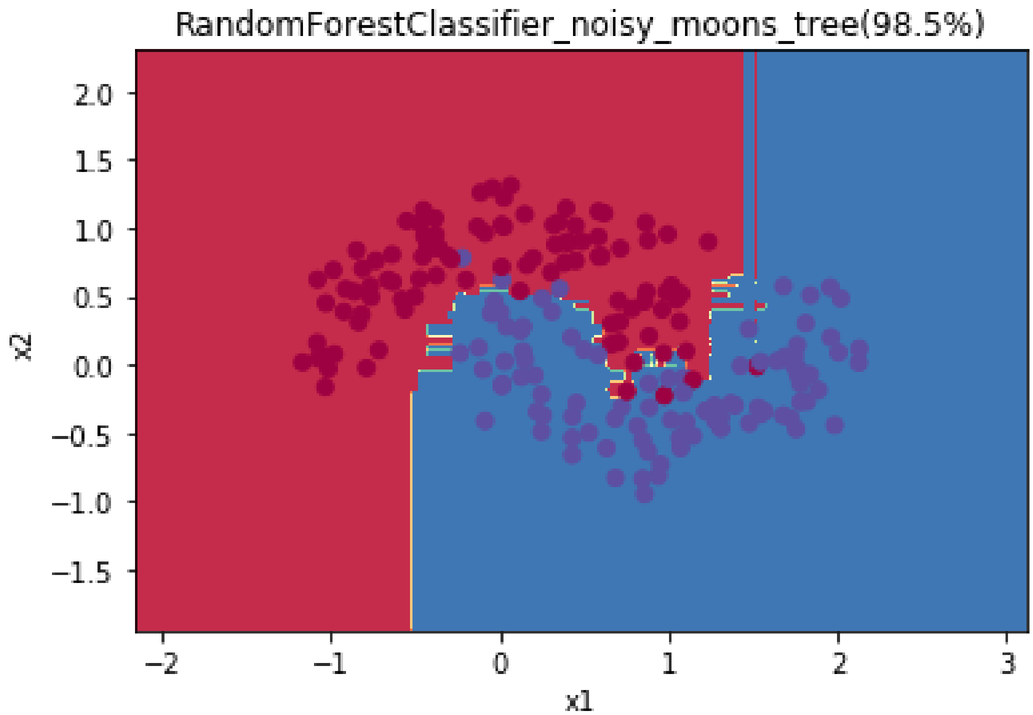



```
Accuracy 100.0%
```

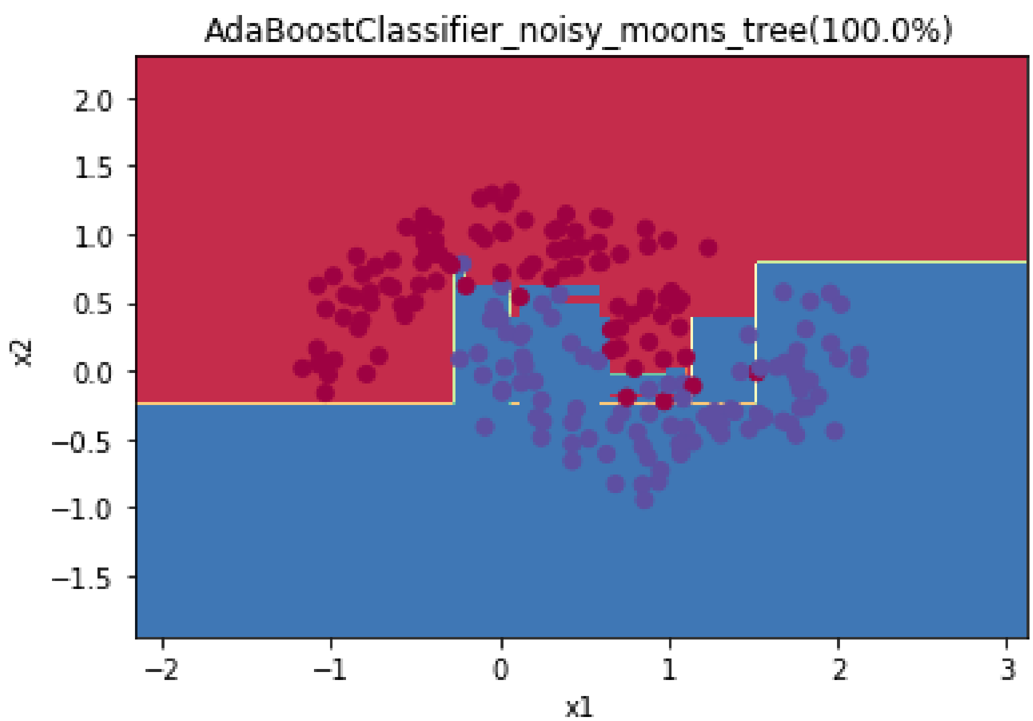



```
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

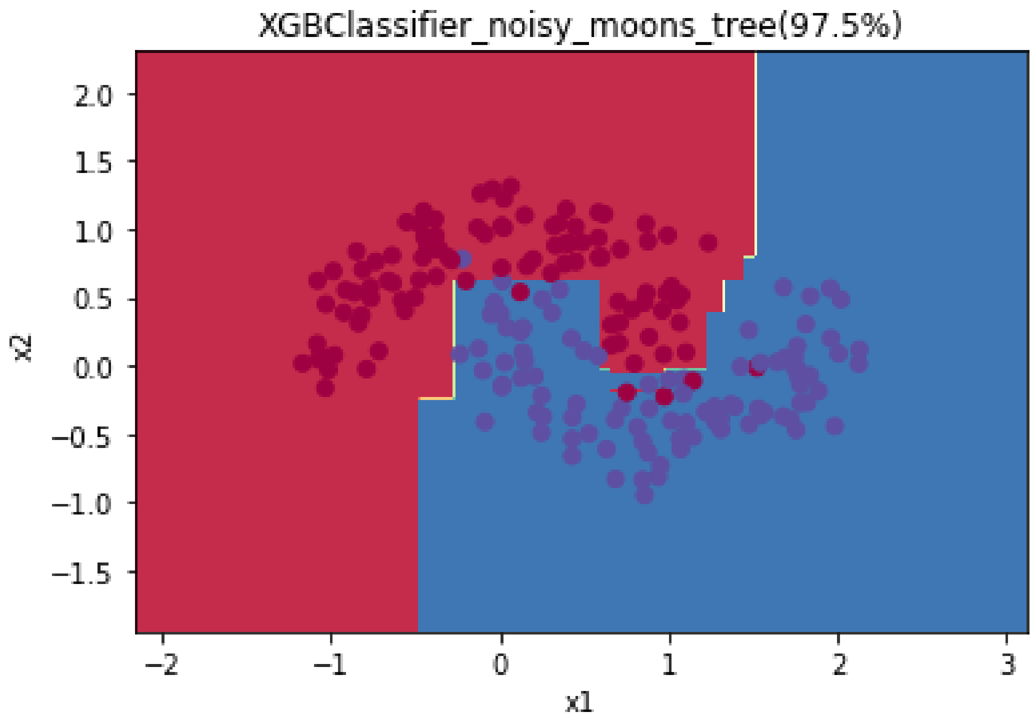
```
Accuracy 98.5%
```



Accuracy 100.0%



```
Accuracy 97.5%
```



9.4 (4). 決策樹的練習

```
In [33]: # 請使用 XGBClassifier() 來訓練 iris dataset
         #=============your works starts===============#
         xgb =
         Y_iris_predict =
         #==============your works ends================#

         print(Y_iris_predict)
         print(Counter(Y_iris_predict))
         # [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
         #  0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
         #  1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
         #  2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
         #  2 2]
         # Counter({0: 50, 1: 50, 2: 50})
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

```
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Counter({0: 50, 1: 50, 2: 50})
```

```
In [34]: accuracy = np.sum(Y_iris_true == Y_iris_predict)/len(Y_iris_predict)
         print("accuracy", accuracy)
```

```
accuracy 1.0
```

```
In [35]: faulse_idxs = np.where(Y_iris_true != Y_iris_predict)[0]
         folwer_type = {
             0:iris.target_names[0],
             1:iris.target_names[1],
             2:iris.target_names[2],
         }
         df = pd.DataFrame(iris.data)
         df.columns = iris.feature_names
         df['type_name'] = [folwer_type.get(i) for i in iris.target]
         df['type'] = iris.target
         df['yhat'] = Y_iris_predict

         print("分類錯誤的 row: ")
         df.loc[faulse_idxs]
```

```
分類錯誤的 row:
```

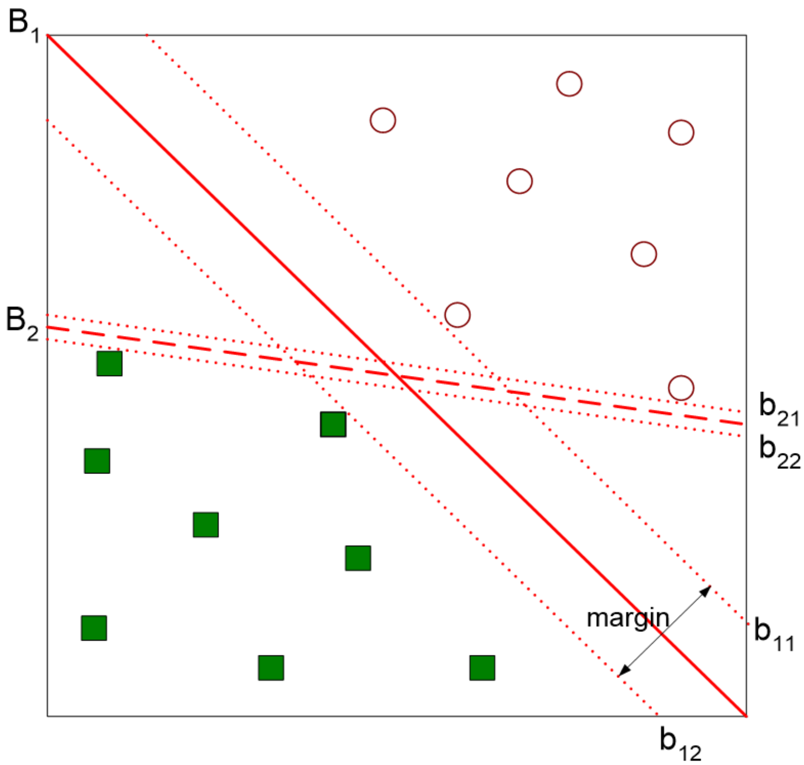
```
Out[35]: Empty DataFrame
         Columns: [sepal length (cm), sepal width (cm), petal length (cm), petal width (cm), ty
         Index: []
```

9.5 (5). 隨機森林、Boosting、Gradient Boosting

1. 隨機森林: 隨機抽取一定比例的 features 跟 rows 跑決策樹，找出最好的樹。
2. Boosting: 在每一輪的 fitting 中加權分類錯誤的 loss，透過 fit 加權過的 y，以提升準確率。
3. Gradient Boosting: 每一輪的 fitting 去 fit 上一輪的 resudual。

10 5. SVM (支持向量機)

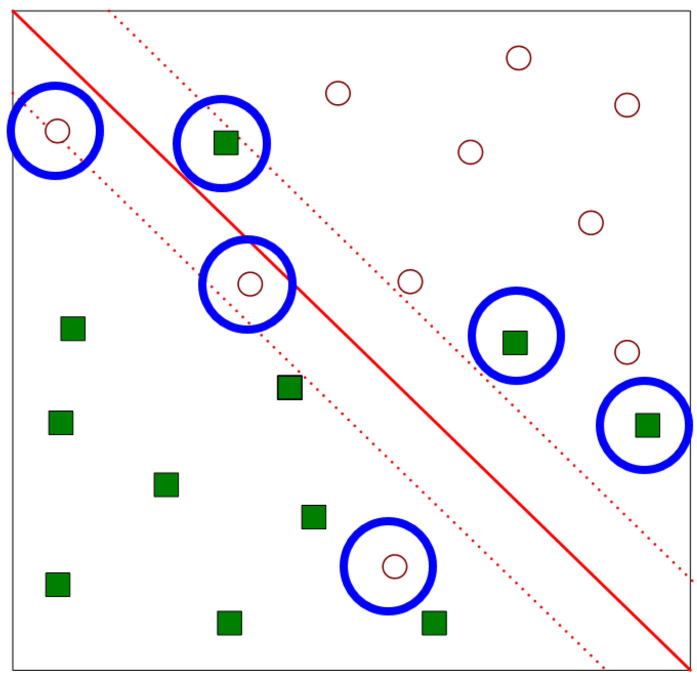
10.1 (1). 理論



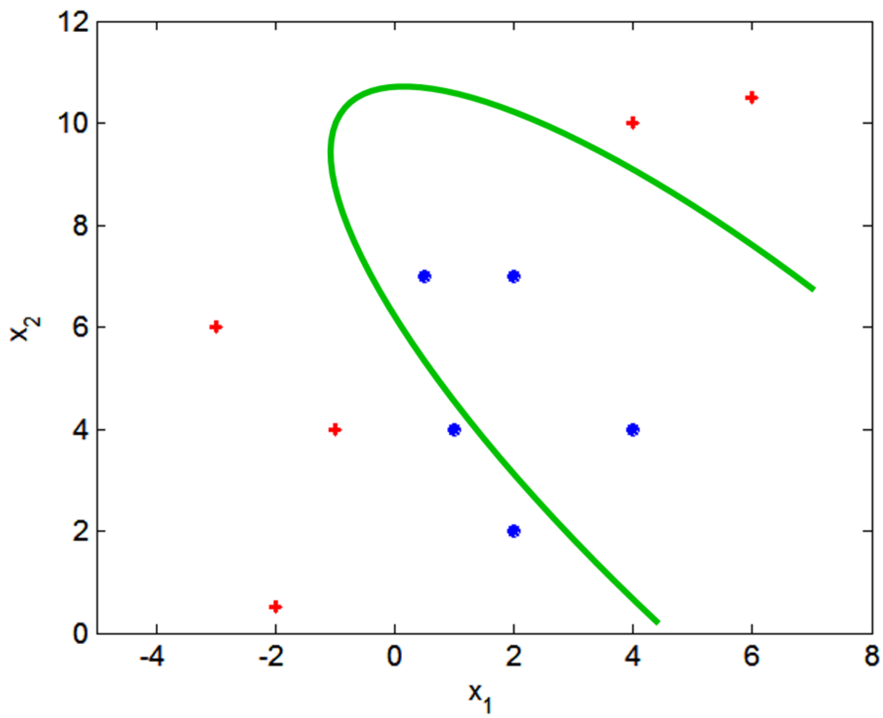
- 基礎
- Error term(Penalty)
- 非線性可分

10.2 (2). 參數

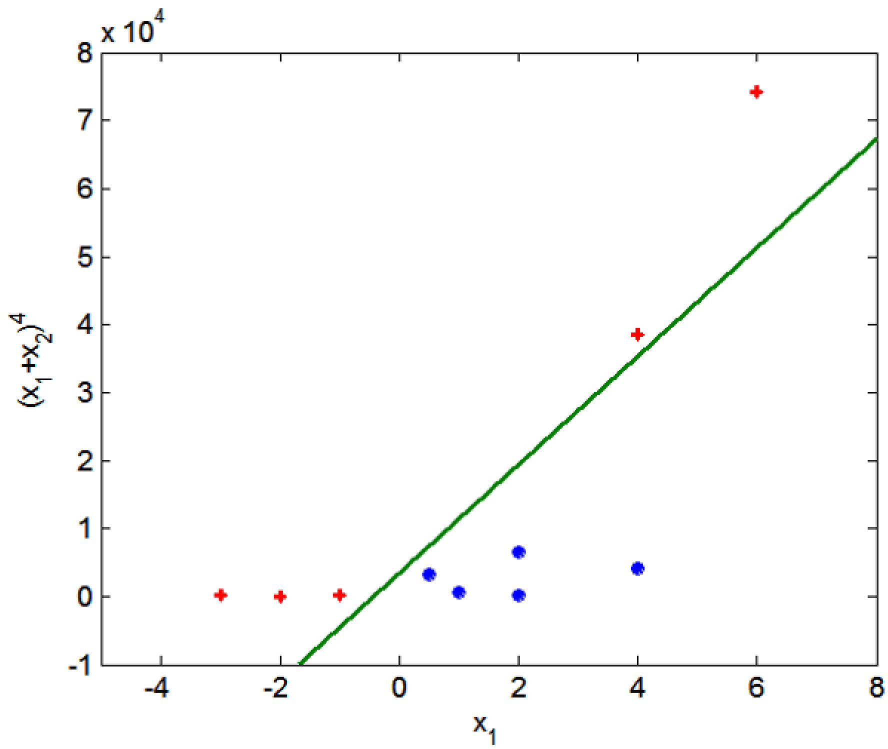
- C : float, optional (default=1.0)
  - 錯誤懲罰項
- kernel : string, optional (default='rbf')
  - 決定分隔線的函數: 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' 或是自定義函數
- degree : int, optional (default=3)
  - polynomial('poly') 分隔函數的 degree，如果使用其他分隔函數將直接被忽略。
- gamma : float, optional (default='auto')
  - 'rbf', 'poly' and 'sigmoid' 的共變異數. 如果 gamma 是'auto' 則預設為 1/n_features。



SVM_error



SVM_nonLinear



SVM_highdim

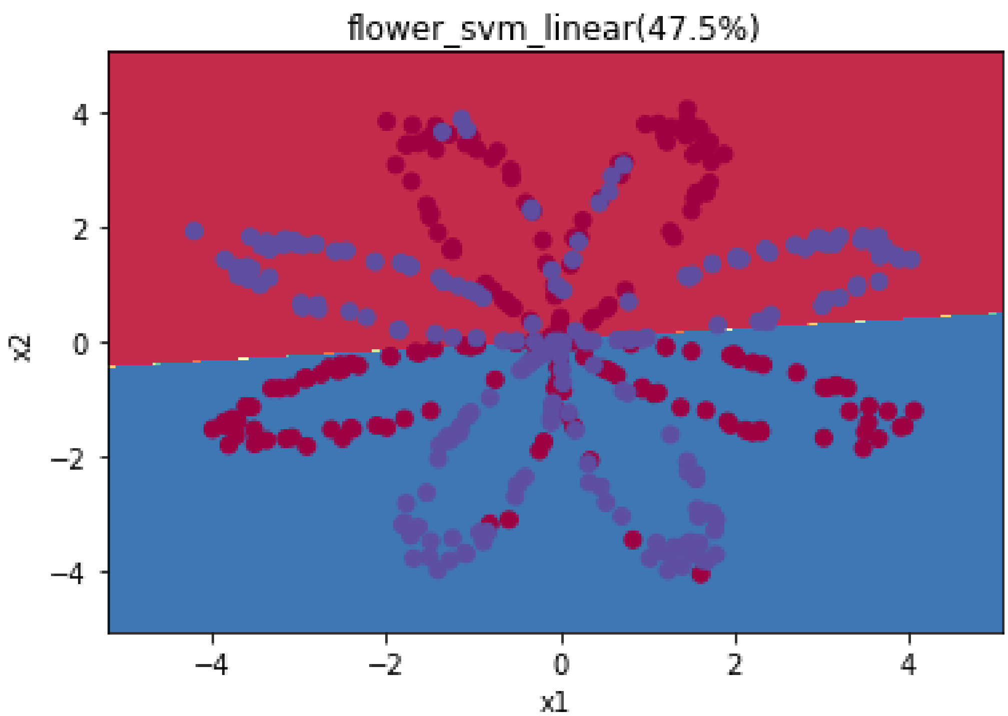
SVM_proj

10.3 (3). SVM 的使用

```
In [36]: from sklearn.svm import SVC
```

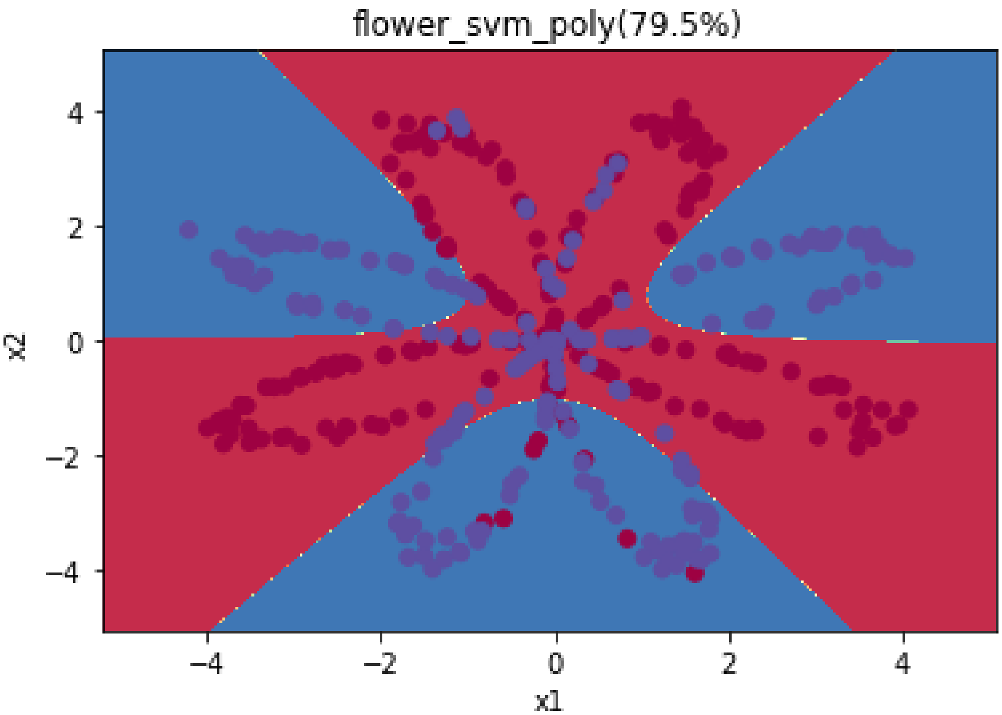
```
In [37]: kernels =['linear', 'poly', 'rbf', 'sigmoid']  ## 選擇 kernel
         for name, X, Y in datas:
             for k in kernels:
                 clf = SVC(C=1.0, kernel=k)  ## 這邊大家可以調整懲罰項 C 試試看
                 clf.fit(X, Y)

                 y_pred = clf.predict(X)
                 print('Accuracy',  str((Y == y_pred).sum()/ X.shape[0]*100)+"%")

                 plot_decision_boundary(lambda x: clf.predict(x), X.T, Y)
                 plt.title(name+'_svm_'+ k +'(' + str((Y == y_pred).sum()/ X.shape[0]*100)+"%)'
                 plt.show()
```

```
Accuracy 47.5%
```

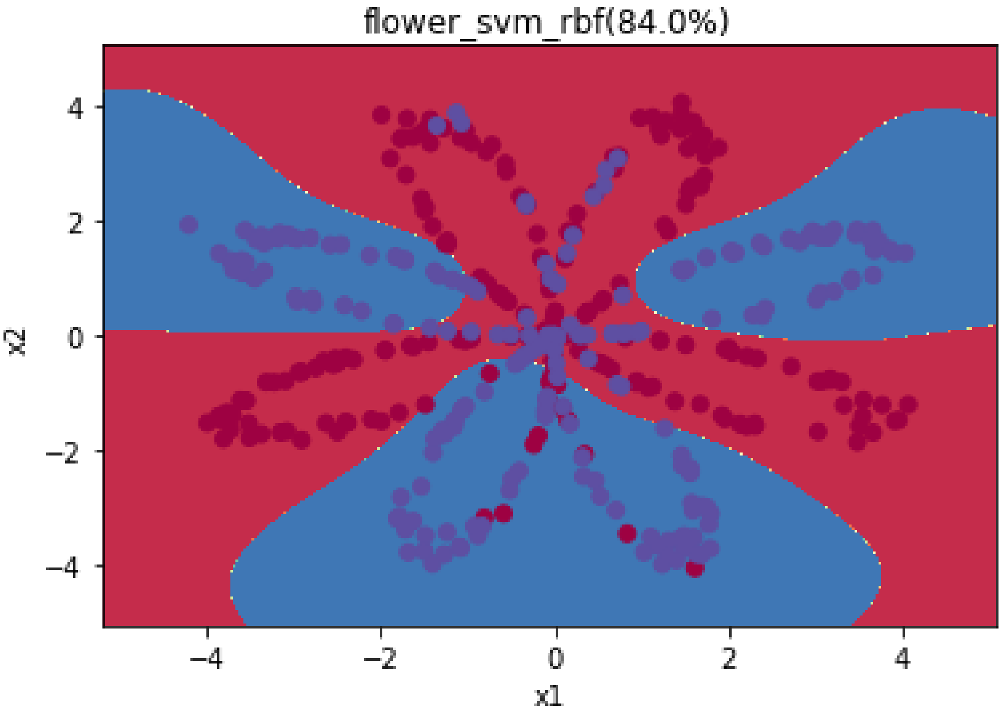



```
  "avoid this warning.", FutureWarning)
```

```
Accuracy 79.5%
```

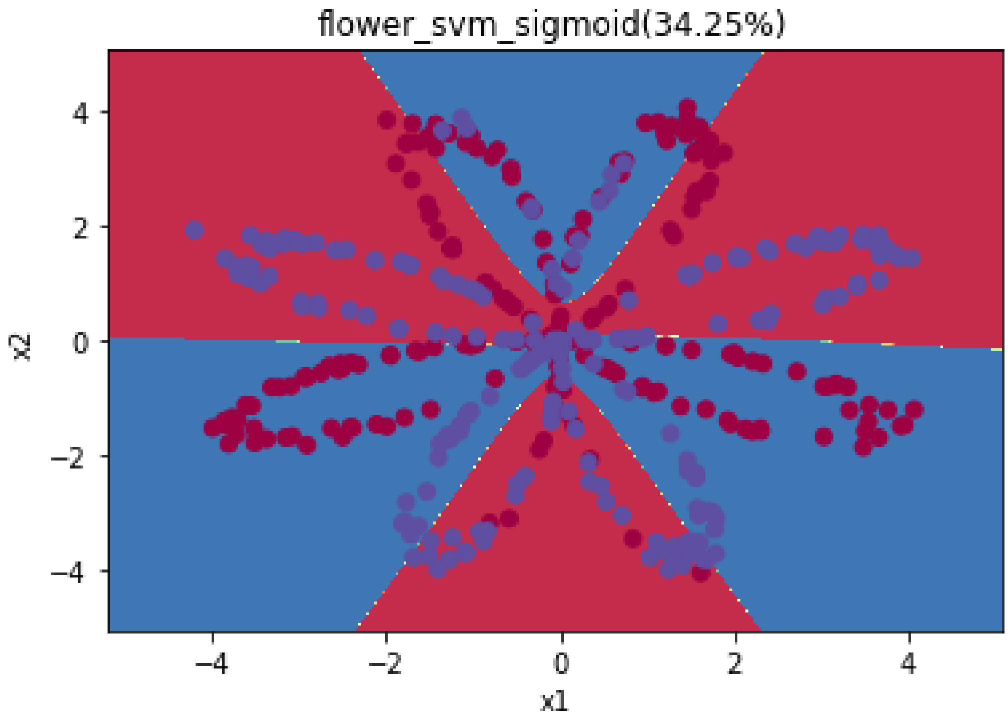



```
  "avoid this warning.", FutureWarning)

Accuracy 84.0%
```

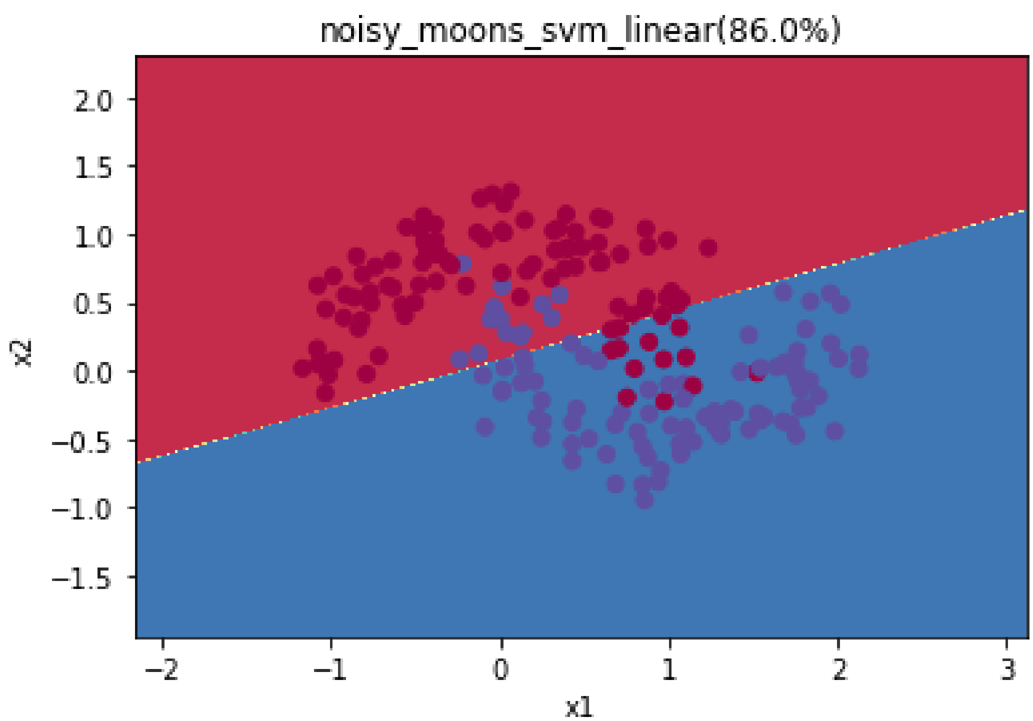



```
  "avoid this warning.", FutureWarning)
```

```
Accuracy 34.25%
```

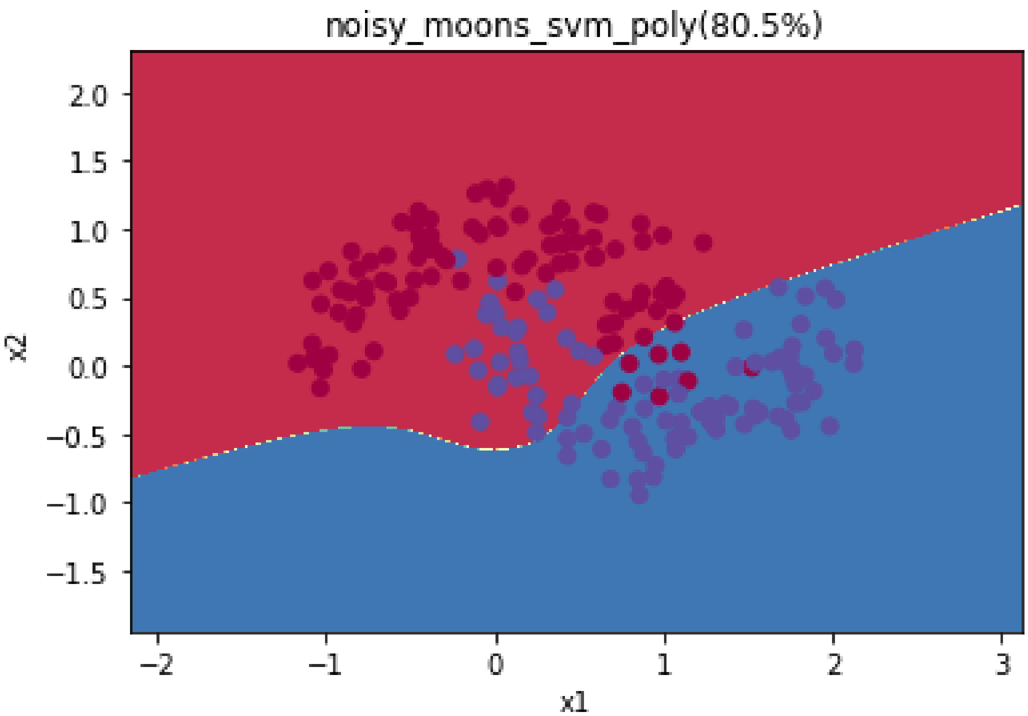



```
Accuracy 86.0%
```



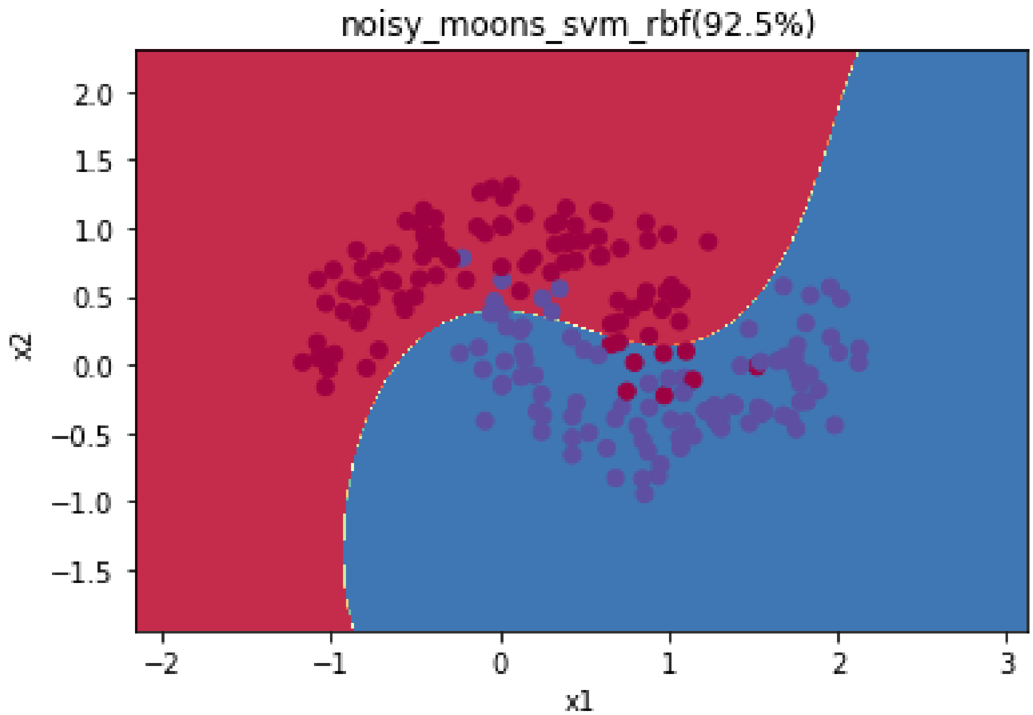
```
  "avoid this warning.", FutureWarning)
```

```
Accuracy 80.5%
```

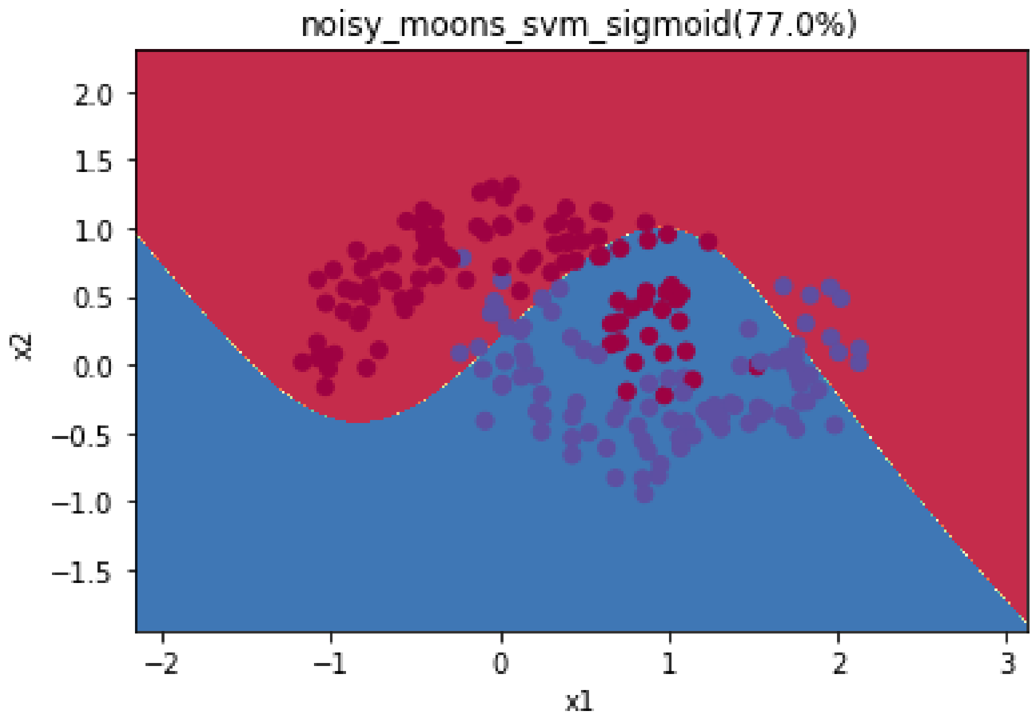



```
  "avoid this warning.", FutureWarning)
```

```
Accuracy 92.5%
```




```
  "avoid this warning.", FutureWarning)

Accuracy 77.0%
```



10.4 (4). SVM 的練習

In [38]:
```python
# 請使用 SVC(C=1.0, kernel='rbf') 來訓練 iris dataset
#=============your works starts===============#
svm =
Y_iris_predict =
#==============your works ends================#

print(Y_iris_predict)
print(Counter(Y_iris_predict))
# [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#  0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
#  1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
#  2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
#  2 2]
# Counter({2: 52, 0: 50, 1: 48})
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Counter({2: 52, 0: 50, 1: 48})
```

```
  "avoid this warning.", FutureWarning)
```

```
In [39]: accuracy = np.sum(Y_iris_true == Y_iris_predict)/len(Y_iris_predict)
         print("accuracy", accuracy)
```

```
accuracy 0.9866666666666667
```

```
In [40]: faulse_idxs = np.where(Y_iris_true != Y_iris_predict)[0]
         folwer_type = {
             0:iris.target_names[0],
             1:iris.target_names[1],
             2:iris.target_names[2],
         }
         df = pd.DataFrame(iris.data)
         df.columns = iris.feature_names
         df['type_name'] = [folwer_type.get(i) for i in iris.target]
         df['type'] = iris.target
         df['yhat'] = Y_iris_predict

         print("分類錯誤的 row: ")
         df.loc[faulse_idxs]
```

```
分類錯誤的 row:
```

```
Out[40]:     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
         77                6.7               3.0                5.0               1.7
         83                6.0               2.7                5.1               1.6

              type_name  type  yhat
         77  versicolor     1     2
         83  versicolor     1     2
```