EXPERIMENT-01

BFS

```
graph = {
  '5' : ['3','7'],
  '3' : ['2', '4'],
  '7' : ['8'],
  '2' : [],
  '4' : ['8'],
  '8' : []
}

visited = []
queue = []

def bfs(visited, graph, node):
  visited.append(node)
  queue.append(node)

  while queue:
    m = queue.pop(0)
    print (m, end = " ")

    for neighbour in graph[m]:
      if neighbour not in visited:
        visited.append(neighbour)
        queue.append(neighbour)


print("Following is the Breadth-First Search")
bfs(visited, graph, '5')
```

OUTPUT:

```
Following is the Breadth-First Search
5 3 7 2 4 8
```

DFS

```
graph = {
  '5' : ['3','7'],
  '3' : ['2', '4'],
  '7' : ['8'],
  '2' : [],
  '4' : ['8'],
  '8' : []
}

visited = set()

def dfs(visited, graph, node):
    if node not in visited:
        print (node)
        visited.add(node)
        for neighbour in graph[node]:
            dfs(visited, graph, neighbour)

print("Following is the Depth-First Search")
dfs(visited, graph, '5')
```

OUTPUT:

```
Following is the Depth-First Search

5

3

2

4

8

7
```

EXPERIMENT-02

A* Algorithm

```
from collections import deque

class Graph:

    def __init__(self, adjacency_list):
        self.adjacency_list = adjacency_list

    def get_neighbors(self, v):
        return self.adjacency_list[v]

    def h(self, n):
        H = {
            'A': 1,
            'B': 1,
            'C': 1,
            'D': 1
        }

        return H[n]

    def a_star_algorithm(self, start_node, stop_node):
        open_list = set([start_node])
        closed_list = set([])

        g = {}

        g[start_node] = 0

        parents = {}
        parents[start_node] = start_node

        while len(open_list) > 0:
            n = None

            for v in open_list:
                if n == None or g[v] + self.h(v) < g[n] + self.h(n):
                    n = v

            if n == None:
                print('Path does not exist!')
                return None

            if n == stop_node:
                reconst_path = []
```

```
                while parents[n] != n:
                    reconst_path.append(n)
                    n = parents[n]

                reconst_path.append(start_node)

                reconst_path.reverse()

                print('Path found: {}'.format(reconst_path))
                return reconst_path

            for (m, weight) in self.get_neighbors(n):
                if m not in open_list and m not in closed_list:
                    open_list.add(m)
                    parents[m] = n
                    g[m] = g[n] + weight

                else:
                    if g[m] > g[n] + weight:
                        g[m] = g[n] + weight
                        parents[m] = n

                        if m in closed_list:
                            closed_list.remove(m)
                            open_list.add(m)

            open_list.remove(n)
            closed_list.add(n)

        print('Path does not exist!')
        return None

adjacency_list = {
'A': [('B', 1), ('C', 3), ('D', 7)],
'B': [('D', 5)],
'C': [('D', 12)]
}
graph1 = Graph(adjacency_list)
graph1.a_star_algorithm('A', 'D')
```

OUTPUT:

```
Path found: ['A', 'B', 'D']
```

EXPERIMENT-03

Prims algorithm

```
import sys
class Graph():
	def __init__(self, vertices):
		self.V = vertices
		self.graph = [[0 for column in range(vertices)]
					for row in range(vertices)]
	def printMST(self, parent):
		print("Edge \tWeight")
		for i in range(1, self.V):
			print(parent[i], "-", i, "\t", self.graph[i][parent[i]])
	def minKey(self, key, mstSet):

		# Initialize min value
		min = sys.maxsize

		for v in range(self.V):
			if key[v] < min and mstSet[v] == False:
				min = key[v]
				min_index = v

		return min_index
	def primMST(self):
		key = [sys.maxsize] * self.V
		parent = [None] * self.V # Array to store constructed MST
		key[0] = 0
		mstSet = [False] * self.V

		parent[0] = -1 # First node is always the root of
```

```
        for cout in range(self.V):
            u = self.minKey(key, mstSet)
            mstSet[u] = True

            for v in range(self.V):
                if self.graph[u][v] > 0 and mstSet[v] == False
                and key[v] > self.graph[u][v]:
                    key[v] = self.graph[u][v]
                    parent[v] = u

        self.printMST(parent)

if __name__ == '__main__':
    g = Graph(5)
    g.graph = [[0, 2, 0, 6, 0],
            [2, 0, 3, 8, 5],
            [0, 3, 0, 0, 7],
            [6, 8, 0, 0, 9],
            [0, 5, 7, 9, 0]]

    g.primMST()
```

OUTPUT:

```
Edge   Weight
0 - 1   2
1 - 2   3
0 - 3   6
1 - 4   5
```

Experiment-04

NQUEEN PROBLEMS

```
print ("Enter the number of queens")

N = int(input())

board = [[0]*N for _ in range(N)]

def is_attack(i, j):

    for k in range(0,N):

        if board[i][k]==1 or board[k][j]==1:

            return True


    for k in range(0,N):

        for l in range(0,N):

            if (k+l==i+j) or (k-l==i-j):

                if board[k][l]==1:

                    return True

    return False

def N_queen(n):

    if n==0:

        return True

    for i in range(0,N):

        for j in range(0,N):

            '''checking if we can place a queen here or not

            queen will not be placed if the place is being attacked
```

```
            or already occupied'''
            if (not(is_attack(i,j))) and (board[i][j]!=1):
                board[i][j] = 1

                if N_queen(n-1)==True:
                    return True
                board[i][j] = 0
    return False
N_queen(N)
for i in board:
    print (i)
```

<u>Output:</u>

```
Enter the number of queens
8
[1, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 1, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 0, 1]
[0, 0, 0, 0, 0, 1, 0, 0]
[0, 0, 1, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 1, 0]
[0, 1, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 1, 0, 0, 0, 0]
```

Experiment 5

```
import random

responses = {
    "hi": ["Hello!", "Hi there!", "Hi!"],
    "how are you": ["I'm doing well, thank you!", "I'm fine, thanks for asking.", "I'm good, thanks!"],
    "what's your name": ["My name is Chatbot.", "I'm Chatbot!", "I'm just a simple chatbot without a name."],
    "bye": ["Goodbye!", "See you later!", "Have a nice day!"],
    "thank you": ["You're welcome!", "No problem!", "Anytime!"],
    "default": ["I'm sorry, I don't understand.", "Can you please rephrase that?", "I'm not sure what you mean."]
}

def chatbot():
    print(random.choice(responses["hi"]))

    while True:
        message = input("> ")

        if "hi" in message.lower():
            print(random.choice(responses["hi"]))
        elif "how are you" in message.lower():
            print(random.choice(responses["how are you"]))
        elif "what's your name" in message.lower():
            print(random.choice(responses["what's your name"]))
        elif "bye" in message.lower():
            print(random.choice(responses["bye"]))
            break
        elif "thank" in message.lower():
            print(random.choice(responses["thank you"]))
        else:
            print(random.choice(responses["default"]))

chatbot()
```

Output :-

```
Hi there!

> hii

Hi there!

> how are you

I'm fine, thanks for asking.

> what is your name

Can you please rephrase that?

> what's your name

My name is Chatbot.

> thank

Anytime!

> bye

Goodbye!
```

Title :- Expert System - Employee performance evaluation

In [1]:

```
# Importing the necessary libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

In [2]:

```
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Importing Raw data

In [3]:

```
# Importing the csv file
data = pd.read_csv('INX_Future_Inc_Employee_Performance_CDS_Project2_Data_V1.8.csv')
```

Exploratory Data Analysis

In [4]:

```
data.shape
```

```
(1200, 28)
```

In [5]:

```
data.columns
```

```
Index(['EmpNumber', 'Age', 'Gender', 'EducationBackground', 'MaritalStatus',
       'EmpDepartment', 'EmpJobRole', 'BusinessTravelFrequency',
       'DistanceFromHome', 'EmpEducationLevel', 'EmpEnvironmentSatisfaction',
       'EmpHourlyRate', 'EmpJobInvolvement', 'EmpJobLevel',
       'EmpJobSatisfaction', 'NumCompaniesWorked', 'OverTime',
       'EmpLastSalaryHikePercent', 'EmpRelationshipSatisfaction',
       'TotalWorkExperienceInYears', 'TrainingTimesLastYear',
       'EmpWorkLifeBalance', 'ExperienceYearsAtThisCompany',
       'ExperienceYearsInCurrentRole', 'YearsSinceLastPromotion',
       'YearsWithCurrManager', 'Attrition', 'PerformanceRating'],
      dtype='object')
```

In [6]:

```
data.head()
```

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	Busines
0	E1001000	32	Male	Marketing	Single	Sales	Sales Executive	Travel_R
1	E1001006	47	Male	Marketing	Single	Sales	Sales Executive	Travel_R
2	E1001007	40	Male	Life Sciences	Married	Sales	Sales Executive	Travel_Fr
3	E1001009	41	Male	Human Resources	Divorced	Human Resources	Manager	Travel_R
4	E1001010	60	Male	Marketing	Single	Sales	Sales Executive	Travel_R

5 rows × 28 columns

In [7]:

```
# Looking for missing data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200 entries, 0 to 1199
Data columns (total 28 columns):
EmpNumber                       1200 non-null object
Age                             1200 non-null int64
Gender                          1200 non-null object
EducationBackground             1200 non-null object
MaritalStatus                   1200 non-null object
EmpDepartment                   1200 non-null object
EmpJobRole                      1200 non-null object
BusinessTravelFrequency         1200 non-null object
DistanceFromHome                1200 non-null int64
EmpEducationLevel               1200 non-null int64
EmpEnvironmentSatisfaction      1200 non-null int64
EmpHourlyRate                   1200 non-null int64
EmpJobInvolvement               1200 non-null int64
EmpJobLevel                     1200 non-null int64
EmpJobSatisfaction              1200 non-null int64
NumCompaniesWorked              1200 non-null int64
OverTime                        1200 non-null object
EmpLastSalaryHikePercent        1200 non-null int64
EmpRelationshipSatisfaction     1200 non-null int64
TotalWorkExperienceInYears      1200 non-null int64
TrainingTimesLastYear           1200 non-null int64
EmpWorkLifeBalance              1200 non-null int64
ExperienceYearsAtThisCompany    1200 non-null int64
ExperienceYearsInCurrentRole    1200 non-null int64
YearsSinceLastPromotion         1200 non-null int64
YearsWithCurrManager            1200 non-null int64
Attrition                       1200 non-null object
PerformanceRating               1200 non-null int64
dtypes: int64(19), object(9)
memory usage: 262.6+ KB
```

Analysis of Department wise Perfomance

In [8]:

```
# A new pandas Dataframe is created to analyze department wise performance as asked.
dept = data.iloc[:,[5,27]].copy()
dept_per = dept.copy()
```

In [9]:

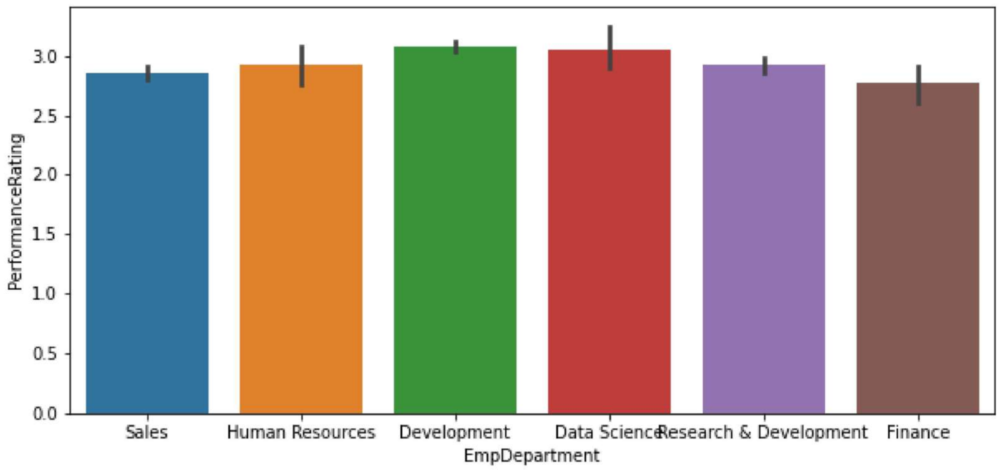
```
# Finding out the mean performance of all the departments and plotting its bar graph using s
dept_per.groupby(by='EmpDepartment')['PerformanceRating'].mean()
```

```
EmpDepartment
Data Science              3.050000
Development               3.085873
Finance                   2.775510
Human Resources           2.925926
Research & Development    2.921283
Sales                     2.860590
Name: PerformanceRating, dtype: float64
```

In [10]:

```
plt.figure(figsize=(10,4.5))
sns.barplot(dept_per['EmpDepartment'],dept_per['PerformanceRating'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x17e0b405fc8>
```



In [11]:

```
# Analyze each department separately
dept_per.groupby(by='EmpDepartment')['PerformanceRating'].value_counts()
```

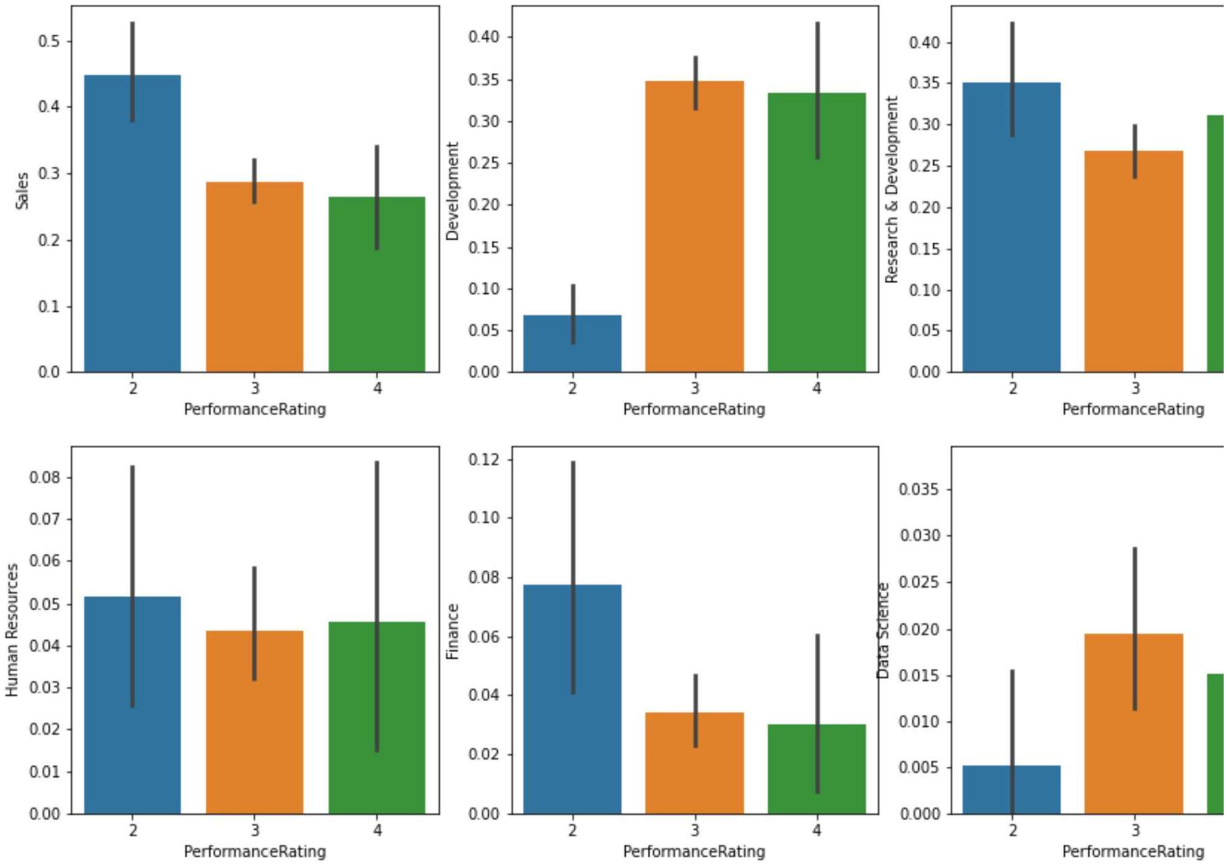
```
EmpDepartment           PerformanceRating
Data Science            3                     17
                        4                      2
                        2                      1
Development             3                    304
                        4                     44
                        2                     13
Finance                 3                     30
                        2                     15
                        4                      4
Human Resources         3                     38
                        2                     10
                        4                      6
Research & Development  3                    234
                        2                     68
                        4                     41
Sales                   3                    251
                        2                     87
                        4                     35
Name: PerformanceRating, dtype: int64
```

In [12]:

```
# Creating a new dataframe to analyze each department separately
department = pd.get_dummies(dept_per['EmpDepartment'])
performance = pd.DataFrame(dept_per['PerformanceRating'])
dept_rating = pd.concat([department,performance],axis=1)
```

In [13]:

```
# Plotting a separate bar graph for performance of each department using seaborn
plt.figure(figsize=(15,10))
plt.subplot(2,3,1)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Sales'])
plt.subplot(2,3,2)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Development'])
plt.subplot(2,3,3)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Research & Development'])
plt.subplot(2,3,4)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Human Resources'])
plt.subplot(2,3,5)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Finance'])
plt.subplot(2,3,6)
sns.barplot(dept_rating['PerformanceRating'],dept_rating['Data Science'])
plt.show()
```



Data Processing/ Data Munging

In [14]:

```
# Encoding all the ordinal columns and creating a dummy variable for them to see if there ar
enc = LabelEncoder()
for i in (2,3,4,5,6,7,16,26):
    data.iloc[:,i] = enc.fit_transform(data.iloc[:,i])
data.head()
```

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	Busines
0	E1001000	32	1	2	2	5	13	2
1	E1001006	47	1	2	2	5	13	2
2	E1001007	40	1	1	1	5	13	1
3	E1001009	41	1	0	0	3	8	2
4	E1001010	60	1	2	2	5	13	2

5 rows × 28 columns

Feature Selection

In [15]:

```
# Finding out the correlation coeffecient to find out which predictors are significant.
data.corr()
```

	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	Emp
Age	1.000000	-0.040107	-0.055905	-0.098368	-0.000104	-0.037
Gender	-0.040107	1.000000	0.009922	-0.042169	-0.010925	0.011
EducationBackground	-0.055905	0.009922	1.000000	-0.001097	-0.026874	-0.012
MaritalStatus	-0.098368	-0.042169	-0.001097	1.000000	0.067272	0.038
EmpDepartment	-0.000104	-0.010925	-0.026874	0.067272	1.000000	0.568
EmpJobRole	-0.037665	0.011332	-0.012325	0.038023	0.568973	1.000
BusinessTravelFrequency	0.040579	-0.043608	0.012382	0.028520	-0.045233	-0.08
DistanceFromHome	0.020937	-0.001507	-0.013919	-0.019148	0.007707	0.022
EmpEducationLevel	0.207313	-0.022960	-0.047978	0.026737	0.019175	-0.01
EmpEnvironmentSatisfaction	0.013814	0.000033	0.045028	-0.032467	-0.019237	0.044
EmpHourlyRate	0.062867	0.002218	-0.030234	-0.013540	0.003957	-0.01
EmpJobInvolvement	0.027216	0.010949	-0.025505	-0.043355	-0.076988	-0.00
EmpJobLevel	0.509139	-0.050685	-0.056338	-0.087359	0.100526	0.004
EmpJobSatisfaction	-0.002436	0.024680	-0.030977	0.044593	0.007150	0.032
NumCompaniesWorked	0.284408	-0.036675	-0.032879	-0.030095	-0.033950	-0.00
OverTime	0.051910	-0.038410	0.007046	-0.022833	-0.026841	0.015
EmpLastSalaryHikePercent	-0.006105	-0.005319	-0.009788	0.010128	-0.012661	0.005
EmpRelationshipSatisfaction	0.049749	0.030707	0.005652	0.026410	-0.050286	-0.04
TotalWorkExperienceInYears	0.680886	-0.061055	-0.027929	-0.093537	0.016065	-0.04
TrainingTimesLastYear	-0.016053	-0.057654	0.051596	0.026045	0.016438	0.004
EmpWorkLifeBalance	-0.019563	0.015793	0.022890	0.014154	0.068875	-0.007
ExperienceYearsAtThisCompany	0.318852	-0.030392	-0.009887	-0.075728	0.047677	-0.00
ExperienceYearsInCurrentRole	0.217163	-0.031823	-0.003215	-0.076663	0.069602	0.019
YearsSinceLastPromotion	0.228199	-0.021575	0.014277	-0.052951	0.052315	0.012
YearsWithCurrManager	0.205098	-0.036643	0.002767	-0.061908	0.033850	-0.00
Attrition	-0.189317	0.035758	0.027161	0.162969	0.048006	0.037
PerformanceRating	-0.040164	-0.001780	0.005607	0.024172	-0.162615	-0.09

27 rows × 27 columns

In [16]:

```
# Dropping the first columns as it is of no use for analysis.
data.drop(['EmpNumber'],inplace=True,axis=1)
```

In [17]:

```
data.head()
```

	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	BusinessTravelFreque
0	32	1	2	2	5	13	2
1	47	1	2	2	5	13	2
2	40	1	1	1	5	13	1
3	41	1	0	0	3	8	2
4	60	1	2	2	5	13	2

5 rows × 27 columns

In [18]:

```
# Here we have selected only the important columns
y = data.PerformanceRating
#X = data.iloc[:,0:-1]  All predictors were selected it resulted in dropping of accuracy.
X = data.iloc[:,[4,5,9,16,20,21,22,23,24]] # Taking only variables with correlation coeffeci
X.head()
```

	EmpDepartment	EmpJobRole	EmpEnvironmentSatisfaction	EmpLastSalaryHikePercent	EmpWorkLifeBal
0	5	13	4	12	2
1	5	13	4	12	3
2	5	13	4	21	3
3	3	8	2	15	2
4	5	13	1	14	3

In [19]:

```
# Splitting into train and test for calculating the accuracy
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

In [20]:

```
# Standardization technique is used
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [21]:

```
X_train.shape
```

```
(900, 9)
```

In [22]:

```
X_test.shape
```

```
(300, 9)
```

Model

We have used Support Vector Machine to calculate the accuracy and found out that gives an accura

Support Vector Machine

In [23]:

```
# Training the model
from sklearn.svm import SVC
rbf_svc = SVC(kernel='rbf', C=100, random_state=42).fit(X_train,y_train)
```

In [24]:

```
# Predicting the model
y_predict_svm = rbf_svc.predict(X_test)
```

In [25]:

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_svm))
print(classification_report(y_test,y_predict_svm))
```

```
0.85
              precision    recall  f1-score   support

           2       0.68      0.76      0.72        37
           3       0.92      0.89      0.90       232
           4       0.60      0.68      0.64        31

    accuracy                           0.85       300
   macro avg       0.73      0.77      0.75       300
weighted avg       0.86      0.85      0.85       300
```

In [26]:

```
confusion_matrix(y_test,y_predict_svm)
```

```
array([[ 28,   9,   0],
       [ 12, 206,  14],
       [  1,   9,  21]], dtype=int64)
```