In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler, StandardScaler, PolynomialFeatures
```

In [ ]:
```
#Import dataset
df = pd.read_csv('project1_1.csv', index_col='Unnamed: 0')
df.head()
```

Out[ ]:

	X	Y	Class
0	0.871319	0.490718	0.0
1	0.715472	-0.458668	1.0
2	1.462538	-0.386599	1.0
3	-0.222521	0.974928	0.0
4	0.327699	-0.240278	1.0

Task 1

Part 1

LDA

In [ ]:
```
#LDA Algorithm
def LDA(class0, class1):
    m0 = class0.mean(axis = 0)
    m1 = class1.mean(axis = 0)
    Sw = (class0-m0).T@(class0-m0) + (class1-m1).T@(class1-m1)
    Sw_inv = np.linalg.pinv(Sw)
    w = Sw_inv.T@(m1-m0)
    w_hat = w / np.linalg.norm(w)
    return w_hat
```

Perceptron

In [ ]:
```
#Perceptron Algorithm
def Perceptron(x, y, epochs):
    x_new = np.insert(x, 0, 1, axis=1)
    w = np.zeros(x_new.shape[1])

    for i in range(epochs): #epochs
        for j in range(x_new.shape[0]):
            z = x_new[j]@w
            y_pred = 1 if z >= 0 else 0
            error = y_pred - y[j]
            w -= error * x_new[j]
    return w
```

Logistic Regression

In [ ]:
```
#Logistic Regression Algorithm
def LogisticRegression(x, y, epochs):
    w = np.zeros(x.shape[1])

    for i in range(epochs):
        z = x@w
```

```
        y_pred = 1 / (1 + np.exp(-z))
        error = y_pred - y
        gradient = np.dot(x.T, error) / len(y)
        w -= gradient
    return w
```

Part 2

In [ ]:

```
#Split dataset into label and target variables
label = df.drop('Class', axis=1)
target = df['Class']

#Split dataset into label and target variables by classification
label0 = df[df['Class'] == 0.0].drop('Class', axis=1).reset_index(drop=True)
target0 = df[df['Class'] == 0.0]['Class'].reset_index(drop=True)
label1 = df[df['Class'] == 1.0].drop('Class', axis=1).reset_index(drop=True)
target1 = df[df['Class'] == 1.0]['Class'].reset_index(drop=True)
```

In [ ]:

```
#Convert to numpy arrays
x = np.array(label)
y = np.array(target)

x0 = np.array(label0)
y0 = np.array(target0)
x1 = np.array(label1)
y1 = np.array(target1)
```

LDA

In [ ]:

```
#Implement LDA algorithm
lda = LDA(x0, x1)
lda_class_guess = []
for i in x:
    guess = 0
    for j in range(len(lda)):
        guess += i[j] * lda[j]
    #Classify prediction
    if guess > 0:
        lda_class_guess.append(1)
    else:
        lda_class_guess.append(0)

print(accuracy_score(y, lda_class_guess))
```

```
0.87
```

Perceptron

In [ ]:

```
#Implement Perceptron algorithm
perceptron = Perceptron(x, y, 100)
perceptron_class_guess = []
for i in x:
    guess = perceptron[0]
    for j in range(len(perceptron)-1):
        guess += i[j] * perceptron[j+1]
    #Classify prediction
    if guess > 0:
        perceptron_class_guess.append(1)
    else:
        perceptron_class_guess.append(0)

print(accuracy_score(y, perceptron_class_guess))
```

```
0.85
```

Logistic Regression

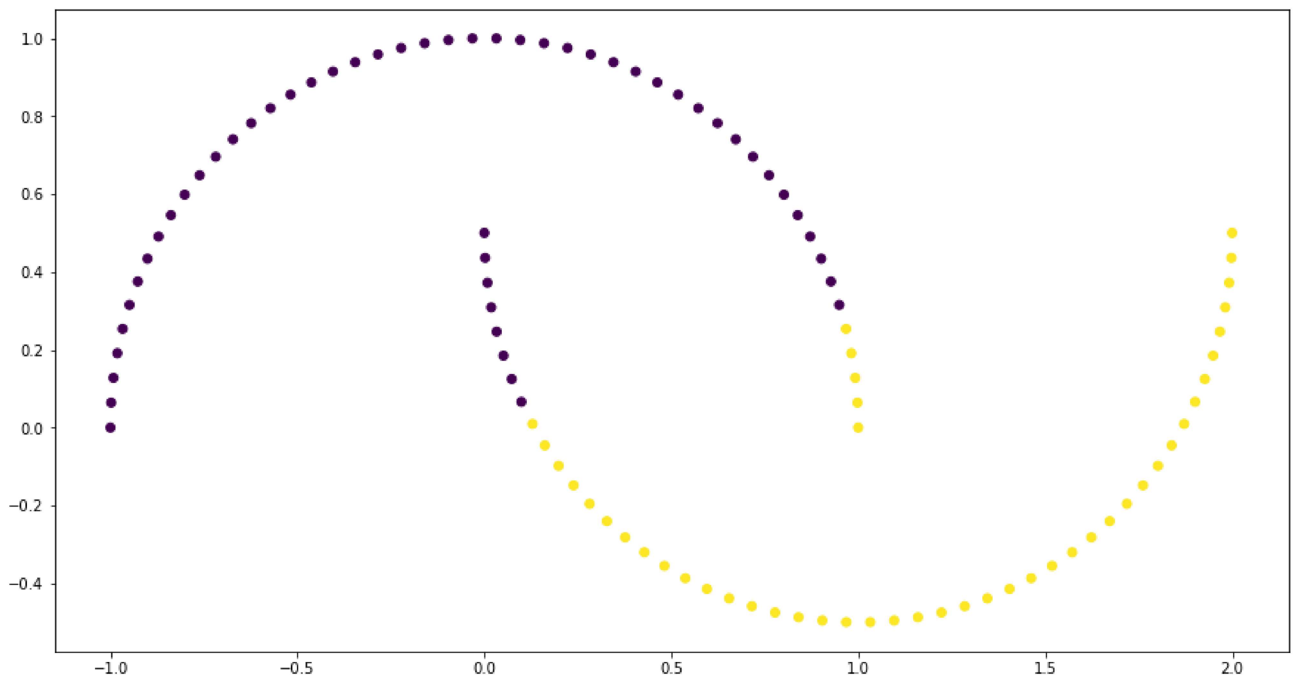
In [ ]:
```
#Implement Logistic Regression algorithm
logreg = LogisticRegression(x, y, 100)
logreg_class_guess = []
for i in x:
    guess = 0
    for j in range(len(logreg)):
        guess += i[j] * logreg[j]
    #Classify prediction
    if guess > 0:
        logreg_class_guess.append(1)
    else:
        logreg_class_guess.append(0)

print(accuracy_score(y, logreg_class_guess))
```

```
0.86
```

Part 3

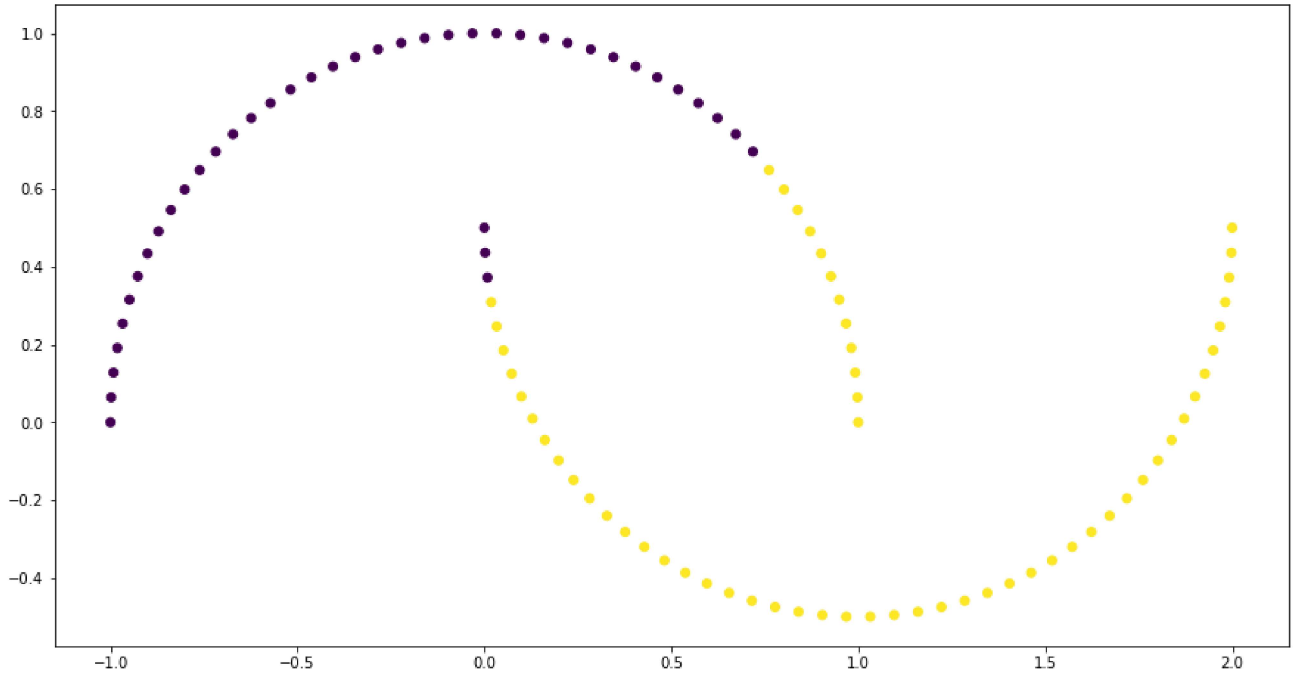
LDA

In [ ]:
```
#Scatter plot of LDA algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label['X'],label['Y'], c=lda_class_guess)
plt.show()
```



Perceptron

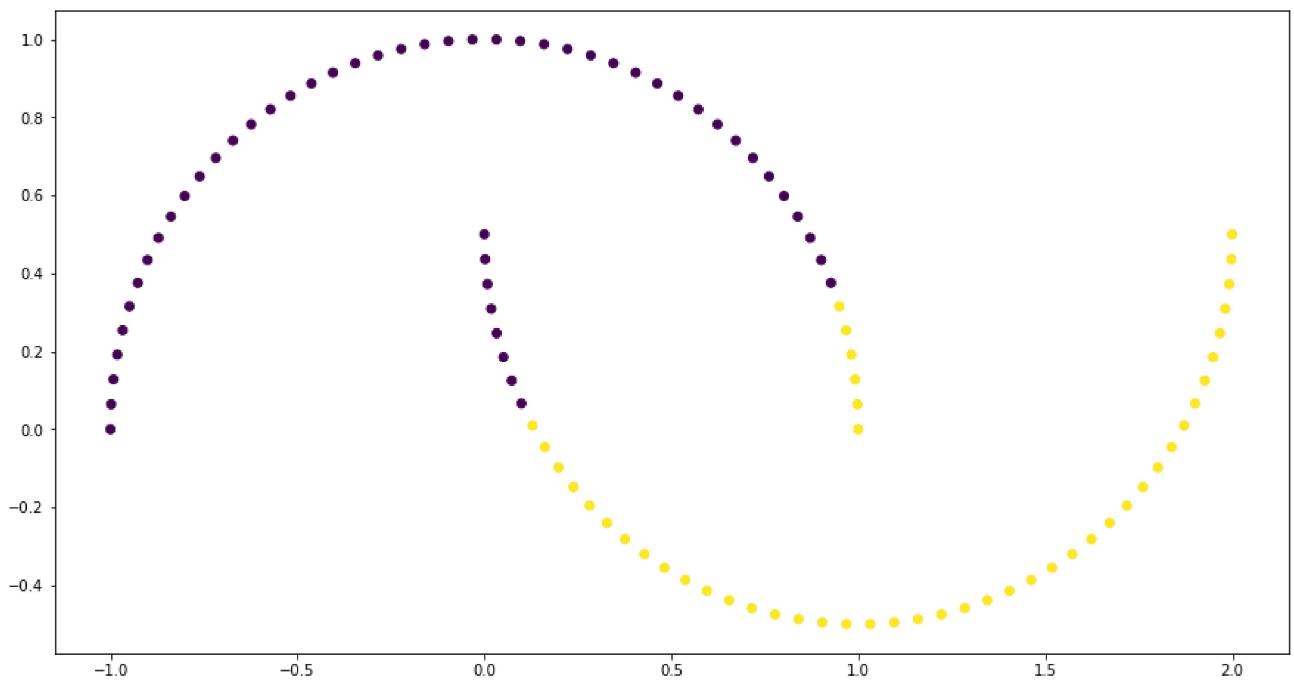
In [ ]:
```
#Scatter plot of Preceptron algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label['X'],label['Y'], c=perceptron_class_guess)
plt.show()
```



Logistic Regression

In [ ]:

```
#Scatter plot of Logistic Regression algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label['X'],label['Y'], c=logreg_class_guess)
plt.show()
```



Task 2

Part 1

In [ ]:

```
#Create copy of data frame
df_new = df.copy(deep = False)
df_new.head()
```

Out[ ]:

	X	Y	Class
0	0.871319	0.490718	0.0
1	0.715472	-0.458668	1.0
2	1.462538	-0.386599	1.0
3	-0.222521	0.974928	0.0
4	0.327699	-0.240278	1.0

In [ ]:

```
#Split dataset into label and target variables
label_new = df_new.drop('Class', axis=1)
target_new = df_new['Class']

#Split dataset into label and target variables by classification
label_new0 = df_new[df_new['Class'] == 0.0].drop('Class', axis=1).reset_index(drop=True)
target_new0 = df_new[df_new['Class'] == 0.0]['Class'].reset_index(drop=True)
label_new1 = df_new[df_new['Class'] == 1.0].drop('Class', axis=1).reset_index(drop=True)
target_new1 = df_new[df_new['Class'] == 1.0]['Class'].reset_index(drop=True)
```

In [ ]:

```
#Convert to numpy arrays
x_new = np.array(label_new)
y_new = np.array(target_new)

x_new0 = np.array(label_new0)
y_new0 = np.array(target_new0)
x_new1 = np.array(label_new1)
y_new1 = np.array(target_new1)
```

In [ ]:

```
#Create 3rd degree polynomial features
poly = PolynomialFeatures(degree=3)
x_poly = poly.fit_transform(x_new)
x_poly0 = poly.fit_transform(x_new0)
x_poly1 = poly.fit_transform(x_new1)
#Based on the plot of the data, the 3rd degree polynomial looks to be the optimal choice
```

In [ ]:

```
#Linearity
ols = LinearRegression()
ols.fit(x_poly, y_new)
print("RSS: %.2f" % np.sum((ols.predict(x_poly) - y_new) ** 2))
print("R^2: %.5f" % ols.score(x_poly, y_new))
#There is an obvious linear relationship between the 3rd degree polynomial features and the classification
```

```
RSS: 0.05
R^2: 0.99793
```

In [ ]:

```
#Independence
corr_matrix = np.c_[x_poly, y_new]
pd.DataFrame(corr_matrix).corr()
#The polynomial features are obviously correlated with X and/or Y, but X and Y themselves are uncorrelated
```

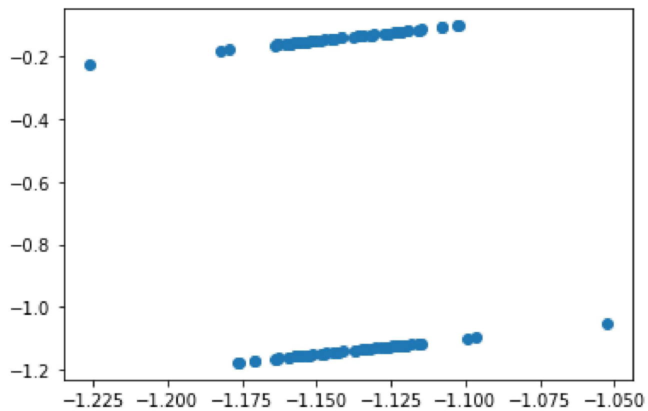
Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	1.000000	-0.436869	0.737474	0.299626	-0.334708	0.838895	-0.057152	0.629767	-0.368772	0.573539
2	NaN	-0.436869	1.000000	-0.322179	0.405879	0.766153	-0.256570	0.529870	-0.264889	0.866861	-0.761706
3	NaN	0.737474	-0.322179	1.000000	0.163572	-0.437711	0.950037	0.195711	0.261665	-0.406028	0.422970
4	NaN	0.299626	0.405879	0.163572	1.000000	0.058343	0.282576	0.711386	0.500918	0.180255	-0.167240
5	NaN	-0.334708	0.766153	-0.437711	0.058343	1.000000	-0.335239	0.092216	-0.107336	0.954244	-0.583584

	0	1	2	3	4	5	6	7	8	9	10
6	NaN	0.838895	-0.256570	0.950037	0.282576	-0.335239	1.000000	0.226794	0.320375	-0.296245	0.518283
7	NaN	-0.057152	0.529870	0.195711	0.711386	0.092216	0.226794	1.000000	-0.029958	0.194312	-0.297558
8	NaN	0.629767	-0.264889	0.261665	0.500918	-0.107336	0.320375	-0.029958	1.000000	-0.200033	0.286501
9	NaN	-0.368772	0.866861	-0.406028	0.180255	0.954244	-0.296245	0.194312	-0.200033	1.000000	-0.642976
10	NaN	0.573539	-0.761706	0.422970	-0.167240	-0.583584	0.518283	-0.297558	0.286501	-0.642976	1.000000

In [ ]:

```
#Homoscadasticity
y_pred = np.sum(ols.coef_ * x_poly, axis = 1)
residuals = y_pred - y_new
plt.scatter(residuals, y_pred)
plt.show()
#While there is an obvious split between classifications, there seems to be no pattern within the
#residuals of each classification
```



Part 2

LDA

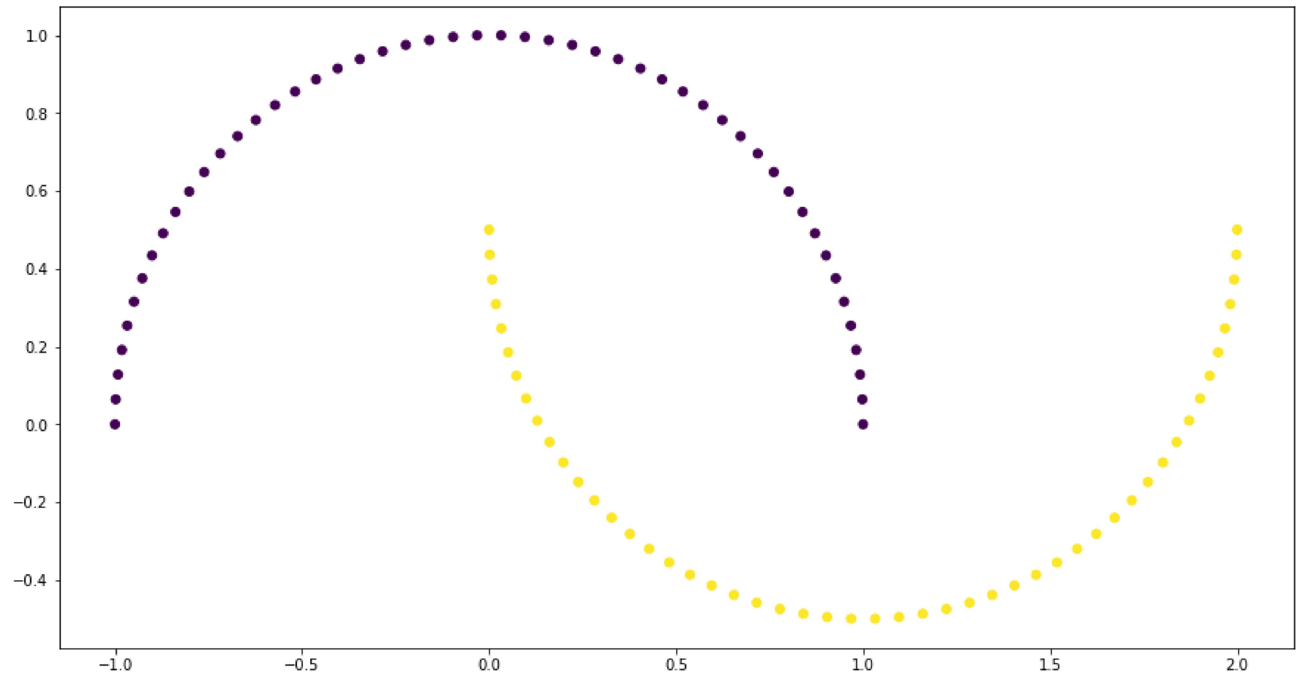
In [ ]:

```
#Implement LDA algorithm using the polynomial features
lda = LDA(x_poly0, x_poly1)
lda_class_guess = []
guess_list = []
for i in x_poly:
    guess = 0
    for j in range(len(lda)):
        guess += i[j] * lda[j]
    guess_list.append(guess)
    if guess > -.1: #Not sure why, but if this value is set to 0 the algorithm classifies everything into
        lda_class_guess.append(1)
    else:
        lda_class_guess.append(0)
print(accuracy_score(y_new, lda_class_guess))
```

```
1.0
```

In [ ]:

```
#Scatter plot of updated LDA algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label_new['X'],label_new['Y'], c=lda_class_guess)
plt.show()
```



Perceptron

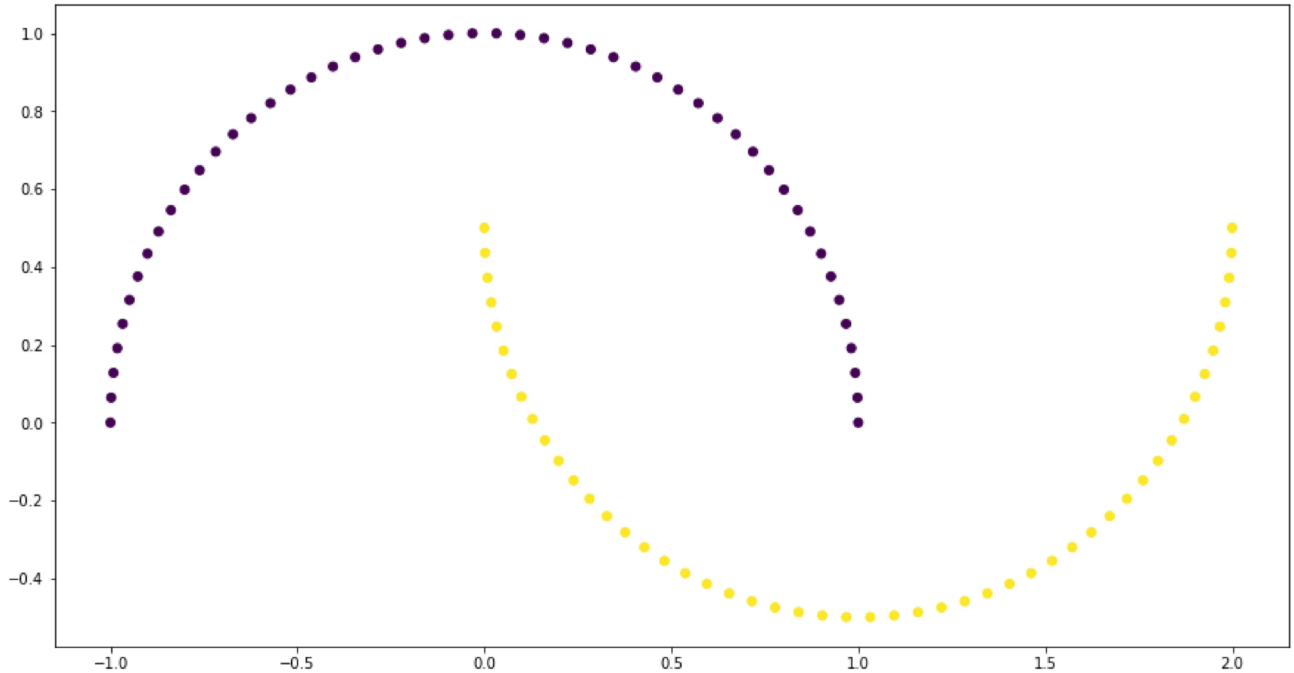
In [ ]:

```
#Implement Perceptron algorithm using the polynomial features
perceptron = Perceptron(x_poly, y_new, 100)
perceptron_class_guess = []
for i in x_poly:
    guess = perceptron[0]
    for j in range(len(perceptron)-1):
        guess += i[j] * perceptron[j+1]
    if guess > 0:
        perceptron_class_guess.append(1)
    else:
        perceptron_class_guess.append(0)

print(accuracy_score(y_new, perceptron_class_guess))
```

```
1.0
```

In [ ]:

```
#Scatter plot of updated Perceptron algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label_new['X'],label_new['Y'], c=perceptron_class_guess)
plt.show()
```



Logistic Regression

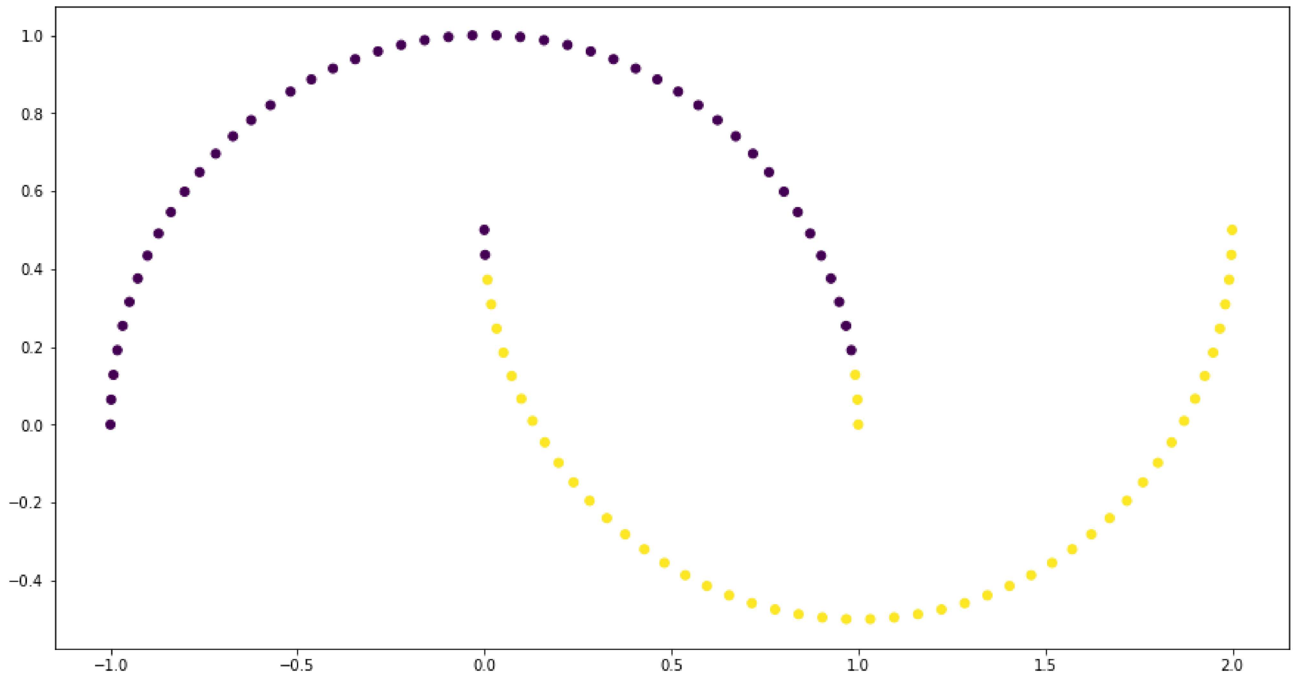
In [ ]:

```
#Implement Logistic Regression algorithm using the polynomial features
logreg = LogisticRegression(x_poly, y_new, 100)
logreg_class_guess = []
for i in x_poly:
    guess = 0
    for j in range(len(logreg)):
        guess += i[j] * logreg[j]
    if guess > 0:
        logreg_class_guess.append(1)
    else:
        logreg_class_guess.append(0)

print(accuracy_score(y_new, logreg_class_guess))
```

```
0.95
```

In [ ]:

```
#Scatter plot of updated Logistic Regression algorithm by classification prediction
plt.figure(figsize=(15, 8))
plt.scatter(label_new['X'],label_new['Y'], c=logreg_class_guess)
plt.show()
```


1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0