MODELOS Y SIMULACION

En la clase de hoy veremos Regresion Logística y kNN.

Para esta semana, siguen abiertas las Office Hours con el mismo link de siempre.

Ya se encuentra disponible la solucion a la practica 3 en Google Drive.

Hoy traemos a clase la siguiente iniciativa: AI For Good

La Iniciativa de las Naciones Unidas para lograr un impacto positivo utilizando AI https://aiforgood.itu.int

Exploramos su sitio y presentamos sus inciativas.

In [329…

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn import neighbors
```

In [330…

```
# Cargamos la data
df = pd.read_csv('Churn_Modelling.csv')
df.head()
```

Out[330…

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiv
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

In [331…

```
# Notemos que hay variables que no aportan al modelo como RowNumber, CustomerId y Surname
df = df.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1)
df.head()
```

Out[331…

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [332…

```
# Tenemos variables que debemos cambiar su forma de representacion como Geography y Gender
# Creamos los valores para geography
geography = pd.factorize(df['Geography'])
geography
```

Out[332…

```
(array([0, 1, 0, ..., 0, 2, 0]),
 Index(['France', 'Spain', 'Germany'], dtype='object'))
```

In [333…

```
# Obtenemos el indice donde se encontraba Geogrpahy
index = df.columns.get_loc('Geography')
# Eliminamos la columna
df = df.drop('Geography', axis=1)
# Insertamos la nueva
df.insert(index, 'Geography', geography[0])
df.head()
```

Out[333…

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	0	Female	42	2	0.00	1	1	1	101348.88	1
1	608	1	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	0	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	0	Female	39	1	0.00	2	0	0	93826.63	0
4	850	1	Female	43	2	125510.82	1	1	1	79084.10	0

In [334…

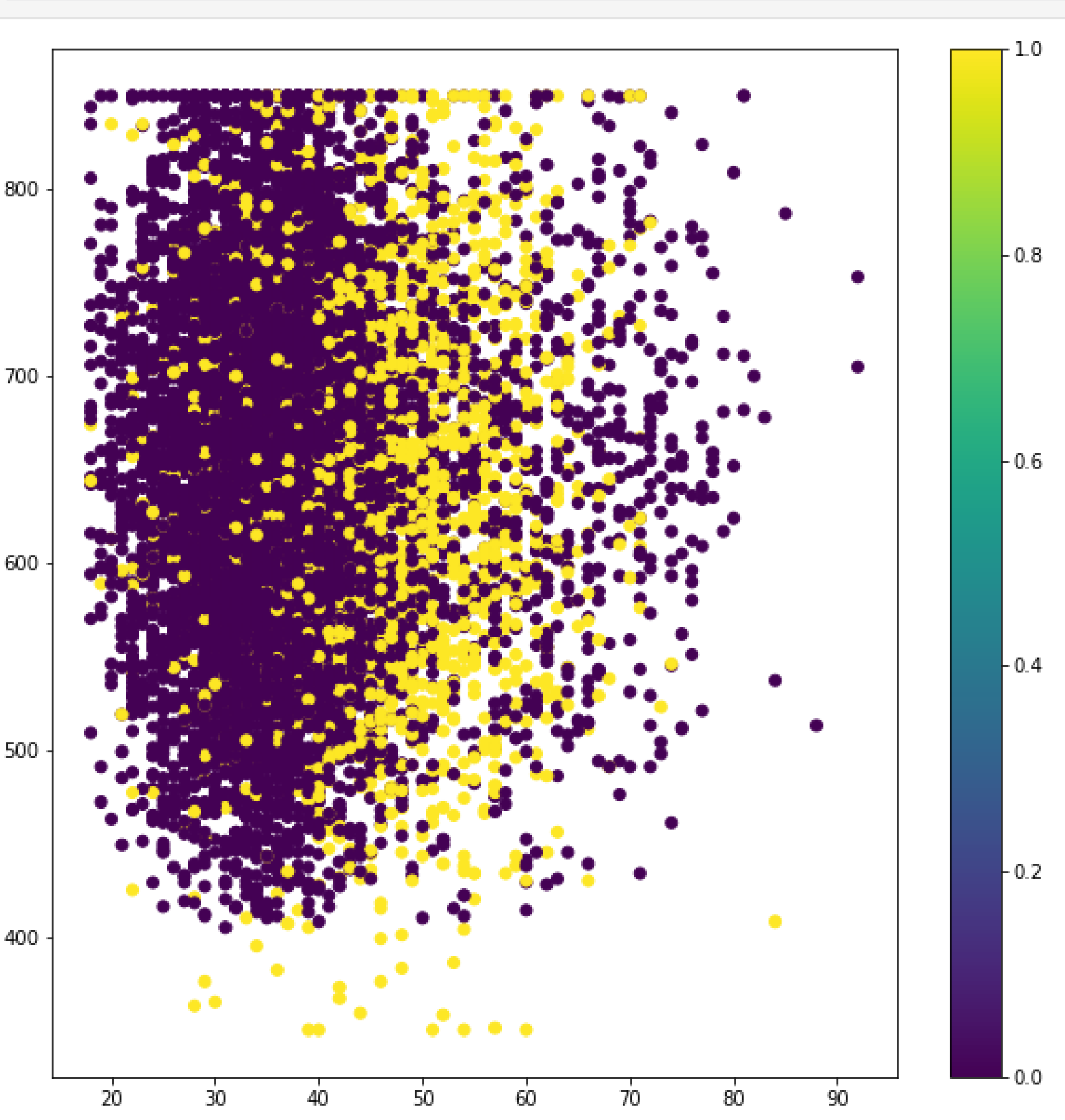
```
# Creamos los valores para Gender
gender = pd.factorize(df['Gender'])
# Obtenemos el indice donde se encontraba Gender
index = df.columns.get_loc('Gender')
# Eliminamos la columna
df = df.drop('Gender', axis=1)
# Insertamos la nueva
df.insert(index, 'Gender', gender[0])
df.head()
```

Out[334…

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	608	1	0	41	1	83807.86	1	0	1	112542.58	0
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	850	1	0	43	2	125510.82	1	1	1	79084.10	0

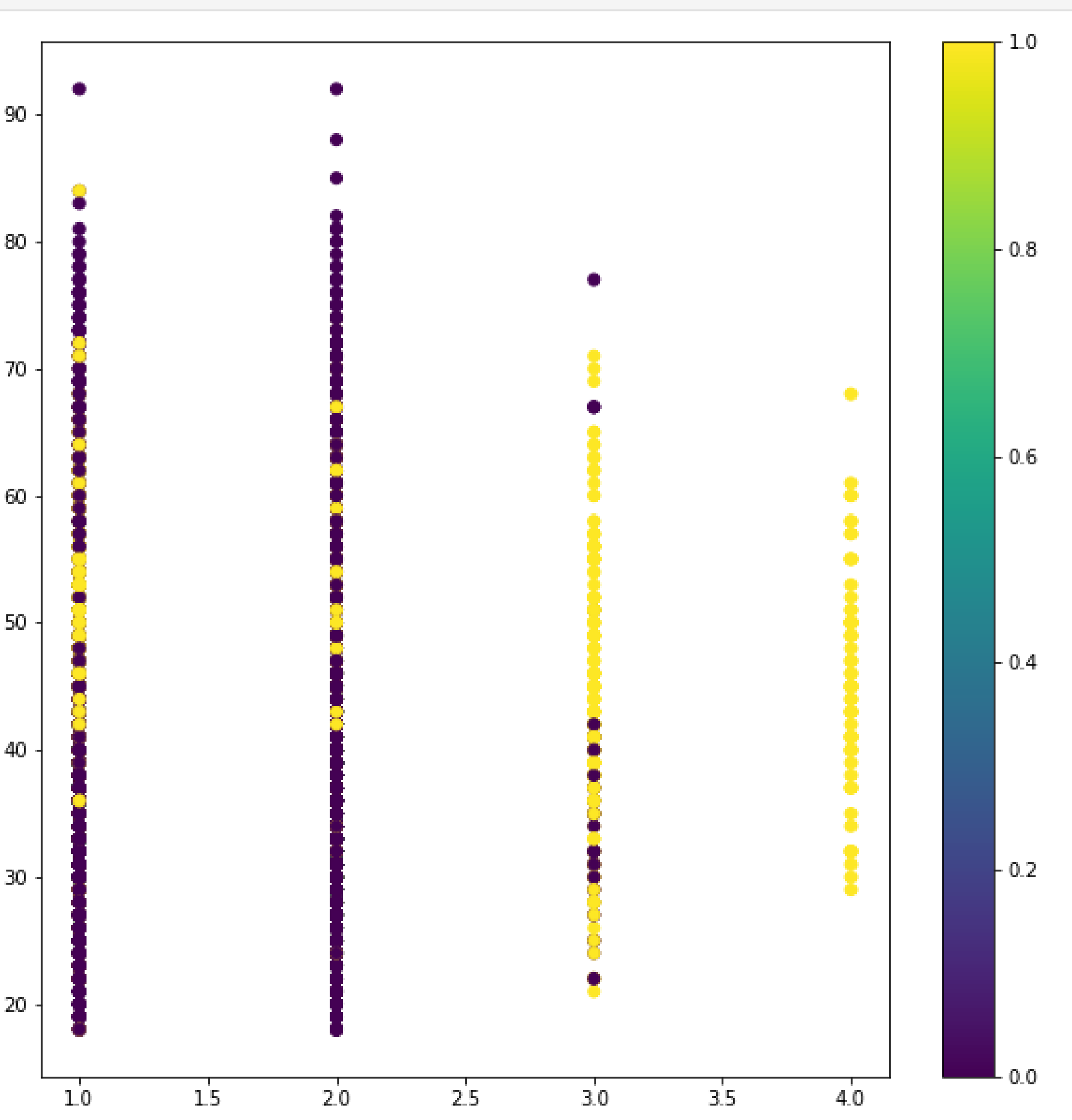
In [335…

```
#Veamos como influye el credit score y la edad en la decision de abandonar el producto
x = df['Age']
y = df['CreditScore']
e = df['Exited']
plt.scatter(x,y,c=e)
plt.colorbar()
plt.show()
```



In [336…

```
#Veamos como influye la edad y la cantidad de productos en la decision de abandonar el producto
x = df['NumOfProducts']
y = df['Age']
e = df['Exited']
plt.scatter(x,y,c=e)
plt.colorbar()
plt.show()
```



Regresión Logística

Vamos a usar la libreria SKLearn para generar y entrenar nuestro modelo. Luego graficaremos el espacio de soluciones

In [337…

```
y = df['Exited']
x = df.drop('Exited', axis=1)
rlog = LogisticRegression().fit(x, y)
# Classes nos devuelve que tipos de etiquetas usa el clasificador
rlog.classes_
```

Out[337…

```
array([0, 1])
```

In [338…

```
# Veamos los coeficientes
rlog.coef_
```

Out[338…

```
array([[-5.03585720e-03,  1.56218586e-03, -1.03853584e-03,
         4.37994243e-02, -1.59075948e-03,  3.61853503e-06,
        -4.45887716e-04, -1.86759998e-04, -1.41742761e-03,
        -1.36186225e-06]])
```

In [339…

```
# Prediccion para cada input
rlog.predict_proba(x)
```

Out[339…

```
array([[0.80550561, 0.19449439],
       [0.75363885, 0.24636115],
       [0.56961686, 0.43038314],
       ...,
       [0.88736952, 0.11263048],
       [0.87067069, 0.12932931],
       [0.91295706, 0.08704294]])
```

In [328…

```
# Y si queremos cambiar el threshold? Default =0.5
x
```

Out[328…

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	0	0	42	2	0.00	1	1	1	101348.88
1	608	1	0	41	1	83807.86	1	0	1	112542.58
2	502	0	0	42	8	159660.80	3	1	0	113931.57
3	699	0	0	39	1	0.00	2	0	0	93826.63
4	850	1	0	43	2	125510.82	1	1	1	79084.10
...	...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0	96270.64
9996	516	0	1	35	10	57369.61	1	1	1	101699.77
9997	709	0	0	36	7	0.00	1	0	1	42085.58
9998	772	2	1	42	3	75075.31	2	1	0	92888.52
9999	792	0	0	28	4	130142.79	1	1	0	38190.78

10000 rows × 10 columns

In [283…

```
# Calculemos el error
y = df['Exited']
x = df.drop('Exited', axis=1)
difference = y - rlog.predict(x)
count = 0
for i in range(0, difference.size):
    # aquellas que calculo bien
    if difference[i] == 0:
        count +=1
accuracy = count/difference.size
accuracy
```

Out[283…

```
0.7899
```

In [284…

```
# Aqui calculado por ela libreria
rlog.score(x, y)
```

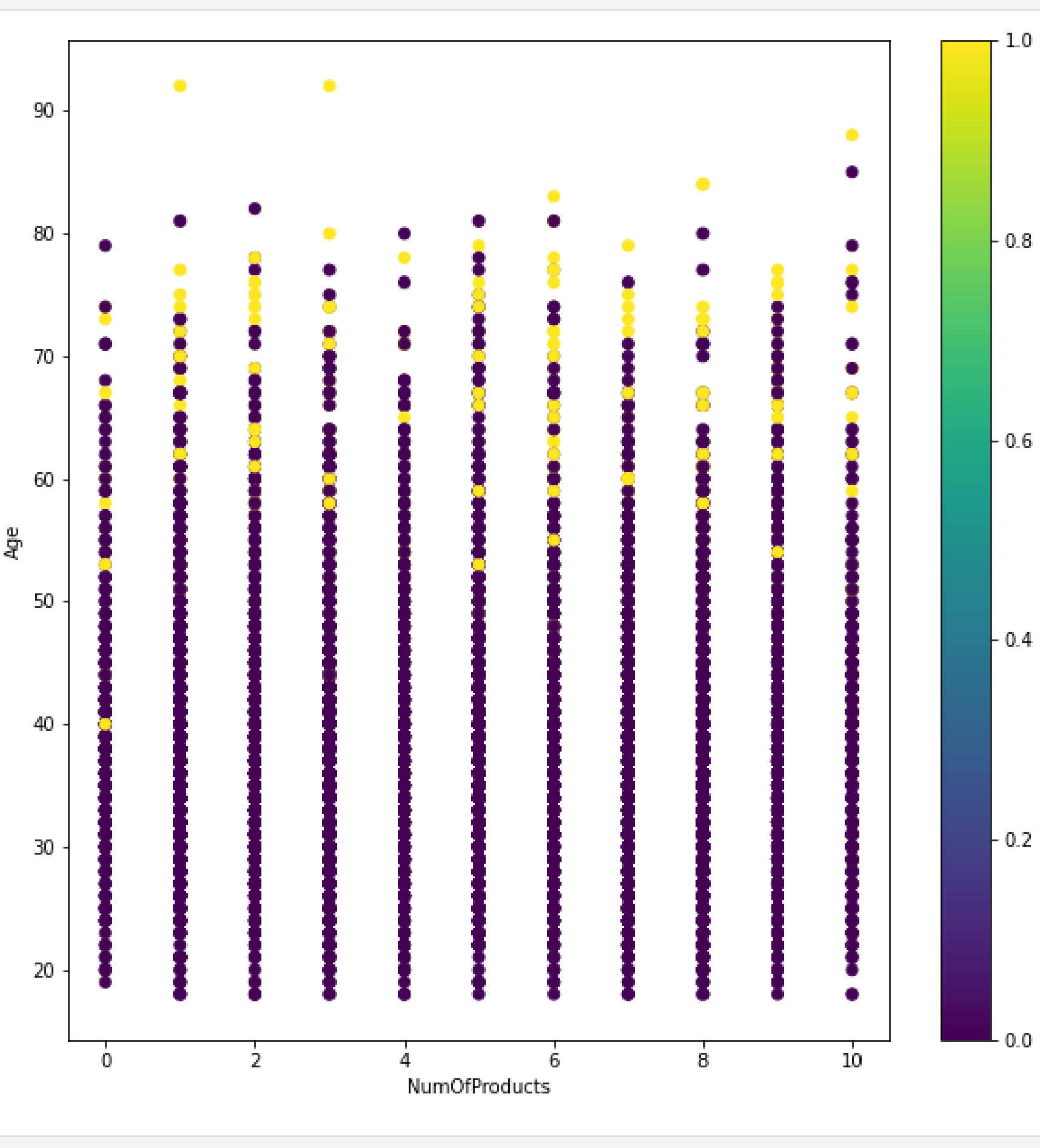
Out[284…

```
0.7899
```

In [322…

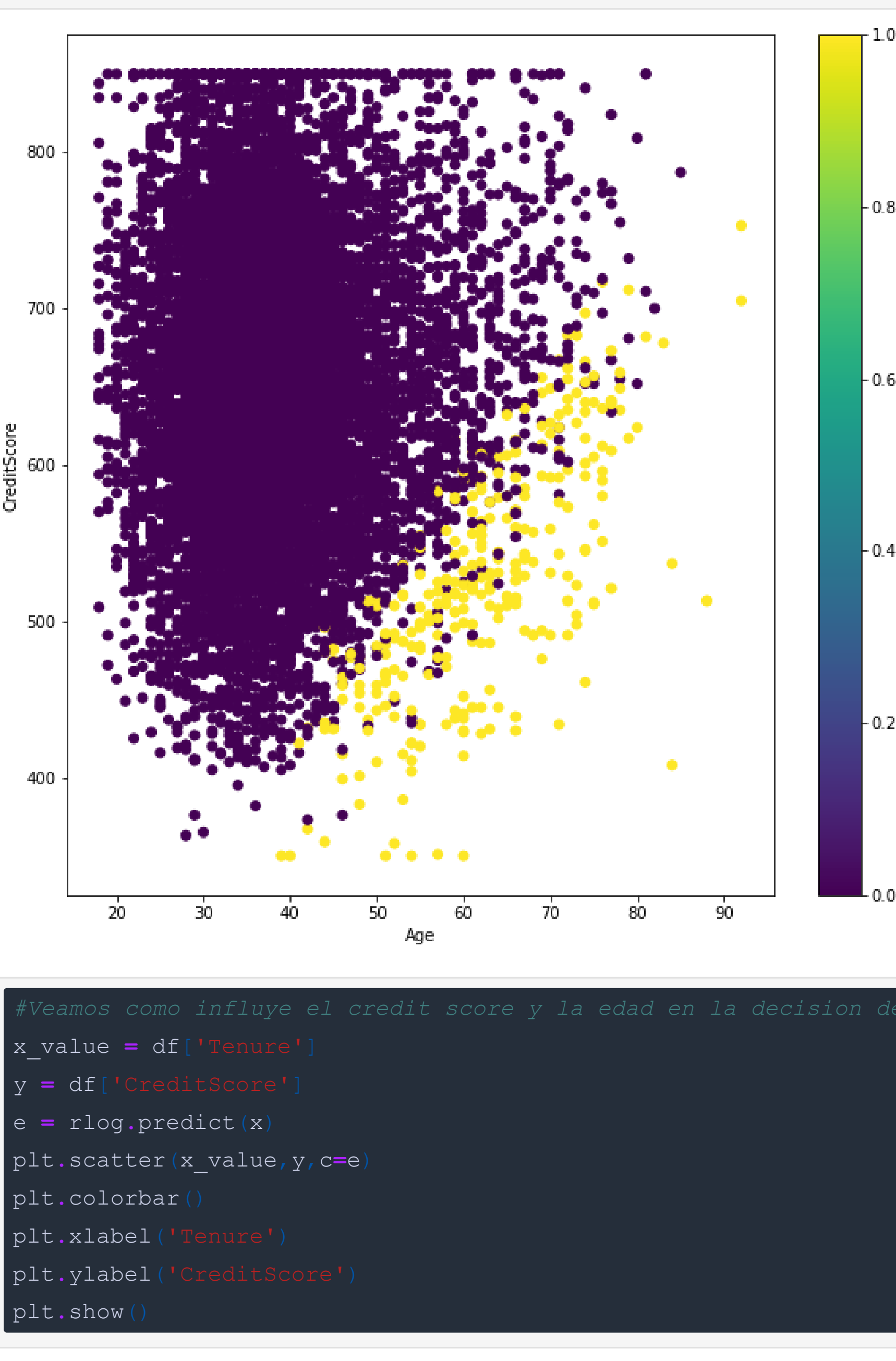
```
# Grafiquemos nuestra solucion
x_values = df['NumOfProducts']
y = df['Age']
e = rlog.predict(x)
plt.scatter(x_value,y,c=e)
plt.colorbar()

plt.xlabel('NumOfProducts')
plt.ylabel('Age')
plt.show()
```



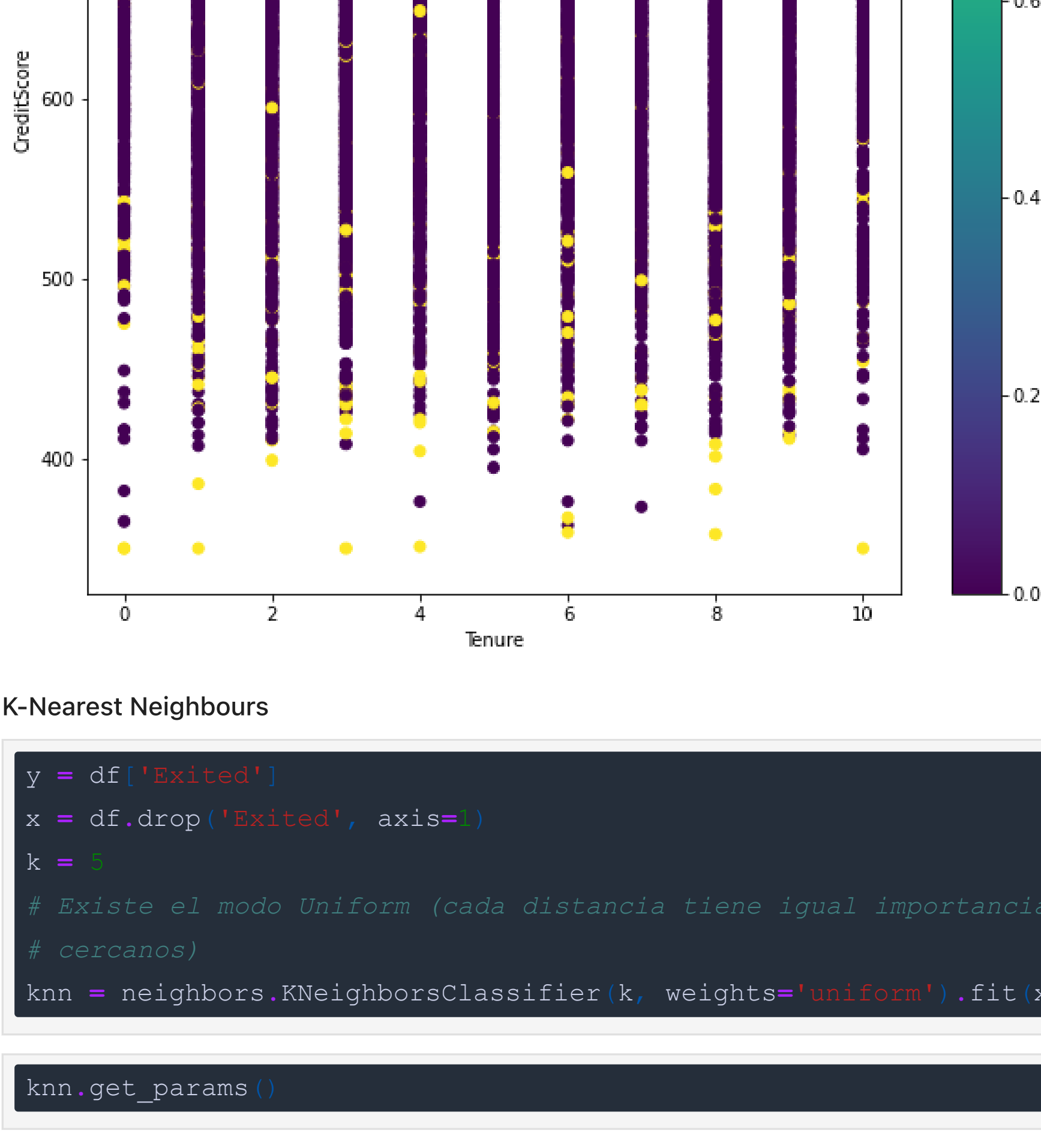
In [323…

```
#Veamos como influye el credit score y la edad en la decision de abandonar el producto
X = df['Age']
y = df['CreditScore']
e = rlog.predict(x)
plt.scatter(X,y,c=e)
plt.colorbar()
plt.xlabel('Age')
plt.ylabel('CreditScore')
plt.show()
```



In [324…

```
#Veamos como influye el credit score y la edad en la decision de abandonar el producto
x_value = df['Tenure']
y = df['CreditScore']
e = rlog.predict(x)
plt.scatter(x_value,y,c=e)
plt.colorbar()
plt.xlabel('Tenure')
plt.ylabel('CreditScore')
plt.show()
```



K-Nearest Neighbours

In [318…

```
y = df['Exited']
x = df.drop('Exited', axis=1)
k = 5
# Existe el modo Uniform (cada distancia tiene igual importancia) o Distance (mas peso a los mas
# cercanos)
knn = neighbors.KNeighborsClassifier(k, weights='uniform').fit(x, y)
```

In [319…

```
knn.get_params()
```

Out[319…

```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 5,
 'p': 2,
 'weights': 'uniform'}
```

In [320…

```
knn.score(x,y)
```

Out[320…

```
0.8163
```

In [325…

```
#Veamos como influye el credit score y la edad en la decision de abandonar el producto
X = df['Age']
y = df['CreditScore']
e = knn.predict(x)
plt.scatter(X,y,c=e)
plt.colorbar()
plt.xlabel('Age')
plt.ylabel('CreditScore')
plt.show()
```