Algoritmos de clasificación

En canvas podrás encontrar la base de datos "iris-data". Borra la variable "Id" de la base de datos, ya que esta no contiene información relevante. Explica los algoritmos que utilizan los métodos de clasificación: regresión logística, Bayes y análisis de discriminate. De ser el caso muestra las ecuaciones correspondientes.

Utiliza los algoritmos de clasificación antes mencionados para predecir el tipo de planta. Utiliza todas las variables de la base de datos como variables regresoras. Muestra la exactitud de cada modelo y su correspondiente matriz de confusión. ¿Qué modelo fue el méjor? ¿Por qué crees que se suceda esto?

```
import numpy as np
import pandas as pd
import sklearn.model_selection
import matplotlib.pyplot as plt

df = pd.read_csv('/content/drive/MyDrive/7mo Semestre/Colab Notebooks/DataSources/Iris.csv')
df.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
df = df.drop('Id', axis = 1)
df
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

```
df['Species'].unique()
```

```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

Seleccionamos nuestras variables regresoras x y la variable a predecir y

```
x = df.iloc[:len(df), [0,1,2,3]].values
y = df.iloc[:len(df), -1]
x
```

```
       [6.3, 2.9, 5.6, 1.8],
       [6.5, 3. , 5.8, 2.2],
       [7.6, 3. , 6.6, 2.1],
       [4.9, 2.5, 4.5, 1.7],
       [7.3, 2.9, 6.3, 1.8],
       [6.7, 2.5, 5.8, 1.8],
       [7.2, 3.6, 6.1, 2.5],
       [6.5, 3.2, 5.1, 2. ],
       [6.4, 2.7, 5.3, 1.9],
       [6.8, 3. , 5.5, 2.1],
       [5.7, 2.5, 5. , 2. ],
       [5.8, 2.8, 5.1, 2.4],
       [6.4, 3.2, 5.3, 2.3],
       [6.5, 3. , 5.5, 1.8],
       [7.7, 3.8, 6.7, 2.2],
       [7.7, 2.6, 6.9, 2.3],
       [6. , 2.2, 5. , 1.5],
       [6.9, 3.2, 5.7, 2.3],
       [5.6, 2.8, 4.9, 2. ],
       [7.7, 2.8, 6.7, 2. ],
       [6.3, 2.7, 4.9, 1.8],
       [6.7, 3.3, 5.7, 2.1],
       [7.2, 3.2, 6. , 1.8],
       [6.2, 2.8, 4.8, 1.8],
       [6.1, 3. , 4.9, 1.8],
       [6.4, 2.8, 5.6, 2.1],
       [7.2, 3. , 5.8, 1.6],
       [7.4, 2.8, 6.1, 1.9],
       [7.9, 3.8, 6.4, 2. ],
       [6.4, 2.8, 5.6, 2.2],
       [6.3, 2.8, 5.1, 1.5],
       [6.1, 2.6, 5.6, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 3.4, 5.6, 2.4],
       [6.4, 3.1, 5.5, 1.8],
       [6. , 3. , 4.8, 1.8],
       [6.9, 3.1, 5.4, 2.1],
       [6.7, 3.1, 5.6, 2.4],
       [6.9, 3.1, 5.1, 2.3],
       [5.8, 2.7, 5.1, 1.9],
       [6.8, 3.2, 5.9, 2.3],
       [6.7, 3.3, 5.7, 2.5],
       [6.7, 3. , 5.2, 2.3],
       [6.3, 2.5, 5. , 1.9],
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

```
y
```

```
0         Iris-setosa
1         Iris-setosa
2         Iris-setosa
3         Iris-setosa
4         Iris-setosa
             ...
145    Iris-virginica
146    Iris-virginica
147    Iris-virginica
148    Iris-virginica
149    Iris-virginica
Name: Species, Length: 150, dtype: object
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2,random_state=42)
x_train
```

```
       [5.1, 3.8, 1.6, 0.2],
       [6.9, 3.1, 5.4, 2.1],
       [5.9, 3. , 4.2, 1.5],
       [6.5, 3. , 5.2, 2. ],
       [5.7, 2.6, 3.5, 1. ],
       [5.2, 2.7, 3.9, 1.4],
       [6.1, 3. , 4.6, 1.4],
       [4.5, 2.3, 1.3, 0.3],
       [6.6, 2.9, 4.6, 1.3],
       [5.5, 2.6, 4.4, 1.2],
       [5.3, 3.7, 1.5, 0.2],
       [5.6, 3. , 4.1, 1.3],
       [7.3, 2.9, 6.3, 1.8],
       [6.7, 3.3, 5.7, 2.1],
       [5.1, 3.7, 1.5, 0.4],
       [4.9, 2.4, 3.3, 1. ],
       [6.7, 3.3, 5.7, 2.5],
       [7.2, 3. , 5.8, 1.6],
       [4.9, 3.1, 1.5, 0.1],
       [6.7, 3.1, 5.6, 2.4],
       [4.9, 3. , 1.4, 0.2],
       [6.9, 3.1, 4.9, 1.5],
       [7.4, 2.8, 6.1, 1.9],
       [6.3, 2.9, 5.6, 1.8],
       [5.7, 2.8, 4.1, 1.3],
       [6.5, 3. , 5.5, 1.8],
       [6.3, 2.3, 4.4, 1.3],
       [6.4, 2.9, 4.3, 1.3],
       [5.6, 2.8, 4.9, 2. ],
       [5.9, 3. , 5.1, 1.8],
       [5.4, 3.4, 1.7, 0.2],
       [6.1, 2.8, 4. , 1.3],
       [4.9, 2.5, 4.5, 1.7],
       [5.8, 4. , 1.2, 0.2],
       [5.8, 2.6, 4. , 1.2],
       [7.1, 3. , 5.9, 2.1]])
```

```
from sklearn.preprocessing import StandardScaler
sc_x = StandardScaler()
x_train = sc_x.fit_transform(x_train)
x_test = sc_x.fit_transform(x_test)
```

Regresión Logística

Procedimiento

```
from numpy.random.mtrand import logistic
from sklearn.linear_model import LogisticRegression
logistic = LogisticRegression()
logistic.fit(x_train,y_train)
log_y_predict = logistic.predict(x_test)
x_test
```

```
array([[ 0.14443512, -0.63451517,  0.45110832, -0.07943674],
       [-0.33701527,  2.00929805, -1.2060243 , -1.20827465],
       [ 2.07023667, -1.16327782,  1.66633891,  1.30025404],
       [ 0.02407252, -0.37013385,  0.34063282,  0.29684256],
       [ 0.98697329, -0.63451517,  0.50634608,  0.17141613],
       [-0.69810306,  0.95177276, -1.3164998 , -1.08284822],
       [-0.45737787, -0.37013385, -0.15650697,  0.04598969],
       [ 1.10733589,  0.15862879,  0.67205934,  1.30025404],
       [ 0.26479771, -2.22080311,  0.34063282,  0.29684256],
       [-0.21665267, -0.8988965 ,  0.00920629, -0.07943674],
       [ 0.6258855 ,  0.42301012,  0.67205934,  0.92397473],
       [-1.42027864, -0.10575253, -1.37173756, -1.45912752],
       [-0.57774046,  1.21615408, -1.42697531, -1.33370109],
       [-1.29991605,  0.15862879, -1.3164998 , -1.45912752],
       [-1.05919085,  2.00929805, -1.3164998 , -1.20827465],
       [ 0.38516031,  0.68739144,  0.45110832,  0.422269  ],
       [ 0.6258855 , -0.10575253,  1.05872362,  1.1748276 ],
       [-0.45737787, -1.42765914,  0.00920629, -0.20486318],
       [-0.33701527, -0.63451517,  0.34063282,  0.04598969],
       [ 0.50552291, -0.63451517,  0.94824811,  1.1748276 ],
       [-1.54064124,  0.42301012, -1.26126205, -1.33370109],
       [ 0.14443512, -0.10575253,  0.56158383,  0.67312186],
       [-1.17955345,  0.95177276, -1.26126205, -1.08284822],
       [ 0.50552291, -0.63451517,  0.94824811,  1.04940117],
       [ 2.31096186,  2.00929805,  1.39015014,  0.92397473],
       [ 0.8666107 , -0.10575253,  0.72729709,  1.30025404],
       [ 0.8666107 , -1.42765914,  1.05872362,  0.67312186],
       [ 0.98697329,  0.42301012,  1.11396137,  1.30025404],
       [-1.42027864, -0.10575253, -1.37173756, -1.20827465],
       [-1.42027864,  0.15862879, -1.26126205, -1.33370109]])
```

```
log_y_predict
```

```
array(['Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa'], dtype=object)
```

```
y_train
```

```
22         Iris-setosa
15         Iris-setosa
65     Iris-versicolor
11         Iris-setosa
42         Iris-setosa
            ...
71     Iris-versicolor
106     Iris-virginica
14         Iris-setosa
92     Iris-versicolor
102     Iris-virginica
Name: Species, Length: 120, dtype: object
```

```
x_train
```

```
array([[-1.47393679,  1.22037928, -1.5639872 , -1.30948358],
       [-0.13307079,  3.02001693, -1.27728011, -1.04292204],
       [ 1.08589829,  0.09560575,  0.38562104,  0.28988568],
       [-1.23014297,  0.77046987, -1.21993869, -1.30948358],
       [-1.7177306 ,  0.32056046, -1.39196294, -1.30948358],
       [ 0.59831066, -1.25412249,  0.72966956,  0.95628954],
       [ 0.72020757,  0.32056046,  0.44296246,  0.42316645],
       [-0.74255534,  0.99542457, -1.27728011, -1.30948358],
       [-0.98634915,  1.22037928, -1.33462153, -1.30948358],
       [-0.74255534,  2.34515281, -1.27728011, -1.44276436],
       [-0.01117388, -0.80421307,  0.78701097,  0.95628954],
       [ 0.23261993,  0.77046987,  0.44296246,  0.55644722],
       [ 1.08589829,  0.09560575,  0.5576453 ,  0.42316645],
       [-0.49876152,  1.8952434 , -1.39196294, -1.04292204],
       [-0.49876152,  1.44533399, -1.27728011, -1.30948358],
       [-0.37686461, -1.47907719, -0.01576889, -0.24323741],
       [ 0.59831066, -0.57925837,  0.78701097,  0.42316645],
       [ 0.72020757,  0.09560575,  1.01637665,  0.82300877],
       [ 0.96400139, -0.12934896,  0.38562104,  0.28988568],
       [ 1.69538284,  1.22037928,  1.36042516,  1.75597417],
       [-0.13307079, -0.35430366,  0.2709382 ,  0.15660491],
       [ 2.18297047, -0.12934896,  1.64713226,  1.22285108],
       [-0.2549677 , -0.12934896,  0.44296246,  0.42316645],
       [-0.86445224,  0.99542457, -1.33462153, -1.30948358],
       [ 2.30486738, -0.57925837,  1.70447368,  1.08957031],
       [-0.01117388, -0.80421307,  0.21359679, -0.24323741],
       [-0.74255534,  0.77046987, -1.33462153, -1.30948358],
       [-0.98634915,  0.99542457, -1.39196294, -1.17620281],
       [-0.86445224,  1.67028869, -1.04791443, -1.04292204],
       [-0.98634915, -2.37889602, -0.13045173, -0.24323741],
       [ 0.59831066, -0.80421307,  0.67232814,  0.82300877],
       [-1.23014297,  0.77046987, -1.04791443, -1.30948358],
       [-0.98634915, -0.12934896, -1.21993869, -1.30948358],
       [-0.86445224,  0.54551516, -1.16259727, -0.90964127],
       [-0.2549677 , -0.80421307,  0.2709382 ,  0.15660491],
       [-0.86445224,  0.77046987, -1.27728011, -1.30948358],
       [-0.13307079, -0.12934896,  0.2709382 ,  0.02332414],
       [ 2.30486738,  1.67028869,  1.70447368,  1.35613185],
       [-1.47393679,  0.32056046, -1.33462153, -1.30948358],
       [ 0.47641375, -0.35430366,  0.32827962,  0.15660491],
       [-0.13307079, -1.25412249,  0.72966956,  1.08957031],
       [-0.37686461,  2.57010752, -1.33462153, -1.30948358],
       [ 0.23261993, -0.12934896,  0.61498672,  0.82300877],
       [-0.01117388, -0.80421307,  0.78701097,  0.95628954],
       [ 0.23261993, -1.9289866 ,  0.15625537, -0.24323741],
       [-0.49876152, -0.12934896,  0.44296246,  0.42316645],
       [ 0.47641375,  0.77046987,  0.95903523,  1.48941263],
       [-0.37686461, -1.7040319 ,  0.15625537,  0.15660491],
       [-0.49876152,  1.8952434 , -1.16259727, -1.04292204],
       [-0.98634915, -1.7040319 , -0.24513457, -0.24323741],
       [ 0.72020757, -0.80421307,  0.90169381,  0.95628954],
       [-0.98634915,  0.54551516, -1.33462153, -1.30948358],
       [-0.98634915,  0.32056046, -1.44930436, -1.30948358],
       [-0.37686461, -1.47907719,  0.04157253, -0.10995664],
       [ 1.08589829, -0.12934896,  0.72966956,  0.68972799],
       [-1.10824606,  0.09560575, -1.27728011, -1.44276436],
       [-0.01117388, -0.57925837,  0.78701097,  1.6226934 ],
       [-0.98634915,  0.77046987, -1.27728011, -1.30948358],
```

Exactitud

```
from sklearn.metrics import accuracy_score
exactitud = accuracy_score(y_test, log_y_predict)
print(exactitud)
```

```
0.9666666666666667
```

```
print("Exactitud del modelo", logistic.score(x_test, y_test))
```

```
Exactitud del modelo 0.9666666666666667
```

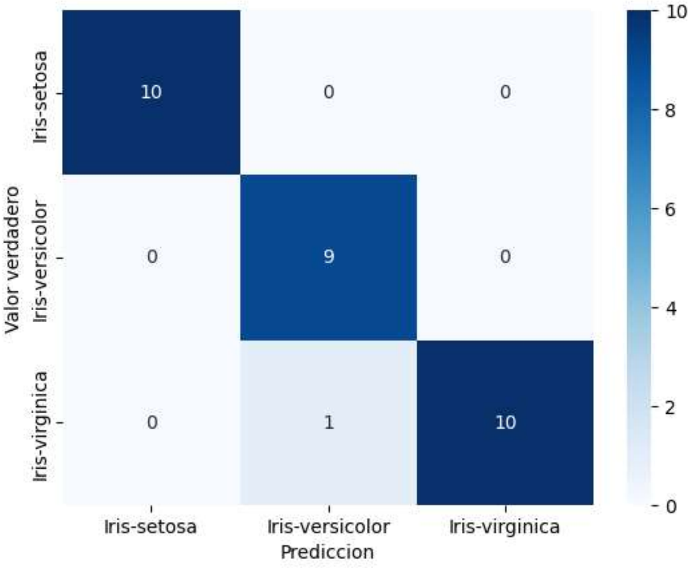
Matríz de Confusión

```
from sklearn.metrics import confusion_matrix
confusion = confusion_matrix(y_test, log_y_predict)
print(confusion)
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  1 10]]
```

```
import matplotlib.pyplot as plt
import seaborn as sns
sns.heatmap(confusion, annot = True, cmap = 'Blues')
class_names = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
tick_marks = [0.5, 1.5, 2.5]
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
plt.ylabel('Valor verdadero')
plt.xlabel('Prediccion')
```

```
Text(0.5, 23.52222222222222, 'Prediccion')
```



Teorema de Bayes

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train, y_train)
```

```
▾ GaussianNB
GaussianNB()
```

```
nb_y_predict = nb.predict(x_test)
print(nb_y_predict)
```

```
['Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-setosa'
 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
```

```
 'Iris-virginica' 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica'
 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica'
 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica'
 'Iris-setosa' 'Iris-setosa']
```

```
exactitud = accuracy_score(y_test, nb_y_predict)
print(exactitud)
```

```
0.9666666666666667
```

```
print("Exactitud del modelo", nb.score(x_test, y_test))
```

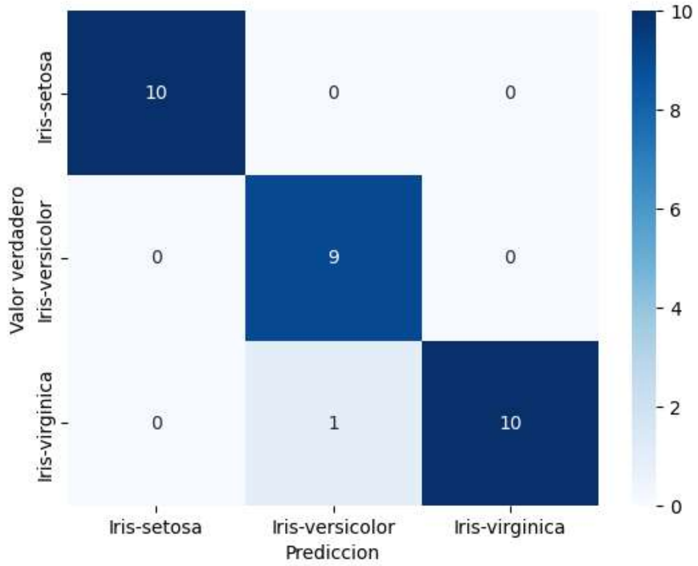
```
Exactitud del modelo 0.9666666666666667
```

```
confusion = confusion_matrix(y_test, nb_y_predict)
print(confusion)
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  1 10]]
```

```
sns.heatmap(confusion, annot = True, cmap = 'Blues')
class_names = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
tick_marks = [0.5, 1.5, 2.5]
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
plt.ylabel('Valor verdadero')
plt.xlabel('Prediccion')
```

```
Text(0.5, 23.52222222222222, 'Prediccion')
```



Análisis del Discriminante

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
adl_model = LinearDiscriminantAnalysis()
adl_model.fit(x_train, y_train)
```

```
▾ LinearDiscriminantAnalysis
LinearDiscriminantAnalysis()
```

```
adl_y_pred =adl_model.predict(x_test)
adl_y_pred
```

```
array(['Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa'], dtype='<U15')
```

```
exactitud = accuracy_score(y_test, adl_y_pred)
print(exactitud)
```

```
0.9666666666666667
```

```
print("Exactitud del modelo", adl_model.score(x_test, y_test))
```

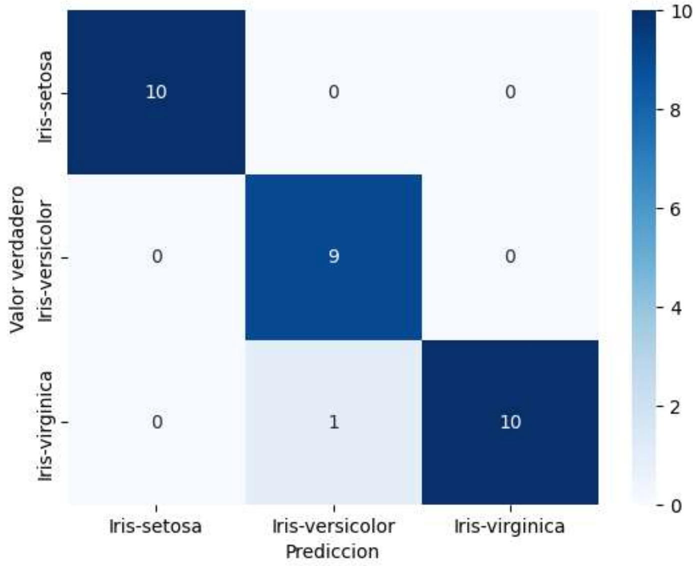
```
Exactitud del modelo 0.9666666666666667
```

```
confusion = confusion_matrix(y_test, adl_y_pred)
print(confusion)
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  1 10]]
```

```
sns.heatmap(confusion, annot = True, cmap = 'Blues')
class_names = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
tick_marks = [0.5, 1.5, 2.5]
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
plt.ylabel('Valor verdadero')
plt.xlabel('Prediccion')
```

```
Text(0.5, 23.52222222222222, 'Prediccion')
```



Conclusiones

Como podemos observar tenemos varios modelos, que practicamente nos dan la misma exactitud y la misma matriz de confusión. Por lo que podemos intuir que para este caso en especial, con estos datos, practicamente cualquiera de los 3 modelos, ya sea la Regresión Logística, con el Teorema de Bayes, o con el Analisis del discriminante, es un buen modelo y es confiable para hacer predicciones para nuestra variable categorica.

✓ 0s completed at 5:42 PM