Regrsión logística para predicciones bancarias

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv("../../../Machine Learning/python-ml-course-master/datasets/bank/bank.csv" , sep=";"
```

In [3]:
```
data.head()
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pd
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	may	fri	...	2	9
1	39	services	single	high.school	no	no	no	telephone	may	fri	...	4	9
2	25	services	married	high.school	no	yes	no	telephone	jun	wed	...	1	9
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	fri	...	3	9
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	mon	...	1	9

5 rows × 21 columns

In [4]:
```
data.shape
```

Out[4]:
```
(4119, 21)
```

In [5]:
```
data.columns.values
```

Out[5]:
```
array(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'], dtype=object)
```

In [6]:
```
data["y"] = (data["y"]=="yes").astype(int) #Transformo los yes a 1 y los no a 0
```

In [7]:
```
data.head()
```

Out[7]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pd
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	may	fri	...	2	9
1	39	services	single	high.school	no	no	no	telephone	may	fri	...	4	9
2	25	services	married	high.school	no	yes	no	telephone	jun	wed	...	1	9
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	fri	...	3	9
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	mon	...	1	9

5 rows × 21 columns

In [8]:
```
data["education"].unique() # Extraemos los únicos campos en la columna educación
```

Out[8]:
```
array(['basic.9y', 'high.school', 'university.degree',
       'professional.course', 'basic.6y', 'basic.4y', 'unknown',
       'illiterate'], dtype=object)
```

In [9]:
```
# Reformamos la base de datos para que quede más bonita la documentacion y que siga la misma sintaxis.
# A esto se le llama "Data cleaning", notar que las educaciones básica están aglomeradas en basic

data["education"] = np.where(data["education"]=="basic.4y", "Basic", data["education"])
data["education"] = np.where(data["education"]=="basic.6y", "Basic", data["education"])
data["education"] = np.where(data["education"]=="basic.9y", "Basic", data["education"])

data["education"] = np.where(data["education"]=="high.school", "High School", data["education"])
data["education"] = np.where(data["education"]=="professional.course", "Professional Course", data["edu
data["education"] = np.where(data["education"]=="university.degree", "University Degree", data["educati

data["education"] = np.where(data["education"]=="illiterate", "Illiterate", data["education"])
data["education"] = np.where(data["education"]=="unknown", "Unknown", data["education"])
```

In [10]:
```
data["education"].unique() #Cambiaron las columnas, son menos y más bonitas
```

Out[10]:
```
array(['Basic', 'High School', 'University Degree', 'Professional Course',
       'Unknown', 'Illiterate'], dtype=object)
```

In [11]:
```
data["y"].value_counts()
```

Out[11]:
```
0    3668
1     451
Name: y, dtype: int64
```

In [12]:
```
data.groupby("y").mean() #Agrupa los yes y no y muestra el promedio
```

Out[12]:

y	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employ
0	39.895311	219.40976	2.605780	982.763086	0.141767	0.240185	93.599677	-40.586723	3.802826	5175.5020
1	41.889135	560.78714	1.980044	778.722838	0.585366	-1.177384	93.417268	-39.786475	2.145448	5093.1186

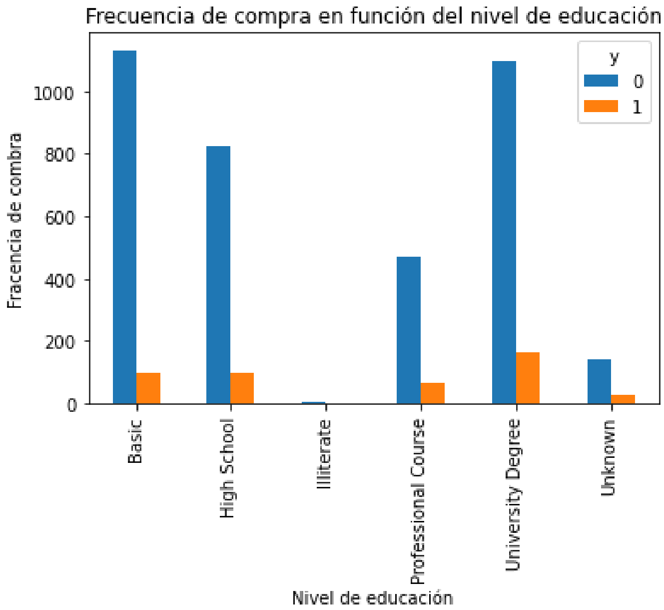
In [13]:
```
data.groupby("education").mean()
```

Out[13]:

education	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m
Basic	42.337124	253.898457	2.429732	978.815597	0.149472	0.237368	93.658600	-41.120552	3.775701
High School	38.097720	258.534202	2.630836	958.022801	0.206298	-0.002497	93.564314	-40.995765	3.511732
Illiterate	42.000000	146.000000	4.000000	999.000000	0.000000	-2.900000	92.201000	-31.400000	0.834000
Professional Course	40.207477	278.816822	2.512150	958.211215	0.194393	0.163925	93.599630	-40.127664	3.701426
University Degree	39.017405	247.707278	2.583070	947.900316	0.207278	-0.009731	93.499109	-39.830063	3.547132
Unknown	42.826347	267.281437	2.538922	939.700599	0.263473	-0.074251	93.637455	-39.487425	3.410174

In [14]:
```
%matplotlib inline
pd.crosstab(data.education, data.y).plot(kind="bar")
plt.title("Frecuencia de compra en función del nivel de educación")
plt.xlabel("Nivel de educación")
plt.ylabel("Fracencia de combra")
```

Out[14]:
```
Text(0, 0.5, 'Fracencia de combra')
```

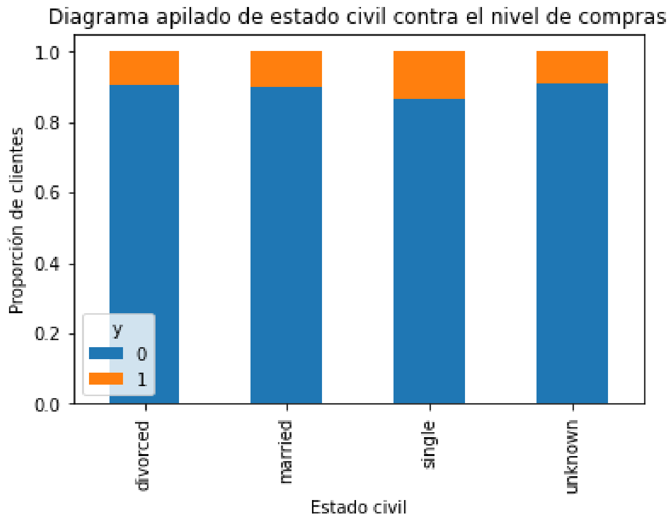


In [15]:

```
table = pd.crosstab(data.marital, data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind="bar", stacked = True)
#Table.sum por filas as type float para que pueda dividir, y luego el resultado por columnas
#Si no dividimos, cada uno de los estados adopta su escala y no sirve para comparar
plt.title("Diagrama apilado de estado civil contra el nivel de compras")
plt.xlabel("Estado civil")
plt.ylabel("Proporción de clientes")
```

Out[15]:

```
Text(0, 0.5, 'Proporción de clientes')
```

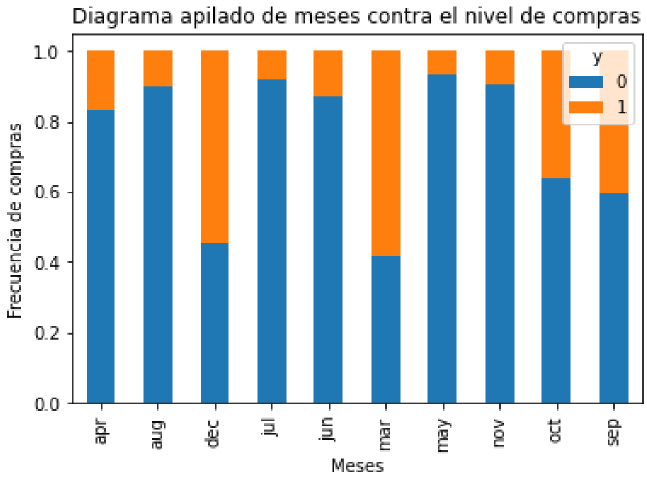


In [16]:

```
table = pd.crosstab(data.month, data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind="bar", stacked = True)
#Table.sum por filas as type float para que pueda dividir, y luego el resultado por columnas
#Si no dividimos, cada uno de los estados adopta su escala y no sirve para comparar
plt.title("Diagrama apilado de meses contra el nivel de compras")
plt.xlabel("Meses")
plt.ylabel("Frecuencia de compras")
```

Out[16]:

```
Text(0, 0.5, 'Frecuencia de compras')
```



In [17]:

```
table
```

Out[17]:

y	0	1
month		
apr	179	36
aug	572	64
dec	10	12
jul	652	59
jun	462	68
mar	20	28
may	1288	90
nov	403	43
oct	44	25
sep	38	26

In [18]:

```
table.div(table.sum(1).astype(float), axis=0)
```

Out[18]:

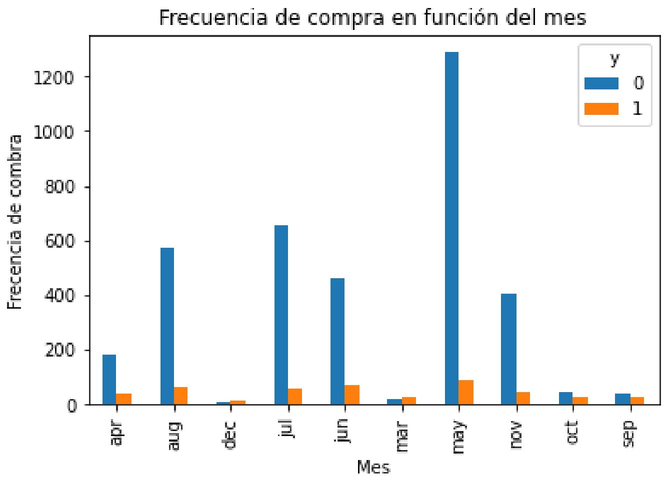
y	0	1
month		
apr	0.832558	0.167442
aug	0.899371	0.100629
dec	0.454545	0.545455
jul	0.917018	0.082982
jun	0.871698	0.128302
mar	0.416667	0.583333
may	0.934688	0.065312
nov	0.903587	0.096413
oct	0.637681	0.362319
sep	0.593750	0.406250

In [19]:

```
%matplotlib inline
pd.crosstab(data.month, data.y).plot(kind="bar")
plt.title("Frecuencia de compra en función del mes")
plt.xlabel("Mes")
```

```
plt.ylabel("Frecencia de combra")
#El mes del año parece ser muy importante, se obseva bastante en vacaciones.
```

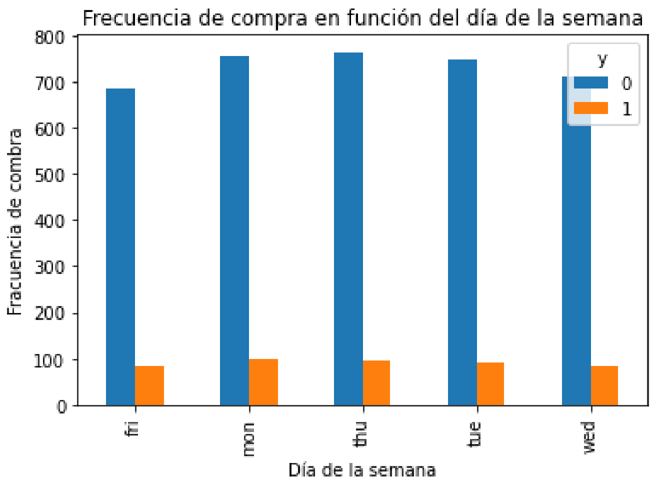
Out[19]: Text(0, 0.5, 'Frecencia de combra')



In [20]:

```
%matplotlib inline
pd.crosstab(data.day_of_week, data.y).plot(kind="bar")
plt.title("Frecuencia de compra en función del día de la semana")
plt.xlabel("Día de la semana")
plt.ylabel("Fracuencia de combra")
#El producto financiero respecto al día no da ninguna pista
```

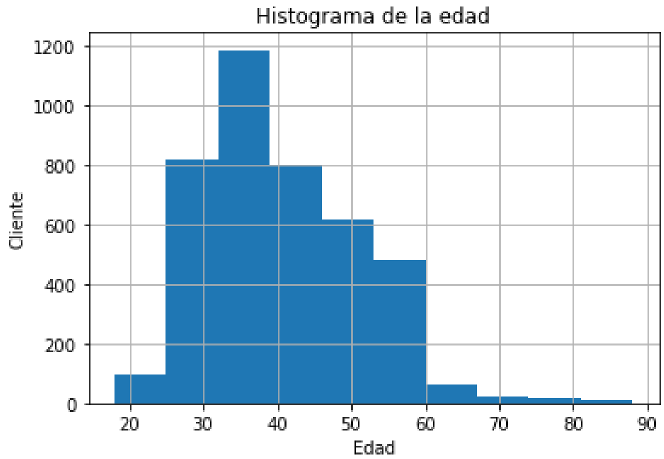
Out[20]: Text(0, 0.5, 'Fracuencia de combra')



In [21]:

```
%matplotlib inline
#pd.crosstab(data.age, data.y).plot(kind="bar")
data.age.hist()
plt.title("Histograma de la edad")
plt.xlabel("Edad")
plt.ylabel("Cliente")
#La mayoría de gente se encuentra entre los treinta y cuarenta años.
```

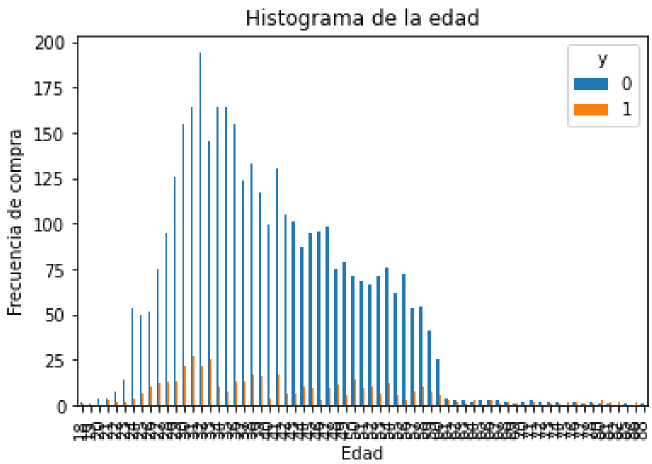
Out[21]: Text(0, 0.5, 'Cliente')



In [22]:

```
%matplotlib inline
pd.crosstab(data.age, data.y).plot(kind="bar")
plt.title("Histograma de la edad")
plt.xlabel("Edad")
plt.ylabel("Frecuencia de compra")
```

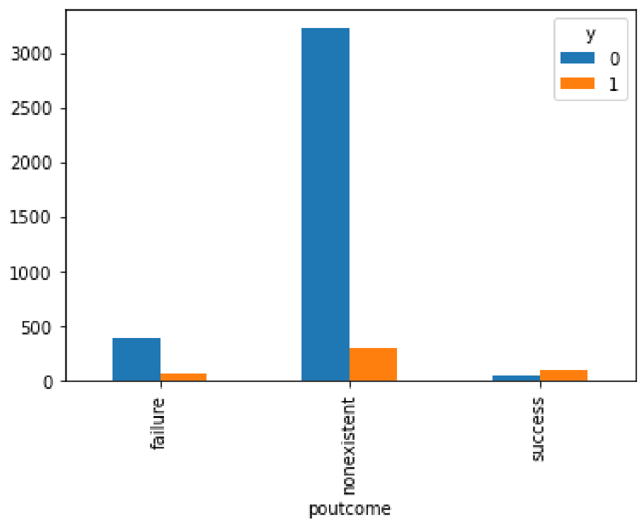
Out[22]: Text(0, 0.5, 'Frecuencia de compra')



In [23]:

```
pd.crosstab(data.poutcome, data.y).plot(kind="bar")
```

Out[23]: <AxesSubplot:xlabel='poutcome'>



Partiendo de un análisis exploratorio de los datos para averigüar cuál es el más releveante, se encunetran entre ellos la edad, el poutcome que se observa que las personas que dijeron que sí, seguramente repitan y el nivel de educación y quizás el mes.

Conversión de las variables categóricas a dummies

In [24]:
```
categories = ["job", "marital", "education", "default", "housing", "loan", "contact", "month", "day_of_w
for category in categories:
    cat_list = "cat" + "_" + category
    cat_dummies = pd.get_dummies(data[category], prefix=cat_list)
    data = data.join(cat_dummies)
```

In [25]:
```
data.columns.values
```

Out[25]:
```
array(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y', 'cat_job_admin.',
       'cat_job_blue-collar', 'cat_job_entrepreneur', 'cat_job_housemaid',
       'cat_job_management', 'cat_job_retired', 'cat_job_self-employed',
       'cat_job_services', 'cat_job_student', 'cat_job_technician',
       'cat_job_unemployed', 'cat_job_unknown', 'cat_marital_divorced',
       'cat_marital_married', 'cat_marital_single', 'cat_marital_unknown',
       'cat_education_Basic', 'cat_education_High School',
       'cat_education_Illiterate', 'cat_education_Professional Course',
       'cat_education_University Degree', 'cat_education_Unknown',
       'cat_default_no', 'cat_default_unknown', 'cat_default_yes',
       'cat_housing_no', 'cat_housing_unknown', 'cat_housing_yes',
       'cat_loan_no', 'cat_loan_unknown', 'cat_loan_yes',
       'cat_contact_cellular', 'cat_contact_telephone', 'cat_month_apr',
       'cat_month_aug', 'cat_month_dec', 'cat_month_jul', 'cat_month_jun',
       'cat_month_mar', 'cat_month_may', 'cat_month_nov', 'cat_month_oct',
       'cat_month_sep', 'cat_day_of_week_fri', 'cat_day_of_week_mon',
       'cat_day_of_week_thu', 'cat_day_of_week_tue',
       'cat_day_of_week_wed', 'cat_poutcome_failure',
       'cat_poutcome_nonexistent', 'cat_poutcome_success'], dtype=object)
```

In [26]:
```
data_vars = data.columns.values.tolist()
```

In [27]:
```
to_keep = (v for v in data_vars if v not in categories) # Extraigo las variables que fueron dumizadas
```

In [28]:
```
bank_data = data[to_keep]
bank_data.columns.values
```

Out[28]:
```
array(['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.var.rate',
       'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed', 'y',
       'cat_job_admin.', 'cat_job_blue-collar', 'cat_job_entrepreneur',
       'cat_job_housemaid', 'cat_job_management', 'cat_job_retired',
       'cat_job_self-employed', 'cat_job_services', 'cat_job_student',
       'cat_job_technician', 'cat_job_unemployed', 'cat_job_unknown',
       'cat_marital_divorced', 'cat_marital_married',
       'cat_marital_single', 'cat_marital_unknown', 'cat_education_Basic',
       'cat_education_High School', 'cat_education_Illiterate',
       'cat_education_Professional Course',
       'cat_education_University Degree', 'cat_education_Unknown',
       'cat_default_no', 'cat_default_unknown', 'cat_default_yes',
       'cat_housing_no', 'cat_housing_unknown', 'cat_housing_yes',
       'cat_loan_no', 'cat_loan_unknown', 'cat_loan_yes',
       'cat_contact_cellular', 'cat_contact_telephone', 'cat_month_apr',
       'cat_month_aug', 'cat_month_dec', 'cat_month_jul', 'cat_month_jun',
       'cat_month_mar', 'cat_month_may', 'cat_month_nov', 'cat_month_oct',
       'cat_month_sep', 'cat_day_of_week_fri', 'cat_day_of_week_mon',
       'cat_day_of_week_thu', 'cat_day_of_week_tue',
       'cat_day_of_week_wed', 'cat_poutcome_failure',
       'cat_poutcome_nonexistent', 'cat_poutcome_success'], dtype=object)
```

Selección de rasgos para el modelo

In [29]:
```
n = 10
```

In [30]:
```
from sklearn import datasets
```

```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
```

In [31]:
```
lr = LogisticRegression(solver='lbfgs', max_iter=5000)
```

In [32]:
```
bank_data_vars = bank_data.columns.values.tolist()
Y = ['y']
X = [v for v in bank_data if v not in Y]
```

In [33]:
```
rfe = RFE(lr, n_features_to_select=n)
rfe = rfe.fit(bank_data[X], bank_data[Y].values.ravel())
```

In [34]:
```
print(rfe.support_)
```

```
[False False False False  True False False False  True False False False
 False False False False  True False False False False False False False
 False False False False False False False False False False False False
 False False False False False False False  True False  True False False
  True  True  True False False False False False False False  True False
  True]
```

In [35]:
```
print(rfe.ranking_)
```

```
[40 49 25 51  1 22 29 28  1 47 27  6  2 42  3 44  1  8 39 35 21 11 23 37
 34 50 30 18  9 26 36 12 41 38 52 14 20 31 43 10 19 13  5  1  7  1 45  4
  1  1  1 16 24 46 32 48 33 15  1 17  1]
```

In [36]:
```
z = zip(bank_data_vars, rfe.support_, rfe.ranking_)
```

In [37]:
```
list(z)
```

Out[37]:
```
[('age', False, 40),
 ('duration', False, 49),
 ('campaign', False, 25),
 ('pdays', False, 51),
 ('previous', True, 1),
 ('emp.var.rate', False, 22),
 ('cons.price.idx', False, 29),
 ('cons.conf.idx', False, 28),
 ('euribor3m', True, 1),
 ('nr.employed', False, 47),
 ('y', False, 27),
 ('cat_job_admin.', False, 6),
 ('cat_job_blue-collar', False, 2),
 ('cat_job_entrepreneur', False, 42),
 ('cat_job_housemaid', False, 3),
 ('cat_job_management', False, 44),
 ('cat_job_retired', True, 1),
 ('cat_job_self-employed', False, 8),
 ('cat_job_services', False, 39),
 ('cat_job_student', False, 35),
 ('cat_job_technician', False, 21),
 ('cat_job_unemployed', False, 11),
 ('cat_job_unknown', False, 23),
 ('cat_marital_divorced', False, 37),
 ('cat_marital_married', False, 34),
 ('cat_marital_single', False, 50),
 ('cat_marital_unknown', False, 30),
 ('cat_education_Basic', False, 18),
 ('cat_education_High School', False, 9),
 ('cat_education_Illiterate', False, 26),
 ('cat_education_Professional Course', False, 36),
 ('cat_education_University Degree', False, 12),
 ('cat_education_Unknown', False, 41),
 ('cat_default_no', False, 38),
 ('cat_default_unknown', False, 52),
 ('cat_default_yes', False, 14),
```

```
 ('cat_housing_no', False, 20),
 ('cat_housing_unknown', False, 31),
 ('cat_housing_yes', False, 43),
 ('cat_loan_no', False, 10),
 ('cat_loan_unknown', False, 19),
 ('cat_loan_yes', False, 13),
 ('cat_contact_cellular', False, 5),
 ('cat_contact_telephone', True, 1),
 ('cat_month_apr', False, 7),
 ('cat_month_aug', True, 1),
 ('cat_month_dec', False, 45),
 ('cat_month_jul', False, 4),
 ('cat_month_jun', True, 1),
 ('cat_month_mar', True, 1),
 ('cat_month_may', True, 1),
 ('cat_month_nov', False, 16),
 ('cat_month_oct', False, 24),
 ('cat_month_sep', False, 46),
 ('cat_day_of_week_fri', False, 32),
 ('cat_day_of_week_mon', False, 48),
 ('cat_day_of_week_thu', False, 33),
 ('cat_day_of_week_tue', False, 15),
 ('cat_day_of_week_wed', True, 1),
 ('cat_poutcome_failure', False, 17),
 ('cat_poutcome_nonexistent', True, 1)]
```

In [38]:

```
cols_auto=[] #Detecto automáticamente las columnas que son trues.
j=0
for i in rfe.support_:
    if i == True:
        cols_auto.append(bank_data_vars[j])
    j+=1
cols_auto
```

Out[38]:

```
['previous',
 'euribor3m',
 'cat_job_retired',
 'cat_contact_telephone',
 'cat_month_aug',
 'cat_month_jun',
 'cat_month_mar',
 'cat_month_may',
 'cat_day_of_week_wed',
 'cat_poutcome_nonexistent']
```

In [39]:

```
X = bank_data[cols_auto]
Y = bank_data["y"]
```

Implementación del modelo en Python con statsmodels.api

In [40]:

```
import statsmodels.api as sm
```

In [41]:

```
logit_model = sm.Logit(Y,X)
```

In [42]:

```
result = logit_model.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.288150
         Iterations 7
```

In [43]:

```
result.summary2()
```

Out[43]:

Model:	Logit	Pseudo R-squared:	0.166
Dependent Variable:	y	AIC:	2393.7830
Date:	2022-04-05 10:48	BIC:	2457.0166
No. Observations:	4119	Log-Likelihood:	-1186.9

Df Model:	9	LL-Null:	-1422.9
Df Residuals:	4109	LLR p-value:	5.4907e-96
Converged:	1.0000	Scale:	1.0000
No. Iterations:	7.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
previous	0.1049	0.0696	1.5074	0.1317	-0.0315	0.2414
euribor3m	-0.5361	0.0349	-15.3524	0.0000	-0.6045	-0.4677
cat_job_retired	0.2227	0.2170	1.0266	0.3046	-0.2025	0.6480
cat_contact_telephone	-0.2189	0.1604	-1.3643	0.1725	-0.5334	0.0956
cat_month_aug	-0.0373	0.1660	-0.2247	0.8222	-0.3627	0.2880
cat_month_jun	0.4573	0.1778	2.5714	0.0101	0.1087	0.8058
cat_month_mar	1.0874	0.3117	3.4890	0.0005	0.4766	1.6983
cat_month_may	-1.0856	0.1340	-8.0991	0.0000	-1.3483	-0.8229
cat_day_of_week_wed	0.0651	0.1393	0.4675	0.6402	-0.2079	0.3382
cat_poutcome_nonexistent	-0.3325	0.1295	-2.5678	0.0102	-0.5863	-0.0787

Implementación del modelo en Python con scikit-learn

In [44]:
```
from sklearn import linear_model
```

In [45]:
```
logit_model = linear_model.LogisticRegression()
logit_model.fit(X,Y)
```

Out[45]:
```
LogisticRegression()
```

In [46]:
```
logit_model.score(X,Y)
```

Out[46]:
```
0.8956057295460063
```

In [47]:
```
1-Y.mean()
```

Out[47]:
```
0.8905074047098811
```

In [48]:
```
logit_model.intercept_
```

Out[48]:
```
array([-0.89307167])
```

In [49]:
```
pd.DataFrame(list(zip(X.columns, np.transpose(logit_model.coef_))))
```

Out[49]:

	0	1
0	previous	[0.5129138891231024]
1	euribor3m	[-0.4890961525383065]
2	cat_job_retired	[0.32914109457357243]
3	cat_contact_telephone	[-0.2581653215873337]
4	cat_month_aug	[0.017839720526623234]
5	cat_month_jun	[0.5198545025764586]
6	cat_month_mar	[1.1438401594864749]
7	cat_month_may	[-0.894992566050582]

	0	1
8	cat_day_of_week_wed	[0.11489898171487398]
9	cat_poutcome_nonexistent	[0.3543769540380019]

La ecuación que quedaría por lo tanto sería:

$$P = \frac{1}{1+e^{-(-0.89307167+0.5129138891231024*previous-0.4890961525383065*euribor3m+0.32914109457357243*cat_job_retired-0.2581653215873337*cat_contact_telephone+0.01783972052662323 4*cat_month_aug}}$$

Validación del modelo logístico

In [50]:
```
from sklearn.model_selection import train_test_split
```

In [51]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=0)
```

X_train y X_test van a ser las X para entrenamiento, que ocupará el 70% de la base de datos para entrenamiento y el 30% para testing, y la Y_train igualmente será el 70% entrenamiento y 30% prueba o testing

In [52]:
```
lm = linear_model.LogisticRegression()
lm.fit(X_train, Y_train)
```

Out[52]:
```
LogisticRegression()
```

In [53]:
```
probs = lm.predict_proba(X_test)
```

In [54]:
```
probs
```

Out[54]:
```
array([[0.93973147, 0.06026853],
       [0.88585785, 0.11414215],
       [0.93692207, 0.06307793],
       ...,
       [0.68264111, 0.31735889],
       [0.9840339 , 0.0159661 ],
       [0.56909263, 0.43090737]])
```

La primer columna es la probabilidad, cómo de seguro estoy de lo que estoy diciendo, la segunda nos dá la probabilidad del valor de salida. Por defecto, si es mayor de 0,5 es más probable que compre y si es menor que 0,5 es mayor la probabilidad de no compra.

In [55]:
```
prediction = lm.predict(X_test)
```

In [56]:
```
prediction
```

Out[56]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

Como vemos, prediction es un array, donde el threshold (límite) es 0,5 o sea, si es mayor que 0,5 lo clasifica como 1 y si es menor que 0,5 lo clasifica como 0. Esto lo hace automáticamente ya que el **THRESHOLD** está siempre seteado en 0,5 por defecto.

$$Y_p = \begin{cases} 0 & si\ p \leq 0.5 \\ 1 & si\ p > 0.5 \end{cases}$$

Si queremos cambiar este **THRESHOLD** a otro nivel, podemos decidir nosotros el nivel.

$$\varepsilon \in (0,1), Y_p = \begin{cases} 0 & si\ p \leq \varepsilon \\ 1 & si\ p > \varepsilon \end{cases}$$

En nuestro caso, si un cliente tiene más de un 10% de posibilidad de compra se le puede catalogar como éxito, ya que sólo el 10% por lo que vimos compra. Entonces se le asigna a la etiquteta probable comprador.

In [57]:
```
prob = probs[:,1]
```

In [58]:
```
prob_df = pd.DataFrame(prob)
threshold = 0.1
prob_df["Prediction"] = np.where(prob_df[0]>threshold, 1, 0)
prob_df.head(5)
```

Out[58]:

	0	Prediction
0	0.060269	0
1	0.114142	1
2	0.063078	0
3	0.050765	0
4	0.081756	0

In [59]:
```
pd.crosstab(prob_df.Prediction, columns = "count")
```

Out[59]:

col_0	count
Prediction	
0	852
1	384

In [60]:
```
390/len(prob_df)*100
```

Out[60]:
```
31.55339805825243
```

In [61]:
```
threshold = 0.15
prob_df["Prediction"] = np.where(prob_df[0]>threshold, 1, 0)
pd.crosstab(prob_df.Prediction, columns = "count")
```

Out[61]:

col_0	count
Prediction	
0	1020
1	216

In [62]:
```
threshold = 0.3
prediction1=np.where(prob_df[0]>threshold, 1, 0)
prediction1
```

Out[62]:
```
array([0, 0, 0, ..., 1, 0, 1])
```

In [63]:
```
225/len(prob_df)*100
```

Out[63]:
```
18.203883495145632
```

In [64]:
```
threshold = 0.12
prob_df["Prediction"] = np.where(prob_df[0]>threshold, 1, 0)
pd.crosstab(prob_df.Prediction, columns = "count")
```

Out[64]:

col_0	count
Prediction	
0	945
1	291

In [65]:
```
879/len(prob_df)*100
```
Out[65]:
```
71.11650485436894
```
In [66]:
```
from sklearn import metrics
```
In [67]:
```
metrics.accuracy_score(Y_test, prob_df["Prediction"]) #Con este framework nos dice cuántos casos le acer
```
Out[67]:
```
0.7872168284789643
```
La eficacia de este modelo, utilizando un conjunto de entremaniento y uno de testing subió del 89% a un 90%.

Validación cruzada en Python

In [68]:
```
from sklearn.model_selection import cross_val_score
```
In [69]:
```
scores = cross_val_score(linear_model.LogisticRegression(), X, Y, scoring="accuracy", cv=10)
```
In [70]:
```
scores
```
Out[70]:
```
array([0.90291262, 0.88834951, 0.90291262, 0.90048544, 0.89805825,
       0.8907767 , 0.88349515, 0.89563107, 0.89320388, 0.88807786])
```
In [71]:
```
scores.mean()
```
Out[71]:
```
0.8943903101599225
```
Con este método, cv es el número de iteraciones que tendrá el modelo, por lo que si sacamos el promedio obtendremos lo que se vió en la teoría, y ciertamente es un buen valor. Con los resultados vistos, podemos decir que es un buen método.

LOOCV

In [72]:
```
from sklearn.model_selection import LeaveOneOut
```
In [73]:
```
loo = LeaveOneOut()
loo.get_n_splits(X)
```
Out[73]:
```
4119
```
In [74]:
```
print(loo)
```
```
LeaveOneOut()
```
In [75]:
```
scores = cross_val_score(linear_model.LogisticRegression(),X,Y, scoring='accuracy', cv=loo, n_jobs=-1)
```
In [76]:
```
len(scores)
```
Out[76]:
```
4119
```
In [77]:
```
scores
```
Out[77]:
```
array([1., 1., 1., ..., 1., 1., 1.])
```
In [78]:
```
scores.mean()
```

Out[78]: 0.8956057295460063

Como hemos visto, con el método del LOOCV (Leave One Out Cross Validation), el equipo tuvo que realizar 4119 iteraciones para que el resultado mejore de 0.894 a 0.895, lo cual es mucho sacrificio computacional para la poca mejora lograda.

Matrices de Confusión y curvas ROC

In [79]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=0)
```

In [225…
```
lm = linear_model.LogisticRegression()
lm.fit(X_train, Y_train)
```

Out[225… LogisticRegression()

In [226…
```
probs = lm.predict_proba(X_test)
```

In [227…
```
prob = probs[:,1]
prob_df=pd.DataFrame(prob)
threshold = 0.1
prob_df["Prediction"] = np.where(prob_df[0]>threshold, 1, 0)
prob_df["Actual"] = list(Y_test) # Con esto Y_test perderá los identificadores antiguos y aparecerán los
prob_df
```

Out[227…

	0	Prediction	Actual
0	0.060269	0	0
1	0.114142	1	0
2	0.063078	0	0
3	0.050765	0	0
4	0.081756	0	0
...	...	...	...
1231	0.050765	0	0
1232	0.038563	0	0
1233	0.317359	1	0
1234	0.015966	0	0
1235	0.430907	1	1

1236 rows × 3 columns

In [228…
```
confusion_matrix = pd.crosstab(prob_df.Prediction, prob_df.Actual)
```

In [229…
```
confusion_matrix
```

Out[229…

Actual	0	1
Prediction		
0	812	40
1	302	82

In [230…
```
TN = confusion_matrix[0][0]
TP = confusion_matrix[1][1]
```

```
FN = confusion_matrix[1][0]
FP = confusion_matrix[0][1]
```

In [231…

```
FN
```

Out[231…

```
40
```

In [232…

```
sens = TP/(TP+FN)
sens
```

Out[232…

```
0.6721311475409836
```

In [233…

```
espc_1 = 1-TN/(TN+FP)
espc_1
```

Out[233…

```
0.2710951526032316
```

In [480…

```
thresholds = [0.04, 0.05, 0.07, 0.10, 0.12, 0.15, 0.18, 0.20, 0.25, 0.30, 0.35, 0.40, 0.50]
sensitivities =[]
especifities_1 = []
especifities_1.append(1)
sensitivities.append(1)
for i in thresholds:
    prob_df["Prediction"] = np.where(prob_df[0]>i, 1, 0)
    prob_df["Actual"] = list(Y_test) # Con esto Y_test perderá los identificadores antiguos y aparecerán
    confusion_matrix = pd.crosstab(prob_df.Prediction, prob_df.Actual)
    TN = confusion_matrix[0][0]
    TP = confusion_matrix[1][1]
    FN = confusion_matrix[1][0]
    FP = confusion_matrix[0][1]
    sens = TP/(TP+FN)
    sensitivities.append(sens)
    espc_1 = 1-TN/(TN+FP)
    especifities_1.append(espc_1)
sensitivities.append(0)
especifities_1.append(0)
```

In [481…

```
sensitivities
```

Out[481…

```
[1,
 0.9426229508196722,
 0.9262295081967213,
 0.7131147540983607,
 0.6721311475409836,
 0.6147540983606558,
 0.5409836065573771,
 0.5163934426229508,
 0.5,
 0.45081967213114754,
 0.36065573770491804,
 0.2786885245901639,
 0.14754098360655737,
 0.11475409836065574,
 0]
```

In [482…

```
especifities_1
```

Out[482…

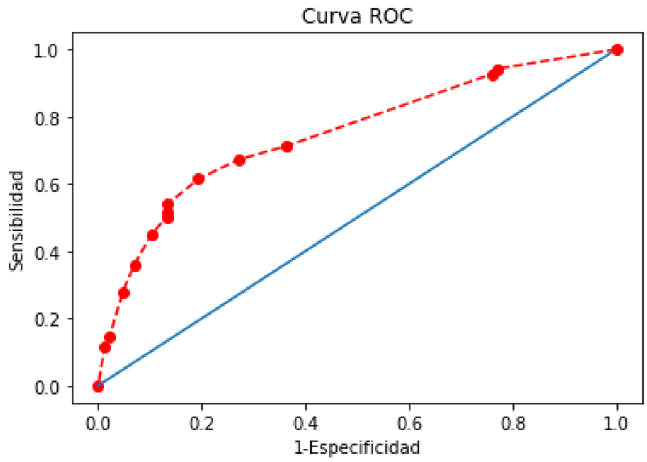
```
[1,
 0.7710951526032316,
 0.7594254937163375,
 0.36445242369838415,
 0.2710951526032316,
 0.19389587073608616,
 0.13464991023339323,
 0.13464991023339323,
 0.13195691202872528,
 0.10323159784560143,
```

```
 0.0700179533213644,
 0.047576301615798955,
 0.022441651705565557,
 0.012567324955116699,
 0]
```

In [297…
```
import matplotlib.pyplot as plt
```

In [298…
```
%matplotlib inline
plt.plot(especifities_1, sensitivities, marker = "o", linestyle = "--", color="r")
x=[i*0.01 for i in range(0,100)]
y=[i*0.01 for i in range(0,100)]
plt.plot(x,y)
plt.xlabel("1-Especificidad")
plt.ylabel("Sensibilidad")
plt.title("Curva ROC")
```

Out[298…
```
Text(0.5, 1.0, 'Curva ROC')
```

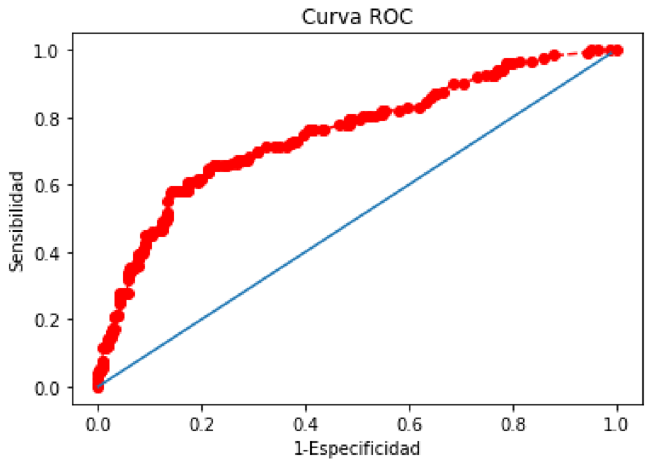


In [122…
```
from sklearn import metrics
from ggplot import *
```

In [124…
```
espec_1, sensit, _ = metrics.roc_curve(Y_test, prob) # División en thresholds de 0.01
```

In [185…
```
%matplotlib inline
plt.plot(espec_1, sensit, marker = "o", linestyle = "--", color="r")
x=[i*0.01 for i in range(0,100)]
y=[i*0.01 for i in range(0,100)]
plt.plot(x,y)
plt.xlabel("1-Especificidad")
plt.ylabel("Sensibilidad")
plt.title("Curva ROC")
```

Out[185…
```
Text(0.5, 1.0, 'Curva ROC')
```



In [125…

```
espec_1
```

Out[125…

```
array([0.        , 0.        , 0.        , 0.        , 0.00179533,
       0.00179533, 0.00359066, 0.005386  , 0.00628366, 0.00628366,
       0.00718133, 0.00718133, 0.00807899, 0.00807899, 0.00897666,
       0.00897666, 0.01615799, 0.01615799, 0.01795332, 0.01885099,
       0.01885099, 0.01974865, 0.01974865, 0.02154399, 0.02154399,
       0.02423698, 0.02423698, 0.02603232, 0.02603232, 0.02782765,
       0.02782765, 0.02872531, 0.03052065, 0.03052065, 0.03231598,
       0.03590664, 0.03680431, 0.03859964, 0.04039497, 0.04039497,
       0.04129264, 0.04129264, 0.04219031, 0.04937163, 0.05206463,
       0.05655296, 0.05655296, 0.05745063, 0.05834829, 0.05834829,
       0.06104129, 0.06104129, 0.06193896, 0.06193896, 0.06732496,
       0.06912029, 0.07001795, 0.07001795, 0.07091562, 0.07271095,
       0.07360862, 0.07630162, 0.07630162, 0.07719928, 0.07899461,
       0.07899461, 0.08258528, 0.08258528, 0.08348294, 0.08797127,
       0.08797127, 0.08976661, 0.08976661, 0.09156194, 0.09156194,
       0.09335727, 0.0951526 , 0.0978456 , 0.1032316 , 0.10412926,
       0.11759425, 0.12208259, 0.12208259, 0.12477558, 0.12477558,
       0.12836625, 0.13016158, 0.13016158, 0.13195691, 0.13285458,
       0.13375224, 0.13375224, 0.13464991, 0.13464991, 0.14003591,
       0.14183124, 0.1427289 , 0.14631957, 0.14721724, 0.1508079 ,
       0.15170557, 0.15709156, 0.16157989, 0.16876122, 0.17145422,
       0.17145422, 0.17235189, 0.17953321, 0.19389587, 0.19389587,
       0.19928187, 0.21184919, 0.21274686, 0.21364452, 0.22262118,
       0.22531418, 0.23070018, 0.24057451, 0.2459605 , 0.24685817,
       0.25763016, 0.26929982, 0.26929982, 0.27199282, 0.27468582,
       0.27558348, 0.27827648, 0.28096948, 0.28545781, 0.28725314,
       0.29174147, 0.3070018 , 0.30789946, 0.32315978, 0.34111311,
       0.35098743, 0.36445242, 0.36894075, 0.37163375, 0.37612208,
       0.38150808, 0.39497307, 0.40664273, 0.40843806, 0.41113106,
       0.41292639, 0.41741472, 0.43267504, 0.43716338, 0.46588869,
       0.47935368, 0.48294434, 0.48384201, 0.48384201, 0.48473968,
       0.48743268, 0.49102334, 0.505386  , 0.51256732, 0.51974865,
       0.52423698, 0.53321364, 0.54667864, 0.5475763 , 0.5475763 ,
       0.5529623 , 0.58168761, 0.59694794, 0.61849192, 0.63195691,
       0.64183124, 0.6481149 , 0.6535009 , 0.66696589, 0.68402154,
       0.7064632 , 0.73249551, 0.74775583, 0.75942549, 0.76122083,
       0.76301616, 0.76570916, 0.77109515, 0.77109515, 0.77289048,
       0.77827648, 0.78096948, 0.78725314, 0.78904847, 0.79174147,
       0.79533214, 0.8016158 , 0.81418312, 0.83572711, 0.85906643,
       0.88061041, 0.94344704, 0.95062837, 0.96319569, 0.98743268,
       1.        ])
```

In [126…

```
sensit
```

Out[126…

```
array([0.        , 0.00819672, 0.02459016, 0.04098361, 0.04098361,
       0.04918033, 0.04918033, 0.04918033, 0.04918033, 0.05737705,
       0.05737705, 0.06557377, 0.06557377, 0.07377049, 0.07377049,
       0.1147541 , 0.1147541 , 0.12295082, 0.12295082, 0.12295082,
       0.13114754, 0.13114754, 0.13934426, 0.13934426, 0.14754098,
       0.14754098, 0.1557377 , 0.1557377 , 0.16393443, 0.16393443,
       0.17213115, 0.17213115, 0.17213115, 0.20491803, 0.20491803,
       0.21311475, 0.21311475, 0.21311475, 0.24590164, 0.25409836,
       0.26229508, 0.2704918 , 0.27868852, 0.27868852, 0.27868852,
       0.27868852, 0.31967213, 0.32786885, 0.32786885, 0.33606557,
       0.33606557, 0.3442623 , 0.3442623 , 0.35245902, 0.35245902,
       0.35245902, 0.35245902, 0.36065574, 0.36065574, 0.36065574,
       0.36065574, 0.36065574, 0.37704918, 0.3852459 , 0.3852459 ,
       0.39344262, 0.39344262, 0.40163934, 0.40163934, 0.40163934,
       0.40983607, 0.41803279, 0.42622951, 0.42622951, 0.45081967,
       0.45081967, 0.45081967, 0.45081967, 0.45081967, 0.45901639,
       0.46721311, 0.46721311, 0.47540984, 0.47540984, 0.49180328,
       0.49180328, 0.49180328, 0.5       , 0.5       , 0.50819672,
       0.50819672, 0.51639344, 0.51639344, 0.54918033, 0.57377049,
       0.58196721, 0.58196721, 0.58196721, 0.58196721, 0.58196721,
       0.58196721, 0.58196721, 0.58196721, 0.58196721, 0.58196721,
       0.59836066, 0.60655738, 0.60655738, 0.60655738, 0.6147541 ,
       0.6147541 , 0.63934426, 0.63934426, 0.64754098, 0.6557377 ,
       0.6557377 , 0.6557377 , 0.6557377 , 0.6557377 , 0.6557377 ,
       0.66393443, 0.66393443, 0.67213115, 0.67213115, 0.67213115,
       0.67213115, 0.67213115, 0.67213115, 0.67213115, 0.67213115,
       0.68032787, 0.69672131, 0.69672131, 0.71311475, 0.71311475,
```

```
       0.71311475, 0.71311475, 0.72131148, 0.72131148, 0.7295082 ,
       0.7295082 , 0.74590164, 0.76229508, 0.76229508, 0.76229508,
       0.76229508, 0.76229508, 0.76229508, 0.76229508, 0.77868852,
       0.77868852, 0.77868852, 0.77868852, 0.79508197, 0.79508197,
       0.79508197, 0.79508197, 0.79508197, 0.80327869, 0.80327869,
       0.80327869, 0.80327869, 0.81147541, 0.81147541, 0.81967213,
       0.81967213, 0.81967213, 0.82786885, 0.82786885, 0.8442623 ,
       0.86065574, 0.86885246, 0.86885246, 0.87704918, 0.90163934,
       0.90163934, 0.91803279, 0.92622951, 0.92622951, 0.92622951,
       0.92622951, 0.92622951, 0.93442623, 0.94262295, 0.94262295,
       0.94262295, 0.94262295, 0.95901639, 0.95901639, 0.95901639,
       0.95901639, 0.95901639, 0.96721311, 0.96721311, 0.97540984,
       0.98360656, 0.99180328, 1.        , 1.        , 1.        ,
       1.        ])
```

In [153…

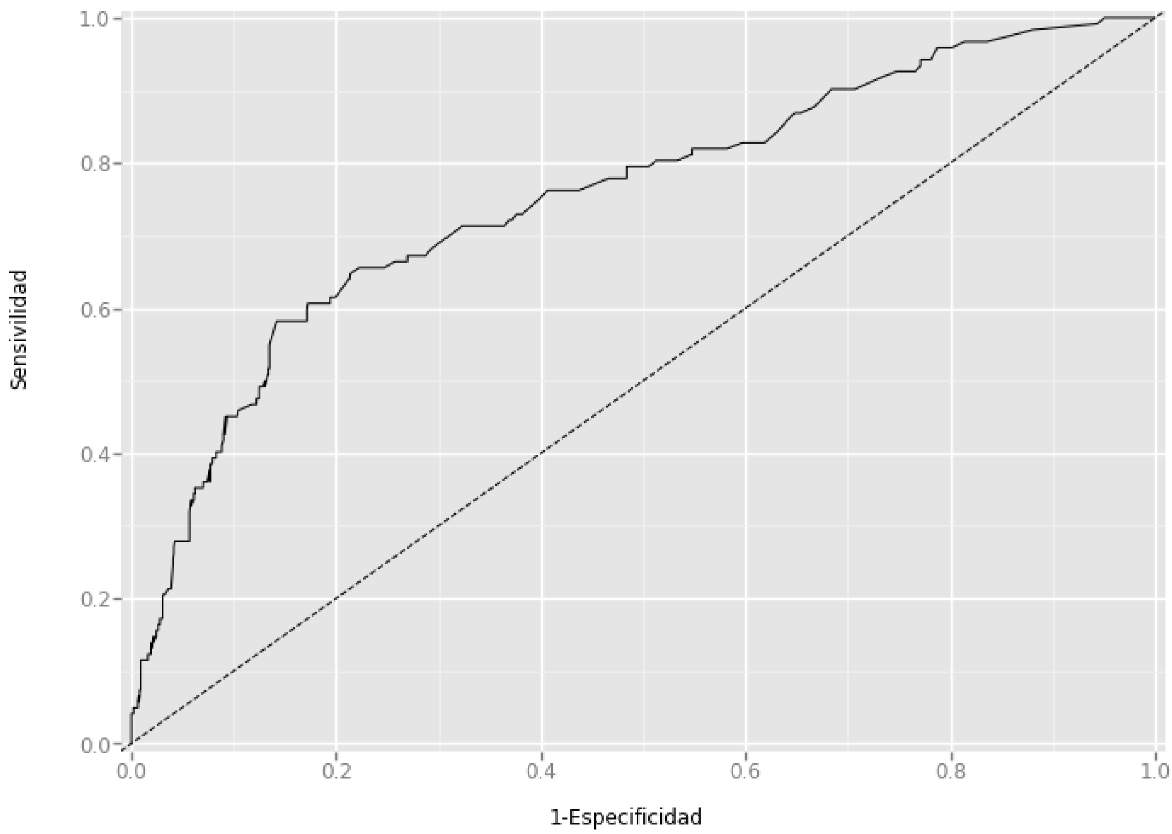
```
df = pd.DataFrame({
    "1-Especificidad": espec_1,
    "Sensivilidad": sensit
})
df.head()
```

Out[153…

	1-Especificidad	Sensivilidad
0	0.000000	0.000000
1	0.000000	0.008197
2	0.000000	0.024590
3	0.000000	0.040984
4	0.001795	0.040984

In [154…

```
ggplot(df, aes(x="1-Especificidad", y="Sensivilidad"))+geom_line()+ geom_abline(linetype="dashed")+xlim
```



Out[154…

```
<ggplot: (157327075642)>
```

In [155…

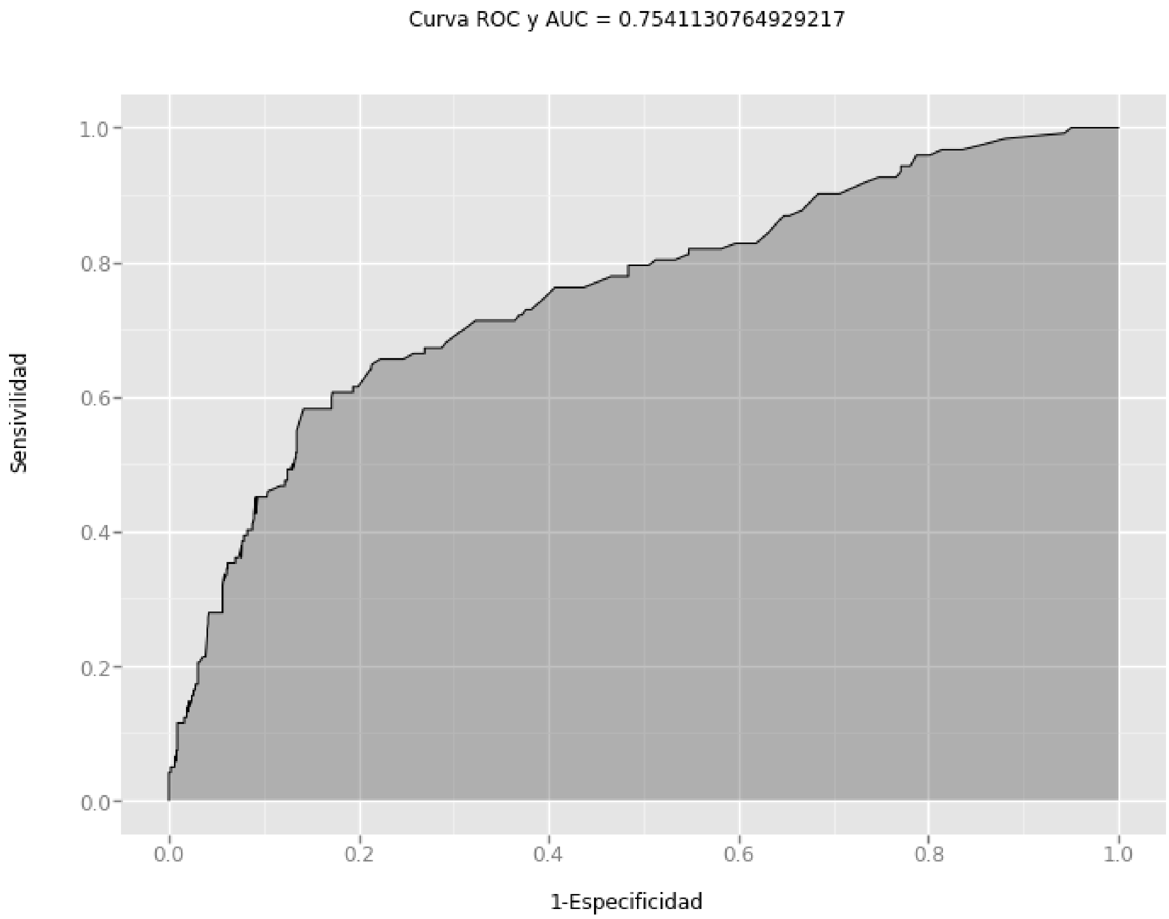
```
auc = metrics.auc(espec_1, sensit)
auc # Area under curve, un valor de 0.75 es bastante bueno
```

Out[155…

```
0.7541130764929217
```

In [156…

```
ggplot(df, aes(x="1-Especificidad", y="Sensivilidad")) + geom_area(alpha=0.3) + geom_line(aes(y="Sensivi
```



Out[156…

```
<ggplot: (157327099429)>
```