Ayudantía - Comparación Estadistica Clasica vs Machine Learling

Wilson Mejías Caballero

Problema 1: Ventas y medios

Introducción

El conjunto de datos contiene información sobre el dinero gastado en publicidad y sus ventas generadas. El dinero se gastó en anuncios de televisión, radio y periódicos. El objetivo es utilizar la regresión lineal para comprender cómo el gasto en publicidad impacta las ventas.

In [1]:
```
#Importar librerias

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import missingno

#Configuración de graficos
plt.style.use('ggplot')

#Ignorar Avisos
import warnings
warnings.filterwarnings("ignore")

#Regresión clasica
from statsmodels.formula.api import ols
import statsmodels.api as sm
import statsmodels.formula.api as smf


#RegresiónLineal Machine
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
```

In [2]:
```
# Carga de data

df = pd.read_csv("Advertising.csv")
```

In [3]:
```
# Revisión de DF
df.head()
```

Out[3]:

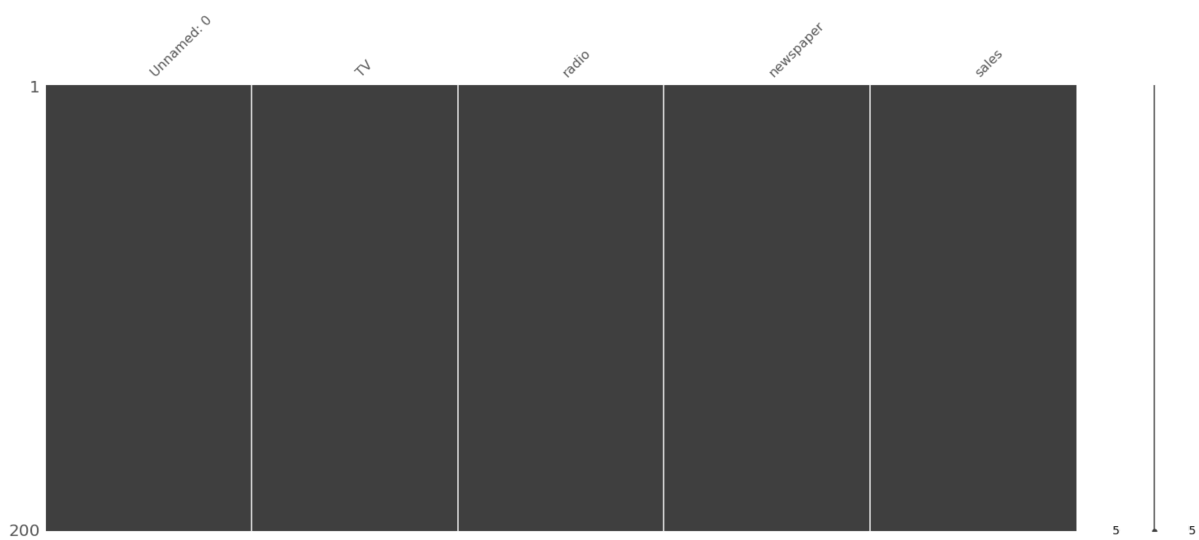
	Unnamed: 0	TV	radio	newspaper	sales
0	1	230.1	37.8	69.2	22.1
1	2	44.5	39.3	45.1	10.4
2	3	17.2	45.9	69.3	9.3
3	4	151.5	41.3	58.5	18.5
4	5	180.8	10.8	58.4	12.9

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
Unnamed: 0    200 non-null int64
TV            200 non-null float64
radio         200 non-null float64
newspaper     200 non-null float64
sales         200 non-null float64
dtypes: float64(4), int64(1)
memory usage: 7.9 KB
```

In [5]:
```
missingno.matrix(df)
```

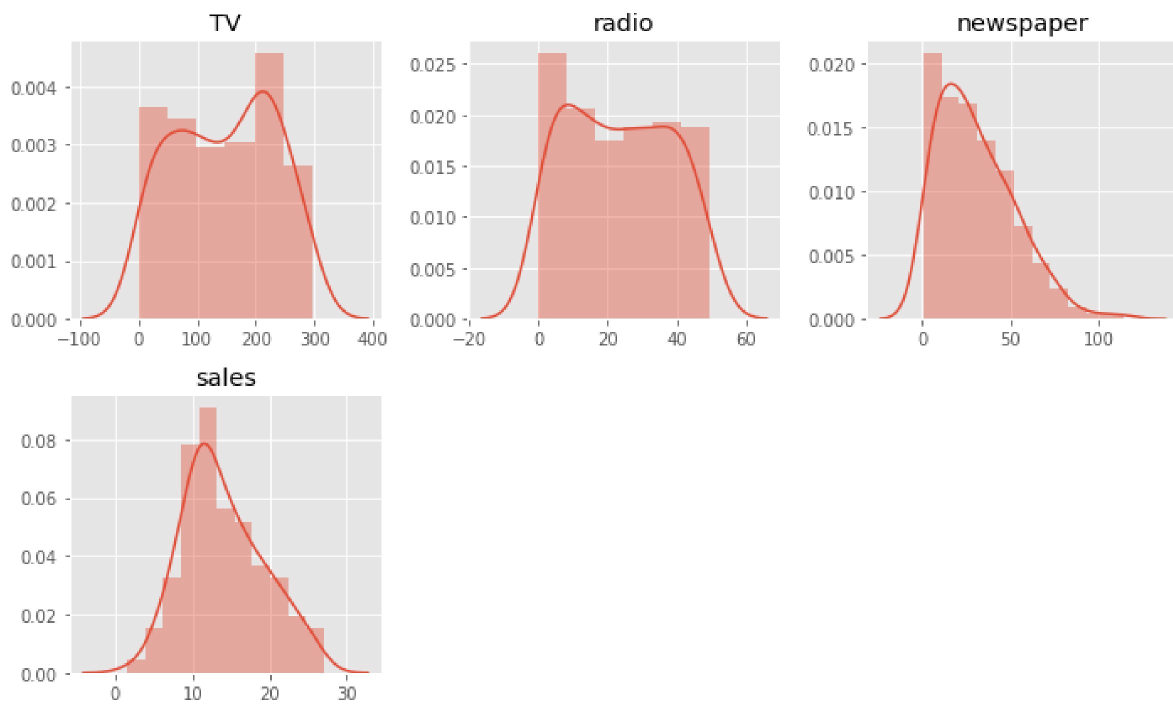
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x22e50295438>



In [6]:
```
#Eliminar columna

df=df.drop(['Unnamed: 0'], axis=1)
```

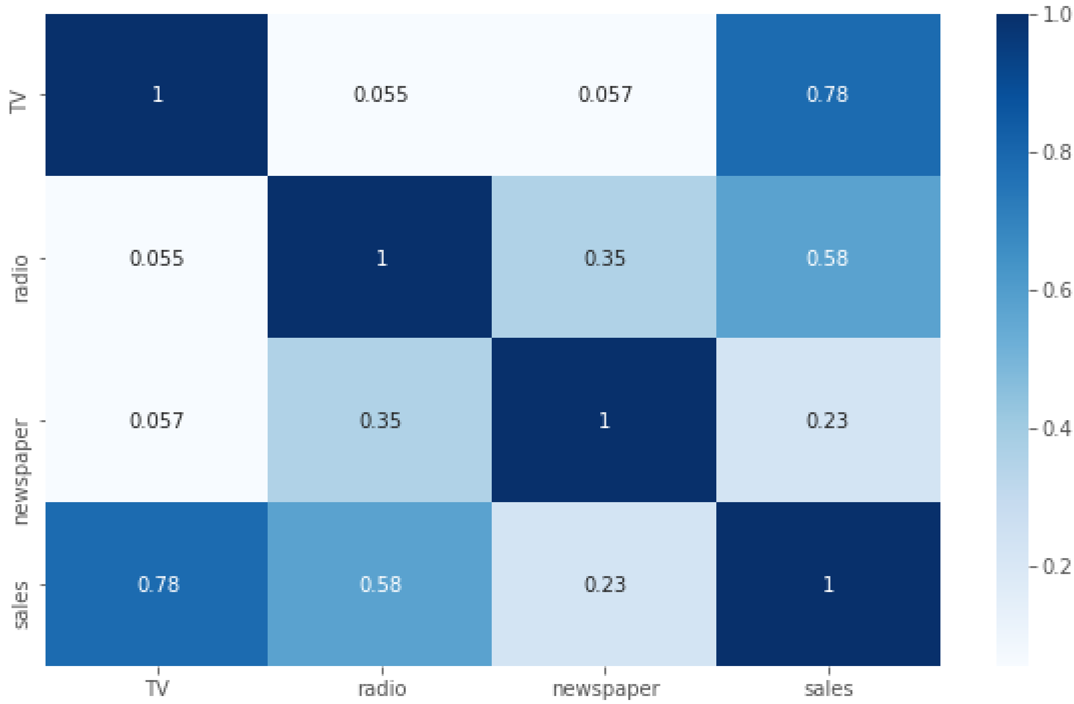
In [7]:
```
#Función para graficar variables en un Data Frame

def explor (df):
    for n, i in enumerate(df):
        plt.subplot((len(list(df.columns))/3)+1,3,n+1)
        if df[i].dtypes ==float:
            sns.distplot(df[i])
            plt.title(i)
            plt.xlabel("")
        elif df[i].dtypes =="object":
            sns.countplot(df[i])
            plt.title(i)
            plt.xlabel("")
        else:
            sns.distplot(df[i],kde=False)
            plt.title(i)
            plt.xlabel("")
    plt.tight_layout()
```

In [8]:
```
#Graficar Variables

plt.rcParams['figure.figsize'] = (10, 6)
explor(df)
```



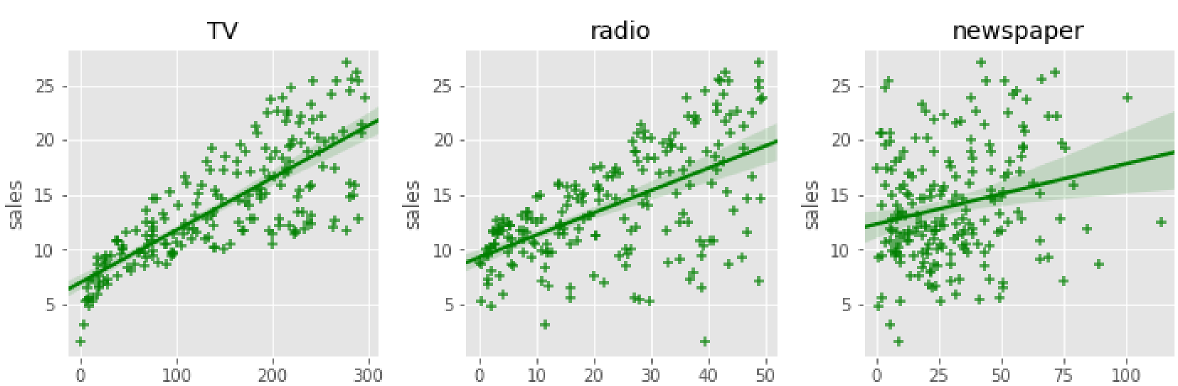
In [9]:
```
#Nivel de Asoción entre variables

sns.heatmap(df.corr( method='pearson'), annot=True, cmap="Blues")
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x22e50573240>

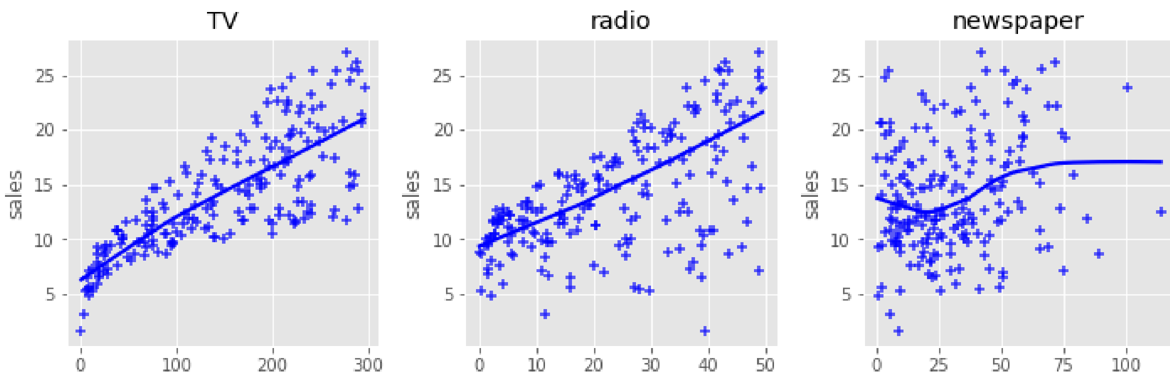


In [10]:
```
#Función regresión

def multireg(y, df,no_lineal=False):
    df_temp=df.drop(y, axis=1)

    if no_lineal=="logistico":
        for n, i in enumerate(df_temp):
            plt.subplot((len(list(df_temp.columns))/3)+1,3,n+1)
            sns.regplot(y=df[y] ,x= df_temp[i],logistic=True,marker="+")
            plt.title(i)
            plt.xlabel("")
    elif no_lineal=="logaritmo":
        for n, i in enumerate(df_temp):
            plt.subplot((len(list(df_temp.columns))/3)+1,3,n+1)
            sns.regplot(y=df[y] ,x= df_temp[i],logx=True ,marker="+")
            plt.title(i)
            plt.xlabel("")

    elif no_lineal=="lowess":
        for n, i in enumerate(df_temp):
            plt.subplot((len(list(df_temp.columns))/3)+1,3,n+1)
            sns.regplot(y=df[y] ,x= df_temp[i],lowess=True,marker="+", color=
"blue")
            plt.title(i)
            plt.xlabel("")

    else :
        for n, i in enumerate(df_temp):
            plt.subplot((len(list(df_temp.columns))/3)+1,3,n+1)
            sns.regplot(y=df[y] ,x= df_temp[i],marker="+",color="green")
            plt.title(i)
            plt.xlabel("")

    plt.tight_layout()
```

In [11]:
```
plt.rcParams['figure.figsize'] = (10, 6)
multireg("sales", df)
```



In [12]:
```
plt.rcParams['figure.figsize'] = (10, 6)
multireg("sales", df, no_lineal="lowess")
```



In [13]:
```
#Separación de la data para pruebas

(x_train,x_test,y_train,y_test)=train_test_split(
    df.drop("sales",axis=1) ,df["sales"], test_size=0.33, random_state=17285)
```

In [14]:
```
#Ahora generemos una función llamada report_scores que ingrese como argumentos

def report_scores (y_hat, y_test):
    mse=mean_squared_error(y_test, y_hat).round(2)
    r2=r2_score(y_test, y_hat).round(2)
    print("Scores del Modelo")
    print("Mean Squared Error: ", mse)
    print("R-cuadrado: ", r2)
```

In [15]:
```
y_train.head()
```

Out[15]:
```
137    20.8
180    10.5
73     11.0
81     12.3
48     14.8
Name: sales, dtype: float64
```

Modelo Lineal desde Estadistica Clasica

In [16]:
```
#Modelo Saturado

df_clasic=pd.DataFrame()
df_clasic=pd.concat([x_train,df_clasic])
df_clasic['sales']=y_train

model = ols('sales ~ TV + radio+ newspaper', data=df_clasic).fit()
model.summary()
```

Out[16]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.883
Model:	OLS	**Adj. R-squared:**	0.880
Method:	Least Squares	**F-statistic:**	327.2
Date:	Wed, 28 Aug 2019	**Prob (F-statistic):**	2.28e-60
Time:	04:03:29	**Log-Likelihood:**	-264.63
No. Observations:	134	**AIC:**	537.3
Df Residuals:	130	**BIC:**	548.9
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.2214	0.378	8.529	0.000	2.474	3.969
TV	0.0470	0.002	24.580	0.000	0.043	0.051
radio	0.1807	0.011	16.880	0.000	0.159	0.202
newspaper	-0.0068	0.008	-0.902	0.369	-0.022	0.008

Omnibus:	49.686	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	128.653
Skew:	-1.475	**Prob(JB):**	1.16e-28
Kurtosis:	6.786	**Cond. No.**	398.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [17]:
```
report_scores(model.predict(x_test), y_test)
```

```
Scores del Modelo
Mean Squared Error:  2.44
R-cuadrado:  0.91
```

In [18]:
```
#Modelo depurado

model = ols('sales ~ TV + radio', data=df_clasic).fit()
model.summary()
```

Out[18]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.882
Model:	OLS	**Adj. R-squared:**	0.881
Method:	Least Squares	**F-statistic:**	491.0
Date:	Wed, 28 Aug 2019	**Prob (F-statistic):**	1.36e-61
Time:	04:03:29	**Log-Likelihood:**	-265.05
No. Observations:	134	**AIC:**	536.1
Df Residuals:	131	**BIC:**	544.8
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.1262	0.362	8.626	0.000	2.409	3.843
TV	0.0467	0.002	24.722	0.000	0.043	0.050
radio	0.1772	0.010	17.723	0.000	0.157	0.197

Omnibus:	47.693	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	114.788
Skew:	-1.450	**Prob(JB):**	1.19e-25
Kurtosis:	6.486	**Cond. No.**	376.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [19]:
```
report_scores(model.predict(x_test), y_test)
```

```
Scores del Modelo
Mean Squared Error:  2.35
R-cuadrado:  0.91
```

Modelo Lineal desde Machine Learling

In [20]:
```
#Instanciar modelo

machine_reg = LinearRegression(fit_intercept=False)

#Ajustar modelo

machine_reg.fit(x_train, y_train)
```

Out[20]:
```
LinearRegression(copy_X=True, fit_intercept=False, n_jobs=None,
         normalize=False)
```

In [21]:
```
report_scores(machine_reg.predict(x_test), y_test)
```

```
Scores del Modelo
Mean Squared Error:  2.95
R-cuadrado:  0.89
```

In [22]:
```
#Ajuste de Hiperparametros

machine_reg = LinearRegression()

#Grilla de busqueda

grilla_parametro={"fit_intercept":[True , False],"normalize":[True , False]}

Grilla=GridSearchCV(machine_reg, param_grid=grilla_parametro, n_jobs=-1, cv=3)
```

In [23]:
```
Grilla.fit(x_train, y_train)
```

```
C:\Users\gladi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:841: DeprecationWarning: The default of the `iid` parameter will change fro
m True to False in version 0.22 and will be removed in 0.24. This will change
numeric results when test-set sizes are unequal.
  DeprecationWarning)
```

Out[23]:
```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=LinearRegression(copy_X=True, fit_intercept=True, n_jobs=Non
e,
         normalize=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'fit_intercept': [True, False], 'normalize': [True, Fals
e]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [24]:
```
Grilla.best_params_
```

Out[24]:
```
{'fit_intercept': True, 'normalize': True}
```

In [25]:
```
#Instanciar modelo

machine_reg_best = LinearRegression(fit_intercept=True, normalize=True )

#Ajustar modelo

machine_reg_best.fit(x_train, y_train)
```

Out[25]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Tru
e)
```

In [26]:
```
report_scores(machine_reg_best.predict(x_test), y_test)
```

```
Scores del Modelo
Mean Squared Error:  2.44
R-cuadrado:  0.91
```

In [27]:
```
machine_reg_best.coef_
```

Out[27]:
```
array([ 0.04698815,  0.18065863, -0.00679921])
```

In [28]:
```
machine_reg_best.intercept_
```

Out[28]:
```
3.2214200622732037
```

Problema 2: Titanic

Introducción

El objetivo de este ejercicio es encontrar un modelo que prediga si un pasajero puede sobrecvivir utilizando las variables del DF.

- PassengerId: correlativo del pasagero
- Pclass: Calse del ticket
- Survived: Variable de Sobrevivencia
- Name: Nombre del pasajero
- Sex: Sexo del pasajero
- Age: Edad del pasajero
- SibSp: Número de hijos/esposos abordo
- Parch: Núde padres / hijos a bordo del Titanic
- Ticket: Númeración del ticket
- Fare: Tarifa del ticket
- Cabin: Número de Cabina
- Embarked: Puerto de embarque

In [29]:
```
df=pd.read_csv('titanic_train.csv')
df.head()
```

Out[29]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

In [30]:
```
df.shape
```

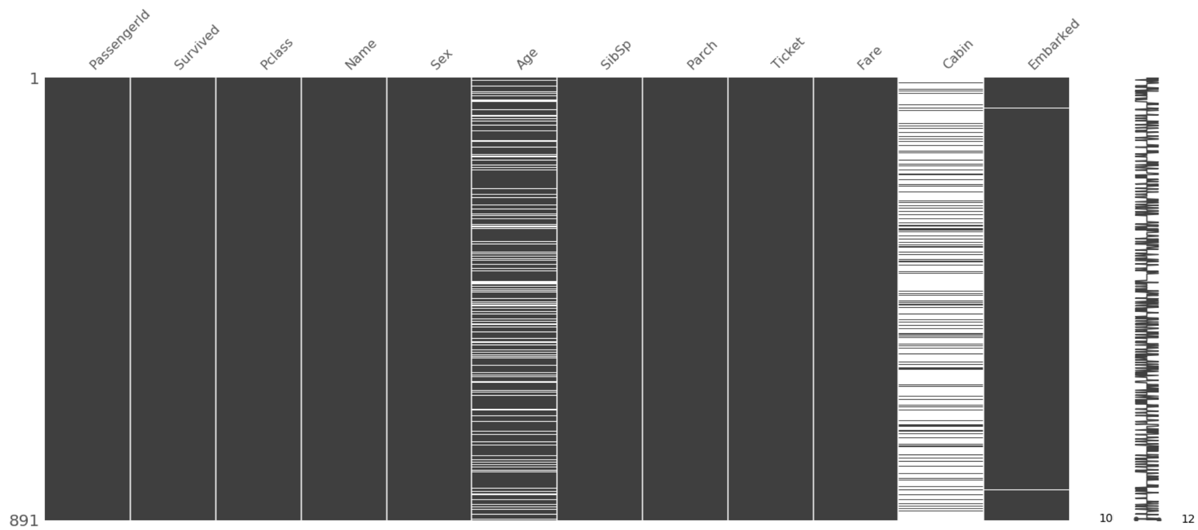
Out[30]:
```
(891, 12)
```

In [31]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

In [32]:
```
#Revisión NA
missingno.matrix(df)
```

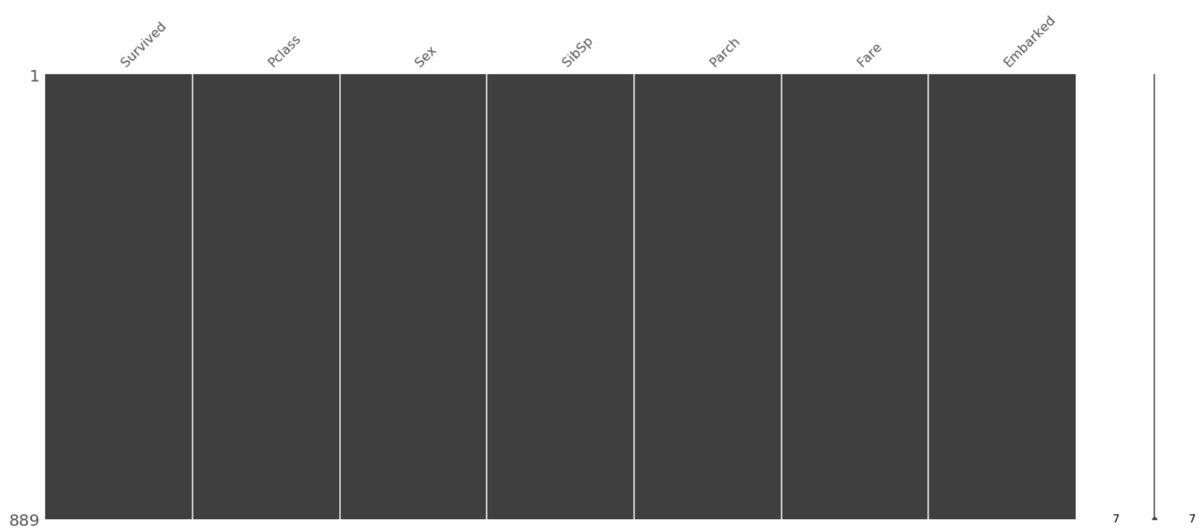
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x22e506e6a58>



In [33]:
```
#Eliminación de columnas con NA

df_drop=df.drop(['Age','Cabin','Name','Ticket','PassengerId'], axis=1)
```

In [34]:
```
df_drop=df_drop.dropna()
missingno.matrix(df_drop)
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x22e5080e2e8>

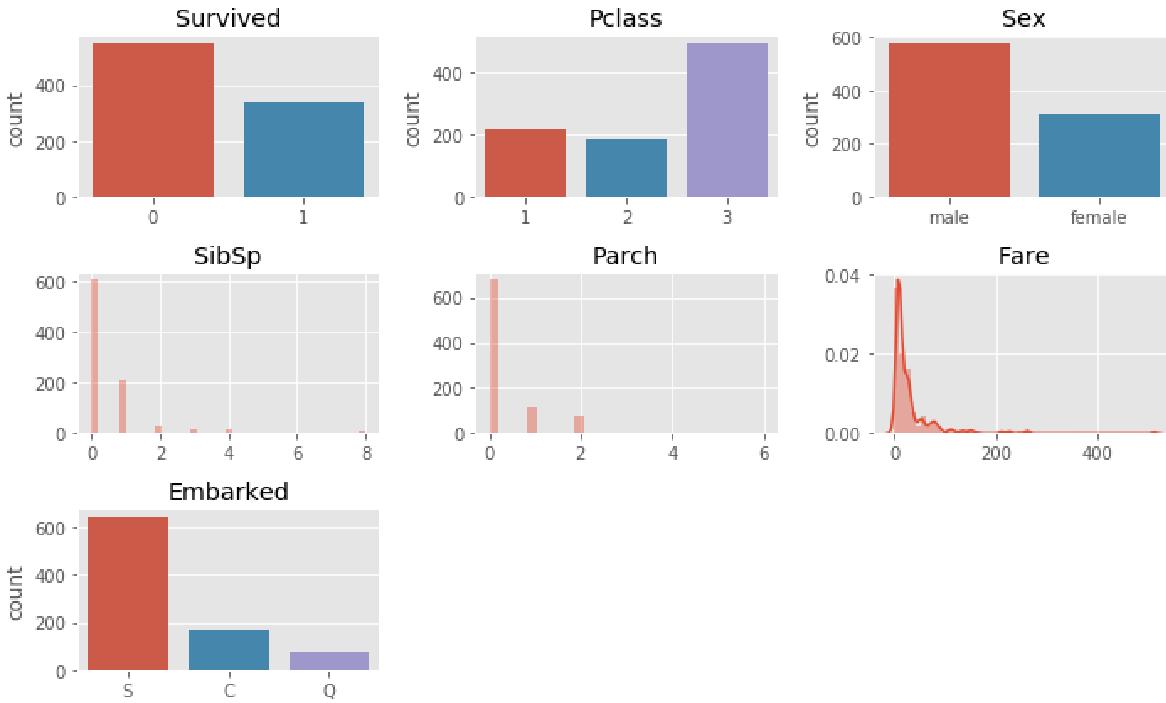


In [35]:
```
df_drop.shape
```

Out[35]: (889, 7)

In [36]:
```
df_drop['Survived']=df_drop['Survived'].astype(str)
df_drop['Pclass']=df_drop['Pclass'].astype(str)
```

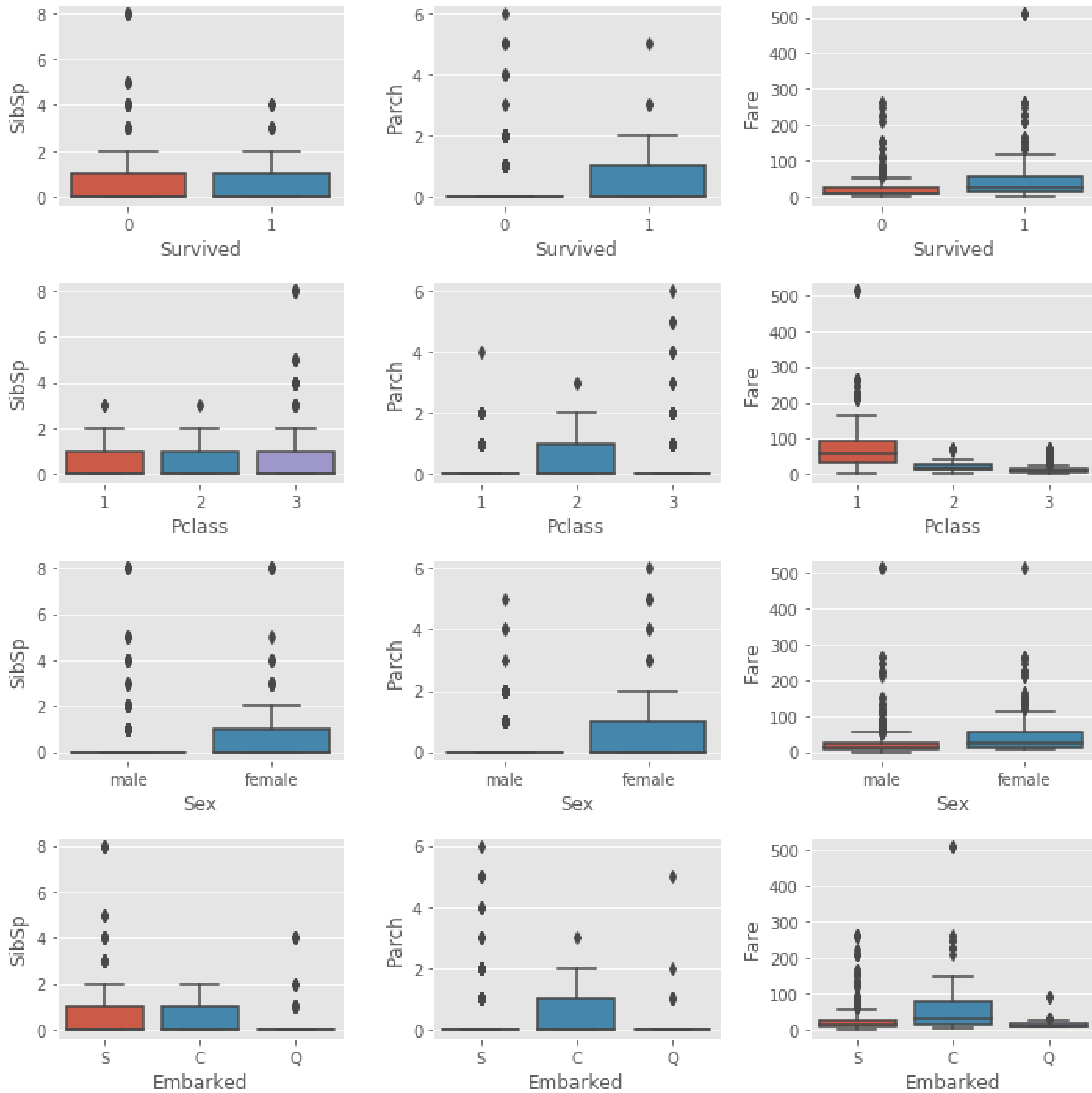
In [37]:
```
explor(df_drop)
```



In [38]:
```
#Realizamos graficos para ver diferencias entre valores

def df_boxplot (df):

    categorica=[]
    numerica=[]

    for n, i in enumerate(df):
        if (df[i].dtypes =="object"):
            categorica.append(i)
        else:
            numerica.append(i)

    print("Las variables numericas son {}".format(numerica))
    print("Las variables cateroricas son {}".format(categorica))

    n=1
    for i in categorica:
        for j in numerica:
            plt.subplot((len(list(df.columns))/3)+2,3,n)
            ax=sns.boxplot(x=i, y=j ,data=df)
            n+=1
    plt.tight_layout()
```

In [39]:
```
plt.rcParams['figure.figsize'] = (10, 10)
df_boxplot (df_drop)
```

```
Las variables numericas son ['SibSp', 'Parch', 'Fare']
Las variables cateroricas son ['Survived', 'Pclass', 'Sex', 'Embarked']
```



In [40]:
```
#Binarizar las variables

#Variables a dummificar

variables=[]

for n, i in enumerate(df_drop.columns):
    if df_drop[i].dtypes ==np.object and i !='Survived':
        variables.append(i)

df_dumm=pd.get_dummies(data=df_drop, columns=variables, prefix=variables,drop_
first=True)
```

In [41]:
```
df_dumm.head()
```

Out[41]:

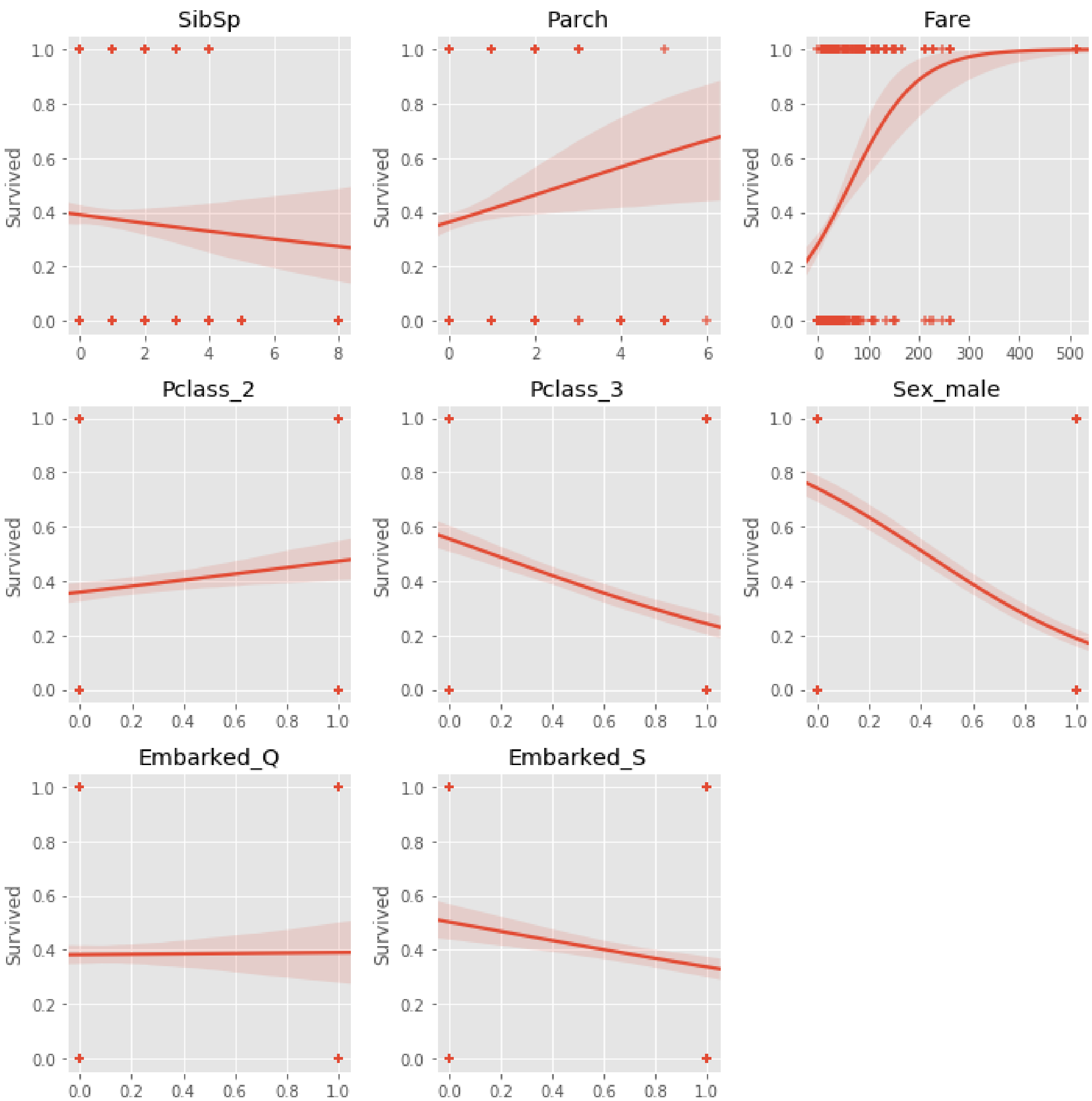
	Survived	SibSp	Parch	Fare	Pclass_2	Pclass_3	Sex_male	Embarked_Q	Embarked_S
0	0	1	0	7.2500	0	1	1	0	1
1	1	1	0	71.2833	0	0	0	0	0
2	1	0	0	7.9250	0	1	0	0	1
3	1	1	0	53.1000	0	0	0	0	1
4	0	0	0	8.0500	0	1	1	0	1

In [42]:
```
df_dumm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 9 columns):
Survived      889 non-null object
SibSp         889 non-null int64
Parch         889 non-null int64
Fare          889 non-null float64
Pclass_2      889 non-null uint8
Pclass_3      889 non-null uint8
Sex_male      889 non-null uint8
Embarked_Q    889 non-null uint8
Embarked_S    889 non-null uint8
dtypes: float64(1), int64(2), object(1), uint8(5)
memory usage: 79.1+ KB
```

In [43]:
```
for i in df_dumm:
    df_dumm[i]=df_dumm[i].astype(float)
```

In [44]:
```
#Relación de la variable objetivo con el resto

multireg("Survived",df_dumm,no_lineal="logistico")
```



In [45]:
```
#Separación de la data para pruebas

(x_train,x_test,y_train,y_test)=train_test_split(
    df_dumm.drop("Survived",axis=1) ,df_dumm["Survived"], test_size=0.33, rand
om_state=17285)
```

Modelo Logistico Clasico

In [46]:

```
#Estimación del modelo saturado

df_clasic=pd.DataFrame()
df_clasic=pd.concat([x_train,df_clasic])
df_clasic['Survived']=y_train


m1_logit=smf.logit('Survived~SibSp+Parch+Fare+Pclass_2+Pclass_3+Sex_male+Embarked_Q+Embarked_S',df_clasic).fit()
m1_logit.summary2()
```

```
Optimization terminated successfully.
         Current function value: 0.465826
         Iterations 6
```

Out[46]:

Model:	Logit	Pseudo R-squared:	0.309
Dependent Variable:	Survived	AIC:	572.3325
Date:	2019-08-28 04:06	BIC:	611.8296
No. Observations:	595	Log-Likelihood:	-277.17
Df Model:	8	LL-Null:	-401.24
Df Residuals:	586	LLR p-value:	4.2596e-49
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	2.3760	0.4165	5.7039	0.0000	1.5595	3.1924
SibSp	-0.2722	0.1245	-2.1873	0.0287	-0.5162	-0.0283
Parch	-0.0956	0.1334	-0.7167	0.4735	-0.3571	0.1659
Fare	0.0054	0.0034	1.5513	0.1208	-0.0014	0.0121
Pclass_2	-0.3826	0.3451	-1.1089	0.2675	-1.0589	0.2937
Pclass_3	-1.4621	0.3347	-4.3687	0.0000	-2.1180	-0.8061
Sex_male	-2.5993	0.2363	-10.9990	0.0000	-3.0625	-2.1362
Embarked_Q	0.2373	0.4748	0.4997	0.6173	-0.6933	1.1678
Embarked_S	-0.4865	0.2824	-1.7230	0.0849	-1.0399	0.0669

In [47]:
```
m2_logit=smf.logit('Survived~Pclass_3+Sex_male',df_clasic).fit()
m2_logit.summary2()
```

```
Optimization terminated successfully.
         Current function value: 0.486346
         Iterations 6
```

Out[47]:

Model:	Logit	Pseudo R-squared:	0.279
Dependent Variable:	Survived	AIC:	584.7523
Date:	2019-08-28 04:06	BIC:	597.9180
No. Observations:	595	Log-Likelihood:	-289.38
Df Model:	2	LL-Null:	-401.24
Df Residuals:	592	LLR p-value:	2.6220e-49
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	1.8660	0.2109	8.8463	0.0000	1.4525	2.2794
Pclass_3	-1.4656	0.2121	-6.9087	0.0000	-1.8814	-1.0498
Sex_male	-2.4884	0.2167	-11.4810	0.0000	-2.9133	-2.0636

Modelo Logistico Machine Learnig

In [72]:
```
#Instancia del Modelo

logistic_machine = LogisticRegression()
```

In [73]:
```
#Entrenamiento

logistic_machine.fit(x_train, y_train)
```

Out[73]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [98]:
```
#Grilla de busqueda

logistic_machine1= LogisticRegression(random_state=17285)

params_log = {'penalty' : ['l1', 'l2'],'C' : [0.001, 0.01, 0.1, 1,10, 100, 100
0, 10000],
              'fit_intercept':[True,False]}

Grilla=GridSearchCV(logistic_machine1, param_grid=params_log, n_jobs=-1, cv=3)
.fit(x_train, y_train)
```

In [99]:
```
Grilla.best_params_
```

Out[99]:
```
{'C': 0.1, 'fit_intercept': True, 'penalty': 'l2'}
```

In [100]:
```
#Instancia del Modelo mejorado

logistic_machine_best = LogisticRegression(C=0.1, penalty= 'l2',fit_intercept=
True)
```

In [101]:
```
#Entrenamiento Mejor

logistic_machine_best.fit(x_train, y_train)
```

Out[101]:
```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

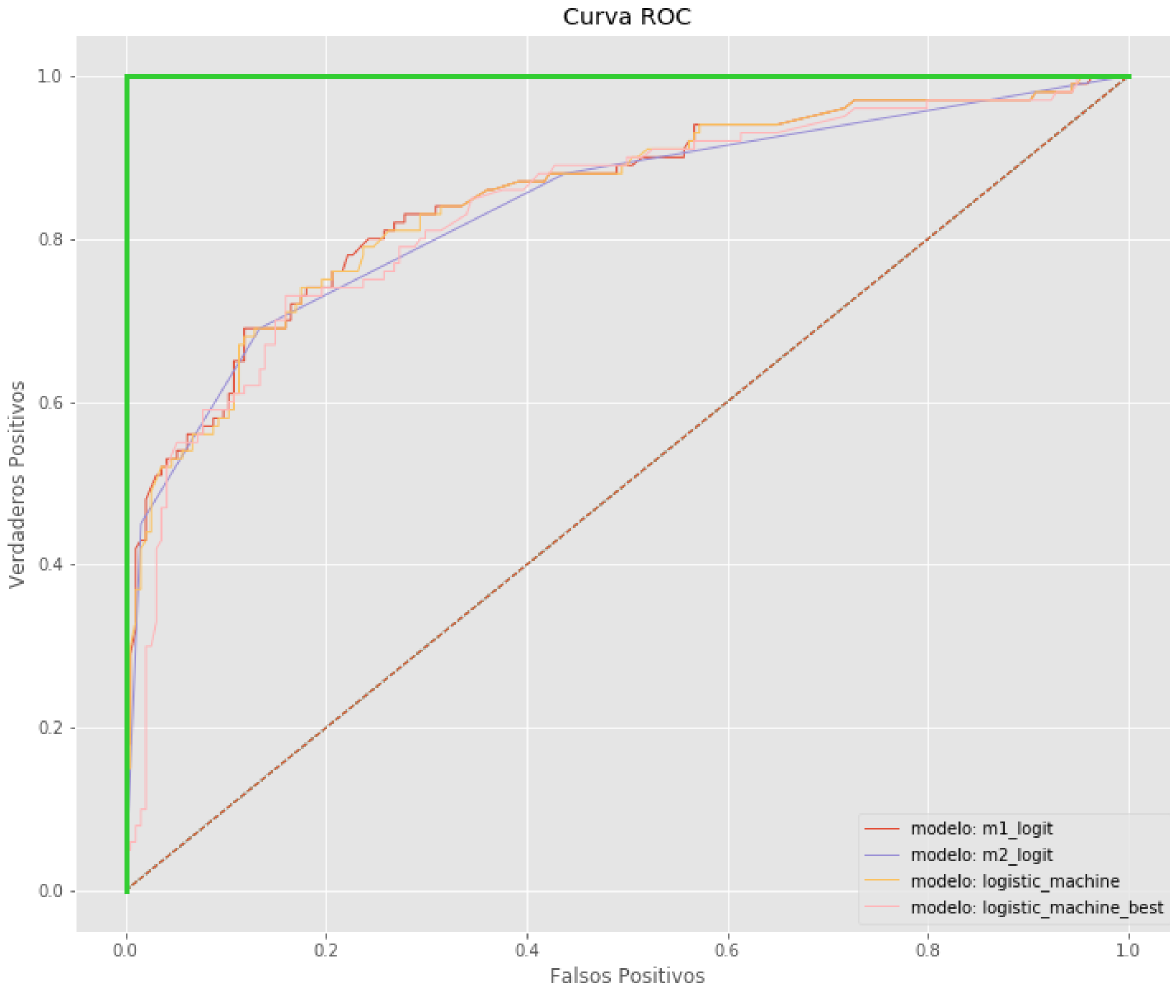
In [54]:
```
def invlogit(x):
    estimate_y = 1 / (1+np.exp(-x))
    return (estimate_y)
```

In [63]:
```
#Importar curva Roc

from sklearn.metrics import classification_report
from sklearn.metrics import auc
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

In [102]:
```
#Curva ROC

plt.rcParams['figure.figsize'] = (12, 10)


modelos=[m1_logit, m2_logit, logistic_machine, logistic_machine_best]

nombres=['m1_logit', 'm2_logit', 'logistic_machine', 'logistic_machine_best']

y_hats=[]
indicador1=[]
indicador2=[]
indicador3=[]


for i in range(len(modelos)):
    if i==2 or i==3:
        y_hats.append(modelos[i].predict_proba(x_test)[:,1])
    else:
        y_hats.append(modelos[i].predict(x_test))
    false_positive, true_positive, threshold = roc_curve(y_test, y_hats [i])
    indicador1.append(false_positive)
    indicador2.append(true_positive)
    indicador3.append(threshold)
    print("Auc del modelo: {} es {}".format(nombres[i],roc_auc_score(y_test, y
_hats [i]).round(2)))

#Plot curva ROC

plt.title('Curva ROC')
for i in range(len(modelos)):
    plt.plot(indicador1[i], indicador2[i], lw=1, label="modelo: {}".format(nom
bres[i]) )
    plt.plot([0, 1], ls="--", lw=1)
plt.plot([0, 0], [1, 0] , c='limegreen', lw=3), plt.plot([1, 1] , c='limegree
n', lw=3)
plt.ylabel('Verdaderos Positivos')
plt.xlabel('Falsos Positivos');
plt.legend()
```

```
Auc del modelo: m1_logit es 0.85
Auc del modelo: m2_logit es 0.84
Auc del modelo: logistic_machine es 0.85
Auc del modelo: logistic_machine_best es 0.83
```

Out[102]: <matplotlib.legend.Legend at 0x22e5253e710>



In [103]:
```
#Metricas de Clasificación

for i in range(4):
    print("==================== {} =====================".format(nombres[i]))
    if i==2 or i==3:
        print(classification_report(y_test, modelos[i].predict(x_test)))
    else:
        print(classification_report(y_test, np.where(modelos[i].predict(x_test
)>0.5,1,0)))
```

```
==================== m1_logit =====================
              precision    recall  f1-score   support

         0.0       0.84      0.86      0.85       194
         1.0       0.72      0.69      0.70       100

   micro avg       0.80      0.80      0.80       294
   macro avg       0.78      0.78      0.78       294
weighted avg       0.80      0.80      0.80       294

==================== m2_logit =====================
              precision    recall  f1-score   support

         0.0       0.84      0.87      0.85       194
         1.0       0.73      0.69      0.71       100

   micro avg       0.81      0.81      0.81       294
   macro avg       0.79      0.78      0.78       294
weighted avg       0.80      0.81      0.80       294

==================== logistic_machine =====================
              precision    recall  f1-score   support

         0.0       0.84      0.87      0.86       194
         1.0       0.73      0.69      0.71       100

   micro avg       0.81      0.81      0.81       294
   macro avg       0.79      0.78      0.78       294
weighted avg       0.81      0.81      0.81       294

==================== logistic_machine_best =====================
              precision    recall  f1-score   support

         0.0       0.82      0.87      0.84       194
         1.0       0.71      0.63      0.67       100

   micro avg       0.79      0.79      0.79       294
   macro avg       0.76      0.75      0.75       294
weighted avg       0.78      0.79      0.78       294
```

In [ ]: