2.1 Proyecto - Predicción de rendimiento financiero en Las empresas del Ecuador realizando un Analisis Predictivo de ROE/ROA a través de indicadores financieros del 2019.

> ## *Prediccion de los años: 2017, 2018, 2020*

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
from scipy.stats import norm
from scipy import stats
import torch
import torch
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,  accuracy_score
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2019_cia.xlsx", index_col=0)
df.sample(5)
```

ID	AÑO	EXPEDIENTE	NOMBRE	RAMA	DESCRIPCIÓN RAMA	RAMA 6 DÍGITOS	SUBRAMA 2 DÍGITOS	LIQUIDEZ CORRIENTE	PRUEBA ÁCIDA	ENDEUDAMIENTO DEL ACTIVO
34374	2019	144777	FACTORINVEST S.A.	N	ACTIVIDADES DE SERVICIOS ADMINISTRATIVOS Y DE ...	N8211.00	N82	1126.883300	1126.883300	0.518959
7827	2019	42707	INMOBILIARIA INMOQUIN SA	L	ACTIVIDADES INMOBILIARIAS.	L6810.01	L68	1.707485	1.707485	0.049491
20010	2019	99154	PROYECTOS L.T.L. S.A.	F	CONSTRUCCIÃ“N.	F4210.11	F42	NaN	NaN	0.969948
84681	2019	726007	IMPORTADORA LICHARD IMPORTLIC S.A.	G	COMERCIO AL POR MAYOR Y AL POR MENOR REPARACIÃ...	G4690.00	G46	NaN	NaN	0.000000
49369	2019	176580	COMPAÃ‘IA DE TRANSPORTE PESADO TRANSLLONMARTZ ...	H	TRANSPORTE Y ALMACENAMIENTO.	H4923.01	H49	3.554761	3.554761	0.281313

5 rows × 37 columns

PRE-PROCESAMIENTO

```
print("Dimensiones antes: {}".format(df.shape))
```

```
Dimensiones antes: (85793, 37)
```

```
df.isnull().sum()
```

```
AÑO                                0
EXPEDIENTE                         0
NOMBRE                             1
RAMA                              19
```

```
DESCRIPCIÓN RAMA                             19
RAMA 6 DÍGITOS                               33
SUBRAMA 2 DÍGITOS                            33
LIQUIDEZ CORRIENTE                        24414
PRUEBA ÁCIDA                              24414
ENDEUDAMIENTO DEL ACTIVO                   4974
ENDEUDAMIENTO PATRIMONIAL                  4771
ENDEUDAMIENTO A CORTO PLAZO               22087
ENDEUDAMIENTO A LARGO PLAZO               22087
COBERTURA DE INTERESES                    47509
ENDEUDAMIENTO DEL ACTIVO FIJO             38116
APALANCAMIENTO                             4771
APALANCAMIENTO FINANCIERO                 23817
FORTALEZA PATRIMONIAL                      4771
ENDEUDAMIENTO PATRIMONIAL CORRIENTE        4771
ENDEUDAMIENTO PATRIMONIAL NO CORRIENTE     4771
APALANCAMIENTO A CORTO Y LARGO PLAZO       4771
ROTACIÓN DE CARTERA                       34707
ROTACIÓN DE ACTIVO FIJO                   38116
ROTACIÓN DE VENTAS                         4974
PERIODO MEDIO DE COBRANZA CORTO PLAZO     28867
PERIODO MEDIO DE PAGO CORTO PLAZO         59555
IMPACTO GASTOS ADMINISTRACIÓN Y VENTAS    28867
IMPACTO DE LA CARGA FINANCIERA            28867
RENTABILIDAD NETA DEL ACTIVO              30147
MARGEN BRUTO                              28867
MARGEN OPERACIONAL                        28867
RENTABILIDAD NETA DE VENTAS               28867
RENTABILIDAD OPERACIONAL DEL PATRIMONIO    4771
RENTABLIDAD FINANCIERA                    30976
UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS      4974
ROE                                        4771
ROA                                        4974
dtype: int64
```

```
df.duplicated().any()
df.dropna(inplace=True)
df.shape
```

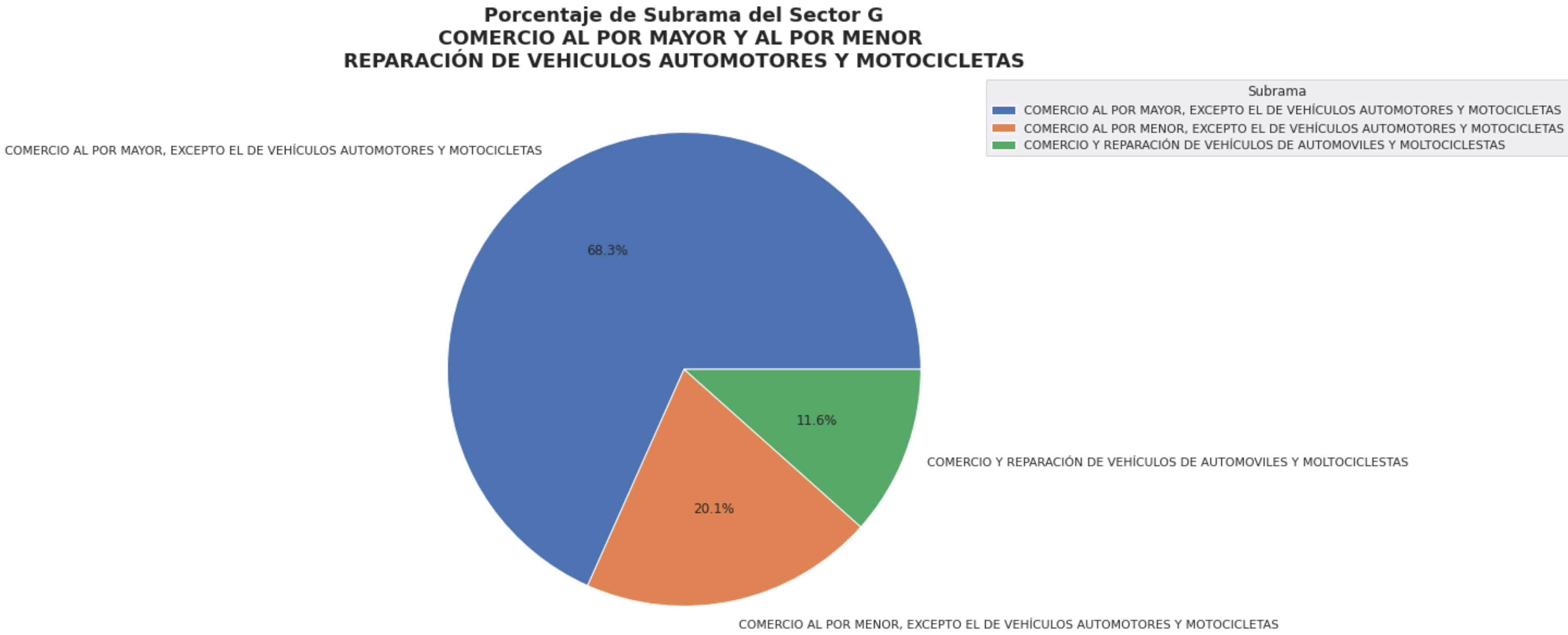
```
(14308, 37)
```

ANÁLISIS EXPLORATORIO CORRELACIONAL

```
sns.set(rc={'figure.figsize':(10,10)})
plt.pie(df['RAMA'].value_counts(), autopct='%1.1f%%', labels=df['DESCRIPCIÓN RAMA'].value_counts().index)
plt.title('% de Rama o Sectores', fontsize=18, fontweight='bold')
plt.legend(title ="Tipos",
          bbox_to_anchor =(1, 0, 0.5, 1))
plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/matplotlib/backends/backend_agg.py:214: RuntimeWarning: Glyph 141 missing from current f
```

```
plt.pie(df[df['RAMA']=='G']['SUBRAMA 2 DÍGITOS'].value_counts(), autopct='%1.1f%%', labels=['COMERCIO AL POR MAYOR, EXCEPTO EL DE VEH
                                                                                                                                'COME
                                                                                                                                'COME
plt.title('Porcentaje de Subrama del Sector G\nCOMERCIO AL POR MAYOR Y AL POR MENOR \nREPARACIÓN DE VEHICULOS AUTOMOTORES Y MOTOCICLE
plt.legend(title ="Subrama",
          bbox_to_anchor =(1, 0, 0.5, 1))
plt.show()
```



ANÁLISIS DE ROE POR RAMAS

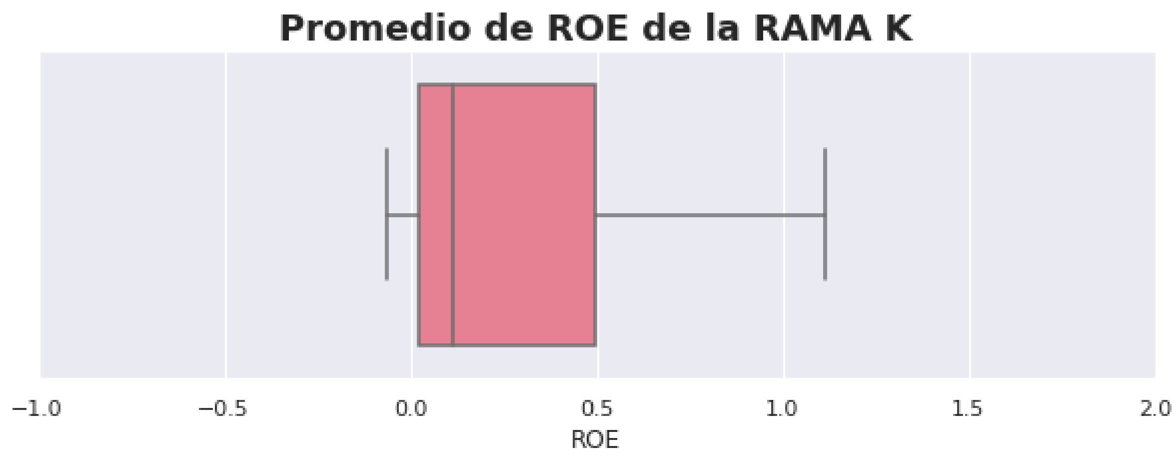
```
print("Skewness: {}".format(df['ROE'].skew()))
print("Kurtosis: {}".format(df['ROE'].kurt()))
print("---------------------------")
print(df['ROE'].describe())
```

```
Skewness: 21.325846842670153
Kurtosis: 6277.201310684813
---------------------------
count    14308.000000
mean        -0.078294
std         14.594107
min      -1062.466900
25%          0.001478
50%          0.062521
75%          0.209866
max       1293.094400
Name: ROE, dtype: float64
```

```
sns.set(rc={'figure.figsize':(10,5)})
plt.bar(df.groupby('RAMA').mean()['ROE'].index, df.groupby('RAMA').mean()['ROE'], align='center')
plt.title("Promedio de ROE por RAMA", fontsize=18, fontweight='bold')
plt.xlabel("RAMAS")
plt.ylabel("Promedio")
plt.ylim(-1, 1)
plt.show()
```

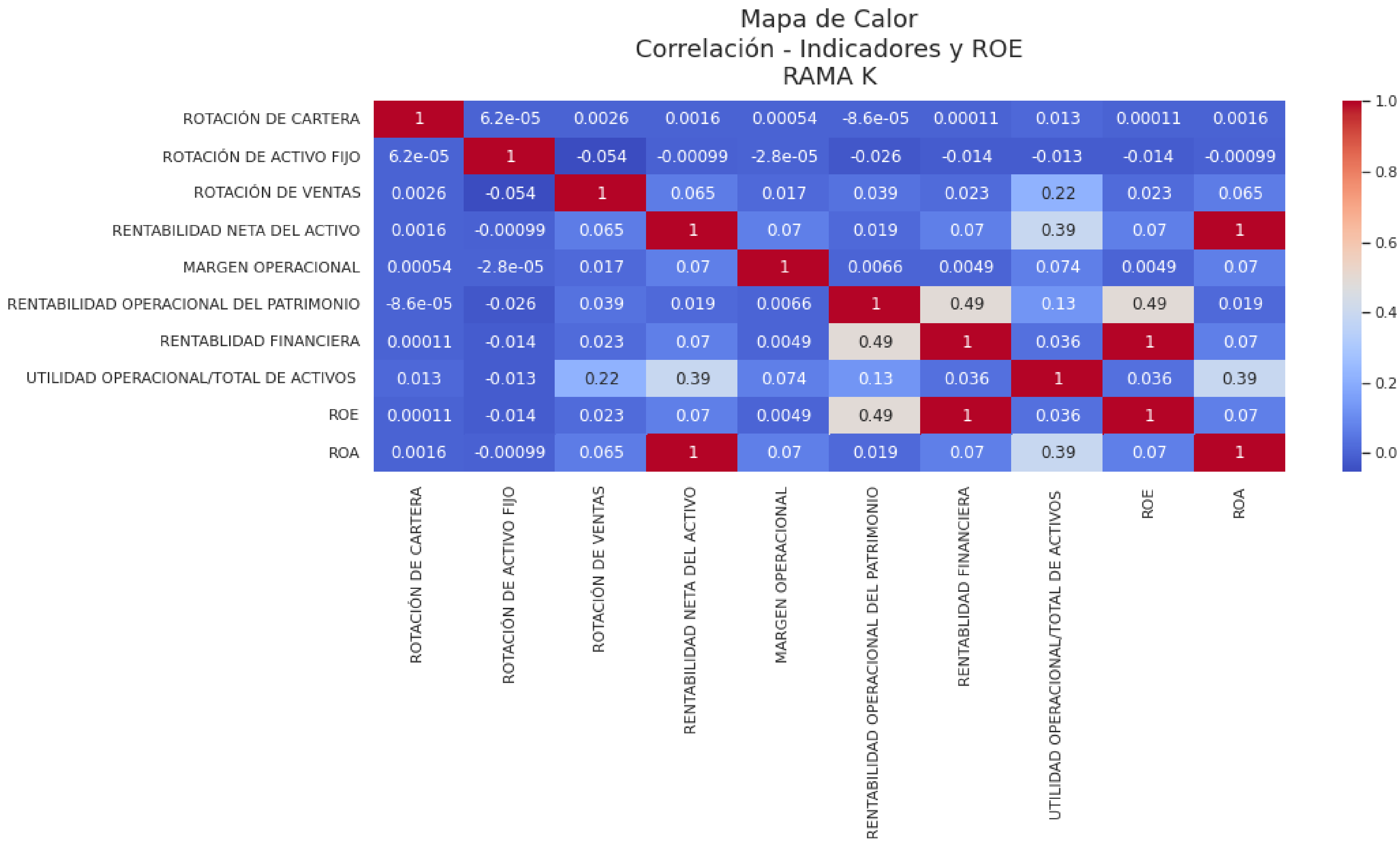

```
sns.set(rc={'figure.figsize':(10,3)})
df_f1 = df[df['RAMA']=='K']
sns.boxplot(orient="h", palette="husl", x="ROE", data=df_f1)
plt.xlim(-1, 2)
plt.title("Promedio de ROE de la RAMA K", fontsize=18, fontweight='bold')
```

```
Text(0.5, 1.0, 'Promedio de ROE de la RAMA K')
```




```
corr_matrix = df_f1.corr()
top_corr_features = corr_matrix.index[abs(corr_matrix["ROE"])>0.4]
plt.figure(figsize=(15,5))
hm = sns.heatmap(df[top_corr_features].corr(),
                annot=True,
                cmap="coolwarm")
hm.set_title('Mapa de Calor\nCorrelación - Indicadores y ROE\nRAMA K', fontdict={'fontsize':18}, pad=12)
```

```
Text(0.5, 1.0, 'Mapa de Calor\nCorrelación - Indicadores y ROE\nRAMA K')
```




```
df_LI = df[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS ',
```

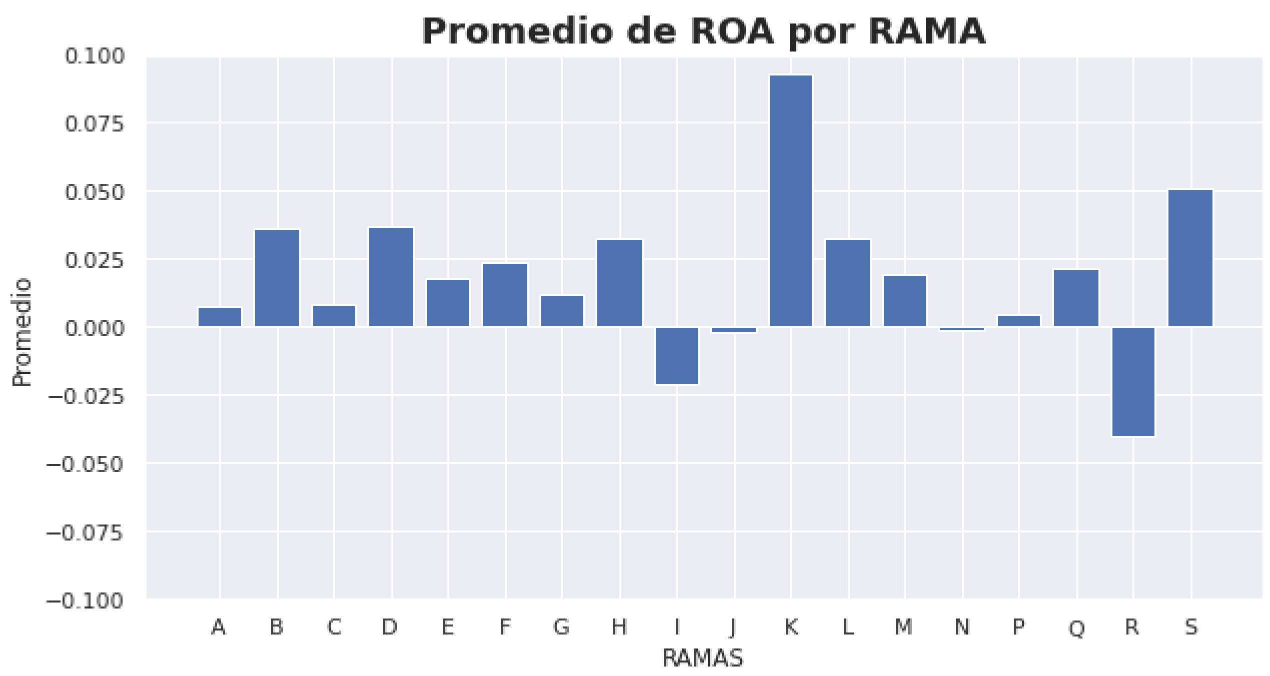
```
df_LI = df_LI[(df_LI['ROE'] > -1) & (df_LI['ROE'] < 1) & (df_LI['ROTACIÓN DE VENTAS'] < 10) & (df_LI['RENTABLIDAD FINANCIERA'] < 100)
          (df_LI['UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS '] > -10) & (df_LI['RENTABILIDAD NETA DEL ACTIVO'] > -3) & (df_LI['MARGEN
```

▾ ANÁLISIS DE ROA POR RAMAS

```
print("Skewness: {}".format(df['ROA'].skew()))
print("Kurtosis: {}".format(df['ROA'].kurt()))
print("---------------------------")
print(df['ROA'].describe())
```

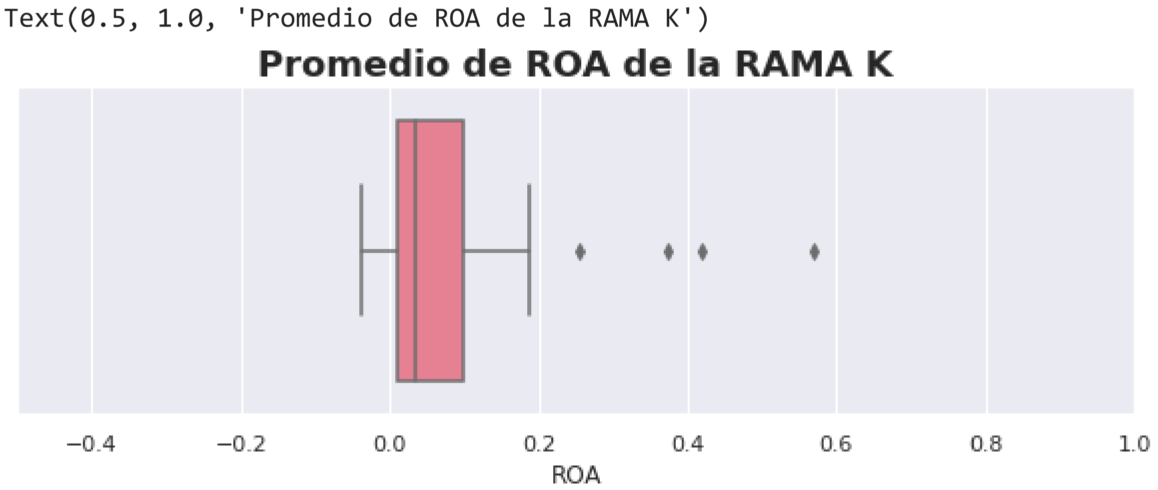
```
Skewness: -10.037858482005094
Kurtosis: 188.38766256816808
---------------------------
count    14308.000000
mean         0.011669
std          0.195766
min         -5.743858
25%          0.000330
50%          0.016086
75%          0.054652
max          1.161803
Name: ROA, dtype: float64
```

```
sns.set(rc={'figure.figsize':(10,5)})
plt.bar(df.groupby('RAMA').mean()['ROA'].index, df.groupby('RAMA').mean()['ROA'], align='center')
plt.title("Promedio de ROA por RAMA", fontsize=18, fontweight='bold')
plt.xlabel("RAMAS")
plt.ylabel("Promedio")
plt.ylim(-0.1, 0.1)
plt.show()
```



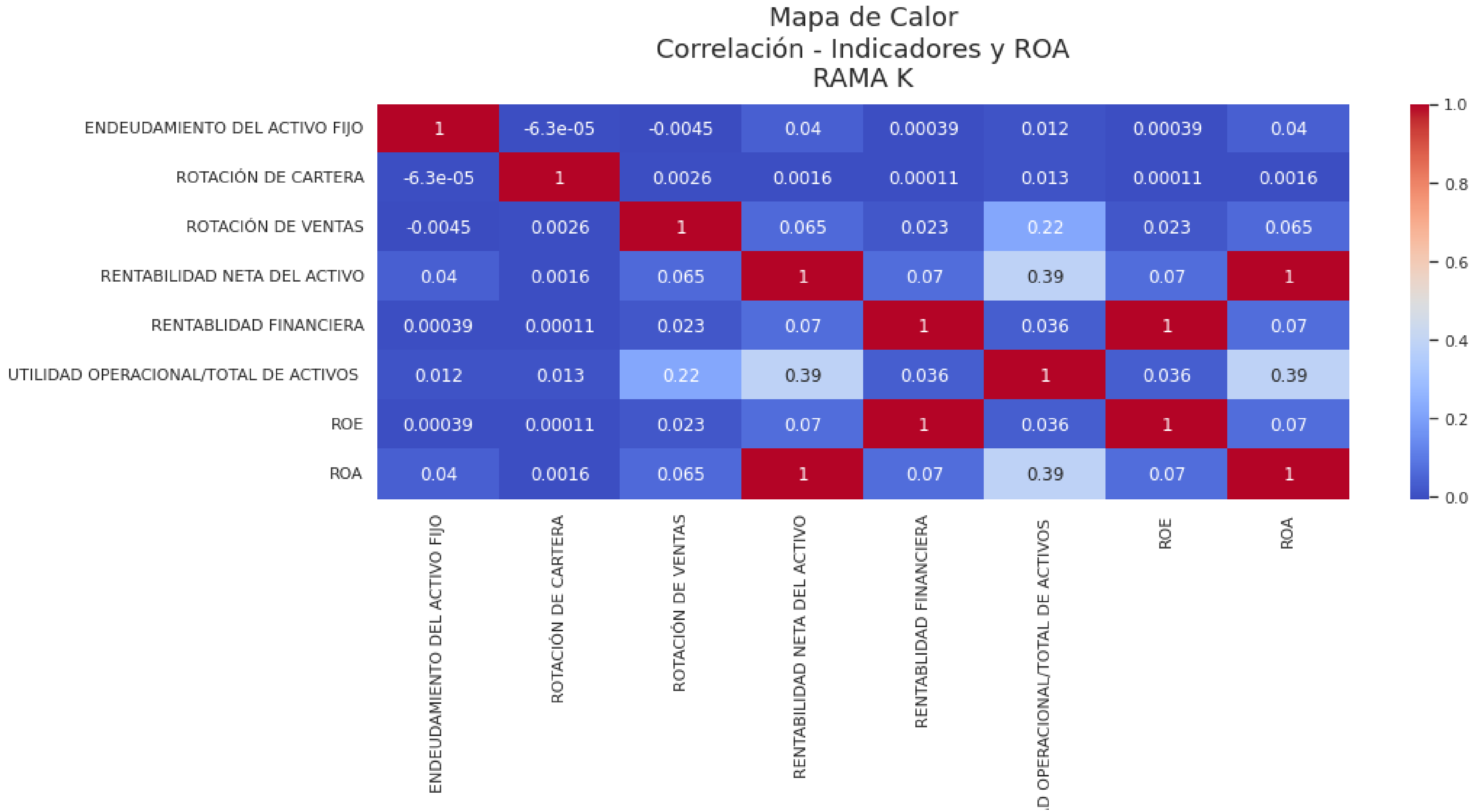

```
sns.set(rc={'figure.figsize':(10,3)})
df_f2 = df[df['RAMA']=='K']
sns.boxplot(orient="h", palette="husl", x="ROA", data=df_f2)
plt.xlim(-0.5, 1)
plt.title("Promedio de ROA de la RAMA K", fontsize=18, fontweight='bold')
```

```
Text(0.5, 1.0, 'Promedio de ROA de la RAMA K')
```




```
corr_matrix = df_f2.corr()
top_corr_features = corr_matrix.index[abs(corr_matrix["ROA"])>0.4]
plt.figure(figsize=(15,5))
hm = sns.heatmap(df[top_corr_features].corr(),
                annot=True,
                cmap="coolwarm")
hm.set_title('Mapa de Calor\nCorrelación - Indicadores y ROA\nRAMA K', fontdict={'fontsize':18}, pad=12)
```

```
Text(0.5, 1.0, 'Mapa de Calor\nCorrelación - Indicadores y ROA\nRAMA K')
```




```
df_LO = df[['ROA','DESCRIPCIÓN RAMA','RAMA','RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  '
df_LO = df_LO[(df_LO['ROA']>-1) & (df_LO['ROA'] < 1) & (df_LO['RENTABILIDAD NETA DEL ACTIVO'] < 500) & (df_LO['RENTABLIDAD FINANCIERA
          (df_LO['ENDEUDAMIENTO A CORTO PLAZO'] > -5) & (df_LO['RENTABILIDAD NETA DE VENTAS'] < 150) & (df_LO['ROTACIÓN DE ACTIVO F
```

Modelo predictivo de regresión lineal del ROE

```
df_LI = df[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS ',
df_LI
```

ID	RENTABLIDAD FINANCIERA	ROTACIÓN DE VENTAS	RENTABILIDAD NETA DEL ACTIVO	UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS	MARGEN OPERACIONAL	ROE
2	0.029656	0.671793	0.013612	0.051820	0.077136	0.029656
3	-0.046171	1.067048	-0.016565	-0.032901	-0.030833	-0.046171
5	0.058648	1.068332	0.016383	0.036057	0.033751	0.058648
8	-0.147701	0.576668	-0.031462	-0.030758	-0.053338	-0.147701
9	0.055154	1.113214	0.028136	0.359713	0.323131	0.055154
...	...	...	...	...	...	...
84796	0.556272	0.808590	0.031278	0.040117	0.049614	0.556272
84842	0.909427	0.712141	0.094858	0.362786	0.509430	0.909427
85220	0.567558	0.332708	0.000869	-0.010504	-0.031573	0.567558
85411	-0.480129	0.020025	-0.053135	-0.052482	-2.620895	-0.480129
85455	0.010929	0.172304	0.001485	0.006483	0.037624	0.010929

14308 rows × 6 columns

```
# Crear los arreglos con los inputs escogidos y el target del ROE
inputs = df_LI[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE ACTIVO
targets = df_LI[['ROE']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [-0.04617107  1.0670478  -0.01656493 -0.03290078 -0.03083346]
Tamaño:  (14308, 5)
Target #1:  [-0.04617106]
Tamaño:  (14308, 1)
```

```
# Normalizar los inputs
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
inputs = scaler.fit_transform(inputs)
#targets = scaler.fit_transform(targets)
```

```
# Cambiar el tipo de dato y crear tensores
X = torch.from_numpy(inputs.astype(np.float32))
Y = torch.from_numpy(targets.astype(np.float32))
n_samples, n_features = X.shape
print(n_samples,n_features)
```

```
14308 5
```

```
#Separar datos de entrenamiento y datos de prueba
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)
```

```
from torch.utils.data import TensorDataset, DataLoader
dataset_train = TensorDataset(X_train, y_train)
```

```
dataset_train[1:2]
```

```
(tensor([[ 0.0636, -0.3086,  0.3239,  0.6815,  0.0847]]), tensor([[0.8499]]))
```

```
# Define la clase del modelo de regresión lineal
bs=64
train_loader = DataLoader(dataset_train,batch_size=bs,shuffle=True)
```

```
class ModeloRegresionLineal(torch.nn.Module):
  def __init__(self):
    super(ModeloRegresionLineal, self).__init__()
    self.linear = torch.nn.Linear(n_features, 1)  #X @ w.t() + b

  def forward(self, x):
    y_pred = self.linear(x)
    return y_pred
```

```
# Define los epochs, learning rate, función de costo y el optimizador
epochs = 30
ta = 1e-9 # Tasa Aprendizaje

model_rl = ModeloRegresionLineal()
funcion_costo = torch.nn.MSELoss(reduction = 'mean')
optimizer = torch.optim.SGD(model_rl.parameters(), lr = ta) #Actualiza los pesos w y el bias b

for i in range(epochs):
  for x,y in train_loader:
    preds = model_rl(x)
    loss = funcion_costo(preds, y)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

  print(f"Epoch {i}/{epochs}: Loss {loss}")
```

```
Epoch 0/30: Loss 0.4285448491573334
Epoch 1/30: Loss 0.5946487188339233
Epoch 2/30: Loss 9.31455135345459
Epoch 3/30: Loss 0.7426868081092834
Epoch 4/30: Loss 10.14592170715332
Epoch 5/30: Loss 25.704723358154297
Epoch 6/30: Loss 0.7936495542526245
Epoch 7/30: Loss 0.10126297920942307
Epoch 8/30: Loss 0.40750259160995483
Epoch 9/30: Loss 31140.6796875
Epoch 10/30: Loss 1.6037739515304565
Epoch 11/30: Loss 20.511751174926758
Epoch 12/30: Loss 0.6074812412261963
Epoch 13/30: Loss 31209.27734375
Epoch 14/30: Loss 1.6176172494888306
Epoch 15/30: Loss 0.7412094473838806
Epoch 16/30: Loss 0.18564684689044952
Epoch 17/30: Loss 9.77913761138916
Epoch 18/30: Loss 0.24114887416362762
Epoch 19/30: Loss 10.19513988494873
```

```
Epoch 20/30: Loss 31141.203125
Epoch 21/30: Loss 0.7967230677604675
Epoch 22/30: Loss 0.42710018157958984
Epoch 23/30: Loss 0.18356266617774963
Epoch 24/30: Loss 25.105409622192383
Epoch 25/30: Loss 0.3895787000656128
Epoch 26/30: Loss 0.833349883556366
Epoch 27/30: Loss 0.4955005347728729
Epoch 28/30: Loss 1.4407721757888794
Epoch 29/30: Loss 0.16915194690227509
```

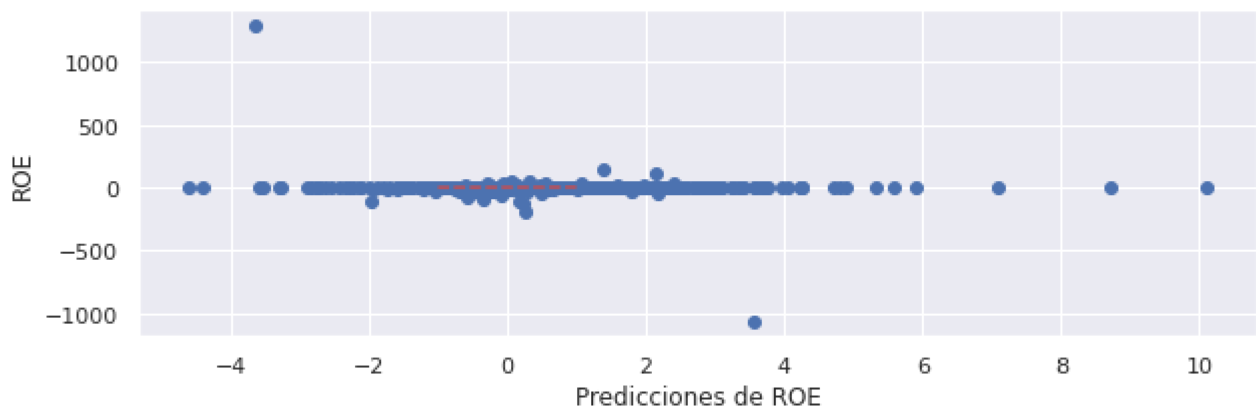
```
model_rl.linear.weight #w
```

```
Parameter containing:
tensor([[-0.0520,  0.2914,  0.0371,  0.3173,  0.0278]], requires_grad=True)
```

```
model_rl.linear.bias #b
```

```
Parameter containing:
tensor([-0.0073], requires_grad=True)
```

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error

y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in train_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROE')
plt.xlabel('Predicciones de ROE')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDATOS DEL AÑO 2019:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```




```
DATOS DEL AÑO 2019:
MAE: 0.8424941301345825
MSE: 261.9762268066406
RMSE: 16.185680389404297
```

PREDICCION POR CATEGORIAS DE AÑO 2019

```
df.plot.scatter(x='ROE',y= 'DESCRIPCIÓN RAMA', figsize=(10,20),title="CATEGORIAS DEL ROE")
```

```
WARNING:matplotlib.axes._axes:*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-m
<matplotlib.axes._subplots.AxesSubplot at
0x7fad89db2a60>/usr/local/lib/python3.8/dist-packages/matplotlib/backends/backend_agg.py:214: RuntimeWarning: Glyph 141 missing
  font.set_text(s, 0.0, flags=flags)
/usr/local/lib/python3.8/dist-packages/matplotlib/backends/backend_agg.py:183: RuntimeWarning: Glyph 141 missing from current f
  font.set_text(s, 0, flags=flags)
```


```
import glob
import os

def CATEGORIAS_LI():


  categ =  df[['RAMA']].values
  df['RAMA'] = categ
  metrics = {"DESCRIPCIÓN": [], "MAE": [], "MSE": [], "RMSE": []}
  grouped =  df.groupby("RAMA")
  for categoria, group in grouped:
      X_Lnl = group[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE A
      Y_Lnl = group[['ROE']].values
      # Escalando
      scaler = StandardScaler()
      inputs = scaler.fit_transform(X_Lnl)
      X_Lnl = torch.from_numpy(inputs.astype(np.float32))
      Y_Lnl = torch.from_numpy(Y_Lnl.astype(np.float32))
      dataset_test = TensorDataset(X_Lnl, Y_Lnl)
      test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)
      # Evaluando el modelo
      y_pred = []
      y_true = []
      model_rl.train(False)
      for inputs, targets in test_loader:
```

```
        y_pred.extend(model_rl(inputs).data.numpy())
        y_true.extend(targets.numpy())
      # Calculando Errores
      mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
      mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
      rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
      metrics["DESCRIPCIÓN"].append(categoria)
      metrics["MAE"].append(mae)
      metrics["MSE"].append(mse)
      metrics["RMSE"].append(rmse)

  metrics_df = pd.DataFrame(metrics)
  metrics_df = metrics_df.sort_values("MSE")
  print("LAS CATEGORIAS MAYORES ERRORES :")
  print(metrics_df.tail(8))
  print("LAS CATEGORIAS MENORES ERRORES :")
  print(metrics_df.head(8))

CATEGORIAS_LI()
```

```
LAS CATEGORIAS MAYORES ERRORES :
   DESCRIPCIÓN       MAE         MSE       RMSE
13           N  0.767580    6.006226   2.450760
2            C  0.639846    9.715785   3.117015
9            J  0.720340   10.789764   3.284778
14           P  1.116344   11.688409   3.418832
17           S  0.858742   13.774165   3.711356
12           M  0.788759   20.722900   4.552241
6            G  0.869720  275.378662  16.594538
0            A  1.579000  747.573303  27.341787
LAS CATEGORIAS MENORES ERRORES :
   DESCRIPCIÓN       MAE       MSE      RMSE
10           K  0.215334  0.090012  0.300020
7            H  0.312487  0.180658  0.425039
11           L  0.318897  0.188932  0.434664
4            E  0.412937  0.277002  0.526310
16           R  0.503054  0.362741  0.602280
1            B  0.400449  0.498010  0.705698
15           Q  0.481493  0.735337  0.857518
5            F  0.424011  1.249428  1.117778
```

PREDICCIONES POR AÑOS

2019

```
x_2019 = torch.from_numpy(np.array([[-0.04617107, 1.0670478, -0.01656493, -0.03290078, -0.03083346]],
  dtype='float32'))
y_2019 = model_rl(x_2019) #predicción
print(y_2019)
```

```
tensor([[0.2942]], grad_fn=<AddmmBackward0>)
```

```
x_2019 = torch.from_numpy(np.array([[-0.04617107, 1.0670478, -0.01656493, -0.03290078, -0.03083346]],
  dtype='float32'))
y_2019 = model_rl(x_2019) #predicción
print(y_2019.mean())
print('prediccion media : ',y_2019.mean())
print('prediccion maxima : ',y_2019.max())
print('prediccion minima : ',y_2019.min())
```

```
tensor(0.2942, grad_fn=<MeanBackward0>)
prediccion media :  tensor(0.2942, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(0.2942, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(0.2942, grad_fn=<MinBackward1>)
```

2017

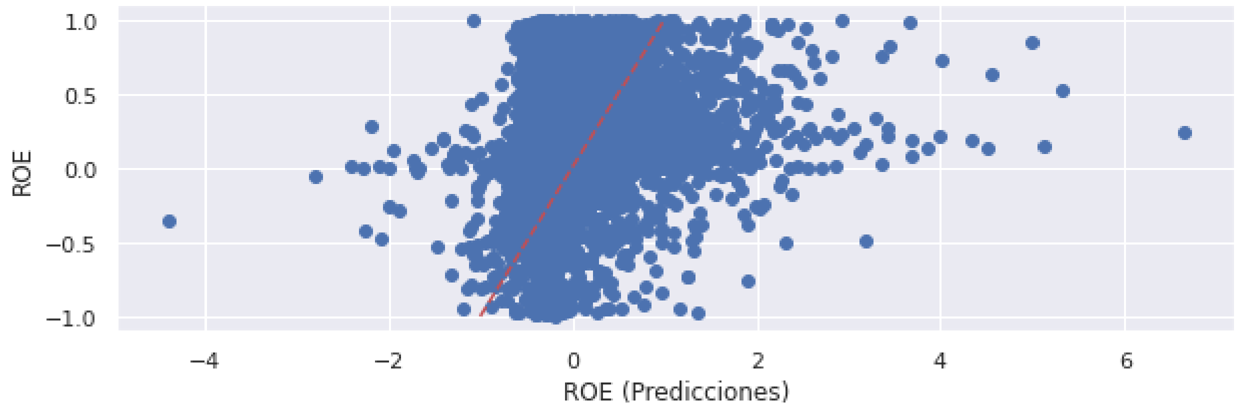
```
df_LI_2017 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2017_cia.xlsx")
df_LI_2017.fillna(0)
df_LI_2017.dropna(inplace=True)
```

```
#Remover Outliers
df_LI_2017 = df_LI_2017[(df_LI_2017['ROE'] > -1) & (df_LI_2017['ROE'] < 1) & (df_LI_2017['ROTACIÓN DE VENTAS'] < 10) & (df_LI_2017['R
```

```
              (df_LI_2017['UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS '] > -10) & (df_LI_2017['RENTABILIDAD NETA DEL ACTIVO'] > -3) & (df_

dfsX_2017 = df_LI_2017[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL D
dfsY_2017 = df_LI_2017[['ROE']].values



# Crear los arreglos con los inputs escogidos y el target del ROE
inputs = df_LI_2017[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE A
targets = df_LI_2017[['ROE']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [-0.13251807  0.87065369 -0.04194727 -0.06638302 -0.07624503]
Tamaño:  (12014, 5)
Target #1:  [-0.13251808]
Tamaño:  (12014, 1)
```

```
scaler = StandardScaler()
inputs = scaler.fit_transform(dfsX_2017)
inputs_rl = np.array(inputs, dtype='float32')
dY_2017 = np.array(dfsY_2017, dtype='float32')
from torch.utils.data import TensorDataset
X_2017 = torch.from_numpy(inputs_rl)
Y_2017 = torch.from_numpy(dY_2017)
dataset_test = TensorDataset(X_2017, Y_2017)
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)
 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROE')
plt.xlabel('ROE (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDATOS DEL AÑO 2017:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```




```
DATOS DEL AÑO 2017:
MAE: 0.3857935070991516
MSE: 0.27093786001205444
RMSE: 0.5205169320106506
```

```
x_2017 = torch.from_numpy(np.array([[-0.13251807, 0.87065369, -0.04194727, -0.06638302, -0.07624503]],
  dtype='float32'))
y_2017 = model_rl(x_2017) #predicción
print(y_2017)
```

```
tensor([[0.2286]], grad_fn=<AddmmBackward0>)
```

```
x_2017 = torch.from_numpy(np.array([[dfsX_2017]],
  dtype='float32'))
y_2017 = model_rl(x_2017) #predicción
print('prediccion media : ',y_2017.mean())
print('prediccion maxima : ',y_2017.max())
print('prediccion minima : ',y_2017.min())
```

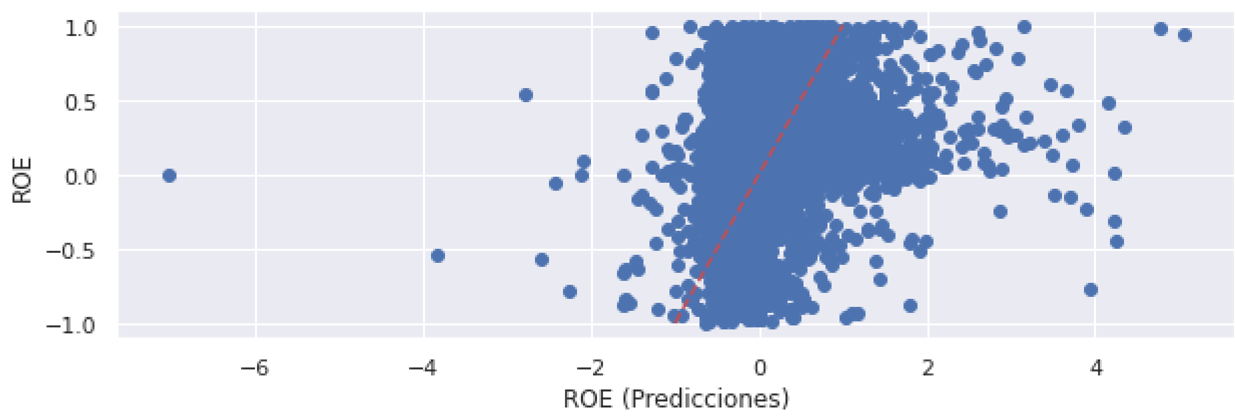
```
prediccion media :  tensor(0.5960, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(5.2616, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-1.6719, grad_fn=<MinBackward1>)
```

2018

```
df_LI_2018 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2018_cia.xlsx")
df_LI_2018.fillna(0)
df_LI_2018.dropna(inplace=True)


#Remover Outliers
df_LI_2018 = df_LI_2018[(df_LI_2018['ROE'] > -1) & (df_LI_2018['ROE'] < 1) & (df_LI_2018['ROTACIÓN DE VENTAS'] < 10) & (df_LI_2018['R
              (df_LI_2018['UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS '] > -10) & (df_LI_2018['RENTABILIDAD NETA DEL ACTIVO'] > -3) & (df_

dfsX_2018 = df_LI_2018[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL D
dfsY_2018 = df_LI_2018[['ROE']].values



# Crear los arreglos con los inputs escogidos y el target del ROE
inputs = df_LI_2018[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE A
targets = df_LI_2018[['ROE']].values
print('Input #1: ', inputs[1], ' - Tamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], ' - Tamaño: ', targets.shape)
```

```
Input #1:  [0.05363422 1.108128   0.01739988 0.00379337 0.00342322]  - Tamaño:  (12751, 5)
Target #1:  [0.05363422]  - Tamaño:  (12751, 1)
```

```
scaler = StandardScaler()
inputs = scaler.fit_transform(dfsX_2018)
inputs_rl = np.array(inputs, dtype='float32')
dY_2018 = np.array(dfsY_2018, dtype='float32')
from torch.utils.data import TensorDataset
X_2018 = torch.from_numpy(inputs_rl)
Y_2018 = torch.from_numpy(dY_2018)
dataset_test = TensorDataset(X_2018, Y_2018)
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)
 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROE')
plt.xlabel('ROE (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDatos del año 2018:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```




```
Datos del año 2018:
MAE: 0.3838843107223511
MSE: 0.2676955759525299
RMSE: 0.5173930525779724
```

```
x_2018 = torch.from_numpy(np.array([[0.05363422, 1.108128,  0.01739988, 0.00379337, 0.00342322]],
  dtype='float32'))
y_2018 = model_rl(x_2018) #predicción
print(y_2018)
```

```
tensor([[0.3148]], grad_fn=<AddmmBackward0>)
```

```
x_2018 = torch.from_numpy(np.array([[dfsX_2018]],
  dtype='float32'))
y_2018 = model_rl(x_2018) #predicción
print('prediccion media : ',y_2018.mean())
print('prediccion maxima : ',y_2018.max())
print('prediccion minima : ',y_2018.min())
```

```
prediccion media :  tensor(0.5829, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(9.4847, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-13.0738, grad_fn=<MinBackward1>)
```

2020

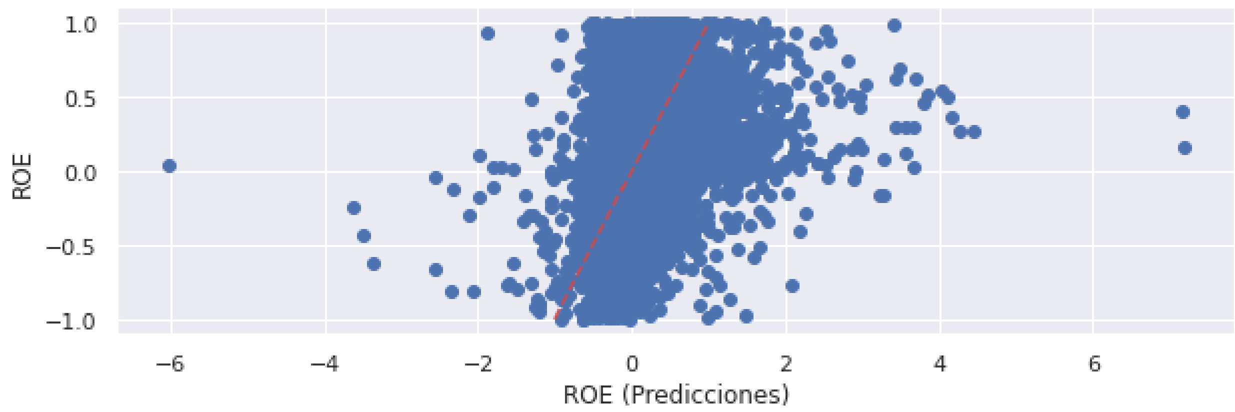
```
df_LI_2020 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2020_cia.xlsx")
df_LI_2020.fillna(0)
df_LI_2020.dropna(inplace=True)
```

```
#Remover Outliers
df_LI_2020 = df_LI_2020[(df_LI_2020['ROE'] > -1) & (df_LI_2020['ROE'] < 1) & (df_LI_2020['ROTACIÓN DE VENTAS'] < 10) & (df_LI_2020['R
              (df_LI_2020['UTILIDAD OPERACIONAL/TOTAL DE ACTIVOS '] > -10) & (df_LI_2020['RENTABILIDAD NETA DEL ACTIVO'] > -3) & (df_

dfsX_2020 = df_LI_2020[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL D
dfsY_2020 = df_LI_2020[['ROE']].values
```

```
# Crear los arreglos con los inputs escogidos y el target del ROE
inputs = df_LI_2020[['RENTABLIDAD FINANCIERA', 'ROTACIÓN DE VENTAS', 'RENTABILIDAD NETA DEL ACTIVO', 'UTILIDAD OPERACIONAL/TOTAL DE A
targets = df_LI_2020[['ROE']].values
print('Input #1: ', inputs[1], ' - Tamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], ' - Tamaño: ', targets.shape)
```

```
Input #1:  [-0.08051773  0.85084701 -0.02910098 -0.04367799 -0.05133472]  - Tamaño:  (12591, 5)
Target #1:  [-0.08051773]  - Tamaño:  (12591, 1)
```

```
scaler = StandardScaler()
inputs = scaler.fit_transform(dfsX_2020)
inputs_rl = np.array(inputs, dtype='float32')
dY_2020 = np.array(dfsY_2020, dtype='float32')
from torch.utils.data import TensorDataset
X_2020 = torch.from_numpy(inputs_rl)
Y_2020 = torch.from_numpy(dY_2020)
dataset_test = TensorDataset(X_2020, Y_2020)
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)
 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROE')
plt.xlabel('ROE (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDatos del año 2018:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```




```
Datos del año 2018:
```

```
x_2020 = torch.from_numpy(np.array([[-0.08051773, 0.85084701, -0.02910098, -0.04367799, -0.05133472]],
  dtype='float32'))
y_2020 = model_rl(x_2020) #predicción
print(y_2020)
```

```
tensor([[0.2285]], grad_fn=<AddmmBackward0>)
```

```
x_2020 = torch.from_numpy(np.array([[dfsX_2020]],
  dtype='float32'))
y_2020 = model_rl(x_2018) #predicción
print('prediccion media : ',y_2020.mean())
print('prediccion maxima : ',y_2020.max())
print('prediccion minima : ',y_2020.min())
```

```
prediccion media :  tensor(0.5829, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(9.4847, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-13.0738, grad_fn=<MinBackward1>)
```

Modelo predictivo de Regresión logística del ROA

```
inputs = df_LO[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO PLAZO'
targets = df_LO[['ROA']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [-1.6564935e-02 -4.6171069e-02 -1.5524080e-02  2.4994294e-01
  2.3307087e+01]
Tamaño:  (13003, 5)
Target #1:  [-0.01656493]
Tamaño:  (13003, 1)
```

```
x = df_LO[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO PLAZO','ROT
y = df_LO[['ROA']]
```

```
y['ROA_DIS'] = pd.qcut(y['ROA'], 5, labels=False)
y['ROA_DESCRIPCION'] = pd.qcut(y['ROA_DIS'], 4, labels=["MALO","REGULAR", "BUENO", "EXCELENTE"])
y
```

```
<ipython-input-197-79d5b338a014>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
  y['ROA_DIS'] = pd.qcut(y['ROA'], 5, labels=False)
<ipython-input-197-79d5b338a014>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
  y['ROA_DESCRIPCION'] = pd.qcut(y['ROA_DIS'], 4, labels=["MALO","REGULAR", "BUENO", "EXCELENTE"])
            ROA  ROA_DIS  ROA_DESCRIPCION
```

```
Y = y[['ROA_DIS']]
Y
```

ID	ROA_DIS
2	2
3	0
5	2
8	0
9	2
...	...
84796	3
84842	4
85220	1
85411	0
85455	1

13003 rows × 1 columns

```
X= np.array(x, dtype='float32')
Y1= Y['ROA_DIS'].values
```

```
print('tamaño de X INDICADORES : ',X.shape) #tamaño de X INDICADORES
print('tamaño de Y ROE : ',Y1.shape) #tamaño de dY ROA
```

```
tamaño de X INDICADORES :  (13003, 5)
tamaño de Y ROE :  (13003,)
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y1,test_size=0.25)
```

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

```
x_train = torch.from_numpy(x_train.astype(np.float32))
x_test = torch.from_numpy(x_test.astype(np.float32))

y_train = torch.from_numpy(y_train.astype(np.int64))
y_test = torch.from_numpy(y_test.astype(np.int64))
```

```
class LR_Model(torch.nn.Module):
  def __init__(self, n_features):
    super(LR_Model,self).__init__()
    self.logt  = torch.nn.Linear(n_features, 5)
    self.softmax = torch.nn.Softmax(dim=1)

  def forward(self, x):
    y_hat = torch.sigmoid(self.logt(x)) #regresión logistica necesita la función sigmoid
    return y_hat
```

```
#función que visualiza la evolución de la perdida y la precisión en cada epoch
def plot_loss(epochs, loss, loss_test, acc):
```

```
  plt.figure(figsize=(10,5))
  xlim = len(loss)
  plt.plot(epochs,loss)
  plt.plot(epochs,loss_test)
  plt.plot(epochs,acc)
  plt.xlabel('Epochs')
  plt.ylabel('Value')
  plt.legend(('Train loss','Test loss','Accuracy'),loc='center right',shadow=True)
  plt.title('Train and Test Loss vs Accuracy')
```

```
#función que realiza el entrenamiento
def train(num_epochs, optimizer, cost, model):
  #listas usadas para guardar los valores de pérdida, precisión, para cada epoch
  #esta información sirve para graficar el proceso de entrenamiento
  loss_vals = []
  loss_test_vals = []
  acc_vals = []
  epoch_vals = []

  #entrenamiento
  for epoch in range(num_epochs):
    y_hat = model(x_train)
    loss = cost(y_hat,y_train)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()

    #se evalua cada 5 epochs
    if (epoch+1)%5 == 0:
      with torch.no_grad():
        loss_vals.append(loss.item())
        y_hat_test = model(x_test)  #se usan los datos de prueba para evaluar el modelo
        loss_test = cost(y_hat_test, y_test)
        loss_test_vals.append(loss_test.item())
        y_hat_class = y_hat_test.argmax(dim=1) #se redondea para saber si la clase es 1 o 0, recordar que sigmoid devuelve valor entr
        accuracy = (y_hat_class.eq(y_test).sum())/float(y_hat_test.shape[0]) #se cuenta las correctas y se divide para el total de da
        acc_vals.append(accuracy.item())
        epoch_vals.append(epoch)
      print(f'epoch:{epoch+1} loss={loss.item()} loss_test={loss_test.item()} accuracy={accuracy.item()}')
  plot_loss(epoch_vals,loss_vals,loss_test_vals,acc_vals)
```

```
print(x_train[1])
print(y_train[1])
```

```
tensor([ 0.0806, -0.0064,  0.0378,  0.9632,  0.0169])
tensor(3)
```

```
n_features = X.shape[1] #en este caso 30 features
lr_model = LR_Model(n_features)
costo =  torch.nn.CrossEntropyLoss()
optim = torch.optim.Adam(lr_model.parameters(),lr=0.01) #gradiente descendente
train(num_epochs=300, optimizer=optim, cost=costo, model=lr_model)
```

```
epoch:5 loss=1.6387180089950562 loss_test=1.632010817527771 accuracy=0.20855121314525604
epoch:10 loss=1.62864089012146 loss_test=1.6209782361984253 accuracy=0.21408797800540924
epoch:15 loss=1.6185014247894287 loss_test=1.6098616123199463 accuracy=0.21839433908462524
epoch:20 loss=1.608323574066162 loss_test=1.598886489868164 accuracy=0.25315287709236145
epoch:25 loss=1.5984264612197876 loss_test=1.5884546041488647 accuracy=0.32328513264656067
epoch:30 loss=1.5888850688934326 loss_test=1.5784411430358887 accuracy=0.33343586325645447
epoch:35 loss=1.5797988176345825 loss_test=1.568900465965271 accuracy=0.33374345302581787
epoch:40 loss=1.5712820291519165 loss_test=1.5599873065948486 accuracy=0.31621038913726807
epoch:45 loss=1.5633301734924316 loss_test=1.5516952276229858 accuracy=0.31990155577659607
epoch:50 loss=1.555988073348999 loss_test=1.5440019369125366 accuracy=0.33035987615585327
epoch:55 loss=1.549252271652217 loss_test=1.5368732213974 accuracy=0.3512765169143677
epoch:60 loss=1.5430513620376587 loss_test=1.5302619934082031 accuracy=0.3669640123844147
epoch:65 loss=1.5373042821884155 loss_test=1.5240880250930786 accuracy=0.3786527216434479
epoch:70 loss=1.5319329500198364 loss_test=1.518279790878296 accuracy=0.3789603114128113
epoch:75 loss=1.5268877744674683 loss_test=1.5127934217453003 accuracy=0.38511228561401367
epoch:80 loss=1.522113800048828 loss_test=1.5075957775115967 accuracy=0.3685019910335541
epoch:85 loss=1.5175814628601074 loss_test=1.5026582479476929 accuracy=0.35742849111557007
epoch:90 loss=1.5132521390914917 loss_test=1.4979511499404907 accuracy=0.35281452536582947
epoch:95 loss=1.509096384048462 loss_test=1.4934433698654175 accuracy=0.34973853826522827
epoch:100 loss=1.5050854682922363 loss_test=1.4891071319580078 accuracy=0.3509689271450043
epoch:105 loss=1.5011987686157227 loss_test=1.484918236732483 accuracy=0.3512765169143677
epoch:110 loss=1.4974194765090942 loss_test=1.4808582067489624 accuracy=0.35404491424560547
epoch:115 loss=1.4937357902526855 loss_test=1.4769128561019897 accuracy=0.35650569200515747
epoch:120 loss=1.490138292312622 loss_test=1.4730722904205322 accuracy=0.35835129022598267
epoch:125 loss=1.4866206645965576 loss_test=1.4693280458450317 accuracy=0.35958167910575867
epoch:130 loss=1.4831780195236206 loss_test=1.465675950050354 accuracy=0.36081206798553467
epoch:135 loss=1.4798067808151245 loss_test=1.4621118307113647 accuracy=0.36327284574508667
epoch:140 loss=1.4765046834945679 loss_test=1.4586323499679565 accuracy=0.36542603373527527
epoch:145 loss=1.473270058631897 loss_test=1.455235481262207 accuracy=0.3663488030433655
epoch:150 loss=1.4701007604599 loss_test=1.4519191980361938 accuracy=0.3681944012641907
epoch:155 loss=1.4669958353042603 loss_test=1.4486812353134155 accuracy=0.3728083670139313
epoch:160 loss=1.4639534950256348 loss_test=1.4455195665359497 accuracy=0.3740387558937073
epoch:165 loss=1.4609726667404175 loss_test=1.4424320459365845 accuracy=0.3761919438838959
epoch:170 loss=1.4580518007278442 loss_test=1.4394171237945557 accuracy=0.37926793098449707
epoch:175 loss=1.4551894664764404 loss_test=1.4364720582962036 accuracy=0.3814210891723633
epoch:180 loss=1.4523845911026 loss_test=1.4335955381393433 accuracy=0.3835742771625519
epoch:185 loss=1.4496351480484009 loss_test=1.4307847023010254 accuracy=0.3857274651527405
epoch:190 loss=1.4469398260116577 loss_test=1.4280375242233276 accuracy=0.3888034522533417
epoch:195 loss=1.444297194480896 loss_test=1.425351858139038 accuracy=0.3903414309024811
epoch:200 loss=1.4417058229446411 loss_test=1.4227261543273926 accuracy=0.3934174180030823
epoch:205 loss=1.4391642808914185 loss_test=1.4201583862304688 accuracy=0.3961857855319977
epoch:210 loss=1.4366710186004639 loss_test=1.4176467657089233 accuracy=0.3980313837528229
epoch:215 loss=1.4342248439788818 loss_test=1.4151887893676758 accuracy=0.4004921615123749
epoch:220 loss=1.4318242073059082 loss_test=1.4127836227416992 accuracy=0.4060289263725281
epoch:225 loss=1.4294676780700684 loss_test=1.4104291200637817 accuracy=0.4066441059112549
epoch:230 loss=1.4271541833877563 loss_test=1.4081230163574219 accuracy=0.4091048836708069
epoch:235 loss=1.424882411956787 loss_test=1.4058644771575928 accuracy=0.4109504818916321
epoch:240 loss=1.4226510524749756 loss_test=1.4036513566970825 accuracy=0.4137188494205475
epoch:245 loss=1.4204589128494263 loss_test=1.4014822244644165 accuracy=0.4161796271800995
epoch:250 loss=1.4183048009872437 loss_test=1.3993555307388306 accuracy=0.4177176356315613
epoch:255 loss=1.4161874055862427 loss_test=1.397269606590271 accuracy=0.4192556142807007
epoch:260 loss=1.414106011390686 loss_test=1.3952230215072632 accuracy=0.4223316013813019
epoch:265 loss=1.4120588302612305 loss_test=1.393214225769043 accuracy=0.4269455671310425
epoch:270 loss=1.4100452661514282 loss_test=1.3912415504455566 accuracy=0.4306367337703705
epoch:275 loss=1.4080638885498047 loss_test=1.3893033266067505 accuracy=0.4346354901790619
epoch:280 loss=1.4061119556427002 loss_test=1.3873965740203857 accuracy=0.4370962679386139
epoch:285 loss=1.4041810035705566 loss_test=1.3855178356170654 accuracy=0.4386342763900757
```

```
print(x_test[1])
```

```
tensor([-0.2242, -0.1057,  0.0286,  0.9980,  0.0176])
```

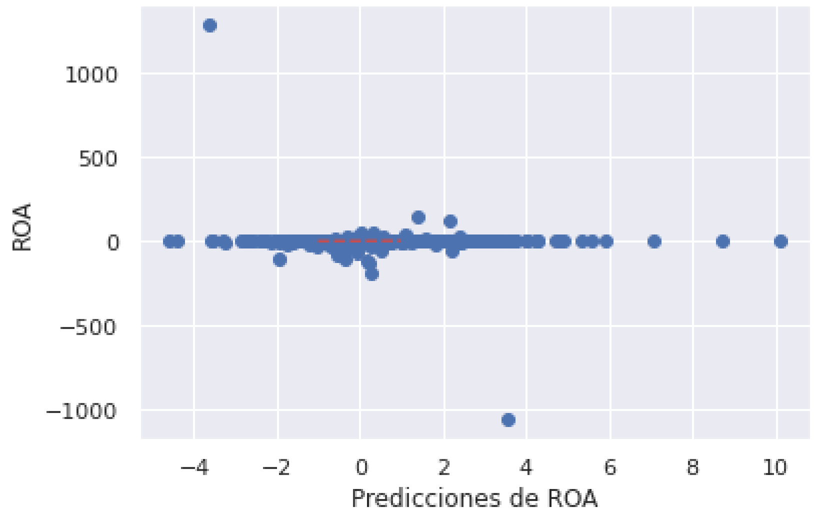


```
features = [-1.6564935e-02, -4.6171069e-02, -1.5524080e-02,  2.4994294e-01, 2.3307087e+01]
y_prueba = lr_model(x_test)
etiquetas = y_prueba.argmax(dim=1)
print(etiquetas)
```

```
tensor([2, 2, 3,  ..., 1, 2, 1])
```


```
# Evaluando el modelo 2019
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in train_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROA')
plt.xlabel('Predicciones de ROA')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
```

```
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDATOS DEL AÑO 2019:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print('Accuracy: {:.2f}%'.format(mse*10))
```

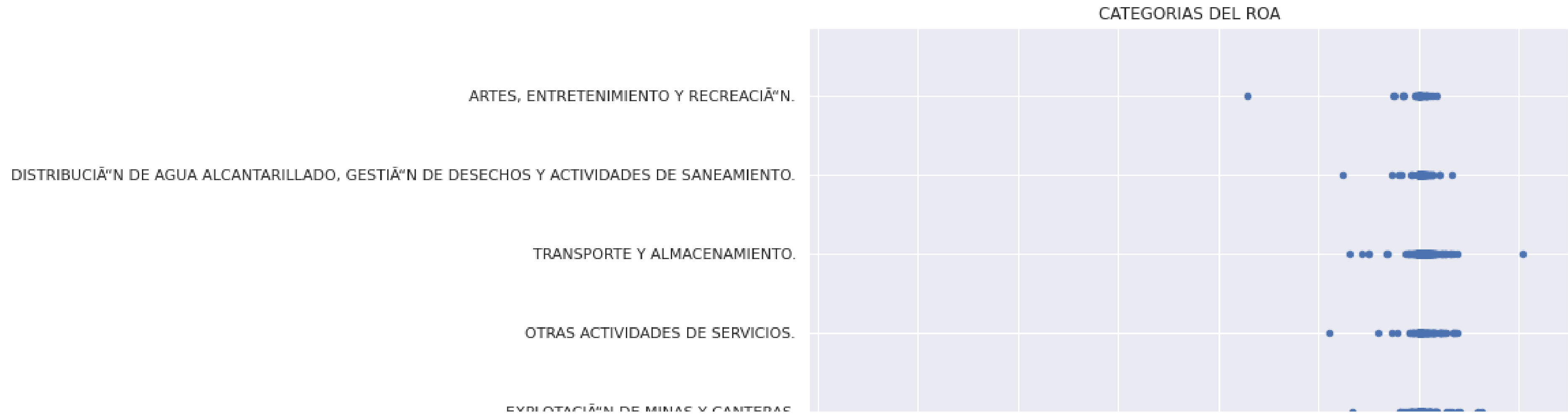



```
DATOS DEL AÑO 2019:
MAE: 0.8424941301345825
MSE: 261.9762268066406
Accuracy: 2619.76%
```

PREDICCION POR CATEGORIAS DE AÑO 2019

```
df.plot.scatter(x='ROA',y= 'DESCRIPCIÓN RAMA', figsize=(10,20),title="CATEGORIAS DEL ROA")
```

```
WARNING:matplotlib.axes._axes:*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-m
<matplotlib.axes._subplots.AxesSubplot at 0x7fad89dd19d0>
```




```
import glob
import os
def CATEGORIAS_LO():
  df ['ROA_DIS'] = pd.qcut(df['ROA'], 4, labels=False)
  categ =  df[['RAMA']].values
  df['RAMA'] = categ
  metrics = {"DESCRIPCIÓN": [],  "MSE": [], "RMSE": [],"ACC": []}
  grouped =  df.groupby("RAMA")
  for categoria, group in grouped:
      X_rlg = group[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO P
      Y_rlg = group[['ROA_DIS']].values
      # Escalando
      scaler = StandardScaler()
      inputs = scaler.fit_transform(X_rlg)
      X_rlg = torch.from_numpy(inputs.astype(np.float32))
      Y_rlg = torch.from_numpy(Y_rlg.astype(np.int64))
      dataset_test = TensorDataset(X_rlg, Y_rlg)
      test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)
      # Evaluando el modelo
      y_pred = []
      y_true = []
      lr_model.train(False)
      for inputs, targets in test_loader:
        y_hat_test = lr_model(inputs).data.numpy()
        y_hat_class = np.argmax(y_hat_test, axis=1)
        y_pred.extend(y_hat_class)
        y_true.extend(targets.numpy())
      # Calculando Errores
      mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
      rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
      acc = accuracy_score(y_true, y_pred)
      metrics["DESCRIPCIÓN"].append(categoria)
      metrics["MSE"].append(mse)
      metrics["RMSE"].append(rmse)
      metrics["ACC"].append(acc)
  metrics_df = pd.DataFrame(metrics)
  metrics_df = metrics_df.sort_values("MSE")
  print("LAS CATEGORIAS MAYORES ERRORES :")
  print(metrics_df.tail(8))
  print("LAS CATEGORIAS MENORES ERRORES :")
  print(metrics_df.head(8))
```

```
CATEGORIAS_LO()
```

```
LAS CATEGORIAS MAYORES ERRORES :
   DESCRIPCIÓN       MSE      RMSE       ACC
6            G  1.450767  1.204478  0.295876
9            J  1.748031  1.322131  0.330709
2            C  1.767623  1.329520  0.255328
0            A  1.901597  1.378984  0.273482
13           N  2.011019  1.418104  0.330579
14           P  2.133333  1.460593  0.355556
8            I  2.486438  1.576844  0.233273
16           R  2.536585  1.592666  0.317073
LAS CATEGORIAS MENORES ERRORES :
   DESCRIPCIÓN       MSE      RMSE       ACC
10           K  0.392857  0.626783  0.714286
7            H  0.711409  0.843451  0.489933
3            D  0.814286  0.902378  0.485714
11           L  0.815668  0.903144  0.419355
17           S  0.824742  0.908153  0.577320
15           Q  0.841121  0.917127  0.514019
```

```
5           F  1.130273  1.063143  0.349876
4           E  1.197531  1.094318  0.320988
```

PREDICCIONES POR AÑOS

2019

```
X_LOG_2019 = torch.from_numpy(np.array([[-1.6564935e-02, -4.6171069e-02, -1.5524080e-02,  2.4994294e-01, 2.3307087e+01]],
  dtype='float32'))
Y_LOG_2019 = model_rl(X_LOG_2019) #predicción
print(Y_LOG_2019)
```

```
tensor([[0.7059]], grad_fn=<AddmmBackward0>)
```

```
x_LO_2019 = torch.from_numpy(np.array([[inputs]],
  dtype='float32'))
y_LOG_2019 = model_rl(x_LO_2019) #predicción
print('prediccion media : ',y_LOG_2019.mean())
print('prediccion maxima : ',y_LOG_2019.max())
print('prediccion minima : ',y_LOG_2019.min())
```

```
prediccion media :  tensor(-1.3777e+13, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(48.6831, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-1.6038e+17, grad_fn=<MinBackward1>)
```

2017

```
df_LO_2017 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2017_cia.xlsx", index_col=0)
df_LO_2017.fillna(0)
df_LO_2017.dropna(inplace=True)


#Remover Outliers
df1_LO_2017 = df_LO_2017[(df_LO_2017['ROA']>-1) & (df_LO_2017['ROA'] < 1) & (df_LO_2017['RENTABILIDAD NETA DEL ACTIVO'] < 500) & (df_
            (df_LO_2017['ENDEUDAMIENTO A CORTO PLAZO'] > -5) & (df_LO_2017['RENTABILIDAD NETA DE VENTAS'] < 150) & (df_LO_2017['ROTAC

X_LO_2017 = df1_LO_2017[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A COR
Y_LO_2017 = df1_LO_2017[['ROA']]
Y_LO_2017['ROA_DIS'] = pd.qcut(Y_LO_2017['ROA'], 5, labels=False)
Y2_LO_2017 = Y_LO_2017[['ROA_DIS']]
```

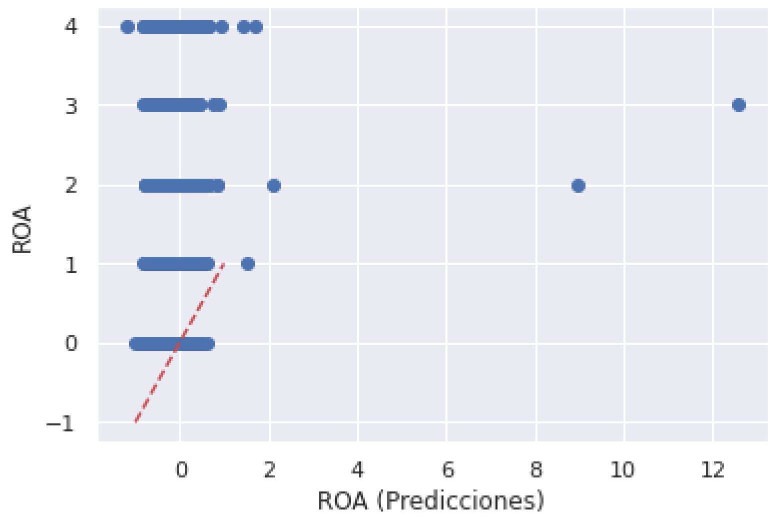
```
<ipython-input-286-eb8d98a7b5e1>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
  Y_LO_2017['ROA_DIS'] = pd.qcut(Y_LO_2017['ROA'], 5, labels=False)
```

```
inputs = df1_LO_2017[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO
targets = df1_LO_2017[['ROA']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [-0.04194727 -0.13251807 -0.04817906  0.26522911 13.475732  ]
Tamaño:  (11947, 5)
Target #1:  [-0.04194728]
Tamaño:  (11947, 1)
```

```
X_2017= np.array(X_LO_2017, dtype='float32')
Y_2017= Y2_LO_2017['ROA_DIS'].values
x_train, x_test, y_train, y_test = train_test_split(X_2017,Y_2017,test_size = 0.25)
# SCALER
scaler = sklearn.preprocessing.StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
#
x_test_2017 = torch.from_numpy(x_test.astype(np.float32))
## describir nuevo paso - numero enteros
y_test_2017 = torch.from_numpy(y_test.astype(np.int64))
dataset_test = TensorDataset(x_test_2017, y_test_2017)
```

```
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)

 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROA')
plt.xlabel('ROA (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nResultados Del año 2017 datos:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print('Accuracy: {:.2f}%'.format(mse*10))
```




```
Resultados Del año 2017 datos:
MAE: 2.0960259307892994
MSE: 6.220399598870354
Accuracy: 62.20%
```

```
X_LO_2017 = torch.from_numpy(np.array([[-0.04194727, -0.13251807, -0.04817906, 0.26522911, 13.475732]],
  dtype='float32'))
Y_LOG_2017 = model_rl(X_LO_2017) #predicción
print(Y_LOG_2017)

y_prueba_2017 = lr_model(x_test_2017)
etiquetas_2017 = y_prueba_2017.argmax(dim=1)
print(etiquetas_2017)
```

```
tensor([[0.4128]], grad_fn=<AddmmBackward0>)
tensor([2, 2, 1,  ..., 2, 3, 3])
```

```
x_LO_2017 = torch.from_numpy(np.array([[inputs]], dtype='float32'))
y_LOG_2017 = model_rl(x_LO_2017) #predicción
print('prediccion media : ',y_LOG_2017.mean())
print('prediccion maxima : ',y_LOG_2017.max())
print('prediccion minima : ',y_LOG_2017.min())
```

```
prediccion media :  tensor(-1.7999e+12, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(96.0370, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-1.0208e+16, grad_fn=<MinBackward1>)
```

2018

```
df_LO_2018 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2018_cia.xlsx", index_col=0)
df_LO_2018.fillna(0)
df_LO_2018.dropna(inplace=True)
```

```
#Remover Outliers
df1_LO_2018 = df_LO_2018[(df_LO_2018['ROA']>-1) & (df_LO_2018['ROA'] < 1) & (df_LO_2018['RENTABILIDAD NETA DEL ACTIVO'] < 500) & (df_
            (df_LO_2018['ENDEUDAMIENTO A CORTO PLAZO'] > -5) & (df_LO_2018['RENTABILIDAD NETA DE VENTAS'] < 150) & (df_LO_2018['ROTAC
```

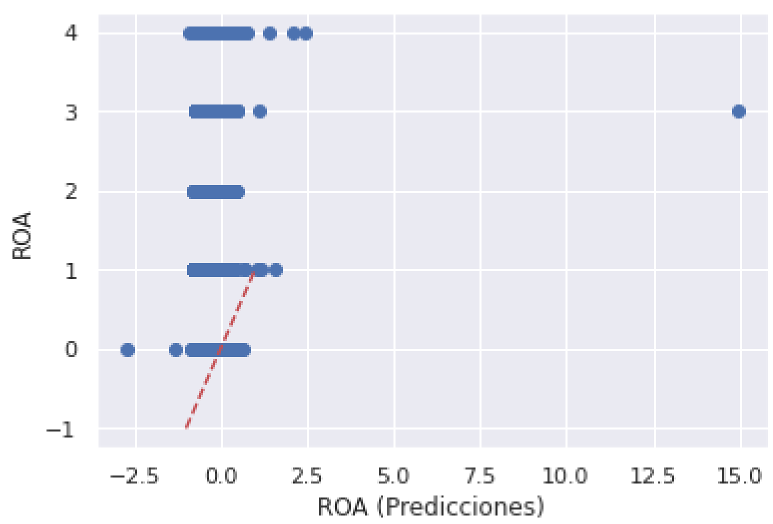
```
X_LO_2018 = df1_LO_2018[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A COR
Y_LO_2018 = df1_LO_2018[['ROA']]
Y_LO_2018['ROA_DIS'] = pd.qcut(Y_LO_2018['ROA'], 5, labels=False)
Y2_LO_2018 = Y_LO_2018[['ROA_DIS']]
```

```
<ipython-input-294-e71f3d476647>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
  Y_LO_2018['ROA_DIS'] = pd.qcut(Y_LO_2018['ROA'], 5, labels=False)
```

```
inputs = df1_LO_2018[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO
targets = df1_LO_2018[['ROA']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [1.7399877e-02 5.3634219e-02 1.5702046e-02 4.4583824e-01 2.3272505e+01]
Tamaño:  (12652, 5)
Target #1:  [0.01739987]
Tamaño:  (12652, 1)
```

```
X_2018= np.array(X_LO_2018, dtype='float32')
Y_2018= Y2_LO_2018['ROA_DIS'].values
x_train, x_test, y_train, y_test = train_test_split(X_2018,Y_2018,test_size = 0.25)
# SCALER
scaler = sklearn.preprocessing.StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
#
x_test_2018 = torch.from_numpy(x_test.astype(np.float32))
## describir nuevo paso - numero enteros
y_test_2018 = torch.from_numpy(y_test.astype(np.int64))
dataset_test = TensorDataset(x_test_2018, y_test_2018)
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)

 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROA')
plt.xlabel('ROA (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDatos del año 2018:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print('Accuracy: {:.2f}%'.format(mse*10))
```




```
Datos del año 2018:
MAE: 2.0657072362937257
MSE: 6.052954244478889
Accuracy: 60.53%
```

```
X_LO_2018 = torch.from_numpy(np.array([[1.7399877e-02, 5.3634219e-02, 1.5702046e-02, 4.4583824e-01, 2.3272505e+01]],
  dtype='float32'))
Y_LOG_2018 = model_rl(X_LO_2018) #predicción
print(Y_LOG_2018)

y_prueba_2018 = lr_model(x_test_2018)
etiquetas_2018 = y_prueba_2018.argmax(dim=1)
print(etiquetas_2018)
```

```
tensor([[0.7956]], grad_fn=<AddmmBackward0>)
tensor([2, 1, 1,  ..., 3, 2, 1])
```

```
x_LO_2018 = torch.from_numpy(np.array([[inputs]], dtype='float32'))
y_LOG_2018 = model_rl(x_LO_2018) #predicción
print('prediccion media : ',y_LOG_2018.mean())
print('prediccion maxima : ',y_LOG_2018.max())
print('prediccion minima : ',y_LOG_2018.min())
```

```
prediccion media :  tensor(-1.6676e+12, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(61.3546, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-1.1621e+16, grad_fn=<MinBackward1>)
```

2020

```
df_LO_2020 = pd.read_excel("/content/drive/MyDrive/datasets/IA/indicadores2020_cia.xlsx", index_col=0)
df_LO_2020.fillna(0)
df_LO_2020.dropna(inplace=True)


#Remover Outliers
df1_LO_2020 = df_LO_2020[(df_LO_2020['ROA']>-1) & (df_LO_2020['ROA'] < 1) & (df_LO_2020['RENTABILIDAD NETA DEL ACTIVO'] < 500) & (df_
            (df_LO_2020['ENDEUDAMIENTO A CORTO PLAZO'] > -5) & (df_LO_2020['RENTABILIDAD NETA DE VENTAS'] < 150) & (df_LO_2020['ROTAC

X_LO_2020 = df1_LO_2020[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A COR
Y_LO_2020 = df1_LO_2020[['ROA']]
Y_LO_2020['ROA_DIS'] = pd.qcut(Y_LO_2020['ROA'], 5, labels=False)
Y2_LO_2020 = Y_LO_2020[['ROA_DIS']]
```

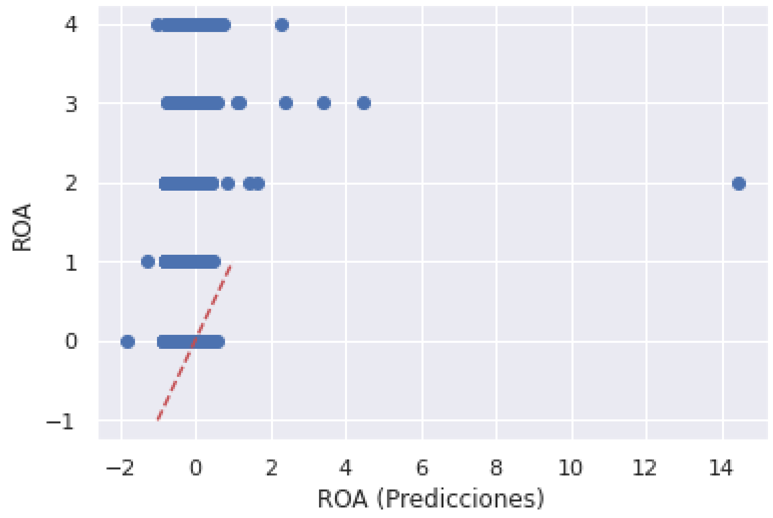
```
<ipython-input-301-6072f85a7925>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
  Y_LO_2020['ROA_DIS'] = pd.qcut(Y_LO_2020['ROA'], 5, labels=False)
```

```
inputs = df1_LO_2020[['RENTABILIDAD NETA DEL ACTIVO','RENTABLIDAD FINANCIERA','RENTABILIDAD NETA DE VENTAS',  'ENDEUDAMIENTO A CORTO
targets = df1_LO_2020[['ROA']].values
print('Input #1: ', inputs[1], '\nTamaño: ', inputs.shape,
      '\nTarget #1: ', targets[1], '\nTamaño: ', targets.shape)
```

```
Input #1:  [-0.02910098 -0.08051773 -0.03420236  0.2134347  20.622047   ]
Tamaño:  (12445, 5)
Target #1:  [-0.02910098]
Tamaño:  (12445, 1)
```

```
X_2020= np.array(X_LO_2020, dtype='float32')
Y_2020= Y2_LO_2020['ROA_DIS'].values
x_train, x_test, y_train, y_test = train_test_split(X_2020,Y_2020,test_size = 0.25)
# SCALER
scaler = sklearn.preprocessing.StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
#
x_test_2020 = torch.from_numpy(x_test.astype(np.float32))
## describir nuevo paso - numero enteros
y_test_2020 = torch.from_numpy(y_test.astype(np.int64))
dataset_test = TensorDataset(x_test_2020, y_test_2020)
test_loader = DataLoader(dataset_test, batch_size=bs, shuffle=True)

 # Evaluando el modelo
y_pred = []
y_true = []
model_rl.train(False)
for inputs, targets in test_loader:
  y_pred.extend(model_rl(inputs).data.numpy())
```

```
  y_true.extend(targets.numpy())
plt.scatter(y_pred, y_true)
plt.ylabel('ROA')
plt.xlabel('ROA (Predicciones)')
plt.plot([-1,1], [-1, 1], '--k', c='r')
plt.show()
    # Calculando Errores
mae = mean_absolute_error(y_true=y_true, y_pred=y_pred)
mse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=True)
rmse = mean_squared_error(y_true=y_true, y_pred=y_pred, squared=False)
print(f"\nDATOS DEL AÑO 2020:")
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print('Accuracy: {:.2f}%'.format(mse*10))
```




```
DATOS DEL AÑO 2020:
MAE: 2.0930176297373886
MSE: 6.181234990097467
Accuracy: 61.81%
```

```
X_LO_2020 = torch.from_numpy(np.array([[-0.02910098, -0.08051773, -0.03420236,  0.2134347,  20.622047]],
  dtype='float32'))
Y_LOG_2020 = model_rl(X_LO_2020) #predicción
print(Y_LOG_2020)

y_prueba_2020 = lr_model(x_test_2020)
etiquetas_2020 = y_prueba_2020.argmax(dim=1)
print(etiquetas_2020)
```

```
tensor([[0.6098]], grad_fn=<AddmmBackward0>)
tensor([2, 2, 3,  ..., 1, 3, 1])
```

```
x_LO_2020 = torch.from_numpy(np.array([[inputs]], dtype='float32'))
y_LOG_2020 = model_rl(x_LO_2020) #predicción
print('prediccion media : ',y_LOG_2020.mean())
print('prediccion maxima : ',y_LOG_2020.max())
print('prediccion minima : ',y_LOG_2020.min())
```

```
prediccion media :  tensor(-4.3949e+12, grad_fn=<MeanBackward0>)
prediccion maxima :  tensor(41.1606, grad_fn=<MaxBackward1>)
prediccion minima :  tensor(-3.9867e+16, grad_fn=<MinBackward1>)
```

RESULTADOS

CATEGORIAS -ROE 2019

CATEGORIAS CON MAYORES ERRORES

DESCRIPCIÓN	RAMA	MAE	MSE	RMSE
SERVICIOS ADMINISTRATIVOS	N	0.767580	6.006226	2.450760
INDUSTRIAS MANUFACTURERAS	C	0.639846	9.715785	3.117015
COMUNICACION	J	0.720340	10.789764	3.284778
ENSEÑANZA	P	1.116344	11.688409	3.418832
OTRAS ACTIVIDADES DE SERVICIOS	S	0.858742	13.774165	3.711356
ACTIVIDADES PROFESIONALES	M	0.788759	20.722900	4.552241
COMERCIO AL POR MAYOR	G	0.869720	275.378662	16.594538
AGRICULTURA	A	1.579000	747.573303	27.341787

CATEGORIAS CON MENORES ERRORES

DESCRIPCIÓN	RAMA	MAE	MSE	RMSE
ACTIVIDADES FINANCIERAS Y DE SEGUROS	K	0.215334	0.090012	0.300020
TRANSPORTE Y ALMACENAMIENTO	H	0.312487	0.180658	0.425039
ACTIVIDADES INMOBILIARIAS	L	0.318897	0.188932	0.434664
DISTRIBUCIÓN DE AGUA ALCANTARILLADO	E	0.412937	0.277002	0.526310
ARTES, ENTRETENIMIENTO Y RECREACIÓN	R	0.503054	0.362741	0.602280
EXPLOTACIÓN DE MINAS Y CANTERAS	B	0.400449	0.498010	0.705698
ACTIVIDADES DE ATENCIÓN DE LA SALUD HUMANA Y DE ASISTENCIA SOCIAL	Q	0.481493	0.735337	0.857518
CONSTRUCCIÓN	F	0.424011	1.249428	1.117778

CATEGORIAS -ROA 2019

CATEGORIAS CON MAYORES ERRORES

DESCRIPCIÓN	RAMA	MSE	RMSE	ACC
COMERCIO AL POR MAYOR	G	1.450767	1.204478	0.295876
COMUNICACION	J	1.748031	1.322131	0.330709
INDUSTRIAS MANUFACTURERAS	C	1.767623	1.329520	0.255328
AGRICULTURA	A	1.901597	1.378984	0.273482
SERVICIOS ADMINISTRATIVOS	N	2.011019	1.418104	0.330579
ENSEÑANZA.	P	2.133333	1.460593	0.355556
SERVICIO DE COMIDAS	I	2.486438	1.576844	0.233273
ARTES	R	2.536585	1.592666	0.317073

**CATEGORIAS CON MENORES ERRORES **

DESCRIPCIÓN	RAMA	MSE	RMSE	ACC
ACTIVIDADES FINANCIERAS	K	0.392857	0.626783	0.714286
TRANSPORTE Y ALMACENAMIENTO	H	0.711409	0.843451	0.489933
SUMINISTRO Y ELECTICIDAD	D	0.814286	0.902378	0.485714
ACTIVIDADES INMOBILIARIAS	L	0.815668	0.903144	0.419355
OTRAS ACTIVIDADES DE SERVICIO	S	0.824742	0.908153	0.577320
SALUD HUMANA	Q	0.841121	0.917127	0.514019
CONSTRUCCION	F	1.130273	1.063143	0.349876
DISTRIBUCIÓN DE AGUA ALCANTARILLADO	E	1.197531	1.094318	0.320988

PREDICCIONES POR AÑO - ROE

ERRORES	2017	2018	2019	2020
MAE	0.313248	0.316394	0.895503	0.316394
MSE	0.185078	0.196501	252.685302	0.196501
RMSE	0.430207	0.443284	15.896078	0.443284

PREDICCIÓN	2017	2018	2019	2020
Mínima	-2.1740	-38.2713	0.0967	-38.2713
Media	-0.0121	-0.0023	0.0967	-0.0023
Máxima	7.0244	53.9339	0.0967	53.9339

PREDICCIONES POR AÑO - ROA

ERRORES	2017	2018	2019	2020
MAE	2.096025	2.065707	0.842494	2.093017
MSE	6.220399	6.052954	261.976226	6.181234
Accuracy	62.20%	60.53%	2619.76%	61.81%

PREDICCIÓN	2017	2018	2019	2020
Mínima	-1.0208e+16	-1.6676e+12	-1.6038e+17	-3.9867e+16
Media	-1.7999e+12	-1.6676e+12	-1.3777e+13	-4.3949e+12
Máxima	96.0370	61.3546	48.6831	41.1606

CONCLUSIONES

¿Qué año predice mejor y peor?

> **En el ROE**

Mediante el Analisis podemos concluir las siguientes predicciones:

El año que predice mejor es:

- Es el 2018 con una prediccion maxima de 53.9339

El año que predice peor es:

- Es 2019 con una prediccion minima de 0.0967

> **En el ROA**

Mediante el Analisis podemos concluir las siguientes predicciones:

El año que predice mejor es:

- Es el 2019 con un accuracy de 2619.76%

El año que predice peor es:

- Es el 2020 con un acuraccy minimo de 61.81%

¿Qué categoría de empresas predice mejor y peor?

> En el ROE 2019

Mediante el Analisis podemos concluir las siguientes predicciones:

El la Categoria que predice mejor es:

- la categoria que mejor predice es la de ACTIVIDADES FINANCIERAS Y DE SEGUROS dentro de la rama K, con una Mae: 0.215334, Mse: 0.090012 y Rmse de 0.300020 con una cantidad de errores bajos

la categoria que peor predice es:

- la categoria que peor predice con una cantida elevada de errores es la ENSEÑANZA de la rama P con una Mae : 1.116344, Mse: 11.688409 y la Rmse: 3.418832

> En el ROA 2019

Mediante el Analisis podemos concluir las siguientes predicciones:

El la Categoria que predice mejor es:

- la categoria que mejor predice es la de ACTIVIDADES FINANCIERAS Y DE SEGUROS dentro de la rama K, con una Mae: 0.392857, Mse: 0.626783 y Rmse de 0.714286 con una cantidad de errores bajos

la categoria que peor predice es:

- la categoria que peor predice con una cantida elevada de errores es la de ARTES de la rama R con una Mae : 3.108108, Mse: 1.762983 y la Rmse: 0.324324.