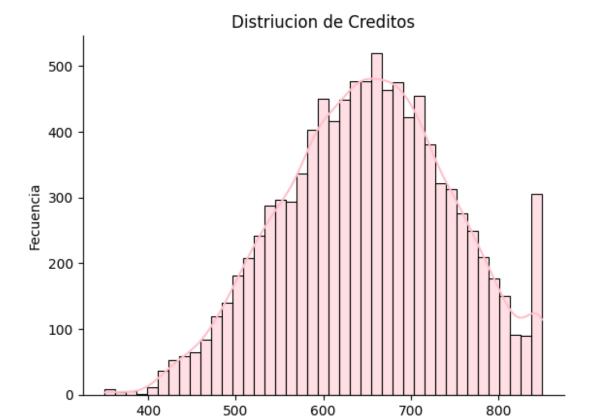
```
import pandas as pd
import numpy as np
df = pd.read csv
('https://raw.githubusercontent.com/yessss28/Estadistica/refs/heads/
main/Churn Modelling%20(1).csv')
df.dropna(inplace=True)
df.drop(columns = ["RowNumber", "CustomerId", "Surname"], inplace =
True)
df
{"summary":"{\n \"name\": \"df\",\n \"rows\": 9998,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
n \"dtype\": \"number\",\n \"std\": 96,\n
\"min\": 350,\n \"max\": 850,\n \"num_unique_values\":
],\n \"semantic_type\":\"\",\n
n },\n {\n \"column\": \"Age\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 10.487985680801943,\n
\"min\": 18.0,\n \"max\": 92.0,\n \"num_unique_values\":
73,\n \"samples\": [\n 29.0,\n
                                                   71.0\
        ],\n \"semantic_type\": \"\",\n
\"num_unique_values\": 11,\n \"samples\": [\n
                                                         3, n
2\n ],\n \"semantic type\": \"\",\n
\"max\": 250898.09,\n \"num_unique_values\": 6379,\n \"samples\": [\n 156834.34,\n 161592.76\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"NumOfProducts\",\n
\"properties\": {\n \"dtype\": \"number\",\n
                                                      \"std\":
0,\n \"min\": 1,\n \"max\": 4,\n
\"num_unique_values\": 4,\n \"samples\": [\n
                                                        3,\n
```

```
],\n \"semantic_type\": \"\",\n
\"HasCrCard\",\n\\"properties\": {\n\\"dtype\": \"number\",\n\\"std\": 0.4558219327223667,\n\
0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n
\"samples\": [\n 0.0,\n
                                        1.0\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"IsActiveMember\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.4998058202347973,\n \"min\": 0.0,\n \"max\": 1.0,\n
\"num_unique_values\": 2,\n
                                \"samples\": [\n
                                                          0.0, n
\"Exited\",\n \"properties\": {\n \"dtype\": \"std\": 0,\n \"min\": 0,\n \"max\": 1,\n
\"num_unique_values\": 2,\n \"samples\": [\n
                                                          0, n
\"description\": \"\"\n }\n ]\n
n}","type":"dataframe","variable name":"df"}
df["Geography"].unique()
array(['France', 'Spain', 'Germany'], dtype=object)
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(Geography)",data=df).fit()
tabla anova = sm.stats.anova lm(modelo)
tabla anova
#No se rechaza la hipotesis nula, no hay diferencia de grupos
{"summary":"{\n \"name\": \"tabla_anova\",\n \"rows\": 2,\n
\"fields\": [\n {\n \"column\": \"df\",\n
                                                   \"properties\":
          \"dtype\": \"number\",\n \"std\":
{\n
7066.118064397169,\n \"min\": 2.0,\n \"max\": 9995.0,\n
\"num_unique_values\": 2,\n \"samples\": [\n 2.0\n ],\n \"semantic_type\": \"\",\n
                                                         9995.0,\n
\"description\": \"\"\n }\n {\n \"column\":
\"sum_sq\",\n\\"properties\": {\n\\"dtype\": \"number\",\n\\"std\": 23375249960878.414,\n\\"min\": 3782055029.3742604,\n\\"max\": 33061377573564.785,\n\\"num_unique_values\": 2,\n
\"samples\": [\n 33061377573564.785,\n
```

```
3782055029.3742604\n
                        ],\n
}\n
                                 \"semantic type\": \"\",\n
                               },\n {\n \"column\":
\"description\": \"\"\n
\"mean_sq\",\n \"properties\": {\n
                                        \"dtype\": \"number\",\
        \"std\": 1001803529.6723961,\n
                                         \"min\":
1891027514.6871302,\n \"max\": 3307791653.18307,\n
\"num_unique_values\": 2,\n
                              \"samples\": [\n
3307791653.18307,\n 1891027514.6871302\n
\"semantic_type\": \"\",\n
                             \"description\": \"\"\n
    },\n {\n \"column\": \"F\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": null,\n \"min\":
0.5716888223196901,\n \"max\": 0.5716888223196901,\n
\"num_unique_values\": 1,\n
                              \"samples\": [\n
0.5716888223196901\n
                        ],\n
                               \"semantic type\": \"\",\n
                        \"description\": \"\"\n
\"PR(>F)\",\n \"properties\": {\n \"dtype\": \"nu\"std\": null,\n \"min\": 0.5645896326325097,\n
                                      \"dtype\": \"number\",\n
                                                     \"max\":
\"semantic type\": \"\",\n \"description\": \"\"\n
    }\n ]\n}","type":"dataframe","variable_name":"tabla_anova"}
import seaborn as sns
import matplotlib.pyplot as plt
sns.histplot(df['CreditScore'], kde = True, color = 'pink')
plt.xlabel('Creditos')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Creditos')
plt.gca().spines['right'].set visible(False)
plt.gca().spines['top'].set visible(False)
# no hay datos atipicos
```



```
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(Geography)",data=df).fit()
tabla anova = sm.stats.anova lm(modelo)
tabla_anova
#No se rechaza la hipotesis nula por que no hay diferencia de grupos
{"summary":"{\n \"name\": \"tabla anova\",\n \"rows\": 2,\n
\"fields\": [\n
                          \"column\": \"df\",\n
                                                    \"properties\":
                  {\n
          \"dtype\": \"number\",\n
{\n
                                     \"std\":
7066.118064397169,\n
                     \"min\": 2.0,\n
                                              \mbox{"max}: 9995.0,\n
\"num_unique_values\": 2,\n
                                  \"samples\": [\n
                                                           9995.0,\n
2.0\n
                      \"semantic type\": \"\",\n
            ],\n
\"description\": \"\"\n
                                                   \"column\":
                                  },\n {\n
                            }\n
\"sum sq\",\n
              \"properties\": {\n
                                            \"dtype\": \"number\",\n
\"std\": 23375249960878.414,\n
\"max\": 33061377573564.785,\n
                                    \"min\": 3782055029.3742604,\n
                                    \"num unique values\": 2,\n
\"samples\": [\n
                         33061377573564.785,\n
3782055029.3742604\n
                           ],\n
                                   \"semantic_type\": \"\",\n
\"description\": \"\"\n
                           }\n
                                   },\n {\n \"column\":
\"mean sq\",\n \"properties\": {\n
                                         \"dtype\": \"number\",\
```

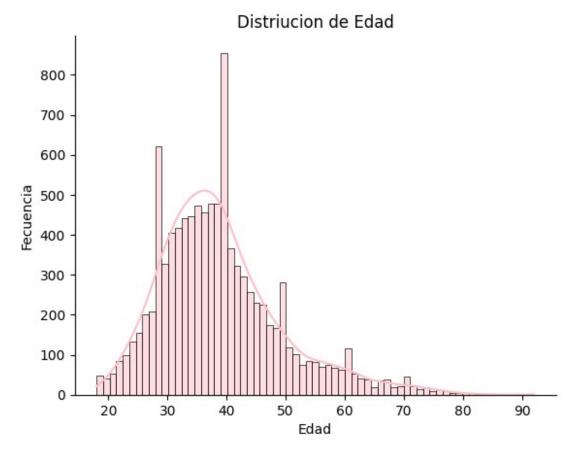
Creditos

```
n \"std\": 1001803529.6723961,\n \"min\":
1891027514.6871302,\n \"max\": 3307791653.18307,\n
\"num_unique_values\": 2,\n \"samples\": [\n
\"dtype\": \"number\",\n \"std\": null,\n \"min\": 0.5716888223196901,\n \"max\": 0.5716888223196901,\n \"num_unique_values\": 1,\n \"samples\": [\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n }\n ]\n}","type":"dataframe","variable_name":"tabla_anova"}
df.drop(columns = ["Geography"], inplace = True)
{"summary":"{\n \"name\": \"df\",\n \"rows\": 9998,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
n \"dtype\": \"number\",\n \"std\": 96,\n \"min\": 350,\n \"max\": 850,\n \"num_unique_values\": 460,\n \"samples\": [\n 716,\n 475,\n
460,\n \"samples\": [\n 716,\n 475,\n 588\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n {\n \"column\": \"Gender\",\n \"num_unique_values\": 2,\n \"samples\": [\n \"Male\",\n \"Female\"\n ],\n \"semantic_type\": \"\"\n }\n {\n \"column\": \"Age\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 10.487985680801943,\n \"min\": 18.0,\n \"max\": 92.0,\n \"num_unique_values\": 73.\n \"samples\": [\n 29.0.\n 71.0\"
73,\n \"samples\": [\n 29.0,\n 71.0\\n ],\n \"semantic_type\": \"\",\n
\"max\": 250898.09,\n \"num_unique_values\": 6379,\n \"samples\": [\n 156834.34,\n 161592.76\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n     },\n     {\n     \"column\": \"NumOfProducts\",\n
\"properties\": {\n     \"dtype\": \"number\",\n     \"std\":
```

```
0,\n \"min\": 1,\n \"max\": 4,\n \"num_unique_values\": 4,\n \"samples\": [\n
                                                                                                                               3,\n
4\n \"semantic_type\": \"\",\n
0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n \"samples\": [\n 0.0,\n 1.0\n 1,\n
\"samples\": [\n 0.0,\n
                                                                                       1.0\n ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"IsActiveMember\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.4998058202347973,\n \"min\": 0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n \"samples\": [\n 0.0,\n
\"num_unique_values\": 2,\n \"samples\": [\n
1\n ],\n \"semantic_type\": \"\",\n
                                                                                                                               0, n
n}","type":"dataframe","variable_name":"df"}
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(Gender)",data=df).fit()
tabla_anova = sm.stats.anova_lm(modelo)
tabla anova
#No rechazamos las hipotesis nula, no hay diferencia de grupos
{"summary":"{\n \"name\": \"tabla_anova\",\n \"rows\": 2,\n
\"fields\": [\n {\n \"column\": \"df\",\n
                                                                                                                \"properties\":
                       \"dtype\": \"number\",\n \"std\":
{\n
7067.532277959543,\n\\"min\\": 1.0,\n\\\"max\\": 9996.0,\n
\"num_unique_values\": 2,\n \"samples\": [\n
                                                                                                                             9996.0.\n
\"samples\": [\n 33063137910429.89\overline{\square},\n 2021718164.2719057\n ],\n \"semantic_type\": \"\",\n \"description\": \"\",\n \"semantic_type\": \"\",\n \"semantic_type\": \"\",\n \"\",\n \"\",\n \"\",\n \"\",\n \\",\n \\",\n
                                                        }\n
\"description\": \"\"\n
                                                                           },\n
                                                                                           {\n \"column\":
```

```
\"mean_sq\",\n \"properties\": {\n \"dtype\": \"number\",\
n \"std\": 909281819.7497585,\n \"min\":
2021718164.2719057,\n \"max\": 3307636845.781302,\n \"num_unique_values\": 2,\n \"samples\": [\n 3307636845.781302,\n \"samples\": [\n 3307636845.781302,\n 2021718164.2719057\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n \\"n \\"column\": \"F\",\n \"properties\": \\"dtype\": \"number\",\n \"std\": null,\n \"min\": 0.6112273682192437,\n \"max\": 0.6112273682192437,\n \"samples\": \\"numunique_values\": \\"\"samples\": \\"\"
\"semantic type\": \"\",\n \"description\": \"\"\n
n }\n ]\n}","type":"dataframe","variable_name":"tabla_anova"}
df.drop(columns = ["Gender"], inplace = True)
{"summary":"{\n \"name\": \"df\",\n \"rows\": 9998,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
n \"dtype\": \"number\",\n \"std\": 96,\n
\"min\": 350,\n \"max\": 850,\n \"num_unique_values\":
}\n    },\n    {\n     \"column\": \"Balance\",\n
\"properties\": {\n          \"dtype\": \"number\",\n
62393.18703475617,\n         \"min\": 0.0,\n         \"max\":
250898.09,\n \"num_unique_values\": 6379,\n \"samples\": [\n 156834.34,\n 161592.76,\n 166883.07\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
```

```
0.0, \n \"max\": 1.0, \n \"num_unique_values\": 2, \n \"samples\": [\n 0.0, \n 1.0\n ], \n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"IsActiveMember\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
0.4998058202347973,\n \"min\": 0.0,\n \"max\": 1.0,\n
\"num_unique_values\": 2,\n \"samples\": [\n
                                                      0.0, n
          1.0\n
\"min\":
11.58,\n \"max\": 199992.48,\n \"num_unique_values\": 9995,\n \"samples\": [\n 51752.18,\n 121408.55\n ],\n \"semantic type\": \"\".\n
\"num_unique_values\": 2,\n \"samples\": [\n
                                                      0, n
1\n ],\n \"semantic_type\": \"\",\n
\"description\": \"\n }\n }\n ]\
n}","type":"dataframe","variable name":"df"}
import seaborn as sns
import matplotlib.pyplot as plt
sns.histplot(df['Age'], kde = True, color = 'pink')
plt.xlabel('Edad')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Edad')
plt.gca().spines['right'].set visible(False)
plt.gca().spines['top'].set visible(False)
# no hay datos atipicos
```

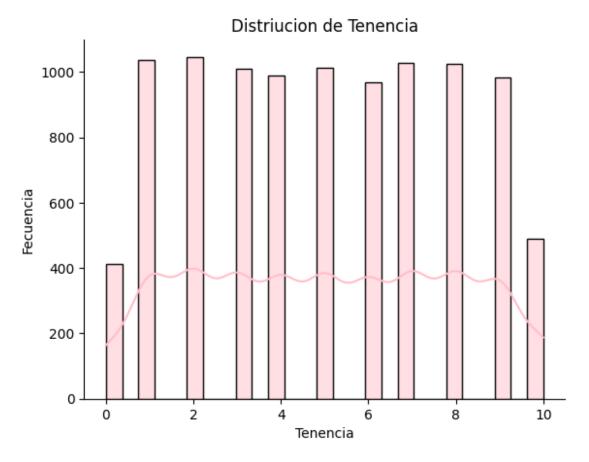


```
import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['Tenure'], kde = True, color = 'pink')
plt.xlabel('Tenencia')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Tenencia')

plt.gca().spines['right'].set_visible(False)
plt.gca().spines['top'].set_visible(False)

# no hay datos atipicos
```



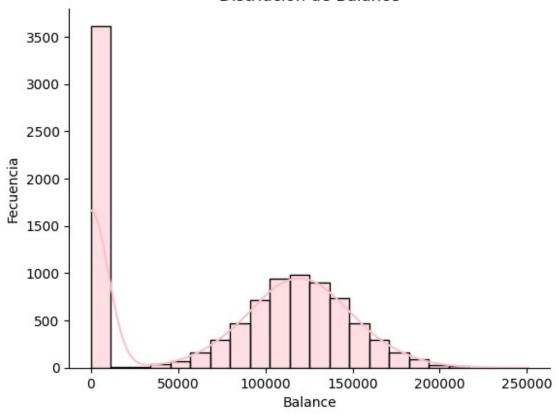
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['Balance'], kde = True, color = 'pink')
plt.xlabel('Balance')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Balance')

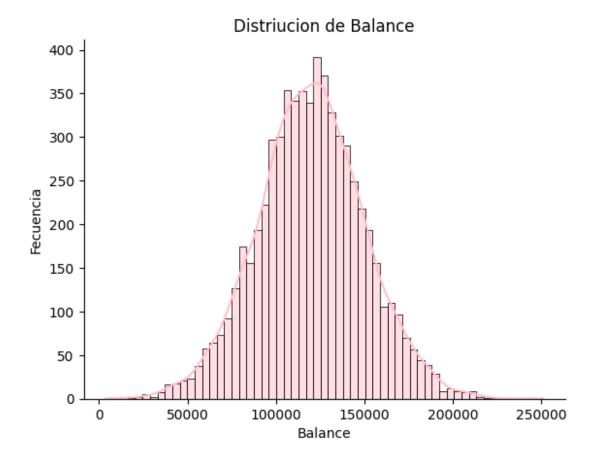
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['top'].set_visible(False)

# este si es atipico
```

## Distriucion de Balance



```
\"num unique values\": 6378,\n
250898.09,\n
                                                                            \"samples\":
                                             142946.18,\n
[\n
                 121863.61,\n
                                                                            125167.74\n
                \"semantic_type\": \"\",\n \"description\": \"\"\n
],\n
}\n },\n {\n \"column\": \"NumOfProducts\",\n
\"properties\": {\n \"dtype\": \"number\",\n
                                                                         \"std\":
0,\n \"min\": 1,\n \"max\": 4,\n
\"num_unique_values\": 4,\n \"samples\": [\n 3,\n
4,\n 1\n ],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n {\n \"column\":
                                                                                 3,\n
\"HasCrCard\",\n\\"properties\": {\n\\"dtype\": \"number\",\n\\"std\": 0.45859377845608573,\n\
0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n \"samples\": [\n 1.0,\n 0.0\n ],\n
\"samples": [\n 1.0,\n]
                                                        0.0\n ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"IsActiveMember\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.4998658949563229,\n \"min\": 0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n \"samples\": [\n 0.0,\n
1.0\n ],\n \"semantic type\": \"\",\n
\"description\": \"\"\n \\n \\n \\n \\"column\": \"EstimatedSalary\",\n \"properties\": \\n \"dtype\": \\"number\",\n \"std\": 57387.54061299657,\n \"min\": 11.58,\n \"max\": 199970.74,\n \"num_unique_values\": 6380,\n \"samples\": [\n 82276.62,\n 138051.19\n ],\n \"semantic_type\": \"\",\n
\"num_unique_values\": 2,\n \"samples\": [\n
0\n ],\n \"semantic_type\": \"\",\n
                                                                                  1, n
\"description\": \"\n }\n }\n ]\
n}","type":"dataframe","variable name":"df"}
import seaborn as sns
import matplotlib.pyplot as plt
sns.histplot(df['Balance'], kde = True, color = 'pink')
plt.xlabel('Balance')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Balance')
plt.gca().spines['right'].set visible(False)
plt.gca().spines['top'].set visible(False)
```



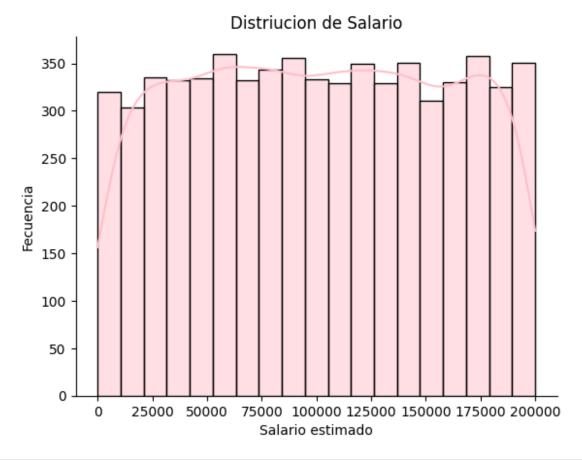
```
df['NumOfProducts'].unique()
array([1, 3, 2, 4])
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(NumOfProducts)",data=df).fit()
tabla anova = sm.stats.anova lm(modelo)
tabla anova
#Se acepta la hipotesis nula
{"summary":"{\n \"name\": \"tabla_anova\",\n \"rows\": 2,\n
                       \"column\": \"df\",\n \"properties\":
\"fields\": [\n
                   {\n
           \"dtype\": \"number\",\n \"std\":
min\": 3.0.\n \"max\": 6378.0,\n
                                           \"std\": 4507.80573006424,\
{\n
         \"min\": 3.0,\n
\"num_unique_values\": 2,\n
                                   \"samples\": [\n
                                                             6378.0,\n
                         \"semantic_type\": \"\",\n
             ],\n
                                   },\n
\"description\": \"\"\n
                                                     \"column\":
                             }\n
                                            {\n
                   \"properties\": {\n
                                              \"dtype\": \"number\",\n
\"sum_sq\",\n
\"std\": 14836100282901.814,\n
                                    \"min\": 16661666675.839527,\n
\"max\": 20998075899482.9.\n
                                    \"num unique values\": 2,\n
                          20998075899482.9,\n
\"samples\": [\n
```

```
\"mean_sq\",\n \"properties\": {\n \"dtype\": \"number\",\
n \"std\": 1599208511.8148003,\n \"min\":
3292266525.475525,\n\\"max\": 5553888891.946509,\n
\"num_unique_values\": 2,\n \"samples\": [\n 3292266525.475525,\n 5553888891.946509\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
     },\n {\n \"column\": \"F\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": null,\n \"min\": 1.6869499625776265,\n \"max\": 1.6869499625776265,\n
\"num_unique_values\": 1,\n \"samples\": [\n
\"PR(>F)\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": null,\n \"min\": 0.1675103678907714,\n \"max\": 0.1675103678907714,\n \"num_unique_values\": 1,\n \"samples\": [\n 0.1675103678907714\n ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
     }\n ]\n}","type":"dataframe","variable_name":"tabla_anova"}
df["HasCrCard"].unique()
array([0., 1.])
df.drop(columns = ["HasCrCard"], inplace = True)
df
<ipython-input-18-05ald017a22e>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df.drop(columns = ["HasCrCard"], inplace = True)
{"summary":"{\n \"name\": \"df\",\n \"rows\": 6382,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
        \"dtype\": \"number\",\n \"std\": 96,\n
\"min\": 350,\n \"max\": 850,\n
                                             \"num unique values\":
450,\n \"samples\": [\n
                                         810,\n
                                                          467.\n
763\n
             ],\n \"semantic_type\": \"\",\n
92.0,\n \"num_unique_values\": 67,\n \"samples\": [\n 47.0,\n 39.0,\n 31.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n \,\n \"roperties\":
         \"dtype\": \"number\",\n \"std\": 2,\n
{\n
```

```
\"min\": 0,\n \"max\": 10,\n \"num_unique_values\": 11,\
n \"samples\": [\n 2,\n 1,\n 5\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n     },\n     {\n     \"column\": \"Balance\",\n
\"properties\": {\n         \"dtype\": \"number\",\n
30100.964691131376,\n         \"min\": 3768.69,\n
250898.09,\n         \"num_unique_values\": 6378,\n
                                                                    \"std\":
                                                                   \"max\":
       121863.61,\n 142946.18,\n \"semantic_typo\": \"\"
                                                                    \"samples\":
                                                                   125167.74\n
[\n
              \"semantic_type\": \"\",\n \"description\": \"\"\n
],\n
0,\n \"min\": 1,\n \"max\": 4,\n
\"num_unique_values\": 4,\n \"samples\": [\n 3,\n
4,\n 1\n ],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n {\n \"column\": \"IsActiveMember\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 0.4998658949563229,\n \"min\":
0.0,\n \"max\": 1.0,\n \"num_unique_values\": 2,\n \"samples\": [\n 0.0,\n 1.0\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"EstimatedSalary\",\n \"properties\": {\n \"dtype\": \"number\",\n 57387.54061299657,\n \"min\": 11.58,\n \"max\
                                                                      \"std\":
                                                               \"max\":
199970.74,\n \"num_unique_values\": 6380,\n \"samples\": [\n 82276.62,\n 138051.19\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"Exited\",\n \"properties\":
}\n ]\n}","type":"dataframe","variable_name":"df"}
df["IsActiveMember"].unique()
array([1., 0.])
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(IsActiveMember)",data=df).fit()
tabla anova = sm.stats.anova lm(modelo)
tabla anova
{"summary":"{\n \"name\": \"tabla anova\",\n \"rows\": 2,\n
\"fields\": [\n {\n \"column\": \"df\",\n \"properties\":
             \"dtype\": \"number\",\n \"std\":
7067.532277959543,\n\"min\": 1.0,\n\\"max\": 9996.0,\n
\"num_unique_values\": 2,\n \"samples\": [\n
                                                                        9996.0,\n
               ],\n \"semantic_type\": \"\",\n
1.0\n
```

```
\"sum sq\",\n \"properties\": {\n \"dtype\": \"number\",\n
\"std\": 23374918049243.47,\n\\"min\": 4016751997.1980176,\n\\"max\": 33061142876596.96,\n\\"num_unique_values\": 2,\n
\"samples\": [\n 33061142876596.96,\n 4016751997.1980176\n ],\n \"seman
                        ],\n \"semantic_type\": \"\",\n
                                 },\n {\n \"column\":
\"description\": \"\"\n }\n
\"mean_sq\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 501561258.8547397,\n \"min\":
3307437262.564722,\n\\"max\": 4016751997.1980176,\n
\"num_unique_values\": 2,\n
                               \"samples\": [\n
},\n {\n \"column\": \"F\",\n \"properties\": {\n
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\"num_unique_values\": 1,\n
                                \"samples\": [\n
\"PR(>F)\",\n \"properties\": {\n
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\"semantic type\": \"\",\n \"description\": \"\"\n
    }\n ]\n}","type":"dataframe","variable name":"tabla anova"}
df.drop(columns = ["IsActiveMember"], inplace = True)
df
<ipython-input-20-13c8f583d392>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df.drop(columns = ["IsActiveMember"], inplace = True)
{"summary":"{\n \"name\": \"df\",\n \"rows\": 6382,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
       \"dtype\": \"number\",\n \"std\": 96,\n
\"min\": 350,\n \"max\": 850,\n
                                        \"num unique values\":
            \"samples\": [\n 810,\n
450,\n
                                                467,\n
           ],\n \"semantic_type\": \"\",\n
763\n
\"column\":
\"Age\",\n \"properties\": {\n \"dtype\": \"number\",\n
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92.0,\n \"num_unique_values\": 67,\n \"samples\": [\n 47.0,\n 39.0,\n 31.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
    },\n {\n \"column\": \"Tenure\",\n \"properties\":
```

```
\"semantic_type\": \"\",\n
                                         \"description\": \"\"\n
],\n
     },\n {\n \"column\": \"Balance\",\n
}\n
\"properties\": {\n \"dtype\": \"number\",\n \\30100.964691131376,\n \"min\": 3768.69,\n
                                                    \"std\":
                                                  \"max\":
250898.09,\n \"num unique values\": 6378,\n
                                                  \"samples\":
[\n
           121863.61,\n 142946.18,\n
                                                   125167.74\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"NumOfProducts\",\n
\"std\":
\"EstimatedSalary\",\n
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11.58,\n \"max\": 199970.74,\n \"num_unique_values\":
             \"samples\": [\n
                                    82276.62,\n
6380,\n
138051.19,\n 108008.65\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"Exited\",\n \"properties\":
{\n \"dtype\": \"number\",\n \"std\": 0,\n
\"min\": 0,\n \"max\": 1,\n \"samples\": [\n 1,\n
                                    \"num unique values\": 2,\n
                                    0\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
    }\n ]\n}","type":"dataframe","variable_name":"df"}
import seaborn as sns
import matplotlib.pyplot as plt
sns.histplot(df['EstimatedSalary'], kde = True, color = 'pink')
plt.xlabel('Salario estimado')
plt.ylabel('Fecuencia')
plt.title('Distriucion de Salario')
plt.gca().spines['right'].set visible(False)
plt.gca().spines['top'].set_visible(False)
```

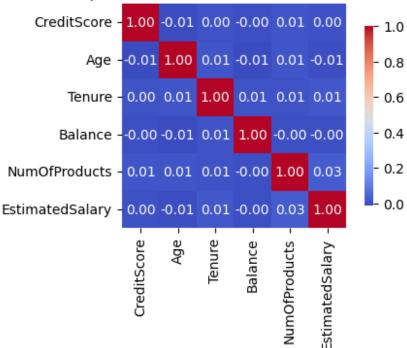


```
df["Exited"].unique()
array([0, 1])
import statsmodels.api as sm
import statsmodels.formula.api as smf
modelo=smf.ols("EstimatedSalary ~ C(Exited)",data=df).fit()
tabla anova = sm.stats.anova lm(modelo)
tabla anova
#Los datos no aportan nada
{"summary":"{\n \"name\": \"tabla_anova\",\n \"rows\": 2,\n
                           \"column\": \"df\",\n
\"fields\": [\n
                   {\n
                                                       \"properties\":
           \"dtype\": \"number\",\n
                                           \"std\":
{\n
4510.634157188987,\n
                      \"min\": 1.0,\n
                                                   \"max\": 6380.0,\n
\"num_unique_values\": 2,\n
                                   \"samples\": [\n
                                                             6380.0,\n
             ],\n
                    \"semantic_type\": \"\",\n
1.0\n
\"description\": \"\"\n
                                   },\n {\n
                             }\n
                                                     \"column\":
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                   \"properties\": {\n
                                              \"dtype\": \"number\",\n
\"std\": 14858493566058.293,\n
\"max\": 21013910341855.88,\n
\"num_unique_values\": 2,\n
\"samples\": [\n
                          21013910341855.88,\n
```

```
\"mean_sq\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1744073255.4668121,\n \"min\":
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},\n {\n \"column\": \"F\",\n \"properties\": {\n
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\"PR(>F)\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": null,\n \"min\": 0.6162821924514956,\n \"max\": 0.6162821924514956,\n \"num_unique_values\": 1,\n \"samples\": [\n 0.6162821924514956\n ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
    }\n ]\n}","type":"dataframe","variable_name":"tabla_anova"}
df.drop(columns = ["Exited"], inplace = True)
df
<ipython-input-24-baclaf30eeba>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
 df.drop(columns = ["Exited"], inplace = True)
{"summary":"{\n \"name\": \"df\",\n \"rows\": 6382,\n \"fields\":
[\n {\n \"column\": \"CreditScore\",\n \"properties\": {\
n \"dtype\": \"number\",\n \"std\": 96,\n
                                    \"num unique_values\":
\"min\": 350,\n \"max\": 850,\n
            \"samples\": [\n 810,\n
450,\n
                                              467,\n
92.0,\n \"num_unique_values\": 67,\n \"samples\": [\n 47.0,\n 39.0,\n 31.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
{\n \"column\": \"Balance\",\n
      },\n
}\n
```

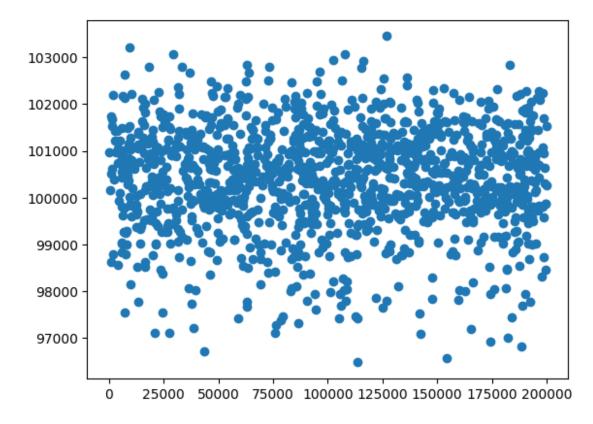
```
\"properties\": {\n \"dtype\": \"number\",\n \\30100.964691131376,\n \"min\": 3768.69,\n
                                                           \"std\":
                                                         \"max\":
250898.09,\n \"num unique values\": 6378,\n
                                                          \"samples\":
             121863.61,\n
                                    142946.18,\n
                                                          125167.74\n
[\n
            \"semantic_type\": \"\",\n \"description\": \"\"\n
],\n
}\n },\n {\n \"column\": \"NumOfProducts\",\n
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                                                              3, n
                                           {\n \"column\":
\"EstimatedSalary\",\n
                            \"properties\": {\n
                                                       \"dtype\":
\"number\",\n \"std\": 57387.54061299657,\n \"min\":
            \"max\": 199970.74,\n \"num_unique_values\":
11.58,\n
6380,\n
               \"samples\": [\n
                                          82276.62,\n
138051.19,\n 108008.65\n
                                         ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
                                                                }\
n }\n ]\n}","type":"dataframe","variable_name":"df"}
import seaborn as sns
import matplotlib.pyplot as plt
matriz de correlacion = df.corr()
plt.figure(figsize=(5, 3))
sns.heatmap(matriz de correlacion, annot=True, cmap='coolwarm',
fmt=".2f", square=True, cbar kws={"shrink": .8})
plt.title('Mapa de Calor de la Matriz de Correlación')
Text(0.5, 1.0, 'Mapa de Calor de la Matriz de Correlación')
```

## Mapa de Calor de la Matriz de Correlación



```
from sklearn.model selection import train test split
from sklearn.metrics import r2 score
import statsmodels.api as sm
import matplotlib.pyplot as plt
X = df[['CreditScore',
                           'Age',
                                       'Tenure', 'Balance']]
Y = df["EstimatedSalary"]
# Datos de entrenamiento y datos de prueba
X train, X test, Y train, Y test = train test split(X, Y, test size =
0.2, random state = 42)
X train constante = sm.add constant(X train)
X test constante = sm.add constant(X test)
modelo = sm.OLS(Y_train, X_train_constante).fit()
Yc = modelo.predict(X test constante)
plt.scatter(Y_test, Yc)
r2 = r2 \ score(Y \ test, Yc)
print(f'Coeficiente de correlacion: {r2: 0.4f}\n')
```

Coeficiente de correlacion: -0.0012



Un coeficiente de correlacion de -0.0012 indica que no hay una relacion lineal aparentemente entre las variables, es decir, no hay correlacion.

```
b0, b1, b2, b3, b4 = modelo.params
Fun = lambda x1, x2, x3, x4: b0 + b1 * x1 + b2 * x2 + b3 * x3 + b4 *
x4

# El salario estimado se puede calcular usando variables como el
puntaje de crédito, edad, antigüedad laboral y saldo financiero , ya
que reflejan estabilidad, experiencia y capacidad de pago.
# Estos datos permiten predecir ingresos mediante modelos estadísticos
o de aprendizaje automático.
Fun(432, 60, 2, 120000)
97992.76900028627
from statsmodels.formula.api import ols
moedo_2 = ols(formula = 'EstimatedSalary ~ CreditScore + Age + Tenure
+ Balance', data = df).fit()
```

```
tabla anova = sm.stats.anova lm(moedo 2, typ = 2)
tabla anova
{"summary":"{\n \"name\": \"tabla anova\",\n \"rows\": 5,\n
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                                                         \"std\":
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9395322884568.426,\n
\"max\": 21009822850002.05,\n
                                    \"num unique values\": 5,\n
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3339432886.04739
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\"num unique values\": 2,\n
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                        \"semantic_type\": \"\",\n
1.0\n
            ],\n
\"description\": \"\"\n
                                         {\n
                                                   \"column\":
                            }\n },\n
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                                                            ],\n
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                                                             }\
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     },\n {\n
                                                   \"properties\":
n
                                          \"std\":
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{\n
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                        0.493072375958044<del>6</del>5,\n
\"samples\": [\n
0.8751358090292845\n
                         ],\n
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\"description\": \"\"\n
                           }\n
                                   }\n ]\
n}","type":"dataframe","variable name":"tabla anova"}
```

CONCLUSIÓN El análisis de regresión lineal múltiple revela que las variables utilizadas en el modelo tienen poca capacidad para explicar la variabilidad del Salario Estimado (EstimatedSalary).

La suma de cuadrados residuales es considerablemente mayor que la de las variables predictoras, lo que indica que la mayor parte de la variabilidad en el salario no se debe a las variables incluidas en el modelo.

Cada variable tiene un grado de libertad, ya que se analizan individualmente, mientras que los residuos cuentan con 6377 grados de libertad.

El estadístico F es muy bajo (por ejemplo, 0.000268 para CreditScore y 0.469869 para Age), lo que sugiere que las variables no explican significativamente la variabilidad en el salario.

Los valores p son altos (todos superiores a 0.05, como 0.986941 para CreditScore y 0.493072 para Age), lo que significa que no hay suficiente evidencia estadística para afirmar que estas variables influyen en el salario estimado.

En resumen, el modelo indica que ni la edad ni el puntaje crediticio tienen un impacto significativo en el salario estimado. Esto sugiere que es necesario explorar otras variables o enfoques alternativos para mejorar la predicción del salario.