Actividad regresión lineal con datos de salario

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```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import statsmodels.formula.api as smf
import statsmodels.api as sm
from scipy import stats
```

```
df = pd.read_csv('/content/ds_salaries.csv')
```

```
df.head()
```

	Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_residence	remote_ratio	company_location	company_size
0	0	2020	MI	FT	Data Scientist	70000	EUR	79833	DE	0	DE	L
1	1	2020	SE	FT	Machine Learning Scientist	260000	USD	260000	JP	0	JP	S
2	2	2020	SE	FT	Big Data Engineer	85000	GBP	109024	GB	50	GB	M
3	3	2020	MI	FT	Product Data Analyst	20000	USD	20000	HN	0	HN	S
4	4	2020	SE	FT	Machine Learning Engineer	150000	USD	150000	US	50	US	L

Se eliminan las variables que no se ocupan

```
df.drop('Unnamed: 0',axis=1,inplace = True)
df.drop('work_year',axis=1,inplace = True)
df.drop('job_title',axis=1,inplace = True)
df.drop('salary_currency',axis=1,inplace = True)
df.drop('employee_residence',axis=1,inplace = True)
df.drop('company_location',axis=1,inplace = True)
df.drop('company_size',axis=1,inplace = True)
```

```
df.head()
```

	experience_level	employment_type	salary	salary_in_usd	remote_ratio
0	MI	FT	70000	79833	0
1	SE	FT	260000	260000	0
2	SE	FT	85000	109024	50
3	MI	FT	20000	20000	0
4	SE	FT	150000	150000	50

Se checa que no existan varibales nulas

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

```
experience_level    0
employment_type     0
salary              0
salary_in_usd       0
remote_ratio        0
dtype: int64
```

Se genera nuevas columnas dummies para trabajar solo con enteros

```
dummies_el = pd.get_dummies(df['experience_level'],prefix='Exp')
dummies_et = pd.get_dummies(df['employment_type'],prefix='Emp')
```

```
df = pd.concat([df,dummies_et],axis=1)
df = pd.concat([df,dummies_el],axis=1)
```

Se eliminan experience level y employment type para tabajar con las creadas previamente

```
df.drop('employment_type',axis=1,inplace = True)
df.drop('experience_level',axis=1,inplace = True)
```

```
df.head()
```

	salary	salary_in_usd	remote_ratio	Emp_CT	Emp_FL	Emp_FT	Emp_PT	Exp_EN	Exp_EX	Exp_MI	Exp_SE
0	70000	79833	0	0	0	1	0	0	0	1	0
2	85000	100024	50	0	0	1	0	0	0	0	1

Se empieza a revisar que los datos sean independientes

```
correlacion = df.corr()
correlacion
```

	salary	salary_in_usd	remote_ratio	Emp_CT	Emp_FL	Emp_FT	Emp_PT	Exp_EN	Exp_EX	Exp_MI	E
salary	1.000000	-0.083906	-0.014608	-0.008268	-0.014568	0.025685	-0.020006	-0.015845	0.014130	0.074626	-0.0
salary_in_usd	-0.083906	1.000000	0.132122	0.092907	-0.073863	0.091819	-0.144627	-0.294196	0.259866	-0.252024	0.3
remote_ratio	-0.014608	0.132122	1.000000	0.065149	-0.016865	-0.023834	-0.002935	-0.010490	0.041208	-0.127850	0.1
Emp_CT	-0.008268	0.092907	0.065149	1.000000	-0.007423	-0.506989	-0.011795	0.066013	0.070739	-0.028817	-0.0
Emp_FL	-0.014568	-0.073863	-0.016865	-0.007423	1.000000	-0.453089	-0.010541	-0.033537	-0.017229	0.068108	-0.0
Emp_FT	0.025685	0.091819	-0.023834	-0.506989	-0.453089	1.000000	-0.719987	-0.167828	-0.008698	-0.006597	0.1
Emp_PT	-0.020006	-0.144627	-0.002935	-0.011795	-0.010541	-0.719987	1.000000	0.204028	-0.027379	-0.013805	-0.1
Exp_EN	-0.015845	-0.294196	-0.010490	0.066013	-0.033537	-0.167828	0.204028	1.000000	-0.087108	-0.302761	-0.3
Exp_EX	0.014130	0.259866	0.041208	0.070739	-0.017229	-0.008698	-0.027379	-0.087108	1.000000	-0.155539	-0.1
Exp_MI	0.074626	-0.252024	-0.127850	-0.028817	0.068108	-0.006597	-0.013805	-0.302761	-0.155539	1.000000	-0.6
Exp_SE	-0.065995	0.343513	0.113071	-0.047768	-0.034520	0.128381	-0.119762	-0.381033	-0.195751	-0.680373	1.0

```
alta_corr = np.where((correlacion>0.95)&(correlacion<1))
alta_corr
```

```
(array([], dtype=int64), array([], dtype=int64))
```

```
baja_corr = np.where((correlacion<-0.95)&(correlacion>-1))
baja_corr
```

```
(array([], dtype=int64), array([], dtype=int64))
```

Debido a que no se necesito estandarizar los datos, se continua con la regresión lineal

Se divide la base de datos para el modelo con una semilla predeterminada

```
entrenamiento,prueba=train_test_split(df,test_size=0.20,random_state=42)
```

```
entrenamiento
```

	salary	salary_in_usd	remote_ratio	Emp_CT	Emp_FL	Emp_FT	Emp_PT	Exp_EN	Exp_EX	Exp_MI	Exp_SE
9	125000	125000	50	0	0	1	0	0	0	0	1
227	75000	88654	50	0	0	1	0	0	0	1	0
591	144854	144854	100	0	0	1	0	0	0	0	1
516	152500	152500	100	0	0	1	0	0	0	0	1
132	38400	38400	100	0	0	1	0	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...
71	37000	42197	50	0	0	1	0	0	0	1	0
106	235000	187442	100	0	0	1	0	0	0	1	0
270	72500	72500	100	0	0	1	0	1	0	0	0
435	70000	91614	100	0	0	1	0	0	0	1	0
102	11000000	36259	50	0	0	1	0	0	0	1	0

485 rows × 11 columns

```
prueba
```

	salary	salary_in_usd	remote_ratio	Emp_CT	Emp_FL	Emp_FT	Emp_PT	Exp_EN	Exp_EX	Exp_MI	Exp_SE
563	140250	140250	100	0	0	1	0	0	0	0	1
289	135000	135000	100	0	0	1	0	0	0	0	1
76	100000	100000	100	0	0	1	0	0	0	1	0
78	270000	270000	100	1	0	0	0	0	0	1	0
182	22000	26005	0	0	0	1	0	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...
249	170000	170000	100	0	0	1	0	0	0	0	1
365	138600	138600	100	0	0	1	0	0	0	0	1
453	120000	120000	100	0	0	1	0	0	0	1	0
548	99050	99050	100	0	0	1	0	0	0	0	1
235	110000	110000	0	0	0	1	0	0	0	1	0

122 rows × 11 columns

Se empieza a trabajar en el modelo

```
#salary_in_usd es la variable dependiente
#Se omite EMP_PT y EXP_SE debido a que quedan implicitas
modelo=smf.ols(formula='salary_in_usd~salary+Exp_EN+Exp_EX+Exp_MI',data=entrenamiento)
modelo = modelo.fit()
print(modelo.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          salary_in_usd   R-squared:                       0.253
Model:                            OLS   Adj. R-squared:                  0.247
Method:                 Least Squares   F-statistic:                     40.70
Date:                Wed, 16 Aug 2023   Prob (F-statistic):           2.24e-29
Time:                        18:16:29   Log-Likelihood:                -6047.6
No. Observations:                 485   AIC:                         1.211e+04
Df Residuals:                     480   BIC:                         1.213e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   1.413e+05   4276.518     33.037      0.000    1.33e+05     1.5e+05
salary        -0.0068      0.003     -2.299      0.022      -0.013      -0.001
Exp_EN     -7.754e+04   8570.685     -9.048      0.000   -9.44e+04   -6.07e+04
Exp_EX      6.913e+04    1.42e+04     4.883      0.000    4.13e+04    9.69e+04
Exp_MI      -4.91e+04   6483.621     -7.573      0.000   -6.18e+04   -3.64e+04
==============================================================================
Omnibus:                      239.858   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1925.137
Skew:                           1.990   Prob(JB):                         0.00
Kurtosis:                      11.912   Cond. No.                     5.07e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.07e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Analizando el resumen obtenido, se observa que:

$r^2 = 0.253$

En este caso la expresión es $y = \beta_0 + \beta_1 X + \ldots + \beta_n X_n$

β_0 siendo Intercept en la tabla mostrada previamente

∴

Tomando en cuenta los p-values, la ecuación matemática que describe el modelo es:

*y = 1.413e+05 - 0.0068 * 'salary' - 7.754e+04 * 'Exp_EN' + 6.913e+04 * Exp_EX - 4.91e+04 * Exp_MI*

```
# y_aprox=9.787e+04-0.0067*prueba['salary']+7.688e+04*prueba['Emp_CT']-7.485e+04*prueba['Exp_EN']+6.662e+04*prueba['Exp_EX']-4.79e+04*prueba['Exp_MI']
y_aprox=1.413e+05-0.0068*prueba['salary']-7.754e+04*prueba['Exp_EN']+6.913e+04*prueba['Exp_EX']-4.91e+04*prueba['Exp_MI']
```

```
tabla=pd.DataFrame({'Real':prueba['salary_in_usd'],'Prediccion':y_aprox,'Error':prueba['salary_in_usd']-y_aprox})
tabla
```

	Real	Prediccion	Error
563	140250	140346.30	-96.30
289	135000	140382.00	-5382.00
76	100000	91520.00	8480.00
78	270000	90364.00	179636.00
182	26005	92050.40	-66045.40
...	...	...	...
249	170000	140144.00	29856.00
365	138600	140357.52	-1757.52
453	120000	91384.00	28616.00
548	99050	140626.46	-41576.46
235	110000	91452.00	18548.00

122 rows × 3 columns

Gráfico de disperción

```
import matplotlib.pyplot as plt
plt.scatter(prueba['salary_in_usd'],y_aprox,color='purple')
plt.plot(prueba['salary_in_usd'],prueba['salary_in_usd'],color='red')
plt.title('Gráfico de dispersión')
plt.xlabel('Datos reales')
plt.ylabel('Prediccion')
```

```
Text(0, 0.5, 'Prediccion')
```

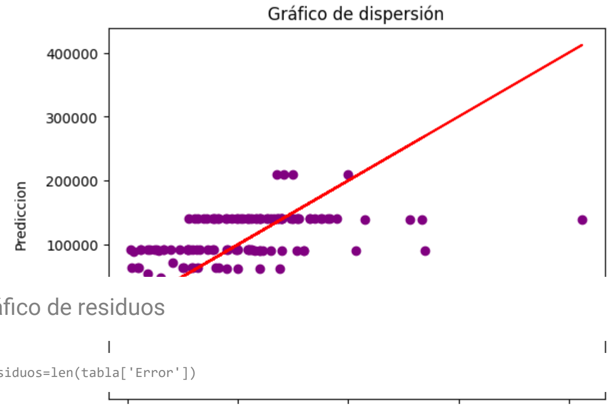
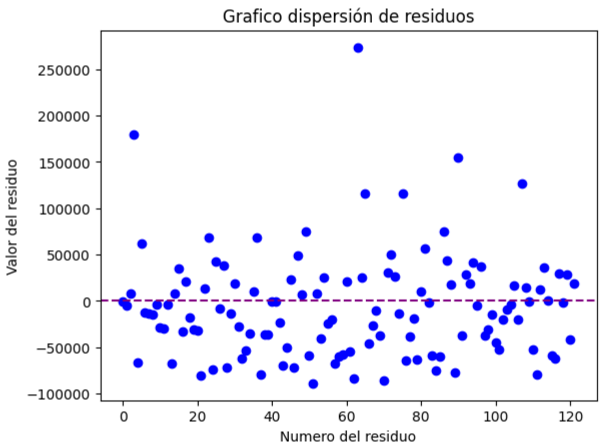


Gráfico de residuos

```
l_residuos=len(tabla['Error'])
```

```
plt.scatter(range(l_residuos),tabla['Error'],color='blue')
plt.axhline(y=0,linestyle='--',color='purple')
plt.title('Gráfico dispersión de residuos')
plt.xlabel('Numero del residuo')
plt.ylabel('Valor del residuo')
```

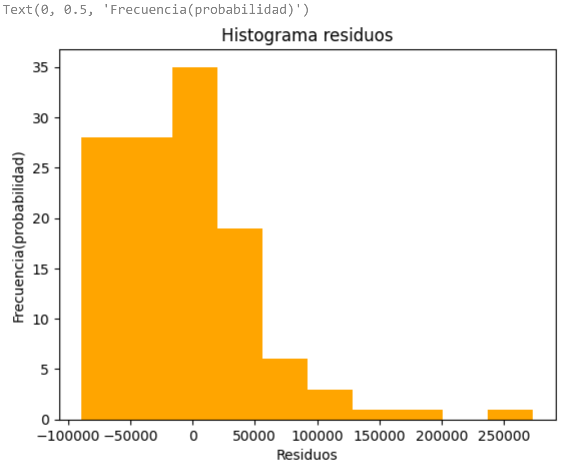
```
Text(0, 0.5, 'Valor del residuo')
```



Histograma

```
plt.hist(x=tabla['Error'],color='orange')
plt.title('Histograma residuos')
plt.xlabel('Residuos')
plt.ylabel('Frecuencia(probabilidad)')
```

```
Text(0, 0.5, 'Frecuencia(probabilidad)')
```




```
media=tabla['Error'].mean()
std=tabla['Error'].std()
Error_est=tabla['Error']-media/std
```

```
stats.kstest(Error_est,'norm')
```

```
#qqplot
QQ=sm.qqplot(tabla['Error'],stats.norm,line='45')
plt.title('Gráfico qqplots')
plt.show()
```

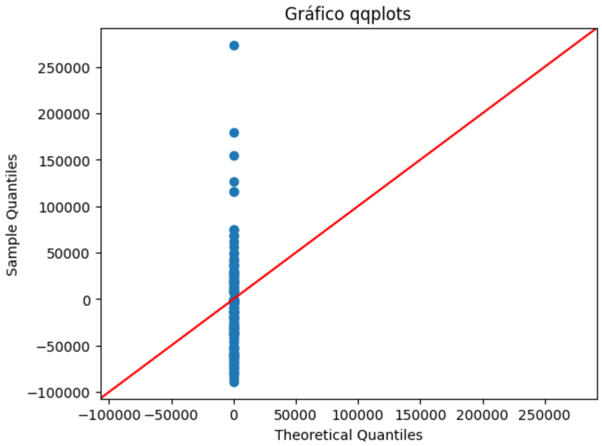


Gráfico qqplots
Sample Quantiles
Theoretical Quantiles
250000
200000
150000
100000
50000
0
−50000
−100000
−100000
−50000
0
50000
100000
150000
200000
250000