Actividad: Regresión Lineal

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Utiliza un modelo de regresión lineal múltiple para predecir el salario en dolares (salary_in_usd) de cada empleado. Las variables regresoras de tu modelo deben de ser las siguientes: nivel de experiencia (experience_level), tipo de empleo (employment_type), salario (salary) y radio remoto (remote_ratio).

1. Importamos librerias

```
import pandas as pd
import numpy as np
```

2. Leemos los datos del archivo ds_salaries.csv para nuestro data frame:

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

	Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	sala
0	0	2020	MI	FT	Data Scientist	70000	
1	1	2020	SE	FT	Machine Learning Scientist	260000	
2	2	2020	SE	FT	Big Data Engineer	85000	

```
df.shape
```

```
(607, 12)
```

3. Checamos si existen valores nulos en alguna de las columnas de nuestros datos:

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

```
Unnamed: 0            0
work_year             0
experience_level      0
employment_type       0
job_title             0
salary                0
salary_currency       0
salary_in_usd         0
employee_residence    0
```

```
remote_ratio         0
company_location     0
company_size         0
dtype: int64
```

4. Analizamos datos unicos en las columnas *experience_level* y *employment_type*:

```
df['experience_level'].unique()
```

```
array(['MI', 'SE', 'EN', 'EX'], dtype=object)
```

```
df['employment_type'].unique()
```

```
array(['FT', 'CT', 'PT', 'FL'], dtype=object)
```

5. Creamos dummies tanto para *experience_level* y *employment_type*:

```
dummiesexplvl = pd.get_dummies(df['experience_level'], prefix='experience_level')
dummiesexplvl.head()
```

	experience_level_EN	experience_level_EX	experience_level_MI	experience_leve
0	0	0	1	
1	0	0	0	
2	0	0	0	
3	0	0	1	
4	0	0	0	

```
dummiesemptype = pd.get_dummies(df['employment_type'], prefix='employment_type')
dummiesemptype.head()
```

	employment_type_CT	employment_type_FL	employment_type_FT	employment_type_PT
0	0	0	1	0
1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0

6. Eliminamos las columnas que ya no nos sirven como *experience_level* y *employment_type* o eliminamos las otras columnas que no son regresoras o de entrada:

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

	salary	salary_in_usd	remote_ratio
0	70000	79833	0
1	260000	260000	0
2	85000	109024	50
3	20000	20000	0
4	150000	150000	50

7. Concatenamos las variables dummiees a nuestro data frame:

```
df = pd.concat([df, dummiesexplvl, dummiesemptype], axis=1)
df.head()
```

	salary	salary_in_usd	remote_ratio	experience_level_EN	experience_level_EX
0	70000	79833	0	0	0
1	260000	260000	0	0	0
2	85000	109024	50	0	0
3	20000	20000	0	0	0
4	150000	150000	50	0	0

8. Checamos la correlacion que existe entre las variables regresoras:

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

	salary	salary_in_usd	remote_ratio	experience_level_EN
salary	1.000000	-0.083906	-0.014608	-0.015845
salary_in_usd	-0.083906	1.000000	0.132122	-0.294196
remote_ratio	-0.014608	0.132122	1.000000	-0.010490
experience_level_EN	-0.015845	-0.294196	-0.010490	1.000000
experience_level_EX	0.014130	0.259866	0.041208	-0.087108
experience_level_MI	0.074626	-0.252024	-0.127850	-0.302761
experience_level_SE	-0.065995	0.343513	0.113071	-0.381033
employment_type_CT	-0.008268	0.092907	0.065149	0.066013
employment_type_FL	-0.014568	-0.073863	-0.016865	-0.033537
employment_type_FT	0.025685	0.091819	-0.023834	-0.167828
employment_type_PT	-0.020006	-0.144627	-0.002935	0.204028

9. Analizamos la alta correlacion (no hay alta correlacion):

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

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

10. Analizamos la baja correlacion (no hay baja correlacion):

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

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

11. Estandarizamos los datos:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_estandar = scaler.fit_transform(df)
df_estandar
```

```
array([[-0.16460538, -0.45790445, -1.74361532, ..., -0.0814463 ,
         0.17975796, -0.12942341],
       [-0.0414754 ,  2.08328151, -1.74361532, ..., -0.0814463 ,
         0.17975796, -0.12942341],
       [-0.15488459, -0.04617667, -0.51437665, ..., -0.0814463 ,
         0.17975796, -0.12942341],
       ...,
       [-0.12637028,  0.2355771 , -1.74361532, ..., -0.0814463 ,
         0.17975796, -0.12942341],
       [-0.11276118,  0.53177399,  0.71486203, ..., -0.0814463 ,
         0.17975796, -0.12942341],
       [-0.08035855,  1.23700468,  0.71486203, ..., -0.0814463 ,
         0.17975796, -0.12942341]])
```

12. Procedemos a realizar la regresion lineal estandar a nuestro data frame:

```
df_estandar = pd.DataFrame(df_estandar, columns = df.columns)
df_estandar.head()
```

salary salary_in_usd remote_ratio experience_level_EN experience_level_EX

13. Entrenamos el modelo con nuestro data frame estandar:

1 -0.041475 2.083282 -1.743615 -0.411773 -0.21154

```
from sklearn.model_selection import train_test_split
entrenamiento, prueba = train_test_split(df_estandar, test_size=0.20, random_state=42)
entrenamiento.head()
```

	salary	salary_in_usd	remote_ratio	experience_level_EN	experience_level_
9	-0.128962	0.179159	-0.514377	-0.411773	-0.211
227	-0.161365	-0.333488	-0.514377	-0.411773	-0.211
591	-0.116096	0.459192	0.714862	-0.411773	-0.211
516	-0.111141	0.567036	0.714862	-0.411773	-0.211
132	-0.185084	-1.042301	0.714862	-0.411773	-0.211

14. Verificamos los resultados de la regresion:

> **R-squared** = 0.264 = 26.4%

R al cuadrado significa en nuestro modelo junto a nuestros datos la variabilidad del salario y las variables de regresion del mismo modelo.

> **Notas:**

- Standard Errors assume that the covariance matrix of the errors is correctly specified.
- The smallest eigenvalue is 1.76e-29. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Esto quiere decir que en alguna de nuestras variables regresoras se encuentre una alta correlacion de las mismas. A pesar de haber estandarizado los datos, se pueden ignorar algunas columnas de nuestro data frame para ver si las variables ignoradas ayuden a mejorar el valor de R al cuadrado.

```
import statsmodels.formula.api as smf
modelo = smf.ols(formula='salary_in_usd~salary+remote_ratio+experience_level_EN+experience_level_EX+experience_level_MI+experience_level_SE+employment_type_CT+employment_type_FL+employment
modelo = modelo.fit()
print(modelo.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          salary_in_usd   R-squared:                       0.264
Model:                            OLS   Adj. R-squared:                  0.252
Method:                 Least Squares   F-statistic:                     21.37
Date:                Fri, 18 Aug 2023   Prob (F-statistic):           8.41e-28
Time:                        05:41:48   Log-Likelihood:                -627.06
No. Observations:                 485   AIC:                             1272.
Df Residuals:                     476   BIC:                             1310.
Df Model:                           8
Covariance Type:            nonrobust
=========================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
```

```
Intercept              0.0167      0.040      0.413      0.680      -0.063       0.096
salary                -0.1455      0.065     -2.251      0.025      -0.272      -0.018
remote_ratio           0.0592      0.040      1.463      0.144      -0.020       0.139
experience_level_EN   -0.2365      0.034     -7.021      0.000      -0.303      -0.170
experience_level_EX    0.2680      0.037      7.230      0.000       0.195       0.341
experience_level_MI   -0.1392      0.027     -5.207      0.000      -0.192      -0.087
experience_level_SE    0.1914      0.025      7.602      0.000       0.142       0.241
employment_type_CT     0.0629      0.036      1.723      0.085      -0.009       0.135
employment_type_FL    -0.0357      0.046     -0.769      0.442      -0.127       0.056
employment_type_FT     0.0201      0.022      0.907      0.365      -0.023       0.064
employment_type_PT    -0.0495      0.033     -1.517      0.130      -0.114       0.015
==============================================================================
Omnibus:                      242.000   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2005.484
Skew:                           2.000   Prob(JB):                         0.00
Kurtosis:                      12.123   Cond. No.                     7.59e+15
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.76e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

15. Verificamos nuevamente los resultados de la regresion:

> **R-squared** = 0.253 = 25.3%

Recordemos que R al cuadrado significa en nuestro modelo junto a nuestros datos la variabilidad del salario y las variables de regresion del mismo modelo. Esta vez disminuida a nuestros resultados pasados pasemos a ver las notas.

> **Notas:**

- Standard Errors assume that the covariance matrix of the errors is correctly specified.

Pudimos quitarnos de la alta correlacion de las variables reegresoras, empeorando el modelo como consecuencia basandonos en los nuevos resultados de la regresion.

```
modelo = smf.ols(formula='salary_in_usd~salary+experience_level_EN+experience_level_EX+experience_level_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:                Fri, 18 Aug 2023   Prob (F-statistic):           2.24e-29
Time:                        05:41:48   Log-Likelihood:                -630.66
No. Observations:                 485   AIC:                             1271.
Df Residuals:                     480   BIC:                             1292.
Df Model:                           4
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept               0.0178      0.041      0.438      0.662      -0.062       0.098
salary                 -0.1487      0.065     -2.299      0.022      -0.276      -0.022
experience_level_EN    -0.3851      0.043     -9.048      0.000      -0.469      -0.301
experience_level_EX     0.1974      0.040      4.883      0.000       0.118       0.277
```

```
experience_level_MI    -0.3305      0.044     -7.573      0.000      -0.416      -0.245
==============================================================================
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.                         1.84
==============================================================================

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

16. Graficamos para visualizar las preedicciones y compararlo con los datos reales:

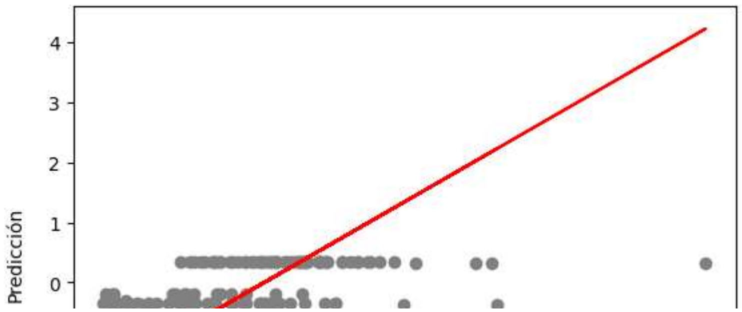
```
y_aprox= -0.1487*prueba['salary']-0.3851*prueba['experience_level_EN']+0.1974*prueba['experience_level_EN']-0.3305*prueba['experience_level_MI']
tabla=pd.DataFrame({'Real': prueba['salary_in_usd'], 'Prediccion': y_aprox, 'Errores': prueba['salary_in_usd']-y_aprox})
tabla
```

	Real	Prediccion	Errores
563	0.394254	0.338001	0.056253
289	0.320205	0.338507	-0.018302
76	-0.173457	-0.350624	0.177168
78	2.224328	-0.367007	2.591334
182	-1.217128	-0.343108	-0.874020
...	...	...	...
249	0.813866	0.335134	0.478732
365	0.370981	0.338160	0.032822
453	0.108636	-0.352552	0.461187
548	-0.186856	0.341971	-0.528827
235	-0.032411	-0.351588	0.319178

122 rows × 3 columns

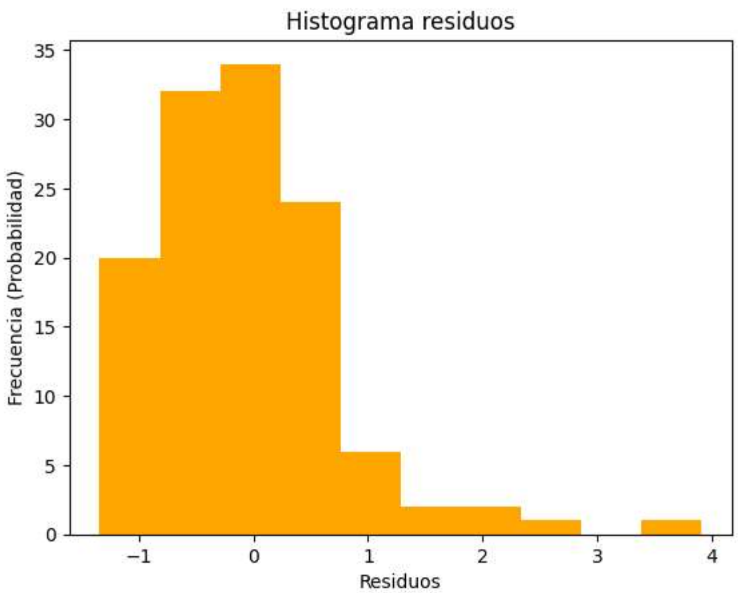
```
import matplotlib.pyplot as plt
plt.scatter(prueba['salary_in_usd'], y_aprox, color='gray')
plt.plot(prueba['salary_in_usd'],prueba['salary_in_usd'], color='red')
plt.xlabel("Datos Reales")
plt.ylabel("Predicción")
```

```
Text(0, 0.5, 'Predicción')
```

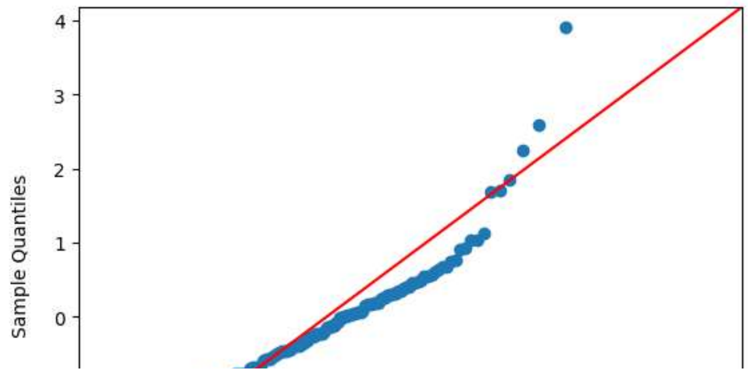



```
plt.hist(x=tabla['Errores'], color='orange')
plt.title('Histograma residuos')
plt.xlabel("Residuos")
plt.ylabel("Frecuencia (Probabilidad)")
```

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




```
import statsmodels.api as sm
from scipy import stats
QQ = sm.qqplot(tabla['Errores'], stats.norm, line='45')
```




```
media = tabla['Errores'].mean()
std = tabla['Errores'].std()
Errores_est=(tabla['Errores']-media)/std
stats.kstest(Errores_est, 'norm')
```

```
KstestResult(statistic=0.07918223576730476, pvalue=0.4076308371884318, statistic_location=0.5229810761201699, statistic_sign=1)
```

Conclusion

Los datos reales con nueestra prediccion no se acercan a la relacion lineal que eestamos buscando. Eso quiere decir que el modelo no se adecua correctamente a nuestros datos y por ende es necesario buscar otro tipo de modelo que logre acertar con mayor exactitud la preediccion de los datos con los reales.