## Actividad de Regresion lineal

```
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```

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

df = pd.read_csv("/content/drive/MyDrive/Inteligencia Artificial/ds_salaries.csv")
```

#### df.head()

₽		Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	salary_
	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	
	3	3	2020	MI	FT	Product Data Analyst	20000	
	$\blacktriangleleft \ $							<b>+</b>

No se encuentran datos faltantes

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

```
Unnamed: 0
work_year
experience_level
employment_type
job_title
salary
salary_currency
                    0
salary_in_usd
                     0
employee_residence
                     0
remote_ratio
                     0
company_location
                     0
company_size
dtype: int64
```

Se eliminan los datos que no se van a utilizar

```
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	7
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	

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

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

```
df['employment_type'].unique()
    array(['FT', 'CT', 'PT', 'FL'], dtype=object)

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

	experience_level_EN	experience_level_EX	experience_level_MI	experience_level
0	0	0	1	
1	0	0	0	
2	0	0	0	
3	0	0	1	
4	0	0	0	
602	0	0	0	
603	0	0	0	
604	0	0	0	
605	0	0	0	
606	0	0	1	
607 rd	ows × 4 columns			<b>+</b>

dummies\_emp\_type = pd.get\_dummies(df['employment\_type'],prefix='employment\_type')
dummies\_emp\_type

	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
602	0	0	1	0
603	0	0	1	0
604	0	0	1	0
605	0	0	1	0
606	0	0	1	0

607 rows × 4 columns

```
df = pd.concat([df,dummies_exp_level,dummies_emp_type],axis=1)
df.drop('experience_level',axis=1,inplace=True)
df.drop('employment_type',axis=1,inplace=True)
df.head()
```

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



## Correlacion de los datos

```
correlacion = df.corr()
alta_corr=np.where((correlacion > 0.95) & (correlacion < 1))</pre>
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))
from \ sklearn.preprocessing \ import \ StandardScaler
scaler = StandardScaler()
df_estandarizada = scaler.fit_transform(df)
df_estandarizada
     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]])
df_estandarizada = pd.DataFrame(df_estandarizada, columns=df.columns)
entrenamiento, prueba=train_test_split(df_estandarizada,test_size=0.20, random_state=42)
```

entrenamiento

	salary	salary_in_usd	remote_ratio	experience_level_EN	experience_level_EX	experience_level_MI	experience_level_SE	emp.
9	-0.128962	0.179159	-0.514377	-0.411773	-0.211543	-0.735261	1.080674	
227	-0.161365	-0.333488	-0.514377	-0.411773	-0.211543	1.360061	-0.925348	
591	-0.116096	0.459192	0.714862	-0.411773	-0.211543	-0.735261	1.080674	
516	-0.111141	0.567036	0.714862	-0.411773	-0.211543	-0.735261	1.080674	
132	-0.185084	-1.042301	0.714862	-0.411773	-0.211543	1.360061	-0.925348	
71	-0.185991	-0.988746	-0.514377	-0.411773	-0.211543	1.360061	-0.925348	
106	-0.057677	1.059879	0.714862	-0.411773	-0.211543	1.360061	-0.925348	
270	-0.162985	-0.561334	0.714862	2.428524	-0.211543	-0.735261	-0.925348	
435	-0.164605	-0.291738	0.714862	-0.411773	-0.211543	1.360061	-0.925348	
102	6.918609	-1.072499	-0.514377	-0.411773	-0.211543	1.360061	-0.925348	
485 rc	ws × 11 colu	ımns						
77:								
4								-

### Generación del modelo

Primer modelo

```
modelo = smf.ols(formula='salary_in_usd~salary+remote_ratio+experience_level_EN+experience_level_EX+experience_level_MI+employment_type_(
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:

Time:	00:	04:03	Log-Likelihood:	,	-627.06	
No. Observations:		485	AIC:		1272.	
Df Residuals:		476	BIC:		1310.	
Df Model:		8				
Covariance Type:	nonr	obust				
	coef	std e	rr t	P> t	[0.025	0.975]
	0.0167		40 0.413	0.680	-0.063	
salary	-0.1455	0.0	65 -2.251	0.025	-0.272	-0.018
remote_ratio	0.0592	0.0	1.463	0.144	-0.020	0.139
experience_level_EN	-0.3717	0.0	-8.423	0.000	-0.458	-0.285
experience_level_EX	0.1902	0.0	4.698	0.000	0.111	0.270
experience_level_MI	-0.3225	0.0	44 -7.387	0.000	-0.408	-0.237
employment_type_CT	0.0980	0.0	50 1.974	0.049	0.000	0.196
employment_type_FL	-0.0042	0.0	-0.073	0.941	-0.117	0.109
employment_type_FT	0.0879	0.0	57 1.531	0.126	-0.025	0.201
=======================================		======		=======		
Omnibus:	24	2.000	Durbin-Watson:		1.979	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		2005.484	
Skew:		2.000	Prob(JB):		0.00	
Kurtosis:	1	2.123	Cond. No.		2.46	
=======================================						

Thu, 17 Aug 2023 Prob (F-statistic):

#### Notes:

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

Segundo modelo eliminando las variables con un p-valor > 0.05

modelo2 = smf.ols(formula='salary\_in\_usd~salary+experience\_level\_EN+experience\_level\_EX+experience\_level\_MI+employment\_type\_CT',data=entr
modelo2 = modelo2.fit()
print(modelo2.summary())

#### OLS Regression Results

Dep. Variable: salary_in_usd R-squared: 0.256 Model: 0LS Adj. R-squared: 0.249 Method: Least Squares F-statistic: 33.04 Date: Thu, 17 Aug 2023 Prob (F-statistic): 5.65e-29 Time: 00:19:25 Log-Likelihood: -629.63 No. Observations: 485 AIC: 1271. Df Residuals: 479 BIC: 1296.
Method:         Least Squares         F-statistic:         33.04           Date:         Thu, 17 Aug 2023         Prob (F-statistic):         5.65e-29           Time:         00:19:25         Log-Likelihood:         -629.63           No. Observations:         485         AIC:         1271.
Date:       Thu, 17 Aug 2023       Prob (F-statistic):       5.65e-29         Time:       00:19:25       Log-Likelihood:       -629.63         No. Observations:       485       AIC:       1271.
Time: 00:19:25 Log-Likelihood: -629.63 No. Observations: 485 AIC: 1271.
No. Observations: 485 AIC: 1271.
Df Posiduals. 470 DTC.
DT RESIDUALS: 4/9 DIC: 1290.
Df Model: 5
Covariance Type: nonrobust
21
coef std err t P> t  [0.025 0.975]
Intercept 0.0179 0.041 0.443 0.658 -0.062 0.098
salary -0.1474 0.065 -2.282 0.023 -0.274 -0.020
experience_level_EN -0.3904 0.043 -9.147 0.000 -0.474 -0.307
experience_level_EX 0.1920 0.041 4.734 0.000 0.112 0.272
experience level MI -0.3292 0.044 -7.549 0.000 -0.415 -0.244
employment_type_CT
Omnibus: 239.133 Durbin-Watson: 1.991
Prob(Omnibus): 0.000 Jarque-Bera (JB): 1932.279
Skew: 1.980 Prob(JB): 0.00
Kurtosis: 11.941 Cond. No. 1.87

#### Notes:

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

Debido a que la R^2 es menor en el segundo modelo nos quedaremos con el primero donde R^2 = 0.264

# Ecuación matematica que describe el modelo

### Ecuacion:

y = -0.1455 \* x1 - 0.3717 \* x2 + 0.1902 \* x3 - 0.3225 \* x4 + 0.0980 \* x5

Variable de respuesta:

• salary\_in\_usd

Variables regresoras:

- x1 = salary
- x2 = experience\_level\_EN
- x3 = experience\_level\_EX
- x4 = experience\_level\_MI

• x5 = employment\_type\_CT

```
y_pre = -0.1455 * prueba['salary'] - 0.3717 * prueba['experience_level_EN'] + 0.1902 * prueba['experience_level_EX'] - 0.3225 * prueba['ε
y_pre
     563
            0.358337
     289
            0.358832
           -0.313609
     78
            0.754617
           -0.306254
     182
            0.355532
     249
     365
            0.358493
     453
           -0.315495
     548
           0.362222
     235
           -0.314552
     Length: 122, dtype: float64
```

## Interpretación de los datos

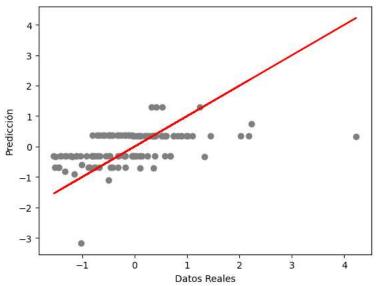
```
tabla = pd.DataFrame({'Real':prueba['salary_in_usd'], 'Prediccion': y_pre, 'Errores':prueba['salary_in_usd']-y_pre})
tabla
```

	Real	Prediccion	Errores	17.	ılı
563	0.394254	0.358337	0.035917	'	
289	0.320205	0.358832	-0.038627		
76	-0.173457	-0.313609	0.140152		
78	2.224328	0.754617	1.469711		
182	-1.217128	-0.306254	-0.910873		
249	0.813866	0.355532	0.458334		
365	0.370981	0.358493	0.012489		
453	0.108636	-0.315495	0.424130		
548	-0.186856	0.362222	-0.549078		
235	-0.032411	-0.314552	0.282141		

122 rows × 3 columns

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

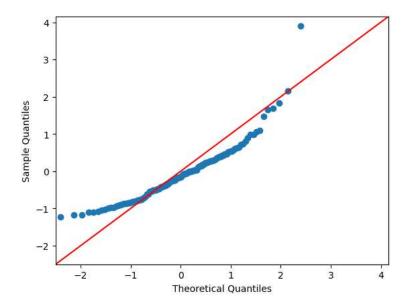
Text(0, 0.5, 'Predicción')



Como se puede apreciar, el modelo no se apega a los datos reales del dataset, esto se puede deber a que R^2 del modelo es muy bajo como para ser un modelo confiable

# QQplot de los errores

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



✓ 0 s completado a las 18:19