Creado por: Isabel Maniega Ejercicio 2 In [1]: # Importing the libraries import numpy as np import matplotlib.pyplot as plt import pandas as pd In [2]: # Importing the dataset dataset = pd.read\_csv('Position\_Salaries.csv') In [3]: dataset Position Level Salary Out[3]: 45000 Business Analyst 1 Junior Consultant 50000 Senior Consultant 60000 3 80000 Manager Country Manager 110000 5 Region Manager 150000 6 Partner 200000 Senior Partner 300000 8 500000 C-level 9 10 1000000 In [4]: X = dataset.iloc[:, 1:2].values y = dataset.iloc[:, 2].values In [5]: # Splitting the dataset into the Training set and Test set 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, random\_state = 0) **Lineal y Polinomial Regression** In [6]: # Fitting Linear Regression to the dataset from sklearn.linear\_model import LinearRegression lin\_reg = LinearRegression() lin\_reg.fit(X, y) Out[6]: ▼ LinearRegression LinearRegression() In [7]: # Fitting Polynomial Regression to the dataset from sklearn.preprocessing import PolynomialFeatures poly\_reg = PolynomialFeatures(degree = 4) X\_poly = poly\_reg.fit\_transform(X) poly\_reg.fit(X\_poly, y) lin reg 2 = LinearRegression() lin\_reg\_2.fit(X\_poly, y) Out[7]: ▼ LinearRegression LinearRegression() Probaremos con un nivel de 6.5 para saber el sueldo que debería de ganar, viendo el sueldo en la tabla, debería estar entre 200.000 y 300.000, entre el puesto de Partner y Senior Partner In [33]: # Predicting a new result with Linear Regression lin\_reg.predict([[6.5]]) Out[33]: array([330378.78787879]) In [34]: # Predicting a new result with Polynomial Regression lin\_reg\_2.predict(poly\_reg.fit\_transform([[6.5]])) Out[34]: array([158862.45265157]) In [9]: print("Valor de pendiente o coeficiente 'a':") print(lin\_reg\_2.coef\_) Valor de pendiente o coeficiente 'a': -211002.33100293 94765.44289063 -15463.28671331 0. 890.15151515] In [10]: print("Precisión del modelo: ") print(lin\_reg\_2.score(X\_poly, y)) Precisión del modelo: 0.9973922891706615 In [11]: # Visualising the Linear Regression results plt.scatter(X, y, color = 'red') plt.plot(X, lin\_reg.predict(X), color = 'blue') plt.title('Truth or Bluff (Linear Regression)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (Linear Regression) 1e6 1.0 0.8 0.6 0.2 0.0 2 8 4 10 Position level In [12]: # Visualising the Polynomial Regression results plt.scatter(X, y, color = 'red') plt.plot(X, lin\_reg\_2.predict(poly\_reg.fit\_transform(X)), color = 'blue') plt.title('Truth or Bluff (Polynomial Regression)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (Polynomial Regression) 1e6 1.0 0.8 0.6 Salary 0.4 0.2 0.0 8 10 6 Position level # Visualising the Polynomial Regression results (for higher resolution and smoother curve) In [13]:  $X_{grid} = np.arange(min(X), max(X), 0.1)$ X\_grid = X\_grid.reshape((len(X\_grid), 1)) plt.scatter(X, y, color = 'red') plt.plot(X\_grid, lin\_reg\_2.predict(poly\_reg.fit\_transform(X\_grid)), color = 'blue') plt.title('Truth or Bluff (Polynomial Regression)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (Polynomial Regression) 1e6 1.0 0.8 0.6 Salary 0.4 0.2 0.0 10 Position level Support Vector Regression (SVR) In [14]: # Fitting SVR to the dataset from sklearn.svm import SVR regressor = SVR(kernel = 'rbf') # regressor = SVR(kernel="linear", C=1.0, epsilon=0.2) regressor.fit(X, y) Out[14]: ▼ SVR SVR() In [15]: # Predicting a new result y\_pred = regressor.predict([[6.5]]) y\_pred Out[15]: array([130001.82883924]) In [16]: y\_pred = regressor.predict(X\_test) y\_pred Out[16]: array([129996.54009563, 130003.51550835]) print("DATOS DEL MODELO VECTORES DE SOPORTE REGRESIÓN") print() print("Precisión del modelo:") print(regressor.score(X\_train, y\_train)) DATOS DEL MODELO VECTORES DE SOPORTE REGRESIÓN Precisión del modelo: -0.1415131652565642 In [18]: # Visualising the SVR results plt.scatter(X, y, color = 'red') plt.plot(X, regressor.predict(X), color = 'blue') plt.title('Truth or Bluff (SVR)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (SVR) 1e6 1.0 0.8 0.6 0.4 0.2 0.0 6 8 10 In [19]: # Visualising the SVR results (for higher resolution and smoother curve)  $X_{grid} = np.arange(min(X), max(X), 0.01) # choice of 0.01 instead of 0.1 step because the data is feature scale$ X\_grid = X\_grid.reshape((len(X\_grid), 1)) plt.scatter(X, y, color = 'red') plt.plot(X\_grid, regressor.predict(X\_grid), color = 'blue') plt.title('Truth or Bluff (SVR)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (SVR) 1e6 1.0 0.8 0.6 0.4 0.2 0.0 8 4 10 Position level **Decision Tree Regression** In [20]: # Fitting Decision Tree Regression to the dataset from sklearn.tree import DecisionTreeRegressor regressor = DecisionTreeRegressor(random\_state = 0) regressor.fit(X, y) Out[20]: DecisionTreeRegressor DecisionTreeRegressor(random\_state=0) In [22]: # Predicting a new result y pred = regressor.predict([[6.5]]) y\_pred Out[22]: array([150000.]) In [23]: y\_pred = regressor.predict(X\_test) y\_pred Out[23]: array([ 60000., 500000.]) In [24]: # Visualising the Decision Tree Regression results (higher resolution)  $X_{grid} = np.arange(min(X), max(X), 0.01)$ X\_grid = X\_grid.reshape((len(X\_grid), 1)) plt.scatter(X, y, color = 'red')
plt.plot(X\_grid, regressor.predict(X\_grid), color = 'blue') plt.title('Truth or Bluff (Decision Tree Regression)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (Decision Tree Regression) 1e6 1.0 0.8 0.6 0.4 0.2 0.0 8 10 6 Position level In [26]: print("Datos del Modelo de árboles de decision Regresión") print() print("Precisión del modelo:") print(regressor.score(X\_train, y\_train)) Datos del Modelo de árboles de decision Regresión Precisión del modelo: 1.0 Random Forest Regression In [27]: # Fitting Random Forest Regression to the dataset from sklearn.ensemble import RandomForestRegressor regressor = RandomForestRegressor(n\_estimators = 10, random\_state = 0) regressor.fit(X, y) Out[27]: ▼ RandomForestRegressor RandomForestRegressor(n\_estimators=10, random\_state=0) In [28]: # Predicting a new result y\_pred = regressor.predict([[6.5]]) y\_pred Out[28]: array([167000.]) In [29]: y\_pred = regressor.predict(X\_test) y\_pred Out[29]: array([ 59000., 470000.]) In [30]: # Visualising the Random Forest Regression results (higher resolution)  $X_{grid} = np.arange(min(X), max(X), 0.01)$ X\_grid = X\_grid.reshape((len(X\_grid), 1)) plt.scatter(X, y, color = 'red') plt.plot(X\_grid, regressor.predict(X\_grid), color = 'blue') plt.title('Truth or Bluff (Random Forest Regression)') plt.xlabel('Position level') plt.ylabel('Salary') plt.show() Truth or Bluff (Random Forest Regression) 1e6 1.0 0.8 0.6 0.4 0.2 0.0 2 8 6 10 4 Position level print("Datos del modelo Bosques Aleatorios Regresión") In [32]: print() print("precisión del modelo:") print(regressor.score(X\_train, y\_train)) Datos del modelo Bosques Aleatorios Regresión precisión del modelo: 0.9675758285151437 Conclusión Los dos mejores modelos son el Polinomial y el Random Forest, como la precisión es más alta nos quedaremos con Polinomial Creado por: Isabel Maniega