TASK 1: PREDICTION USING SUPERVISED LEARNING AUTHOR : TEJASWIDEVI GRIP: THE SPARKS FOUNDATION DATA SCIENCE AND BUSINESS ANALYTICS INTERN In [1]: #IMPORT LIBRARIES import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import scipy.stats as stats import statsmodels.formula.api as smf from sklearn.model_selection import train_test_split from sklearn.neighbors import KNeighborsClassifier In [2]: # IMPORT DATA SET USING PANDAS READ_CSV df = pd.read_csv('https://raw.githubusercontent.com/AdiPersonalWorks/Random/master/student_s cores%20-%20student_scores.csv') In [3]: df.head() Out[3]: **Hours Scores** 0 2.5 21 5.1 47 1 3.2 27 3 75 8.5 3.5 30 **EXPLORATORY DATA ANALYSIS** In [4]: df.columns Out[4]: Index(['Hours', 'Scores'], dtype='object') In [5]: df.dtypes Out[5]: Hours float64 Scores int64 dtype: object In [6]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 25 entries, 0 to 24 Data columns (total 2 columns): # Column Non-Null Count Dtype Hours 25 non-null float64 1 Scores 25 non-null int64 dtypes: float64(1), int64(1)memory usage: 528.0 bytes In [7]: df.isnull().sum() Out[7]: Hours Scores 0 dtype: int64 In [8]: | df.describe() Out[8]: Hours Scores **count** 25.000000 25.000000 5.012000 51.480000 mean 2.525094 25.286887 std 1.100000 17.000000 25% 2.700000 30.000000 4.800000 47.000000 **75%** 7.400000 75.000000 max 9.200000 95.000000 In [9]: df.corr() Out[9]: Hours Scores **Hours** 1.000000 0.976191 **Scores** 0.976191 1.000000 **Remove Outliers** In [10]: def outlier_detection(df): ### Written by: Sujay Rittikar # Detecting the Null or NaN values and remo ving them first # to ensure that the numerical columns can be detected correctly. r = []for col in df.columns: for i in df.index: if df.loc[i, col] == 'Null' or df.loc[i, col] == np.nan: r.append(i) df = df.drop(list(set(r))) df = df.reset_index() df = df.drop('index', axis=1) # Finding out the columns having numerical values. $num_cols = []$ for col in df.columns: if df[col].dtype == 'object': try: df[col] = pd.to_numeric(df[col]) num_cols.append(col) except ValueError: pass # Removing the rows having values which can be called outliers # on the basis of their z-scores of >3 or <-3count = 0 t = []for i in num_cols: z = np.abs(stats.zscore(df[i])) for j in range(len(z)): **if** z[j]>3 **or** z[j]<-3: t.append(j) count+=1 df = df.drop(list(set(t))) df = df.reset_index() df = df.drop('index', axis=1) print(count) return df In [11]: | df = outlier_detection(df) Distribution In [12]: sns.distplot(df["Scores"]) plt.show() sns.distplot(df["Scores"], kde=False, rug=True) plt.show() 0.0175 0.0150 0.0125 0.0100 0.0075 0.0050 0.0025 0.0000 -20 80 100 120 140 0 20 40 60 Scores 12 10 2 · 50 20 30 40 60 Scores In [13]: sns.jointplot(df['Hours'], df['Scores'], kind = "reg").annotate(stats.pearsonr) plt.show() C:\Users\Tejaswi\anaconda3\lib\site-packages\seaborn\axisgrid.py:1848: UserWarning: JointGrid annotation is deprecated and will be removed in a future release. warnings.warn(UserWarning(msg)) 140 pearsonr = 0.98; p = 9.1e-17120 100 80 60 40 0 -20 7.5 10.0 12.5 -2.5 0.0 2.5 5.0 Performing Simple Linear Regression In [14]: mean_x = np.mean(df['Hours']) mean_y = np.mean(df['Scores']) num = 0den = 0x = list(df['Hours']) y = list(df['Scores']) for i in range(len(df)): $num += (x[i]-mean_x)*(y[i]-mean_y)$ $den += (x[i]-mean_x)**2$ B1 = num/den In [15]: B1 Out[15]: 9.775803390787475 In [16]: B0 = mean_y - B1*mean_x In [17]: B0 Out[17]: 2.4836734053731746 **Making Predictions** In [18]: df['predicted_Scores'] = B0 + B1*df['Hours'] In [19]: df.head() Out[19]: Hours Scores predicted_Scores 2.5 21 26.923182 5.1 47 52.340271 33.766244 27 3.2 8.5 75 85.578002 3.5 30 36.698985 In [20]: plt.scatter(df['Hours'], df['Scores']) plt.scatter(df['Hours'], df['predicted_Scores']) plt.plot() Out[20]: [] 80 60 -**Prediction of given value: 9.25** In [21]: B0 + B1*9.25 Out[21]: 92.90985477015732 In [22]: y = list(df['Scores'].values) y_pred = list(df['predicted_Scores'].values) **RMSE** In [25]: $s = sum([(y_pred[i] - y[i])**2$ for i in range(len(df))]) rmse = (np.sqrt(s/len(df)))/mean_y In [26]: rmse Out[26]: 0.10439521325937494 **OLS Model** In [27]: model = smf.ols('Scores ~ Hours', data = df) model = model.fit() In [28]: df['pred_ols'] = model.predict(df['Hours']) In [29]: plt.figure(figsize=(12, 6)) plt.plot(df['Hours'], df['pred_ols']) # regression line plt.plot(df['Hours'], df['Scores'], 'ro') # scatter plot showing actual data plt.title('Actual vs Predicted') plt.xlabel('Hours') plt.ylabel('Scores') plt.show() Actual vs Predicted 90 80 -70 60 Š 50 40 30 20 Hours We can observe that the predicted value for 9.25 hours is around 92 Additional conclusions: Categorical Prediction In [30]: # Consider a threshold to come to a conclusion whether the student passed or not! # Let's consider here 40 as the cut-off to pass. $cut_off = 40$ In [31]: | df['Result'] = df['Scores']>=40 In [32]: df.head() Out[32]: Hours Scores predicted_Scores pred_ols Result 2.5 21 5.1 47 52.340271 52.340271 1 3.2 27 33.766244 33.766244 False 3 8.5 75 85.578002 85.578002 3.5 30 36.698985 36.698985 False In [33]: | feature = df['Hours'].values.reshape(-1, 1) target = df['Result'].values In [34]: X_train, X_test, y_train, y_test = train_test_split(feature, target, random_state=0) In [35]: knn = KNeighborsClassifier(n_neighbors=5) knn.fit(X_train, y_train) Out[35]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=None, n_neighbors=5, p=2, weights='uniform') **ACCURACY** In [36]: knn.score(X_train, y_train)

Out[37]: 0.8571428571428571

In [38]: get_results = [[9.25]]

In [39]: knn.predict(get_results)

Out[39]: array([True])

Out[40]: array([True])

Out[41]: array([False])

In []:

In [40]: knn.predict([[14]])

In [41]: knn.predict([[3]])

In [37]: knn.score(X_test, y_test)

Predicting the outcomes