Business Problem

"The labor problem" is the economics term widely used toward the turn of the twentieth century with various applications.It has been defined in many ways, such as "the problem of improving the conditions of employment of the wage-earning classes." It encompasses the difficulties faced by wage-earners and employers who began to cut wages for various reasons including increased technology, desire for lower costs or to stay in business.

Now the laor organization, https://labour.gov.in/lcandilasdivision/india-ilo the indian version of this recently published the data for the 1974 and 1975 and wanted to demo of data science such that the data of 1978 labor can be predicted. Now the problem is the data is a copy of USA version and have race in it.

Data Contains Age, Race, Educational detail and Labour earning for 1974, 1975. The problem we are solving is the prediction of the future labours earning. The earning can be dependant on many of the variables. We have data for following

Age of the person.

Race : Is he/she is black or not black.

Education Details : How qualified the person is?

Hispanic : Is that person is Hispanic or not?

Married : Does marriage affect the earnings. And other informations.

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.stats.stattools import durbin_watson
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Load the dataset
data = pd.read_csv('/content/The labor problem.csv')
```

```
# Display basic information about the dataset
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15992 entries, 0 to 15991
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Age            15992 non-null  int64  
 1   Eduacation     15992 non-null  object 
 2   Race           15992 non-null  object 
 3   Hisp           15992 non-null  object 
 4   MaritalStatus  15992 non-null  object 
 5   Nodeg          15992 non-null  int64  
 6   Earnings_1974  15992 non-null  float64
 7   Earnings_1975  15992 non-null  float64
 8   Earnings_1978  15992 non-null  float64
dtypes: float64(3), int64(2), object(4)
memory usage: 1.1+ MB
None
```

```
# Preprocessing: OneHotEncode categorical variables
categorical_cols = ['Eduacation', 'Race', 'Hisp', 'MaritalStatus']
data = pd.get_dummies(data, columns=categorical_cols, drop_first=True)
```

```
# Define features (X) and target (y)
X = data.drop(['Earnings_1978'], axis=1)
y = data['Earnings_1978']
```

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Initialize and fit the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
# Predict on the test set
y_pred = model.predict(X_test)
```

```
# Evaluate the model using RMSE
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print(f'Root Mean Squared Error: {rmse}')
```

```
Root Mean Squared Error: 6973.217621811093
```

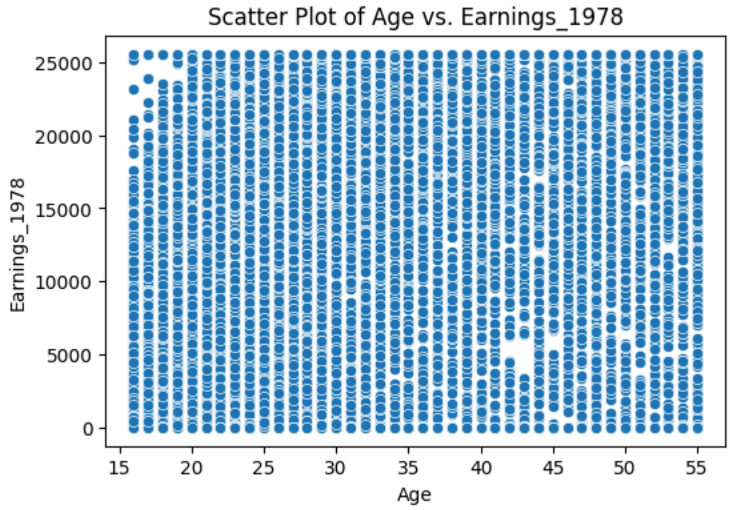
Solution Approach:

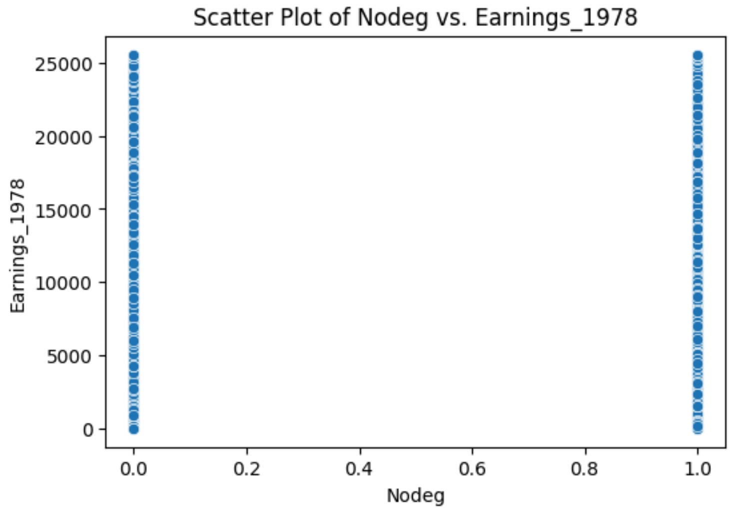
As we need to predict Labour earning for 1978 which is continuous in nature, Linear Regression can be used for prediction

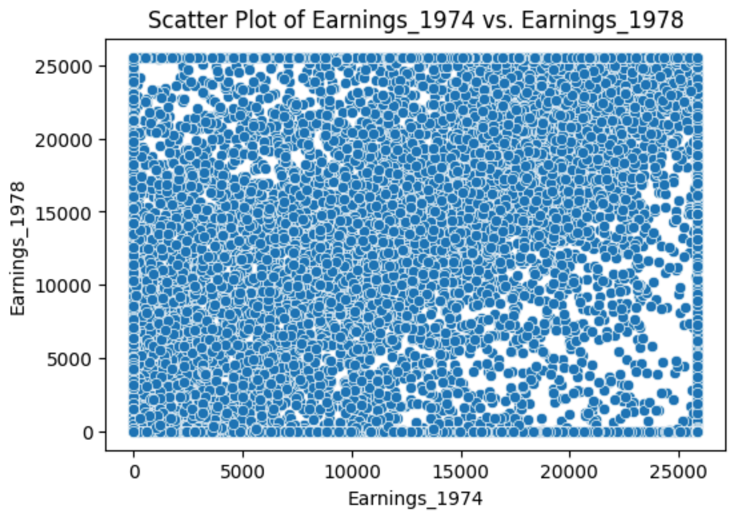
1. Check all the Linear Regression assumptions
2. Check if all the Linear Regression assumptions are verified or not

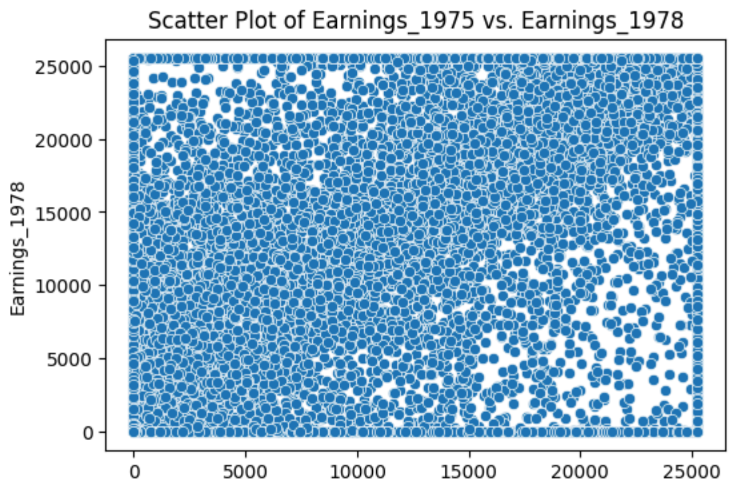
```
# 1. Check Linear Regression Assumptions

# Linearity Assumption
print("Checking Linearity Assumption...")
for column in X.columns:
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=data[column], y=y)
    plt.title(f'Scatter Plot of {column} vs. Earnings_1978')
    plt.xlabel(column)
    plt.ylabel('Earnings_1978')
    plt.show()
```

```
Checking Linearity Assumption...
```

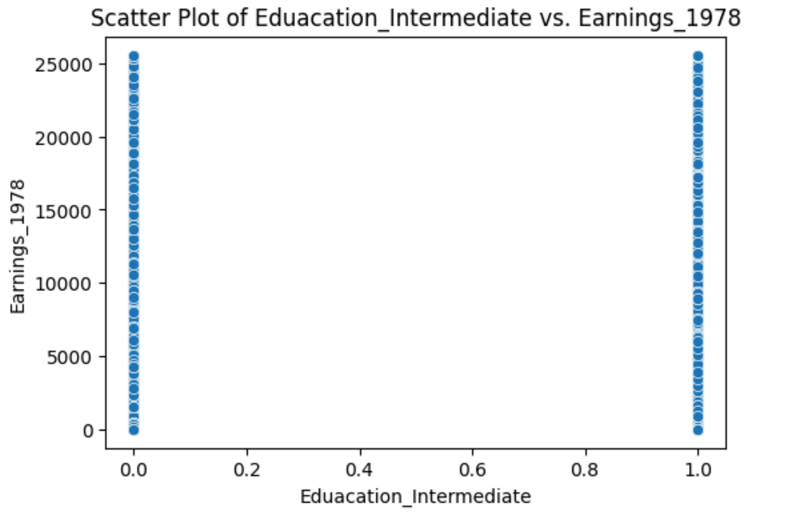


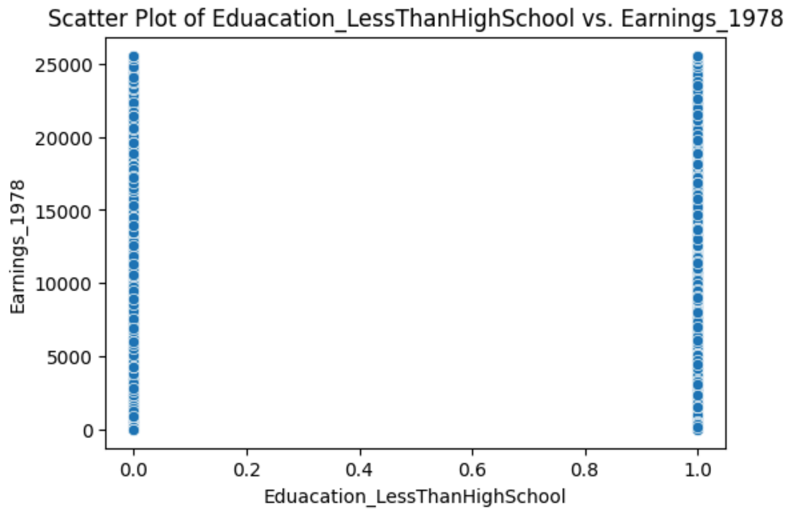


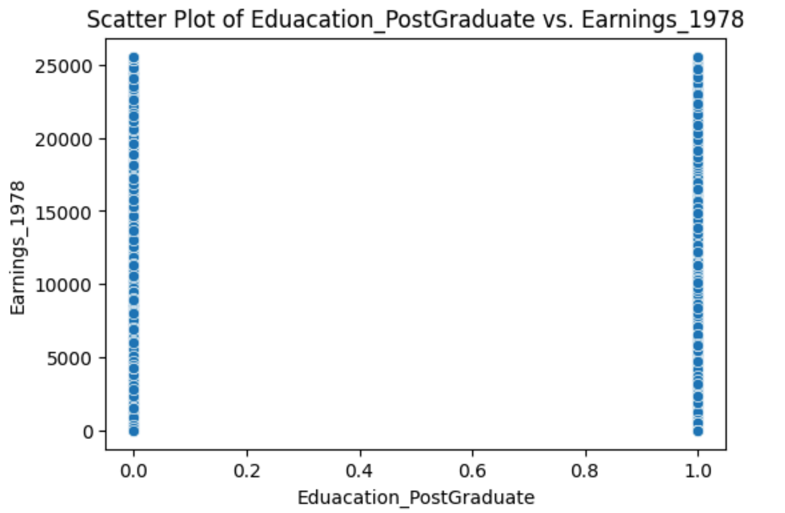


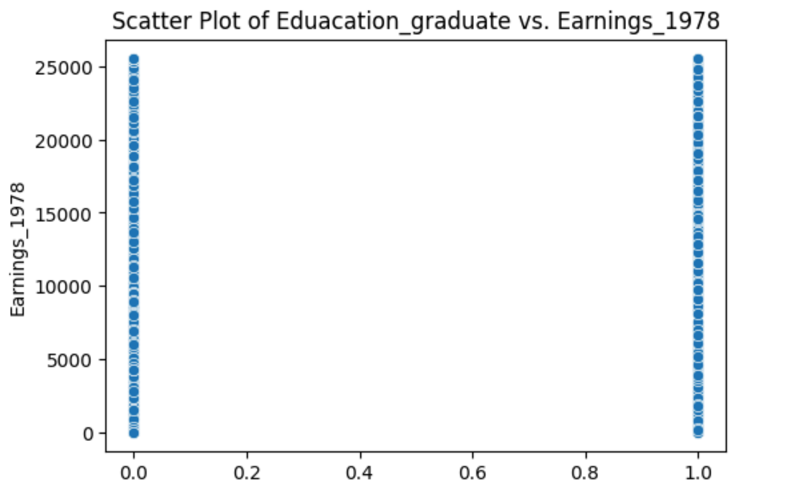


Earnings_1975

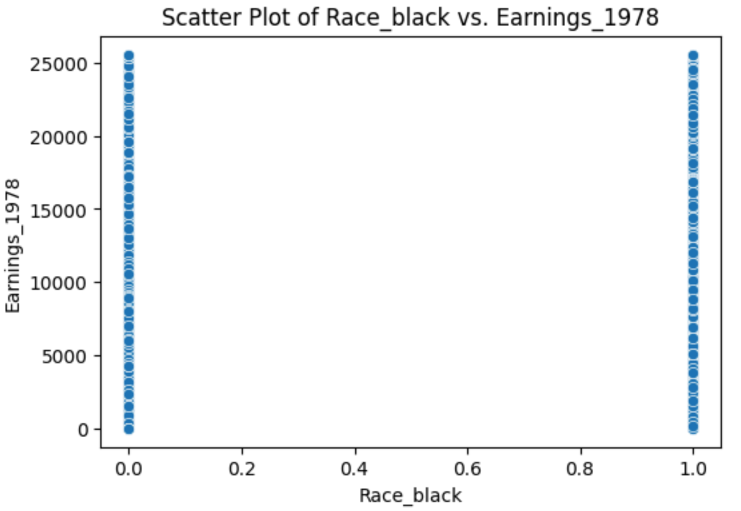


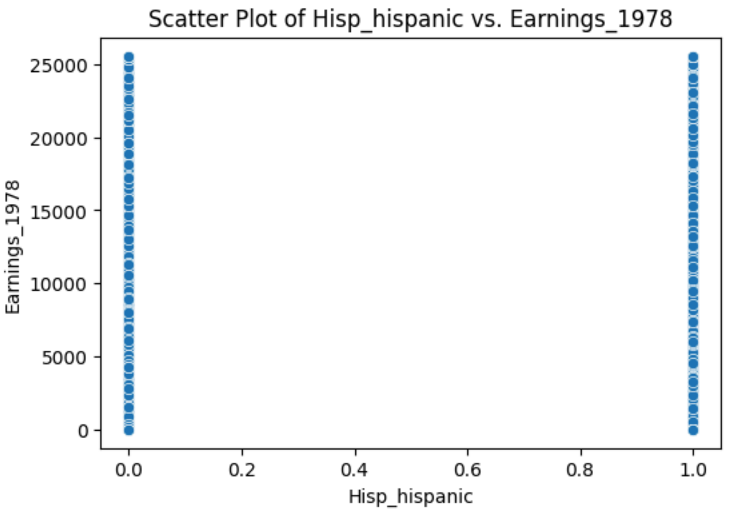


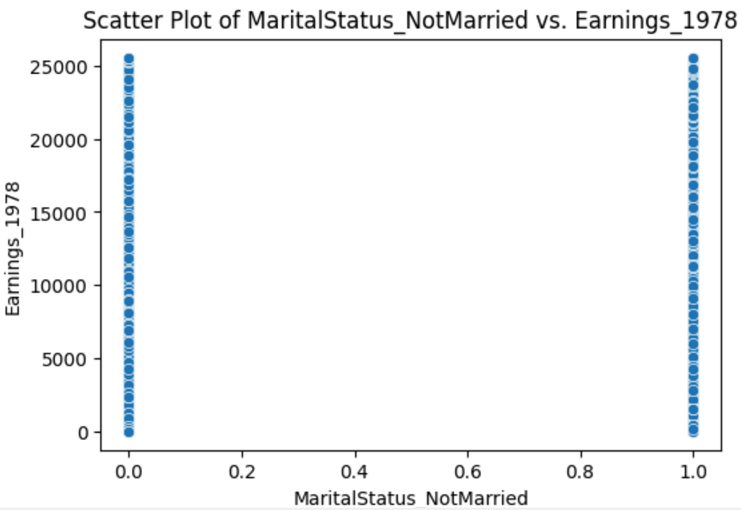




Eduacation_graduate







```
# Normality of Residuals
print("Checking Normality of Residuals...")
y_pred_train = model.predict(X_train)
residuals = y_train - y_pred_train
```

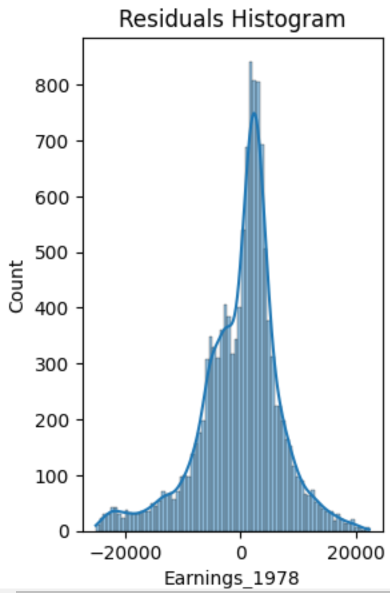
```
Checking Normality of Residuals...
```

```
plt.figure(figsize=(10, 5))
```

```
<Figure size 1000x500 with 0 Axes>
<Figure size 1000x500 with 0 Axes>
```

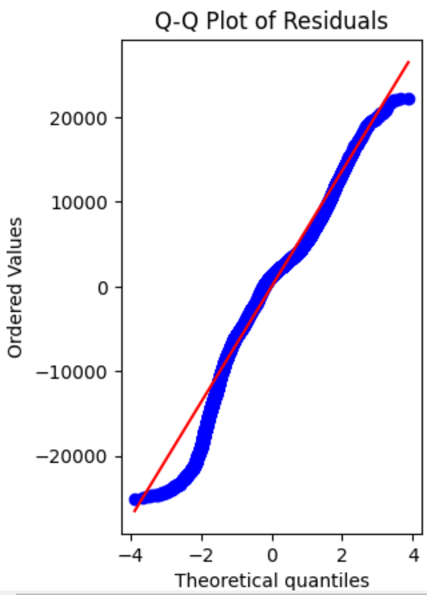
```
# Histogram of residuals
plt.subplot(1, 2, 1)
sns.histplot(residuals, kde=True)
plt.title('Residuals Histogram')
```

```
Text(0.5, 1.0, 'Residuals Histogram')
```




```
# Q-Q Plot
plt.subplot(1, 2, 2)
stats.probplot(residuals, dist="norm", plot=plt)
plt.title('Q-Q Plot of Residuals')
```

```
Text(0.5, 1.0, 'Q-Q Plot of Residuals')
```

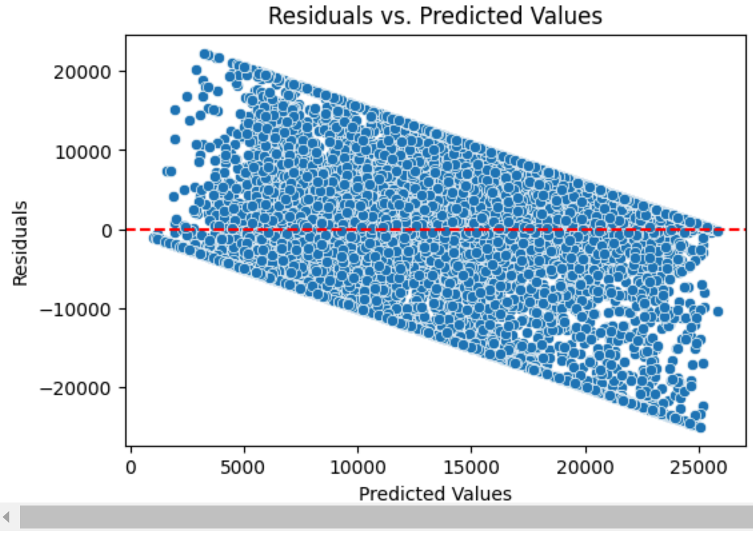



```
plt.show()
```

```
# Homoscedasticity
print("Checking Homoscedasticity...")
plt.figure(figsize=(6, 4))
```

```
sns.scatterplot(x=y_pred_train, y=residuals)
plt.axhline(0, color='red', linestyle='--')
plt.title('Residuals vs. Predicted Values')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```

```
Checking Homoscedasticity...
```




```
# Multicollinearity
print("Checking Multicollinearity...")
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

# Convert X to numeric, handling errors
X_numeric = X.apply(pd.to_numeric, errors='coerce').fillna(0)

# Explicitly convert all columns to float
for col in X_numeric.columns:
    X_numeric[col] = X_numeric[col].astype(float)

vif_data["VIF"] = [variance_inflation_factor(X_numeric.values, i)
                   for i in range(X_numeric.shape[1])]
print(vif_data)
```

```
Checking Multicollinearity...
/usr/local/lib/python3.10/dist-packages/statsmodels/stats/outliers_influence.py:197: RuntimeWarning: divide by zero encountered in s
  vif = 1. / (1. - r_squared_i)
                        feature        VIF
0                           Age   5.799295
1                         Nodeg        inf
2                 Earnings_1974  13.852094
3                 Earnings_1975  12.992214
4        Eduacation_Intermediate   1.357750
5  Eduacation_LessThanHighSchool        inf
6        Eduacation_PostGraduate   1.136485
7            Eduacation_graduate   1.191066
8                    Race_black   1.099107
9                  Hisp_hispanic   1.105774
10      MaritalStatus_NotMarried   1.326203
```

```
# Independence of Residuals
print("Checking Independence of Residuals...")
dw_stat = durbin_watson(residuals)
print(f'Durbin-Watson Statistic: {dw_stat}')
```

```
Checking Independence of Residuals...
Durbin-Watson Statistic: 2.007240881854767
```

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