### Gestational Diabetes Dataset

---

Source: https://www.kaggle.com/datasets/rasooljader/gestational-diabetes

[23]:
```
import pandas as pd
df=pd.read_csv('/content/Gestational Diabetes.csv')
df
```

[23]:
```
       Age  Pregnancy No  Weight  Height   BMI  Heredity  Prediction
0     17.0           1.0    48.0   165.0  17.6         0           0
1     17.0           1.0    49.0   145.0  23.3         0           0
2     17.0           1.0    50.0   140.0  25.5         0           0
3     17.0           1.0    50.0   145.0  23.8         0           0
4     17.0           1.0    49.0   146.0  23.0         0           0
…     …            …     …      …     …       …         …
1007  35.0           3.0    89.0   159.0  35.2         1           1
1008  41.0           4.0    87.0   165.0  32.0         0           0
1009  34.0           2.0    67.0   160.0  26.2         1           0
1010  33.0           3.0    65.0   167.0  23.3         0           1
1011  28.0           2.0    68.0   156.0  27.9         0           0

[1012 rows x 7 columns]
```

[24]:
```
df.head()
```

[24]:
```
    Age  Pregnancy No  Weight  Height   BMI  Heredity  Prediction
0  17.0           1.0    48.0   165.0  17.6         0           0
1  17.0           1.0    49.0   145.0  23.3         0           0
2  17.0           1.0    50.0   140.0  25.5         0           0
3  17.0           1.0    50.0   145.0  23.8         0           0
4  17.0           1.0    49.0   146.0  23.0         0           0
```

### Exercise 1: Analyzing a Health-Related Dataset

---

[25]:
```
# Calculate basic descriptive statistics
 print("Mean:\n", df.mean())
```

```python
print("\nMedian:\n", df.median())
print("\nMode:\n", df.mode().iloc[0])
print("\nStandard Deviation:\n", df.std())
print("\nVariance:\n", df.var())
# Additional descriptive statistics
print("\nRange:\n", df.max() - df.min())
print("\nSkewness:\n", df.skew())
print("\nKurtosis:\n", df.kurt())
```

```
Mean:
 Age              30.357708
Pregnancy No      2.517787
Weight           72.988142
Height          158.154150
BMI              29.256818
Heredity          0.226285
Prediction        0.214427
dtype: float64

Median:
 Age              30.0
Pregnancy No      2.0
Weight           70.0
Height          158.0
BMI              28.9
Heredity          0.0
Prediction        0.0
dtype: float64

Mode:
 Age              23.0
Pregnancy No      2.0
Weight           65.0
Height          160.0
BMI              31.6
Heredity          0.0
Prediction        0.0
Name: 0, dtype: float64

Standard Deviation:
 Age              7.022960
Pregnancy No     1.530656
Weight          12.552712
Height           7.367421
BMI              5.092321
Heredity         0.418632
Prediction       0.410627
```

```
dtype: float64

Variance:
 Age              49.321968
Pregnancy No      2.342908
Weight          157.570581
Height           54.278885
BMI              25.931734
Heredity          0.175253
Prediction        0.168615
dtype: float64

Range:
 Age             29.0
Pregnancy No     8.0
Weight          83.0
Height          61.0
BMI             38.3
Heredity         1.0
Prediction       1.0
dtype: float64

Skewness:
 Age             0.161460
Pregnancy No    1.256361
Weight          0.748643
Height          0.381251
BMI             0.665234
Heredity        1.310254
Prediction      1.393667
dtype: float64

Kurtosis:
 Age            -0.861067
Pregnancy No    1.534562
Weight          1.099075
Height          0.515864
BMI             1.073525
Heredity       -0.283798
Prediction     -0.057812
dtype: float64
```

[26]:

```
import scipy.stats as stats

# Select the feature for analysis
feature = 'BMI'  # Replace with your desired feature
```

```
# Define the hypothesized value
hypothesized_value = 29.42699440206 # Replace with your hypothesized value

# Extract the data for the selected feature
data = df[feature]

# Perform a one-sample t-test
t_stat, p_value = stats.ttest_1samp(data, hypothesized_value)

# Print the results
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Determine if the hypothesis should be rejected
alpha = 0.05  # Significance level
if p_value < alpha:
    print("Reject the null hypothesis. The average BMI is significantly␣
 ↪different from the hypothesized value.")
else:
    print("The null hypothesis is accepted. There is no significant difference␣
 ↪between the average BMI and the hypothesized value.")

# Calculate the 95% confidence interval
confidence_level = 0.95
degrees_of_freedom = len(data) - 1
confidence_interval = stats.t.interval(confidence_level, degrees_of_freedom,␣
 ↪loc=data.mean(), scale=stats.sem(data))

# Print the confidence interval
print(f"95% Confidence Interval for the mean of {feature}:␣
 ↪{confidence_interval}")
```

```
T-statistic: -1.063098123519172
P-value: 0.2879913138277411
The null hypothesis is accepted. There is no significant difference between the
average BMI and the hypothesized value.
95% Confidence Interval for the mean of BMI: (28.942699440206496,
29.57093692342987)
```

**Exercise 2: Exploring Regression Analysis on a New Dataset**

---

[27]:
```
import statsmodels.formula.api as smf

# Define the regression model
model = smf.ols('Prediction ~ Age', data=df)
```

```python
# Fit the model
results = model.fit()

# Print the summary of the regression results
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Prediction   R-squared:                       0.116
Model:                            OLS   Adj. R-squared:                  0.115
Method:                 Least Squares   F-statistic:                     132.6
Date:                Thu, 05 Sep 2024   Prob (F-statistic):           6.32e-29
Time:                        14:35:13   Log-Likelihood:                -472.28
No. Observations:                1012   AIC:                             948.6
Df Residuals:                    1010   BIC:                             958.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.3903      0.054     -7.243      0.000      -0.496      -0.285
Age            0.0199      0.002     11.517      0.000       0.017       0.023
==============================================================================
Omnibus:                      151.139   Durbin-Watson:                   1.737
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              225.486
Skew:                           1.156   Prob(JB):                     1.09e-49
Kurtosis:                       3.001   Cond. No.                         138.
==============================================================================

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

# 1 Explanation of the values:

---

# 2 R-squared:

This value indicates the proportion of variance in the dependent variable (Prediction) that is explained by the independent variable (Age).

A higher R-squared value suggests a stronger relationship between the variables.

# 3 Adjusted R-squared:

This is a modified version of R-squared that accounts for the number of predictors in the model. It helps to prevent overfitting.

# 4 Coefficients:

These values represent the estimated change in the dependent variable (Prediction) for a one-unit change in the independent variable (Age).

The intercept represents the predicted value of the dependent variable when the independent variable is zero.

# 5 P-values:

These values indicate the statistical significance of the coefficients. A p-value less than the significance level (usually 0.05) suggests that the coefficient is statistically significant.

# 6 Standard Errors:

These values indicate the variability of the estimated coefficients.

# 7 F-statistic and p-value:

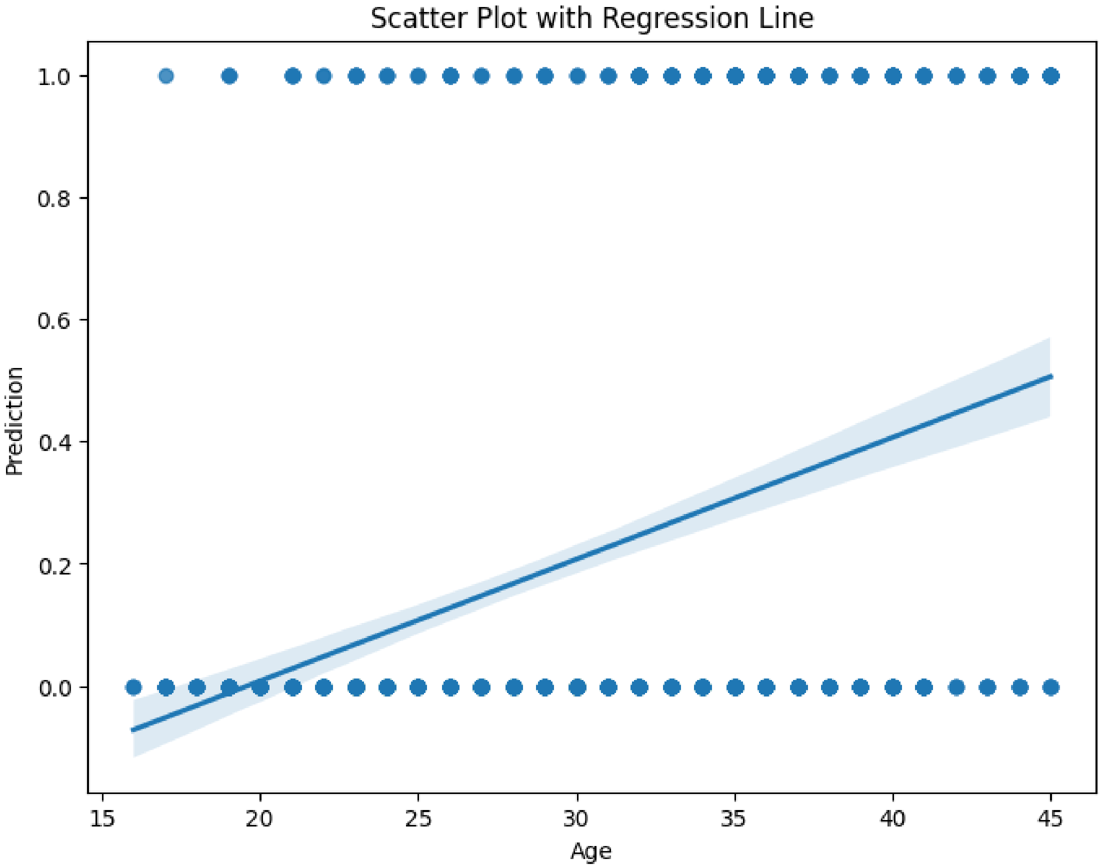
These values test the overall significance of the regression model. A low p-value indicates that the model is statistically significant.

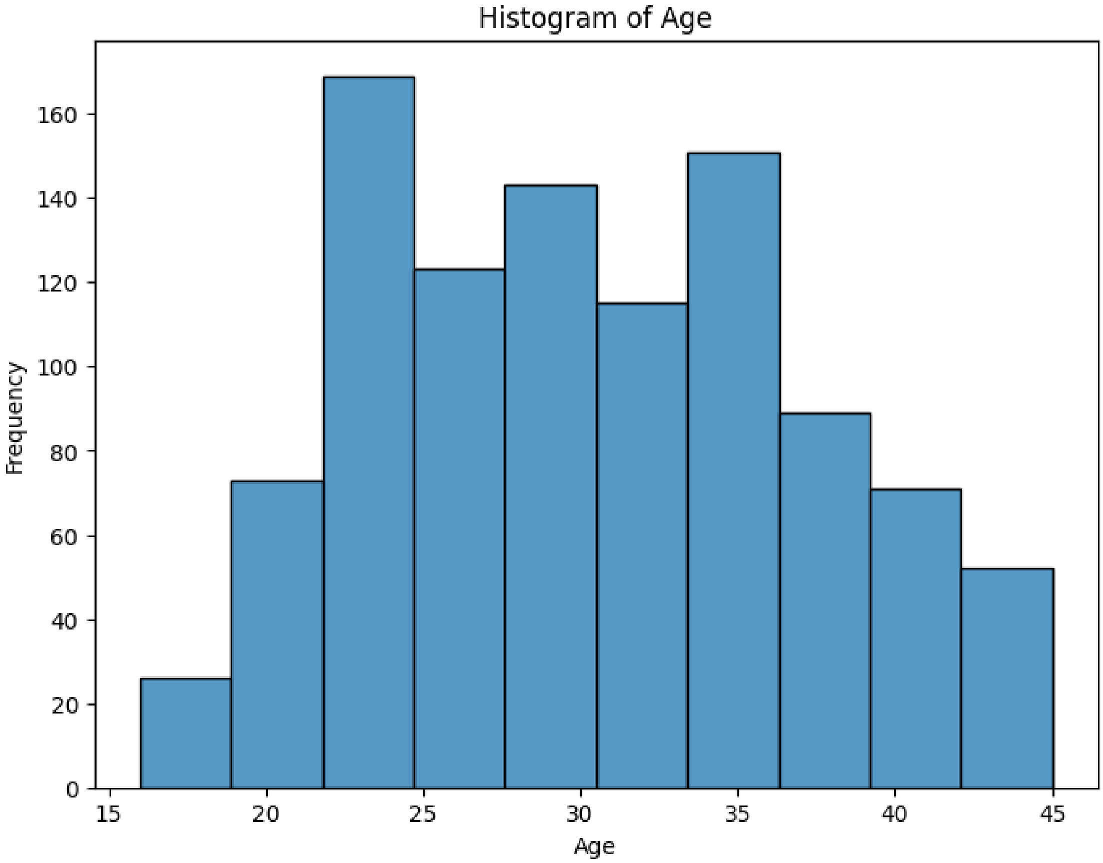
[28]:

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Scatter plot with regression line
plt.figure(figsize=(8, 6))
sns.regplot(x='Age', y='Prediction', data=df)
plt.title('Scatter Plot with Regression Line')
plt.xlabel('Age')
plt.ylabel('Prediction')
plt.show()

# Histogram of Age
plt.figure(figsize=(8, 6))
sns.histplot(df['Age'], bins=10)
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```


Scatter Plot with Regression Line
Prediction
1.0
0.8
0.6
0.4
0.2
0.0
Age
15
20
25
30
35
40
45


Histogram of Age
Frequency
0
20
40
60
80
100
120
140
160
15
20
25
30
35
40
45
Age

[ ]: