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Fundamentals of Business Analytics - Week 10 Session 1

Notes

- Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the data.

- A scatter plot can be used to:

  - Visualize the relationship between X and Y variables.
- Only one independent variable, X.

- Relationship between X and Y is described by a linear function.

- Changes in Y are assumed to be related to changes in X.

Simple Linear Regression Model

- Yi = β0 + β1Xi + εi

- Dependent Variable = Population Y intercept + (Population Slope Coefficient * Independent Variable) + Random Error term

- The simple linear regression equation provides an estimate of the population regression line.

- b0 is the estimated mean value of Y when the value of X is zero.

- b1 is the estimated change in the mean value of Y as a result of a one-unit increase in X.

  - homoscedascitcty

In [ ]:

```

```

House Price Prediction Using Simple Linear Regression

A real estate agent wishes to examine the relationship between the selling price of a home and its size (measured in square feet). This notebook reads house price data from a CSV file, visualizes it with a scatter plot, and performs simple linear regression to model the relationship between house size and price.

In [1]:
```
# IMPORT OUR LIBRARIES
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
from statsmodels.stats.anova import anova_lm

# plotting defaults
sns.set(style='whitegrid')
%matplotlib inline
```

STEP 1 - SET OBJECTIVE

t test for a population slope:

Is there a linear relationship between House prices and Size?

Null and alternative hypotheses:

H0: β1 = 0 (no linear relationship)

H1: β1 ≠ 0 (linear relationship does exist)

Significance level: 0.05 (95% CI)

In [2]:
```
# Main analysis: load data, visualize, fit OLS, report t-test and 95% CI for slope
df = pd.read_csv('https://raw.githubusercontent.com/Kartavya-Jharwal/Kartavya_Busin
print("Loaded 'house_prices.csv'.")

# quick head
print(df.head())
```

```
Loaded 'house_prices.csv'.
   price  area
0    245  1400
1    312  1600
2    279  1700
3    308  1875
4    199  1100
```

Scatter Plot

In [3]:
```
# Create a scatter plot
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x="area", y="price", s=100, color='navy')
plt.title("House price model: Scatter Plot", fontsize=16)
plt.xlabel("Square Feet", fontsize=12)
```

```
plt.ylabel("House Price ($1000s)", fontsize=12)
plt.grid(False)
plt.xlim(0)
plt.ylim(0)
plt.tight_layout()
plt.show()
```

RUN THE LINEAR REGRESSION

In [4]:

```
# Linear regression
X = df["area"]
y = df["price"]
# Use formula-based interface instead of sm.OLS
model = smf.ols('price ~ area', data=df).fit()
print('\n=== OLS Summary ===')
print(model.summary())
```

```
=== OLS Summary ===
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.581
Model:                            OLS   Adj. R-squared:                  0.528
Method:                 Least Squares   F-statistic:                     11.08
Date:                Mon, 10 Nov 2025   Prob (F-statistic):             0.0104
Time:                        14:50:12   Log-Likelihood:                -50.290
No. Observations:                  10   AIC:                             104.6
Df Residuals:                       8   BIC:                             105.2
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     98.2483     58.033      1.693      0.129     -35.577     232.074
area           0.1098      0.033      3.329      0.010       0.034       0.186
==============================================================================
Omnibus:                        1.066   Durbin-Watson:                   3.222
Prob(Omnibus):                  0.587   Jarque-Bera (JB):                0.779
Skew:                           0.399   Prob(JB):                        0.677
Kurtosis:                       1.890   Cond. No.                     7.82e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 7.82e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Check Residual Assumptions

NORMALITY OF ERROR

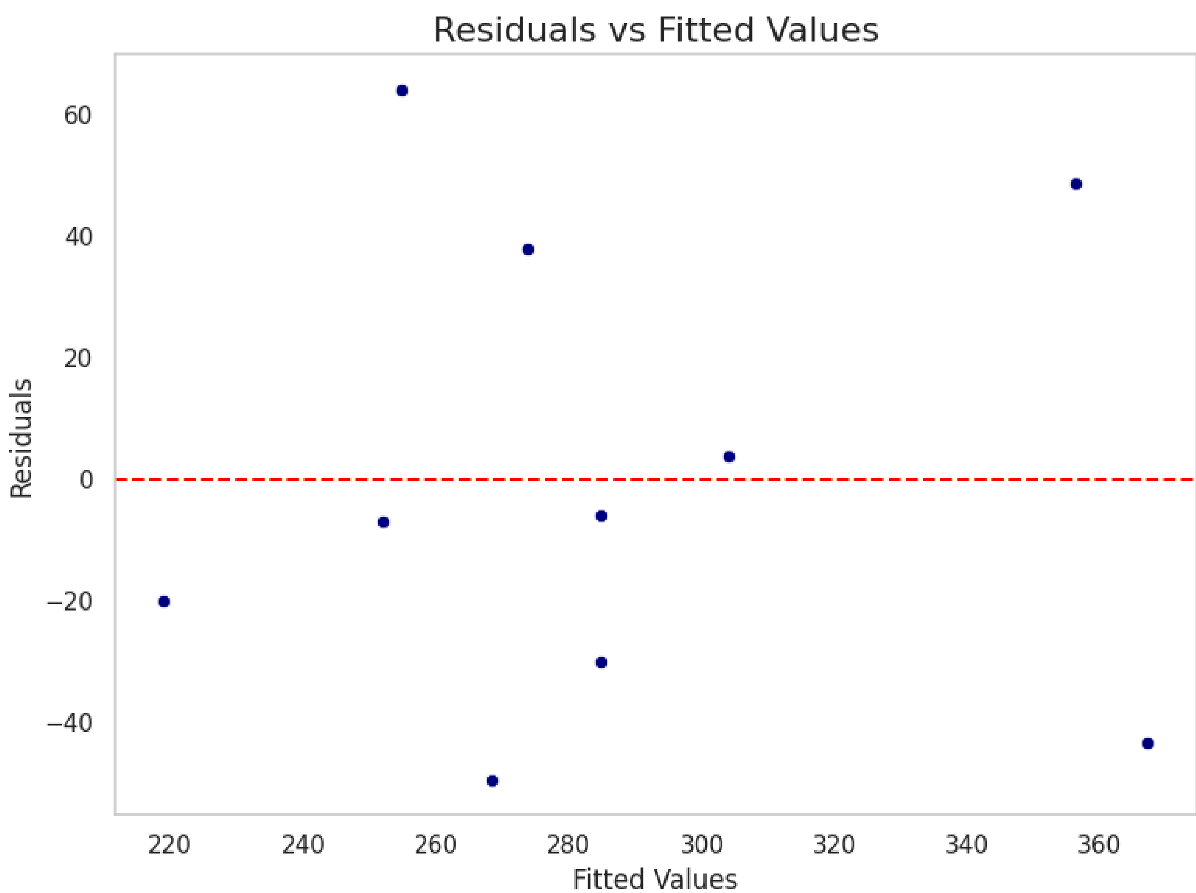
In [5]:

```
from scipy.stats import shapiro

# Get the residuals from the model
residuals = model.resid

# Perform the Shapiro-Wilk test for normality
shapiro_test = shapiro(residuals)

# Print the results
print(f"Shapiro-Wilk Test Statistic: {shapiro_test.statistic:.4f}")
print(f"Shapiro-Wilk p-value: {shapiro_test.pvalue:.4f}")

# Interpret the results
alpha = 0.05
if shapiro_test.pvalue > alpha:
    print("The residuals appear to be normally distributed (fail to reject H0)")
else:
    print("The residuals do not appear to be normally distributed (reject H0)")
```

```
Shapiro-Wilk Test Statistic: 0.9353
Shapiro-Wilk p-value: 0.5017
The residuals appear to be normally distributed (fail to reject H0)
```

EQUAL VARIANCE CHECK

In [6]:
```python
import statsmodels.stats.api as sms

# Get fitted values
fitted_values = model.fittedvalues
# Create a scatter plot of residuals vs fitted values
plt.figure(figsize=(8, 6))
sns.scatterplot(x=fitted_values, y=residuals, color='navy')
plt.axhline(y=0, color='red', linestyle='--')
plt.title("Residuals vs Fitted Values", fontsize=16)
plt.xlabel("Fitted Values", fontsize=12)
plt.ylabel("Residuals", fontsize=12)
plt.grid(False)
plt.tight_layout()
plt.show()
```



Simple Linear Regression Prediction

Making a prediction of house price based on area in square feet. We have fitted a simple linear regression model to predict house price based on square footage using the equation:

y^ = Predicted house price (in $1000s)

Prediction Example

To predict the price of a house with 2000 square feet:

y^ = 98.24833+0.10977·2000

Predicted House Price: $317,790 y^ = 98.24833 + 219.54 = 317.79

The python linear model object contains a .predict() method, predictions can be generated by calling this method and providing the input values in a DataFrame the names of the variables must match the model

---

model.predict(pd.DataFrame({'area': [2000]}))

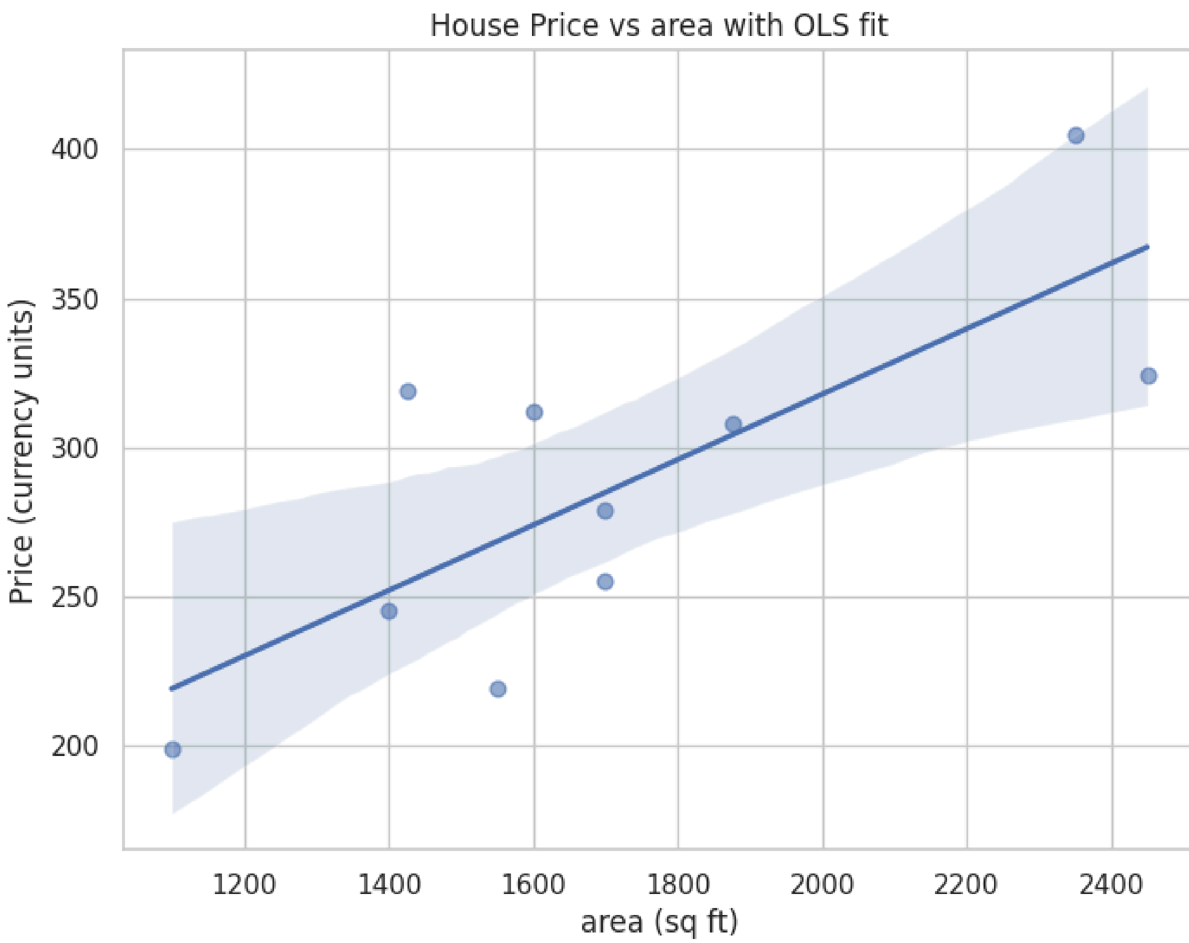
In [7]:
```python
# Get the coefficients from the trained model
intercept = model.params['Intercept']
slope = model.params['area']

# Prompt the user for an area input
try:
    input_area = float(input("Enter the house area in square feet (e.g., 1500): "))

    # Use the model's predict method with a DataFrame input
    predicted_price = model.predict(pd.DataFrame({'area': [input_area]}))[0]

    # Pretty print the results
    print(f"\n--- Prediction Result ---")
    print(f"Input Area: {input_area:,.0f} sq ft")
    print(f"Predicted Price: ${predicted_price:,.2f} (in $1000s)")
    print(f"Using formula: price = {intercept:.4f} + {slope:.4f} * area")
except ValueError:
    print("Invalid input. Please enter a numerical value for the area.")
```

```
Enter the house area in square feet (e.g., 1500): 2000

--- Prediction Result ---
Input Area: 2,000 sq ft
Predicted Price: $317.78 (in $1000s)
Using formula: price = 98.2483 + 0.1098 * area
```

Plot R2

In [8]:
```python
# plot regression line
plt.figure(figsize=(8,6))
sns.regplot(x='area', y='price', data=df, ci=95, scatter_kws={'s':40, 'alpha':0.6})
plt.title('House Price vs area with OLS fit')
plt.xlabel('area (sq ft)')
```

```
plt.ylabel('Price (currency units)')
plt.show()
```



Hypothesis Test for the Slope Using the Student's t-Distribution

To test whether the independent variable (e.g., area) significantly predicts the dependent variable (e.g., price), we perform a t-test on the slope coefficient using the Student’s t-distribution.

Hypotheses: Null Hypothesis (no relationship between area and price) H0: $\beta 1 = 0$

Alternative Hypothesis (a significant linear relationship exists)
H1:$\beta 1 \neq 0$

The t-statistic measures how many standard errors the estimated slope is away from zero

In [9]:
```
# t-test for slope (area)
slope_t = model.tvalues['area']
slope_p = model.pvalues['area']
ci = model.conf_int(alpha=0.05).loc['area']
```

```python
print(f"\nSlope t-statistic: {slope_t:.4f}")
print(f"Slope p-value: {slope_p:.4e}")
print(f"95% CI for slope: [{ci[0]:.4f}, {ci[1]:.4f}]")

alpha = 0.05
if slope_p < alpha:
    print('\nConclusion: Reject H0 — there is evidence of a linear relationship bet
else:
    print('\nConclusion: Fail to reject H0 — no evidence of linear relationship at
```

```
Slope t-statistic: 3.3294
Slope p-value: 1.0394e-02
95% CI for slope: [0.0337, 0.1858]

Conclusion: Reject H0 — there is evidence of a linear relationship between area and
Price at alpha=0.05.
```