

CHAPTER 7: CORRELATION AND REGRESSION ANALYSIS

(Week 13: Lecture Notes)

1. INTRODUCTION: RELATIONSHIP BETWEEN VARIABLES

In engineering, systems do not depend on a single parameter. Variables affect each other.

- **If Temperature increases** → Metal expands.
- **If Speed increases** → Fuel consumption changes.

In this chapter, we will answer two fundamental questions:

1. **Correlation:** Do the two variables move together? How strong is the relationship?
 2. **Regression:** Can we formulate this relationship and predict the future?
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2. COVARIANCE (Direction of Relationship)

Before moving to correlation, we must understand the cornerstone of the relationship: **Covariance**.

2.1. What is Covariance? (S_{xy})

It measures how the deviations of two variables (x and y) from their means change together.

The Logic:

- **Positive Covariance:** As x increases, y also increases (Move together).
- **Negative Covariance:** As x increases, y decreases (Inverse movement).
- **Zero Covariance:** No relationship between them (Independent).

The Problem: Covariance depends on units.

- If you take length in "meters", covariance is small; if "millimeters", it is huge.
 - Therefore, we cannot use Covariance to compare the strength of the relationship.
We need a "standardized" measure. That is **Correlation**.
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3. CORRELATION ANALYSIS (Strength of Relationship)

It is the unit-free (normalized) version of covariance.

3.1. Pearson Correlation Coefficient (r)

A coefficient ranging from -1 to +1 that measures the direction and intensity of the relationship.

Formula:

$$r = \frac{\text{Covariance}(x, y)}{\text{StdDev}(x) \times \text{StdDev}(y)}$$
$$r = \frac{S_{xy}}{\sqrt{S_{xx}} \times \sqrt{S_{yy}}}$$

Interpretation:

- $r = +1$: Perfect Positive Relationship.
- $r = -1$: Perfect Negative Relationship.
- $r = 0$: No Relationship.

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In [1]: import matplotlib.pyplot as plt
import random

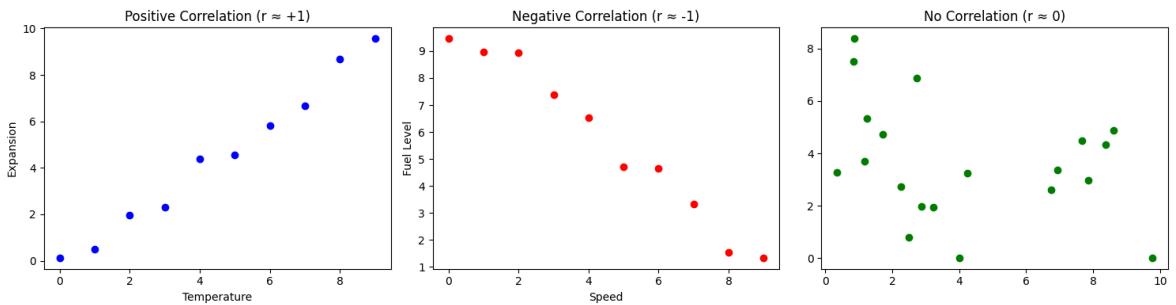
# Visualization of Different Correlations
plt.figure(figsize=(15, 4))

# 1. Positive Correlation
x1 = list(range(10))
y1 = [i + random.uniform(-1, 1) for i in x1]
plt.subplot(1, 3, 1)
plt.scatter(x1, y1, color='blue')
plt.title("Positive Correlation (r ≈ +1)")
plt.xlabel("Temperature"); plt.ylabel("Expansion")

# 2. Negative Correlation
x2 = list(range(10))
y2 = [10 - i + random.uniform(-1, 1) for i in x2]
plt.subplot(1, 3, 2)
plt.scatter(x2, y2, color='red')
plt.title("Negative Correlation (r ≈ -1)")
plt.xlabel("Speed"); plt.ylabel("Fuel Level")

# 3. Zero Correlation
x3 = [random.uniform(0, 10) for _ in range(20)]
y3 = [random.uniform(0, 10) for _ in range(20)]
plt.subplot(1, 3, 3)
plt.scatter(x3, y3, color='green')
plt.title("No Correlation (r ≈ 0)")

plt.tight_layout()
plt.show()
```



3.2. Outlier Warning

Correlation is very sensitive to Outliers.

- **Example:** Imagine a perfect line of 100 data points ($r = 1$). If you add just one single erroneous "extreme" data point (outlier), the r value can suddenly drop to 0.5.
- **Lesson:** Do not trust the r value alone without seeing the graph (Scatter Plot).

3.3. The Causality Trap

"Correlation does not imply Causation."

Classic Example: In a research conducted during summer months:

1. Ice Cream Sales increase.
 2. Drowning Cases increase.
- **Correlation:** $r = 0.8$ (Very high).

Question: Does eating ice cream cause drowning? **Answer:** No! There is a common hidden cause increasing both: **TEMPERATURE**. (As engineers, finding correlation is not enough; we must understand the mechanism).

4. SIMPLE LINEAR REGRESSION (Model Building)

If there is a relationship, we want to turn it into a mathematical function.

4.1. Real Life Model (With Error Term)

No relationship in nature is straight as if drawn by a ruler. There is always a deviation.

True Model:

$$y = \beta_0 + \beta_1 x + \epsilon$$

- y : Dependent variable (Output).
- x : Independent variable (Input).
- β_0, β_1 : True coefficients.
- ϵ (Epsilon): **Error Term (Noise)**. Random effects we cannot measure or know.

4.2. Prediction Model (What We Find)

We cannot know ϵ , we only estimate. Our equation:

$$\hat{y} = b_0 + b_1 x$$

- \hat{y} : Predicted value.
- b_0 (Intercept): Where the line cuts the y-axis.
- b_1 (Slope): How much y increases if x increases by one unit.

4.3. Model Assumptions (LINE Rule)

To use these formulas, the data must meet these conditions:

1. **Linearity**: The relationship must really be linear (Not curved).
 2. **Independence**: Errors must be independent of each other.
 3. **Normality**: Errors (ϵ) must follow a Normal Distribution.
 4. **Equal Variance**: The size of errors should not grow as x changes (Must remain constant).
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5. CALCULATING COEFFICIENTS (Least Squares)

The goal is to find the line that minimizes the sum of squared distances to the points.

Slope (b_1) Formula:

$$b_1 = \frac{S_{xy}}{S_{xx}}$$

Intercept (b_0) Formula:

$$b_0 = \bar{y} - (b_1 \times \bar{x})$$

6. RESIDUALS AND MODEL CHECK

We built the model, but is it good? We look at **Residuals (Errors)**.

Definition:

$$\text{Residual}(e) = \text{RealValue}(y) - \text{PredictedValue}(\hat{y})$$

Residual Analysis: When we plot residuals, we should see a random cloud.

- If there is a "U shape" or "Expanding funnel shape" in residuals, your model is **WRONG**. (Linear model is not suitable).

7. STEP-BY-STEP NUMERICAL EXAMPLE

An engineer measures the relationship between **Bitumen Ratio (x)** and **Hardness (y)** in asphalt.

Data:

- x : 2, 3, 4, 5, 6
- y : 20, 24, 30, 32, 40

STEP 1: Summary Statistics

- Mean $\bar{x} = 4$
- Mean $\bar{y} = 29.2$

STEP 2: Calculate Variations (S)

(Note: Sum of squares is found via table method)

x (Bitumen)	y (Hardness)	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
2	20	-2	-9.2	4	18.4
3	24	-1	-5.2	1	5.2
4	30	0	0.8	0	0
5	32	1	2.8	1	2.8
6	40	2	10.8	4	21.6
Sum				10 (S_{xx})	48 (S_{xy})

STEP 3: Find Slope and Intercept

- **Slope (b_1):** $48/10 = 4.8$
 - (Comment: If bitumen increases by 1%, hardness increases by 4.8 points).
- **Intercept (b_0):** $29.2 - (4.8 \times 4) = 29.2 - 19.2 = 10$

STEP 4: Equation

$$y = 10 + 4.8x$$

Prediction: What happens if Bitumen ratio is 7?

$$y = 10 + (4.8 \times 7) = 43.6$$

```
In [2]: # --- ASPHALT PROBLEM CODE ---
import matplotlib.pyplot as plt

# Data
x_vals = [2, 3, 4, 5, 6]
y_vals = [20, 24, 30, 32, 40]

# 1. Calculate Means
n = len(x_vals)
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x_bar = sum(x_vals) / n
y_bar = sum(y_vals) / n

# 2. Calculate S_xx and S_xy
S_xx = sum([(xi - x_bar)**2 for xi in x_vals])
S_xy = sum([(xi - x_bar) * (yi - y_bar) for xi, yi in zip(x_vals, y_vals)])

# 3. Calculate Coefficients
b1 = S_xy / S_xx
b0 = y_bar - (b1 * x_bar)

print(f"--- RESULTS ---")
print(f"Slope (b1): {b1:.2f}")
print(f"Intercept (b0): {b0:.2f}")
print(f"Equation: y = {b0:.1f} + {b1:.1f}x")

# Prediction for x=7
pred_7 = b0 + b1 * 7
print(f"Prediction for x=7: {pred_7:.1f}")

# --- PLOTTING ---
# Generate line points for plotting
line_x = [1, 8] # range for drawing the line
line_y = [b0 + b1 * xi for xi in line_x]

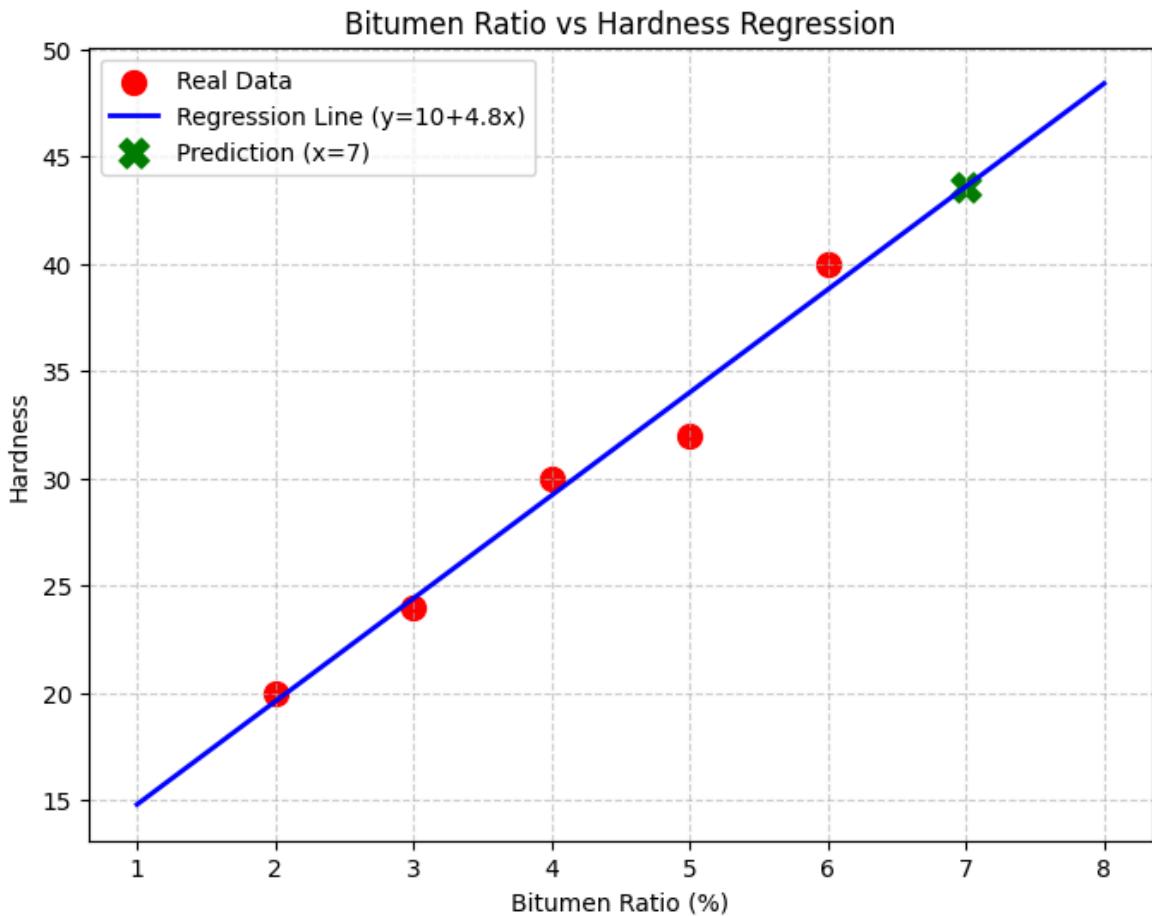
plt.figure(figsize=(8, 6))
plt.scatter(x_vals, y_vals, color='red', s=100, label='Real Data')
plt.plot(line_x, line_y, color='blue', linewidth=2, label=f'Regression Line (y={

# Show prediction point
plt.scatter([7], [pred_7], color='green', marker='X', s=150, label='Prediction (


plt.title("Bitumen Ratio vs Hardness Regression")
plt.xlabel("Bitumen Ratio (%)")
plt.ylabel("Hardness")
plt.grid(True, linestyle='--', alpha=0.6)
plt.legend()
plt.show()

```

--- RESULTS ---
 Slope (b1): 4.80
 Intercept (b0): 10.00
 Equation: $y = 10.0 + 4.8x$
 Prediction for x=7: 43.6



8. ADVANCED CONCEPTS (Vision Box)

Concepts you need to know as an engineer, although we won't calculate them in this course:

1. **Confidence and Prediction Intervals:** The value $y = 43.6$ we found is a single point (Point Estimate). In real life we look at:
 - **Confidence Interval:** "Average hardness is 95% likely to be between 42 and 45."
 - **Prediction Interval:** "Hardness of a single sample is 95% likely to be between 40 and 47." (Prediction interval is always wider).
2. **Multiple Regression:** Hardness is not only affected by bitumen. Temperature, aggregate size etc. also affect it.

$$y = b_0 + b_1 x_1 + b_2 x_2 + \dots$$

(This is covered in Masters or Advanced Statistics).

3. **Coefficient of Determination (R^2):** Success of the model. If $R^2 = 0.90$, it means "Our formula explains 90% of the change in hardness, 10% is unknown factors".

9. Lecture Summary

1. **Do Not Extrapolate:** Our data was between $x = 2$ and $x = 6$. Do not calculate for $x = 50$ using this formula. Physical behavior may change in that region.
2. **Check Correlation Visually:** r might be 0.9, but data could be "parabolic" (U-shaped). Always draw the graph first.
3. **Error Term:** ϵ (Epsilon) is the "measure of our ignorance" in engineering. Everything we couldn't include in the model is there.