

EXPT NO:3	
DATE: 12.01.2026	

Designing Multivariate Patterns

PRE-LAB QUESTIONS (PROVIDE BRIEF ANSWERS TO THE FOLLOWING QUESTIONS)

1. Why is multivariate analysis essential in real-world AI problems?
2. What challenges arise when visualizing high-dimensional data?
3. How does correlation analysis support feature selection?
4. What are ethical concerns in healthcare data visualization?
5. Give examples of multivariate data in AI systems.

ANSWERS:

1. Multivariate analysis is essential in real-world AI problems because it analyzes multiple variables together, helping models understand complex relationships and improve prediction accuracy.
2. Visualizing high-dimensional data is challenging because it causes cluttered plots, overlapping information, and difficulty in interpreting patterns beyond three dimensions.
3. Correlation analysis supports feature selection by identifying redundant features, reducing dimensionality, and improving model efficiency and performance.
4. Ethical concerns in healthcare data visualization include patient privacy, data security, misrepresentation of data, bias, and potential misuse of sensitive information.
5. Examples of multivariate data in AI systems include healthcare records, customer behavior data, financial transaction data, and sensor data from autonomous systems.

IN-LAB EXERCISE:

OBJECTIVE:

To discover relationships among multiple variables using multivariate visualization.

SCENARIO:

A hospital analytics team studies patient health records to identify relationships between age, BMI, glucose levels, and blood pressure for early disease prediction.

IN-LAB TASKS (Using R Language)

- Generate scatter plot matrix
- Apply color encoding for age groups
- Identify correlated health indicators

CODE:

```
1 "Student name: Sai Vaishnavi R"
2 "roll no:23BAD094"
3 # 2. Load libraries
4 library(GGally)
5 library(dplyr)
6
7 # 3. Load healthcare dataset
8 health <- read.csv("C:/Users/student/Downloads/3.healthcare_data.csv")
9
10 # 4. Check dataset structure
11 str(health)
12 head(health)
13
14
15 # 5. Create Age Groups for color encoding
16 health <- health %>%
17   mutate(
18     Age_Group = cut(
19       Age,
20       breaks = c(0, 30, 50, 100),
21       labels = c("Young", "Middle", "Senior"))
22   )
23
24
25 # 6. Scatter Plot Matrix
26 ggpairs(
27   health,
28   columns = c("Age", "Blood_Pressure", "Cholesterol", "Glucose_Level"),
29   aes(color = Age_Group),
30   title = "Scatter Plot Matrix of Health Indicators"
31 )
32
33
34 # 7. Select numeric variables for correlation
35 health_numeric <- health %>%
36   select(Age, Blood_Pressure, Cholesterol, Glucose_Level)
37
38 # 8. Correlation matrix
39 correlation_matrix <- cor(health_numeric, use = "complete.obs")
40
41 # 9. Display correlation matrix
42 print(correlation_matrix)
```

OUTPUT:

```

> "Student name: Sai Vaishnavi R"
[1] "Student name: Sai Vaishnavi R"
> "roll_no:23BA0D094"
[1] "roll_no:23BA0D094"
> # 2. Load libraries
> library(GGally)
> library(dplyr)
>
> # 3. Load healthcare dataset
> # health <- read.csv("C:/Users/student/Downloads/3.healthcare_data.csv")
>
> # 4. Check dataset structure
> str(health)
'data.frame': 50 obs. of 8 variables:
 $ Patient_ID : int 3001 3002 3003 3004 3005 3006 3007 3008 3009 3010 ...
 $ Age          : int 31 45 65 53 68 33 45 64 46 28 ...
 $ Gender       : chr "Male" "Male" "Female" "Male" ...
 $ BMI          : num 23.6 33.9 18.1 21.8 24.2 26.3 23.9 19.5 31.7 18.9 ...
 $ Blood_Pressure: int 104 113 127 124 138 158 151 149 139 98 ...
 $ Glucose_Level : int 111 84 180 102 107 166 102 155 135 79 ...
 $ Cholesterol  : int 255 241 180 158 200 178 227 189 190 235 ...
 $ Disease_Risk : chr "Low" "High" "High" "High" ...
> head(health)
Patient_ID Age Gender BMI Blood_Pressure Glucose_Level Cholesterol Disease_Risk
1 3001 31 Male 23.6 104 111 255 Low
2 3002 45 Male 33.9 113 84 241 High
3 3003 65 Female 18.1 127 180 180 High
4 3004 53 Male 21.8 124 102 158 High
5 3005 68 Male 24.2 138 107 200 High
6 3006 33 Male 26.3 158 166 178 Medium

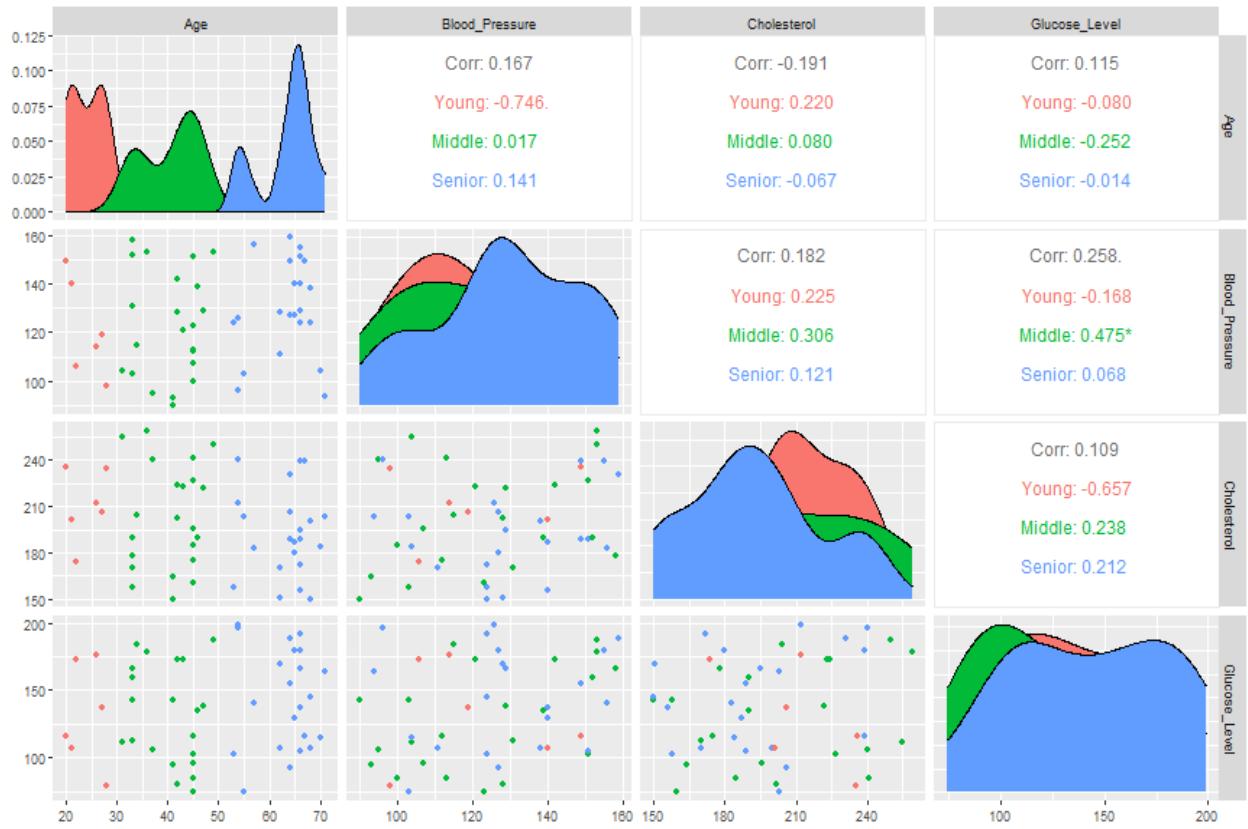
> # 5. Create Age Groups for color encoding
> health <- health %>
+   mutate(
+     Age_Group = cut(
+       Age,
+       breaks = c(0, 30, 50, 100),
+       labels = c("young", "Middle", "senior"))
+   )
>
> # 6. Scatter Plot Matrix
> ggpairs(
+   health,
+   columns = c("Age", "Blood_Pressure", "Cholesterol", "Glucose_Level"),
+   aes(color = Age_Group),
+   title = "Scatter Plot Matrix of Health Indicators"
+ )
>

> # 7. Select numeric variables for correlation
> health_numeric <- health %>
+   select(Age, Blood_Pressure, Cholesterol, Glucose_Level)
>
> # 8. Correlation matrix
> correlation_matrix <- cor(health_numeric, use = "complete.obs")
>
> # 9. Display correlation matrix
> print(correlation_matrix)

                    Age Blood_Pressure Cholesterol Glucose_Level
Age    1.00000000 0.1672128 -0.1911136 0.1146740
Blood_Pressure 0.1672128 1.0000000 0.1819998 0.2582461
Cholesterol   -0.1911136 0.1819998 1.0000000 0.1088433
Glucose_Level  0.1146740 0.2582461 0.1088433 1.0000000

```

Scatter Plot Matrix of Health Indicators



POST-LAB QUESTIONS (PROVIDE BRIEF ANSWERS TO THE FOLLOWING QUESTIONS)

1. Which health parameters show strong correlation?
2. Why correlation does not imply causation in medical data?
3. How can these patterns assist predictive healthcare AI?
4. What visualization limitations exist for high-dimensional data?
5. How can dimensionality reduction improve visualization?

ANSWERS:

1. No health parameters show a strong correlation. The highest observed correlation is between blood pressure and glucose level (≈ 0.26), which indicates only a weak to moderate positive relationship, while all other correlations are weak.
2. Correlation does not imply causation because health variables may be related due to confounding factors, coincidence, or indirect effects. Medical outcomes are influenced by multiple biological, environmental, and lifestyle factors, so a correlation alone cannot establish a cause–effect relationship.
3. These patterns assist predictive healthcare AI by helping identify relevant features, understand relationships among health indicators, and improve risk prediction models through better feature selection.
4. High-dimensional data visualization becomes complex and cluttered, making patterns difficult to interpret. Scatter plot matrices grow large, overlap increases, and important relationships may be overlooked.
5. Dimensionality reduction improves visualization by compressing multiple variables into fewer meaningful components, simplifying plots, revealing hidden patterns, and making high-dimensional data easier to interpret and analyze.

ASSESSMENT

Description	Max Marks	Marks Awarded
Pre Lab Exercise	5	
In Lab Exercise	10	
Post Lab Exercise	5	
Viva	10	
Total	30	
Faculty Signature		