

## **Data Warehousing & Data Mining – Practical Lab Manual with Solutions**

### **Practical 1: Visualization Features in WEKA**

Solution:

1. Open WEKA → Explorer → Open File → Select dataset (e.g., iris.arff).
2. Go to the “Visualize” tab.
3. Scatter plot matrix appears showing relationships between attributes.
4. Identify patterns:
  - Iris-setosa is clearly separable in PetalLength vs PetalWidth.
  - Iris-versicolor and virginica overlap slightly.

Conclusion: Visualization helps detect separability and outliers.

### **Practical 2: Data Preprocessing & Association Rule Mining**

Solution:

1. Load dataset → Preprocess tab.
2. Apply filters:
  - Remove → delete specific attributes.
  - Normalize → scale attributes.
3. To perform association mining:
  - Associate tab → Choose Apriori.
  - Set minimum support = 0.1, confidence = 0.9.
4. Click Start.

Sample Output Rule:

petalwidth < 0.3  $\Rightarrow$  class=setosa (confidence 1.0)

Conclusion: Apriori finds strong rules that describe attribute relationships.

### **Practical 3: Classification on Datasets**

Solution:

1. Load dataset → Classify tab.

2. Choose classifier → J48 (Decision Tree).

3. Test Options:

- Use Training Set
- Percentage split = 70%

4. Start.

Sample Result:

Accuracy: 94%

Confusion Matrix:

	a	b	c
a	50	0	0
b	2	44	4
c	0	3	47

Conclusion: J48 performs strongly on structured datasets like Iris.

#### Practical 4: Clustering on Datasets

Solution:

1. Load dataset → Cluster tab.
2. Choose SimpleKMeans → set k = 3.
3. Start.

Output:

Cluster 0: mostly setosa

Cluster 1: mixed virginca/versicolor

Cluster 2: mixed virginca/versicolor

Conclusion: K-means clusters based on attribute similarity but is unsupervised; labels are not used.

#### Practical 5: German Credit Data

Solution:

1. Load german\_credit.arff → Preprocess.

2. Handle missing values (ReplaceMissingValues filter).

3. Classify → Choose NaiveBayes or J48.

4. Start.

Result example:

Accuracy: 72%

Conclusion: German Credit dataset is noisy and complex, giving lower accuracy than Iris.

### **Practical 6: Decision Tree with Cross Validation**

Solution:

1. Load dataset → Classify tab.

2. Choose J48 → Test Option: 10-fold cross-validation.

3. Record accuracy.

Compare:

- Training set accuracy: 98%

- Cross-validation accuracy: 94%

Reason: Training accuracy is higher due to overfitting.

Conclusion: Cross-validation gives realistic performance measures.

### **Practical 7: Check Bias Against Attributes**

Solution:

1. Load German Credit dataset.

2. Remove attribute 'foreign\_worker'.

3. Train model → Record accuracy.

4. Remove attribute 'personal\_status'.

Accuracy Comparison:

- Original: 72%

- Without foreign\_worker: 72% (no change)

- Without personal\_status: 70% (slight drop)

Conclusion: No major bias found against foreign workers. Personal status has some predictive importance.

### **Practical 8: Attribute Combination Testing**

Solution:

Steps:

1. Use Attribute Selection Filter → Ranker + InfoGain.
2. Select top attributes: credit\_amount, duration, checking\_status.

Model Accuracy:

- Using all attributes: 72%
- Using top 5 attributes: 71%

Conclusion: Reduced attributes give similar performance; some attributes are redundant.

### **Practical 9: Decision Tree vs Cross Validation**

Solution:

Normal Training:

Accuracy: 97%

Cross-validation:

Accuracy: 93%

Difference Reason:

- Training uses same data for testing → overly optimistic.
- CV uses unseen data → more realistic.

Conclusion: Cross-validation should be preferred.

### **Practical 10: Decision Tree Complexity vs Bias**

Solution:

Steps:

1. In J48 settings → change pruning confidence:
  - High confidence (0.5) → Larger tree (low bias, high variance).
  - Low confidence (0.1) → Smaller tree (high bias, low variance).

Observed:

- Larger tree accuracy (training): 98%
- Smaller tree accuracy (CV): 93%

Conclusion: Higher complexity reduces bias but increases variance; balanced pruning gives best results.