```
In [36]: import csv
         import math
         from collections import Counter
In [37]: # ------ 1. Preprocessing ------
In [38]: def read_csv(path):
             with open(path, 'r') as file:
                 reader = csv.reader(file, delimiter=';')
                 header = next(reader)
                 data = [row for row in reader]
             return header, data
In [39]: def encode_data(header, data):
             encoders = {}
             encoded_data = []
             target_col_index = len(header) - 1
             for col_index in range(len(header)):
                 col_values = [row[col_index].strip('"') for row in data]
                 if col_index == target_col_index:
                     mapping = {'no': 0, 'yes': 1}
                     for row in data:
                         row[col_index] = mapping[row[col_index].strip('"')]
                     encoders[header[col_index]] = mapping
                     continue
                     [float(v) for v in col_values]
                     encoders[header[col_index]] = None
                 except:
                     unique_vals = sorted(set(col_values))
                     mapping = {val: idx for idx, val in enumerate(unique_vals)}
                     for row in data:
                         row[col_index] = mapping[row[col_index].strip('"')]
                     encoders[header[col_index]] = mapping
             for row in data:
                 encoded_data.append([float(value) for value in row])
             return encoded_data, encoders
In [40]: def split_dataset(data):
             return data[:4000], data[4000:4400], data[4400:]
In [41]: def split_features_labels(dataset):
             X = [row[:-1] for row in dataset]
             y = [row[-1] for row in dataset]
             return X, y
In [42]: # ------ 2. ID3 -----
In [43]: def entropy(labels):
             total = len(labels)
             counts = Counter(labels)
             return -sum((count / total) * math.log2(count / total) for count in counts.values())
In [44]: def info_gain(X, y, feature_index):
             total_entropy = entropy(y)
             subsets = {}
             for xi, yi in zip(X, y):
                 key = xi[feature_index]
                 if key not in subsets:
                     subsets[key] = {'X': [], 'y': []}
                 subsets[key]['X'].append(xi)
                 subsets[key]['y'].append(yi)
             weighted_entropy = 0
             total = len(y)
             for group in subsets.values():
                 proportion = len(group['y']) / total
                 weighted_entropy += proportion * entropy(group['y'])
             return total_entropy - weighted_entropy
In [45]: def build_id3(X, y, features):
             if len(set(y)) == 1:
                 return {'label': y[0]}
             if not features:
                 return {'label': Counter(y).most_common(1)[0][0]}
             gains = [info_gain(X, y, f) for f in features]
             best_feature = features[gains.index(max(gains))]
             tree = {'feature': best_feature, 'branches': {}}
             for value in set([xi[best_feature] for xi in X]):
                 subset_X, subset_y = [], []
                 for xi, yi in zip(X, y):
                     if xi[best_feature] == value:
```

```
new_xi = xi[:best_feature] + xi[best_feature+1:]
                          subset_X.append(new_xi)
                         subset_y.append(yi)
                 new_features = [f if f < best_feature else f - 1 for f in features if f != best_feature]</pre>
                 tree['branches'][value] = build_id3(subset_X, subset_y, new_features)
             return tree
In [46]: def majority_class(tree):
             labels = []
             def collect_labels(t):
                 if 'label' in t:
                     labels.append(t['label'])
                 else:
                     for child in t['branches'].values():
                         collect_labels(child)
             collect_labels(tree)
             return Counter(labels).most_common(1)[0][0]
In [47]: def predict_id3(tree, x):
             while 'label' not in tree:
                  feature_index = tree['feature']
                 value = x[feature_index]
                 if value in tree['branches']:
                     tree = tree['branches'][value]
                     x = x[:feature_index] + x[feature_index+1:]
                 else:
                     return majority_class(tree)
             return tree['label']
In [48]: # ------ 3. CART -----
In [49]: def gini_index(groups, classes):
             total = sum(len(group) for group in groups)
             gini = 0.0
             for group in groups:
                 size = len(group)
                 if size == 0:
                     continue
                 score = 0.0
                 counts = Counter(group)
                 for c in classes:
                     p = counts[c] / size
                     score += p * p
                 gini += (1 - score) * (size / total)
             return gini
In [50]: def get_best_split(X, y):
             best_index, best_value, best_score, best_groups = None, None, float('inf'), None
             classes = list(set(y))
             for index in range(len(X[0])):
                  values = set([row[index] for row in X])
                  for value in values:
                     left_y = [y[i] for i in range(len(X)) if X[i][index] == value]
                     right_y = [y[i] for i in range(len(X)) if X[i][index] != value]
                      gini = gini_index([left_y, right_y], classes)
                     if gini < best_score:</pre>
                          best_index, best_value, best_score = index, value, gini
                          best_groups = (
                              [X[i] for i in range(len(X)) if X[i][index] == value],
                              [y[i] for i in range(len(X)) if X[i][index] == value],
                              [X[i] for i in range(len(X)) if X[i][index] != value],
                              [y[i] for i in range(len(X)) if X[i][index] != value]
             return {'index': best_index, 'value': best_value, 'groups': best_groups}
In [51]: def build_cart(X, y, max_depth, depth=0):
             if len(set(y)) == 1 or depth >= max_depth:
                 return {'label': Counter(y).most_common(1)[0][0]}
             node = get_best_split(X, y)
             left_X, left_y, right_X, right_y = node['groups']
             node['left'] = build_cart(left_X, left_y, max_depth, depth+1)
             node['right'] = build_cart(right_X, right_y, max_depth, depth+1)
             return node
In [52]: def predict_cart(tree, x):
             if 'label' in tree:
                 return tree['label']
             if x[tree['index']] == tree['value']:
                 return predict_cart(tree['left'], x)
             else:
                 return predict_cart(tree['right'], x)
```

```
In [53]: # ------ 4. Naive Bayes -----
In [54]: def train_naive_bayes(X, y):
             summaries = {}
             class_counts = Counter(y)
             total = len(y)
             for class_val in class_counts:
                  indices = [i for i in range(len(y)) if y[i] == class_val]
                 class_data = [X[i] for i in indices]
                  summaries[class_val] = {
                      'prior': class_counts[class_val] / total,
                      'features': list(zip(*class_data))
             return summaries
In [55]: def predict_naive_bayes(model, x):
             probs = {}
              for class_val, info in model.items():
                 prob = info['prior']
                  for i in range(len(x)):
                     values = info['features'][i]
                     count = values.count(x[i])
                     prob *= (count + 1) / (len(values) + len(set(values))) # Laplace smoothing
                 probs[class_val] = prob
             return max(probs, key=probs.get)
In [56]: # ----- 5. Accuracy -----
In [57]: def accuracy(y_true, y_pred):
             return sum(1 for yt, yp in zip(y_true, y_pred) if yt == yp) / len(y_true)
In [58]: # ------ 6. Run Everything -----
In [59]: header, raw_data = read_csv('bank.csv')
         encoded_data, encoders = encode_data(header, raw_data)
         train_set, val_set, pred_set = split_dataset(encoded_data)
In [60]: X_train, y_train = split_features_labels(train_set)
         X_val, y_val = split_features_labels(val_set)
         X_pred = [row[:-1] for row in pred_set]
In [61]: # ID3
         features = list(range(len(X_train[0])))
         id3_tree = build_id3(X_train, y_train, features)
          id3_preds = [predict_id3(id3_tree, x) for x in X_val]
         acc_id3 = accuracy(y_val, id3_preds)
In [62]: # CART
         cart_tree = build_cart(X_train, y_train, max_depth=5)
         cart_preds = [predict_cart(cart_tree, x) for x in X_val]
         acc_cart = accuracy(y_val, cart_preds)
In [63]: # Naive Bayes
         nb_model = train_naive_bayes(X_train, y_train)
         nb_preds = [predict_naive_bayes(nb_model, x) for x in X_val]
         acc_nb = accuracy(y_val, nb_preds)
In [64]: # Comparison
         print(f"ID3 Accuracy: {round(acc_id3 * 100, 2)}%")
          print(f"CART Accuracy: {round(acc_cart * 100, 2)}%")
         print(f"Naive Bayes Accuracy: {round(acc_nb * 100, 2)}%")
         ID3 Accuracy: 85.0%
         CART Accuracy: 88.5%
         Naive Bayes Accuracy: 78.0%
In [65]: from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
         y_val_true = [int(y) for y in y_val]
          id3_pred = [int(p) for p in id3_preds]
          cart_pred = [int(p) for p in cart_preds]
          nb_pred = [int(p) for p in nb_preds]
         def print_metrics(name, y_true, y_pred):
             print(f"\n{name} Metrics:")
             print(f"Accuracy : {accuracy_score(y_true, y_pred) * 100:.2f}%")
             print(f"Precision: {precision_score(y_true, y_pred) * 100:.2f}%")
             print(f"Recall : {recall_score(y_true, y_pred) * 100:.2f}%")
             print(f"F1 Score : {f1_score(y_true, y_pred) * 100:.2f}%")
         print_metrics("ID3", y_val_true, id3_pred)
print_metrics("CART", y_val_true, cart_pred)
         print_metrics("Naive Bayes", y_val_true, nb_pred)
```

```
ID3 Metrics:
       Accuracy : 85.00%
       Precision: 23.81%
       Recall : 10.20%
       F1 Score : 14.29%
      CART Metrics:
       Accuracy : 88.50%
       Precision: 61.54%
       Recall : 16.33%
       F1 Score : 25.81%
      Naive Bayes Metrics:
       Accuracy : 78.00%
       Precision: 27.59%
       Recall : 48.98%
       F1 Score : 35.29%
In [66]: #best model classifier
       best\_model = max([('ID3', acc\_id3), ('CART', acc\_cart), ('NB', acc\_nb)], key=lambda x: x[1])[0]
       print(f"Best Algorithm: {best_model}")
       Best Algorithm: CART
In [67]: # Final Predictions
       if best_model == 'ID3':
          final_preds = [predict_id3(id3_tree, x) for x in X_pred]
       elif best_model == 'CART':
          final_preds = [predict_cart(cart_tree, x) for x in X_pred]
       else:
          final_preds = [predict_naive_bayes(nb_model, x) for x in X_pred]
In [68]: # Reverse Label encoding
       label_decoder = {v: k for k, v in encoders['y'].items()} if 'y' in encoders else {0: 'no', 1: 'yes'}
       final_preds_decoded = [label_decoder[int(p)] for p in final_preds]
In [69]: print("Final Predictions:")
print(" ".join(final_preds_decoded))
       Final Predictions:
       In [ ]:
```