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In [3]: import numpy as np
         import matplotlib.pyplot as plt
          from sklearn.metrics import accuracy_score, matthews_corrcoef
         from sklearn.metrics import confusion_matrix
         # Define global probabilities for easy access
         fair_probs = [1/6] * 6
         loaded_probs = [1/10, 1/10, 1/10, 1/10, 1/10, 1/2]
          # Generate dice throws for testing
         def genDieNumbers(n):
              states = ['fair', 'loaded']
              current_state = 'fair' if np.random.rand() < 0.5 else 'loaded'</pre>
              dice = []
              throws = []
              for _ in range(n):
                  if current_state == 'fair':
                      throws.append(np.random.choice(range(1, 7), p=fair_probs))
                      throws.append(np.random.choice(range(1, 7), p=loaded_probs))
                  dice.append(current_state)
                  if current_state == 'fair' and np.random.rand() < 0.1:</pre>
                      current_state = 'loaded'
                  elif current_state == 'loaded' and np.random.rand() < 0.2:</pre>
                      current_state = 'fair'
              return np.array(throws), np.array(dice)
         # Viterbi Algorithm Implementation
         def viterbi(observations):
              states = ['fair', 'loaded']
              start_prob = {'fair': 0.5, 'loaded': 0.5}
              trans_prob = {'fair': {'fair': 0.95, 'loaded': 0.05}, 'loaded': {'fair': 0.05, 'loaded': 0.95}}
              em_prob = {
                  'fair': dict(zip(range(1, 7), fair_probs)),
                  'loaded': dict(zip(range(1, 7), loaded_probs))
              n = len(observations)
              probs = np.zeros((n, len(states)))
              prev = np.zeros((n, len(states)), dtype=int)
              for i, state in enumerate(states):
                  probs[0, i] = start_prob[state] * em_prob[state][observations[0]]
              for t in range(1, n):
                  for i, state in enumerate(states):
                      prob_trans = [probs[t-1, j] * trans_prob[prev_state][state] for j, prev_state in enumerate(states)]
                      best_prev_state = np.argmax(prob_trans)
                      probs[t, i] = prob_trans[best_prev_state] * em_prob[state][observations[t]]
                      prev[t, i] = best_prev_state
              # Backtrack
              opt = np.zeros(n, dtype=int)
              opt[-1] = np.argmax(probs[-1, :])
              for t in range(n-2, -1, -1):
                  opt[t] = prev[t + 1, opt[t + 1]]
              return [states[state] for state in opt]
         # evaluate the Viterbi algorithm with test examples
         def evaluate_viterbi(n):
              throws, actual_dice = genDieNumbers(n)
              predicted_dice = viterbi(throws)
              accuracy = accuracy_score(actual_dice, predicted_dice)
              mcc = matthews_corrcoef(actual_dice, predicted_dice)
              return accuracy, mcc, throws, actual_dice, predicted_dice
         # Test the function for n = 200
         accuracy, mcc, throws, actual_dice, predicted_dice = evaluate_viterbi(200)
         print("Accuracy:", accuracy)
         print("MCC:", mcc)
         print("First 20 throws:", throws[:20])
         print("Actual dice types for first 20 throws:", actual_dice[:20])
         print("Predicted dice types for first 20 throws:", predicted_dice[:20])
        Accuracy: 0.775
        MCC: 0.3646859721191225
        First 20 throws: [1 5 4 6 1 4 5 1 5 1 4 5 3 3 5 5 1 1 6 6]
        Actual dice types for first 20 throws: ['fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair'
         'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair' 'fair']
        Predicted dice types for first 20 throws: ['fair', 'fair', 'fa
        r', 'fair']
In [4]: def decode_dice_sequence(throws):
              predicted_dice = viterbi(throws)
              rolls_str = 'Rolls\n' + ' '.join(map(str, throws))
              die_str = 'Die\n' + ''.join('F' if d == 'fair' else 'L' for d in predicted_dice)
              viterbi_str = 'Viterbi\n' + ''.join('F' if d == 'fair' else 'L' for d in predicted_dice)
              formatted_output = '\n'.join([rolls_str, die_str, viterbi_str])
              return formatted_output
          # Test implementation with different sequence lengths.
         test_lengths = [200, 300, 400]
         for length in test_lengths:
              throws, actual_dice = genDieNumbers(length)
              predicted_dice = viterbi(throws)
              formatted_output = decode_dice_sequence(throws)
              # Print the formatted output.
              print(f"Test with sequence length {length}:")
              print(formatted_output)
              print("\n" + "-"*50 + "\n")
        Test with sequence length 200:
        153335266666426652422613664662214415631656441416251264262315236166466236551516353631423136145655
        254615432336541663634334266455236623352164616612215245652145456211546314634145125566666521366145
        FFFFFFFF
        FFFFFFFF
        Test with sequence length 300:
        6\ 1\ 1\ 6\ 1\ 5\ 2\ 5\ 6\ 3\ 3\ 2\ 4\ 4\ 6\ 6\ 6\ 5\ 6\ 3\ 2\ 2\ 3\ 3\ 5\ 6\ 1\ 6\ 5\ 4\ 5\ 3\ 5\ 1\ 1\ 6\ 2\ 1\ 6\ 6\ 1\ 4\ 5\ 1\ 4\ 5\ 3\ 2\ 5\ 3\ 2\ 5\ 4\ 6\ 4\ 4\ 6\ 5\ 4\ 6\ 3\ 3\ 5\ 1\ 6\ 6\ 6\ 6\ 5\ 5\ 5\ 6\ 1\ 4\ 2\ 3\ 1\ 1\ 3\ 6\ 6\ 5\ 5\ 3\ 6\ 4\ 6\ 1\ 1
        3\ 2\ 1\ 5\ 4\ 2\ 4\ 3\ 1\ 3\ 1\ 5\ 2\ 2\ 4\ 2\ 2\ 5\ 6\ 6\ 4\ 4\ 5\ 6\ 6\ 2\ 6\ 3\ 6\ 3\ 6\ 6\ 6\ 6\ 6\ 1\ 6\ 1\ 5\ 4\ 1\ 3\ 5\ 6\ 4\ 3\ 2\ 6\ 5\ 6\ 6\ 5\ 2\ 6\ 5\ 4\ 1\ 6\ 3\ 4\ 3\ 1\ 5\ 5\ 3\ 4\ 2\ 2\ 3\ 3\ 6\ 4\ 2\ 1\ 1\ 6\ 6\ 4\ 6\ 5\ 4\ 2\ 1
        Test with sequence length 400:
        f3 6 f2 5 f3 4 f3 5 f4 6 f3 6 f3 4 f5 6 f3 6 f4 6 f5 6 f4 6 f4 6 f5 6 f4 6 f5 6 f4 6 f5 6 f5 6 f5 6 f5 7 f5
        5\ 3\ 3\ 1\ 3\ 5\ 5\ 2\ 2\ 1\ 2\ 6\ 1\ 3\ 3\ 1\ 4\ 3\ 4\ 1\ 1\ 4\ 4\ 3\ 4\ 1\ 5\ 4\ 2\ 2\ 2\ 5\ 5\ 5\ 1\ 4\ 5\ 3\ 3\ 1\ 1\ 4\ 2\ 4\ 3\ 4\ 5\ 5\ 5\ 2\ 4\ 3\ 2\ 2\ 1\ 6\ 4\ 3\ 6\ 5\ 6\ 6\ 6\ 6\ 2\ 1\ 2\ 6\ 2\ 2\ 6\ 4\ 6\ 2\ 2\ 3\ 6\ 1\ 6\ 5\ 5\ 3\ 5\ 1\ 4\ 2\ 5\ 4\ 1\ 6\ 1\ 6\ 3\ 3\ 5\ 6
        6 6 3 1 6 4 6 2 6 1 6 2 4 6 3 2
        Viterbi
        LLLLLLLLLLLLLLLL
In [7]: def calculate_performance_metrics(actual, predicted):
              # Calculate confusion matrix
              performance = confusion_matrix(actual, predicted, labels=['fair', 'loaded'])
              # interpret the confusion matrix
              TP, FN, FP, TN = performance[0][0], performance[0][1], performance[1][0], performance[1][1]
              # Calculate Accuracy
              accuracy = (TP + TN) / (TP + TN + FP + FN)
              # Calculate MCC
              mcc_numerator = (TP * TN) - (FP * FN)
              mcc_denominator = np.sqrt((TP + FN) * (TP + FP) * (TN + FP) * (TN + FN))
              mcc = mcc_numerator / mcc_denominator if mcc_denominator != 0 else 0
              return accuracy, mcc
         # Main program to evaluate the Viterbi algorithm's effectiveness
         def evaluate_viterbi_algorithm():
              n_range = range(100, 2001, 100) # From 100 to 2000 with step size of 100
              results = []
              for n in n_range:
                  accuracies = []
                  mccs = []
                  for _ in range(10): # Repeat 10 times for each n
                      throws, actual_dice = genDieNumbers(n) # Simulate the dealer
                      predicted_dice = viterbi(throws) # Predict using Viterbi algorithm
                      # Calculate accuracy and MCC
                      accuracy, mcc = calculate_performance_metrics(actual_dice, predicted_dice)
                      accuracies.append(accuracy)
                      mccs.append(mcc)
                  # Calculate average accuracy and MCC for this input size n
                  avg_accuracy = np.mean(accuracies)
                  avg_mcc = np.mean(mccs)
                  results.append((n, avg_accuracy, avg_mcc))
              return results
         # Run the evaluation
         performance_results = evaluate_viterbi_algorithm()
         performance_results
Out[7]: [(100, 0.708, 0.30213777126609753),
           (200, 0.74, 0.4151732742237805),
           (300, 0.7203333333333333, 0.30854968192560095),
           (400, 0.69, 0.2907620947267026),
           (500, 0.6926, 0.2563768120830407),
           (600, 0.682499999999999, 0.26505933324126774),
           (700, 0.682999999999999, 0.18633485634129052),
           (800, 0.675375, 0.17908221849792536),
           (900, 0.65977777777778, 0.1674326009957896),
           (1000, 0.679, 0.1757036876879906),
           (1100, 0.6938181818181819, 0.1446246389328692),
           (1200, 0.6953333333333334, 0.15042736163702924),
           (1300, 0.6718461538461538, 0.1345555413653207),
           (1400, 0.6667142857142856, 0.13309025723101364),
           (1500, 0.6791333333333334, 0.16618359608621988),
           (1600, 0.6756875, 0.13953876261481338),
           (1700, 0.6722941176470589, 0.12447971334760552),
           (1800, 0.6774444444444445, 0.09588215321367874),
           (1900, 0.6834210526315789, 0.13392926835933325),
           (2000, 0.6702, 0.10633011522945975)]
In [ ]:
In [
In [10]: def plot_results(results):
              sizes = [r[0] for r in results]
              accuracies = [r[1] for r in results]
              mccs = [r[2] for r in results]
              plt.figure(figsize=(12, 5))
              plt.subplot(1, 2, 1)
              plt.plot(sizes, accuracies, marker='o', color='blue')
              plt.title('Accuracy vs Number of Throws')
              plt.xlabel('Number of Throws')
              plt.ylabel('Accuracy')
              plt.subplot(1, 2, 2)
              plt.plot(sizes, mccs, marker='o', color='red')
              plt.title('MCC vs Number of Throws')
              plt.xlabel('Number of Throws')
              plt.ylabel('MCC')
              plt.tight_layout()
              plt.show()
         # Use this function after running 'evaluate_viterbi_algorithm'
         plot_results(performance_results)
                                  Accuracy vs Number of Throws
                                                                                                                      MCC vs Number of Throws
            0.74 -
                                                                                             0.40
            0.73
                                                                                             0.35
            0.72 -
                                                                                            0.30
           0.71
           0.70
         Acc
           0.69
                                                                                            0.20
           0.68
```

0.15

0.10

250

500

1000

Number of Throws

1250

750

1500

1750

2000

0.67

0.66

250

500

1000

Number of Throws

750

1250

1500

1750

2000