Discrete HMM for DNA Sequence Analysis and Gene Region Prediction

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In [12]:
         import numpy as np
         from hmmlearn import hmm
         from collections import Counter
         from hmmlearn.hmm import CategoricalHMM
In [4]:
         # Mapping nucleotides and gene states to integers
         nucleotide_mapping = {'A': 0, 'C': 1, 'G': 2, 'T': 3}
         state mapping = {'N': 0, 'G': 1}
In [5]: # Inverse mapping for decoding
         inv_state_mapping = {0: 'N', 1: 'G'}
In [6]: # Synthetic training data (sequences and labeled gene/non-gene states)
         train_sequences = ["ATGCG", "TTCGA", "GGGTT"]
         train_states = ["GGGGG", "NNNGG", "GGGNN"]
In [7]: # Convert sequences and states to numerical format
         observed_sequences = [np.array([nucleotide_mapping[nuc] for nuc in seq]).reshape(-1, 1)
                               for seq in train_sequences]
         state_sequences = [np.array([state_mapping[state] for state in states])
                            for states in train_states]
In [8]: # Concatenate all sequences for training
         X = np.concatenate(observed_sequences)
         lengths = [len(seq) for seq in observed_sequences]
In [9]: # Initialize a Multinomial HMM with 2 hidden states: Gene (G) and Non-Gene (N)
         n_states = 2 # Gene, Non-Gene
         n_observations = len(nucleotide_mapping)
In [13]:
         model = hmm.CategoricalHMM(n_components=n_states, n_iter=100, tol=1e-4, verbose=True)
         model.n_features = n_observations
In [14]: # Train the model using Maximum Likelihood Estimation (MLE)
         model.fit(X, lengths)
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64
                       -18.08058659
                                         +0.00017862
                65
                       -18.08044884
                                         +0.00013774
                66
                       -18.08034266
                                         +0.00010618
                67
                       -18.08026083
                                         +0.00008183
Out[14]:
                                           CategoricalHMM
         CategoricalHMM(n_components=2, n_features=4, n_iter=100,
                         random state=RandomState(MT19937) at 0x28FCA358E40, tol=0.0001,
                         verbose=True)
In [15]:
         print("Initial Probabilities (\pi):")
         print(model.startprob_)
         print("\nTransition Probabilities (A):")
         print(model.transmat )
         print("\nEmission Probabilities (B):")
         print(model.emissionprob_)
        Initial Probabilities (\pi):
        [0.35263532 0.64736468]
        Transition Probabilities (A):
        [[0.78324568 0.21675432]
         [0.40475911 0.59524089]]
        Emission Probabilities (B):
        [[6.82116014e-02 2.32920347e-01 6.98761034e-01 1.07017613e-04]
         [2.20522388e-01 1.31530440e-12 9.31494853e-09 7.79477603e-01]]
In [16]: # Example test DNA sequence
         test sequence = "ATGGC"
         test_observed = np.array([nucleotide_mapping[nuc] for nuc in test_sequence]).reshape(-1, 1)
In [17]: # Predict hidden states using Viterbi algorithm
         predicted_states = model.predict(test_observed)
         predicted_labels = [inv_state_mapping[state] for state in predicted_states]
In [18]: # Display results
         print("\nTest DNA sequence:
                                          ", test_sequence)
         print("Predicted gene regions: ", "".join(predicted_labels))
        Test DNA sequence:
                                  ATGGC
        Predicted gene regions:
                                  GGNNN
```

In []: