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In [2]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

def viterbi_decode(observations, states, initial_probabilities, transition_mat
    """
    Implements the Viterbi algorithm to find the most likely sequence of hidden

    Args:
        observations (list): The sequence of observations (indices).
        states (list): The list of possible hidden states (S1, S2, ...).
        initial_probabilities (np.array): The starting probability for each st
        transition_matrix (np.array): The state transition probabilities (A).
        emission_matrix (np.array): The observation emission probabilities (B)

    Returns:
        tuple: (most_likely_sequence, max_probability, V, P, best_path_indices)
               V and P are the Viterbi probability and traceback tables.
    """

    # N = number of states (4)
    N = len(states)
    # T = length of the observation sequence (4)
    T = len(observations)

    # 1. Initialization: Create Viterbi probability table (V) and Path traceback
    # V[t, i]: max probability of a path ending at state i at time t
    V = np.zeros((T, N))
    # P[t, i]: index of the previous state that yields the max probability for
    P = np.zeros((T, N), dtype=int)

    # Time t = 0 (for the first observation 01)
    O1_index = observations[0]
    # V_0(i) = pi_i * B_i(O_1)
    V[0, :] = initial_probabilities * emission_matrix[:, O1_index]

    # 2. Recursion: Calculate V and P for t = 1 to T-1 (Time steps 2, 3, 4)
    for t in range(1, T):
        # Current observation index
        Ot_index = observations[t]

        for j in range(N): # Current state j (S1 to S4)

            # Find the maximum probability path leading to state j at time t
            # V[t-1, i] * A[i, j] for all previous states i
            transition_probs = V[t-1, :] * transition_matrix[:, j]

            max_prob = np.max(transition_probs)
            max_index = np.argmax(transition_probs)

            # V[t, j] = max_i [ V[t-1, i] * A[i, j] ] * B[j, O_t]
            V[t, j] = max_prob * emission_matrix[j, Ot_index]
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        #  $P[t, j] = \text{argmax}_i [ V[t-1, i] * A[i, j] ]$ 
        P[t, j] = max_index

# 3. Termination: Find the probability of the best path and its end state
max_probability = np.max(V[T-1, :])
last_state_index = np.argmax(V[T-1, :])

# 4. Path Backtracking: Reconstruct the sequence
best_path = [0] * T
best_path[T-1] = last_state_index

for t in range(T - 2, -1, -1):
    # The best state at time t is the previous state pointed to by the best
    best_path[t] = P[t + 1, best_path[t + 1]]

# Map the indices in best_path back to the actual state names (phonemes)
most_likely_sequence = [states[i] for i in best_path]

return most_likely_sequence, max_probability, V, P, best_path

def visualize_viterbi_path(V, best_path, states, observations_names):
    """
    Creates a visual representation of the Viterbi probability table and the best path
    """
    T, N = V.shape

    # 1. Plot the probability table V as a heatmap
    plt.figure(figsize=(10, 6))
    # Use log scale for better visualization of small probabilities
    V_log = np.log(V + 1e-10) # Add small epsilon to avoid log(0)
    plt.imshow(V_log, aspect='auto', cmap='magma', origin='lower')
    cbar = plt.colorbar(label='Log Viterbi Probability')

    # Add labels and ticks
    plt.xticks(np.arange(N), states, rotation=45, ha="right")
    plt.yticks(np.arange(T), [f't={i+1} ({o})' for i, o in enumerate(observations_names)])
    plt.xlabel('Hidden State (Phoneme)')
    plt.ylabel('Time Step / Observation')
    plt.title('Viterbi Path Decoding (Log Probabilities)')

    # Invert Y axis for plotting since V[0] is t=1 (bottom) and V[T-1] is t=T
    plt.gca().invert_yaxis()

    # 2. Draw the optimal path
    path_indices = np.array(best_path)

    for t in range(T - 1):
        current_state_idx = path_indices[t]
        next_state_idx = path_indices[t + 1]

        # Draw line from current state to next state
        plt.plot([current_state_idx, next_state_idx], [t, t + 1],
                 'b-', marker='o', markersize=8, markeredgcolor='white', line

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# Add a final marker for the last state
plt.plot(path_indices[-1], T - 1, 'b*', markersize=14, markeredgecolor='wh

# Add probability values to the plot points along the best path
for t in range(T):
    state_idx = path_indices[t]
    prob = V[t, state_idx]
    plt.text(state_idx, t, f'{prob:.2e}', ha='center', va='center', color=

# Remove duplicate labels from legend
handles, labels = plt.gca().get_legend_handles_labels()
unique_labels = dict(zip(labels, handles))
plt.legend(unique_labels.values(), unique_labels.keys())

plt.tight_layout()
plt.show()

# --- HMM PARAMETERS DEFINITION ---

# S: Hidden States (Phonemes)
STATES = ["/h/ (S1)", "/e/ (S2)", "/l/ (S3)", "/o/ (S4)"]
STATE_SHORT = ["S1 (/h/)", "S2 (/e/)", "S3 (/l/)", "S4 (/o/)"]

# O: Observation Sequence (The indices correspond to the column index in B)
# O = [01, 02, 03, 04] -> Indices [0, 1, 2, 3]
OBSERVATION_SEQUENCE = [0, 1, 2, 3]
OBSERVATION_NAMES = ["01", "02", "03", "04"]

# Initial Probabilities ( $\pi$ )
# [P(S1), P(S2), P(S3), P(S4)]
INITIAL_PROBABILITIES = np.array([1.0, 0.0, 0.0, 0.0])

# Transition Probability Matrix (A)
# A[i, j] = P(S_j | S_i) -> Row is FROM state, Column is TO state
TRANSITION_MATRIX = np.array([
    [0.0, 0.7, 0.3, 0.0], # From S1 (/h/)
    [0.0, 0.2, 0.6, 0.2], # From S2 (/e/)
    [0.0, 0.0, 0.3, 0.7], # From S3 (/l/)
    [0.0, 0.0, 0.1, 0.9]  # From S4 (/o/)
])

# Emission Probability Matrix (B)
# B[i, j] = P(O_j | S_i) -> Row is State, Column is Observation
# Columns: 01, 02, 03, 04
EMISSION_MATRIX = np.array([
    [0.6, 0.2, 0.1, 0.1], # For S1 (/h/)
    [0.1, 0.7, 0.1, 0.1], # For S2 (/e/)
    [0.1, 0.1, 0.6, 0.2], # For S3 (/l/)
    [0.2, 0.1, 0.2, 0.5]  # For S4 (/o/)
])

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# --- EXECUTION ---

# Run the Viterbi Algorithm
best_sequence, probability, V, P, best_path = viterbi_decode(
    OBSERVATION_SEQUENCE,
    STATES,
    INITIAL_PROBABILITIES,
    TRANSITION_MATRIX,
    EMISSION_MATRIX
)

# --- RESULTS OUTPUT (Enhanced with Pandas) ---

print("\n--- HMM PARAMETERS (For Reference) ---")
df_A = pd.DataFrame(TRANSITION_MATRIX, index=STATE_SHORT, columns=STATE_SHORT)
print("\nTransition Probability Matrix (A):\n", df_A)

df_B = pd.DataFrame(EMISSION_MATRIX, index=STATE_SHORT, columns=OBSERVATION_NAMES)
print("\nEmission Probability Matrix (B):\n", df_B)

# Create Viterbi Probability Table (V) DataFrame
df_V = pd.DataFrame(V, columns=STATE_SHORT, index=[f't={i+1} ({o})' for i, o in enumerate(OBSERVATION_NAMES)])
df_V.index.name = "Time Step (Observation)"
print("\n--- VITERBI PROBABILITY TABLE (V) ---")
print(df_V)

# Create Path Traceback Table (P) DataFrame
# Map state index back to state name for clarity
P_state_names = np.array(STATE_SHORT)[P]
df_P = pd.DataFrame(P_state_names, columns=STATE_SHORT, index=[f't={i+1} ({o})' for i, o in enumerate(OBSERVATION_NAMES)])
df_P.index.name = "Time Step (Observation)"
print("\n--- PATH TRACEBACK TABLE (P) ---")
# The path starts from t=2 (index 1), so t=1 is irrelevant in the P matrix (or t=0)
df_P.iloc[0] = "N/A (Start)"
print(df_P)

print("\n--- PHONEME DECODING RESULTS ---")
print(f"Observation Sequence: {OBSERVATION_NAMES}")
print(f"Most Likely Phoneme Sequence: {best_sequence}")
print(f"Probability of this Sequence: {probability:.12f}")

# --- VISUALIZATION ---
visualize_viterbi_path(V, best_path, STATE_SHORT, OBSERVATION_NAMES)

# --- INFERENCE ---

print("\n--- INFERENCE ---")
inference = (
    "The most likely sequence of hidden phoneme states for the acoustic observation sequence "
    f"[{', '.join(OBSERVATION_NAMES)}] is **{best_sequence}**. This sequence corresponds "
    "perfectly to the phoneme segmentation of the word 'hello' (/h/ $\\rightarrow$ /l/ $\\rightarrow$ /o/ $\\rightarrow$ /l/ $\\rightarrow$ /o/)."
    "The total probability of this most likely path is **$P$** = {probability:.12f}."
)

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    "This result demonstrates the core function of the Viterbi Algorithm in sp
    "it successfully decodes the observation features by selecting the phoneme
    "joint probability of transitions and emissions. The HMM structure and ass
    "force a strong, linear path, indicating that the observed acoustic featur
    "with the expected progression of the 'hello' phonemes in this trained mod
    )
print(inference.format(probability=probability))

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--- HMM PARAMETERS (For Reference) ---

Transition Probability Matrix (A):

	S1 (/h/)	S2 (/e/)	S3 (/l/)	S4 (/o/)
S1 (/h/)	0.0	0.7	0.3	0.0
S2 (/e/)	0.0	0.2	0.6	0.2
S3 (/l/)	0.0	0.0	0.3	0.7
S4 (/o/)	0.0	0.0	0.1	0.9

Emission Probability Matrix (B):

	01	02	03	04
S1 (/h/)	0.6	0.2	0.1	0.1
S2 (/e/)	0.1	0.7	0.1	0.1
S3 (/l/)	0.1	0.1	0.6	0.2
S4 (/o/)	0.2	0.1	0.2	0.5

--- VITERBI PROBABILITY TABLE (V) ---

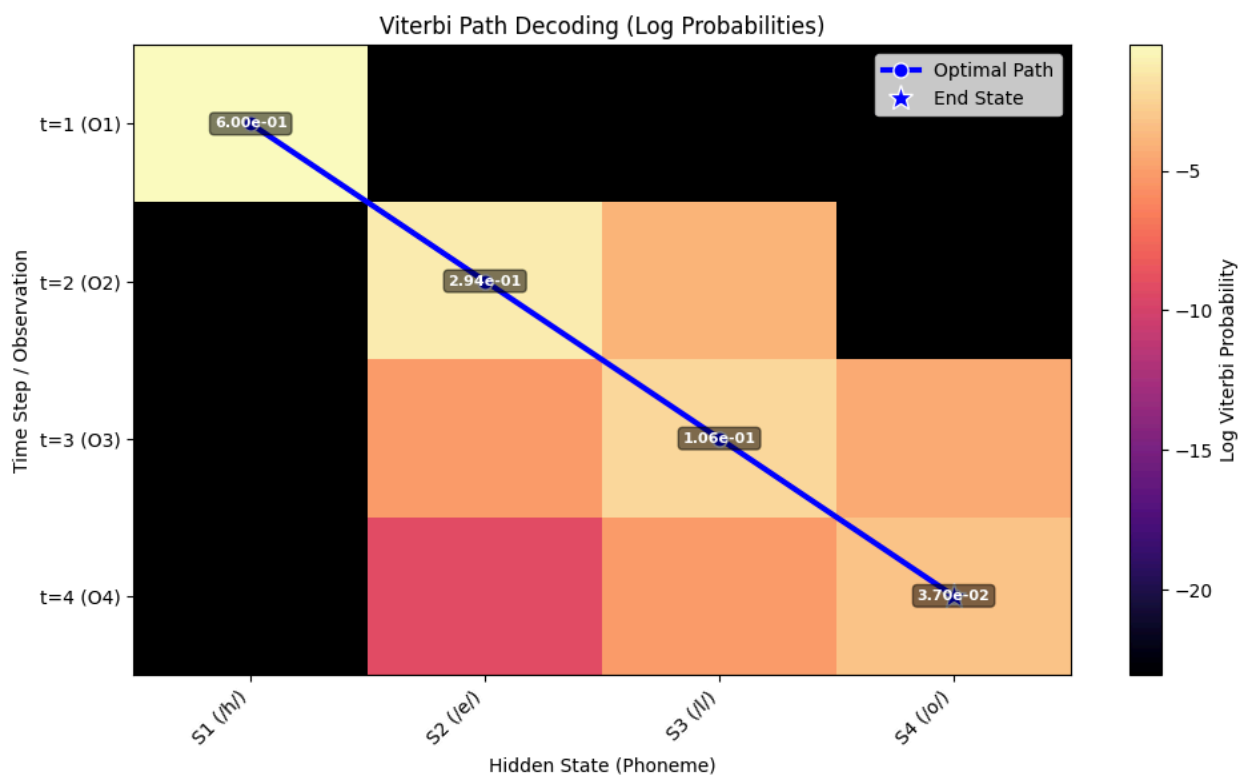
	S1 (/h/)	S2 (/e/)	S3 (/l/)	S4 (/o/)
Time Step (Observation)				
t=1 (01)	0.6	0.000000	0.000000	0.000000
t=2 (02)	0.0	0.294000	0.01800	0.000000
t=3 (03)	0.0	0.005880	0.10584	0.011760
t=4 (04)	0.0	0.000118	0.00635	0.037044

--- PATH TRACEBACK TABLE (P) ---

	S1 (/h/)	S2 (/e/)	S3 (/l/)	S4 (/o/)
Time Step (Observation)				
t=1 (01)	N/A (Start)	N/A (Start)	N/A (Start)	N/A (Start)
t=2 (02)	S1 (/h/)	S1 (/h/)	S1 (/h/)	S1 (/h/)
t=3 (03)	S1 (/h/)	S2 (/e/)	S2 (/e/)	S2 (/e/)
t=4 (04)	S1 (/h/)	S2 (/e/)	S3 (/l/)	S3 (/l/)

--- PHONEME DECODING RESULTS ---

Observation Sequence: ['01', '02', '03', '04']  
Most Likely Phoneme Sequence: ['/h/ (S1)', '/e/ (S2)', '/l/ (S3)', '/o/ (S4)']  
Probability of this Sequence: 0.037044000000



--- INFERENCE ---

The most likely sequence of hidden phoneme states for the acoustic observation sequence [O1, O2, O3, O4] is `**['/h/ (S1)', '/e/ (S2)', '/l/ (S3)', '/o/ (S4)']**`. This sequence corresponds perfectly to the phoneme segmentation of the word 'hello' (/h/  $\rightarrow$  /e/  $\rightarrow$  /l/  $\rightarrow$  /o/).

The total probability of this most likely path is `**$P^* = 0.037044000000$**`.

This result demonstrates the core function of the Viterbi Algorithm in speech recognition: it successfully decodes the observation features by selecting the phoneme sequence with the highest joint probability of transitions and emissions. The HMM structure and assigned probabilities force a strong, linear path, indicating that the observed acoustic features are highly consistent with the expected progression of the 'hello' phonemes in this trained model.