Using Hidden Markov Model (HMM) for Home Energy Consumption Analysis

1. Observations: The HMM would use measurable data such as time-series power consumption readings (in watts or kilowatt-hours) from smart meters or IoT sensors attached to household appliances (e.g., fridge, TV, washing machine). Additional observations could include timestamped usage patterns (e.g., on/off states, duration of use) and environmental factors like time of day or temperature, which influence appliance usage.

2. Type of HMM Problem: Since the hidden states (e.g., specific appliances or their operational modes like "on," "off," or "standby") are not known in advance and must be inferred from the data, this is a learning problem (unsupervised HMM). The model identifies hidden states and their transitions from observed power consumption patterns.

3. Training Algorithm:

a. Known Values at Start: The observed data (power consumption readings, usage durations, and contextual factors like time) and the number of hidden states (e.g., estimated number of appliances or modes) are known. Initial guesses for model parameters (e.g., random transition and emission probabilities) are also set.

b. Unknown Values to be Learned: The hidden states (e.g., which appliance or mode corresponds to each state), transition probabilities (likelihood of switching between states, e.g., fridge "on" to "off"), and emission probabilities (likelihood of observed power readings given a state, e.g., TV "on" emits ~100W) need to be learned.

4.Parameter Updates: The training algorithm (Baum-Welch algorithm) will update:

a.Transition probabilities: Probabilities of moving between hidden states (e.g., appliance switching from "on" to "standby").

b.Emission probabilities: Probabilities of observing specific power consumption values for each hidden state (e.g., fridge "on" state emitting ~150W).

c.Initial state probabilities: Likelihood of starting in a particular hidden state (e.g., TV "off" at the beginning of the day).