Using Hidden Markov Models in a Live Automated Traffic Light Management System

1. Describe the Observations

In this system, the observations are sequences of measurable traffic data over time, such as: Vehicle count per lane from sensors or image processing, Average vehicle speed ,Waiting time per lane ,Pedestrian presence.

These observed values form time-series data streams, captured every few seconds or minutes. Each observation is a snapshot of the current state of traffic, representing the input to the HMM at that time step.

2. Type of HMM Problem

This is a partially observable sequence modeling problem. We can observe traffic conditions (the data), but we do not know the true underlying traffic state directly. These states are hidden and must be inferred, making this an unsupervised HMM task.

3. Training Algorithm

a. Known at the Start:

Observed traffic metrics (e.g., vehicle count, speed, wait time), An assumption about the number of hidden traffic states (e.g., 3-5 states) ,General structure of the model (states change over time, based on traffic patterns)

b. Unknown and to be Learned:

Transition probabilities between hidden traffic states (e.g., how likely it is to go from “moderate” to “heavy” traffic) , Emission probabilities: likelihood of observing certain traffic metrics given a hidden state , Initial state distribution (probability of starting in each traffic state)

4. Parameter Updates

The training process updates:

Transition Matrix (A): Probability of moving from one traffic state to another , Emission Matrix (B): Probability of observing a traffic pattern given a hidden state ,Initial State Distribution (π): Starting probabilities of traffic states

Conclusion

In your system, HMM can learn and predict traffic patterns over time, enabling the traffic light controller to anticipate future congestion and adjust signal durations proactively. This leads to smarter, data-driven traffic flow optimization, especially in unpredictable or rapidly changing traffic environments.