Report on HMM-MDP

HMM

Day	Observation	Probabilities	Sunny	Cloudy	Rainy
1	***WALK***	V0(?)	0.333	0.333	0.333
		P(W|?)	1.0	0.67	0.33
		V1(?)=V0(?)*P(W)?)	0.333	0.223	0.111
2	***UMBRELLA***	V1(S)*P(?|S)	0.0000	0.22	0
		V1(C)*P(?|C)	0.0000	0	0.14
			0.0000	0.03	0.03
			0.0000	0.33	0.67
			0.0000	0.072	0.09
3	***WALK***	V2(S)*P(?|S)	0	0	0
		V2(C)*P(?|C)	0.002	0	0.006
		V2(R)*P(?|R)	0.029	0.029	0.029
		P(W|?)	1	0.67	0.33
		V3(?)=max(?)*P(W?)	0.029	0.019	0.009

MDP

Current State	Action	Next State Probabilities
Low (L)	A	80% Stay in L, 20% Move to M
Low (L)	C	60% Stay in L, 40% Move to M
Medium (M)	C	70% Stay in M, 30% Move to H
Medium (M)	A	50% Stay in M, 50% Move to H
High (H)	C	90% Stay in H, 10% Drop to M
High (H)	A	70% Stay in H, 30% Drop to M

Hidden Markov Models (HMM) and Markov Decision Processes (MDP)

Hidden Markov Models (HMM) and Markov Decision Processes (MDP) are both foundational concepts in probabilistic modeling and decision-making under uncertainty. While they share some similarities in their use of Markov properties, they serve different purposes.

Hidden Markov Models (HMM)

An HMM is a statistical model used to represent systems with hidden (latent) states and observable outcomes. It consists of:

- **States (S)**: The system transitions between hidden states over time.
- **Observations (O)**: The visible outcomes generated by the underlying states.
- **Transition Probabilities (A)**: The probability of moving from one state to another.
- **Emission Probabilities (B)**: The probability of observing an outcome given a hidden state.
- **Initial Probabilities (π)**: The probability distribution over initial states.

HMMs are widely used in speech recognition, bioinformatics, and financial modeling, where the goal is to infer hidden states from observed data.

Markov Decision Processes (MDP)

MDPs extend the Markov model by incorporating decision-making through actions. An MDP consists of:

- **States (S)**: The set of possible system conditions.
- **Actions (A)**: Choices available to an agent.
- **Transition Probabilities (T)**: The likelihood of reaching a new state given an action.
- **Rewards (R)**: The immediate reward received after a transition.
- **Policy (π)**: A strategy mapping states to actions to maximize long-term rewards.

MDPs are essential in reinforcement learning, robotics, and AI for optimal sequential decision-making.

Comparison and Applications

While both models rely on probabilistic state transitions, HMMs are primarily used for prediction and inference of hidden states, whereas MDPs focus on optimizing decision-making in dynamic environments. Understanding these models is crucial in AI-driven applications such as autonomous navigation, natural language processing, and intelligent systems.