Hidden Markov Models in Wildlife Monitoring for South Sudan

Project Context:
In South Sudan's conservation areas, poaching and wildlife movement often occur without direct observation. Hidden Markov Models (HMMs) are well-suited for modeling systems where we observe indirect signals (like animal tracks or sounds), but the actual state (presence of poachers or animals) is hidden. Integrating HMMs can help predict animal movement patterns or detect poaching risks over time based on sequences of observations.

1. Observations

The HMM will use measurable inputs such as:

- Camera trap image detections (e.g., "elephant seen", "human detected", "nothing detected")
- GPS location data of recent sightings
- Sensor readings (e.g., sound triggers, motion sensors)
- Time of day and weather conditions

Each time step gives us a set of observations that can help infer the hidden state.

2. Type of HMM Problem

This is a learning and inference task with unknown hidden states a partially observable system.
We don't directly observe the true activity (e.g., whether a poacher is present nearby or an animal is on the move), so it's a decoding and learning problem, such as:

- State estimation (decoding): Inferring the most likely hidden state sequence given observed data
- Training (learning): Estimating HMM parameters from observed sequences

3. Training Algorithm

a. Known values at the start:

- Observation sequences (e.g., time-stamped camera detections, GPS logs)

- Number of hidden states (can be hypothesized as: “safe”, “animal nearby”, or “poacher nearby”)

b. Unknown values to be learned:

- Transition probabilities between hidden states (e.g., likelihood of movement from “animal nearby” to “poacher nearby”)
- Emission probabilities (likelihood of observing a sensor reading or camera detection given a hidden state)
- Initial state distribution (e.g., starting with “safe”)

4. Parameter Updates

During training, the following HMM parameters will be updated:

- **Transition probabilities:** How likely the system moves from one hidden state to another (e.g., from “safe” → “threat”)
- **Emission probabilities**: How likely we are to observe specific data given a hidden state (e.g., “human detection” when in a “poacher nearby” state)
- **Initial state probabilities:** Starting likelihoods of each hidden state

Conclusion

Integrating HMMs into your wildlife monitoring system can help model time-based predictions, such as the movement of endangered animals or the detection of potential poaching threats. It offers a probabilistic, data-driven way to support real-time decision-making for ranger teams even when observations are partial or noisy.