Hidden Markov Models for Road Infrastructure Prioritization

Observations

The project uses Hidden Markov Models (HMMs) to analyze satellite imagery augmented with other data for pavement condition assessment on trade routes, aiming to evaluate economic impacts from poor transportation infrastructure and prioritize maintenance. The sub-problem addressed here involves determining if a trade route needs repair/upgrade based on:

- **Crack Density (%)**: Derived from satellite or street view imagery.
- **Pothole Count**: Obtained from crowdsourced reports.
- **Surface Roughness**: Measured via mobile device accelerometer data, if available.
- **Traffic Volume**: Collected from toll gates and GPS data.
- **Previous Maintenance Records**: Binary flags indicating recent repairs.

What type of HMM problem does this study primarily address?

Given that the status of a trade route (hidden state) is not explicitly known in advance, the immediate problem presented is a Learning problem to ascertain the parameters (A, B, π).

Which algorithm is used to train the HMM?

The algorithm used will be the Baum-Welch algorithm which is used to learn the model parameters assuming the observations are given.

What value(s) is/are “Known”?

- Observations: For example, Pothole count, crack density
- Number of Hidden States (N): Assumed (e.g., 2 or 3 states).

What value(s) is/are “Unknown”?

- Transition Matrix (A): Probabilities between hidden states (e.g., P(Fair → Poor)).
- Emission Probabilities (B): Distribution of observations per state.
- Initial State Probabilities (π): Likelihood of starting in each state.

Parameters updated in each iteration of the training process

The Baum-Welch (EM) algorithm iteratively updates:

1. Transition Probabilities (A): How likely a road transitions between states.
2. Emission Probabilities (B): Observations correlation with states (e.g., "High cracks likely mean Poor state").
3. Initial State Probabilities (π): Baseline distribution of states.