Hidden Markov Model

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Method

Research Design

- Objective: Understand Hidden Markov Model

Results

Terminology

Hidden Markov Models:

It allows us to observe some evidence at each timestep, which can potentially affect the belief distribution in each state.

- HMMs are defined by:
    - + Initial distribution: $P(X_0)$
    - + Transition model: $P(X_t \mid X_{t = t - 1})$
    - + Sensor model: $P(E_t \mid X)$
- All above them are stationary
- Belief distribution: $B(W_i) = P(W_i | f_1, \ldots, f_i)$

Inference task

Inference tasks:

- Filtering: belief state: input to the decision process
- Prediction: filtering without evidence
- Smoothing: better estimate of past states
- Most likely explanation: most probable path

The Forward Algorithm

- A filtering algorithm: Compute belief distribution at any given timestep
- Time elapse updates that iteratively incorporate new evidence into our model.
- Formulation: $f_{1:t+1}$ = Forward($f_{1:t}$, e_{t+1}) $f_{1:t}$ is $P(X_t \mid e_{1:t})$

- Consider observation matrix O given evidence E_t and transition matrix T. We have: $f_{1:t+1} \propto O_{t+1} T^T f_{1:t}$

Viterbi Algorithm

- A most likely explanation algorithm
- The algorithm consists of two passes: the first runs forward in time and computes the probability of the best to each tuple given the evidence observed so far and the second pass runs backward in time: to find the terminate state that lies on the path with the highest probability and then traverses backward through time along the path that leads into this state
- State trellis: a graph of states and transitions over time
- In Viberbi Algorithm, we compute: arg max P(x1:N,e1:N) (for $x_1 \ldots x_N$)
- $m_t[x_t] = P(e_t|x_t) \max P(x_t|x_{t-1}) m_{t-1}[x_{t-1}]$ (for all value x_{t-1})