Modeling People Count in a Building With Hidden Markov Model

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Research Goals

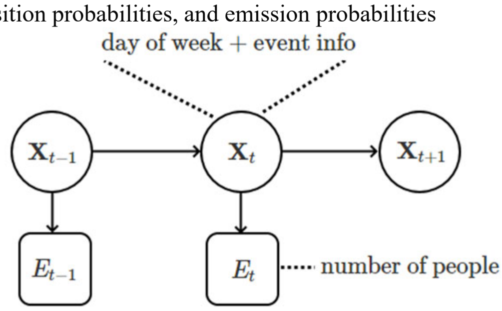
- **To model a sequential, discrete-time-series data set with Hidden Markov Model (HMM)**
  - Represent environment as a single hidden state variable and an observable evidence variable
  - Apply the trained model on test data to investigate the generalizability of HMM in the particular setting

Dataset

- **CalIt2 Building People Counts Data Set[1]**
  - Count of people entering or exiting the CalIt2 building at UCI
  - Measured over 48 consecutive 30-minute intervals for 15 weeks
  - Record of events within the building, such as a conference
  - People count influenced by regular pattern (e.g. day of week), as well as anomalous event (e.g. conferences)[2]

Methodology

- **Hidden Markov Model settings**
  - Hidden state incorporates:
    - Seven days of week information (e.g. Monday)
    - Variable number of possible values representing the information regarding the progress of events (e.g. no event)
  - Evidence variable: Number of people moving in and out (counted twice) during the day, divided into 20 equal segments
  - Time steps considered in units of days
  - Additional heuristics to the initialization of start probabilities, transition probabilities, and emission probabilities



- Train HMM with first 75 days of observation via Baum-Welch algorithm[3]
- Test HMM on the next 20 days
  - Find most likely state sequence with Viterbi algorithm[4]
  - Determine log likelihood of the most likely sequence

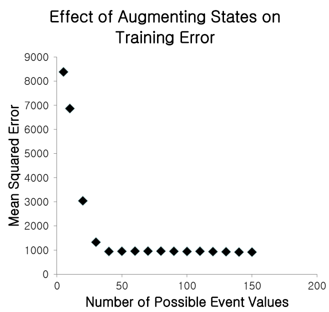
Viterbi probability
$$v_t(j) = \max_i \left[v_{t-1}(i) \times a_{ij} \times b_j(o_t) \right]$$

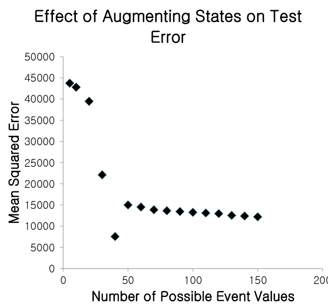
E-step
$$\gamma_t(j) = \frac{\alpha_t(j)\beta_t(j)}{\alpha_T(q_F)}$$
$$\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\alpha_t(q_F)}$$

M-step
$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1}\xi_t(i,j)}{\sum_{t=1}^{T-1}\sum_{k=1}^{N}\xi_t(i,k)}$$
$$\hat{b}_j(v_k) = \frac{\sum_{t=1\, s.t. O_t=v_k}^{T}\gamma_t(j)}{\sum_{t=1}^{T}\gamma_t(j)}$$

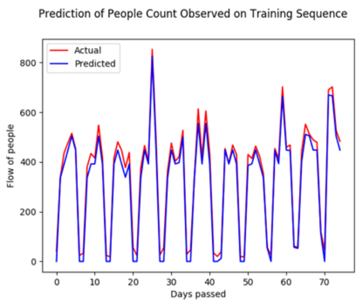
Experimental Results

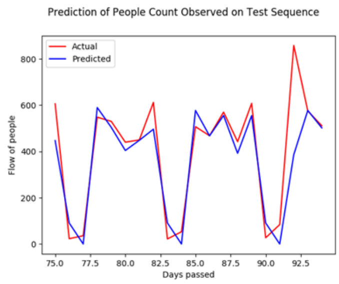
- **Effects of increasing the number of possible values representing the event information**
  - MSE (Mean-squared error) consistently decreases and stabilizes





- **Reconstruct observation sequence out of most likely sequence output from Viterbi algorithm**
  - Prediction seems to highly match the actual data for both training and test sequence





- **High MSE for test set indicates poor generalization**
- Possible improvements:
  - Higher order HMMs
  - Model periodic and anomalous patterns separately[2]

Reference

1. Dua, D. and Graff, C. (2019). *UCI Machine Learning Repository* [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.
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3. Baum, L. E., Petrie, T., Soules, G., & Weiss, N. (1970). A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *The annals of mathematical statistics*, *41*(1), 164-171.
4. Forney Jr, G. D. (2005). The viterbi algorithm: A personal history. *arXiv preprint cs/0504020*.