Nonparametric Bayesian Dynamic Systems Analysis Applied to a Large Eyetracking Corpus

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Available at: https://works.bepress.com/joseph_houpt/46/
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Joseph W. Houpt  Mary E. Frame

Society for Mathematical Psychology Annual Meeting
Outline

1. The Problem
2. The Model
3. The Data
4. The Results
5. Conclusions
Existing Approaches
Outline

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The Model

Vector Autoregressive Process

\[ y_t = \sum_{l \in (0, t-1)} a_l y_l + e_t \quad e_t \sim N(0, \sigma^2) \]
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The Model

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\[ y_{t}^{(i)} = \sum_{l \in (0, t-1)} a_l y_{l}^{(i)} + e_{t}^{(i)} \quad e_t \sim N(0, \Sigma) \]
The Model

Hidden Markov Model

\[
\begin{align*}
\pi_1^{(i)} & \quad \pi_2^{(i)} & \quad \pi_3^{(i)} & \quad \pi_4^{(i)} & \quad \pi_5^{(i)} & \quad \ldots \\
\pi_{11} & \quad \pi_{12} & \quad \pi_{13} & \quad \pi_{14} & \quad \pi_{15} & \quad \ldots \\
\pi_{21} & \quad \pi_{22} & \quad \pi_{23} & \quad \pi_{24} & \quad \pi_{25} & \quad \ldots \\
\pi_{31} & \quad \pi_{32} & \quad \pi_{33} & \quad \pi_{34} & \quad \pi_{35} & \quad \ldots \\
\pi_{41} & \quad \pi_{42} & \quad \pi_{43} & \quad \pi_{44} & \quad \pi_{45} & \quad \ldots \\
\pi_{51} & \quad \pi_{52} & \quad \pi_{53} & \quad \pi_{54} & \quad \pi_{55} & \quad \ldots \\
\end{align*}
\]

\(\pi_j \sim \text{Dirichlet}\)
Beta Process – Bernoulli Process
The Model

The BP-HMM

The BP-HMM model consists of features $k = 1, \ldots, \infty$ connected to $\omega_k$, which in turn is connected to $\theta_k$. The parameter $\alpha$ and $\gamma$ are used to connect these elements. The time series $i = 1, \ldots, N$ is connected to $\pi^{(i)}$, $\eta^{(i)}$, $z^{(i)}_1$, $z^{(i)}_2$, $\ldots$, $z^{(i)}_t$, $\ldots$, $z^{(i)}_{T_i}$, and $y^{(i)}_1$, $y^{(i)}_2$, $\ldots$, $y^{(i)}_t$, $\ldots$, $y^{(i)}_{T_i}$.
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The DIEM Project


- Project led by John Henderson (UC Davis)
- Overview: https://thediemproject.wordpress.com/
- Examples: https://vimeo.com/visualcognition/
- Data: https://www.mediafire.com/?mpu3ot0m2o384
Technical Details

- 85 Video Clips
- Sports, TV Shows, Advertisements, Viral Videos, etc.
- Varying sizes and lengths
- > 250 total participants
- Many viewers per clip (over 100 for some clips)

- Eyelink 2000, 1000Hz for each eye (down-sampled to 30Hz)
- 21” Viewsonic Monitor at 1280 × 960, 120Hz
- Observers at 90cm; using chin and headrest
  - Task was to rate enjoyment of the clip
- 10 Video Clips
- 10 Observers Each
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Distribution of Features
The Results

Features
Fixations

**Maximum Distance from Onset**
- $\mu = 0.370^\circ$
- $\sigma = 0.367^\circ$

**Maximum Speed**
- $\mu = 6.982^\circ$/s
- $\sigma = 2.329^\circ$/s

**Duration**
- $\mu = 0.289$ s
- $\sigma = 0.305$ s
The Results

Saccades

**Maximum Distance from Onset**
- $\mu = 2.716^\circ$
- $\sigma = 1.943^\circ$

**Maximum Speed**
- $\mu = 90.861^\circ/s$
- $\sigma = 61.828^\circ/s$

**Duration**
- $\mu = 0.042\ s$
- $\sigma = 0.017\ s$

Houpt & Frame (Wright State)
The Results

Glissades?

- Maximum Distance from Onset:
  - $\mu = 0.745$ s
  - $\sigma = 0.728$ s

- Maximum Speed:
  - $\mu = 23.190$ s
  - $\sigma = 16.242$ s

- Duration:
  - $\mu = 0.083$ s
  - $\sigma = 0.081$ s
## Feature Transitions

### Forward

<table>
<thead>
<tr>
<th>From</th>
<th>Fix</th>
<th>Scd</th>
<th>Gls</th>
</tr>
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### The Results

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## The Results

### Correspondence with Eyelink Parsing

<table>
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<tr>
<td>Fixation</td>
<td>0.88</td>
<td>0.05</td>
<td>0.08</td>
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<tr>
<td>Saccade</td>
<td>0.44</td>
<td>0.45</td>
<td>0.11</td>
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Data driven discrimination of eye-movement patterns

- Across multiple videos and observers
- A statistical model (i.e., we have a distribution over parse and parameters)
- Described 100 time series with 3+ features
- Based on limited data (30Hz rather than 1000Hz)
- Features are similar to a priori categories: fixations, saccades, and glissades.
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Future: Parse based on more information (particularly location)
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Thank you!

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