Eye-tracking and electroencephalogram data analysis using hidden semi-Markov models to identify reading strategies

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Study proposal

- Textual information search is an unhomogeneous process in time (Simola, 2008)
- ↳ Reading strategies and decision processes are intertwined
- Proposal: use a data-driven approach in order to separate these processes
- Have the reading strategy contrasted characteristics in terms of EEGs?

Experiment description

- 15 participants, 60 texts per participant
- Presentation of a goal topic, e.g. in French "chasse aux oiseaux" (bird hunting), and a text, extracted from LeMonde, 1999
- Question: is the text related to the topic ?

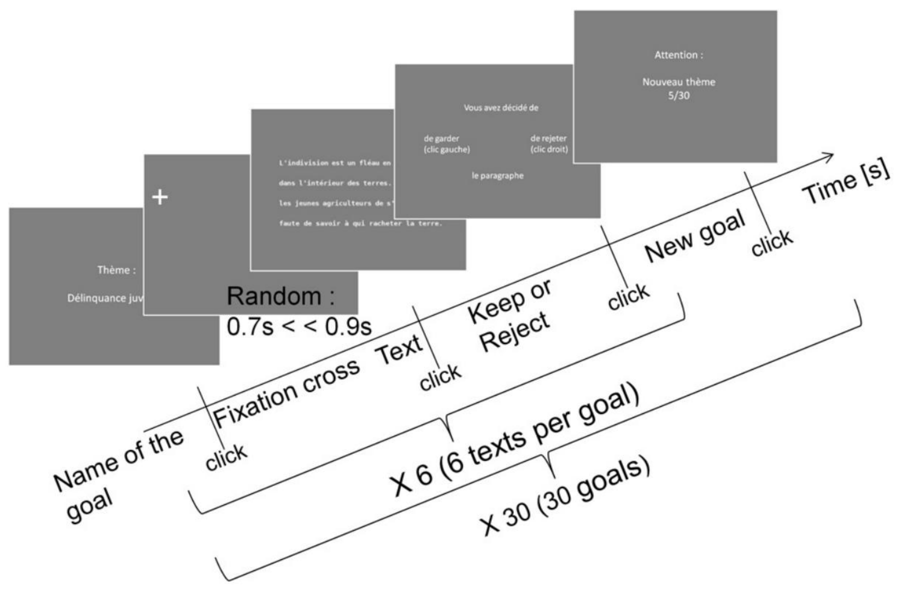


Figure: Frey, 2013

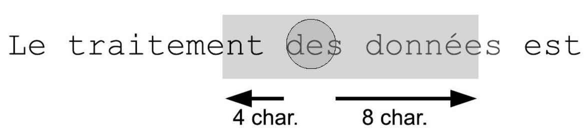
- Measurements of eye positions over time and 30-channel EEG

Data pre-processing

Raw data: For each Participant and each text: coordinates X,Y of fixations at each time t, fixation duration, saccade amplitude.

Data augmentation:

- Word(s) gazed at each fixation (foveal, and parafoveal regions)



- Number of skipped words in one saccade
- Semantic proximity of the words in each text to the target topic (Latent Semantic Analysis + Cosine distance)

Observed process: Readmode: number of skipped words in one saccade, and direction of the saccade $\mathcal{V} = \{v_1 : > 1, v_2 : 1, v_3 : 0, v_4 : -1, v_5 : < -1\}$

Model covariates: Fixation duration, saccade amplitude, semantic proximity of the fixated word to the topic

Problems

- Identify reading strategies, obtain a segmentation of scanpaths with meaningful EEG interpretation
- Markov-switching model to catch phase changes
- The sojourn time may not have Geometric distributions (Non-Markovian)

Hidden semi-Markov models (Yu 2010)

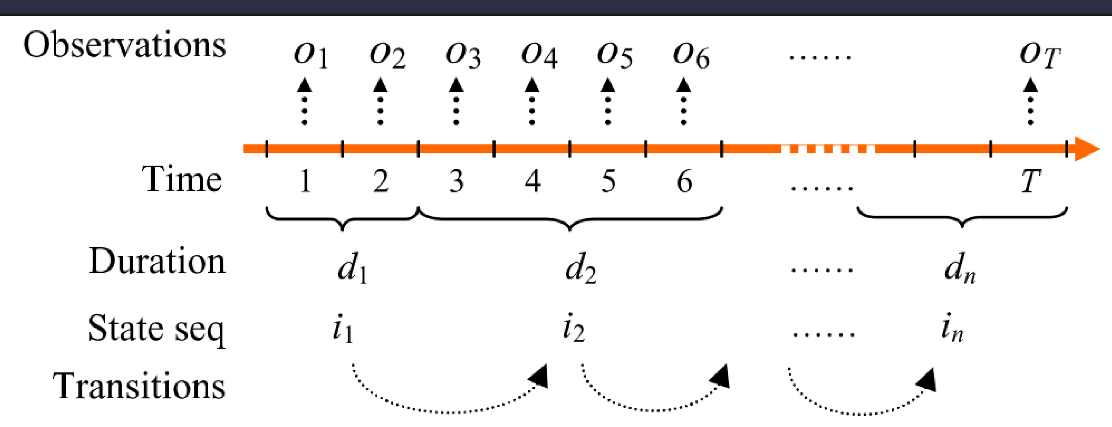


Figure: Yu, 2010

Notations:

- The set of observable values $\mathcal{V} = \{v_1, \ldots, v_K\}$ where $O_t \in \mathcal{V}$ is the state at time t. $O_{1:T}$ is the observed state sequence, $o_{1:T}$ a realization
- The set of hidden states $\mathcal{S} = \{1, \ldots, M\}$ where $S_t \in \mathcal{S}$ is the state at time t. $S_{1:T}$ is the hidden state sequence, $s_{1:T}$ a realization
- The state duration $D \in \mathcal{D} = \{1, \ldots, \infty\}$

Model: Explicit-duration HMM, assuming process starts at $t = 1$ and ends at T

- Initial distribution:

$$\pi_j p_{\theta_j}(d) \equiv P(S_1 = j)P(D = d, S_{1:d} = j, S_{d+1} \neq j | S_1 = j) = P(D = d, S_{1:d} = j, S_{d+1} \neq j)$$

- State transition probability from (i, d') to (j, d), $i \neq j$:

$$a_{(i,d')(j,d)} = a_{ij} p_{\theta_j}(d)$$
$$a_{ij} \equiv P(S_{t+1} = j | S_t = i)$$
$$p_{\theta_j}(d) \equiv P(D = d, S_{t+1:t+d} = j, S_{t+d+1} \neq j | S_t \neq j)$$

- Emission probability:

$$b_j(v_k) \equiv P(O_t = v_k | S_t = j)$$

- Parameters of the model: $\lambda \equiv \{a_{(i,d')(j,d)}, b_j(v_k), \pi_j, \theta_j\}$

Inference & Learning in HSMM

Inference: Forward-Backward algorithm to maintain tractability in inference problems. (e.g. probabilities such as $P(o_1, \ldots, o_T | \lambda)$)

Learning: MLE of $\hat{\lambda}$ via the iterative **Expectation-Maximization** algorithm:
E-step: decomposition of $E[\ln P(S_{1:T}, O_{1:T} | \lambda) | O_{1:T}, \lambda^{old}]$ and simplification
M-step: maximize with respect to λ

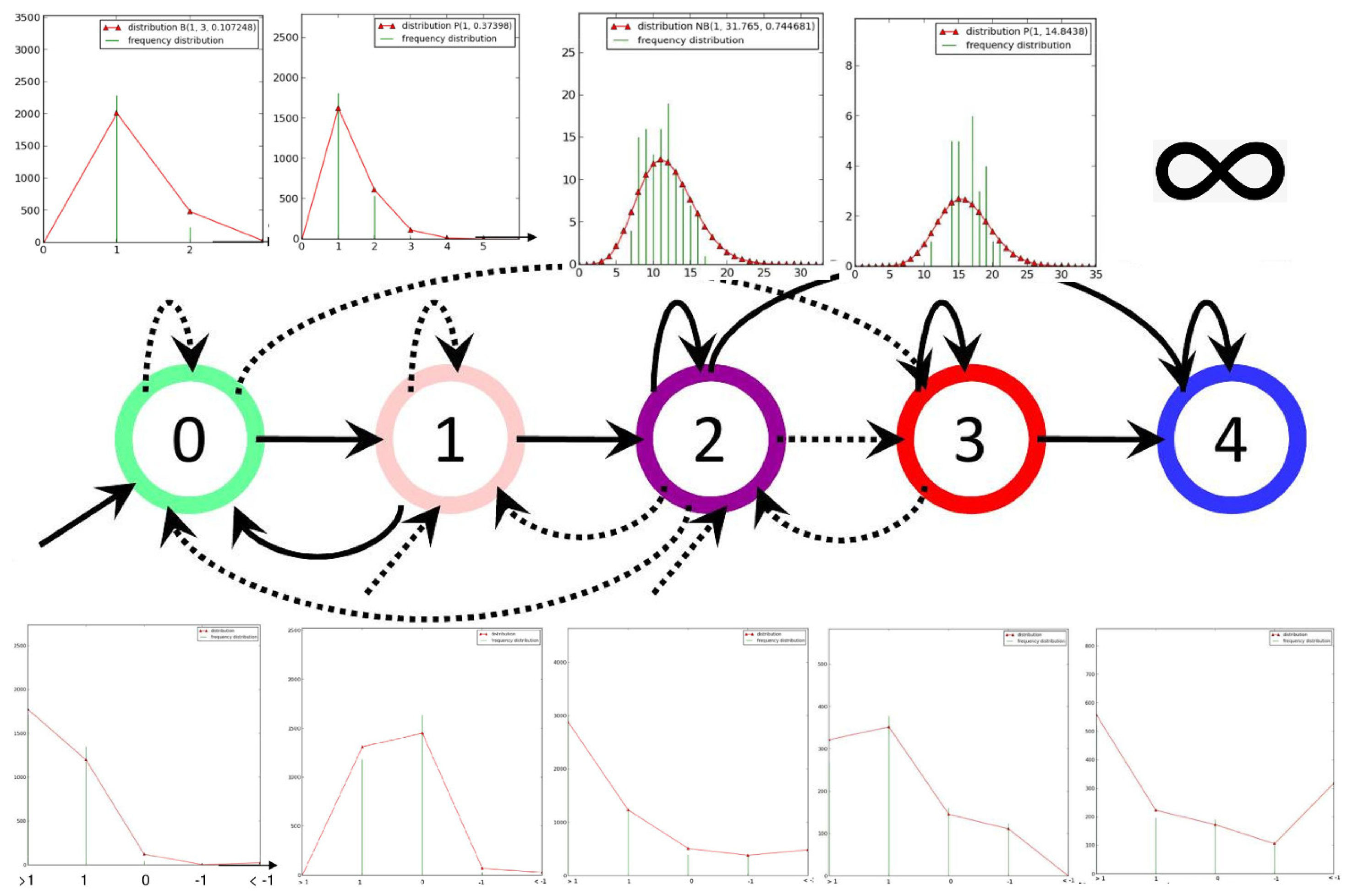
Restoration: Estimation of the most likely state sequence, $\hat{s}_{1:T}$, given an observed sequence, $o_1, \ldots, o_T$, by the MAP principle

$$\hat{s}_t = \arg\max_j \max_d P(S_{t-d} \neq j, S_{t-d+1:t} = j, S_{t+1} \neq j, o_{1:t} | \hat{\lambda})$$

using the **Viterbi** algorithm.

Application to eye-movement data

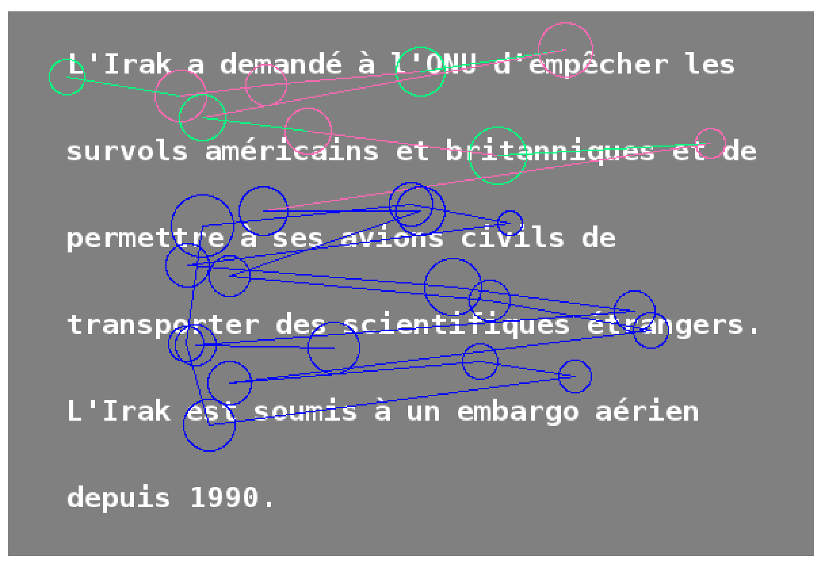
- The time index t corresponds to a fixation.
- $M = 5$ reading strategies estimated by maximizing BIC criterion

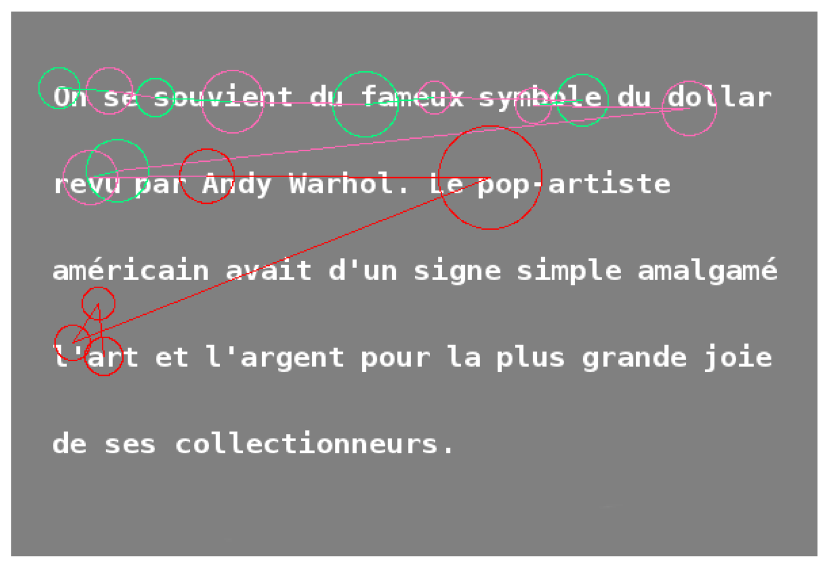


HSMM. top bar charts: sojourn time distributions. automaton: transition probabilities. bottom bar charts: emission probabilities.

4 interpretable strategies uncovered and validated according to reading theory and by analyzing covariates (fixation duration, saccade amplitude, semantic proximity of the word fixated to the goal):

$\mathcal{S} = \{$0-1: Normal reading, 2: Speed reading, 3: Careful reading, 4: Confirmation$\}$





Issues adressed:

- Text variability: evolution of text relativeness to the topic
- Individual variability: trained vs. careful readers

Perspectives

- Variability in the text and individuals → propose a clustering approach to reduce variability of the model (mixtures of HSMM)
- Couple eye-movement and EEG data into a single HSMM framework handling signal overlap

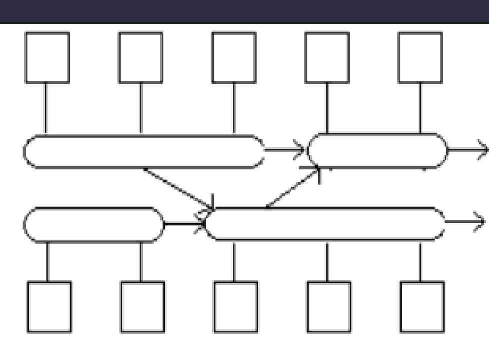


Figure: Natarajan, 2007

References

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