Joint analysis of eye-movements and electroencephalograms using coupled hidden Markov and topic models

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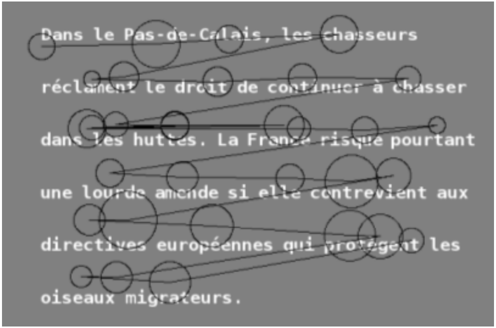
Outline

The context

- A cross-disciplinary PhD between Statistics and Cognitive Science (CS)
- What is CS ?
  - Studying the mind and its processes
  - *"Thinking can best be understood in terms of representational structure in the mind and computational procedures that operate on those structures"*[1]
  - Early 1930's : first variant of **artificial neural networks** inspired from biological neural networks
  - 1973 : first use of the term "Cognitive Science" and creation of the CS journal
- More precisely we are interested in **oculometry**, the science which study the eye-movement

[1] P. Thagard, Cognitive Science, the Stanford encyclopedia of Philosophy, 2008

General goals



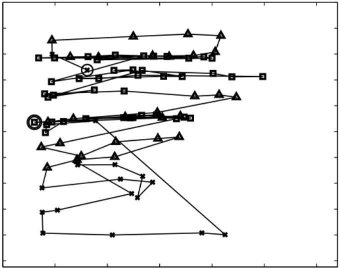
Oculometric data : **scanpath** example

Alternation of **fixations** (circles) and **saccades** (lines)

- **Decipher** underlying cognitive phases in the cognitive processes of a press review-like task while recording the **scanpath** of eye-movement
- **Characterize** these phases with eye-movements
- **Explain** the phase changes using the local text properties

Simola2008[2]

- Use a model on eye-movement series to **infer phases in the reading process** which can be interpreted as steps in the cognitive processes leading to the decision



Example of eye movement trajectories for a Q&A task

× : *scanning* phase

△ : *reading* phase

□ : *decision* phase

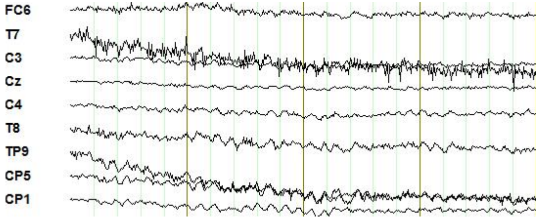
⊕ 3 reading phrases are identified and discriminated with an accuracy of 60.2% (33% pure chance)

⊖ Eye-movement analysis implies two linked phenomenon. What one read guide his thoughts, the thoughts guide what is going to be read after

[2] J. Simola, J. Salojärvi, I. Kojo, *Cognitive Systems Research*, 2008

Obermaier2001[3]

- A model is used for the analysis of EEGs



Example of EEG data for given channels

⊕ The EEG analysis has been widely studied and there are **known EEG patterns** in order to characterize cognitive processes

⊖ In our case, it does not take into account the text properties and the way it is processed

[3] B. Obermaier, C. Guger, C. Neuper, G. Pfurtscheller, *Pattern Recognition Letters*, 2001

Reviewed goals

- Couple eye-movement data with EEG data and text properties in a new coherent model using a single coupled model[4]
- Further, the goal is to model "human data mining"
- The main difficulty of jointly modeling eye-movements and EEGs is due to **material variability**, **people variability** and **signal overlapping**[5]

More generally,

- we need to deal with **sequential data**
- we need **change point detection** to catch the changes of phase

$\rightarrow$ What kind of model can we use ?

[4] S. Zhong, J. Ghosh, *Department of Electrical and Computer Engineering*, 2001

[5] A. Frey et al., *Frontiers in Systems Neuroscience*, 2013

Hidden Markov Model, discrete space and time case I

- $(x_1, ..., x_T)$ denotes the observed data produced by the R.V. $(X_1, ..., X_T)$, with $X_t \in \mathcal{V} = \{v_1, ..., v_K\}$, where $\mathcal{V}$ is the set of **observed states**, and $t = 1, ..., T$ are the time instants
- $(z_1, ..., z_T)$ denotes the latent data produced by the R.V. $(Z_1, ..., Z_T)$, with $Z_t \in \mathcal{S} = \{1, ..., M\}$, where $\mathcal{S}$ is the set of **hidden states**, and $t = 1, ..., T$
- At each time t, an observation is associated to a latent variable in order to obtain a segmentation

Hidden Markov Model, discrete space and time case II

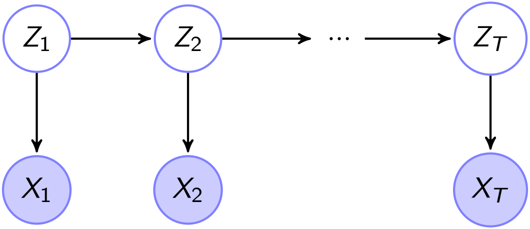


Figure: Graphical model corresponding to the 1st order HMM

- In order to deal with **tractability**, the trick is to use the d-separation property and assume the following conditional independence :

  $Z_t \perp Z_{1..t-1} | Z_{t-1}, \forall t = 2..T$
  $X_t \perp X_{1..t-1}, Z_{1..t-1} | Z_t, \forall t = 2..T$
- Therefore, the **joint probability distribution** is denoted :

  $$p(x_1..x_T, z_1...z_T) = p(z_1)\Big[\prod_{t=2}^{T} p(z_t|z_{t-1})\Big] \prod_{t=1}^{T} p(x_t|z_t)$$

Hidden Markov Model, discrete space and time case III

- The **model parameters** can be identified as :

$$a(i,j) = p(Z_t = j|Z_{t-1} = i), \quad i,j \in \mathcal{S}$$
$$b_i(v_t) = p(X_t = v_t|Z_t = i), \quad v_t \in \mathcal{V}, i \in \mathcal{S}$$
$$\pi(j) = p(Z_1 = j), \quad j \in \mathcal{S}$$

- Parameters estimation is carried out by an **Expectation-Maximization** (EM) algorithm while inference is achieved via a **Forward/Backward** algorithm

⊖ **Limit** : The sojourn duration distribution of each hidden state is necessarily Geometric

Hidden Semi-Markov Model[6] I

- We now consider that a hidden state has a **variable duration** d, with a corresponding number of observations produced in this state
- In HSMM, the state duration distribution can either be parametric (e.g. exponential distributions) or non-parametric

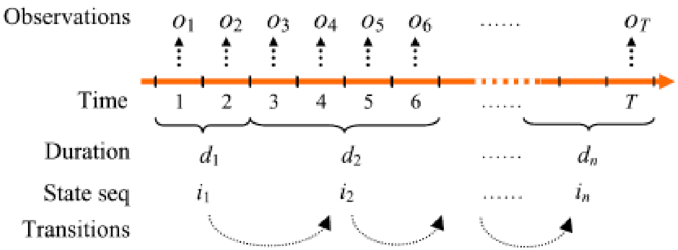


Figure: General HSMM

[6] S-Z. Yu *Artificial Intelligence*, 2010

Hidden Semi-Markov Model II

- In the most general case, the state transition probability distribution from (i, d') to (j, d), $i \neq j$ is :

  $$a(i, d')(j, d) \equiv p[Z_{[t:t+d-1]} = j \mid Z_{[t-d':t-1]} = i]$$

- For simplicity and tractability, we will make the following assumption on the transition probability distribution and get a specific model called **Explicit Duration HMM** :

  $$a(i, d')(j, d) = a_{ij} p_j(d)$$
  $$a_{ij} = p[Z_{[t} = j \mid Z_{t-1]} = i]$$
  $$p_j(d) \equiv p[Z_{t:t+d-1} = j \mid Z_{[t} = j]$$

- Afterwards, assumptions can be made on $p_j(d)$ to simplify the model and fit other distributions than the geometric one in the classic HMM case
- Parameters can also be retrieved via an EM algorithm while inference is achieved using a F/B algorithm

Application of HSMM on eye-movement data I

- Reminder :
  - Text skimming for Q&A tasks
  - Segment scanpaths into interpretable zones
- The observed variable $X_t \in \mathcal{V}$ at time t characterizes the **eye fixation**
- The set of observed states is the **read mode** $\mathcal{V} = \{v_0, ..., v_4\}$, with v_0 : *word skip*, v_1 : *next word*, v_2 : *same word*, v_3 : *previous word*, v_4 : *further backward*
- The hidden variable $Z_t \in \mathcal{S} = \{0, ..., 4\}$ characterize the **reading strategies**
- The number of hidden state is deduced using BIC criterion

Application of HSMM on eye-movement data II

Using Explicit Duration HMM, the parameters are as follows :

- The transition probabilities from reading strategy i to reading strategy j, $i \neq j$: $a_{ij} \equiv p[Z_{[t} = j \mid Z_{t-1]} = i]$
- The sojourn duration distributions d in reading strategy j : $p_j(d) \equiv p[Z_{t:t+d-1} = j \mid Z_{[t} = j]$
- The emission probabilities, observe a read mode v_t while using reading strategy j : $b_{j,d}(v_t) \equiv p[v_{t:t+d-1} | Z_{t:t+d-1} = j]$

Application of HSMM on eye-movement data III

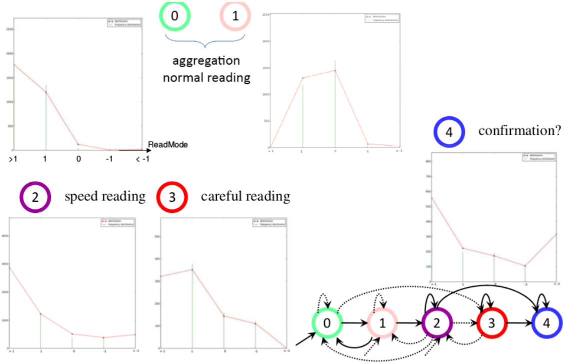


Figure: Reading strategies

- state 0 and 1 are combined according to their duration distribution for a better interpretation

Application of HSMM on eye-movement data IV

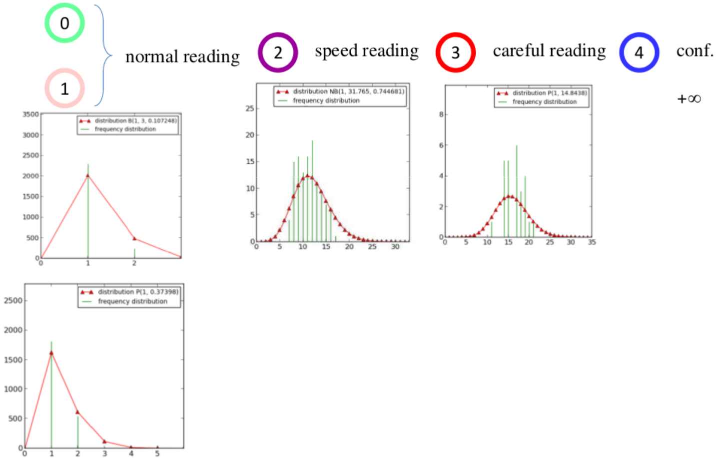
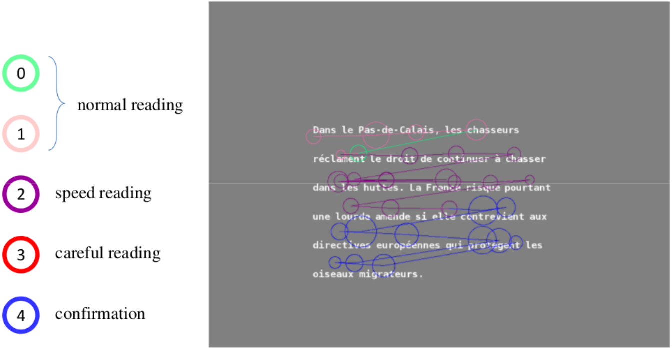


Figure: Sojourn duration distributions

Application of HSMM on eye-movement data V



Individual 4, text 9 (bird hunting)

Figure: Segmentation of reading strategies

- $\hat{Z}_1 \ldots \hat{Z}_T = argmax_{Z_1,\ldots Z_T} p[Z_1, \ldots, Z_T | X_1, \ldots X_T]$

Conclusion

Advantages :

- Using HSMM allowed us to provide a **better discrimination** of the reading strategies changes
- Identification of variability that prevent us to give global conclusions on the experience

Ongoing work and perspectives :

- Improve issues related to material variability, people variability and signal overlapping
- **Build a single framework** to jointly handle eye movement data and EEG data for a better discrimination and interpretation of the reading strategies and related cognitive processes

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