Switching HMM
and
HMM Classification

Lecture 4

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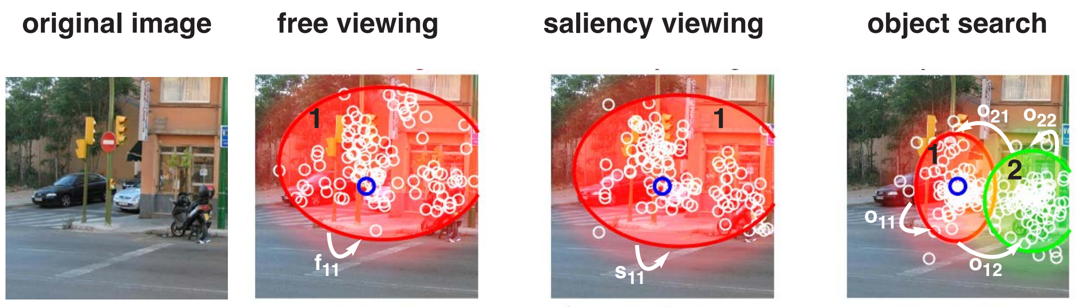
Outline

- Switching HMM: Modeling changes in Cognitive Task
- SMAC: Scanpath Modeling and Classification with HMMs

- Mini-Project: Finalize data analysis and work on project presentations

Modeling High-Level Tasks

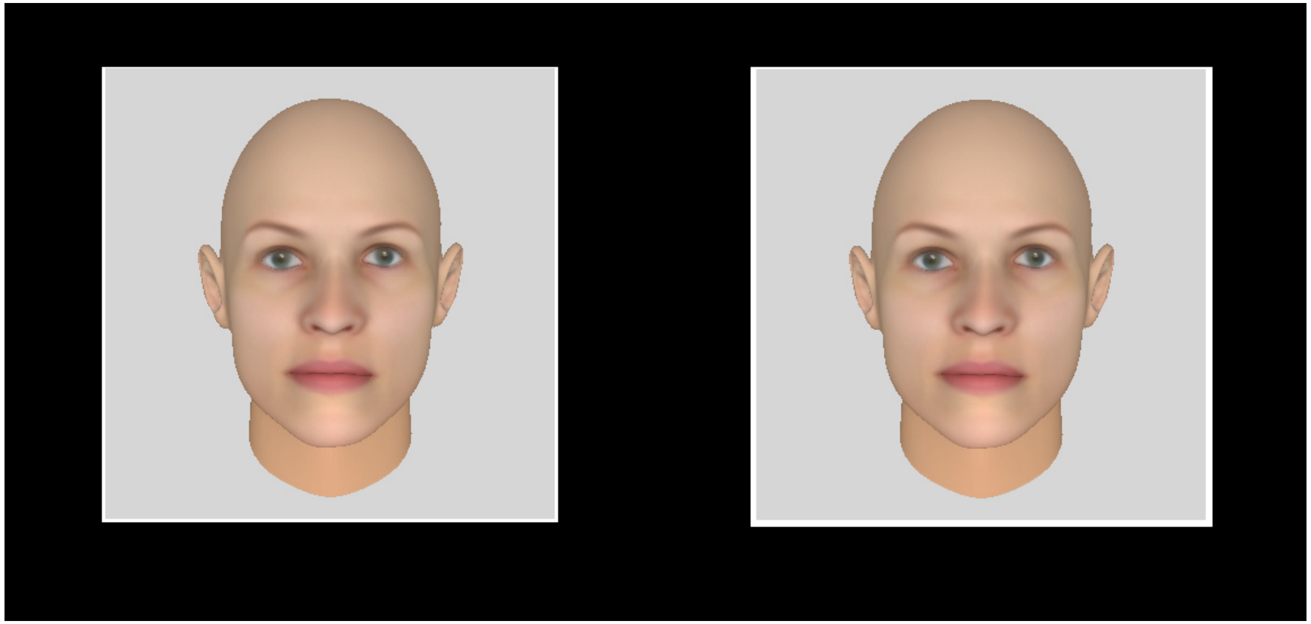
- Previous method uses an eye gaze model for each task – each trial consists of one task.



  - What if in each trial the participant performs two tasks?
  - Can we model eye gaze as it switches between tasks?
- Switching hidden Markov Model
  - Eye gaze patterns change with task over time.
  - Study individual differences in gaze cascade effect.

Experiment Design

- 2AFC Task, 24 participants
- Computer-generated faces (60 male 60 female)
- Procedure:
  - 1) Rate the level of attractiveness of all the faces (1 to 7)
  - 2) The ones received similar ratings were paired up. Participants had to choose which one they preferred.

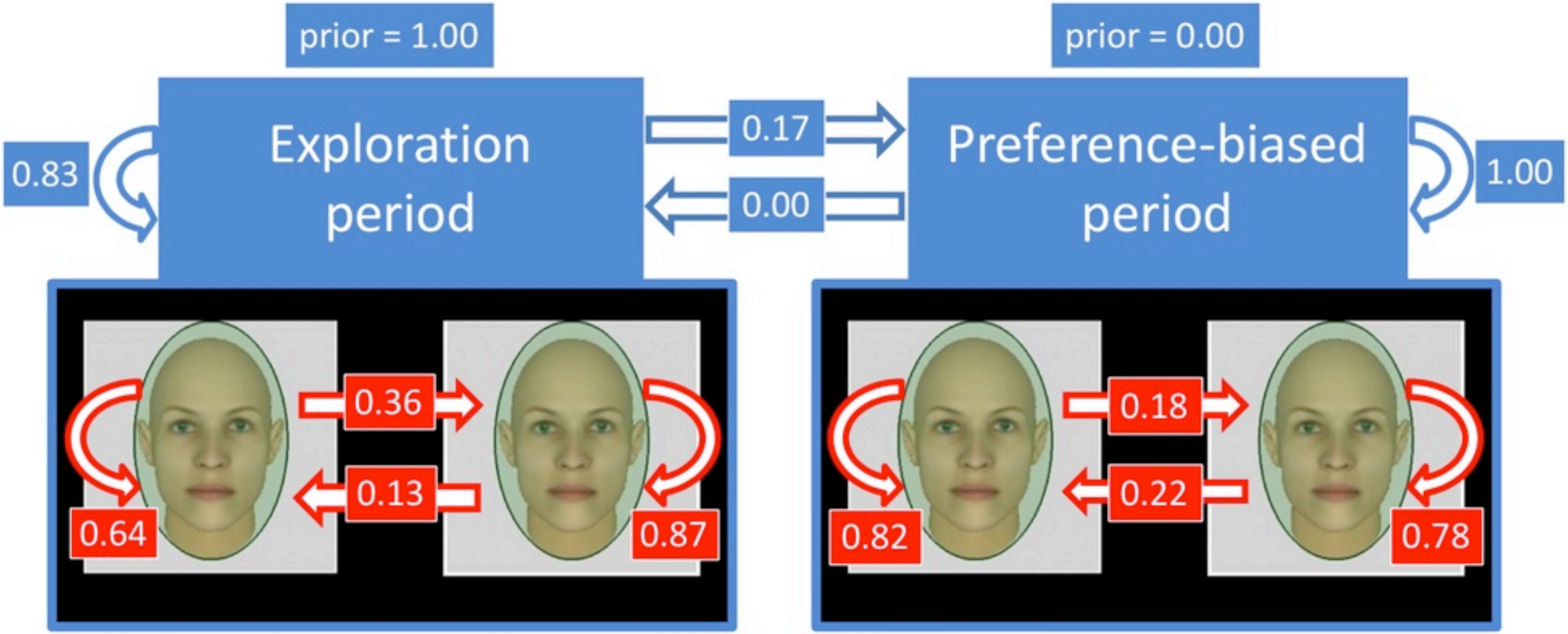


Previous Studies

- Shimojo et al., 2003 showed that the eye movements a person made during a trial can be different:
  - at the **exploration stage**, the person spends time looking at both images.
  - at the **preference-biased** stage, the person spends more time looking at the to-be-chosen image.

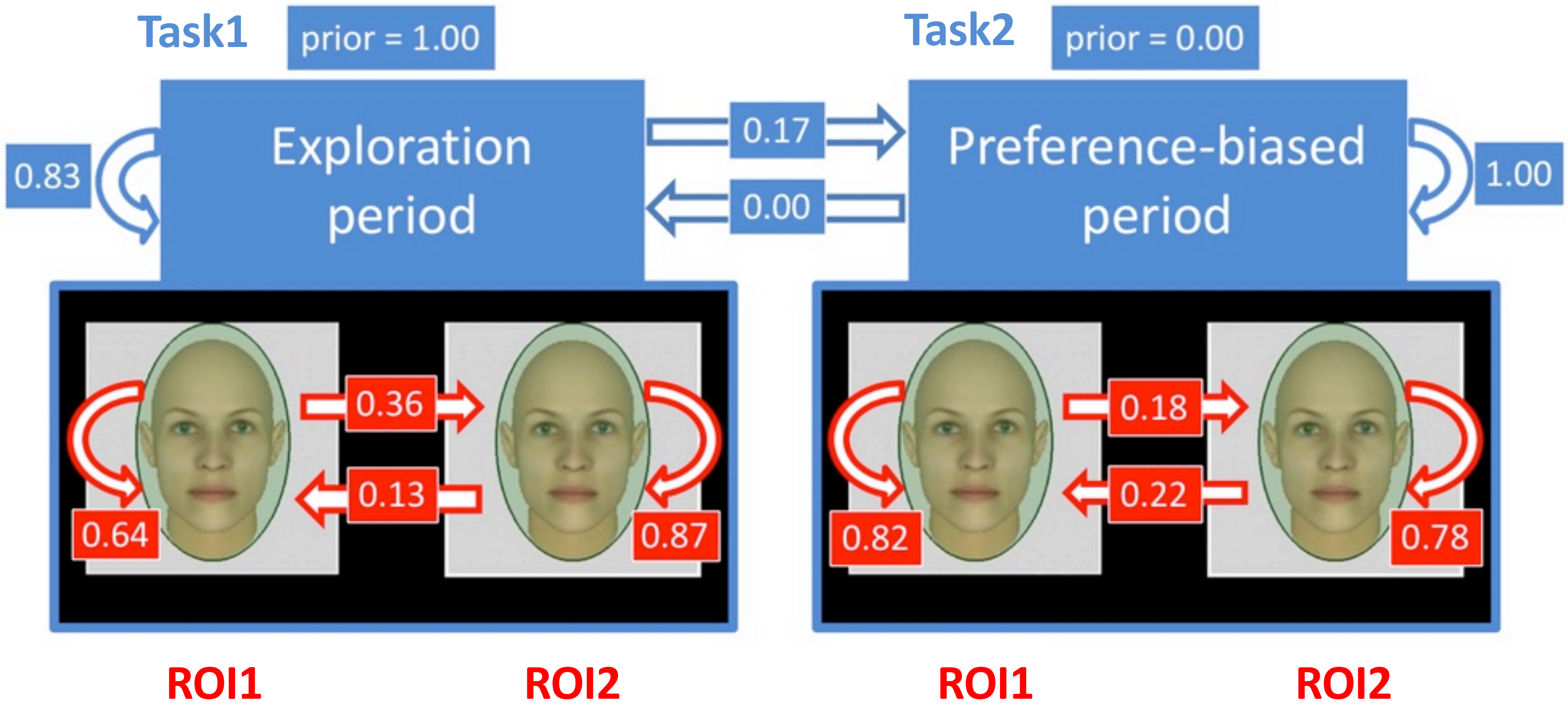
Switching hidden Markov model

- The model has two levels:
  - high-level states (switching between high-level tasks)
  - low level states (eye movement patterns)



Switching hidden Markov model

- Two transition matrices encode:
  - High-level: Switching between tasks.
  - Low-level: Switching between ROIs (depends on the task).
    - Although the low-level transitions are different, the ROIs are shared among the high-level states.



Methodology

- **Modeling**
  - For each participant, learn a switching HMM on their eye gaze data.
    - assume one-way transition from exploration to preference-biased (zero probability to move from preference to exploration)
    - Learn separate HMM for left- and right-selected trials, then combine them.
  - Cluster into 2 groups using k-means clustering on the high-level transition matrices.
- **Analysis**
  - Examine the “exploration” and “preference-biased” HMMs.
    - *Are there differences in preference-biased period?*
  - Gaze cascade plots
  - Inferring selected face from fixations

Switching HMM for all Subjects

- Use VHEM to summarize exploration and preference-biased HMMs over all 24 subjects.

high-level transition matrix

	Exploration	Preference
Prior	1.00	0.00
Exploration	0.55	0.45
Preference	0.00	1.00

exploration transition matrix

	Left	Right
Prior	0.70	0.30
Left	0.64	0.36
Right	0.12	0.88

Briefly examine left and then right side

Preference-biased transition matrix

	to Chosen	to Not-chosen
Prior	0.53	0.47
from Chosen	0.77	0.23
from Not-chosen	0.33	0.67

Preference to look at chosen side. Consistent with gaze cascade effect.

Switching HMMs for 2 Groups

Group A (11 participants)

High-level	Exploration	Preference
Prior	1.00	0.00
Exploration	0.68	0.32
Preference	0.00	1.00

Exploration	Left	Right
Prior	0.76	0.24
Left	0.67	0.33
Right	0.17	0.83

Pref-biased	Chosen	Not-chosen
Prior	0.50	0.50
Chosen	0.83	0.17
Not-chosen	0.25	0.75

Group A has longer exploration period

Group A looks at left side longer than Group B

Group B (13 participants)

High-level	Exploration	Preference
Prior	1.00	0.00
Exploration	0.45	0.55
Preference	0.00	1.00

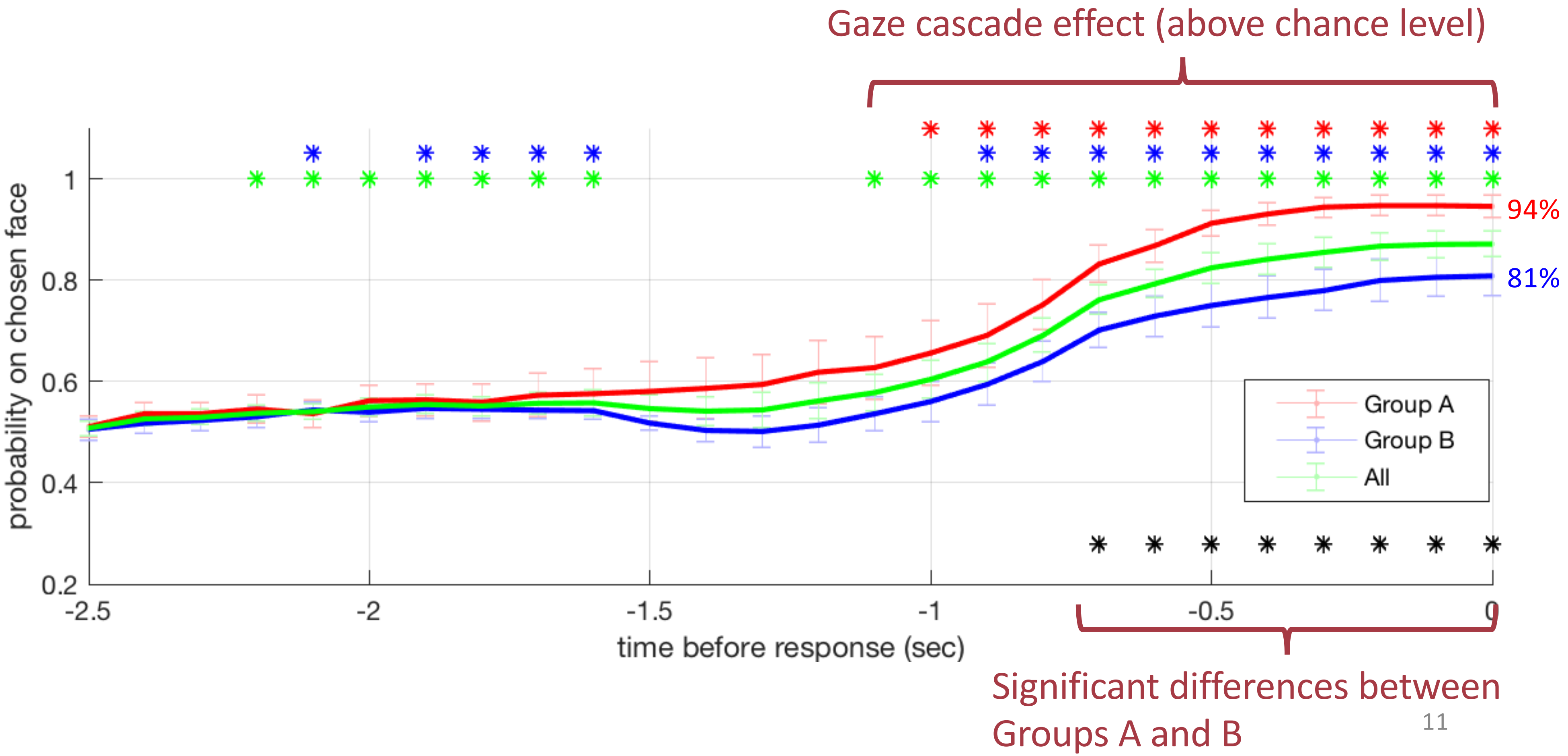
Exploration	Left	Right
Prior	0.64	0.36
Left	0.60	0.40
Right	0.09	0.91

Pref-biased	Chosen	Not-chosen
Prior	0.54	0.46
Chosen	0.71	0.29
Not-chosen	0.39	0.61

Group A had stronger bias towards chosen side, and switches sides less often.

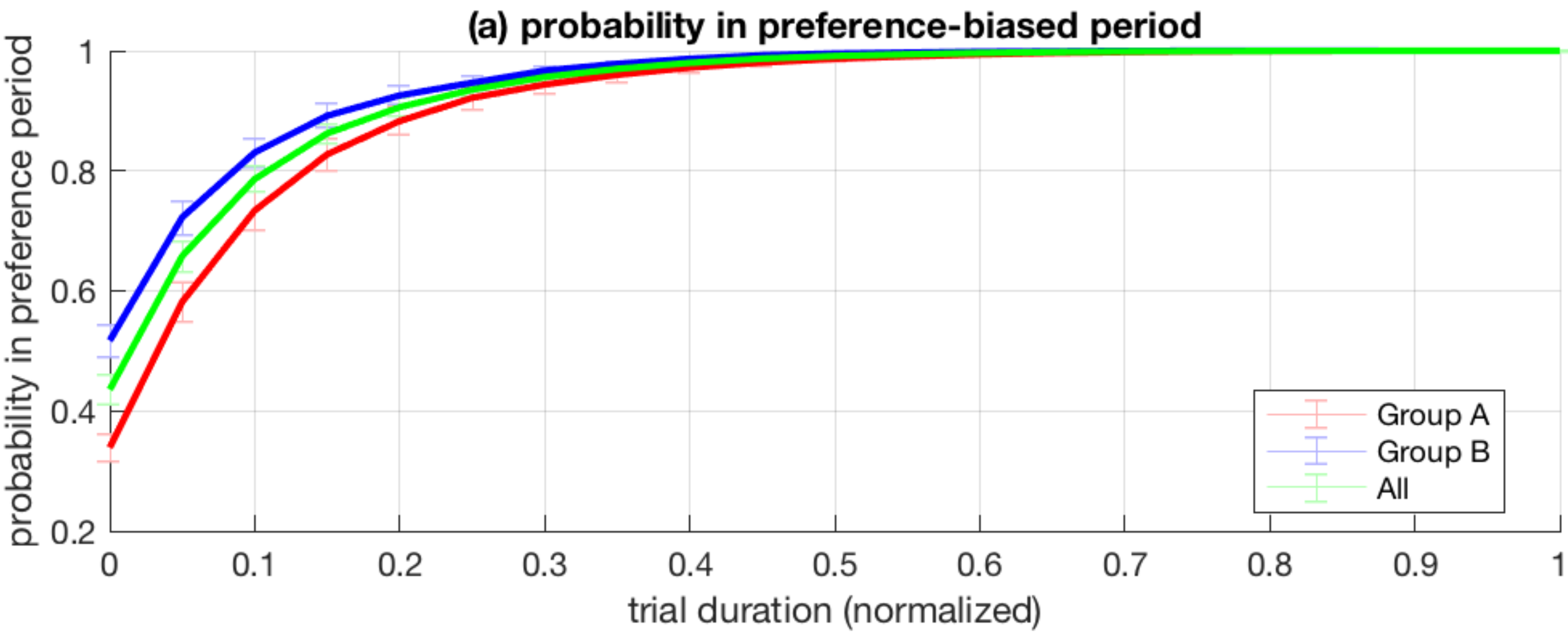
Gaze Cascade Plots

- Plot the percentage of time viewing the chosen face for the last 2.5 seconds of each trial.
    - For Group A, the gaze cascade effect happened earlier and was stronger.
    - For Group B, the gaze cascade effect started later and was weaker.



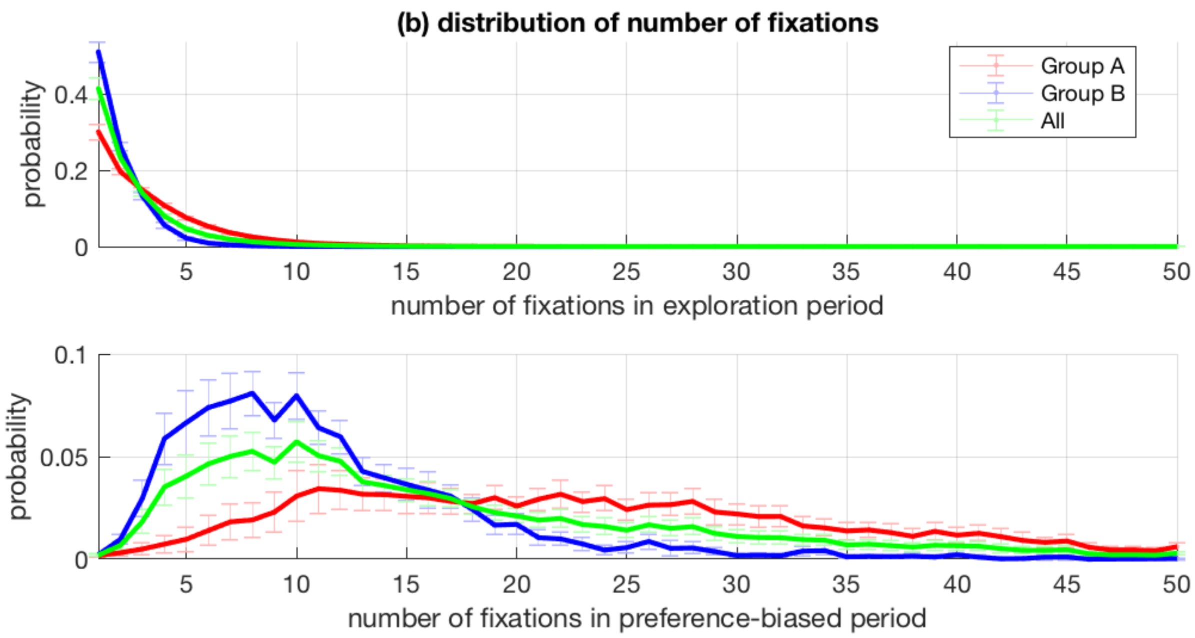
Time in Exploration/Preference-biased Periods

- Probability in preference-biased period within a normalized time-segment of a trial.
  - Group B had a higher % in the beginning, although the cascade effect is weaker.
  - Group A entered preference-biased period later, but had stronger cascade effect.



Number of Fixations

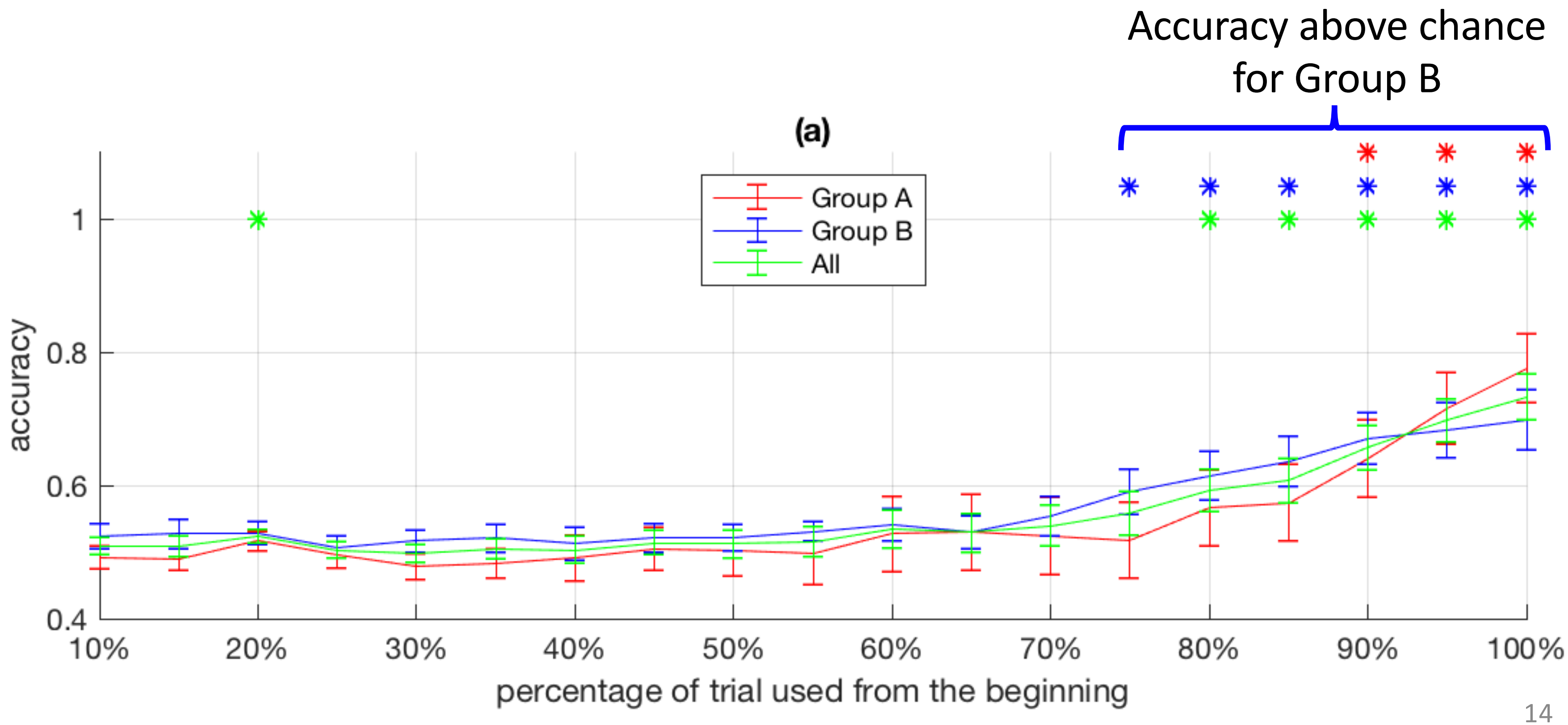
- Group A had more fixations (29) vs Group B (13.3)
  - Group A has more fixations in exploration and preference-biased periods than Group B.
  - Group A had more ROI switches (5.6) vs Group B (4.1)
- When normalizing for number of fixations in a trial
  - Groups did not differ in % of fixations in the two periods.
  - Group A had smaller % of ROI switches.



Group A tended to explore stimulus longer before switching to another stimulus.

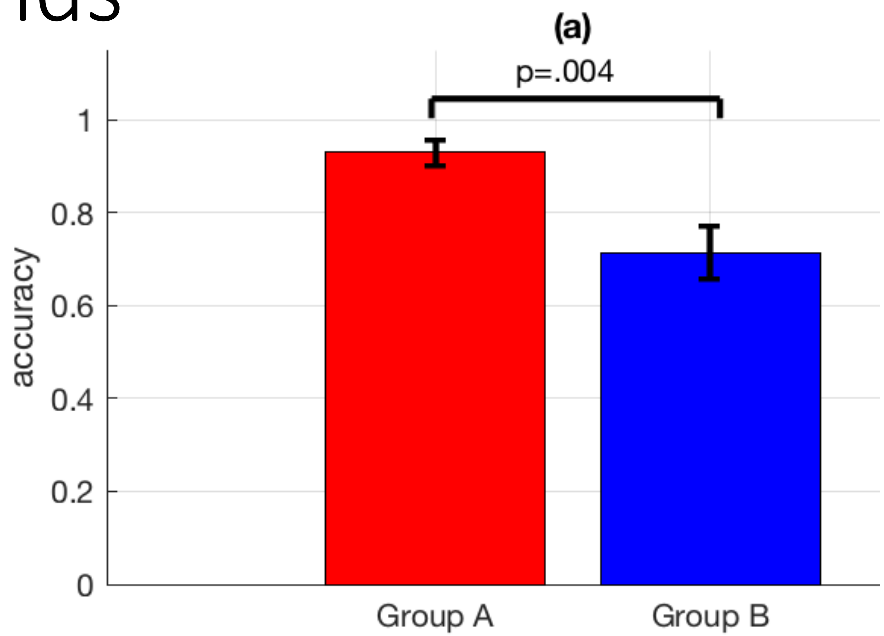
Inferring Participant's Decision

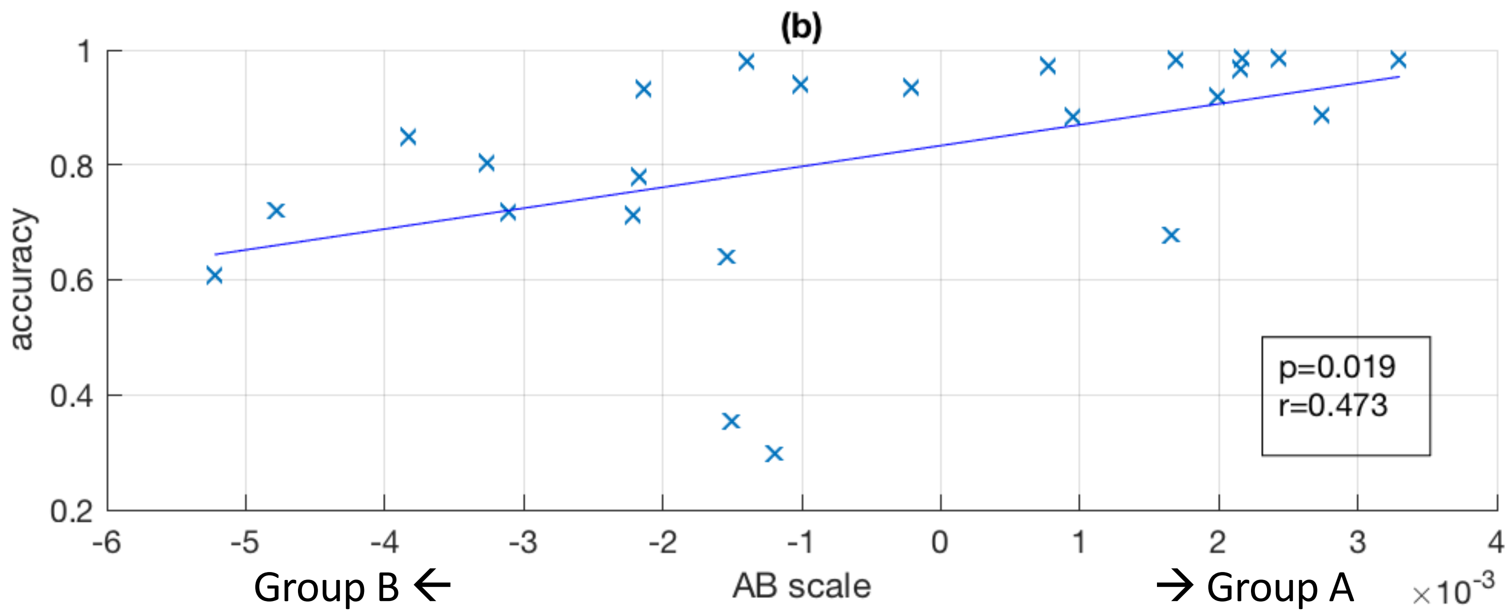
- Using eye movements to infer people's decisions
  - Leave-one-trial-out cross-validation.
  - Combine left- and right-selected HMMs, and infer the final high-level state.
  - Using a percentage of fixations from the start of the trial.
  - Group B revealed their preference earlier.



Inference in Last 2 Seconds

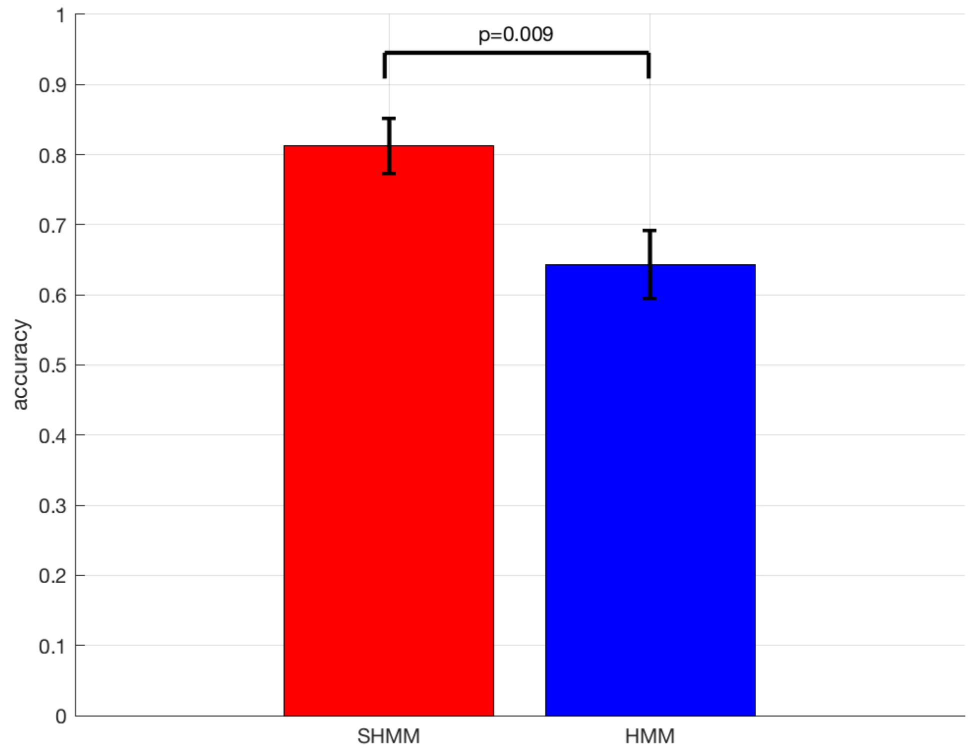
- Infer the chosen face using the fixations from the last 2 seconds
  - Group A (0.93) was significantly higher than group B (0.73), *p*= .004.
  - The more similar to Group A, the higher the inference accuracy.





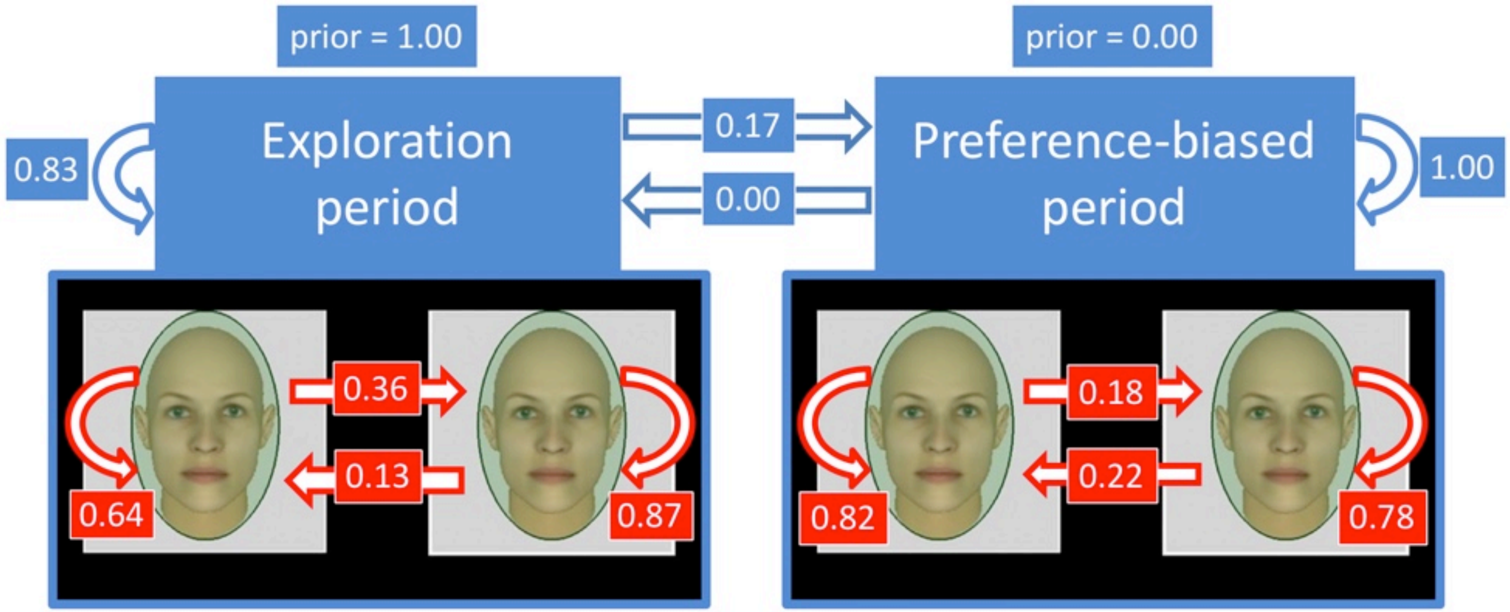
Inference using standard HMM

- Perform the same inference task using HMM
  - Average inference accuracy was higher for SHMM (0.81) vs HMM (0.64).
  - Shows the advantage of using switching HMM in tasks involving cognitive state changes.



Summary: Switching HMM

- Model changes in eye gaze patterns due to changes in high-level task.
- In preference decision making task
  - Discovered different types of cascade effect.
  - Model individual differences in gaze cascade effect and inference accuracy.



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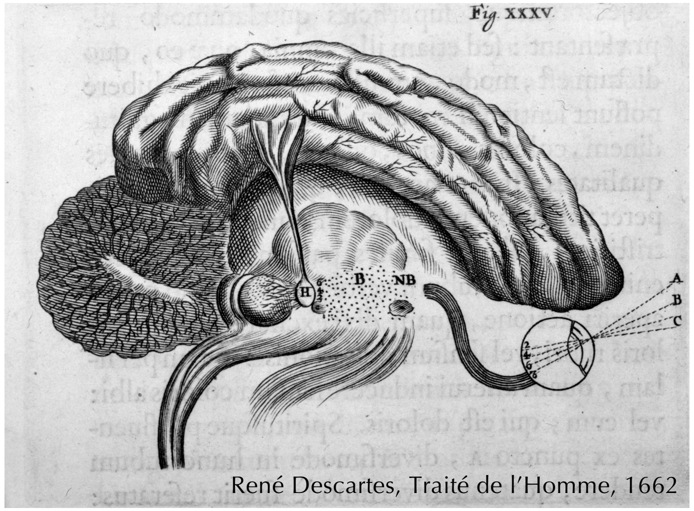
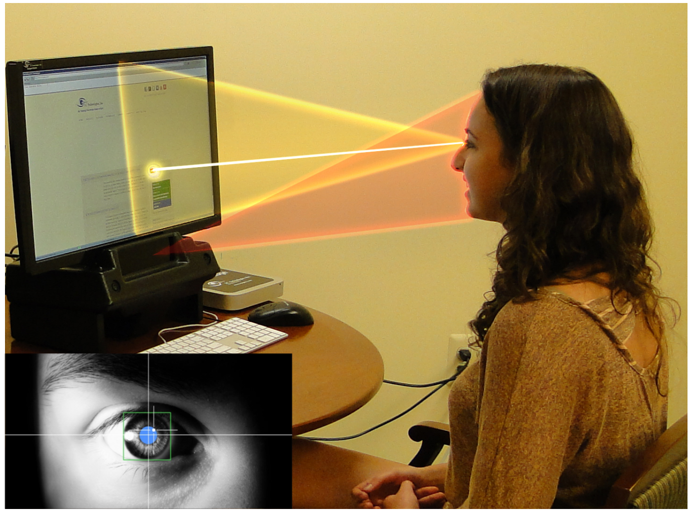
Gaze behaviour

Eye movements are an exceptionally rich source of information. They provide a high-resolution spatio-temporal measure of cognitive and visual processes.



René Descartes, Traité de l'Homme, 1662

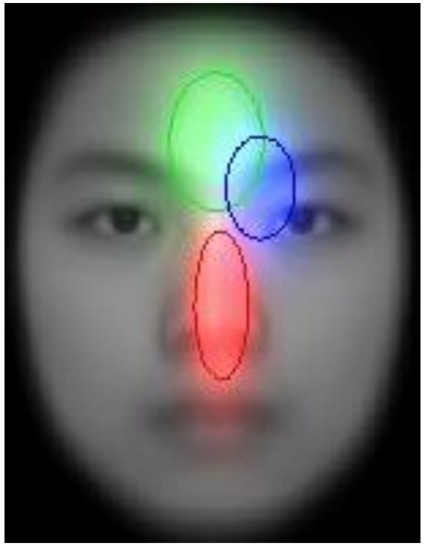
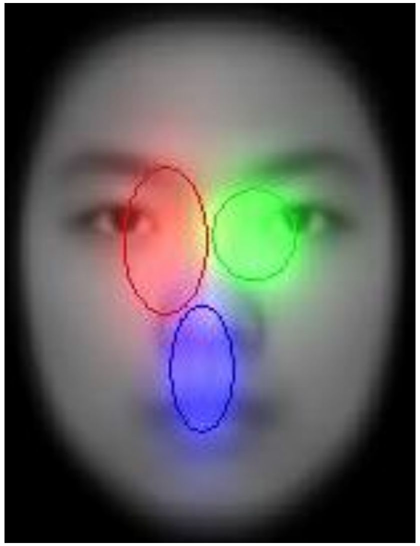


What can we predict about the viewer from eye gaze?

- What are they looking at? What is their task? What will they do next?
- What are the markers that allow such a prediction?

Clustering Individuals’ HMMs

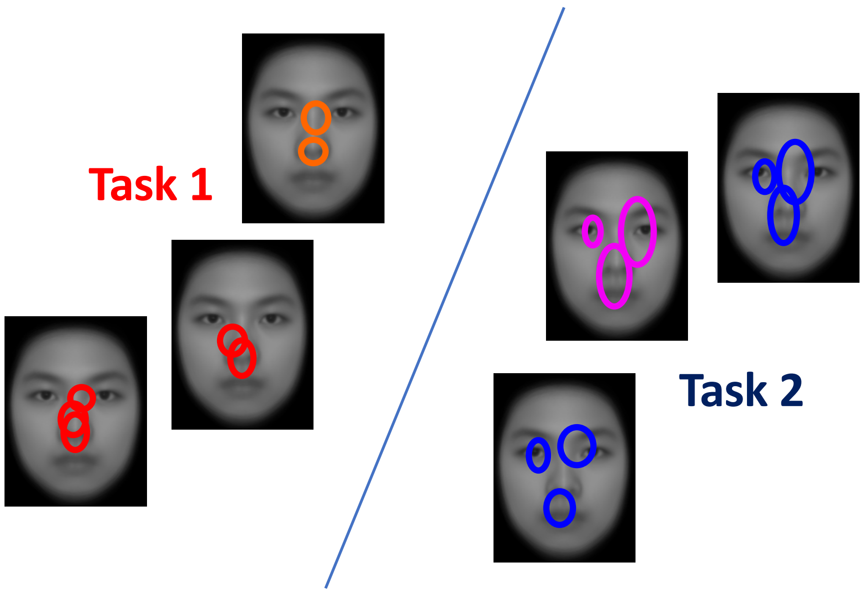
- Learn an HMM from individual’s eye fixations.
- Previous work focused on clustering HMMs to discover common patterns.
  - Individuals in each group have similar patterns…

  - but does not say how the groups are different.

Classifying Individuals’ HMMs

- Suppose we have additional information about the individual (e.g., their task)
  - We can train a classifier to predict the task from an individual’s HMM.
  - The classifier is discriminatively trained, meaning that it finds differences in patterns that are diagnostic of the task.

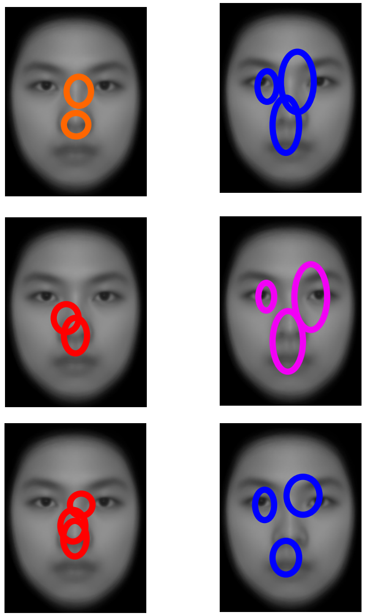


HMM Classification

- Individual is represented with a vector of their HMMs parameters (prior, transition prob., ROI mean, ROI variance).
- Use linear discriminant analysis for classification.
  - LDA coefficients indicate which part of the HMM that is diagnostic for predicting the class.

<u>Learn Individuals' HMMs</u>

Task 1 **Task 2**



<u>Vectors of HMM parameters</u>

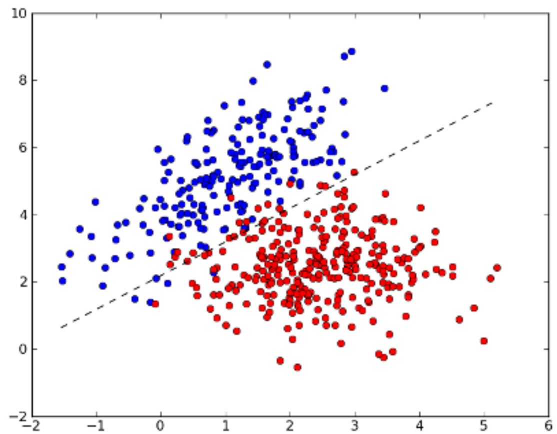
Task 1

x_1, x_2, x_3

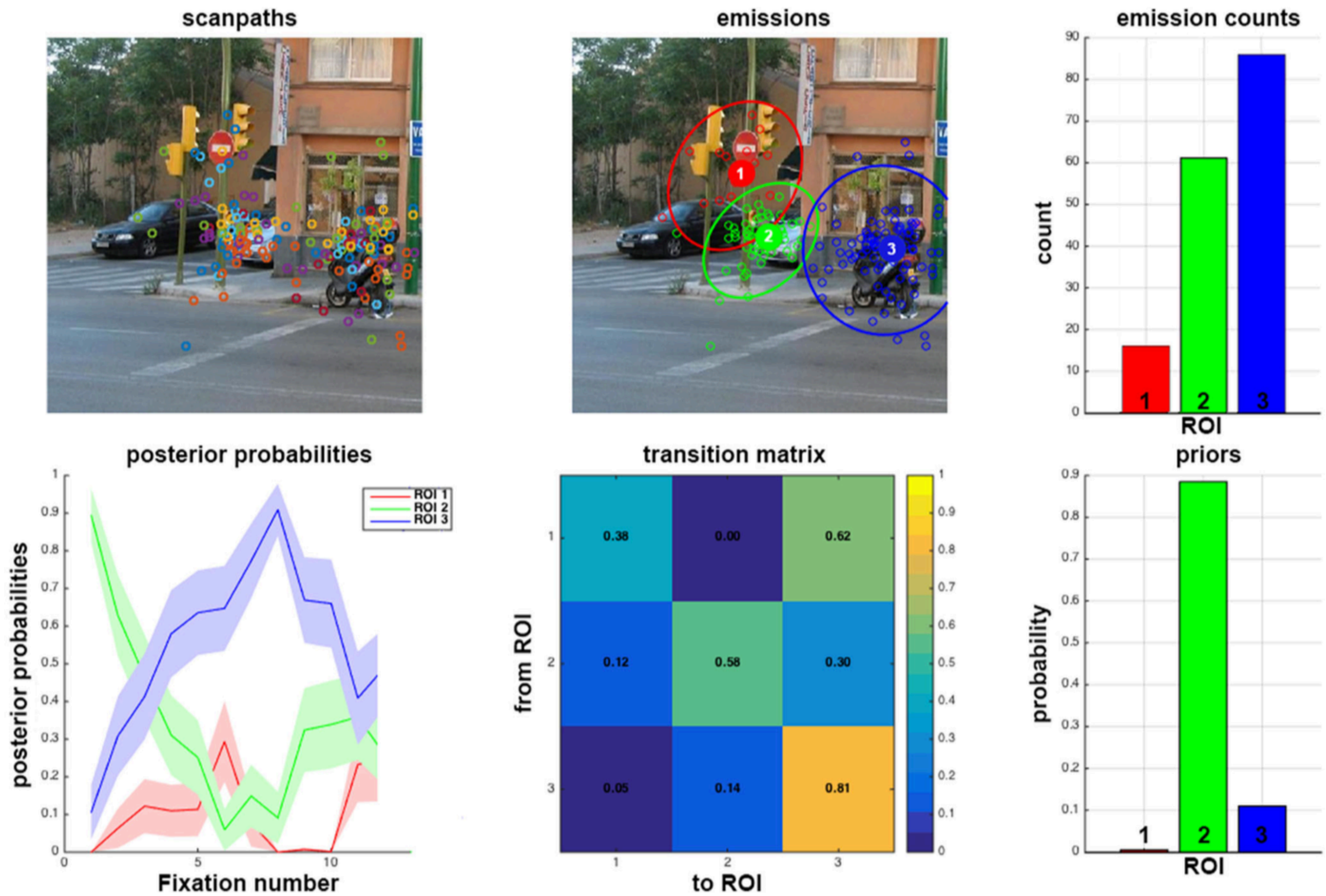
Task 2

x_4, x_5, x_6

<u>Linear Discriminant Analysis</u>



Example HMM for Image Viewing



Coutrot, Hsiao & Chan, Behavior Research Methods, 2017

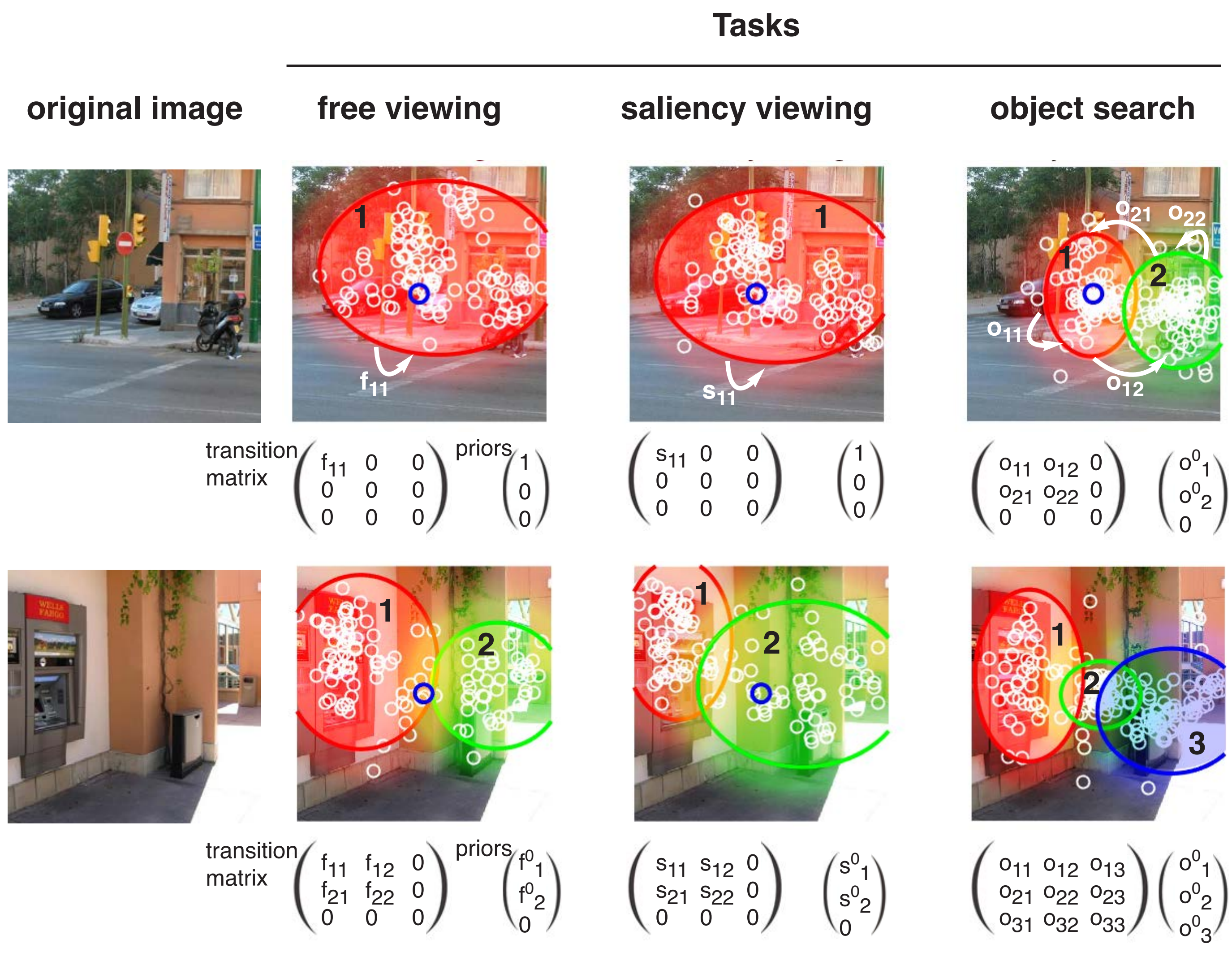
Gaze-based Task Inference

Koehler's Dataset

158 participants

800 static images

3 tasks



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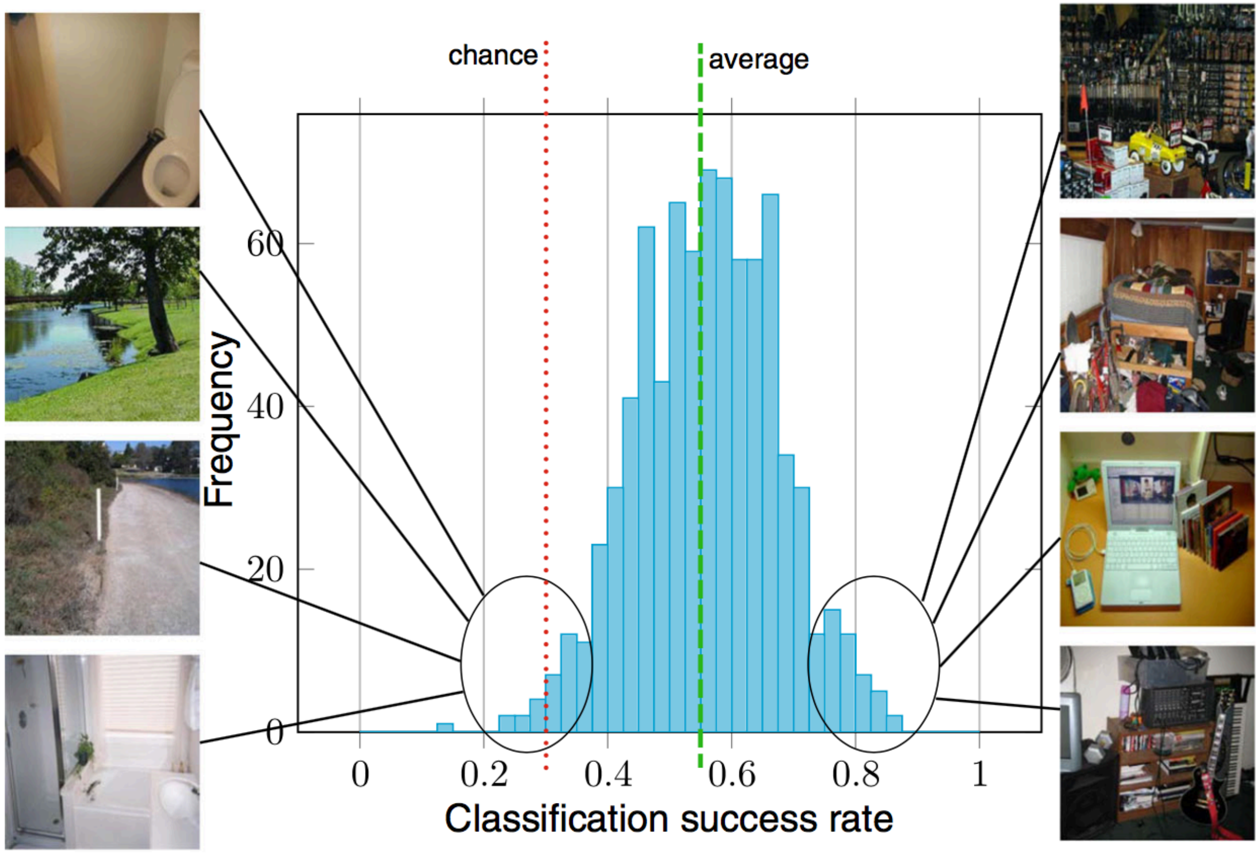
Gaze-based task inference

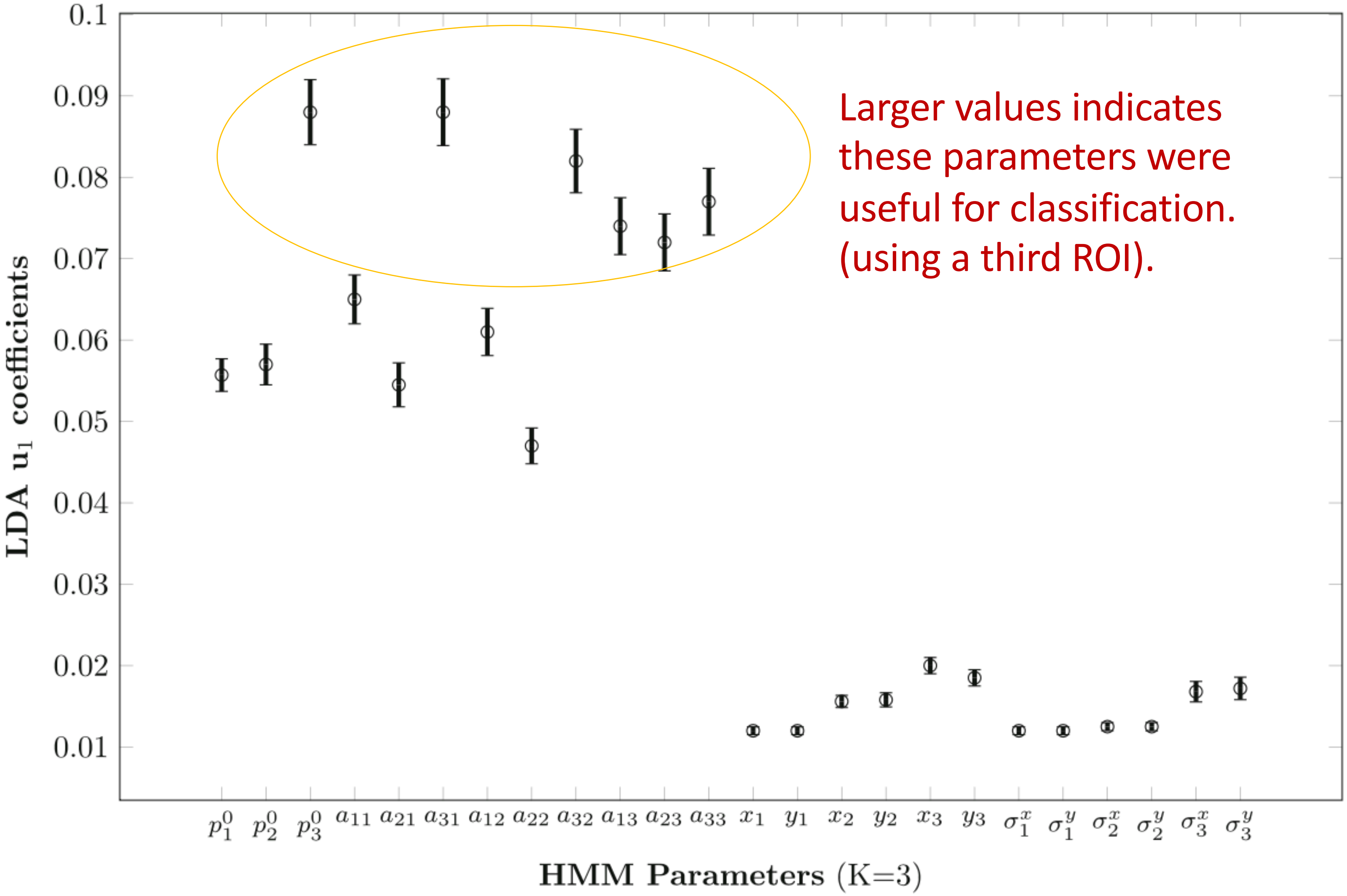
Results

- Leave-one-out cross-validation.
- 51.9 % correct classification of the task at hand (chance = 33 %).



Classifier performs better when there are salient objects.

LDA Coefficients



Larger values indicates these parameters were useful for classification. (using a third ROI).

Gaze-based Stimuli Inference

Dataset

36 participants
15 conversational videos
2 auditory condition: with and without original soundtrack.

Results

81.2 % correct classification of the auditory condition (chance = 50 %).

Video with original soundtrack

Video without original soundtrack

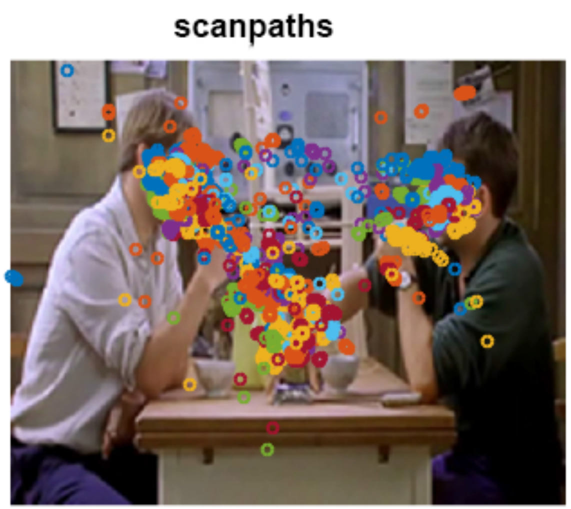
transition matrix $\begin{pmatrix} s_{11} & s_{12} & 0 \\ s_{21} & s_{22} & 0 \\ 0 & 0 & 0 \end{pmatrix}$ priors $\begin{pmatrix} s^0{}_1 \\ s^0{}_2 \\ 0 \end{pmatrix}$

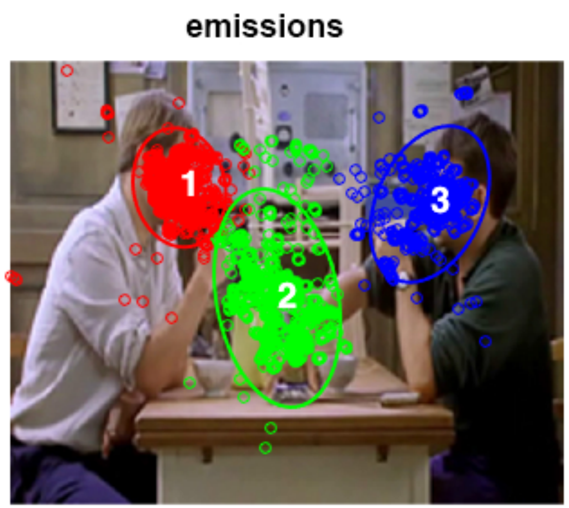
$\begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{pmatrix}$ $\begin{pmatrix} m^0{}_1 \\ m^0{}_2 \\ m^0{}_3 \end{pmatrix}$

Coutrot, Hsiao & Chan, Behavior Research Methods, 2017

Summary

- HMMs can effectively capture information about the observer and what is being observed.
  - Can discover characteristic differences in eye gaze patterns.
- Toolbox available: **SMAC with HMM.**
  - http://antoinecoutrot.magix.net/public/code.html





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