Modeling the cognitive process during experimental games using hidden Markov models

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Motivations

How to model the dynamic strategic reasoning using choice process data: eye-tracking and mouse tracking?

- **Generalizable**: Easy to apply to any games
- **Explainable**: Help us better understand the cognitive process
- **Dimension Reduction:** Be able to see the main effect

Background

- Crawford, Costa-gomes and Broseta (2001), mouse-tracking and information search.

- Wang, Spezio and Camerer (2010) , Polonio Guida and Coricelli (2015), Polonio, Devetag and Guida (2016), Zonca, Coricelli and Polonio (2019), eye-tracking on different non-cooperative games, pre-specified patterns

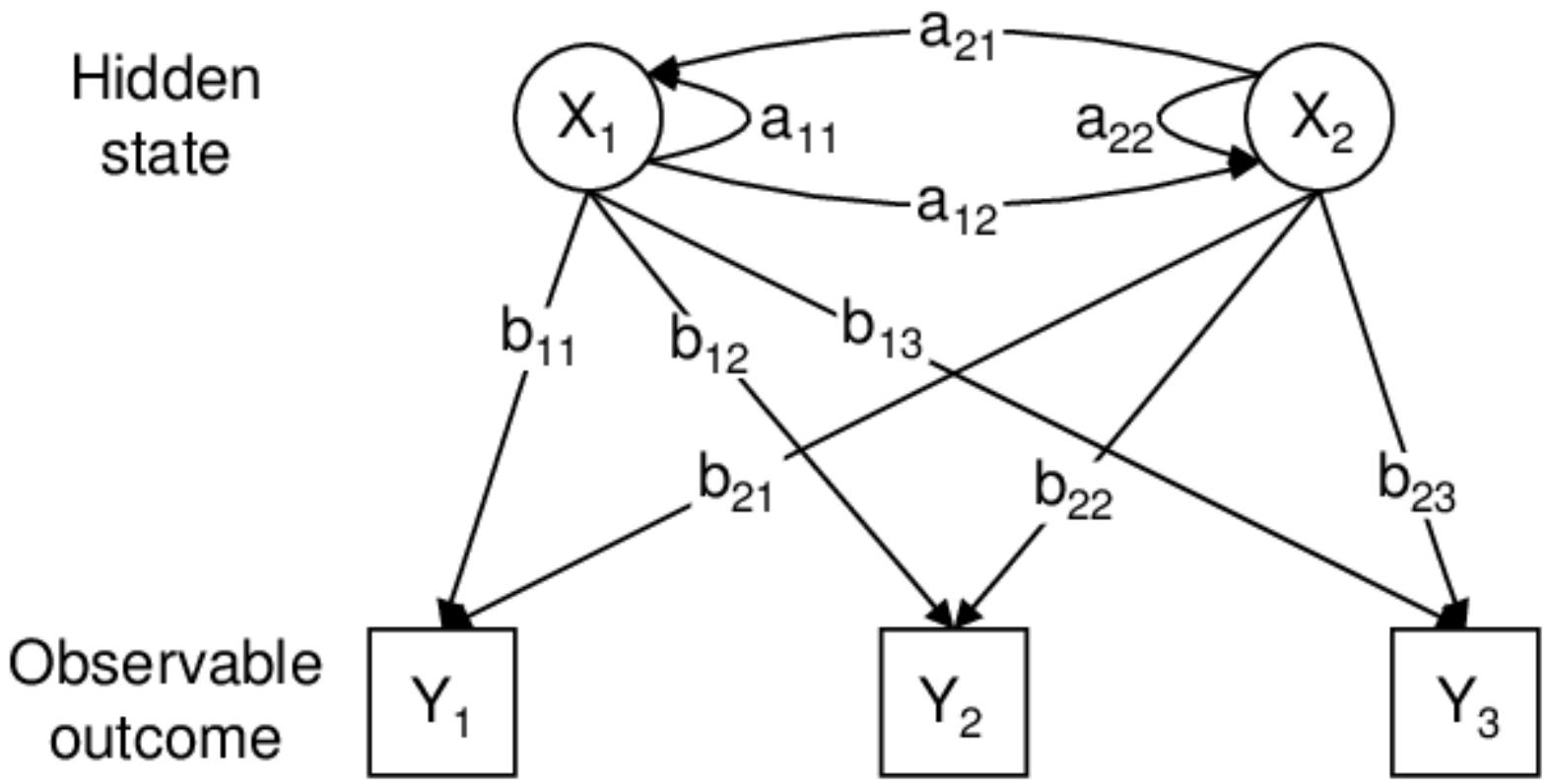
- Krajbich, Armel and Rangel (2010), Krajbich and Rangel (2011): Sequential sampling method to model gaze (DDM)

Hidden Markov Model

HMM is a machine learning model for problems where the goal is to recover a data sequence that is not immediately observable

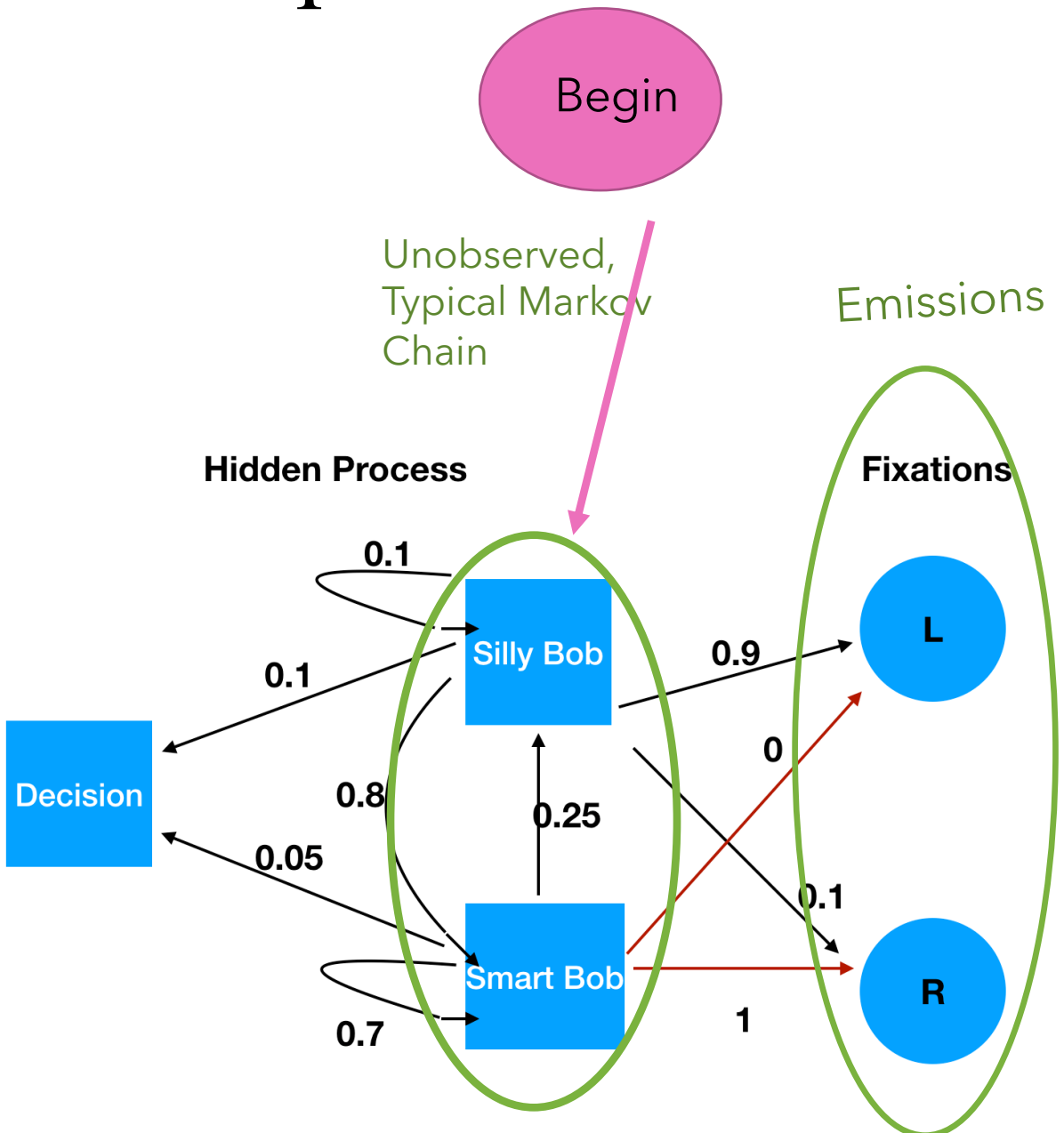
Unobserved?
Thoughts

Observed?
Gaze



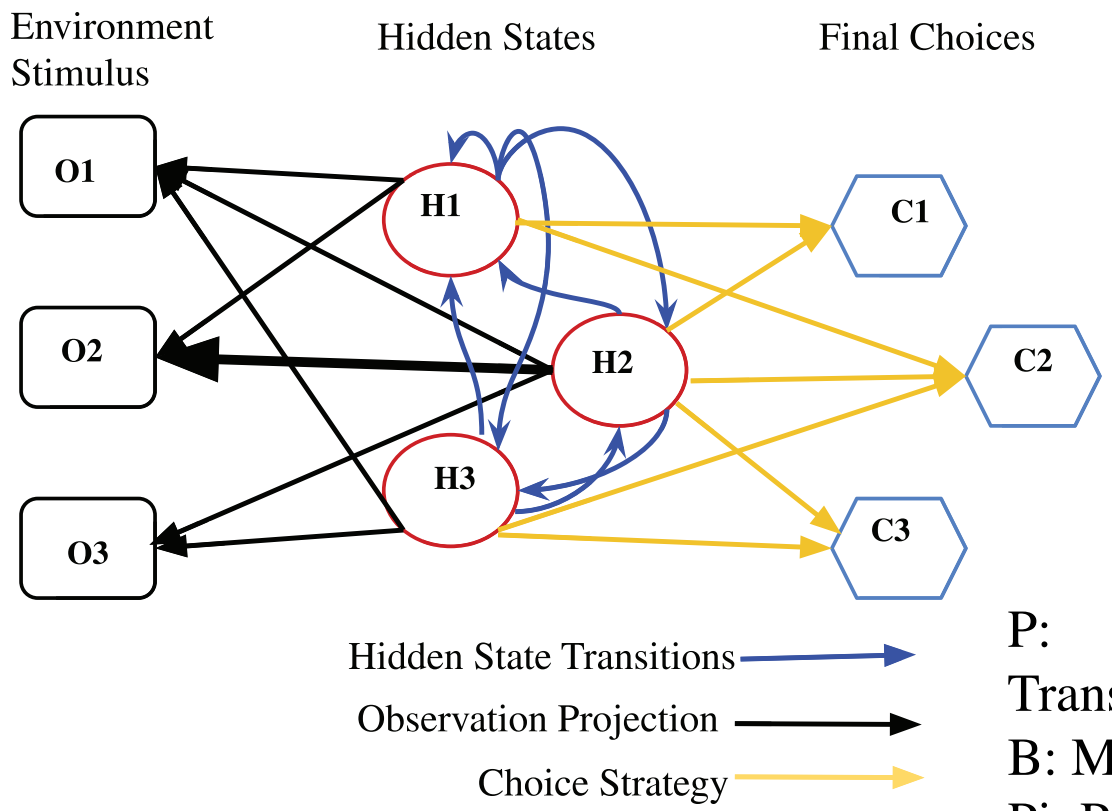
A Naïve example

Bob \ *Ann*	L	R
T	(0,1)	**(1,0)**
B	**(1,0)**	(0,1)



Hidden Markov Model in Strategic Games

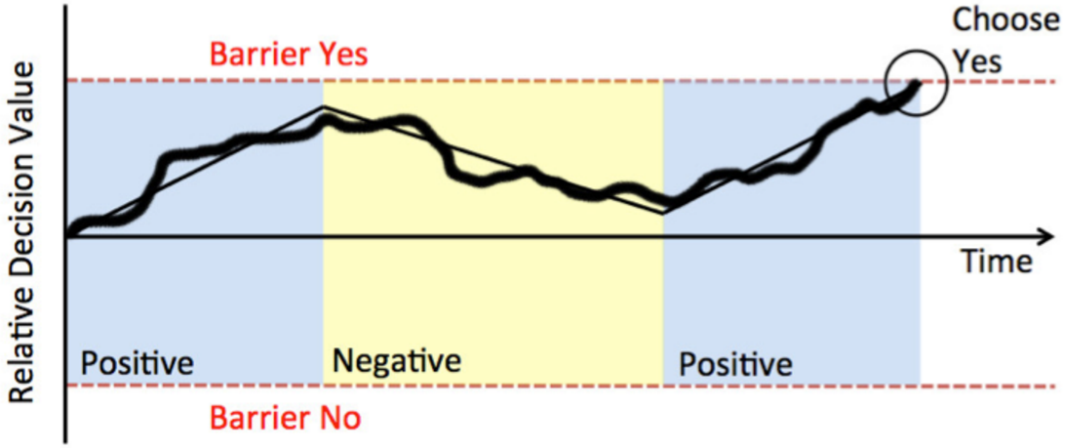
$$Model =< P, B, \Pi >$$



P:
Transition Probabilities in hidden states
B: Mapping: hidden states to observations
Pi: Prior distribution

Why we need HMM?

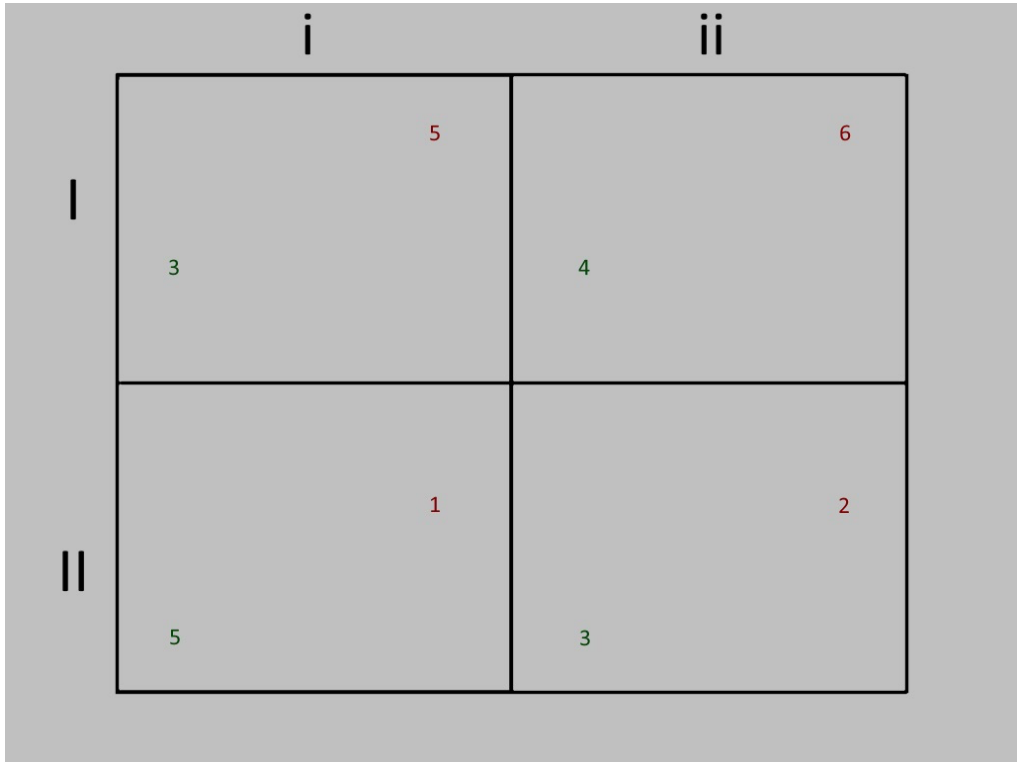
- DDM restricts the fixation data only on choices themselves, it cannot incorporate other information like counterpart payoff.
- DDM limits in the number of choices, it works best for a two choices problem.



Application 1: Normal Form Games

Dataset – Zonca, Coricelli and Polonio (2019)

- 48 games, 16 DSS, 16 DSO, 16 multiple equilibria
- N=100
- Mean Fixation Number = 25
- Only row players
- Fixations: eight AOIs (payoffs)

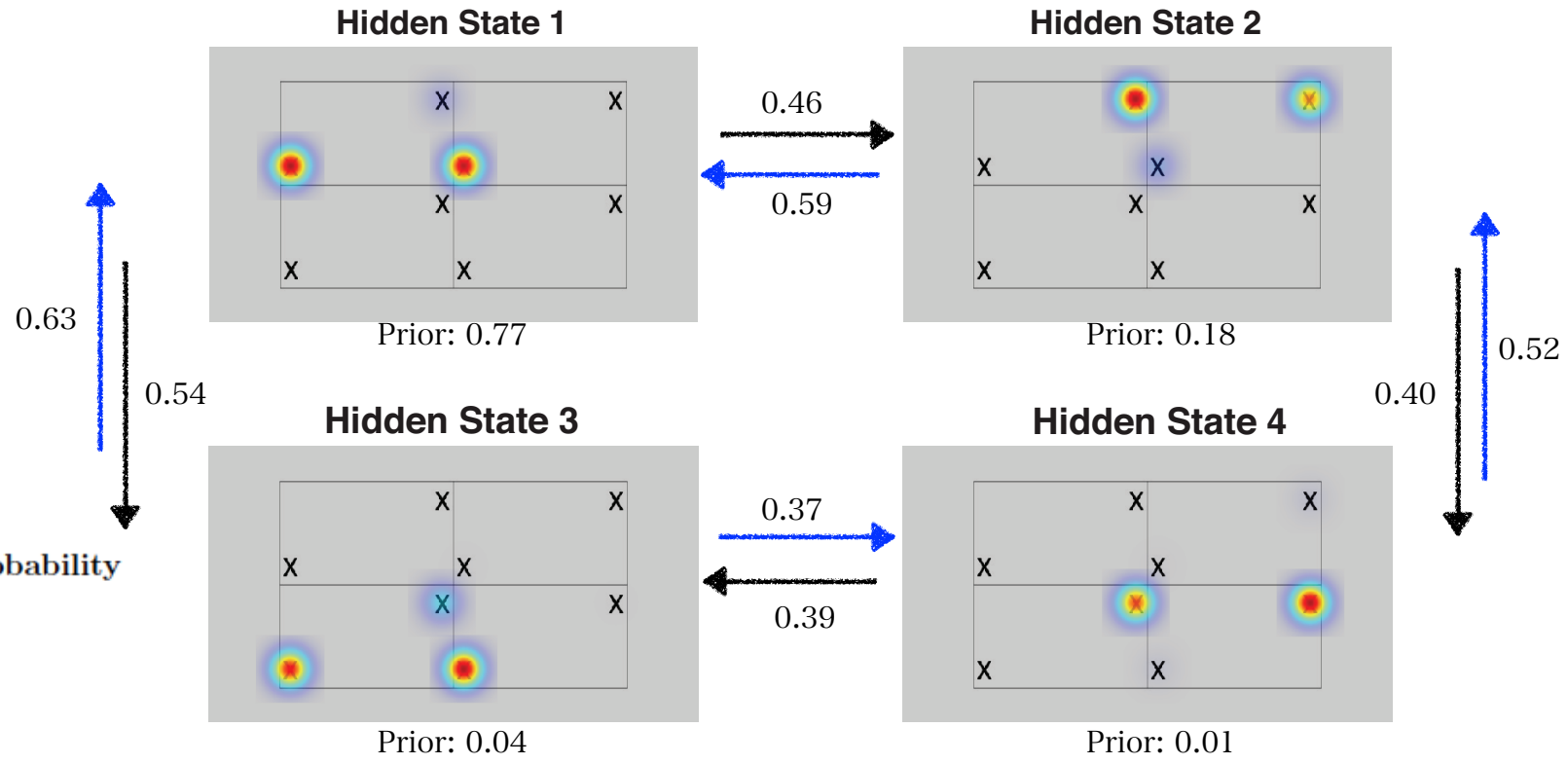


HMM in normal-form games

1. Strong saliency effect
2. Information structure

Action x Role

3. No diagonal transfer
4. "Hypothetical play"



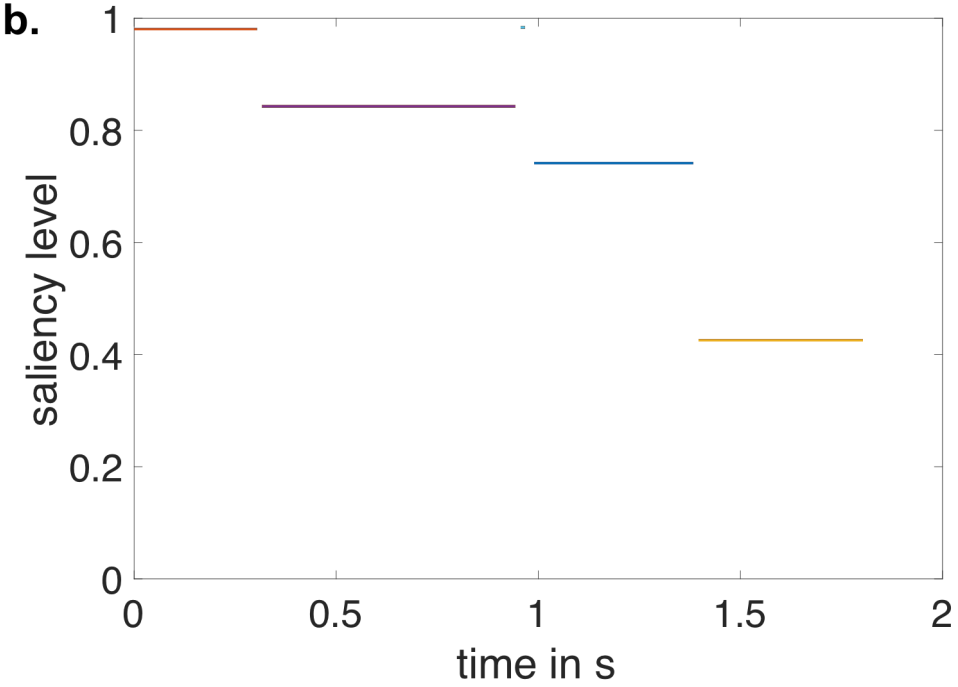
	Top	Bottom	Decision Probability
Hidden State 1	0.99	0.01	0.05
Hidden State 2	0.98	0.02	0.01
Hidden State 3	0.09	0.91	0.07
Hidden State 4	0.05	0.95	0.01

Application 1: Locations games

Fixation Data

a.

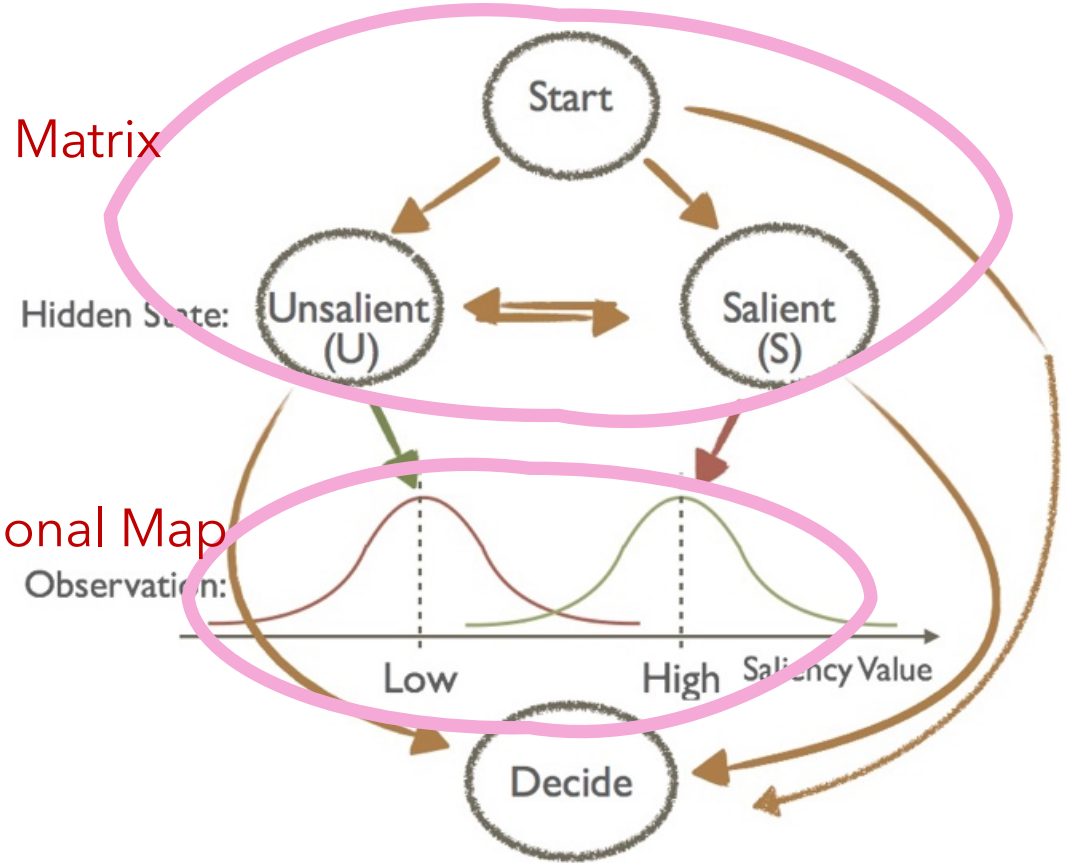
b.



Gaussian hidden markov model (gHMM)

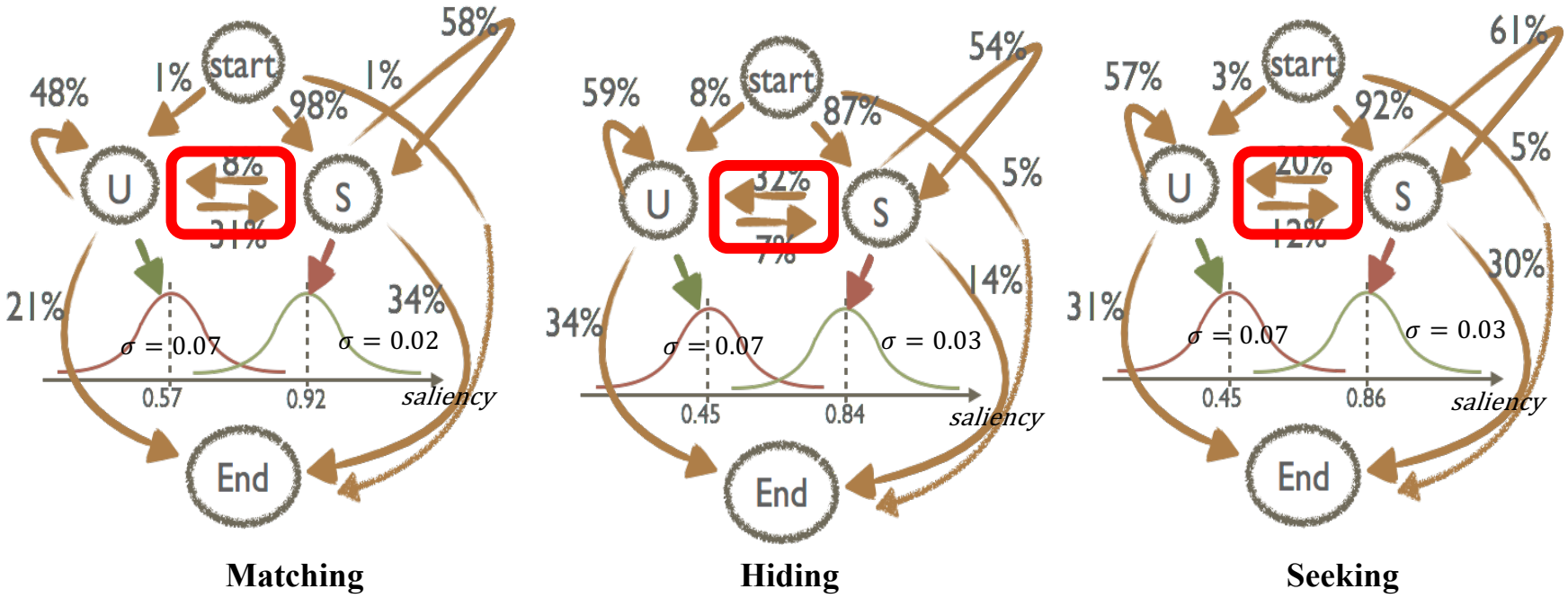
Transition Matrix

Observational Map



States	Saliency
Start	Start
S	0.9
U	0.3
S	0.7
U	0.4
Decide	Decide

Fitted Model



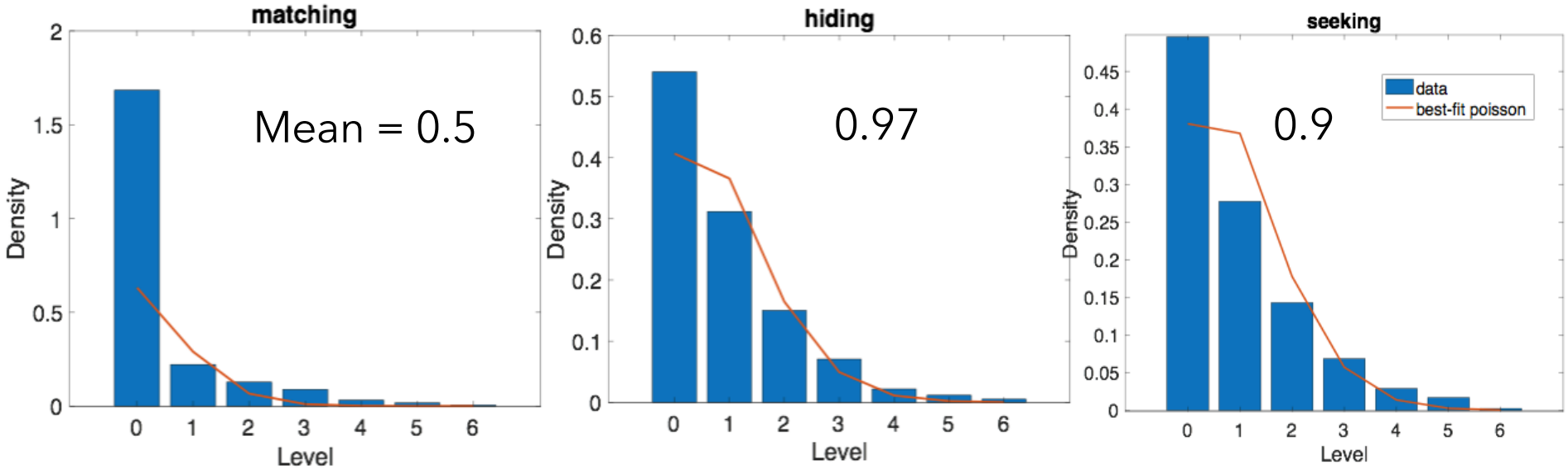
Matching **Hiding** **Seeking**

Estimate the model using a standard Baum–Welch algorithm

Gaze predicted strategic levels

- Levels are defined as transitions among hidden states along the direction of the best response function.

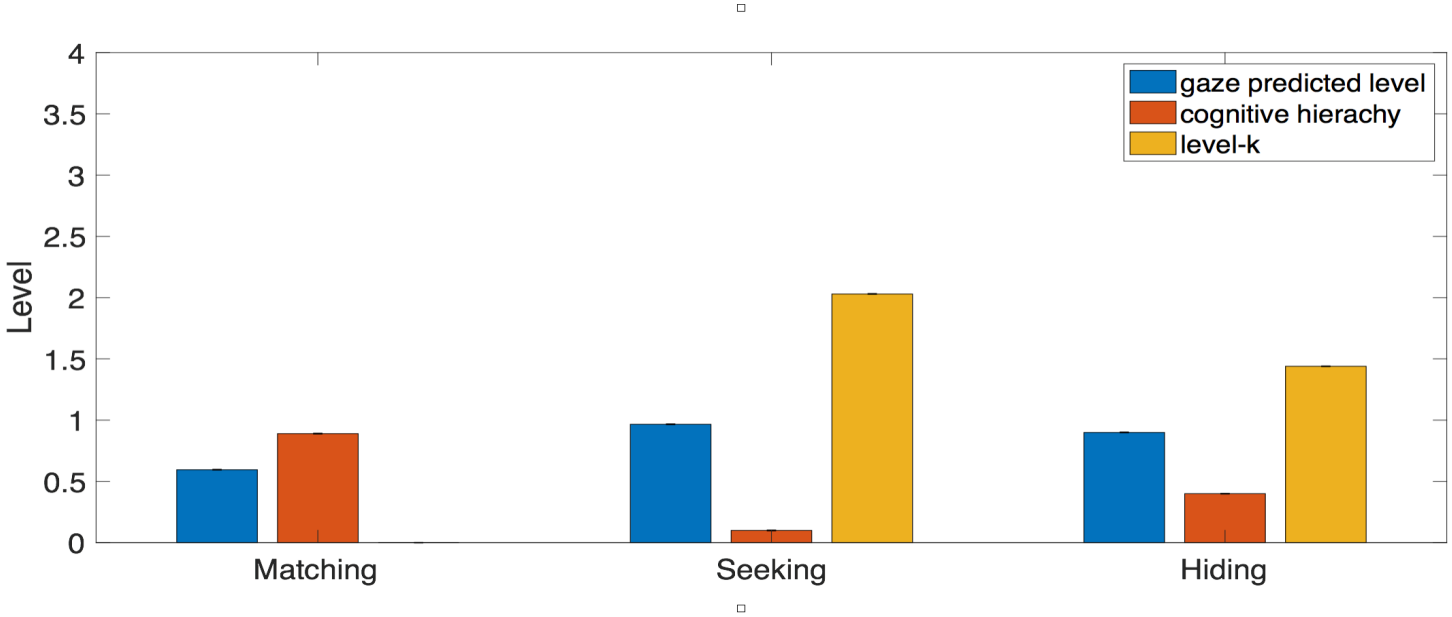
Example: { S, U , S}, level 2, { S, U}, level 1, { S}, level 0



Gaze-predicted strategic levels

Advantages:

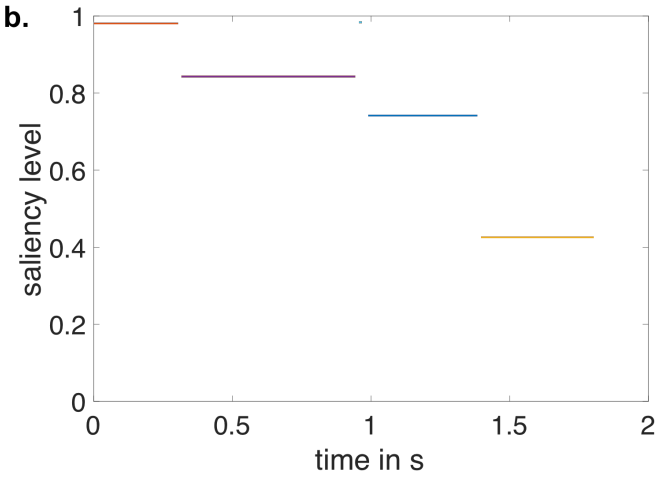
- It is directly defined on mental states transitions
- No assumption for level zero behaviors
- Defined on a trial basis instead of individual basis
- Connects well to the traditional definition for validations



Continuous-time gaussian hidden markov model (ctHMM)

a.

b.



Discrete Emission: U -- S – U – S – End

Continuous Emission: U -.2s- S -.1s- U -.4s- S -.7- End

- Include fixation duration time to the HMM model
- Now, the observation matrix are known!
- Need to modify: the hidden transition matrix changes from P to P(t).
- $P_{ij}(t)$: at each time point, condition on that I am at i state, the probability I will transit to j state.

Use cgtHMM to predict time pressure effect

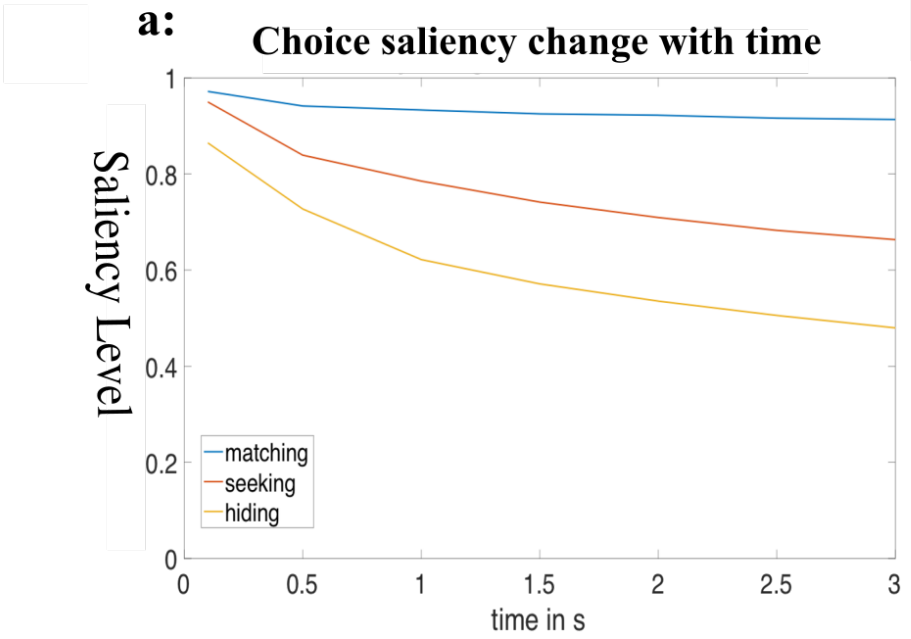
State transitions: U, S, U, S, S, U, End

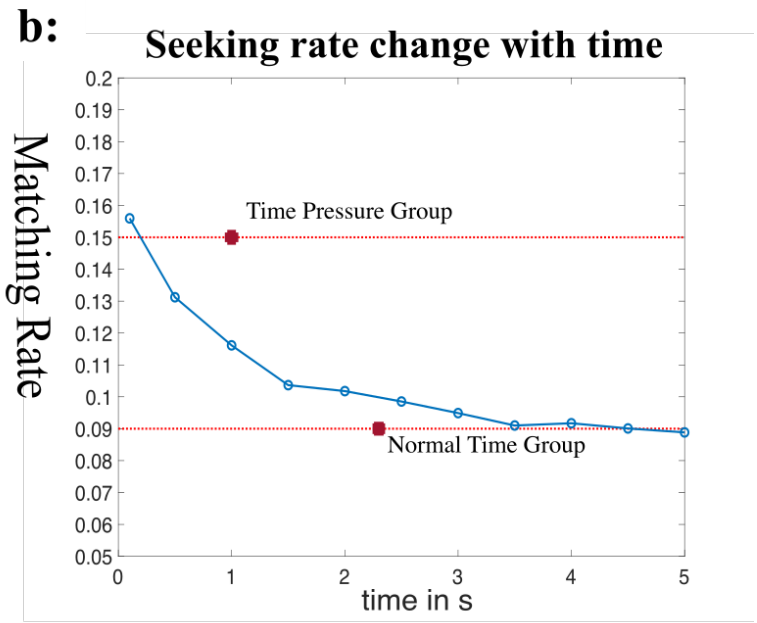
Time in s: 0.3, 0.4, 0.5, 0.3, 0.2, 0.4, End

Hard Stop

Natural Stop

Force a Choice





Conclusion

Proposed a new method, HMM, to dynamically model eye-tracking data.
1. Easy to generalize and estimate. 2. Noise resistant and learns principle components.

Two applications:

1) In normal form games, discrete action space, information space: payoff and actions.

    Learned that people do levels of reasoning from a common start point

2) In location games, continuous action space, information space: non-neutral frame/images without payoff.

    Still see a transitional effect and strong saliency effect.

HMM induces a new system of levels that have many advantages.

HMM can further incorporate duration time and make predictions about time effect.