# Point process latent variable models of larval zebrafish behavior

Anuj Sharma Columbia University\* Robert E. JohnsonFlorian EngertHarvard UniversityHarvard University

\*Anuj is currently a research engineer at Imagen Technologies

Scott W. Linderman Columbia University

#### Why larval zebrafish behavior?

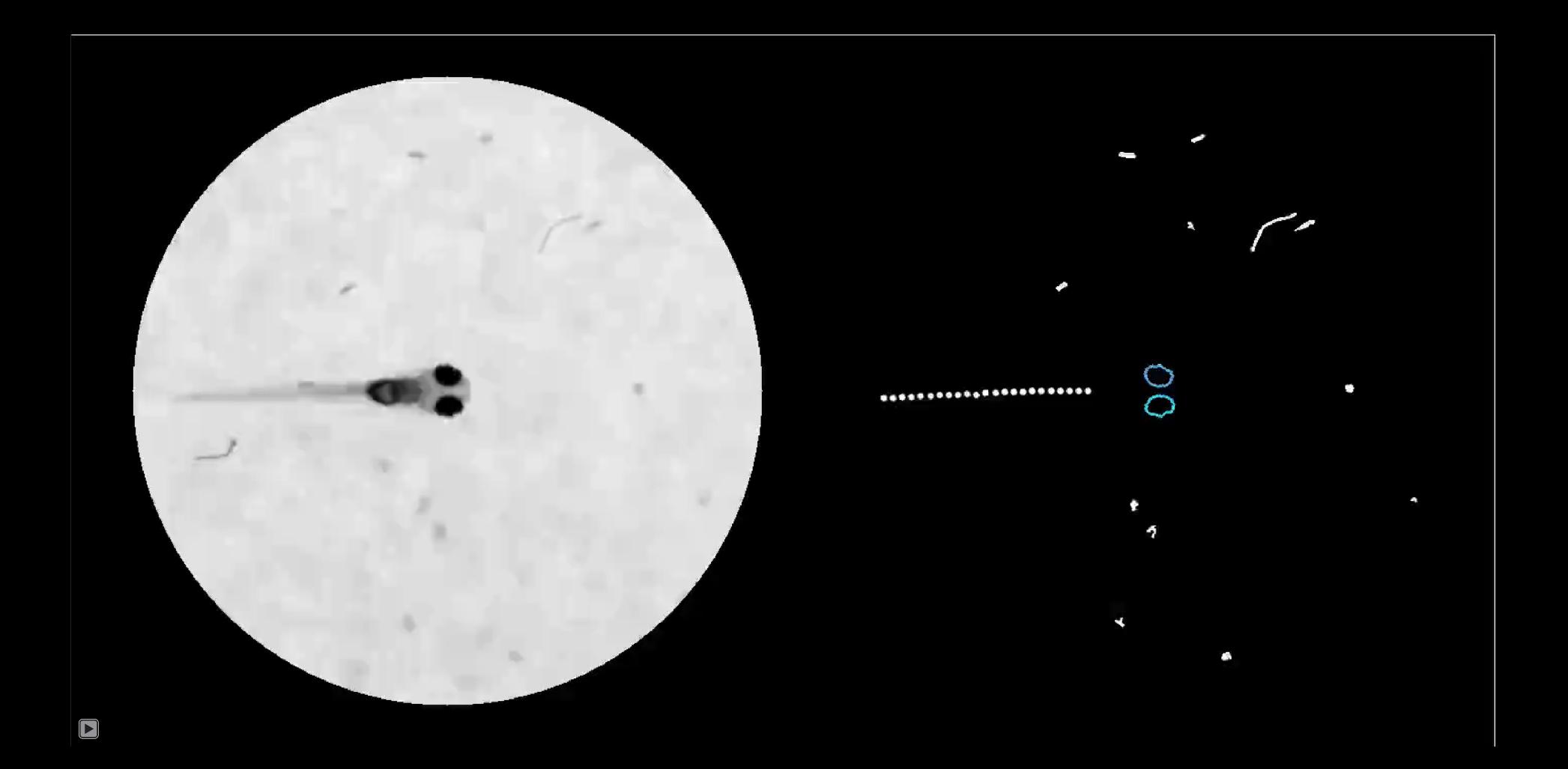


### to understand its behavioral outputs.

To understand the computations of the nervous system, we need



#### Real recording of a freely behaving larval zebrafish





#### **Key questions**

**Q1**: How should we characterize types of swim bouts?

#### **Key questions**

Q2: What dynamics govern how swim bouts are sequenced together over time?

- **Q1**: How should we characterize types of swim bouts?

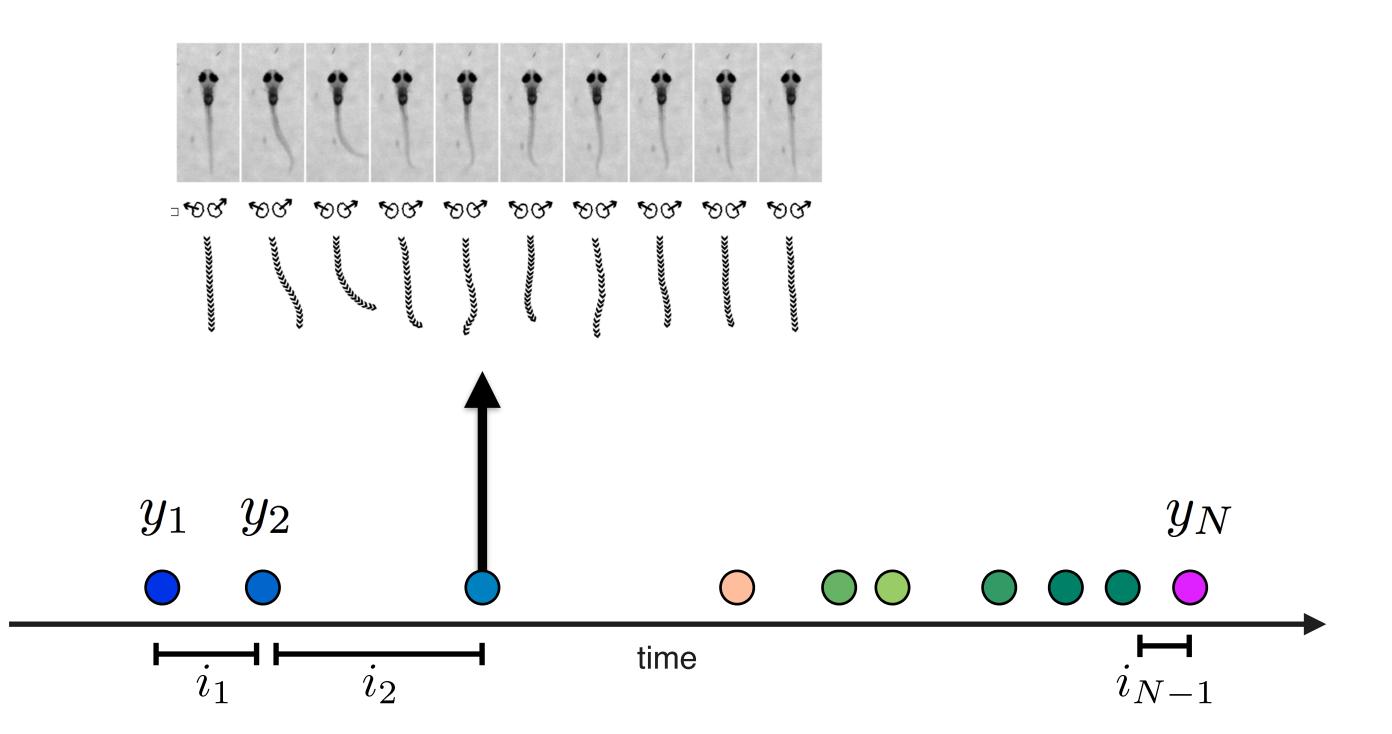
#### **Key questions**

**Q2**: What dynamics govern how swim bouts are sequenced together over time?

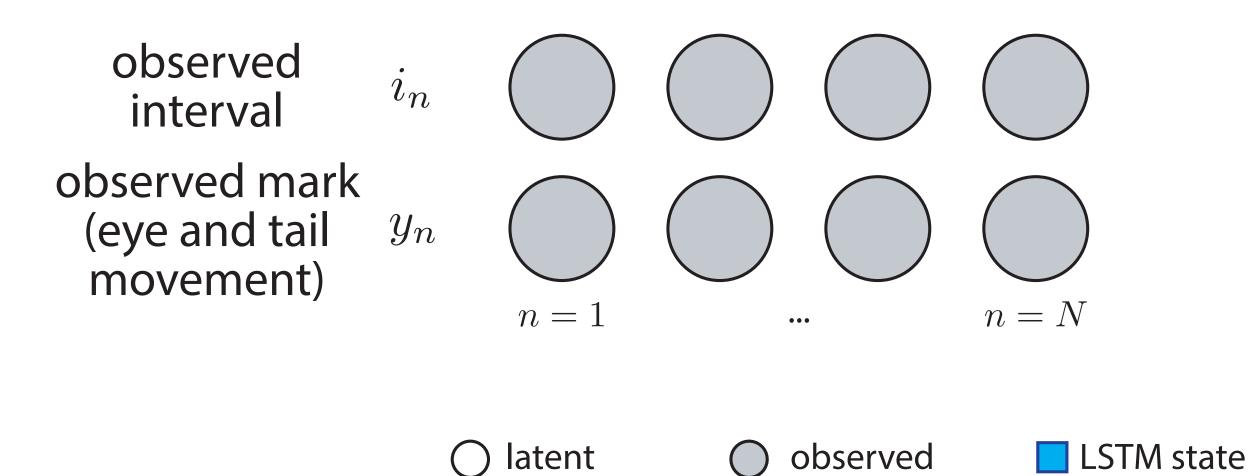
like hunger?

- **Q1**: How should we characterize types of swim bouts?
- Q3: How are these dynamics modulated by internal states

#### Modeling larval zebrafish behavior as a marked point process

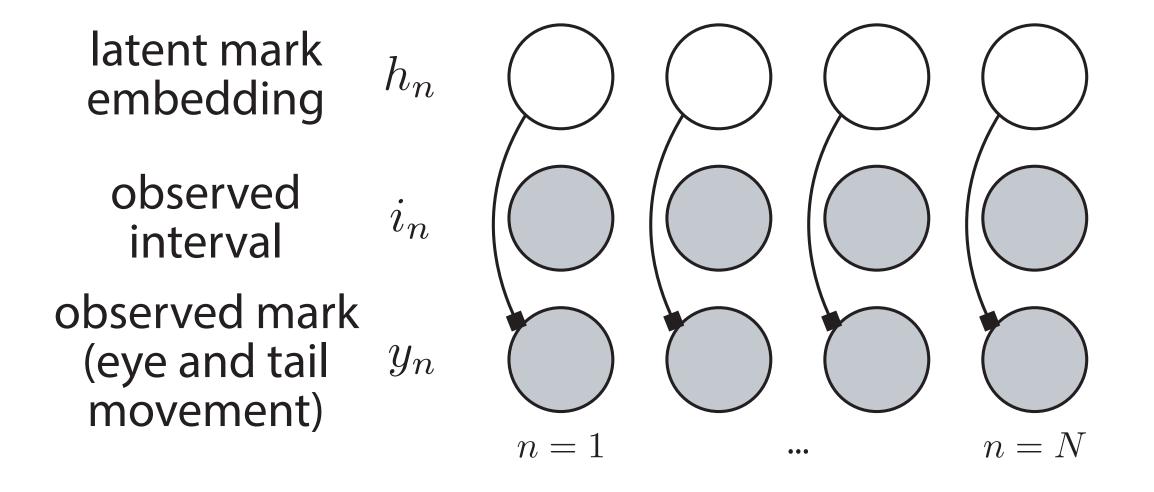


**Full Generative Model** 



ate -> dependency -= neural net dep. -- clique

**Full Generative Model** 



 $\bigcirc$ 

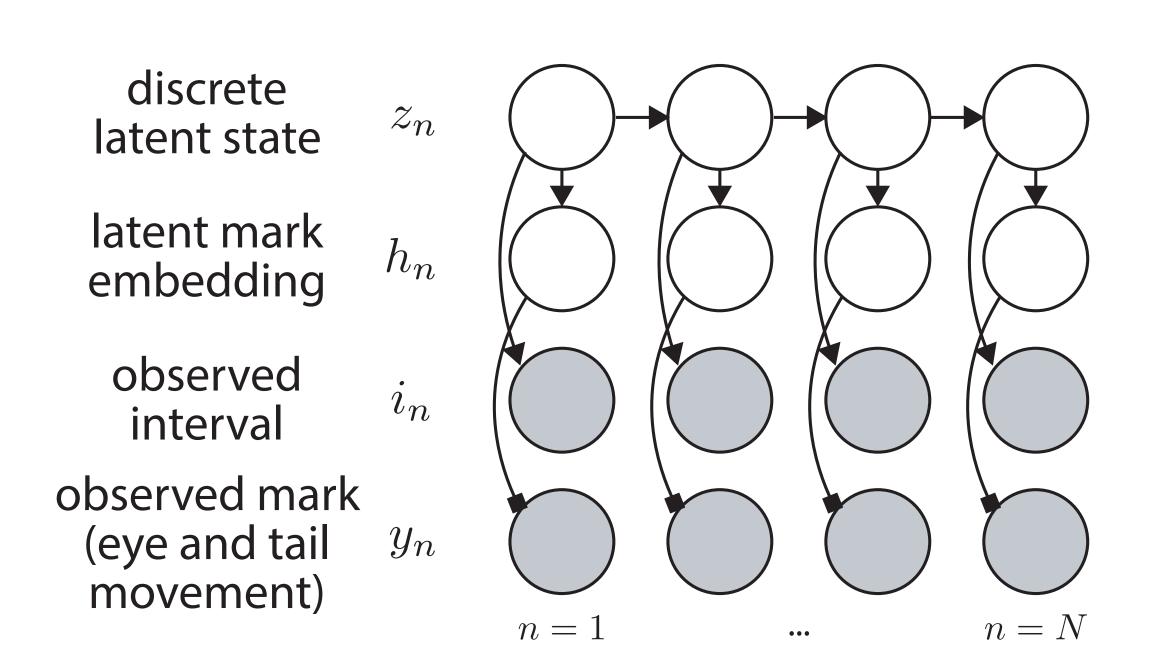


■ LSTM state → dependency — neural net dep. — clique

**Full Generative Model** 

observed

 $\bigcirc$ 

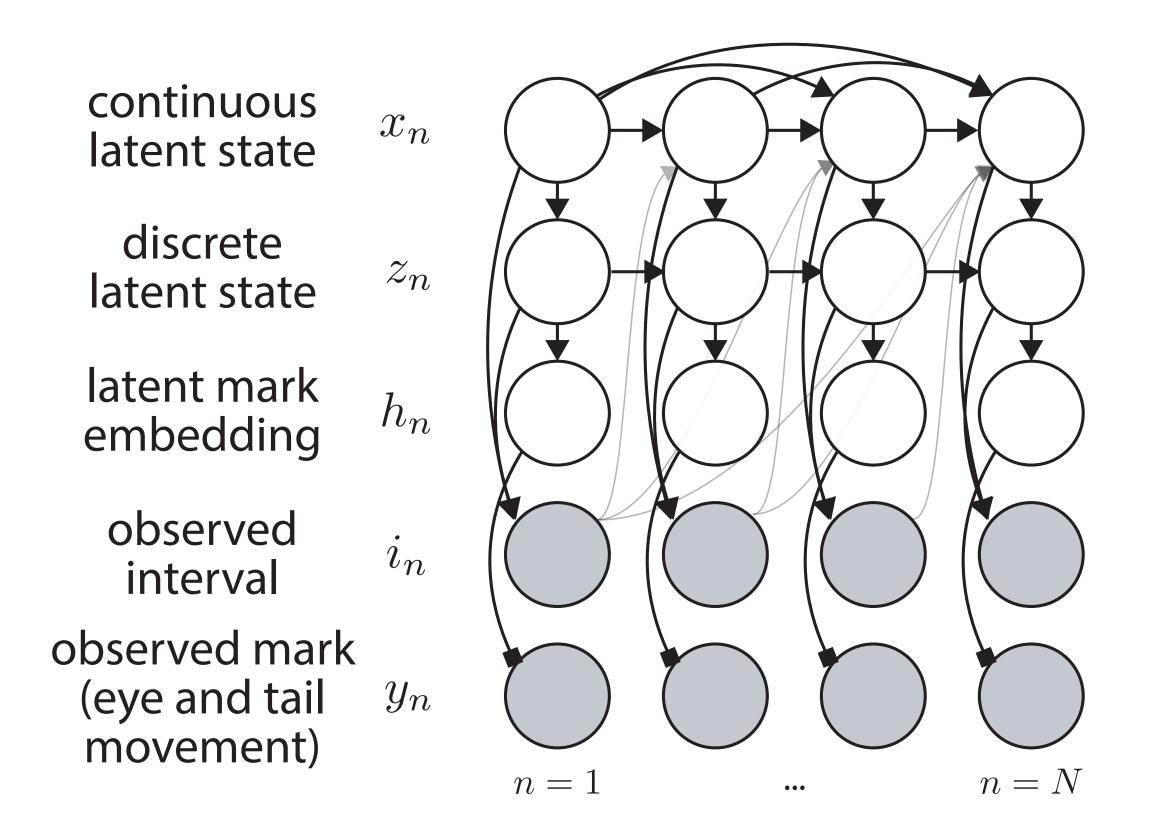


latent

 $\bigcirc$ 

■ LSTM state → dependency — neural net dep. — clique

#### **Full Generative Model**



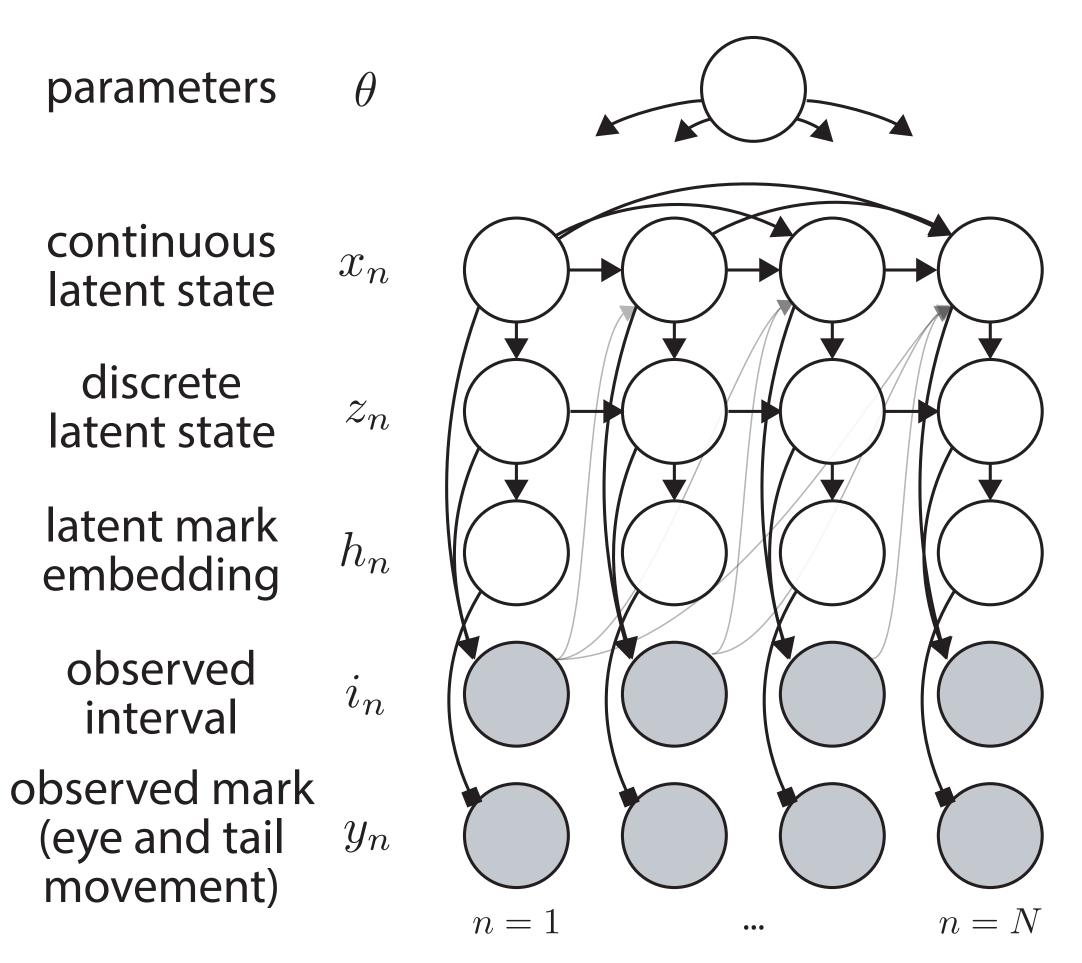
 $\bigcirc$ 





ate -> dependency -= neural net dep. -- clique

#### **Full Generative Model**

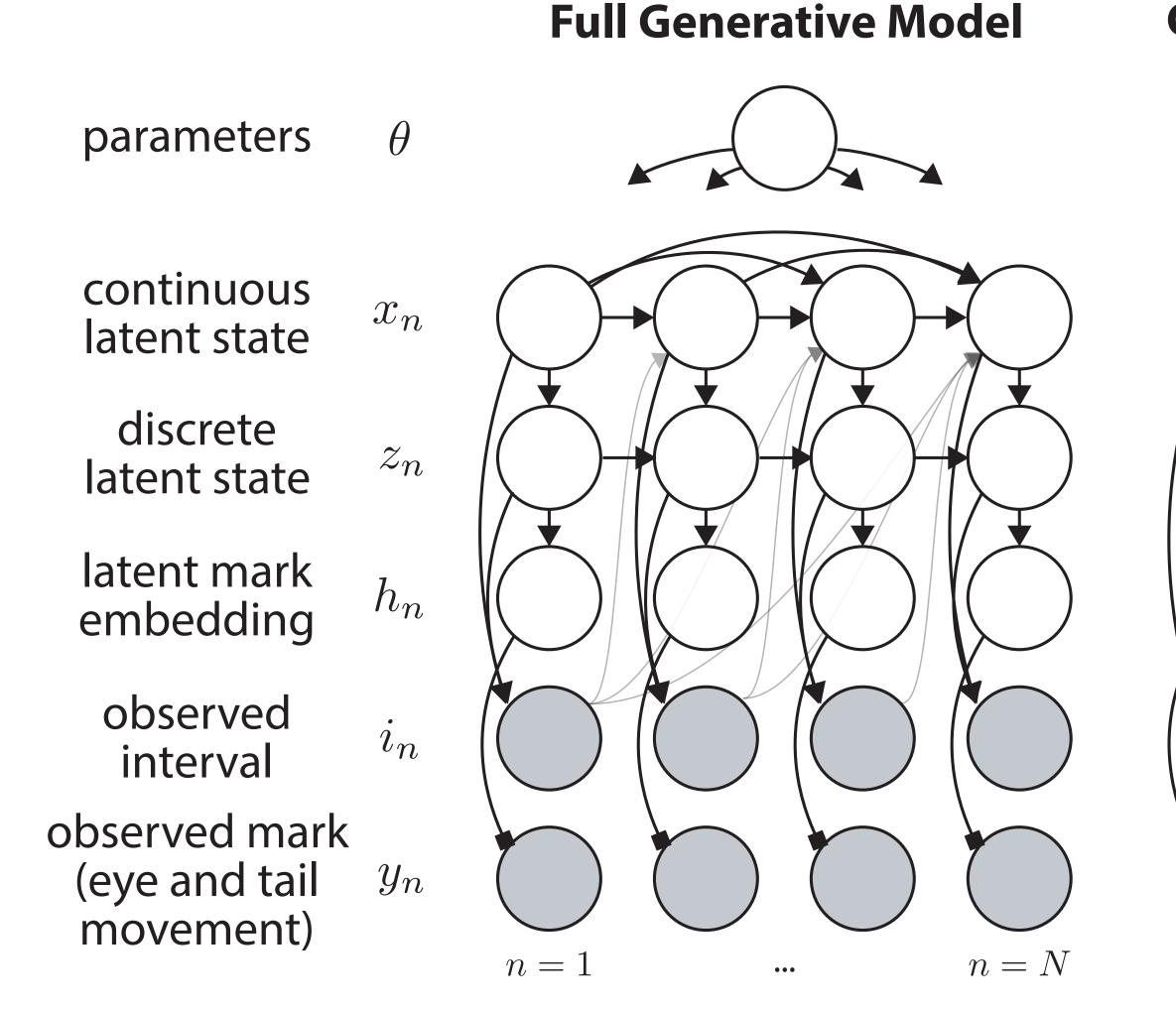


 $\bigcirc$ 





ate -> dependency -= neural net dep. -- clique

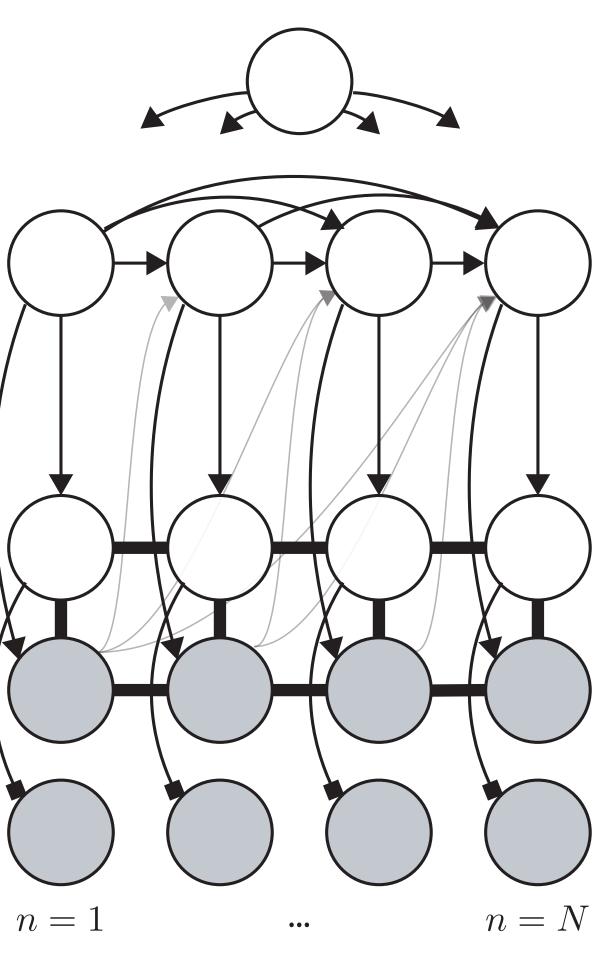




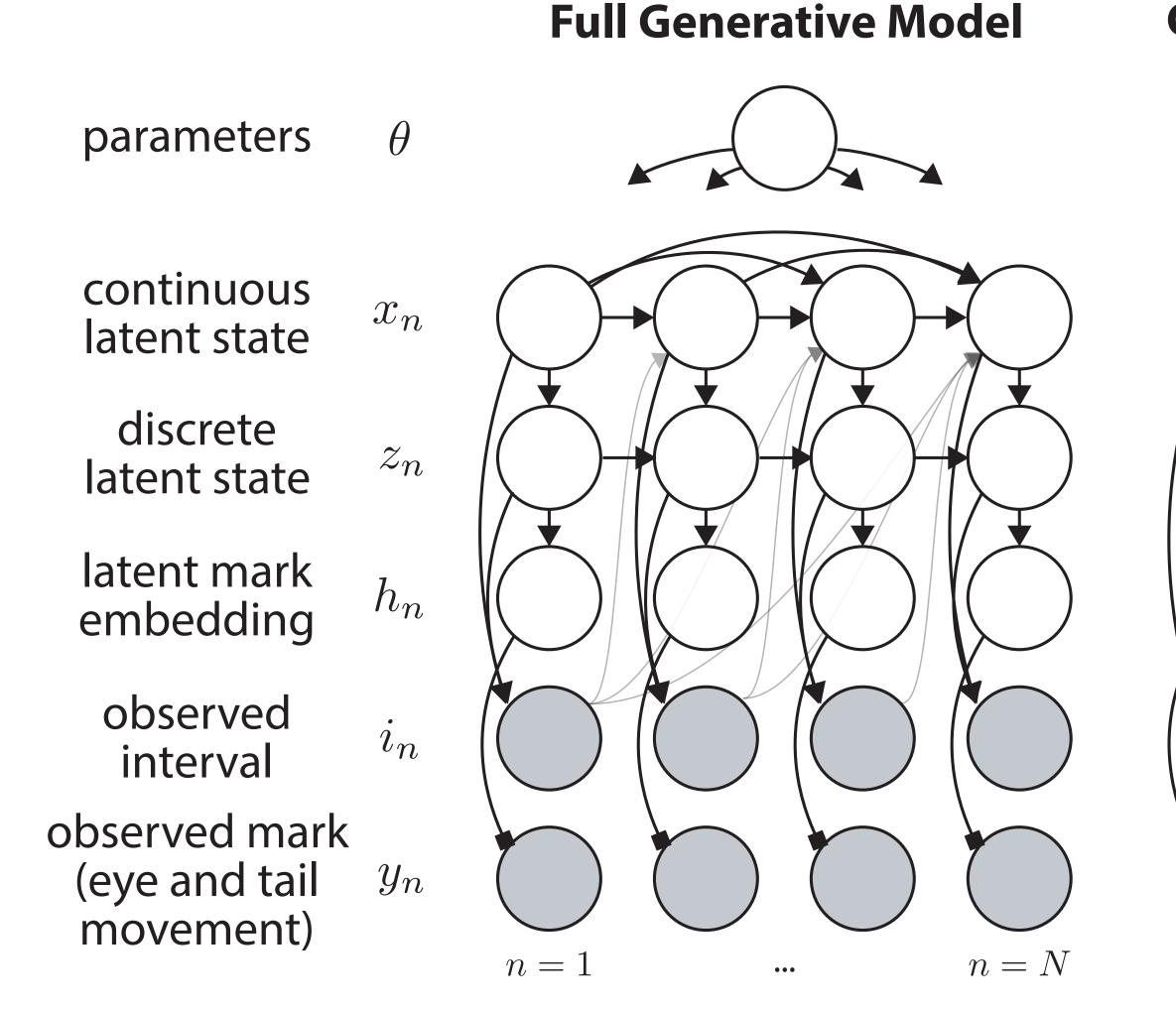
 $\bigcirc$ 



**Collapsed Generative Model** 



ite -> dependency -= neural net dep. -= clique

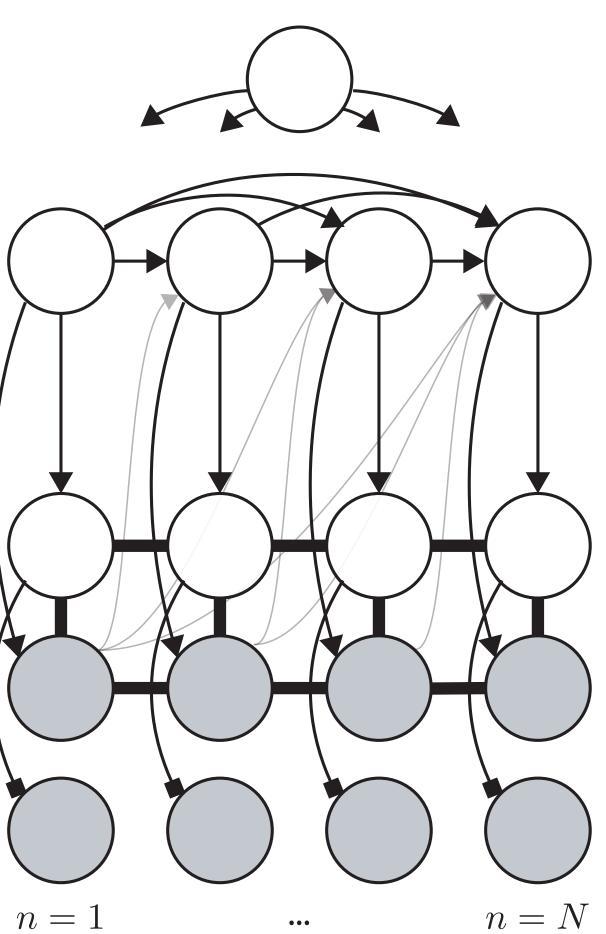




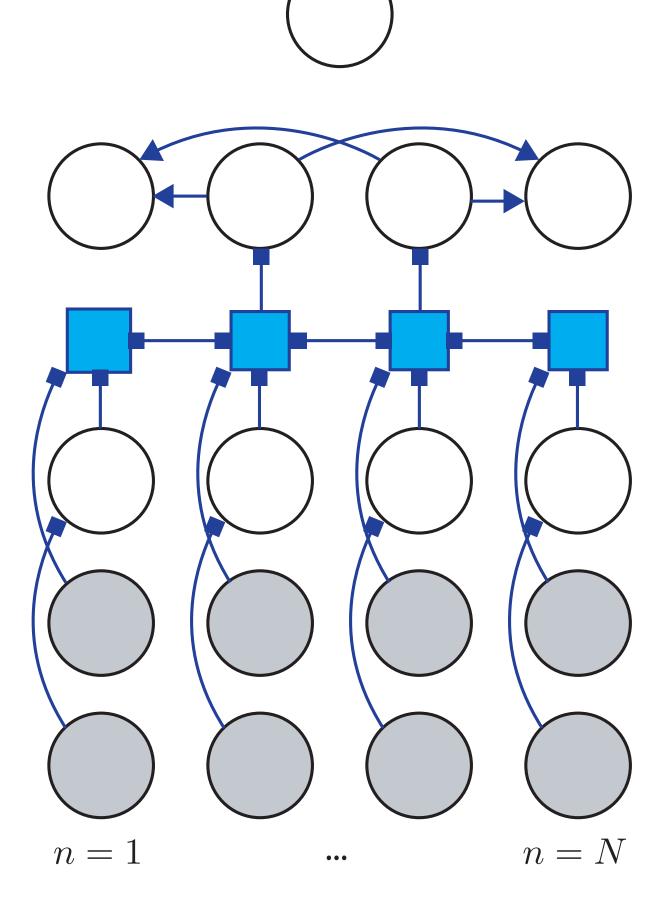
 $\bigcirc$ 







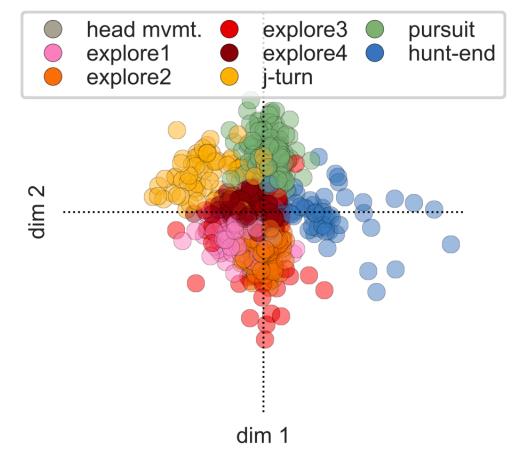
**Bidirectional LSTM Recognition Network** 



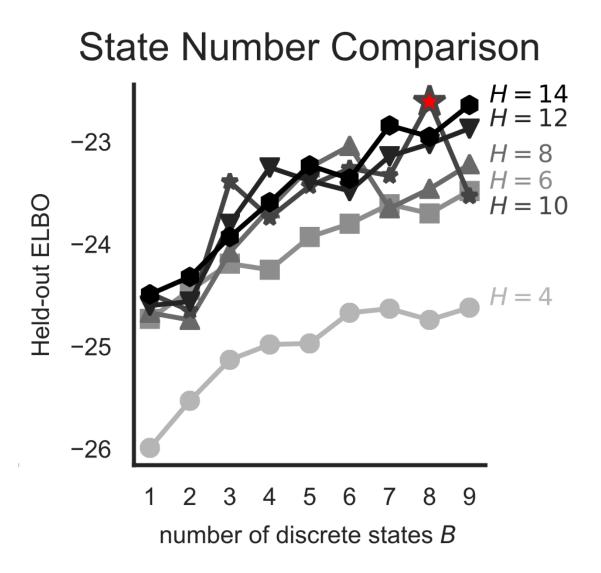
## **PPLVMs help answer key questions**

A1: Bouts cluster into discrete types in low-d latent space.

#### Inferred Clusters & Embedding



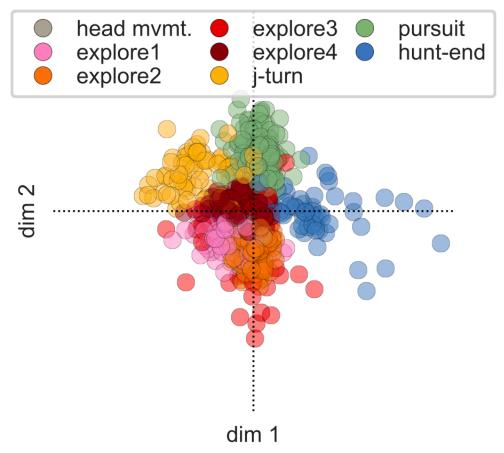
A1': Held-out likelihood offers a quantitative metric for comparing representations.



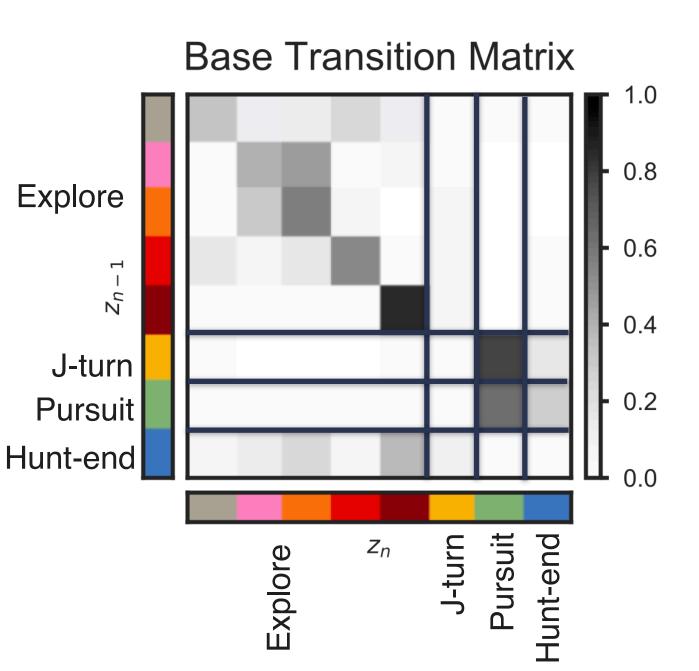
# **PPLVMs help answer key questions**

A1: Bouts cluster into discrete types in low-d latent space.

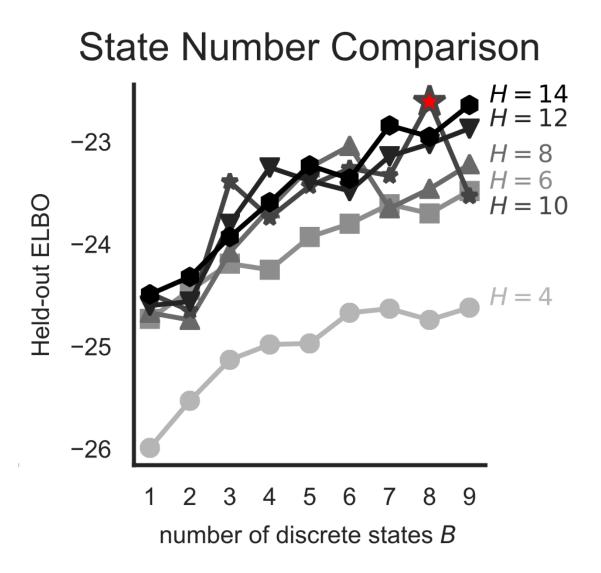
#### Inferred Clusters & Embedding



A2: Bout types follow characteristic transition patterns between hunting and exploring.



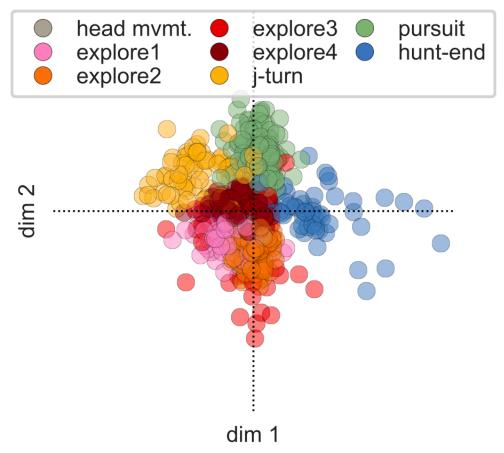
A1': Held-out likelihood offers a quantitative metric for comparing representations.



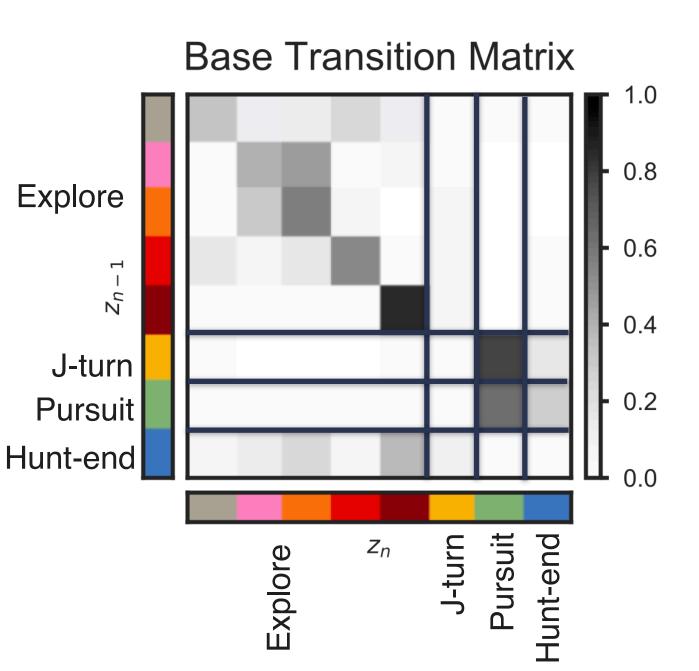
# **PPLVMs** help answer key questions

A1: Bouts cluster into discrete types in low-d latent space.

#### Inferred Clusters & Embedding



A2: Bout types follow characteristic transition patterns between hunting and exploring.



A1': Held-out likelihood offers a quantitative metric for comparing representations.

A3: These transition patterns change over time as a function of hunger.

interval (s)

State Number Comparison -23 Held-out ELBO -24 -25 -26 6 7 8 9 3 5 number of discrete states B hunt-end j-turn pursuit transition bias 000000 fed starved , which is the second state of the second stat time (min) time (min) time (min)

Extend our model to include

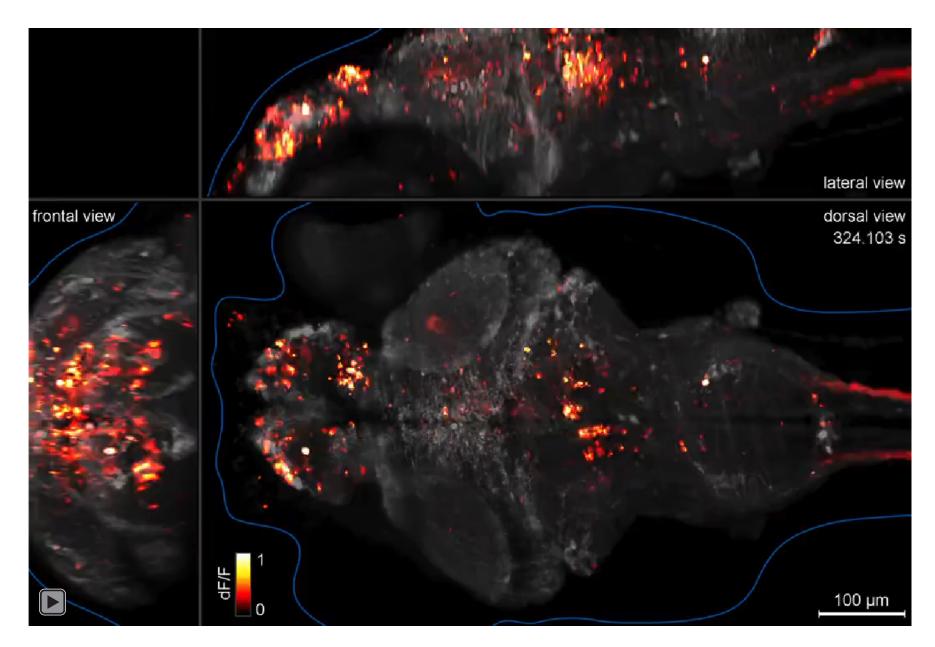
- Environmental dependencies (prey) locations, sizes, dynamics)
- Whole brain neural activity dynamics

Apply PPLVMs to other domains:

- Healthcare
- Social media
- Consumer behavior

Acknowledgements: Misha Ahrens (video), John Cunningham, Kristian Herrera (animations), Liam Paninski, Haim Sopolinsky (video), SWL: Simons Foundation SCGB-418011; FE: National Institutes of Health's Brain Initiative U19NS104653, R24NS086601 and R43OD024879, Simons Foundation SCGB-542973 and 325207

#### **Come to our poster!**



Ahrens et al (Nature Methods, 2013)