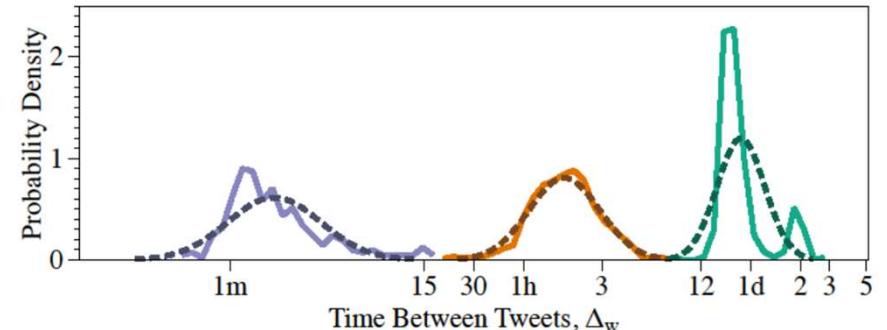
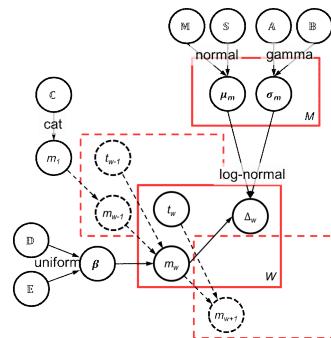
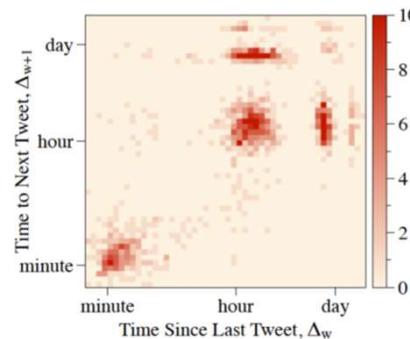


Exceptional service in the national interest



Estimating users' mode transition functions and activity levels from social media

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Social Media Modeling

We consider social media research as analogous to language modeling research: build a model to explain the data.

- Language models are likelihood estimators that support many tasks...
 - Translation
 - Automatic summary
 - Bot detection
- Social media models should support diverse tasks as well.
 - Electric power load prediction
 - Network traffic analysis
 - Disease spread modeling & forecasting
 - Market segmentation
 - Bot detection
 - Clustering

Temporal Analysis of Social Media



- This work focused on modeling Twitter post time patterns
 - Post times & post intervals
 - Changing patterns throughout the day
 - Diversity among users
- Temporal model presented is in the context of broader social media analysis
 - Temporal properties
 - Text analysis
 - Social network structure

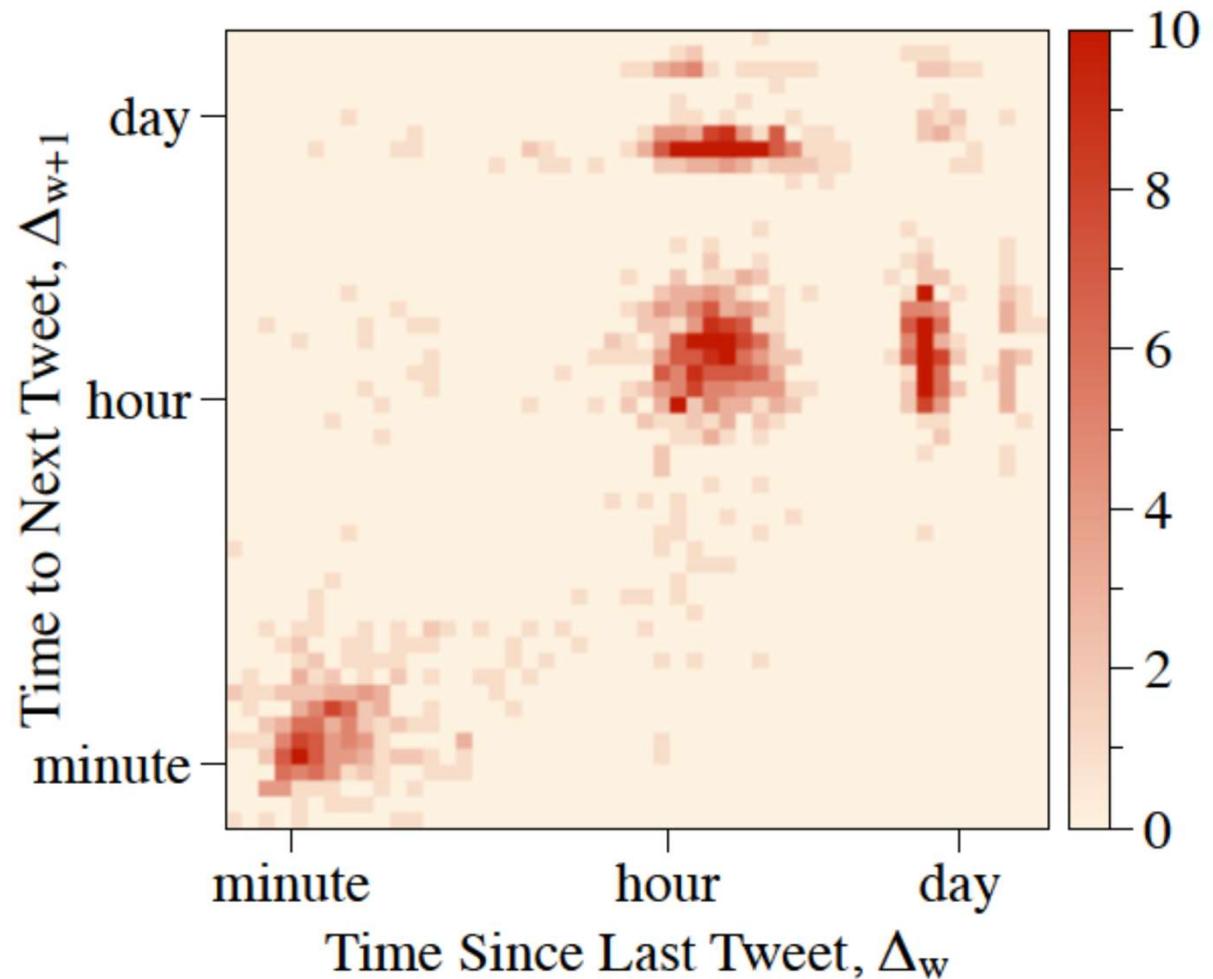
Developing a New Model

- Observed phenomenon of “modal” behavior & formed hypothesis
- LDA suggested discrete variable chosen in a user-specific mixture, influencing likelihood of observations.
 - Topics -> Activities (Modes)
 - Topic Mixture -> Mode transition function
 - Words -> Intervals
- Final model structure isn’t recognizable as LDA and isn’t trained the same way. Other point processes also could be used.

Observation

Many users appear to have discrete “modes” of behavior.

When they are excited, they tend to tweet rapidly for a while. When they are sedate, they tend to tweet at a lower frequency for several messages.

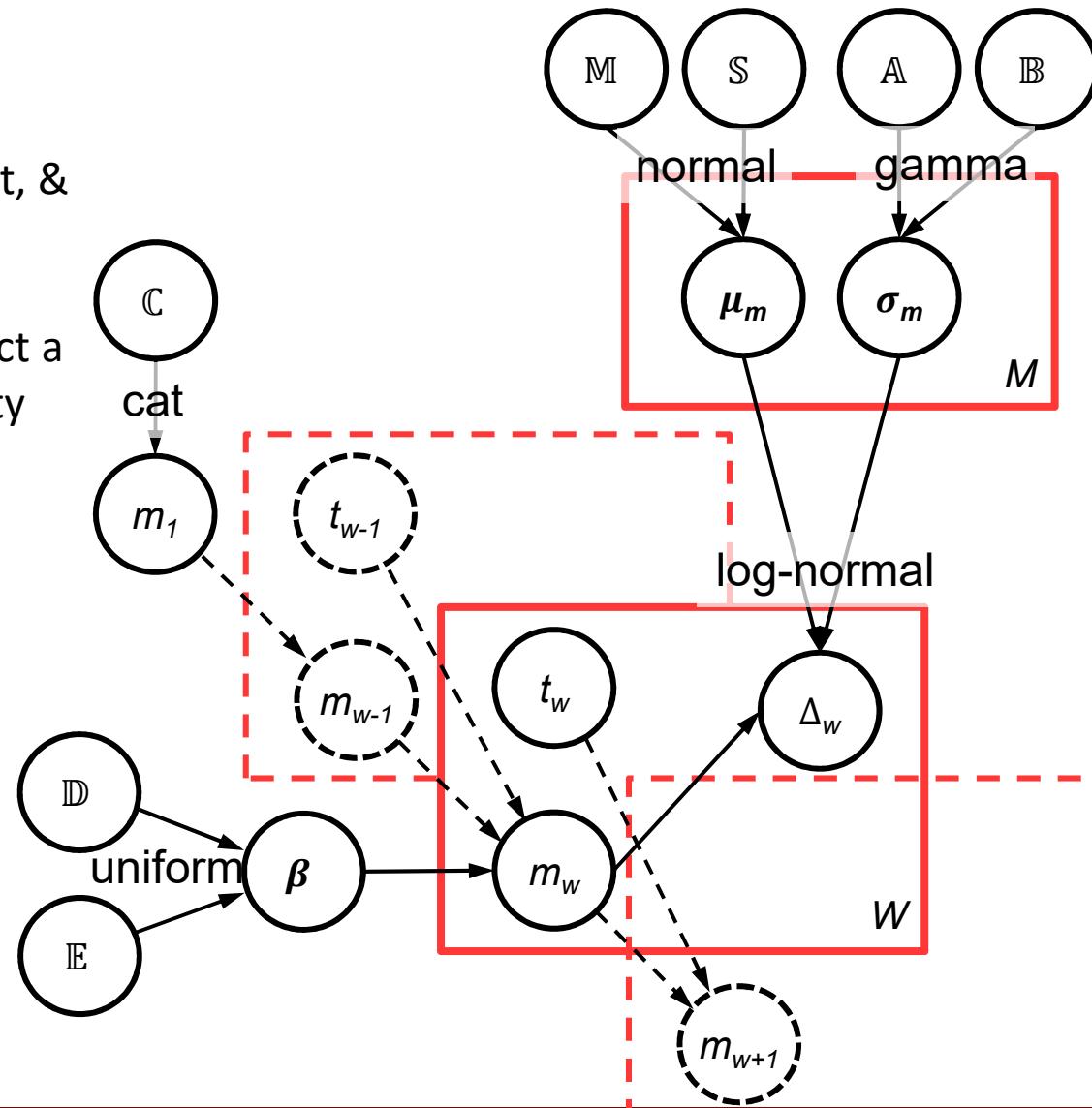


Hypothesis

We'd like to

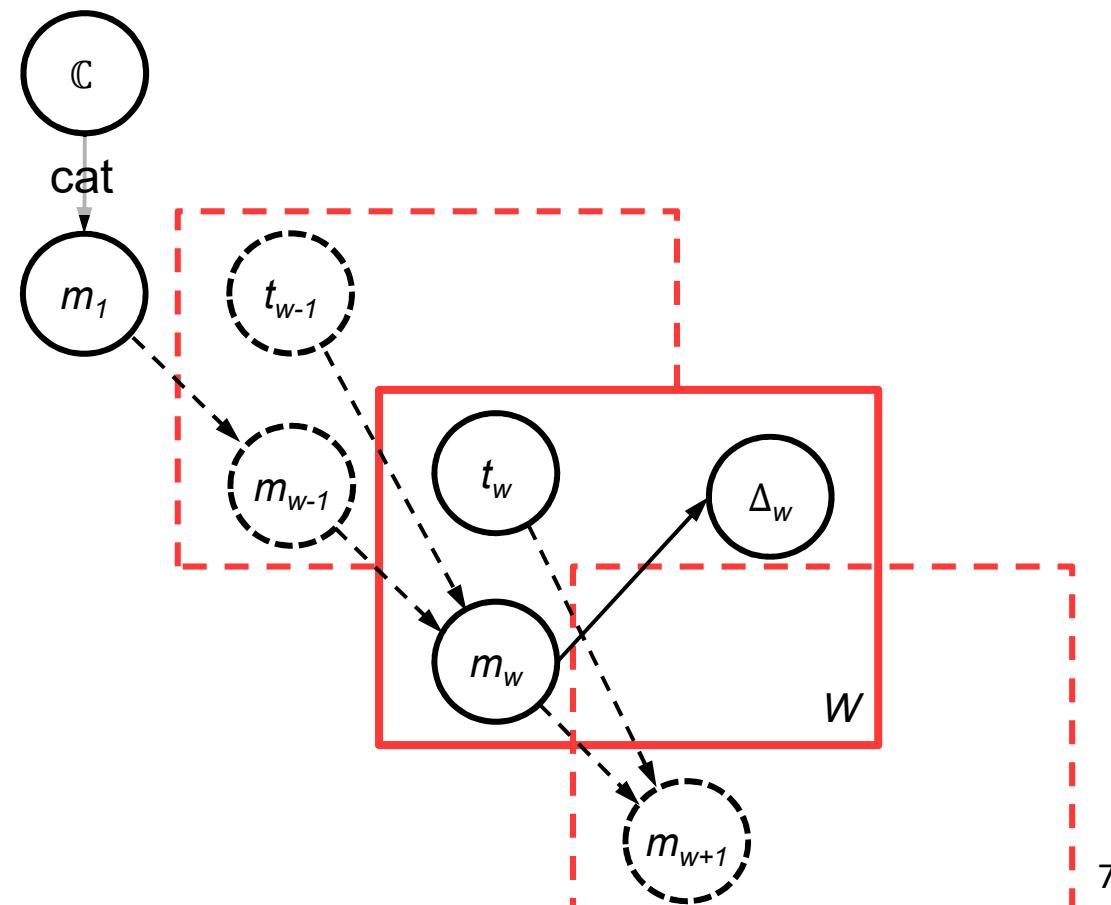
- formalize this pattern,
- quantify our confidence in it, &
- apply this insight.

To do this we chose to construct a Bayesian conditional probability model relating unknowns to observables.



Constructing the Model

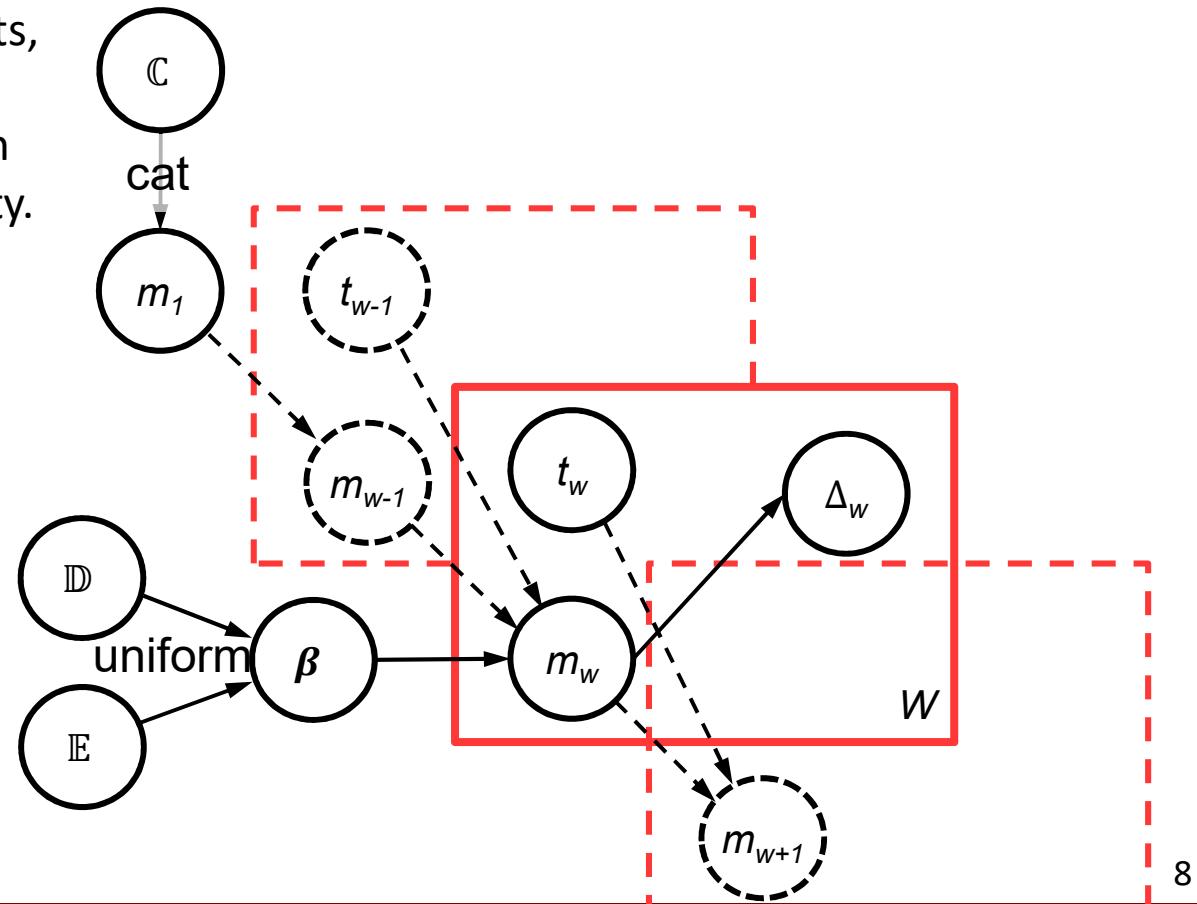
Consider a hidden Markov model, with a user that proceeds through different states of excitation.



Constructing the Model

We do not expect the current state to be sufficient.

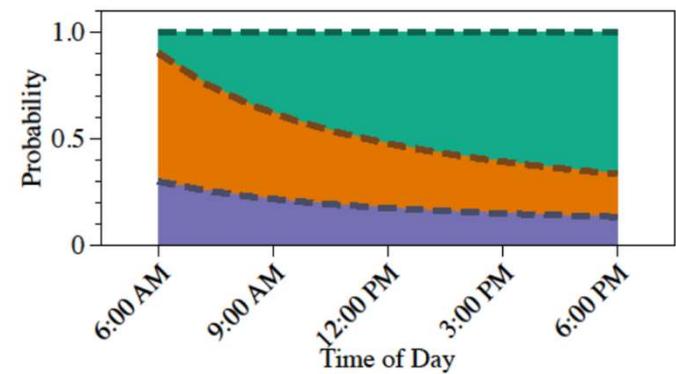
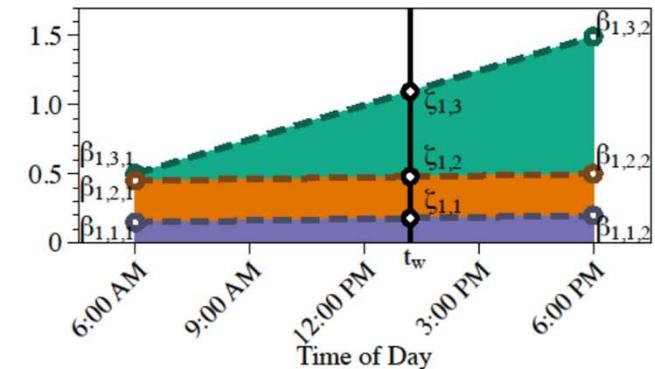
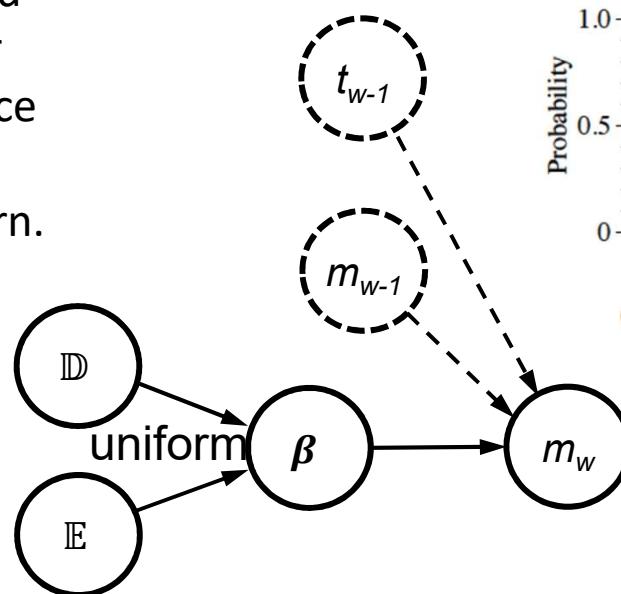
Many people have daily habits, and we extend the model to account for the time of day in the state transition probability.



Testing

The state transition probability is a function of the current mode, and the relative proportion of linear functions of time of day.

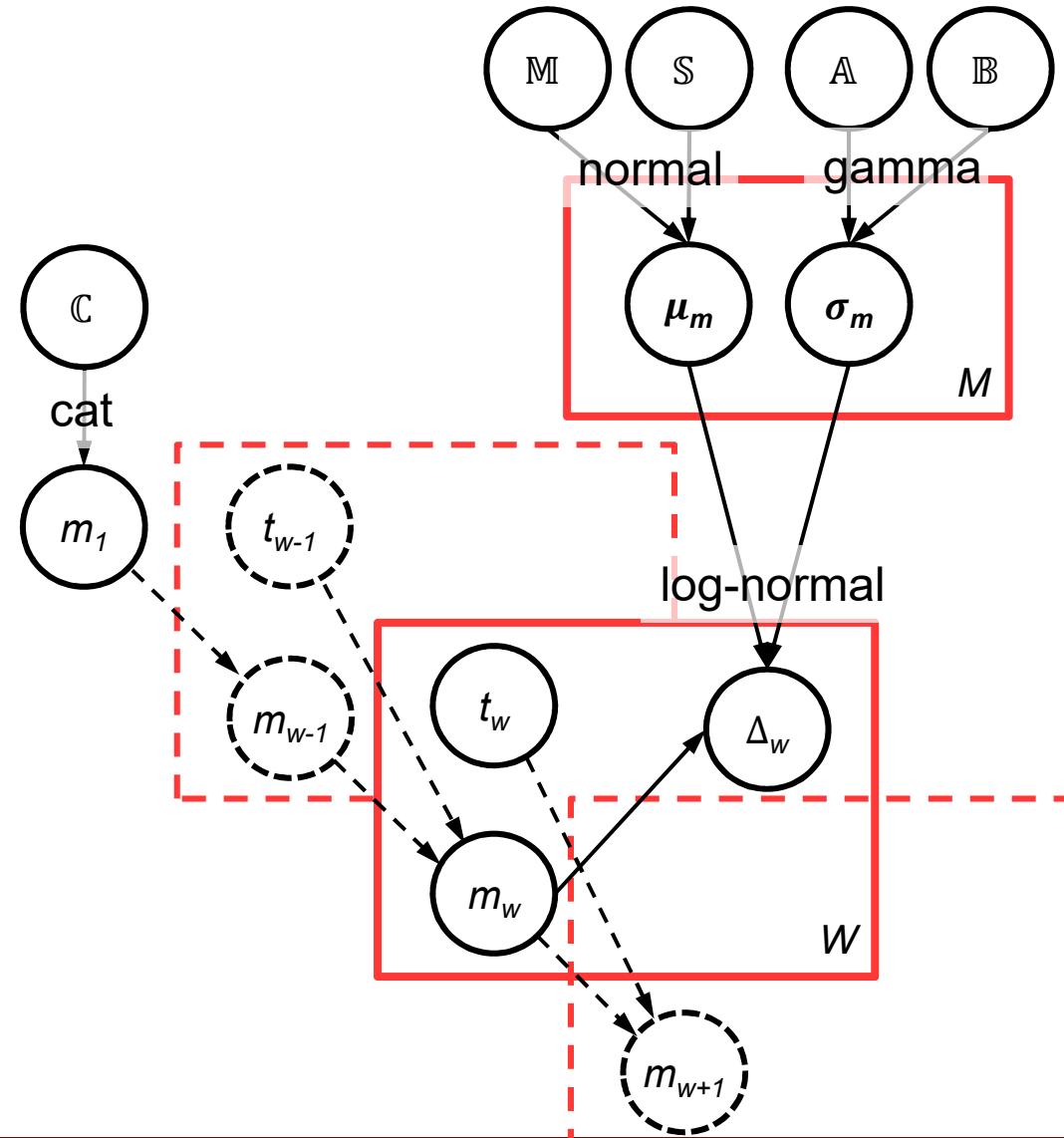
More complex functions could be used. This one provides for some nonlinear behavior (once normalized) and has a small number of parameters to learn.



Constructing the Model

The likelihood of interval observations is a parameterized function of the mode.

Log-normal distributions are used with k unknown means & standard deviations.



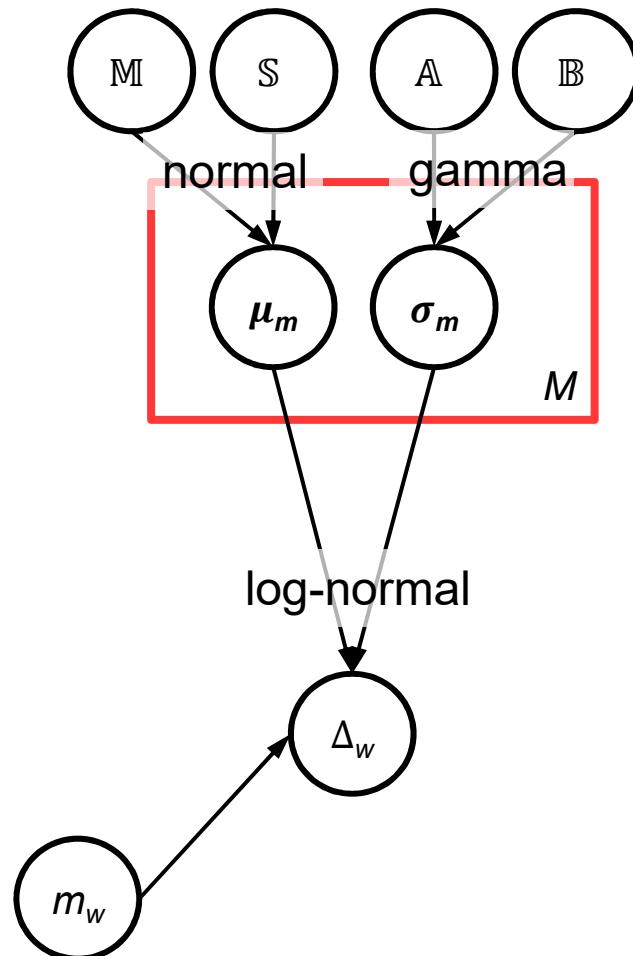
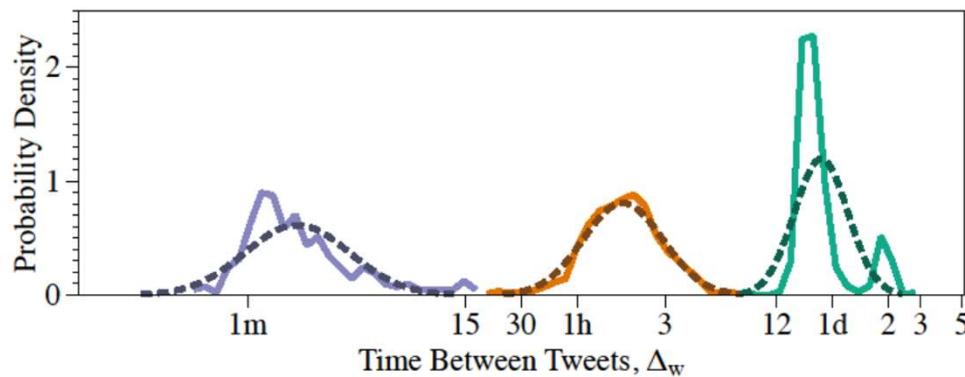
Testing

Log-normal was chosen after observation of interval distributions in several domains of human activity.

- Instant messenger traffic, Twitter
- Facebook
- Video attention

Mixture model fits data except...

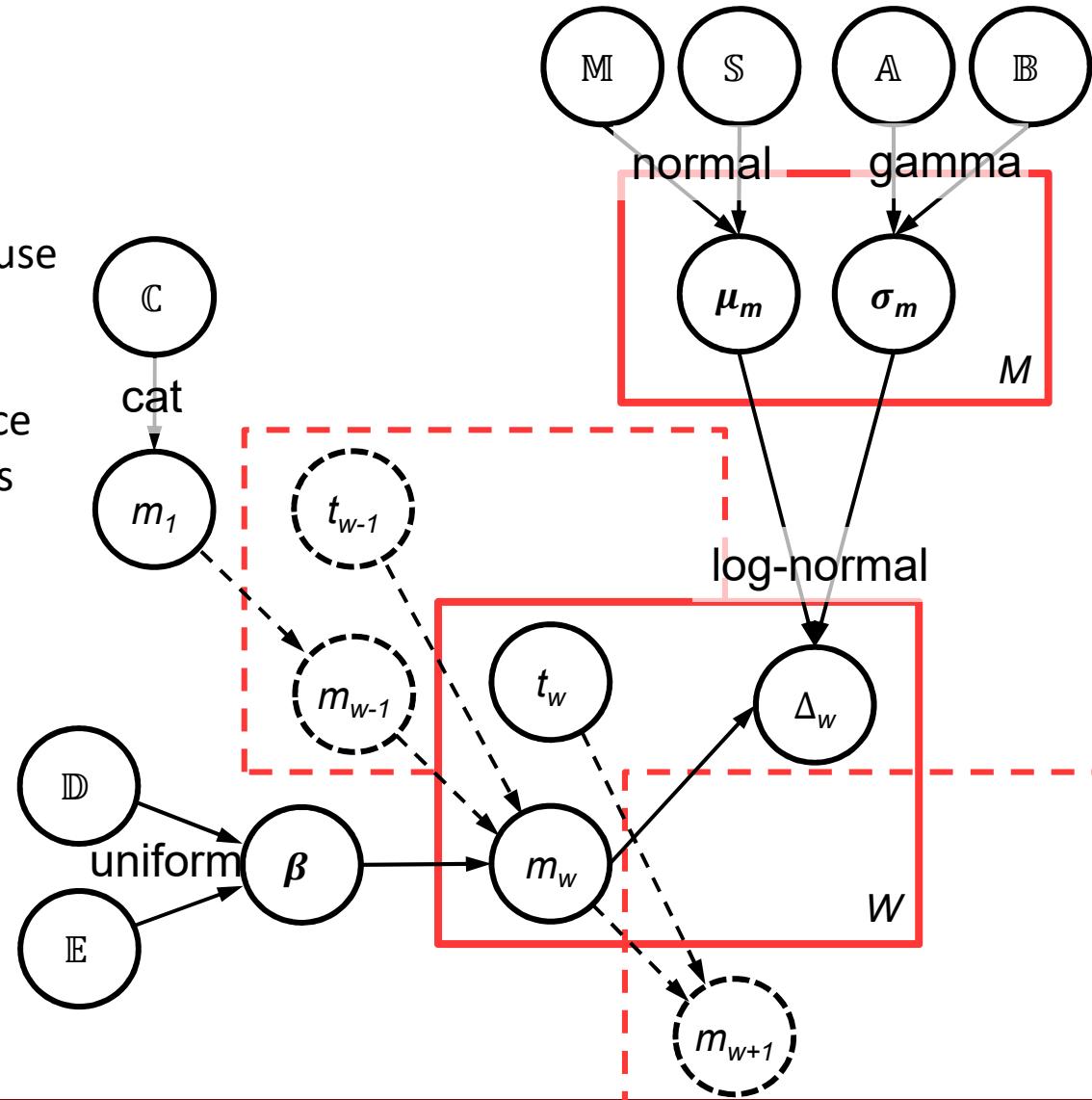
- Very low energy modes are underrepresented
- Mode-to-mode sequence is not arbitrary



Constructing the Model

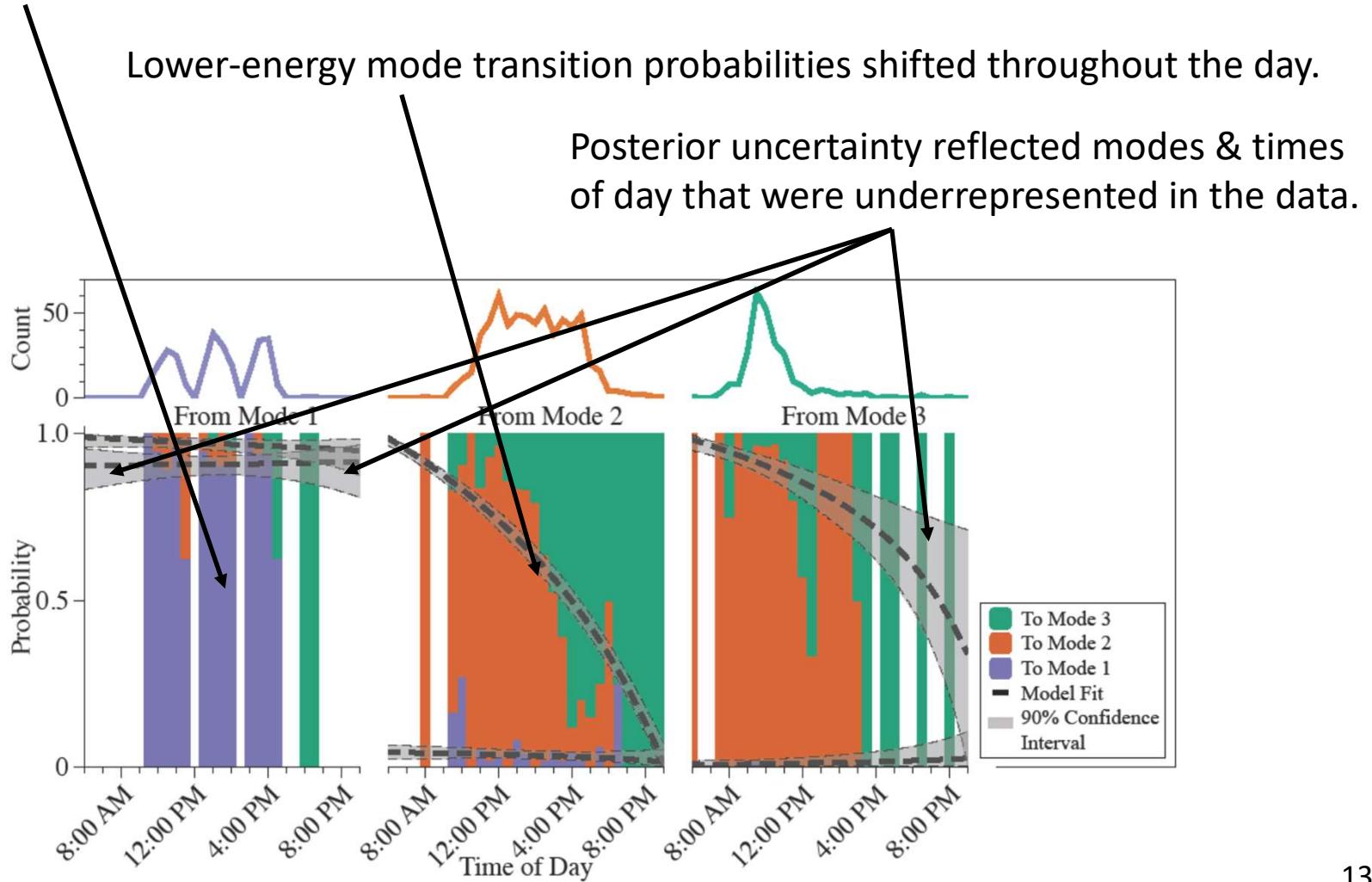
JAGS worked well for this problem.

- Discrete mode precluded use of HMC (via Stan)
- Built model in pieces
- Extended model to produce posterior predictive checks

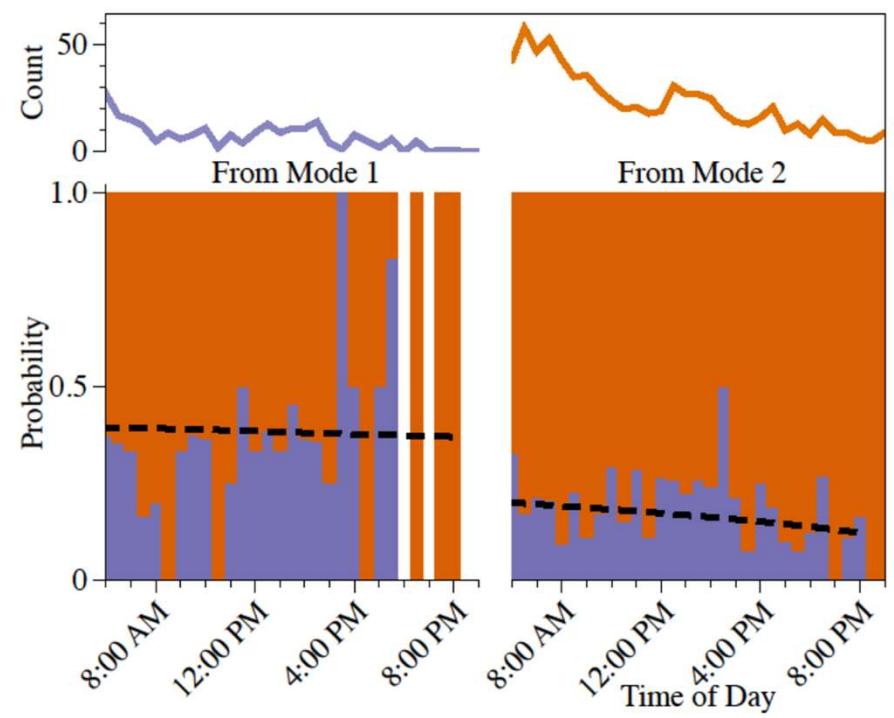
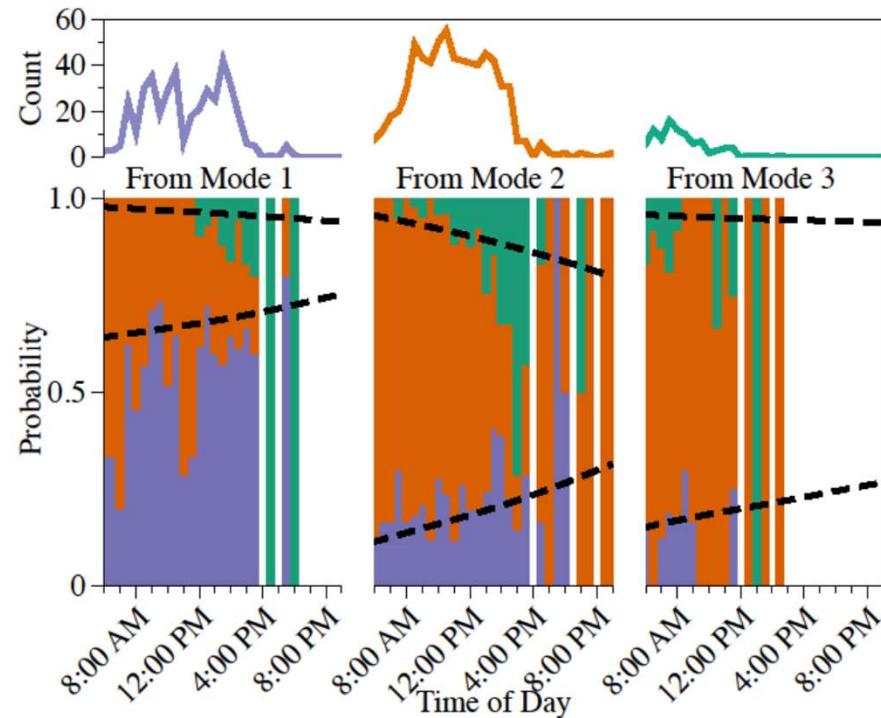
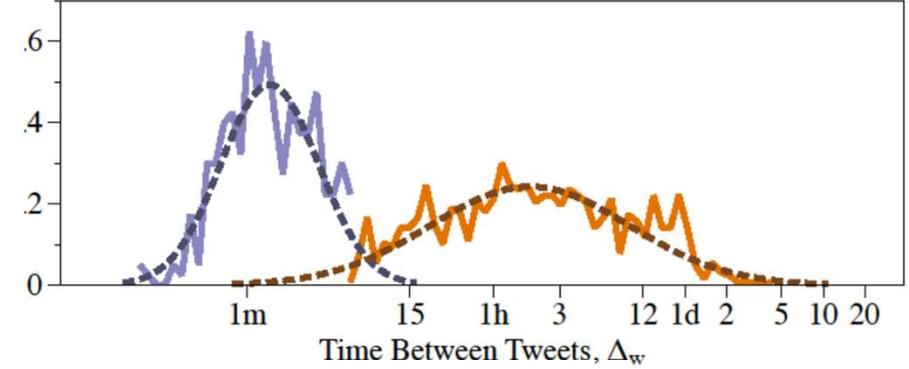
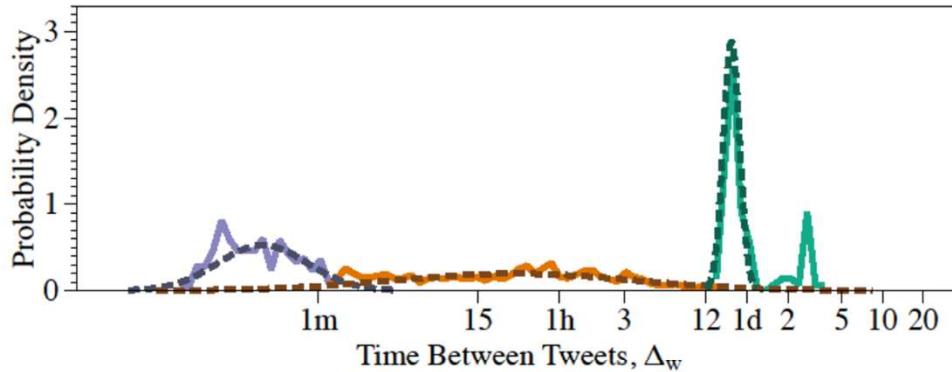


Posterior Predictive Checks

High-energy modes were more likely to be sustained.



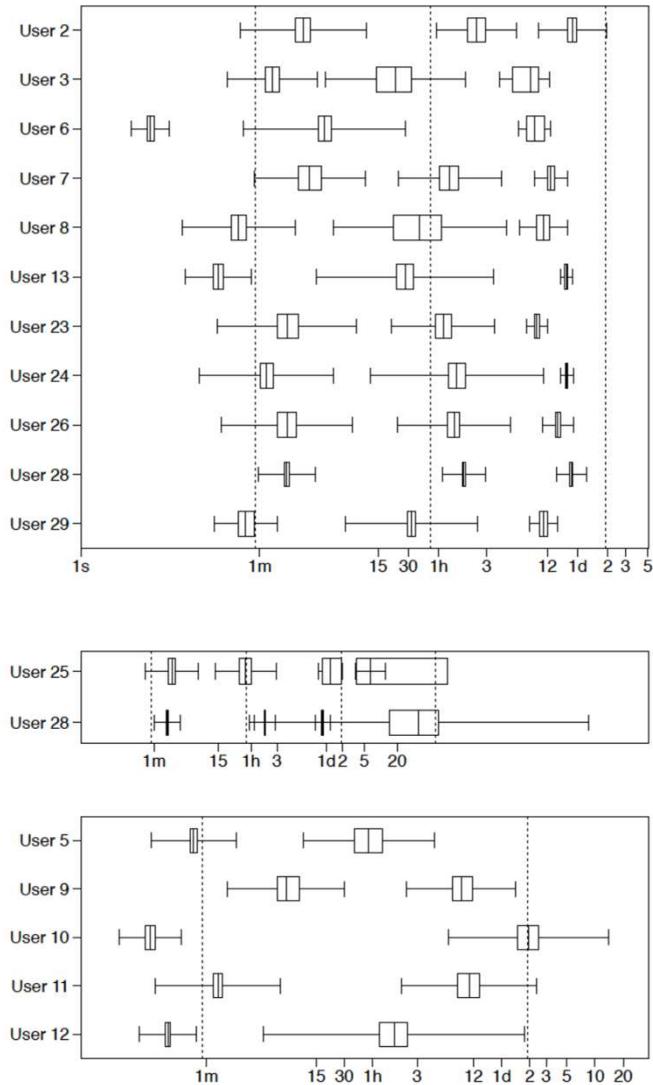
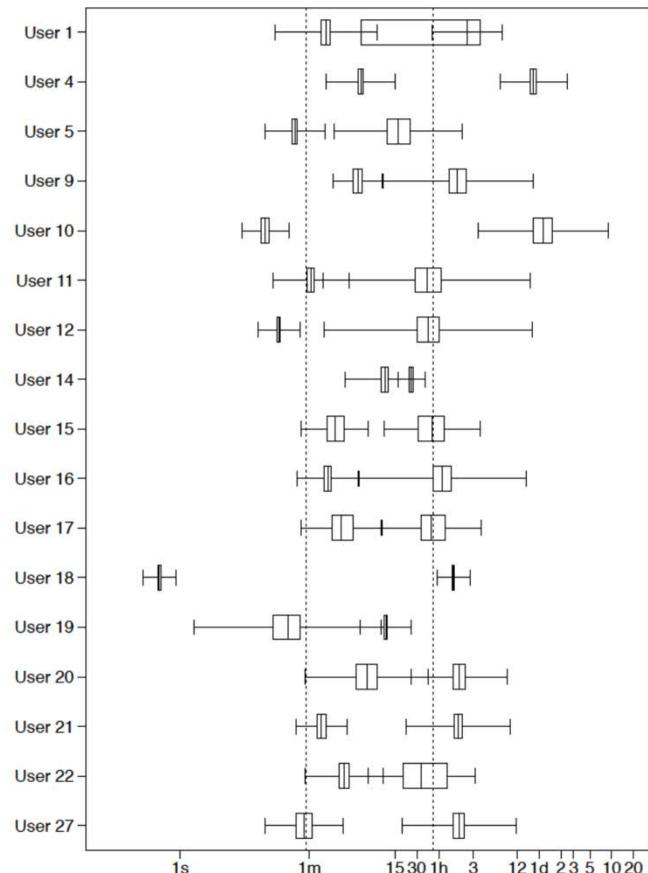
Posterior Predictive Checks



Sensitivity to Priors

Checking a model with different priors is important.

We found our model was somewhat sensitive to prior mean/stddev (but not too badly).

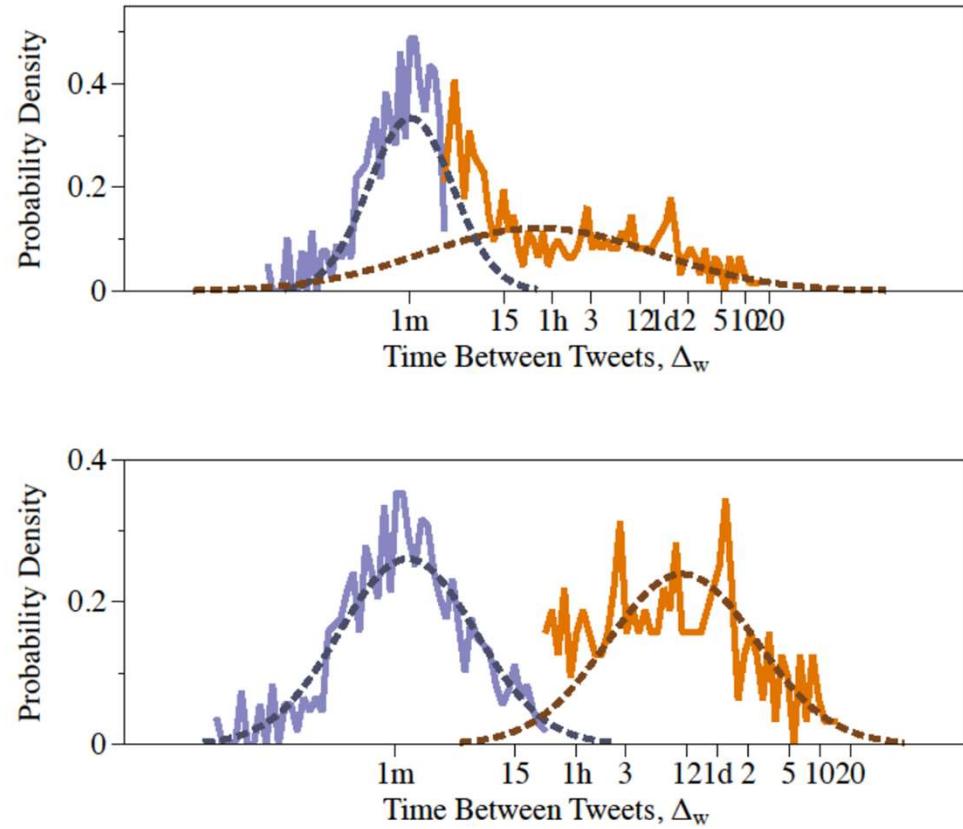


Sensitivity to Priors

In our system, sensitivity to priors had the effect of biasing the posterior mode assignments.

In this example, the equal probability point of assigning mode 1 or 2 to a message shifts from about 10 minutes to about 30 minutes.

More data would overcome the choice of prior, or the prior uncertainty in the means and std devs could be increased.



Conclusions

- Model converges well
- Model uncertainty appears in reasonable places
- Model demonstrates flexibility when fit to diverse users
- Priors are stronger than we'd like
- Current model works well enough for some applications
 - Multi-agent simulation for disease spread modeling
 - Market segmentation
 - Bot detection

Next Steps

- Model extensions
 - Better transition function representation
 - Periodic instead of a fixed window
 - Time zone inference
 - Accounting for topic & other evidence conditioned on mode
 - Estimating 'k'
 - Population parameter distributions
 - Perplexity/data likelihood comparisons vs. competing models
- Application extensions
 - Market segmentation (distinguishing bots, people, and organizations)
 - Load forecasting (relating social media activity to power demand)
 - Network security (repurposing model to handle network traffic)

Questions?

- Thank you for your time.
- Those interested in this work may reach me at
helink@sandia.gov