

## Goal

Learn statistical models from heterogeneous data produced by related, but unique, generative processes.

Data may be large, siloed, and private making pooling impractical.

Distributed hierarchical Bayesian modeling too communication inefficient to be applicable.

## Contributions

We develop **meta models** for efficiently combining models learned from local data.

Local parameters can exhibit **arbitrary permutations**. We learn **permutation invariant** global parameters.

Bayesian nonparametrics allows **adaptive learning of global model size**.

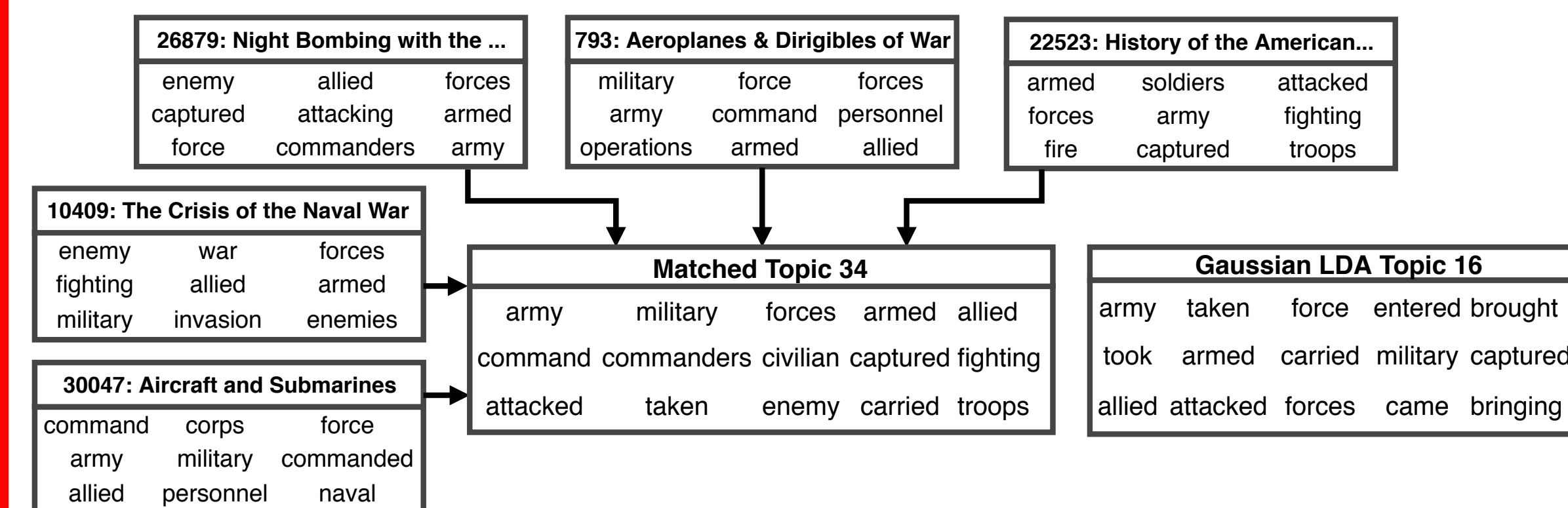
We make minimal assumptions; widely applicable.

## Results

Code: <https://github.com/IBM/SPAHM>

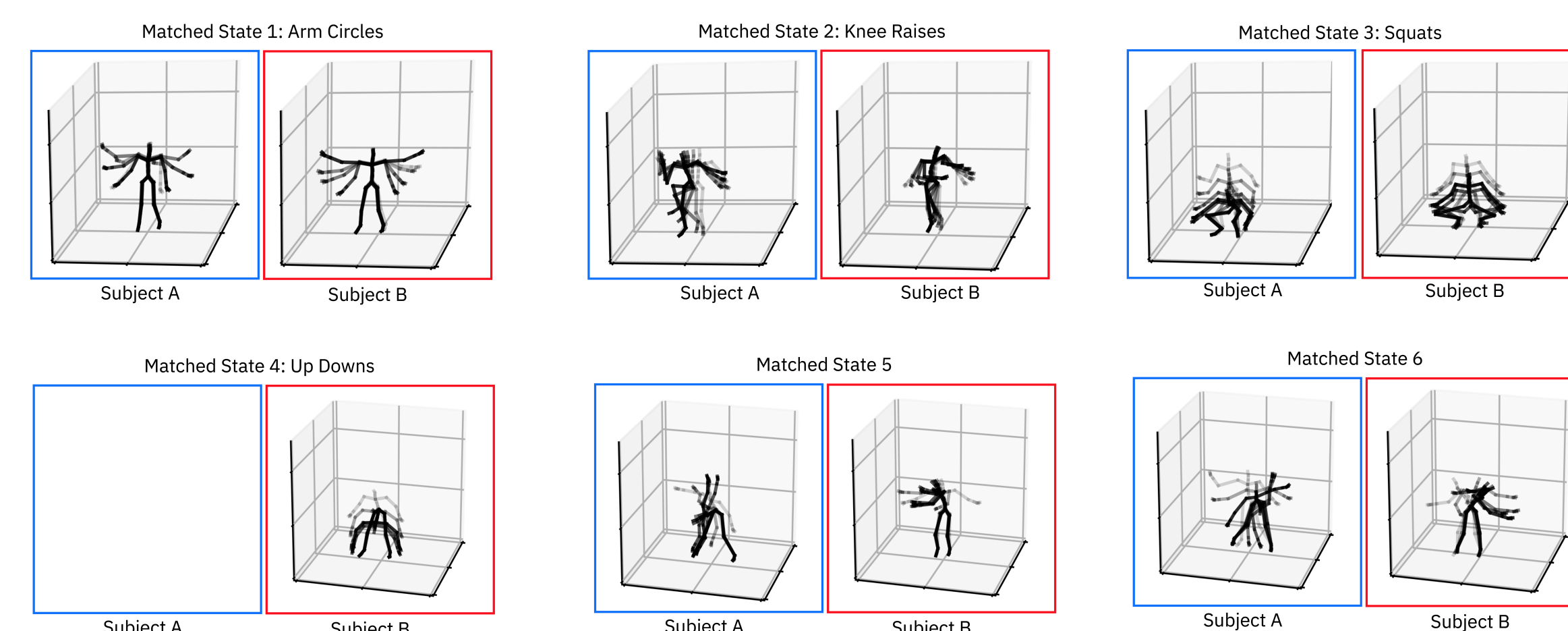
### Topic Modeling

Gaussian topics learned from Gutenberg books  
**1400 times faster** than Gibbs sampling, **higher** coherence



### Motion Capture Activity Discovery

HDP-HMM for modeling MoCAP exercise sequences  
**Twice as fast** with comparable performance to memoized VI



### Related:

- Scalable inference of topic evolution via models for latent geometric structures. NeurIPS'19. Wed 10:45 AM -- 12:45 PM @ East Exhibition Hall B + C #190
- Bayesian nonparametric federated learning of neural networks. ICML' 19.

## Bayesian nonparametric Meta Model

Draw a measure  $G$  from a Beta process with base measure  $H$

$$G = \sum_{i=1}^{\infty} p_i \delta_{\theta_i}; \theta_i \sim H$$

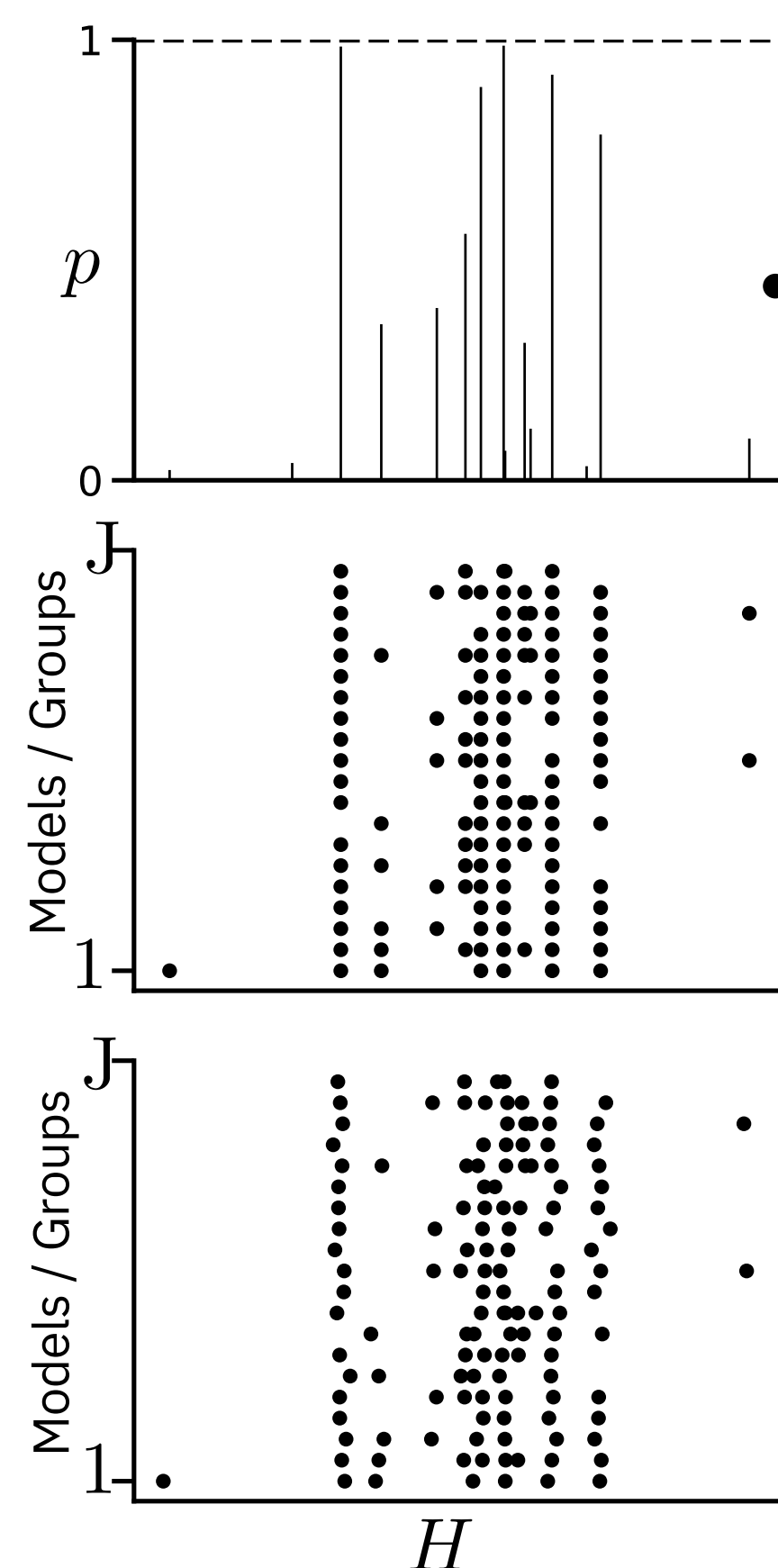
For each model  $j$  draw from a Bernoulli process (BeP) centered at  $G$ ,  $Q_j | G$

$$b_{ji} | p_i \sim \text{Bern}(p_i)$$

$$Q_j = \sum_{i=1}^{\infty} b_{ji} \delta_{\theta_i}$$

Generate **parameters** of model  $j$  centered around global parameters selected by  $Q_j$  indexed by  $l$

$$\tilde{\theta}_{jl} | \theta_{jl} \sim F(\cdot | \theta_{jl})$$



## Inference

$$\theta_i | b_{\cdot}, \tilde{\theta}$$

MAP estimate of global parameters

$$b_{j\cdot} | \tilde{\theta}_{j\cdot}, b_{j\cdot}$$

Estimating binary assignments can be cast as a linear sum **assignment problem**. We use the Hungarian algorithm to solve it

$$\tilde{\theta}_{jl} | \mathbf{x}_j$$

Local inference using **your favorite algorithm**

