Personalizing Gesture Recognition Using Hierarchical Bayesian Neural Networks

Ajjen Joshi[1], Soumya Ghosh[2], Margrit Betke[1], Stan Sclaroff[1], Hanspeter Pfister[3]
[1]Boston University, [2]IBM T.J. Watson Research Center, [3]Harvard University

Overview

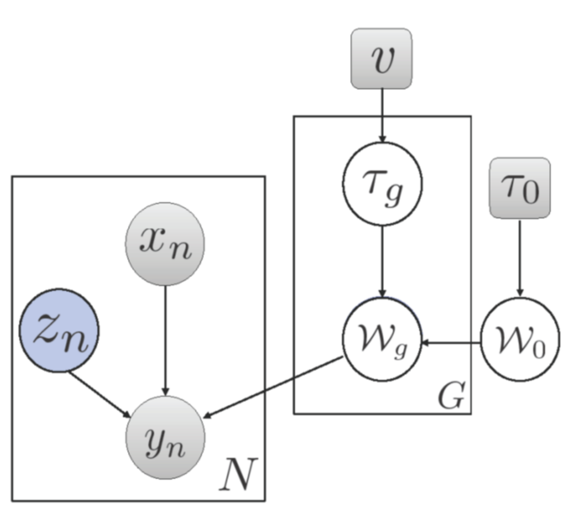
Problem Statement

- It is challenging to recognize gestures given subject-specific variations in gesture production.

Contributions

- We formulate Hierarchical Bayesian Neural Networks (HBNN) that capture group-specific variations in gesture performance.
- Our model can adapt to new subjects.
- Our active learning mechanism improves personalization in resource-constrained scenarios.

Hierarchical Bayesian Neural Networks



- Given a dataset $\mathcal{D} = \{x_n, y_n\}_{n=1}^{N}$, each subject is endowed with its own conditional distribution $p(y_n \mid z_n = g, f(x_n, \mathcal{W}_g))$.

$$p(\mathcal{W}_g \mid \mathcal{W}_0, \tau_g) = \prod_{l=1}^{L} \prod_{i=1}^{V_{l-1}} \prod_{j=1}^{V_l} \mathcal{N}(w_{ij,l}^{g} \mid w_{ij,l}^{0}, \tau_g^{-1})$$

$$p(\mathcal{W}_0 \mid \tau_0) = \prod_{l=1}^{L} \prod_{i=1}^{V_{l-1}} \prod_{j=1}^{V_l} \mathcal{N}(w_{ij,l}^{0} \mid 0, \tau_0^{-1})$$

$$p(\gamma_g \mid v) = \mathcal{N}(\gamma_g \mid 0, v); \quad \tau_g^{-1/2} = |\gamma_g|$$

- The joint distribution is given by:

$$p(\mathcal{W}_0, \mathcal{W}, \mathcal{T}, \mathbf{y} \mid \mathbf{x}, \mathbf{z}, \tau_0, v) = p(\mathcal{W}_0 \mid \tau_0^{-1}) \prod_{g=1}^{G} p(\gamma_g \mid v) p(\mathcal{W}_g \mid \mathcal{W}_0, \tau_g^{-1}) \prod_{n=1}^{N} \prod_{g=1}^{G} p(y_n \mid f(\mathcal{W}_g, x_n))^{\mathbf{1}[z_n = g]}$$

Inference

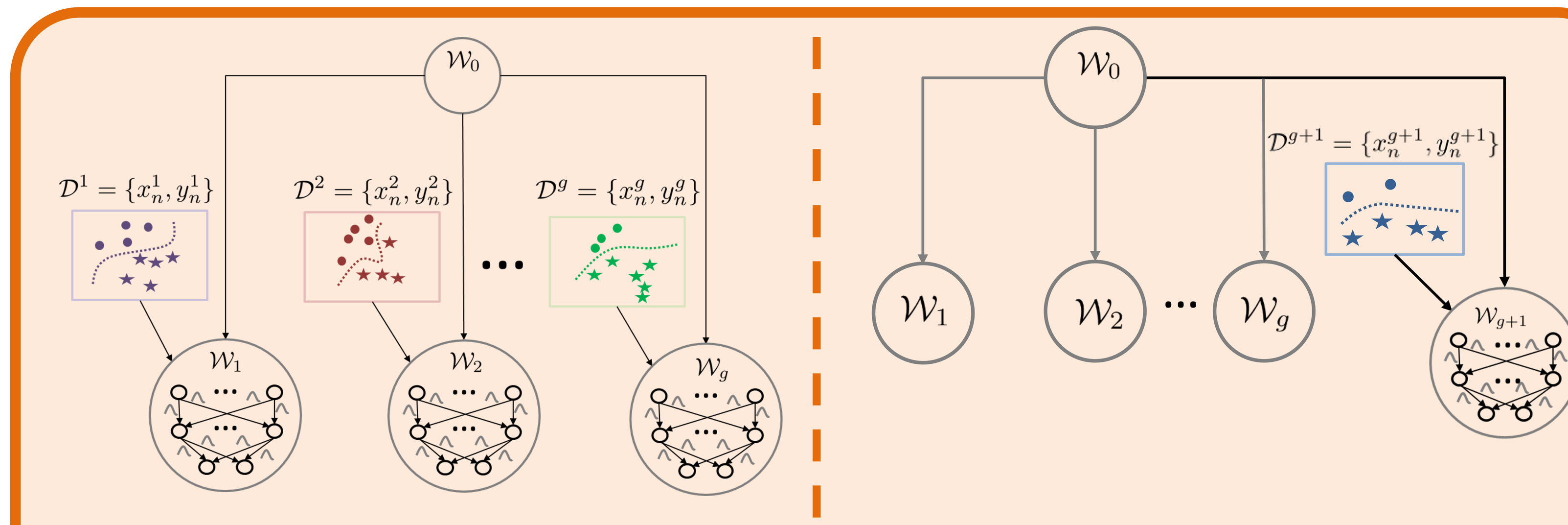
- We approximate the intractable posterior with a fully factorized approximation,

$$q(\mathcal{W}_0, \mathcal{W}, \mathcal{T} \mid \phi) = q(\mathcal{W}_0 | \phi_0) \prod_{g=1}^{G} q(\mathcal{W}_g | \phi_g) q(\tau_g^{-1/2} | \phi_{\tau_g})$$

- The Evidence Lower Bound (ELBO) is then maximized with respect to the variational parameters using variational Bayes.

$$\mathcal{L}(\phi) = \mathbb{E}_{q_\phi}[\ln p(\mathcal{W}_0, \mathcal{W}, \mathcal{T}, \mathbf{y} \mid \mathbf{x}, \mathbf{z}, \tau_0, v)] - \mathbb{E}_{q_\phi}[\ln q(\mathcal{W}_0, \mathcal{W}, \mathcal{T} \mid \phi)]$$

- In computing the Monte Carlo estimate of the gradients, we use the local reparameterization trick.
- Unobserved group memberships of held-out data are inferred via a separate inference network.



Hierarchical Bayesian Neural Network

Personalization

Personalization

- $\{\mathcal{W}_g\}_{g=1}^{G+1}$ are conditionally independent given $\mathcal{W}_0$.
- Given a model trained on $\mathcal{D}$, we only update $\mathcal{W}_{G+1}$ while keeping everything else fixed.
- To best utilize limited labeling resources, we adopt the Bayesian Active Learning by Disagreement (BALD) algorithm to adaptively select training instances for the new group.

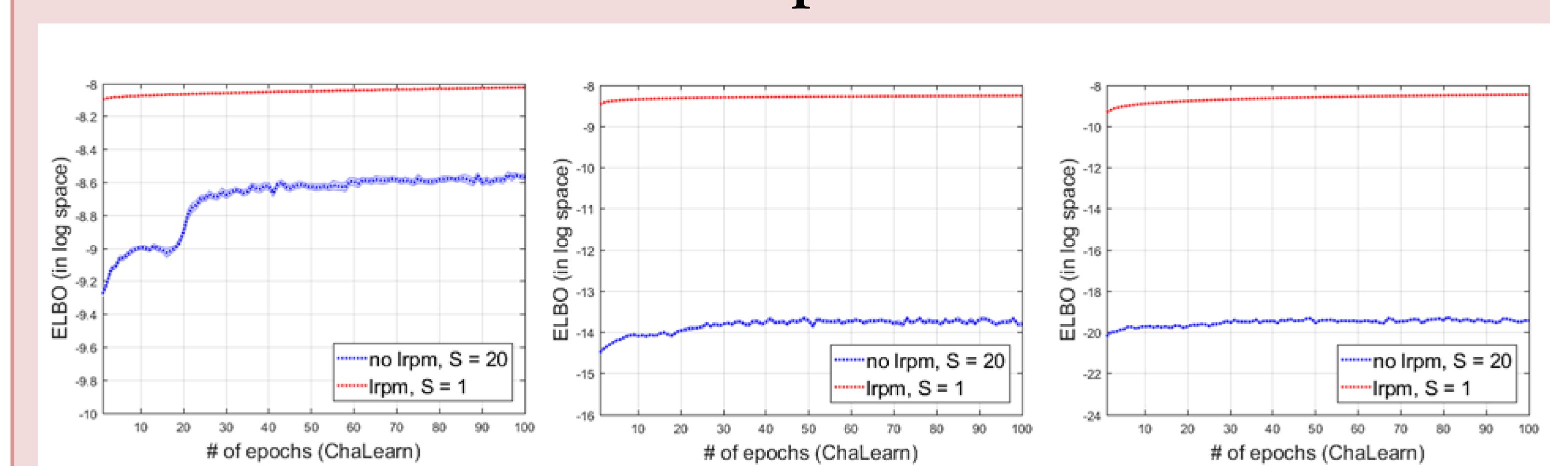
$$x_l = \underset{x \in X_{pool}}{\operatorname{argmax}} \mathbb{H}[y \mid x, \mathcal{D}] - \mathbb{E}_{\mathcal{W}_g \sim p(\mathcal{W}_g | \mathcal{D})} \mathbb{H}[y \mid x, \mathcal{W}_g]$$

Results

We test our method on 3 gesture datasets:

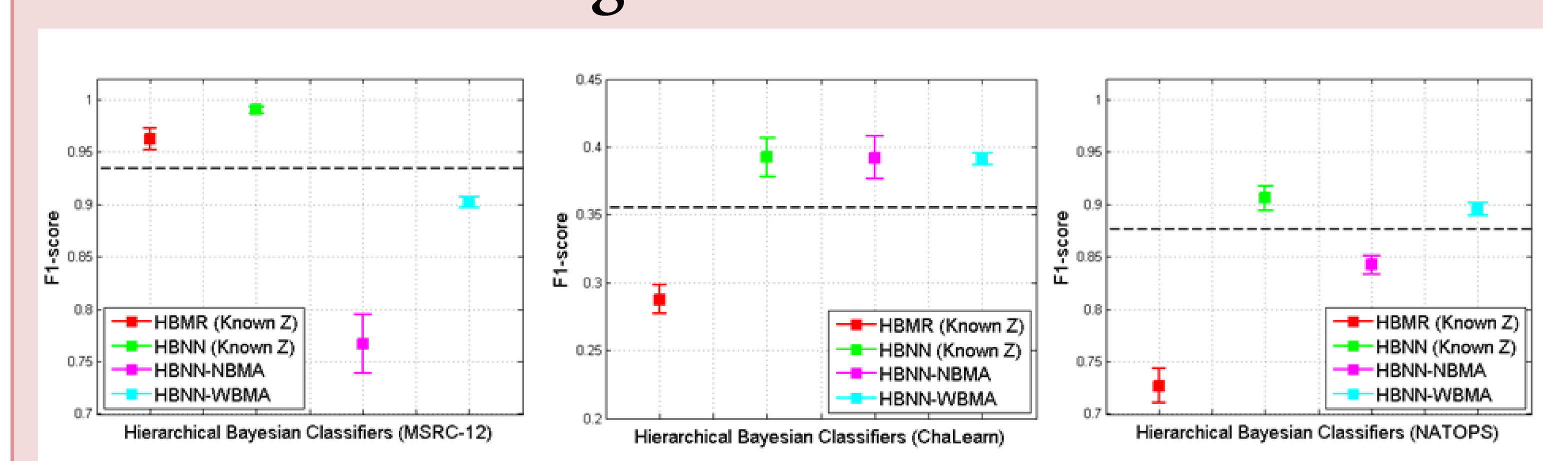
MSRC-12 ChaLearn 2013 NATOPS

1. Benefits of Local Reparameterization



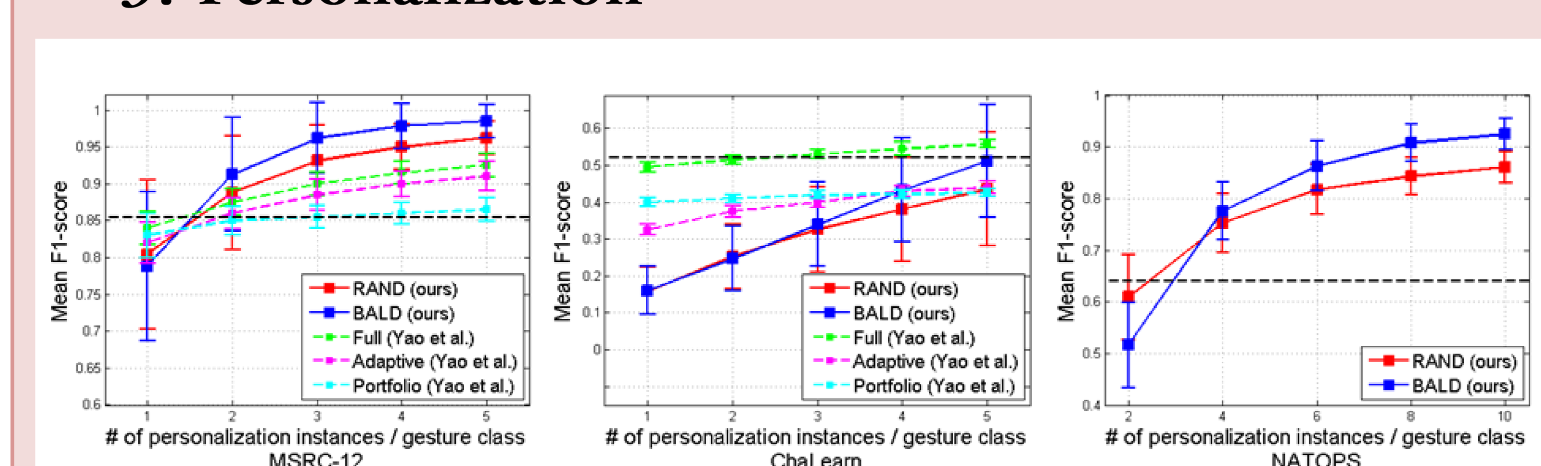
lrpm: local reparameterization

2. Gesture Recognition



HBMR: Hierarchical Bayesian Multinomial Regression model
HBNN: Hierarchical Bayesian Neural Network model with 2 hidden layers

3. Personalization



References:

Yao, Angela, Luc Van Gool, and Pushmeet Kohli. "Gesture recognition portfolios for personalization." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2014.