Uncertainty propagation in neural networks for sparse coding

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1-LISTA 2-BayesLISTA Reconstruct $\boldsymbol{\beta}$ from observations \mathbf{y} collected as $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, such • Add priors for NN weights that elements $\boldsymbol{\beta}$ contain zeros. • Perform full Bayesian inference • Estimate uncertainty of predictions • Represent iterative soft-thresholding algorithm as a recurrent neural network with shared weights • Learn weights with backpropagation through time 4-BackProp-PBP Overfitting • No uncertainty estimation Blocktext **Require:** observation **y**, current weights **W**, **S**, number of layers Initialisation. Dense layer $\mathbf{b} \leftarrow \mathbf{W}\mathbf{y}$ 2: Initialisation. Soft-thresholding nonlinearity $\widehat{\beta}_0 \leftarrow h_{\lambda}(\mathbf{b})$ 5-Results 3: $\mathbf{for}\ l = 1\ \mathbf{to}\ L\ \mathbf{do}$ Dense layer $\mathbf{c}_l \leftarrow \mathbf{b} + \mathbf{S}\widehat{\boldsymbol{\beta}}_{l-1}$ Soft-thresholding nonlinearity $\hat{\boldsymbol{\beta}}_l \leftarrow h_{\lambda}(\mathbf{c}_l)$ 6: end for 7: $\mathbf{return} \ \ \widehat{oldsymbol{eta}} \leftarrow \widehat{oldsymbol{eta}}_L$ 3-Uncertainty propagation Fig. 1: Different depth performance At every step the output of soft-thresholding can be closely approximated with spike and slab distribution 1. $\mathbf{b} = \mathbf{W}\mathbf{y}$ is Gaussian-distributed 2. $\widehat{\boldsymbol{\beta}}_0 = h_{\lambda}(\mathbf{b})$ is approximated with the spike and slab distribution Fig. 2: Different observation size performance 3. $\mathbf{e}_l = \mathbf{S}\hat{\boldsymbol{\beta}}_{l-1}$ is approximated with the Gaussian distribution 4. $\mathbf{c}_l = \mathbf{b} + \mathbf{e}_l$ is Gaussian-distributed 5. $\widehat{\boldsymbol{\beta}}_l = h_{\lambda}(\mathbf{c}_l)$ is approximated with the spike and slab distribution • All latent variables are modelled with parametrised distributions • We can apply approximate Bayesian inference methods Fig. 3: Posterior parameters for an image of digit 7 Fig. 4: Samples from the posterior for an image of digit 7 Use the estimated uncertainty to choose next training data with largest variance Fig. 5: Sequential pool additions

6-Summary

Blocktext

Notetext