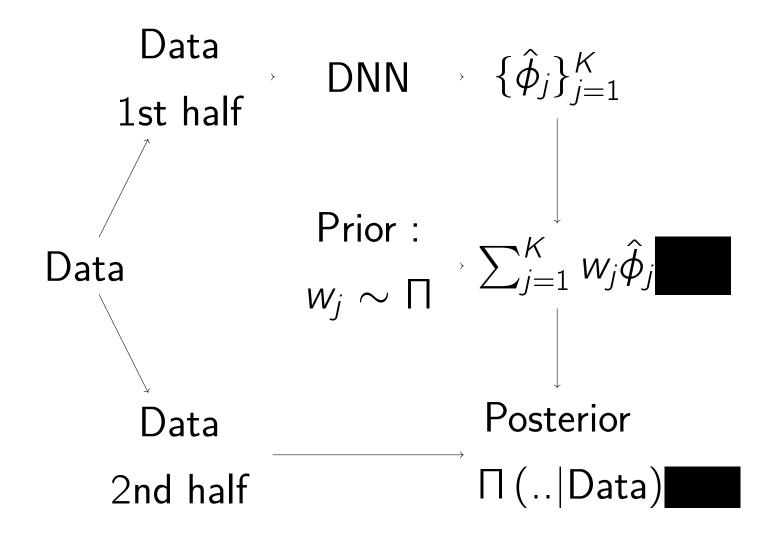
## This work in under 60 seconds

### **Selling points**

- First methodology with theoretical guarantees
- Significantly faster than bootstrap and fully Bayesian approaches
- Easy to implement
- Easily adapted to new statistical tasks

## Set up



# Uncertainty quantification

Credible balls with suitably blown up radius give coverage

- log(n) in simulations
- $\log(n)^3$  in theory

#### Conclusion

Empirical Bayesian deep neural networks provide a great way to do uncertainty quantification.

# Fast uncertainty quantification in Deep learning

#### Introduction

We provide the first methodology for uncertainty quantification using deep neural networks and a theoretical study.

#### **Earlier results**

- Johannes
- Suzuki
- Judith + Botond

## Assumptions

- True function is  $\beta$ -smooth
- Have  $k_n = n^{1/(2\beta+d)}$  basis functions
- Have found a good (local) optimizer of the deep neural network
- Sparse deep neural networks<sup>1</sup>
- Near orthogonal basis functions<sup>2</sup>

<sup>1</sup>Needed in theory to get best rates

<sup>2</sup>Needed in theory to get control on radius of credible ball

#### Simulation studies

Simulations were done using dense neural networks and gradient descent

Regression

Classification

# Theoretical guarantees for regression

Denote  $\epsilon_n = n^{\frac{-\beta}{2\beta+d}}$  and  $\tilde{\epsilon_n} = \epsilon_n \log(n)^3$ .

**Theorem 0.1.** Let  $\beta$ , M > 0. Under some conditions

■ The posterior contracts at near minimax rate:

$$\limsup_{n\to\infty} \sup_{f_0\in W_M^\beta} \mathbb{E}_{f_0}\left(\Pi\left(\|f-f_0\|_2 \geq M_n \tilde{\epsilon}_n | \mathcal{D}_n\right)\right) = 0,$$

for all  $M_n \to \infty$ .

The credible balls have uniform near optimal coverage: There exists  $L_{\epsilon,\alpha}$  such that if  $B(c_{\alpha},R_{\alpha})$  is an  $\alpha$ -credible ball, the ball  $B=B(c_{\alpha},L_{\epsilon,\alpha}\log(n)^3R_{\alpha})$  satisfies

$$\liminf_n \inf_{f_0 \in \mathcal{W}^eta_M([0,1]^d)} \mathbb{P}^{(n)}_{f_0}(f_0 \in B) \geq 1 - \epsilon$$

■ The credible balls have uniform near optimal size:

$$\liminf_n \inf_{f_0 \in W^{eta}_M([0,1]^d)} \mathbb{P}^{(n)}_{f_0}(R_lpha \leq C\epsilon_n) \geq 1-\epsilon$$

for some large enough C > 0.