

Bayesian Neural Network

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Outline

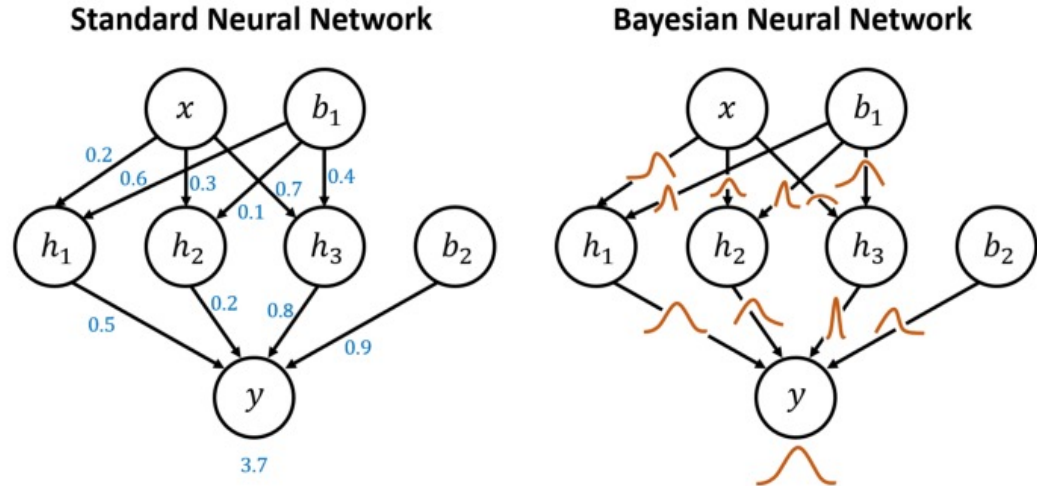
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Traditional Artificial neural networks (ANN) tend to overfit. $l_i = s_i(\mathbf{W}_i l_{i-1} + \mathbf{b}_i)$

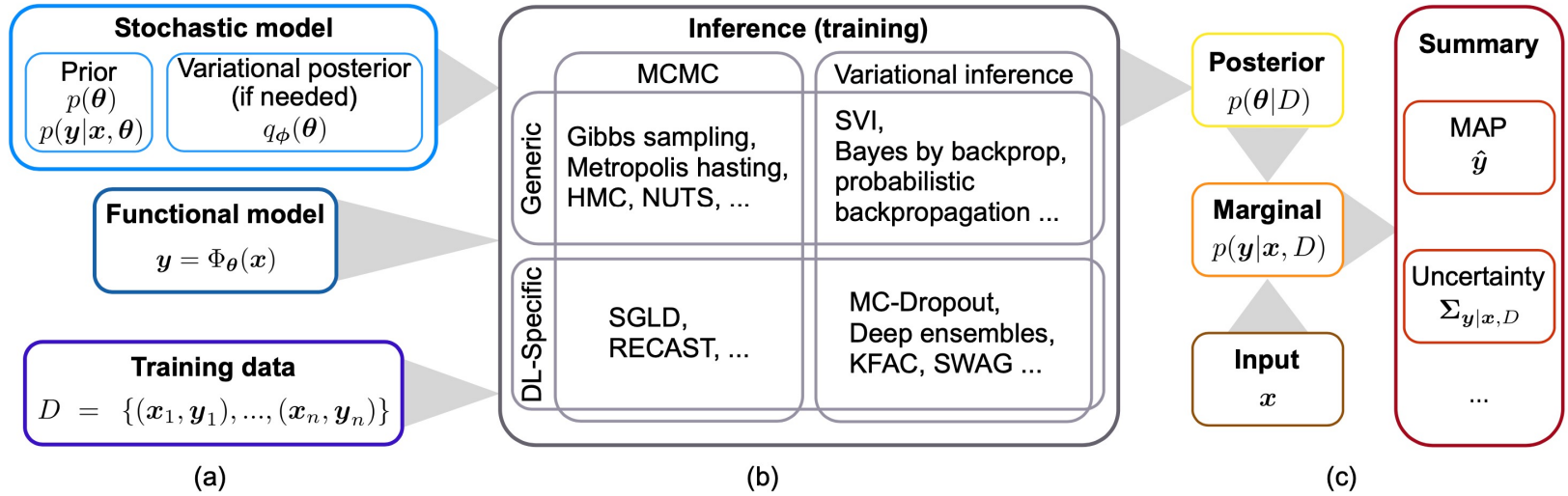
Bayesian neural networks (BNN) are NNs in a Bayesian framework

BNNs can better estimate confidence levels

$$p(\theta|D) = \frac{p(D_y|D_x, \theta) p(\theta)}{\int p(D_y|D_x, \theta') p(\theta) d\theta'} \propto p(D_y|D_x, \theta) p(\theta)$$


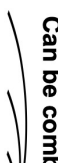
BNN

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MCMC and Variational Inference

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	Benefits	Limitations	Use cases	
MCMC (V.A)	Directly samples the posterior	Requires to store a very large number of samples	Small and average models	Can be combined 
Classic methods (HMC, NUTS)(§V-A)	State of the art samplers limit autocorrelation between samples	Do not scale well to large models	Small and critical models	
SGLD and derivates (§V-E2a)	Provide a well behaved Markov Chain with minibatches	Focus on a single mode of the posterior	Models with larger datasets	
Warm restarts (§V-E2a)	Help a MCMC method explore different modes of the posterior	Requires a new burn-in sequence for each restart	Combined with a MCMC sampler	
Variational inference (V.B)	The variational distribution is easy to sample	Is an approximation	Large scale models	Can be combined 
Bayes by backprop (§V-C)	Fit any parametric distribution as posterior	Noisy gradient descent	Large scale models	
Monte Carlo-Dropout (§V-E1)	Can transform a model using dropout into a BNN	Lack expressive power	Dropout based models	
Laplace approximation (§V-E2b)	By analyzing standard SGD get a BNN from a MAP	Focus on a single mode of the posterior	Unimodals large scale models	
Deep ensembles (§V-E2b)	Help focusing on different modes of the posterior	Cannot detect local uncertainty if used alone	Multimodals models and combined with other VI methods	

Bayes-by-backprop

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Draw epsilon from q

Deterministic transformation

Loss function with variational inference

Normal backpropagation

Algorithm 5 Bayes-by-backprop algorithm.

```
 $\phi = \phi_0;$   
for  $i = 0$  to  $N$  do  
  Draw  $\varepsilon \sim q(\varepsilon);$   
   $\theta = t(\varepsilon, \phi);$   
   $f(\theta, \phi) = \log(q_\phi(\theta)) - \log(p(D_{\mathbf{y}}|D_{\mathbf{x}}, \theta)p(\theta));$   
   $\Delta_\phi f = \text{backprop}_\phi(f);$   
   $\phi = \phi - \alpha \Delta_\phi f;$   
end for
```

Performance Metrics

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Distribution, not point Estimate

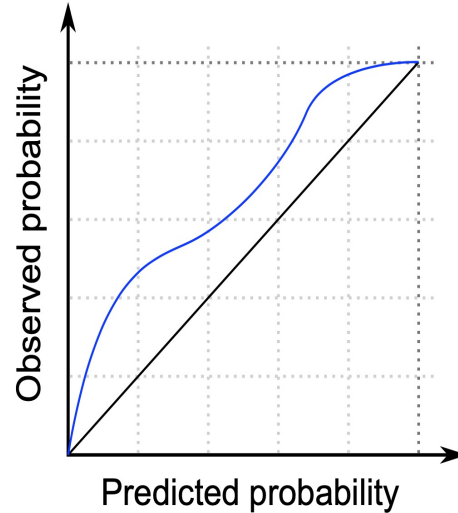
Calibration graph:

- predicted probability p
- observed probability q

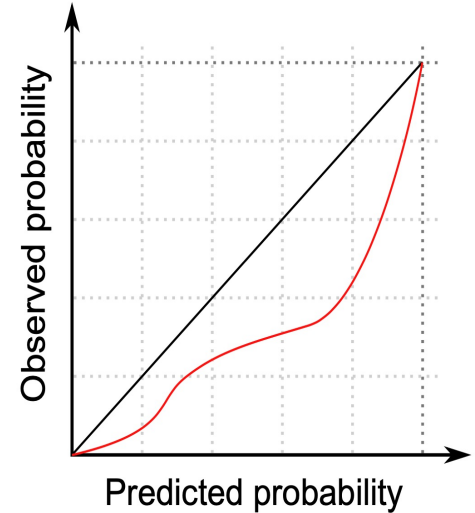
If $q > p$ – underconfident

If $q < p$ – overconfident

If $q \approx p$ – well calibrated



(a)



(b)

Discussion

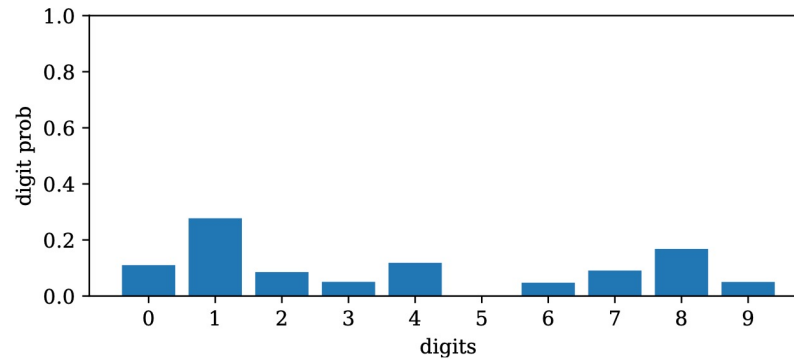
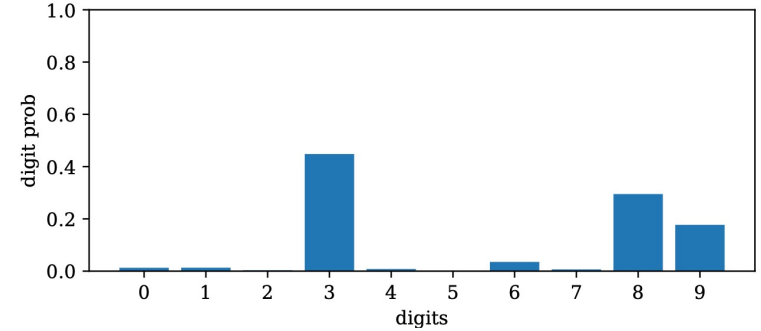
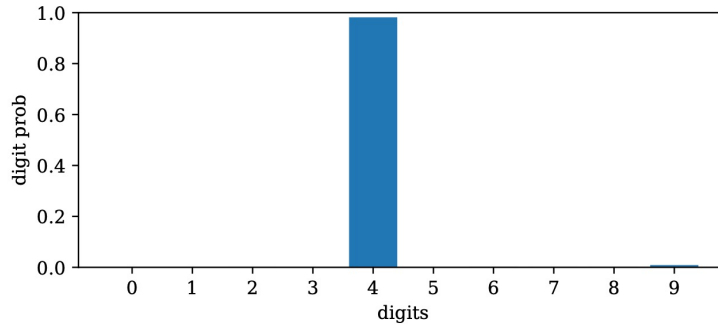
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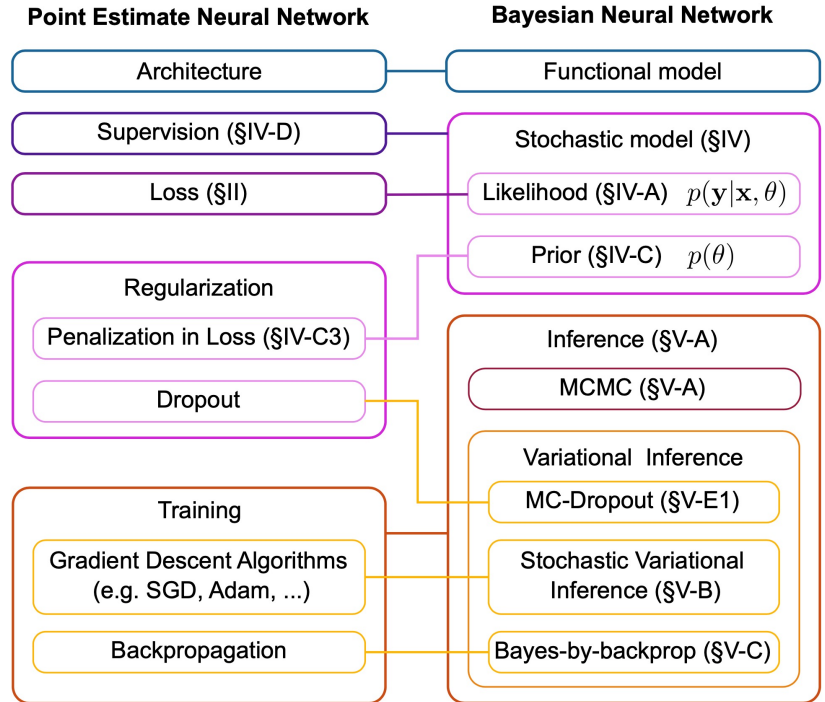
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Appropriate confidence intervals

Always use the right tool for the task

- BNN
- ANN



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Laurent Valentin Jospin, Wray L. Buntine, Farid Boussaïd, Hamid Laga, Mohammed Bennamoun:
“*Hands-on Bayesian Neural Networks – A Tutorial for Deep Learning Users*”.

Submitted on 14 Jul 2020 (v1). Last revised 3 Jan 2022 (v3).

<https://arxiv.org/abs/2007.06823>

Figure slide 2:

<https://towardsdatascience.com/why-you-should-use-bayesian-neural-network-aaf76732c150>

Acknowledgements

- D. Jason Koskinen for feedback on the relevance of the topic.

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Extras