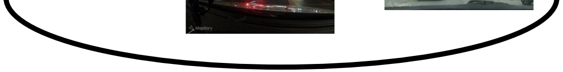
Dpto. Informática e Ingeniería de Sistemas.

Images: Wikipedia, Nando de Freitas.

http://www.cs.ox.ac.uk/people/yarin.gal/website/blog_2248.html


f_2
x^*
x



I. J. Goodfellow, J. Shlens, and C. Szegedy, Explaining and harnessing adversarial examples, *arXiv:1412.6572*, 2014
https://openai.com/blog/multimodal-neurons/

Image: Yarin Gal

Image: Yarin Gal

Image: Yarin Gal

Image: Yarin Gal

$p(D')$

$$p(w) = N(w|w_0, \Sigma_0)$$

with: $\lambda = \frac{\sigma^2}{\tau^2}$ ...which is again ridge regression!

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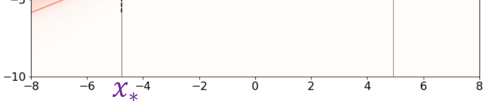
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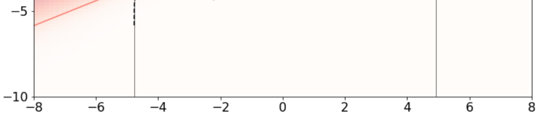
x_*


−5
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0
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reducible by additional training data

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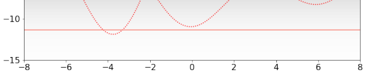
Alex Kendall and Yarin Gal. What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?, NeurIPS, 2017 https://papers.nips.cc/paper_files/paper/2017/hash/2650d6089a6d640c5e85b2b88265dc2b-Abstract.html

F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable Bayesian deep learning methods for robust computer vision, CVPRW. 2020.
https://openaccess.thecvf.com/content_CVPRW_2020/papers/w20/Gustafsson_Evaluating_Scalable_Bayesian_Deep_Learning_Methods_for_Robust_Computer_Vision_CVPRW_2020_paper.pdf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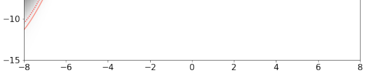
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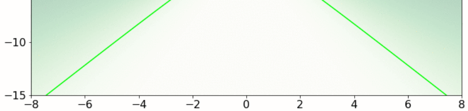
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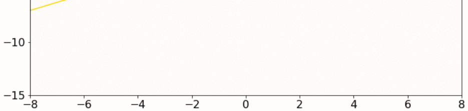
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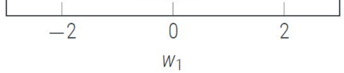


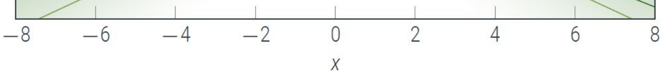
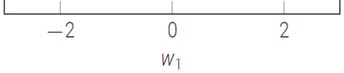


Image: Philipp Hennig



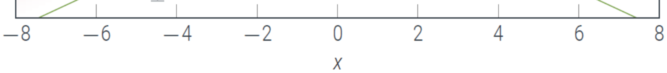


Image: Philipp Hennig

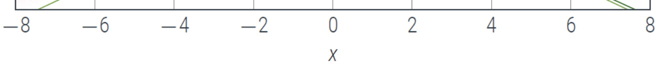


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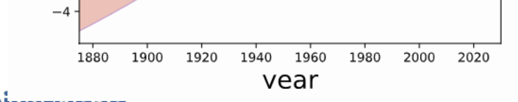
Image: Philipp Hennig

$$(f_*) \quad (\quad [\quad k(x_*, X) \quad\quad k(x_*, x_*)])$$

Left: a Bayesian neural network with two hidden layers, transforming a 3-dimensional input into a two-dimensional output. **Right**: output probability density function induced by the random weights of the network. **Video**: as the width of the network increases, the output distribution simplifies, ultimately converging to a multivariate normal in the infinite width limit. https://en.wikipedia.org/wiki/Large_width_limits_of_neural_networks

https://arxiv.org/pdf/1402.5836.pdf

- 1904 Olympic marathon
  - Unusually high temperatures and humidity, coupled with poor organization and planning, meant that the marathon in 1904 had the slowest winning time and most bizarre outcome in Olympic history. https://www.statista.com/statistics/1099351/olympics-marathon-gold-medal-times-since-1896/



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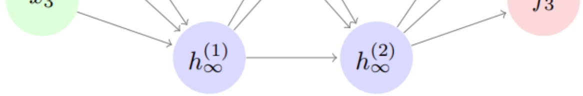
Example by Neil Lawrence: http://inverseprobability.com/talks/notes/deep-gaussian-processes.html


$h_\infty^{(1)}$
$h_\infty^{(2)}$

- Heteroscedastic!

F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable bayesian deep learning methods for robust computer vision, CVPRW. 2020.

- Homoscedastic noise $\sigma_W^2(\boldsymbol{x}) = \sigma_{MAP}^2$

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F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable bayesian deep learning methods for robust computer vision, CVPRW. 2020.

Image: Brendan Hasz

$$KL(q||p) = \mathbb{E}_q[\log q(x)] - \mathbb{E}_q[\log p(x)] = -\mathbb{E}_q[\log p(x)] - \mathcal{H}(q(x))$$

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$$q(w_i) \sim N(\mu_i, \sigma_i)$$

- We want to maximize ELBO → Loss = negative ELBO more approximations. [Osawa et al. 2019]

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$$p(\mathbf{w}|\mathbf{X}, \mathbf{y}) \approx q(\mathbf{w}) = \frac{\exp\left(\frac{1}{2}(\mathbf{w} - \mathbf{w}^*)^T H(\mathbf{w}^*)(\mathbf{w} - \mathbf{w}^*)\right)}{\int \exp\left(\frac{1}{2}(\mathbf{w} - \mathbf{w}^*)^T H(\mathbf{w}^*)(\mathbf{w} - \mathbf{w}^*)\right) d\mathbf{w}}$$

Image: Philipp Hennig


θ_{MAP}

(a) Full **(b)** LRank **(c)** KFAC **(d)** Diag.

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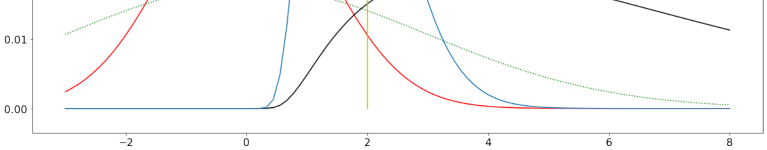
Daxberger E, Kristiadi A, Immer A, Eschenhagen R, Bauer M, Hennig P. Laplace redux-effortless bayesian deep learning. Advances in Neural Information Processing Systems. 2021 Dec 6;34:20089-103.
https://github.com/AlexImmer/Laplace

- Then the posterior is: $y_{\mathrm{lin}} \sim \mathcal{N}\left(f_{\mathbf{w}^*}(\mathbf{x}), J(\mathbf{x}) H(\mathbf{w}^*)^{-1} J(\mathbf{x})^T\right)$

Khan 2019: https://proceedings.neurips.cc/paper_files/paper/2019/file/b3bbccd6c008e727785cb81b1aa08ac5-Paper.pdf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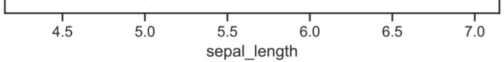
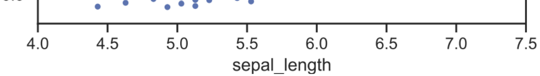
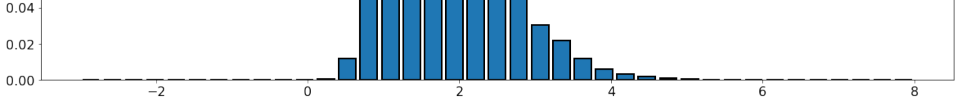




Kevin P. Murphy, Probabilistic Machine Learning: An introduction, section 4.6.7.2, MIT Press, 2021, https://probml.github.io/pml-book/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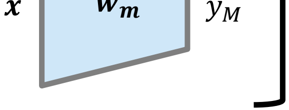

- We can only use a small number of samples! $\mathcal{O}(M)$

epistemic aleatoric

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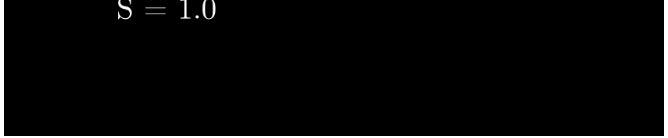
Y. Gal and Z. Ghahramani, Dropout as a Bayesian approximation: Representing model uncertainty in deep learning, ICML, 2016

- Masksensembles



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different networks)

- Better than local approximations

B. Lakshminarayanan, A. Pritzel, and C. Blundell, Simple and scalable predictive uncertainty estimation using deep ensembles, NeurIPS, 2017

$outputs$ = (● , ... , ●)

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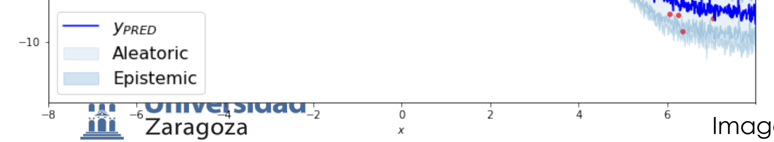
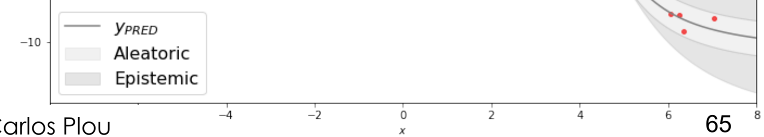
Image: Carlos Plou





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Images: Carlos Plou

- See K.P. Murphy Book2 Chapter 17 https://probml.github.io/pml-book/book2.html

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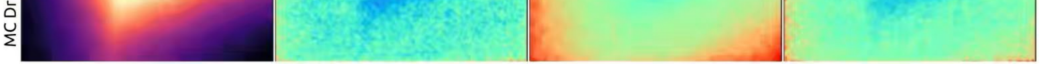
(a) Input Image (b) Ground Truth (c) Semantic Segmentation (d) Aleatoric Uncertainty (e) Epistemic Uncertainty

Alex Kendall and Yarin Gal. What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?, NeurIPS, 2017



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Javier Rodríguez-Puigvert, Rubén Martínez-Cantín, Javier Civera, Bayesian Deep Networks for Supervised Single-View Depth Learning, IEEE-RAL, 2021

Javier Rodríguez-Puigvert, Rubén Martínez-Cantín, Javier Civera, Bayesian Deep Networks for Supervised Single-View Depth Learning, IEEE-RAL, 2021

Figure 5: NYUv2 Depth results. From left: input image, ground truth, depth regression, aleatoric uncertainty, and epistemic uncertainty.

Alex Kendall and Yarin Gal. What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?, NeurIPS, 2017

M Deep Ensembles

Student

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M Deep Ensembles

Student

Background	Contain	Cut	Display	Engine	Grasp	Hit	Pound	Support	W-Grasp

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Mur-Labadia, Lorenzo, Martinez-Cantin, Ruben and Guerrero, Jose J. (2023) *Bayesian deep learning for affordance segmentation in images*. In Proc. of the IEEE International Conference on Robotics and Automation.

Mur-Labadia, Lorenzo, Martinez-Cantin, Ruben and Guerrero, Jose J. (2023) *Bayesian deep learning for affordance segmentation in images.* In Proc. of the IEEE International Conference on Robotics and Automation.


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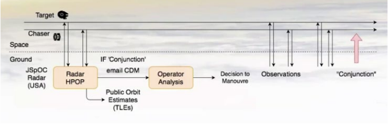
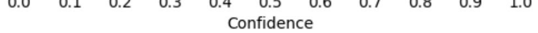


its probability as the predicted confidence (p).

F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable Bayesian deep learning methods for robust computer vision, CVPRW. 2020.
https://openaccess.thecvf.com/content_CVPRW_2020/papers/w20/Gustafsson_Evaluating_Scalable_Bayesian_Deep_Learning_Methods_for_Robust_Computer_Vision_CVPRW_2020_paper.pdf

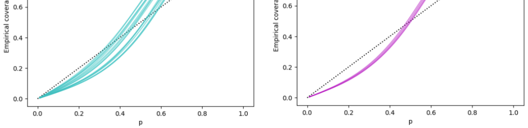
- n: number of samples

C. Guo, G. Pleiss, Y. Sun, K. Q. Weinberger, On calibration of modern neural networks, ICML 2017



F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable Bayesian deep learning methods for robust computer vision, CVPRW. 2020.

- $|\tilde{p} - p|$ for multiple p
- In a well calibrated model $|\tilde{p} - p| = 0$.



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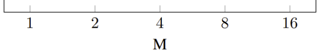
P(rain)=0,7, rain=1.00, BS=(0,7-1)^2=0,09

G. W. Brier. Verification of forecasts expressed in terms of probability. Monthly weather review, 1950.



F. K. Gustafsson, M. Danelljan, T. B. Schon, Evaluating scalable Bayesian deep learning methods for robust computer vision, CVPRW. 2020.

- Csaba Szepesvari, Algorithms of Reinforcement Learning
  - https://sites.ualberta.ca/~szepesva/rlbook.html