# What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? A Review

Bayesian Non Parametric & Bayesian ML Project

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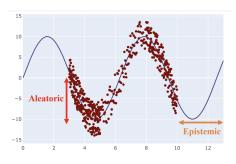
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## Main Concepts

Kendall & Gal (2017) Aleatoric & epistemic uncertainties



#### Two types of uncertainty:

- Aleatoric uncertainty: Captures noise inherent in the observations.
- Epistemic uncertainty:
  Accounts for uncertainty in
  the model, which can be
  explained away with enough
  data.

#### Traditional methods

Capturing **Epistemic Uncertainty** using Bayesian Neural Networks with MC dropout:

$$\mathcal{L}_{\mathsf{BNN}}(\theta, p) = -\frac{1}{N} \sum_{i=1}^{N} \log \mathbb{P}(y_i | f_{\hat{W}_i}(x_i)) + \frac{1-p}{2N} ||\theta||^2$$

Capturing Heteroscedastic Aleatoric Uncertainty

$$\mathcal{L}_{\mathsf{NN}}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{2\sigma(x_i)^2} \|y_i - f(x_i)\|^2 + \frac{1}{2} \log \sigma(x_i)^2 \right)$$

## Key Results

$$\hat{y}_{\hat{\mathbf{W}}}(\mathbf{x}) \qquad \hat{\sigma}_{\hat{\mathbf{W}}}^{2}(\mathbf{x})$$

$$[\hat{y}, \hat{\sigma}^{2}] = \mathbf{f}^{\hat{\mathbf{W}}}(\mathbf{x}) \qquad \hat{\mathbf{W}} \sim q(\mathbf{W})$$

$$\mathbf{x}$$

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \log \mathcal{N}(y_{i}; \hat{y}_{\hat{\mathbf{W}}}(\mathbf{x}), \hat{\sigma}_{\hat{\mathbf{W}}}^{2}(\mathbf{x}))$$

# Aleatoric Uncertainty with Probabilistic Deep Learning

### Modeling Aleatoric Uncertainty with Probabilistic Deep Learning

	Deep Learning	Probabilistic Deep Learning
Model	$[\hat{y}] = f(x)$	$[\hat{y}, \hat{\sigma}^2] = f(x)$
Regression	$Loss = \ y - \hat{y}\ ^2$	$Loss = \frac{\ y - \hat{y}\ ^2}{2\hat{\sigma}^2} + \log \hat{\sigma}^2$
Classification	$\textit{Loss} = \textit{SoftmaxCrossEntropy}(\hat{y}_t)$	$\hat{y}_{t} = \hat{y} + \epsilon_{t} \qquad \epsilon_{t} \sim N(0, \hat{\sigma}^{2})$ $Loss = \frac{1}{T} \sum SoftmaxCrossEntropy(\hat{y}_{t})$

# Experiments

#### Semantic Segmentation Performance on CamVid

CamVid Results	IoU Accuracy
DenseNet (State of the art baseline)	67.1
+ Aleatoric Uncertainty	67.4
+ Epistemic Uncertainty	67.2
+ Aleatoric & Epistemic	67.5

#### Monocular Depth Regression Performance

NYU Depth Results	Rel. Error
DenseNet (State of the art baseline)	0.167
+ Aleatoric Uncertainty	0.149
+ Epistemic Uncertainty	0.162
+ Aleatoric & Epistemic	0.145















(b) Ground Truth

(c) Semantic Segmentation