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

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NIPS

## 1. Types of Uncertainty

In Bayesian modelling, there are two main types of uncertainty we can model [1]:

- *Epistemic uncertainty*: uncertainty in the model, capturing what our model doesn't know due to lack of training data. Can be explained away with increased training data.
- *Aleatoric uncertainty*: information which our data cannot explain. Can be explained away with increased sensor precision.

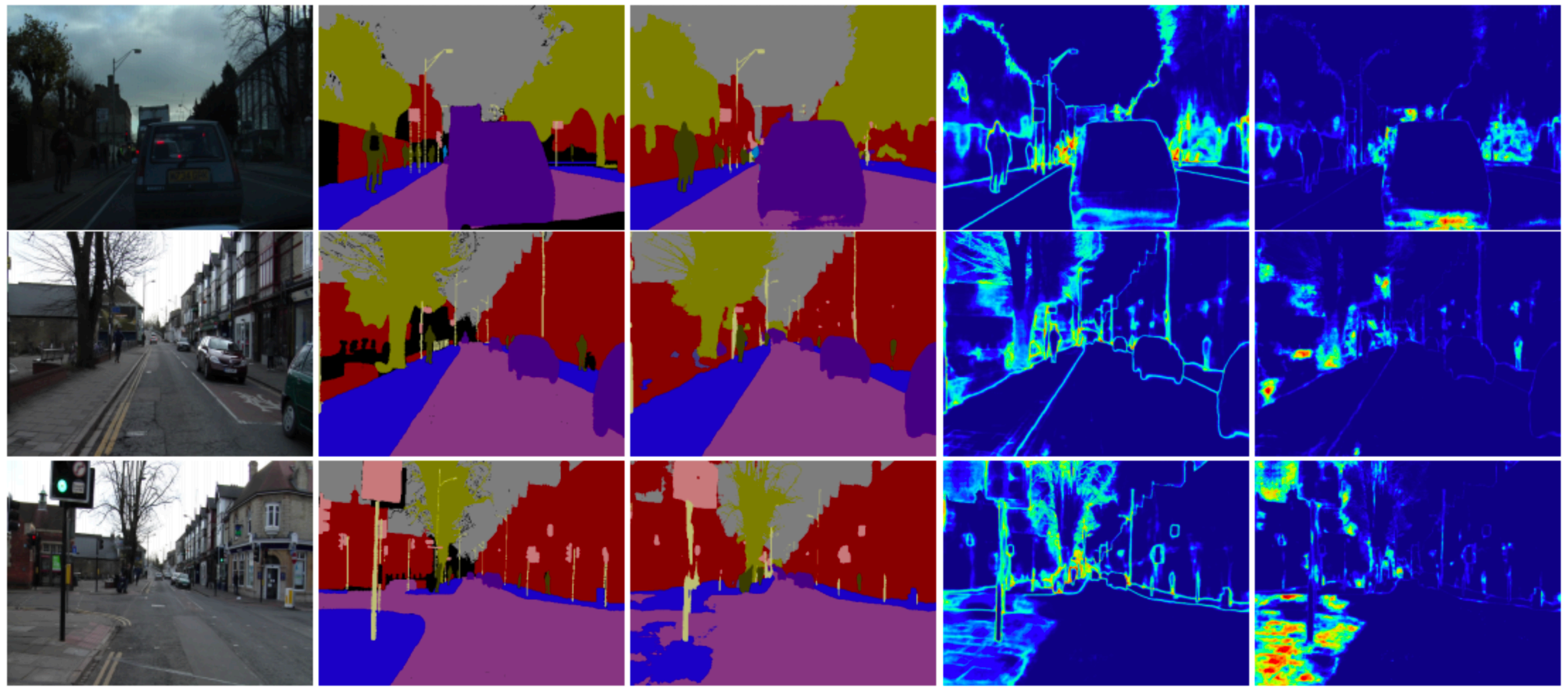
## 2. We jointly model aleatoric and epistemic uncertainty

with deep learning. Our model's uncertainty for pixel output $y_i$ is given by:

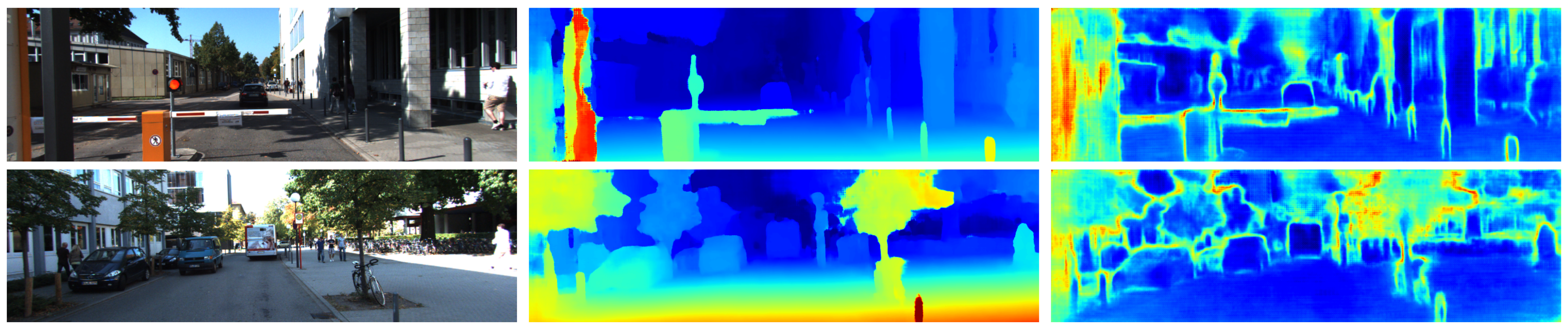
$$Var(y_i) \approx \frac{1}{T}\sum_{T} \sigma(x_t)^2 + \frac{1}{T}\sum_{T} f(x_t)^2 - \left(\frac{1}{T}\sum_{T} f(x_t)\right)^2$$

Using Monte Carlo dropout samples, T, learning aleatoric uncertainty with loss:

$$Loss(\theta) = \frac{1}{D}\sum_{i} \frac{1}{2\sigma(x)_i} \left\| y_i - f(x)_i \right\|^2 + \log \sigma(x)_i$$



*Input Image* *Ground Truth* *Model Segmentation* *Aleatoric Uncertainty* *Epistemic Uncertainty*



*Input Image* *Depth Regression* *Uncertainty*

## 3. SOTA performance

for semantic segmentation and per-pixel depth regression datasets.

We use a convolutional network based on DenseNet [20] with 103 layers and 9.4M parameters

| CamVid | IoU |
|---|---|
| SegNet [28] | 46.4 |
| FCN-8 [29] | 57.0 |
| DeepLab-LFOV [24] | 61.6 |
| Bayesian SegNet [22] | 63.1 |
| Dilation8 [30] | 65.3 |
| Dilation8 + FSO [31] | 66.1 |
| DenseNet [20] | 66.9 |
| *This work:* | |
| DenseNet (Our Implementation) | 67.1 |
| + Aleatoric Uncertainty | 67.4 |
| + Epistemic Uncertainty | 67.2 |
| + Aleatoric & Epistemic | **67.5** |

| Make3D | rel | rms | $\log_{10}$ |
|---|---|---|---|
| Karsch et al. [33] | 0.355 | 9.20 | 0.127 |
| Liu et al. [34] | 0.335 | 9.49 | 0.137 |
| Li et al. [35] | 0.278 | 7.19 | 0.092 |
| Laina et al. [26] | 0.176 | 4.46 | 0.072 |
| *This work:* | | | |
| DenseNet Baseline | 0.167 | 3.92 | 0.064 |
| + Aleatoric Uncertainty | **0.149** | 3.93 | **0.061** |
| + Epistemic Uncertainty | 0.162 | **3.87** | 0.064 |
| + Aleatoric & Epistemic | **0.149** | 4.08 | 0.063 |

Modelling uncertainty allows the model to learn to attenuate the effect from erroneous labels and learn loss attenuation.

## 4. Uncertainty with Distance from Training Data

Experiments training on one dataset and testing on another.

- Aleatoric uncertainty cannot be explained away with more data,
- Aleatoric uncertainty does not increase for out-of-data examples (situations different from training set),
- Epistemic uncertainty increases with decreasing training size,
- Epistemic uncertainty increases with examples out of the training distribution.

| Train dataset | Test dataset | RMS | Aleatoric variance | Epistemic variance |
|---|---|---|---|---|
| Make3D / 4 | Make3D | 5.76 | 0.506 | 7.73 |
| Make3D / 2 | Make3D | 4.62 | 0.521 | 4.38 |
| Make3D | Make3D | 3.87 | 0.485 | 2.78 |
| Make3D / 4 | NYUv2 | - | 0.388 | 15.0 |
| Make3D | NYUv2 | - | 0.461 | 4.87 |

*Per-pixel depth regression*

## 5. Conclusions

It is important to model ***aleatoric*** uncertainty for:

- Large data situations, where epistemic uncertainty is explained away,
- Real-time applications, because we can form aleatoric models without expensive MC samples.
- Noisy data, because we can learn to attenuate erroneous labels.

And ***epistemic*** uncertainty is important for:

- Safety-critical applications, because epistemic uncertainty is required to understand examples which are different from training data,
- Small datasets where the training data is sparse.