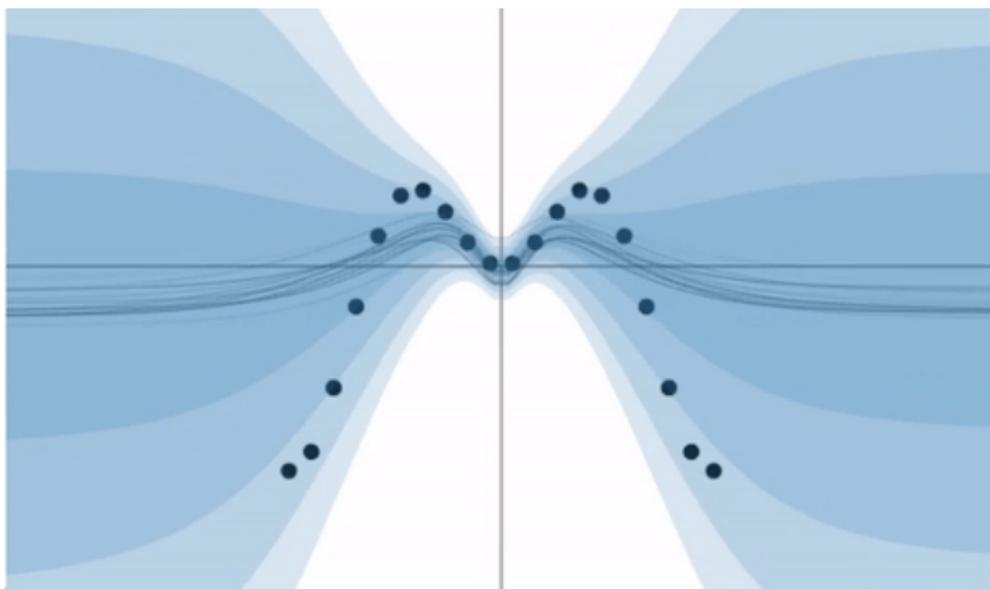




What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?

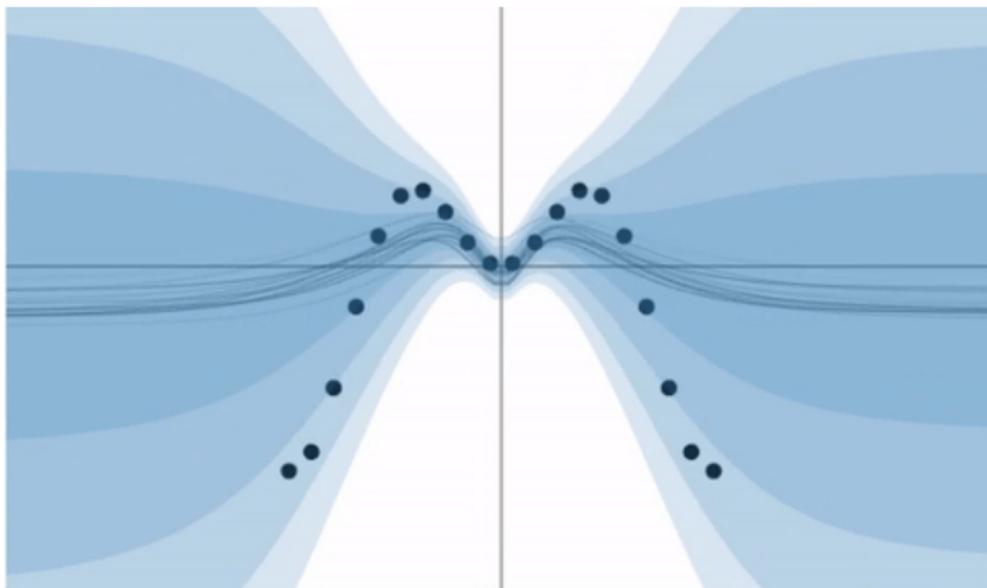
Alex Kendall • Yarin Gal

University of Cambridge • University of Oxford • The Alan Turing Institute
yarin@cs.ox.ac.uk



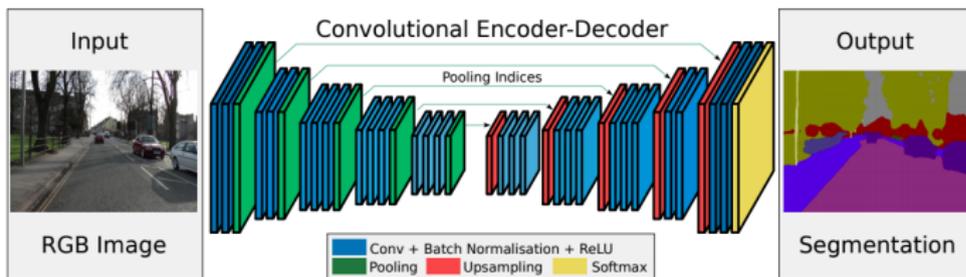
For example:

```
1 | y = []  
2 | for _ in xrange(10):  
3 |     y.append(model.output(x, dropout=True))  
4 | y_mean = numpy.mean(y)  
5 | y_var = numpy.var(y)
```



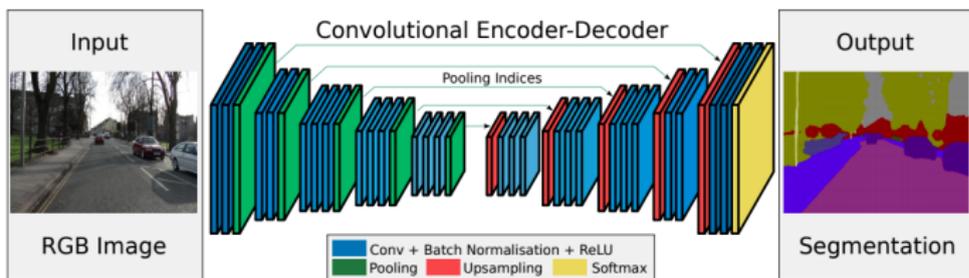
- ▶ What if we could capture uncertainty in modern computer vision?
 - ▶ Detect anomalies with image data
 - ▶ Identify adversarial examples
 - ▶ Learn with small amounts of labelled image data

- ▶ Not a new idea...
 - ▶ Particle filtering [Blake, Curwen, and Zisserman, 1993],
 - ▶ Conditional random fields [He, Zemel, and Carreira-Perpinan, 2004]
- ▶ Using BDL we can estimate uncertainty for modern computer vision models.
E.g., Segnet: [Badrinarayanan, Kendall, and Cipolla, 2015]



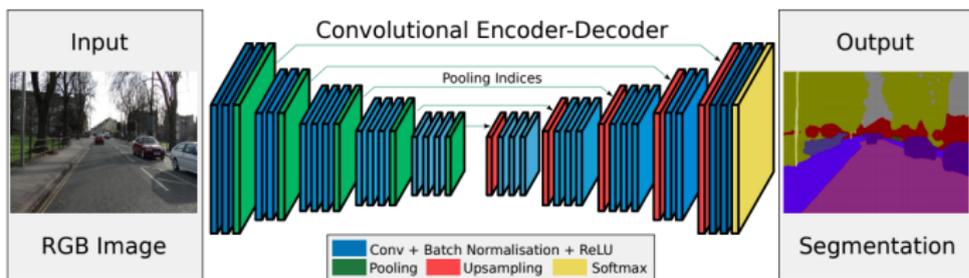
- ▶ But what uncertainty do we even want?
There are many different types of uncertainty, including:
 - ▶ *Aleatoric uncertainty*, capturing inherent noise in the data
 - ▶ *Epistemic uncertainty*, capturing model's lack of knowledge

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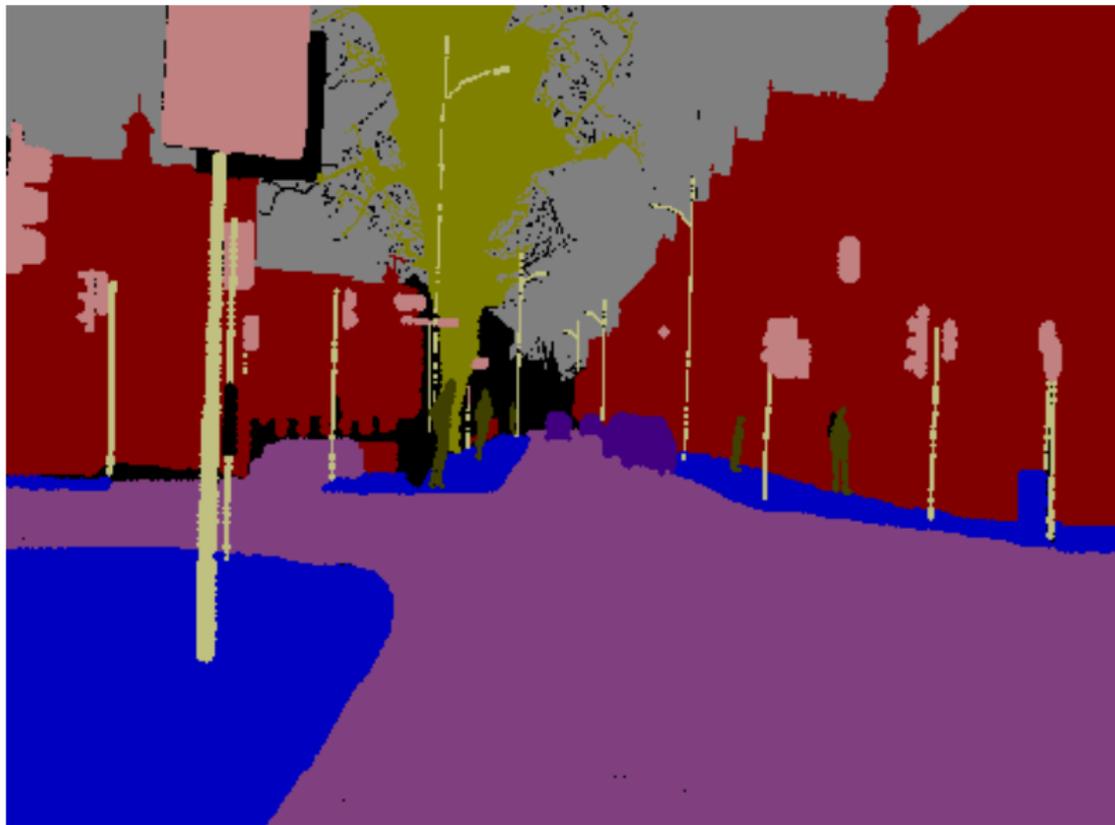
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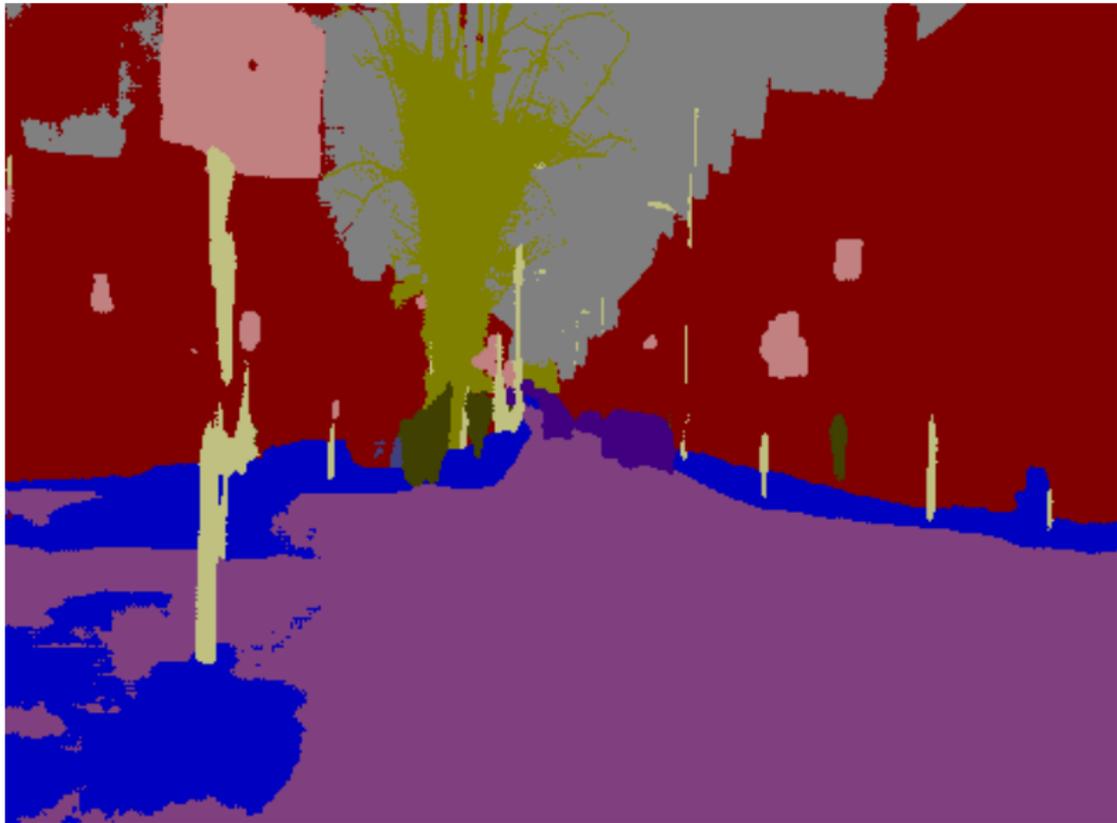


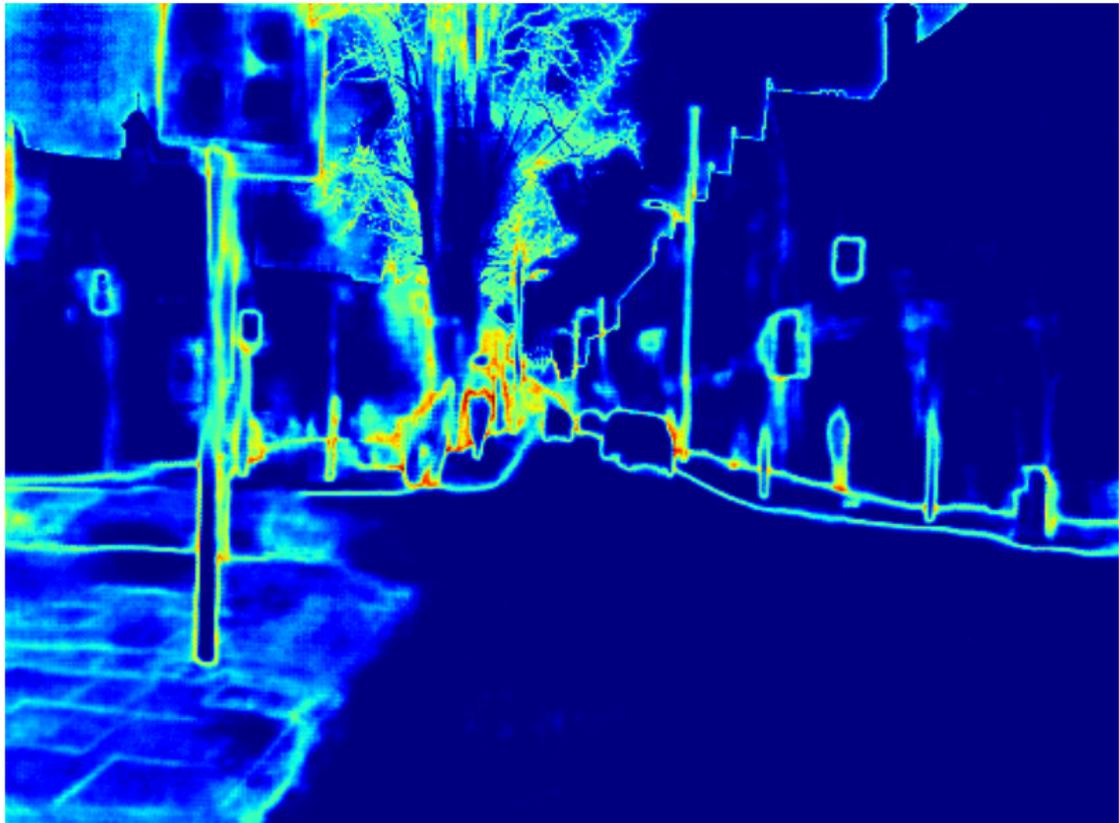
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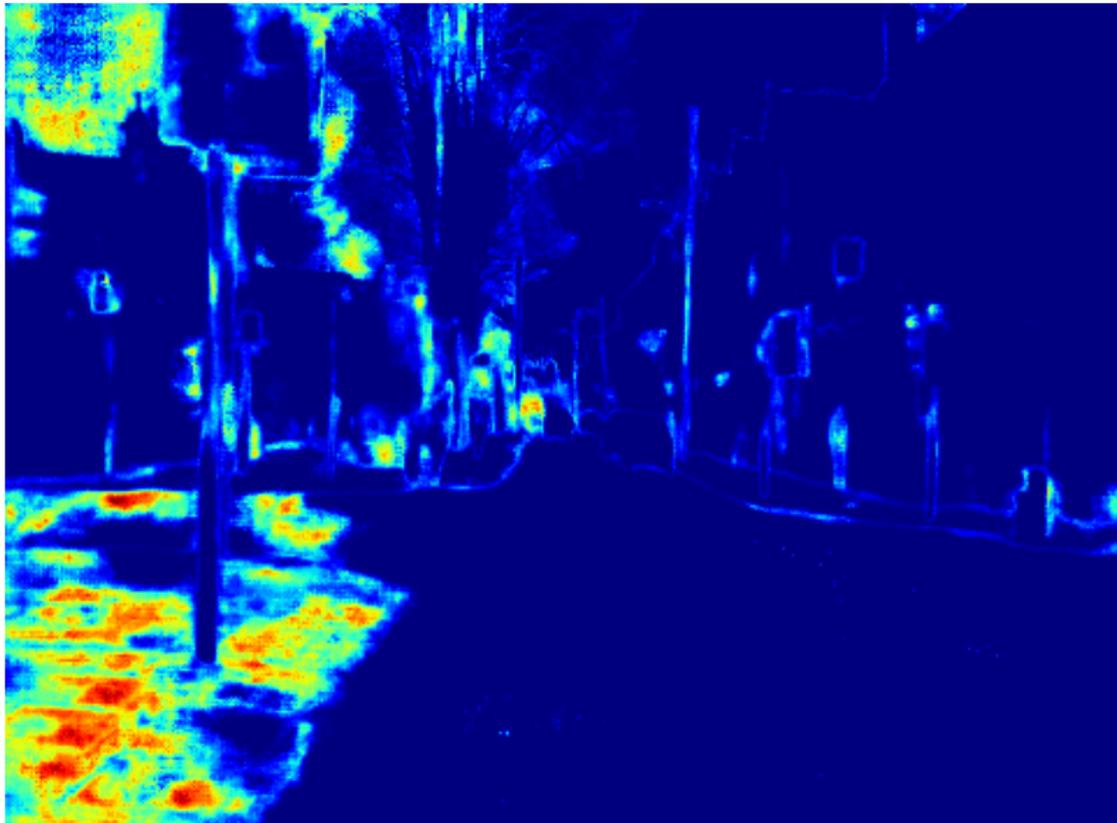
Uncertainty in Computer Vision



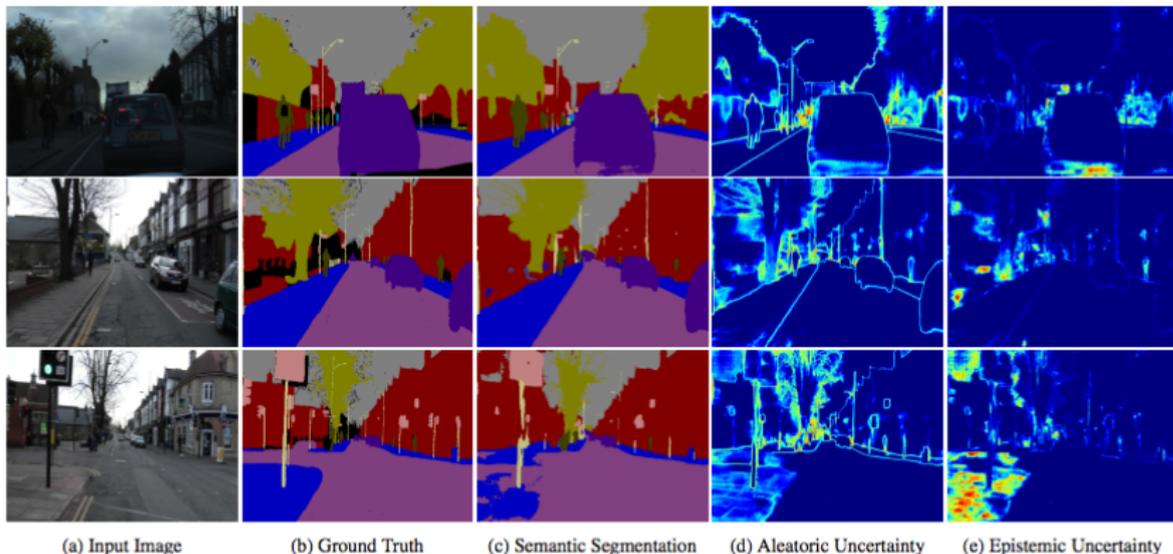








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What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? [Kendall & Gal, NIPS, 2017]

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Can we detect anomalies with Segnet?

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

(a) Regression

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What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? [Kendall & Gal, NIPS, 2017]

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



Alex Kendall (agk34@cam.ac.uk) and Yarin Gal (yarin@cs.ox.ac.uk)



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.

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
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Per-pixel depth regression

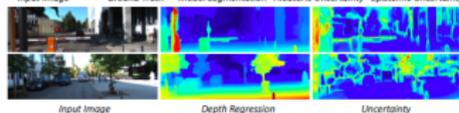
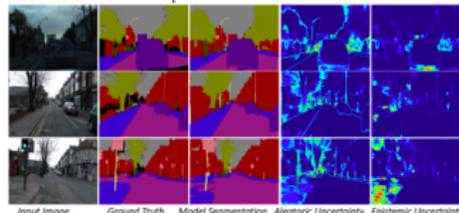
2. We jointly model aleatoric and epistemic uncertainty

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

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

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

$$\text{Loss}(\theta) = \frac{1}{D} \sum_x \frac{1}{2\sigma(x_i)} \|y_i - f(x_i)\|^2 + \log \sigma(x_i)$$



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.

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 [24]	46.4
FC7-8 [26]	57.0
DeepLab-LPOW [24]	61.6
Bayesian SegNet [22]	63.1
DilatedR [30]	65.3
DilatedR + 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	rd	rms	log ₁₀
Karsch et al. [33]	0.355	0.30	0.127
Liu et al. [34]	0.355	0.40	0.137
Liu et al. [35]	0.278	3.19	0.062
Laina et al. [26]	0.176	4.46	0.072

This work:

DenseNet Baseline	0.167	3.02	0.064
+ Aleatoric Uncertainty	0.149	3.05	0.061
+ Epistemic Uncertainty	0.162	3.05	0.064
+ Aleatoric & Epistemic	0.149	3.08	0.063

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

► Tue Dec 5th 06:30 – 10:30 PM Pacific Ballroom #95

What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? [Kendall & Gal. NIPS. 2017]