Simple & Scalable Predictive Uncertainty Estimation using Deep Ensembles

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Joint work with Alexander Pritzel & Charles Blundell

DeepMind

Uncertainty Quantification In Deep Learning

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Our contribution: A simple yet powerful non-Bayesian baseline

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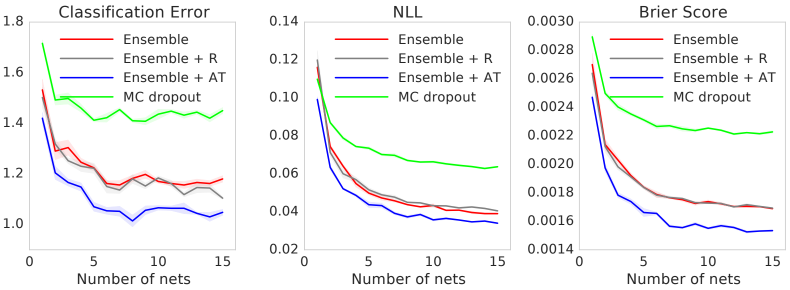
Model combination & not Bayesian Model Averaging

Classification Results on MNIST



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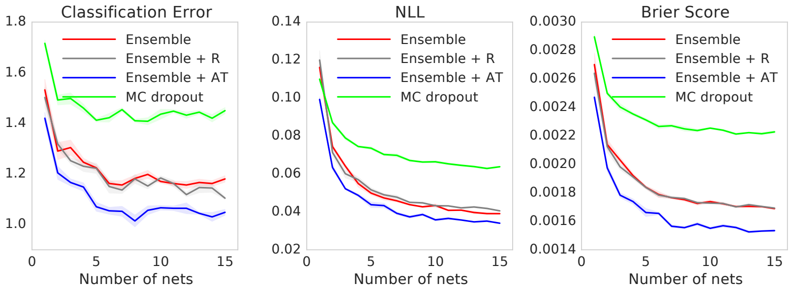

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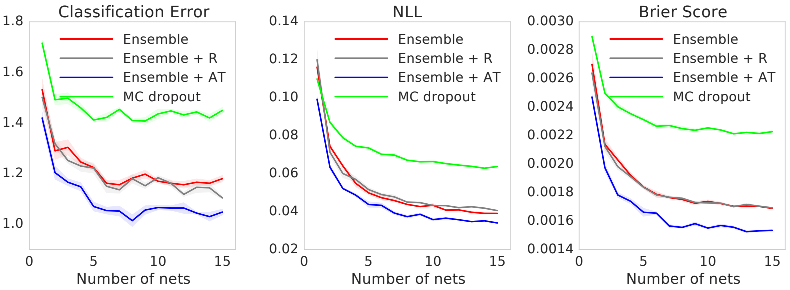

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- Similar results on SVHN, ImageNet & regression

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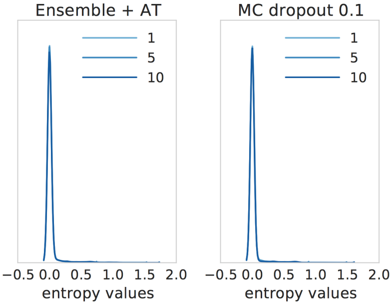

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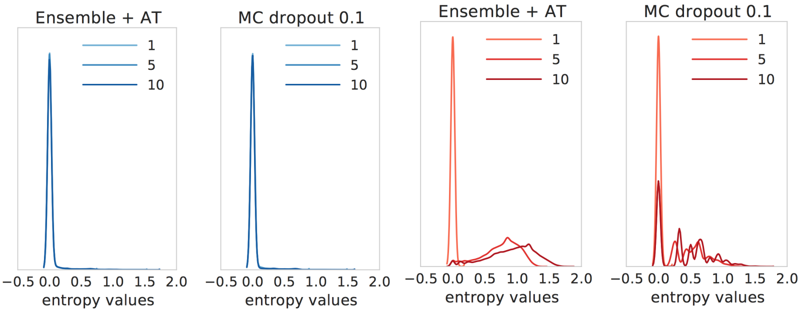

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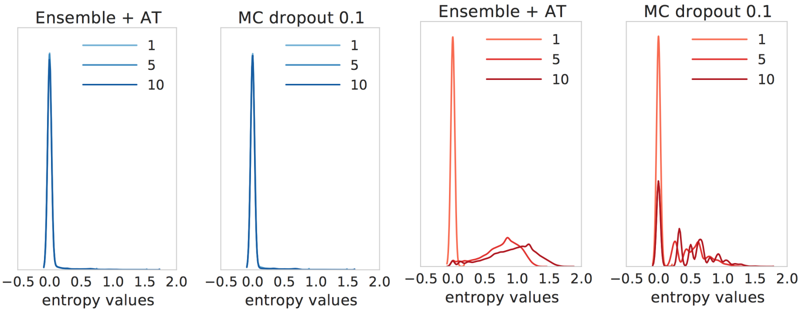

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Similar results on ImageNet (dogs vs no-dogs).

Poster # 133

Thanks!