SAFEAL 2020

BENCHMARKING UNCERTAINTY ESTIMATION METHODS FOR DEEP LEARNING WITH SAFETY-RELATED METRICS MAXIMILIAN HENNE, ADRIAN SCHWAIGER, KARSTEN ROSCHER, GEREON WEISS



UNCERTAINTY QUANTIFICATION

Softmax: Default network output

Monte-Carlo Dropout (MCDO): Sample over same network with different dropout masks

Deep Ensembles (DE): Sample over multiple, differently initialized networks

Evidential Deep Learning (EDL): Learn parameters of a predictive Dirichlet distribution

Learned Confidence (LC): Additional confidence head

EVALUATION METRICS

- Incorporate uncertainty in addition to the correctness of a prediction
 - CT: Certain True, CF: Certain False, UT: Uncertain True, UF: Uncertain False
 - Depends on a threshold for the certainty
- Remaining Error Rate
 - $RER = \frac{CF}{N}$, Error ratio when discarding uncertain predictions
- Remaining Accuracy Rate
 - $RAR = \frac{CT}{N}$, Accuracy ratio when discarding uncertain predictions

EXPERIMENTS SETUP

- Task: Image classification
- Network Architectures
 - VGG16 and a simple 6-Layer CNN (SimpleCNN)
 - Both perform very similar wrt. accuracy
 - SimpleCNN used for most of the evaluation, except when using learned confidences
- Datasets
 - CIFAR-10
 - MNIST
 - German Traffic Sign Recognition Benchmark (GTSRB)

CALIBRATION ON CIFAR-10



REMAINING ERROR RATE VS REMAINING ACCURACY RATE (CIFAR-10)



REMAINING ERROR RATE VS REMAINING ACCURACY RATE (GTSRB)



SUMMARY AND OUTLOOK

Conclusions

- No single best method
- Tested sampling-free approaches generally more cautious
- No guarantees can be given for any of the considered uncertainty quantification methods

• Future Work

- Combination of approaches
- Embedding in a safety concept
- More complicated datasets, out-of-distribution examples and other perception tasks

THANK YOU FOR YOUR

ATTENTION!



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UNCERTAINTY RATIOS (CIFAR-10)



REMAINING ERROR RATE VS REMAINING ACCURACY RATE



(CI

REMAINING ERROR RATE VS REMAINING ACCURACY RATE (MNIST)



SIMPLECNN ARCHITECTURE

Layer (type)	Output Shape	Param #
inputLayer	[(None, 32, 32, 3)]	0
Conv2D	(None, 32, 32, 32)	896
BatchNormalization	(None, 32, 32, 32)	128
Conv2D	(None, 32, 32, 32)	9248
BatchNormalization	(None, 32, 32, 32)	128
MaxPooling2D	(None, 16, 16, 32)	0
Dropout	(None, 16, 16, 32)	0
Conv2D	(None, 16, 16, 64)	18496
BatchNormalization	(None, 16, 16, 64)	256
Conv2D	(None, 16, 16, 64)	36928
BatchNormalization	(None, 16, 16, 64)	256
MaxPooling2D	(None, 8, 8, 64)	0
Dropout	(None, 8, 8, 64)	0
Conv2D	(None, 8, 8, 128)	73856
BatchNormalization	(None, 8, 8, 128)	512
Conv2D	(None, 8, 8, 128)	147584
BatchNormalization	(None, 8, 8, 128)	512
MaxPooling2D	(None, 4, 4, 128)	0
Dropout	(None, 4, 4, 128)	0
Flatten	(None, 2048)	0
Dense	(None, 10)	20490