Improving reliability of attention branch network by introducing uncertainty

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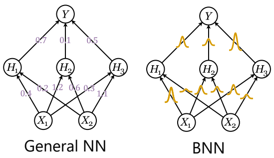
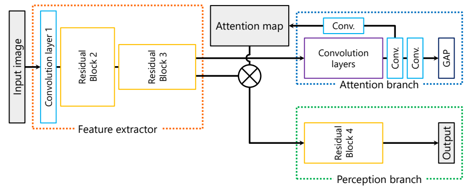
MPRG MACHINE PERCEPTION AND ROBOTICS GROUP

Background

- Convolutional Neural Networks (CNN)
  - Used in various fields to achieve high recognition accuracy
- Problem of existing CNN
  - Difficult to measure the reliability of CNN output
  - Does not consider uncertainty



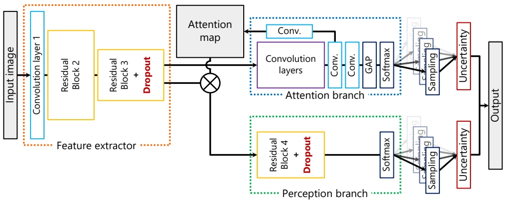
- Bayesian Neural Network (BNN) [Blundell+, ICML2015]
  - Represent the weight of a network model by probability distribution
  - Uncertainty can be estimated along with prediction results
- Monte Carlo dropout (MCDO) [Gal+, ICML2016]
  - Approximate inference of large-scale and complex models
  - Apply dropout and represent weights with a Bernoulli distribution
- Attention Branch Network (ABN) [Fukui+, CVPR2019]
  - Introduce an attention mechanism
  - Provides visual explanation by attention map



- Research Objective & Approach
  - Improving CNN reliability by considering uncertainty
  - Apply MCDO to ABN to introduce uncertainty

Proposed method

- Bayesian Attention Branch Network (Bayesian ABN)
  - Improve accuracy and reliability of CNN
  - Introduce uncertainty estimation into ABN
- Structure of Bayesian ABN
  - Added dropout
    - Apply feature extractor and perceptual branch
  - Use dropout during learning and evaluation



- Uncertainty estimation
  - Sample the output of attention branch and perception branch
  - Estimate the prediction distribution $\boldsymbol{p}_{\mathrm{branch}}$ from the average of the outputs
  - The uncertainty $H(\boldsymbol{p}_{\mathrm{branch}})$ is estimated by the entropy of the predicted distribution P_c for each class $c = 1, \ldots, C$:

$$H(\boldsymbol{p}_{\mathrm{branch}}) = -\sum_{c=1}^{C} P_c \ln P_c$$

- Estimating prediction results using uncertainty
  - Use the predicted distribution $\boldsymbol{p}$ with the lowest uncertainty as a result

$$\boldsymbol{p} = \begin{cases} \boldsymbol{p}_{\mathrm{att}} & H(\boldsymbol{p}_{\mathrm{att}}) < H(\boldsymbol{p}_{\mathrm{per}}) \\ \boldsymbol{p}_{\mathrm{per}} & H(\boldsymbol{p}_{\mathrm{att}}) \geqq H(\boldsymbol{p}_{\mathrm{per}}) \end{cases}$$

$\boldsymbol{p}_{\mathrm{att}}$: Predicted distribution of attention branch

$\boldsymbol{p}_{\mathrm{per}}$: Predicted distribution of perception branch

Experiment

- Datasets (3 types)
  1. CIFAR-10 dataset
  2. CIFAR-100 dataset
  3. ImageNet-1K dataset
- Comparative methods (3 types)
  1. Base network
  2. Base network + ABN
  3. Base network + Bayesian ABN
- Base network (4 types)
  1. Residual Network (ResNet)
  2. Wide Residual Network (WRN)
  3. Dense Convolutional Network (DenseNet)
  4. ResNeXt

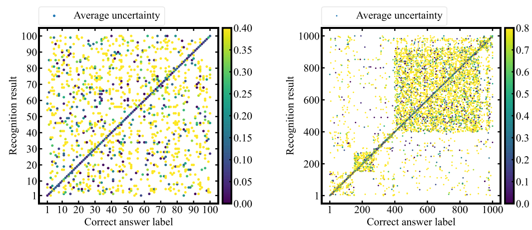
- Evaluation of recognition accuracy

[Unit : %]

Methods			CIFAR-10 dataset		CIFAR-100 dataset		ImageNet-1K dataset	
Base	ABN	Bayesian ABN	Top-1 accuracy	Top-5 accuracy	Top-1 accuracy	Top-5 accuracy	Top-1 accuracy	Top-5 accuracy
ResNet			93.57	–	75.86	–	77.81	–
	✓		94.25	99.77	76.09	92.80	79.35	94.55
		✓	**94.28**	**99.78**	**78.97**	**94.58**	**80.31**	**95.01**
WRN			95.83	–	79.50	–	76.61	–
	✓		96.04	99.89	82.01	95.53	76.93	92.97
		✓	**96.06**	**99.90**	**82.04**	**95.75**	**77.75**	**93.20**
DenseNet			94.08	–	75.85	–	77.80	–
	✓		94.48	99.79	76.51	93.57	75.85	92.87
		✓	**94.75**	**99.83**	**79.47**	**94.87**	**78.61**	**94.16**
ResNeXt			96.42	–	81.68	–	77.60	–
	✓		96.93	99.91	82.05	96.73	78.48	94.10
		✓	**96.97**	**99.93**	**83.11**	**96.94**	**79.39**	**94.62**

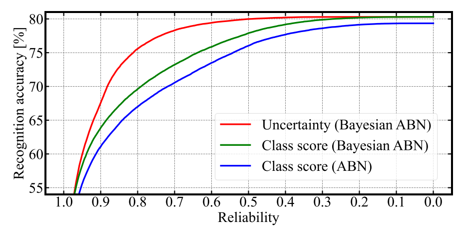
➔ Bayesian ABN achieved the highest recognition accuracy

- Analyze the effectiveness of uncertainty
  - Visualization of uncertainty



CIFAR-100 dataset   ImageNet-1K dataset

  - Recognition accuracy over different reliability threshold



➔ Introducing uncertainty improves reliability