Improving Group Fairness in Knowledge Distillation via Laplace Approximation of Early Exits

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CS 769
Optimization in Machine Learning

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Overview

1. Recap from Seminar
2. Experiments And Results
3. Analysis And Future Work

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- DEDIER loss

$$\mathcal{L}_{student} = \sum_{D_w} (1 - \lambda) \cdot l_{ce} + \lambda \cdot \mathbf{wt} \cdot l_{kd}$$

where $\mathbf{wt} = \exp^{\beta.\mathbf{cm}.\alpha}$ and $\mathbf{cm}(\mathbf{p}) = \mathbf{p_{max}} - \max_{\mathbf{p_k} \in \mathbf{p} - \mathbf{p_{max}}} \mathbf{p_k}$

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- [Meronen et al., 2023] used Laplace approximation for bayesian posterior at exit layer.
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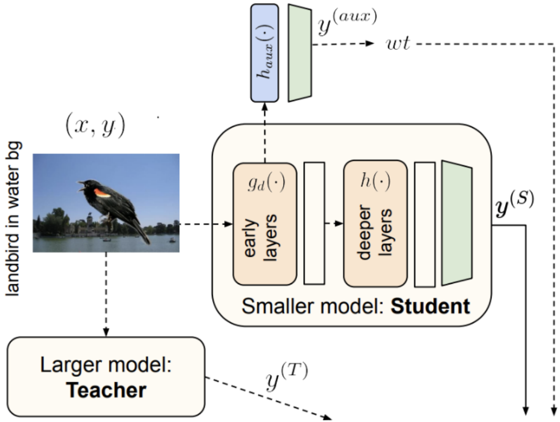
- Experiment: Laplace Approximation based uncertainity estimate to reweight both the losses.

Recap from Seminar

Figure:



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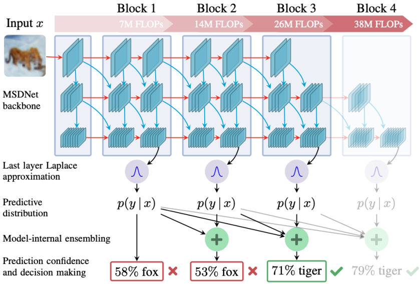

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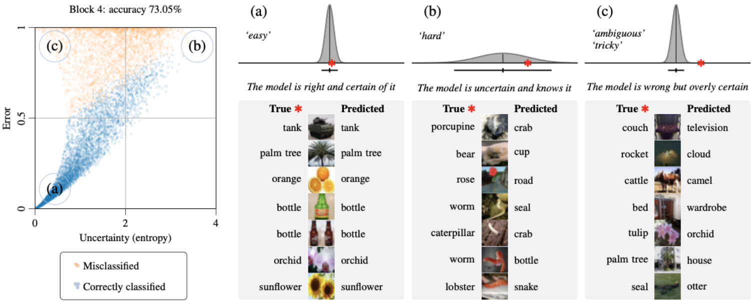

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- Bayesian treatment of parameters

$$p(\boldsymbol{\theta} \mid \mathcal{D}_{\text{train}}) = \frac{p(\mathcal{D}_{\text{train}} \mid \boldsymbol{\theta})\, p(\boldsymbol{\theta})}{\int_{\boldsymbol{\theta}} p(\mathcal{D}_{\text{train}}, \boldsymbol{\theta})\, d\boldsymbol{\theta}} = \frac{[\text{likelihood}] \times [\text{prior}]}{[\text{model evidence}]}$$

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$$p(\hat{\mathbf{z}}_i \mid \mathbf{x}_i) = \mathcal{N}(\hat{\mathbf{W}}_{\text{MAP}}^{\top} \hat{\phi}_i, (\hat{\phi}_i^{\top} \mathbf{V} \hat{\phi}_i) \mathbf{U})$$

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- Samples

$$\hat{\mathbf{z}}_i^{(l)} = \hat{\mathbf{W}}_{\text{MAP}}^\top \hat{\phi}_i + (\hat{\phi}_i^\top \mathbf{V} \hat{\phi}_i)^{\frac{1}{2}} (\mathbf{L}\mathbf{g}^{(l)})$$

$\mathbf{g}^{(l)} \sim \mathcal{N}(0, \mathbf{I})$ and $\mathbf{L}$ is the Cholesky factor of $\mathbf{U}$

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Early-Exit Neural Networks with Nested Prediction Sets.
arXiv:2311.05931 [cs, stat].

Meronen, L., Trapp, M., Pilzer, A., Yang, L., and Solin, A. (2023).
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Version Number: 4.