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

Section Overview

Recap from Seminar

- Knowledge Distillation as an effective way to distill knowledge from teacher to student

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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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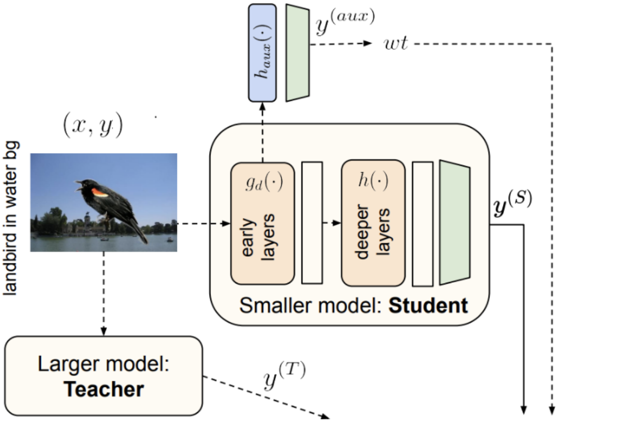
- Experiment: Laplace Approximation based uncertainity estimate to reweight both the losses.

Recap from Seminar

Figure:



$$\mathcal{L}_{student} = (1-\lambda) \cdot l_{\text{ce}}(y^{(S)}, y) + \lambda \cdot \boldsymbol{wt} \cdot l_{\text{kd}}(y^{(S)}, y^{(T)})$$

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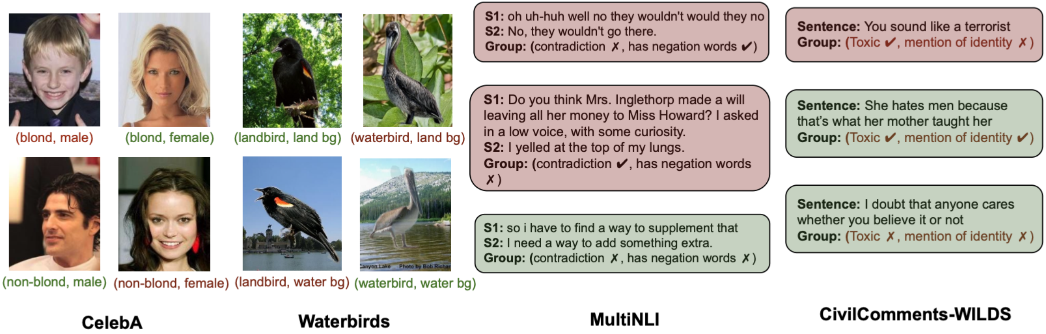

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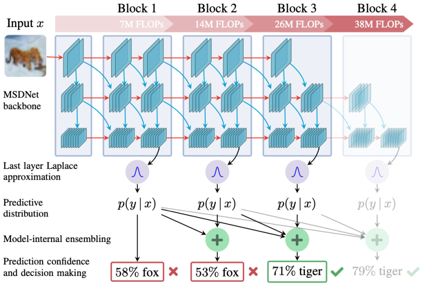

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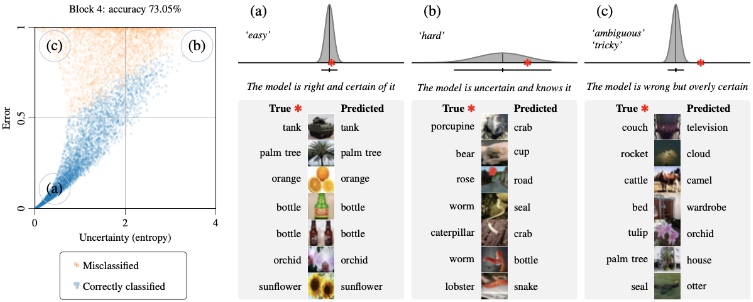

Recap from Seminar

- 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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Experiments And Results

- The MultiNLI dataset [Williams et al., 2018] was used

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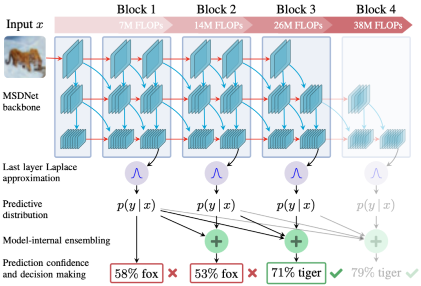

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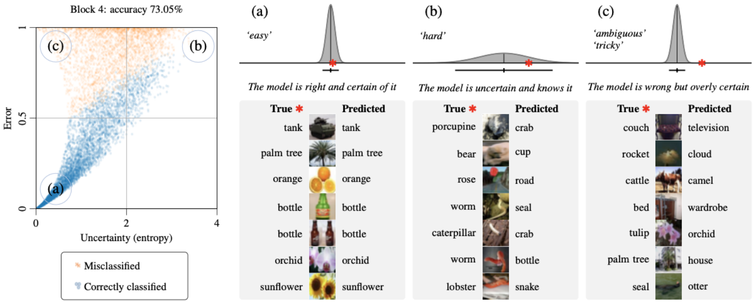

Section Overview

References

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