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

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CS 769 Optimization in Machine Learning

2 May 2025

Overview

1. Recap from Seminar

2. Experiments And Results

3. Analysis And Future Work

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

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- DEDIER loss

$$\mathcal{L}_{ extit{student}} = \sum_{D_{w}} (1 - \lambda) \cdot I_{ extit{ce}} + \lambda \cdot \mathbf{wt} \cdot I_{ extit{kd}}$$

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.

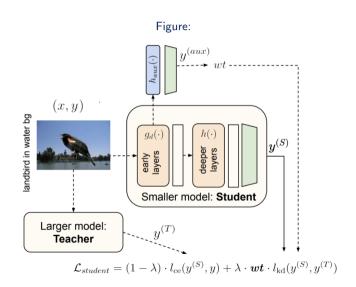


Figure:



(blond, male)







(landbird, land bg) (waterbird, land bg)



S1: oh uh-huh well no they wouldn't would they no S2: No. they wouldn't go there. Group: (contradiction X, has negation words ✔)

S1: Do you think Mrs. Inglethorp made a will leaving all her money to Miss Howard? I asked in a low voice, with some curiosity. S2: I yelled at the top of my lungs. Group: (contradiction . has negation words

S1: so i have to find a way to supplement that S2: I need a way to add something extra. Group: (contradiction X, has negation words X) Sentence: You sound like a terrorist Group: (Toxic ✓, mention of identity X)

Sentence: She hates men because that's what her mother taught her Group: (Toxic ., mention of identity .)

Sentence: I doubt that anyone cares whether you believe it or not Group: (Toxic X, mention of identity X)

(non-blond, male) (non-blond, female) (landbird, water bg) (waterbird, water bg)

CelebA

Waterbirds

MultiNLI

CivilComments-WILDS

Figure:

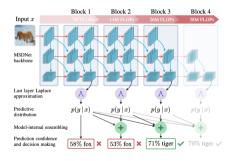
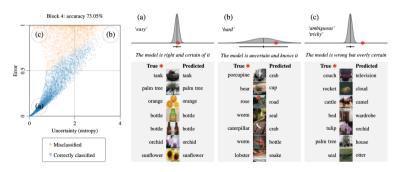


Figure:



• Bayesian treatment of parameters

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

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MAP estimate can be found by maximising the unnormalised posterior:

$$\hat{m{ heta}} = rg \max_{m{ heta}} \log p(\mathcal{D}_{\mathsf{train}} \mid m{ heta}) + \log p(m{ heta})$$

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Gaussian distribution via laplace approximation

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

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Samples

$$\hat{\mathbf{z}}_{i}^{(I)} = \hat{\mathbf{W}}_{\mathsf{MAP}}^{\top} \hat{\boldsymbol{\phi}}_{i} + (\hat{\boldsymbol{\phi}}_{i}^{\top} \mathbf{V} \hat{\boldsymbol{\phi}}_{i})^{\frac{1}{2}} (\mathsf{Lg}^{(I)})$$

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



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Meronen, L., Trapp, M., Pilzer, A., Yang, L., and Solin, A. (2023). Fixing Overconfidence in Dynamic Neural Networks. Version Number: 4.