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

Edvin 24V0074 Sagar 24D0367

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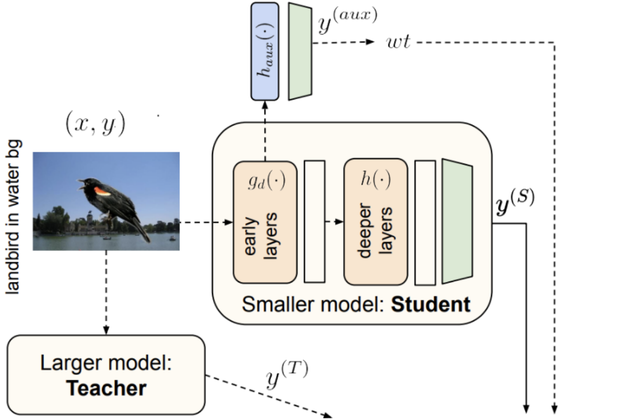
- Experiment: Laplace Approximation based uncertainity estimate to reweight both the losses.

Recap from Seminar

Figure



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

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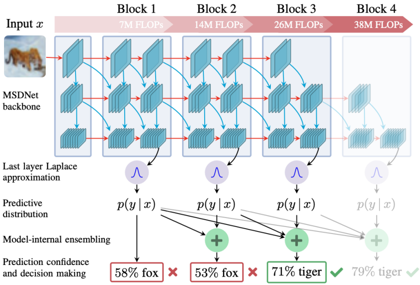

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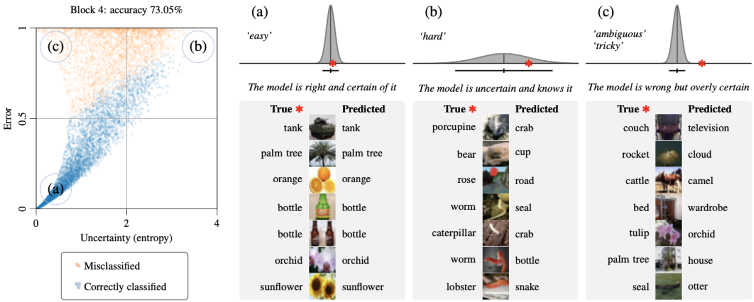

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- $$p(\boldsymbol{\theta} \mid \mathcal{D}_{\text{train}}) = \frac{p(\mathcal{D}_{\text{train}} \mid \boldsymbol{\theta})\, p(\boldsymbol{\theta})}{\int_{\boldsymbol{\theta}} p(\mathcal{D}_{\text{train}}, \boldsymbol{\theta})\, d\boldsymbol{\theta}}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

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- Gaussian distribution via laplace approximation
$$p(\hat{\mathbf{z}}_i \mid \mathbf{x}_i) = \mathcal{N}(\hat{\mathbf{W}}_{\text{MAP}}^\top \hat{\phi}_i, (\hat{\phi}_i^\top \mathbf{V} \hat{\phi}_i)\mathbf{U})$$
$$\mathbf{V}^{-1} \otimes \mathbf{U}^{-1} = \mathbf{H}^{-1}$$

  where H is
$$\mathbf{H} := -\nabla^2_{\boldsymbol{\theta}} \log p(\boldsymbol{\theta}|\mathcal{D})\Big|_{\boldsymbol{\theta}_{\text{MAP}}}$$

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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.
- Determine if premise entails, contradicts, or is neutral given a hypothesis.
- Major Diffrences with DEDIER: The auxiliary reweighting is done in every epoch, as student trained for five epochs.
- The auxiliary network used is a simple, single layer network.
- Models Used
  - **Teacher model:** `bert-base-uncased` (12-layer BERT, hidden size 768)
  - **Student model:** `distilbert-base-uncased` (6-layer DistilBERT, hidden size 768)
  - **Auxiliary network:** One-layer linear classifier trained on the students third layer.

Experiments And Results

- Hyperparameters
  - **Teacher fine-tuning**
    - Epochs: $E_T = 3$
    - Learning rate: 2×10^{-5}
    - Optimizer: AdamW
  - **Student training**
    - Epochs: $E_S = 5$
    - Learning rate: 2×10^{-5}
    - Optimizer: AdamW
    - Distillation temperature: $\tau = 2.0$
- Training and Evaluation
  - Batch size: 16
  - Dataset: MultiNLI (via HuggingFace `datasets`)
  - Evaluation: Accuracy and per-group performance (negation vs. non-negation)
  - Tokenization: `bert-base-uncased` tokenizer with padding and truncation
  - Learning rate scheduler: Linear schedule with warm-up

Experiments And Results

Metric	Teacher	Student (Aux layer 3)	Student (Aux layer 6)	Group
Average Accuracy	0.845	0.835	0.832	All

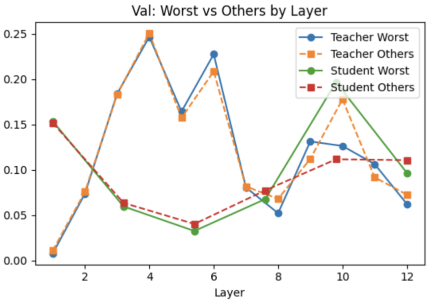
Table: Results of Dedier with Laplace

Experiments And Results

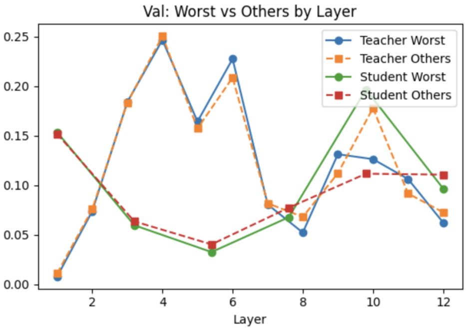
Metric	Teacher	Student
Final Test Accuracy	0.841	0.830

Table: Original DEDIER performance with same teacher

Experiments And Results



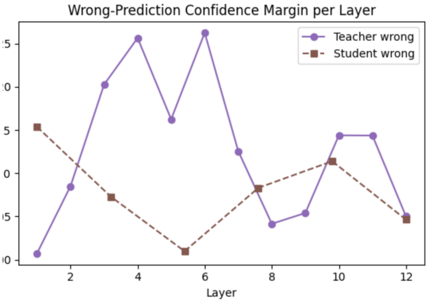
(a) Auxiliary network on layer 3



(b) Auxiliary network on layer 6 (last layer)

Figure: Confidence margins per layer on worst group predictions and all predictions

Experiments And Results



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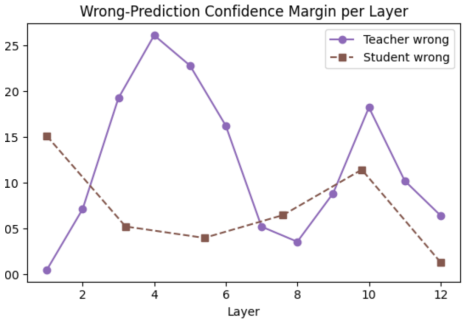

(b) Auxiliary network on layer 6 (last layer)

Figure: Confidence margins in student and teacher on the predictions that were wrong

Section Overview

Analysis And Future Work

- Minor improvement in accuracy of the student model by the proposed approach over DEDIER on MultiNLI
- Still more testing needed, on varied datasets and teacher models for justifying its use.
- The confidence margins are generally lower than one used in DEDIER work.
- Need to study effects of increasing layers of Aux network
- Hyperparameter tuning

Conclusion

- Cheap, effective uncertainty via Laplace in early exits.
- Uncertainty reweights KD loss in student models.
- Reduces reliance on simple features.

References

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arXiv:2311.05931 [cs, stat].

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