The key idea is to learn a binary mask that indicates whether a weight should be frozen or not when fine-tuning on the target domain.

**Motivation + Hypothesis**

- The key idea is to modularize the weights of a network into those specialized for the source task and those we can reuse and fine-tune for the target task.
- If we only fine-tune these weights and freeze the specialized weights, the hypothesis is that we will not lose too much performance on the source dataset.
- We provide three methods to learn a binary mask that indicates whether a weight should be frozen or not when fine-tuning on the target domain.

**Problem Statement + Dataset**

Problem Statement:
A model f_s is trained on a source domain S. There is a target domain T to which we would like to generalize.

Goal: generalize to target domain T while retaining strong performance on S.

Dataset:
We utilize the PACS dataset. PACS consists of 4 domains: photos, art, cartoon, and sketch. Each domain consists of the 7 classification classes.

**Methodology**

Naive Masking
- We identified that the weights after training on S are distributed normally and hence re-initialized the weights that were one within one standard deviation from the mean.
- The idea is that extremes contribute more to the output than the non-extremes.

Edit Masking (A)
- Learn a real-valued edit for each weight after training on S such that the cross-entropy loss on S does not decrease too much.
- Regularizer: "edit as many weights without affecting performance on S".
- The actual weights W are frozen during mask training.
- If a weight is edited more than a certain threshold after mask training, we hypothesise that it is not specialized to S and re-initialize it.

Binary Masking (B)
- Instead of learning a real-valued mask and thresholding it to get a binary mask, learn a binary mask directly.
- During mask training, sample binary masks from the real-valued logits using Gumbel-Sigmoid and a straight-through estimator so it is end-to-end differentiable.
- Once we sample a mask, multiply it with the frozen W to mask out some weights and learn a mask that doesn't reduce cross entropy loss too much and the regularizer encourages masking as many weights as possible.
- After mask training, re-initialize weights with negative logits and freeze the other weights.

**Future Work**

- Information-theoretic masking strategies: identify weights that give maximum information about logits; mask weights such that distance between output probability distributions before and after masking are similar.
- Linear algebraic masking strategies: make edits on the low-rank approximation of the weight matrix preserving the eigenvectors corresponding to larger eigenvalues.
- Extending to multi-task and continual learning settings.

**Experimental Results**

Target Domain Performance
- Binary masking consistently yields the strongest performance when the fine-tuned model is evaluated in the source domain.
- Edit and naive masking surpass the no-masking baseline at times.
- Hypothesis: edit and naive masking are sensitive to the threshold at which to binarize; binary masking provides a more natural way to obtain a binary mask.

**Discussion and Analysis**

How should $\theta_{new}$ be initialized?

- We explore 3 methods for initializing $\theta_{new}$ values before starting source domain training ($\theta_{source}$), values after source domain training ($\theta_{source}$), and random.
- Values are similar across strategies, but $\theta_{source}$ yields the best performance most often, similar to the findings in the Lottery Ticket Hypothesis.

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