Hierarchical Prototypical Networks for Fine-Grained Image Classification

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Outline

Problem Description

Classification generally suffers in case of small intra class variations and do badly on such closely related dataset. Intra class differences across data points of similar sub-classes of particular class, are in general hard to capture through basic models. Embedding space for each subclass could be considered to capture this differences.

A Simple Inductive Bias

- There exists a latent space where samples from same class are close together and far away from samples from other classes.
- A class prototype is defined by the mean embedding vector of all samples of that class.
- Given all class prototypes, a sample can be classified by giving it a label of its closest prototype.

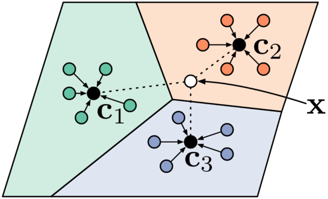

Figure: Prototypical Network

This bias reduces the classification task to finding the corresponding latent space.

Training Algorithm

Initialize the Prototypical Neural Network

$\hookrightarrow$ prototypical network maps an image to the latent space

Sample N_C number of subclasses from the dataset

▶ Finding Prototypes using Support set

for *each subclass in the* $[N_C]$ **do**

  Sample support set and query set of that dataset;

  Obtain the subclass prototypes using support set;

end

▶ Optimizing Network using Query set

for *each subclass in the* $[N_C]$ **do**

  for *each sample in the query set* **do**

    Assign the sample to its closest prototype in the latent space.

    Calculate the cross entropy loss

  end

end

Update the Network to minimize the sum of Cross Entropy loss.

Further Improvements

- Maximizing the pairwise Prototypical distance of all prototypes
  ↪ After the gradient update from previous step
  - Recalculate the prototypes using Support Set
  - Calculate S = sum of pairwise distances of all prototypes
  - Update the Network to maximize S

Note : This combined with previous optimization step forms an alternating optimization schedule.

Hierarchical Cross-Entropy Loss Function

- Our Hierarchical Cross-Entropy loss is defined as

$$loss = -\left[\alpha \sum_{c=1}^{M} y_{o,c} \log p_{o,c} + (1-\alpha)\frac{1}{2} \sum_{d \notin S_o} \log\left(1 - p_{o,d}\right)\right]$$

where S_o is all the sister subclasses of correct subclass of object o.
and α is a weighting parameter

- If a image gets classified to a subclass label in other class higher loss is incurred.
- If a image gets classified to a subclass label of same parent class less loss is incured.

Dataset

We are using dataset of following coarse classes and corresponding sub classes (fine grained classes).

CUBS Birds Dataset - 200 sub classes

Dataset

FGVC-Aircraft dataset - 120 sub classes.

Dataset

Stanford Cars Dataset - 196 sub classes.

Dataset

Stanford Dogs Dataset - 120 sub classes.

Thank You