50.021 – AI

Alex

Week 04: Fine Tuning of neural networks

[The following notes are compiled from various sources such as textbooks, lecture materials, Web resources and are shared for academic purposes only, intended for use by students registered for a specific course. In the interest of brevity, every source is not cited. The compiler of these notes gratefully acknowledges all such sources.]

1 Homework

Due: as announced

- check the AMI that I shared with your amazon account: it is oregon zone, search for owner: 277133844599. You should see an AMI with ubuntu18_.....
- take the imageclef dataset, select those data samples which are either indoor or outdoor (index 13 and 14 if count starts at 0) and write a dataset class which can work with a train/val/test split for it.
- take any deep network you like which has pretrained weights (a resnet18 or a mobilenet are training fast, keep your AWS money for the project rather than NASNets or VGG or other dinosaurs of computations)
- train a deep neural network in three different modes:

  A once without loading weights and training all layers.

  B once with loading model weights before training and training all layers,

  C once with loading model weights before training and training only the last trainable layer (note: for quite some problems, the approach B is better than C), for the two imageclef classes below C is the better option

For each of these 2 modes select the best epoch by its performance on the validation set. Typically less than 30-40 epochs should suffice for training when using finetuning. You can run also optionally a selection over a few learning rates. If you use amazon AWS please do not use more than 6 GPU hours. You will need them later for a project. For me the ImageCLEF job with a resnet18 trains 90 seconds on a RTX2080 Ti for 30 iterations, on Kepler K80 from 2014 GPUs it could be 6 minutes or the like.

- what loss to choose for this multiclass dataset?

  what do you need to do for steps when you start with a code like the MNIST training code?

  - write a new dataloader for your training dataset
  - adjust paths for data (and if necessary for label paths/files or files determining splits into train/val/test)
  - decide on some at least basic data augmentation (how to load the images into a fixed size: resizing+some cropping, do more at training time? do what at test time ?)
  - use some deep learning model from the model zoo, load its weights before training
  - think of what results to report for homework submission. a naked code will not do it!

- A note: Calling a model constructor with `pretrained=True` does not tell you what really goes on when one. Check `https://github.com/pytorch/vision/blob/master/torchvision/models/resnet.py` to see what routine is used to load a model.

- for the homework report at least the following:

  - for each of the 3 settings curves of training loss, validation loss and validation accuracy as a function of epochs (for the best setting you found)
  - for each of the 3 settings the test accuracy of the best model
  - observe differences between the validation and the test accuracy of these models
  - report the baseline accuracy given the test set frequencies for these two classes.

- outside of homework I (for self-study): if you want to see a setting where B beats C, check the 102 flowers dataset and play with it. Its just another dataloader and 102 instead of 2 classes.

- outside of homework II (for self-study): if you want a reasonable result on a harder problem with small sample size like classes $9, 10, 11, 12$, then try

the following. Do not create train and val, but create a trainval dataset, and split it into 5 cross-validation slices. Then train 5 models – each of them trained on 4/5 and evaluated on the disjoint 1/5-th. For each of the five models you use another 1/5-th of trainval. For prediction on the test set you use the average of all these 5 models. I keep this out of homework because this is more complicated to code.

- do not try some very hard and subjective classes like 70 *cute*. You do not have enough data to generalize to such a diverse class directly. You can though improve learning on it by exploiting class correlations between cute and other class labels.