Regularization, Data Augmentation and Self-supervised Learning

Efficient Deep Learning - Session 4

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Course organisation

Sessions

1. Introduction/Refresher on Deep Learning
2. Quantization,
3. Pruning,
4. Regularization, Data Augmentation,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL,
8. Final session.

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Why this session ?

Regularization

Constrain the training for faster convergence and better generalization.

Data Augmentation (DA)

Help generalization by sampling training examples from a larger distribution using randomized transforms.

Self-supervised Learning (SSL)

Exploit DA and regularization tricks for learning representations, without labels

Significance

- In some (most?) cases, DA regularizes training and is needed.
- Large networks can't be trained without regularization.

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Regularization

Weight Decay

An old idea (Krogh and Herz 1991): ℓ_2 penatly term is added to the loss, limits the growth of model weights.

Has been shown to increase generalization and suppresses irrelevant model weights.

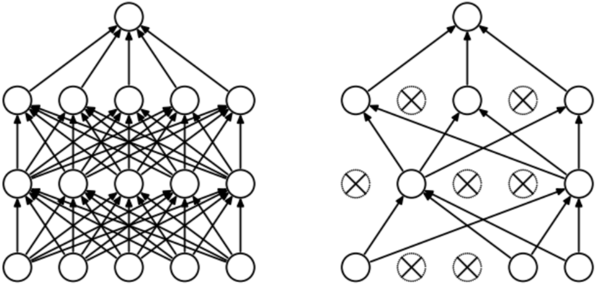
Ressources :

- https://proceedings.neurips.cc/paper/1991/file/8eefcfdf5990e441f0fb6f3fad709e21-Paper.pdf
- https://ja.d2l.ai/chapter_deep-learning-basics/weight-decay.html
- Readily available in pytorch (optimizer options)

Regularization

Dropout

Randomly "drops" some units during training with a certain probability.



(a) Standard Neural Net (b) After applying dropout.

- Was introduced to train very large networks
- Can prevent overfitting
- Adds hyperparameters : where to drop ? How often ?

https://www.jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf

Regularization

Batch Normalization (Ioffe & Szegedy, 2015)

Normalize feature distributions to the standard distribution by learning batch statistics.

- Consider a batch X
- Calculate $m = E(X)$ and $\sigma = Var(X)$
- Compute $\hat{X} = \frac{X-m}{\sigma}$
- m and σ are continuously updated across batches using running statistics

Notes

- Has been shown to accelerate training, increase generalization
- Can remove the need for DropOut
- Should be included by default after convolutions

`http://proceedings.mlr.press/v37/ioffe15.pdf`

Data Augmentation using image transformations

Translations, rotations, Scaling, Shifting in RGB, Crops, ...

Image from Albumentations `https://albumentations.ai/docs/examples/pytorch_classification/`

Mixup, Cutout and Cutmix

Mixup

For a network F trained using Cross Entropy (CE),

- Sample x_i, x_j from the training data, associated to labels y_i, y_j.
- Defined mixed up data samples as $\tilde{x} = x_i + (1 - \lambda)x_j$
- $loss = \lambda CE(F(\tilde{x}), y_i) + (1 - \lambda)CE(F(\tilde{x}), y_j)$, where $\lambda \in [0, 1]$
- Train with backprop

Notes

- Has been shown to regularize training and achieves better generalization.
- Should be included most of the time when training classification networks !
- See Lab4.md for a proposed implementation

`https://arxiv.org/pdf/1710.09412.pdf`

Mixup, Cutout and Cutmix

	ResNet-50	Mixup [47]	Cutout [3]	CutMix
Image				
Label	Dog 1.0	Dog 0.5 Cat 0.5	Dog 1.0	Dog 0.6 Cat 0.4
ImageNet Cls (%)	76.3 (+0.0)	77.4 (+1.1)	77.1 (+0.8)	**78.6** **(+2.3)**
ImageNet Loc (%)	46.3 (+0.0)	45.8 (-0.5)	46.7 (+0.4)	**47.3** **(+1.0)**
Pascal VOC Det (mAP)	75.6 (+0.0)	73.9 (-1.7)	75.1 (-0.5)	**76.7** **(+1.1)**

Table 1: Overview of the results of Mixup, Cutout, and our CutMix on ImageNet classification, ImageNet localization, and Pascal VOC 07 detection (transfer learning with SSD [23] finetuning) tasks. Note that CutMix significantly improves the performance on various tasks.

https://openaccess.thecvf.com/content_ICCV_2019/papers/Yun_CutMix_Regularization_Strategy_to_Train_Strong_Classifiers_With_Localizable_Features_ICCV_2019_paper.pdf

Application to Self supervised Learning

Self-Supervised Learning

Learn representations of input samples without labels or annotations

How ?

Train encoders (e.g. ResNet) on pre-text tasks:

- Self-Prediction
- Contrastive Learning

Trained encoders are expected to learn general features that generalize to supervised tasks.

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Contrastive Learning : SimCLR.

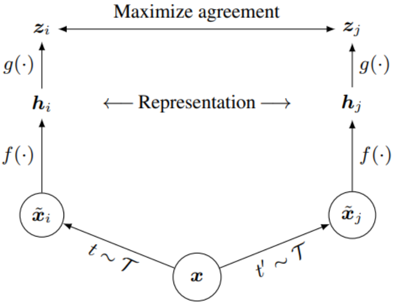

Figure 2. A simple framework for contrastive learning of visual representations. Two separate data augmentation operators are sampled from the same family of augmentations ($t \sim \mathcal{T}$ and $t' \sim \mathcal{T}$) and applied to each data example to obtain two correlated views. A base encoder network $f(\cdot)$ and a projection head $g(\cdot)$ are trained to maximize agreement using a contrastive loss. After training is completed, we throw away the projection head $g(\cdot)$ and use encoder $f(\cdot)$ and representation $\boldsymbol{h}$ for downstream tasks.

https://arxiv.org/pdf/2002.05709.pdf