

Regularization, Data Augmentation and Self-Supervised Learning

Efficient Deep Learning - Session 4



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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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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.

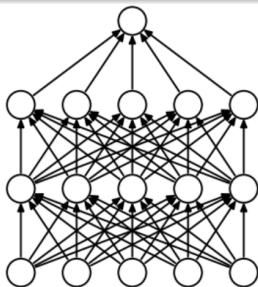
Ressources :

- <https://proceedings.neurips.cc/paper/1991/file/8eefcfd5990e441f0fb6f3fad709e21-Paper.pdf>
- https://ja.d2l.ai/chapter_deep-learning-basics/weight-decay.html
- Readily available in pytorch (optimizer options)

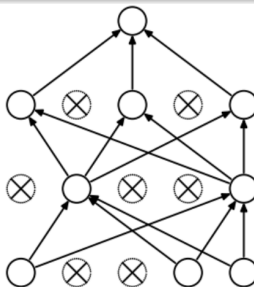
Regularization

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 $\sigma = \text{Var}(X)$
- Compute $\hat{X} = \frac{X-m}{\sigma} * \gamma + \beta$
- m and σ are continuously updated across batches using running statistics, and γ and β are learnable parameters (by default set to 1 and 0, respectively)

Notes

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

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 $\tilde{x} = \lambda x_i + (1 - \lambda)x_j$
- $loss = \lambda CE(F(\tilde{x}), y_i) + (1 - \lambda)CE(F(\tilde{x}), y_j)$, 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 ?

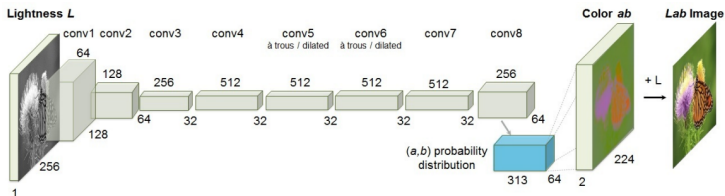
Train encoders (e.g. ResNet) on pre-text tasks:

- Self-Prediction
- Contrastive Learning

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

Application to Self supervised Learning

Self-Prediction : Colorful Image Colorization



<https://arxiv.org/pdf/1603.08511.pdf>

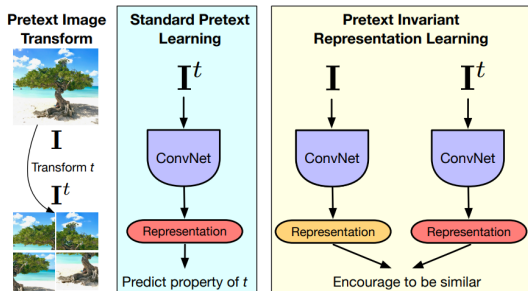
Colorful Image Colorization

Learn feature representations by restoring colored version of images :

- Given lightness L , predict a and b color channels (CIE Lab colorspace)
- A loss penalty is computed between the predicted and the original image

Application to Self supervised Learning

Contrastive Learning : Pretext-Invariant Representations Learning (PIRL)



<https://arxiv.org/pdf/1912.01991.pdf>

PIRL

Train a discriminative feature extractor :

- Images and their augmented version should have similar representations
- Different images should have dissimilar representations