Regularization, Data Augmentation and Self-Supervised Learning

Efficient Deep Learning - Session 2

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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Course organisation

Sessions

1. Intro Deep Learning,
2. Data Augmentation and Self Supervised Learning,
3. Quantization,
4. Pruning,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL,
8. Presentations for challenge.

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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 penalty term is added to the loss, limits the growth of model weights.

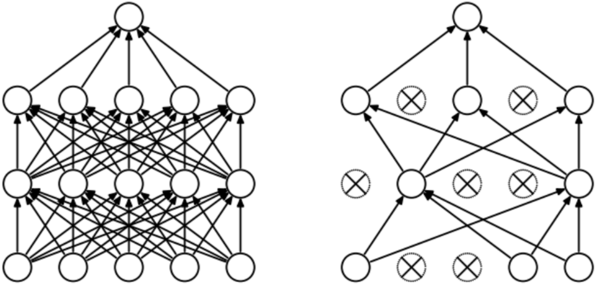
Has been shown to increase generalization and suppresses irrelevant model weights.
Ressources :

- `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 $\hat{X} = \frac{X-m}{\sigma} * \gamma + \beta$
- 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

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

Self supervised Learning

Self-Supervised Learning

Learn representations of input samples without labels or annotations

How ?

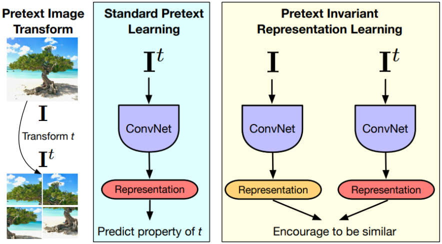
Train encoders (e.g. ResNet) on pre-text tasks:

- Contrastive Learning
- Self-Prediction

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

Self supervised Learning

Contrastive Learning : Pretext-Invariant Representations Learning (PIRL)



`https://https://arxiv.org/pdf/1912.01991.pdf`

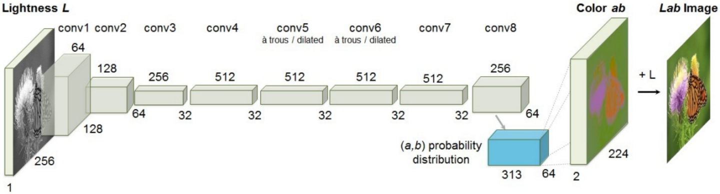
PIRL

Train a discriminative feature extractor :

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

Self supervised Learning

Self-Prediction : Colorful Image Colorization



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

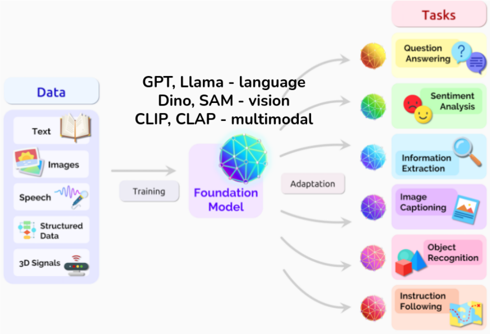
Colorful Image Colorization

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

Self supervised Learning

SSL to pretrain foundation models

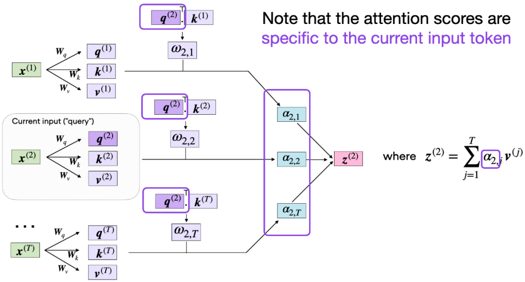


https://arxiv.org/pdf/2108.07258.pdf

Foundation Model

- Pretrained on internet-scale data with SSL
- Able to learn general features from data
- Perform (or can be easly adapted to) multipurpose tasks

Self-Attention



Self-Attention in foundation models

- Grasp relationships between parts of the inputs (context)
- Attention weights ω: dot product input query **q** and all other inputs key **k**
- The input **x** is transformed in the context vector **z**, which is an attention-weighted version of the original query input

https://sebastianraschka.com/blog/2023/self-attention-from-scratch.html

Self-Attention

Self-Attention and Transformers

- Self-Attention is found in the basic architecture of foundation models: **Transformers**
- No convolutions, inputs are transformed taking in account attention weights
- Best generalization in many domains, but need large scale data

https://arxiv.org/pdf/1706.03762.pdf