PyTorch Tutorial: Part II

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Outline

In this tutorial, some advanced models will be introduced.
* All the materials included in the slides are only used for the purpose of academic education.

Normalization

Why do we need normalization?

- Batch Norm: Reduce internal co-variate shift.
- Instance Norm: Reduce the influence of contrast.

* Instance Norm is a special case of Batch Norm($batchsize = 1$).

Batch Norm Paper: `https://arxiv.org/pdf/1502.03167.pdf`

Instance Norm Paper: `https://arxiv.org/pdf/1607.08022.pdf`

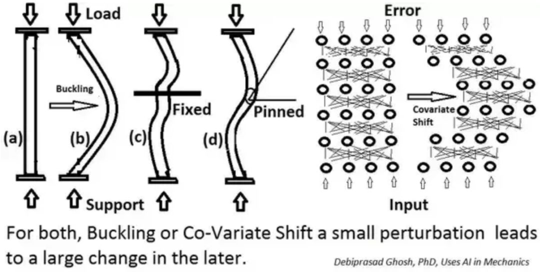


Figure: Visual explanation from Quora: Co-Variate Shift

Normalization

Ideally, all the samples are i.i.d, but it's almost impossible. That's why we need normalization.
It not only accelerates the speed of convergence, but also increases the accuracy.

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Figure: Core Algorithm of Batch Normalization

Autoencoder

Autoencoder is useful for information compression. Training an autoencoder to minimize reconstruction error amounts to maximizing a lower bound on the **mutual information** between input and learnt representation in latent space. [Stacked Denoising Autoencoders]

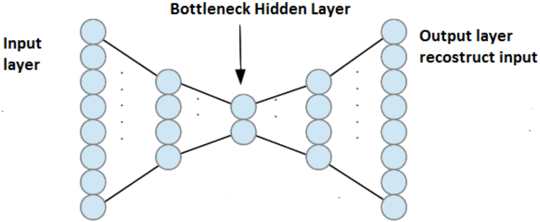


Figure: autoencoder architecture

ResNet

ResNet Paper: `https://arxiv.org/pdf/1512.03385.pdf`

- Understand why the gradients are unstable. [gradient problem]
- Using residual blocks makes training arbitrarily deep neural nets become possible.

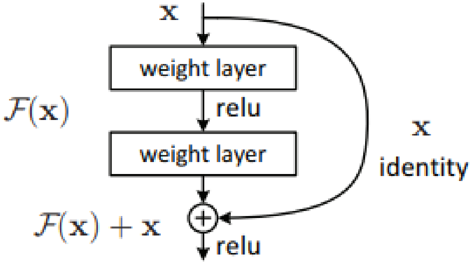
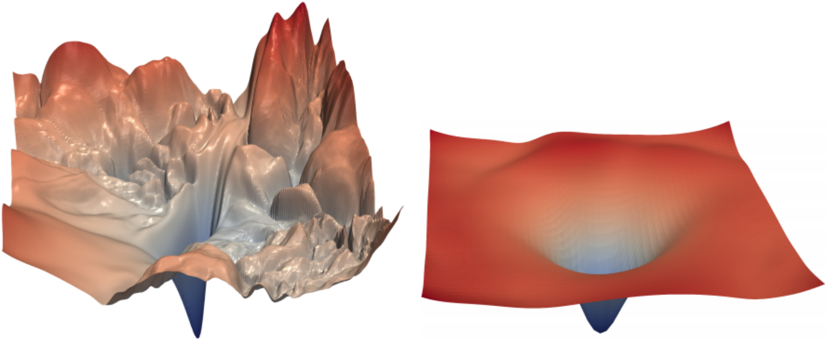


Figure: Residual block

Skip-connection

Effect of skip-connection: `https://arxiv.org/pdf/1712.09913.pdf`



(a) without skip connections (b) with skip connections

Figure: The loss surfaces of ResNet-56 with/without skip connections.

VisualBackProp: Efficient visualization of CNNs

VisualBackProp Paper: `https://arxiv.org/pdf/1611.05418.pdf`
Intuition: The feature maps contain less and less irrelevant information to the prediction decision when moving deeper into the network.

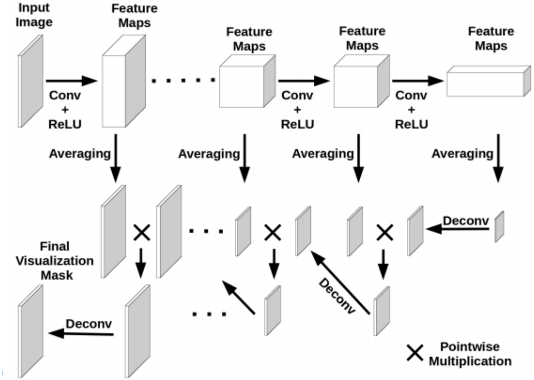


Figure: VisualBackProp

U-Net

U-net Paper: `https://arxiv.org/pdf/1505.04597.pdf`. U-Net was first used for image segmentation but itself is also a great autoencoder architecture.

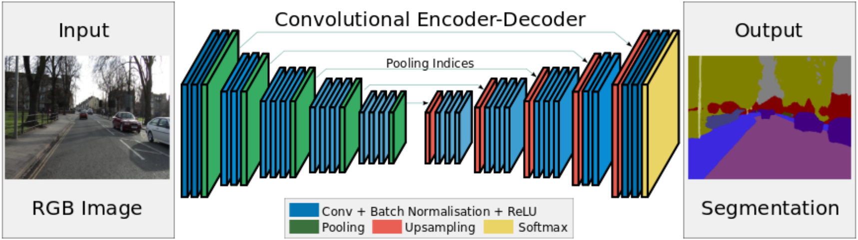


Figure: SegNet

Generative Adversarial Nets

GAN Paper: `https://arxiv.org/pdf/1406.2661.pdf`

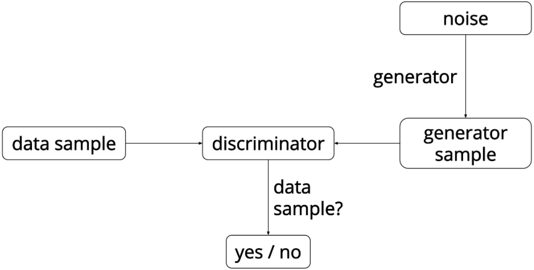


Figure: Generative adversarial nets

Extended Reading:

- Minimax: `https://en.wikipedia.org/wiki/Minimax`