Lecture 7. Convolutional Neural Networks, advanced technics

Alex Avdyushenko

Kazakh-British Technical University

October 24, 2022

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Hello, today we continue to talk about Convolutional Neural Networks, advanced optimization methods ans architecture.

And again we will start with three questions for five minutes based on the materials of the previous lecture.

Five-minutes block

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Please, write answers or send photos with them directly to me in private messages here in Teams, so that others cannot read your message. Last time, a lot of people did it, so I believe that this time you all will succeed.

Five-minutes block

- Define a convolution operation for neural networks
- Write down the main features of the AlexNet network
- Write the formulas for updating the weights in the Momentum method

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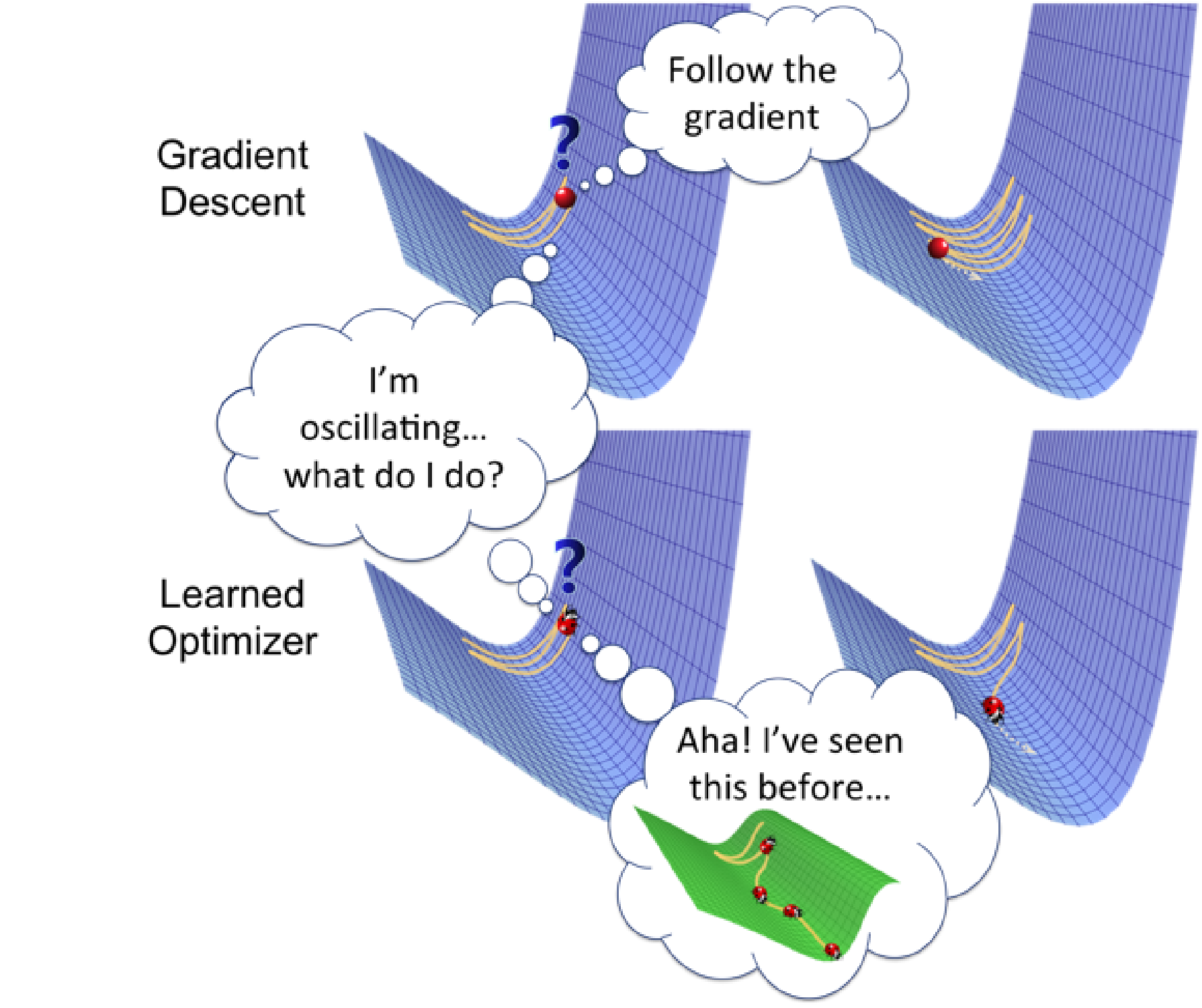
Gradient Descent
Follow the gradient
?
I'm oscillating… what do I do?
Learned Optimizer
?
Aha! I've seen this before…

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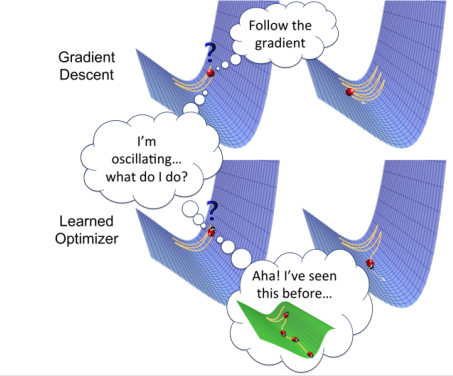

Let's look at this picture. In many ways, it reflects the entire content of today's lecture.

Neural networks optimization methods

Recall the Momentum method

A very popular method for improving the convergence of SGD is the momentum accumulation method. In it, from a physical point of view, the derivative of the loss function becomes the acceleration of the change in model parameters, and not the speed as in classical SGD.

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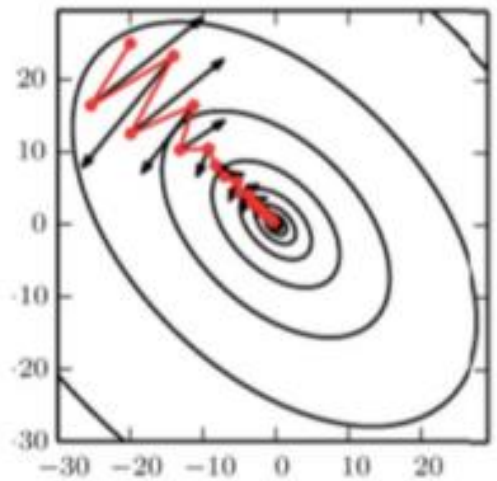

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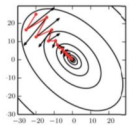

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AdaGrad

Another interesting approach is the adaptive gradient method. You accumulate squares of gradient vector and then change the model parameters by the component-wise way.

AdaGrad

$$G = G + \mathcal{L}'_i(w) \odot \mathcal{L}'_i(w)$$
$$w = w - \eta_t \mathcal{L}'_i(w) \oslash \sqrt{G + \varepsilon}$$

η_t can be fixed, for example $\eta_t = 0.01$,
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The development of AdaGrad is RMSProp — optimization method, which you really have in modern libraries.

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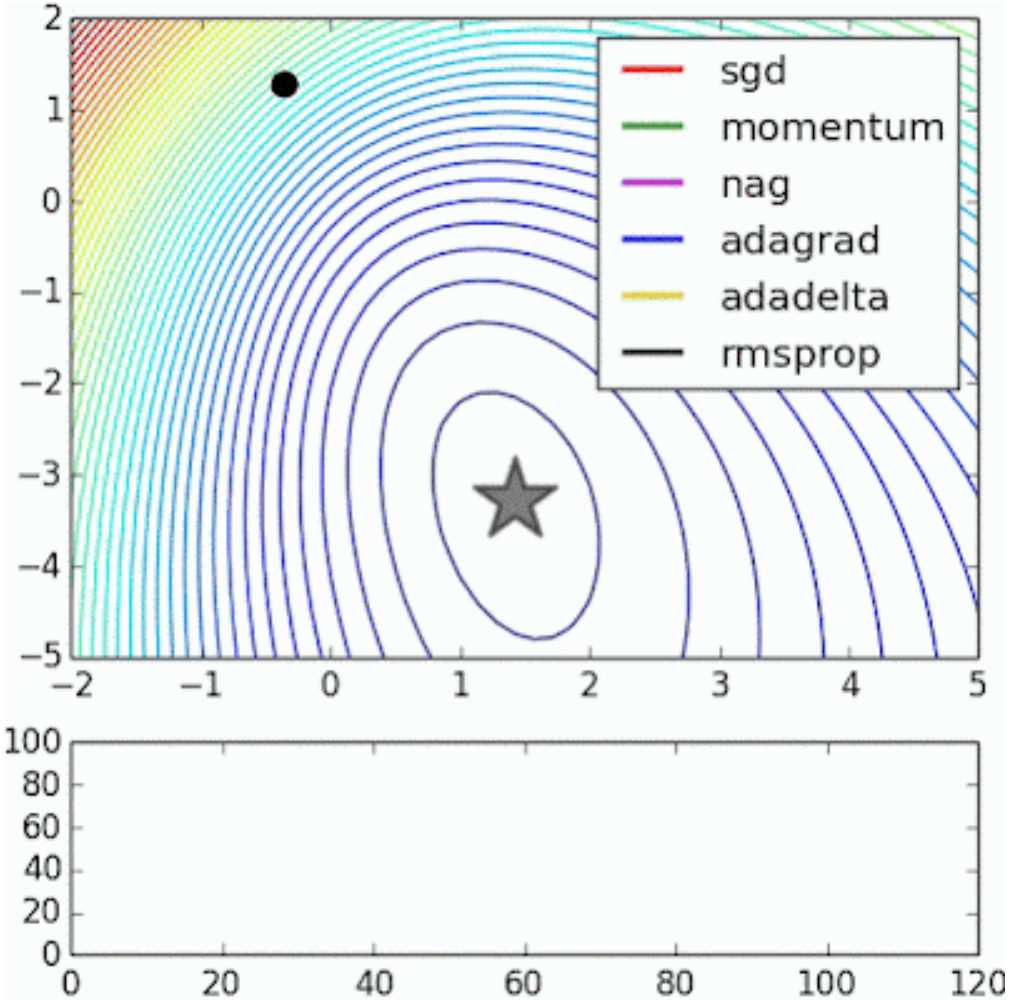
And Nadam (Nesterov-accelerated adaptive momentum) — is modern modification of Adam method.

Convergence example



Source: http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html

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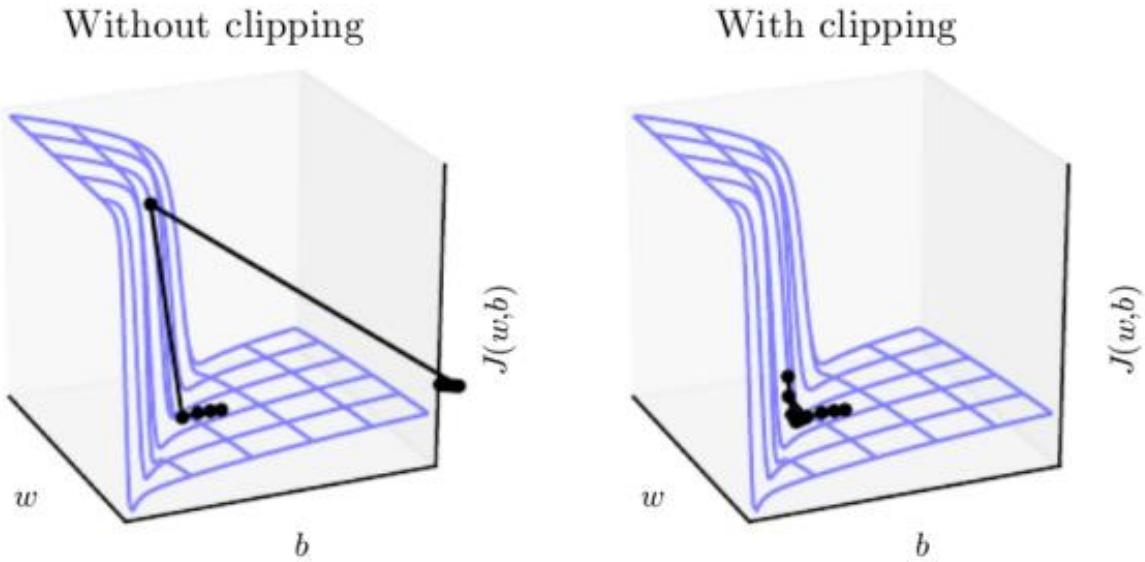
Let's look on example of convergence of considered optimization methods.

Question

Which method and how to choose?

Gradient exploding



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Source: https://neptune.ai/blog/understanding-gradient-clipping-and-how-it-can-fix-exploding-gradients-problem

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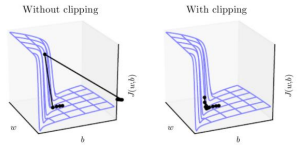
Gradient exploding

There is typical problem in neural network optimization, it is gradient exploding.

Gradient exploding



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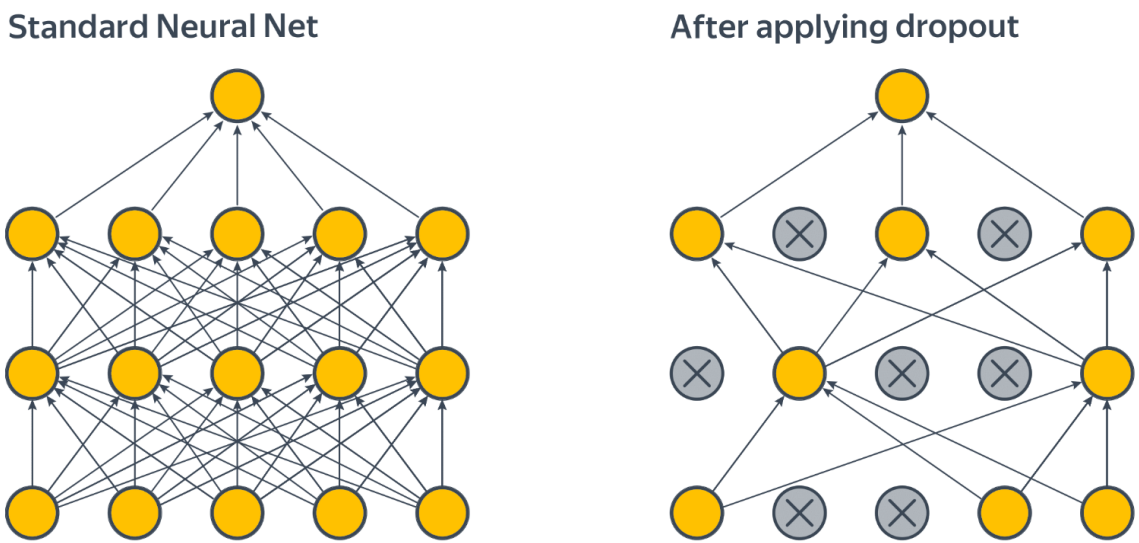

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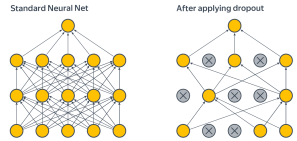

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Question

What is the peculiarity of this case of dropout implementation?

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Application stage doesn't require neither modification nor knowledge of p_ℓ:

$$x_{ih}^{\ell+1} = \sigma_h\Big(\sum_j w_{jh}x_{ij}^\ell\Big)$$

L_2-regularization prevents growth of training parameters:

$$\mathcal{L}_i(w) + \frac{\lambda}{2}\|w\|^2 \to \min_w$$

Gradient step with Dropout and L_2 regularization:

$$w = w(1-\eta\lambda) - \eta\frac{1}{1-p_\ell}\xi_h^\ell \mathcal{L}_i'(w)$$

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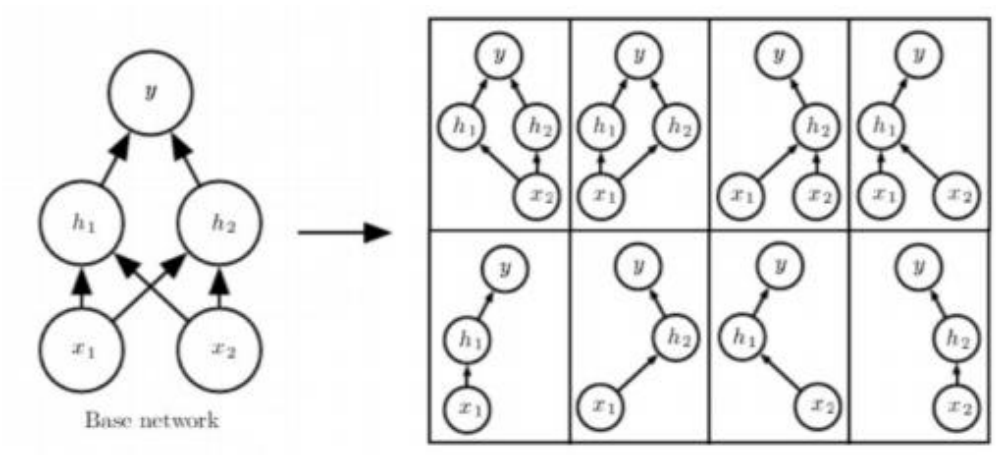

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3. Parameters $\gamma_j^\ell, \beta_j^\ell$ are configured by BackProp

Initial Approximation of the Weights

Monitoring changes in variances

Both of neuron values and backpropagation gradients

Equalization of variances of both neurons and gradients in different layers — Xavier initialization for tanh:

$$w_j \sim U\left[-\frac{6}{\sqrt{n_{in}+n_{out}}}, \frac{6}{\sqrt{n_{in}+n_{out}}}\right]$$

n_{in}, n_{out} — the number of neurons in the previous and current layers, respectively

The proof and details are in the SHAD textbook (in Russian yet).

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Question

What to do in case of ReLU activation?

Other ways of initialization

1. Layer-by-layer training of neurons as linear models
   - or by random subsample
   - or by a random subset of inputs
   - or from various random initial distributions

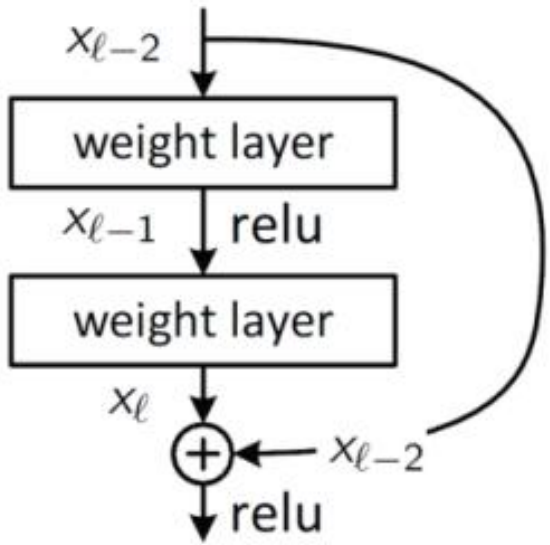
   This ensures the diversity of neurons.
2. Weight initialization of a pre-trained model (for example, an autoencoder)

ResNet — Residual Net

Skip-connection of the ℓ layer with the previous $\ell - d$ layer:

$$x_\ell = \sigma(Wx_{\ell-1}) + x_{\ell-d}$$

The ℓ layer learns not the new vector representation x_ℓ, but its increment $x_\ell - x_{\ell-d}$



- (main) it is possible to increase the number of layers
- increments are more stable $\rightarrow$ convergence is better

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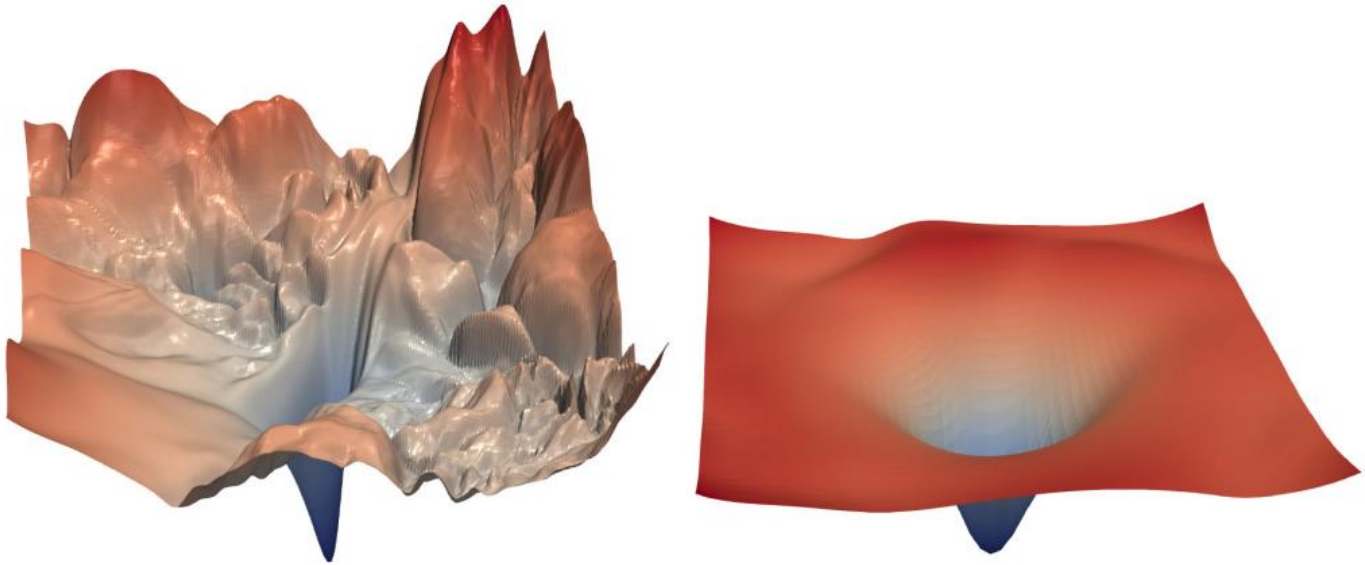
Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun. Deep Residual Learning for Image Recognition. 2015.
R.K. Srivastava, K. Greff, J. Schmidhuber. Highway Networks. 2015

ResNet: visualization of loss function



without skip connections

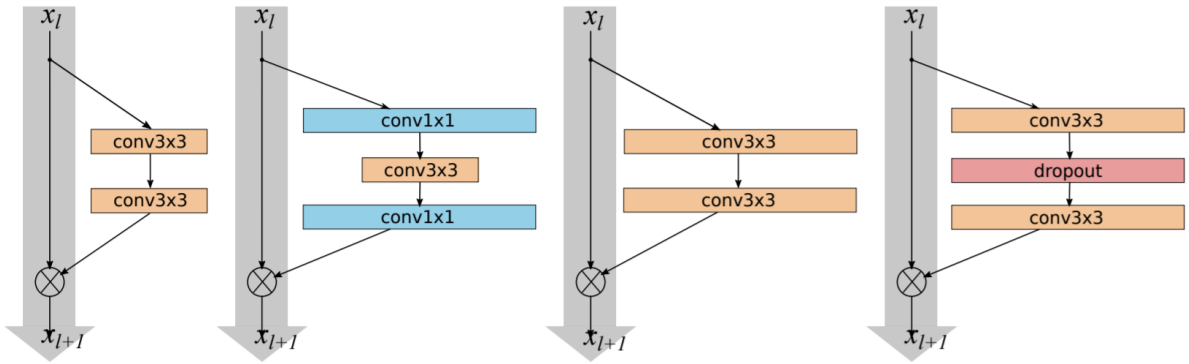
with skip connections

Hao Li et al. Visualizing the Loss Landscape of Neural Nets. 2018.

WideResNet — WRN

Disadvantages of ResNet

- is too deep — up to 1000 layers :)
- take a long time to train to SotA



(a) basic (b) bottleneck (c) basic-wide (d) wide-dropout

- a simple WRN network of 16 layers defeated all ResNets
- WRN-40-4 (i.e. 40 layers and 4x width) trains 8 times faster than ResNet-1001

S. Zagoruyko, N. Komodakis Wide Residual Networks, 2017

Summary

- Convolutional networks are very well suited for image processing
- Various optimization algorithms: adam, RMSProp
- Regularization methods: dropout, L_2 and batch normalization
- The choice of the initial approximation is also important (weight initialization)
- ResNet and skip-connections, WideResNet

Summary

- Convolutional networks are very well suited for image processing
- Various optimization algorithms: adam, RMSProp
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- ResNet and skip-connections, WideResNet

What else can you see?

- Course lecture at Stanford about convolutional networks

Levenberg-Marquardt Diagonal Method

Reminder

Newton-Raphson method (second order):

$$w = w - \eta(\mathcal{L}_i''(w))^{-1}\mathcal{L}_i'(w),$$

where $\mathcal{L}_i''(w) = \frac{\partial^2 \mathcal{L}_i(w)}{\partial w_{jh}\partial w_{j'h'}}$ — Hessian

Heuristics. We assume that the Hessian is diagonal:

$$w_{jh} = w_{jh} - \eta\left(\frac{\partial^2 \mathcal{L}_i(w)}{\partial w_{jh}^2} + \mu\right)^{-1}\frac{\partial \mathcal{L}_i(w)}{\partial w_{jh}},$$

η is the learning rate, we can assume $\eta = 1$

μ — a parameter that prevents the denominator from being set to zero

The ratio η/μ is the learning rate on flat sections of the functional $\mathcal{L}_i(w)$, where the second derivative vanishes.