# Residual Networks

## Outline

by Alexander Kowsik

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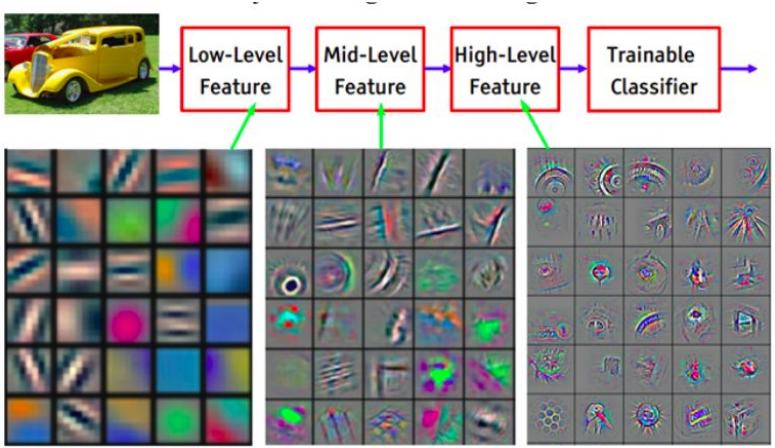
- Introduction/Motivation
  - layers learn increasingly abstract features
  - idea: more layers = better performance
  - problem: vanishing/exploding gradients → at some point, networks not trainable anymore (25+ layer) → error rate increases
  - solution: ResNets
- Residual Networks
  - allows training for DEEP networks (up to 2000 layers)
  - main idea: skip connections
  - skip connections can be identity function
  - rough idea: if layer hurts performance: “skip” it



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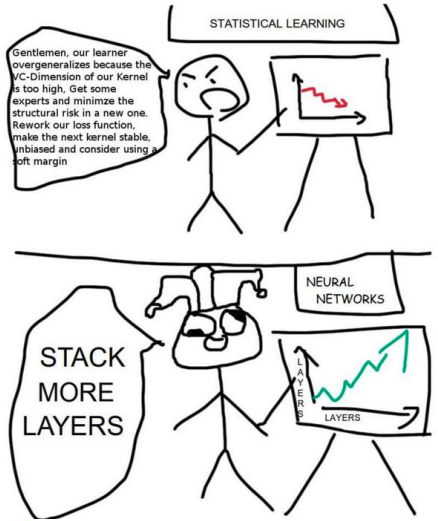


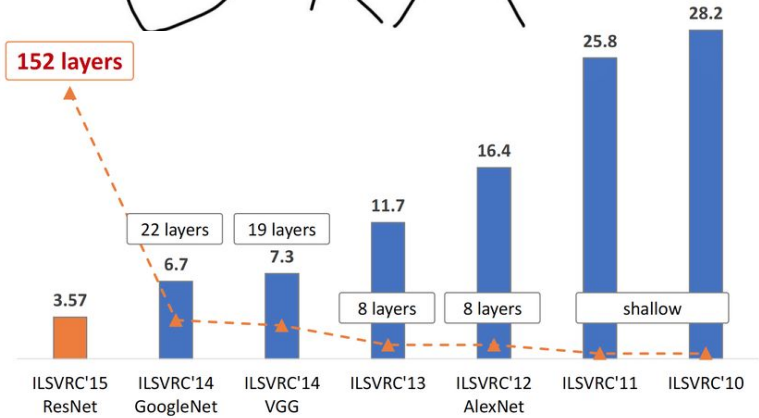

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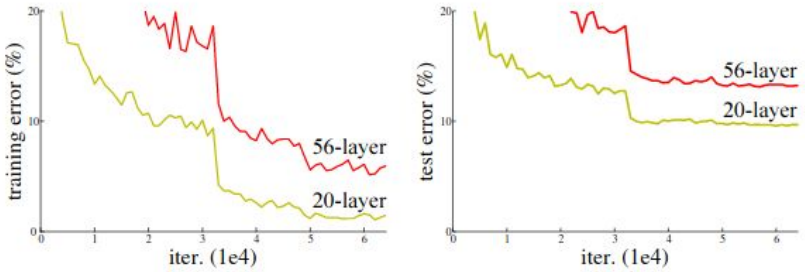

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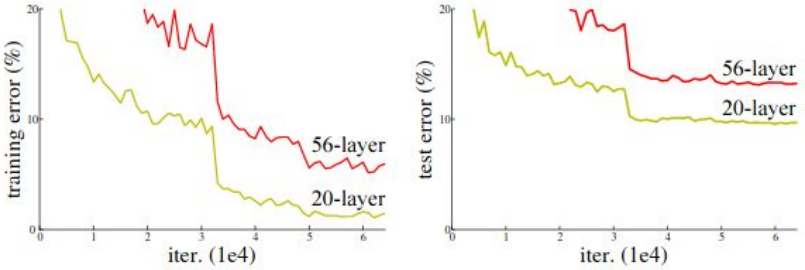


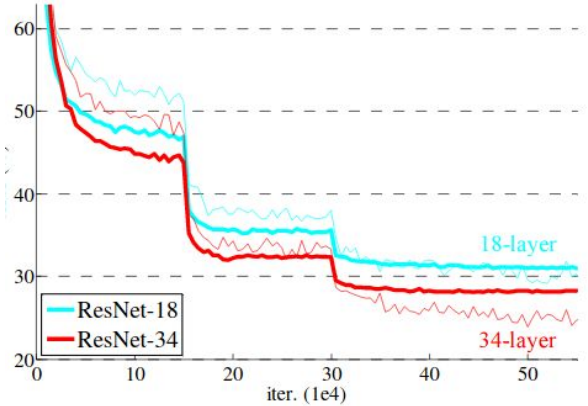

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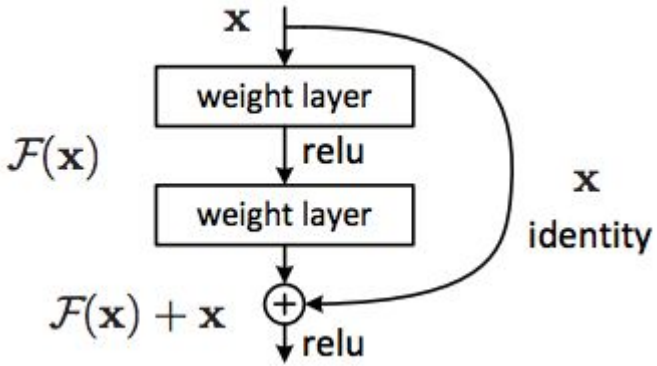

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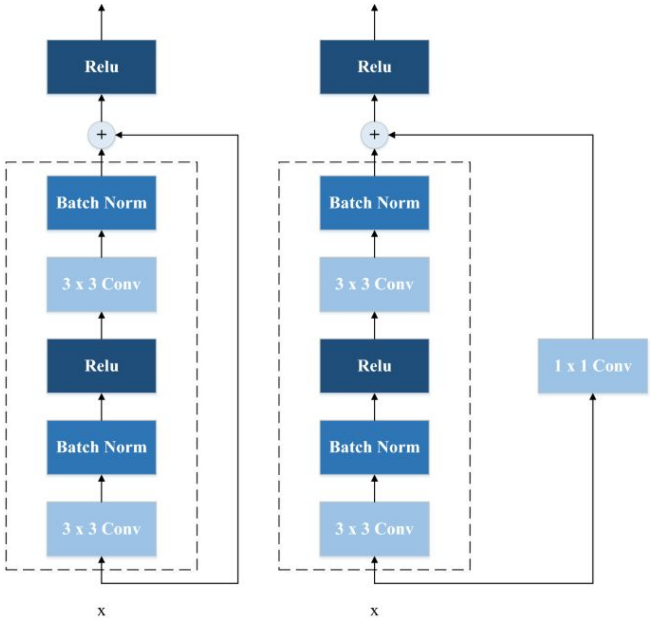
- Structure/Variants
  - structure in detail (ReLU before/after skip connection, ...)
  - skip distances
  - **dimension differences** + solutions: 1x1 convolutions, padding, pooling, ...
  - different network architectures (HighwayNets, DenseNets, ...)
- ResNets Internals
  - Forward propagation
  - Backprop
  - Training of ResNets: Gradient Descent, ...
  - advantages/disadvantages/performances
- Summary/Conclusion



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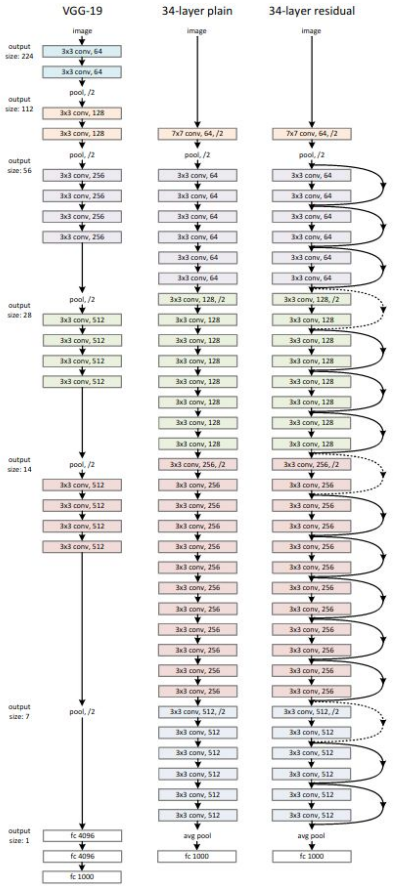

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During backpropagation learning for the normal path

$$\Delta w^{\ell-1,\ell} := -\eta \frac{\partial E^{\ell}}{\partial w^{\ell-1,\ell}} = -\eta a^{\ell-1} \cdot \delta^{\ell}$$

and for the skip paths (nearly identical)

$$\Delta w^{\ell-2,\ell} := -\eta \frac{\partial E^{\ell}}{\partial w^{\ell-2,\ell}} = -\eta a^{\ell-2} \cdot \delta^{\ell}.$$

# Structure of the site

- site will be built with **pandoc**
- video at the top (**kdenlive?**)
  - slides with powerpoint
  - presentation of the topic
- rest of site: topic in detail
  - written elaboration
  - supportive graphics and diagrams (maybe animations or interactive elements if possible)
  - goal: something similar to *distill.pub* articles