

Residual Networks & Densly Connected Convolutional Networks

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Outline

ResNet (published 2015)

- Architecture
- Properties

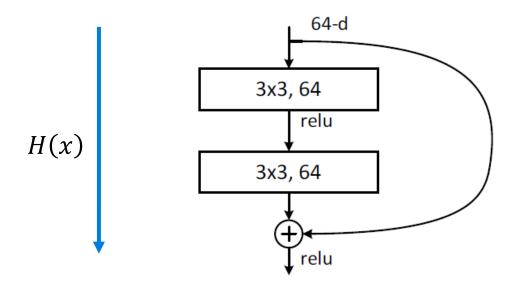
DenseNet (published 2018)

- Architecture
- Properties

Experiments

ResNet Residual Unit

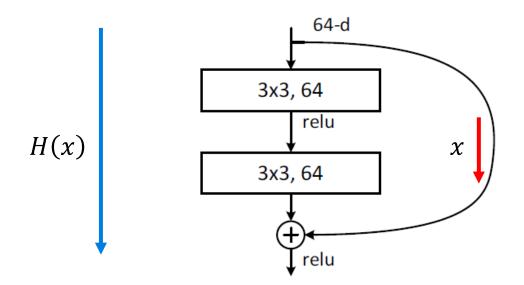
• H(x) old mapping



Source: (modified) Paper "Deep Residual Learning for Image Recognition"

ResNet Residual Unit

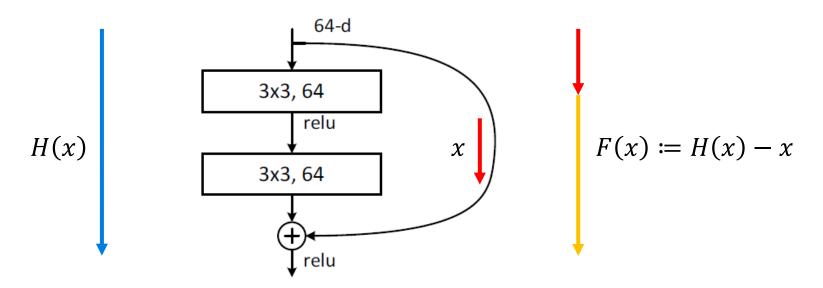
- H(x) old mapping
- x skip connection / identity



Source: (modified) Paper "Deep Residual Learning for Image Recognition"

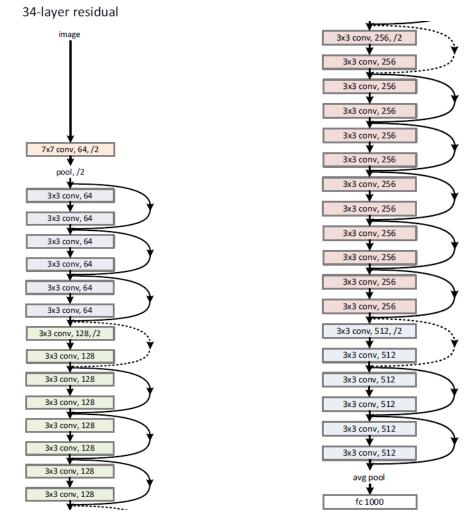
ResNet Residual Unit

- H(x) old mapping
- x skip connection / identity
- F(x) new mapping with skip connection



Source: (modified) Paper "Deep Residual Learning for Image Recognition"

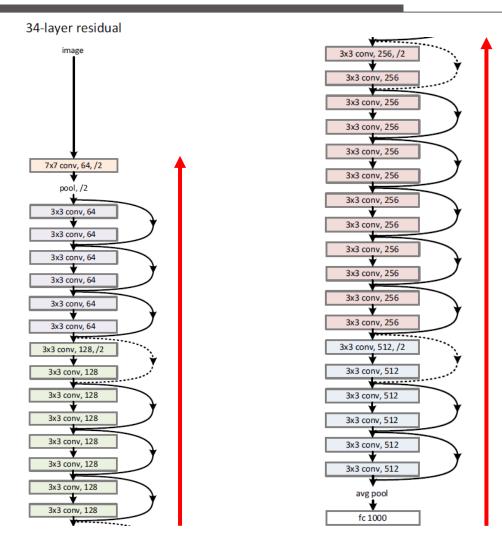
ResNet Architecture



Source: "Deep Residual Learning for Image Recognition"

ResNet Gradient Flow

Improved gradient flow through skip connections

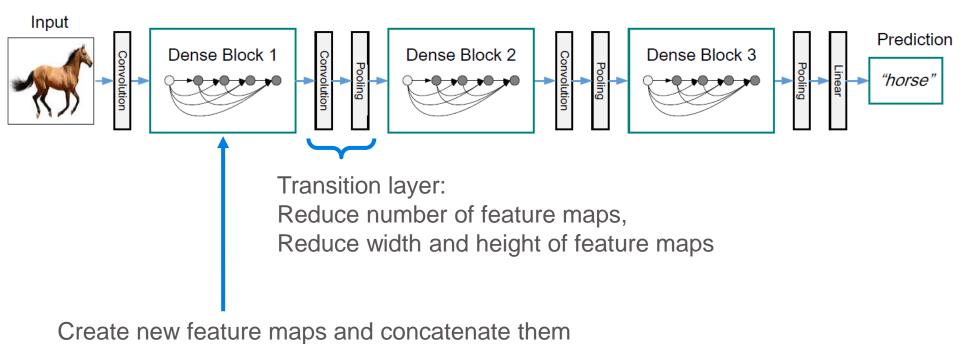


Source: (modified) Paper "Deep Residual Learning for Image Recognition"

ResNet Properties

- Improved gradient flow
 - Less prone to vanishing gradients
 - Deeper networks are trainable
- Feauture propagation through skip connections
- Skip connections are computationally cheap

DenseNet Architecture



Source: Paper "Densely Connected Convolutional Networks"

DenseNet Architecture II

• $H(\cdot)$ Composite function (Batch Norm., ReLU, Conv., Pooling) e.g. Transition layer:

$$H(x_l) = Conv(Pooling(x_l))$$

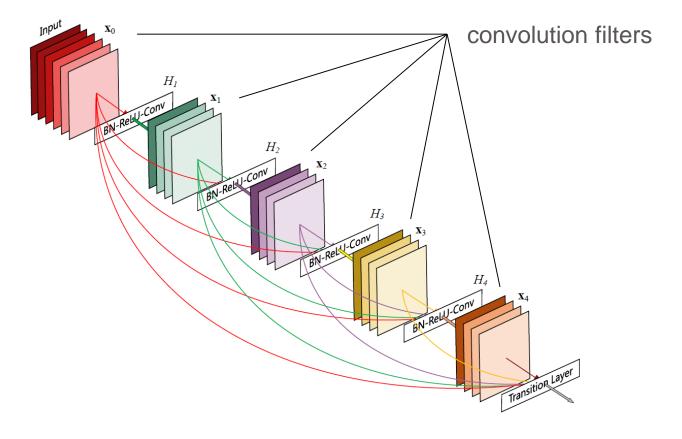
ResNet:

$$x_l = H_l(x_{l-1}) + x_{l-1}$$

DenseNet:

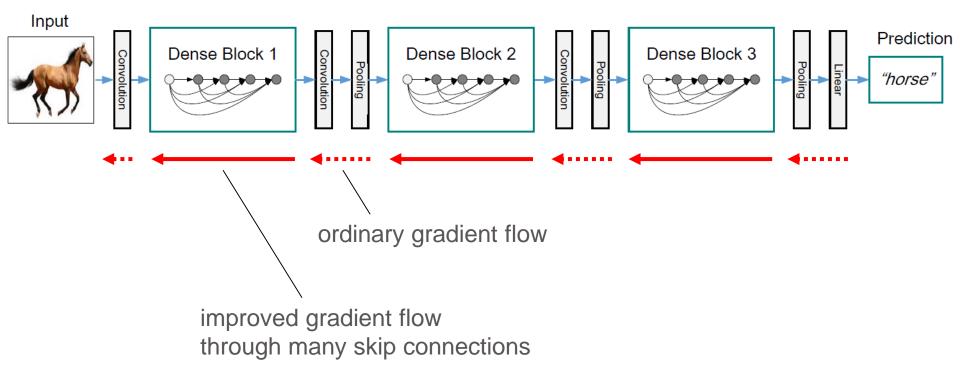
$$x_l=H_l([x_0,x_1,\dots,x_{l-1}])$$

DenseNet Dense Block Architecture



Source: Paper "Densely Connected Convolutional Networks"

DenseNet Gradient Flow



Source: Paper "Densely Connected Convolutional Networks"

DenseNet Properties

Similarities compared to ResNet:

- Uses skip connections
- Less prone to vanishing gradients

Differences compared to ResNet:

- Deeper networks are trainable
- Less parameters to learn
 - Less filters per convolution layer
- Combine feature maps by concatenation
 - Enables feature reuse
- Better accuracy

Experiments

Dataset

- Data from HS Offenburg Sweaty team
- Small dataset excerpt:
 - 8 Classes
 - 4917 Training images
 - 1230 Test images



Source: https://sweaty.hs-offenburg.de/projekt/

Dataset



Ball



Goal post



Obstacle



L-Line



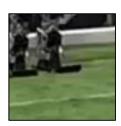
X-Line



T-Line



Penalty spot



Robot foot

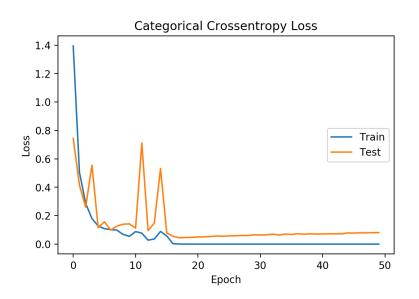
ResNet-50 Performance Overview

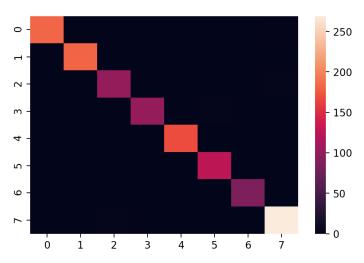
2,5 h Training time

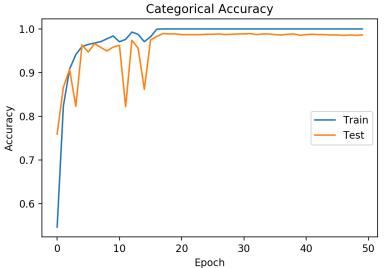
1230 Test images

17 False predictions

1,38% Error rate







ResNet-50 Performance False Predictions



Robot foot (Ball)



Robot foot (X-Line)



Goal post



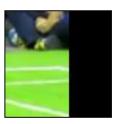
Goal post (T-Line)



Goal post (Obstacle)



Penalty spot

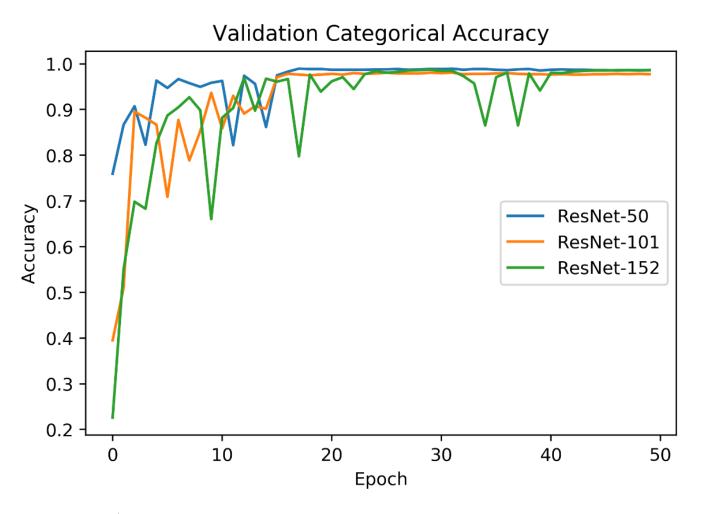


T-Line (L-Line)

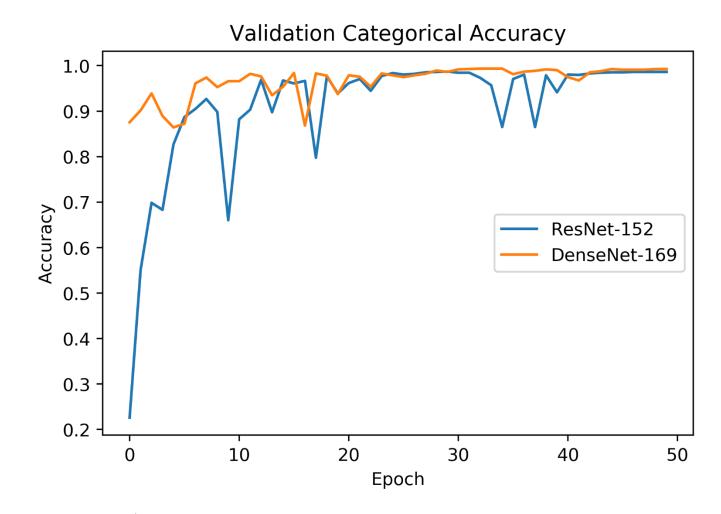


Obstacle (Robot foot)

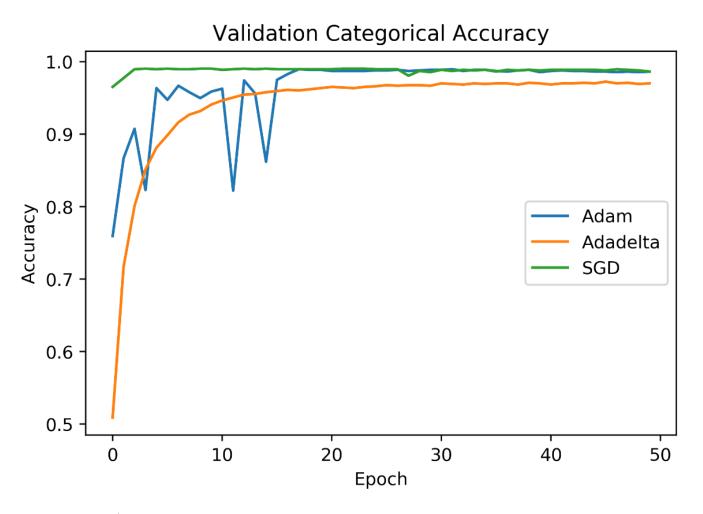
ResNet-50 -101 - 152



ResNet-152 & DenseNet-169



Optimizers



Summary

Deeper networks are trainable

ResNet: through skip connections

DenseNet: through many skip connections in dense units

Skip connections allow the gradients to flow better

 Skip connections "artificially flatten the network" such that deeper models are trainable

DenseNet improves ResNet

- Better information flow (concatenation of feature maps)
- Even more deeper networks possible (many skip connections in dense blocks)
- Less parmeters to learn (less filters per convolution layer)
- Better accuracy

Literature

Colab Notebook:

https://github.com/abieren/DL-Seminar-ResNet-DenseNet

Source code and documentation:

Keras ResNet Documentation https://keras.io/applications/#resnet

"Tutorial Keras: Transfer Learning with ResNet50"

https://www.kaggle.com/suniliitb96/tutorial-keras-transfer-learning-with-resnet50

GitHub: "How to add and remove new layers in keras after loading weights?"

https://stackoverflow.com/questions/41668813/how-to-add-and-remove-new-layers-in-keras-after-loading-weights

ResNet Paper:

"Deep Residual Learning for Image Recognition" https://arxiv.org/abs/1512.03385

DenseNet Paper:

"Densely Connected Convolutional Networks" https://arxiv.org/abs/1608.06993

Sweaty HS Offenburg:

https://sweaty.hs-offenburg.de/projekt/