HIGH PERFORMANCE
ARTIFICIAL INTELLIGENCE

Deep Learning - MAI

Convolutional neural networks

THEORY

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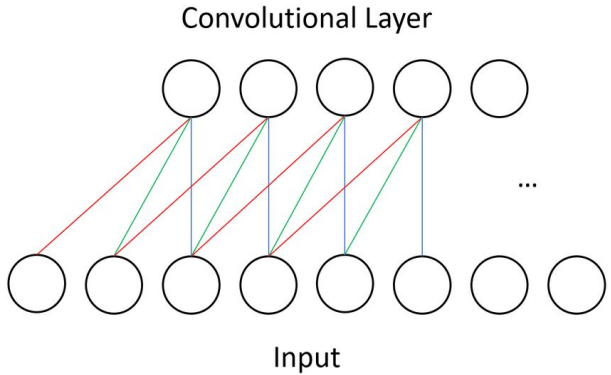
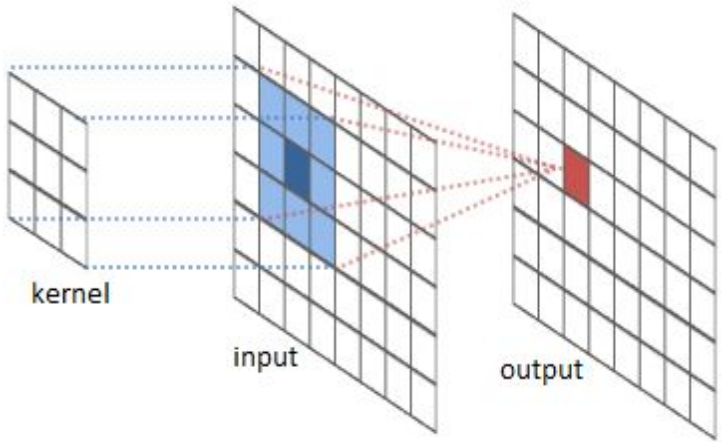
Spatial Connectivity

- Some data has spatial correlations that can be exploited
  - 1D, 2D, 3D, …
- Near-by data points are more relevant than far-away.
- Sparsify connectivity to reduce complexity and ease the learning





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Weight Sharing

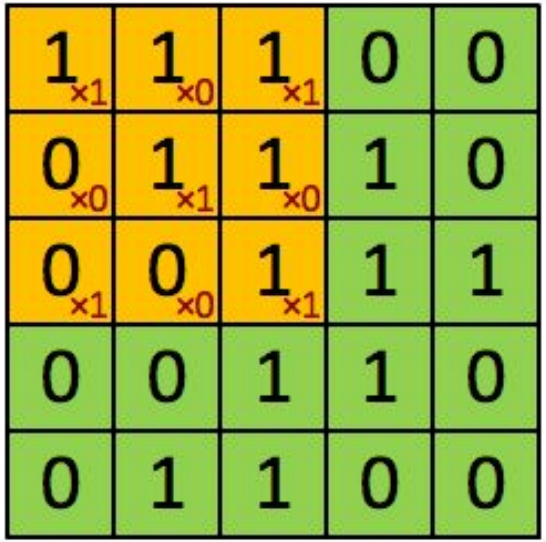
- Sparse connectivity is nice, but we want to apply filters everywhere.
- Each filter will get convolved all over the image: 2D activations matrix
- In static we have sets of neurons sharing weights
- In this context, what is a neuron?

Convolution in Action

Kernel size 3x3
(neuron input = 9)

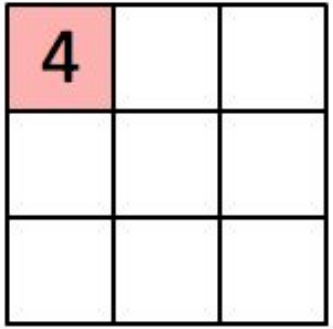
1 0 1
0 1 0
1 0 1

Detect ‘X’



Image

Filter convolution process



Convolved Feature

Activations (pre-func.)

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Image Transformations

- Convolving filters transform the image
- Let the model learn the kernels it needs

Edge detection	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Gaussian blur 3 × 3	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

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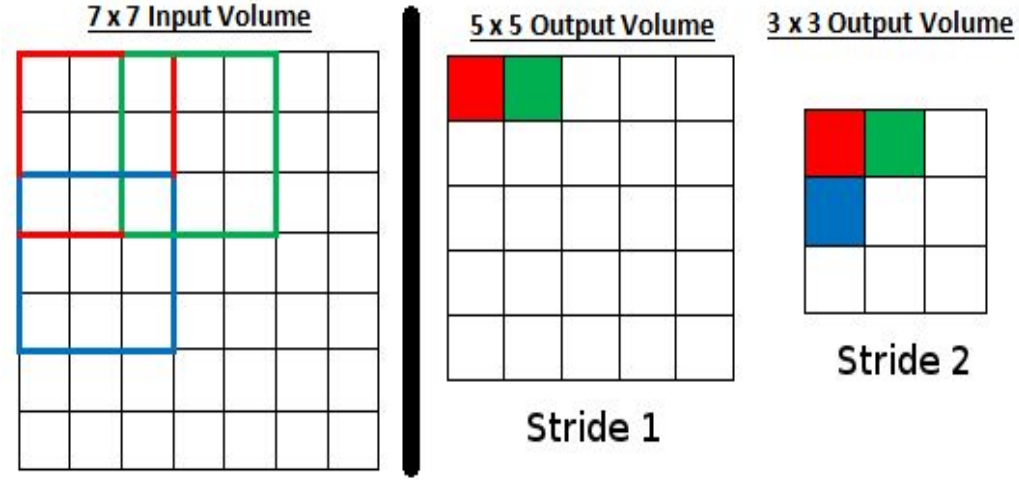
Convolution Details

Kernel size: Size of the receptive field of convolutional neurons

Stride: Steps size of convolution

Padding: Allows focus on border



$$OutputSize = \frac{InputSize - KernelSize + 2 * Padding}{Stride} + 1$$

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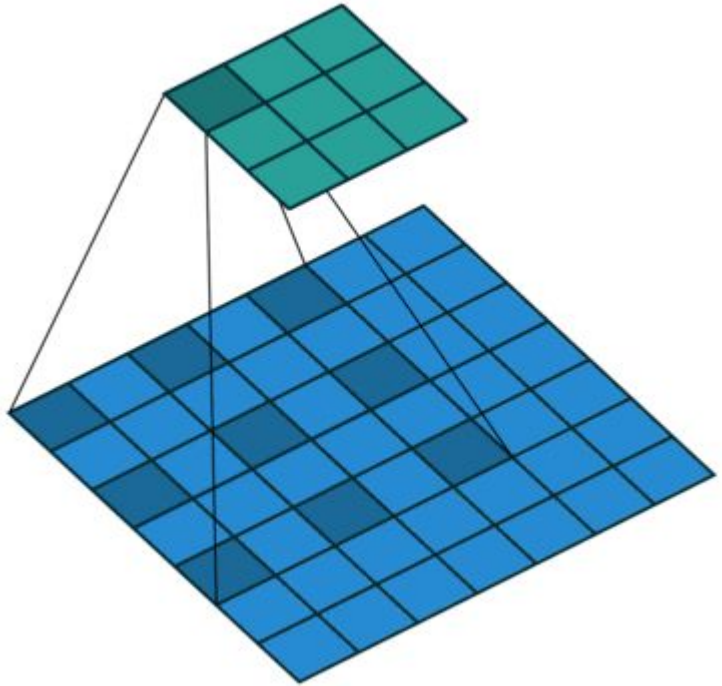
Dilated/Atrous Convolutions

Sparsify the kernel

- Increases perceptive field without added complexity
- Loses details, gains context
- Another hyperparam :(
- Used for
  - Down/Upsampling (segmentation)
  - High Resolution inputs



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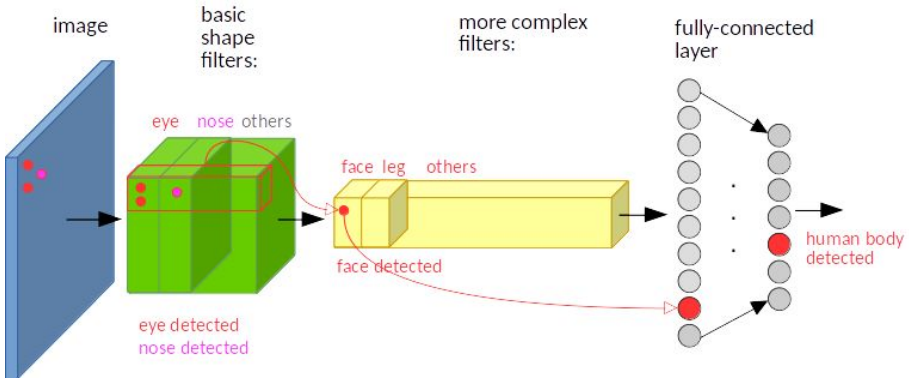
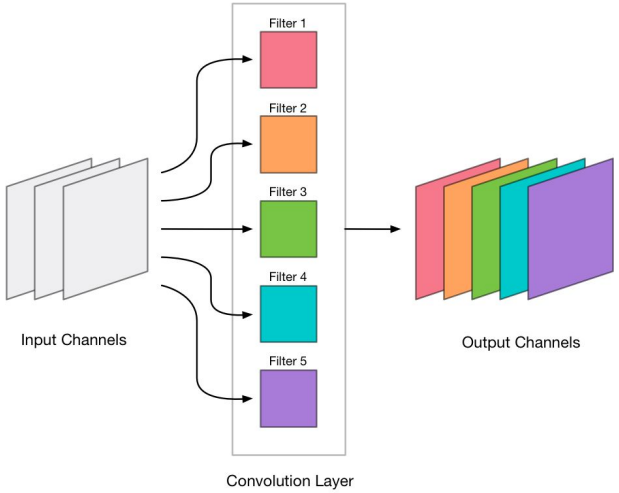
Output Volumes

- Typically, conv filters are full depth (**N*N*input_depth**)
- Each conv filter (often 3D) convolved generates a 2D plane of data
- Depth provides all the *views* on a part of the input
- Output volume: New representation of input with different dimensions





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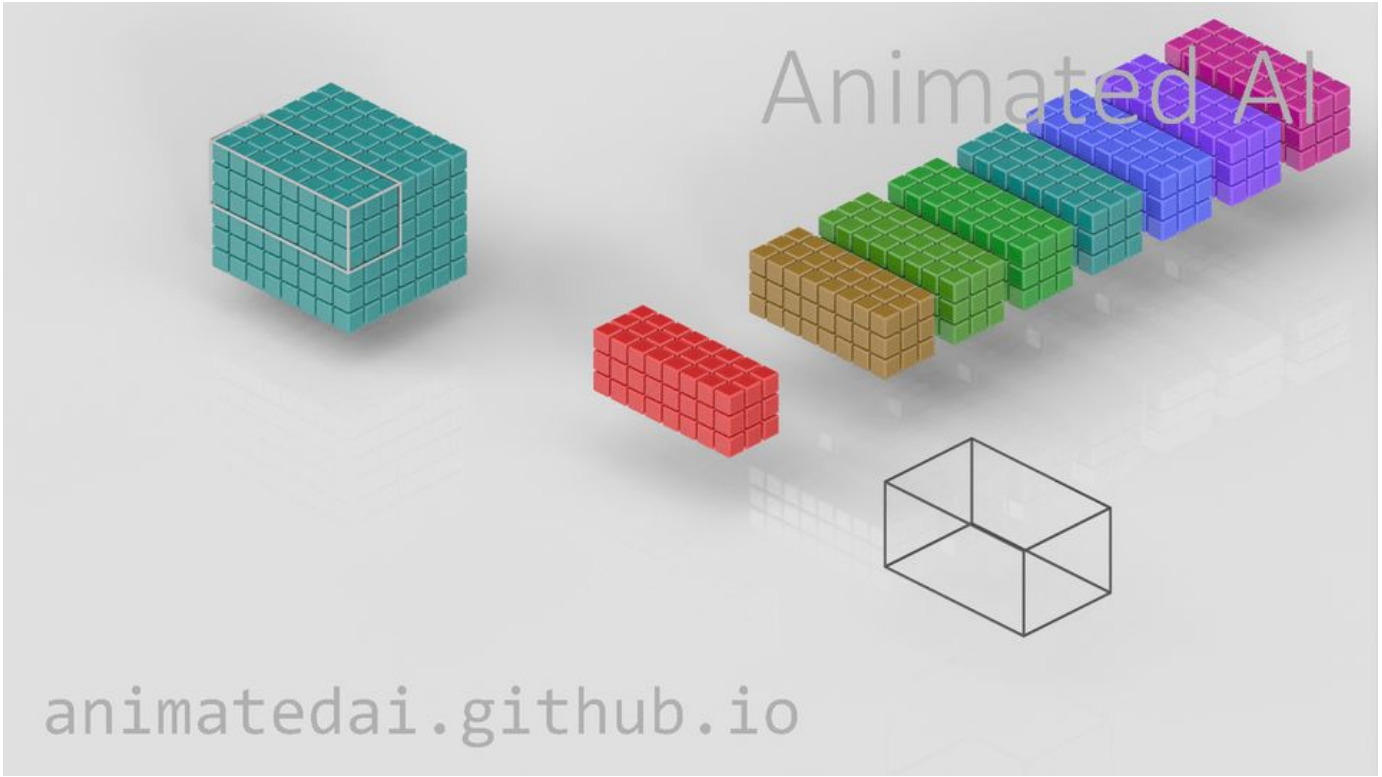
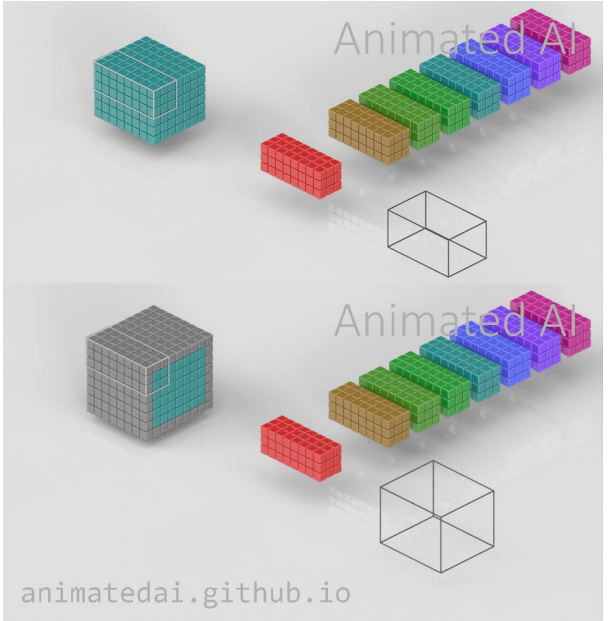
Output Volumes



Padding policies

- Size
  - Valid (no padding): Internal only. May skip data. Reduces dims.
  - Same: Keep dimensionality with stride 1
- Filling
  - Zeros
  - Reflect
  - Circular
  - ...



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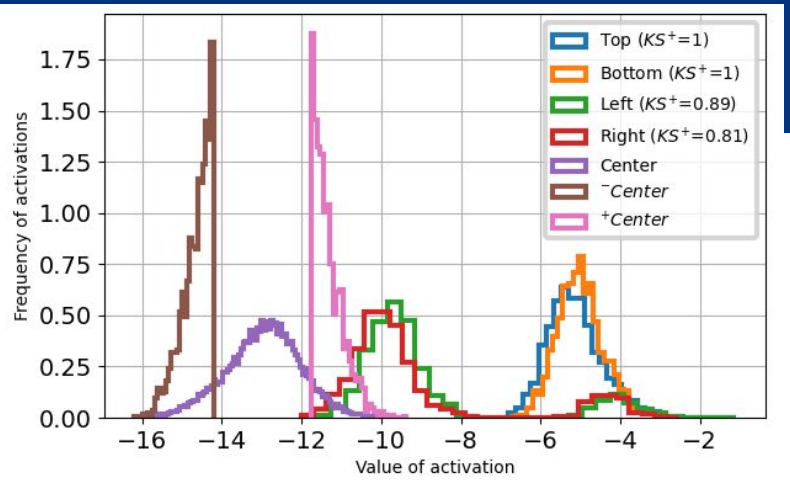
PANs

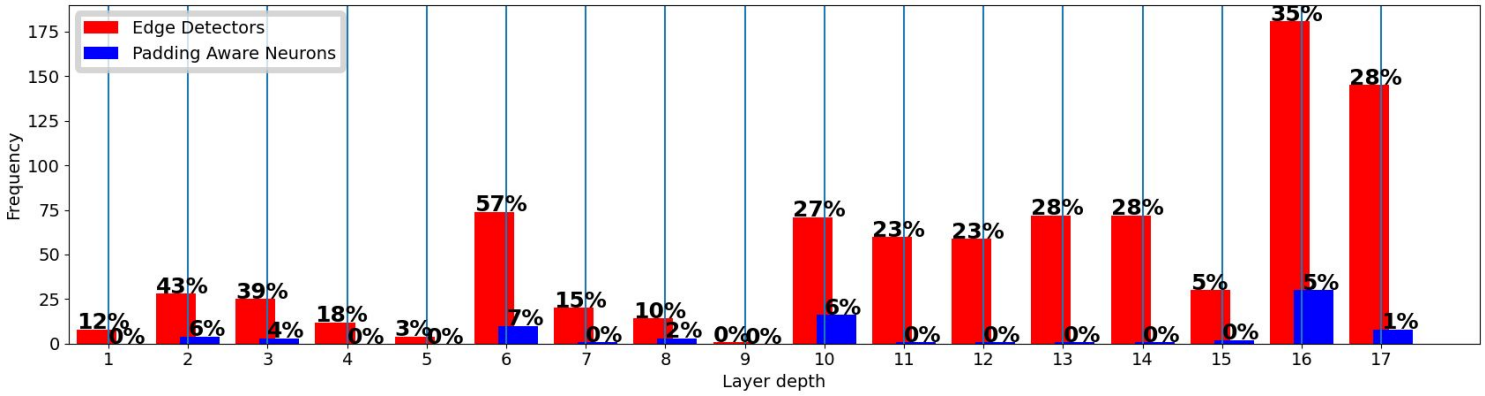
- Too much bias

-2	1	1
-2	1	1
-2	1	1

-3	2	-1
-3	2	-1
-3	2	-1

0	0	0	0	0	0	0
0						0
0	A					0
0						0
0				B		0
0						0
0	0	0	0	0	0	0





Depth-wise Separable Convolutions

- Depth-wise convolutions (spatial)
  - Filters: **N*N*1**
- Point-wise convolution (depth)
  - Filters: **1*1*input_depth**

- Params: **N*N+N**
  - Decrease in complexity & cost

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[51, 39, 38]

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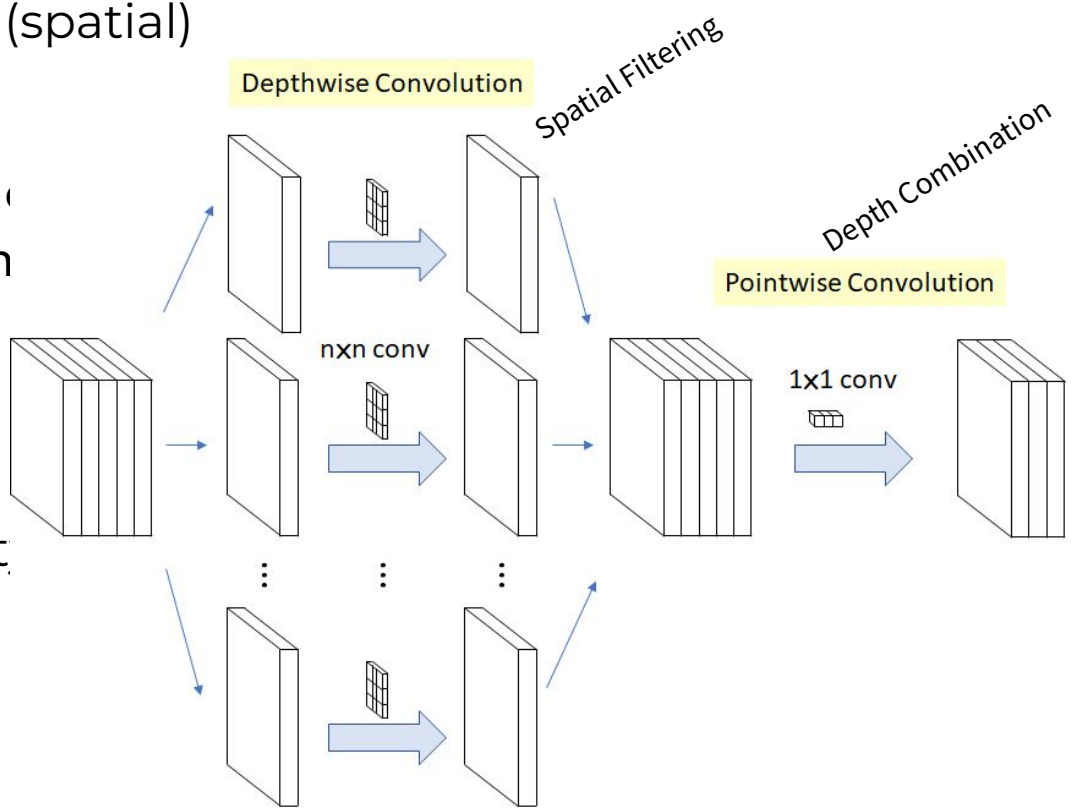

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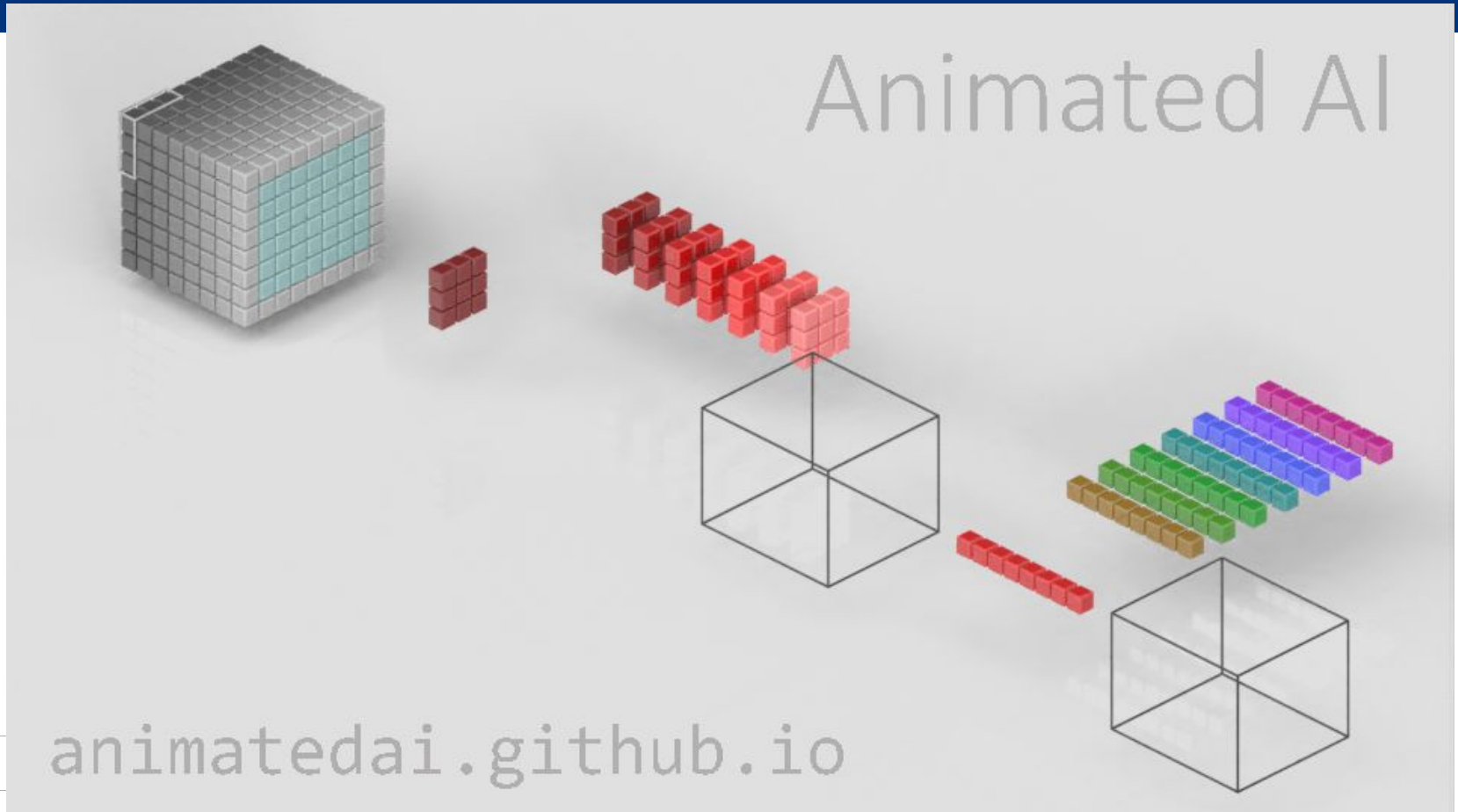
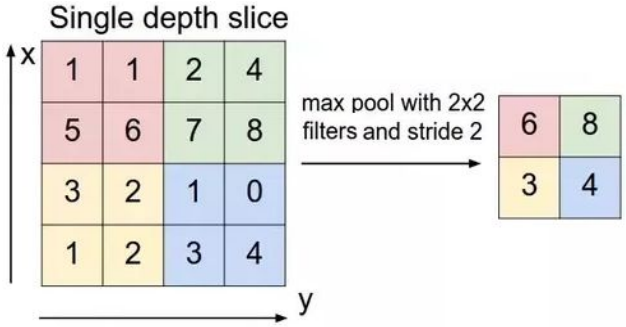
[51, 39, 38]

Depth-wise Separable Convolutions



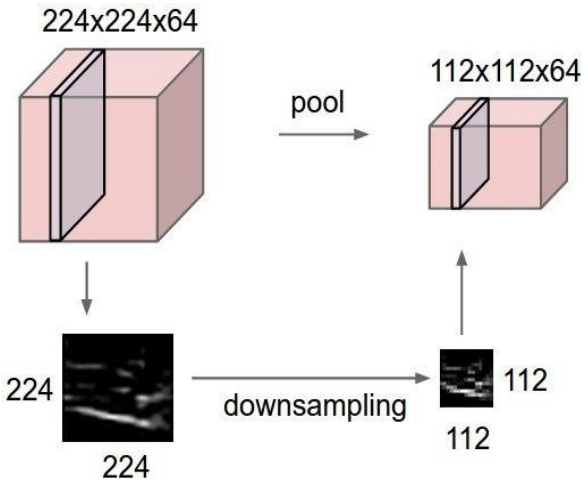
To Pool Or Not To Pool

- Operation: **Max** or Avg
- Dimensionality reduction (along *x* and *y* only)
- Rarely applied full depth
- Parameter free layer
- Hyperparams: Size & Stride
- Loss in spatial precision / Robust to invariance



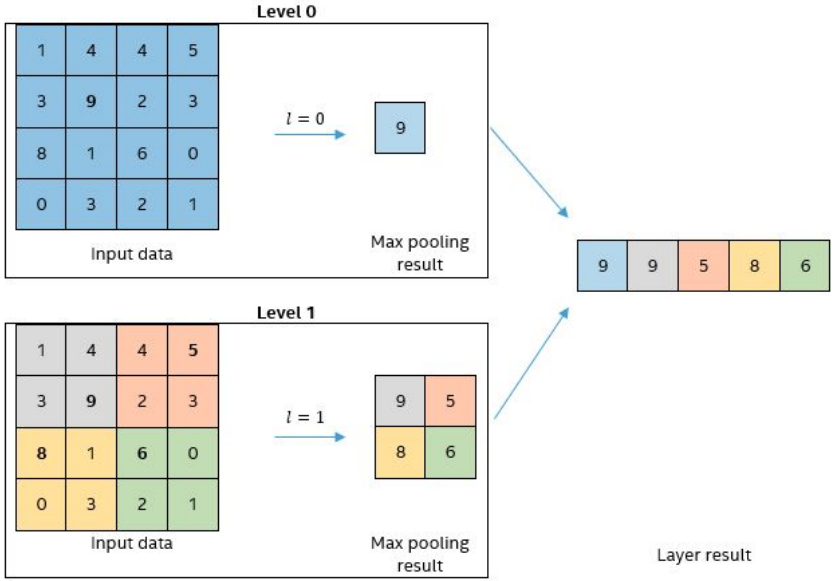
Other means to reduce complexity

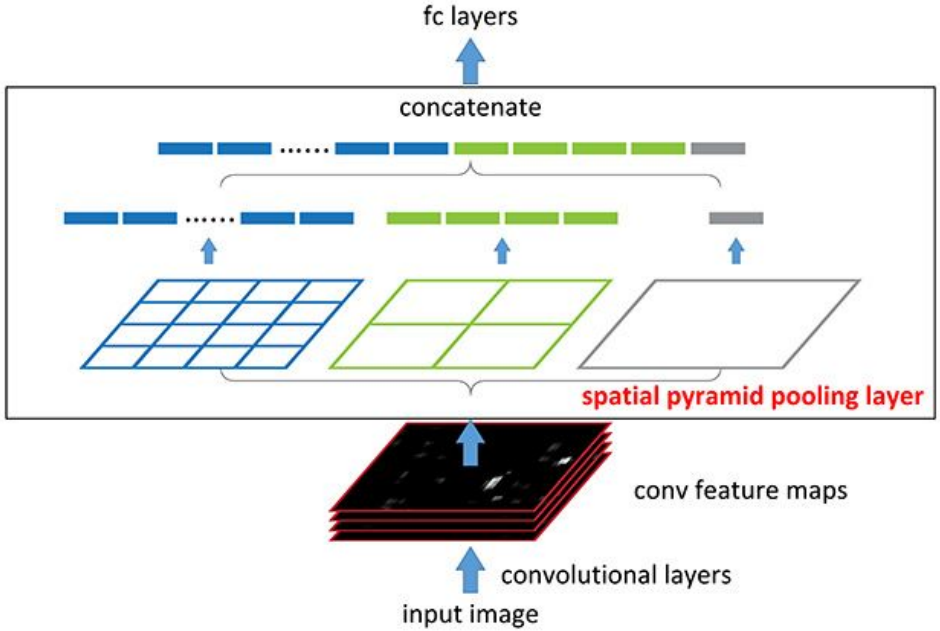
- Depth-wise separable convs, bigger conv. strides



Spatial Pyramid Pooling (SPP)

- Multi-scale Pool (by powers of 2)
- Often used between conv and fc





More alternatives: Atrous spatial PP, Global average pooling, Pyramid pooling module, Adaptive PP

Practical Tips XI

Convolutional

- Small/big filters (3x3, 5x5, 7x7)
  - Cheap/Expensive
  - Local/General
  - Bigger/Smaller outputs (stride)
- Kernel Size = input size: fc
- Kernel size = 1x1: Alter depth)

Pooling

- 2x2, stride 1 is the least invasive

Hyperparameters incomplete list #4

- ❑ Kernel size (conv & pool)
- ❑ Stride (conv & pool)
- ❑ Padding (conv & pool)
- ❑ Num. filters
- ❑ Dilatation rate

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CNNs

Emerging regularizers

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Data Augmentation for CNNs

Apply what is safe for each case

- Problem specific
- Limited impact
- Computation
- Train/Val/Test

Advanced image regularization/augmentation

Increase train variance forcing attention on full input (adds *noise*)

- MixUp (merge two samples), AdaMixup (manifold intrusion)
- CutOut (remove a patch)
- CutMix (merge samples w/ patch)
- Auto/DeepAugment (learn <*op.*,*mag.*> from the data. Danger!)

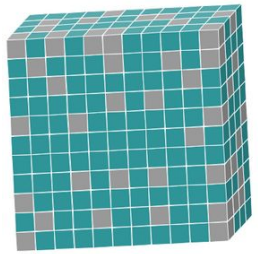
Beware. **More data** is always better than more augmentation.

[40,41,42,43,44,50]

Spatial Dropout

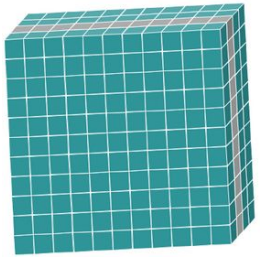
Standard Dropout is suboptimal for spatially related data

- Consecutive inputs can be strongly redundant



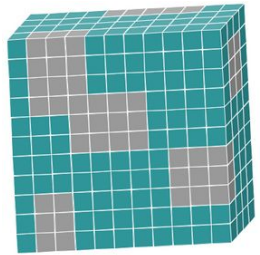
Spatial Dropout

- Drop entire feature maps, aka channels



Cutout

- Drop connected components along width, height and/or depth



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[45,46,47]

Noisy Student (not only for CNNs)

A semi-supervised training paradigm

1. Train model A (teacher) with the labeled data
2. Use A to generate pseudo-labels for an unlabeled data set
3. Train model B (student) with both labeled and pseudo-labeled data

- Iterate, re-labeling the unlabeled data each time
- Highly regularized (noise!) student to guarantee improvement
- Each student has more capacity than the previous

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CNNs

Architectures

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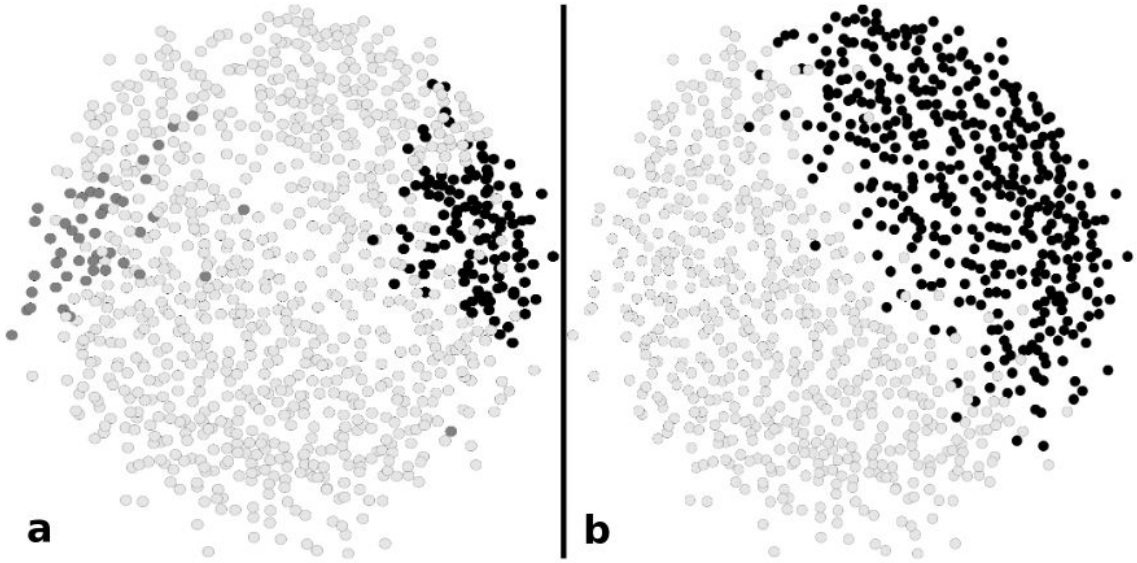
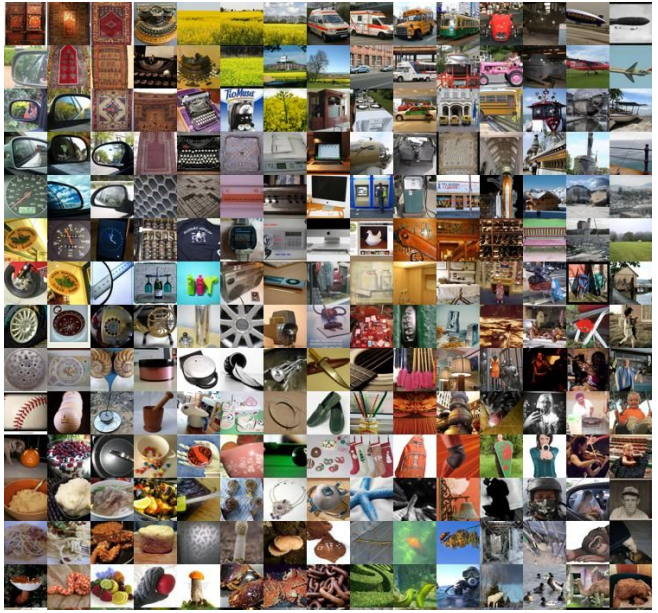
ILSVRC'12 (aka "Imagenet")

- Classification: 1K classes
- Train: 1.2M, Val: 50K





ImageNet today

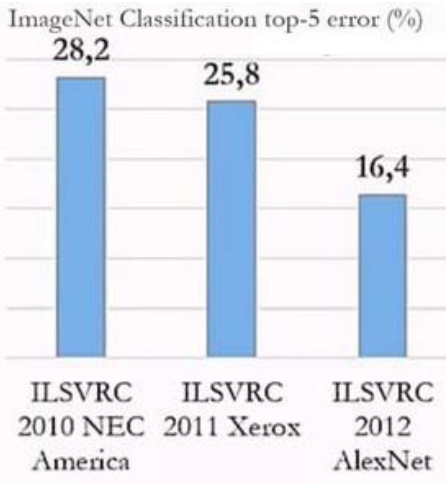
- Noisy
  - Multiclass
  - Wrong (6%)
- Overkilled
  - 90% pruning -> 3% perf. loss
- Overused
  - -10% performance on new test set

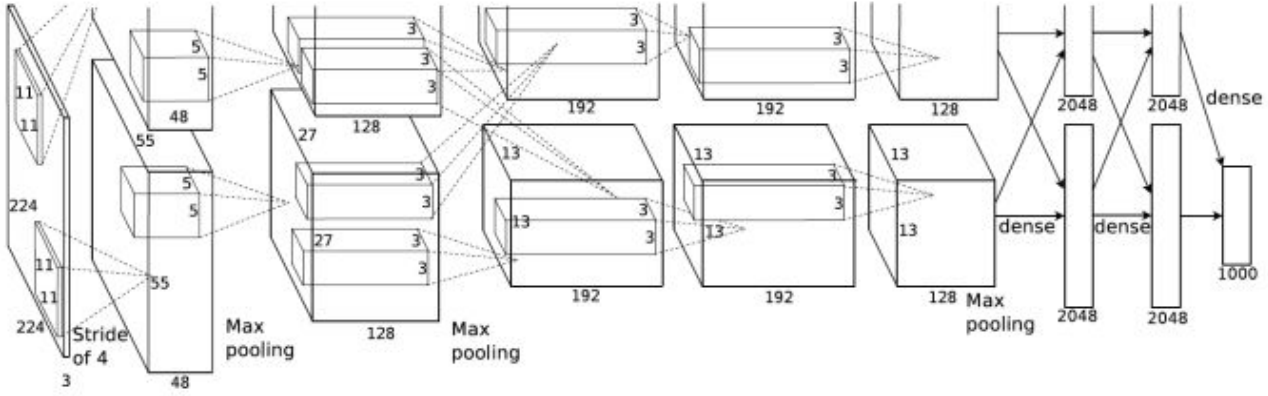
[49,56,57]

CNNs Big Bang (1st gen.)

AlexNet (2012)

- Breakthrough in ILSVRC
- 5 convs+pools, ReLU, 2 dense, and dropout
- 62M parameters



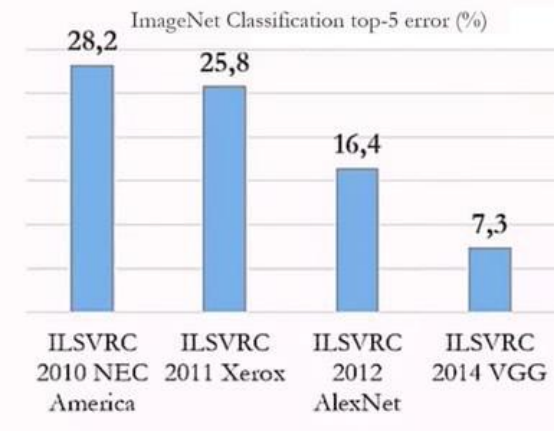


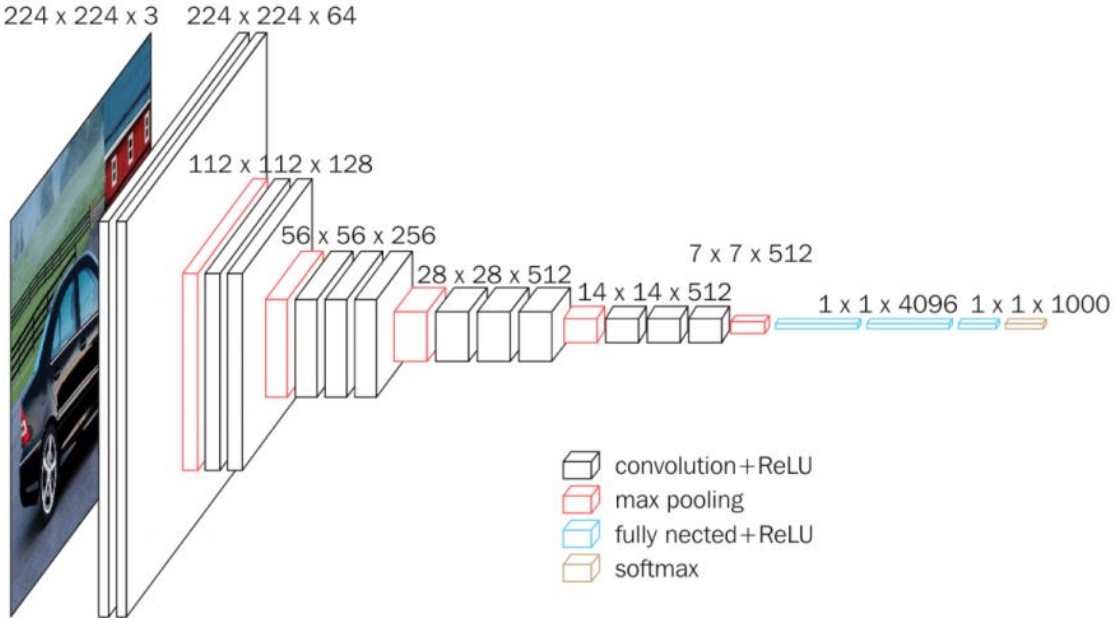
On the shoulders of giants

Optimizing cp*f (1st gen.)

VGG 11/13/16/19 (2014)

- Prototype of **(conv-pool)*+dense*** architecture
- 133-144M parameters
- 3x3 convs only

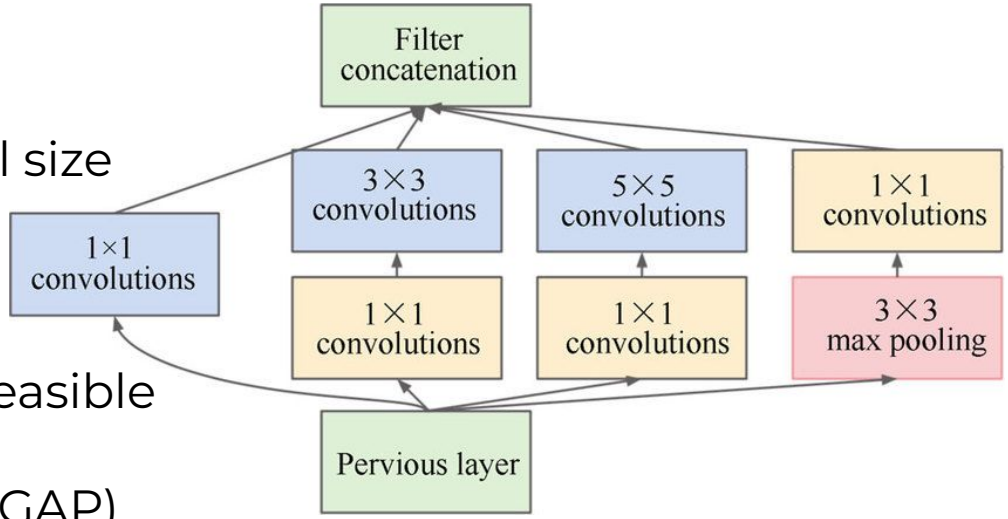




The Inception Family (2nd gen.)

GoogLeNet (2014)

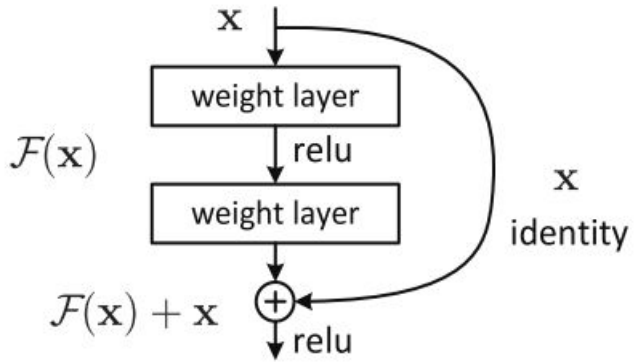
- The Inception block
- Let the model decide the kernel size
- Better scale adaptation
- Bottleneck 1x1 conv to make it feasible
- No FC: Global Average Pooling (GAP)

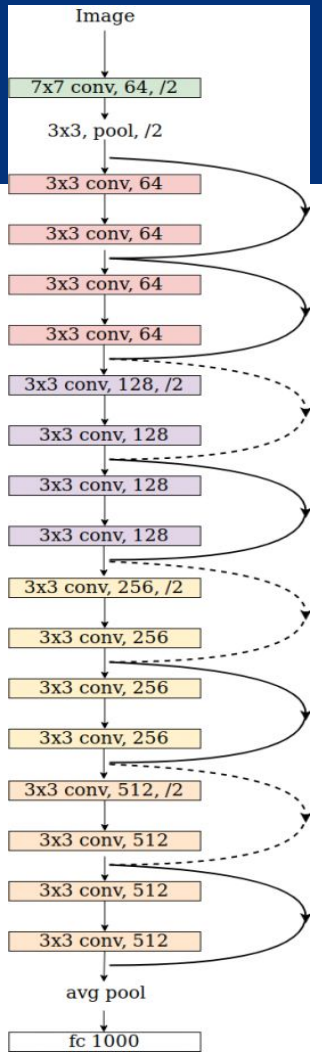


The Skipped Connection (2nd gen.)

ResNet (2015)

- Residual blocks / Skip connections
- Deeper should never be worse
  - Learning the identity is hard
  - Learning to cancel out is easy
- Shallow ensemble of nets
- Train up to 1K layers (do not!)
- ILSVRC'12 human level





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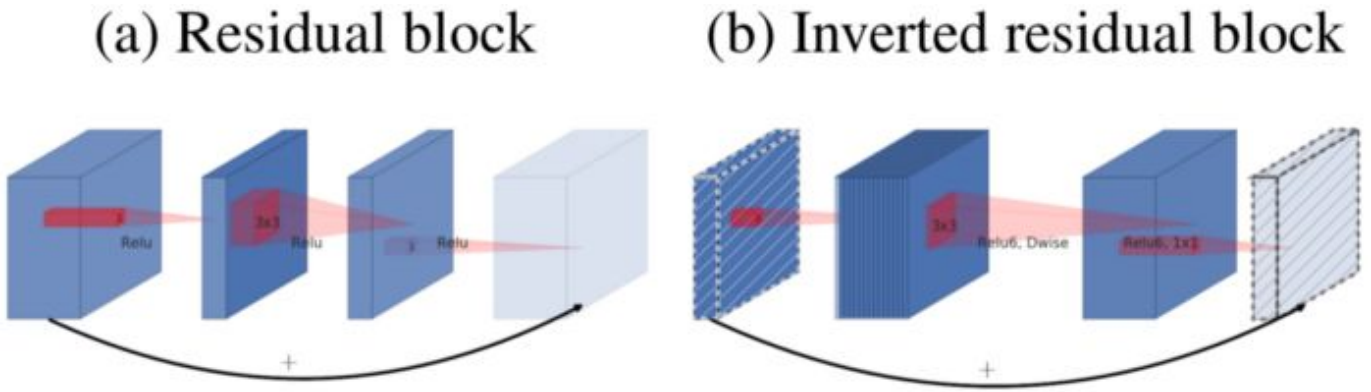
[13]

Inverted Residuals & Linear Bottlenecks

1. Upsample depth
2. Depth-wise conv
3. Point-wise conv



- Linear act at end
- Non-linear mid
- Residual link
- Efficient

Sponsored by:
The manifold hypothesis

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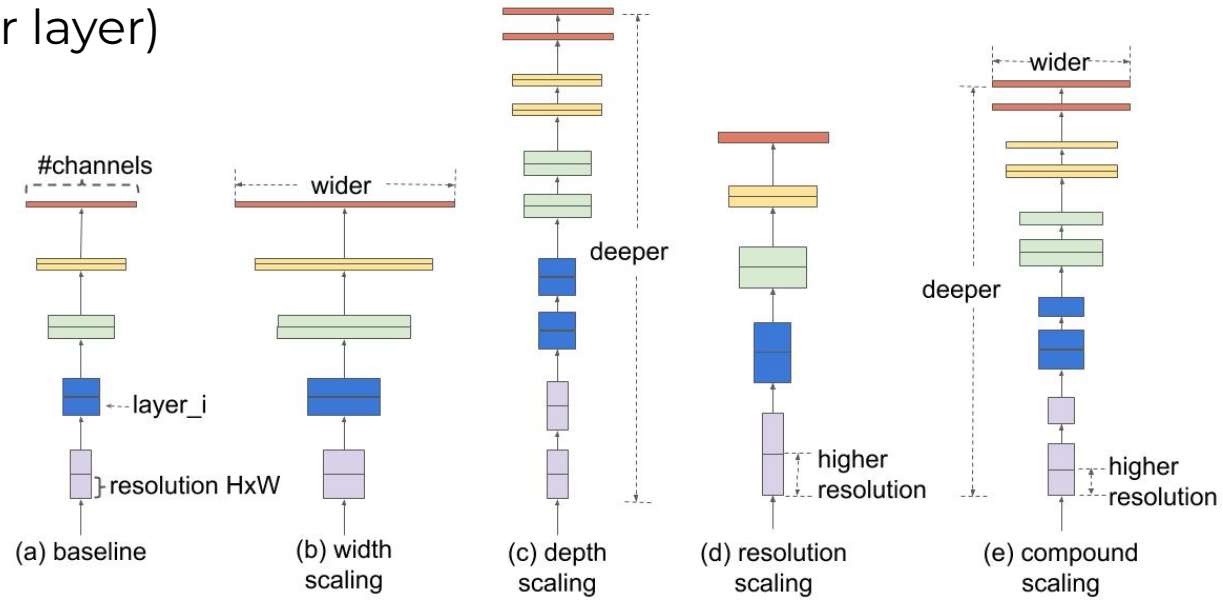
[38]

EfficientNet (3rd gen.)

Should I go deeper, wider or bigger?

- Find a balance between them (all related)
  - Width (neurons per layer)
  - Depth (layers)
  - Resolution (input)
- Choose a size
  - B0 to B7



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ConvNext, transforming CNNs (3rd gen.)

ViT learnt from CNN (Swin Transformer). Retribution

- AdamW (L2 regularization after step computation. Safe.)
- Regularize: Data augmentation (MixUp, Cutmix, ...), Label smoothing, ...
- Compute distribution (pool separated blocks): (3,4,6,3) -> (3,3,9,3)
- Patchify: First layer 4x4 stride 4 conv
- Depth-wise conv (spatial *or* channel mix). Inverted bottleneck.
- Larger kernels: 7x7
- GeLU. Sparsely activation functions & normalization layers (LN by BN).

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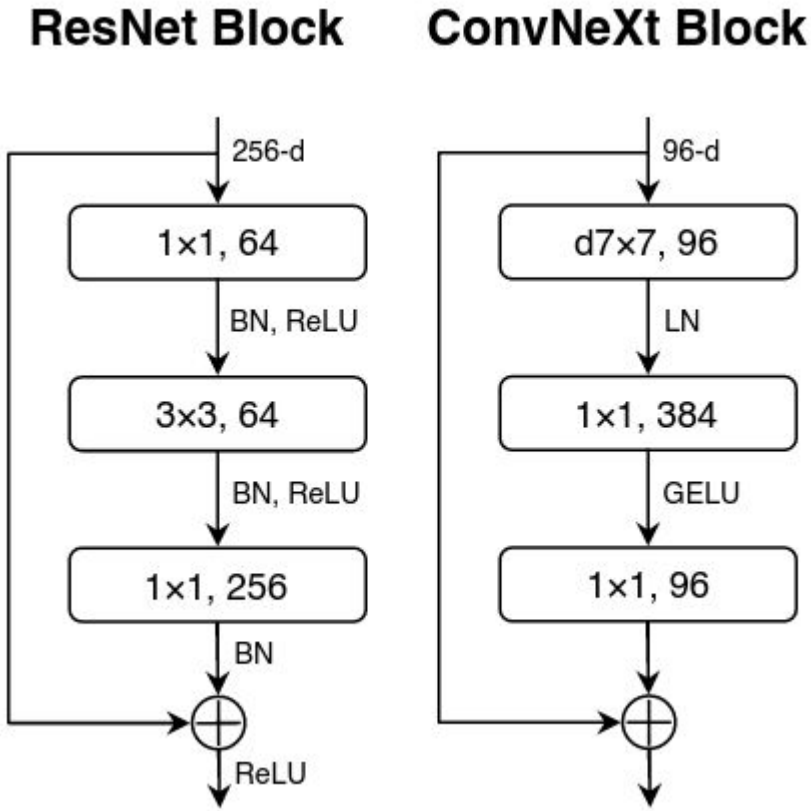
[52,53,54]

ConvNext, transforming CNNs (3rd gen.)

1. Patchify
2. Depth-wise conv
3. Inverted bottleneck
4. Larger kernels: 7x7
5. GeLU
6. Less activation functions
7. LN instead of BN
8. Less normalization layers



[52,53,54]

Practical Tips XII

CNN design policies

- Few filters at the beginning
- Hierarchy
- Max. complexity 2/3ds in

Things to monitor

- Volume sizes
- Num. parameters

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Visualizing CNNs

Biases everywhere

The Basics

- NN are representation learning techniques
- CNNs build hierarchically complex features
  - From Gabor filters to dog faces
  - Induced by convolution
  - Tend to focus on the “non obvious for humans”
    - Backgrounds, textures
- The closer to the loss, more classifier (task) and less representation (data)

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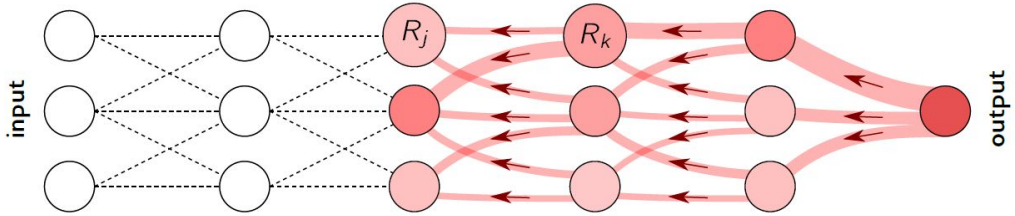
[25,26]

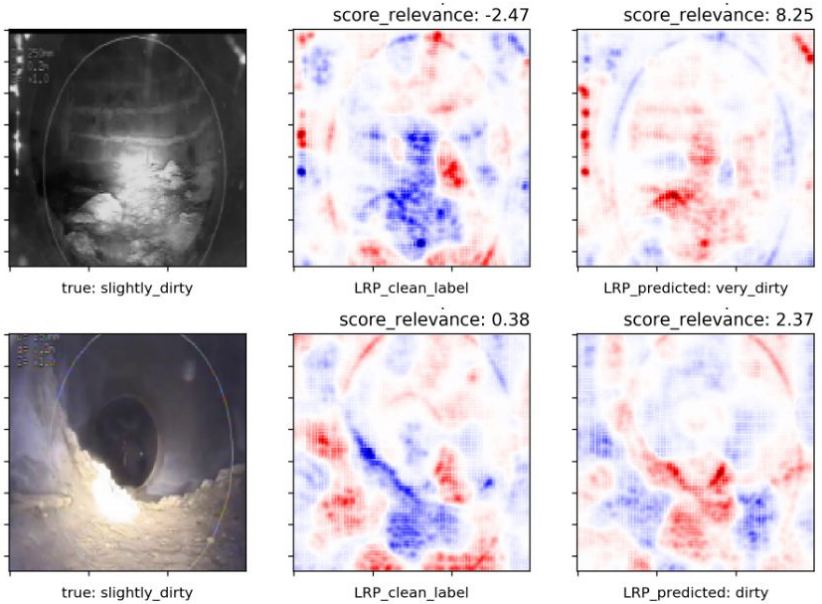
Ways of Looking at CNNs

- *Feature Attribution*: **Where** is the network looking?
  - Grounded. Instance based.
  - Explainability in practice.
- *Feature Visualization*: **What** is the network seeing?
  - Uncontextualized. Maximization based.
  - Diagnosys & Insight
- *Exemplification*: **How** does the network react?
  - Max. activations
  - Samples from a distribution

Attribution

- Finding the importance of pixels
- Layerwise Relevance Propagation (LRP)
  - Backpropagate *an* output. Find the relevance of each neuron
    - Weighted by CNN parameters





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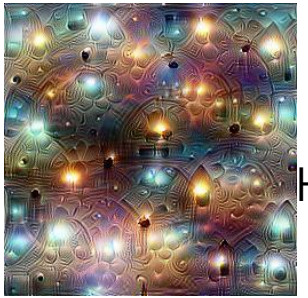
[29]

Feature Visualization

- Optimizing the input to maximize the output
  - A neuron
    - A channel
  - A layer (DeepDream)



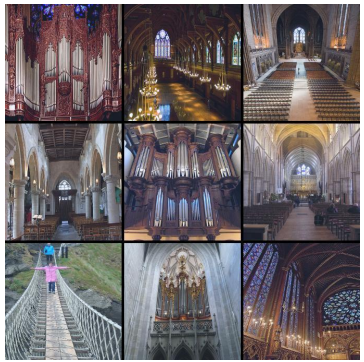
Low level

High level

Exemplification

- Finding images within a dataset maximizing outputs

  - Subjective
  - Partial
  - Stochastic



Bias in DL

“All models are wrong, some are useful” - George Box

-

“All DL models are biased, some are usefully biased”

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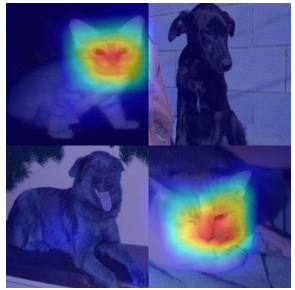
Bias in DL

- Bias is what makes ML work. Is a form of generalization.
  - *Identification*: What bias?
    - Bonus track: Human bias (Pareidolia)
  - *Appreciation*: Desirable bias?
  - *Mitigation*: Altering dataset or model?

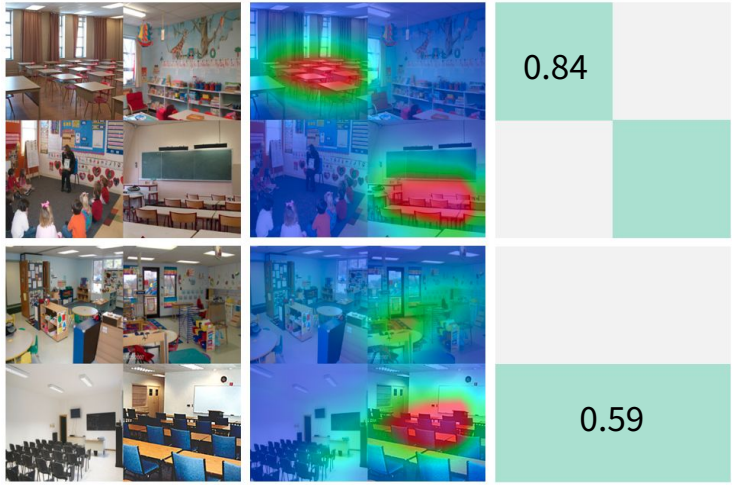
Bias Detection through XAI Attribution

Focus & Mosaics: An eye-tracking game

Why is this mosaic of class “cat”?



- Identification: Many examples needed
- Appreciation: Expert decision
- Mitigation:
  - Shared bias:
    - Add target samples without bias
    - Add non-target samples with bias
  - Missing bias: Add target samples with bias



[48]

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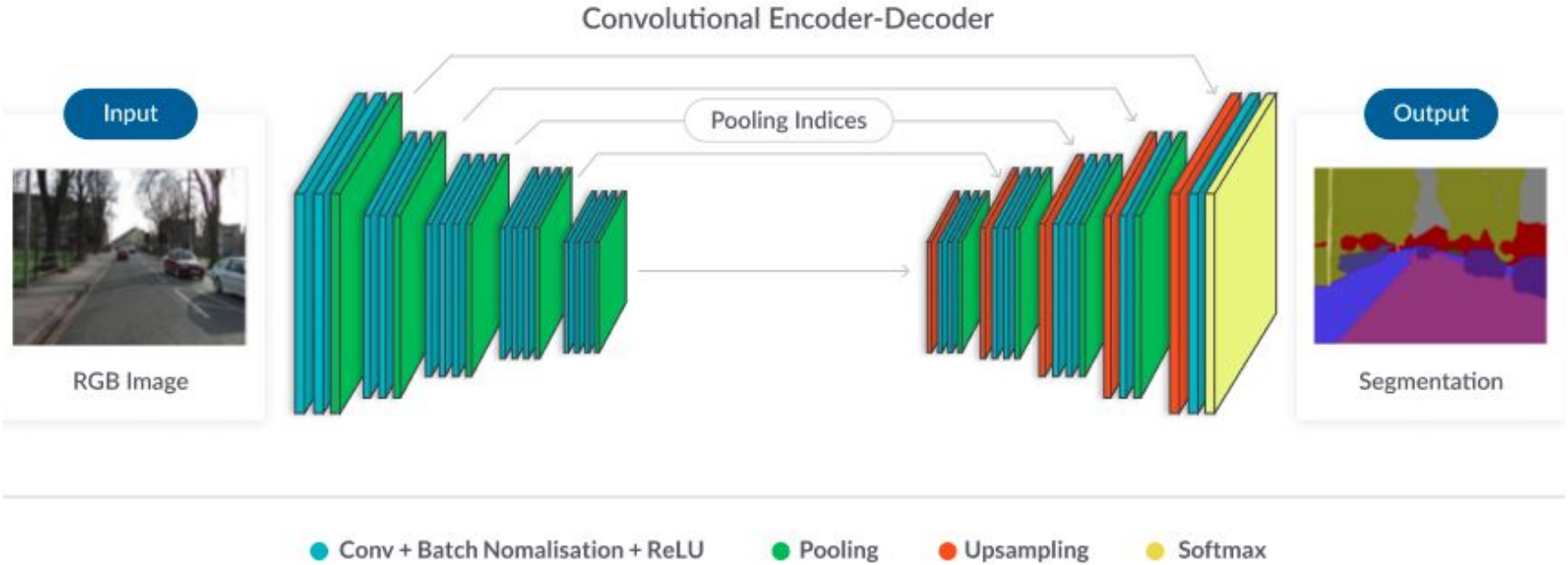
Playing with CNNs

Encoder-Decoder CNNs

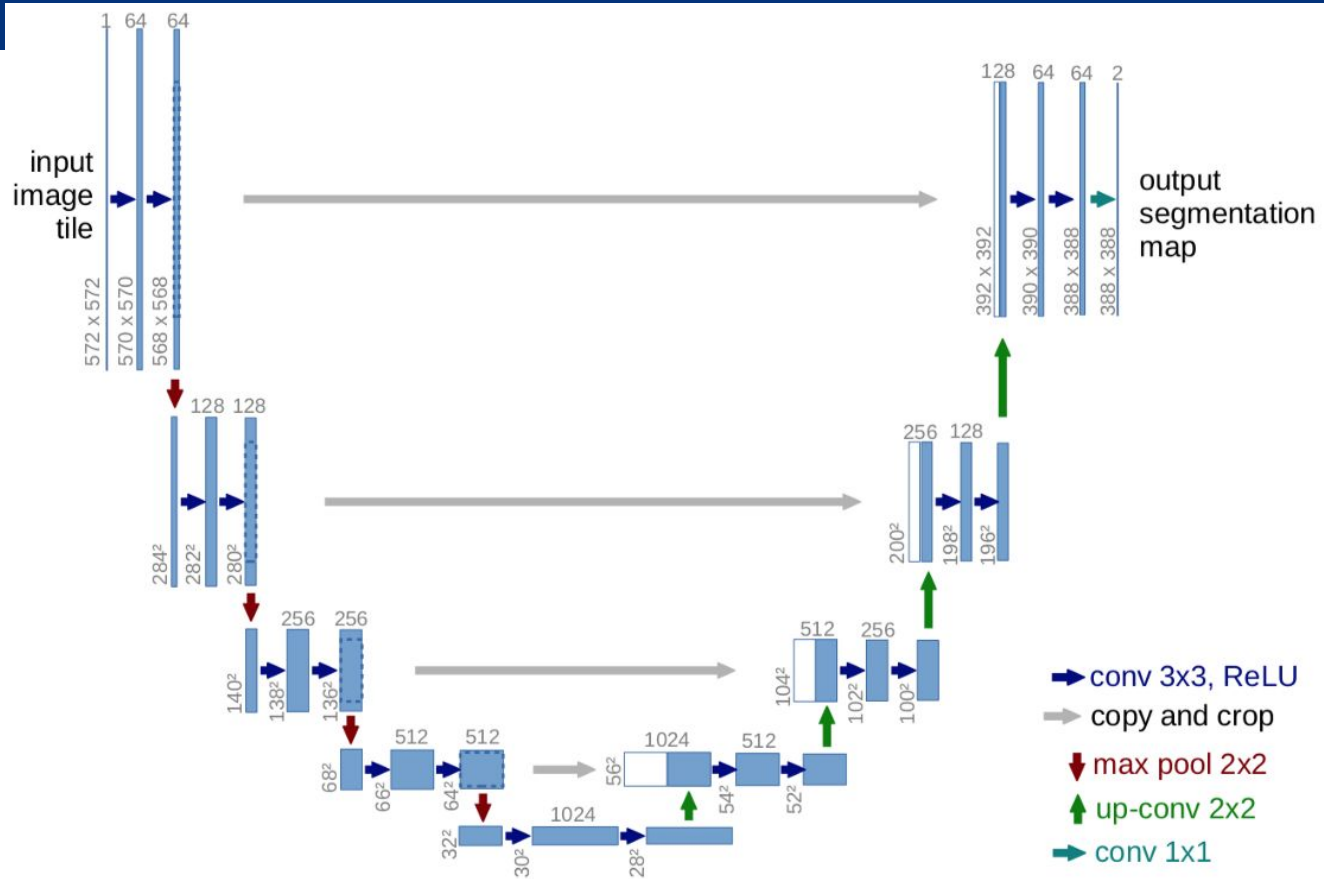
- Pixel-wise classification task (image reconstruction loss)
- Bottlenecking makes it cheaper



[14]

A standard

- U-Net



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Automatic Image Colorization

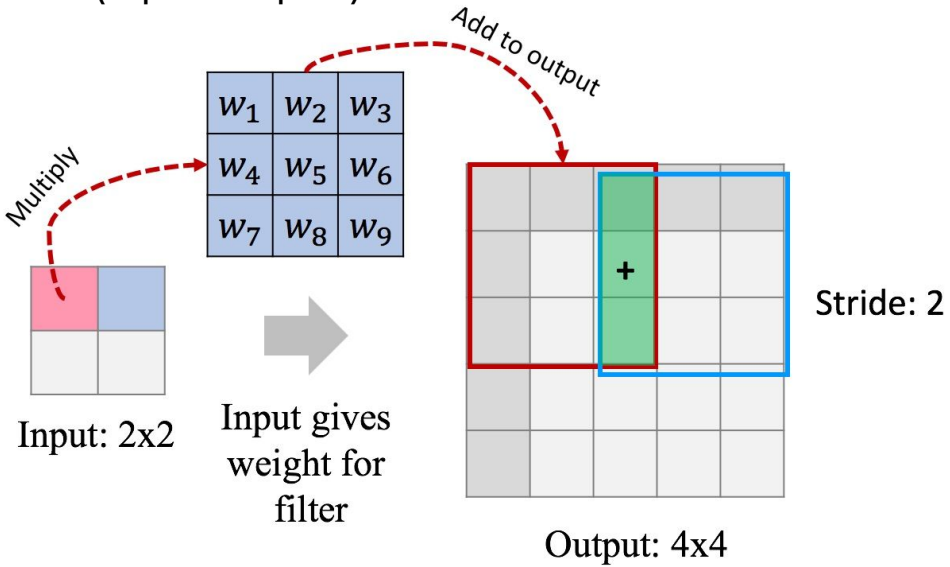
- Another pixel-wise classification application

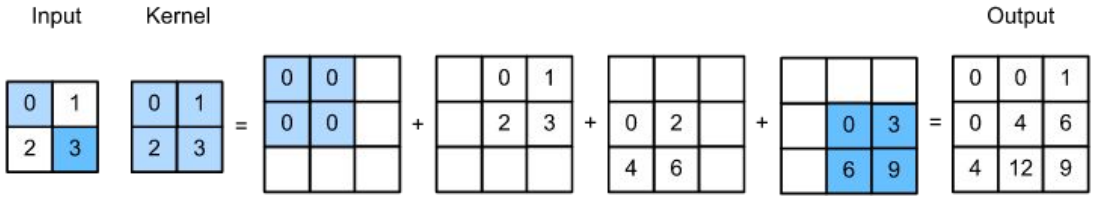
(a) Colorado National Park, 1941 (b) Textile Mill, June 1937 (c) Berry Field, June 1909 (d) Hamilton, 1936

[15,16]

Transposed Convolution ~~Deconvolution~~

- Reverse effect of regular convolution (upsample)
- Learnt interpolation
- Applications
  - Segmentation
  - GANs
  - Super-Resolution
  - Conv. Autoencoders





Faster Segmentation

- ~~Pixel wise classification~~ Object detection (bounding box)
  - Can be done with a “regular” CNN
- R-CNN: Propose crops (SVM). Extract features (CNN). Classify crops (SVM)
- Fast R-CNN: Extract features. Propose crops. Classify/Bounding Box (CNN)
- Faster R-CNN: Propose crops through a specific sub-net (RPN)
- YOLO v? (no regions, faster, less accurate)
  - Divide into grid. Predict class and bounding box for each cell.

Better Segmentation

- Mask R-CNN
  - Faster R-CNN for object detection
  - FCN for instance segmentation (pixel classification)
- Xception
  - Depth-wise separable Convs (inverted order & w/o non-linearity)
  - Skip connections
  - Atrous SPP

[17,18]

Style Transfer

- What do the correlation of activations intra-layer tell us?
  - What if we force it on another image?

- Gram matrix represents the *style*
  - Channel-wise (cXc)
  - Several mid layers
- Activations represents the *content*
  - One mid layer

- Optimize the **input** to minimize 2 losses
- Use a pre-trained net frozen
- Improved and extended

[19,20,21,22]

References

[1] http://vordenker.de/ggphilosophy/mcculloch_a-logical-calculus.pdf
[2]http://www-public.tem-tsp.eu/~gibson/Teaching/Teaching-ReadingMaterial/Rosenblatt58.pdf
[3] http://www.dtic.mil/dtic/tr/fulltext/u2/236965.pdf
[4] https://en.wikipedia.org/wiki/Perceptrons_(book)
[5]http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/
[6] https://en.wikipedia.org/wiki/Perceptrons_(book)
[7] Werbos et al. "Beyond regression:" new tools for prediction and analysis in the behavioral sciences." Ph. D. dissertation, Harvard University (1974).
[8] Rummelhart et al. "Learning Internal Representations by Error Propagation". MIT Press (1986).

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

References

[9]https://towardsdatascience.com/effect-of-gradient-descent-optimizers-on-neural-net-training-d44678d27060
[10] https://arxiv.org/abs/1711.05101
[11] https://bbabenko.github.io/weight-decay/
[12] https://towardsdatascience.com/weight-decay-l2-regularization-90a9e17713cd
[13] Veit, Andreas, Michael J. Wilber, and Serge Belongie. "Residual networks behave like ensembles of relatively shallow networks." Advances in neural information processing systems. 2016.
[14] https://thegradient.pub/semantic-segmentation/
[15] https://arxiv.org/pdf/1603.08511
[16] https://pdfs.semanticscholar.org/5c6a/0a8d993edf86846ac7c6be335fba244a59f8.pdf

References

[17] https://arxiv.org/pdf/1606.00915.pdf
[18] https://arxiv.org/pdf/1610.02357.pdf
[19] https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Gatys_Image_Style_Transfer_CVPR_2016_paper.pdf
[20] https://arxiv.org/abs/1603.08155
[21] https://arxiv.org/abs/1603.03417
[22] https://ai.googleblog.com/2016/10/supercharging-style-transfer.html
[23] https://arxiv.org/pdf/1903.07291.pdf
[24] http://nvidia-research-mingyuliu.com/gaugan
[25] Geirhos, Robert, et al. "ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness." arXiv preprint arXiv:1811.12231 (2018).

References

[26] Beery, Sara, Grant Van Horn, and Pietro Perona. "Recognition in terra incognita." Proceedings of the European Conference on Computer Vision (ECCV). 2018.
[27] https://distill.pub/2017/feature-visualization/
[28] https://distill.pub/2018/building-blocks/
[29] Montavon, Grégoire, et al. "Layer-wise relevance propagation: an overview." Explainable AI: interpreting, explaining and visualizing deep learning. Springer, Cham, 2019. 193-209.
[30] https://medium.com/machine-intelligence-report/how-do-neural-networks-work-57d1ab5337ce
[31] Hebb, D.O. (1949), The organization of behavior, New York: Wiley

References

[32] Dauphin, Yann N., et al. "Identifying and attacking the saddle point problem in high-dimensional non-convex optimization." Advances in neural information processing systems. 2014.
[33] Ruder, Sebastian. "An overview of gradient descent optimization algorithms." arXiv preprint arXiv:1609.04747 (2016).
[34] Viazovetskyi, Yuri, Vladimir Ivashkin, and Evgeny Kashin. 'StyleGAN2 Distillation for Feed-Forward Image Manipulation'. 7 March 2020. http://arxiv.org/abs/2003.03581.
[35] https://medium.com/@jonathan_hui/gan-stylegan-stylegan2-479bdf256299
[36] https://www.justinpinkney.com/making-toonify/
[37] http://chengao.vision/FGVC/files/FGVC.pdf
[38] Sandler, Mark, et al. "Mobilenetv2: Inverted residuals and linear bottlenecks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

References

[39] Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." arXiv preprint arXiv:1704.04861 (2017).
[40] https://arxiv.org/abs/1710.09412v2
[41] https://arxiv.org/abs/1708.04552
[42] https://arxiv.org/pdf/1905.04899.pdf
[43] https://arxiv.org/abs/1809.02499
[44] https://openaccess.thecvf.com/content_CVPR_2019/papers/Cubuk_AutoAugment_Learning_Augmentation_Strategies_From_Data_CVPR_2019_paper.pdf
[45] https://towardsdatascience.com/12-main-dropout-methods-mathematical-and-visual-explanation-58cdc2112293

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

References

[46] J. Tompson, R. Goroshin, A. Jain, Y. LeCun, and C. Bregler, Efficient object localization using convolutional networks
[47] T. DeVries and G. W. Taylor, Improved regularization of convolutional neural networks with cutout
[48] Arias-Duart, Anna, Ferran Parés, and Dario Garcia-Gasulla. "Focus! Rating XAI Methods and Finding Biases with Mosaics" arXiv preprint arXiv:2109.15035 (2021).
[49] Recht, Benjamin, Rebecca Roelofs, Ludwig Schmidt, and Vaishaal Shankar. "Do imagenet classifiers generalize to imagenet?." In International Conference on Machine Learning, pp. 5389-5400. PMLR, 2019.
[50] https://blog.insightdatascience.com/automl-for-data-augmentation-e87cf692c366
[51] Chollet, François. "Xception: Deep learning with depthwise separable convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

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References

[52] Liu, Ze, et al. "Swin transformer: Hierarchical vision transformer using shifted windows." Proceedings of IEEE/CVF international conference on computer vision. 2021.
[53] Liu, Zhuang, et al. "A convnet for the 2020s." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.
[54] https://towardsdatascience.com/why-adamw-matters-736223f31b5d
[55] Garcia-Gasulla, Dario, et al. "A visual embedding for the unsupervised extraction of abstract semantics." Cognitive Systems Research 42 (2017): 73-81.
[56] Trevor Gale, Erich Elsen, and Sara Hooker. The state of sparsity in deep neural networks. CoRR, abs/1902.09574, 2019. URL http://arxiv.org/abs/1902.09574
[57] Northcutt, Curtis G., Anish Athalye, and Jonas Mueller. "Pervasive label errors in test sets destabilize machine learning benchmarks." arXiv preprint arXiv:2103.14749 (2021).

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