Foundations of Deep Learning, Winter Term 2021/22

Week 8: Practical Methodology and Architectures

Practical Methodology and Architectures

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Overview of Week 8

1. Normalization Layers
2. Transfer Learning
3. General Methodology
4. Parameter Initialization
5. CNN Architectures
6. Detection and Segmentation
7. Summary, Further Reading, References

Lecture Overview

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Foundations of Deep Learning, Winter Term 2021/22

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Normalization Layers

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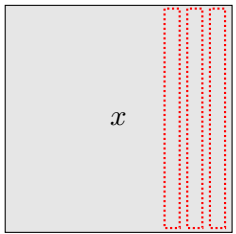
Batch Normalization

Consider a batch of activations at some layer. To make each dimension zero-mean and unit-variance, apply:

$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathsf{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

Batch Normalization (cont.)

Consider an input x of shape $N \times D$

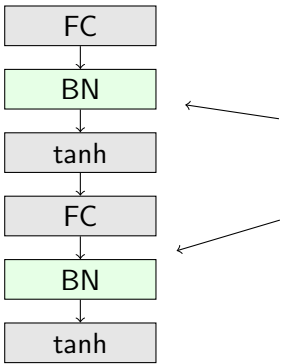


$$\mu_j \leftarrow \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$ Per-channel mean, shape D

$$\sigma_j^2 \leftarrow \frac{1}{N}\sum_{i=1}^{N}(x_{i,j} - \mu_j)^2$$ Per-channel variance, shape D

$$\widehat{x}_{i,j} \leftarrow \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$ Normalized x, shape $N \times D$

Batch Normalization (cont.)



Usually inserted after fully connected or convolutional layers, but before nonlinearity.

Batch Normalization (cont.)

Consider an input x of shape $N \times D$

- Learnable scale and shift parameters: γ, β of shape D.
- Learning $\gamma_j = \sigma_j$ and $\beta_j = \mu_j$ recovers the identity function.

$$y_{i,j} \leftarrow \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}} \cdot \gamma - j + \beta_j \quad \text{Output, shape } N \times D$$

$\cdot$ denotes the element-wise multiplication

Batch Normalization at Test Time

- During testing batch norm becomes a linear operator.
- It can be fused with the previous fully-connected or convolution layer.

$\mu_j \leftarrow$ Moving average over the μ_j's seen during training.
$\sigma_j \leftarrow$ Moving average over the σ_j's seen during training.

Batch Normalization for CNNs

Batch normalization for **fully-connected** layers (`torch.nn.BatchNorm1d`).

$$x : N \times D$$

Normalize

$$\mu, \sigma : 1 \times D$$
$$\gamma, \beta : 1 \times D$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Batch normalization for **convolutional** layers (`torch.nn.BatchNorm2d`).

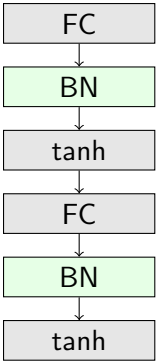
$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma : 1 \times C \times 1 \times 1$$
$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Batch Normalization for CNNs (cont.)



- Makes deep networks much easier to train.
- Improves gradient flow.
- Allows higher learning rates, faster convergence.
- Networks become more robust to initialization.
- Acts as regularization during training.
- Does not perform well with small mini-batch sizes and while having recurrent connections.

Layer Normalization

Batch normalization for fully-connected layers

$$x : N \times D$$

Normalize

$$\mu, \sigma : 1 \times D$$
$$\gamma, \beta : 1 \times D$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Layer normalization for fully-connected layers behaves the same during training and testing. It can be used in RNNs and transformers.

$$x : N \times D$$

Normalize

$$\mu, \sigma : N \times 1$$
$$\gamma, \beta : 1 \times D$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Instance Normalization

Batch Normalization for convolutional layers.

$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma : 1 \times C \times 1 \times 1$$
$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Instance Normalization for convolutional layers. Same behavior for train and test.

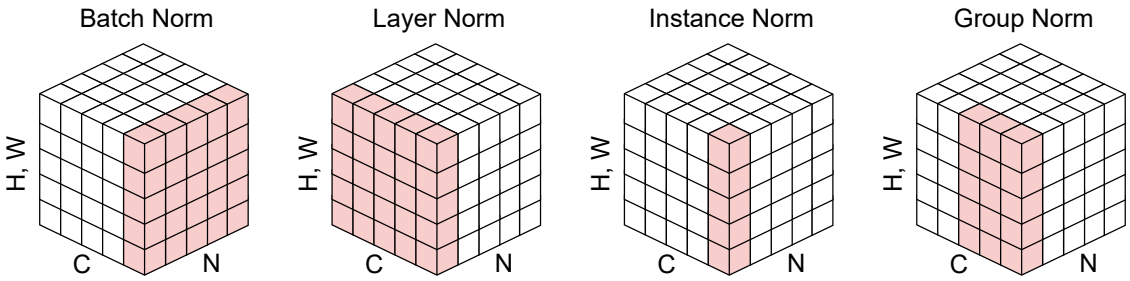
$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma : N \times C \times 1 \times 1$$
$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y \leftarrow \gamma \widehat{x} + \beta$$

Comparison of Normalization Layers



Questions to Answer for Yourself / Discuss with Friends

- Repetition: What are two scenarios in which batch normalization does not perform well?
- Repetition: Which normalization should you use for RNNs?
- Repetition: Which normalization has been demonstrated to perform well for style transfer?

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Week 8: Practical Methodology and Architectures

Transfer Learning

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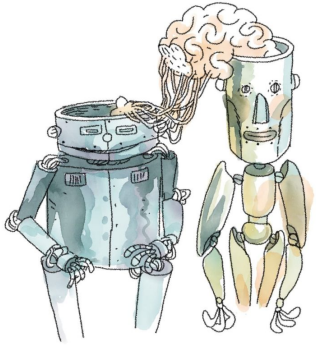
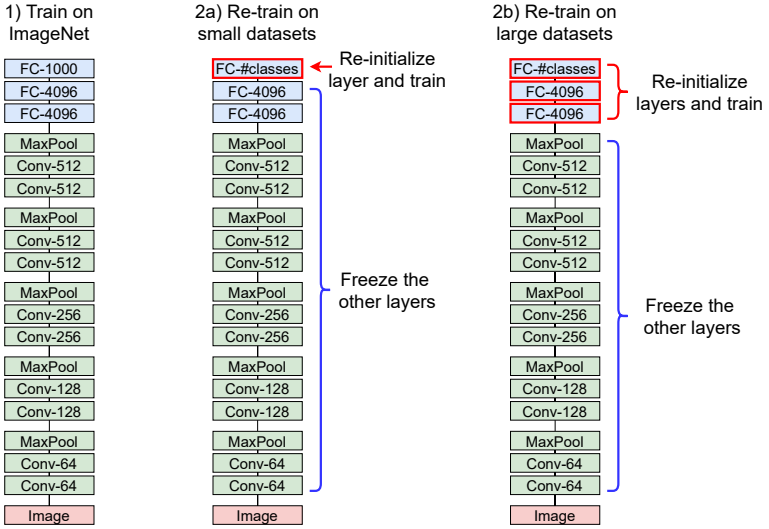
Transfer Learning



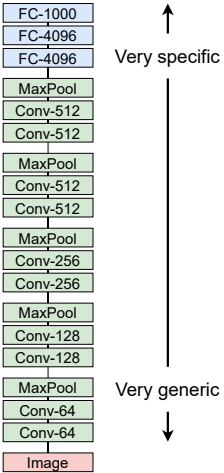
- Idea: Make use of a large related dataset.
- Initialize model for small dataset with weights found on a large dataset.

[Image source: https://thedatafrog.com/en/articles/image-recognition-transfer-learning]

Transfer Learning with CNNs



Transfer Learning with CNNs – Strategies



	Similar dataset	**Different dataset**
Little data	Add linear classifier to top layer.	Difficult to resolve. Try linear classifier at different stages.
Much data	Fine-tune some layers.	Fine-tune many layers.

Self-Supervised Learning

It can be beneficial to first train without human supervision.

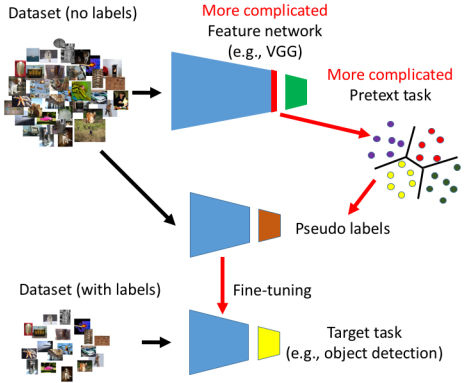


Figure: Vision [Noroozi et al., 2018].

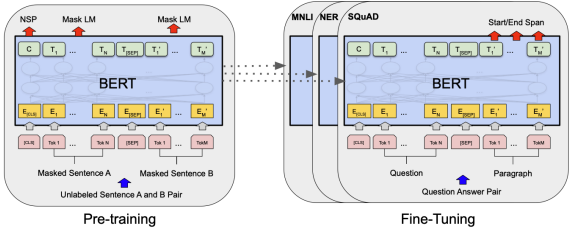


Figure: Natural language processing [Devlin et al., 2019].

Transfer Learning in Vision

- Self-supervised Learning
- Image Classification

⋮

- Image Classification
- Image Captioning
- Object Detection
- Image Segmentation

⋮

Transfer Learning in NLP

- Language Modeling
- Masked Language Modeling

⋮

- Question Answering
- Sentiment Classification
- Entailment Classification
- Grammar Checking
- Machine Translation

⋮

Questions to Answer for Yourself / Discuss with Friends

- Repetition: How will you perform transfer learning when you have very little data but your data is similar to ImageNet?
- Application of what you just learned: Can you still perform transfer learning if the network architecture that you used to first pre-train on ImageNet is completely different from the architecture that you are going to use for training on your small dataset?

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General Methodology

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What Deep Learning Model Should I Apply?

- Fixed-size vectors as input?
  - ⇝ Feedforward network with fully connected layers
- Input with topological structure (e.g., images)?
  - ⇝ Convolutional network
  - ⇝ Transformer
- Input (and output) is a sequence?
  - ⇝ Gated recurrent net (LSTM, GRU)
  - ⇝ Transformer

Recommended Practical Design Process

- Determine your goals, including performance metrics.
- Establish a working end-to-end pipeline as early as possible.
  - If task is similar to a previous one, use the same type of model or copy weights (e.g., ImageNet features).
- Determine the bottlenecks in performance: diagnose and debug.
- Repeatedly make incremental changes.
  - Gather new data.
  - Adjust hyperparameters.

Debugging Strategies

- Fit a tiny dataset.
- Visualize the exact inputs.
- Visualize the model in action.
- Visualize the worst mistakes.
- Check your derivatives with finite differences.
- Monitor histograms of activations and gradient.

Fit a Tiny Dataset

- If the training error does not vanish on a tiny dataset, something is wrong:
  - Some software bug.
  - Problem in the optimizer.
  - $\rightsquigarrow$ Very cheap check, very effective.

- Related: feed in random data as input.
  - Allows diagnosing whether output biases reflect class distribution.

Visualize the Exact Inputs

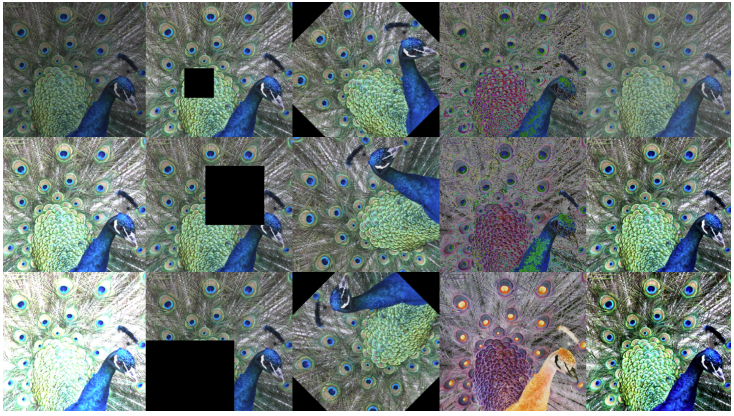
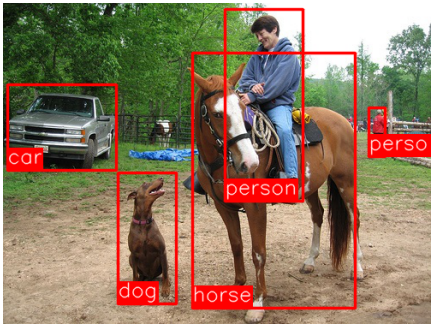


Figure: E.g., visualize the inputs of a neural network after applying augmentations.

Visualize the Model in Action



Directly observe model performance:

- Visualize the detections proposed by the model.
- Listen to speech samples if the model generates speech.
- Quantitative performance measurement, e.g., accuracy, log-likelihood, etc.

[Image source: https://cdn-images-1.medium.com/max/1600/1*E-8oQW8ZO-hHgTf6laWhhQ.png]

Visualize the Worst Mistakes

- View the training set examples that are hardest to model correctly.
- Example: Incorrectly transcribed street numbers.

[Image source: Goodfellow et al., 2013]

Check Your Derivatives with Finite Differences

- Incorrect implementation of the gradient expression is a common mistake when dealing with gradients.
- Using finite difference to verify correctness:

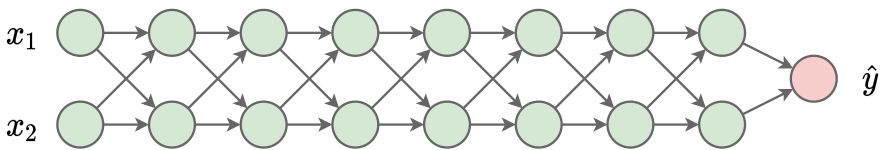
$$f'(x) = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon) - f(x)}{\varepsilon}$$

$$f'(x) \approx \frac{f(x+\varepsilon) - f(x)}{\varepsilon}$$

$$f'(x) \approx \frac{f\left(x+\frac{\varepsilon}{2}\right) - f\left(x-\frac{\varepsilon}{2}\right)}{\varepsilon}$$

- To check gradient on a vector-valued function $g : R^m \to R^n$,
  - simply run finite differentiation $m \times n$ times or
  - sample random directions $\mathbf{u}$ and $\mathbf{v}$ and check derivatives along those: $f(x) = \mathbf{u}^T g(\mathbf{v}x)$.

Monitor Histograms of Activations and Gradient



- Monitor gradient values to detect vanishing/exploding gradients.
- Monitor activations, e.g., how often are rectifiers off?

Questions to Answer for Yourself / Discuss with Friends

- Repetition: You have trained your network and you find that it performs really poorly in the quantitative metrics, how would you debug this?
- Repetition: You have an innovative idea for a completely new type of activation function or layer and want to implement it yourself. Which checks should you do to make sure it works as expected?

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Parameter Initialization

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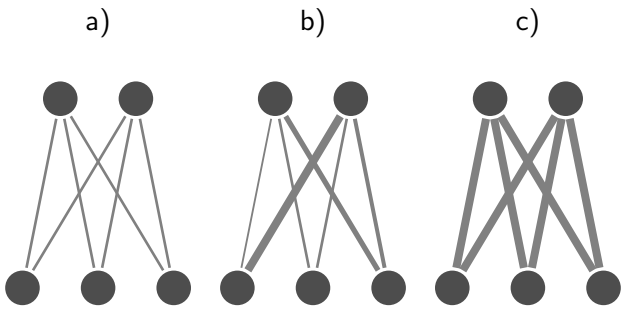
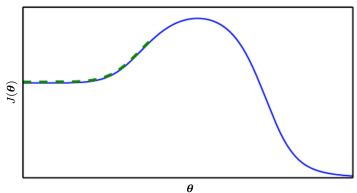
Parameter Initialization



Before we can start SGD, we need to define with what weights to start!

Parameter Initialization Strategies

- Initial point affects *convergence*, *minimal cost*, and *generalization error*.



- Current research topic, often just *simple heuristics*.
- Break the symmetry: weights of hidden units in the same layer would always remain the same if initialized the same.
  - Rather initialize weights for units to compute maximally-different functions.
- Random weights (constant bias).
- More advanced: pre-training, meta-learning.

[Image source: Goodfellow et al., 2016, p. 288, Fig. 8.4]

Parameter Initialization Strategies – Weights

- Uniform or normal distribution.
- Scale is important:
  - Break symmetry, activation flow $\rightarrow$ large
  - Gradient explosion, generalization $\rightarrow$ small
- E.g., normalized initialization (also known as Xavier initialization):

$$\mathrm{W}_{i,j} \sim U\left(-\sqrt{\frac{6}{m+n}}, \sqrt{\frac{6}{m+n}} \right)$$

  - For fully connected layer with m inputs and n outputs.
  - To compromise between goals of initializing all layers to have the same activation variance and gradient variance.
- In practice: scale of weights is a layer-dependent hyperparameter to be tuned.
- Try to preserve norm of activations & gradient when propagated through the network.
  - Can be checked and adjusted on a few mini-batches.

Parameter Initialization Strategies – Biases

- Often 0, except
  1. Output units: set bias vector $\mathbf{b}$ to match desired output statistics.
     - E.g., to output the average class proportions c_i with a softmax unit, solve $\text{softmax}(\mathbf{b}) = \mathbf{c}$.
  2. ReLU units: $\mathbf{b} \approx 0.1$ (not 0 to avoid saturation).

     Gating units: $\mathbf{b} \approx 1$ (to open the gate):
     - Gating units $h \in [0, 1]$, to be multiplied by units with output u to form uh.
     - Initialize biases to make $h \approx 1$, so that u has a chance to learn.
     - E.g., initialize the bias of the forget gate in LSTMs to 1.

Other Initialization Strategies: Meta-Learning and Warm-Starting

Both meta-learning and warm-starting techniques can be used to initialize networks.

- **Warm-starting**: initialize with weights that have been optimized on a different task.
- **Meta-learning**: learning the "best" weight initialization strategy for different tasks.

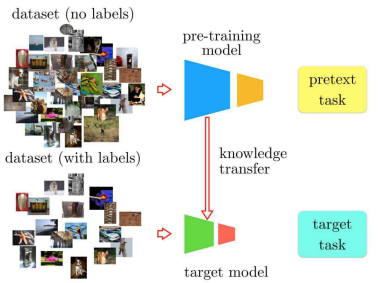


Figure: Warm-start [Noroozi et al., 2018].

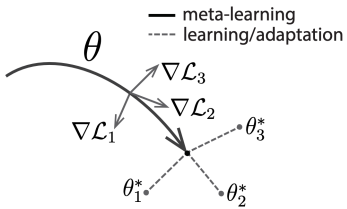


Figure: Meta-learning in MAML [Finn et al., 2017].

Questions to Answer for Yourself / Discuss with Friends

- Activation of what you just learned: Why would you want to preserve the norm of activations and gradients when propagated through the network?
- Transfer: Can you think of some examples of tasks that could be used to perform transfer learning for each other?

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CNN Architectures

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LeNet-5 (1998)

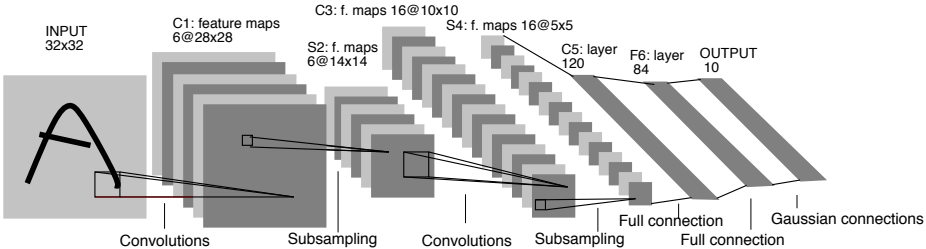


Figure: Architecture of LeNet-5 [LeCun et al., 1998].

- First wave of successful application of CNNs, e.g., reading zip codes, digits, etc.
- Key points:
  - Overall architecture: CONV $\rightarrow$ POOL $\rightarrow$ CONV $\rightarrow$ POOL $\rightarrow$ CONV $\rightarrow$ FC $\rightarrow$ FC
  - Average pooling $\rightsquigarrow$ today, max pooling is used
  - Tanh activation function $\rightsquigarrow$ today, replaced by ReLU and others
- Reminder: Valid convolutions reduce the size (height, width).

The ImageNet Challenge

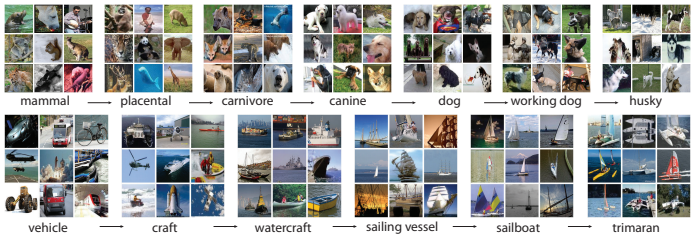


Figure: Examples of the ImageNet dataset [Jia et al., 2009].

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
- Annually held from 2010 to 2017.
- Evaluation of algorithms for object detection and image classification at large scale:
  - 1.3M training images
  - 1,000 object classes
- Often used for pre-training.

AlexNet (2012 winner)

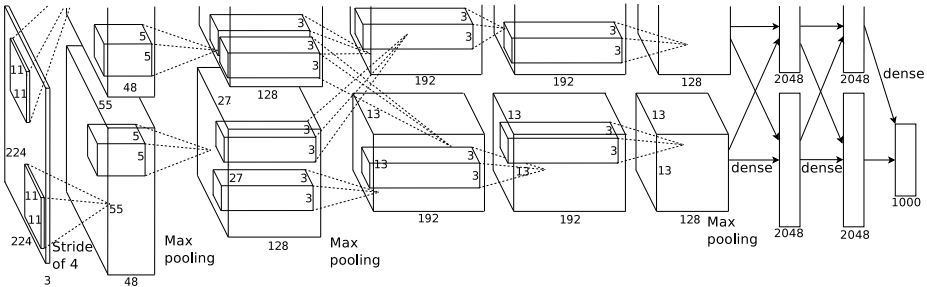


Figure: Architecture of AlexNet [Krizhevsky et al., 2012].

- Popularized CNNs for Computer Vision tasks.
- Key points:
  - Stacking multiple convolutional layers $\rightsquigarrow$ deep networks
  - First use of ReLU activation $\rightsquigarrow$ increase speed and accuracy
  - Normalization layers $\rightsquigarrow$ not commonly used anymore
  - Dropout
  - Heavy data augmentation

ZFNet (2013 winner)

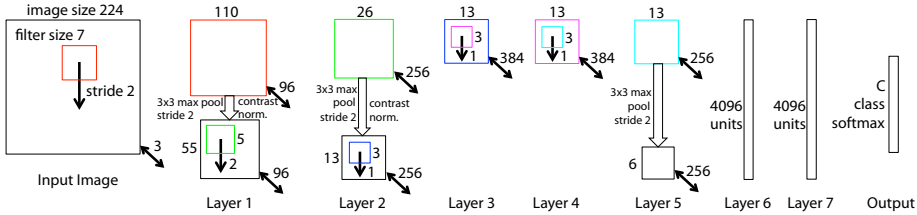


Figure: Architecture of ZFNet [Zeiler and Fergus, 2014].

- Optimize network hyperparameters.
- Key points:
  - Change AlexNet hyperparameters
  - 1st conv layer: decreased filter size and stride
  - Mid conv layers: increased number of channels

VGGNet (2014 runner-up)

- Deep networks with small filters.
- Key points:
  - Stack of three 3×3 filters have the same receptive field as one 7×7 filter.
  - Reduce number of parameters.
    $\rightsquigarrow 3(3^2C^2)$ vs 7^2C^2 (C is channels per layer)
  - Downside: more non-linearities.
  - Downside: many parameters (140M) make inference expensive.
    $\rightsquigarrow$ 1st FC layer has been removed since then without loss in performance.

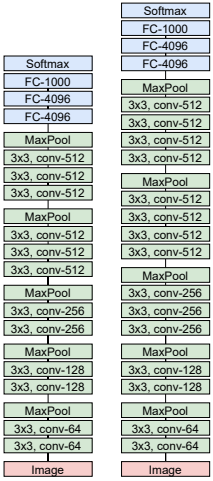


Figure: Architectures of VGGNet-16 and VGGNet-19.

GoogLeNet (2014 winner)

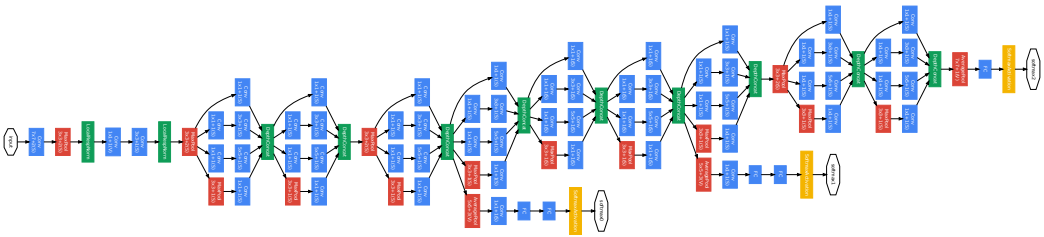


Figure: Architecture of GoogLeNet [Szegedy et al, 2015].

- Focus towards deep networks that are computationally efficient.
- Key points:
  - Inception module $\rightsquigarrow$ reduce number of parameters (AlexNet: 60M, GoogLeNet: 4m)
  - Average pooling instead of FC layers $\rightsquigarrow$ remove parameters without contribution

GoogLeNet – Inception Module

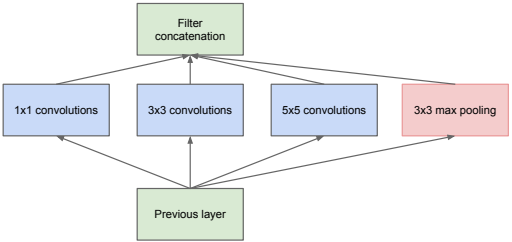


Figure: Naïve version [Szegedy et al, 2015].

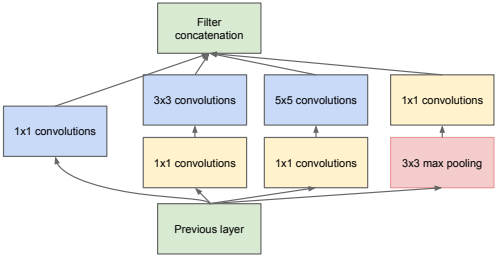


Figure: "Bottleneck" version [Szegedy et al, 2015].

- Design a good local network topology and then stack these modules.
- Key idea: apply parallel filters of different sizes and concatenate the output.
- The naïve version has high computational complexity. $\rightsquigarrow$ very expensive
- The "bottleneck" version reduces the dimensionality via 1×1 convolutions.

ResNet – Motivation

What happens when we continue stacking deeper layers on a "plain" convolutional neural network?

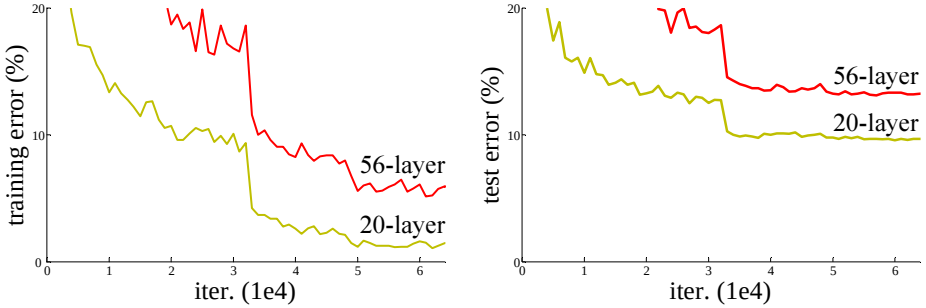


Figure: Error on CIFAR-10 with "plain" networks [He et al., 2016].

The deeper model should be able to perform at least as well as the shallower model.

ResNet – Residual Learning

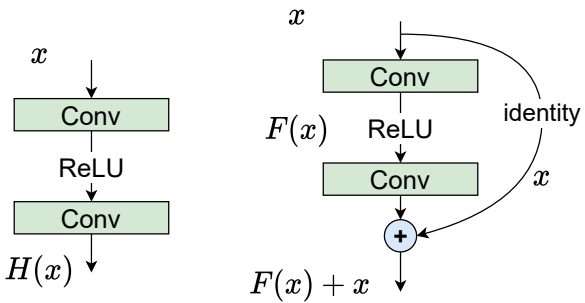


Figure: "Plain" (left) vs residual building block (right).

- Use a small network to fit a residual mapping instead of directly trying to fit a desired underlying mapping. $\rightsquigarrow F(x) = H(x) - x$
- Key idea: make each layer the identity by default.
  - Enable the network to skip layers.

ResNet (2015 winner)

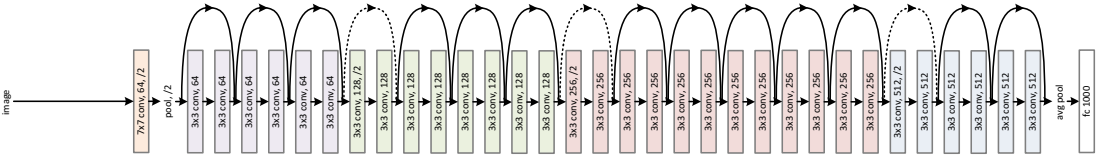


Figure: Architecture of ResNet-34 [He et al., 2016].

- Very deep networks with residual connections.
- Key points:
  - Skip connections (residual building blocks)
  - Batch normalization
  - Only a single FC layer at the end
- Deeper variants, e.g., ResNet-50, use bottleneck blocks.
  $\rightsquigarrow$ Similar idea as Inception module.
- Better than human performance on ImageNet challenge [Russakovsky et al, 2015].

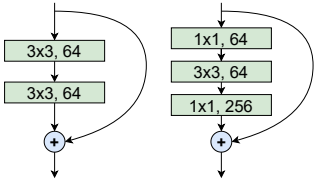


Figure: Normal (left) vs bottleneck block (right).

Variants of ResNet – ResNeXt (2016 runner-up)

Now, focus on efficiency since already superior than human performance.

- From authors of ResNet.
- Increase the width of a residual block by introducing parallel pathways ("cardinality").
- The idea behind the pathways is similar to the Inception module.

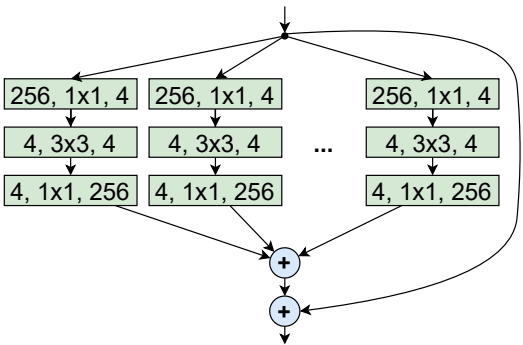


Figure: ResNeXt building block.

Variants of ResNet - DenseNet

Now, focus on efficiency since already superior than human performance.

- Dense block, where each layer is connected to all later layers.
- Advantages:
  - Mitigates vanishing gradient.
  - Encourages feature propagation and re-use.
- Shallow 50-layer can outperform ResNet-152.

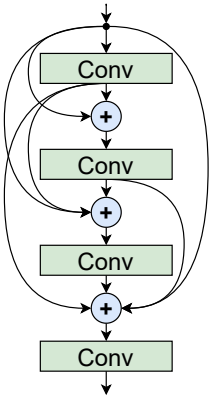


Figure: DenseNet building block.

MobileNets

- Focus towards efficient networks for deployment on mobile devices.
- Replace standard convolutions by two layers (depthwise separable filter):
  - Depthwise convolution
  - Pointwise convolution

  $\rightsquigarrow$ Reduce number of computations and hence increase efficiency.
- Inspired many follow-up works, e.g., MobileNetV2 [Sandler et al., 2018] and ShuffleNet [Zhang et al., 2018].

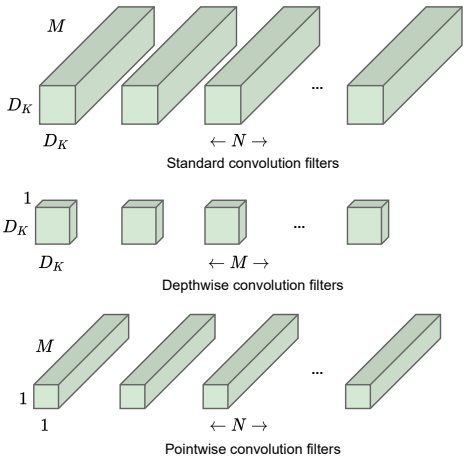


Figure: Depthwise separable filter consisting of depthwise convolutions and pointwise convolutions.

EfficientNet – Structured Model Scaling

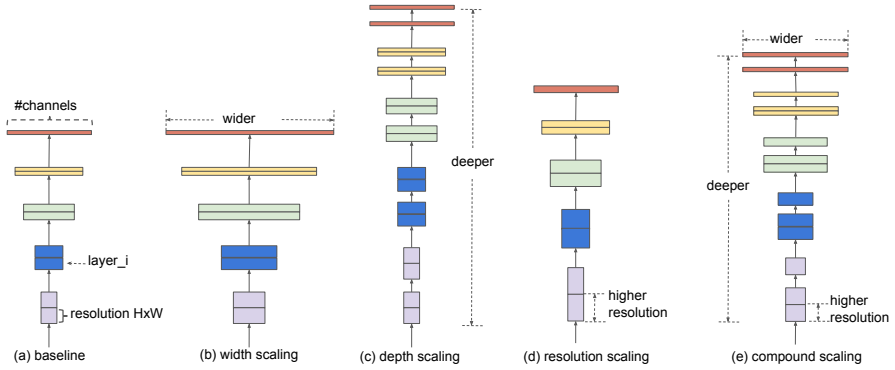


Figure: Various model scaling methods [Tan et al., 2019].

- Commonly, models are developed at a fixed resource cost and then scaled up.
- Conventionally, network dimensions are arbitrarily scaled, e.g., width, depth, etc.
- Compound model scaling balances scaling of dimensions against available resources.

EfficientNet

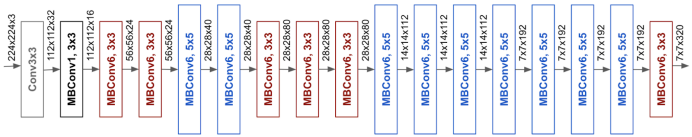


Figure: EfficientNet-B0 baseline architecture.

- Effectiveness of method relies on baseline network.
  $\rightsquigarrow$ EfficientNet allows for simple and clean scaling.
- Key points:
  - Designed via neural architecture search.
  - Using inverted bottleneck convolutions (MBConv), similar to MobileNetV2 [Sandler et al., 2018].

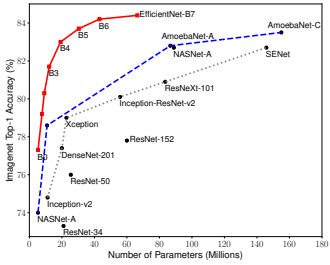
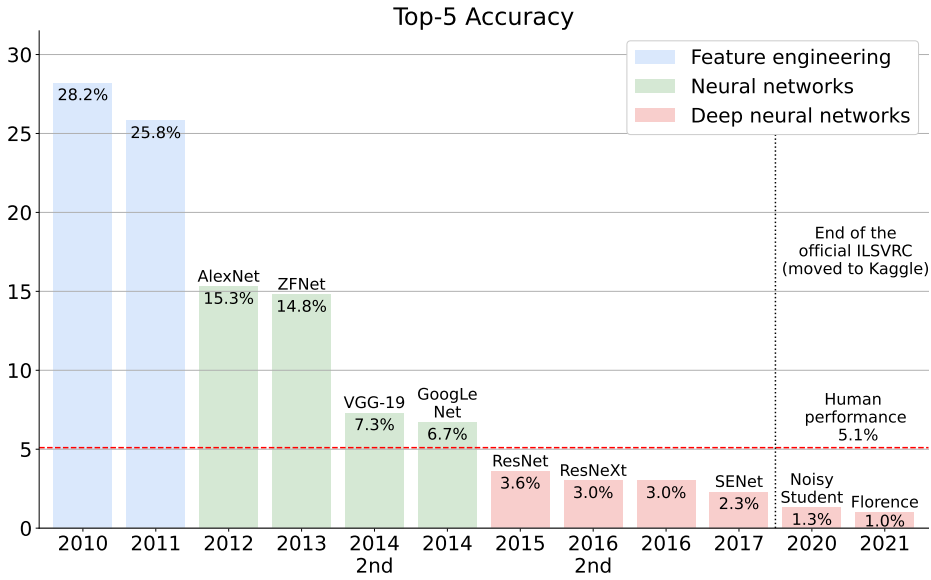


Figure: Model size vs. accuracy comparison [Tan et al., 2019].

ImageNet Challenge – Overview Results



Questions to Answer for Yourself / Discuss with Friends

- Application of what you just learned: What is the best strategy to take while designing CNNs?
- Repetition: What are some methods to keep the number of parameters and computational burden low?
- Repetition: What are some good practices that we can follow to increase the performance of the model in terms of only the metrics?

Lecture Overview

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4. Parameter Initialization
5. CNN Architectures
6. Detection and Segmentation
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Week 8: Practical Methodology and Architectures

Detection and Segmentation

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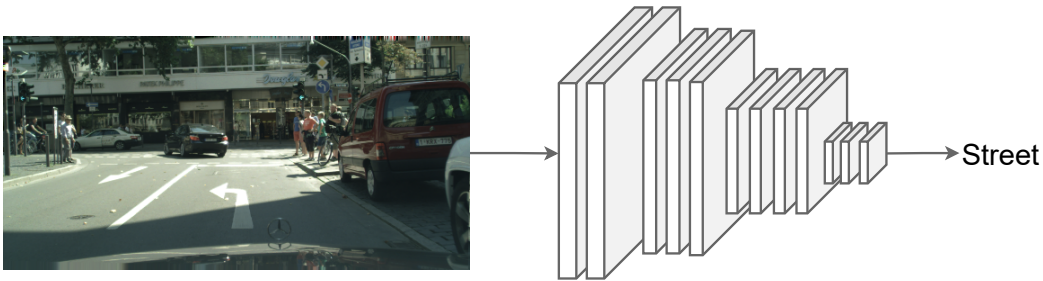
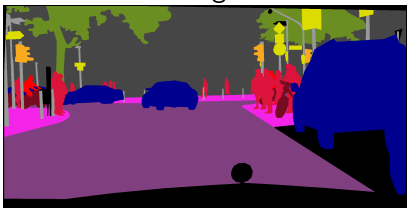
Image Classification



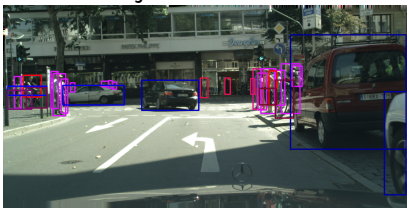
- Assign a single label to the entire image.
- A commonly used benchmark is the ImageNet dataset.

Image Recognition Tasks

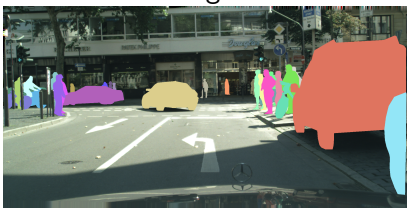
Semantic Segmentation



Object Detection



Instance Segmentation

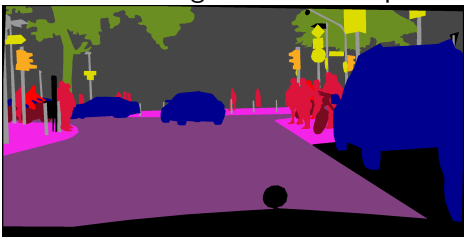


Panoptic Segmentation

Semantic Segmentation

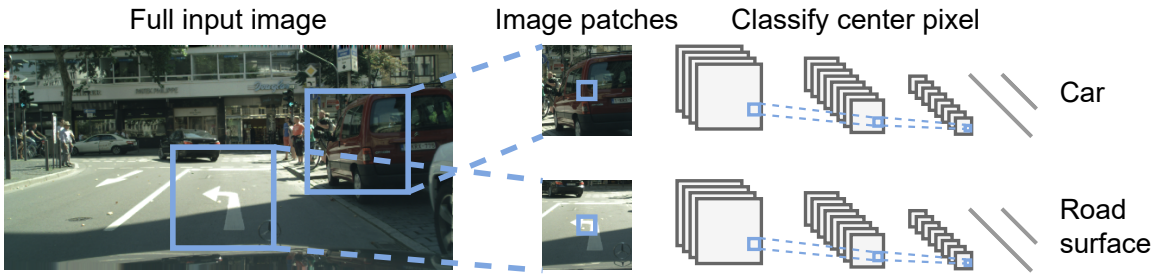
Input Image

Semantic Segmentation Output



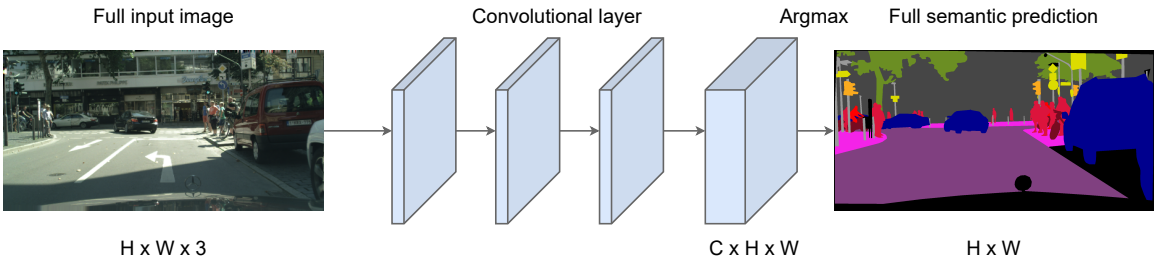
- Assign a class label to each pixel in the image.
- Do not differentiate between different instances of the same class.
- Consider the full scene context, i.e., object classes, location, and shape of all scene elements including the background.

Semantic Segmentation – Sliding Window Approach



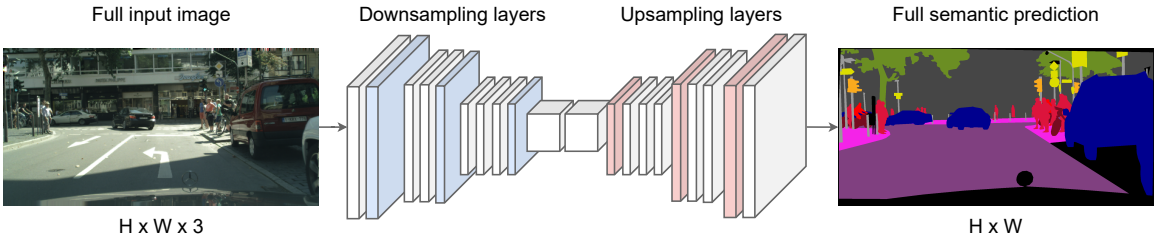
Problem: Very inefficient since overlapping patches do not reuse shared features.

Semantic Segmentation – Fully Convolutional Approach



- Design a convolutional network to predict classes for all pixels simultaneously.
- Problem: Convolutions at the original image resolution will be very expensive.

Semantic Segmentation – Fully Convolutional Approach (cont.)

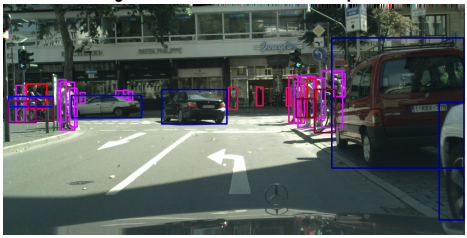


- Design a convolutional network with down- and upsampling layers.
- Downsampling: pooling or dilated convolutions.
- Upsampling: unpooling or transposed convolutions.

Object Detection

Input Image

Object Detection Output



- One of the most fundamental and extensively researched topics in machine vision.
- Requires both identification and localization of objects, e.g., person, vehicles, etc.
- Generate bounding boxes around the given specific target class.

Object Detection – Two-Stage vs. Single-Stage Detectors

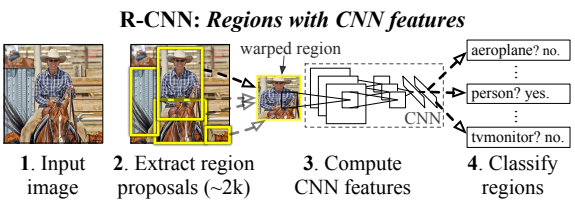


Figure: Two-stage detector, e.g., R-CNN [Ross et al., 2014].

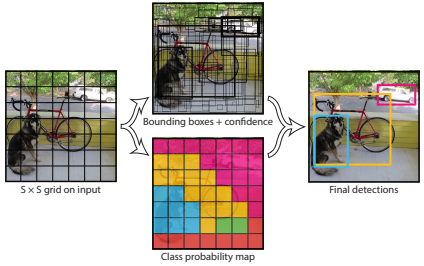


Figure: Single-stage detector, e.g., YOLO [Redmon et al., 2016].

- Two subtasks: object classification and box regression.
- Employ a multi-task loss.
- Two-stage detectors first perform box regression and then classification.
- Single-stage detectors use one CNN for box regression and classification.

Object Detection – Two-Stage Detectors: R-CNN to Faster R-CNN

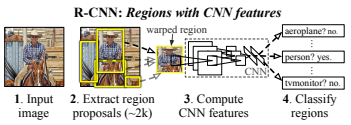


Figure: R-CNN [Ross et al., 2014].

- Extract region proposals from input image.
  No learning!
- CNN-based features for individual boxes.
- SVM for box offset values and object presence.

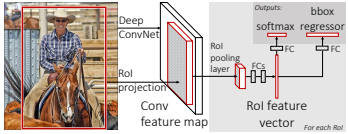


Figure: Fast R-CNN [Girshick, 2015].

- Feed image to CNN.
- Extract region proposals from global feature map.
  Still the bottleneck!
- FCN for regression and classification.

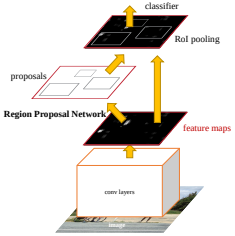


Figure: Faster R-CNN [Shaoqing et al., 2016].

- Learn region proposals with a separate network.

Object Detection – Single-Stage Detectors

Input Image

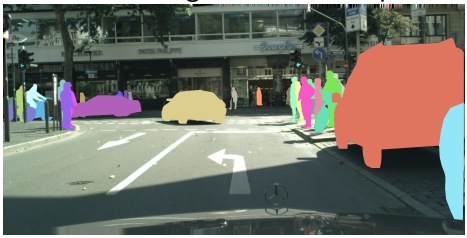
Grid Overlay

- For each grid cell:
  - For each base box, regress a final box with five values: (dx, dy, dh, dw, confidence).
  - Predict scores for each class including the background.
  - Similar to Region Proposal Network but specific for each class.
- Popular examples are YOLO [Redmon et al., 2016], SSD [Liu et al., 2016], and RetinaNet [Lin et al., 2017].

Instance Segmentation

Input Image

Instance Segmentation Output



- Detect and delineate distinct objects of interest in the image.
- Assign different labels for separate instances of the same class.
- Generate pixel-wise annotations.

Instance Segmentation – Mask R-CNN

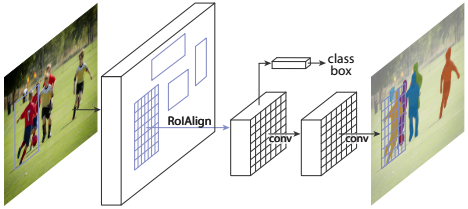


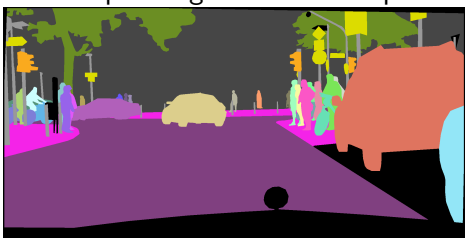
Figure: The Mask R-CNN framework [He et al., 2017].

- When proposed, Mask R-CNN (and its variants) set a long-standing state-of-the-art.
- *Detect-then-segment* approach:
  1) Extract bounding boxes via object detection.
  2) Perform binary segmentation inside each box (object vs. background).
- Builds on top of Faster R-CNN. Problem: Inherits its drawbacks:
  - Slow execution preventing real-time usage.
  - Masks have a fixed resolution.
- Single-stage methods (anchor-free) mitigate these issues, e.g., SOLOv2 [Wang et al., 2020].

Panoptic Segmentation

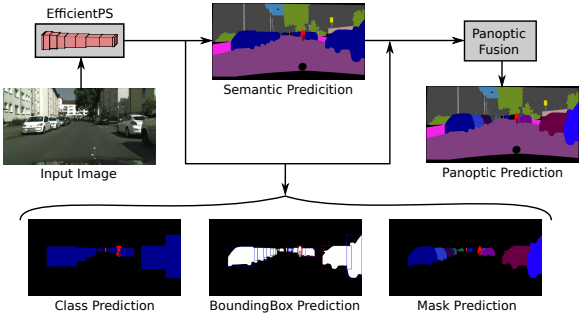
Input Image

Panoptic Segmentation Output



- Combination of semantic and instance segmentation.
- Differ between *stuff* (sky, building, etc.) and *thing* classes (cars, pedestrians, etc.).
- *Stuff* classes receive class labels. *Thing* classes receive both class and instance labels.

Panoptic Segmentation (cont.)



- Most approaches rely on solving multiple sub-tasks.
- *Top-down* methods tackle these in parallel and resolve contradicting results, e.g., overlapping masks, in a fusion module. $\rightsquigarrow$ superior performance
- *Bottom-up* methods use a sequential approach, e.g., semantic segmentation followed by a grouping step to generate instance masks. $\rightsquigarrow$ faster inference speed

[Image source: Mohan and Valada, 2021]

Questions to Answer for Yourself / Discuss with Friends

- Repetition: What is the most naïve approach to perform semantic segmentation with CNNs that you should not do?
- Application of what you just learned: What could be the advantage of performing panoptic segmentation, instead of just doing regular semantic segmentation or instance segmentation?

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Week 8: Practical Methodology and Architectures

Summary, Further Reading, References

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Summary by Learning Goals

Having heard this lecture, you can now ...

- describe the different normalization techniques and explain which to use when.
- describe the principle behind transfer learning and explain how you would perform it.
- explain the practical design considerations and debugging strategies.
- describe the reasons for the importance of parameter initialization.
- explain specific practical parameter initialization strategies.
- describe basic architectures of segmentation and detection networks.
- explain how the different image recognition tasks built on top of each other.
- explain the main innovation behind milestone CNN architectures for object classification.

Further Reading

- Resources for this lecture: Deep Learning Book [Goodfellow et al., 2016, chapters 8 & 11]

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