Two (very) Deep Networks

Deep Residual Learning for Image Recognition
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Rethinking the Inception Architecture
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VGG Reading Group, 2 Feb 2016
Ankush Gupta
Deep Residual Learning
Revolution of Depth

AlexNet, 8 layers (ILSVRC 2012)  VGG, 19 layers (ILSVRC 2014)  ResNet, 152 layers (ILSVRC 2015)

Why can’t we just stack layers?

Shouldn’t Deep $\geq$ Shallow?

- A deeper model should not have higher training error

A solution by construction:
original layers: copied from a learned shallower model
extra layers: set as identity $\Rightarrow$ at least the same training error

Optimization Difficulties
Solvers cannot find the solution when going deeper
Residual Mapping

• Instead of relying on the solver to find the identity mapping, explicitly add it in.

• Number of layers range up to 152

• Performance continues to improve with depth

Suppose, we wanted the network to learn a mapping \( H(x) \):

Decompose as: \( H(x) = F(x) + x \)

\[ \Rightarrow F(x) = H(x) - x \]

\[ \Rightarrow F(x) \text{ is the “residual” mapping} \]

Residual Mapping (2)

- If identity were optimal, easy to set weights as 0.
- If optimal mapping is closer to identity, easier to find small fluctuations.

\[ H(x) = F(x) + x \]

Network Design

• Inspired by VGG:
  • 3x3 filters
  • Spatial-size/2 => #filters x2

• No max-pooling – use stride-2 convolution instead
• No dropout – use Batch Normalization instead
• No hidden fc – drastically reduces the number of parameters (by 90%)

• 19% of VGG FLOP/forward-pass:
  3.6 billion (ResNet 34 layers) vs. 19.6 billion (VGG-19)

ImageNet Experiments

ImageNet plain nets

solid: test/val
dashed: train

34-layer
18-layer

Deep ResNets can be trained without difficulties
Deeper ResNets have lower training error, and also lower test error


ImageNet Experiments

- Deeper ResNets have lower error

<table>
<thead>
<tr>
<th>Model</th>
<th>10-crop testing, top-5 val error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet-152</td>
<td>5.7</td>
</tr>
<tr>
<td>ResNet-101</td>
<td>6.1</td>
</tr>
<tr>
<td>ResNet-50</td>
<td>6.7</td>
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<tr>
<td>ResNet-34</td>
<td>7.4</td>
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</tbody>
</table>
Rethinking the Inception Architecture
“Inception” inspiration...

Network in network

We need to go deeper
Four Design Principles
Design Principle #1

Avoid representational bottlenecks early on

Representation size should gently decrease from input to output
Design Principle #2

Use higher dimensional representations

Disentangled features $\Rightarrow$ faster training
Reduce the representation dimension before convolution

This is also used in Residual nets: see pg. 6, Figure 5, section “Deeper Bottleneck Architectures”
Design Principle #4

**Balance** width (#filters) and depth (#layers)

Increase them together
Making Inception Efficient
The Inception Module

- Capture spatial correlations at multiple scales
- 1x1 convolutions to reduce dimensions (efficiency)

Recommendations
Factorizing into **Smaller Conv.**

- Reduce parameters by factorizing 5x5 into sequence of two 3x3 convolutions: same receptive field ($\frac{(9+9)}{25} = 28\%$ savings)
- Use ReLU in b/w
Factorizing into **Asymmetric Conv.**

- Reduce parameters by approximating $nxn$ conv. using two $nx1$ and $1xn$ convolutions: $\frac{2n}{n^2}$ savings. (33% cheaper for $n=3$)

- Does not work in early layers. Good in later layers.
Auxiliary Classifiers

- Originally introduced to strengthen the back-propagation signal
- Does not work for early layers
- Helps convergence towards the end
Other Optimizations

• Reducing spatial size of features:
  use stride-2 convolutions and max-pooling

• Do label smoothing:
  – encourage model to be less confident
    (reduce over-fitting and smoother gradients)
  – improves top-1 and top-5 error by 0.2% (absolute)
That’s It!