Deep Learning

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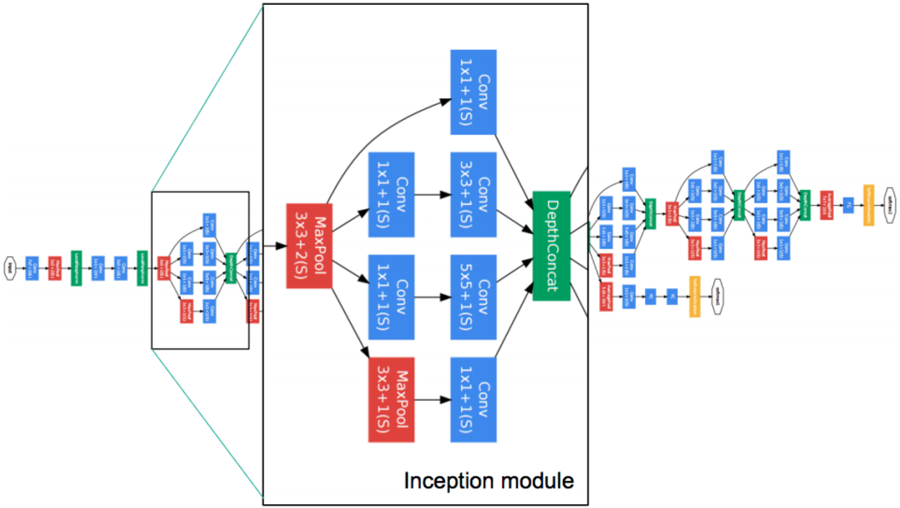
GoogLeNet/Inception v1 (2014)



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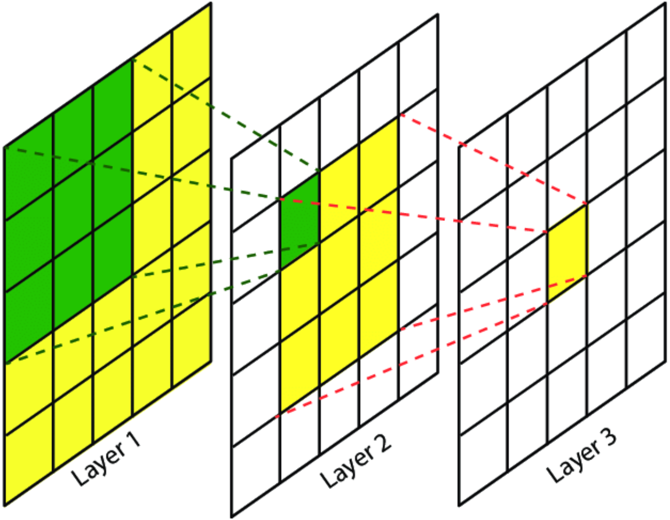

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- replace $n \times n$ convolution layers with asymmetric consequent convolution layers of sizes $n \times 1$ and $1 \times n$.

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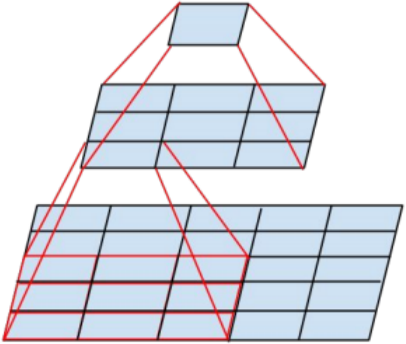

Figure 1. Mini-network replacing the 5×5 convolutions.

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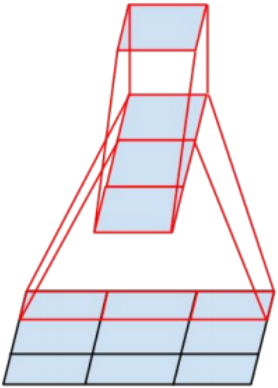

Figure 3. Mini-network replacing the 3×3 convolutions. The lower layer of this network consists of a 3×1 convolution with 3 output units.

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- The best result on ImageNet: Top1=88.5%, Top5=98.7% with 480M parameters.

Outline

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- Training takes a long time.

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Variations:

- Same domain, different task.
- Different domain, same task.

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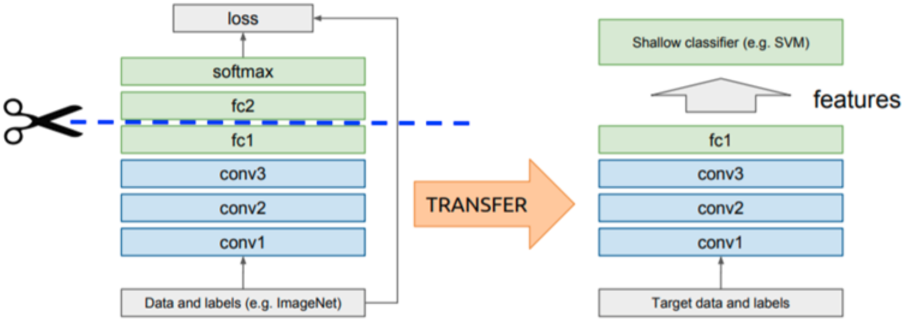
- Low level features from A could be helpful for learning B.

Fixed feature extractor

For example take a NN pretrained on some big dataset, remove the last fully-connected layer, then treat the rest of the NN as a fixed feature extractor for the new dataset. Then train a classifier (e.g. Linear SVM or Softmax classifier) for the new dataset.

Fixed feature extractor



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The last two points are motivated by the observation that the earlier features of the network contain more generic features.

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Transfer learning in image specific tasks

Transfer learning in NLP

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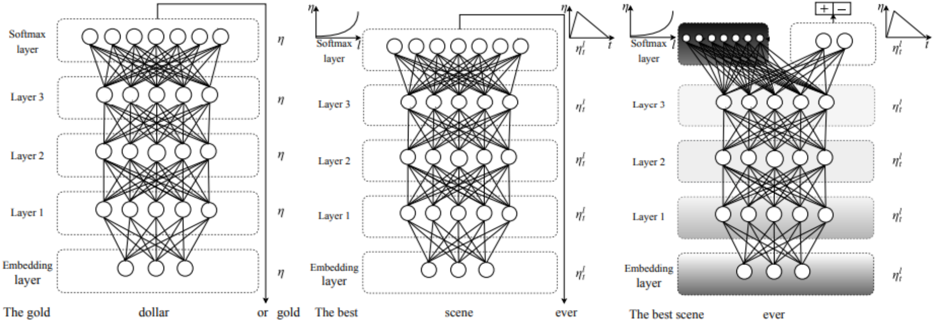
ULMFiT



(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

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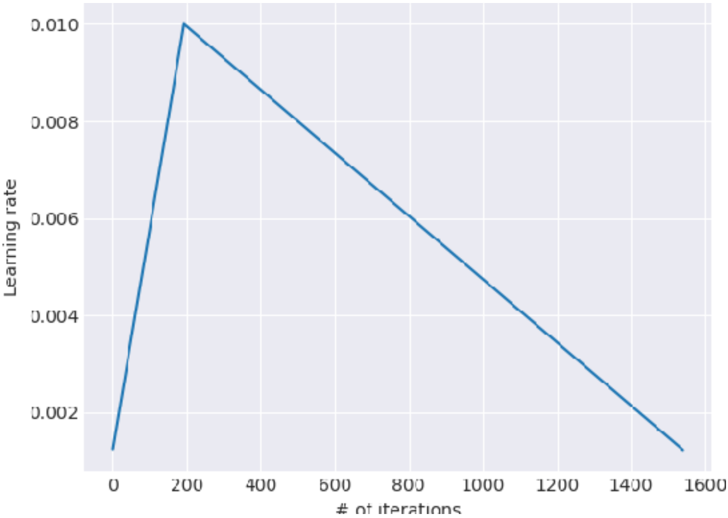
- Gradual unfreezing

  During the classification training, the LM model is gradually unfreezed starting from the last layer.

STLR



0.010
0.008
0.006
0.004
0.002
Learning rate
0
200
400
600
800
1000
1200
1400
1600
# of iterations

Outline

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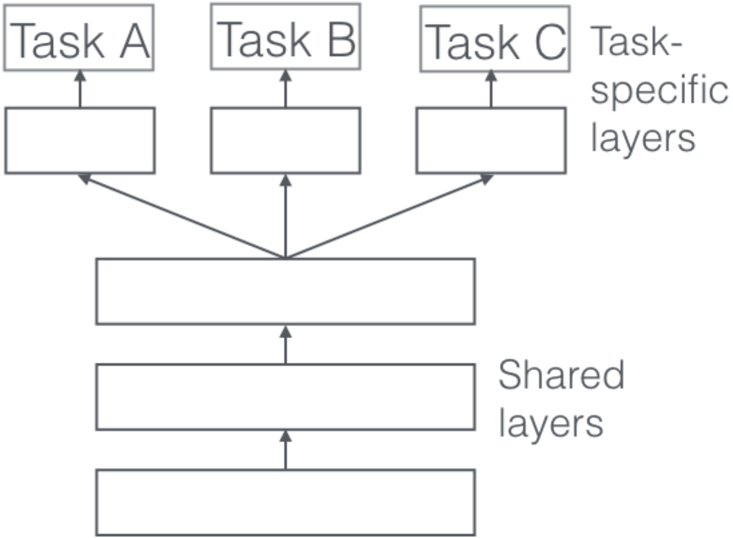

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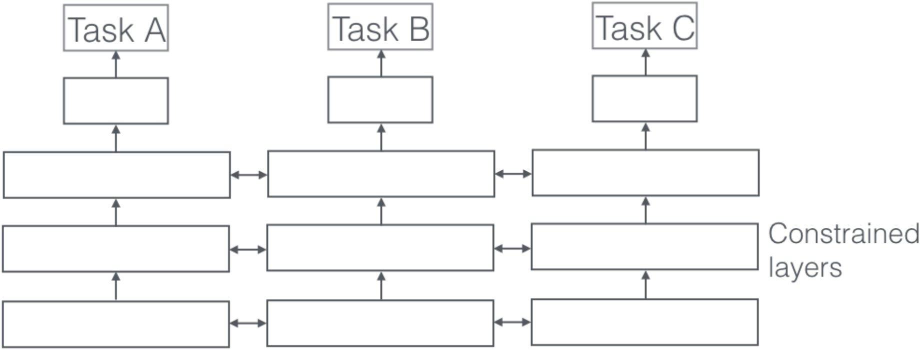

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- Amount of data you have for each task is quite similar.
- Can train a big enough neural network to do well on all the tasks.