# Deep Learning

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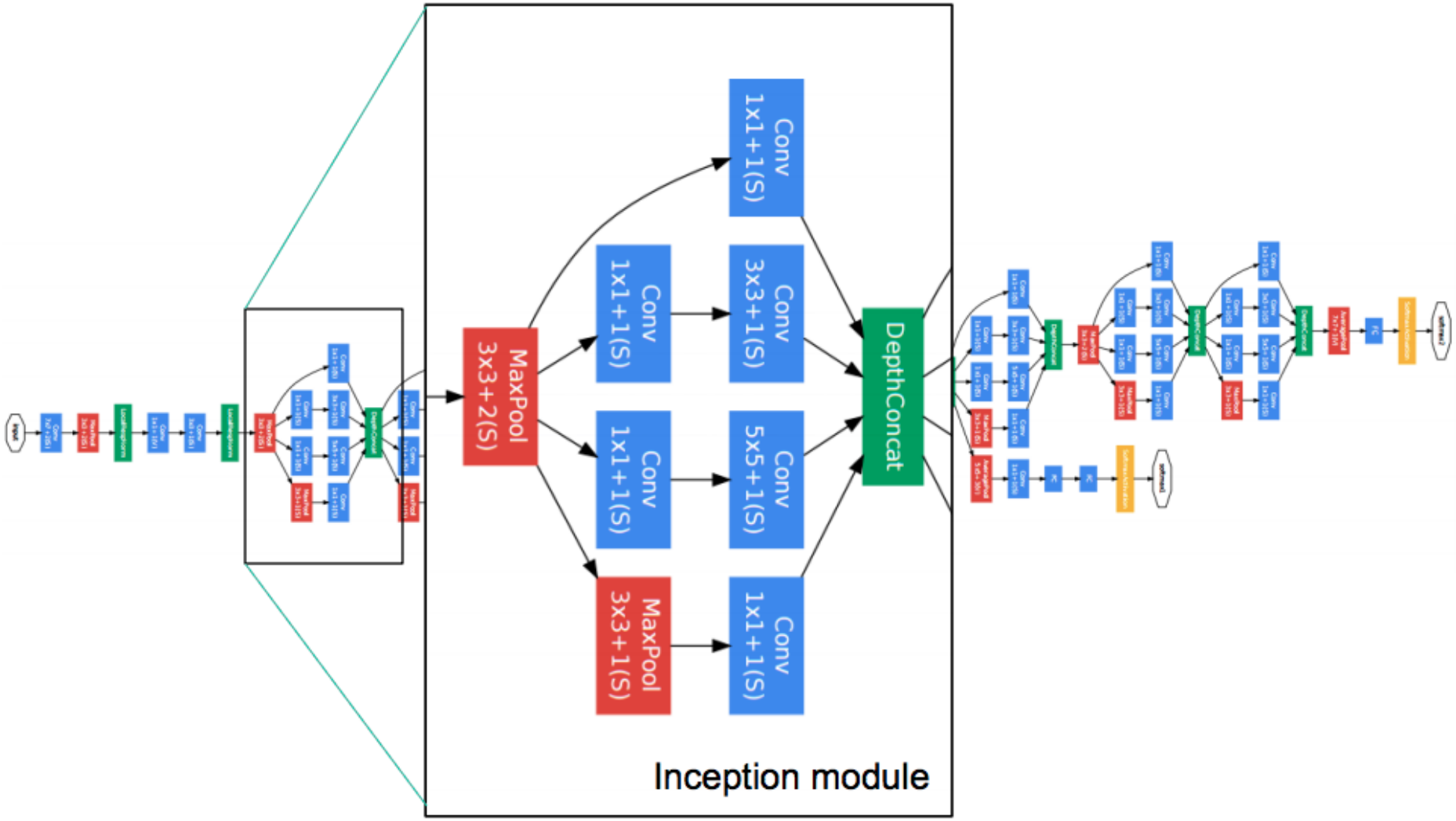
November 21, 2020

FAST DISCOVERING THE FUTURE

# GoogLeNet/Inception v1 (2014)



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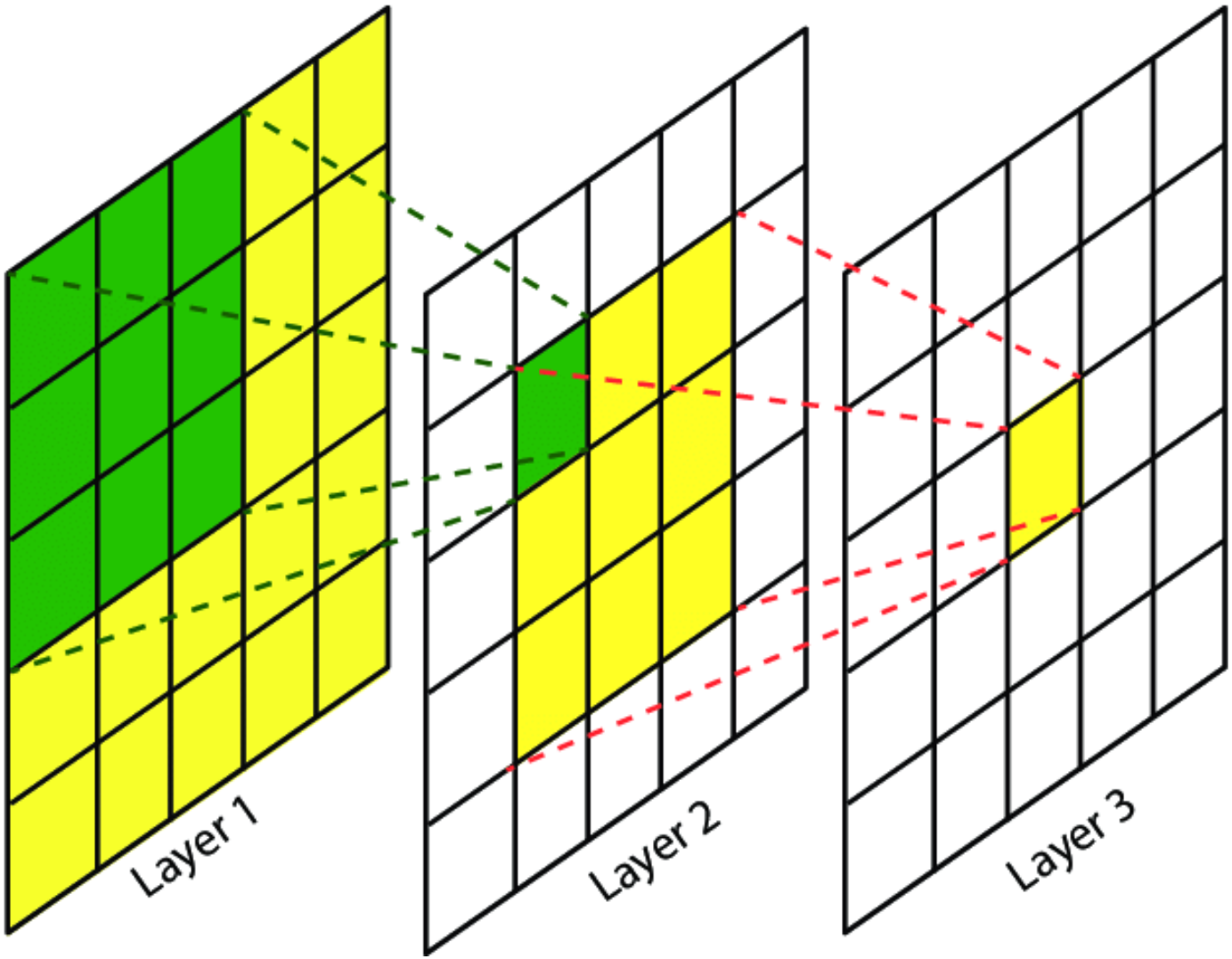

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So the natural need arises to enlarge the size of the receptive field of the network, or keep the size of receptive field the same but decrease the number of computations. For the latter purpose the approach of convolution factorization is appropriate.

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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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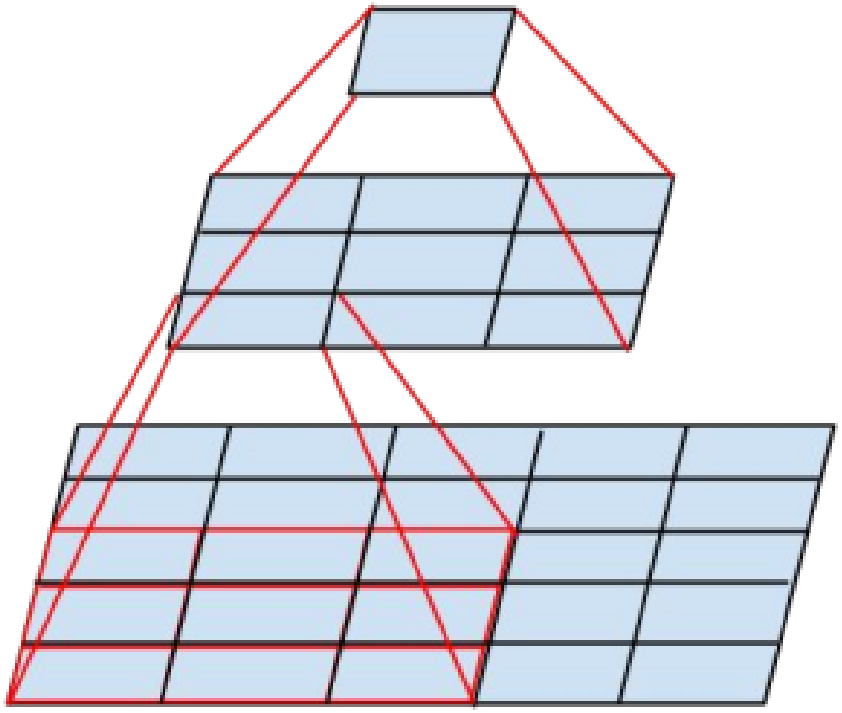

Figure 1. Mini-network replacing the $5 \times 5$ convolutions.

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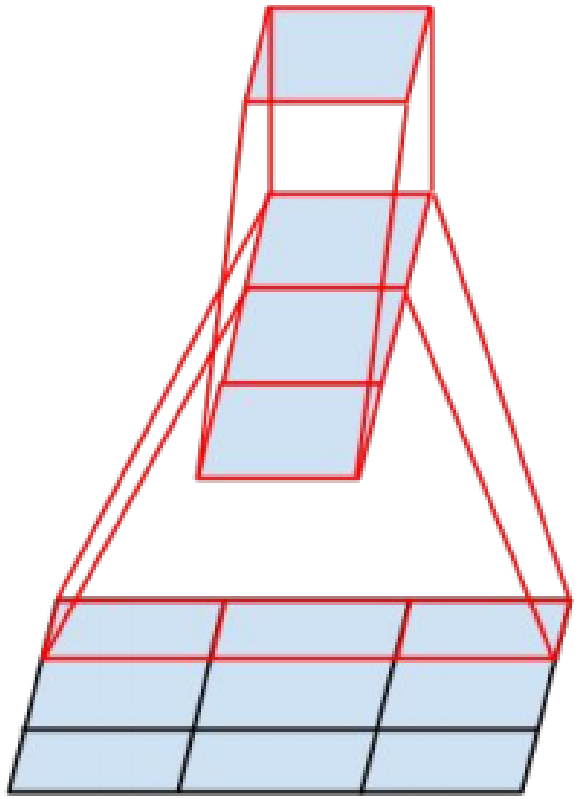

Figure 3. Mini-network replacing the $3 \times 3$ convolutions. The lower layer of this network consists of a $3 \times 1$ convolution with 3 output units.

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

# Outline

# Problems of deep learning

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- Training takes a long time.

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- Different domain, same task.

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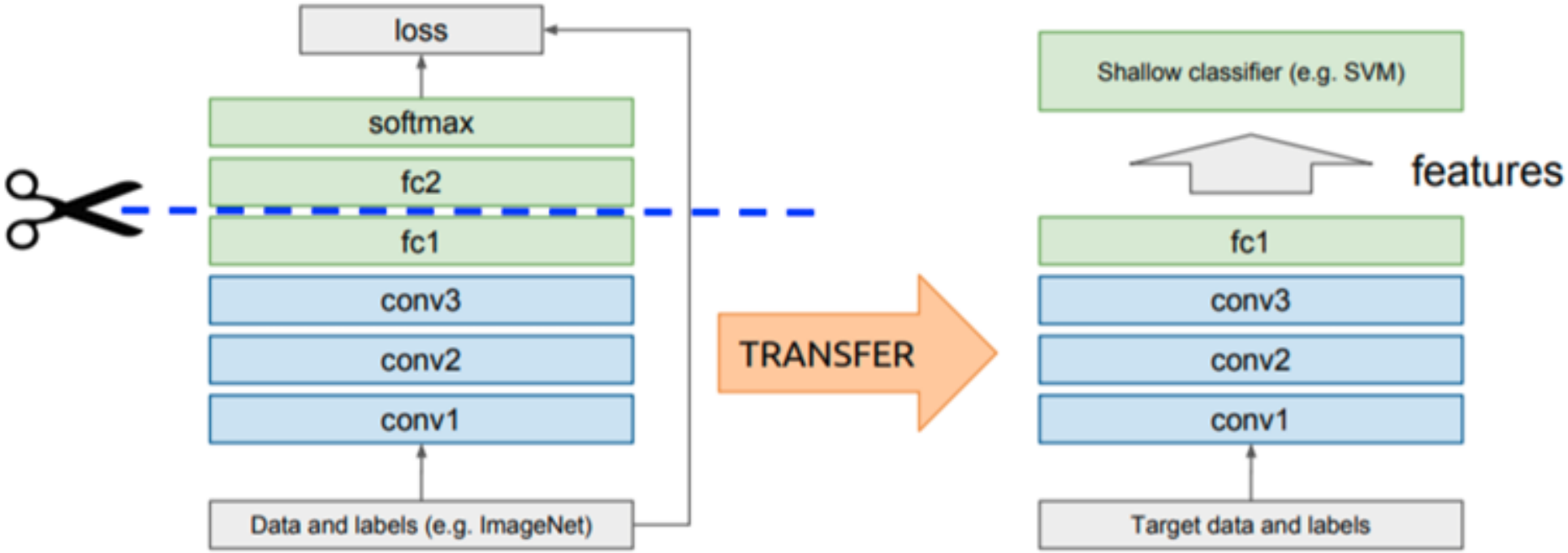
- You have a lot of more data for Task A than Task B.
- Low level features from A could be helpful for learning B.

# 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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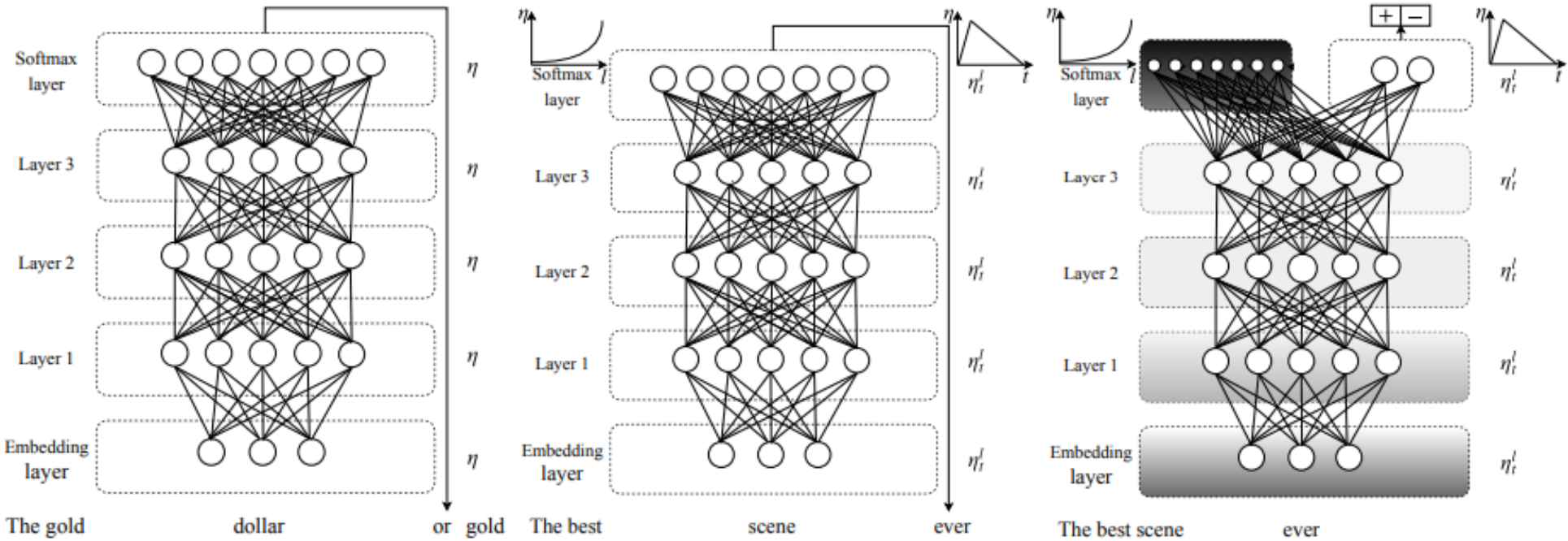
# ULMFiT




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

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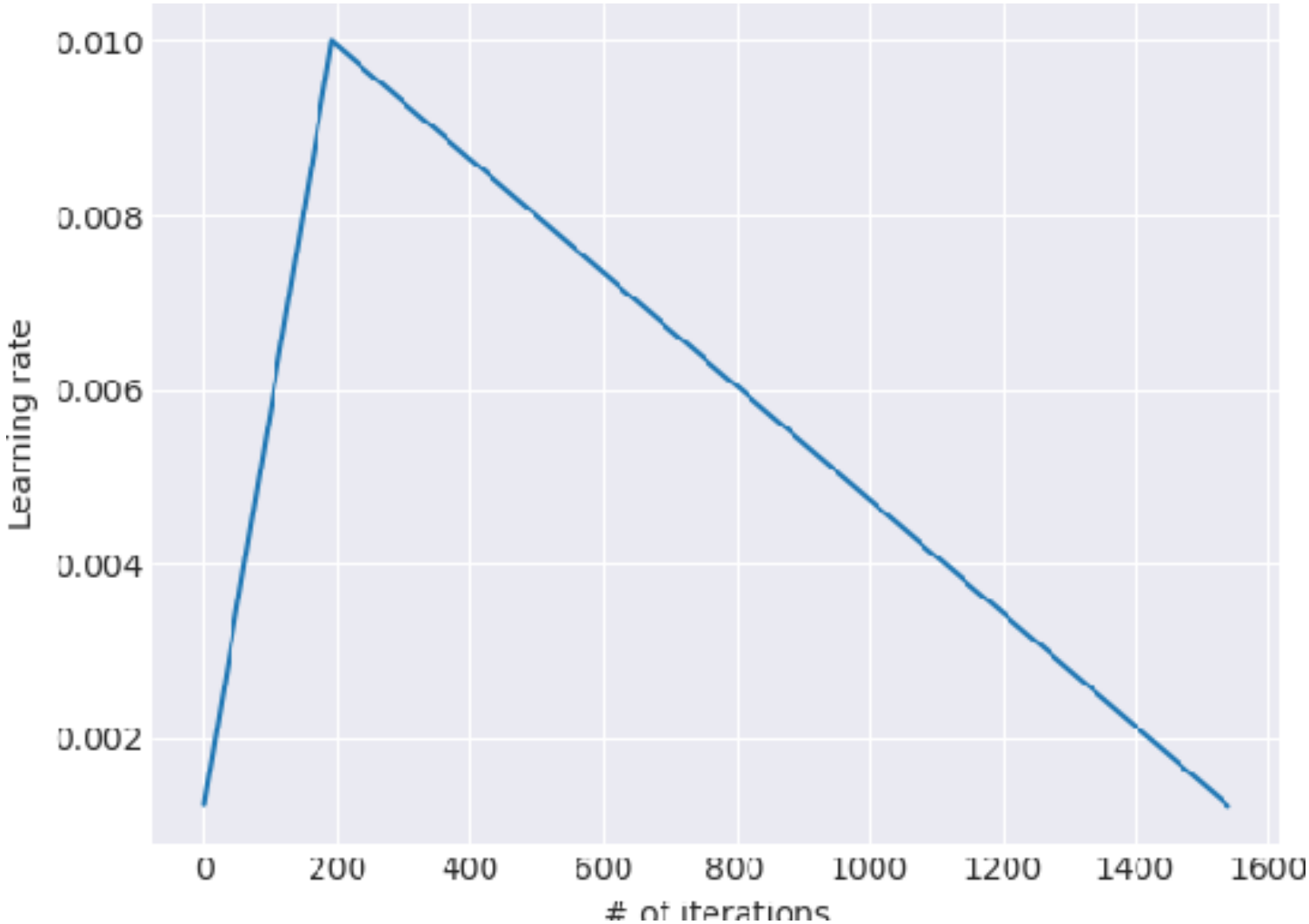
- Gradual unfreezing

  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