Deep Learning

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Outline

Problems of deep learning

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- The high cost of GPUs needed to run advanced deep learning algorithms.
- Training takes a long time.

Idea of transfer learning

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Variations:

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

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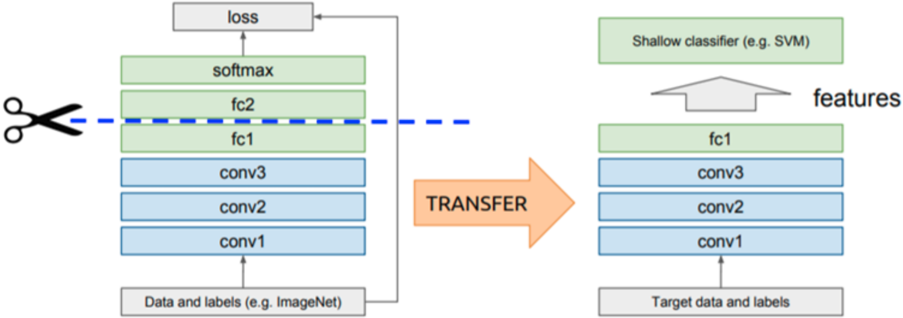
- You have a lot of more data for Task A than Task B.
- Low level features from A could be helpful for learning B.

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



Fine-tuning

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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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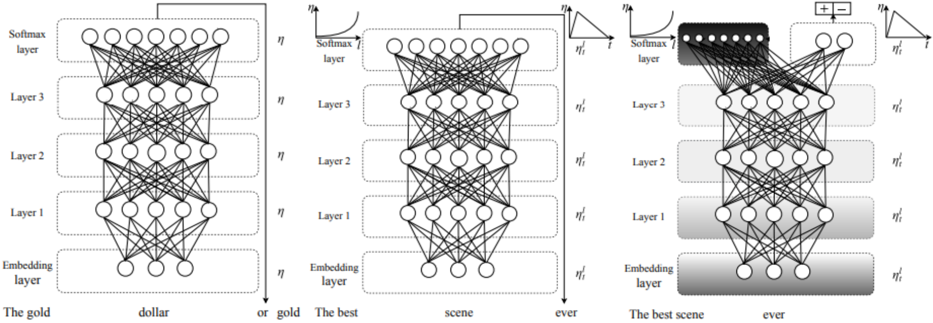
ULMFiT



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

Main ideas in ULMFiT

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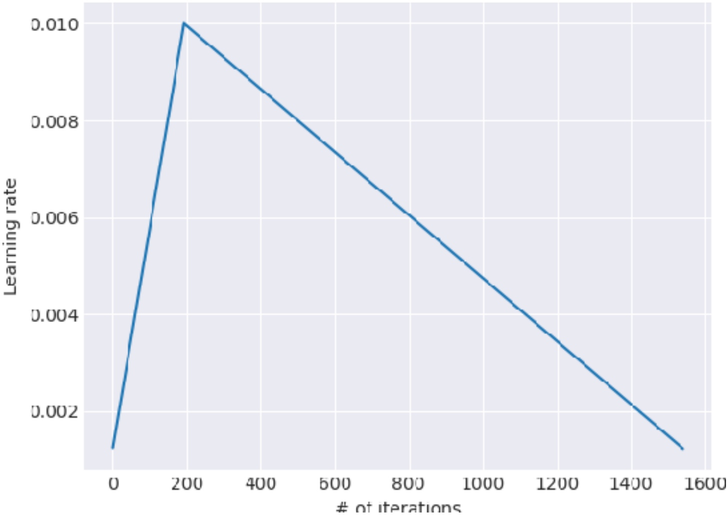
- Gradual unfreezing

  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

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Multi-Task Learning

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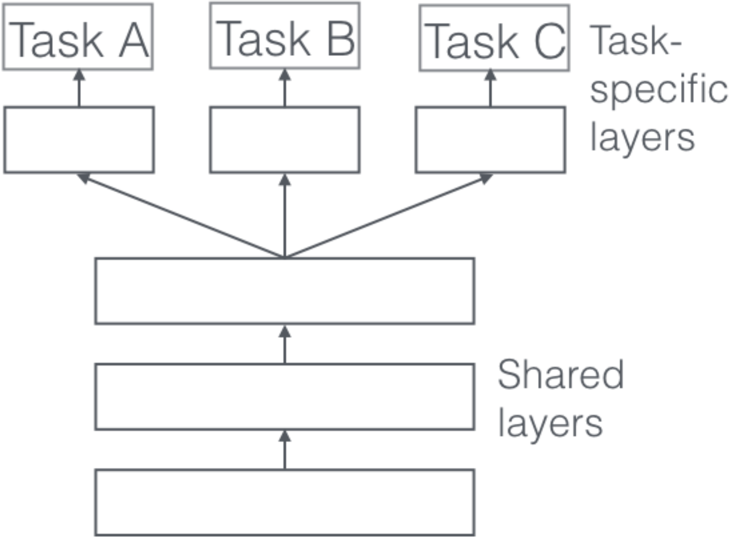

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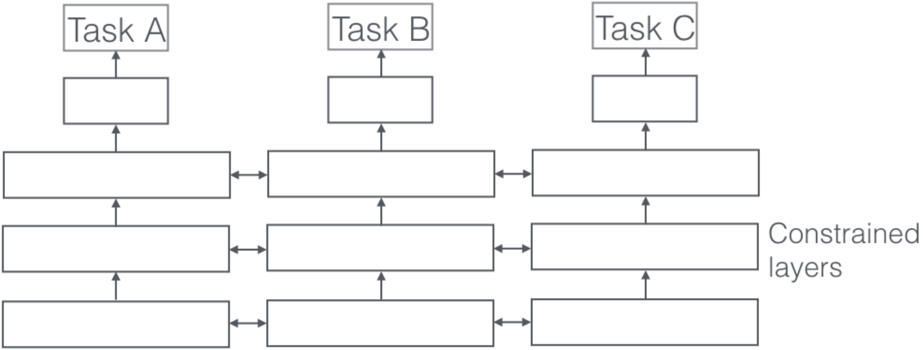

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- Amount of data you have for each task is quite similar.
- Can train a big enough neural network to do well on all the tasks.

Outline

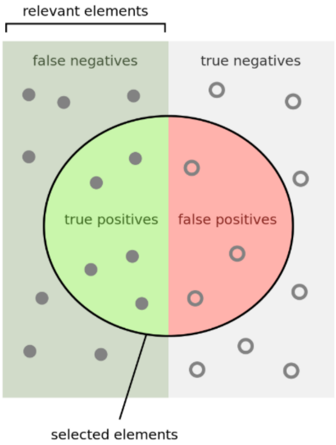
Accuracy

Definition 1

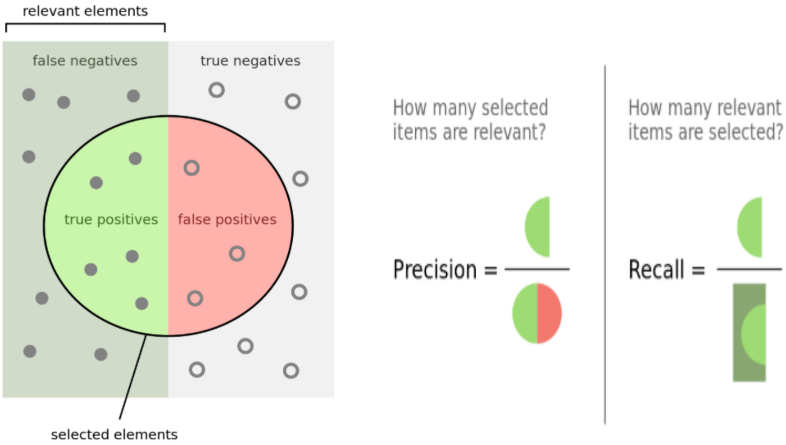
Accuracy in classification problems is the percent of correct predictions made by the model over all kinds predictions made:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ numbers\ of\ predictions\ made}$$

Precision and Recall



Precision and Recall



F1 Score

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Why don't to use arithmetic mean instead of harmonic mean?
Answer: If $Precision = 0.1$ and $Recall = 0.95$, then their mean is equal to 0.525 and $F1 \approx 0.18$.