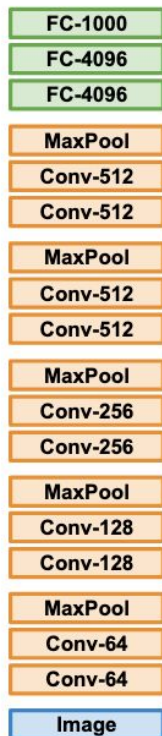


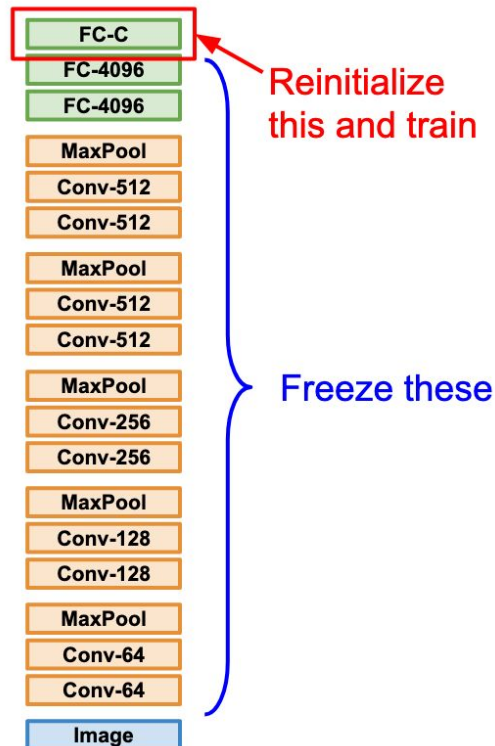
Transfer learning

Transfer learning key points

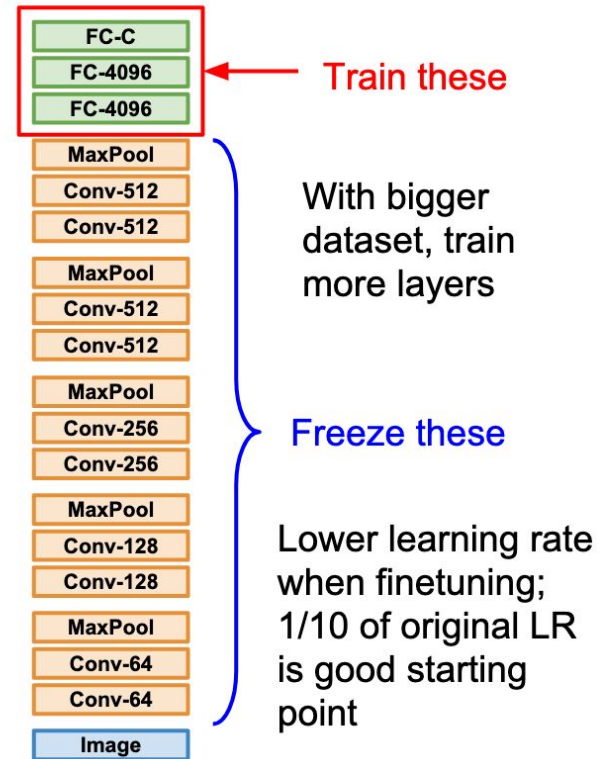
1. Train on Imagenet



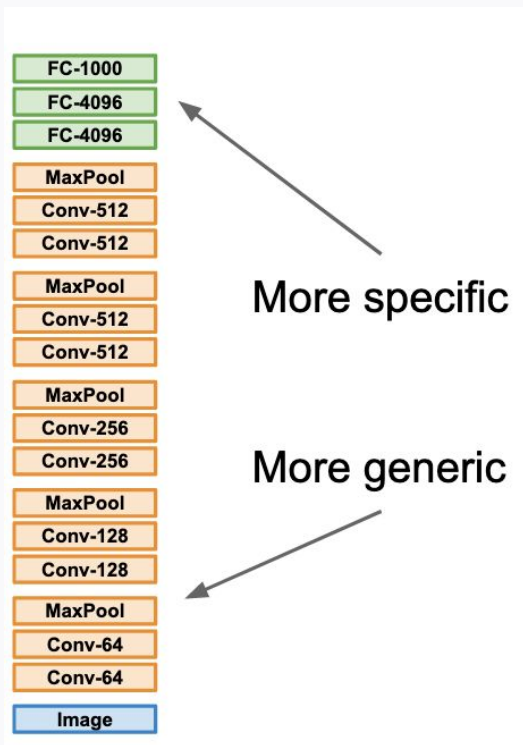
2. Small Dataset (C classes)



3. Bigger dataset

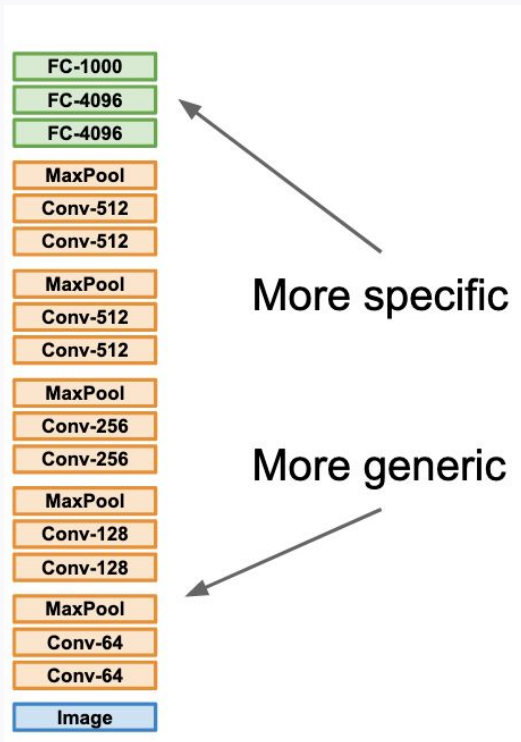


Transfer learning key points



	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?

Transfer learning key points



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble... Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Universal Language Model Fine-tuning for Text Classification (ULMFiT)

- Sebastian Ruder (DeepMind researcher, [blogger](#)) & Jeremy Howard ([fast.ai](#))
- Discriminative fine-tuning

$$\theta_t^l = \theta_{t-1}^l - \eta^l \cdot \nabla_{\theta^l} J(\theta)$$

We empirically found it to work well to first choose the learning rate η^L of the last layer by fine-tuning only the last layer and using $\eta^{l-1} = \eta^l / 2.6$ as the learning rate for lower layers.

- Gradual unfreezing
- Slanted triangular learning rate

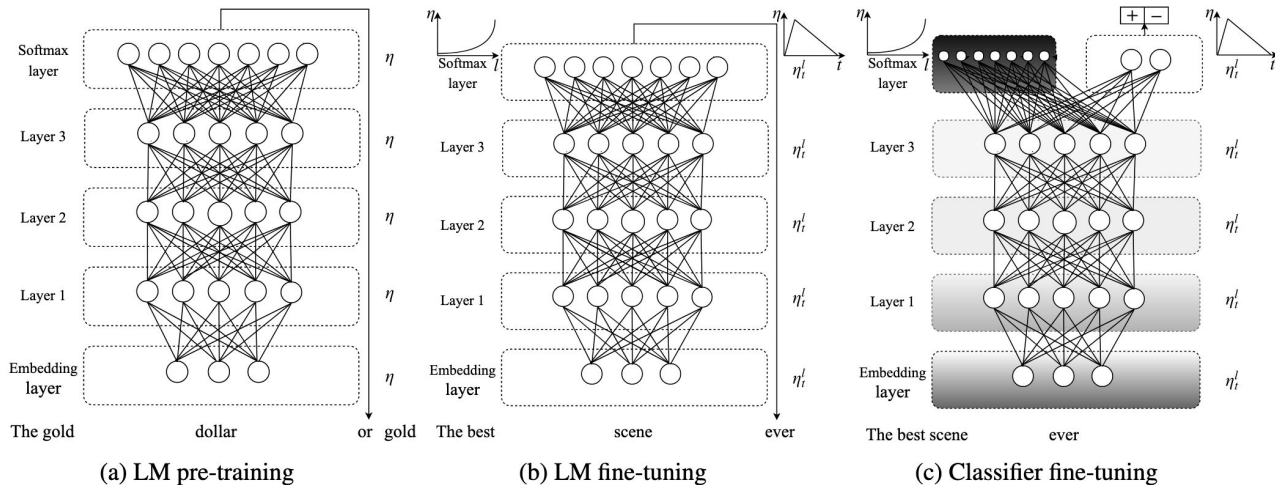
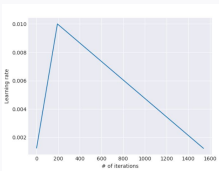
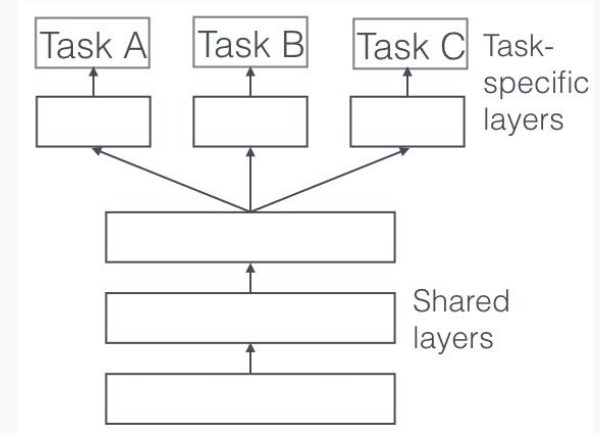
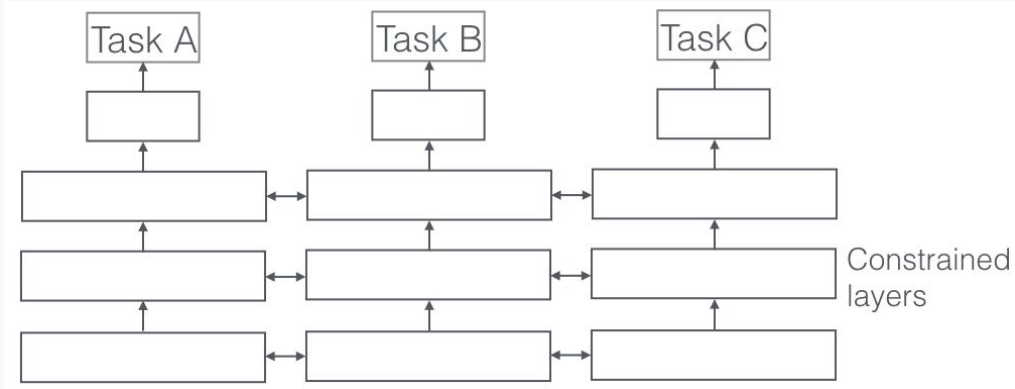


Figure 1: ULMFiT consists of three stages: a) The LM is trained on a general-domain corpus to capture general features of the language in different layers. b) The full LM is fine-tuned on target task data using discriminative fine-tuning (*'Discr'*) and slanted triangular learning rates (STLR) to learn task-specific features. c) The classifier is fine-tuned on the target task using gradual unfreezing, *'Discr'*, and STLR to preserve low-level representations and adapt high-level ones (shaded: unfreezing stages; black: frozen).

Multi-task learning



Tf.Hubs

- [Transfer learning with Hubs](#)
- [Available models](#)

Using pretrained CNN

- [Transfer learning with a pretrained ConvNet](#)