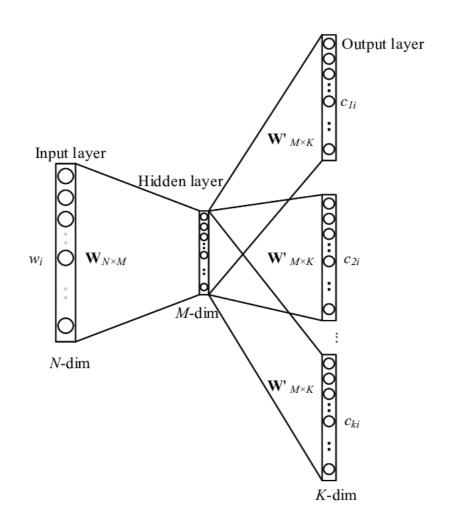
Word Embeddings

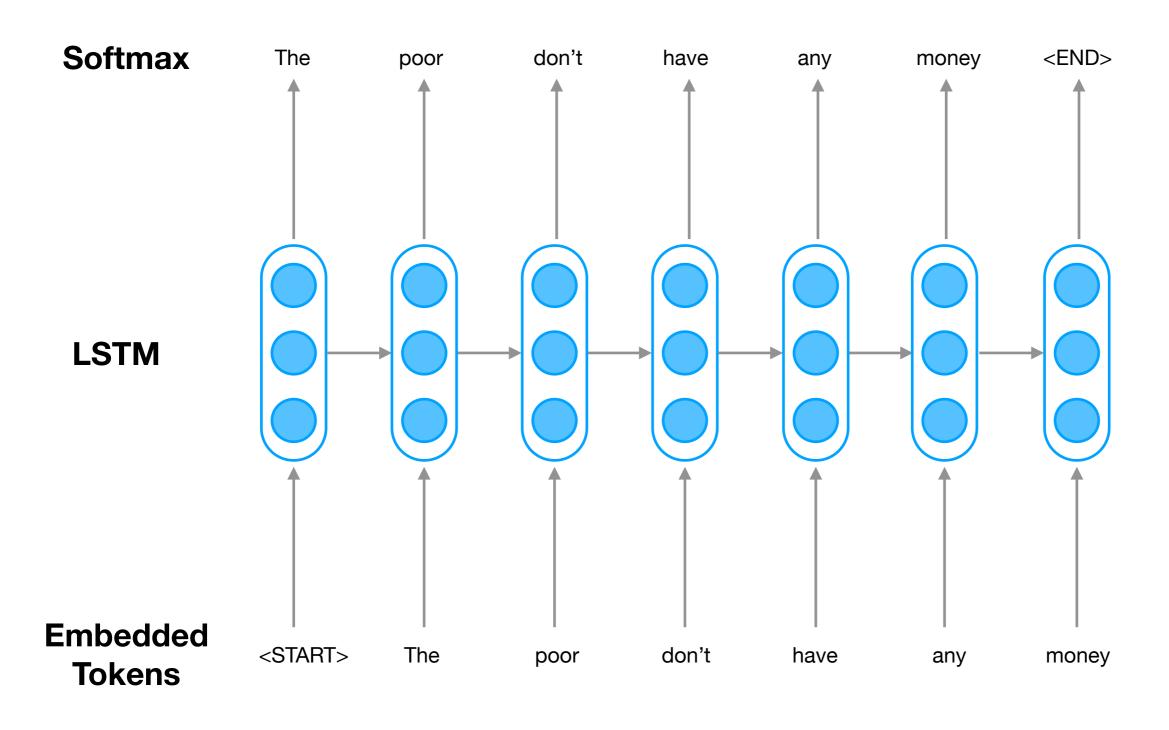
w2v, glove, etc

- Just key—value storage at inference
- Don't change from relationships with other words in the current text

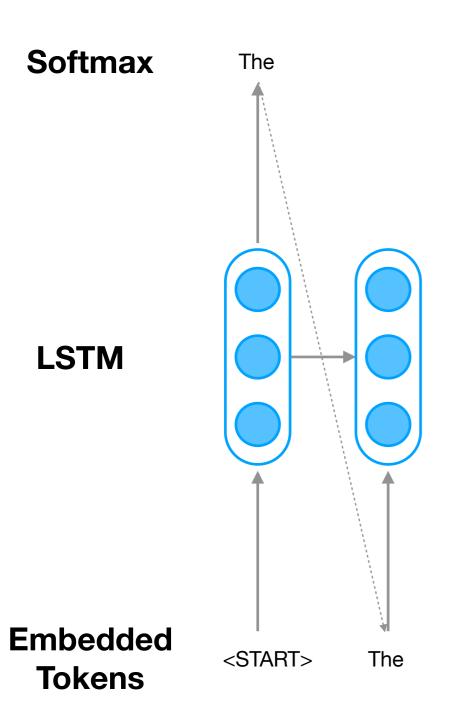




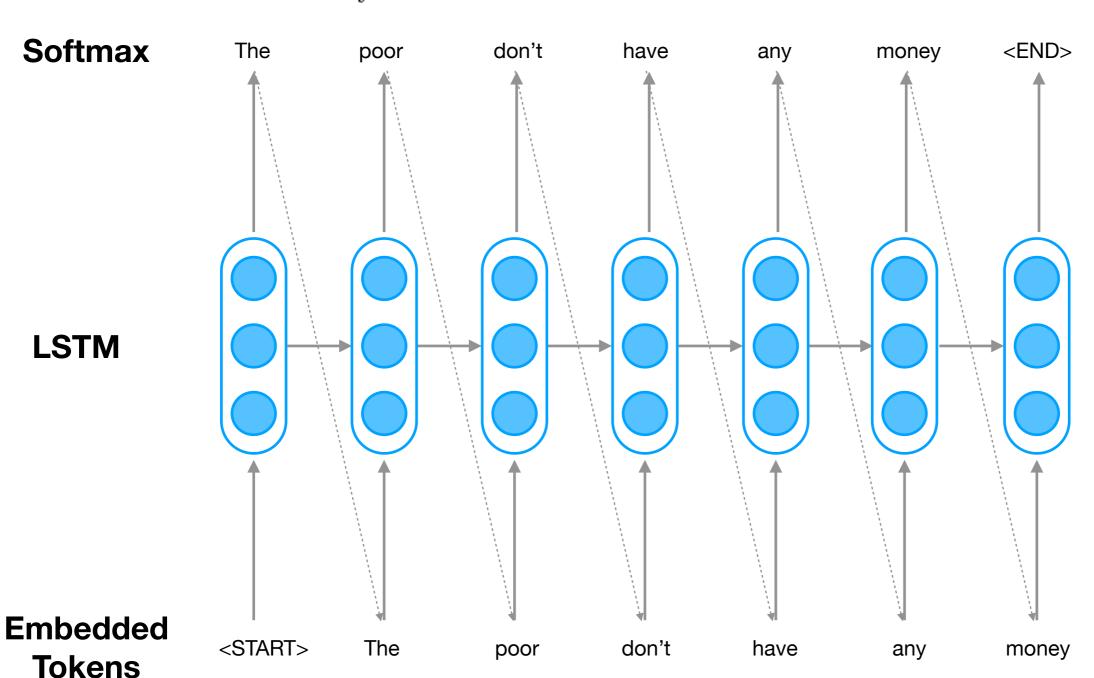
Training

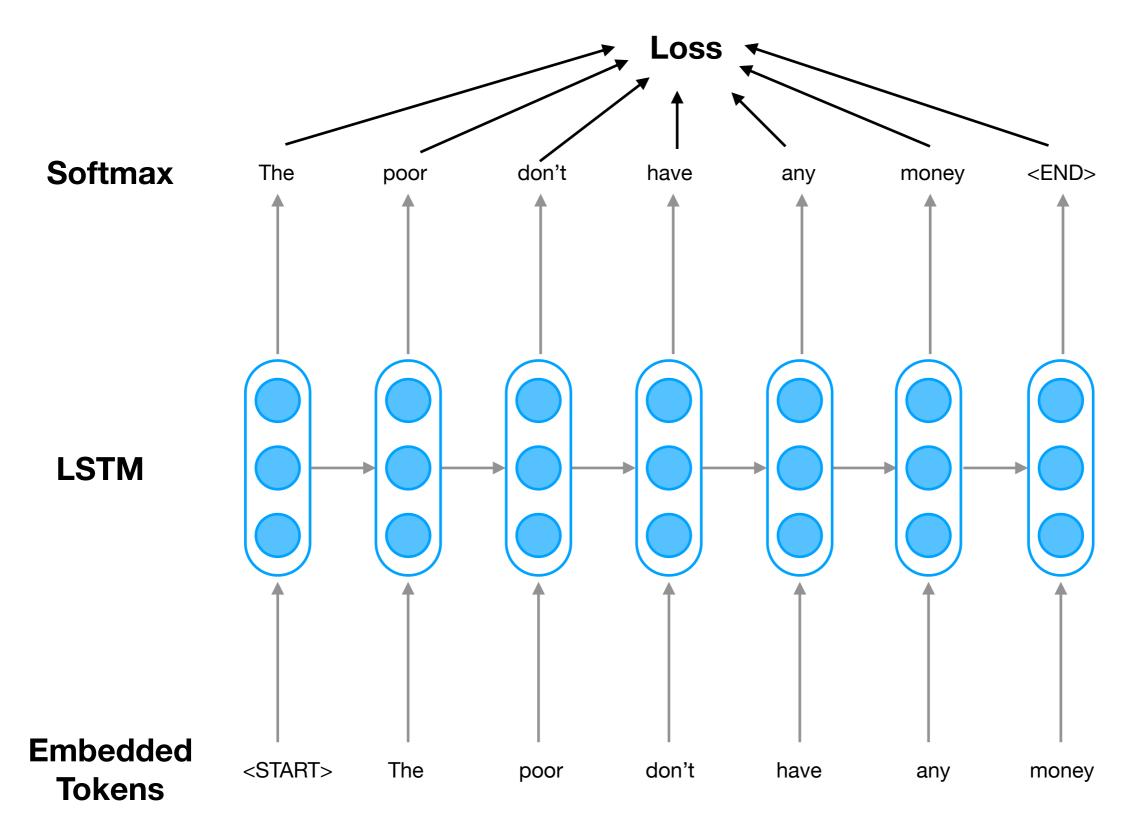


Prediction



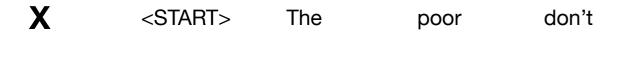
$$p(\mathbf{x}) = \prod_{i} p(x|x_{< i}) = p(x_0)p(x_1|x_0)p(x_2|x_0, x_1)\dots$$





```
X <START> The poor

Y
```



Y have

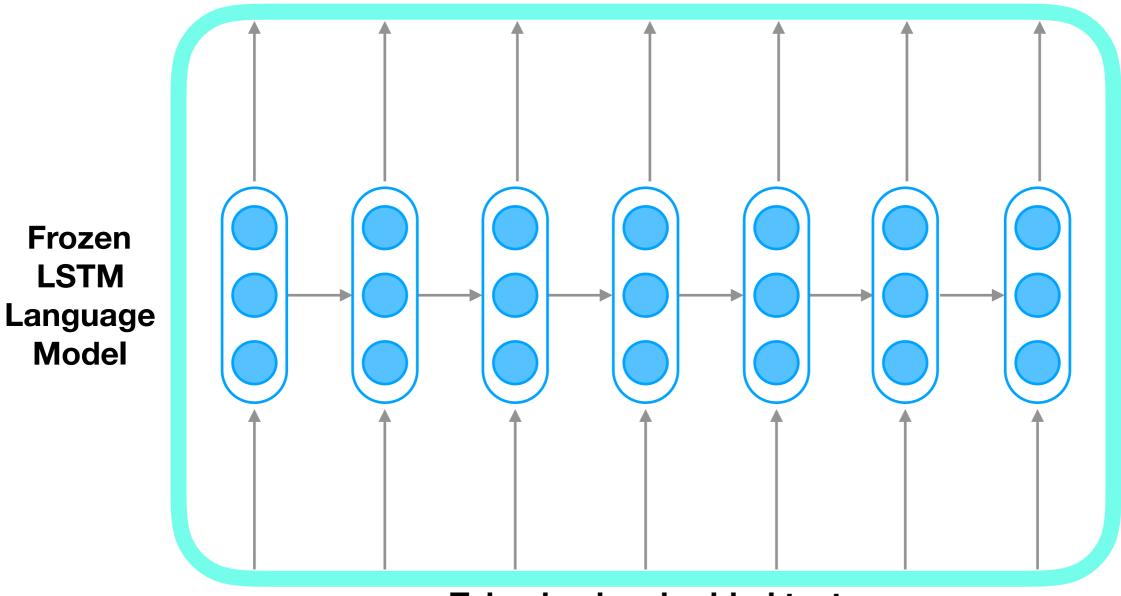
any



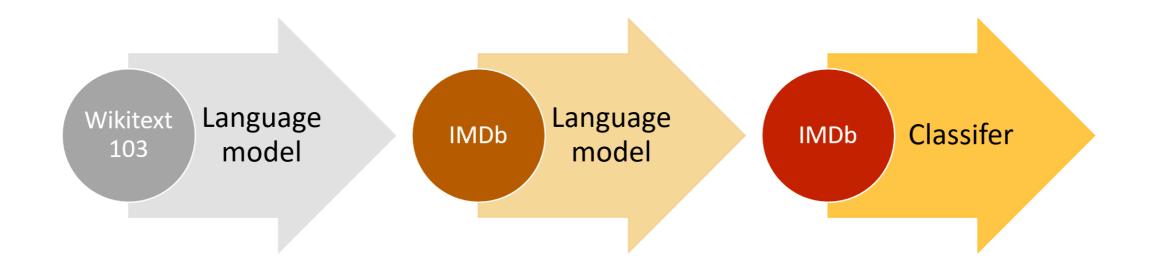
NLP LM Transfer Learning

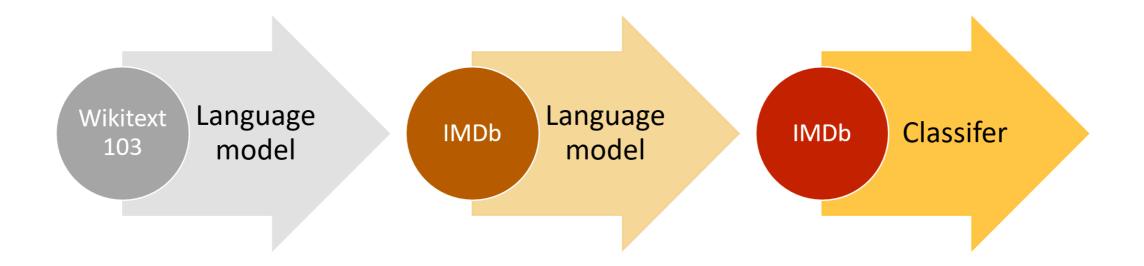
Your typical classifier

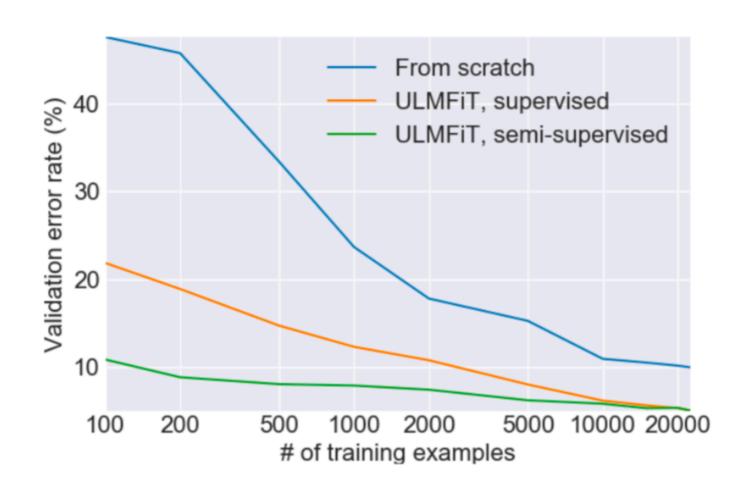
Contextualized word embeddings



Tokenized embedded text







 $\mathbf{h}_c = [\mathbf{h}_T, \mathtt{maxpool}(\mathbf{H}), \mathtt{meanpool}(\mathbf{H})]$

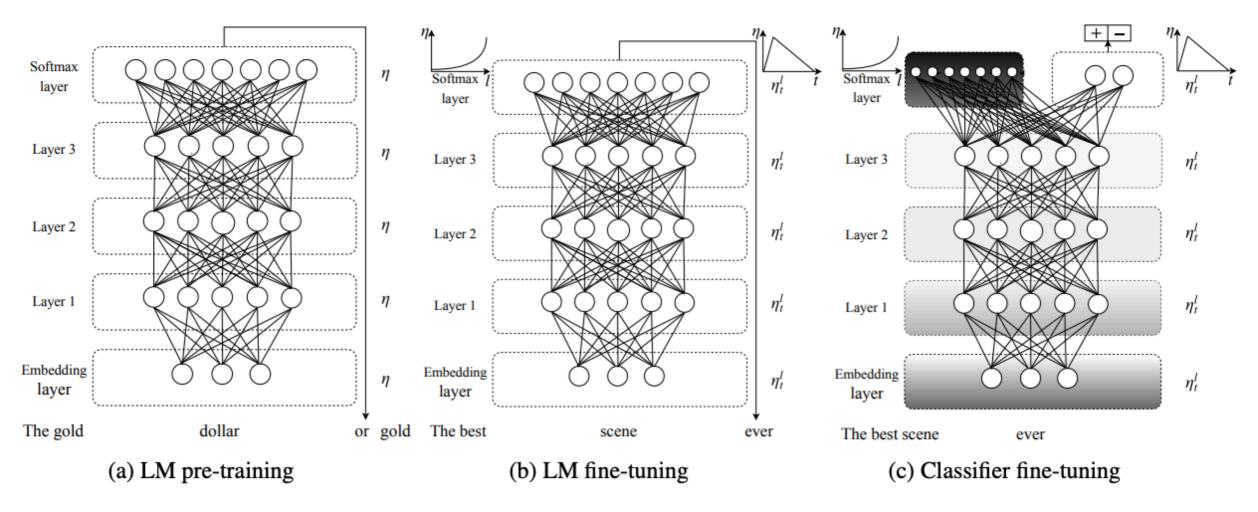


Figure 1: ULMFiT consists of three stages: a) The LM is trained on a general-domain corpus to capture general features of the language in different layers. b) The full LM is fine-tuned on target task data using discriminative fine-tuning ('Discr') and slanted triangular learning rates (STLR) to learn 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).

Scheduling

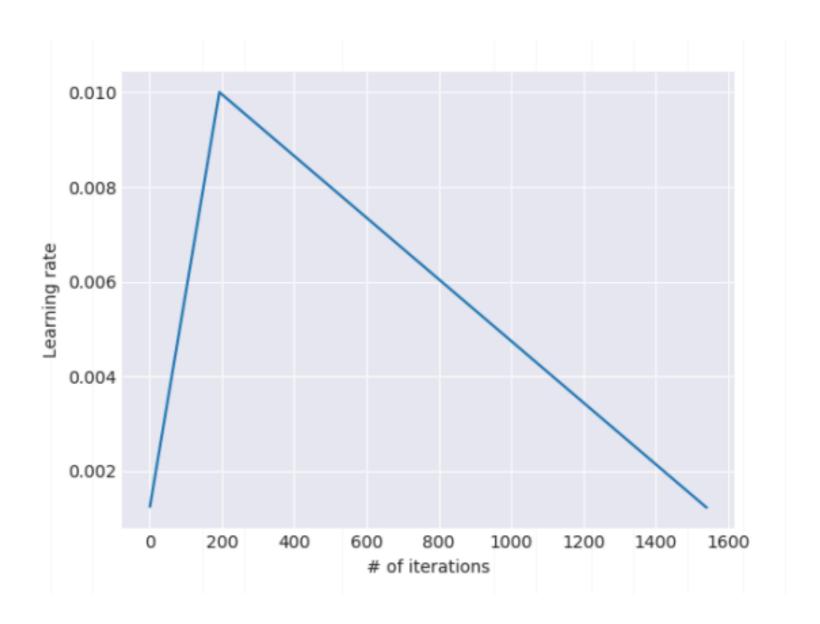
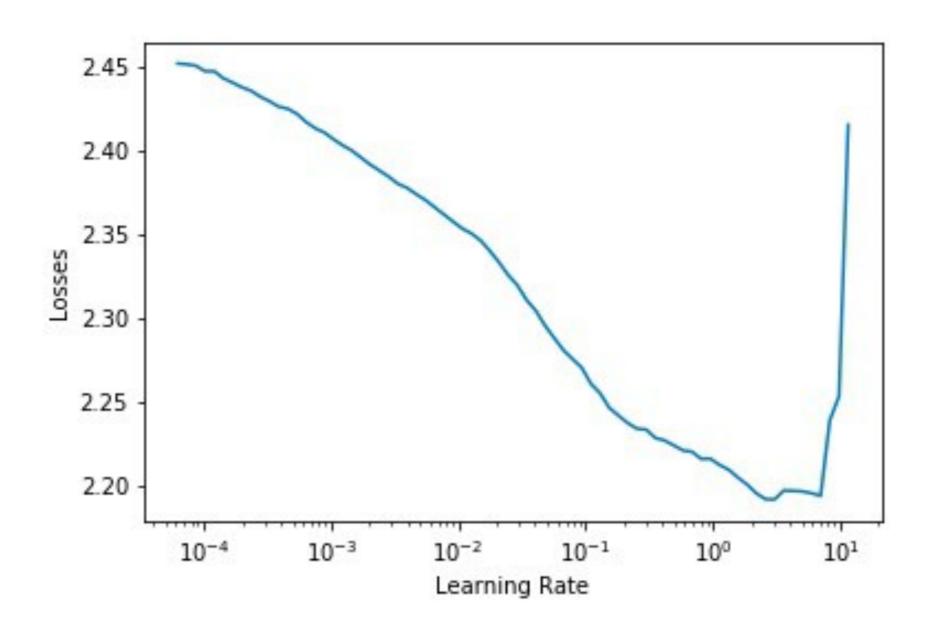


Figure 2: The slanted triangular learning rate schedule used for ULMFiT as a function of the number of training iterations.

LR Finder



Gradual Unfreezing (Catastrophic Forgetting)

 $\mathbf{h}_c = [\mathbf{h}_T, \mathtt{maxpool}(\mathbf{H}), \mathtt{meanpool}(\mathbf{H})]$

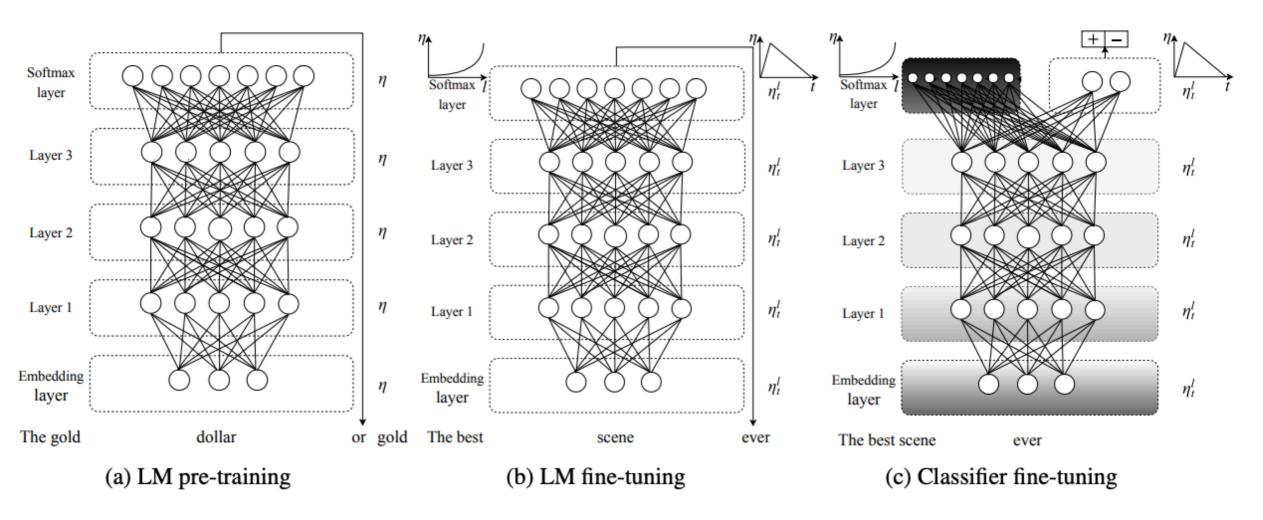


Figure 1: ULMFiT consists of three stages: a) The LM is trained on a general-domain corpus to capture general features of the language in different layers. b) The full LM is fine-tuned on target task data using discriminative fine-tuning ('Discr') and slanted triangular learning rates (STLR) to learn 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).

Classifier

```
\mathbf{h}_c = [\mathbf{h}_T, \mathtt{maxpool}(\mathbf{H}), \mathtt{meanpool}(\mathbf{H})]
```

```
(1): PoolingLinearClassifier(
    (layers): Sequential(
        (0): BatchNorm1d(900, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): Dropout(p=0.4)
        (2): Linear(in_features=900, out_features=50, bias=True)
        (3): ReLU(inplace)
        (4): BatchNorm1d(50, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (5): Dropout(p=0.1)
        (6): Linear(in_features=50, out_features=2, bias=True)
    )
)
```

ENCODER D	ROPOUT								
	before dropout								
	token	d1	d2		token	d1	d2		
		0.399	0.75379	0.62616	_	0	0	0	
	love	0.88533	0.29449	0.15856	love	0.88533	0.29449	0.15856	
	cats	0.48927	0.04071	0.21427	cats	0.48927	0.04071	0.21427	
	dogs	0.72918	0.86882	0.77136	dogs	0.72918	0.86882	0.77136	

ENCODER D	ROPOUT								
	before dropout								
	token	d1	d2		token	d1	d2		
	I	0.399	0.75379	0.62616	I	0	0	0	
	love	0.88533	0.29449	0.15856	love	0.88533	0.29449	0.15856	
	cats	0.48927	0.04071	0.21427	cats	0.48927	0.04071	0.21427	
	dogs	0.72918	0.86882	0.77136	dogs	0.72918	0.86882	0.77136	

INPUT DROP	POUT								
batch: [I love cats, I love dogs]									
before dropout					after dropout				
	- 1	0	0	0	1	0	0	0	
	love	0.88533	0.29449	0.15856	love	0	0.29449	0.15856	
	cats	0.48927	0.04071	0.21427	cats	0	0.04071	0.21427	
	before dropout				after dropout				
	1	0	0	0	1	0	0	0	
	love	0.88533	0.29449	0.15856	love	0.88533	0.29449	0	
	dogs	0.72918	0.86882	0.77136	dogs	0.72918	0.86882	0	

