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

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Paper and Author Infos

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Abstract

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1 Introduction

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Text classification is a category of Natural Language Processing (NLP) tasks with real-world applications such as spam, fraud, and bot detection (Jindal and Liu, 2007; Ngai et al., 2011; Chu et al., 2012), emergency response (Caragea et al., 2011), and commercial document classification, such as for legal discovery (Roitblat et al., 2010).

While Deep Learning models have achieved state-of-the-art on many NLP tasks, these models are trained from scratch, requiring large datasets, and days to converge. Research in NLP focused mostly on *transductive* transfer (Blitzer et al., 2007). For *inductive* transfer, fine-tuning pretrained word embeddings (Mikolov et al., 2013), a simple transfer technique that only targets a model's first layer, has had a large impact in practice and is used in most state-of-the-art models. Recent approaches that concatenate embeddings derived from other tasks with the input at different layers (Peters et al., 2017; McCann et al., 2017; Peters et al., 2018) still train the main task model from scratch and treat pretrained embeddings as fixed parameters, limiting their usefulness.

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We show that not the idea of LM fine-tuning but our lack of knowledge of how to train them effectively has been hindering wider adoption. LMs overfit to small datasets and suffered catastrophic forgetting when fine-tuned with a classifier. Compared to CV, NLP models are typically more shallow and thus require different fine-tuning methods.

We propose a new method, Universal Language Model Fine-tuning (ULMFiT) that addresses these issues and enables robust inductive transfer learning for any NLP task, akin to fine-tuning ImageNet models: The same 3-layer LSTM architecture—with the same hyperparameters and no additions other than tuned dropout hyperparameters—outperforms highly engineered models and trans-

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Overview

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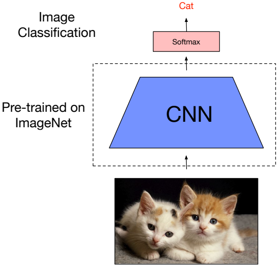

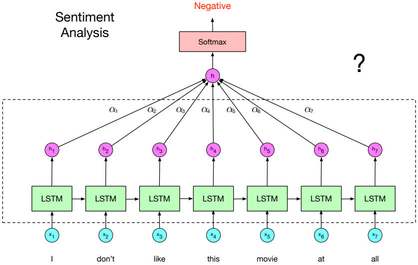

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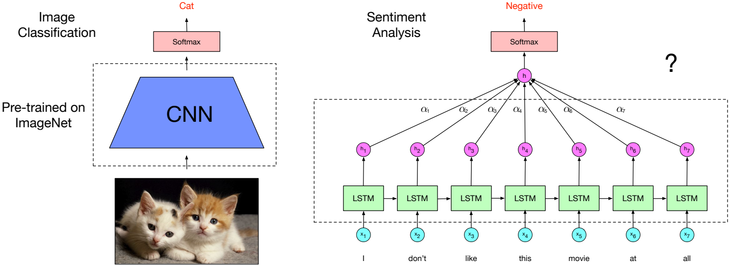

- Computer Vision (CV) models rarely trained from scratch;

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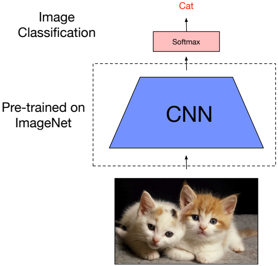

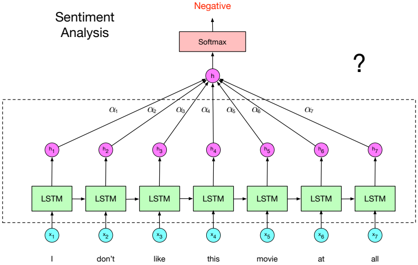

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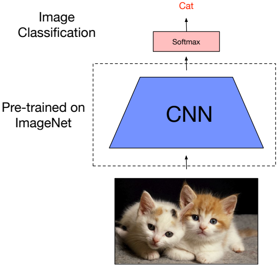

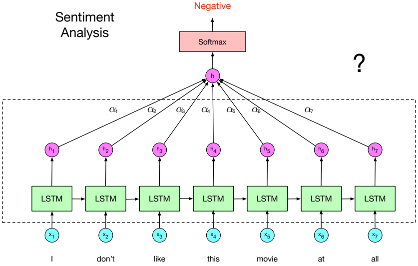

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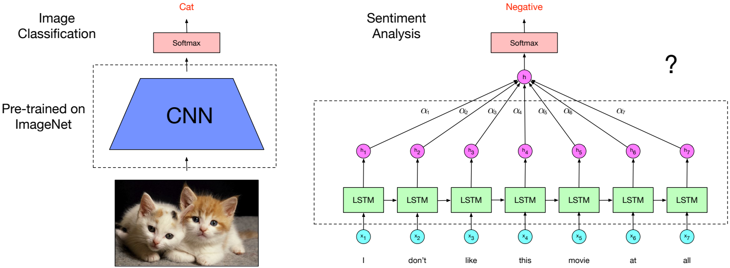

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- How to transfer learn from pretrained LM for NLP tasks?

Motivation

How to design specific techniques to fine-tune LM effectively?

Related Work

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Transfer learning in CV

- General to task-specific [Yosinski et al. 2014]
- Transferring and fine-tune layers [Long et al. 2015, Sharif et al. 2014]

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- Jointly train LM and main tasks [Rei et al. 2017, Liu et al. 2018]

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Fine-tuning

- Fine-tune LM, require lots of examples [Dai et al. 2015]

Overview

Universal Language Model Fine-tuning

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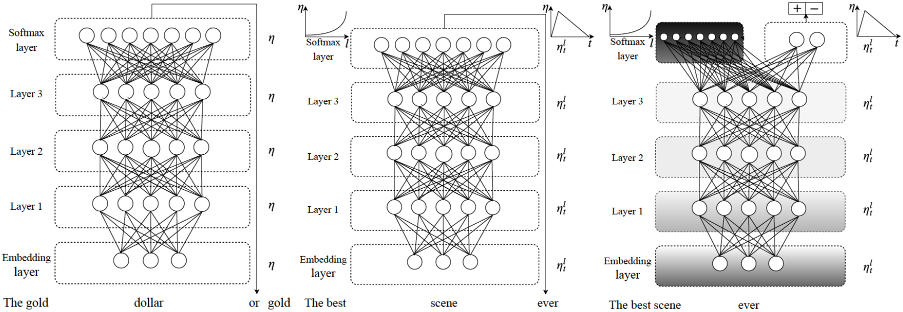

(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

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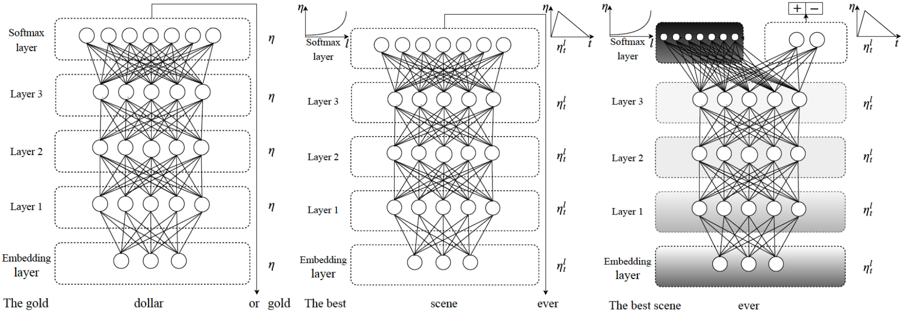

(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

- LM ($\mathcal{T}_S$) $\rightarrow$ Text Classification ($\mathcal{T}_T$)
- Universal novel techniques for LM fine-tuning
- Based on AWD-LSTM [Merity et al. 2017]

General-domain LM pretraining

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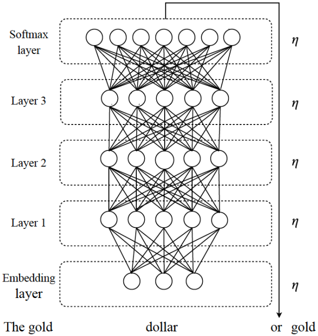
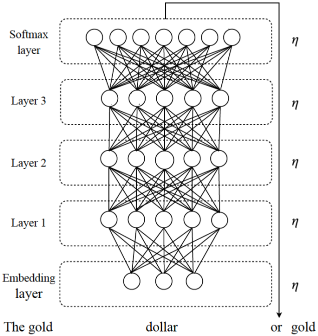


General-domain LM pretraining



$\mathcal{T}_S$ LM pretraining

- $P(x_t|x_1, \ldots, x_{t-1})$
- Wikitext-103: $28,595$ articles and 103M words;

Target task LM fine-tuning

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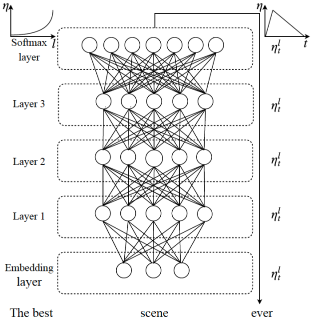

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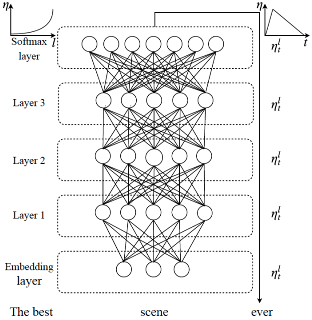

$\mathcal{T}_T$ LM pretraining

- Discriminative fine-tuning
- Slanted triangular learning rates

Target task LM fine-tuning

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Discriminative fine-tuning

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

$$\eta^{l-1} = \eta^l / 2.6$$

Target task LM fine-tuning

Discriminative fine-tuning

$$\theta_t^l = \theta_{t-1}^l - \eta^l \cdot \nabla_{\theta^l} J(\theta)$$
$$\eta^{l-1} = \eta^l / 2.6$$

Slanted triangular learning rates

$$cut = \lfloor T \cdot cut\_frac \rfloor$$
$$p = \begin{cases} t/cut, & \text{if } t < cut \\ 1 - \frac{t-cut}{cut \cdot (1/cut\_frac - 1)}, & \text{otherwise} \end{cases}$$
$$\eta_t = \eta_{max} \cdot \frac{1 + p \cdot (ratio - 1)}{ratio}$$

Slanted Triangular Learning Rates

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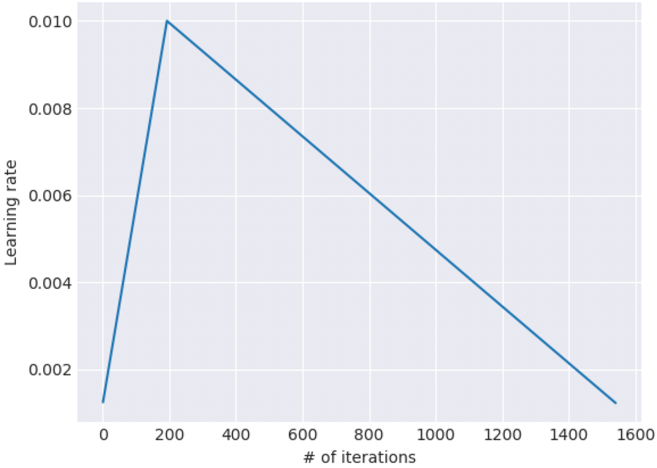

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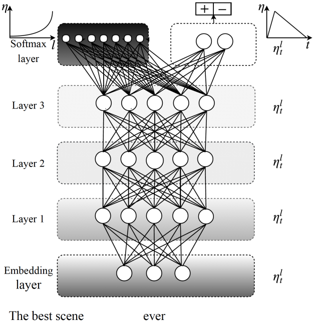

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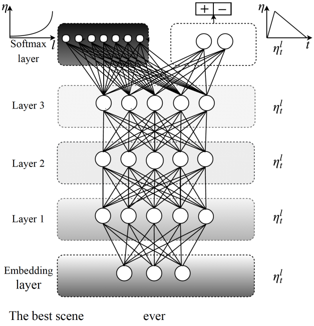

Classifier fine-tuning

- Two additional linear blocks;
- Concat pooling & Gradual unfreezing;
- BPTT for Text Classification (BTT3C);
- Bidirectional LM;

Target task classifier fine-tuning

Target task classifier fine-tuning

Concat Pooling

$$\mathbf{h}_c = [\mathbf{h}_T, \mathsf{maxpool}(\mathbf{H}), \mathsf{meanpool}(\mathbf{H})]$$
$$\mathbf{H} = \{\mathbf{h}_1, \ldots, \mathbf{h}_T\}$$

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Gradual Unfreezing

- Unfreeze layers one by one from the last;

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Gradual Unfreezing

- Unfreeze layers one by one from the last;

BPT3C

- Fixed length batches for LM fine-tuning;

Bidirectional LM

- Pretrain both forward and backward LM;
- Average prediction for fine-tuned classifier;

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Tasks and Datasets

- Sentiment Analysis: IMDb & Yelp reviews;
- Question Classification: TREC;
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Baselines

- IMDb & TREC-6: CoVe [Mccann et al. 2017];
- AG, Yelp, DBpedia: [Johnson et al. 2017];

Results

Results

	Model	Test		Model	Test
IMDb	CoVe (McCann et al., 2017)	8.2	TREC-6	CoVe (McCann et al., 2017)	4.2
	oh-LSTM (Johnson and Zhang, 2016)	5.9		TBCNN (Mou et al., 2015)	4.0
	Virtual (Miyato et al., 2016)	5.9		LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**4.6**		ULMFiT (ours)	**3.6**

Table 2: Test error rates (%) on two text classification datasets used by McCann et al. (2017).

	AG	DBpedia	Yelp-bi	Yelp-full
Char-level CNN (Zhang et al., 2015)	9.51	1.55	4.88	37.95
CNN (Johnson and Zhang, 2016)	6.57	0.84	2.90	32.39
DPCNN (Johnson and Zhang, 2017)	6.87	0.88	2.64	30.58
ULMFiT (ours)	**5.01**	**0.80**	**2.16**	**29.98**

Table 3: Test error rates (%) on text classification datasets used by Johnson and Zhang (2017).

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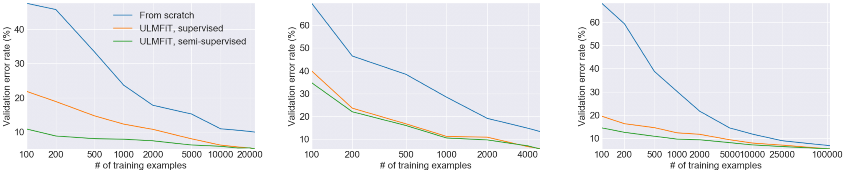

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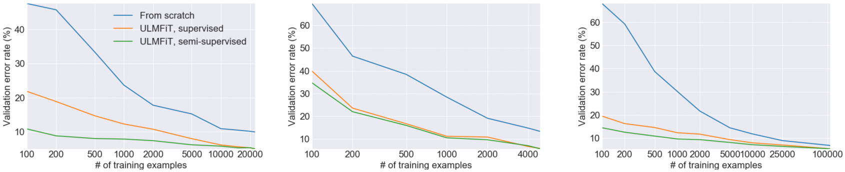

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Pretraining	IMDb	TREC-6	AG
Without pretraining	5.63	10.67	5.52
With pretraining	**5.00**	**5.69**	**5.38**

Table 4: Validation error rates for ULMFiT with and without pretraining.

LM Quality & Fine-tuning

LM Quality & Fine-tuning

LM	IMDb	TREC-6	AG
Vanilla LM	5.98	7.41	5.76
AWD-LSTM LM	**5.00**	**5.69**	**5.38**

Table 5: Validation error rates for ULMFiT with a vanilla LM and the AWD-LSTM LM.

LM Quality & Fine-tuning

LM	IMDb	TREC-6	AG
Vanilla LM	5.98	7.41	5.76
AWD-LSTM LM	**5.00**	**5.69**	**5.38**

Table 5: Validation error rates for ULMFiT with a vanilla LM and the AWD-LSTM LM.

LM fine-tuning	IMDb	TREC-6	AG
No LM fine-tuning	6.99	6.38	6.09
Full	5.86	6.54	5.61
Full + discr	5.55	6.36	5.47
Full + discr + stlr	**5.00**	**5.69**	**5.38**

Table 6: Validation error rates for ULMFiT with different variations of LM fine-tuning.

Classifier Fine-tuning

Classifier Fine-tuning

Classifier fine-tuning	IMDb	TREC-6	AG
From scratch	9.93	13.36	6.81
Full	6.87	6.86	5.81
Full + discr	5.57	6.21	5.62
Last	6.49	16.09	8.38
Chain-thaw	5.39	6.71	5.90
Freez	6.37	6.86	5.81
Freez + discr	5.39	5.86	6.04
Freez + stlr	5.04	6.02	5.35
Freez + cos	5.70	6.38	**5.29**
Freez + discr + stlr	**5.00**	**5.69**	5.38

Table 7: Validation error rates for ULMFiT with different methods to fine-tune the classifier.

Classifier Fine-tuning Behavior

Classifier Fine-tuning Behavior

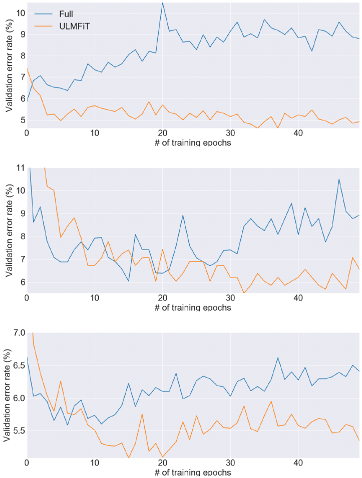

Figure 4: Validation error rate curves for fine-tuning the classifier with ULMFiT and '*Full*' on IMDb, TREC-6, and AG (top to bottom).

Overview

Thank You!
Questions & Comments?

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