Natural Language Processing
Contextualized Embeddings, Pre-Training, Fine-Tuning and Large Language Models

Felipe Bravo-Marquez

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Representations for a word

- So far, we've basically had one representation of words, the word embeddings we've already learned: Word2vec, GloVe, fastText.[1].
- These embeddings have a useful semi-supervised quality, as they can be learned from unlabeled corpora and used in our downstream task-oriented architectures (LSTM, CNN, Transformer).
- However, they exhibit two problems.
- Problem 1: They always produce the same representation for a word type regardless of the context in which a word token occurs
- We might want very fine-grained word sense disambiguation
- Problem 2: We just have one representation for a word, but words have different aspects, including semantics, syntactic behavior, and register/connotations

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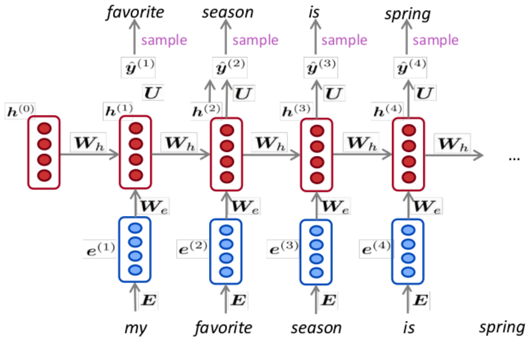
[1] These slides are based on the Stanford CS224N: Natural Language Processing with Deep Learning course:
`http://web.stanford.edu/class/cs224n/`

Neural Language Models can produce Contextualized Embeddings

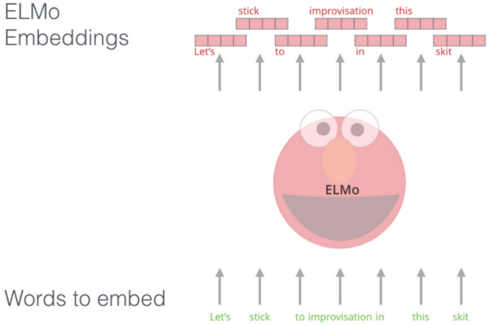
- In, a Neural Language Model (NLM), we immediately stuck word vectors (perhaps only trained on the corpus) through LSTM layers
- Those LSTM layers are trained to predict the next word.
- But these language models produce context-specific word representations in the hidden states of each position.



ELMo: Embeddings from Language Models

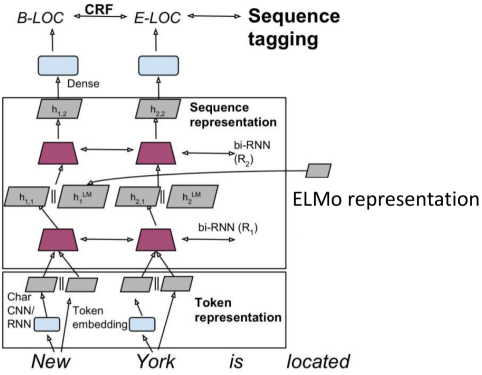
- Idea: train a large language model (LM) with a recurrent neural network and use its hidden states as “contextualized word embeddings” [Peters et al., 2018].
- ELMO is bidirectional LM with 2 biLSTM layers and around 100 million parameters.
- Uses character CNN to build initial word representation (only)
- 2048 char n-gram filters and 2 highway layers, 512 dim projection
- User 4096 dim hidden/cell LSTM states with 512 dim projections to next input
- Uses a residual connection
- Parameters of token input and output (softmax) are tied.

ELMo: Embeddings from Language Models



ELMo: Use with a task

- First run biLM to get representations for each word.
- Then let (whatever) end-task model use them.
- Freeze weights of ELMo for purposes of supervised model.
- Concatenate ELMo weights into task-specific model.



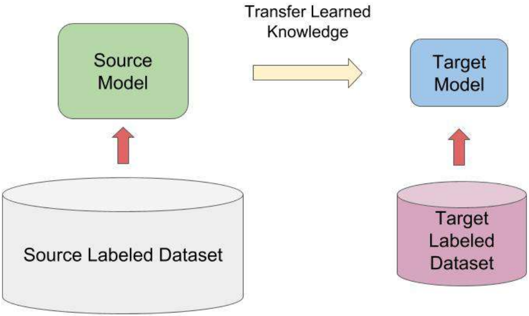
$$\mathbf{h}_{k,1} = [\overrightarrow{\mathbf{h}}_{k,1}; \overleftarrow{\mathbf{h}}_{k,1}; \mathbf{h}_k^{LM}]$$

ELMo: Results

Name	Description	Year	F1
ELMo	ELMo in BiLSTM	2018	92.22
TagLM Peters	LSTM BiLM in BiLSTM tagger	2017	91.93
Ma + Hovy	BiLSTM + char CNN + CRF layer	2016	91.21
Tagger Peters	BiLSTM + char CNN + CRF layer	2017	90.87
Ratinov + Roth	Categorical CRF+Wikipeda+word cls	2009	90.80
Finkel et al.	Categorical feature CRF	2005	86.86
IBM Florian	Linear/softmax/TBL/HMM ensemble, gazettes++	2003	88.76
Stanford	MEMM softmax markov model	2003	86.07

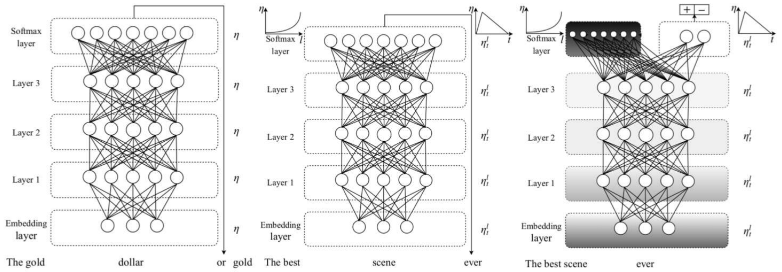
ULMfit

- Howard and Ruder (2018) Universal Language Model Fine-tuning for Text Classification [Howard and Ruder, 2018].
- Same general idea of transferring NLM knowledge
- Here applied to text classification



ULMfit

- Train LM on big general domain corpus (use biLM)
- Tune LM on target task data
- Fine-tune as classifier on target task



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

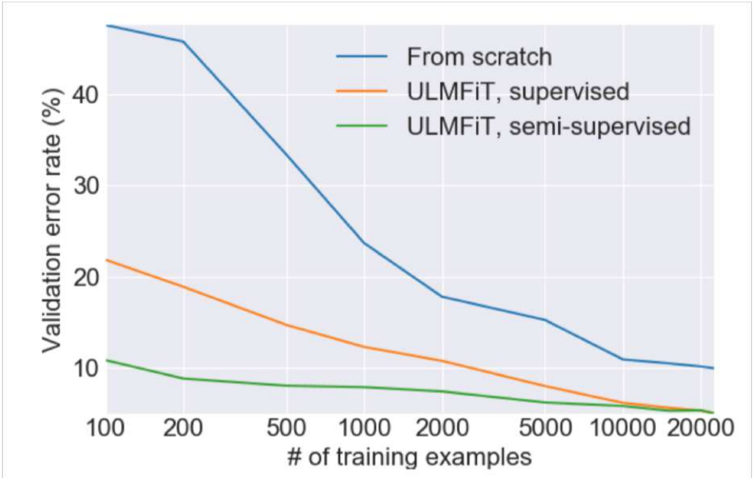
ULMfit emphases

- Use reasonable-size “1 GPU” language model not really huge one
- A lot of care in LM fine-tuning
- Different per-layer learning rates
- Slanted triangular learning rate (STLR) schedule
- Gradual layer unfreezing and STLR when learning classifier
- Classify using concatenation [h_T,maxpool(h),meanpool(h)]

	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**

Text classifier error rates

ULMfit transfer learning



Let's scale it up!

ULMfit

Jan 2018

Training:

1 GPU day

fast.ai

GPT

June 2018

Training

240 GPU days

OpenAI

BERT

Oct 2018

Training

256 TPU days

~320–560

GPU days

Google AI

GPT-2

Feb 2019

Training

~2048 TPU v3 days according to a reddit thread

OpenAI

GPT-2 language model (cherry-picked) output

Human provided prompt:
In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.
Model Completition:
The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.
Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.
Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Transformer models

All of these models are Transformer architecture models … so maybe we had better learn about Transformers?

ULMfit	GPT	BERT	GPT-2
Jan 2018	June 2018	Oct 2018	Feb 2019
Training:	Training	Training	Training
1 GPU day	240 GPU days	256 TPU days ~320–560 GPU days	~2048 TPU v3 days according to a reddit thread

fast.ai

OpenAI

Google AI

OpenAI

BERT (Bidirectional Encoder Representations from Transformers)

- Idea: combine ideas from ELMO, ULMFit and the Transformer [**?**].
- How: Train a large model (335 million parameters) from a large unlabeled corpus using a Transformer encoder and then fine-tune it for other downstream tasks.
- The parallelizable properties of the Transformer (unlike RNNs, which must be processed sequentially) allow the model to scale to more parameters.
- This model is related but a little bit different from a standard Language Model.

Questions?

Thanks for your Attention!

References I

Howard, J. and Ruder, S. (2018).
Universal language model fine-tuning for text classification.
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Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. (2018).
Deep contextualized word representations.
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