Unsupervised learning methods based on huge data for the needs of supervised learning methods using small training sets

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Difficulties

- supervised learning methods using small training sets
 - classification
 - extraction
- increasing the amount of small training sets
- ▶ noisy data (types, ORC error, rare words)
- unbalanced training sets
- time and costs

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Neural language model

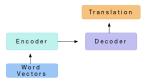
- use different architectures:
 - word level
 - char level
 - sentence level
- evaluation models:
 - perplexity
 - guest gap
- ▶ OCR types tolerant

Neural language model

- ▶ use embedding of models:
 - ► CoVe [1]
 - ► ELMo [2]
- compare with:
 - ► word2vec [3]
 - ► fastText [4]

CoVe

- inspired by the pretrained ImageNet
- train an encoder and transfer the encoder to other tasks
- training an attentional sequence-to-sequence model for English-to-German translation



ightharpoonup CoVe(w) = MT-LSTM(GloVe(w)), w - sequence of words

CoVe

	Model	Test		Model	Test
SST-2	P-LSTM [Wieting et al., 2016]	89.2	REC-6	SVM [da Silva et al., 2011]	95.0
	CT-LSTM [Looks et al., 2017]	89.4		SVM [Van-Tu and Anh-Cuong, 2016]	95.2
	TE-LSTM [Huang et al., 2017]	89.6		DSCNN-P [Zhang et al., 2016]	95.6
	NSE [Munkhdalai and Yu, 2016a]	89.7		BCN+Char+CoVe (Ours)	95.8
	BCN+Char+CoVe (Ours)	90.3		TBCNN [Mou et al., 2015]	96.0
	bmLSTM [Radford et al., 2017]	91.8		LSTM-CNN [Zhou et al., 2016]	96.1
SST-5	MVN [Guo et al., 2017]	51.5	SEC-5	SVM [Loni et al., 2011]	89.0
	DMN [Kumar et al., 2016]	52.1		SNoW [Li and Roth, 2006]	89.3
	LSTM-CNN [Zhou et al., 2016]	52.4		BCN+Char+CoVe (Ours)	90.2
	TE-LSTM [Huang et al., 2017]	52.6		RulesUHC [da Silva et al., 2011]	90.8
	NTI [Munkhdalai and Yu. 2016b]	53.1		SVM [Van-Tu and Anh-Cuong, 2016]	91.6
	BCN+Char+CoVe (Ours)	53.7		Rules [Madabushi and Lee, 2016]	97.2
	BCN+Char+CoVe (Ours)	91.8	SN	DecAtt+Intra [Parikh et al., 2016]	86.8
IMDb	SA-LSTM [Dai and Le, 2015]	92.8		NTI [Munkhdalai and Yu, 2016b]	87.3
	bmLSTM [Radford et al., 2017]	92.9		re-read LSTM [Sha et al., 2016]	87.5
	TRNN [Dieng et al., 2016]	93.8		btree-LSTM [Paria et al., 2016]	87.6
	oh-LSTM [Johnson and Zhang, 2016]	94.1		600D ESIM [Chen et al., 2016]	88.0
	Virtual [Miyato et al., 2017]	94.1		BCN+Char+CoVe (Ours)	<i>88.1</i>

ELMo (Embeddings from Language Models)

- function of all of the internal layers of the biLM
- lower-level LSTM states model aspects of syntax
- higher-level LSTM states capture context-dependent aspects of word meaning
- ► ELMo outperforms CoVe

ELMo (Embeddings from Language Models)

TASK	PREVIOUS SOTA		OUR BASELINE	ELMO + BASELINE	INCREASE (ABSOLUTE/ RELATIVE)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

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Data sets

- ► Get more data
 - Common Crawl
 - Wikipedia
- ► Extract in-domain data sets [?]
- Data augmentation

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References I

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