Paper Reading Dec 10th

2 papers about LMs One focus on Interpretability(夹带私货 \rightarrow_\rightarrow) One focus on injecting knowledge into LMs

Perturbed Masking: Parameter-free Probing for Analyzing and Interpreting BERT *Zhiyong Wu*, Yun Chen, Ben Kao, Qun Liu





HUAWEI | NOAH'S ARK LAB

Background

An emerging body of NLP work asks "Does my neural network implicitly learns **Y** from plain text?"

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Pretrained LM e.g., ELMo, BERT

parts-of-speech syntax semantics

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An emerging body of NLP work asks "Does my neural network implicitly learns Y from plain text?" Pretrained LM e.g., ELMo, BERT Probing: supervised analysis of representations



NN

mat

sit

Cats

on the















Shall we give credit to the **representation**? and/or the **probe**?



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Fix it: control tasks (Hewitt and Liang 2019) MDL(Elena et al., 2020)



Shall we give credit to the **representation**? and/or the **probe**?

Fix it: control tasks (Hewitt and Liang 2019) MDL(Elena et al., 2020) This work: **parameter-free(unsupervised) probing**



Perturbed Masking



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 $e = E(Cats|S \setminus \{Cats\})$

Example: Calculate impact <u>sit</u> has on <u>Cats</u>: f(Cats, sit) = d(e, e')



Perturbed Masking

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 $e = E(Cats|S \setminus \{Cats\})$



 $e' = E(Cats|S \setminus \{Cats, sit\})$



Perturbed Masking

Example: Calculate impact <u>sit</u> has on <u>Cats</u>: f(Cats, sit) = d(e, e')

 $e = E(Cats|S \setminus \{Cats\})$





f(Cats, sit) = d(e, e') = Distance between e and e'

Impact Matrix

	Cats	sit	on	the	mat
Cats	-	f(Cat,sit)			
sit	f(sit,Cats)	-			
on			-		
the				-	
mat					-

Supervised Probe: learning to map representations to task Ours: Impact Matrix + task specific algo => task



1. Perturb input sentence and extract an impact matrix.

2. Use task-specific algorithm to extract taskrelated knowledge from the impact matrix

Application 1: Dependency probe

Using graph-based dependency parsing algorithm to extract dependency trees out of impact matrixes.

Madal	Parsing UAS				
	WSJ10-U	PUD			
Right-chain	49.5	35.0			
Left-chain	20.6	10.7			
Random BERT	16.9	10.2			
Eisner+Dist	58.6	41.7			
Eisner+Prob	52.7	34.1			
CLE+Dist	51.5	33.2			

Application 1: Dependency probe

- 1. Despite its parameter-free nature, our probe corroborates findings from previous studies
- 2. However, we also observe that the structures induced from BERT only correlate with human-designed syntax weakly

Model	Parsing UAS				
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Application 1: Dependency probe

- 1. Despite its parameter-free nature, our probe corroborates findings from previous studies
- 2. However, we also observe that the structures induced from BERT only correlate with human-designed syntax weakly

Would BERT learn **better** dependency structures?

Model	Parsing UAS				
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Empirical usefulness of the induced structure

Input sentence: **s** Parser generated dep tree for s: **dep tree** BERT generated dep tree for s: **BERT tree**



Empirical usefulness of the induced structure

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Madal	L	aptop	Restaurant			
widdei	Acc	Macro-F1	Acc	Macro-F1		
LSTM	69.63	63.51	77.99	66.91		
PWCN						
+Pos	75.23	71.71	81.12	71.81		
+Dep	76.08	72.02	80.96	72.21		
+Eisner	75.99	72.01	81.21	73.00		
+right-chain	75.64	71.53	81.07	72.51		
+left-chain	74.39	70.78	80.82	72.71		

Other applications

- Other probes (refer to paper)
- Unsupervised syntactic parsing (Kim et al., 2020; Li et al., 2020)
- Chinese word segmentation
- LM pre-training



The 2020 Conference on Empirical Methods in Natural Language Processing

FMNI P 2020

Vokenization:

Improving Language Understanding with Contextualized, Visual-Grounded Supervision

Hao Tan, Mohit Bansal

UNC Chapel Hill haotan, mbansal@cs.unc.edu

thetimes.co.uk/article/feline-philosophy-by-john-gray-review-what-cats-teach-us-about-the-meaning-of-life-bgzwkqpqm

Visual Supervision to Language

Look, this is a "cat"!



Peters, Matthew E., et al. "Deep contextualized word representations." NAACL 2018 Radford, Alec, et al. "Language models are unsupervised multitask learners."

Causal Language Model (e.g., ELMo, GPT2)

Next Tokens in the Sentence



Masked Language Model (e.g., BERT)

Masked Tokens



(Masked) Language Input

Visually-Supervised Language Model

Vokens (Token-Related Images)



Language Input

Visually-Supervised Language Model

Vokens (Token-Related Images)



Language Input

Available Resources and Our Goal





Challenges 1: Data Divergence





The man at bat readies to swing at the pitch while the umpire looks on.

A large bus sitting next to a very tall building.





A horse carrying a large load of hay and two people sitting on it.

Bunk bed with a narrow shelf sitting underneath it.

MS COCO Captioning: 7M Tokens

COVID-19 pandemic

Several terms redirect here. For other uses, see Coronavirus outbreak (disambiguation) and 2019-2020 outbreak (disambiguation

The COVID-19 pandmic, also income as the decrementary pandmice, is an origin guardenic of community mices 2019 (COVID 19) quarked by the treatment of service acids regulation synchrone concension 2 (SARS-COV-2), which uses find identified in Decomer 2019 in WAans, Ohma¹¹⁴ The them-outheak was dedared a Public Health Emergency of International Concern (PMEC) p. January 2020, and a pandmice in March 2020. A or 12 Conceler 2020, news that it million cases have been confined, with more than 1.12 million dashes abladed to COVID-110¹¹

Common symptoms include lever, cough, tatigue, treating difficulties, and loss of amell. Complications may include preventia and acute respiratory distress syndrome. The includation period is figibility acuted free days but may range from one to 14 days.^[11] There are severed inacchic candidates in development, although none have proven their safety and efficiency. There is no increase syndrome from their safety and efficiency. There is no increase syndrome from their safety and efficiency. There is no increase syndrome from their safety and efficiency.



English Wikipedia: ~2800M Tokens

The **amount** of grounded language is much less than plain language.

Challenges 1: Data Divergence

Example: A cat sits in the shadow of a blue doorway.

MS COCO Captioning: 11.8 tokens / sentence

Example:

It is the only domesticated species in the family Felidae and is often referred to as the domestic cat to distinguish it from the wild members of the family.

English Wikipedia: 24.1 tokens / sentence

The **distribution** of grounded language is different from plain language.

Challenges 1: Data Divergence

Example: A cat sits in the shadow of a blue doorway.

MS COCO Captioning: Vocab Size - 9K Example:

It is the only domesticated species in the family Felidae and is often referred to as the domestic cat to distinguish it from the wild members of the family.

> English Wikipedia: Vocab Size - 29K

The **distribution** of grounded language is different from plain language.

Solution 1: Extrapolation



Challenges 2: Low Grounding Ratio

Bold Blue: Visually-Grounded Unbold Blue: Unsure

Example: A **cat sits** in the **shadow** of a **blue doorway**. Example:

A cat can either be a house cat, a farm cat or a feral cat; the latter ranges freely and avoids human contact.

MS COCO Captioning: Grounding Ratio - 54.8% English Wikipedia: Grounding Ratio - 27.7%

Visually-Grounded (informal definition): If the word could be mapped to a visual image.

Challenges 2: Low Grounding Ratio

Bold Blue: Visually-Grounded Unbold Blue: Unsure

Example: A **cat sits** in the **shadow** of a **blue doorway**. Example:

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MS COCO Captioning: Grounding Ratio - 54.8% English Wikipedia: Grounding Ratio - 27.7%

Problem: if the grounding ratio is small, it's hard to provide dense visual supervision.

Solution 2: Contextualized Grounding

Bold Blue:Visually-GroundedUnbold Blue:UnsureBold Red:Contextually Visually-GroundedBold Red:Unsure

Example: A cat sits in the shadow of a blue doorway. Example:

A cat can either be a house cat, a farm cat or a feral cat; the latter ranges freely and avoids human contact.

MS COCO Captioning: Grounding Ratio - 54.8% English Wikipedia: Grounding Ratio - 27.7%

Contextually Visually-Grounded (informal definition): If the (word, context) pair is visually-grounded.

https://possibility-cp.com/the-2-mistakes-to-avoid-when-recruiting-board-members/ https://zhuanlan.zhihu.com/p/67822808

Solution 2: Contextualized Grounding





A cat can either be a house cat, a farm cat or a feral cat; the latter ranges freely and **avoids** human contact.

Contextualized Grounding

avoids

Grounding (Token-Level Grounding)

Solution 2: Contextualized Grounding





Grounding (Token-Level Grounding)



A cat can either be a house cat, a farm cat or a feral cat; the latter ranges freely and avoids human CONTACT. Contextualized Grounding

Vokenization = Extrapolation + Contextual Grounding



Vokenizer: Modeling



Positive Pair



Vokenizer: Inference



Final learning objective



Pranav Rajpurkar, et al. SQuAD. EMNLP 2016 Adina Williams, et al. MNLI. NAACL 2018 Rowan Zellers, et al. Swag. EMNLP 2018

Experiment Setups





The man at bat readies to swing at the pitch while the umpire looks on.

A large bus sitting next to a very tall building.





A horse carrying a large load of hay and two people sitting on it. Bunk bed with a narrow shelf sitting underneath it.



Train the Vokenizer



Note: Long passages in SQuAD need sequence length 512 but our computational resources only support sequence length 128. Other experiments are not affected by this. Please refer to got detailed implementation of SQuAD (the sliding window approach): https://github.com/google-research/bert/blob/master/run_squad.py

Results with BERT Backbone

	Pre-trained on	SST-2	QNLI	QQP	MNLI				
	MS COCO	83.7	60.6	82.1	69.3				
	Wiki103*	85.8	77.9	84.8	73.9				
Method		SST-2	QNLI	QQP	MNLI	SQuAD v1.1	SQuAD v2.0	SWAG	Avg.
BERT _{6L/512H}		88.0	85.2	87.1	77.9	71.3/80.2	57.2/60.8	56.2	75.6
$BERT_{6L/512H} + V$	Voken-cls	89.7	85.0	87.3	78.6	71.5/80.2	61.3/64.6	58.2	76.8
BERT _{12L/768H}		89.3	87.9	83.2	79.4	77.0/85.3	67.7/71.1	65.7	79.4
BERT _{12L/768H} +	Voken-cls	92.2	88.6	88.6	82.6	78.8/86.7	68.1/71.2	70.6	82.1

Small experiments on Wiki103 (reproducible to the community). **1.2%** average improvement.

Note: We did some simplifications (constant sequence length, no NSP task) to standardize training process. We also excludes the unavailable BookCopus but only kept English Wikipedia.

Results with BERT Backbone

2.7% average improvement when pre-trained on Wikipedia.

Method	SST-2	QNLI	QQP	MNLI	SQuAD v1.1	SQuAD v2.0	SWAG	Avg.
BERT _{6L/512H}	88.0	85.2	87.1	77.9	71.3/80.2	57.2/60.8	56.2	75.6
BERT _{6L/512H} + Voken-cls	89.7	85.0	87.3	78.6	71.5/80.2	61.3/64.6	58.2	76.8
BERT _{12L/768H}	89.3	87.9	83.2	79.4	77.0/85.3	67.7/71.1	65.7	79.4
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Method	SST-2	2 QNLI	QQ	P M	NLI	SQuAD v1.1	SQuAD v2.0	SWAG	Avg.
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BERT _{12L/768H}	89.3	87.9	83.	2 79	9.4	77.0/85.3	67.7/71.1	65.7	79.4
$BERT_{12L/768H}$ + Voken-cl	s 92.2	88.6	88.	6 82	2.6	78.8/86.7	68.1/71.2	70.6	82.1
BERT-BASE (Devlin et al. 20	19) 00 3	80.6	88 /	1 8'	$\frac{1}{2}$				
Trained with 800M BooksCorp	ous	89.0	00	+ 0.	2.4	System		Dev	Test
						ESIM+G	loVe	51.9	52.7
	a .	P				ESIM+E	LMo	59.1	59.2
	System	D EM	ev F1	EM F	F1	OpenAI (GPT	-	78.0
Top Le	eaderboard Syst	tems (Dec	10th, 2	018)		BERTBAS	SE	81.6	_
Human	-	-	- 8	82.3 91	1.2	BERTLAT	RGE	86.6	86.3
#1 Ensembl	e - nlnet	-	- 8	86.0 9 1	1.7				
#2 Ensembl	e - QANet	-	- 8	84.5 90	0.5	Human (expert) [†]	-	85.0
	Publ	ished				Human (5 annotations) ^{\dagger}	-	88.0
BiDAF+EL	Mo (Single)	-	85.6	- 83	5.8		-		
R.M. Reade	r (Ensemble)	ible) 81.2 87		82.3 88	8.5	CWAC D.			⁺ TT
	O	ırs				SWAG De	ev and rest ac	curacie	es. 'H
BERT _{BASE} ((Single)	80.8	88.5	-	-				39

Hao Tan and Mohit Bansal. LXMERT, EMNLP 2019 Xiujun Li, et al. Oscar: Object-semantics aligned pre-trainingfor vision-language tasks. ECCV 2020

Vision-and-Language Pre-training

Model	Init. with BERT?	Diff. to BERT Weight	SST-2	QNLI	QQP	MNLI
ViLBERT (Lu et al., 2019)	Yes	0.0e-3	90.3	89.6	88.4	82.4
VL-BERT (Su et al., 2020)	Yes	6.4e-3	90.1	89.5	88.6	82.9
VisualBERT (Li et al., 2019)	Yes	6.5e-3	90.3	88.9	88.4	82.4
Oscar (Li et al., 2020a)	Yes	41.6e-3	87.3	50.5	86.6	77.3
LXMERT (Tan and Bansal, 2019)	No	42.0e-3	82.4	50.5	79.8	31.8
BERT _{BASE} (Devlin et al., 2019)	-	0.0e-3	90.3	89.6	88.4	82.4
BERT _{BASE} + Weight Noise	-	89.9	89.9	88.4	82.3	
	BERT _{12L/76}	_{88H} + Voken-cls	92.2	88.6	88.6	82.6

OSCAR on MNLI: 77.3% (- 2.1%)

LXMERT on MNLI: 31.8% (- 47.6%)

Visualization





humans



listening



speaking



language

reading

bv

Note: The goal of vokenization is not to build the perfect token-level image retriever but to improve understanding of other types of language with related visual information.









by







salle

love









meet

and

down

