



The Chinese Causative-Passive Homonymy Disambiguation: an Adversarial Dataset for NLI and a Probing Task

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Motivation

Leaderboard Version: 2.0															
	Rank	Name	Model	URL	Score	BoolQ	СВ	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	A
+	1	Liam Fedus	ST-MoE-32B		91.2	92.4	96.9/98.0	99.2	89.6/65.8	95.1/94.4	93.5	77.7	96.6	72.3	96.1/9
	2	Microsoft Alexander v-team	Turing NLR v5		90.9	92.0	95.9/97.6	98.2	88.4/63.0	96.4/95.9	94.1	77.1	97.3	67.8	93.3/9
	3	ERNIE Team - Baidu	ERNIE 3.0		90.6	91.0	98.6/99.2	97.4	88.6/63.2	94.7/94.2	92.6	77.4	97.3	68.6	92.7/9
	4	Yi Tay	PaLM 540B		90.4	91.9	94.4/96.0	99.0	88.7/63.6	94.2/93.3	94.1	77.4	95.9	72.9	95.5/9
+	5	Zirui Wang	T5 + UDG, Single Model (Google Brain)		90.4	91.4	95.8/97.6	98.0	88.3/63.0	94.2/93.5	93.0	77.9	96.6	69.1	92.7/9
+	6	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.3	90.4	95.7/97.6	98.4	88.2/63.7	94.5/94.1	93.2	77.5	95.9	66.7	93.3/9
	7	SuperGLUE Human Baselines	SuperGLUE Human Baselines	♂	89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	76.6	99.3/

Screenshoot from <u>super.gluebenchmark.com</u> (retrieved on 06.05.2022)

- Pretrained language models (PLMs) achieve fantastic performance in NLU tasks.
- Do language models understand language?



Natural Language Inference (NLI) Task

Premise: Today is Friday

Hypothesis: Tomorrow is Saturday

Entailment

Premise: Today is Friday

Hypothesis: It is April

Non-entailment



NLI Dataset Examples

SNLI (Bowman et al.2015)

Premise:

A soccer game with multiple males playing.

Hypothesis:

Some men are playing a sport.

Entailment

OCNLI (Hu et al. 2020)

Premise:

嗯,今天星期六我们这儿,嗯哼. En, it's Saturday today in our place, yeah.

Hypothesis:

昨天是星期天 It was Sunday yesterday.

Contradiction/ Non-entailment

<u>A large annotated corpus for learning natural language inference</u> (Bowman et al., EMNLP 2015) <u>OCNLI: Original Chinese Natural Language Inference</u> (Hu et al. 2020., Findings of EMNLP 2020)



Adversarial NLI Datasets

- PLMs often exploit superficial patterns, and fail on examples with high lexical overlap
- HANS: carefully designed adversarial NLI dataset

(McCoy et al.2019)

Non-entailment

The doctor near the actor danced. \rightarrow The actor danced.

- However:
 - templates only for English
 - difficult to find the templates from scratch



Contributions

- We create the first Chinese adversarial NLI test set CANLI.
- Using the linguistic phenomenon Causative-Passive Homonymy (CPH).
- SOTA NLI system (RoBERTa finetuned on OCNLI) performs poorly on CANLI.
- We use word sense disambiguation as a probing task.
- The probe results demonstrate that RoBERTa's performance on CANLI does not correspond to its internal representation of CPH.



The Causative-Passive Homonymy (CPH)

Canonical

1a. She gets them to do the cleaning. (causative : get + infinitive)

1b. Her wallet was stolen. (passive: be + past participle).

Causative - Passive Homonymy (CPH)

2a. She got them arrested (by the police). (Causative, get + past participle)

2b. She got her wallet stolen (by someone). (Passive, get + past participle)

- CPH also be observed in Korean, Chinese, Japanese, Manchu Tungusic languages, and others.
- There are no differences in the verbal constructions of CPH; it is the context that determines whether the verb should be read as causative or passive.



CPH in Chinese

```
(4)
a. 经济危机
                               倒闭
                      公司
  jingji-weiji rang gongsi
                               daobi
  ecnomic-crisis CAUS company close-down PFV
'The economic crisis caused the company to close down.'
            公司
                    开除
b. 他 让
                    kaichu le
  ta rang gongsi
  he PASS company
                           PFV
                    fire
'He was fired by the company.'
```



Construction of CANLI

	Ca	usative	P		
	Entailment	Non-entailment	Entailment	Non-entailment	Total
Train	200 200		200	200	800
Test	200	200	200	200	800
Total		800			

Premises collection:

- CPH sentences marked by the CPH morpheme rang.
- Drawn from the genre of modern literature in the CCL online corpus
- Collected and annotated by a Chinese native speaker with a linguistics background

Hypothesis generation:

- Generated with templates.
- Proofread and edited by a native publishing house editor.
- The first author of this paper has double-checked the data after the editing process.



CANLI Template I

Template:

Premise: N1 rang N2 VP (passive)

Hypothesis 1: N1 VP N2 Non-entailment Non-entailment

Hypothesis 2: N2 VP N1

Entailment

Example:

Premise: Wo rang Baoqing chao xing le

"I was woken up by Baoqing"

Hypothesis 1: Wo chao xing le Baoqing.

"I woke Baoqing up."

Non-entailment

Hypothesis 1: Baoqing chao xing le Wo.

"Baoqing woke me up."

Entailment



CANLI Template II

Template:

Premise: N1 rang N2 VP (causative)

Hypothesis 1: N1 VP

Hypothesis 2: N2 VP



Non-entailment

Example:

Premise: Jing ji wei ji rang gong si dao bi le.

"The economic crisis caused the company to close down."

Non-entailment Hypothesis 1: Jing ji wei ji dao bi le.

"The economic crisis closed down.

Hypothesis 1: Gong si dao bi le.

"The company closed down."





Experiments

- hfl/chinese-roberta-wwm-ext- large (Cui et al. 2020)
- sequence classification head on top from the transformers library (Wolf et al. 2020)
- Fine-tuned on OCNLI training set (Xu et al. 2020)



Results

Test data	OCNLI.val				CANLI.test					
Fine-tuning data	accuracy	P	R	F1	accuracy	P	R	F1		
OCNLI.train	87.4 (0.3)	81.5 (0.8)	78.8 (1.0)	80.1 (0.5)	48.1 (1.3)	48.9 (0.8)	88.2 (2.6)	62.9 (1.2)		
OCNLI.train	87.2 (0.2)	81.4 (0.4)	77.7 (0.2)	79.5 (0.3)	97.3 (0.6)	97.4 (0.6)	97.3	97.3		
+ CANLI.train					97.3 (0.0)	97.4 (0.0)	(0.9)	(0.7)		
Human Performance					93.2 (2.4)	93.5 (7.2)	93.1 (5.10)	93.0 (2.5)		

- The OCNLI-fine-tuned model performed poorly on the CANLI.test
- Fine-tuning with CANLI.train set indeed helps substantially when testing on CANLI.test
- Has the model learned the linguistic feature of CPH after augmenting?
- To what extent can we find the CPH feature in the model's internal representation?



The Representation of CPH

- There are no differences in the verbal constructions of CPH; it is the context that determines whether the verb should be read as causative or passive.
- Embeddings provided by Transformers depend on context.
- Hypothesis: The model has learned the CPH after fine-tuning with CANLI. -> CPH feature is captured in the model's representation



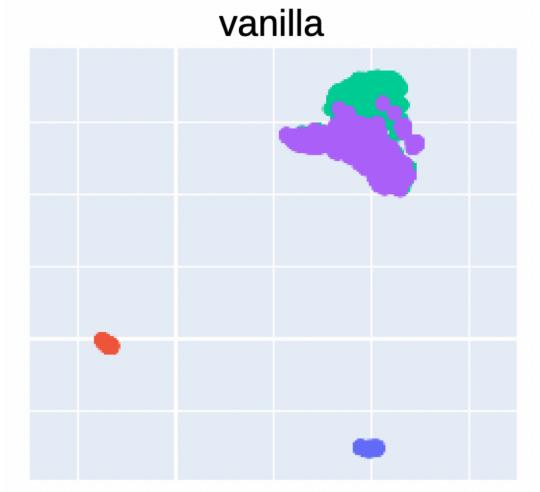
Visualization with UMAP

green: embeddings of *rang* from 200 passive sentences in the CANLI train set

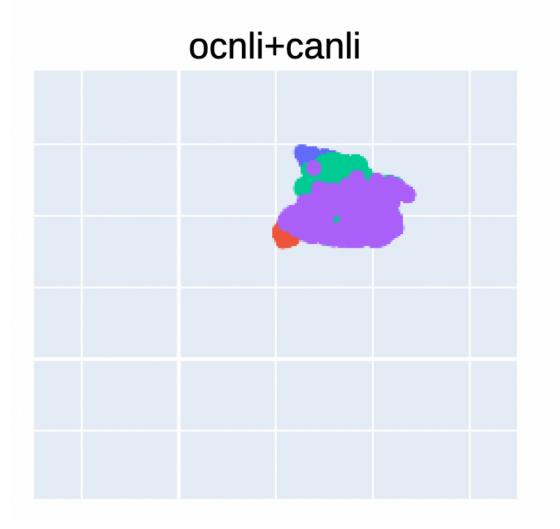
purple: embeddings of *rang* from 200 causative sentences in the CANLI train set

blue: embeddings of *bei* (canonical passive marker) from 40 sentence drawn from CCL corpus.

red: embeddings of *shi* (canonical causative marker) 40 sentence drawn from CCL corpus



Embeddings pulled from the vanilla RoBERTA



Embeddings pulled from RoBERTA fine-tuned with OCNLI + CANLI



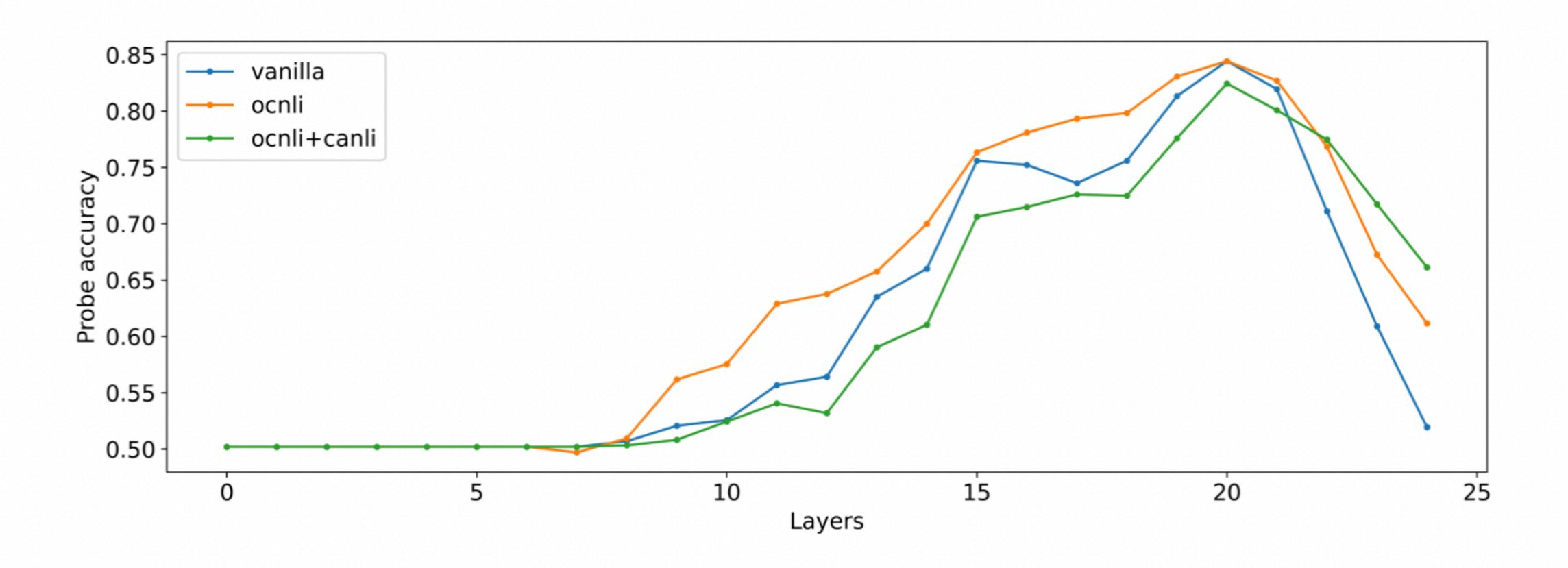
Quantitative Analysis

Causative/Passive disambiguation as a probing task

- Inspired by the method of Word Sense Disambiguation (WSD). (Coenen et al, 2019)
- Nearest-centroid classifier as probe.
- As the probe is not trained, selectivity is assured.
- Gold causative centroid: the centroid of 40 contextualized embeddings of *shi* (canonical causative marker)
- Gold passive centroid: the centroid of 40 contextualized embeddings of *bei* (canonical passive marker)



Probe Accuracies





Conclusions

- We present CANLI, the first adversarial NLI dataset for Chinese.
- The poor performance using RoBERTA fine-tuned on OCNLI demonstrates that CANLI is challenging for a state-of-the-art NLI system.
- WSD as probing task
- RoBERTa's performance on CANLI does not correspond to its internal representation of CPH
- CANLI available @ https://huggingface.co/datasets/sxu/CANLI