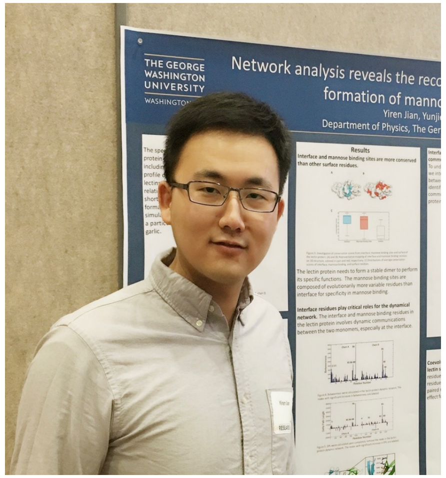
NAACL2022

DARTMOUTH
Department of Computer Science

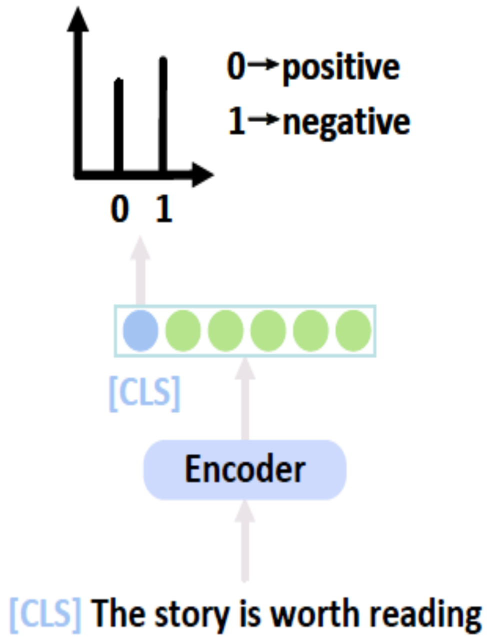
Northwestern | McCORMICK SCHOOL OF ENGINEERING
Computer Science

Contrastive Learning for Prompt-based Few-shot Language Learners

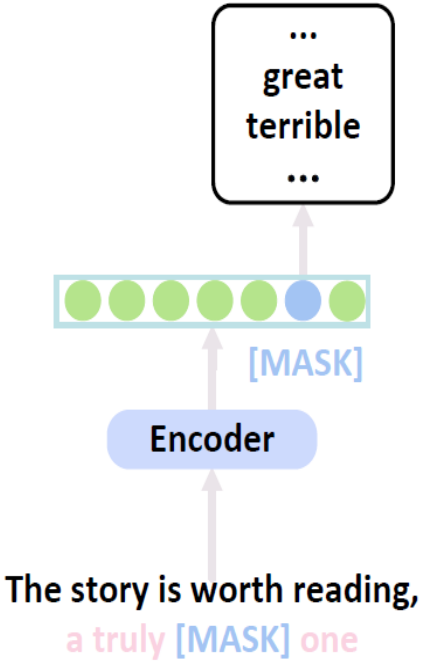


Yiren Jian | Chongyang Gao | Soroush Vosoughi

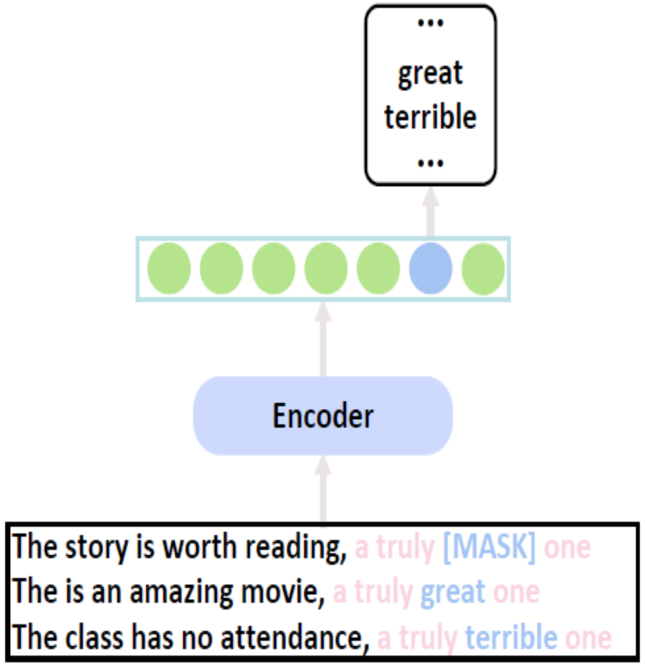
Conventional finetuning, prompts and demonstrations



Conventional fine tuning, classifying at hidden states of [CLS].



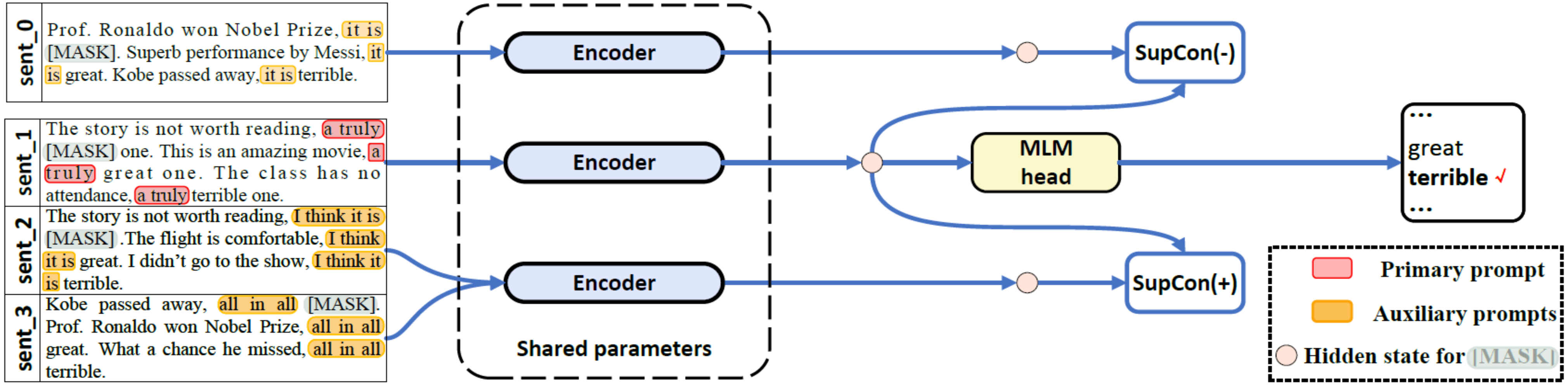
Prompt-based fine tuning, predicting the best suited missing word.



Prompt-based fine tuning with demonstrations to help model to know what is “great” / “terrible”. [1]

[1] Gao et al, Making Pre-trained Language Models Better Few-shot Learners, ACL 2022

Contrastive Learning for Prompt-based Few-shot Language Learners



Besides the standard prompt-base MLM loss on label words "great" and "terrible", we introduce a SupCon loss on multi-views of input text. The positive pair is sentences (with sampled templates and/or demonstrations) in the same class, e.g. sent1 and sent3, or itself with a different template and demonstrations, e.g. sent1 and sent2. The negative sentence pair is input sentences (with sampled templates and/or demonstrations) in different classes, e.g. sent1 and sent0.

Experimental results

Task	LM-BFF	LM-BFF + ours	PET	PET + ours
SST-2 (acc)	89.2 (1.3)	**90.6** (0.1)	88.4 (1.0)	**89.9** (0.6)
Subj (acc)	88.6 (3.3)	**90.4** (1.1)	89.2 (1.5)	**90.6** (1.6)
SST-5 (acc)	47.9 (0.8)	**49.5** (1.1)	46.0 (0.9)	**48.8** (1.2)
CoLA (Matt.)	6.1 (5.3)	**10.2** (5.8)	3.5 (3.4)	**5.9** (3.3)
TREC (acc)	82.8 (3.1)	**83.3** (1.5)	77.8 (9.1)	**82.3** (4.6)
MNLI (acc)	61.0 (2.1)	**64.0** (2.0)	58.2 (1.1)	**58.9** (3.1)
MNLI-mm (acc)	62.5 (2.1)	**65.5** (2.7)	59.8 (1.2)	**61.0** (3.3)
SNLI (acc)	66.9 (2.4)	**69.9** (2.4)	63.1 (2.5)	**65.7** (3.9)
QNLI (acc)	60.7 (1.7)	**66.4** (3.5)	61.5 (3.3)	**63.5** (3.7)
QQP (acc)	62.5 (2.6)	**68.8** (3.8)	61.9 (3.5)	**65.7** (4.3)
RTE (acc)	64.3 (2.7)	**65.1** (3.5)	60.9 (4.7)	**65.1** (3.5)
MRPC (F1)	75.5 (5.2)	**78.2** (3.1)	70.6 (6.0)	**75.7** (6.1)
MR (acc)	83.3 (1.4)	**85.8** (0.6)	85.0 (0.6)	**85.2** (0.9)
MPQA (acc)	83.6 (1.8)	**84.6** (1.5)	81.3 (2.6)	**81.8** (2.4)
CR (acc)	88.9 (1.0)	**89.4** (1.0)	89.3 (1.0)	**90.5** (0.5)

Our framework can improve two different kinds of prompt-based few-shot learning: the one with demonstrations (LM-BFF) and the other one without demonstration (PET).

Ablations: different augmentations for multi-views in contrastive learning

Task	LM-BFF	SR	RI	RS	RD	EDA	ours
SST-2	89.2	90.7	**90.8**	90.7	90.7	90.5	90.6
Subj	88.6	90.6	90.8	**91.0**	90.5	89.1	90.4
SST-5	47.9	47.7	49.2	48.2	47.9	46.7	**49.5**
CoLA	6.1	5.8	6.5	4.9	4.0	3.9	**10.2**
TREC	82.8	78.1	80.7	79.0	80.7	80.6	**83.3**
MNLI	61.0	61.8	62.4	61.0	58.1	58.9	**64.0**
-mm	62.5	63.6	64.8	62.7	60.3	60.9	**65.5**
SNLI	66.9	63.1	66.4	67.2	65.2	62.2	**69.9**
QNLI	60.7	65.3	65.3	**67.4**	64.8	62.5	$66.4^{\dagger}$
QQP	62.5	64.5	65.8	68.0	63.2	61.0	**68.8**
RTE	64.3	61.4	61.4	61.3	62.1	61.1	**65.1**
MRPC	75.5	77.6	77.7	**79.3**	78.7	79.1	$78.2^{\dagger}$
MR	83.3	85.5	85.5	85.5	85.3	85.6	**85.8**
MPQA	83.6	82.2	84.4	84.4	83.9	82.8	**84.6**
CR	88.9	88.9	88.2	88.3	88.5	87.1	**89.4**

We show that our method of appending sampled templates and demonstrations which would not hurt the semantic and completeness of sentences outperforms augmentations at lexical space.

Thank you!