







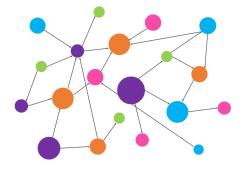
PALT: Parameter-Lite Transfer of Language Models for Knowledge Graph Completion

Findings of EMNLP 2022

Jianhao Shen, Chenguang Wang, Ye Yuan, Jiawei Han, Heng Ji, Koushik Sen, Ming Zhang, Dawn Song

Form

(head entity, relation, tail entity)
(Steve Jobs, founder of, Apple Inc.)



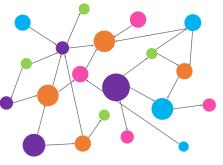
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Instances



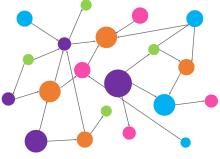






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Instances

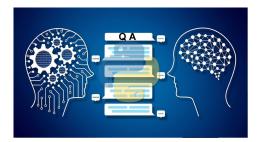
Freebase





Application





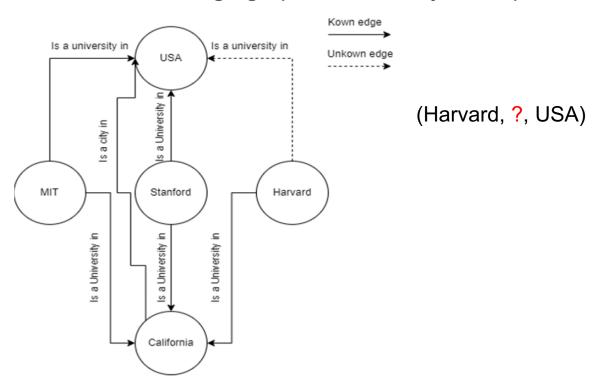


Knowledge Graph Completion

Real-world knowledge graphs are usually incomplete

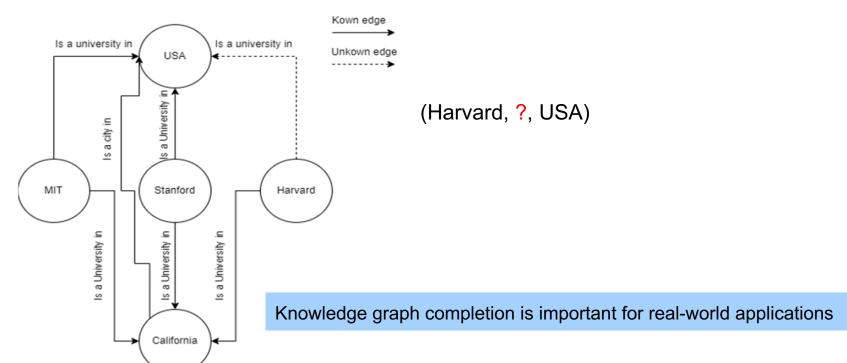
Knowledge Graph Completion

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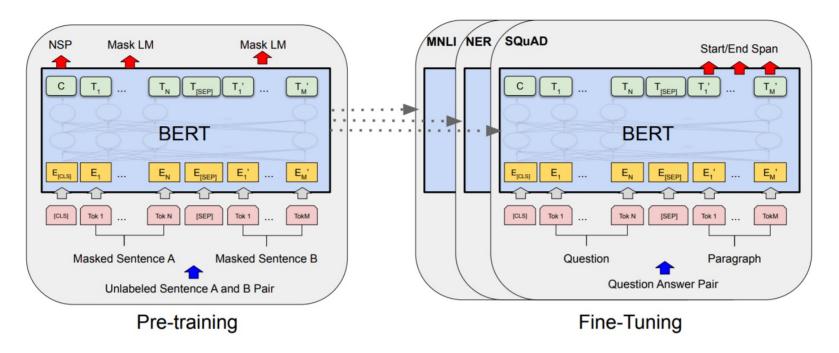


Knowledge Graph Completion

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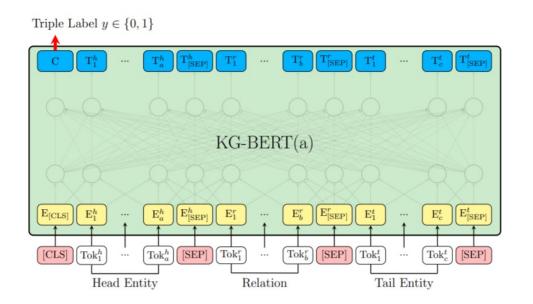


Pretrained Language Models



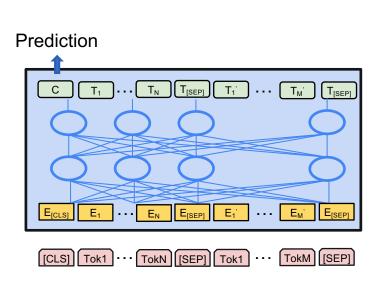
Pretrained language models have enabled downstream transfer

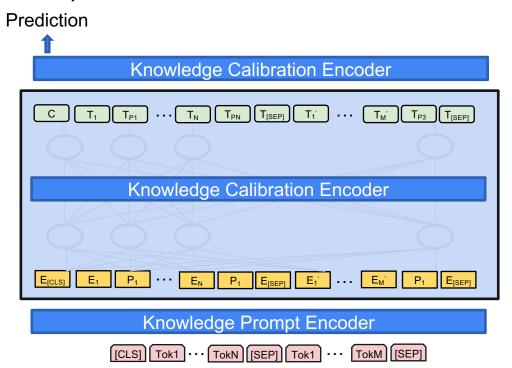
Finetuning to Knowledge Graph Completion



Finetuning requires high computational and storage resources

PArameter-Lite Transfer (PALT)

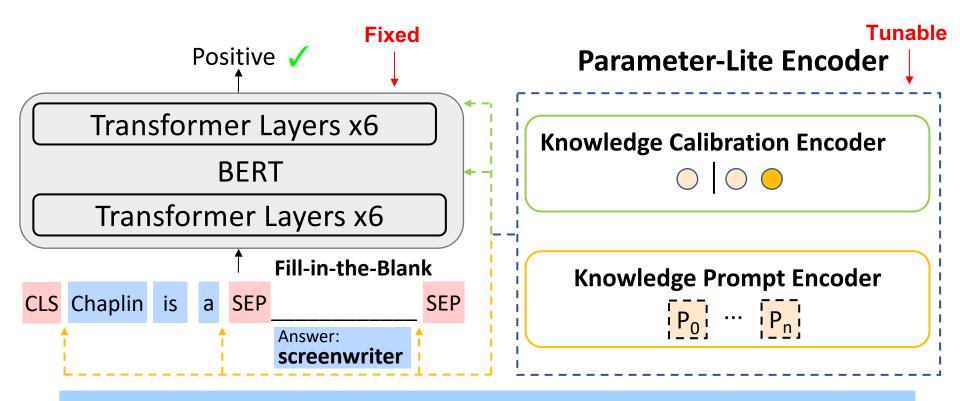




Finetuning

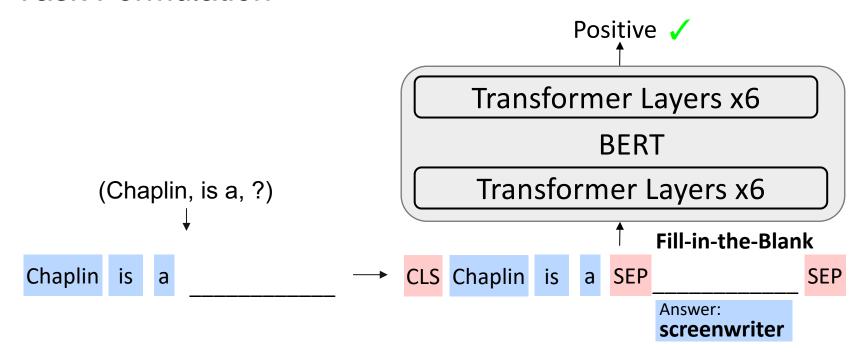
PALT

PArameter-Lite Transfer (PALT)

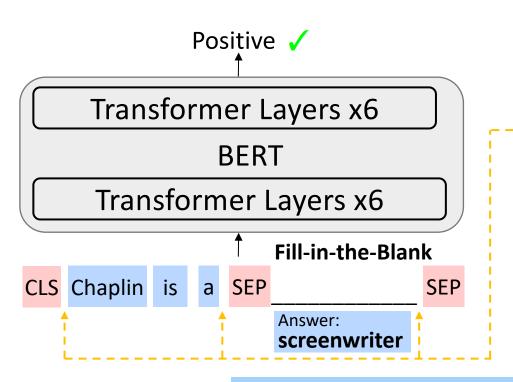


Prepare a proper context to recall knowledge and align the output distribution with the task of interest

Task Formulation



Knowledge Prompt Encoder



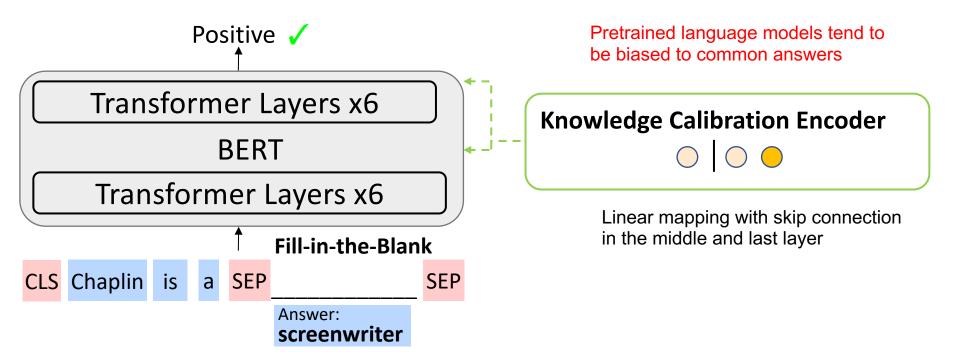
Task-specific context helps to recall relevant knowledge

Knowledge Prompt Encoder

$$P_0 \cdots P_n$$

- Continuous virtual tokens
- Linear mapping with skip connection on top of the embedding layer

Knowledge Calibration Encoder



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Training

- Only tune parameter-lite encoders and keep PLM parameters fixed
- Training objective:
 - NSP prediction about whether two sentences are correctly connected

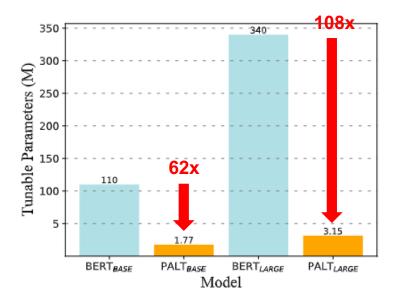
$$L_h = -\log\Pr(1|h,r,t) - \sum_{i}^{n_{\rm ns}} \mathbb{E}_{\tilde{h}_i \sim E \setminus \{h\}} \log\Pr(0|\tilde{h}_i,r,t) \\ \qquad \qquad \uparrow \qquad \qquad \uparrow \qquad \qquad \uparrow \qquad \qquad \\ \text{Positive samples} \qquad \qquad \qquad \qquad \text{Negative samples}$$

Experiment

Method	WN11	FB13	Avg
Task-specific models			
NTN (Socher et al., 2013)	86.2	90.0	88.1
TransE (Bordes et al., 2013)	75.9	81.5	78.7
TransH (Wang et al., 2014)	78.8	83.3	81.1
TransR (Lin et al., 2015)	85.9	82.5	84.2
TransD (Ji et al., 2015)	86.4	89.1	87.8
TEKE (Wang and Li, 2016)	86.1	84.2	85.2
TransG (Xiao et al., 2016)	87.4	87.3	87.4
TranSparse-S (Ji et al., 2016)	86.4	88.2	87.3
DistMult (Yang et al., 2015)	87.1	86.2	86.7
DistMult-HRS (Zhang et al., 2020a)	88.9	89.0	89.0
AATE (An et al., 2018)	88.0	87.2	87.6
ConvKB (Nguyen et al., 2018)	87.6	88.8	88.2
DOLORES (Wang et al., 2020b)	87.5	89.3	88.4
General models			
KG-BERT (Yao et al., 2019)	93.5	90.4	91.9
PALT _{BASE} (ours)	93.3	91.3	92.3
PALT _{LARGE} (ours)	93.8	91.7	92.8

Triplet Classification

Number of Parameters



PALT achieves better performance than finetuning with only 1% tunable parameters

Ablation Study

Method	WN11
PALT _{BASE}	93.3
w/o Prompt	91.7
w/o Calibration _{middle}	92.2
w/o Calibration _{last}	93.0
w/o Calibration _{both}	89.3
w/o Encoder	73.7
Finetuning	93.2

All components have a positive effect

Conclusion

- We propose parameter-lite transfer (PALT) for knowledge graph completion
 - Task formulation is important to use knowledge in language models
 - Novel prompt encoders and calibration encoders which can be used for other models
- PALT achieves state-of-the-art performance
- It should be useful for broad knowledge-intensive NLP applications
- Knowledge graph completion is a knowledge benchmark for language models

Thank you for your time!

Code: https://github.com/yuanyehome/PALT

