

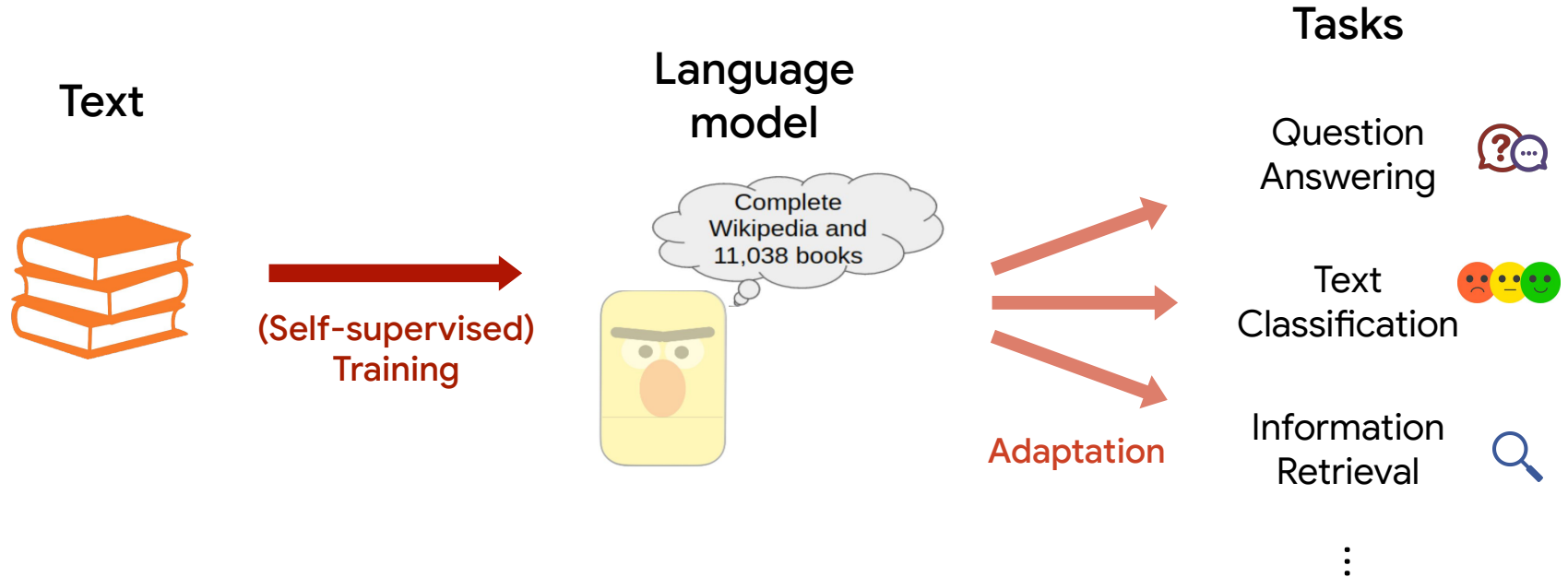
DRAGON: Deep Bidirectional Language-Knowledge Pretraining

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Foundation Model Pretraining



Text & KG offer complementary information

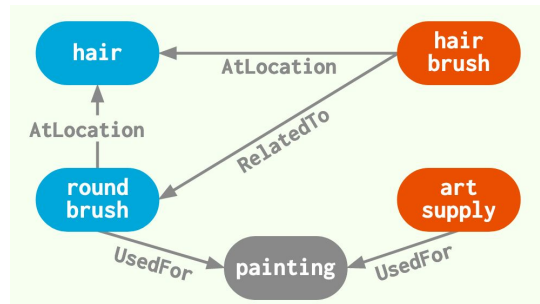
Text & Pretrained Language Model (LM)

- Broad coverage (e.g. [Gao+2020](#))
- Captures rich context



Knowledge Graph (KG)

- Latent, structured relations
- Multihop reasoning (e.g. [Yasunaga+2021](#))



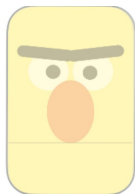
Goal: Combine text & KG for pretraining

Text

- Broad coverage (e.g. [Gao+2020](#))
- Captures rich context



WIKIPEDIA



Complete
Wikipedia and
11,038 books

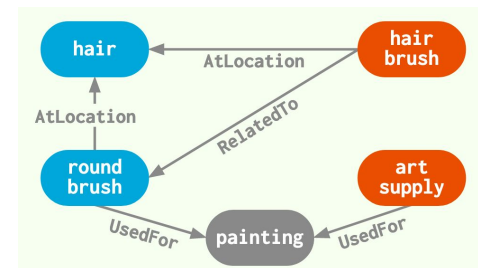
Joint Pretraining



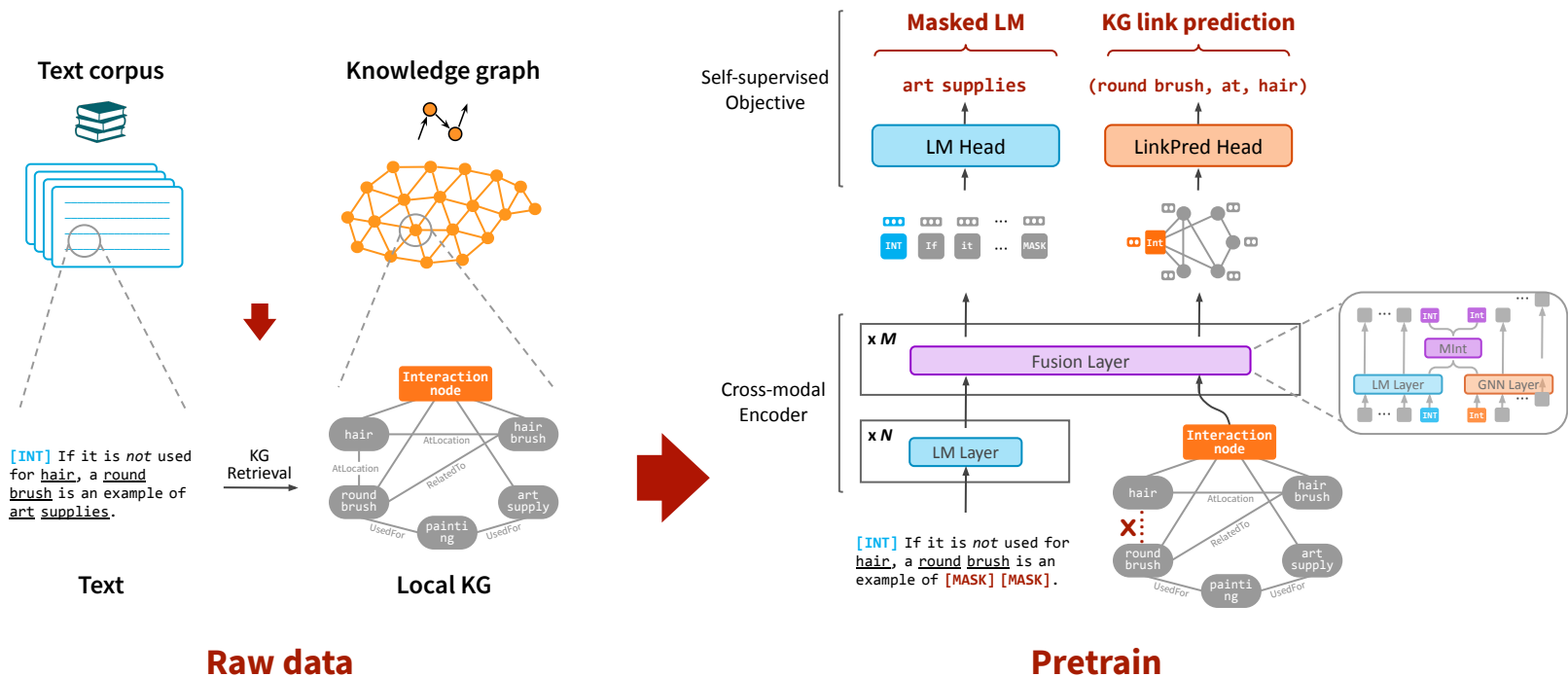
Language-Knowledge Foundation Model

Knowledge Graph (KG)

- Latent, structured relations
- Multihop reasoning
(e.g. [Yasunaga+2021](#))

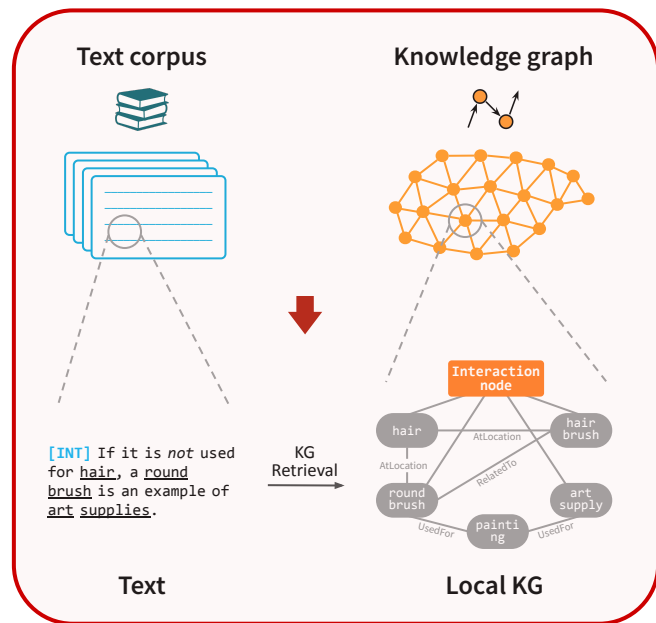


Proposed Method: DRAGON

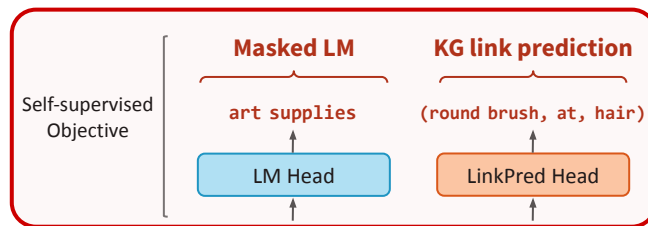


Proposed Method: DRAGON

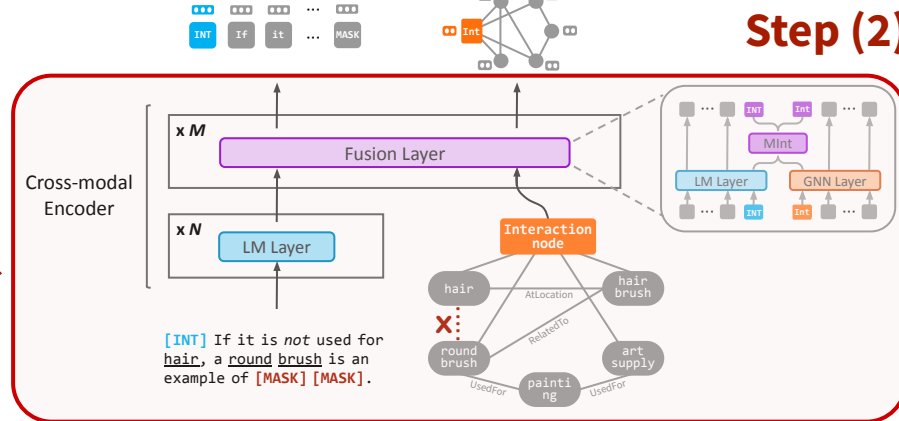
Step (1)



Raw data



Step (3)



Step (2)

Pretrain

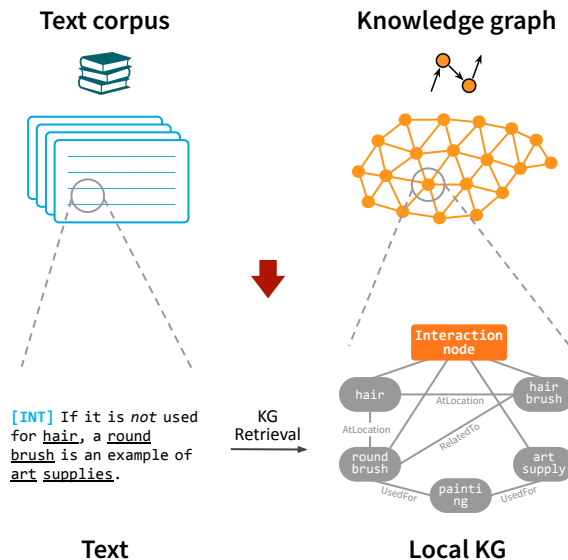
(1) Text-KG Input

Motivation

- Informative pair of (text, local KG):
Text can contextualize the KG
KG can ground the text

Idea

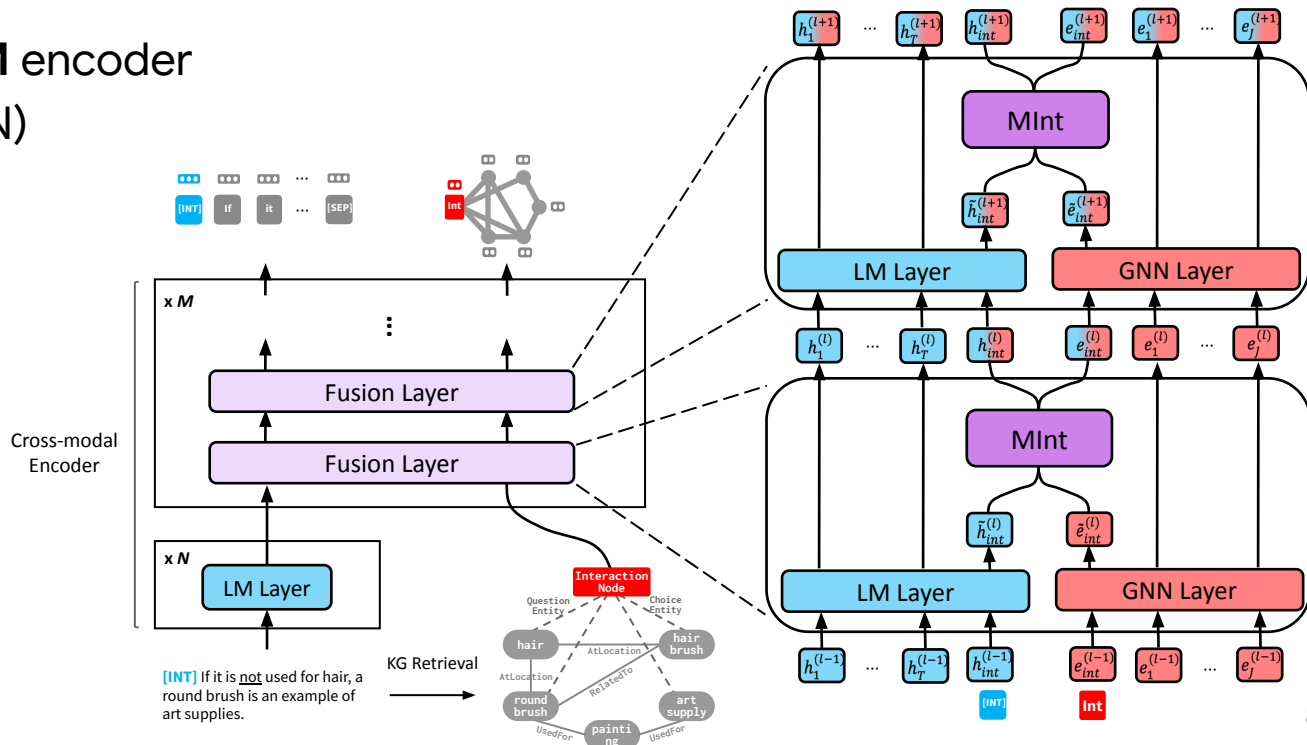
- Given text corpus and KG, sample a text segment and retrieve a relevant knowledge subgraph by entity linking
⇒ **Aligned pairs of (text, local KG)**



(2) Deep Bidirectional Cross-Modal Model

Idea

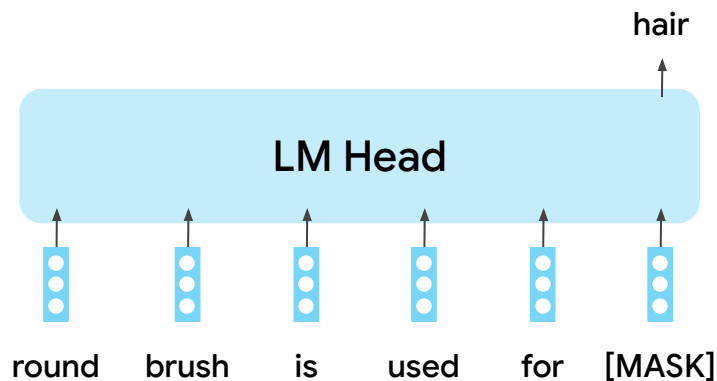
- Use the **GreaseLM** encoder (Transformer+GNN)
- Fuse text tokens & KG nodes bidirectionally for multiple layers



(3) Bidirectional Self-Supervision

Idea: Pretrain with two self-supervised reasoning tasks

Masked LM

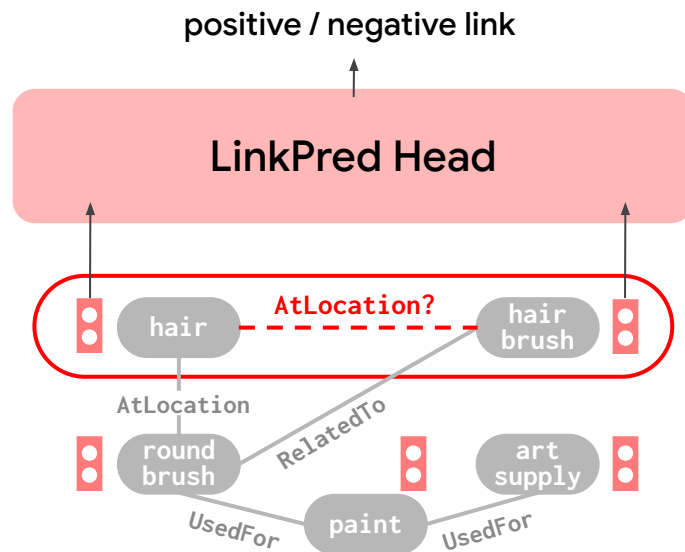


Joint training

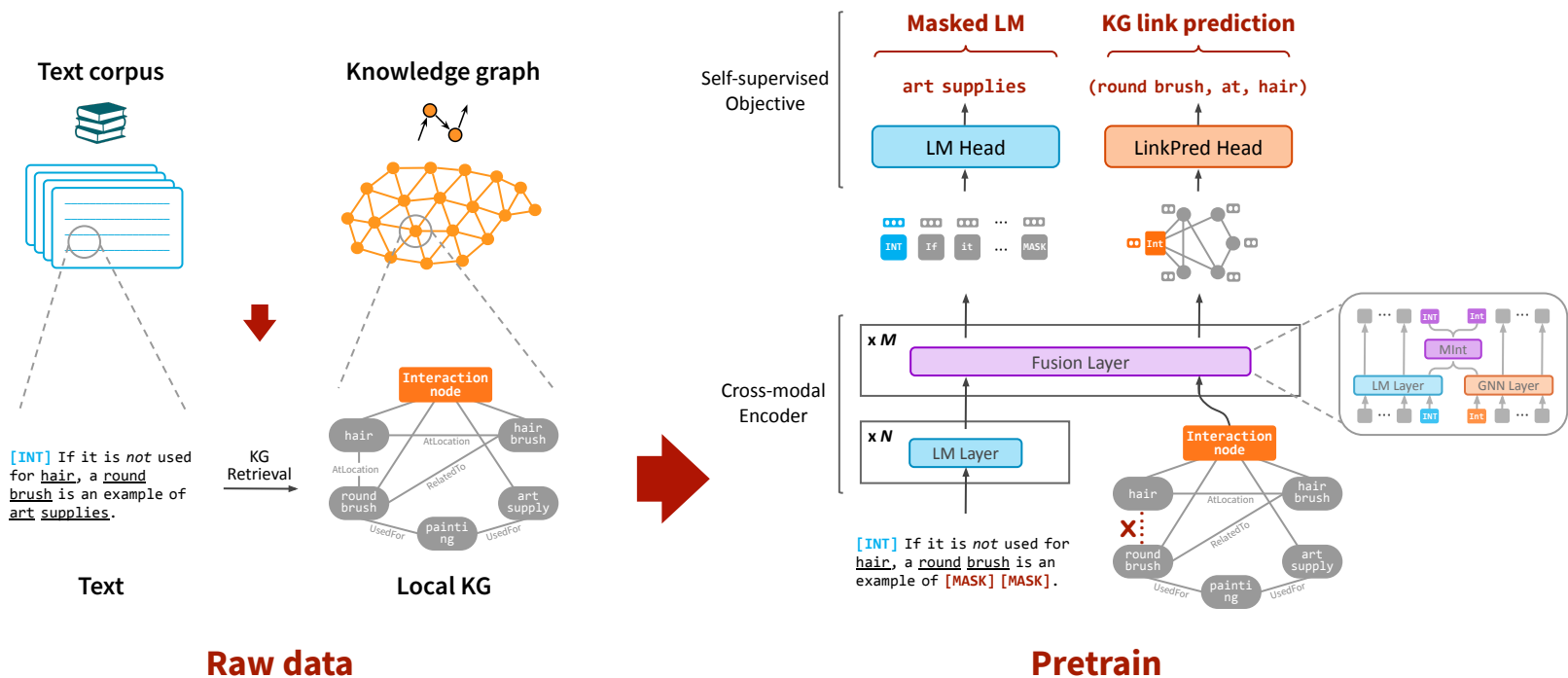


**Text & KG
mutually inform
each other**

KG Link Prediction



Proposed Method: DRAGON



Experiments

	General domain	Biomedical domain
Pretraining data	Text: BookCorpus (6GB) KG: ConceptNet (800K nodes, 2M edges)	Text: PubMed (20GB) KG: UMLS (300K nodes, 1M edges)
Downstream tasks	Commonsense reasoning (OBQA , RiddleSense , CommonsenseQA , CosmosQA , HellaSwag , PIQA , SIQA , aNLI , ARC)	Biomedical reasoning (PubMedQA , BioASQ , MedQA-USMLE)
Baseline: LM	RoBERTa (Liu+2019)	BioLinkBERT (Yasunaga+2022)
Baseline: LM finetuned with KG	RoBERTa + GreaseLM	BioLinkBERT + GreaseLM

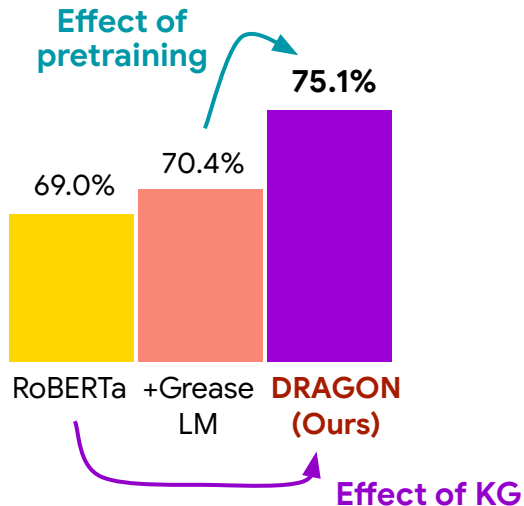
Ours (DRAGON): LM pretrained with KG

Performance

DRAGON makes consistent improvement across tasks and domains

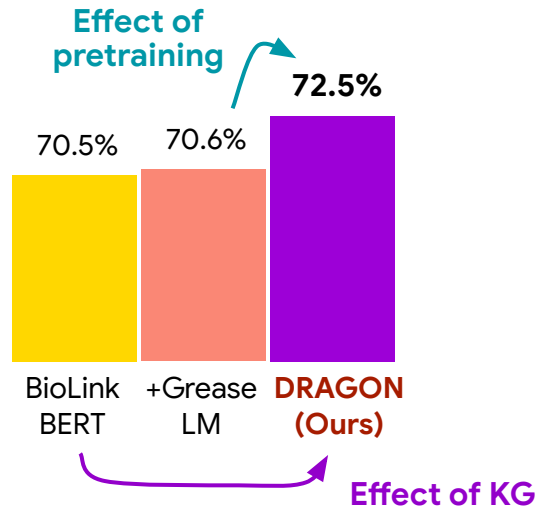
Commonsense reasoning tasks

(e.g. OBQA, RiddleSense)



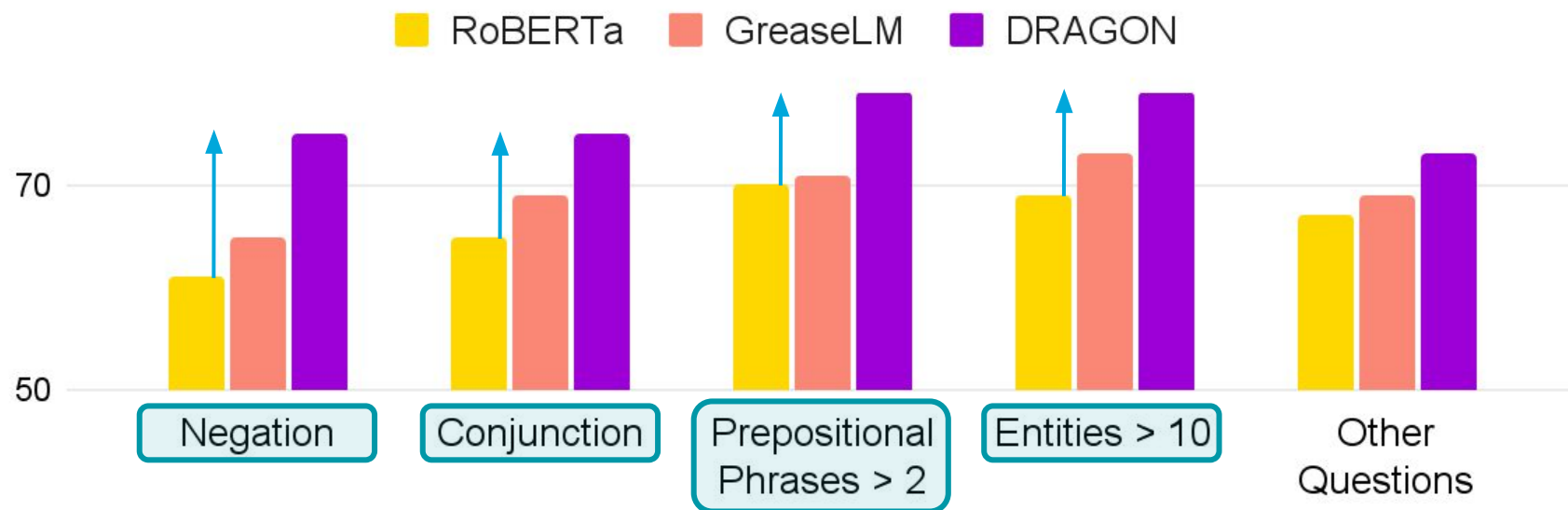
Biomedical reasoning tasks

(e.g. PubMedQA, MedQA)



Benefit 1: Complex Reasoning

Large gains on QA examples involving complex reasoning

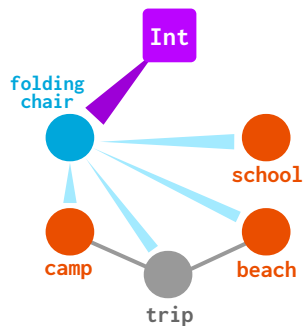


Benefit 1: Complex Reasoning

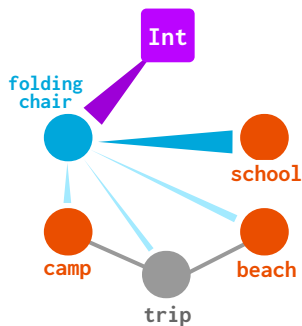
Conjunction

Where would you use a **folding chair** and store one?

A. camp **B. school** C. beach



DRAGON
GNN 1st Layer



DRAGON
GNN Final Layer

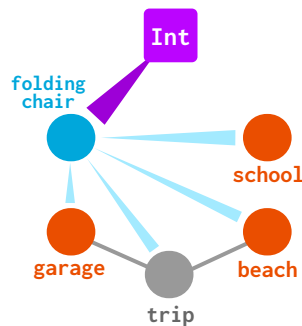
RoBERTa:
A. camp (✗)
GreaseLM:
C. camp (✗)
DRAGON:
B. school (✓)

Model
Prediction

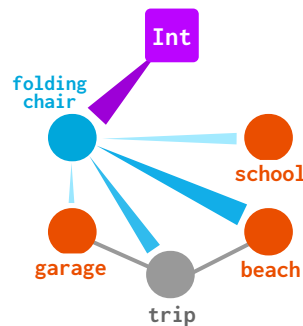
Negation + Conjunction

Where would you use a **folding chair** but not store one?

A. garage B. school **C. beach**



DRAGON
GNN 1st Layer



DRAGON
GNN Final Layer

RoBERTa:
B. school (✗)
GreaseLM:
B. school (✗)
DRAGON:
C. beach (✓)

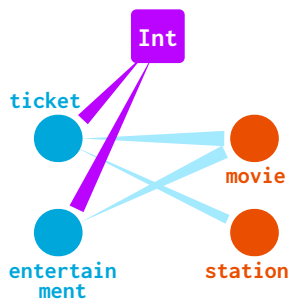
Model
Prediction

In DRAGON, KG serves as **scaffold** for performing **structured reasoning**

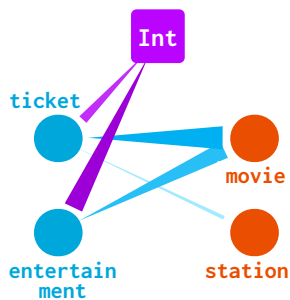
Benefit 1: Complex Reasoning

Single context

You will buy a **ticket** for entering what building for **entertainment**?
A. **station** B. **movie theater**



DRAGON
GNN **1st** Layer



DRAGON
GNN **Final** Layer

RoBERTa:
B. movie theater (✓)

GreaseLM:
B. movie theater (✓)

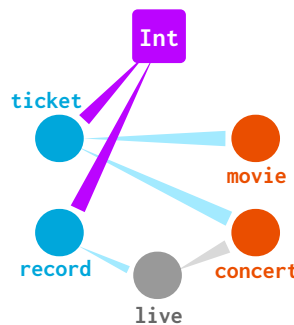
DRAGON:
B. movie theater
(✓)

Model
Prediction

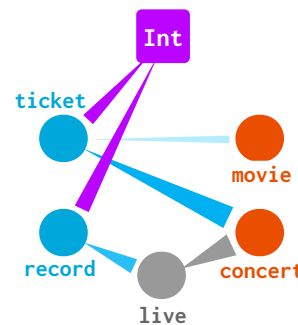


Multi context (extra reasoning step)

You don't enjoy watching **pre-recorded** performance. You will
buy a **ticket** for entering what building for **entertainment**?
A. **station** B. **movie theater** C. **concert hall**



DRAGON
GNN **1st** Layer



DRAGON
GNN **Final** Layer

RoBERTa:
B. movie theater (✗)

GreaseLM:
B. movie theater (✗)

DRAGON:
C. concert hall
(✓)

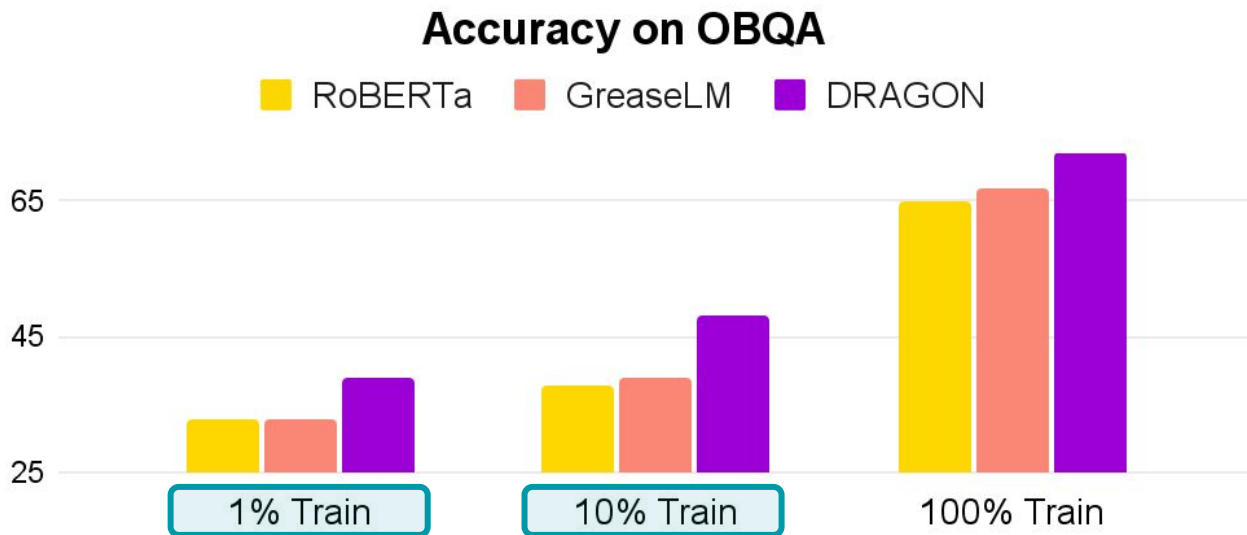
Model
Prediction

Pretraining with KG helps **extrapolate** to harder test examples that need **multi-step reasoning**.

Benefit 2: Low-Resource QA

Large gains on few-shot and low-resource QA

⇒ Intuition: self-supervision helps learn more knowledge

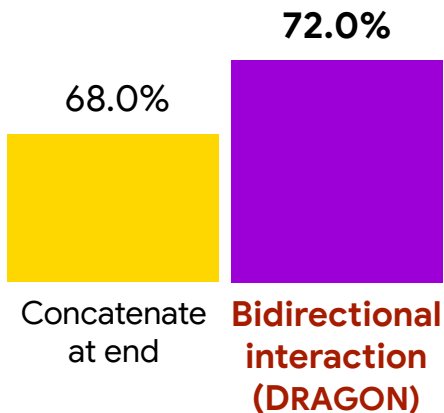


Key Design Choices: Modeling

Cross-modal fusion for text+KG

- Bidirectional interaction (DRAGON)
- Concatenate representations at end

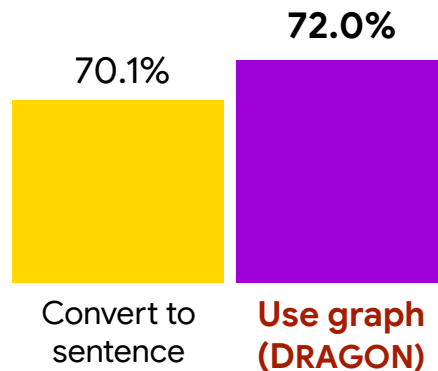
Accuracy on OBQA



KG structure

- Use graph and GNN (DRAGON)
- Convert to sentence and add to text

Accuracy on OBQA



Key Design Choices: Self-Supervision

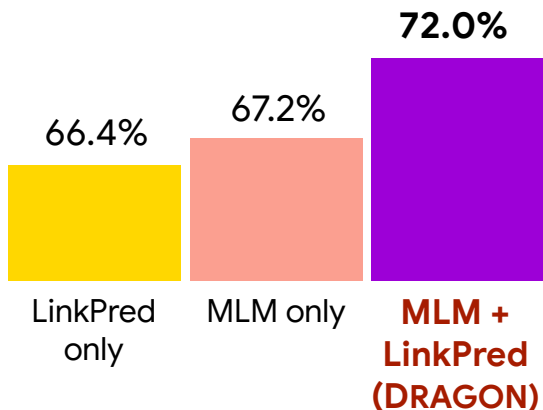
Pretraining objective

- Joint MLM + LinkPred (DRAGON)
- MLM only
- LinkPred only

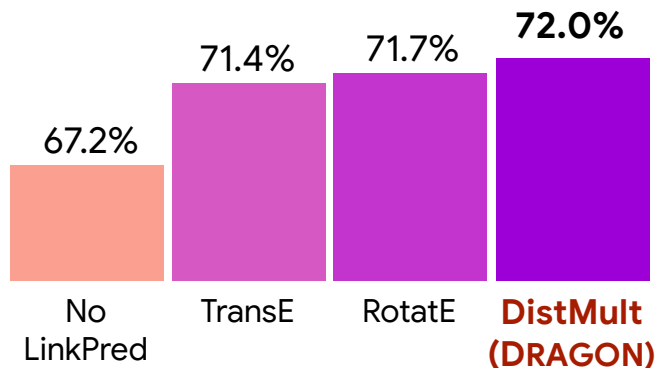
LinkPred head

- [DistMult](#) (Final DRAGON)
 - [TransE](#)
 - [RotatE](#)
- ⇒ All help

Accuracy on OBQA



Accuracy on OBQA



Summary

DRAGON: Pretrain a foundation model jointly on text & KG

Approach

- Deeply bidirectional model for the two modalities to interact
- Self-supervised objective to learn joint reasoning over text and KG at scale

Result

- Improved performance on knowledge- and reasoning-intensive applications (e.g. low-resource QA, multi-step reasoning)

Thanks!



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Paper: Deep Bidirectional Language-Knowledge Graph Pretraining. NeurIPS 2022.

Code: <https://github.com/michiyasunaga/DRAGON>

