Connecting the Dots:
A Knowledgeable Path Generator for Commonsense Question Answering

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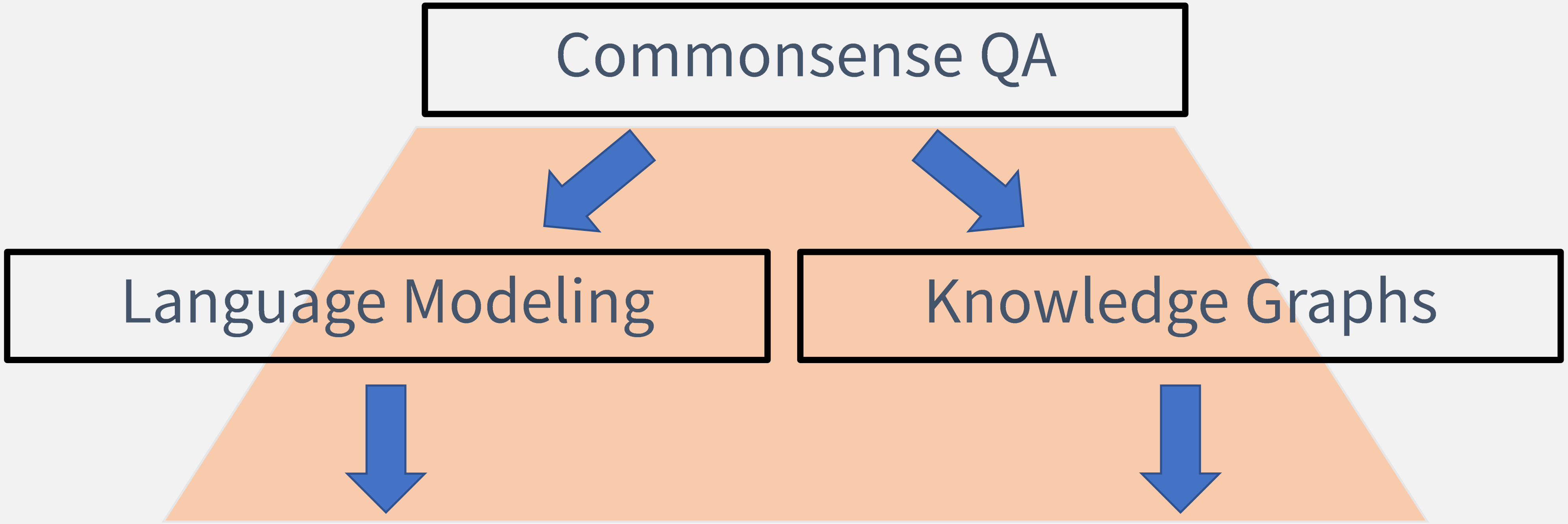
01 Problem Statement

How can we empower the Knowledge Graphs(KG) for Commonsense QA?

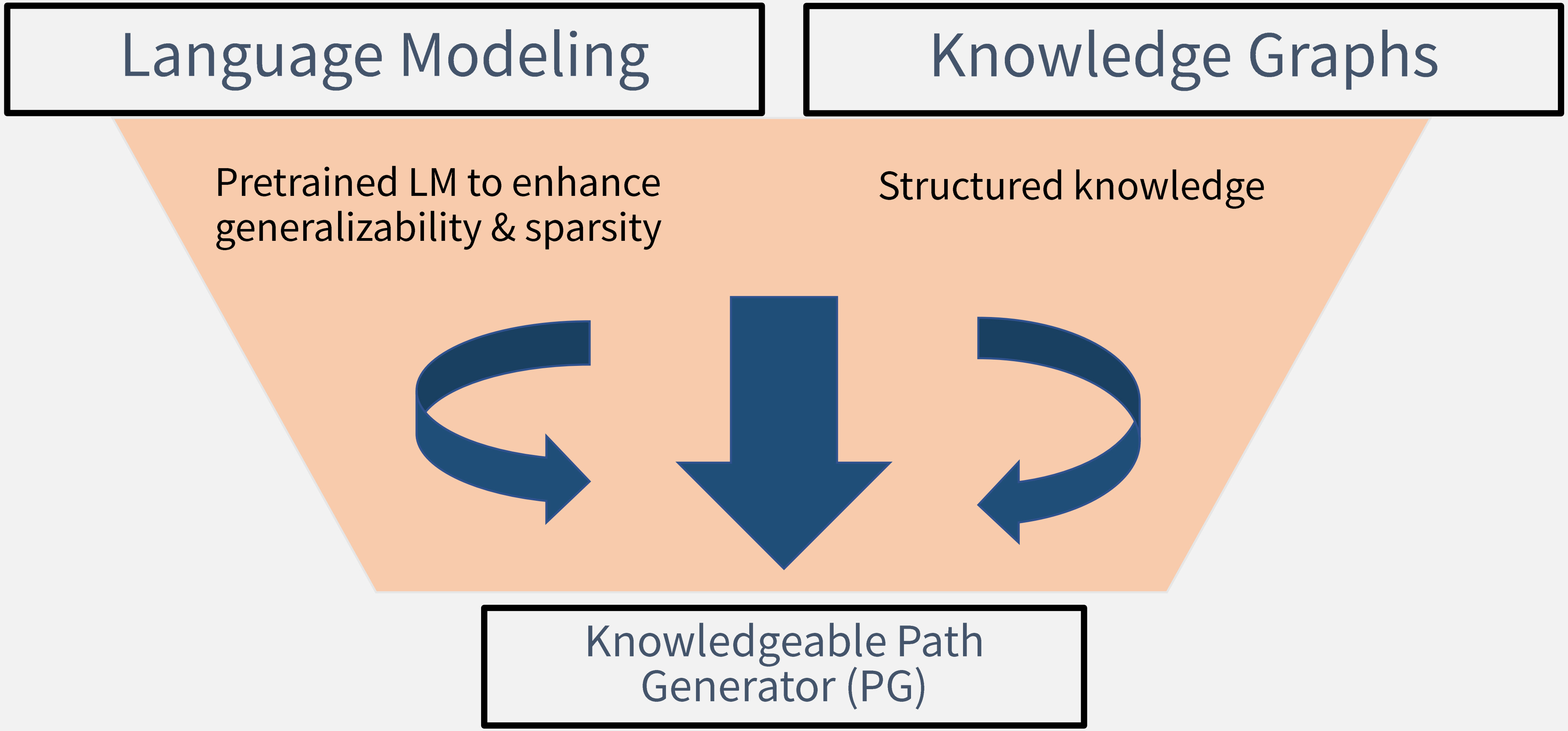
Motivation



- Commonsense reasoning vs Spurious correlation
- Uninterpretable

- Sparsity Problem
- Contextualization Problem

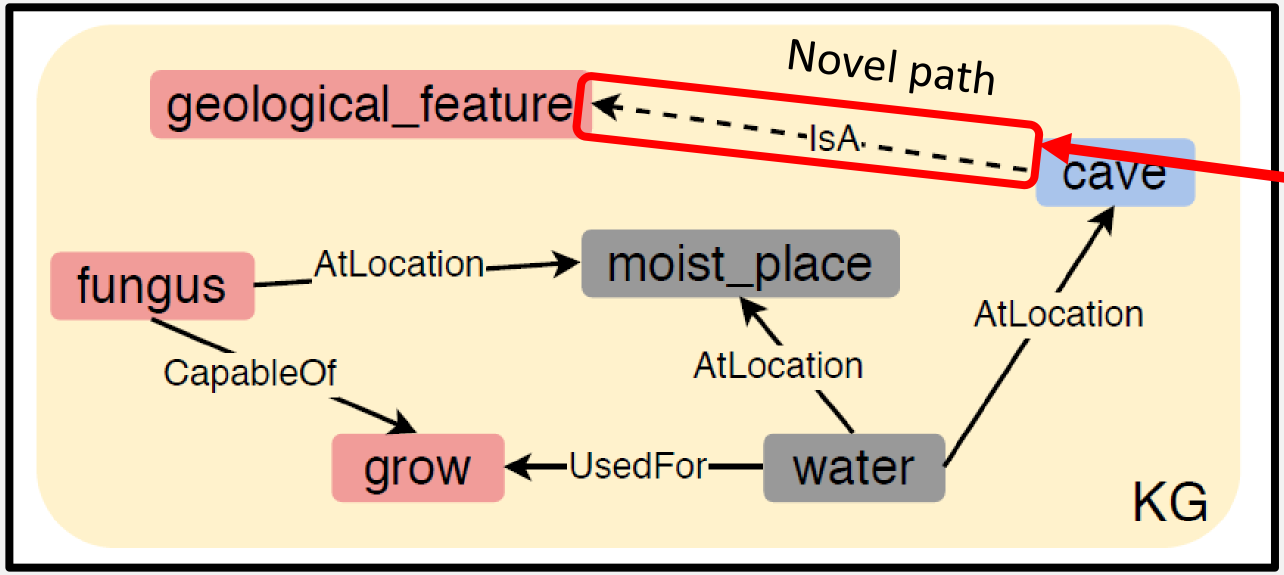
02 Motivation



02 Motivation

Q: In what geological feature will you find fungus growing?

A: shower stall B: toenails C: basement D: forest E: cave



Knowledgeable Path Generator (PG)

03 Contribution

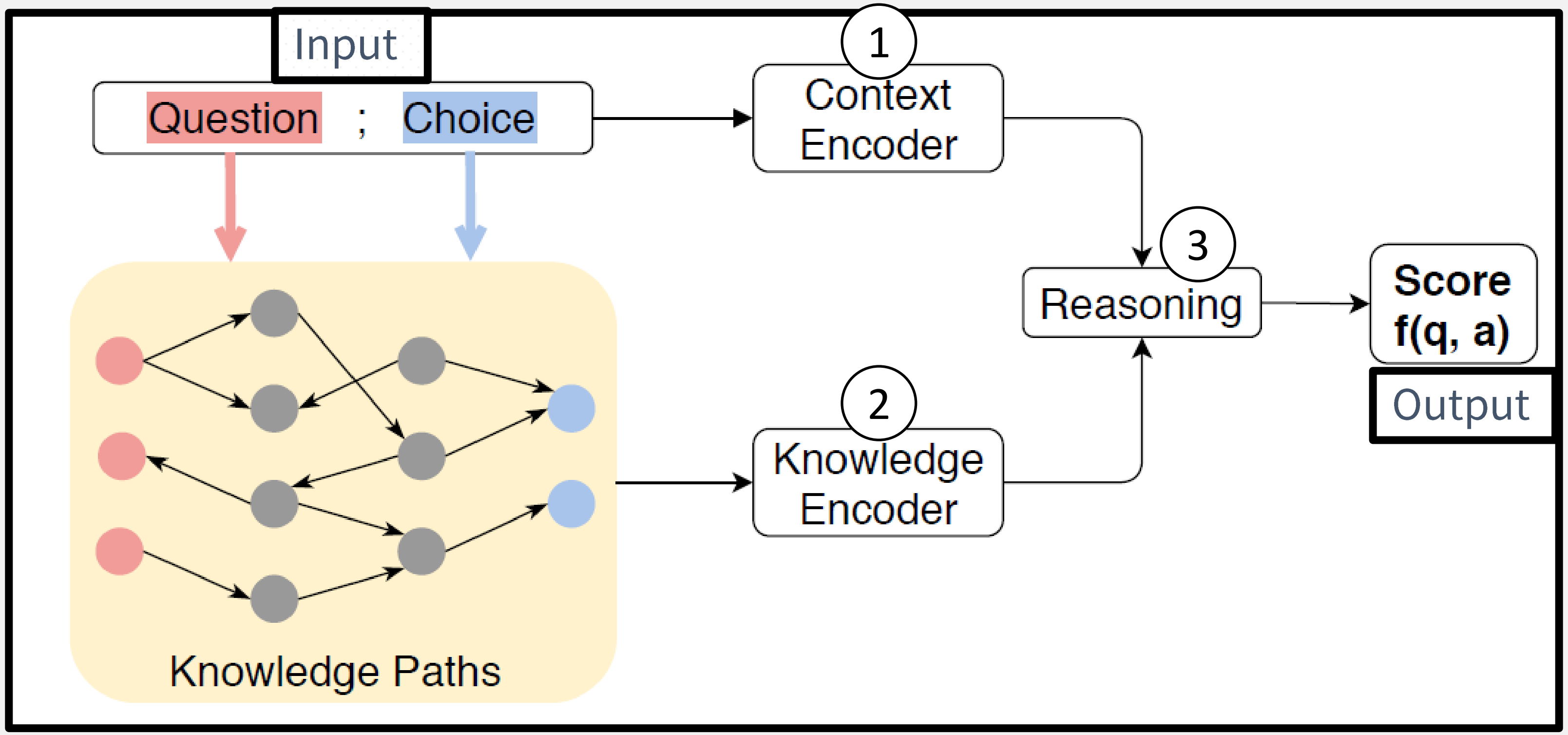
1) Proposes a method to generate task-relevant knowledge paths that may not **exist** in the original KG

2) Design and implement a QA framework with the **Knowledgeable Path Generator(PG)**

3) Demonstrates **effectiveness** of the method by extensive experiments on **two benchmark datasets** (CQA & OBQA)

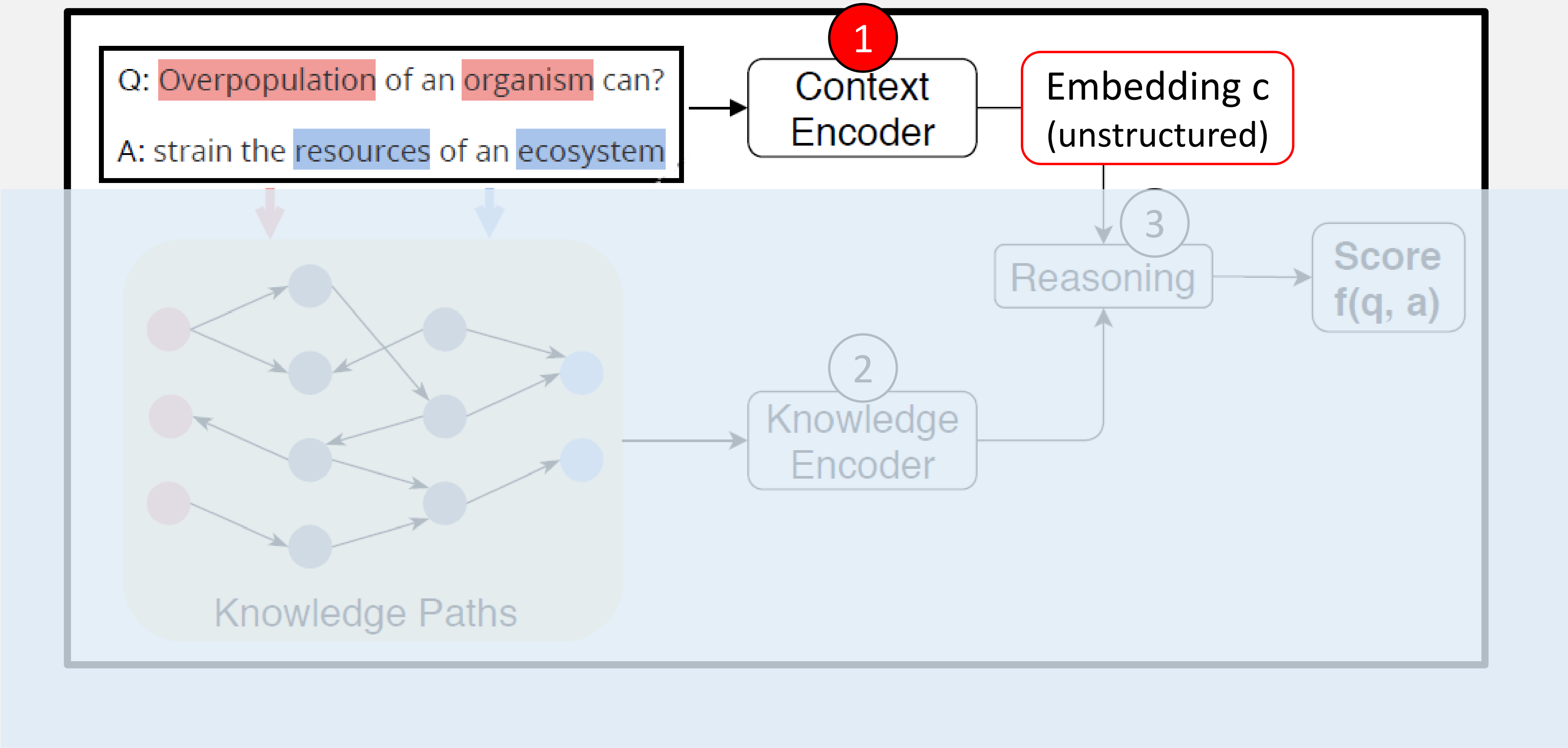
04 Model

KG-augmented QA Framework



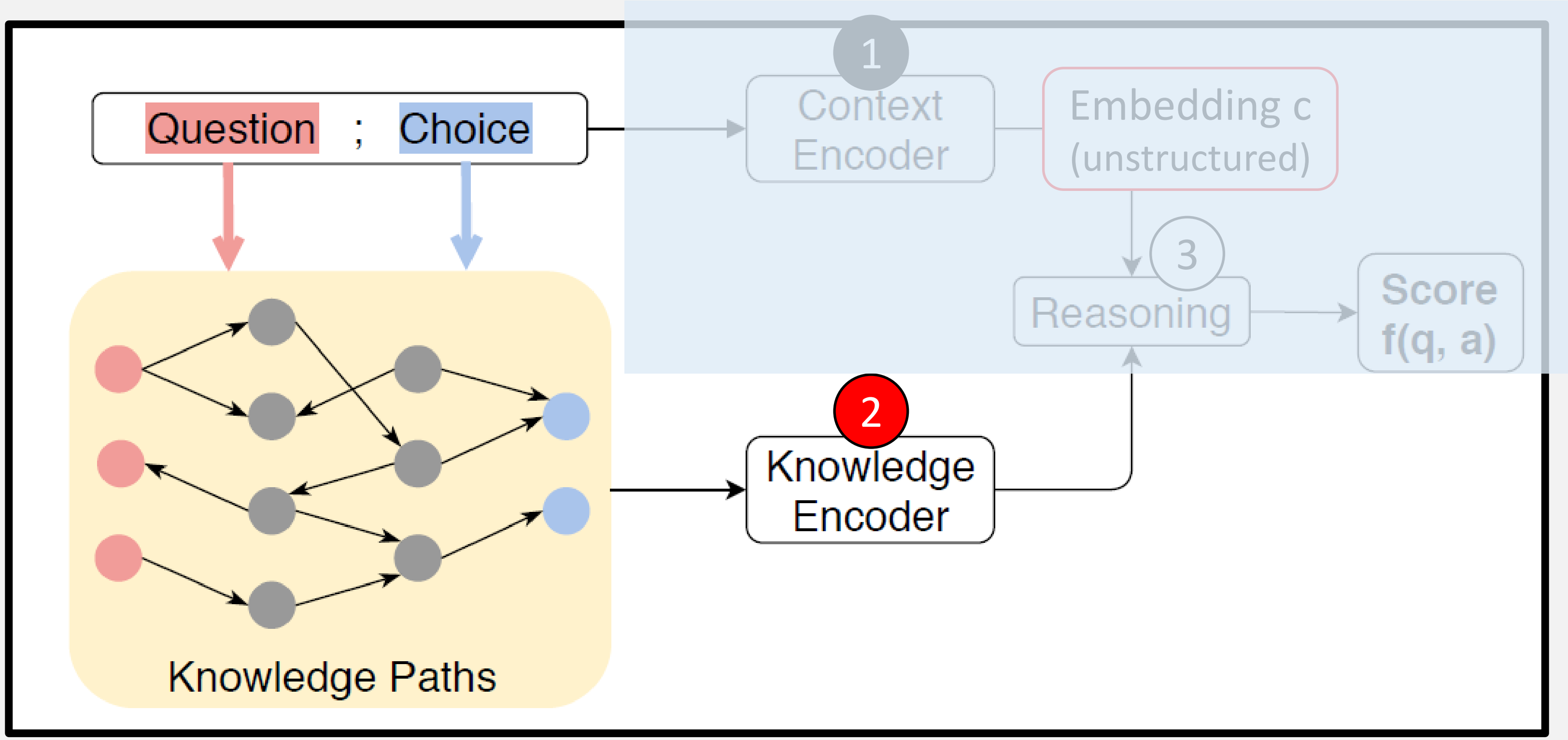
04 Model

KG-augmented QA Framework: Context Module

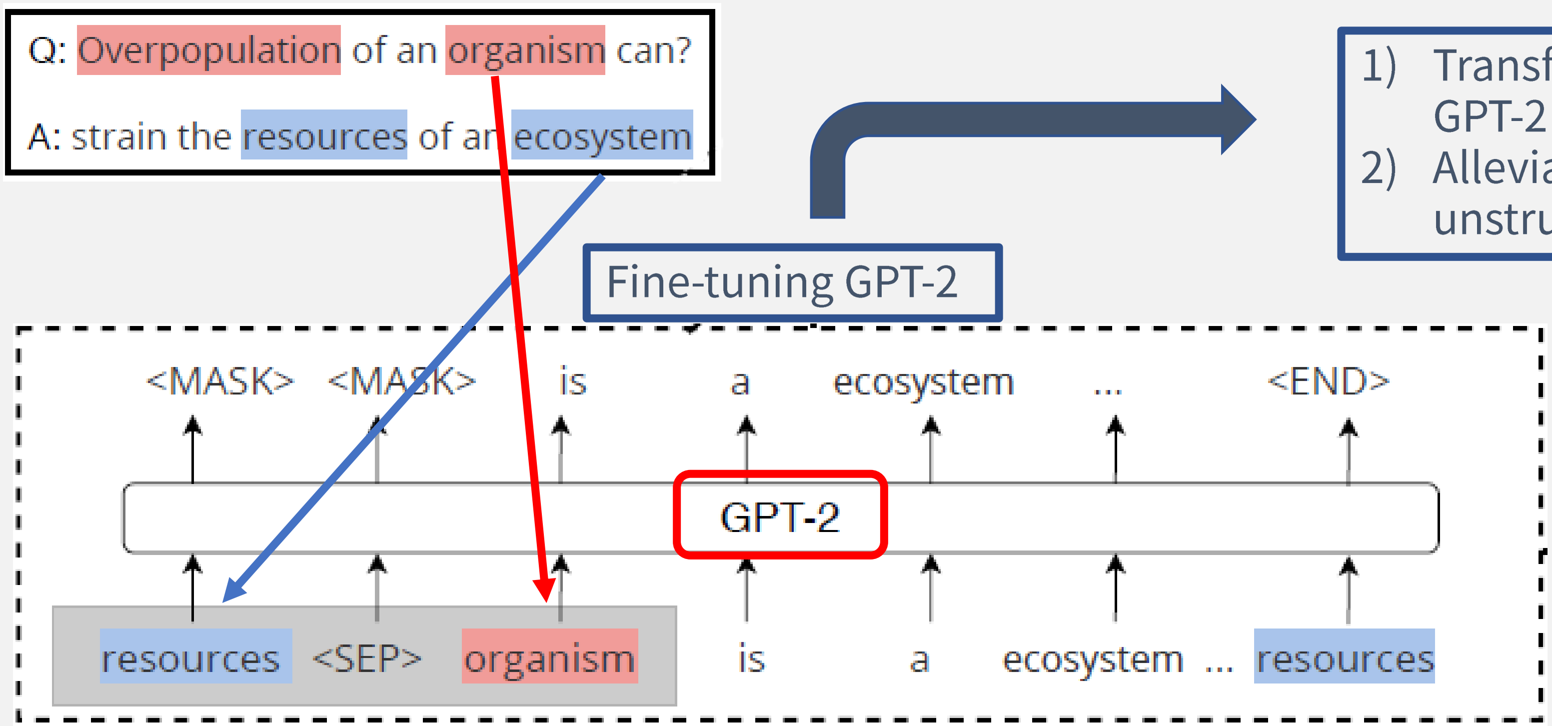


04 Model

KG-augmented QA Framework: Knowledge Module

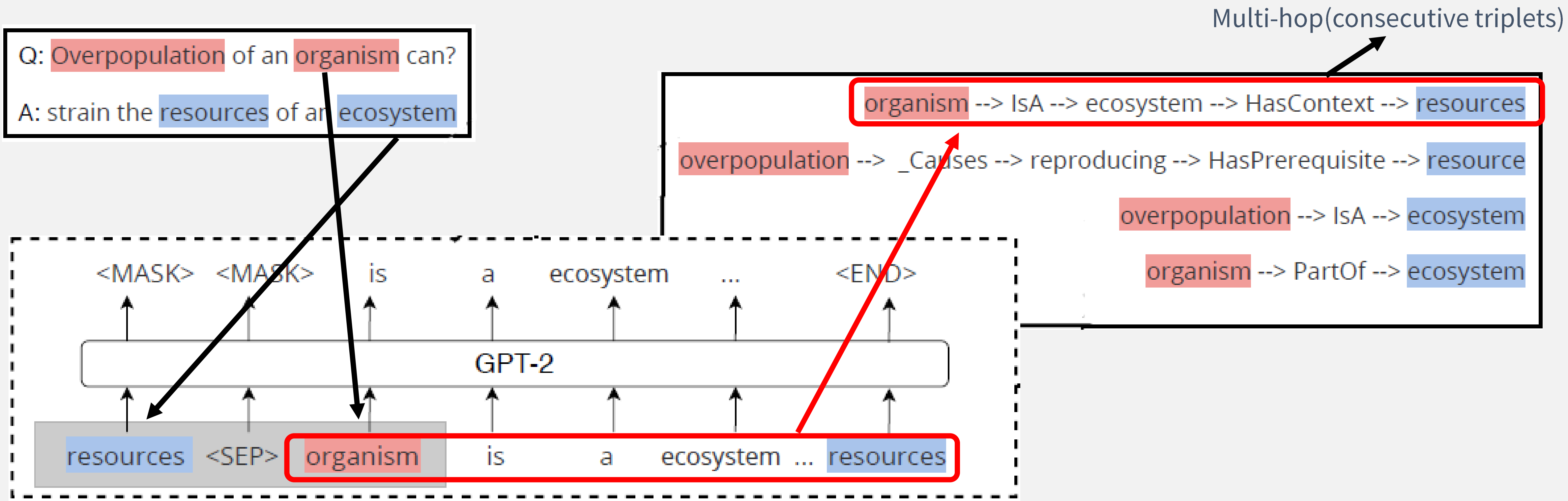


KG-augmented QA Framework: Knowledge Module – Path Generator



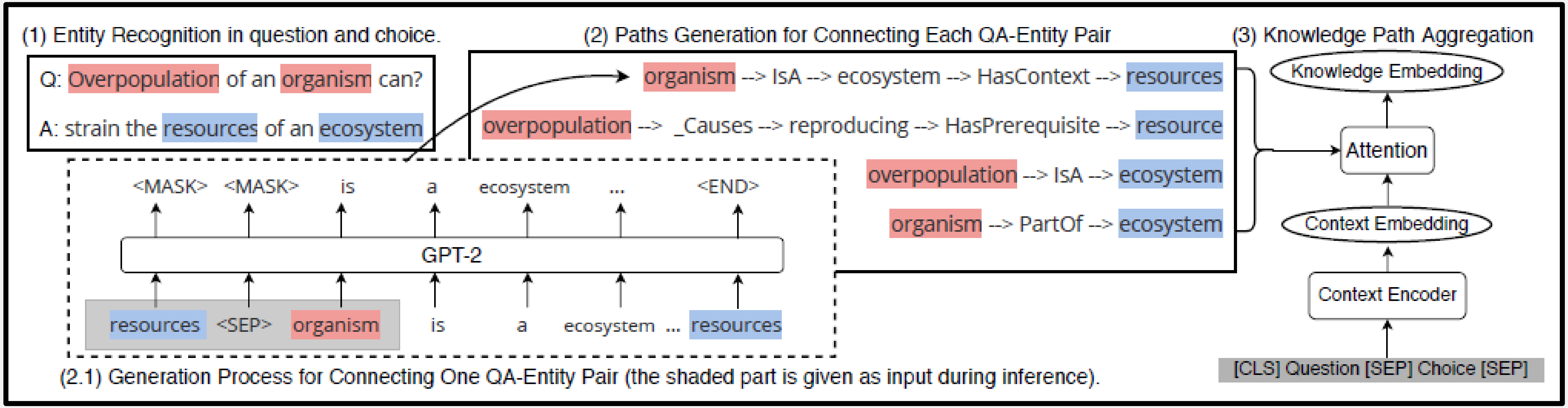
1) Transfer knowledge of pre-trained GPT-2 to PG
2) Alleviate sparsity problem with unstructured knowledge in GPT-2

KG-augmented QA Framework: Knowledge Module – Path Generator

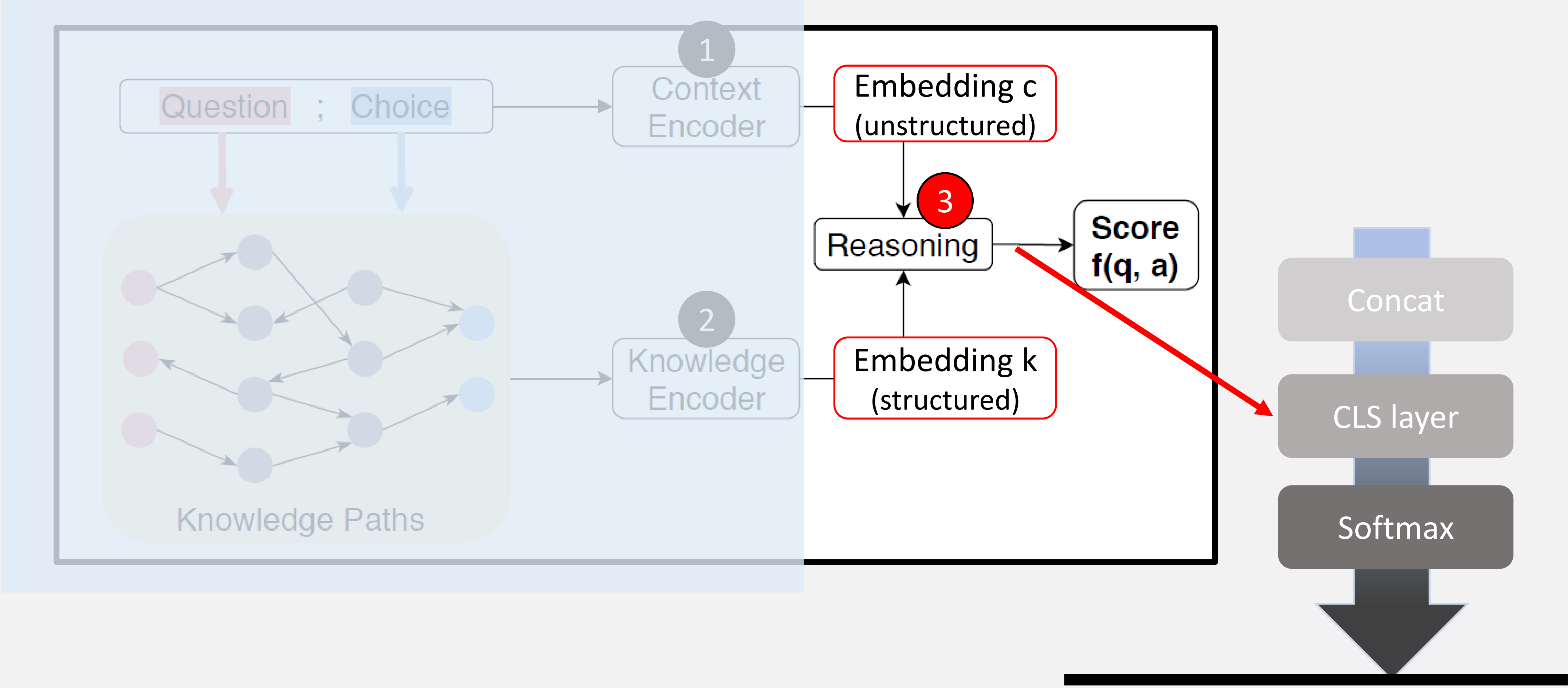


04 Model

KG-augmented QA Framework: Knowledge Module



KG-augmented QA Framework: Reasoning Module



05 Datasets / Code / Settings

[Dataset]

Commonsense QA [Test set unavailable]

https://www.tau-nlp.org/commonsenseqa

Openbook QA

https://leaderboard.allenai.org/open_book_qa/submissions/public

[Code]

https://github.com/wangpf3/Commonsense-Path-Generator

05 Datasets / Code / Settings

[Entity Recognition]

– Conceptnet(Speer et al., 2017)

[Path Sampling]

- Hops: 1~3
- Global Sampling: 2.8 mil paths
- Local Sampling: 133k paths(CQA)
  105k paths(OBQA)
- Split: 90:5:5 (train/dev/test)

[Path Generator Training]

– Fine-tune GPT-2
- LR: 1e-5
- Batch size: 64
- Early Stopping : 2 epochs of consecutive loss

(Context Module Settings in Appendix)

06

Baselines

Fine-tuned LM (w/o KG)

Static KG Models

1) Relational Network (RN)
2) Relational Graph Convolutional Network (RGCN)
3) GconAttn

Link Prediction Model – 1 hop path embedding

07 Experiments

OBQA Test Accuracy

Methods	RoBERTa-large	AristoRoBERTa
Fine-tuned LMs (w/o KG)	64.80 (±2.37)	78.40 (±1.64)
+ RN	65.20 (±1.18)	75.35 (±1.39)
+ RGCN	62.45 (±1.57)	74.60 (±2.53)
+ GconAtten	64.75 (±1.48)	71.80 (±1.21)
+ Link Prediction	66.30 (±0.48)	77.25 (±1.11)
+ PG-Local	70.05 (±1.33)	79.80 (±1.45)
+ PG-Global	68.40 (±0.31)	**80.05** (±0.68)
+ PG-Full	**71.20** (±0.96)	79.15 (±0.78)

Commonsense QA Test Accuracy

Methods	Single	Ensemble
RoBERTa (Liu et al., 2019)	72.1	72.5
RoBERTa+FreeLB (Zhu et al., 2019)	-	73.1
RoBERTa+HyKAS (Ma et al., 2019)	73.2	-
XLNet+DREAM	73.3	-
RoBERTa+KE	-	73.3
RoBERTa+KEDGN	-	74.4
XLNet+GraphReason (Lv et al., 2019)	75.3	-
Albert (Lan et al., 2019)	-	76.5
UnifiedQA* (Khashabi et al., 2020)	79.1	-
Albert+PG-Full	75.6	78.2

07 Experiments

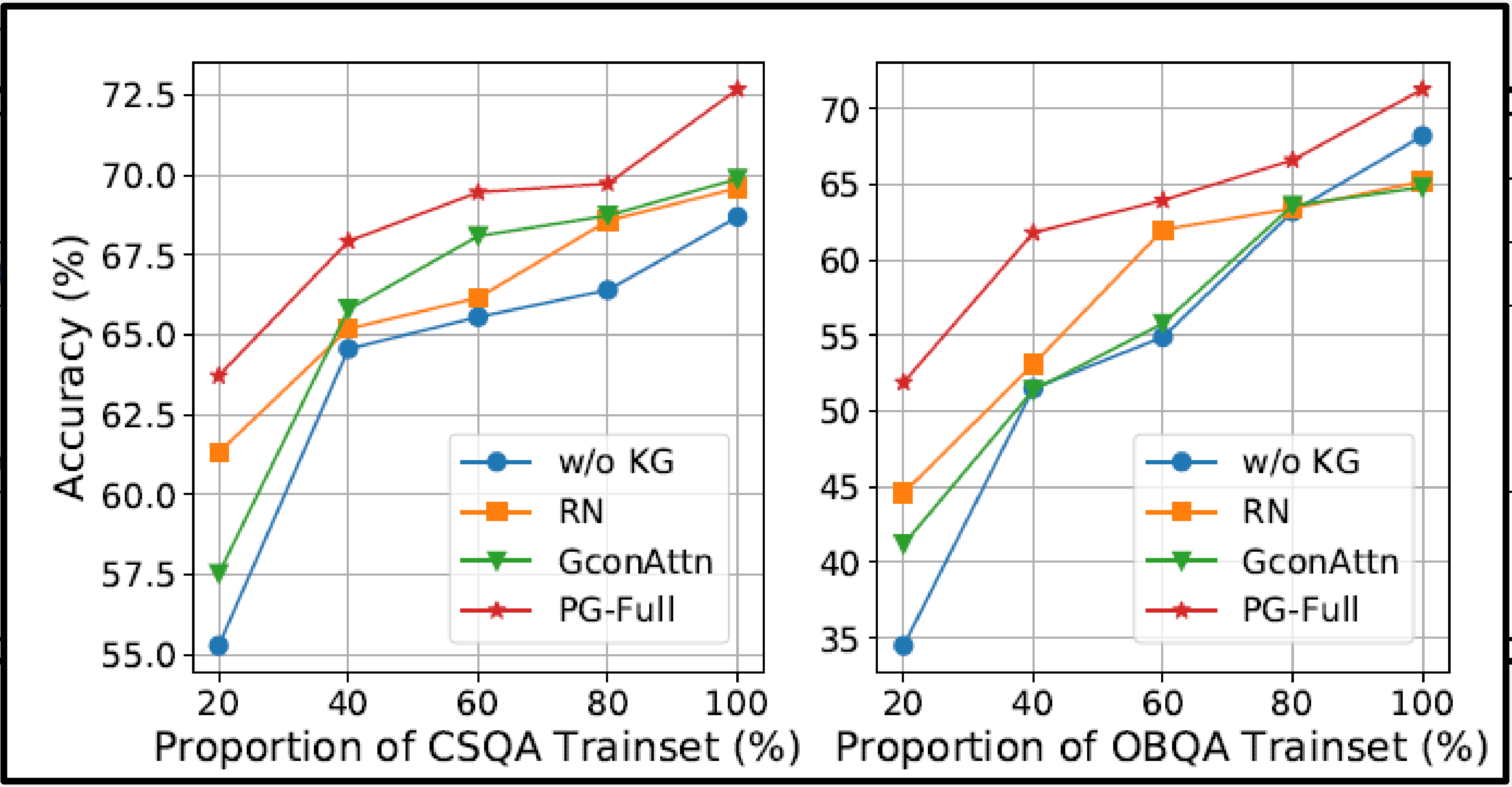
Commonsense QA Test Accuracy with varying proportion of train data

Methods	BERT-large			RoBERTa-large		
	20% Train	60% Train	100% Train	20% Train	60% Train	100% Train
Fine-tuned LM (w/o KG)	46.25 (±0.63)	52.30 (±0.16)	55.39 (±0.40)	55.28 (±0.35)	65.56 (±0.76)	68.69 (±0.56)
+ RN	45.12 (±0.69)	54.23 (±0.28)	58.92 (±0.14)	61.32 (±0.68)	66.16 (±0.28)	69.59 (±3.80)
+ RGCN	48.67 (±0.28)	54.71 (±0.37)	57.13 (±0.36)	58.58 (±0.17)	68.33 (±0.85)	68.41 (±0.66)
+ GconAttn	47.95 (±0.11)	54.96 (±0.69)	56.94 (±0.77)	57.53 (±0.31)	68.09 (±0.63)	69.88 (±0.47)
+ Link Prediction	47.10 (±0.79)	53.96 (±0.56)	56.02 (±0.55)	60.84 (±1.36)	66.29 (±0.29)	69.33 (±0.98)
+ PG-Local	50.20 (±0.31)	55.68 (±0.07)	56.81 (±0.73)	61.56 (±0.72)	67.77 (±0.83)	70.43 (±0.65)
+ PG-Global	49.89 (±1.03)	55.47 (±0.92)	57.21 (±0.45)	62.93 (±0.82)	68.65 (±0.02)	71.55 (±0.99)
+ PG-Full	**51.97** (±0.26)	**57.53** (±0.19)	**59.07** (±0.30)	**63.72** (±0.77)	**69.46** (±0.23)	**72.68** (±0.42)

07 Experiments

Common

Methods	100% Train
Fine-tuned LM (	68.69 (±0.56)
+ RN	69.59 (±3.80)
+ RGCN	68.41 (±0.66)
+ GconAttn	69.88 (±0.47)
+ Link Predictio	69.33 (±0.98)
+ PG-Local	70.43 (±0.65)
+ PG-Global	71.55 (±0.99)
+ PG-Full	**72.68** (±0.42)



Ablation Study

Methods	CQA	OBQA
Scratch (fine-tune X)	68.75	65.50
Full (fine-tune)	72.68	71.20

1) Scratch approximates what static KG already has

2) Pre-trained GPT-2 complements missing knowledge of a static KG

08 Limitation

Model	Affiliation	Date	Accuracy	Accuracy (*Uses ConceptNet)
Human		03/10/2019	88.9	
ALBERT+DESC-KCR (ensemble model)	Microsoft Cognitive Services Research	12/02/2020		83.3
Albert+KD (ensemble model)	HIT-SCIR-QA	12/30/2020		80.9
ALBERT+DESC-KCR (single model)	Microsoft Cognitive Services Research	12/02/2020		80.7
ALBERT+KD (single model)	HIT-SCIR-QA	12/10/2020		80.3
Albert + KCR(knowledge chosen by relations, single model)	ITNLP (Harbin Institute of Technology)	07/12/2020		79.5
UnifiedQA (single model)	Allen Institute for AI	04/23/2020	79.1	
Albert + KRD(single model)	SudaNLP	12/04/2020	78.4	
Albert + PathGenerator (ensemble model)	USC MOWGLI / INK Lab	05/14/2020		78.2
T5 (single model)	Allen Institute for AI	04/23/2020	78.1	
TeGBERT (single model)	anonymous	07/22/2020		76.8
ALBERT (ensemble model)	Zhiyan Technology	12/18/2019	76.5	

08 Conclusion

1) Addresses the **contextualization** and **sparsity** challenges of original KGs

2) Design and implement a QA framework with the **Knowledgeable Path Generator(PG)**

3) Demonstrates effectiveness of the method in its **robustness** to limited training data.

Q&A