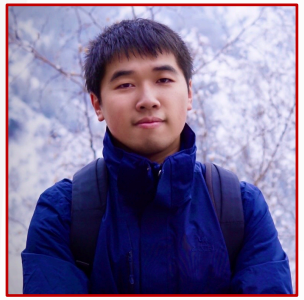
WSDM 2023 Tutorial

Incorporating Commonsense Knowledge into Neural NLP Models



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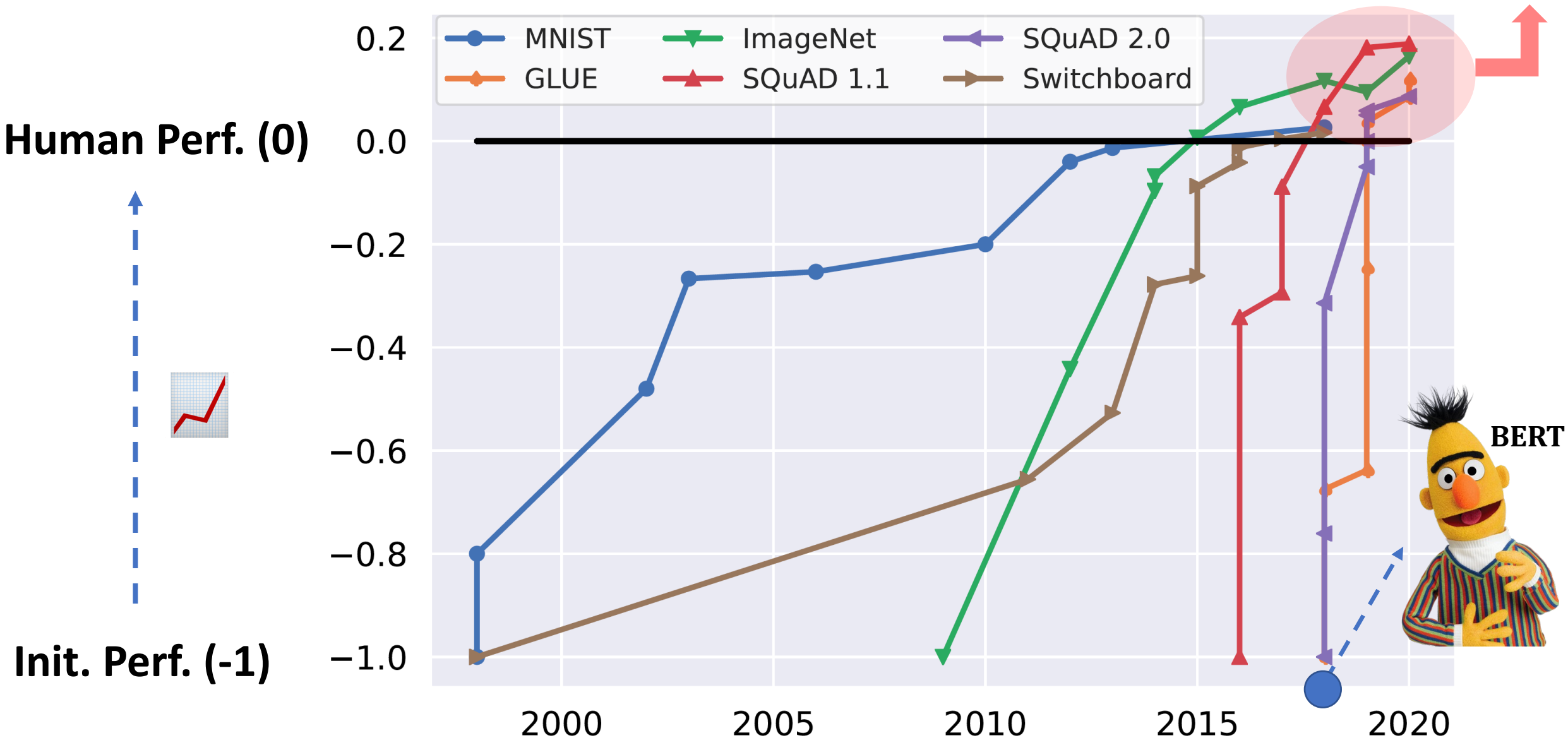
[1]University of Southern California, [2]Allen Institute for AI

Human-level AI?

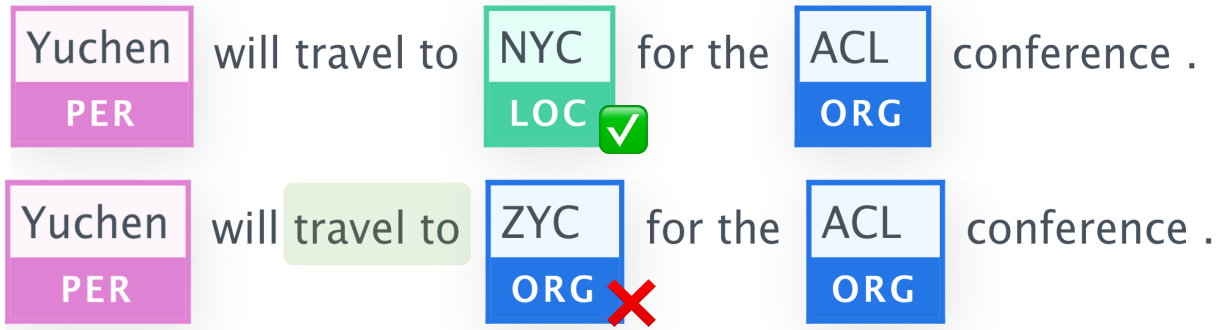


Initial baseline performance and human performance are normalized to **-1** and **0** respectively (Credit: Kiela et al., 2021).

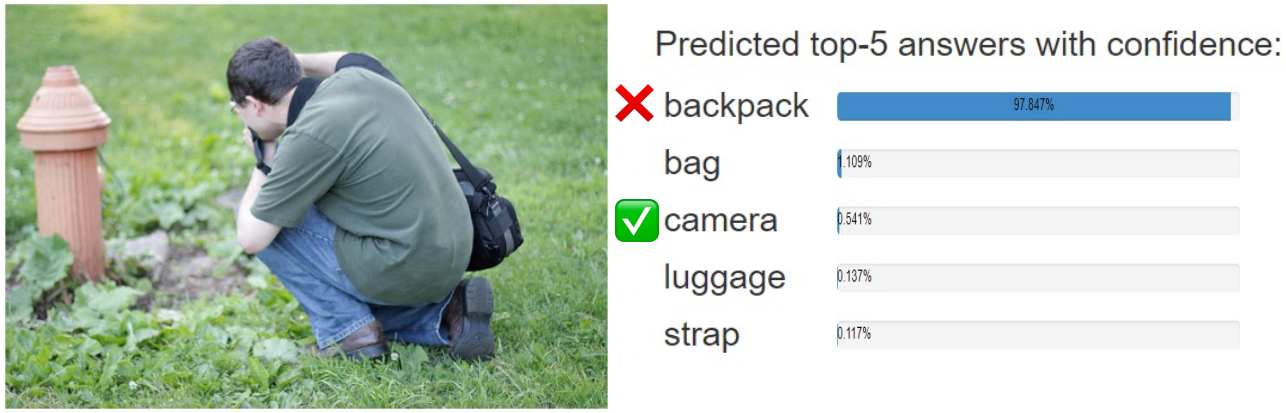
Modern NLP models still lack commonsense knowledge.

The/ **fruit flies**/ **like**/ a banana/. ✅

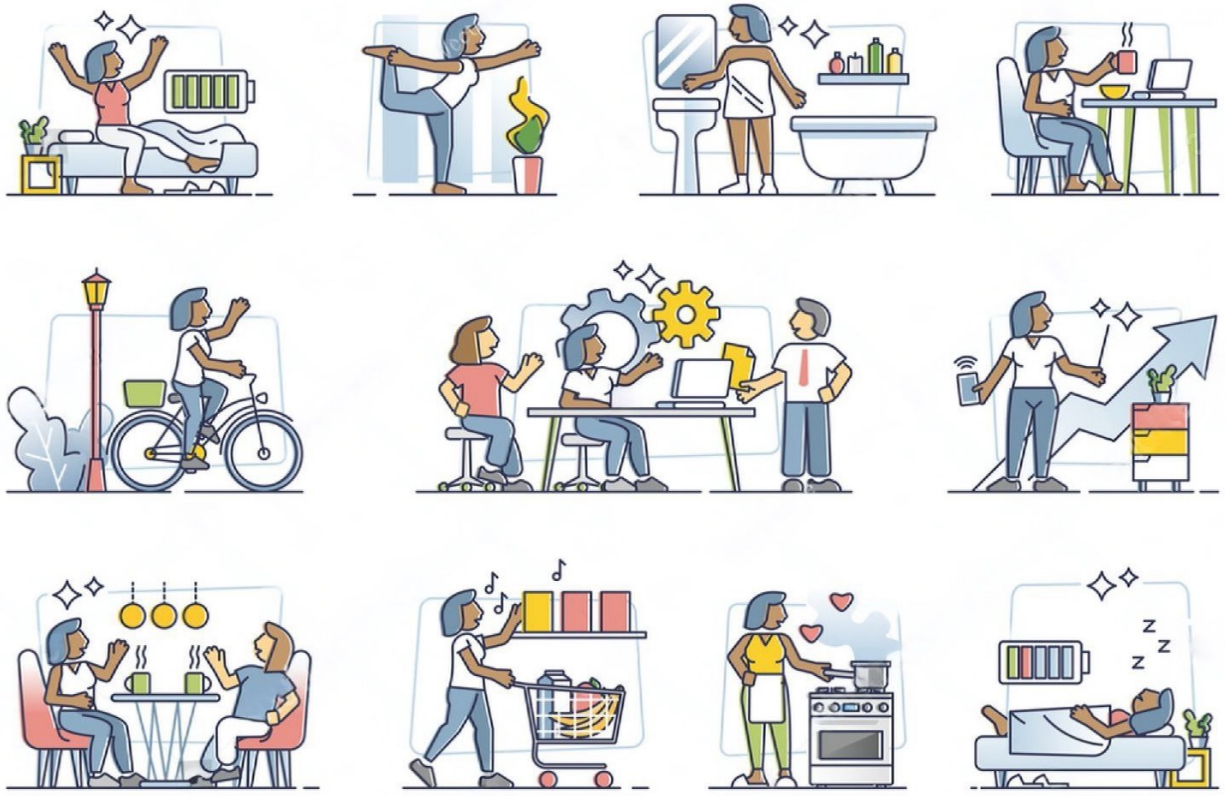
The **fruit**/ **flies**/ **like** a banana/. ❌



Question: What is the man holding in his hands?



“ **commonsense reasoning is** a **human-like ability** to make presumptions about the type and essence of **ordinary situations** humans encounter every day. ”

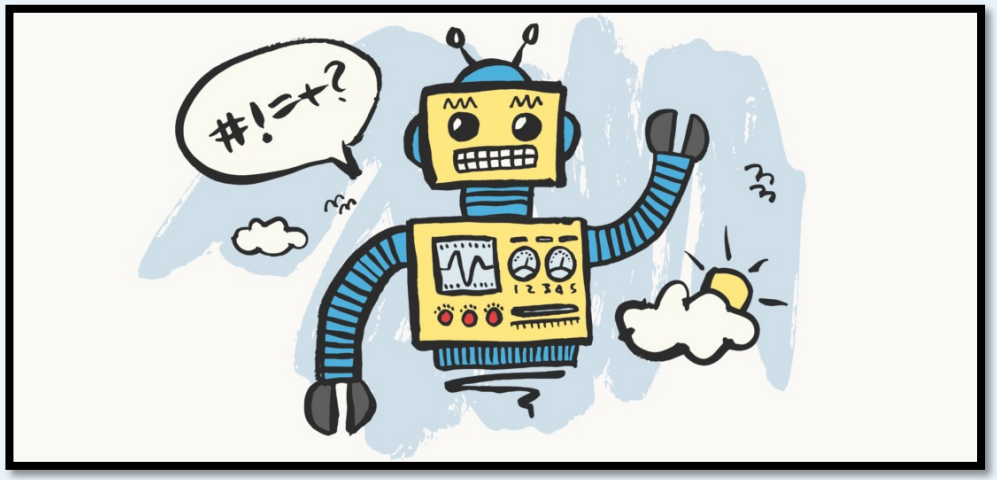


Human-level AI !

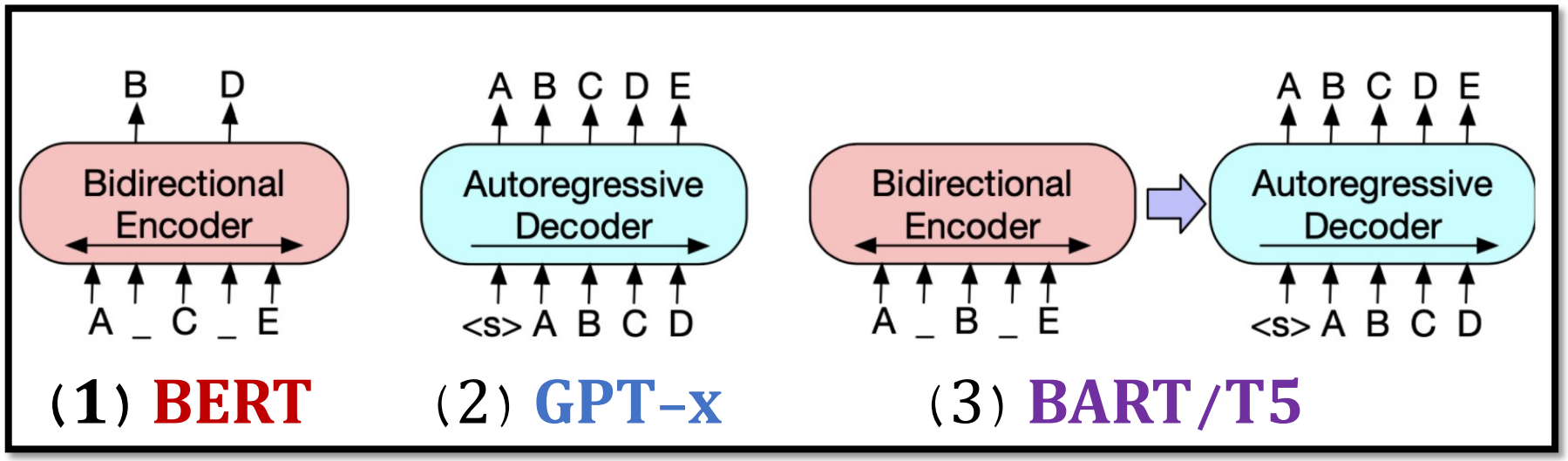
Everyday Situations 🌍

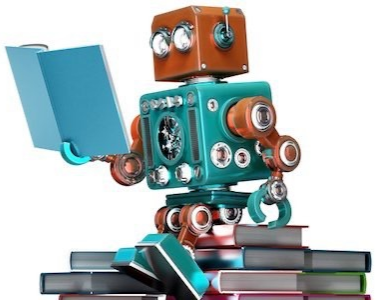
Think 🤔
Talk 💬
Act 💪

Common-Sense Reasoning



Neural Language Models



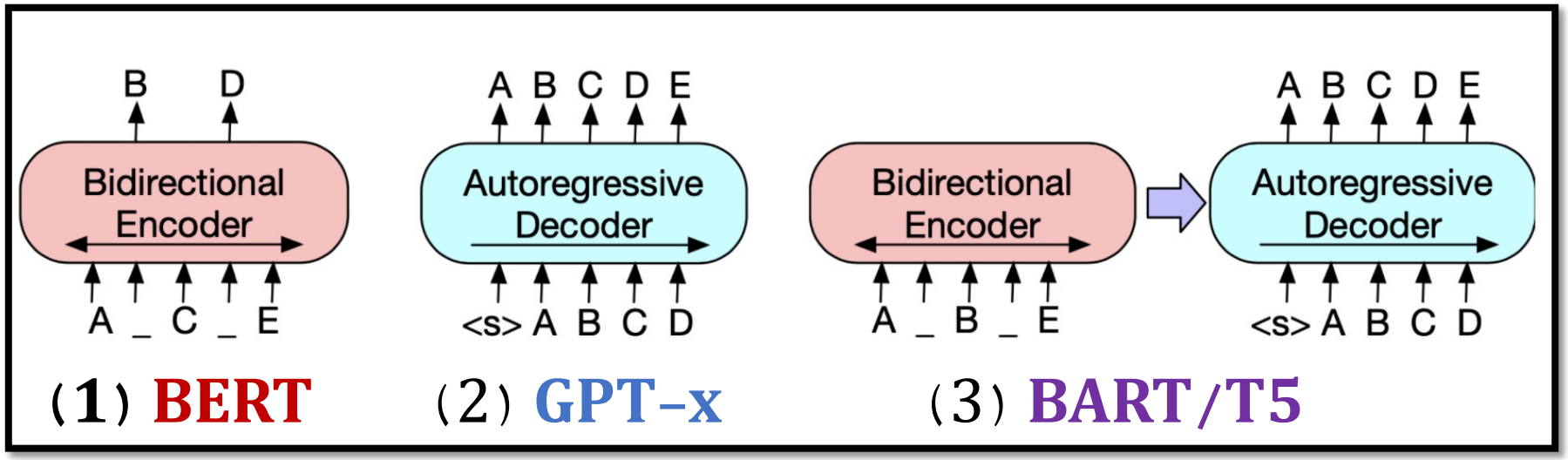


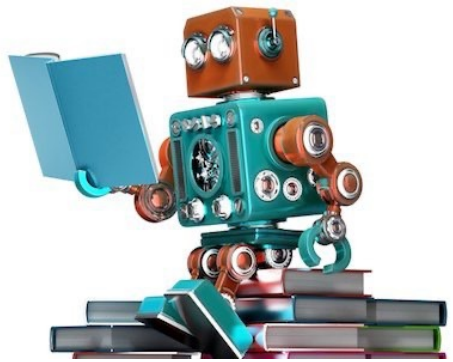
How do we incorporate commonsense knowledge into neural NLP models?

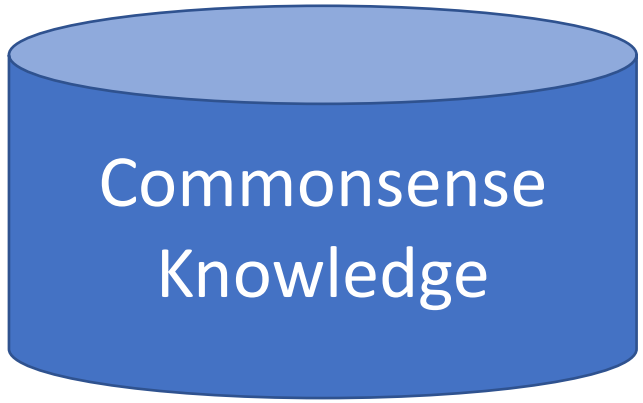
Outline

- → Background of Commonsense Reasoning in NLP
- Incorporating Structured Commonsense Knowledge
- Incorporating Unstructured Commonsense Knowledge
- Incorporating Commonsense Knowledge for Generation

Neural Language Models







Do LMs have common sense? (masked LMs)

Birds usually can [MASK].

Masked LMs
(e.g., BERT)

Tigers usually have [MASK] **legs**.

LAMA (Petroni et al. 2019)

Prediction	Score	
Birds usually can **fly** .	33.1%	✅
Birds usually can **sing** .	8.2%	✅
Birds usually can **survive** .	3.5%	

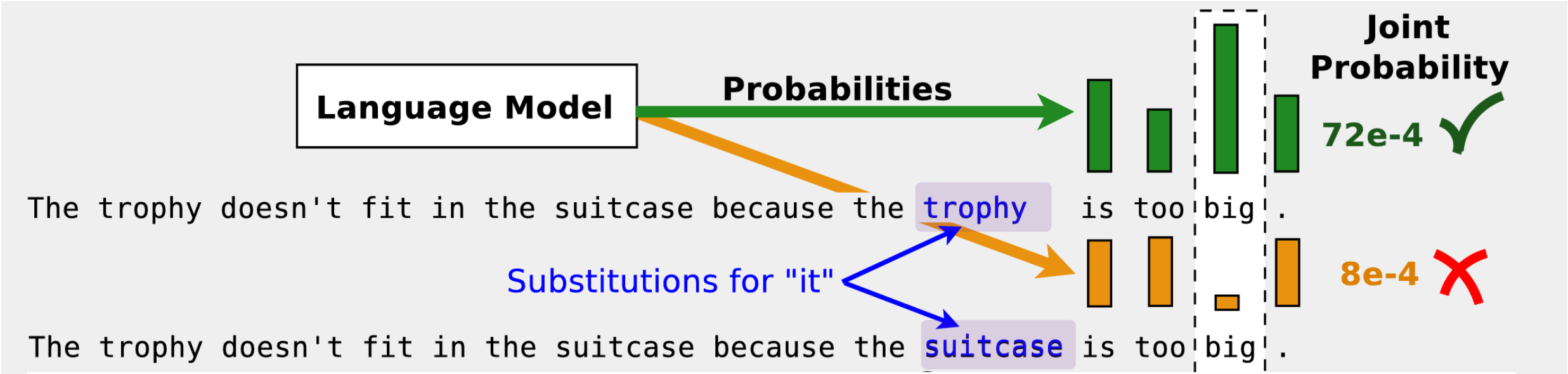
NumerSense (Lin et al. 2020)

Prediction	Score	
Tigers usually have **two** legs .	14.1%	❌
Tigers usually have **short** legs .	11.2%	
Tigers usually have **four** legs .	8.8%	✅

(demo w/ AllenNLP) AllenNLP

Do LMs have common sense? (auto-regressive LMs)

The trophy doesn't fit in the suitcase because it **is too big.**



RNN-based LMs on WSC-237

→ acc: 63.7% (random = 50%)

Trinh & Le (2018)

Do LMs have common sense? (encoder–decoder LMs)

Input:

What do you fill with ink to write notes on a piece of copy paper?

(A) fountain pen (B) pencil case (C) printer (D) notepad

UNIFIED-QA *A T5-based multi-task LM for **QA***

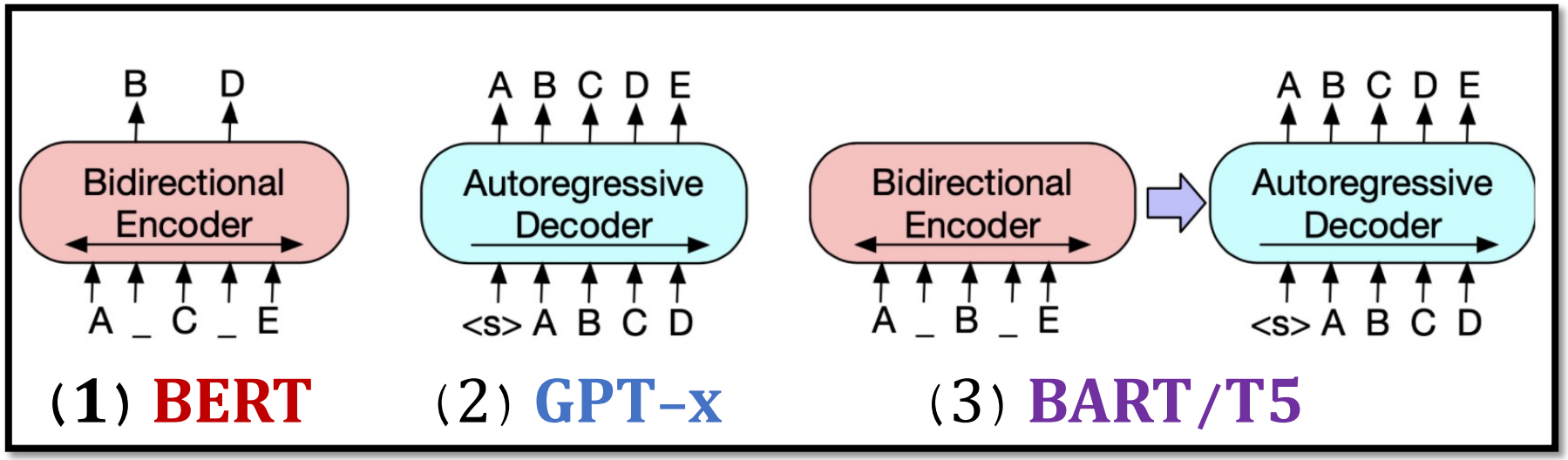
Output:

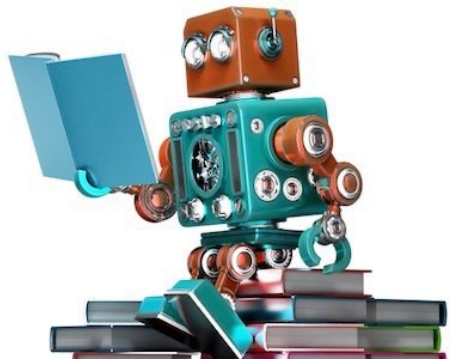
Prediction [small, 60 million parameters]: pencil case

Prediction [large, 770 million parameters]: printer

(Khashabi et al. 2020)

Neural Language Models





Better performance
Interpretable
Trustworthy

Commonsense Knowledge

MULTIPLE-CHOICE QA

What do you fill with ink to write notes on a piece of copy paper?

(A) fountain pen (B) pencil case (C) printer (D) notepad

UNIFIED-QA → State-of-the-art QA Model

Prediction [small, 60 million parameters]: pencil case

Prediction [large, 770 million parameters]: printer

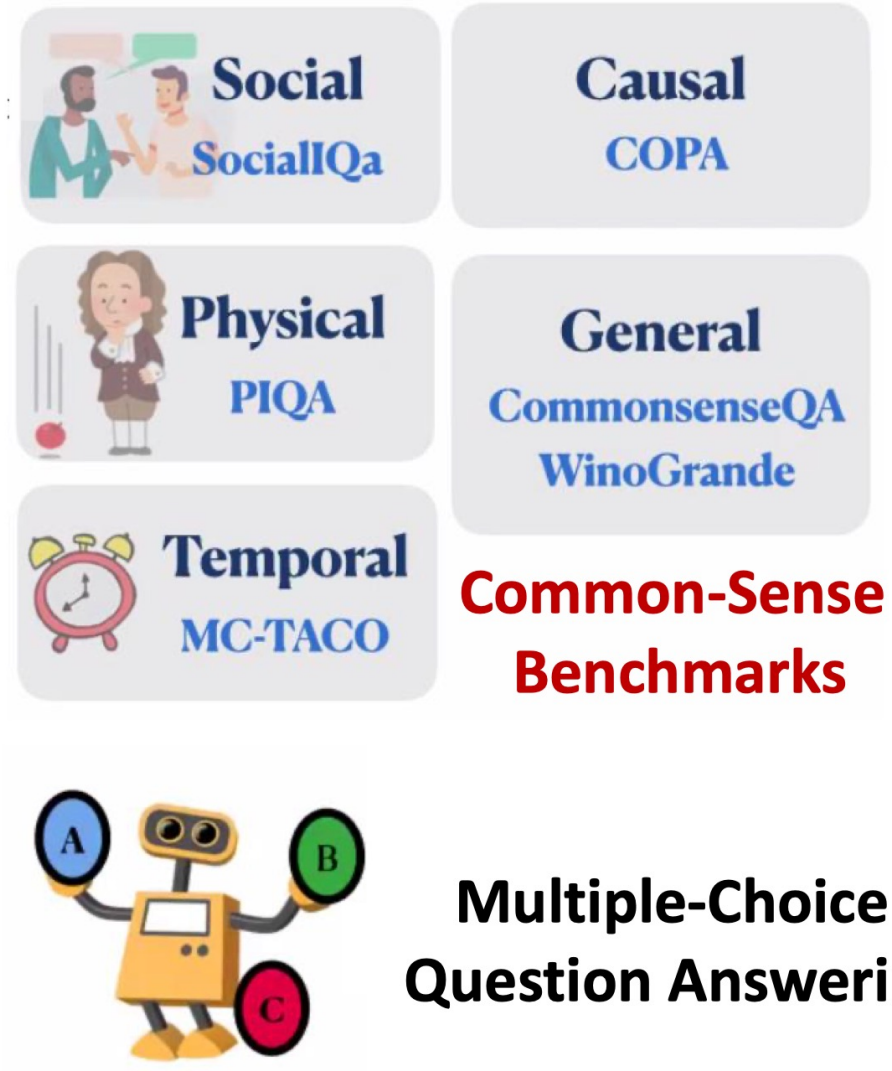
CommonsenseQA (Talmor et al. 2019)

In the school play, Robin played a hero in the struggle to the death with the angry villain.

Q: How would others feel afterwards?

A: (a) sorry for the villain
(b) hopeful that Robin will succeed ✓
(c) like Robin should lose

Social IQA (Sap et al. 2019)



Open-Ended QA & Text Generation

OpenCSR (NAACL 2021)

Q: What can help alleviate global warming?

Open-Ended CSR
Input: a question only

A large text corpus of commonsense **facts**

Carbon dioxide is the major greenhouse gas contributing to global warming .

Trees remove *carbon dioxide* from the atmosphere through photosynthesis .

renewable energy, *tree*, solar battery, ...

Output: a ranked list of concepts as answers.

CommonGen (EMNLP 2020)

Concept-Set: a collection of objects/actions.

dog | frisbee | catch | throw

Generative Commonsense Reasoning

Expected Output: everyday scenarios covering all given concepts.

[Humans]
- A dog leaps to catch a thrown frisbee.
- The dog catches the frisbee when the boy throws it.
- A man throws away his dog 's favorite frisbee expecting him to catch it in the air.

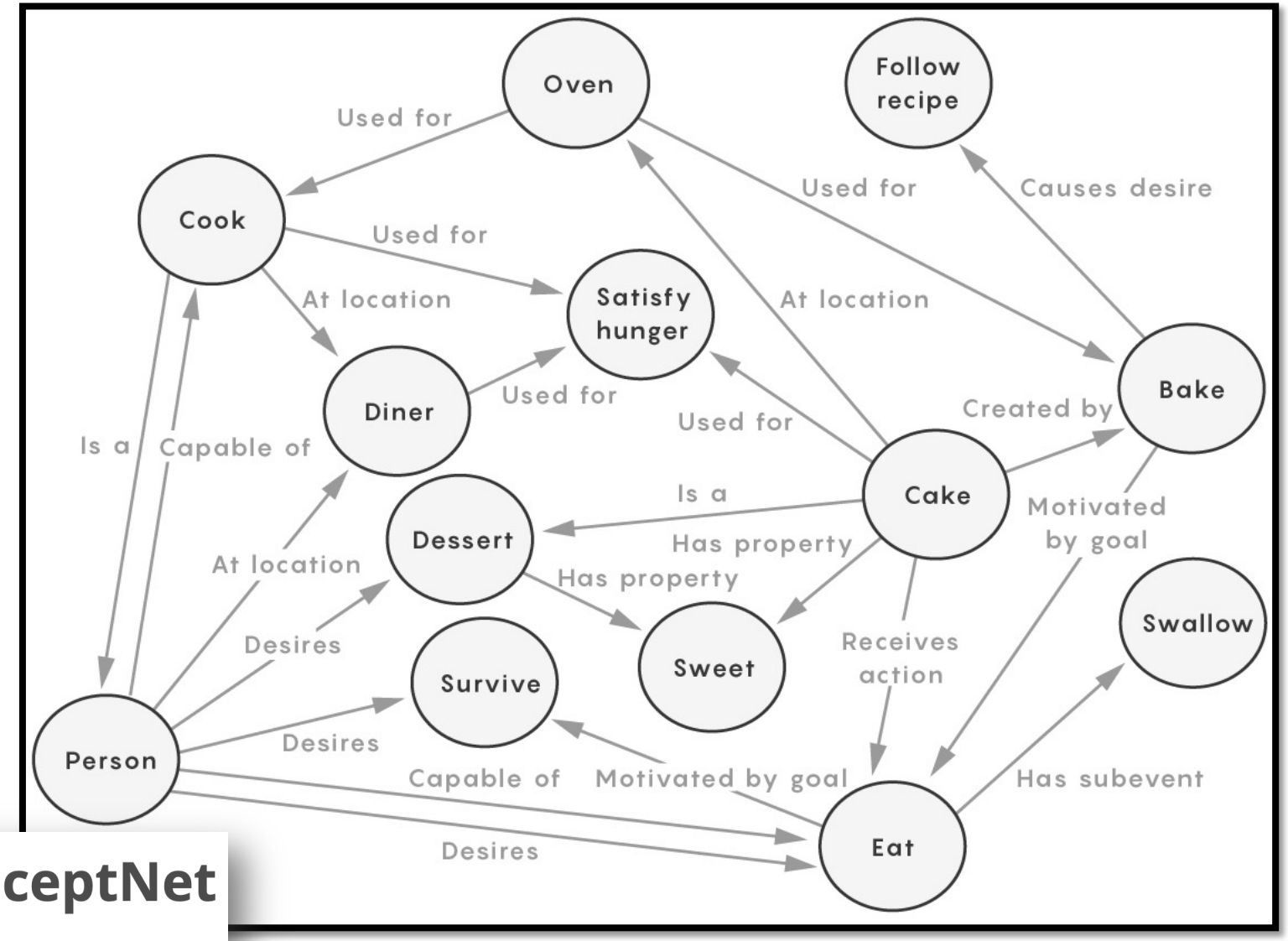
[Machines]
GPT2: A dog throws a frisbee at a football player.
UniLM: Two dogs are throwing frisbees at each other .
BART: A dog throws a frisbee and a dog catches it.
T5: dog catches a frisbee and throws it to a dog

Outline

- ~~Background of Commonsense Reasoning in NLP~~
- → **Incorporating Structured Commonsense Knowledge**
  - **KagNet (EMNLP 2019)**
  - **MHGRN (EMNLP 2020)**
  - **QA-GNN (NAACL 2021)**
  - GreaseLM (ICLR 2022)
  - GSC (ICLR 2022)

- Incorporating Unstructured Commonsense Knowledge
- Incorporating Commonsense Knowledge for Generation

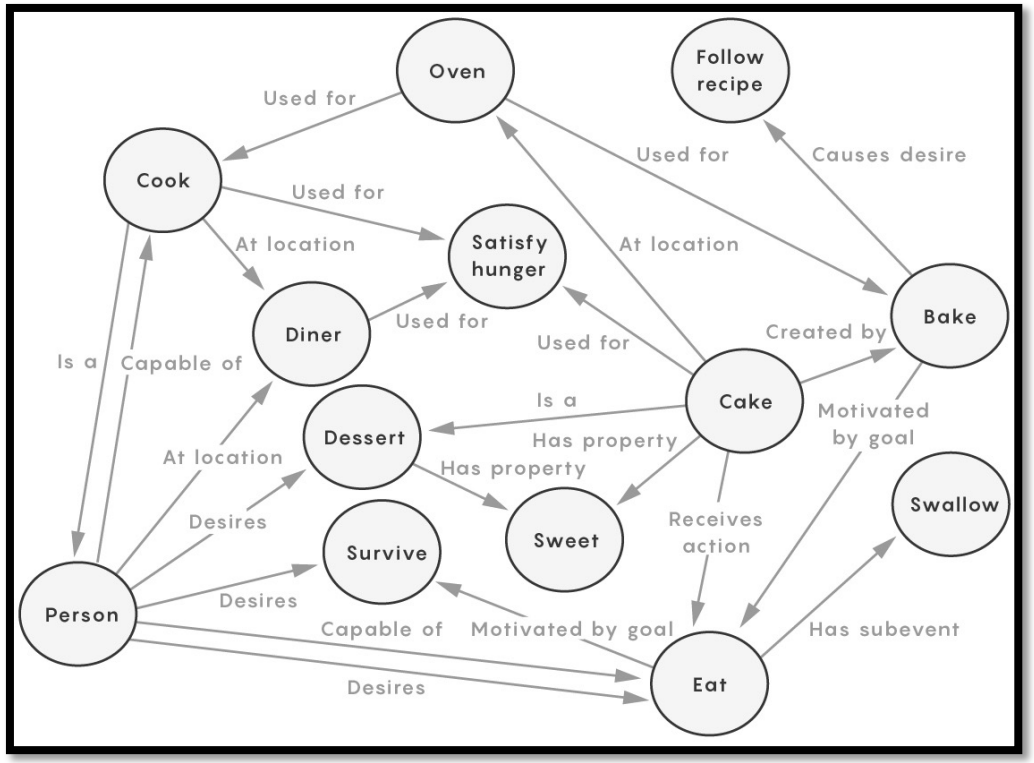
STRUCTURED COMMONSENSE KNOWLEDGE BASE



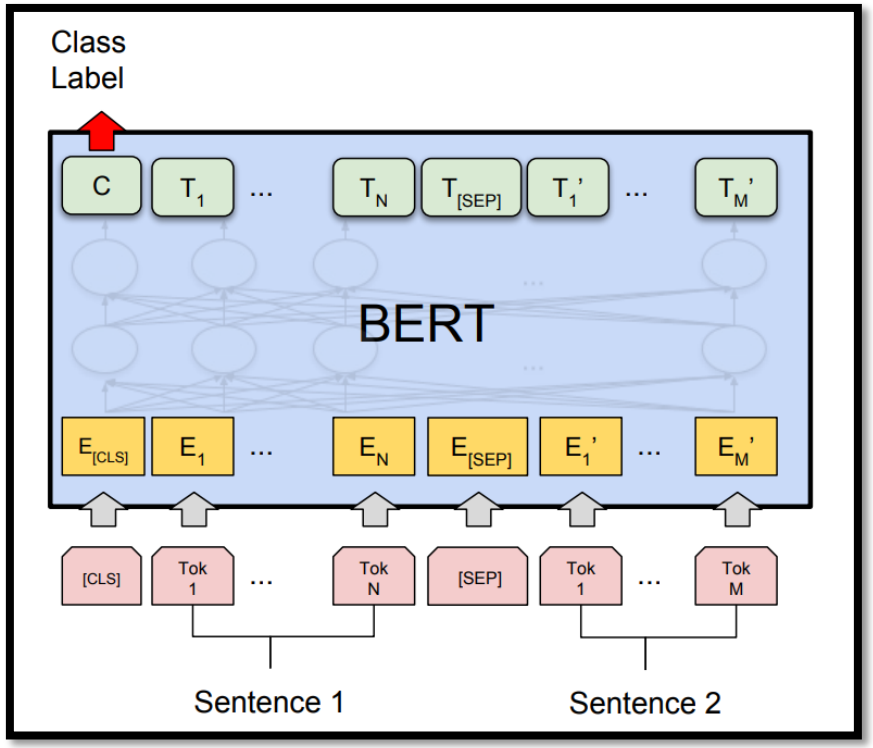
ConceptNet

STRUCTURED CSKB & NEURAL LMs

symbolic knowledge



neural networks

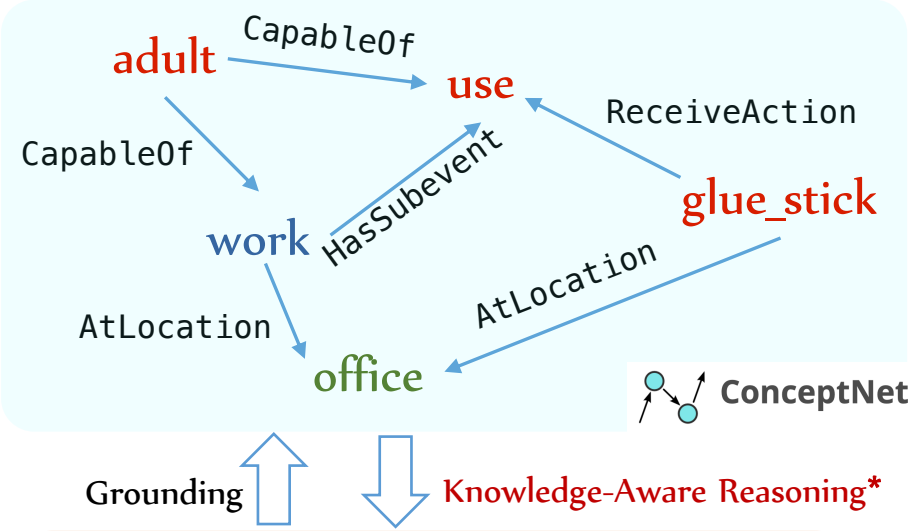


Structured Commonsense Knowledge Graphs
(e.g., ConceptNet)

Pre-Trained Neural Language Models
(e.g., BERT)

Using Structured Commonsense KGs!

Symbol Space



A Schema Graph
for the choice **B: office**

Semantic Space

Where do adults use glue sticks?

Question

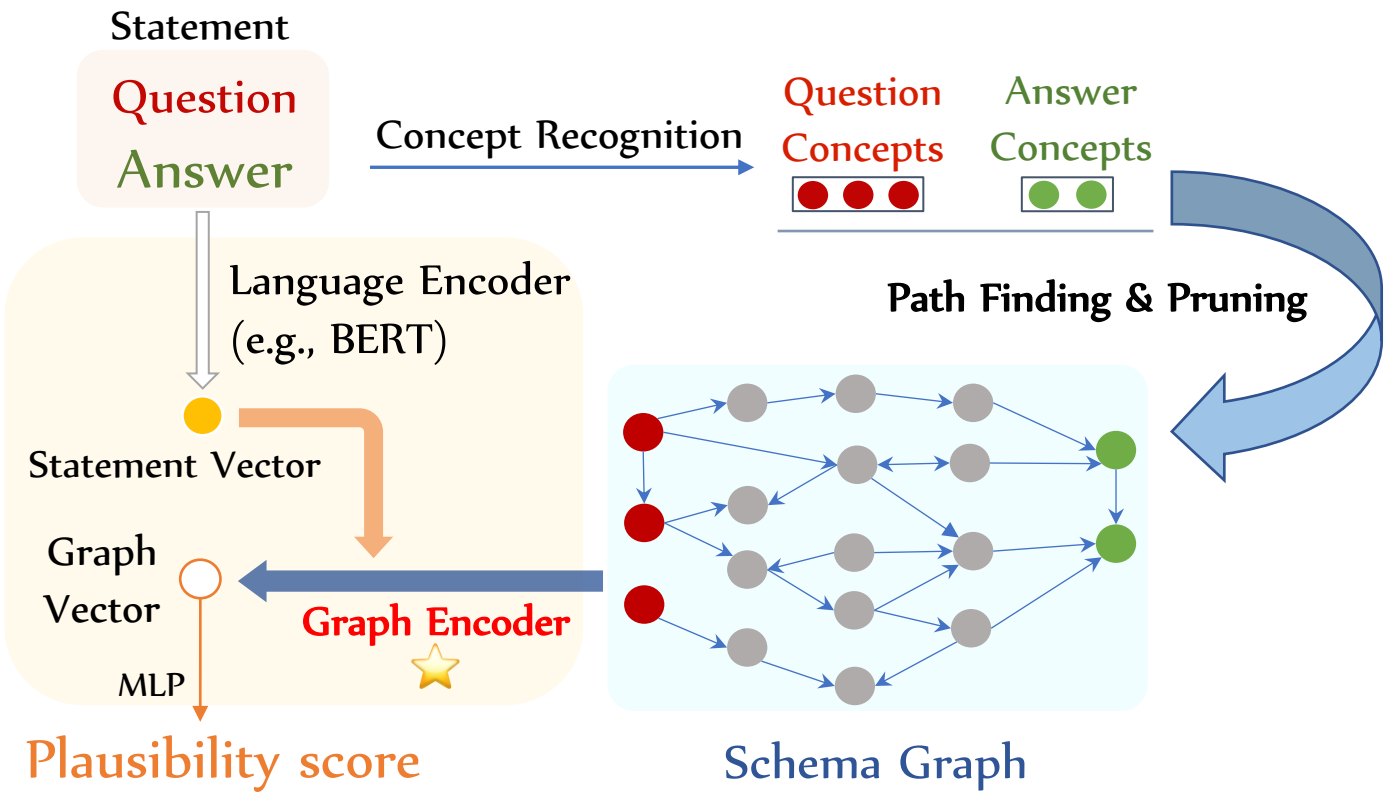
A: classroom B: office C: desk drawer

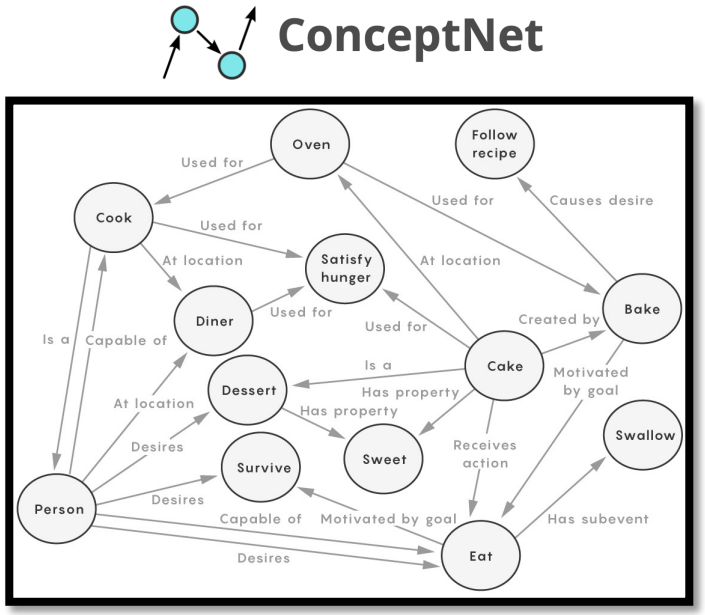
Answer Options

Key Motivation:

*using **commonsense knowledge graphs** (CSKGs) to support **language reasoning**!*

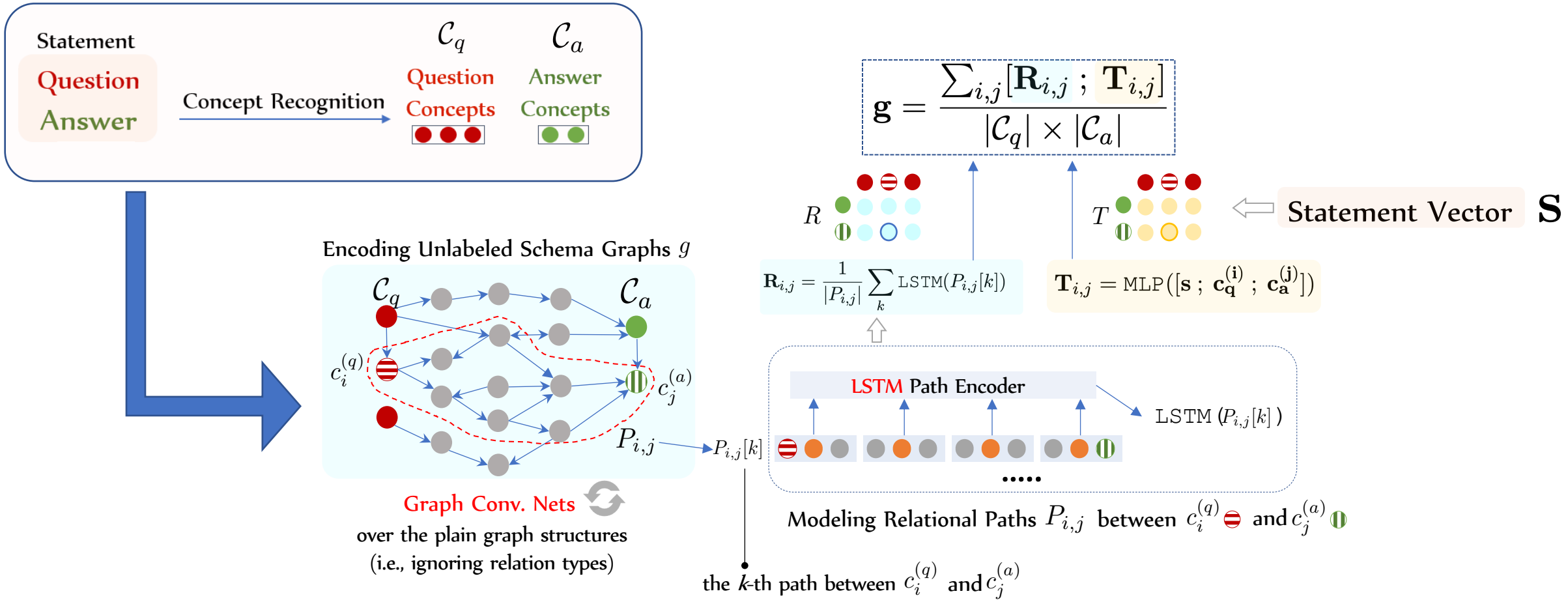
KagNet: Knowledge-Aware Graph Neural Networks





Knowledge Graph-Augmented Language Reasoning

KagNet: Knowledge-Aware Graph Neural Networks



Path-based Relational Graph Encoder + Language Representation

KagNet: Knowledge-Aware Graph Neural Networks

- Two average pooling:
  - Assuming all QA-concept pairs are equally important $\mathbf{g} = \frac{\sum_{i,j}[\mathbf{R}_{i,j}\ ;\ \mathbf{T}_{i,j}]}{|\mathcal{C}_q| \times |\mathcal{C}_a|}$
  - Assuming all paths are equally relevant $\mathbf{R}_{i,j} = \frac{1}{|P_{i,j}|}\sum_k \texttt{LSTM}(P_{i,j}[k])$

- Modeling the two-level importance as latent weights:

$$\alpha_{(i,j,k)} = \mathbf{T}_{i,j}\ \mathbf{W}_1\ \texttt{LSTM}(P_{i,j}[k]),$$
$$\hat{\alpha}_{(i,j,\cdot)} = \texttt{SoftMax}(\alpha_{(i,j,\cdot)}),$$
$$\hat{\mathbf{R}}_{i,j} = \sum_k \hat{\alpha}_{(i,j,k)} \cdot \texttt{LSTM}(P_{i,j}[k])$$

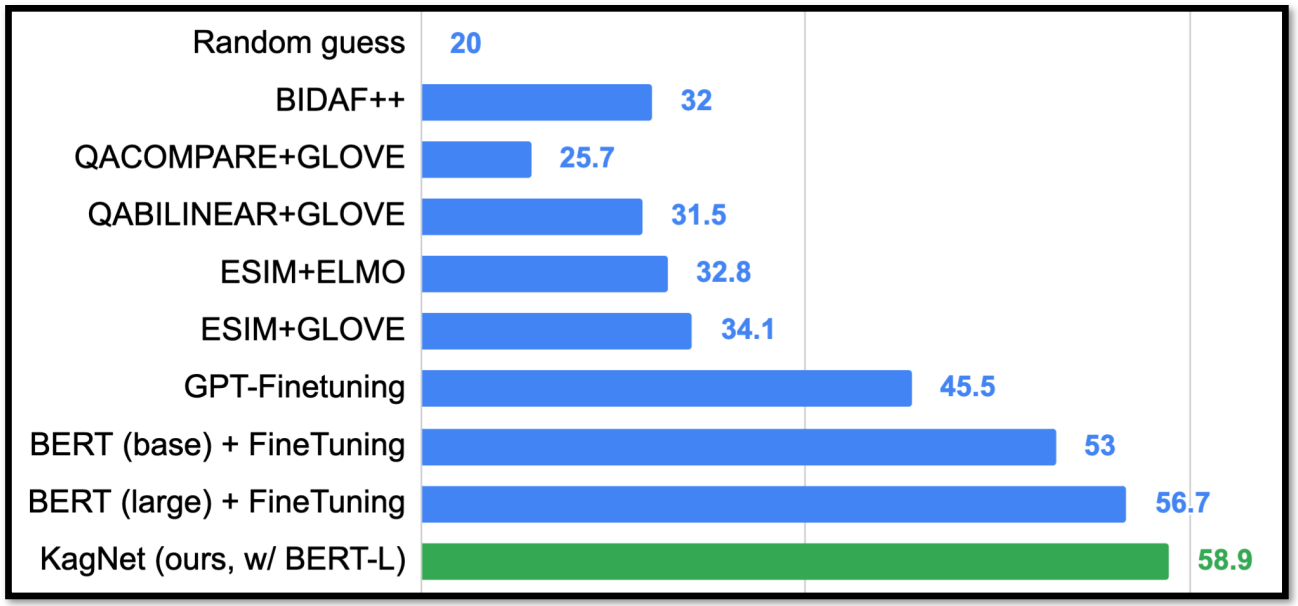
Path-Level Attention
(attending on semantic space)

$$\beta_{(i,j)} = \mathbf{s}\ \mathbf{W}_2\ \mathbf{T}_{i,j}$$
$$\hat{\beta}_{(\cdot,\cdot)} = \texttt{SoftMax}(\beta_{(\cdot,\cdot)})$$
$$\hat{\mathbf{g}} = \sum_{i,j} \hat{\beta}_{(i,j)}[\hat{\mathbf{R}}_{i,j}\ ;\ \mathbf{T}_{i,j}]$$

Pair-Level Attention
(attending on statement)

+ Hierarchical Path-based Attention

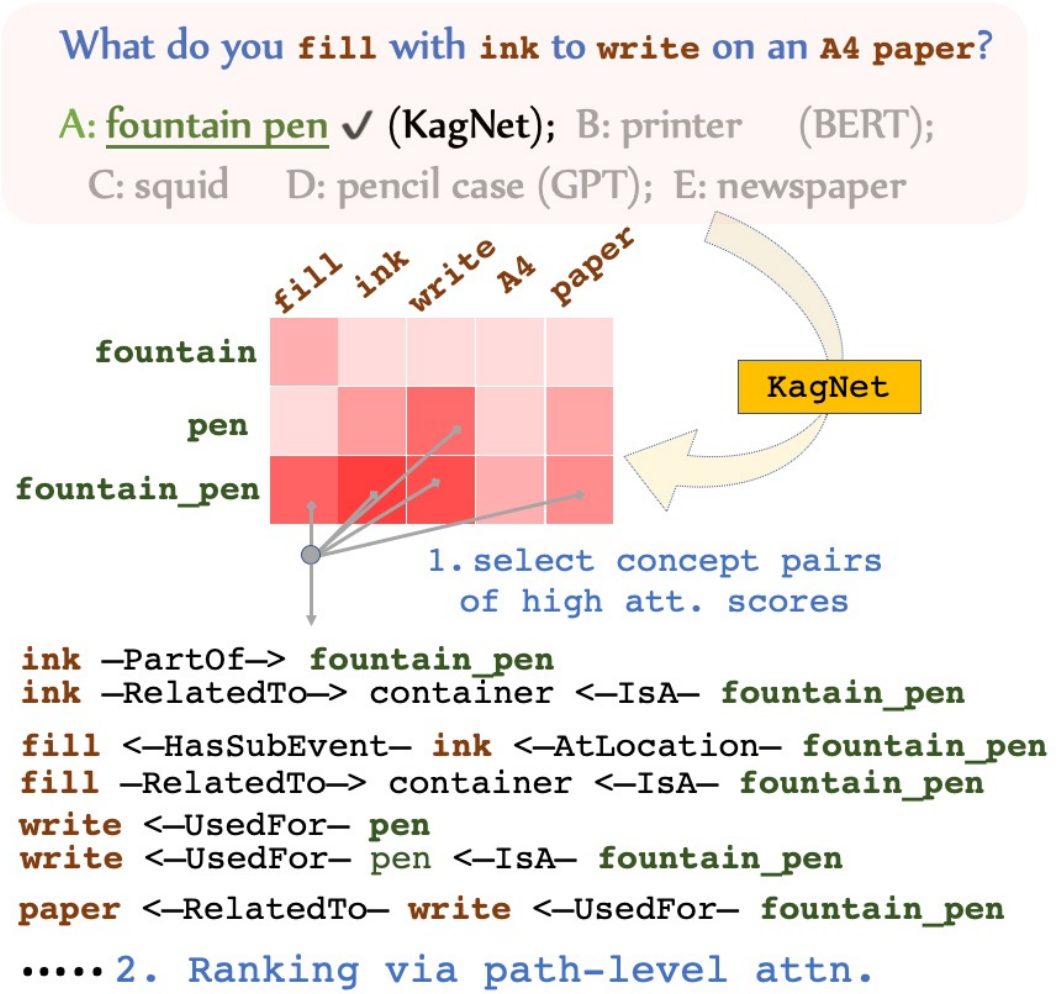
Experimental Results



(as of the publication time)

The latest results on the official leaderboard:

https://www.tau-nlp.org/csqa-leaderboard.

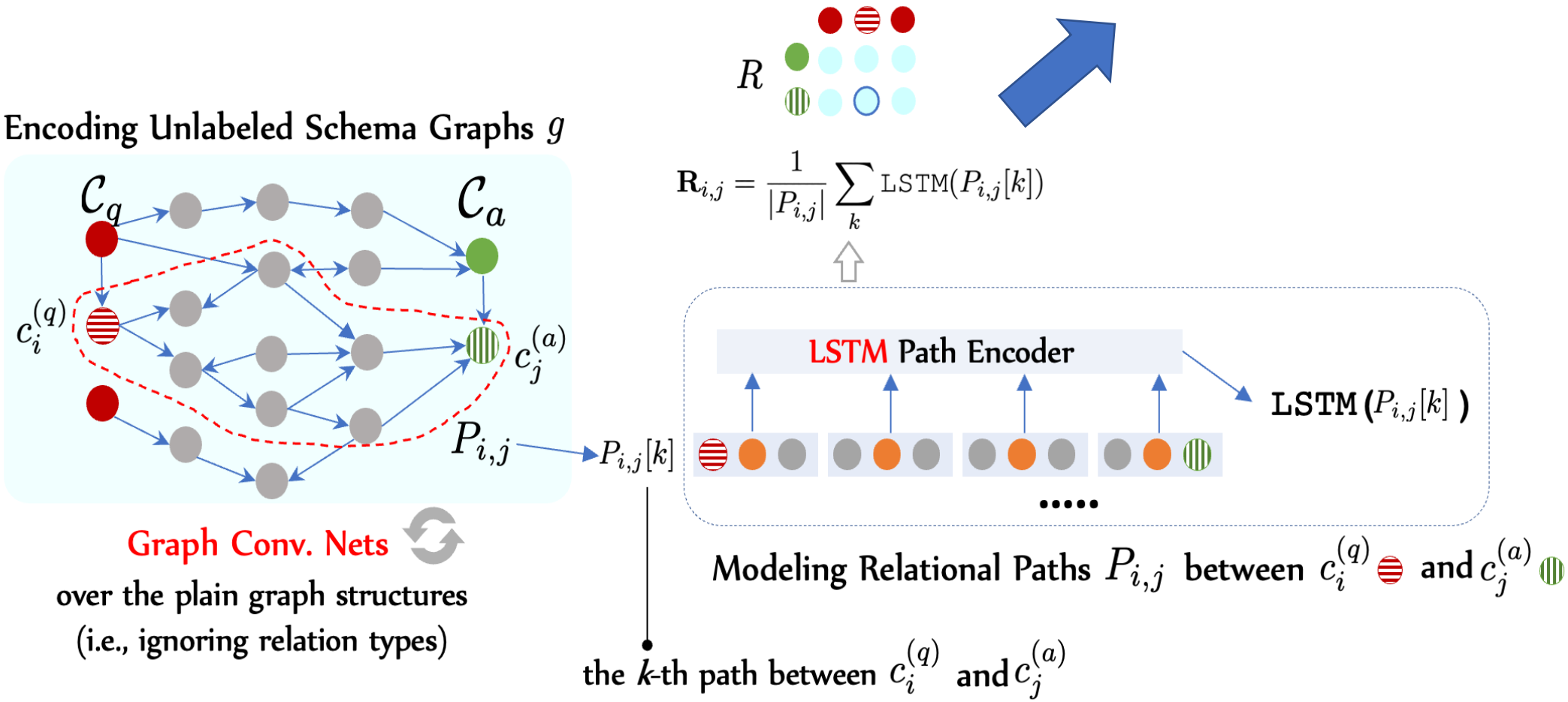


An **interpretable** reasoning process!

KagNet: The Scalability Issue

⚠ Larger number of paths.

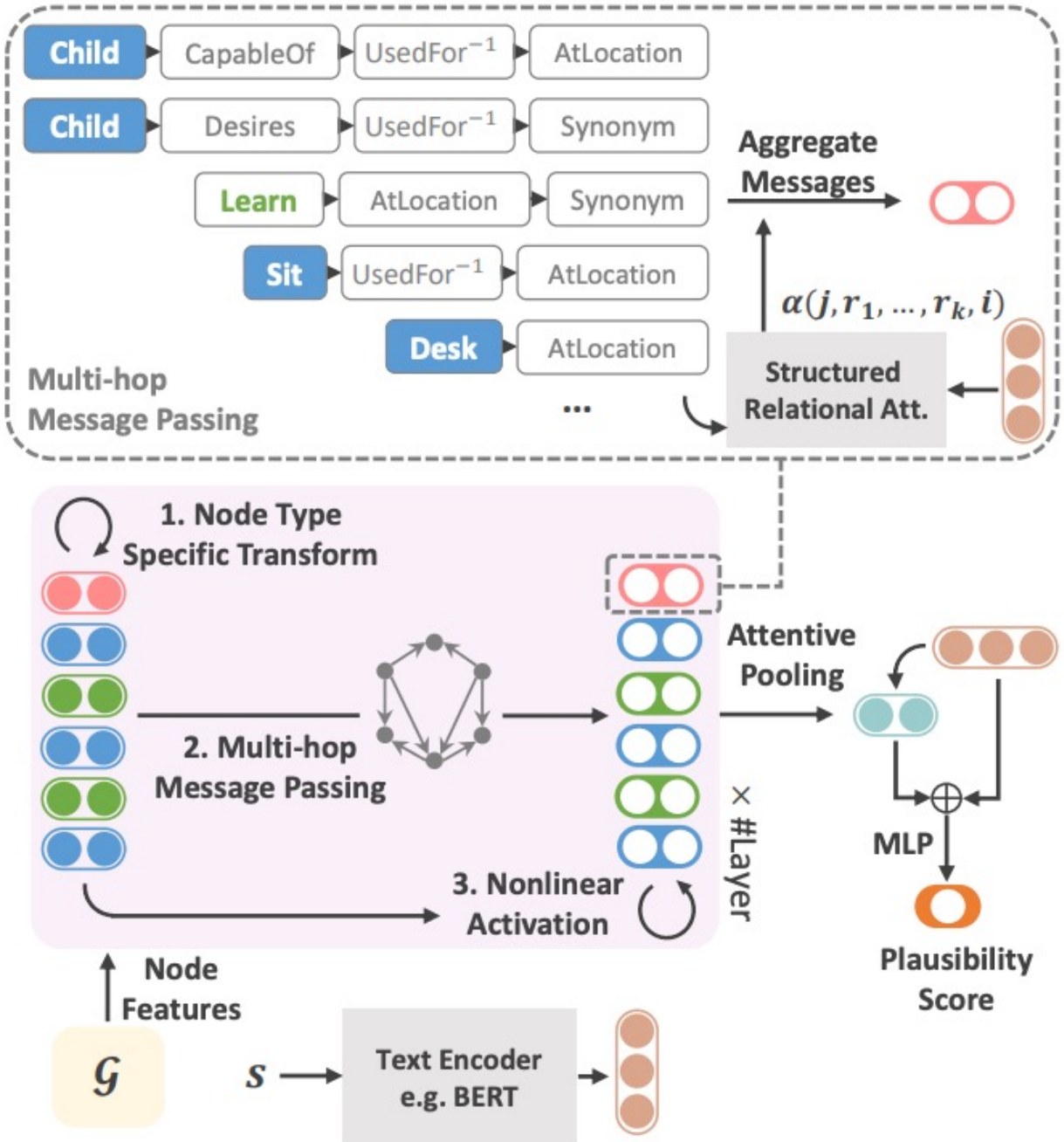
⚠ Longer sequence of triples.



MHGRN (EMNLP 20)

Can we **directly** model **multi-hop massage passing** in **relational** graph networks?

Relational paths can be modeled as **multi-hop message passing** with **multi-layer** graph **attention** networks.



$$\mathrm{GNN}(\mathcal{G}) = \mathrm{Pool}(\{\boldsymbol{h}'_1, \boldsymbol{h}'_2, \ldots, \boldsymbol{h}'_n\}).$$

$$\boldsymbol{h}'_i = \sigma\left(\left(\sum_{r\in\mathcal{R}} |\mathcal{N}_i^r|\right)^{-1} \sum_{r\in\mathcal{R}} \sum_{j\in\mathcal{N}_i^r} \boldsymbol{W}_r \boldsymbol{h}_j\right)$$

Relational GNN (e.g., R-GCN)

Simple, fast
Bad representation of k-hop

Normalized Attention

Path-based, with attention
Slow, cannot scale

$$\textsc{KagNet}(\mathcal{G}) = \mathrm{Pool}\Big(\{\mathrm{LSTM}(j, r_1, \ldots, r_k, i) \mid (j, r_1, j_1), \cdots, (j_{k-1}, r_k, i) \in \mathcal{E}, 1 \le k \le K\}\Big)$$

KagNet (paths are pre-filtered)

Multi-Hop Graph Relation Nets

$$\Phi_k = \{(j, r_1, \ldots, r_k, i) \mid (j, r_1, j_1), \cdots, (j_{k-1}, r_k, i) \in \mathcal{E}\} \quad (1 \le k \le K).$$

$$\boldsymbol{z}_i^k = \sum_{(j,r_1,\ldots,r_k,i)\in\Phi_k} \alpha(j, r_1, \ldots, r_k, i)/d_i^k \cdot \boldsymbol{W}_0^K \cdots \boldsymbol{W}_0^{k+1} \boldsymbol{W}_{r_k}^k \cdots \boldsymbol{W}_{r_1}^1 \boldsymbol{x}_j \quad (1 \le k \le K)$$

$$\boldsymbol{W}_r^t (1 \le t \le K, 0 \le r \le m)$$

low-rank approximation

$$\{m \times \cdots \times m\}_k \times d \times d$$

$$\boldsymbol{z}_i = \sum_{k=1}^{K} \mathrm{softmax}\big(\mathrm{bilinear}\big(\boldsymbol{s}, \boldsymbol{z}_i^k\big)\big) \cdot \boldsymbol{z}_i^k$$

$$\boldsymbol{h}'_i = \sigma\left(\boldsymbol{V}\boldsymbol{h}_i + \boldsymbol{V}'\boldsymbol{z}_i\right)$$

Model	Time	Space
	$\mathcal{G}$ is a dense graph	
K-hop KagNet	$\mathcal{O}\left(m^K n^{K+1} K\right)$	$\mathcal{O}\left(m^K n^{K+1} K\right)$
K-layer RGCN	$\mathcal{O}\left(mn^2 K\right)$	$\mathcal{O}\left(mnK\right)$
MHGRN	$\mathcal{O}\left(m^2 n^2 K\right)$	$\mathcal{O}\left(mnK\right)$
$\mathcal{G}$ is a sparse graph with maximum node degree $\Delta \ll n$		
K-hop KagNet	$\mathcal{O}\left(m^K nK\Delta^K\right)$	$\mathcal{O}\left(m^K nK\Delta^K\right)$
K-layer RGCN	$\mathcal{O}\left(mnK\Delta\right)$	$\mathcal{O}\left(mnK\right)$
MHGRN	$\mathcal{O}\left(m^2 nK\Delta\right)$	$\mathcal{O}\left(mnK\right)$

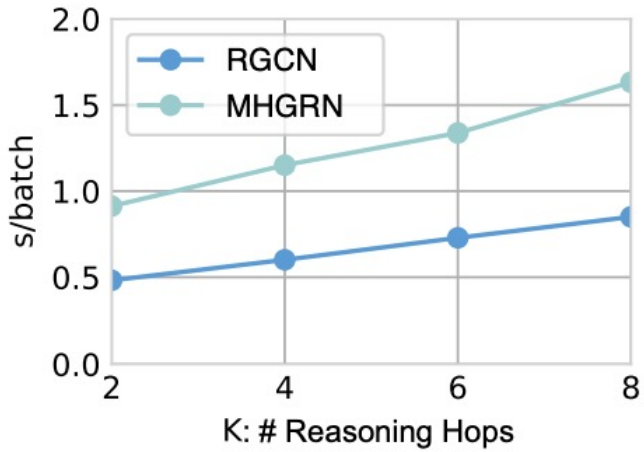
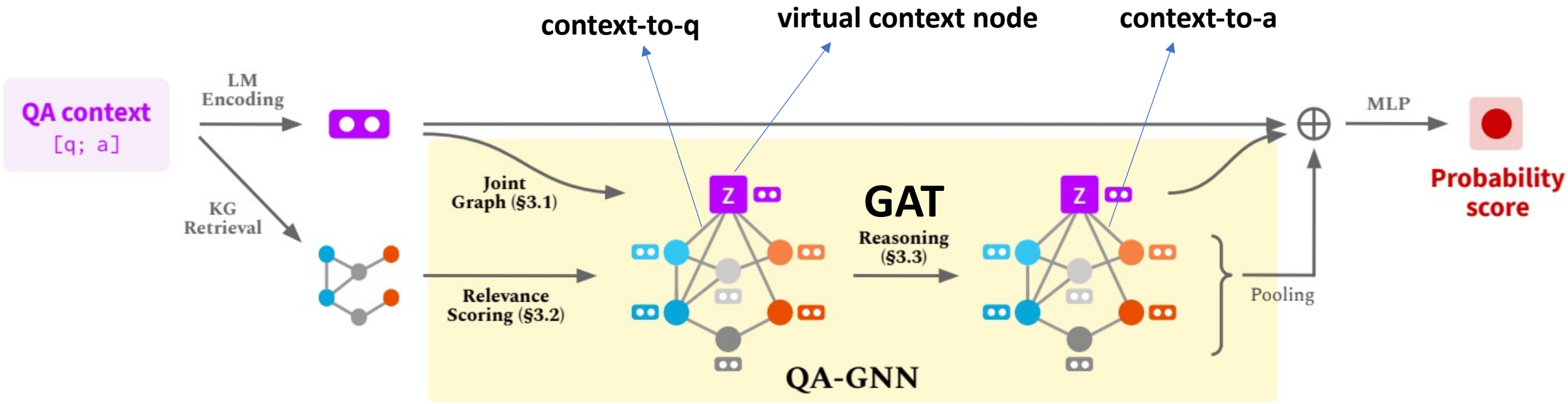


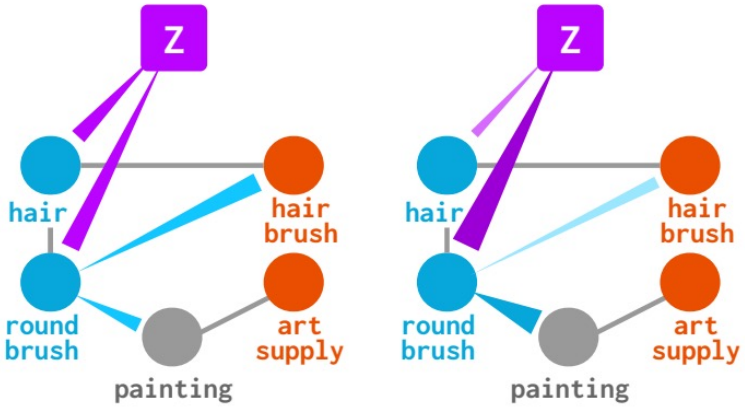
Figure 7: **Analysis of model scalability**. Comparison of per-batch training efficiency w.r.t. # hops K.

QA-GNN (NAACL 2021)



C

If it is **not** used for **hair**, a **round brush** is an example of what?
A. hair brush B. **art supply***



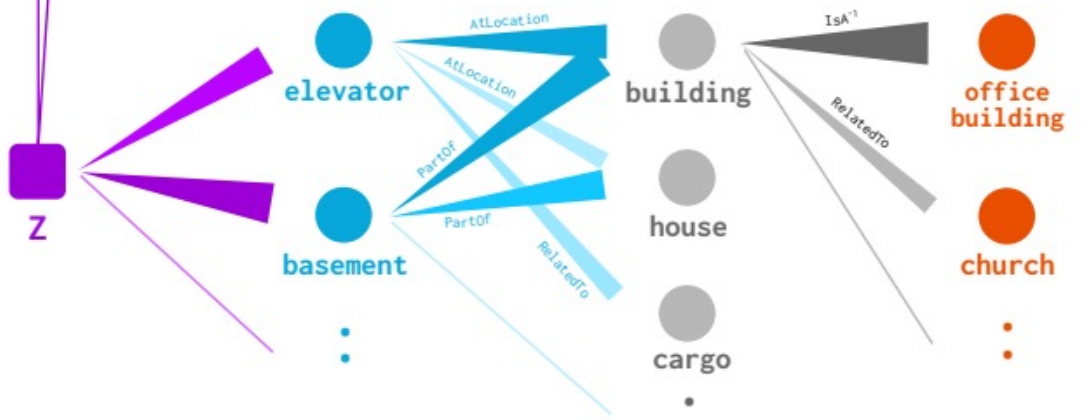
A. hair brush (0.38)

B. art supply (0.64)

GNN **1st** Layer | GNN **Final** Layer | Model Prediction

(a) Attention visualization direction: BFS from Q

Where would you find a **basement** that can be accessed with an **elevator**?
A. closet B. church C. **office building***



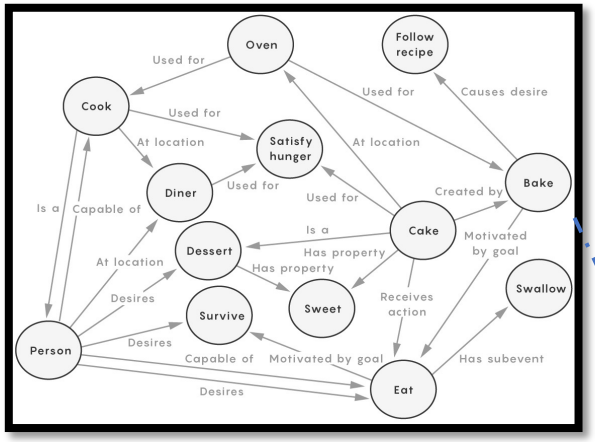
KagNet vs MHGRN vs QA–GNN

Methods	IHdev-Acc. (%)	IHtest-Acc. (%)
RoBERTa-large (w/o KG)	73.07 (±0.45)	68.69 (±0.56)
+ RGCN (Schlichtkrull et al., 2018)	72.69 (±0.19)	68.41 (±0.66)
+ GconAttn (Wang et al., 2019a)	72.61(±0.39)	68.59 (±0.96)
+ KagNet (Lin et al., 2019)	73.47 (±0.22)	69.01 (±0.76)
+ RN (Santoro et al., 2017)	74.57 (±0.91)	69.08 (±0.21)
+ MHGRN (Feng et al., 2020)	74.45 (±0.10)	71.11 (±0.81)
+ QA-GNN (**Ours**)	**76.54** (±0.21)	**73.41** (±0.92)

Table 2: **Performance comparison on *Commonsense QA* in-house split** (controlled experiments). As the official test is hidden, here we report the in-house Dev (IHdev) and Test (IHtest) accuracy, following the data split of Lin et al. (2019).

Outline

- ~~Background of Commonsense Reasoning in NLP~~
- ~~Incorporating Structured Commonsense Knowledge~~
- **→ Incorporating Unstructured Commonsense Knowledge**
  - **DrFact (NAACL 2021)**
- Incorporating Commonsense Knowledge for Generation



Unstructured Commonsense Knowledge Base

(e.g., GenericsKB)

Trees are perennial plants that have long woody trunks.

Most trees add one new ring for each year of growth.

Trees produce oxygen by absorbing carbon dioxide from the air.

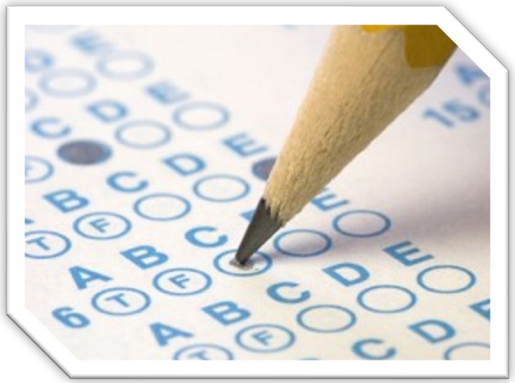
Trees are large, generally single-stemmed, woody plants.

Trees grow using photosynthesis, absorbing carbon dioxide and releasing oxygen.

Structured Commonsense KGs

(e.g., ConceptNet)

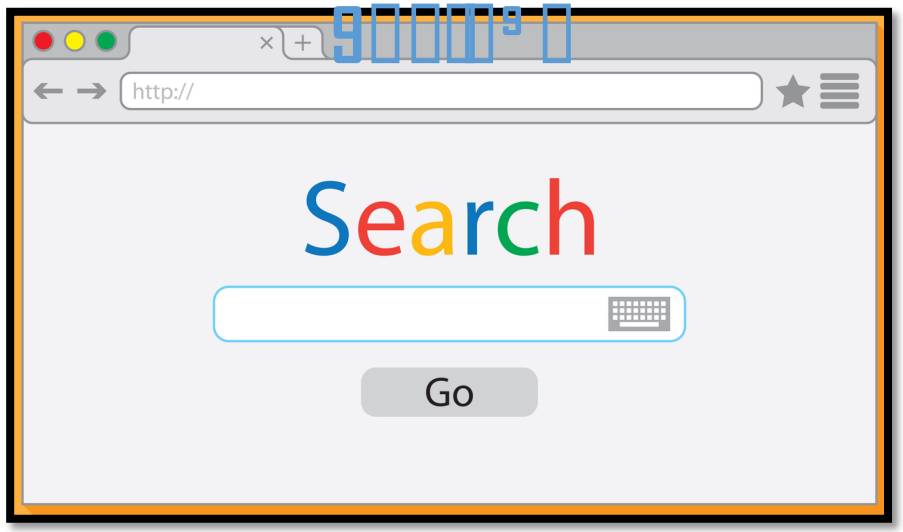
- **binary**
- **limited**
- **noisy & incomplete**



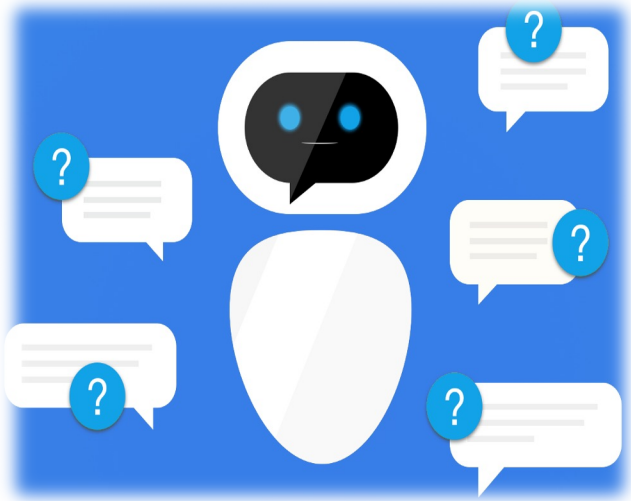
Open-Ended Question Answering
(i.e., no choices provided)

Is multiple-choice QA useful in realistic applications?

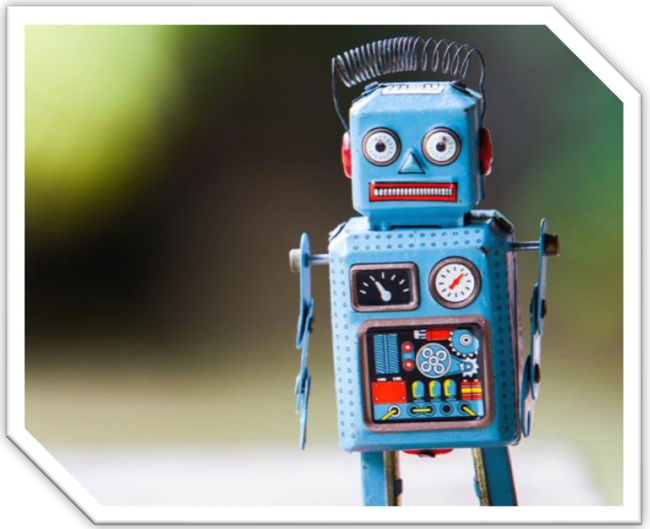
{ª AÅ
9 ª



Chatbots



Robots



Common Sense as a Service for practical AI applications.

Real users usually do **NOT** have any ***answer candidates***
when querying commonsense knowledge.

Open-Ended Commonsense Reasoning

Q: What can help alleviate global warming?

Open-Ended CSR

Input: a question only

A large text corpus of commonsense **facts**

Carbon dioxide is the major greenhouse gas contributing to global warming .

Trees remove *carbon dioxide* from the atmosphere through photosynthesis .

renewable energy, ***tree***, solar battery, ...

Output: a ranked list of concepts as answers.

Multiple-Choice/Closed CSR

Input: a question + a few choices

A) air conditioner B) fossil fuel

C) renewable energy D) carbon dioxide

?

*Can machines learn to **reason** without answer candidates?*

Why is OpenCSR challenging?

1) Latent Multi-Hop Structures (vs. factoid questions).

Who voices the *dog* in the TV show *Family Guy* ?

A multi-hop, factoid question from **HotpotQA**.

q_1= the dog in the TV show Family Guy

q_2= who voices [q_1. **answer**]

Clear, **explicit** hints for querying **evident relations** between **named entities**.

What can help alleviate global warming?

q_1= what *contributes to* global warming

q_2= what *removes* [q_1. **answer**]

Latent, **implicit** hints for querying **complex relations** between **concepts**.

2) Very Large Search Space (vs. multiple-choice setting).

3) Much Denser Entity Links (vs. named entities).

Notations for DrFact

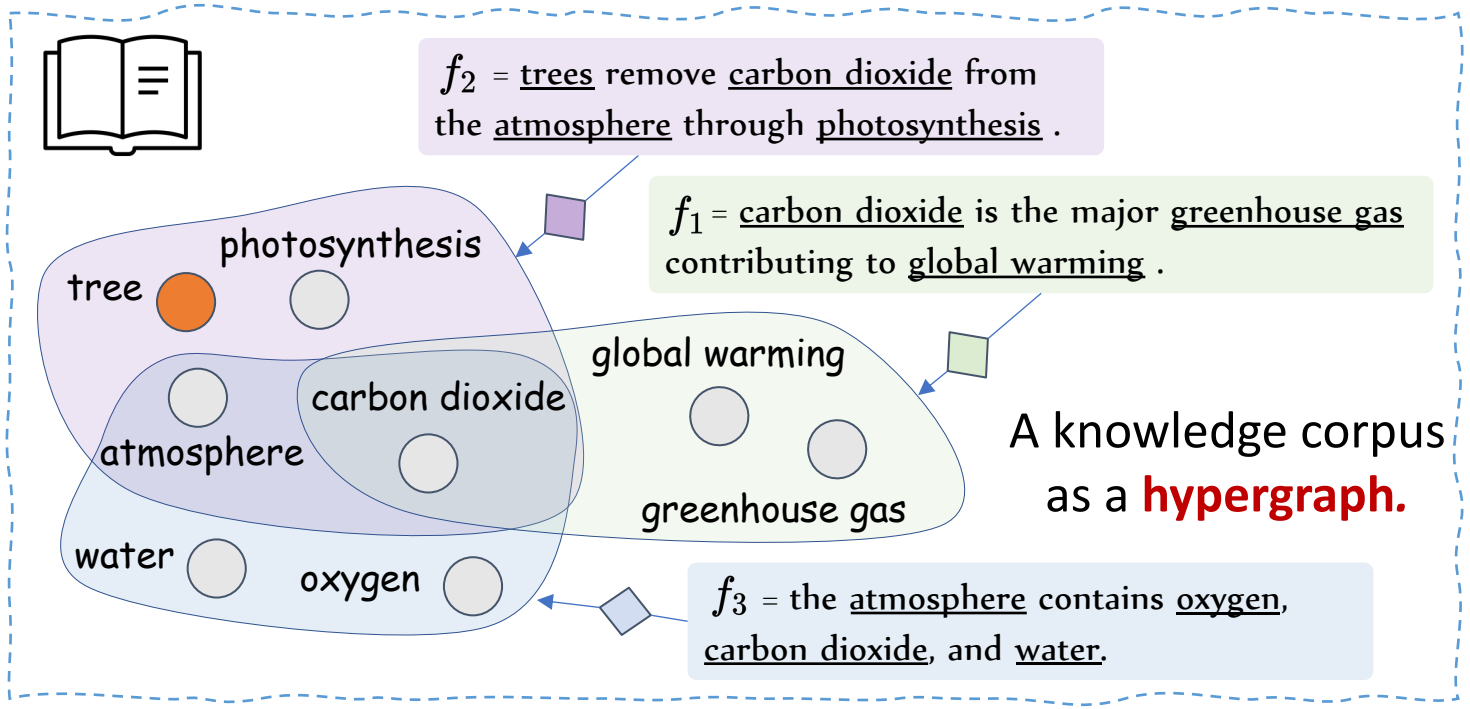
a **corpus** of common-sense facts, e.g., **GenericsKB**. $\mathcal{F}$

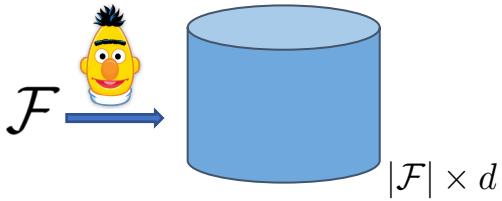
$f_i \in \mathcal{F}$

A **fact** is a sentence of generic commonsense knowledge

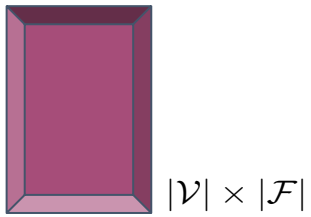
$c_j \in \mathcal{V}$

A **concept** is a noun or noun-chunk that are mentioned in $\mathcal{F}$

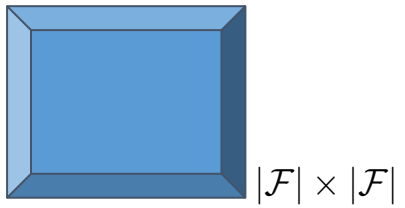




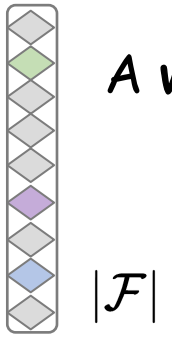
Dense Matrix of **Fact Embeddings**



Sparse Matrix of **Concept-to-Fact** Links

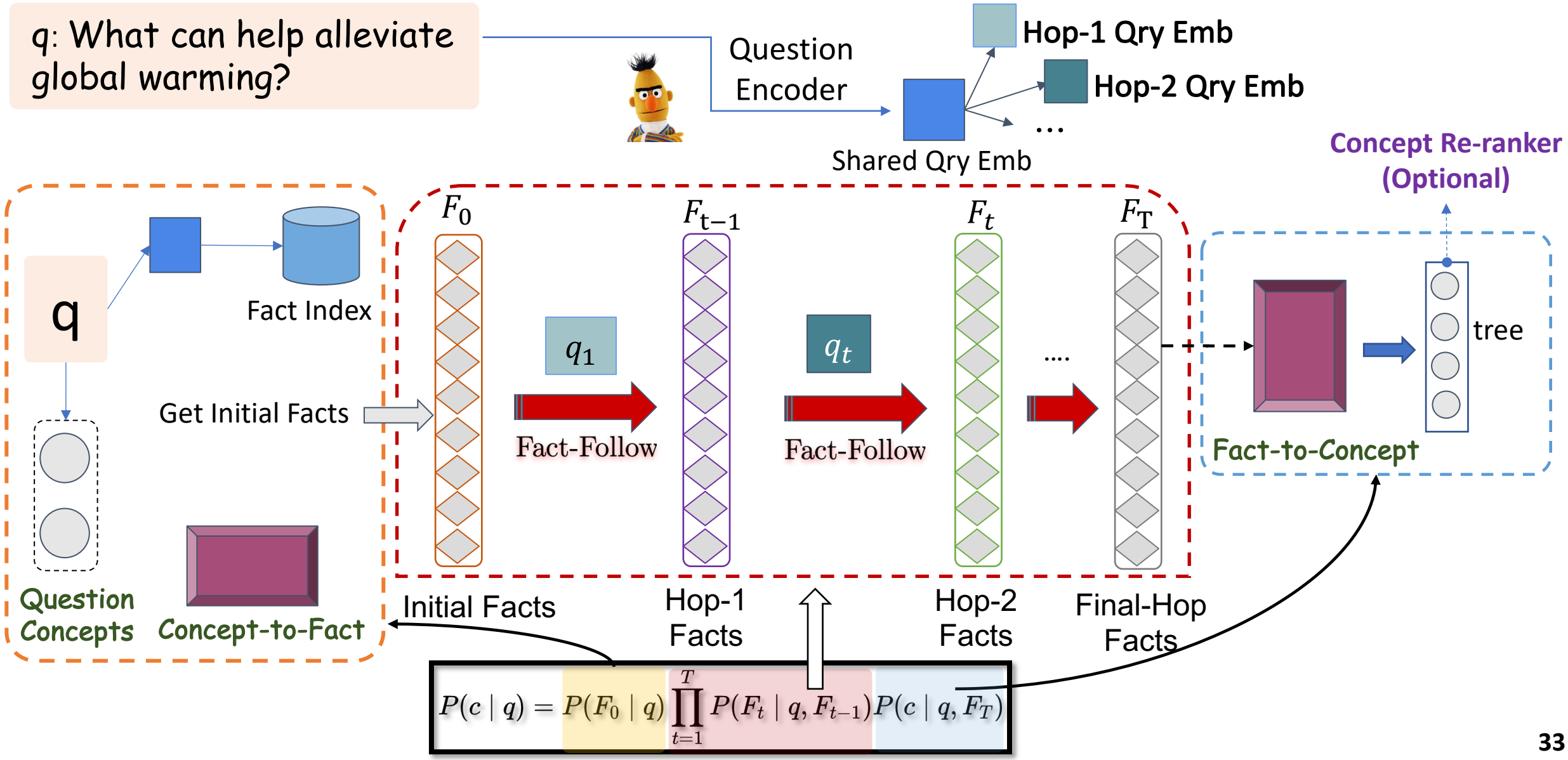


Sparse Matrix of **Fact-to-Fact** Links

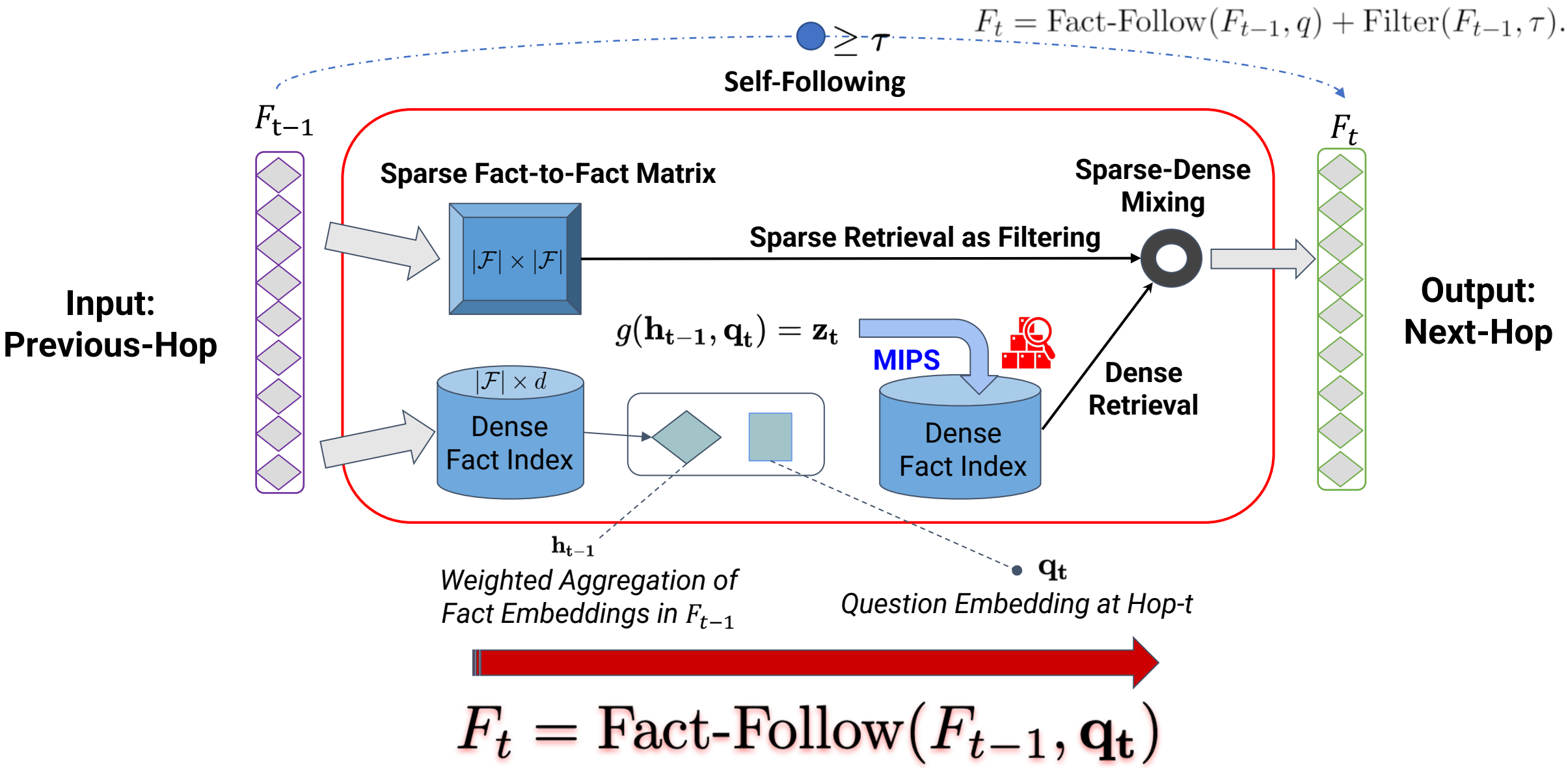


A weighted set of facts
→
A sparse vector.

Overall Workflow of DrFact



DrFact: Differentiable Fact-Following Operation



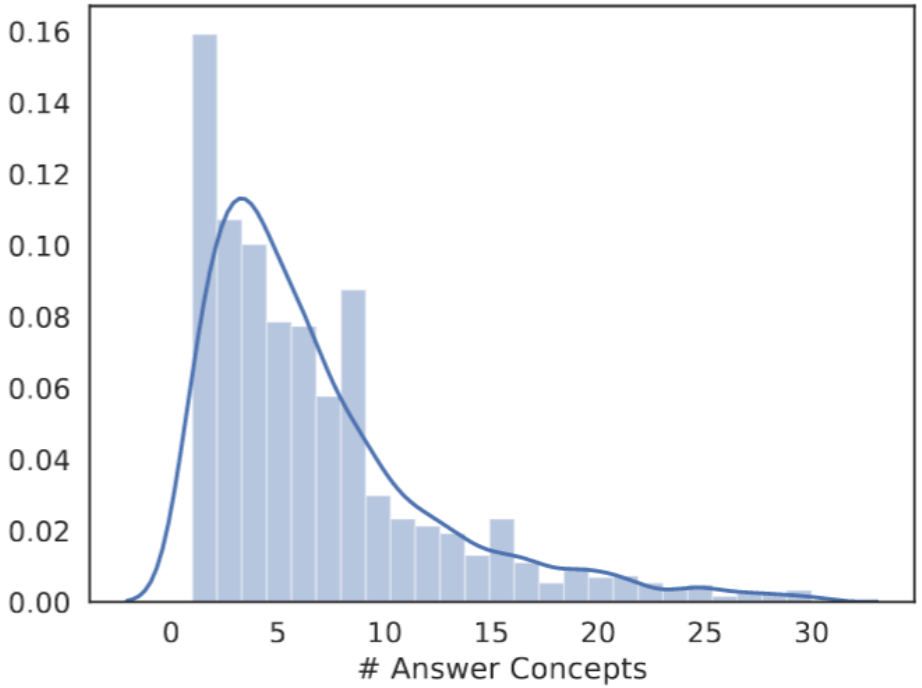
Comparisions with baseline methods.

Methods	BM25 (off-the-shelf)	DPR (EMNLP 2020)	DrKIT (ICLR 2020)	DrFact (NAACL 2021)
Knowledge Structure	A set of documents	A set of documents	Mention-Entity Bipartite Graph	Concept-Fact Hypergraph
Multi-hop Reasoning Formulation	N/A	N/A	Entity-Following	Fact-Following
Index for Dense Retrieval	N/A	Dense Fact Embeddings	Dense Mention Embedding	Dense Fact Embeddings
Sparse Retrieval Method	TF-IDF based Index+ BM25 Ranking Func.	N/A	Entity Cooccurrence	Fact-to-Fact Matrix
Multi-Hop Questions	N/A	N/A	Aggregating Multiple Models	A single model w/ Self-Following
Intermediate Supervision	N/A	N/A	N/A	Distant Supervision

Evaluation Setup

OpenCSR Dataset

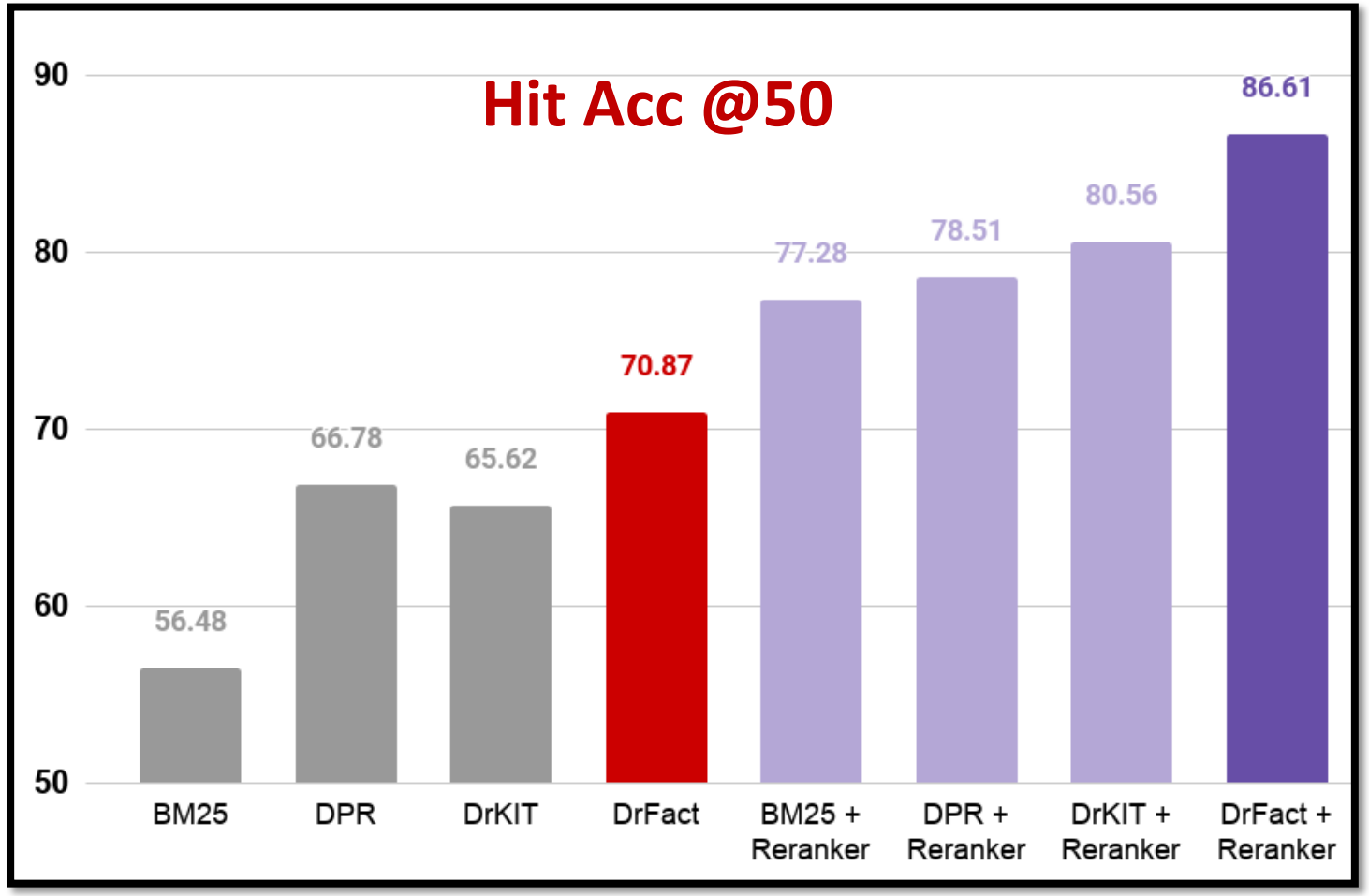
- Reformatted 3 Multiple-Choice QA Datasets (ARC, OBQA, QASC)
- + **Human-Annotated Answers** **(7 answer concepts per question on average)**

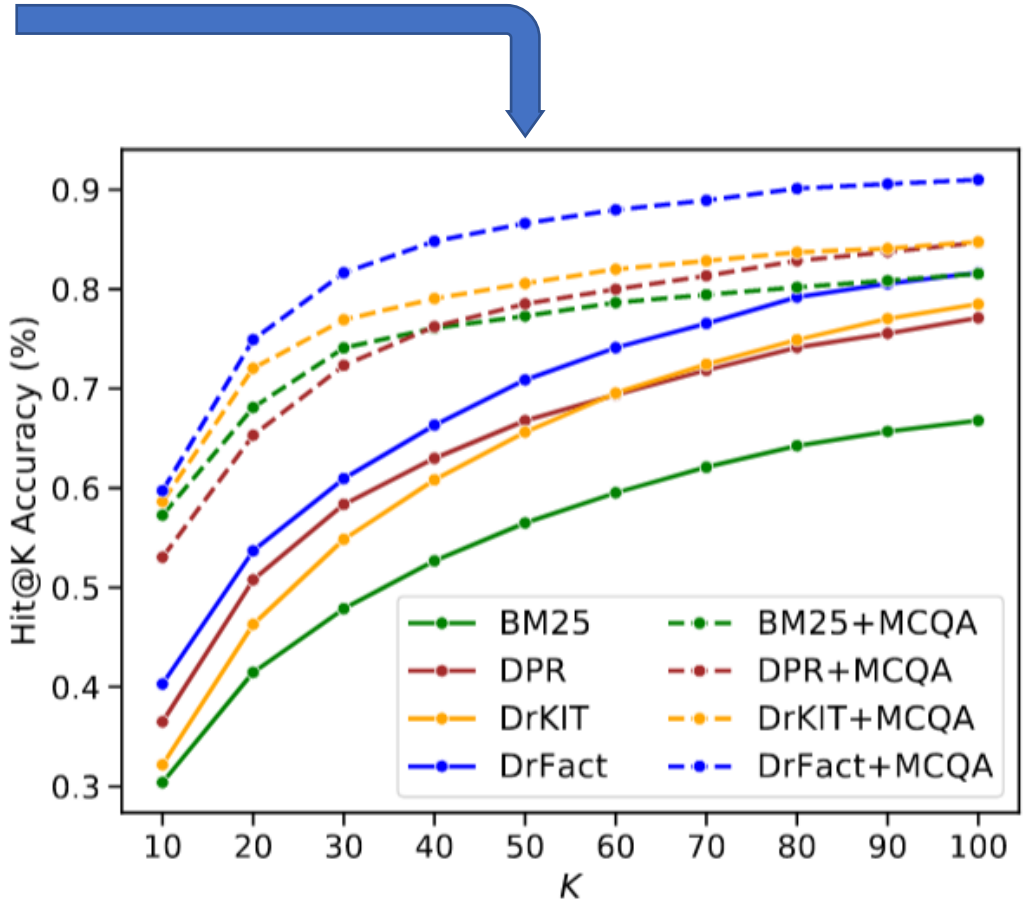


Metrics for evaluation

- **Hit Acc @ K <-- In the top K retrieved facts, there is at least one fact containing a correct answer (1 or 0).**
- **Ret Acc @ K <-- In the top K retrieved facts, the percentage of the recalled answer concepts (over all the correct answer concepts).**
- Both are reported as an **average** over all examples in the **test set**.

Main Experimental Results





Experimental Results

Methods	Major Computations	Speed (sec/q)
BM25	Sparse Retrieval	0.14
DPR	BERT-base + MIPS	0.08
DrKIT	BERT-base + T*(MIPS+ sp_{e2m})	0.47
DrFact	BERT-base + T*(MIPS+ sp_{f2f})	0.23
X+ MCQA	X + K * BERT-Large	+ *14.12*

	ARC	QASC	OBQA	Overall
T=1	69.3%	70.1%	65.0%	68.1%
T=2	71.1%	72.2%	68.3%	70.5%
T=3 ✓	71.6%	72.0%	69.0%	70.9%
w/o. Self-follow	70.9%	70.4%	68.4%	69.9%
w/o. Aux. loss	70.6%	70.1%	68.0%	69.6%

DPR vs DrFact: Faithfulness and Interpretability

Q: "What will separate iron filings from sand? "

f1= angle irons reinforce the thinnest section of the ring ."
f2= sieves are used for separating fossils from sand..."
f3= stainless steel has a rough surface just after filing ." **DPR**

iron filings show the *magnetic fields* . (in F0) **DrFact**
magnets *produce a magnetic field with a north ...* (in F1)
magnets *attract magnetic metals through magnetism* (in F2)

Findings and Take-Home Messages

- **OpenCSR is a novel setting to study CSR**
  - more **realistic** and **challenging** .
  - new **data** annotation for evaluation.

- **DrFact is an effective and efficient method for OpenCSR.**
  - **differentiable** Fact-Follow operation for **end-to-end** learning.
  - **state-of-the-art** performance comparing to strong baselines.
  - improve the explanations for multi-hop questions.

Outline

- ~~Background of Commonsense Reasoning in NLP~~
- ~~Incorporating Structured Commonsense Knowledge~~
- ~~Incorporating Unstructured Commonsense Knowledge~~
- **→ Incorporating Commonsense Knowledge for NLG**
  - **CommonGen (EMNLP 2020)**
    - A constrained text generation benchmark requires CS knowledge
  - Recent knowledge-augmentation methods for CommonGen
    - **KG-BART (AAAI 2021), KGR^4 (AAAI2022), I&V (ICLR 2022), etc.**

What is CommonGen?

- Most current tasks for machine commonsense focus on discriminative reasoning.
  - CommonsenseQA, SWAG.

- Humans not only use **commonsense knowledge** for understanding text, but also for **generating sentences**.

Concept-Set: a collection of objects/actions.

dog, frisbee, catch, throw

Generative Commonsense Reasoning

Expected Output: everyday scenarios covering all given concepts.

- A dog leaps to catch a thrown frisbee. [Humans]
- The dog catches the frisbee when the boy throws it.
- A man throws away his dog 's favorite frisbee expecting him to catch it in the air.

Input:

-A set of common concepts (actions & objects)

Output:

-A sentence that describes an everyday scenario the given concepts.

Why is it hard? Two key Challenges of CommonGen

(1) Relational knowledge are **latent** and **compositional**.

{ exercise, rope, wall, tie, wave }

Underlying Relational Commonsense Knowledge

(exercise, HasSubEvent , releasing energy)

(rope, UsedFor, tying something)

(releasing energy, HasPrerequisite, motion)

(wave, IsA, motion) ; (rope, UsedFor, waving)

The motion costs more energy if ropes are tied to a wall.

Relational Reasoning for Generation

A woman in a gym exercises by waving ropes tied to a wall.

Category	Relations	1-hop	2-hop
Spatial knowledge	AtLocation, LocatedNear	9.40%	39.31%
Object properties	UsedFor,CapableOf,PartOf, ReceivesAction,MadeOf, FormOf, HasProperty,HasA	9.60%	44.04%
Human behaviors	CausesDesire,MotivatedBy, Desires,NotDesires,Manner	4.60%	19.59%
Temporal knowledge	Subevent, Prerequisite, First/Last-Subevent	1.50%	24.03%
General	RelatedTo, Synonym, DistinctFrom, IsA, HasContext,SimilarTo	74.89%	69.65%

Why is it hard? Two key Challenges of CommonGen

(2) Compositional Generalization for unseen concept compounds.

x_1 = { apple, bag, put } — Training

y_1 = a girl puts an apple in her bag

x_2 = { apple, tree, pick }

y_2 = a man picks some apples from a tree

x_3 = { apple, basket, wash }

y_3= a boy takes an apple from a basket and washes it.

Compositional Generalization

x = { pear, basket, pick, put, tree }, y = ?

Reference: "a girl picks some pear from a tree and put them in her basket." — Test

Unseen Concept in Training

Statistics	Train	Dev	Test
# Concept-Sets	**32,651**	**993**	**1,497**
-Size = 3	25,020	493	-
-Size = 4	4,240	250	747
-Size = 5	3,391	250	750
# Sentences	67,389	4,018	6,042
per Concept-Set	2.06	4.04	4.04
Average Length	10.54	11.55	13.34
# Unique Concepts	4,697	766	1,248
# Unique Concept-Pairs	59,125	3,926	8,777
# Unique Concept-Triples	50,713	3,766	9,920
% Unseen Concepts	-	6.53%	8.97%
% Unseen Concept-Pairs	-	96.31%	100.00%
% Unseen Concept-Triples	-	99.60%	100.00%

Experimental Results

Model \ Metrics	ROUGE-2/L		BLEU-3/4		METEOR	CIDEr	SPICE	Coverage
bRNN-CopyNet (Gu et al., 2016)	7.61	27.79	10.70	5.70	15.80	4.79	15.00	51.15
Trans-CopyNet	8.78	28.08	11.90	7.10	15.50	4.61	14.60	49.06
MeanPooling-CopyNet	9.66	31.14	10.70	6.10	16.40	5.06	17.20	55.70
LevenTrans. (Gu et al., 2019)	10.58	32.23	19.70	11.60	20.10	7.54	19.00	63.81
ConstLeven. (Susanto et al., 2020)	11.82	33.04	18.90	10.10	24.20	10.51	22.20	94.51
GPT-2 (Radford et al., 2019)	17.18	39.28	30.70	21.10	26.20	12.15	25.90	79.09
BERT-Gen (Bao et al., 2020)	18.05	40.49	30.40	21.10	27.30	12.49	27.30	86.06
UniLM (Dong et al., 2019)	21.48	**43.87**	38.30	27.70	29.70	14.85	30.20	89.19
UniLM-v2 (Bao et al., 2020)	18.24	40.62	31.30	22.10	28.10	13.10	28.10	89.13
BART (Lewis et al., 2019)	**22.23**	41.98	36.30	26.30	**30.90**	13.92	30.60	**97.35**
T5-Base (Raffel et al., 2019)	14.57	34.55	26.00	16.40	23.00	9.16	22.00	76.67
T5-Large (Raffel et al., 2019)	22.01	42.97	**39.00**	**28.60**	30.10	**14.96**	**31.60**	95.29
Human Performance	48.88	63.79	48.20	44.90	36.20	43.53	63.50	99.31

(1) Seq2seq models

(2) Fine-tuning pre-trained LMs

(3) Agreement

Manual Eval.

	C.Leven	GPT	BERT-G.	UniLM	BART	T5
Hit@1	3.2	21.5	22.3	21.0	26.3	**26.8**
Hit@3	18.2	63.0	59.5	69.0	69.0	**70.3**
Hit@5	51.4	95.5	95.3	96.8	96.3	**97.8**

Case Study & Transfer Learning

Concept-Set: { hand, sink, wash, soap }

[bRNN-CopyNet]: a hand works in the sink .

[MeanPooling-CopyNet]: the hand of a sink being washed up

[ConstLeven]: a hand strikes a sink to wash from his soap.

[GPT-2]: hands washing soap on the sink.

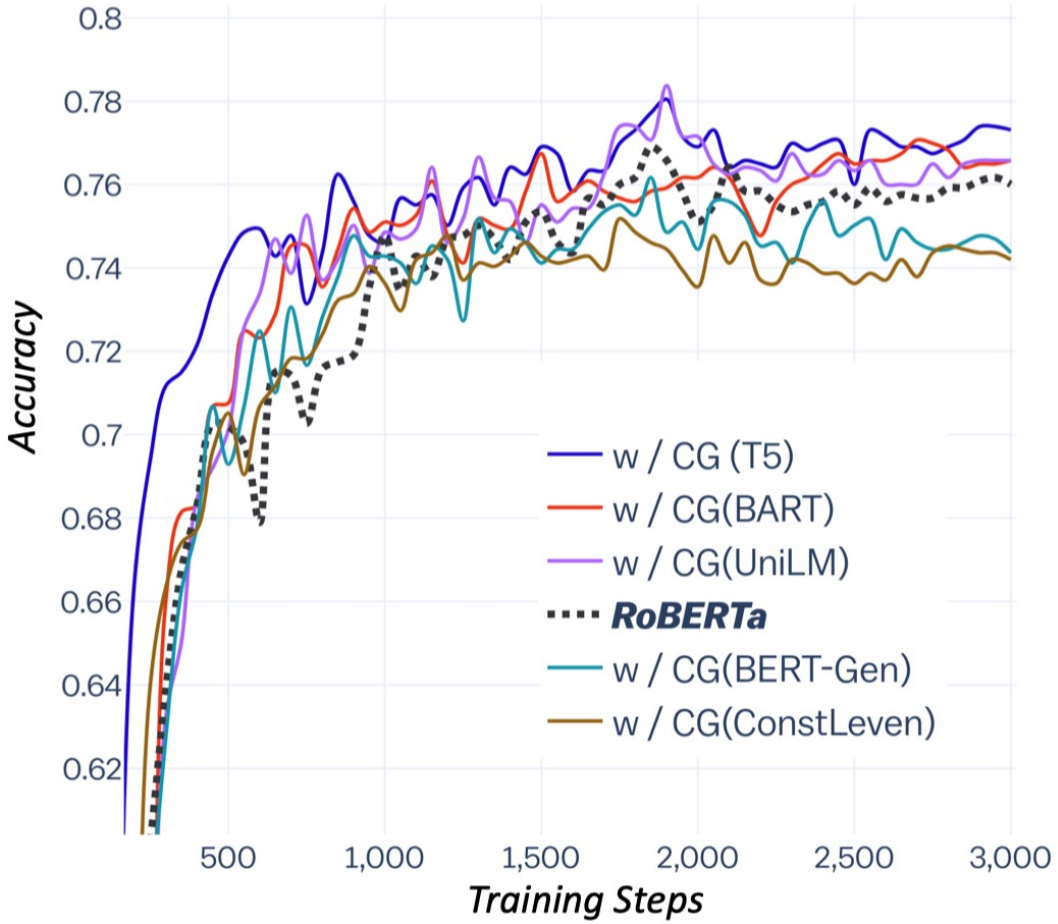
[BERT-Gen]: a woman washes her hands with a sink of soaps.

[UniLM]: hands washing soap in the sink

[BART]: a man is washing his hands in a sink with soap and washing them with hand soap.

[T5]: hand washed with soap in a sink.

1. A girl is washing her hands with soap in the bathroom sink.
2. I will wash each hand thoroughly with soap while at the sink.
3. The child washed his hands in the sink with soap.
4. A woman washes her hands with hand soap in a sink.
5. The girl uses soap to wash her hands at the sink.



Learning curve for the transferring study (acc on dev). We use trained CommonGen models to generate choice-specific context for the CommonsenseQA task.

Rank	Model	BLEU-4	CIDEr	**SPICE**
	Upper Bound	46.49	37.64	52.43
1 Jun 09, 2021	**KFCNet** *MSRA and Microsoft Ads* Email Paper (EMNLP'21)	43.619	18.845	33.911
2 May 18, 2021	**KGR^4** *Alibaba and Xiamen University.* Email Paper (AAAI 2022)	42.818	18.423	33.564
3 Mar 23, 2021	**KFC (v1)** *MSRA and Microsoft Ads* Email Paper (EMNLP'21)	42.453	18.376	33.277
4 April 25, 2021	**R^3-BART** *Anonymous (under review).* Email Document (placeholder)	41.954	17.706	32.961
5 July 1, 2021	**WittGEN + T5-large** *Anonymous (under review)*	38.233	18.036	31.682
6 Jan 28, 2022	**Imagine-and-Verbalize** *USC/ISI* Email Paper (ICLR22)	40.565	17.716	31.291

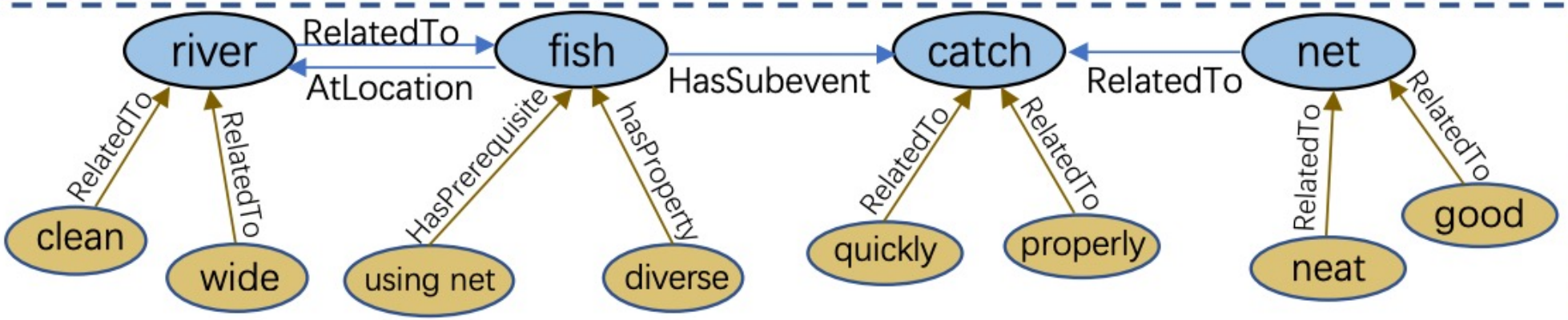
KG-BART (AAAI 2021)

Concept Set: {river, fish, net, catch}

[Expected Output]: everyday scenarios covering all given concepts.

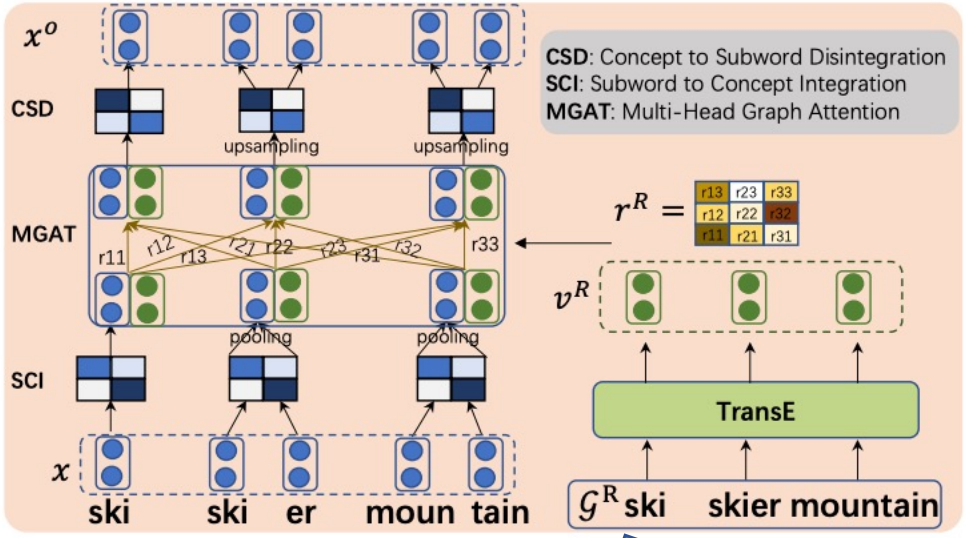
1. Fisherman uses a strong net to catch plentiful fishes in the river.
2. Men like to catch fishes in the wide river with a net in the afternoon.

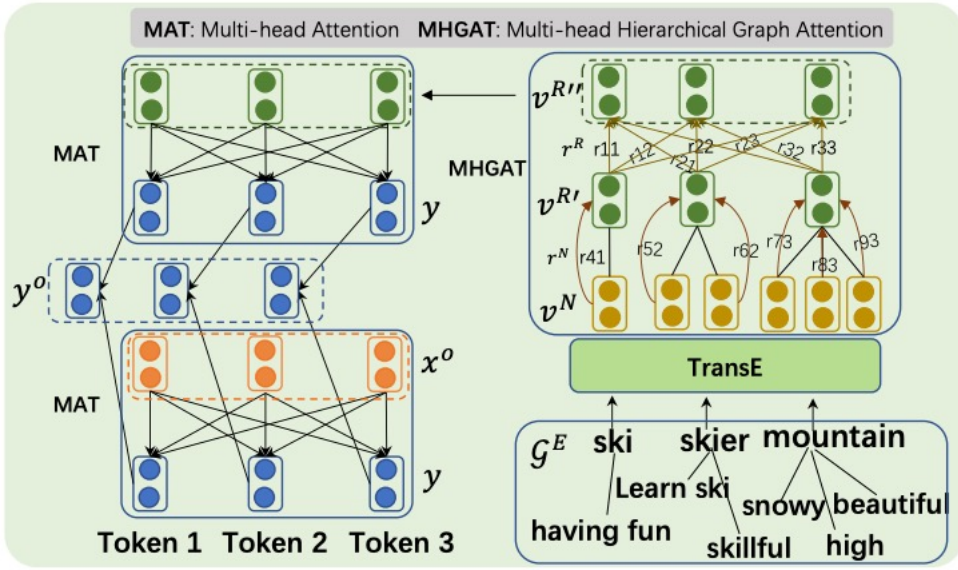
[GPT-2]: A fish is catching in a net
[UniLM]: A net catches fish in a river
[T5]: Fish are caught in a net in the river.
[BART]: A man catches a fish with a net in the river

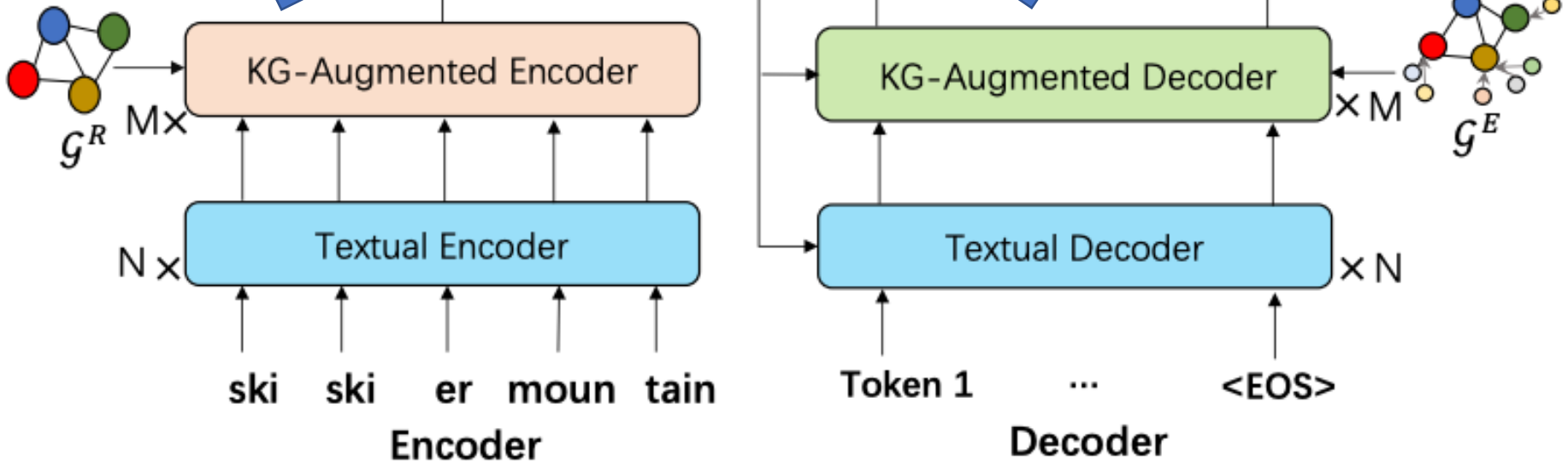


[KG-BART]: A fisherman catches fishes by using good net in the clean river.

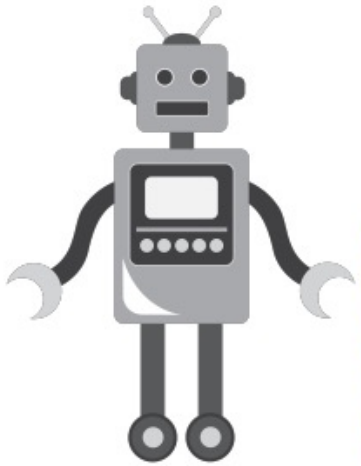
KG-BART (AAAI 2021)







KGR^4 (AAAI 2022)



hand, sink, wash, soap

Retrieval

P1: A man is washing his hands in a bathroom sink.
P2: Someone thoroughly washing their hands with soap in a bathroom sink
P3: Two kids are standing in front of a sink washing their hands with kid soap,
...

Retrospect

Edited: A man is washing his hands with soap in a sink with soap.
Copied: A man is washing his hands in a bathroom sink.

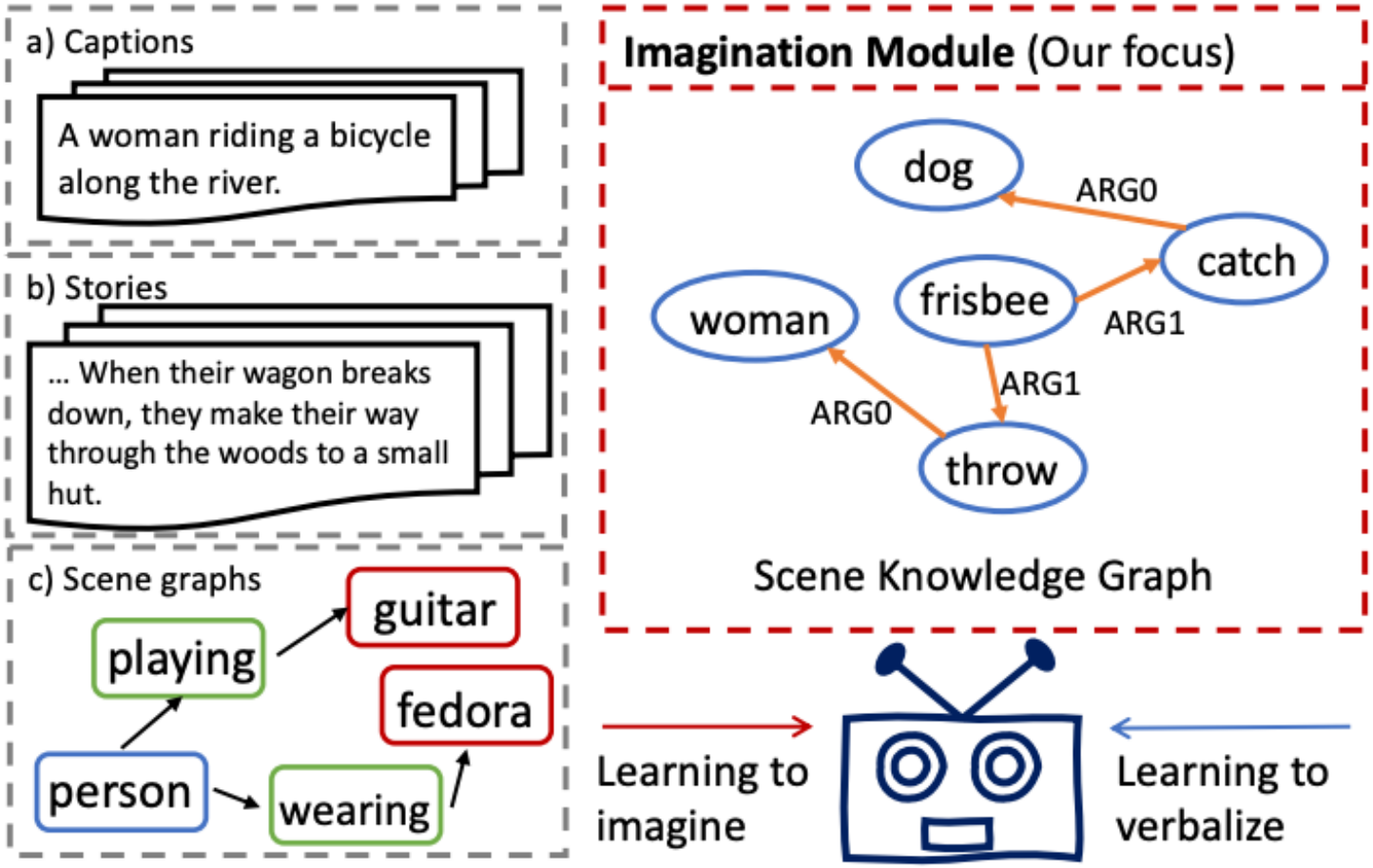
Refine

Edited: A man is washing his hands with soap in a sink.
Copied: A man is washing his hands in a bathroom sink.

Rethink

A man is washing his hands with soap in a sink.

Imagine & Verbalize (ICLR 2022)



Verbalization Module

A woman throws a frisbee and a dog catches it in the air.

- Task 1: Concept2Sentence

Input	Concepts: {dog, frisbee, throw, catch}
Output	"A woman throws a frisbee and a dog catches it."

- Task 2: Concept2Story

Input	Context: "My sister arrived early to help me with the family BBQ." Concepts[1]: {everyone, arrive} ... Concepts[K]: {day, end, fireworks, shoot}
Output	"Everyone else arrived soon after... We ended the day shooting off some fireworks."

Review

- Background of Commonsense Reasoning in NLP
- Incorporating **Structured** Commonsense Knowledge
  - KagNet (EMNLP 2019), MHGRN (EMNLP 2020), QA-GNN (NAACL 2021)
  - ~~GreaseLM (ICLR 2022), GSC (ICLR 2022)~~
- Incorporating **Unstructured** Commonsense Knowledge
  - DrFact (NAACL 2021)
- Incorporating Commonsense Knowledge for **NLG**
  - CommonGen (EMNLP 2020)
  - KG-BART (AAAI 2021), KGR^4 (AAAI2022), I&V (ICLR 2022), etc.