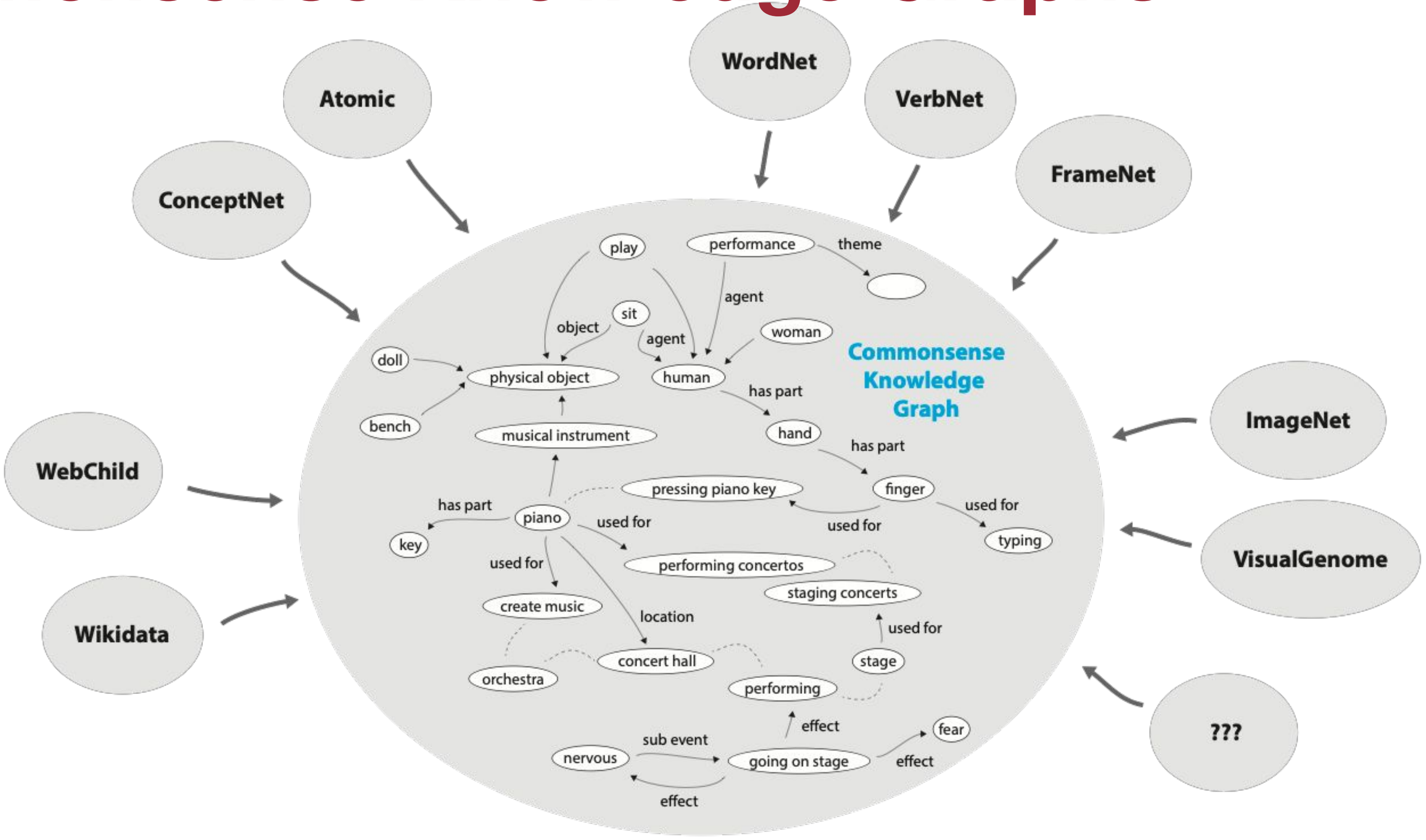
Agenda

08:00 PST	1 hr 50 mins	**Part I - Review of CSKGs**
	15 min	Introduction to commonsense knowledge (slides) - Pedro
	25 min	Review of top-down commonsense knowledge graphs (slides) - Mayank
	70 min	Review of bottom-up commonsense knowledge graphs (slides+demo) - Mayank, Filip, Pedro
	10 min	**Break**
10:00 PST	45 min	**Part II - Integration and analysis**
	35 min	Consolidating commonsense graphs (slides) - Filip
	10 min	Consolidating commonsense graphs (demo) - Pedro
	10 min	**Break**
10:55 PST	1 hr 05 mins	**Part III - Downstream use of CSKGs**
	50 min	Answering questions with CSKGs (slides+demo) - Filip
	15 min	Wrap-up (slides) - Mayank

Answering Questions with CSKGs

Filip Ilievski

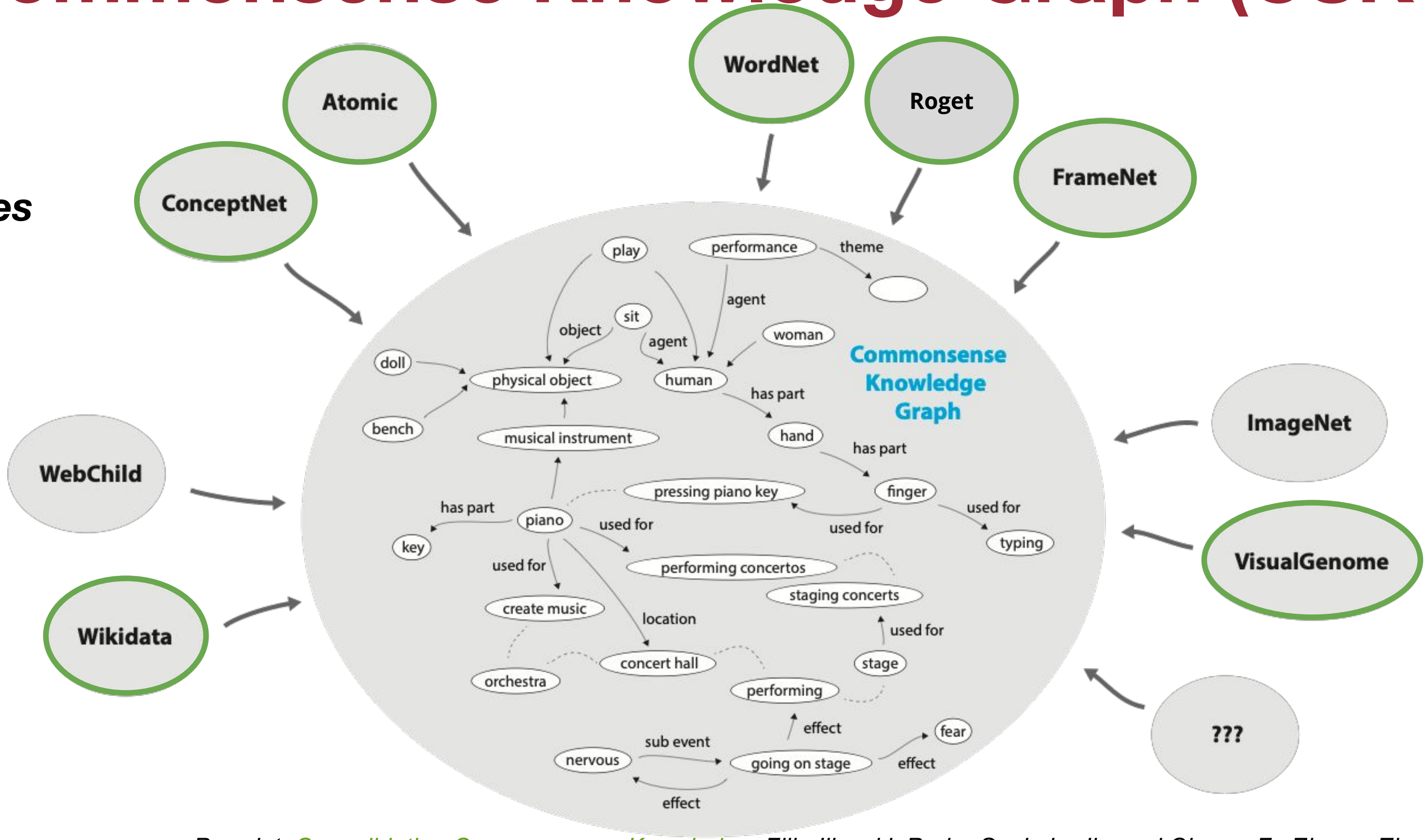
Commonsense Knowledge Graphs



The Commonsense Knowledge Graph (CSKG)

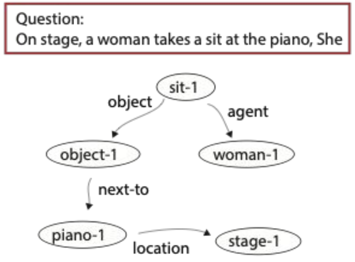
7 sources

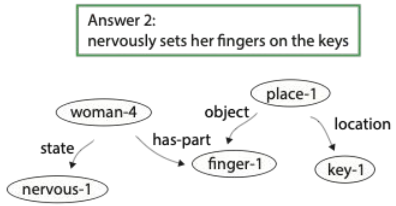
2.3M nodes
6M edges

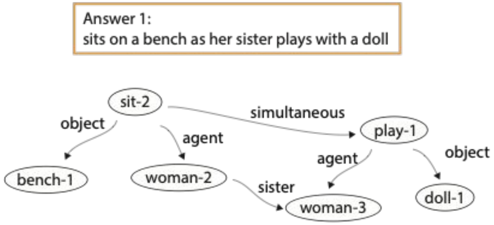


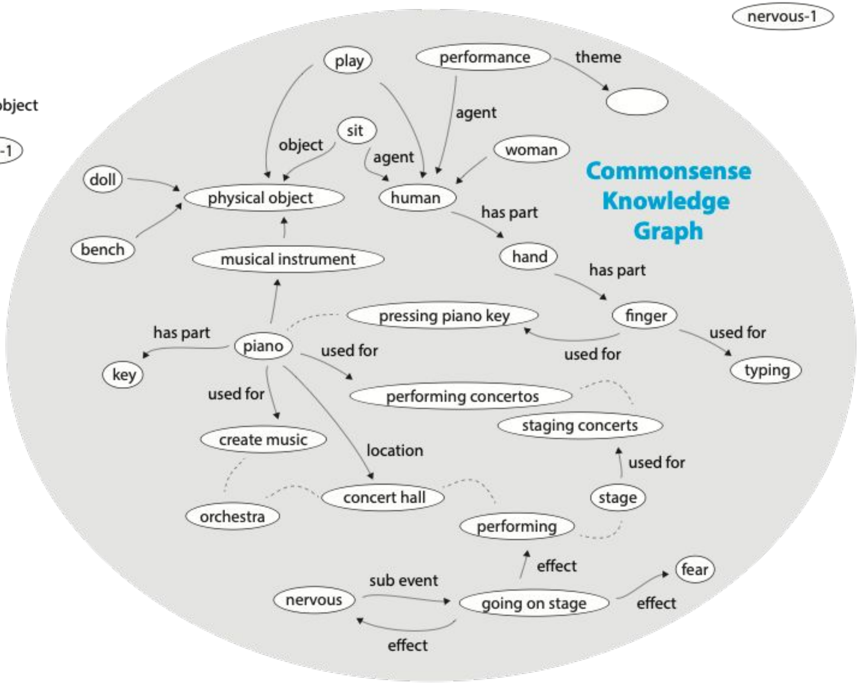
Preprint: [Consolidating Commonsense Knowledge](). Filip Ilievski, Pedro Szekely, Jingwei Cheng, Fu Zhang, Ehsan Qasemi.

Semantic Parsing



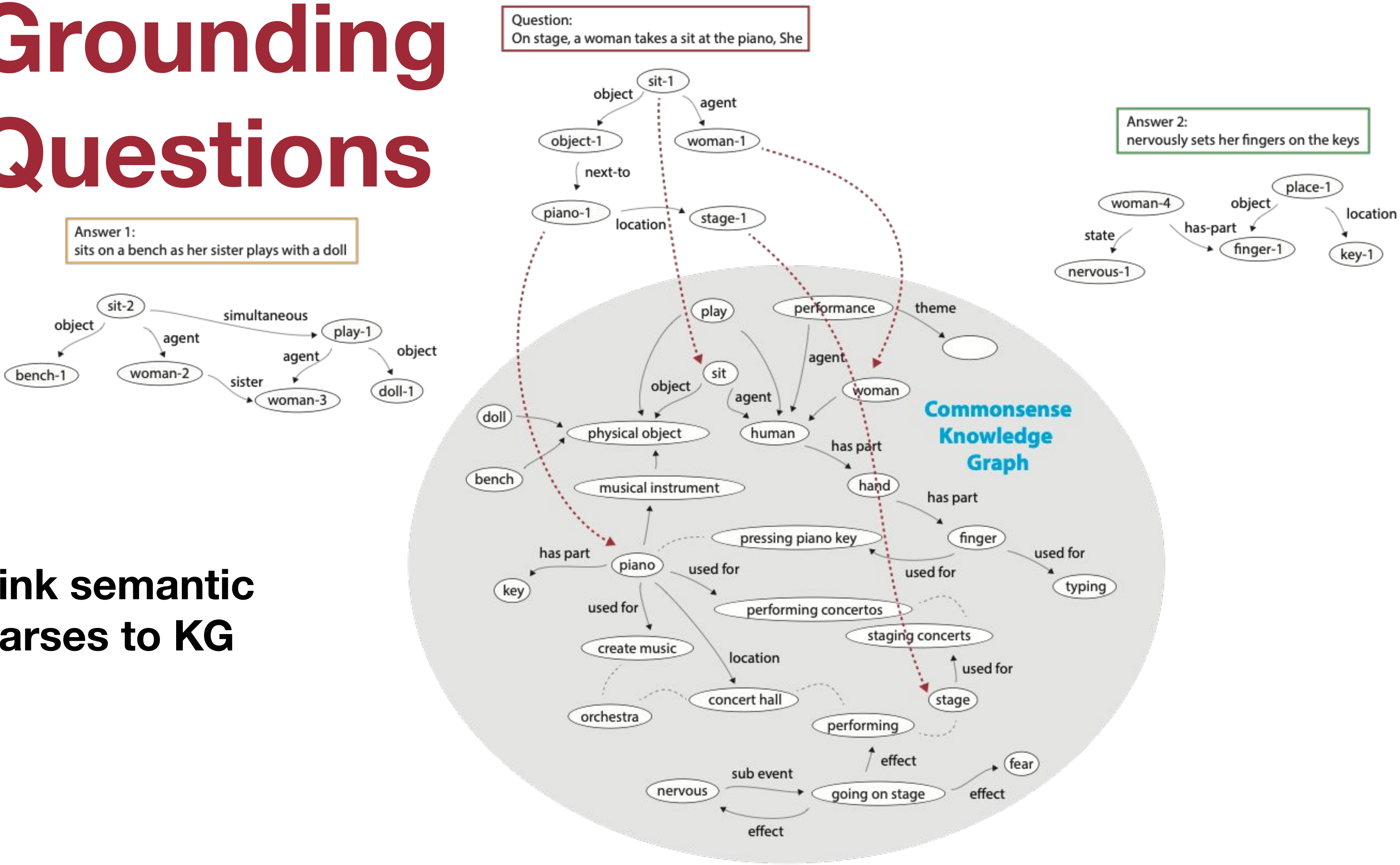






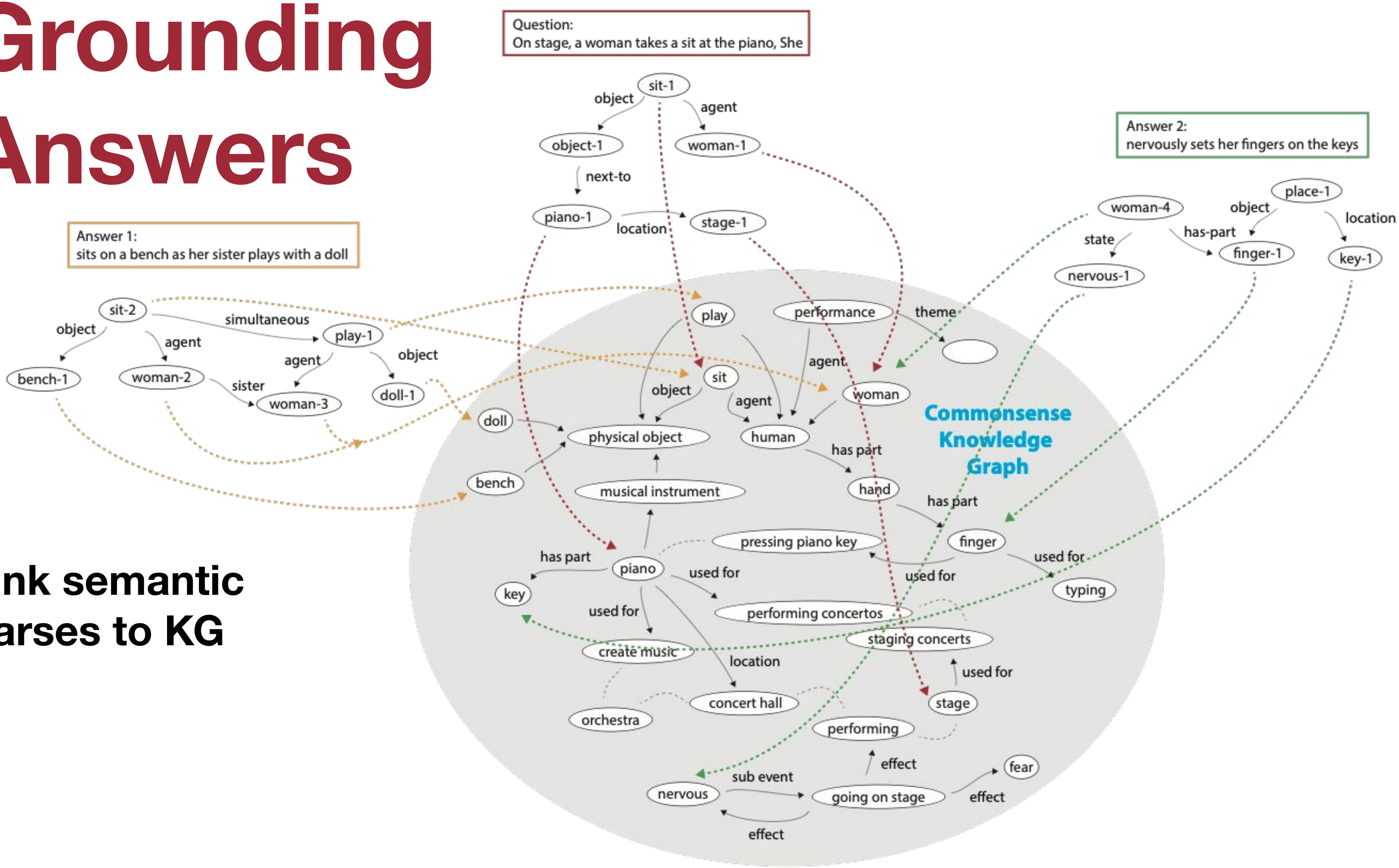
Construct semantic representations of question and answers

Grounding Questions



Link semantic parses to KG

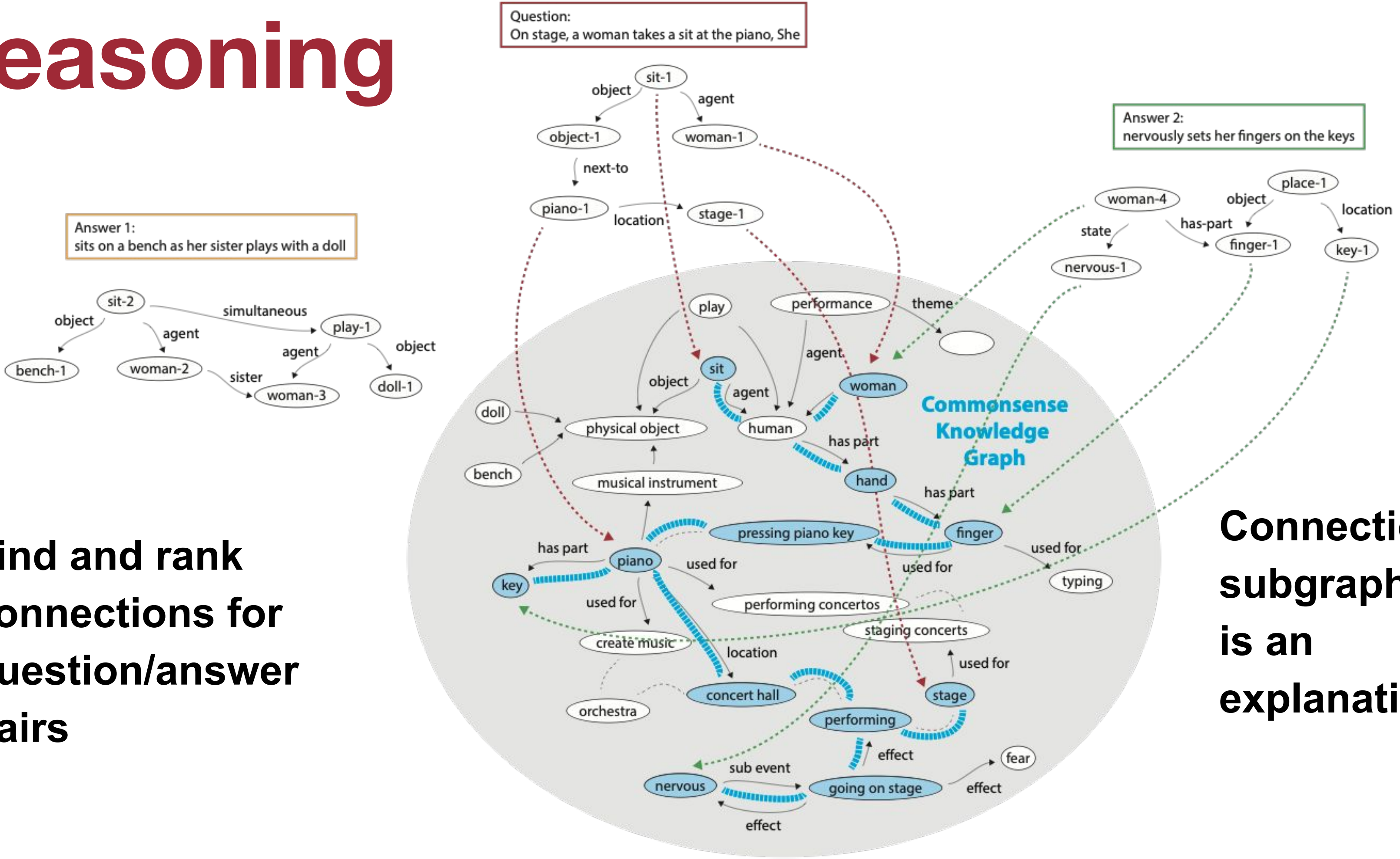
Grounding Answers



Link semantic parses to KG

Reasoning

Find and rank connections for question/answer pairs



Connection subgraph is an explanation

Grounding

Slides adapted from:
Anthony Chen, Robert Logan, Sameer Singh
UC Irvine

Motivating Example

When boiling butter, when it's ready, you can…

pour it on a plate

pour it into a jar

Source: Physical IQA

Motivating Example

When boiling butter, when it's ready, you can...

pour it on a plate

pour it into a jar

Required Common Sense:

- Things that boil are liquid (when they're ready)
- Liquids can be poured
- Butter can be a liquid
- Jars hold liquids
- Plates (typically) do not contain liquids

Captured in CSKG!

Required Linguistic Understanding:

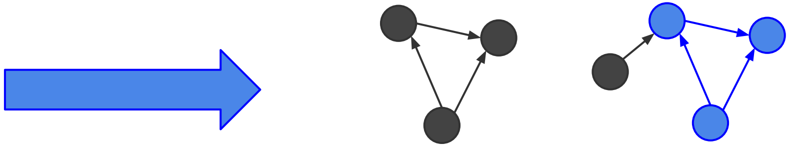
- The antecedent of '*it*' is '*butter*'

Source: Physical IQA

Semantic Parsing: Text to Meaning Representation

When boiling butter, when it’s ready, you can...

..pour it on a plate



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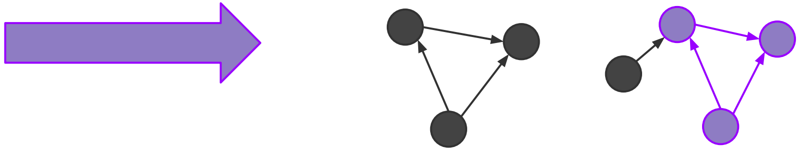


Semantic Parsing: Text to Meaning Representation

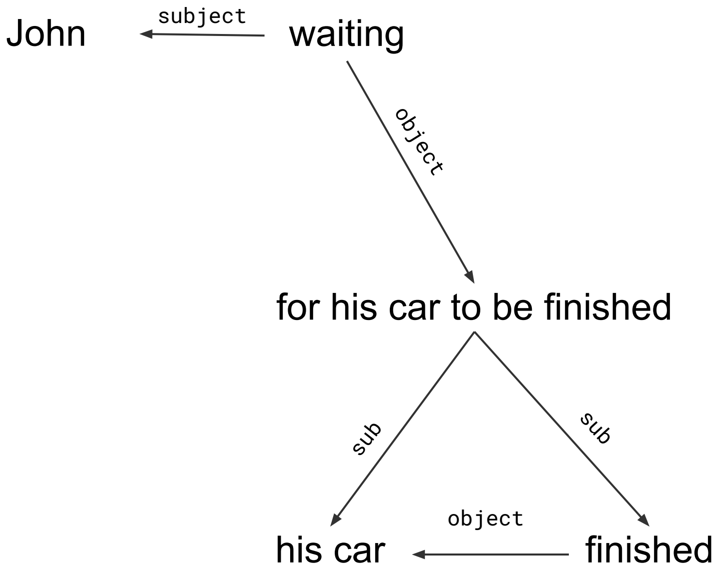
Three steps:

1. **Semantic Role Labeling**
   - Graphical encoding of dependencies between subjects/verbs in a sentence.
2. **Coreference Resolution**
   - Link mentions of entity within and across sentences.
3. **Named Entity Recognition**
   - Map fine-grained entities (e.g., “John”) to common entities (e.g., “Person”).
   - Better generalization

Semantic Role Labeling

Labels predicates (verbs) and their associated arguments.

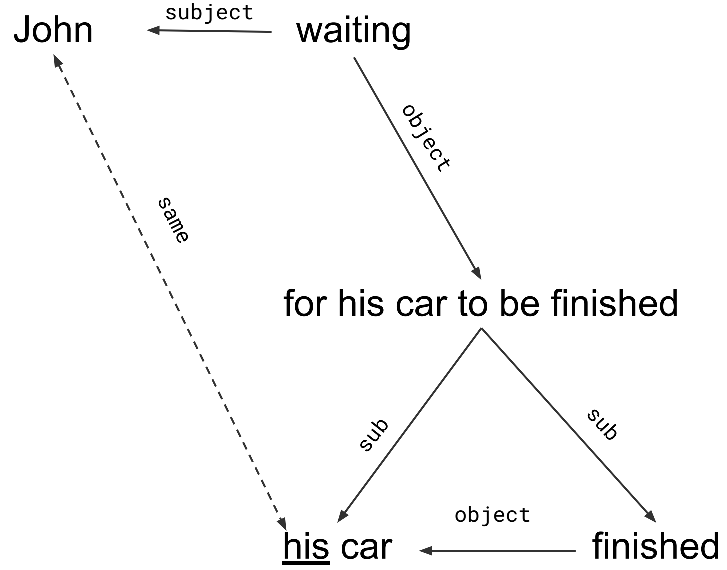
John is waiting for his car to be finished.



Coreference Resolution

Links mentions of a single entity in a sentence or across sentences.

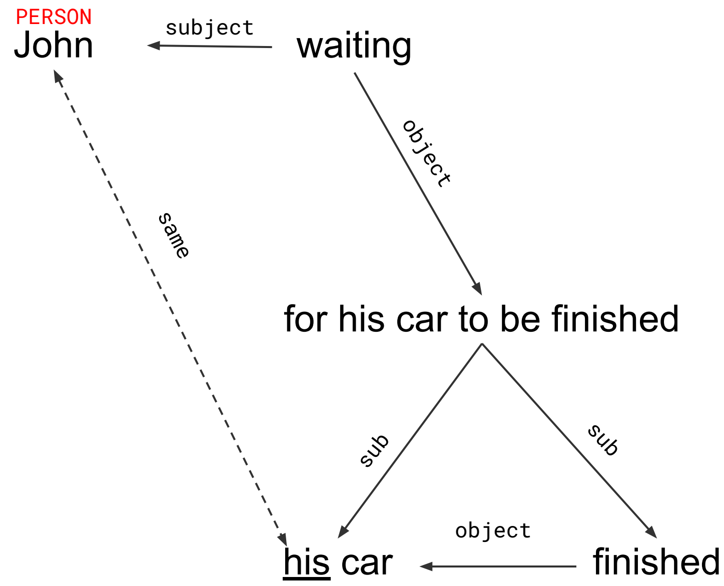
John is waiting for his car to be finished.



Named Entity Recognition

Marks each node if it is a named entity along with the entity type.

John is waiting for his car to be finished.



Semantic Parse: Question/Context

Which answer choice is better?

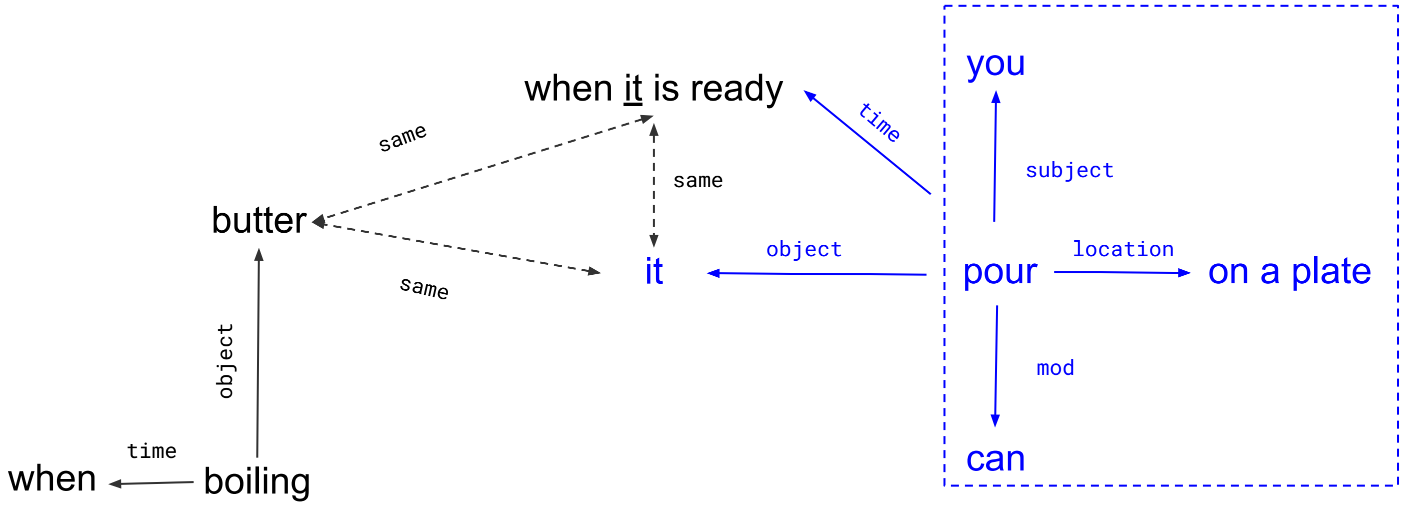
Q. When boiling butter, when it is ready, you can…

Ans 1 pour it on a plate.

Ans 2 pour it into a jar

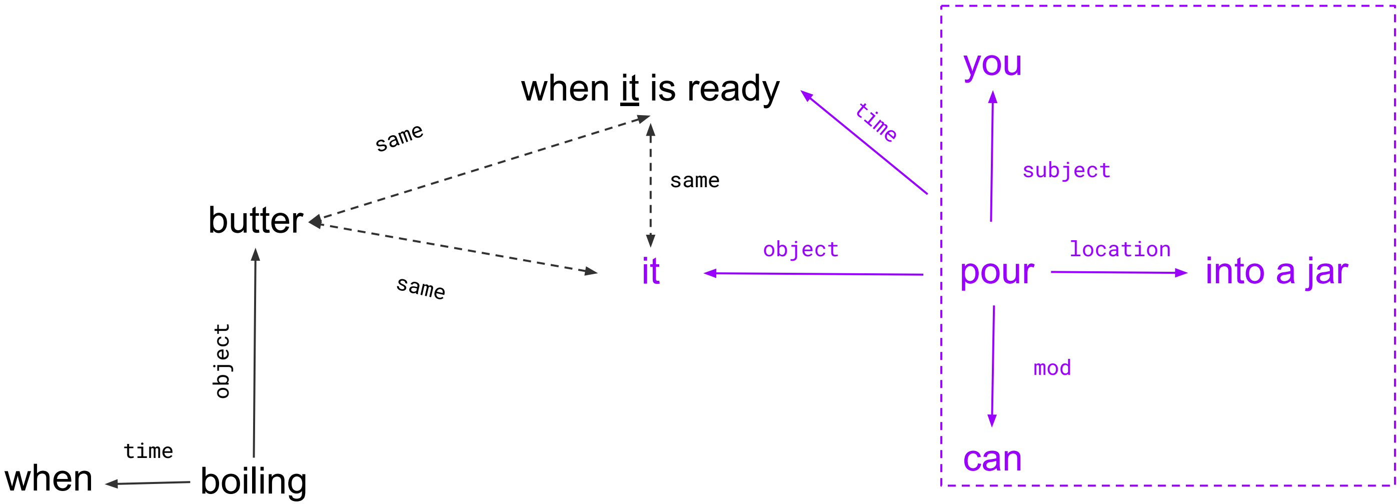
Semantic Parse: Answer 1

When boiling butter, when it is ready, you can pour it on a plate.



Semantic Parse: Answer 2

When boiling butter, when it is ready, you can pour it into a jar.



Shortcomings and Future Directions

Many different ways to parse a sentence/sentences

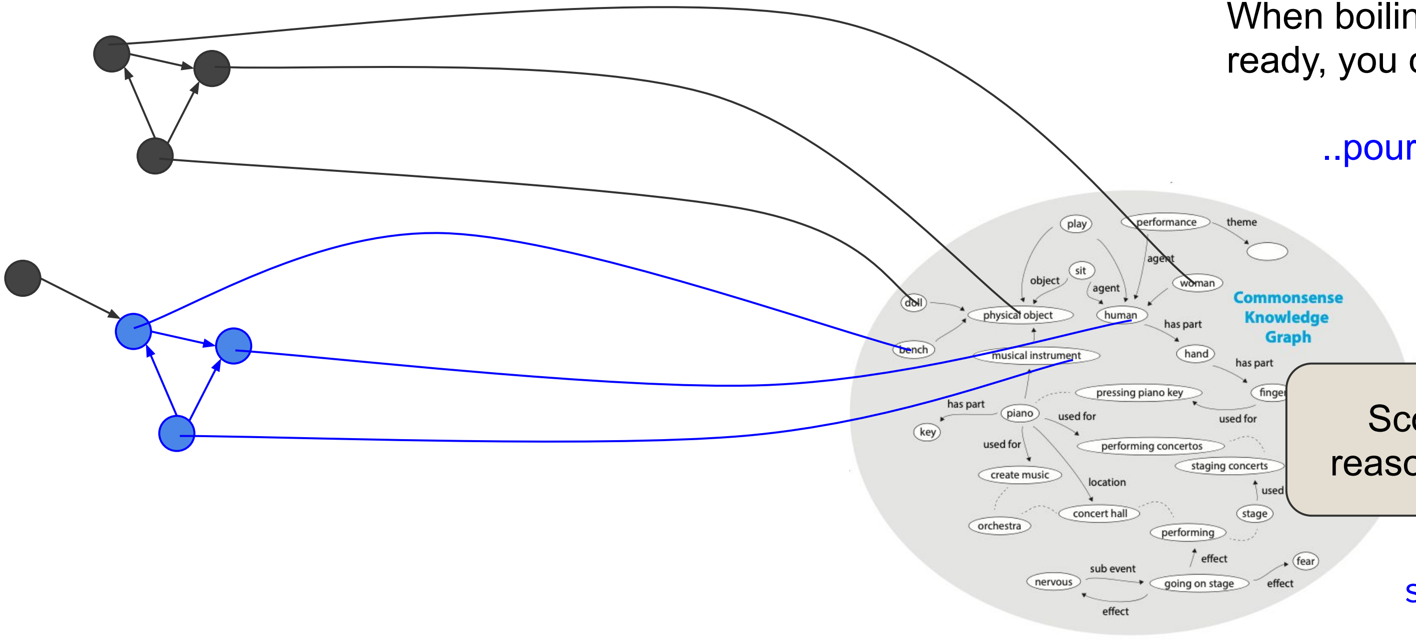
- Semantic role labeling focuses on predicates, but ignores things like prepositional phrases.
- Can incorporate dependency parsing, abstract meaning representations (AMR), etc.

Future Work: Explore other meaning representations, including logic

Linking to Commonsense KG

When boiling butter, when it's ready, you can...

..pour it on a plate

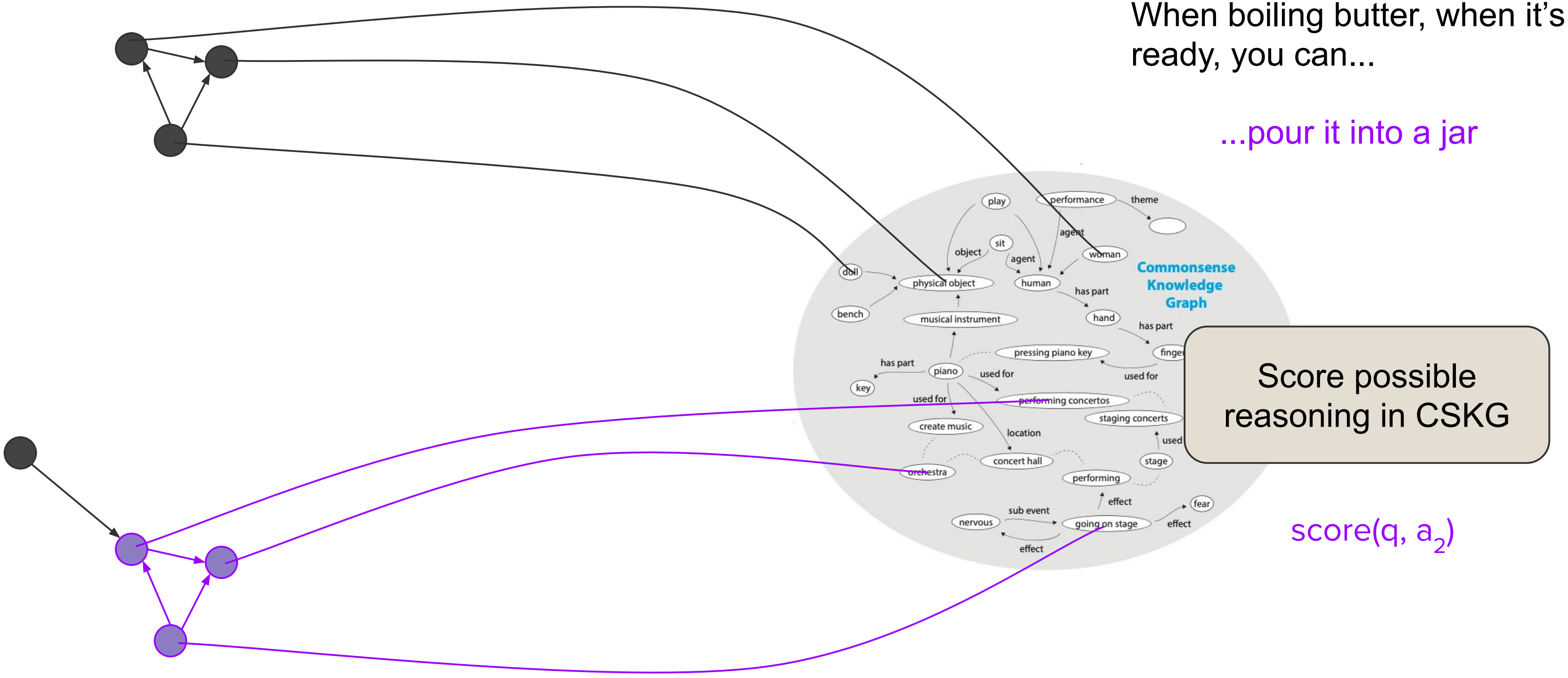


Score possible reasoning in CSKG

score(q, a_1)

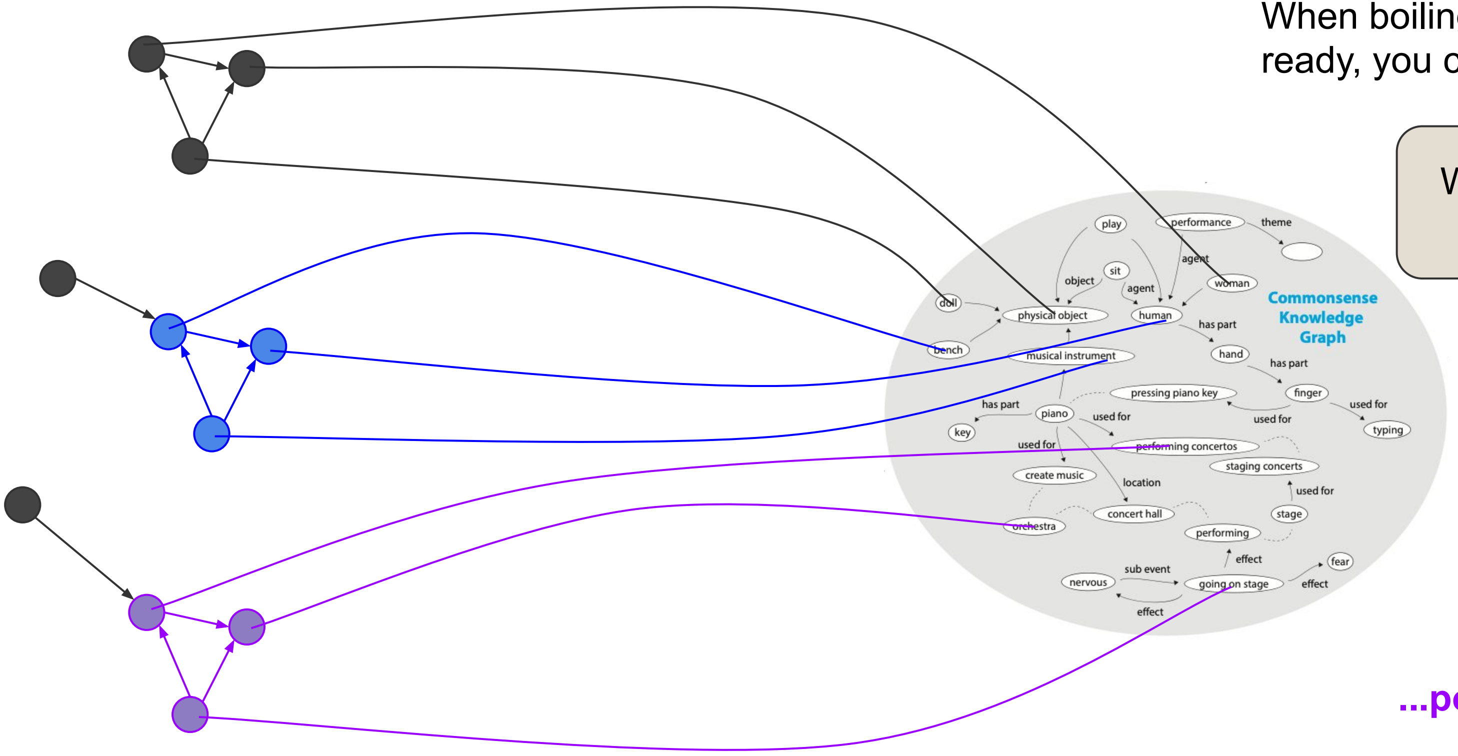
Linking to Commonsense KG

When boiling butter, when it's ready, you can...



Linking to Commonsense KG

When boiling butter, when it's ready, you can...



Which reasoning is better?

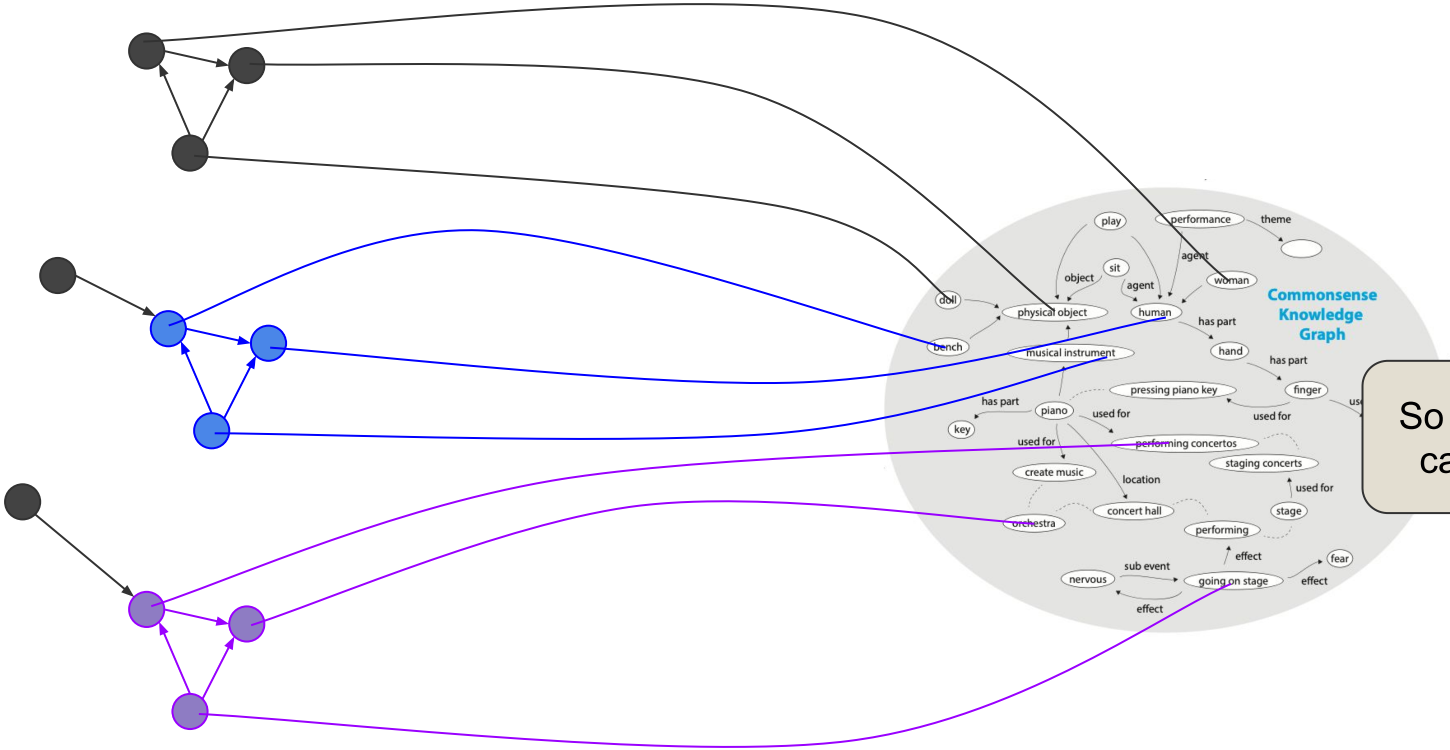
score(q, a_1)

$\wedge$

score(q, a_2)

...pour it into a jar

Linking to CSKG



So that reasoning can take place!

Linking to CSKG: Question/Context

The boy loved telling scary stories.

The boy — /c/en/boy

loved — /c/en/loved

telling — /c/en/telling

scary stories — /c/en/horror_stories

Generalizes to concepts
(not just lexical)

Approach

- **Embed words and phrases**
  - Tokenization/concept matching
    - “*Natural language processing*” or “*Natural*”, “*language*”, “*processing*”?
  - Use embeddings
    - ConceptNet Numberbatch [Speer et al., AAAI 2017]
    - BERT [Devlin et al., 2018]
  - Node representation = function of word embeddings
- **Compute alignment between text and KG embeddings**
  - Cosine/L2 distance

Examples

“amused” -> *amused* (0.0), *amusedness* (0.04), *amusedly* (0.12), …

“Tina, a teenager” -> *teenager* (0.0), *tina* (0.0), *subteen* (0.01), …

“With how popular her mother is” -> *mother* (0.0), *with* (0.0), *is* (0.0), …

“Scary stories” -> *stories* (0.0), *scary* (0.0), *scarisome* (0.02), …

Examples

"amused" -> *amused* (0.0), *amusedness* (0.04), *amusedly* (0.12), ...

"Tina, a teenager" -> *teenager* (0.0), *tina* (0.0), *subteen* (0.01), ...

"With how popular her mother is" -> *mother* (0.0), *with* (0.0), *is* (0.0), ...

"Scary stories" -> *stories* (0.0), *scary* (0.0), *scarisome* (0.02), ...

- Potentially better links: *scary_story*, *horror_story*
  - *horror_story* appears in the top-5 using original averaging method

Challenges

Multi-word phrases: His car -> /c/en/his? /c/en/car?

- Average embedding is closer to his. Car is not linked.
- Alternatives:
  - **Link each word. Simple, but not compositional.**
  - **Link root of dependency parse. Discards even more information.**

Polysemous words: “Doggo is *good* boy” vs. “Toilet paper is a scarce *good*”

- Only one entry in ConceptNet: /c/en/good.
- Can perform word sense disambiguation/link to WordNet nodes instead.
  - **Better to handle at linking or graph reasoning step?**

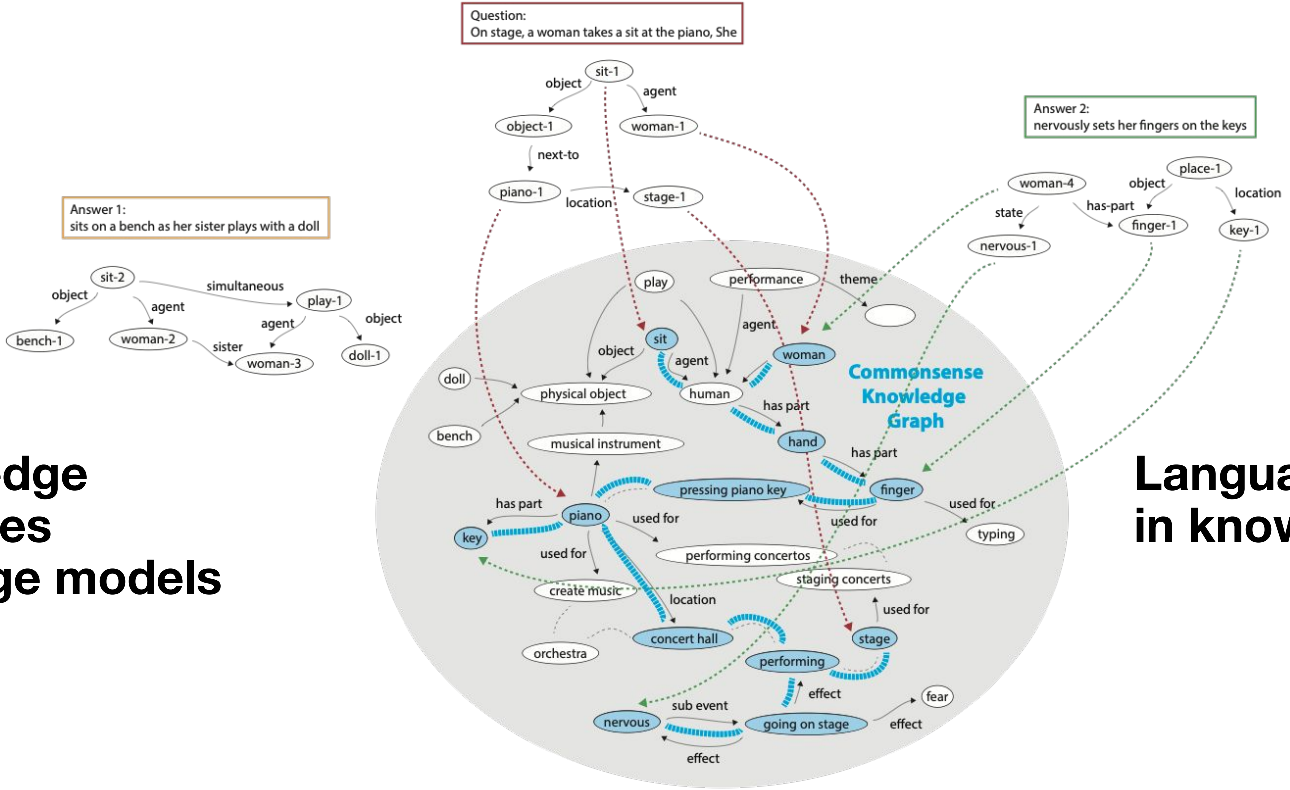
Evaluation

Fidelity vs. Utility Trade-off

- Exact matches may exist, but are not always useful
- Incorporate node degree?

Neuro-symbolic Reasoning Approaches

Neuro-Symbolic Reasoning Approaches

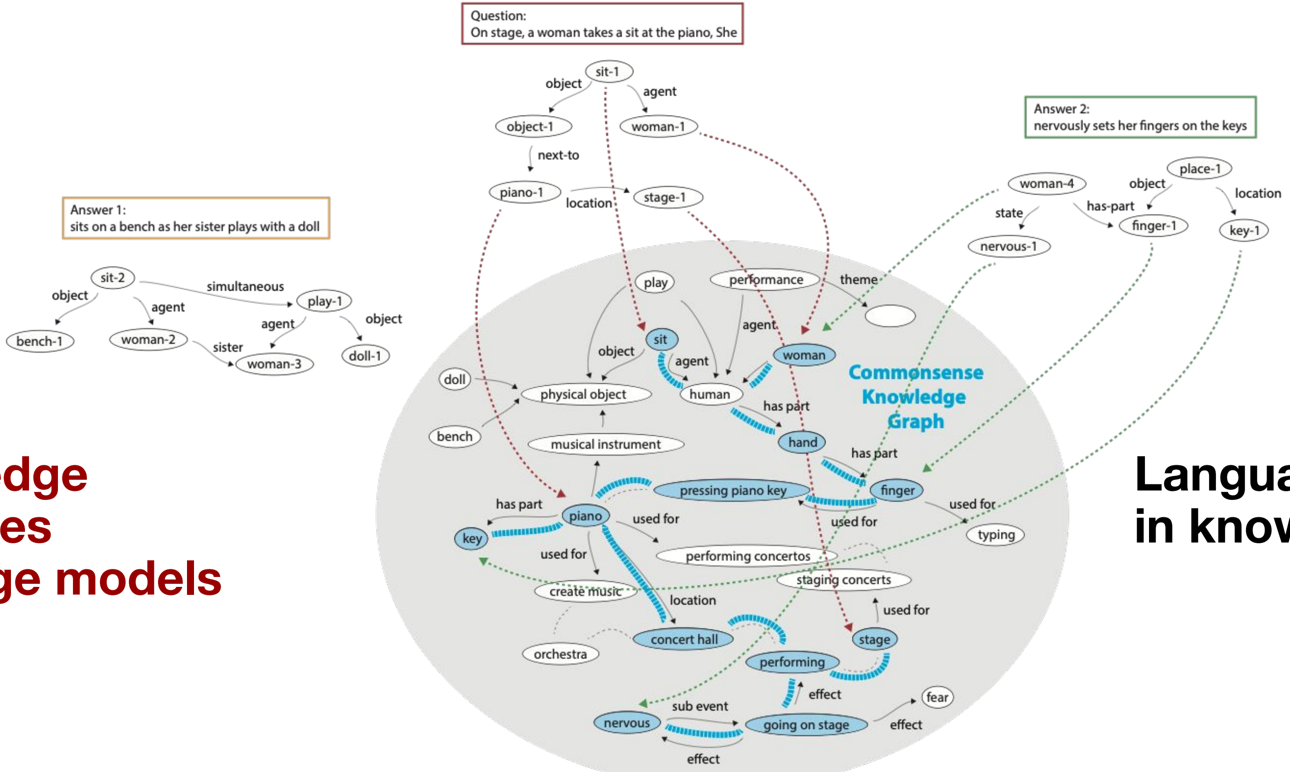


Knowledge enhances language models

Language models fill in knowledge gaps

Neuro-Symbolic Reasoning Approaches

Knowledge enhances language models



Language models fill in knowledge gaps

Kaixin Ma, Filip Ilievski, Jon Francis, Yonatan Bisk, Eric Nyberg, Alessandro Oltramari. In prep.

Structured evidence in CSKGs

Q: Bob the lizard lives in a warm place with lots of water. Where does he probably live?

A: tropical rainforest

Structured evidence in CSKGs

Q: Bob the lizard lives in a warm place with lots of water. Where does he probably live?

A: tropical rainforest

AtLocation
(ConceptNet)

Structured evidence in CSKGs

Q: Bob the lizard lives in a warm place with lots of water. Where does he probably live?

HasInstance (FrameNet-ConceptNet)

A: tropical rainforest

AtLocation (ConceptNet)

Structured evidence in CSKGs

Q: Bob the lizard lives in a warm place with lots of water. Where does he probably live?

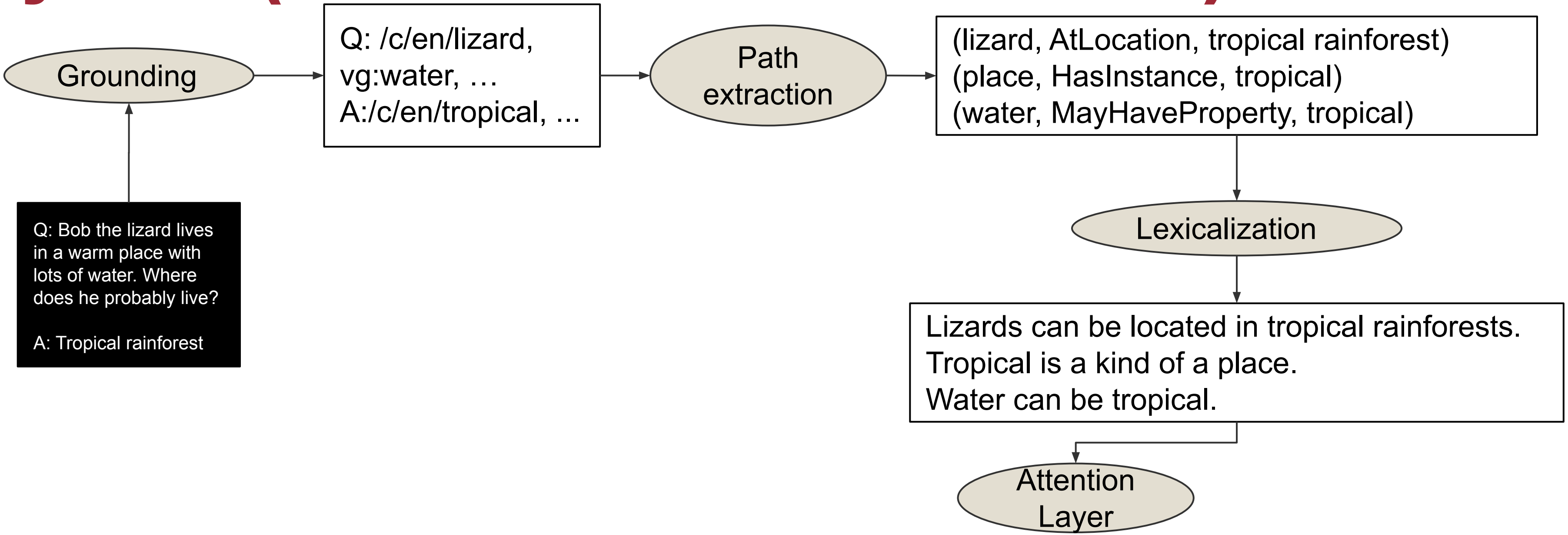
HasInstance
(FrameNet-ConceptNet)

MayHaveProperty
(Visual Genome)

A: tropical rainforest

AtLocation
(ConceptNet)

HyKAS (based on Ma et al. 2019)



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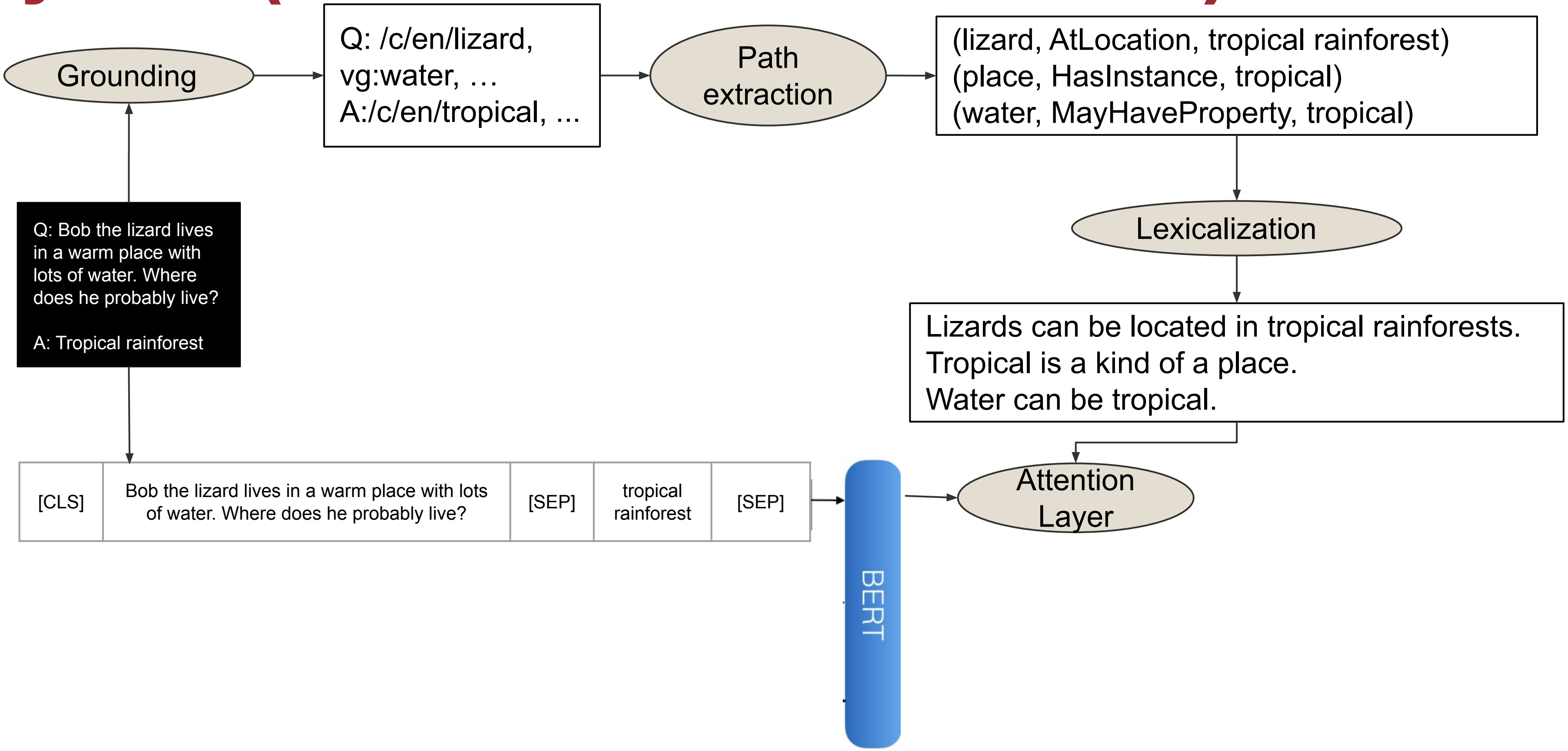

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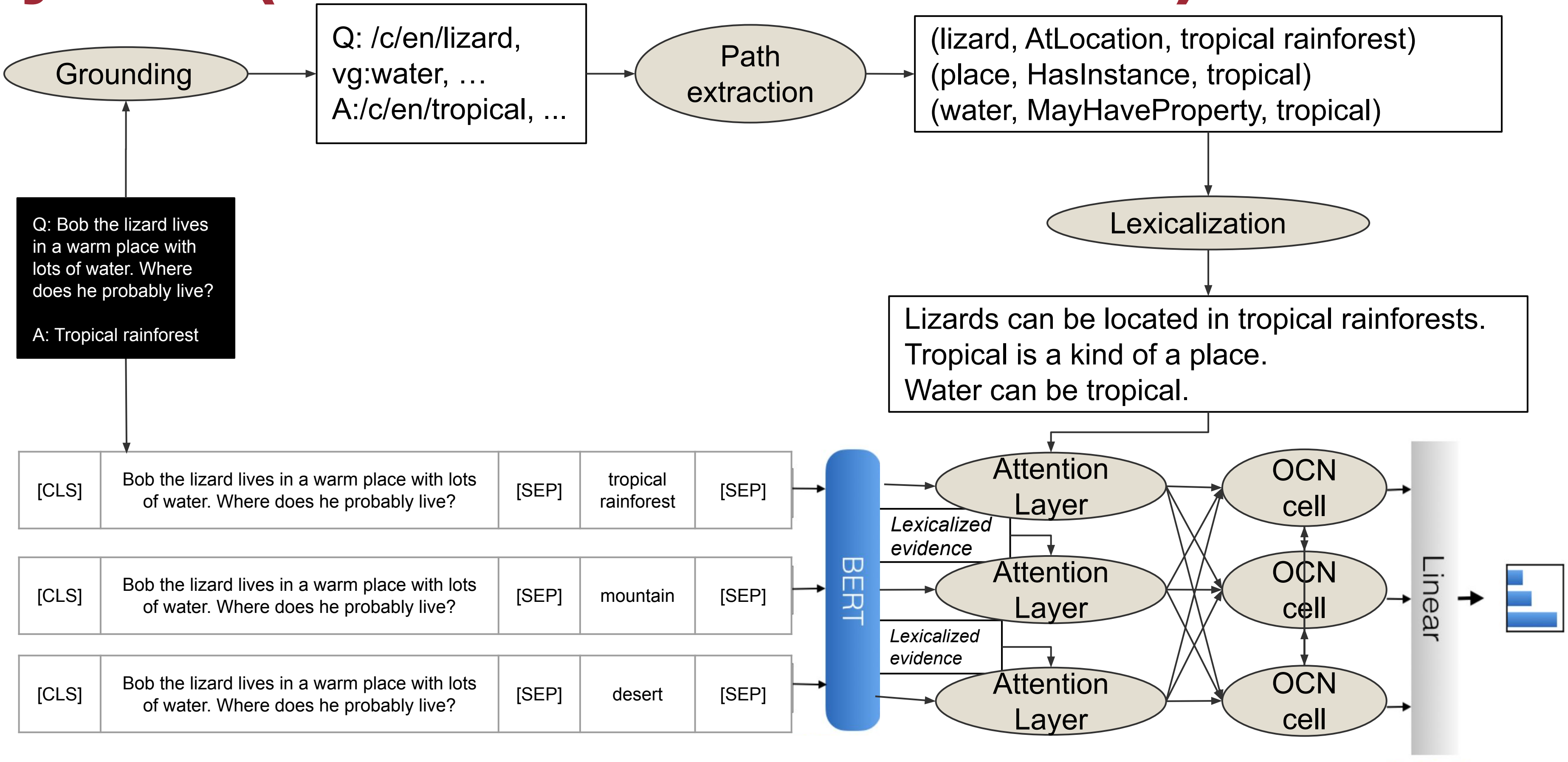

‘No-knowledge’ baseline is strong

SocialIQA

Train knowledge	Inference Knowledge	Dev acc
-	-	78.7
ATOMIC	ATOMIC	**79.04**
CSKG	CSKG	78.56
CSKG	-	*77.22*
CSKG	*-Visual Genome*	*78.4*
CSKG	*ConceptNet*	*78.61*
CSKG	*Visual Genome*	*78.04*
CSKG	*ConceptNet+Visual Genome*	<u>*78.81*</u>
CSKG	*-RelatedTo*	*78.4*
CSKG	*-Synonym-Antonym*	*78.66*

CommonSense QA

Train+inference Knowledge	Dev acc
-	76.7
ATOMIC	77.1
ConceptNet	80.1
CSKG	79.5
CSKG -symmetric -overlapping	79.7
CSKG in a separate OCN	<u>80.1</u>
ConceptNet (2-hop)	**80.5**

Adding knowledge helps

CommonSense QA

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Different knowledge helps different problems

CommonSense QA

Train+inference Knowledge	Dev acc
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More knowledge is not always better

CommonSense QA

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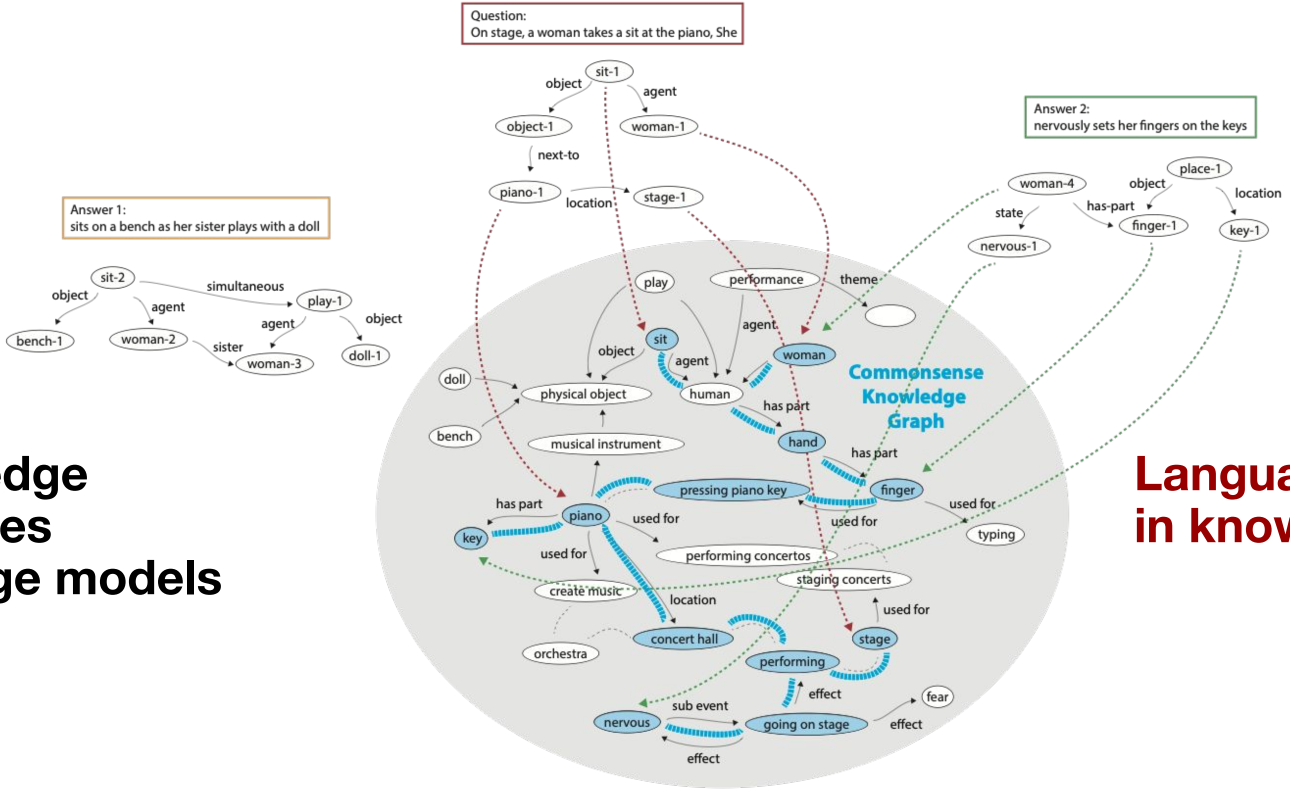
Enhancing CSKGs with Language Models

Wang et al. (2020). Connecting the Dots: A Knowledgeable Path Generator for Commonsense Question Answering.

EMNLP Findings 2020

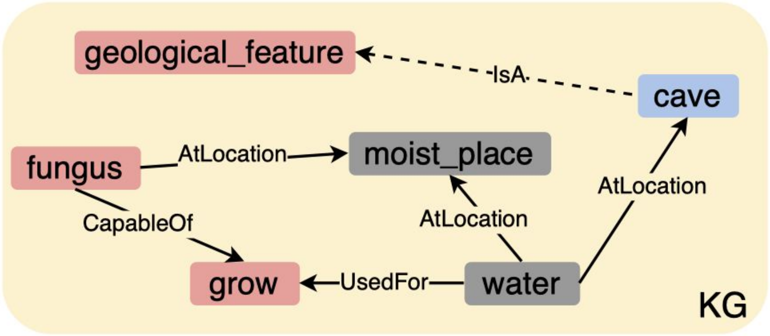
Neuro-Symbolic Reasoning Approaches



Knowledge enhances language models

Language models fill in knowledge gaps

Retrieving KG facts does not suffice



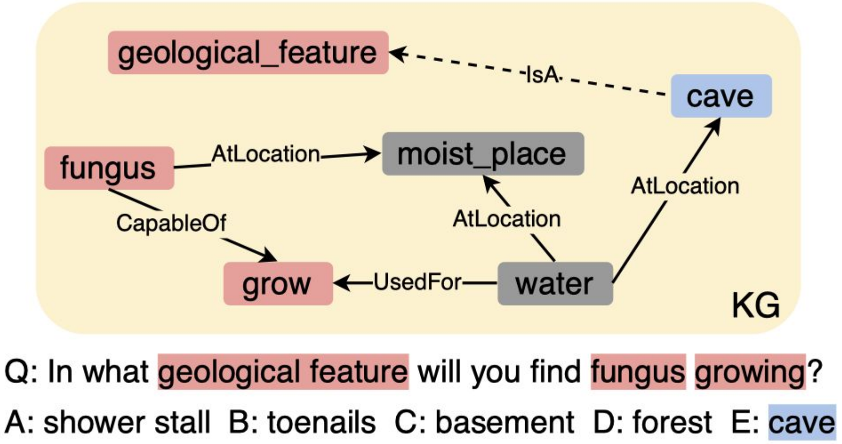
Q: In what geological feature will you find fungus growing?

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

Challenges

- KG incompleteness
- Introducing irrelevant facts

Retrieving KG facts does not suffice



Challenges

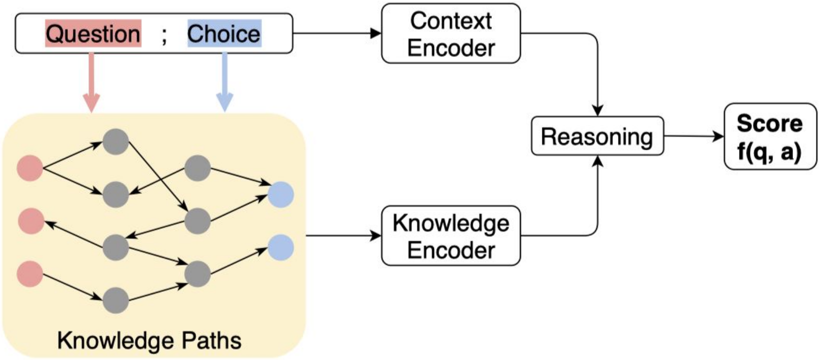
- KG incompleteness
- Introducing irrelevant facts

Solution

- Learn a **path generator** to connect entities mentioned in context with novel multi-hop knowledge paths

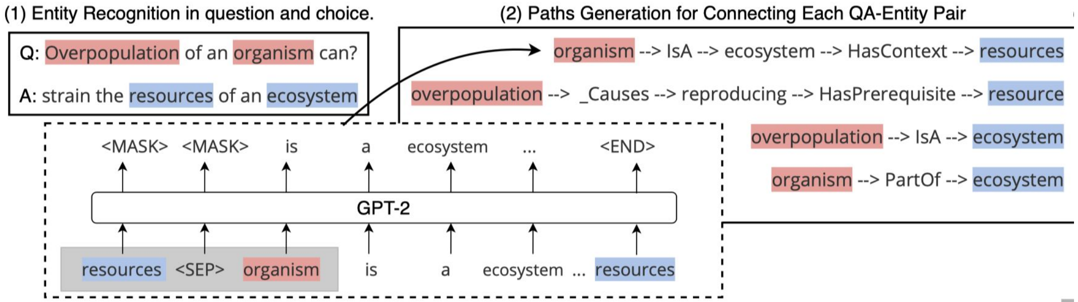
A KG-augmented QA Framework

- **Context Module**
  - Encode question and answer choices as unstructured evidence
- **Knowledge Module**
  - Encode knowledge facts (paths) as structured evidence
- **Reasoning Module**
  - Score a question-choice pair based on un/structured evidence



Path Generator for Connecting Dots

Goal: generate a multi-hop path between two entities



(2.1) Generation Process for Connecting One QA-Entity Pair (the shaded part is given as input during inference).

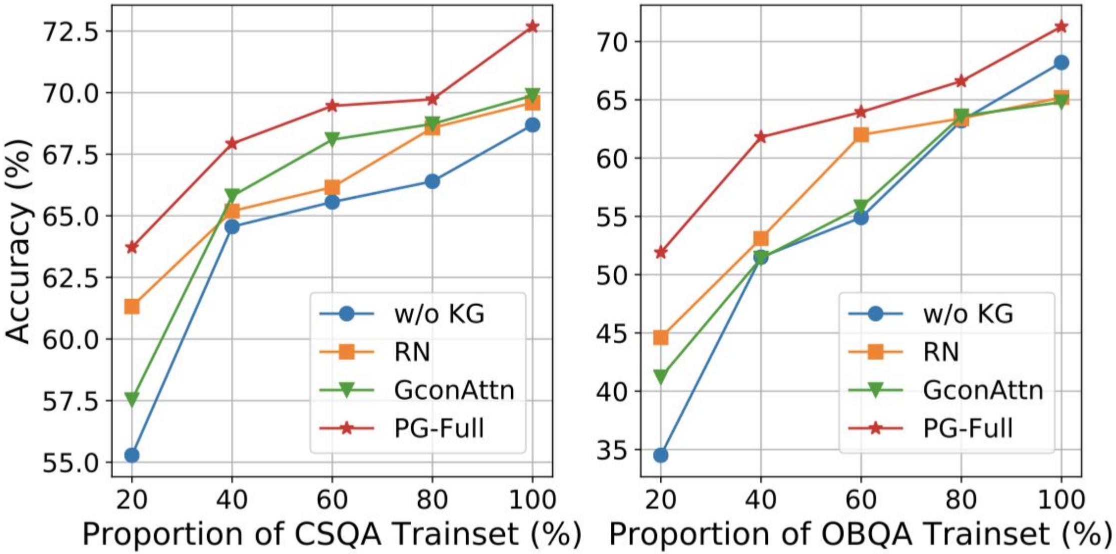
1. **Path Sampling** with KG random walk
2. **Training** by fine-tuning GPT-2
3. **Inference** by using greedy decoding

Generating knowledge paths is better than merely *retrieving* them

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)

Test Accuracy on OpenBookQA

Consistent improvements with less training data



Test Accuracy on CommonsenseQA and OpenBookQA with different amount of training data.

Interpretability with “real” structured paths

Q1: Where would you find **magazines** along side many other printed works? A: doctor. B^* : *bookstore*. C: market. D: train station. E: mortuary. PG-Global (2-hop): {magazine, IsA, book, AtLocation, bookstore} PG-Scratch: {magazine, _IsA, magazine, AtLocation, bookstore}
Q2: If you want **harmony**, what is something you should try to do with the world? A: take time. B. make noise. C. make war. D^* .*make peace*. E. make haste. PG-Global (2-hop): {harmony, _MotivatedByGoal, make better world, HasPrerequisite, make peace} PG-Scratch: {harmony, _UsedFor, committing perjury, Causes, make peace}
Q3: Janet was watching the **film** because she liked what? A: rejection. B: laughter. C^* : *being entertained*. D: fear. E: bordem. PG-Global (1-hop): {film, _CausesDesire, being entertained} PG-Scratch: {film, _HasContext, being entertained}

Role of knowledge

Existing benchmarks

New benchmarks?

Few shot, zero shot

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	15 min	Wrap-up (slides) - Mayank

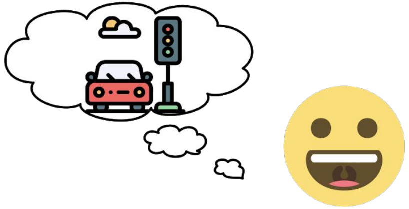
Wrap-up

What Is Common Sense?

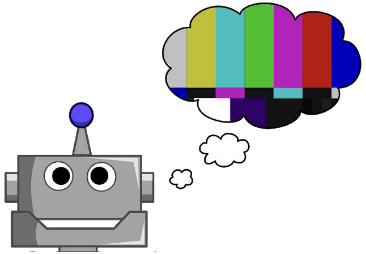
Common sense is sound practical judgement concerning everyday matters,

or a basic ability to perceive, understand, and judge that is shared by ("common to") nearly all people.

Wikipedia



Essential for humans to live and interact with each other in a reasonable and safe way.



Essential for AI to understand human needs and actions better

For example, it's ok to keep the closet door open, but it's not ok to keep the fridge door open, as the food inside might go bad.

Slide by Yejin Choi

A Common Sense Task

Input: a set of common concepts

dog | frisbee | catch | throw

Output: a sentence using these 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.

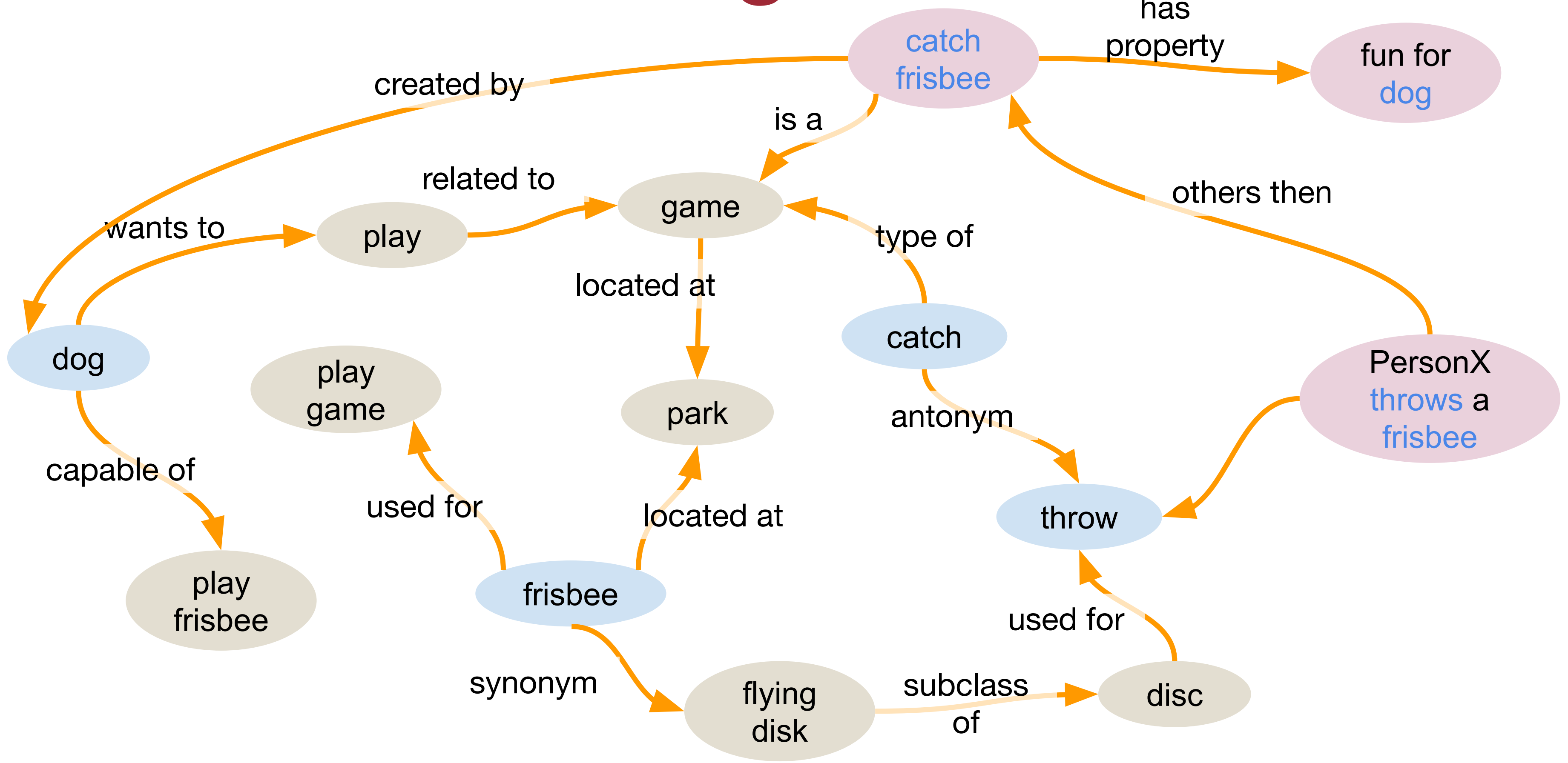
UniLM: Two dogs are throwing frisbees at each other .

BART: A dog throws a frisbee and a dog catches it.

T5: dog catches a frisbee and throws it to a dog

https://inklab.usc.edu/CommonGen/

Role Of Knowledge



Common Sense Knowledge Graphs

COMET
[Bosselut et al., 2019]

Atomic
[Sap et al., 2019]

WebChild
[Tandon et al., 2014]

WebChild 2.0
[Tandon et al., 2017]

Open Mind Common Sense
[Minski, Singh, Havasi,1999]

ConceptNet
[Liu, Singh, 2004]

ConceptNet 5.5
[Speer et al., 2017]

NELL
[Carlson et al., 2010]

NELL
[Mitchell et al., 2015]

Wikidata
[Vrandečić, 2012]

Cyc
[Lenat et al., 1984]

OpenCyc 4.0
[Lenat 2012]

Dimensions Of Common Sense Knowledge

Representation

- symbolic
- natural language
- neural

Creation method

- expert input
- crowdsourcing
- information extraction, machine learning

Knowledge type

- entities and actions
- inferential/rules

Topic

- general
- social

COMET

Atomic

WebChild

ConceptNet

NELL

Wikidata

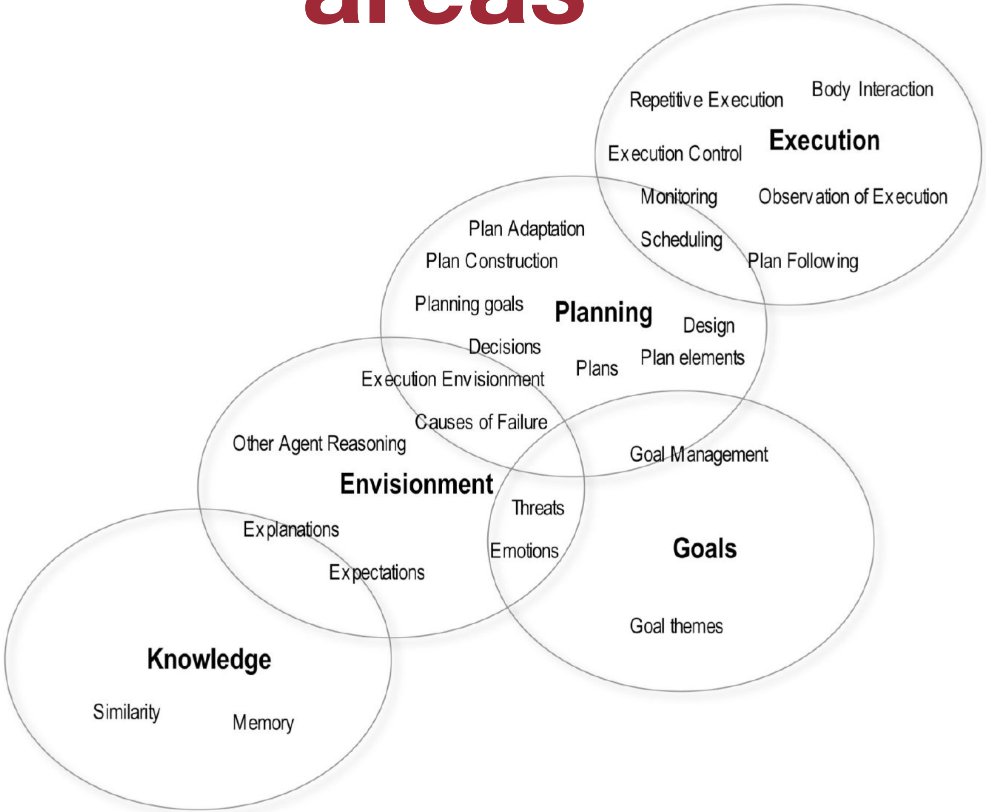
OpenCyc

Why is top-down knowledge necessary?

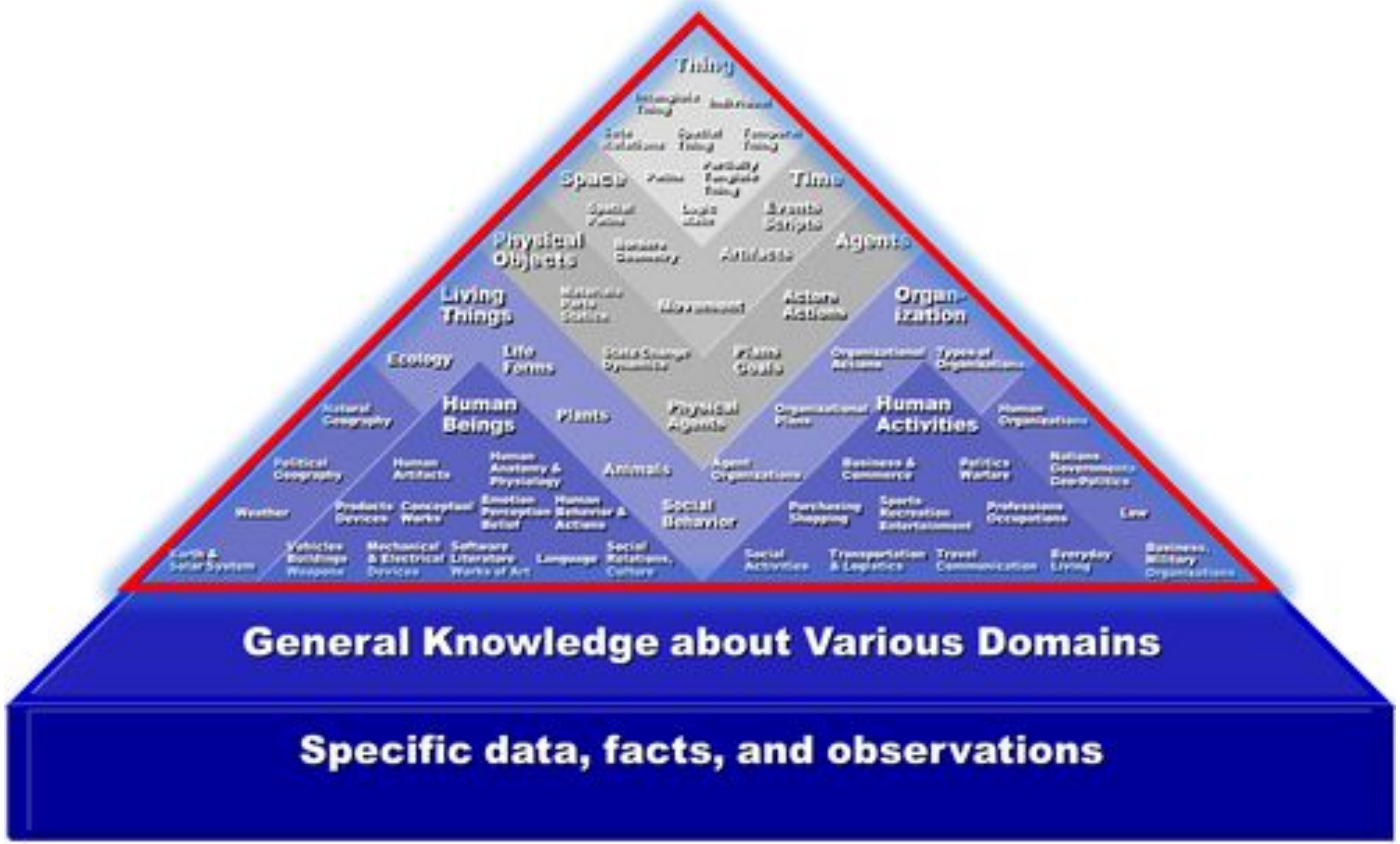
"In Artificial intelligence, commonsense knowledge is the set of background information that an individual is intended to know or assume and the ability to use it when appropriate."

Argument: This knowledge cannot be acquired simply through text (or in an otherwise 'inductive' fashion)

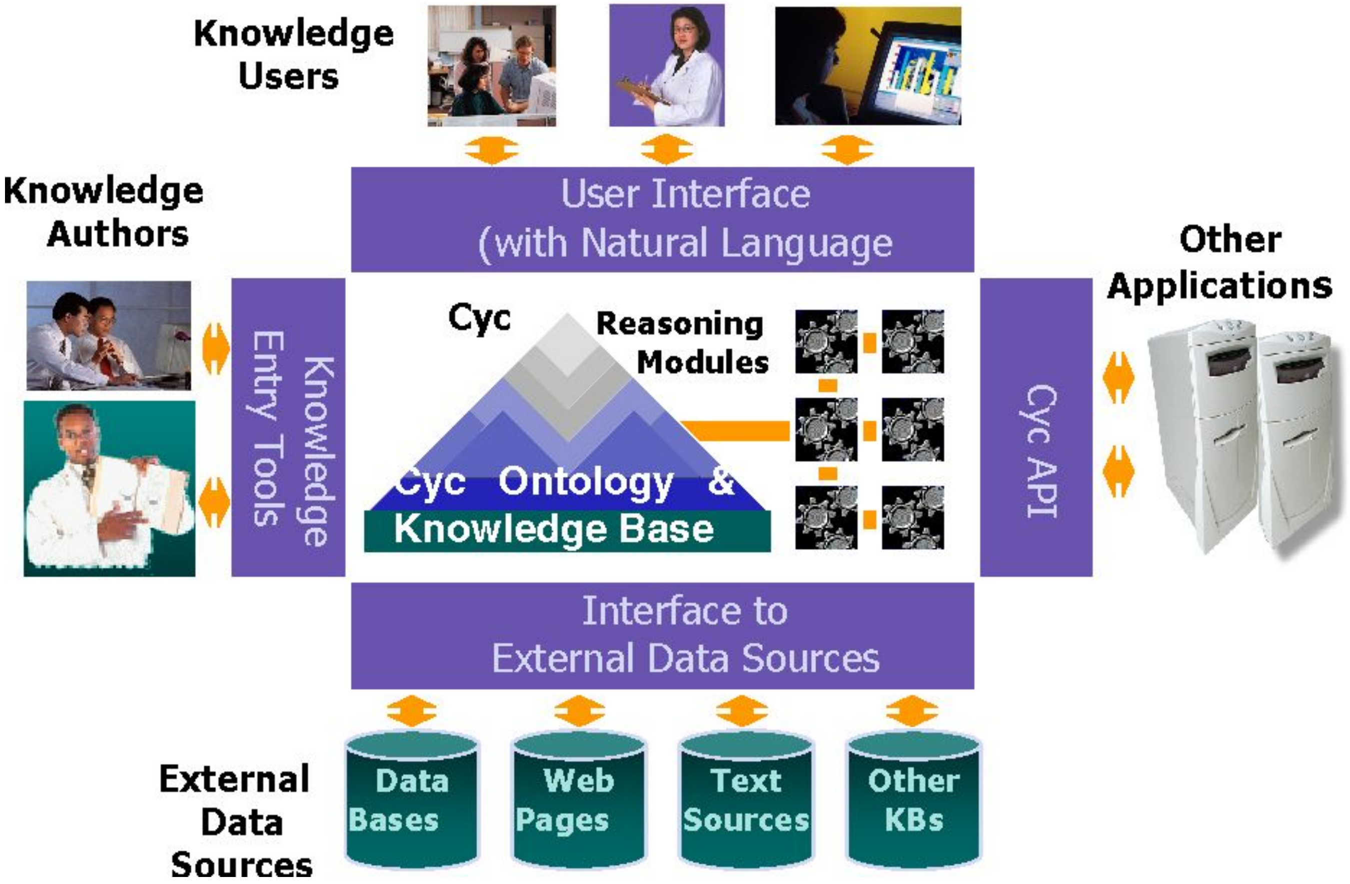
Taxonomy of 30 representational areas



Example of a ‘top-down’ CSKG: Cyc



Evolution of Cyc

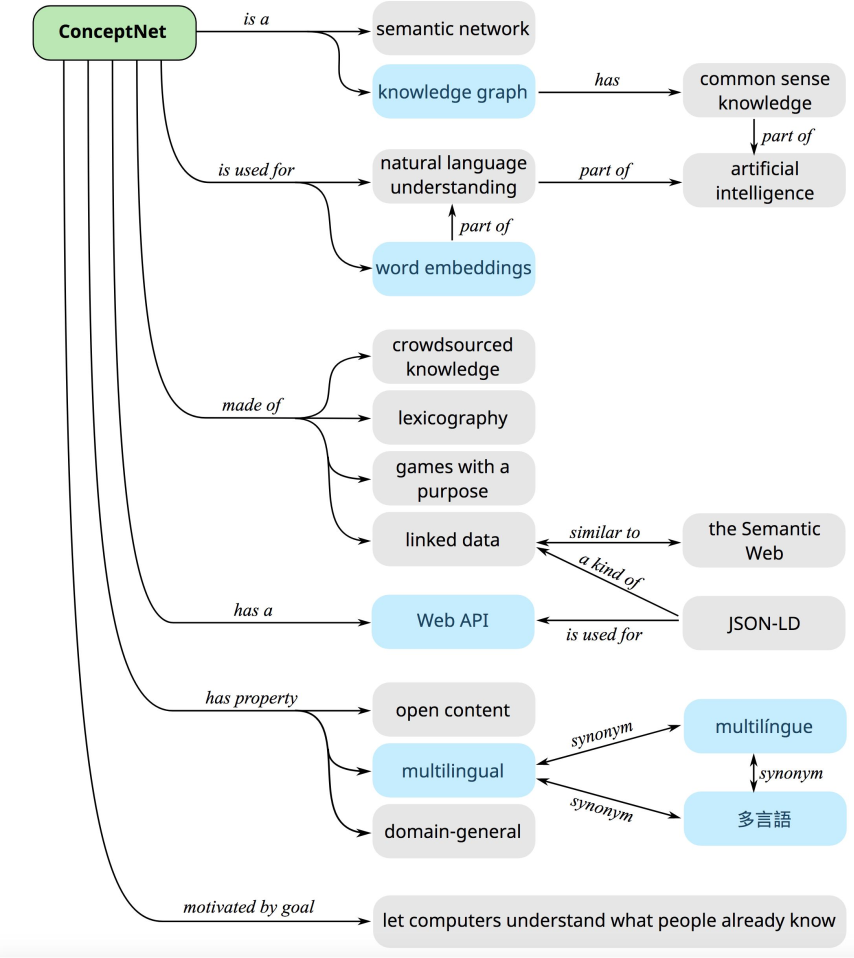


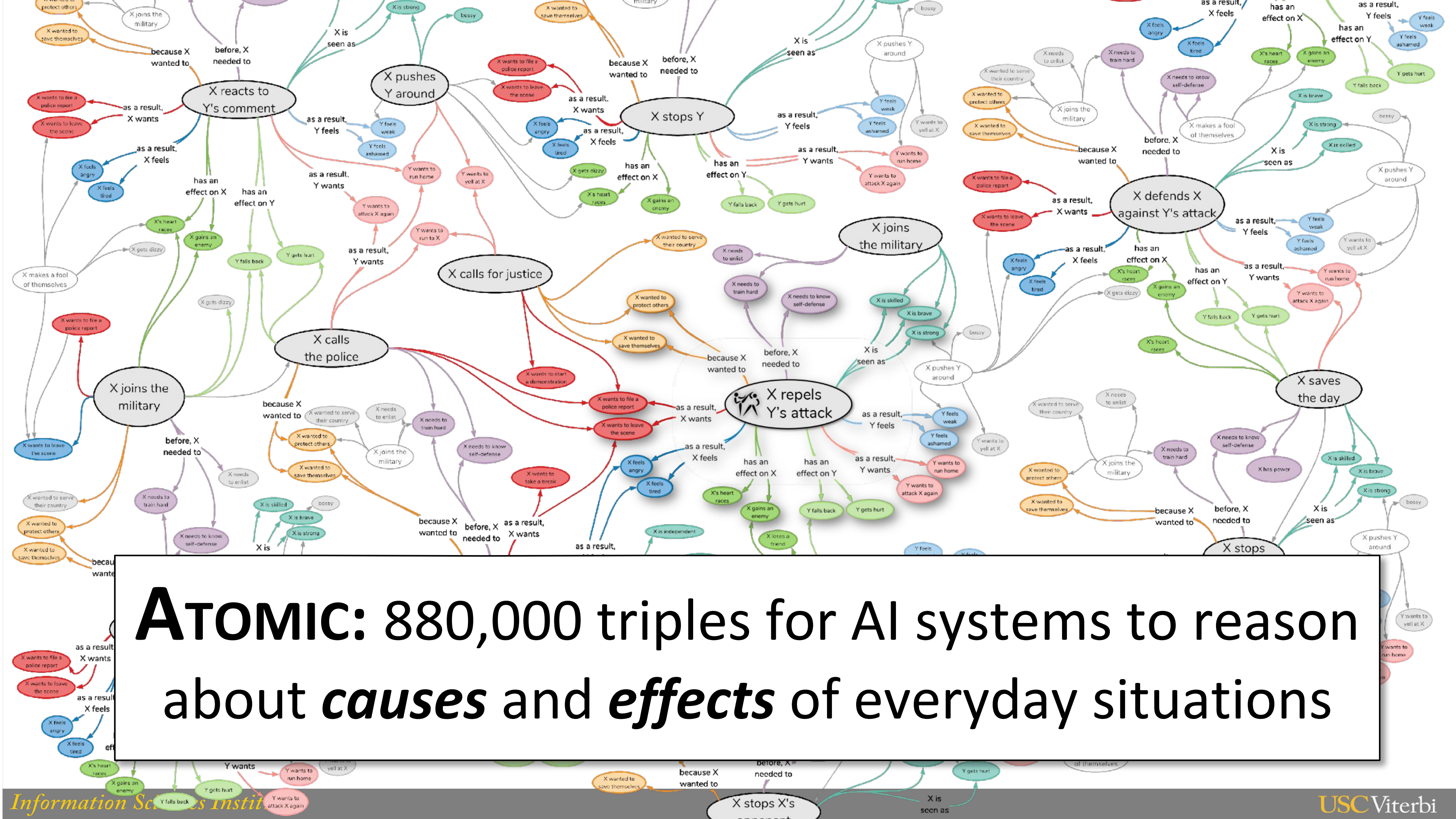
Limitations of top-down CSKGs

Many of the same issues that other top-down systems (including, famously, expert systems) have, such as brittleness, expense of acquisition...

Even if it were possible, we can never get away from language models completely

The many faces of ConceptNet





ATOMIC: 880,000 triples for AI systems to reason about ***causes*** and ***effects*** of everyday situations

Commonsense Knowledge in Wikidata

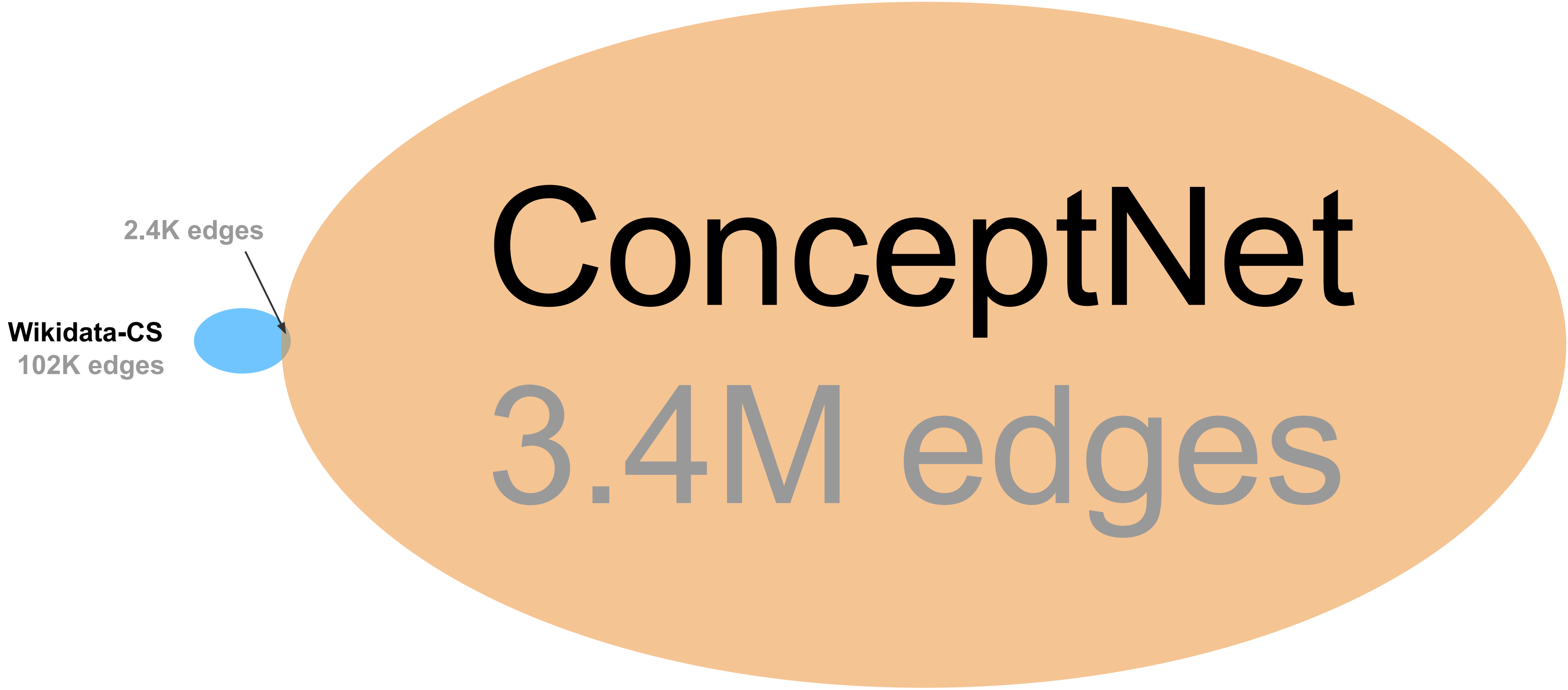
shower part of bathroom

reading uses written work

queen follows jack

political opposition opposite of government

Wikidata-CS Is Small But Novel



Commonsense Knowledge Sources

- ConceptNet
  - Information about everyday objects, actions, states and relationships among them, extensive links to WordNet
  - Incomplete coverage, “related-to” accounts for 75% of statements
- ATOMIC
  - Pre- and post-states for events and their participants, physical and mental aspects covered
  - Only 25% of nodes have links to ConceptNet, difficult to combine with other resources
- WordNet
  - Meanings of words & relationships to other words, high coverage, many resources have links to WordNet, example sentences
  - No description of the properties of objects or roles in verbs, only is-a and part-of relations
- VerbNet, FrameNet
  - Defines participants/roles for a large number of situations/frames, links to verbs, syntactic forms and example sentences
  - No semantic typing of roles, many roles are very abstract (e.g., Agent), lacks info about state changes, or pre-post conditions
- Visual Genome
  - “Visual” commonsense, many possible attributes, relationships/actions among objects, linked to WordNet, many edges for a KG
  - No abstraction mechanism to understand prevalence of relations
- Wikidata
  - Comprehensive descriptions of objects, both specific (named entities) and generic (nouns)
  - Sparse information about events and states, much knowledge is on instance-level and abstraction is non-trivial

Consolidation Hypothesis

Integrating multiple knowledge sources in CSKG is beneficial for downstream reasoning tasks.

Principles for a modular and useful CSKG

P1. Embrace heterogeneity of nodes

objects, classes, words, actions, frames, states

P2. Reuse edge types across resources

/r/HasProperty from ConceptNet applicable for attributes in Visual Genome

P3. Leverage external links

many sources map to WordNet

P4. Generate high-quality probabilistic links

many facts not explicitly stated

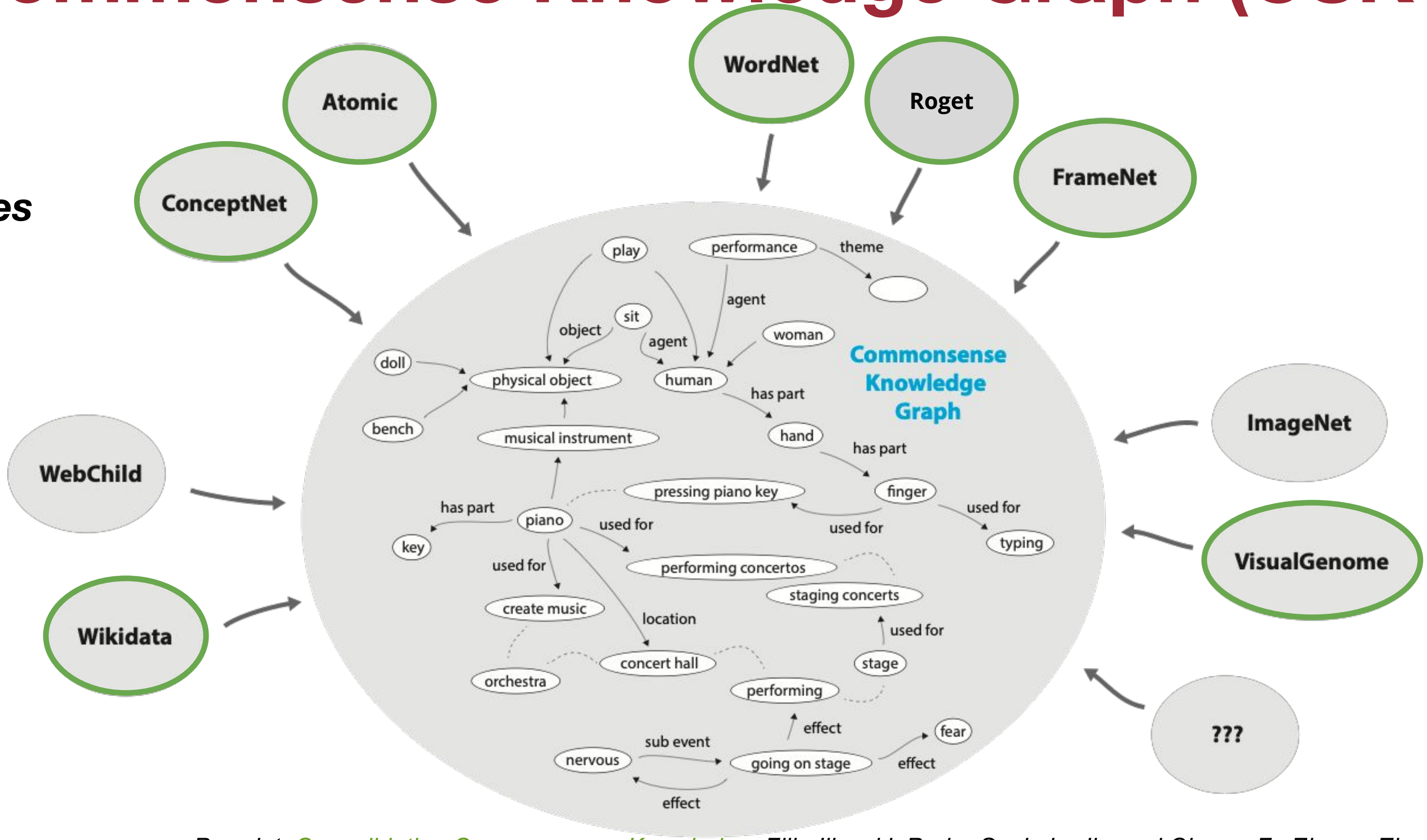
P5. Enable access to labels

text labels and aliases are the key, in particular for NLP use cases

The Commonsense Knowledge Graph (CSKG)

7 sources

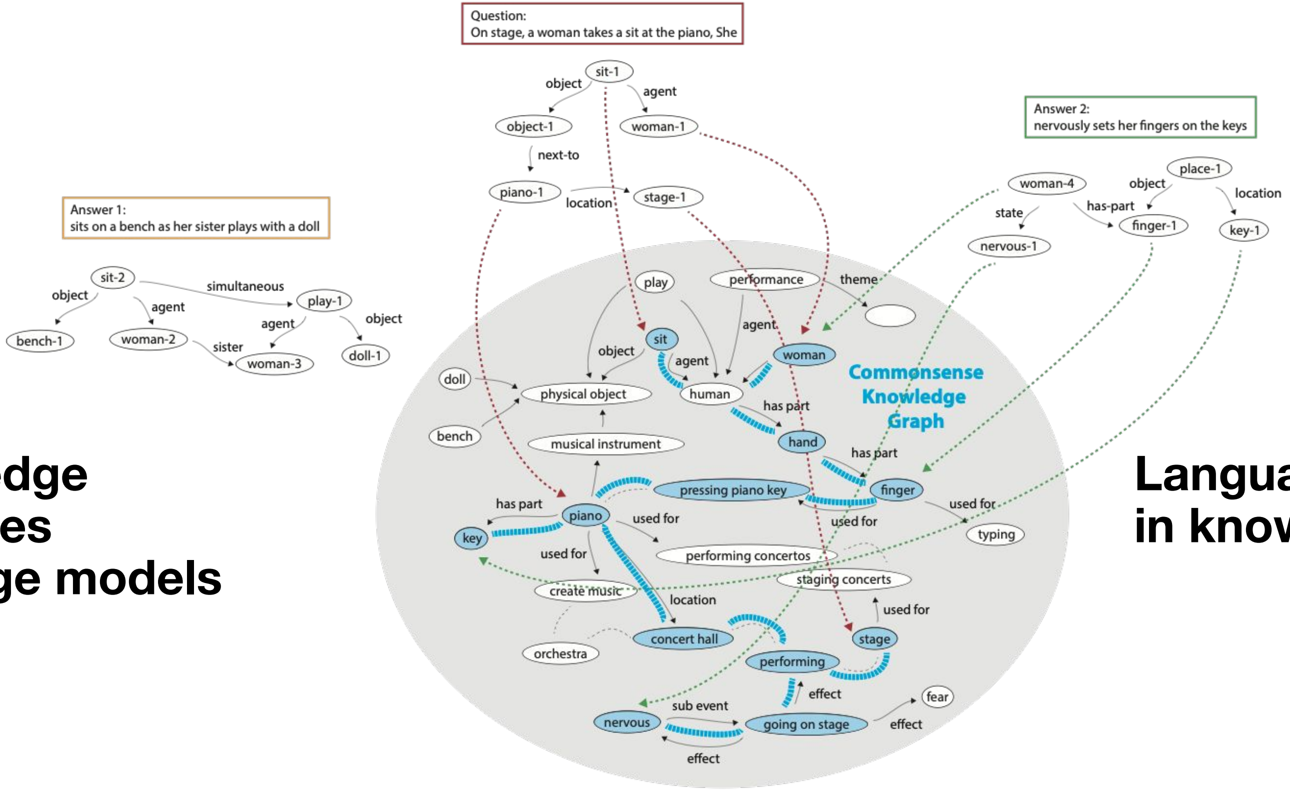
2.3M nodes
6M edges



Preprint: Consolidating Commonsense Knowledge. Filip Ilievski, Pedro Szekely, Jingwei Cheng, Fu Zhang, Ehsan Qasemi.

Neuro-Symbolic Reasoning Approaches

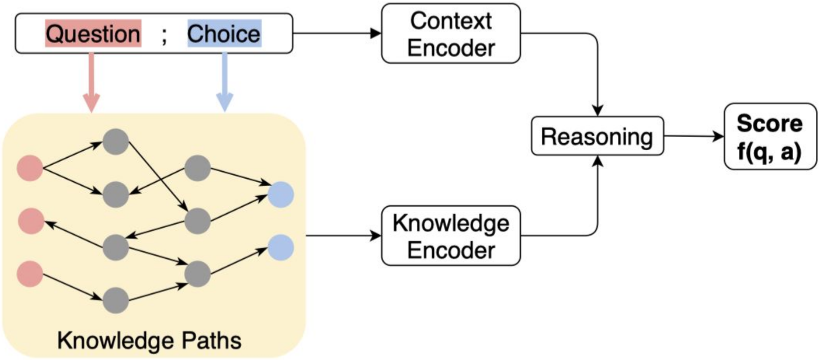
Knowledge enhances language models



Language models fill in knowledge gaps

A KG-augmented QA Framework

- **Context Module**
  - Encode question and answer choices as unstructured evidence
- **Knowledge Module**
  - Encode knowledge facts (paths) as structured evidence
- **Reasoning Module**
  - Score a question-choice pair based on un/structured evidence



Our final takeaways

- Commonsense (CS) reasoning is a difficult general AI problem that has come of age
    - Ironically, exposed both the strengths and limitations of neural networks, including language representation learning
    - We hypothesize that a neuro-symbolic approach is necessary for CS reasoning
- CS knowledge, appropriately contextualized, is critical for robust CS reasoning and QA
- Much progress has been achieved in integrating multiple sources into a single CSKG, but many open challenges remain

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