Graph-Based Reasoning over Heterogeneous External Knowledge for Commonsense Question Answering

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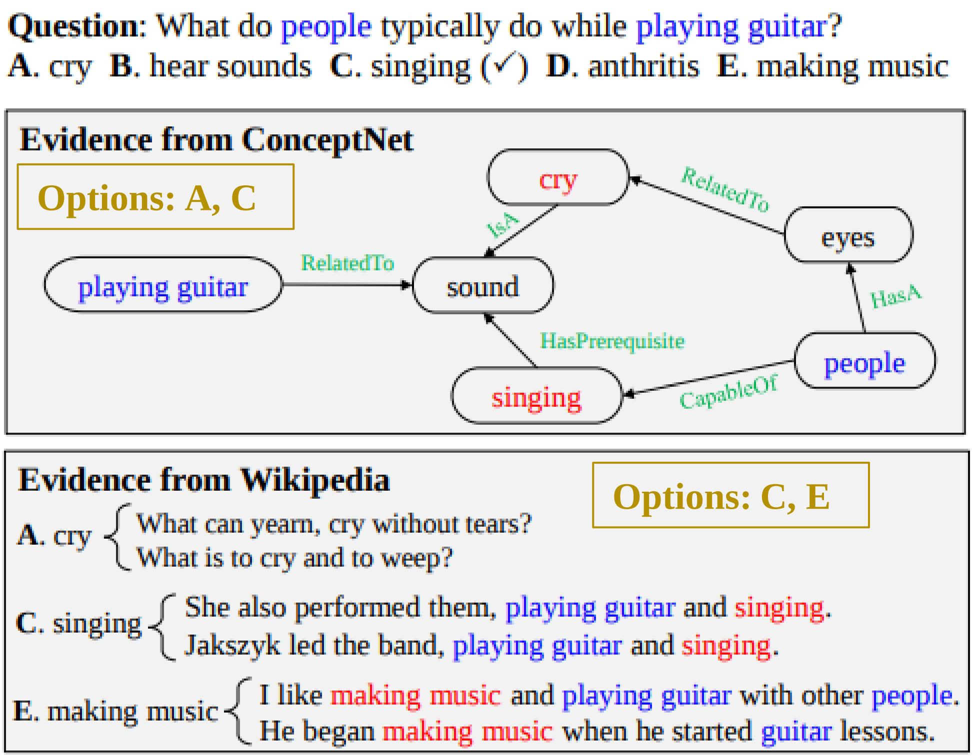
Motivation



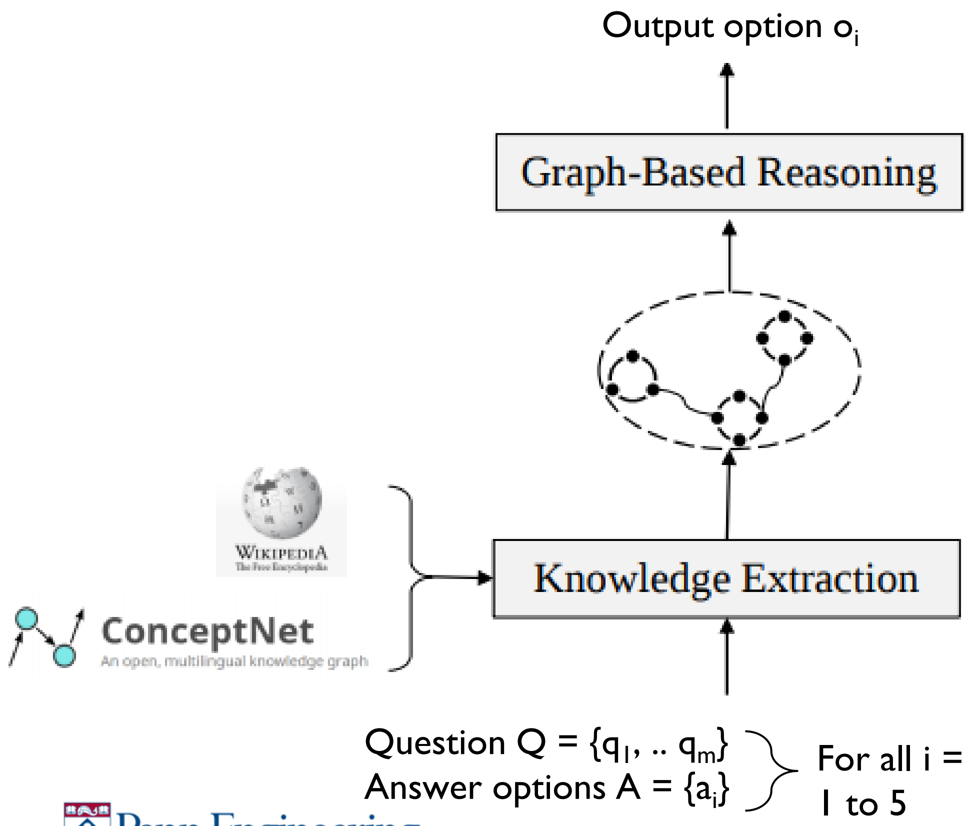
- Combining evidence from ConceptNet & Wikipedia gives the option C
- Commonsense QA
  - Collect background knowledge and reason over it
- Structured KBs: relations beneficial for reasoning
  - But low coverage is an issue
- Unstructured text: abundant coverage

Contributions

- Main: Combine heterogenous knowledge sources together into the same representation space
- Graph modules to leverage structure for reasoning
  - Context representation learning module
  - Inference module
- New state-of-the-art performance: 75.3%

Contents

Problem: Overview

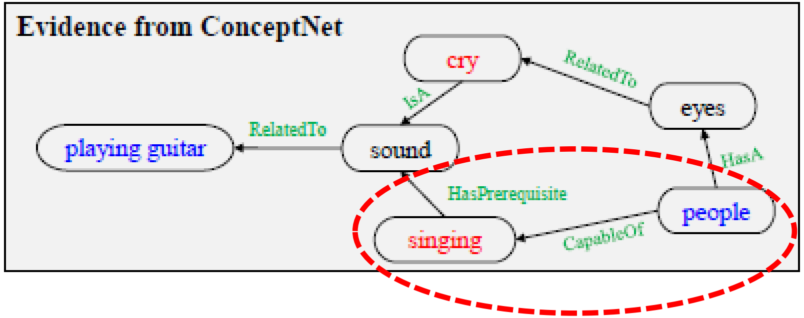


- Dataset:
  - CommonsenseQA [1]
  - Questions lack evidence, rely on background knowledge
- Evaluation:
  - Accuracy
  - Ablation Study
  - Error Analysis

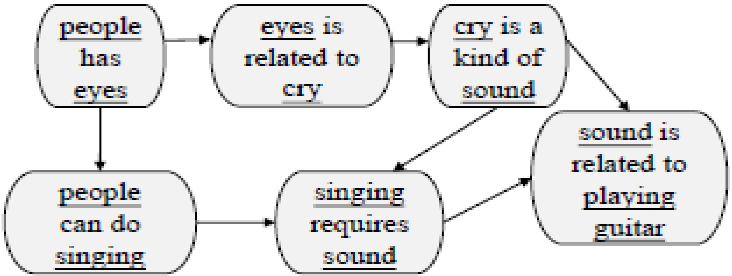
Knowledge Extraction ConceptNet → Concept-Graph

- Commonsense Knowledge Base
- Locate and search for path from question entities → answer choice entities (< 3 hops)
- Merge triples as nodes in graph
  - Edge from s_i to s_j if they contain same entity
- Convert triples to natural language sentences

Question: What do people typically do while playing guitar?
A. cry B. hear sounds C. singing (✓) D. anthritis E. making music



ConceptNet triple



Knowledge Extraction Wikipedia → Wiki-Graph

- Top 10 Wiki sentences from Elastic Search for (question + choices)
- Semantic Role Labeling: Nodes are **subject, predicate, object**
- Edges:
  - (subject, predicate)
  - (predicate, object)
  - Node A is contained in node B and the #words (A) > 3 - - - - - - ▸
  - Node A and node B only have one different word and #words(A) and #words(B) > 3

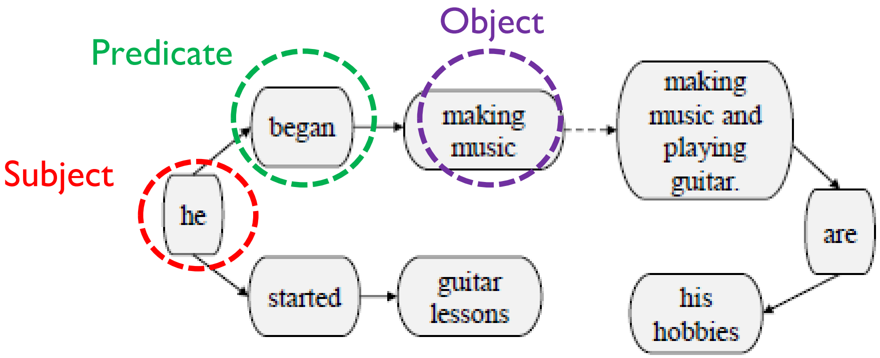
Question: What do people typically do while playing guitar?
A. cry **B**. hear sounds **C**. singing (✓) **D**. anthritis **E**. making music

Evidence from Wikipedia

A. cry { What can yearn, cry without tears? / What is to cry and to weep?

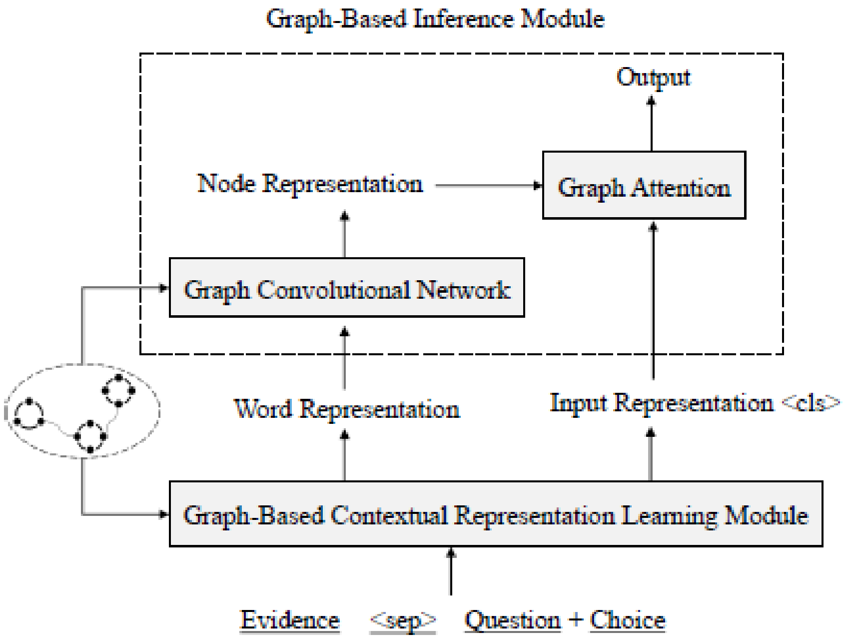
C. singing { She also performed them, playing guitar and singing. / Jakszyk led the band, playing guitar and singing.

E. making music { Making music and playing guitar are his hobbies. / He began making music when he started guitar lessons.

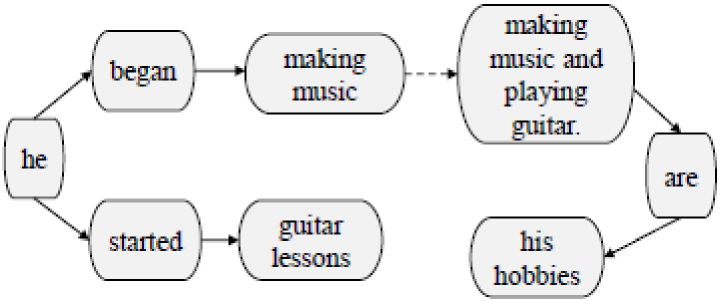


Graph-Based Reasoning

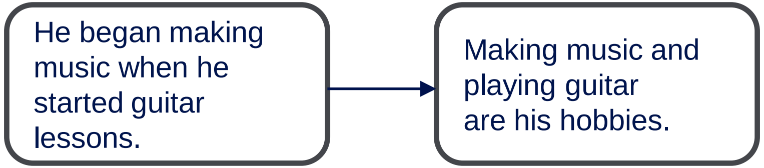
- Evidence
  - Concept-Graph
  - Wiki-Graph
- Context Representation Learning
- Inference
  - Graph Convolutional Network
  - Graph Attention
- Output



Contextual Representation Learning Module



Wiki-Graph



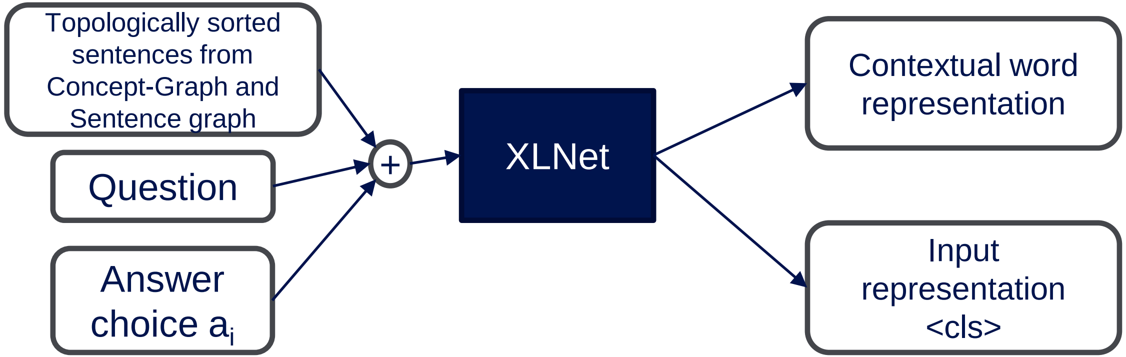
Sentence Graph

- If $p \in s_i$, $q \in s_j$ and (p,q) is an edge in Wiki-Graph, then (s_i, s_j) in an edge in sentence

- Topological sort on Concept-Graph & sentence graph
- Goal: Shorten distance between semantically similar nodes

Contextual Representation Learning Module

- XLNet: captures long term dependencies



- Goal:
  - Obtain better contextual word representations
  - Fuse two knowledge sources in same representation space

Topology Sort Algorithm (for reference)

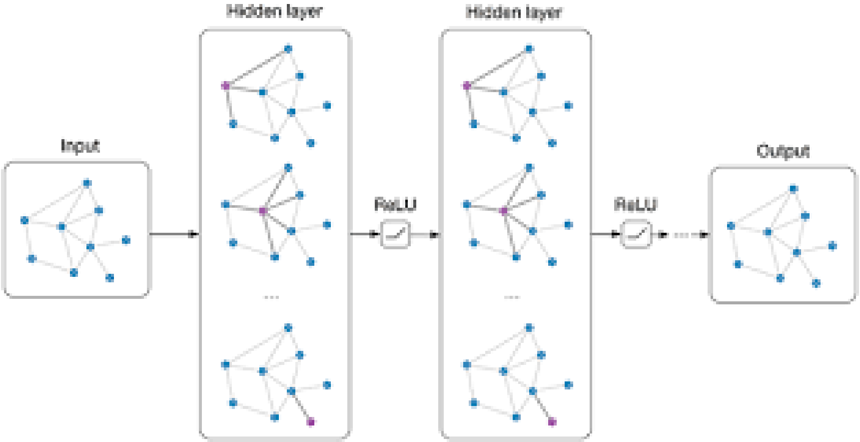
Algorithm 1 Topology Sort Algorithm.

Require: A sequence of nodes $S = \{s_i, s_2, \cdots, s_n\}$; A set of relations $R = \{r_1, r_2, \cdots, r_m\}$.

function DFS(node, visited, sorted_sequence)
    for each child s_c in node's children **do**
        if s_c has no incident edges and visited[s_c]==0 **then**
            visited[s_c]=1
            sorted_sequence.append(0, s_c)
            Remove the incident edges of s_c
            DFS(s_c, visited, sorted_sequence)
        end if
    end for
end function
sorted_sequence = []
visited = [0 for i in range(n)]
S,R = to_acyclic_graph(S,R)
for each node s_i in S **do**
    if s_i has no incident edges and visited[i] == 0 **then**
        visited[i] = 1
        sorted_sequence.append(s_i)
        DFS(s_i, visited, sorted_sequence)
    end if
end for
return sorted_sequence

Inference Module

- Graph Convolutional Networks (GCNs)
  - Use Concept-Graph and Wiki-Graph
  - Update graph node representations using features of neighboring nodes
- The i^{th} node representation in layer 0



$$h_i^0 = \sigma(W \sum_{w_j \in s_i} \frac{1}{|s_i|} h_{w_j}) , \quad (1)$$

XLNet representation for token w_j

Evidence sentence

- Subsequent layers

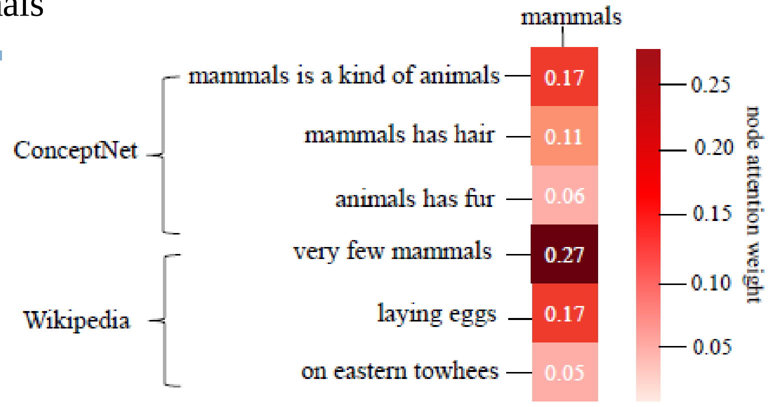
$$z_i^l = \sum_{j \in N_i} \frac{1}{|N_i|} V^l h_j^l , \quad (2)$$

Aggregated neighbor information for i^{th} node at layer l

$$h_i^{l+1} = \sigma(W^l h_i^l + z_i^l) . \quad (3)$$

Inference Module

Q: Animals who have hair and don't lay eggs are what?
A: Mammals



- Graph Attention (multiplicative)
  - Attention function: alignment score between <cls> and final GCN representation of i^{th} node
  - Aggregate over all nodes of graph
  - Obtain normalized score, compare across options

input representation <cls>

i^{th} node representation in last layer of GCN

Importance of node i

$$\alpha_i = \frac{h^c \sigma(W_1 h_i^L)}{\sum_{j \in N} h^c \sigma(W_1 h_j^L)}, \quad (4)$$

Graph representation

$$h^g = \sum_{j \in N} \alpha_j^L h_j^L . \quad (5)$$

Normalized scoring

$$score(q,a) = MLP(h_g . h_c)$$

$$p(q,a) = \frac{e^{score(q,a)}}{\sum_{a' \in A} e^{score(q,a')}} .$$

Correct option = $\operatorname{argmax}_{a \in A} p(q,a)$

Experiments

Models without descriptions

Models without extracted knowledge

Models without extracted structured knowledge

Models without extracted unstructured knowledge

Group	Model	Dev Acc	Test Acc
Group 1	SGN-lite	-	57.1
	BECON (single)	-	57.9
	BECON (ensemble)	-	59.6
	CSR-KG	-	61.8
	CSR-KG (AI2 IR)	-	65.3
Group 2	BERT-large	-	56.7
	XLNet-large	-	62.9
	RoBERTa(single)	78.5	72.1
	RoBERTa(ensemble)	-	72.5
Group 3	KagNet	-	58.9
	BERT + AMS	-	62.2
	RoBERTa + CSPT	76.2	69.6
Group 4	Cos-E	-	58.2
	BERT + OMCS	68.8	62.5
	HyKAS	-	62.5
	AristoBERTv7	-	64.6
	DREAM	73.0	66.9
	RoBERT + KE	77.5	68.4
	RoBERTa + CSPT	76.2	69.6
	RoBERTa + IR	78.9	72.1
	Our Model	**79.3**	**75.3**

Ablation Studies

Components of graph-based reasoning

Model	Dev Acc
XLNet + E	75.8
XLNet + E + Topology Sort	77.7
XLNet + E + Graph Inference	77.2
XLNet + E + Topology Sort + Graph Inference	**79.3**

- Topology sort change the relative position between words for better contextual word representation
- GCN and graph attention can aggregate both word and node representations to infer answers
- Both together: complementary

Heterogenous knowledge sources

Knowledge Sources	Dev Acc
None	68.9
ConceptNet	75.3
Wikipedia	73.5
ConceptNet + Wikipedia	**79.3**

- None: XLNet large model
- Both sources individually bring about improvement
- Combining both: much larger benefit

Conclusion

- Knowledge Extraction into graphs
  - ConceptNet (structured)
  - Wikipedia (unstructured)

  Heterogeneous background knowledge
- Graph-based reasoning
  - Contextual word representation learning module (Top. Sort + XLNet)
  - Inference module (GCN + Attention)
- State-of-the-art performance: 75.3%
- Graph structure of evidence sentences: basis for reasoning in commonsense question answering task

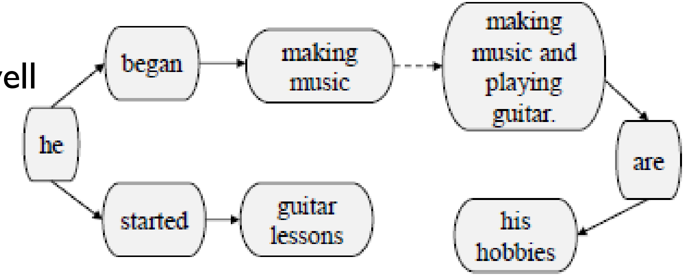
Issues

- Opening example in paper:

  Question: What do people typically do while playing guitar?
  A. cry **B**. hear sounds **C**. singing (✓) **D**. anthritis **E**. making music

  – Claim: "Dataset built in a way that answer choices share the same relation with question concept" ✘
- Semantic Role Labeling: typing errors
  – "Subjective" refers to → "subject"
  – "Objective" refers to → "object"

  Does not reflect well
- Wiki-Graph example
  – "Node A is contained in node B and the #words (A) > 3"



- Uses **only** entities in question to extract knowledge
  – Replacing "typically" with "never" would not change Concept-Graph, rely only on Wiki-Graph ✘
- Removal of stopwords during Wikipedia (Elastic Search)
  – Words like "not" would be skipped, this would give opposite results
  – BERT-Large baseline can't deal with negation either [1]
- Robustness: case studies of failed examples absent

Discussion

- Error Analysis (in paper): extracted evidence lack answer; two options too similar
- Limitations (opinion) for other graph-based reasoning (not commonsense)
    - ➢ Question Answering via Integer Programming over Semi-Structured Knowledge [3]
    - ➢ Question Answering as Global Reasoning over Semantic Abstractions [4]
  - This paper and [4] use SRL. [3] uses table schema, WordNet-based entailment score.
    - Support graph mathematically rigorous than Concept/Wiki graphs
  - Both use structure of graph to formulate ILP problem
  - XLNet representations vs. ILP
    - Pre-trained models perhaps perform better, but representations/constraints not explainable
  - Using SRL for unstructured → structured knowledge: important advantage
  - Does it address limitations of those papers?
    - Reasoning fails to exploit requisite knowledge from graph ✘
    - Natural language modules fail to represent the underlying phenomena of context ✘

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