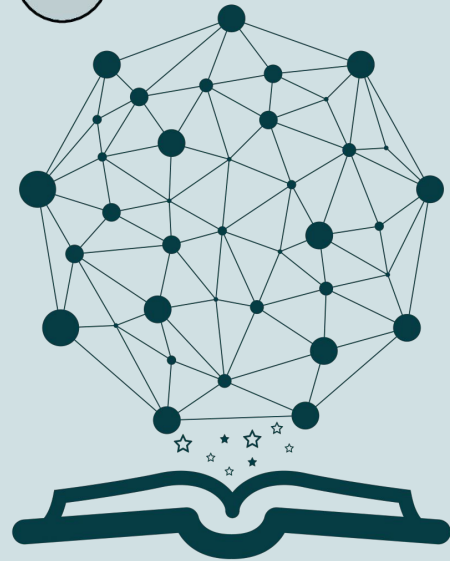
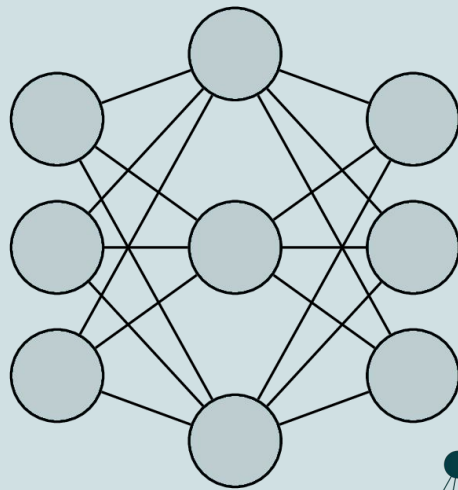


# Neural and Symbolic Models of Commonsense Reasoning

Vered Shwartz

July 5th, 2020





**Katrina had the financial means to afford a new car while Monica did not, since \_\_\_\_ had a high paying job.**



# Modern Neural Architecture

[CLS] Katrina had the financial means to afford a new car while Monica did not, since [SEP] **Katrina** had a high paying job.

[CLS] Katrina had the financial means to afford a new car while Monica did not, since [SEP] **Monica** had a high paying job.



0.51

0.49

**Sentence:**

Katrina had the financial means to afford a new car while Monica did not, since  
[MASK] had a high paying job.

**Predictions:**

11.8% ↩

8.8% **She**

6.3% **I**

6.2% **So**

5.2% **Monica**

← **Undo**

**Sentence:**

Katrina had the financial means to afford a new car while Monica did not, since  
[MASK] had a high paying job.

**Predictions:**

11.8% ↩

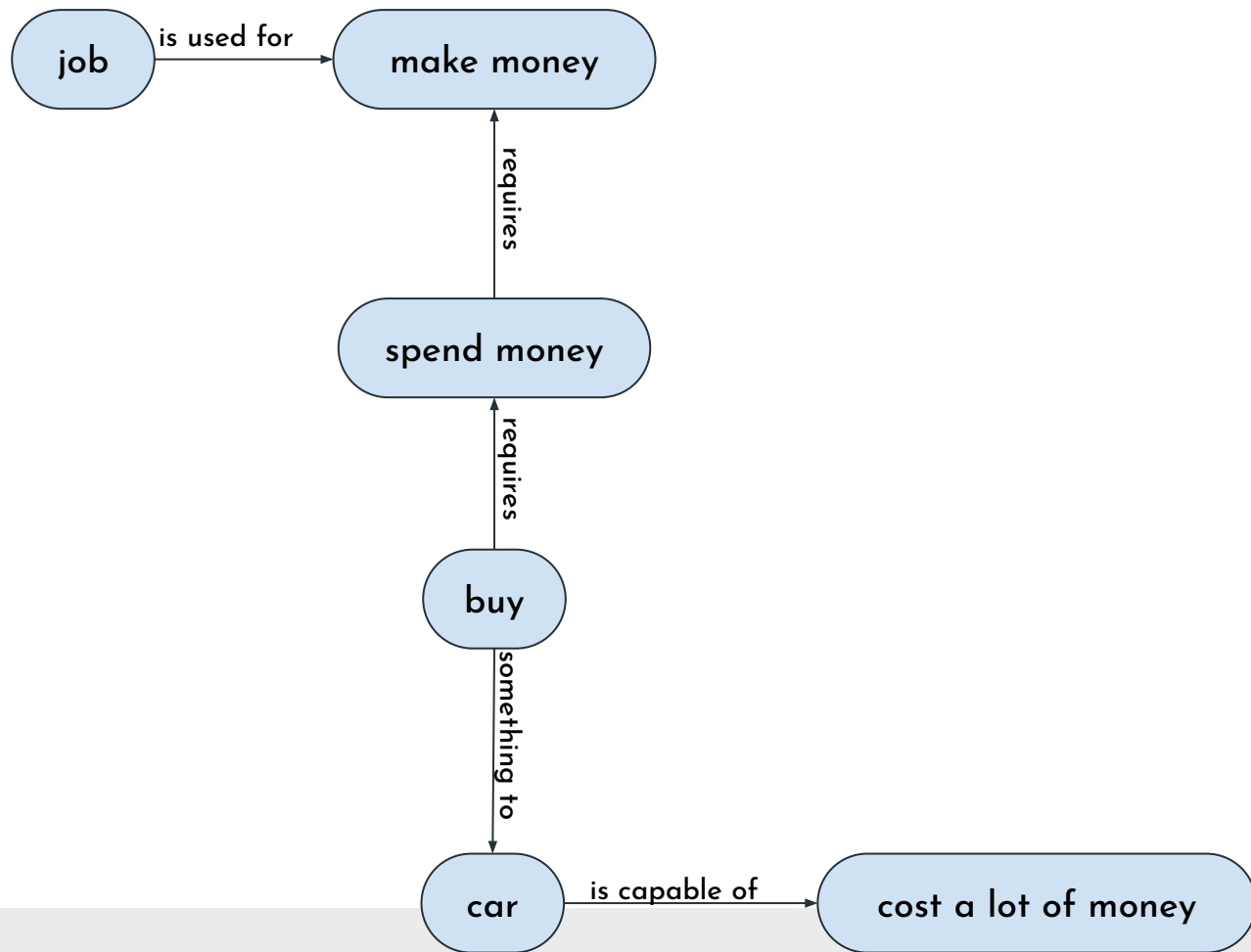
8.8% **She**

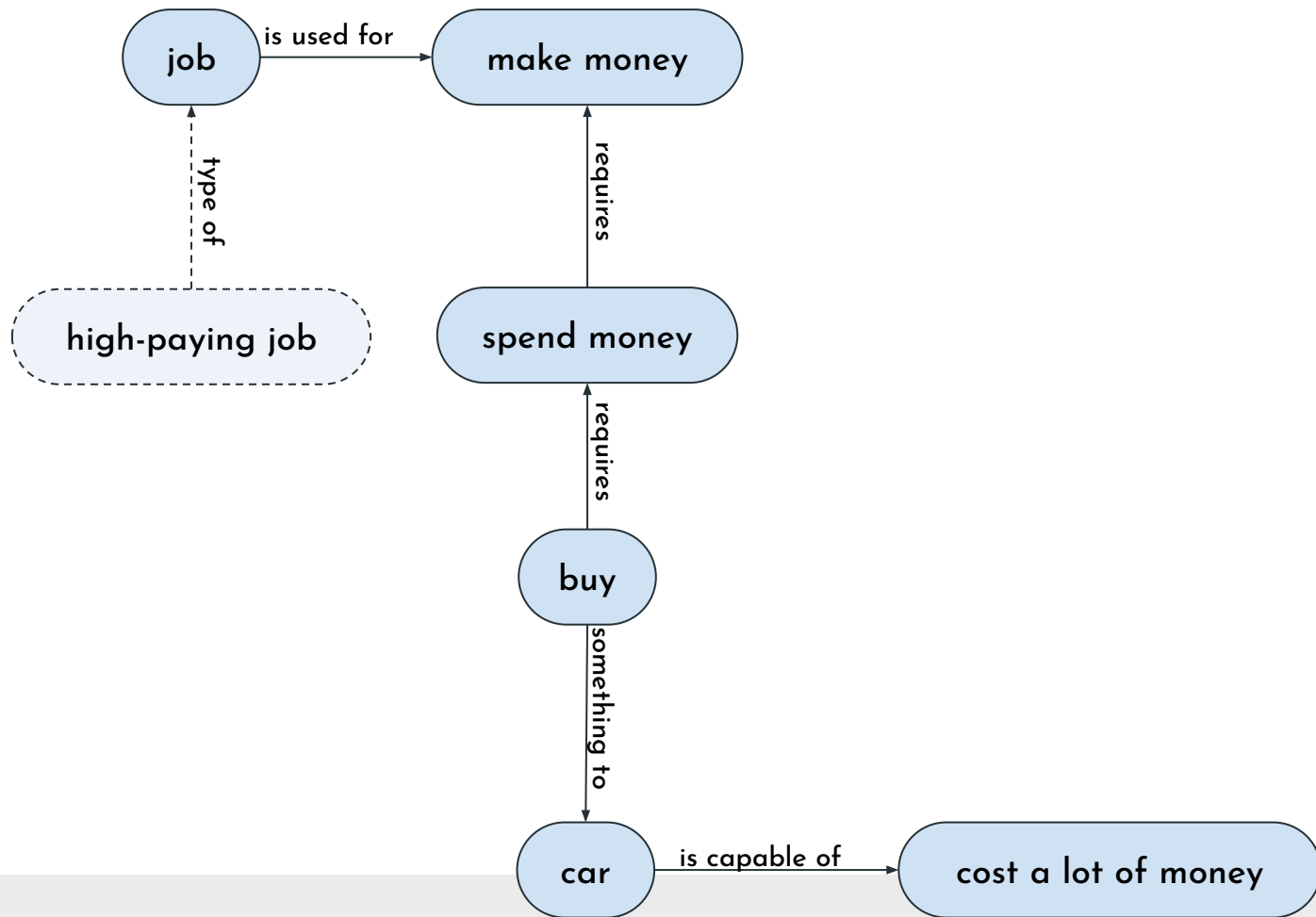
6.3% **I**

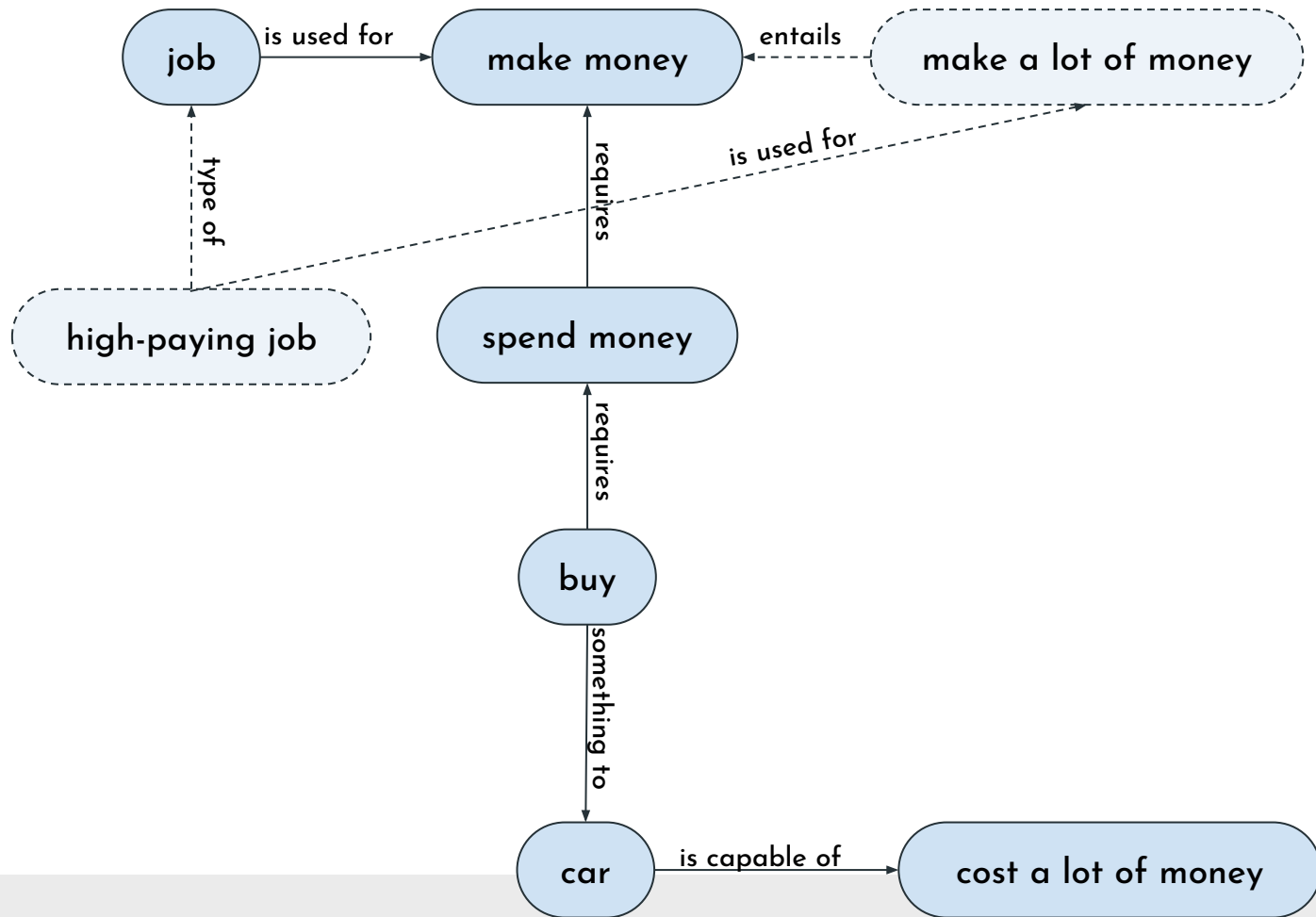
6.2% **So**

5.2% **Monica**

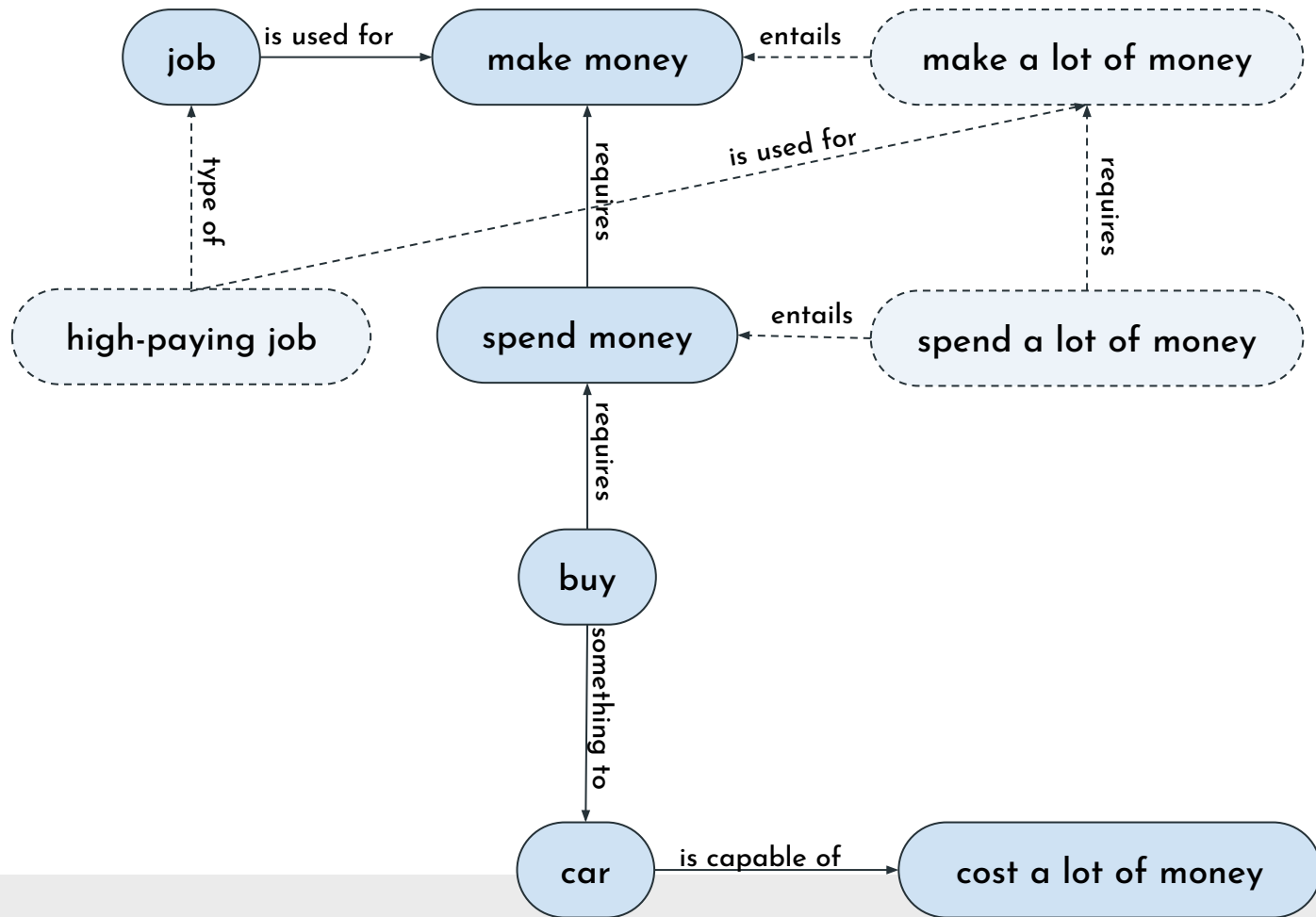
← **Undo**

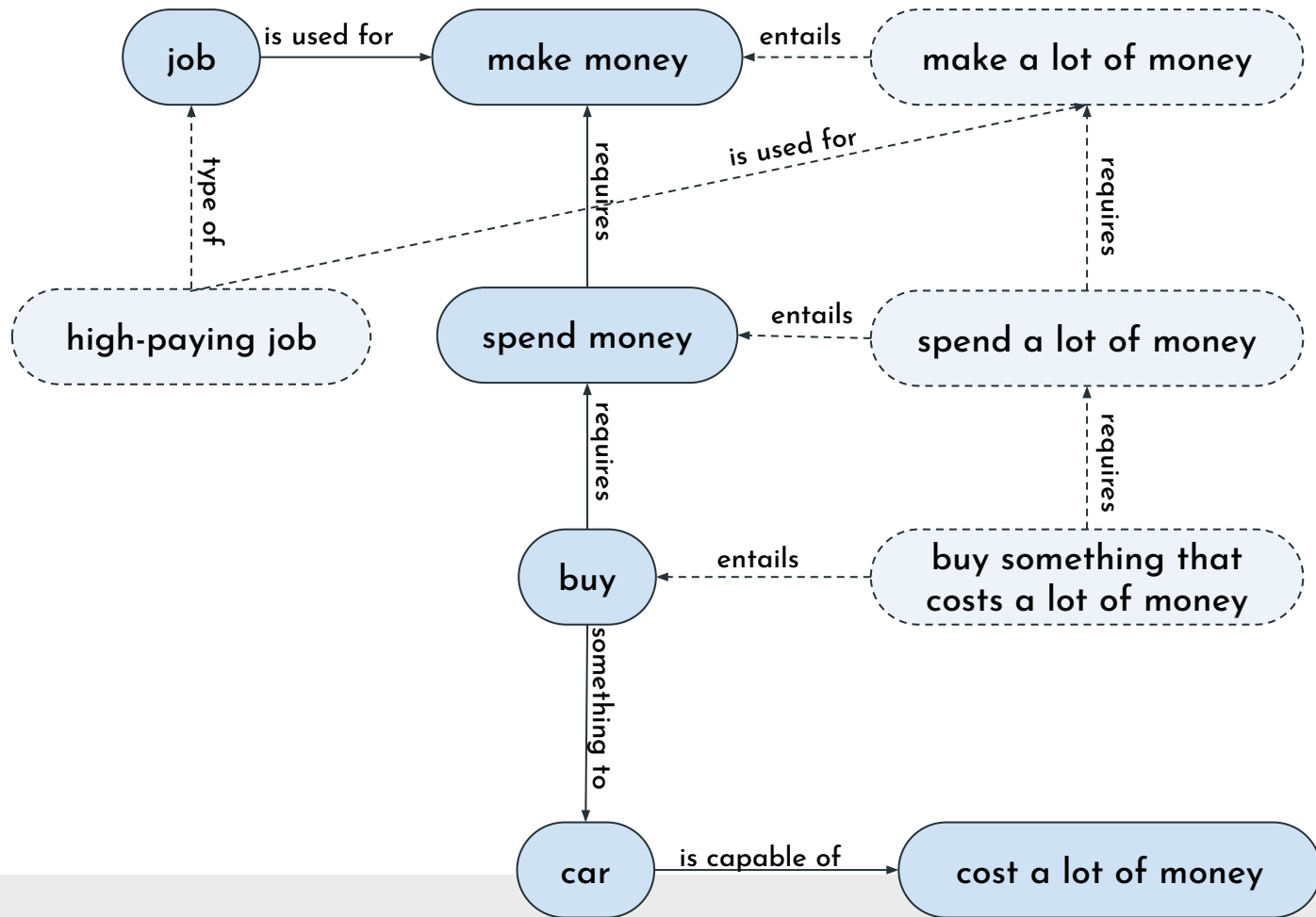


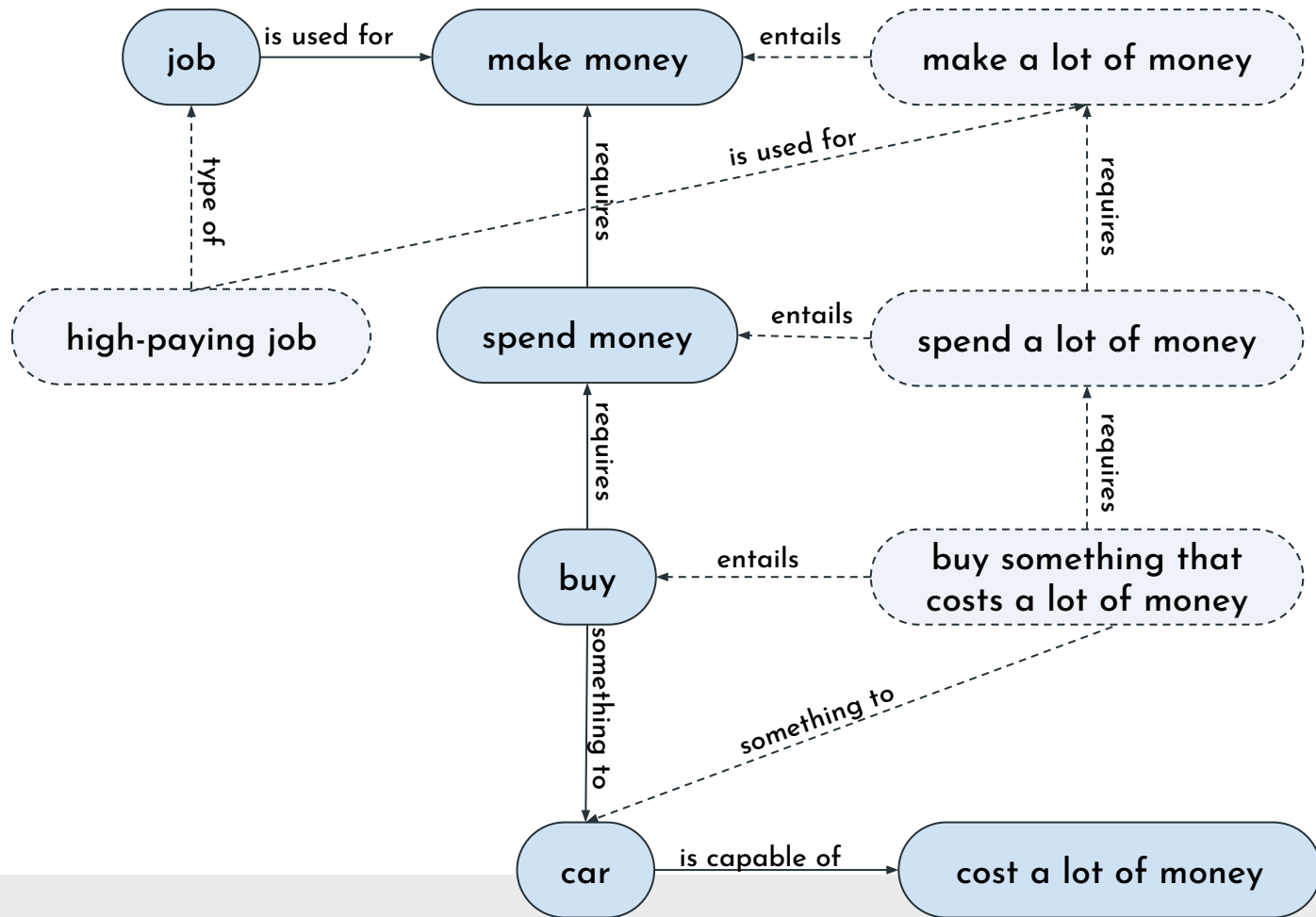


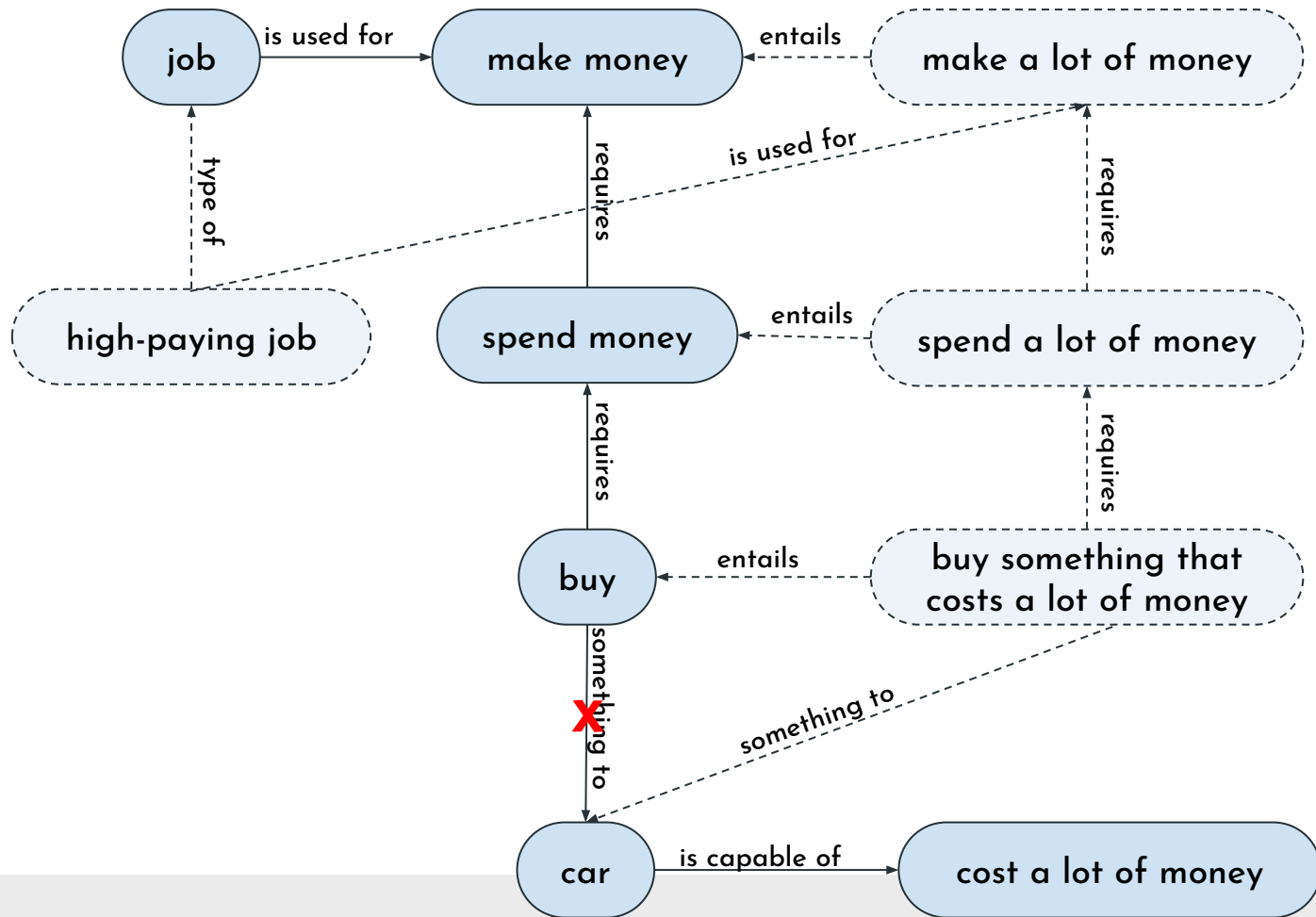






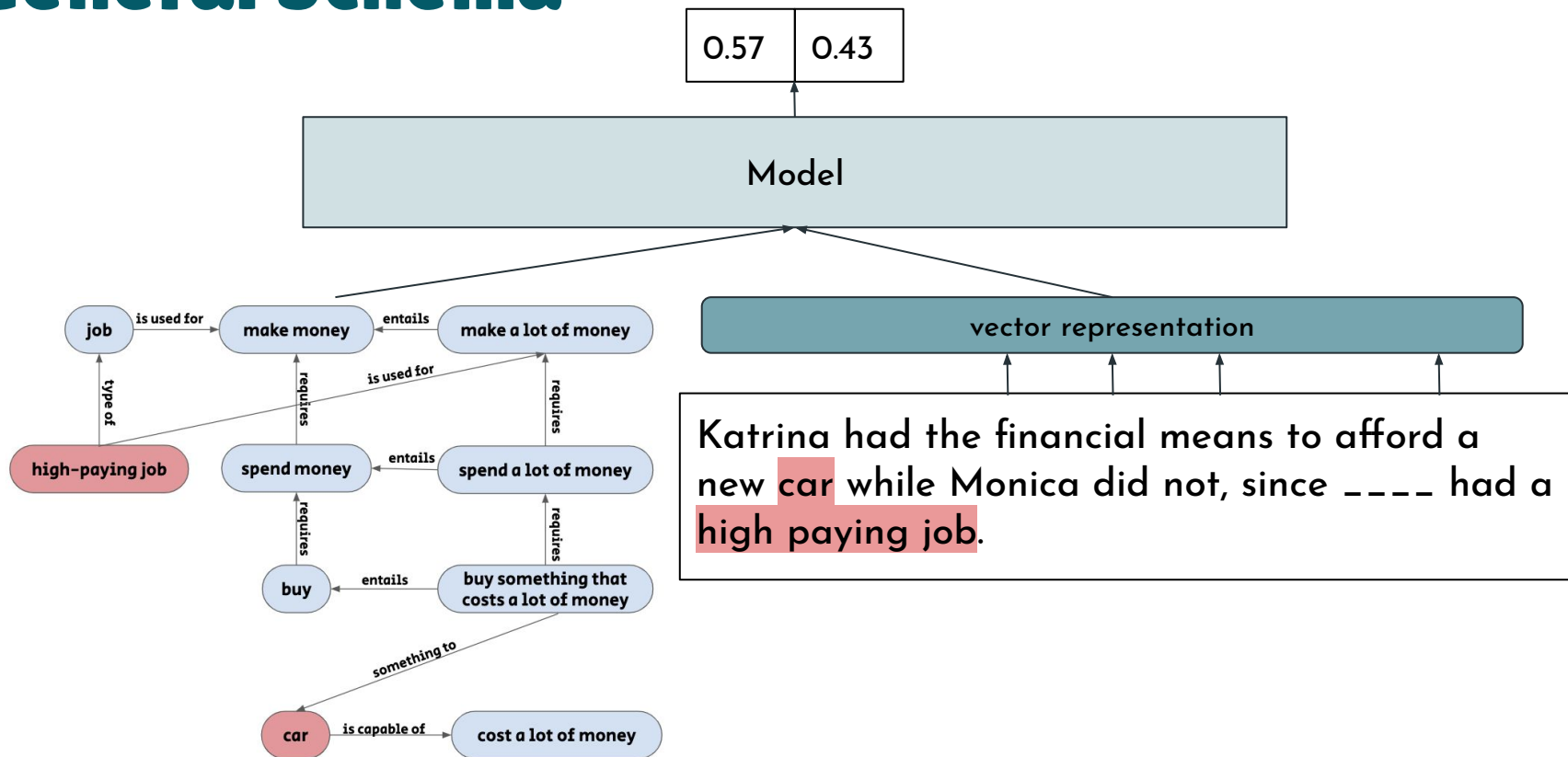






# Incorporating External Knowledge into Neural Models

## General Schema

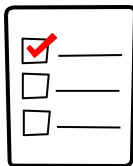


# Incorporating External Knowledge into Neural Models

## Recipe

### Task

Story ending,  
Machine Comprehension  
Social common sense  
NLI



# Incorporating External Knowledge into Neural Models

## Recipe

### Task

Story ending,  
Machine Comprehension  
Social common sense  
NLI



### Knowledge Source

Knowledge bases,  
extracted from text,  
hand-crafted rules

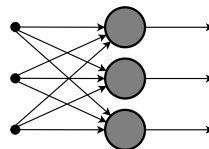
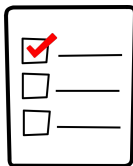


# Incorporating External Knowledge into Neural Models

## Recipe

### Task

Story ending,  
Machine Comprehension  
Social common sense  
NLI



### Neural Component

Pre/post pre-trained  
language models

### Knowledge Source

Knowledge bases,  
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hand-crafted rules



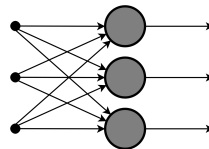
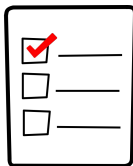


# Incorporating External Knowledge into Neural Models

## Recipe

### Task

Story ending,  
Machine Comprehension  
Social common sense  
NLI

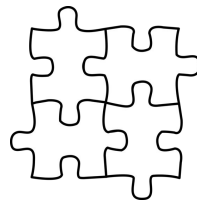


### Neural Component

Pre/post pre-trained  
language models

### Knowledge Source

Knowledge bases,  
extracted from text,  
hand-crafted rules



### Combination Method

Attention, pruning, word  
embeddings, multi-task  
learning

# Story Ending (RocStories)

Agatha had always wanted pet birds.  
So one day she purchased two pet finches.  
Soon she couldn't stand their constant noise.  
And even worse was their constant mess.



Agatha decided to buy two more. (Wrong)  
Agatha decided to return them. (Right)

Task

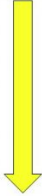
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# Machine Comprehension

## ProPara

Paragraph (seq. of steps):		Participants:				
		water	light	CO2	mixture	sugar
	state0	soil	sun	?	-	-
<i>Roots absorb water from soil</i>						
	state1	roots	sun	?	-	-
<i>The water flows to the leaf.</i>						
	state2	leaf	sun	?	-	-
<i>Light from the sun and CO2 enter the leaf.</i>						
	state3	leaf	leaf	leaf	-	-
<i>The light, water, and CO2 combine into a mixture.</i>						
	state4	-	-	-	leaf	-
<i>Mixture forms sugar.</i>						
	state5	-	-	-	-	leaf

Time



## Task

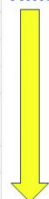
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		water	light	CO2	mixture	sugar
state0	<i>Roots absorb water from soil</i>	soil	sun	?	-	-
state1	<i>The water flows to the leaf.</i>	roots	sun	?	-	-
state2	<i>Light from the sun and CO2 enter the leaf.</i>	leaf	sun	?	-	-
state3	<i>The light, water, and CO2 combine into a mixture.</i>	leaf	leaf	leaf	-	-
state4	<i>Mixture forms sugar.</i>	-	-	-	leaf	-
state5		-	-	-	-	leaf

Time



## NarrativeQA

**Question:** How is Oscar related to Dana?

**Answer:** her son

**Snippet:** [...] She continues digging in her purse while Frank leans over the buggy and makes funny faces at the baby, OSCAR, a very cute nine-month old boy. [...]

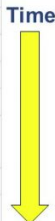
Task

<input checked="" type="checkbox"/>	_____
<input type="checkbox"/>	_____
<input type="checkbox"/>	_____

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## NarrativeQA

**Question:** How is Oscar related to Dana?

**Answer:** her son

**Snippet:** [...] She continues digging in her purse while Frank leans over the buggy and makes funny faces at the baby, OSCAR, a very cute nine-month old boy. [...]

## MCScript

**T** I wanted to plant a tree. I went to the home and garden store and picked a nice oak. Afterwards, I planted it in my garden.

**Q1** What was used to dig the hole?

- a. a shovel                      b. his bare hands

**Q2** When did he plant the tree?

- a. after watering it              b. after taking it home

## Task

<input checked="" type="checkbox"/>	_____
<input type="checkbox"/>	_____
<input type="checkbox"/>	_____

# Machine Comprehension

## ProPara

Paragraph (seq. of steps):	Participants:					
	water	light	CO2	mixture	sugar	
state0	soil	sun	?	-	-	Time ↓
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<i>The water flows to the leaf.</i>	leaf	sun	?	-	-	
<i>Light from the sun and CO2 enter the leaf.</i>	leaf	leaf	leaf	-	-	
<i>The light, water, and CO2 combine into a mixture.</i>	leaf	leaf	leaf	-	-	
<i>Mixture forms su</i>	-	-	-	leaf	-	

## CommonsenseQA

Where on a river can you hold a cup upright to catch water on a sunny day?

👍 waterfall, 👎 bridge, 👎 valley, 👎 pebble, 👎 mountain

Where can I stand on a river to see water falling without getting wet?

👎 waterfall, 👍 bridge, 👎 valley, 👎 stream, 👎 bottom

I'm crossing the river, my feet are wet but my body is dry, where am I?

👎 waterfall, 👎 bridge, 👍 valley, 👎 bank, 👎 island

Name

Question

Answer

Snippet

Purpose

makes runny faces at the baby, OSCAR, a very cute nine-month old boy. [...]

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☒ ☐ ☐

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Name

Question

Answer

Snippet

Purpose

makes runny faces at the baby, OSCAR, a very cute nine-month old boy. [...]

## ARC

Which property of a mineral can be determined just by looking at it?

- (A) luster
- (B) mass
- (C) weight
- (D) hardness

## MCScrip

T I wa  
and g  
ward

Q1 What was used to dig the hole?

- a. a shovel
- b. his bare hands

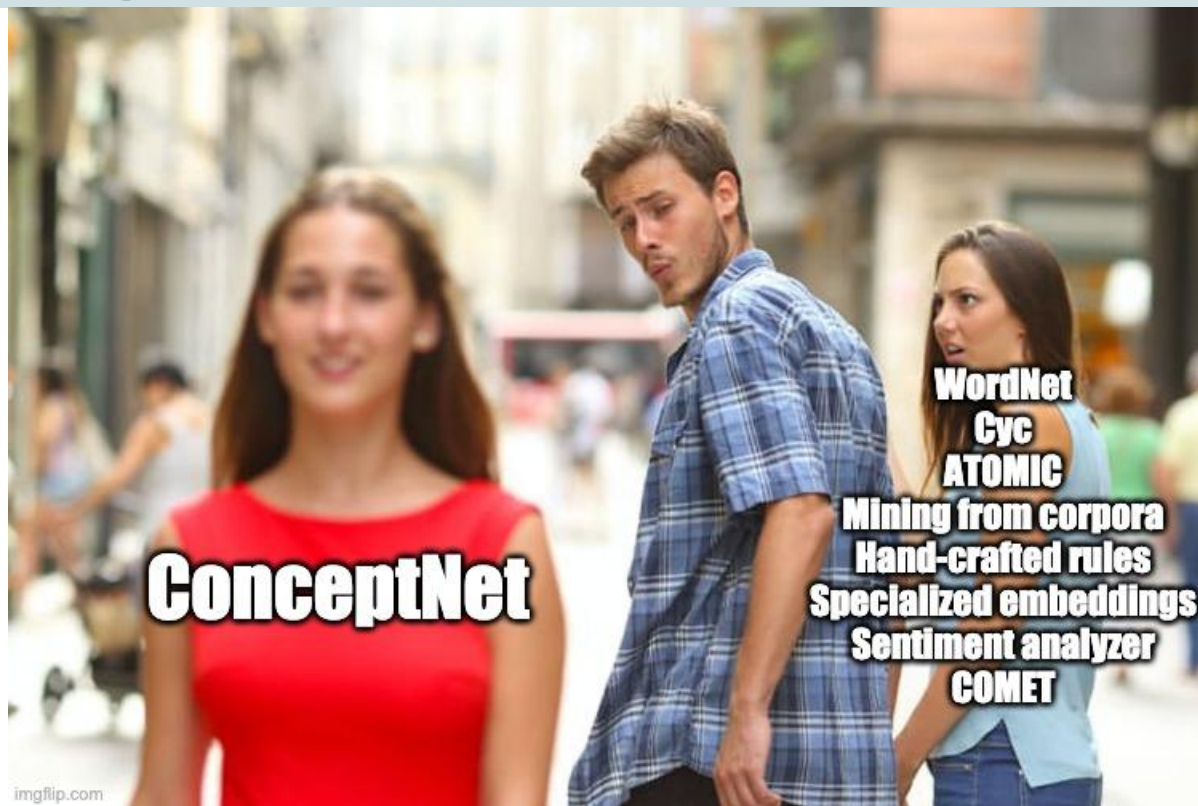
ter taking it home

## Task

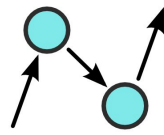
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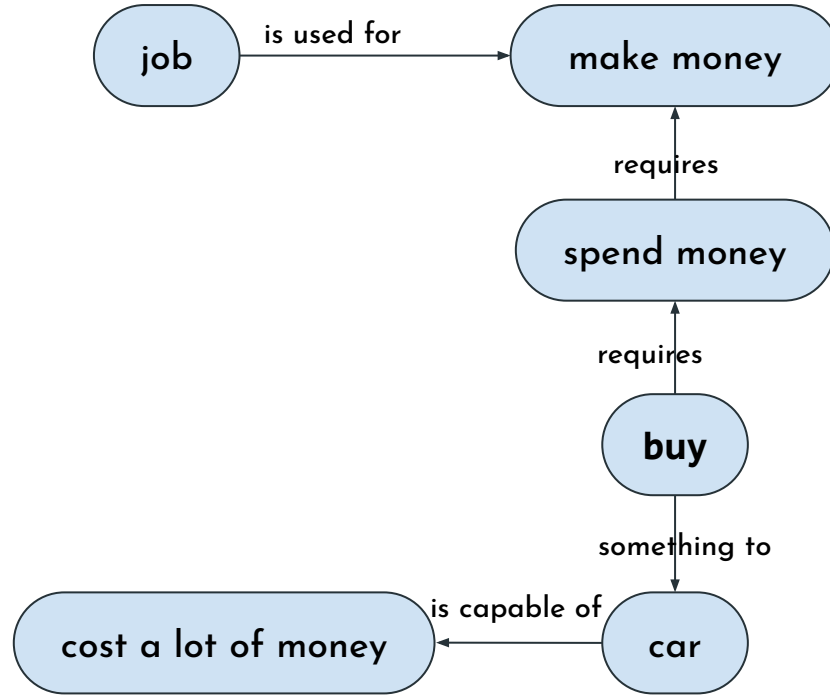
# Knowledge Source



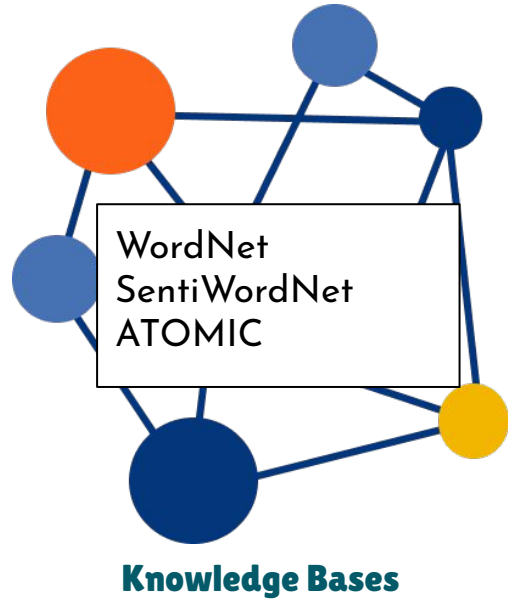




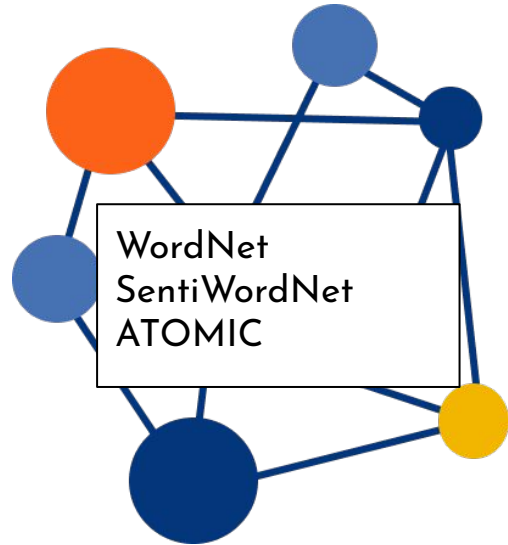
# ConceptNet



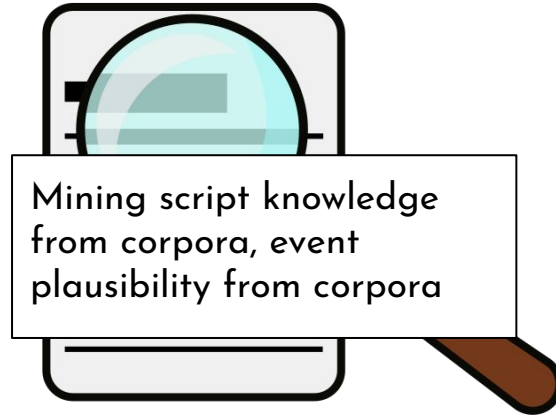
## Other Knowledge Sources



# Other Knowledge Sources

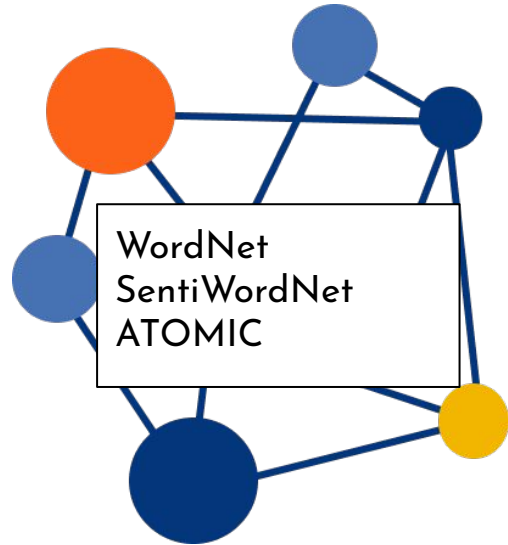


**Knowledge Bases**

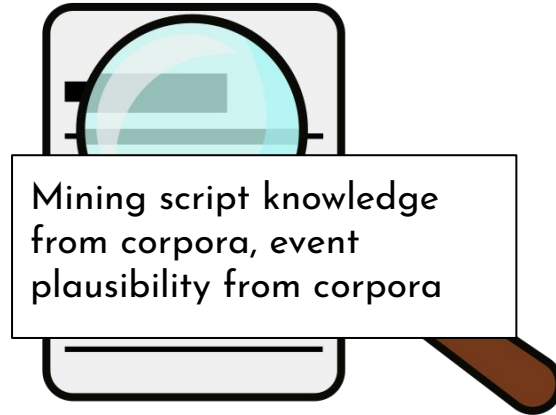


**Mining from Text**

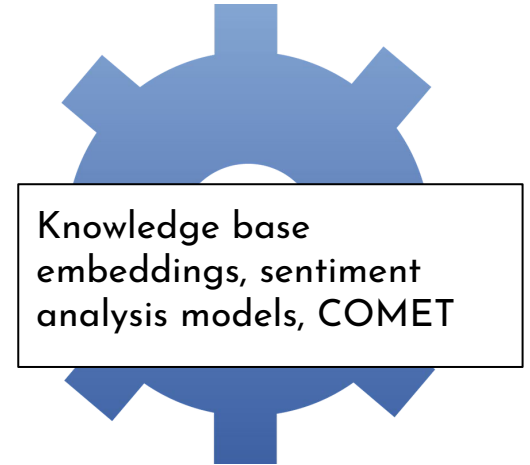
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**Knowledge Bases**



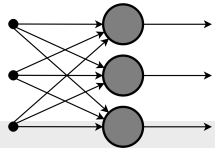
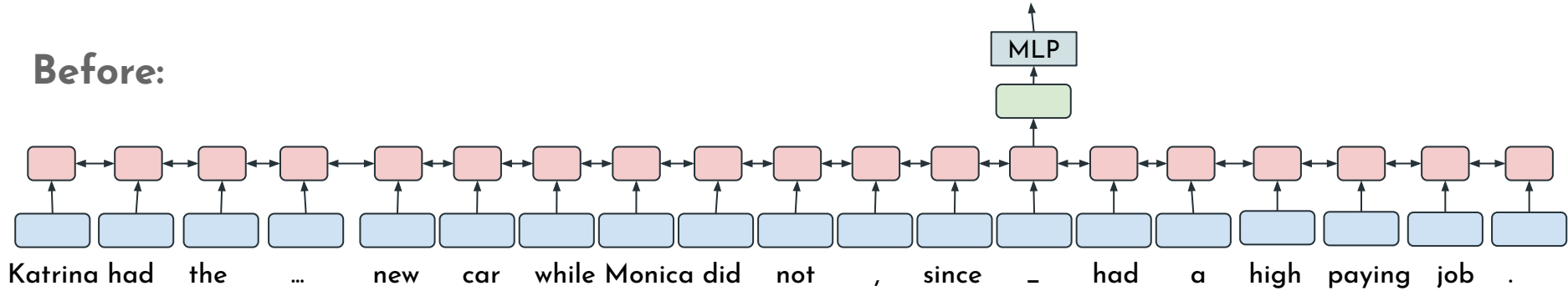
**Mining from Text**



**Tools**

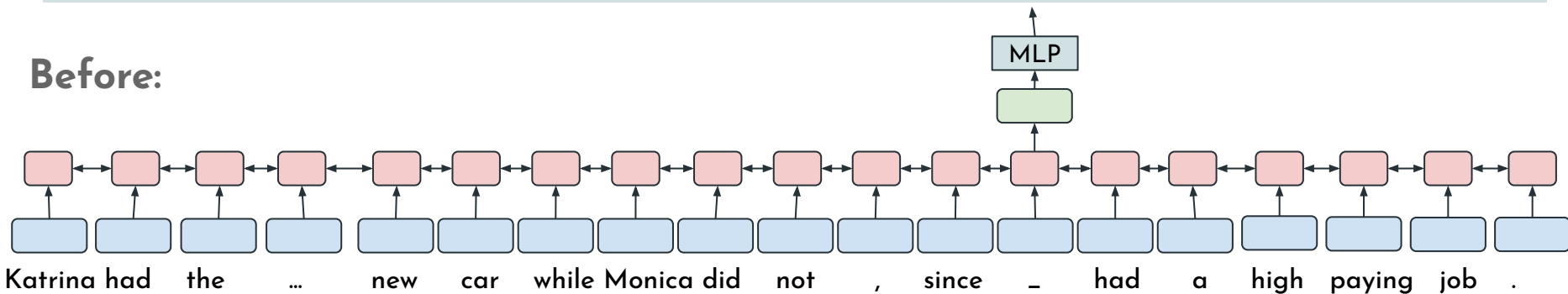
# Neural Component

Before:



# Neural Component

Before:



After:

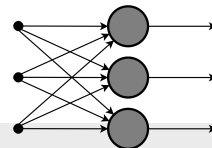
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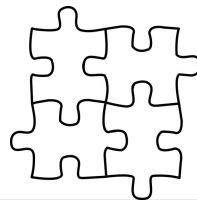
0.51

0.49



# Combination Method

1. Incorporate into scoring function
2. Symbolic  $\rightarrow$  vector representation
  - (+attention)
3. Multi-task learning



# Incorporating External Knowledge into Neural Models

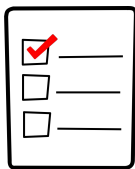
## Example #1



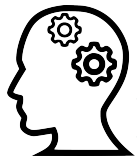


# Incorporating External Knowledge into Neural Models

## Example #1



RocStories



### Inference Rules (with costs)

**WordNet:** restaurant→eatery (1.0)

**Wikipedia:** restaurant→business (1.0)

**Script knowledge:**

*X went to a restaurant*→*X ate* (0.32)

**Relatedness:** restaurant→food (0.71)

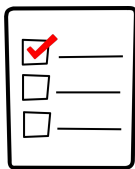
Hand-crafted negation rules

Sentiment

...

# Incorporating External Knowledge into Neural Models

## Example #1



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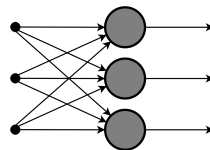
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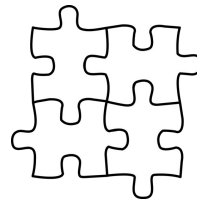
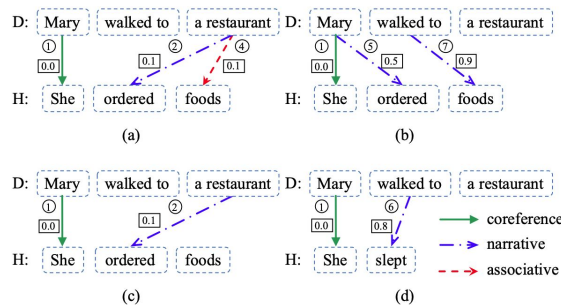
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Sentiment

...

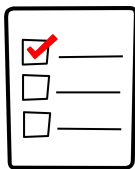


1. For each sentence in the story (premise), find a set of inference rules that “cover” a story ending (hypothesis): **reason**.



# Incorporating External Knowledge into Neural Models

## Example #1



RocStories



### Inference Rules (with costs)

**WordNet:** restaurant→eatery (1.0)

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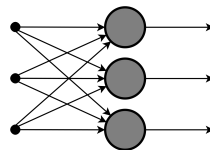
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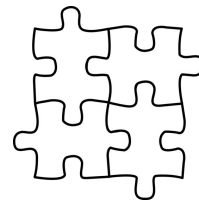
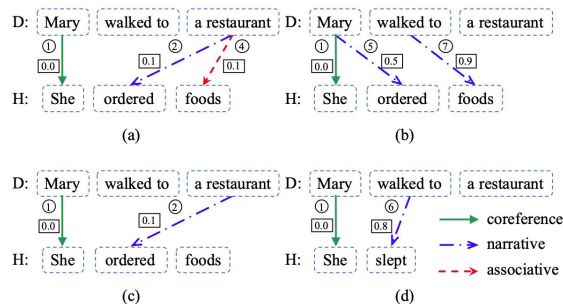
Hand-crafted negation rules

Sentiment

...



1. For each sentence in the story (premise), find a set of inference rules that “cover” a story ending (hypothesis): **reason**.



2. Learn to score a reason according to costs, inference types, and relatedness between the involved words, using **attention mechanism**.

# Incorporating External Knowledge into Neural Models

## Example #1



RocStories



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**WordNet:** restaurant  $\rightarrow$  eatery (1.0)

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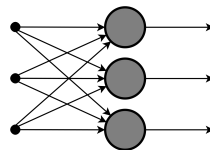
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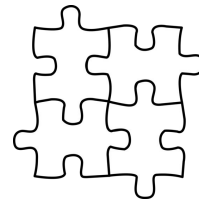
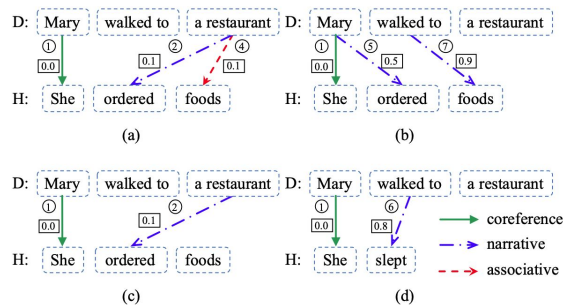
Hand-crafted negation rules

Sentiment

...



1. For each sentence in the story (premise), find a set of inference rules that “cover” a story ending (hypothesis): **reason**.



2. Learn to score a reason according to costs, inference types, and relatedness between the involved words, using **attention mechanism**.

3. Aggregate across all the sentences in the story.

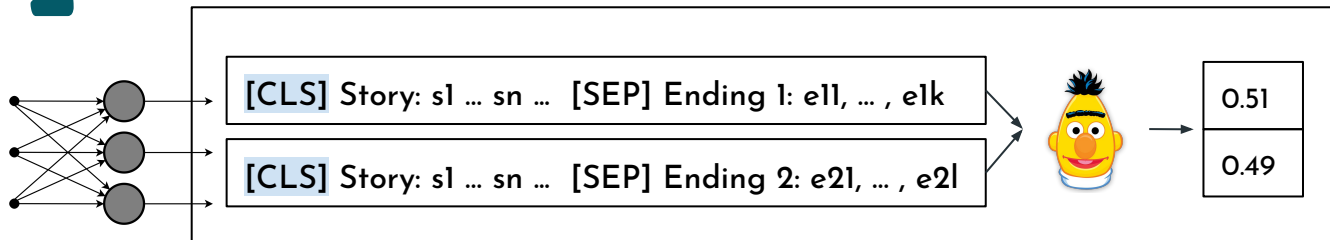
# Incorporating External Knowledge into Neural Models

## Example #2



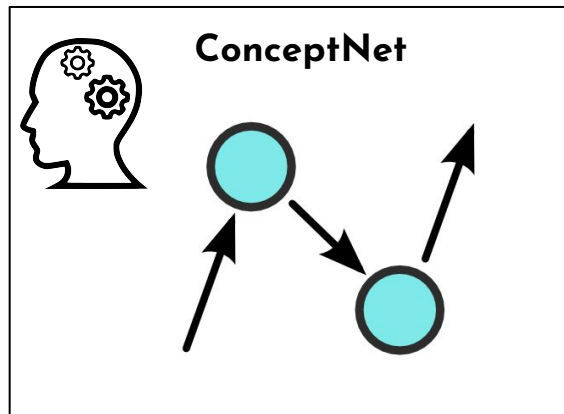
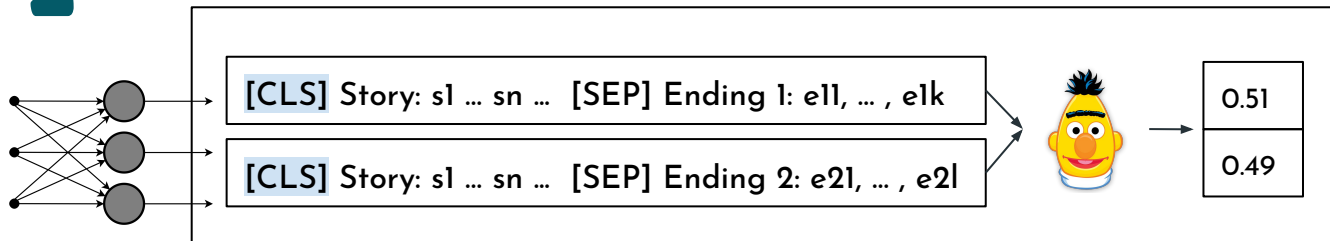
# Incorporating External Knowledge into Neural Models

## Example #2



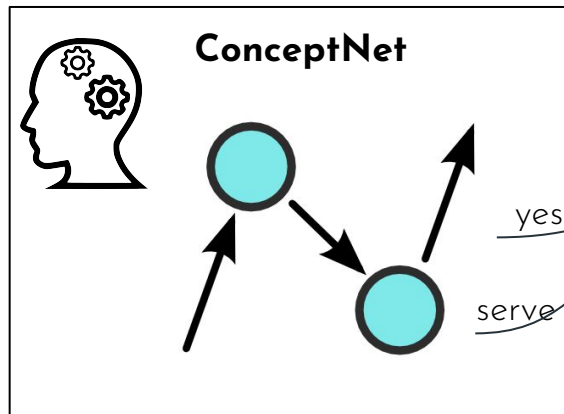
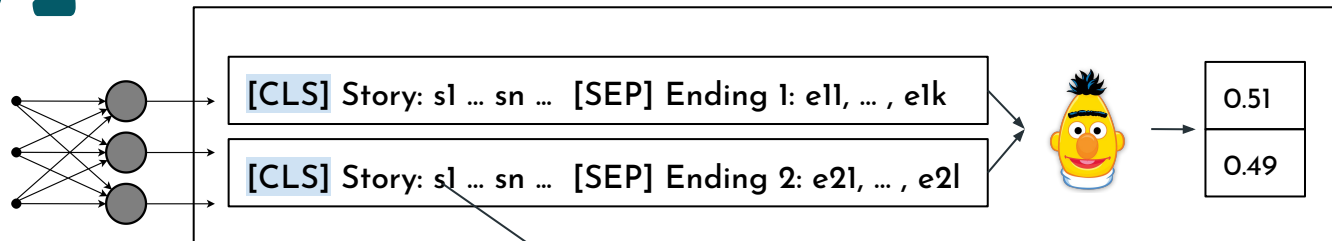
# Incorporating External Knowledge into Neural Models

## Example #2



# Incorporating External Knowledge into Neural Models

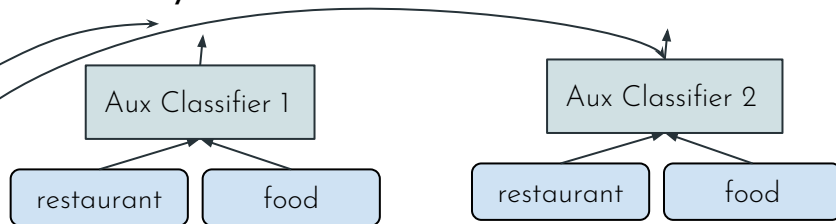
## Example #2



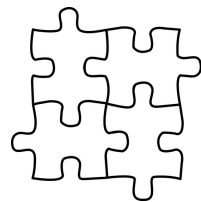
### Multi-task Learning

1. Are they related?

2. What's the relation?



$S_i = \text{restaurant}$   $E_j = \text{food}$





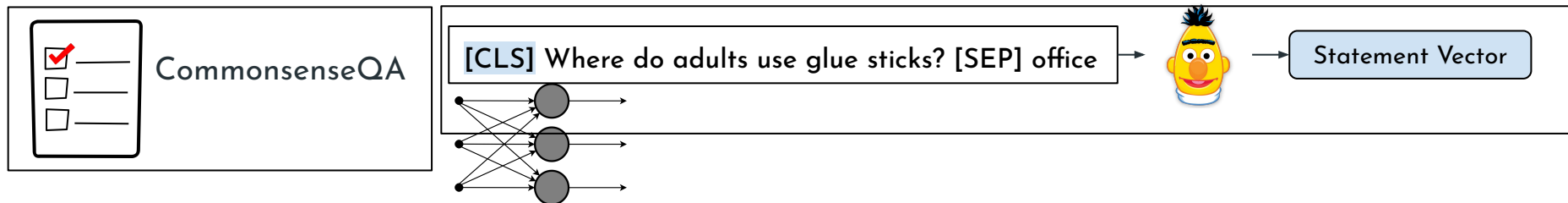
# Incorporating External Knowledge into Neural Models

## Example #3



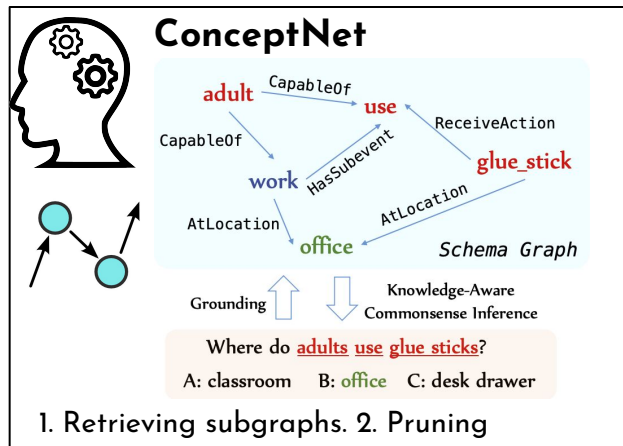
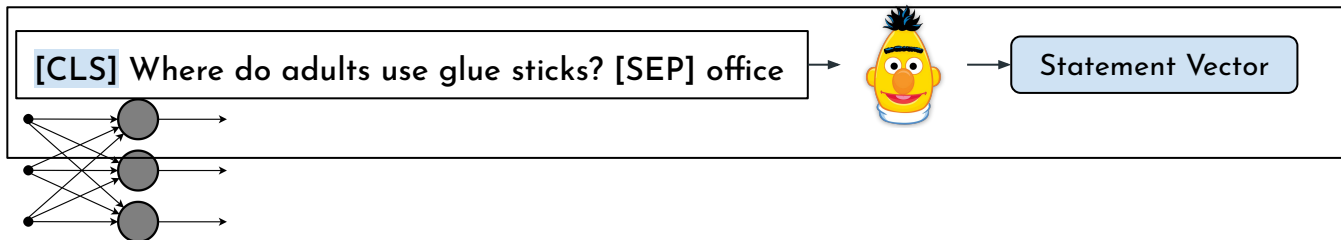
# Incorporating External Knowledge into Neural Models

## Example #3



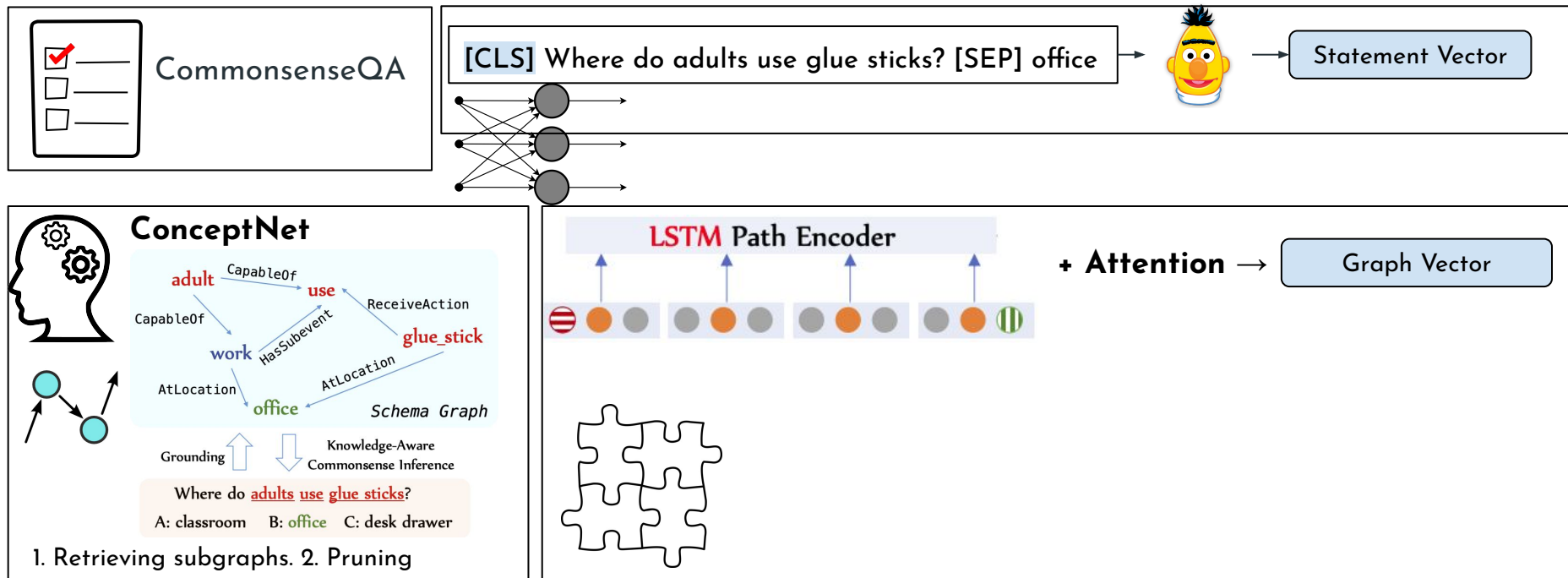
# Incorporating External Knowledge into Neural Models

## Example #3



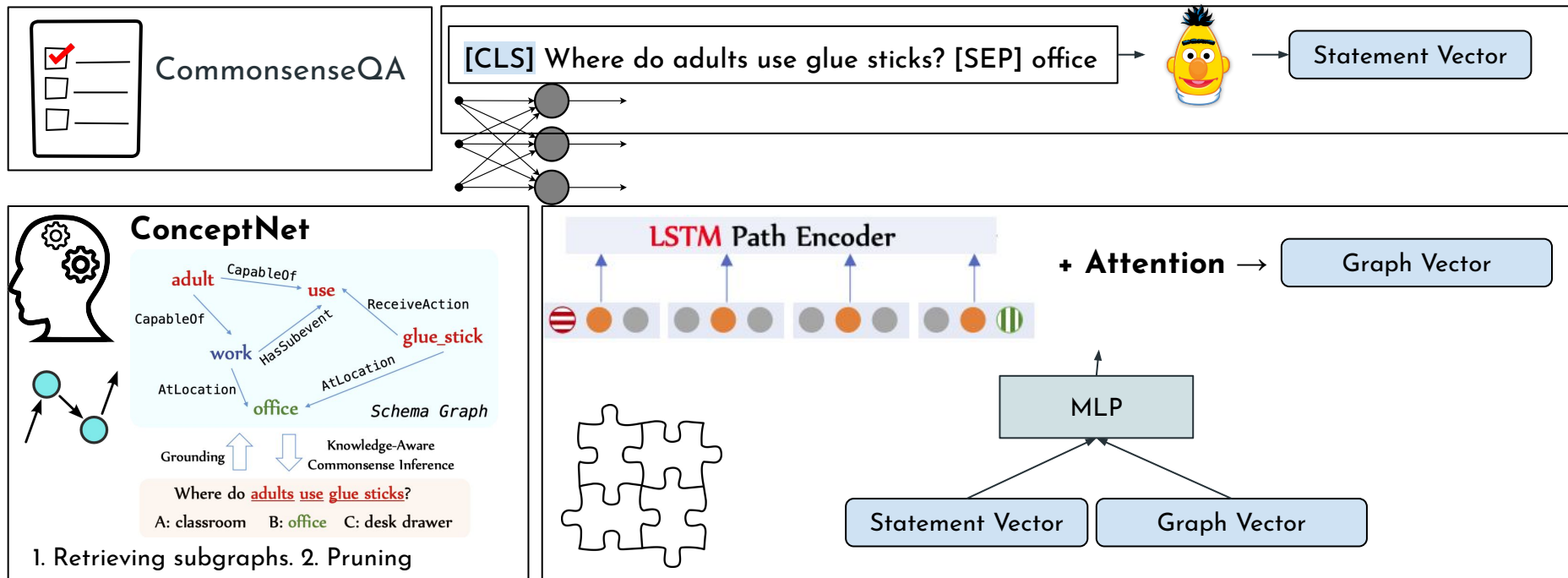
# Incorporating External Knowledge into Neural Models

## Example #3



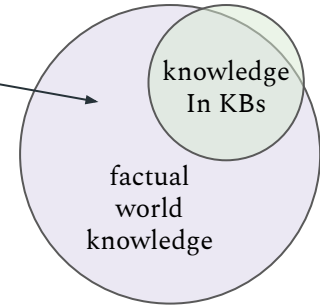
# Incorporating External Knowledge into Neural Models

## Example #3



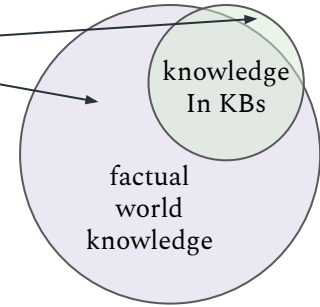
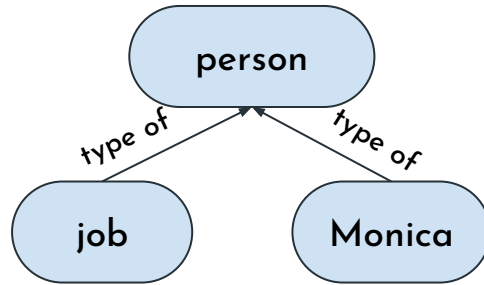
# Limitations

- Insufficient Coverage



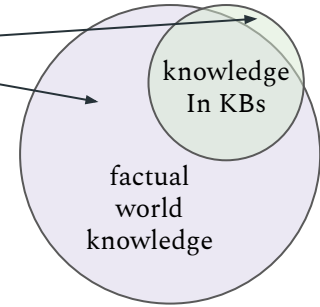
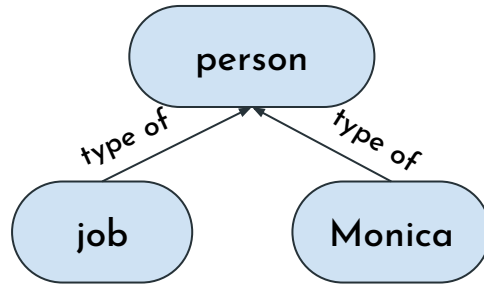
# Limitations

- Insufficient Coverage
- Not 100% accurate



# Limitations

- Insufficient Coverage
- Not 100% accurate



- Easy to incorporate simple resources with stationary facts (ConcpetNet) but they are limited in expressiveness:





# Thank you!

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# References + Additional Reading

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- [7] Incorporating Relation Knowledge into Commonsense Reading Comprehension with Multi-task Learning. Jiangnan Xia, Chen Wu, and Ming Yan. CIKM 2019.
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- [11] Improving Question Answering over Incomplete KBs with Knowledge-Aware Reader. Wenhan Xiong, Mo Yu, Shiyu Chang, Xiaoxiao Guo, and William Yang Wang. ACL 2019.
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