Neurosymbolic Knowledge Bases

10/29/2024
CMSC 491/691 - INTERACTIVE FICTION AND TEXT GENERATION
DR. LARA J. MARTIN

SLIDES ADAPTED FROM THE ACL 2020 COMMONSENSE TUTORIAL BY YEJIN CHOI, VERED SHWARTZ, MAARTEN SAP, ANTOINE BOSSELUT, AND DAN ROTH

Learning Objectives

- Recall how neural networks and symbolic methods can be combined
- Follow examples of integrated and post-hoc knowledge graph integration

Review: Definition of Common Sense

The basic level of **practical knowledge** and **reasoning**
concerning **everyday situations** and events
that are **commonly shared** among **most** people.

It's OK to keep the closet door open	It's not OK to keep the refrigerator door open because the food might go bad
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

Review:
Desirable properties for a commonsense resource

Coverage

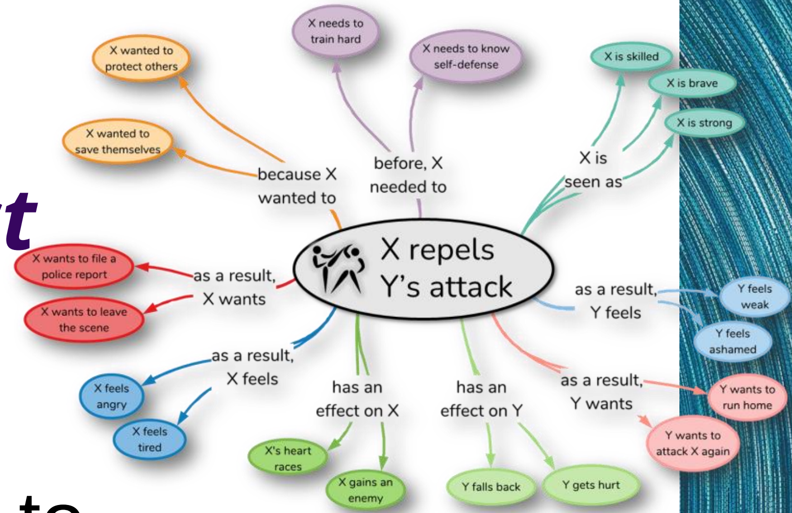
- Large scale
- Diverse knowledge types

Useful

- High quality knowledge
- Usable in downstream tasks

Multiple resources tackle different knowledge types

Review:
Atomic: knowledge of *cause* and *effect*



Humans have **theory of mind**, allowing us to

- make inferences about **people's mental states**
- understand **likely events** that precede and follow (Moore, 2013)

AI systems struggle with ***inferential*** reasoning

- only find **complex correlational patterns** in data
- **limited to the domain** they are trained on

(Pearl; Davis and Marcus 2015; Lake et al. 2017; Marcus 2018)

M. Sap *et al.*, "ATOMIC: An Atlas of Machine Commonsense for If-Then Reasoning," *AAAI Conference on Artificial Intelligence (AAAI)*, vol. 33, no. 1, pp. 3027–3035, 2019, doi: 10.1609/aaai.v33i01.33013027.

Review:
Ways of categorizing existing knowledge bases

Represented in **symbolic logic**
(e.g., LISP-style logic)

Represented in **natural language**
(how humans *talk* and *think*)

NELL
(Mitchell et al., 2015)

OpenCyc 4.0
(Lenat, 2012)

ConceptNet 5.5
(Speer et al., 2017)

Knowledge of "***what***"
(taxonomic: `A isA B`)

Knowledge of "***why***" and "***how***"
(inferential: *causes* and *effects*)

ATOMIC
(Sap et al., 2019)

Review:
Some commonsense cannot be extracted

Text is subject to reporting bias (Gordon & Van Durme, 2013)

Noteworthy events

- Murdering 4x more common than exhaling

Commonsense is not often written

- Grice's maxim of quantity

found when extracting commonsense knowledge on four large corpora using Knext (Gordon & Van Durme, 2013)

When communicating, people try to be as informative as they possibly can, and give as much information as is needed, and no more.

Review:
Why combine [neural and symbolic methods]?

Neural Networks

Statistical patterns over data

Easy to generate new text from

Need a lot of data to train (and might need to be labeled)

Hard to control

Examples: sequence-to-sequence networks, transformers (LLMs)

Symbolic Methods

Structured information

Easy for people to understand (interpretable)

Hard to make

- Need experts or a lot of time

Limited set of information

Examples: knowledge bases, planning domains/problems, scripts

Ways of combining them

- During training
  - Such as in reinforcement learning or retrieval-augmented generation (RAG)
- After training
  - Like a symbolic “wrapper” – helps validate what the NN is doing
- Others??

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- Others??

Adding neural networks to knowledge bases

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

WINOGRANDE: An Adversarial Winograd Schema Challenge at Scale.
Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. AAAI 2020.

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

Masked Language Models

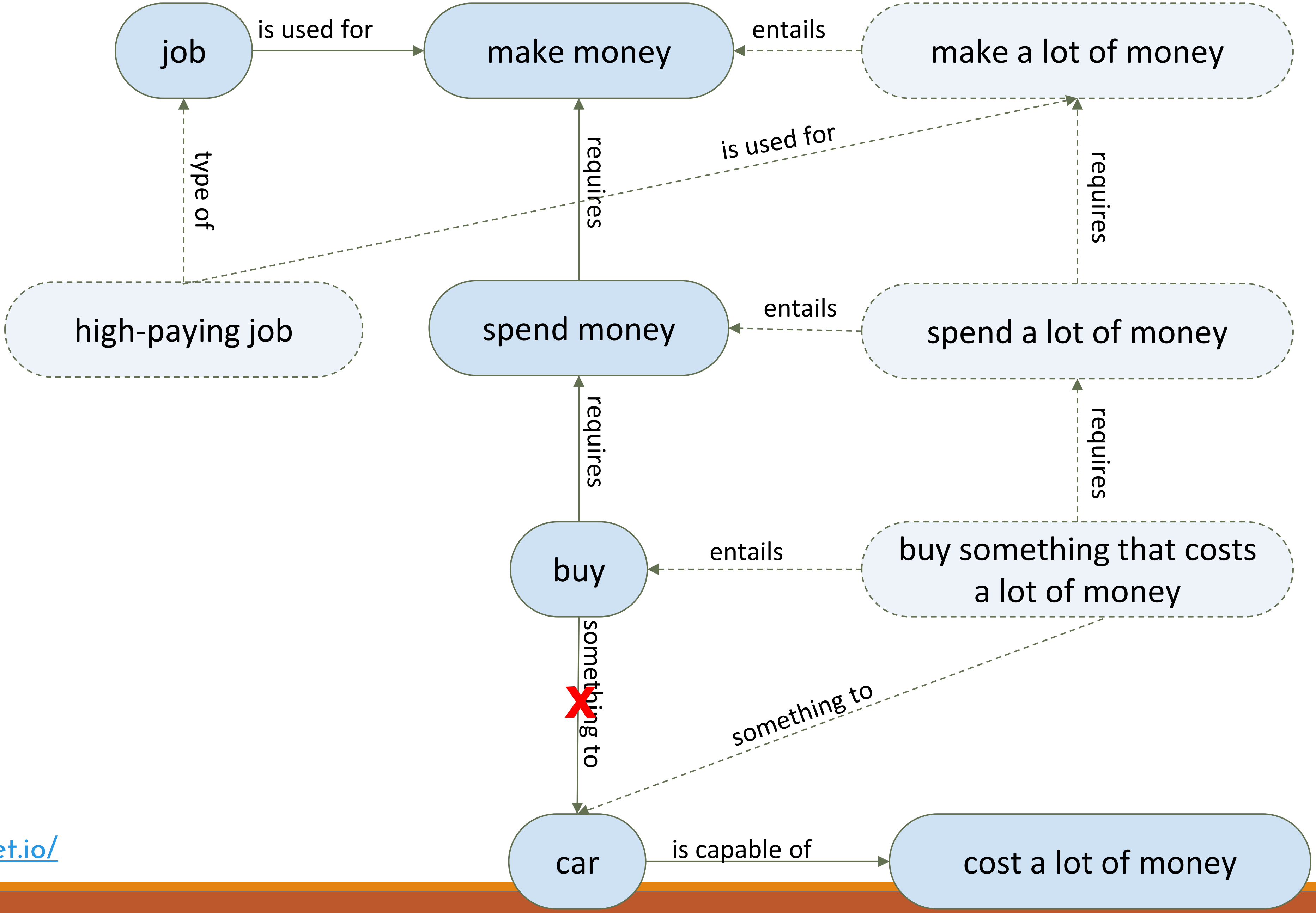
Sentence:

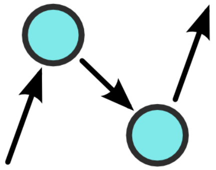
Katrina had the financial means to afford a new car while Monica did not, since [MASK] had a high paying job.

Predictions:

11.8% ↵
8.8% She
6.3% I
6.2% So
5.2% Monica
← Undo

~~https://demo.allennlp.org/masked-lm~~

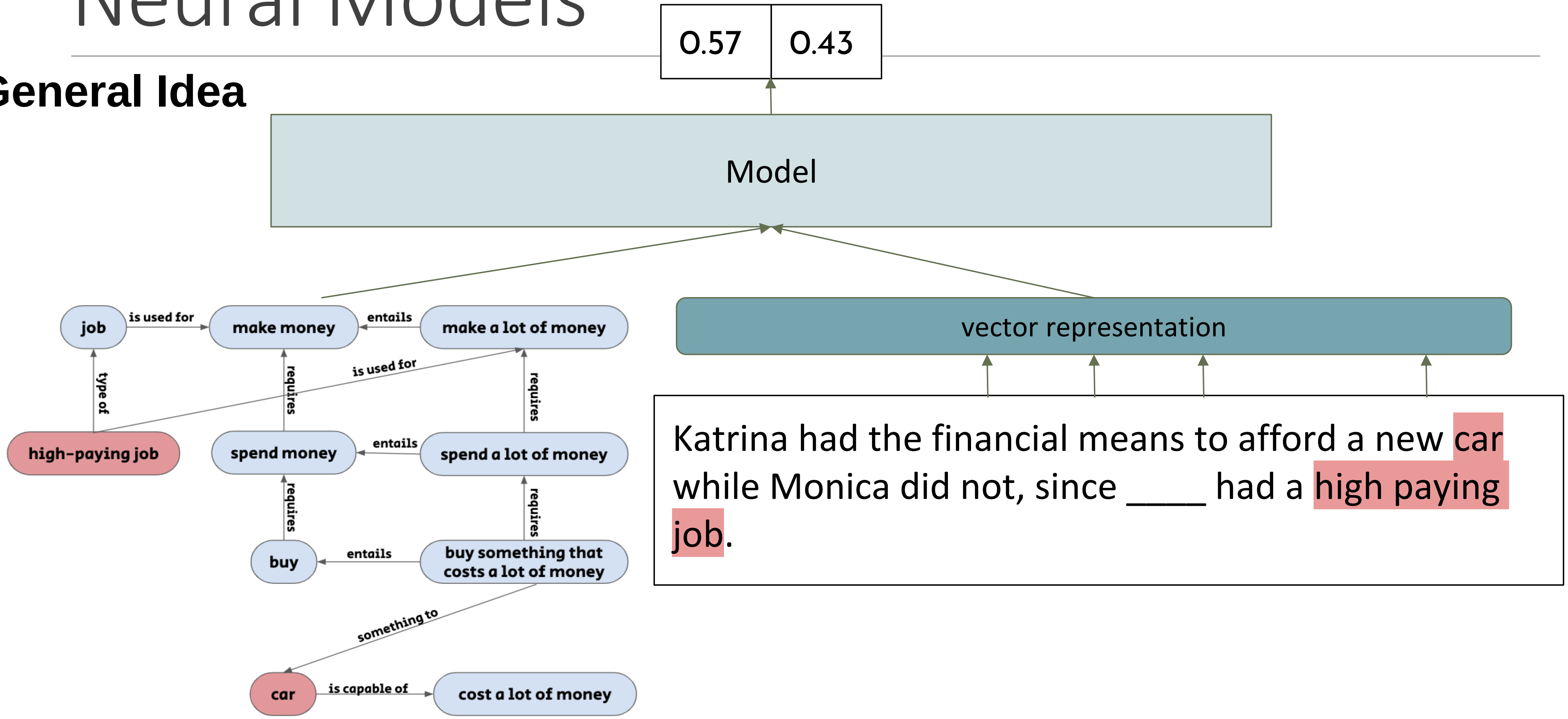




https://conceptnet.io/

Incorporating External Knowledge into Neural Models

General Idea

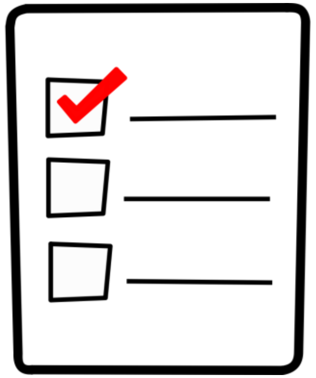


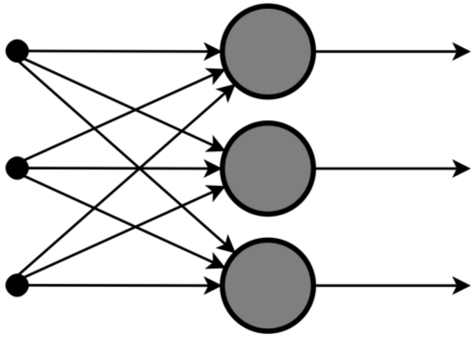
Incorporating External Knowledge into Neural Models

Recipe

- **Task**

Story ending,
Machine Comprehension
Social common sense
NLI



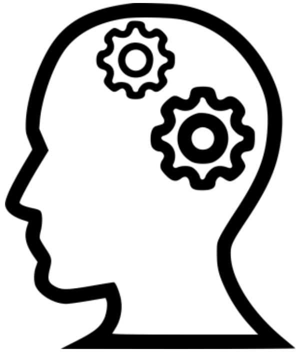


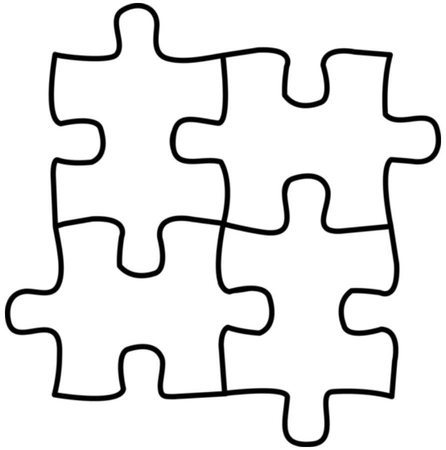
Neural Component

Pre/post pre-trained language models

Knowledge Source

Knowledge bases,
extracted from text,
hand-crafted rules





Combination Method

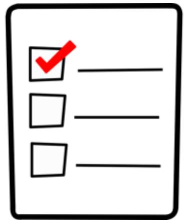
Attention, pruning,
word embeddings,
multi-task learning

Story Ending Task (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.

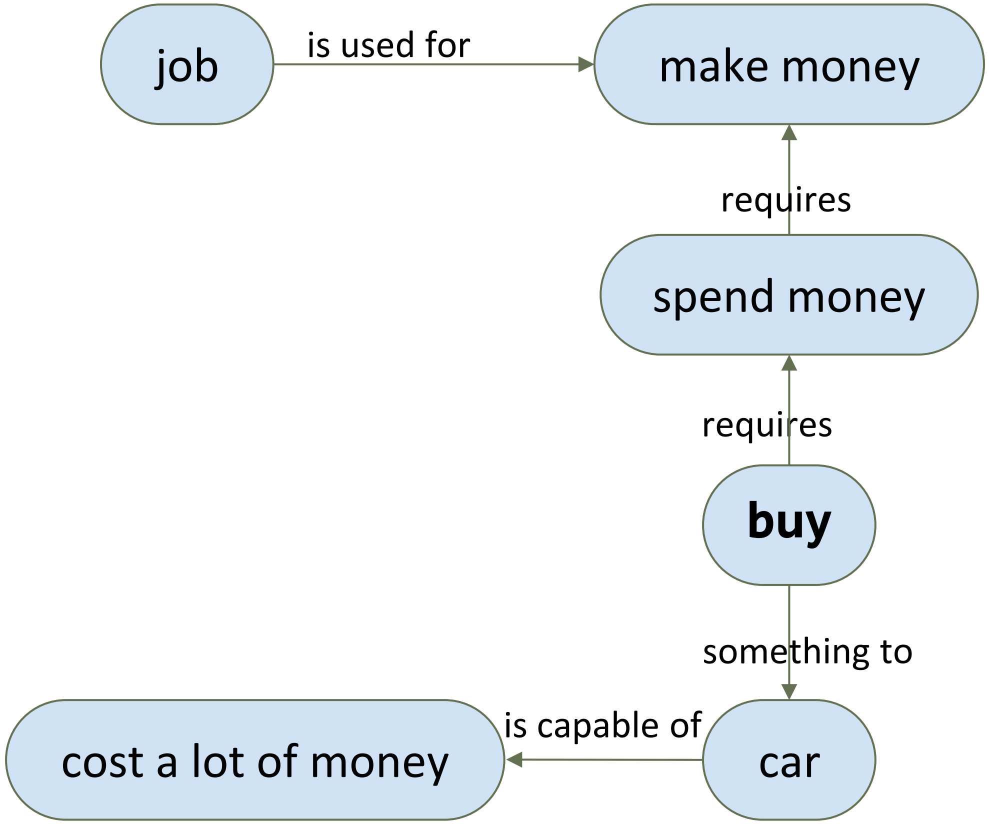
Agatha decided to buy two more. (Wrong)
Agatha decided to return them. (Right)

Task



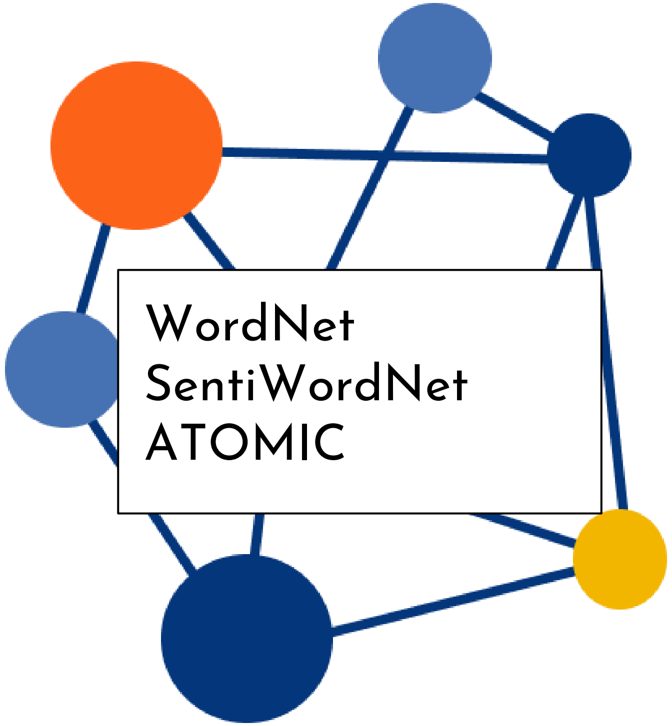
A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen.* NAACL 2016.

ConceptNet



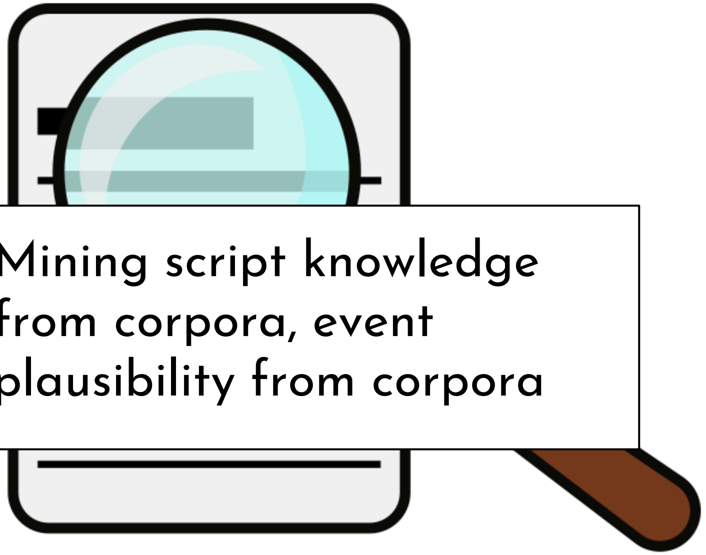
Conceptnet 5.5: An open multilingual graph of general knowledge. *Robyn Speer, Joshua Chin, and Catherine Havasi.* AAAI 2017.

Other Knowledge Sources



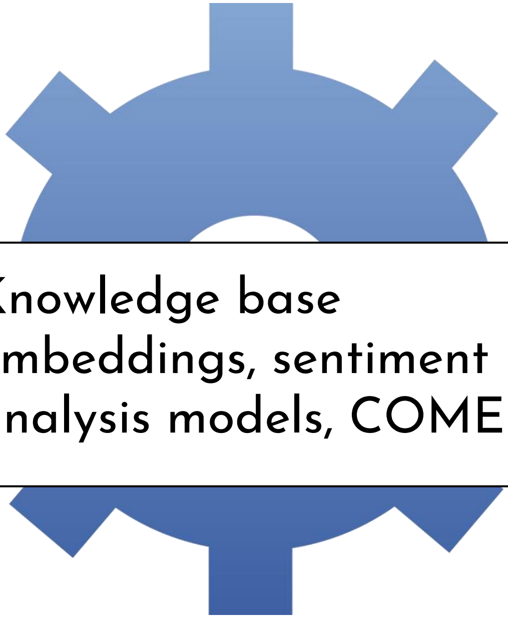
WordNet
SentiWordNet
ATOMIC

Mining from Text



Mining script knowledge from corpora, event plausibility from corpora

Knowledge Bases



Knowledge base embeddings, sentiment analysis models, COMET

Tools

Neural Component

[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
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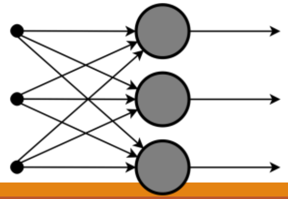
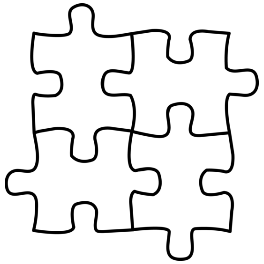
Neural



Combination Method

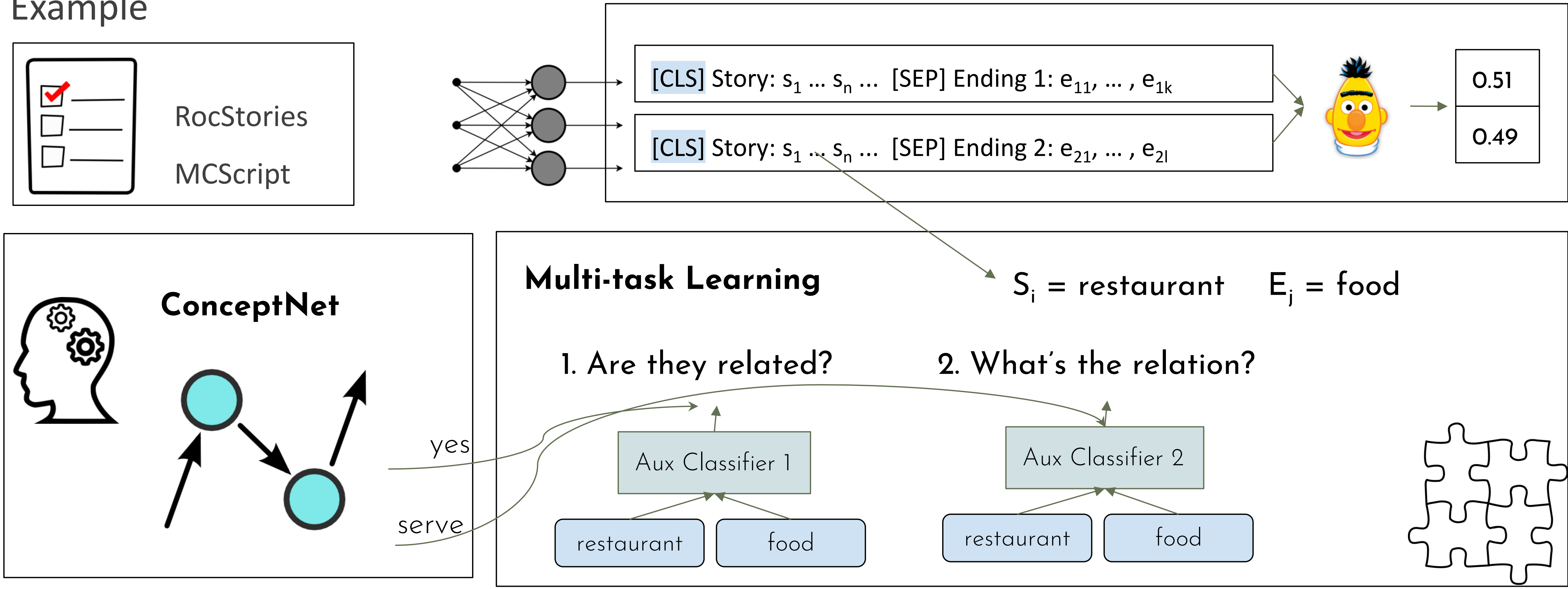
- Incorporate into scoring function
- Symbolic → vector representation
  (+attention)
- Multi-task learning

Combined



Incorporating External Knowledge into Neural Models

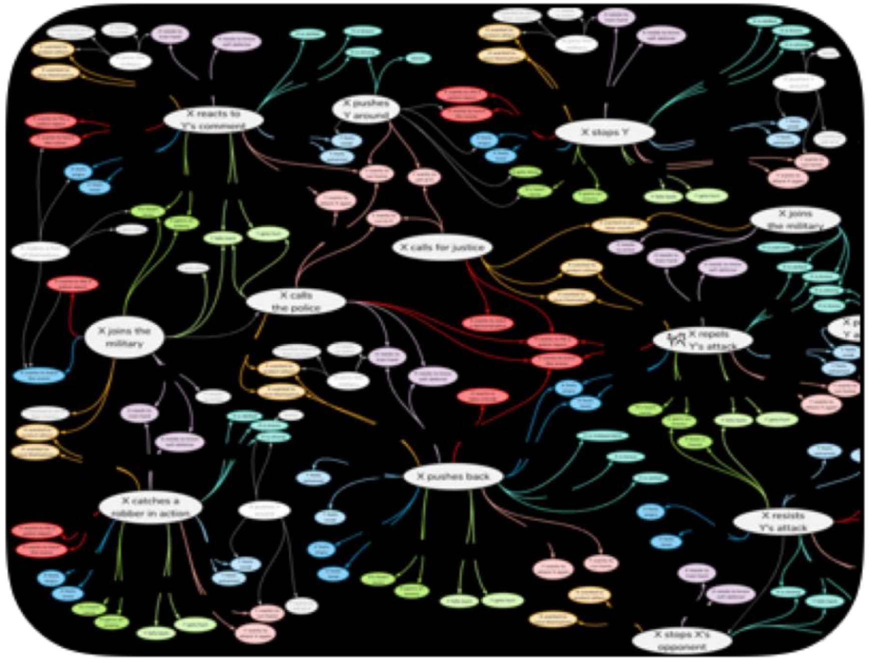
Example



Incorporating Commonsense Reading Comprehension with Multi-task Learning. *Jiangnan Xia, Chen Wu, and Ming Yan.* CIKM 2019.

Limitations of Knowledge Graphs

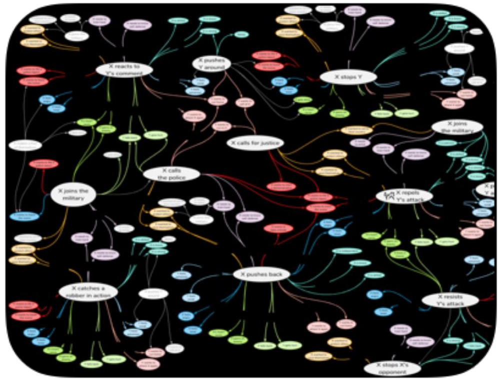
- Insufficient Coverage
- Not 100% Accurate
- Limited expressivity



Limitations of Knowledge Graphs

- Situations rarely found as-is in commonsense knowledge graphs

ATOMIC



(Sap et al., 2019)

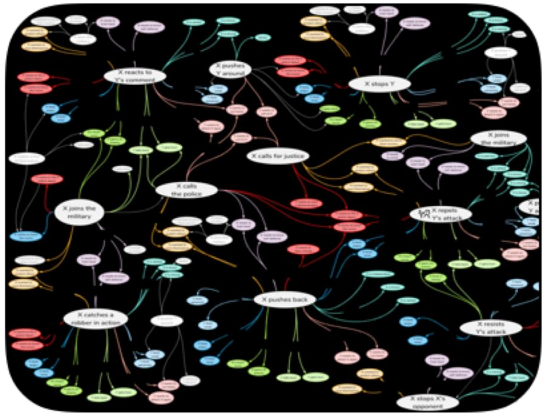
(X goes to the mall, Effect on X, buys clothes)

(X goes the mall, Perception of X, rich)

(X gives Y some money, Reaction of Y, grateful)

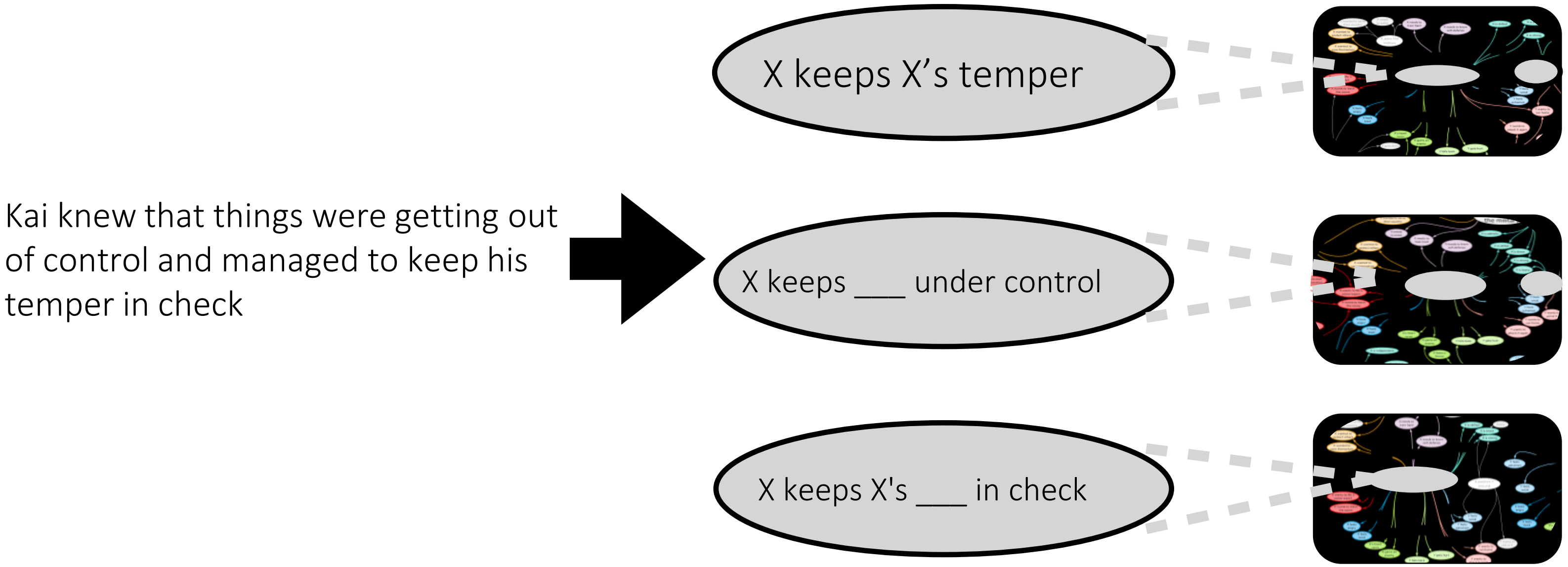
Limitations of Knowledge Graphs

Kai knew that things were getting out of control and managed to keep his temper in check



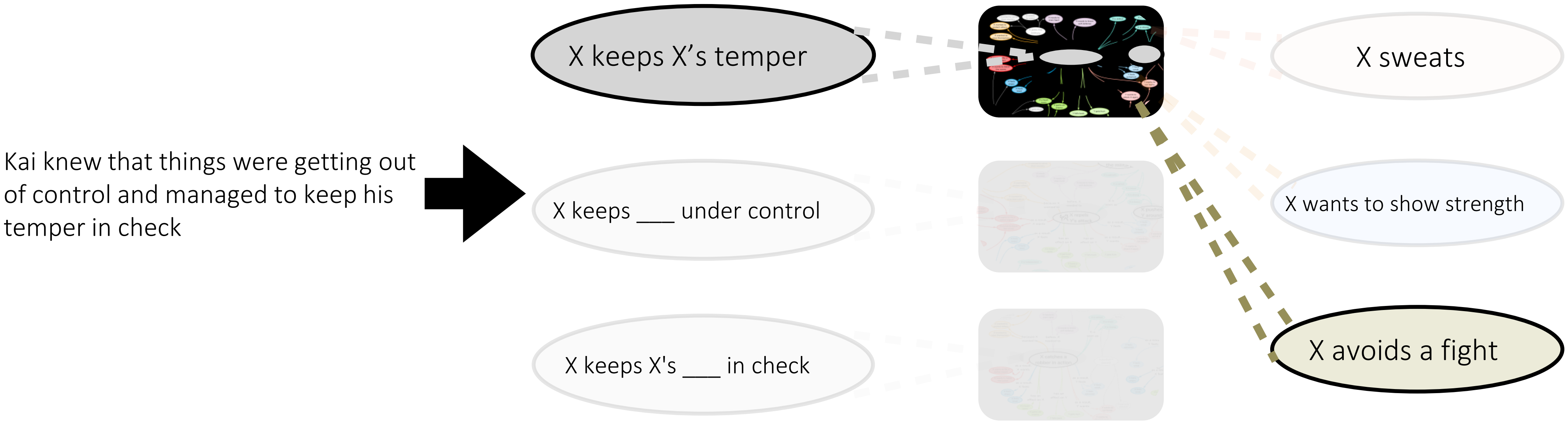
Limitations of Knowledge Graphs

- Situations rarely found as-is in commonsense knowledge graphs
- Connecting to knowledge graphs can yield incorrect nodes



Limitations of Knowledge Graphs

- Situations rarely found as-is in commonsense knowledge graphs
- Connecting to knowledge graphs can yield incorrect nodes
- Suitable nodes are often uncontextualized



Challenge

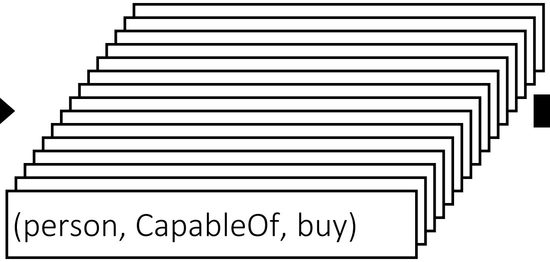
- How do we provide machines with large-scale commonsense knowledge?

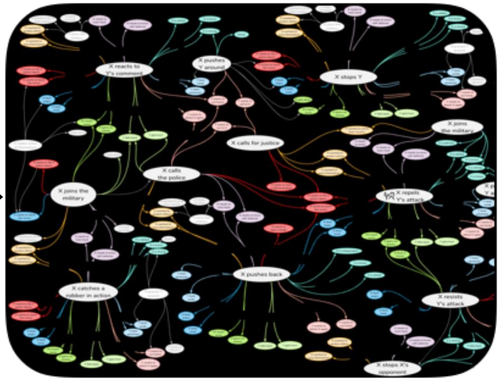
Constructing Knowledge Graphs

Observe world

Write commonsense knowledge facts

Store facts in knowledge graph



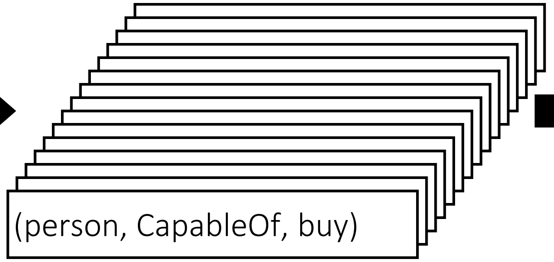


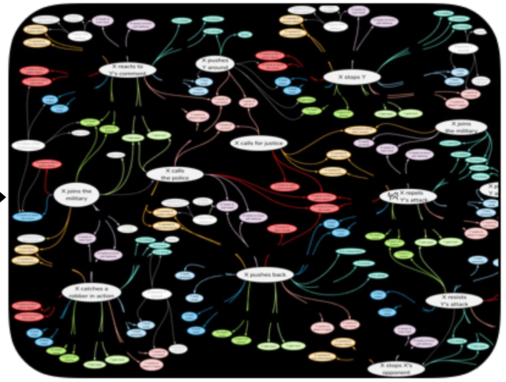
Constructing Symbolic Knowledge Graphs

Observe world

Write commonsense knowledge facts

Store facts in knowledge graph





(Miller, 1995)

(Singh et al., 2002)

(Lenat, 1995)

(Sap et al., 2019)

Challenges of Prior Approaches

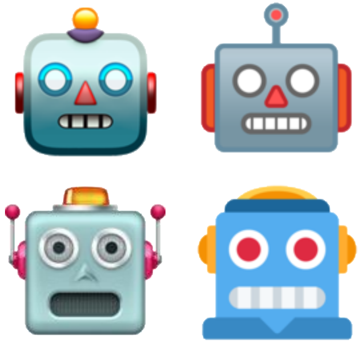
- Commonsense knowledge is immeasurably vast, making it impossible to manually enumerate

Constructing Knowledge Graphs Automatically

Gather Textual Corpus

John went to the grocery **store** to buy some **steaks**. He was going to prepare **dinner** for his **daughter**'s **birthday**. She was turning 5 and would be starting elementary **school** soon.

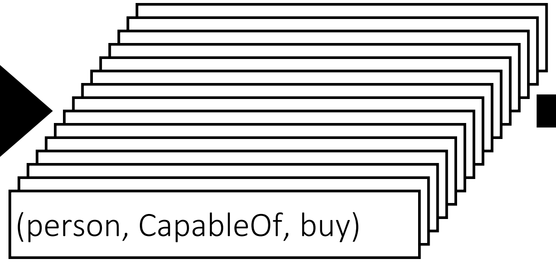
Automatically extract knowledge



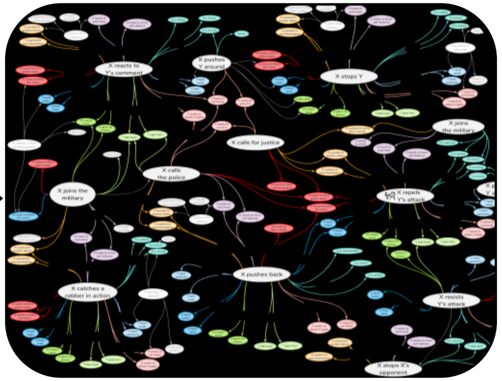
(Schubert, 2002)

(Banko et al., 2007)

(Zhang et al., 2020)



Store in knowledge graph



ConceptNet
An open, multilingual knowledge graph

(Speer et al., 2017)

Webchild

(Tandon et al., 2019)

Encyclopedic vs. Commonsense Knowledge

Encyclopedic Knowledge	Commonsense Knowledge
Explicitly written in text	Often assumed Grice's Maxim of Quantity
Ontological Mentions	
Deviations rarely written	

Encyclopedic vs. Commonsense Knowledge

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Explicitly written in text	Often assumed Grice's Maxim of Quantity
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Encyclopedic vs. Commonsense Knowledge

Encyclopedic Knowledge	Commonsense Knowledge
Explicitly written in text	Often assumed Grice's Maxim of Quantity
Ontological Mentions	Complex Mentions e.g., Causal If-Then Knowledge
Deviations rarely written	Reporting Bias murders 4x more common than breating

Challenges of Prior Approaches

- Commonsense knowledge is **immeasurably vast**, making it **impossible to manually enumerate**

- Commonsense knowledge is often implicit, and often **can't be directly extracted from text**

Constructing Knowledge Graphs Automatically

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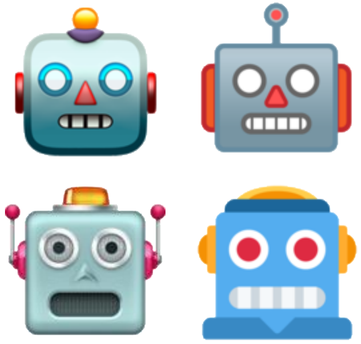


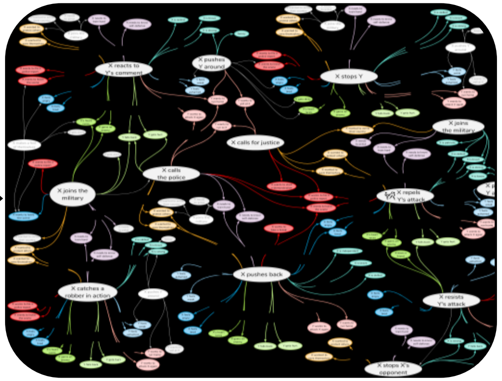
(Schubert, 2002)

(Banko et al., 2007)

(Zhang et al., 2020)

(person, CapableOf, buy)

Store in knowledge graph



ConceptNet
An open, multilingual knowledge graph

(Speer et al., 2017)

Webchild

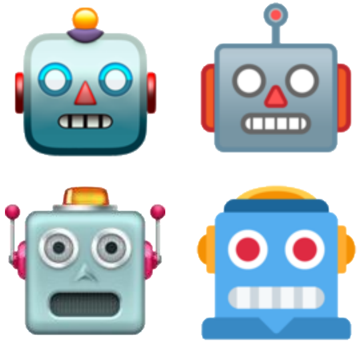
(Tandon et al., 2019)

Knowledge Base Completion

Gather training set of knowledge tuples

(person, CapableOf, buy)

Learn relationships among entities



(Socher et al., 2013)

(Bordes et al., 2013)

(Riedel et al., 2013)

(Toutanova et al., 2015)

(Yang et al., 2015)

(Trouillon et al., 2016)

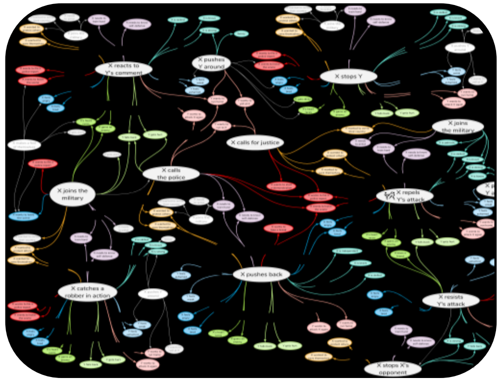
(Nguyen et al., 2016)

(Dettmers et al., 2018)

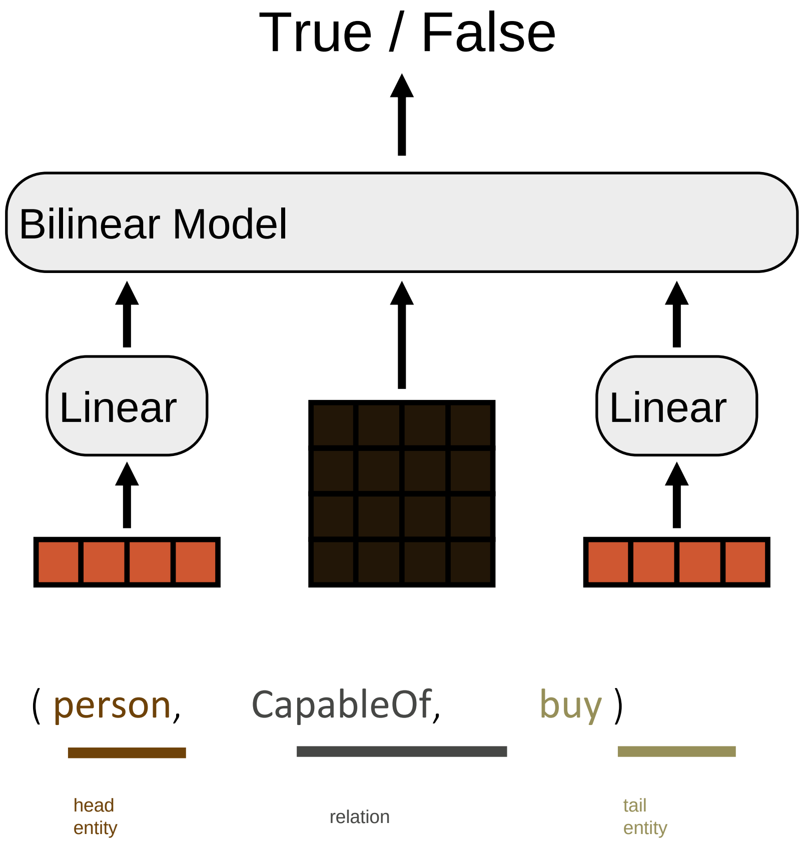
Predict new relationships

(person, CapableOf,)?

Store in knowledge graph



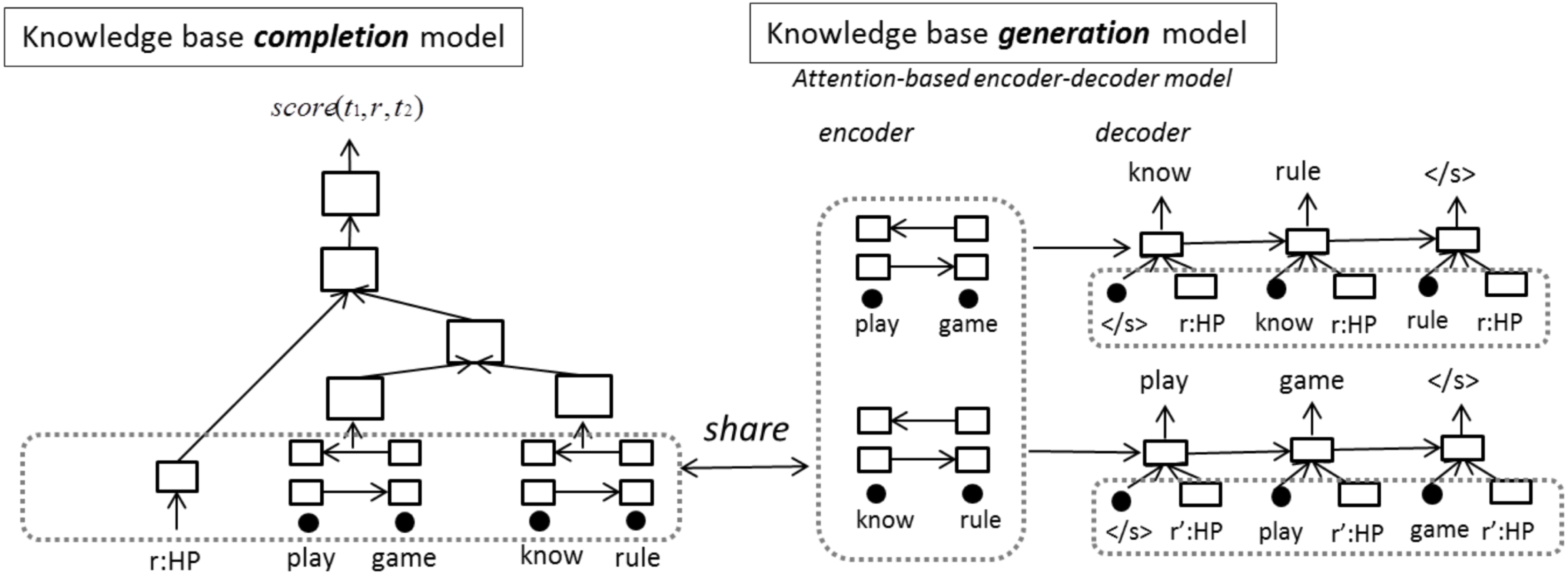
Commonsense Knowledge Base Completion



Li et al., 2016

Jastrzebski et al., 2018

Commonsense Knowledge Base Completion and Generation!



Saito et al., 2018

Challenges of Prior Approaches

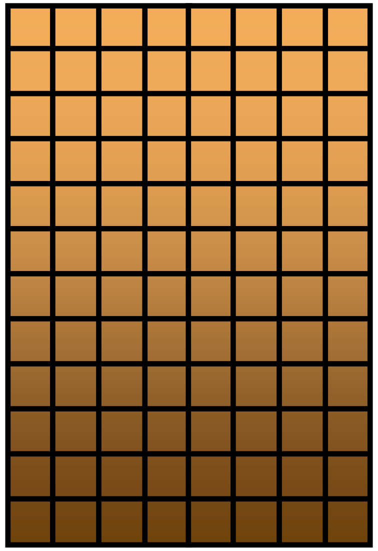
- Commonsense knowledge is **immeasurably vast**, making it **impossible to manually enumerate**

- Commonsense knowledge is often implicit, and often **can't be directly extracted from text**

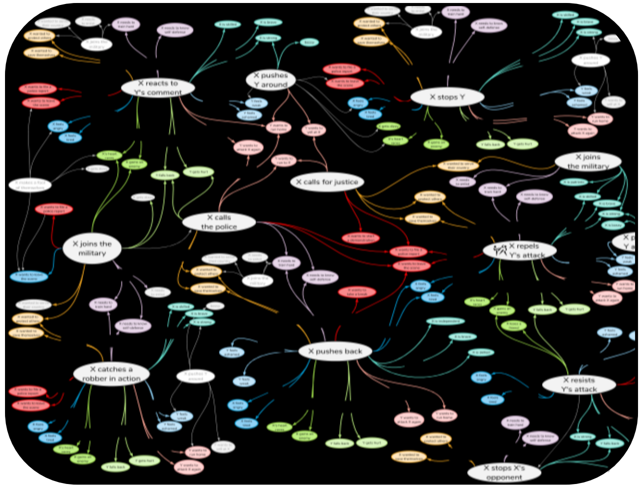
- Commonsense knowledge resources are quite sparse, making them **difficult to extend by only learning from examples**

Solution Outline

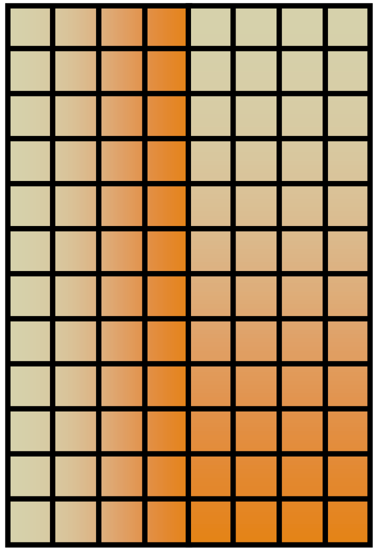
- Leverage manually curated commonsense knowledge resources
- Learn from the examples to induce new relationships
- Scale up using language resources



Learn word embeddings from language corpus



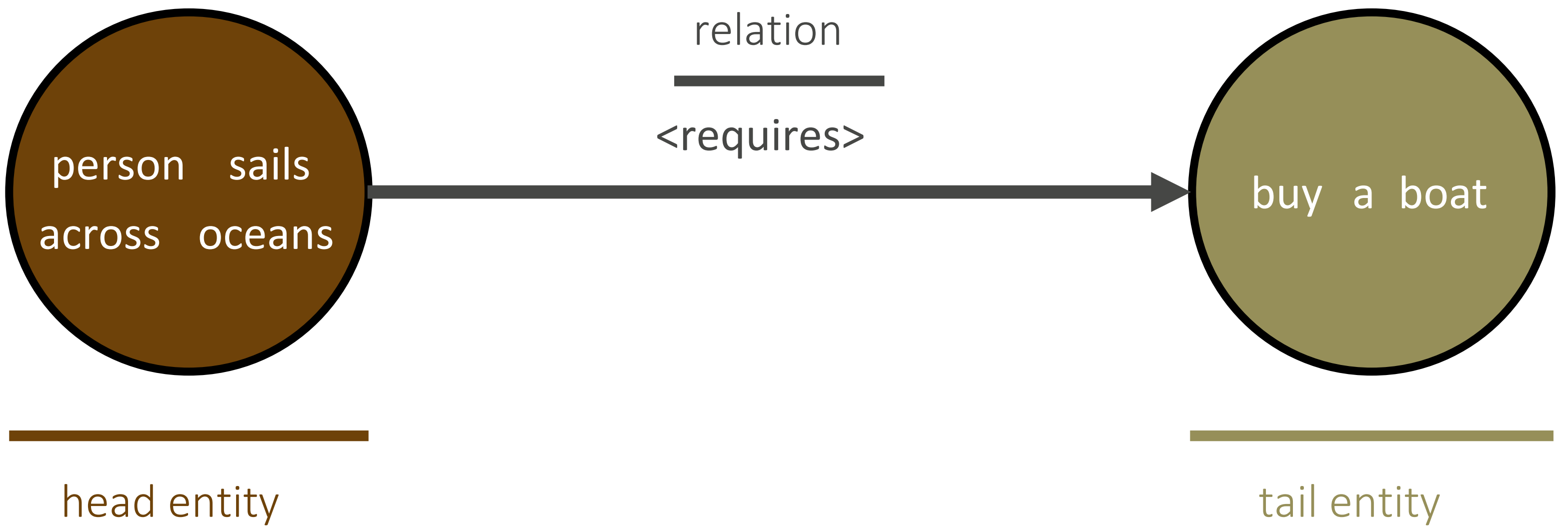
Retrofit word embeddings on semantic resource



Learn knowledge-aware embeddings

Faruqui et al., 2015, Speer et al., 2017

Structure of Knowledge Tuple

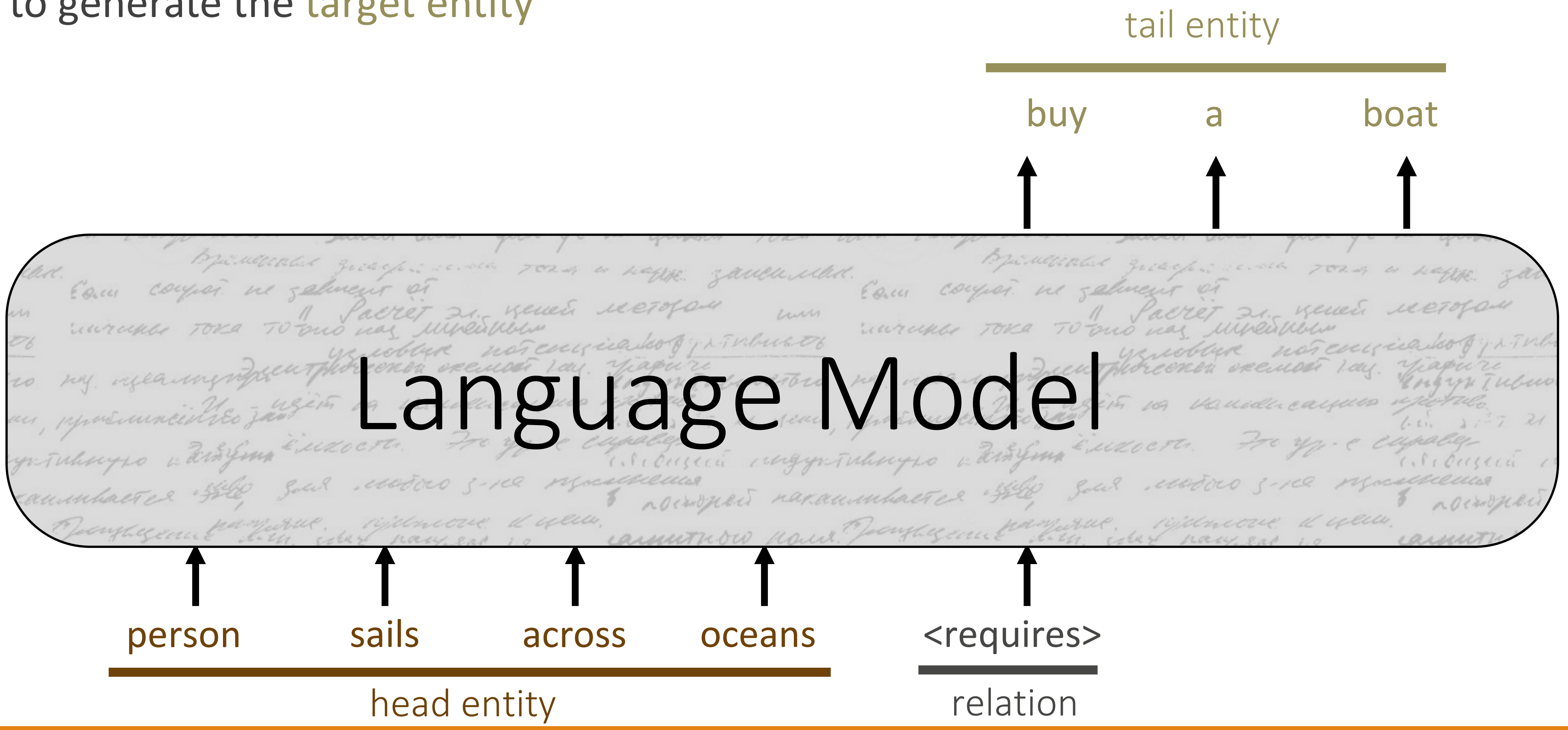


(entity to generate)

Learning Structure of Knowledge

- Given a seed entity and a relation, learn to generate the target entity

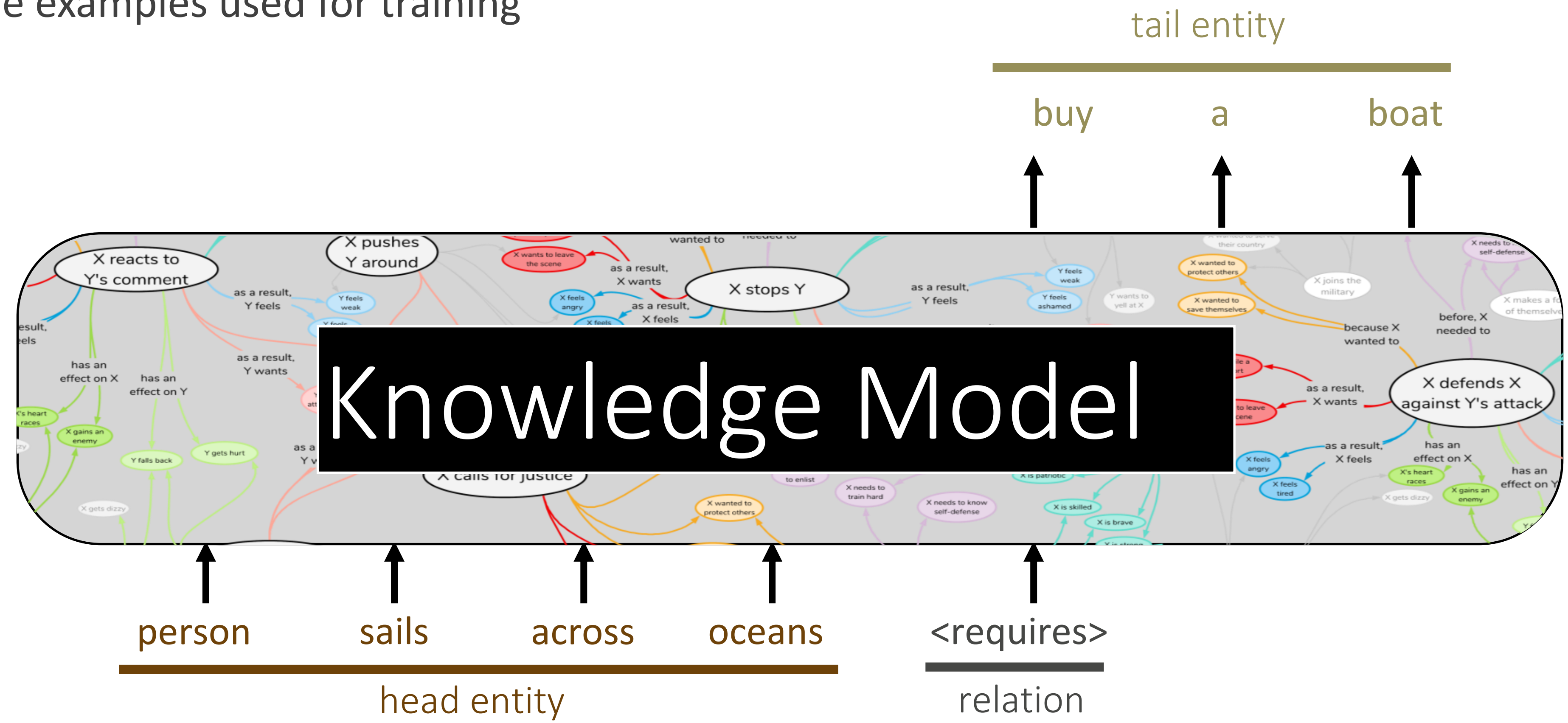
$$\mathcal{L} = -\sum \log P(\textit{target words} \mid \textit{seed words, relation})$$



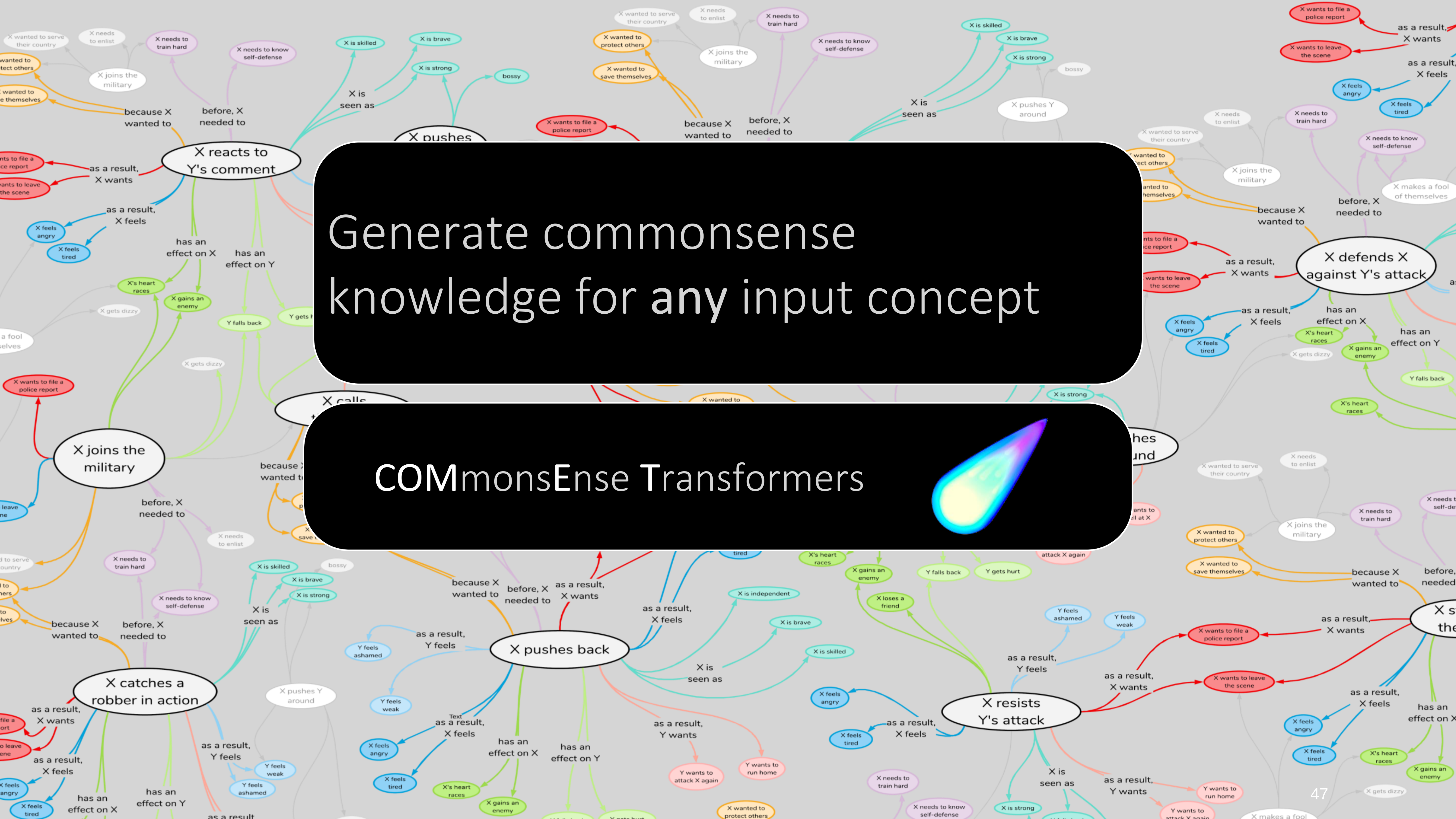
(Bosselut et al., 2019)

Learning Structure of Knowledge

- Language Model → Knowledge Model: generates knowledge of the structure of the examples used for training



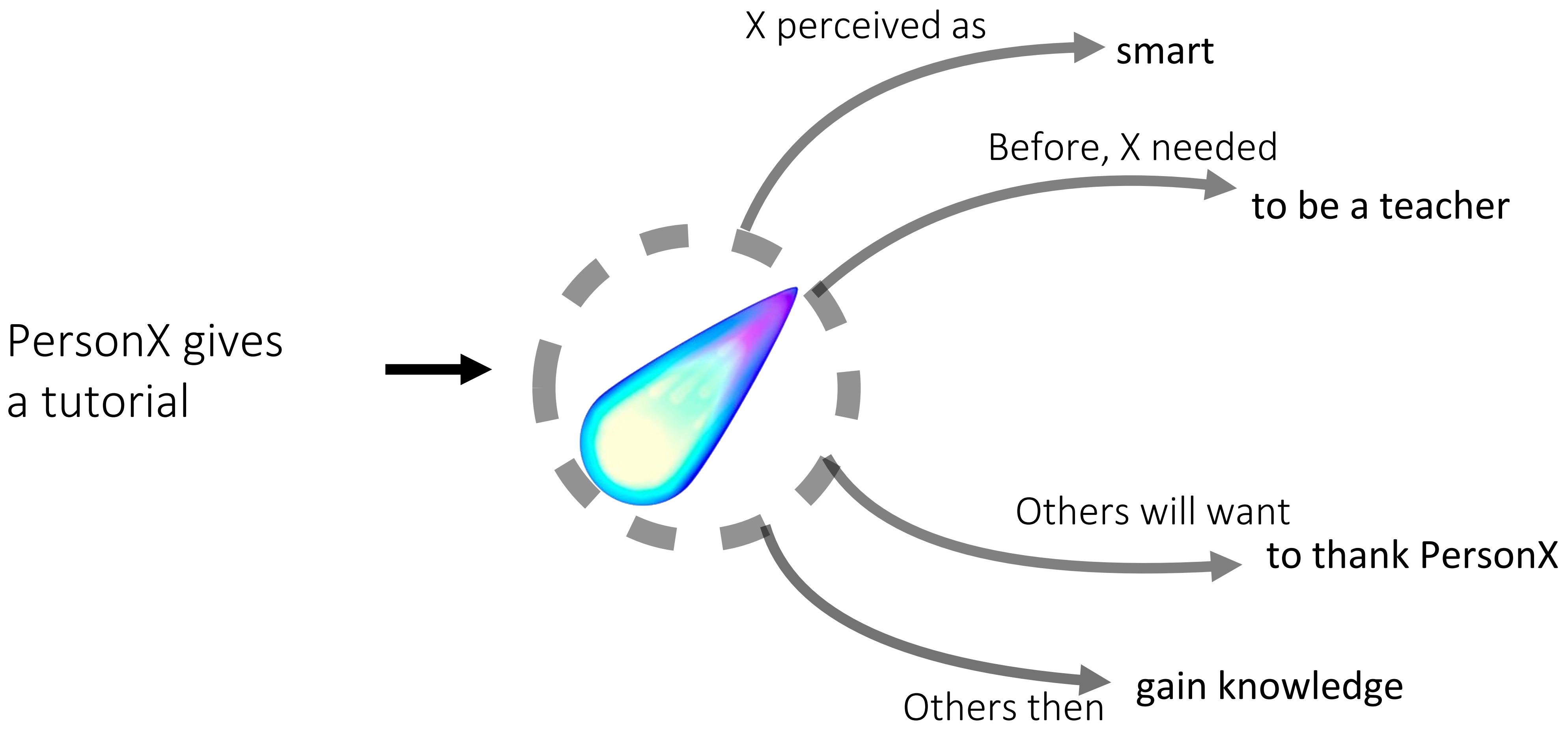
(Bosselut et al., 2019)



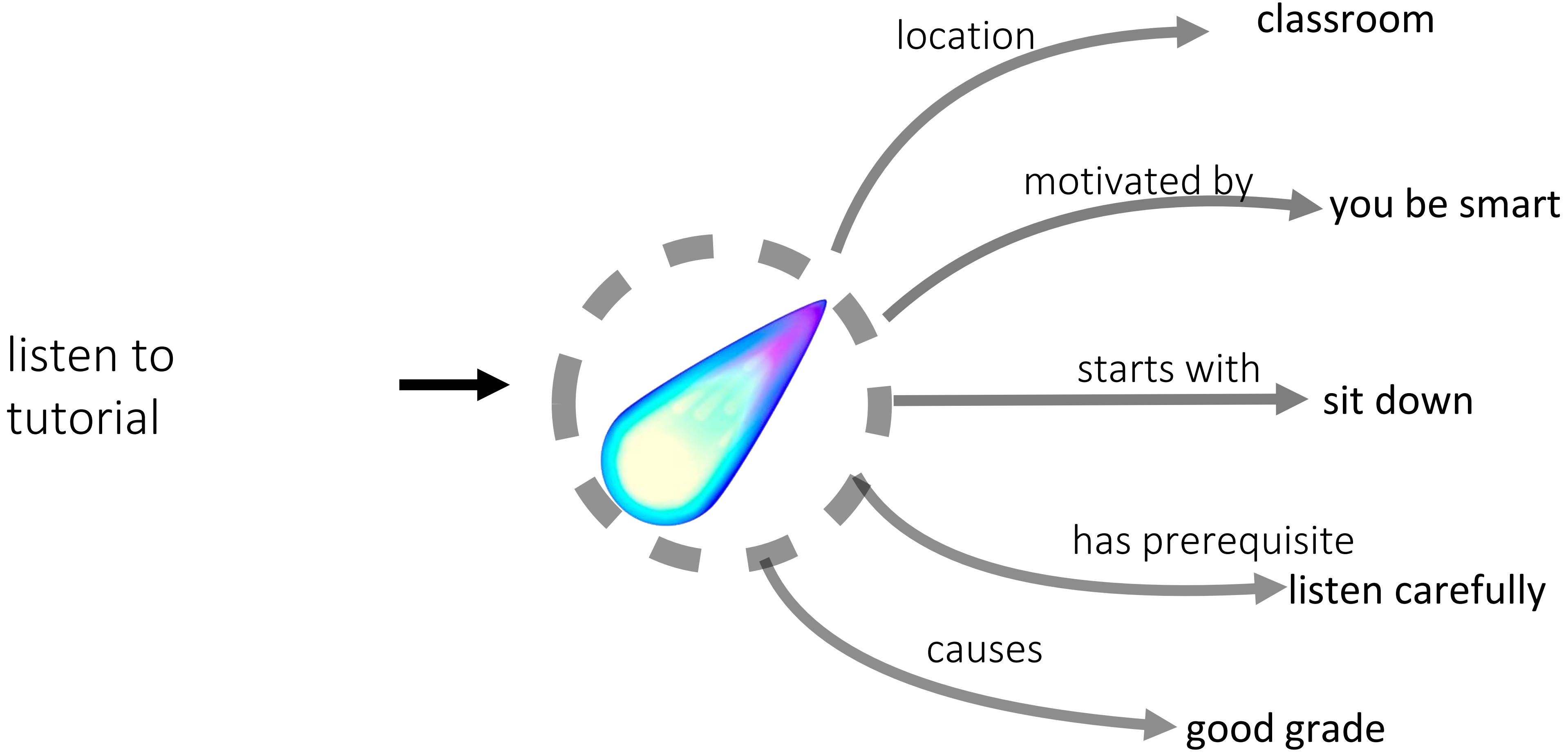
Generate commonsense knowledge for **any** input concept

COMmons**E**nse **T**ransformers

COMET - ATOMIC



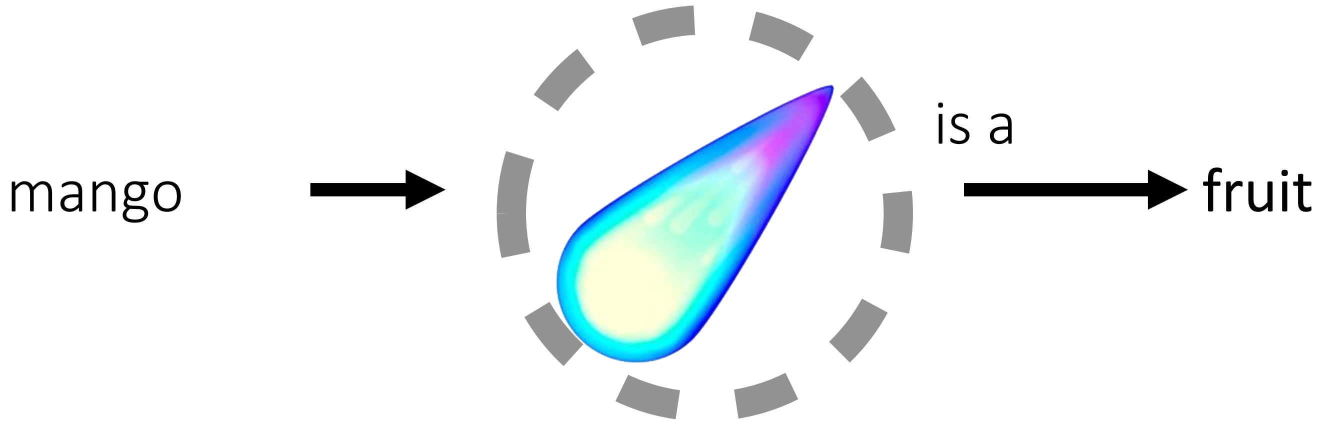
COMET - ConceptNet



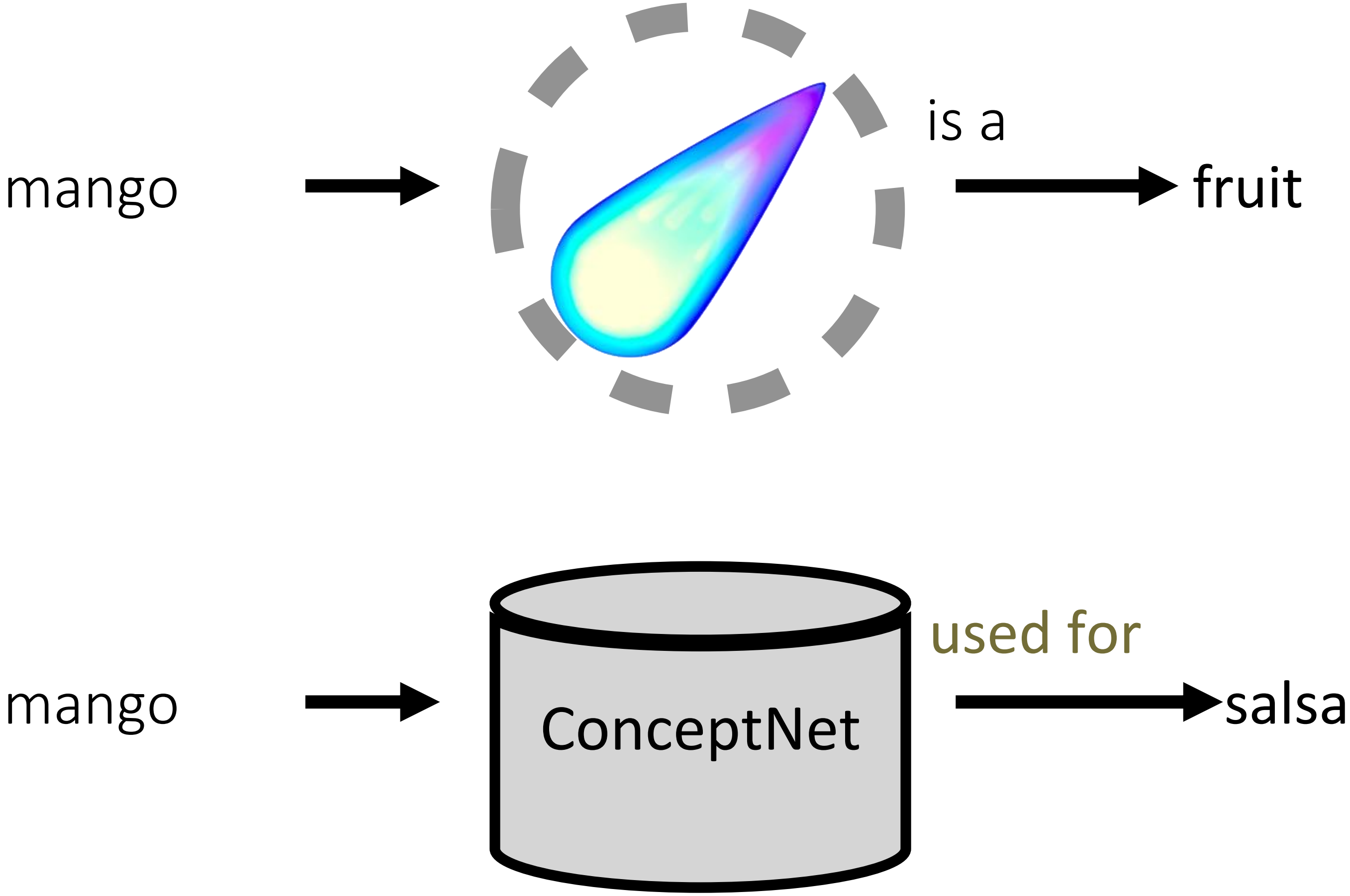
Question

Why does this work?

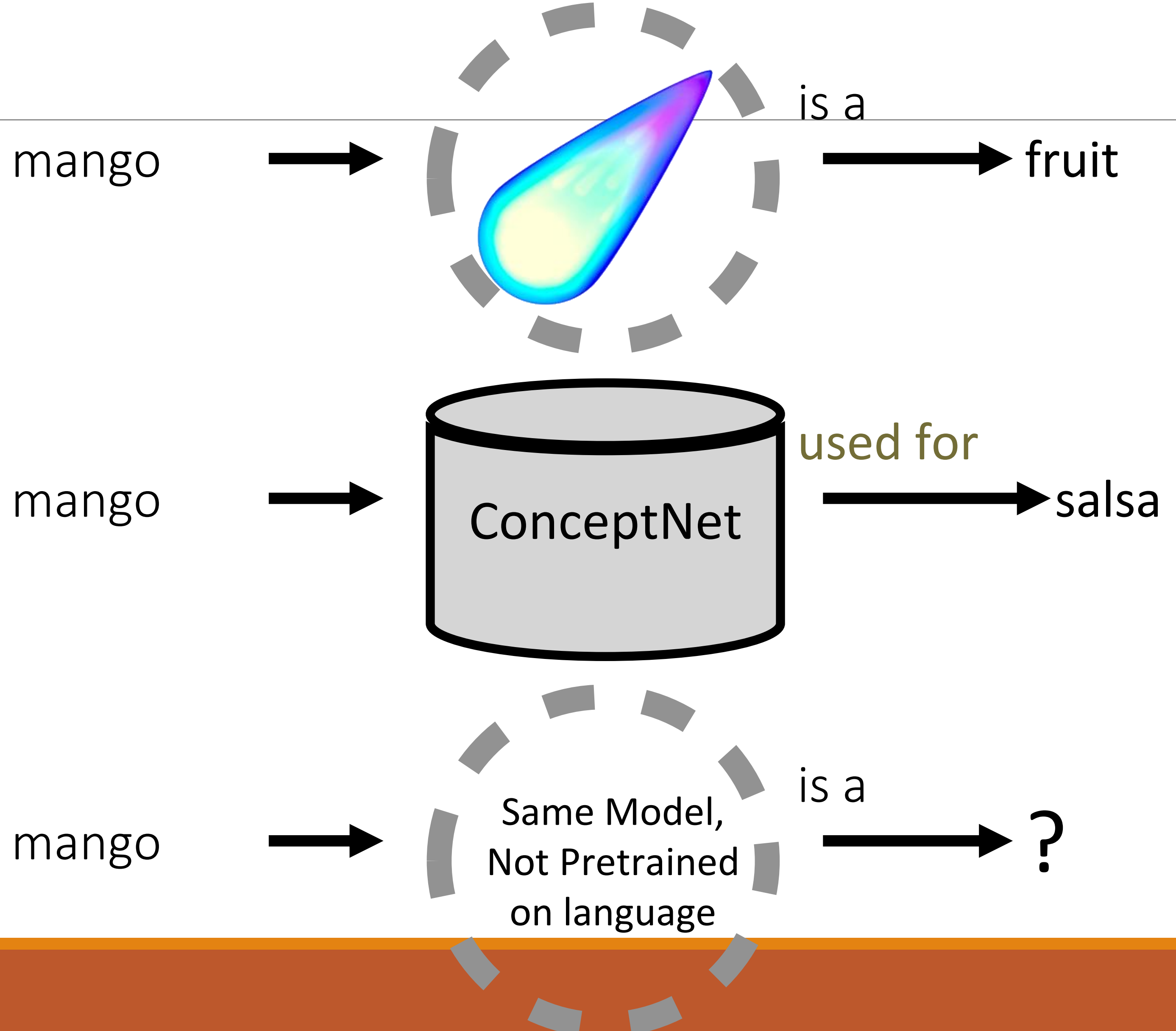
Transfer Learning from Language



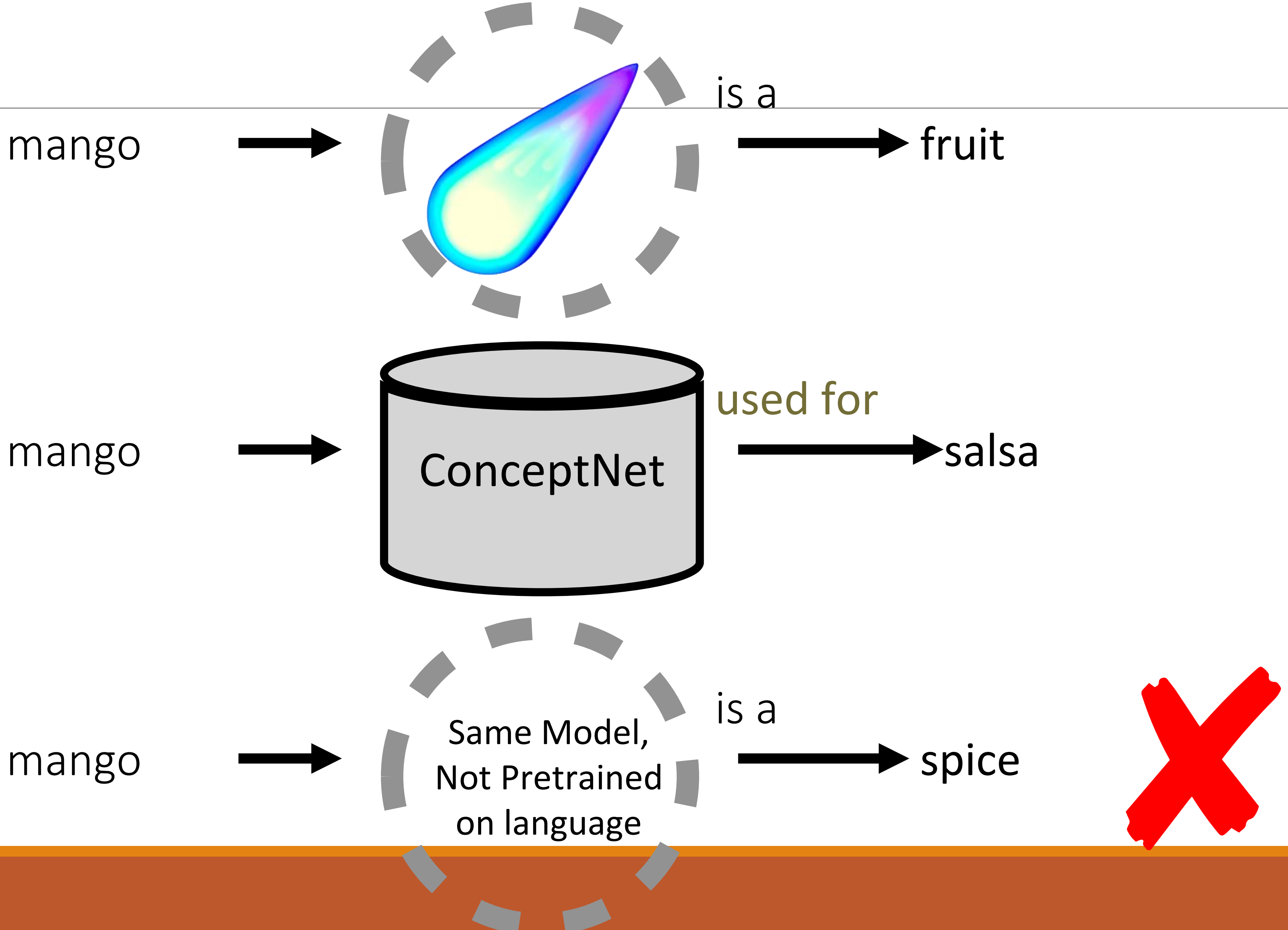
Transfer Learning from Language



Transfer Learning from Language



Transfer Learning from Language



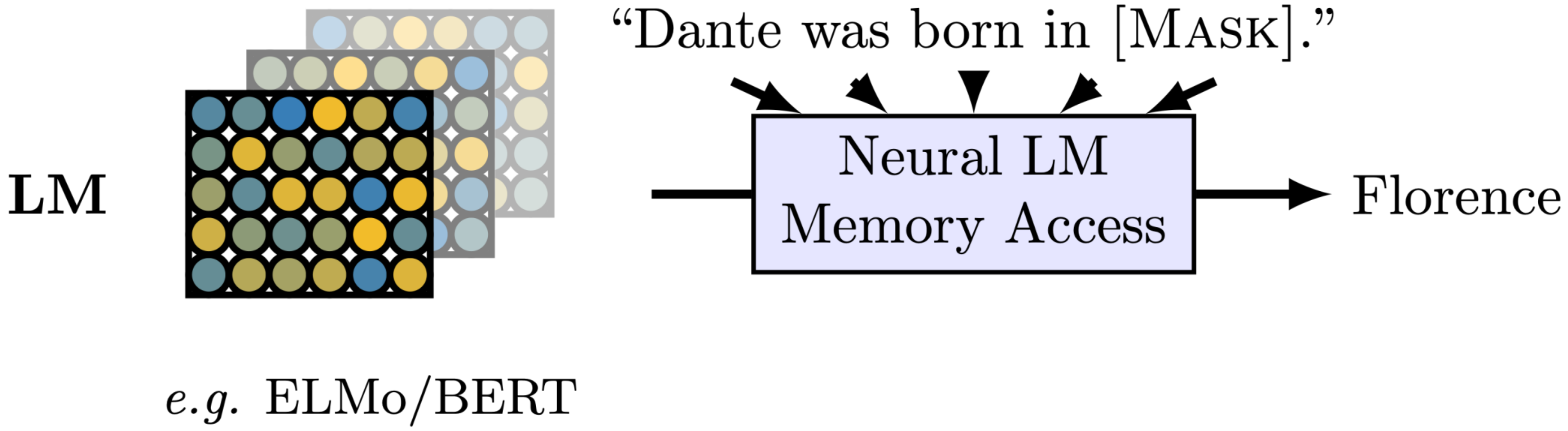
Question

Can’t a off-the-shelf language model do the same thing?

Unsupervised Commonsense Probing

(Dante, <born_in>, ?)

map relation to one or more natural language sentences



Petroni et al., 2019; Feldman et al., 2019

Do Language Models know this?

Sentence:

mango is a

Predictions:

2.1% **great**

1.9% **very**

1.2% **new**

1.0% **good**

1.0% **small**

← Undo

https://demo.allennlp.org/next-token-lm

Do Language Models know this?

Sentence:

mango is a

Predictions:

- 2.1% great
- 1.9% very
- 1.2% new
- 1.0% good
- 1.0% small
- ← Undo

a mango is a

- 4.2% good
- 4.0% very
- 2.5% great
- 2.4% delicious
- 1.8% sweet
- ← Undo

Do Language Models know this?

Sentence:

mango is a

Predictions:

2.1% great
1.9% very
1.2% new
1.0% good
1.0% small
← Undo

Sentence:

a mango is a

Predictions:

4.2% good
4.0% very
2.5% great
2.4% delicious
1.8% sweet
← Undo

Sentence:

A mango is a

Predictions:

4.2% fruit
3.5% very
2.5% sweet
2.2% good
1.5% delicious
← Undo

Do *Masked* Language Models know this?

Sentence:

mango is a [MASK]

Mask 1 Predictions:
69.7% **.**
9.3% **;**
1.7% **!**
0.8% **vegetable**
0.7% **?**

Sentence:

mango is a [MASK] .

Mask 1 Predictions:
7.6% **staple**
7.6% **vegetable**
4.6% **plant**
3.5% **tree**
3.5% **fruit**

Sentence:

A mango is a [MASK] .

Mask 1 Predictions:
16.0% **banana**
12.1% **fruit**
5.9% **plant**
5.5% **vegetable**
2.5% **candy**

Sensitivity to cues

Candidate Sentence S_i	$\log p(S_i)$
"musician can playing musical instrument"	-5.7
"musician can be play musical instrument"	-4.9
"musician often play musical instrument"	-5.5
"a musician can play a musical instrument"	$-\mathbf{2.9}$

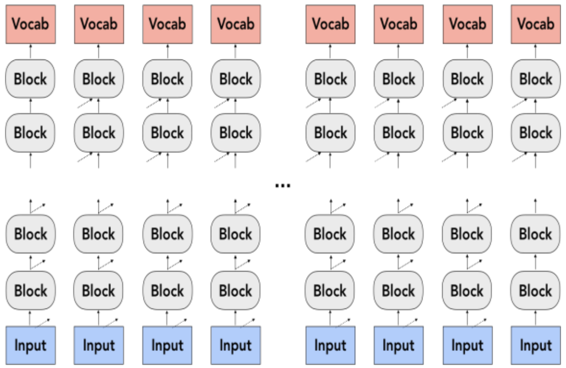
Feldman et al., 2019

Prompt	**Model Predictions**
A ____ has fur.	dog, cat, fox, ...
A ____ has fur, is big, and has claws.	cat, **bear**, lion, ...
A ____ has fur, is big, has claws, has teeth, is an animal, eats, is brown, and lives in woods.	**bear**, wolf, cat, ...

Weir et al., 2020

Commonsense Transformers

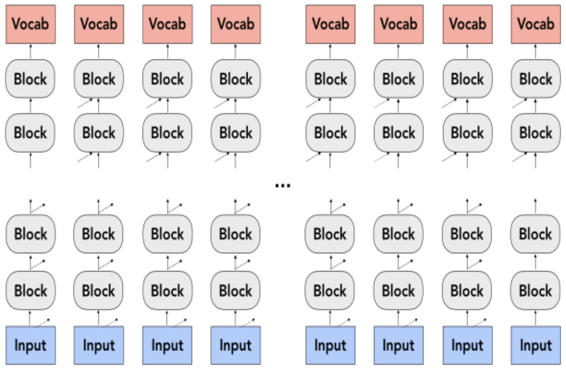
- Language models **implicitly represent knowledge**



Pre-trained
Language Model

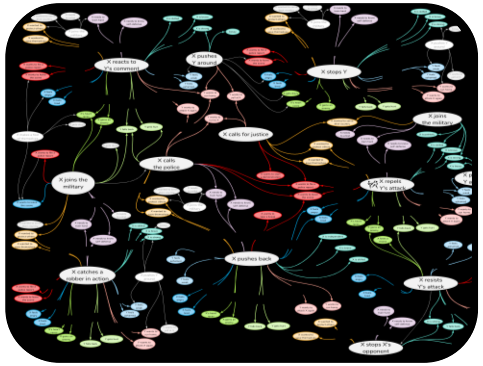
Commonsense Transformers

- Language models **implicitly represent knowledge**
- Re-train them on knowledge graphs to **learn structure of knowledge**



Pre-trained
Language Model

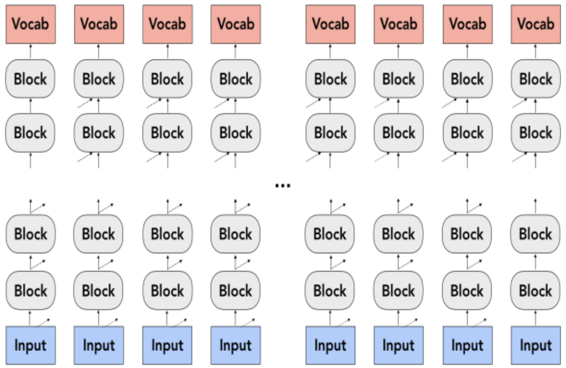
+



Seed Knowledge
Graph Training

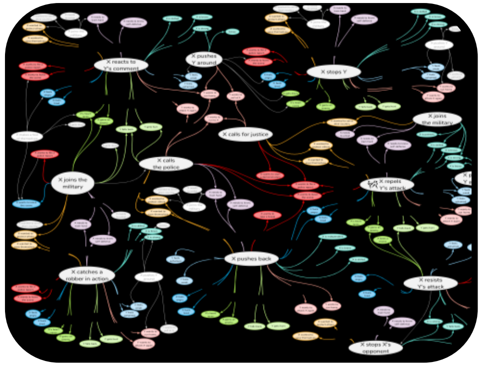
Commonsense Transformers

- Language models **implicitly represent knowledge**
- Re-train them on knowledge graphs to **learn structure of knowledge**
- Resulting knowledge model **generalizes structure** to other concepts



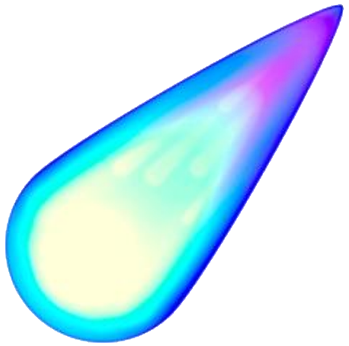
Pre-trained
Language Model

+



Seed Knowledge
Graph Training

=



COMET

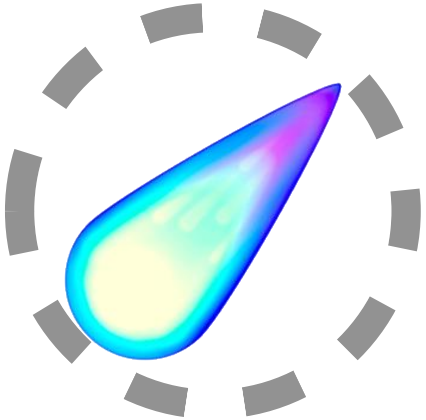
Question

What are the implications of this knowledge representation?

Commonsense Knowledge for any Situation

- transformer-style architecture — input format is natural language
  - event can be fully parsed

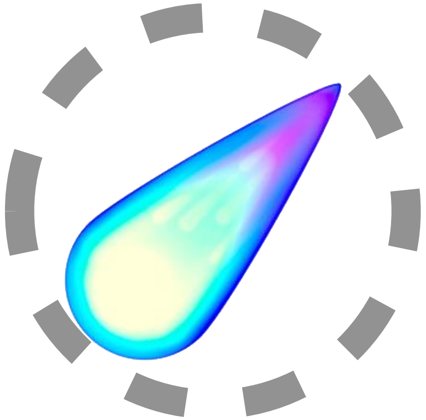
Kai knew that things were getting out of control and managed to keep his temper in check



Commonsense Knowledge for any Situation

- transformer-style architecture — input format is natural language
  - event can be fully parsed
  - knowledge generated dynamically from neural knowledge model

Kai knew that things were getting out of control and managed to keep his temper in check



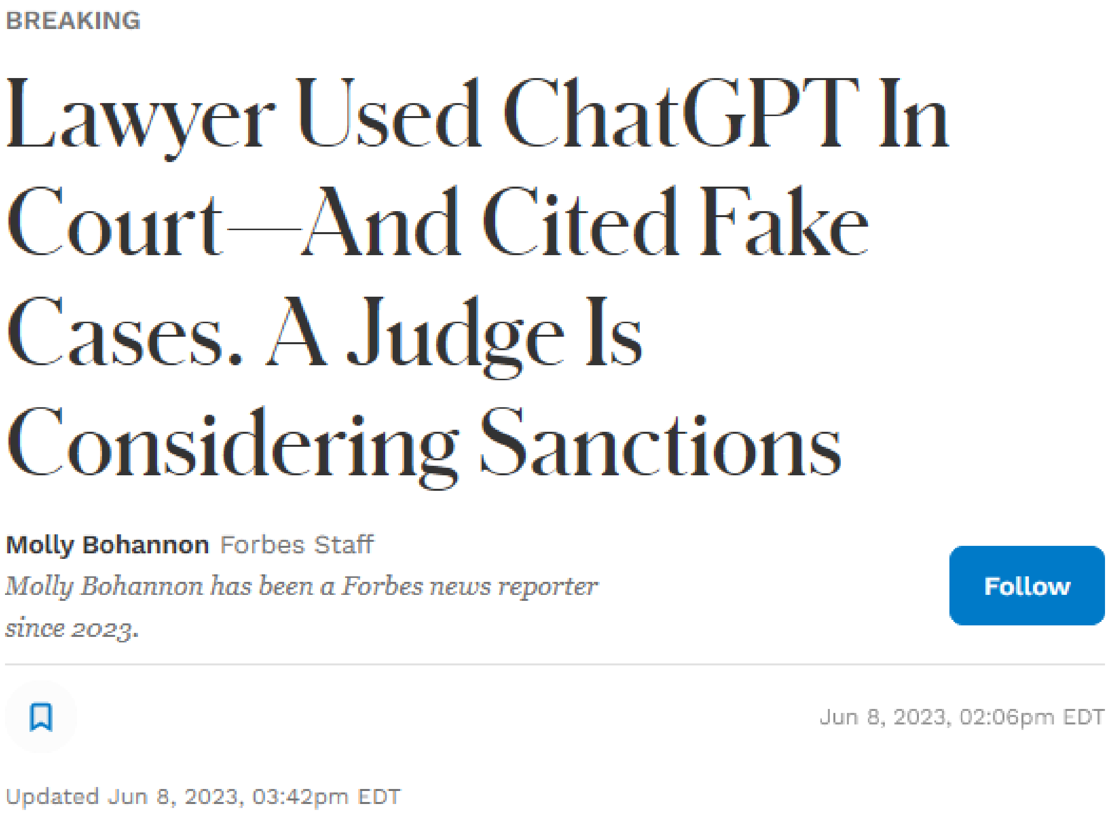
Kai wants to avoid trouble

Kai intends to be calm

Kai stays calm

Kai is viewed as cautious

But sometimes LMs can't be trusted



BREAKING

Lawyer Used ChatGPT In Court—And Cited Fake Cases. A Judge Is Considering Sanctions

Molly Bohannon Forbes Staff

Molly Bohannon has been a Forbes news reporter since 2023.

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Jun 8, 2023, 02:06pm EDT

Updated Jun 8, 2023, 03:42pm EDT

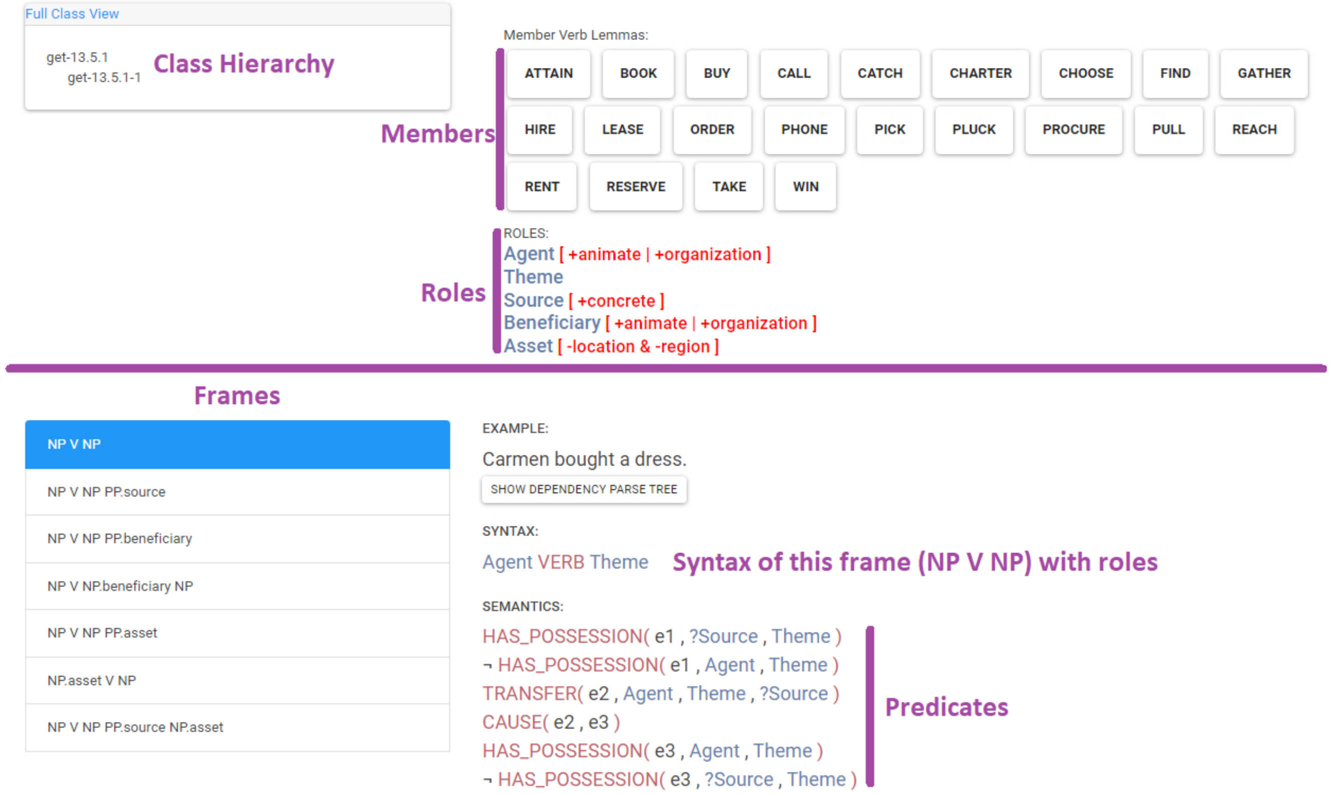
https://www.forbes.com/sites/mollybohannon/2023/06/08/lawyer-used-chatgpt-in-court-and-cited-fake-cases-a-judge-is-considering-sanctions/

Ways of combining them

- During training
  - Such as in reinforcement learning or retrieval-augmented generation (RAG)
- After training
  - Like a symbolic “wrapper” – helps validate what the NN is doing
- Others??

VerbNet v3.4

- https://verbs.colorado.edu/verbnet/
- Verb classes based on Beth Levin (1993)
- **Data Source:** hand-crafted
- **Languages:** English
- **Use:** raw data or my code
- **Demo:** https://uvi.colorado.edu/uvi_search



K. Kipper Schuler, “VerbNet: A Broad-Coverage, Comprehensive Verb Lexicon,” University of Pennsylvania, 2005.
Levin, B. (1993) “English Verb Classes and Alternations: A Preliminary Investigation”, University of Chicago Press, Chicago, IL.

Using VerbNet

Jen sent the book to Remy from Baltimore.

ROLES Agent Theme Destination Initial_Location

has_location(e1, book, Baltimore)
do(e2, **Jen**)
cause(e2, e3)
motion(e3, book)
!has_location(e3, book, Baltimore)
has_location(e4, book, Remy)

PREDICATES

Initial_Location : location

Theme : concrete

Agent : animate or organization

SELECTIONAL RESTRICTIONS

L. J. Martin, “Neurosymbolic Automated Story Generation,” PhD, Georgia Institute of Technology, Atlanta, GA, 2021. https://smartech.gatech.edu/handle/1853/64643

Pre-Conditions and Effects

Jen sent the book to Remy from Baltimore.

Pre-Conditions

has_location(e1, book, Baltimore)

Baltimore : location

book : concrete

Jen : animate or organization

Effects

~~do(e2, **Jen**)~~

~~cause(e2, e3)~~

~~motion(e3, book)~~

!has_location(e3, book, Baltimore)

has_location(e4, book, Remy)

L. J. Martin, "Neurosymbolic Automated Story Generation," PhD, Georgia Institute of Technology, Atlanta, GA, 2021. https://smartech.gatech.edu/handle/1853/64643

Pre-Conditions and Effects

Jen sent the book to Remy from Baltimore.

Pre-Conditions → Event → Effects

Pre-Conditions

has_location(book, Baltimore)
Baltimore : location
book : concrete
Jen : animate or organization

Effects

!has_location(book, Baltimore)
has_location(book, Remy)

L. J. Martin, "Neurosymbolic Automated Story Generation," PhD, Georgia Institute of Technology, Atlanta, GA, 2021. https://smartech.gatech.edu/handle/1853/64643

Resulting State Representation

Jen sent the book to Remy from Baltimore.

Baltimore : location
book : concrete
Jen : animate or organization
!has_location(book, Baltimore)
has_location(book, Remy)

L. J. Martin, "Neurosymbolic Automated Story Generation," PhD, Georgia Institute of Technology, Atlanta, GA, 2021. https://smartech.gatech.edu/handle/1853/64643

How does a neural network fit in here?