Neuro-symbolic Representations of Commonsense Knowledge

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University of Washington
Allen Institute for AI
Limitations of Knowledge Graphs

- Insufficient Coverage
- Not 100% Accurate
- Limited expressivity
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

**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

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- Connecting to knowledge graphs can yield **incorrect** nodes

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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

(person, CapableOf, buy)
Constructing Symbolic Knowledge Graphs

Observe world → Write commonsense knowledge facts → Store facts in knowledge graph

(person, CapableOf, buy)

(Observe world)

Write commonsense knowledge facts

Store facts in knowledge graph

ATOMIC: ATlas O of Machinery (Miller, 1995)

Commonsense (Sap et al., 2019)

Constructing Symbolic Knowledge Graphs

(Miller, 1995)

(Sap et al., 2019)

(Lenat, 1995)

(Singh et al., 2002)
Constructing Symbolic Knowledge Graphs

Observe world → Write commonsense knowledge facts → Store facts in knowledge graph

(person, CapableOf, buy)

(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)

(person, CapableOf, buy)

Store in knowledge graph

(Speer et al., 2017)
(Tandon et al., 2019)
# Encyclopedic vs. Commonsense Knowledge

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<tr>
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<th>Commonsense Knowledge</th>
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<td>“black sheep problem”</td>
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- Commonsense knowledge is often implicit, and often *can’t be directly extracted from text*.
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Store in knowledge graph
(person, CapableOf, buy)
(Speer et al., 2017)
(Tandon et al., 2019)
Knowledge Base Completion

Gather training set of knowledge tuples

Learn relationships among entities

Predict new relationships

Store in knowledge graph

(person, CapableOf, buy)

(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)
## Commonsense KBs are Different

<table>
<thead>
<tr>
<th>Knowledge Graph</th>
<th># Entities</th>
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<tr>
<td>ConceptNet - 100k</td>
<td>78088</td>
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<td>1.25</td>
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<td>256570</td>
<td>610536</td>
<td>2.25</td>
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<tr>
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Malaviya et al., 2020
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Knowledge base completion assumes explicit connectivity

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Knowledge base completion assumes explicit connectivity

Malaviya et al., 2020
Commonsense Knowledge Base Completion

Li et al., 2016
Commonsense Knowledge Base Completion

True / False

Bilinear Model

Linear

Linear

( person, head entity)

CapableOf, relation

buy )

tail entity

Only high confidence predictions are validated

Low Novelty

Li et al., 2016

Jastrzebski et al., 2018
Commonsense Knowledge Base Completion and Generation!

Knowledge base completion model

Knowledge base generation model

Attention-based encoder-decoder model

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
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Learn word embeddings from language corpus

Retrofit word embeddings on semantic resource

Learn knowledge-aware embeddings

Faruqui et al., 2015, Speer et al., 2017
Transformer Language Models

Allen sailed across oceans in bought a boat <END>

Stacked Transformer Blocks

Predict Next Word

Input Vector

(Radford et al., 2018, 2019)
Learning in Language Models

Text Corpus

Transformer Language Model

Used to Learn

(Critics say that current voting systems used in the United States are inefficient and often lead to the inaccurate counting of votes. Miscounts can be especially damaging if an election is closely contested. Those critics would like the traditional systems to be replaced with far more efficient and trustworthy computerized voting systems.

In traditional voting, one major source of inaccuracy is that people accidentally vote for the wrong candidate. Voters usually have to find the name of their candidate on a large sheet of paper containing many names—the ballot—and make a small mark next to that name. People with poor eyesight can easily mark the wrong name. The computerized voting machines have an easy-to-use touch-screen technology: to cast a vote, a voter needs only to touch the candidate’s name on the screen to record a vote for that candidate; voters can even have the computer magnify the name for easier viewing.

Another major problem with old voting systems is that they rely heavily on people to count the votes. Officials must often count the votes one by one, going through every ballot and recording the vote. Since they have to deal with thousands of ballots, it is almost inevitable that they will make mistakes. If an error is detected, a long and expensive recount has to take place. In contrast, computerized systems remove the possibility of human error, since all the vote counting is done quickly and automatically by the computers. Finally, some people say it is too risky to implement complicated voting technology nationwide. But without giving it a thought, governments and individuals alike trust other complex computer technology every day to be perfectly accurate in banking transactions as well as in the communication of highly sensitive information.)

(Radford et al., 2018, 2019)
# Knowledge in Language Models

<table>
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<tr>
<th>Sentence</th>
<th>Predictions</th>
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<tbody>
<tr>
<td>I wanted to learn to <strong>sail</strong>, so I bought a</td>
<td>14.2% <strong>boat</strong>&lt;br&gt;5.4% sail&lt;br&gt;2.6% <strong>new</strong>&lt;br&gt;2.0% <strong>small</strong>&lt;br&gt;1.4% canoe</td>
</tr>
<tr>
<td>I wanted to learn to drive, so I bought a</td>
<td>7.5% <strong>new</strong>&lt;br&gt;7.0% <strong>car</strong>&lt;br&gt;1.7% <strong>Honda</strong>&lt;br&gt;1.7% <strong>BMW</strong>&lt;br&gt;1.3% <strong>Ford</strong>&lt;br&gt;← Undo</td>
</tr>
<tr>
<td>I wanted to learn to read, so I bought a</td>
<td>17.2% <strong>book</strong>&lt;br&gt;15.2% copy&lt;br&gt;3.4% <strong>Kindle</strong>&lt;br&gt;2.4% new&lt;br&gt;1.7% <strong>few</strong>&lt;br&gt;← Undo</td>
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<tr>
<td>I wanted to learn to fly, so I bought a</td>
<td>5.5% <strong>plane</strong>&lt;br&gt;3.8% <strong>new</strong>&lt;br&gt;1.6% <strong>small</strong>&lt;br&gt;1.6% <strong>Boeing</strong>&lt;br&gt;1.5% jet&lt;br&gt;← Undo</td>
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[https://demo.allennlp.org/next-token-lm](https://demo.allennlp.org/next-token-lm)
From Unstructured to Structured Knowledge

Transformer Language Model

Used to Generate

...
From Unstructured to Structured Knowledge

Transformer Language Model

Used to Generate

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Voc...
Allen sailed across oceans in bought a boat <END>

(Radford et al., 2018, 2019)
Transformer Language Models

- Trained to generate the next word given a set of preceding words

Language Model

Allen sailed across oceans in ... bought a boat <END>
Structure of Knowledge Tuple
Structure of Knowledge Tuple

- **head entity**

  - person sails across oceans
Structure of Knowledge Tuple

head entity

relation

<requires>

person sails across oceans
Structure of Knowledge Tuple

head entity

person sails across oceans

relation

<requires>

buy a boat

tail entity

(entity to generate)
Learning Structure of Knowledge

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

(Bosselut et al., 2019)
Learning Structure of Knowledge

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

(Bosselut et al., 2019)
Learning Structure of Knowledge

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

(Bosselut et al., 2019)
Learning Structure of Knowledge

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

(Bosselut et al., 2019)
Learning Structure of Knowledge

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

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

(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.
Generate commonsense knowledge for any input concept

COMmonsEnse Transformers
PersonX gives a tutorial
COMET - ATOMIC

PersonX gives a tutorial

X perceived as smart
COMET - ATOMIC

Person X gives a tutorial

X perceived as smart

Before, X needed to be a teacher
COMET - ATOMIC

PersonX gives a tutorial

X perceived as smart

Before, X needed to be a teacher

Others will want to thank PersonX
COMET - ATOMIC

PersonX gives a tutorial

X perceived as

Before, X needed to be a teacher

Others will want to thank PersonX

Others then none
COMET - ATOMIC

PersonX gives a tutorial

X perceived as smart

Before, X needed to be a teacher

Others will want to thank PersonX

Others then gain knowledge
COMET - ConceptNet

listen to tutorial
COMET - ConceptNet

listen to tutorial

location → classroom
COMET - ConceptNet

listen to tutorial

location -> classroom

motivated by you be smart
COMET - ConceptNet

listen to tutorial

location

classroom

motivated by

you be smart

starts with

sit down
listen to tutorial

COMET - ConceptNet

location → classroom

motivated by → you be smart

starts with → sit down

has prerequisite → listen carefully
COMET - ConceptNet

- listen to tutorial
- location
- classroom
- motivated by
- you be smart
- starts with
- sit down
- has prerequisite
- listen carefully
- causes
- good grade
Transfer Learning from Language

mango → is a → fruit
Transfer Learning from Language

mango → is a fruit

mango → used for salsa

ConceptNet
Transfer Learning from Language

mango → is a fruit

ConceptNet

mango → used for salsa

mango → Same Model, Not Pretrained on language → is a ?
Transfer Learning from Language

mango → is a fruit

ConceptNet

mango → used for salsa

mango → Same Model, Not Pretrained on language → is a spice
Transfer Learning from Language

mango $\rightarrow$ is a $\rightarrow$ fruit

mango $\rightarrow$ used for $\rightarrow$ salsa

mango $\rightarrow$ Same Model, Not Pretrained on language $\rightarrow$ spice
Unsupervised Commonsense Probing

(\text{Dante, <born\textunderscore in>, ?})

map relation to one or more natural language sentences

"Dante was born in [MASK]."

LM

\text{Neural LM Memory Access}

Florence

e.g. ELMo/BERT

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

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

Sentence:

a mango is a

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

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

https://demo.allennlp.org/masked-lm
## Sensitivity to cues

<table>
<thead>
<tr>
<th>Candidate Sentence $S_i$</th>
<th>$\log p(S_i)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>“musician can playing musical instrument”</td>
<td>-5.7</td>
</tr>
<tr>
<td>“musician can be play musical instrument”</td>
<td>-4.9</td>
</tr>
<tr>
<td>“musician often play musical instrument”</td>
<td>-5.5</td>
</tr>
<tr>
<td>“a musician can play a musical instrument”</td>
<td><strong>2.9</strong></td>
</tr>
</tbody>
</table>

Feldman et al., 2019

<table>
<thead>
<tr>
<th>Prompt</th>
<th>Model Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>A ____ has fur.</td>
<td>dog, cat, fox, ...</td>
</tr>
<tr>
<td>A ____ has fur, is big, and has claws.</td>
<td>cat, <strong>bear</strong>, lion, ...</td>
</tr>
<tr>
<td>A ____ has fur, is big, has claws, has teeth, is an animal, eats, is brown, and lives in woods.</td>
<td><strong>bear</strong>, wolf, cat, ...</td>
</tr>
</tbody>
</table>

Weir et al., 2020
Commonsense Transformers

- Language models **implicitly** represent knowledge
Commonsense Transformers

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

![Diagram of Commonsense Transformers]

Pre-trained Language Model + Seed Knowledge Graph Training
- Language models implicitly represent knowledge
- Re-train them on knowledge graphs to learn structure of knowledge
- Resulting knowledge model generalizes structure to other concepts
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
Reasoning with Knowledge Graphs

Kai knew that things were getting out of control and managed to keep his temper in check.
Reasoning with Knowledge Graphs

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Commonsense Knowledge for any Situation

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Commonsense Knowledge for any Situation

- transformer-style architecture — input format is natural language
  - event can be fully parsed
  - dynamically generated knowledge passed to downstream model

Liu et al., 2020
Commonsense Knowledge for any Situation
Commonsense Knowledge for any Situation

Kearns et al., 2020

<table>
<thead>
<tr>
<th>Invite</th>
<th>Grounding Responses</th>
<th>Question Answering</th>
<th>Therapeutic Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HI Darren, is now a good time to talk? 5:00 PM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sure I’m leaving work now. 5:05 PM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Great. How are you feeling today? 5:05 PM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I’ve been busy with lesson plans. 5:06 PM</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>RESPONSE PREVIEW</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>You sound very [dedicated to your work], but I can see how that may also make you feel [stressed].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In our last session, I asked you to rate your [stress] between 0 and 10 with 0 being extremely low and 10 being extremely high. You rated your [stress] as [8].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>What would you rate your current [stress] level?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>GROUNDING RESPONSES</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Simple Reflection</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- I can see this really [negative emotion] you.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- I can see how that could be [negative emotion].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- So sorry to hear you are [negative emotion].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Glad to hear you are [positive emotion].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- That sounds really [positive / negative emotion].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Affirmation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- You sound very [positive attribute], but I can see how that may also make you feel [negative emotion].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Others must think you are very [positive attribute].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Supportive</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- I will help you [positive action].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- I will try to [positive action].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- We will work together to [positive action].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>They may want to...</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- take a break</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- learn</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- be successful</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- get a good grade</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>They may feel...</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- happy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- tired</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- stressed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- satisfied</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>They may be seen as...</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- busy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- determined</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- focused</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- dedicated</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Others may want to...</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- listen to them</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- learn more</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- thank them</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>They may next...</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- get stressed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- lose time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- get tired</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- get a headache</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Search</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stress</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In our last session, I asked you to rate your [symptom] between 0 and 10 with 0 being extremely low and 10 being extremely high. You rated your [symptom] as [number].</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>What would you rate your current [symptom] level?</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feeling stressed is normal for caregivers. But constant worrying, unrelenting doubts and pre-occupation with the “what ifs” and worst-case scenarios can be unproductive and even paralyzing.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Setting personal health goals such as working out is a strategy for dealing with caregiver stress.</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>And some physical activity is better than none. By adding physical activity, this can help with stress. As a person moves from 150 minutes a week toward 300 minutes a week, the health benefits become more extensive.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Commonsense Knowledge for any Situation**

- transformer-style architecture — input format is natural language
  - event can be fully parsed
  - knowledge representations passed to downstream model

---

**Transformer**

- Commonsense+Contextualized Word Representations

**COMeT Commonsense Transformers**

\[
\begin{align*}
&<o1> \omega_1^1 \ldots \omega_m^1 </o1> <o2> \omega_1^2 \ldots \omega_m^2 </o2>
\end{align*}
\]
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
Dynamic Construction of Reasoning Graphs

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

Bosselut et al., 2020
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.
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

Dynamic Construction of Reasoning Graphs

Root Node

Generated Commonsense Inference Nodes

Bosselut et al., 2020
Kai knew that things were getting out of control and managed to keep his temper in check.
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

$\ell = 1$

Bosselut et al., 2020
Kai knew that things were getting out of control and managed to keep his temper in check.

\[ \ell = 1 \]

- Kai wants to avoid trouble
- Kai intends to be calm
- Kai stays calm
- Kai is viewed as cautious
- Kai feels relieved
- Others want to avoid trouble

\[ \ell = 2 \]

- Kai then avoids trouble
- Kai wants to be safe
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.

$\ell = 1$

$\ell = L$
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.

Kai intends to be calm.

Kai is viewed as cautious.

\[ \ell = 1 \]

\[ \ell = L \]

Kai intends to be calm.

Kai is viewed as cautious.

Kai wants to avoid trouble.

Kai is viewed as cautious.

\[ \ell = L \]

Kai is viewed as cautious.

Kai is viewed as cautious.

Kai is viewed as cautious.

relieved

scared

anxious
<table>
<thead>
<tr>
<th>Situation</th>
<th>Top Reasoning Paths</th>
<th>Answers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jesse drove Ash to the airport and dropped</td>
<td><strong>Jesse wants to go home</strong></td>
<td>a) <strong>drained ✓</strong></td>
</tr>
<tr>
<td>them off at the airport with ease.</td>
<td></td>
<td>b) went to the ticket counter</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) dropped me off at the airport</td>
</tr>
<tr>
<td>How would Jesse feel afterwards?</td>
<td><strong>Jesse wanted to be helpful</strong></td>
<td>a) drained</td>
</tr>
<tr>
<td></td>
<td></td>
<td>b) <em>went to the ticket counter X</em></td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) dropped me off at the airport</td>
</tr>
<tr>
<td>After jumping off the roof of his house</td>
<td><strong>Quinn gets hurt</strong></td>
<td>a) <strong>foolish ✓</strong></td>
</tr>
<tr>
<td>Quinn had trouble breathing.</td>
<td></td>
<td>b) patient</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) light-headed</td>
</tr>
<tr>
<td>How would you describe Quinn?</td>
<td><strong>Quinn wants to get medical</strong></td>
<td>a) foolish</td>
</tr>
<tr>
<td>help</td>
<td></td>
<td>b) patient</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) <em>light-headed X</em></td>
</tr>
<tr>
<td>Alex took notice of the children who</td>
<td><strong>Alex is happy</strong></td>
<td>a) hurt the children</td>
</tr>
<tr>
<td>were singing at the playground.</td>
<td></td>
<td>b) <strong>joy ✓</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) tell the children to stop</td>
</tr>
<tr>
<td>What will happen to Alex?</td>
<td><strong>Alex wants to go home</strong></td>
<td>a) hurt the children</td>
</tr>
<tr>
<td></td>
<td></td>
<td>b) joy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) <em>tell the children to stop X</em></td>
</tr>
<tr>
<td>Taylor was close to winning the game.</td>
<td><strong>Taylor wants to celebrate</strong></td>
<td>a) try to get over that they did win</td>
</tr>
<tr>
<td>Taylor ran straight for home plate.</td>
<td></td>
<td>b) <em>celebrate the win X</em></td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) wanted to score</td>
</tr>
<tr>
<td>What will Taylor want to do next?</td>
<td><strong>Taylor wants to be home</strong></td>
<td>a) try to get over that they did win</td>
</tr>
<tr>
<td></td>
<td></td>
<td>b) celebrate the win</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) <em>wanted to score ✓</em></td>
</tr>
</tbody>
</table>
Path Knowledge Models

PersonX saw a fight was breaking out <xWant> wants to avoid trouble <xEffect> leaves

Wang et al., 2020
Path Knowledge Models

Path entities

<want> wants to avoid trouble <effect>

Language Model

Head entity

PersonX saw a fight was breaking out

Tail entity

leaves

Wang et al., 2020
Path Knowledge Models

Path entities

<xWant> wants to avoid trouble <xEffet>

PersonX saw a fight was breaking out

X pushes Y around

X stops Y

Tail entity

Multi-step Knowledge Model
Visual Commonsense Knowledge Graphs

Park et al., 2020
VisualCOMET

Language Model

Visual Context | Head entity | <relation> | Tail entity

<Person2> is holding onto a ... <after> Gasp for air

Park et al., 2020
VisualCOMET

Language Model

Person2 is holding onto a...

Visual Context

Head entity <relation> Tail entity

<after> Gasp for air

Park et al., 2020
VisualCOMET

Language Model

Visual Context  
Head entity  
<relation>  
Tail entity

ROI Feature  
ROI Feature

<Person2> is holding onto a ...  <after>  Gasp  for  air

Park et al., 2020
Park et al., 2020
VisualCOMET

Multimodal Knowledge Model

Tail entity

gasp
for
air
(END)

Head entity

<Person2> is holding onto a ...

<after>
Gasp
for
air

Visual Context

ROI Feature
ROI Feature

Park et al., 2020
Limitations of Knowledge Models

- Base Self-supervised Model
  - biases in language model will be in COMET

- Seed Knowledge Graph
  - bias, relations, schema

- Generation Algorithm
  - diversity

PersonX gives a tutorial

X perceived as smart

Before, X needed to be a teacher

Others will want to thank PersonX

Others then none
Kai knew that things were getting out of control and managed to keep his temper in check.

- **Static vs. Dynamic**
  - Link to **static** Knowledge Graph
    - X keeps ___ under control
    - X keeps X's temper
    - X avoids a fight
    - X wants to show strength
    - X sweats
    - X wants to show strength
  - Generate **dynamic** graph with COMET
    - Kai stays calm
    - Kai is viewed as cautious
    - Kai wants to avoid trouble
    - Kai intends to be calm
    - no linking
    - contextual knowledge

- **Bad links**
  - X keeps ___ under control
  - X keeps X's temper
  - X avoids a fight
  - X wants to show strength
  - X sweats
  - X wants to show strength
Resources

Code: atcbosselut.github.io

Demo: mosaickg.apps.allenai.org
References & Additional Reading


References & Additional Reading


