Commonsense Reasoning

These slides are from the ACL 2020 Commonsense Tutorial by Yejin Choi, Vered Shwartz, Maarten Sap, Antoine Bosselut, and Dan Roth
Monsters in a Tunnel

- **Two monsters are running** (rather than standing still on one foot)
- **One is chasing another** (rather than trying to copy his movements)
- **The chaser has hostile intentions and the chased is afraid** (even though two faces are identical)

Important Observations:

- A great deal of **intuitive inferences** are **commonsense inferences**, which can be described in **natural language**.
- None of these inferences is absolutely true. The inferences are **stochastic** in nature. Everything is **defeasible** with additional context.
- Commonsense inferences are about **predicting new information** that is **likely to be true** based on partially available information.
Claims of AI systems reaching a “human level”

Google's AI translation system is approaching human-level accuracy

But there's still significant work to be done

Google's AI translation system is approaching human-level accuracy

Microsoft claims new speech recognition record, achieving a super-human 5.1% error rate

Microsoft, Google Beat Humans at Image Recognition

Deep learning algorithms compete at ImageNet challenge

R. Colin Johnson
2/18/2015 08:15 AM EST
14 comments

Alibaba and Microsoft AI beat human scores on Stanford reading test

Neural networks edged past human scores on the measure of machine reading.
We may be “solving” datasets rather than the underlying “task”.

Where did Tesla move in 1880? **Chicago**

A horse standing in the grass.

Object Recognition

Giant panda + Gibbon =

Szegedy et al, 2014

VQA

Jabri et al, 2017

We may be “solving” datasets rather than the underlying “task”.

A horse standing in the grass.

Captioning

MacLeod et al, 2017

Where did Tesla move in 1880? **Chicago**

Tadakatsu moved to Chicago in 1881.
## Theory of Core Knowledge

<table>
<thead>
<tr>
<th>Domain</th>
<th>Description</th>
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<tbody>
<tr>
<td>Objects</td>
<td>supports reasoning about objects and the laws of physics that govern them</td>
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<tr>
<td>Agents</td>
<td>supports reasoning about agents that act autonomously to pursue goals</td>
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<tr>
<td>Places</td>
<td>supports navigation and spatial reasoning around an environment</td>
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<tr>
<td>Number</td>
<td>supports reasoning about quality and how many things are present</td>
</tr>
<tr>
<td>Forms</td>
<td>supports representation of shapes and their affordances</td>
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<tr>
<td>Social Beings</td>
<td>supports reasoning about Theory of Mind and social interaction</td>
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Developmental psychologists have shown that children develop the ability to reason about these domains early in life. Such reasoning is important for later learning.
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
CIS 700: Interactive Fiction and Text Generation

Commonsense resources
Grandma’s glasses

Tom’s grandma was reading a new book, when she dropped her glasses.

She couldn’t pick them up, so she called Tom for help.

Tom rushed to help her look for them, they heard a loud crack.

They realized that Tom broke her glasses by stepping on them.

Promptly, his grandma yelled at Tom to go get her a new pair.
Humans reason about the world with **mental models** [Graesser, 1994]

**Personal experiences** [Conway et al., 2000]

**World knowledge and commonsense** [Kintsch, 1988]

**Commonsense resources** aim to be a bank of knowledge for machines to be able to reason about the world in tasks
Tom’s grandma was reading a new book, when she dropped her glasses.

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Overview of existing resources

NELL knowledge fragment

Open Mind Common Sense
(Minsky, Singh & Havasi, 1999)

Cyc
(Lenat et al., 1984)

Cyc
(Lenat et al., 2019)

OpenCyc
(Lenat, 2004)

OpenCyc 4.0
(Lenat, 2012)

ResearchCyc
(Lenat, 2006)

ConceptNet
(Liu & Singh, 2004)

ConceptNet
5.5
(Speer et al., 2017)

Web Child
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NELL
(Carlson et al., 2010)

NELL
(Mitchell et al., 2015)

today
How do you create a commonsense resource?
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
Creating a commonsense resource

Representation
- Symbolic
- Natural language

Knowledge type
- Domain-specific
- Semantic
- Inferential
CONCEPTNET:

*semantic* knowledge in *natural language* form
**Related terms**
- book →
- books →
- book →

**Effects of reading**
- learning →
- ideas →
- a headache →

**reading is a subevent of...**
- you learn →
- turning a page →
- learning →

**reading**
An English term in ConceptNet 5.8

**Subevents of reading**
- relaxing →
- study →
- studying for a subject →

**Things used for reading**
- article →
- a library →
- literature →
- a paper page →

**Types of reading**
- browse (n, communication) →
- bumf (n, communication) →
- clock time (n, time) →
- miles per hour (n, time) →
What is ConceptNet?

General commonsense knowledge

21 million edges and over 8 million nodes (as of 2017)
  • Over 85 languages
  • In English: over 1.5 million nodes

Knowledge covered:
  • Open Mind Commonsense assertions
  • Wikipedia/Wiktionary semantic knowledge
  • WordNet, Cyc ontological knowledge

http://conceptnet.io/
ATOMIC: inferential knowledge in natural language form

https://mosaickg.apps.allenai.org/kg_atomic
ATOMIC: 880,000 triples for AI systems to reason about causes and effects of everyday situations
X repels Y's attack

because X wanted to

before, X needed to

has an effect on X

has an effect on Y

as a result, Y feels

as a result, Y wants

as a result, Y feels weak

as a result, Y feels ashamed

as a result, Y wants to run home

as a result, Y wants to attack X again

X is skilled

X is brave

X is strong

X is seen as

X wants to file a police report

X wants to leave the scene

X feels angry

X feels tired

X wanted to protect others

X wanted to save themselves

X needs to train hard

X needs to know self-defense
X repels Y’s attack

because X wanted to

before, X needed to

nine inference dimensions

X is seen as

as a result, Y feels

as a result, Y wants

as a result, Y gets hurt

Y falls back

Y feels ashamed

Y feels weak

Y wants to run home

Y wants to attack X again

X feels angry

X feels tired

X’s heart races

X gains an enemy

X is skilled

X is brave

X is strong

X is

X wants to file a police report

X wants to leave

X wanted to protect others

X wanted to save themselves

X needs to train hard

X needs to know self-defense
Causes

X wanted to protect others

X wanted to save themselves

because X wanted to

before, X needed to

X needs to train hard

X needs to know self-defense

Effects

X repels Y’s attack

as a result, Y feels

Y feels weak

Y feels ashamed

as a result, Y wants

Y wants to run home

as a result, X feels

X feels angry

X feels tired

has an effect on X

X’s heart races

X gains an enemy

has an effect on Y

Y falls back

Y gets hurt

as a result, X wants

X wants to file a police report

X wants to leave the scene
X repels Y's attack

Dynamic

- X wants to file a police report
- X wants to leave the scene
- X feels angry
- X feels tired
- X's heart races
- X gains an enemy
- Y feels weak
- Y feels ashamed
- Y wants to run home
- Y wants to attack X again
- Y gets hurt
- as a result, Y wants
- as a result, Y feels
- as a result, X feels
- has an effect on X
- has an effect on Y

Static

- X wanted to save themselves
- X wanted to protect others
- X needs to train hard
- X needs to know self-defense
- X is skilled
- X is brave
- X is strong
- X is seen as
- because X wanted to
- before, X needed to
Involuntary repels Y’s attack

Voluntary

X wanted to protect others
X wanted to save themselves
X wanted to train hard
X needs to know self-defense

because X wanted to
before, X needed to

X is skilled
X is strong
X is brave

as a result, Y feels
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Y gets hurt
Y falls back
X gains an enemy
X’s heart races

X feels angry
X feels tired

X wants to file a police report
X wants to leave the scene

Penn Engineering
X repels Y's attack

before, X needed to
because X wanted to

X is skilled
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Y wants to run home
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has an effect on X
X feels angry
X feels tired
X's heart races
X gains an enemy

has an effect on Y
Y falls back
Y gets hurt

Agent
X wanted to protect others
X wanted to save themselves
X wanted to file a police report
X wants to leave the scene

Theme
X needs to train hard
X needs to know self-defense

Penn Engineering
X repels Y's attack

300,000 event nodes to date

880,000 if-Event-then-* knowledge triples
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)
Overview of existing resources

- **Open Mind Common Sense** (Minsky, Singh & Havasi, 1999)
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- **ConceptNet 5.5** (Speer et al., 2017)
- **ATOMIC** (Sap et al., 2019)

* today
Existing knowledge bases

- **ATOMIC**
  (Sap et al., 2019)

- **NELL**
  (Mitchell et al., 2015)

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Existing knowledge bases

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

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

- **ConceptNet 5.5**
  (Speer et al., 2017)

- **ATOMIC**
  (Sap et al., 2019)

```latex
(#$implies
  (#$and
    (#$isa ?OBJ ?SUBSET)
    (#$genls ?SUBSET ?SUPERSET))
  (#$isa ?OBJ ?SUPERSET))
```
Existing knowledge bases

Represented in **symbolic logic**
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Knowledge of “**what**”
(taxonomic: A isA B)

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

**ATOMIC**
(Sap et al., 2019)
Q: How do you gather commonsense knowledge at scale?

A: It depends on the type of knowledge
Extracting commonsense from text

Based on information extraction (IE) methods
1. Read and parse text
2. Create candidate rules
3. Filter rules based on quality metric

Advantage:
can extract knowledge automatically

Example system:
Never Ending Language Learner (NELL; Carlson et al., 2010)
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**

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

Experts create knowledge base

Advantages:
• Quality guaranteed
• Can use complex representations (e.g., CycL, LISP)

Drawbacks:
• Time cost
• Training users

Non-experts write knowledge in natural language phrases

Natural language
• Accessible to non-experts
• Different phrasings allow for more nuanced knowledge

Fast and scalable collection
• Crowdsourcing
• Games with a purpose

OpenCyc 4.0 (Lenat, 2012)
WordNet (Miller et al., 1990)

ATOMIC (Sap et al., 2019)
ConceptNet 5.5 (Speer et al., 2017)
Knowledge bases and mitigating biases

PersonX clutches a gun because X wanted to

Jaquain clutches a gun because X wanted to

Karen clutches a gun because X wanted to

COMET (Bosselut et al., 2019): ATOMIC + OpenAI

ATOMIC (Sap et al., 2019)
Neural and Symbolic Models of Commonsense Reasoning
Katrina had the financial means to afford a new car while Monica did not, since ____ had a high paying job.
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.
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
A car costs a lot of money, and is capable of making a high-paying job, which is used for a job that entails making money. Spending money requires buying something that costs a lot of money, which entails buying something to spend a lot of money.
Incorporating External Knowledge into Neural Models

General Idea

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

**Neural Component**
- Pre/post pre-trained language models

**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)
ConceptNet


- **Car**
  - **Cost a lot of money**
  - **Requires**
  - **Something to**
  - **Is capable of**

- **Job**
  - **Is used for**
  - **Requires**
  - **Is capable of**

- **Make money**
  - **Requires**
  - **Is used for**

- **Spend money**
  - **Requires**

- **Buy**

---

Other Knowledge Sources

Mining from Text
- WordNet
- SentiWordNet
- ATOMIC

Knowledge Bases
- Mining script knowledge from corpora, event plausibility from corpora

Tools
- Knowledge base embeddings, sentiment analysis models, COMET
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.
1. Incorporate into scoring function

2. Symbolic → vector representation
   ○ (+attention)

3. Multi-task learning
Incorporating External Knowledge into Neural Models

**Example**

RocStories
MCScript

**ConceptNet**

![ConceptNet diagram](image)

**Multi-task Learning**

1. Are they related?
2. What's the relation?

- **Aux Classifier 1**
  - restaurant
  - food

- **Aux Classifier 2**
  - restaurant
  - food

**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
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

(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)

(Sap et al., 2019)
Limitations of Knowledge Graphs

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

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

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- Suitable nodes are often *uncontextualized*
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*

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

(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

(person, CapableOf, buy)

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

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Grice’s Maxim of Quantity

- Grice’s Maxim of Quantity
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- Grice’s Maxim of Quantity
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
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

(person, CapableOf, buy)

Gather Textual Corpus

(Schubert, 2002)
(Banko et al., 2007)
(Zhang et al., 2020)

Store in knowledge graph

(Webchild)

(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 Knowledge Base Completion

True / False

Bilinear Model

Linear

( person, CapableOf, buy )

head entity
relation
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

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

person sails across oceans \( \xrightarrow{\text{<requires>}} \) buy a boat

head entity

relation

tail entity

(entity to generate)
Learning Structure of Knowledge

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

\[ \mathcal{L} = -\sum \log P(\text{target words}|\text{seed words}, \text{relation}) \]
Learning Structure of Knowledge

Language Model $\rightarrow$ Knowledge Model:
generates knowledge of the structure of the examples used for training

(Bosselut et al., 2019)
Generate commonsense knowledge for any input concept

COMmonsEnse Transformers
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

- Classroom
- Motivated by you be smart
- Starts with sit down
- Has prerequisite listen carefully
- Causes good grade
- Location

Listen to tutorial
Question

Why does this work?
Transfer Learning from Language

mango \rightarrow \text{is a} \rightarrow \text{fruit}
Transfer Learning from Language

mango $\rightarrow$ mango

is a $\rightarrow$ fruit

ConceptNet $\rightarrow$ used for

salsa
Transfer Learning from Language

mango → is a fruit

mango → ConceptNet → used for salsa

mango → Same Model, Not Pretrained on language → is a ?

mango
Transfer Learning from Language

mango → mango is a fruit

mango → ConceptNet is a fruit

mango → ConceptNet used for salsa

mango → mango is a spice

mango → mango is a spice, Not Pretrained on language
Can’t a language model do the same thing?
Unsupervised Commonsense Probing

\[
(\text{Dante}, <\text{born_in}>, ? )
\]

map relation to one or more natural language sentences

"Dante was born in [MASK]."

LM

e.g. ELMo/BERT

Neural LM Memory Access

Florence

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
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
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2.5% great
2.4% delicious
1.8% sweet
← Undo

Sentence:

a mango is a

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

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>$-2.9$</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, bear, 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>bear, wolf, cat, ...</td>
</tr>
</tbody>
</table>

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**
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
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
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