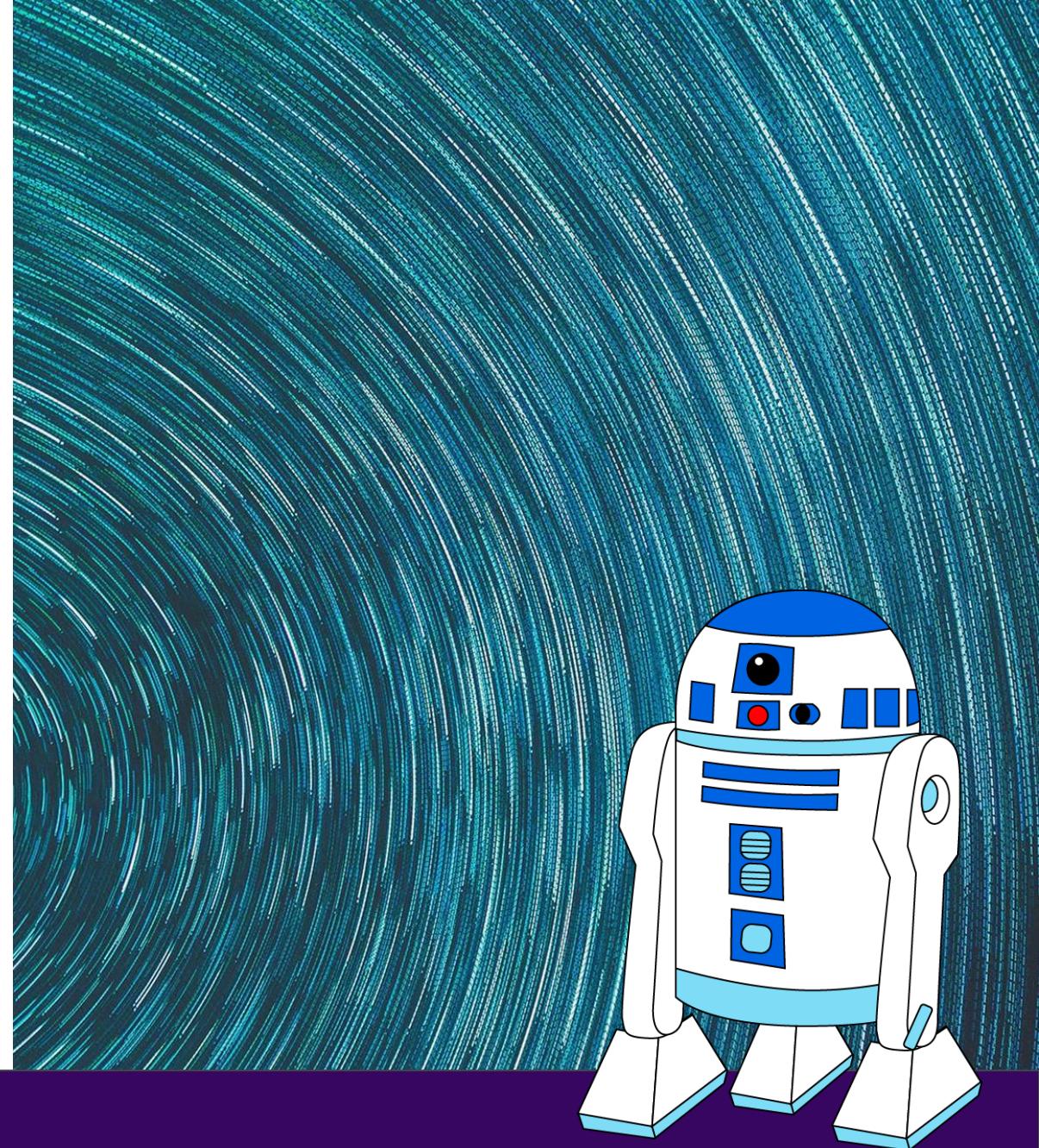


CMSC 491/691: Interactive
Fiction and Text Generation

Commonsense Reasoning

These slides adapted from the [ACL 2020
Commonsense Tutorial](#) by Yejin Choi,
Vered Shwartz, Maarten Sap, Antoine Bosselut,
and Dan Roth

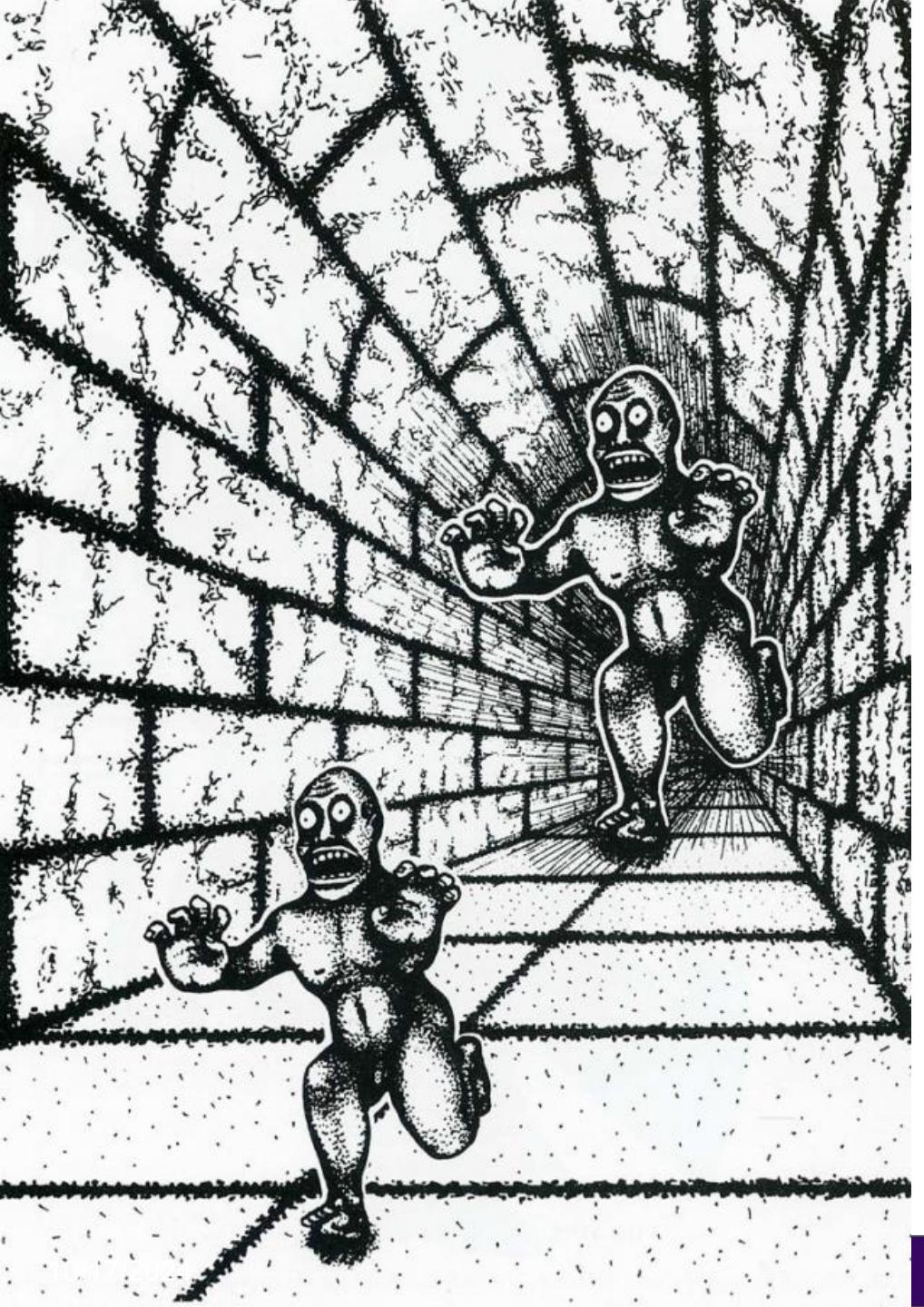


Announcements

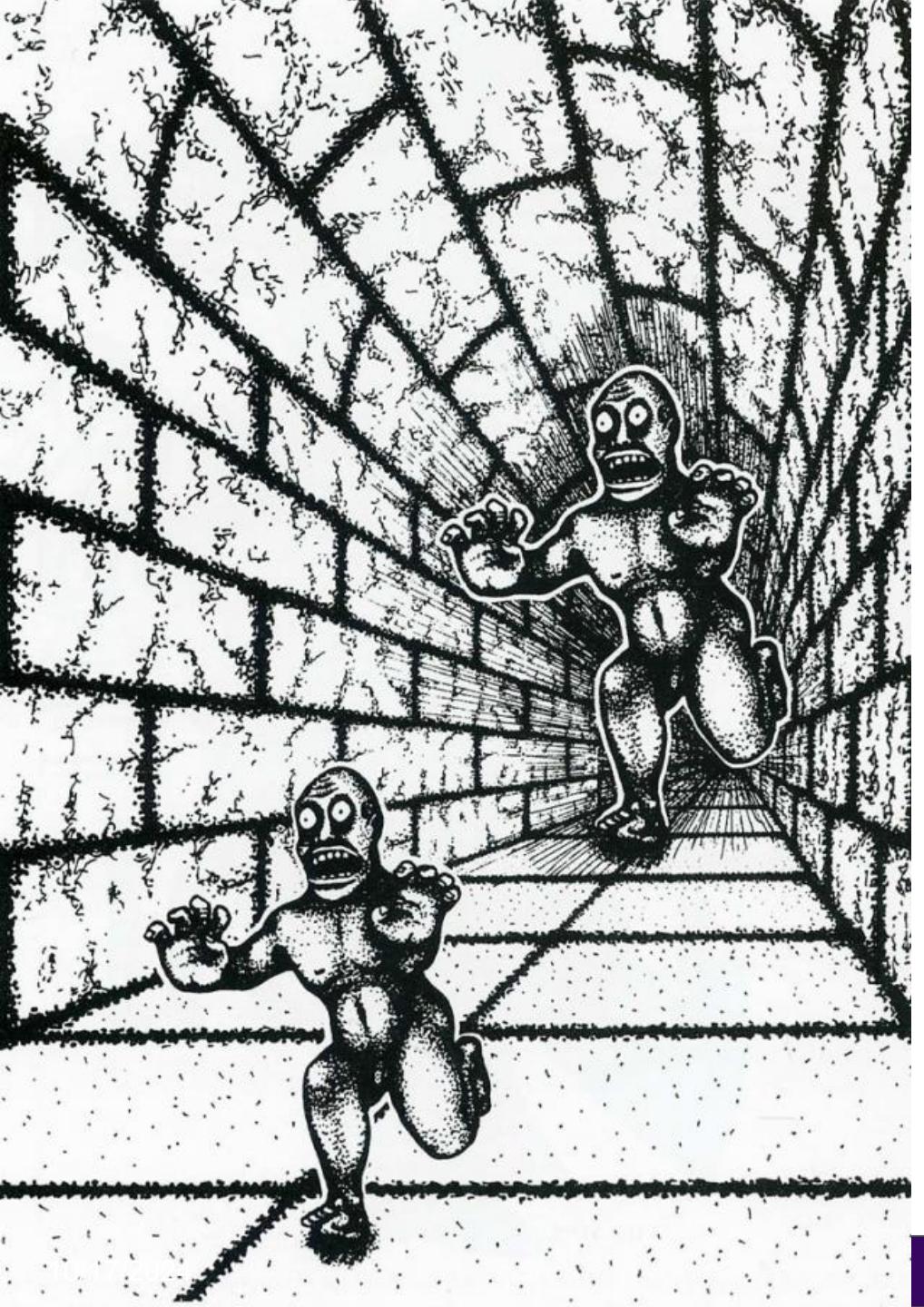
- HW 3
 - Due 10/28 (same day as project milestone)
 - Next Tuesday will be grad paper presentations
 - Midpoint feedback due 10/22 – hard deadline
 - knowledge check point
 - All homeworks are up 2% (most are 12% now, HW1 is 7%)
 - Final presentations will be in SHER 150 on 12/12

Learning Objectives

- Consider the difference between human commonsense and machine reasoning
- Find out about existing commonsense knowledge bases
- Distinguish when you would use one knowledge base over another



What does this picture show?



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”

CADE METZ

BUSINESS MAY 22, 2017 3:12 PM

ChatGPT passes exams from law and business schools

By Samantha Murphy Kelly, CNN Business

4 minute read · Updated 1:35 PM EST, Thu January 26, 2023

JULY 12, 2022 | 6 MIN READ

Google Engineer Claims AI Chatbot Is Sentient: Why That Matters

Is it possible for an artificial intelligence to be sentient?

BY LEONARDO DE COSMO

AlphaGo Is Back to Battle Mere Humans—and It's Smarter Than Ever

s in China to take on the world's top-ranked e there for every move.

Newsweek

Tech

Joe Rogan

The Joe Rogan Experience

SUBSCRIBE FOR \$1

Login



Who Is Joe Rogan Voting For? We Asked ChatGPT

Published Oct 15, 2024 at 6:38 AM EDT

Updated Oct 15, 2024 at 6:07 PM EDT

AI in real-life usage: Can't win an argument with your partner? Get ChatGPT to do it for you

Girlfriend goes viral for using ChatGPT to make her arguments when couple disagrees, apparently telling her partner that they lack 'emotional bandwidth.'



Darren Allan
Tech Reporter

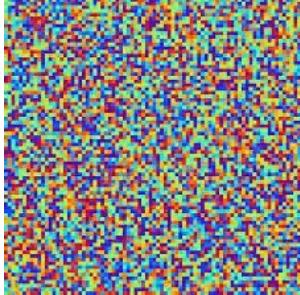
Published Oct 17, 2024 9:05 AM CDT

3 minutes read time





+



=



Giant panda Object Recognition

Gibbon

Szegedy et al,
2014....



Jabri et al,
2017

VQA



A horse standing in the grass.

Captioning

MacLeod
et al, 2017

QA

Jia et al,
2017

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

a Tesla moved to
Prague in 1880. ... Tadakatsu
moved to Chicago in 1881.

Theory of Core Knowledge

Domain	Description
Objects	supports reasoning about objects and the laws of physics that govern them
Agents	supports reasoning about agents that act autonomously to pursue goals
Places	supports navigation and spatial reasoning around an environment
Number	supports reasoning about quality and how many things are present
Forms	supports representation of shapes and their affordances
Social Beings	supports reasoning about Theory of Mind and social interaction

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

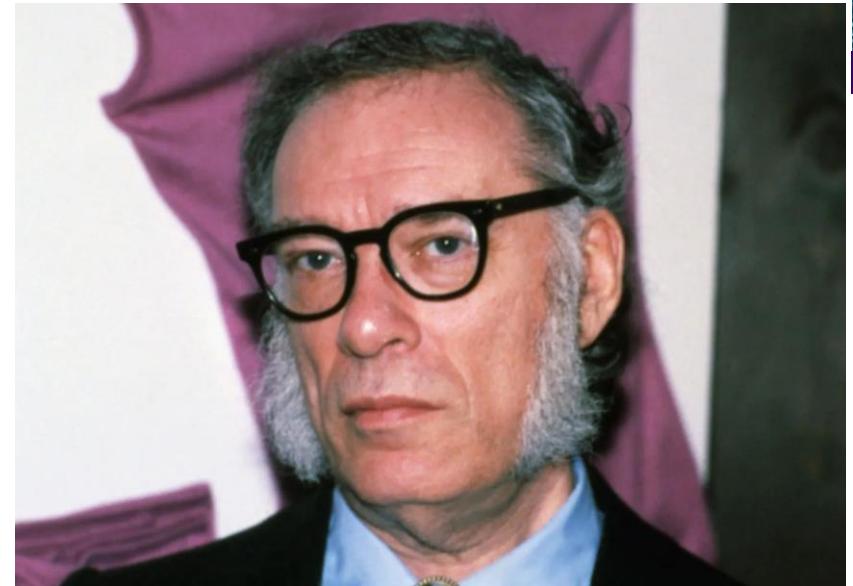
Essential for humans to live and interact with each other in a reasonable and safe way

Essential for AI to understand human needs and actions better

Isaac Asimov's "Three Laws of Robotics"

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

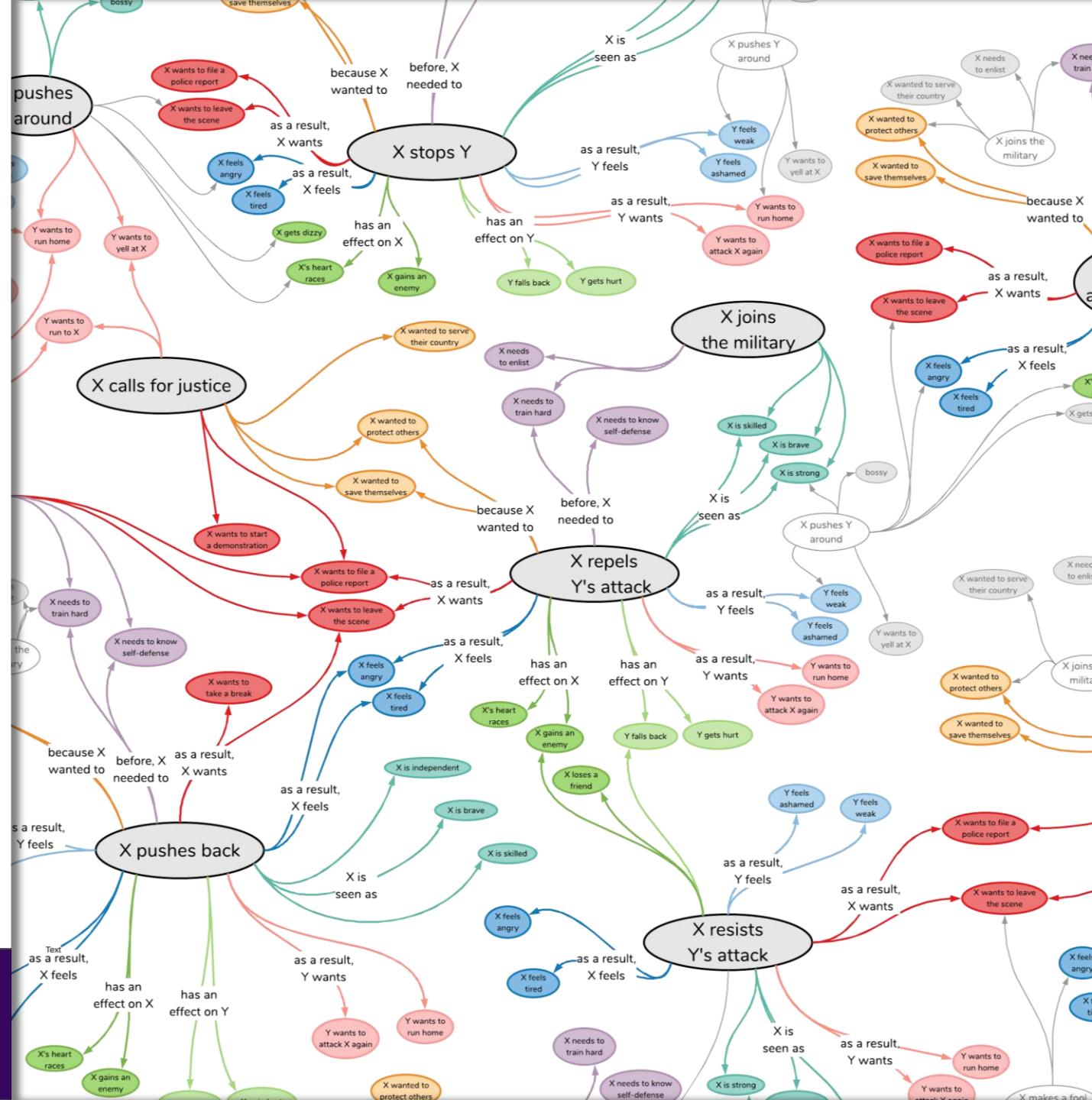
- Isaac Asimov, 1942 short story "Runaround"



<https://cdn.britannica.com/82/195182-050-97684526/Isaac-Asimov-1979.jpg>

CMSC 491/691: 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.

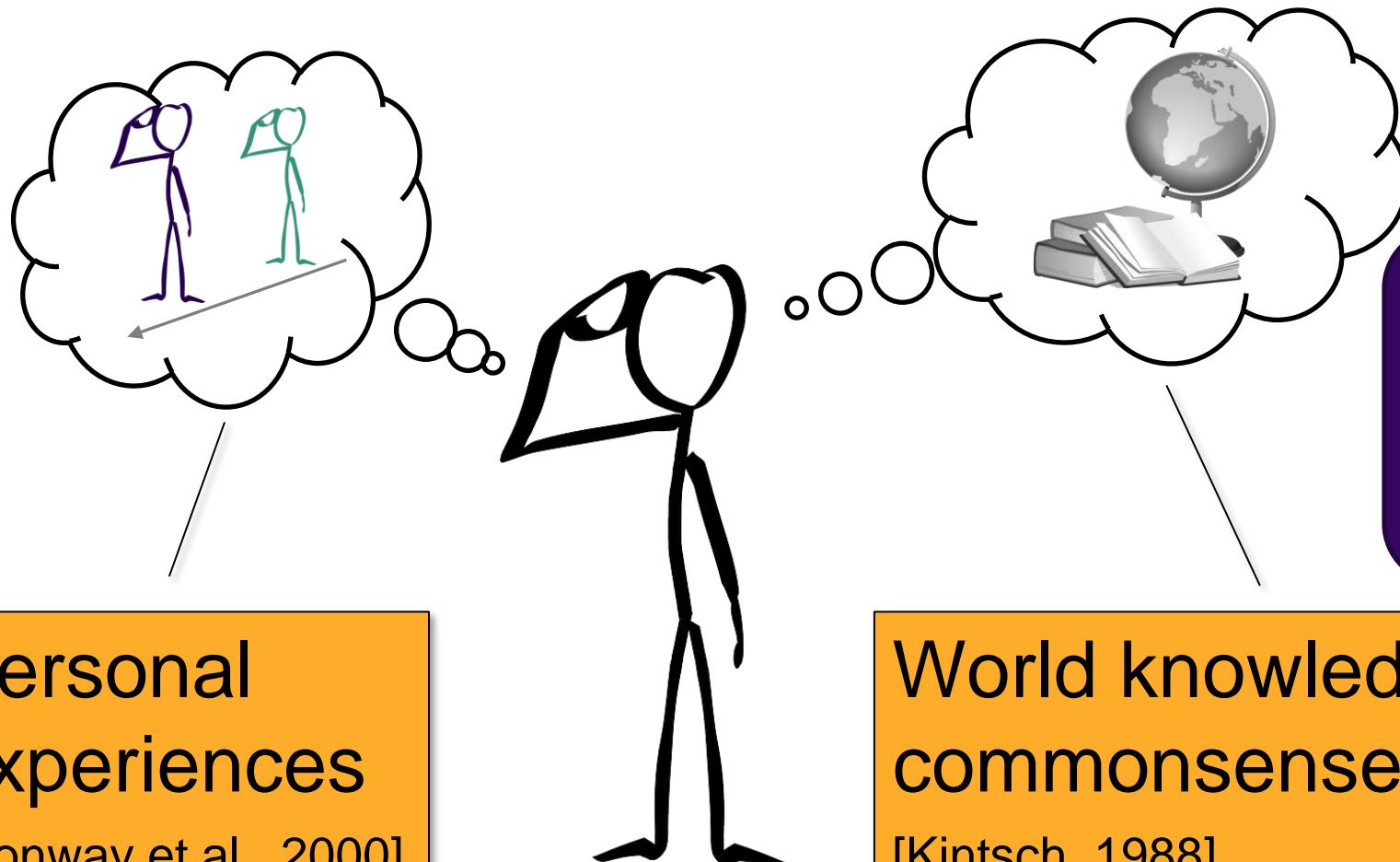
Tom rushed to help her look for them, they heard a loud crack.

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]

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.

ConceptNet

ATOMIC

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

```
graph LR; reading[reading] -- usedFor --> glasses[glasses]
```

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

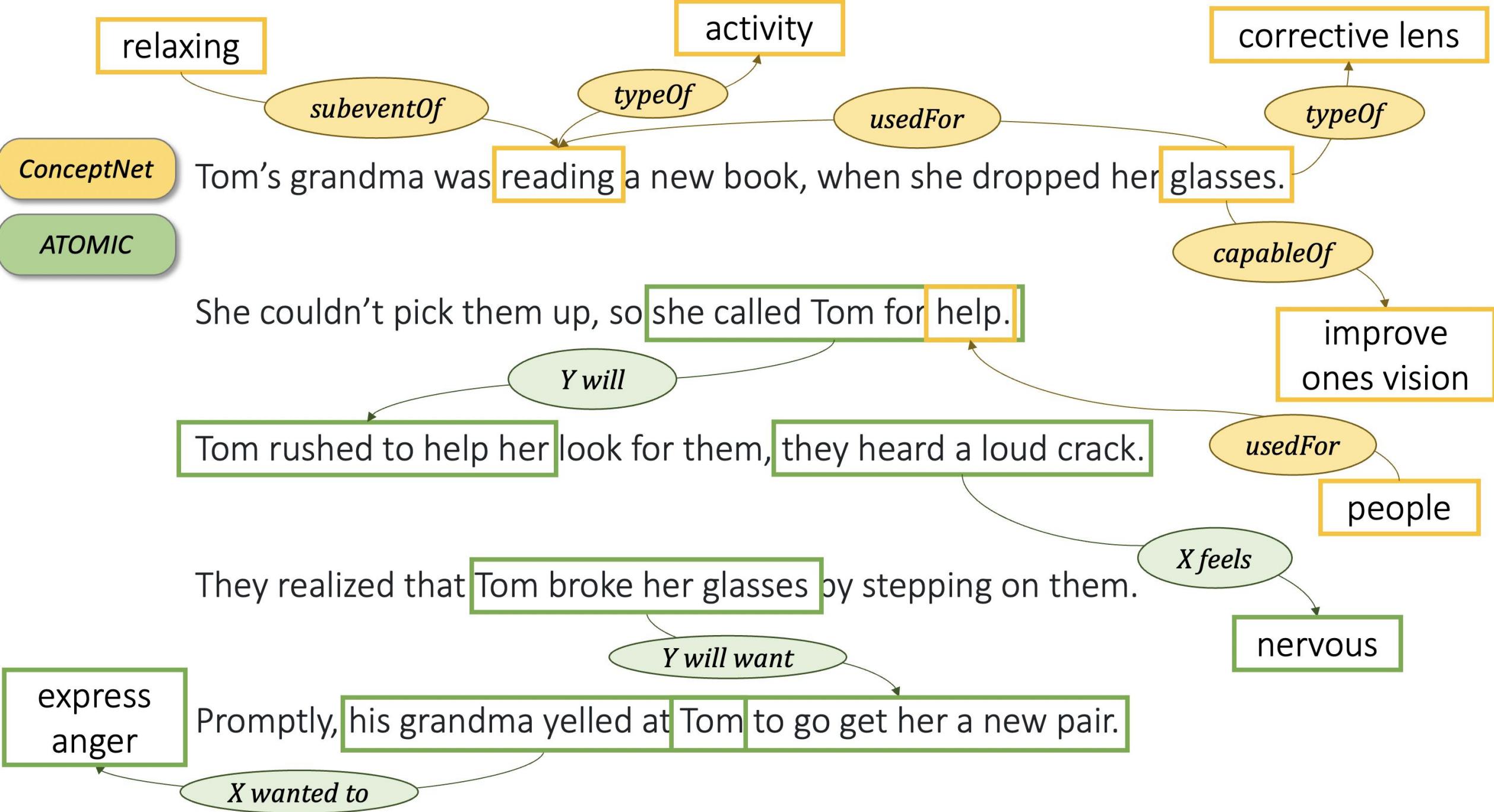
Y will

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

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

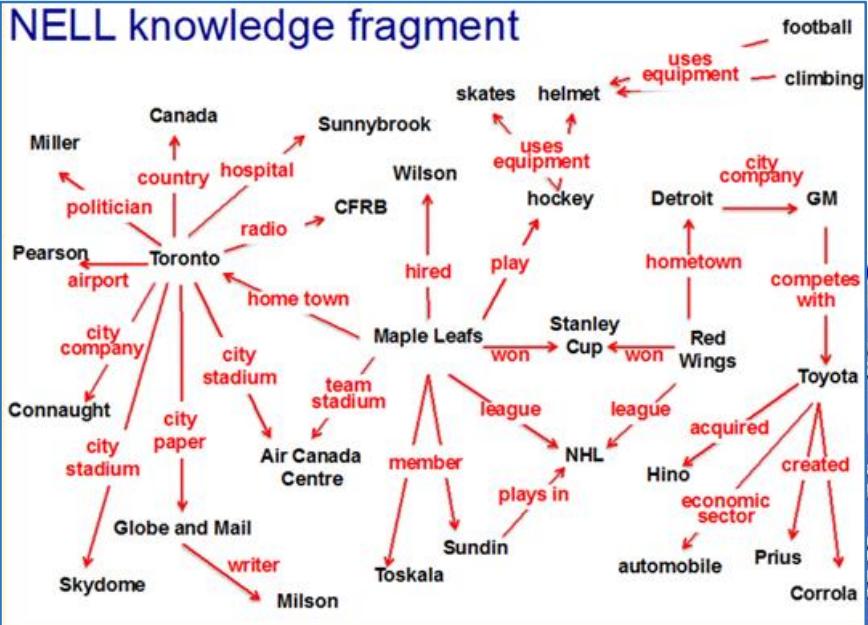
Y will want

Promptly, his grandma yelled at Tom to go get her a new pair.

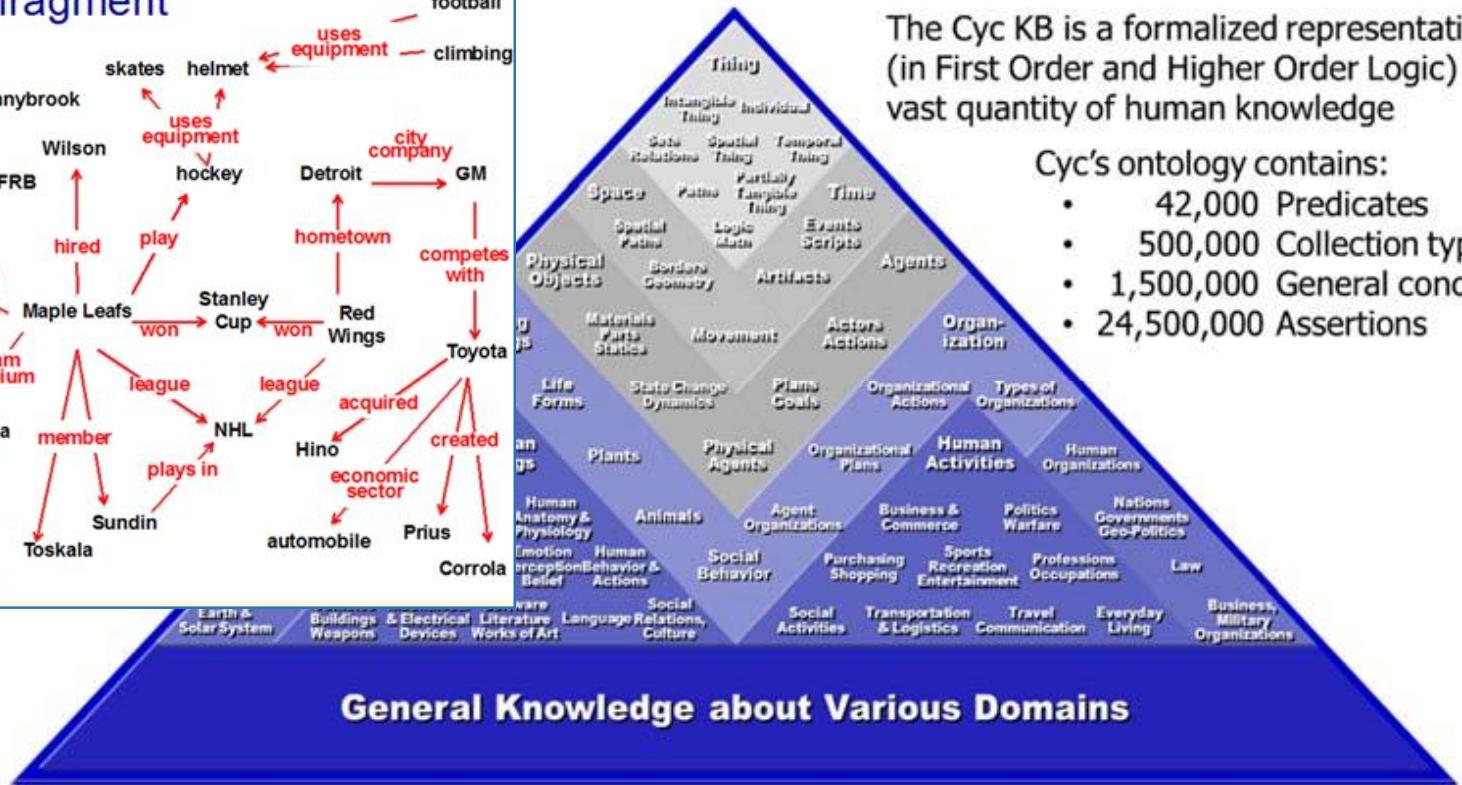


Some important resources

NELL knowledge fragment



Open Mind Comm
(Minsky, Singh &
1999)



Cyc
(Lenat et al.,
1984)

OpenCyc
(Lenat,
2004)

ResearchCyc
(Lenat, 2006)

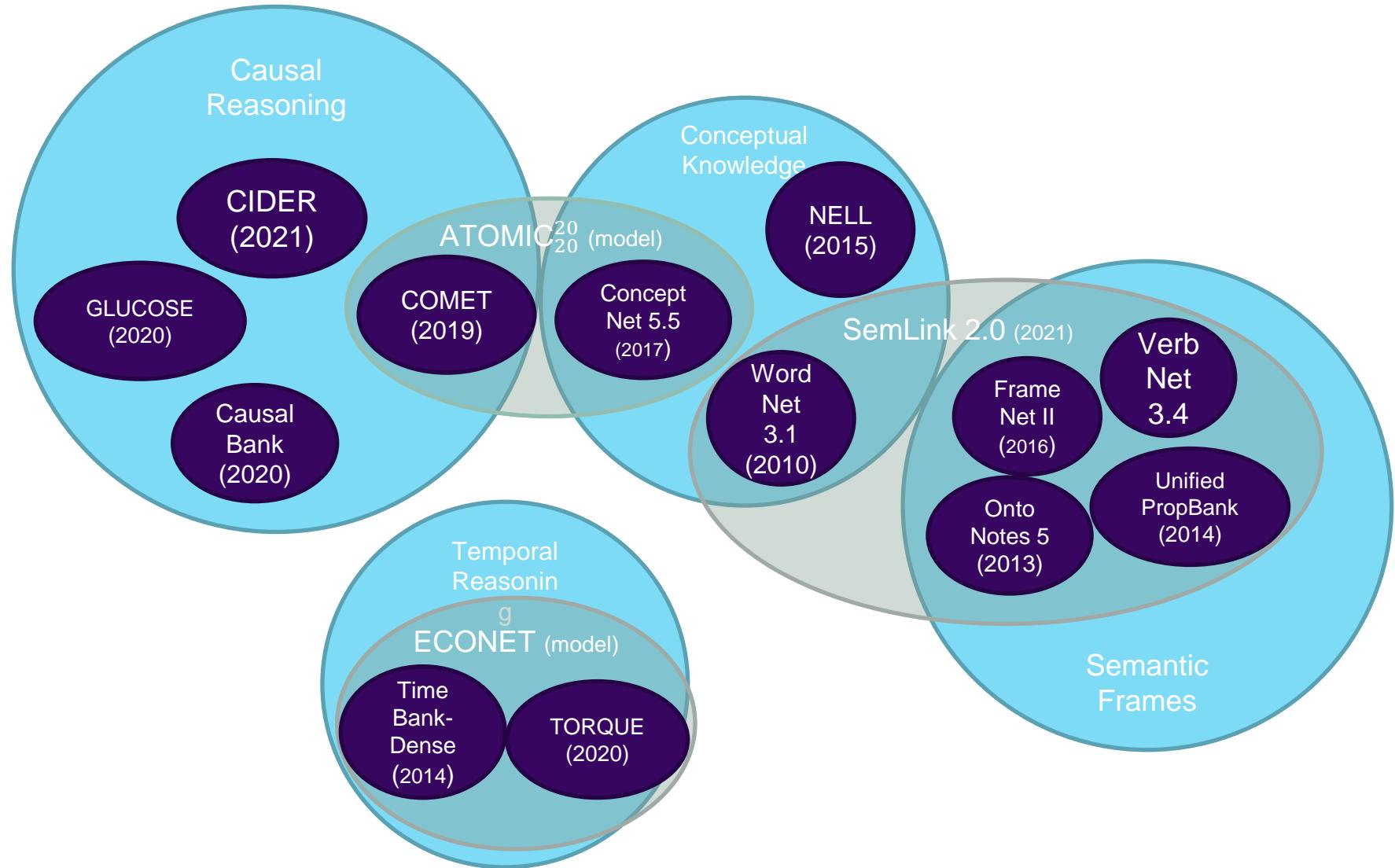
OpenCyc 4.0
(Lenat, 2012)

ATOMIC
(ap et al., 2019)

World 2.0
(et al.,
7)

Net 5.5
(al., 2017)

today



How do you create a commonsense resource?

Desirable properties for a commonsense resource

Coverage

Large scale

Diverse knowledge types

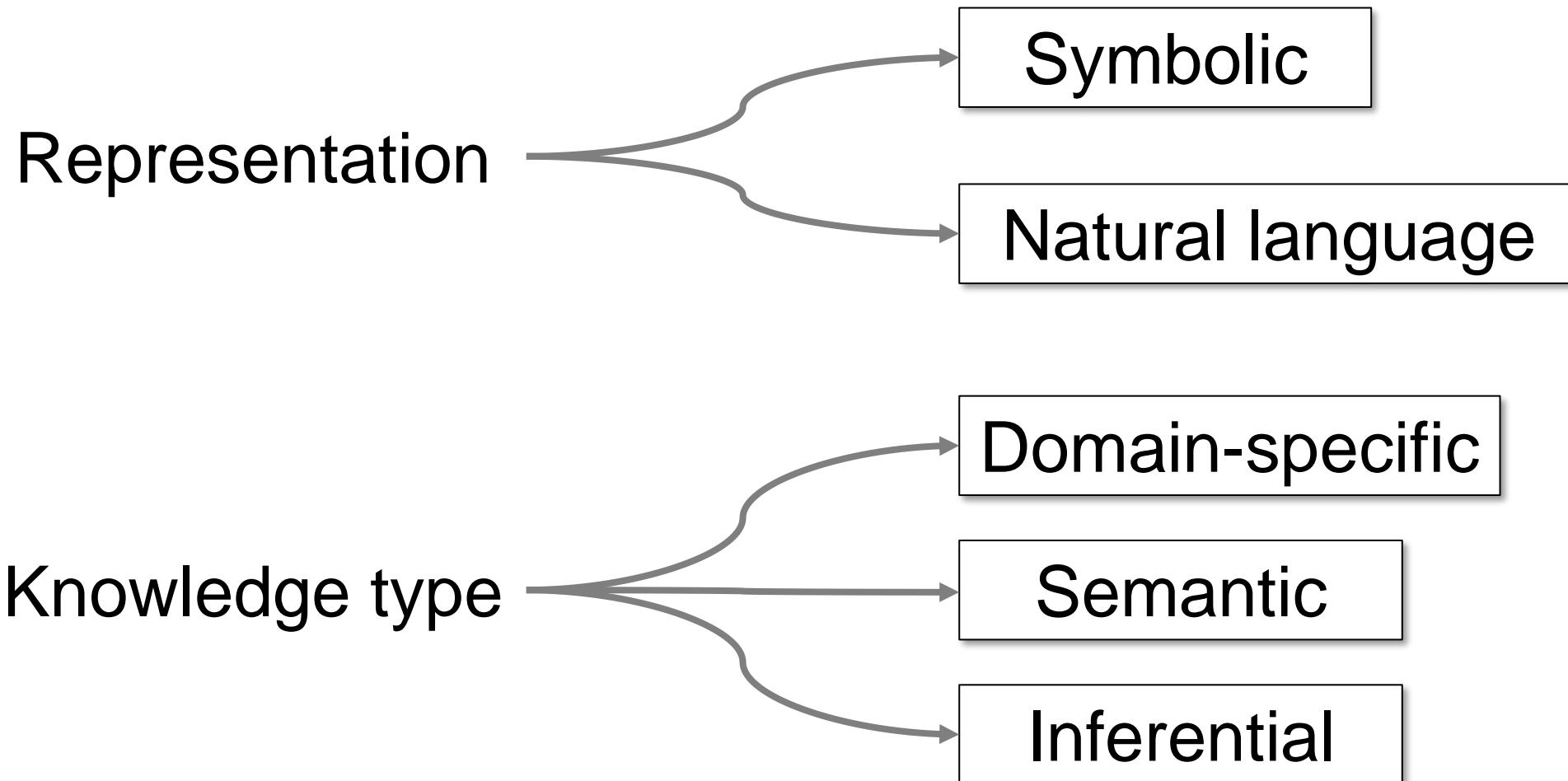
Useful

High quality knowledge

Usable in downstream tasks

Multiple resources tackle different
knowledge types

Creating a commonsense resource



What is a semantic frame?

“people understand the meaning of words largely by virtue of the frames which they evoke”

- Understanding words in context
- Based on recurring experiences

Josef Ruppenhofer, Michael Ellsworth, Miriam R. L. Petrucc, Christopher R. Johnson, Collin F. Baker, & Jan Scheffczyk. *FrameNet II: Extended Theory and Practice* (Revised November 1, 2016.)

Fillmore, Charles J. (1982). "Frame semantics". In The Linguistic Society of Korea, eds. *Linguistics in the Morning Calm*. Seoul: Hanshin. 111-37.

CONCEPTNET:

semantic knowledge in natural language form

Related terms

- en book →
- en books →
- en book →

Effects of reading

- en learning →
- en ideas →
- en a headache →

reading is a subevent
of...

- en you learn →
- en turning a page →
- en learning →

en reading
An English term in ConceptNet 5.8

Subevents of reading

- en relaxing →
- en study →
- en studying for a subject →

Things used for reading

- en article →
- en a library →
- en literature →
- en a paper page →

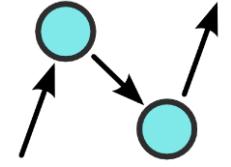
reading is a type of...

- en an activity →
- en a good way to learn →
- en one way of learning →
- en one way to learn →

Types of reading

- en browse (n, communication) →
- en bumf (n, communication) →
- en clock time (n, time) →
- en miles per hour (n, time) →

What is ConceptNet?



General commonsense knowledge

21 million edges and over 8 million nodes (as of 2017)

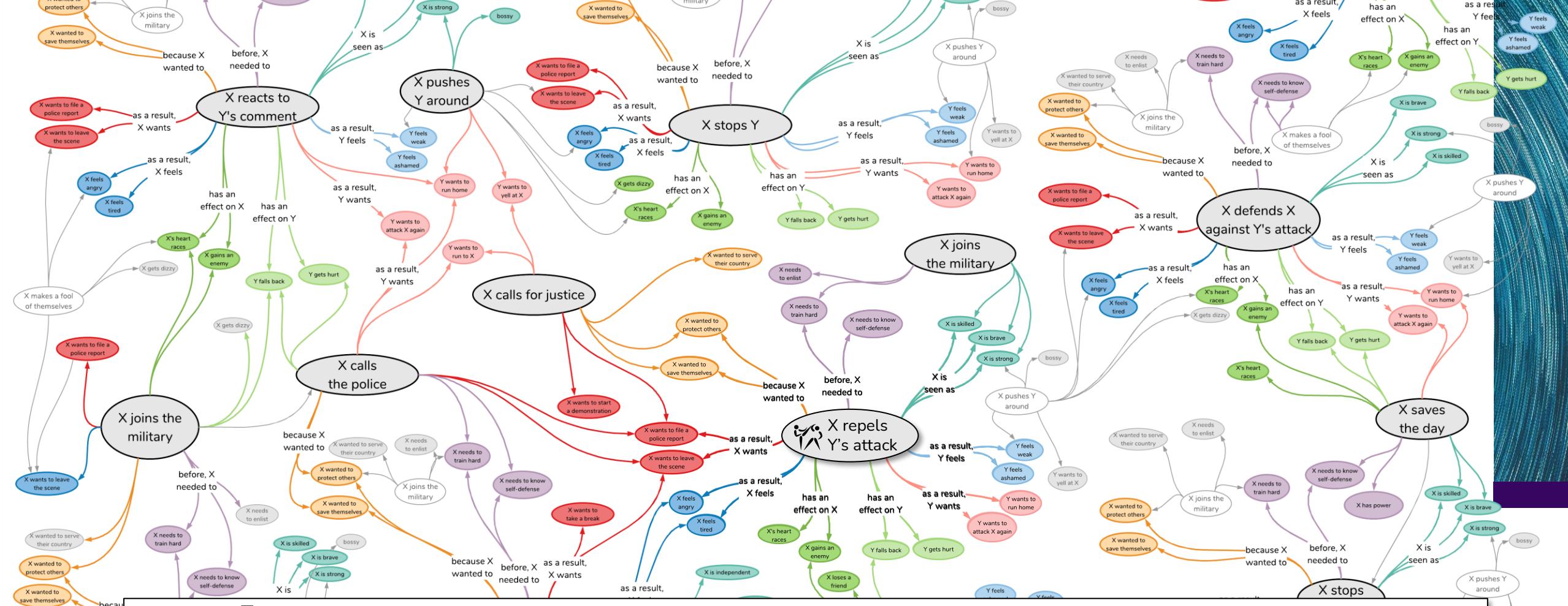
- Over 85 languages
- In English: over 1.5 million nodes

Knowledge covered:

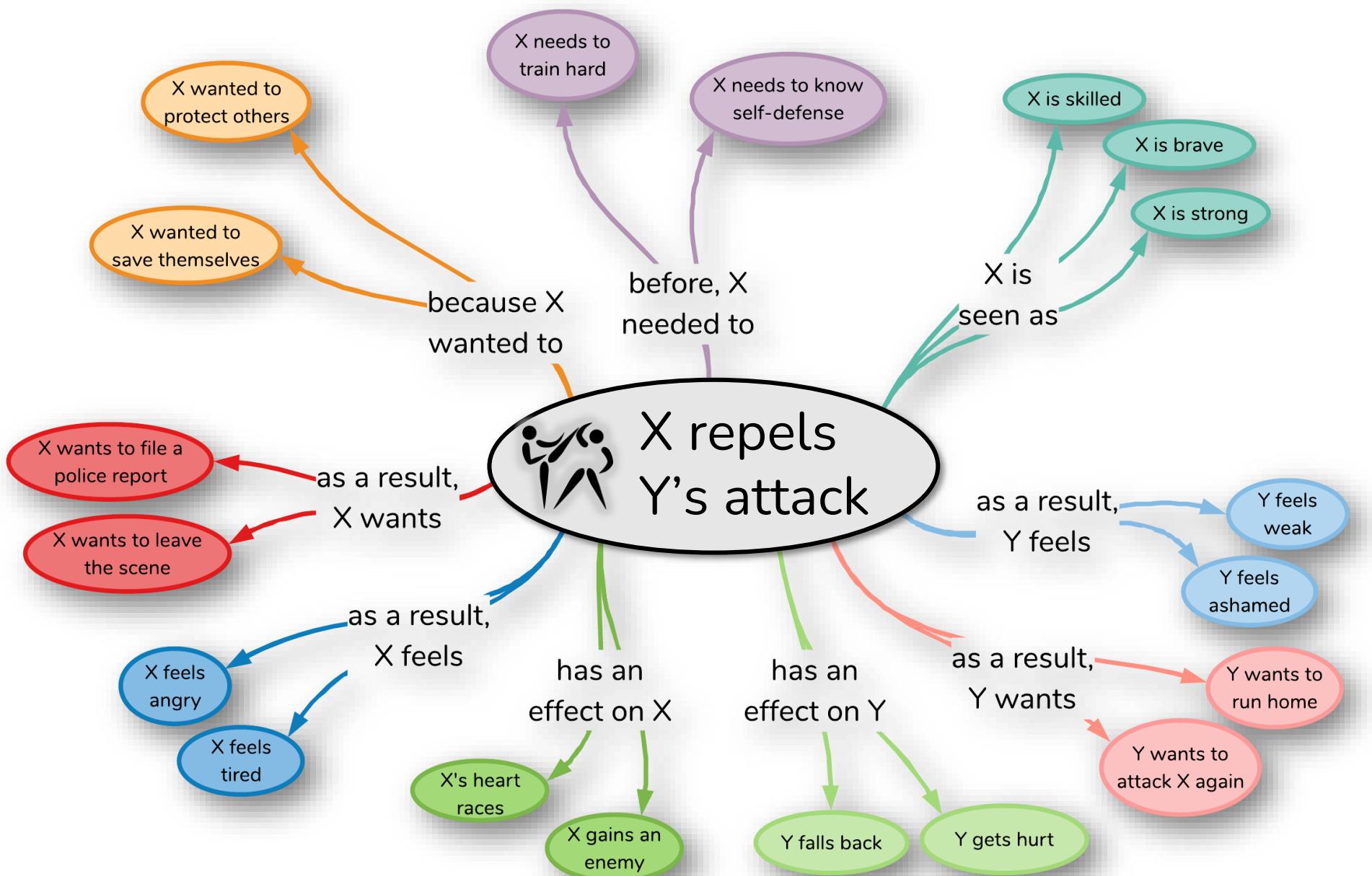
- Open Mind Commonsense assertions
- Wikipedia/Wiktionary semantic knowledge
- WordNet, Cyc ontological knowledge

ATOMIC: *inferential* knowledge in *natural language* form

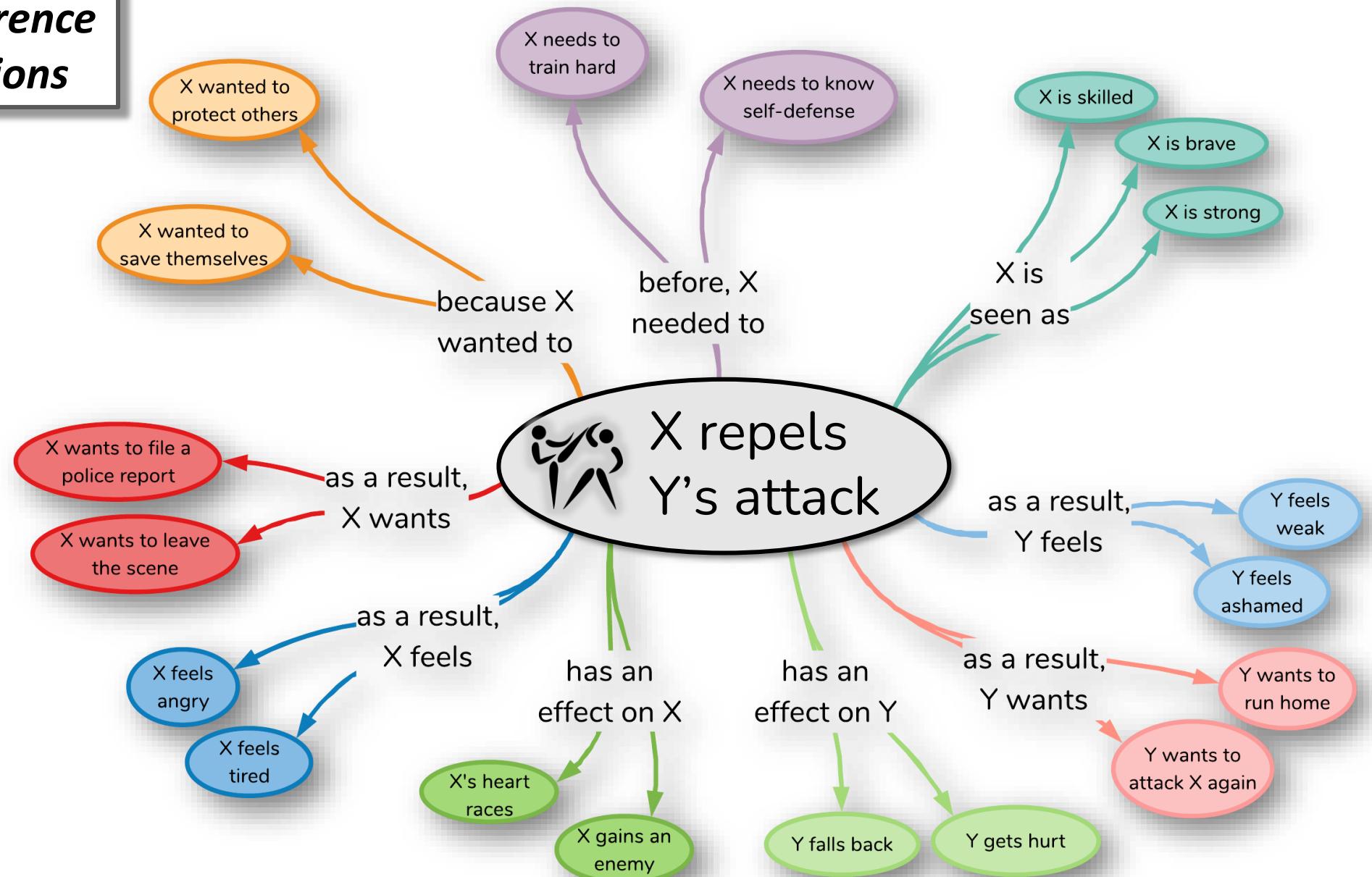
<https://github.com/allenai/comet-atomic-2020>



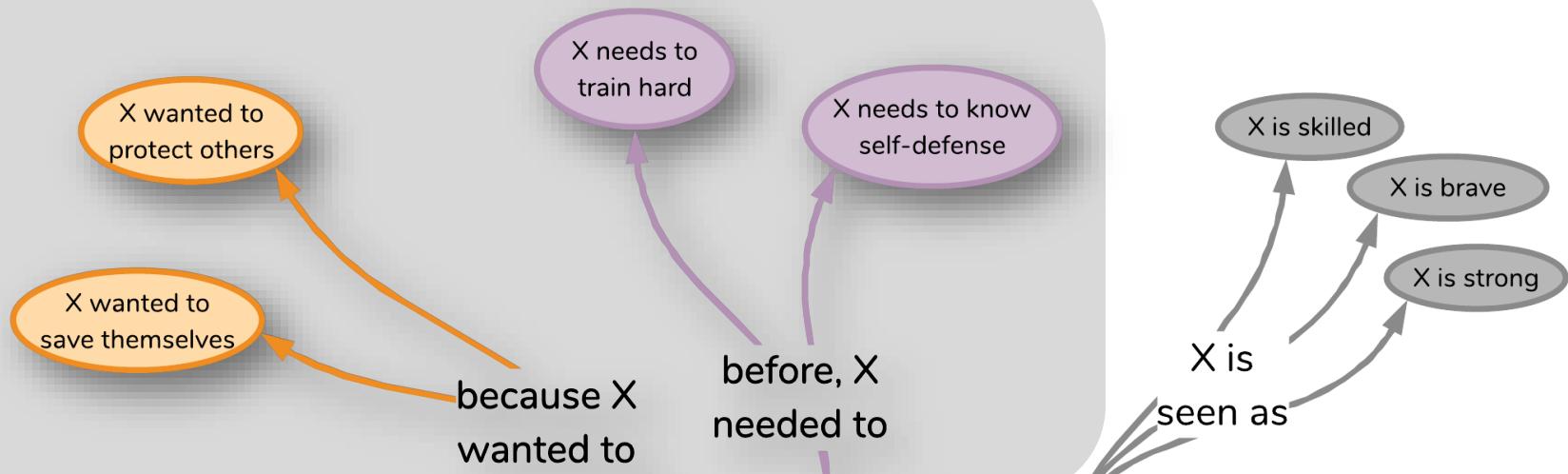
ATOMIC: 880,000 triples for AI systems to reason about **causes** and **effects** of everyday situations



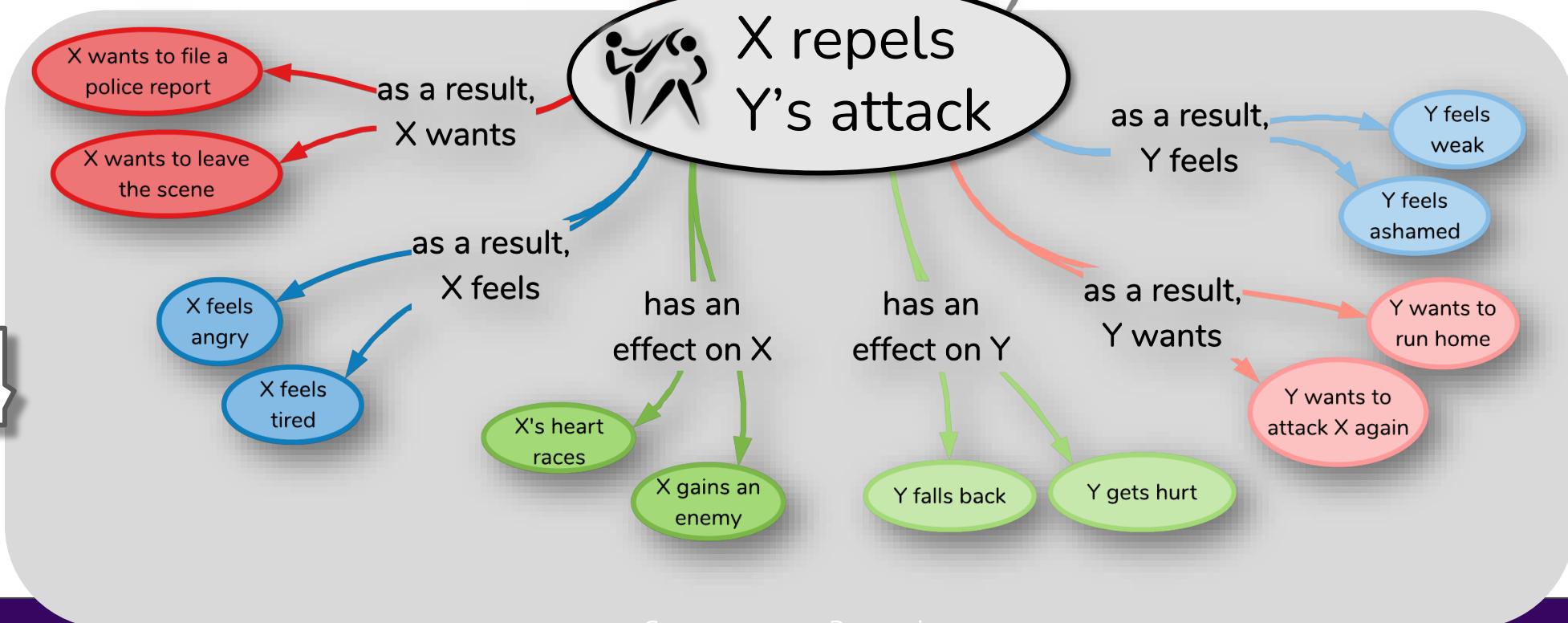
nine inference dimensions



Causes

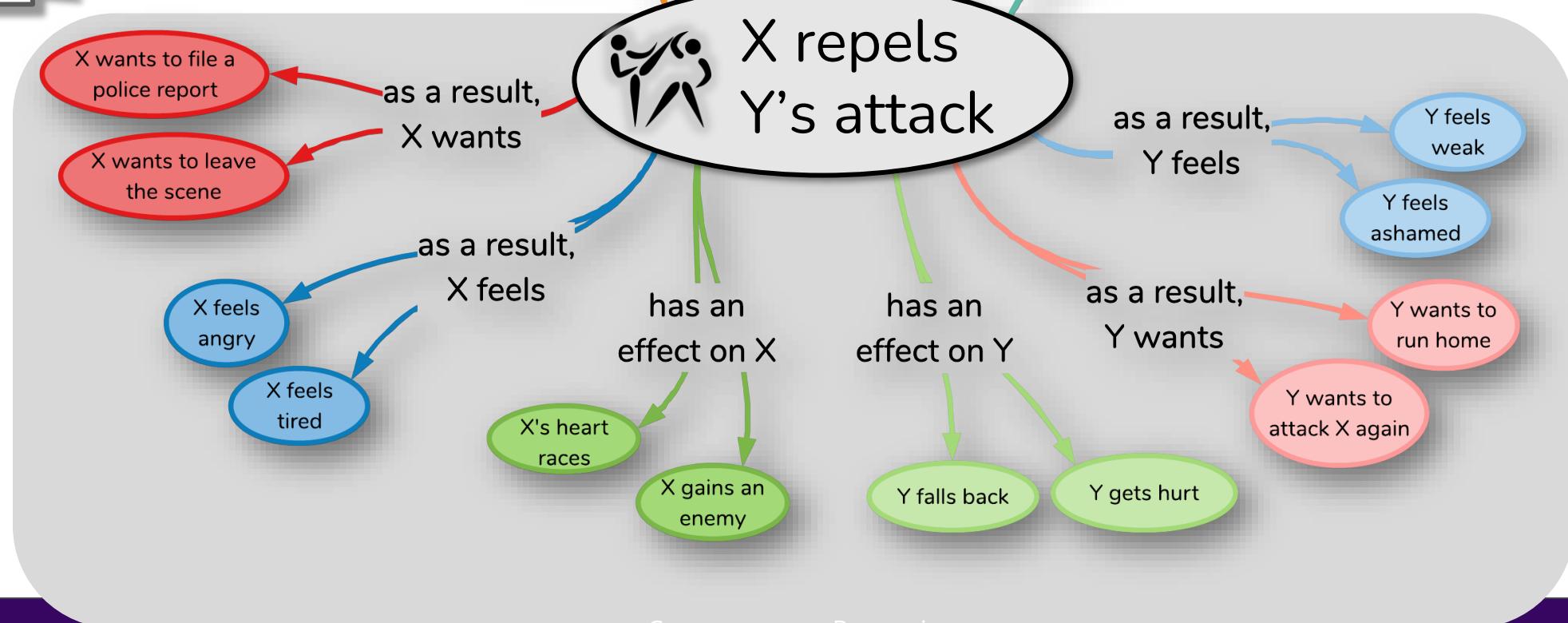


Effects

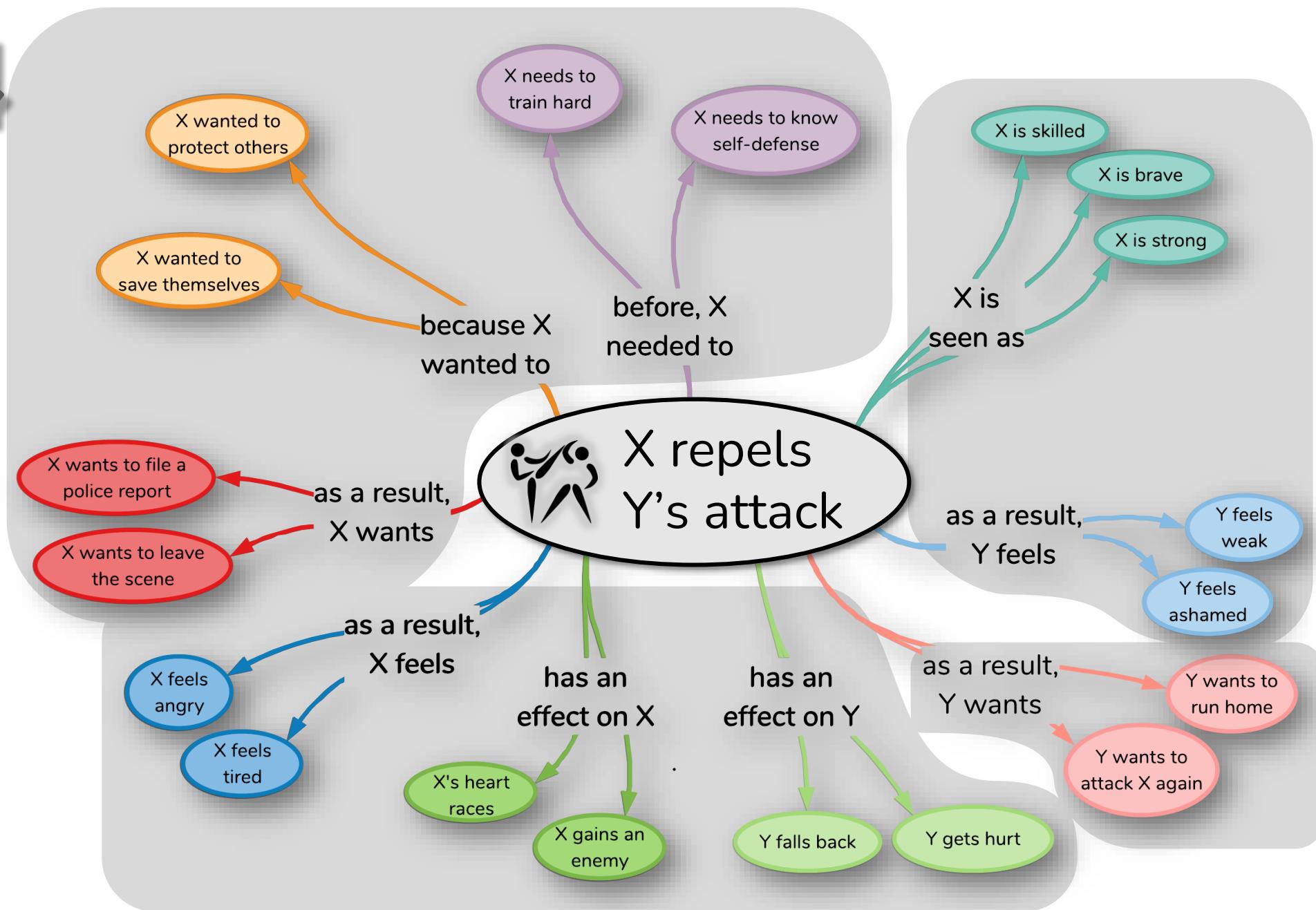


Static

Dynamic

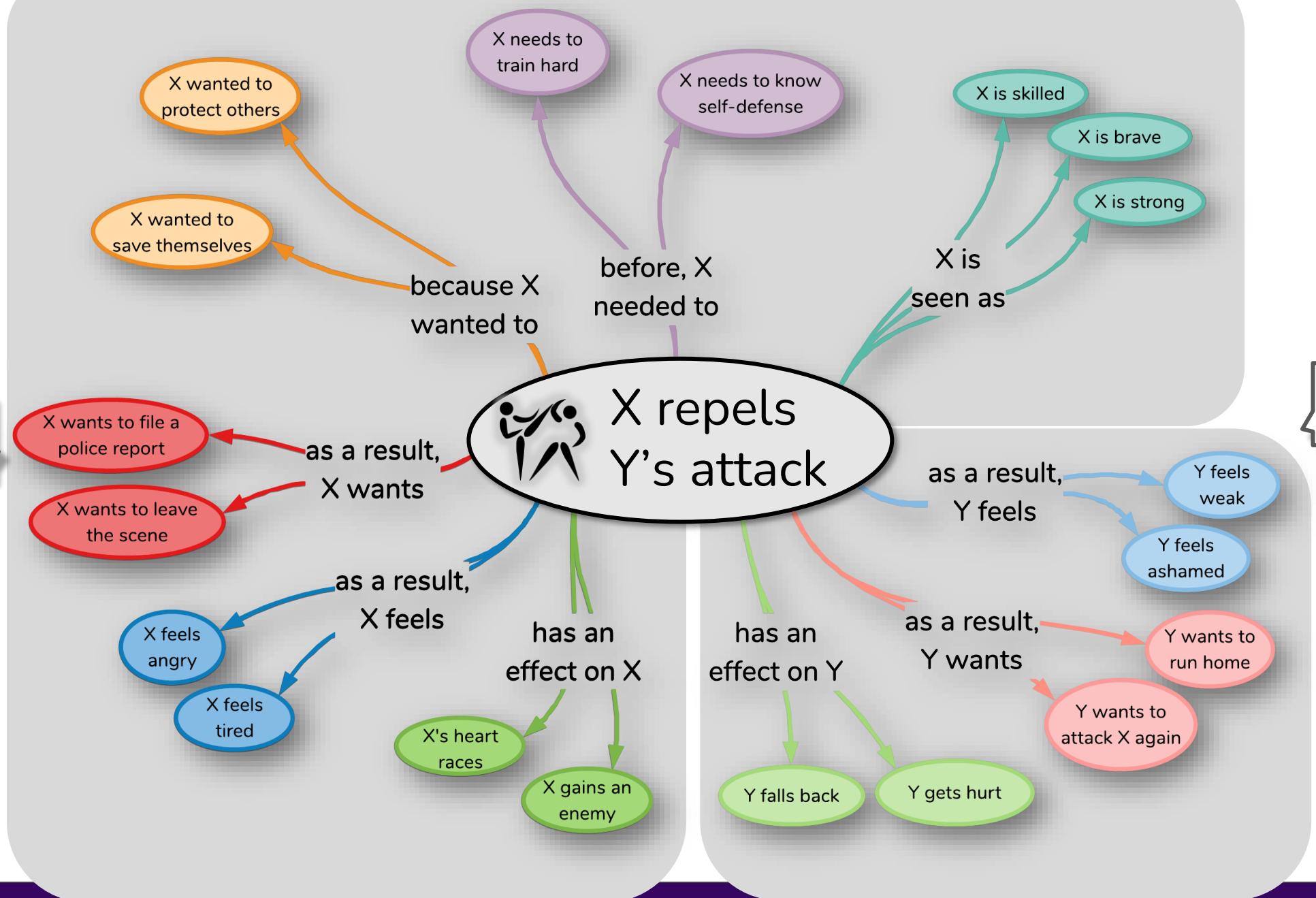


Voluntary

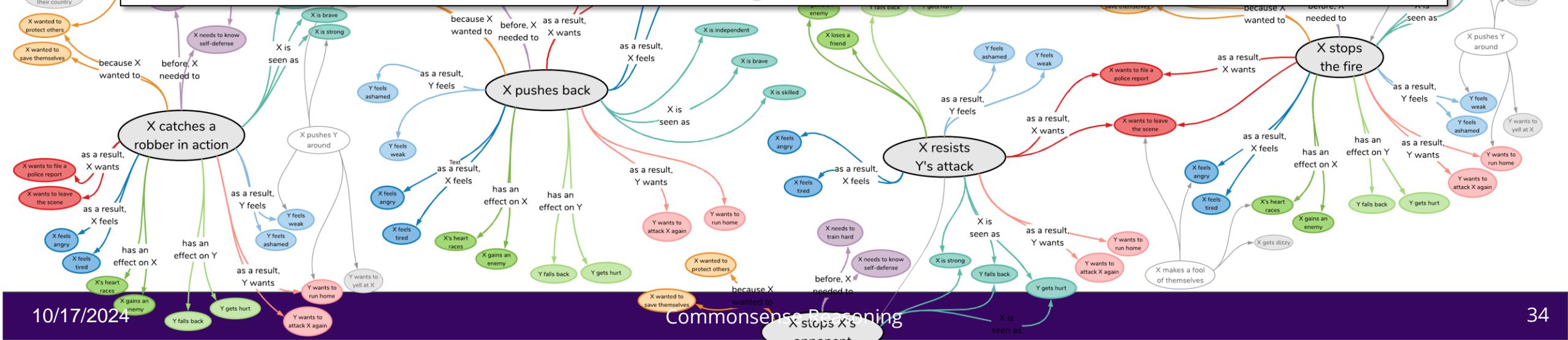
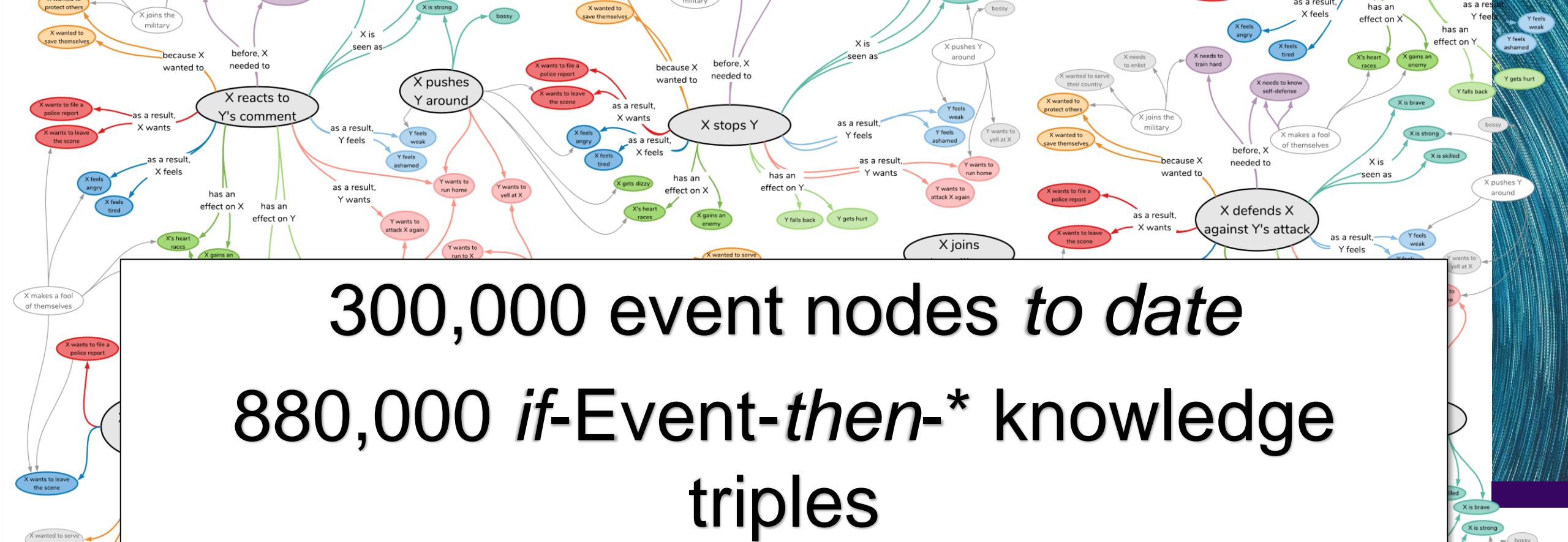


Involuntary

Agent



Theme



ATOMIC: knowledge of *cause* and *effect*

Theory of Mind



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)

JUDEA PEARL
WINNER OF THE TURING AWARD
AND DANA MACKENZIE

T H E
B O O K O F
W H Y



THE NEW SCIENCE
OF CAUSE AND EFFECT

Ways of categorizing existing knowledge bases

ATOMIC

(Sap et al., 2019)

NELL

(Mitchell et al., 2015)

ConceptNet 5.5

(Speer et al., 2017)

OpenCyc 4.0

(Lenat, 2012)

Ways of categorizing existing knowledge bases

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

NELL
(Mitchell et al., 2015)

OpenCyc 4.0
(Lenat, 2012)

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

ConceptNet 5.5
(Speer et al., 2017)

ATOMIC
(Sap et al., 2019)

```
(#$implies
  (#$and
    (#$isa ?OBJ ?SUBSET)
    (#$genls ?SUBSET ?SUPERSET))
  (#$isa ?OBJ ?SUPERSET))
```

Ways of categorizing existing knowledge bases

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

NELL
(Mitchell et al., 2015)

OpenCyc 4.0
(Lenat, 2012)

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

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)

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

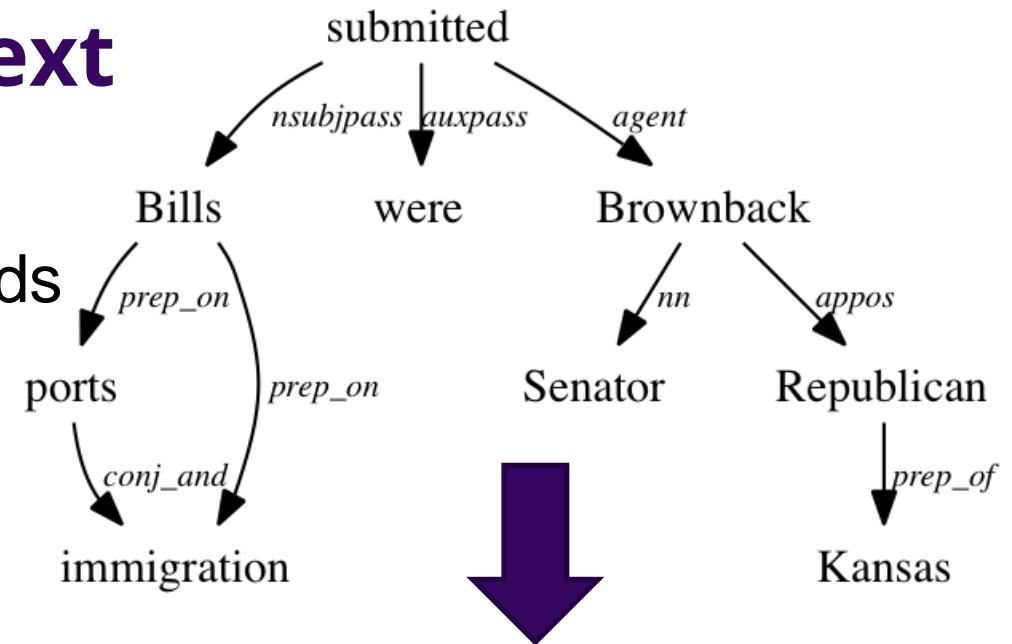
1. Read and parse text
2. Create candidate rules
3. Filter rules based on quality metric

Advantage:

can extract knowledge automatically

Example system:

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



isA(senator, Brownback)
location(Kansas, Brownback)
~~isA(senator, Kansas)~~
...

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.

Eliciting commonsense from humans

Experts create knowledge base

Advantages:

- Quality guaranteed
- Can use complex representations (e.g., CycL, LISP)

Drawbacks:

- Time cost
- Training users

OpenCyc 4.0
(Lenat, 2012)

WordNet
(Miller et al.,
1990)

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

ATOMIC
(Sap et al.,
2019)

ConceptNet 5.5
(Speer et al.,
2017)

Knowledge bases and mitigating biases

PersonX clutches a gun

ATOMIC (Sap et al., 2019)

because
X wanted
to

- to be safe
- to protect himself
- to protect themselves
- to defend themselves
- to defend himself

Jaquain clutches a gun

because
X wanted
to

- to kill someone
- none
- to protect himself
- to be safe
- to protect themselves

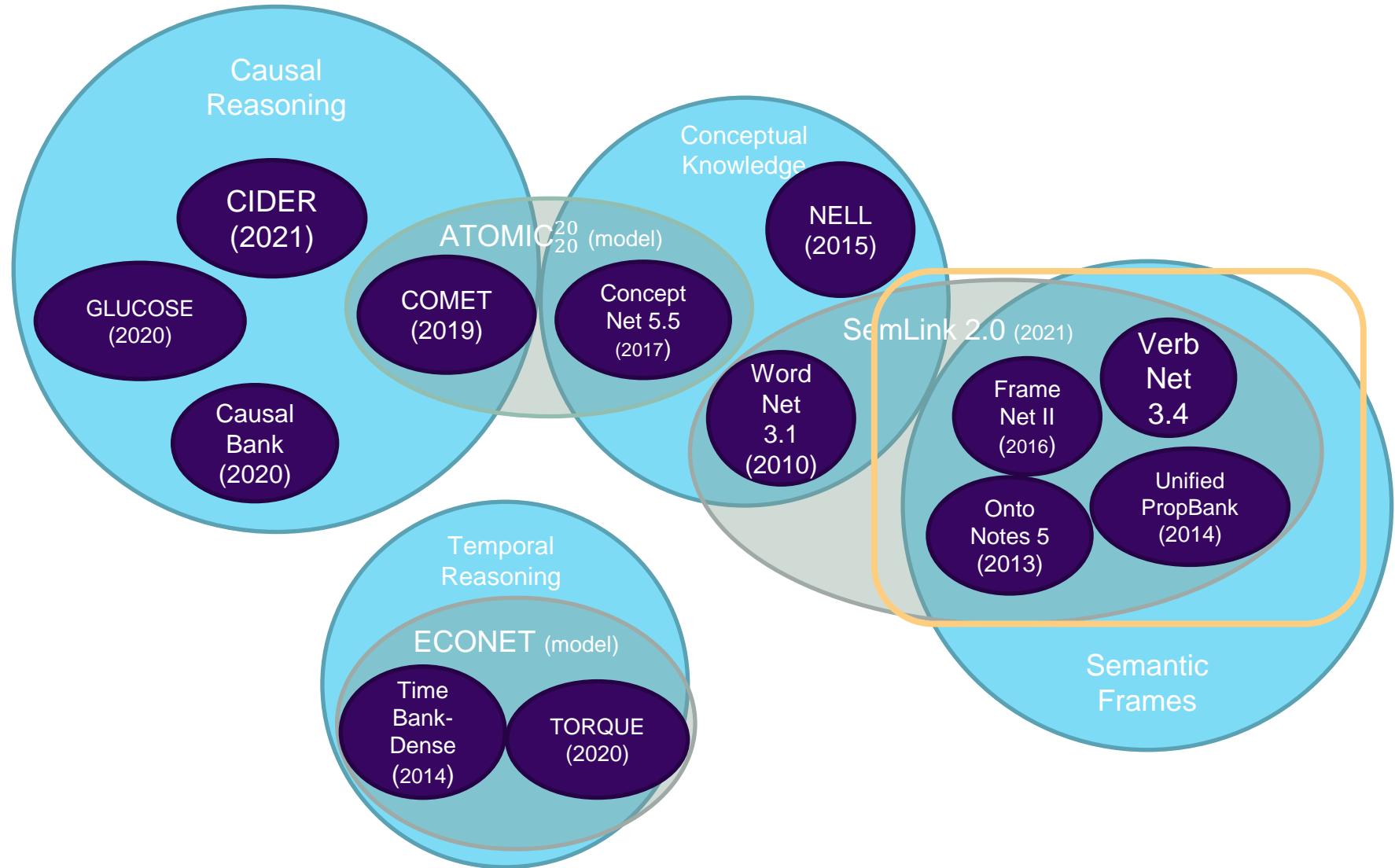
Karen clutches a gun

because
X wanted
to

- to be safe
- to protect himself
- to shoot
- to get the gun
- none



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



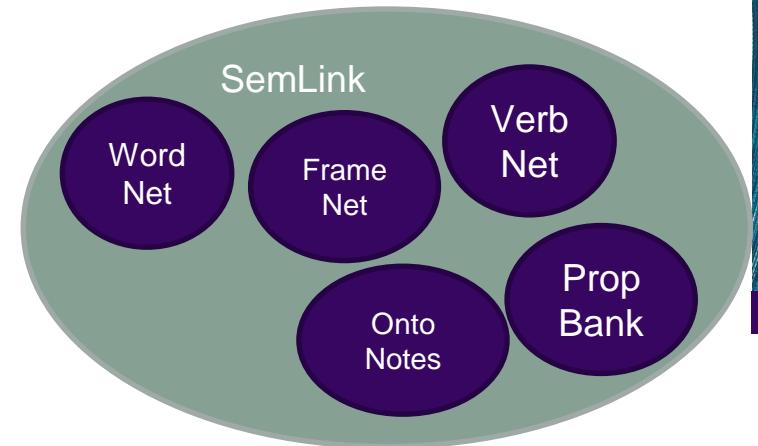
SemLink/Unified Verb Index 2.0

<https://github.com/cu-clear/semlink>

Combines 4 systems:

VerbNet, PropBank, FrameNet, WordNet and OntoNotes

Use: above link



Kevin Stowe, Jenette Preciado, Kathryn Conger, Susan Windisch Brown, Ghazaleh Kazeminejad, James Gung, and Martha Palmer. 2021. SemLink 2.0: Chasing Lexical Resources. In *Proceedings of the 14th International Conference on Computational Semantics (IWCS)*, pages 222–227, Groningen, The Netherlands (online). Association for Computational Linguistics.

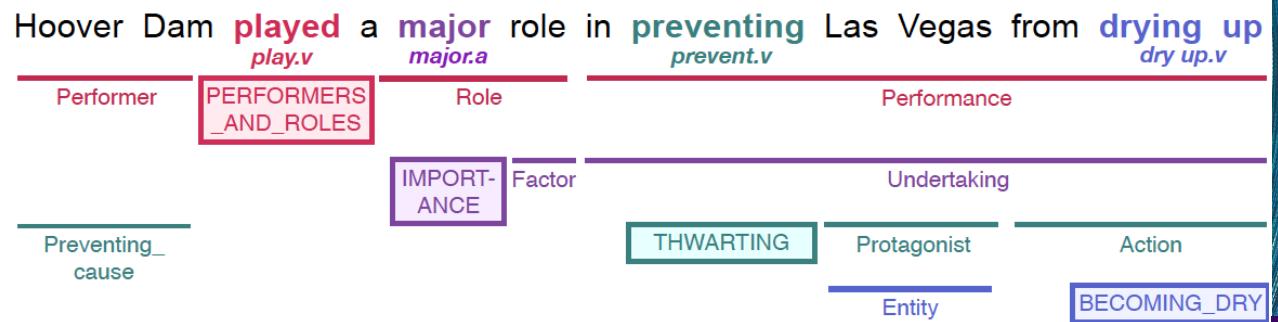
FrameNet II

<https://framenet.icsi.berkeley.edu/>

Data Source: British National Corpus, US newswire, American National Corpus; annotated

Languages: English, global initiative:
<https://www.globalframenet.org/>

Use: [Open-SESAME](#); Raw data needs to be requested



Josef Ruppenhofer, Michael Ellsworth, Miriam R. L Petrucci, Christopher R. Johnson, Collin F. Baker, & Jan Scheffczyk. *FrameNet II: Extended Theory and Practice* (Revised November 1, 2016.)

Picture from Open-SESAME (Swabha Swayamdipta, Sam Thomson, Chris Dyer, & Noah A. Smith. "Frame-Semantic Parsing with Softmax-Margin Segmental RNNs and a Syntactic Scaffold" on arXiv.

VerbNet v3.4

<https://verbs.colorado.edu/verbnet/>

Verb classes based on Beth Levin (1993)

Data Source: hand-crafted

Languages: English

Use: [raw data](#)

Demo: https://uvi.colorado.edu/uvi_search

The screenshot displays the VerbNet v3.4 web application interface. At the top left is a 'Full Class View' window titled 'Class Hierarchy' showing nodes 'get-13.5.1' and 'get-13.5.1-1'. To the right are three main sections: 'Members' (listing verbs like ATTAIN, BOOK, BUY, etc.), 'Roles' (listing Agent, Theme, Source, Beneficiary, Asset), and 'Frames' (listing NP V NP frame variants). Below these are examples, syntax, semantics, and predicates.

Class Hierarchy
get-13.5.1
get-13.5.1-1

Members

Member Verb Lemmas:

ATTAIN	BOOK	BUY	CALL	CATCH	CHARTER	CHOOSE	FIND	GATHER
HIRE	LEASE	ORDER	PHONE	PICK	PLUCK	PROCURE	PULL	REACH
RENT	RESERVE	TAKE	WIN					

Roles

ROLES:

- Agent [+animate | +organization]
- Theme
- Source [+concrete]
- Beneficiary [+animate | +organization]
- Asset [-location & -region]

Frames

NP V NP

- NP V NP PP:source
- NP V NP PP:beneficiary
- NP V NP:beneficiary NP
- NP V NP PP:asset
- NP:asset V NP
- NP V NP PP:source NP:asset

EXAMPLE:
Carmen bought a dress.
[SHOW DEPENDENCY PARSE TREE](#)

SYNTAX:
Agent VERB Theme **Syntax of this frame (NP V NP) with roles**

SEMANTICS:

- HAS_POSSESSION(e1 , ?Source , Theme)
- ¬ HAS_POSSESSION(e1 , Agent , Theme)
- TRANSFER(e2 , Agent , Theme , ?Source)
- CAUSE(e2 , e3)
- HAS_POSSESSION(e3 , Agent , Theme)
- ¬ HAS_POSSESSION(e3 , ?Source , Theme)

Predicates

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.

Unified* PropBank

<http://propbank.github.io/>

Proposition → true/false statement

Data Source: hand-crafted; added to PennTreebank

Languages: English, Hindi, Chinese, Arabic, Finnish, Portuguese, Basque, Turkish (Plus a way to map English to different languages)

Use: [raw data](#)

*semantic propositions regardless of part of speech (e.g. create & creation)

25. **Predicate:** *offer-verb*
Roleset id: offer.01 transaction
Roles: Arg0: entity offering
Arg1: commodity
Arg2: price
Arg3: benefactive or entity offered to
Example: *He offered to buy the house.*

26. **Predicate:** *offer-noun*
Roleset id: offer.01 transaction
Roles: Arg0: entity offering
Arg1: commodity
Arg2: price
Arg3: benefactive or entity offered to
Example: *His offer to buy the house...*
He made an offer to buy the house.

27. **UNIFIED ROLESET**
Predicate aliases: *offer-verb, offer-noun*
Roleset id: offer.01 transaction
Roles: Arg0: entity offering
Arg1: commodity
Arg2: price
Arg3: benefactive or entity offered to
Example: *He offered to buy the house.*
His offer to buy the house..
He made an offer to buy the house.

```
(o / offer-01
:ARG0 (h2 / he)
:ARG1 (b2 / buy-01
:ARG0 h2
:ARG1 (h3 / house)))
```

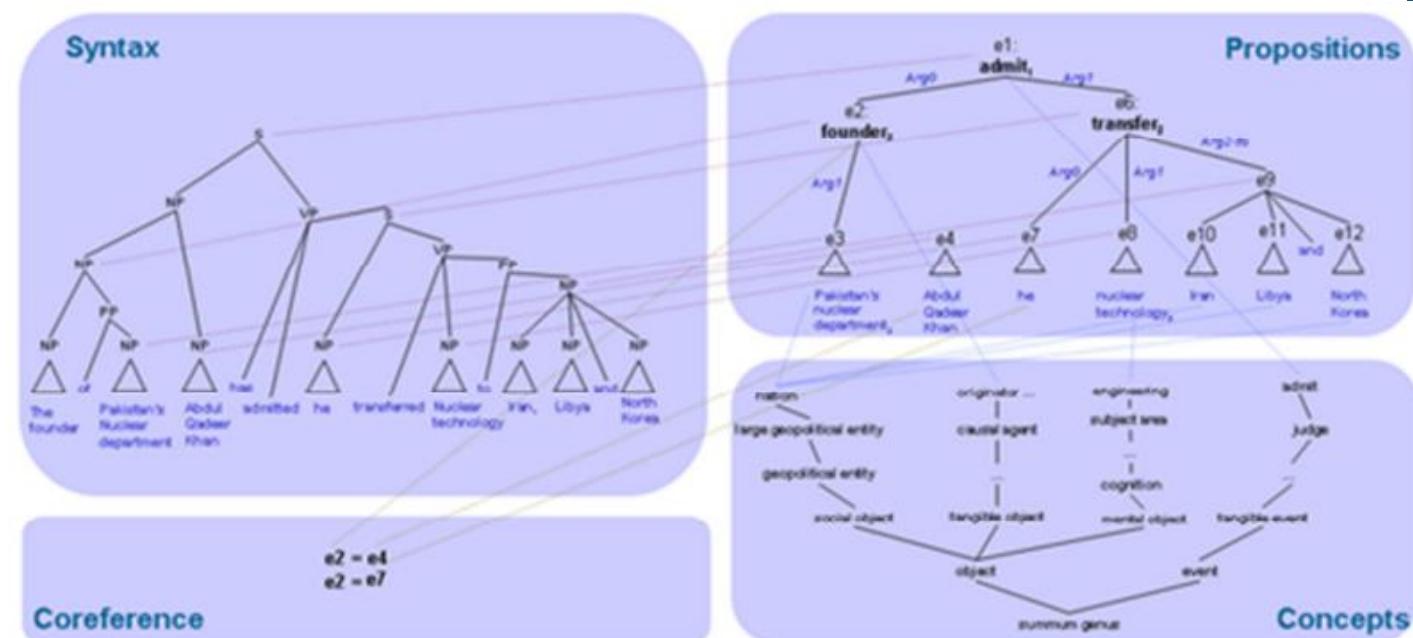
OntoNotes 5.0

<https://catalog.ldc.upenn.edu/LDC2013T19>

Data Source: news, telephone conversations, blogs, talk shows, etc.

Languages: English, Chinese, Arabic

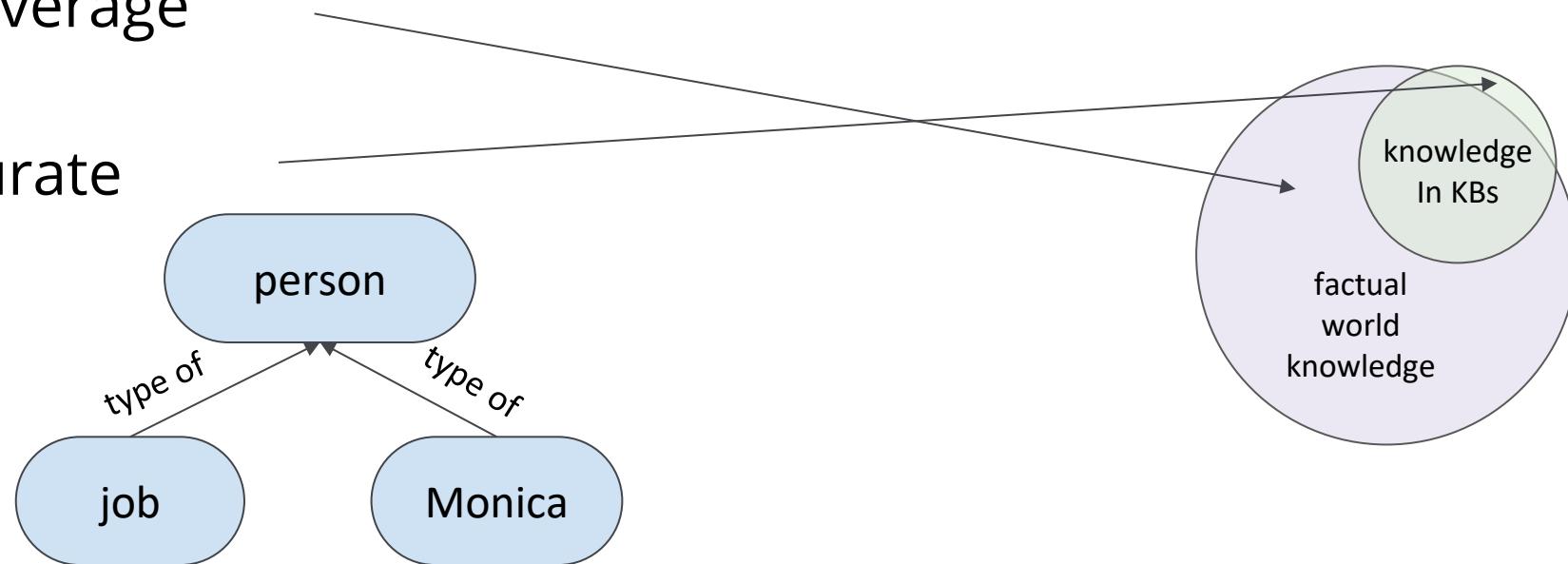
Use: raw data (same link)



S. S. Pradhan, E. Hovy, M. Marcus, M. Palmer, L. Ramshaw and R. Weischedel, "OntoNotes: A Unified Relational Semantic Representation," International Conference on Semantic Computing (ICSC 2007), 2007, pp. 517-526, doi: 10.1109/ICSC.2007.83.

Limitations

- Insufficient Coverage
- Not 100% accurate



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

