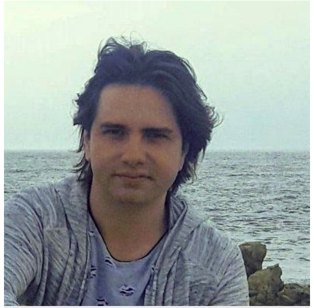
Commonsense Knowledge Graphs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Agenda

08:00 PST	1 hr 50 mins	**Part I - Review of CSKGs**
	15 min	Introduction to commonsense knowledge (slides) - Pedro
	25 min	Review of top-down commonsense knowledge graphs (slides) - Mayank
	70 min	Review of bottom-up commonsense knowledge graphs (slides+demo) - Mayank, Filip, Pedro
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	15 min	Wrap-up (slides) - Mayank

Introduction to commonsense knowledge

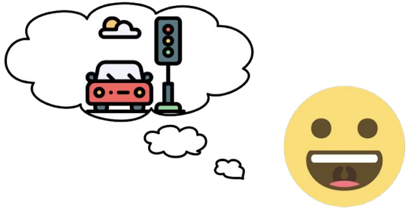
Pedro Szekely

What Is Common Sense?

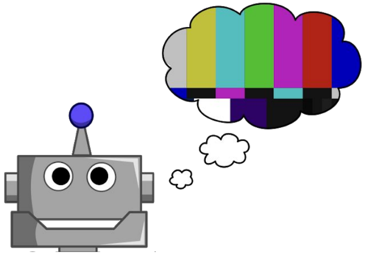
Common sense is sound practical judgement concerning everyday matters,

or a basic ability to perceive, understand, and judge that is shared by ("common to") nearly all people.

Wikipedia



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

For example, it's ok to keep the closet door open,
but it's not ok to keep the fridge door open,
as the food inside might go bad.

Slide by Yejin Choi

Humans reason about the world with **mental models** [Graesser, 1994]

Personal experiences

[Conway et al., 2000]

World knowledge

[Kintsch, 1988]

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World knowledge

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A Common Sense Task

Input: a set of common concepts

dog | frisbee | catch | throw

Output: a sentence using these concepts

https://inklab.usc.edu/CommonGen/

A Common Sense Task

Input: a set of common concepts

Output: a sentence using these concepts

dog | frisbee | catch | throw

[Humans]

- A dog leaps to catch a thrown frisbee.
- The dog catches the frisbee when the boy throws it.
- A man throws away his dog 's favorite frisbee expecting him to catch it in the air.

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A Common Sense Task

Input: a set of common concepts

Output: a sentence using these concepts

dog | frisbee | catch | throw

[Humans]

- A dog leaps to catch a thrown frisbee.
- The dog catches the frisbee when the boy throws it.
- A man throws away his dog 's favorite frisbee expecting him to catch it in the air.

[Machines]

GPT2: A dog throws a frisbee at a football player.

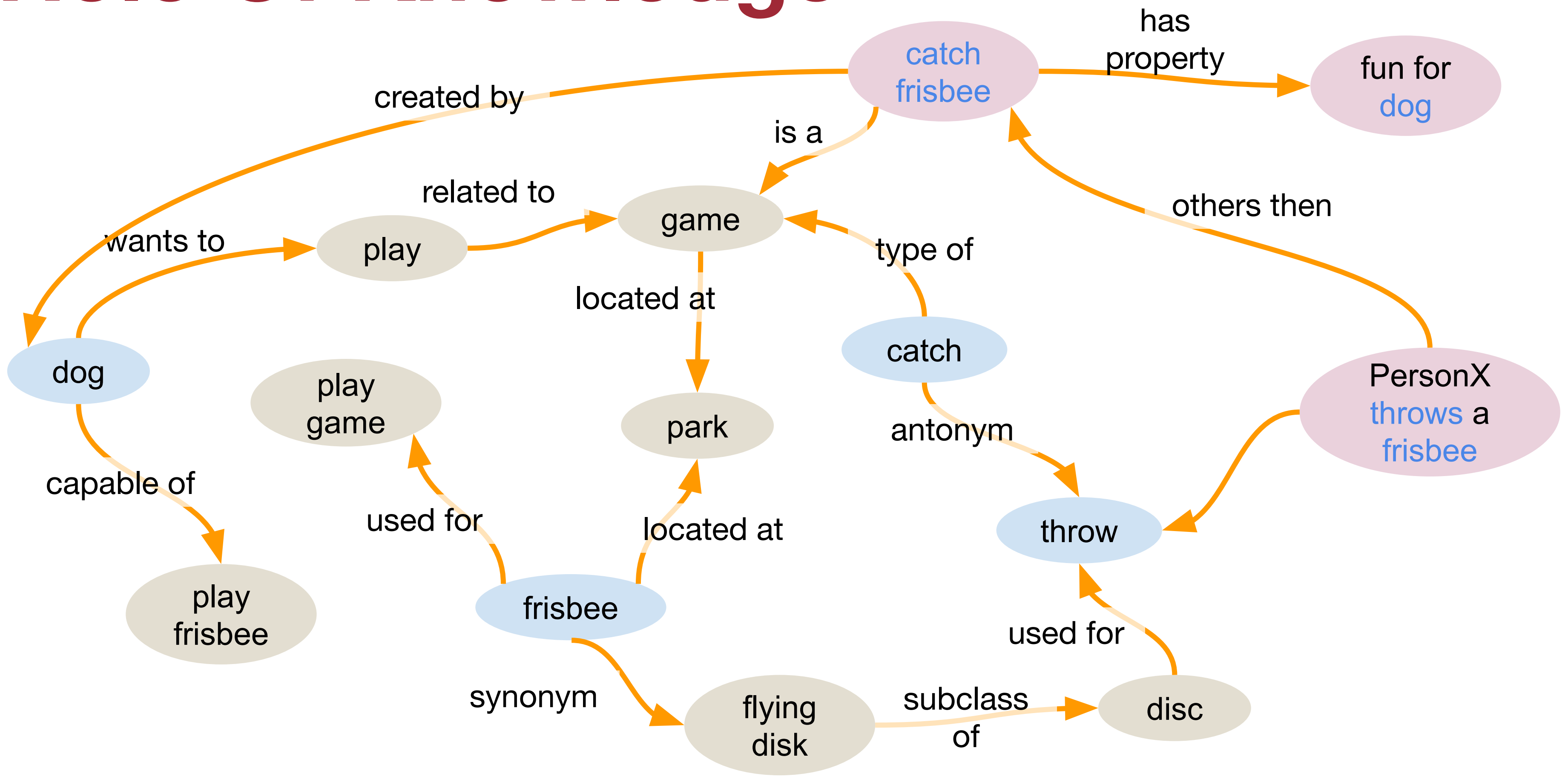
UniLM: Two dogs are throwing frisbees at each other .

BART: A dog throws a frisbee and a dog catches it.

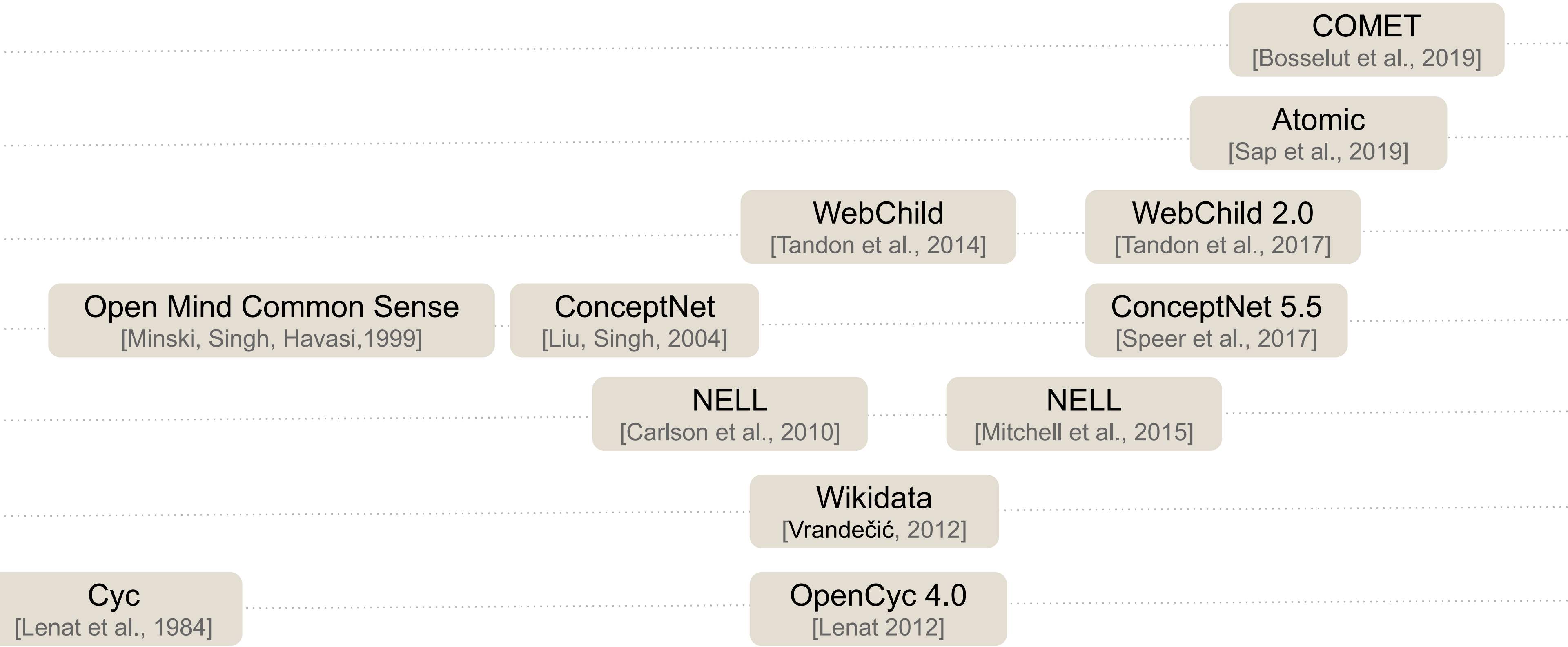
T5: dog catches a frisbee and throws it to a dog

https://inklab.usc.edu/CommonGen/

Role Of Knowledge



Common Sense Knowledge Graphs



Dimensions Of Common Sense Knowledge

Representation

- symbolic
- natural language
- neural

Creation method

- expert input
- crowdsourcing
- information extraction, machine learning

Knowledge type

- entities and actions
- inferential/rules

Topic

- general
- social

COMET

Atomic

WebChild

ConceptNet

NELL

Wikidata

OpenCyc

Representation Method

Representation

- symbolic: frisbee, dog
- natural language: "PersonX throws a frisbee"
- neural: <black box>

Creation method

- expert input
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Creation Method

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Knowledge Type

Representation

- symbolic
- natural language
- neural

Creation method

- expert input
- crowdsourcing
- information extraction, machine learning

Knowledge type

- entities and actions: frisbee, dog, throw, catch
- inferential/rules:
  PersonX throws frisbee, as a result
  others then, catches frisbee

Topic

- general
- social

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Topic

Representation

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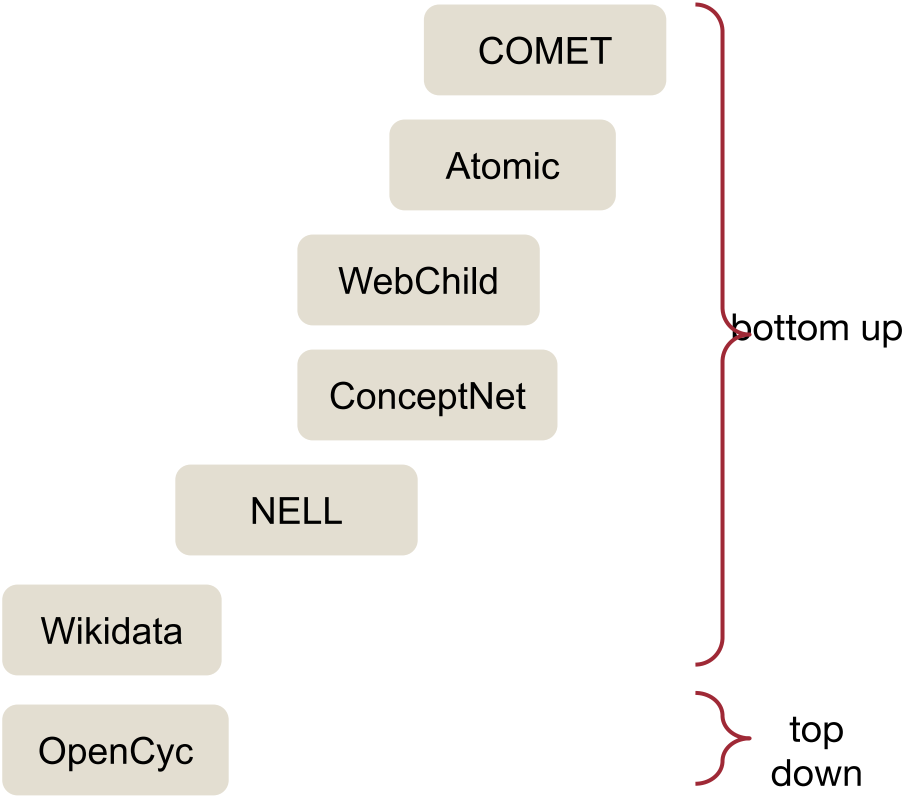
Design Approach

Representation
- symbolic
- natural language
- neural

Creation method
- expert input
- crowdsourcing
- information extraction, machine learning

Knowledge type
- entities and actions
- inferential/rules

Topic
- general
- social



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Review of top-down commonsense knowledge graphs

Mayank Kejriwal

Why is top-down knowledge necessary?

"In Artificial intelligence, commonsense knowledge is the set of background information that an individual is intended to know or assume and the ability to use it when appropriate."

Argument: This knowledge cannot be acquired simply through text (or in an otherwise 'inductive' fashion)

Some important concepts necessary in a top-down CSKG

- Scales, time, spaces and dimension, material, causal connections, (in other domains) force, shape, systems and functionality, hitting, abrasion, wear (and related concepts)
- Competency vs. coverage theories
- Naive physics vs. psychology theories

All reasoning (ultimately) depends on axioms...

What are the ‘axioms’ of commonsense ‘psychology’?

This is a controversial question

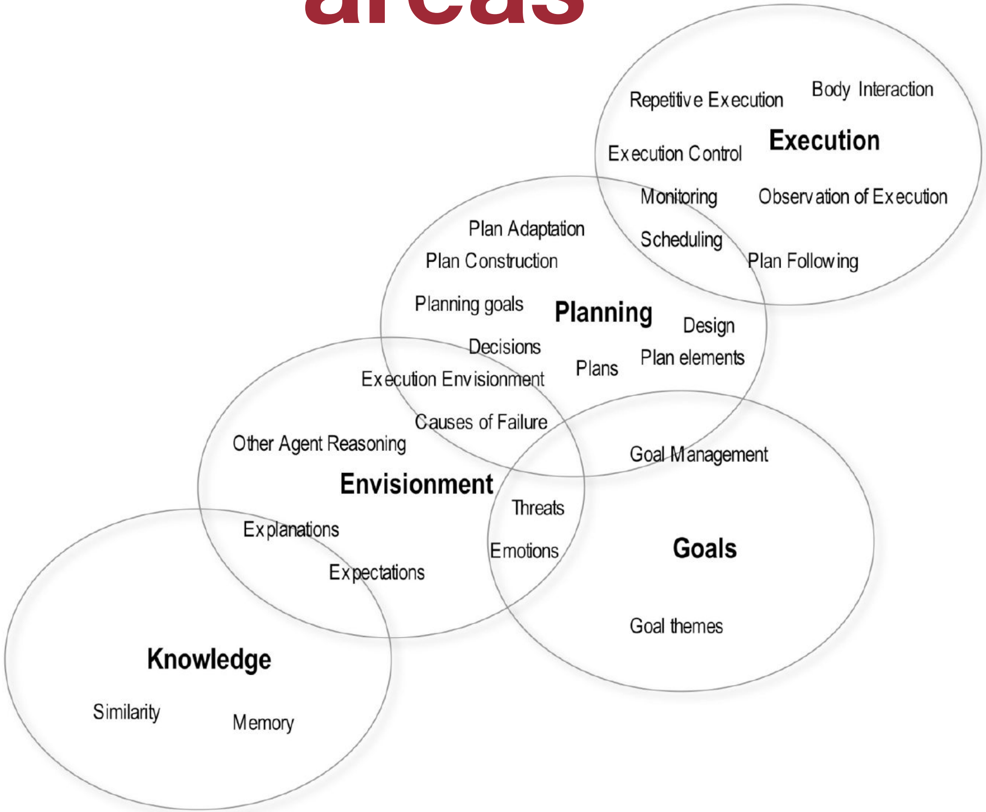
A more fruitful approach might be to understand the ‘representational areas’ of commonsense psychology (Gordon and Hobbs, 2004)

30 representational areas

Gordon (2001a) noted that there is an interesting relationship between concepts that participate in commonsense psychology theories and planning strategies

Described 30 representational areas by studying planning strategy

Taxonomy of 30 representational areas



Examples of representational areas

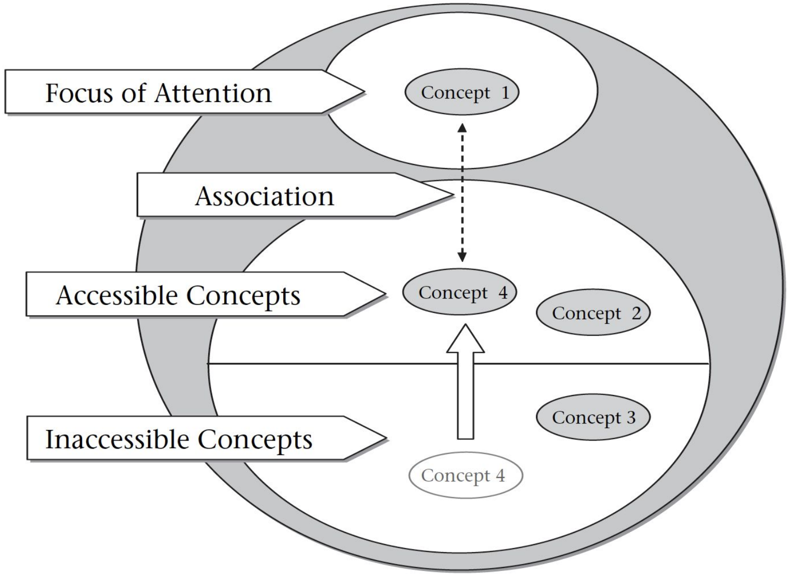
Explanations: the process of generating satisfying explanations for effects that have unknown causes

Similarity Comparison: the mental process of making comparisons and drawing analogies in order to find similarities and differences

Managing knowledge: concepts of knowledge, belief, assumptions, justifications and the mental processes that manipulate these concepts in reasoning

Example of 'theory': Accessibility by association

- Memory retrieval by association is well-known in psychology
- 'Encode' it as a theory by defining appropriate predicates and concepts



‘Encoding knowledge’ of commonsense psychology

Not an easy problem, reminiscent of ‘expert system’ era

Two eventualities e_1 and e_2 are “causally linked” in a set of “causally involved” relations if there is a chain of relations in s between e_1 and e_2, regardless of direction.

$$
\begin{aligned}
&(\forall\, e1, e_2, s)[\mathit{causally\text{-}linked}(e_1, e_2, s) \\
&\quad \equiv [(\exists\, r)[\mathit{causally\text{-}involved}'(r, e_1, e_2) \wedge \mathit{member}(r, s)] \\
&\quad\quad \vee (\exists\, r)[\mathit{causally\text{-}involved}'(r, e_2, e_1) \wedge \mathit{member}(r, s)] \\
&\quad\quad \vee (\exists\, e_3, r)[[\mathit{causally\text{-}involved}'(r, e_1, e_3) \vee [\mathit{causally\text{-}involved}'(r, e_3, e_1)] \\
&\quad\quad\quad\quad \wedge \mathit{member}(r, s) \wedge \mathit{causally\text{-}linked}(e_3, e_2, s - \{r\}]]]
\end{aligned}
$$

Open question how we can encode such knowledge in a way that makes it robust to noisy or incomplete data

Some more examples (belief in goals)

It will be useful below to state that if one believes he or she has a goal, then defeasibly he or she really does have the goal. Though not always true, we are usually pretty reliable about knowing what we want.

```
(forall (e e1 a)
   (if (and (goal' e e1 a)(believe a e))
       (Rexist e)))
```

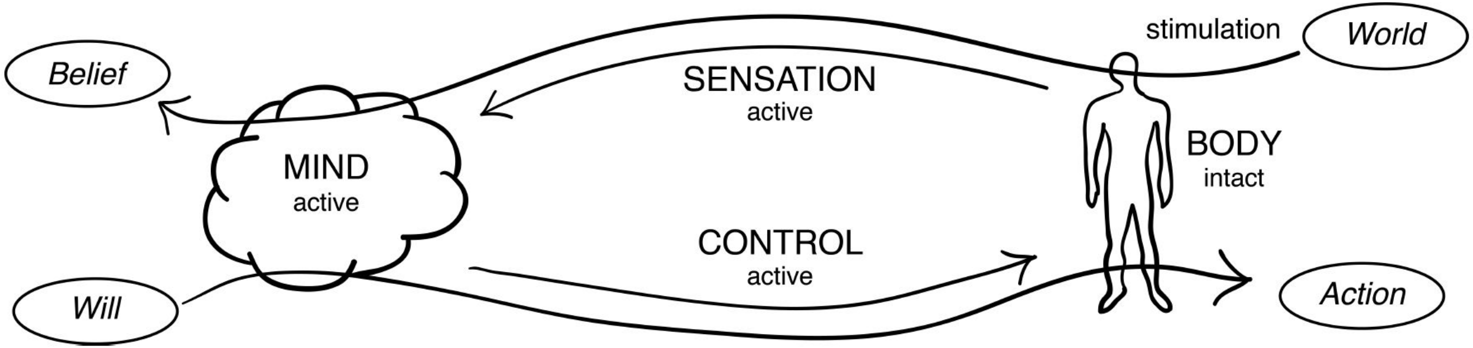
However, it is possible for an agent to have a goal without knowing it.

Some more examples (trying, succeeding and failing)

When we try to bring about some goal, we devise at least a partial plan to achieve it, including subgoals of the original goal which are actions on our part, and we execute some of those subgoals. Moreover, our executing those actions is a direct result of our having those actions as subgoals. We can take this as a definition of “trying”.

```
(forall (e a e1)
   (iff (try’ e a e1)
        (exist (e0 e2 e3 e4)
           (and (goal e1 a)(subgoal’ e3 e2 e1 a)
                (instanceOf e4 e2)(Rexist’ e0 e4)
                (agentOf a e4)(cause e3 e0)(gen e e0)))))
```

Other representational work



A person has a body and a mind.

```
(forall (p)                                    (1)
 (if (person p)
  (exists (b m)
   (and (body b p)
    (mind m p)))))
```

Bodies are intact, damaged, or destroyed.

```
(forall (b p)                                  (2)
 (if (body b p)
  (xor (intact b)
   (damaged b)
    (destroyed b)))))
```

Minds are active, impaired, or inactive.

```
(forall (m p)                                  (3)
 (if (mind m p)
  (xor (active m)
   (impaired m)
    (inactive m)))))
```

AI Magazine Volume 6 Number 4 (1985) (© AAAI)

CYC: Using Common Sense Knowledge to Overcome Brittleness and Knowledge Acquisition Bottlenecks

Doug Lenat, Mayank Prakash, & Mary Shepherd

Microelectronics & Computer Technology Corporation, 9430 Research Boulevard, Austin, Texas 78759

The major limitations in building large software have always been (a) its brittleness when confronted by problems that were not foreseen by its builders, and (b) the amount of manpower required. The recent history of expert systems, for example, highlights how constricting the brittleness and knowledge acquisition bottlenecks are. Moreover, standard software methodology (*e.g.*, working from a detailed "spec") has proven of little use in AI, a field which by definition tackles ill-structured problems.

How can these bottlenecks be widened? Attractive, elegant answers have included machine learning, automatic programming, and natural language understanding. But decades of work on such systems (Green *et al.*, 1974; Lenat *et al.*, 1983; Lenat & Brown, 1984; Schank & Abelson, 1977) have convinced us that each of these approaches has difficulty "scaling up" for want of a substantial base of real world knowledge.

Making AI Programs More Flexible

> [Expert systems'] performance in their specialized domains are often very impressive. Nevertheless, hardly any of them have certain commonsense knowledge and ability possessed by any non-feeble-minded human. This lack makes them "brittle." By this is meant that they are difficult to expand beyond the scope originally contemplated by their designers, and they usually do not recognize their own limitations. Many important applications will require commonsense abilities... Common-sense facts and methods are only very partially understood today, and extending this understanding is the key problem facing artificial intelligence. — John McCarthy, 1983, p. 129.

We would like to thank MCC and our colleagues there and elsewhere for their support and useful comments on this work. Special thanks are due to Woody Bledsoe, David Bridgeland, John Seely Brown, Al Clarkson, Kim Fairchild, Ed Feigenbaum, Mike Genesereth, Ken Haase, Alan Kay, Ben Kuipers, John McCarthy, John McDermott, Tom Mitchell, Nils Nilsson, Elaine Rich, and David Wallace

How do people flexibly cope with unexpected situations? As our specific "expert" knowledge fails to apply, we draw on increasingly more general knowledge. This general knowledge is less powerful, so we only fall back on it reluctantly.

"General knowledge" can be broken down into a few types. First, there is real world factual knowledge, the sort found in an encyclopedia. Second, there is common sense, the sort of knowledge that an encyclopedia would assume the reader knew without being told (*e.g.*, an object can't be in two places at once).

Abstract

MCC's CYC project is the building, over the coming decade, of a large knowledge base (or KB) of real world facts and heuristics and—as a part of the KB itself—methods for efficiently reasoning over the KB. As the title of this article suggests, our hypothesis is that the two major limitations to building large intelligent programs might be overcome by using such a system. We briefly illustrate how common sense reasoning and analogy can widen the knowledge acquisition bottleneck. The next section ("How CYC Works") illustrates how those same two abilities can solve problems of the type that stymie current expert systems. We then report how the project is being conducted currently: its strategic philosophy, its tactical methodology, and a case study of how we are currently putting that into practice. We conclude with a discussion of the project's feasibility and timetable.

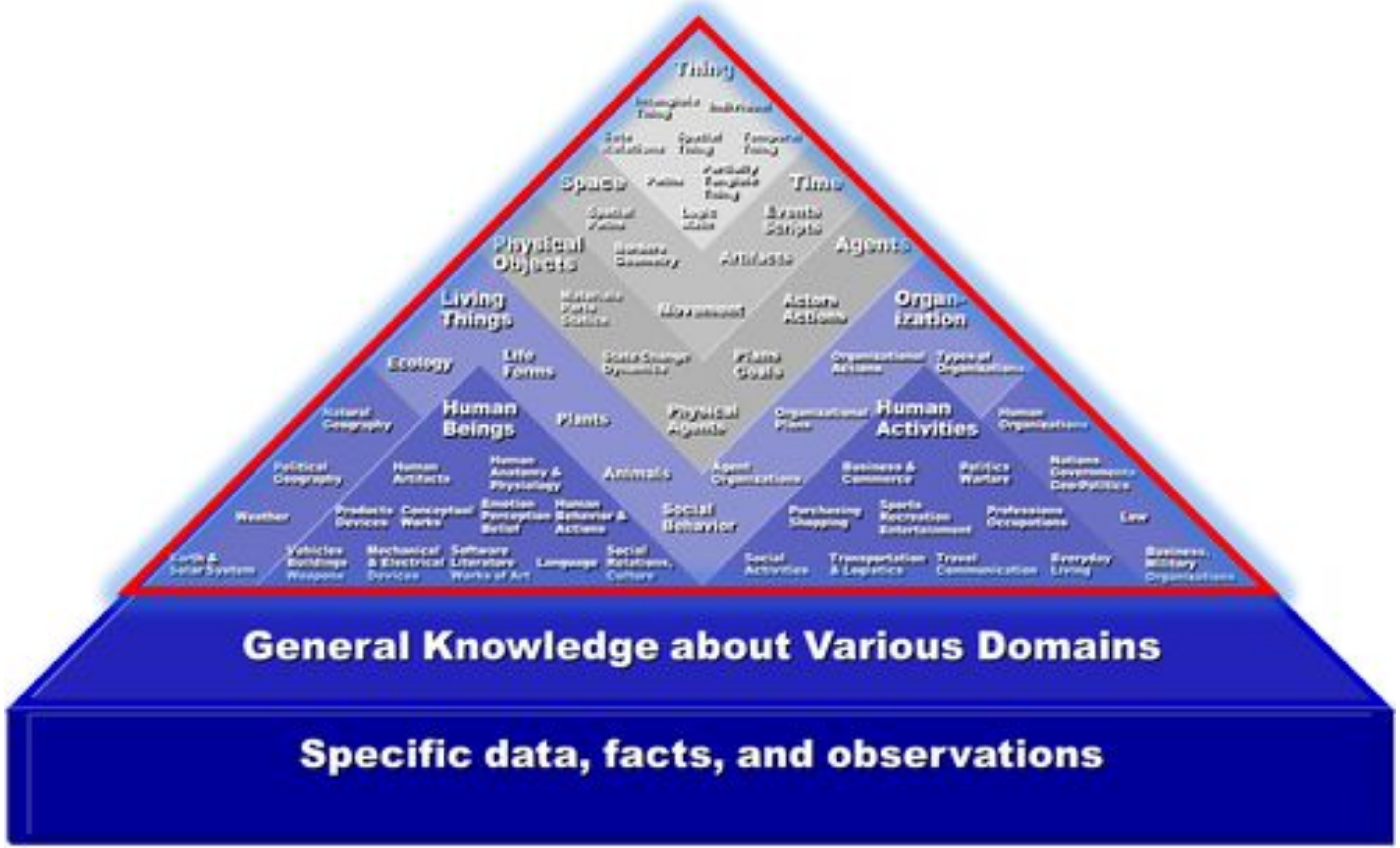
What is Cyc?

- Very large, multi-contextual knowledge base and inference engine.
- Founded in 1984 by Stanford professor Doug Lenat (president and founder of the Cycorp, Inc.).

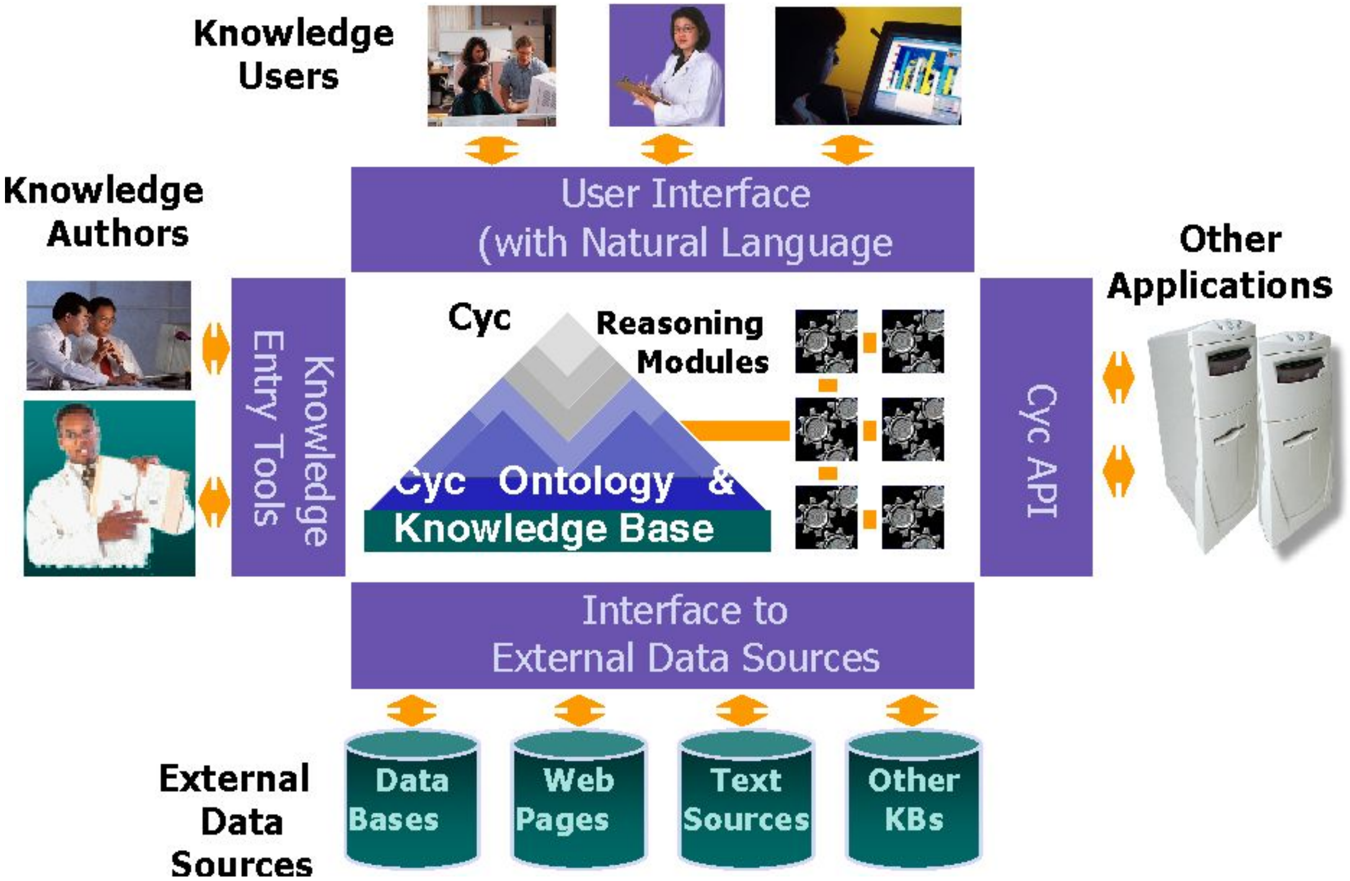
cYcorp

- What is the objective of Cyc?
  - to assemble an comprehensive ontology and Knowledge Base of common sense knowledge.
  - to codify, in machine-usable form, millions of pieces of knowledge that comprise human common sense.
  - Example:
    - "Every tree is a plant" && "Plants eventually die" from which we can infer "All trees die".

Example of a ‘top-down’ CSKG: Cyc



Evolution of Cyc



Limitations of top-down CSKGs

- Many of the same issues that other top-down systems (including, famously, expert systems) have, such as brittleness, expense of acquisition…
- When does work in AI stop, and work in philosophy and psychology begin?
- Even if it were possible, we can never get away from language models completely

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Review of bottom-up commonsense knowledge graphs: ConceptNet

Mayank Kejriwal

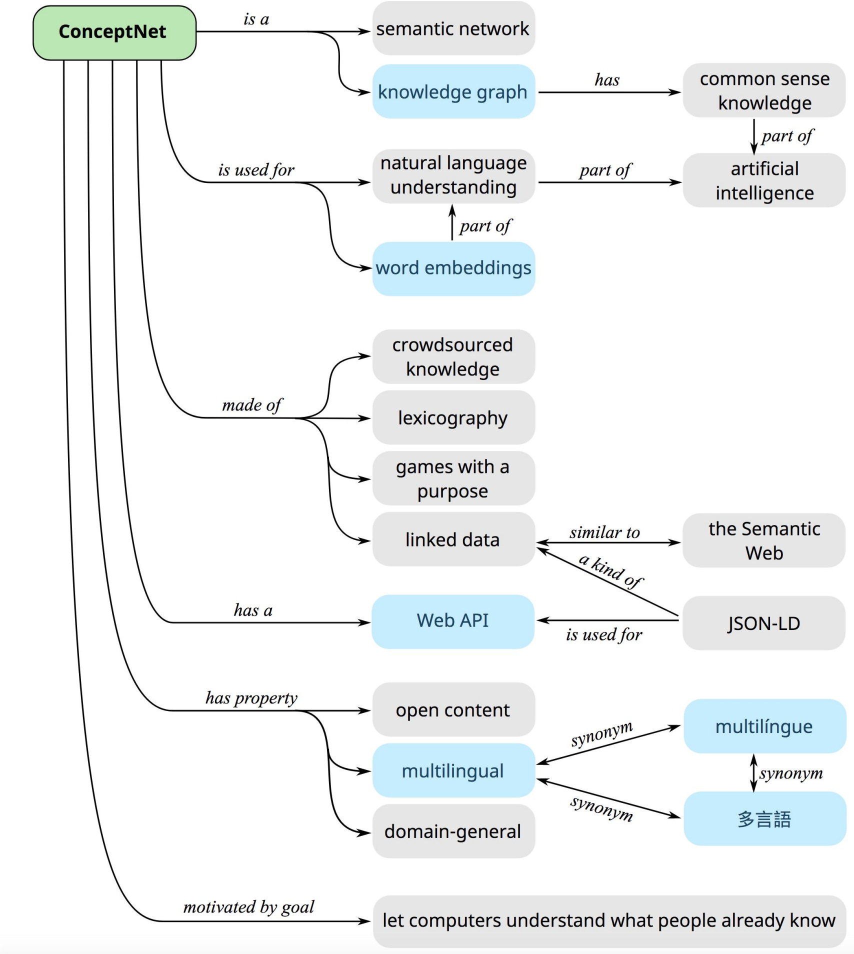
ConceptNet: An introduction

"a freely-available **semantic network**, designed to help computers understand the meanings of words that people use"

"an open, multi-lingual **knowledge graph**"

https://www.conceptnet.io/

The many faces of ConceptNet



Sources of knowledge

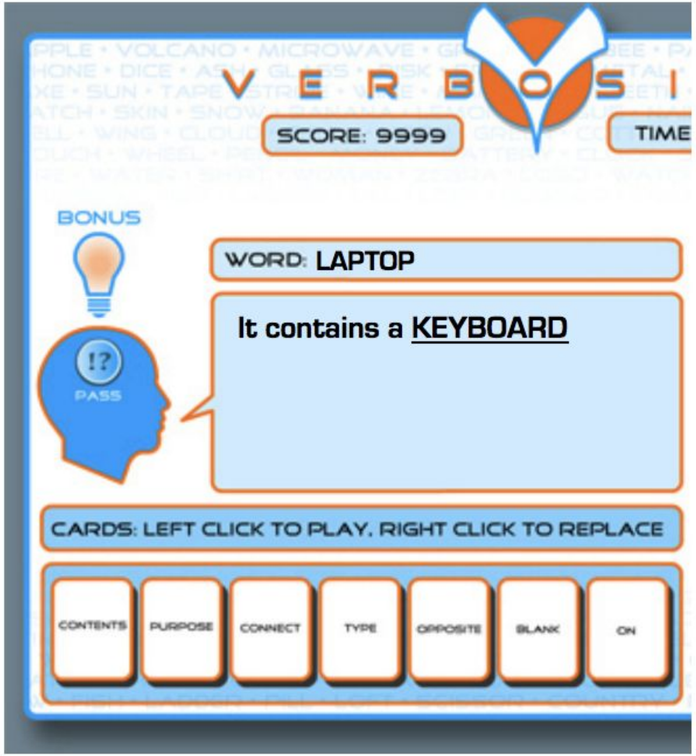
- Similar to previous versions, relational knowledge contributed to Open Mind Common Sense and its sister projects in other languages
- Subset of DBpedia
- Wiktionary (a dominant source)
  - Dictionary-style information also used from Open Multilingual WordNet
- High-level ontology from OpenCyc

Human-generated knowledge: Games with a purpose (GWAP)

“multi-player online game that is designed to be fun and accomplish tasks that are easy for humans but beyond the capability of today's computers.”

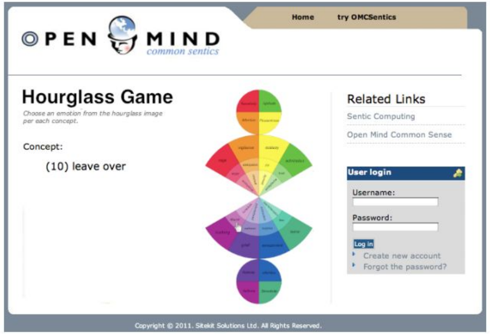
https://www.cmu.edu/homepage/computing/2008/summer/games-with-a-purpose.shtml

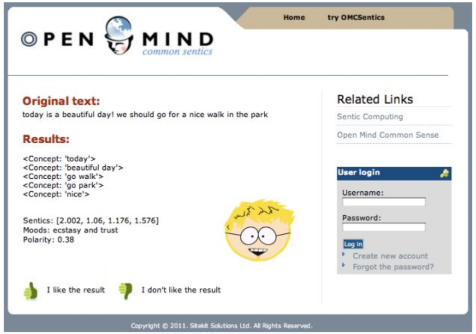
Example: Verbosity

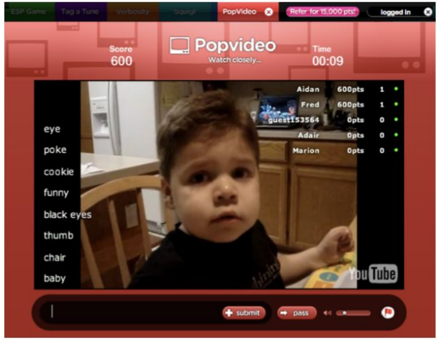


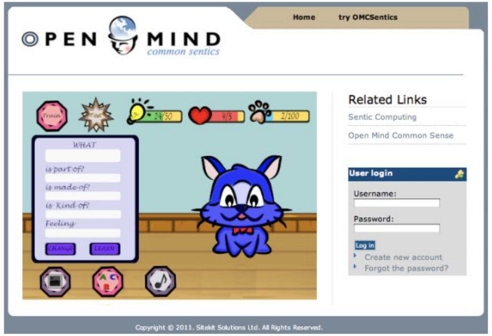
https://www.cs.cmu.edu/~biglou/Verbosity.pdf

Lesson: GWAPs are useful for acquiring crowdsourcing CS acquisition









Accessing ConceptNet

- ConceptNet has a Linked Open Data API
    - Available as JSON-LD
- ExternalURL links in ConceptNet are used to fulfill LD Principle 4
    - Linked to several other vocabularies, including WordNet, DBPedia, and OpenCyc
- API documentation: https://github.com/commonsense/conceptnet5/wiki/API


```
@id:            "/a/[/r/UsedFor/,/c/en/example/,/c/en/explain/]"
dataset:        "/d/conceptnet/4/en"
end:
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  label:        "explain something"
  language:     "en"
  term:         "/c/en/explain"
license:        "cc:by/4.0"
rel:
  @id:          "/r/UsedFor"
  label:        "UsedFor"
sources:
  0:
    activity:     "/s/activity/omcs/omcs1_possibly_free_text"
    contributor:  "/s/contributor/omcs/pavlos"
start:
  @id:          "/c/en/example"
  label:        "an example"
  language:     "en"
  term:         "/c/en/example"
surfaceText:    "You can use [[an example]] to [[explain something]]"
weight:         1
@context:
  0:            "//api.conceptnet.io/ld/conceptnet5.7/context.ld.json"
  1:            "//api.conceptnet.io/ld/conceptnet5.7/pagination.ld.json"
```
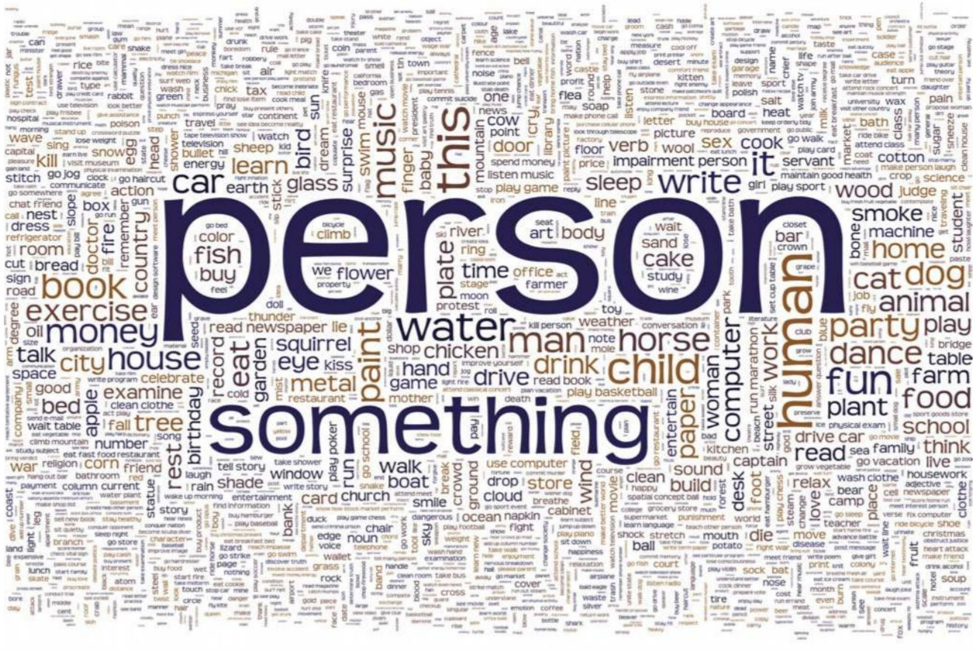

With all this knowledge...

- **Why not use it to understand the nature of commonsense knowledge?**
- **Key idea: Analyzing ConceptNet using a rigorous methodology can enable data-driven understanding of concepts like ‘context’ and ‘negation’**

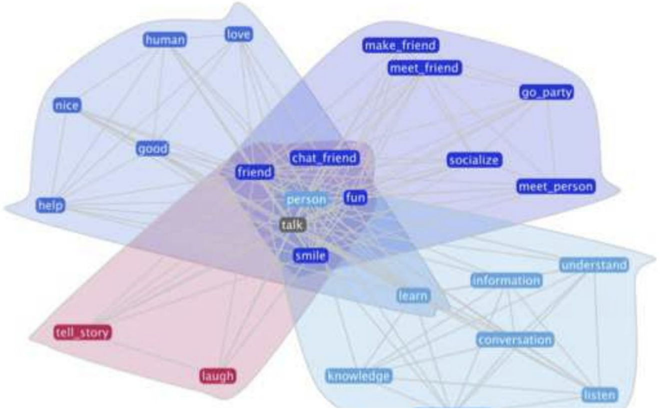
Early work

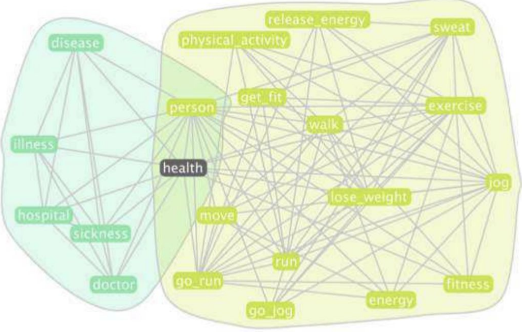
- In 2013, a report showed what we would expect from inductively derived KGs like ConceptNet: inconsistency
- Structural analysis showed that some concepts are much more frequent than others



More recent work: using ConceptNet to study 'context'

- What is context and why is it important?
- We used PBG for getting KG embeddings on a 4 million-triples sample, and Fit-SNE for visualizations



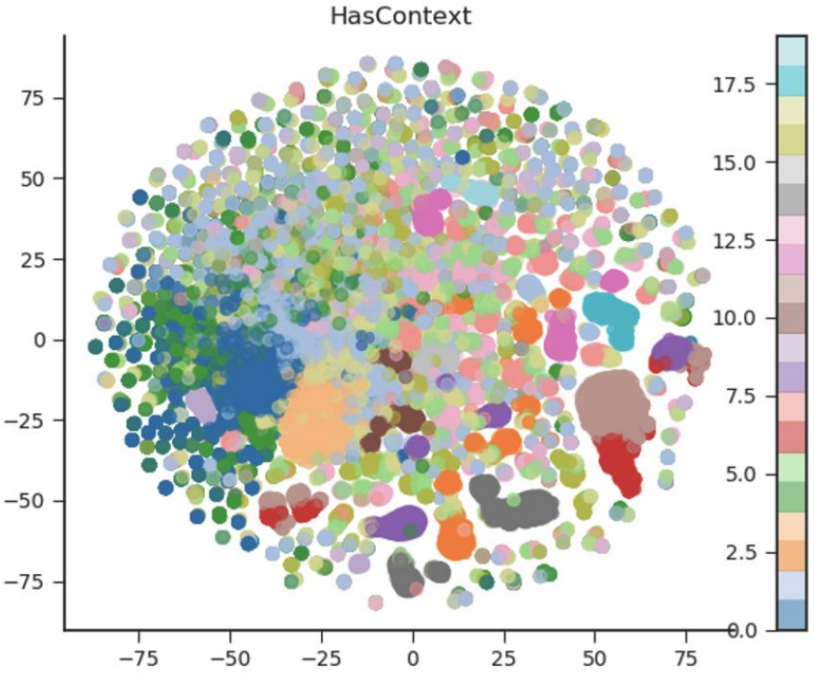


Findings: HasContext sub-structures

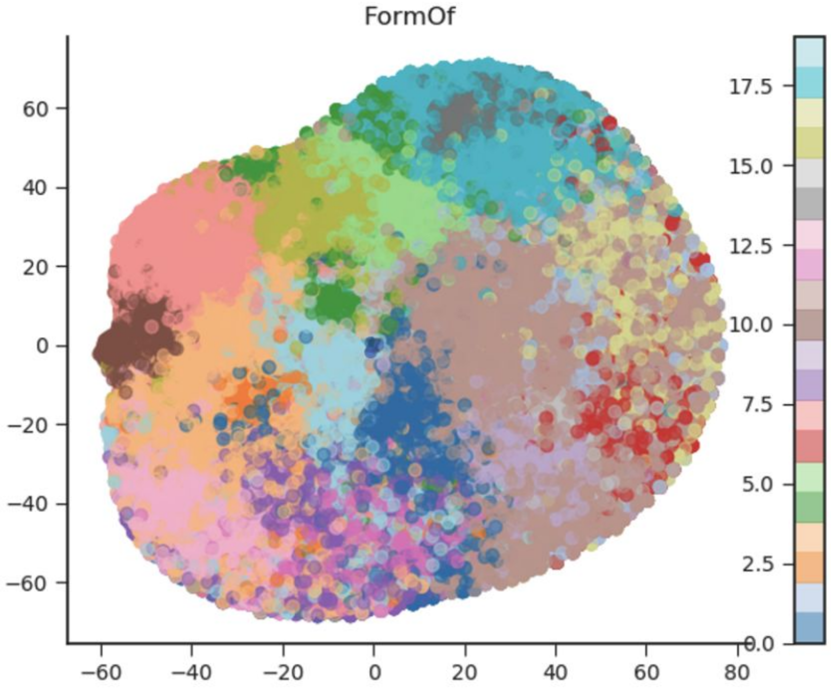
Example triples from two ‘obvious’ clusters (1 and 6)

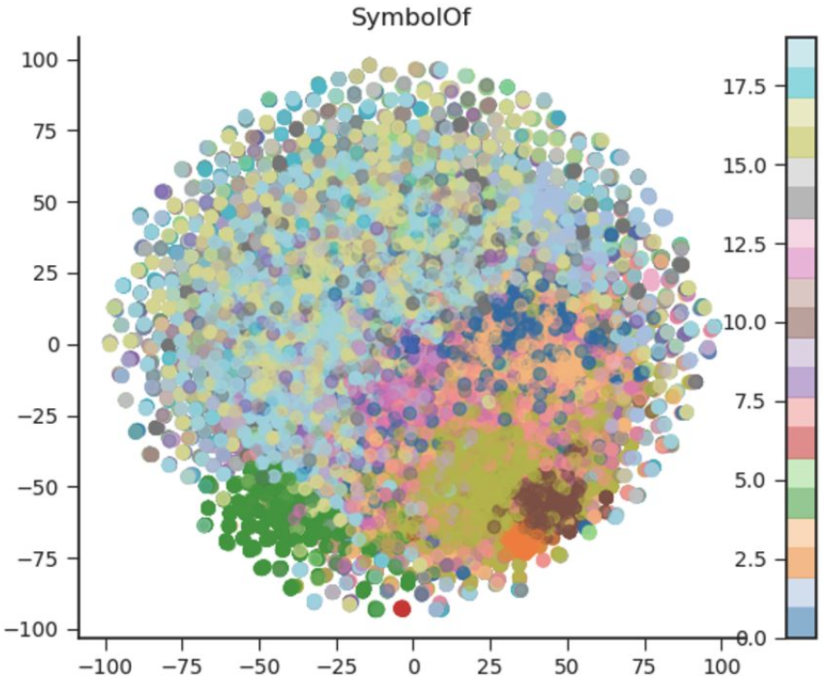
1	/c/fr/sapide/a	/c/en/literary
	/c/hu/szir?n/n	/c/en/literary
	/c/ga/eo/n/wikt/en_3	/c/en/literary
	/c/af/elk/n	/c/en/literary
	/c/ga/gair/v/wikt/en_1	/c/en/literary

6	/c/en/azodicarbonamide/n	/c/en/chemistry
	/c/en/ricinoleate/n	/c/en/chemistry
	/c/fi/rikkiyhdiste/n	/c/en/chemistry
	/c/en/test/v/wikt/en_1	/c/en/chemistry
	/c/en/vinyl_acetate/n	/c/en/chemistry



Similar results



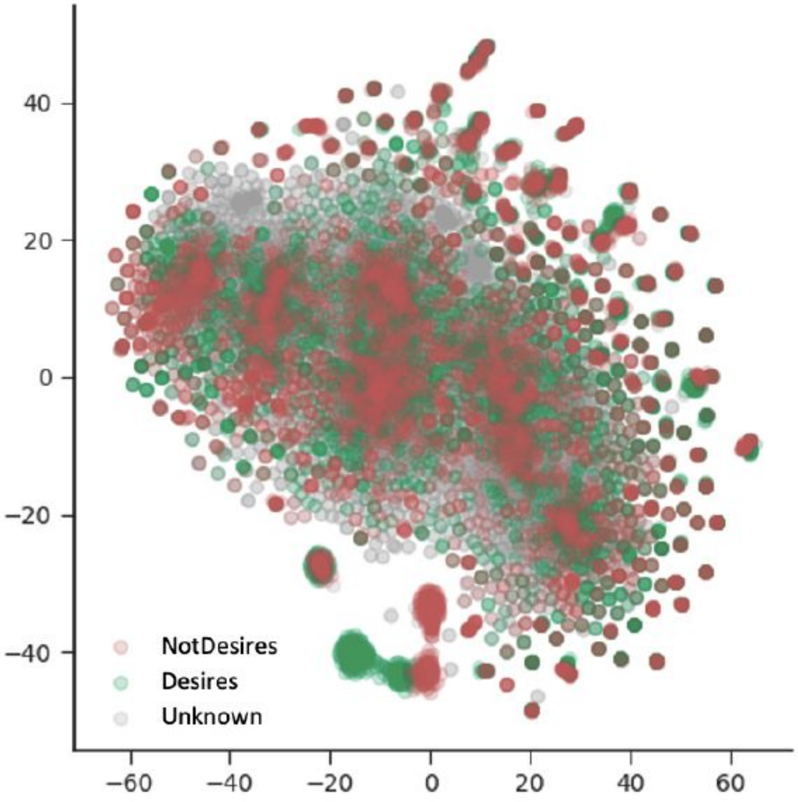


Another experiment: Understanding ‘negation’

- Can we distinguish between a relation, its negation and its ‘unknowns’ in a visual space?
- What if we train a classifier on the embeddings?

Results (Desires/NotDesires)

- Answer to the first question is no, though 'unknowns' are more distinctive
- Answer to the second question is yes
- May help explain why language models don't (or can't) do well on negation tasks without extra work



Review of bottom-up commonsense knowledge graphs: Other KGs

Filip Ilievski

ATOMIC:
inferential knowledge in *natural language* form

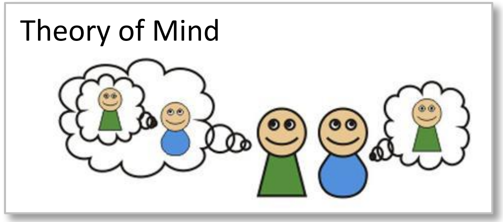
https://mosaickg.apps.allenai.org/kg_atomic

Slides adapted from Sap et al. https://homes.cs.washington.edu/~msap/acl2020-commonsense/

Knowledge of causes and effects

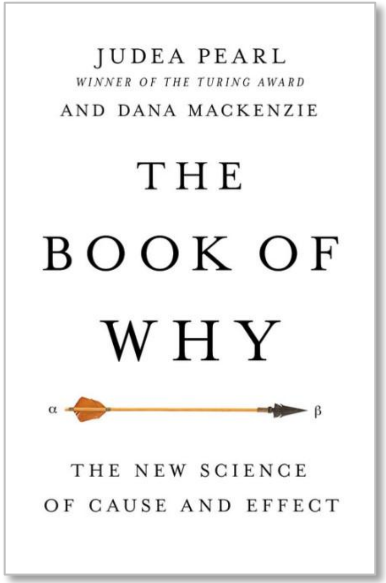
- Humans have **theory of mind**, allowing us to
  - make inferences about **people's mental states**
  - understand **likely events** that precede and follow

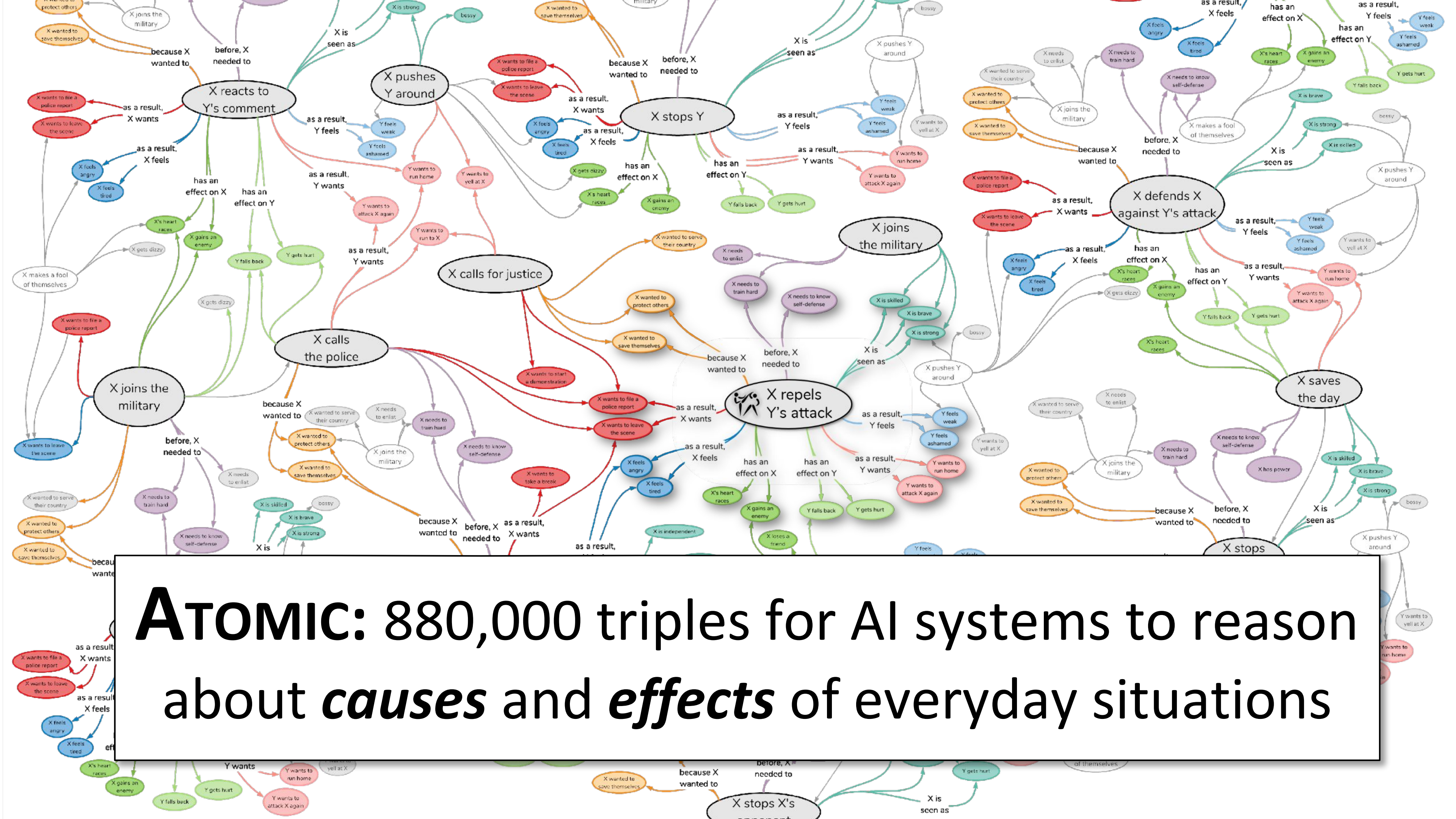
    (Moore, 2013)



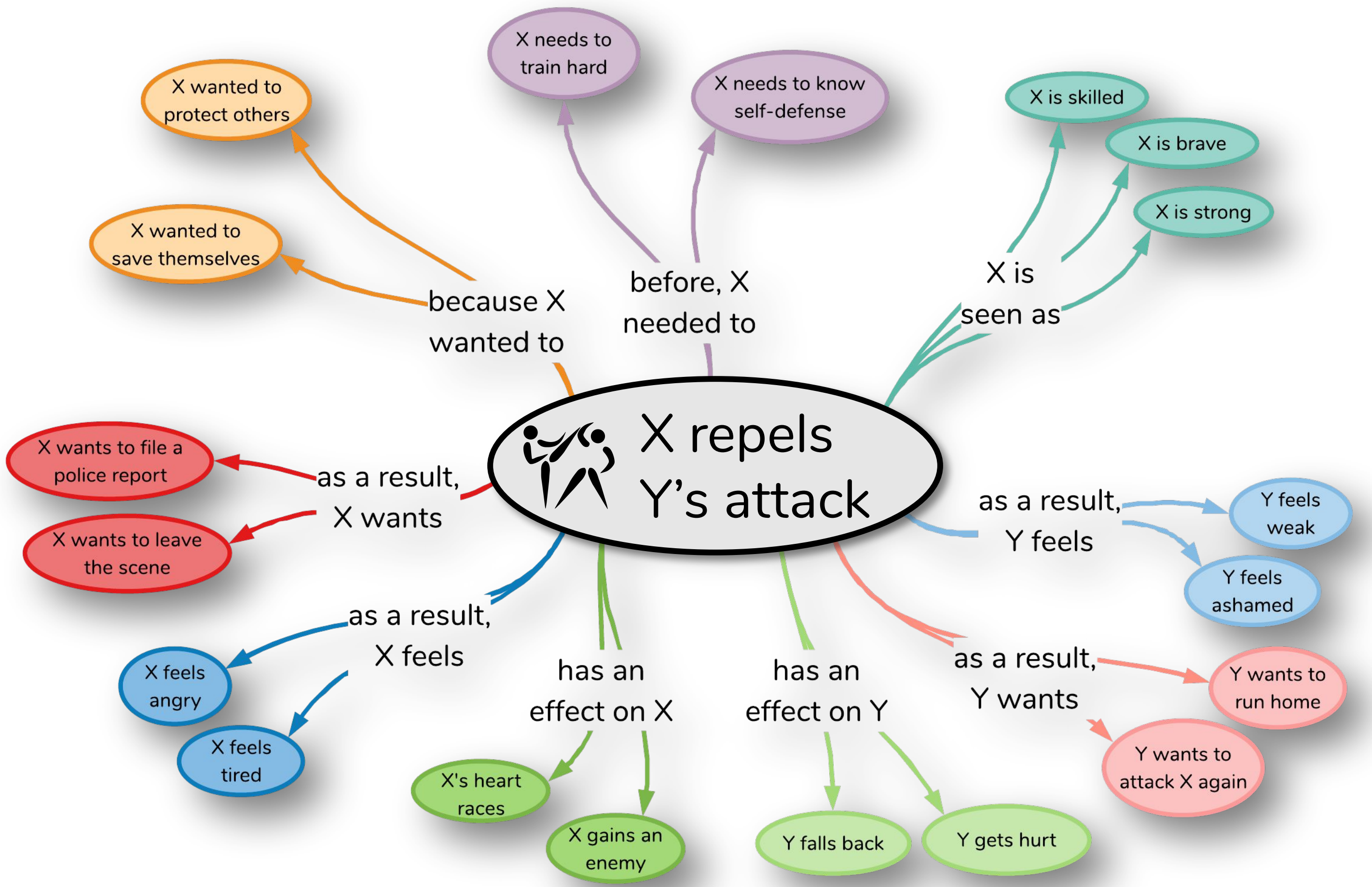
- AI systems struggle with ***inferential*** reasoning
  - only find **complex correlational patterns** in data
  - **limited to the domain** they are trained on

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

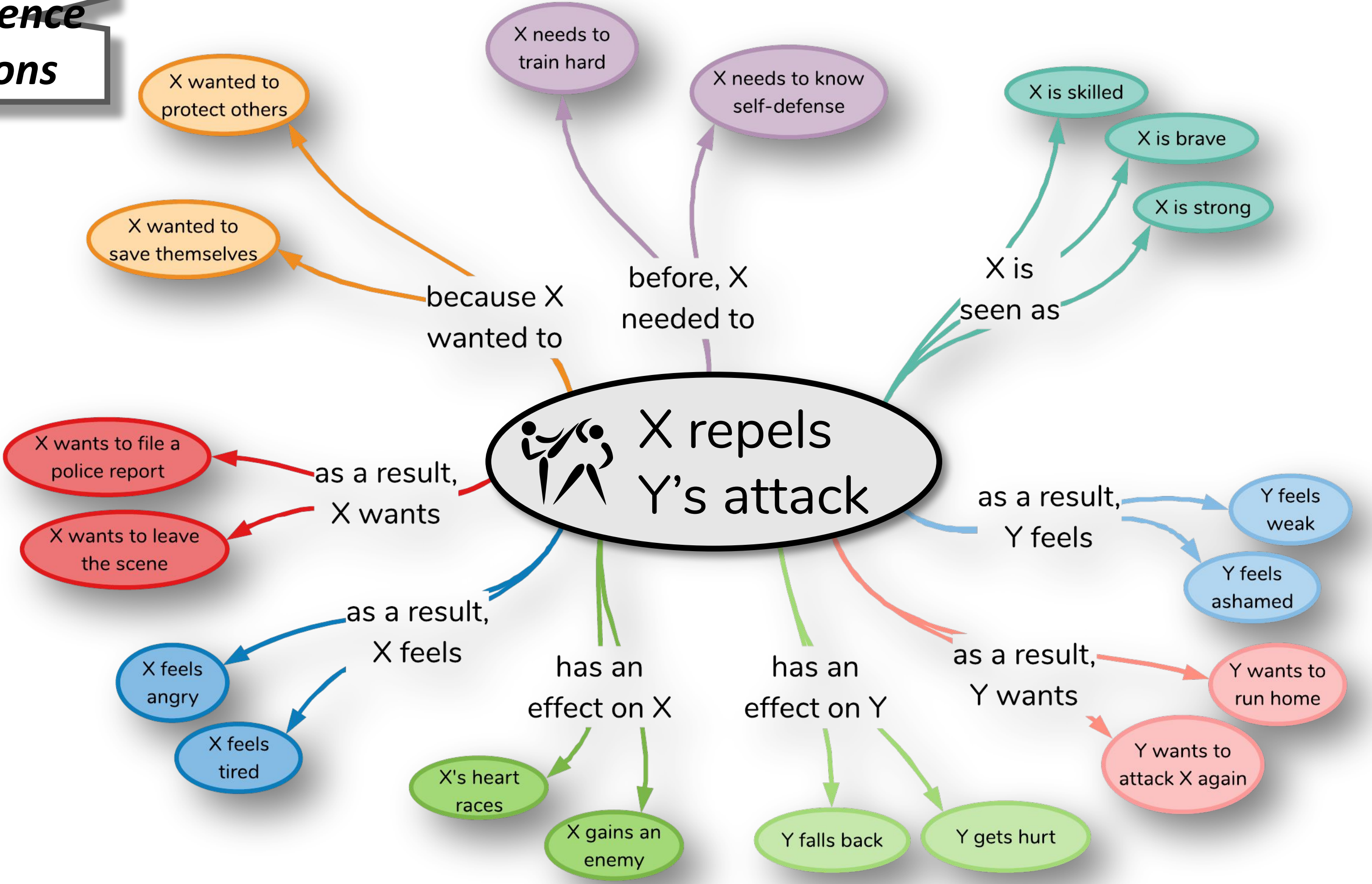


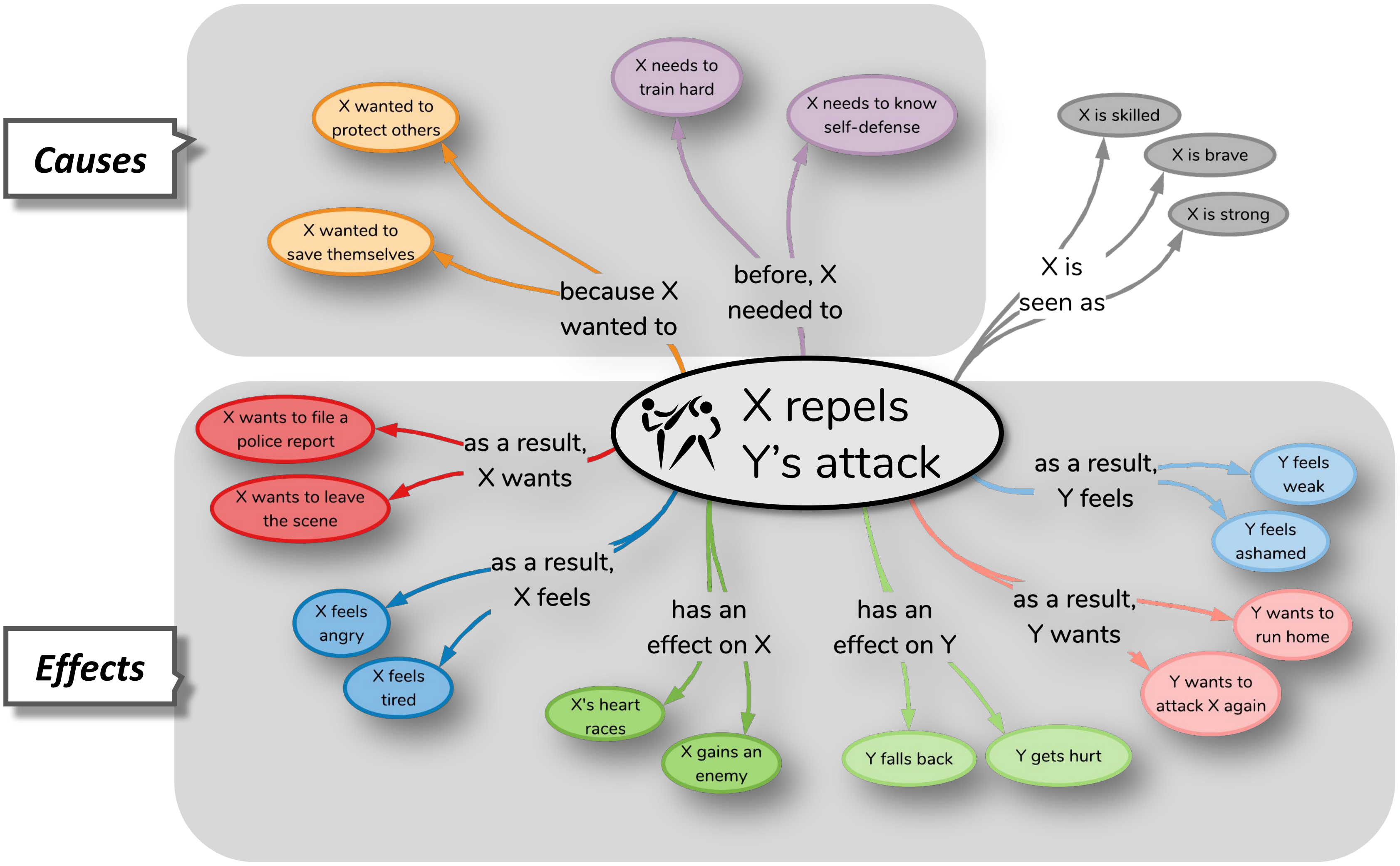


ATOMIC: 880,000 triples for AI systems to reason about ***causes*** and ***effects*** of everyday situations

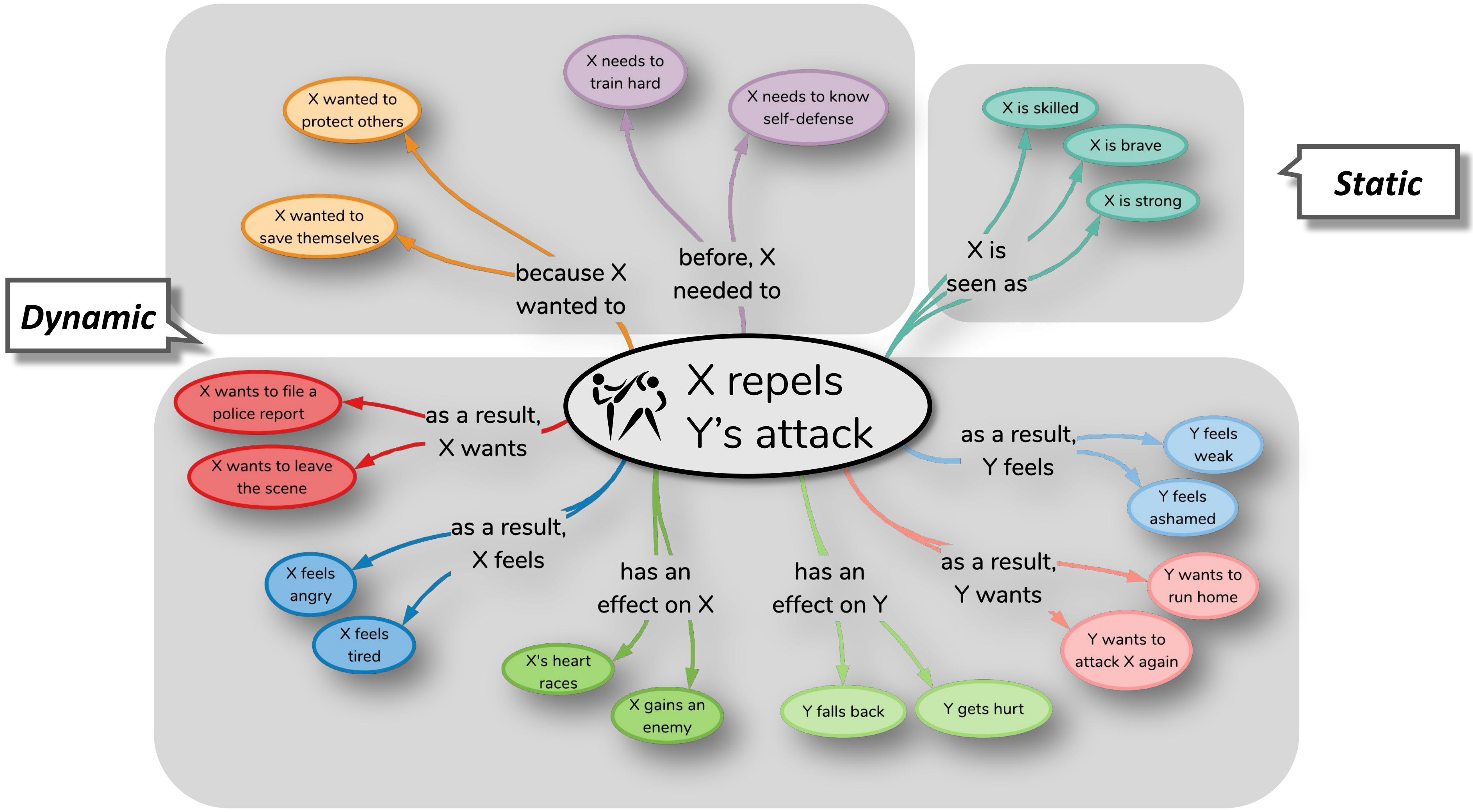

X repels Y's attack
because X wanted to
X wanted to protect others
X wanted to save themselves
before, X needed to
X needs to train hard
X needs to know self-defense
X is seen as
X is skilled
X is brave
X is strong
as a result, X wants
X wants to file a police report
X wants to leave the scene
as a result, Y feels
Y feels weak
Y feels ashamed
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, Y wants
Y wants to run home
Y wants to attack X again

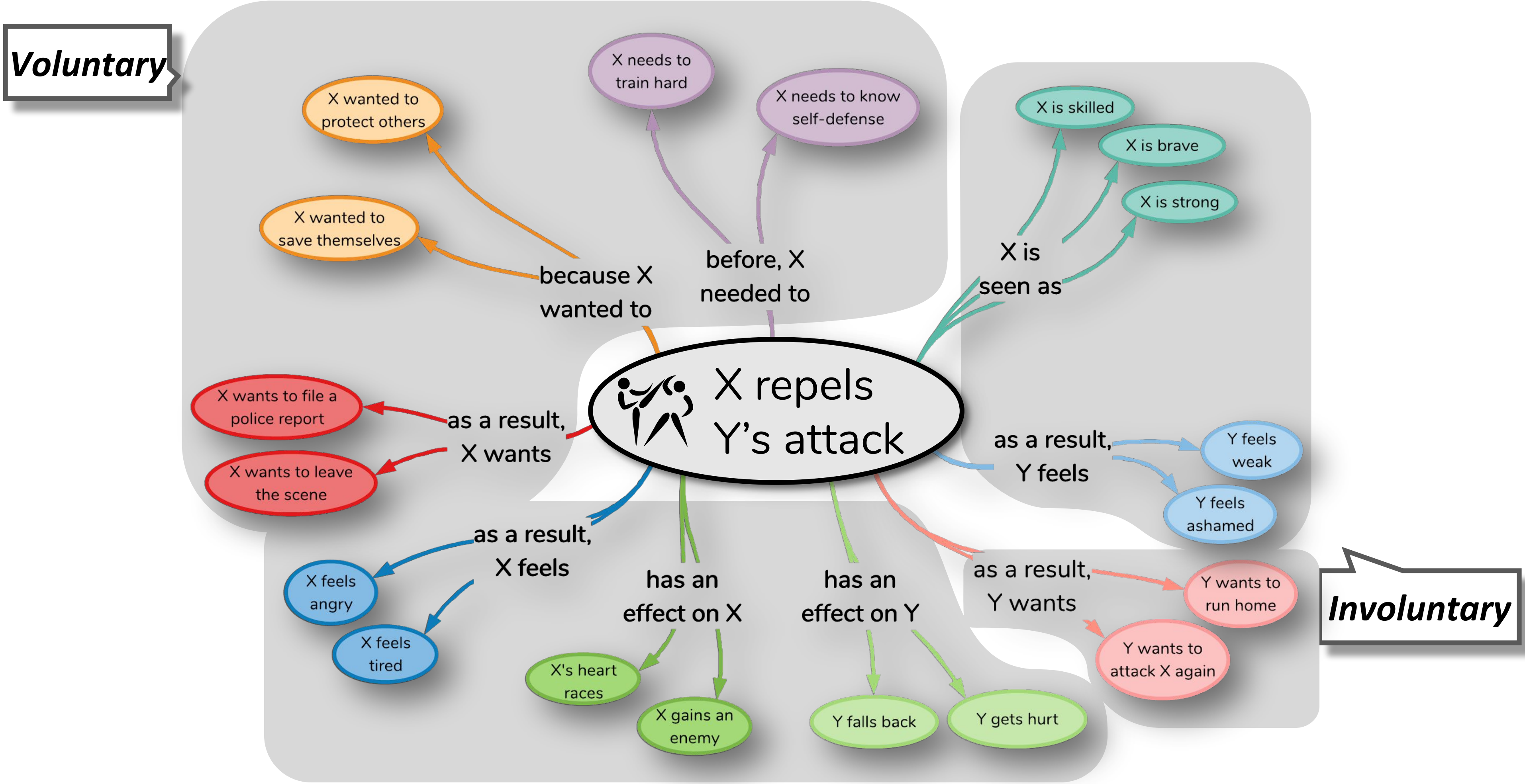
nine inference dimensions

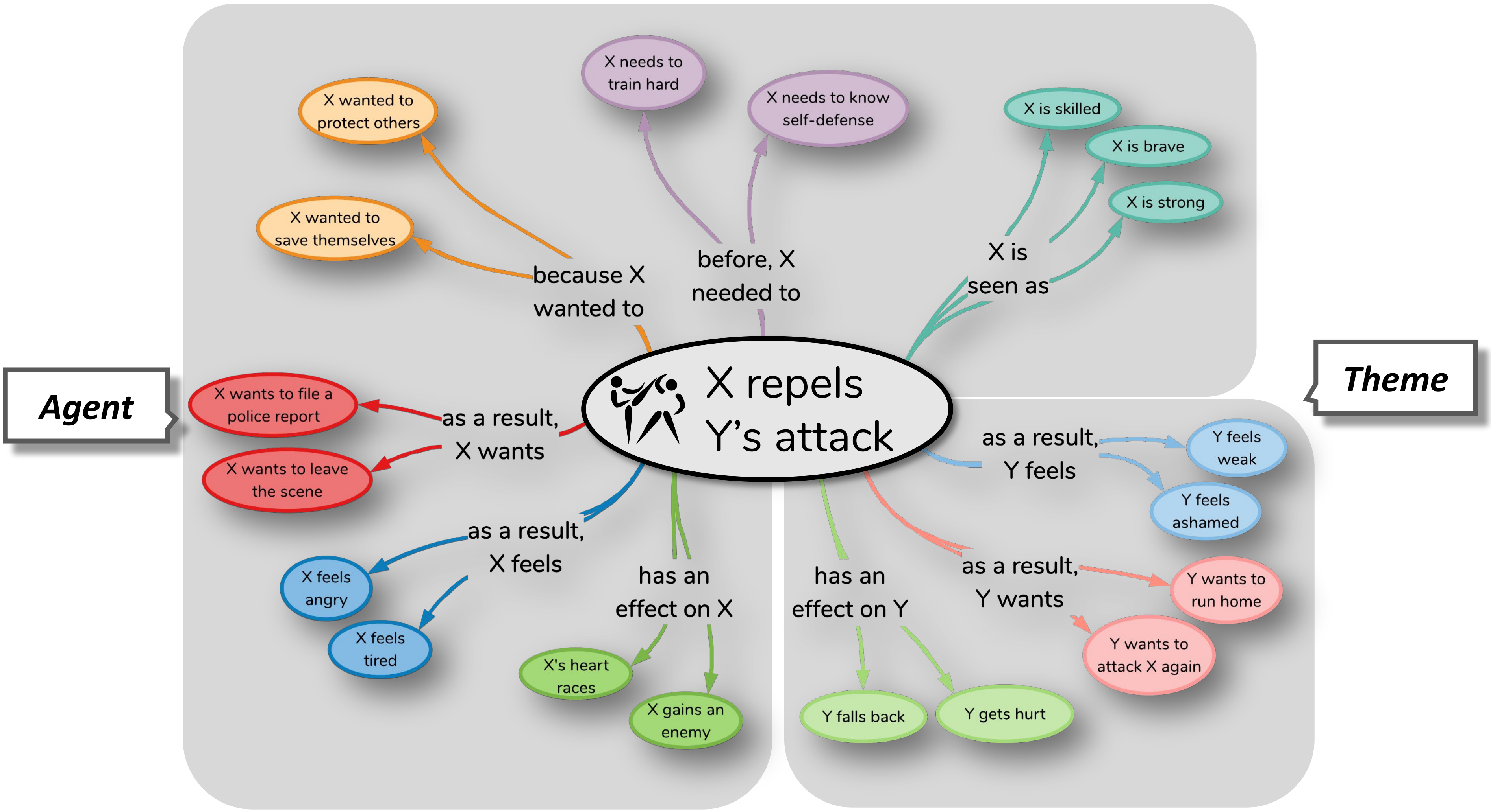


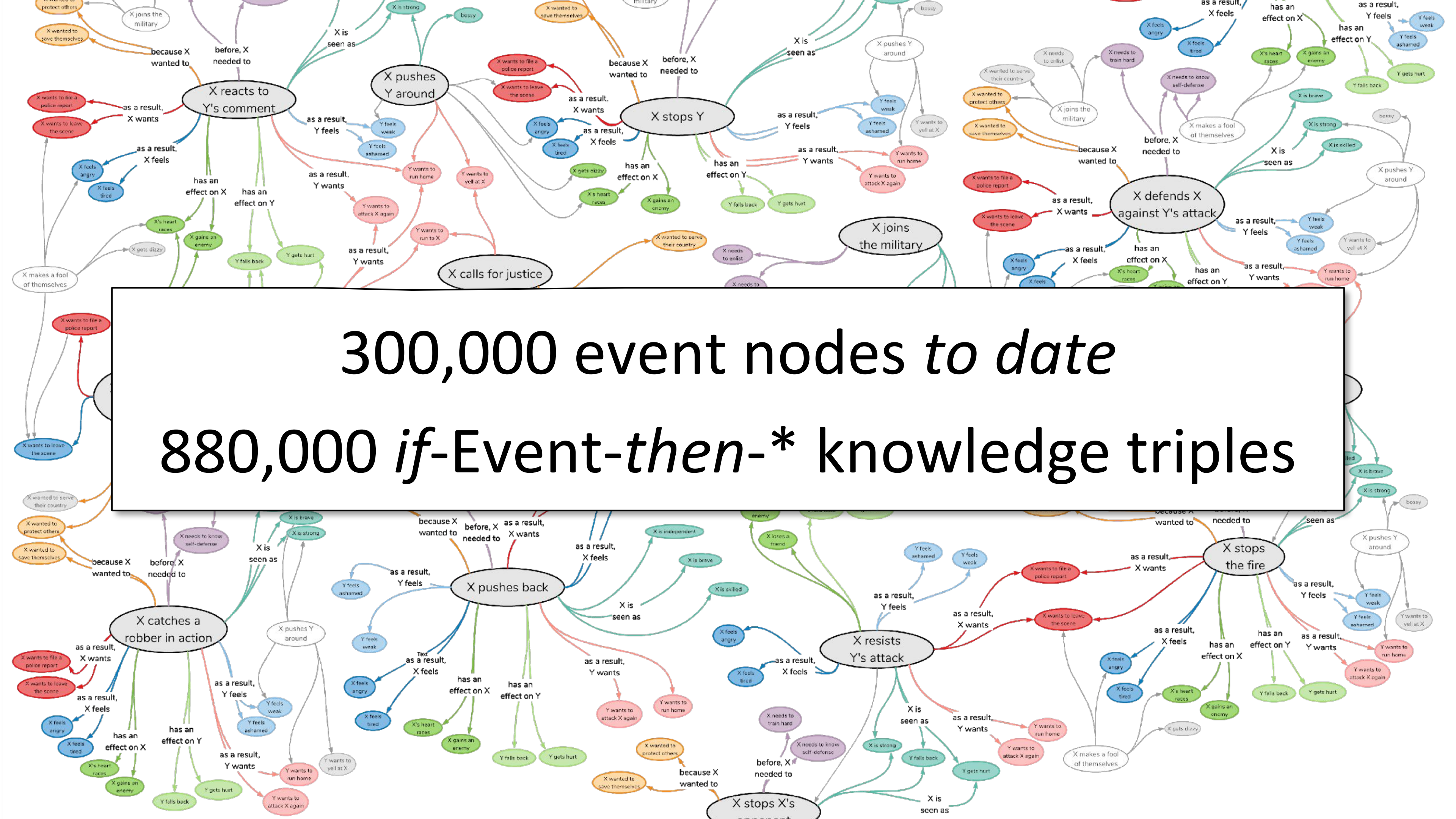


Causes
Effects
X repels Y's attack
because X wanted to
X wanted to protect others
X wanted to save themselves
before, X needed to
X needs to train hard
X needs to know self-defense
X is seen as
X is skilled
X is brave
X is strong
as a result, X wants
X wants to file a police report
X wants to leave the scene
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, Y wants
Y wants to run home
Y wants to attack X again
as a result, Y feels
Y feels weak
Y feels ashamed


Static
Dynamic
X repels Y's attack
because X wanted to
X wanted to protect others
X wanted to save themselves
before, X needed to
X needs to train hard
X needs to know self-defense
X is seen as
X is skilled
X is brave
X is strong
as a result, X wants
X wants to file a police report
X wants to leave the scene
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, Y wants
Y wants to run home
Y wants to attack X again
as a result, Y feels
Y feels weak
Y feels ashamed


Voluntary
X wanted to protect others
X wanted to save themselves
X needs to train hard
X needs to know self-defense
because X wanted to
before, X needed to
X is skilled
X is brave
X is strong
X is seen as
X repels Y's attack
X wants to file a police report
X wants to leave the scene
as a result, X wants
as a result, Y feels
Y feels weak
Y feels ashamed
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, Y wants
Y wants to run home
Y wants to attack X again
Involuntary


X repels Y's attack
Agent
Theme
because X wanted to
X wanted to protect others
X wanted to save themselves
before, X needed to
X needs to train hard
X needs to know self-defense
X is seen as
X is skilled
X is brave
X is strong
as a result, X wants
X wants to file a police report
X wants to leave the scene
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, Y wants
Y wants to run home
Y wants to attack X again
as a result, Y feels
Y feels weak
Y feels ashamed



300,000 event nodes *to date*

880,000 *if*-Event-*then*-* knowledge triples

Event	Type of relations	Inference examples	Inference dim.
"PersonX pays PersonY a compliment"	If-Event-Then-Mental-State	PersonX wanted to be nice	xIntent
		PersonX will feel good	xReact
		PersonY will feel flattered	oReact
	If-Event-Then-Event	PersonX will want to chat with PersonY	xWant
		PersonY will smile	oEffect
		PersonY will compliment PersonX back	oWant
	If-Event-Then-Persona	PersonX is flattering	xAttr
		PersonX is caring	xAttr
"PersonX makes PersonY's coffee"	If-Event-Then-Mental-State	PersonX wanted to be helpful	xIntent
		PersonY will be appreciative	oReact
		PersonY will be grateful	oReact
	If-Event-Then-Event	PersonX needs to put the coffee in the filter	xNeed
		PersonX gets thanked	xEffect
		PersonX adds cream and sugar	xWant
	If-Event-Then-Persona	PersonX is helpful	xAttr
		PersonX is deferential	xAttr
"PersonX calls the police"	If-Event-Then-Mental-State	PersonX wants to report a crime	xIntent
		Others feel worried	oReact
	If-Event-Then-Event	PersonX needs to dial 911	xNeed
		PersonX wants to explain everything to the police	xWant
		PersonX starts to panic	xEffect
		Others want to dispatch some officers	oWant
	If-Event-Then-Persona	PersonX is lawful	xAttr
		PersonX is responsible	xAttr

Best-effort mappings to ConceptNet

- **Wants**: MotivatedByGoal, HasSubevent, HasFirstSubevent, CausesDesire
- **Effects**: Causes, HasSubevent, HasFirstSubevent, HasLastSubevent
- **Needs**: MotivatedByGoal, Entails, HasPrerequisite
- **Intents**: MotivatedByGoal, CausesDesire, HasSubevent, HasFirstSubevent
- **Reactions**: Causes, HasLastSubevent, HasSubevent
- **Attributes**: HasProperty

COMET: Commonsense Transformers for Automatic Knowledge Graph Construction

Antoine Bosselut [♢♠] Hannah Rashkin [♢♠] Maarten Sap [♢♠] Chaitanya Malaviya [♢]
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[♢]Allen Institute for Artificial Intelligence, Seattle, WA, USA
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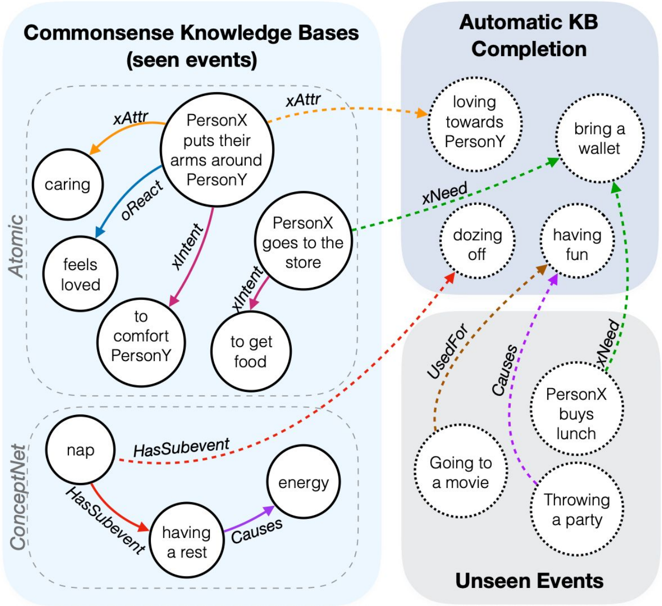
Abstract

We present the first comprehensive study on automatic knowledge base construction for two prevalent commonsense knowledge graphs: ATOMIC (Sap et al., 2019) and ConceptNet (Speer et al., 2017). Contrary to many conventional KBs that store knowledge with canonical templates, commonsense KBs only store loosely structured open-text descriptions of knowledge. We posit that an important step toward automatic commonsense completion is the development of *generative* models of commonsense knowledge, and propose ***COMmonsEnse Transformers*** (COMET) that learn to generate rich and



Building Common Sense KGs Is Hard

- 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**

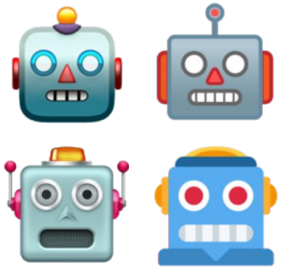
Slide by Antoine Bosselut

Traditional KB Completion

Gather training set of knowledge tuples

(person, CapableOf, buy)

Learn relationships among entities

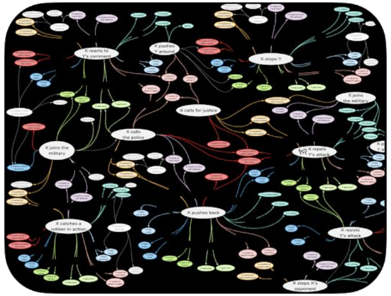


(Socher et al., 2013)
(Bordes et al., 2013)
(Riedel et al., 2013)
(Toutanova et al., 2015)
(Yang et al., 2015)
(Trouillon et al., 2016)
(Nguyen et al., 2016)
(Dettmers et al., 2018)

Predict new relationships

(person, CapableOf, **?**)

Store in knowledge graph



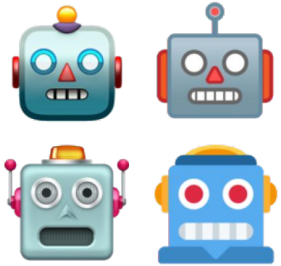
Slide by Antoine Bosselut

COMET Idea

Gather training set of knowledge tuples

(person, CapableOf, buy)

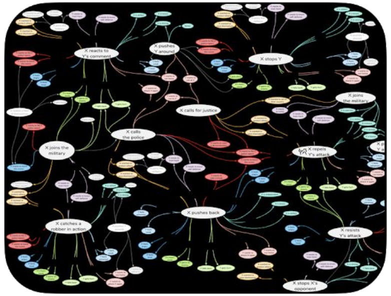
Learn relationships among entities



Predict new relationships

(person, CapableOf, **?**)

Store in knowledge graph

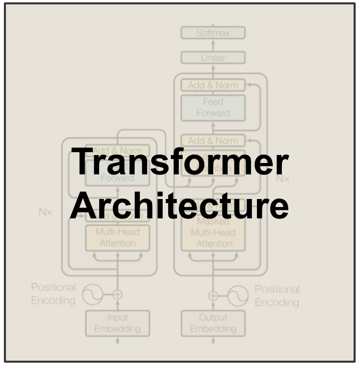


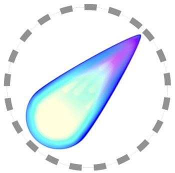
ATOMIC Input Template and ConceptNet Relation-only Input Template

s tokens	mask tokens	*r* token	*o* tokens
PersonX goes to the mall	[MASK]	<xIntent>	to buy clothes

ConceptNet Relation to Language Input Template

s tokens	mask tokens	*r* tokens	mask tokens	*o* tokens
go to mall	[MASK] [MASK]	has prerequisite	[MASK]	have money





COMET

Symbolic Knowledge Graph

Knowledge stored as triples

Knowledge is not contextualized

Knowledge is incomplete

Symbolic Knowledge Graph

Knowledge stored as triples

Knowledge is not contextualized

Knowledge is incomplete

COMET Knowledge Base Transformer

Knowledge generated dynamically

Input format is natural language

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

Randomly selected novel generations from ATOMIC

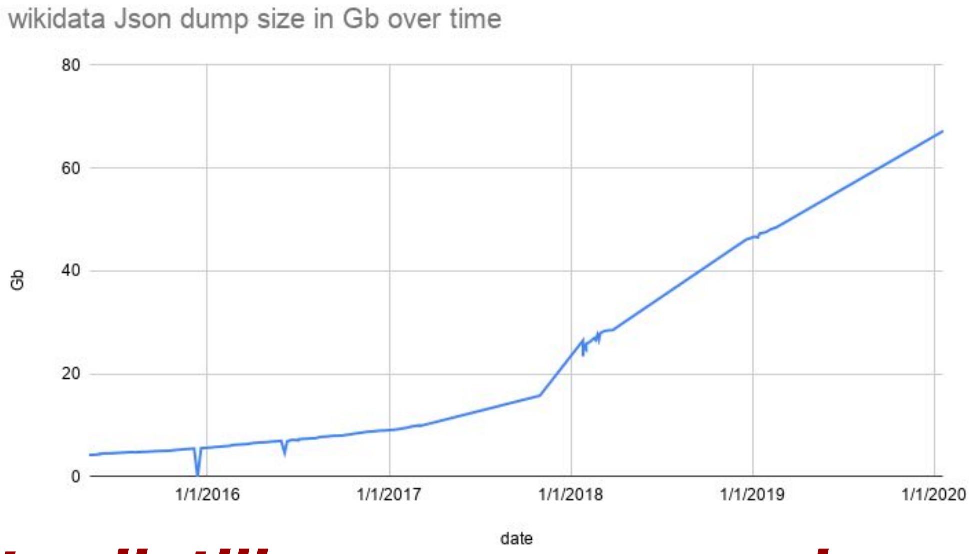
Seed Concept	Relation	Generated	Plausible
X holds out X's hand to Y	xAttr	helpful	✓
X meets Y eyes	xAttr	intense	✓
X watches Y every ___	xAttr	observant	✓
X eats red meat	xEffect	gets fat	✓
X makes crafts	xEffect	gets dirty	✓
X turns X's phone	xEffect	gets a text	
X pours ___ over Y's head	oEffect	gets hurt	✓
X takes Y's head off	oEffect	bleeds	✓
X pisses on Y's bonfire	oEffect	gets burned	
X spoils somebody rotten	xIntent	to be mean	
X gives Y some pills	xIntent	to help	✓
X provides for Y's needs	xIntent	to be helpful	✓
X explains Y's reasons	xNeed	to know Y	✓
X fulfils X's needs	xNeed	to have a plan	✓
X gives Y everything	xNeed	to buy something	✓
X eats pancakes	xReact	satisfied	✓
X makes ___ at work	xReact	proud	✓
X moves house	xReact	happy	✓
X gives birth to the Y	oReact	happy	✓
X gives Y's friend ___	oReact	grateful	✓
X goes ___ with friends	oReact	happy	✓
X gets all the supplies	xWant	to make a list	✓

Randomly selected novel generations from ConceptNet

Seed	Relation	Completion	Plausible
piece	`PartOf`	machine	✓
bread	`IsA`	food	✓
planet	`AtLocation`	space	✓
dust	`AtLocation`	fridge	
puzzle	`AtLocation`	your mind	🤔
college	`AtLocation`	town	✓
dental chair	`AtLocation`	dentist	✓
finger	`AtLocation`	your finger	
sing	`Causes`	you feel good	✓
doctor	`CapableOf`	save life	✓
post office	`CapableOf`	receive letter	✓
dove	`SymbolOf`	purity	✓
sun	`HasProperty`	big	✓
bird bone	`HasProperty`	fragile	✓
earth	`HasA`	many plant	✓
yard	`UsedFor`	play game	✓
get pay	`HasPrerequisite`	work	✓
print on printer	`HasPrerequisite`	get printer	✓
play game	`HasPrerequisite`	have game	✓
live	`HasLastSubevent`	die	✓
swim	`HasSubevent`	get wet	✓
sit down	`MotivatedByGoal`	you be tire	✓
all paper	`ReceivesAction`	recycle	✓
chair	`MadeOf`	wood	✓
earth	`DefinedAs`	planet	✓

Wikidata

90M nodes **>1.1B edges** **8k properties**



How to distill commonsense knowledge?

Slides from Ilievski et al. (2020). Commonsense Knowledge in Wikidata. Wikidata Workshop at ISWC 2020

Principles of Commonsense Knowledge

P1: Concepts, not entities

houses have rooms

Versailles Palace has 700 rooms

WD guidelines on entity capitalization

Principles of Commonsense Knowledge

P1: Concepts, not entities

houses* have *rooms

Versailles Palace* has *700 rooms

WD guidelines on entity capitalization

P2: Common concepts

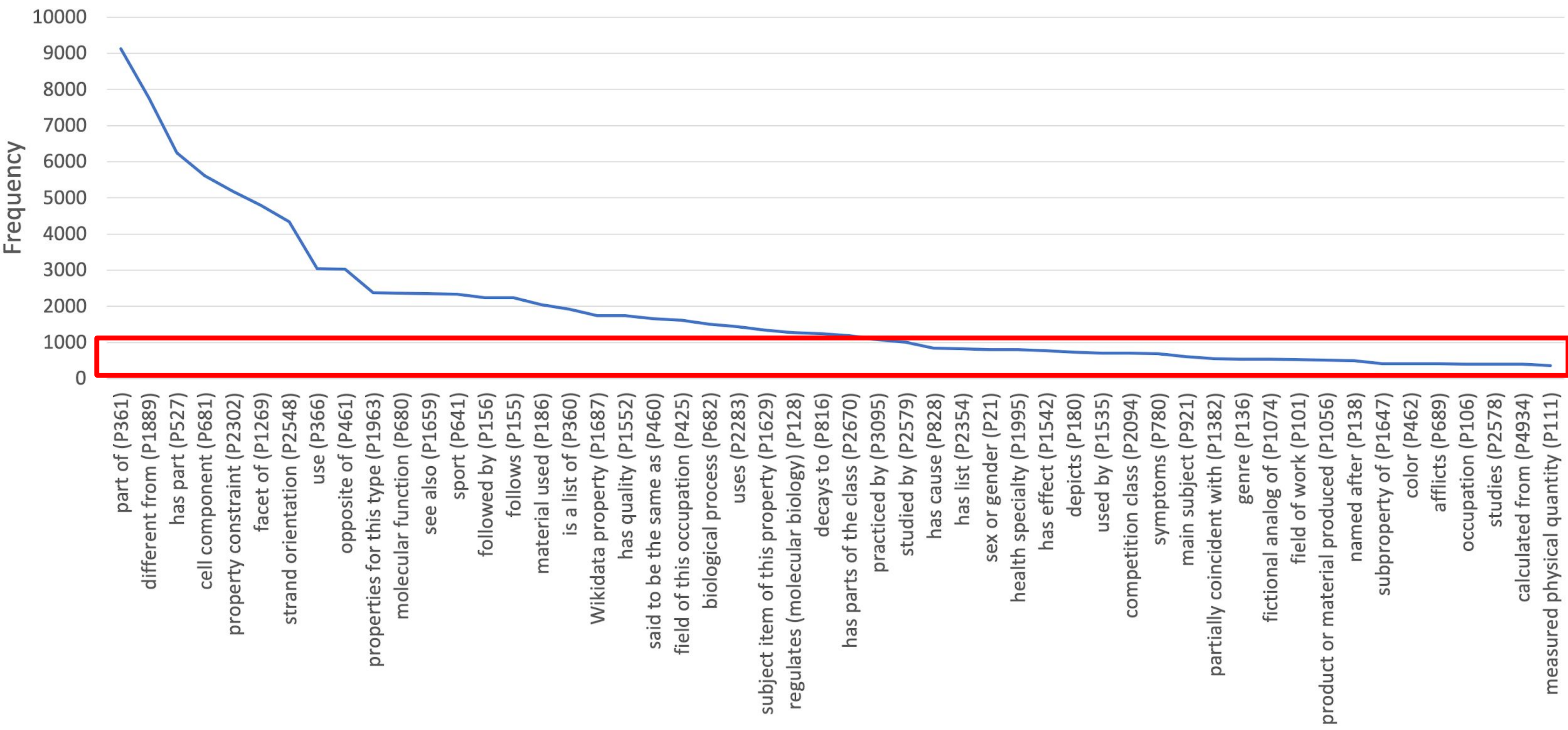
Container* used for *storage

Noma* subclass of *aphthous stomatitis

Corpus frequency

After step 1 & 2: 414 relations 421k edges

Relation	#edges	Examples
subclass of (P279)	172,535	saxophone - woodwind instrument
instance of (P31)	141,499	happiness - positive emotion
part of (P361)	9,118	shower - bathroom
different from (P1889)	7,767	vein - artery
has part (P527)	6,252	senses - touch
cell component (P681)	5,607	cholesterol - cell membrane
property constraint (P2302)	5,180	votes received - integer constraint
facet of (P1269)	4,792	wind - weather
strand orientation (P2548)	4,345	sac-1 - forward strand
use (P366)	3,045	crystal ball - psychic reading
opposite of (P461)	3,028	political opposition - government
properties for this type (P1963)	2,382	human - date of birth
molecular function (P680)	2,369	protein kinase - kinase activity
see also (P1659)	2,344	position held - member of
sport (P641)	2,338	head stand - gymnastics
followed by (P156)	2,244	middle school - secondary school
follows (P155)	2,234	queen - jack
material used (P186)	2,047	ice cream cone - wafer
is a list of (P360)	1,914	list of major opera composers - human
Wikidata property (P1687)	1,746	president - head of government
has quality (P1552)	1,739	elder sister - female
said to be the same as (P460)	1,664	belief - conviction
field of this occupation (P425)	1,616	jockey - horse racing
biological process (P682)	1,509	hypothetical protein - cell differentiation
uses (P2283)	1,431	reading - written work


Frequency
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
part of (P361)
different from (P1889)
has part (P527)
cell component (P681)
property constraint (P2302)
facet of (P1269)
strand orientation (P2548)
use (P366)
opposite of (P461)
properties for this type (P1963)
molecular function (P680)
see also (P1659)
sport (P641)
followed by (P156)
follows (P155)
material used (P186)
is a list of (P360)
Wikidata property (P1687)
has quality (P1552)
said to be the same as (P460)
field of this occupation (P425)
biological process (P682)
uses (P2283)
subject item of this property (P1629)
regulates (molecular biology) (P128)
decays to (P816)
has parts of the class (P2670)
practiced by (P3095)
studied by (P2579)
has cause (P828)
has list (P2354)
sex or gender (P21)
health specialty (P1995)
has effect (P1542)
depicts (P180)
used by (P1535)
competition class (P2094)
symptoms (P780)
main subject (P921)
partially coincident with (P1382)
genre (P136)
fictional analog of (P1074)
field of work (P101)
product or material produced (P1056)
named after (P138)
subproperty of (P1647)
color (P462)
afflicts (P689)
occupation (P106)
studies (P2578)
calculated from (P4934)
measured physical quantity (P111)

Principles of Commonsense Knowledge

P1: Concepts, not entities

houses have rooms

Versailles Palace has 700 rooms

WD guidelines on entity capitalization

P2: Common concepts

Container used for storage

Noma subclass of aphthous stomatitis

Corpus frequency

P3: General-domain relations

wheel is part of a car

cholesterol has component cell membrane

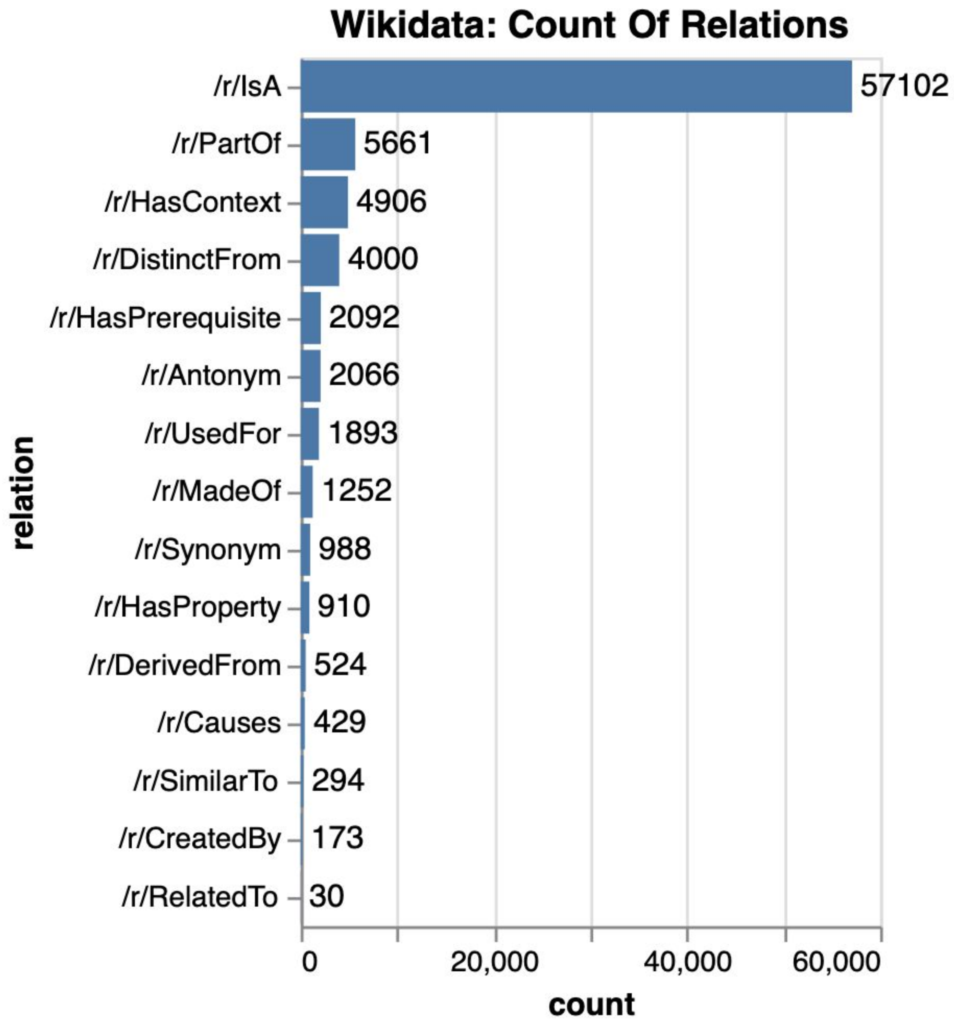
Mapping to ConceptNet

Mapping general-domain relations to ConceptNet

Category	ConceptNet	Wikidata
distinctness	/r/DistinctFrom	different from (P1889)
antonymy	/r/Antonym	opposite of (P461)
synonymy	/r/Synonym	said to be the same as (P460)
similarity	/r/SimilarTo	partially coincident with (P1382)
derivation	/r/DerivedFrom	named after (P138), fictional analog of (P1074)
inheritance	/r/IsA	instance of (P31), subclass of (P279), subproperty of (P1647)
meronymy	/r/PartOf	part of (P361), *has part (P527), *has parts of the class (P2670)
material	/r/MadeOf	material used (P186), is a list of (P360), *has list (P2354)
attribution	/r/CreatedBy	*product or material produced (P1056)
utility	/r/UsedFor	use (P366), *uses (P2283), used by (P1535)
properties	/r/HasProperty	color (P462), has quality (P1552), properties of this type (P1963), Wikidata property (P1687), sex or gender (P21)
causation	/r/Causes	*has cause (P828), has effect (P1542), symptoms (P780)
ordering	/r/HasPrerequisite	*followed by (P156), follows (P155)
context	/r/HasContext	facet of (P1269), sport (P641), field of this occupation (P425), health specialty (P1995), competition class (P2094), genre (P136), studied by (P2579), field of work (P101), afflicts (P689), *practiced by (P3095), depicts (P180), main subject (P921)
other	/r/RelatedTo	see also (P1659), subject item of this property (P1629)

Wikidata-CS = 0.01% * Wikidata

	Wikidata-CS	Wikidata	Ratio
# nodes	71,243	84 million	***0.08%***
# edges	***101,771***	1.5 billion	***0.01%***


Wikidata: Count Of Relations
relation
/r/IsA
/r/PartOf
/r/HasContext
/r/DistinctFrom
/r/HasPrerequisite
/r/Antonym
/r/UsedFor
/r/MadeOf
/r/Synonym
/r/HasProperty
/r/DerivedFrom
/r/Causes
/r/SimilarTo
/r/CreatedBy
/r/RelatedTo
57102
5661
4906
4000
2092
2066
1893
1252
988
910
524
429
294
173
30
0
20,000
40,000
60,000
count

Commonsense Knowledge in Wikidata

shower part of bathroom

reading uses written work

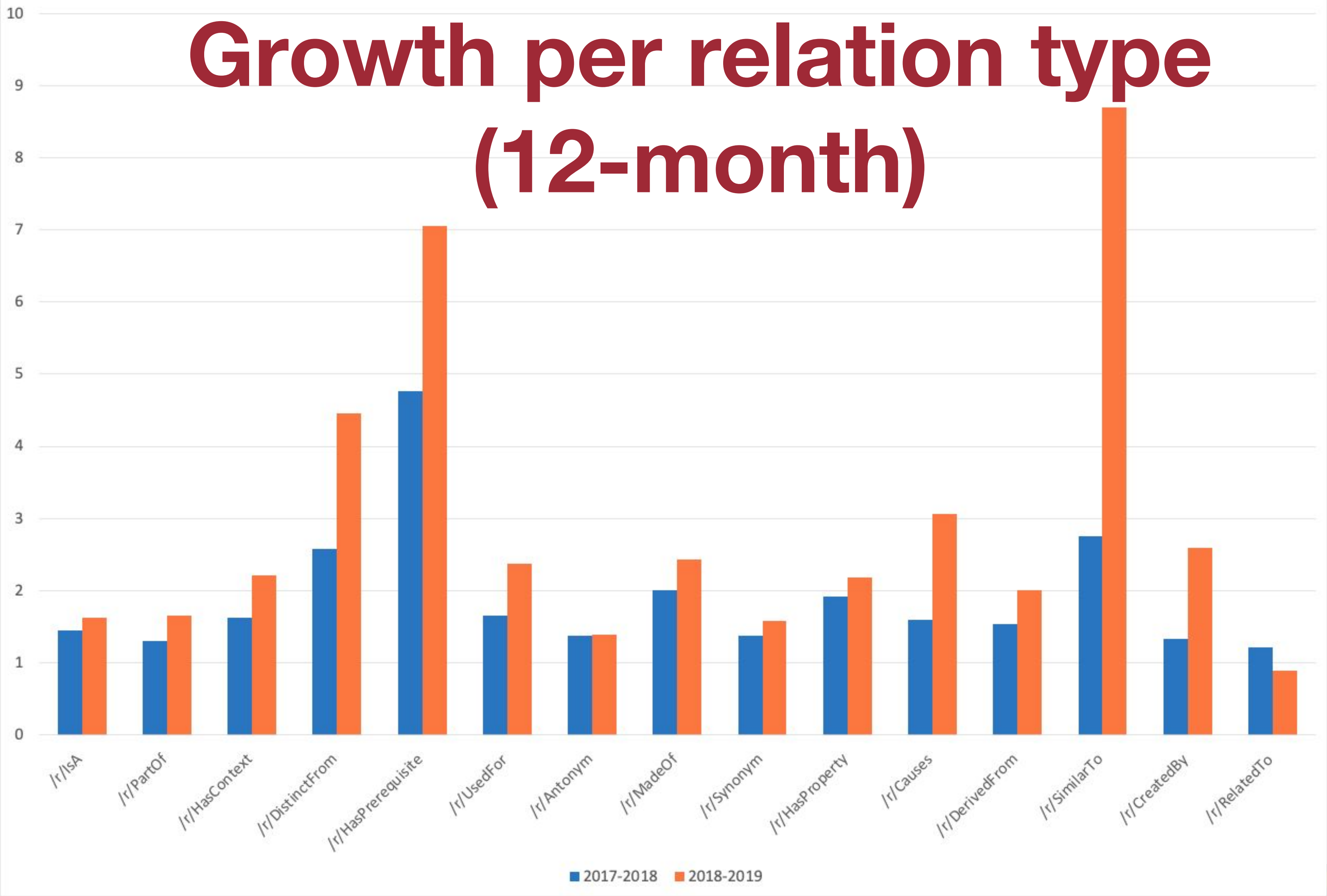
queen follows jack

political opposition opposite of government

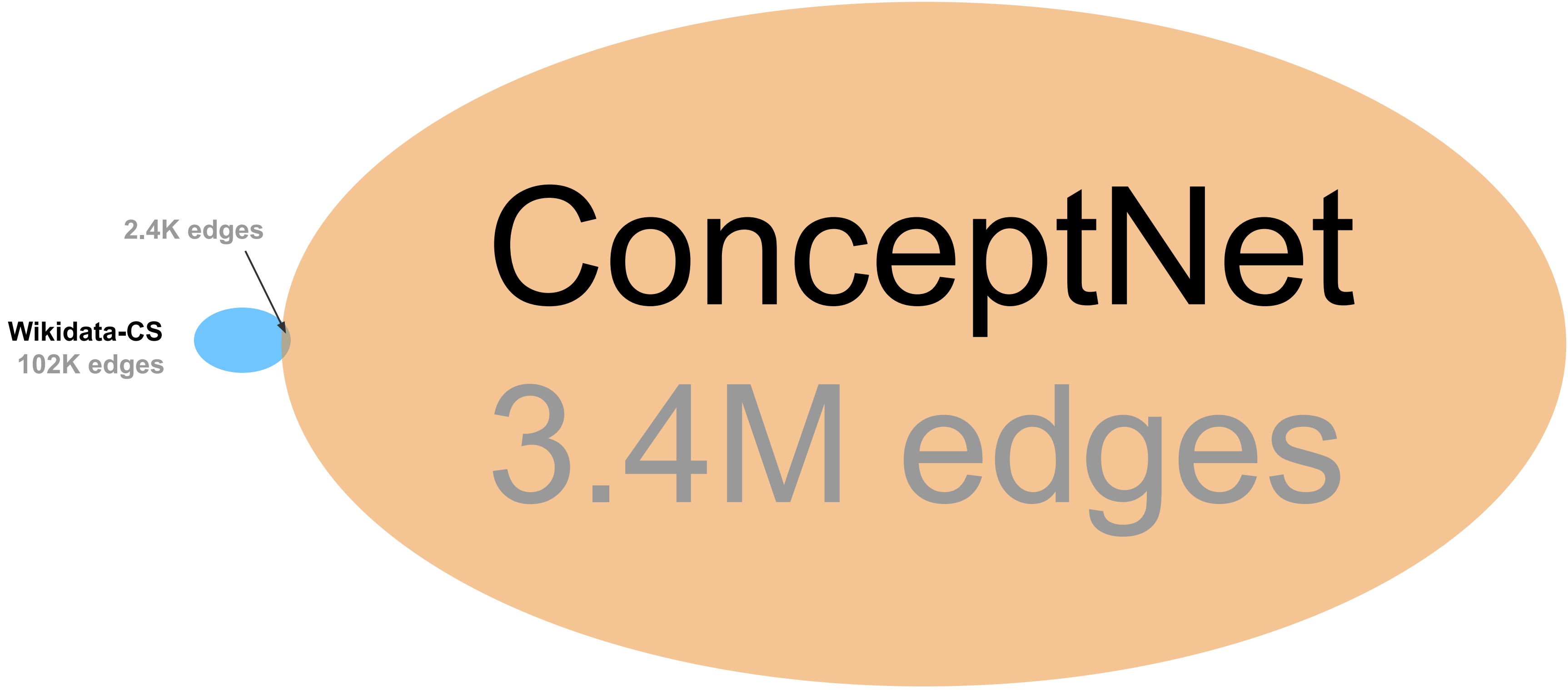
Has it been growing over time?

	2017-12-27	2018-12-10	2020-05-04
/r/IsA	31,668	45,606 (144%)	72,707 (230%)
/r/PartOf	3,390	4,416 (130%)	7,938 (234%)
/r/HasContext	1,968	3,189 (162%)	6,152 (313%)
/r/DistinctFrom	782	2,011 (257%)	4,934 (631%)
/r/HasPrerequisite	413	1,965 (476%)	4,131 (1,000%)
/r/UsedFor	735	1,215 (165%)	2,469 (336%)
/r/Antonym	1,109	1,530 (138%)	2,184 (197%)
/r/MadeOf	415	834 (201%)	1,426 (344%)
/r/Synonym	478	655 (137%)	1,070 (224%)
/r/HasProperty	339	650 (192%)	1,049 (309%)
/r/Causes	150	238 (159%)	651 (434%)
/r/DerivedFrom	190	293 (154%)	540 (284%)
/r/SimilarTo	28	77 (275%)	345 (1,232%)
/r/CreatedBy	51	68 (133%)	187 (367%)
/r/RelatedTo	33	40 (121%)	42 (127%)
edges (Wikidata-CS)	41,769	62,787 (150%)	101,771 (244%)
edges (Wikidata)	405,081,219	696,605,955 (172%)	1,105,944,515 (273%)
nodes (Wikidata-CS)	32,620	47,056	71,243
nodes (Wikidata)	42,187,222	53,004,762	84,601,621

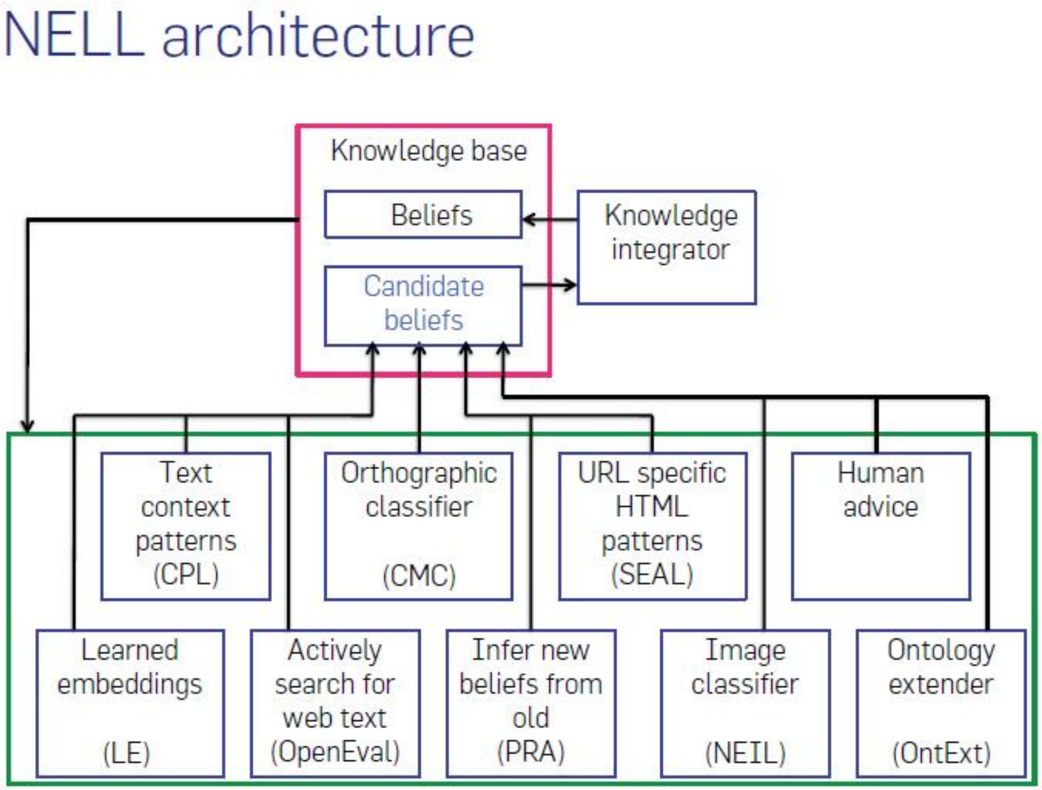
Growth per relation type (12-month)



Wikidata-CS Is Small But Novel

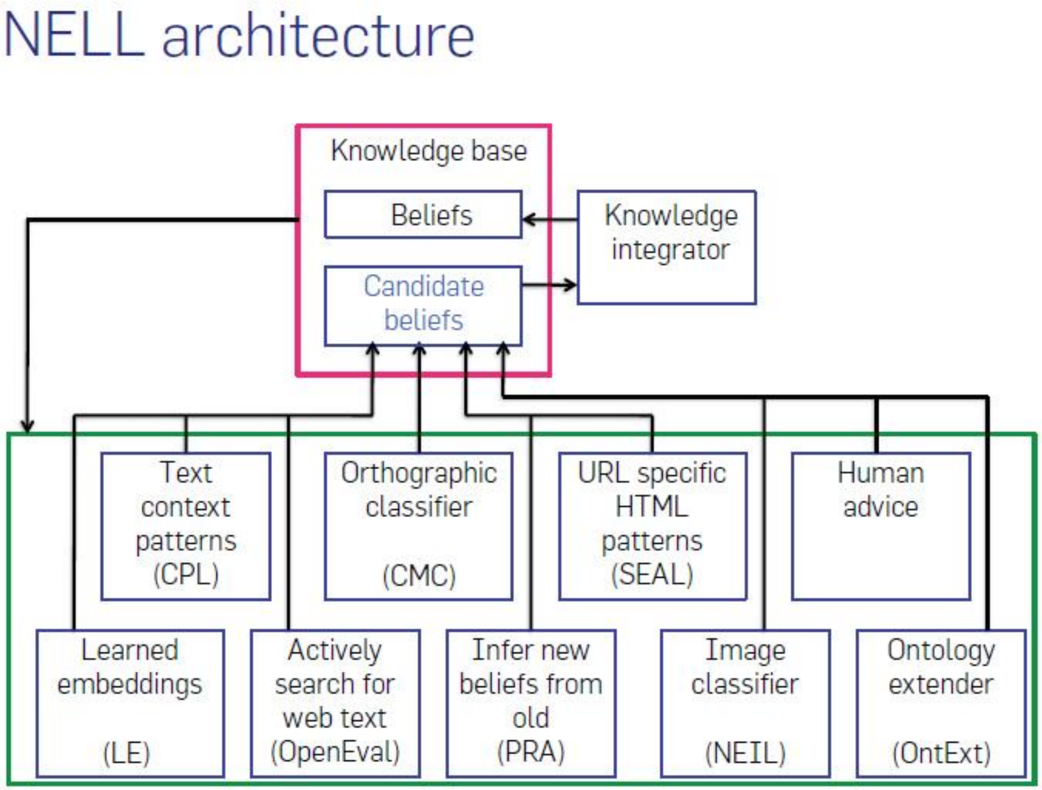


Never-Ending Language Learning (NELL)



https://cacm.acm.org/magazines/2018/5/227193-never-ending-learning/fulltext

NELL statistics



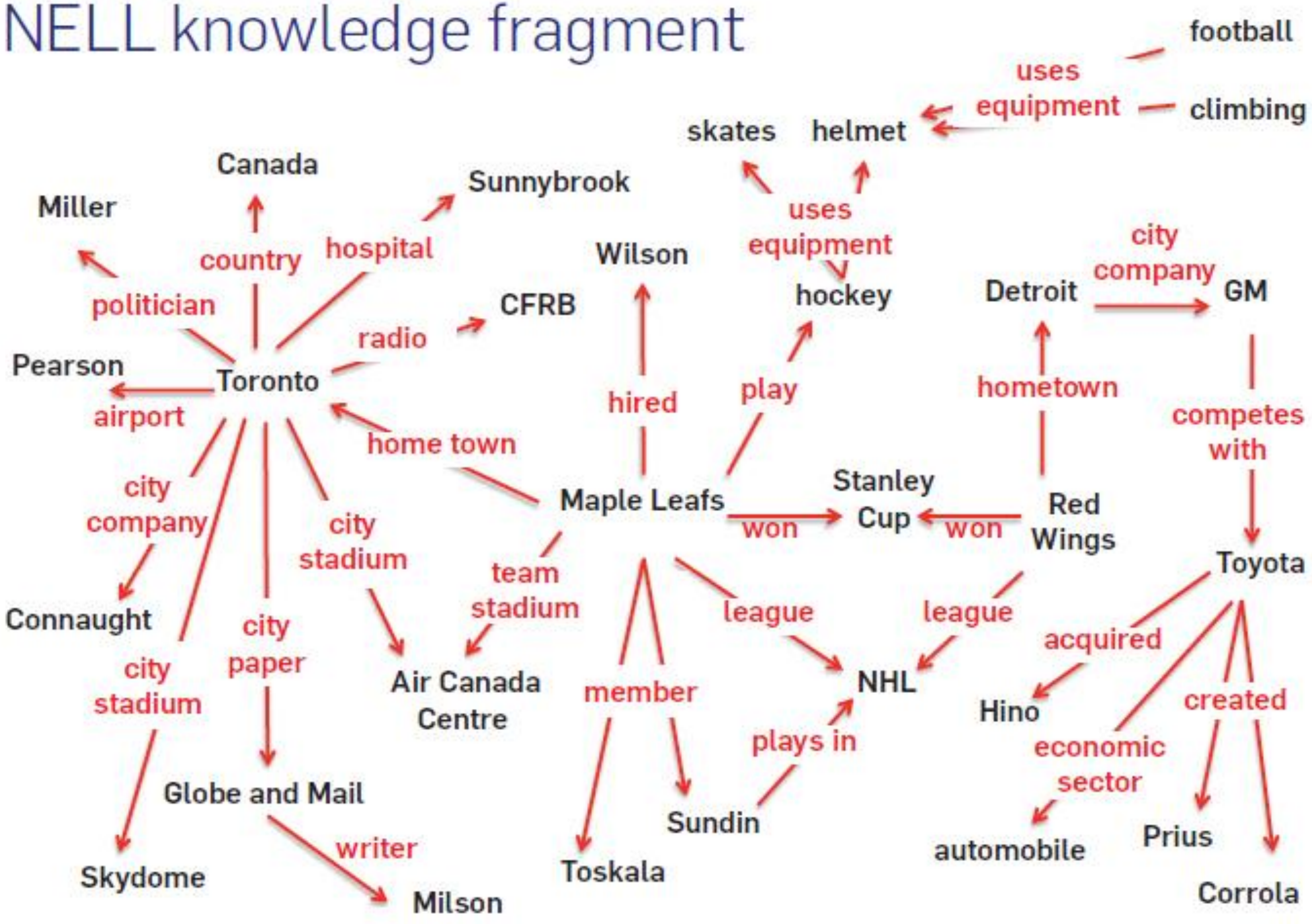
100M candidate beliefs

3M high-confidence facts

~3K predicates

https://cacm.acm.org/magazines/2018/5/227193-never-ending-learning/fulltext

NELL knowledge fragment



https://cacm.acm.org/magazines/2018/5/227193-never-ending-learning/fulltext

Latest learned facts

Recently-Learned Facts

twitter

Refresh

instance	iteration	date learned	confidence
translucent_paper is an office supply	1111	06-jul-2018	93.4
the_barbirolli_string_quartet is a musical artist	1111	06-jul-2018	99.2
private_support is an event outcome	1111	06-jul-2018	99.8
vancouver_olympic_games is an instance of the olympics	1111	06-jul-2018	95.2
eddie_mathews is a person	1111	06-jul-2018	98.9
roswell_road is a street in the city atlanta	1116	12-sep-2018	93.8
james_madison is a U.S. politician who holds the office of secretary	1115	03-sep-2018	98.4
rice was born in the city orleans	1116	12-sep-2018	100.0
republic is a country also known as china	1111	06-jul-2018	100.0
dodge is a specific automobile maker dealer in utah	1115	03-sep-2018	93.8

WebChild

Automatic acquisition and organization of common sense

>18M assertions

>2M disambiguated concepts and activities

Tandon et al. (2017). [Webchild 2.0: Fine-grained commonsense knowledge distillation](). ACL 2017

WebChild relations

1. object properties

hasTaste, hasShape, evokesEmotion

2. comparative

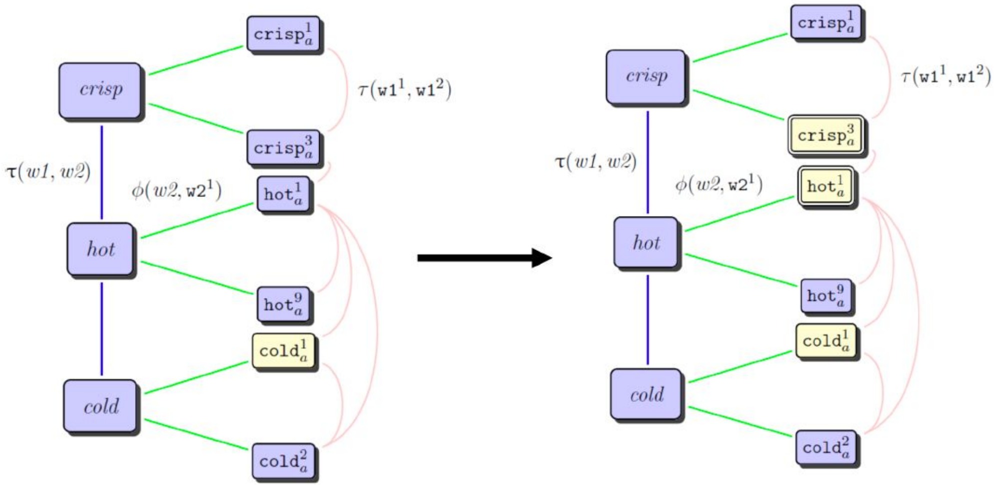
fasterThan, smallerThan

3. part-of

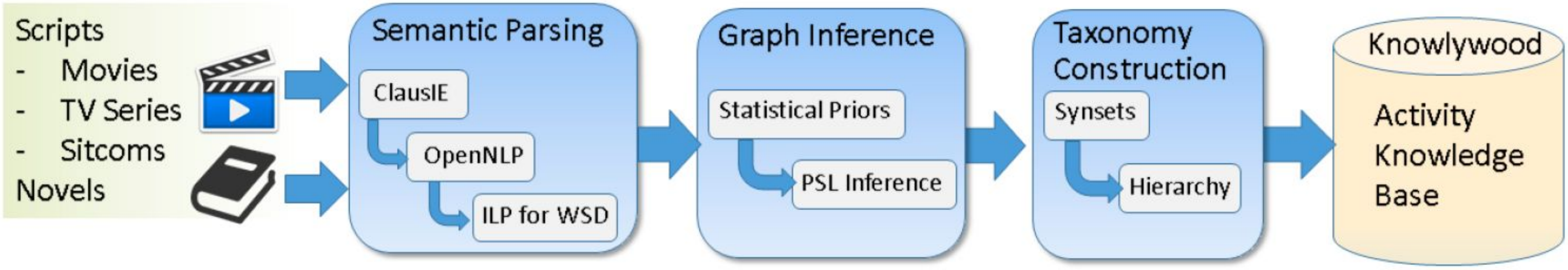
member of, physical part of, substance of

4. activities

WebChild label propagation



WebChild activity extraction



Example

mountain: a land mass that projects well above its surroundings; higher than a hill

TYPE OF	natural elevation
	size to **object**, under the category of **mountaineering**
PHYSICAL PROPERTIES	large · high · heavy · cold · hard · More
ABSTRACT PROPERTIES	elegant · old · safe · holy · risky · More
COMPARABLES	mountain,hill · mountain,mount · mountain, high hill · valley,mountain · More
HAS PHYSICAL PARTS	mountain peak · mountainside · slope · tableland · hill · More
HAS SUBSTANCE	mixture · metallic element · material · page · wood · More
IN SPATIAL PROXIMITY	coast · tunnel · lake · sea · river · More
ACTIVITIES	climb mountain · cross mountain · move mountain · see mountain · ascend mountain

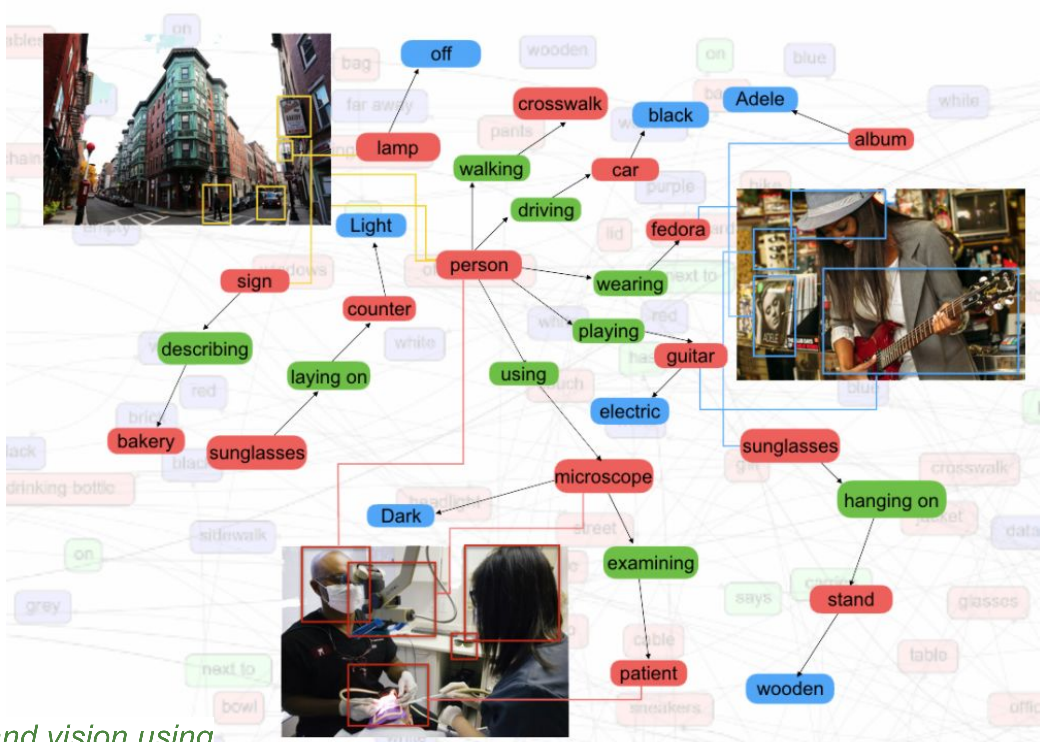
Demo

Visual Genome

108k images

annotated with scene graphs

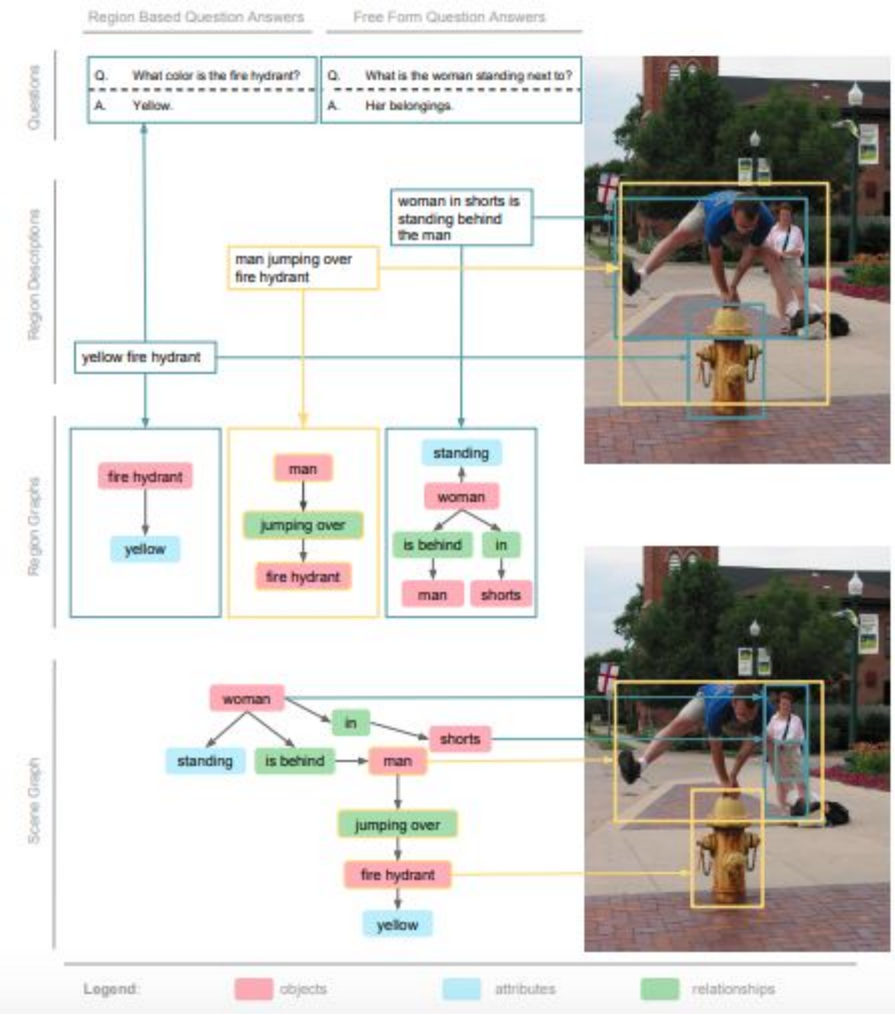
canonicalized to WordNet senses



Krishna et al. (2017). [Visual genome: Connecting language and vision using crowdsourced dense image annotations.](#) International journal of computer vision

Components

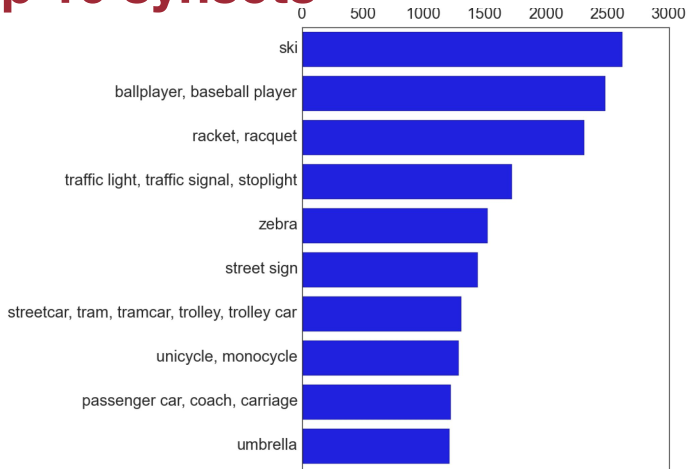
1. region descriptions
2. objects
3. attributes
4. relationships
5. region graphs
6. scene graphs
7. question-answer pairs



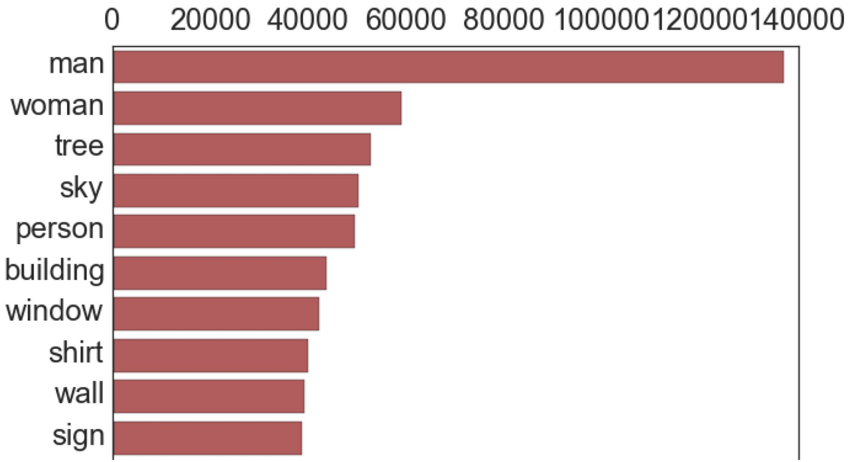
Statistics

- 108,077 images
- 50 descriptions per image
- objects
  - 3.8M in total (35 objects per image)
  - 33,877 categories (synsets)
- attributes
  - 26 per image
  - 68,111 categories (synsets)
- relationships
  - 21 per image
  - 42,374 categories (synsets)
- QA pairs
  - 1.7 million

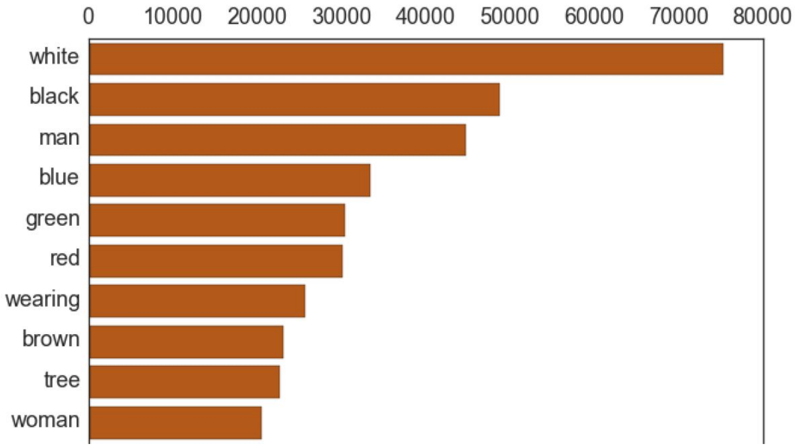
Top 10 synsets



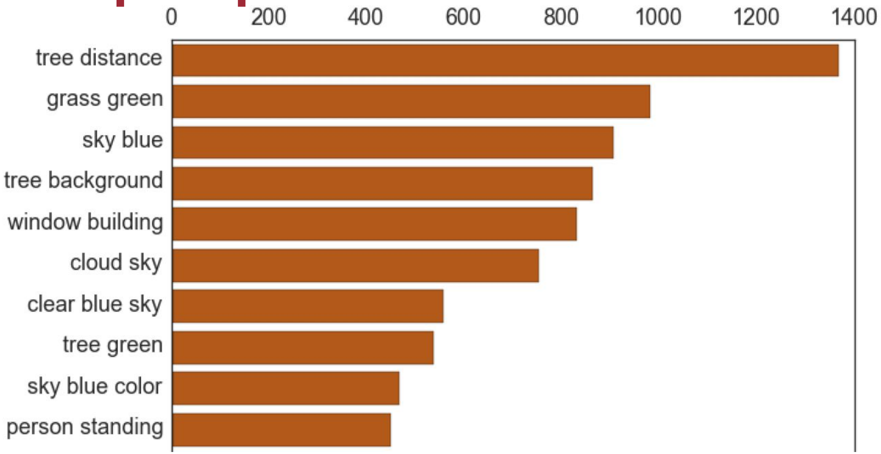
Top 10 object categories



Top 10 words



Top 10 phrases



Visual Genome as a KG

Objects = WordNet senses

‘red shoe’ is the label

shoe#n#1 is the node

Visual Genome as a KG

Objects = WordNet senses

'red shoe' is the label

shoe#n#1 is the node

Relationships = proximity

'on top of' is the label

/r/LocatedNear is the relation

Visual Genome as a KG

Objects = WordNet senses

‘red shoe’ is the label

shoe#n#1 is the node

Relationships = proximity

‘on top of’ is the label

/r/LocatedNear is the relation

Attributes

(POS=v) /r/CapableOf

(POS=a) mw:MayHaveProperty

(POS=n) -

Some other CKGs

WordNet

FrameNet

VerbNet

ROGET

Tuple KB

Quasimodo KB

PropStore

Demos

https://caninehq.com/best-dog-breeds-for-playing-frisbee/

Dog and Frisbee

Wikidata:

https://sqid.toolforge.org/#/view?id=Q144 (dog)
https://sqid.toolforge.org/#/view?id=Q131689 (frisbee)

ConceptNet:

https://www.conceptnet.io/c/en/dog
https://www.conceptnet.io/c/en/dogs
http://conceptnet.io/c/en/frisbee
https://www.conceptnet.io/c/en/dogs_catching_frisbees

VisualGenome

https://visualgenome.org/VGViz/explore?query=throwing%20frisbee%20dog

ATOMIC:

https://mosaickg.apps.allenai.org/kg_atomic/?l=PersonX%20throws%20a%20frisbee

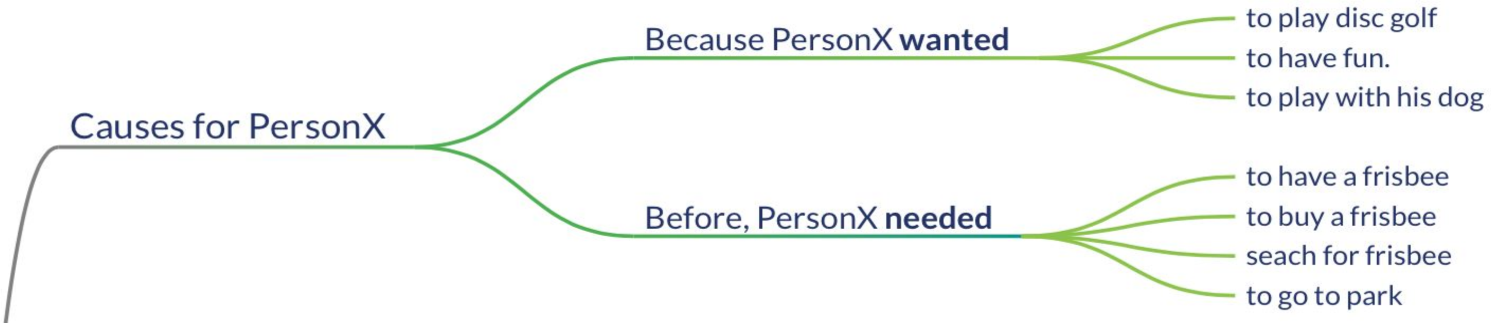
COMET:

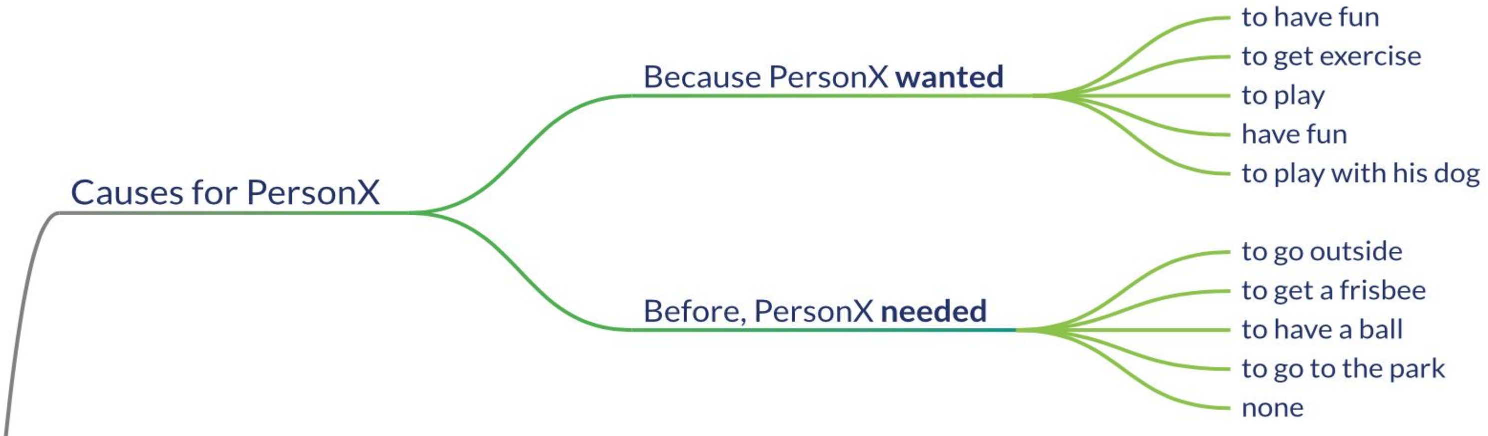
comet dog
https://mosaickg.apps.allenai.org/comet_atomic/?l=PersonX%20throws%20frisbee

DICE

https://dice.mpi-inf.mpg.de/subject/dog

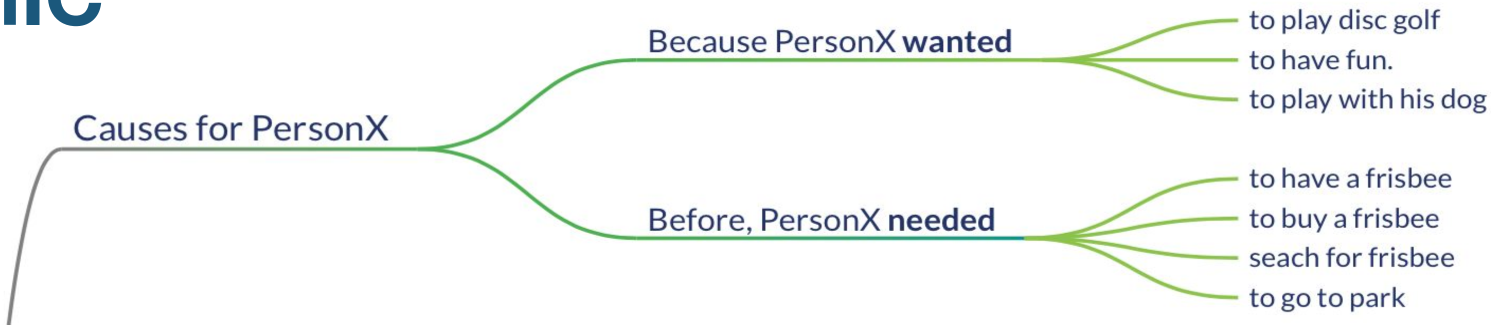
PersonX throws frisbee
ATOMIC or COMET?



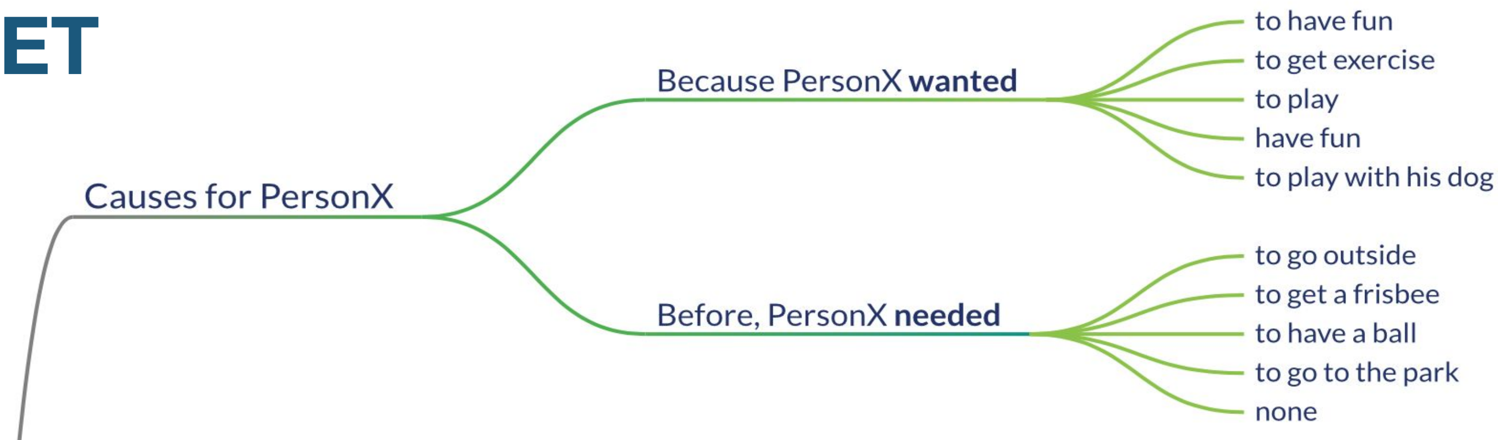


PersonX throws frisbee

ATOMIC



COMET



PersonX throws frisbee
ATOMIC or COMET?

- As a result, others **feel**
  - none
  - happy
  - playful
  - excited
  - competitive
- As a result, others **want**
  - none
  - to have fun
  - to catch the frisbee
  - to catch it
  - to play
- Others **then**
  - none
  - catches the frisbee
  - gets exercise
  - gets hit by frisbee
  - gets hit

- As a result, others **feel**
  - none
  - happy.
- As a result, others **want**
  - none
- Others **then**
  - none
  - person y catches frisbee
  - person y throws frisbee back

PersonX throws frisbee

COMET

- As a result, others **feel**
  - none
  - happy
  - playful
  - excited
  - competitive
- As a result, others **want**
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ATOMIC

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  - none
  - person y catches frisbee
  - person y throws frisbee back

baseball-1615665-1920.jpg

1200px-Thomas_Röhler_2011.jpg

Catch and Throw

Wikidata:
- https://sqid.toolforge.org/#/view?id=Q17144564 (throw)
- https://sqid.toolforge.org/#/view?id=Q91553195 (catch)

ConceptNet:
- https://www.conceptnet.io/c/en/throw
- https://www.conceptnet.io/c/en/catch

VisualGenome
- https://visualgenome.org/VGViz/explore?query=catch%20frisbee

Agenda

08:00 PST	1 hr 50 mins	**Part I - Review of CSKGs**
	15 min	Introduction to commonsense knowledge (slides) - Pedro
	25 min	Review of top-down commonsense knowledge graphs (slides) - Mayank
	70 min	Review of bottom-up commonsense knowledge graphs (slides+demo) - Mayank, Filip, Pedro
	10 min	**Break**
10:00 PST	45 min	**Part II - Integration and analysis**
	35 min	Consolidating commonsense graphs (slides) - Filip
	10 min	Consolidating commonsense graphs (demo) - Pedro
	10 min	**Break**
10:55 PST	1 hr 05 mins	**Part III - Downstream use of CSKGs**
	50 min	Answering questions with CSKGs (slides+demo) - Filip
	15 min	Wrap-up (slides) - Mayank