

Course

## Knowledge-based Systems

### Lecture 09: Commonsense Reasoning

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# Recall ...

- **(Artificial) intelligence:** the ability acquire knowledge and adopt that knowledge to new environment and tasks to achieve goals.
- **Knowledge base (KB)** is the core of KB systems
- **Two types of KBs (based on knowledge representations):**  
Symbolic, Connectionist
- **Evaluating KBs using semantic relatedness tasks**
  - Semantic relations between words
- **Multilingual KBs**
- **Commonsense and factual knowledge**

# Any other open questions?



# In this lecture, you learn about ...

- Commonsense knowledge sources
- Commonsense knowledge reasoning

**Today**

# Introduction

# Commonsense knowledge and reasoning

- **Commonsense knowledge** is the information that is generally accepted by the **majority of people** concerning **everyday life**, encapsulating the **practical knowledge** about **how the world works**.
- **Reasoning with commonsense knowledge** is at the **core of building natural language understanding models** and, more broadly, **AI systems that can reason about the world in the same way as humans do**.

# Commonsense Knowledge Sources

# Desiderata for ideal commonsense KBs

## ▪ Coverage

- Large scale
- Diverse knowledge types

## ▪ Usefulness

- High quality knowledge
- Usable in downstream tasks

# Factors in creating commonsense KBs

- **Representation**

- Symbolic
- Natural language
- Neural

- **Commonsense knowledge type**

- Semantics: Knowledge of “**What**”, **A isA B**
- Inferential: Knowledge of “**why**” and “**How**”, **if-then** or **cause** and **effect**

- **Creation method**

- Expert input
- Crowdsourcing
- Information extraction

# NELL (Mitchell, 2015): Never Ending Language Learner

- **Representation:** Symbolic
- **Type:** Semantic
- **Creation method:** Information extraction

# NELL (Mitchell, 2015): Never Ending Language Learner

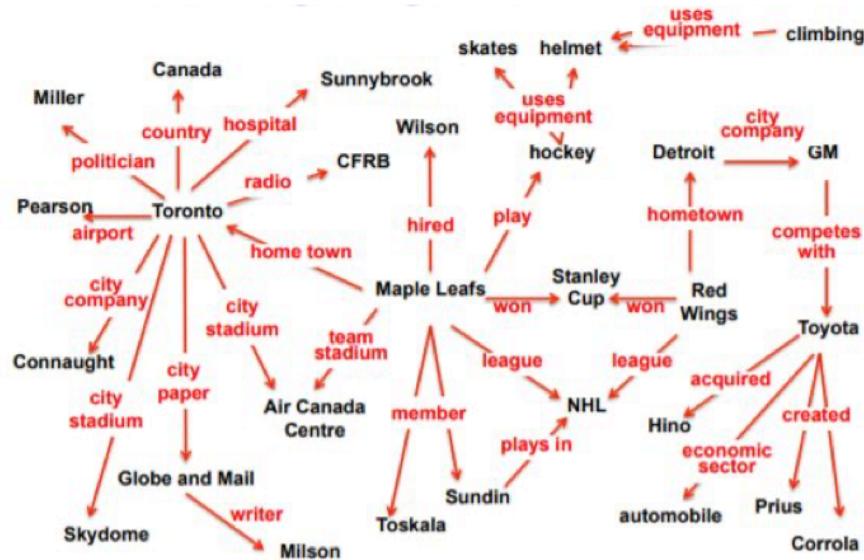


Figure from the paper

# NELL (Mitchell, 2015): Never Ending Language Learner

- <http://rtw.ml.cmu.edu/rtw/>

**Read the Web**  
Research Project at Carnegie Mellon University

Home    Project Overview    Resources & Data    Publications    People

**NELL: Never-Ending Language Learning**

Can computers learn to read? We think so. "Read the Web" is a research project that attempts to create a computer system that learns over time to read the web. Since January 2010, our computer system called NELL (Never-Ending Language Learner) has been running continuously, attempting to perform two tasks each day:

- First, it attempts to "read," or extract facts from text found in hundreds of millions of web pages (e.g., `playsInstrument(George_Harrison, guitar)`).
- Second, it attempts to improve its reading competence, so that tomorrow it can extract more facts from the web, more accurately.

So far, NELL has accumulated over 50 million candidate beliefs by reading the web, and it is considering these at different levels of confidence. NELL has high confidence in 2,810,379 of these beliefs — these are displayed on this website. It is not perfect, but NELL is learning. You can track NELL's progress below or [@cmunell on Twitter](#), browse and download its [knowledge base](#), read more about our [technical approach](#), or join the [discussion group](#).

**Recently-Learned Facts** [twitter](#) [refresh](#)

instance	iteration	date learned	confidence
<a href="#">michigan_city_hotels</a> is a <a href="#">hotel</a>	1111	06-jul-2018	94.7%
<a href="#">slaughter_mountain</a> is a <a href="#">mountain</a>	1111	06-jul-2018	100.0%
<a href="#">national_science_foundation_research</a> is a <a href="#">part of the government</a>	1111	06-jul-2018	100.0%
<a href="#">n1995_national_league_division_series</a> is a <a href="#">sports</a>	1111	06-jul-2018	99.9%

- **Representation:** Natural language
- **Type:** Semantic
- **Creation method:** Information extraction from OpenMind Common Sense Corpus

## 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) →

# ATOMIC ([paper](#))

- **Representation:** Natural language
- **Type:** Inferential (if-then)
- **Creation method:** Crowdsourcing

Event  
PersonX pays PersonY a compliment

Before

1. Does PersonX typically **need** to do anything **before** this event?

After

2. What does PersonX likely **want** to do next **after** this event?

3. Does this event affect people other than PersonX?

(e.g., PersonY, people included but not mentioned in the event)

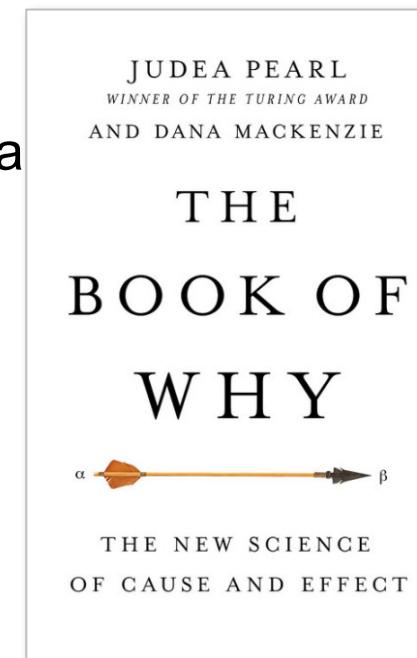
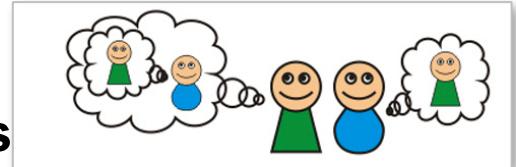
Yes    No

- a). What do they likely **want** to do next **after** this event?

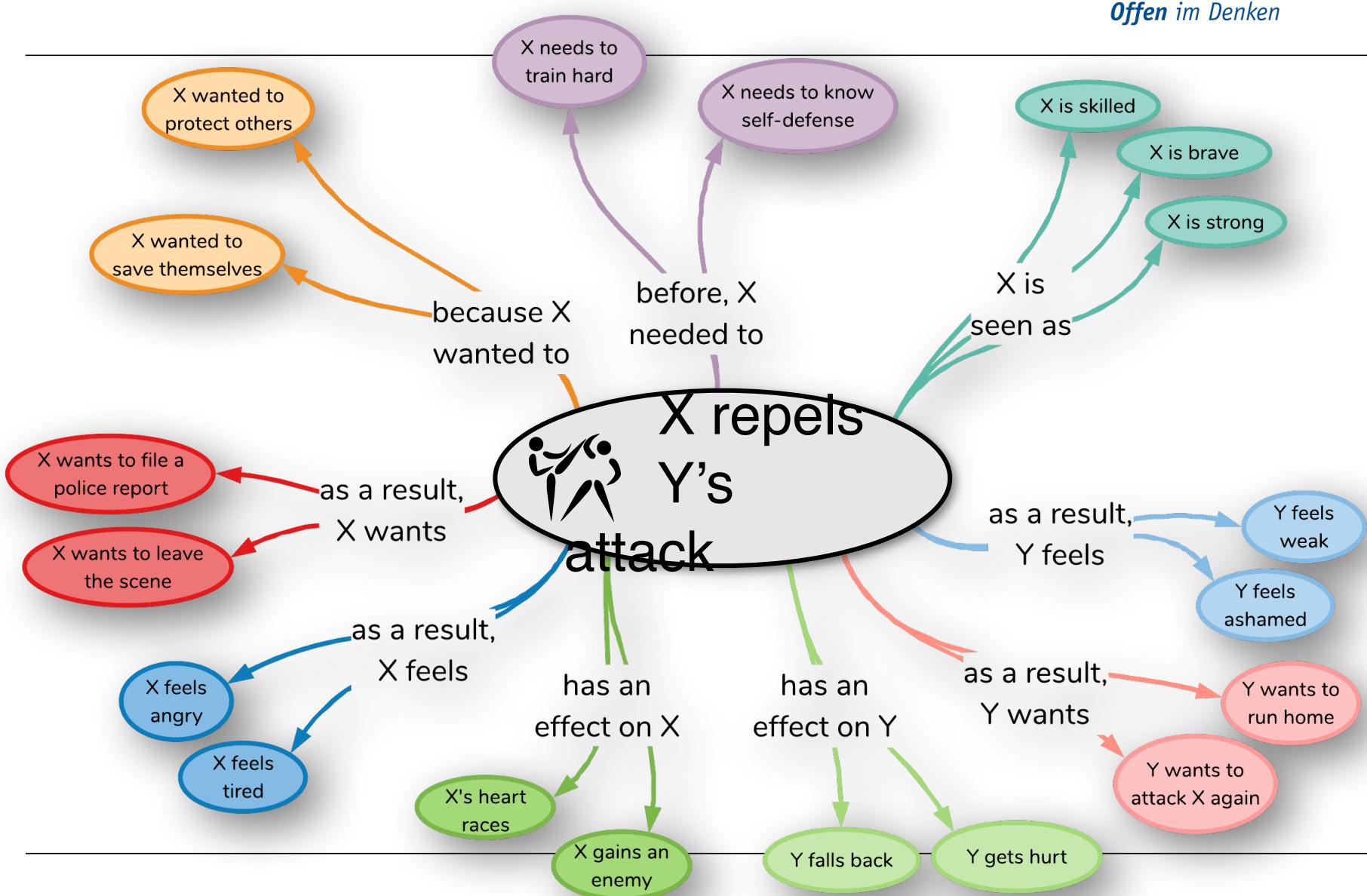
  
  

Figure from the paper

- Humans have **theory of mind**, allowing us to
  - **make inferences** about people's **mental states**
  - **understand likely events** that precede and follow
- AI agents struggle with **inferential reasoning**
  - only find **complex correlational patterns** in data
  - limited to the **domain they are trained on**



# ATOMIC





# ConceptNet

WordNet  
Cyc  
**ATOMIC**

Mining from corpora  
Hand-crafted rules  
Specialized embeddings  
Sentiment analyzer  
**COMET**

# Pre-trained language models

- **Representation:** neural
- **Type:** ?
- **Creation method:** machine learning
- **Topic:** general

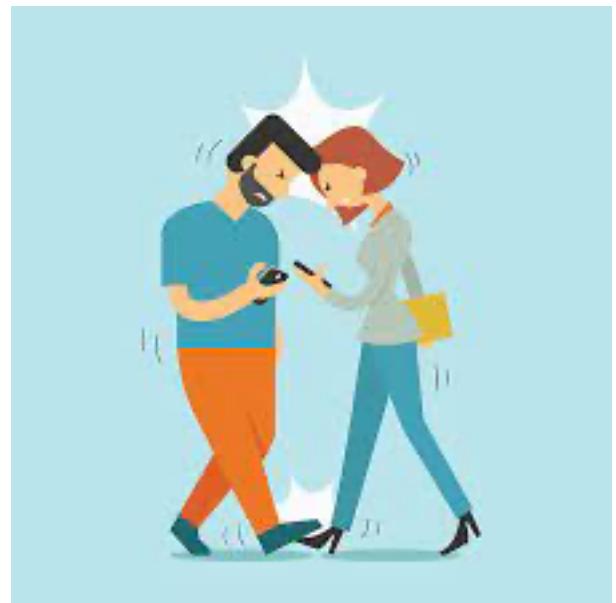
# Pre-trained language models (PLMs)

- PLMs work well on **categorization**, i.e., **knowledge types that are ontological in nature**, such as “mango isA fruit” (Hwang et al. 2021).
- PLMs can **compare physical objects** along a particular attribute such as weight or size (e.g., a chair is *smaller than* a room) (Goel et al. 2019).
- PLMs **do not generalize well on entities not encountered** during pre-training due to their heavy reliance on memorization in the pre-training process (Logan et al. 2019).

# Common Sense Reasoning

# Today

- Humans navigate everyday situations seamlessly with the help of their commonsense knowledge and their ability to reason on such knowledge
  - “bumping into people annoys them”
  - “rain makes the road slippery”



# Three well-known reasoning methods

- **Deduction:** conclusions from give axiom (facts or observations)
  - *All humans are mortal.* —> *axiom*
  - *Socrates is a human.* —> *(fact/premise)*
  - =?

# Three well-known reasoning methods

- **Deduction:** conclusions from give axiom (facts or observations)
  - *All humans are mortal.* —> *axiom*
  - *Socrates is a human.* —> *(fact/premise)*
  - =? *Therefore, it follows that Socrates is mortal.* —> *(conclusion)*

# Three well-known reasoning methods

- **Induction:** Generalization from background knowledge or observations
  - *Socrates is a human* —> (*background knowledge*)
  - *Socrates is mortal* —> (*observation/example*)
  - =?

# Three well-known reasoning methods

- **Induction:** Generalization from background knowledge or observations
  - *Socrates is a human —> (background knowledge)*
  - *Socrates is mortal —> (observation/example)*
  - *=? Therefore, I hypothesize that all humans are mortal. —> (generalization)*

# Three well-known reasoning methods

- **Abduction:** Simple and most likely observation, given observations
  - All humans are mortal. —> (theory)
  - Socrates is mortal. —> (observation/example)
  - =?

# Three well-known reasoning methods

- **Abduction:** Simple and most likely observation, given observations
  - All humans are mortal. —> (*theory*)
  - Socrates is mortal. —> (*observation/example*)
  - =? Therefore, Socrates must have been a human. —> (*diagnosis*)

# Some active reasoning tasks

- Linguistic reasoning
- Reasoning about physical world
- Abductive reasoning
- Multimodal reasoning

# Linguistic Reasoning

- **Goal:** understanding text for which the correct interpretation **requires commonsense knowledge**.
- **Benchmark:** WinoGrande (a more difficult version of Winograd)
- **How do PLMs work on this task?**
  - BERT fails to distinguish between the two sentences “**Birds cannot [MASK]**” and “**Birds can [MASK]**”
  - PLMs perform poorly on **numerical knowledge**
    - given the sentence “**Cats have [MASK] legs**”, BERT predicts “**two**” to be the answer, suggesting that pre-training does not facilitate the acquisition of numerical knowledge.
    - Try: <https://demo.allennlp.org/masked-lm>
  - BERT fails in riddles, where it is required to understand figurative language
  - **[MASK] has to be broken before you can use it?**

# Reasoning about physical world

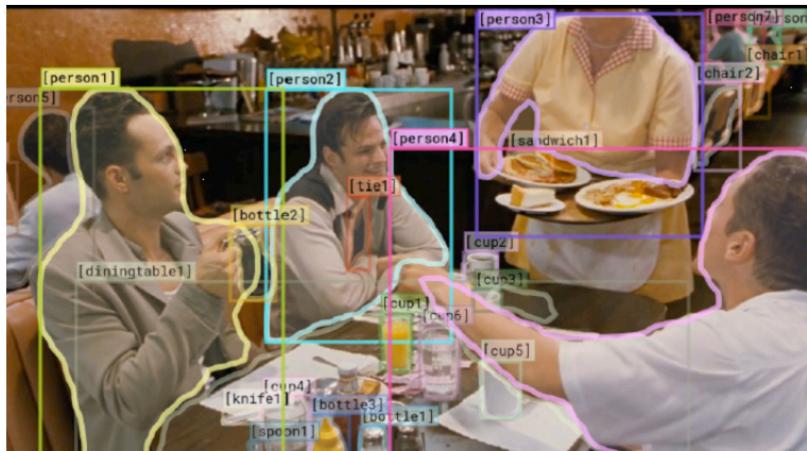
- **Goal:** understanding concepts based on the physical **properties** of objects ("boats require fuel"), the **affordances** of objects (i.e., the actions applicable to them, "boats can be driven") and **how they can be manipulated**.
- **Benchmark:** PIQA (Bisk et al. 2020)
  - the goal is to fill in the blank with one of two answer options
    - "When boiling butter, when it's ready, you can ..."
      - "Pour it onto a plate"
      - "Pour it onto a jar"
- **How do PLMs work for this task?**
  - PLMs **know property associations** that **are explicitly mentioned in text during pre-training**
  - PLMs **struggle** to understand **fundamental relations** (e.g., "**before/after**", "**top/bottom**")
  - PLMs fail to reason when common **objects are used in unconventional ways** (e.g., "a glue stick is used as a paper-weight").

# Abductive Reasoning

- **Goal:** finding the most likely **explanation** for a set of incomplete observations.
- **Benchmark:**
  - **COSMOSQA** (Huang et al. 2019): **choose the answer** to the **question** based on the **context from four answer candidates**. This benchmark contains questions that require abductive reasoning, such as "**what might I continue to do after the situation described in the context?**"
  - **HellaSwag** (Zellers et al. 2019b) **choose the best plausible ending** of a given context out of four options.
- **How do PLMs work for this task?**
  - PLMs struggle on examples **where understanding the context requires cross-sentence interpretation and reasoning**
  - PLMs struggle with selecting the **most plausible ending**: given context a question can have **multiple correct endings**. Determining which one would be the most plausible **requires prior reasoning of what humans relate to the most with their commonsense knowledge**. When more **surface cues** are **eliminated**, PLMs are **less likely to be able to predict the most plausible** ending even though it might be trivial for humans to do so.

# Multimodal reasoning

- **Goal:** Textual representations are restricted to what can be expressed through natural language. Humans use other modalities for reasoning. Can machines do the same?
- For example, **inferring the intentions of the entities in images** can only be well dealt with if we have **some prior information** (either behavioral or temporal) to rely on to make **justifiable inferences**.



Why is [person4] pointing at [person1]?

- a) He is telling [person3] that [person1] ordered the pancakes.
- b) He just told a joke.
- c) He is feeling accusatory towards [person1].
- d) He is giving [person1] directions.

I chose  
because...

- a) [person1] has the pancakes in front of him.
- b) [person4] is taking everyone's order and asked for clarification.
- c) [person3] is looking at the pancakes and both she and [person2] are smiling slightly.
- d) [person3] is delivering food to the table, and she might not know whose order is whose.

# Multimodal reasoning

- **Goal:** Textual representations are restricted to what can be expressed through natural language. Humans use other modalities for reasoning. Can machines do the same?
- For example, **inferring the intentions of the entities in images** can only be well dealt with if we have **some prior information** (either behavioral or temporal) to rely on to make **justifiable inferences**.
- **Benchmark:** Visual commonsense reasoning (VSR) (Zellers et al. 2019a) seeks to answer cognition-level questions from images.
- **How do PLM-based model work?**
  - visual features help make higher quality commonsense inferences.

# Summary

- How to acquire commonsense knowledge?
- What is reasoning and what are active tasks in reasoning?

# References

- **Mandatory**
  - Commonsense Knowledge Reasoning and Generation with Pre-trained Language Models: A Survey

**Today**

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# Thank You