Course

Knowledge-based Systems

Lecture 09: Commonsense Reasoning

Dr. Mohsen Mesgar

Universität Duisburg-Essen

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

Introduction

Commonsense knowledge and reasoning

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- **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.**

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Commonsense Knowledge Sources

Desiderata for ideal commonsense KBs

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- **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

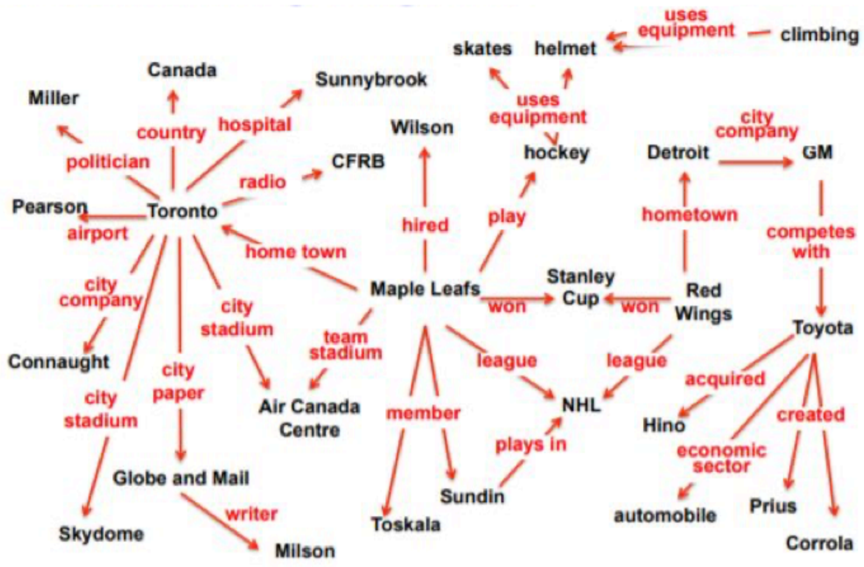

Figure from the paper

NELL (Mitchell, 2015): Never Ending Language Learner

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

ConceptNet

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

ConceptNet

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en reading

An English term in ConceptNet 5.8

Related terms

- en book →
- en books →
- en book →

Effects of reading

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

reading is a type of...

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

reading is a subevent of...

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

Types of reading

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

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 →

ATOMIC (paper)

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

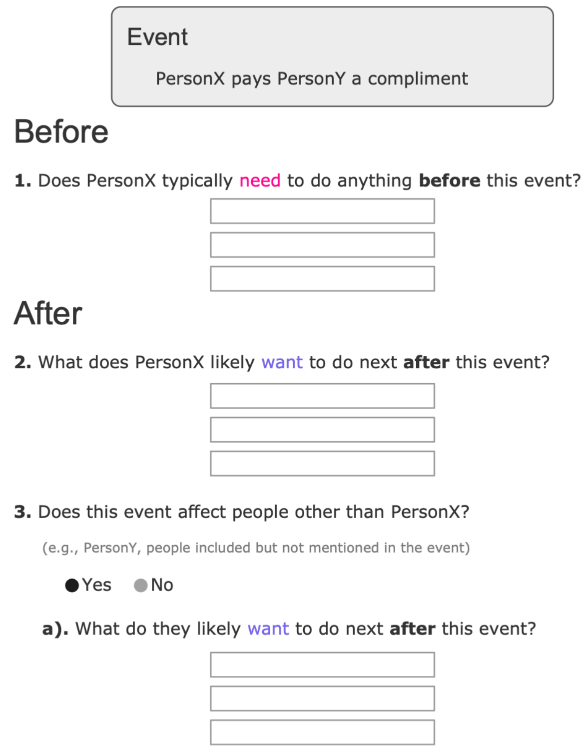
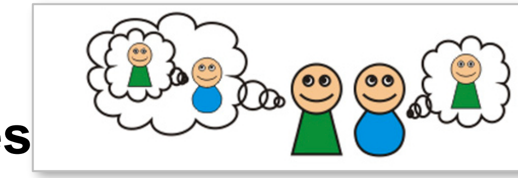


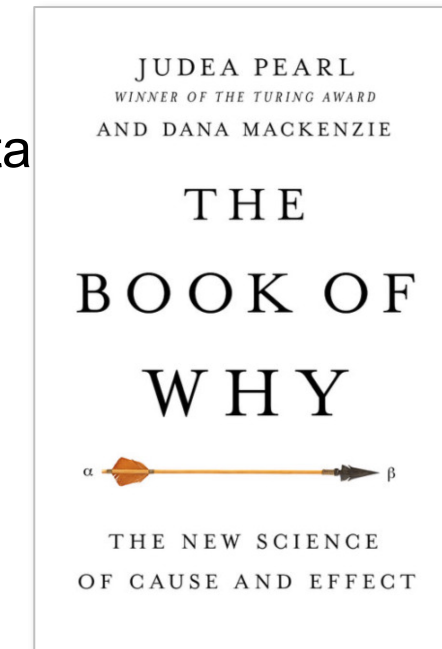
Figure from the paper

ATOMIC

- 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

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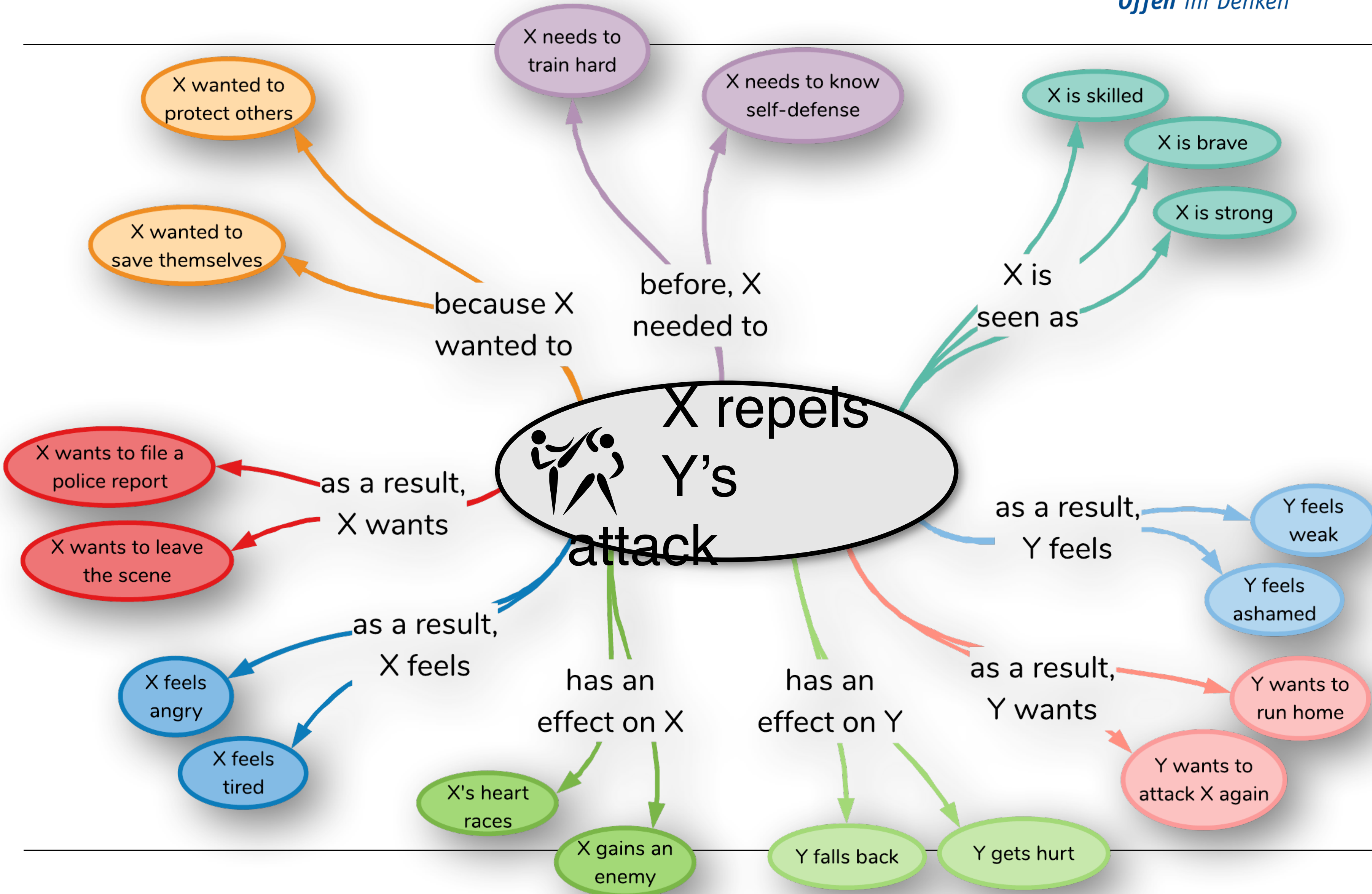


ConceptNet
WordNet
Cyc
ATOMIC
Mining from corpora
Hand-crafted rules
Specialized embeddings
Sentiment analyzer
COMET
imgflip.com

Pre-trained language models

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- **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).

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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

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- **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

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

Three well-known reasoning methods

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- **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

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- ***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

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

Linguistic Reasoning

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- **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

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- **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

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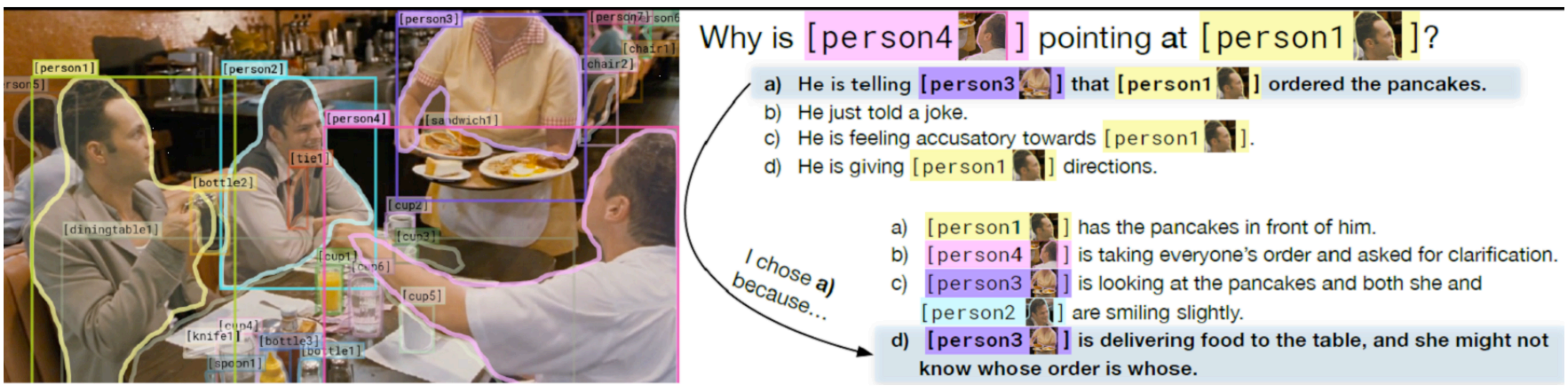
- **Goal:** Textual representations are restricted to what can be expressed through natural language. Humans use other modalities for reasoning. Can machines do the same?
- For example, **inferring the intentions of the entities in images** can only be well dealt with i**f we have some prior information**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



Multimodal reasoning

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- For example, **inferring the intentions of the entities in images** can only be well dealt with i**f 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

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- 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

Thank You