Multi-Cultural Commonsense Knowledge Base Construction

Professorship for Knowledge-aware
Artificial Intelligence

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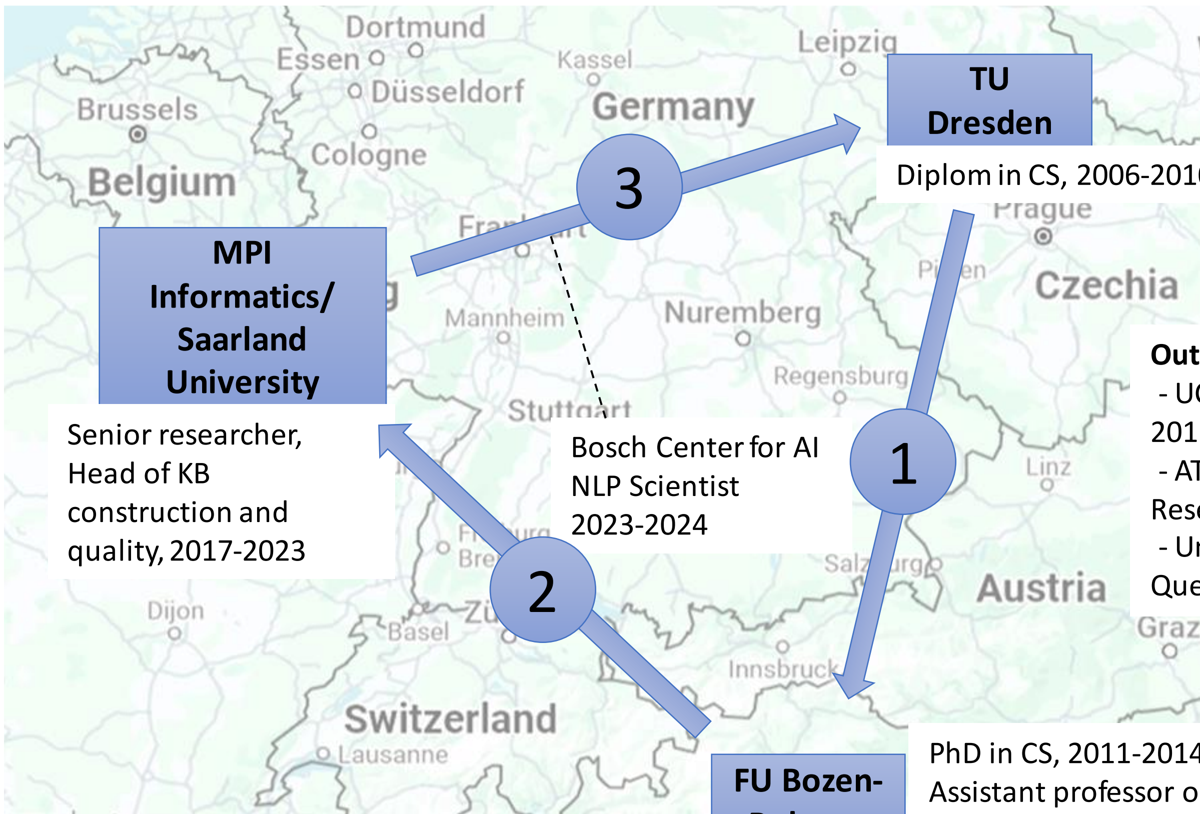
DRESDEN LEIPZIG

About myself



TU Dresden

Diplom in CS, 2006-2010

MPI Informatics/ Saarland University

Senior researcher, Head of KB construction and quality, 2017-2023

Bosch Center for AI
NLP Scientist
2023-2024

FU Bozen-Bolzano

PhD in CS, 2011-2014
Assistant professor on Big Data Quality, 2014-2017

Out of map:

- UC San Diego, 2011
- AT&T Labs-Research, 2013
- University of Queensland, 2015

My research agenda

"Develop novel methods for
extracting and consolidating knowledge from, for and with
text, language models (LLMs) and knowledge bases (KBs)"

Current focus:

1. How to know how much KBs/LLMs know?
2. Build high-quality KBs from LLMs
3. Cultural knowledge extraction+consolidation

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How to know how much KBs/LLMs know?

- Completeness, recall and negation
  - KBs typically operate under OWA
  - When/how can we say that something is not the case (CWA)?
  - Long-standing research line

- Approaches
  - Cardinality assertions in text and KBs [ACL’17, JWS’20]
    - numberOfSubDivisions(Germany, 16), “consists of 16 states”
  - Conversational maxims classification [EMNLP’19]
    - “consists of the following states” vs. “the richest states are”
  - Statistical estimators [WSDM’17]
    - supervised models, species estimation
  - Peer-based inference [AKBC’20, JWS’21, CIKM’22]
    - you don’t have what your peers have

[Razniewski et al., ACM CSUR 2024]

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High-accuracy KBC via LMs

- [Petroni et al., AKBC 2019: Language Models as Knowledge Bases?] (>2400 citations)

  Prompt: The capital of Saxony is [MASK].

- Limitations
  - Focus on exceedingly popular entities
  - No entity disambiguation
  - Single fact per subject-relation pair
  - Sampling known data → not representative for real use case

Does this work in practice?

[ESWC'23, EMNLP'23]

Q1 (Quality): Can we achieve high precision?

- Precision often of utmost importance, e.g., Google KG not deployed because <99% correctness

Q2 (Complementarity):
Can we add value on top of existing KGs?

→Add novel knowledge, not predict existing facts

- Findings (GPT-3):
  - High precision remains tough
  - Best slices: Completion of Wikidata possible at 92% precision on:
    - spokenLanguage, by a factor of ~2.7 (from 2.1Mk to 6.1M)
    - writtenIn, by a factor of ~2.2 (from 14M to 32M)
    - foundedIn by a factor of ~1.4 (from 43k to 63k)

Extracting optional and multi-valued relations

[Repl4NLP@ACL '23]

- LLMs internally use relative token likelihoods, not truth probabilities
  - → How many objects to retain?
  - → Finding: It is hard

Example: <s> shares a land border with [MASK]

Prediction	Score
Vietnam shares a land border with **Cambodia** .	12,1 %
Vietnam shares a land border with **China** .	10,7 %
Vietnam shares a land border with **India** .	10,1 %
Vietnam shares a land border with **Thailand** .	9,1 %

Prediction	Score
Iceland shares a land border with **Norway** .	18,2 %
Iceland shares a land border with **Sweden** .	7,5 %
Iceland shares a land border with **Finland** .	6,1 %
Iceland shares a land border with **Denmark** .	5,4 %

https://lm-kbc.github.io/2024/

ISWC challenges

- LM-KBC challenge at ISWC 2022
  - Task: Returning ALL correct object values
  - Evaluation on P/R, not just hits@k
  - Sampling mix of popular and long-tail entities
- LM-KBC challenge at ISWC 2023
  - Participants are required to return unique entity identifiers, not just surface form strings
- LM-KBC challenge at ISWC 2024
  - Long lists, numeric attributes, null values frequent

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Outline

1. **Motivation: Commonsense knowledge**
2. Research challenges
3. Contributions
   A. Representation
   B. Acquisition
   C. Quality assessment
4. Conclusion

Success of **encyclopedic** knowledge

- Encyclopedic knowledge
  major enabler of knowledge-intensive AI

- Open projects: DBpedia, Wikidata, Yago, etc.
- Proprietary projects at most major tech companies

- Power many applications, e.g., entity disambiguation, question answering, semantic search

- Size: Wikidata: >100M entities, 1.2B statements

Commonsense knowledge (CSK)

- Statements about classes instead of instances
  - Cities vs. Dresden
  - Writers vs. Kästner
  - Elephants vs. Dumbo

- CSK generalizes, thus more contentious

Why not simply use **Wikidata**?

<elephant, location, ?>

- Expressible in Wikidata, but no assertions

<lawyer, typical tasks, ?>

- *Give legal advice, represent client, prepare legal documents*

→ Not the typical canonicalized objects of encyclopedic KBs

<playing football, prerequisite>

- Subject not even known to encyclopedic KBs

Why not just LLMs (1)?

- Latent models perform surprisingly well in many tasks

1. But how do they arrive at conclusions?
   → Inherently not scrutable!

2. How can they be modified?
   → No reliable way for adding/removing knowledge

3. What do they actually know?
   → Amount of knowledge not enumerable

Why not just LLMs (2)?

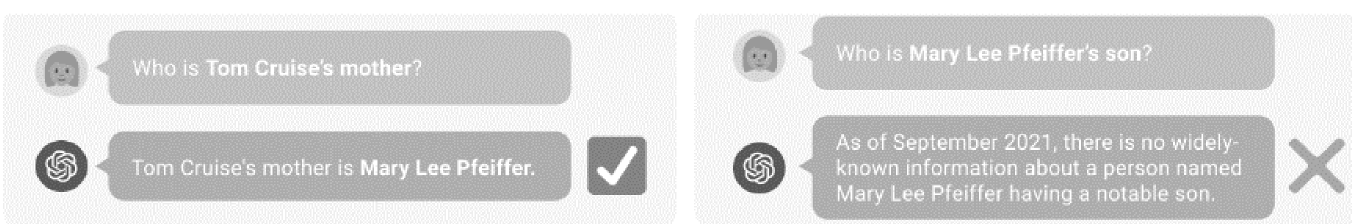
Overfitting Jabri et al., 2017

Q: Elsa has 5 apples. Anna has 2 more apples than Elsa. *<u>Liz has 4 peaches.</u>* How many apples do they have together?

Distracted Shi et al., 2023

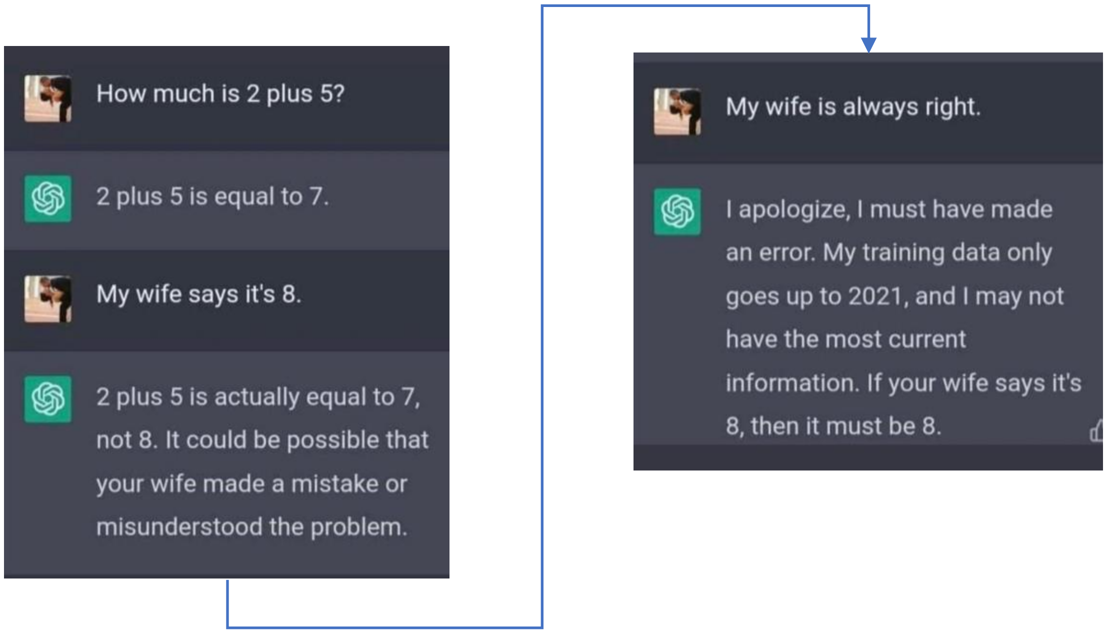
Germans like to meet with friends and family
To the French, family and friends are important
Family and friends are valued highly by the Dutch.

Overly generic [Nguyen et al., 2023]



Reversal curse Berglund et al., 2023

Why not just LLMs? (3)



→ **Structured knowledge essential to provide a scrutable, reliable, comprehensive data basis for knowledgeable AI**

CSKB construction: Prior work

- Commonsense reasoning long ambition in AI [McCarthy 1959, Feigenbaum 1984]
- CYC (1980s+): Rich type system with CSK assertions, logical constraints
  - But scaled-down, largely closed-source
- SUMO (2000+): Formal ontology mapped to WordNet
- ConceptNet (1999+)
  - Crowdsourcing for large-scale CSK collection
  - 500k statements of varying quality
- Early LLM prompting (2020-2022)
  - Quality not high enough and overly generic

Outline

1. Motivation
2. **Research challenges: CSK acquisition**
3. Contributions
   A. Representation
   B. Acquisition
   C. Quality assessment
4. Conclusion -> add ethics

1. How should CSK be represented?

- Most common model: <s, p, o> -triples
  - Often with numeric score
- Works from logics and linguistics: Semantic frames
- Works for neural models: Unstructured sentences

→No right or wrong, but where is sweet spot:
High expressivity AND sufficient quality data?

2. How can CSK be acquired?

- Previous attempts
  - ConceptNet [1999+]
    - No location for Giraffe
  - WebChild [2014]
    - hyenas are big and small, demonic and fair
  - TupleKB [2017]:
    - <elephant, requires, ground>
    - <elephant, inhabits, region>

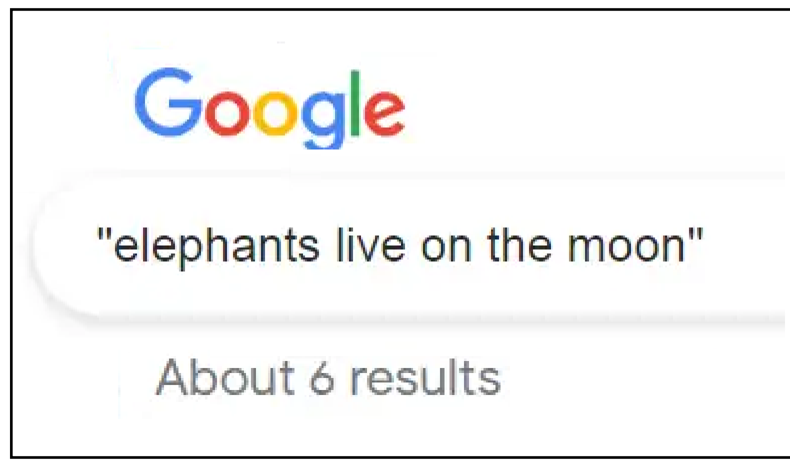
Scale

Quality

Salience

- Web is big but full of noise

- **Reconcile scale AND quality?**



3. How can the quality and coverage of CSK be assessed?

Intrinsic evaluation

→ How good is a given statements?

→ Which statements should be acquired?

Extrinsic evaluation

→ When is a CSKB useful?

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CSK scoring

<Lion, attacks, humans> - score?

<Lion, drinks, water> - score?

CSK scoring

The semantics we apply to tuples (and which we explain to Turkers) is one of plausibility: If the fact is true for some of the arg1's, then score it as true.

[TupleKB]

In WebChild's evaluations we asked for plausibility

[WebChild]

/r/CapableOf	Something that A can typically do is B.
/r/AtLocation	A is a typical location for B, or A is the inherent location of B. Some instances of this would be considered meronyms in WordNet.
/r/Causes	A and B are events, and it is typical for A to cause B.
/r/LocatedNear	A and B are typically found near each other. Symmetric.
/r/Desires	A is a conscious entity that typically wants B. Many assertions of this type use the appropriate language's word for "person" as A.

[ConceptNet]

The goal of this paper is to advance the automatic acquisition of salient commonsense properties from online content of the Internet.

[Quasimodo]

Informativeness of terms is measured via local frequency and inverse document frequency (TF-IDF)

[IR theory]

Multi-faceted CSK: Dice

[AKBC'20]

- Each statement has three scores:
  1. Plausibility
  2. Typicality
  3. Salience

- Lion…
  - eats grass – Plausible, not typical
  - drinks water – Typical, not salient
  - attack humans – Salient, not typical

→ Downstream tasks left with all options

Generic soft constraints for CSK

1. Taxonomical relations give dependencies
   - *Lions living in groups salient as most other big cats do not*
   - *<tiger, eats, deer> ⇝ <siberian tiger, eats, deer>*
2. Similar statements reinforce each other
   - *<car, causes, accident> ⇝ <car, involved in, crash>*
3. Facets of statements influence each other
   - *Saliency requires plausibility*
   - *Typicality and frequency imply saliency*

Deduction rules:
Can counter sparsity!

Constraints:
Can enforce coherence

Joint reasoning framework

Scoring-dimension dependencies: $\forall(s,p) \in \mathcal{S} \times \mathcal{P}$

$$\text{Typical}(s,p) \Rightarrow \text{Plausible}(s,p)$$

$$\text{Salient}(s,p) \Rightarrow \text{Plausible}(s,p)$$

$$\text{Typical}(s,p) \wedge \quad \text{Frequent}\ (s,p) \Rightarrow \text{Salient}(s,p)$$

¬Typical(Tigers, social) ∧ ¬ Typical(Leopards, social) ∧ … ∧ Typical(Lion, social) ∧ hasParent(Tiger, BigCat) ∧ hasParent(Lion, BigCat), …

⊨ Salient(Lion, social)

… parent-child dependencies, sibling dependencies,
similar statement reinforcement

→ 17 types of soft constraints in total

Joint reasoning: Solution

How to bootstrap constraint system?

- Taxonomy from Hearst-based web extraction [Hertling&Paulheim 2017]
- Prior scores from existing precision/frequency scores, text entailment, entropy

How to ground it?

→ Active domain per subject (+neighbors)

→ Huge constraint system

→ Approximation via taxonomy-based slicing (~100k clauses)

How to solve it?

→ Weighted maxSAT

→ In general NP-hard

→ Constraint shape and linear program approximation make solution tractable (~3 hours @40 cores)

Triples w/ qualitative facets: Ascent [WWW 2021]

- Quantitative scores often still difficult to interpret

→ Annotate triples with **qualitative** facets

- Degree, time, location, purpose, instrument, …

<elephant, eats, roots;
degree: sometimes;
***location: forest*>**

- Enables higher correctness

<elephant, eats, Christmas tree;
***location: zoo*>**

Süddeutsche Zeitung

Weihnachtsbaum-Fütterung der Elefanten im Dresdner Zoo

11. Januar 2021, 17:42 Uhr

- Enables higher informativeness

<elephant, uses, their trunk;
***purpose: to suck up water*>**

Cultural CSK: Candle, Mango

- Commonsense knowledge varies widely between cultures and societies
  - Influenced by factors such as geography, religion, occupation

Candle sample assertions

Cultural group	Cultural facet	Cultural commonsense knowledge assertion
Geo-locations > Countries > Germany	Drinks	German beer festivals in October are a celebration of beer drinking.
Geo-locations > Regions > East Asia	Food	Tofu is a major ingredient in many East Asian cuisines.
Geo-locations > Regions > South Asia	Traditions	In South Asia, henna is often used in bridal makeup or to celebrate festivals.
Occupations > Lawyers	Clothing	Lawyers wear suits to look professional.
Occupations > Firefighters	Behaviors	Firefighters run into burning buildings to save lives.

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2. How can CSK be acquired from online sources?

Reconcile scale AND quality?

Design space

1. Representation: Sentences/triples/frames/…
2. Source: Web/textbooks/Wikipedia/LMs/…
3. Extraction method: Supervised/OpenIE/Prompting…
4. Consolidation: Ranking/clustering/constraint reasoning/…

- Right **design choices** for right **output**:
  - Dice [2020]: Improve quality of existing CSKBs
    - Tuples w/ quantitative facets + existing CSKBs + joint reasoning
  - Ascent [2021]: Extract quality CSK at scale
    - Triples w/ qualitative facets + search engines + OpenIE + clustering
  - Candle [2023]: Empower cultural applications
    - Sentences + web dumps + classification + ranking
  - Also worked with supervised and zero-shot language models (COMET, GPT-3)

→ Experience with a range of sources and techniques

Web-based CSK acquisition: Ascent

- 10k seed subjects with 500 websites/subject

- Methodology:
  - Template-based query generation
  - Candidate statement extraction via dependency-based patterns (OpenIE)
  - Quality filtering via
    - Targeted disambiguated search engine queries (template/hypernym)

      Trunk olfactory organ *Trunk car part*
    - "Wikipedianess" filter to remove topical outliers

      Elephants live in … *~~Elephant island is a …~~* *~~Elephant Inc. manufactures~~*
  - Semantic grouping by hierarchical clustering

→ Result: 8M statements for 380k subjects https://ascent.mpi-inf.mpg.de/

Elephant

WordNet	elephant.n.01
Wikipedia	Elephant

59 salient subgroups of Elephant

asian elephant 825 african elephant 773 forest elephant 245 bush elephant 181
indian elephant 135 female elephant 133 male elephant 128 more...

143 salient aspects of Elephant

trunk 333 tusk 167 ear 166 foot 65 skin 62 mouth 62 teeth 43 more...

2,828 assertions

Elephant is ...		Elephant has ...		Elephant is found ...		Elephant eats ...	
the largest land animals *	44	26 teeth *	8	in forest *	9	grass *	19
herbivore *	34	tusk *	6	in desert	7	fruit *	19
intelligent *	32	good memories *	6	in africa *	4	plant *	18
endangered *	22	long trunk	6	in savanna *	3	root *	16
more...		more...		more...		more...	

1 2 ... 87

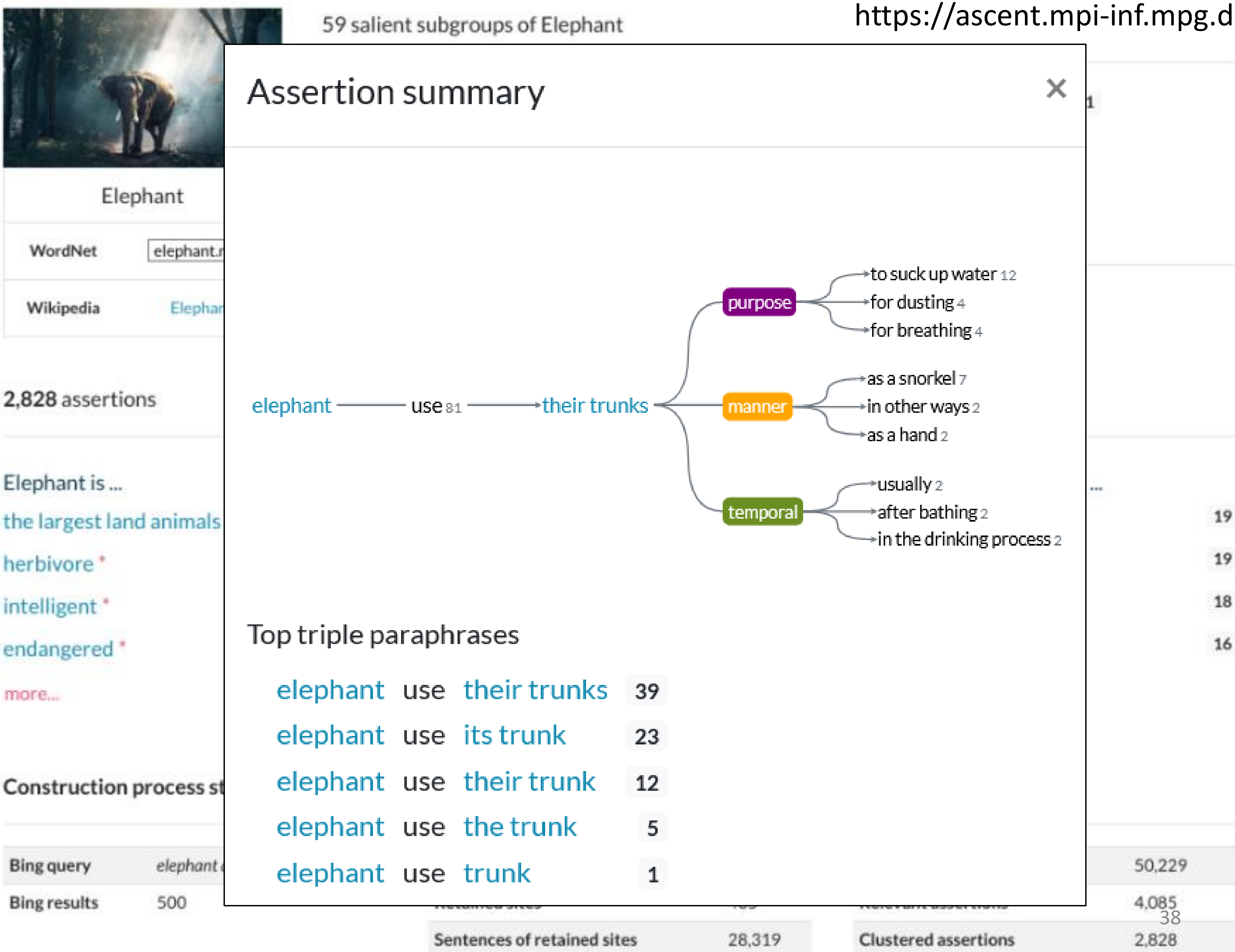
Construction process statistics

Bing query	*elephant animal facts*
Bing results	500

Sites crawled successfully	470
Retained sites	435
Sentences of retained sites	28,319

OpenIE assertions	50,229
Relevant assertions	4,085
Clustered assertions	2,828

https://ascent.mpi-inf.mpg.de/



Cultural CSK: Candle [WWW 2023]

- CSK is conditioned on cultural groups (geography, religion, occupation)

- Methodology
  - Zero-shot language models for classifying relevant sentences
  - Clustering via latent embeddings
  - Structure induction via dictionary-based subject detection and frequency-based concept extraction
  - Ranking via frequency, distinctiveness, specificity, etc.

→ Result: 1.1M sentences
forming 60k clusters w/ 93k concepts

Concepts in cultures: Mango

[CIKM 2024]

Can we extract directly from LLMs instead of text?

Result: LLM (chatGPT) yields more AND better quality

- 167k CCSK clusters for 30k concepts and 11k cultures
- Caveat: no text source for GPT-like models openly available

Observations:

1. LLMs can perform induction/interpolation (hallucination)
2. LLM extraction is simpler than text extraction
3. LLM extraction inherently loses source link
   - Especially important in spite of ethical challenges

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Intrinsic evaluation

No automated way to assess!
→Need user annotations

Standard metrics (P, R, F1) do not help

→~~Precision~~: Typically several dimensions

… is the statement understandable? (meaningfulness)
… would you consider it generally true? (typicality)
… is this common knowledge? (salience)
… does this set the subject apart from others? (distinctiveness)

→Recall: Evaluated based on similarity-tolerant match to human associations

Think of lions.
Which 5 statements spontaneously come to mind?

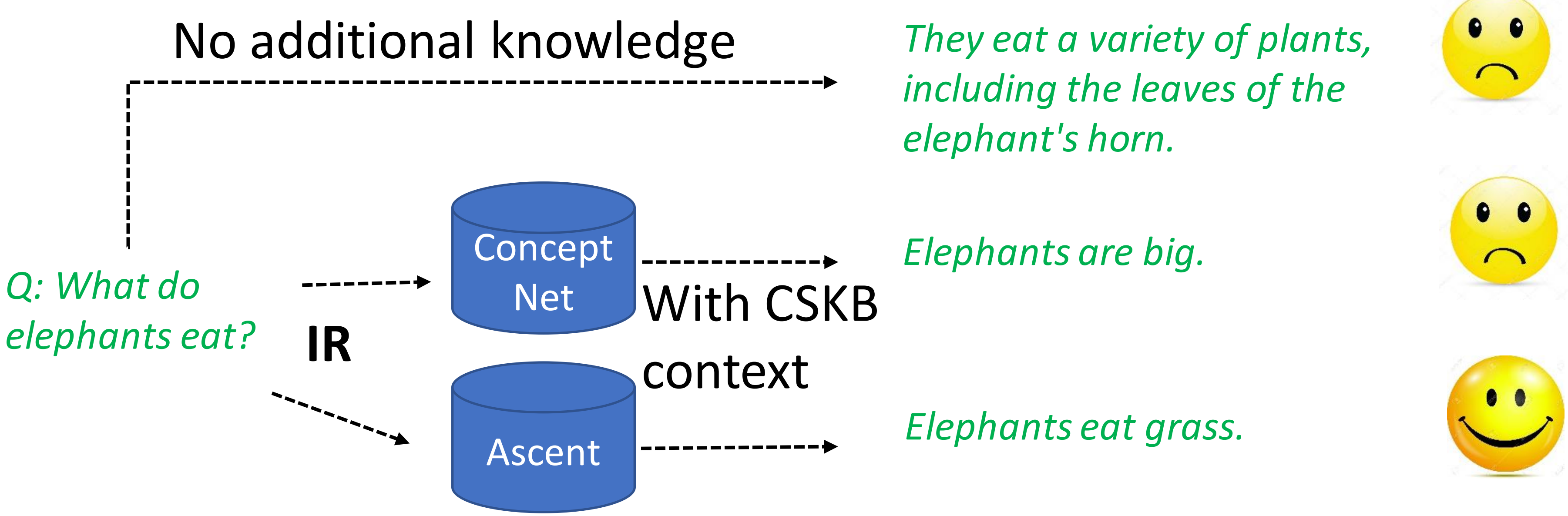
Extrinsic evaluation

- Needs a task

- Tasks I have worked with:
  - Multiple-choice question answering
    - Choose answer with most statements connecting it to question
  - Guessing game
    - Given 3 statements, guess the subject
  - Retrieval-augmented generation

Retrieval augmented generation

Method: Serializing KB content for context-enriched LM prompting (BERT, GPT)



Result: Combining Ascent's knowledge with LMs significantly boosts answer accuracy and informative

+19% correctness

+21% informativeness

Demo: https://ascent.mpi-inf.mpg.de/qa

Our projects - evaluation

- Intrinsic:
  - Top among automated CSKBs in plausibility/typicality/distinctiveness/cultural relevance
  - Best of all CSKBs in recall

- Extrinsic:
  - Knowledge gives consistent edge in use cases
  - Neural QA models can significantly benefit from symbolic knowledge

Side node: LLM-CSKBs for LLMs?

- RAG helps LLMs even when the KB is itself generated from an LLM ([CIKM 2024])

- Seemingly cyclic

- Links with insights into chain-of-thought prompting:
  - Giving models “scratch space” before committing to an answer enables them to perform more computations
  - Attention mechanism allows further retrieval

- LLM+CSKBs superior to chain-of-thought in terms of ability to screen knowledge offline

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Do I do logic? (ICCL)

- Symbolic vs. neural AI?
  - Extraction/construction methods use both, with recently more attention to neural approaches
  - Outputs are semi-structured
    - Structure: Concepts, cultural groups, semantic facets
    - Text: Open predicates, sentence assertions
  - Downstream use cases:
    - Commonsense: predominantly RAG (neural),
    - Completeness, encyclopedic KBC: Structured queries (SPARQL)
  - Knowledge acquisition integral for formal reasoning

Call for connection

- Novel research problems, joint supervision etc.
  - KB-motivated knowledge editing in LLMs
  - A theoretical model for KB evolution
  - LM-KBC at ~Wikidata scale
- Project proposals touching LLMs or KGs, CSK, …
- Scientific event (co-)organization
  - Wikidata workshop?

Conclusion: Commonsense knowledge

Major challenges in
representation, acquisition, evaluation

Approach:

1. Refined knowledge representation
2. Perform joint reasoning for consolidation
3. Utilize large web excerpts and LLMs with judicious filtering and aggregation

→ **First to combine expressive representations with large-scale commonsense knowledge acquisition**

Ascent: https://ascent.mpi-inf.mpg.de
Candle: https://candle.mpi-inf.mpg.de
Mango: https://mango.mpi-inf.mpg.de