Agenda

08:30 PST	10 mins	**Introduction to commonsense knowledge (Filip)**
08:40 PST	25 min	**Part I - Axiomatization of commonsense knowledge (Mayank)**
09:05 PST	40 min	**Part II - Consolidating commonsense knowledge (Filip)**
09:45 PST	15 min	Break
10:00 PST	45 min	**Part III - Extracting and contextualizing commonsense knowledge (Simon)**
10:45 PST	45 min	**Part IV - Language models, QA, and evaluation challenges (Antoine)**
11:30 PST	15 min	**Way forward: KGs+LMs+axioms? (Filip)**

Part III: Extracting and contextualizing commonsense knowledge

Simon Razniewski

Max Planck Institute for Informatics

Outline – Extracting and contextualizing CSK

1. **Background**
2. Recipe
3. Example projects
4. Take-away

Background

- Earliest projects on CSKB construction were manually authored (Cyc, ConceptNet)
- Challenges in scale
  - Atomic: ~100k$ annotator expenses
- Automated information extraction and KB construction field with long history
  - Focus traditionally on crisp ``encyclopedic'' knowledge (cf. DBpedia, YAGO, NELL, DeepDive, …)
- Can we use automated IE and KBC for CSK?

Graham Neubig
@gneubig

Following

One commonly cited argument about the difficulty of learning common-sense reasoning is that "no-one writes down common sense". A counter-argument is "well, the web is big": instructables.com/id/How-To-Open…

How to Open a Door

Step 1: Locate Desired Door

Step 2: Locate Door Handle or Knob

Step 3: Turn Knob or Handle and Pull or Push

Challenges of automated CSKB construction

- Underspecified text semantics
  - “Lions attack humans” – all/some/all the time/once/..?
- Reporting bias
  - “woman kills” vs. ”woman breathes” – 1.5M vs. 0.1M web search results
  - “pink elephant” vs. “grey elephant” – 6.9M vs. 1.9M web search results
- Sparse observations of quadratic+ space of possible statements
  - Do computer programmers drink water?
- Noise and polysemy
  - Pigs can fly - idiom
  - Lynx: Constellation, web browser, animal

Outline – Extracting and contextualizing CSK

1. Background
2. **Recipe**
3. Example projects
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(Textual) information extraction

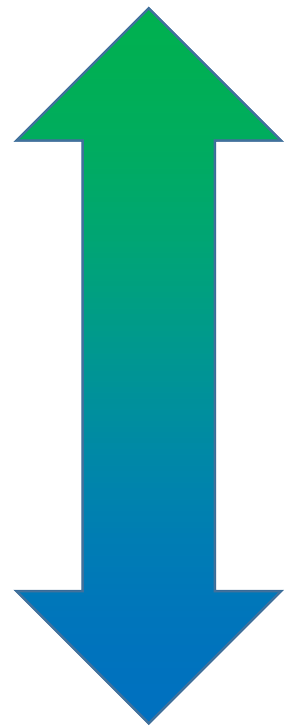
- Textual information extraction long attention in KBC/NLP
- Idea: Exploit patterns/commonalities in natural language in order to extract commonsense knowledge
  - *Lynx eat hares*
  - *Elephants eat grass*

  → <s> eats <o> - pattern for (s, diet, o)
- Generic design points
  1. Sources
  2. Extraction method
  3. Type of contextualization
  4. Consolidation method

Design point 1 – Source choices

- *“Where to extract from?”*
  - Wikipedia
  - Books and other dedicated sources
    - ARC science corpus
    - Project Gutenberg
  - Web search
  - Forums
    - Reddit
    - Quora
    - Yahoo Answers
  - Search engine query logs
  - Web crawls
    - ClueWeb
    - CommonCrawl
  - …

Precision
Coherence



Recall
Redundancy

Extraction source - considerations

- (CS)KB projects stand and fall with source selection
- Precision: *Topic-specific sources >> random web*
  - Event knowledge – Wikihow [HowToKB, WWW 2017]
  - Cultural knowledge – Movie scripts [Knowlywood, CIKM 2015]
  - Science knowledge – Science textbooks [GenericsKB, Arxiv 2020]

- With considerable cleaning, frequency signals may be stronger from general web dumps

- Intermediate setting: Targeted web search [TupleKB, Ascent]

Design point 2 – Extraction method options

- *“How to extract”*

1. Manual patterns [WebChild, WSDM 2014]
    - Hearst patterns etc.
2. Co-occurrence [DoQ, ACL 2019]
    - Window, same sentence, …
3. Open information extraction [TupleKB, Quasimodo, Ascent]
    - Any verb phrase
4. Relation-specific supervised learning

Extraction method - considerations

- Preferred method depends on desired knowledge representation
  - E.g.,
    - Few non-overlapping relation → Co-occurrence
    - Moderate relations → Supervised extractors
    - Many relations → OpenIE

- Has implications downstream
  - Extraction confidences (supervised extractors) for quantitative contextualization
  - Text context for qualitative contextualization
  - OpenIE with many unspecific extractions

Design point 3 – Contextualization

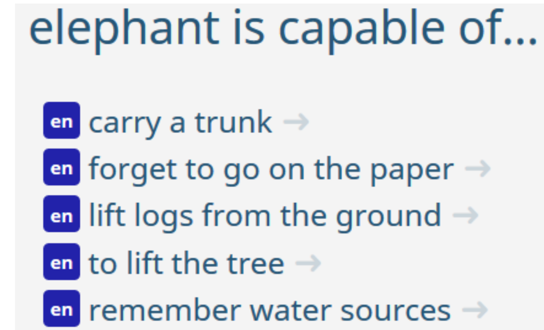
"What do we annotate statements with?"

1. Observation frequency [WebChild 2.0, DoQ]
   - *Elephant, has, tusks, 155*
   - *Elephant, has, tail, 84*
2. Quantitative [0,1] truth labels [TupleKB, Quasimodo]
   - *Elephant, lives in, group, 0.87*
3. Qualitative truth labels [Ascent]
   - *Elephant, lives in, group, **temp**: during wet season*
   - ***Subgroup**: <u>Female</u> elephant, lives in, group*

Contextualization - considerations

- Frequencies trivial to interpret, but do not qualify degree of truth
- Quantitative truth labels nontrivial semantics
- Qualitative labels easier to interpret, but harder to compare
- Expressive proposals from KR exist (e.g., modal logics)
  - Actual implementation not easy
    - Sparse realization in natural language
    - Correct extraction nontrivial

Design point 4 – Consolidation



"What do we do with redundant and competing extractions?"

- Similar statements may be seen several times
- Redundancy and contradictions may require additional inference

Cats, are, solitary
Lions, live in, groups

Lions, are, cats

- Common consolidation methods
  1. Keep all [DoQ]
  2. Frequency cutoff [Ascent]
     - E.g., at least seen 5 times
  3. Per-statement consolidation [TupleKB, Quasimodo]
     - Feature-based classification/ranking
  4. Joint consolidation [WebChild, Dice, Ascent]
     - E.g., BERT-based clustering, MaxSAT, …

Consolidation - considerations

- Redundancy challenge and blessing
- Exploiting redundancy requires strong text similarity/entailment modules
- Previous projects often stuck to per-statement consolidation due to lack of strong similarity/entailment modules
- Recent advances on pretrained LMs give hope for joint consolidation (see e.g., Dice, Ascent)

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2. Recipe
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Example projects

1. **Webchild 1.0 [Tandon et al., WSDM 2014]**
   - Disambiguated noun-adjective pairs
2. TupleKB [Mishra et al., TACL 2017]
   - Open science triples
3. Quasimodo [Romero et al., CIKM 2019]
   - Salient general triples
4. DoQ [Elazar et al., ACL 2019]
   - Quantitative knowledge
5. Dice [Chalier et al., AKBC 2020]
   - Multifaceted quantitative contextualization and joint consolidation
6. Ascent [Nguyen et al., WWW 2021]
   - Qualitative contextualization and state-of-the-art extraction

WebChild

- Among the first large-scale attempts at text extraction
- Named for getting children's knowledge from the web
- Focus: Linking nouns with plausible adjectives
- Source: Google web search 5-gram corpus
- Extraction method: patterns, ~20 copula verbs (be, look, feel, …)
- Contextualization: Single numeric score
- Consolidation: Jointly (label propagation on graph)

[Tandon et al., WSDM 2014]

Key ideas of WebChild

Text extraction needs semantic refinement

1. **Fine-grained relations** for commonsense knowledge: hasAppearance, hasTaste, hasTemperature, hasShape, evokesEmotion, …..
2. **Sense-disambiguation of arguments** of knowledge triples (mapped to WordNet):
   pop-singer-n^1 hasAppearance hot-a^3
   chili-n^1 hasTaste hot-a^9
   volcano-n^1 hasTemperature hot-a^1

Steps

2. Domain Population

3. Computing Assertion

1. Range Population

Refine: **salsa-n^1** **hasTaste** **hot-a^9**

what has taste

how does it taste

2. Domain Population	3. Computing Assertion	1. Range Population
pizza-n^1	chocolate-n^2 , sweet-a^1	spicy-a^1
sauce-n^1	milk-n^1, tasty-a^1	hot-a^9
java-n^2	…	sweet-a^1
…		…

Approach

For **range and domain population**:

Extract a large list of ambiguous (potentially noisy) candidates.

Construct a weighted graph of ambiguous words and their senses.

Mark few seed nodes in the graph.

Use propagation concept: similar nodes (beautiful) (lovely) have similar labels

For **computing assertion**:

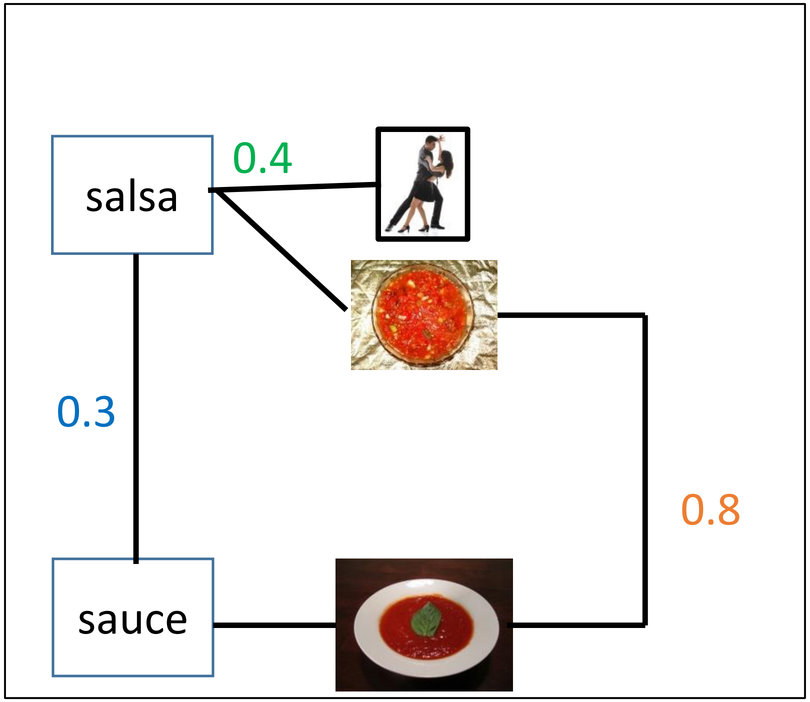
Use the range and domain to prune search space of assertions (for a relation)

Use propagation concept: similar nodes (car, sweet) (car, lovely) similar labels.

Graph construction per relation (e.g. hasTaste)

- Edge weight:
  taxonomic (between senses) ,
  co-occurrence statistics (between words),
  distributional (between word, senses).

One graph per attr. (here, **hasTaste**)



WebChild: Examples

Domain (hasShape)
face-n^1
leaf-n^1
…

Range (hasShape)
triangular-a^1
tapered-a^1
…

Assertions (hasSshape)
lens-n^1, spherical-a^2
palace-n^2, domed-a^1
…

Sense disambiguation: keyboard-n^1

Top 10 adjectives	ergonomic, foldable, sensitive, black, comfortable, compact, lightweight, comfy, pro, waterproof

Sense disambiguation: keyboard-n^2

Top 10 adjectives	universal, magnetic, small, ornamental, decorative, solid, heavy, white, light, cosmetic

WebChild: Summary

- Graph method helps to overcome sparsity of observations in text

- **WebChild**: Commonsense KB with fine-grained relations and disambiguated arguments; 4.6 million assertions including domain and range for 19 relations

  www.mpi-inf.mpg.de/yago-naga/webchild/

	#instances	Precision
Noun senses	221 K	0.80
Adj senses	7.7 K	0.90
Assertions	4.6 M	0.82

Example projects

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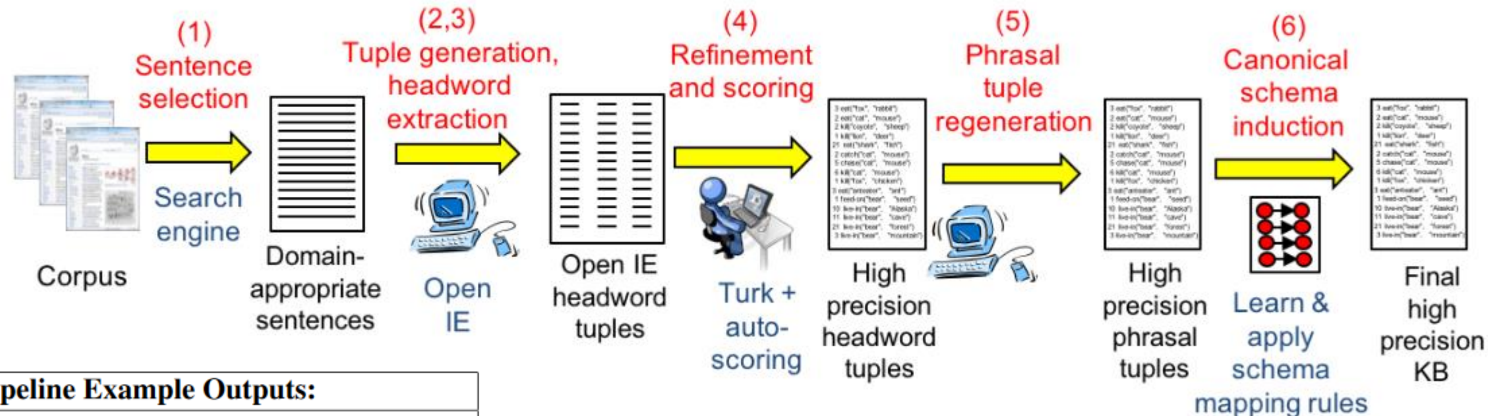
TupleKB

- Knowledge about science topics

- Source: Relevant websites via subject-specific keyword queries (template-based)
- Extraction method: OpenIE
- Contextualization: Single numeric score
- Consolidation: Supervised regression per statement

[Mishra et al., TACL 2017]

TupleKB



Pipeline Example Outputs:
Inputs: corpus + vocabulary + types
1. Sentence selection:
"In addition, green leaves have chlorophyll.")
2. Tuple Generation:
("green leaves" "have" "chlorophyll")
3. Headword Extraction:
("leaf" "have" "chlorophyll")
4. Refinement and Scoring:
("leaf" "have" "chlorophyll") @0.89 (score)
5. Phrasal tuple generation:
("leaf" "have" "chlorophyll") @0.89 (score)
("green leaf" "have" "chlorophyll") @0.89 (score)
6. Relation Canonicalization:
("leaf" "have" "chlorophyll") @0.89 (score)
("green leaf" "have" "chlorophyll") @0.89 (score)
("leaf" "contain" "chlorophyll") @0.89 (score)
("green leaf" "contain" "chlorophyll") @0.89 (score)

Example projects

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Quasimodo

= Query Logs and QA Forums for
Salient Commonsense Definitions


(The Hunchback of Notre Dame)

- Focus on salient knowledge
  - Human associations, curiosity

- Source: Query logs and QA forum questions
- Extraction method: OpenIE
- Contextualization: Supervised precision + IDF
- Consolidation: Largely per-statement regression

[Romero et al., CIKM 2019]

Starting point:
Humans vs. automated IE

Manual constructions:
- Salient but few

[ConceptNet]

elephant is capable of...

en carry a trunk →
en remember water sources →

(6 more)

Automated construction:
- Many but boring

[TupleKB]

***Elephant**:*
- require, ground
- inhabit, region
- (95 more)

How to reconcile the two?

Salient knowledge: Utterance context

Key idea: Questions convey salient knowledge

- Why do cats purr?
- Why do Americans love guns?
- Why are airplanes white?

a) So someone knows these!
b) That someone cares enough to ask!

Salient knowledge: Premier sources

- QA forums:
  - Reddit
  - Quora
  - Yahoo answers
  - Ask.com
- Search engine query logs
  - Bing
  - Google

Tapping search engine query logs

- Autocomplete gives only 10 suggestions/query
  → Exhaustive suffix probing
  - *Why do cats a*
  - *Why do cats b*
  - *Why do cats …*
  - *Why do cats aa*
  - *Why do cats ab*
  - *…*

Statement extraction

- Questions → statements → tuples using OpenIE

Why are lions hunting zebras?

Q2S → *Lions are hunting zebras*

OpenIE → *(lions, are hunting, zebras)*

Normalize → *(lion, hunt, zebras)*

Per-statement consolidation

- Reduce noise using additional co-occurrence signals from :
  - Wikipedia and Simple Wikipedia
  - Answer snippets from search engines
  - Google Books
  - Image Tags from OpenImages and Flickr
  - Google's Conceptual Captions dataset

Wildlife Photographer of the Year award goes to Yongqing Bao for image of Tibetan fox attacking marmot

- Train classifier from all signals in 700 manually annotated triples

Anecdotal Examples

Practical human knowledge	**(car, slip on, ice)**
Problems linked to a subject	**(pen, can, leak)**
Emotions linked to events	**(divorce, can, hurt)**
Human behaviors	**(ghost, scare, people)**
Visual facts	**(road, has_color, black)**
Cultural knowledge (USA)	**(school, have, locker)**
Comparative knowledge	**(light, faster than, sound)**

Quasimodo – Summary

- Highest salience resource to date

- Significantly outperforms other resources in saliency-centric tasks like multiple-choice QA and word guessing (Taboo)

- Limitations:
  - Questions sometimes go towards the odd
    - Why does car leak oil, catch fire, not start …
    - Not: Car transports people, consumes fuel, …
  - How to fit phrases into triples?
    - Lawyers, can make, the world a better place?
    - Lawyers, are, good for a fair judicial system?

Example projects

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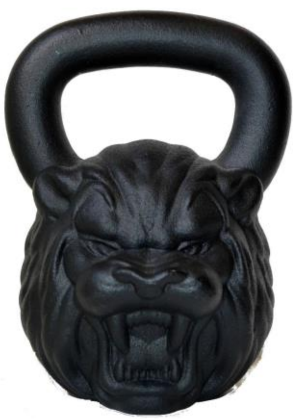
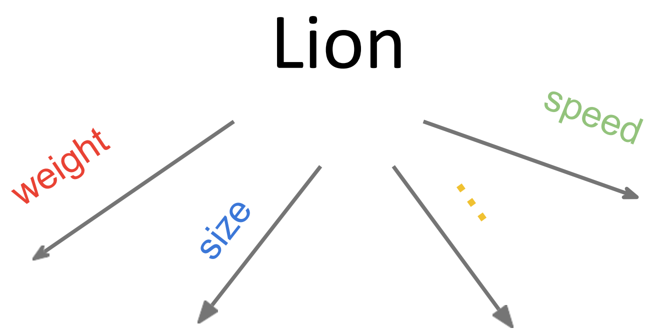
Distribution over quantities (DoQ)

- Understanding numerical properties and the way they relate to words.





Physical attributes

- Focus on items which can be measured objectively

[Elazar et al., ACL 2019]

Distribution over quantities (DoQ)

- Source: Google search engine document index
- Extraction scheme: Text window co-occurrence of subject, quantity and dimension keyword
- Contextualization: Frequency
- Consolidation: none/distribution

Example - Measurement Detection

“These breeds can vary in weight from a

0.46 kg *teacup poodle ...”*

Detect numerical measurements using a set of rules: kg/kgs/kilogram -> MASS
Normalize (kg -> g)

Example - Co-Occurring objects

Noun Verb Noun

"These breeds can vary in weight from a

***0.46 kg** teacup poodle ..."*

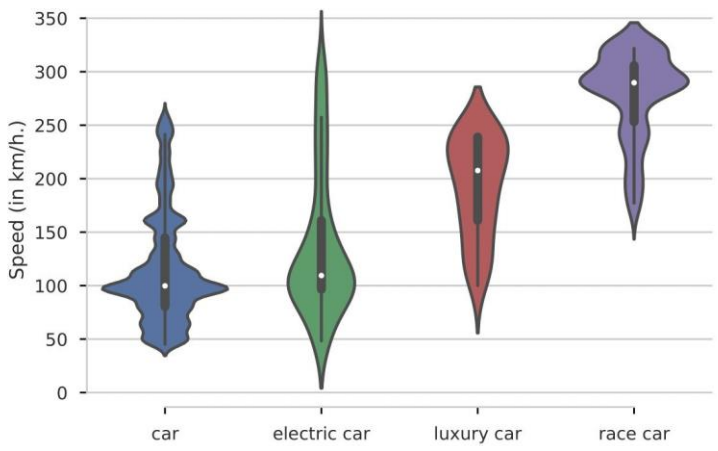
$\underbrace{\text{teacup poodle}}_{NP}$

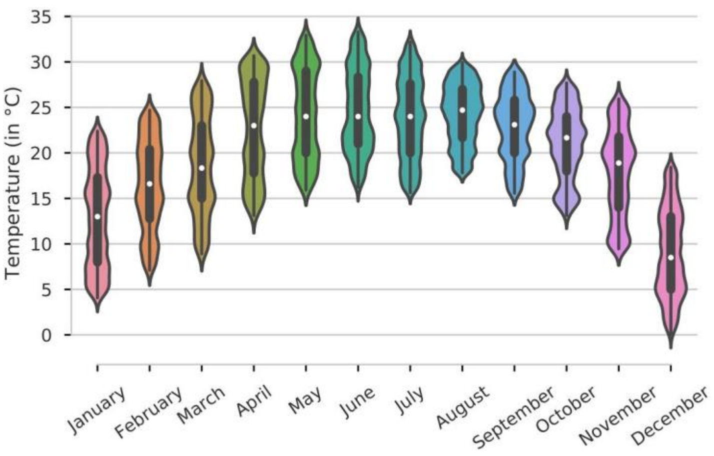
$0.46\ kg \rightarrow$ **460 gram**

Detect objects of interest (Nouns, Adjectives and Verbs) using a POS tagger.

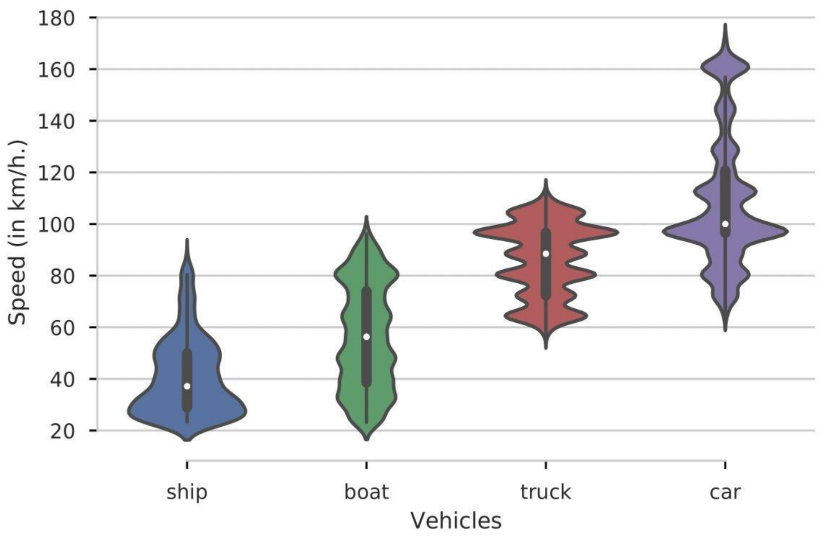
```
objects_distribution['poodle']['mass'] += [460]
objects_distribution['breeds']['mass'] += [460]
...
```

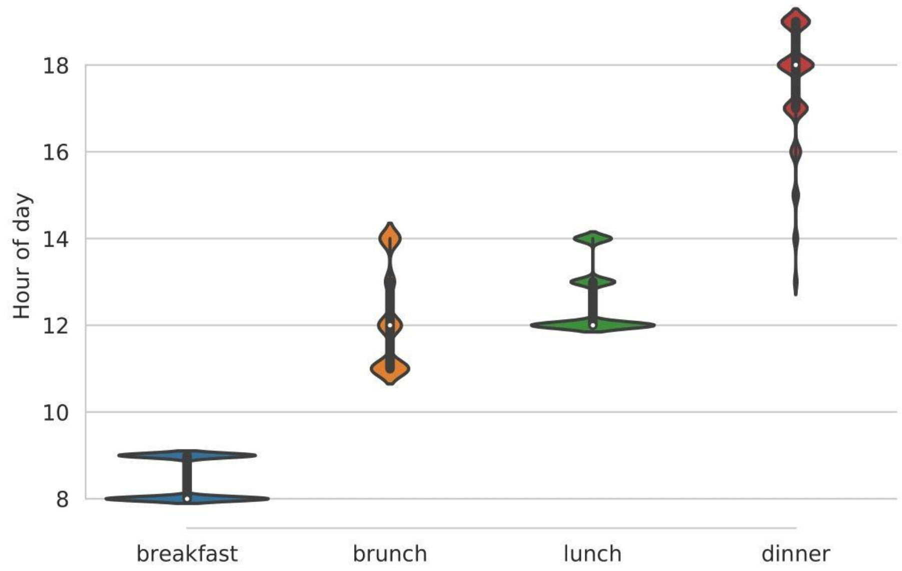
Example - Aggregating Measurements





More examples

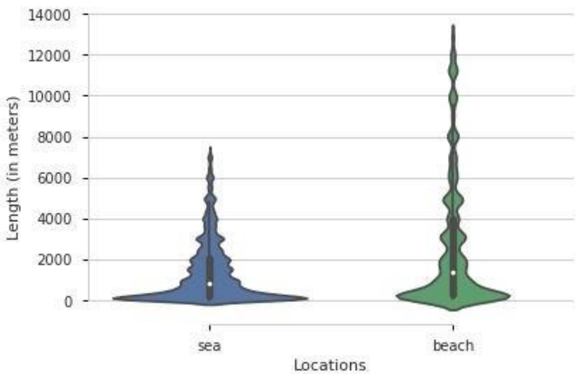


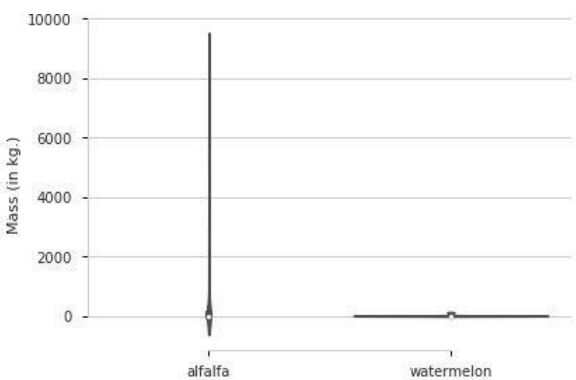


Intrinsic Evaluation

- Extract the median of “popular” noun distributions
- Expand to a range
  - 20 mm $\longrightarrow$ 10-100 mm
- Ask annotators if the item fits the range
  - “Is the usual length of a screw between 10-100mm?”
- 69% agreement with predictions
- Not perfect, but a reasonable start

Co-occurrence limitations





"Elevation ranges from **3,000 feet** ... above ***sea*** level."

"***Alfalfa*** is the most cultivated legume ... reaching around **454 million tons** ..."

Resource Statistics - DoQ

- **D**istributions **o**ver **Q**uantities (DoQ)
- A very large and diverse resource

- ~120M Unique tuples (object, measurement)
    - ~350K with >= 1000 occurrences
- Measurement types:
    - Length, mass, currency, temperature, …
- 27 In total

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Dice

- A reasoning framework for contextualizing existing CSKBs by four numeric facets
  - Plausibility, typicality, remarkability, salience

- Source: Any existing CSKB
- Extraction method: -
- Contextualization: Four numeric facets
- Consolidation: Joint taxonomy and similarity-based reasoning

[Chalier et al., AKBC 2020]

A step back – CSK semantics

Lions, attack, humans

A step back – CSK semantics

The semantics we apply to tuples (and which we ex-
plain to
is true f

In WebChild's evaluations

ion]

/r/Ca

/r/At

/r/Causes

/r/LocatedNear

/r/Desires

for "person" as A.

ce
nt

odo]

[ConceptNet]

Remarkability of terms is captured via inverse document frequency (IDF)
[Information theory 101]

Multi-faceted CSK: Dice

- Each statement (s, p) has four facets:
  1. Plausibility
  2. Typicality
  3. Remarkability
  4. Salience

- Lions drink milk – Plausible, not typical
- Lions eat meat – Typical, not salient
- Lions attack humans – Salient, not typical

→ Downstream tasks left with all options

Joint reasoning

- Consolidation in TupleKB, Quasimodo:
  Each statement in isolation
- In traditional DBs: Joint constraints
  - *Functionality, single-value constraints, disjointness, (a)symmetry, …*
- In KBs expert knowledge
  - Humans two parents, marriage temporally functional, birth before death, …
  - Prominent frameworks: PSL (DeepDive), MaxSAT (SOFIE)
  - Not suited for open KBs

  → No hope for CSK consolidation?

Key idea: Generic soft constraints apply to CSK

Generic soft constraints for CSK

1. Taxonomical relations give dependencies
   - *Penguins not flying remarkable when most taxonomical siblings do fly*
   - *Macaques eating bananas makes it likely that also stump-tailed macaques eat bananas*
2. Similar statements reinforce each other
   - *Being able to swim correlates with being able to dive*
   - *Lifting logs from the ground correlates with carrying trees*
3. Facets of statements influence each other
   - *Being salient requires being plausible*
   - *Being remarkable and typical implies being salient*

Can combat sparsity!

Can encode coherence expectations!

Dice: Joint reasoning framework

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

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

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

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

Sibling dependencies: $\forall (s_1,p) \in \mathcal{S} \times \mathcal{P}, \forall s_2 \in \text{siblings}(s_1)$

$$\text{Remarkable}(s_1,p) \Rightarrow \neg\text{Remarkable}(s_2,p)$$

$$\text{Typical}(s_1,p) \Rightarrow \neg\text{Remarkable}(s_2,p)$$

$$\neg\text{Plausible}(s_1,p) \wedge \text{Plausible}(s_2,p) \Rightarrow \text{Remarkable}(s_2,p)$$

… parent-child dependencies, similar statement reinforcement

- 17 kinds of soft dependencies in total

Dice: Implementation

Huge constraint system (weighted maxSAT)

How to bootstrap constraint system?

- Taxonomy from Hearst-based web extraction [Hertling&Paulheim 2017]
- Prior scores from
    - Precision/frequency scores in existing CSKBs,
    - Text entailment models,
    - Statement entropy w.r.t. neighbourhood

How to ground it?

→ Active domain per subject (+neighbors)

→ Still huge constraint system

→ Approximation via taxonomy-based slicing

DICE About Dialogues Browse full collection

subject: polar bear

Related concepts

Parents bear, brown bear, mammal, wild animal, predator

Siblings arctic fox, black bear, grizzly bear, panda bear, moose

Facts about 'polar bear'

Click on a property for more details on the statement. Click on a column header to use it as a sorting key.

Show scores as: absolute percentiles

Filter by source: ConceptNet Quasimodo

Property	Score	Plausible	Typical	Remarkable	Salient	Source
adapt in summer	0.83	0.19	0.54	0.15	0.15	Quasimodo
adapt to environment	0.83	0.52	0.38	0.93	0.76	Quasimodo
adapt to tundra	0.83	0.10	0.40	0.14	0.10	Quasimodo
be at in arctic	0.67	0.17	0.29	0.93	0.18	ConceptNet
be at risk	0.83	0.62	0.54	0.88	0.80	Quasimodo
be at zoo	0.75	0.10	0.03	0.39	0.37	ConceptNet
be found in arctic	0.91	0.34	0.44	0.51	0.32	Quasimodo
be important to canada	0.92	0.43	0.70	0.27	0.29	Quasimodo
be in danger	0.82	0.91	0.93	0.77	0.97	Quasimodo
be under threat	0.83	0.83	0.80	0.85	0.95	Quasimodo
be used to snow	0.46	0.20	0.51	0.17	0.19	ConceptNet
be white	0.46	0.07	0.68	0.16	0.13	ConceptNet

https://dice.mpi-inf.mpg.de/subject/polar-bear

Dice: Open challenges

- Weak priors for facets make task hard
  - 0.58..0.69 ppref in pairwise statement ranking
- Stronger priors difficult to identify
- Quantitative contextualization with limitations
  - Typicality ranking
    "lions hunt in packs vs. lions have manes"?

Example projects

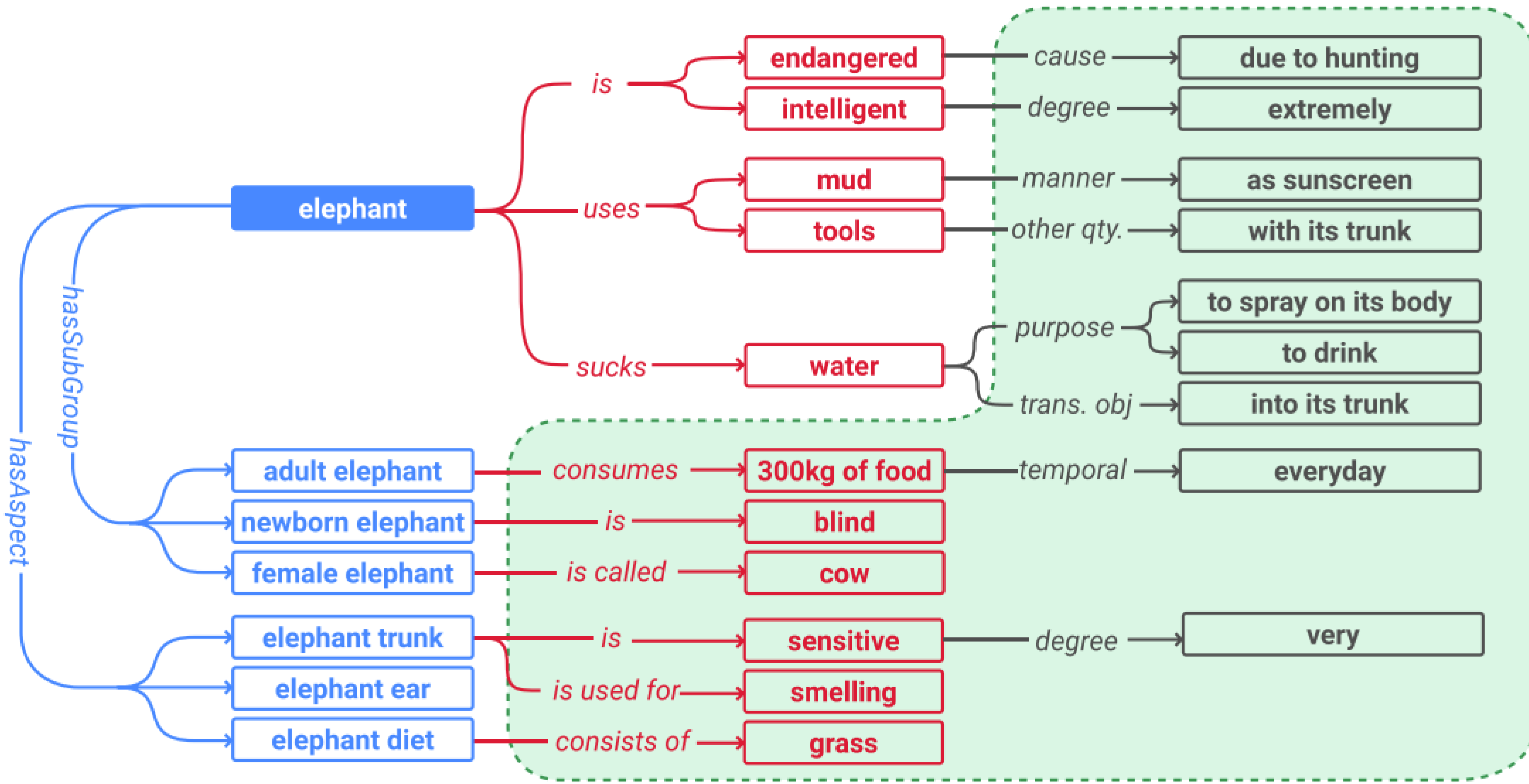
1. WebChild 1.0 [Tandon et al., WSDM 2014]
   - Disambiguated noun-adjective pairs
2. TupleKB [Mishra et al., TACL 2017]
   - Open science triples
3. Quasimodo [Romero et al., CIKM 2019]
   - Salient general triples
4. DoQ [Elazar et al., ACL 2019]
   - Quantitative knowledge
5. Dice [Chalier et al., AKBC 2020]
   - Multifaceted quantitative contextualization and joint consolidation
6. **Ascent [Nguyen et al., WWW 2021]**
   - Qualitative contextualization and state-of-the-art extraction

Ascent

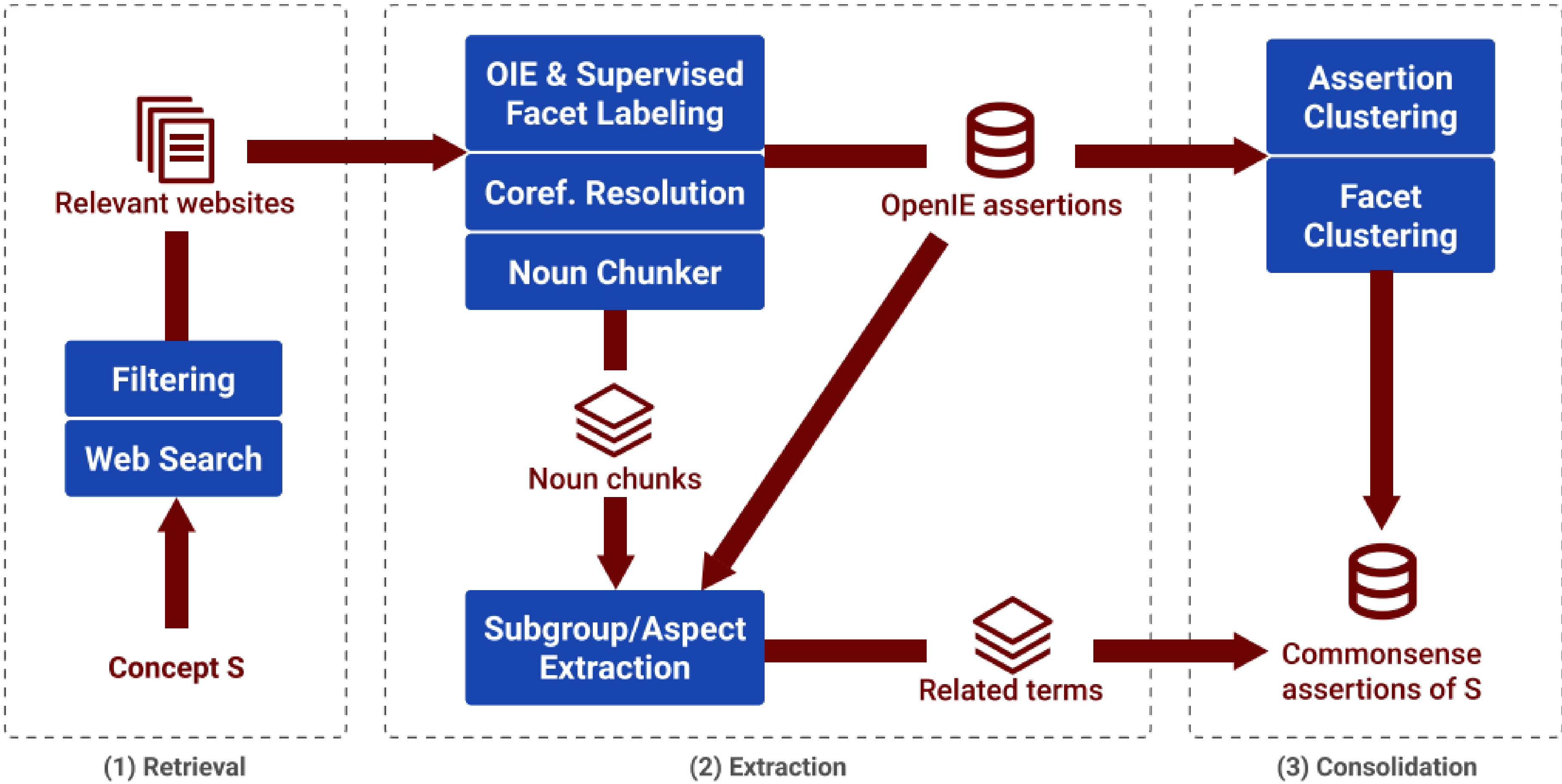
- Source: Targeted web search
  - Queries created from WordNet hypernyms, e.g., “bank financial institution”
- Extraction method: Facet-centric OpenIE
  - Facets give qualitative contextualizations for triples, e.g., location, time, cause, mode
- Contextualization: Frequency, qualitative facets, subgroups and aspects
  - ***Female** elephants, live in, groups, **loc**: in Africa, 13*
- Consolidation: BERT-based clustering

[Nguyen et al., WWW 2021]

Ascent – qualitative contextualization



Ascent - Architecture



Ascent – BERT-based clustering

Top triple paraphrases

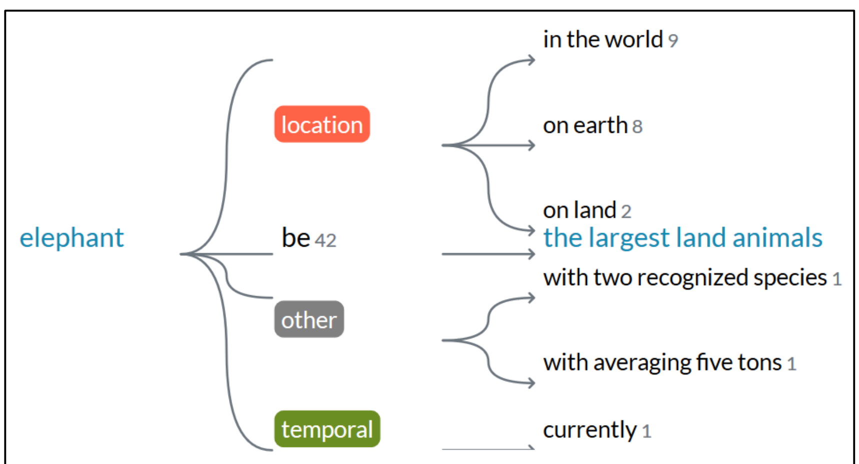
elephant	eat	fruit	13
elephant	consume	fruit	3
elephant	feed on	fruit	2
elephant	feast on	fruit	1
elephant	consume	other fruits	1

▾ 18 source sentences

- Elephants consume grasses, small plants, bushes, fruit, twigs, tree bark, and roots.
- Elephants are herbivorous and will eat leaves, twigs, fruit, bark and roots.
- Elephants tend to feast on small plants, bushes, fruit, twigs, tree bark, and roots and consume up to 330-
- Elephants eat things such as fruits, bark, grasses, plants, roots and bushes.
- Elephants are more likely to feed on plants or fruits when these are readily available.
- – elephants feed on grass, leaves, tree barks, tender stems and even fruits.
- They eat grasses, tree foliage, bark, bamboo, shrubs, roots and fruit.
- Elephants eat an extremely varied vegetarian diet, including grass, leaves, twigs, bark, fruit and seed pod
- Elephants in Babille Elephant Sanctuary consume leaves and fruit of cherimoya, papaya, banana, guava a
- Elephants are herbivores, consuming ripe bananas, leaves, bamboo, tree bark, and other fruits.
- They eat roots, grasses, bark and fruit and will even use their tusks to pull off the tree bark or dig in the g

Ascent web interface

Elephant is ...		Elephant has ...		Elephant eats ...	
the largest land animals *	42	26 teeth *	8	fruit *	20
herbivore *	35	long trunk	6	grass *	19
intelligent *	32	good memories *	6	plant *	19
endangered *	19	tusk *	6	leaf *	17
good swimmers *	16	four molars *	6	root *	17
more...		more...		more...	



https://ascentkb.herokuapp.com

Outline – Extracting and contextualizing CSK

1. Background
2. Recipe
3. Example projects
4. **Take-away**

Summary

1. Sources
   - Domain-specific selection pays off
2. Extraction method
   - OpenIE vs. trained extractors
3. Contextualization
   - Expressivity-extractability tradeoff
   - Quantitative vs. qualitative
4. Consolidation
   - Advances in text similarity detection enable joint consolidation

State of the art

- Automatically extracted CSKBs competitive with manually-built projects
  - Usually huge gains in recall, moderate loss in precision

Overview – major projects

	Domain	1. Sources	2. Extraction	3. Contextualization	4. Consolidation	Size (#statements)
WebChild	General noun-adjective pairs	Books	Manual patterns	Single precision	Joint ILP	4.6 M
TupleKB	Science triples	Targeted web search	OpenIE	Single precision	Supervised per-statement	0.3 M
Quasimodo	General triples	User questions	OpenIE	Single precision	Supervised per-statement	4 M (v1.3)
DoQ	Quantity triples	Web crawls	Co-occurrence	Frequency	-	(120 M)
Dice	General triples	Existing structured CSKBs	-	Four quantitative facets	Joint MaxSAT	-
Ascent	General triples	Targeted web search	Facet-based OpenIE	Qualitative facets, subject constraints, frequency	Similarity clustering	8.6 M

Outlook

- Advance of pre-trained LMs suggest hybrid extraction schemes
  - LMs can contextualize existing uncontextualized CSKBs with plausibility scores
  - Extract salient knowledge directly from LMs
  - Tail knowledge and qualitative contextualizations so far not in reach of pretrained LMs

  → See next part

- Contextualization of CSK still with gaps
  - Plausibility vs. typicality vs. salience scores?
  - What kind of qualitative facets?
  - Opportunity for AI community

References – Major projects

1. Tandon, Niket, et al. "Webchild: Harvesting and organizing commonsense knowledge from the web." *WSDM*. 2014.
2. Mishra, Bhavana Dalvi, Niket Tandon, and Peter Clark. "Domain-targeted, high precision knowledge extraction." *TACL.* 2017
3. Romero, Julien, et al. "Commonsense properties from query logs and question answering forums." *CIKM*. 2019.
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