Enriching Large-Scale Eventuality Knowledge Graph with Entailment Relations

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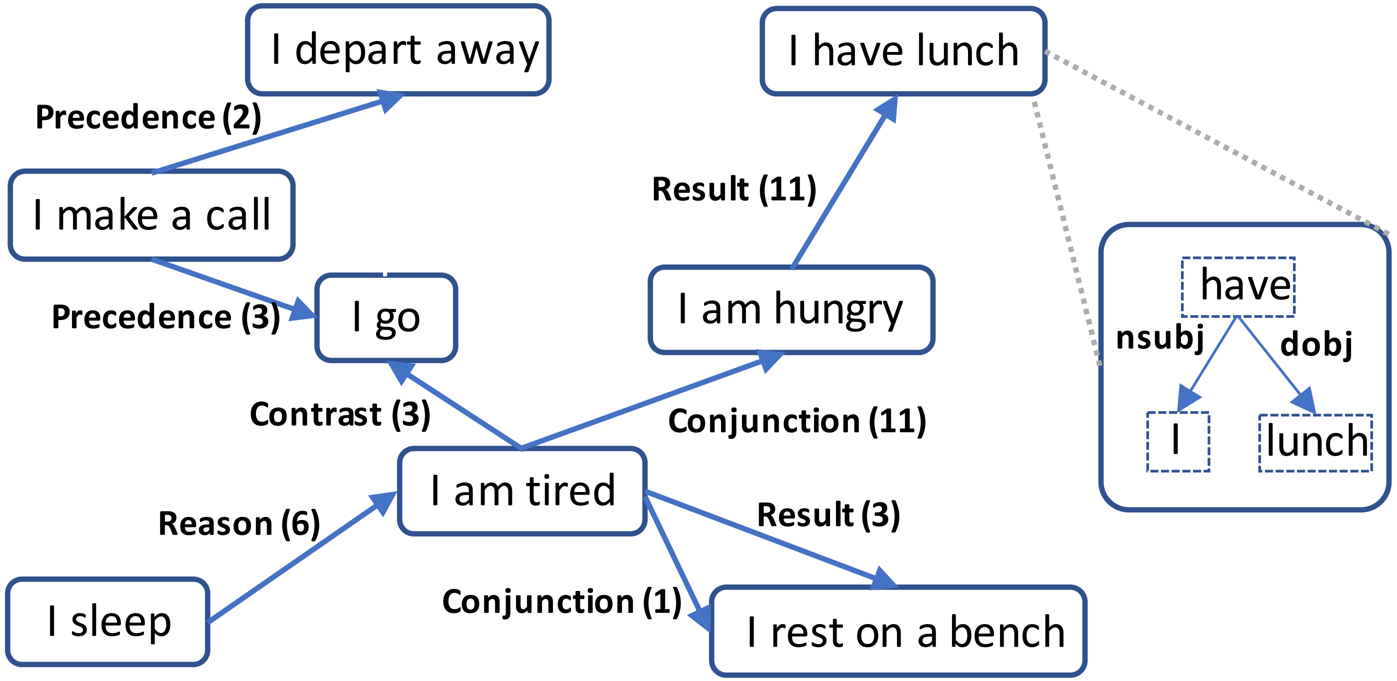
AUTOMATED KNOWLEDGE BASE CONSTRUCTION

Outline

1. ASER: Eventuality Knowledge Graph
2. Entailment Graph
3. Three-step Construction Method
4. Evaluation and Potential Applications

ASER: Eventuality Knowledge Graph



Sparsity issues of current ASER:
1. Concept Transitivity
2. Verb’s Entailment Relations

→ Eventuality Entailment

- Eventuality Node: 194 Million mined from 14 linguistic patterns.

n1-nsubj-dobj -n2	I have lunch
n1-nsubj-v1	I sleep
n1-nsubj-a1-cop-be	I am hungry
n1-nsubj-v1-nmod-n2-case-p1	I rest on a bench

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- Eventuality Relations: 64 Million with 14 discourse relations.

Precedence	before/then/till
Result	so/thus/therefore
Reason	because
Contrast	but/however
Conjunction	and/also

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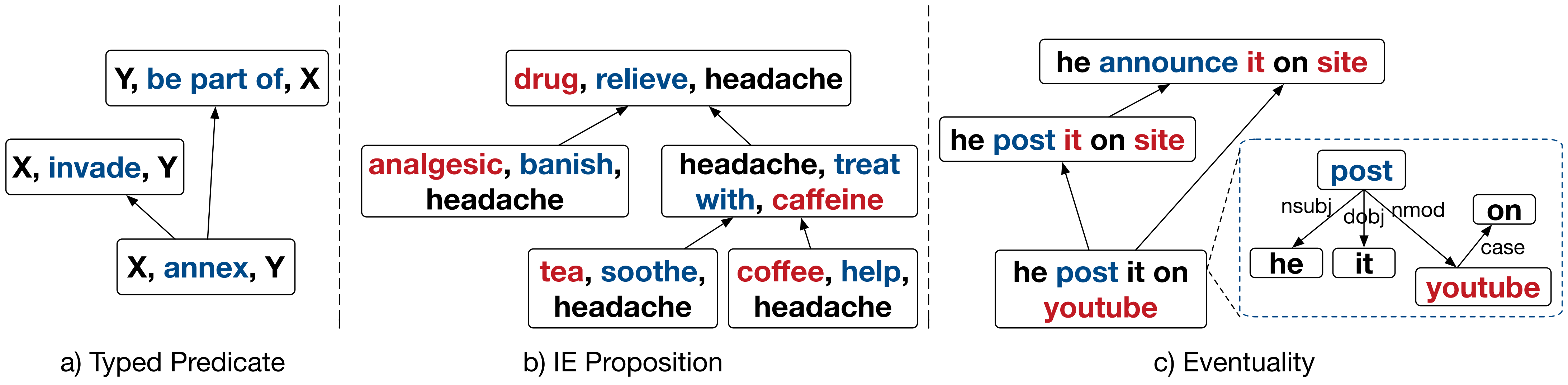
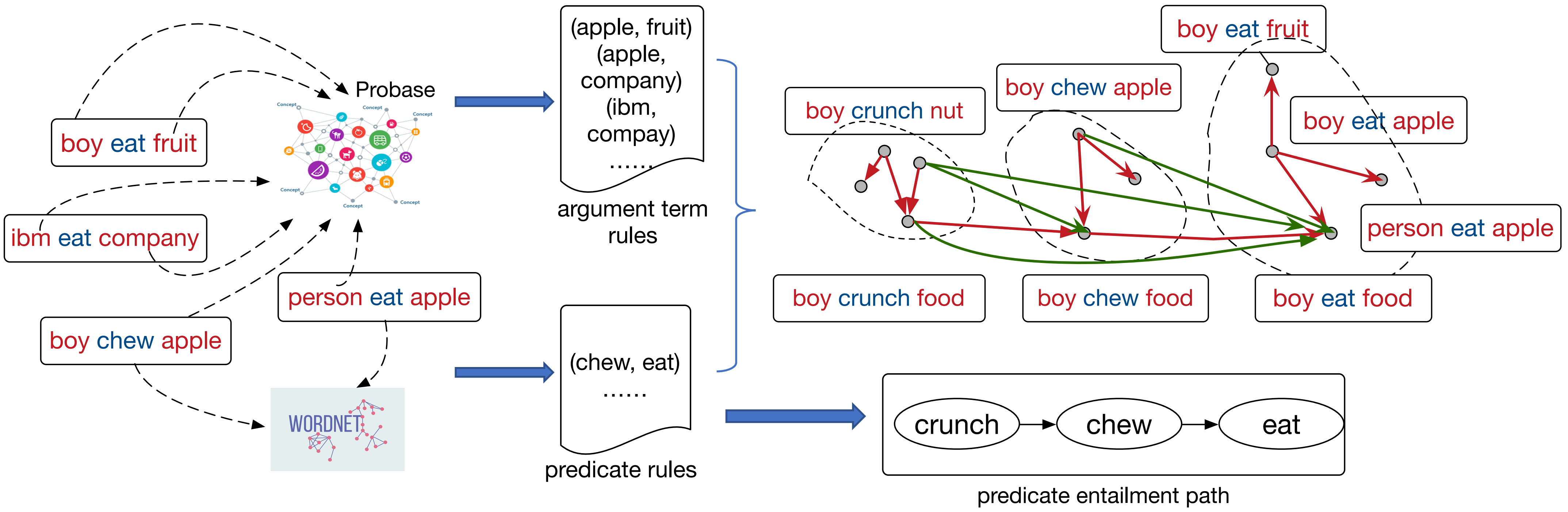
Hongming Zhang*, Xin Liu*, Haojie Pan*, Yangqiu Song, and Cane Wing-Ki Leung. ASER: A Large-scale Eventuality Knowledge Graph. WWW. 2020.

Eventuality Entailment Graph



Node Type	Reference	#Graphs	#Nodes	#Edges	Domain
Typed Predicate	Berant et al., ACL, 2011 Hosseini et al. TACL, 2018	2,303 363	10,672 101K	263,756 66M	Place/disease News
Open IE Proposition	Levy et al., CoNLL, 2014	30	5,714	1.5M	Healthcare
Textual Fragment	Kotlerman et al., NLE, 2015	457	756	7,862	Email
Eventuality	Ours	473	10M	103M	Commonsense

Three-step Construction Method



Step2 : Compositional Local Inference

Step1 : Eventuality Pre-processing

Step3 : Global Inference Along Predicate Entailment Path

Evaluation and Result

For each type of the eventuality entailment, random sample 100 rules to ask five workers for annotation in the Amazon MTurk platform.

		# Eventuality	# ER(global)	# ER(local)	Acc (local)	Acc (all)
Activities/ Events	s-v ⊨ s-v	3.3M	32.7M	10.7M	89.1%	85.7%
	s-v-o ⊨ s-v-o	5.3M	45.2M	14.8M	90.1%	89.3%
	s-v-p-o ⊨ s-v-p-o	1.9M	12.6M	5.3M	88.3%	87.4%
	s-v-o-p-o ⊨ s-v-o	0.5M	0.8M	0.8M	91.4%	90.0%
	s-v-p-o ⊨ s-v-o	1.1M	2.7M	0.9M	88.5%	87.2%
	s-v-o ⊨ s-v-p-o	0.9M	5.4M	2.2M	87.8%	86.7%
	s-v-o-p-o ⊨ s-v-o-p-o	2.4M	3.2M	2.1M	89.4%	88.4%
States	s-v-a ⊨ s-be-a	0.2M	0.1M	0.1M	97.9%	97.9%
	s-be-a-p-o ⊨ s-be-a	0.8M	0.4M	0.4M	96.0%	95.8%
	s-be-a-p-o ⊨ s-be-a-p-o	0.1M	0.1M	0.1M	95.1%	94.7%
	Overall	10.0M*	103.2M	37.4M	91.4%	90.3%

- The global inference step increased the scale of entailment rules by averagely three times.
- Moreover the global inference does not lead to heavy drop of the performance, which proves the effectiveness of our method.

Potential Applications and Conclusion

- Enhance TransOMCS[1]: Provide ASER with more powerful inference ability and generate more reliable commonsense knowledge.
- Testbed for Probing Tasks[2]: Whether QA models / pretrained language models have taxonomic reasoning ability.
- External Rule Base[3]: Provide large-scale explicit general knowledge for complementing implicit reasoning.

Large Scale Eventuality Entailment Graph with 10M nodes and 103M relations. Our resources and code are at:

https://github.com/HKUST-KnowComp/ASER-EEG

1. Hongming Zhang, Daniel Khashabi, Yangqiu Song, and Dan Roth. TransOMCS: From Linguistic Graphs to Commonsense Knowledge. IJCAI. 2020
2. Kyle Richardson, and Ashish Sabharwal. What Does My QA Model Know? Devising Controlled Probes using Expert Knowledge. Arxiv 2020
3. Peter Clark, Oyvind Tafjord, Kyle Richardson. Transformers as Soft Reasoners over Language. IJCAI 2020