An Overview of Commonsense Knowledge Graph Construction and Reasoning at HKUST

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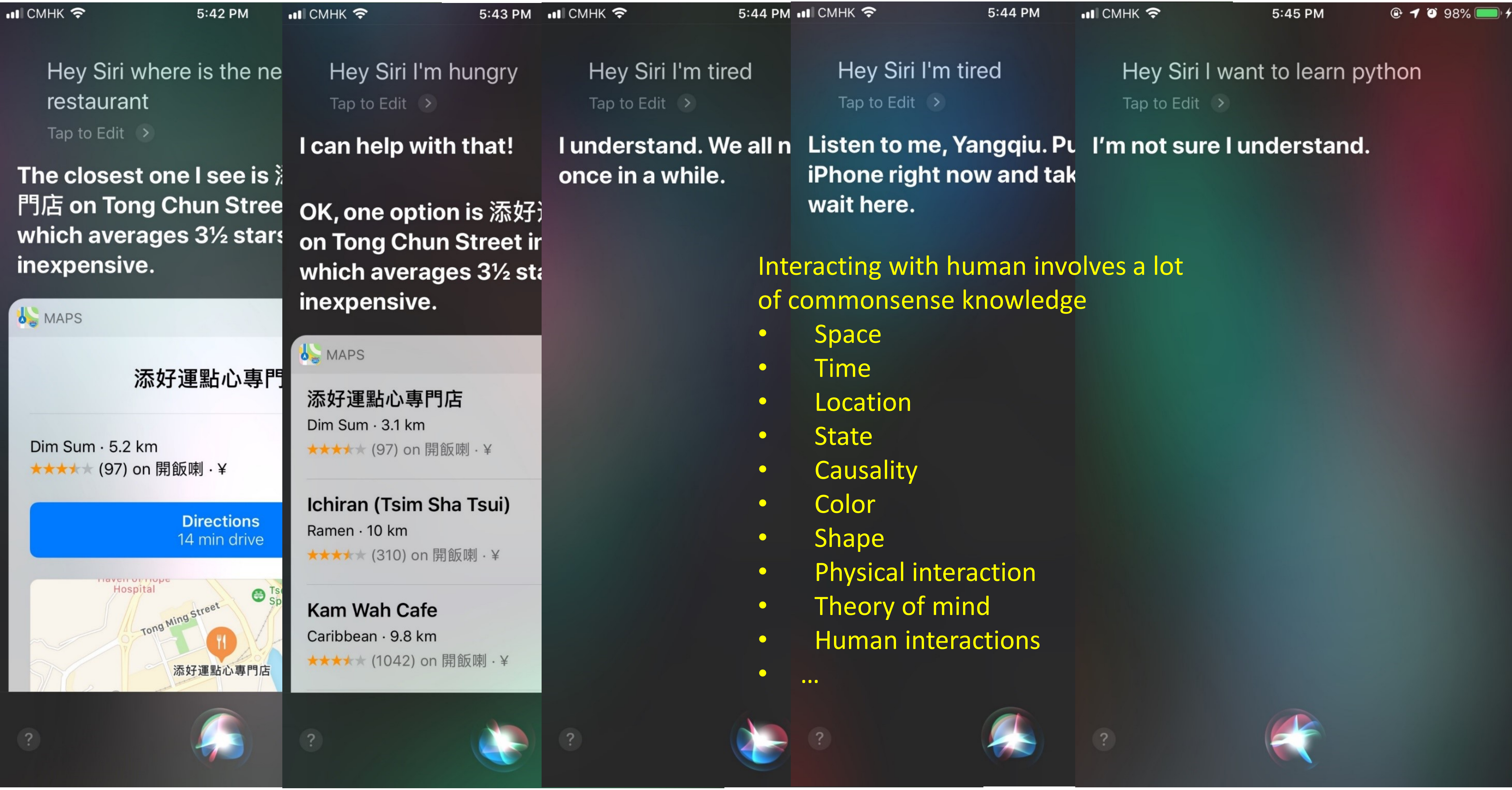
Outline

- Motivation: NLP and commonsense knowledge
- Consideration: selectional preference
- New proposal: large-scale and higher-order selectional preference
- Extensions



Interacting with human involves a lot of commonsense knowledge

- Space
- Time
- Location
- State
- Causality
- Color
- Shape
- Physical interaction
- Theory of mind
- Human interactions
- …

Judy Kegl, The boundary between word knowledge and world knowledge, TINLAP3, 1987
Ernie Davis, Building AIs with Common Sense, Princeton Chapter of the ACM, May 16, 2019

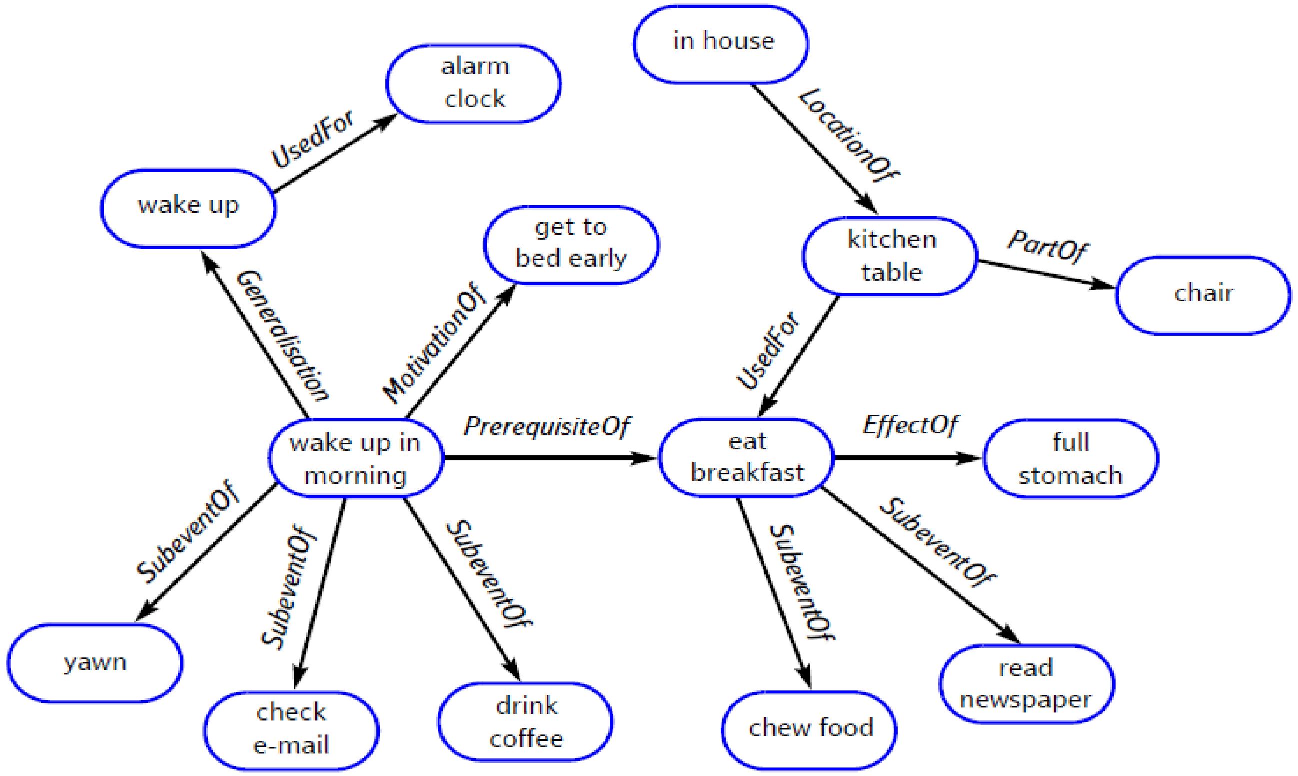
Commonsense Knowledge is the Key

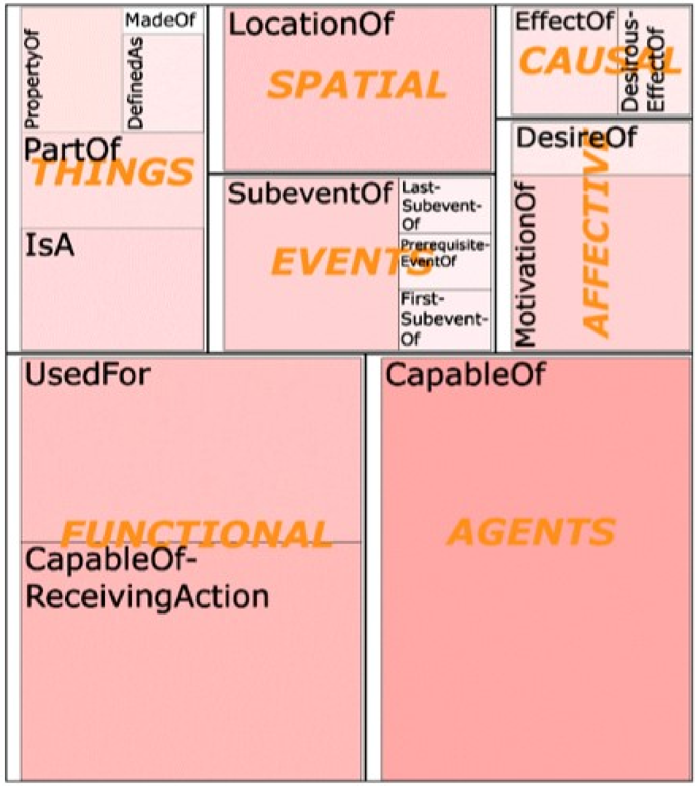
- How to define commonsense knowledge? (Liu & Singh, 2004)
  - "While to the average person the term 'commonsense' is regarded as synonymous with 'good judgement', "
  - "in the AI community it is used in a technical sense to refer to the millions of basic facts and understandings possessed by most people."
  - "Such knowledge is typically omitted from social communications", e.g.,
    - If you forget someone's birthday, they may be unhappy with you.

H Liu and P Singh, ConceptNet - a practical commonsense reasoning tool-kit, BTTJ, 2004

How to collect commonsense knowledge?

- ConceptNet5 (Speer and Havasi, 2012)
  - Core is from Open Mind Common Sense (OMCS) (Liu & Singh, 2004)





  - Essentially a crowdsourcing based approach + text mining

The Scale

- "A founder of AI, Marvin Minsky, once estimated that '...commonsense is knowing maybe 30 or 60 million things about the world and having them represented so that when something happens, you can make analogies with others'." (Liu & Singh, 2004)

- ConceptNet
  - 2004: 1.6 million relations among 300,000 nodes
  - 2017: 21 million edges over 8 million nodes
    - 1.5 million nodes are English

Slides credit: Haixun Wang

What contribute to ConceptNet5.5 (21 million edges and over 8 million nodes)?

- Facts acquired from Open Mind Common Sense (OMCS) (Singh 2002) and sister projects in other languages (Anacleto et al. 2006)
- Information extracted from parsing Wiktionary, in multiple languages, with a custom parser ("Wikiparsec")
- "Games with a purpose" designed to collect common knowledge (von Ahn, Kedia, and Blum 2006) (Nakahara and Yamada 2011) (Kuo et al. 2009)
- Open Multilingual WordNet (Bond and Foster 2013), a linked-data representation ofWordNet (Miller et al. 1998) and its parallel projects in multiple languages
- JMDict (Breen 2004), a Japanese-multilingual dictionary
- OpenCyc, a hierarchy of hypernyms provided by Cyc (Lenat and Guha 1989), a system that represents commonsense knowledge in predicate logic
- A subset of DBPedia (Auer et al. 2007), a network of facts extracted from Wikipedia infoboxes

Most of them are entity-centric knowledge, there are only 116,097 edges among 74,989 nodes about events

Speer, Chin, and Havasi, ConceptNet 5.5: An Open Multilingual Graph of General Knowledge. AAAI 2017.

Most Existing KBs are Entity-centric

- Many large-scale knowledge graphs about entities and their attributes (property-of) and relations (thousands of different predicates) have been developed
  - Millions of entities and concepts
  - Billions of relationships

WIKIPEDIA
The Free Encyclopedia

BabelNet

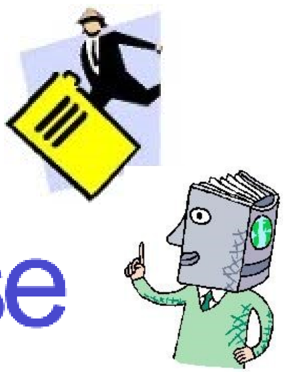
Freebase Labs

NELL

yago select knowledge

DBpedia

ProBase



Google Knowledge Graph (2012)
570 million entities and 18 billion facts

However,

- Semantic meaning in our language can be described as 'a finite set of mental primitives and a finite set of principles of mental combination (Jackendoff, 1990)'.
- The primitive units of semantic meanings include
  - Thing (or Object, Entity, Concept, Instance, etc.),
  - Property,
  - Place,
  - Path,
  - Amount,
  - Activity,
  - State,
  - Event,
  - etc.

Eventuality

How to collect more knowledge about eventualities rather than entities and relations?

Ray Jackendoff. (Ed.). (1990). Semantic Structures. Cambridge, Massachusetts: MIT Press.

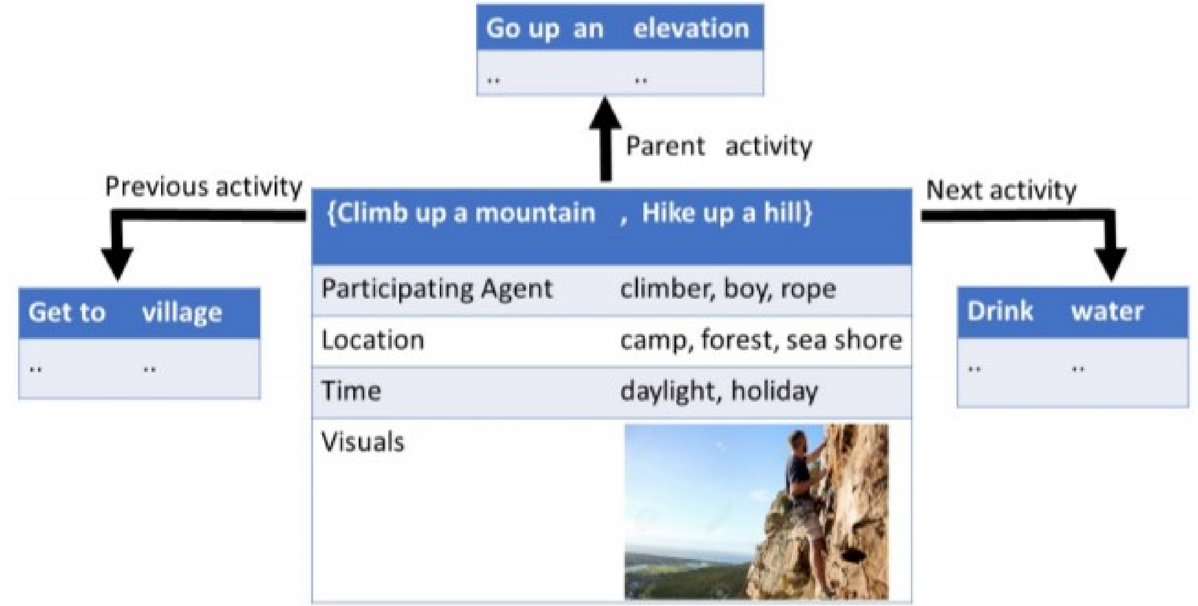
ATOMIC

- Crowdsourcing 9 Types of IF-THEN relations
- All personal entity information has been removed to reduce ambiguity
- Arbitrary texts

Maarten Sap, Ronan LeBras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A. Smith, Yejin Choi: ATOMIC: An Atlas of Machine Commonsense for If-Then Reasoning. AAAI, 2019.

KnowlyWood

- Perform information extraction from free text
  - Mostly movie scripts and novel books
- Four relations: previous, next, parent, similarity
- Only verb+object



Niket Tandon, Gerard de Melo, Abir De, Gerhard Weikum: Knowlywood: Mining Activity Knowledge From Hollywood Narratives. CIKM 2015: 223-232

How to define and scale up the commonsense knowledge acquisition and inference?

Outline

- Motivation: NLP and commonsense knowledge
- Consideration: selectional preference
- New proposal: large-scale and higher-order selectional preference
- Application on the Winograd Schema Challenge
- Extensions

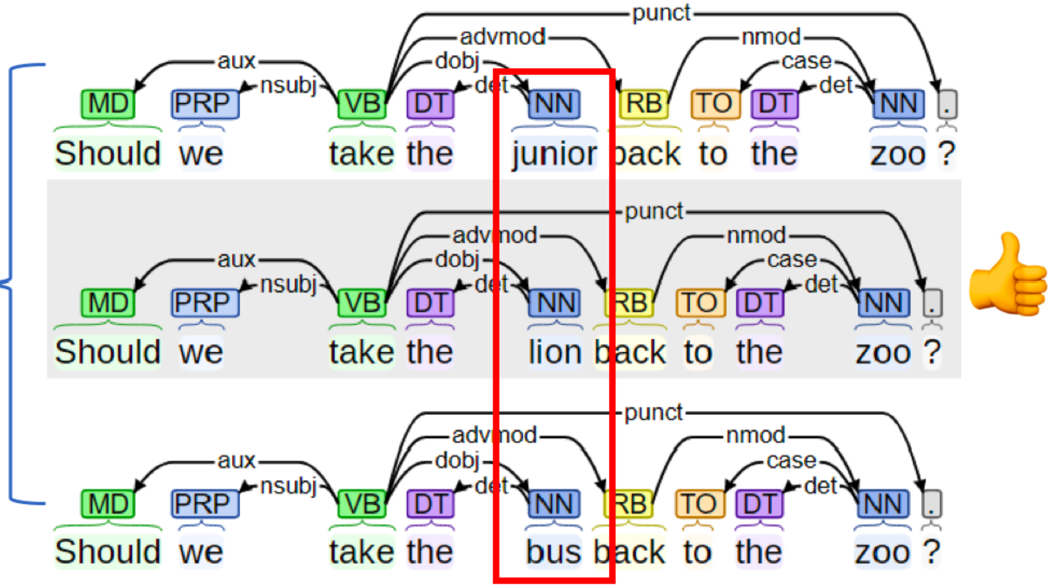
"Linguistic description – grammar = semantics"
The lower bound of a semantic theory (Katz and Fodor, 1963)

- Disambiguation needs both "the speaker's knowledge of his language and his knowledge about the world" (Katz and Fodor, 1963)

- Compare semantic meanings by fixing grammar
  - Syntactically unambiguous

Principle #1

It is dangerous.



Katz, J. J., & Fodor, J. A. (1963). The structure of a semantic theory. Language, 39(2), 170–210.

Selectional Preference (SP)

Principle #2

- The need of language inference based on ‘**partial information** (in John MaCarthy’s phrase)**’** (Wilks, 1975)
  - The soldiers fired at the women, and we saw several of them fall.
  - The needed partial information: hurt things tending to fall down
    - “not invariably true”
    - “tend to be of a very high degree of generality indeed”

(hurt, X) connection (X, fall)

- Selectional preference (Resnik, 1993)
  - A relaxation of selectional restrictions (Katz and Fodor, 1963) and as syntactic features (Chomsky, 1965)
  - Applied to isA hierarchy in WordNet and verb-object relations

Yorick Wilks. 1975. An intelligent analyzer and understander of English. Communications of the ACM, 18(5):264–274.
Katz, J. J., & Fodor, J. A. (1963). The structure of a semantic theory. Language, 39(2), 170–210.
Noam Chomsky. 1965. Aspects of the Theory of Syntax. MIT Press, Cambridge, MA.
Philip Resnik. 1993. Selection and information: A class-based approach to lexical relationships. Ph.D. thesis, University of Pennsylvania.

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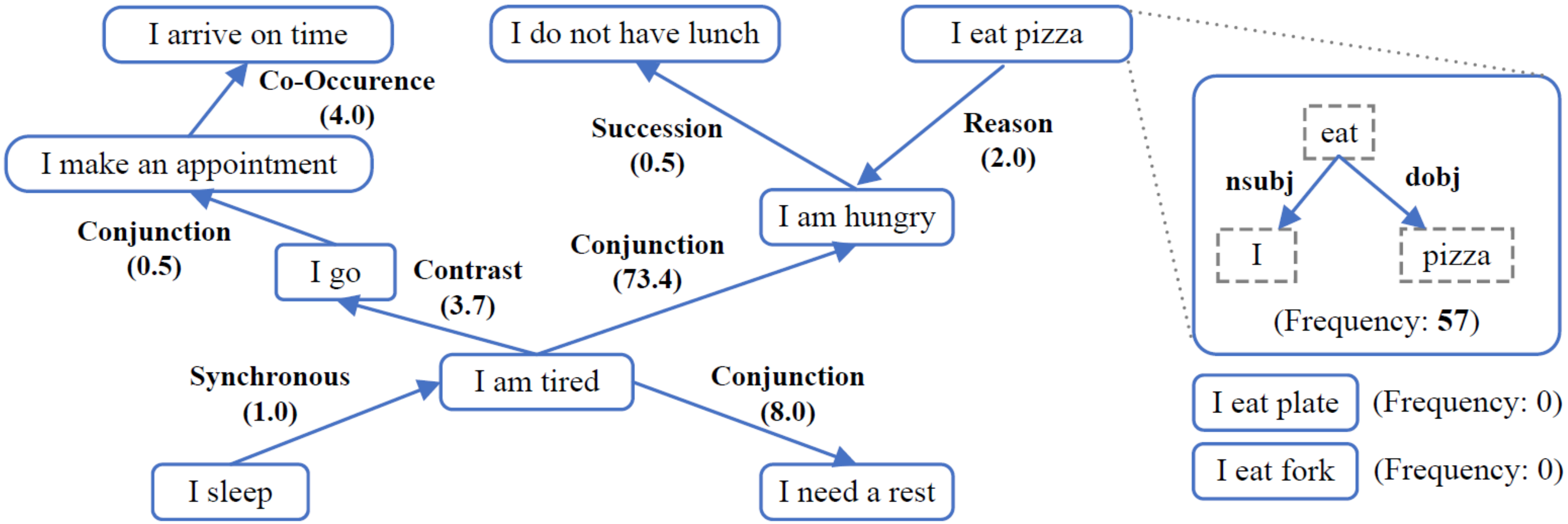
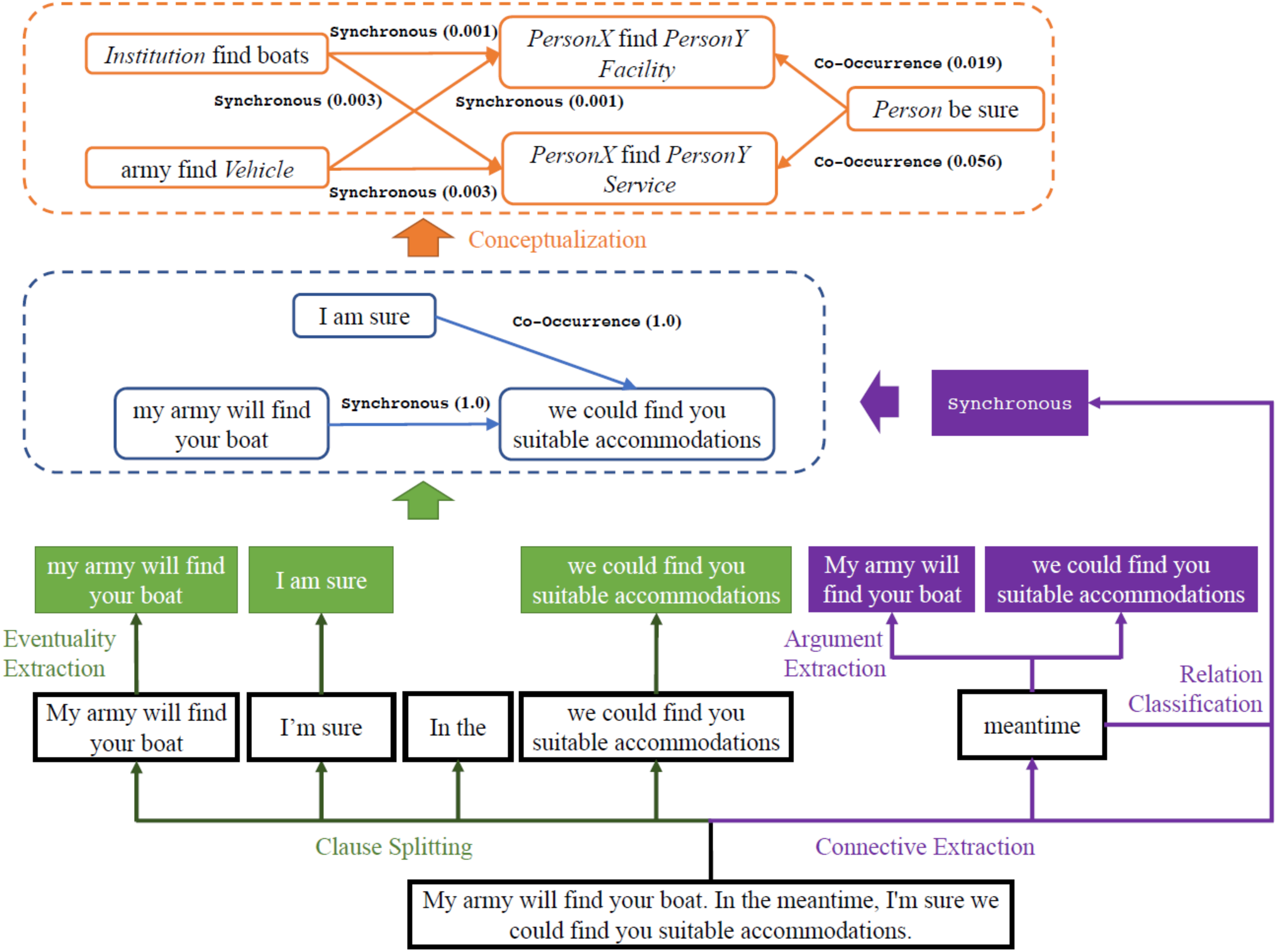
A New Eventuality Knowledge Graph: ASER
Activities, **S**tates, **E**vents, and their **R**elations

- Use verb-centric patterns from dependency parsing
  - Principle #1: to compare semantics by fixing syntax (Katz and Fodor, 1963)
- Maintain a set of key tags and a set of auxiliary tags
  - Principle #2: to obtain frequent 'partial information' (Wilks, 1975)



A hybrid graph of
- Each eventuality is a hyper-edge of words
- Heterogeneous edges among eventualities

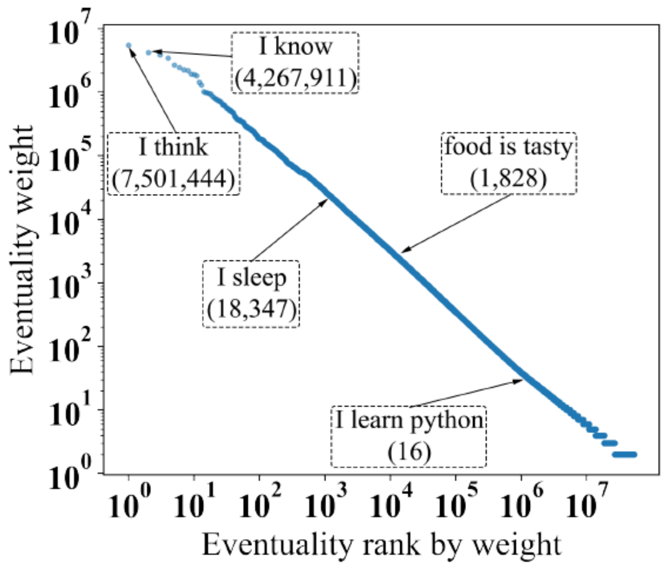
A Running Example



Eventualities

- Using patterns to collect partial information
- Six relations are also kept but treated as auxiliary edges
  - advmod,
  - amod,
  - nummod,
  - aux,
  - compound,
  - neg

Pattern	Code	Example
n1-nsubj-v1	s-v	`The dog barks'
n1-nsubj-v1-dobj-n2	s-v-o	`I love you'
n1-nsubj-v1-xcomp-a	s-v-a	`He felt ill'
n1-nsubj-(v1-iobj-n2)-dobj-n3	s-v-o-o	`You give me the book'
n1-nsubj-a1-cop-be	s-be-a	`The dog is cute'
n1-nsubj-v1-xcomp-a1-cop-be	s-v-be-a	`I want to be slim'
n1-nsubj-v1-xcomp-n2-cop-be	s-v-be-o	`I want to be a hero'
n1-nsubj-v1-xcomp-v2-dobj-n2	s-v-v-o	`I want to eat the apple'
n1-nsubj-v1-xcomp-v2	s-v-v	`I want to go'
(n1-nsubj-a1-cop-be)-nmod-n2-case-p1	s-be-a-p-o	`It' cheap for the quality'
n1-nsubj-v1-nmod-n2-case-p1	s-v-p-o	`He walks into the room'
(n1-nsubj-v1-dobj-n2)-nmod-n3-case-p1	s-v-o-p-o	`He plays football with me'
n1-nsubjpass-v1	spass-v	`The bill is paid'
n1-nsubjpass-v1-nmod-n2-case-p1	spass-v-p-o	`The bill is paid by me'



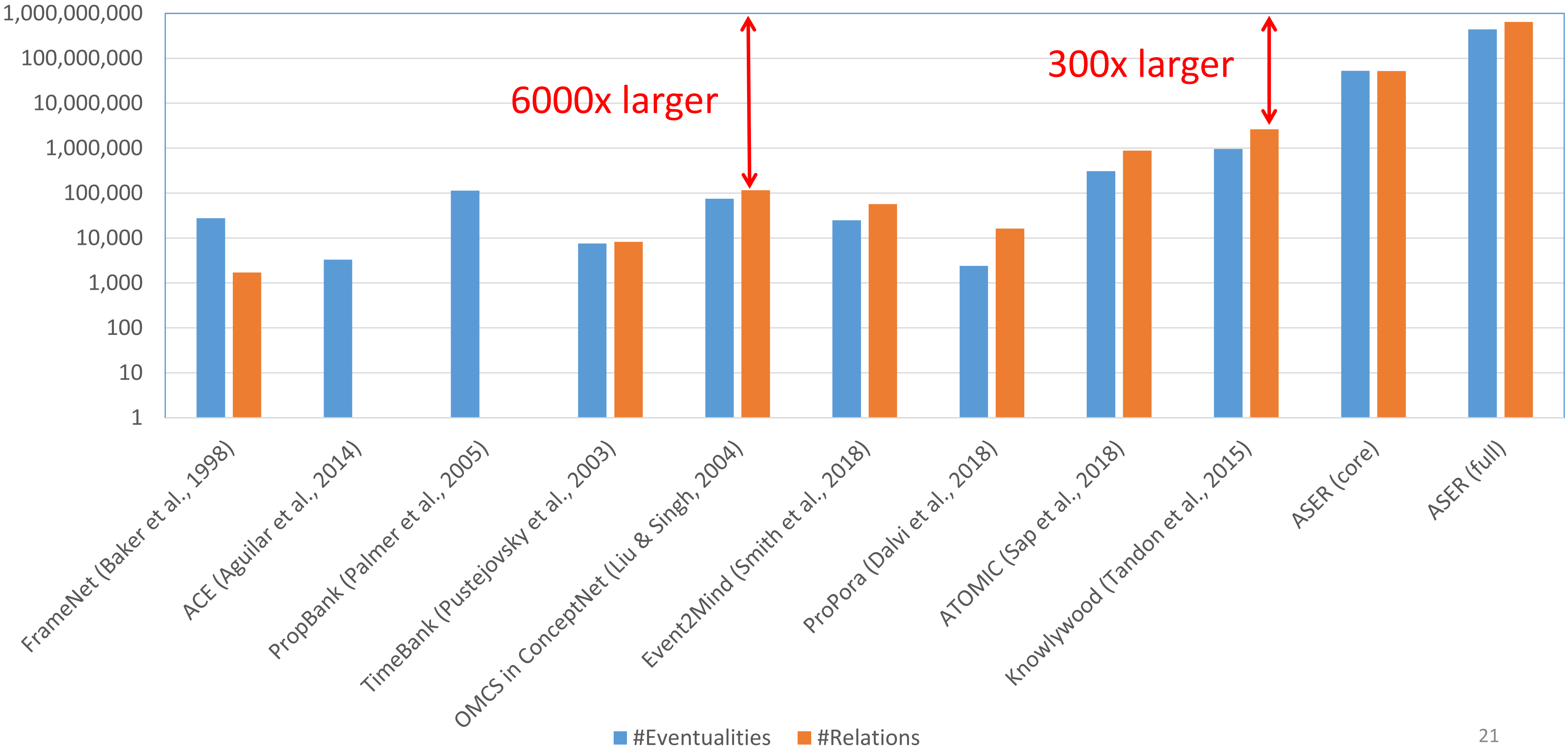
Eventuality Relations

- Classifiers trained on Penn Discourse Treebank (PDTB) (Prasad et al., 2007)
- 14 relations taking from CoNLL shared task
  - More frequent relations
- Less ambiguous connectives
  - ‘so that’ 31 times only in ‘Result’ relations
- Some are ambiguous
  - ‘while’: Conjunction 39 times, Contrast 111 times, Expectation 79 times, and Concession 85 times

Relation Type	Examples
Precedence	E1 **before** E2; E1 , **then** E2; E1 **till** E2; E1 **until** E2
Succession	E1 **after** E2; E1 **once** E2
Synchronous	E1, **meanwhile** E2; E1 **meantime** E2; E1, **at the same time** E2
Reason	E1, **because** E2
Result	E1, **so** E2; E1, **thus** E2; E1, **therefore** E2; E1, **so that** E2
Condition	E1, **if** E2; E1, **as long as** E2
Contrast	E1, **but** E2; E1, **however** E2; E1**, by contrast** E2; E1, **in contrast** E2; E1 , **on the other hand**, E2; E1, **on the contrary**, E2
Concession	E1, **although** E2
Conjunction	E1 **and** E2; E1, **also** E2
Instantiation	E1, **for example** E2; E1, **for instance** E2
Restatement	E1, **in other words** E2
Alternative	E1 **or** E2; E1, **unless** E2; E1, **as an alternative** E2; E1, **otherwise** E2
ChosenAlternative	E1, E2 **instead**
Exception	E1, **except** E2

Prasad, R., Miltsakaki, E., Dinesh, N., Lee, A., Joshi, A., Robaldo, L., & Webber, B. L. (2007). The penn discourse treebank 2.0 annotation manual.
Nianwen Xue, Hwee Tou Ng, Sameer Pradhan, Rashmi Prasad, Christopher Bryant, Attapol T. Rutherford. The CoNLL-2015 Shared Task on Shallow Discourse Parsing.

Scales of Verb Related Knowledge Graphs



Partial Information Aggregation

- “hurt things tending to fall down”

(hurt, X) connection (X, fall)

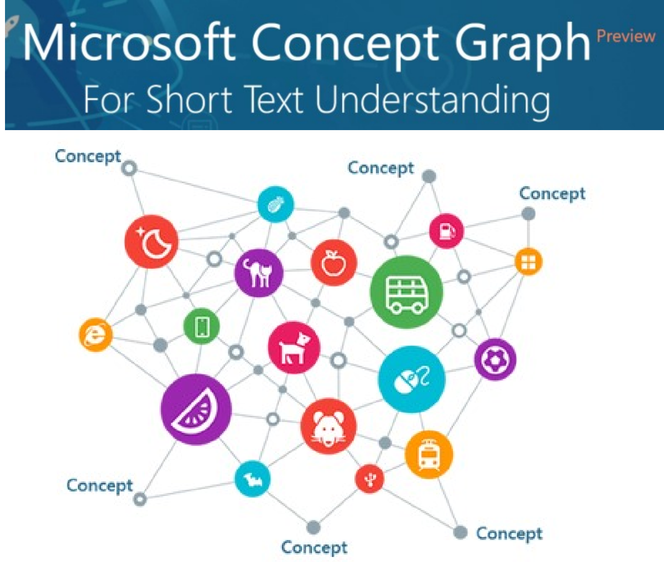
- “stocks price may increase when company X acquire a start-up”

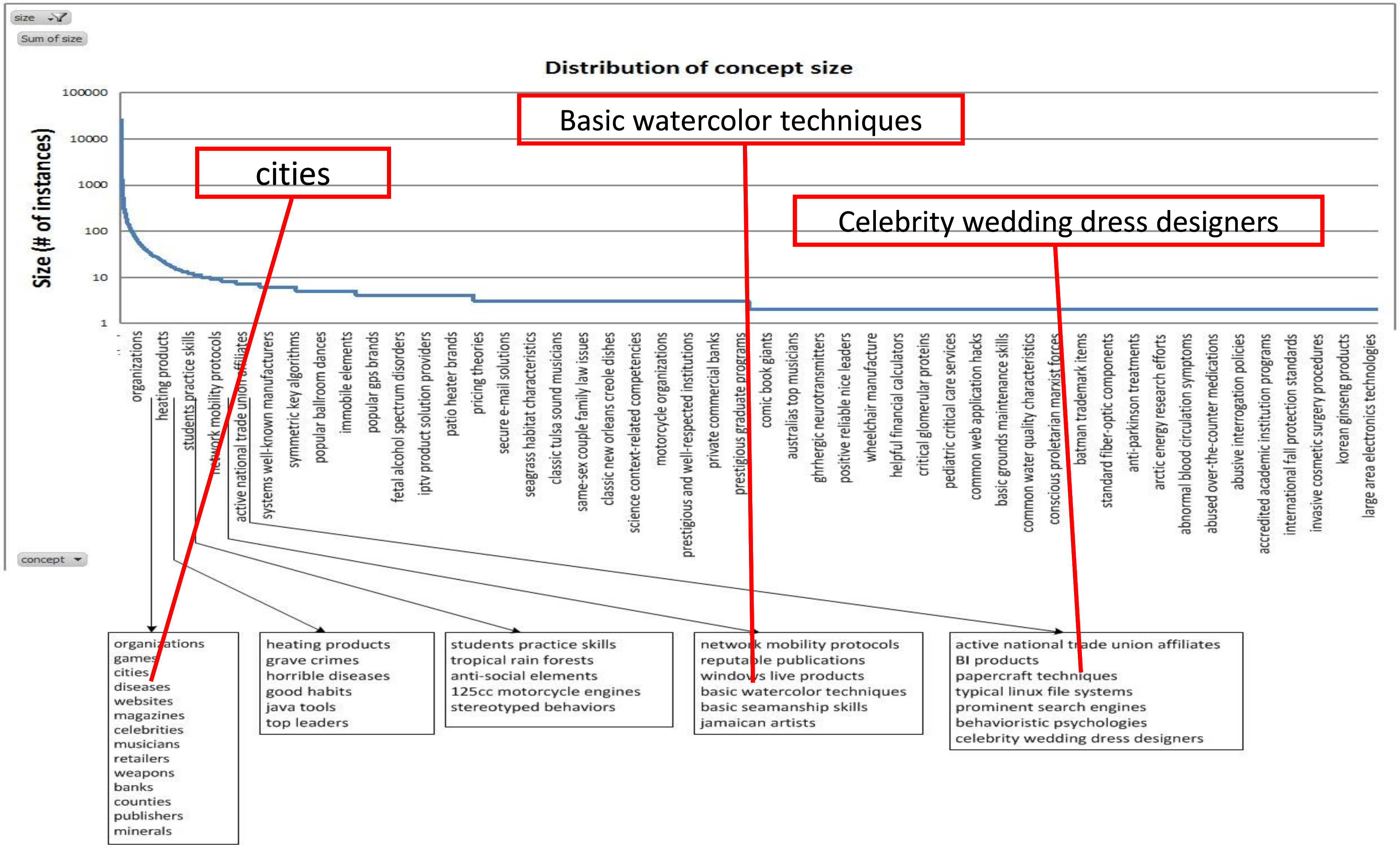
(company, acquire, start-up) result-in (stock, increase)

Normalization

			Probability
He, she, I, Bob, …	⟶	__PERSON__	1.0
1996, 2020, 1949, …	⟶	__YEAR__	1.0
23, 20, 333, ….	⟶	__DIGIT__	1.0
www.google.com, …	⟶	__URL__	1.0

Conceptualization with ProBase





Concepts are the glue that holds our mental world together.

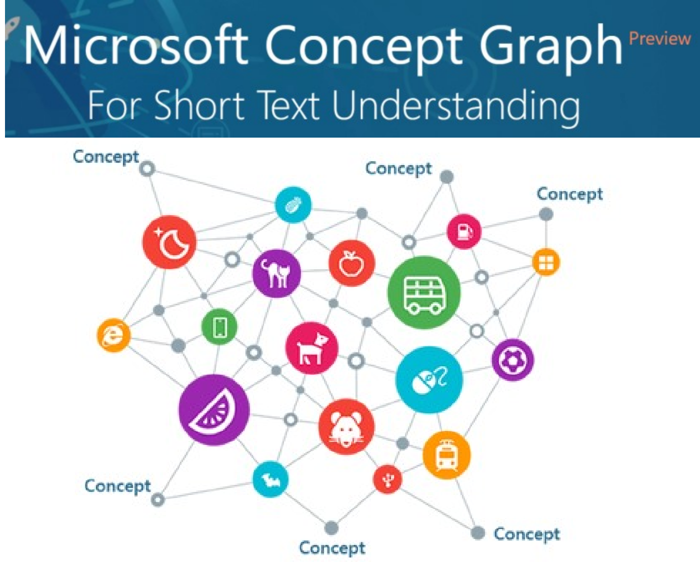
Gregory L. Murphy
NYU

Probase is a *large, universal, probabilistic* knowledge base with **an extremely large concept space**

Data are available at https://concept.research.microsoft.com/

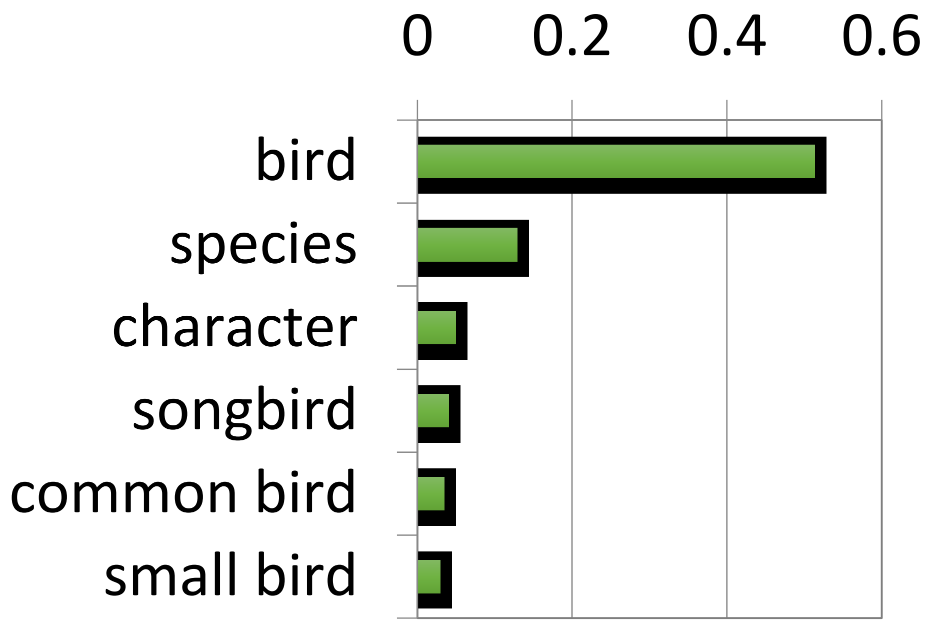
Wentao Wu, Hongsong Li, Haixun Wang, Kenny Qili Zhu: Probase: a probabilistic taxonomy for text understanding. SIGMOD Conference 2012: 481-492

Conceptualization with ProBase

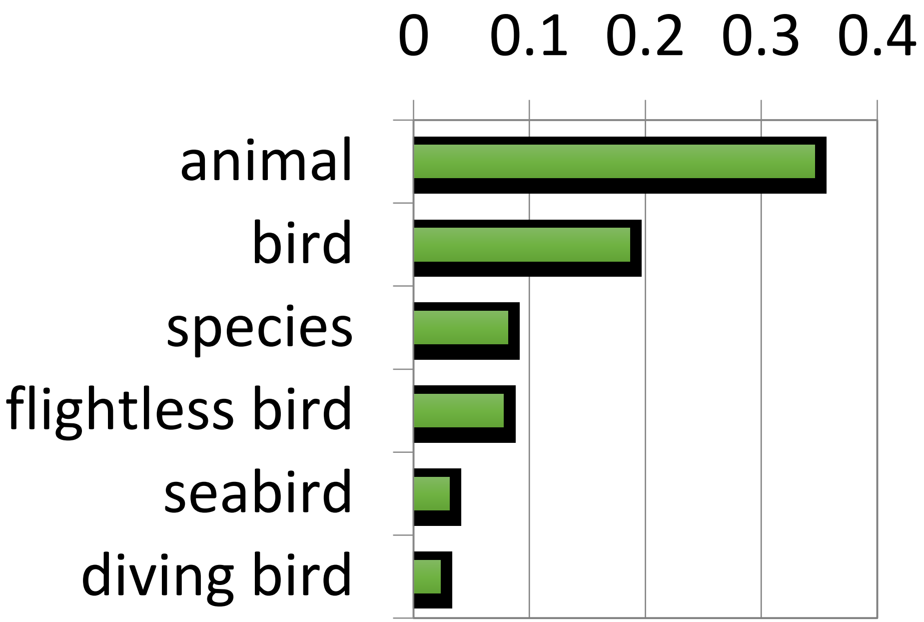


Typicality $P(concept \mid instance) = \dfrac{\#(concept, instance)}{\#(instance)}$

- Robin



- Penguin



Data are available at https://concept.research.microsoft.com/

Wentao Wu, Hongsong Li, Haixun Wang, Kenny Qili Zhu: Probase: a probabilistic taxonomy for text understanding. SIGMOD Conference 2012: 481-492
Yangqiu Song, Haixun Wang, Zhongyuan Wang, Hongsong Li, Weizhu Chen: Short Text Conceptualization Using a Probabilistic Knowledgebase. IJCAI 2011: 2330-2336

A Running Example

Obama

(politician, 0.0855)
(democrat, 0.0560)
(liberal, 0.0560)

dog

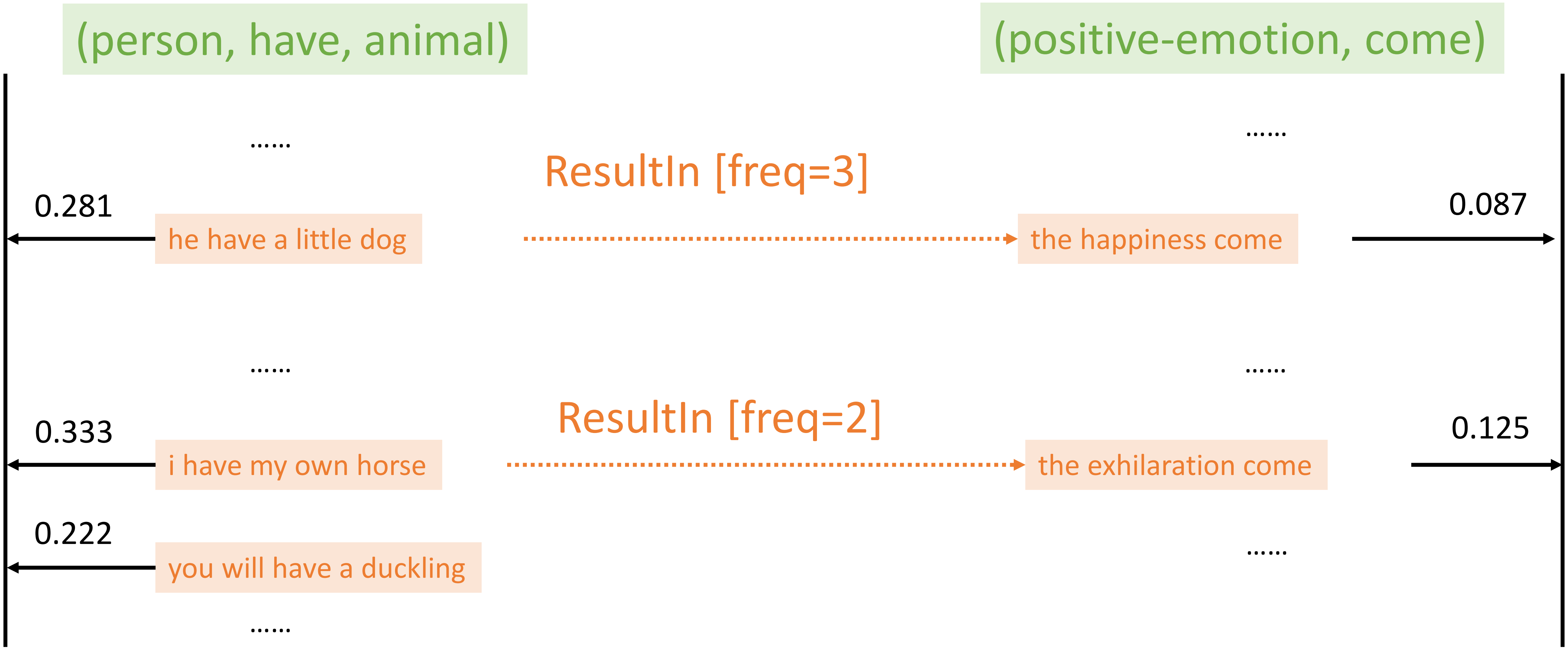
(animal, 0.2811)
(pet, 0.1377)
(domestic animal, 0.0525)

(Obama, have, dog)

(obama have animal, 0.2811)
(obama have pet, 0.1377)
(politician have dog, 0.0855)
(democrat have dog, 0.05604)
...
(politician have animal, 0.0240)
(democrat have animal, 0.01575)
...

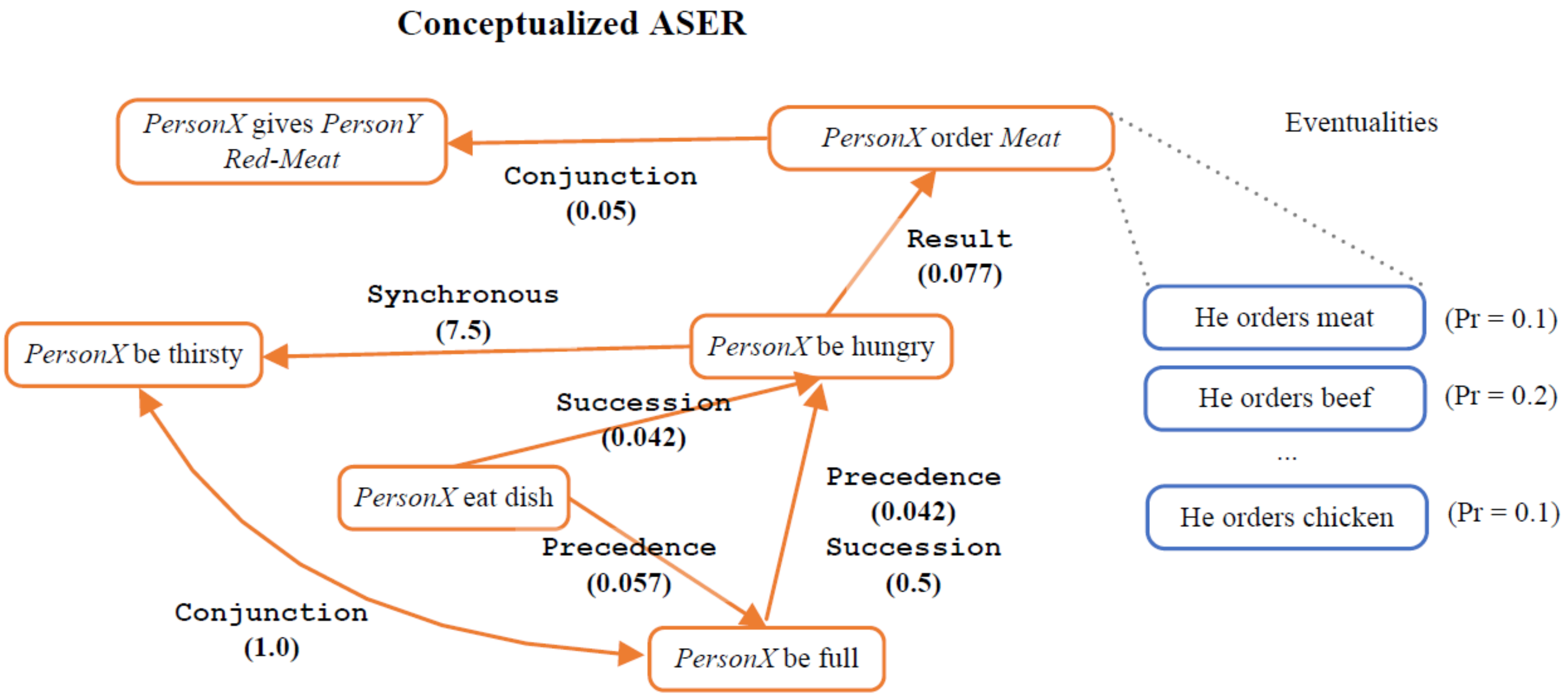
$$\prod_{i=1}^{N} P\left(C_{i,k} | E_i\right)$$

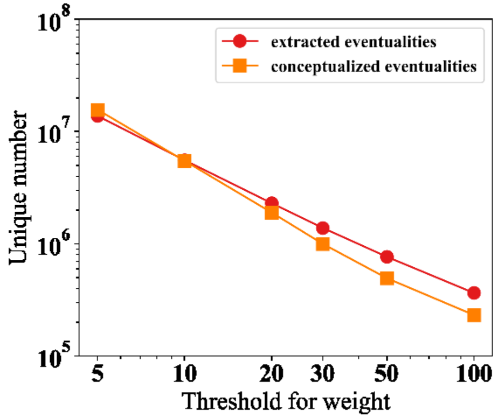
$$P(politician \mid Obama) \times P(animal \mid dog) = 0.0855 \times 0.2811 = 0.0240$$

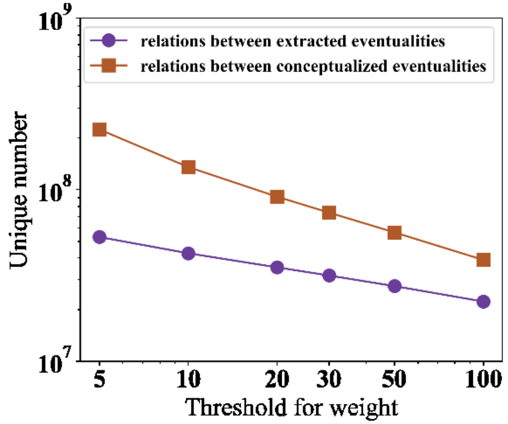


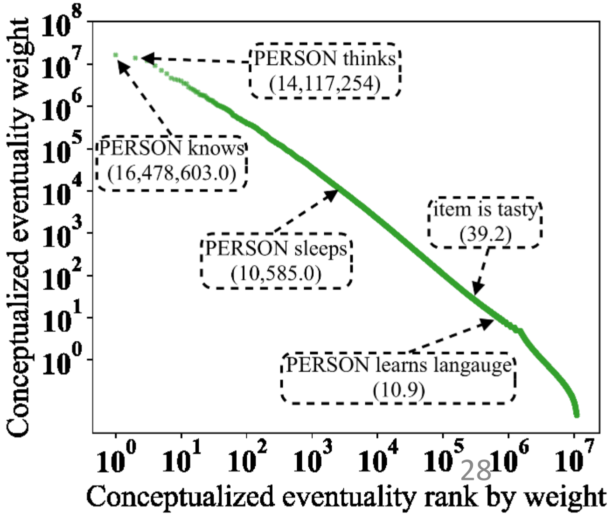
P(ResultIn | (person, have, animal) , (positive-emotion, come)) $= 0.281 \times 3 \times 0.087 + 0.333 \times 2 \times 0.125$
$= 0.157$

Conceptualization Results









ASER 2.0

- 1.0: Rule based extraction (14 Eventuality Patterns, Improved Version)

Data	#Unique Eventualities	#Unique Relations
Core	34,212,258	15,339,027
Full	272,206,675	205,758,398

- 2.0: Discourse Parser (18 Eventuality Patterns + Wang and Lan 2015)

Data	#Unique Eventualities	#Unique Relations
Core	52,940,258	52,296,498
Full	438,648,952	648,514,465

- Conceptualization Core (threshold=5):
  - Concepts: 15,640,017 (based on 13,766,746 eventualities, 1.X times)
  - Concept Relations: 224,213,142 (based on 52,927,979 eventuality relations, 4.X times)

Jianxiang Wang and Man Lan. A Refined End-to-End Discourse Parser. CONLL Shared Task 2015.

Graph Inference Examples

- One hop relations $\Pr(E_t|E_h, T_1) = \frac{w^{(r)}_{\langle E_h, T_1, E_t \rangle}}{\sum_{E'_t, s.t., (E_h, T_1, E'_t) \in \mathcal{R}} w^{(r)}_{\langle E_h, T_1, E'_t \rangle}},$

- Eventualities
  - ⟨"I drink coffee", `Reason`, "I enjoy the flavor"⟩
  - ⟨"You go to restaurant", `Precedence`, "You got sick"⟩
  - ⟨"It is a cat", `Condition`, "It is a tiger"⟩

- Concepts
  - ⟨"*Company* be *Stakeholder-Group*", `Condition`, "*PersonX* be successful"⟩
  - ⟨"*PersonX* hurt *Insect*", `Condition`, "*PersonX* help *Insect*"⟩
  - ⟨"*PersonX* be *Emotion*", `Succession`, "*PersonX* marry"⟩

Graph Inference Examples

- Two hop relations $$\Pr(E_t|E_h, T_1, T_2) = \sum_{E_m \in \mathcal{E}_m} \Pr(E_m|E_h, T_1)\Pr(E_t|E_m, T_2),$$
- Eventualities
  - ⟨"I go to bed", `Conjunction`, ["I sleep early"], `Result`, "I am healthy"⟩
  - ⟨"We have lunch", `Conjunction`, ["We really hit it off"], `Contrast`, "She has a boyfriend at time"⟩
  - ⟨"I go to restaurant", `Reason`, ["I have a coupon"], `Contrast`, "It is expired"⟩
- Concepts
  - ⟨"*PersonX* wait for *PersonY*", `Precedence`, ["*PersonX* be tired"], `Result`, "*PersonX* go to sleep"⟩
  - ⟨ "*PersonX* be cranky", `Synchronous`, ["*PersonX* be hungry"], `Result`, "*PersonX* order *Meat*" ⟩
  - ⟨ "*PersonX* be *Artist*", `Condition`, ["*PersonX* strike *PersonY*"], `Synchronous`, "*PersonY* interview *PersonX*" ⟩

Rule Mining: Concepts

- Mine Rules using AMIE+ $< E_a, T_1, E_b > \wedge < E_b, T_2, E_c > \Rightarrow < E_a, T_3, E_b >,$

Rule	$E_a \xrightarrow{Reason} E_f \wedge E_b \xrightarrow{Succession} E_f \Rightarrow E_a \xrightarrow{Reason} E_b$
Instances	I ask → I am not sure ∧ I do not know → I am not sure ⇒ I ask → I do not know We are lucky → We notice ∧ We order → We notice ⇒ We are lucky → We order I remember it → I see it ∧ I realize → I see it ⇒ I remember it → I realize
Rule	$E_a \xrightarrow{Concession} E_f \wedge E_b \xrightarrow{Precedence} E_f \Rightarrow E_a \xrightarrow{Contrast} E_b$
Instances	I am unconscious → I wake up ∧ I see → I wake up ⇒ I am unconscious → I see I swear → I guess ∧ I do not know → I guess ⇒ I swear → I do not know I can not believe → It is great ∧ I think → It is great ⇒ I can not believe → I think
Rule	$E_a \xrightarrow{Alternative} E_e \wedge E_e \xrightarrow{Exception} E_b \Rightarrow E_a \xrightarrow{Exception} E_b$
Instances	It is not → It is wrong ∧ It is wrong → It is ⇒ It is not → It is I really want → I think ∧ I think → I know ⇒ I really want → I know It is not → I suppose ∧ I suppose → You know ⇒ It is not → You know

Luis Galárraga, Christina Teflioudi, Katja Hose, and Fabian Suchanek. Fast Rule Mining in Ontological Knowledge Bases with AMIE+. *The VLDB Journal*, Springer, 2015.

Rule Mining: Concepts

- Mine Rules using AMIE+ $< E_a, T_1, E_b > \wedge < E_b, T_2, E_c > \Rightarrow < E_a, T_3, E_b >,$

Rule	$E_e \xrightarrow{Instantiation} E_a \wedge E_e \xrightarrow{Instantiation} E_b \Rightarrow E_a \xrightarrow{Conjunction} E_b$
Instances	*PersonX* realize → *PersonX* point out ∧ *PersonX* realize → PersonX have *information* ⇒ *PersonX* point out → *PersonX* have *information*
	PersonX have → *PersonX* get ∧ *PersonX* have → *PersonX* own ⇒ *PersonX* get → *PersonX* own
	PersonX know → *PersonX* be sure ∧ *PersonX* know → *PersonX* remember ⇒ *PersonX* be sure → *PersonX* remember
Rule	$E_e \xrightarrow{Concession} E_b \wedge E_e \xrightarrow{Restatement} E_a \Rightarrow E_a \xrightarrow{Contrast} E_b$
Instances	*PersonX* order *dish* → *PersonX* be hungry ∧ *PersonX* order *dish* → *PersonX* order ⇒ *PersonX* order → *PersonX* be hungry
	PersonX wish → *PersonX* doubt ∧ *PersonX* wish → *PersonX* need ⇒ *PersonX* doubt → *PersonX* need
	PersonX love it → *PersonX* hate it ∧ *PersonX* love it → it be good ⇒ *PersonX* hate it → it be good
Rule	$E_e \xrightarrow{Exception} E_b \wedge E_e \xrightarrow{Succession} E_a \Rightarrow E_a \xrightarrow{Contrast} E_b$
Instances	*item* be ready → *PersonX* wait ∧ *item* be ready → *PersonX* check ⇒ *PersonX* check → *PersonX* be wait
	PersonX say → *PersonX* be sorry ∧ *PersonX* say → *PersonX* be surprised ⇒ *PersonX* be sorry → *PersonX* be surprised
	it be → *PersonX* guess ∧ it be → it be *factor* ⇒ *PersonX* guess → it be *factor*

Luis Galárraga, Christina Teflioudi, Katja Hose, and Fabian Suchanek. Fast Rule Mining in Ontological Knowledge Bases with AMIE+. *The VLDB Journal*, Springer, 2015.

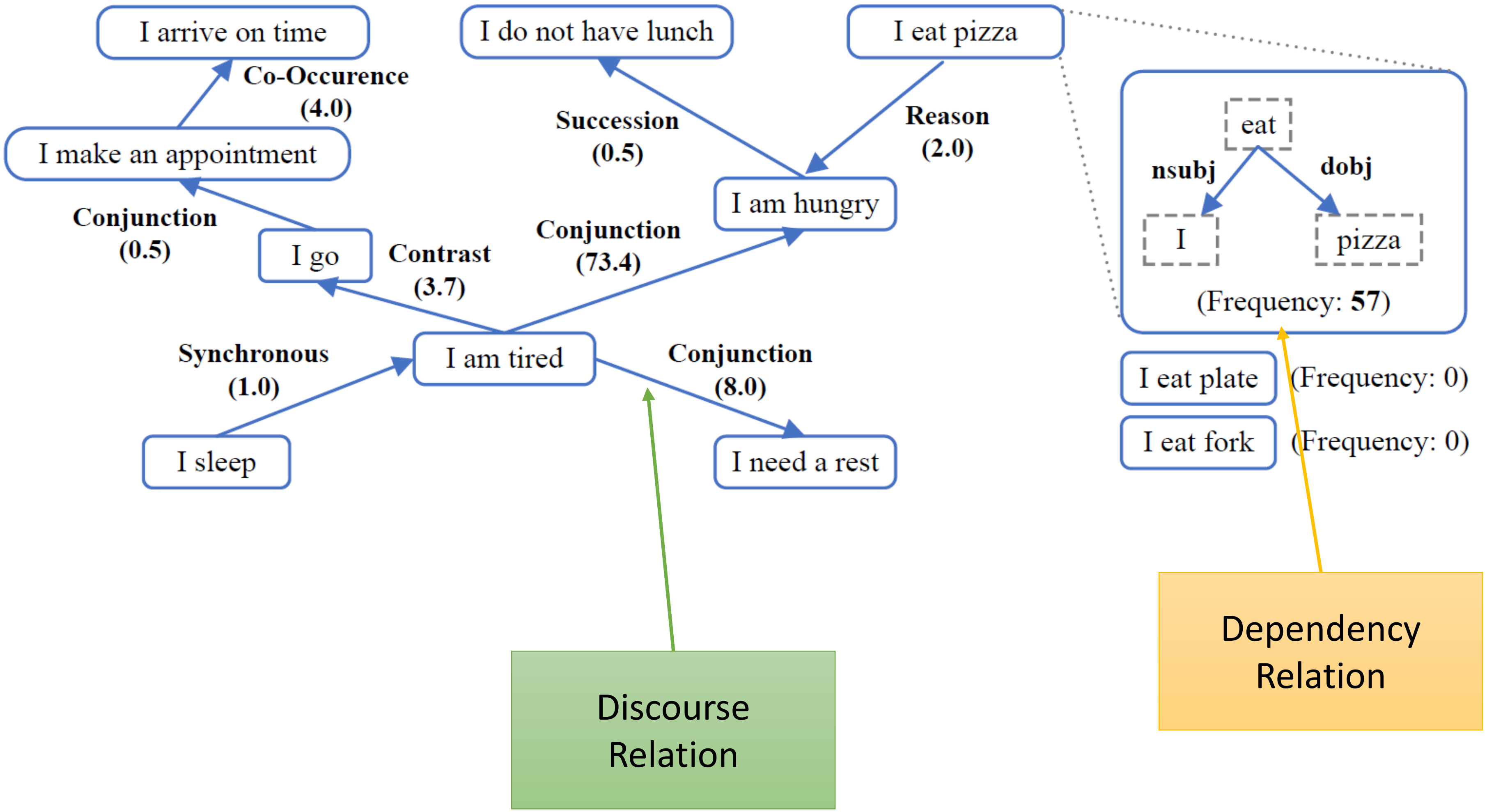
Meta-path Mining

#Hop	meta-path	Instances
2	$E_1 \xrightarrow{\texttt{Conjunction}} E_2 \xrightarrow{\texttt{Contrast}} E_3$	I go to bed → I go to sleep → I wake up I have breakfast → I have milk → I feel sick I take bus → I go to work → I go home
	$E_1 \xrightarrow{\texttt{Precedence}} E_2 \xrightarrow{\texttt{Precedence}} E_3$	You go to sleep → You wake up → You hit the ground You drink alcohol → You go to toilet → You have to pee You go to restaurant → You are sick → You go to hospital
	$E_1 \xrightarrow{\texttt{Conceptualization}} C_1 \xrightarrow{\texttt{ConceptInstantiation}} E_2$	He is psychiatrist → *PersonX* is *Specialist* → I am attorney I want milk → *PersonX* want *Animal-Product* → He wants burgers You make reservation → *PersonX* make *Service* → He makes statement
	$E_1 \xrightarrow{\texttt{Conjunction}} E_2 \xrightarrow{\texttt{Conjunction}} E_3$	I go to gym → I have to wait → I go home I am vegan → My wife is vegan → I used to eat meat It is a cat → It is fine → It is beautiful
	$E_1 \xrightarrow{\texttt{Reason}} E_2 \xrightarrow{\texttt{Result}} E_3$	I go to bar → I have many friends → I have parties I go to school → We could afford → I get my first job I am in pain → I am alone → I sit at bar
3	$E_1 \xrightarrow{\texttt{Precedence}} E_2 \xrightarrow{\texttt{Conjunction}} E_3 \xrightarrow{\texttt{Precedence}} E_4$	The rain comes down → The engine whistles → The train starts → The train moves on The moon arises → The weather is pleasant → The snow ceases → The night is still She sleeps → The phone rings → We gets home → She hangs up the phone
	$E_1 \xrightarrow{\texttt{Conjunction}} E_2 \xrightarrow{\texttt{Conceptualization}} C_1 \xrightarrow{\texttt{ConceptInstantiation}} E_3$	I play piano → I am musician → *PersonX* be *Artist* → He is actor I am chill → It is a snake → It be *Predator* → It is a bear It is hot → I am sweating → *PersonX* be *Symptom* → She is in a coma
	$E_1 \xrightarrow{\texttt{Condition}} E_2 \xrightarrow{\texttt{Reason}} E_3 \xrightarrow{\texttt{Conjunction}} E_4$	Everyone knows him → He comes off the bench → He makes his debut for club → He scores his first goal I am healthy → I sleep → I am exhausted → I am cold We get the check → We order dessert → I am still hungry → We eat everything
	$E_1 \xrightarrow{\texttt{Result}} E_2 \xrightarrow{\texttt{Contrast}} E_3 \xrightarrow{\texttt{Conjunction}} E_4$	I am tired → I go to bed → The sun is shining → The wind blows There is a storm coming → The rain falls → The sky is clear → The air is warm I have you number → I call you → I have a meeting → I have a presentation
	$E_1 \xrightarrow{\texttt{Contrast}} E_2 \xrightarrow{\texttt{Reason}} E_3 \xrightarrow{\texttt{Reason}} E_4$	I am a vegan → I eat meat → I enjoy it → It tastes good The painting is controversial → It is a masterpiece → It belongs in museum → It is valuable I get over it quickly → i be go to mall → Reason → i have a job interview

Outline

- Motivation: NLP and commonsense knowledge
- Consideration: selectional preference
- New proposal: large-scale and higher-order selectional preference
- Extensions
  - Transform to ConceptNet
  - Transform to ATOMIC

ASER is Essentially a Knowledge Graph based on Linguistics

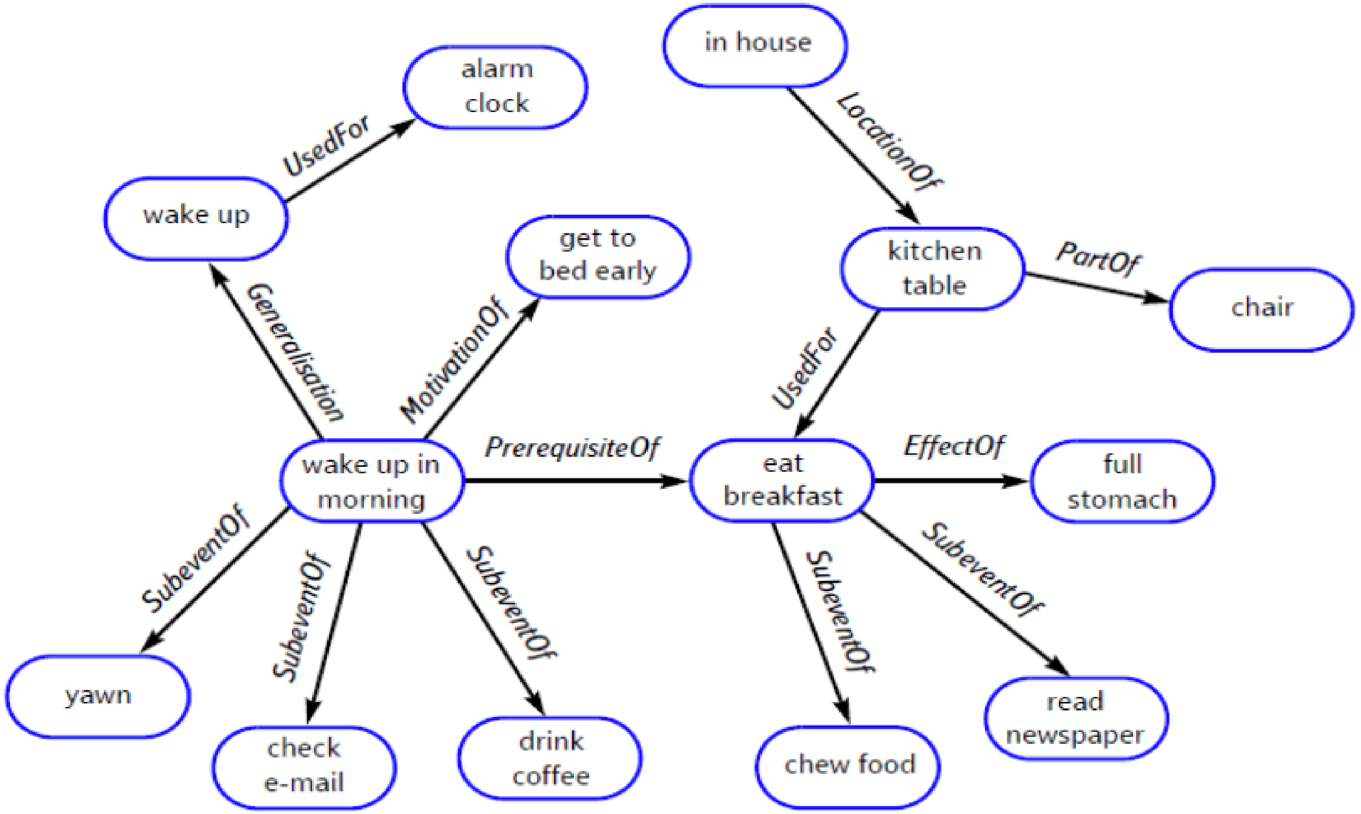


How is it transferrable from linguistic knowledge to existing definition of commonsense knowledge?

ConceptNet (Speer & Havasi, 2012)

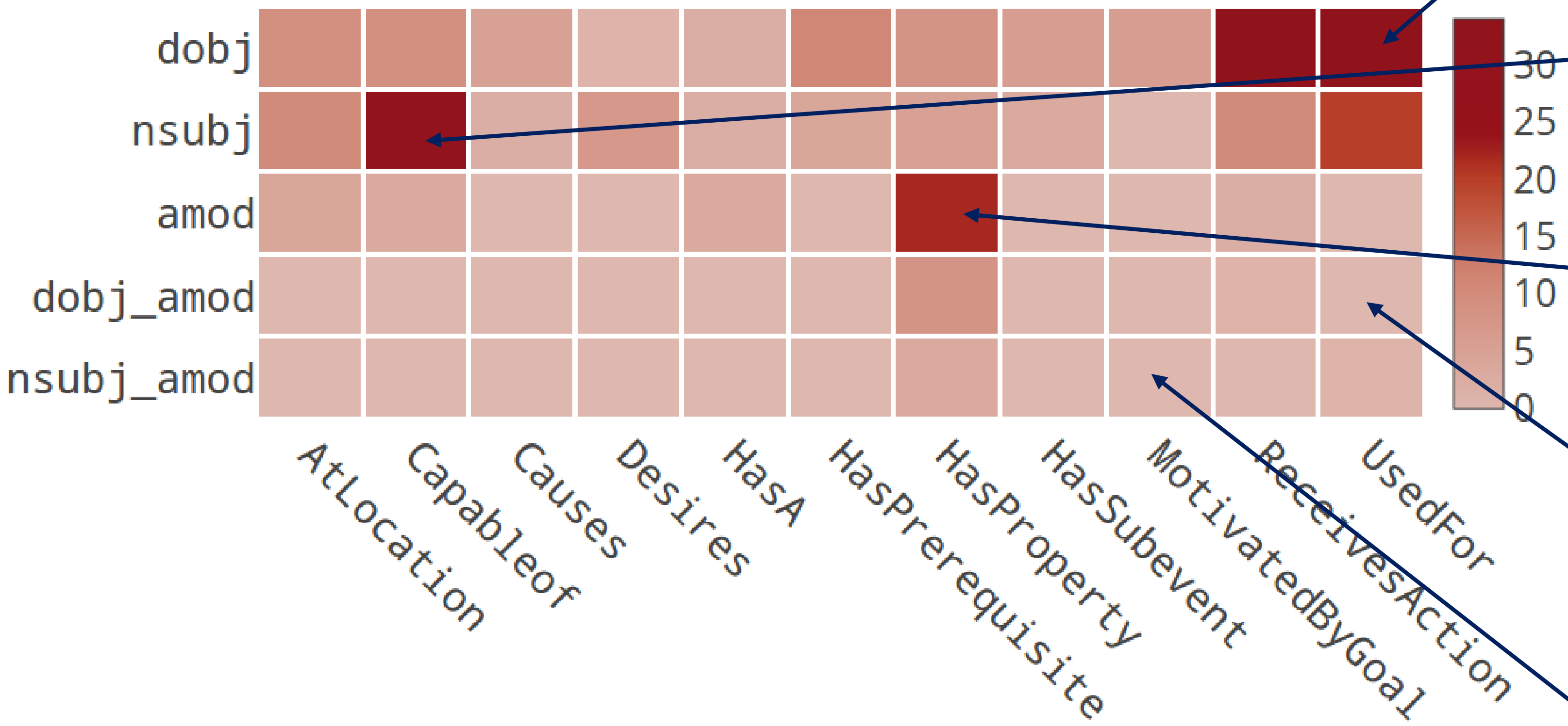
Core is OMCS (Liu & Singh 2004)

- Commonsense knowledge base
  - Commonsense knowledge about noun-phrases, or entities.



Speer and Havasi. "Representing General Relational Knowledge in ConceptNet 5." *LREC*. 2012.

Revisit the Correlations of SP and OMCS



(sing, song) (dobj, 9.25)
(song, UsedFor, sing)

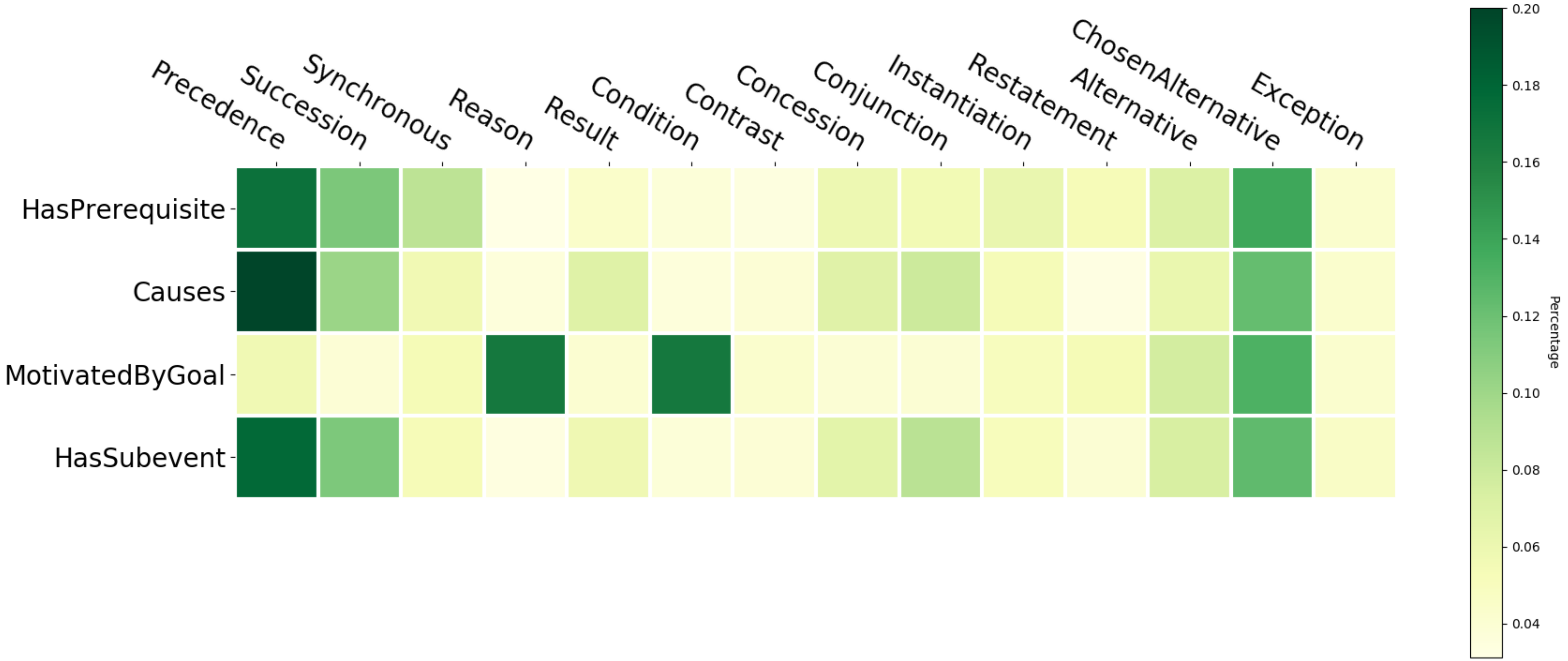
(phone, ring) (nsubj, 8.75)
(phone, CapableOf, ring)

(cold, water) (amod, 8.86)
(water, HasProperty, cold)

(create, new) (dobj_amod, 8.25)
(create idea, UsedFor, invent new things)

(hungry, eat) (nsubj_amod, 10.00)
(eat, MotivatedByGoal, are hungry)

Revisit the Correlations of ASER and OMCS



TransOMCS

Relation: `AtLocation`

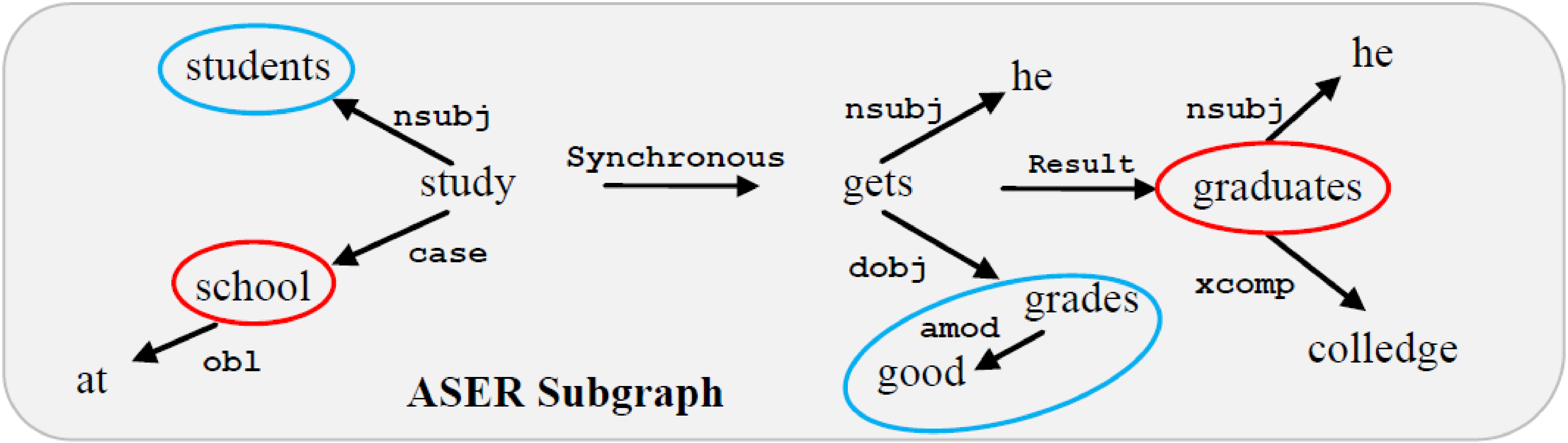
Pattern: (***H***)<-nsubj<-((***T***)-obl-(at))

Knowledge: `(Student, AtLocation, School)`

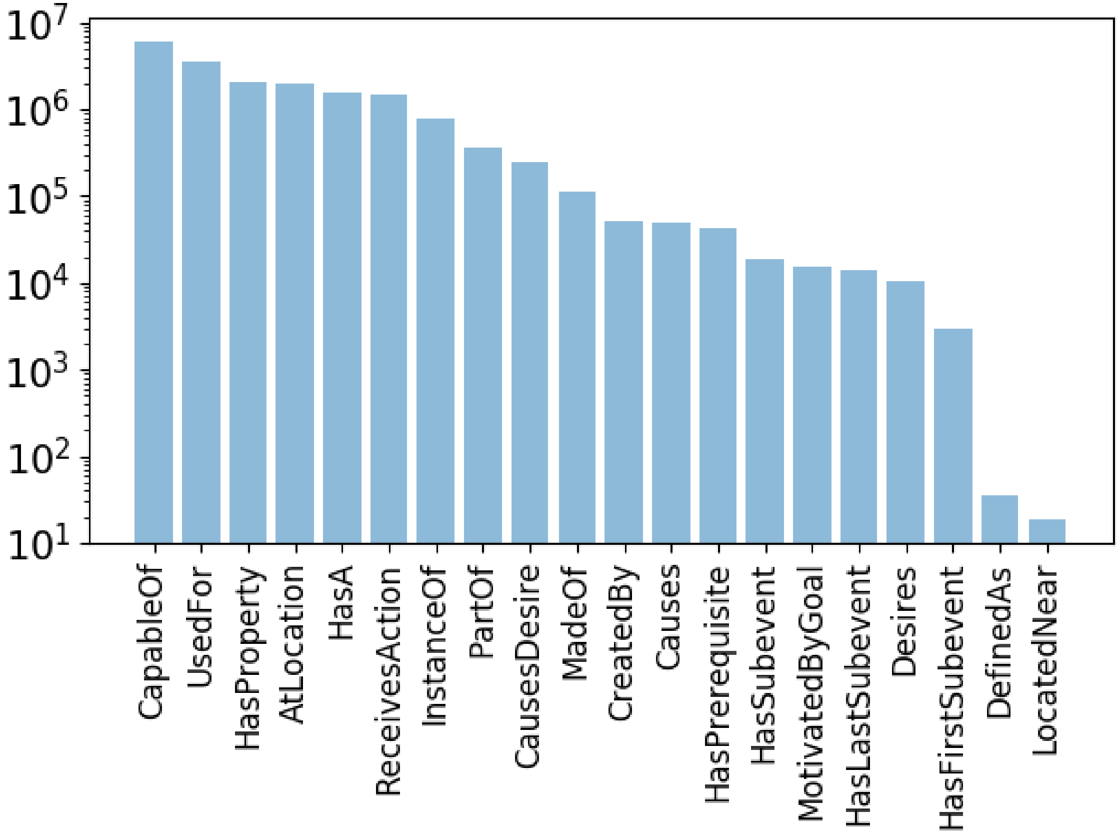
Relation: `Causes`

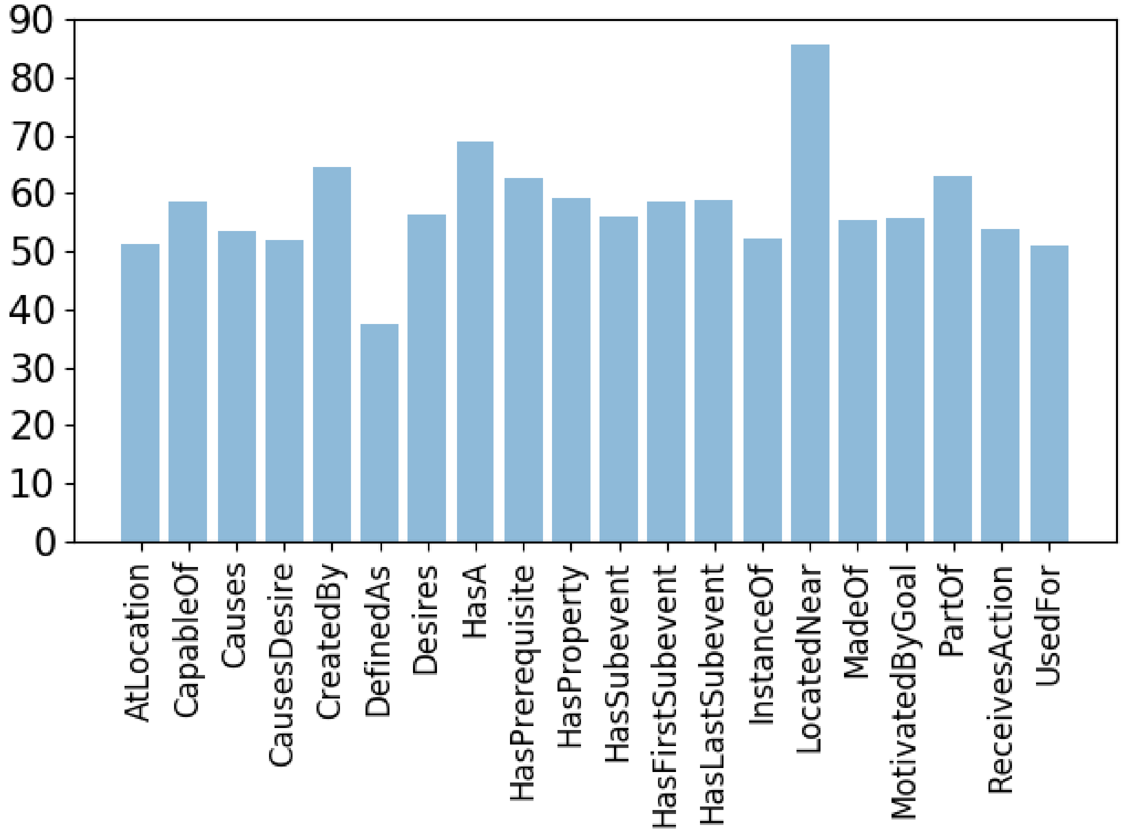
Pattern: (***H***)<-dobj<-()<-Result<-(***T***)

Knowledge: `(Good grades, Causes, Graduate)`



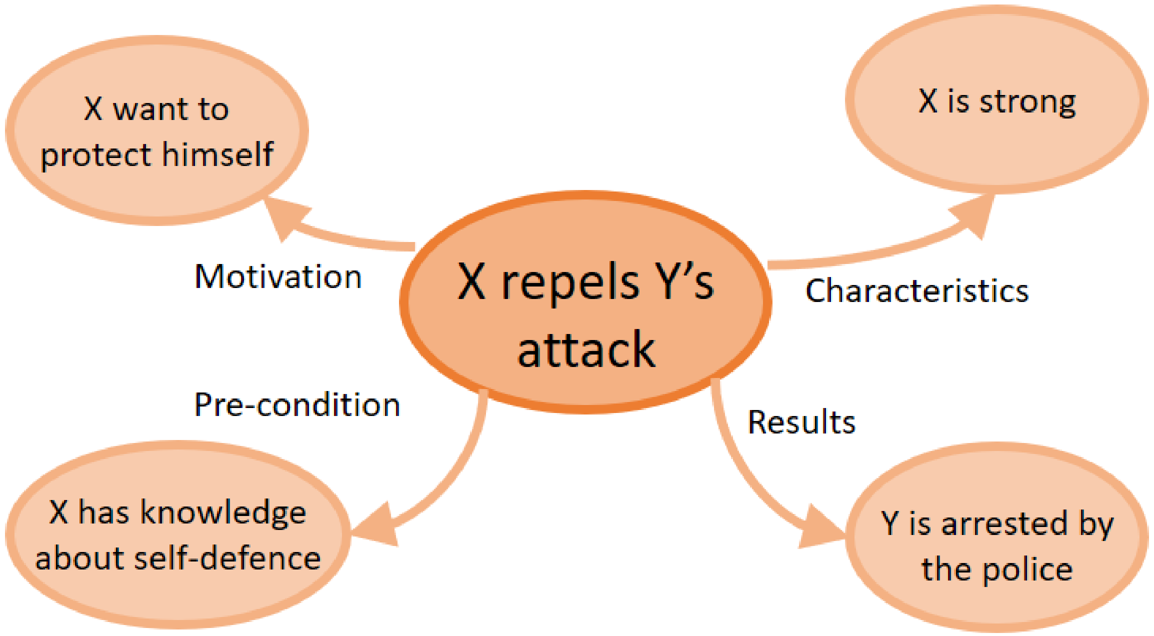
Distribution of Relations and Accuracy





ATOMIC (Sap, Maarten, et al. 2019)

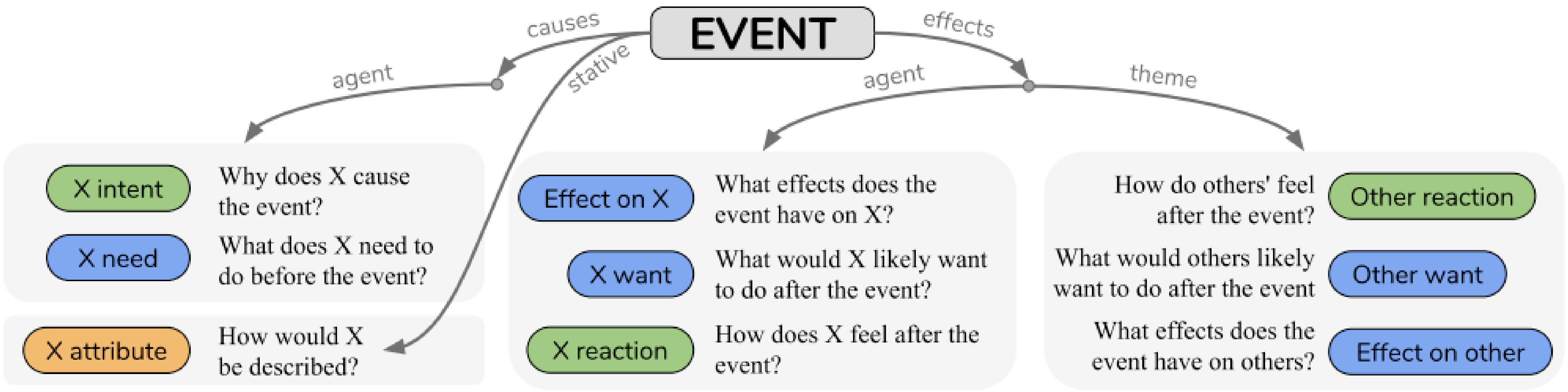
- Everyday if-then commonsense knowledge These are day-to-day knowledge that help us understand each other.
  - If a person *X did* something, human beings are able to inference:
    - Motivation: Why person X did this.
    - Pre-conditions: What enables X to do this.
    - Characteristics: What are attributes of X.
    - Result: What will affect X/others



Sap, Maarten, et al. "Atomic: An atlas of machine commonsense for if-then reasoning.", *AAAI* 2019.

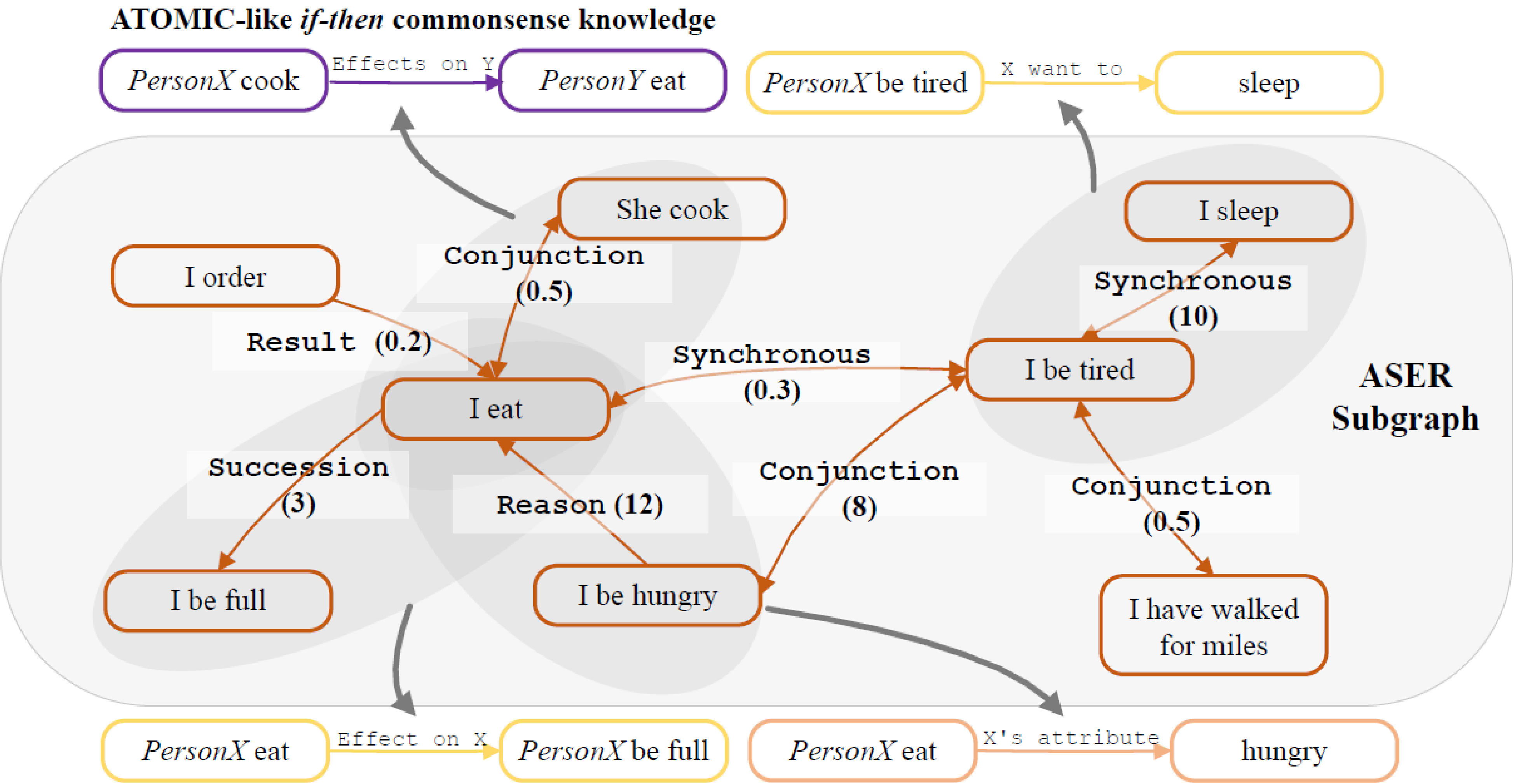
ATOMIC (Sap, Maarten, et al. 2019)

- Define 4 categories of if-then relations:
    - Causes-agent (Motivation & Pre-condition): xIntend, xNeed
    - Stative (Characteristics): xAttr
    - Effects-agent (Results on X): xWant, xReact, xEffect
    - Effects-theme (Results on others): oWant, oReact, oEffect

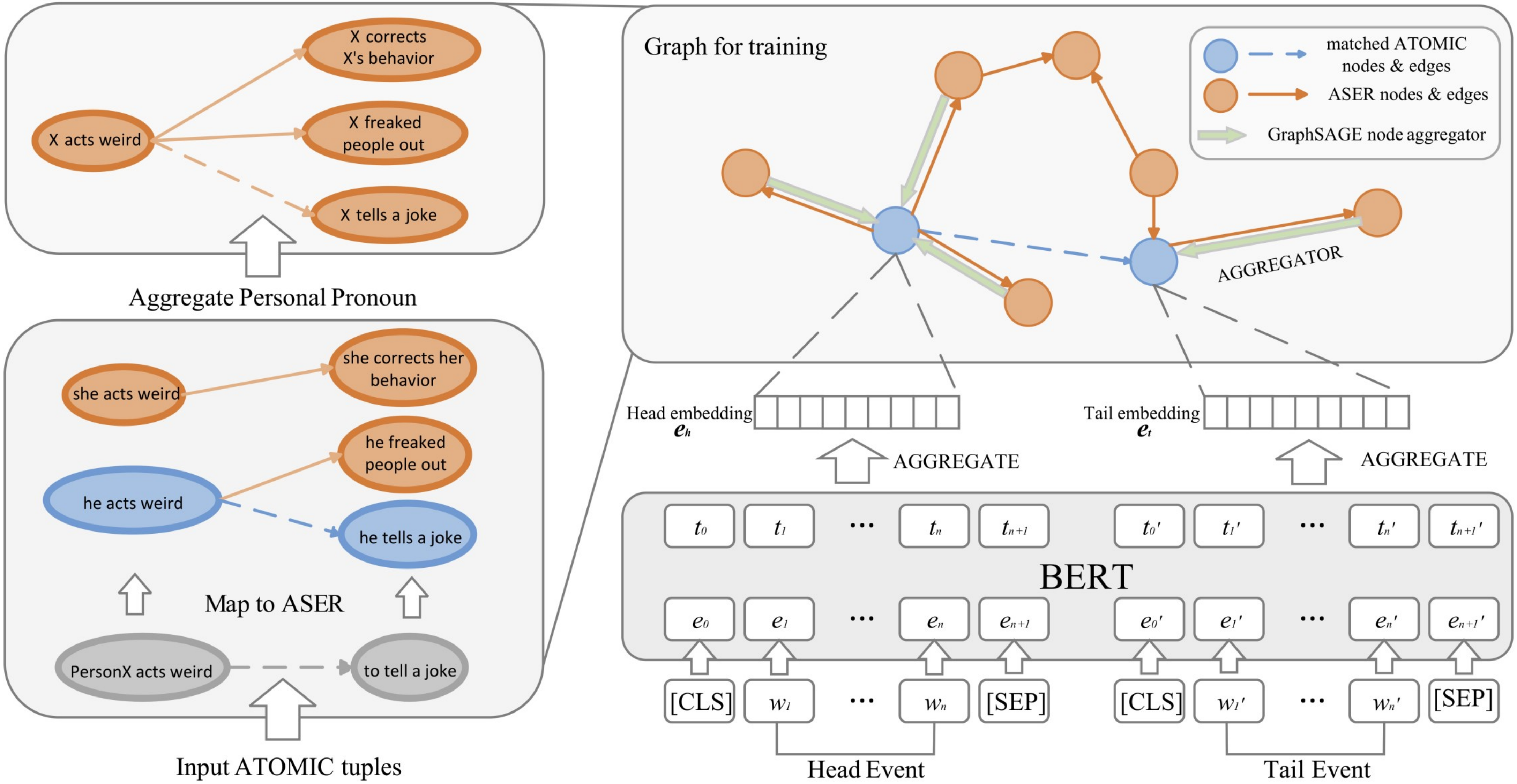


Sap, Maarten, et al. “Atomic: An atlas of machine commonsense for if-then reasoning.”, *AAAI* 2019.

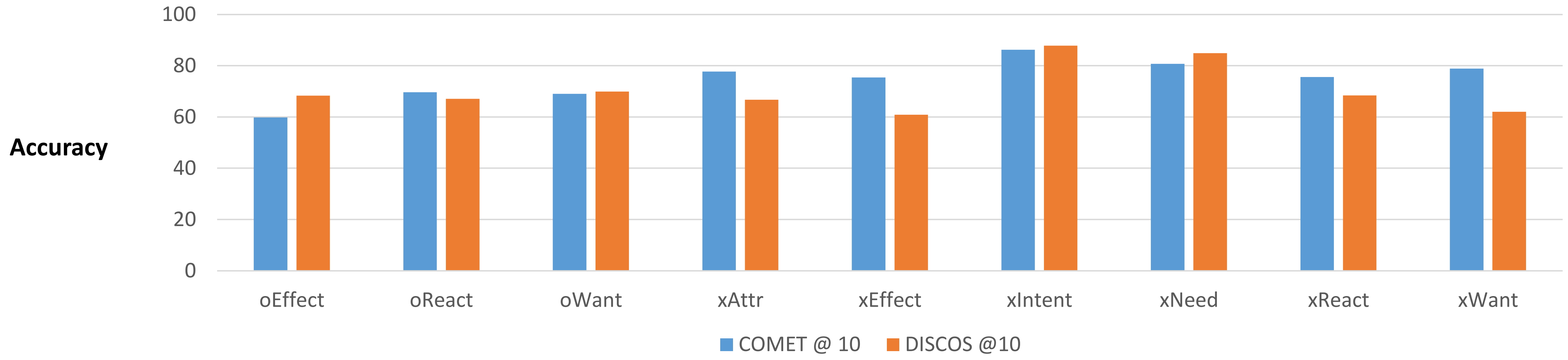
DISCOS: Transform to ATOMIC



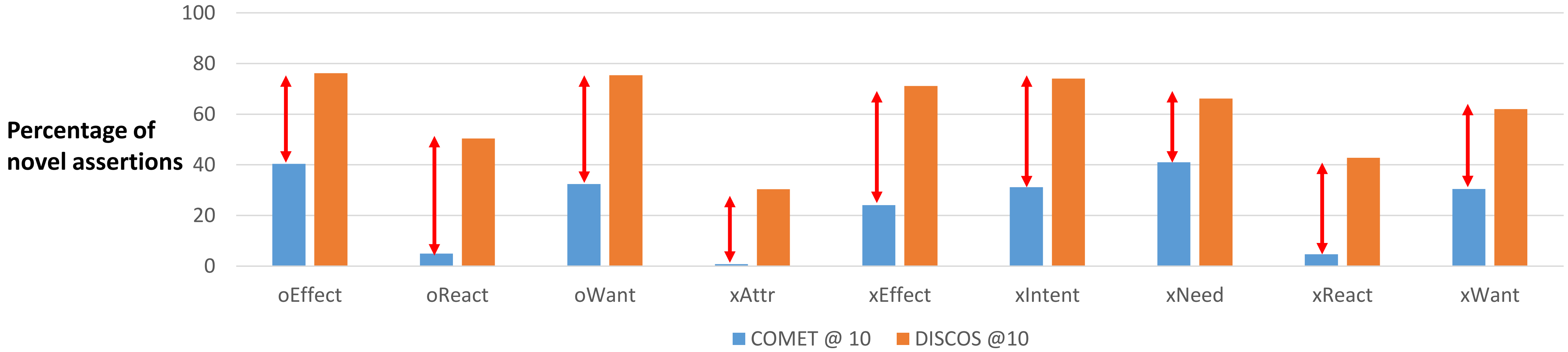
DISCOS Framework



DISCOS Result



Quality



Novelty

Future Work

- We have proven that ASER can be transferred to other commonsense knowledge graphs:
  - OMCS/ConceptNet: TransOMCS (IJCAI 2020)
  - ATOMIC: DISCOS (WWW 21)
  - Social Chemistry 101?
- Multi-modality ASER?
- Applications of ASER?
  - Event detection and reasoning
  - Other NLP tasks
    - Legal AI
    - …