

USC Viterbi



"What Are You Trying To Do" Semantic Typing of Event Processes

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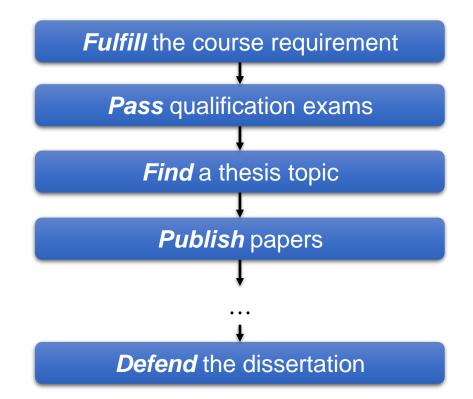
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Understanding Event Processes



Natural language always involves descriptions of event processes.

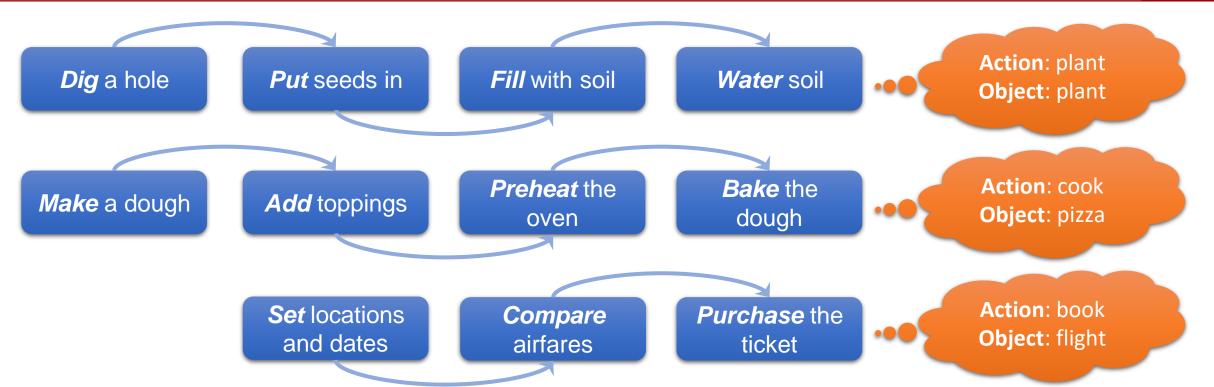
Earning a PhD in Computer Science typically takes around 5 years. It first involves *fulfilling the course requirements* and *passing qualification exams*. Then within several years, the student is expected to *find a thesis topic*, *publish several papers* about the topic and *present them in conferences*. The last one or two years are often about *completing the dissertation proposal, writing* and *defending the dissertation*.



An event process: a chain of events that happen sequentially.

Understanding Event Processes





Event processes are directed by the **central goal**, or the **intention** of its performer [Zacks+, Nature Neuroscience 2001].

- Inherent to human's common sense.
- Missing from current computational methods.
- Important to machine commonsense reasoning, summarization, schema induction, etc.



Three Contributions of This Work

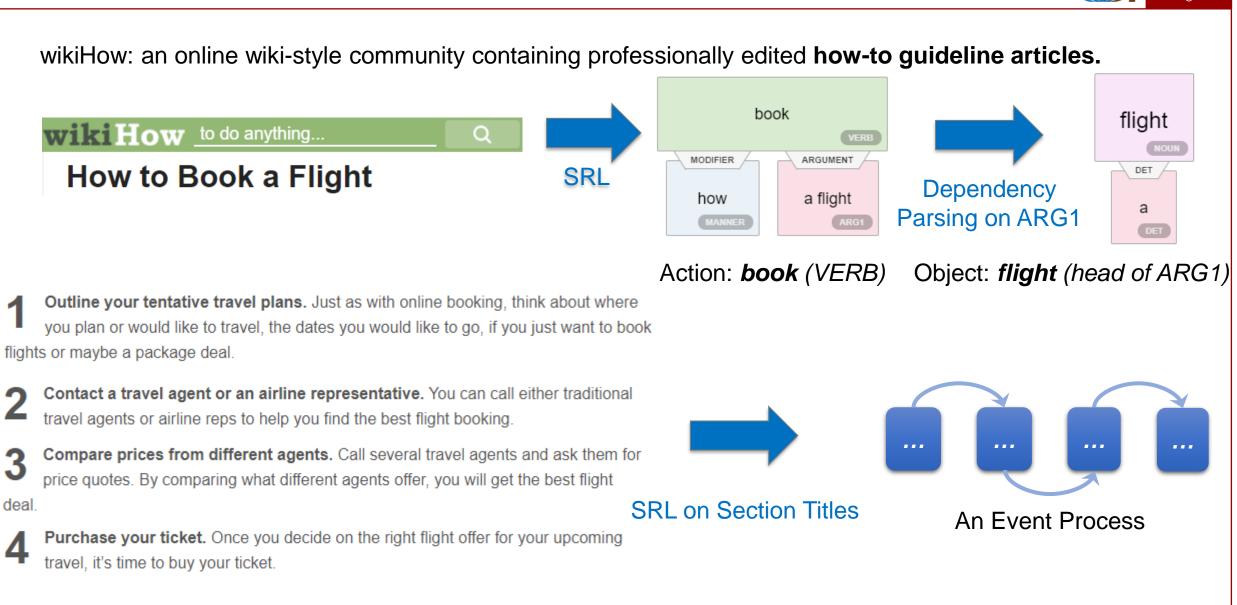
A new (cognitively motivated) **semantic typing task** for understanding event processes in natural language. Two **type axes**:

- What action the event process seeks to take? (action type)
- What type of **object**(s) it should affect? (**object type**)

This research also contributes with

- A large dataset of typed event processes (>60k processes)
- A hybrid learning framework for event process typing based on indirect supervision

A Large Event Process Typing Dataset



A Large Event Process Typing Dataset



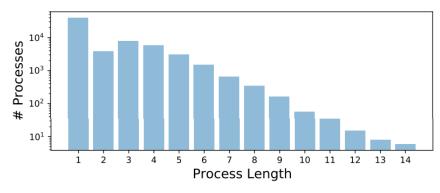
A large dataset of typed event processes

• 60,277 event processes with free-form labels of action and object types

A challenging typing system

- Diversity: 1,336 action types and 10,441 object types (in free froms)
- Few-shot cases: 85.9% labels appear less than 10 times, (~half 1-shot).
- External labels: in 91.2% (84.2%) processes, the action (object) type label does not appear in the process body.

A non-trivial learning problem with ultra fine-grained and extremely few-shot labels.



How

Figure 2: Distribution of process lengths.

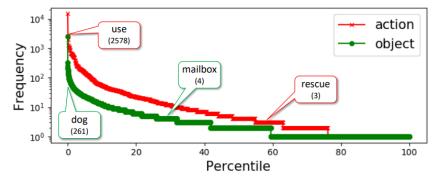
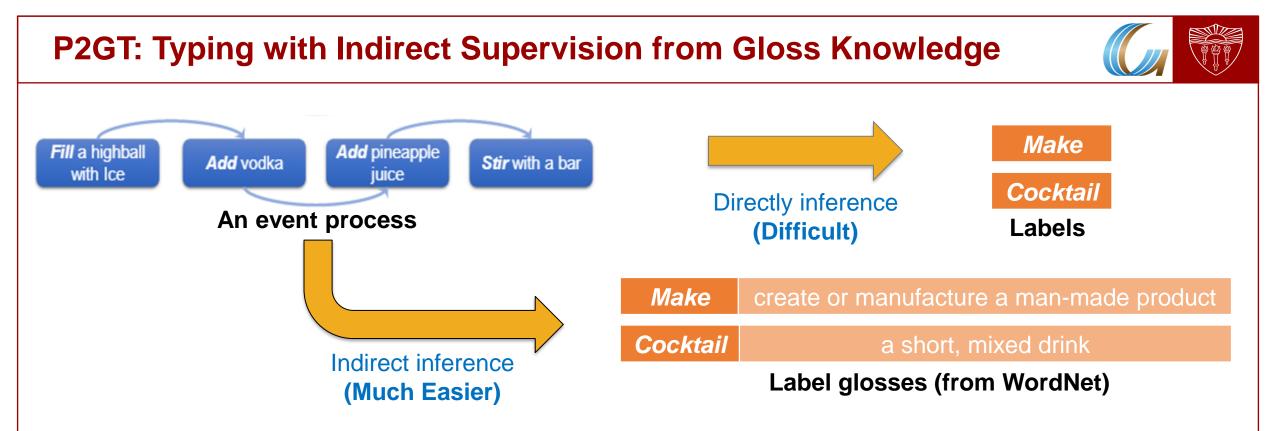


Figure 3: Distribution of actions and objects. Number of frequencies are shown in the brackets.

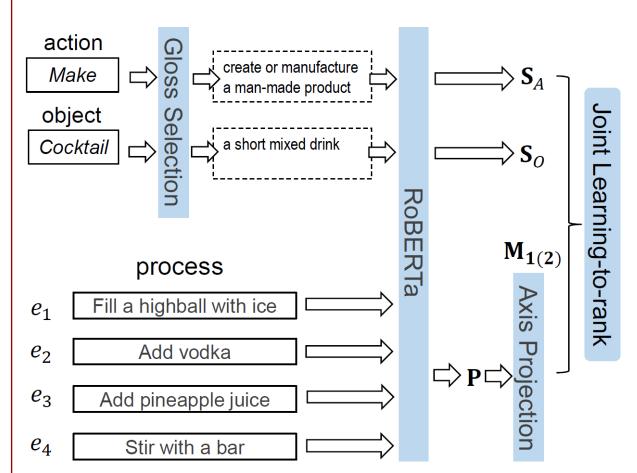


Why using label glosses?

- Semantically richer than labels themselves
- Capturing the association of a process-gloss pair (two sequences) is much easier
- Jump-starting few-shot label representations (and benefiting with fairer prediction)

P2GT: Typing with Indirect Supervision from Gloss Knowledge





How to represent the process?

• RoBERTa encodes concatenated event contents (VERB and ARG1).

How to represent a label?

The same RoBERTa encodes the label gloss

Which gloss for a polysemous label?

- WSD [Hadiwinoto+, EMNLP-19]
- MFS (Most frequent sense)

Learning objective?

 Joint learning-to-rank for both type axes (different projection)

Inference?

Ranking all glosses for all labels in the vocab



Evaluation protocol

- 60,277 event processes
- 80/10/10 train/dev/test split

Compared methods

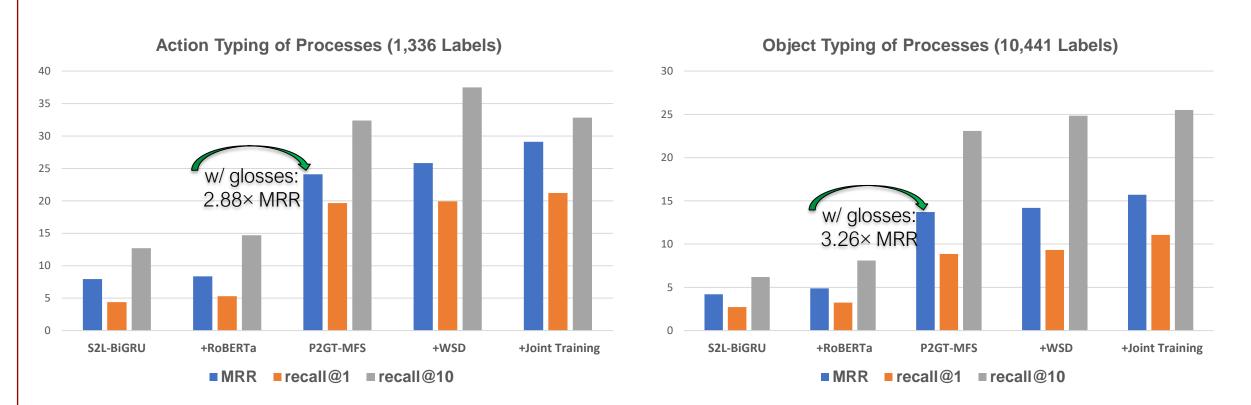
- Sequence to label generators (S2L) [Rashkin+, ACL-18]
 - Different encoders: pooling, BiGRU, RoBERTa
- Variants of P2GT
 - w/ or w/o multi-axis joint training
 - w/ or w/o WSD-based gloss selection
 - Partial information for event representation (VERB only or ARG only)

Ranking metrics

- recall@1, recall@10
- Mean Reciprocal Rank (MRR)

Main Results

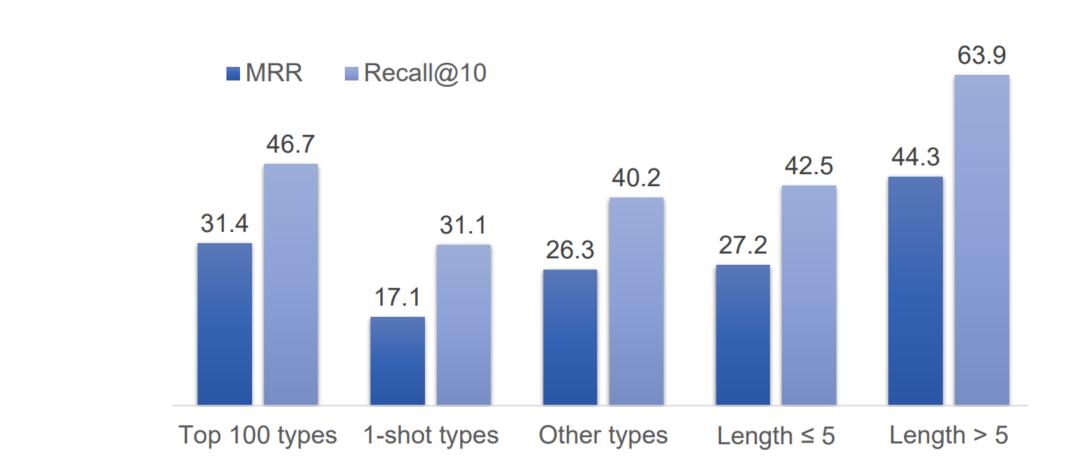




- Gloss knowledge brings along the most improvement (2.88~3.26 folds of MRR)
- Joint training indicates the effectiveness of leveraging complementary supervision signals
- Sense selection (WSD) leads to lesser improvement (predominant senses are representative enough)

Error Analysis





- Performance is better on more frequent labels (as expected)
- On 1-shot cases, it performs reasonably well
- Longer processes are easier to type (w/ more contextual information of associated events)

Case Study



Event processes	Predictions	
Make explosive materials \Rightarrow Obtain a container \Rightarrow Obtain shrapnel \Rightarrow Install a	A: detonate, assemble, blacken	
trigger	O: grenade, blaster, mine	
Go to DMV \Rightarrow Take photos \Rightarrow Take vision test \Rightarrow Take permit test \Rightarrow Take road test	A: obtain, verify, explore	
Go to Diviv \Rightarrow Take photos \Rightarrow Take vision test \Rightarrow Take permit test \Rightarrow Take toad test	O: license, check, visa	
Ignore order \Rightarrow Enter area \Rightarrow Enforce blockade \Rightarrow Force to retreat from area	A: conquer, disarm, invade	
	O: barrier, soldier, fortress	
Capture two opposition posts \Rightarrow Kill many fighters \Rightarrow Destroy three armed trucks	A: kill, demolish, fight	
\Rightarrow Confiscate artillery guns	O: melee, conflict, stronghold	
Cooperate with the counsel investigation \Rightarrow Open his remarks \Rightarrow Apologize many	A: respond, disagree, accept	
times \Rightarrow Try to restore public trust	O: apology, disagreement, slander	
Travel in a presidential motorcade \Rightarrow Be shot once in the back \Rightarrow Be taken to	A: survive, die, tackle	
hospital \Rightarrow Be pronounced dead	O: assassin, crash, roadkill	
Give advance notice \Rightarrow Give notice \Rightarrow Issue dividends	A: honor, pay, reward	
Give advance notice \Rightarrow Give notice \Rightarrow issue dividends	O: finance, equity, subsidy	
Target quotes \Rightarrow Target shares quotes \Rightarrow Ask to clarify offer \Rightarrow Challenge to merge	A: compare, maximize, negotiate	
agreement \Rightarrow Challenge to merge businesses	O: prospectus, quote, settlement	
Clean windows \rightarrow Ruy plants \rightarrow Hang pictures \rightarrow Doint walls \rightarrow Correct floors	A: redecorate, decorate, refurbish	
Clean windows \Rightarrow Buy plants \Rightarrow Hang pictures \Rightarrow Paint walls \Rightarrow Carpet floors	O: room, bedroom, makeover	

Table 3: Case study for typing event processes in the news domain. The predictions are given by Joint P2GT-WSD trained on our full dataset. Each case is given top 3 predictions on both axes, whereof reasonably correct ones are boldfaced, and relevant ones are italic. Few-shot labels appearing up to 10 times in our dataset are in blue.

System Demonstration



A web demonstration of our prototype system is running at http://dickens.seas.upenn.edu:4035/

Examples

Decoration

Event process (choose an example or write the subevents of a process separated by '@' to get its intention)

clean windows @ buy plants @ paint walls @ hang pictures @ carpet floors @ reorganize furniture

Get intention >

redecorate room

Cosine similarity	Action	Object	Cosine similarity
0.678	redecorate	room	0.623
0.650	stage	atmosphere	0.599
0.500	brighten	mosaic	0.589
0.427	preoccupy	suite	0.574
0.418	furnish	interior	0.573

Conclusion



This work provided

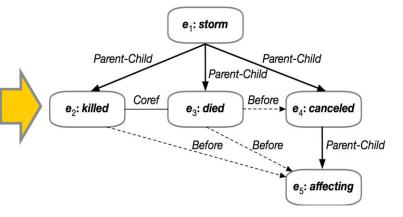
- A new (cognitively motivated) task for event understanding, *multi-axis event process typing*, to infer the types of the overall action and affected object(s).
- A large event process dataset with ultra diverse and fine-grained type vocabularies.
- A simple yet effective method of process typing based on indirect supervision from gloss knowledge

Meaningful future research

- Identifying salient events in processes
- More downstream applications of commonsense reasoning, summarization and narrative prediction
- Event schema induction and instantiation with the produced language model

Our Parallel Works About Event-centric NLU

On Tuesday, there was a typhoon-strength $(e_1:storm)$ in Japan. One man got $(e_2:killed)$ and thousands of people were left stranded. Police said an 81-year-old man $(e_3:died)$ in central Toyama when the wind blew over a shed, trapping him underneath. Later this afternoon, with the agency warning of possible tornadoes, Japan Airlines $(e_4:canceled)$ 230 domestic flights, $(e_5:affecting)$ 31,600 passengers.



Haoyu Wang, Muhao Chen, Hongming Zhang, Dan Roth. Joint Constrained Learning for Event-event Relation Extraction. EMNLP 2020



Hongming Zhang, Muhao Chen, Haoyu Wang, Yangqiu Song, Dan Roth. *Analogous Process Structure Induction for Sub-event Sequence Prediction*. **EMNLP** 2020



School of Engineering





Thank You

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