Connecting the Dots: Event Graph Schema Induction with Path Language Modeling

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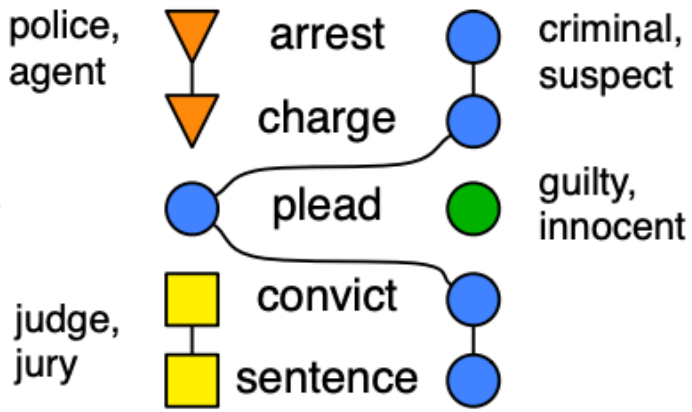
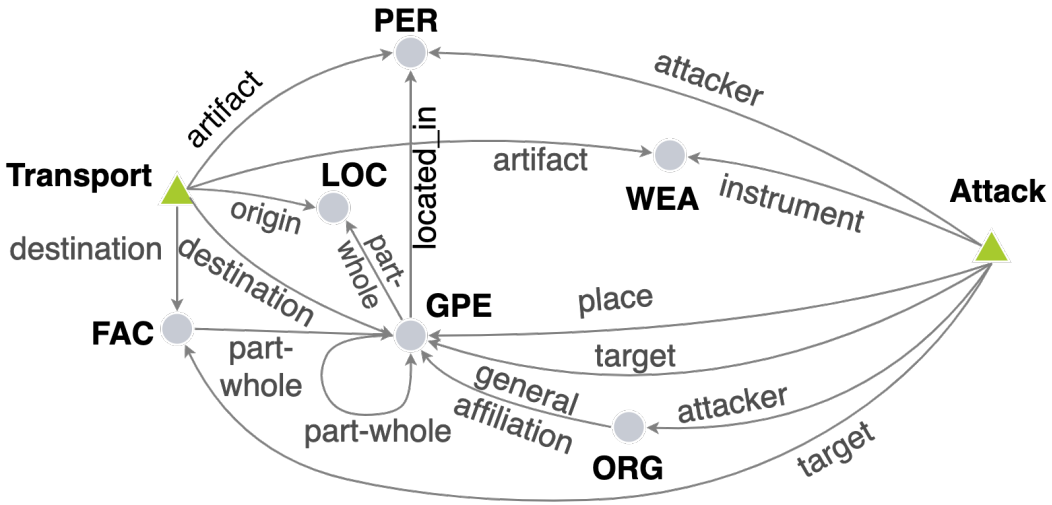
Event Schema Induction Related Work

- How to capture complex connections among events?
  - Temporal relations exist between almost all events, even those that are not semantically related
  - Causal relations have been hobbled by low inter-annotator agreement (Hong et al., 2016).
- Two events are connected through entities and their relations



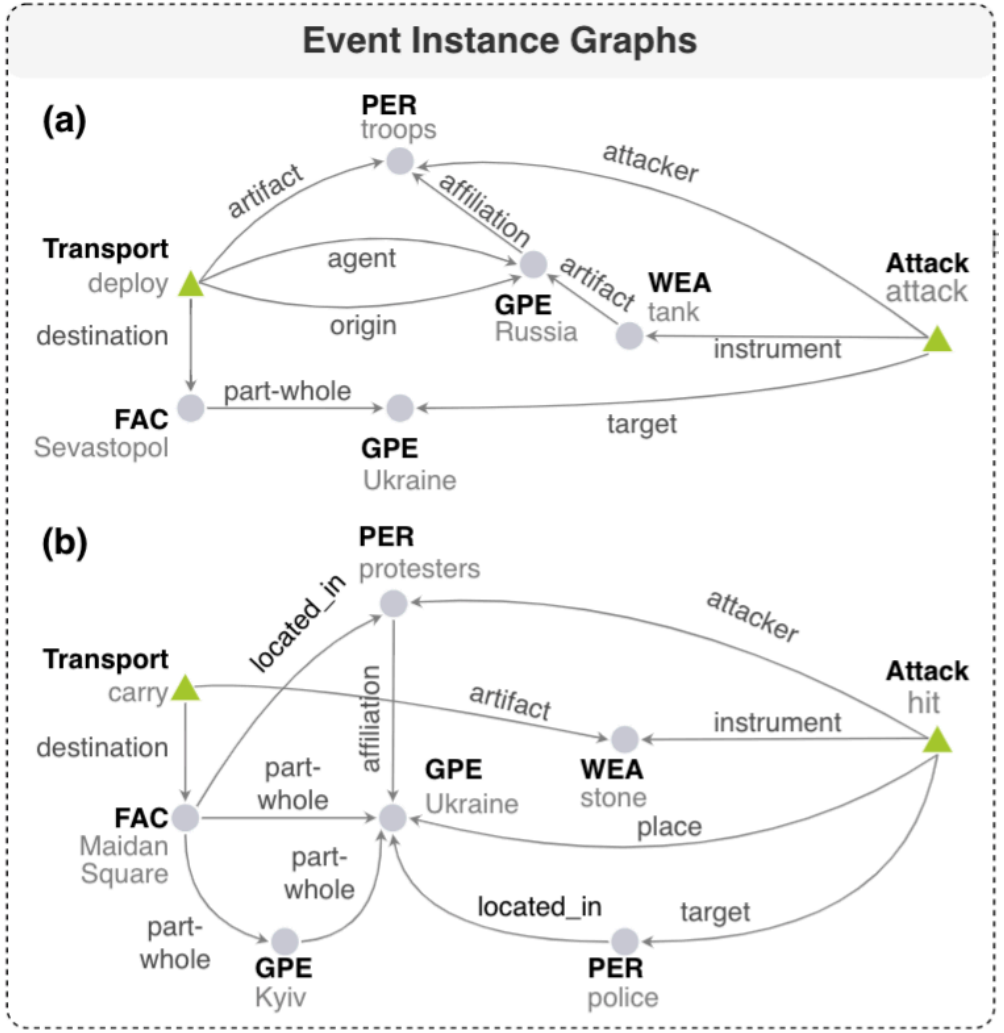
Previous Work:
Event Narrative Chain (Chambers and Jurafsky, 2008, 2009, 2010)

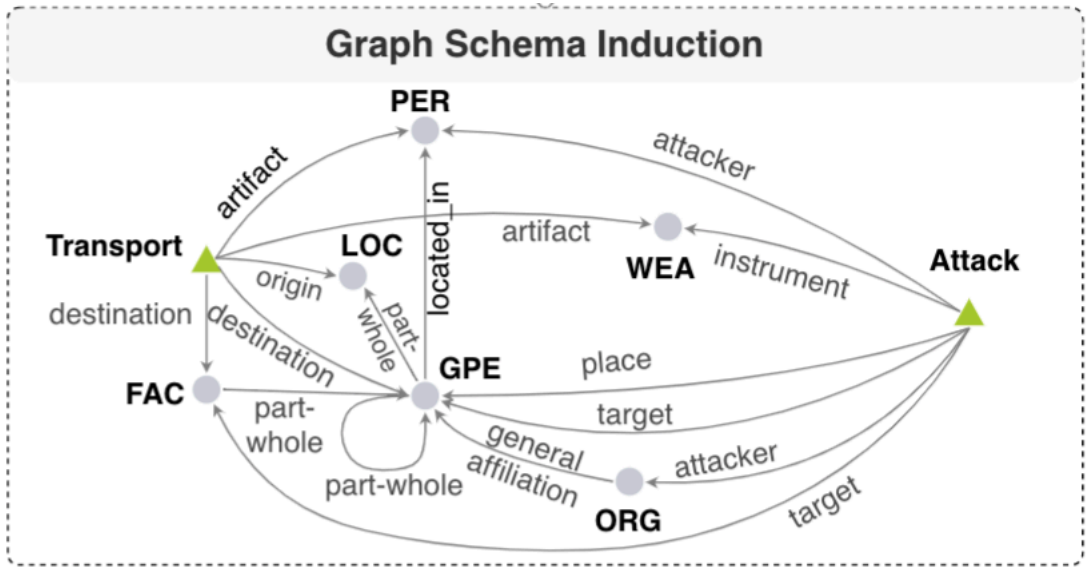


Our Paper:
Event Narrative Graph Schema

Problem Formulation

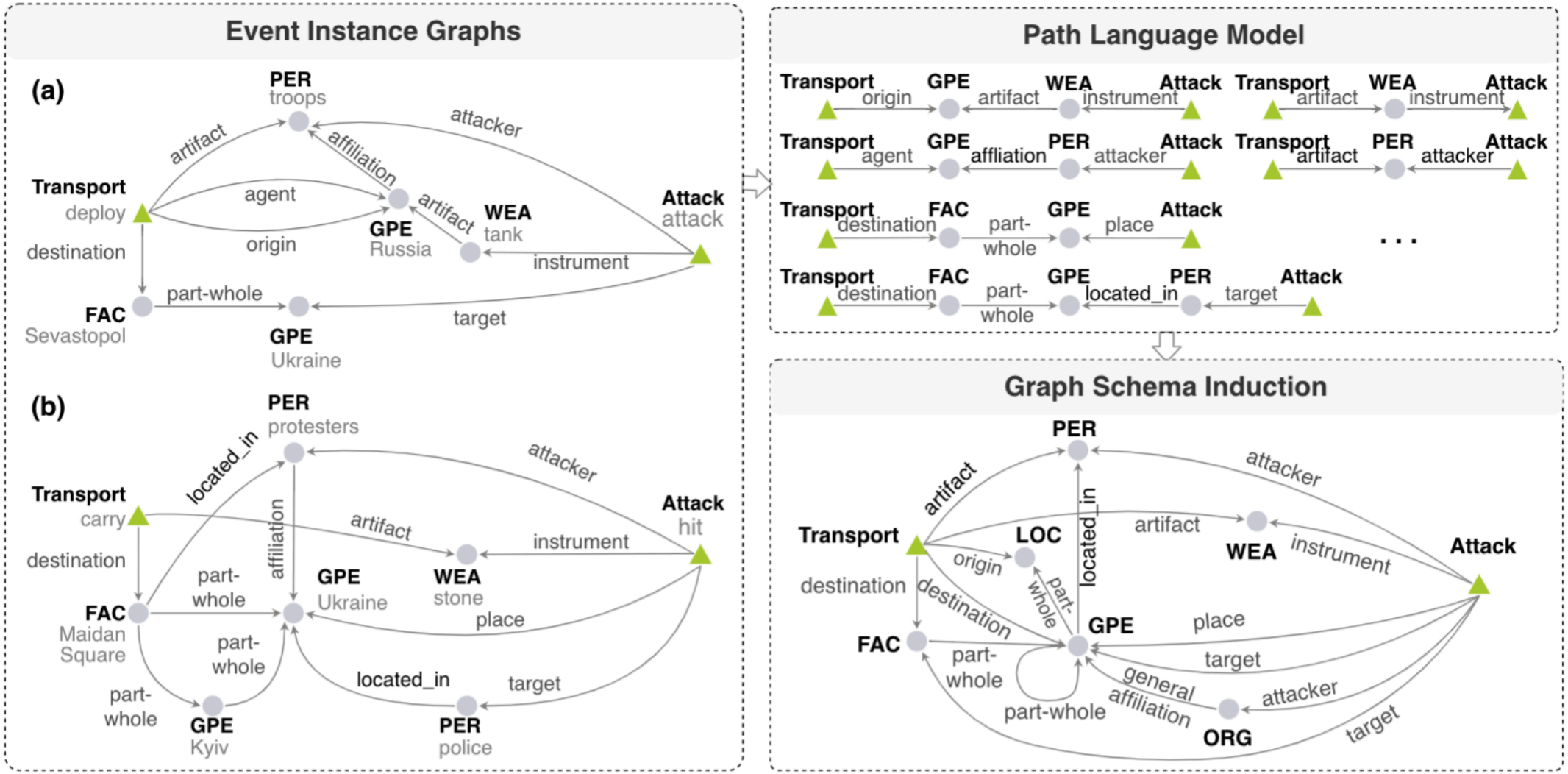
- **Input**: Instance graphs, where each node is an entity or event, each edge is an argument role or relation.
- **Output**: Graph schemas between two event types, where each node is an entity type or event type.
- Instance graphs (a) and (b) refer to very different event instances, but they both illustrate a same scenario.





Event Graph Schema Induction Framework

- We select **salient** and **coherent** paths based on Path Language Model, and merge them into graph schemas.



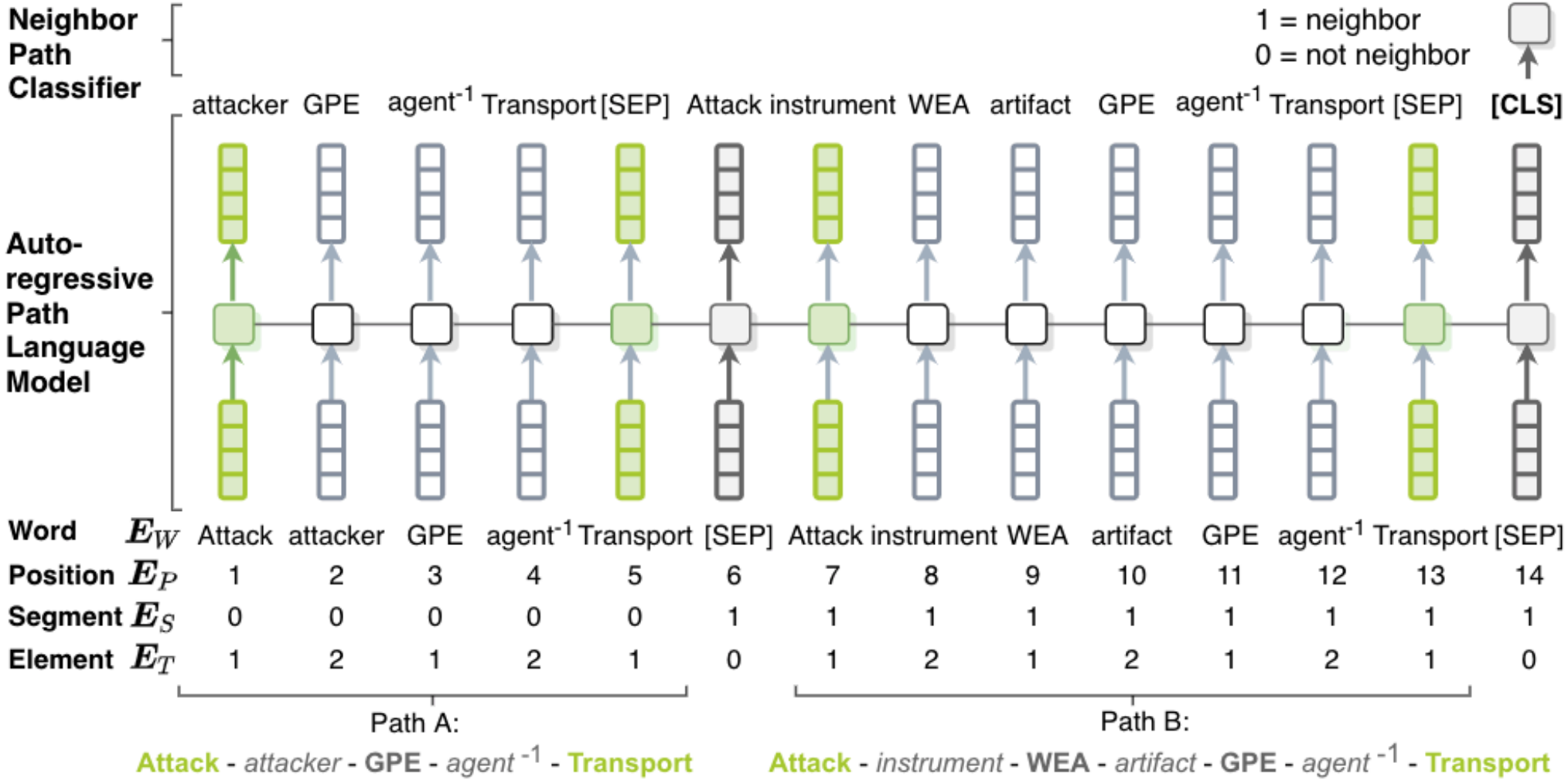
What is a good graph schema?

- A good graph schema for two event types consists of **salient** and **coherent** paths between them.
  - Salience: recurring event-event connection patterns
  - Coherence: semantically coherent

Criteria			Examples	Frequency
Single Path	Salience	High	Transport —agent→ GPE ←affiliation— PER ←attacker— Attack	31
		Low	Transport —destination→ GPE ←affiliation— PER ←attacker— Attack	2
	Semantic Coherence	High	Transport —origin→ FAC —part-whole→ LOC ←part-whole— GPE ←affiliation— PER ←attacker— Attack	9
		Low	Transport —agent→ GPE ←affiliation— PER —affiliation→ GPE ←resident— PER ←target— Attack	24
Multiple Paths	Semantic Consistency	High	Transport —destination→ GPE —place→ Attack Transport —artifact→ PER —located_in→ GPE ←place— Attack	20
		Low	Transport —destination→ GPE —place→ Attack Transport —origin→ GPE ←place— Attack	0

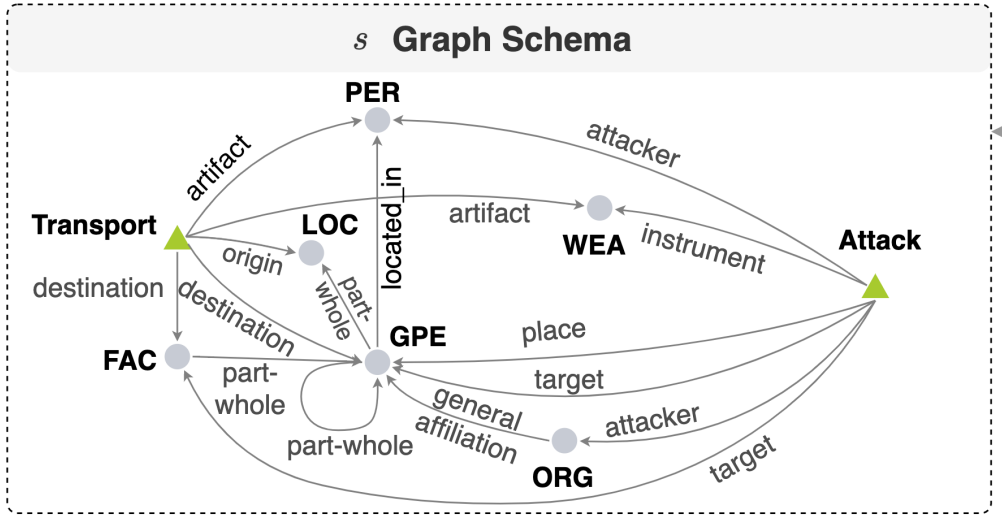
Path Language Model

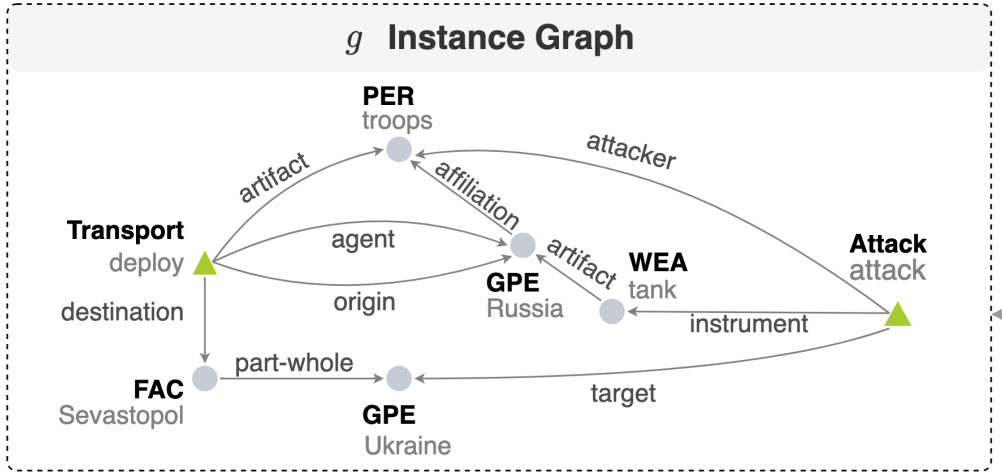
- Path Language Model is trained on two tasks
  - Autoregressive Language Model Loss: capturing the frequency and coherence of a single path
  - Neighbor Path Classification Loss: capturing co-occurrence of two paths



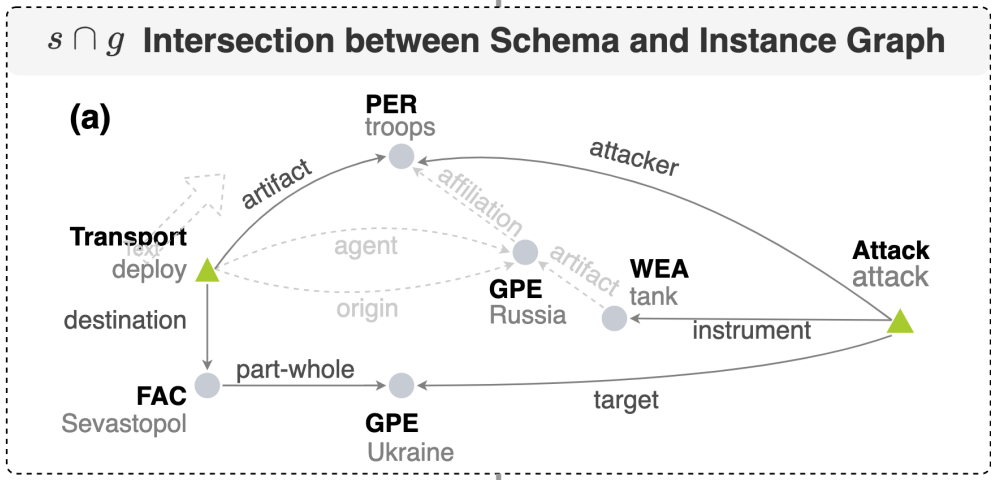
Experiment: Instance Coverage

- A salient schema can serve as a skeleton to recover instance graphs
  - We use each graph schema to match back to each ground-truth instance graph and evaluate their intersection in terms of Precision and Recall.





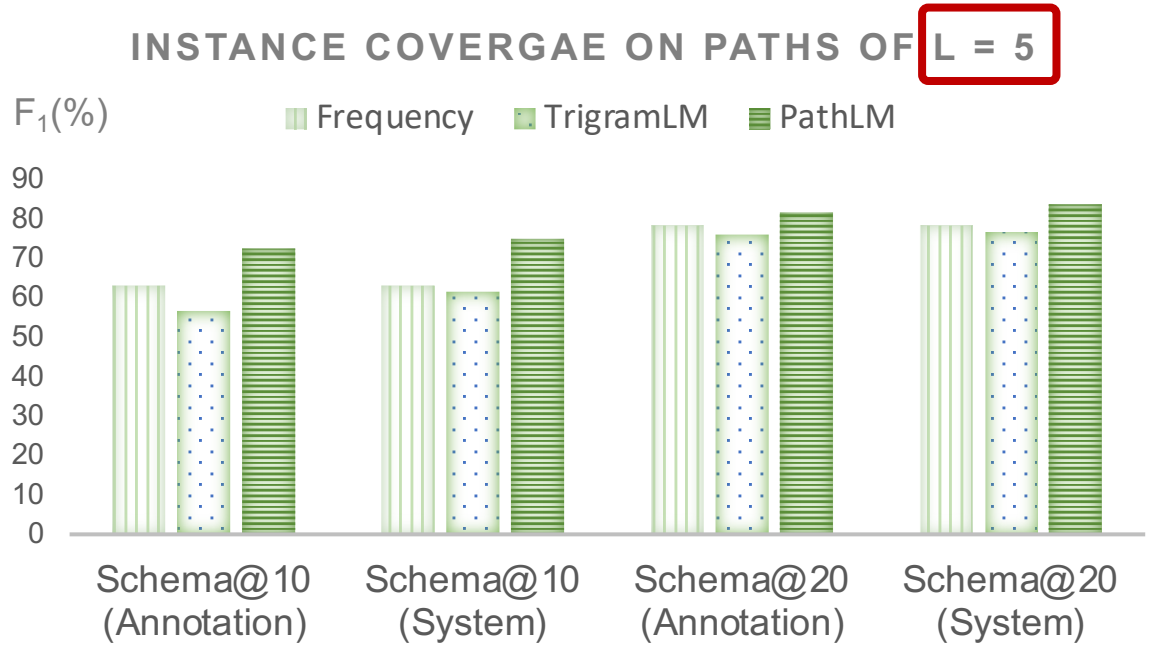
$$\text{Precision} = \frac{\sum_{s \in \mathcal{S}} \sum_{g \in \mathcal{G}} |g \cap s|_{\mathbb{S}}}{\sum_{s \in \mathcal{S}} |s|_{\mathbb{S}}}$$

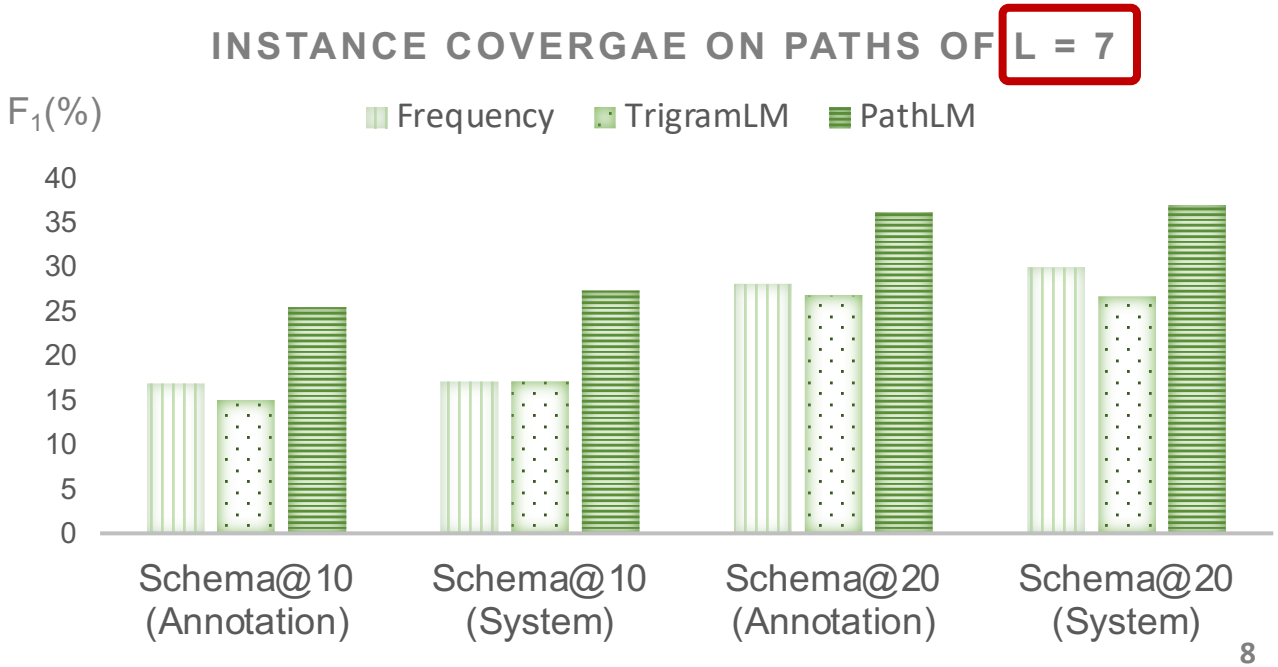


$$\text{Recall} = \frac{\sum_{s \in \mathcal{S}} \sum_{g \in \mathcal{G}} |g \cap s|_{\mathbb{I}}}{\sum_{g \in \mathcal{G}} |g|_{\mathbb{I}}}$$

Experiment: Instance Coverage

- We evaluate the intersection by substructures of the schema graph, i.e., paths of different lengths
- Proves ability of PathLM:
  - Higher gains on longer path queries (e.g. l = 7) → able to capture complex graph structures involving long distance between related events.
  - Larger gains compared to baselines on Schema@10 than Schema@20, demonstrating the effectiveness of our ranking approach, especially on top ranked ones.
  - Schemas induced from automatically constructed and manually constructed event graph instances have comparable performance → robust to extraction noise





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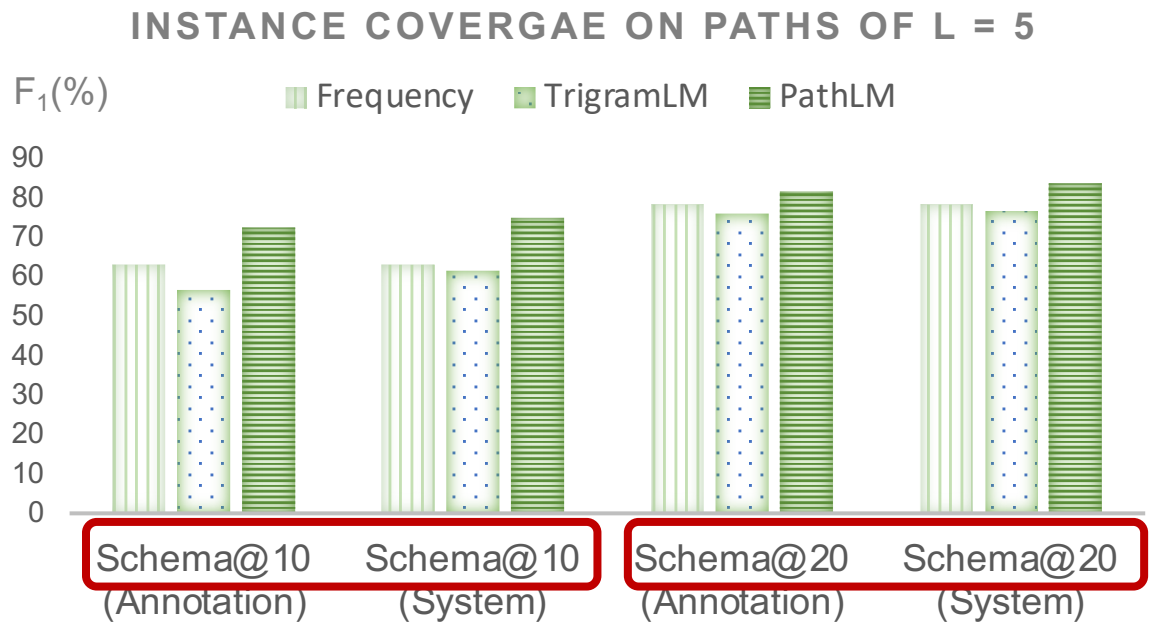

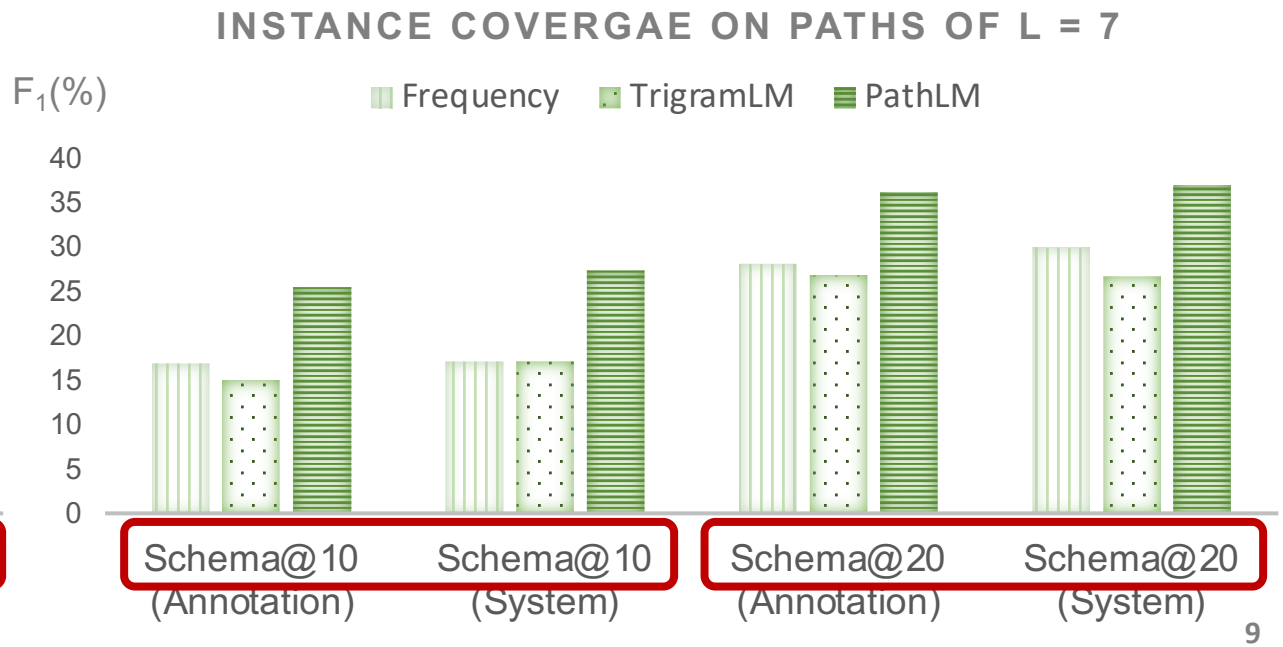

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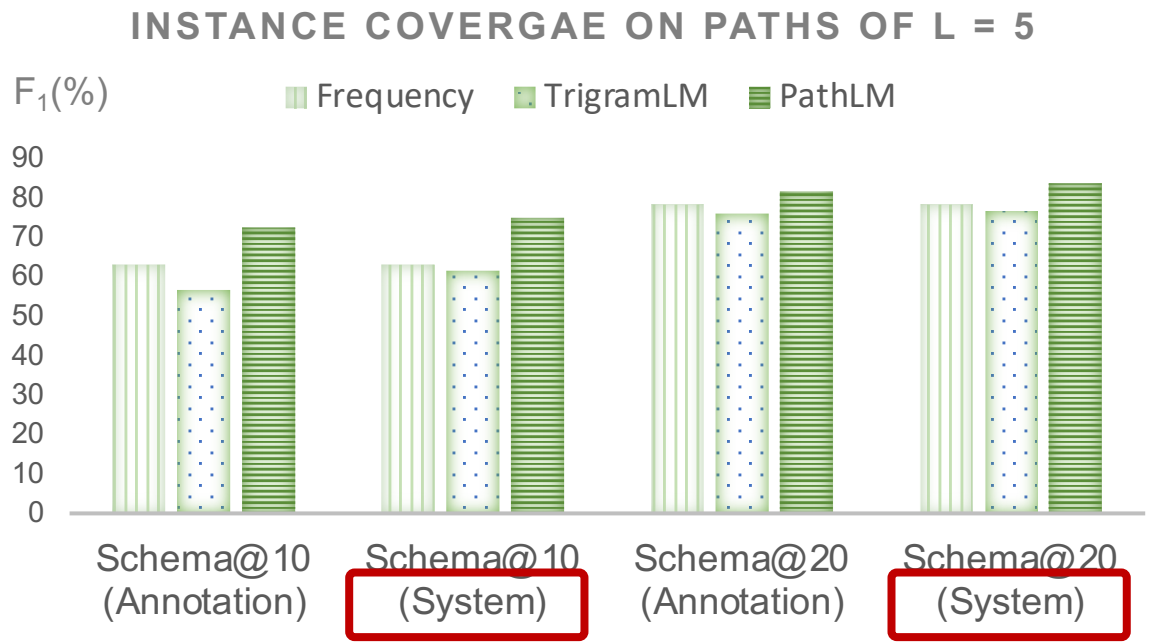
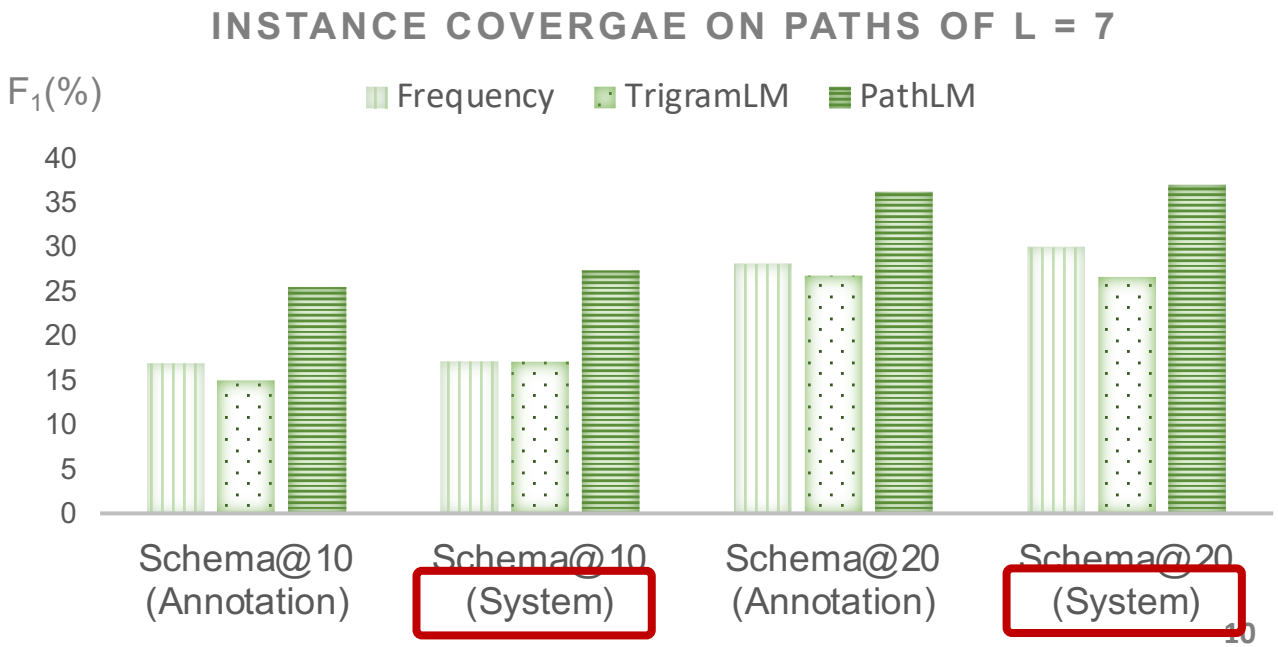
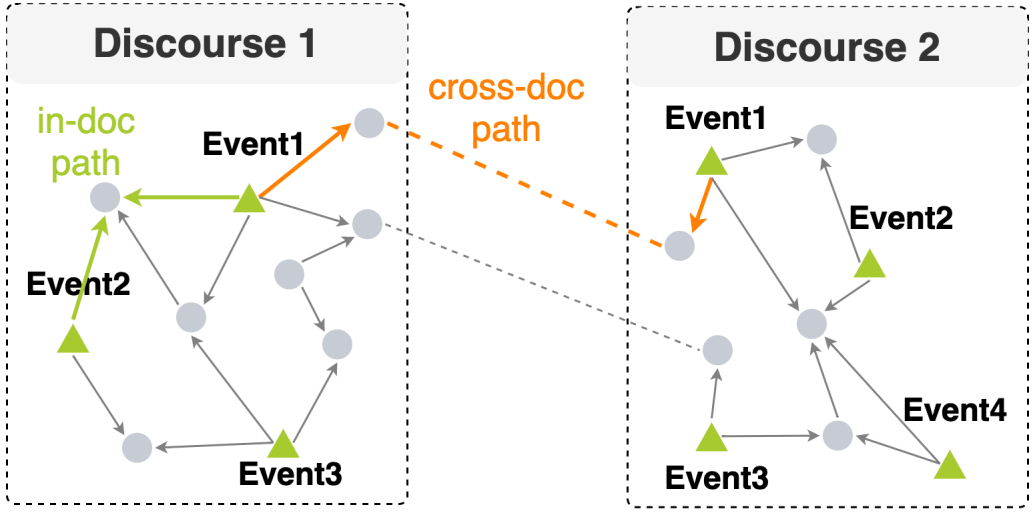




Experiment: Instance Coherence

- we hypothesize that an instance graph between two events *v* and *v′* is coherent if *v* and *v′* are from the same discourse (e.g., a news document)
- We carefully select 24 documents with each document talking about a unique complex event such as *Iraq War* or *North Korea Nuclear Test*
- We define **Instance Coherence** as the proportion of in-doc path instances

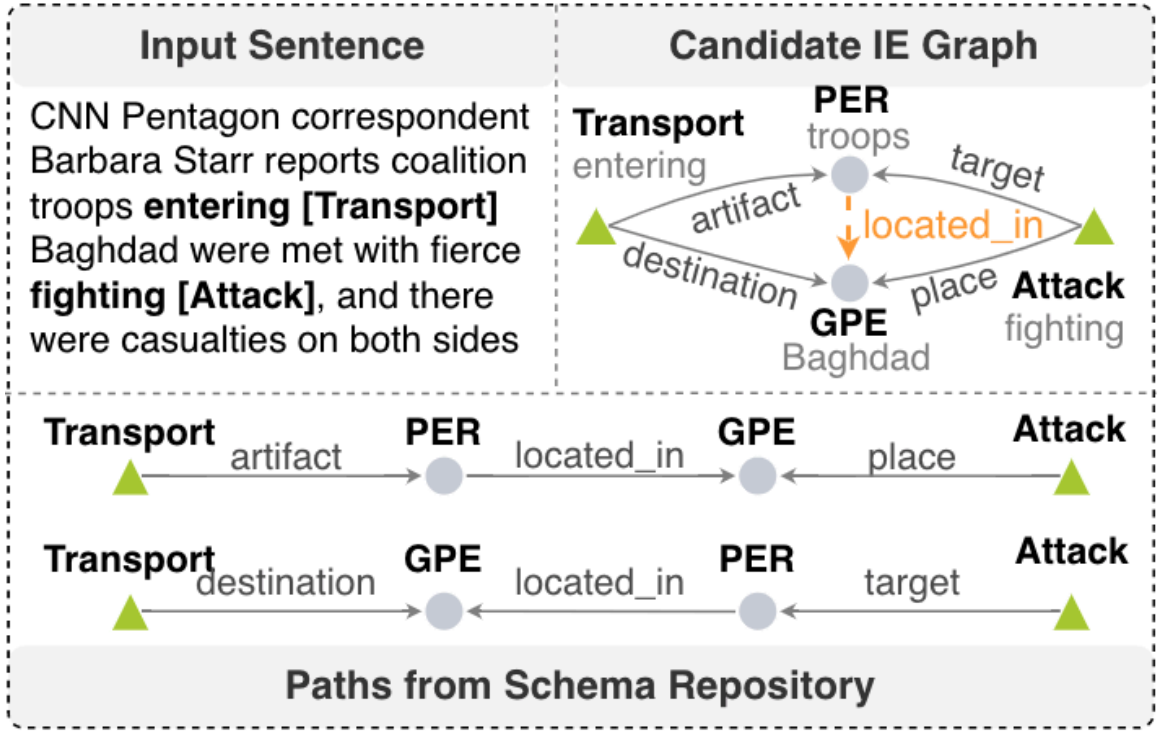


$$\text{Coherence} = \frac{\sum_{s \in \mathcal{S}} \sum_{g \in \mathcal{G}} \sum_{p \in g \cap s} f(p) \cdot \mathbb{I}_g}{\sum_{s \in \mathcal{S}} \sum_{g \in \mathcal{G}} \sum_{p \in g \cap s} f(p)};$$

Historical	Models	Schema@10 (%)	Schema@20 (%)
Annotation	Frequency	67.8	65.6
	UnigramLM	62.4	69.9
	BigramLM	59.0	67.5
	TrigramLM	56.6	64.9
	PathLM	**76.0**	**79.9**
	w/o CLS_NP	75.3	79.2
System	Frequency	60.1	65.6
	UnigramLM	61.8	70.0
	BigramLM	59.7	69.6
	TrigramLM	55.8	65.8
	PathLM	**76.4**	**78.5**
	w/o CLS_NP	73.9	77.1

Schema-Guided Information Extraction

- Use the state-of-the-art IE system OneIE (Lin et al, 2020) to decode converts each input document into an IE graph
- Each path in the graph schema is encoded as a single global feature for scoring candidate IE graphs
- OneIE promotes candidate IE graphs containing paths matching schema graphs
- http://blender.cs.illinois.edu/software/oneie
- F-scores (%) on ACE2005 data [Lin et al., ACL2020]:



Dataset	Entity	Event Trigger Identification	Event Trigger Classification	Event Argument Identification	Event Argument Classification	Relation
Baseline	90.3	75.8	72.7	57.8	55.5	44.7
+PathLM	90.2	**76.0**	**73.4**	**59.0**	**56.6**	**60.9**








THANK YOU!