Knowledge Graph and Corpus Driven Segmentation and Answer Inference for Telegraphic Entity-seeking Queries

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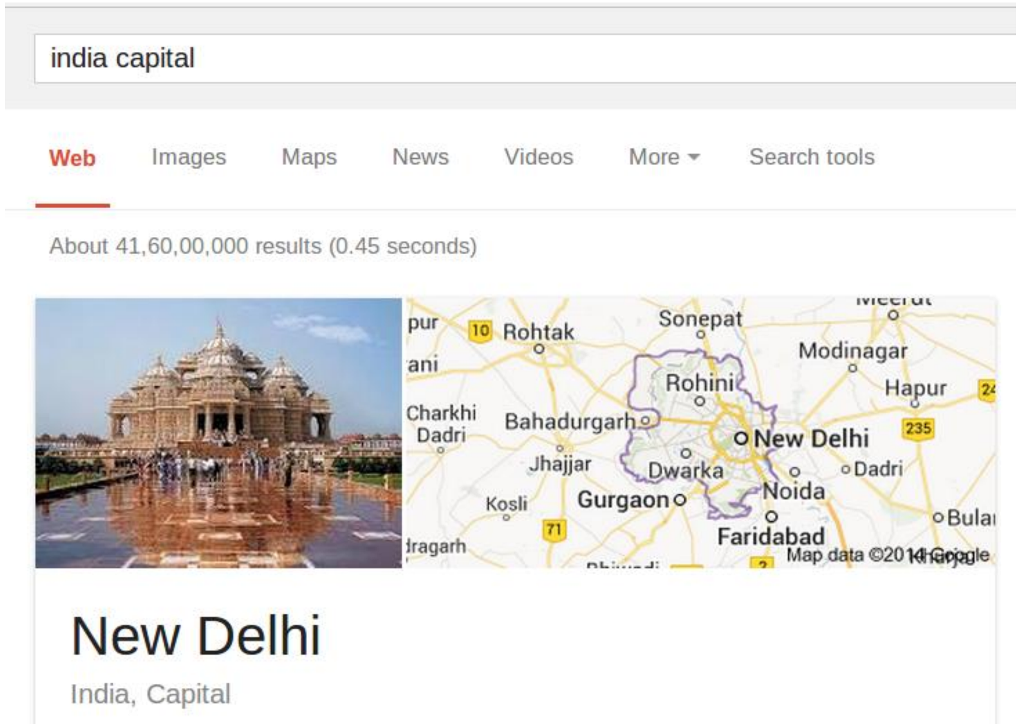
Entity-seeking Telegraphic Queries



- Short
- Unstructured (like natural language questions)
- Expect entities as answers

Challenges

- No reliable syntax clues
  - Free word order
  - No or rare capitalization, quoted phrases
- Ambiguous
  - Multiple interpretations
  - `aamir khan films`
    - Aamir Khan - the Indian actor or British boxer
    - Films - appeared in, directed by, or about
- Previous QA work
  - Convert to structured query
  - Execute on knowledge graph (KG)

WHY DO WE NEED THE CORPUS?

- KG is high precision but incomplete
  - Work in progress
  - Triples can not represent all information
  - Structured – unstructured gap
- Corpus provides recall
- `fastest odi century batsman`

> ... Corey Anderson hits **fastest ODI century**. This was the first time two **batsmen** have hit hundreds in under 50 balls in the same **ODI**.

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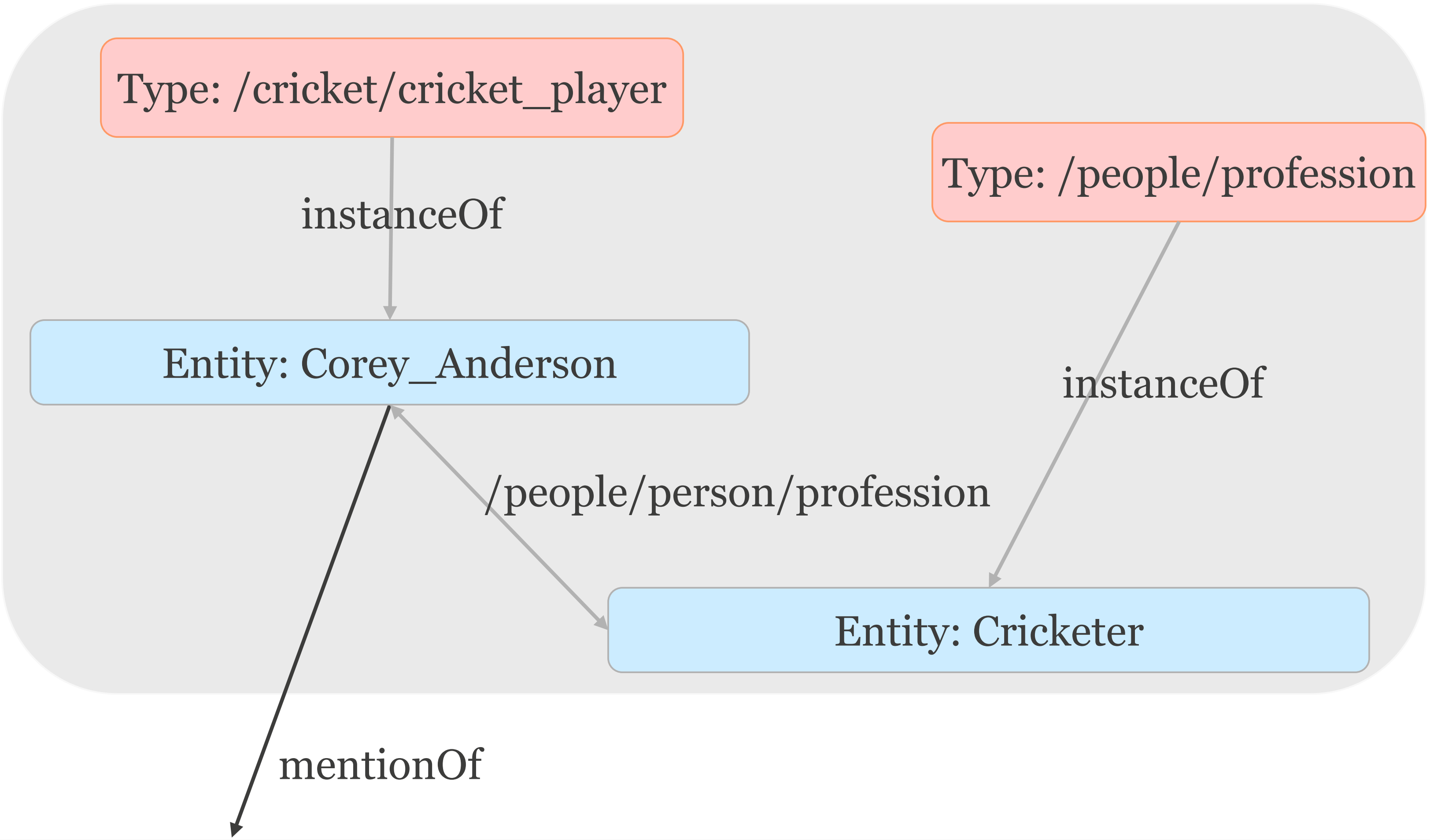
> .. Corey Anderson hits **fastest ODI century**. This was the first time two **batsmen** have hit hundreds in under 50 balls in the same **ODI**.

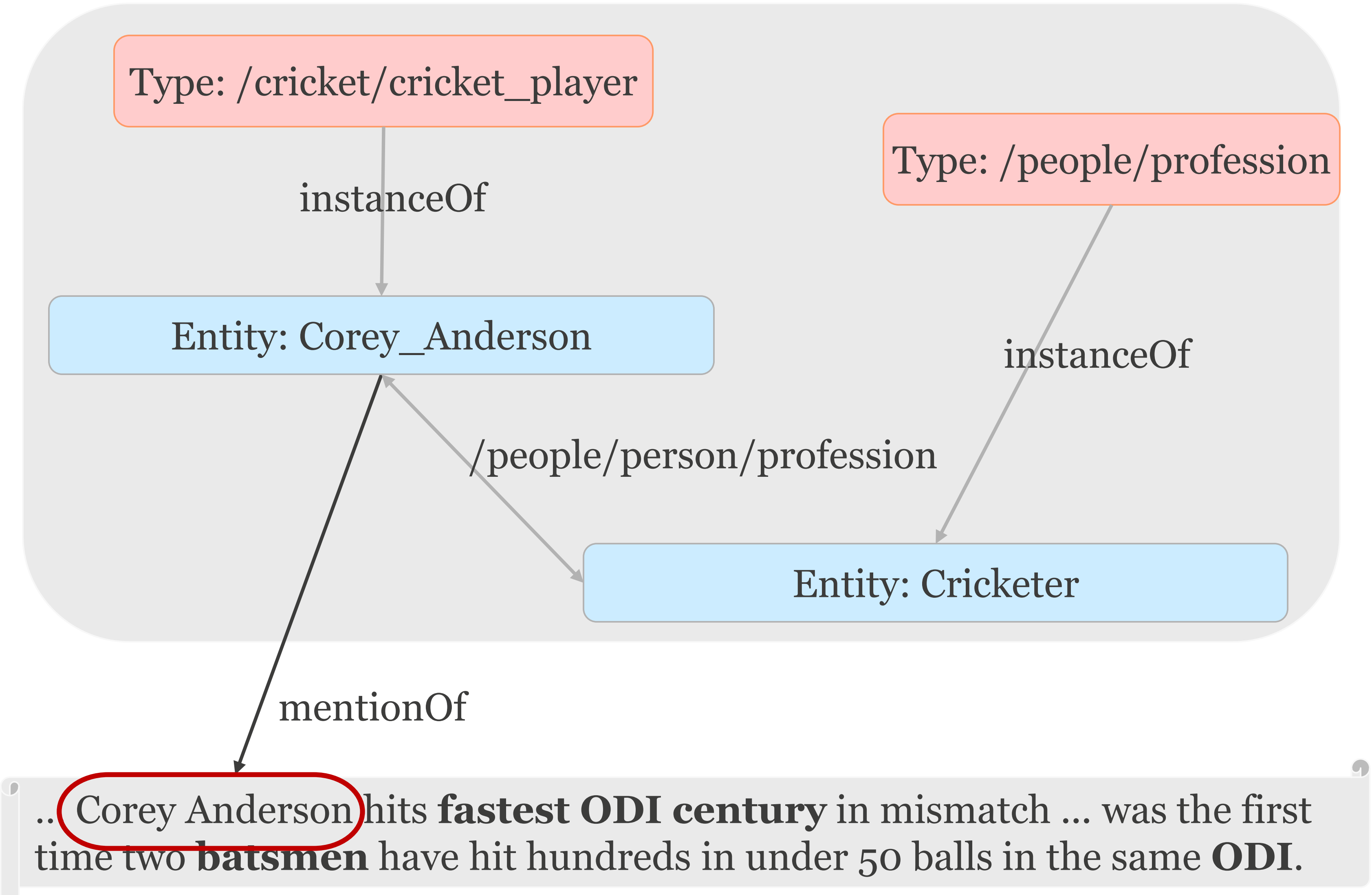
ANNOTATED WEB WITH KNOWLEDGE GRAPH



... Corey Anderson hits **fastest ODI century** in mismatch ... was the first time two **batsmen** have hit hundreds in under 50 balls in the same **ODI**.

Annotated document

Annotated Web with Knowledge Graph



Annotated document

Interpretation via Segmentation

Signals from the Query

- Queries seek answer entities (e_2)
- Contain (query) *entities* (e_1) , *target types* (t_2), *relations* (r), and *selectors* (s).

query	e_1	r	t_2	s
`washington first governor`	washington	governor	governor	first
	washington	-	governor	first
`spider automobile company`	spider	-	automobile company	-
	automobile	company	company	spider

Assignment of tokens to columns for illustration only; not necessarily optimal

Segmentation and Interpretation

- Interpretation = Segmentation + Annotation
- Segmentation of query tokens into 3 partitions
  - Query entity (E_1)
  - Relation and Type (T_2/R)
  - Selectors (S)
- Multiple ways to annotate each partition

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washington first governor

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E_1 partition S partition T_2/R partition

1. Washington (State)
2. Washington_D.C. (City)

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washington first governor

E_1 partition

S partition

T_2/R partition

1. Washington (State)
2. Washington_D.C. (City)

r: governorOf t2: us_state_governor
r: null t2: us_state_governor

Combining KG and Corpus Evidence

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Segmentation Z

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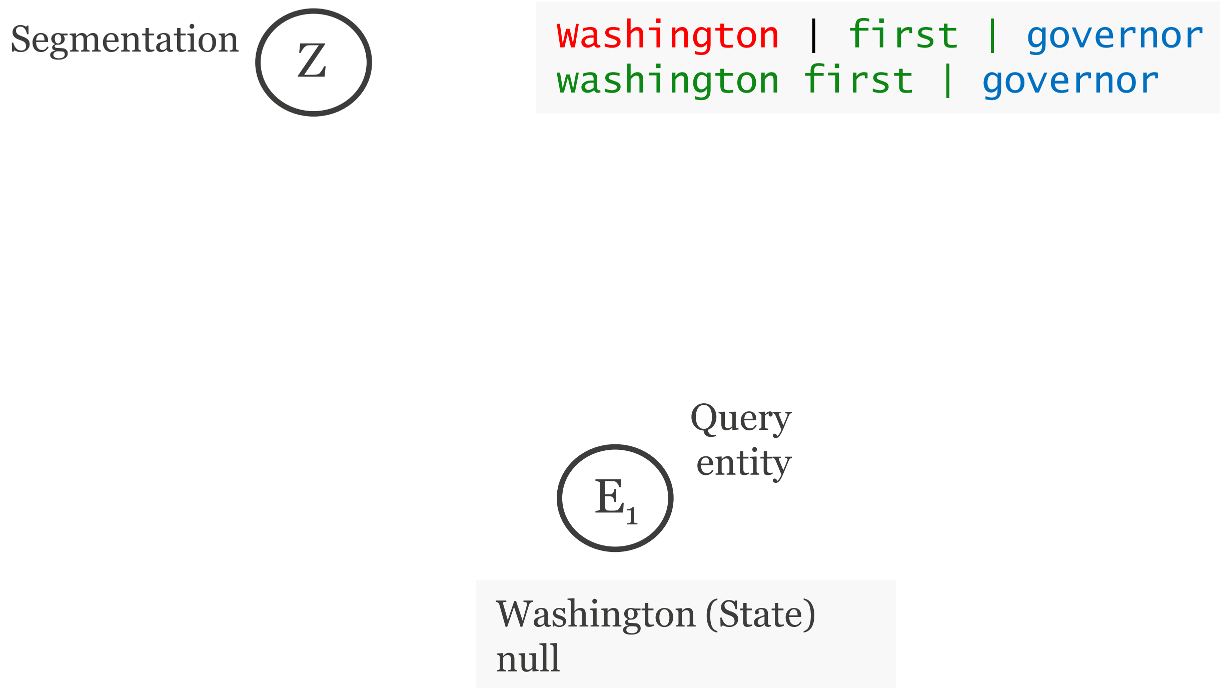
Segmentation Z

```
Washington | first | governor
washington first | governor
```

Combining KG and Corpus Evidence



Combining KG and Corpus Evidence

Segmentation Z

Washington | first | governor
washington first | governor

Target type T_2

us_state_governor
governor_general

Query entity E_1

Washington (State)
null

Combining KG and Corpus Evidence

Segmentation Z

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Selectors

S

first
washington first

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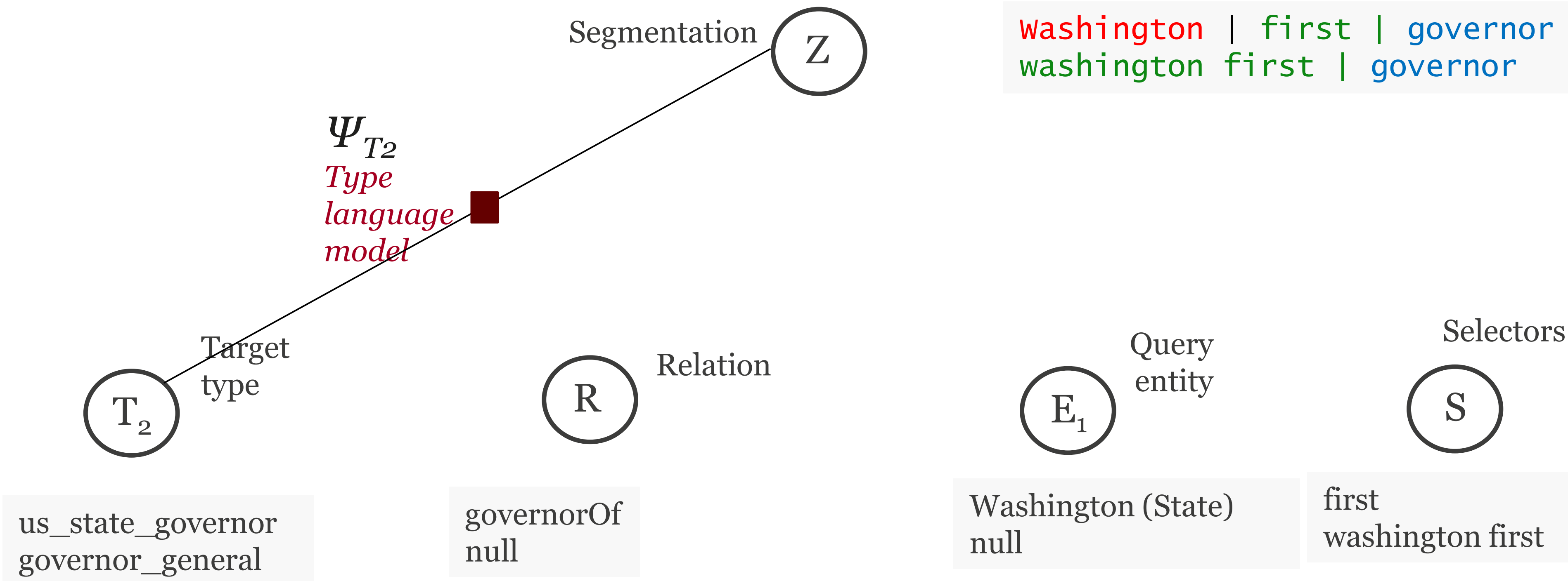

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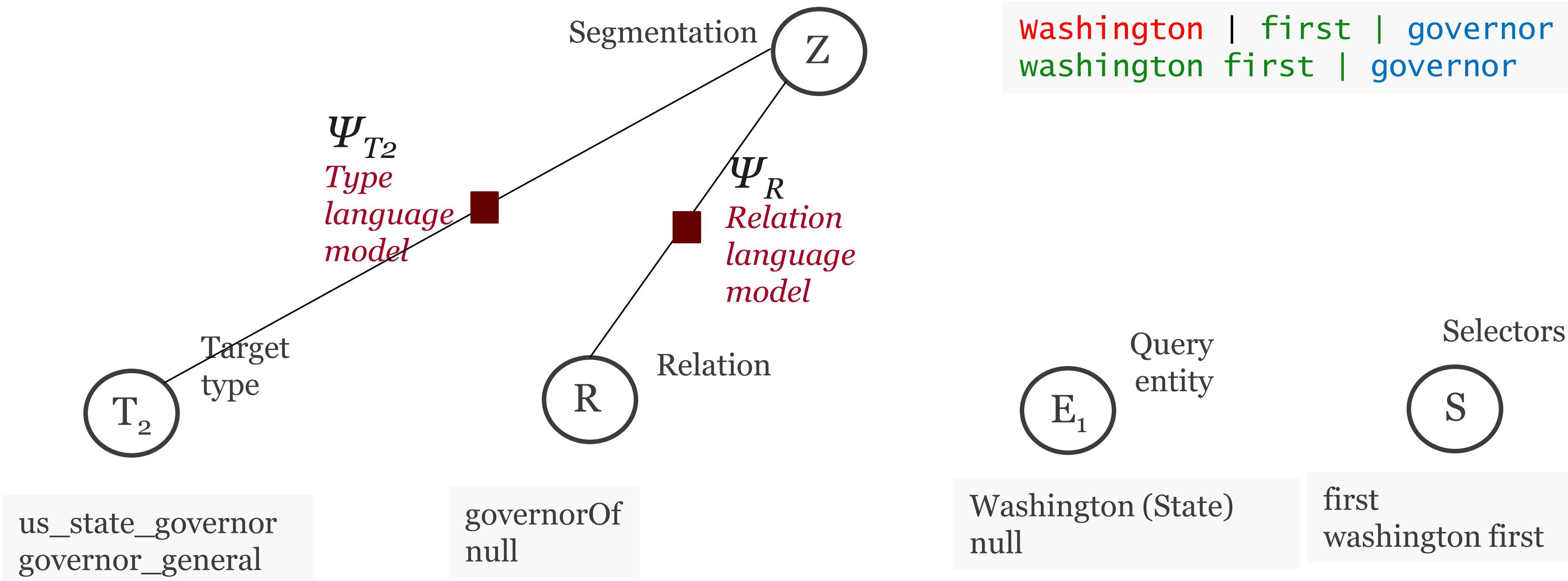

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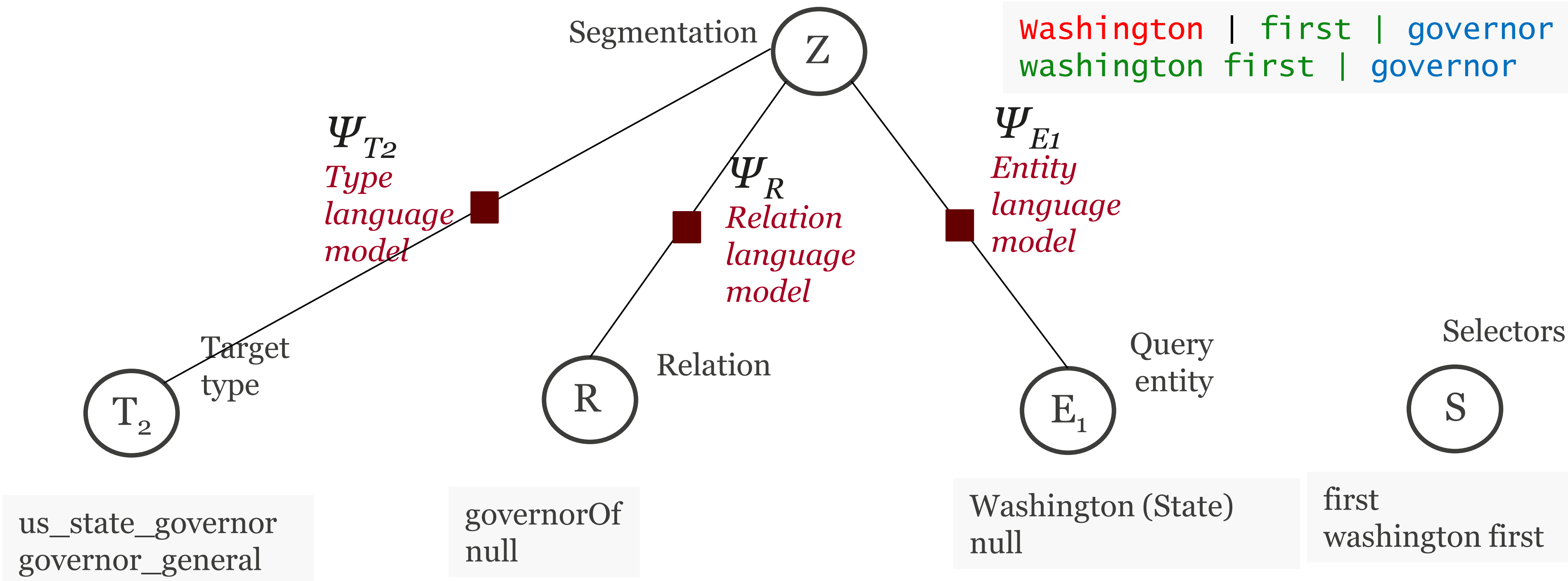

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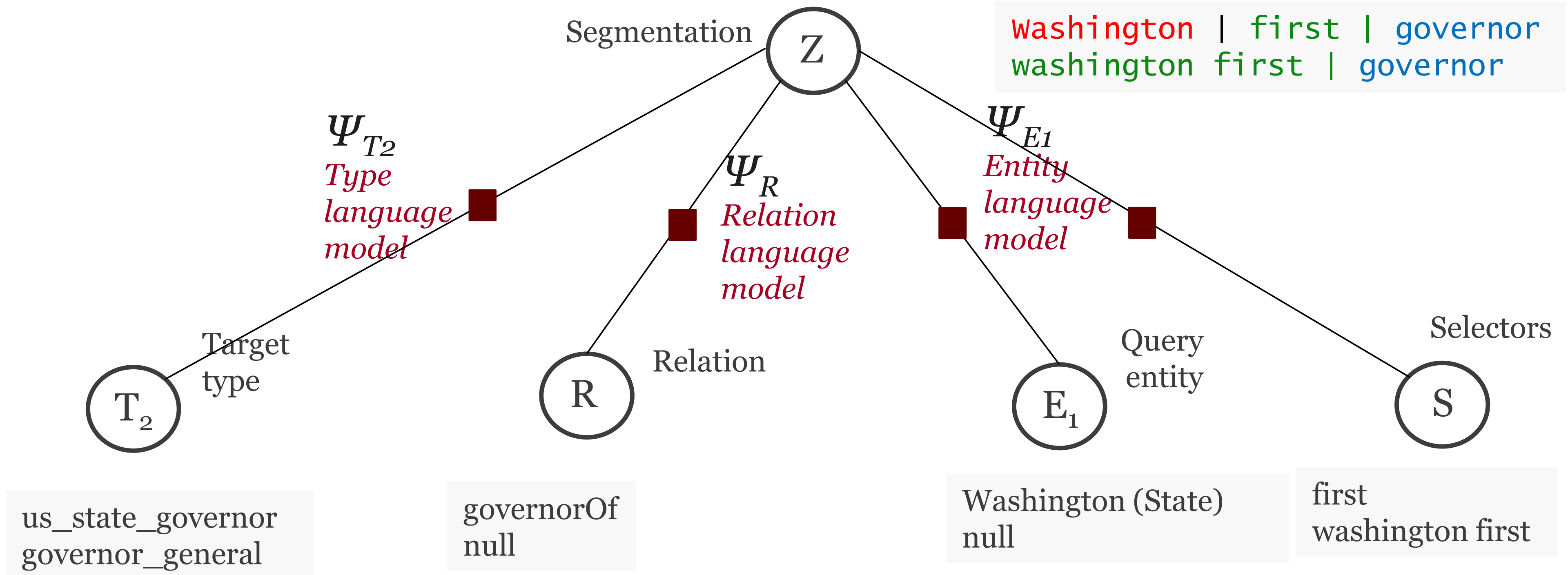

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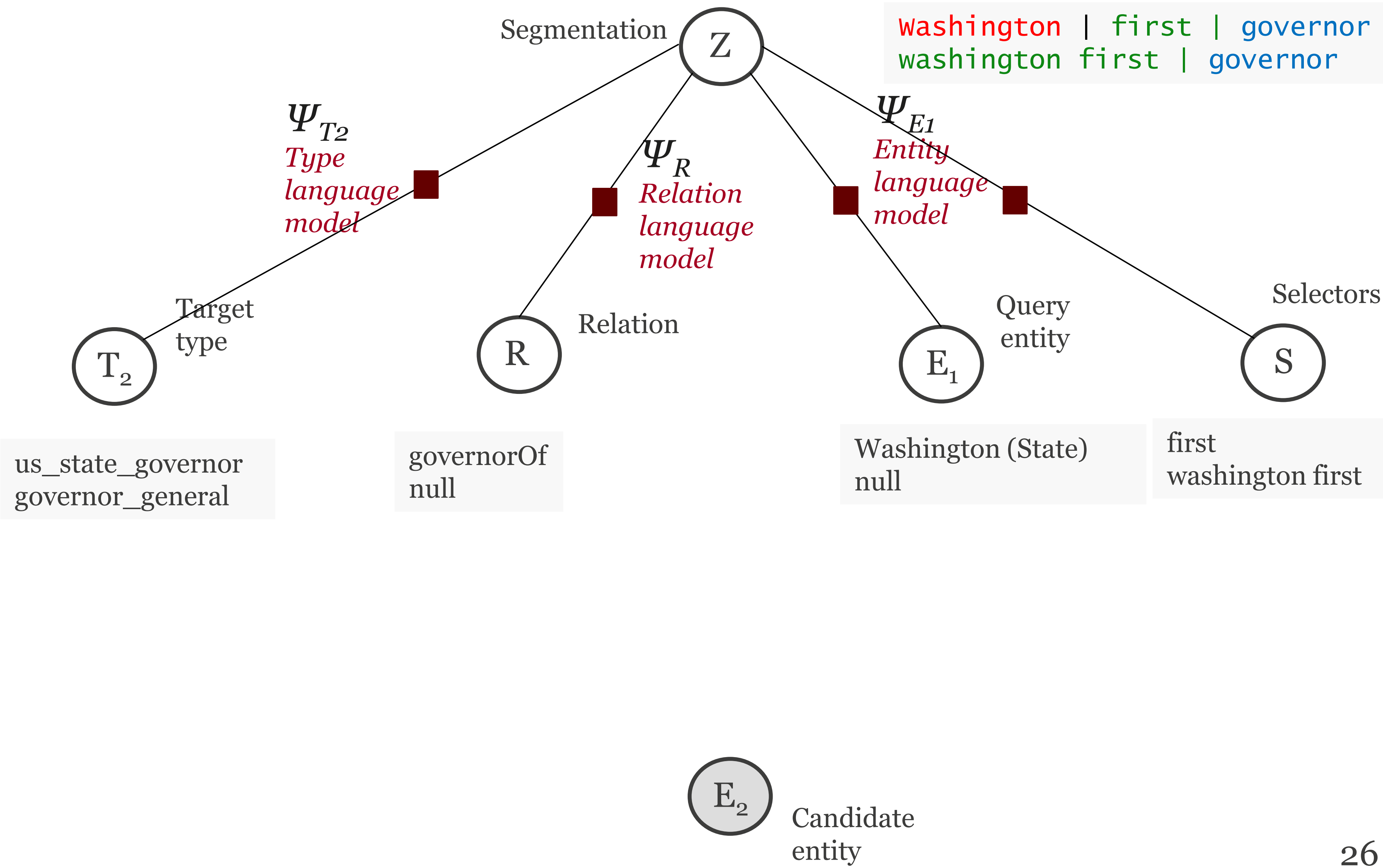

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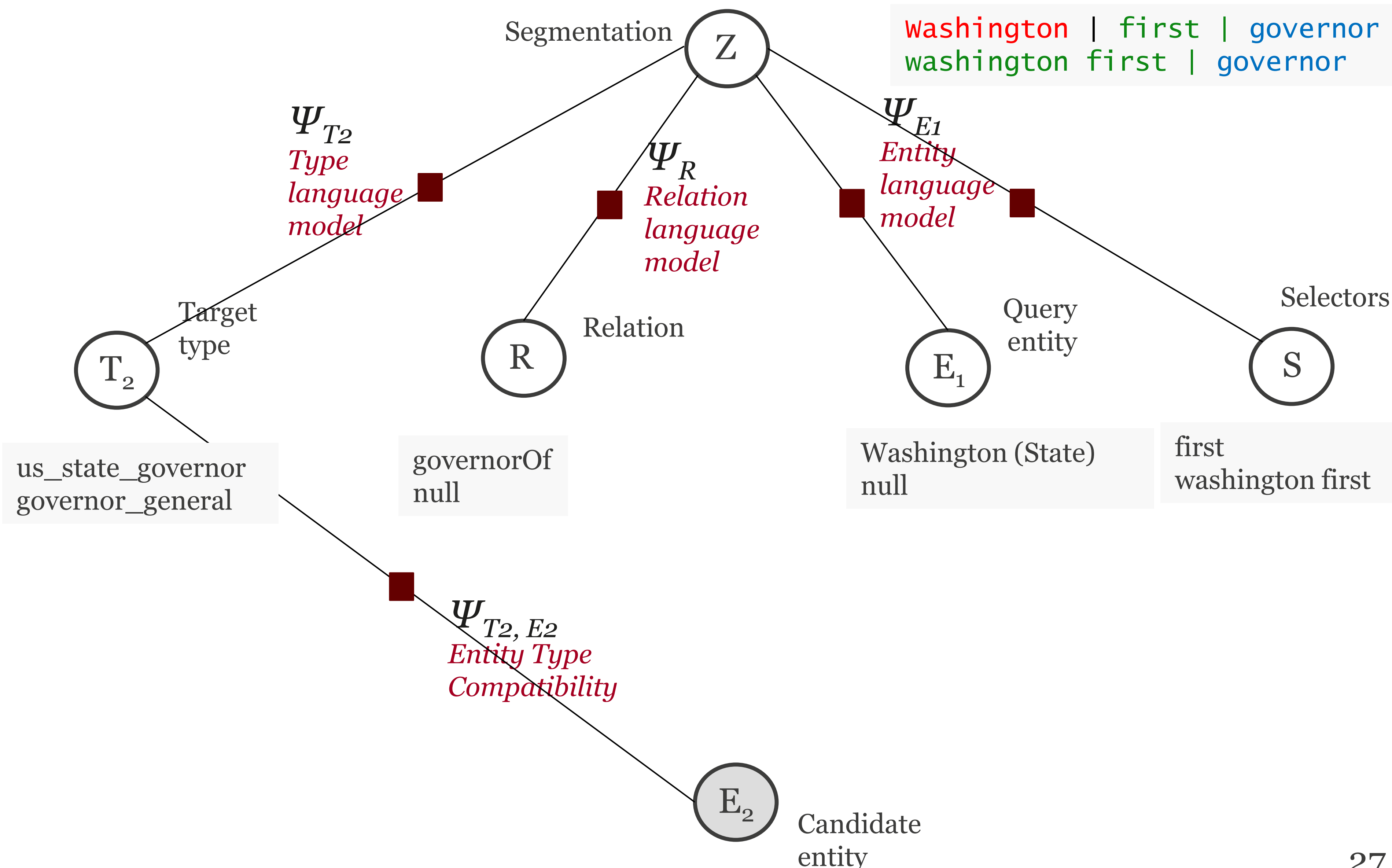

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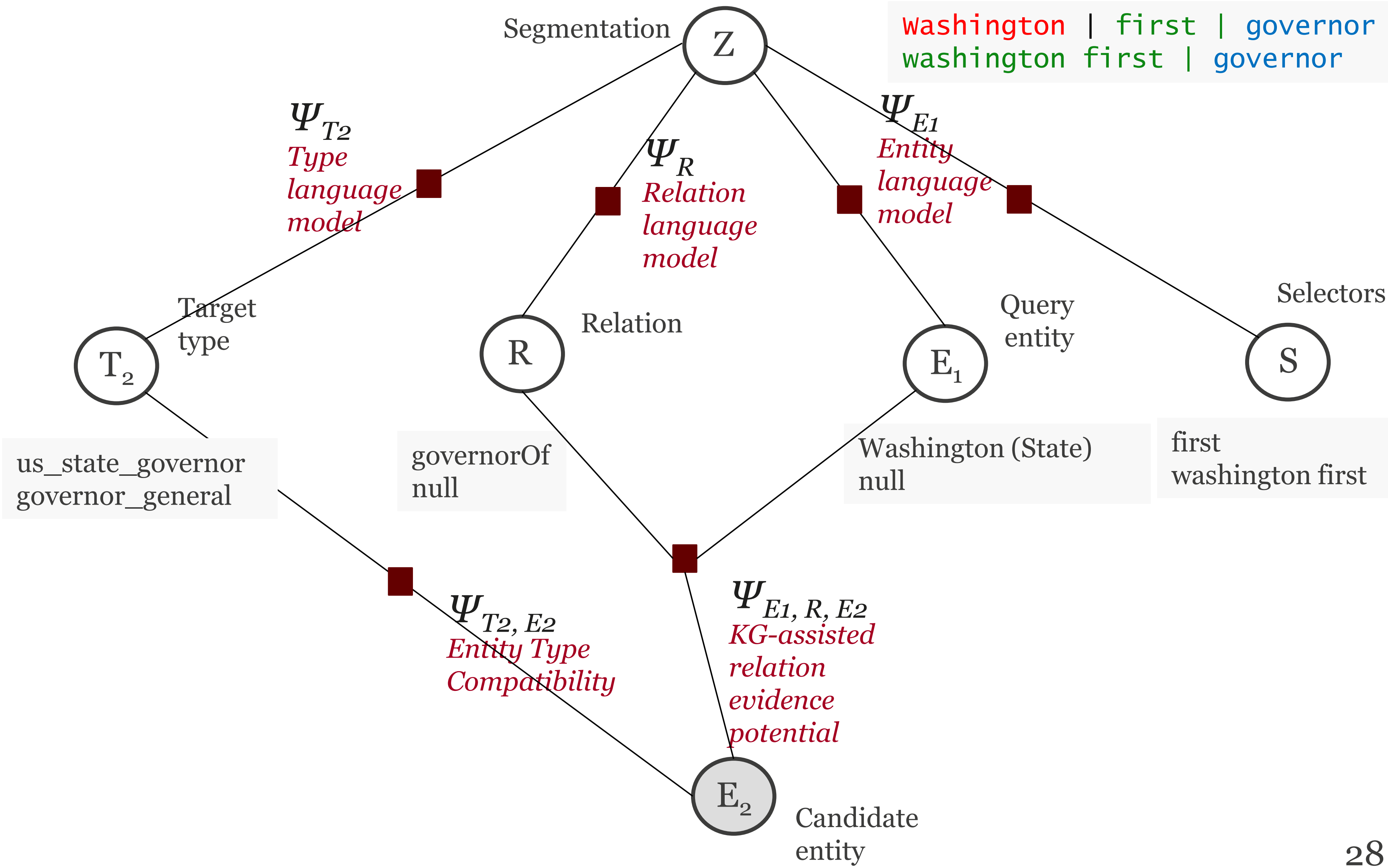

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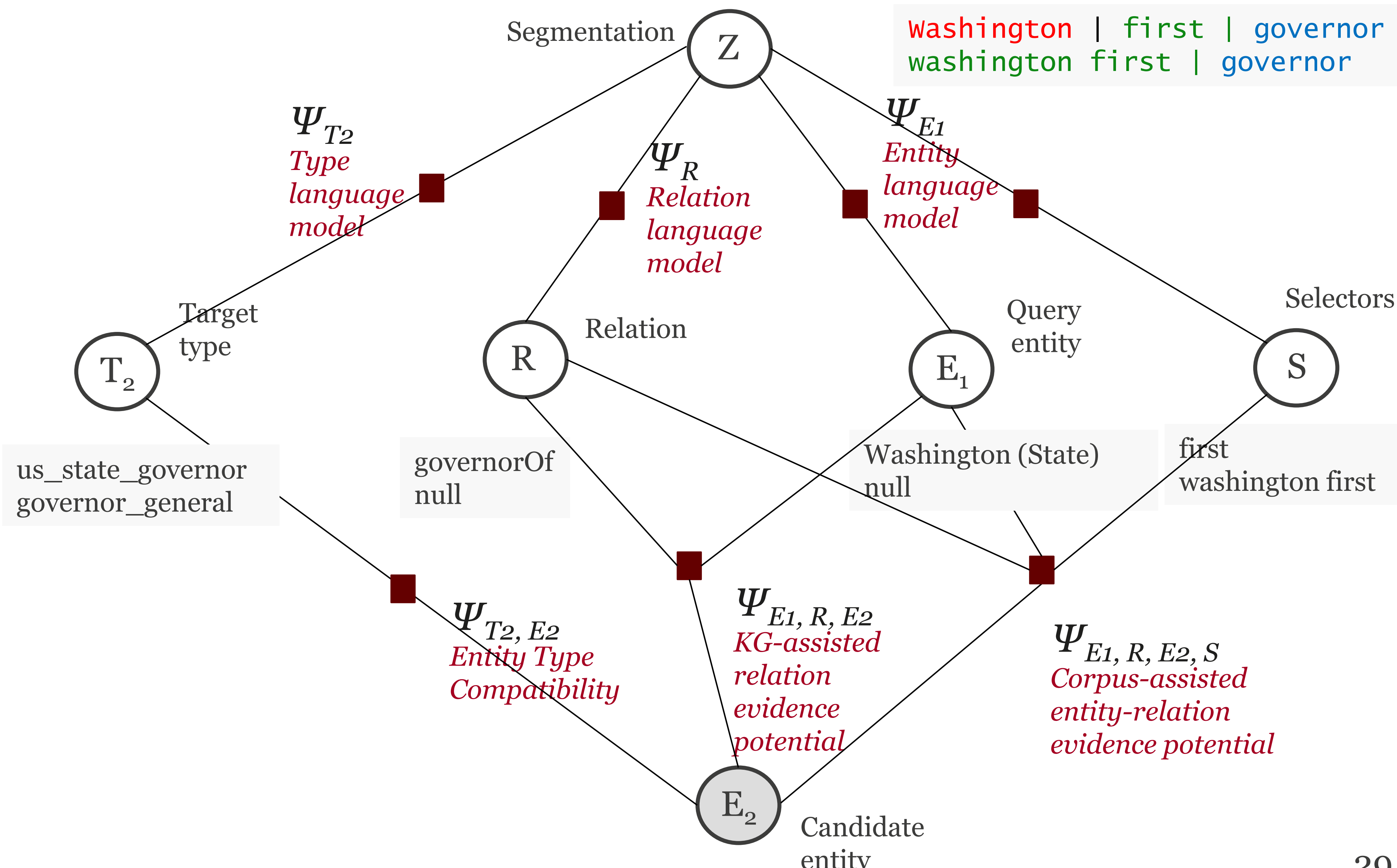

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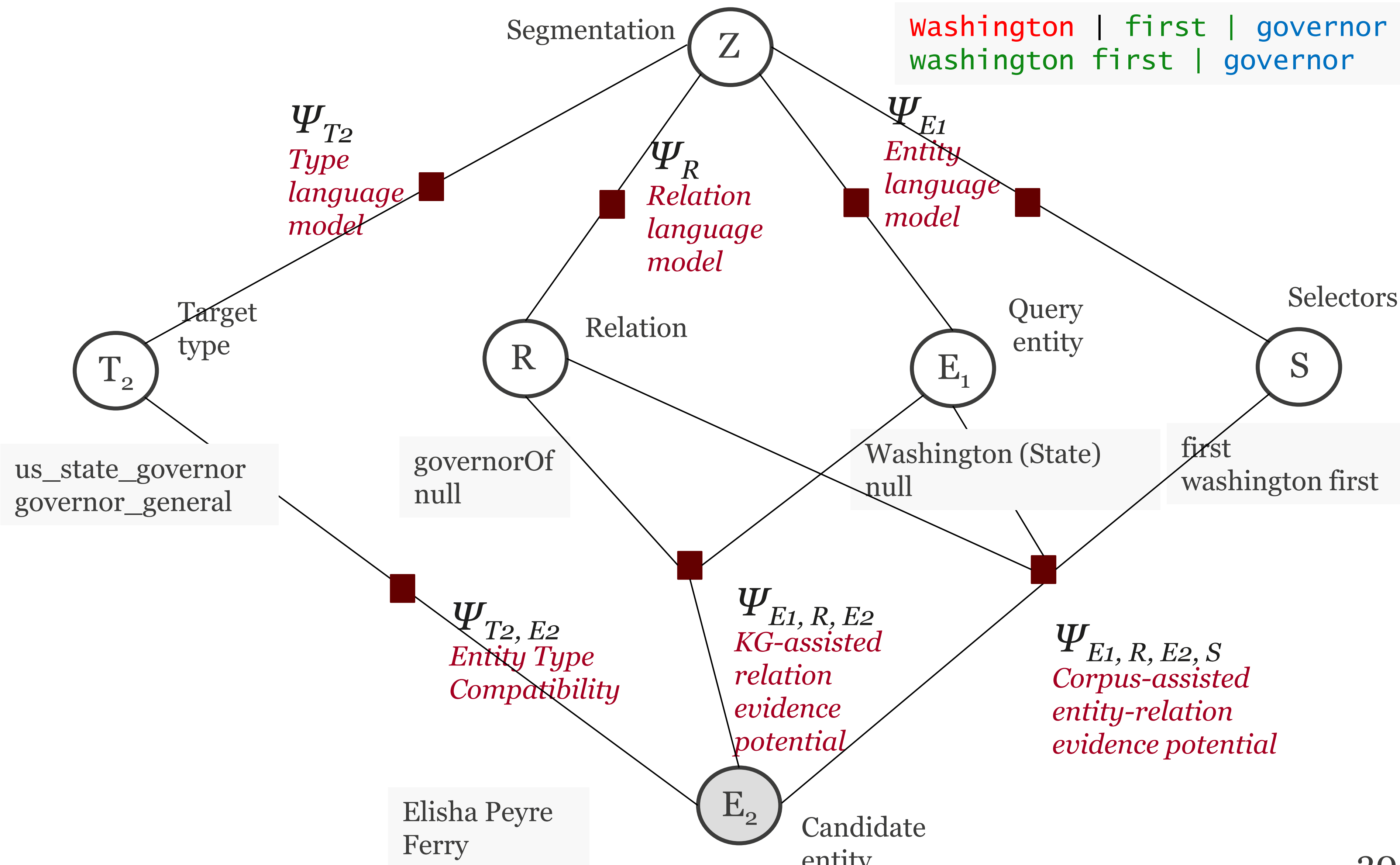

From query to Answer Entity

- Generate interpretations
- Retrieve snippets for each interpretation
- Construct candidate answer entities (e_2) set
  - Top *k* from corpus based on snippet frequency
  - By KG links that are in interpretations set
- Inference

$$score(e_2) = \max_{z,t_2,r,e_1} \Psi_{T_2}(q,z,t_2)\ \Psi_R(q,z,r)\ \Psi_{E_1}(q,z,e_1)\ \Psi_{E_2,T_2}(e_2,t_2)\ \Psi_{E_1,R,E_2,S}(e_1,r,e_2,s)\ \Psi_{E_1,R,E_2}(e_1,r,e_2)$$

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evidence from KG and corpus

Relation and Type Models

- Objective: To map relation (or type) mentions in query to Freebase relation (or types)
- Relation Language Model (Ψ_R)
  - Use annotated ClueWeb09 + Freebase triples
  - Locate Freebase relation endpoints in corpus
  - Extract dependency path words between entities
  - Maintain co-occurrence counts of <words, rel>
  - Assumption: Co-occurrence implies relation
- Type Language Model (Ψ_{T2})
  - Smoothed Dirichlet language model using Freebase type names

Corpus Potential

- Estimates support to e_1-r-e_2-s in corpus
- Snippet retrieval and scoring
- Snippets scored using RankSVM
- Partial list of features
  - #snippets with distance(e_2 , e_1) < k (k = 5, 10)
  - #snippets with distance(e_2 , r) < k (k = 3, 6)
  - #snippets with relation r = ⊥
  - #snippets with relation phrases as prepositions
  - #snippets covering fraction of query IDF > k (k = 0.2, 0.4, 0.6, 0.8)

Latent Variable Discriminative Training (LVDT)

- Constraints are formulated using the best scoring interpretation
- Training

$$\max_{q,z,e_1,t_2,r} w \cdot \phi(q,z,e_1,t_2,r,e_2^+) + \xi$$
$$\geq 1 + \max_{q,z,e_1,t_2,r} w \cdot \phi(q,z,e_1,t_2,r,e_2^-)$$

- Inference

$$\max_{q,z,e_1,t_2,r} w \cdot \phi(q,z,e_1,t_2,r,e_2),$$

- q, e_2 are observed; e_1, t_2, r and z are latent
- Non-convex formulation

Experiments

TEST BED

- Freebase entity, type and relation knowledge graph
  - ~29 million entities
  - 14000 types
  - 2000 selected relation

- Annotated corpus
  - Clueweb09B Web corpus having 50 million pages
  - Google (FACC1), ~ 13 annotations per page
  - Text and Entity Index

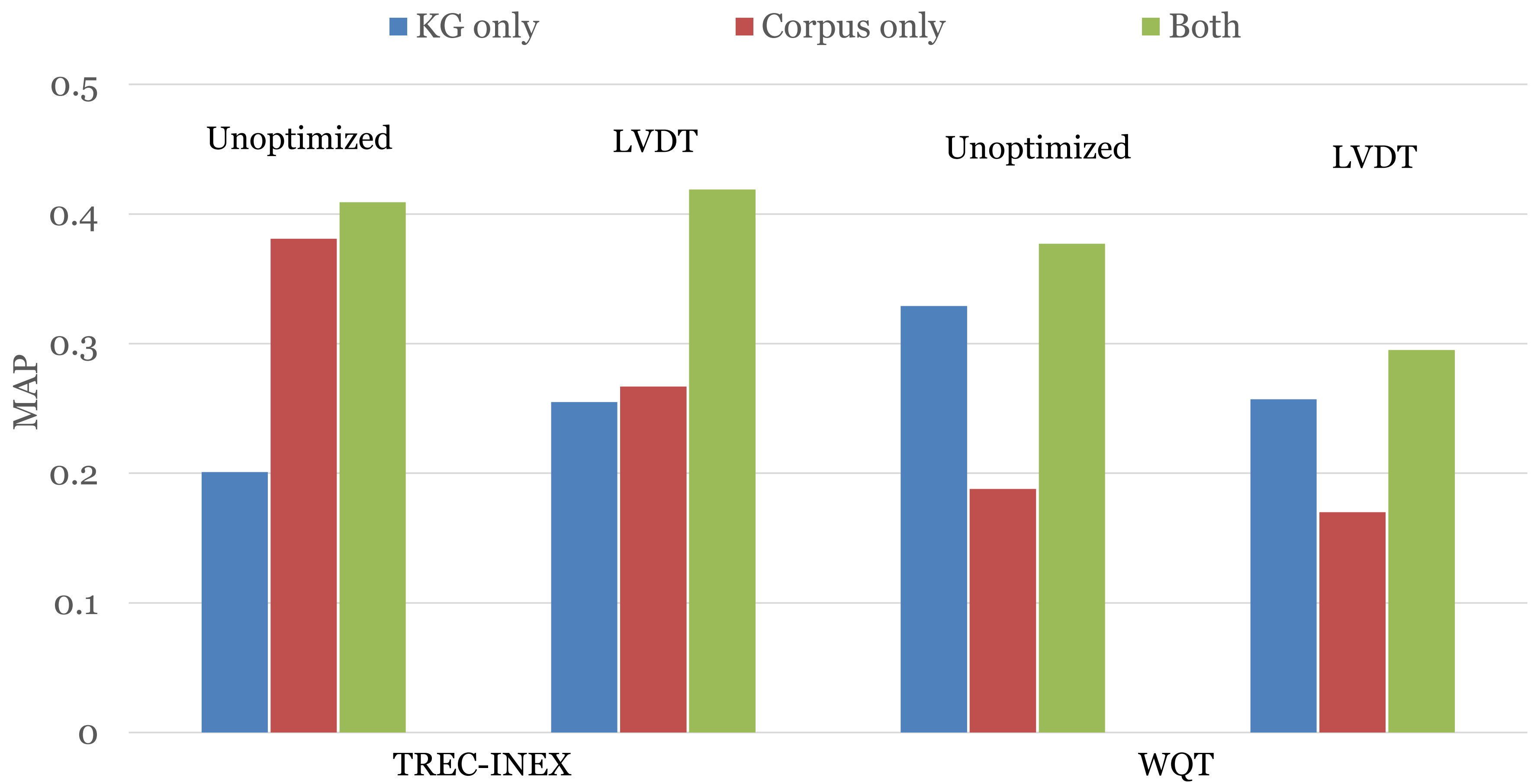
TEST BED

- Query sets
  - TREC-INEX: 700 entity search queries
  - WQT: Subset of ~800 queries from WebQuestions (WQ) natural language query set [1], manually converted to telegraphic form
  - Available at http://bit.ly/Spva49

TREC-INEX	WQT
Has type and/or relation hints	Has mostly relation hints
Answers from KG and corpus collected by volunteers	Answers from KG only collected by turkers.
Answer evidence from corpus (+ KG)	Answer evidence from KG

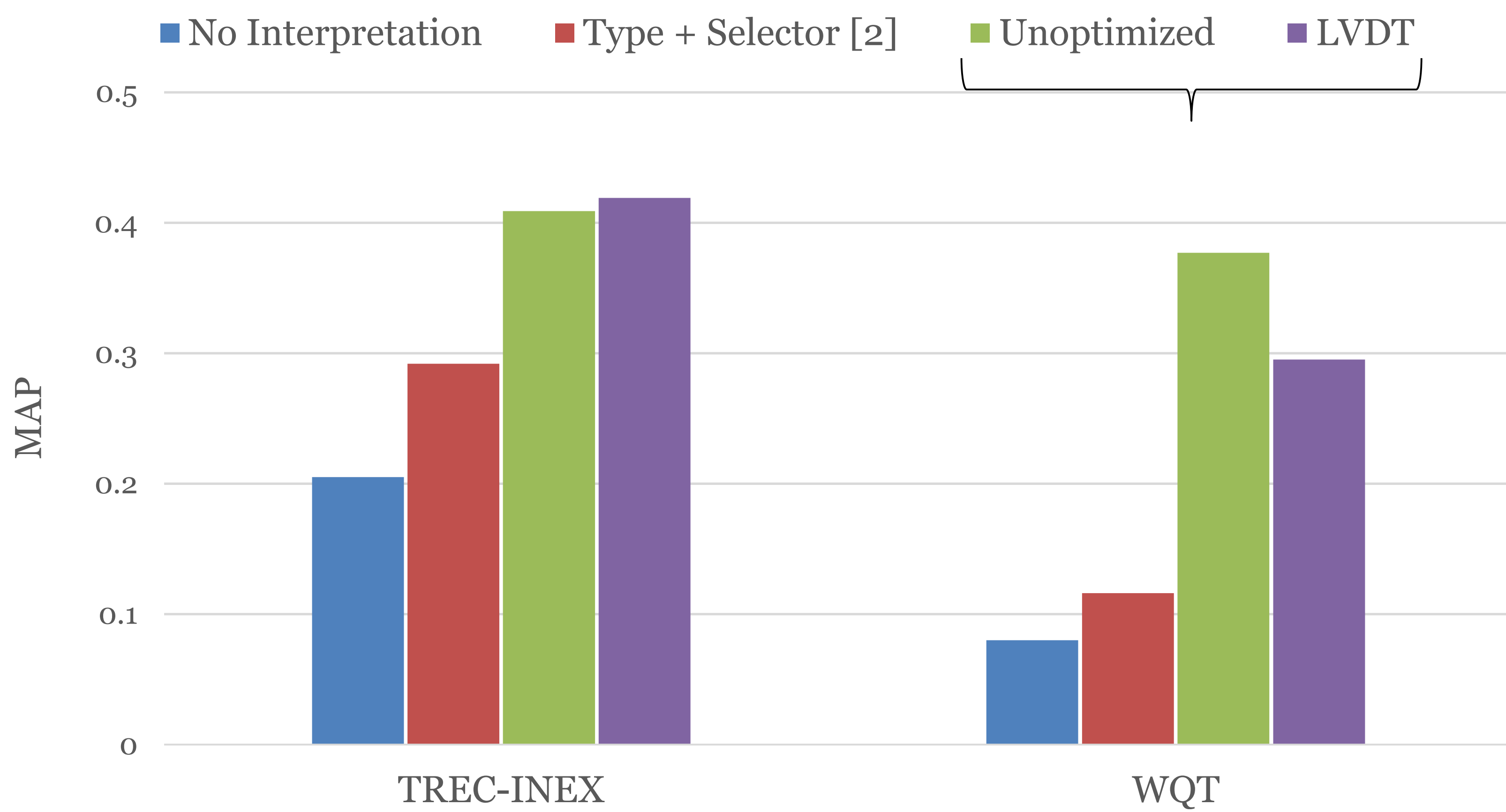
[1] Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Empirical Methods in Natural Language Processing (EMNLP).

Synergy Between KG and Corpus



Corpus and knowledge graph help each other to deliver better performance

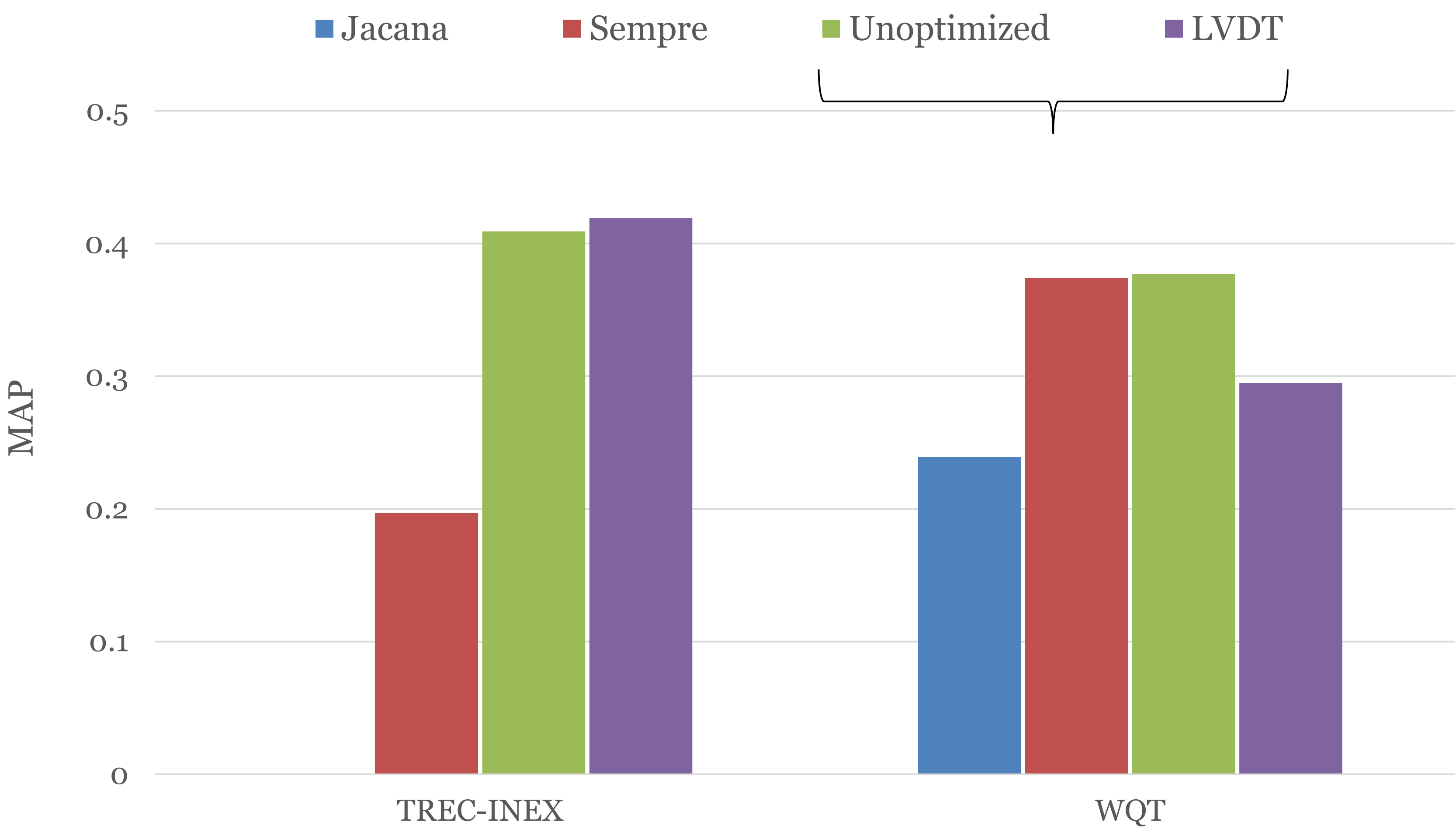
QUERY TEMPLATE COMPARISON



Entity-relation-type-selector template provides yields better accuracy than type-selector template

[2] Uma Sawant and Soumen Chakrabarti. 2013. Learning joint query interpretation and response ranking. In WWW Conference, Brazil.

COMPARISON WITH SEMANTIC PARSERS



QUALITATIVE COMPARISON

- Benefits of collective inference
  - `automobile company makes spider`
  - Entity model fails to identify e_1 (Alfa Romeo Spider)
  - Recovery: `automobile company makes spider`

- Limitations
  - Sparse corpus annotations
  - `south africa political system`
  - Few corpus annotations for e_2: Constitutional Republic
  - Can't find appropriate t_2 (/../form_of_government) and r (/location/country/form_of_government)

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    e_1: Automobile

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Qualitative Comparison

- Benefits of collective inference
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  - Entity model fails to identify e_1 (Alfa Romeo Spider)
  - Recovery: `automobile` `company` `makes spider`

    e_1: Automobile t_2: /../organization r : /business/industry/companies

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Summary

- Query interpretation is rewarding, but non-trivial
- Segmentation based models work well for telegraphic queries
- Entity-relation-type-selector template better than type-selector template
- Knowledge graph and corpus provide complementary benefits

REFERENCES

- S&C: Uma Sawant and Soumen Chakrabarti. 2013. Learning joint query interpretation and response ranking. In WWW Conference, Brazil.
- Sempre: Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Empirical Methods in Natural Language Processing (EMNLP).
- Jacana: Xuchen Yao and Benjamin Van Durme. 2014. Information extraction over structured data: Question answering with Freebase. In ACL Conference. ACL.

DATA

- TREC-INEX and WQT
  - Short URL http://bit.ly/Spva49
  - Long URL https://docs.google.com/spreadsheets/d/1AbKBdFOIXum_NwXeWuboSdeG-y8Ub4_ub8qTjAw4Qug/edit#gid=0
- Project page
  - http://www.cse.iitb.ac.in/~soumen/doc/CSAW/

THANK YOU!
QUESTIONS?