



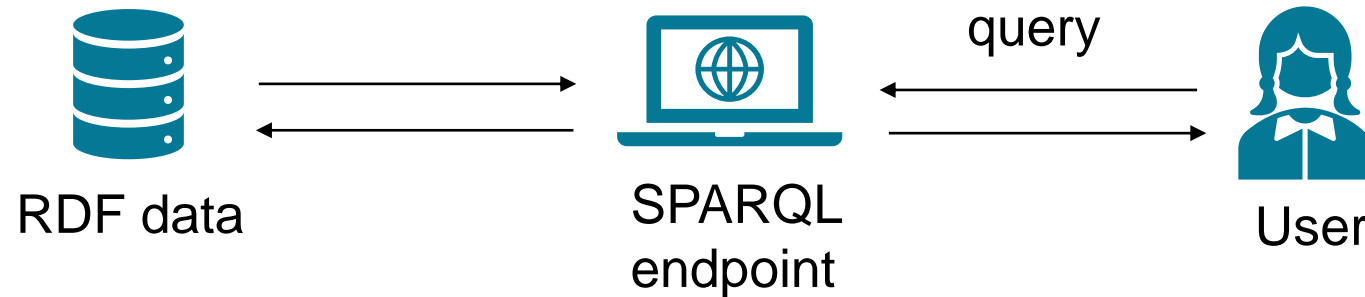
# Revealing Secrets in SPARQL Session Level

Xinyue Zhang, Meng Wang, Muhammad Saleem, Axel-Cyrille  
Ngonga Ngomo, Guilin Qi, and Haofen Wang.

# 1. Background

---

- Knowledge graphs help users to discover **information of interest** by using **live SPARQL services**.



# 1. Background

---

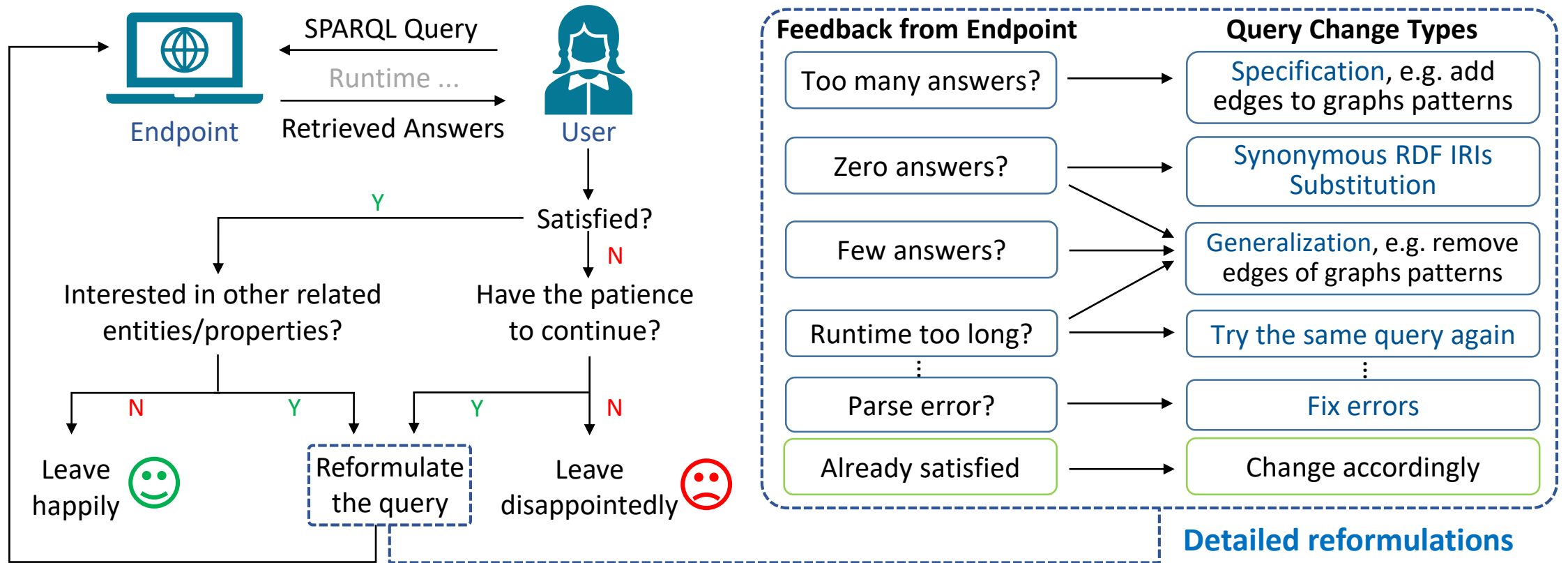
- Users often **fail** to express their information needs in **one succinct query**.

Because of their **unfamiliarity** with:

- the ontology underlying the endpoints,
- SPARQL syntax.

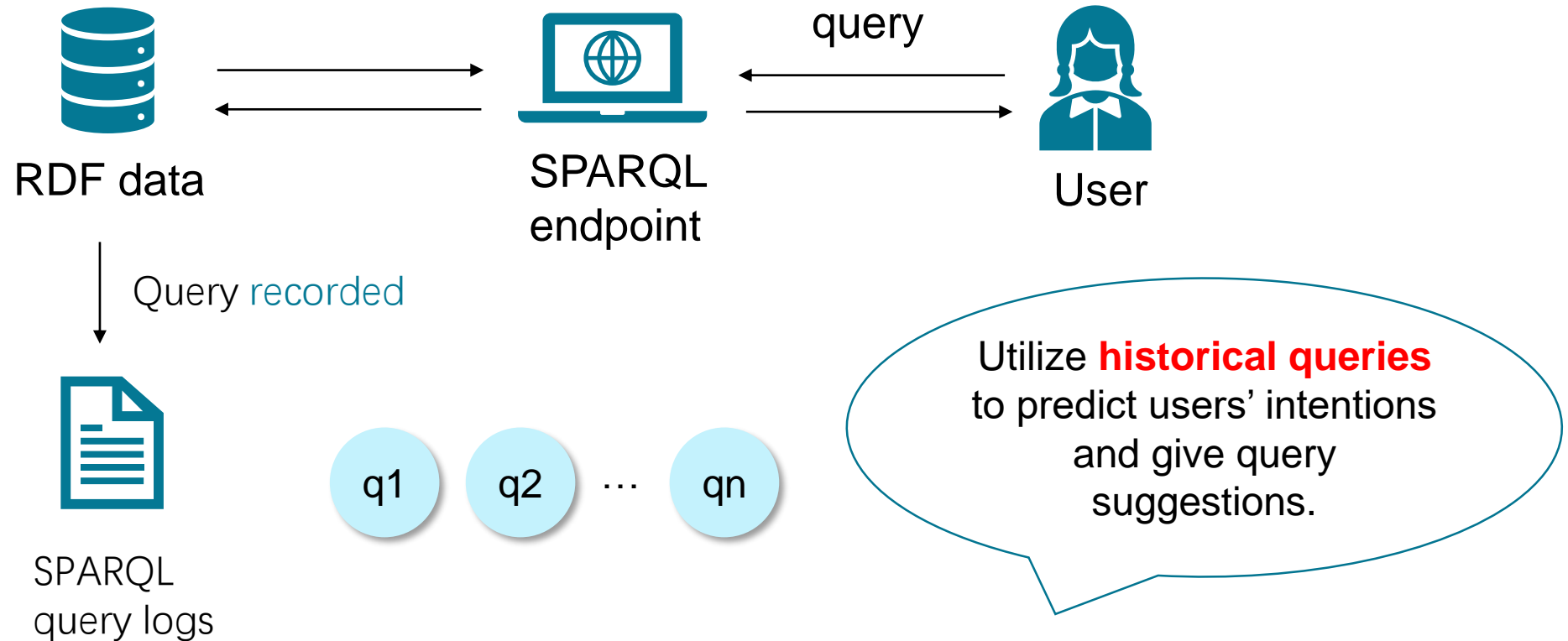
# 1. Background

- Therefore, SPARQL queries are **continuous refined** to retrieve satisfying results.



# 1. Background

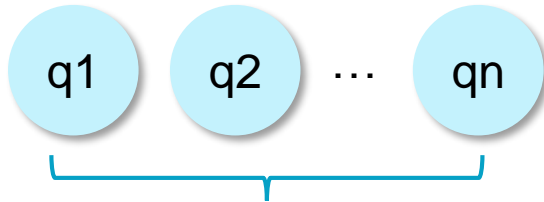
- How to help users?



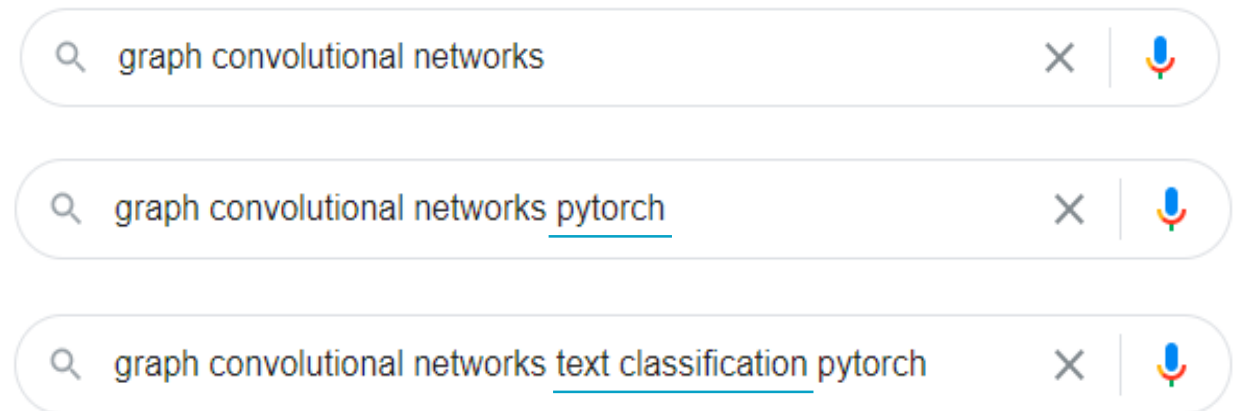
## 2. Our work: SPARQL query log analysis in session level

- Research Object

- SPARQL Search Sessions



1. Executed by **one user**.
2. Within a fixed time threshold (1h).
3. Continuous query pairs  $(q_i, q_{\{i+1\}})$  share **at least one** common variable or IRI.



## 2. Our work: SPARQL query log analysis in session level

---

### Challenges:

- The information we could utilize in sessions.

Implicit Feedback	Traditional IR Field	SPARQL Scenario
Dwell Time in webpages	✓	✗
Clicked URLs	✓	✗
Query Reformulations	✓	✓

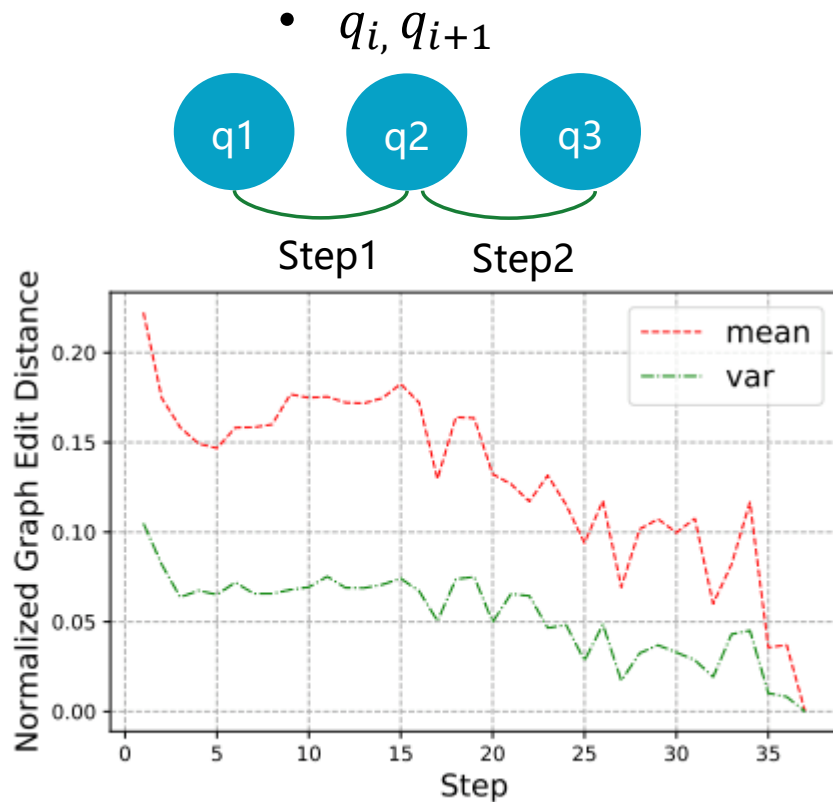


Focus on the **query changes!**

## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Structural** changes evaluated by **Graph Edit Distance (GED)**.



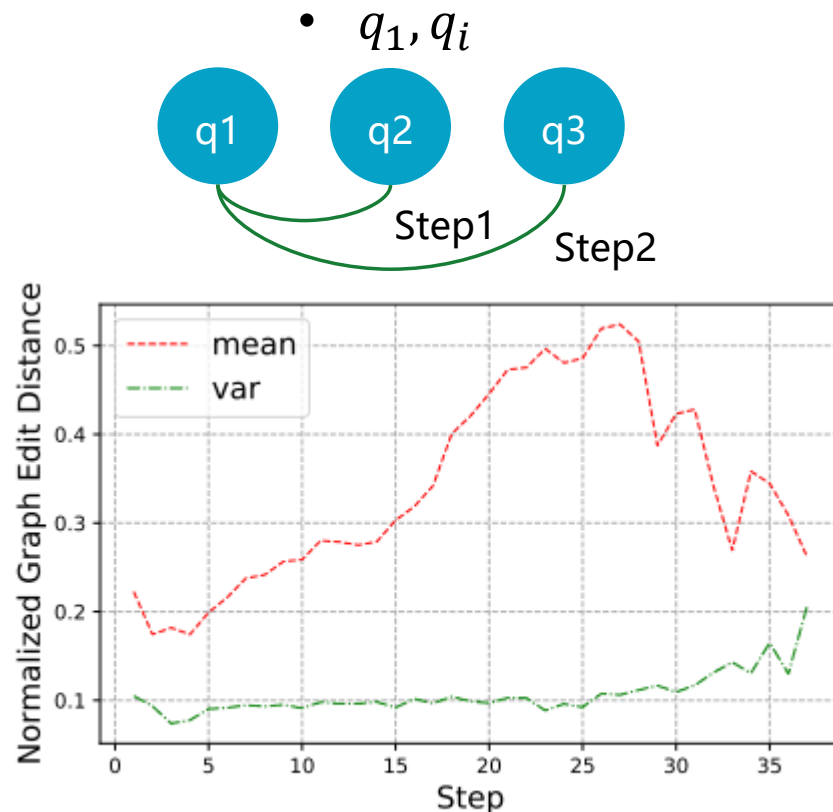
Query changes between two continuous queries is **increasingly indistinct** as users getting closer to their information needs.



## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Structural** changes evaluated by **Graph Edit Distance (GED)**.



GEDs between  $(q_1, q_i)$  **increase consistently at first, then decrease**. Users may use **prior query structures** with different IRIs to explore other related information.

## 2. Our work: SPARQL query log analysis in session level

---

Query changes in SPARQL search sessions:

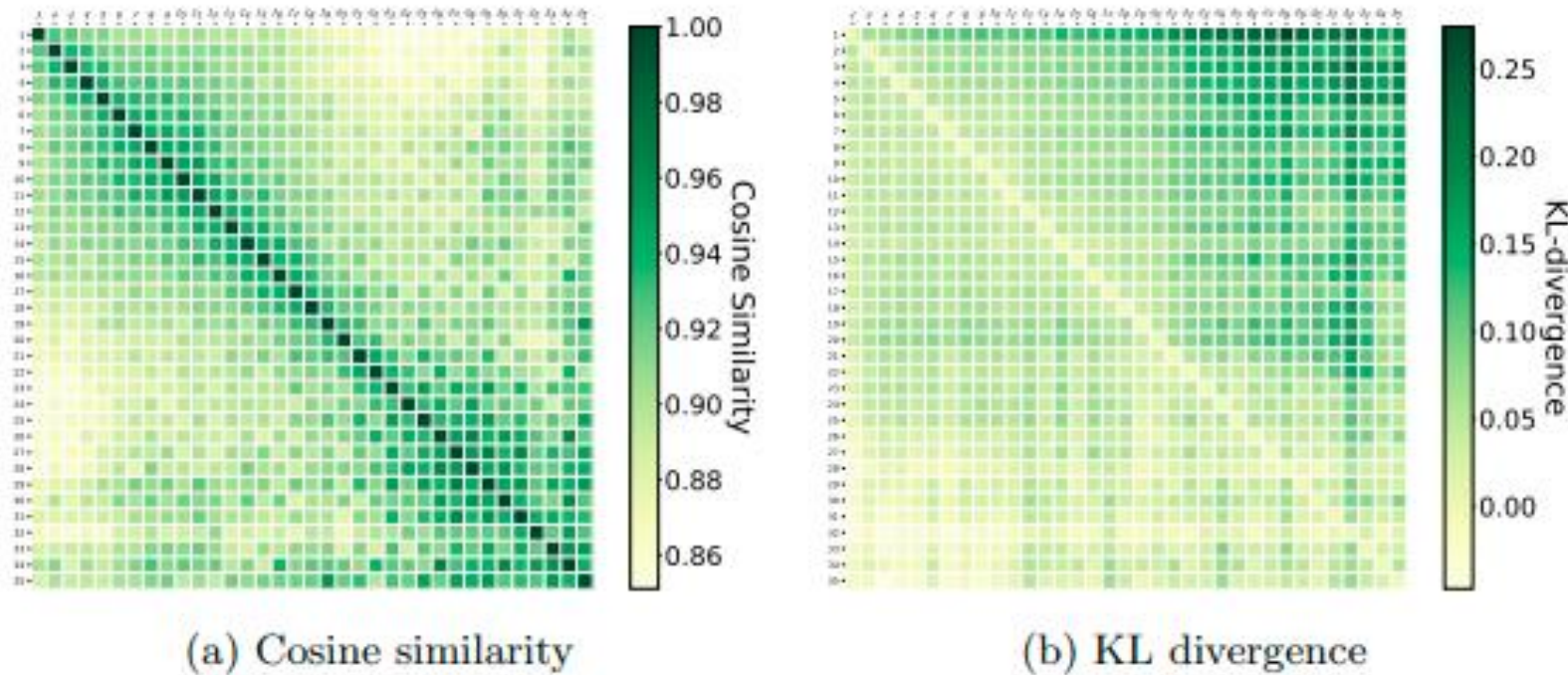
- **Structural** changes evaluated by graph pattern similarity.

$$V = [ \#triplePatterns, \#BGP, \#Projection, \#SinkJoinVertex, \\ \#StarJoinVertex, \#HybridJoinVertex, \#PathJoinVertex, \\ MaxJoinDegree, MinJoinDegree, MeanJoinDegree ].$$

## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Structural** changes evaluated by graph pattern similarity.



Users usually change the **structure of graph patterns slightly**.

Fig. 6: Graph pattern similarity of query sequence  $Q$  in sessions.

## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Structural** changes evaluated by **IRI term similarity**.

Q1: SELECT ?who

WHERE {<http://dbpedia.org/resource/Minecraft> <http://dbpedia.org/ontology/designer> ?who. }



**Bags of Words** are used to construct a IRI-term vector to present each SPARQL query.

<http://dbpedia.org/resource/Minecraft>	<http://dbpedia.org/ontology/designer>	Other IRIs ...	
1	1	...0...	1

1 if this IRI present else 0

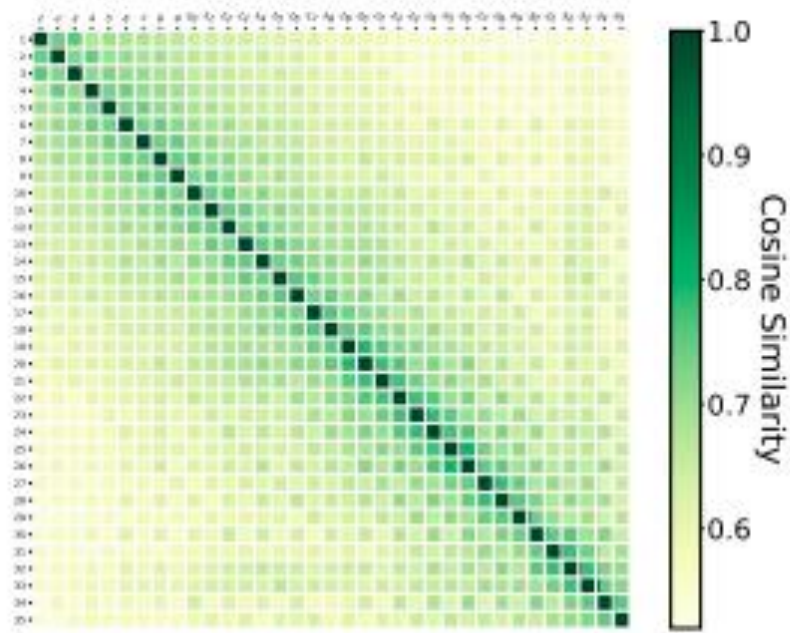
All 0

This column is used to avoid all-zero vectors.

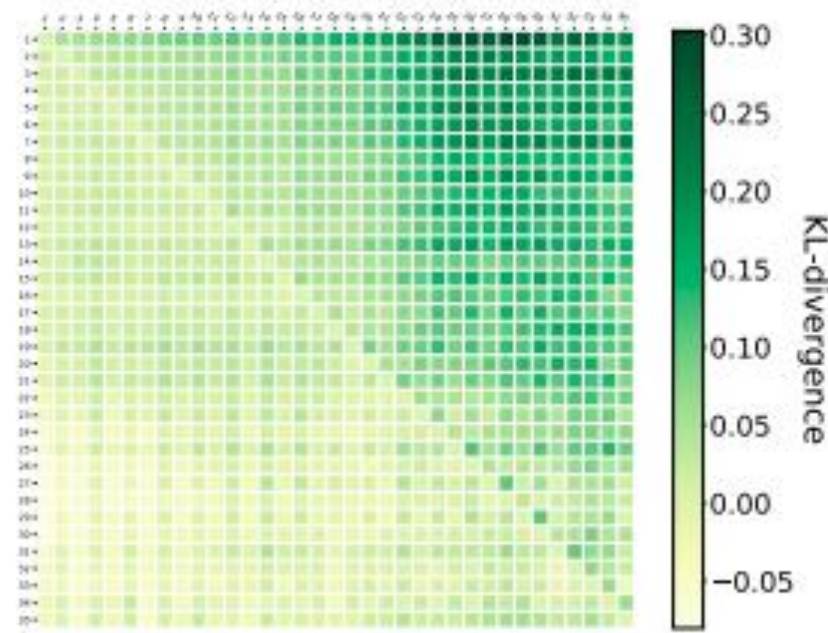
## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Structural** changes evaluated by **IRI term similarity**.



(a) Cosine similarity



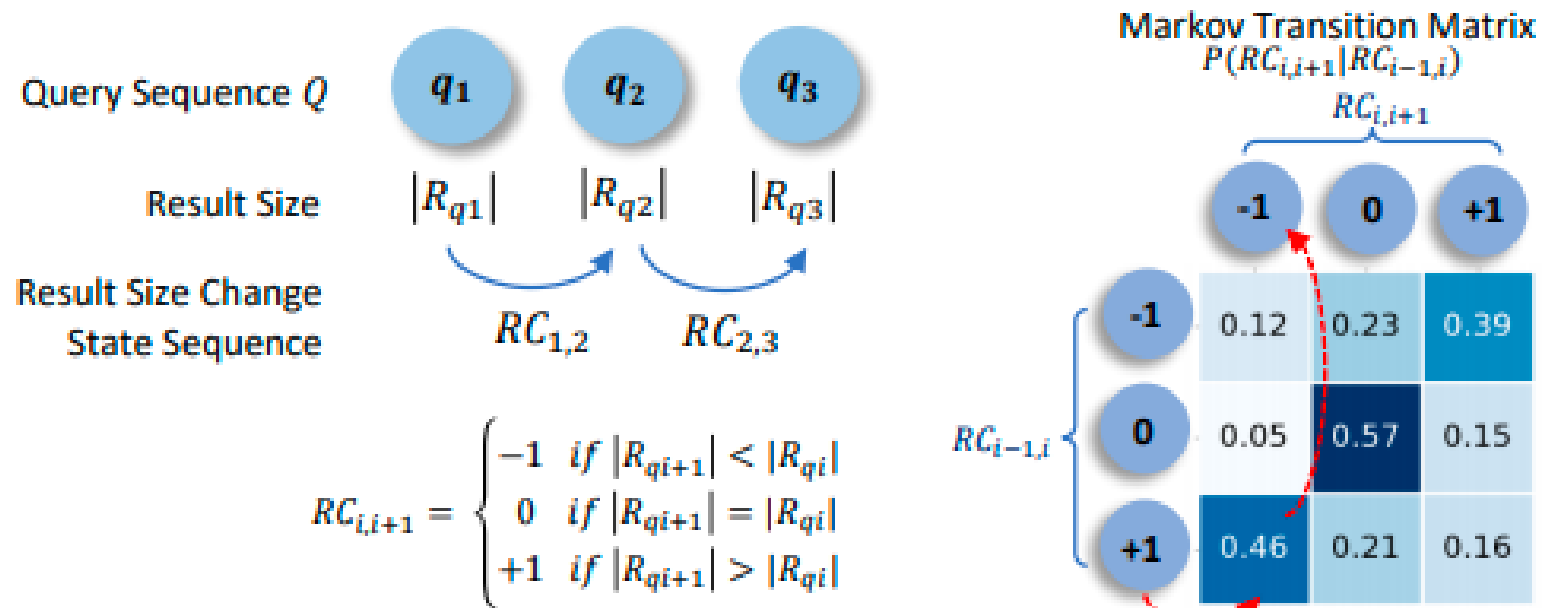
(b) KL divergence

Users tend to **include more IRI terms** and express a clearer intention **as the session move forward**.

## 2. Our work: SPARQL query log analysis in session level

Query changes in SPARQL search sessions:

- **Intention** changes evaluated by **changes of result set size**.



Previous result size change does **influence** the intention of the current query.

## 2. Our work: SPARQL query log analysis in session level

---

### Query changes in SPARQL search sessions:

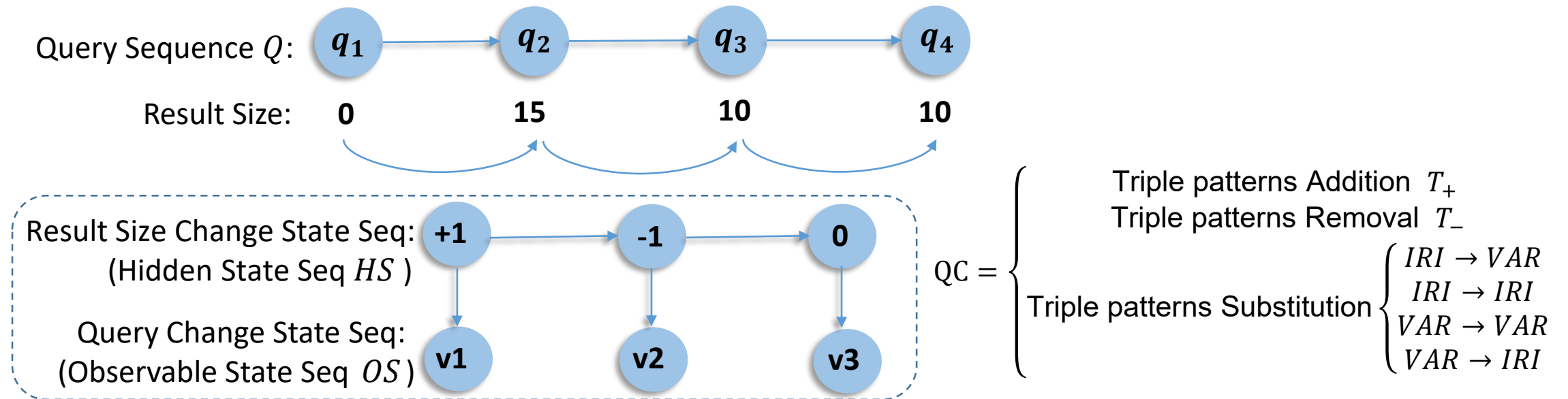
- Distribution of detailed reformulation strategies.
  - **Additions/deletions of operators.**
  - **Additions/deletions of triple patterns.**
  - **Substitutions of individual elements of triple patterns.**
  - **Substitutions on different join vertex types and their neighbors.**
  - **Additions/deletions/substitutions of FILTER constraints.**



### 3. An application example

#### Hidden Markov Model:

	Hidden states $H$	Observable states $U$
Human users	Abstract intentions	Query reformulations
Our application	Result Size Change States $RC$	Query Change States $QC$





# 3. An application example

## Parameters of HMM

$\pi$ : Initial State Distribution

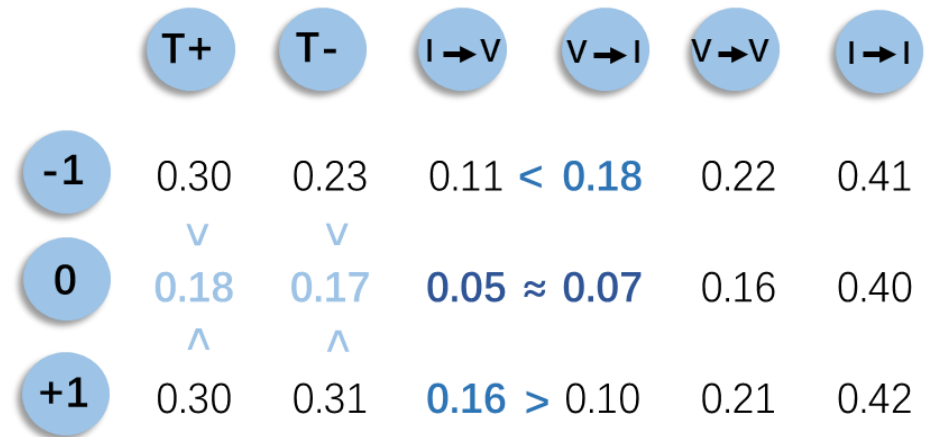


+1: #Results Increase      T+: Triples Addition  
 -1: #Results Decrease      T-: Triples Removal  
 0: #Results remain the same      V: Variable      I: IRI

A: Transition Probability



B: Emission Probability



The simple demo we present here is capable of:

- **predicting user behavior** (evaluation problem: given parameters of HMM  $\lambda = (A, B, \pi)$ , calculate  $p(O|\lambda)$ )
- **understanding user intentions** (decoding problem: given  $\lambda = (A, B, \pi)$  and  $O = (o_1, o_2 \dots o_t)$ , calculate a sequence  $I = (i_1, i_2 \dots i_t)$  that maximize  $P(I|O)$ )

# 4. Conclusions

---

- **Define** the SPARQL search **session**.
- Investigate **potential relations between queries** in single search **sessions**.
- Conduct a comprehensive analysis of **query reformulations**.
- Provide an **example application** to illustrate the potentiality of utilizing user behaviors in a search session.

Thanks!