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Fast ObjectRank for Large Knowledge Databases

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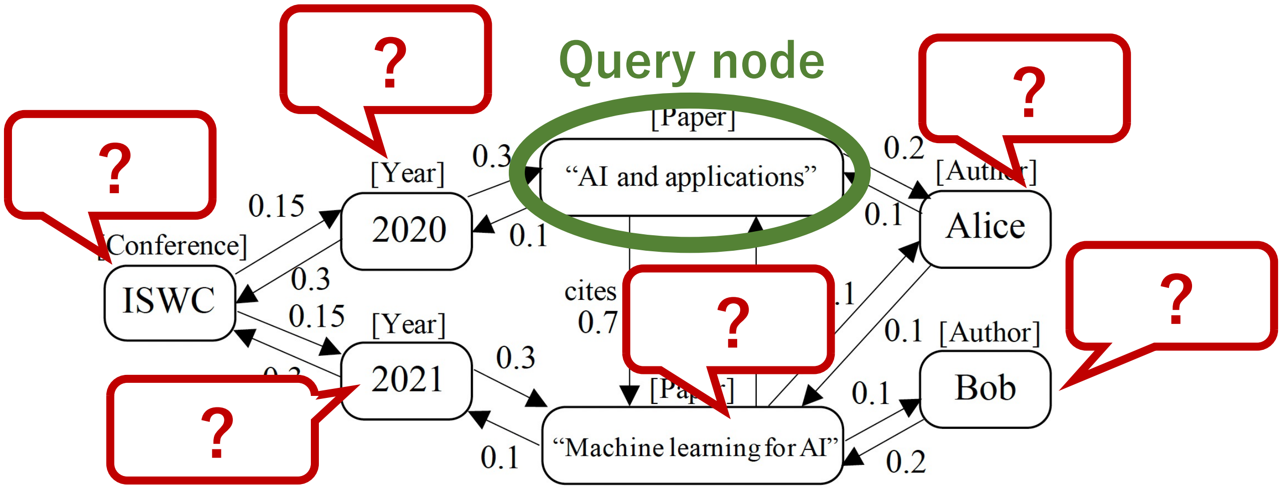
ObjectRank [Hiristidis, Hwang and Papakonstantinou, 2008]

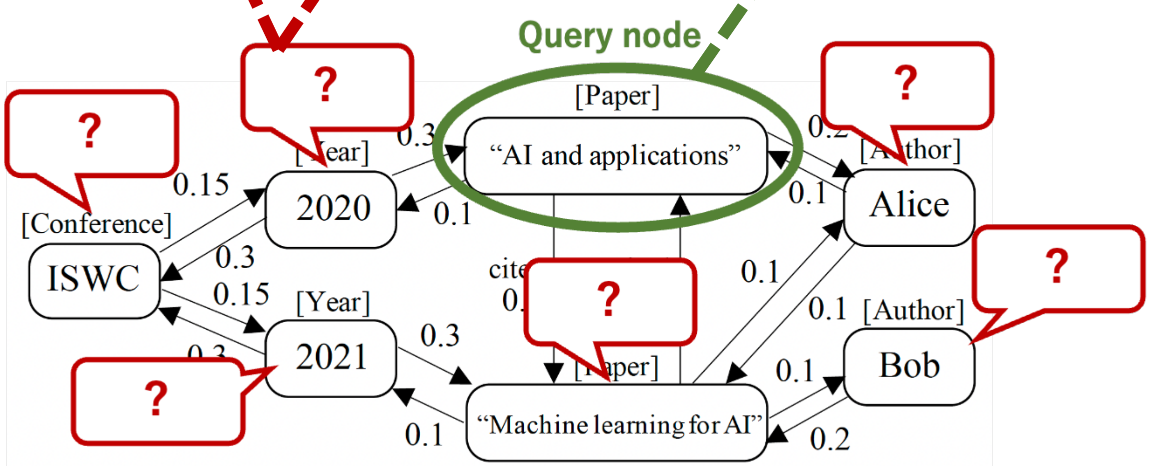
- **Relevant entity search algorithm for KGs**
  - **Given:** a KG $G_D(V_D, E_D, W_D)$, and a query nodes $\boldsymbol{V_q} \subseteq \boldsymbol{V_D}$
  - **Return:** an importance vector $\mathbf{r} = (\boldsymbol{r_1}, \boldsymbol{r_2}, \ldots, \boldsymbol{r_{|V_D|}})^{\mathbf{T}}$, where r_i denotes a relevance between $v_i \in V_D$ and V_q



Importance Computation

- **Iterative Random-walk with Restart (RWR)**
  - ObjectRank iteratively runs the following a matrix-vector multiplication until $\mathbf{r}$ converges.

$$\mathbf{r} = \alpha \mathbf{A}\mathbf{r} + (1-\alpha)\mathbf{q}$$



Efficiency Problem of ObjectRank

- **Iterative RWR incurs expensive costs**
  - ObjectRank needs to update the importance vector for all entities (nodes) included in V_D until convergence.
  - It incurs $\boldsymbol{O}((|\boldsymbol{V_D}| + |\boldsymbol{E_D}|)\boldsymbol{t_D})$ time, where $|V_D|, |E_D|$ and t_D are # of nodes and edges in a KG, and # of iterations, respectively.

- **Recent Semantic Web applications**
  - KGs are becoming larger and larger…
  - In many cases, we need to handle at least $|V_D| \geq 10^6$ entities.

Can ObjectRank handle such massive KGs?

Goal & Contributions

How can we efficiently compute ObjectRank without sacrificing the top-k search quality?

- **Proposed Method:** ***SchemaRank***
  - Schema-aware top-k search algorithm for fast/exact ObjectRank.
- **Contributions**
  - **Efficient:** Up to 644.7 times faster than SOTAs.
  - **Exact:** Guarantees the same results as those of ObjectRank.
  - **Easy to deploy:** Requires no user-specified parameters.
  - **Codes are available:**

https://github.com/LazyShion/SchemaRank

Key Observation

- **The skewness in the importance distribution**
  - Real graphs have **highly skewed importance distribution**.
  - The vast majority of nodes practically yield low importance.

Question: Can we find such nodes with low importance **before** the importance evaluation?

- **ShemaRank: Schema-aware two-phase RWRs**

① Coarse-grained RWR

It estimates the importance of node-types from a schema of KGs.

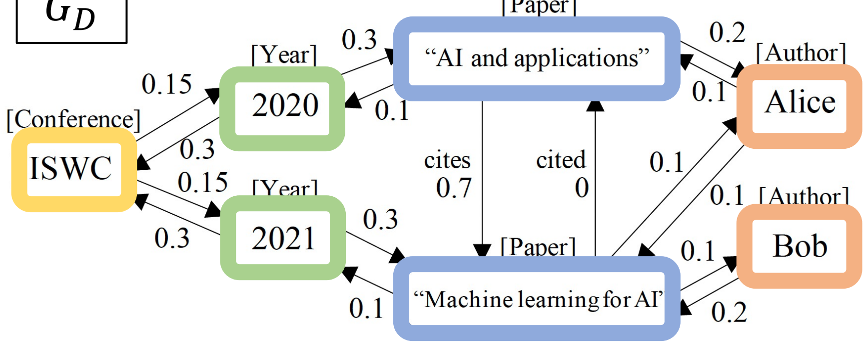
② Coarse-grained RWR

It incrementally prunes unpromising nodes to find top-k nodes using the importance of node-types.

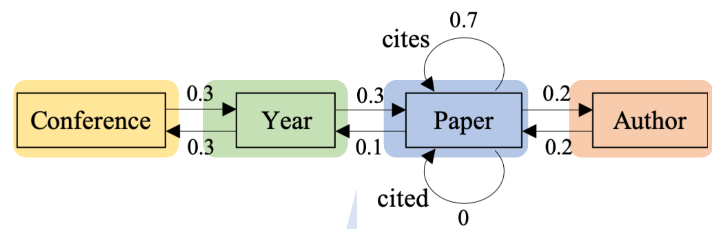
Coarse-grained RWR (CR)

- **Schema-level importance estimation**
  - Finds node-types that yield low importance score from a schema.

G_D



G_S(a schema graph of G_D)

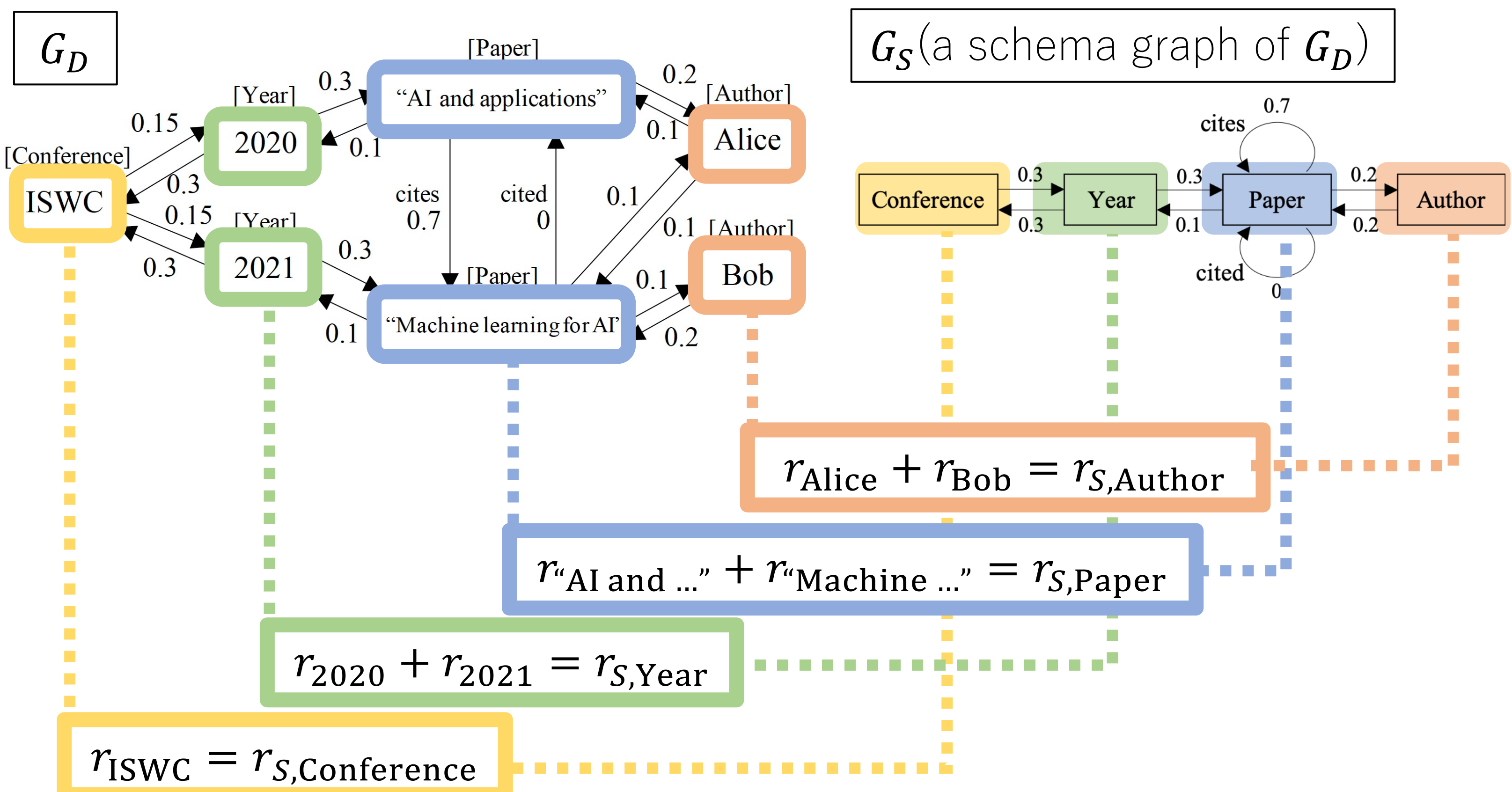


$$\mathbf{r}_S = \alpha \mathbf{A}_S \mathbf{r}_S + (1 - \alpha)\mathbf{q}_S$$

$\mathbf{r}_S$ and $\mathbf{q}_S$ are the vectors projected from G_D to G_S.
$\mathbf{A}_S$ is the adjacency matrix of G_S.

Important Property of CR

- $\mathbf{r}_S$ is a good approximation of $\mathbf{r}$



Fine-grained RWR (FR) (1/2)

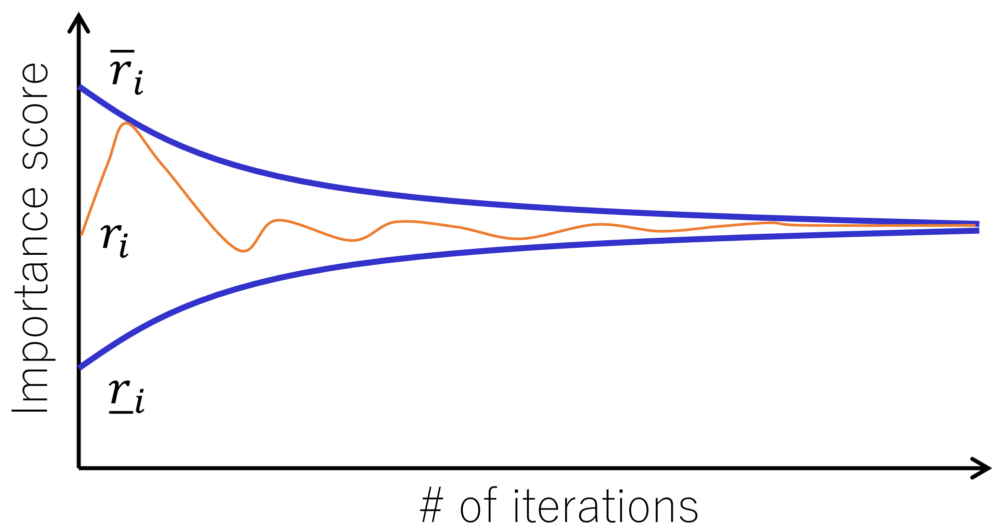
- **Explores top-k important nodes on a KG using $\mathbf{r}_S$**
  - SchemaRank derives the following bounds from $\mathbf{r}_S$.

Lower bound of r_i

$$\underline{r}_i^{(t)} = \begin{cases} (1-\alpha)q_i & (t=0) \\ \underline{r}_i^{(t-1)} + (1-\alpha)\alpha^t p_i^{(t)} & (t>0) \end{cases},$$

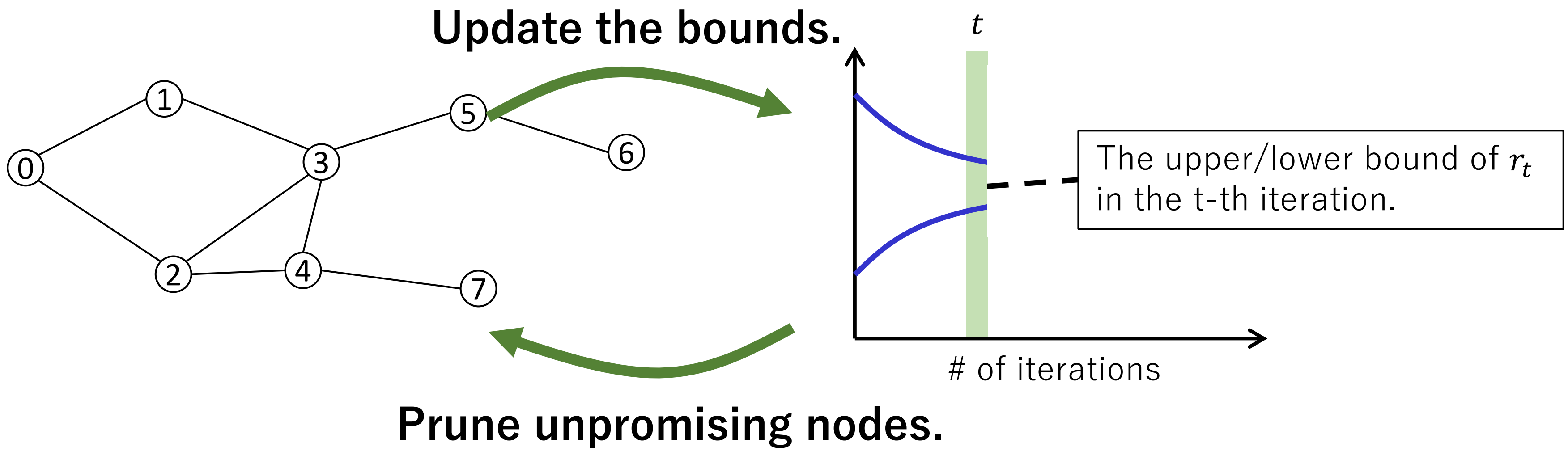
Upper bound of r_i

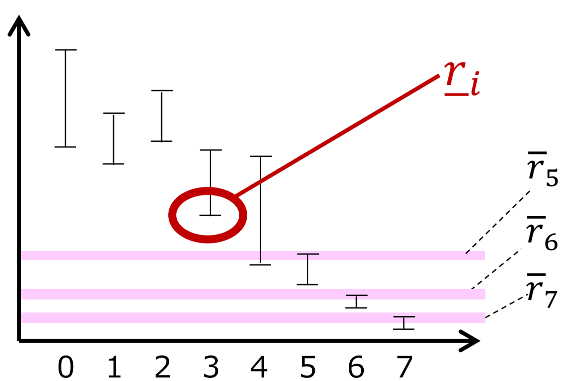
$$\overline{r}_i^{(t)} = \begin{cases} b_i^{(0)} + \frac{\alpha}{1-\alpha}\overline{A}_i & (t=0) \\ \underline{r}_i^{(t-1)} + \alpha^t b_i^{(t)} + \frac{\alpha^{t+1}}{1-\alpha}\Delta^{(t)}\overline{A}_i & (t>0) \end{cases},$$



$$\underline{r}_i^{(\infty)} = \overline{r}_i^{(\infty)} = r_i$$

Fine-grained RWR (FR) (2/2)





Prune nodes whose upper bound is smaller than the k-th largest lower bound.

Runtime Efficiency

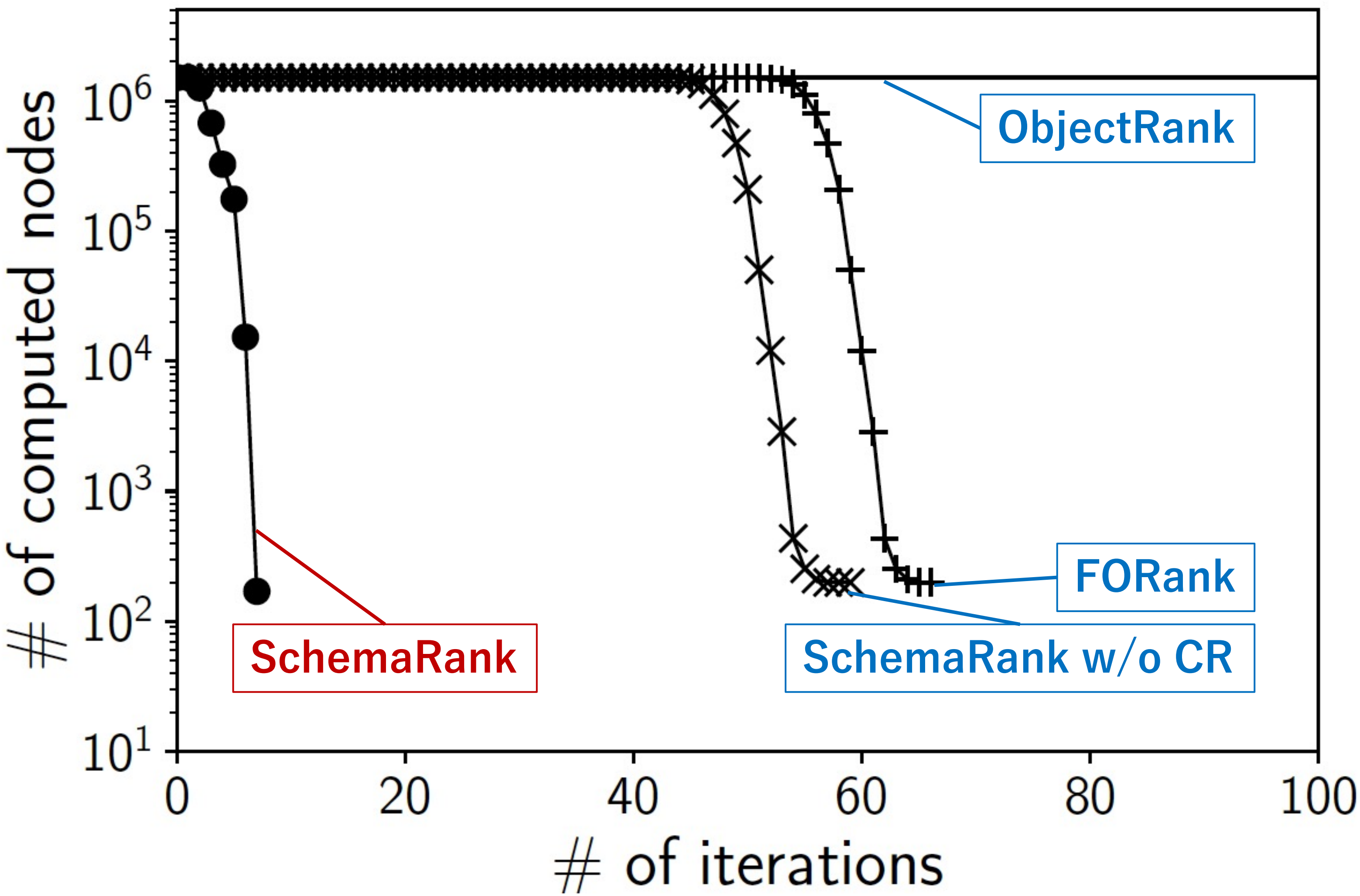
(b) DBLP (small)

Methods	Skewed	Uniform	Pre-comp.
SchemaRank ($k=10^2$)	**1.91** (±0.003) **sec.**	**2.54** (±0.003) **sec.**	—
SchemaRank ($k=10^3$)	**2.08** (±0.002) **sec.**	**2.63** (±0.003) **sec.**	—
ObjectRank	22.8 (±0.011) sec.	22.7 (±0.009) sec.	—
BinRank	6.42 (±0.009) sec.	7.22 (±0.011) sec.	17.9 hours
LORank	16.4 (±0.008) sec.	17.2 (±0.008) sec.	—
SimMat ($k=10^2$)	N/A	N/A	$>$24 hours
SimMat ($k=10^3$)	N/A	N/A	$>$24 hours
FORank ($k=10^2$)	6.77 (±0.002) sec.	7.45 (±0.003) sec.	—
FORank ($k=10^3$)	8.68 (±0.003) sec.	9.03 (±0.004) sec.	—

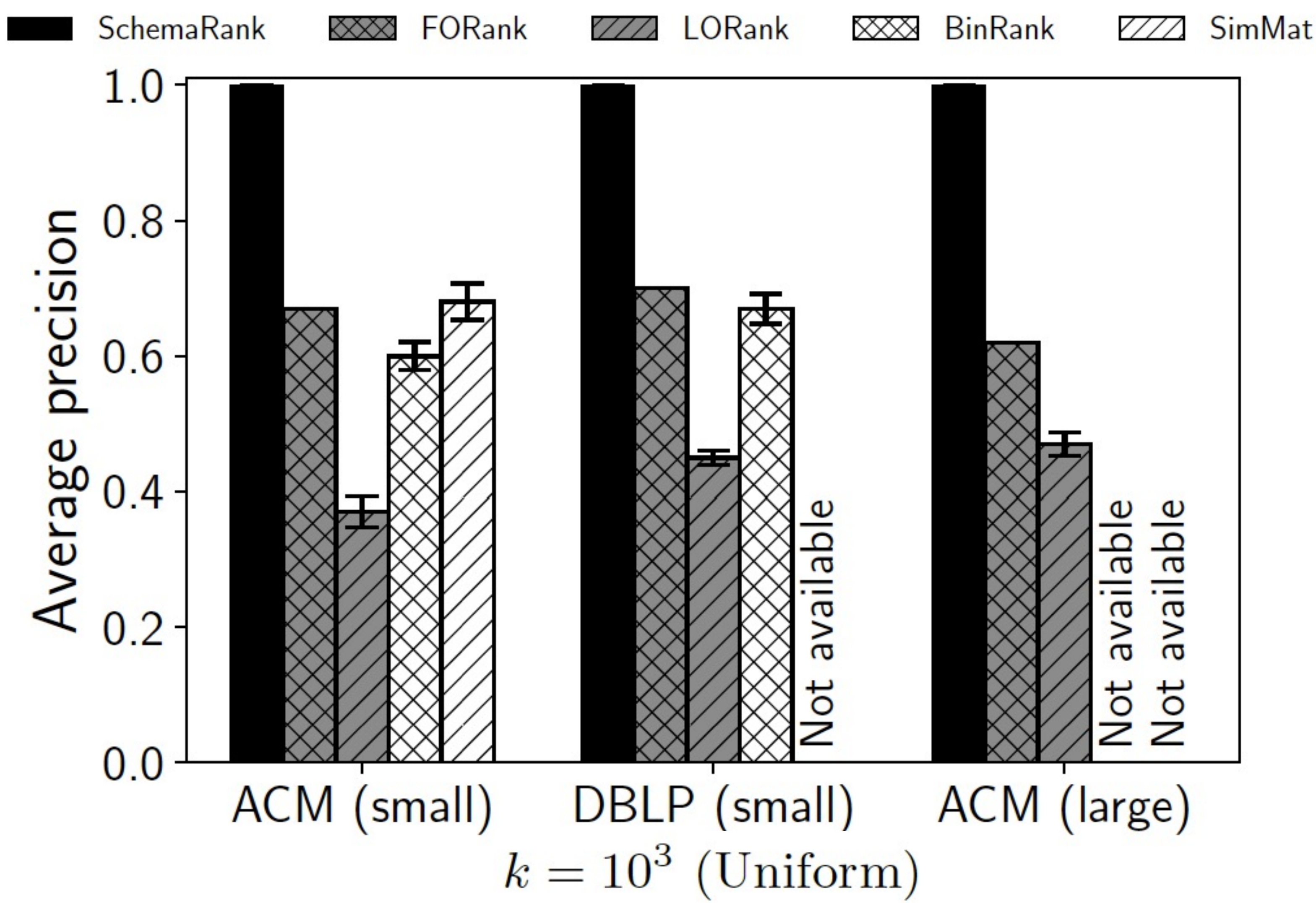
(d) DBLP (large)

Methods	Skewed	Uniform	Pre-comp.
SchemaRank ($k=10^2$)	**134** (±0.195) **sec.**	**169** (±0.106) **sec.**	—
SchemaRank ($k=10^3$)	**168** (±0.173) **sec.**	**241** (±0.122) **sec.**	—
ObjectRank	$>$24 hours	$>$24 hours	—
BinRank	N/A	N/A	$>$24 hours
LORank	$>$24 hours	$>$24 hours	—
SimMat ($k=10^2$)	N/A	N/A	$>$24 hours
SimMat ($k=10^3$)	N/A	N/A	$>$24 hours
FORank ($k=10^2$)	2,209 (±1.908) sec.	2,677 (±1.966) sec.	—
FORank ($k=10^3$)	2,431 (±1.912) sec.	3,137 (±1.903) sec.	—

How CR Effectively Works?



Average Precision (Top-K)



Summary

- **Research Question**
  - How can we efficiently compute ObjectRank without sacrificing the top-k search quality on large knowledge databases?
- **Proposed method: *SchemaRank***
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- **Contributions**
  - **Efficient:** Up to 644.7 times faster than SOTAs.
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