Graph databases:
Where theory meets pactice

Gabor Szarnyas

Simonyi Conference 2025

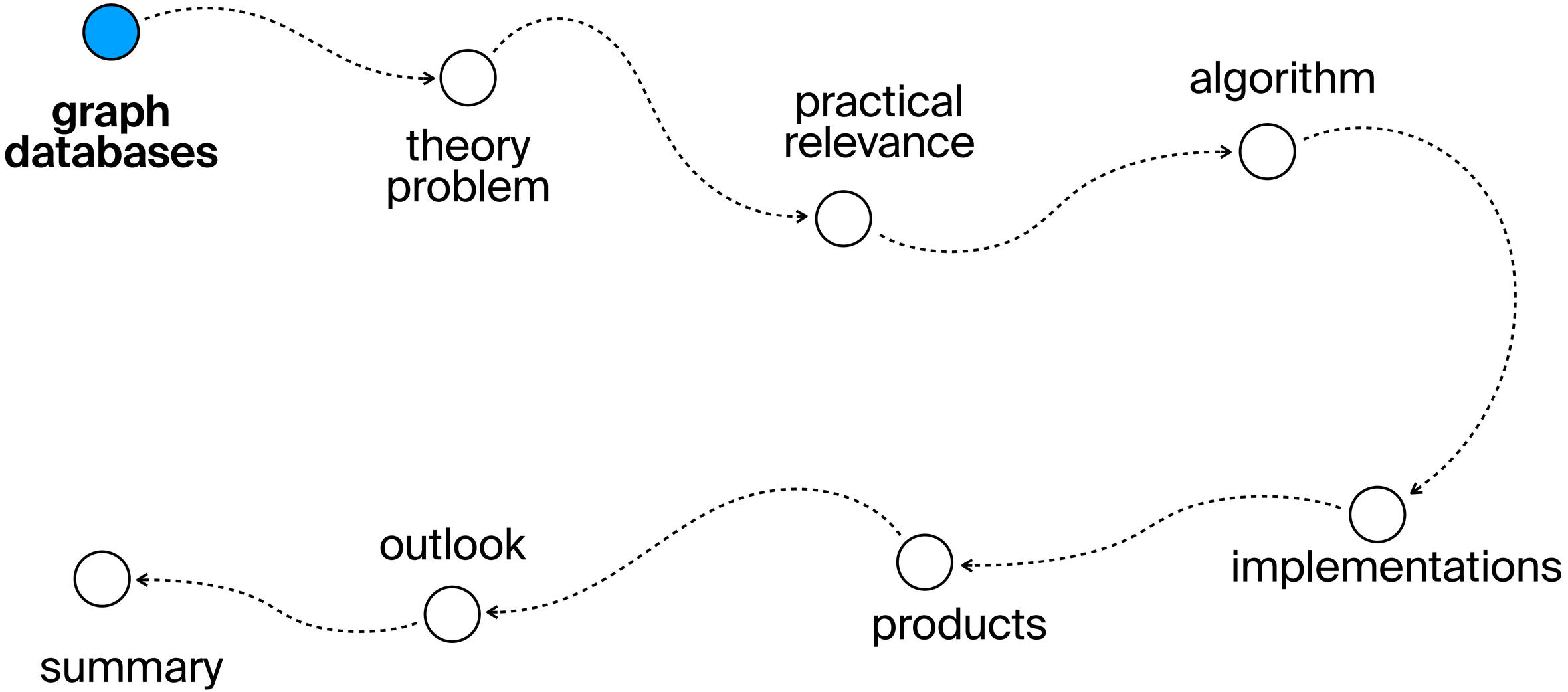
My career in databases

ftsrg

CWI

DuckDB Labs

2010 2013 2020 2023


graph databases
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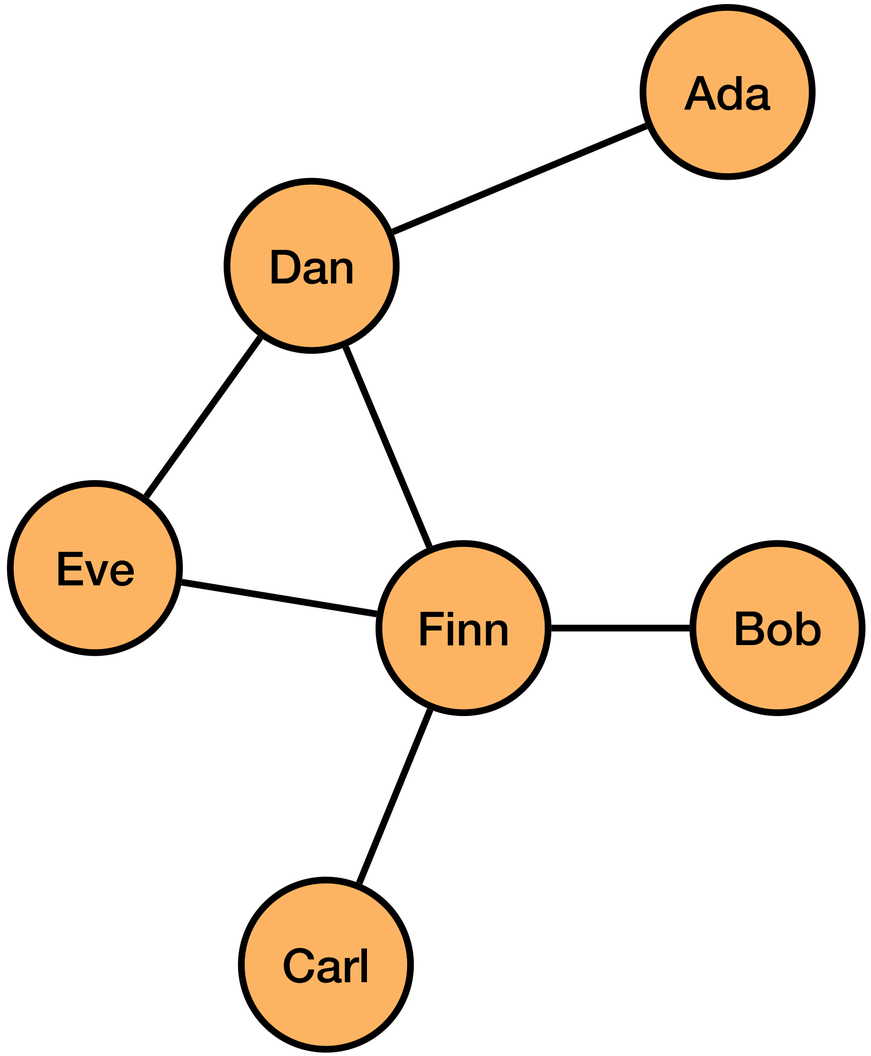
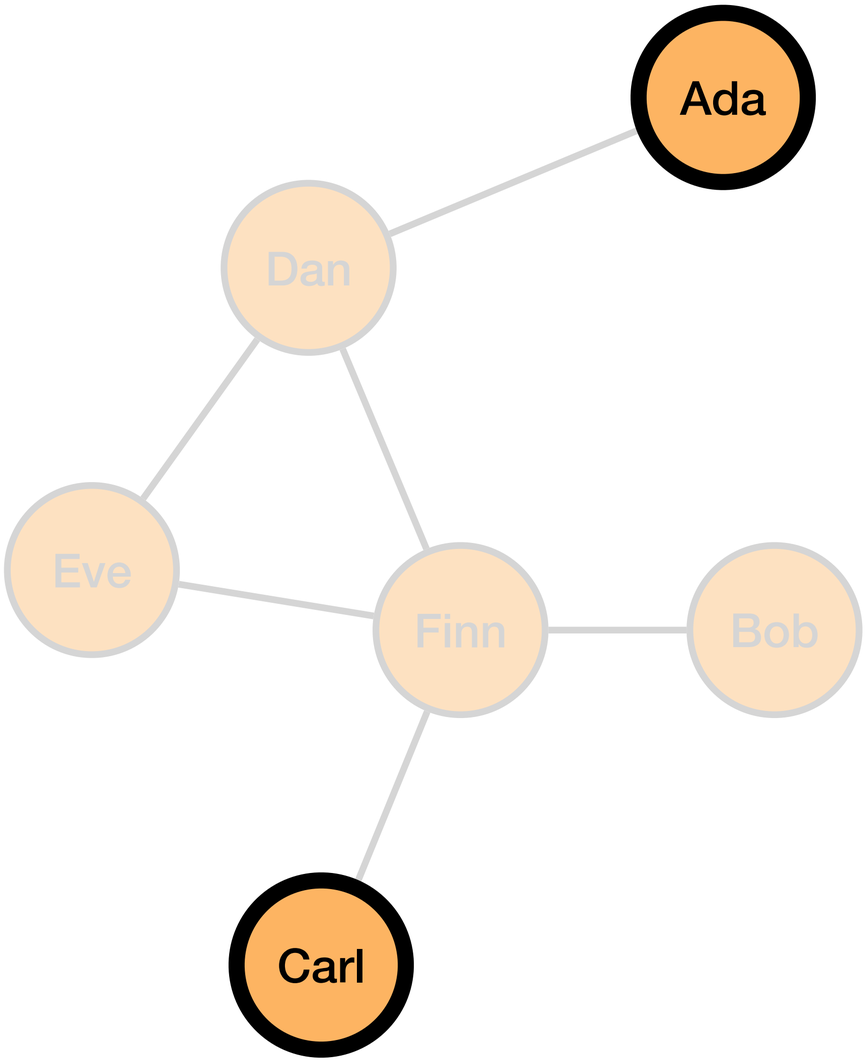


graph

$$G = (V, E)$$

path finding

q: shortest path between two nodes
BFS (breadth-first search) Dijkstra's algorithm



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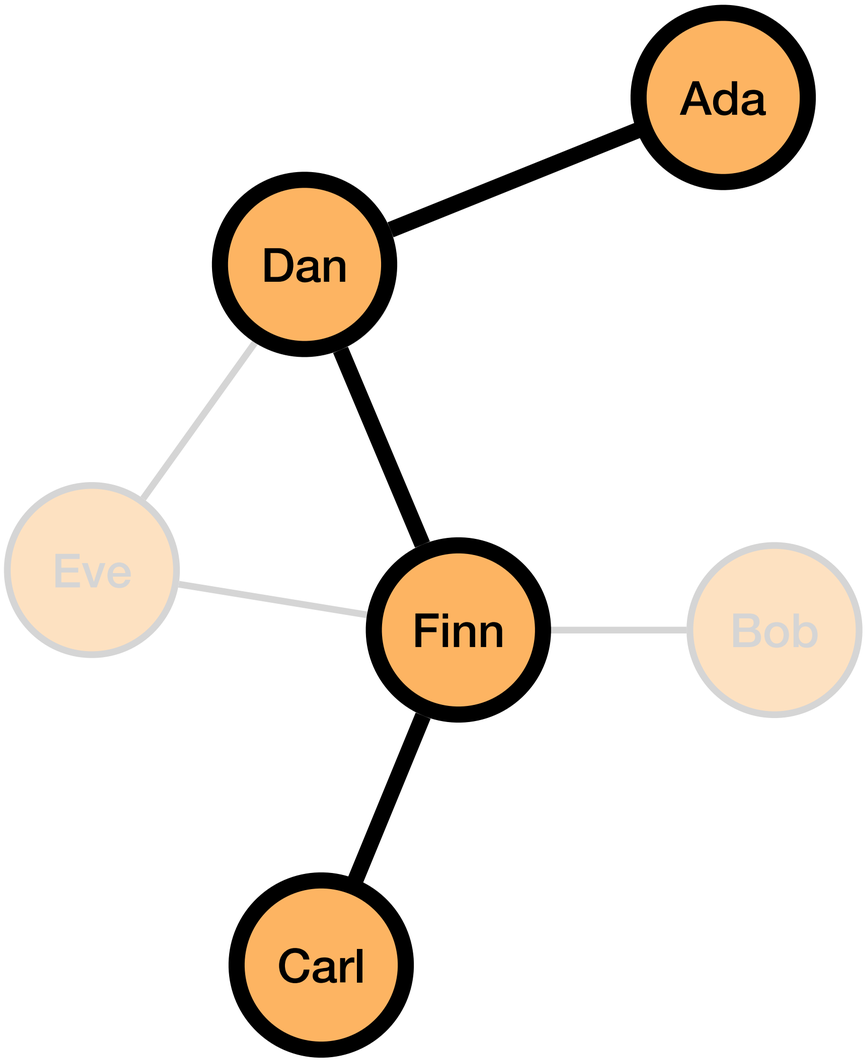

path finding

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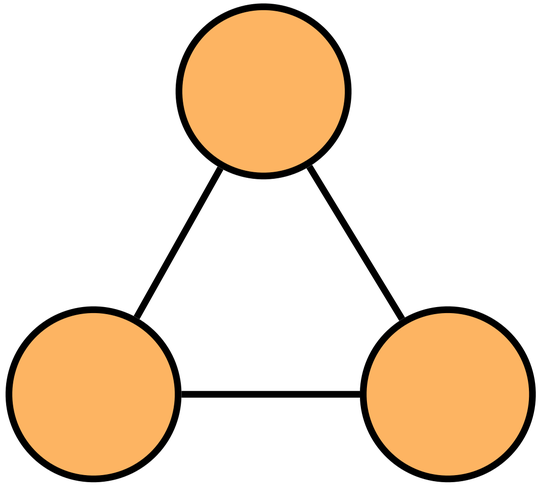
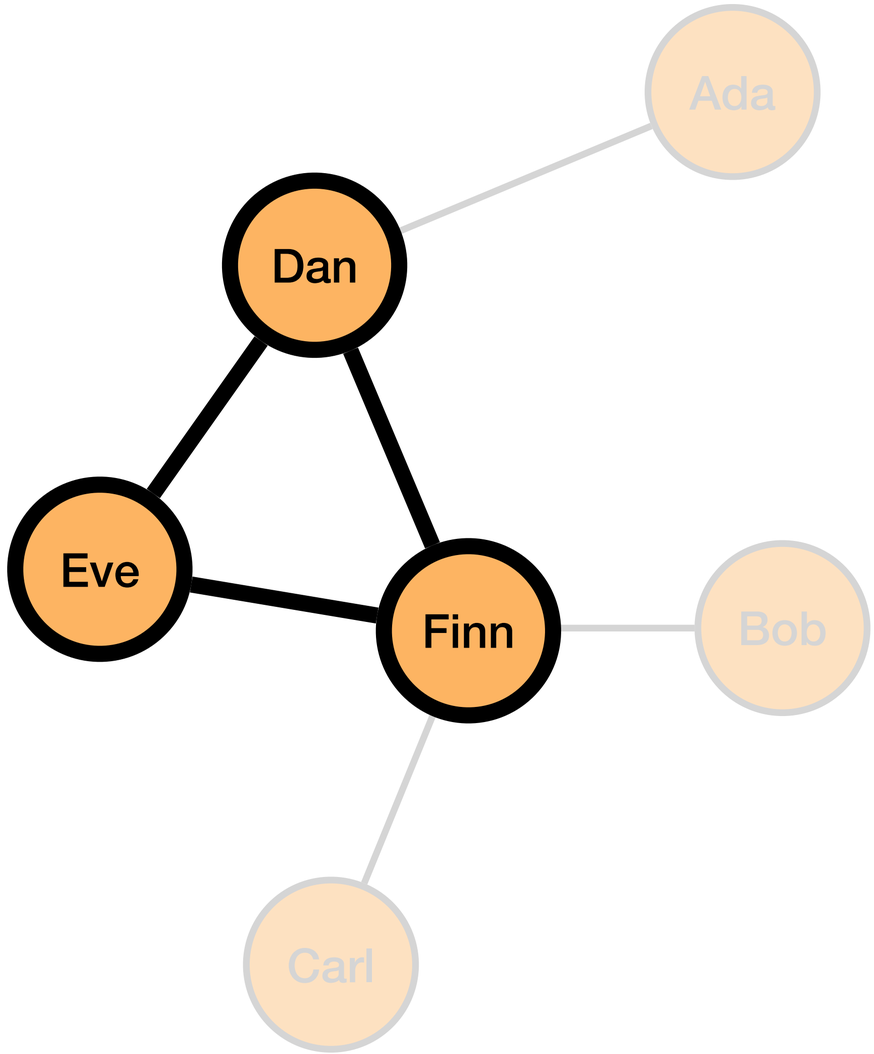
BFS (breadth-first search) Dijkstra's algorithm

graph pattern matching

q: triangle-shaped subgraphs





graph pattern matching

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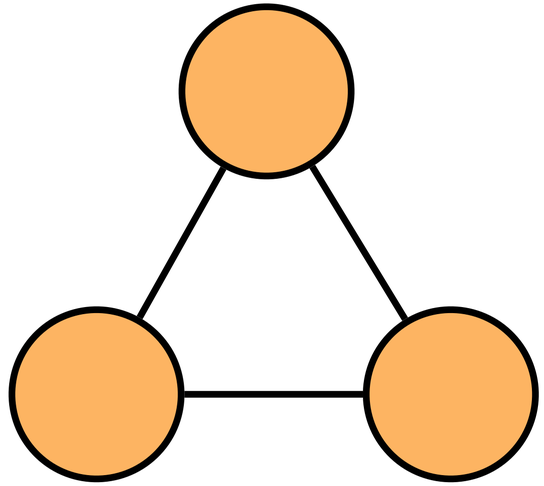
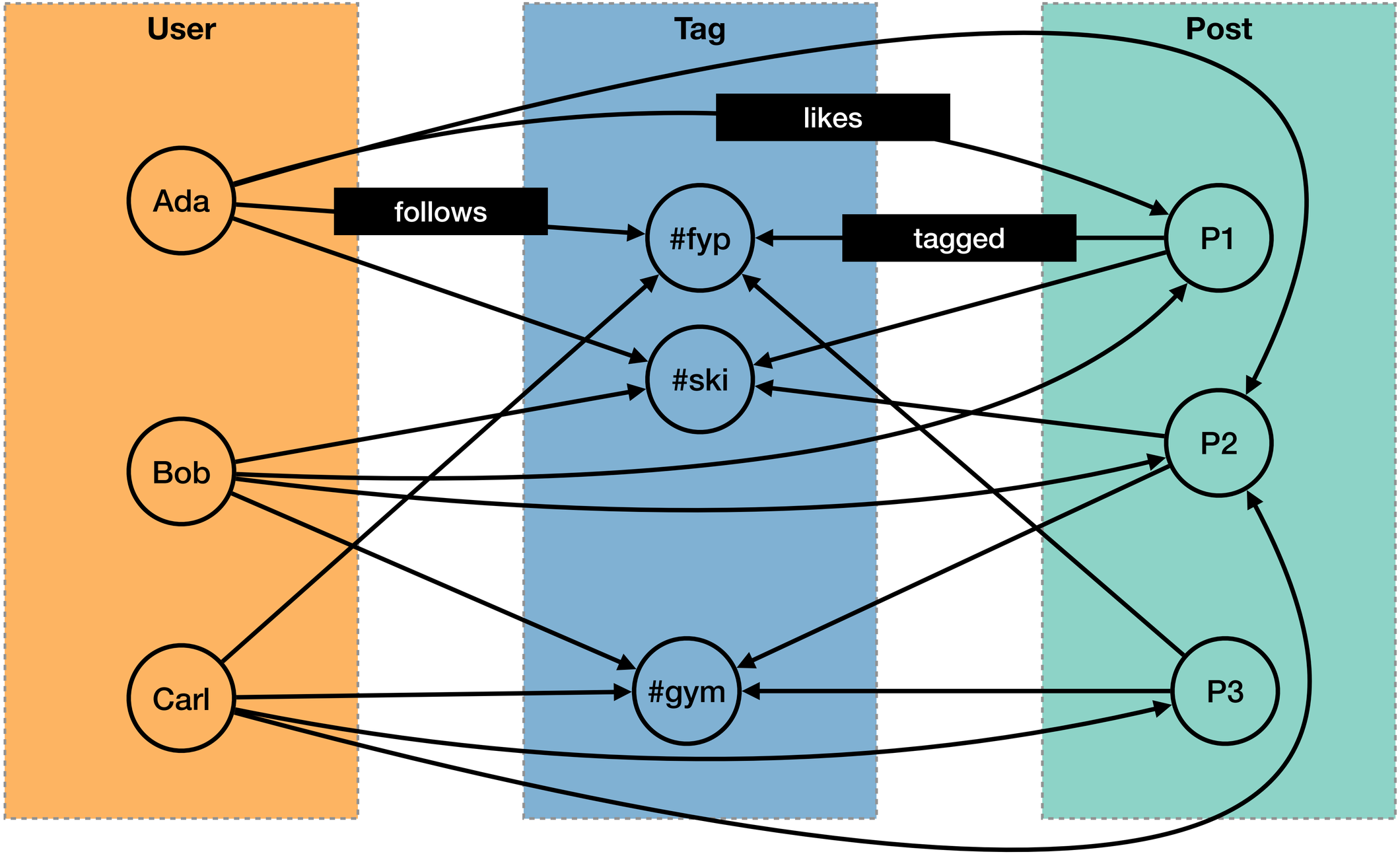
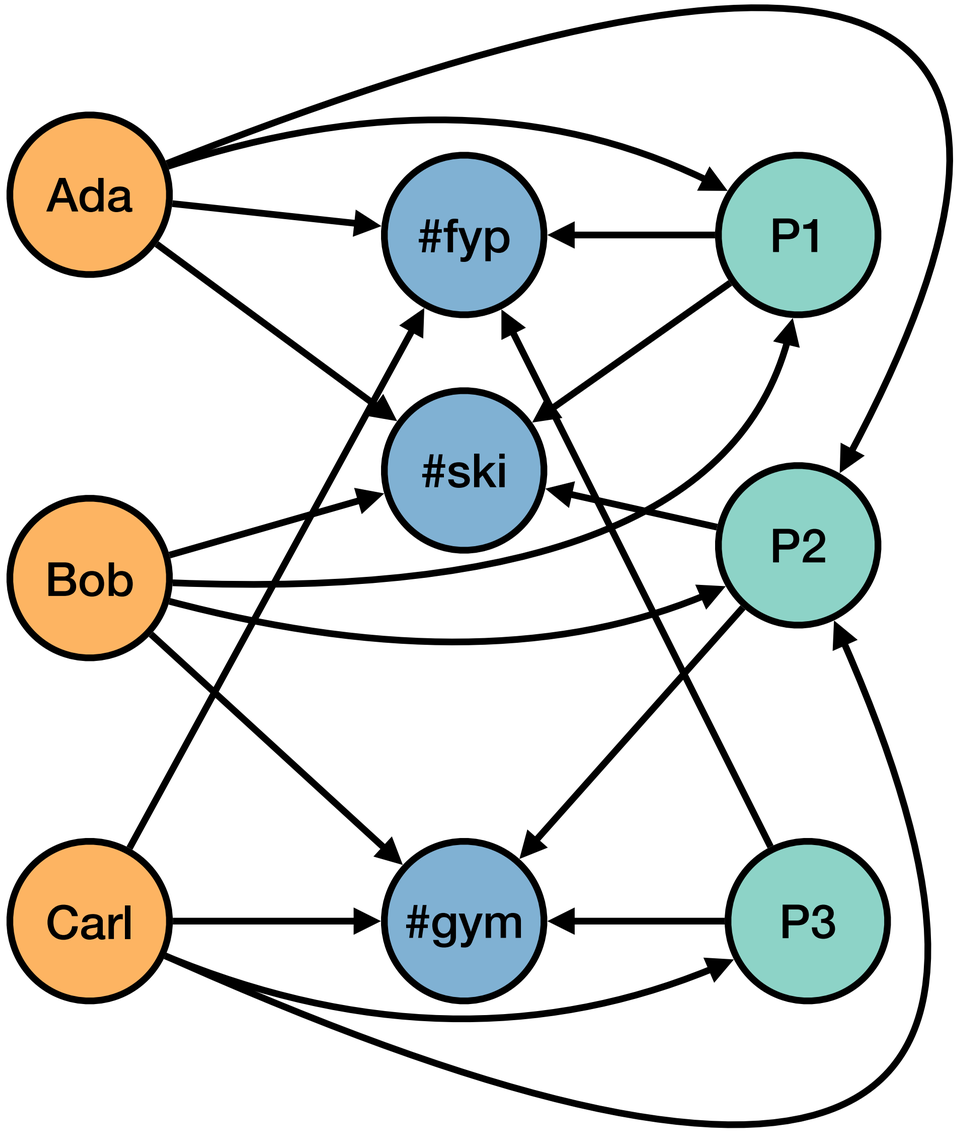


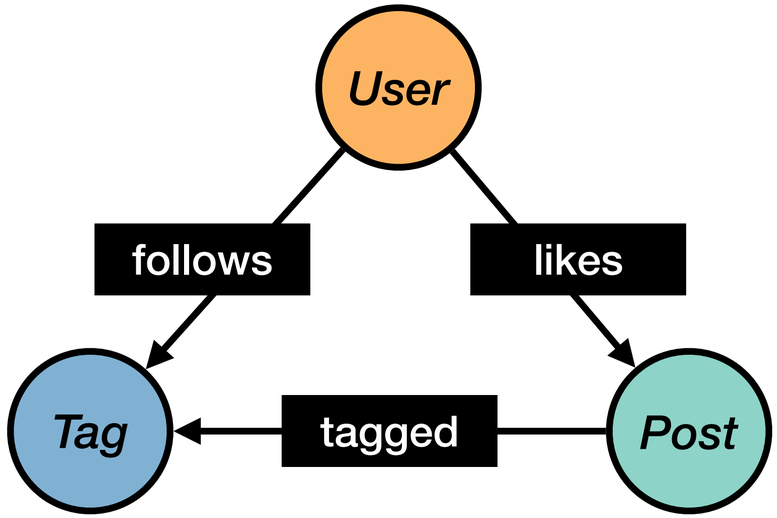
Social network

Social network


User
Tag
Post
likes
Ada
follows
#fyp
tagged
P1
#ski
Bob
P2
Carl
#gym
P3



q: User-Tag-Post triangles



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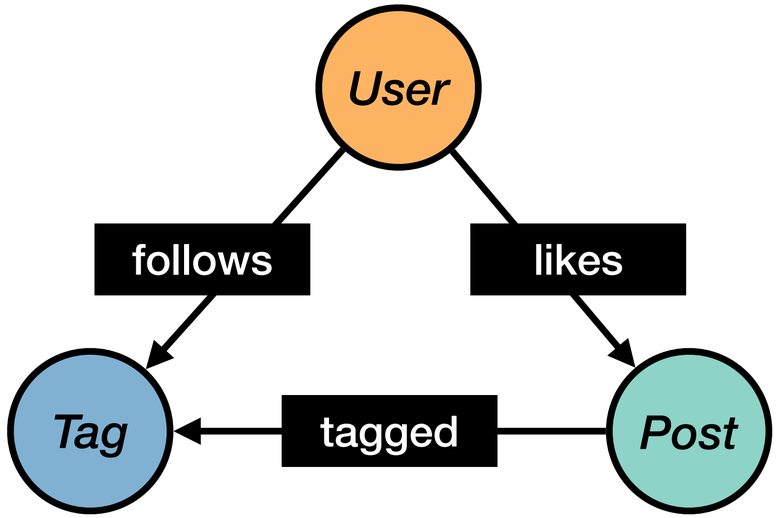

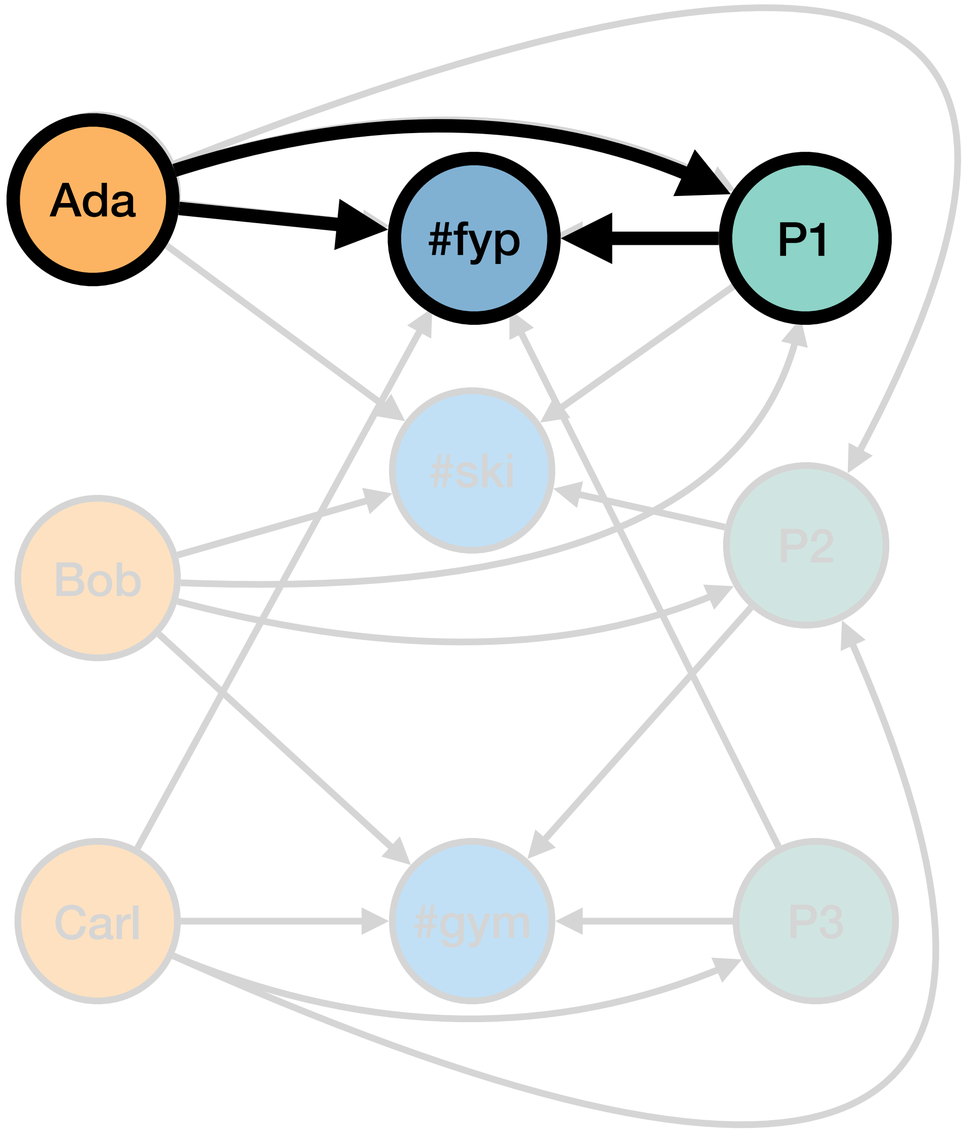

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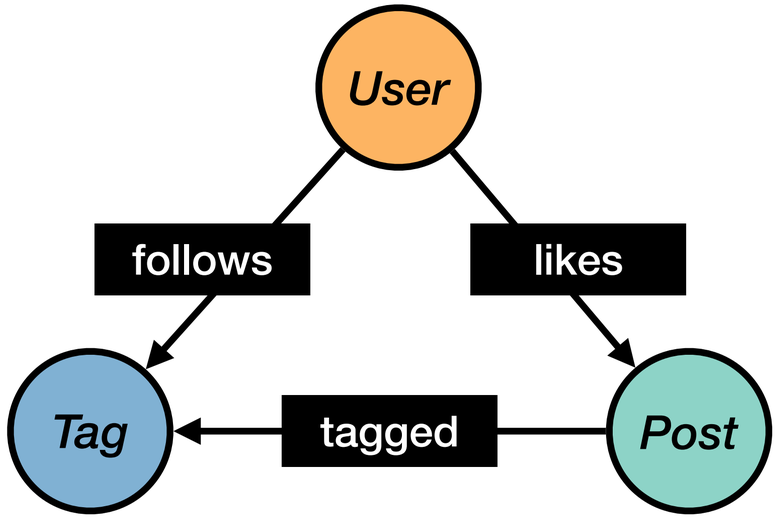

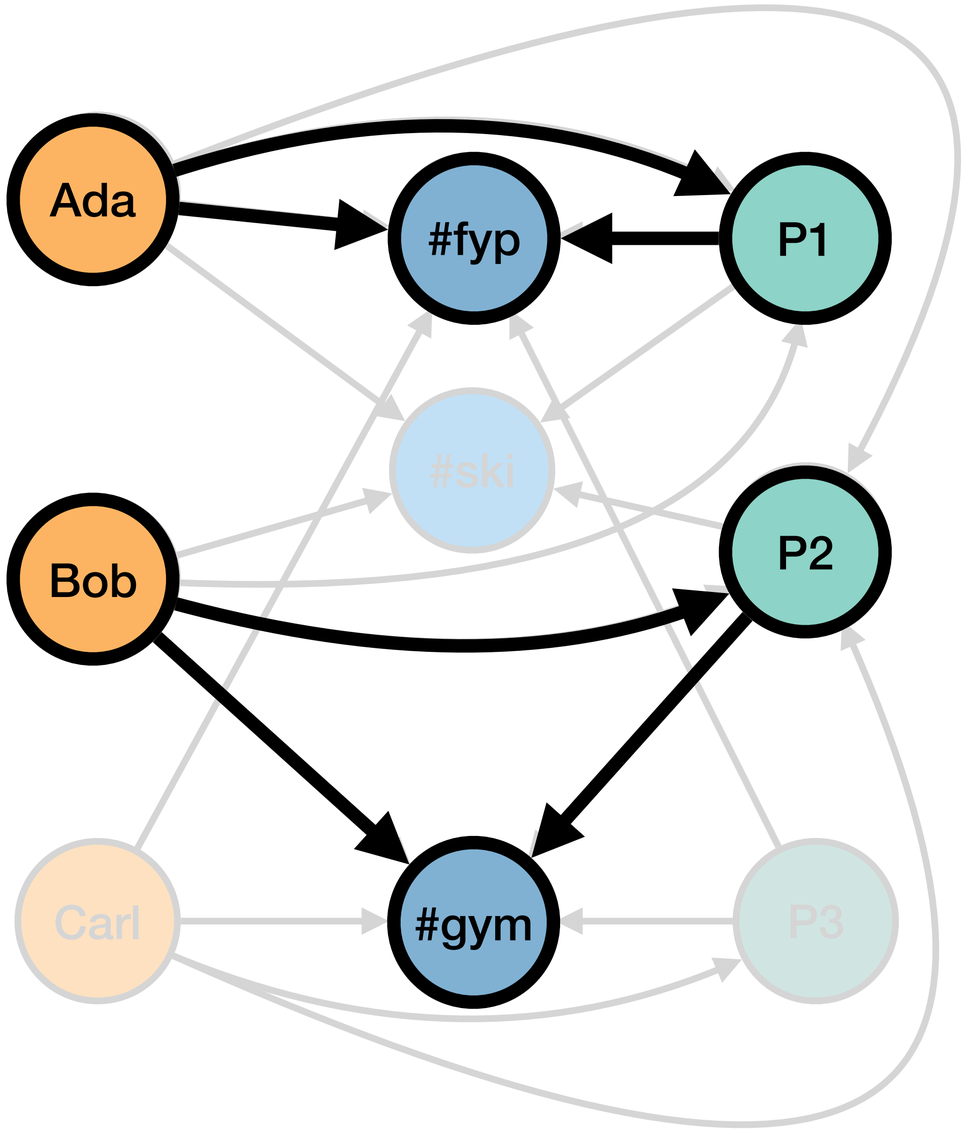

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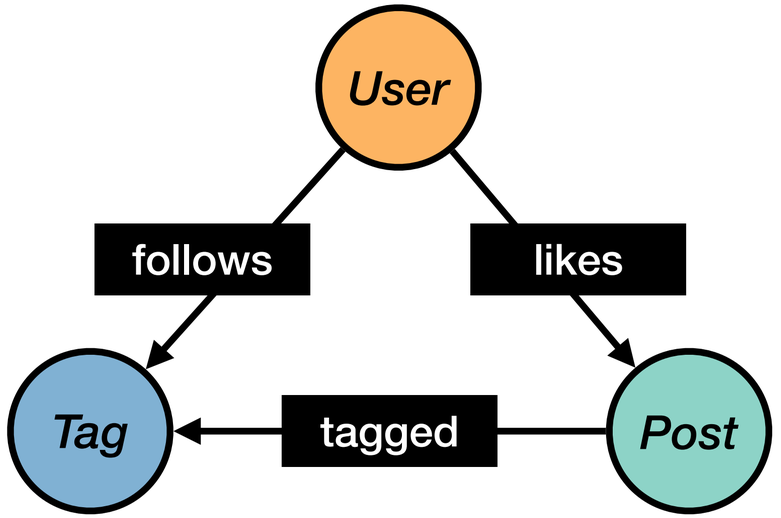

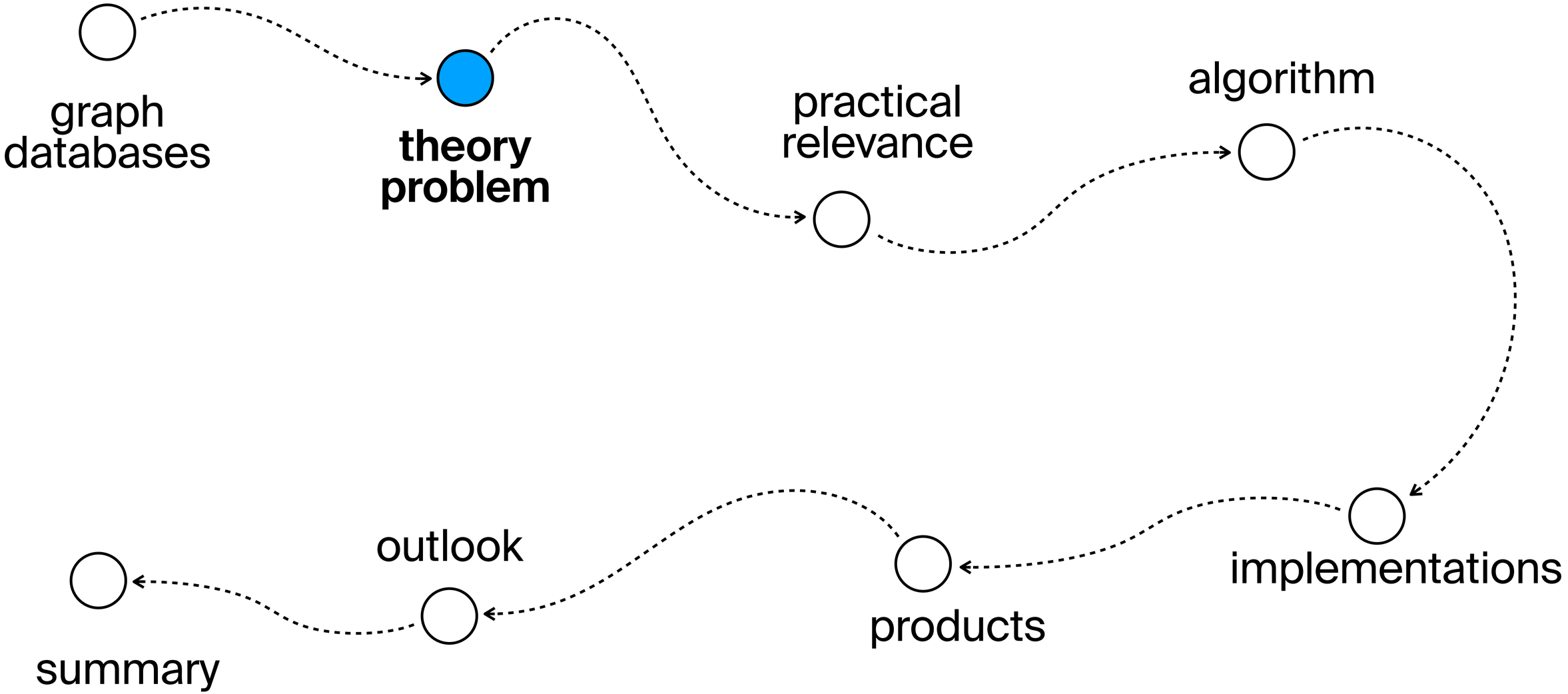
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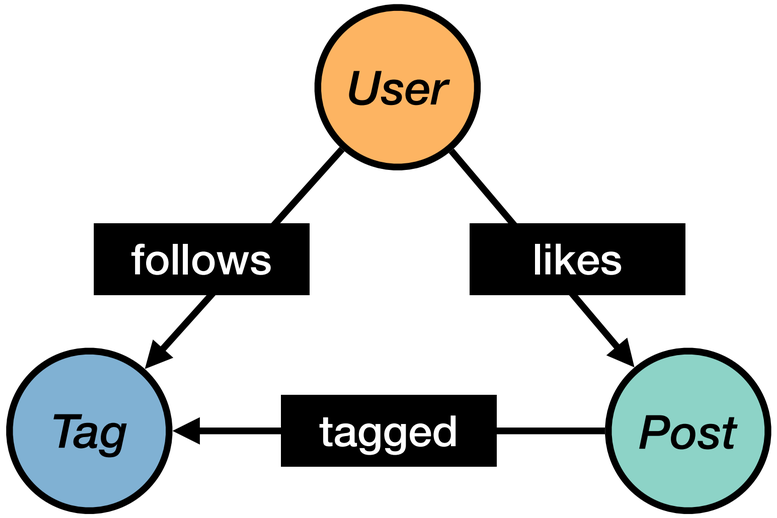


⋈: join

```
SELECT *
FROM follows
NATURAL JOIN tagged
NATURAL JOIN likes;
```

follows

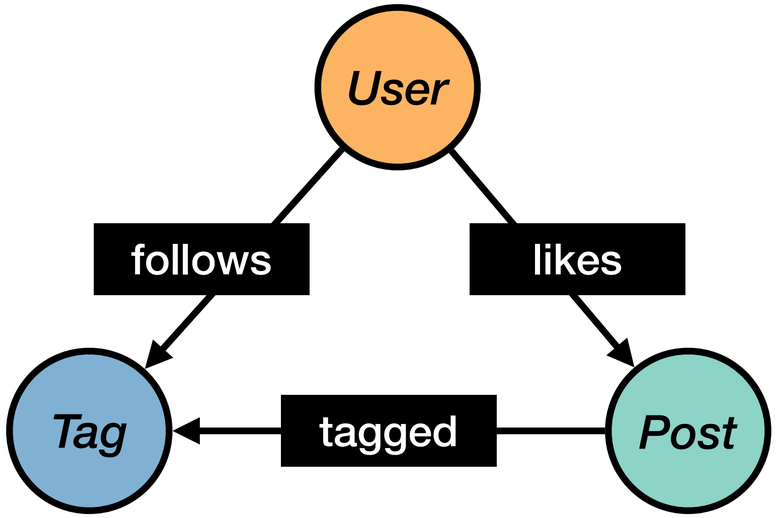
User	Tag
Ada	#fyp
Ada	#ski
Bob	#ski
Bob	#gym
Carl	#fyp
Carl	#gym

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3



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Bob	P2
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follows ⋈ tagged ⋈ likes

User	Tag	Post
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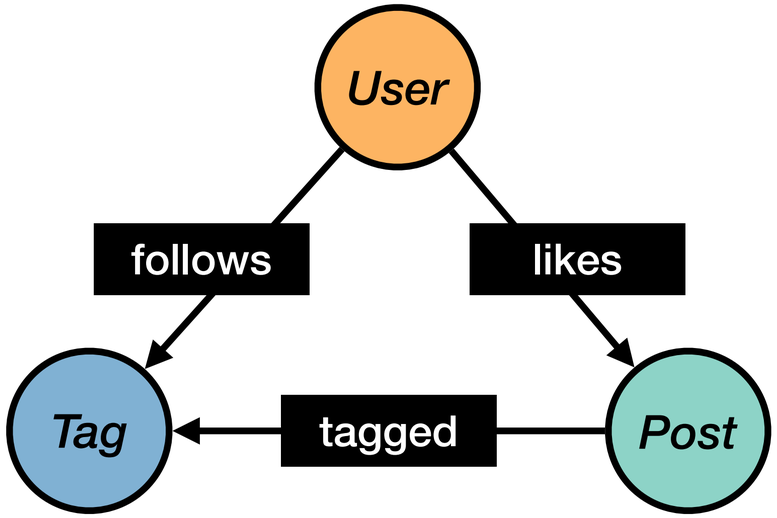
Ada	#fyp	P1
Bob	#ski	P1
Bob	#ski	P2
Bob	#gym	P2
Carl	#fyp	P3
Carl	#gym	P2
Carl	#gym	P3

9▲



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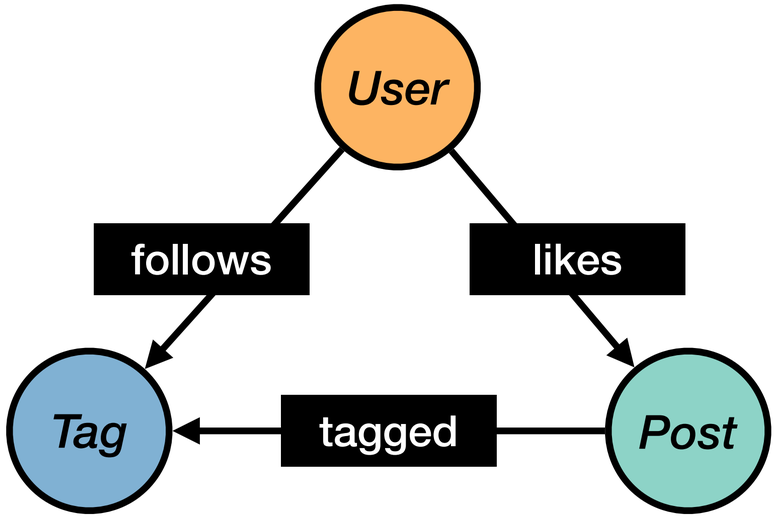
Ada	#fyp	P1
Ada	#fyp	P3
Bob	#ski	P1
Bob	#ski	P2
Bob	#gym	P2
Bob	#gym	P3
Carl	#fyp	P1
Carl	#fyp	P3
Carl	#gym	P2
Carl	#gym	P3

12 rows



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P2	#gym
P3	#gym

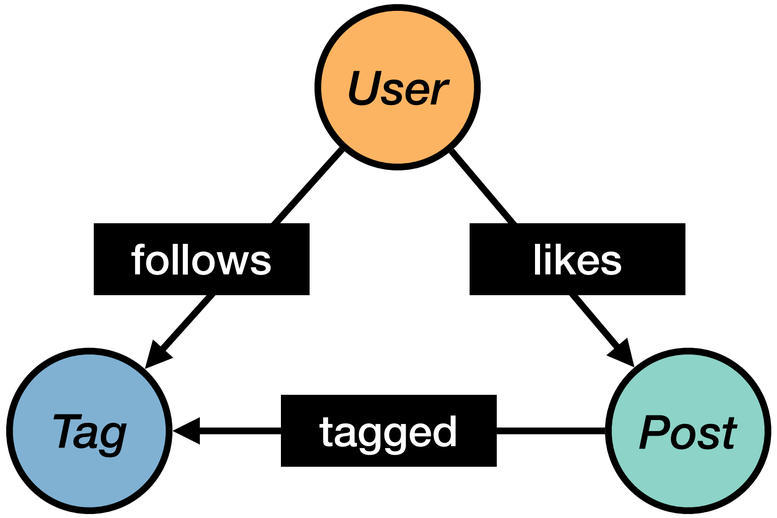
likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

tagged ⋈ likes

Post	Tag	User
P1	#ski	Ada
P1	#ski	Bob
P1	#fyp	Ada
P1	#fyp	Bob
P2	#ski	Ada
P2	#ski	Bob
P2	#ski	Carl
P2	#gym	Ada
P2	#gym	Bob
P2	#gym	Carl
P3	#fyp	Carl
P3	#gym	Carl

12 rows



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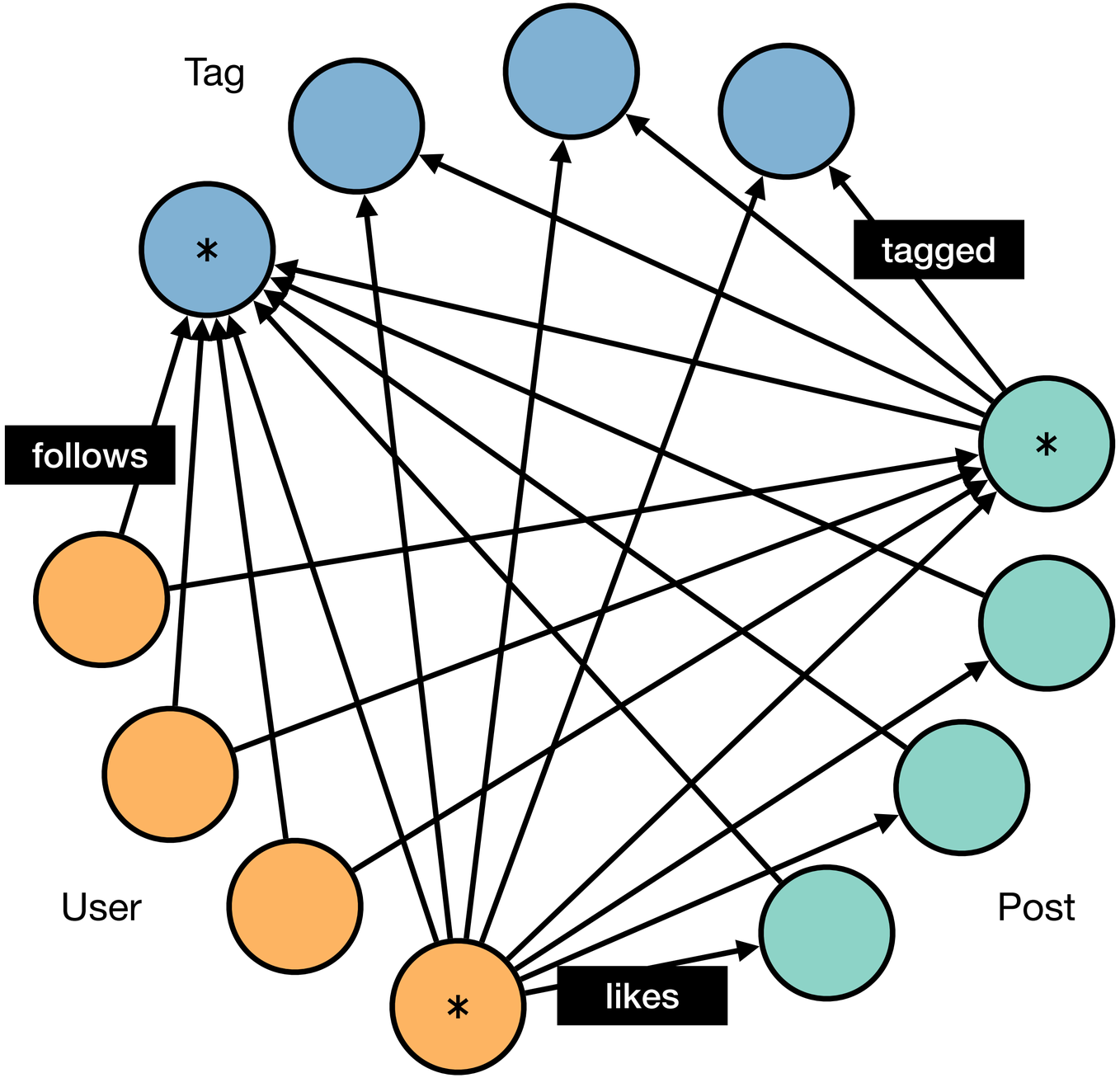
Bob	#gym	P1
Bob	#gym	P2
Carl	#fyp	P2
Carl	#fyp	P3
Carl	#gym	P2
Carl	#gym	P3

12 rows

What's the complexity of the algorithm?

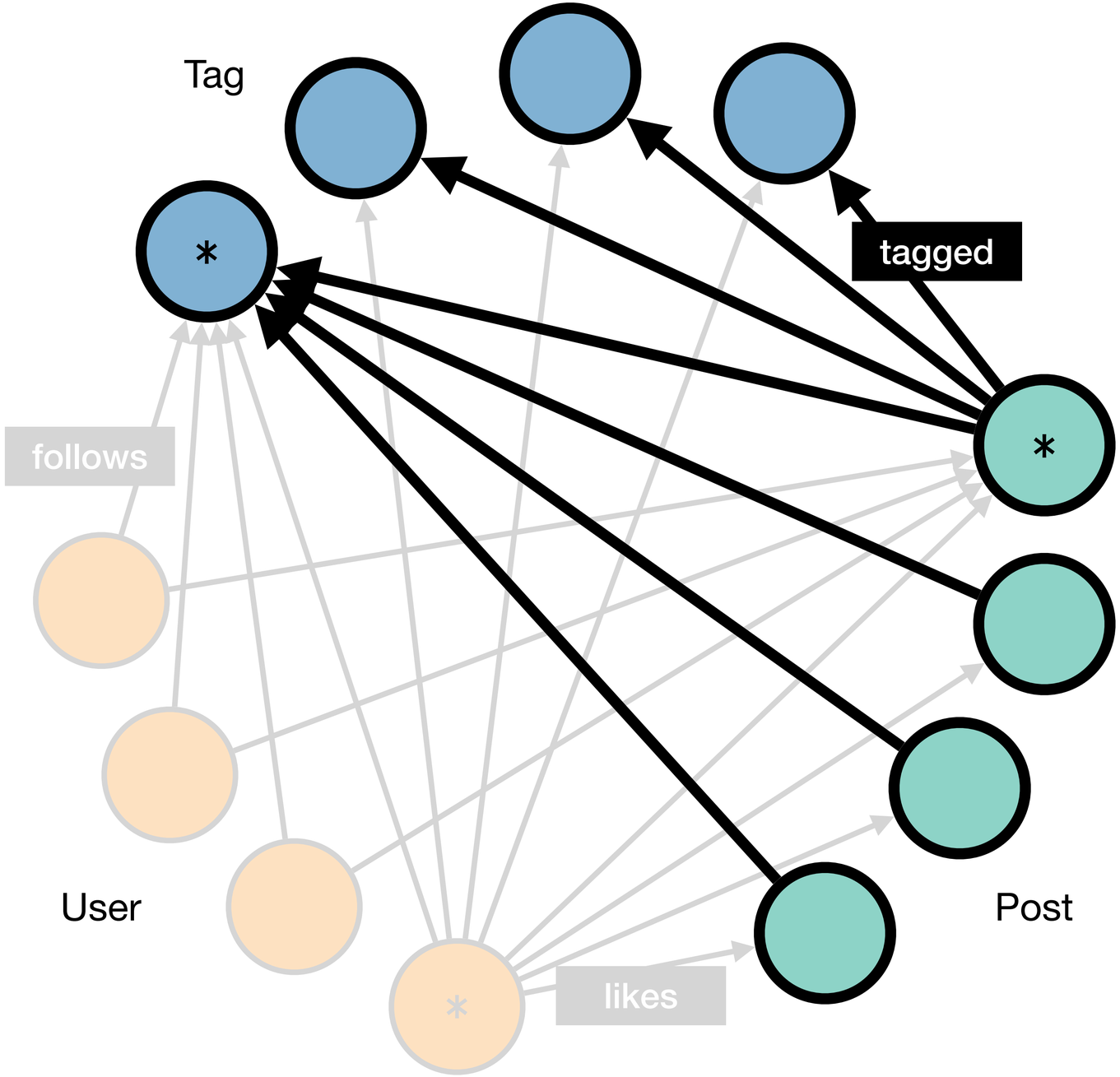
⇒ Let's look at a *worst-case* input

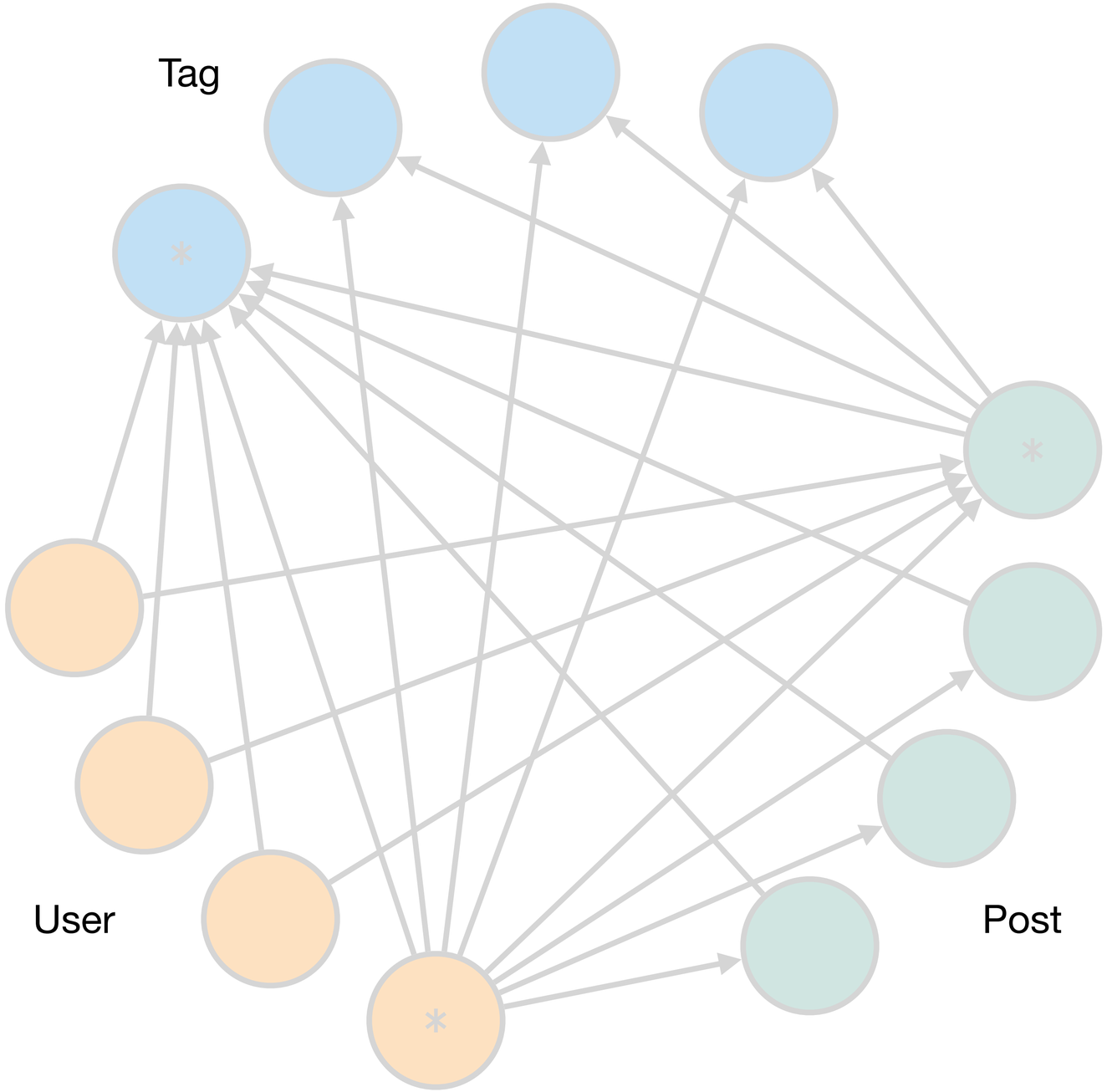


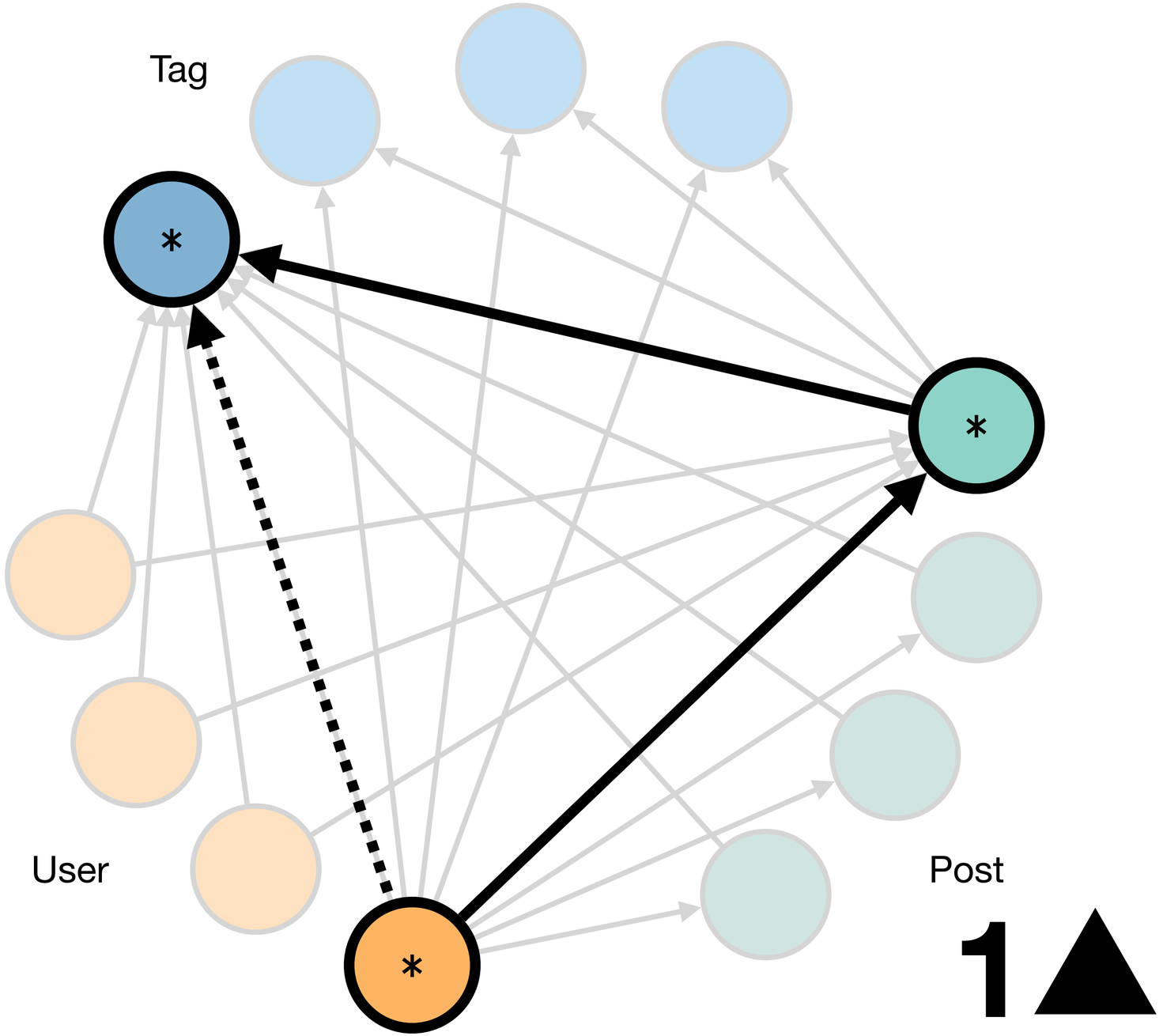
From all three node types, we have 1 distinguished ($*$) and k regular instances.

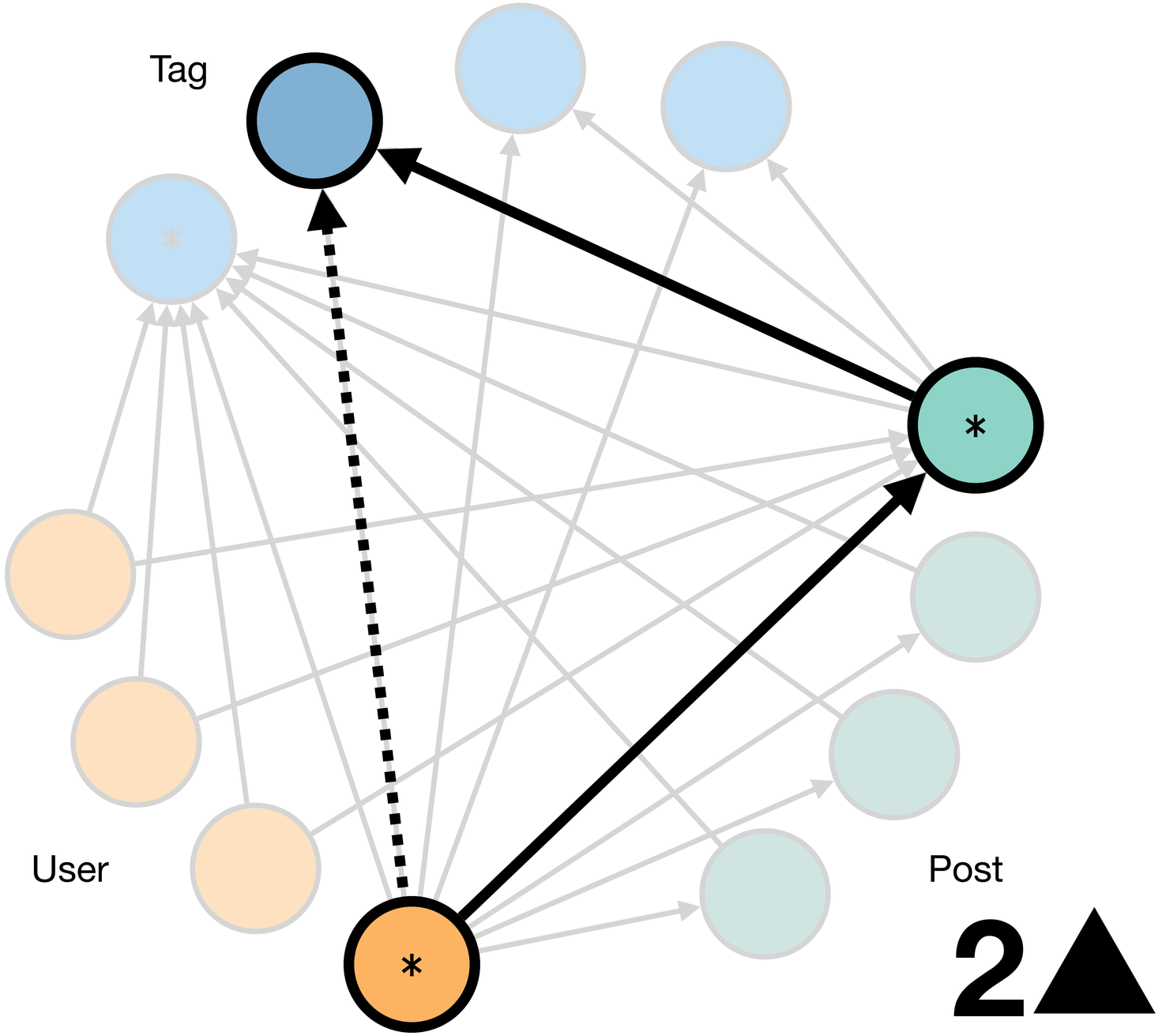
1 distinguished nodes

k regular nodes


Tag
*
tagged
*
follows
User
*
likes
Post


Tag
User
Post


Tag
*
*
User
*
Post
1



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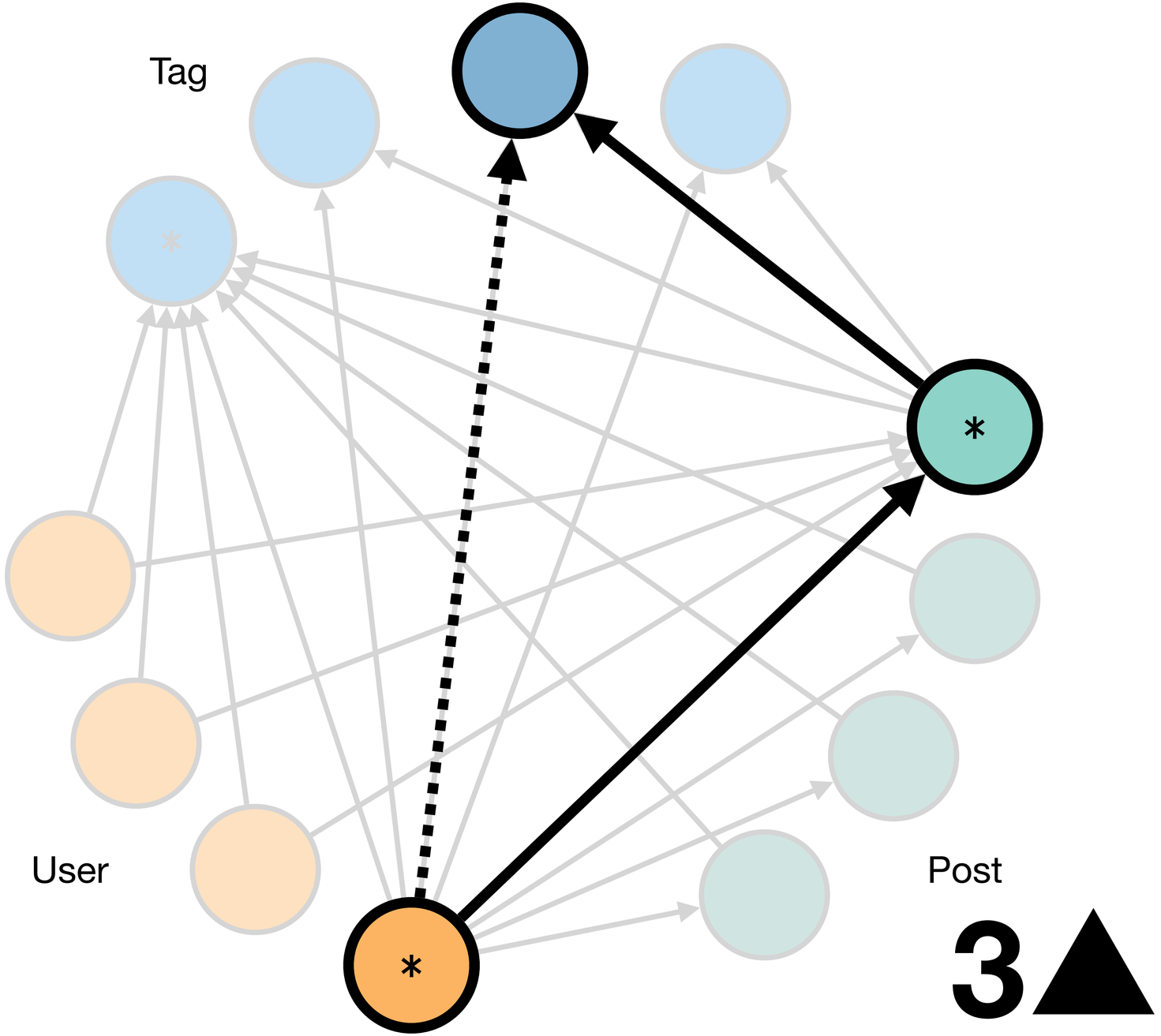
Tag
*
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User
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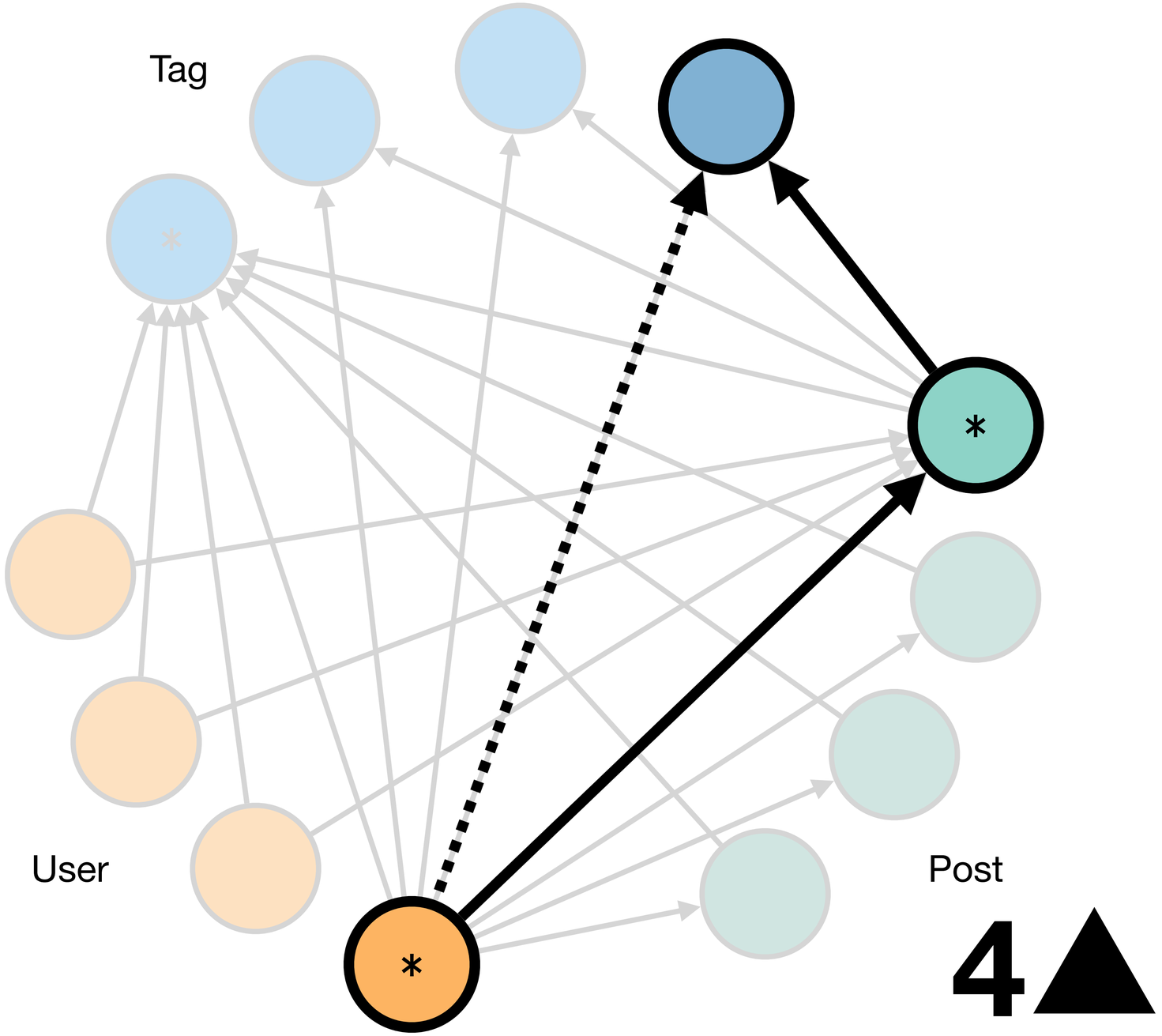
Post
3



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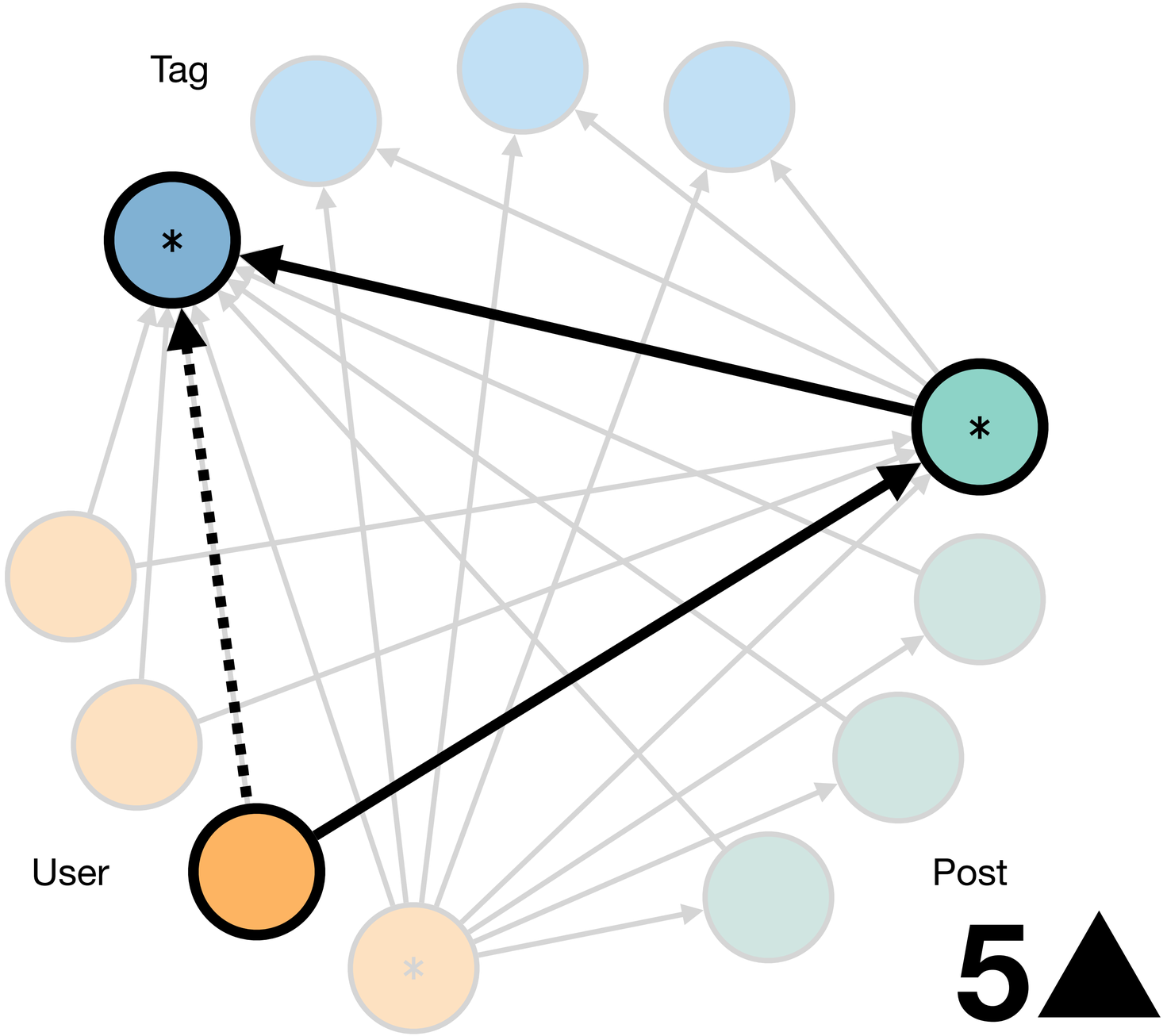

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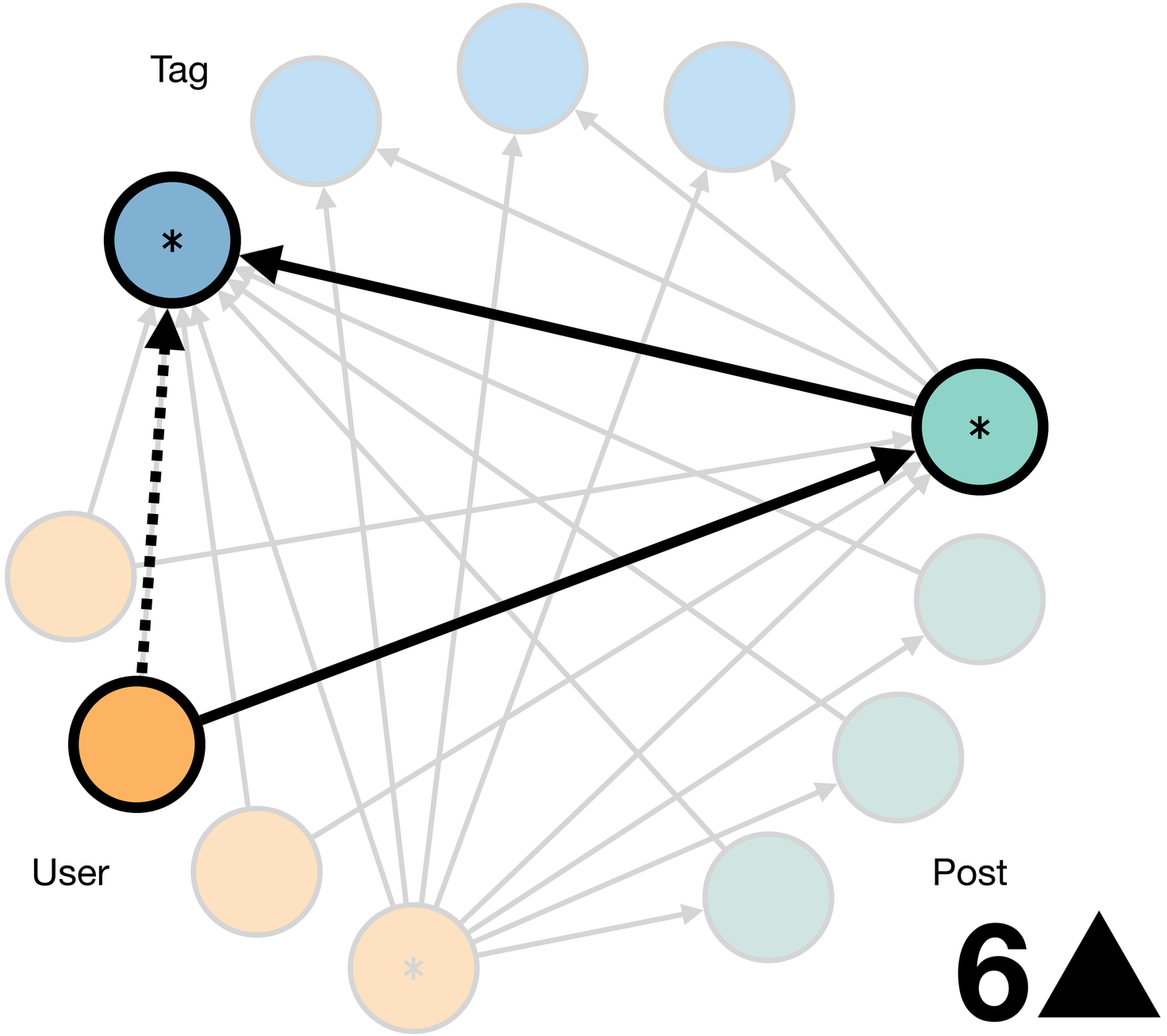

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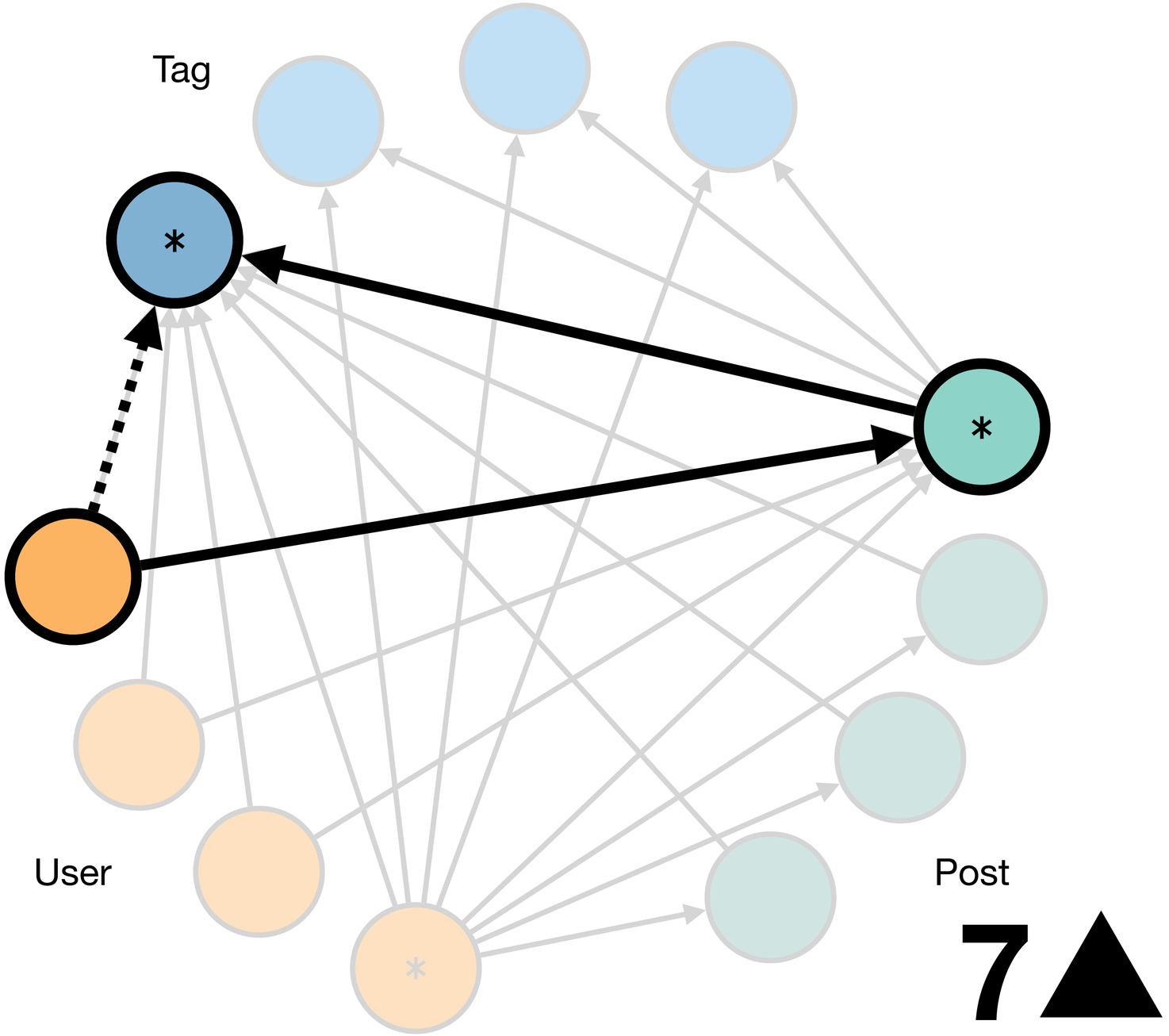

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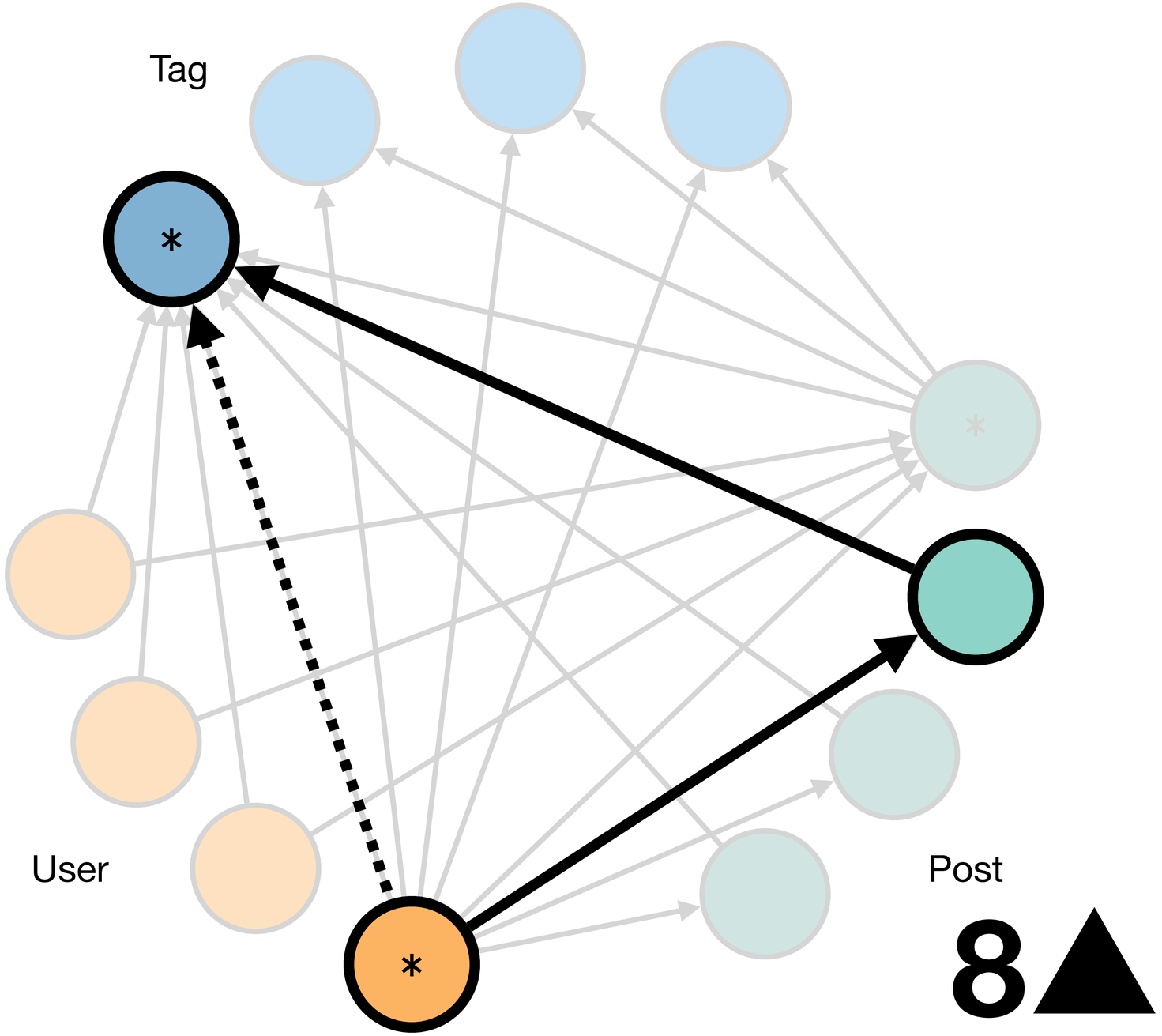

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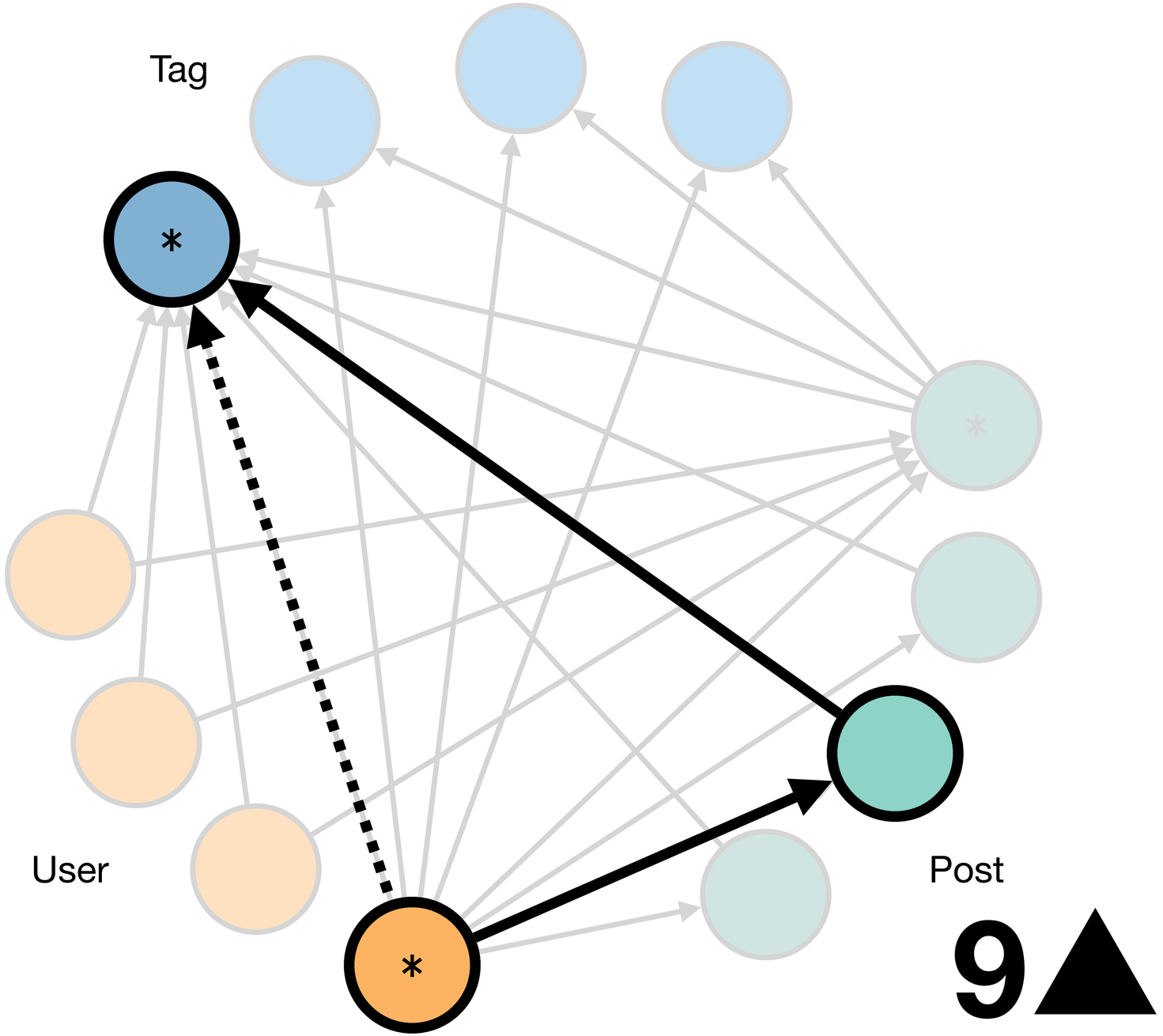
Tag
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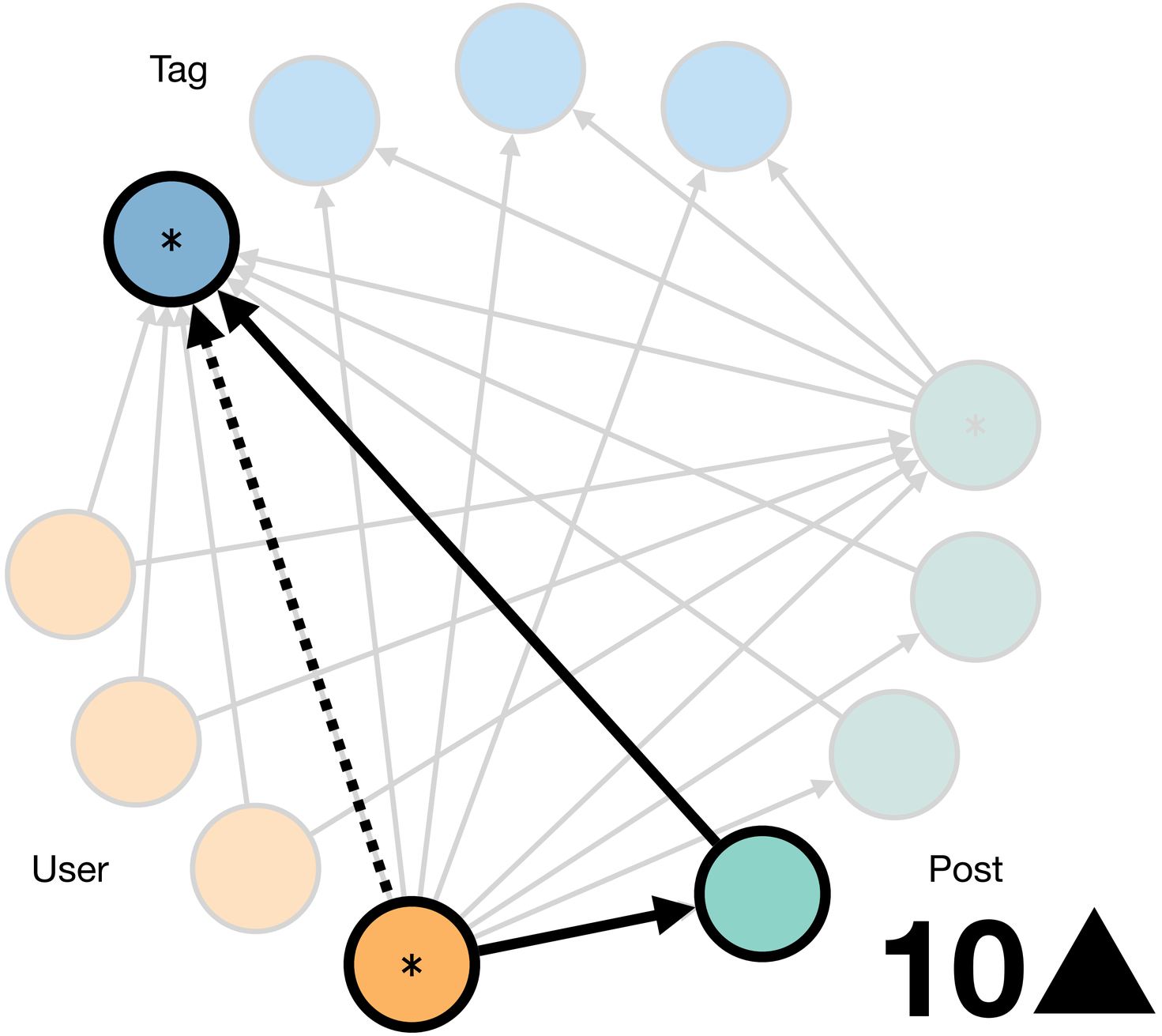
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User
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Post
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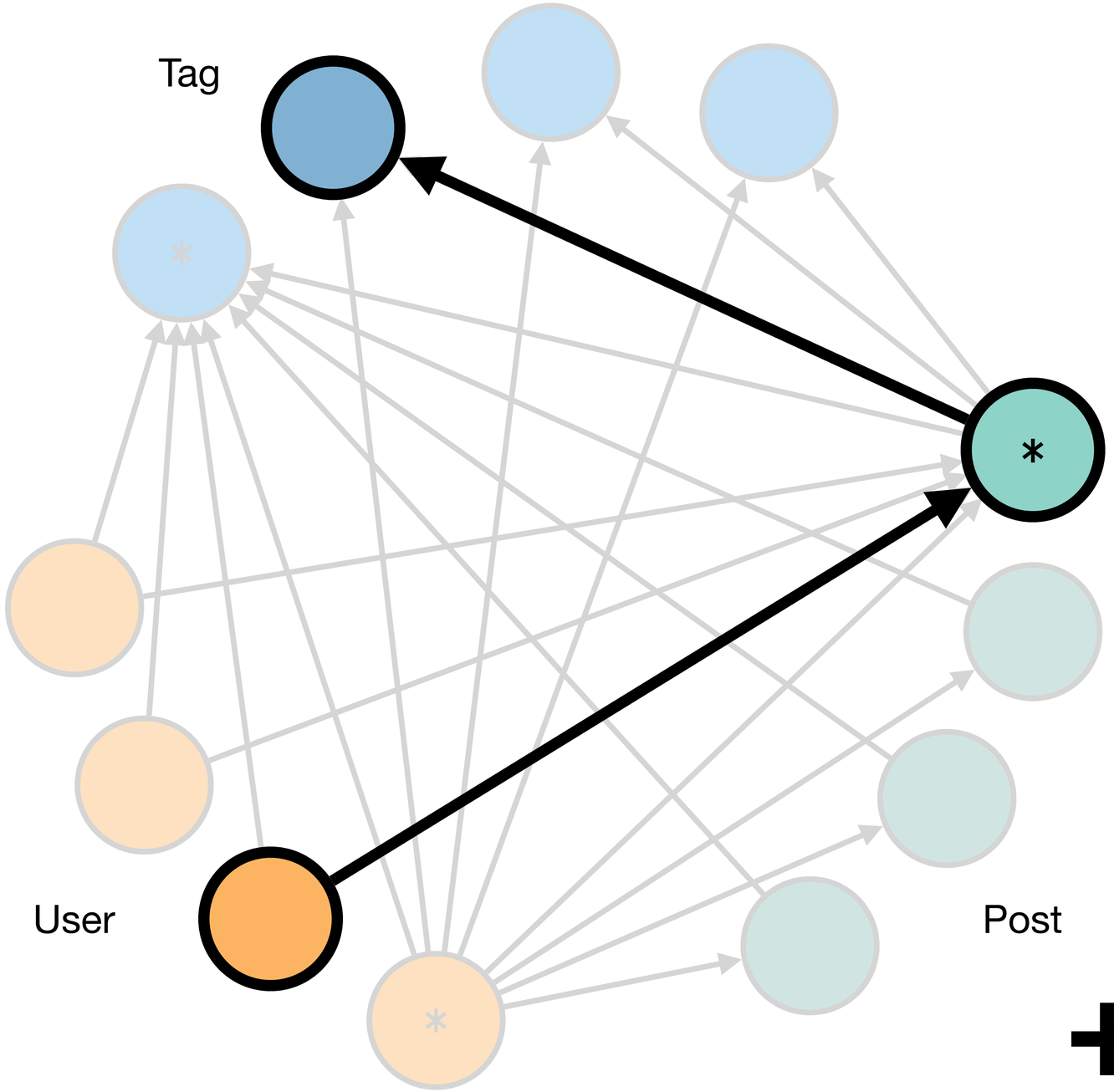

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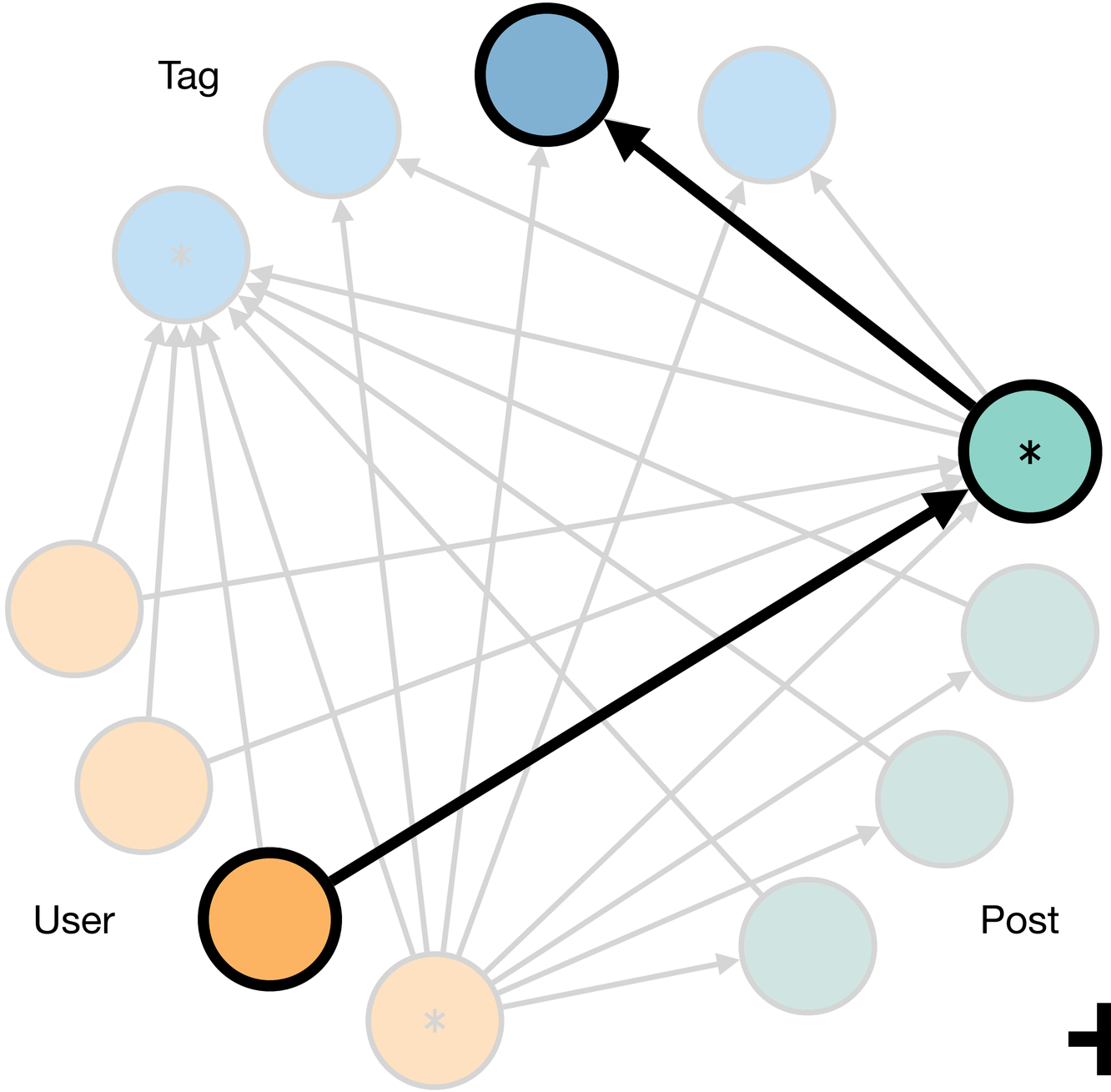

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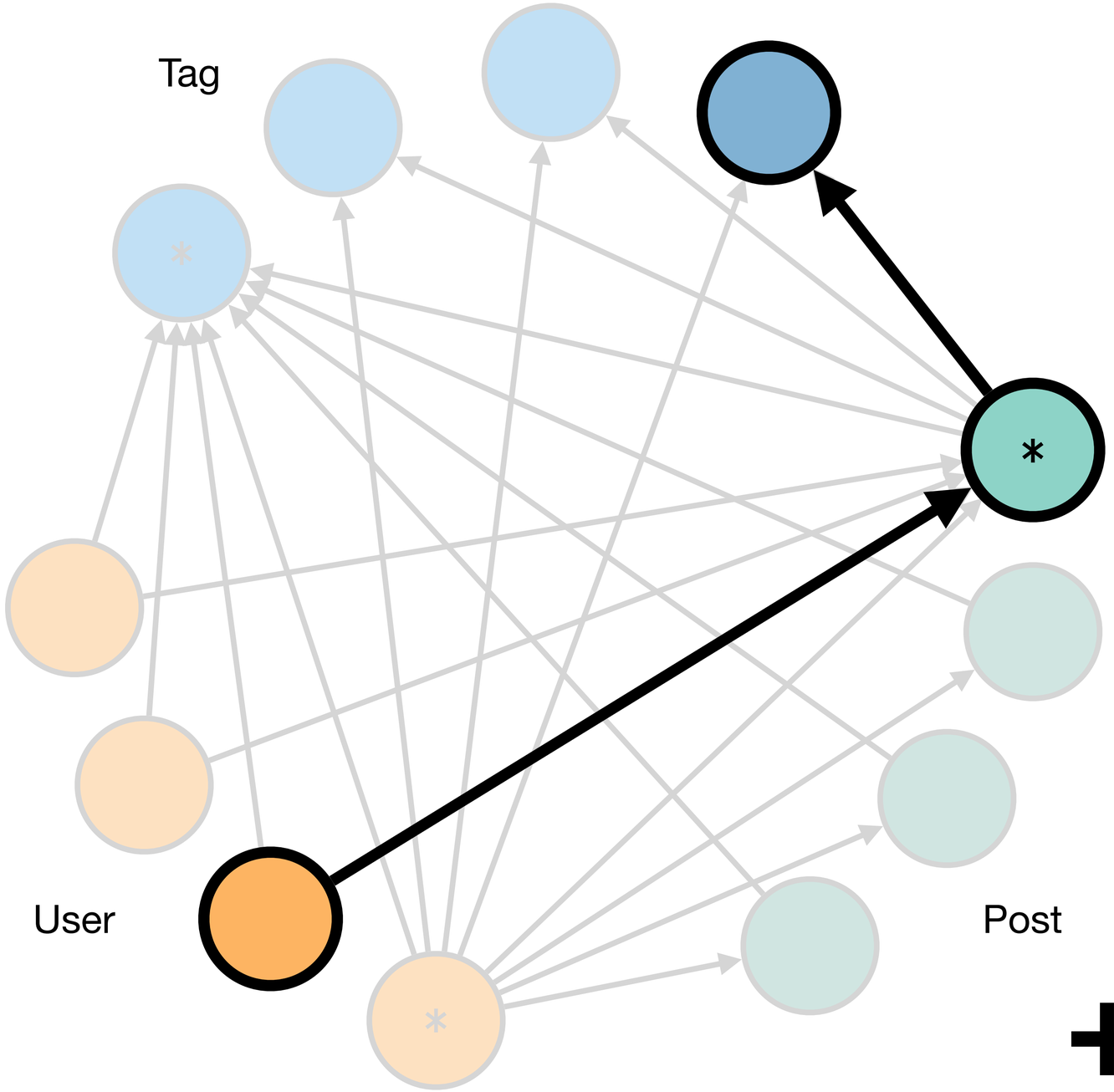

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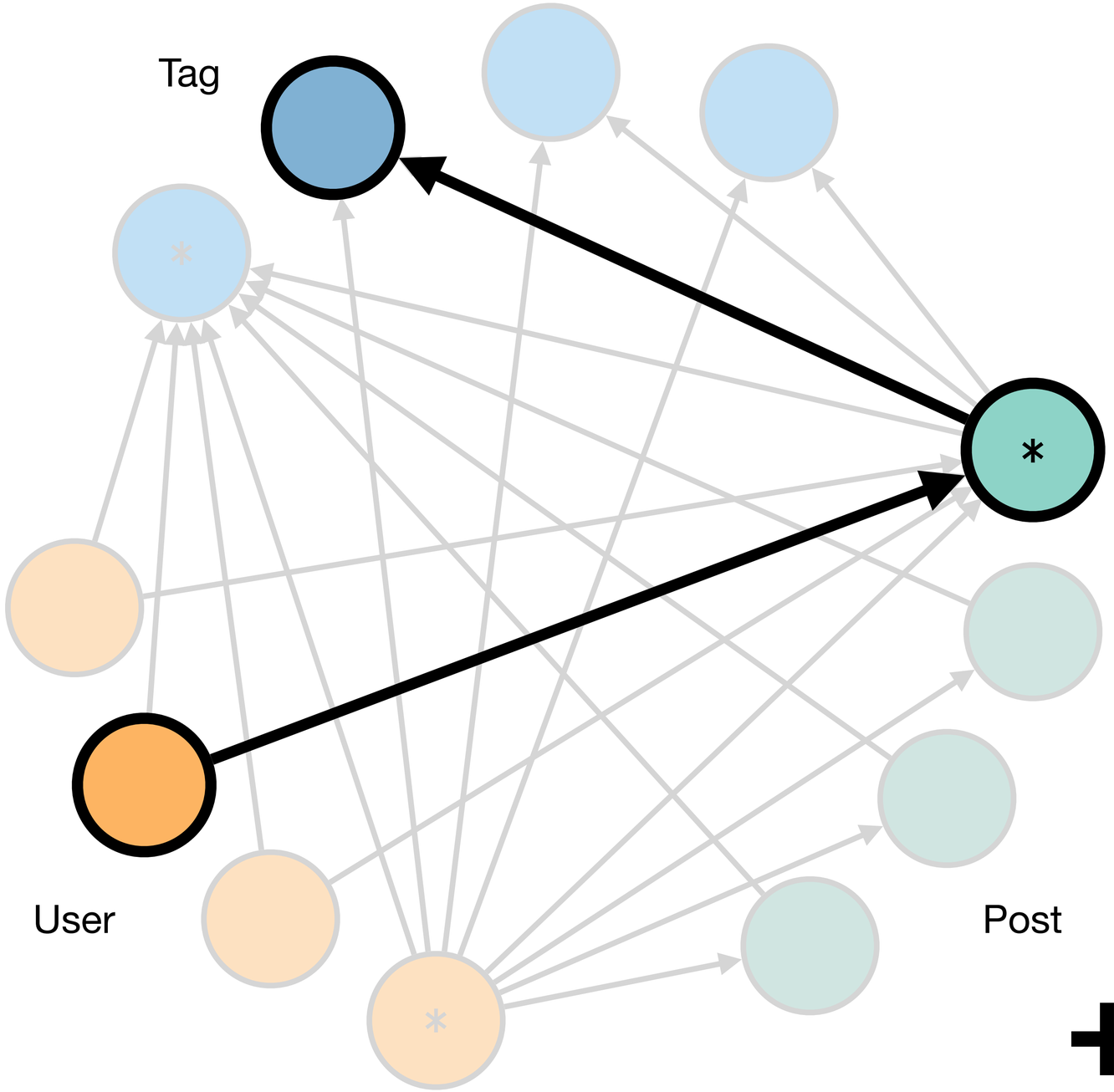

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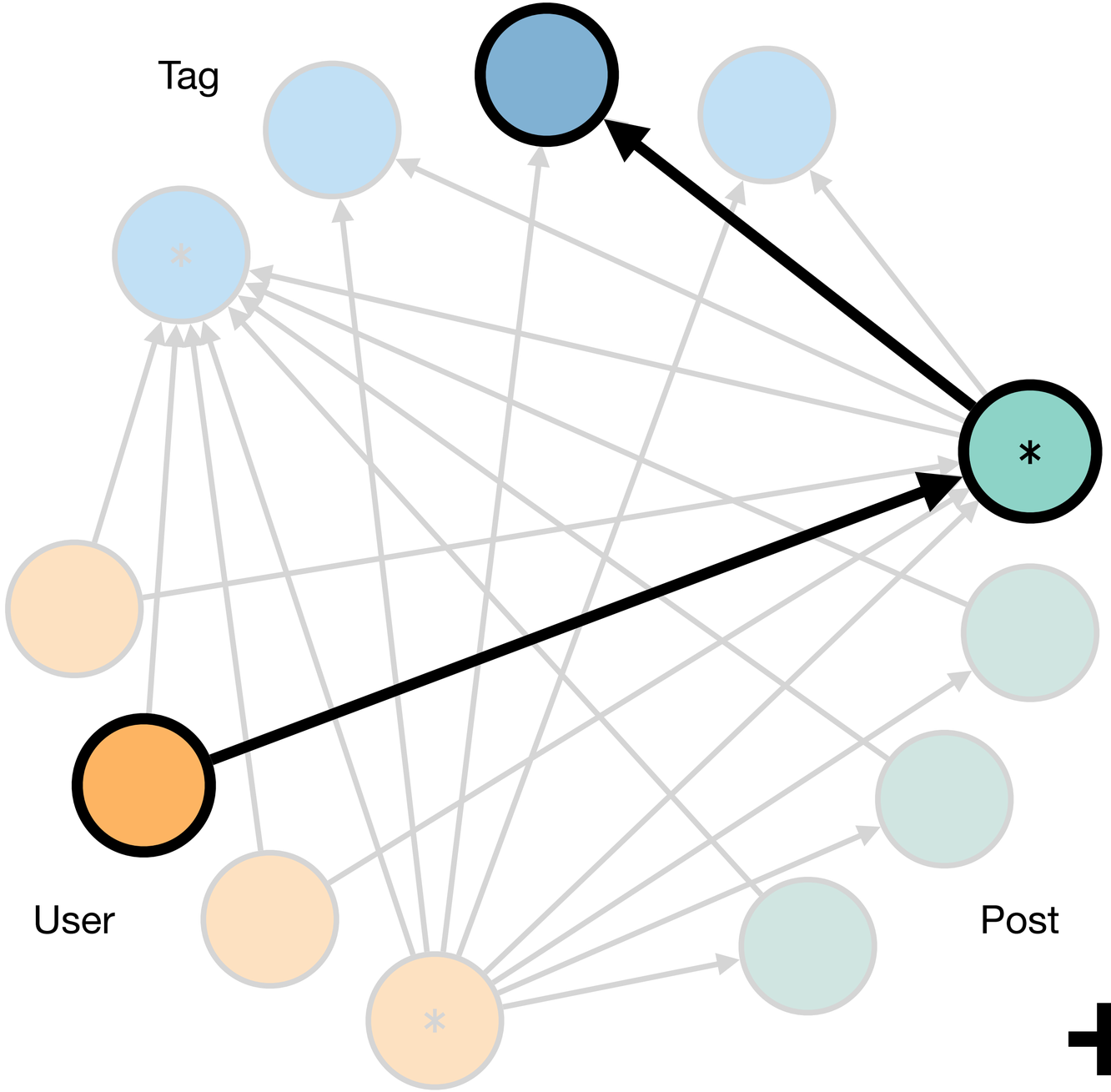

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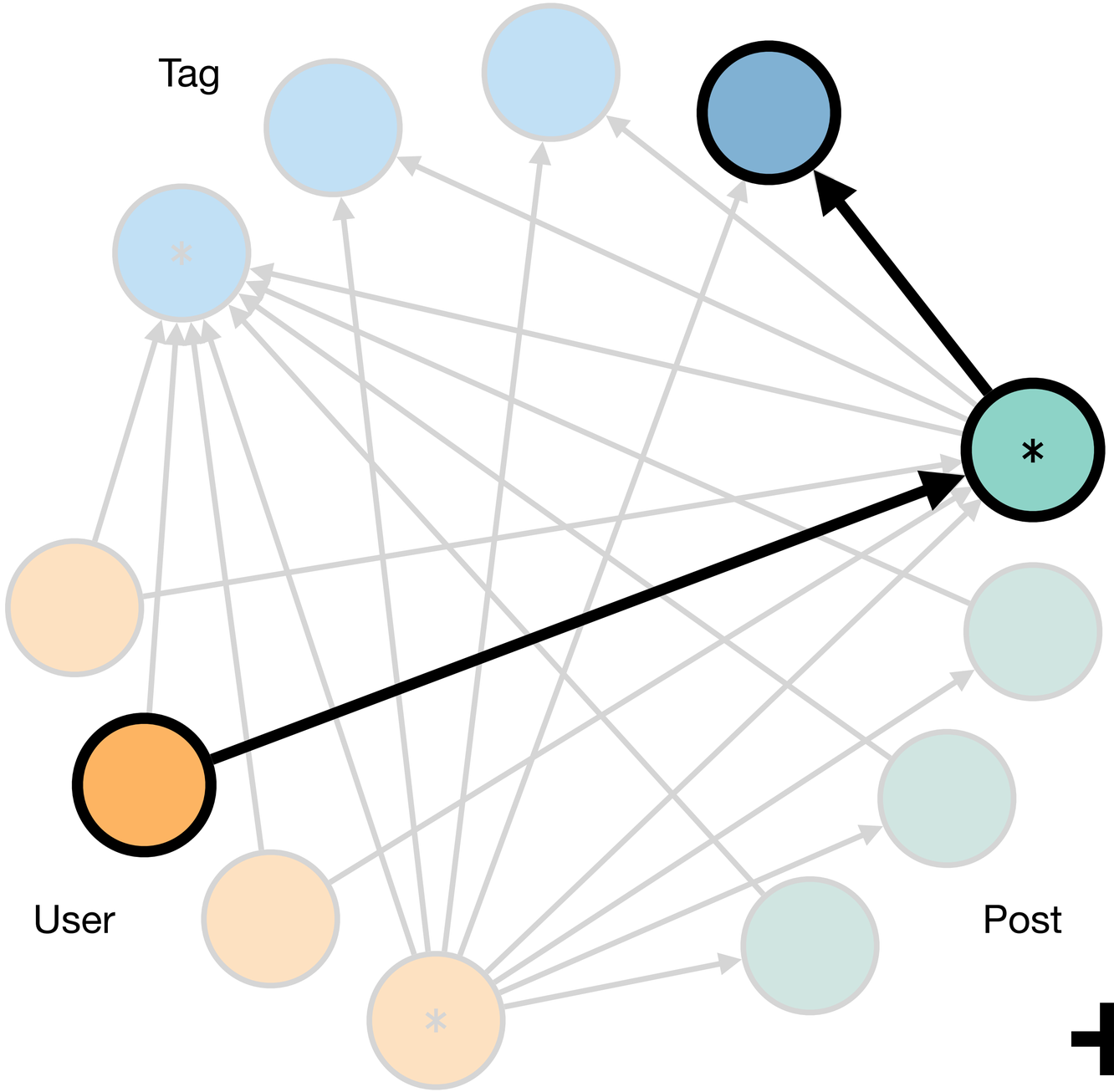

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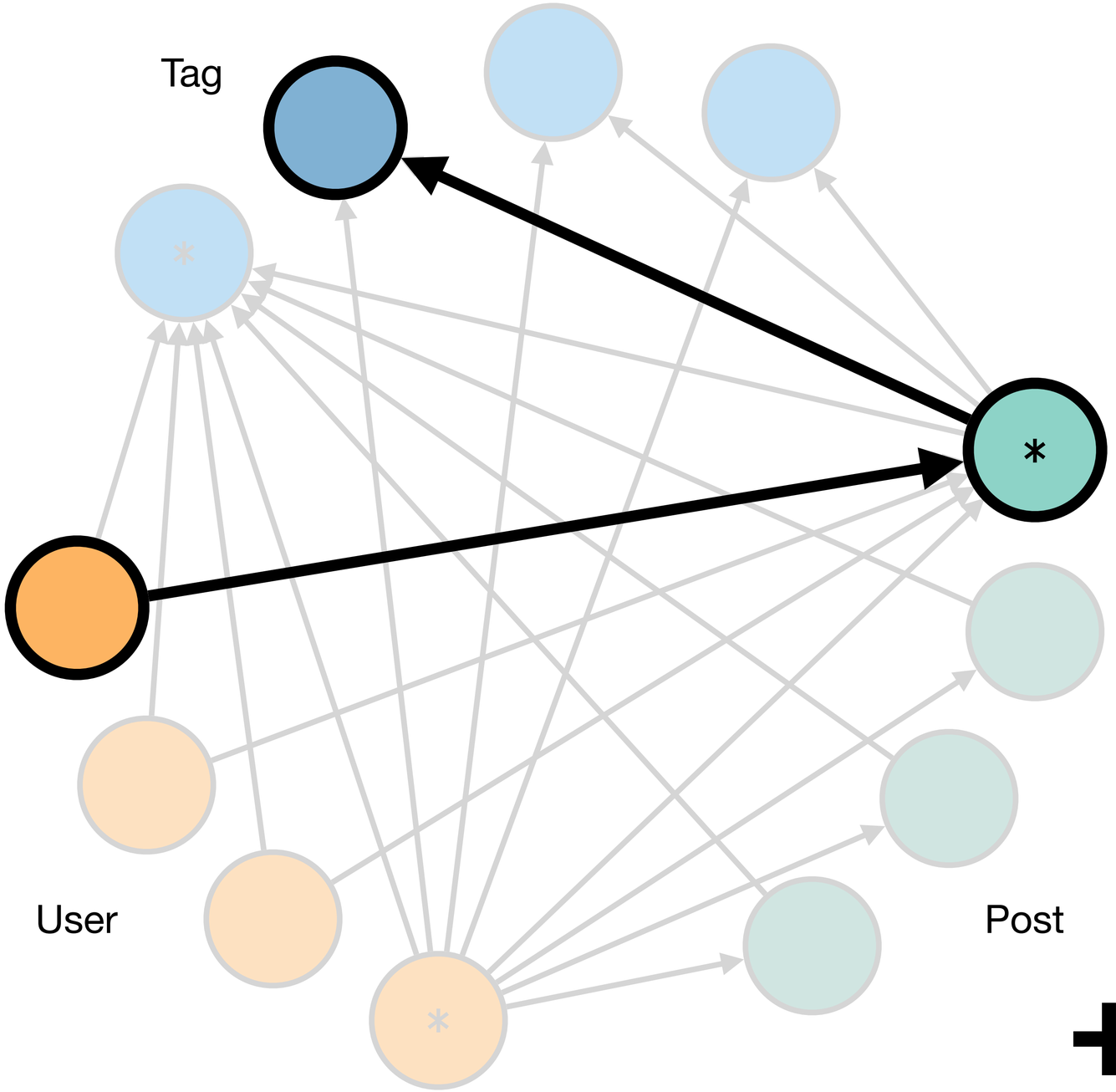

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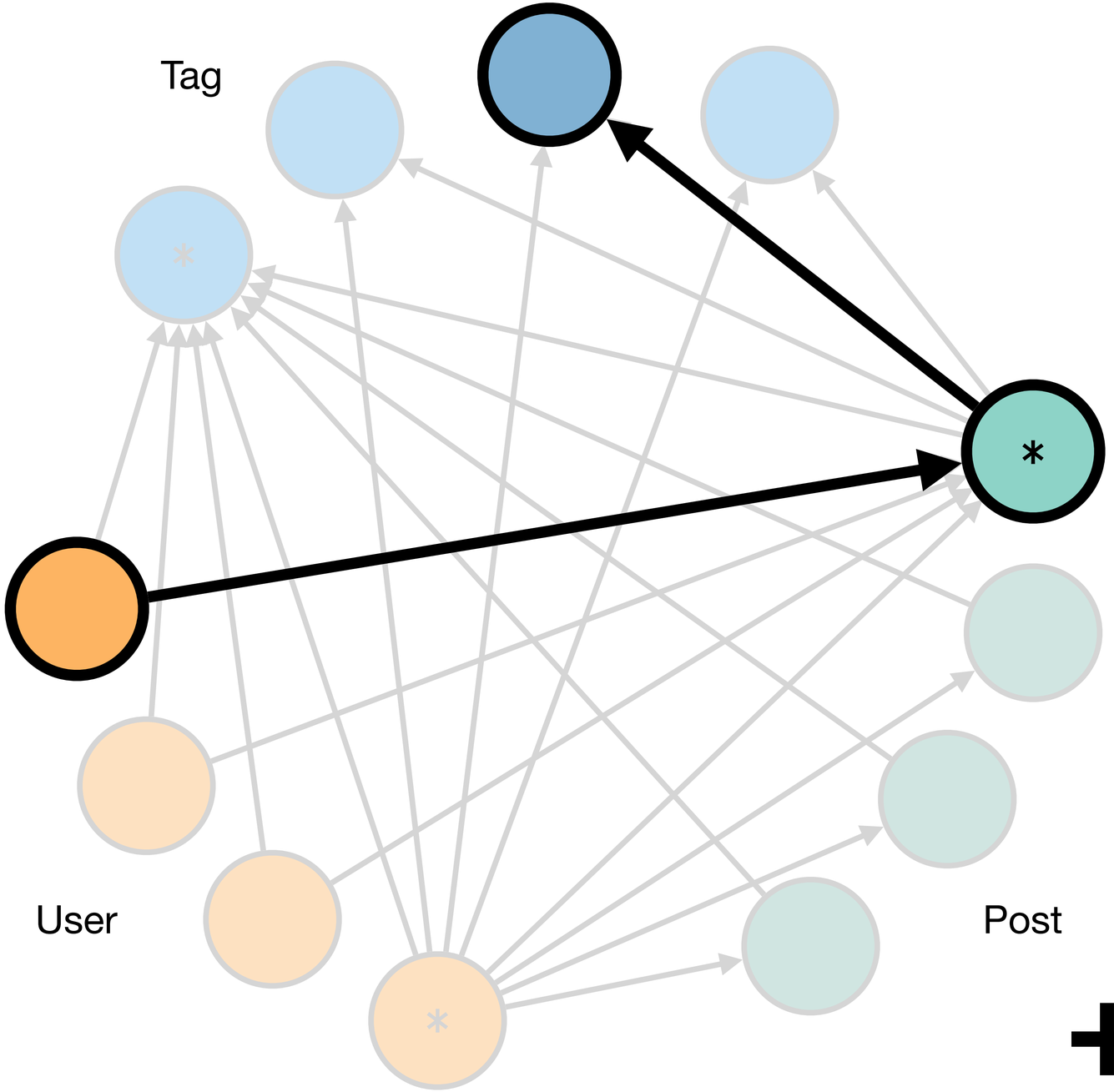

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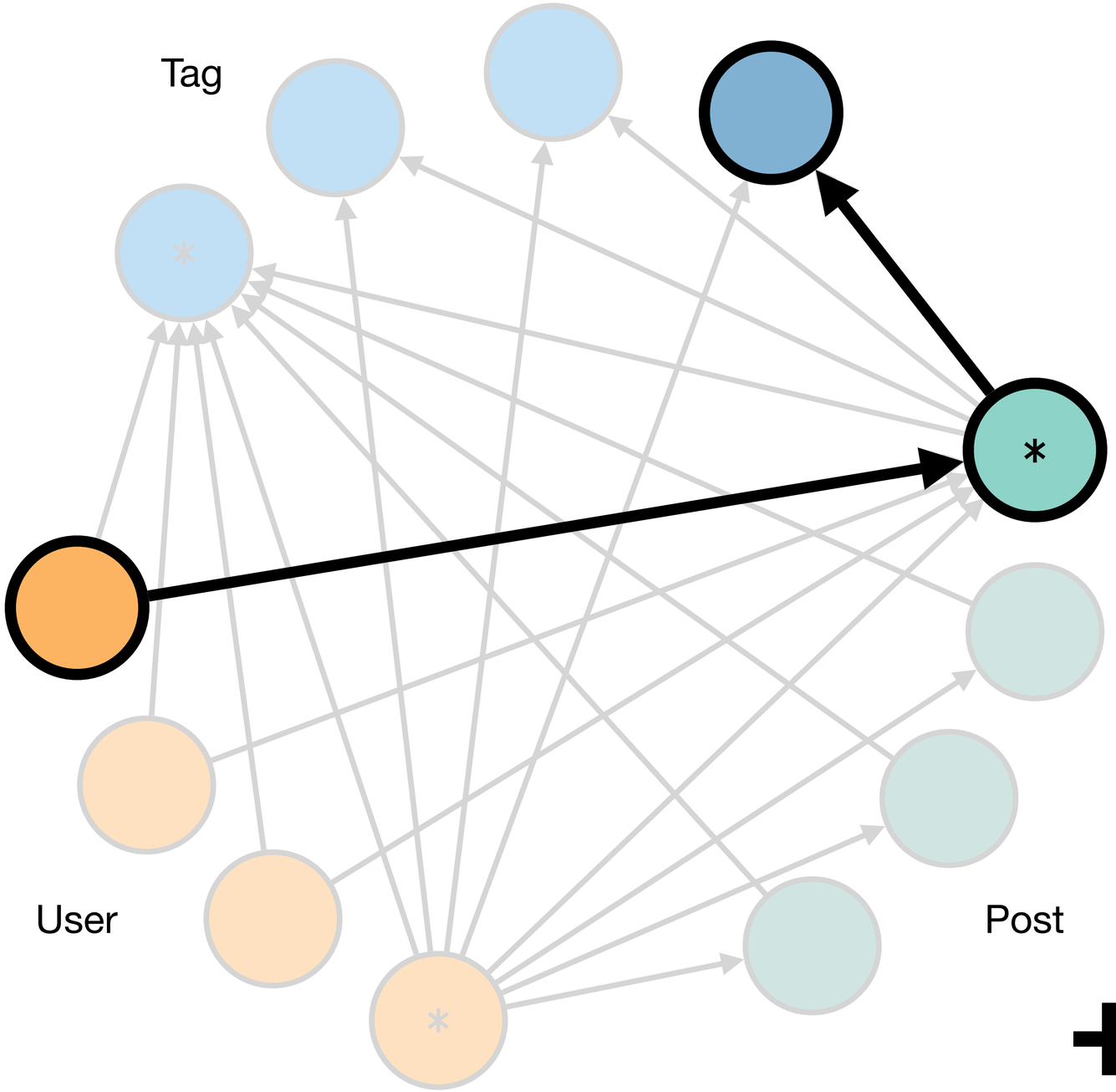

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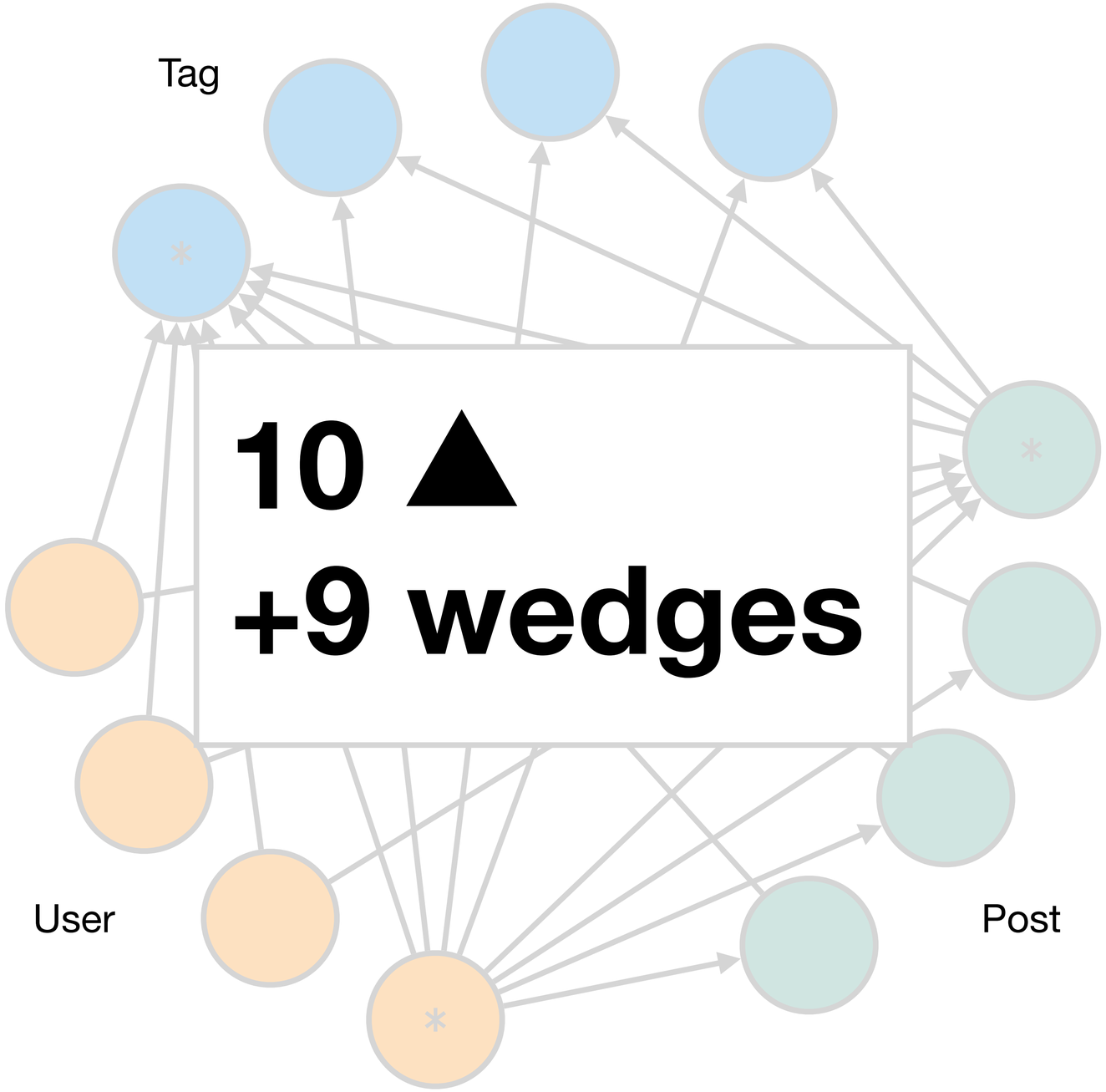


From all three node types, we have 1 distinguished $(*)$ and k regular instances.

Size of tables:

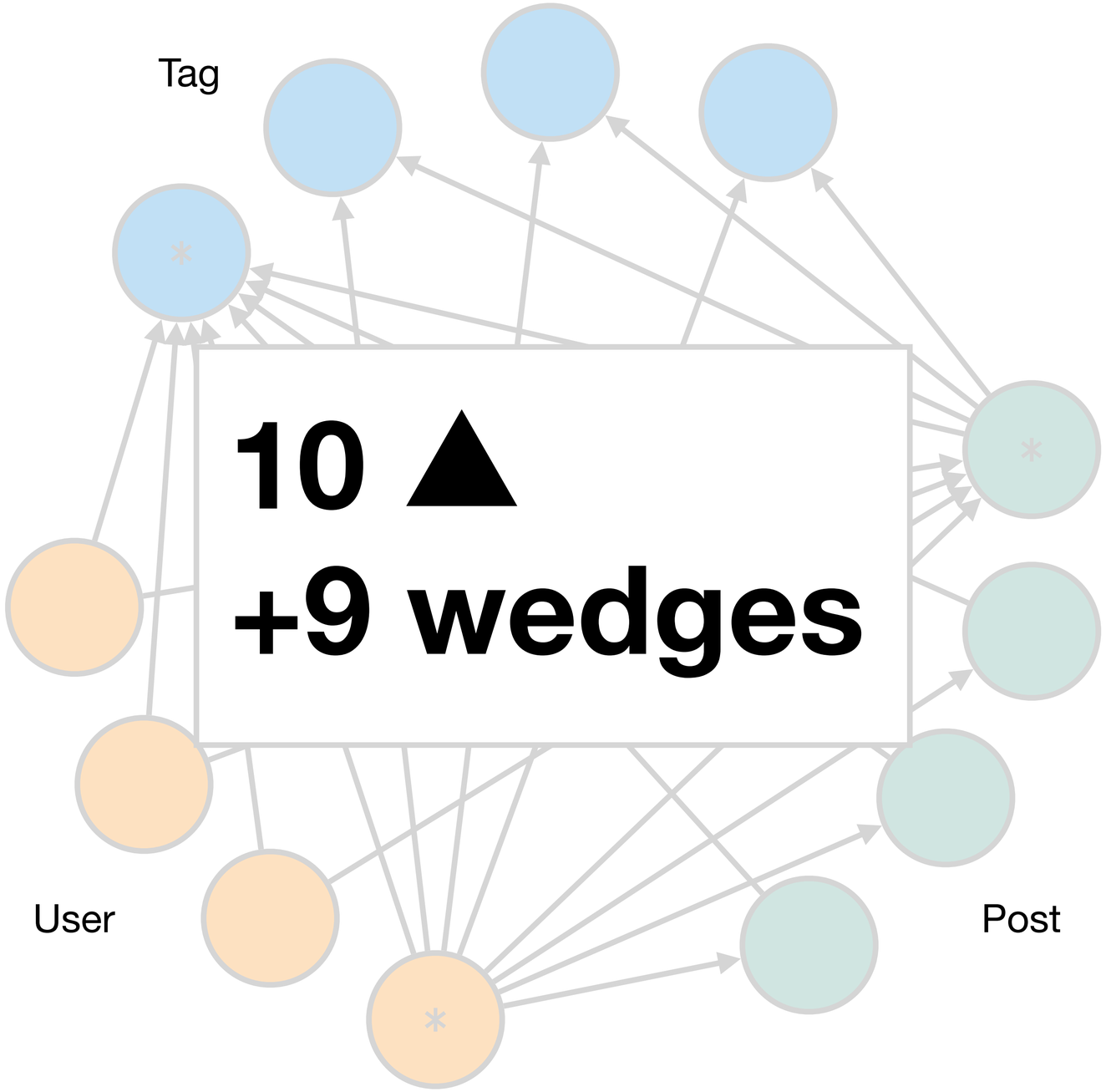
$$n = 2k + 1$$

Number of triangles:

$$q_{\triangle} = 3k + 1$$

Size of the first join:

$$q_{<} = k^2 + 3k + 1$$



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Foundations of Computer Science, 2007

Size Bounds and Query Plans for Relational Joins

Albert Atserias
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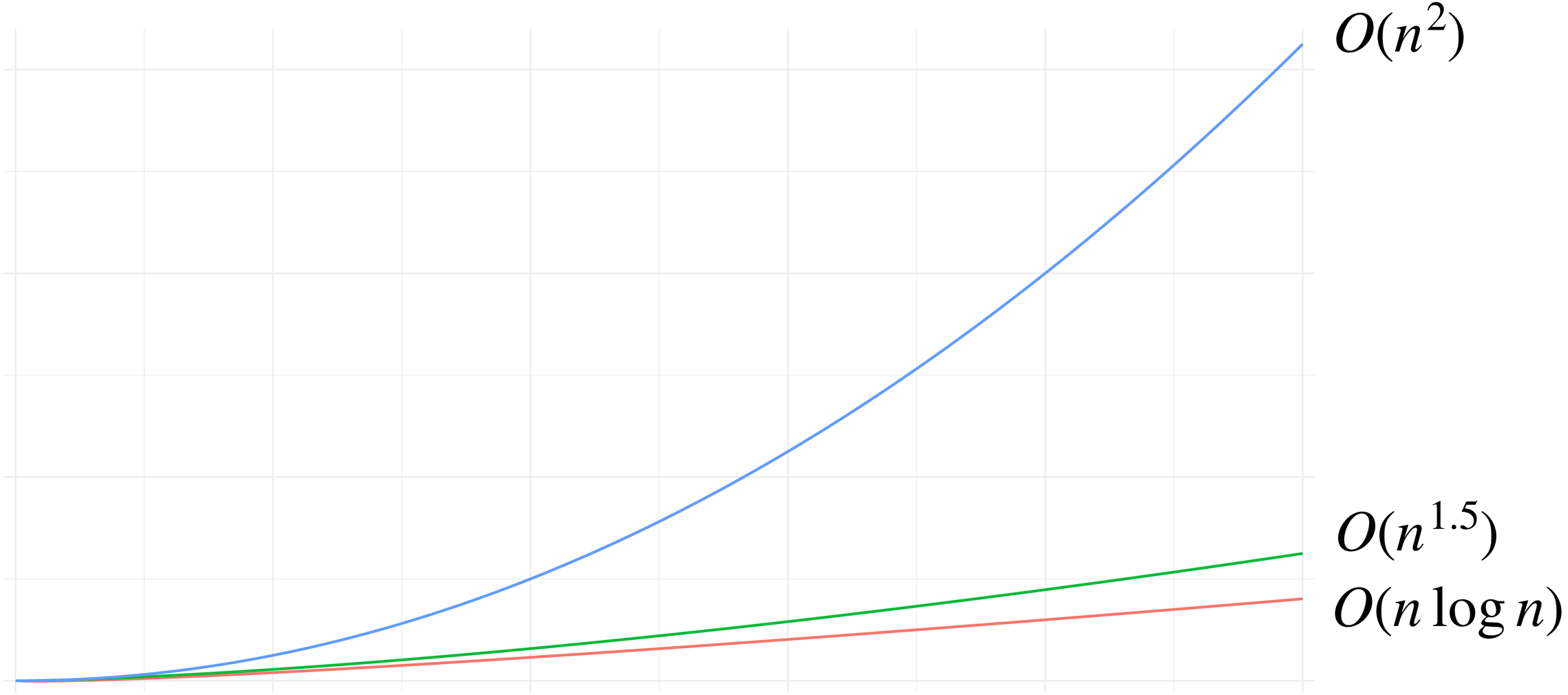
Dániel Marx*
Budapest University of Technology and Economics
Budapest, Hungary
dmarx@cs.bme.hu

On a graph with n edges, computing $q_{\triangle}$ with joins takes $O(n^2)$

The output size of $q_{\triangle}$ is $\Theta(n^{1.5})$

Complexity: $n^{1.5}$ vs. n^2



Foundations of Computer Science, 2007

Size Bounds and Query Plans for Relational Joins

Albert Atserias
Universitat Politècnica de Catalunya
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Martin Grohe
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Dániel Marx*
Budapest University of Technology and Economics
Budapest, Hungary
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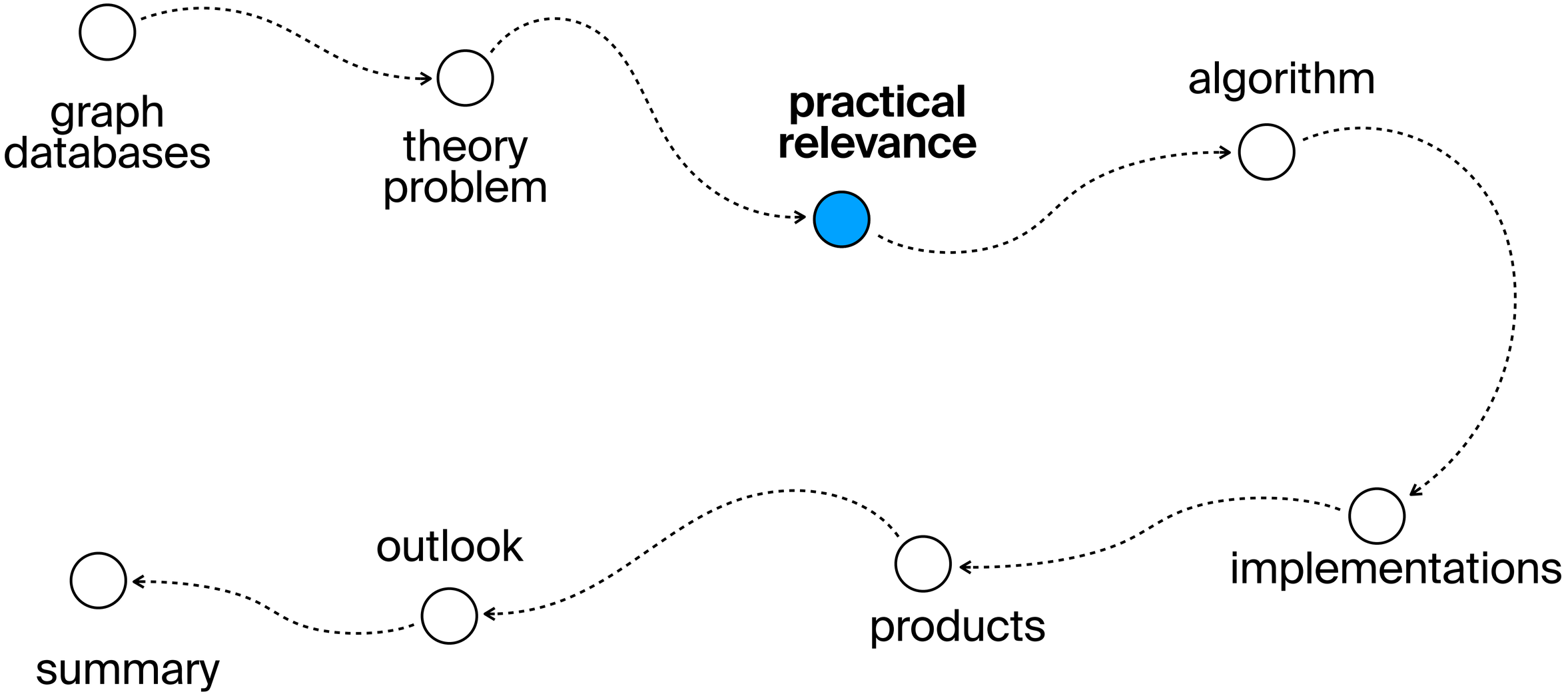
On a graph with n edges, computing $q_{\triangle}$ with joins takes $O(n^2)$

The output size of $q_{\triangle}$ is $\Theta(n^{1.5})$

The paper doesn't give an algorithm for computing the join.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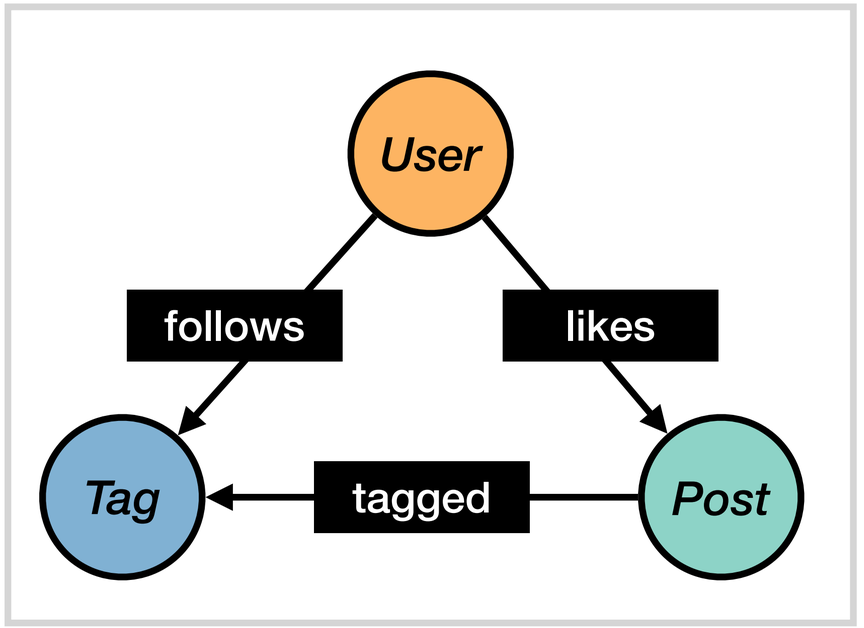
When does this problem occur?

Conditions:

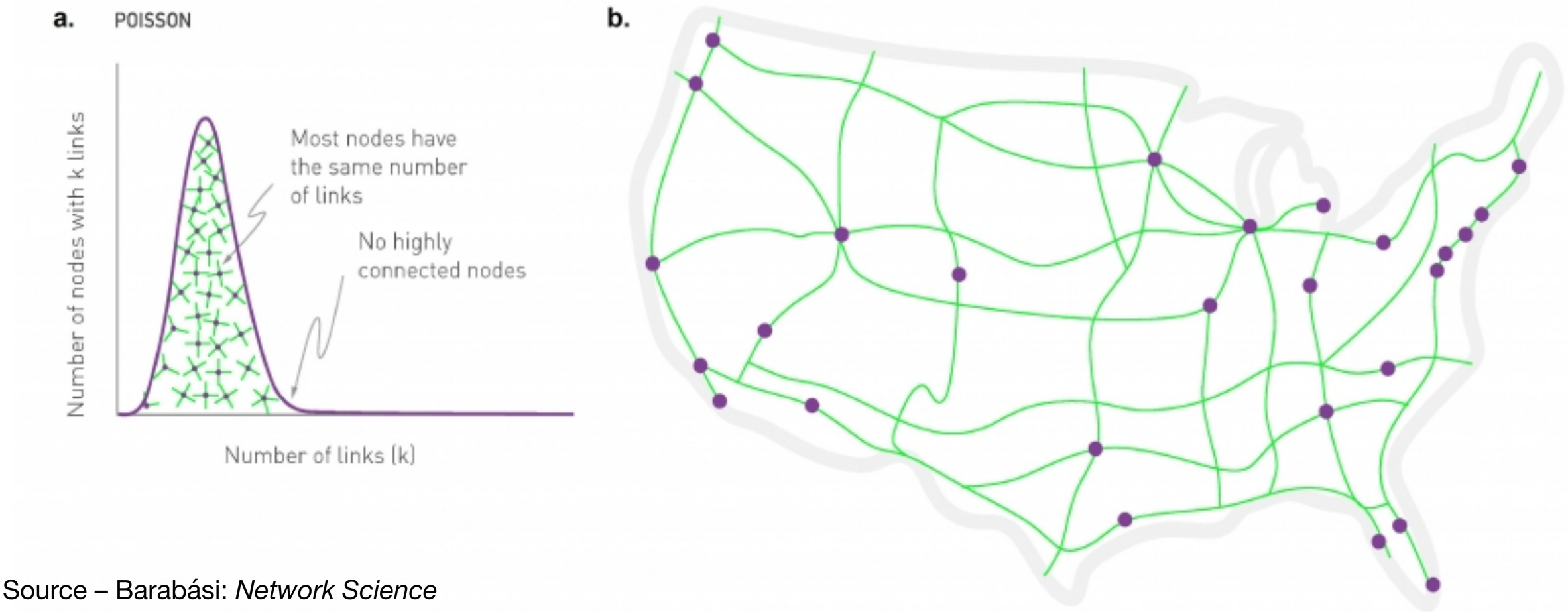
- cyclic graph pattern
- many-to-many cardinality edges
- asymmetric (skewed) degree distribution



These conditions can hold in any database but are more common in graph databases.

Degree distributions – Network science

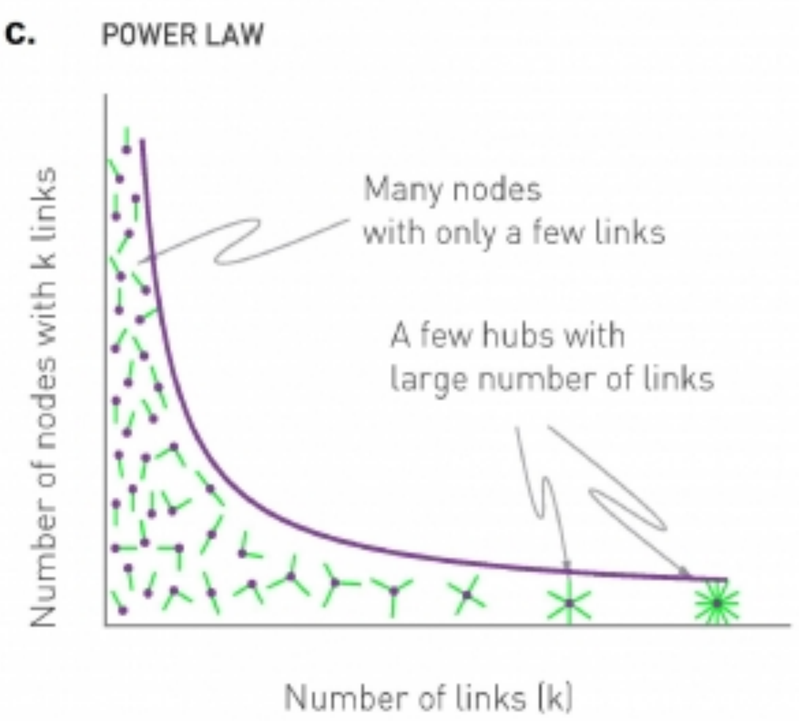
Poisson distribution



Source – Barabási: *Network Science*

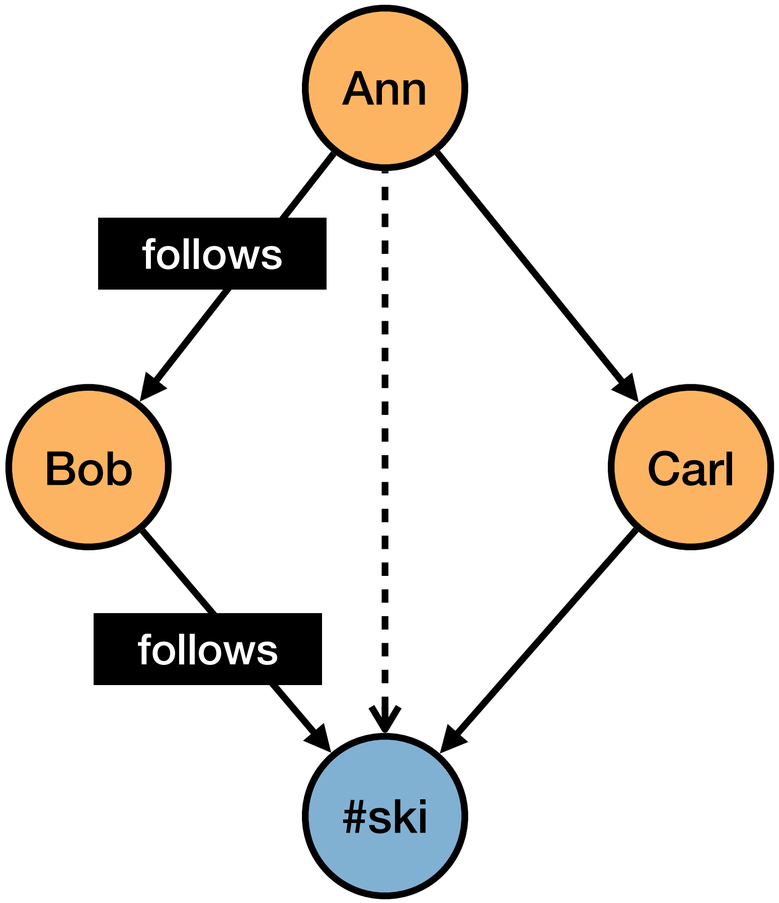
Degree distributions – Network science

Power law distribution

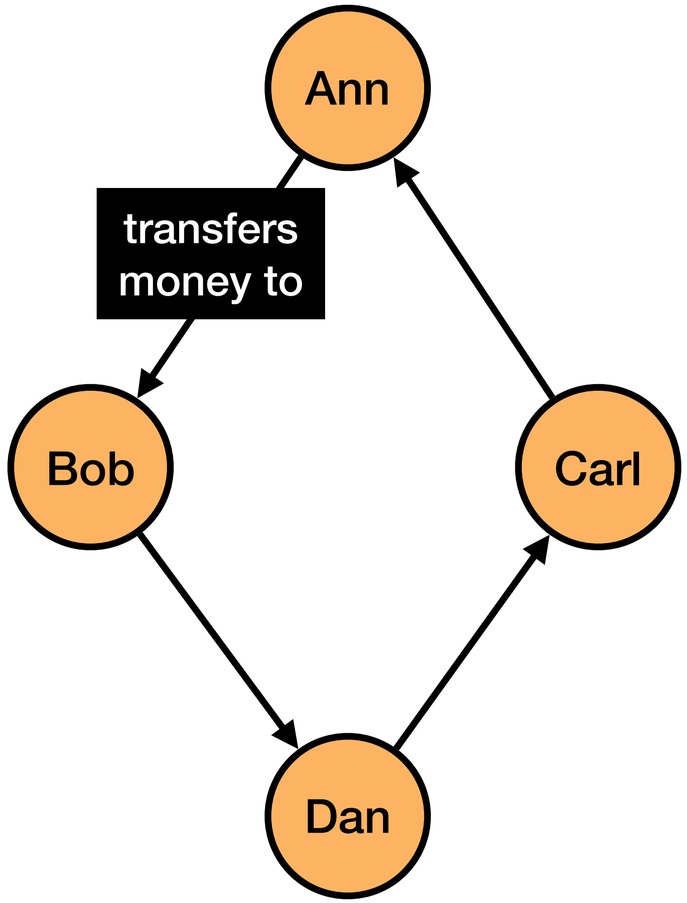


Source – Barabási: *Network Science*

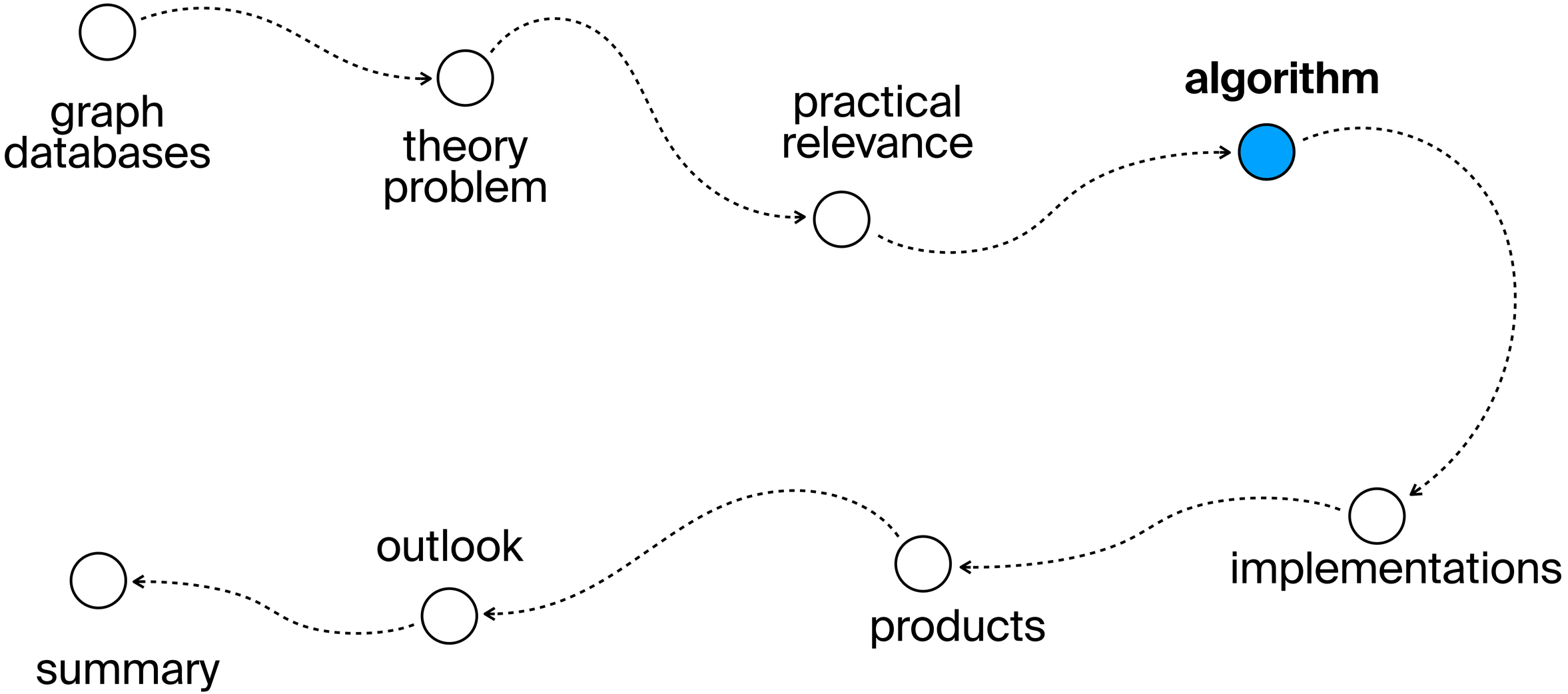
Cyclic graph queries in practice



recommendation algorithm



detecting money laundering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summary

Principles of Database Systems 2012

Worst-case Optimal Join Algorithms

Hung Q. Ngo
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Christopher Ré
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chrisre@cs.wisc.edu

Atri Rudra
University at Buffalo, SUNY
atri@buffalo.edu

To understand the spirit of AGM's results, consider the following example where we have a schema with three attributes, A, B, and C, and three relations, $R(A,B)$, $S(B,C)$ and $T(A,C)$, defined over those attributes. Consider the following natural join query:

$$q = R \bowtie S \bowtie T \qquad (1)$$

Algorithm for computing $q_{\triangle}$

in $O(n^{1.5})$ steps

"Traditionally", join is a binary operator.

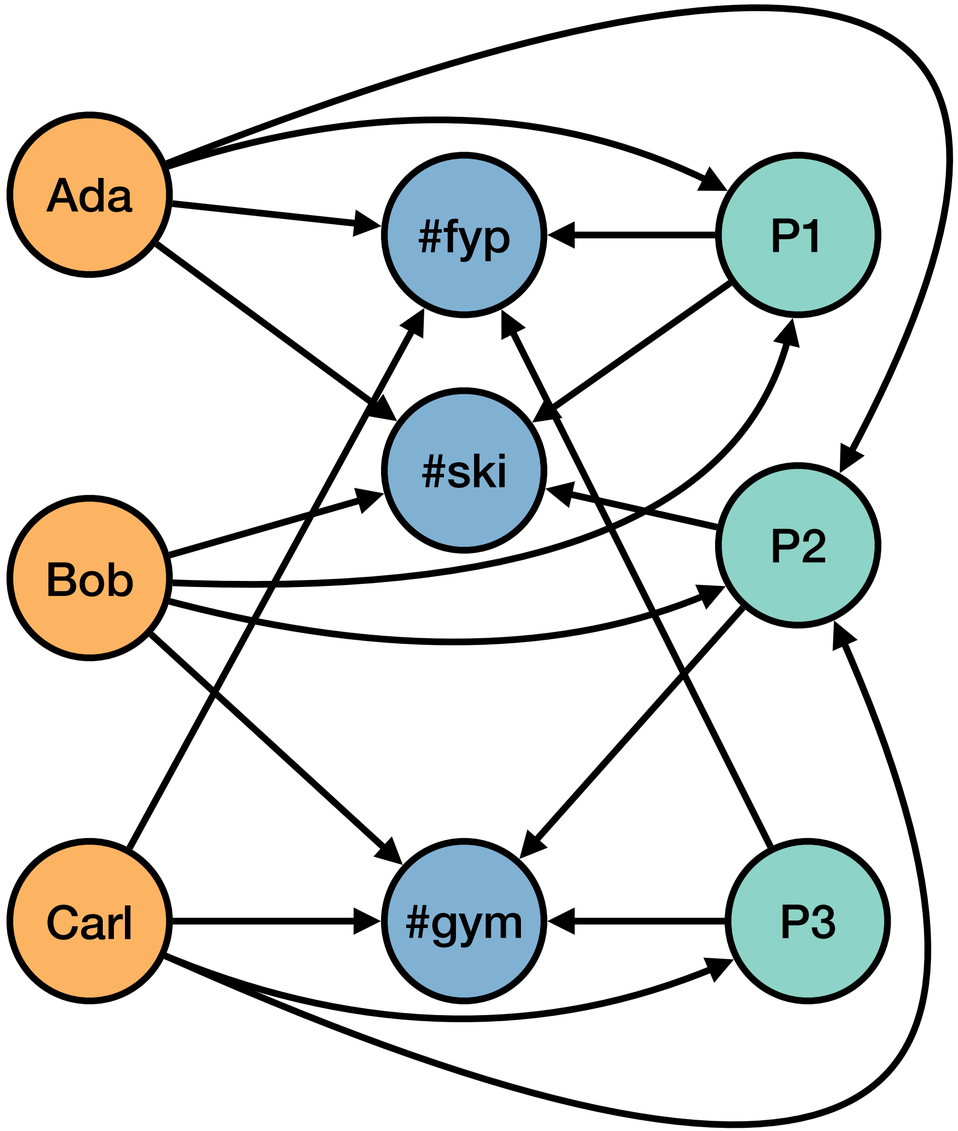
```
follows ⋈ tagged ⋈ likes
```

Idea: treat joins are n-ary operators *(multiway join)*:

```
⋈ (follows, tagged, likes)
```

The paper gives two algorithms, both using repeated intersections.

These are asymptotically optimal join algorithms, known as *worst-case optimal join algorithms.*



follows

User	Tag
Ada	#fyp
Ada	#ski
Bob	#ski
Bob	#gym
Carl	#fyp
Carl	#gym

tagged

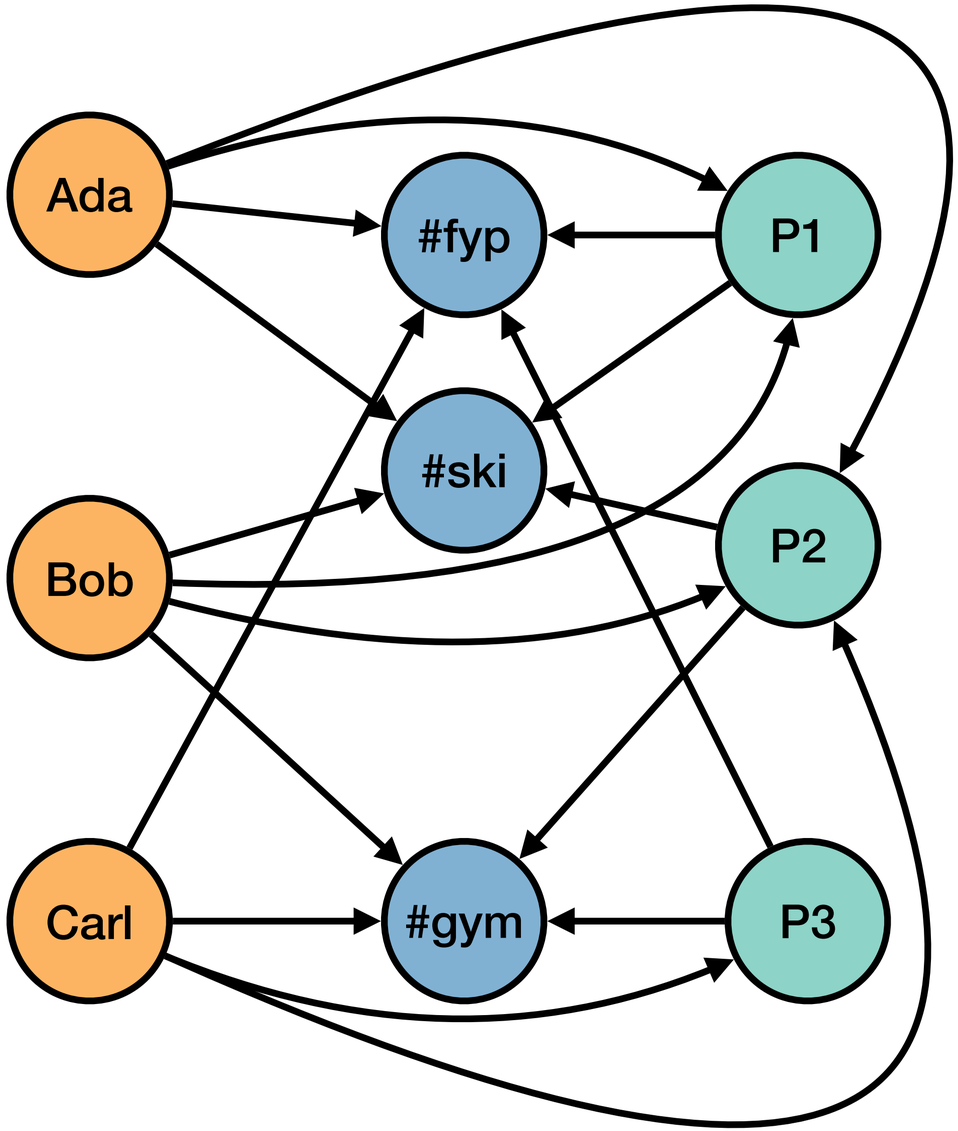
Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

∩

User
Ada
Bob
Carl



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P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

User	Post
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Ada	P2
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Carl	P2
Carl	P3

∩

User
Ada
Bob
Carl

User	Tag
Ada	#fyp
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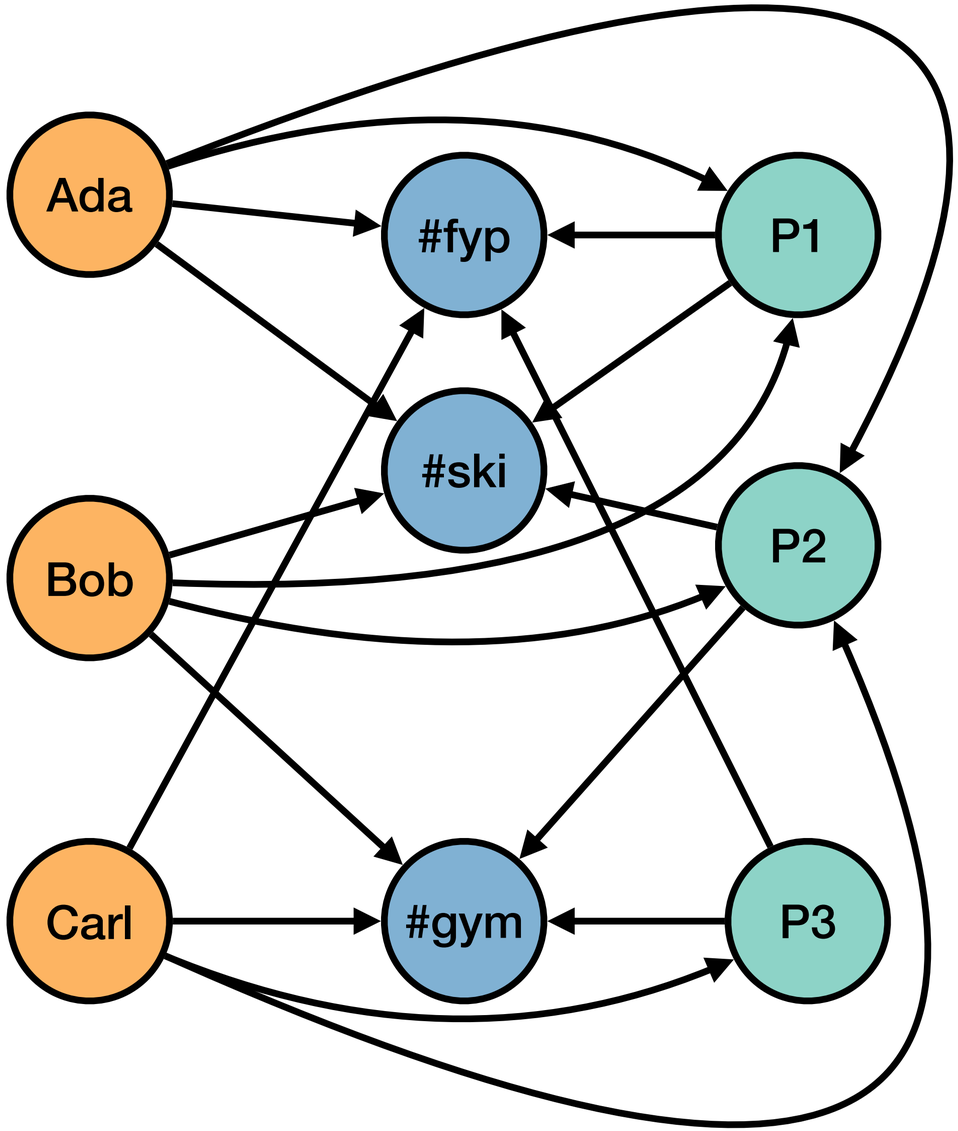

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P2	#ski
P2	#gym
P3	#gym

likes

User	Post
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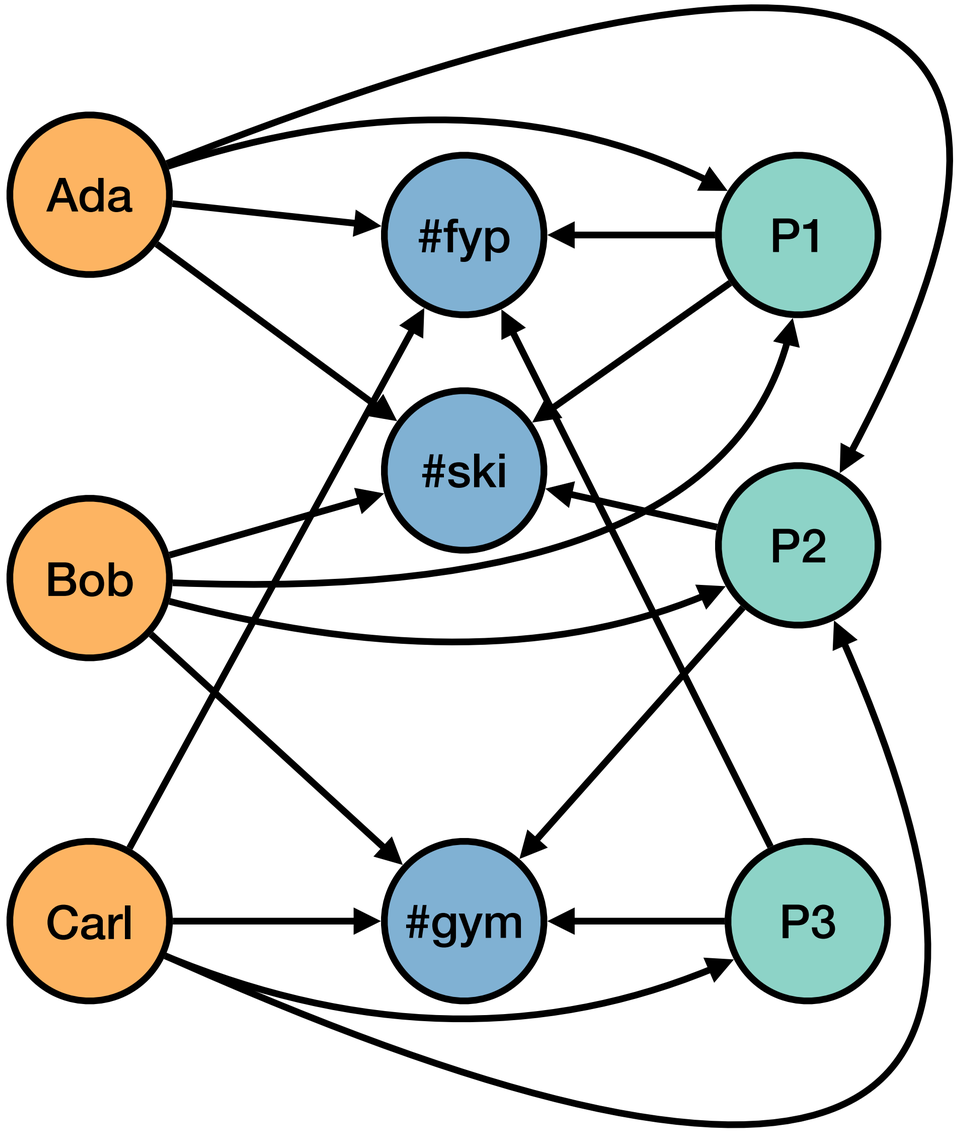
Bob	P2
Carl	P2
Carl	P3

∩

User
Ada
Bob
Carl

User	Tag
Ada	#fyp
Ada	#ski
Bob	#gym
Bob	#ski



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User
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Bob
Carl

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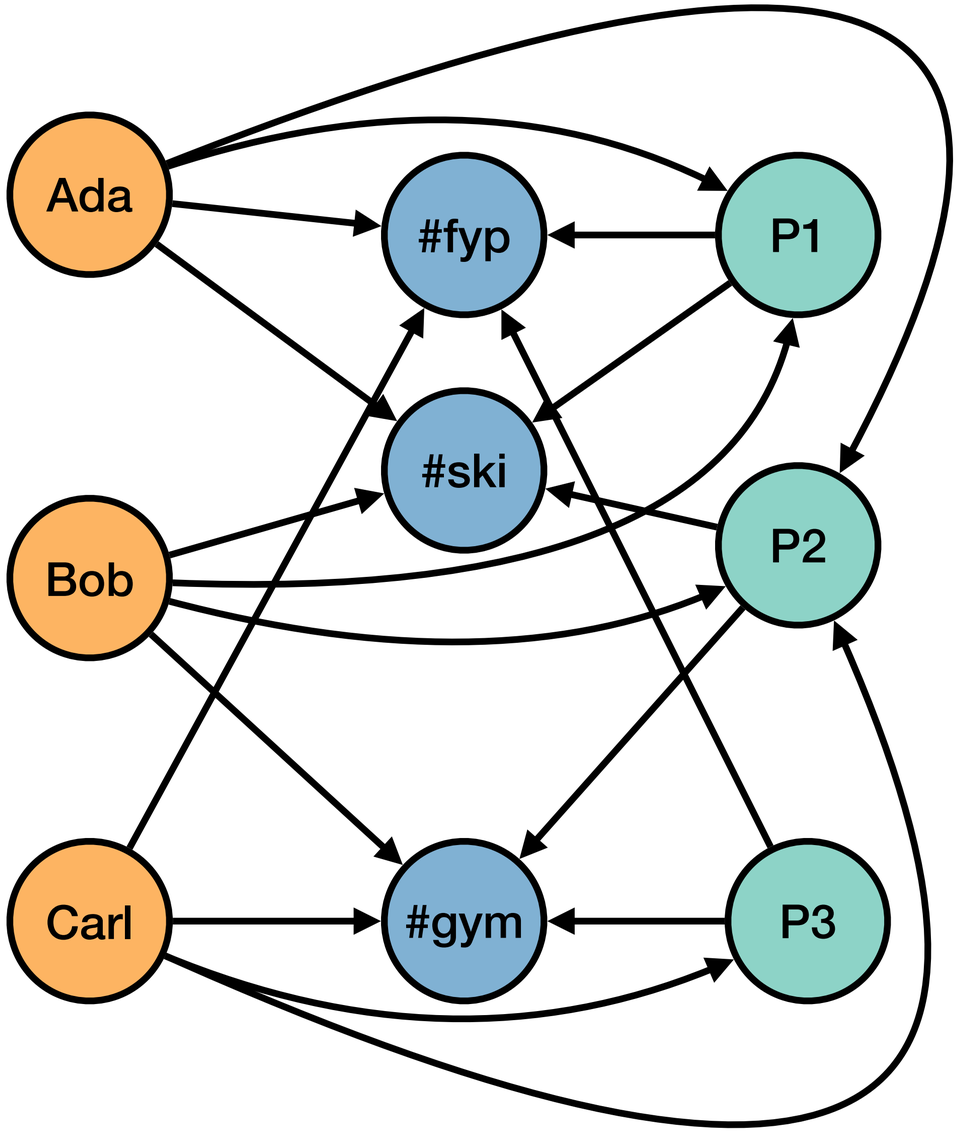

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P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

User	Post
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Ada	P2
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Bob	P2
Carl	P2
Carl	P3

∩

User	Tag
Ada	#fyp
Ada	#ski
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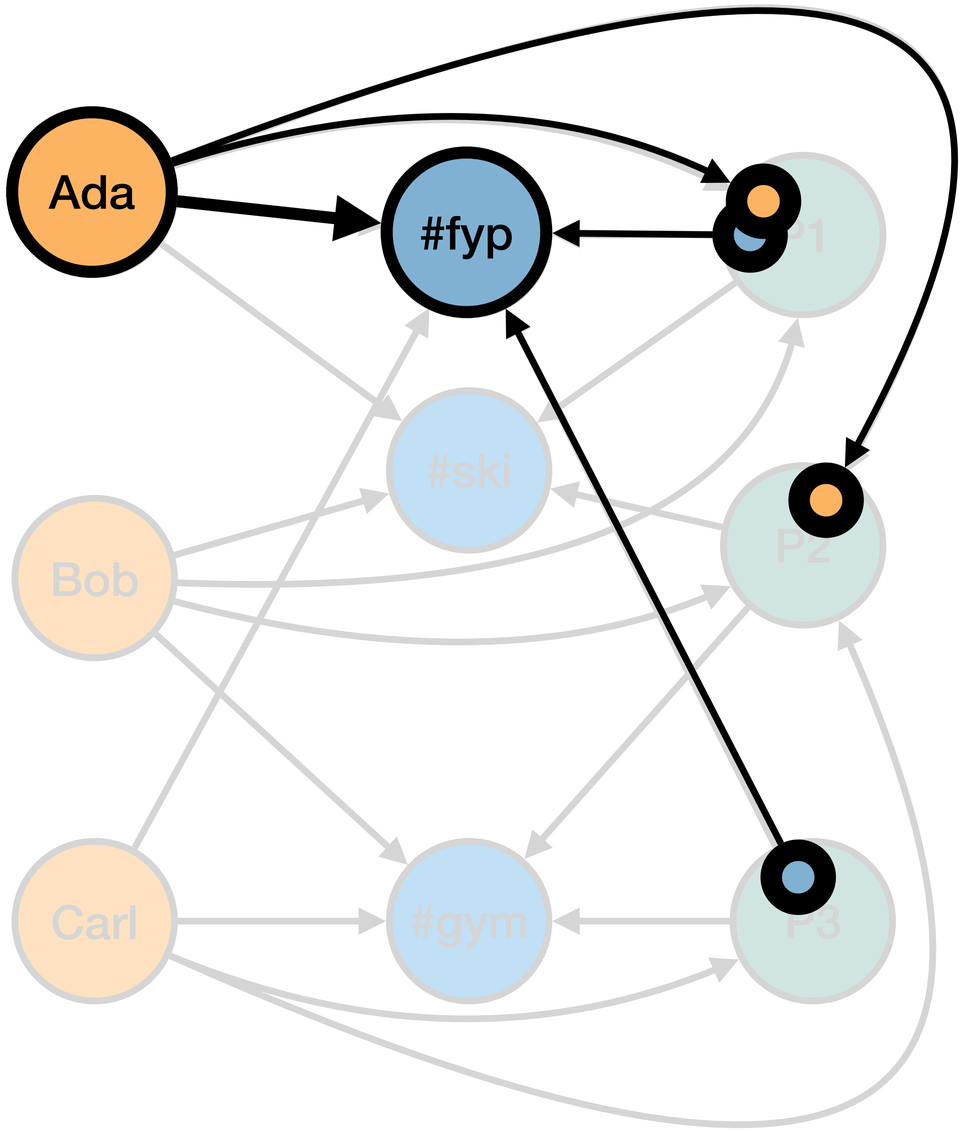
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
Ada	#fyp	P1



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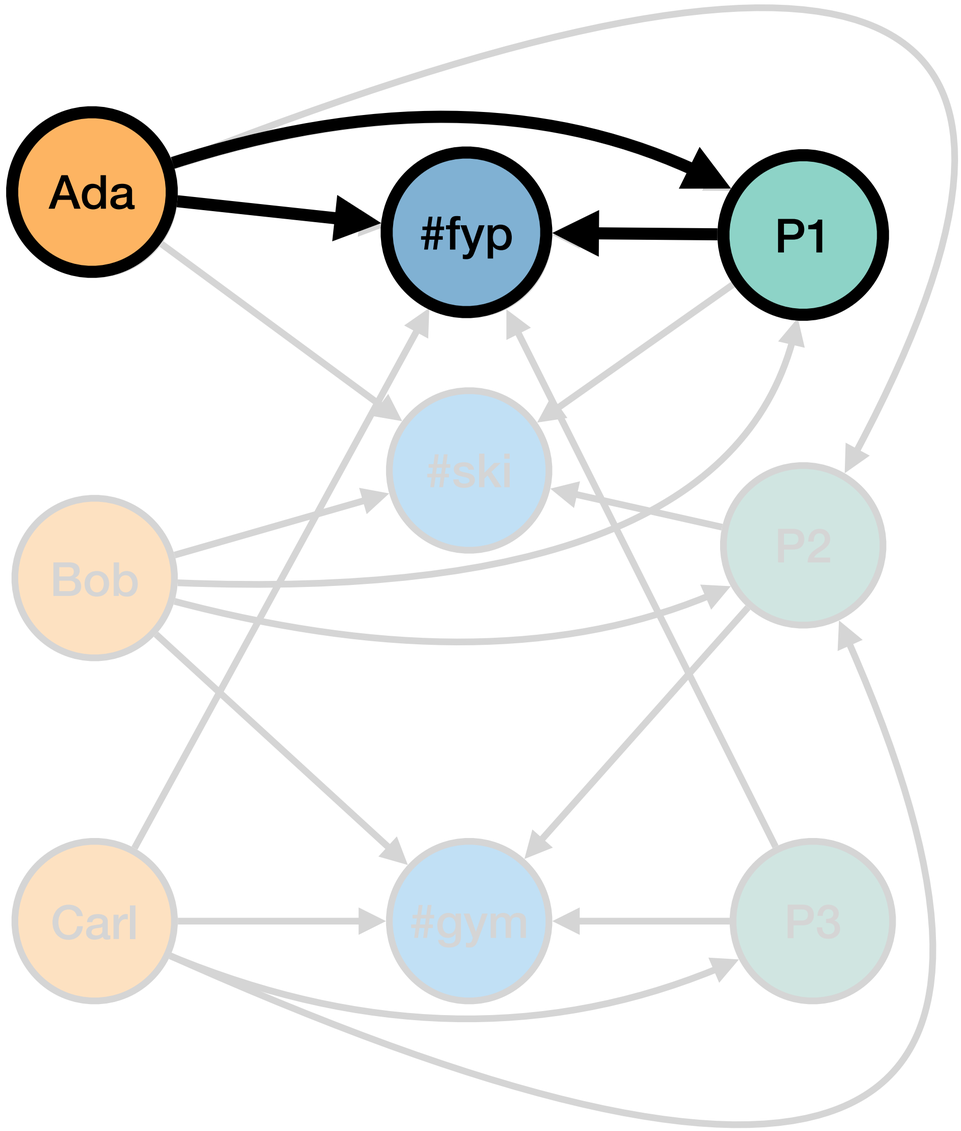
Ada	#fyp	P1



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P2	#gym
P3	#gym

likes

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Bob	P2
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Carl	P3

∩

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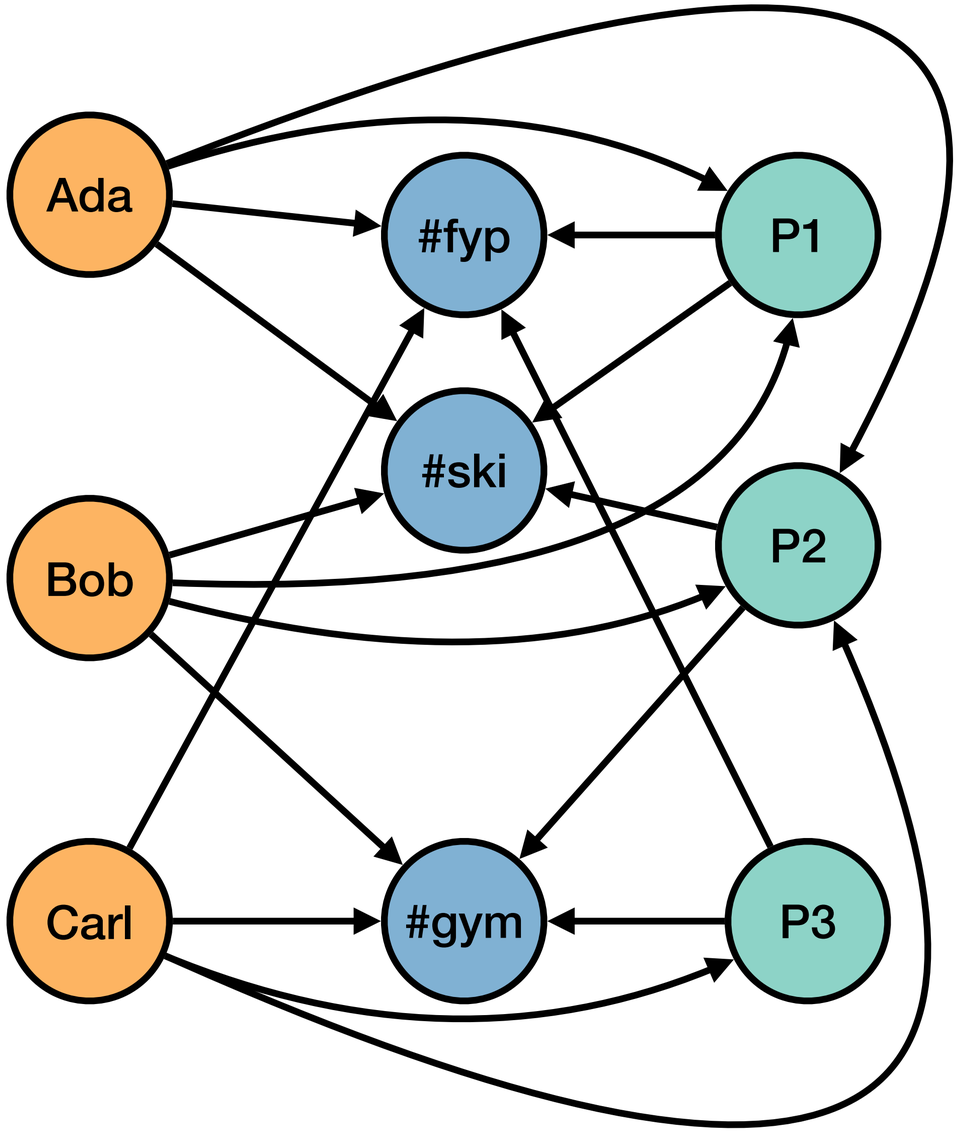
User	Tag	Post
Ada	#fyp	P1



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Ada	#ski
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Carl	#gym

tagged

Post	Tag
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P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

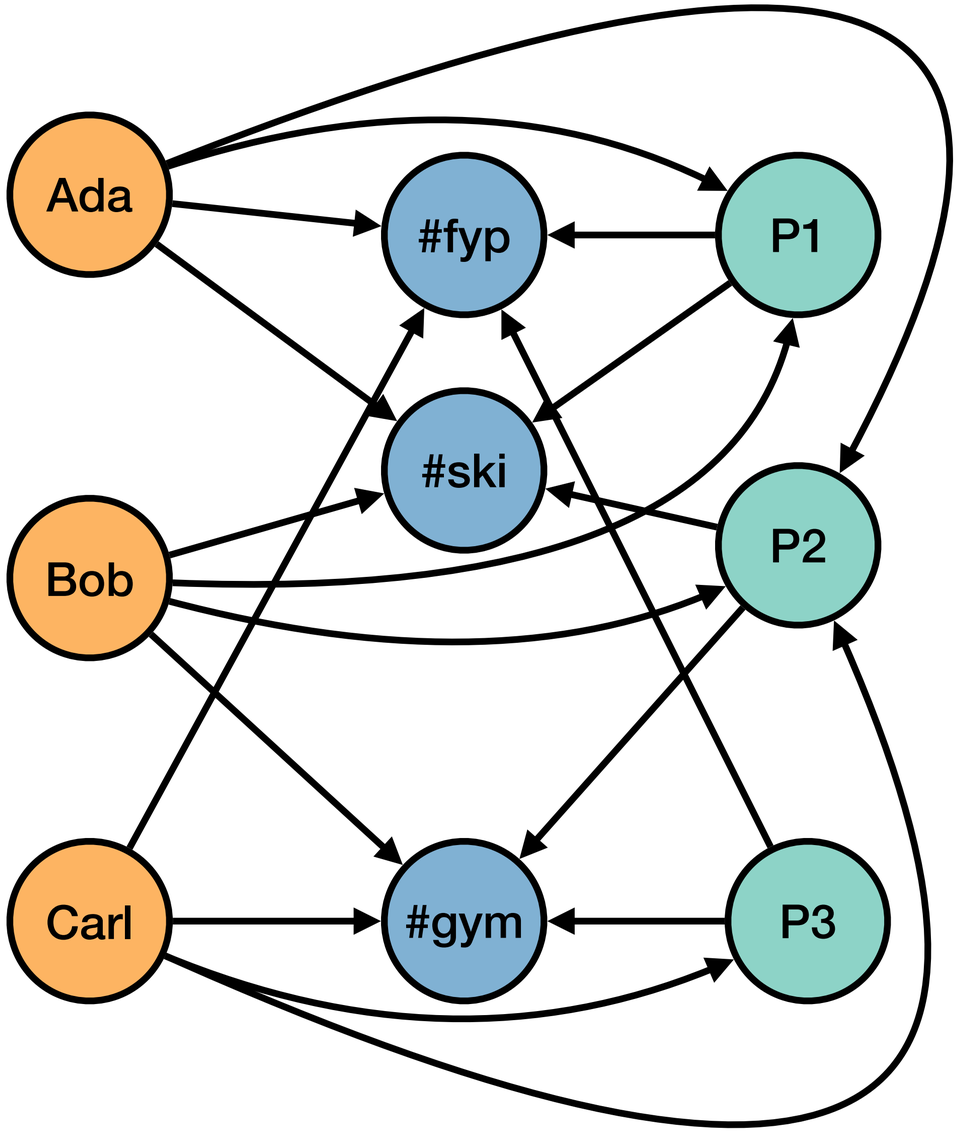
likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

∩

User	Tag
Ada	#fyp
Ada	#ski
Bob	#gym
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
Ada	#fyp	P1
Ada	#ski	P1
Ada	#ski	P2



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Carl	#gym

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P2	#ski
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P3	#gym

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Bob	P2
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∩

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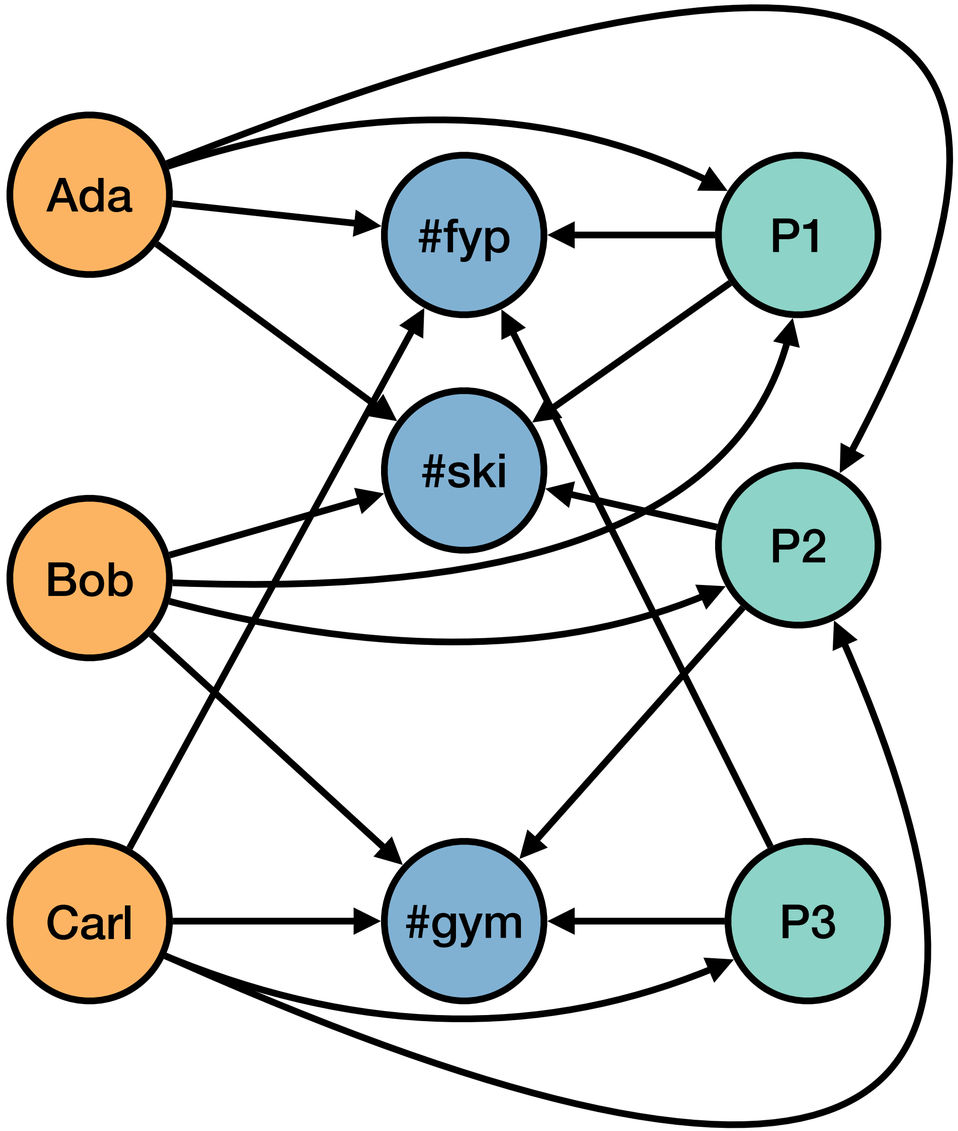
Ada	#ski
Bob	#gym
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
Ada	#fyp	P1
Ada	#ski	P1
Ada	#ski	P2
Bob	#gym	P2



follows

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Ada	#ski
Bob	#ski
Bob	#gym
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Carl	#gym

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

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Bob	P2
Carl	P2
Carl	P3

∩

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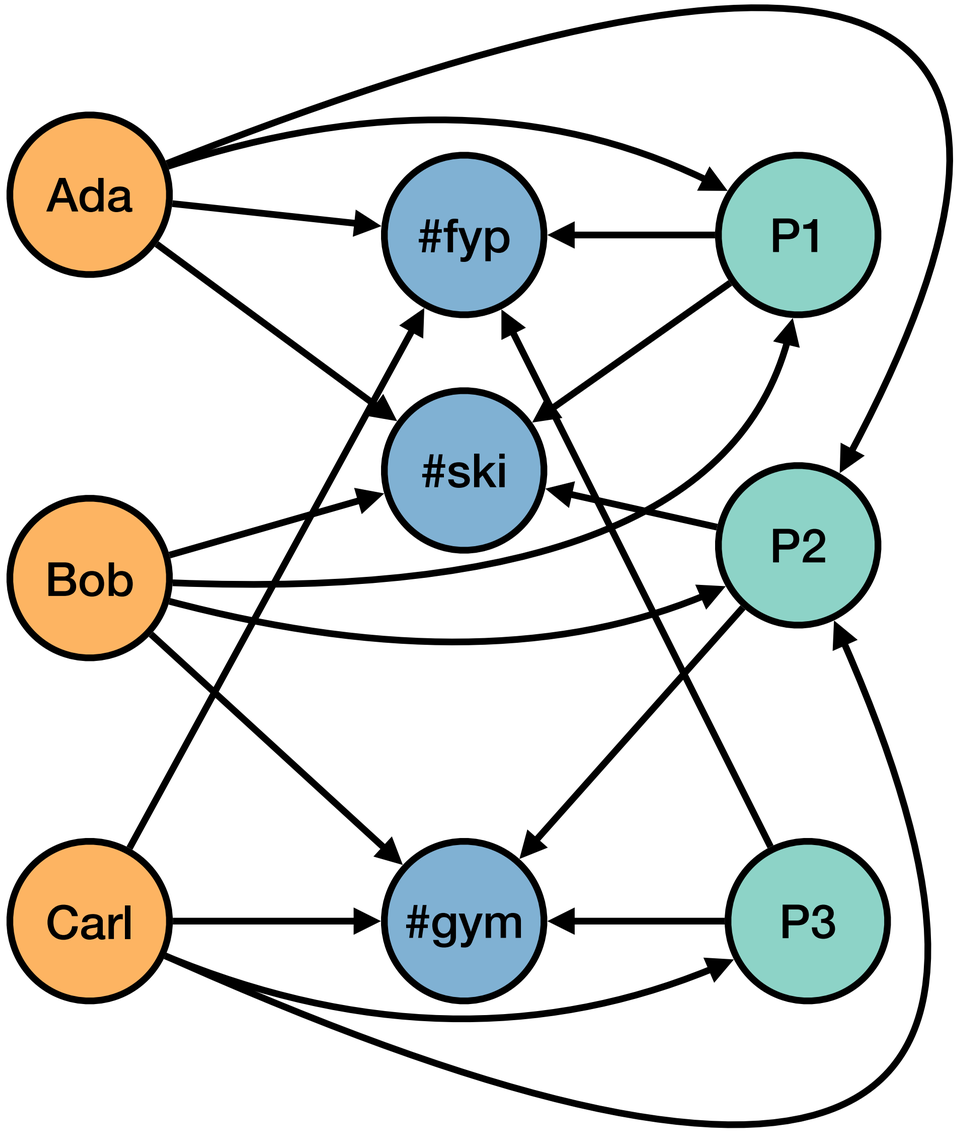
Ada	#ski
Bob	#gym
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
Ada	#fyp	P1
Ada	#ski	P1
Ada	#ski	P2
Bob	#gym	P2
Bob	#ski	P1
Bob	#ski	P2



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P3	#gym

likes

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Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

∩

User	Tag
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Ada	#ski
Bob	#gym
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
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Ada	#ski	P1
Ada	#ski	P2
Bob	#gym	P2
Bob	#ski	P1
Bob	#ski	P2
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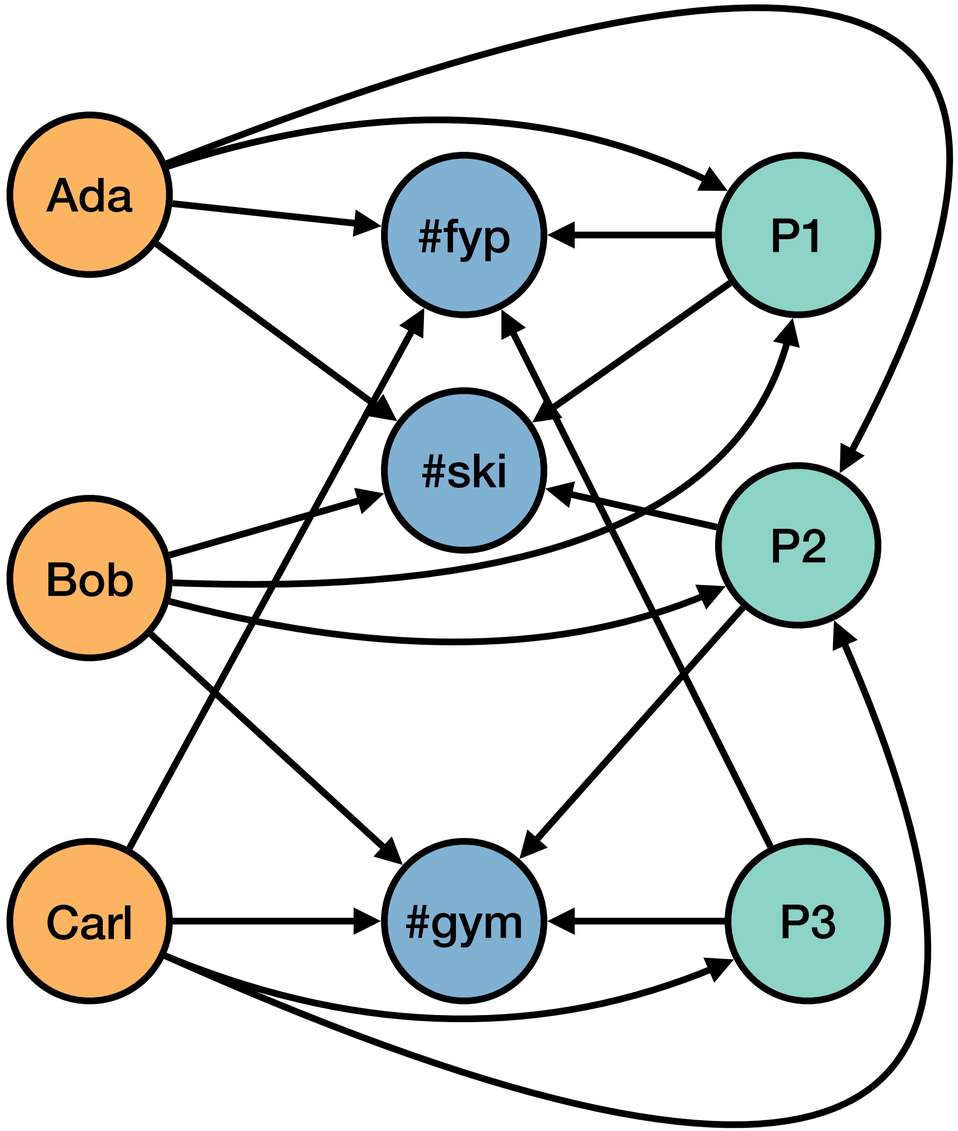

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Carl	#gym

tagged

Post	Tag
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P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes

User	Post
Ada	P1
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Bob	P1
Bob	P2
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Carl	P3

∩

User	Tag
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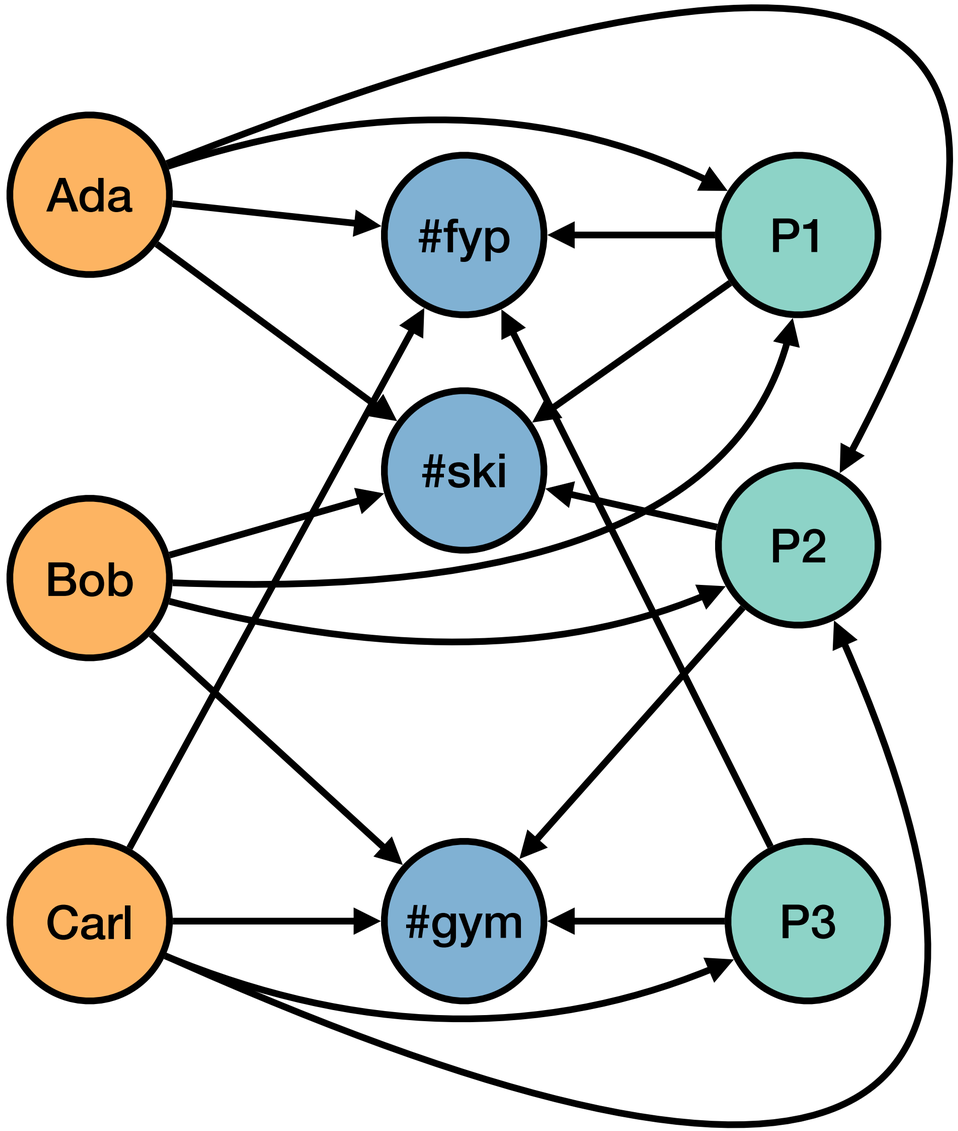
Ada	#ski
Bob	#gym
Bob	#ski
Carl	#fyp
Carl	#gym

User	Tag	Post
Ada	#fyp	P1
Ada	#ski	P1
Ada	#ski	P2
Bob	#gym	P2
Bob	#ski	P1
Bob	#ski	P2
Carl	#fyp	P3
Carl	#gym	P2
Carl	#gym	P3



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Carl	#gym

tagged

Post	Tag
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P1	#ski
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P2	#gym
P3	#gym

likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
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User	Tag	Post
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Ada	#ski	P1
Ada	#ski	P2
Bob	#gym	P2
Bob	#ski	P1
Bob	#ski	P2
Carl	#fyp	P3
Carl	#gym	P2
Carl	#gym	P3

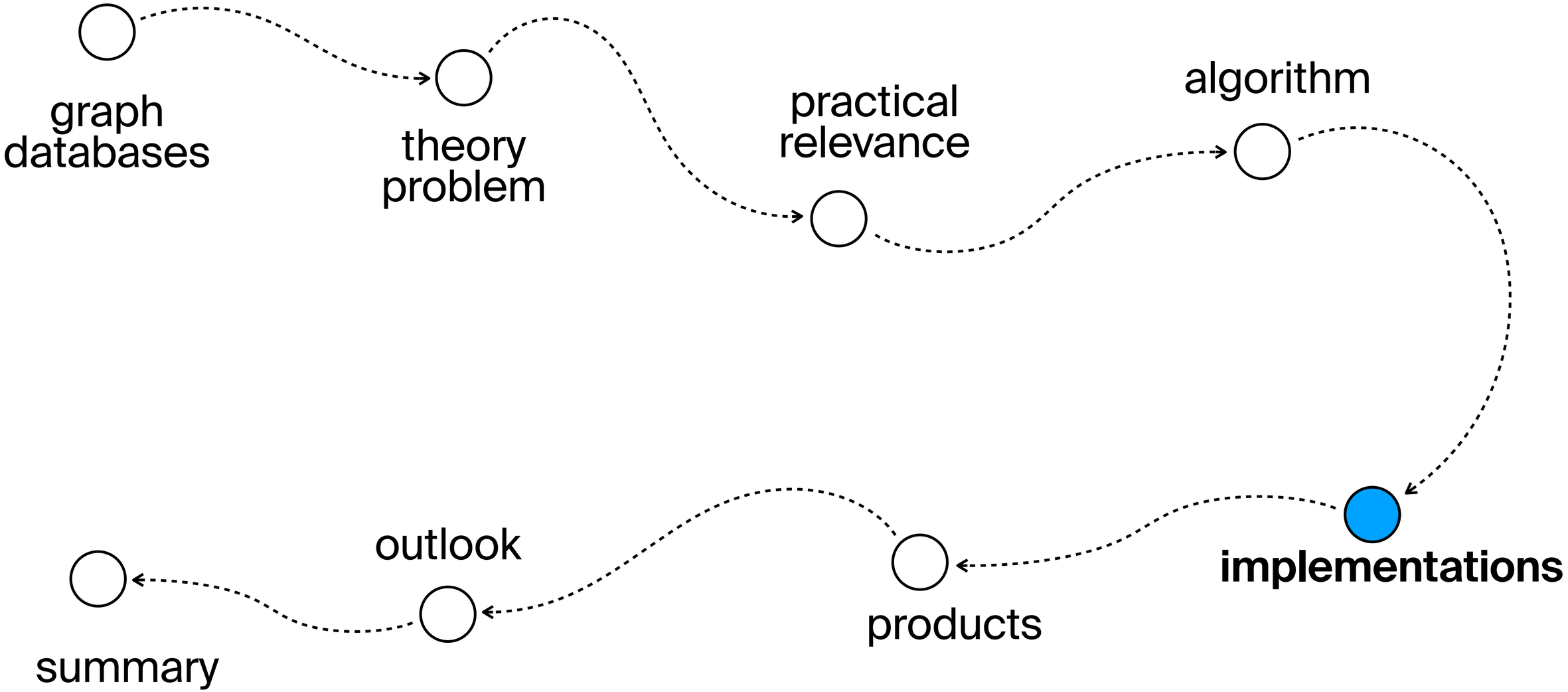
Very Large Databases 2019

Optimizing Subgraph Queries by Combining Binary and Worst-Case Optimal Joins

Amine Mhedhbi
University of Waterloo
amine.mhedhbi@uwaterloo.ca

Semih Salihoglu
University of Waterloo
semih.salihoglu@uwaterloo.ca

When to choose binary vs. multiway joins and how to **order them**?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SIGMOD 2016

EmptyHeaded: A Relational Engine for Graph Processing

Christopher R. Aberger
Stanford University
caberger@stanford.edu

Susan Tu
Stanford University
sctu@stanford.edu

Kunle Olukotun
Stanford University
kunle@stanford.edu

Christopher Ré
Stanford University
chrismre@cs.stanford.edu

Very Large Databases 2020

Adopting Worst-Case Optimal Joins in Relational Database Systems

Michael Freitag, Maximilian Bandle, Tobias Schmidt, Alfons Kemper, Thomas Neumann
Technische Universität München
{freitagm, bandle, tobias.schmidt, kemper, neumann}@in.tum.de

Hash table-based implementation

3.2.4 *Complexity Analysis*

In the following, we present a formal investigation of the time and space complexity of the proposed hash trie join approach, proving in particular that its runtime is indeed worst-case optimal.

THEOREM 1. *The build phase of the proposed approach has time and space complexity in* $O(n \cdot \sum_{E_j \in \mathcal{E}} |R_j|)$.

PROOF. As outlined above, the same operations are performed for each input relation R_j during the build phase, hence we focus on a given R_j in the following. The initial materialization of R_j in a linked list clearly requires time and space proportional to $|R_j|$. Moving on to Algorithm 2, we note that each tuple in the input linked list L is moved to exactly one of the linked lists that are processed recursively. That is, no additional space is required for tuple storage, and the overall set of tuples that is processed in each recursive step of Algorithm 2 is some partition of R_j. As there are at most n join attributes in a relation, we obtain a total time and space complexity of $O(n \cdot |R_j|)$ for the build phase of a single relation R_j. □

3.2.4 *Complexity Analysis*

In the following, we present a formal investigation of the time and space complexity of the proposed hash trie join approach, proving in particular that its runtime is indeed worst-case optimal.

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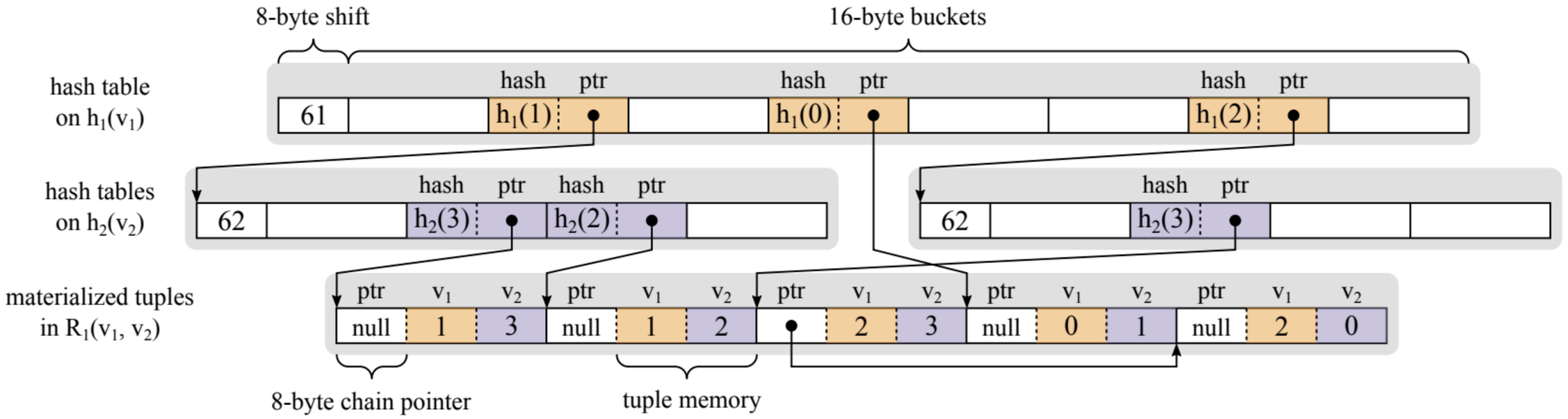
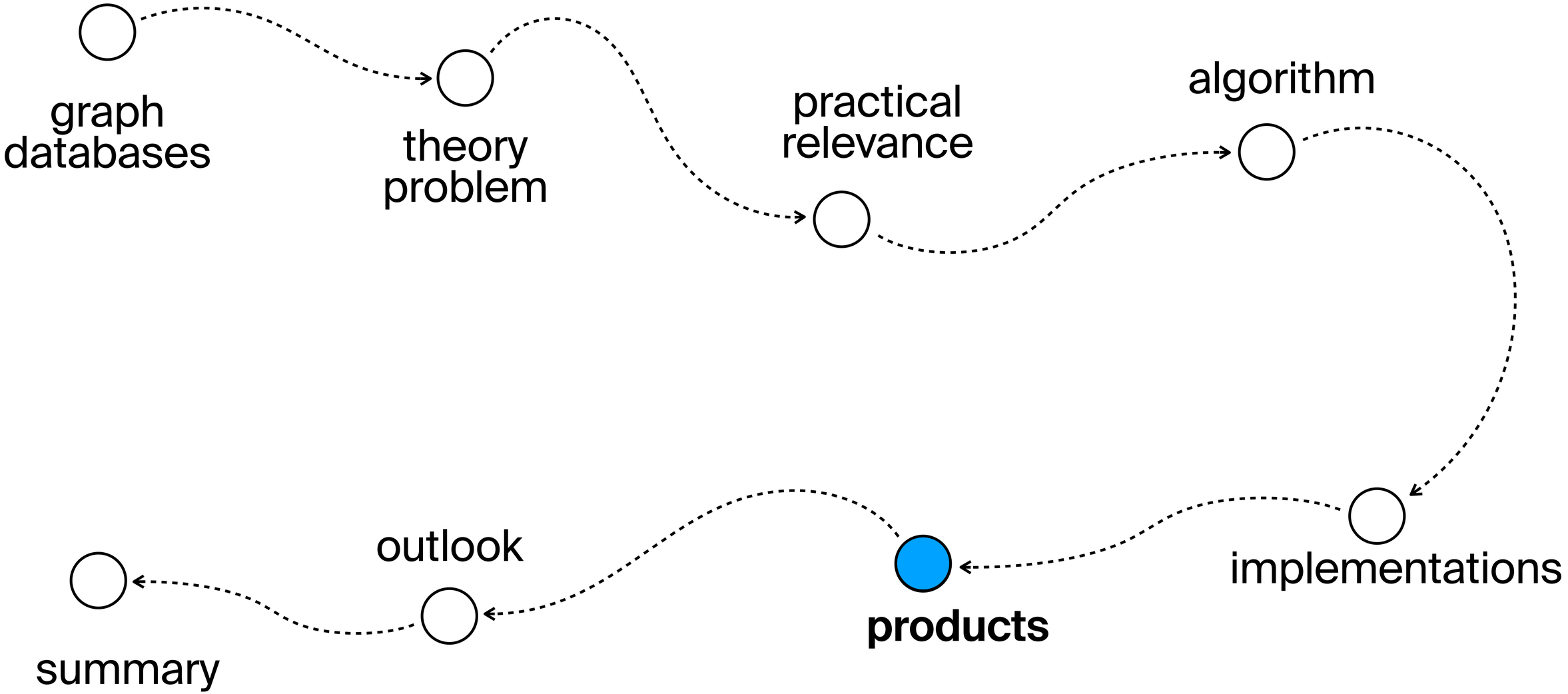


Figure 3: Memory layout of the hash trie in Figure 2. The gray boxes correspond to the individual hash tables and materialized input tuples. No nested hash table is built for the tuple $(0, 1)$ due to singleton pruning.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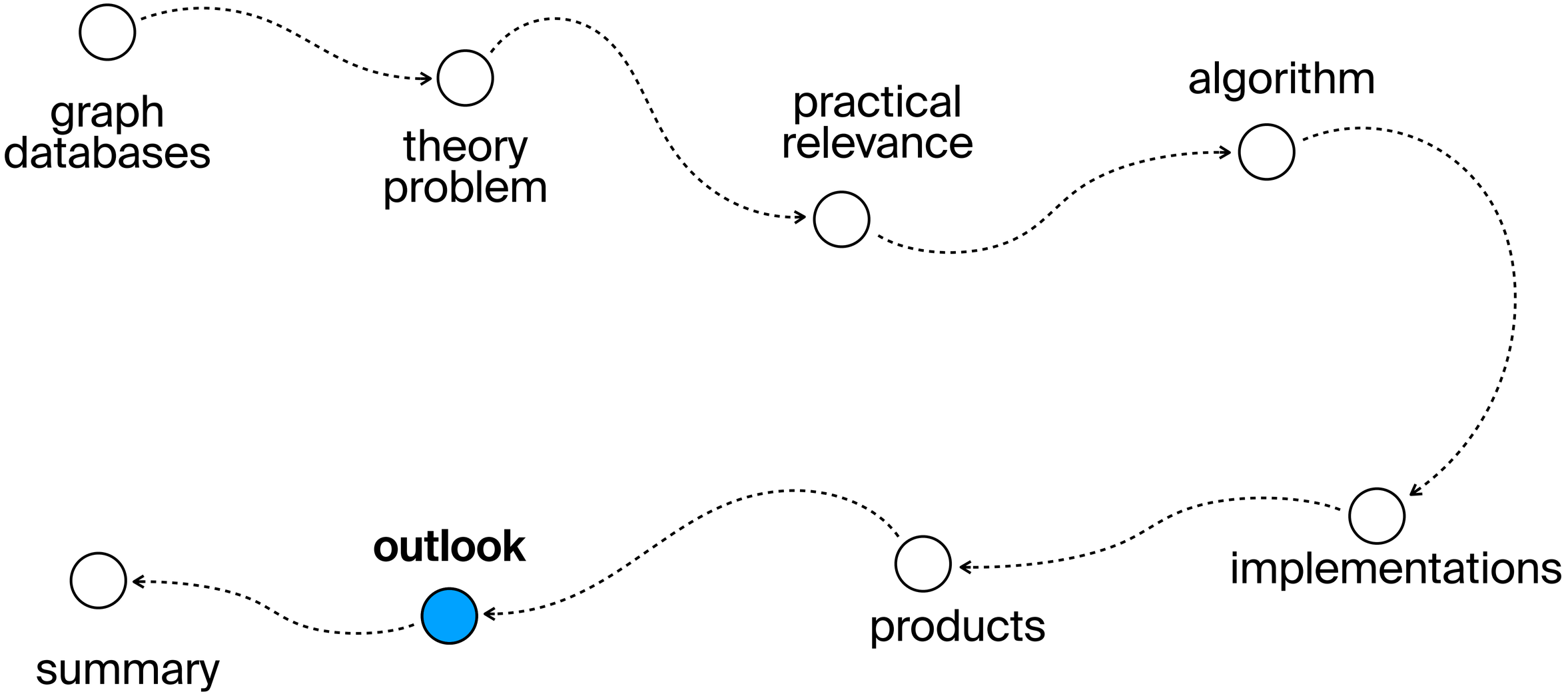
Database systems that support multiway joins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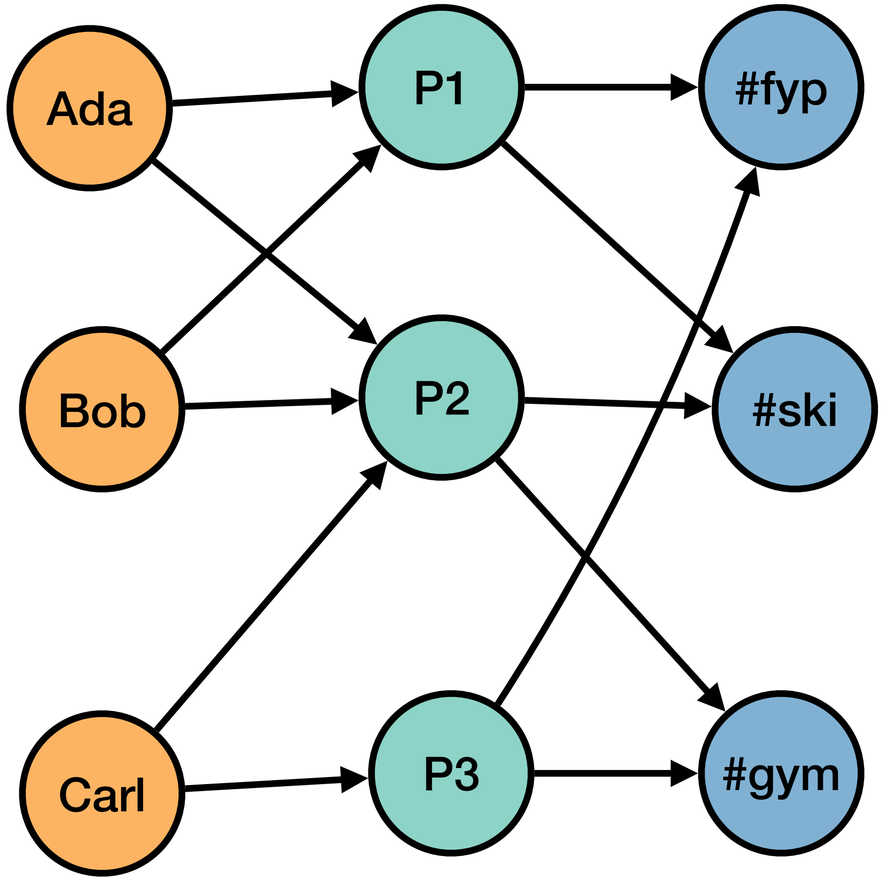


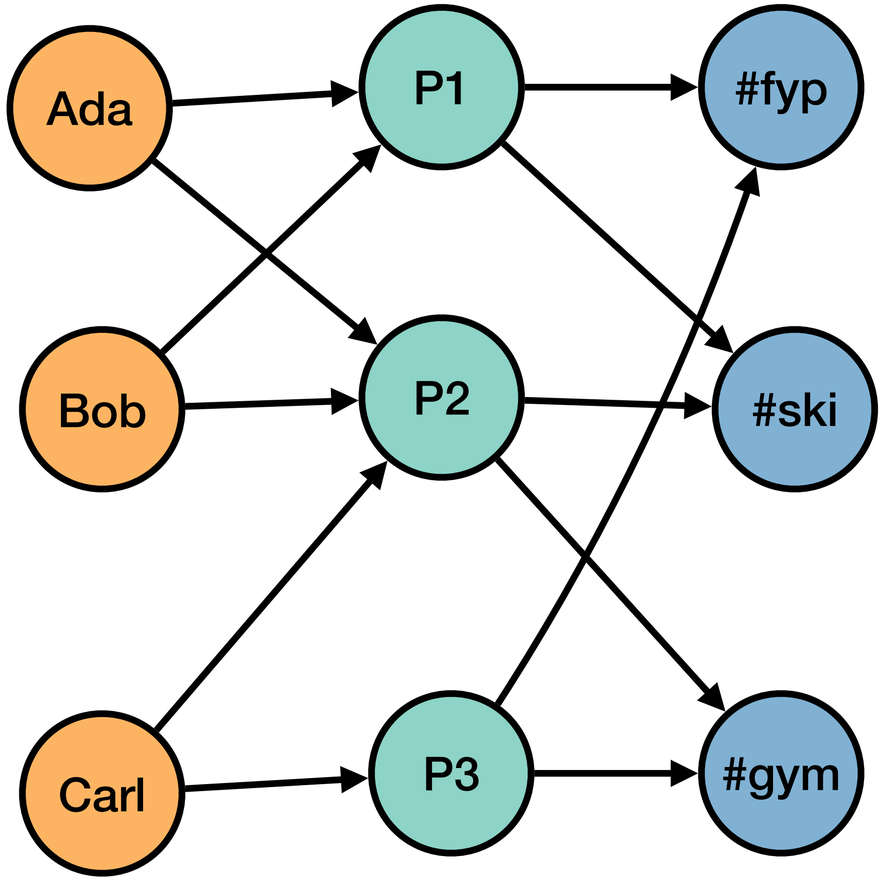

```
SELECT post
FROM likes
NATURAL JOIN tagged
GROUP BY post
HAVING count(distinct user) > count(distinct tag);
```

likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

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NATURAL JOIN tagged
GROUP BY post
HAVING count(distinct user) > count(distinct tag);
```

likes ⋈ tagged

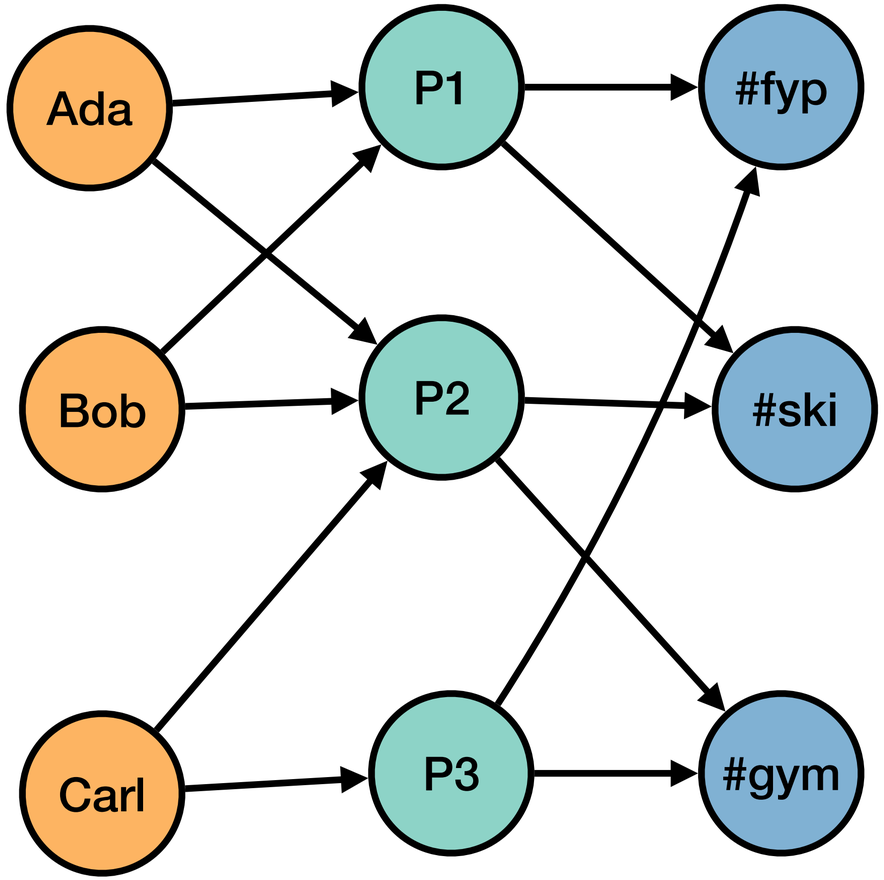
User	Post	Tag
Ada	P1	#ski
Bob	P1	#ski
Ada	P1	#fyp
Bob	P1	#fyp
Ada	P2	#gym
Bob	P2	#gym
Carl	P2	#gym
Ada	P2	#ski
Bob	P2	#ski
Carl	P2	#ski
Carl	P3	#gym
Carl	P3	#fyp

likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
Carl	P2
Carl	P3

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym




```
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likes

User	Post
Ada	P1
Ada	P2
Bob	P1
Bob	P2
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Carl	P3

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
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P3	#gym

likes ⋈ tagged

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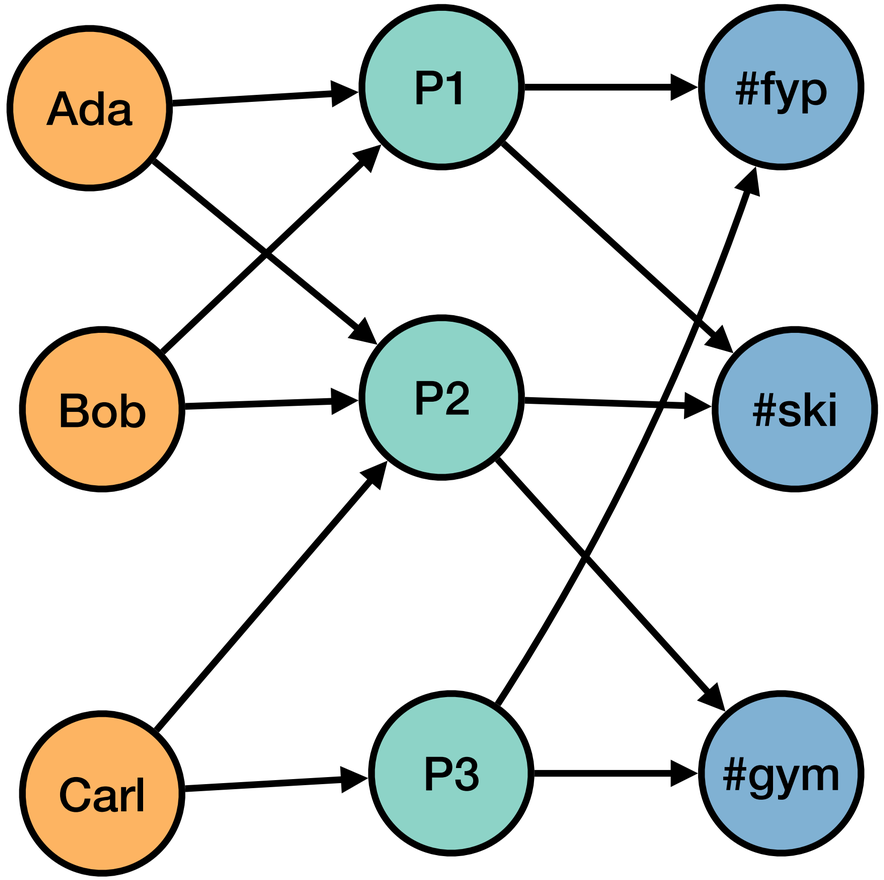
Bob	P1	#ski
Ada	P1	#fyp
Bob	P1	#fyp

count[user, tag] (likes ⋈ tagged)

Post	num_users	num_tags
P1	2	2
P2	3	2
P3	1	2

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tagged

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P3	#fyp
P1	#ski
P2	#ski
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P3	#gym

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Post	num_users	num_tags
P1	2	2
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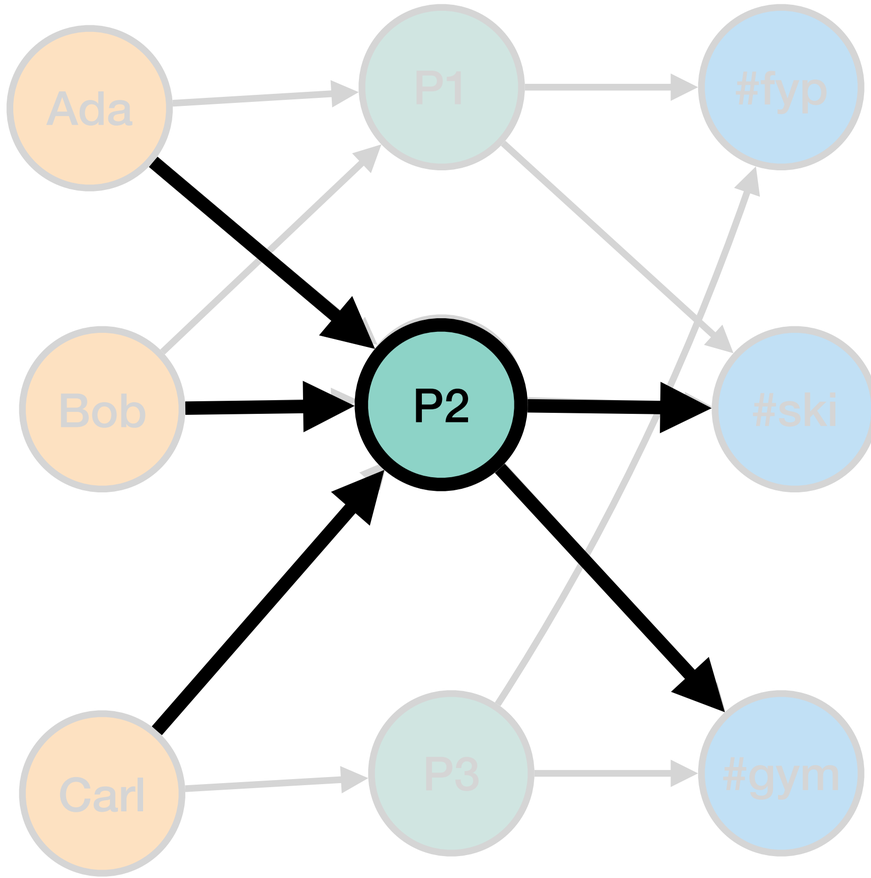
P3	1	2

result

Post
P2

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Post	Tag
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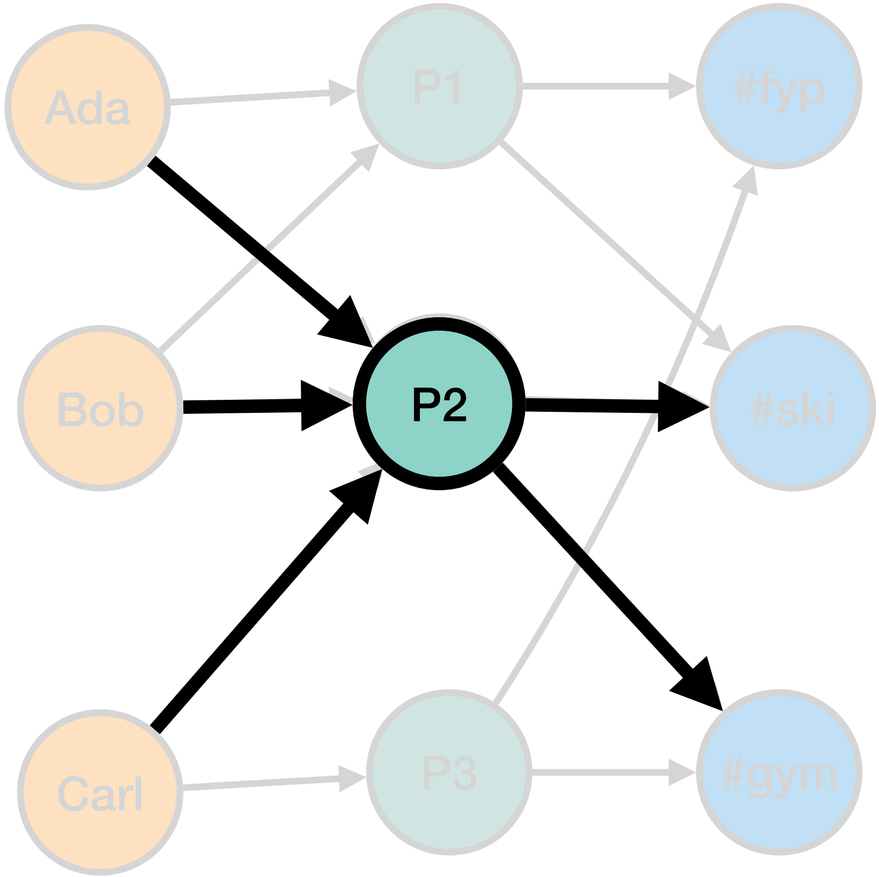
P3	#gym

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SELECT post
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factorization: lossless compression

likes

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Ada	P2
Bob	P1
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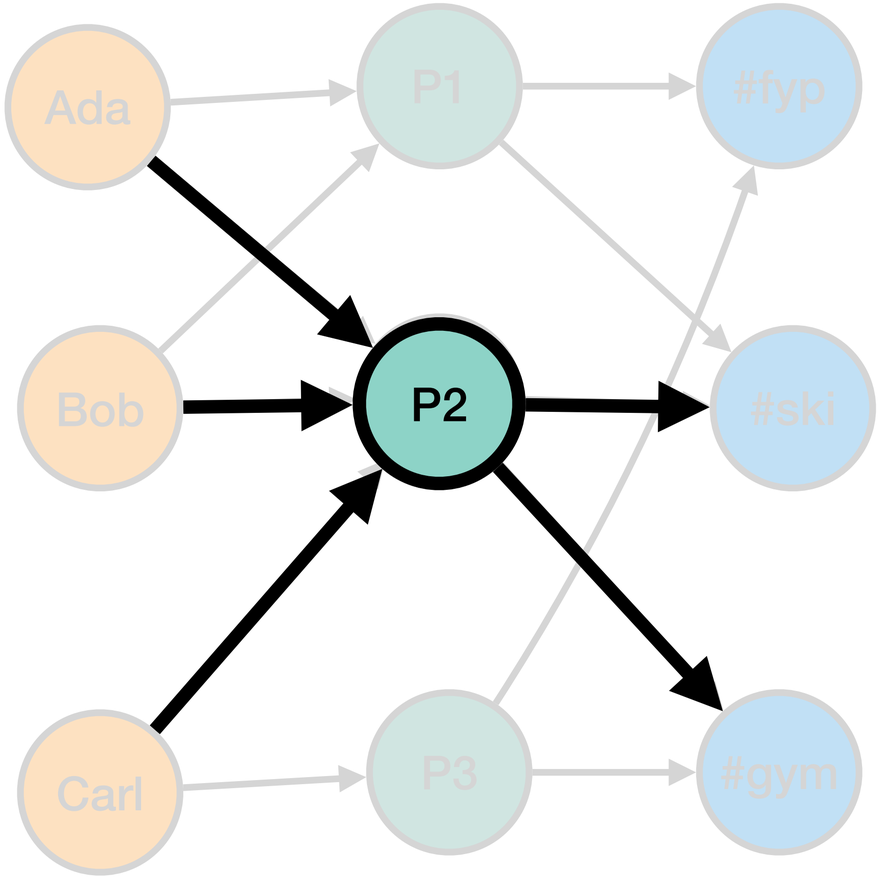
Carl	P3

tagged

Post	Tag
P1	#fyp
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

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Carl	P3

tagged

Post	Tag
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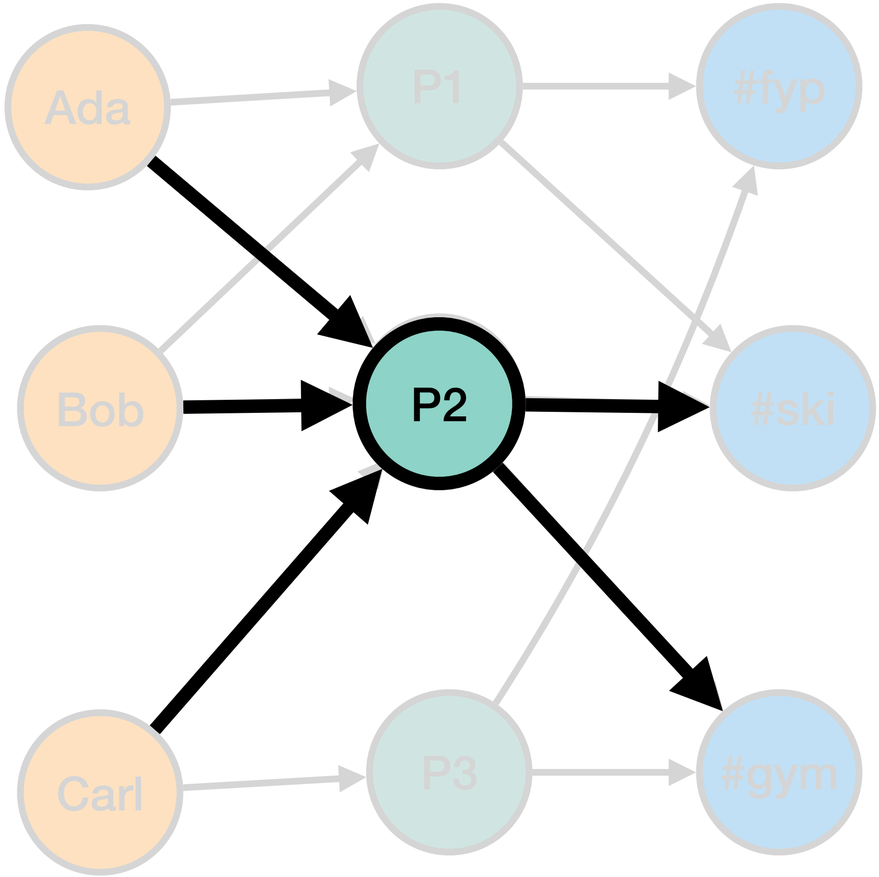
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes ⋈ tagged

User	Post	Tag
{Ada, Bob} {Ada, Bob, Carl} {Carl}	P1 P2 P3	{#ski, #fyp} {#gym, #ski} {#fyp, #gym}

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tagged

Post	Tag
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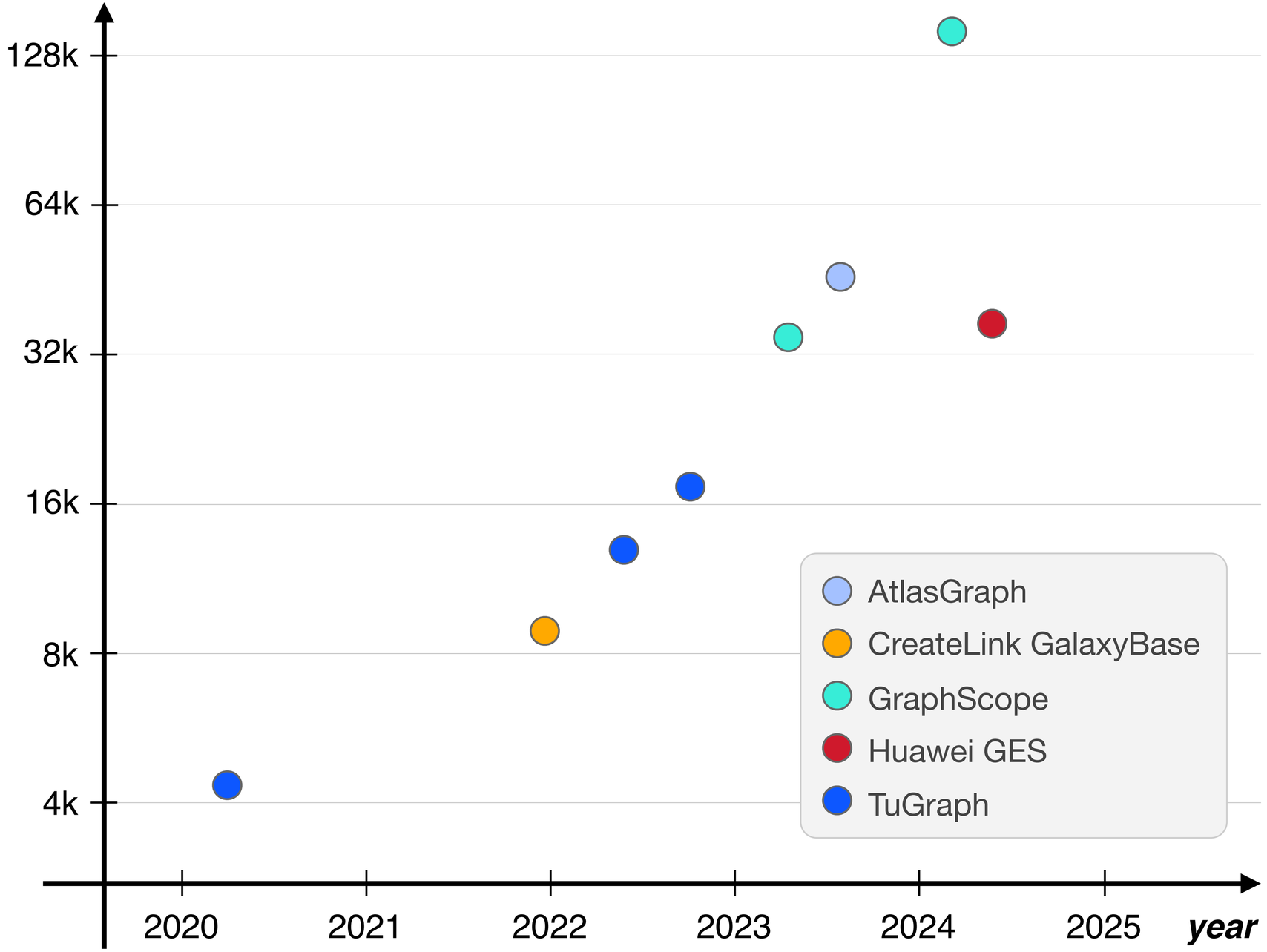
P3	#fyp
P1	#ski
P2	#ski
P2	#gym
P3	#gym

likes ⋈ tagged

User	Post	Tag
{Ada, Bob}	P1	{#ski, #fyp}
{Ada, Bob, Carl}	P2	{#gym, #ski}
{Carl}	P3	{#fyp, #gym}

Industry

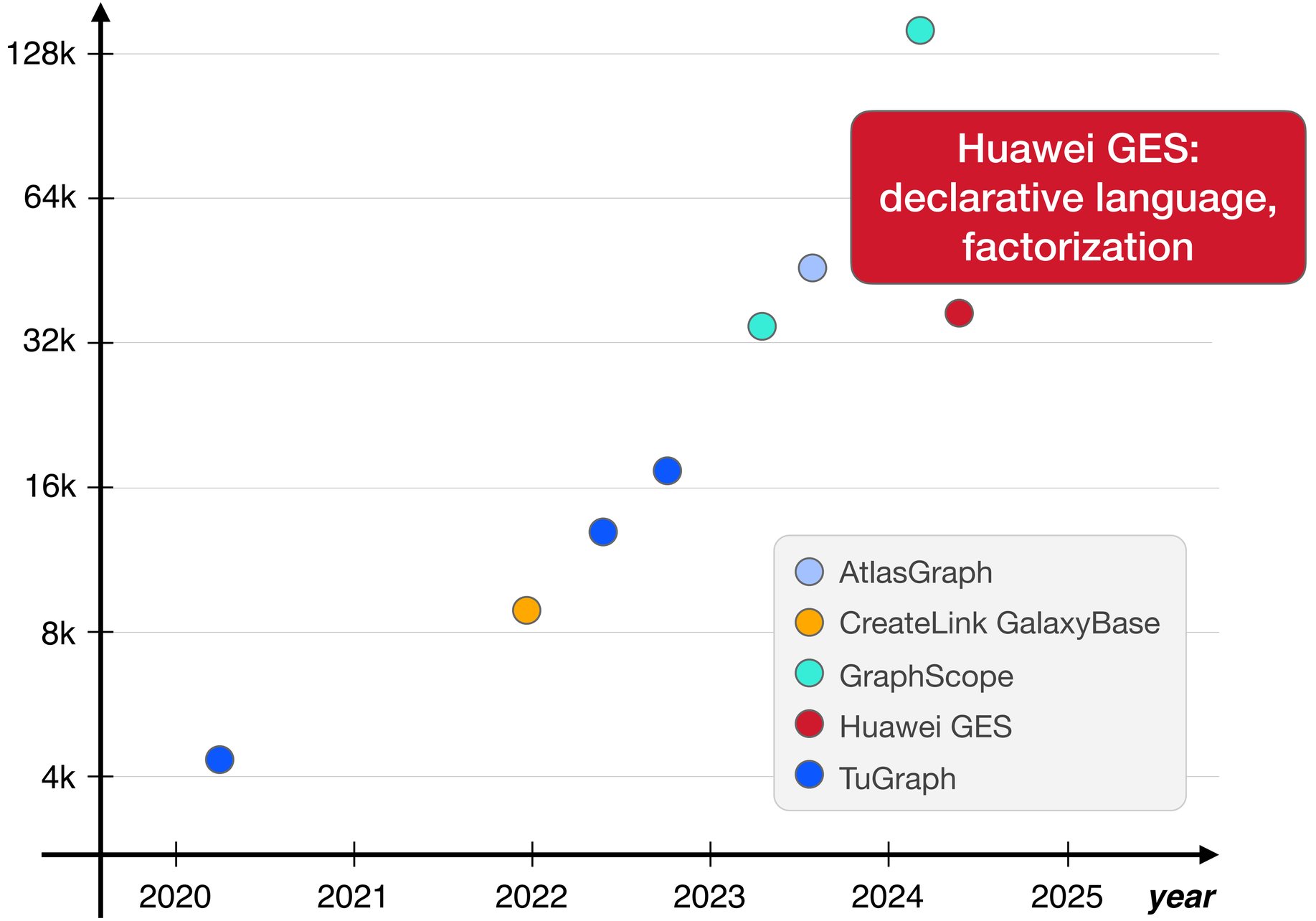
Competition is spurred by standardized benchmarks



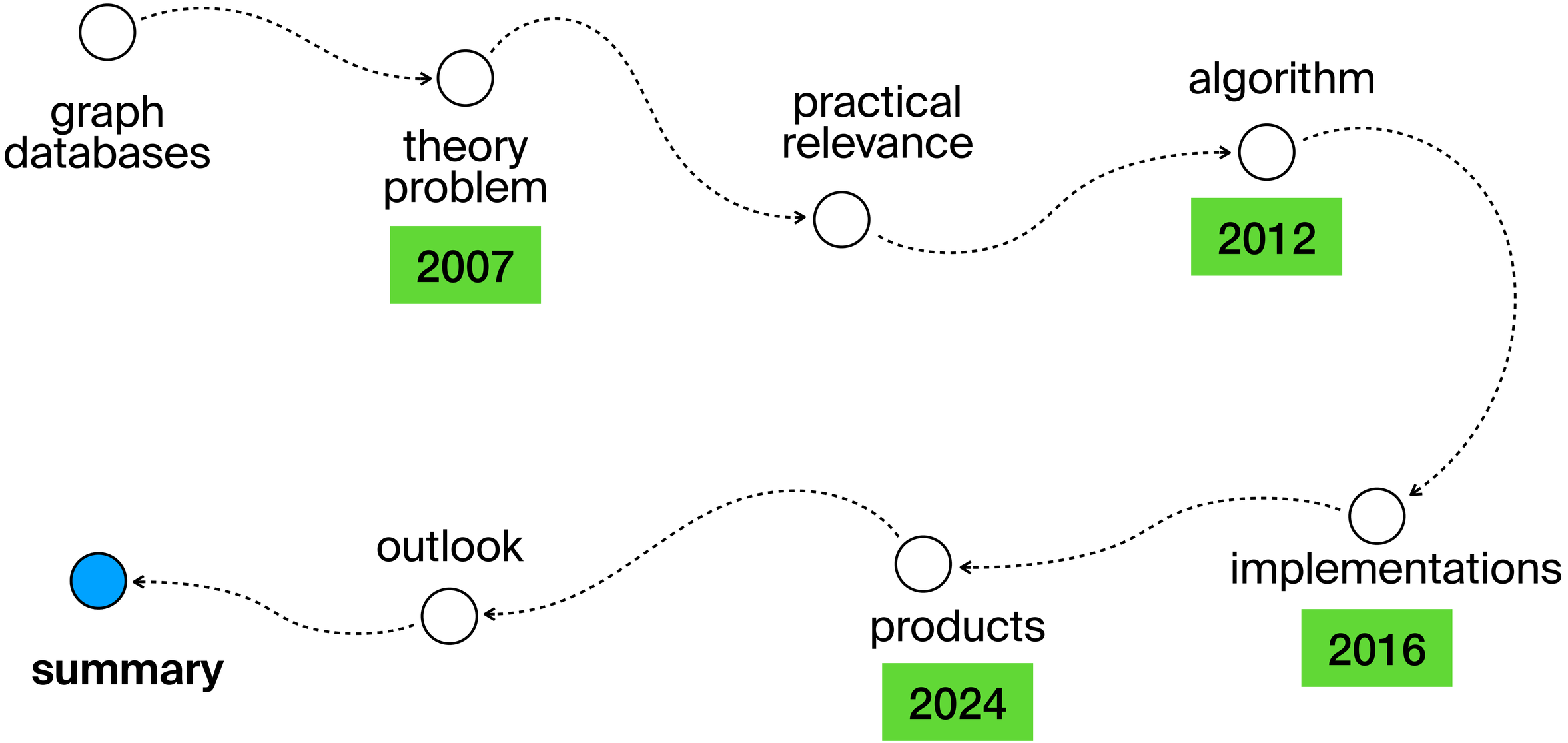
LDBC

Industry

Competition is spurred by standardized benchmarks



LDBC


graph databases
theory problem
2007
practical relevance
algorithm
2012
implementations
2016
products
2024
outlook
summary