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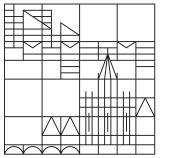
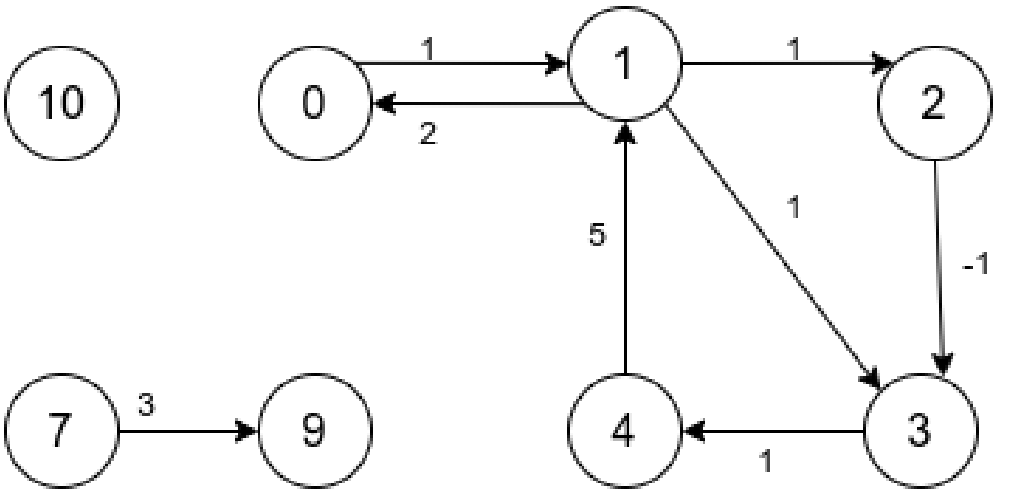


Locality Optimization for traversal-based Queries on Graph Databases

Fabian Klopfer

Databases and Information Systems Group
Department of Computer and Information Science
University of Konstanz, 30.04.2021

Graphs



Data Structures I

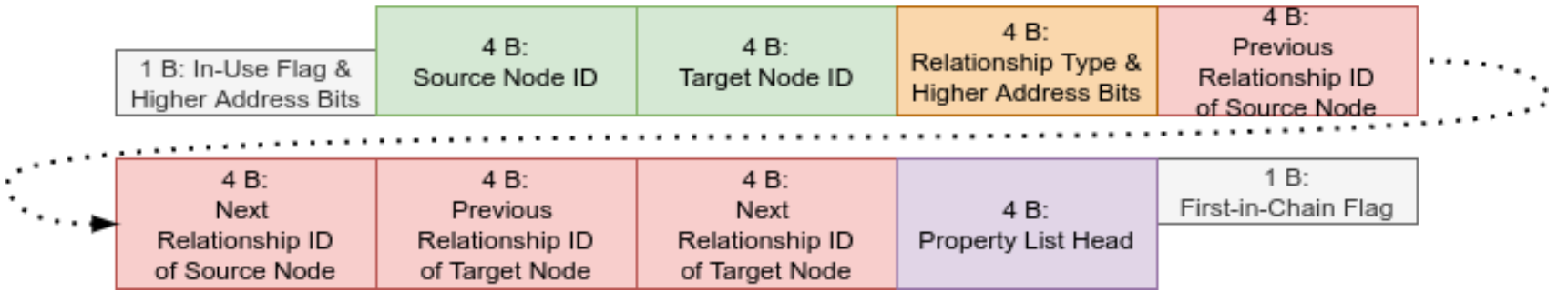
Two essential record structures:

1. Node records
2. Relationship records

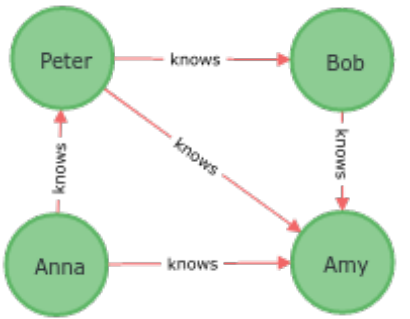
Inspired by Neo4J [1], [2].

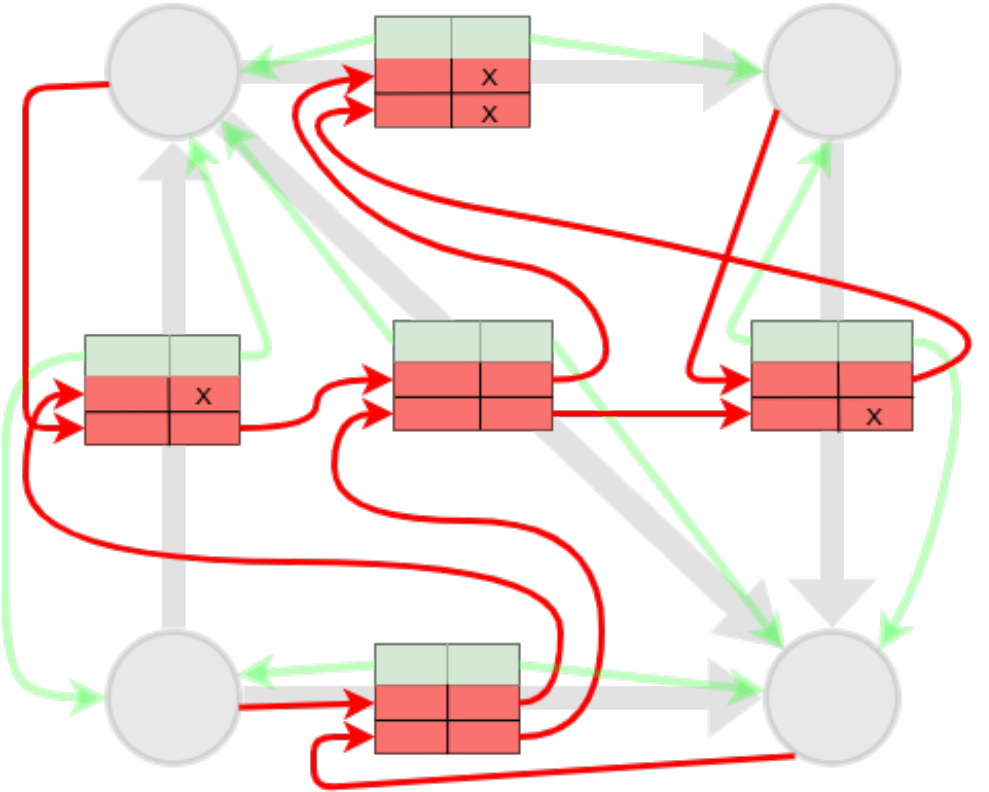
Data Structures II

Data Structures III



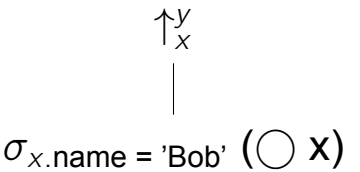
Data Structures – Example




X
X
X
X

Example Query

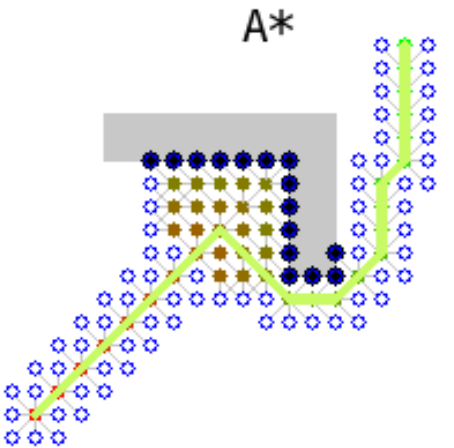
Show me all people that Bob knows:



$\Rightarrow$ Scaning and filtering read sequential.

$\Rightarrow$ `Expand` does not necessarily.

Traversal-based Query



Motivation

- `Expand`'s access pattern depends on the query, record and incidence list order.

- When these factors are not considered, access is random.

  Potentially leads to

  ⇒ hard-to-predict access patterns.
  ⇒ cache & prefetch misses, thrashing and pollution.
  ⇒ inadequate page eviction behavior.

Traversals rely primarily on `expand`!

Locality I

- “memory references tend to be localized in time and space” [3].
- Tendency to access nearby memory locations based on previous accesses [4].
- Enables usage of memory hierarchy.

⇒ The more localized the access the less IO ops are necessary [5].

Locality II

Temporal locality based on blocks

$$P(X_{t+\Delta} = B | X_t = B)$$

Spatial locality in the same sense

$$P(X_{t+\Delta} = B \pm \varepsilon | X_t = B)$$

with $\varepsilon = \lceil \frac{p}{b} \rceil$ [5].

Problem Definition

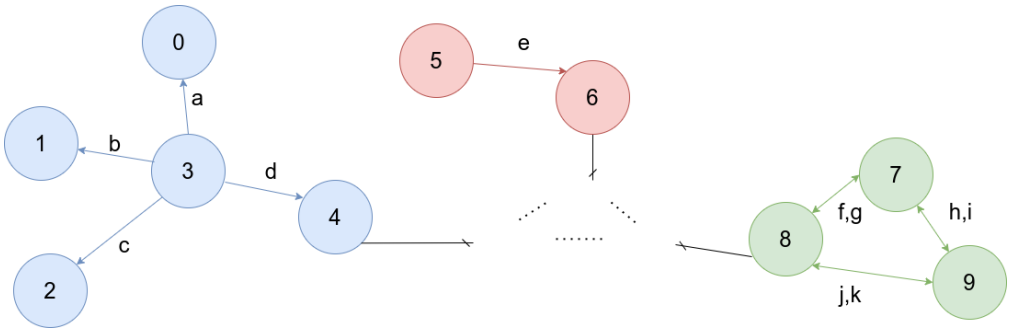
Given a graph G, logical block size b, page size p.

Desired is

1. A partition of G into blocks of size b,
2. permutations π_v, π_e of the blocks,

such that locality is as high as possible for traversal-based queries.

Example: Block Formation and Order



node.db	0, 5, 7	1, 4, 9	2, 6, 8	3		
edge.db	a, f	b, g	c, h	d, i	e, j	k

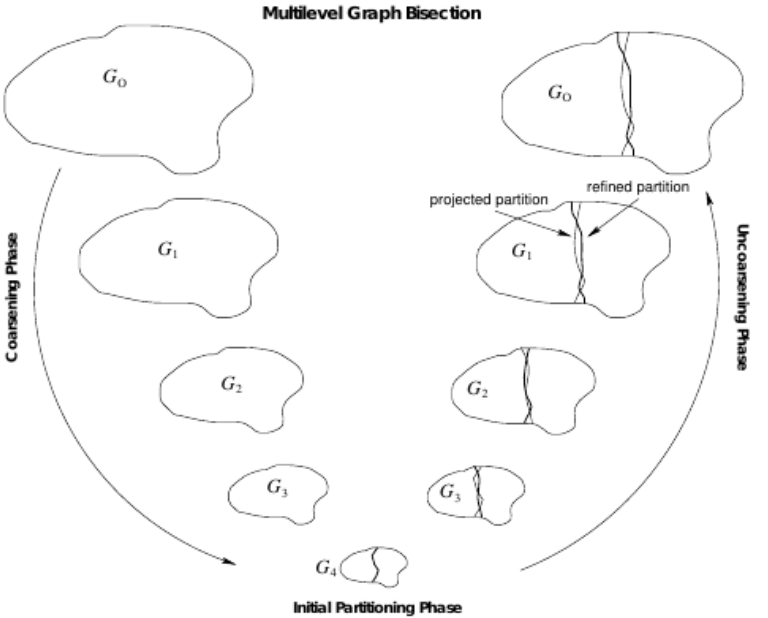
node.db	7, 8, 9	0, 1, 3	2, 4, 5	6		
edge.db	f, h	g, k	i, j	a, b	c, d	e

Record Layout Methods: Overview

- Existing methods
  - G-Store [6]
  - ICBL [7]

- Our approach
  - Community detection — Louvain method [8].
  - Incidence list reordering

G-Store I

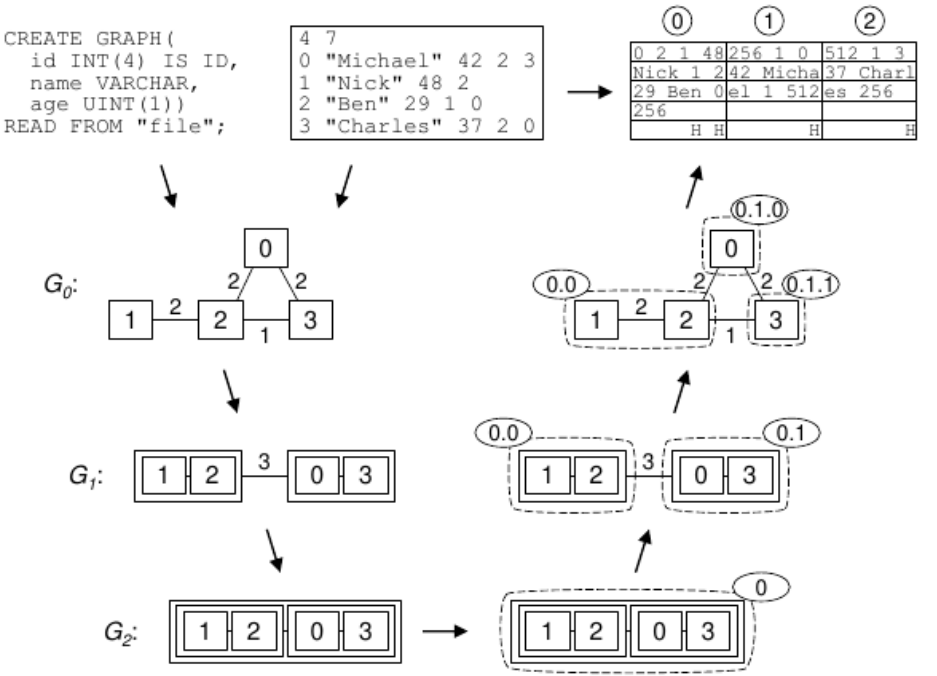

Multilevel Graph Bisection
G_0
G_1
G_2
G_3
G_4
Coarsening Phase
Uncoarsening Phase
projected partition
refined partition
Initial Partitioning Phase

G-Store II

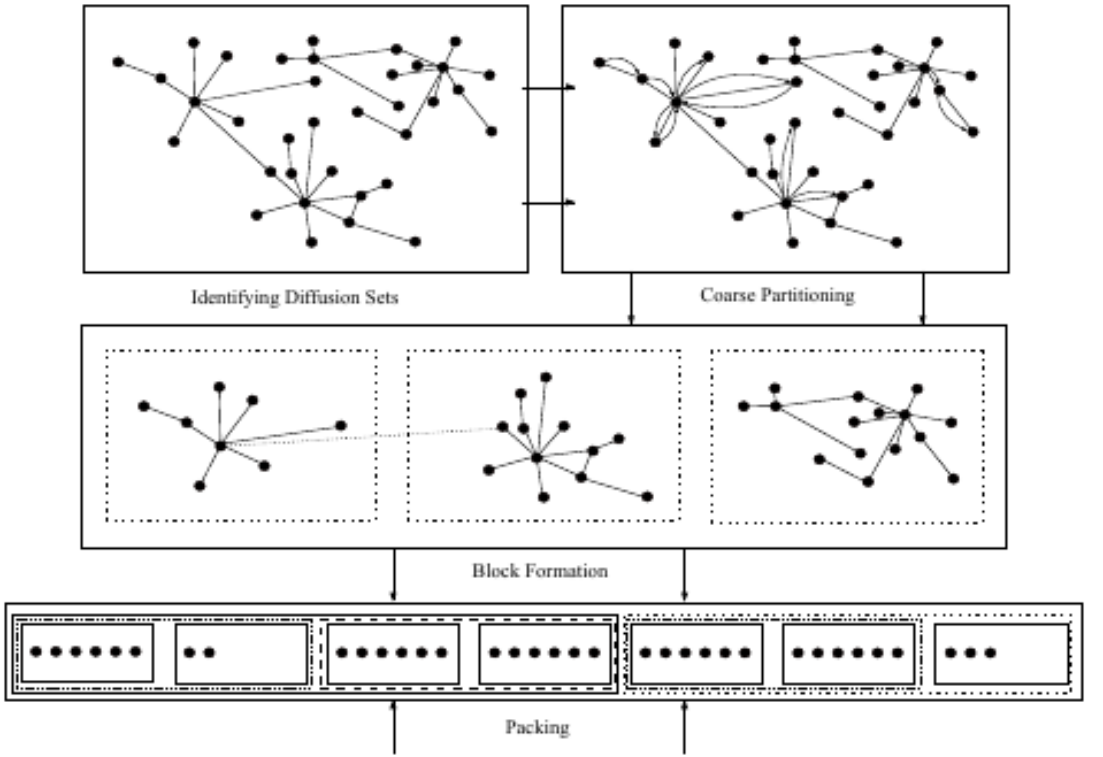
1. Coarsening: Heavy-Edge Matching [9]
2. Turn-around
3. Uncoarsening
   - 3.1 Project
   - 3.2 Reorder
   - 3.3 Refine

$$\min \sum_{(u,v)\in E} |\phi(u) - \phi(v)|$$

G-Store III


CREATE GRAPH(
id INT(4) IS ID,
name VARCHAR,
age UINT(1))
READ FROM "file";
4 7
0 "Michael" 42 2 3
1 "Nick" 48 2
2 "Ben" 29 1 0
3 "Charles" 37 2 0
0 1 2
0 2 1 48 256 1 0 512 1 3
Nick 1 2 42 Micha 37 Charl
29 Ben 0 el 1 512 es 256
256
H H H H
G0:
G1:
G2:
0.0
0.1
0.1.0
0.1.1

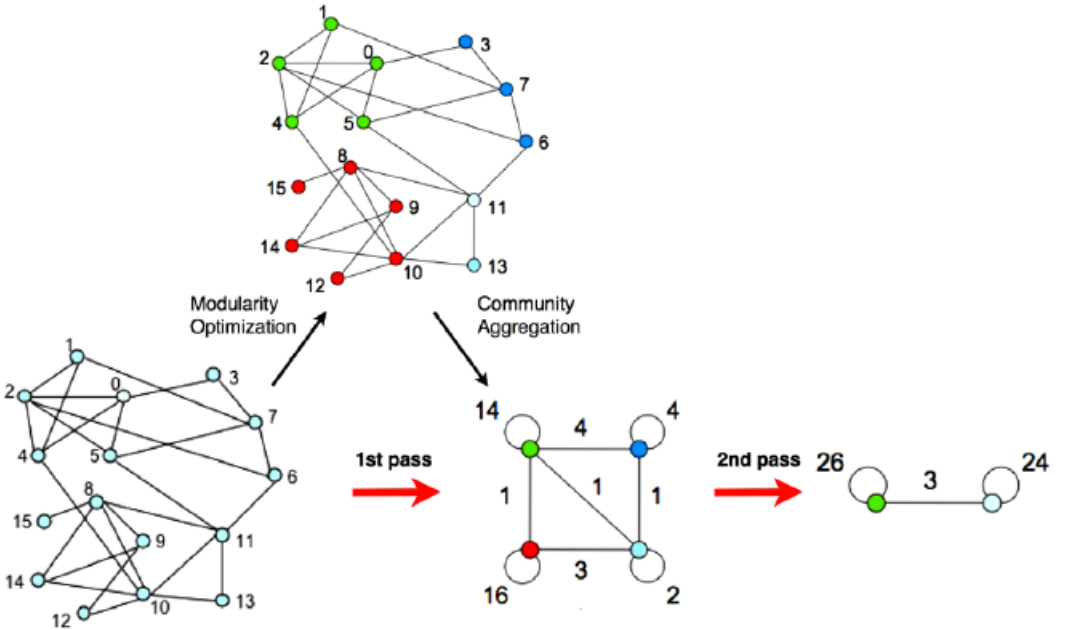
ICBL I


Identifying Diffusion Sets
Coarse Partitioning
Block Formation
Packing

ICBL II

I Feature extraction: Do t random walks [10] of length l.
C Coarse clustering: Adapted K-Means [11].
B Block Formation: Agglomerative hierarchical clustering [12].
L Layout Blocks: Sort blocks and subgraphs

Louvain Method I

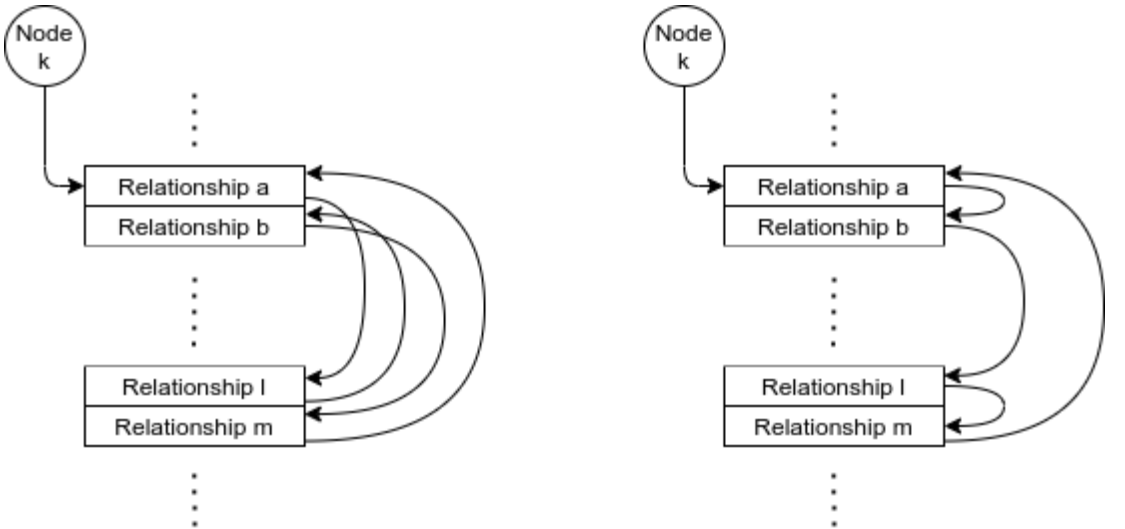


Louvain Method II

1. Initialize all nodes in singleton community.
2. Merge community into a neighboring community where modularity gain is maximal, until modularity gain is below threshold.
3. Construct new graph from aggregated communities and go to 1.

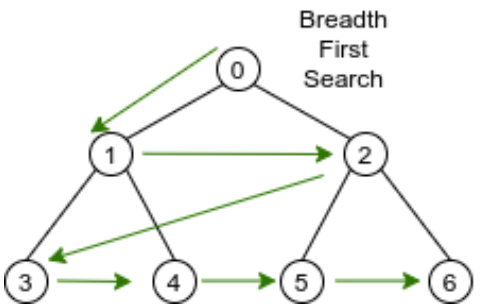
$$\frac{1}{2m} \sum_{u,v \in V} \left(w_{(u,v)} - \frac{w_u w_v}{2m} \right) \cdot \delta(c_u, c_v)$$

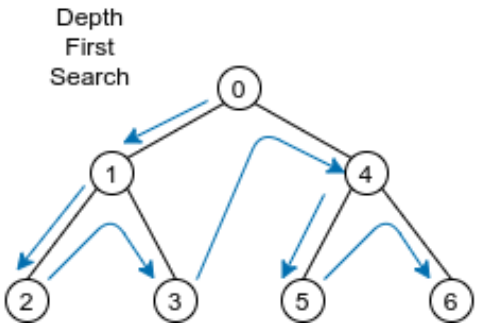
Incidence List Rearrangement

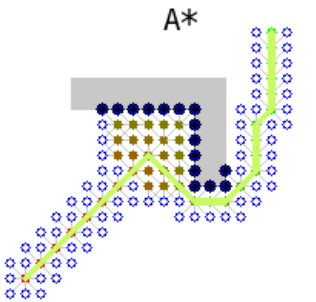


Setup I

- Queries: BFS, DFS, Dijkstra, A*, ALT.







Setup II

- Datasets: $[131, 1'134'890]$ nodes, $[764, 2'987'624]$ edges, average degree $[2.6, 25.5]$

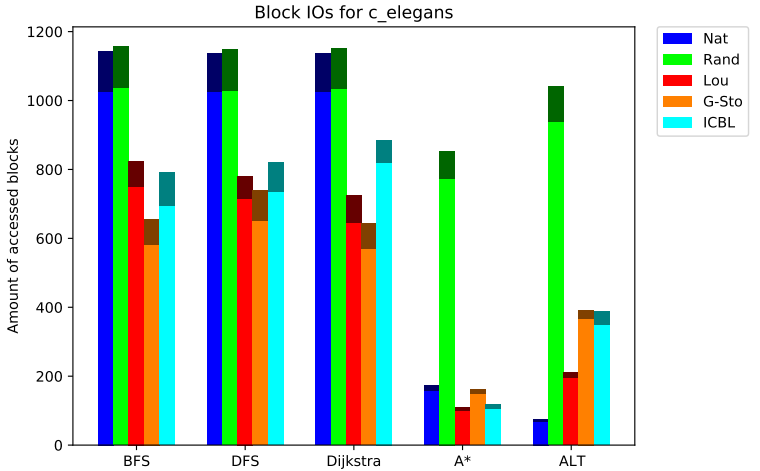
- Domains include biological neural net, e-mails, co-authors, frequent item sets, video channel subscriptions [13].

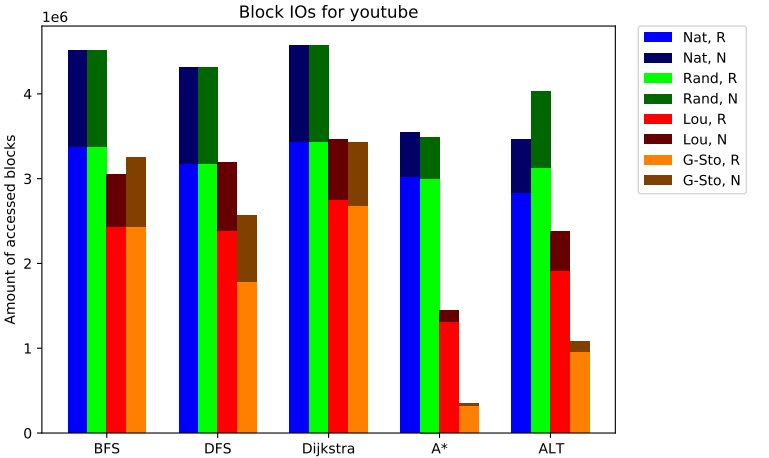
Setup III

- Simulate IOs using in-memory access layer, queries and record IDs.
- Block no. = record ID · `sizeof(`record struct`)` / block size
- Consecuive accesses to same block require no IO op.
- All other accesses count as one IO op.

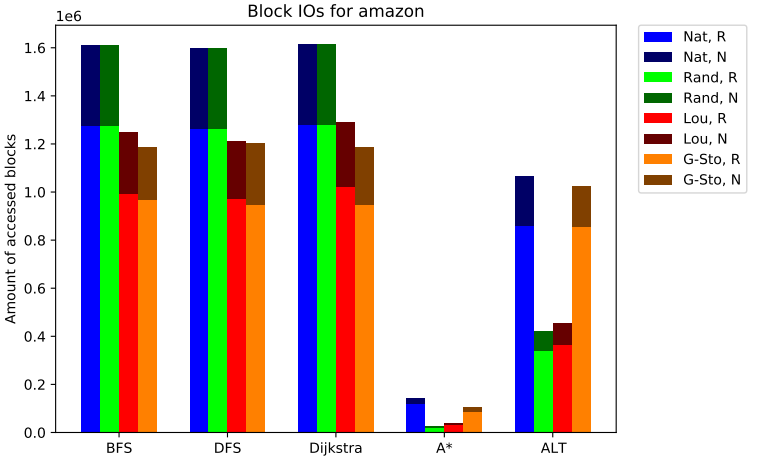
1. Import dataset.
2. Run query and log IDs of accessed nodes and relationships.
3. Calculate sequence of block no. from sequence of IDs.
4. Calculate sequence of page no. from sequence of block no.

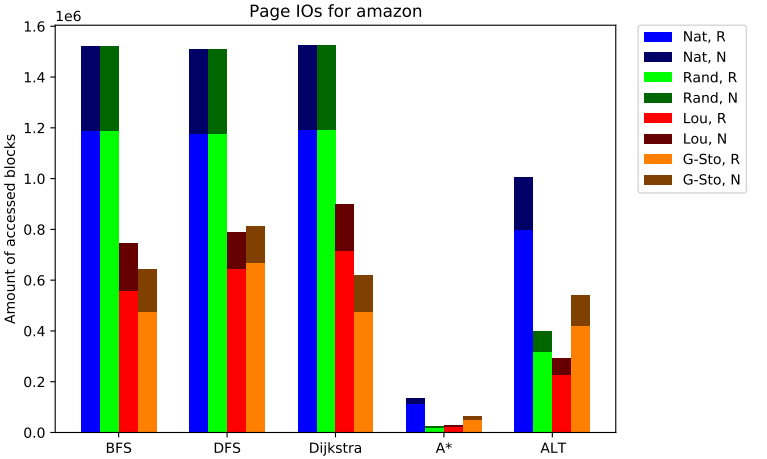
Results I


Block IOs for c_elegans
Amount of accessed blocks
0
200
400
600
800
1000
1200
BFS
DFS
Dijkstra
A*
ALT
Nat
Rand
Lou
G-Sto
ICBL

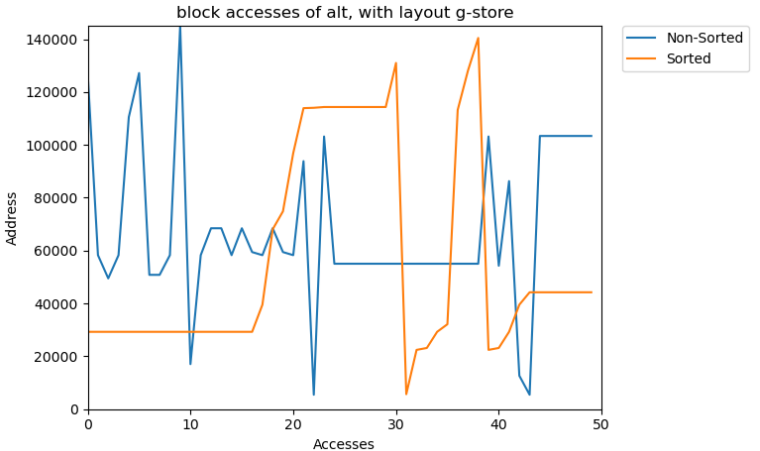

Block IOs for youtube
1e6
Amount of accessed blocks
0
1
2
3
4
BFS
DFS
Dijkstra
A*
ALT
Nat, R
Nat, N
Rand, R
Rand, N
Lou, R
Lou, N
G-Sto, R
G-Sto, N

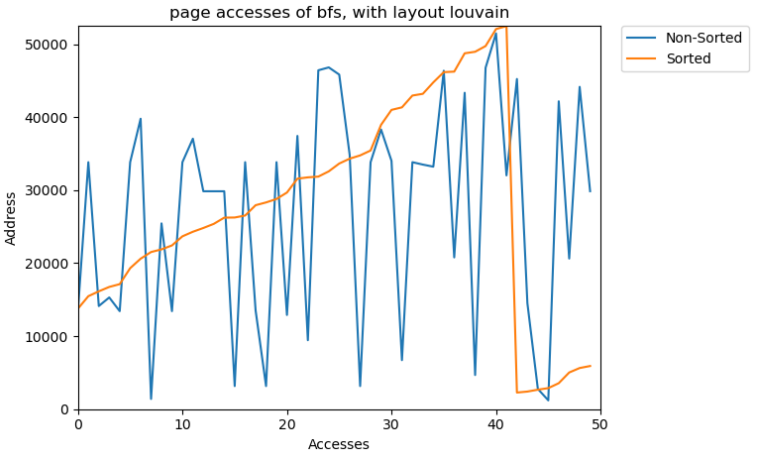
Results II


Block IOs for amazon
1e6
Amount of accessed blocks
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
BFS
DFS
Dijkstra
A*
ALT
Nat, R
Nat, N
Rand, R
Rand, N
Lou, R
Lou, N
G-Sto, R
G-Sto, N

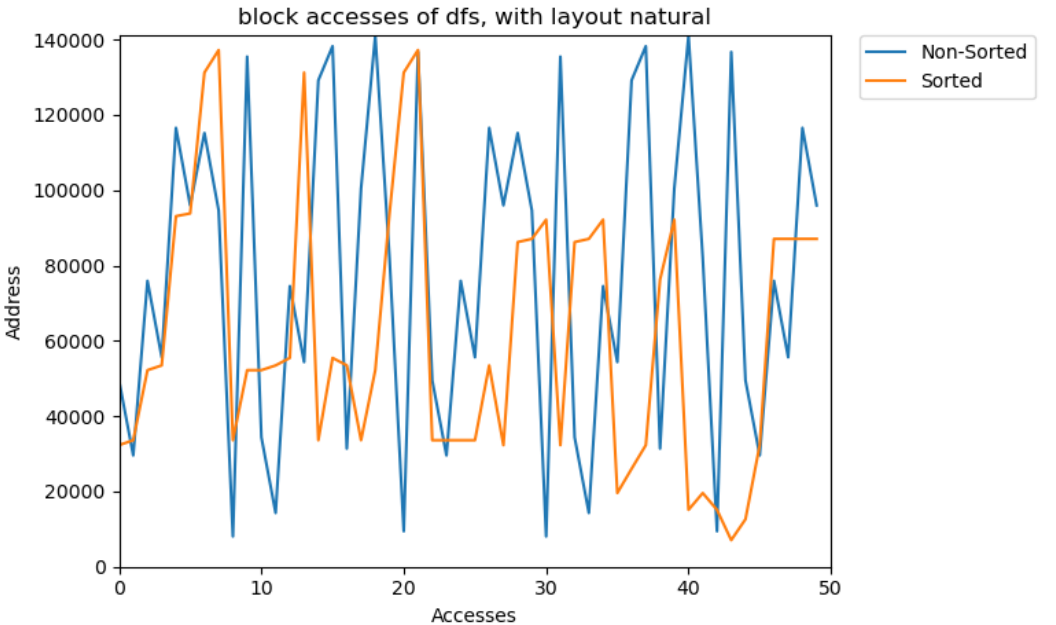

Page IOs for amazon
1e6
Amount of accessed blocks
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
BFS
DFS
Dijkstra
A*
ALT
Nat, R
Nat, N
Rand, R
Rand, N
Lou, R
Lou, N
G-Sto, R
G-Sto, N

Results III


block accesses of alt, with layout g-store
Non-Sorted
Sorted
Address
Accesses
0
20000
40000
60000
80000
100000
120000
140000
0
10
20
30
40
50


page accesses of bfs, with layout louvain
Non-Sorted
Sorted
Address
Accesses
0
10000
20000
30000
40000
50000
0
10
20
30
40
50

Results IV


block accesses of dfs, with layout natural
Address
Accesses
Non-Sorted
Sorted
0
20000
40000
60000
80000
100000
120000
140000
0
10
20
30
40
50

Summary

- Static rearrangement methods increase locality.
  $\Rightarrow$ decrease number of block accesses

- The order of blocks is important for spatial locality

- Sorting the incidence lists leads to more sequential access sequences.

- Results differ between queries

Future Work

- Leiden [14] instead of Louvain
- RCM-based [15] rearrangement
- Dynamic Rearrangement
  - Query-based
  - History-based

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