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Big Data Processing and Analytics Inside DBMS

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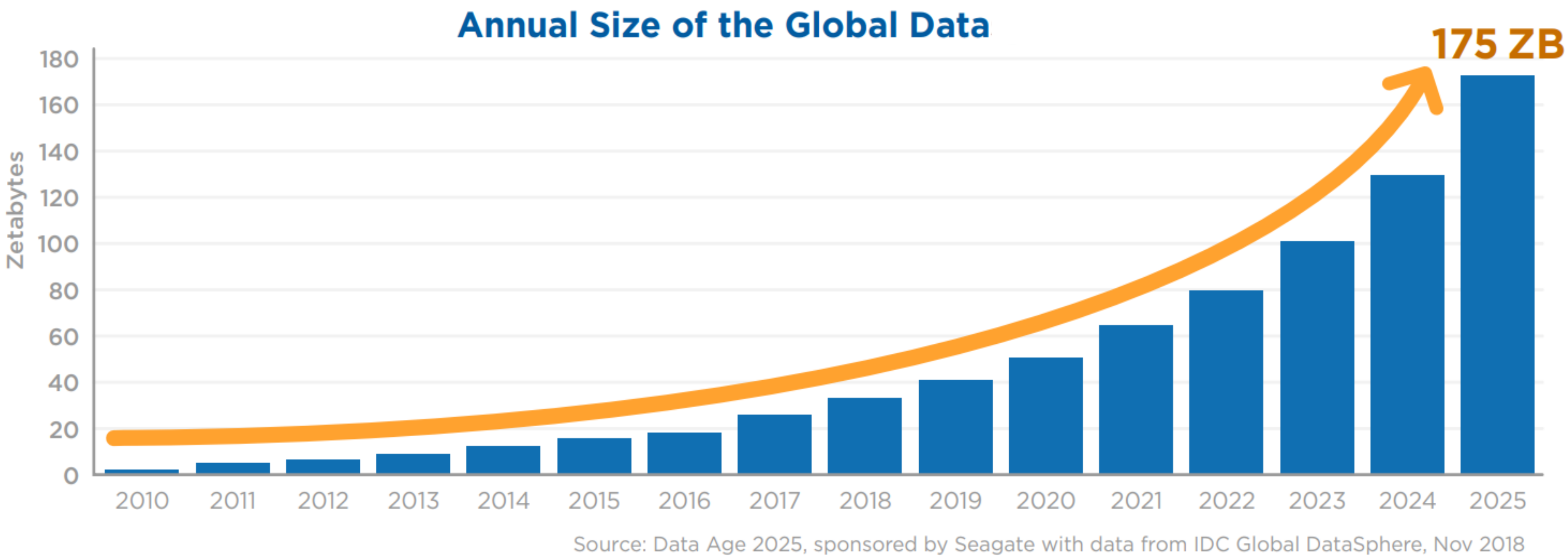
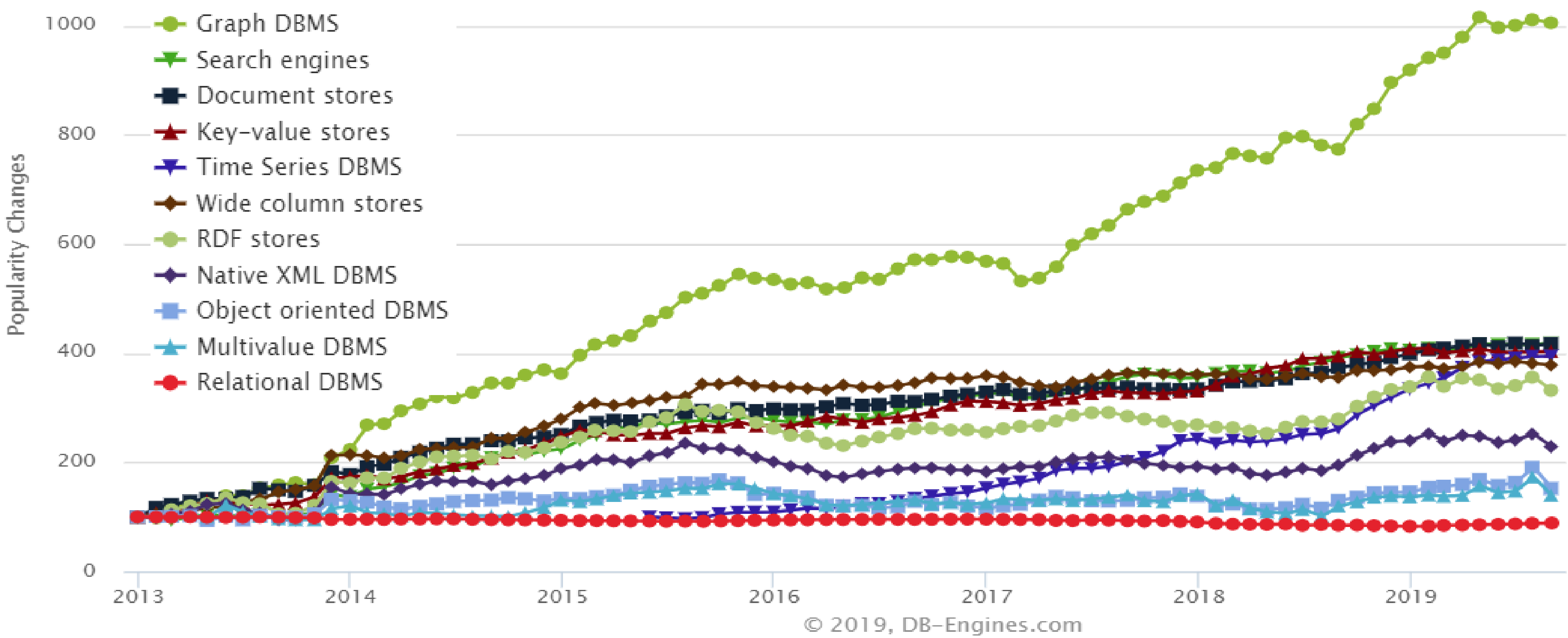
Big Challenges of Big Data

Huge amounts of various data grow fast



What data management systems do we need?

NoSQL systems dominate?

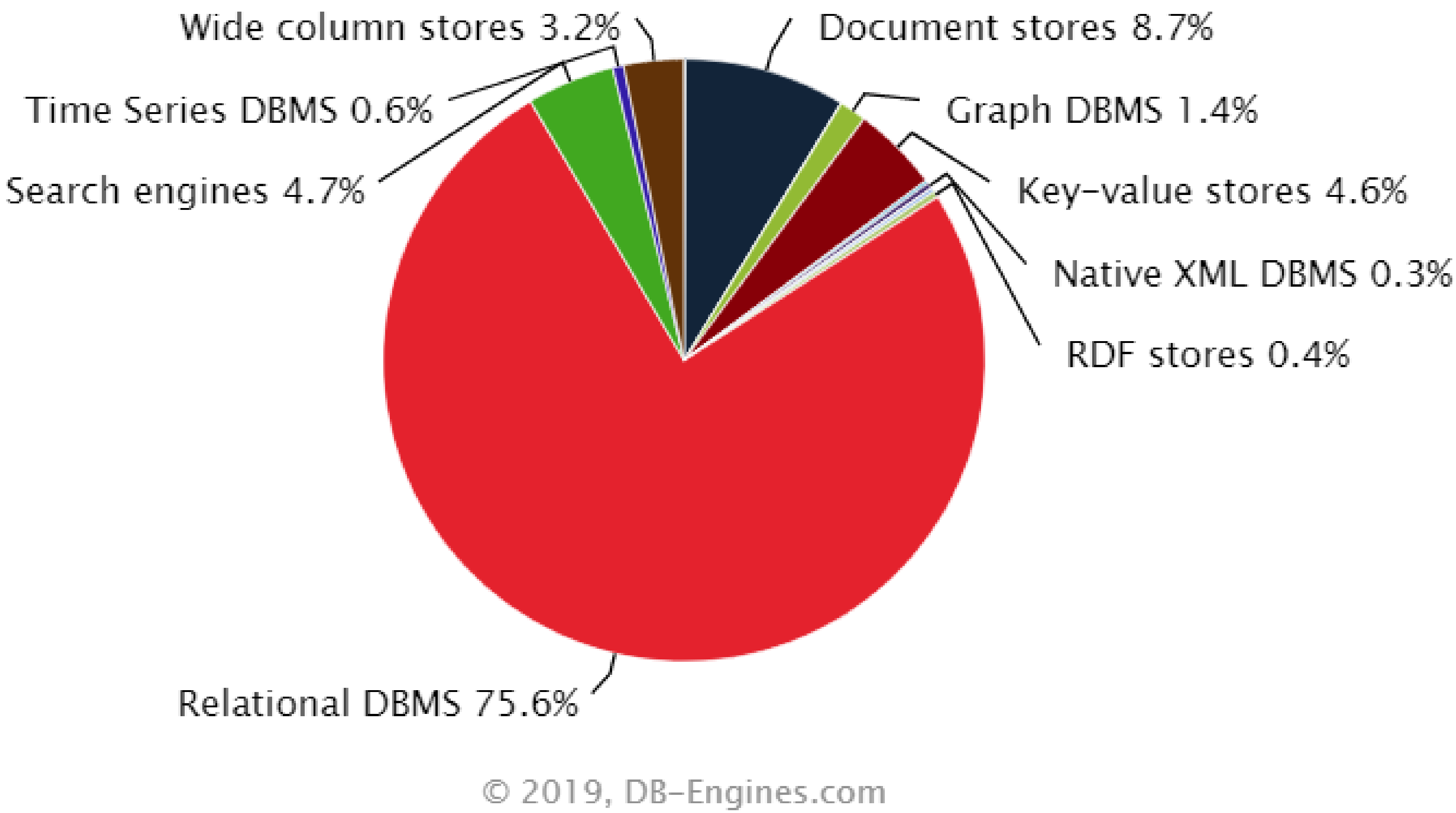


Popularity of systems by their mentions in

- Google Trends
- Newsfeeds (Google, Yandex, etc.)
- Tech discussions (Stack Overflow, etc.)
- Job offers (Simply hired, etc.)
- Professional nets (LinkedIn, etc.)
- Social nets (Twitter, etc.) ,

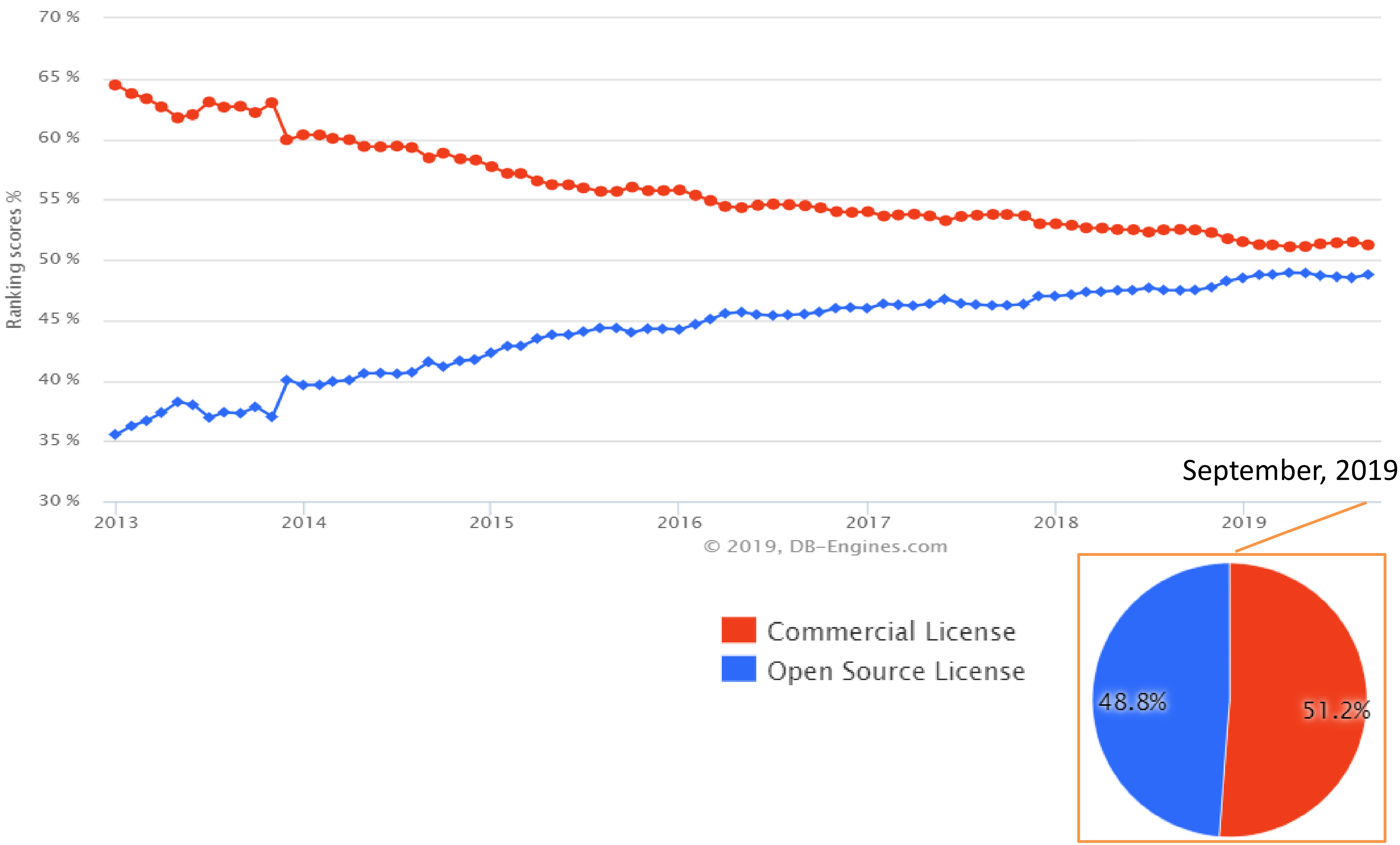
September 2019

Indeed, No! RDBMSs dominate!

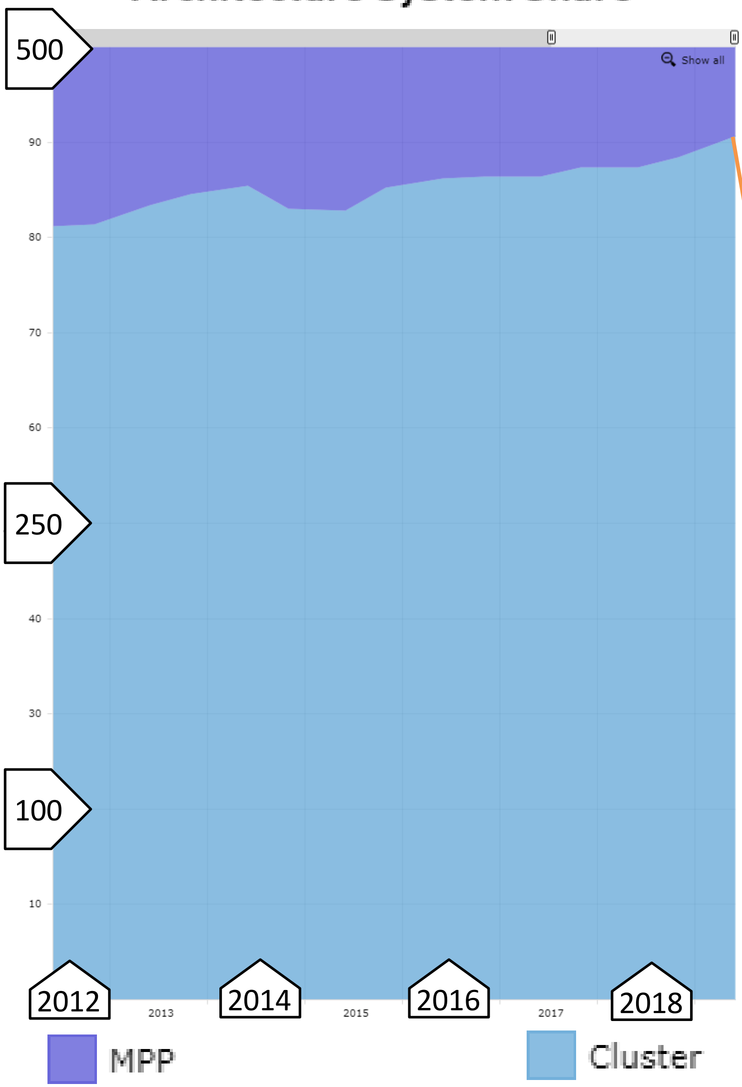


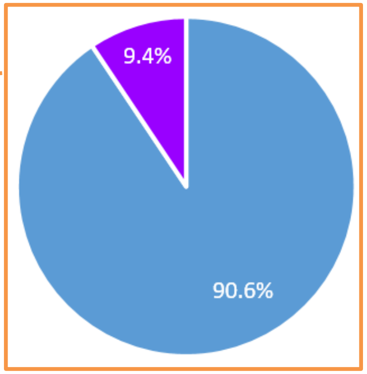
Popularity of systems per category, September 2019

Open source vs Commercial



TOP 500 The List.: HPC clusters dominate





https://top500.org

Cluster

MPP

Why embed parallelism into serial DBMS?

- **Proprietary parallel DBMSs** are very expensive to buy or develop from scratch

PDBMS	Price per year
IBM DB2 Parallel Edition	**$11,016**
Oracle Real Application Cluster	**$29,692**
Teradata Data Warehouse Appliance	**$4,597,784**

- **Open-source DBMSs** are mostly serial but can be (softly) modified to make it parallel
- At last (but not least), in Russia, **import substitution** matters!

How can we parallelize query execution?

**Partition data and apply SPMD paradigm
(Single Program, Multiple Data)**

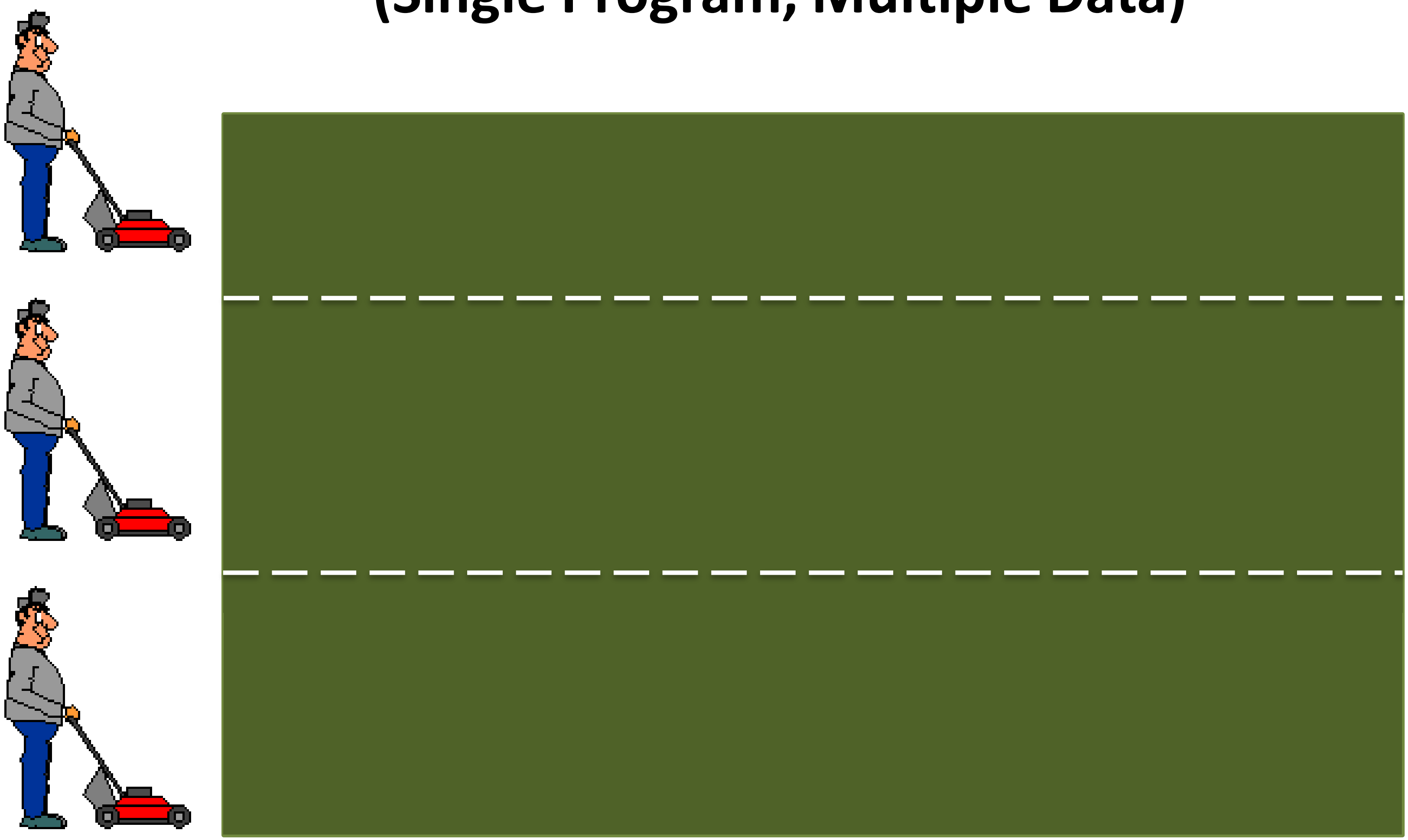
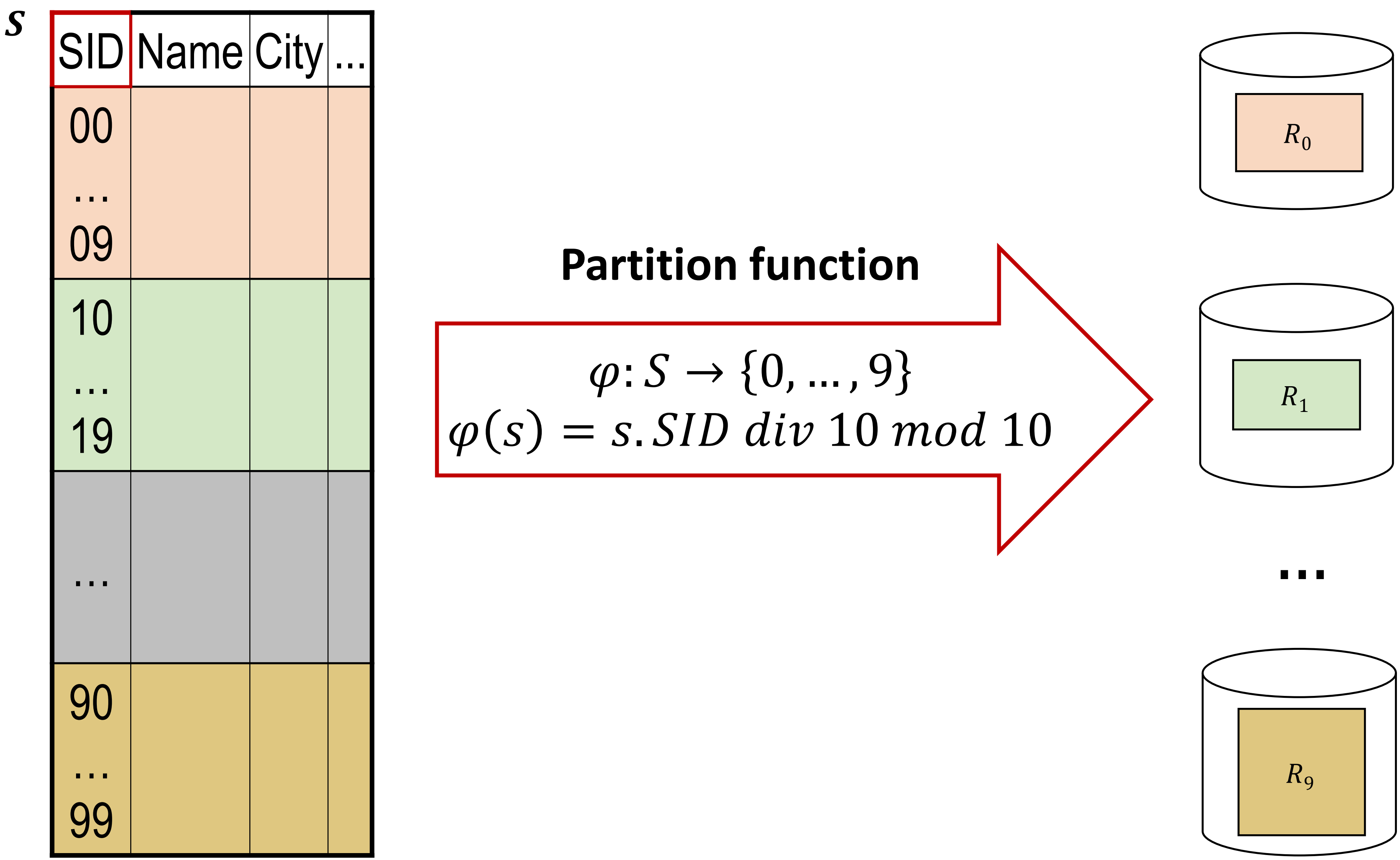
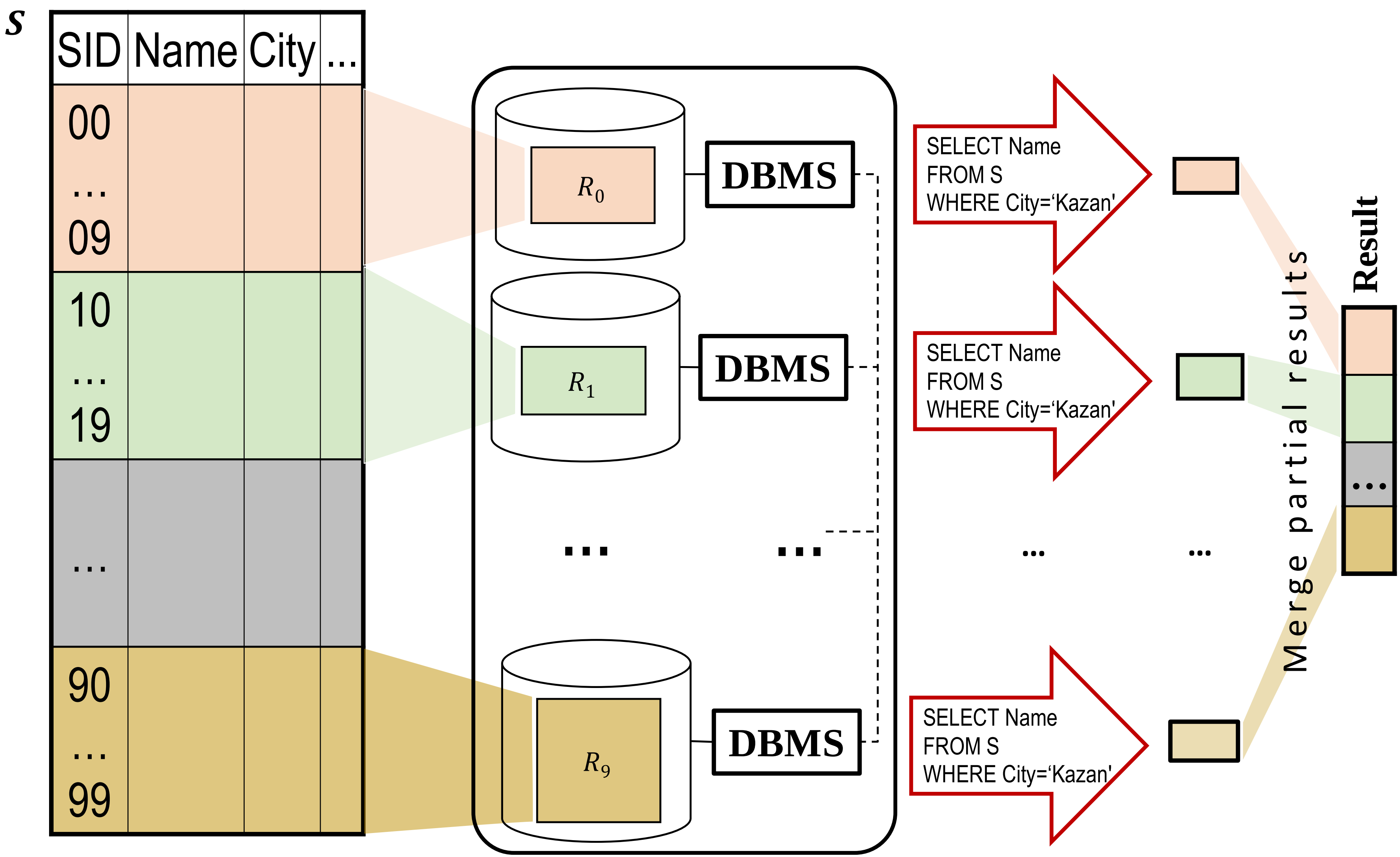


Table partitioning



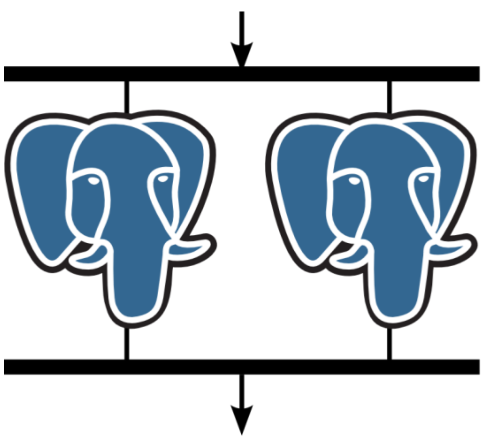
Parallel query execution



From serial to parallel DBMS

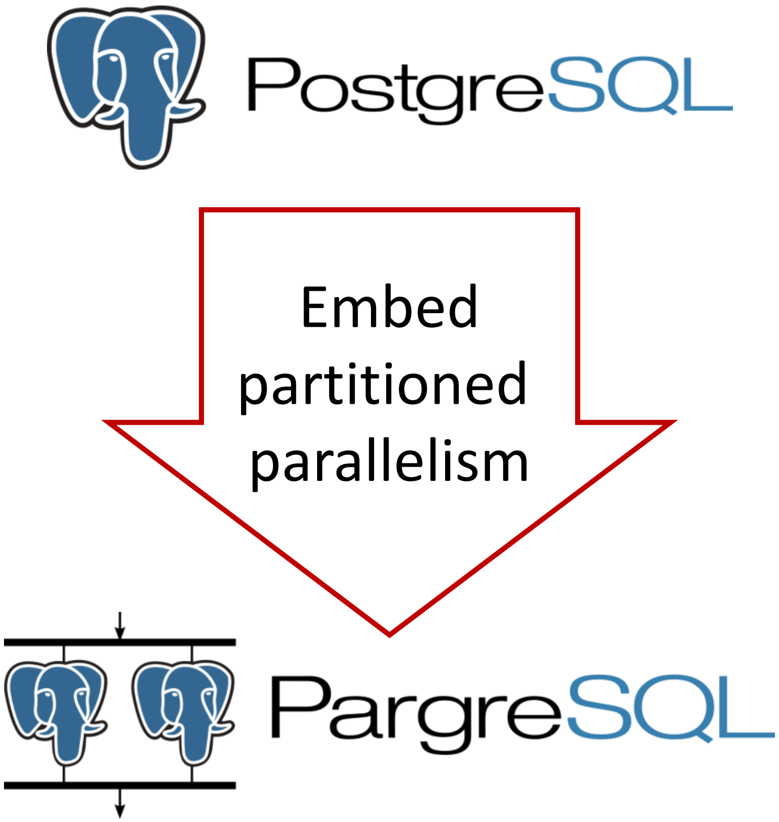
PostgreSQL

Embedding partitioned parallelism



PargreSQL

Basic “How to?”s



1. Partition a table
2. Disseminate a query
3. Merge results
4. Exchange data
5. Run an application

Table partitioning

PostgreSQL

CREATE TABLE T
(A int, B int);

PargreSQL

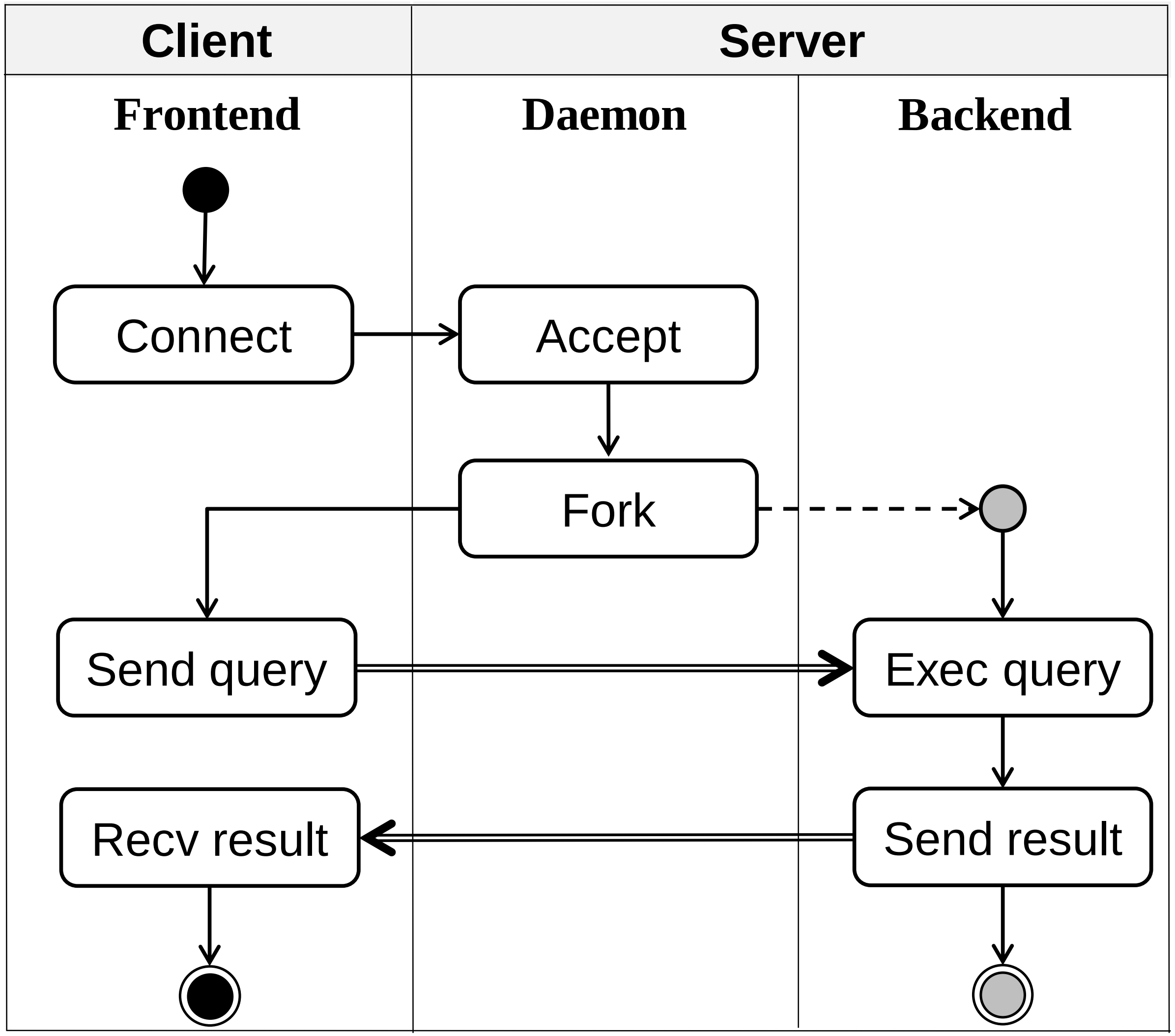
CREATE TABLE T
(A int, B int)
WITH (FRAGATTR = B);

Partitioning function:

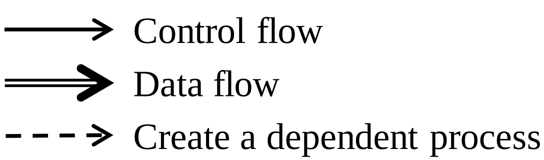
$$\varphi(t) = t.B \ mod \ P$$

where P is number of servers

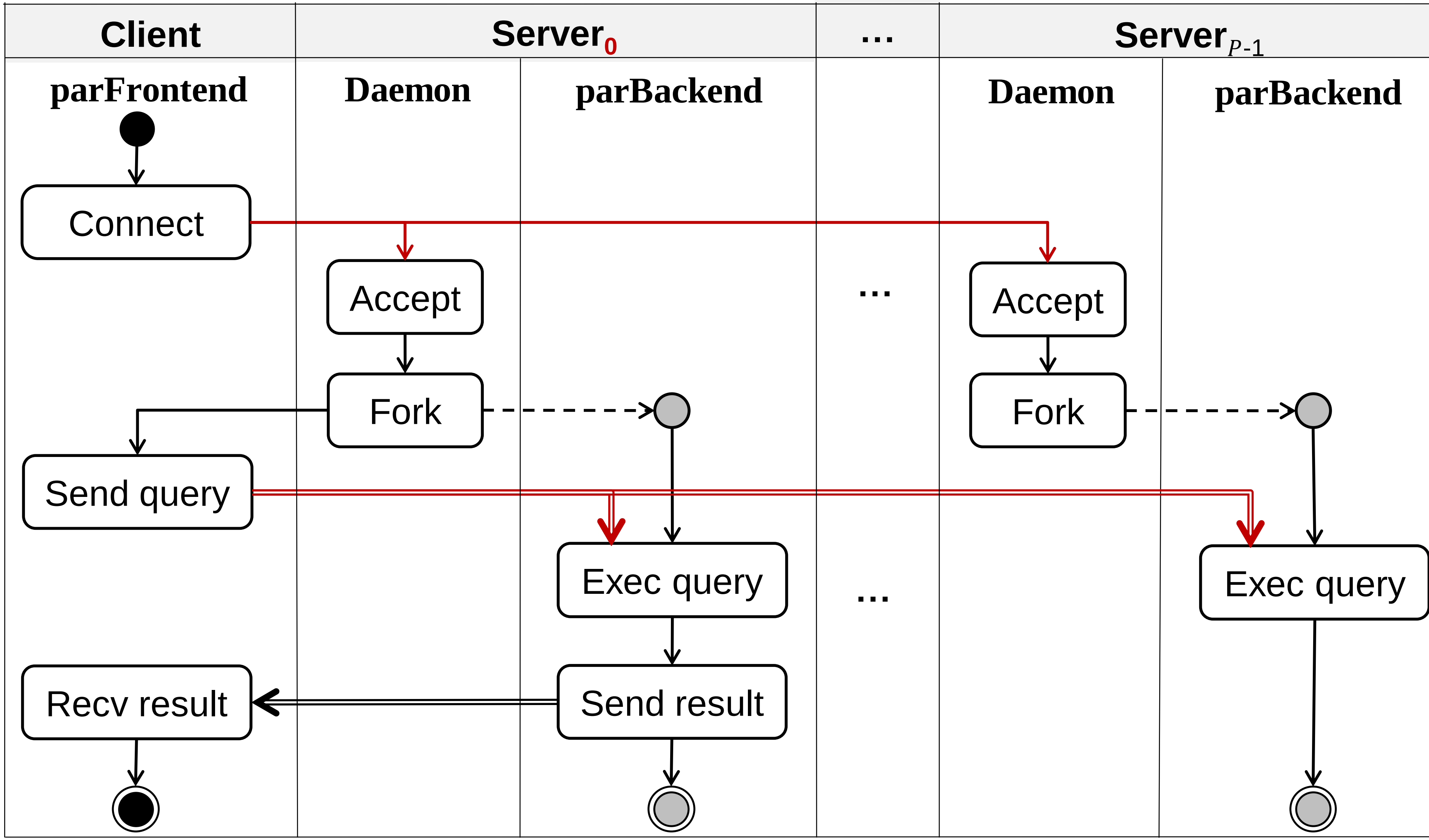
Processes



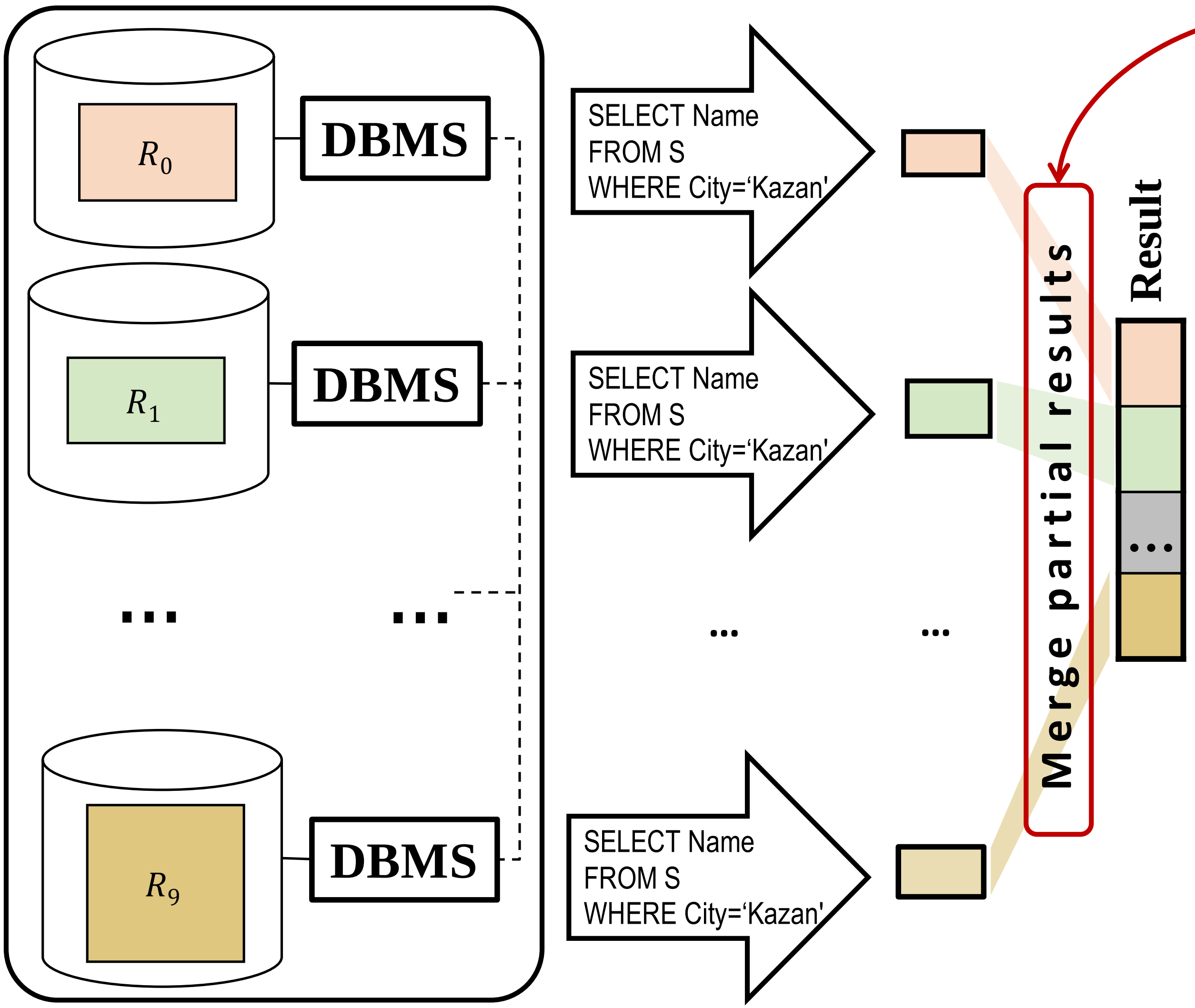
- **Frontend**
  client application with PostgreSQL's libpq-fe library
- **Daemon**
  server process to accept client's connection and create Backend instance to process client's queries
- **Backend**
  server process to execute client's query and send the results to the client



PargreSQL Processes



Merging results



How 0th server **merges partial results** and **sends the result to a client**?

An example on data exchanges: join tables

S

SID	Name	City	…
00	Horns&Hoofs	Odessa	
11	RaznoExport	Moscow	
22	UralTrak	Chelyabinsk	
…	…	…	

$$\varphi(s) = s.SID\ div\ 10\ mod\ 10$$

P

PID	Name	Price	…
00	Nail	100	
11	Bolt	75	
99	Screw	10	
…	…	…	

$$\varphi(p) = p.PID\ div\ 10\ mod\ 10$$

SP

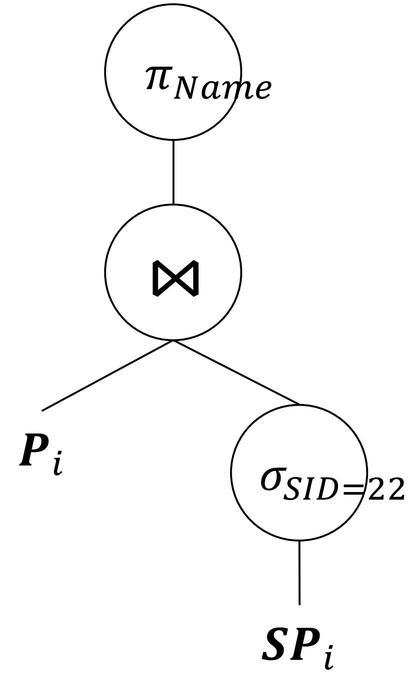
SID	PID	Qty
00	02	5000
11	01	500
22	00	50
11	02	100
22	02	500

$$\varphi(sp) = sp.PID\ div\ 10\ mod\ 10$$

Data exchanges not needed

Get the names of parts supplied by supplier with ID 22:

```
SELECT Name
FROM P, SP
WHERE P.PID=SP.PID AND SP.SID=22
```



P

PID	Name	Price	...
00	Nail	100	
11	Bolt	75	
99	Screw	10	
...	...	...	

$\varphi(p) = p.PID\ div\ 10\ mod\ 10$

SP

SID	PID	Qty
00	02	5000
01	11	500
22	99	50
...	...	...

$\varphi(sp) = sp.PID\ div\ 10\ mod\ 10$

All records are processed by the servers on which these records are stored, so **no records to be transferred**

Data exchanges needed

Get the names of suppliers who supply part with ID 99:

```
SELECT Name
FROM S, SP
WHERE S.SID=SP.SID AND SP.PID=99
```

$\boldsymbol{S}$

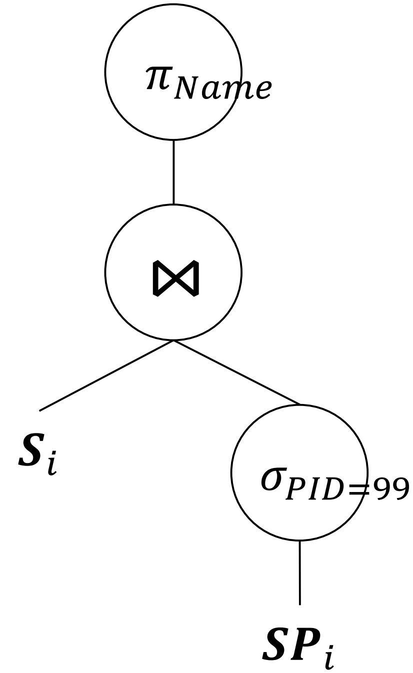
SID	Name	City	…
00	Horns&Hoofs	Odessa	
11	RaznoExport	Moscow	
22	UralTrak	Chelyabinsk	
…	…	…	

$\varphi(s) = s.SID\ div\ 10\ mod\ 10$

$\boldsymbol{SP}$

SID	PID	Qty
00	02	5000
01	11	500
22	99	50
…	…	…

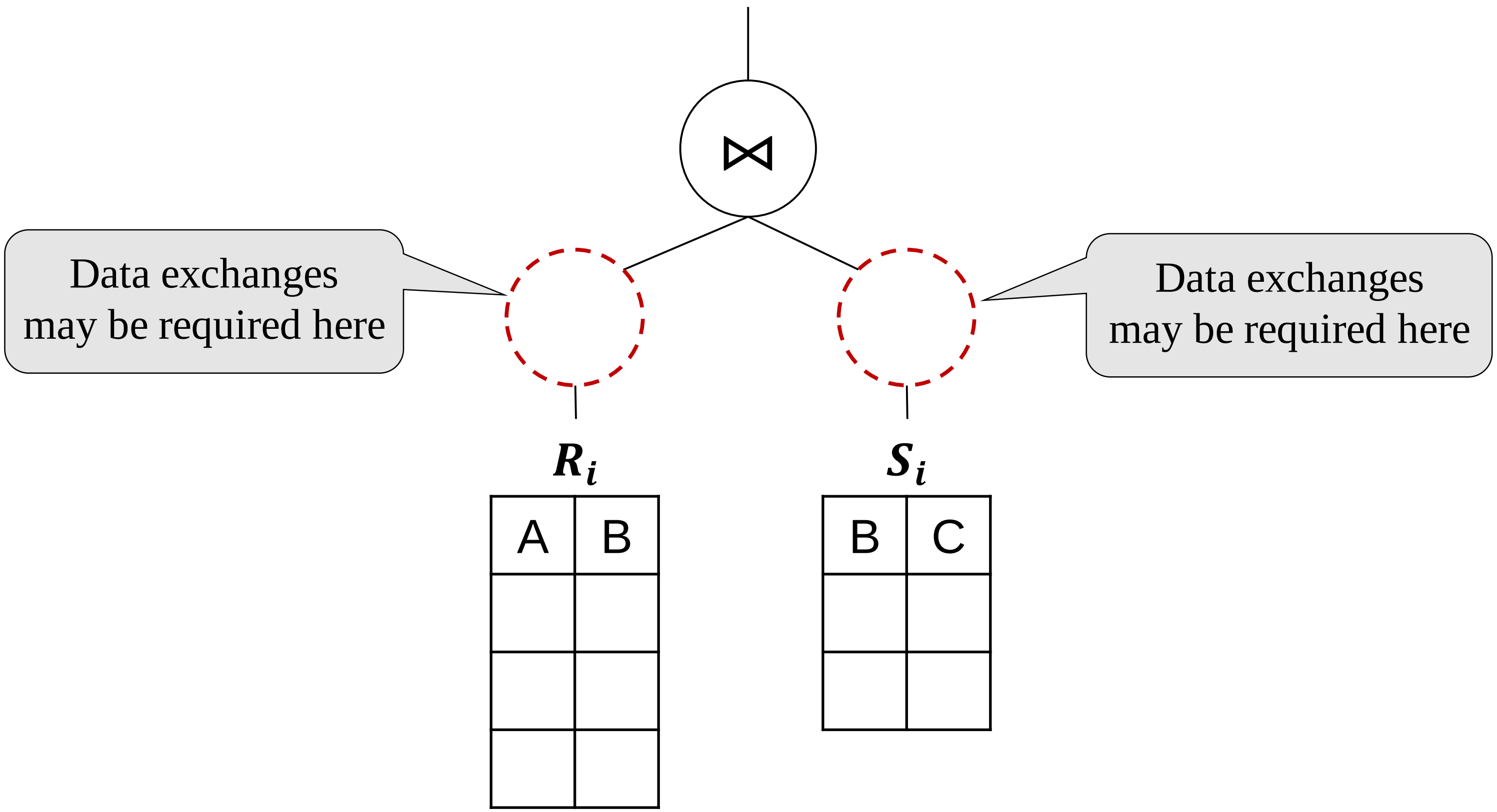
$\varphi(sp) = sp.PID\ div\ 10\ mod\ 10$



This record is **stored on the 9th server** but to be processed it **must be transferred to the 2th server**

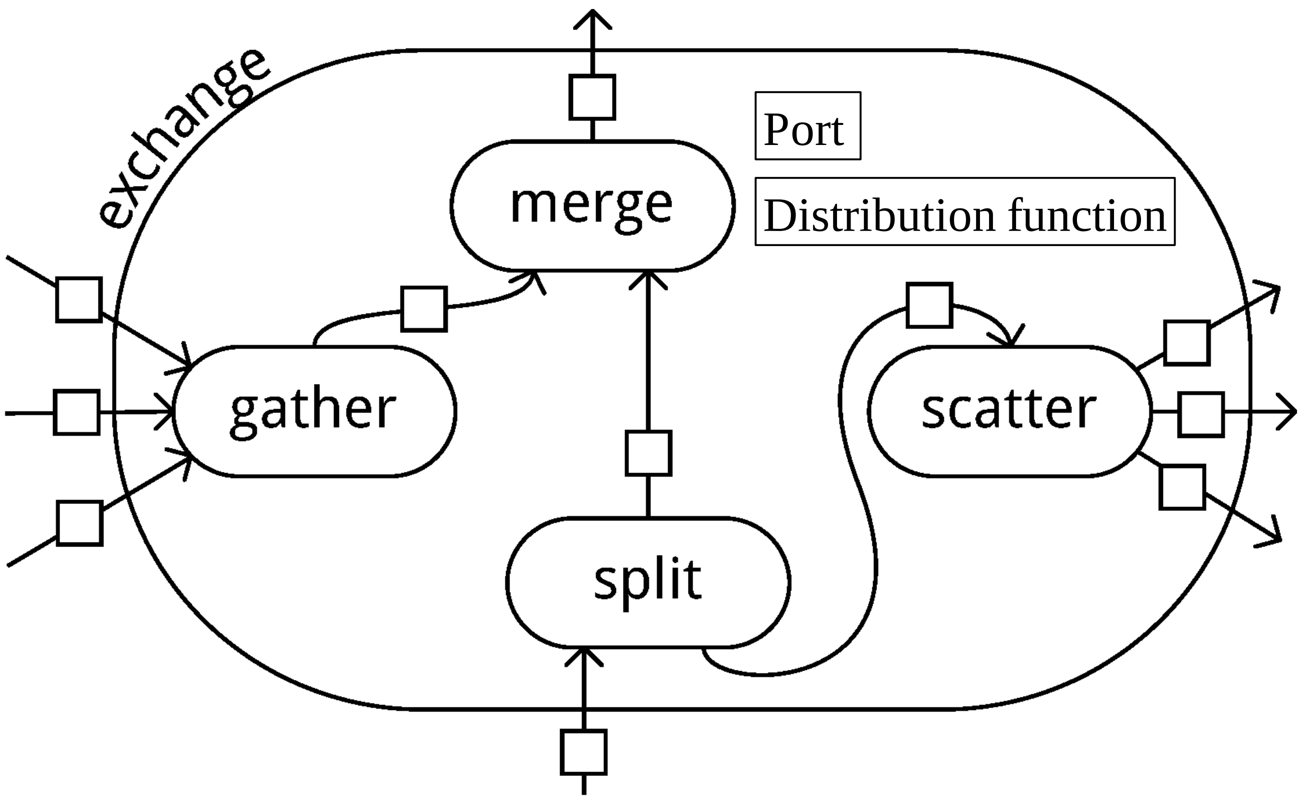
So, we need exchanges

$$R \bowtie S$$

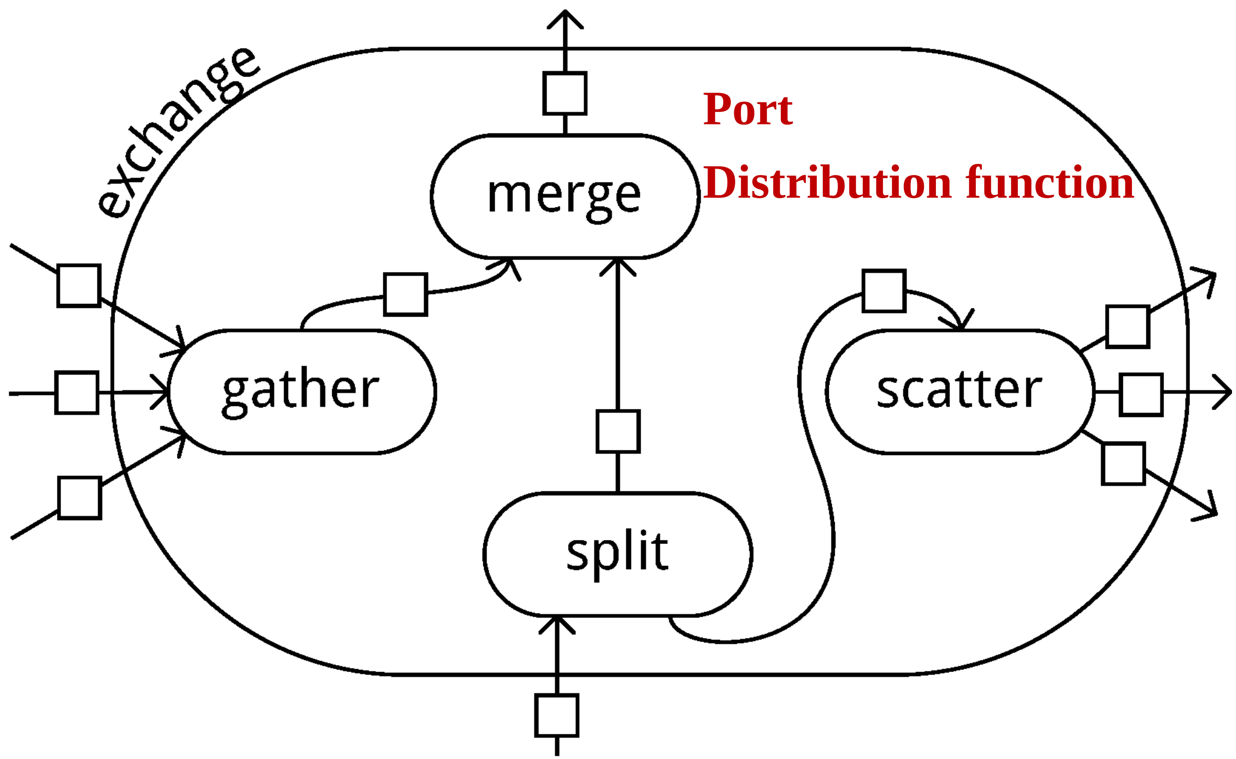


Did you want an EXCHANGE? We have it…

It is an **empty operator of relational algebra**,
which is **executed by the serial DBMS engine in normal mode**
but it **encapsulates the parallelism**

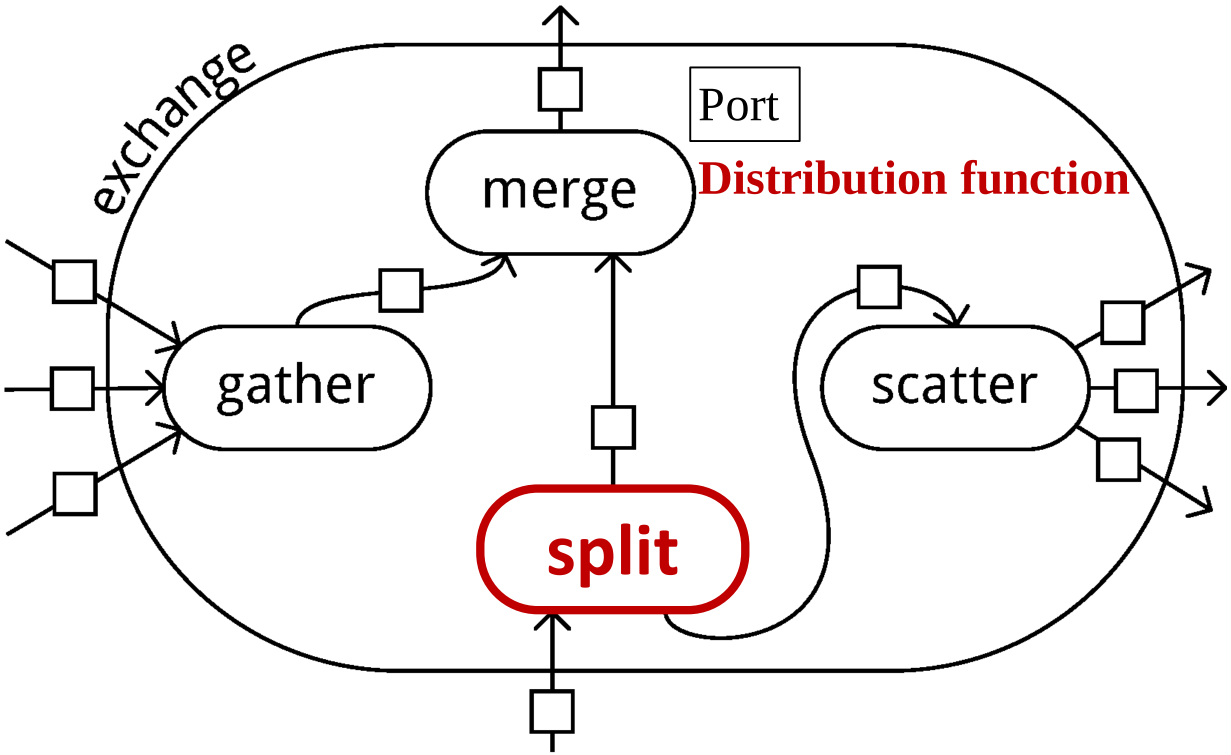


EXCHANGE operator



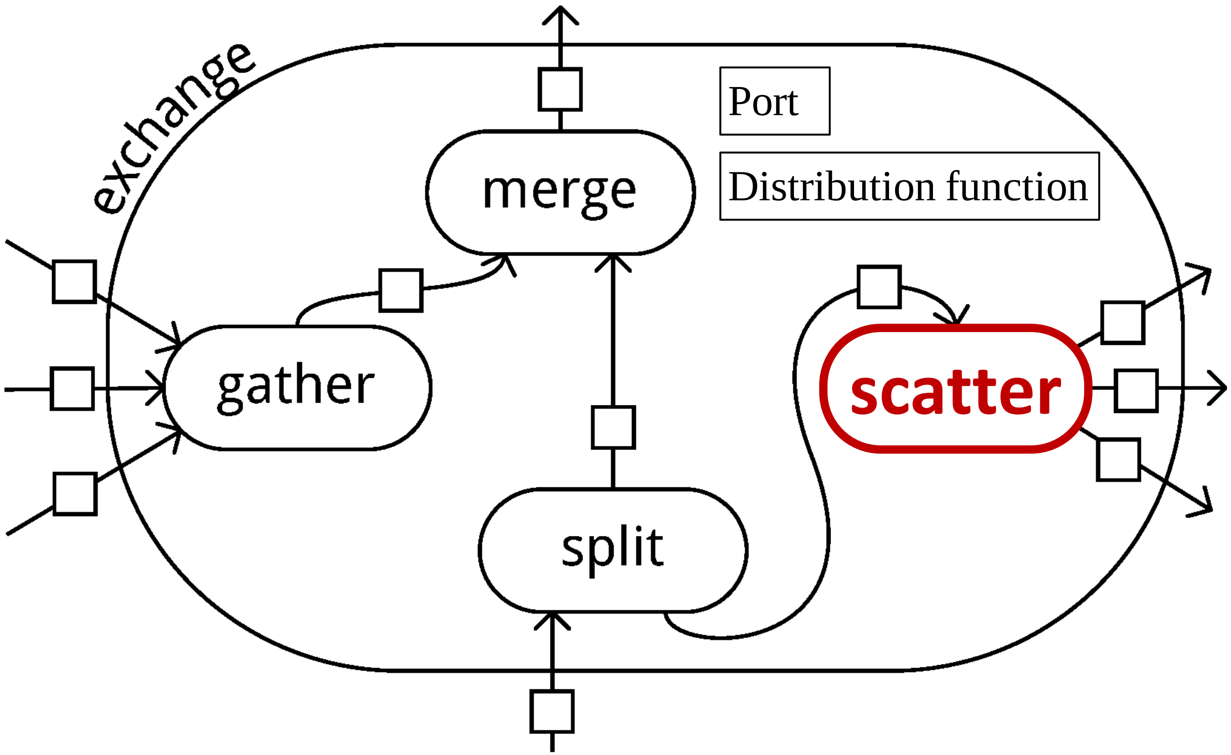
- **Port** is a serial number of EXCHANGE in a query
- **Distribution function** $\psi: R \rightarrow \{0, \ldots, P-1\}$ calculates a server where the given record must be processed

EXCHANGE operator



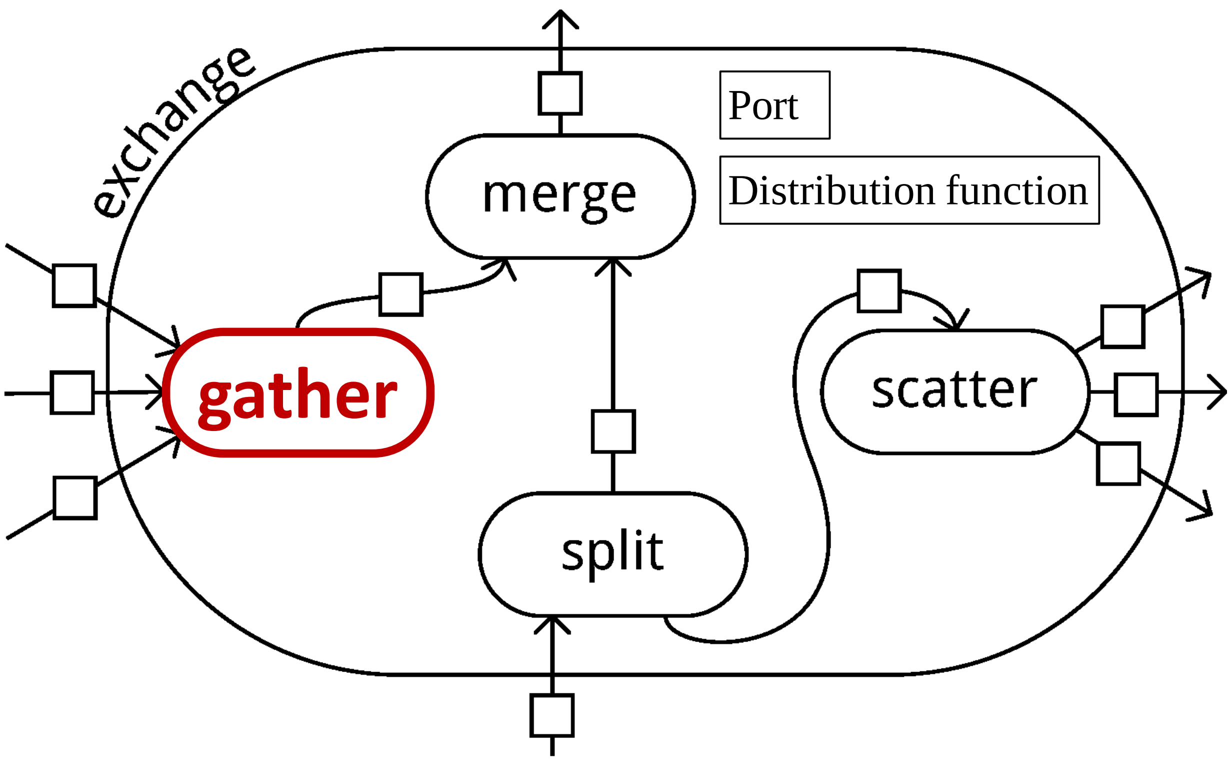
- **Split** calculates the distribution function ψ from the given record
- If ψ returns current server then the record is passed to Merge otherwise it is passed to Scatter

EXCHANGE operator



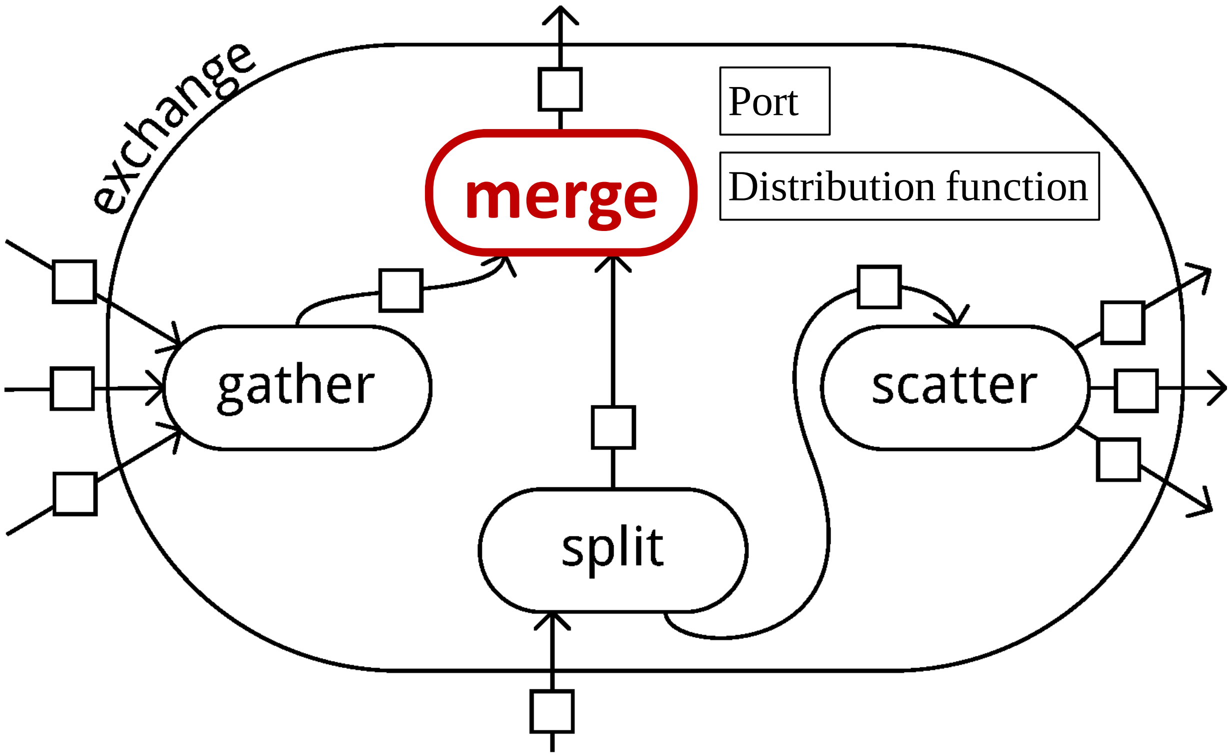
- **Scatter** transfers the given record to alien servers

EXCHANGE operator



- **Gather** receives the current server's records from alien servers and pass them to Merge

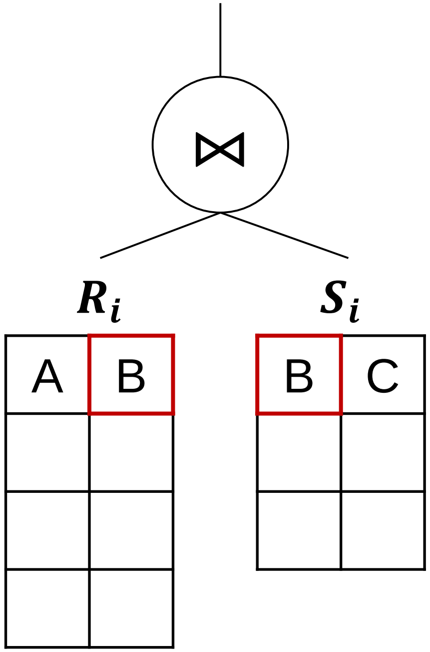
EXCHANGE operator

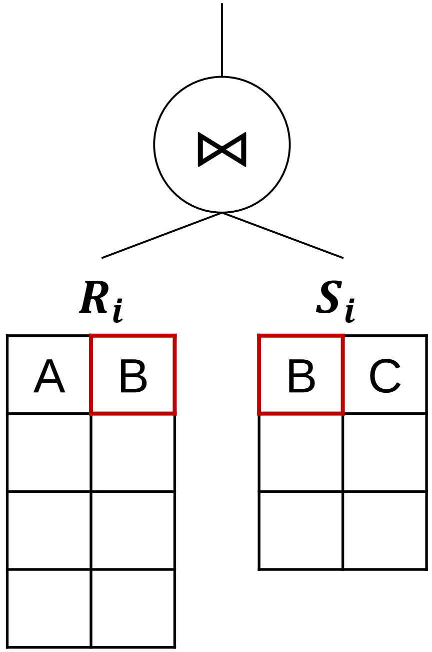


- **Merge** outputs records
  from Gather and Split by rotation

Query parallelization, case 1

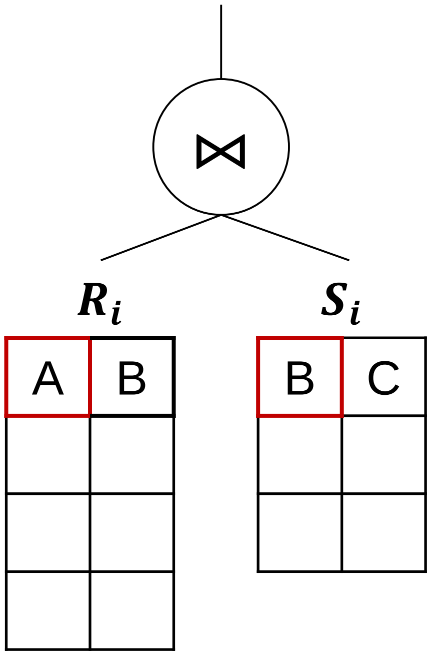
R and S are partitioned by the join attribute using the same partition function

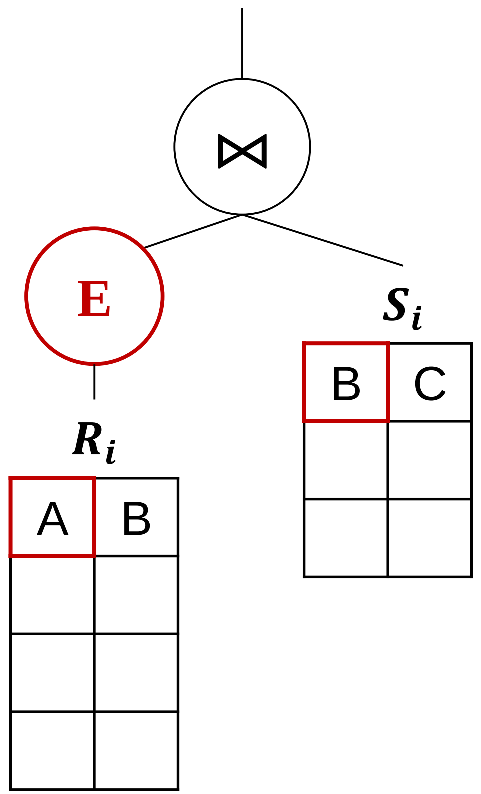




Query parallelization, case 2

R is partitioned by A and S is partitioned by B using the φ_S partition function



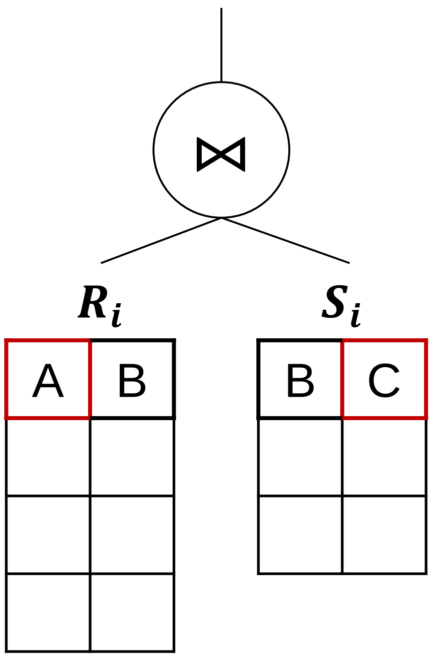


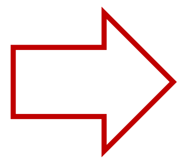
Distribution function:

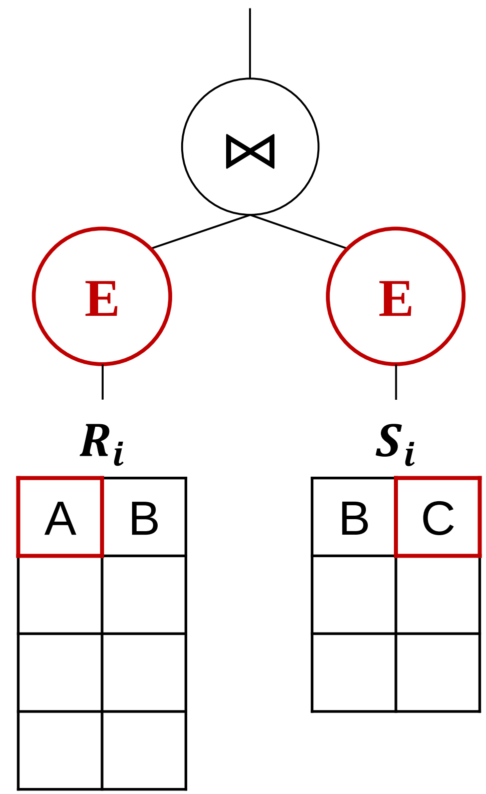
$\psi_R(r.B) = \varphi_S(r.B)$

Query parallelization, case 3

R is partitioned by A and S is partitioned by C







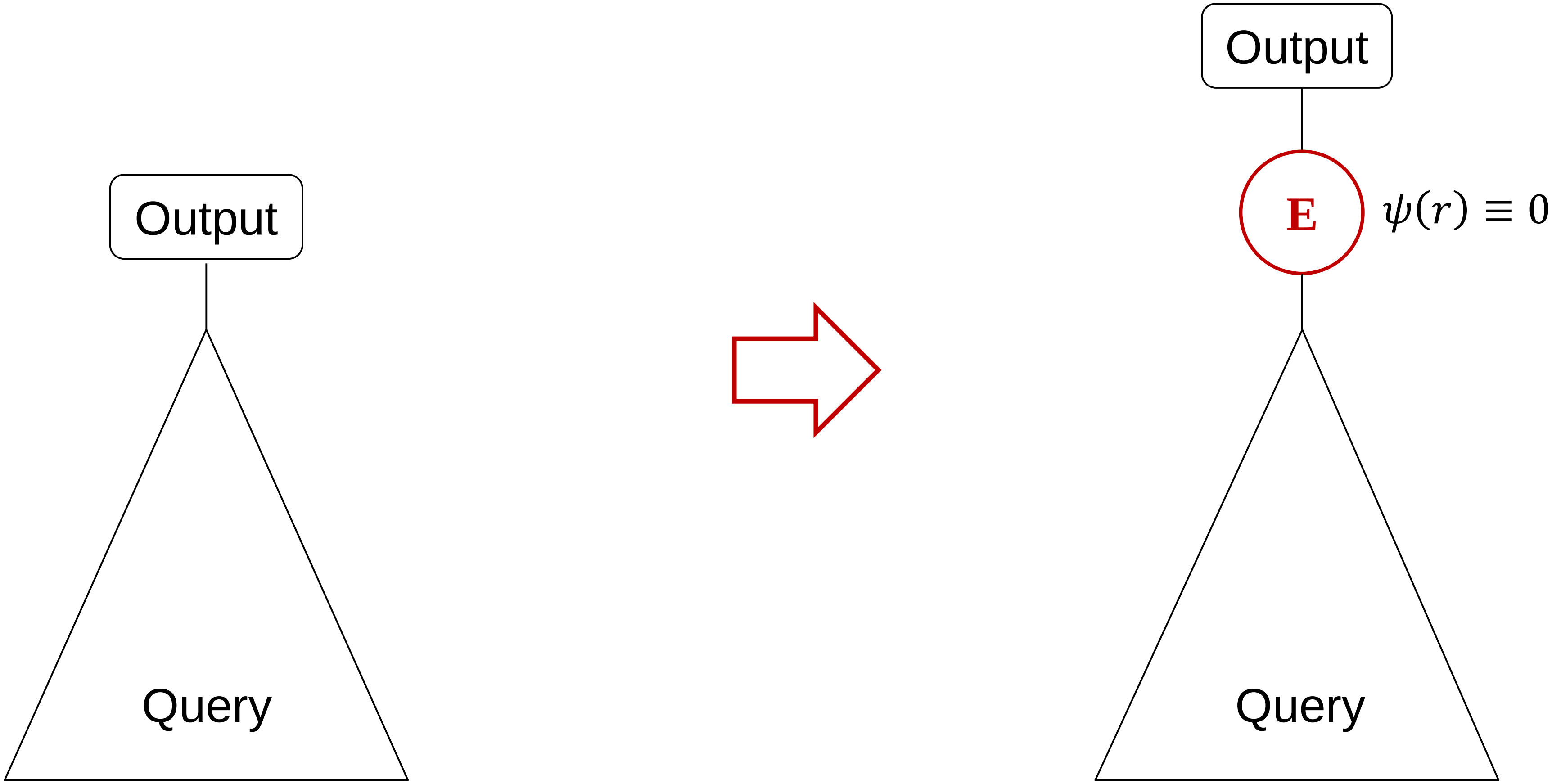
Distribution functions:

$$\psi_R(r.B) = f(r.B)$$
$$\psi_S(s.B) = f(s.B)$$

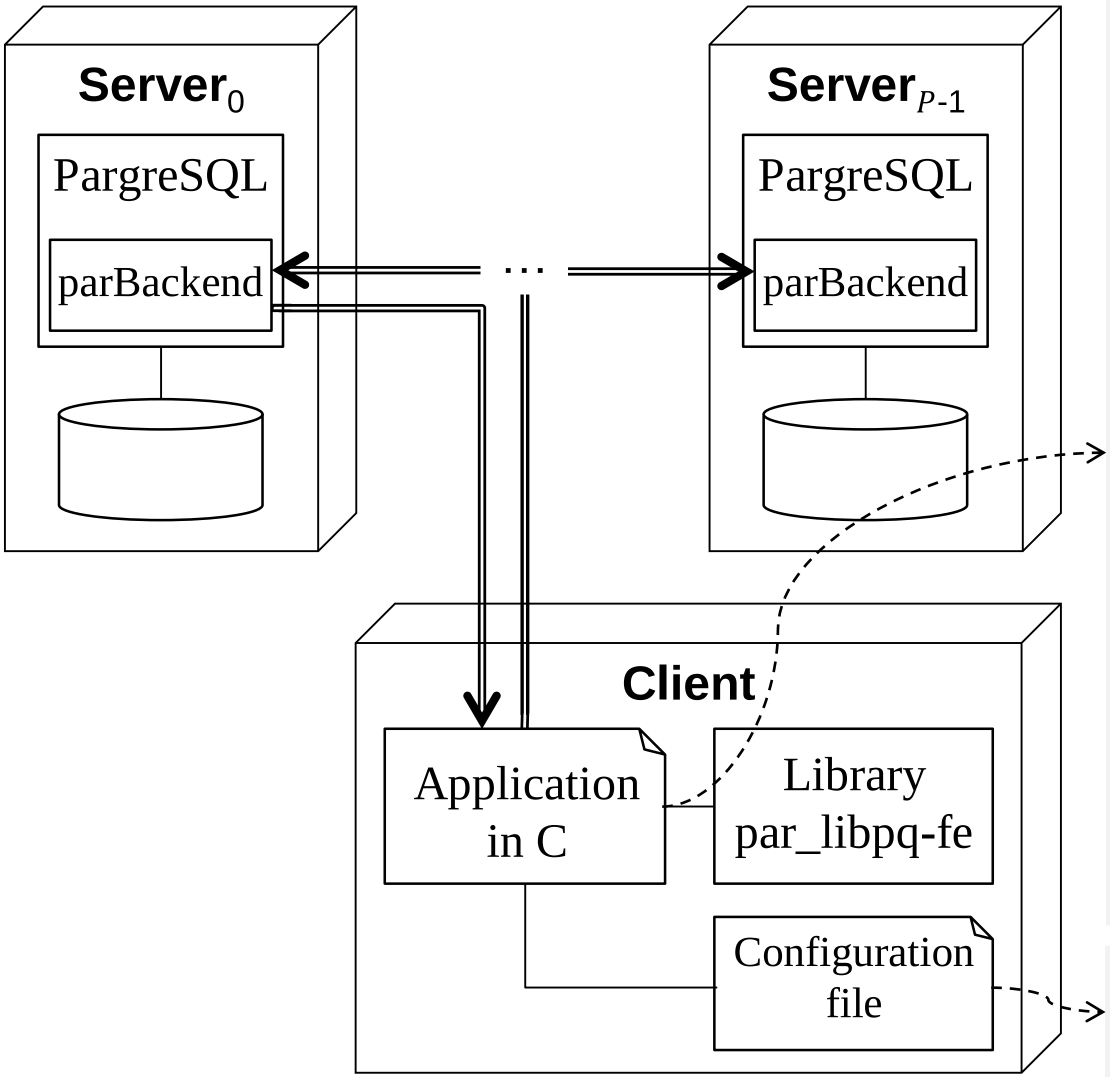
$$f: D_B \rightarrow \{0, \ldots, P-1\}$$

Merging partial results

To merge partial results on the 0th server, we just need **one more EXCHANGE with trivial distribution function**



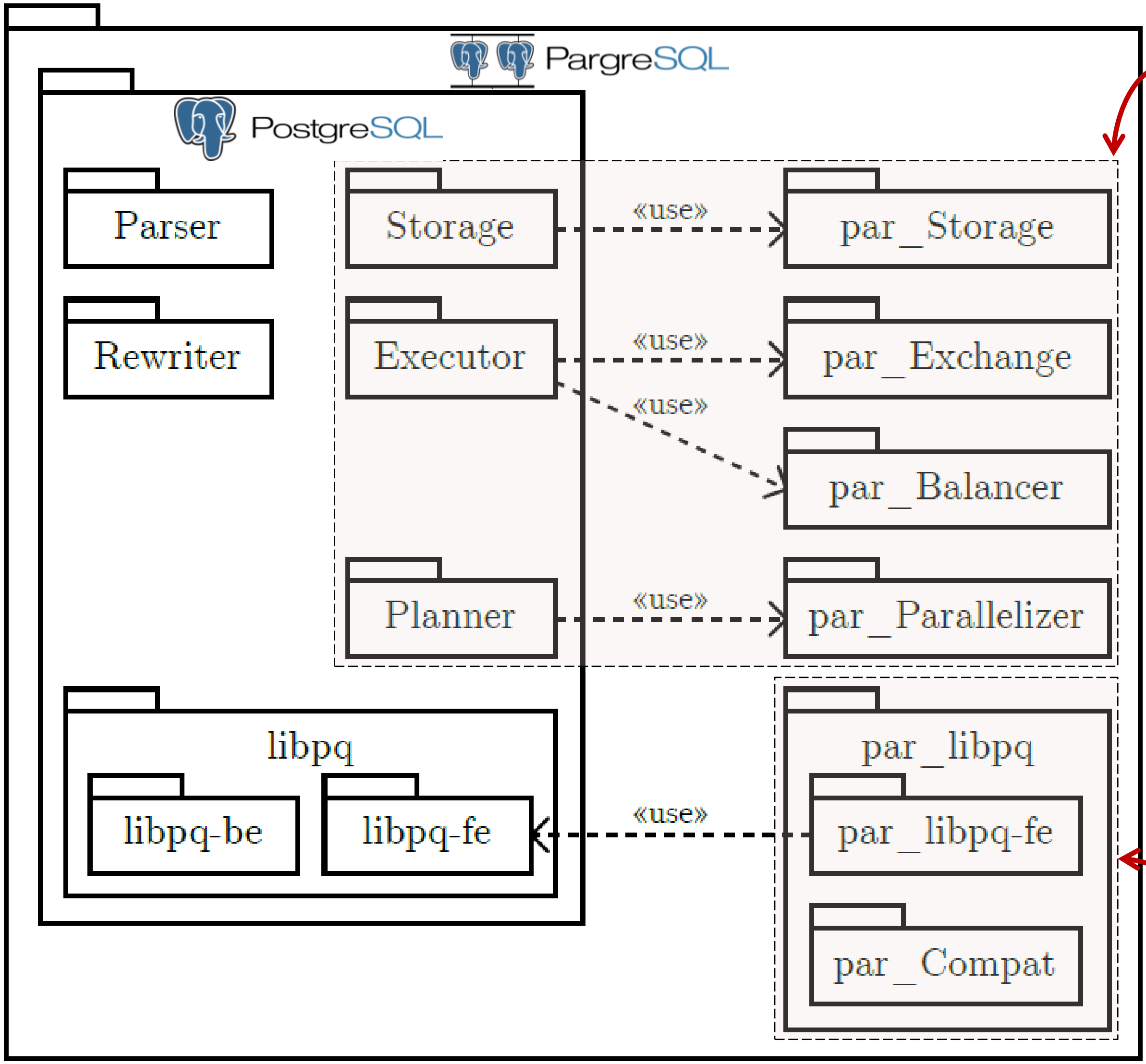
Running PargreSQL application



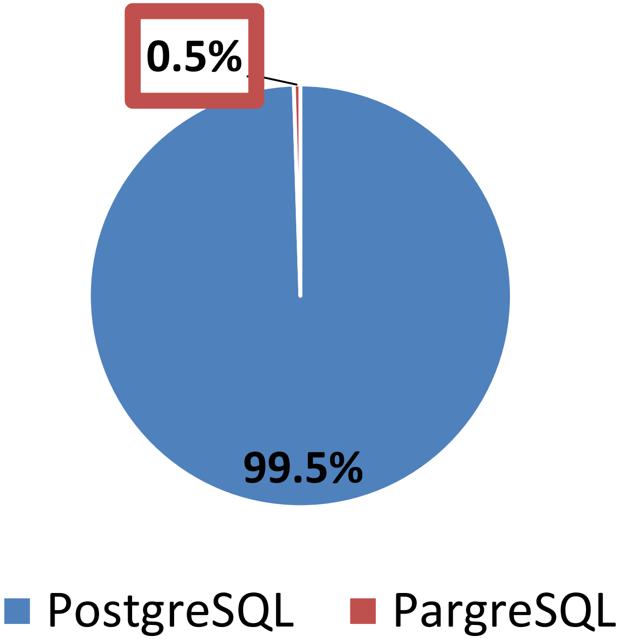

```
#include <par_libpq-fe.h>

PGconn *conn;
char *conninfo = "dbname=… hostaddr=… port=… ";
PGresult *res;

void main(int argc, char * argv[]) {
  conn = PQconnectdb (conninfo);

  res = PQexec(conn,
    "CREATE TABLE R (A INT, B INT)
  WITH (FRAGATTR = B);");

  res = PQexec(conn,
    "INSERT INTO R VALUES (2501, 1755);
    INSERT INTO R VALUES (2, 4);
    INSERT INTO R VALUES (8, 1); ");

  res = PQexec(conn, "SELECT * FROM R;");
  PQprint(stderr, res);

  PQclear(res);
  PQfinish(conn);
}
```

```
# Connection strings for each PargreSQL instance
dbname=postgres hostaddr=10.4.5.204 port=5432
dbname=postgres hostaddr=10.4.5.205 port=5432
```

ParqreSQL is just a prototype



Modified PostgreSQL source codes



New ParqreSQL source codes

PargreSQL is just a prototype…

TPC-C test results

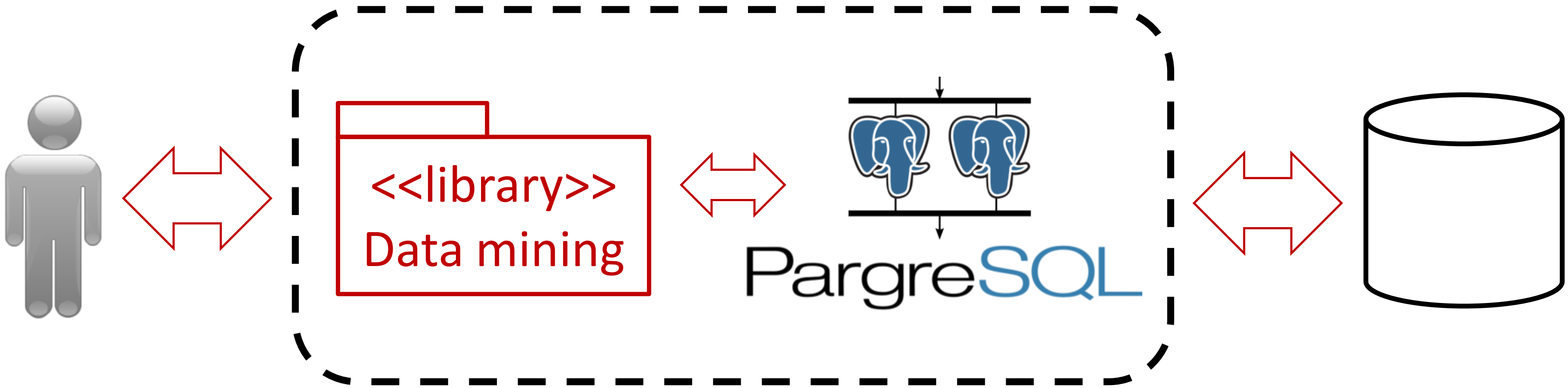
Rank	Company	System	Performance (tpmC)	DBMS	OS
1	Oracle	SPARC SuperCluster with T3-4 Servers	30 249 688	Oracle Database 11g R2 Enterprise Edition w/RAC w/Partitioning	Oracle Solaris 10 09/10
2	IBM	IBM Power 780 Server Model 9179-MHB	10 366 254	IBM DB2 9.7	AIX Version 6.1
3	Oracle	Sun SPARC Enterprise T5440 Server Cluster	7 646 486	Oracle Database 11g Enterprise Edition w/RAC w/Partitioning	Sun Solaris 10 10/09
	SUSU	Tornado SUSU supercomputer	2 202 531	PargreSQL	Linux CentOS 6.2
4	HP	HP Integrity rx5670 Cluster Itanium2/1.5 GHz-64p	1 184 893	Oracle Database 10g Enterprise Edition	Red Hat Enterprise Linux AS 3

Why Data Mining inside DBMS?

Significant OVERHEAD

Why Data Mining inside DBMS?

Let us move algorithms closer to data!

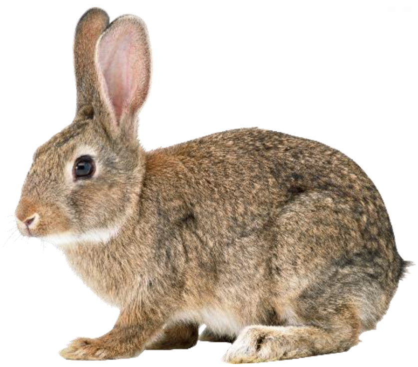


- No export and import data overhead
- All the DBMS services are available for free (query optimization, indexing, data security, etc.)

Data mining inside PDBMS: fuzzy clustering

A

B



C

D

E

Objects	C_1	C_2
A	0.90	0.10
B	0.80	0.20
C	0.15	0.85
D	0.30	0.70
E	0.25	0.75

Fuzzy *c*-Means (FCM) algorithm generalizes *k*-Means and performs clustering where **each object belongs to all clusters** at the same time with different *membership degree*

Fuzzy c-Means clustering

- Input
  - $X = \{x_1, x_2, \ldots, x_n\}$ is a set of objects, $x_i \in \mathbb{R}^d$
  - k is number of clusters
- Output
  - $U \in \mathbb{R}^{n \times k}$ is *membership matrix* where $u_{ij} \in (0,1)$ is a membership degree of object x_i in cluster c_j:

$$\forall i \sum_{j=1}^{k} u_{ij} = 1$$

  - $C \in \mathbb{R}^{k \times d}$ is *matrix of centroids* where row c_j is center of j-th cluster

x	$x_{i,1}$	$\ldots$	$x_{i,d}$
1			
$\ldots$			
n			

u	1	$\ldots$	k
1			
$\ldots$			
n			

c	$c_{j,1}$	$\ldots$	$c_{j,d}$
1			
$\ldots$			
k			

Fuzzy c-Means clustering

- *Objective function* to be minimized

$$J_{FCM}(X,k,m) = \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij}^2\, ED^2(x_i, c_j)$$

- Computation of centroids

$$c_{j\ell} = \frac{\sum_{i=1}^{n} u_{ij}^2 \cdot x_{i\ell}}{\sum_{i=1}^{n} u_{ij}^2}$$

- Computation of memberships

$$u_{ij} = \sum_{t=1}^{k} \frac{ED(x_i, c_t)}{ED(x_i, c_j)}$$

Fuzzy c-Means clustering

- **Input:** X, k
- **Output:** U, C
- **Method**

$s := 0$

$U^{(0)} := rand(0..1)$

repeat

  Compute $C^{(s)}$ as in **(1)**

  Compute $U^{(s)}$ **and** $U^{(s+1)}$ as in **(2)**

  $s := s + 1$

until $\max_{ij}\left\{\left|u_{ij}^{(s)} - u_{ij}^{(s-1)}\right|\right\} \geq \varepsilon$

(1) $c_{j\ell} = \frac{\sum_{i=1}^{n} u_{ij}^2 \cdot x_{i\ell}}{\sum_{i=1}^{n} u_{ij}^2}$

(2) $u_{ij} = \sum_{t=1}^{k} \frac{ED(x_i, c_t)}{ED(x_i, c_j)}$

pgFCM: relational schema

Object matrix $\boldsymbol{X}$

	x_1	$\cdots$	x_d
1	1.0	$\cdots$	2.1
$\vdots$	$\vdots$	$\ddots$	$\vdots$
n	3.4	$\cdots$	2.9

Vertical object table SV

i	l	val
1	1	1.0
$\vdots$	$\vdots$	$\vdots$
n	d	2.9

Horizontal object table SH

i	x_1	$\cdots$	x_d
1	1.0	$\cdots$	2.1
$\vdots$	$\vdots$	$\ddots$	$\vdots$
n	3.4	$\cdots$	2.9

Centroid matrix $\boldsymbol{C}$

	x_1	$\cdots$	x_d
1	2.2	$\cdots$	8.1
$\vdots$	$\vdots$	$\ddots$	$\vdots$
k	3.4	$\cdots$	6.9

Centroid table C

j	l	val
1	1	2.2
$\vdots$	$\vdots$	$\vdots$
k	d	6.9

Now we can use queries with **aggregation by rows SUM()**

Membership matrix $\boldsymbol{U}$

	1	$\cdots$	k
1	0.2	$\cdots$	0.1
$\vdots$	$\vdots$	$\ddots$	$\vdots$
n	0.8	$\cdots$	0.1

Membership table $U^{(s)}$

i	j	val
1	1	0.2
$\vdots$	$\vdots$	$\vdots$
n	k	0.1

Membership table $UT^{(s+1)}$

i	j	val
1	1	0.2
$\vdots$	$\vdots$	$\vdots$
n	k	0.1

pgFCM: computations

- **Computing centroids**

```
INSERT INTO C
  SELECT R.j, SV.l, sum(R.s * SV.val) / sum(R.s) AS val
  FROM (
    SELECT i, j, U.val^m AS s
    FROM U) AS R, SV
  WHERE R.i = SV.i
  GROUP BY j, l;
```

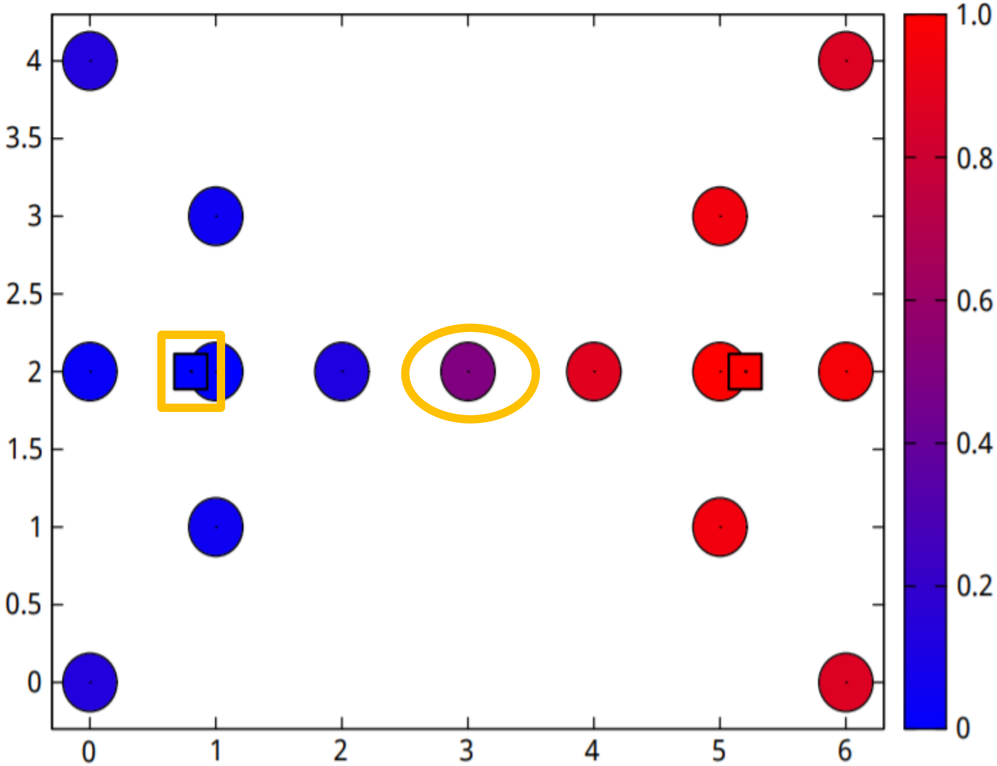
- **Computing Euclidean distances**

```
INSERT INTO SD
  SELECT i, j, sqrt(sum((SV.val - C.val)^2)) as dist
  FROM SV, C
  WHERE SV.l = C.l;
  GROUP BY i, j;
```

- **Computing memberships**

```
INSERT INTO UT
  SELECT i, j, SD.dist^(2.0^(1.0 - m)) * SD1.den AS val
  FROM (
    SELECT i, 1.0 / sum(dist^(2.0^(m - 1.0))) AS den
    FROM SD
    GROUP BY i) AS SD1, SD
  WHERE SD.i = SD1.i;
```

pgFCM: results



$k = 2$

Membership table U

i	j	val
1	1	0.86
1	2	0.13
2	1	0.97
2	2	0.02
…	…	…
8	1	0.49
8	2	0.50
…	…	…
15	1	0.13
15	2	0.86

Horizontal object table SH

i	x_1	x_2
1	0	0
2	0	2
3	0	4
8	3	2
	…	
15	6	0

Centroid table C

j	l	val
1	1	0.79
1	2	2.0
2	1	5.2
2	2	1.99

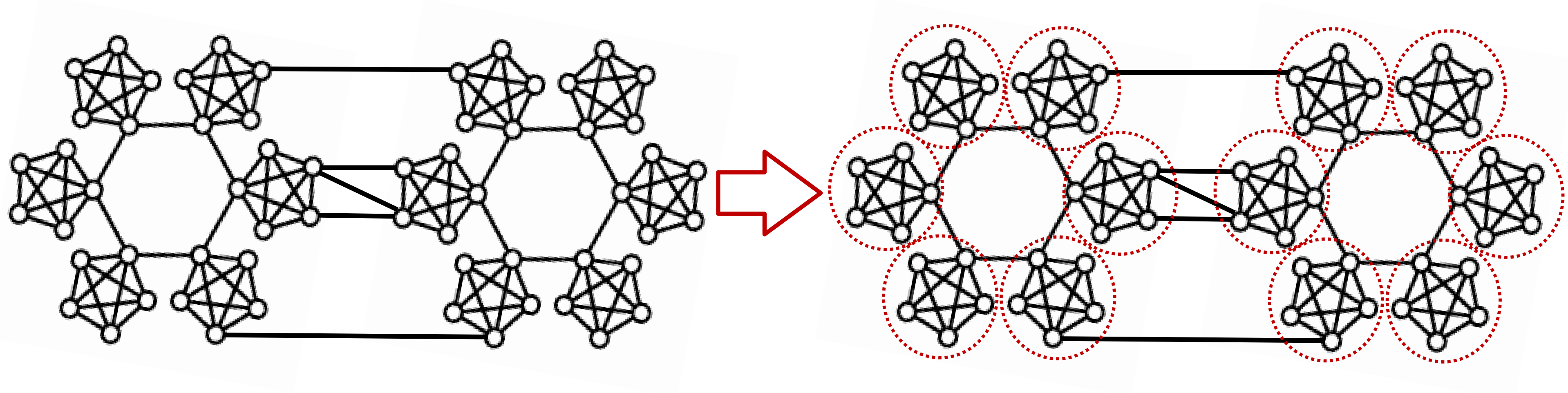
pgFCM vs analogs

Algorithm	Dataset		Time, sec.				*pgFCM*, sec.
	n	d	Clustering	**Export**	**Import**	Total	
WCFC [1)]	$4.9 \cdot 10^6$	41	5100	**203**	**10**	5 313	**5 182**
BigFCM [2)]	$1.1 \cdot 10^7$	28	189	**397**	**25**	611	**531**

[1)] Hidri M.S., *et al.* Speeding up the large-scale consensus fuzzy clustering for handling Big Data. Fuzzy Sets and Systems. 2018. vol. 348. pp. 50–74.

[2)] Ghadiri N., *et al*. BigFCM: Fast, precise and scalable FCM on Hadoop. Future Generation Comp. Syst. 2017. vol. 77. pp. 29–39.

Data mining inside PDBMS: communities

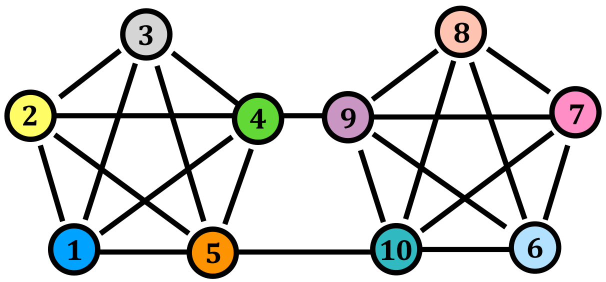


Community detection problem:

Split a big social graph into a set of subgraphs where vertices of each subgraph have dense connections with each other and sparse connections with vertices of other subgraphs

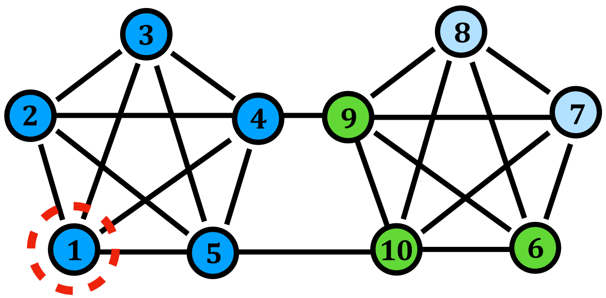
Community detection: ideas

Input graph



for each vertex v
 Assign a community label to v

Label propagation



repeat
 for each vertex v
  for each neighbor vertex u
   Compute their affinity as

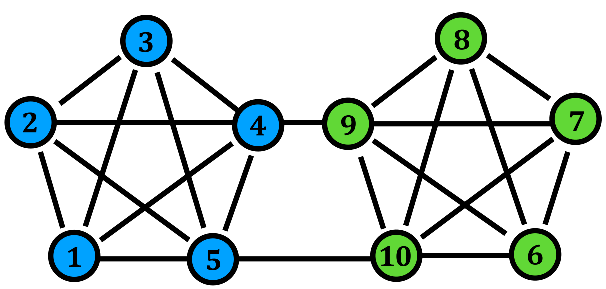
$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

  for each community C
   Compute v's degree of membership as

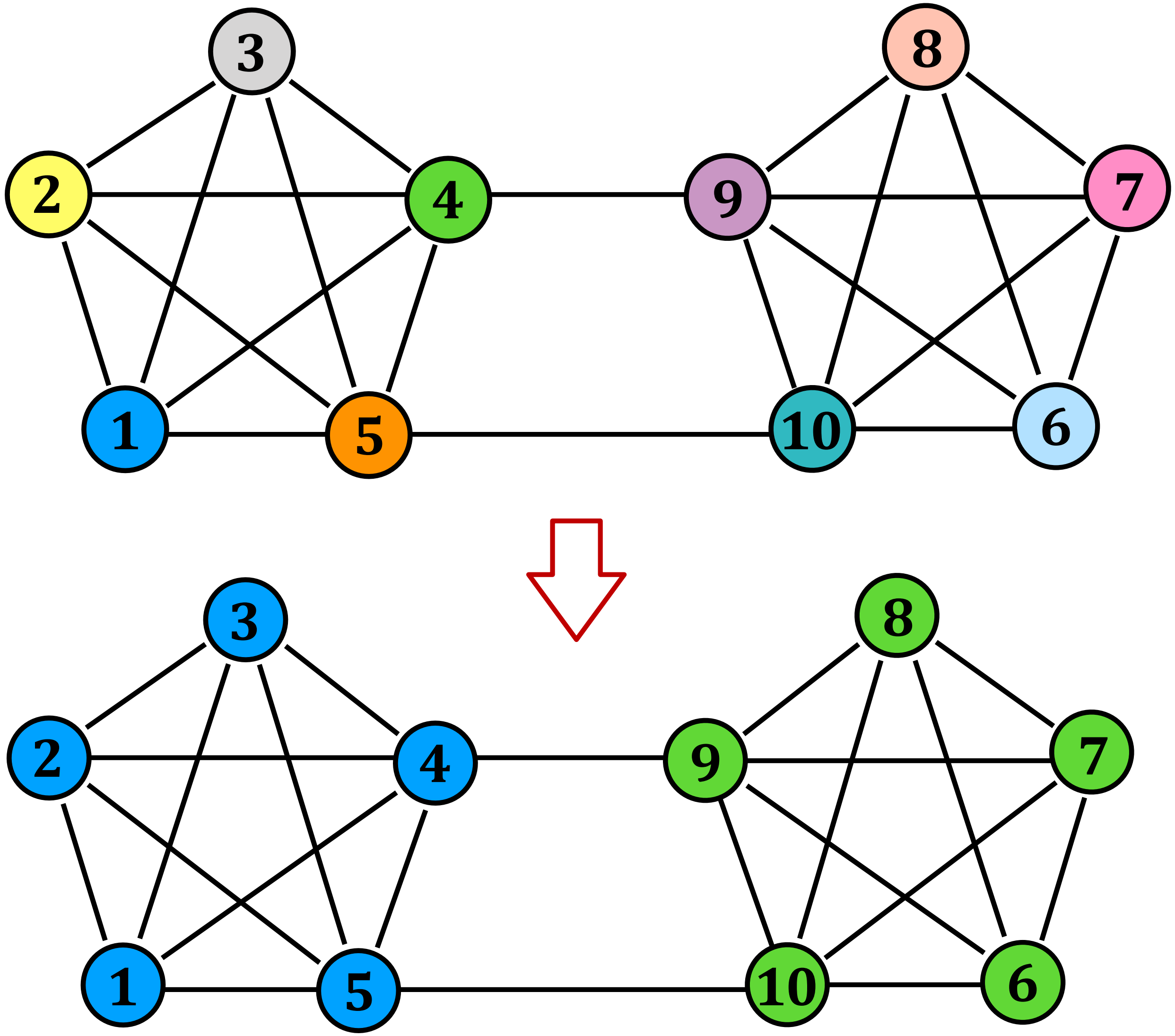
$$d(v,C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v,u)}{\sum_{u \in \mathcal{N}_v} afty(v,u)}$$

  Assign a community label with highest d
until a given part or all vertices keep labels

Final graph



Community detection: relational schema



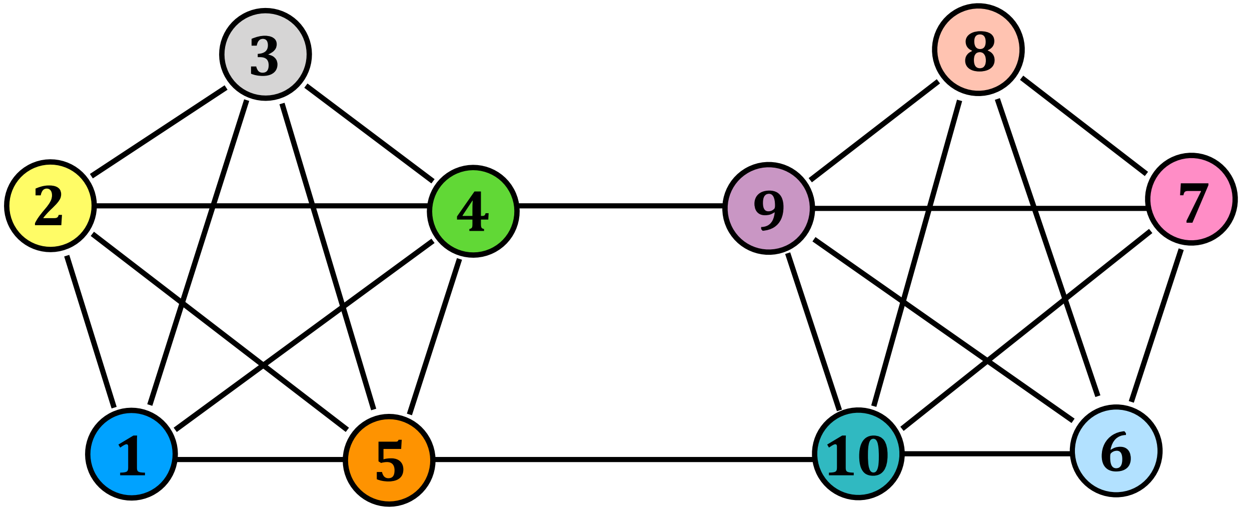
GRAPH table

v	u	w
1	2	1
1	3	1
…		
8	9	1
9	10	1

VERTEX table

v	c
1	1
2	1
…	
9	4
10	4

Community detection: label propagation



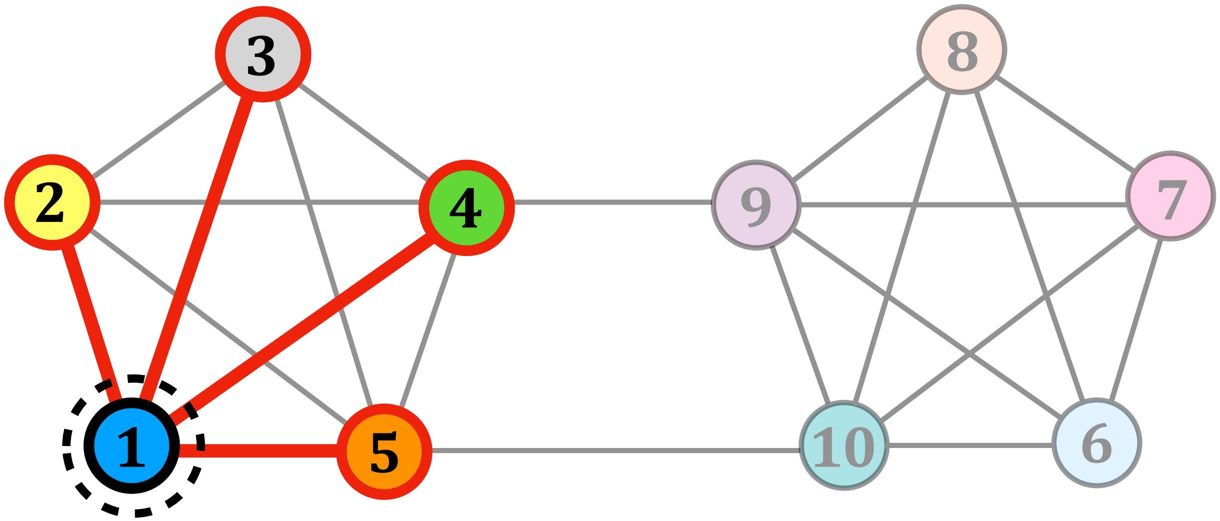
$$afty(v,u) = \frac{w(v,u)}{\sum_{i\in\mathcal{N}_v} w(v,i)}$$

AFF_TMP_WNBR

v	wnbr
…	

```
INSERT INTO AFF_TMP_WNBR
    SELECT v, sum(w) as wnbr
    FROM AFF_TMP_SUBG
    GROUP BY v;
```

Community detection: label propagation



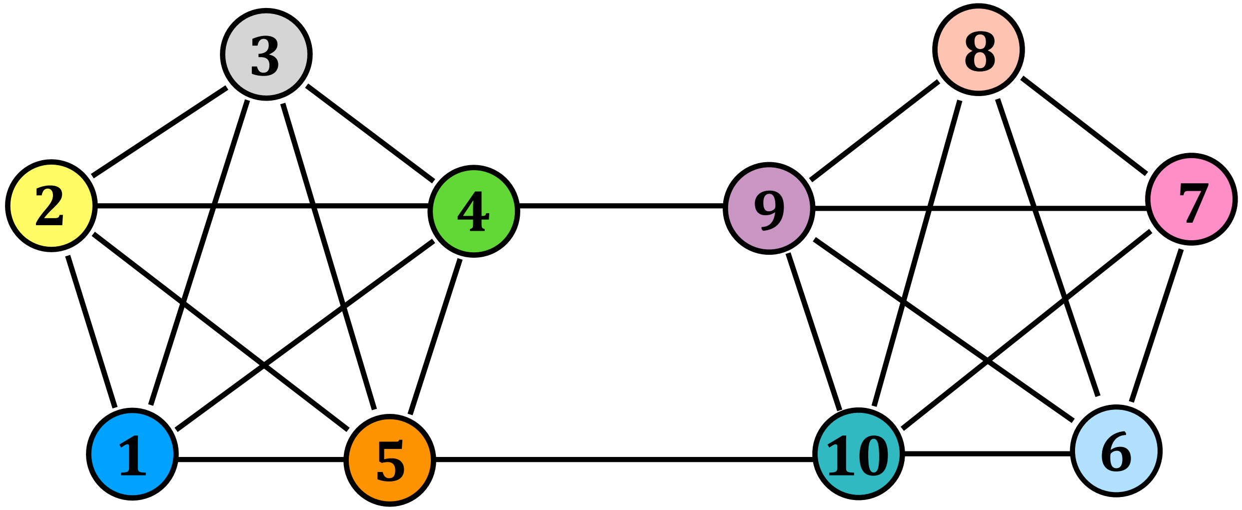
$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

AFF_TMP_WNBR

v	wnbr
1	4
…	

INSERT INTO **AFF_TMP_WNBR**
SELECT v, sum(w) as wnbr
FROM AFF_TMP_SUBG
GROUP BY v;

Community detection: label propagation



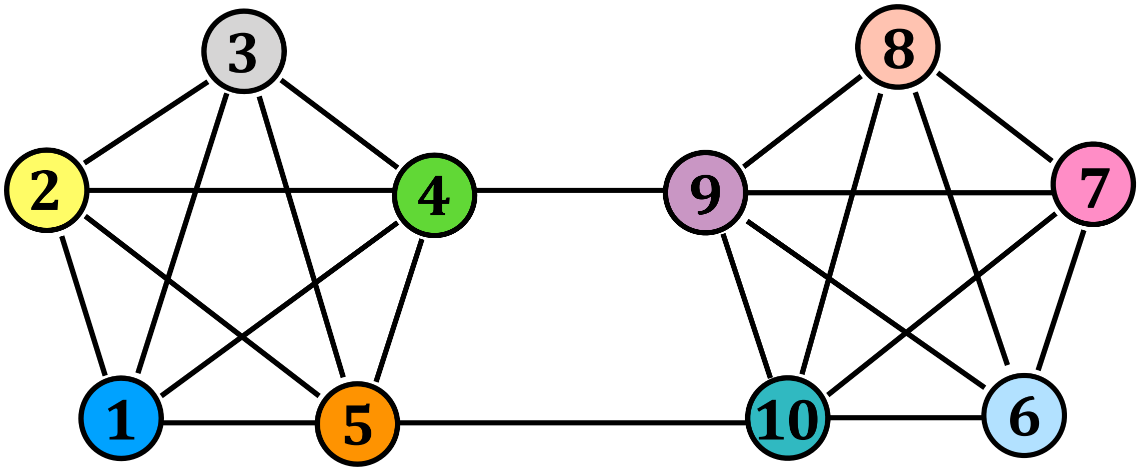
$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

AFF_TMP_WNBR

v	wnbr
1	4
2	4
…	
9	5
10	5

INSERT INTO **AFF_TMP_WNBR**
SELECT v, sum(w) as wnbr
FROM AFF_TMP_SUBG
GROUP BY v;

Community detection: label propagation



$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

- INSERT INTO **AFF_TMP_WNBR**
  SELECT v, sum(w) as wnbr
  FROM AFF_TMP_SUBG
  GROUP BY v;
- INSERT INTO **AFFINITY**
  SELECT X.v, u, w/wnbr as afty
  FROM AFF_TMP_SUBG AS X,
  AFF_TMP_WNBR AS Y
  WHERE X.v = Y.v;

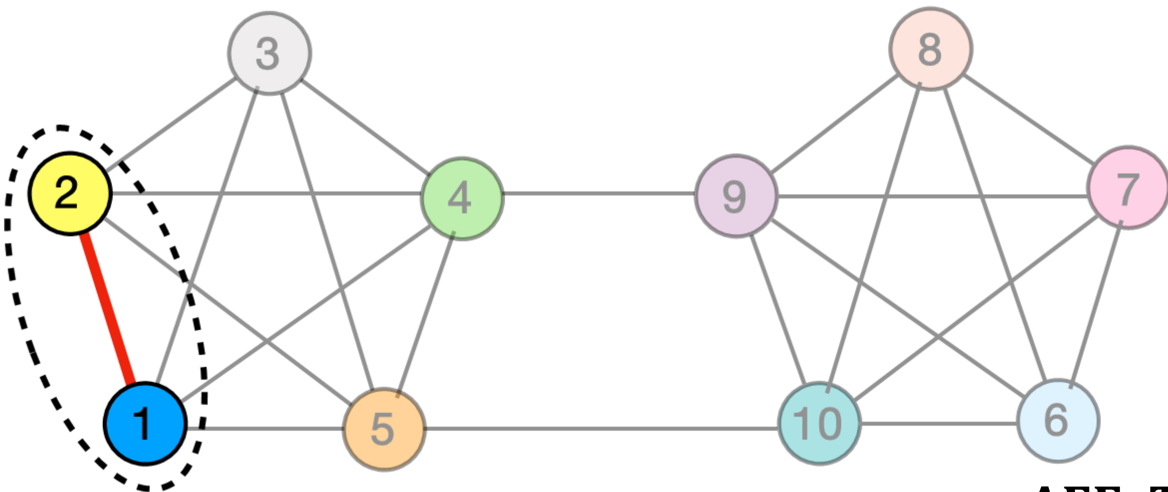
AFF_TMP_WNBR

v	wnbr
1	4
2	4
…	
9	5
10	5

AFFINITY

v	u	afty
…		

Community detection: label propagation



$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

- INSERT INTO **AFF_TMP_WNBR**
  SELECT v, sum(w) as wnbr
  FROM AFF_TMP_SUBG
  GROUP BY v;
- INSERT INTO **AFFINITY**
  SELECT X.v, u, w/wnbr as afty
  FROM AFF_TMP_SUBG AS X,
  AFF_TMP_WNBR AS Y
  WHERE X.v = Y.v;

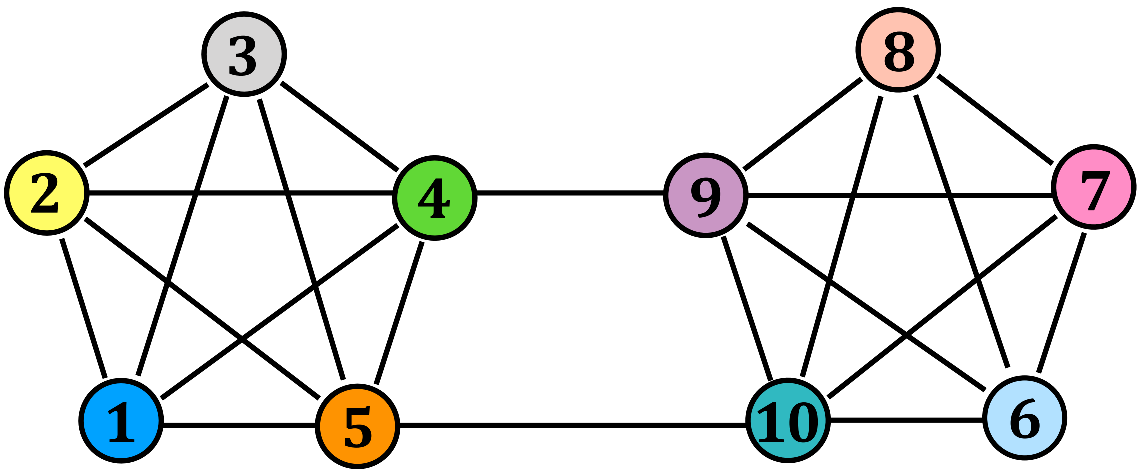
AFF_TMP_WNBR

v	wnbr
1	4
2	4
…	
9	5
10	5

AFFINITY

v	u	afty
1	2	$\frac{1}{4} = 0.25$
…		

Community detection: label propagation



$$afty(v,u) = \frac{w(v,u)}{\sum_{i \in \mathcal{N}_v} w(v,i)}$$

- INSERT INTO **AFF_TMP_WNBR**
  SELECT v, sum(w) as wnbr
  FROM AFF_TMP_SUBG
  GROUP BY v;
- INSERT INTO **AFFINITY**
  SELECT X.v, u, w/wnbr as afty
  FROM AFF_TMP_SUBG AS X,
  AFF_TMP_WNBR AS Y
  WHERE X.v = Y.v;

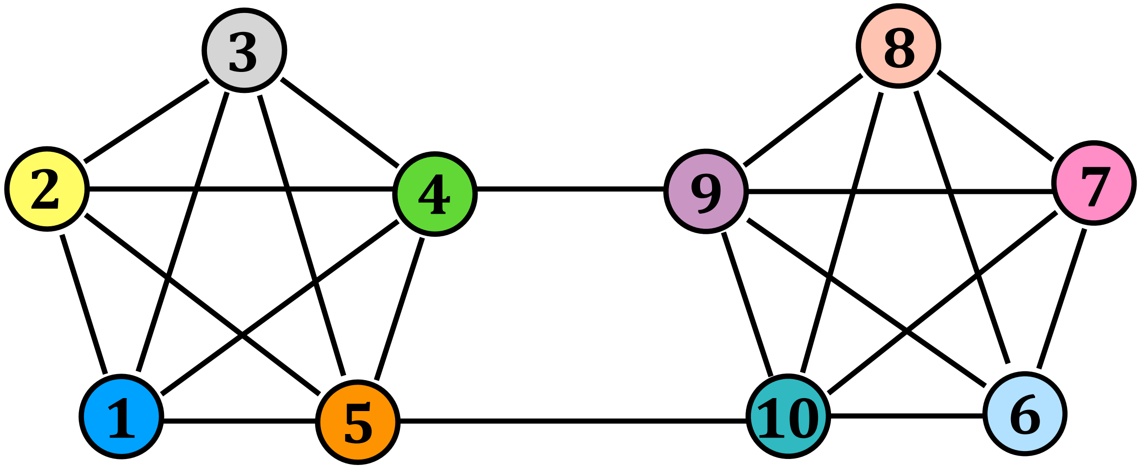
AFF_TMP_WNBR

v	wnbr
1	4
2	4
…	
9	5
10	5

AFFINITY

v	u	afty
1	2	0.25
1	3	0.25
1	4	0.25
…		
10	7	0.2
10	8	0.2
10	9	0.2

Community detection: label propagation



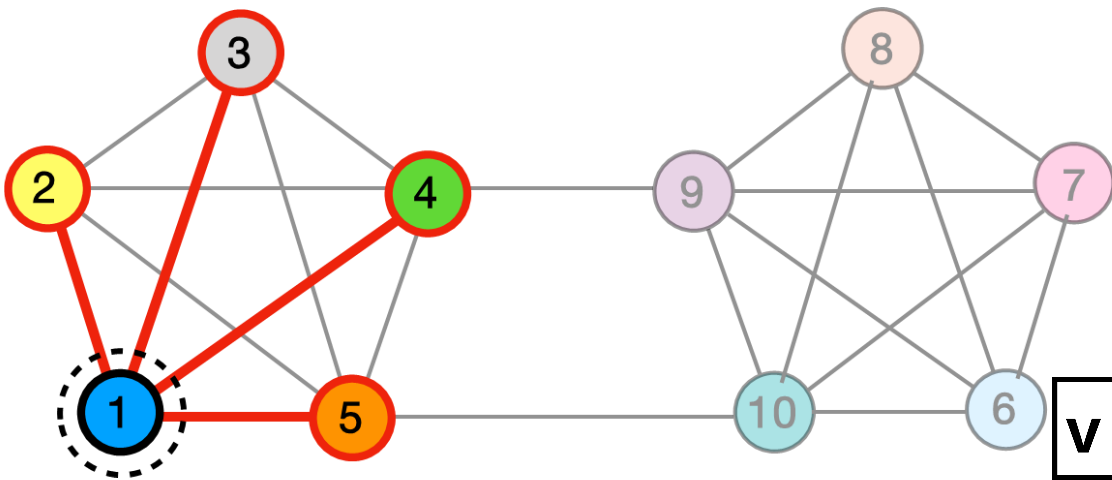
$$d(v,C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v,u)}{\sum_{u \in \mathcal{N}_v} afty(v,u)}$$

```
INSERT INTO COMM_TMP_AFNBRALL
        SELECT v, sum(afty) as afnrall
        FROM AFFINITY
        GROUP BY v;
```

COMM_TMP_AFNRALL

v	afnrall
...	

Community detection: label propagation



$$d(v, C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v, u)}{\sum_{u \in \mathcal{N}_v} afty(v, u)}$$

```
INSERT INTO COMM_TMP_AFNBRALL
    SELECT v, sum(afty) as afnrall
    FROM AFFINITY
    GROUP BY v;
```

AFFINITY

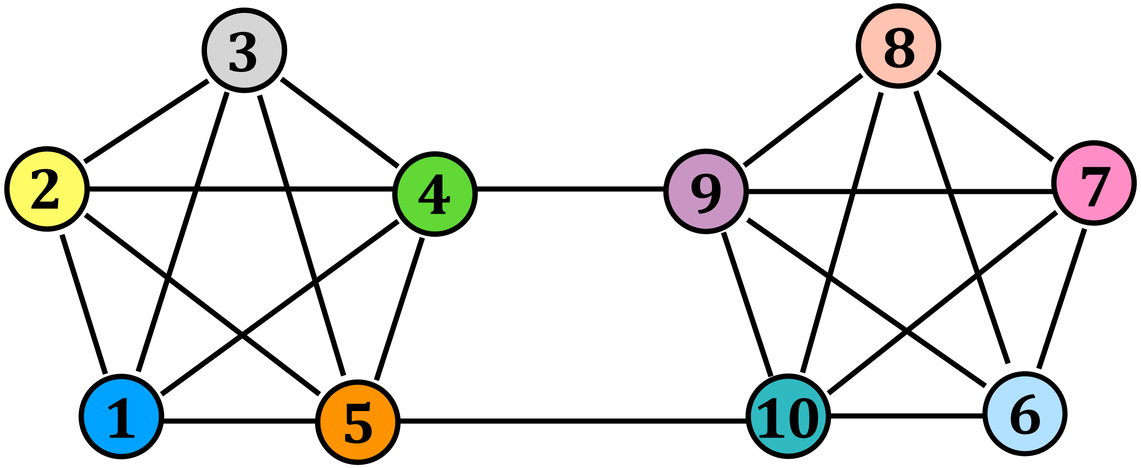
v	u	afty
1	2	0.25
1	3	0.25
1	4	0.25
1	5	0.25
...		
10	8	0.2
10	9	0.2

$\sum$

COMM_TMP_AFNBRALL

v	afnrall
1	1
...	

Community detection: label propagation



$$d(v, C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v,u)}{\sum_{u \in \mathcal{N}_v} afty(v,u)}$$

- INSERT INTO **COMM_TMP_AFNBRALL**
  SELECT v, sum(afty) as afnrall
  FROM AFFINITY
  GROUP BY v;
- INSERT INTO **COMM_TMP_AFNBRCOM**
  SELECT AFFINITY.v, VERTEX.c, sum(afty)
  FROM AFFINITY, VERTEX
  WHERE AFFINITY.u = VERTEX.v
  GROUP BY AFFINITY.v, VERTEX.c;

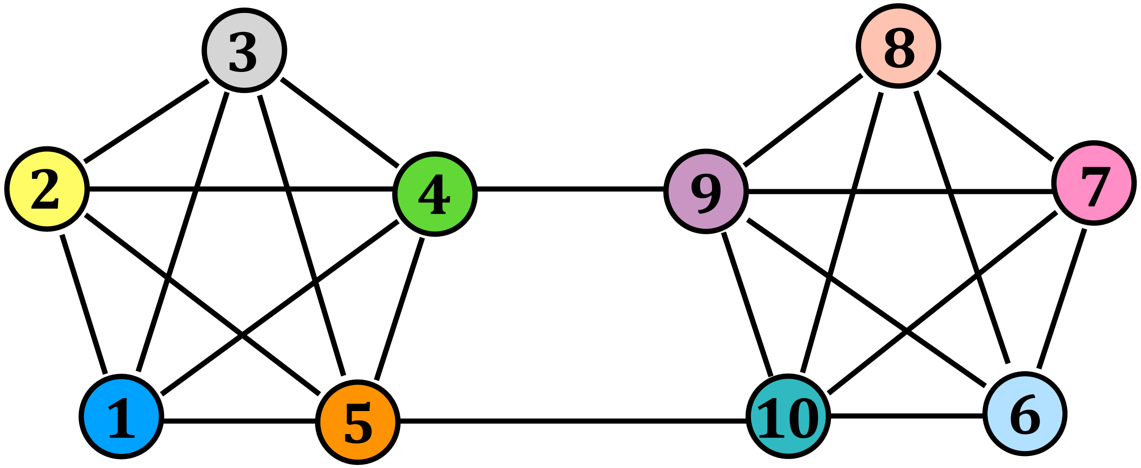
COMM_TMP_AFNBRALL

v	afnrall
1	1
2	1
…	
9	1
10	1

COMM_TMP_AFNBRCOM

v	u	afty
1	2	0.25
1	3	0.25
1	4	0.25
…		
10	7	0.2
10	8	0.2
10	9	0.2

Community detection: label propagation



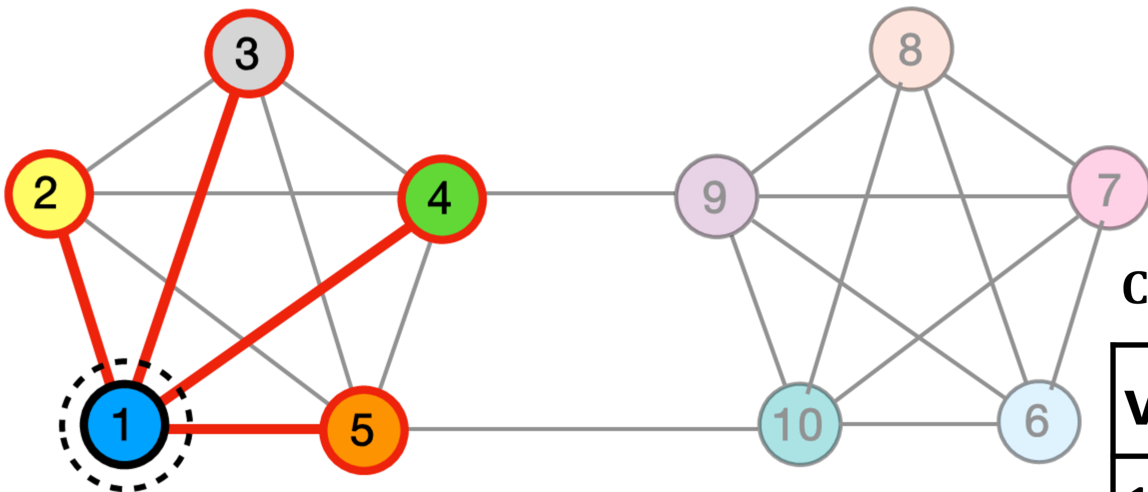
$$d(v,C)=\frac{\sum_{u\in\mathcal{N}_v \wedge \mathcal{L}_u=C} afty(v,u)}{\sum_{u\in\mathcal{N}_v} afty(v,u)}$$

COMMUNITY

v	c	d
1	2	0.25
1	3	0.25
1	4	0.25
…		
10	7	0.2
10	8	0.2
10	9	0.2

```
INSERT INTO COMMUNITY
        SELECT X.v, c, afnbrcom/afnbrall as d
        FROM COMM_TMP_AFNBRALL as X,
            COMM_TMP_AFNBRCOM as Y
        WHERE X.v = Y.v;
```

Community detection: label propagation



$$d(v, C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v, u)}{\sum_{u \in \mathcal{N}_v} afty(v, u)}$$

- INSERT INTO **COMMUNITY**
  SELECT X.v, c, afnbrcom/afnbrall as d
  FROM COMM_TMP_AFNBRALL as X,
  COMM_TMP_AFNBRCOM as Y
  WHERE X.v = Y.v;

- INSERT INTO **COMM_TMP_DMAX**
  SELECT v, max(d) as dmax
  FROM COMMUNITY
  GROUP BY v;

COMMUNITY

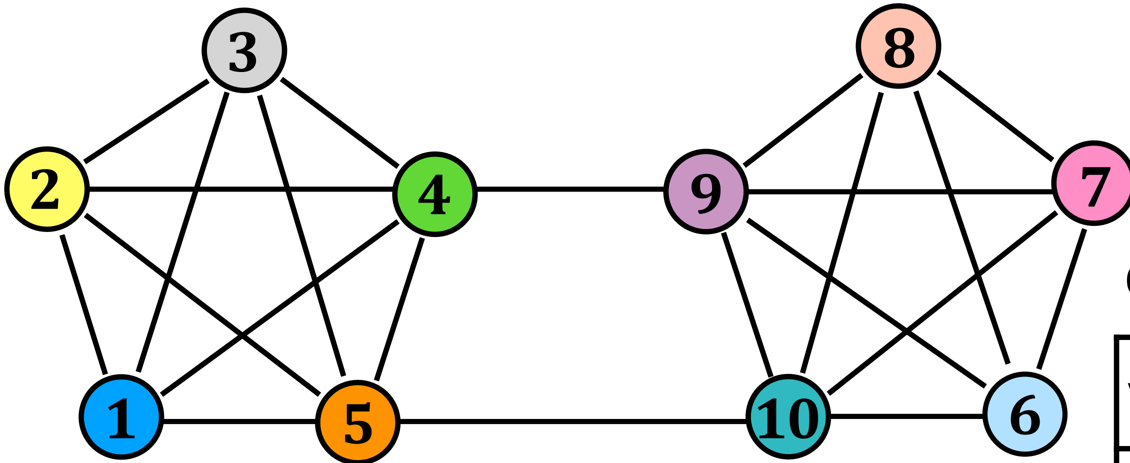
v	c	d
1	2	0.25
1	3	0.25
1	4	0.25
1	5	0.25
…		
10	8	0.2
10	9	0.2

max

COMM_TMP_DMAX

v	dmax
1	0.25
…	

Community detection: label propagation



$$d(v, C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v, u)}{\sum_{u \in \mathcal{N}_v} afty(v, u)}$$

- INSERT INTO **COMMUNITY**
  SELECT X.v, c, afnbrcom/afnbrall as d
  FROM COMM_TMP_AFNBRALL as X,
  COMM_TMP_AFNBRCOM as Y
  WHERE X.v = Y.v;
- INSERT INTO **COMM_TMP_DMAX**
  SELECT v, max(d) as dmax
  FROM COMMUNITY
  GROUP BY v;

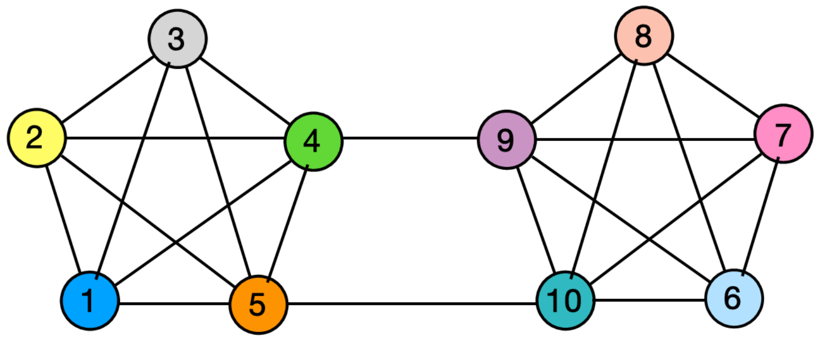
COMMUNITY

v	c	d
1	2	0.25
1	3	0.25
1	4	0.25
1	5	0.25
…		
10	8	0.2
10	9	0.2

COMM_TMP_DMAX

v	dmax
1	0.25
2	0.25
…	
9	0.2
10	0.2

Community detection: label propagation



$$d(v,C) = \frac{\sum_{u \in \mathcal{N}_v \wedge \mathcal{L}_u = C} afty(v,u)}{\sum_{u \in \mathcal{N}_v} afty(v,u)}$$

COMMUNITY as X

v	c	d
1	2	0.25
1	3	0.25
1	4	0.25
1	5	0.25
…		
10	8	0.2
10	9	0.2

COMM_TMP_ DMAX as Y

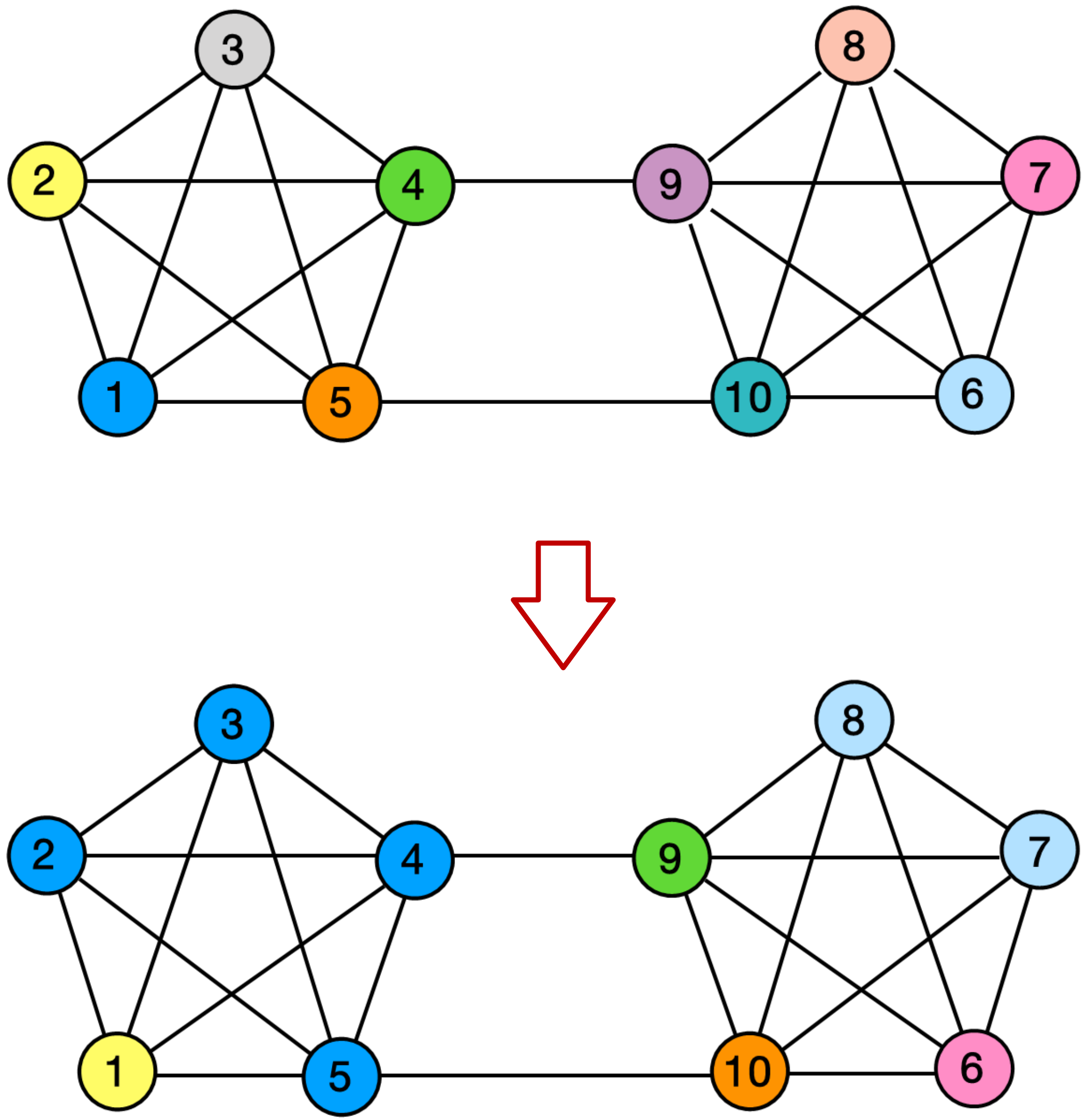
v	dmax
1	0.25
2	0.25
…	
9	0.2
10	0.2

$$\gamma_{a,min(c)}(\pi_{v,c}(X \bowtie Y))$$

VERTEX

v	c
1	2
2	1
…	
9	4
10	5

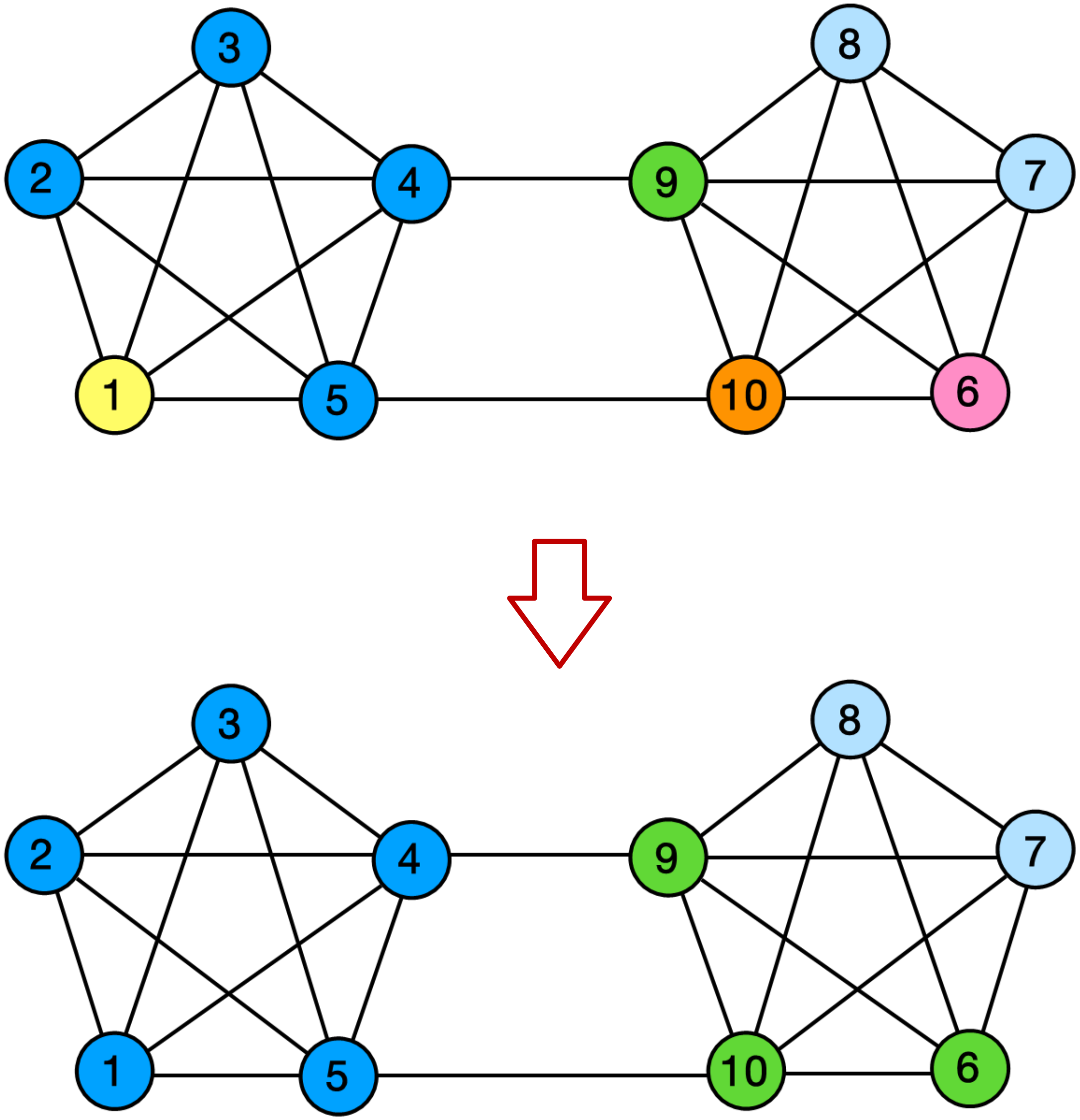
Community detection



VERTEX

v	c
1	2
2	1
3	1
4	1
5	1
6	7
7	6
8	6
9	4
10	5

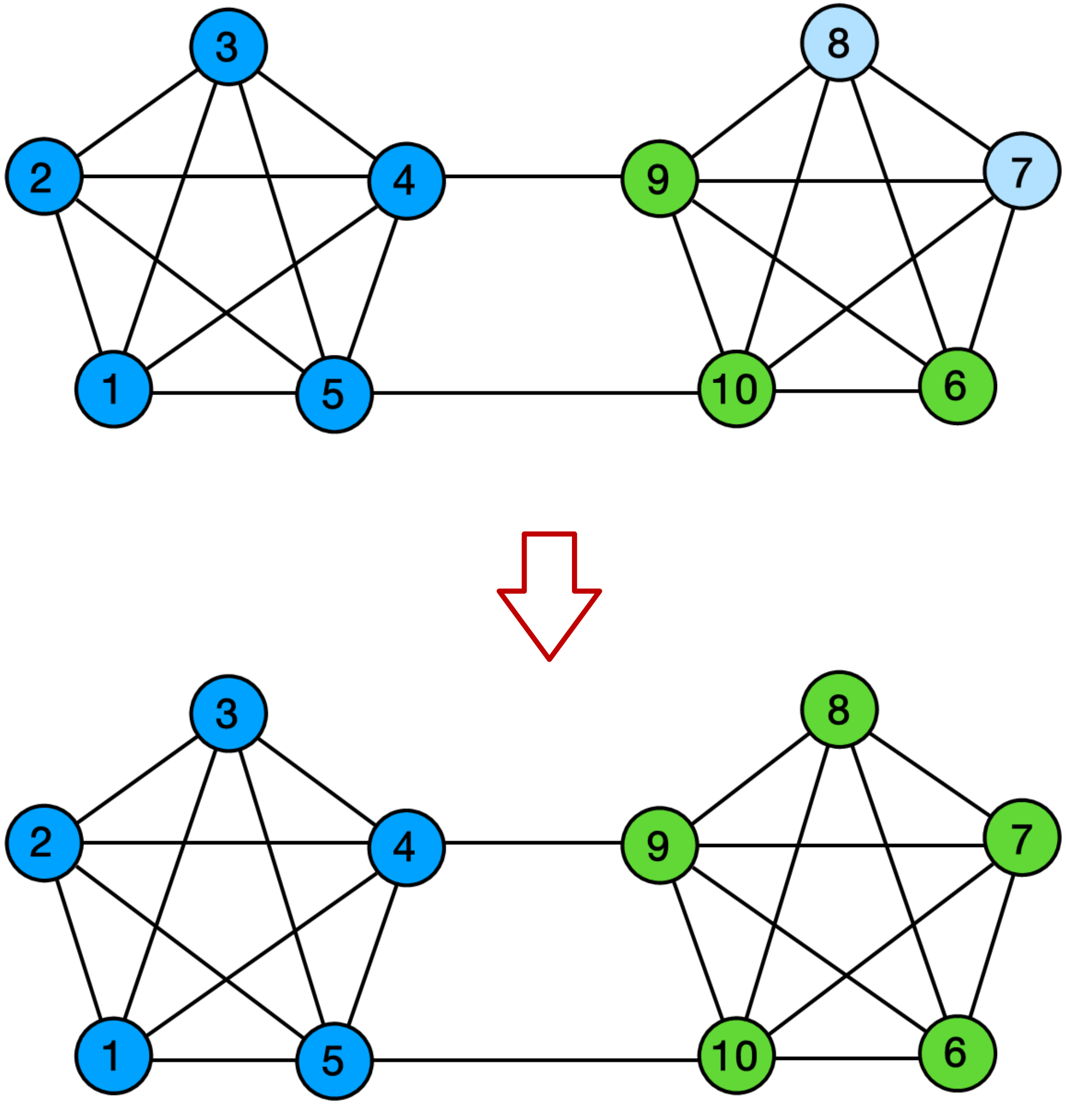
Community detection



VERTEX

v	c
1	1
2	1
3	1
4	1
5	1
6	4
7	6
8	6
9	4
10	4

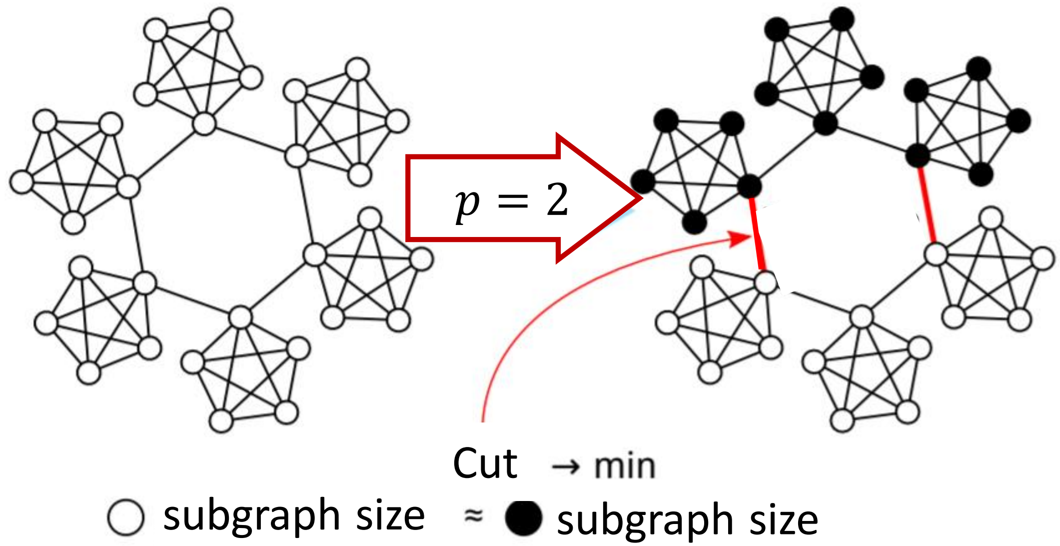
Community detection



VERTEX

v	c
1	1
2	1
3	1
4	1
5	1
6	4
7	4
8	4
9	4
10	4

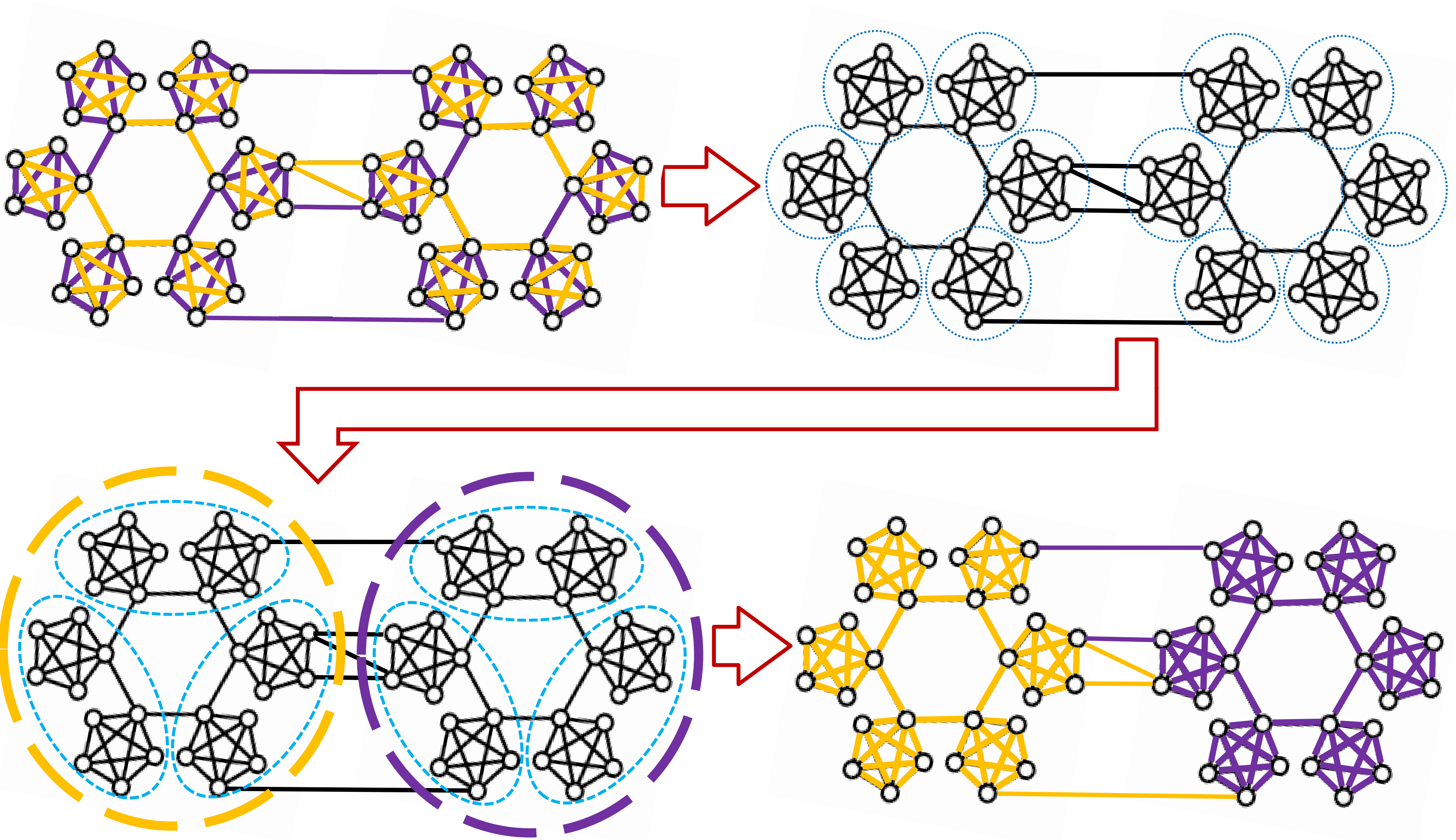
Even more! Graph partitioning in PDBMS



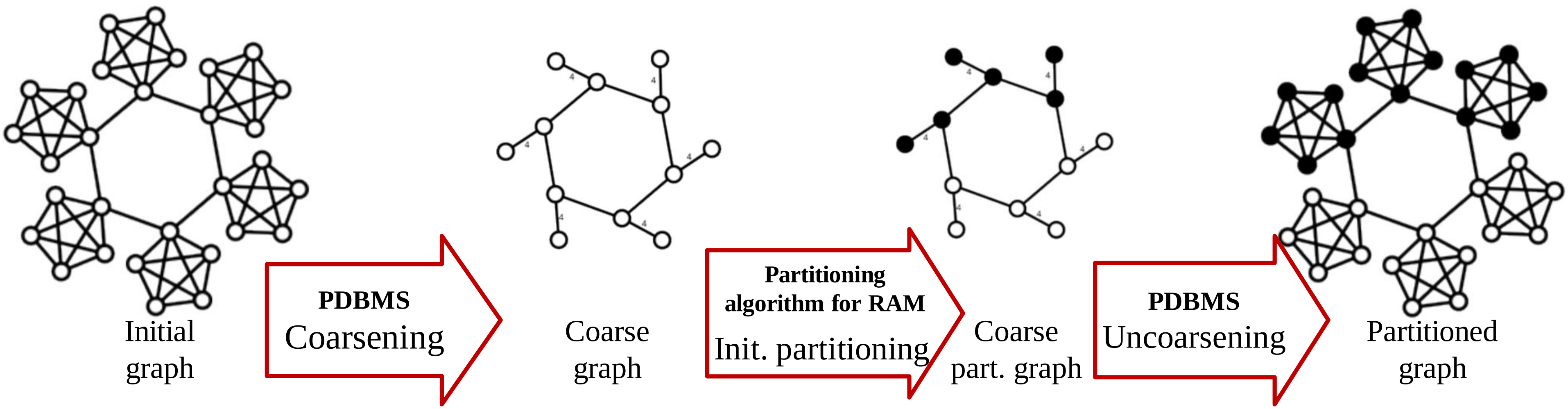
$$G(N, E, w)$$

1. $N = \cup_{i=1}^{p} N_i,\ \forall i \neq j\ N_i \cap N_j = \emptyset,\ p > 1$
2. $w(N_i) \approx \frac{w(N)}{p}\ \ \forall i \in \{1, \dots, p\}$
3. $Cut\ W_{cut} \rightarrow \min,\ W_{cut} \coloneqq \sum_{e \in E_{cut}} w(e),$
   $E_{cut} \coloneqq \{(u, v) \in E \mid u \in N_i, v \in N_j, 1 \leq i, j \leq p, i \neq j\}$

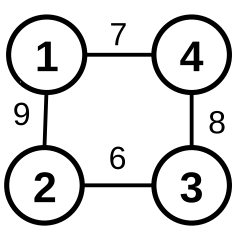
Graph partitioning in PDBMS



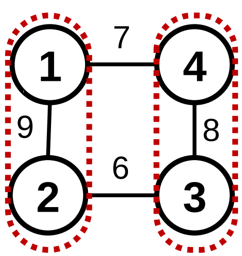
Multilevel graph partitioning in PDBMS



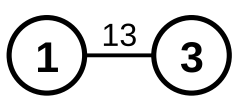
U	*V*	*W*
1	2	9
2	3	6
3	4	8
4	1	7



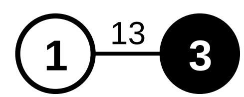
U	*V*
1	2
3	4



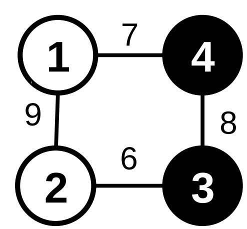
U	*V*	*W*
1	3	13



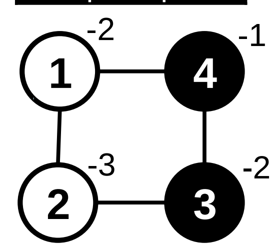
U	*P*
1	**1**
3	**0**



U	*P*
1	**1**
2	**1**
3	**0**
4	**0**



A	*P*	*G*
1	**1**	-2
2	**1**	-3
3	**0**	-2
4	**0**	-1

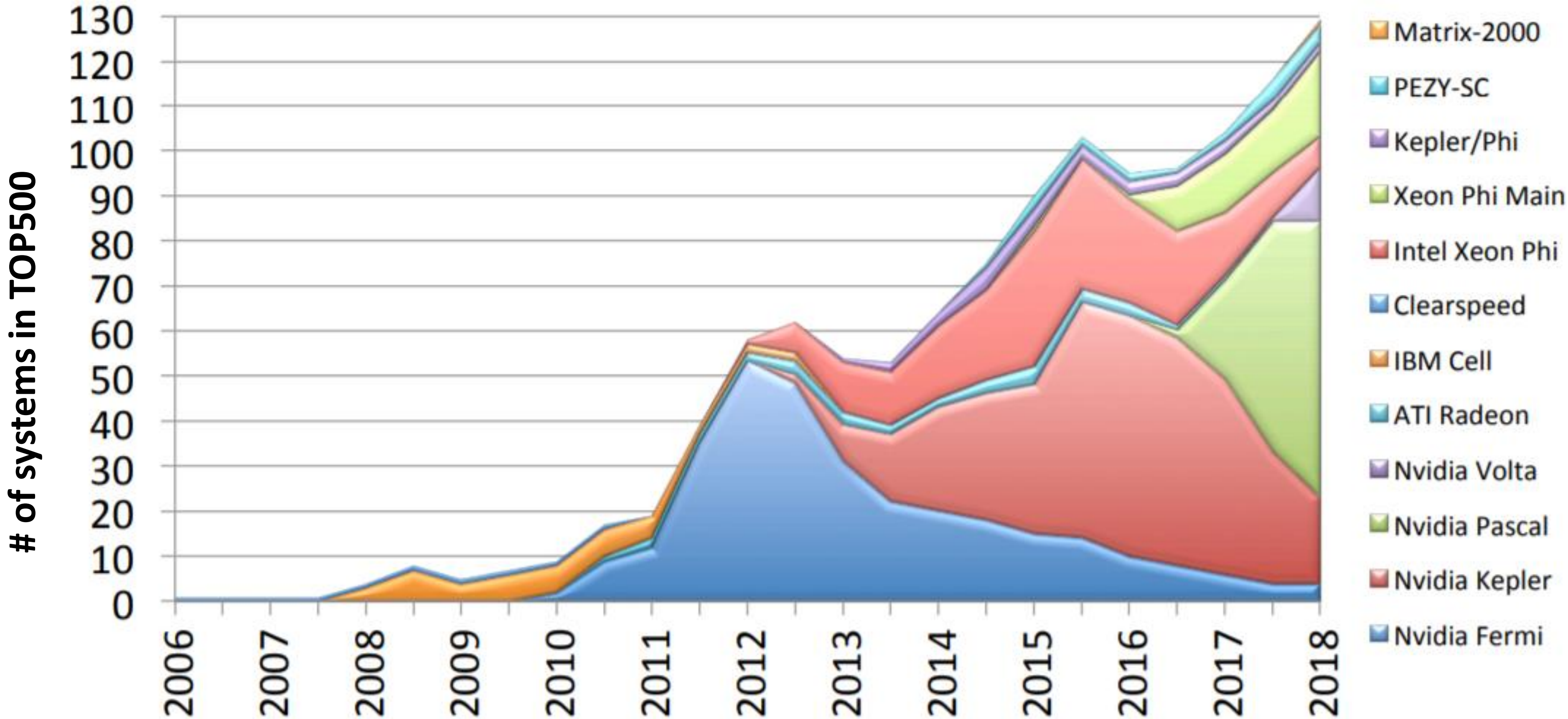


Comparison with analogs

Algorithm	Graph		Time, sec.				***dbPar graph,*** sec.
	$\|N\|$	$\|E\|$	Detection	**Export**	**Import**	Total	
MSP [1)]	10^7	$5 \cdot 10^7$	962	307	36	1 305	**1 189**
ParMETIS [2)]	$7.7 \cdot 10^6$	$1.33 \cdot 10^8$	500	474	30	1 004	**886**
PT-Scotch [3)]	$2.3 \cdot 10^7$	$1.75 \cdot 10^8$	417	652	79	1 148	**897**

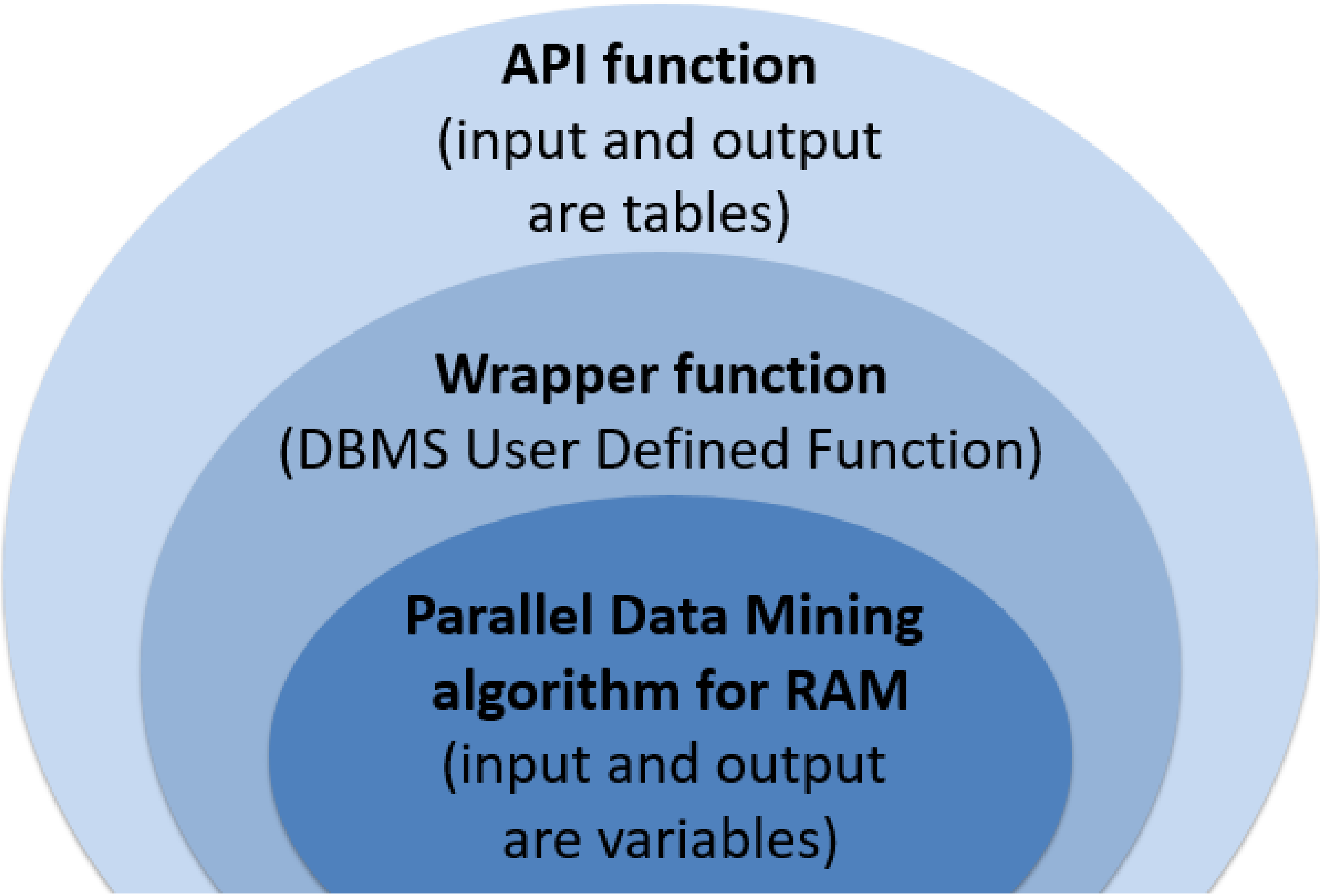
[1)] Zeng Z., *et al.* A parallel graph partitioning algorithm to speed up the large-scale distributed graph mining. BigMine 2012. pp. 61–68.
[2)] Karypis G. METIS and ParMETIS. Enc. of Parallel Computing (Ed. by D.A. Padua). Springer, 2011. pp. 1117–1124.
[3)] Chevalier C., Pellegrini F. PT-Scotch: A tool for efficient parallel graph ordering. Parallel Computing. 2008. vol. 34, no. 6-8. pp. 318–331.

TOP 500 The List.: Many-core accelerators are coming



… and we can use it for in-DBMS Data Mining!

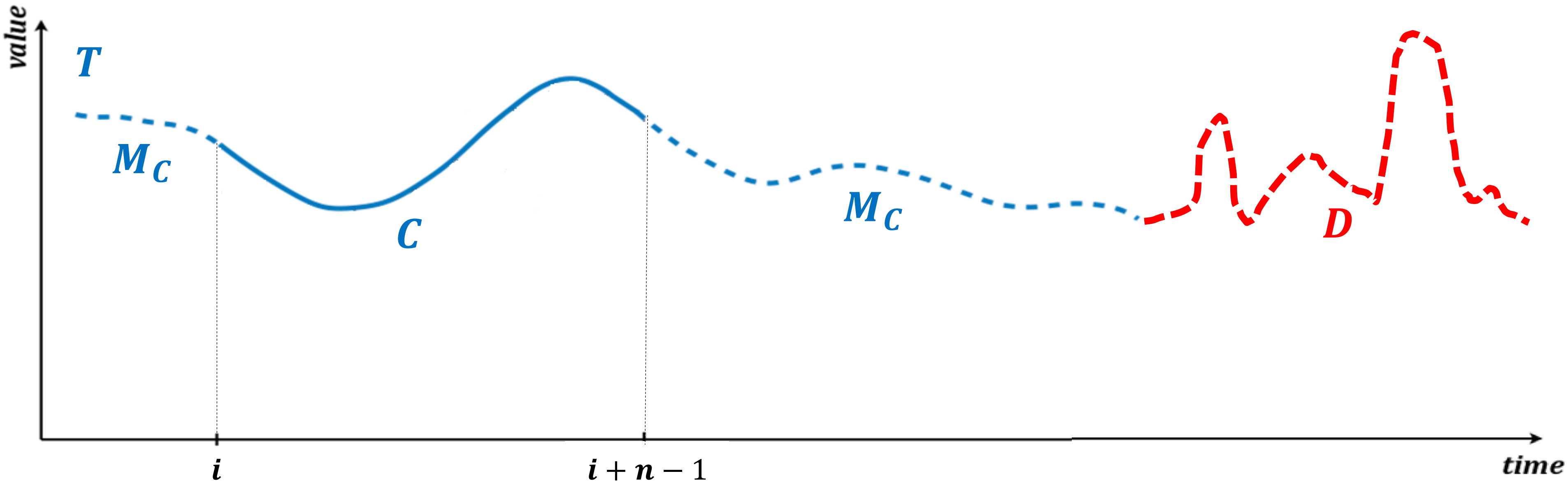
Embedding parallel DM algorithms into DBMS



How should we parallelize algorithms for accelerators?

- **SIMD processing and auto-vectorization**
  - Single Instruction Multiple Data
  - Computations should be organized as **for**-loops without data dependencies, so the compiler will be able to change a set of scalar statements in loop body to one vector operation
- **Data alignment**
  - Data element size should be multiple of vector register size to avoid loop peeling

Accelerating anomaly detection in time series



- Time series: $T := (t_1, \ldots, t_m), t_i \in \mathbb{R}$
- Subsequence: $C := T_{i,n}$ where $n \ll m$
- Non-self match subsequence for C : $M_C := T_{j,n}, |i-j| \geq n$
- **Anomalous subsequence** D:

$$\forall C, M_C \in T \min(ED(D, M_D)) > \min(ED(C, M_C))$$

Anomaly detection: ideas

- We need **index structures** to effectively iterate subsequences of the given time series
- We differ the following types of subsequences
  - **NearAnomalies** are the rarest, and **Others**
  - **Neighbors** are close to the given subsequence, and **Strangers**
- We can avoid brute force and **prune** clearly unpromising subsequences

$$
\begin{array}{l}
d_{anomaly} \leftarrow 0;\ d_{NN} \leftarrow \infty \\
\textbf{for } C_i \in \boldsymbol{NearAnomalies}, \boldsymbol{Others} \\
\quad \textbf{for } C_j \in \boldsymbol{Neighbors}, \boldsymbol{Strangers} \\
\quad\quad d \leftarrow ED^2(C_i, C_j) \\
\quad\quad \textbf{if } \ d < d_{anomaly} \\
\quad\quad\quad \textbf{break} \\
\quad\quad d_{NN} \leftarrow \min(d, d_{NN}) \\
\quad d_{anomaly} \leftarrow \max\left(d_{NN}, d_{anomaly}\right) \\
\quad C_{anomaly} \leftarrow C_i \\
\textbf{return } \{C_{anomaly}, d_{anomaly}\}
\end{array}
$$

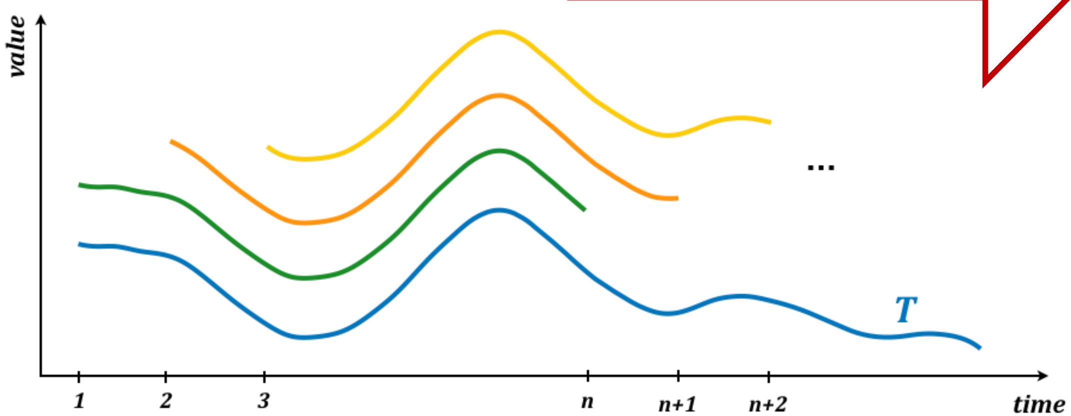
Index structures: Subsequence matrix

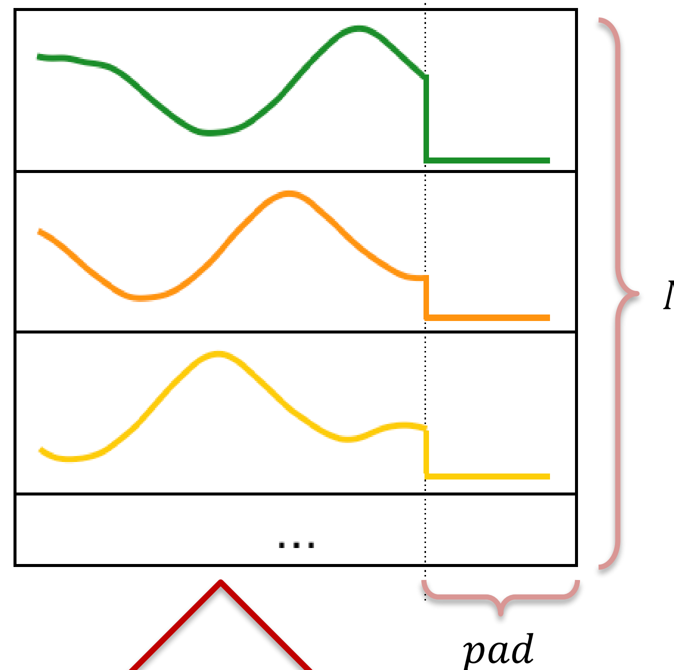
$T \in \mathbb{R}^m$

Alignment

$(n + pad) \vdots width_{VPU}$

$\boldsymbol{S} \in \mathbb{R}^{N \times (n+pad)}$





$N := |T| - n + 1$

$width_{VPU}$

z-normalization

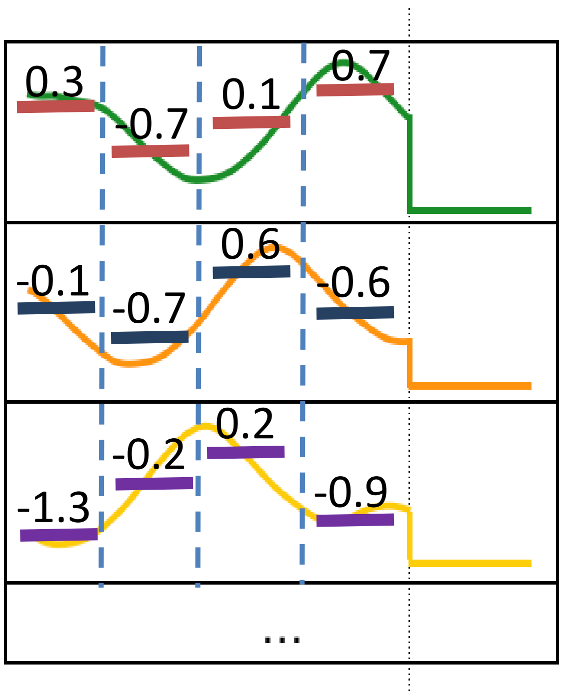
$$\hat{S} = (\hat{s}_1, \hat{s}_2, \dots, \hat{s}_n)$$

$$\hat{s}_i = \frac{s_i - \mu}{\sigma},\ \mu = \frac{1}{n}\sum_{i=1}^{n} s_i\,,\ \sigma^2 = \frac{1}{n}\sum_{i=1}^{n} s_i^2 - \mu^2$$

PAA transformation

Subsequence matrix

$$\boldsymbol{S} \in \mathbb{R}^{N\times(n+pad)}$$



Piecewise Aggregate Approximation

$$PAA(i,k) = \frac{w}{n} \sum_{j=\left(\frac{n}{w}\right)(i-1)+1}^{\left(\frac{n}{w}\right)i} S(k,j)$$

Matrix of PAA codes

$$\boldsymbol{PAA} \in \mathbb{R}^{N\times w}$$

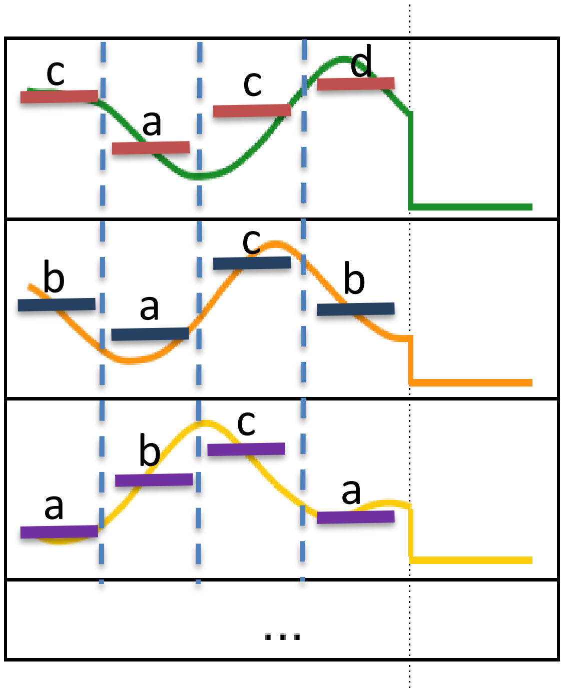
0.3	-0.7	0.1	0.7
-0.1	-0.7	0.6	-0.6
-1.3	-0.2	0.2	-0.9
	...		

w – compression degree (typically w=4)

SAX transformation

Subsequence matrix

$$\boldsymbol{S} \in \mathbb{R}^{N\times(n+pad)}$$



Symbolic Aggregate ApproXimation

$(-\infty; -0.67)$	$[-0.67; 0)$	$[0; 0.67)$	$[0.67; \infty)$
a	b	c	d

Coding table in alphabet A
(typically $|A|$=4)

Matrix of SAX codes

$$\boldsymbol{SAX} \in \mathbb{N}^{N\times w}$$

c	a	c	d
b	a	c	b
a	b	c	a
...			

Indices of SAX codes and near anomalies

Matrix of SAX codes

$$\boldsymbol{SAX} \in \mathbb{N}^{N \times w}$$

1	a	b	d	d
2	c	d	a	b
3	a	b	d	c
	…			
j	a	b	d	c
ℓ	c	d	a	b
u	c	d	a	b
k	a	b	d	d

Count word frequencies

Frequency index of SAX codes

$$\boldsymbol{F_{SAX}} \in \mathbb{N}^{N}$$

2
3
2
…
2
3
3
2
…

Building an index

Index of near anomalies

$$\boldsymbol{Cand} \in \mathbb{N}^{N}$$

1
3
j
k
-
-
-
-

Dictionary and its indices

Dictionary

$\boldsymbol{W_A} \in \mathbb{N}^{|A|^w \times w}$

a	a	a	a
a	a	a	b
…			
a	b	d	c
a	b	d	d
….			
c	d	a	b
…			
d	d	d	d

Matrix of SAX codes

$\boldsymbol{SAX} \in \mathbb{N}^{N \times w}$

1	a	b	d	d
2	c	d	a	b
3	a	b	d	c
	…			
j	a	b	d	c
ℓ	c	d	a	b
u	c	d	a	b
k	a	b	d	d
	…			

Frequency index

$\boldsymbol{F_W} \in \mathbb{N}^{|A|^w}$

0
0
…
2
2
…
3
…
0

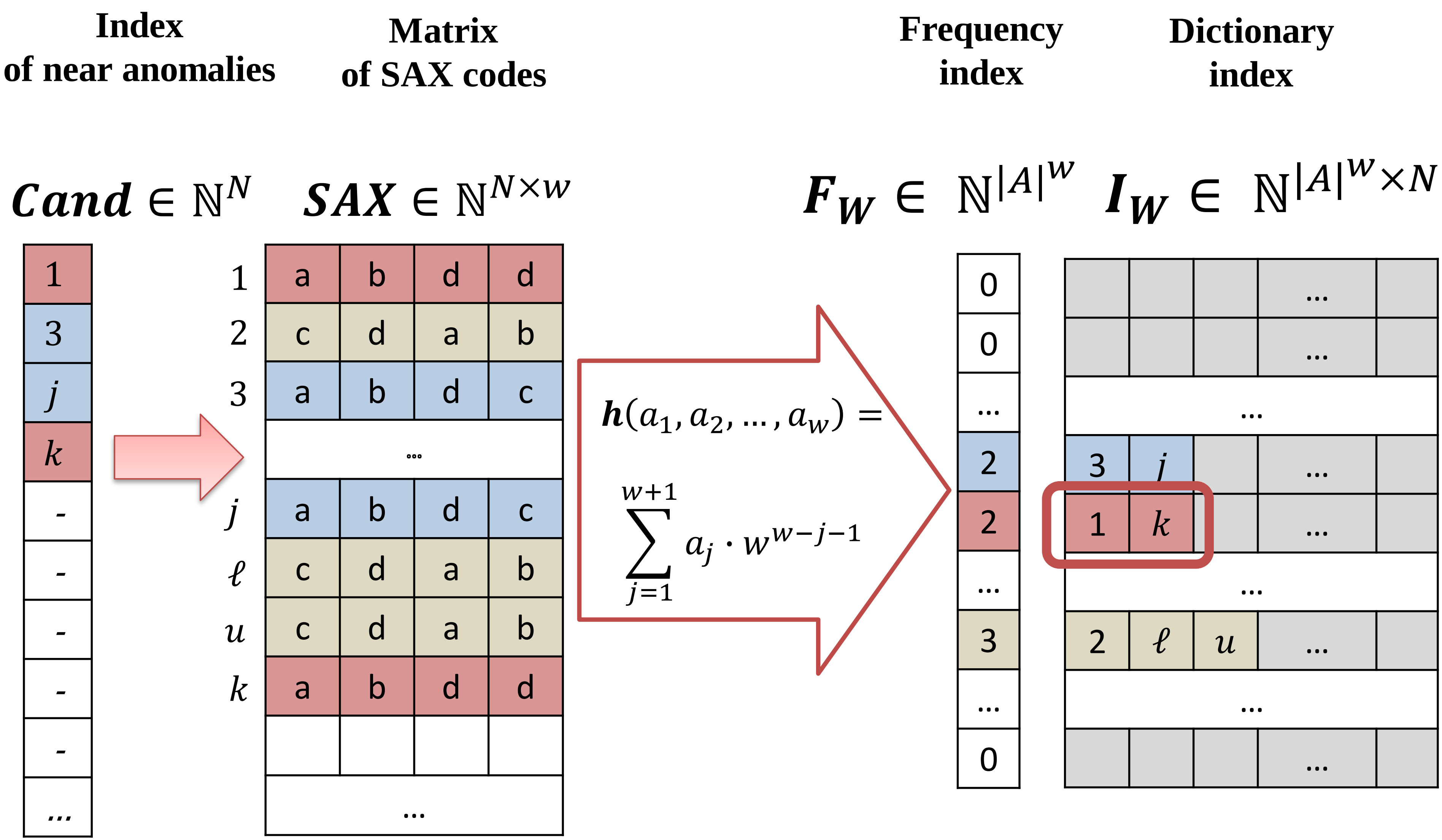
Dictionary index

$\boldsymbol{I_W} \in \mathbb{N}^{|A|^w \times N}$

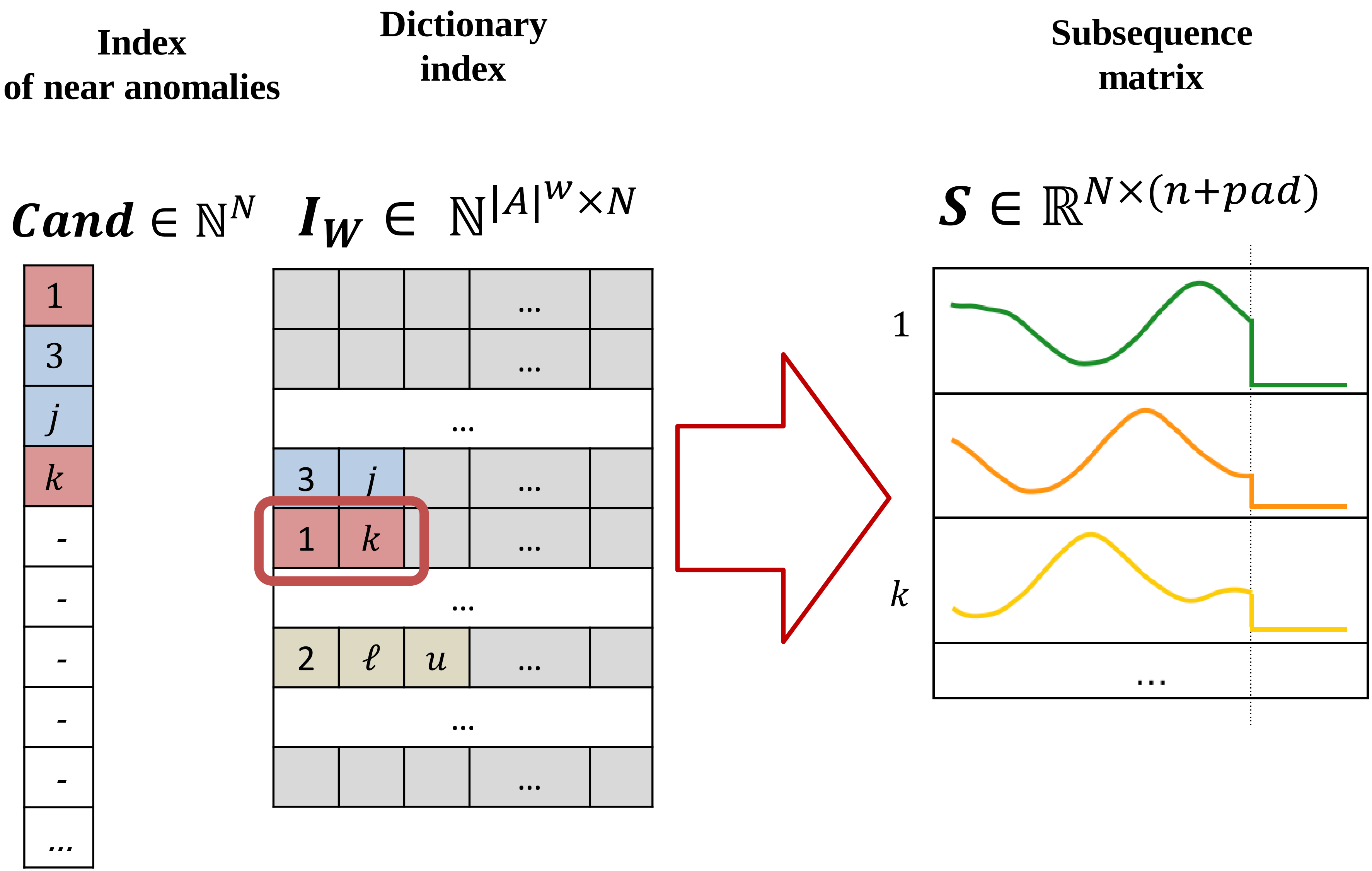
			…	
			…	
…				
3	j		…	
1	k		…	
…				
2	ℓ	u	…	
…				
			…	

Placement of characters in alphabet A by w characters with repetitions

Indirect access to subsequences



Iteration of subsequences



Parallel anomaly detection

1. Select candidates

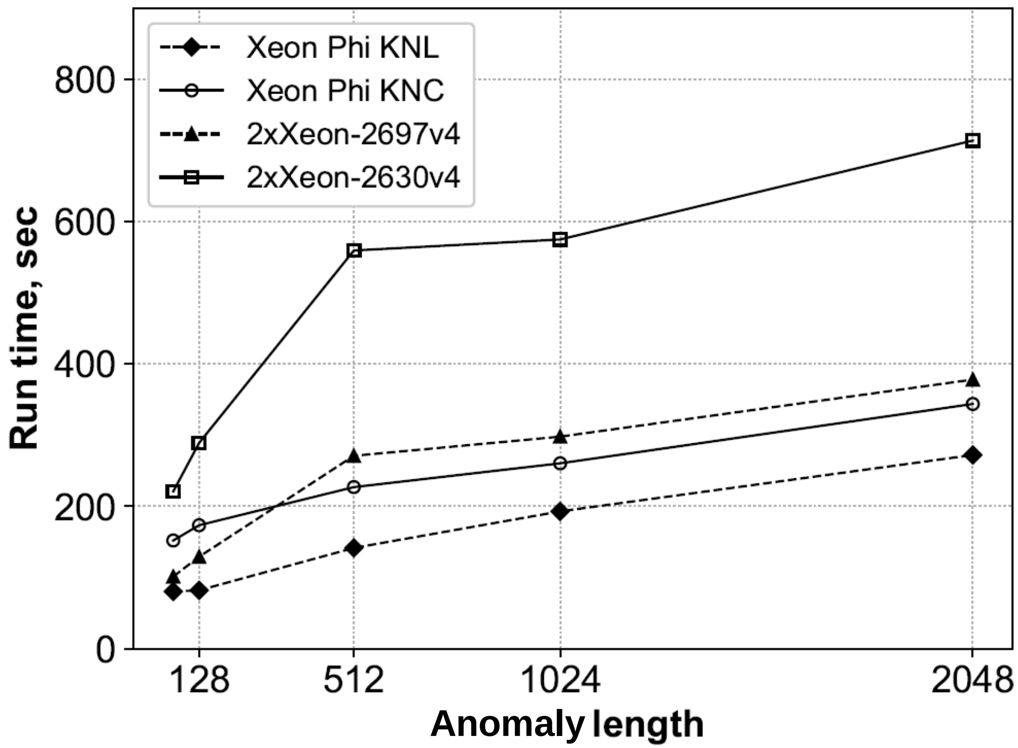
$d_{anomaly} \leftarrow 0$; $d_{NN} \leftarrow \infty$
for $C_i \in \boldsymbol{NearAnomalies}$
  PARALLEL
  for $C_j \in \boldsymbol{Neighbors}, \boldsymbol{Strangers}$
    $d \leftarrow \boldsymbol{ED}^2\,(C_i, C_j)$
    if $d < d_{anomaly}$
      break
    $d_{NN} \leftarrow \min(d, d_{NN})$
  $d_{anomaly} \leftarrow \max(d_{NN}, d_{anomaly})$
  if $d_{anomaly} < d_{NN}$ **then**
    $C_{anomaly} \leftarrow C_i$
return $\{C_{anomaly}, d_{anomaly}\}$

2. Refine

$d_{NN} \leftarrow \infty$
PARALLEL
for $C_i \in \boldsymbol{Others}$
  for $C_j \in \boldsymbol{Neighbors}, \boldsymbol{Strangers}$
    $d \leftarrow \boldsymbol{ED}^2\,(C_i, C_j)$
    if $d < d_{anomaly}$
      break
    $d_{NN} \leftarrow \min(d, d_{NN})$
  $d_{anomaly} \leftarrow \max(d_{NN}, d_{anomaly})$
  if $d_{anomaly} < d_{NN}$ **then**
    $C_{anomaly} \leftarrow C_i$
return $\{C_{anomaly}, \sqrt{d_{anomaly}}\}$

Speedup

Feature \ Device	Intel Xeon Phi SE10X (**KNC**)	Intel Xeon Phi 7290 (**KNL**)	2× Intel Xeon E5-2697v4	2× Intel Xeon E5-2630v4
Number of cores	**61**	**72**	2×16	2×10
Frequency, GHz	1.1	1.5	**2.6**	**2.2**
Peak. performance, TFLOPS	1.076	3.456	0.600	0.390



Conclusions

Big Data processing and analytics inside Parallel Relational DBMS – it is possible and feasible!

Thank you for paying attention! Questions?

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