B4M36DS2, BE4M36DS2: Database Systems 2

https://cw.fel.cvut.cz/b211/courses/b4m36ds2/

Lecture 12

Advanced Aspects

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11. 12. 2022

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Graph Databases

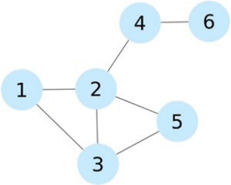
A bit of theory

- Data: a set of entities and their relationships
  - e.g., social networks, travelling routes, …
  - We need to efficiently represent graphs
- Basic operations: finding the neighbours of a node, checking if two nodes are connected by an edge, updating the graph structure, …
  - We need efficient graph operations
- $G = (V, E)$ is commonly modelled as
  - set of nodes (vertices) V
  - set of edges E
  - $n = |V|$, $m = |E|$
- Which data structure should be used?

Adjacency Matrix

- Bi-dimensional array A of n x n Boolean values
  - Indexes of the array = node identifiers of the graph
  - The Boolean junction A_{ij} of the two indices indicates whether the two nodes are connected
- Variants:
  - Directed graphs
  - Weighted graphs
  - …

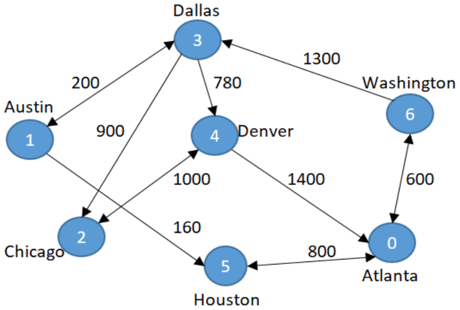
Adjacency Matrix



$$\begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

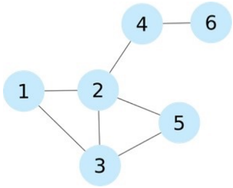
- Pros:
  - □ Adding/removing edges
  - □ Checking if two nodes are connected
- Cons:
  - □ Quadratic space with respect to *n*
    - We usually have sparse graphs → lots of 0 values
  - □ Addition of nodes is expensive
  - □ Retrieval of all the neighbouring nodes takes linear time with respect to *n*

Adjacency Matrix



		[0]	[1]	[2]	[3]	[4]	[5]	[6]
[0]	Atlanta	0	0	0	0	**-1400**	800	600
[1]	Austin	0	0	0	200	0	160	0
[2]	Chicago	0	0	0	**-900**	1000	0	0
[3]	Dallas	0	200	900	0	780	0	**-1300**
[4]	Denver	1400	0	1000	**-780**	0	0	0
[5]	Houston	800	**-160**	0	0	0	0	0
[6]	Washington	600	0	0	1300	0	0	0

Adjacency Matrix



$$\begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

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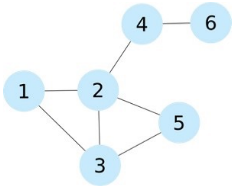
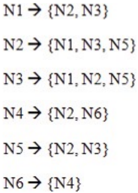
Adjacency List

- A set of lists where each accounts for the neighbours of one node
    - A vector of *n* pointers to adjacency lists
- Undirected graph:
    - An edge connects nodes *i* and *j* => the list of neighbours of *i* contains the node *j* and vice versa
- Often compressed
    - Exploitation of regularities in graphs, difference from other nodes, …

Adjacency List





N1 → {N2, N3}

N2 → {N1, N3, N5}

N3 → {N1, N2, N5}

N4 → {N2, N6}

N5 → {N2, N3}

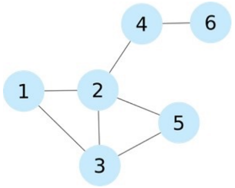
N6 → {N4}

- Pros:
  - Obtaining the neighbours of a node
  - Cheap addition of nodes to the structure
  - More compact representation of sparse matrices
- Cons:
  - Checking if there is an edge between two nodes
    - Optimization: sorted lists => logarithmic scan, but also logarithmic insertion

Incidence Matrix

- Bi-dimensional Boolean matrix of *n* rows and *m* columns
  - A column represents an edge
    - Nodes that are connected by a certain edge
  - A row represents a node
    - All edges that are connected to the node

Incidence Matrix



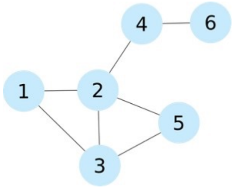
$$\begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

- pros:
  - For representing hypergraphs, where one edge connects an arbitrary number of nodes
- Cons:
  - Requires n x m bits

Laplacian Matrix

- Bi-dimensional array of *n* x *n* integers
  - Diagonal of the Laplacian matrix indicates the degree of the node
  - The rest of positions are set to -1 if the two vertices are connected, 0 otherwise

Laplacian Matrix



$$\begin{pmatrix} 2 & -1 & -1 & 0 & 0 & 0 \\ -1 & 4 & -1 & -1 & -1 & 0 \\ -1 & -1 & 3 & 0 & -1 & 0 \\ 0 & -1 & 0 & 2 & 0 & -1 \\ 0 & -1 & -1 & 0 & 2 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$$

- Pros:
  - Allows analyzing the graph structure by means of spectral analysis
    - Calculates the eigenvalues

Improving Data Locality

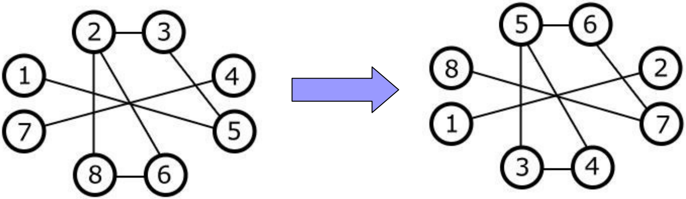
- Idea: take into account computer architecture in the data structures to reach a good performance
  - The way data is laid out physically in memory determines the locality to be obtained
  - Spatial locality = once a certain data item has been accessed, the nearby data items are likely to be accessed in the following computations
    - e.g., graph traversal
- Strategy: in graph adjacency matrix representation, exchange rows and columns to improve the cache hit ratio

Breadth First Search Layout (BFSL)

- Trivial algorithm
- Input: sequence of vertices of a graph
- Output: a permutation of the vertices which obtains better cache performance for graph traversals
- BFSL algorithm:
  1. Selects a node (at random) that is the origin of the traversal
  2. Traverses the graph following a breadth first search algorithm, generating a list of vertex identifiers in the order they are visited
  3. Takes the generated list and assigns the node identifiers sequentially
- Pros: optimal when starting from the selected node
- Cons: starting from other nodes

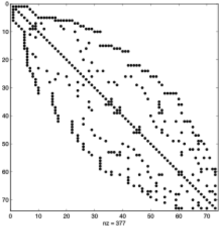
Bandwidth of a Matrix

- Graphs ↔ matrices
- Locality problem = minimum bandwidth problem
  - Bandwidth of a row in a matrix = the maximum distance between nonzero elements, with the condition that one is on the left of the diagonal and the other on the right of the diagonal
  - Bandwidth of a matrix = maximum of the bandwidth of its rows
- Matrices with low bandwidths are more cache friendly
  - Non zero elements (edges) are clustered across the diagonal
- Bandwidth minimization problem (BMP) is NP hard
  - For large matrices (graphs) the solutions are only approximated



$$
\begin{pmatrix}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 1 & 0 & 1 \\
0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 1
\end{pmatrix}
\longrightarrow
\begin{pmatrix}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1
\end{pmatrix}
$$

Cuthill-McKee (1969)



- Popular bandwidth minimization technique for sparse matrices
- Re-labels the vertices of a matrix according to a sequence, with the aim of a heuristically guided traversal
- Algorithm:
  1. Node with the first identifier (where the traversal starts) is the node with the smallest degree in the whole graph
  2. Other nodes are labeled sequentially as they are visited by BFS traversal
     - □ In addition, the heuristic prefers those nodes that have the smallest degree

Graph Partitioning

- Some graphs are too large to be fully loaded into the main memory of a single computer
  - Usage of secondary storage degrades the performance of graph applications
  - Scalable solution distributes the graph on multiple computers
- We need to partition the graph reasonably
  - Usually for particular (set of) operation(s)
  - The shortest path, finding frequent patterns, BFS, spanning tree search, …

One and Two Dimensional Graph Partitioning

- Aim: partitioning the graph to solve BFS more efficiently
  - Distributed into shared-nothing parallel system
  - Partitioning of the adjacency matrix
- 1D partitioning
  - Matrix rows are randomly assigned to the *P* nodes (processors) in the system
  - Each vertex and the edges emanating from it are owned by one processor

$$
\begin{array}{c|cccccccccccc}
 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 \\
\hline
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\
2 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
3 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
\hline
4 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
5 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
6 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
\hline
7 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 \\
8 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
\hline
10 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
11 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 \\
12 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0
\end{array}
$$

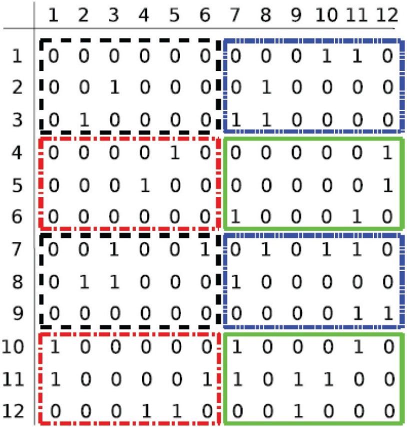
One and Two Dimensional Graph Partitioning

- BFS with 1D partitioning
  - Input: starting node *s* having level 0
  - Output: every vertex *v* becomes labeled with its level, denoting its distance from the starting node

1. Each processor has a set of frontier vertices *F*
   - At the beginning it is node *s* where the BFS starts
2. The edge lists of the vertices in *F* are merged to form a set of neighbouring vertices *N*
   - Some owned by the current processor, some by others
3. Messages are sent to all other processors to (potentially) add these vertices to their frontier set *F* for the next level
   - A processor may have marked some vertices in a previous iteration => ignores messages regarding them

One and Two Dimensional Graph Partitioning

- 2D partitioning
  - Processors are logically arranged in an R x C processor mesh
  - Adjacency matrix is divided C block columns and R x C block rows
  - Each processor owns *C* blocks
- Note: 1D partitioning = 2D partitioning with *C = 1* (or *R = 1*)
- Consequence: each node communicates with at most *R + C* nodes instead of all *P* nodes
  - In step 2 a message is sent to all processors in the same row
  - In step 3 a message is sent to all processors in the same column



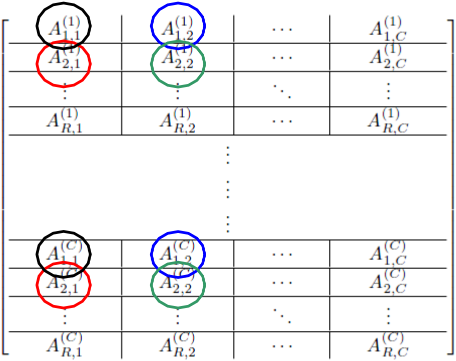
$$\begin{array}{c|cccccc|cccccc}
 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 \\
\hline
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\
2 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
3 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
\hline
4 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
5 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
6 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
\hline
7 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 \\
8 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
\hline
10 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
11 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 \\
12 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0
\end{array}$$

$A^{(*)}_{i,j}$

= block owned by processor *(i,j)*

Partitioning of vertices:

Processor *(i, j)* owns vertices corresponding to block row *(j−1) x R + i*

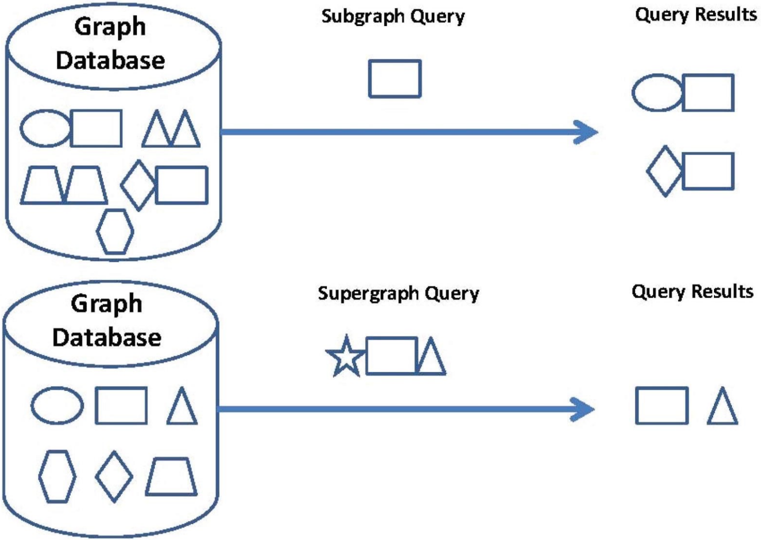


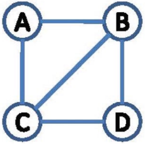
$$\left[\begin{array}{c|c|c|c}
A^{(1)}_{1,1} & A^{(1)}_{1,2} & \cdots & A^{(1)}_{1,C} \\
\hline
A^{(1)}_{2,1} & A^{(1)}_{2,2} & \cdots & A^{(1)}_{2,C} \\
\hline
\vdots & \vdots & \ddots & \vdots \\
\hline
A^{(1)}_{R,1} & A^{(1)}_{R,2} & \cdots & A^{(1)}_{R,C} \\
\hline
\multicolumn{4}{c}{\vdots} \\
\multicolumn{4}{c}{\vdots} \\
\multicolumn{4}{c}{\vdots} \\
\hline
A^{(C)}_{1,1} & A^{(C)}_{1,2} & \cdots & A^{(C)}_{1,C} \\
\hline
A^{(C)}_{2,1} & A^{(C)}_{2,2} & \cdots & A^{(C)}_{2,C} \\
\hline
\vdots & \vdots & \ddots & \vdots \\
\hline
A^{(C)}_{R,1} & A^{(C)}_{R,2} & \cdots & A^{(C)}_{R,C}
\end{array}\right]$$

Transactional Graph Databases

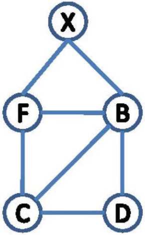
Types of Queries

- Sub-graph queries
  - Searches for a specific pattern in the graph database
  - A small graph or a graph, where some parts are uncertain
    - e.g., vertices with wildcard labels
  - More general type: sub-graph isomorphism
- Super-graph queries
  - Searches for the graph database members of which their whole structures are contained in the input query
- Similarity (approximate matching) queries
  - Finds graphs which are similar, but not necessarily isomorphic to a given query graph
  - Key question: how to measure the similarity

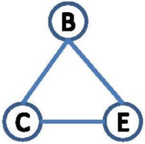

Graph Database
Subgraph Query
Query Results
Graph Database
Supergraph Query
Query Results



g_1



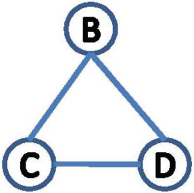
g_2



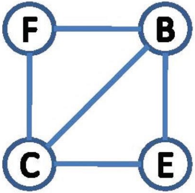
g_3

sub-graph:
q_1: g_1, g_2
q_2: $\varnothing$

super-graph:
q_1: $\varnothing$
q_2: g_3



q_1



q_2

Performance Tuning
Goals

Example from 2010: Tweets add up to 12 Terabytes per day. This amount of data needs around 48 hours to be written to a disk at a speed of about 80 Mbps.

- MapReduce creates a bottleneck-free way of scaling out
- To reduce latency
  - □ Latency:
    - Non-parallel systems: time taken to execute the entire program
    - Parallel systems: time taken to execute the smallest atomic sub-task
  - □ Strategies:
    - Reducing the execution time of a program
    - Choosing the most optimal algorithms for producing the output
    - Parallelizing the execution of sub-tasks
- To increase throughput
  - □ Throughput = the amount of input that can be manipulated to generate output within a process
  - □ Non-parallel systems:
    - Constrained by the available resources (amount of RAM, number of CPUs)

□ Parallel systems:

- “No” constraints
- Parallelization allows for any amount of commodity hardware

Performance Tuning

Linear Scalability

- Typical horizontally scaled MapReduce-based model: linear scalability
  - □ "One node of a cluster can process ***x*** MBs of data every second → ***n*** nodes can process ***x*** × ***n*** amounts of data every second."
    - Time taken to process *y* amounts of data on a single node = t seconds
    - Time taken to process *y* amounts of data on *n* nodes = *t / n* seconds
- Assumption: tasks can be parallelized into equally balanced units

Performance Tuning

$$S(N) = \frac{1}{(1-P) + \frac{P}{N}}$$

Amdahl's Law

- Formula for finding the maximum improvement in performance of a system when a part is improved
  - P = the proportion of the program that is parallelized
  - $1 - P$ = the proportion of the program that cannot be parallelized
  - N = the times the parallelized part performs as compared to the non-parallelized one
    - i.e., how many times faster it is
      - e.g., the number of processors
    - Tends to infinity in the limit
- Example: a process that runs for 5 hours (300 minutes); all but a small part of the program that takes 25 minutes to run can be parallelized
  - Percentage of the overall program that can be parallelized: 91.6%
  - Percentage that cannot be parallelized: 8.4%
  - Maximum increase in speed: 1 / (1 – 0.916) = ~11.9 times faster
    - N tends to infinity

Performance Tuning

$L = kW$

Little's Law

- Origins in economics and queuing theory (mathematics)
- Analyzing the load on stable systems
  - □ Customer joins the queue and is served (in a finite time)
- "The average number of customers (*L*) in a stable system is the product of the average arrival rate (*k*) and the time each customer spends in the system (*W*)."
  - □ Intuitive but remarkable result
  - □ i.e., the relationship is not influenced by the arrival process distribution, the service distribution, the service order, or practically anything else
- Example: a gas station with cash-only payments over a single counter
  - □ 4 customers arrive every hour
  - □ Each customer spends about 15 minutes (0.25 hours) at the gas station
  - ⇒ There should be on average 1 customer at any point in time
  - ⇒ If more than 4 customers arrive at the same station, it would lead to a bottleneck

Performance Tuning

Message Cost Model

initialization

$C = a + bN$

linear dependence on size

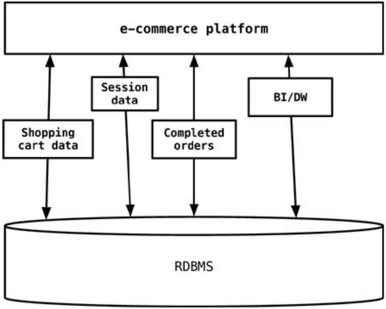
- Breaks down the cost of sending a message from one end to the other in terms of its fixed and variable costs
  - C = cost of sending the message from one end to the other
  - a = the upfront cost for sending the message
  - b = the cost per byte of the message
  - N = number of bytes of the message
- Example: gigabit Ethernet
  - a is about 300 microseconds = 0.3 milliseconds
  - b is 1 second per 125 MB
    - Implies a transmission rate of 125 MBps.
  - 100 messages of 10 KB => take 100 × (0.3 + 10/125) ms = 38 ms
  - 10 messages of 100 KB => take 10 × (0.3 + 100/125) ms = 11 ms
  - A way to optimize message cost is to send as big packet as possible each time

0,08

0,8

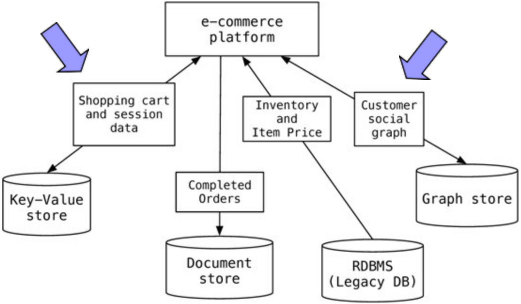
Polyglot Persistence

- Different databases are designed to solve different kinds of problems
- Using a single database engine for all of the requirements usually leads to partially non-performant solutions
- Example: e-commerce
  - Many types of data
    - Business transactions, session management data, reporting, data warehousing, logging information, …
  - Do not need the same properties of availability, consistency, or backup requirements



Polyglot Persistence

- Polyglot programming (2006)
  - Applications should be written in a mix of languages
  - Different languages are suitable for tackling different problems
- Polyglot persistence
  - Hybrid approach to persistence
  - e.g., a data store for the shopping cart which is highly available vs. finding products bought by the customers' friends

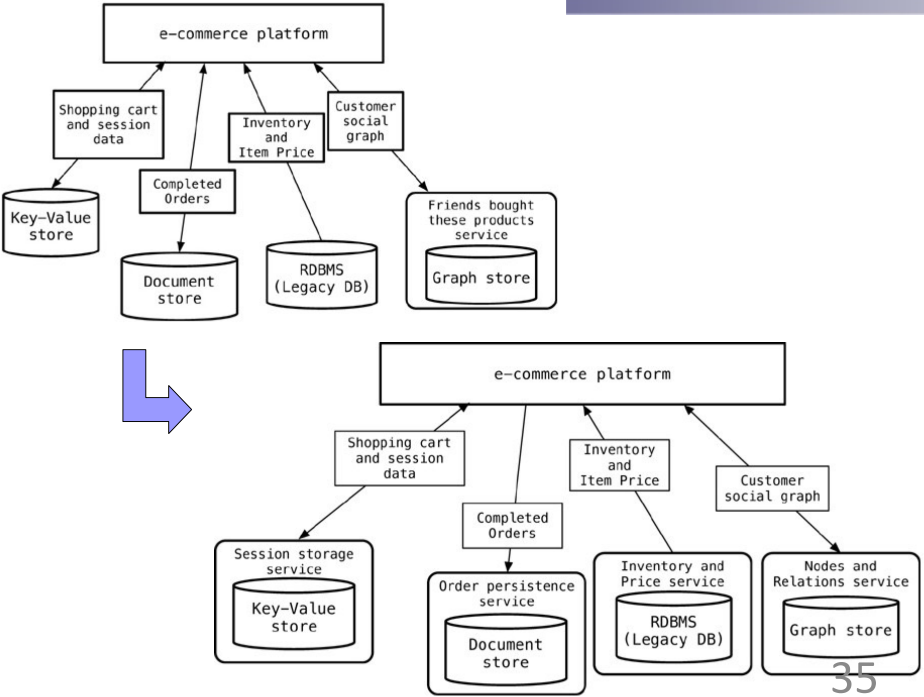


Polyglot Persistence

- There may be other applications in the enterprise
  - □ e.g., the graph data store can serve data to applications that need to understand which products are being bought by a certain segment of the customer base

⇒ Instead of each application talking independently to the graph database, we can wrap the graph database into a service

- □ Assumption:
  - Nodes can be saved in one place
  - Queried by all the applications
- □ Allows for the databases inside the services to evolve without having to change the dependent applications


e-commerce platform
Shopping cart and session data
Completed Orders
Inventory and Item Price
Customer social graph
Key-Value store
Document store
RDBMS (Legacy DB)
Friends bought these products service
Graph store
e-commerce platform
Shopping cart and session data
Completed Orders
Inventory and Item Price
Customer social graph
Session storage service
Key-Value store
Order persistence service
Document store
Inventory and Price service
RDBMS (Legacy DB)
Nodes and Relations service
Graph store