GPU-accelerated Data Management
Advanced Topics in Databases

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Motivation

Graphics Processing Unit: Architecture

GPU-accelerated Database Operators

Hybrid Query Optimization

Outlook
Motivation – Big Picture

• **Big Data Analysis**: Should we always scale out, e.g., use the cloud to analyze our data?
Motivation – Big Picture

Taken from [Appuswamy et al., 2013]
Motivation – Big Picture

- Approximately 50% of the job sizes are smaller than 10 GB
- Approximately 80% of the job sizes are smaller than 1 TB

→ A majority of big data analysis jobs can be processed in one scale up machine!

[Appuswamy et al., 2013]

Taken from [Appuswamy et al., 2013]
Motivation – Big Picture

How to scale up a server?
Base Configuration
Scale Up: Add More CPUs
Scale Up: Add GPUs
Focus of this Lecture Topic

How can we speed up database query processing using GPUs?
Graphics Processing Unit: Architecture
Recapitulation: The Central Processing Unit (CPU)

- General purpose processor

- Goal is low response time:
  → optimized to execute one task as fast as possible (pipelining, branch prediction)

- Processes data dormant in the main memory
Graphics Processing Unit (1)

- Specialized processor, can be programmed similar to CPUs
- GPUs achieve high performance through massive parallelism → Problem should be easy to parallelize to gain most from running on the GPU
- Single Instruction, Multiple Data (SIMD): Each multiprocessor only has a single instruction decoder → Scalar processors execute the same instruction at a time
- Optimized for computation
Graphics Processing Unit (2)
Example: Fermi Architecture of NVIDIA

Picture taken from [Breß et al., 2013b]
GPU Performance Pitfalls

Data transfers between host and device:

- One of the most important performance factors in GPU programming
  → All data has to pass across the PCIexpress bus
  → bottleneck

Divergent code paths:

- Data-dependent conditionals causes some threads in a workgroup to diverge
  → Multiprocessor has to serialize the code paths, leading to performance losses
  → General rule: Avoid control structures in kernels
GPU Performance Pitfalls (2)

- Limited memory capacity (1 to 16GB)
  → Efficient memory management necessary

→ GPU algorithm can be faster than its CPU counterpart

[Gregg and Hazelwood, 2011]
Summary: CPU vs. GPU

CPU is likely to be better if
- Algorithm needs much control flow or cannot be parallelized
- Data set is relatively small or exceeds capacity of GPU RAM

GPU is likely to be better if
- Algorithm can be parallelized and need moderate control flow
- Data set is relatively large but still fits in the GPU RAM

Rule of Thumb:
- Use CPU for little and GPU for large datasets
Graphics Processing Unit: Programming Model
How to program a GPU? (1)

GPUs are programmed using the *kernel programming model*.

Kernel:
- Is a simplistic program
- Forms the basic unit of parallelism
- Scheduled concurrently on several scalar processors in a SIMD fashion → Each kernel invocation (thread) executes the same code on its own share of the input

Workgroup:
- Logically grouping of all threads running on the same multiprocessor
How to program a GPU? (2)

Host Code:
- Executed on the CPU
- Manages all processing on the GPU

Device Code:
- The *kernel*, is the GPU program
- Executed massively parallel on the GPU
- General limitations: no dynamic memory allocation, no recursion
Processing Data on a GPU: Basic Structure

1. CPU instructs to copy all data needed for a computation from the RAM to the GPU RAM

2. CPU launches the GPU kernel

3. CPU instructs to copy the result data back to CPU RAM
Processing Data on a GPU: Basic Structure (2)

- CPU may wait (synchronous kernel launch) or perform other computations (asynchronous kernel launch) while the kernel is running

- GPU executes the kernel in parallel

- GPU can only process data located in its memory
  → Manual data placement using special APIs
Frameworks for GPU Programming

Compute Unified Device Architecture (CUDA):
- NVIDIA’s Architecture for parallel computations
- Program GPUs in CUDA C using the CUDA Toolkit

Open Computing Language (OpenCL):
- Open Standard
- Targets parallel programming of heterogeneous systems
- Runs on a broad range of hardware (CPUs or GPUs)
Programming a GPU: An Example with CUDA
Example: Vector Addition

```c
void add( int *a, int *b, int *c ) {
    for (i=0; i < N; i++) {
        c[i] = a[i] + b[i];
    }
}
```

Taken from [Sanders and Kandrot, 2010]
**Example: Parallel Vector Addition with two Threads**

**CPU Core 1**

```c
void add( int *a, int *b, int *c ){
    int tid = 0;
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 2;
    }
}
```

**CPU Core 2**

```c
void add( int *a, int *b, int *c ){
    int tid = 1;
    while (tid < N) {
        c[tid] = a[tid] + b[tid];
        tid += 2;
    }
}
```

Taken from [Sanders and Kandrot, 2010]
Example: Cuda Host Code for Vector Addition

1 // allocate the memory on the GPU for a, b, and c
2 cudaMalloc( (void**)&dev_a, N * sizeof(int) ); ...
3 // fill the arrays 'a' and 'b' on the CPU
4 // copy the arrays 'a' and 'b' to the GPU
5 cudaMemcpy( dev_a, a, N * sizeof(int), cudaMemcpyHostToDevice ); ...
6 // launch kernel, with one block per vector element
7 add<<<N,1>>>( dev_a, dev_b, dev_c );
8 // copy the array 'c' back from the GPU to the CPU
9 cudaMemcpy( c, dev_c, N * sizeof(int), cudaMemcpyDeviceToHost );

Taken from [Sanders and Kandrot, 2010]
Example: Cuda Kernel for Vector Addition

```c
__global__ void add( int *a, int *b, int *c ) {
    int tid = blockIdx.x;
    // handle the data at this index
    if (tid < N)
        c[tid] = a[tid] + b[tid];
}
```

**blockIdx:**
- Built-in variable, defined by CUDA runtime
- Contains the block index for the block currently running the device code

Taken from [Sanders and Kandrot, 2010]
Further Reading


You want to learn more about how to program a GPU?

→ There is lecture on this: ”GPU-Programmierung” by Jun.-Prof. Dr. Thorsten Grosch
Graphics Processing Unit: General Problems for Data Processing
GPU-accelerated DBMS: General Problems

1. Data placement strategy

2. Predicting the benefit of GPU acceleration

3. Force in-memory database

4. Increased complexity of query optimization

[Breß et al., 2013b]
Data placement strategy

Problem:

- Data transfer between CPU and GPU is the main bottleneck
- GPU memory capacity limited → database does not fit in GPU RAM

Data placement:

- GPU-accelerated databases try to keep relational data cached on the device to avoid data transfer
- Only possible for a subset of the data
- **Data placement strategy:** Deciding which part of the data should be offloaded to the GPU
→ Difficult problem that currently remains unsolved
Predicting the benefit of GPU acceleration

- Operators may generate a large result
- Often unfit for GPU-offloading
- Result size of an operation is typically not known before execution (estimation errors propagate through the query plan, estimation is typically bad for operations near the root)

→ Predicting whether a given operator will benefit from the GPU is a hard problem
Force in-memory database

- GPU-accelerated operators are of little use, when most time is spent on disk I/O
- Time savings will be small compared to the total query runtime
- GPU improves performance only once the data is in main memory
- Disk-resident databases are typically very large, making it harder to find an optimal data placement strategy
Increased complexity of query optimization

Option of running operations on a GPU increases the complexity of query optimization:

- The plan search space is drastically larger
- Require cost function that compares run-times across architectures
- GPU-aware query optimization remains an open challenge
Graphics Processing Unit: Architectural Considerations for DBMS
Row Stores vs. Column Stores

Store a Table row wise:

<table>
<thead>
<tr>
<th>Produkt</th>
<th>Ort</th>
<th>Umsatz</th>
<th>Jahr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Merlot</td>
<td>Magdeburg</td>
<td>4325</td>
<td>2010</td>
</tr>
<tr>
<td>Guinness</td>
<td>Magdeburg</td>
<td>2341</td>
<td>2010</td>
</tr>
<tr>
<td>Merlot</td>
<td>Ilmenau</td>
<td>5543</td>
<td>2010</td>
</tr>
<tr>
<td>Pinot Noir</td>
<td>Ilmenau</td>
<td>4944</td>
<td>2010</td>
</tr>
</tbody>
</table>

Store a Table column wise:

<table>
<thead>
<tr>
<th>Produkt</th>
<th>Ort</th>
<th>Umsatz</th>
<th>Jahr</th>
</tr>
</thead>
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<tr>
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</tr>
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<td>2341</td>
<td>2010</td>
</tr>
<tr>
<td>Merlot</td>
<td>Ilmenau</td>
<td>5543</td>
<td>2010</td>
</tr>
<tr>
<td>Pinot Noir</td>
<td>Ilmenau</td>
<td>4944</td>
<td>2010</td>
</tr>
</tbody>
</table>
Row Stores vs. Column Stores

A column store is more suitable for a GPU-accelerated DBMS than a row store.

Column stores:

• Allow for coalesced memory access on the GPU
• Achieve higher compression rates, an important property considering the current memory limitations of GPUs
• Reduce the volume of data that needs to be transferred to GPU RAM
Processing Model

There are basically two alternative processing models that are used in modern DBMS:

- **Tuple-at-a-time volcano model** [Graefe, 1990]
  - Operator requests next tuple, processes it, and passes it to the next operator

- **Operator-at-a-time bulk processing** [Manegold et al., 2009]
  - Operator consumes its input and materializes its output
Tuple-at-a-time processing

Advantages:
• Intermediate results are very small
• Pipelining parallelism
• The "classic" approach

Disadvantages:
• A higher per tuple processing overhead
• High miss rate in the instruction cache
Operator-at-a-time Processing

Advantages:

- Cache friendly memory access patterns → Making effective usage of the memory hierarchy
  
  [Manegold et al., 2009]

- Parallelism inside an operator, multiple cores used for processing a single operation → Intra-operator parallelism

Disadvantages:

- Increased memory requirement, since intermediate results are materialized [Manegold et al., 2009]

- No pipeline parallelism
Operator-at-a-time processing is more promising than tuple-at-a-time processing, because:

- Data can be most efficiently transferred over the PCIe bus by using large memory chunks
- Tuple-wise processing is not possible on the GPU, because inter-kernel communication is undefined [NVIDIA, 2012] → No pipelining possible
- Operator-at-a-time processing can be easily combined with operator-wise scheduling
GPU-accelerated Database Operators
State of the Art: GPUs in Databases

GPUs are utilized for accelerating query processing like:

- Relational operations

- XML path filtering [Moussalli et al., 2011]

- Online aggregation [Lauer et al., 2010]

- Compression [Andrzejewski and Wrembel, 2010, Fang et al., 2010]

- Scans [Beier et al., 2012]

GPUs are as well utilized for accelerating query optimization: e.g., GPU based selectivity estimation

Co-processing in a DBMS

**GPU Co-Processing in Database Systems**

- Query Processing
  - Relational
    - Selection
    - Projection
    - Join
  - Other
    - Online Aggregation
    - Sorting
    - Map Reduce
- Query Optimization
  - Selectivity Estimation
- Database Tasks
  - Compression
  - Update Merging in Column Stores
  - Transaction Management

**Searching**
- Index Lookups
- knn-Search
- Range Queries

**XML**
- XPath Selection

**Figure:** Classification of Co-Processing Approaches

[Breß et al., 2013a]
Selection

Choose a subset of elements from a relation $R$ satisfying a predicate and discard the rest:

pred: $\text{val} < 5$

<table>
<thead>
<tr>
<th>val</th>
<th>res</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>

algorithm:

```c
unsigned int i=0;
for(i=0;i<n;i++){
    if(pred(val[i]))
        res.add(val[i]);
}
```
Selection

How to parallelize a selection efficiently?

Points to consider:

• Concurrent writes may corrupt data structures
  → Usually, correctness is ensured by locks

• Locks may serialize your threads and nullify the performance
gained by parallel execution
  → We need a way to ensure correctness and consistency
  without using locks

→ pre-compute write locations
Prefix Scans

• Important building block for parallel programs

• Applies a binary operator to an array

• Example: prefix sum

• Given an input array $R_{in}$, $R_{out}$ is computed as follows:
  
  $R_{out}[i] = R_{in}[0] + \ldots + R_{in}[i - 1]$ \hspace{1em} (1 \leq i < |R_{in}|)
  
  $R_{out}[0] = 0$

[He et al., 2009]
Example: Prefix Sum

```
R_{in}    R_{out}
---    ---
  1    0
  0    1
  1    1
  0    2
  1    2
  1    3
```
Parallel Selection

• Create an array `flags` of the same size as `R` and init with zeros

• For each tuple set corresponding flag in `flags` if and only if the current tuple matches the predicate
  → `flags` array contains a 1 if the corresponding tuple in `R` is part of the result
  → The sum of the values in `flags` is the number of result tuples `#rt`

• Compute the prefix sum of `flags` and store it in array `ps`
  → Now we have the write locations for each tuple in the result buffer

[He et al., 2009]
Parallel Selection

- Create the result buffer \( \text{res} \) of size \( \#rt \)
- Scan flags: if(flags[i] == 1) write R[i] to position ps[i] in the result buffer:

\[
\begin{align*}
1 & \text{ do in parallel:} \\
2 & \text{ for(unsigned int } i=0; i<n; i++) \{
3 & \quad \text{ if(flags[i]==1)} \{
4 & \quad \quad \text{ unsigned int } \text{ res_write_index}=\text{ps}[i]; \\
5 & \quad \quad \text{ res[res_write_index]}=\text{R}[i]; \\
6 & \quad \} \\
7 & \} 
\end{align*}
\]

[He et al., 2009]
Parallel Selection: Example

build flag array:
if(pred(val[i]))
  flags[i]=1;
else
  flags[i]=0;

compute prefix sum from flags

scan flags and write val[i] to position ps[i] in result array
Joins

• Non Indexed Nested Loop Join

• Indexed Nested Loop Join

• Sort Merge Join

• Hash Join

We will not discuss the individual parallelism strategies, but we focus on the common problems here!
Joins

General Problems:

- Exact result size not known in advance (exception: primary-key/foreign-key join)

- Join result may or may not fit in GPU RAM

- Need lock free processing to fully exploit parallelism of GPU
  → Pre-compute write locations for each thread
Joins

Joins use a three-step output scheme:

1. Each thread counts the number of join partners for its share of the input

2. Using the result size for each thread, we compute a prefix sum, to get the write location for each thread

3. The host allocates the memory of the size of the join result and all threads write their results to the device memory according to the their write locations

→ lock free processing scheme

[He et al., 2009]
Hybrid Query Optimization
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Outlook

Notation

operation on CPU
operation on GPU
performs computation on GPU
performs computation on CPU
copies data from the CPU RAM to the GPU RAM
copies data back from the GPU RAM to the CPU RAM
logical query plan

\[ T_1 \bowtie T_2 \]
logical query plan

CPU only plan
(cost: 100)
logical query plan

CPU only plan
(cost: 100)

GPU only plan
(cost: 80)
logical query plan

CPU only plan
(cost: 100)

hybrid plan
(cost: 60)

GPU only plan
(cost: 80)
• Problems during hybrid Query Processing

• Selecting Processors: A Decision Model

• Hybrid Query Optimization
Problems during hybrid Query Processing [Breß et al., 2012d]

logical query plan
Problems during hybrid Query Processing

\[ \pi \rightarrow \sigma \bowtie T_1 \bowtie T_2 \rightarrow \sigma \]
Problems during hybrid Query Processing

Concurrent Copying?
Problems during hybrid Query Processing

Concurrent Copy Operations:

- Concurrent copy operations in the same direction are not possible [NVIDIA, 2012]
  → Copy operations need to be serialized, and the following selections have to be serialized as well

- Possible approach: combine two data streams in one copy operation and reorganize the data in the GPU RAM
  → Can be faster, because the PCIe Bus is better utilized
Problems during hybrid Query Processing

Impact of Concurrent Kernel Invocation?
Problems during hybrid Query Processing

Concurrent Kernel Execution:

- Database operations can be executed in parallel (e.g., two selections can be processed concurrently)

- Concurrent processing of kernels is possible for current GPUs [NVIDIA, 2012]
  → But it is hard to predict the influence on execution times.
Problems during hybrid Query Processing

Pipelining on GPUs?
Problems during hybrid Query Processing

Pipelining:

• Kernels can be enqueued and processed concurrently, but inter-kernel communication is undefined [NVIDIA, 2012]
  → Regular pipelining between two GPU algorithms is not possible

• However: possible to integrate two operations in one kernel

• Example: Combine and compile several kernels at run-time (if OpenCL is used) [Heimel, M., 2011]
Problems during hybrid Query Processing

Further problems:

- Number of concurrent kernel executions and the PCIe Bus bandwidth are limited [NVIDIA, 2012]

→ Not every query can benefit from the GPU

→ Need heuristic, which chooses ”critical queries” that
  - benefit from the GPU usage
  - have a certain degree of ”importance”

- Estimate how the optimization of one query influences the performance of another hybrid query
Selecting Processors: A Decision Model
Goal

**Question:** When should we execute operations on the CPU and when on the GPU?

**Answer:** Depends on

- The operation to execute
- Features of the input data set (e.g., data size, selectivity, skew)
- Computational power of CPU and GPU (e.g., cores, clock rate, memory bandwidth)
- The algorithms implementation details
- Storage location of data (CPU/GPU RAM)
- Current load condition on CPU and GPU
Idea

- Algorithm as central component of abstraction, bound to a processing device (e.g., CPU or GPU)

- Learn execution behavior of algorithms

- Pick algorithm that is likely to be the fastest for execution → Selection of an algorithm assign an operator to a processing device
Overview of Decision Model [Breß et al., 2012a, Breß et al., 2013a]

![Diagram of decision model]

- **Operation**
  - Algorithm pool
    - CPU
    - GPU

- **Input Dataset**
  - Algorithms

- **Optimization Criterion**
  - Estimated execution times
  - Estimation refinement
  - Execute algorithm

- **Decision Component**
Estimation Component

Idea:

- Treat algorithms as black boxes
- Use statistical methods to deduce estimated execution times from measured execution times

Assign each Algorithm:

- A statistical method
- An approximation function
- A measurement pair list

Updating Model:

- Recompute approximation function using statistical method and measurement pair list
**Decision Component**

**Goal:** Choose algorithm $A$ of operation $O$ with lowest execution time for a data set $D$ → optimize for response time

**Implementation:** Choose the algorithm with the smallest estimated execution time

![Graph showing execution time vs. data size for different algorithms]

Execution time

Data size
**Decision Component**

**Goal:** Choose algorithm $A$ of operation $O$ with lowest execution time for a data set $D \rightarrow$ optimize for response time

**Implementation:** Choose the algorithm with the smallest estimated execution time

![Graph showing execution time vs. data size for different algorithms](chart.png)
Load Balancing

Optimal scheduling of $n$ tasks on $m$ heterogeneous processors is an active research area, too large to cover it here.

→ We discuss the HyPE framework only, because it focuses on scheduling and load balancing of database operators.
Load Balancing

**Problem:** Choosing the fastest algorithm is not always optimal:

- Cannot achieve a performance improvement in case a processor always outperforms other processors
  → GPU or CPU algorithm always faster
  → Unbalanced load distribution on (co-)processors → Performance degradation

**Solution:** Consider load on each processor, and schedule operators to underutilized processors
Load Balancing

How can we quantify “load” for a processor?

- Number of rows to process on a processor
- Number of operators scheduled on a processor
- Accumulated execution time of all operators scheduled on a processor
Load Tracking in HyPE

Waiting time until operator starts processing as indicator for load on devices:

- Add a ready queue $OQ_X$ to each processing device $X$
- Keep track of each operator’s estimated execution time $T_{est}(Op_{cur})$ and the estimated completion time for each queue $T_{est}(OQ_X)$
- Select the processing device where the overall time of the operator to finish is minimal:

$$\min(T_{est}(OQ_X) + T_{fin}(Op_{run}) + T_{est}(Op_{cur}))$$

[Breß et al., 2013c]
Load Tracking in HyPE

Operator to Schedule

Ready Queues

Processing Devices

Test(Op\text{cur}, X)

Test(OQ_X)

Test(Op\text{run}, X)

Operator to Schedule

Scheduled Operator

Running Operator

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Outlook
Hybrid Query Optimization
Hybrid Query Optimization

Idea:

- Use decision model to estimate cost of algorithms for each operation in a query

- Pick GPU algorithm only if estimated execution time is lower than its CPU counterpart including data transfer

- Minimize accesses on decision model to keep overhead low
Greedy Algorithm

Phase 1:
- For each operation in the query, use decision model to select fastest algorithm
- Consider time for data transfer in decision

Phase 2:
- Remove unnecessary copy operations
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\[ \sigma \bowtie \sigma \bowtie \pi \sigma \]

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Hybrid Query Optimization
Outlook
2-Copy Heuristic

- Very likely that an optimal hybrid query sequence contains a minimum of copy operations.

- Allow maximal 2 copy operations in one hybrid query sequence:
  \[ A_1^{CPU}, \ldots, A_i^{CPU}, A_{cpy}, A_{i+1}^{GPU}, \ldots, A_j^{GPU}, A_{cpy}, A_{j+1}^{CPU}, \ldots, A_n^{CPU} \]

- Allowed set of sequences are:
  - Pure CPU plans
  - Pure GPU plans
  - Real subset of all possible hybrid plans

- Choose plan with lowest cost for execution.
2-Copy Heuristic – Example Plans
2-Copy Heuristic – Example Plans

Diagram showing the 2-Copy Heuristic with example plans.
2-Copy Heuristic – Example Plans

Diagram with three plans:
1. Blue circles connected in sequence.
2. Blue circles, followed by a yellow circle, then a green circle, ending with a blue circle.
3. Yellow circle, followed by green circles connected in sequence, ending with a red circle.
2-Copy Heuristic – Example Plans
Outlook
Hybrid Query Processing Engine

Hybrid Query Processing Engine (HyPE):

- Distributes database operations response time minimal on CPU/GPU
- Tries to utilize the processing device most suited for an operation while keeping track of the load situation

[Breß et al., 2012c, Breß et al., 2012a, Breß et al., 2012d, Breß et al., 2012b, Breß et al., 2013a]
CoGaDB

CoGaDB (Column Oriented GPU accelerated DBMS):

- Designed as In-Memory Column Store
- Basis for investigating different query optimization strategies
  
  [Breß et al., 2012d]

- Prototype for advanced co-processing techniques for column-oriented DBMS  
  [Breß et al., 2013b]
Open Research Questions:

- How can GPU-acceleration be integrated in column stores, and – in particular – how should an efficient data-placement and query optimization strategy for a GPU-aware DBMS look like?

- Which parts of a database engine should be hardware-conscious (fine-tuned to a particular architecture), and which parts should be hardware-oblivious (implemented in a general framework like OpenCL, that can be mapped to multiple architectures at runtime)?

[Breß et al., 2013b]
Open Research Questions:

- How does the performance differ when comparing distributed-query-processing approaches with tailor-made approaches for hybrid CPU/GPU systems?
- What is a suitable transaction protocol that ensures ACID properties over all (co-)processors?
- Is it feasible to include GPU-acceleration in an existing DBMS by changing the architecture successively (e.g., Ocelot) or are the necessary changes on DBMS architecture and software so invasive and expensive that a rewrite from scratch is necessary (e.g., CoGaDB)?

[Breß et al., 2013b]
Invitation

Your are invited to join our research on GPU-accelerated data management, e.g., in form of:

- Bachelor or master thesis (also as internship at TU Dortmund University)
- Scientific team project
  → "Scientific Project on Databases and Software Engineering" next winter term
- Scientific individual project

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Thank you for your attention!

Are there any questions or suggestions?
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