Data Processing on Modern Hardware

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Lecture 3: Cache awareness
for query execution models
Cache awareness for query execution models
The processing model of a database defines how the system executes the query plan.

The four main approaches are:
- **Iterator** model (volcano, tuple-at-a-time)
- **Materialization** model (operator-at-a-time, column-at-a-time)
- **Vectorization** model (vector-at-a-time, batch, block-wise)
- **Pushing tuples up** model

There are different trade-offs depending on the workload type and the underlying hardware.

→ cf. Database Systems on Modern CPU Architectures (chapter 5)
Most classical systems implement the **Volcano iterator model**:

- Operators request tuples from their input using `next()`
  - On each invocation, the operator returns either a single tuple or `null` if there are no more tuples

- Data is processed **tuple-at-a-time** in a **pipelined** fashion
  - Also called the Volcano or pipeline model

- Each operator keeps its own **state**
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

\[ \pi \ R.id, S.value \]
\[ \Join \ R.id = S.id \]
\[ \sigma \ value > 100 \]

\[ R \rightarrow S \]

\[ \text{for } t \text{ in } \text{child.Next()}:\]
\[ \quad \text{emit}(\text{projection}(t)) \]

\[ \text{for } t_1 \text{ in } \text{left.Next()}:\]
\[ \quad \text{buildHashTable}(t_1) \]
\[ \text{for } t_2 \text{ in } \text{right.Next()}:\]
\[ \quad \text{if } \text{probe}(t_2): \text{emit}(t_1 \land t_2) \]

\[ \text{for } t \text{ in } \text{child.Next()}:\]
\[ \quad \text{if } \text{evalPred}(t): \text{emit}(t) \]
\[ \quad \text{else } \text{emit}(\text{null}) \]

\[ \text{if } R.\text{hasNext}(): \]
\[ \quad \text{emit}(R.\text{next}()) \]
\[ \quad \text{else } \text{emit}(\text{null}) \]

\[ \text{if } S.\text{hasNext}(): \]
\[ \quad \text{emit}(S.\text{next}()) \]
\[ \quad \text{else } \text{emit}(\text{null}) \]
**Iterator model – Example**

**SQL Example:**

```sql
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```

**Diagram:**

- **Selection:** \( \pi \) R.id, S.value
- **Join:** \( \bowtie \) R.id = S.id
- **Filter:** \( \sigma \) value > 100

**Code Example:**

```java
for t in child.Next():
    emit(projection(t))
```

```java
for t1 in left.Next():
    buildHashTable(t1)
    for t2 in right.Next():
        if probe(t2):
            emit(t1 \( \bowtie \) t2)
```

```java
for t in child.Next():
    if evalPred(t):
        emit(t)
```

```java
if R.hasNext() :
    emit(R.next())
else emit(null)
```

```java
if S.hasNext() :
    emit(S.next())
else emit(null)
```

**Single tuple**
**Iterator model – Example**

**SQL Query**

```
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```
This is used in almost every RDBMS.

- Allows for tuple pipelining.
- Some operators must block until their children emit all their tuples:
  - Joins, subqueries, sort, group-by, etc.

**Implications on cache usage efficiency:**

- All operators in a plan run *tightly interleaved*
  - Their *combined* instruction *footprint* may be *large*
  - Many *instruction cache misses*
- Operators constantly call each other’s functionality
  - Results in a big *function call overhead*
- The combined *state of the operators* may be too large to fit into caches
  - *e.g.*, hash tables, cursors, partial aggregates
  - Results in many *data cache misses*
Example: Query Q1 from the TPC-H benchmark on MySQL

```sql
SELECT  
    l_returnflag, l_linenstatus, SUM(l_quantity) AS sum_qty, 
    SUM(l_extendedprice) AS sum_base_price, 
    SUM(l_extendedprice*(1-l_discount)) AS sum_disc_price, 
    SUM(l_extendedprice*(1-l_discount)*(1+l_tax)) AS sum_charge, 
    AVG(l_quantity) AS avg_qty, AVG(l_extendedprice) AS avg_price, 
    AVG(l_discount) AS avg_disc, COUNT(*) AS count_order 
FROM lineitem 
WHERE l_shipdate <= DATE '1998-09-02' 
GROUP BY l_returnflag, l_linenstatus
```

- Scan query with arithmetics on aggregated tuples without a join

Results taken from MonetDB/X100: Hyper-Pipelining Query Execution *CIDR 2005*
Show results from executing the query

<table>
<thead>
<tr>
<th>time [sec]</th>
<th>calls</th>
<th>instr./call</th>
<th>IPC</th>
<th>function name</th>
</tr>
</thead>
<tbody>
<tr>
<td>11.9</td>
<td>846M</td>
<td>6</td>
<td>0.64</td>
<td>ut_fold_ulong_int_pair</td>
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<tr>
<td>8.5</td>
<td>0.15M</td>
<td>27K</td>
<td>0.71</td>
<td>ut_fold_binary</td>
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<tr>
<td>5.8</td>
<td>77M</td>
<td>37</td>
<td>0.85</td>
<td>memcpy</td>
</tr>
<tr>
<td>3.1</td>
<td>23M</td>
<td>64</td>
<td>0.88</td>
<td>Item_sum_sum::update_field</td>
</tr>
<tr>
<td>3.0</td>
<td>6M</td>
<td>247</td>
<td>0.83</td>
<td>row_search_for_mysql</td>
</tr>
<tr>
<td>2.9</td>
<td>17M</td>
<td>79</td>
<td>0.70</td>
<td>Item_sum_avg::update_field</td>
</tr>
<tr>
<td>2.6</td>
<td>108M</td>
<td>11</td>
<td>0.60</td>
<td>rec_get_bit_field_1</td>
</tr>
<tr>
<td>2.5</td>
<td>6M</td>
<td>213</td>
<td>0.61</td>
<td>row_sel_store_mysql_rec</td>
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<tr>
<td>2.4</td>
<td>48M</td>
<td>25</td>
<td>0.52</td>
<td>rec_get_nth_field</td>
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<td>2.4</td>
<td>60</td>
<td>19M</td>
<td>0.69</td>
<td>ha_print_info</td>
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<tr>
<td>2.4</td>
<td>5.9M</td>
<td>195</td>
<td>1.08</td>
<td>end_update</td>
</tr>
<tr>
<td>2.1</td>
<td>11M</td>
<td>89</td>
<td>0.98</td>
<td>field_conv</td>
</tr>
<tr>
<td>2.0</td>
<td>5.9M</td>
<td>16</td>
<td>0.77</td>
<td>Field_float::val_real</td>
</tr>
<tr>
<td>1.8</td>
<td>5.9M</td>
<td>14</td>
<td>1.07</td>
<td>Item_field::val</td>
</tr>
<tr>
<td>1.5</td>
<td>42M</td>
<td>17</td>
<td>0.51</td>
<td>row_sel_field_store_in_mysql</td>
</tr>
<tr>
<td>1.4</td>
<td>36M</td>
<td>18</td>
<td>0.76</td>
<td>buf_frame_align</td>
</tr>
<tr>
<td>1.3</td>
<td>17M</td>
<td>38</td>
<td>0.80</td>
<td>Item_func_mul::val</td>
</tr>
<tr>
<td>1.4</td>
<td>25M</td>
<td>25</td>
<td>0.62</td>
<td>pthread_mutex_unlock</td>
</tr>
<tr>
<td>1.2</td>
<td>206M</td>
<td>2</td>
<td>0.75</td>
<td>hash_get_nth_cell</td>
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<tr>
<td>1.2</td>
<td>25M</td>
<td>21</td>
<td>0.65</td>
<td>mutex_test_and_set</td>
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<tr>
<td>1.0</td>
<td>102M</td>
<td>4</td>
<td>0.62</td>
<td>rec_get_1byte_offs_flag</td>
</tr>
<tr>
<td>1.0</td>
<td>53M</td>
<td>9</td>
<td>0.58</td>
<td>rec_1_get_field_start_offs</td>
</tr>
<tr>
<td>0.9</td>
<td>42M</td>
<td>11</td>
<td>0.65</td>
<td>rec_get_nth_fieldExtern_bit</td>
</tr>
<tr>
<td>1.0</td>
<td>11M</td>
<td>38</td>
<td>0.80</td>
<td>Item_func_minus::val</td>
</tr>
<tr>
<td>0.5</td>
<td>5.9M</td>
<td>38</td>
<td>0.80</td>
<td>Item_func_plus::val</td>
</tr>
</tbody>
</table>

Each call only processes a **single tuple** → **millions of calls**

Only **10% of the time** spent on actual query task.

Very low **instructions-per-cycle** (IPC) ratio.
Further observations

Much time spent on field access (e.g., \texttt{rec\_get\_nth\_field()}).
- Row-store $\rightarrow$ polymorphic operators.

**Single-tuple functions are hard to optimize (by compiler):**
- Low IPC ratio – empty pipelines make the CPU stall
- Optimization across functions not possible (or very difficult)
- Function call overhead is high
- Vector instructions (SIMD) are hardly applicable

**Example:**
- Let's consider the \texttt{Item\_func\_plus::val} function from the previous table
  - $\frac{38 \text{ instr.}}{0.8 \text{ instr./cycle}} = 48 \text{ cycles vs. 3 instructions for load/add/store assembly}$
  - One explanation for this high cost is the absence of \textit{loop pipelining}, dependent instructions $\rightarrow$ 20 cycles
  - High cost of a function (routine) call ($\sim 20 \text{ cycles}$) that cannot be amortized
Materialization model

Each operator processes its input all at once and then stores its output all at once (in one buffer).

- Operators consume and produce **full columns** (or tables).
- Each (sub-)result is **fully materialized** (in memory)
- *No* pipelining (rather a sequence of statements)
- Each operator runs exactly once.

The output can be either a whole tuple (row-store) or subsets of columns (column-store).
Materialization model – Example

```sql
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```
Materialization model – Example

```
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```

```
\pi \ R.id, S.value
\bowtie \ R.id = S.id
\sigma \ value > 100
```

1. `out = []`
   ```python
   for t in child.Output():
       out.append(projection(t))
   return out
   ```

2. `out = []`
   ```python
   for t_1 in left.Output():
       buildHashTable(t_1)
   for t_2 in right.Output():
       if probe(t_2):
           out.append(t_1 \bowtie t_2)
   return out
   ```

3. `out = []`
   ```python
   for t in R
       out.append(t)
   return out
   ```

4. `out = []`
   ```python
   for t in child.Output():
       if evalPred(t):
           out.append(t)
   return out
   ```

5. `out = []`
   ```python
   for t in S
       out.append(t)
   return out
   ```
Materialization model – Example

```
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```

1. `out = []`
   - for `t` in `child.Output()`:
     - `out.append(projection(t))`
   - `return out`

2. `out = []`
   - for `t1` in `left.Output()`:
     - `buildHashTable(t1)`
   - for `t2` in `right.Output()`:
     - if `probe(t2)`:
       - `out.append(t1 ⨉ t2)`
   - `return out`

3. `out = []`
   - for `t` in `R`
     - `out.append(t)`
   - `return out`

4. `out = []`
   - for `t` in `child.Output()`:
     - if `evalPred(t)`:
       - `out.append(t)`
   - `return out`

5. `out = []`
   - for `t` in `S`
     - `out.append(t)`
   - `return out`
Materialization model – analysis

Much fewer number of function calls

Due to such operator-at-a-time processing, its tight loops

- Conveniently *fit into instruction caches*
- Can be optimized effectively by modern compilers
  - *Loop unrolling*
  - *Vectorization* (use of SIMD instructions)
- Can leverage modern CPU features (*hardware prefetching*)
- Far less expensive function calls are now *out of the critical code path*
The materialization (operator-at-a-time) model is a two-edged sword:
- Cache-efficient with respect to code and operator state
- Tight loops, optimizable code

But, each operator reads in and out everything, so
- Data won’t fully fit into the cache:
  - Repeated scans will fetch data from memory over and over
  - Strategy falls apart when intermediate (materialized) results no longer fit in memory/caches

Can we aim for the middle-ground between the two extremes?

- tuple-at-a-time (iterator model)
- vector-at-a-time (vectorization model)
- operator-at-a-time (materialization model)
Idea: use volcano-style iteration

But for each `next()` call return a *batch of tuples* instead of a single tuple

- Vector in MonetDB/X100 terminology
- The operator’s internal loop processes multiple tuples at a time
- The size of the batch can vary based on the hardware and query properties
Vectorization model – Example

```
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```

**Diagram:**
- **Projection:** \( \pi \) R.id, S.value
- **Join:** \( \bowtie \) R.id = S.id
- **Selection:** \( \sigma \) value > 100

**Code Snippets:**

1. 
   ```python
   out = []
   for t in child.Output():
       out.append(projection(t))
   if |out|>n: emit(out)
   ```

2. 
   ```python
   out = []
   for t1 in left.Output():
       buildHashTable(t1)
   for t2 in right.Output():
       if probe(t2): out.append(t1\&t2)
   if |out|>n: emit(out)
   ```

3. 
   ```python
   out = []
   while R.hasNext() & |out|<n:
       out.append(R.next())
   emit(out)
   ```

   ```python
   while S.hasNext() & |out|<n:
       out.append(S.next())
   emit(out)
   ```
Vectorization model – Example

**SQL Query**

```
SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```

**Diagram Notes**

1. `out = []
   for t in child.Output():
   out.append(projection(t))
   if |out|>n: emit(out)`

2. `out = []
   for t in child.Output():
   out.append(t)
   if |out|>n: emit(out)`

3. `out = []
   while R.hasNext() & |out|<n
   out.append(R.next())
   emit(out)`

4. `out = []
   while S.hasNext() & |out|<n
   out.append(S.next())
   emit(out)`

5. `out = []
   for t in child.Output():
   out.append(projection(t))
   if |out|>n: emit(out)`

**Query Breakdown**

- **Selection** `R.id, S.cdate`
- **Join** `R JOIN S ON R.id = S.id`
- **Filter** `WHERE S.value > 100`
Vectorization model – analysis

Uses the best of both worlds (iterator and materialization models):
- Reduces the number of invocations per operator
- Allows for operators to use vectorized (SIMD) instructions to process batches of tuples

Imperative to choose a vector size that is:
- Large enough to amortize the iteration overhead (e.g., function calls, instruction cache misses, etc),
- Small enough to not thrash data caches

Will there be such a vector size?
- Or will caches be thrashed long before iteration overhead is compensated?
Observations:

- Vectorized execution quickly compensates for iteration overhead
- 1000 tuples should conveniently fit into caches
Vectorized execution in MonetDB/X100

M. Zukowski, Balancing Vectorized Query Execution with Bandwidth Optimized Storage, PhD thesis, CWI Amsterdam, 2009
Vectorized execution in SQL Server 11

Microsoft SQL Server supports vectorized ("batched" in MS jargon) execution since version 11.

- Storage via new **column-wise index** (with compression and prefetching improvements)

- New operators with **batch-at-a-time processing**

- Typical pattern:
  - Scan, pre-filter, project, aggregate data early in the plan using **batch operators**
  - **row operators** may be needed to finish the operation

- Good for scan-intensive workloads (OLAP), **not** for point queries (OLTP workloads)

- Internally, the optimizer treats batch processing as new **physical property** (like being sorted) to combine operators in a proper way.

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src: Per-Ake Larson et al. SQL Server Column Store Indexes. SIGMOD 2011
SQL Server: Performance

Performance impact (TPC-DS, scale factor 100, ~ 100GB)

Graph showing execution time for queries Q1 to Q4, comparing row store and column store performance.
Vectorized execution in PostgreSQL

- Organize query plan into **execution groups**
- Add **buffer operator** between execution groups
- The buffer operator provides tuple-at-a-time interface to the outside, but **batches up** tuples internally.
- Similar to the example we covered previously

```c
function: next()
// Read a batch of input tuples if buffer is empty
if empty and !end-of-tuples then
  while !full do
    append child.next() to buffer
    if end-of-tuples then
      break;
  // Return tuples from buffer
  return next tuple in buffer;
```
Buffer operators in PostgreSQL

## Comparison of processing models

Overview of the discussed execution models

<table>
<thead>
<tr>
<th>Execution model</th>
<th>iterator (tuple)</th>
<th>materialization (operator)</th>
<th>vectorization (vector)</th>
</tr>
</thead>
<tbody>
<tr>
<td>query plans</td>
<td>simple</td>
<td>complex</td>
<td>simple</td>
</tr>
<tr>
<td>instruction cache utilization</td>
<td>poor</td>
<td>extremely good</td>
<td>very good</td>
</tr>
<tr>
<td>function calls</td>
<td>many</td>
<td>extremely few</td>
<td>very few</td>
</tr>
<tr>
<td>attribute access</td>
<td>complex</td>
<td>direct</td>
<td>direct</td>
</tr>
<tr>
<td>most time spent on</td>
<td>interpretation</td>
<td>processing</td>
<td>processing</td>
</tr>
<tr>
<td>CPU utilization</td>
<td>poor</td>
<td>good</td>
<td>very good</td>
</tr>
<tr>
<td>compiler optimizations</td>
<td>limited</td>
<td>applicable</td>
<td>applicable</td>
</tr>
<tr>
<td>materialization overhead</td>
<td>very cheap</td>
<td>expensive</td>
<td>cheap</td>
</tr>
<tr>
<td>scalability</td>
<td>good</td>
<td>limited</td>
<td>good</td>
</tr>
</tbody>
</table>

src: M. Zukowski, Balancing Vectorized Query Execution with Bandwidth Optimized Storage, PhD thesis, CWI Amsterdam, 2009
Pushing the envelope further with query compilation

- Database operators tend to be extremely simple:
  - Selection, arithmetic, etc.
  - Even operators like hash probes are quite simple

- Even a cache access can incur a noticeable cost
  - Keep tuples in registers between operators?

- Pipeline breakers
  - Tuples must be moved out of CPU registers on input side
  - Try to keep data in registers in-between pipeline breakers
Pushing tuples up execution model

- **HyPer**
  - *Fuse all* adjacent non-blocking operators of a query pipeline in a *single, tight loop*
  - *Compile* query plans into *machine code*

- **Trick:**
  - *Push-based* (rather than pull-based) model
  - each code block *consumes* from one pipeline breaker and *pushes* into next
  - Carefully *keep data in registers* within one code block
Pushing tuples up execution model

Example:

```
// initialize memory of \( \bowtie_{a=b} \), \( \bowtie_{c=z} \), and \( \Gamma_z \)
for each tuple \( t \) in \( R_1 \)
  if \( t.x = 7 \)
    // materialize \( t \) in hash table of \( \bowtie_{a=b} \)
  for each tuple \( t \) in \( R_2 \)
    if \( t.y = 3 \)
      // aggregate \( t \) in hash table of \( \Gamma_z \)
      for each tuple \( t \) in \( \Gamma_z \)
        // materialize \( t \) in hash table of \( \bowtie_{c=z} \)
        for each tuple \( t_3 \) in \( R_3 \)
          for each match \( t_2 \) in \( \bowtie_{c=z} [t_3.c] \)
            for each match \( t_1 \) in \( \bowtie_{a=b} [t_3.b] \)
              output \( t_1 \circ t_2 \circ t_3 \)
```

Code blocks don’t quite match operator boundaries, e.g., build/probe parts of hash join

*Operator-centric* → *Data-centric* execution

HyPer – compiled query execution

- Use **LLVM** (Low Level Virtual Machine) to generate code instead of C++
  - assembly-style code
  - *platform-independent*
  - automatic *register assignment*
  - strong *type checking*

- Mix generated code with pre-compiled libraries
  - *e.g.*, memory management, error handling
  - Written in C++ anyway, no need to re-compile at runtime
HyPer performance

- Showing both compilation and execution time

- Also the size of the generated machine code, the fraction of the machine code that was generated at runtime using LLVM, and the fraction of the time spent in the generated code

<table>
<thead>
<tr>
<th>TPC-H #</th>
<th>compile</th>
<th>executed code</th>
<th>HyPer generated</th>
<th>time in generated</th>
<th>runtime</th>
<th>Vectorwise runtime</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13ms</td>
<td>5.6KB</td>
<td>42%</td>
<td>98%</td>
<td>9.0s</td>
<td>33.4s</td>
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<tr>
<td>2</td>
<td>37ms</td>
<td>10.9KB</td>
<td>58%</td>
<td>86%</td>
<td>2.4s</td>
<td>2.7s</td>
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<tr>
<td>3</td>
<td>15ms</td>
<td>6.6KB</td>
<td>36%</td>
<td>89%</td>
<td>27.5s</td>
<td>25.6s</td>
</tr>
<tr>
<td>4</td>
<td>12ms</td>
<td>6.2KB</td>
<td>33%</td>
<td>93%</td>
<td>21.6s</td>
<td>22.4s</td>
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<td>5</td>
<td>23ms</td>
<td>8.1KB</td>
<td>42%</td>
<td>86%</td>
<td>31.4s</td>
<td>29.7s</td>
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<tr>
<td>6</td>
<td>5ms</td>
<td>1.1KB</td>
<td>82%</td>
<td>96%</td>
<td>5.5s</td>
<td>7.1s</td>
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<tr>
<td>7</td>
<td>31ms</td>
<td>9.4KB</td>
<td>51%</td>
<td>88%</td>
<td>23.8s</td>
<td>28.2s</td>
</tr>
<tr>
<td>geo. mean (all 22)</td>
<td>19ms</td>
<td>6.8KB</td>
<td>47%</td>
<td>81%</td>
<td>16.2s</td>
<td>21.5s</td>
</tr>
</tbody>
</table>

**Insights:** most of the critical code path is generated, the compilation time is quite low, and performance is often better than Vectorwise.
Compiling query plans in other systems

- HyPer was a pioneering system implementing the data-centric code generation

- Other systems that compile queries (not necessarily with LLVM) are:
  - Microsoft’s Hekaton
    - compiles stored procedures into native code using C as intermediary language
  - Cloudera Impala
    - LLVM JIT compilation for predicate evaluation and record parsing
  - MemSQL
    - High-level imperative DSL $\rightarrow$ second language of opcodes $\rightarrow$ LLVM IR $\rightarrow$ native code,
  - Apache Spark
    - WHERE clause expression trees $\rightarrow$ Scala AST $\rightarrow$ JVM bytecode,
  - PostgreSQL added support for JIT compilation in 2018
    - Automatically compiles Postgres’ back-end C code into LLVM C++ code to remove iterator calls
    - etc.

Compiled vs. vectorized query execution

- Single test system compares the fundamental properties of the execution model of a compilation-based pushing tuples up engine (Typer) and a vectorization based engine (Tectorwise).

- Selected OLAP queries from TPC-H with SF 1
  - Q1: fixed-point arithmetic, (4 groups) aggregation
  - Q6: selective filters
  - Q3: join (build: 147k entries, probe: 3.2m entries)
  - Q9: join (build: 320k entries, probe: 1.5m entries)
  - Q18: high-cardinality aggregation (1.5m groups)

There is no clear winner:
- Typer is faster for Q1 and Q18
- TW is better for Q6, Q3 and Q9

Understanding the results, requires more in-depth analysis on the CPU/cache characteristics.
## Compiled vs. vectorized query execution

- **Micro-architectural analysis for the TPC-H queries, main observations:**
  - TW executes significantly more instructions (up to 2.4x) and has more L1-d cache misses (up to 3.3x).

<table>
<thead>
<tr>
<th></th>
<th>cycles</th>
<th>IPC</th>
<th>instr.</th>
<th>L1 miss</th>
<th>LLC miss</th>
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<tr>
<td>Q1 Typer</td>
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<td>Q18 Typer</td>
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<td>0.37</td>
</tr>
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**Query 1**: dominated by fixed point arithmetic operations and a cheap in-cache aggregation.

**TW intermediate results must be materialized, which is as expensive as the computation itself.**

**Typer** can often keep intermediate results in CPU registers and perform the same operations with less instructions.

- **Typer** is more efficient for **computational** queries that can hold intermediate results in CPU registers and have few cache misses.
Micro-architectural analysis for the TPC-H queries, main observations:
- Typer’s complex loops induce more memory stalls and branch misses

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Q3 and Q9’s performance is determined by the efficiency of hash table probing.

TW’s simple loops for hash probing allow for generating many outstanding memory loads.

Observation: **TW** (vectorization) is better at hiding cache-miss latencies.
Compiled vs. vectorized query execution

- Micro-architectural analysis for the TPC-H queries, main observations:
  - Typer’s complex loops induce more memory stalls and branch misses
  - TW (vectorization) is better at hiding cache-miss latencies.

- TW (vectorization) is better at hiding cache-miss latencies.

Typer’s performance suffers due to memory stalls more than TW’s.

Both systems observe more CPUs spent on memory stalls as data size increases.
## Compiled vs. vectorized query execution

### Qualitative analysis and comparison

<table>
<thead>
<tr>
<th>Execution model</th>
<th>Compilation-based engines</th>
<th>Vectorized engines</th>
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<tr>
<td>Computation</td>
<td>More efficient code</td>
<td>Less efficient (data not in registers)</td>
</tr>
<tr>
<td>Parallel data access</td>
<td>Less good at hiding memory latencies</td>
<td>Can generate more parallel memory requests</td>
</tr>
<tr>
<td>SIMD vectorization</td>
<td>Good (but, more complex to implement)</td>
<td>Very good (better match to leverage SIMD)</td>
</tr>
<tr>
<td>Parallelization</td>
<td>Good</td>
<td>Good</td>
</tr>
<tr>
<td>OLTP</td>
<td>Can generate fast stored procedures</td>
<td>Slower</td>
</tr>
<tr>
<td>Language support</td>
<td>Easy to write portable code</td>
<td>More complex</td>
</tr>
<tr>
<td>Compile time</td>
<td>Has overhead</td>
<td>Primitives are pre-compiled</td>
</tr>
<tr>
<td>Profiling</td>
<td>More complex for performance debugging</td>
<td>Naturally can attribute profiling to primitives</td>
</tr>
<tr>
<td>Adaptivity</td>
<td>Possible by switching from interpretation to compilation</td>
<td>Possible to swap execution primitives mid-flight</td>
</tr>
<tr>
<td>Debugging</td>
<td>Runtime and compile time co-exist</td>
<td>Simple (like every c++)</td>
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Timo Kersten et al. *Everything You Always Wanted to Know About Compiled and Vectorized Queries But Were Afraid to Ask*. VLDB 2018
Relaxed Operator Fusion

- **Idea: Relax** the pipeline breakers to create *mini-batches*
  - Good for operators that can be vectorized
  - Leverage software prefetching to hide memory stalls
  - Use data-level parallelism (e.g., using SIMD)

- Implemented in the Peloton DMBS (2017)

- If the query optimizer can correctly decide when to break a pipeline, this approach can be faster than both standard models (vectorized vs compiled).
Results of Relaxed Operator Fusion

- Performance comparison of baseline (compiled query execution) vs. optimized (relaxed operator fusion)
  - For selected TPC-H queries, with scaling factor 10 (~ 10GB data)

Q1 only marginal improvement. Time is spent primarily on selection and aggregation.

The big performance improvements for Q3 is for the memory-intensive operators, the joins, mainly due to pre-fetching and SIMD.

Q13 gets 34% improvement solely due to efficient pre-fetching.
Memory-intensive operations (e.g., join and aggregation) deserve attention on their own.

How can we optimize their performance for the memory sub-system?

Next week we will look into how we can optimize the hash joins using techniques such as:
- “blocking” or partitioning
- software-based prefetching
- software write-combining
- non-temporal writes
- etc.
Various papers cross-referenced in the slides

- Boncz et al. MonetDB/X100: Hyper-Pipelining Query Execution CIDR 2005
- Zukowski Balancing Vectorized Query Execution with Bandwidth Optimized Storage, PhD thesis, CWI Amsterdam 2009
- Larson et al. SQL Server Column Store Indexes. SIGMOD 2011
- Neumann. Efficiently Compiling Efficient Query Plans for Modern Hardware. VLDB 2011
- Kersten et al. Everything You Always Wanted to Know About Compiled and Vectorized Queries But Were Afraid to Ask. VLDB 2018

Lecture: Database Systems on Modern CPU Architectures by Prof. Thomas Neumann (TUM)
Lecture: Data Processing on Modern Hardware by Prof. Jens Teubner (TU Dortmund, past ETH)
Lecture: Advanced Databases by Prof. Andy Pavlo (CMU)

Check out the code from Timo Kersten and play around with the TPC-H queries from Typer and Tectorwise (TW):
- https://github.com/TimoKersten/db-engine-paradigms

References