Special Topics:
Self-Driving Database Management Systems

Workload Modeling I

@Yingjie_Ling // 15-799 // Spring 2022
Previously

- Index recommendation
- Knob/Parameter Tuning
- Partitioning
- Workload Modeling (Forecasting)
TODAY’S AGENDA

• Motivation
• QB5000
  • Overview
  • Pre-Processor
  • Clusterer
  • Forecaster
• Experimental Analysis
• Parting Thoughts
Self-Driving Car

Perception

Action Model

Planning

Source: Lin Ma
Self-Driving Database

Perception

Workload Forecasting

Action Model

Behavior Modeling

Planning

Action Planning

Source: Lin Ma
Workload Patterns

- Bus Tracker: Cycles
- Admissions: Growth and Spikes
- MOOC: Workload Evolution

Figure 1: Workload Patterns – Examples of three common workload patterns in database applications.
TODAY’S AGENDA

• Motivation

• QB5000

• Experimental Analysis

• Parting Thoughts
Figure 2: QB5000 Workflow – The framework receives SQL queries from the DBMS. This data is first passed into the Pre-Processor that identifies distinct templates in the workload and records their arrival rate history. Next, the Clusterer combines the templates with similar arrival rate patterns together. This information is then fed into the Forecaster where it builds models that predict the arrival rate of templates in each cluster.
Pre-Processor

<table>
<thead>
<tr>
<th></th>
<th>Admissions</th>
<th>BusTracker</th>
<th>MOOC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Queries</td>
<td>2546M</td>
<td>1223M</td>
<td>95M</td>
</tr>
<tr>
<td>Total Num of Templates</td>
<td>4060</td>
<td>334</td>
<td>885</td>
</tr>
<tr>
<td>Num of Clusters</td>
<td>1950</td>
<td>107</td>
<td>391</td>
</tr>
<tr>
<td>Reduction Ratio</td>
<td>1.3M</td>
<td>10.5M</td>
<td>0.24M</td>
</tr>
</tbody>
</table>

Table 2: Workload Reduction – Breakdown of the total number of queries that QB5000 must monitor after applying the reduction techniques in the Pre-Processor and Clusterer.
Clusterer

• Motivation: still too many templates, not feasible to build a model for each template

• Clusterer must generate stable mapping independent of the state of the database

• Need to be adaptable to the change of workload (when clustered based on time-dependent information)
Clustering Criteria

- Possible similarity features:
  - Physical features
    - # Tuples Read
    - # Tuples Write
    - Latency
  - Logical features
    - Query Type
    - Columns referenced
    - # JOINs
  - Arrival rate features

| Source: Lin Ma |
Clusterer Implementation

- Modified DBSCAN using cluster centers
- Use threshold to determine similarity

Source: Lin Ma
Clusterer Implementation

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Forecaster

• Each of the top clusters has its own forecasting model
• Combine LR and RNN to build an ensemble for patterns with short periods (ENSEMBLE)
• Use KR for rare but periodic spikes
• Altogether is the HYBRID model
• Trust the KR if its predicted workload volume is above that of ENSEMBLE by more than a threshold
TODAY’S AGENDA

- Motivation
- QB5000
- Experimental Analysis
- Parting Thoughts
Terminology

Historical data
Prediction

Prediction Horizon

Prediction Interval

1 Min
1 Hour

Source: Lin Ma
Analysis: Number of Clusters

- **Efficiency**: a small number of clusters capture most of the workload information.

- **Stability**: cluster shift is minimal.

**Figure 5: Cluster Coverage** – The average ratio between the volume of the largest clusters and the total workload volume.

**Figure 6: Cluster Change** – The number of clusters that changed among the five largest clusters between two consecutive days.
Analysis: Prediction Accuracy

- LR models perform well for shorter horizons
- RNN models is better for longer horizons
- ENSEMBLE cannot predict rare spikes
- HYBRID is the overall winner by correcting spike predictions with KR

Figure 7: Forecasting Model Evaluation – The average prediction accuracy of the different forecasting models over prediction horizons ranging from one hour to one week for the Admissions, BusTracker, and MOOC workloads.
Analysis: Prediction Accuracy

- Prediction for a shorter horizon is more accurate
- Predicted arrival rate pattern matches the actual pattern even for a longer horizon
- Only KR can predict the spike pattern with reasonable accuracy

**Figure 8: Prediction Results** – Actual vs. predicted query arrival rates for the highest-volume cluster in the BusTracker workload with prediction horizons of one hour and one week.

**Figure 9: Prediction Results** – Actual vs. predicted query arrival rates for the combined clusters in the Admissions workload with spike patterns.
Analysis: Prediction Interval

- Prediction accuracy is higher for models with shorter interval
- More time consuming to train models with shorter interval
- Models trained with shorter interval are larger and more complex

Figure 10: Prediction Interval Evaluation – The average prediction accuracy and training time with different intervals for BusTracker.
Analysis: Computation & Storage Overhead

- Reasonable storage overhead overall
- Training the RNN models is the most time-consuming
- GPU speeds up training for RNN models
- KR models consumes higher storage

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<tr>
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<th>Clusterer</th>
<th>LR</th>
<th>RNN</th>
<th>KR</th>
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</thead>
<tbody>
<tr>
<td>Admissions</td>
<td>0.043ms/query</td>
<td>15s/day</td>
<td>GPU:0.3s</td>
<td>GPU:9s</td>
<td>GPU:0.16s</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>CPU:0.3s</td>
<td>CPU:58s</td>
<td>CPU:0.18s</td>
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<tr>
<td>BusTracker</td>
<td>0.05ms/query</td>
<td>3s/day</td>
<td>CPU:0.12s</td>
<td>GPU:33s</td>
<td>GPU:0.02s</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GPU:0.13s</td>
<td>CPU:221s</td>
<td>CPU:0.02s</td>
</tr>
<tr>
<td>MOOC</td>
<td>0.048ms/query</td>
<td>12s/day</td>
<td>GPU:0.54s</td>
<td>GPU:5s</td>
<td>GPU:0.04s</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CPU:0.51s</td>
<td>CPU:18s</td>
<td>CPU:0.04s</td>
</tr>
</tbody>
</table>

Table 4: Computation & Storage Overhead – The measurements for QB5000’s different components.
Analysis: Automatic Index Selection

- **AUTO**: candidate indexes generated using the predicted workload of the three largest clusters
- **STATIC**: same index selection algorithm but applied to a fixed workload sample
- **AUTO-LOGICAL**: clustered based on logical feature

**Figure 11: Index Selection (MySQL)** – Performance measurements for the Admissions workload using different index selection techniques.

**Figure 12: Index Selection (PostgreSQL)** – Performance measurements for the BusTracker workload using different index selection techniques.
TODAY’S AGENDA

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PARTING THOUGHTS

• A better clustering criterion that not only captures the arrival rate but also the semantics?
• Can a single forecaster predict the arrival rate for all/multiple clusters?
• How does QB5000 perform with more challenging workload, such as the MOOC workload?
• How else can the forecaster be used?
References