Self-Driving Database Management Systems

Paper:
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Contributions

• Presents an architectural model for a “self-driving” database management system (DBMS).
  • Should allow DBMS to adapt without any human intervention.
  • Optimizes system for the predicted future workloads.
  • Measures effects of actions to better schedule deployment.

• Presents Peloton.
  • A skeleton implementation of the theoretical architecture.
Previous Self-Tuners

• Must prepare workload samples.
• Requires spare hardware to test on.
• Requires intuition into the DBMS’s internals.
• External to the DBMS.
  • Limited actions that can be taken.
• Reactionary as they cannot predict future workloads.
• Cannot take a holistic view that considers more than one problem at a time.
• Often require restarting on change.
• Many actions too slow.
Application Workloads

- **Online Transaction Processing (OLTP)**
  - Row-oriented.
  - Optimizes writes.
- **Online Analytical Processing (OLAP)**
  - Column-oriented.
  - Optimizes reads.
- **Hybrid Transaction-Analytical Processing (HTAP)**
  - Execute OLAP queries as soon as data is written.
Application Workloads

• Could deploy separate databases.
  • Stream updates.

• Could optimize for different database segments.

• Self-driving DBMS needs to:
  • Forecast resource utilization trends.
  • Choose action to optimize database.
  • Deploy optimization at time of least impact.

• Cannot:
  • Require applications to be rewritten.
  • Rely on program analysis tools that only support certain programming environments.
## Actions

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</table>
Workload Classification:

- Clusterer uses unsupervised learning. (DBSCAN algorithm)
- Can use runtime metrics or logical semantics.
  - Runtime more sensitive to changes in contents, design or concurrent workloads.
  - Logical semantics isn’t as accurate.
- Uses standard cross validation to detect when clusters are no longer correct and require rebuilding.
Workload Forecasting:

• Train forecast model that predicts each cluster’s arrival rate.
• Identifies periodicity and data growth trends.
• Recurrent Neural Networks (RNNs) are effective at predicting time-series patterns for non-linear systems.
• Specifically uses Long Short-Term Memory (LSTM).
  • Contains special blocks that determine whether to retain old information and when to output it into the network.
• Maintains multiple RNNs that forecast workloads at different time horizons and interval granularities.
• Tracking all queries increases storage and training costs.
Action Generation:

- Searches for actions that might improve performance.
- Guided by forecasting model.
- Stores along with resource requirements and history of effects.
Action Planning:

- Uses control theory, Receding-Horizon Control Model (RHCM).

- At each time epoch:
  - Estimates workload for time horizon using forecasts.
  - Searches for a sequence of actions that minimize objective function (latency).
  - Performs first action.

- Avoids recently invoked then reversed actions.

- Uses a cost-benefit model:
  - Cost is estimate of deployment latency and cost on performance.
  - Benefit is change in queries’ latencies.

- Deploys actions in a non-blocking manner.
Peloton Implementation

• Assumes queries are already clustered correctly.
  • Clusterer not tested.

• Integrated Google TensorFlow to perform workload forecasting.
  • Uses two stacked LSTM layers on input, connected to a linear regression layer.
  • Uses a 10% dropout rate to avoid over-fitting.

• Uses 1 hour time horizon with 1 minute granularity.
  • Input is per-minute workload over past 2 hours.

• Uses 24 hour time horizon with 1 hour granularity.
  • Input is previous day’s workload.
Peloton Implementation

- Uses 75% of a 4 week data set to train the model.
- Training took 11 and 18 minutes on a Nvidia GeForce GTX 980 GPU.
- Validates using other 25%.
- Predicts with 11.3% for 1-hour and 13.2% for 24-hour.
Peloton Implementation

- Migrates table to row or column layout based on types of queries.
- Hot tuples are stored in a row-oriented layout.
- Cold tuples are stored in a column-oriented layout.
Criticisms

• Shows only a small gain over simply using the column layout.

• Peleton is only tested on a very predictable workload with simple behaviour patterns.

• Peleton is not tested under any drastic changes such as failures or erratic traffic.

• It claims to be able to do almost everything, yet is only shown to do one very simple change.
  • Could have been scheduled by an administrator.
Criticisms

• The cost of the extra work and resources for such are not properly addressed.

• The action generator is not tested at all as only one action is made available to Peleton.

• Assumes latency is most important metric.

• No kind of possible distribution of the database is mentioned.
Questions?