Using Data-Driven and Zero-Shot Learning to learn DBMS Components

Abstract

Workload-driven learning is a technique to replace a DBMS component with a machine learning model

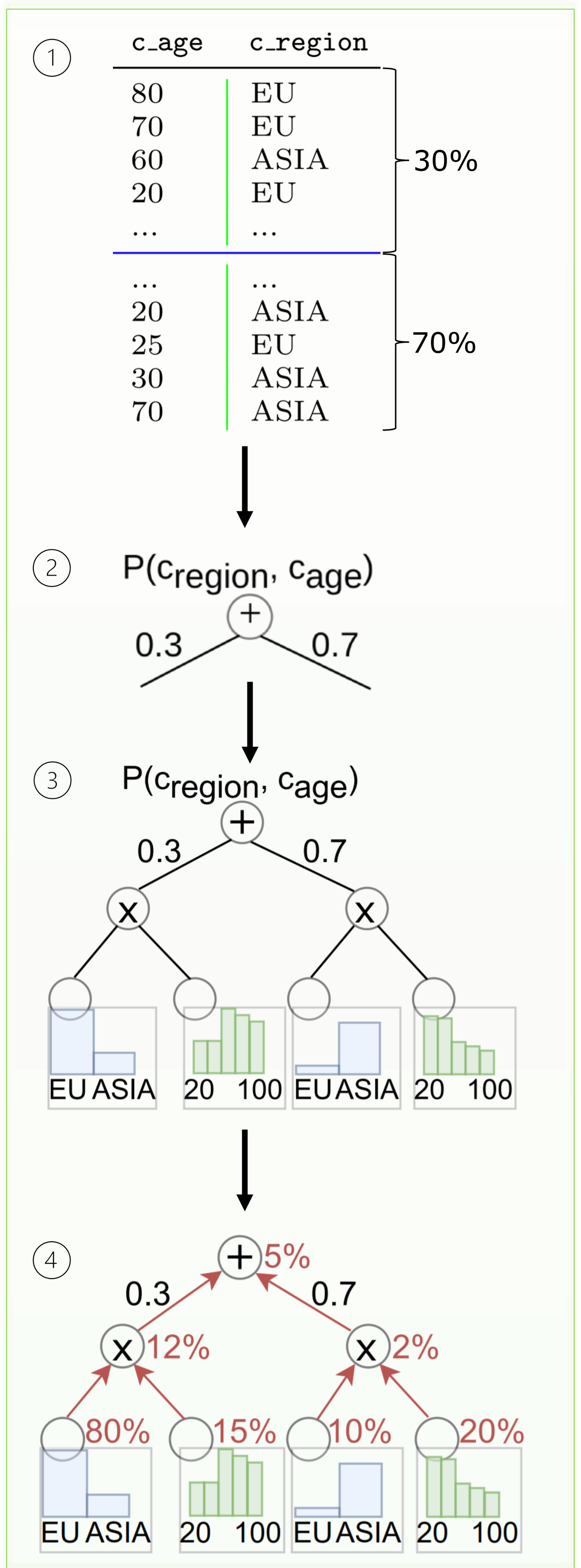
- **Issue**: For each new database or component, a new model must be trained. This makes it very inflexible and expensive to train.
- **Solution**: Use data-driven and transfer learning approaches to reduce training effort and make the model generalizable to unseen databases

Data-Driven Learning

Idea: Model **learns data characteristics** like the data's distribution and correlation across complex relational databases

- No training workload needed as the model relies on data only
- Retraining the model only takes a few minutes
- Support for tasks that do not consider workload (cardinality estimation, AQP, indexing)

Goal: Construct Relational Sum-Product Network (RSPN) from database



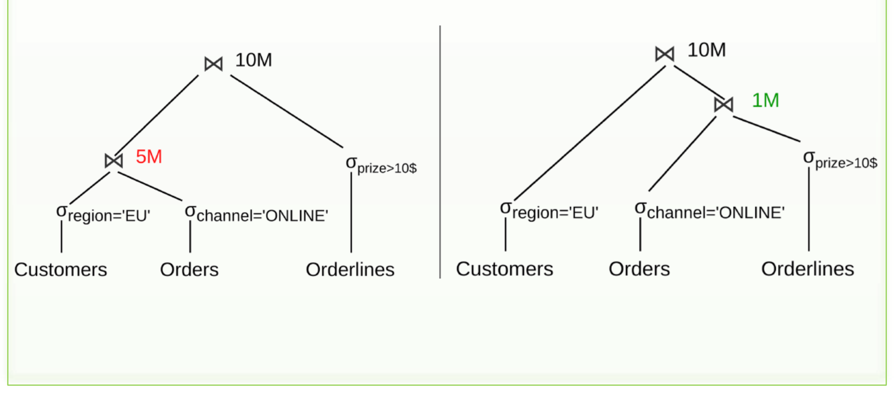
① Split independent rows into row clusters (e.g. using KMeans)

② Use sum node and add weights corresponding to the row cluster sizes to the edges

③
- In each row cluster, split independent columns into column clusters (product node)
- If not all columns are independent, start again with the first step, otherwise continue

④
- Use RSPN to compute probabilities on arbitrary attributes of the table
- Example: `SELECT COUNT(*) FROM Customer C WHERE c_region='EU' AND c_age<30` yields 5%

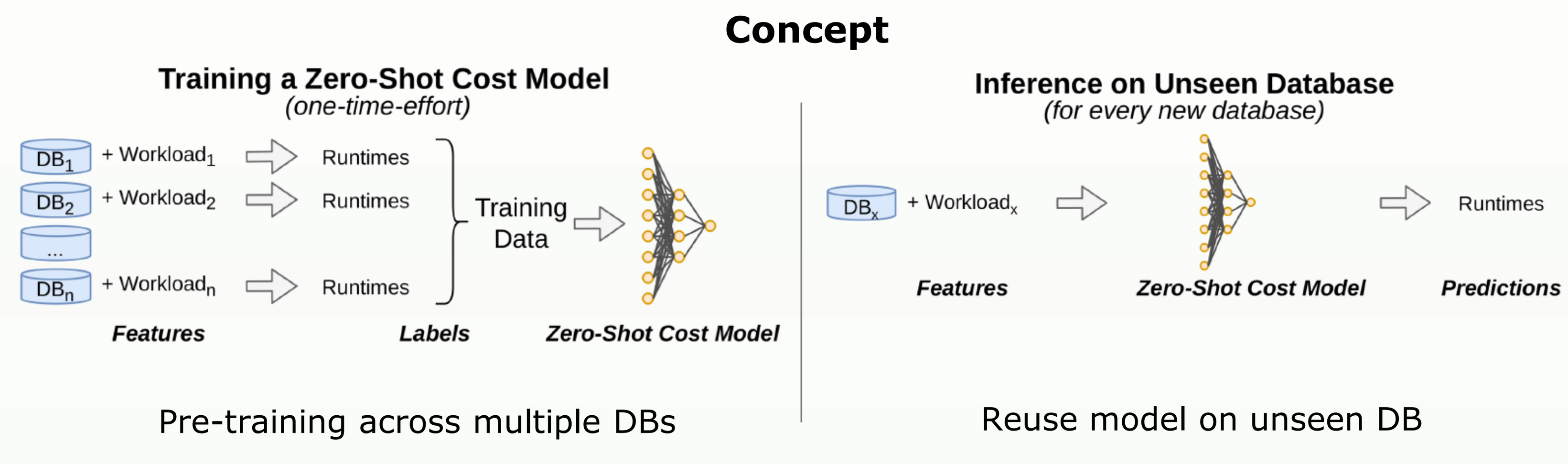
⑤ Estimated value can be used to **select optimal query plan**



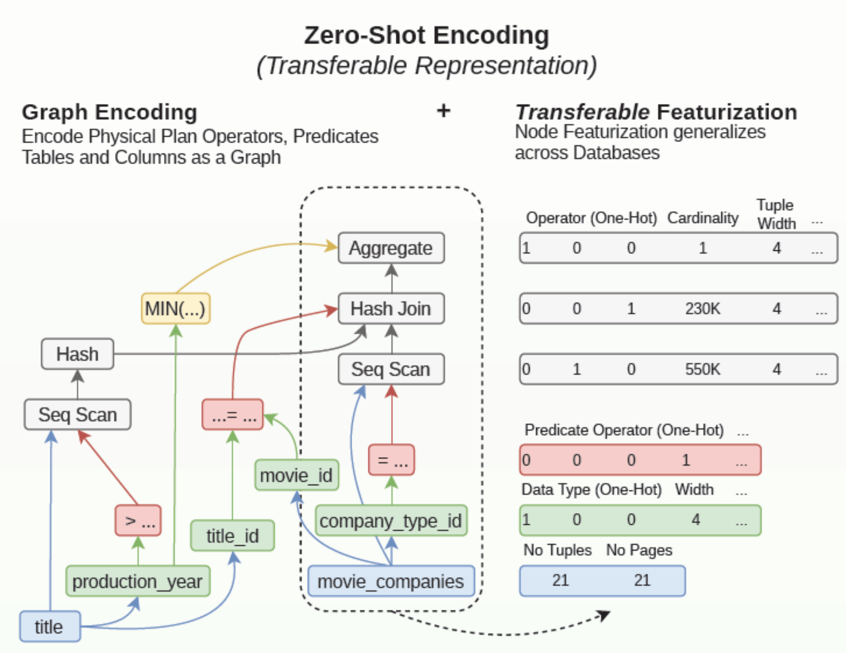
Zero-Shot Learning for Databases

Idea: Inline to other zero-shot approached (e.g. GPT-3), train a model that can **generalize to unseen databases out-of-the-box**.

- No queries on database are required for training
- Broader applicability to different tasks (physical cost estimation, knob tuning, physical design tuning)

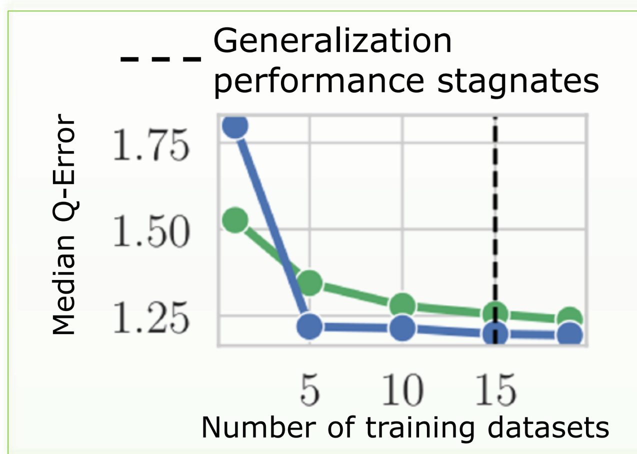


Key Challenges



1. Challenge: Query encoding that generalizes across databases

- **Problem**: Can't use representation of workload-driven models as they don't allow transfer across DBs
- **Solution**:
  - Capture query plans as graph encoding
  - Lean how expensive a certain operation on a dataset is
  - Encode information (e.g. data type, tuple width) of data where operations are executed on
  - Annotate operators with the intermediate sizes they are executed on (⟶ informed by data-driven models)



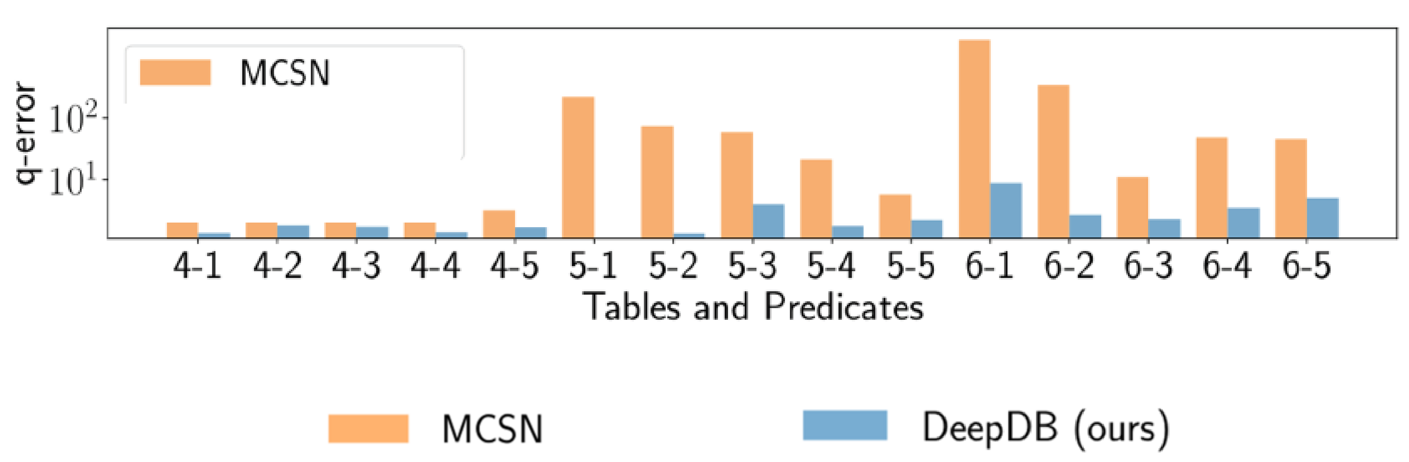
2. Challenge: Sufficient training

- **Goal**: Find out when model is sufficiently trained
- **Idea**: Estimate using holdout databases. If estimated performance is acceptable or stagnates, stop
- **Assumption**: Every DB and workload is sampled i.i.d.

Evaluation

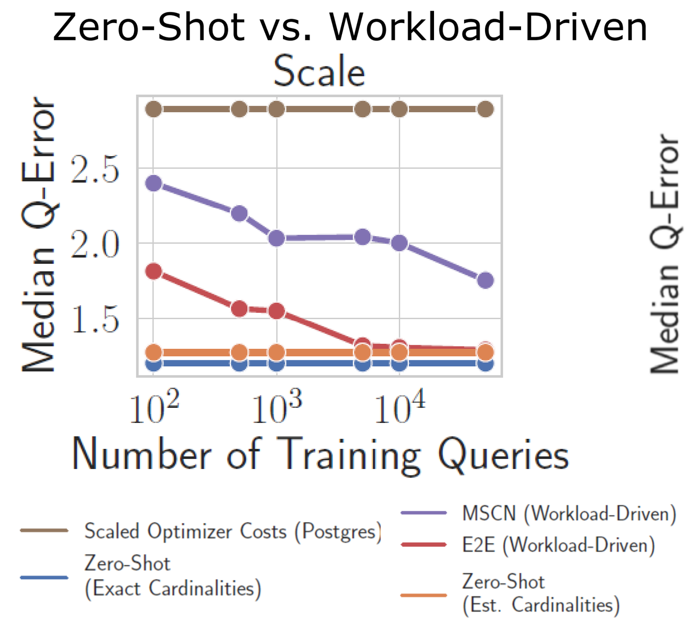
Generalizability to larger joins

Data-Driven vs. Workload-Driven

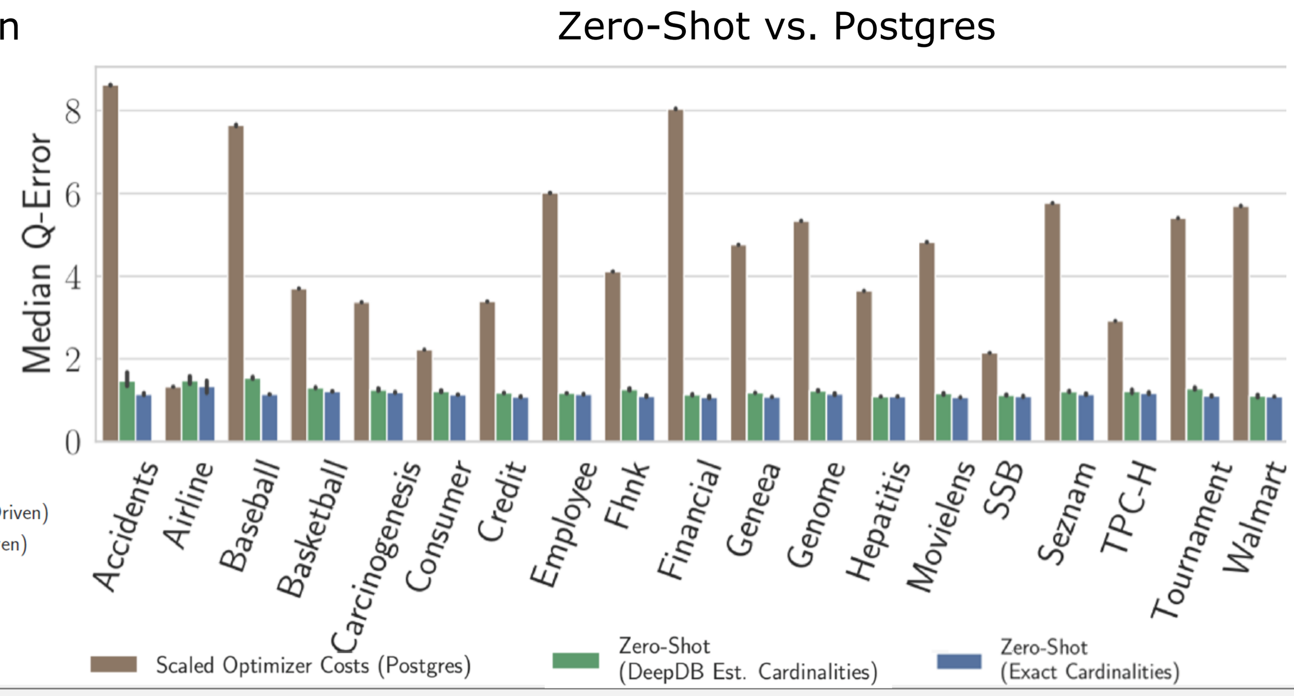


Query runtime estimation

Zero-Shot vs. Workload-Driven



Zero-Shot vs. Postgres



Vincent Melisch
Diploma Computer Science Student at the TU Dresden

E-Mail: vincent.melisch@tu-dresden.de

Resources
Based on Prof. Dr. Carsten Binnig's lecture *Learned DBMS Components* as part of the Lecture Series on Database Research

Graphics are taken from the slides of Prof. Dr. Carsten Binnig

HPI Hasso Plattner Institut