OSNABRÜCK UNIVERSITY

Embedded Software Systems

Understanding Product Line Runtime Performance with Behaviour Models and Regression Model Trees

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September 4th, 2025

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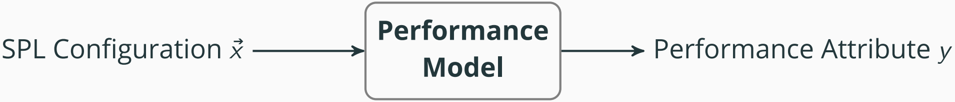
The State of Runtime Performance Models



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SPL Configuration $\vec{x}$ → **Performance Model** → Performance Attribute y

- x264 video encoder [Zha+15; Guo+18; Sie+15; Sie+13; DAS21]
  - runtime flags → latency, output file size
- Database management systems systems [Guo+13; Sar+15; Nai+17; Per+21]
  - Static features → latency, throughput, . . .

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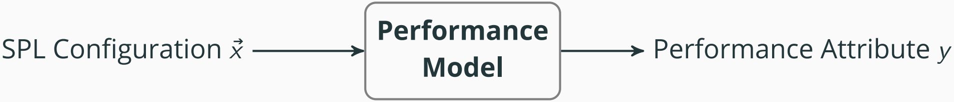

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  - Input file length, resolution $\overset{?}{\to}$ latency, output file size
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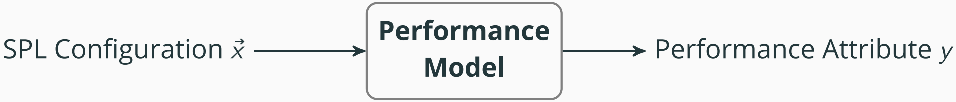
  - Database size, query sequence $\overset{?}{\to}$ latency, throughput, . . .

Performance Models: Workload as a Black Box



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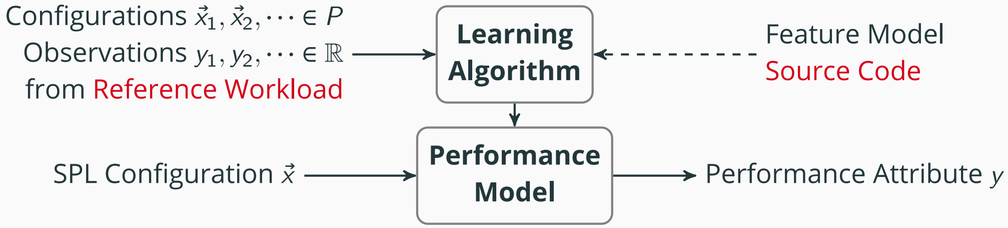

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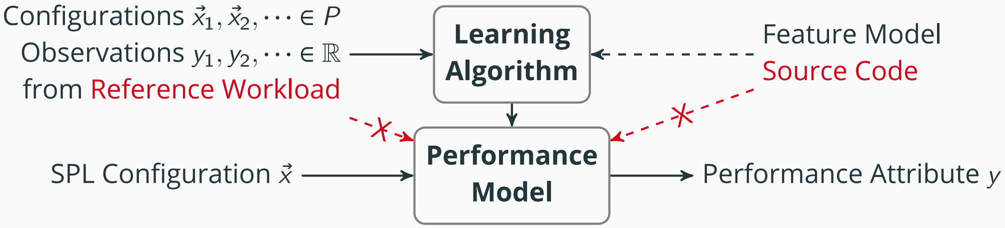

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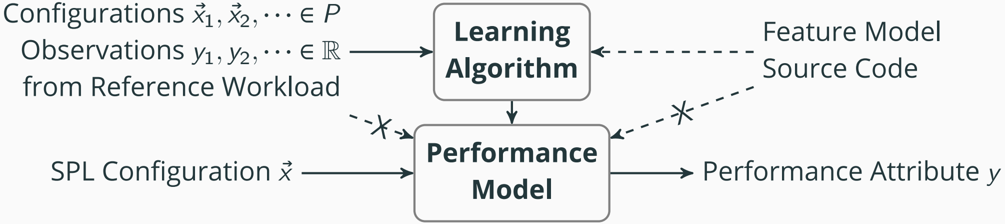

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- Performance bottlenecks → no link to workload / source code

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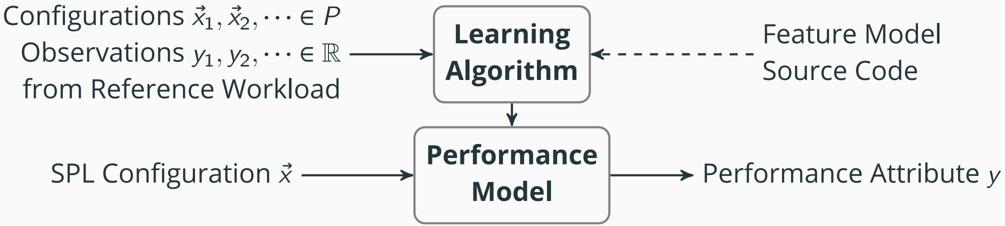

- Workload changes → re-run benchmarks and re-build model
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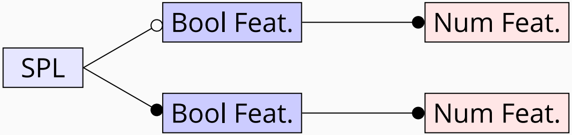
- Proposal: Workload-aware and interpretable performance models

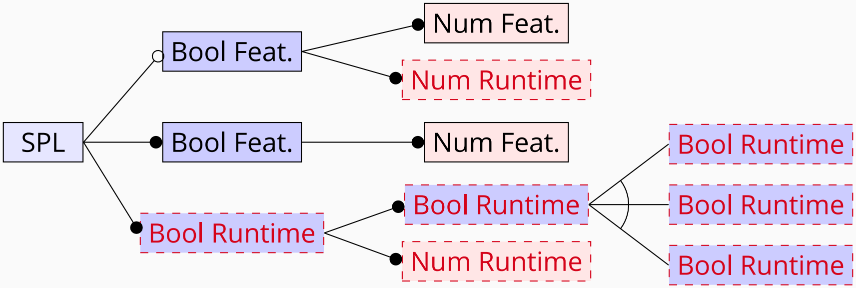
→ ① runtime variability, ② workload model, ③ performance annotations

① Runtime Variability Model



- Feature model: static features only, unaware of runtime variability

① Runtime Variability Model



- Feature model + runtime-only variability (e.g. input file length, table size)

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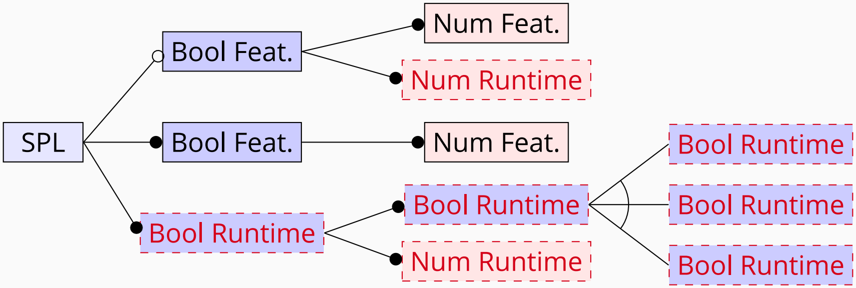
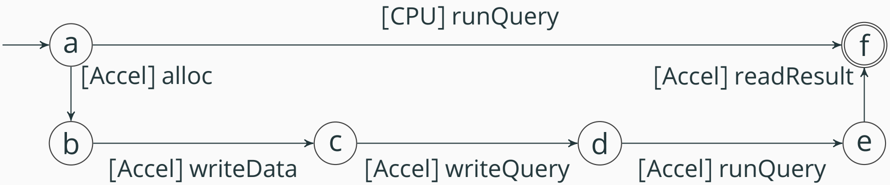


- Feature model + runtime-only variability (e.g. input file length, table size)
- Extension of Dynamic Software Product Lines (DSPLs) [Hal+08]
  - Compile-time defaults can be changed at runtime
  - DSPLs: no support for runtime variability ∉ product line features

② Workload Model

- Example: DBMS with optional offloading engines (query accelerators)



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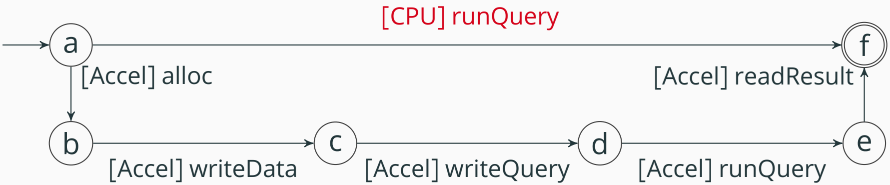

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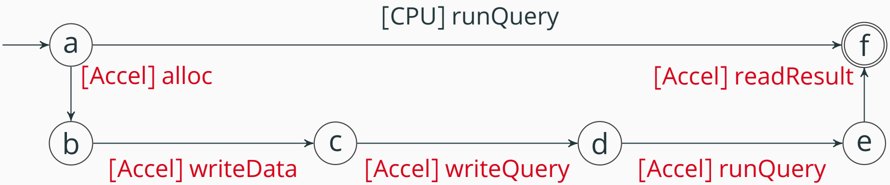

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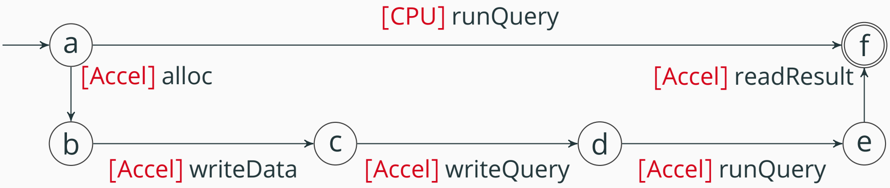
  - Feature guards: transitions may depend on feature configuration



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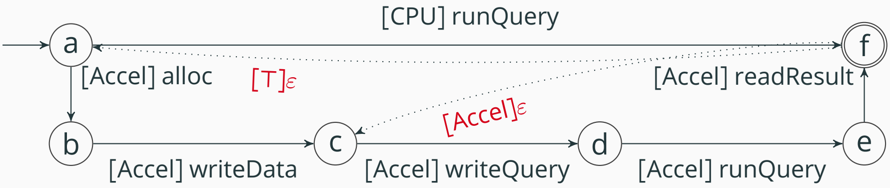

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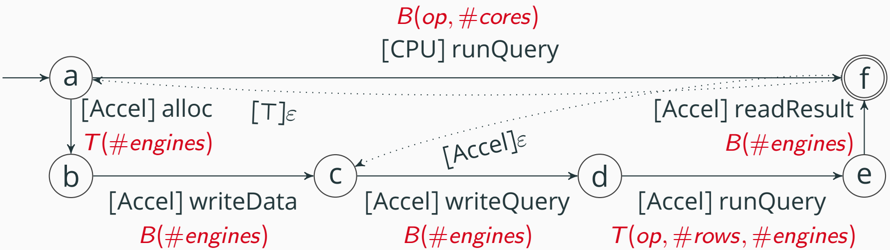

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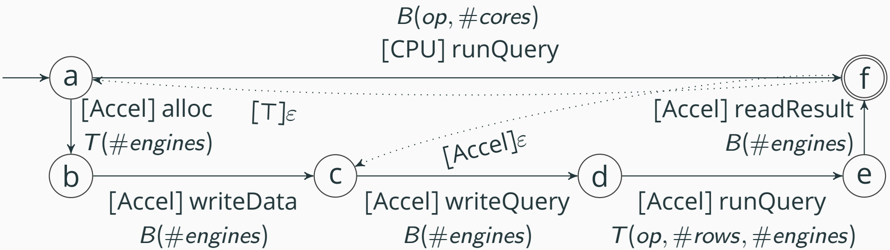
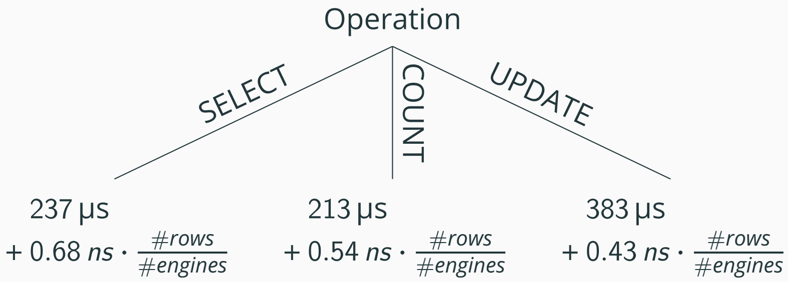
- Extension of featured transition systems [AFL15; Cla+13; Cla+14]



③ Regression Model Trees



Regression model trees [FS22]

= regression trees [Bre+84]

\+ unsupervised least-squares [FBS18]

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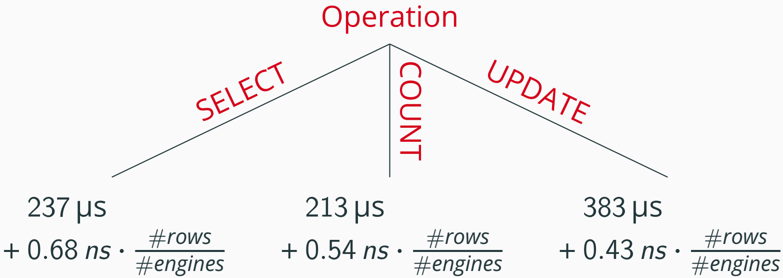

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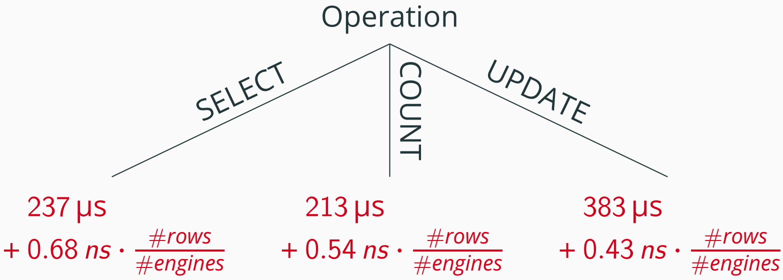

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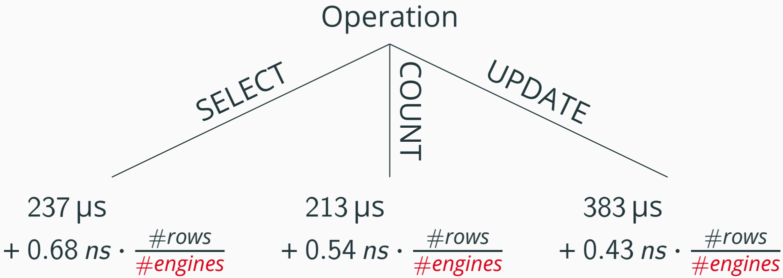

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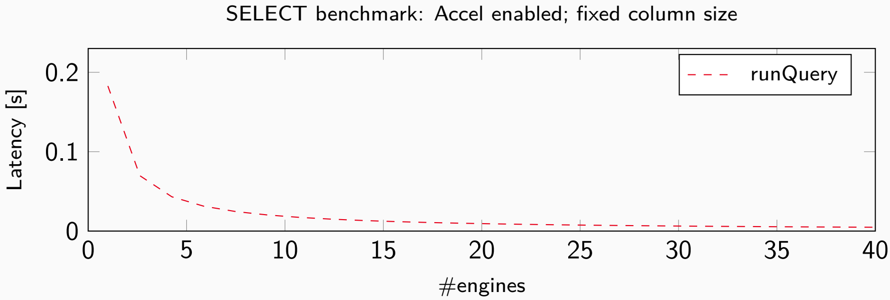
- Accurate and interpretable
- runQuery example: linear scaling with # accelerator engines

Understanding Product Line Behaviour



- runQuery scales linearly with #engines

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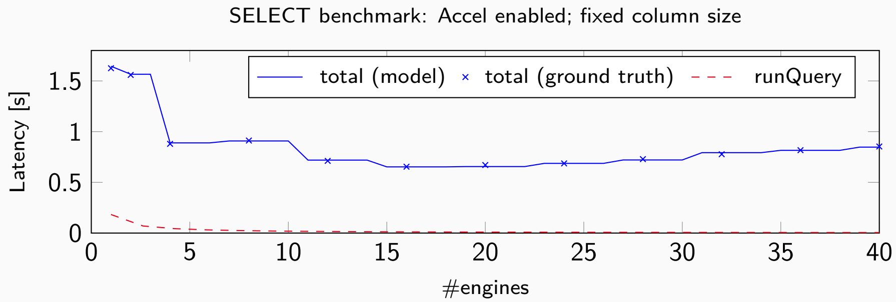

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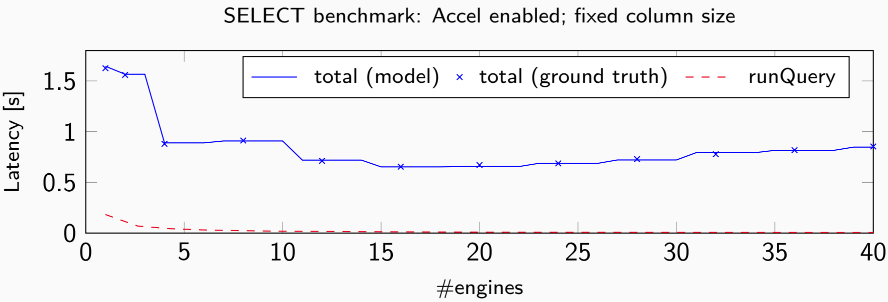

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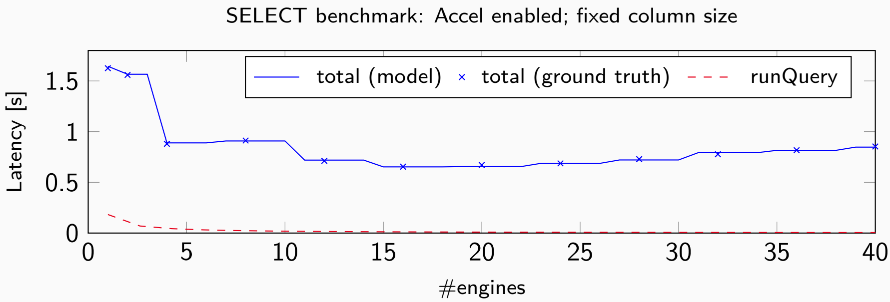
- Neither minimum nor maximum are optimal

→ Why?

Understanding Product Line Behaviour



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→ Why? (explanation in the paper)

Quantitative Evaluation

- Case study: DBMS with query accelerators
- Four models:
  - CART: conventional performance model
  - CART+B: ① CART with runtime variability
  - BM+CART: ① ② behaviour model with CART annotations
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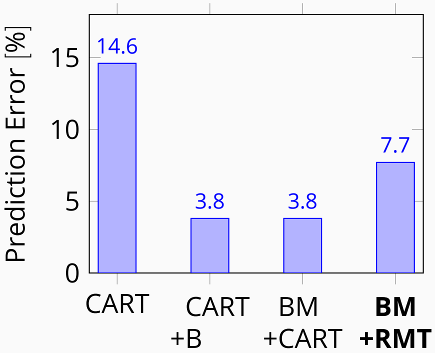
- Evaluation metrics:
  - Latency prediction error: variable configuration and query sequences (10-fold cross validation)
  - Model complexity (# tree nodes + # regression weights)

Evaluation Results



⇒ Sufficient accuracy for reasoning about runtime performance

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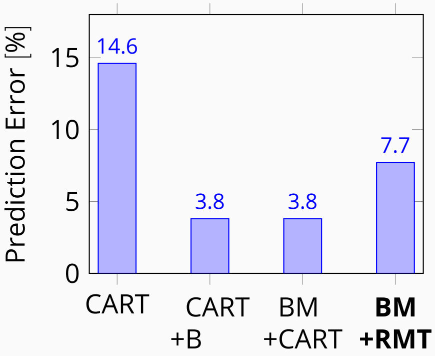
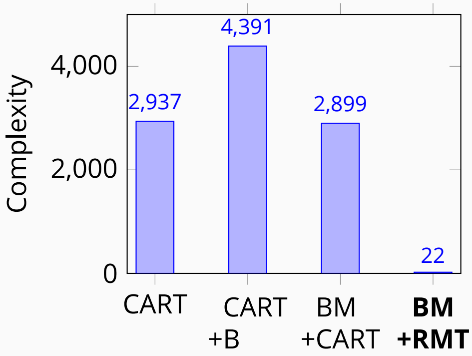


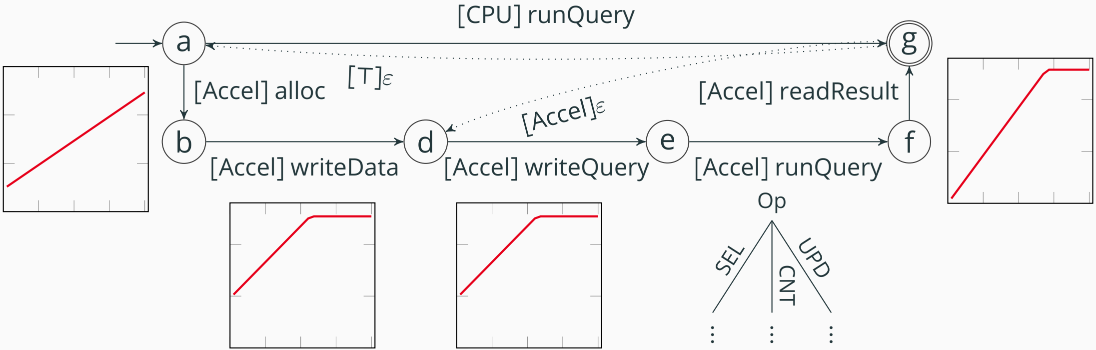


⇒ Sufficient accuracy for reasoning about runtime performance

⇒ Two orders of magnitude lower complexity → interpretable models

Conclusion

- Behaviour Models and Regression Model Trees:
  flexible, interpretable, workload-independent performance models



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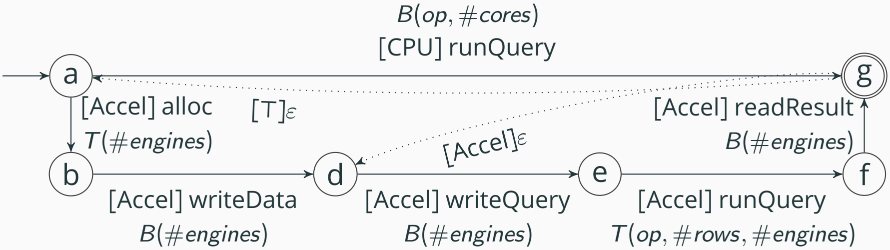

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  - Artifacts available and functional: `zenodo.org/records/15827230` [Fri25]

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- Learning behaviour models from application traces:
  work in progress; proof of concept to appear @ CCMCC'25 [FS25]

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