Adversarial Query Synthesis via Bayesian Optimization

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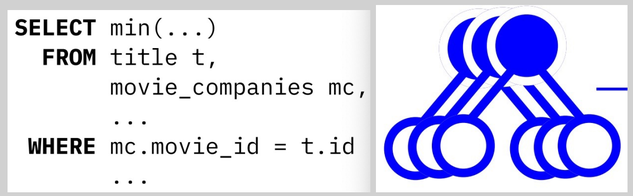
Adversarial Query Synthesis

As an optimization problem:

$\mathcal{A}$: {  ... }

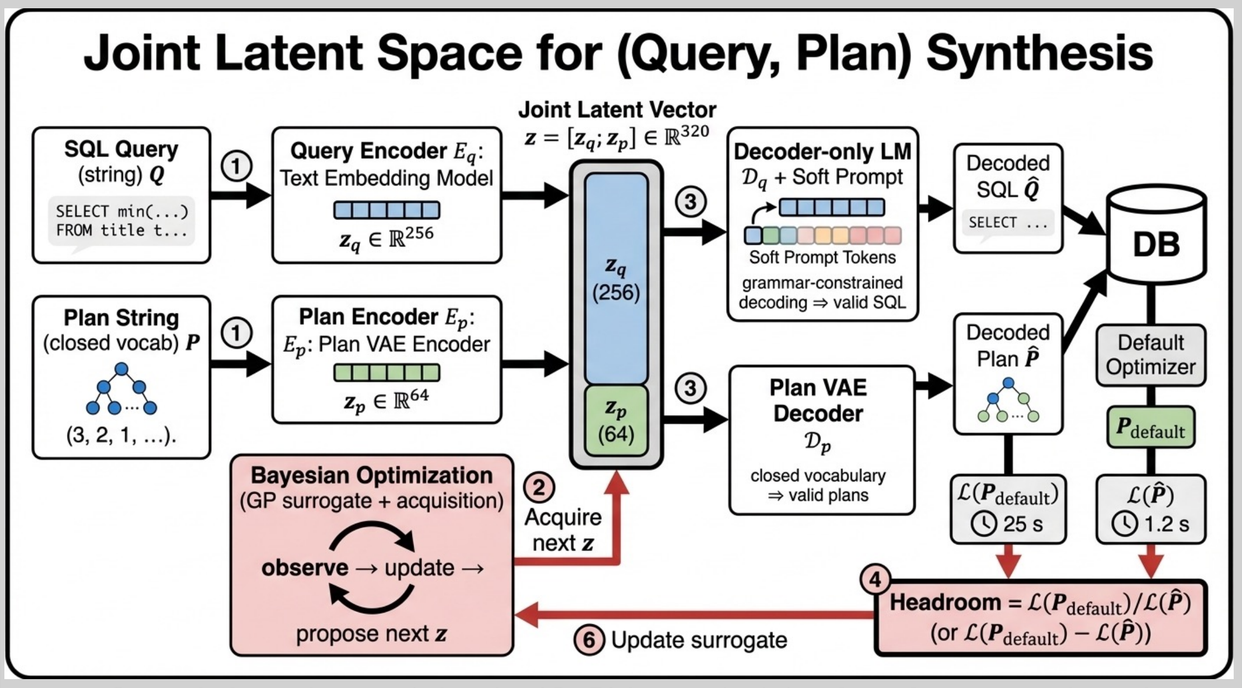
$$\max_{(Q,P)\in\mathcal{A}} \text{Headroom}(Q,P)$$

Maximize optimization headroom

$$\text{Relative}(Q,P) = \frac{L(P_{\text{default}})}{L(P)}$$
$$\text{Absolute}(Q,P) = L(P_{\text{default}}) - L(P)$$

Challenge: Optimizing over the space of all SQL queries and plans is hard

Joint Latent Space BO

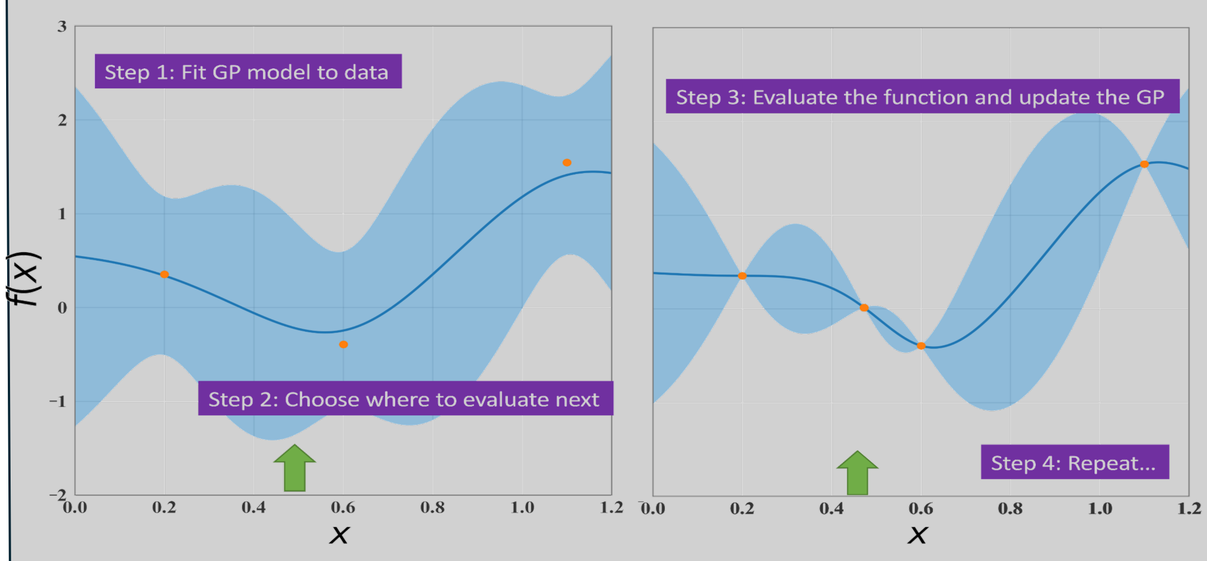


- Search for *adversarial pairs* (Q, P) by optimizing **headroom** against the DB's default plan
- Embed both query + plan into a **joint continuous latent** $z = [z_q; z_p]$ and run **Bayesian optimization** in z

Output is a benchmark entry: **decoded SQL** $\hat{Q}$ **+ witness plan** $\hat{P}$

Bayesian Optimization (BO)

BO: A model-based global optimization technique for black-box optimization.

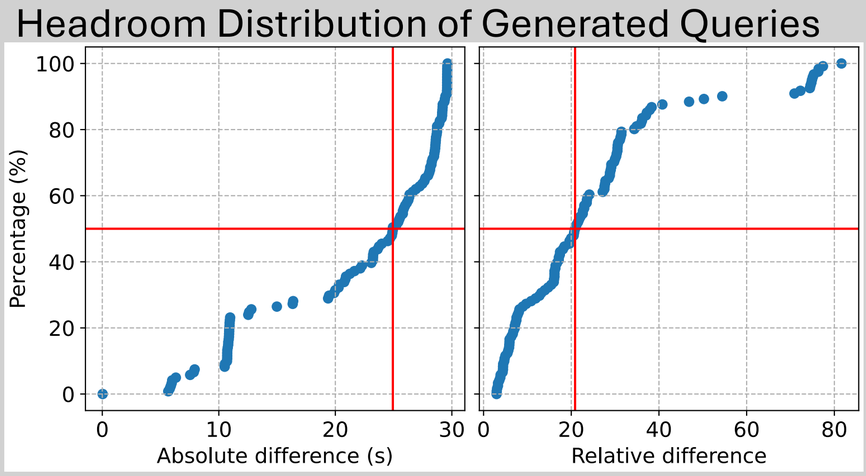


The literature supports: constraints, multi objective, diverse solutions, and more!

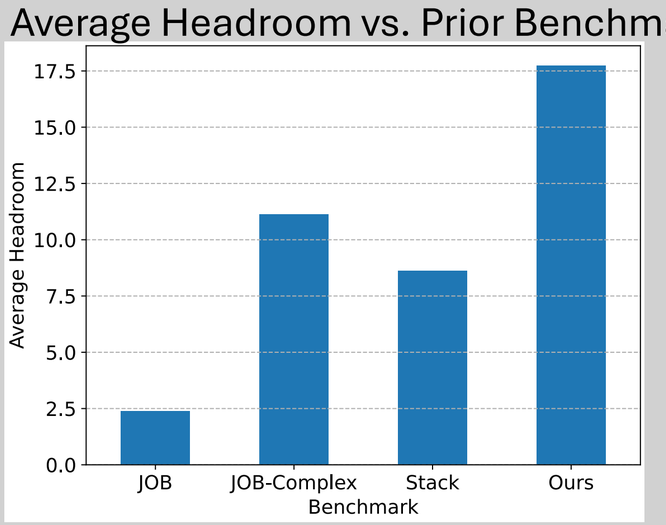
Historically: not very useful for high dimensional optimization, discrete/structured optimization, ...

Results

Headroom Distribution of Generated Queries

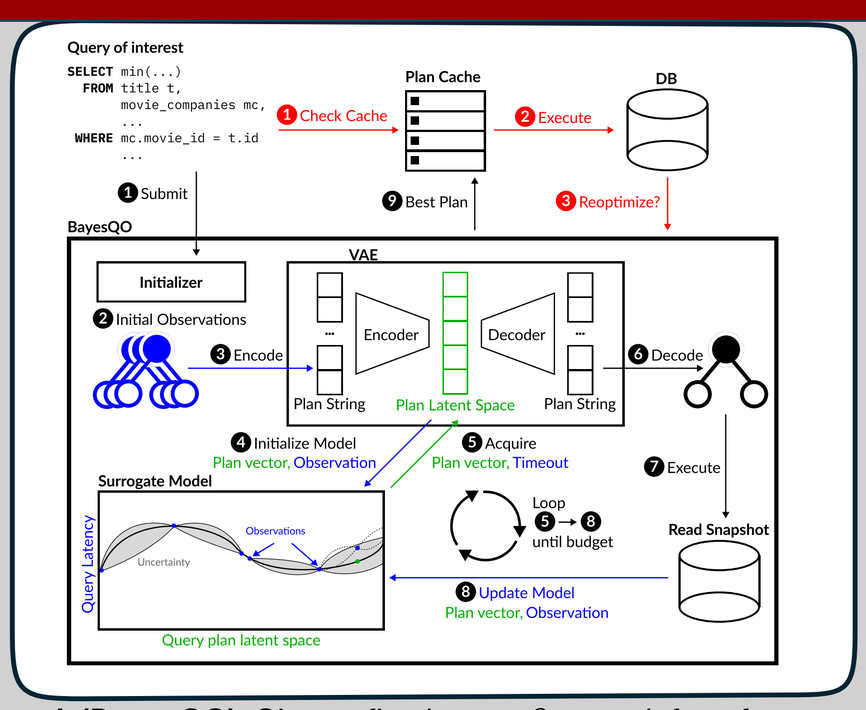


Average Headroom vs. Prior Benchmarks



- **Median** headroom is **~25s** absolute and **~20×** relative (red cross / lines).
- Tail queries are very hard: up to **~30s** absolute gap and **~80×** relative speedup.
- our synthesized queries provide **more optimization "room to improve"**
- Comparison uses reported values for JOB / JOB-Complex / Stack; "Ours" is computed w.r.t. our witness plans.

Query Optimization with BO



Prior work (BayesQO): Given a fixed query Q, search for a faster execution plan P under a limited execution budget.
Key idea: represent discrete plans in a continuous latent space (VAE) and run Bayesian optimization (GP + acquisition) to propose plans, execute, and update.

Difference: BayesQO optimizes plans for one query; we *synthesize (query, plan) pairs* to maximize headroom.

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