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Robust Contour Discovery for Plan Bouquets

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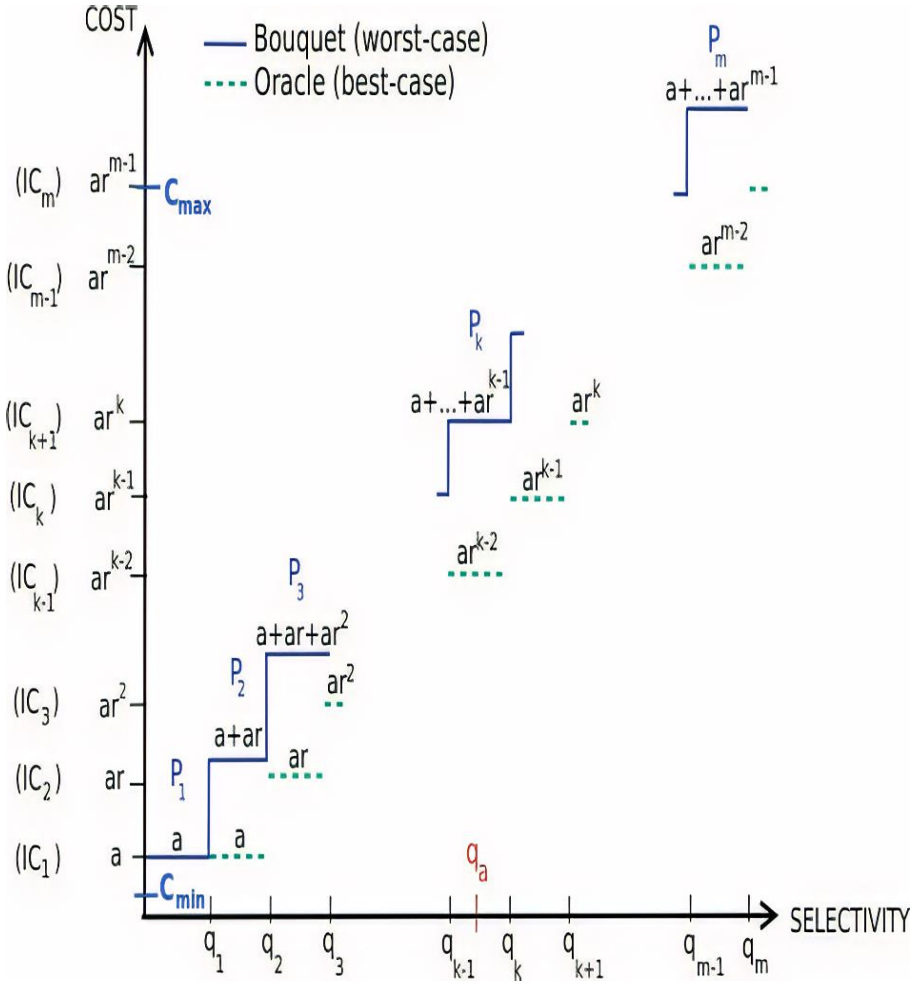
Introduction

- SQL queries are declarative in nature
- Many execution strategies for a SQL query are possible, each is called $query\ plan$
- Database optimizer selects the best plan for execution
- Plan choices are suboptimal, as they are based on selectivity estimation
- $Plan\ bouquets$ was proposed to provide worst case performance guarantees for OLAP queries

Plan Bouquets



$$C_{pb}(q_a) = CC_1 + CC_2 + \cdots + CC_k$$

$$= a * r_{pb}^0 + a * r_{pb}^1 + \cdots + a * r_{pb}^{k-1}$$

$$= \frac{a(r_{pb} - 1)}{r_{pb} - 1}$$

$$SubOpt(*, q_a) \leq \frac{a * \left(r_{pb}^k - 1\right) \Big/ \left(r_{pb} - 1\right)}{a * r_{pb}^{k-2}}$$

$$\leq \frac{r_{pb}^2}{r_{pb} - 1}$$

$$Using\ r_{pb} = 2, MSO = 4$$

Performance Metrics

- Suboptimality

$$Subopt(q_e, q_a) = \frac{Cost(P_{opt}(q_e), q_a)}{Cost(P_{opt}(q_a), q_a)} \qquad Subopt(*, q_a) = \frac{\sum_{exec \in BS} Budget(exec)}{Cost(P_{opt}(q_a), q_a)}$$

- Worst Suboptimality

$$Subopt_{worst}(q_a) = \max_{q_e \in ESS} Subopt(q_e, q_a)$$

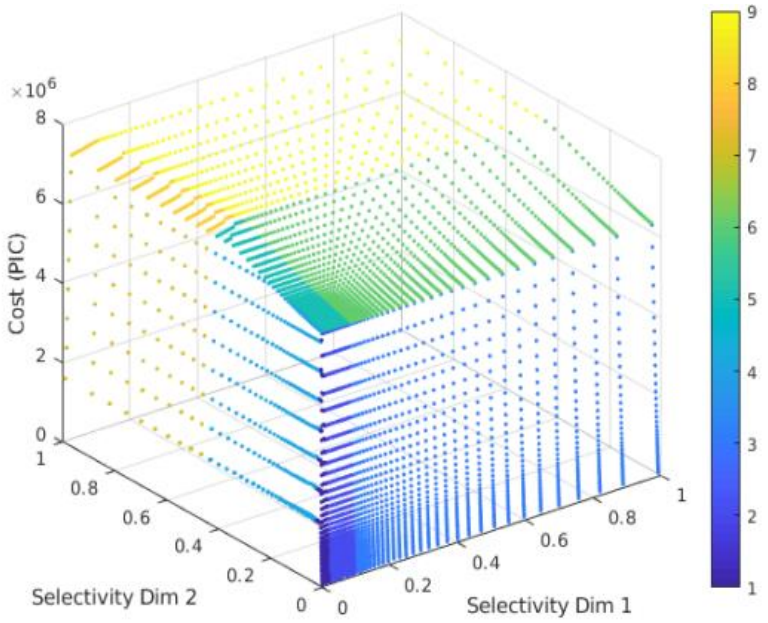
- Maximum Suboptimality (MSO)

$$MSO = \max_{q_a \in ESS} Subopt_{worst}(q_a) \qquad MSO = \max_{q_a \in ESS} Subopt(*, q_a)$$

Assumptions

- Plan Cost Monotonicity (PCM)
- Axis Parallel Concave (APC)
- Perfect Cost Model of Optimizer
- Bounded Cost Growth (BCG)
- Piece-wise Axis Parallel Linear (APL)
- Selectivity Independence

Linearity & BCG of OCS



(a) Exemplar piecewise linear OCS

For any PCF $\mathcal{F}_p$

$$\mathcal{F}_p(\alpha * q.j) \leq f(\alpha) * \mathcal{F}_p(q.j)$$

$$\forall j \in \{1, \ldots, D\}, \forall \alpha \geq 1$$

Common observation is

$$f(\alpha) = \alpha$$

(b) Definition of BCG

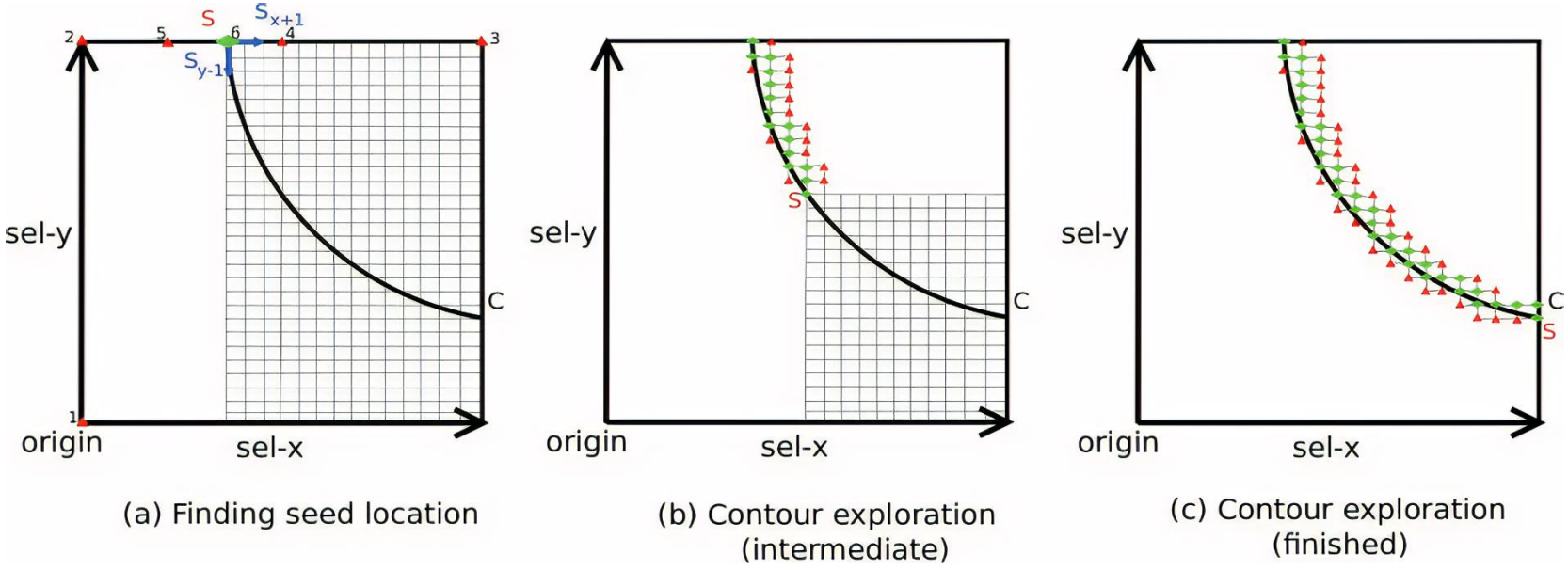
Note: APL and BCG behavior of Plan Cost Functions implies similar behavior of OCS

Bouquets Compilation

- Full Space Exploration
  - Do optimizer calls at all points, and take only feasible points, i.e. those whose cost lies in $[CC_i, CC_i(1+\alpha)]$
  - Total calls made are $\Theta(RES^{Dim})$
- NEXUS
  - Initial seed on one boundary is located
  - Neighboring points of seed are explored to create contours
  - Worst case calls made are $\Theta\left(m * Dim * RES^{Dim-1}\right)$
  - Speed-up guaranteed when $m * Dim < RES$

Understanding NEXUS

- Reduces optimizer calls by avoiding all points of ESS
- $n - dimensional$ version solved by multiple 2D exploration in recursive fashion



MSO_g on Cost Deviation

Let,

The total number of contours be k (IC_1, IC_k)

Cost of all contours except IC_{k-1} *is deviated by* $(1+\alpha)$

Cost Incurred due to Bouquet Sequence

$$BS_{cost} = CC_{k-1} + (1+\alpha) * (CC_k + \sum_{i=1}^{k-2} CC_i)$$

Best possible cost

$$OPT_{cost} = \lim_{h \to 0} (CC_{k-1} + h) = CC_{k-1}$$

$$MSO_g = \frac{BS_{cost}}{OPT_{cost}} = \frac{(1+\alpha) * \sum_{i=1}^{k} CC_i \; - \; \alpha * CC_{k-1}}{CC_{k-1}}$$

$$= (1+\alpha) * \frac{r_{pb}^2}{r_{pb}-1} - \alpha$$

$$\leq \frac{r_{pb}^2}{r_{pb}-1} * (1+\alpha) = \frac{r_{pb}^2}{r_{pb}-1} * \eta$$

Using $r_{pb} = 2$, *we will get* MSO_g

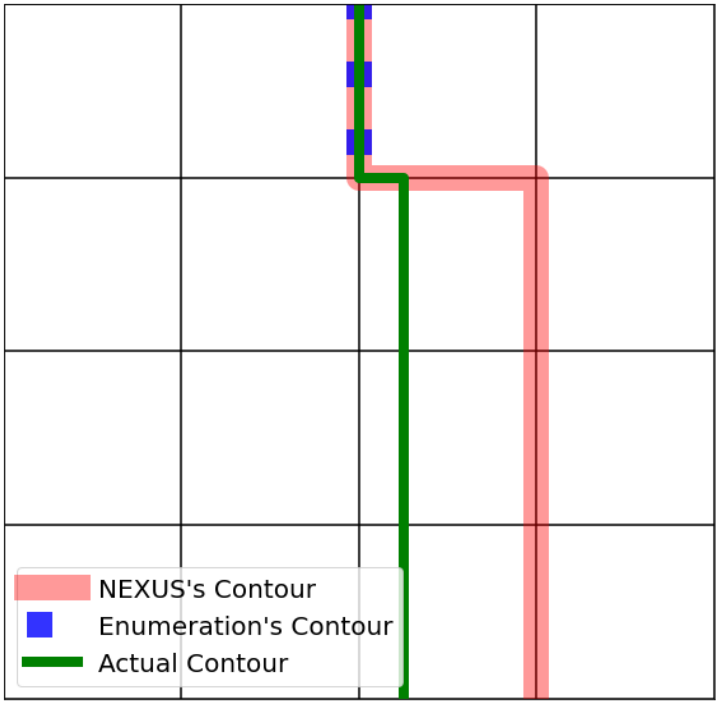
$$4 * (1+\alpha) = 4 * \eta$$

Cost Deviation (η) *should always respect*

$$1 \leq (1+\alpha) = \eta \ll r_{pb}$$

Cons of existing methods

- Discretization limits the search to finite number of points
- Cost deviated from ideal cost CC_i of contour IC_i
- May lead to slits in IC_i when used with the full space exploration



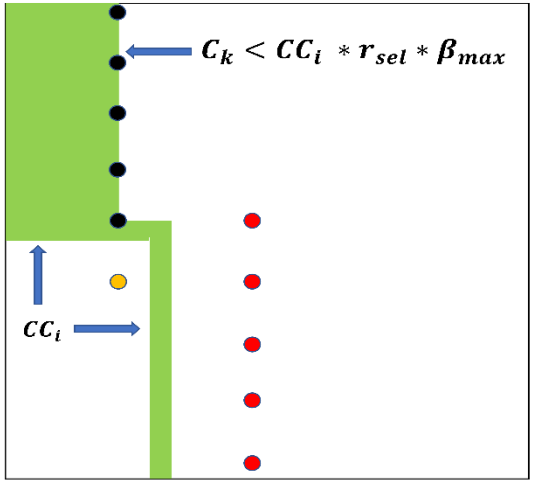
NEXUS Cost Deviation

Assume $\beta_{max} = 1$ in BCG assumption, r_{sel} is the ratio to discretize ESS, r_{cost} is cost ratio change per step in ESS

$$r_{cost} \leq r_{sel} \qquad r_{sel} = \left(\sqrt[(RES-1)]{\varepsilon}\right)^{-1}$$

Black points have cost C_k, where

$$C_k = \lim_{h \to 0^+} \left(\frac{CC_i * r_{sel}}{(1+h)}\right)$$



Yellow point have cost < CC_i, in that case Blind-search of NEXUS will choose a next red point now

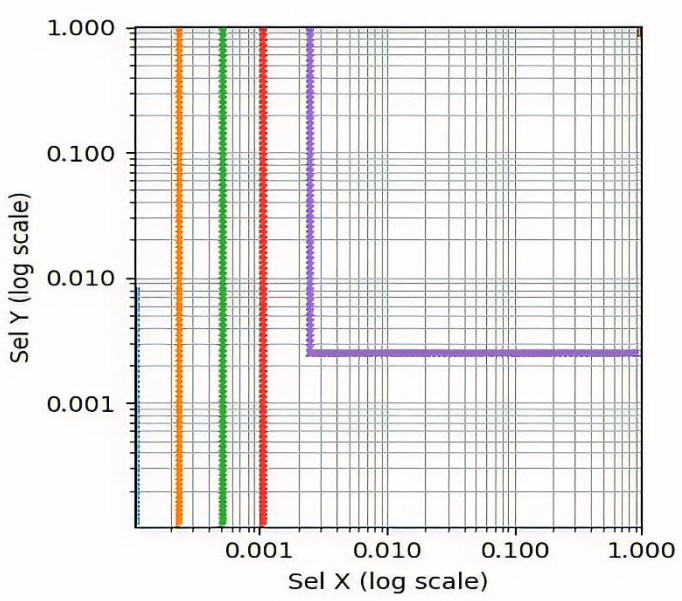
Cost of red point be C_r, where C_r due to BCG is

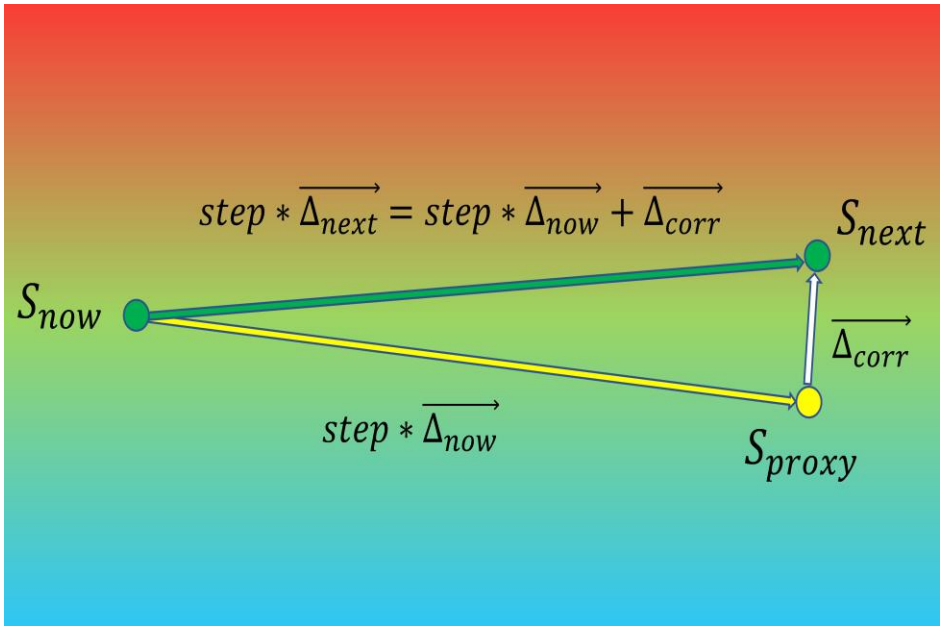
$$C_r \leq \lim_{h \to 0^+} \left(\frac{CC_i * r_{sel}}{(1+h)}\right) * r_{sel} \leq CC_i * r_{sel}^2 = CC_i * \eta$$

So, for NEXUS

$$\boldsymbol{\eta = r_{sel}^2}$$

AdaNEXUS





- Piece-wise linear contours are observed in practice
- Step sizes during contour discovery can be increased exponentially when the further points are in a desired cost interval
- When the next given direction is wrong, aggressive search finds it

AdaNEXUS

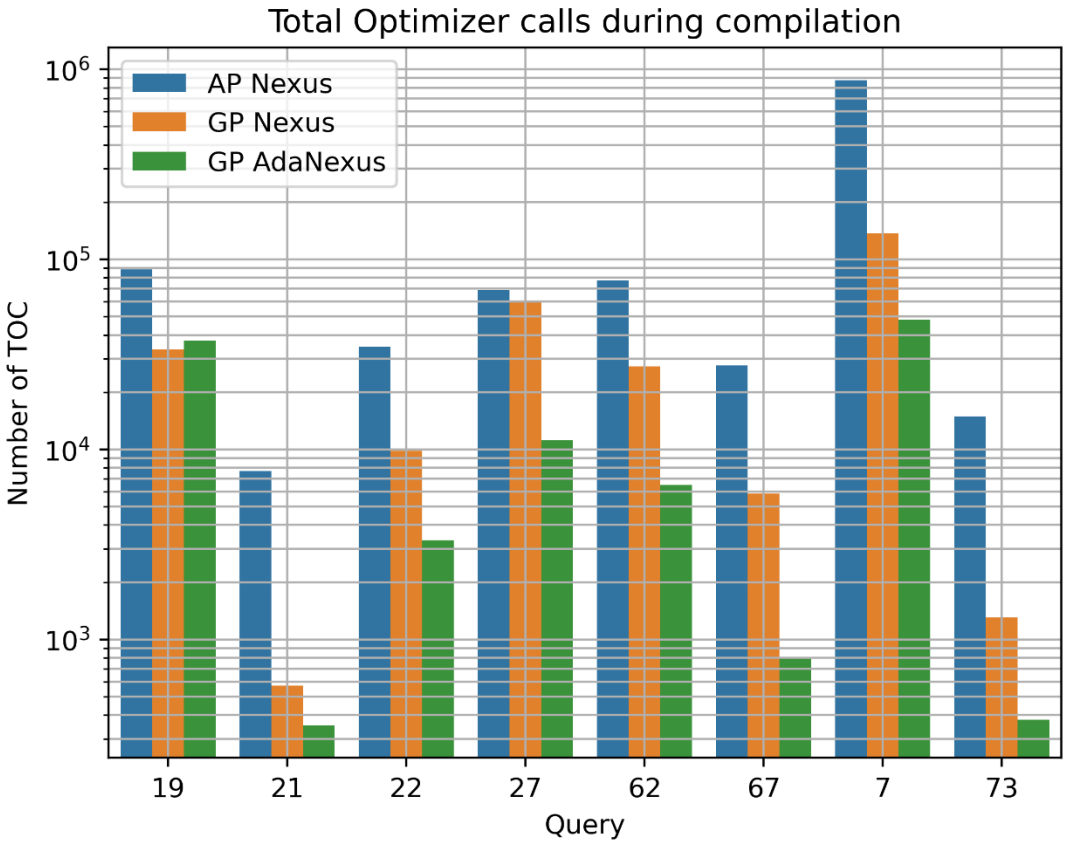
```
def bisectionEXP(left, right):
    P_L, P_R = P_opt(left), P_opt(right)
    if (left ≤ right) and (P_L != P_R):
        mid = (left+right) / 2
        P_M = P_opt(mid)
        if (P_L != P_M):
            bisectionEXP(left, mid)
        if (P_R != P_M):
            bisectionEXP(mid, right)
```

```
def AdaNEXUS(CC_i):
    S_now, P_now = InitializeSeed(CC_i)
    C_now = Cost(P_opt, S_now)
    step, Δ_now = 1, [0, −1]
    while (There exist next point):
        S_proxy = S_now + step * Δ_now
        C_proxy, P_proxy = Cost(P_opt, S_proxy)
        S_next, Δ_next = Correct(CC_i, C_proxy)
        C_next, P_next = Cost(P_opt, S_next)
        if (max(C_next/CC_i, CC_i/C_next) ≤ (1 + α)):
            Δ_now = TuneDir(Δ_now, Δ_next, step)
            bisectionEXP(S_now, S_next)
            S_now, step = S_next, 2 * step
        else:
            if step > 1:
                step = step / 2
            else:
                Δ_now = Rotate(S_now, CC_i)
```

Experiments

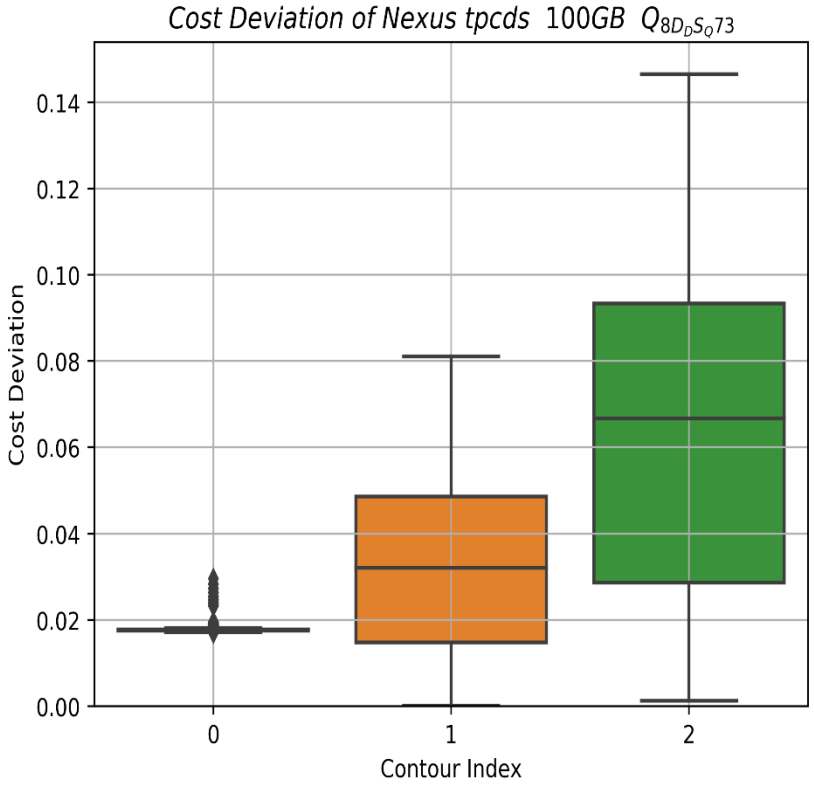
- Database Environment
  - Evaluation on 8 TPC-DS SQL queries
  - Dimension of ESS from 3 to 5
  - DB instances in range of 1GB to 250GB via CODD
  - FPC module is used for Foreign Plan Costing
- System Environment
  - DB engine is modified version of Postgres-9.4
  - Intel© Core™ i9 CPU, 32GB 2666MHz RAM, 2TB Storage

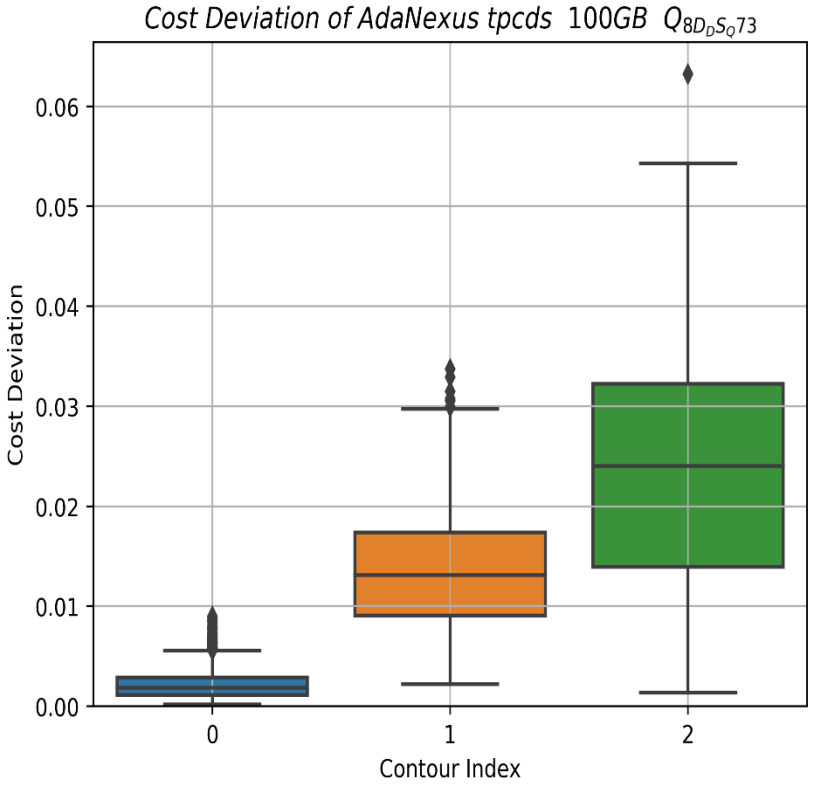
Lesser Optimizer Calls



Reduced Cost Deviation

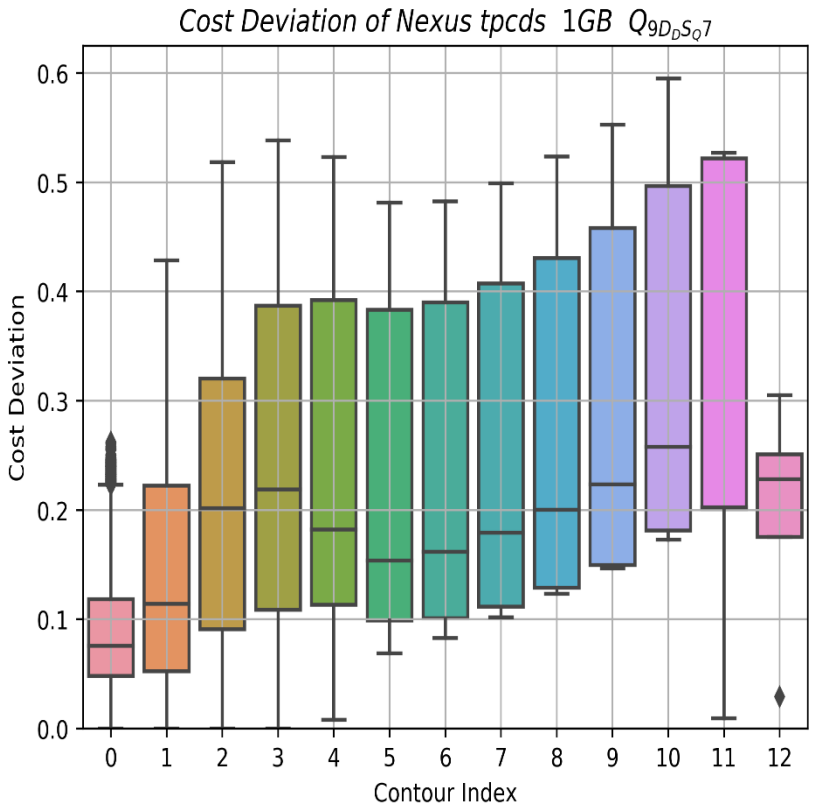
Query 73, 100GB instance

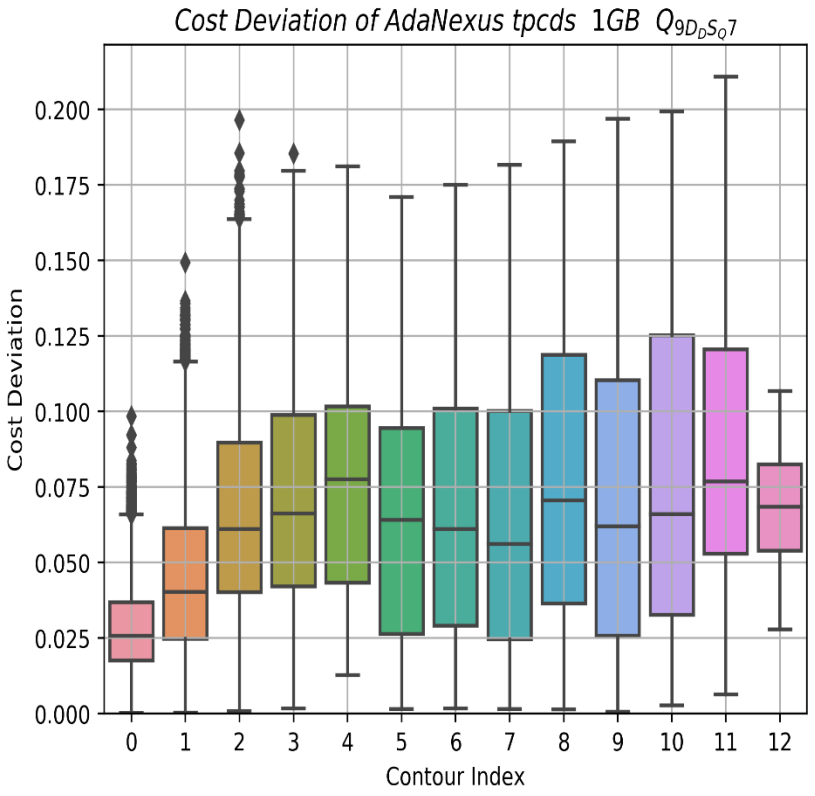




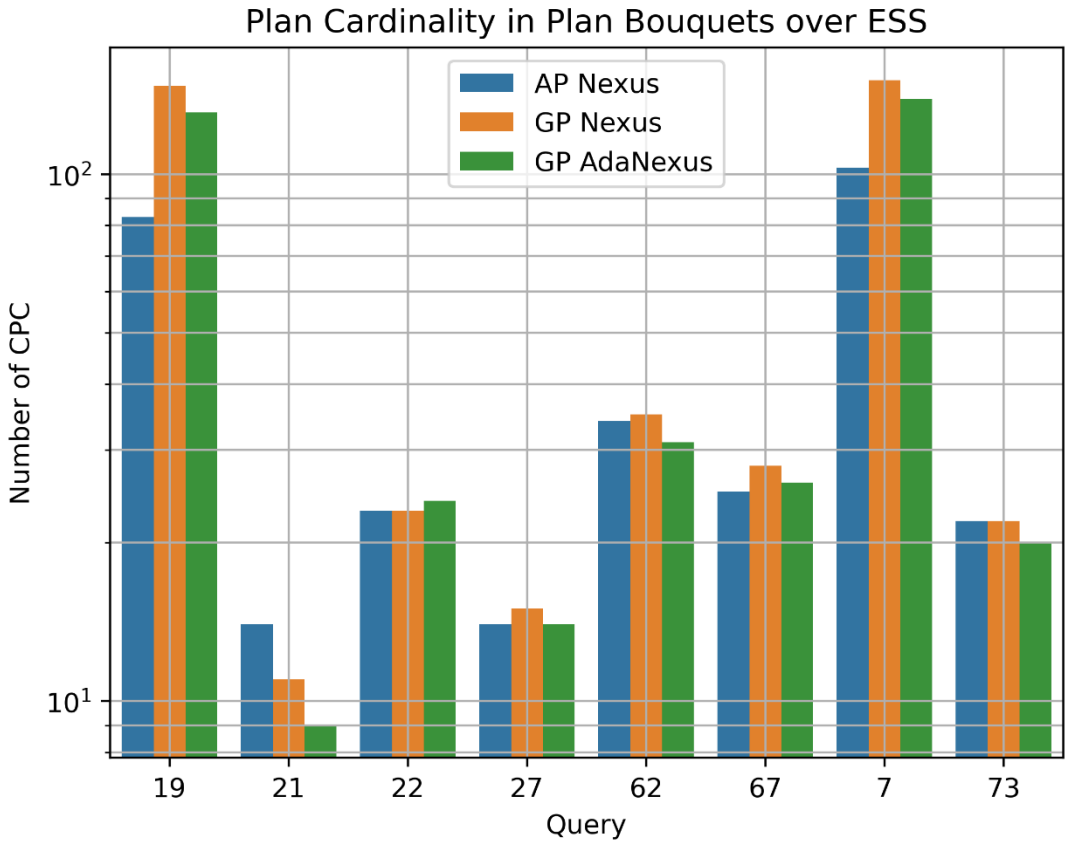
Reduced Cost Deviation

Query 7, 1GB instance





Plan Cardinalities



Conclusion & Future Work

- Discretization of ESS is now removed in AdaNEXUS.
- Exponentially varying step size leads to bounded cost deviation.
- Speed up in contour discovery is obtained (with lesser cost deviation) by using slope information of piece-wise linear contours

- Adjacent sub-problems can share information for further speed-up for constructing a contour.
- Direction of contour discovery can be tuned using a full learnable PID controller or any (robust and interpretable) machine learning model.

Thank You!