Robust Contour Discovery for Plan Bouquets

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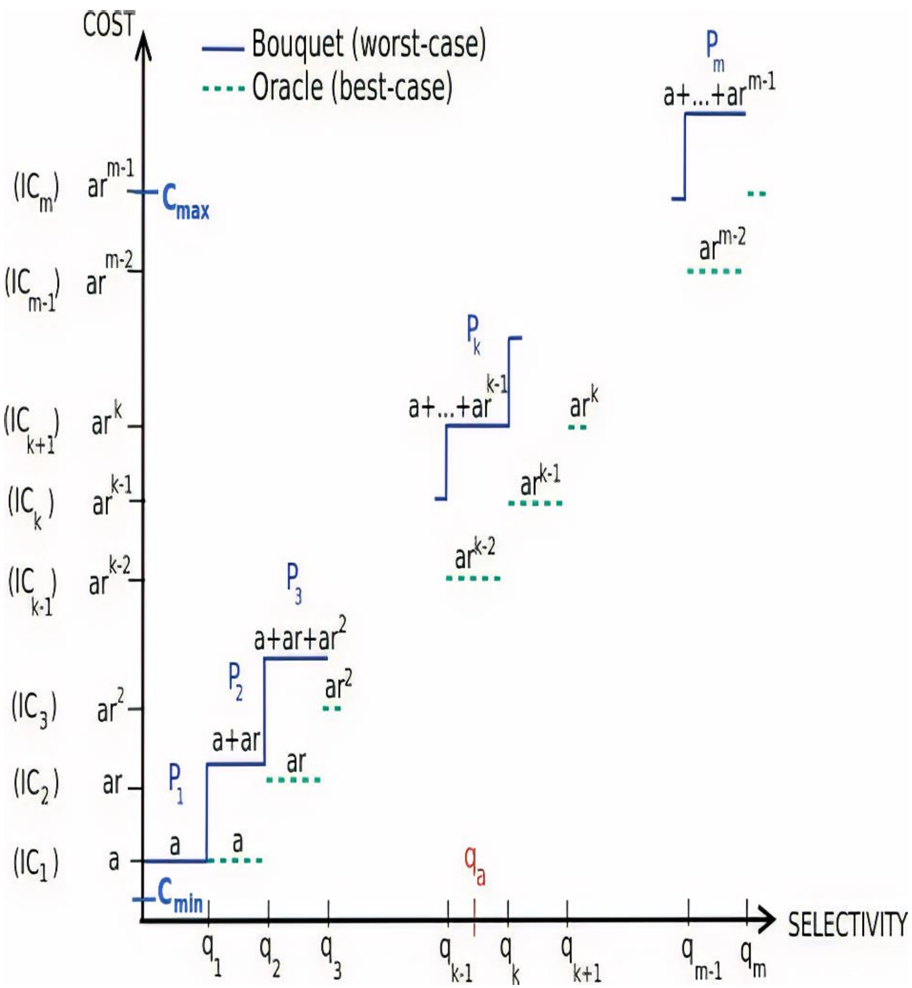
Introduction

- SQL queries are declarative in nature
- Many execution strategies for a SQL query are possible, each is called $query\ plan$
- Database optimizer select a 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



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

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

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

$$SubOpt(*, q_a)$$

$$\leq \frac{a * (r_{pb}^k - 1) \Big/ (r_{pb} - 1)}{a * r_{pb}^{k-2}}$$

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

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

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

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

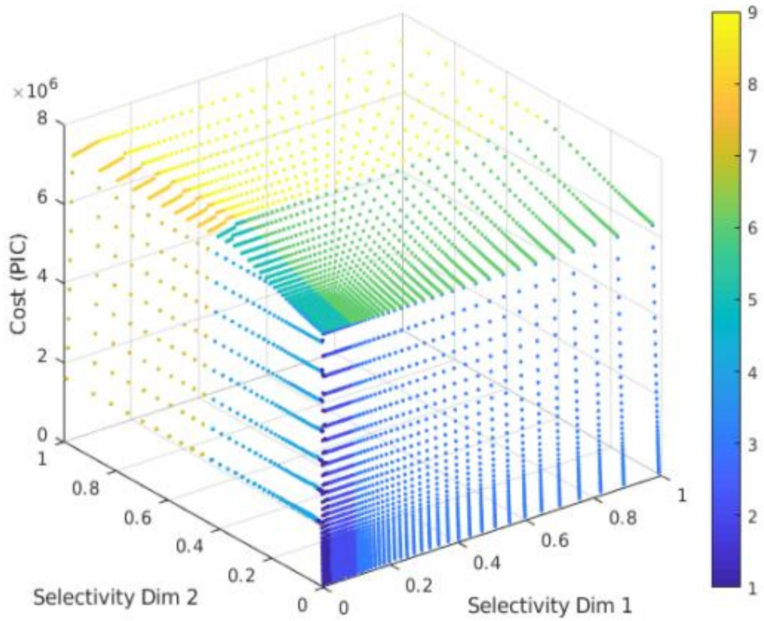
- Maximum Suboptimality (MSO)

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

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



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

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

(a) Exemplar piecewise linear OCS

(b) Definition of BCG

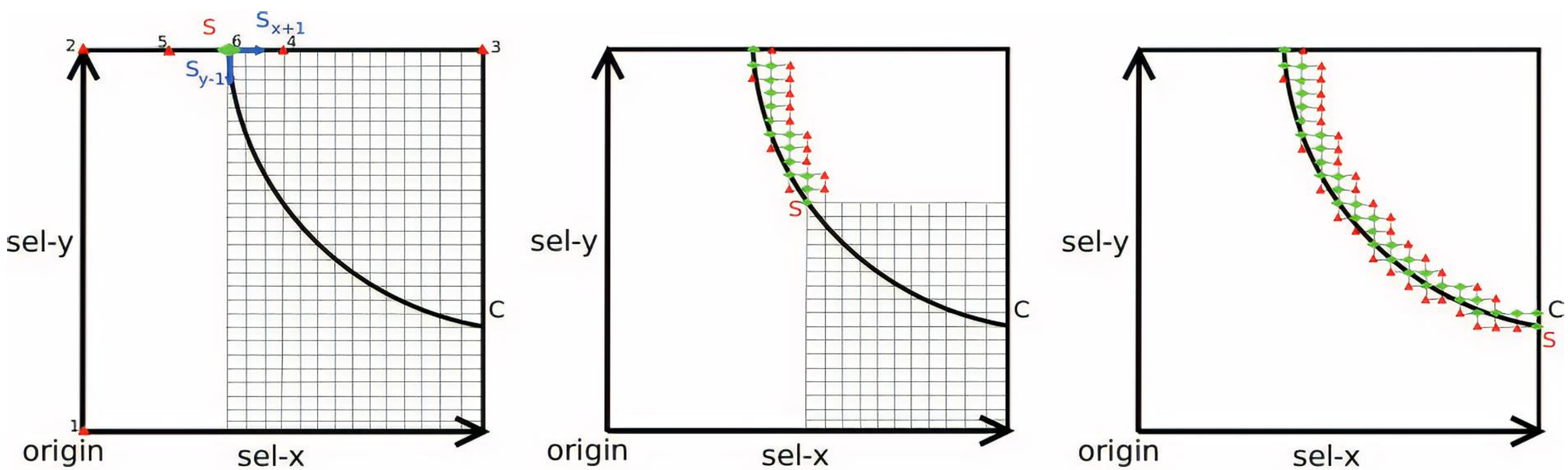
Note: APL and BCG behavior of Plan Cost Functions implies similar behavior of OCS

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 $\Theta(m * Dim * RES^{Dim-1})$
  - 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



(a) Finding seed location (b) Contour exploration (intermediate) (c) Contour exploration (finished)

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

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

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

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

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

$Using\ r_{pb} = 4, we\ will\ get\ MSO_g$

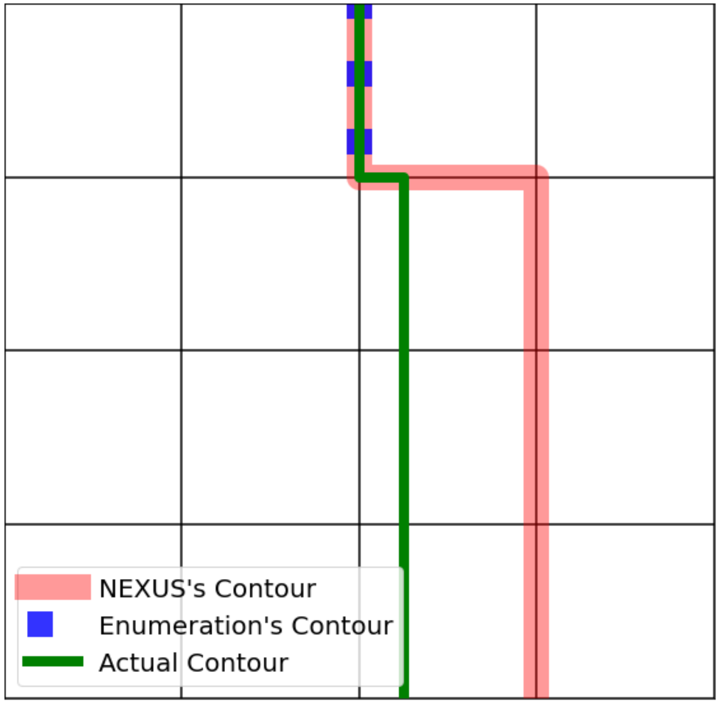
$$4 * (1+\alpha) = 4 * \eta$$

$Cost\ Deviation\ (\eta)\ should\ always\ respect$

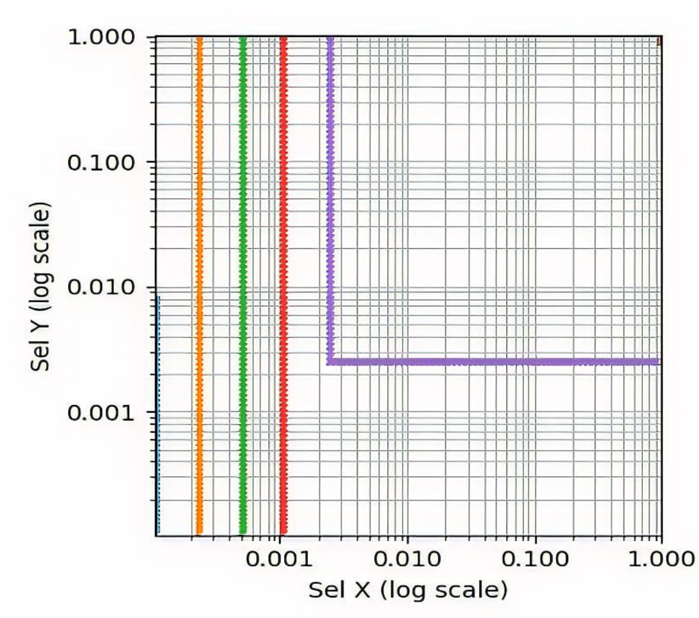
$$1 \leq (1+\alpha) = \eta \ll r_{pb}$$

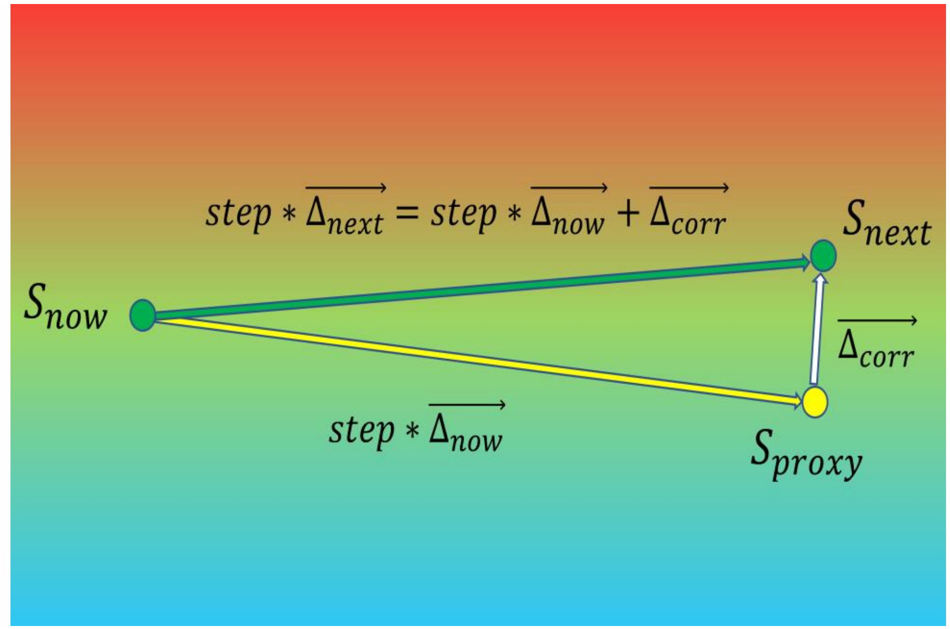
Cons of existing methods

- 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



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)
```

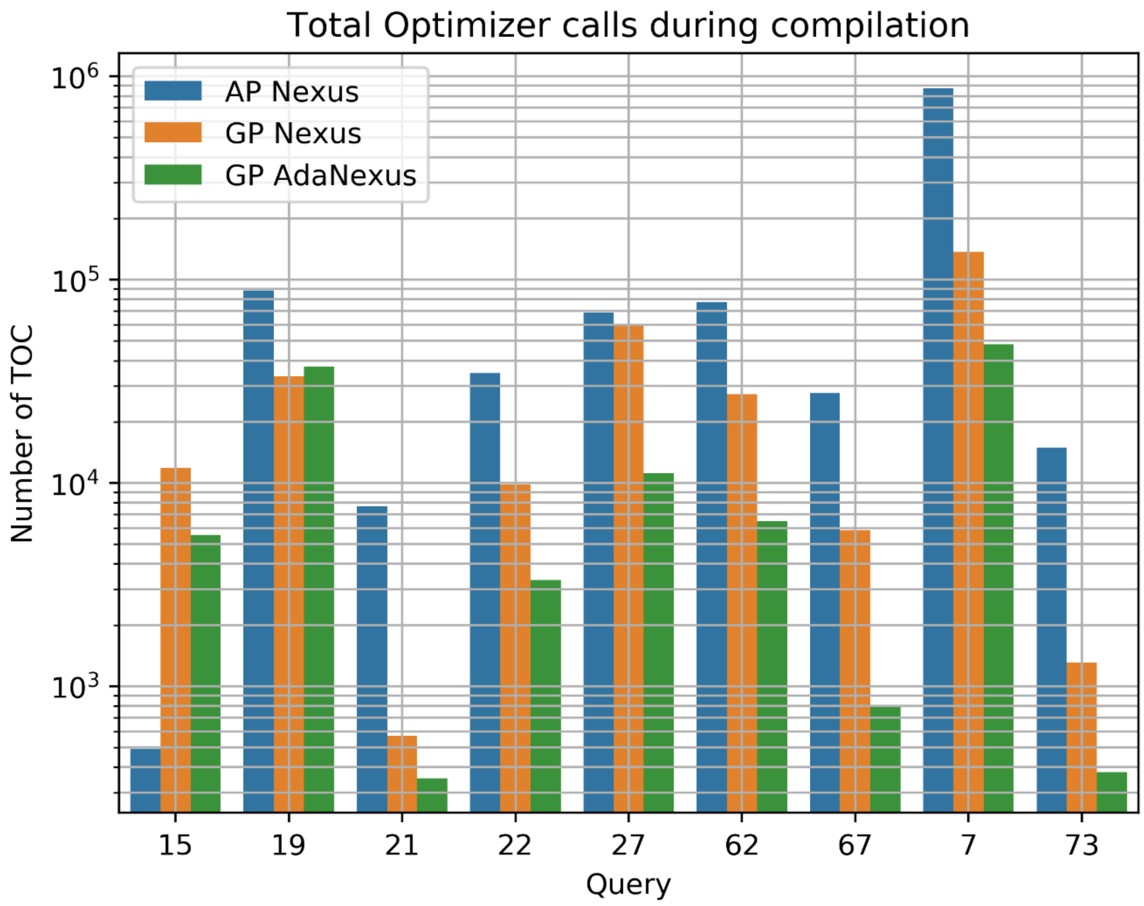
$$\begin{array}{l}
\text{def } bisectionEXP(left, right): \\
\quad P_L, P_R = P_{opt}(left), P_{opt}(right) \\
\quad if\ (left \leq right)\ and\ (P_L\ != P_R): \\
\quad\quad mid = \frac{left+right}{2} \\
\quad\quad P_M = P_{opt}(mid) \\
\quad\quad if\ (P_L != P_M): \\
\quad\quad\quad bisectionEXP(left,\ mid) \\
\quad\quad if\ (P_R != P_M): \\
\quad\quad\quad bisectionEXP(mid,\ right)
\end{array}$$

$$\begin{array}{l}
\text{def } AdaNEXUS(CC_i): \\
\quad S_{now},\ P_{now} = InitializeSeed(CC_i) \\
\quad C_{now} = Cost(P_{opt}, S_{now}) \\
\quad step,\ \Delta_{now} = 1,\ [-1, 0] \\
\quad while\ (There\ exist\ next\ point): \\
\quad\quad S_{proxy} = S_{now} + step * \Delta_{now} \\
\quad\quad C_{proxy}, P_{proxy} = Cost(P_{opt}, S_{proxy}) \\
\quad\quad S_{next}, \Delta_{next} = Correct(CC_i, C_{proxy}) \\
\quad\quad C_{next}, P_{next} = Cost(P_{opt}, S_{next}) \\
\quad\quad if\ \left(\max\left(\frac{C_{next}}{CC_i}, \frac{CC_i}{C_{next}}\right) \leq (1+\alpha)\right): \\
\quad\quad\quad \Delta_{now} = TuneDir(\Delta_{now}, \Delta_{next}, step) \\
\quad\quad\quad bisectionEXP(S_{now},\ S_{next}) \\
\quad\quad\quad S_{now}, step = S_{next}, 2 * step \\
\quad\quad else: \\
\quad\quad\quad if\ step > 1: \\
\quad\quad\quad\quad step = step\ /\ 2 \\
\quad\quad\quad else: \\
\quad\quad\quad\quad \Delta_{now} = Rotate(S_{now}, CC_i)
\end{array}$$

Experiments

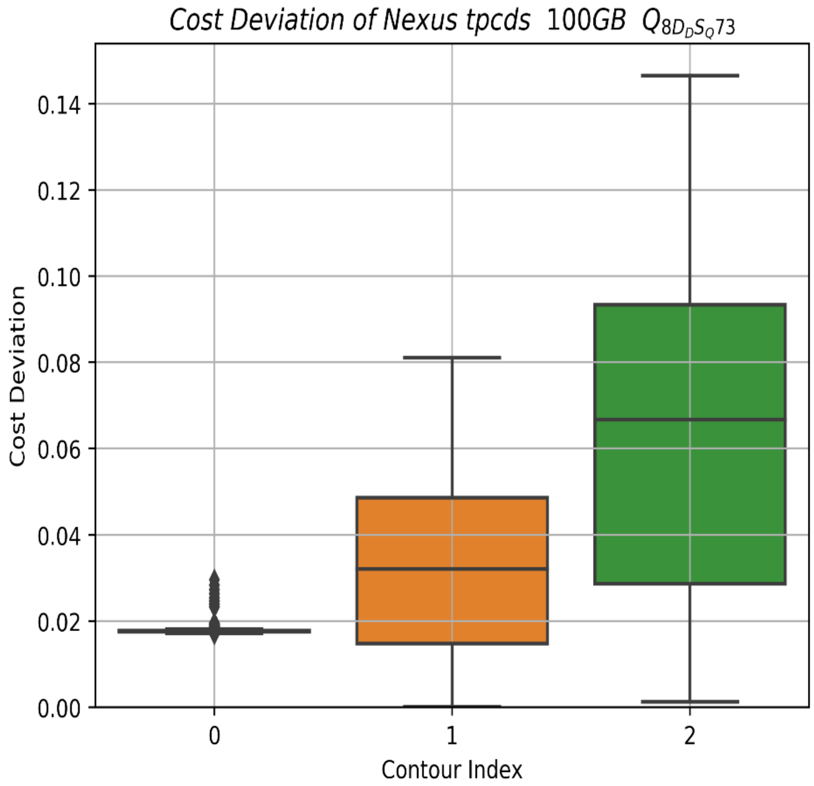
- Database Environment
  - Evaluation on 8 TPC-DS SQL queries
  - Dimension of ESS from 3 to 5
  - DB instances in range of 1GB to 250GB via CODD
  - FPC module is used for Foreign Plan Costing
- System Environment
  - DB engine is modified version of Postgres-9.4
  - Intel© Core™ i9 CPU, 32GB 2666MHz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

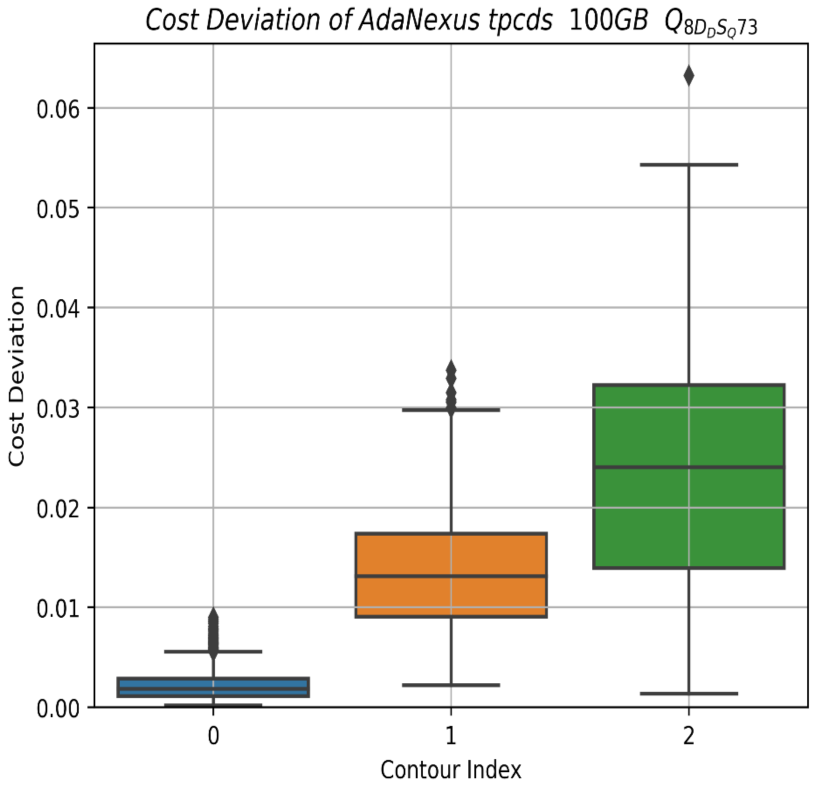
Lesser Optimizer Calls



Reduced Cost Deviation

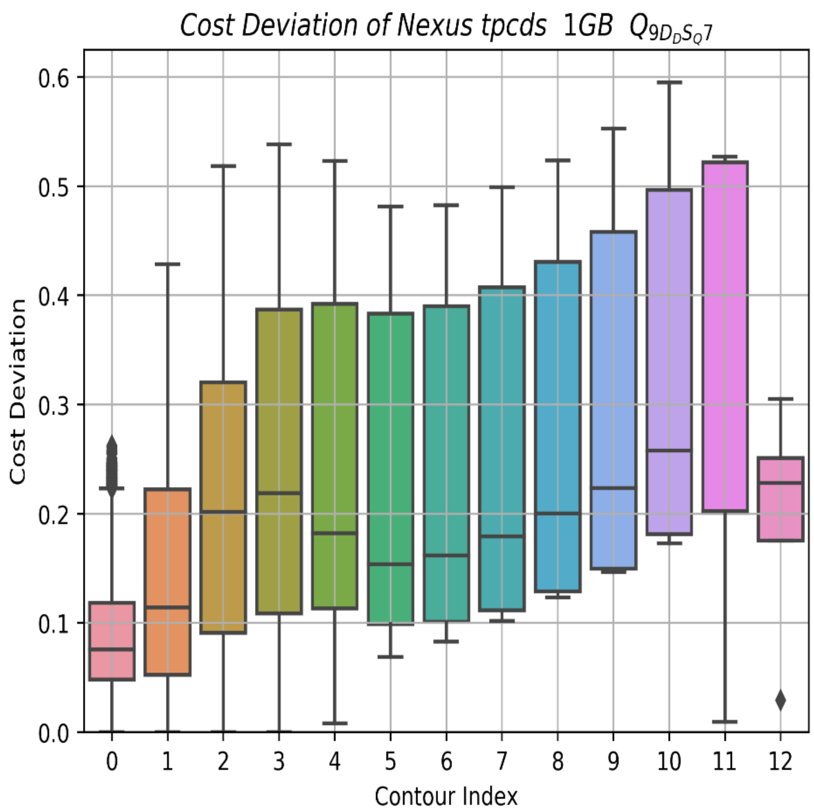
Query 73 100GB instance

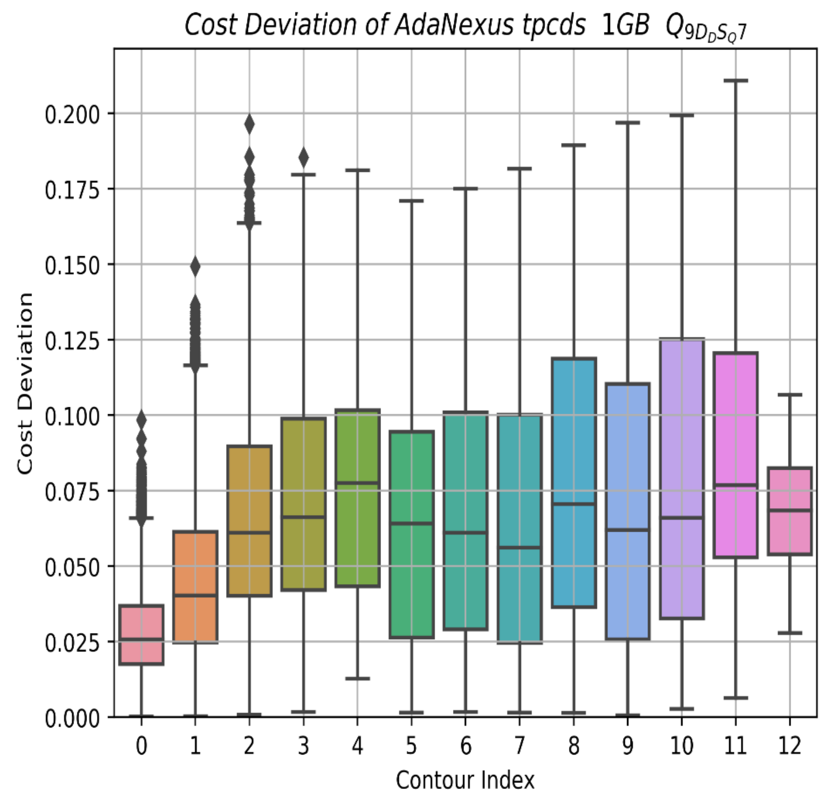




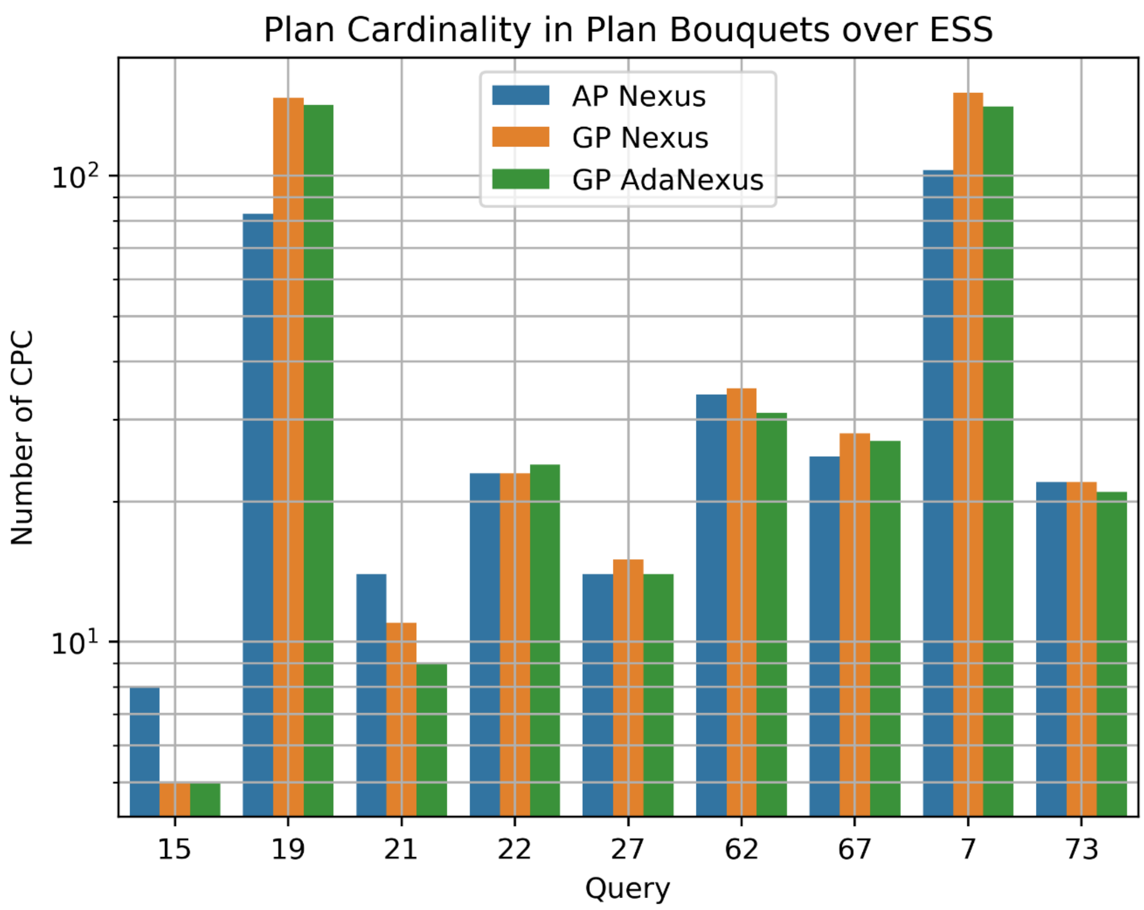
Reduced Cost Deviation

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!