Statistical Learning Techniques for Costing XML Queries

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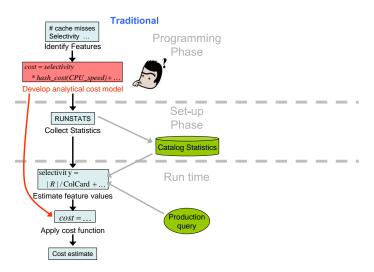
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VLDB 2005

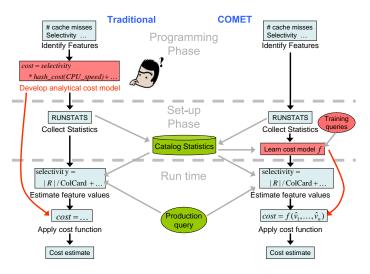


COMET: A New Cost-Modeling Approach





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Advantages of COMET Approach

Can handle complex operators using statistical learning

- Operators not decomposable into simple scans, joins, etc.
- Operators with highly non-sequential data access patterns
- Used successfully to cost UDFs, remote DB systems (Lee et al. 2004, He et al. 2004, Rahal et al. 2004)



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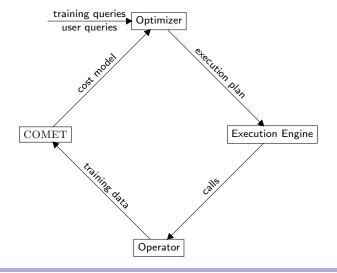
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Simplifies cost-model development

- Reduces need for painstaking code analysis used in analytical modeling
- Easier to incorporate new operators into optimizer
- Helps avoid brittle simplifying assumptions
- Avoids need to explicitly incorporate HW parameters



COMET Permits Optimizer to be Self Tuning



Our Motivation: XML Query Optimization

```
Query q_1:
<bib>
Ł
  for $b in
    doc("bib.xml")/bib/book
  where
   $b/authors//last = "Stevens"
   and $b/@year > 1991
  return
    <book>
      { $b/title }
    </book>
}
</bib>
```

Need to cost candidate execution plans:

- 1. Navigational plan:
 - navigate the bib.xml tree
 - check pred's for each book

2. Value-based index plan:

- find elements with "Stevens" or "1991" using value-based index
- navigate up to **book** and check remaining conditions
- 3. Structure-based index plan:
 - look up matching tree structures using a path/twig index
 - check pred's for each book



Today's Talk: Application of COMET Approach to an XML Operator

XML operator to be modeled:

- XNAV operator (complex and dynamic, so hard to model)
- Adaptation of TurboXPath (Josifovski et al. 2005)
- Will model CPU costs (nontrivial component of overall cost)
 - prior work has focused primarily on cardinality estimation



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Nontrivial steps in applying COMET methodology:

- Step 1: Identify XNAV features
- Step 2: Determine statistics for estimating feature values
- Step 3: Determine formulas for feature-value estimation
- Step 4: Identify appropriate statistical learning algorithm for fitting cost model



XNAV: A Complex XML Navigational Operator

What is XNAV?

- XNAV_{XPath}(XMLTrees) → list of matching XML nodes
- XNAV is complex:
 - equivalent to non-decomposable N-way join
 - data stored as paged tree

High-level description of XNAV algorithm:

- XNAV traverses the XML tree in a single pass, with possible skipping of nodes
- XNAV maintains internal states and buffers for matching the query tree during the traversal



Step 1: Identifying XNAV Features

Basis for feature identification

- Knowledge of XNAV algorithm (involves human interaction)
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Some features for XNAV:

- #visits : # of XML nodes actually traversed
- **#p_requests** : **#** of pages read
- ... more features given in the paper



Step 2: Novel Statistics for Estimating Features

How to choose statistics ?

- "As simple as possible, but not simpler"
 - Easy to collect and maintain, less error-prone
- Need to balance space and time requirements
 - Storing redundant stats can speed up feature-value estimation



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Example — Simple Path (SP) Statistics

- cardinality: |p|, where p is a "simple" path (no branching, no wildcards, etc.)
- children and descendant cardinality: |p/*| and |p//*|
- page cardinality: ||p||
- ... more in the paper

Step 3: Feature-Value Estimation Using Stats

Can estimate all needed feature values using SP stats

- Analysis required, but much easier than analyzing entire XNAV operator
- See paper for detailed formulas (algorithms)
- Formulas tend to overestimate feature values, but COMET automatically compensates for bias (see below)



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Example

• **#visits** =
$$\sum_{p \in S} |p/*| + \sum_{q \in C} |q//*|$$

where S is a set of root-to-non-leaf simple path in the query tree whose next step is connected by a /-axis; C is a set of root-to-non-leaf simple path in the query tree whose next step is connected by a //-axis

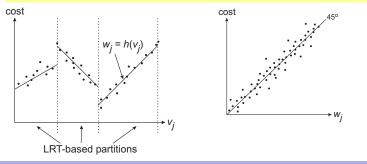


Step 4: Fitting The Cost Model

Use Transform Regression (Pednault 2004)

- "Linear regression on steroids"
- Handles discontinuities and nonlinearities in cost function
- Fully automated (no statistician needed) and highly efficient
- Seamlessly handles both numerical and categorical features

Uses 1-level linear regression tree to "linearize" each feature



Uses multivariate linear regression on linearized features

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Uses "gradient boosting" to capture feature interactions

- First-order model: models the cost
- *i*th-order model: models the error in (i 1)st-order model



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Model learned from estimated feature values

• So COMET is robust to systematic bias in feature-value estimation



Experimental Study

Training data and queries:

- Synthetic and real-world data sets (Including TPC-H, XMark, NASA, and XBench)
- Randomly generated queries:
 - Simple linear paths (e.g., /a/b/c)
 - Branching paths (e.g., /a[b][c]/d)
 - Complex paths (e.g., /a[.//b][c//d]//e)



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Model evaluation:

- Use 5-fold cross-validation
- Plot predicted vs. actual costs
- Calculate accuracy measurements

Evaluating COMET's Accuracy

Error metrics:

• NRMSE (Normalized Root-Mean-Squared Error): measures the average (relative) prediction error

NRMSE =
$$\frac{1}{\overline{c}} \left(\frac{1}{n} \sum_{i=1}^{n} (c_i - \hat{c}_i)^2 \right)^{1/2}$$

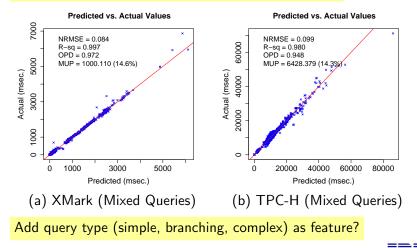
where c_i and \hat{c}_i are the actual and estimated costs for *i*th query, and $\bar{c} = \operatorname{average}(c_1, c_2, \ldots, c_n)$

• Other metrics discussed in paper: R², OPD, MUP



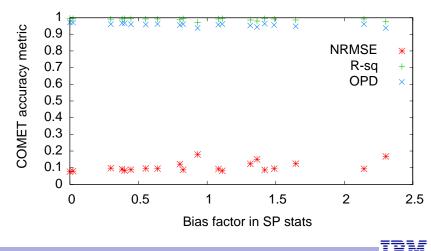
Accuracy of COMET

COMET does decent-to-excellent job in most cases:



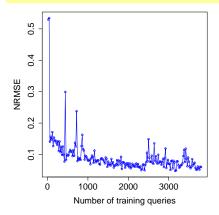
Effect of Errors in SP Statistics

COMET is not sensitive to systematic errors in SP stats:



Effect of Training-set Size

Training-set is of reasonable size for reasonable accuracy:



Model build time for 1000 training queries: < 1 second



Conclusion

Summary

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- COMET can accurately model XNAV cost
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Future Work

- Automatic identification of features
- Smarter generation of training queries
- Extensions to handle I/O costs, multi-user environments (will identify appropriate features)
- Incorporation of selectivity-estimation technology
- Improve dynamic model maintenance (incremental model building)
- Apply to other operators (XML, relational, text)

