Statistical Learning Techniques for Costing XML Queries

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COMET: A New Cost-Modeling Approach

Identify Features

Cost estimate:
\[
cost = selectivity \times hash\_cost(CPU\_speed) + \ldots
\]

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Traditional

Programming Phase

Set-up Phase

Run time

Catalog Statistics

RUNSTATS

Collect Statistics

Estimate feature values

Apply cost function

Cost estimate
COMET: A New Cost-Modeling Approach

Traditional

Identify Features

# cache misses
Selectivity ...

Develop analytical cost model

RUNSTATS
Collect Statistics

Estimate feature values

selectivity = |R| / ColCard + ...

Apply cost function

Cost estimate

Catalog Statistics

Set-up Phase

COMET

Identify Features

# cache misses
Selectivity ...

Learn cost model \( f \)

RUNSTATS
Collect Statistics

Estimate feature values

selectivity = |R| / ColCard + ...

Apply cost function

Cost estimate

Training queries

Production query

Run time

1. \( \hat{\text{cost}} = \text{selectivity} \times \text{hash_cost}(\text{CPU\_speed}) + \ldots \)
2. Cost estimate
3. \( \text{selectivity} = |R| / \text{ColCard} + \ldots \)
4. Cost estimate

Ning Zhang
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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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 $q_1$:

```xml
<bib>
{
  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?

• $XNAV_{XPath}(XMLTrees) \rightarrow$ 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)
- Trial and error experimentation (with cross-validation)
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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

Example — Simple Path (SP) Statistics

- \(|p|\) where \(p\) is a “simple” path (no branching, no wildcards, etc.)
- \(|p/\ast|\) and \(|p//\ast|\)
- Page cardinality: \(\|p\|\)
- ... more in the paper
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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/\ast| + \sum_{q \in C} |q//\ast|

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
Step 4: Transform Regression—Continued

Uses multivariate linear regression on linearized features

- Greedy forward stepwise-regression
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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

Model learned from estimated feature values

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

  \[
  \text{NRMSE} = \frac{1}{\bar{c}} \left( \frac{1}{n} \sum_{i=1}^{n} (c_i - \hat{c}_i)^2 \right)^{1/2}
  \]

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

- Other metrics discussed in paper: \(R^2, \text{OPD, MUP}\)
Accuracy of COMET

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

(a) XMark (Mixed Queries)  
(b) TPC-H (Mixed Queries)

Add query type (simple, branching, complex) as feature?
Effect of Errors in SP Statistics

COMET is not sensitive to systematic errors in SP stats:

![Graph showing the relationship between bias factor in SP stats and COMET accuracy metric. The graph indicates that COMET is not sensitive to systematic errors in SP stats.](image-url)
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

• Statistical learning increasingly needed as data and its management become increasingly complicated
• COMET can accurately model XNAV cost
• COMET cost model is fast to construct and adaptable to changing environment
• A promising approach for costing complex query operators

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
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