AutoSys: The Design and Operation of Learning-Augmented Systems

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Microsoft Research, Peking University, USTC, Bing Platform, Bing Ads
Learning-Augmented Systems

• Systems whose design methodology or control logic is at the intersection of traditional heuristics and machine learning
  - Not a stranger to academic communities: “Workshop on ML for Systems”, “MLSys Conference”, ...

• This work reports our years of experience in designing and operating learning-augmented systems in production
  1. AutoSys framework
  2. Long-term operation lessons
Our Scope in This Paper:
Auto-tuning System Config Parameters

- The problem is simple...
  - A great application of black-box optimization
  - Find the configuration that best optimizes the performance counters
Our Scope in This Paper: Auto-tuning System Config Parameters

• *But,* the problem is very difficult for system operators in practice...
  • Vast system-specific parameter search space
  • Continual optimization based on system-specific triggers
Our Scope in This Paper: Bing Web Search

Selection Service
- Selection engines
  - Keyword-based
  - Semantics-based
- Inverted index
- Vectorized index

Ranking Service
- Ranking engines
  - ML/DL Models
- Per-document forward index

Re-ranking Service
- Re-ranking engines
- KV cluster
- Key-value store engines
  - RocksDB
  - MLFT

Search query → Search results
Our Scope in This Paper: Bing Web Search

Auto-tuning Selection engines to optimally select relevant documents
Our Scope in This Paper: Bing Web Search

Auto-tuning Ranking models to optimally rank documents
Our Scope in This Paper: Bing Web Search

**Selection Service**
- Server
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  - Keyword-based
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**Ranking Service**
- Server
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**Re-ranking Service**
- Server

- RocksDB
- MLFT

Auto-tuning key-value stores to reduce lookup latency
Towards A Unified Framework - *AutoSys*

- **Addressing common pain points in building learning-augmented systems**
  - Job scheduling and prioritization for sequential optimization approaches
  - Handling learning-induced system failures (due to ML inference uncertainty)
  - Generality and extensibility

- **Lowering the cost of bootstrapping new scenarios, by sharing data and models**
  - System deployments typically contain replicated service instances
  - Different system deployments can contain the same service

- **Facilitating computation resource sharing**
  - Difficult to provision job resources
  - Jobs in AutoSys are ad-hoc and nondeterministic
Jobs Within AutoSys

<table>
<thead>
<tr>
<th>Types</th>
<th>Descriptions</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tuners</td>
<td>Executes (1) ML/DL model training and inferencing, and (2) optimization solver</td>
<td>Hyperband, TPE, SMAC, Metis, random search, ...</td>
</tr>
<tr>
<td>Trials</td>
<td>Executes system explorations</td>
<td>RocksDB, ...</td>
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</tbody>
</table>

- **AutoSys jobs are ad-hoc:**
  - Jobs are triggered in response to system and workload dynamics

- **AutoSys jobs are nondeterministic:**
  - Jobs are spawned as necessary, according to optimization progress at runtime
  - Job completion time depends on system benchmarks and runtime (e.g., cache warmup)
Overview – Learning

Target System #1
- Control Interface

Training Plane
- Trial Manager
- Candidate Generator
- Model Trainer
- Model Repository

Inference Plane
- Rule Engine
- Inference Runtime

Target System #2
- Control Interface

Inference Plane
- Rule Engine
- Inference Runtime
1.) From assessing current model progress, AutoSys generates benchmark candidates to iteratively improve the model
• Exploration: benchmarks that are of high uncertainty
• Exploitation: benchmarks that are likely being optimal
• Re-sampling: benchmarks that likely contain measurement noises or outliers
2.) AutoSys prioritizes benchmark candidates, according to how likely they would help discover the optimum in the search space

- E.g., its Metis tuner uses Gaussian process to estimate the information gain
- E.g., its TPE tuner uses two GMM to estimate the likelihood of a candidate being the optimum
Overview – Auto-Tuning Actuations

Target System #1
- Control Interface

Target System #2
- Control Interface

Training Plane
- Trial Manager
- Candidate Generator
- Model Trainer
- Model Repository

Inference Plane
- Rule Engine
- Inference Runtime

Inference Plane
- Rule Engine
- Inference Runtime
3.) As it is difficult to formally verify ML/DL correctness, AutoSys opts to validate ML/DL outputs with a rule-based engine.

- Useful for validating parameter value constraints and dependencies
- Useful for preventing known bad configurations from being applied
- Useful for implementing triggers based on the system’s actuation feedback
### Summary of Production Deployments

<table>
<thead>
<tr>
<th>Component</th>
<th>Tuning time</th>
<th>Key results (vs. long-term expert tuning)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Keyword-based Selection Engine (KSE)</td>
<td>1 week</td>
<td>Up to 33.5% and 11.5% reduction in 99-percentile latency and CPU utilization, respectively</td>
</tr>
<tr>
<td>Semantics-based Selection Engine (SSE)</td>
<td>1 week</td>
<td>Up to 20.0% reduction in average latency</td>
</tr>
<tr>
<td>Ranking Engine (RE)</td>
<td>1 week</td>
<td>3.4% improvement in NDCG@5</td>
</tr>
<tr>
<td>RocksDB key-value cluster (RocksDB)</td>
<td>2 days</td>
<td>Lookup latency on-par with years of expert tuning</td>
</tr>
<tr>
<td>Multi-level Time and Frequency-value cluster (MLTF)</td>
<td>1 week</td>
<td>16.8% reduction on avg in 99-percentile latency</td>
</tr>
</tbody>
</table>
Long-term Lessons Learned

Higher-than-expected learning costs

• Various types of system dynamics can frequently trigger re-training
  • System deployments can scale up/down over time
  • Workloads can drift over time

• Learning large-scale system deployments can be costly
  • Testbeds might not match the scale and fidelity of the production environment
  • It is typically infeasible to explore system behavior in the production environment
Long-term Lessons Learned

Pitfalls of human-in-the-Loop

- Human experts can inject biases into training datasets
  - E.g., human experts can provide labeled data points for certain search space regions
- Human errors can prevent AutoSys from functioning correctly
  - E.g., wrong parameter value ranges
Long-term Lessons Learned

System control interfaces should abstract system measurements and logs to facilitate learning

• Many systems distribute configuration parameters and error messages over a set of not-well documented files and logs
• Many system feedbacks are not natively learnable, e.g., stack traces and core dump
• Some systems require customized measurement aggregation and cleaning
Conclusion

• This work reports our years of experience in designing and operating learning-augmented systems in production
  1. AutoSys framework, for unifying the development at Microsoft
  2. Long-term operation lessons

• Core components of AutoSys are publicly available at https://github.com/Microsoft/nni
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