AutoSys: The Design and Operation of Learning-Augmented Systems

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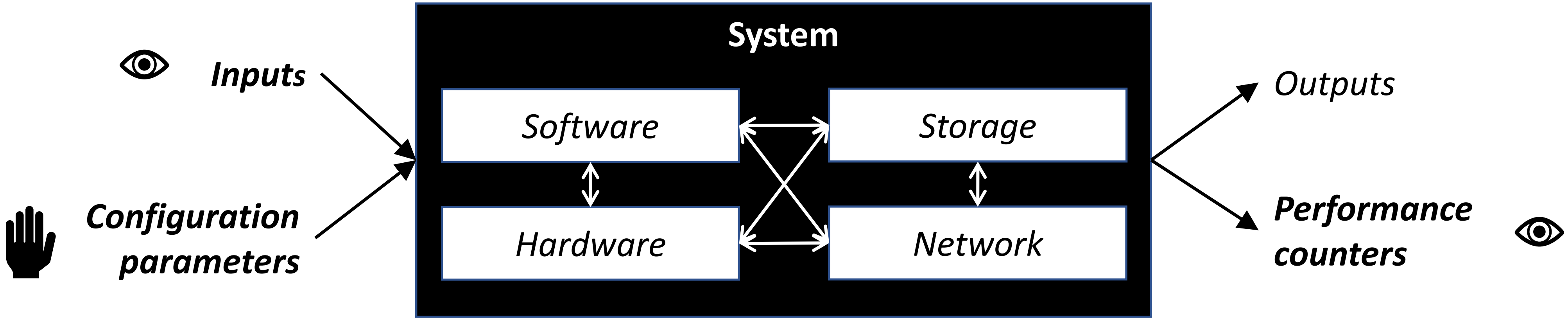
Learning-Augmented Systems

- **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

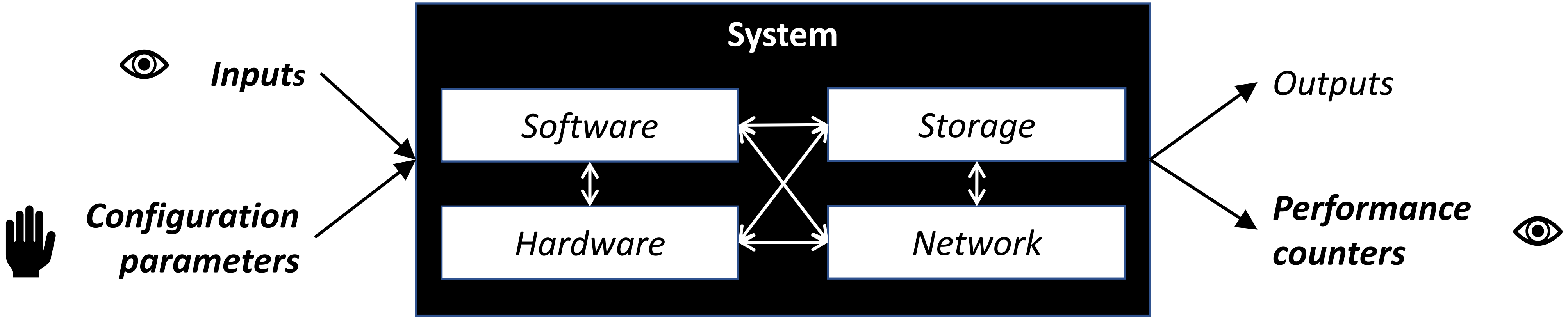
Our Scope in This Paper: Auto-tuning System Config Parameters

- **The problem is simple…**
  - A great application of black-box optimization
  - Find the configuration that best optimizes the performance counters

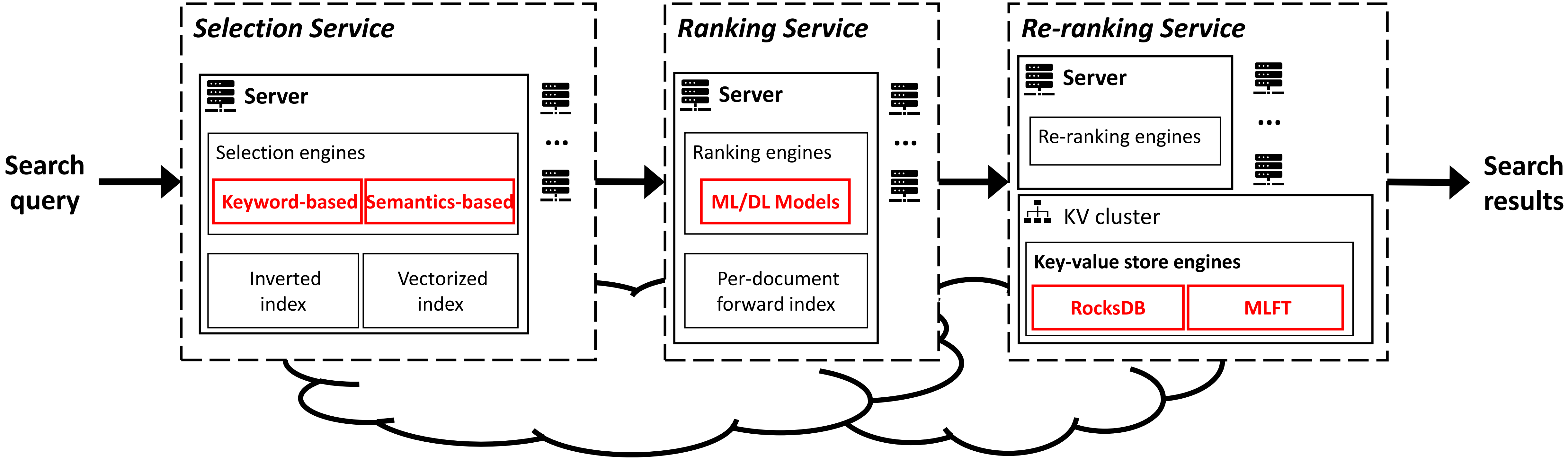


Our Scope in This Paper: Auto-tuning System Config Parameters

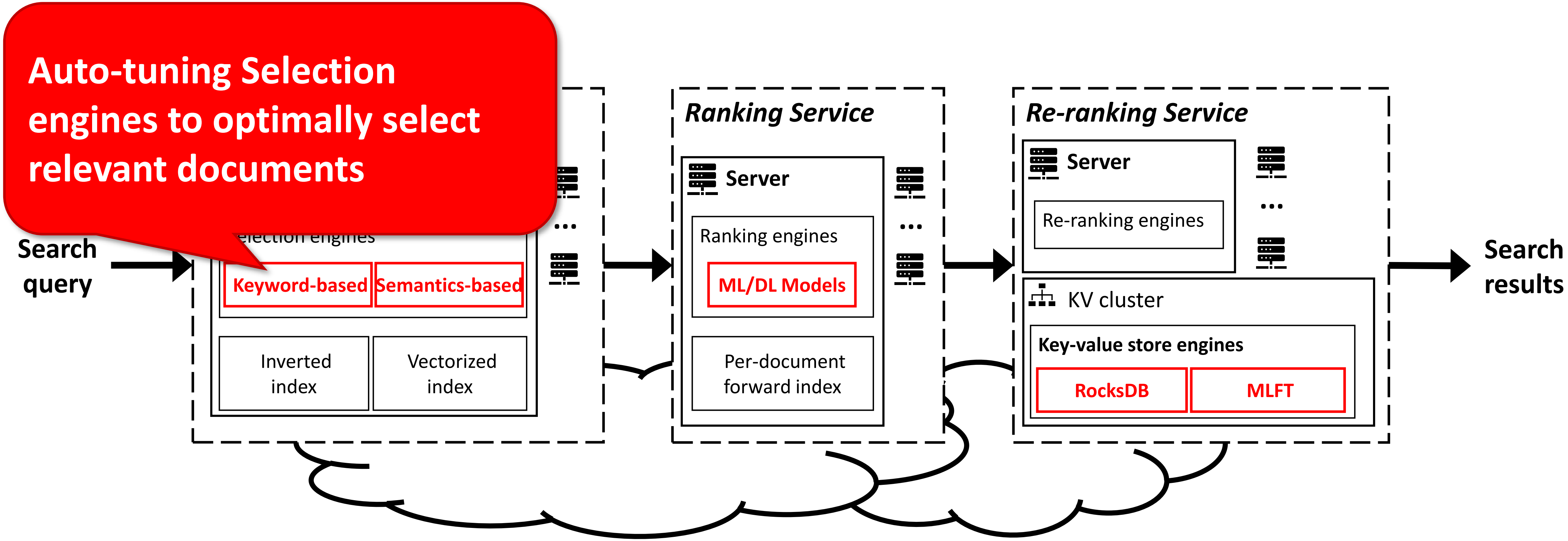
- ***But*, the problem is very difficult for system operators in practice…**
  - Vast system-specific parameter search space
  - Continual optimization based on system-specific triggers



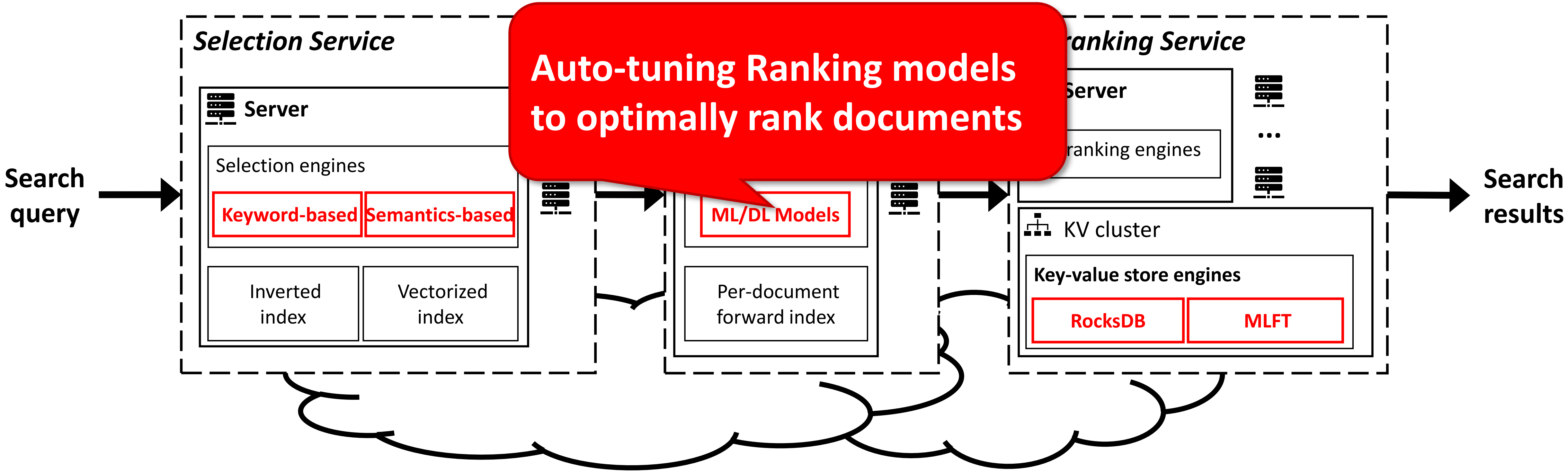
Our Scope in This Paper: Bing Web Search



Our Scope in This Paper:
Bing Web Search



Our Scope in This Paper: Bing Web Search



Our Scope in This Paper:
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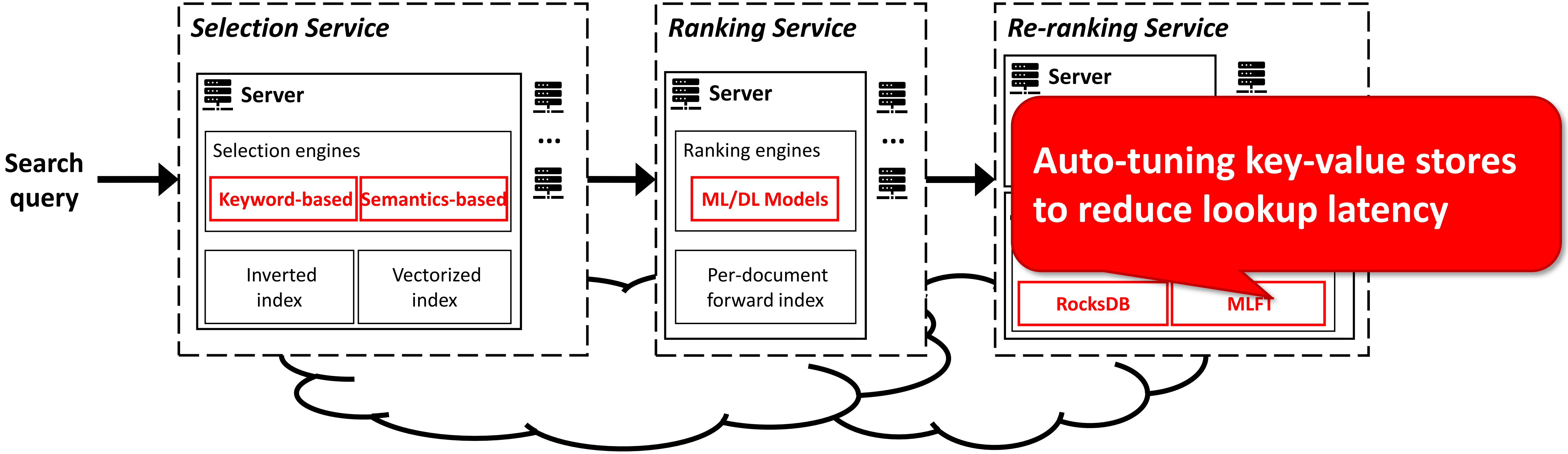


Towards A Unified Framework - *AutoSys*

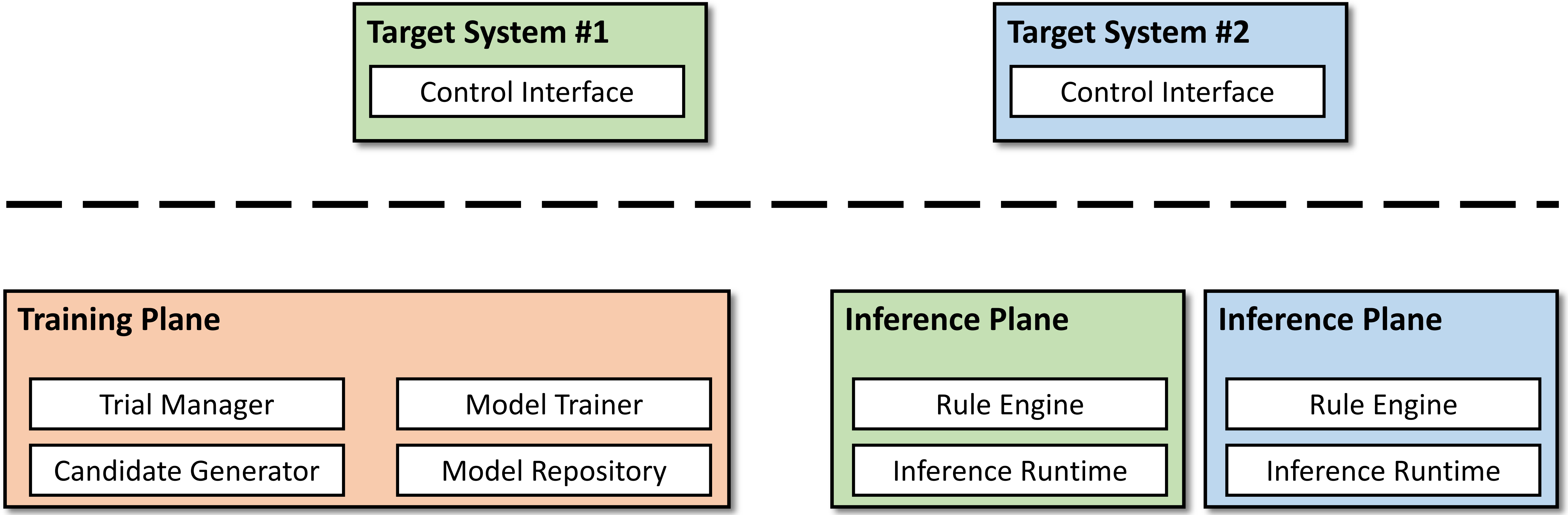
- **Addressing common pain points in building learning-augmented systems**
  - Job scheduling and prioritization for sequential optimization approaches
  - Handling learning-induced system failures (due to ML inference uncertainty)
  - Generality and extensibility
- **Lowering the cost of bootstrapping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

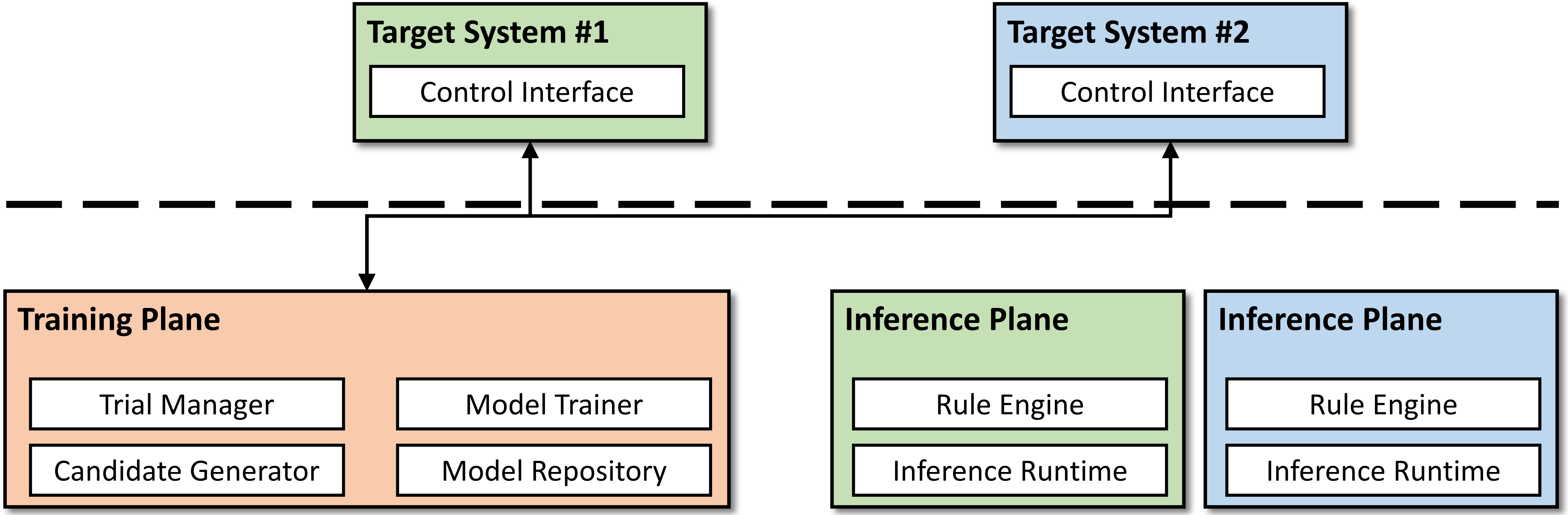
Types	Descriptions	Examples
Tuners	Executes **(1)** ML/DL model training and inferencing, and **(2)** optimization solver	Hyperband, TPE, SMAC, Metis, random search, …
Trials	Executes system explorations	RocksDB, …

- **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


Target System #1
Control Interface
Target System #2
Control Interface
Training Plane
Trial Manager
Model Trainer
Candidate Generator
Model Repository
Inference Plane
Rule Engine
Inference Runtime
Inference Plane
Rule Engine
Inference Runtime

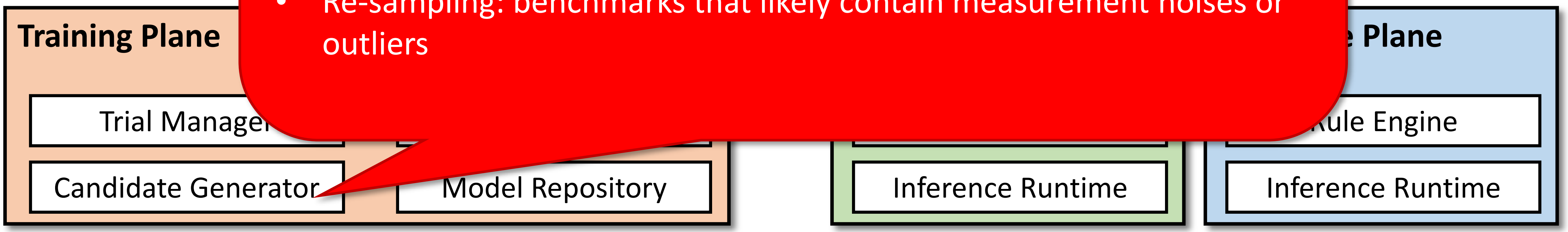
Overview – Learning



Overview – Learning

1.) From assessing current model progress, AutoSys generates benchmark candidates to iteratively improve the model

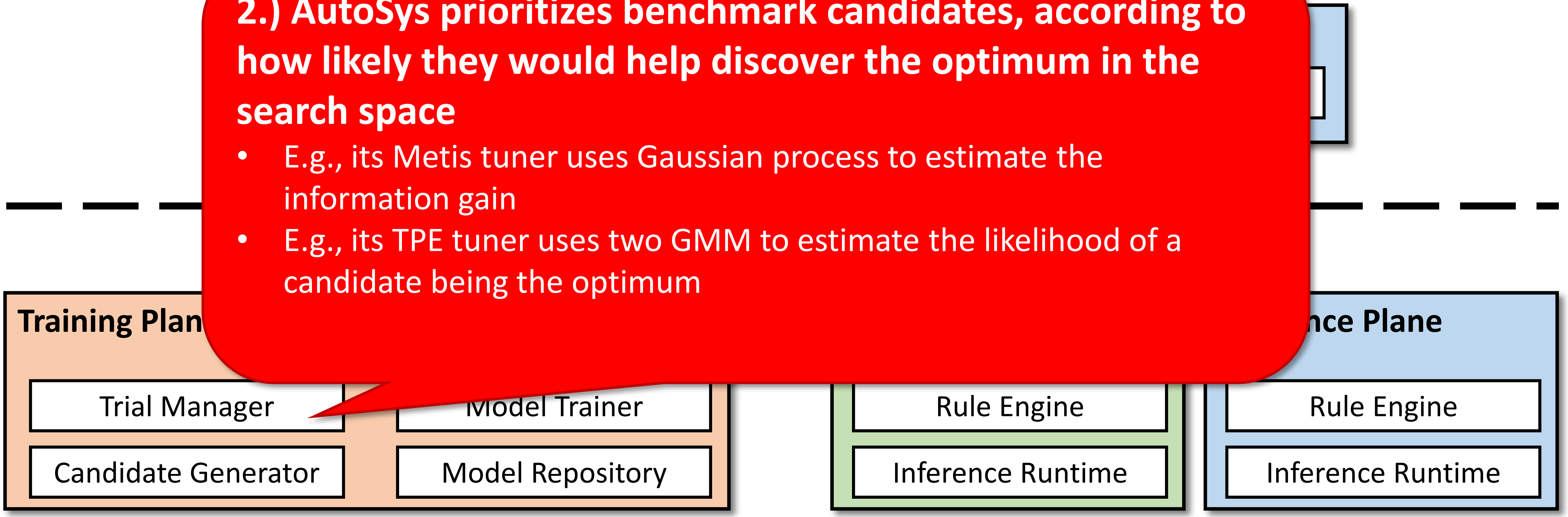
- Exploration: benchmarks that are of high uncertainty
- Exploitation: benchmarks that are likely being optimal
- Re-sampling: benchmarks that likely contain measurement noises or outliers



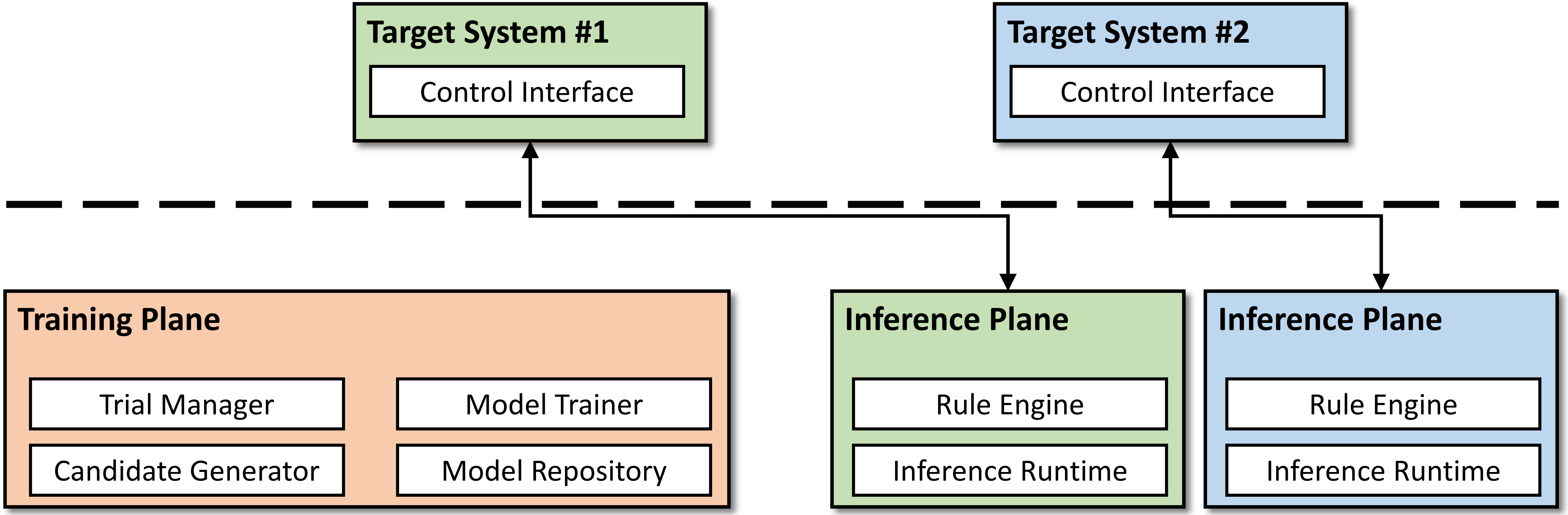
Overview – Learning

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



Overview – Auto-Tuning Actuations

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 be applied
- Useful for implementing triggers based on the system’s actuation feedback

Training Plane

Trial Manager

Model Trainer

Candidate Generator

Model Repository

Rule Engine

Inference Runtime

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Rule Engine

Inference Runtime

Summary of Production Deployments

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

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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