CherryPick: Adaptively Unearthing the Best Cloud Configurations for Big Data Analytics

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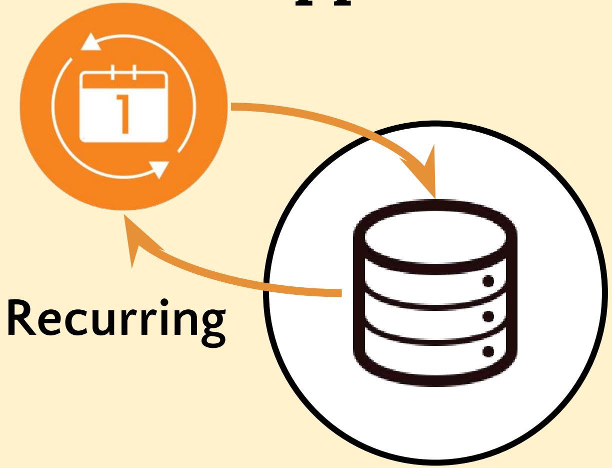
Recurring jobs are popular

Apps & Data



Frameworks

Microsoft reports 40% of key jobs at Bing are rerun periodically.

Providers	Machine Type	Cluster Size
	r3.8xlarge, i2.8xlarge, m4.8xlarge, c4.8xlarge,	
Azure	A12, D1, D2, D3, L4s, …	
	n1-standard-4, n1-highmem-2, n1-highcpu-4, f1-micro, ... **+ configurable VMs**	

Hundreds of instance types and instance count combinations

Choosing a good configuration is important

Better performance:

- For the same cost: best/worst running time is up to 3x
  - Worst case has good CPUs whereas the memory is bottlenecked.

Lower cost:

- For the same performance: best/worst cost is up to 12x
  - No need for expensive dedicated disks in the worst config.
  - 2$ vs. 24$ per job with 100s of monthly runs

How to find the best cloud configuration

One that minimizes the cost given a performance constraint

for a recurring job, given its representative workload?

High Accuracy

Close the optimal configurations

Adaptivity

Works across all big-data apps

Key Challenges

Modeling

Searching

Low Overhead

Only runs a few configuration

Existing solution: searching

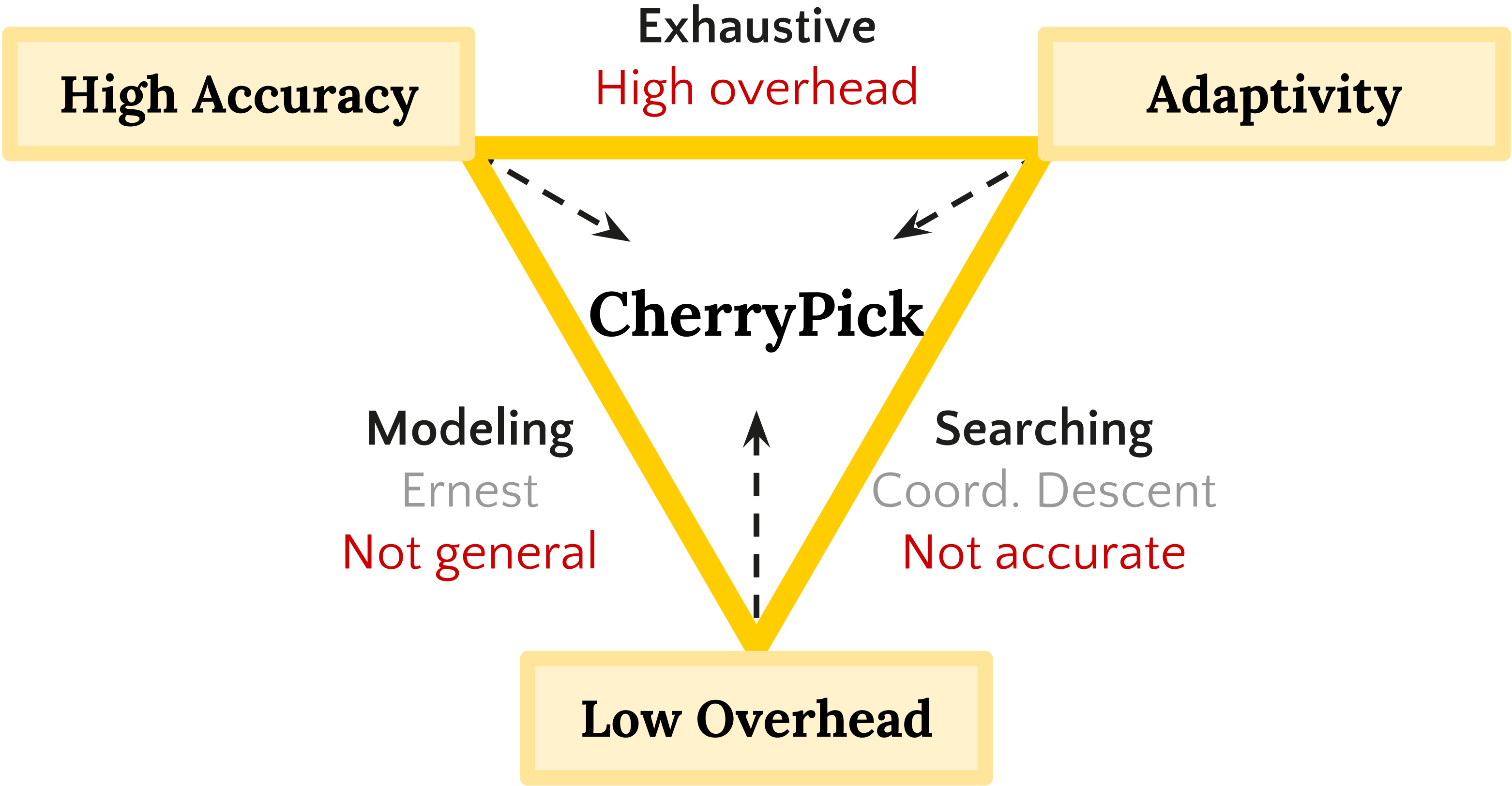
- Systematically search each dimension (Coordinate descent)
  - On each resources: RAM, CPU, disk, cluster sizes

- Problem: not accurate
  - Non-convex performance/cost curves across many resources
  - If you search one dimension, drop early, it would mislead you later

Existing solution: modeling

- Modeling the resource-perf/cost tradeoffs
  - Ernest [NSDI 16] models machine learning apps for each machine type

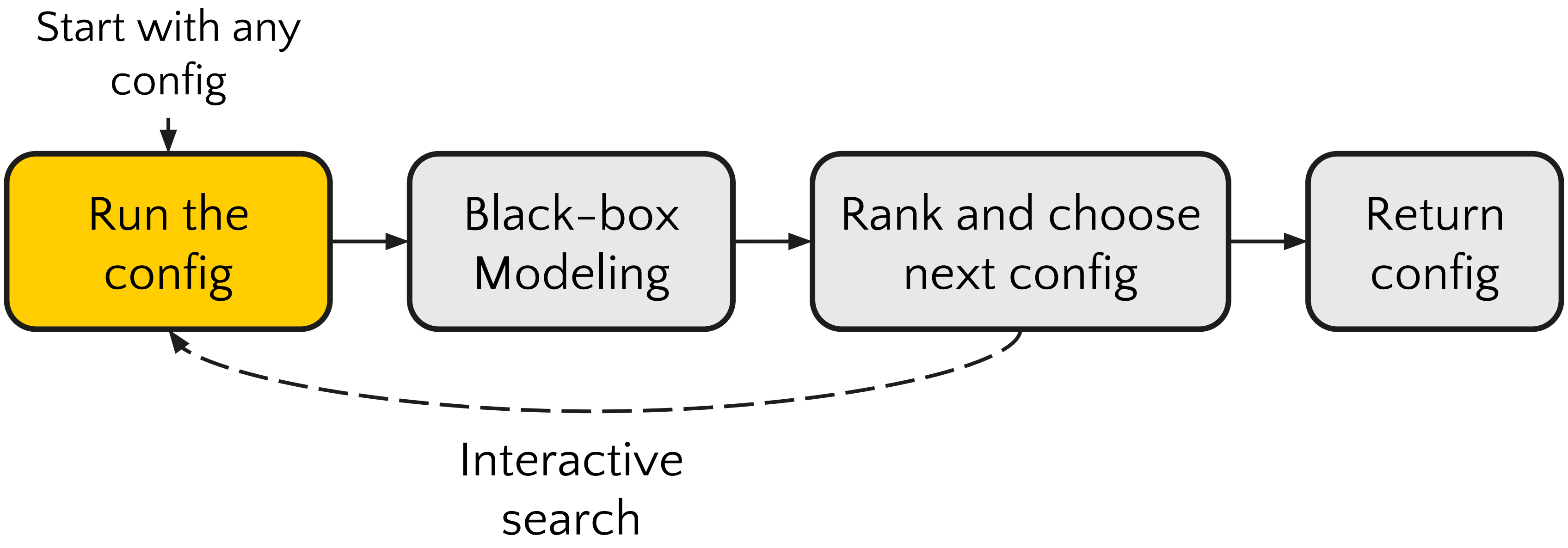
- Problem: not adaptive
  - Frameworks (e.g., MapReduce or Spark)
  - Applications (e.g., machine learning or database)
  - Machine type (e.g., memory vs CPU intensive)


Exhaustive
High overhead
High Accuracy
Adaptivity
CherryPick
Modeling
Ernest
Not general
Searching
Coord. Descent
Not accurate
Low Overhead

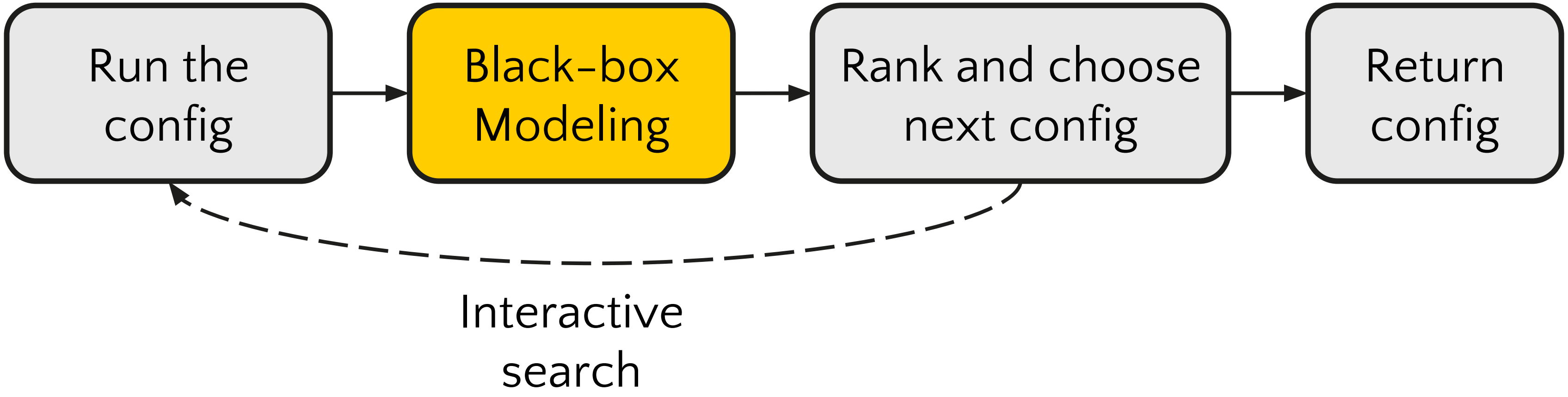
Key idea of CherryPick

- Adaptivity: black-box modeling
  - Without knowing the structure of each application
- Accuracy: modeling for ranking configurations
  - No need to be accurate everywhere
- Low overhead: interactive searching
  - Smartly select next run based on existing runs

Workflow of CherryPick



Workflow of CherryPick



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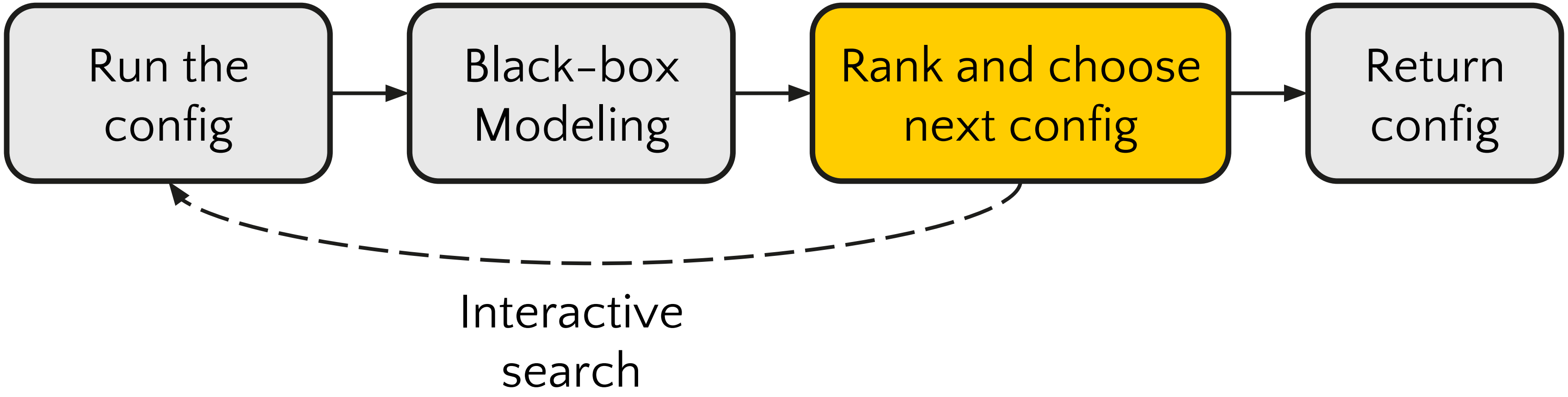

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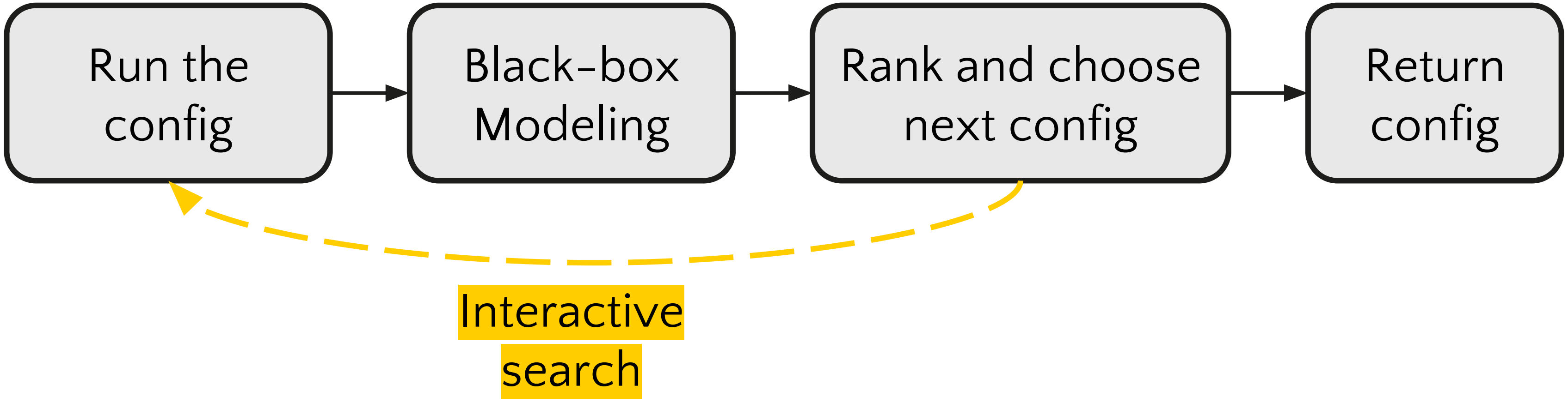

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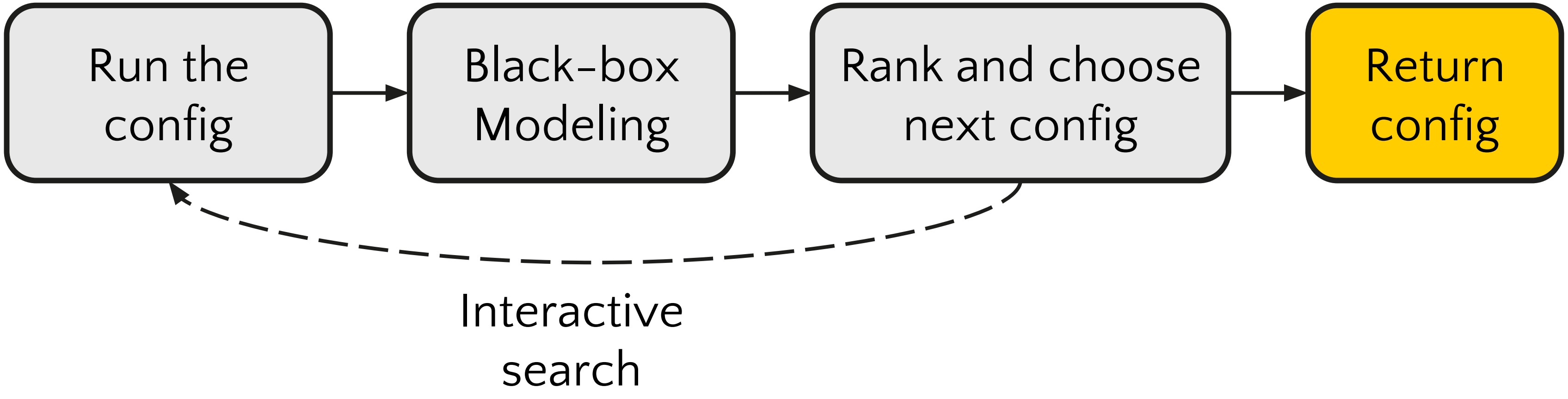

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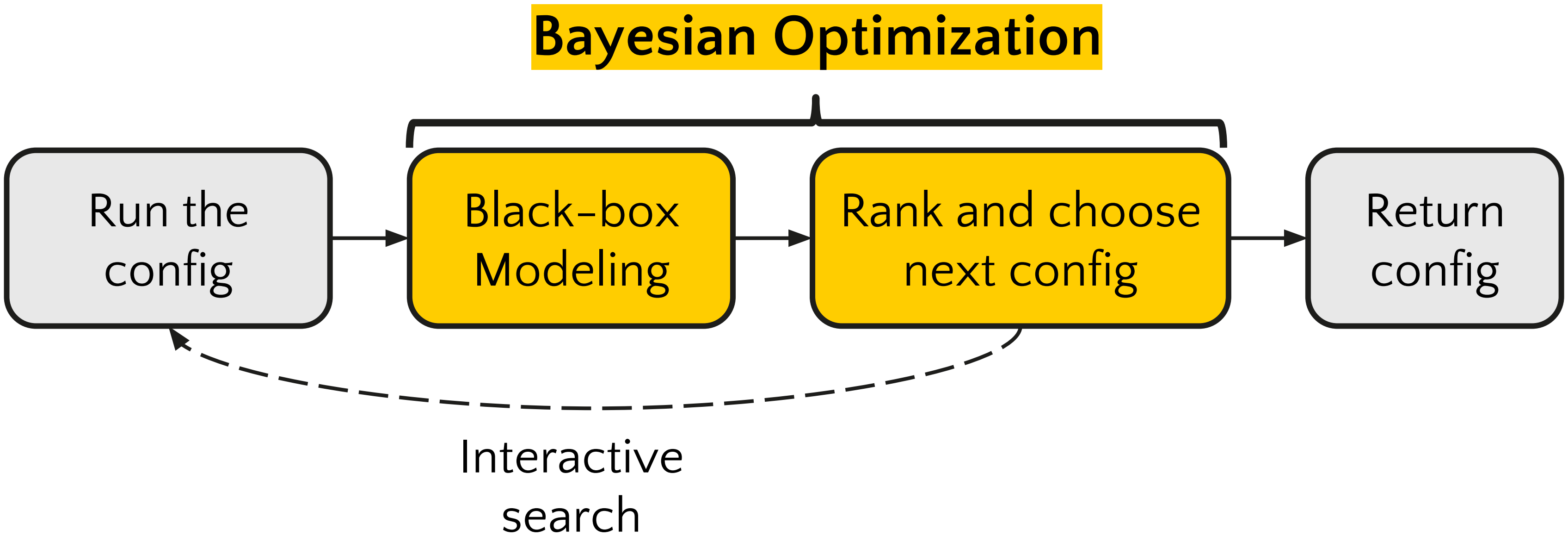

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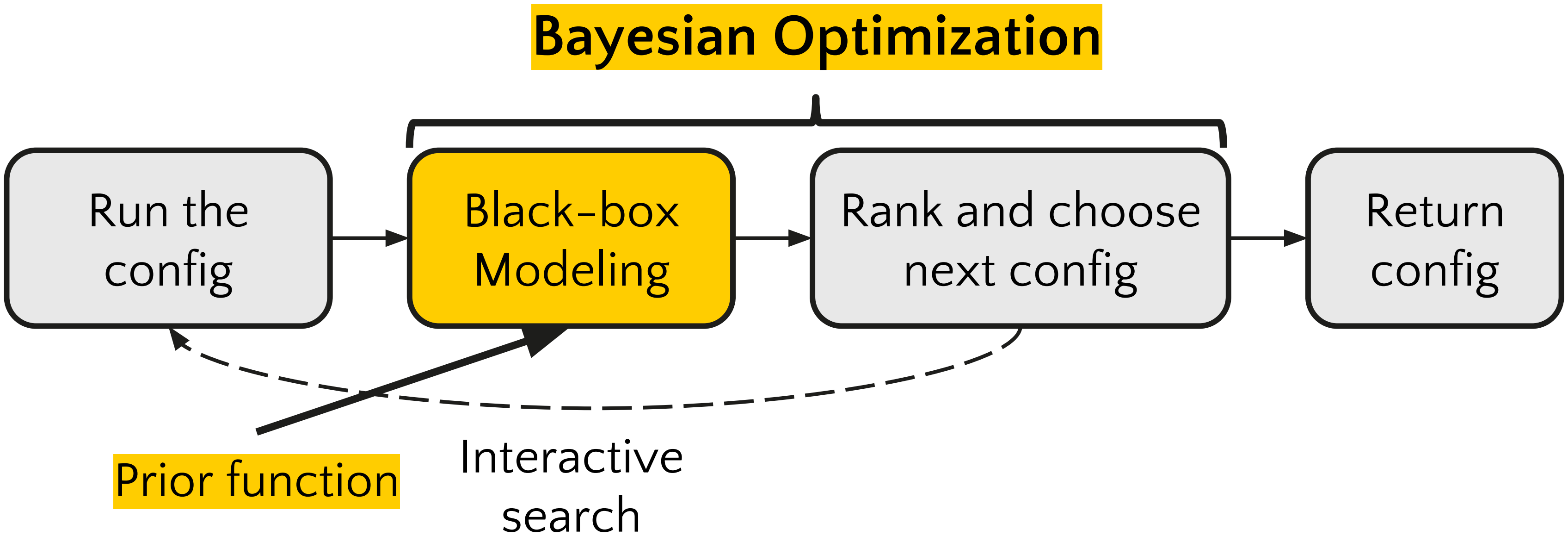

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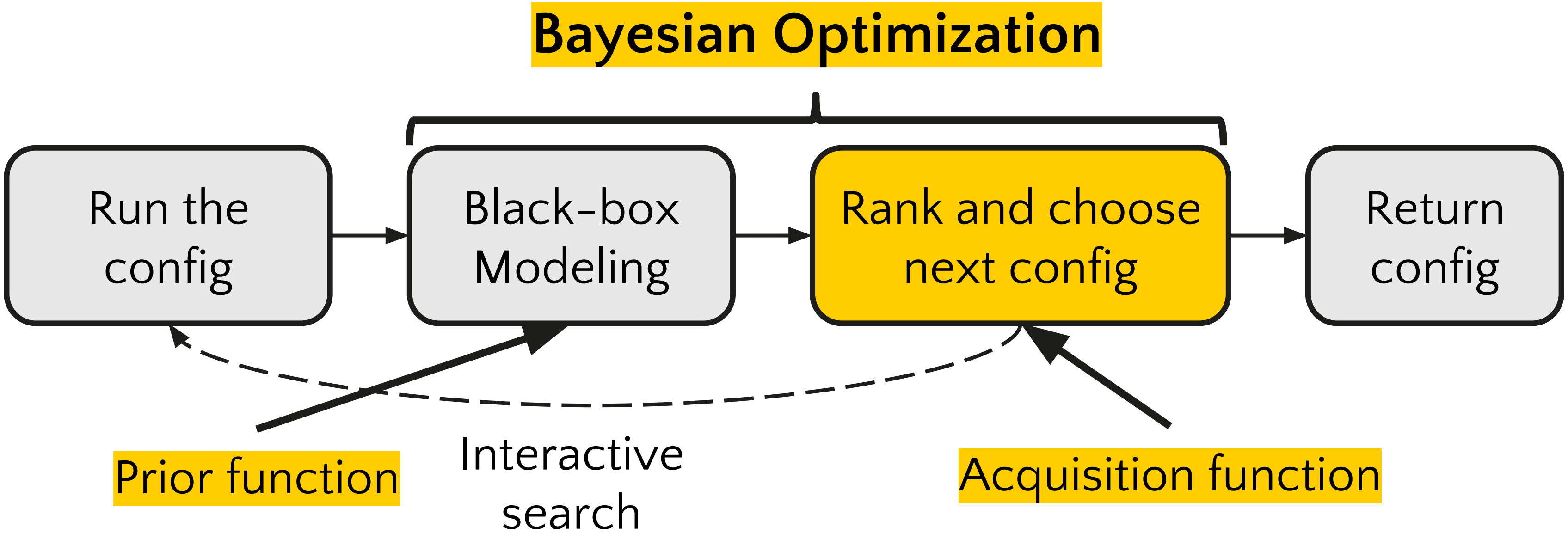

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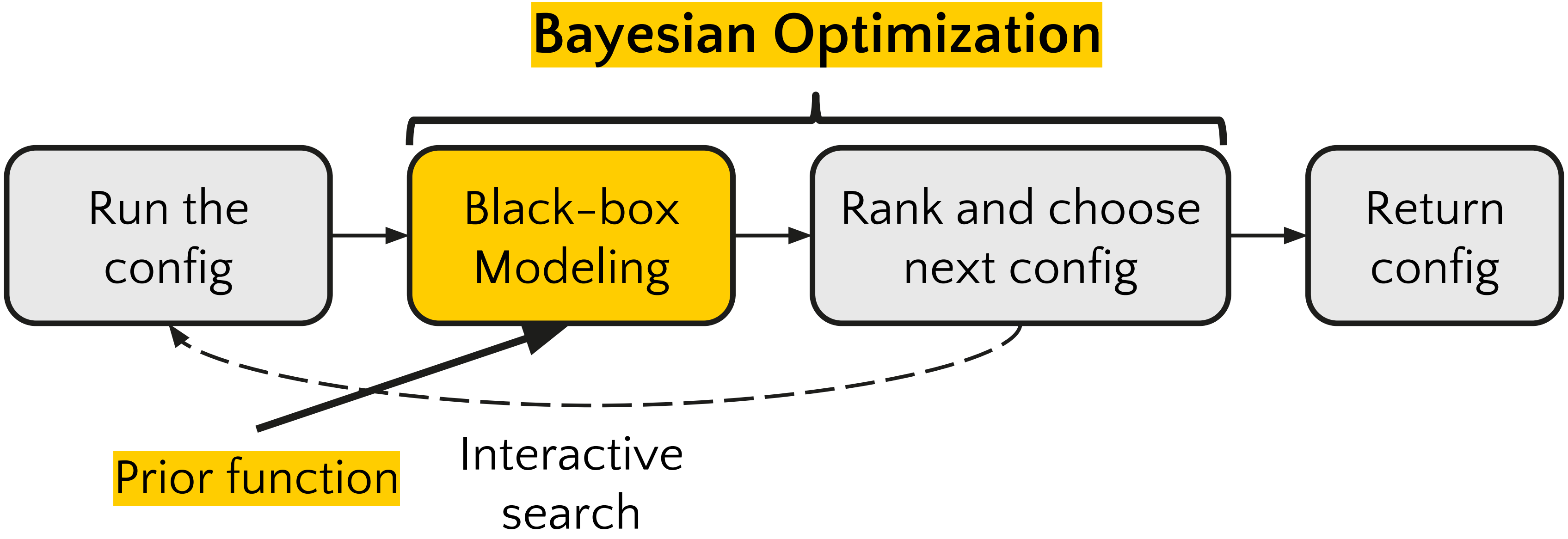
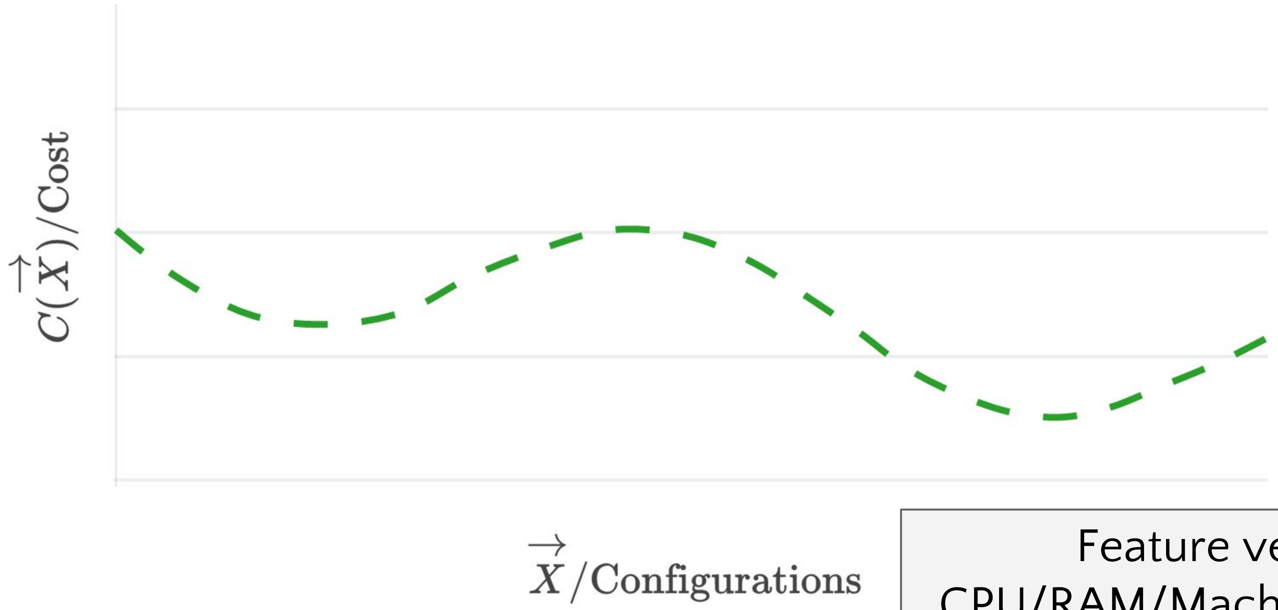


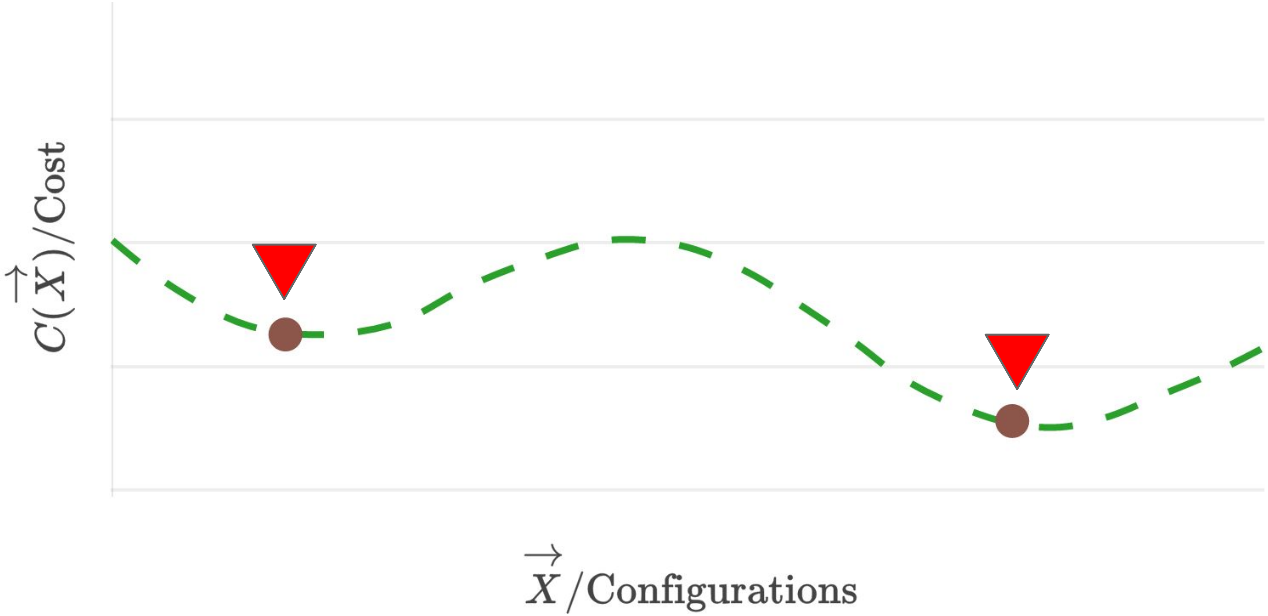
Prior function for black box modeling



Feature vector:
CPU/RAM/Machine count/...

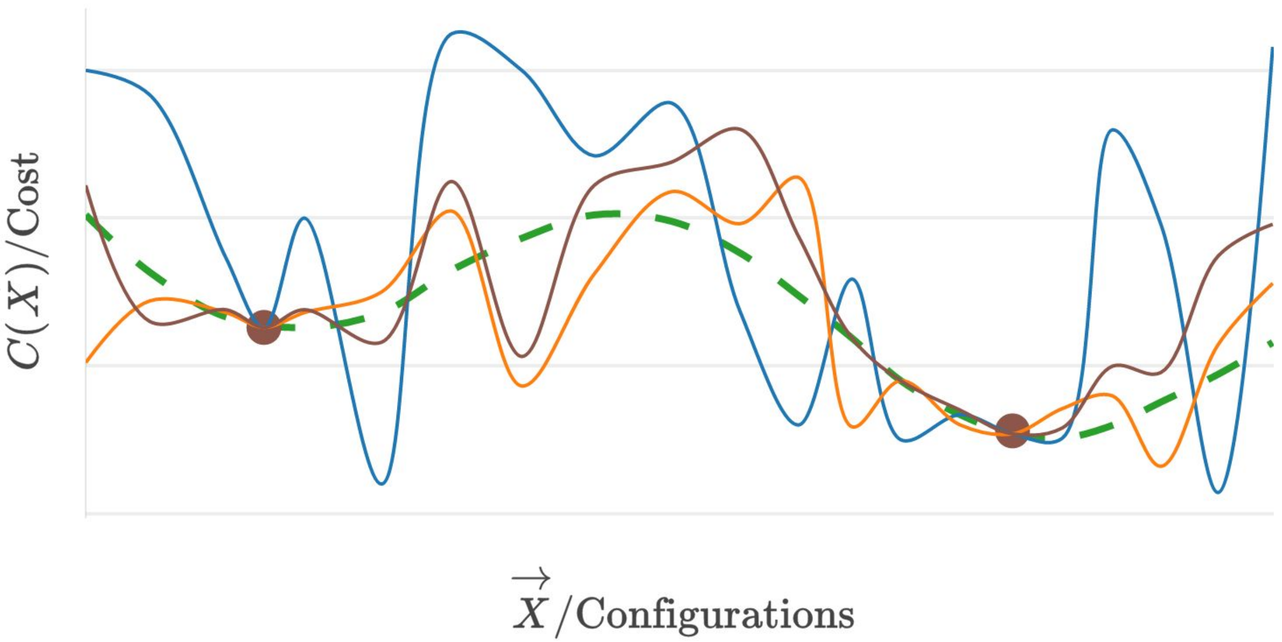
This is the actual cost function curve across all configurations.

Prior function for black box modeling



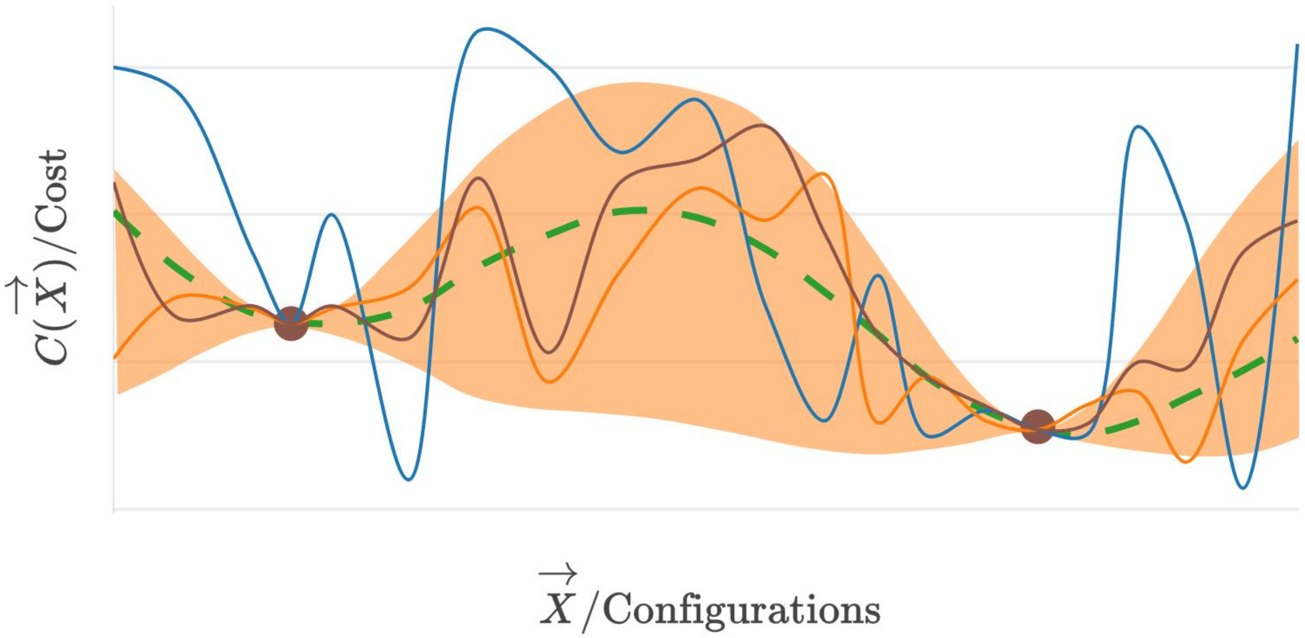
Challenge: what can we infer about configurations with two runs?

Prior function for black box modeling



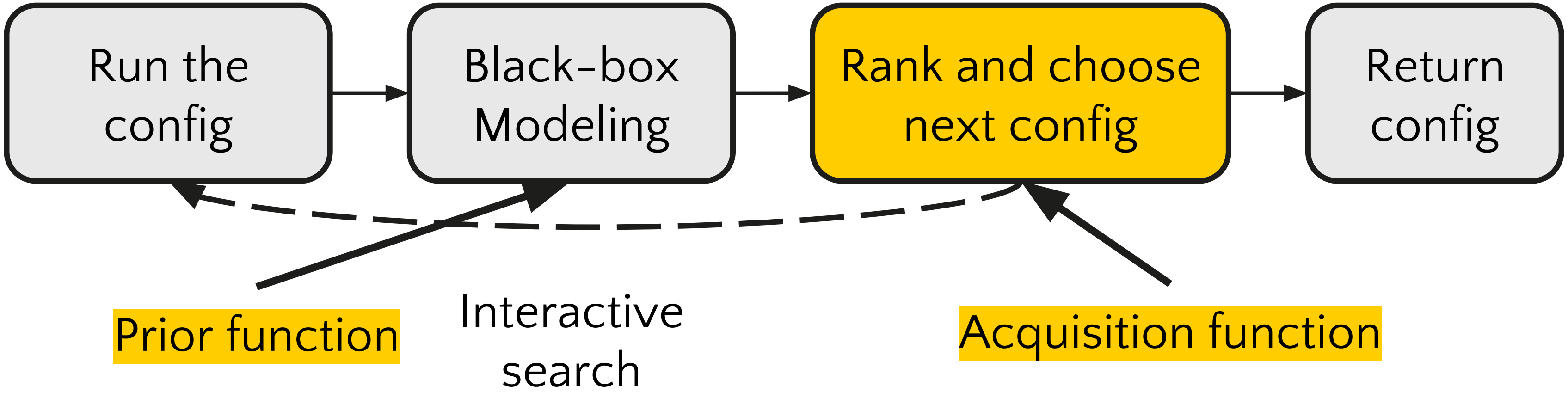
Challenge: what can we infer about configurations with two runs?
There are many valid functions passing through two points

Prior function for black box modeling

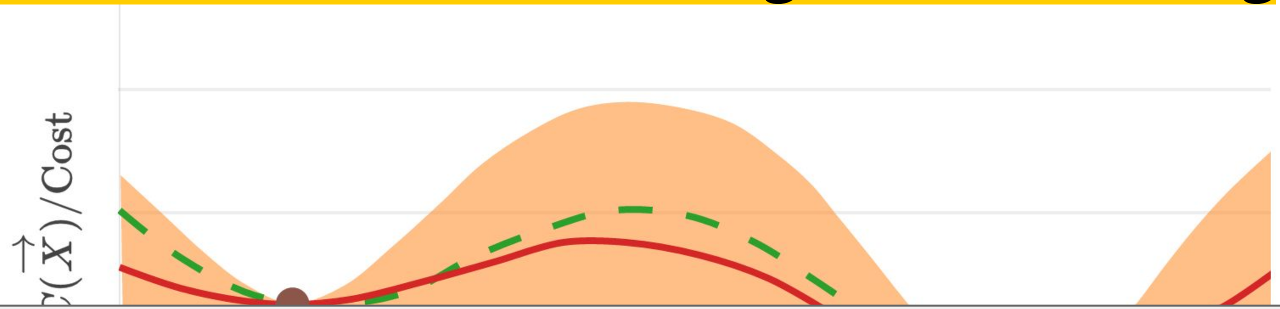


Challenge: what can we infer about configurations with two runs?
Solution: confidence intervals capture where the function likely lies

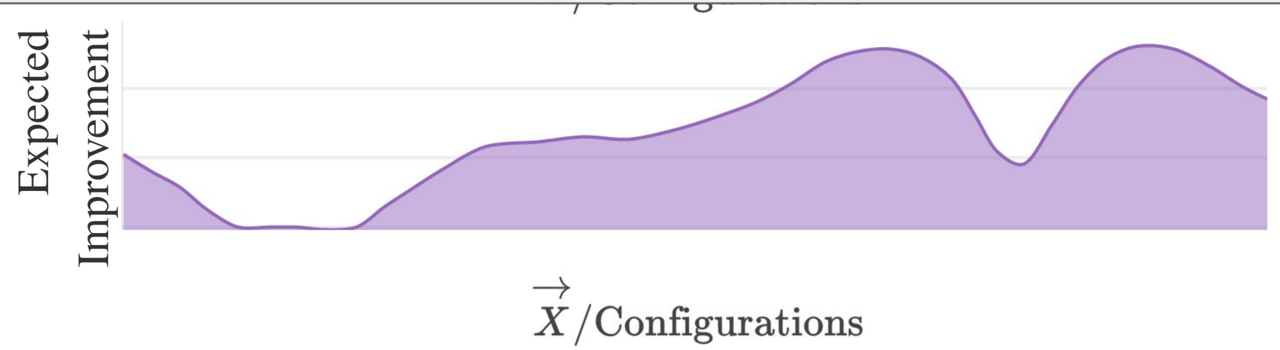
Workflow of CherryPick



Acquisition function for choosing the next config



Build an acquisition function based on the prior function
Calculate the expected improvement in comparison to the current best configuration



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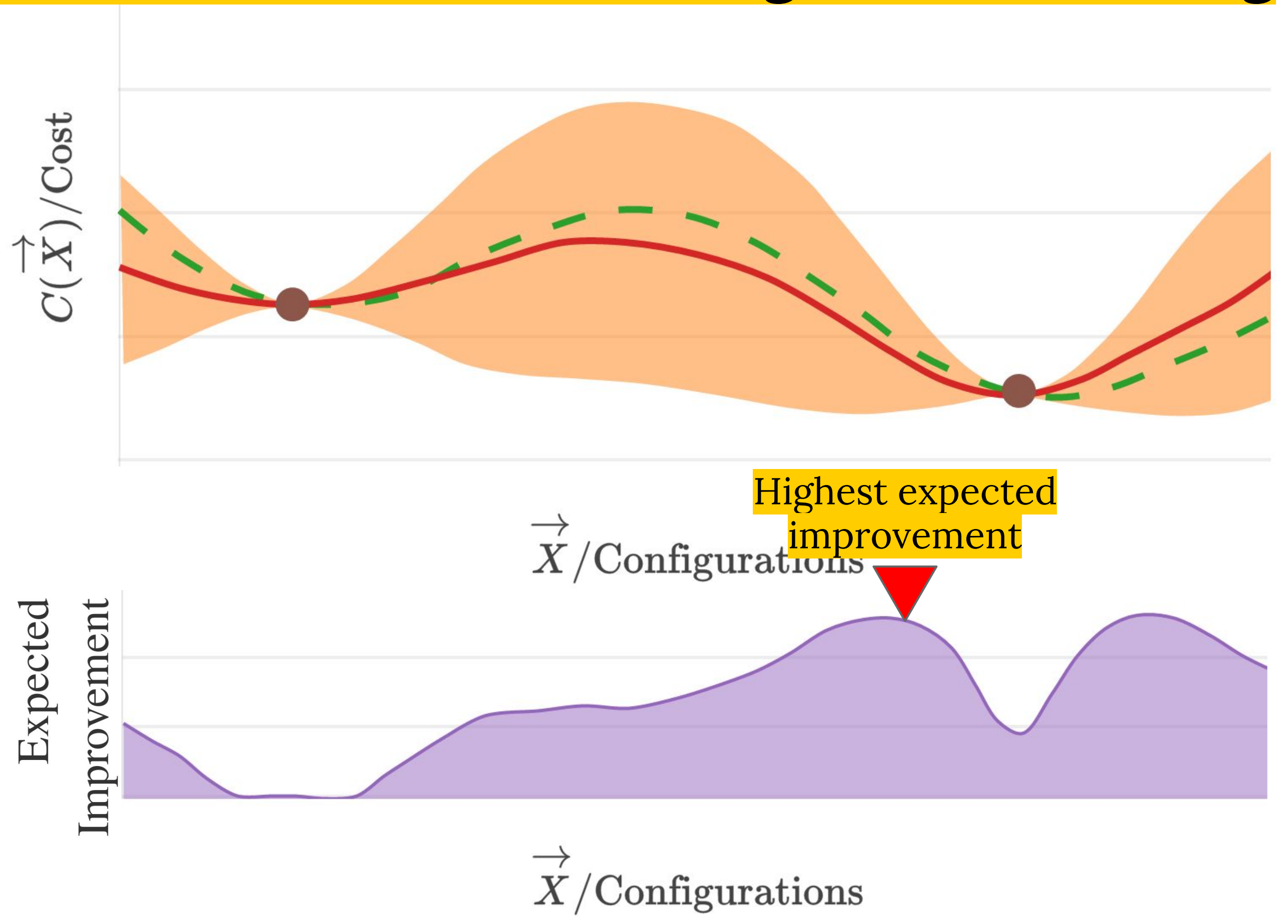

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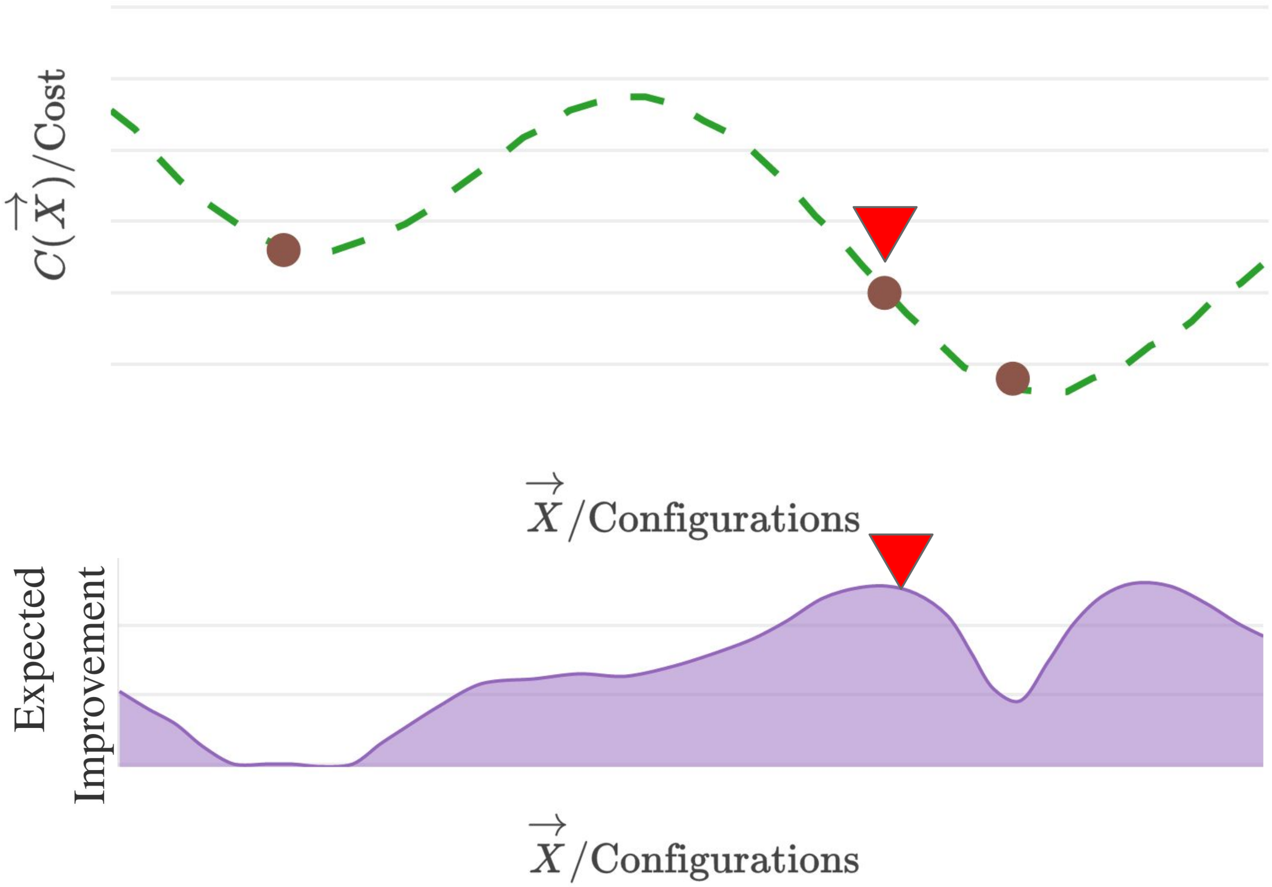
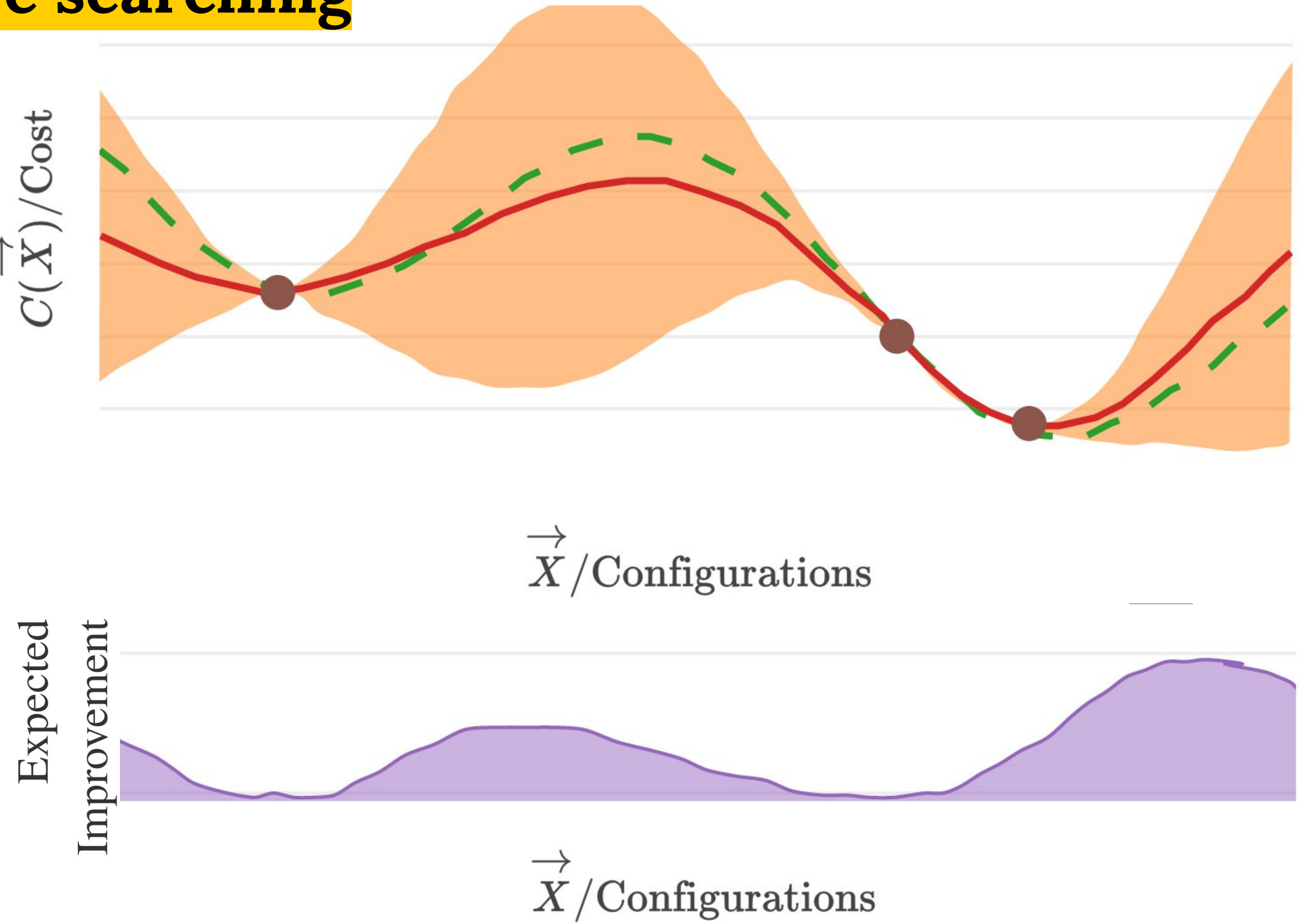
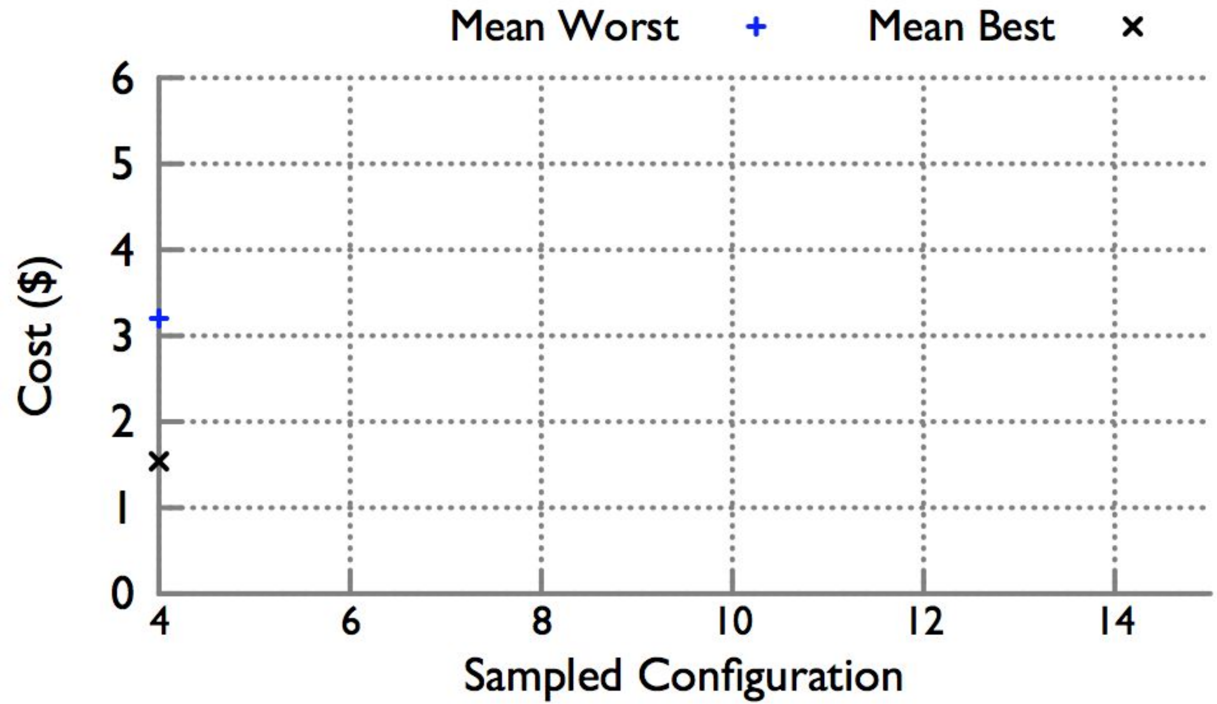


Iterative searching

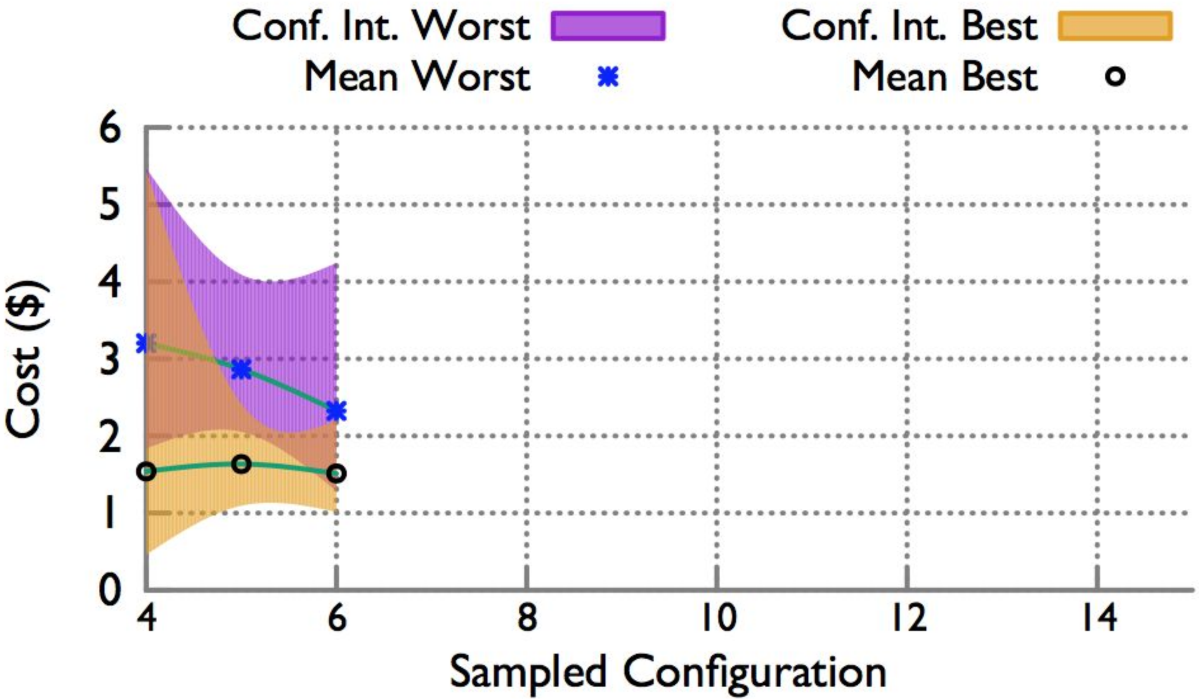


CherryPick searches in the area that matters



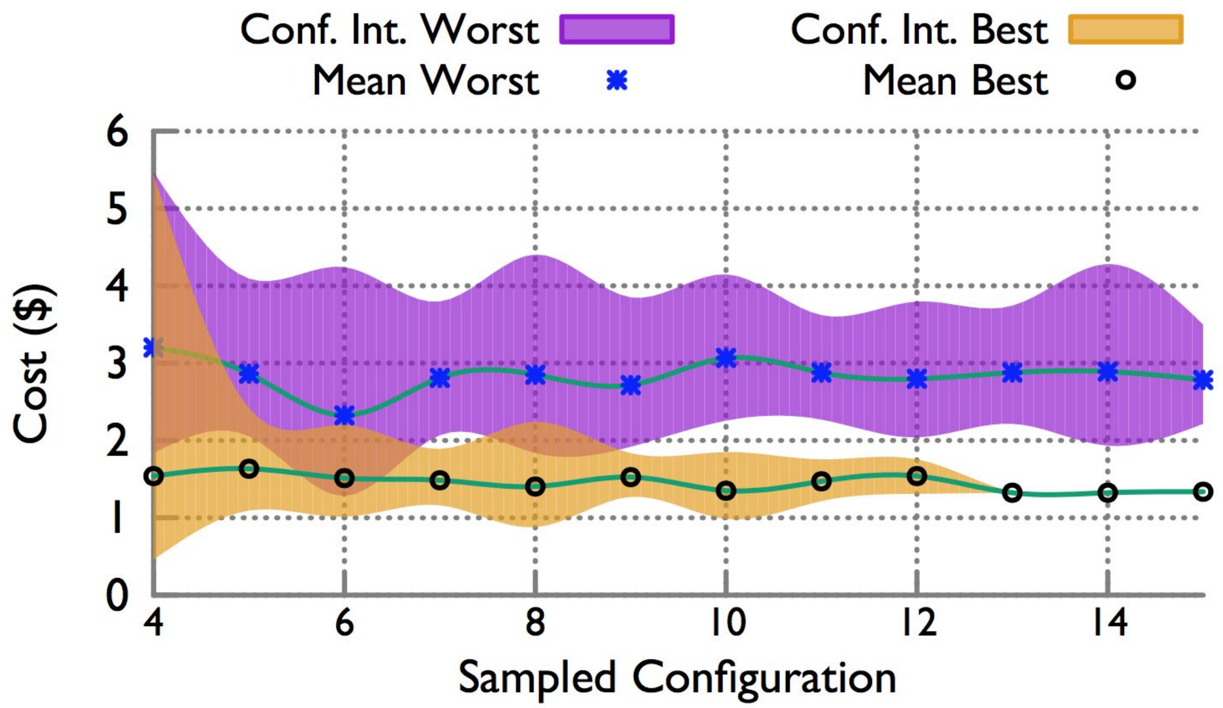
A database application with 66 configurations

CherryPick searches in the area that matters



A database application with 66 configurations

CherryPick searches in the area that matters



A database application with 66 configurations

Noises in the cloud

- Noises are common in the cloud
  - Shared environment means inherent noise from other tenants
  - Even more noisy under failures, stragglers
  - **Strawman solution:** run multiple times, but high overhead.
  -
- Bayesian optimization is good at handling additive noise
  - Merge the noise in the confidence interval

$$f(\overrightarrow{X}) + \epsilon \longleftarrow \text{Noise}$$

(learned by monitoring or historical data)

Challenge: Multiplicative noise

A lot of the noise in cloud is multiplicative

- Example: if VMs IO slows down due to overloading
  - Writing 1G to disk (5 sec normally) now takes 6 secs (by 20%)
  - Writing 10G to disk (50 sec normally) now takes 60 secs (by 20%)

$$\hat{C}(\vec{X}) = C(\vec{X}) \boxed{\times (1 + \epsilon)}$$

The max. relative variance in a given cloud.

Use the log function to change to additive noise

$$\log \hat{C}(\vec{X}) = \log C(\vec{X}) \boxed{+ \log(1 + \epsilon)}$$

Further customizations

- Discretize features:
  - Deal with infeasible configs and large searching space
  - Discretize the feature space
- Stopping condition:
  - Trade-off between accuracy and searching cost
  - Use the acquisition function knob
- Starting condition:
  - Should fully cover the whole space
  - Use quasi-random search

Evaluation settings

5 big-data benchmarks

- Database:
  - TPC-DS
  - TPC-H
- MapReduce:
  - TeraSort
- Machine Learning:
  - SparkML Regression
  - SparkML Kmeans

66 cloud configurations

- 30 GB–854 GB RAM
- 12–112 cores
- 5 machine types

Evaluation Settings

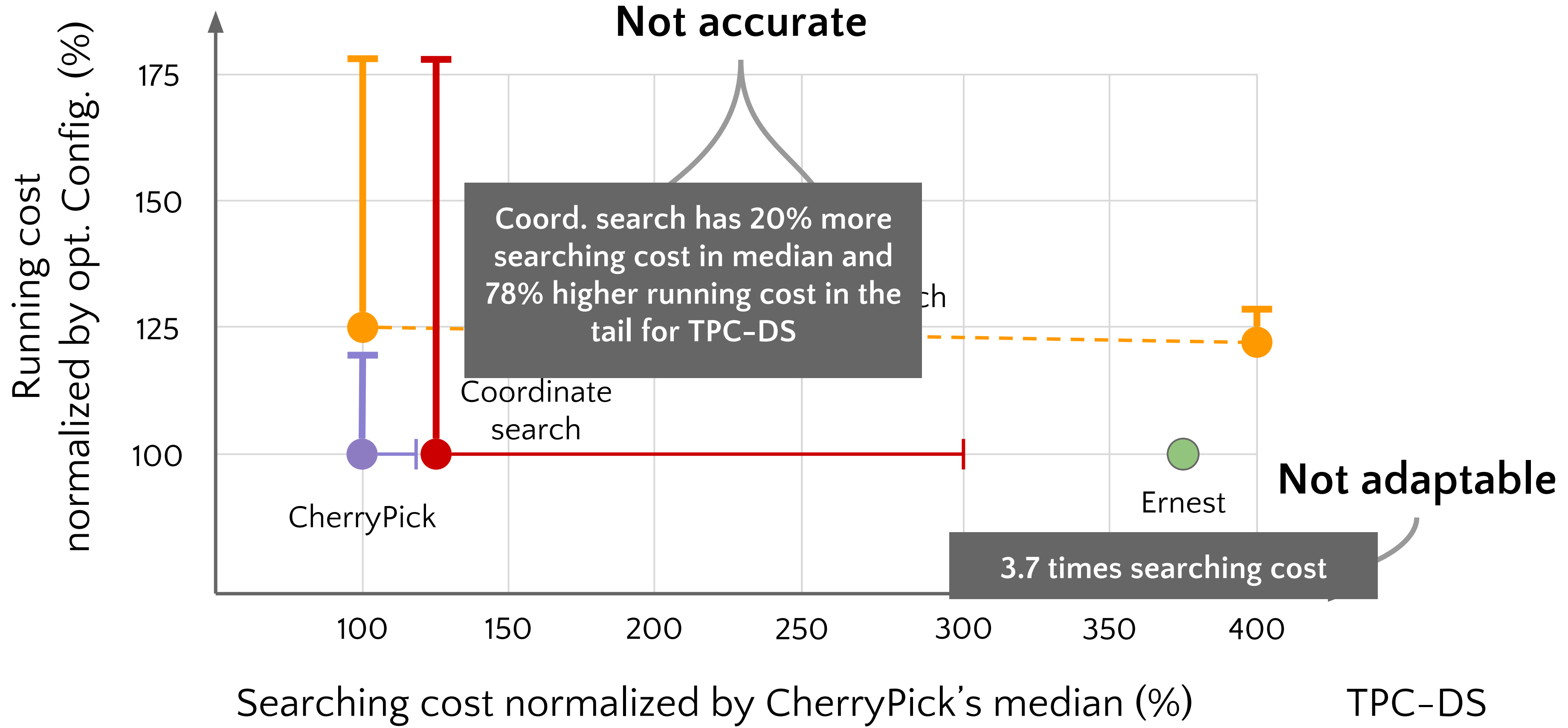
Metrics

- Accuracy: running cost compared to the optimal configuration
- Overhead: searching cost of suggesting a configuration

Comparing with

- Searching: random search, coordinate descent
- Modeling: Ernest [NSDI'16]

CherryPick has high accuracy with low overhead



CherryPick corrects Amazon guidelines

- Machine type
  - AWS suggests R3,I2,M4 as good options for running TPC-DS
  - CherryPick found that at our scale C4 is the best.

- Cluster size
  - AWS has no suggestion
  - Choosing a bad cluster size can have 3 times higher cost than choosing a right cluster config.

- Combining the two becomes even harder.

Conclusions

Adaptivity

Black-box modeling:
Requires running the cloud configuration.

Low overhead

Restricted amount of information:
Only a few runs available.

High accuracy

"… do not solve a more general problem …
try to get the answer that you really need"
—Vladimir Vapnik

Thanks!

Please try our tool at:

https://github.com/yale-cns/cherrypick