



Using AI to Build a Self-Driving Query Optimizer

Shivnath Babu, Adrian Popescu

#AI7SAIS

Meet the speakers



Shivnath Babu

- Cofounder and CTO at Unravel, Adjunct Professor at Duke University
- Focusing on ease-of-use and manageability of data-intensive systems
- Recipient of US National Science Foundation CAREER Award, three IBM Faculty Awards, HP Labs Innovation Research Award



Adrian Popescu

- Data engineer at Unravel
- PhD from EPFL, Switzerland
- 8+ years of experience in performance monitoring & modeling of data management systems
- Focusing on tuning and optimization of Big Data apps

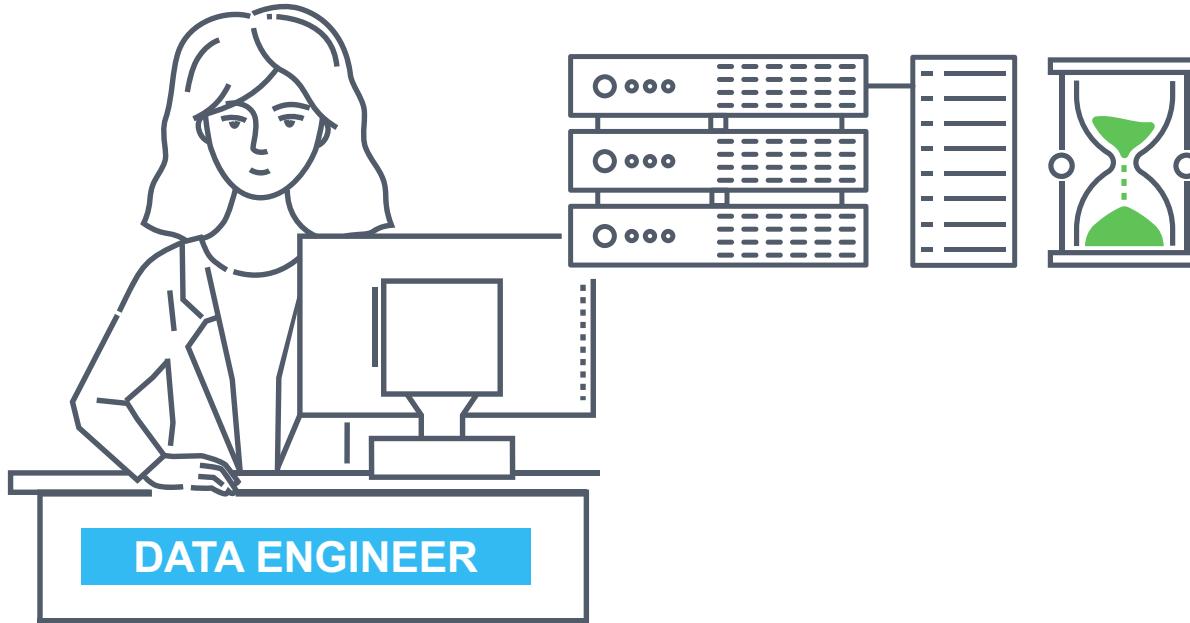
My app often fails with Out of Memory...



How can I make it more reliable?

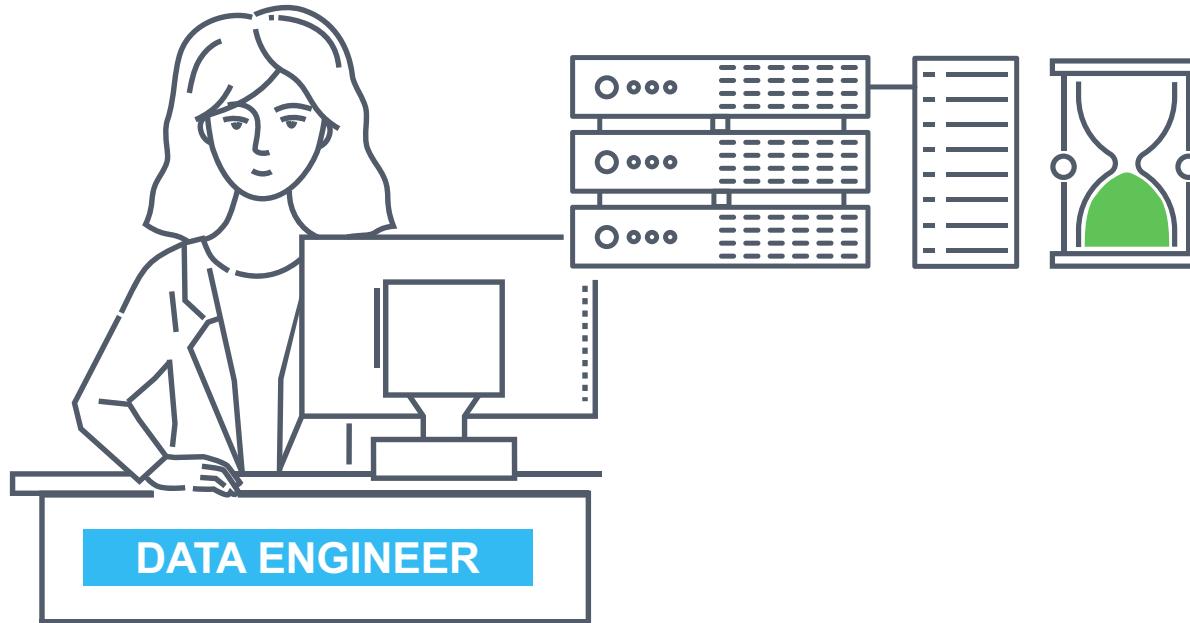


My app is too slow...



DATA ENGINEER

I need to make it faster...



My app is missing SLA...



DATA PIPELINE OWNER

How can I tune my app to guarantee SLAs?



This rogue app is wasting resources and reducing cluster throughput



Can this app use less resources while finishing on time?

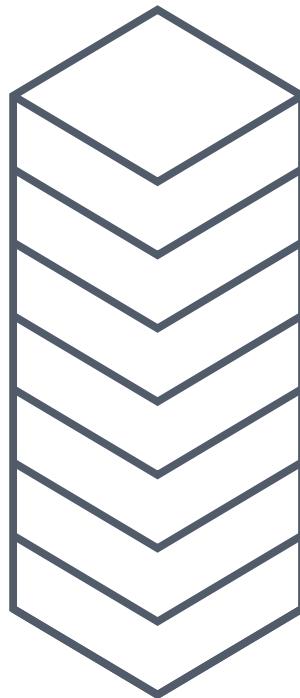


Current approach: Find the needle in the hay STACKS

1 System

1 User

1 App



1. Find the app. Review Spark/YARN UI to find the app
2. Review metrics on web UI
3. Review stages associated with the app
4. Identify executors associated with the stages and outliers
5. Deep dive into “outlier” stage
6. Identify problematic “executors”
7. Review and debug container logs
8. Rinse & repeat across other executor/container logs to identify the problem

Now imagine the problem at scale

10x Systems
100x Users
1000x Apps

Imagine a new world

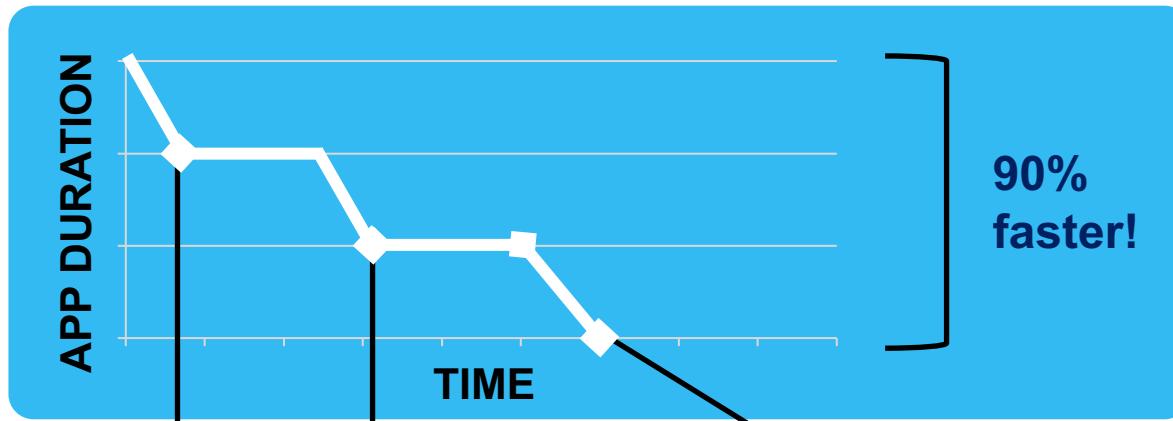


INPUTS

1. App = Spark Query
2. Goal = Speedup

“I need to make this app faster”

Imagine a new world

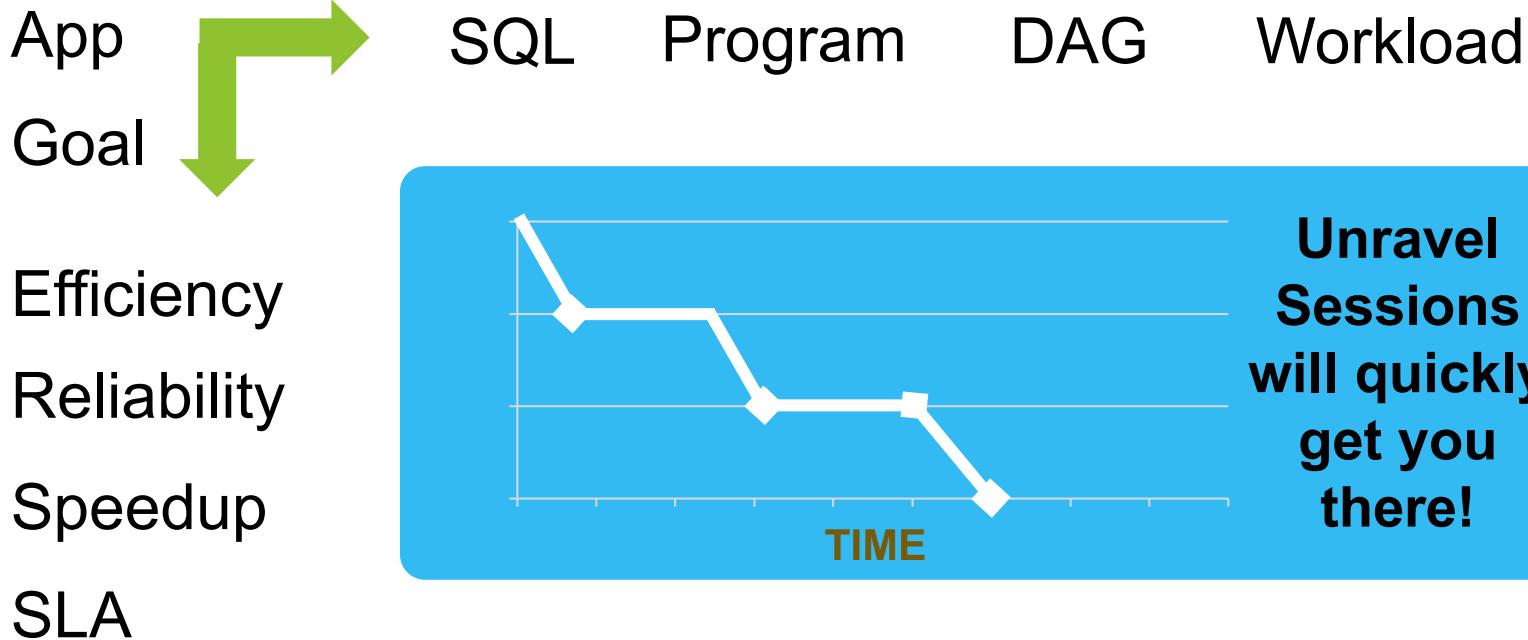


At Unravel, we want to bring
the **new world** to you today

Introducing Unravel Sessions

Demo

Unravel Sessions



Demo

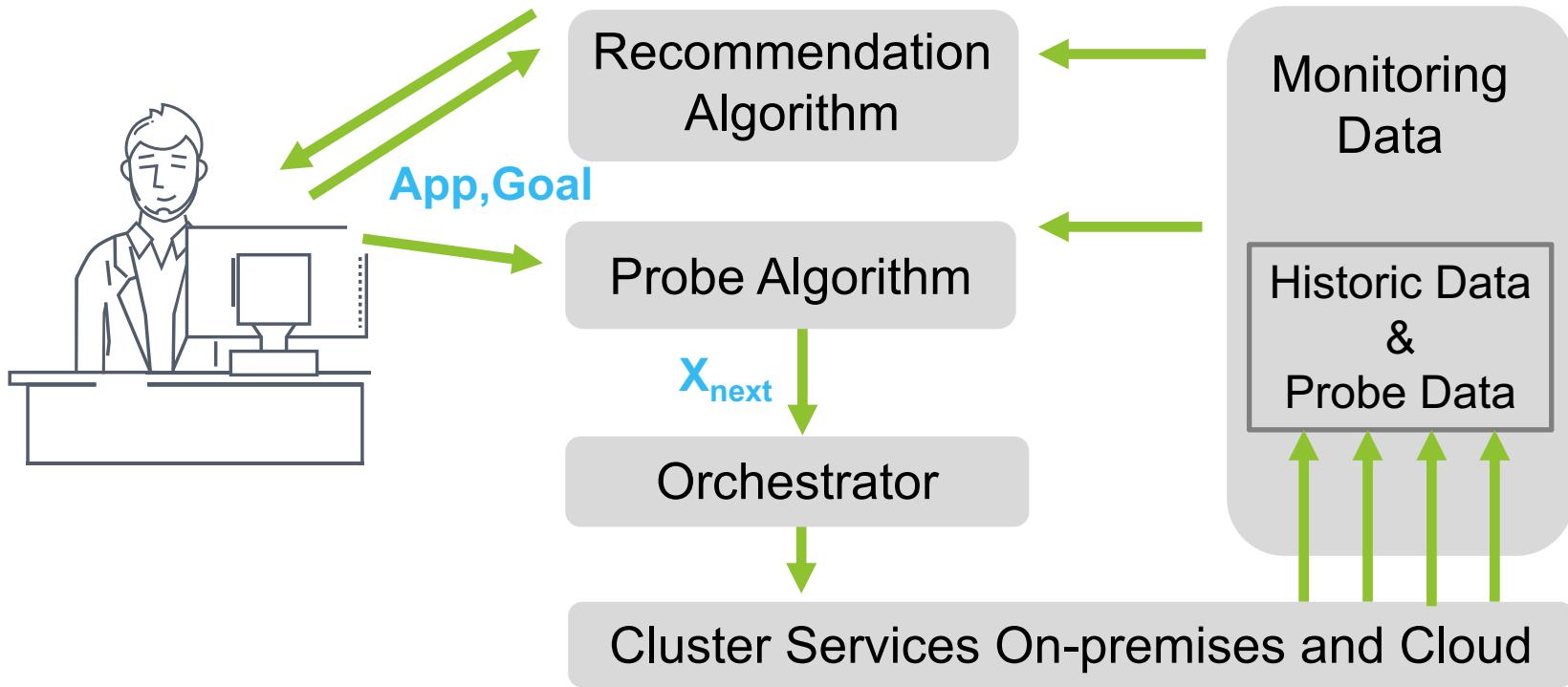
How Unravel Sessions work

AI

for

Application Performance Management

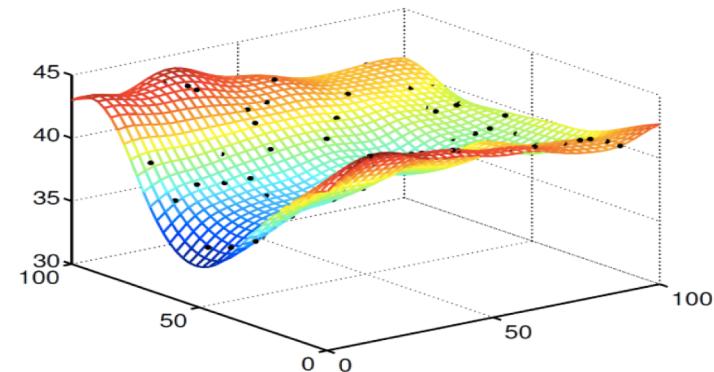
Unravel Sessions Architecture



<code>spark.driver.cores</code>	2
<code>spark.executor.cores</code>	10
...	
<code>spark.sql.shuffle.partitions</code>	300
<code>spark.sql.autoBroadcastJoinThreshhold</code>	20MB
...	
<code>SKEW('orders', 'o_custId')</code>	true
<code>spark.catalog.cacheTable("orders")</code>	true
...	

We represent the setting as vector X

PERFORMANCE

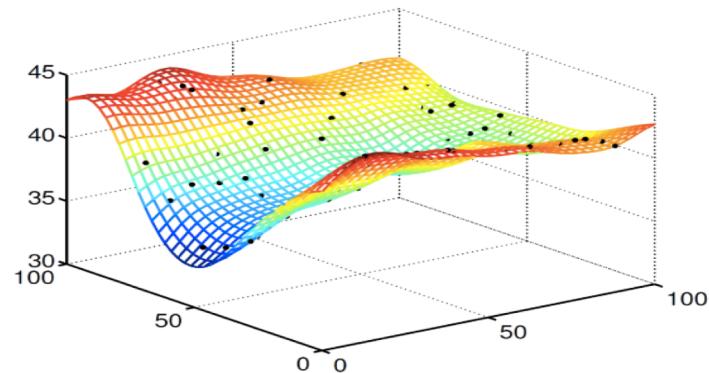


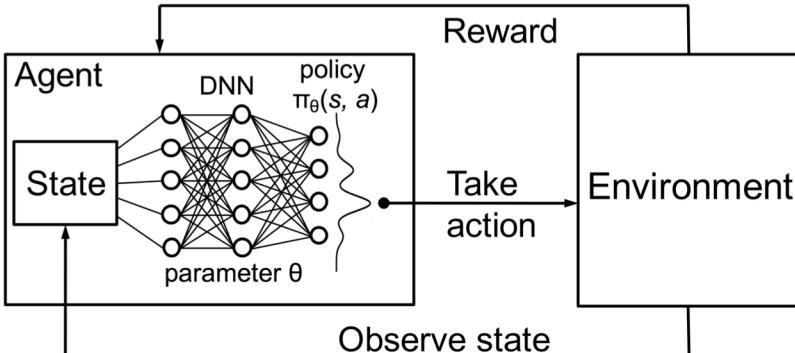
X

Given: App + Goal

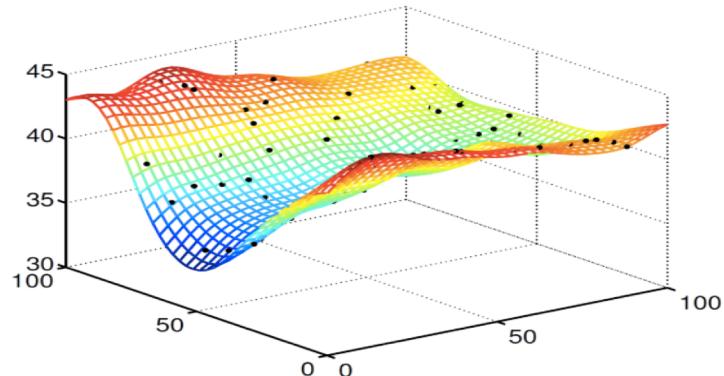
- **Goal:** Find the setting of X that best meets the goal
- **Challenge:** Response surface $y = f(X)$ is unknown

PERFORMANCE





Reinforcement Learning



Response Surface Methodology

Tuning Database Configuration Parameters with iTuned

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ABSTRACT

Database systems have a large number of configuration parameters that control memory distribution, I/O optimization, costing of query plans, parallelism, many aspects of logging, recovery, and

Amy recalls that the database has *configuration parameters*. For lack of better understanding, she had set them to default values during installation. The parameters may need tuning, so Amy pulls out the 1000+ page database tuning manual. She finds many dozens

Xplus: A SQL-Tuning-Aware Query Optimizer

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ABSTRACT

The need to improve a suboptimal execution plan picked by the query optimizer for a repeatedly run SQL query arises routinely. Complex expressions, skewed or correlated data, and changing con-

step in to lead the optimizer towards a good plan [6]. This process of improving the performance of a “problem query” is referred to in the database industry as *SQL tuning*. Tuning a problem query is critical in two settings:

Challenge: Response surface $y = f(X)$ is unknown

Model the response surface as

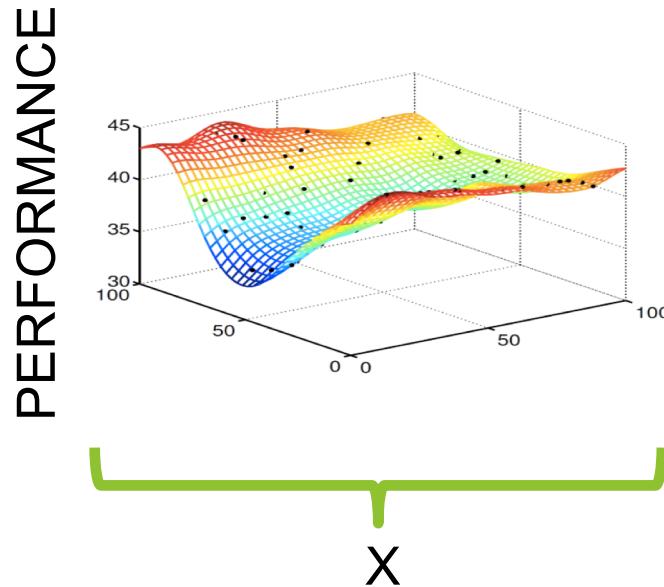
$$\hat{y}(X) = \vec{f}^t(X)\vec{\beta} + Z(X)$$

Here:

$\vec{f}^t(X)\vec{\beta}$ is a regression model

$Z(X)$ is the residual captured as a
Gaussian Process

The Gaussian Process model captures the
uncertainty in our current knowledge of the
response surface



Opportunity

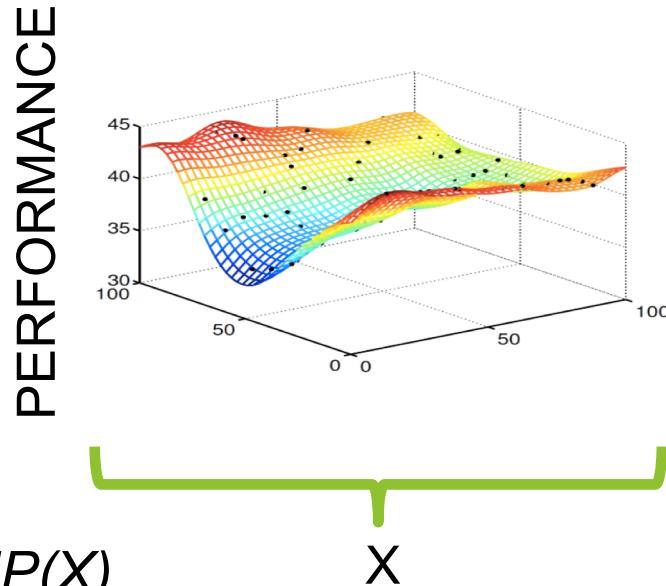
We can now estimate the **expected improvement** $EIP(X)$ from doing **a probe** at any setting X

$$EIP(X) = \int_{p=-\infty}^{p=y(X^*)} (y(X^*) - p) pdf_{\hat{y}(X)}(p) dp$$

Improvement at any setting X over the best performance seen so far

Probability density function (uncertainty estimate)

Gaussian Process model helps estimate $EIP(X)$



Bootstrap

1

Get initial set of monitoring data from history or via probes: $\langle X_1, y_1 \rangle, \langle X_2, y_2 \rangle, \dots, \langle X_n, y_n \rangle$



Probe Algorithm

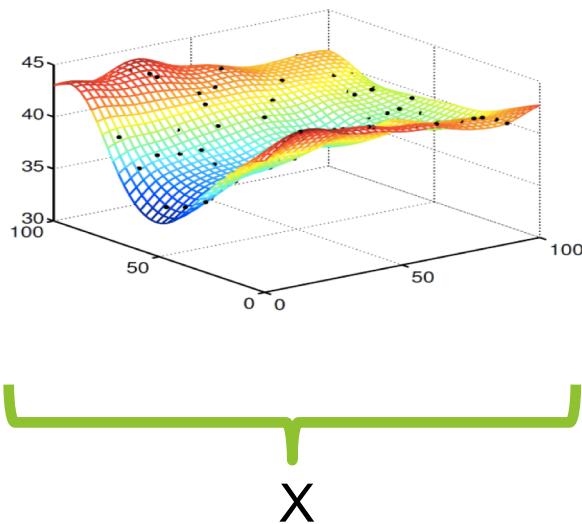
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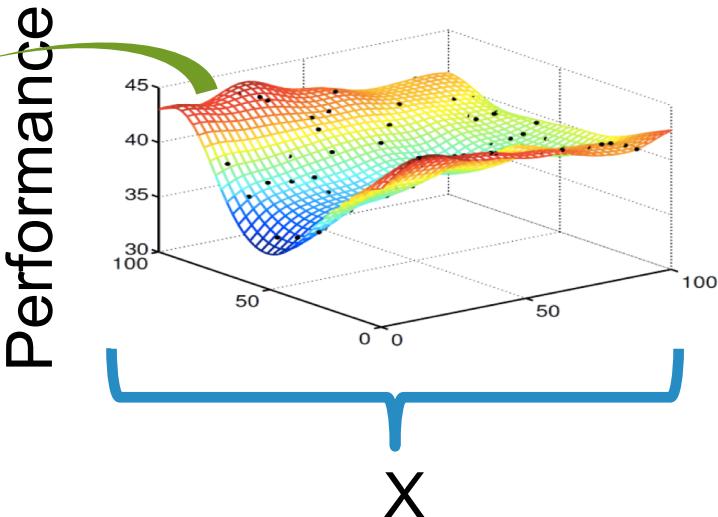
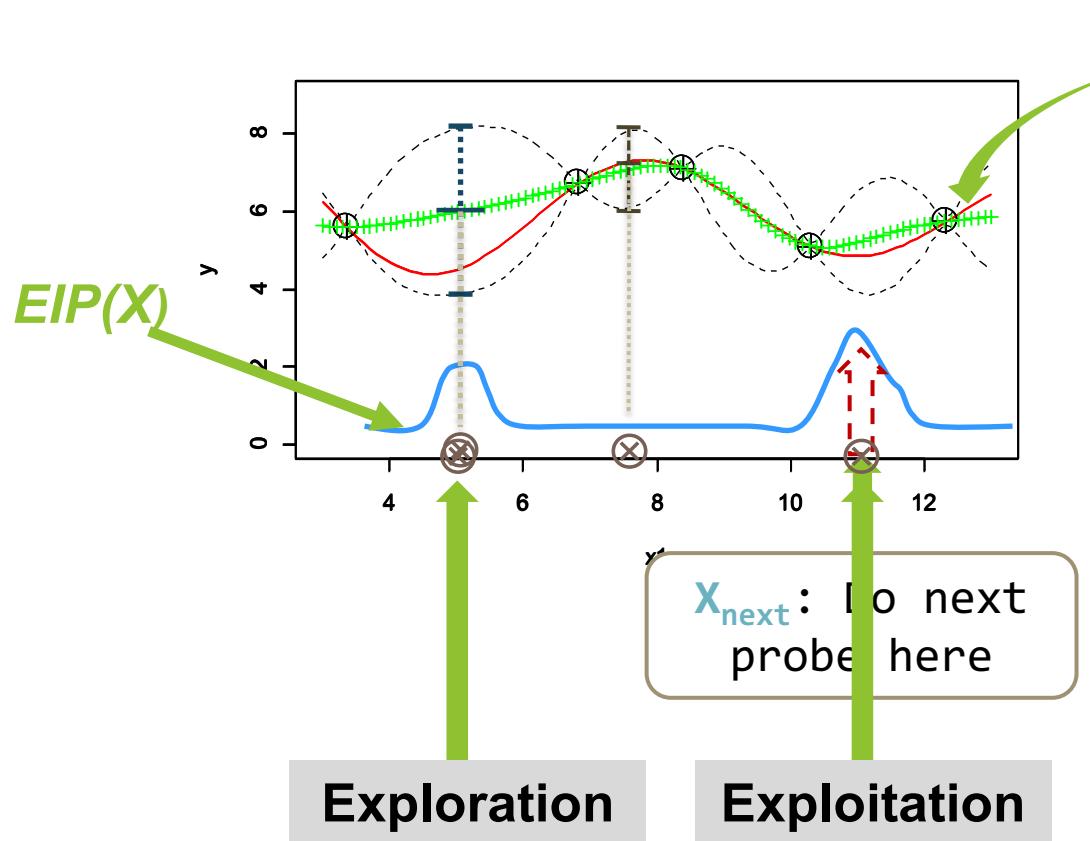
Select *next probe* X_{next} based on all history and probe data available so far to calculate the setting with *maximum expected improvement EIP(X)*

Until the stopping condition is reached

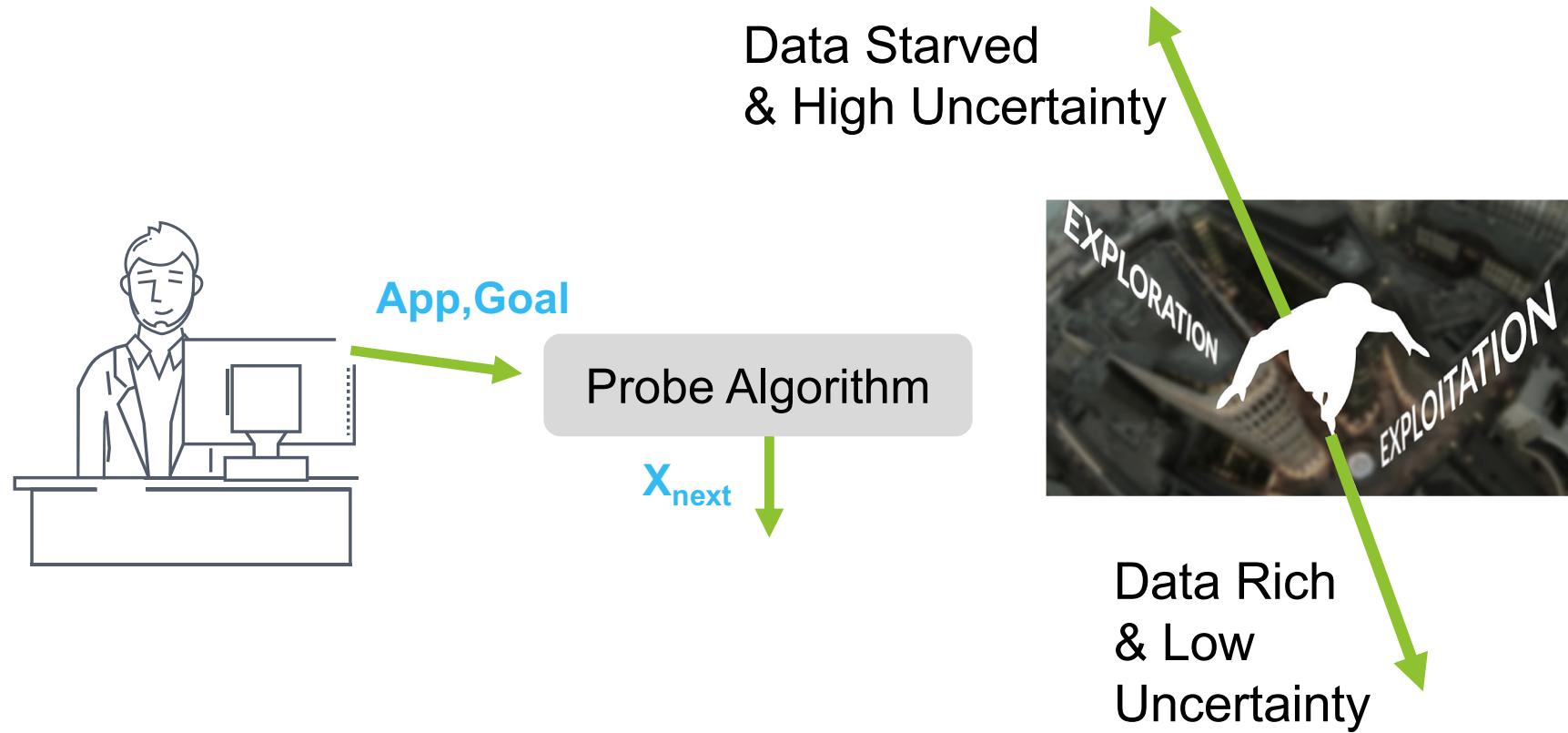


PERFORMANCE

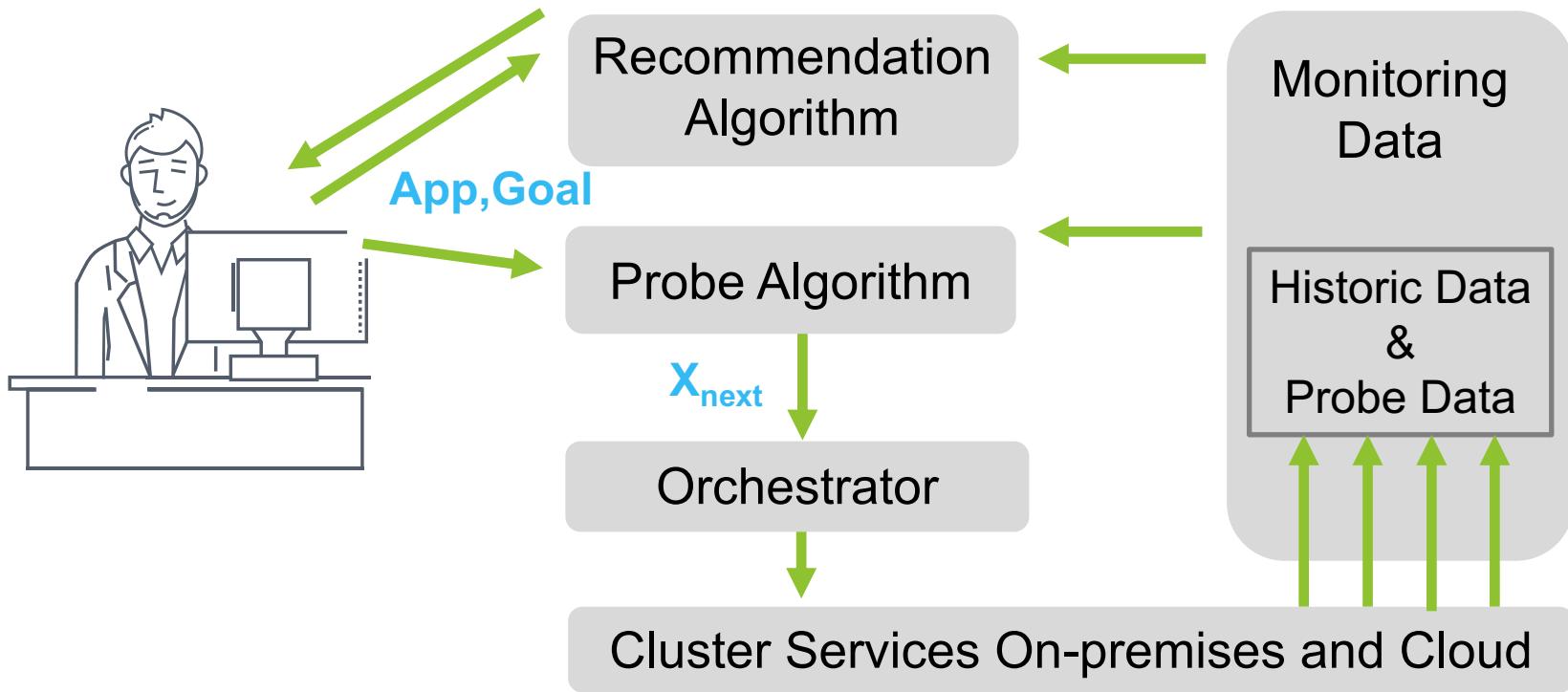




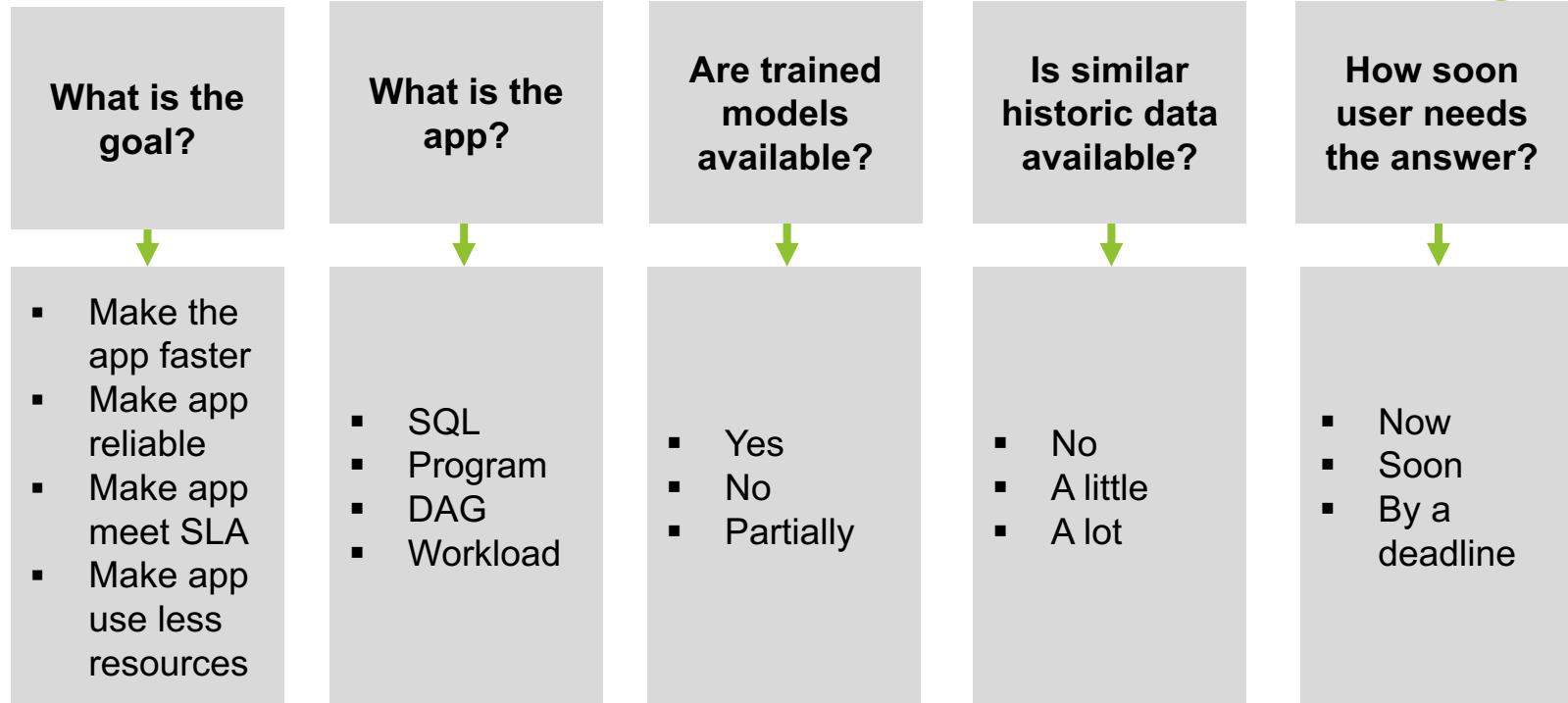
This approach balances Exploration Vs. Exploitation



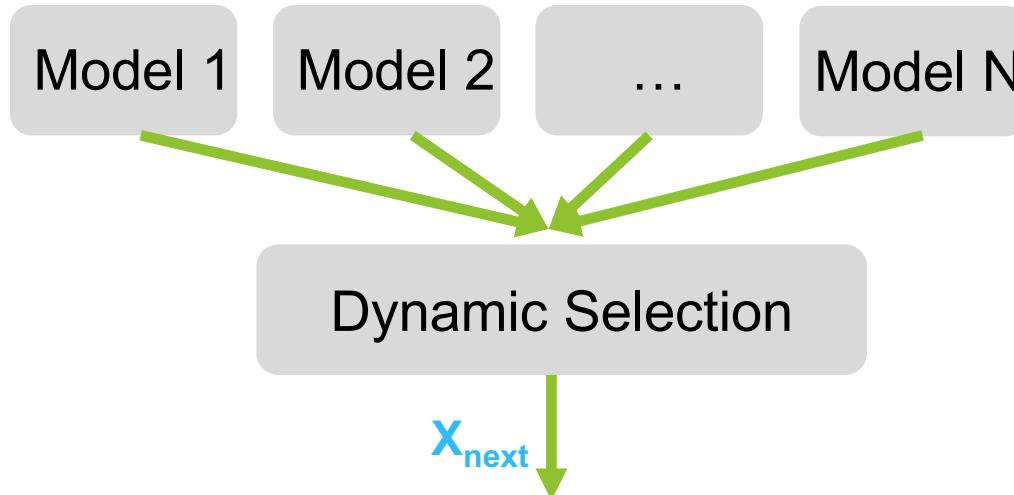
Unravel Sessions Architecture



Probe Algorithm: Has to deal with a diverse space of data & uncertainty



Probe Algorithm: Use Model Ensembles

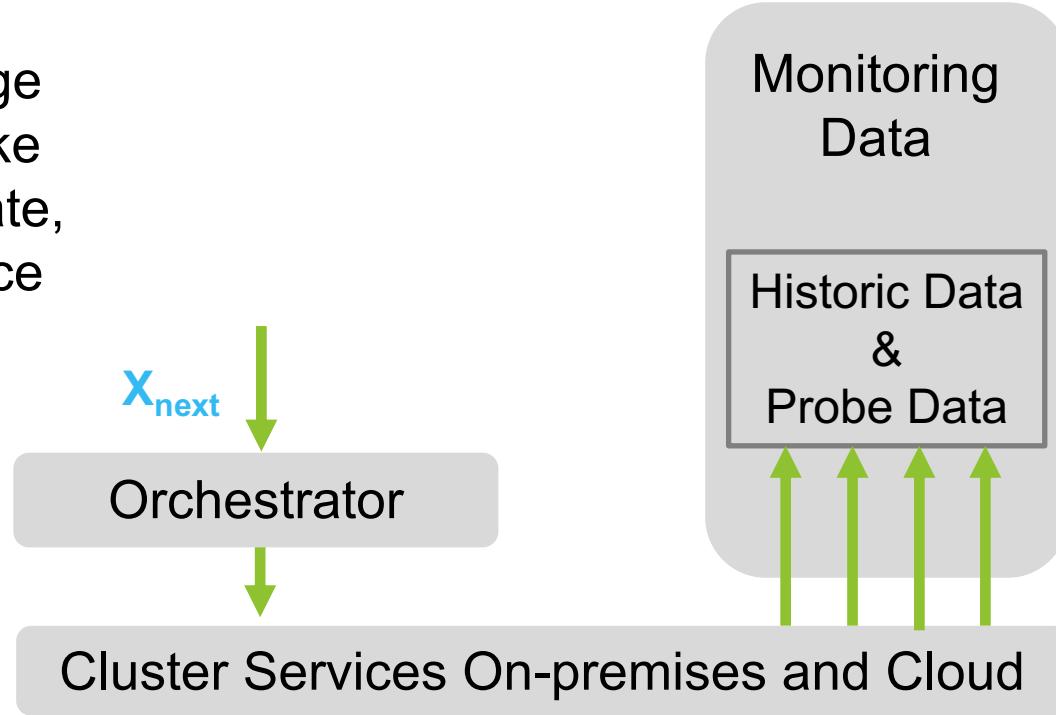


Lessons Learned Building the Unravel Sessions Architecture

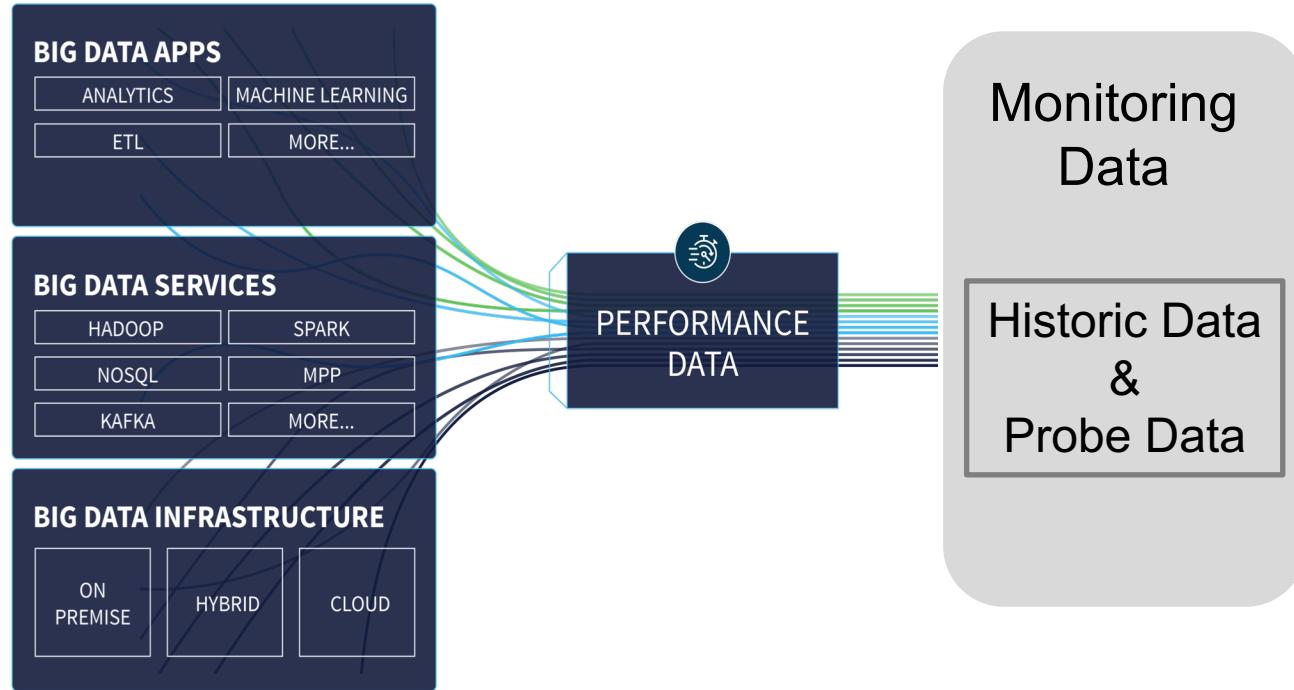
- Probe Algorithm: Use model ensembles
- Orchestrator: Use cheap probes when possible
- Monitoring data: Use full-stack data collection
- Recommendation Algorithm: Keep user in the loop

Lessons Learned: Cheap Probes

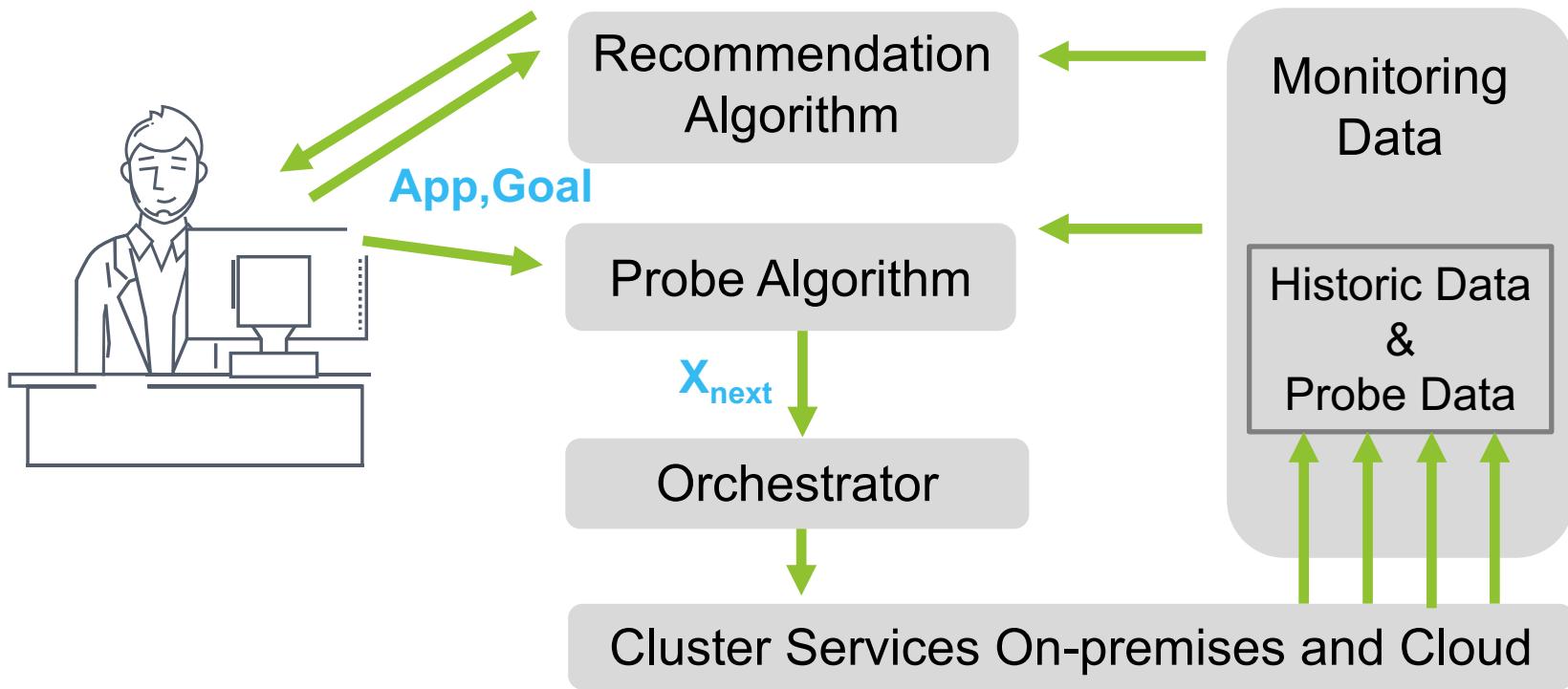
Orchestrator can leverage cost-based optimizers like Catalyst as an approximate, but very fast, performance model in some cases



Lessons Learned: Full Stack



Lessons Learned: User in the Loop



In Summary

AI for Application Performance Management

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