Cirrus:
A Serverless Framework for End-to-end ML Workflows

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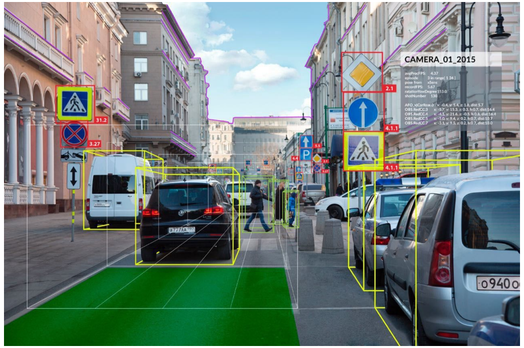
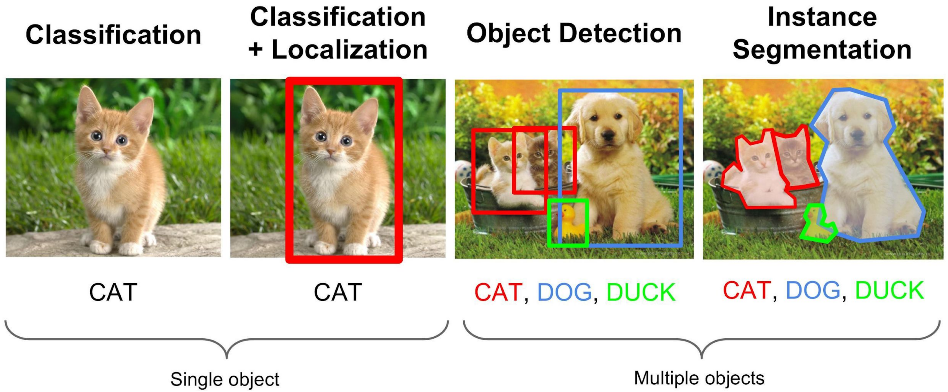
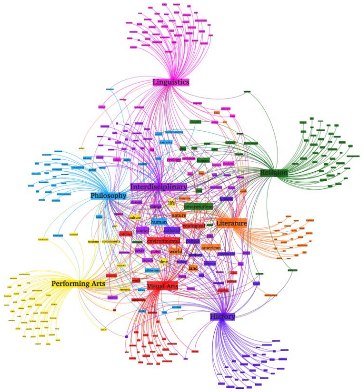
Machine Learning







End-to-end ML workflows

- Modern end-to-end ML workflows are complex

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- ML workflows consist of 3 heterogeneous stages

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Dataset Preprocessing

End-to-end ML workflows

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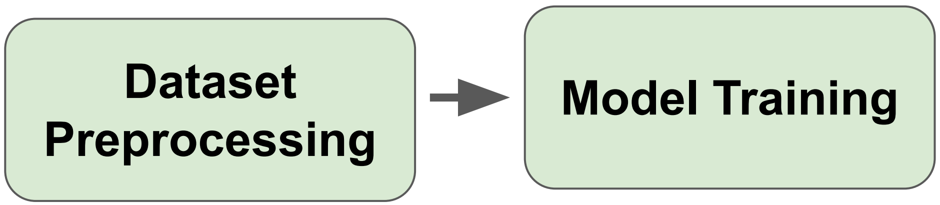

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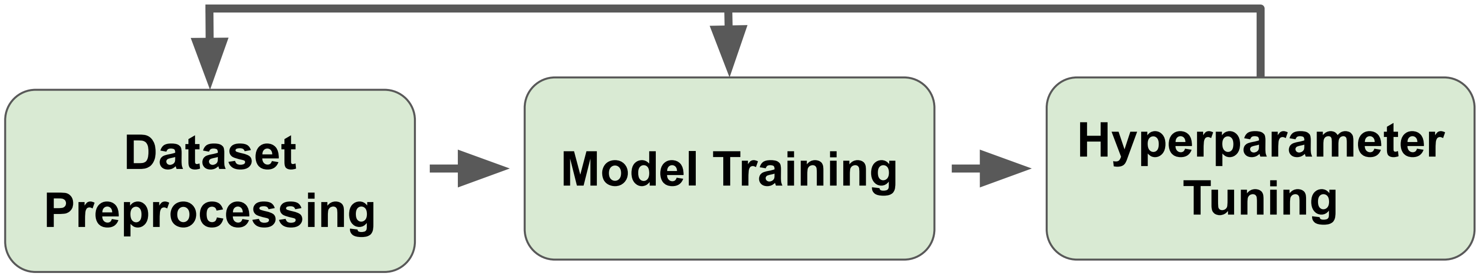

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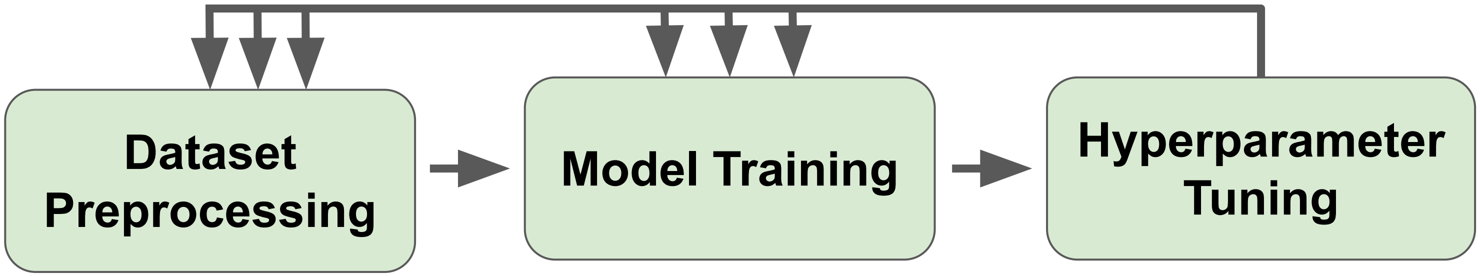


ML workflows are **interactive** and **iterative**

Provisioning ML workflows

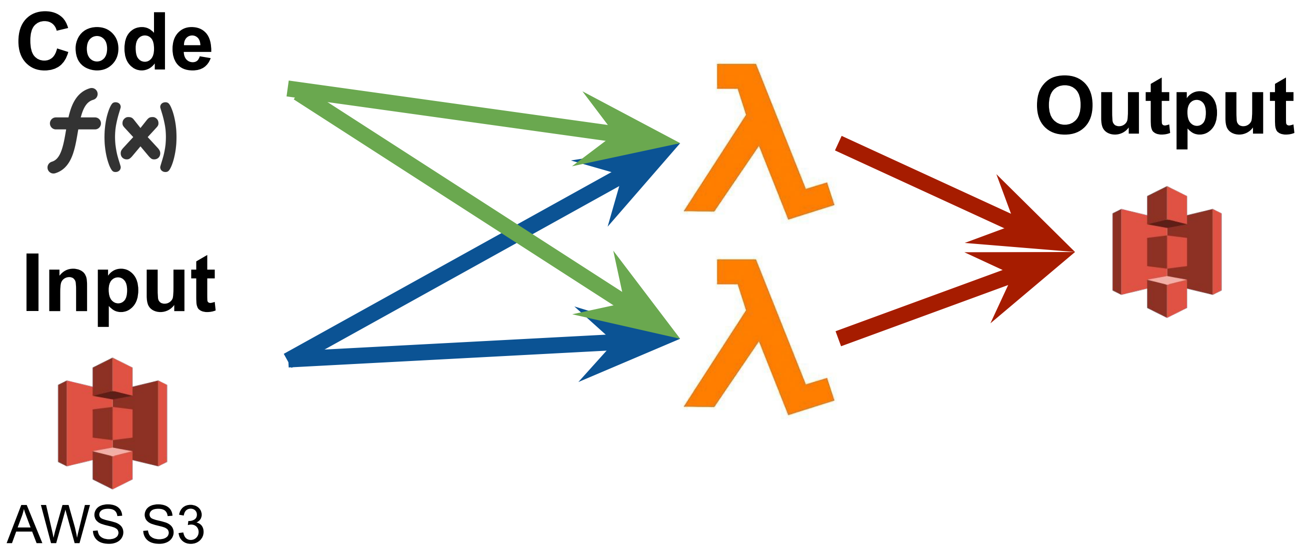
Provisioning ML workflows is challenging

Hard to accurately estimate resource demands of each stage

Data scientists have limited systems expertise

- Complex infrastructure management **detracts from ML work**
- **Resource waste** due to overprovisioning of resources

Serverless computing



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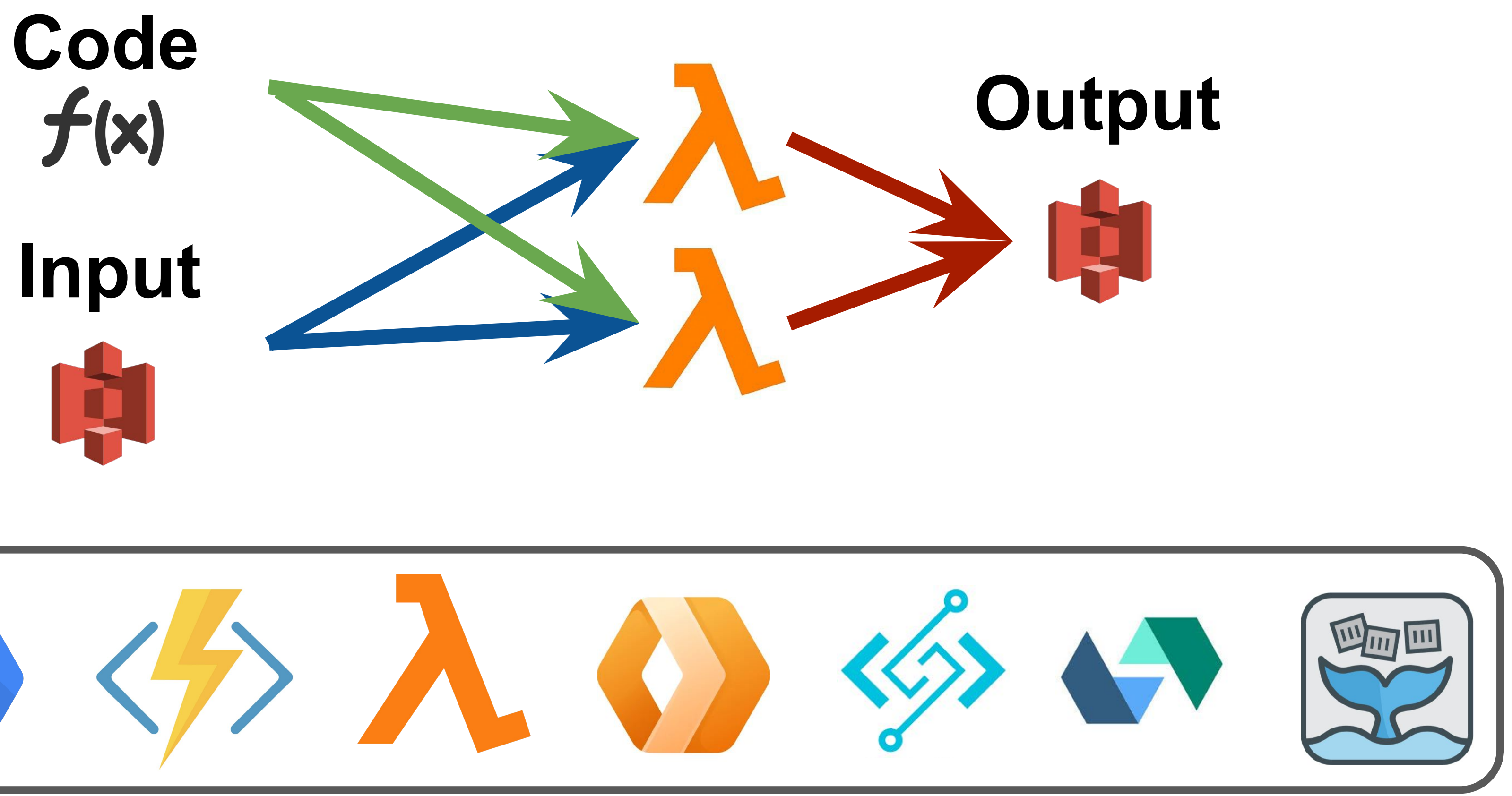
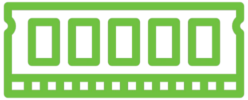


Serverless computing benefits

Tight provisioning of resources

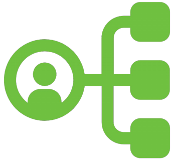
Fine-grained billing



Fine-grained resources

High elasticity

Simplifying infrastructure management



Automatic resource configuration / provisioning / maintenance

Challenges of serverless

Small local memory and storage

Low bandwidth and no P2P communication

Limited lambda package size

Lack of fast shared storage

Short-lived and unpredictable launch times

Existing approaches

Serverless Frameworks

Machine Learning Frameworks

Existing approaches

Serverless Frameworks

corral PyWren faast.js

Limit. Pkg size

Download dependencies from S3

No fast storage

High-latency communication through S3

Unpred. launch

Stragglers

Machine Learning Frameworks

Existing approaches

<u>Serverless Frameworks</u>

corral PyWren faast.js

Limit. Pkg size — Download dependencies from S3

No fast storage — High-latency communication through S3

Unpred. launch — Stragglers

<u>Machine Learning Frameworks</u>

TensorFlow Apache Spark

Small mem. — Unable to launch runtimes in lambdas

No P2P comm. — No ring/tree reduces
No driver-to-worker comm.

Unpred. launch — Precludes MPI

Cirrus: a framework for serverless end-to-end ML workflows

Cirrus: design principles

1) Addressing serverless challenges

Low memory

Limited package size

No P2P communication

No fast storage

Short lifetimes and unpredictable launch

Ultra-lightweight runtime + data prefetching

High-perf. data store (parameter-server and KV)

Robust handling of lambda termination

Cirrus: design principles

2) Achieving benefits for end-to-end ML

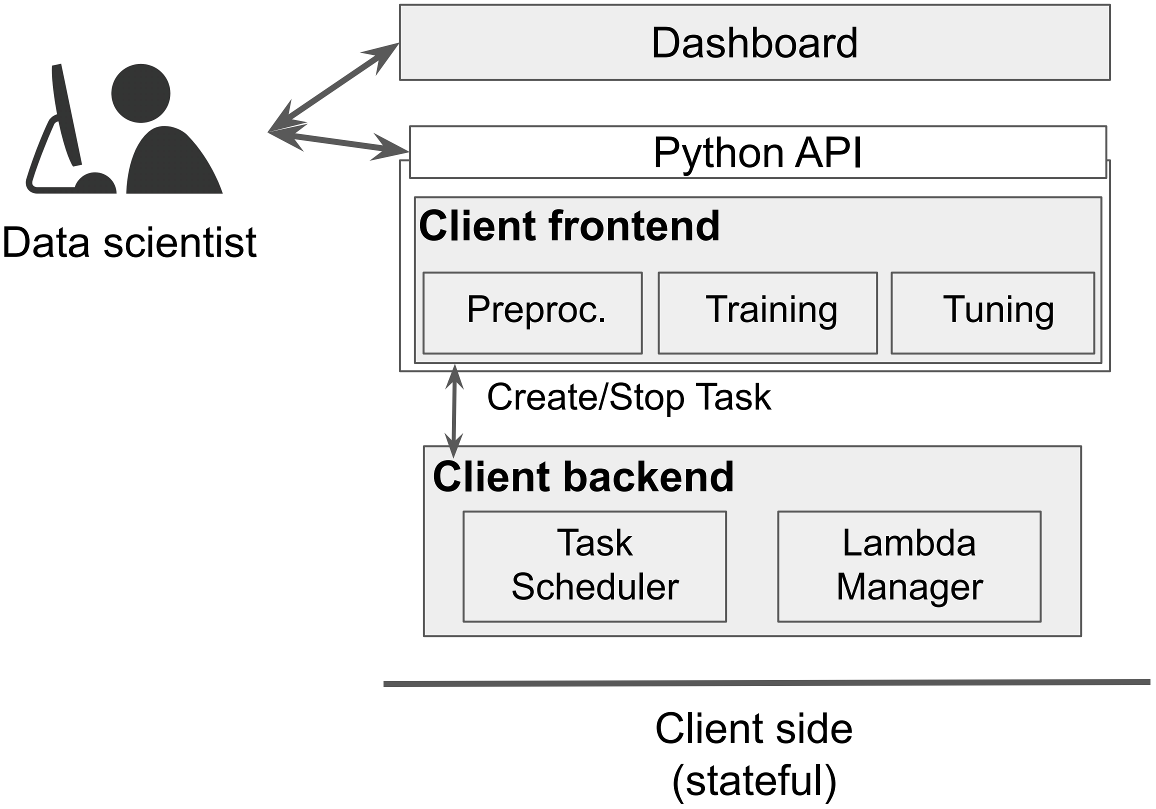
Tight provisioning of resources

Per-stage fine-grained variable agile scalability

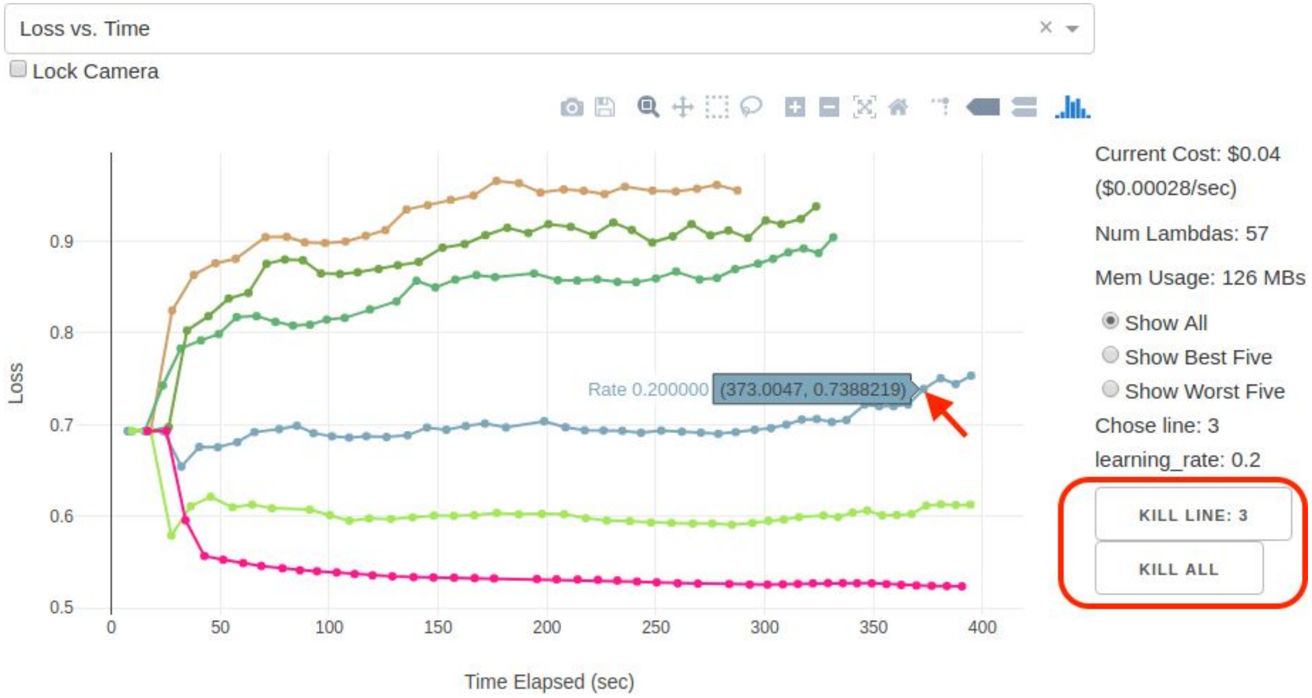
Simplifying infrastructure management

High-level API supports end-to-end ML

Cirrus architecture (client side)



Cirrus Dashboard



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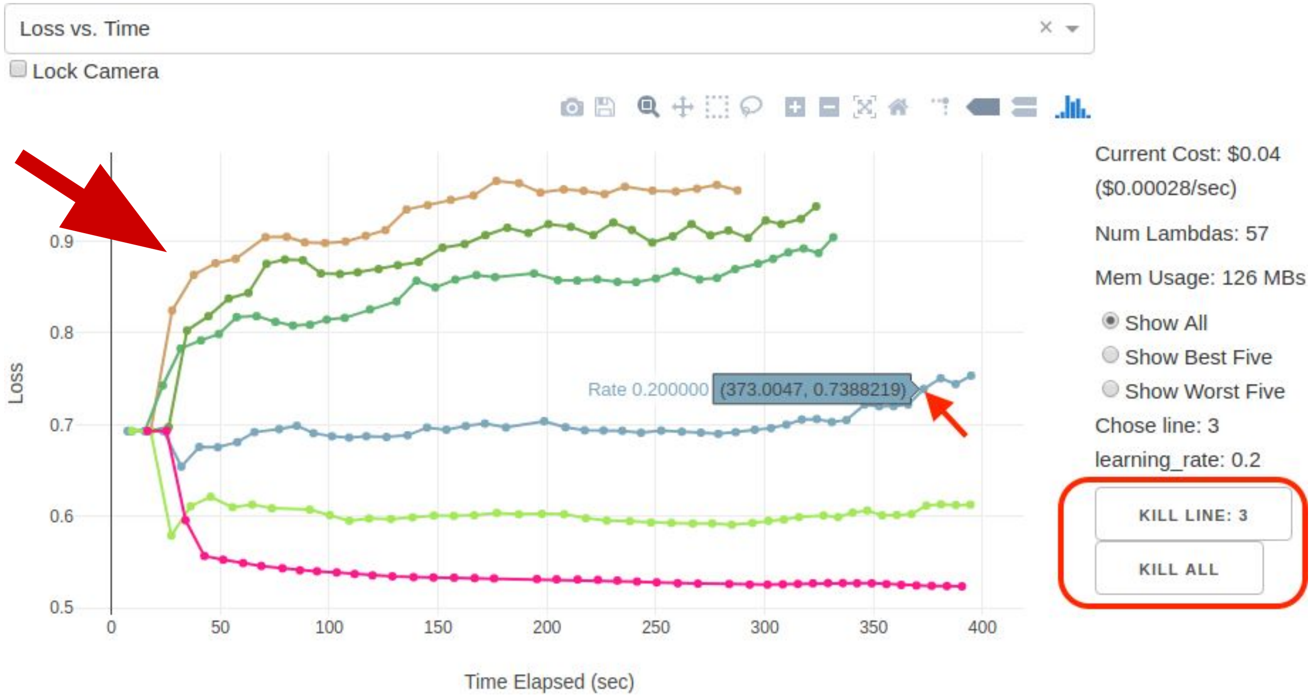

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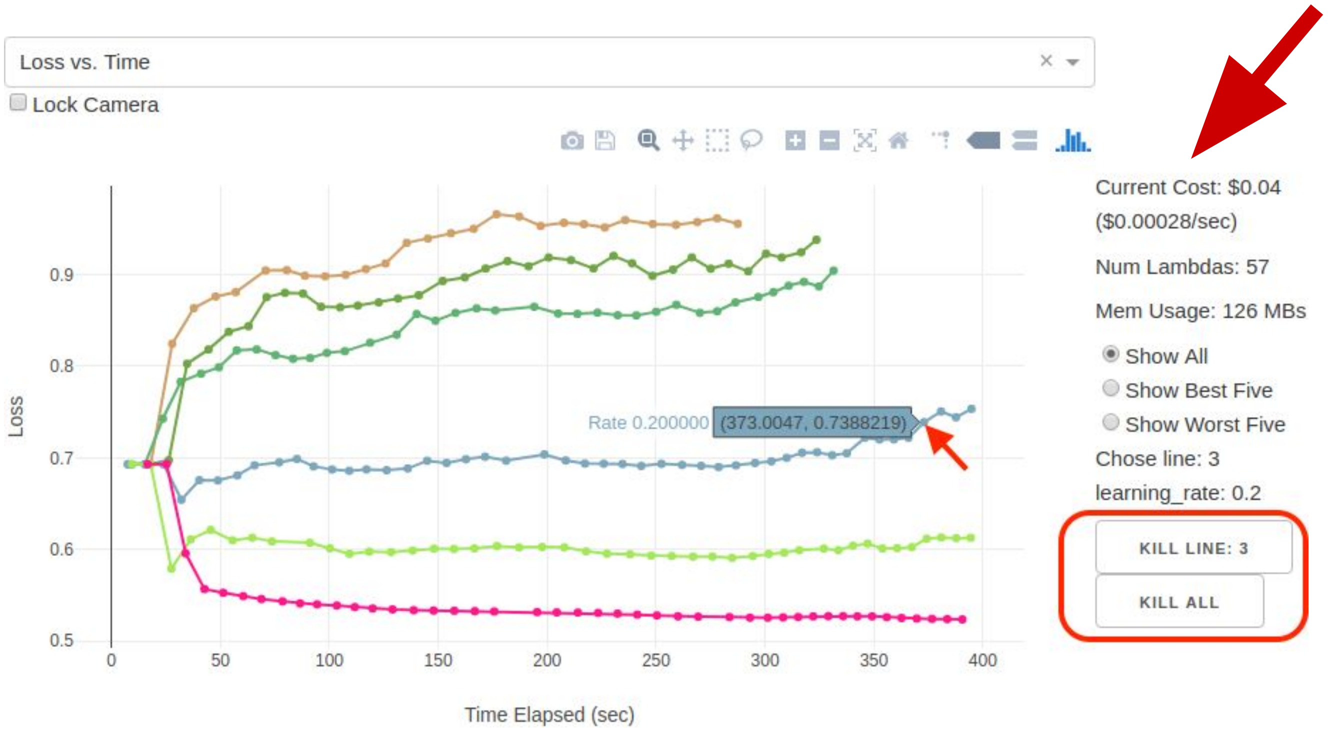

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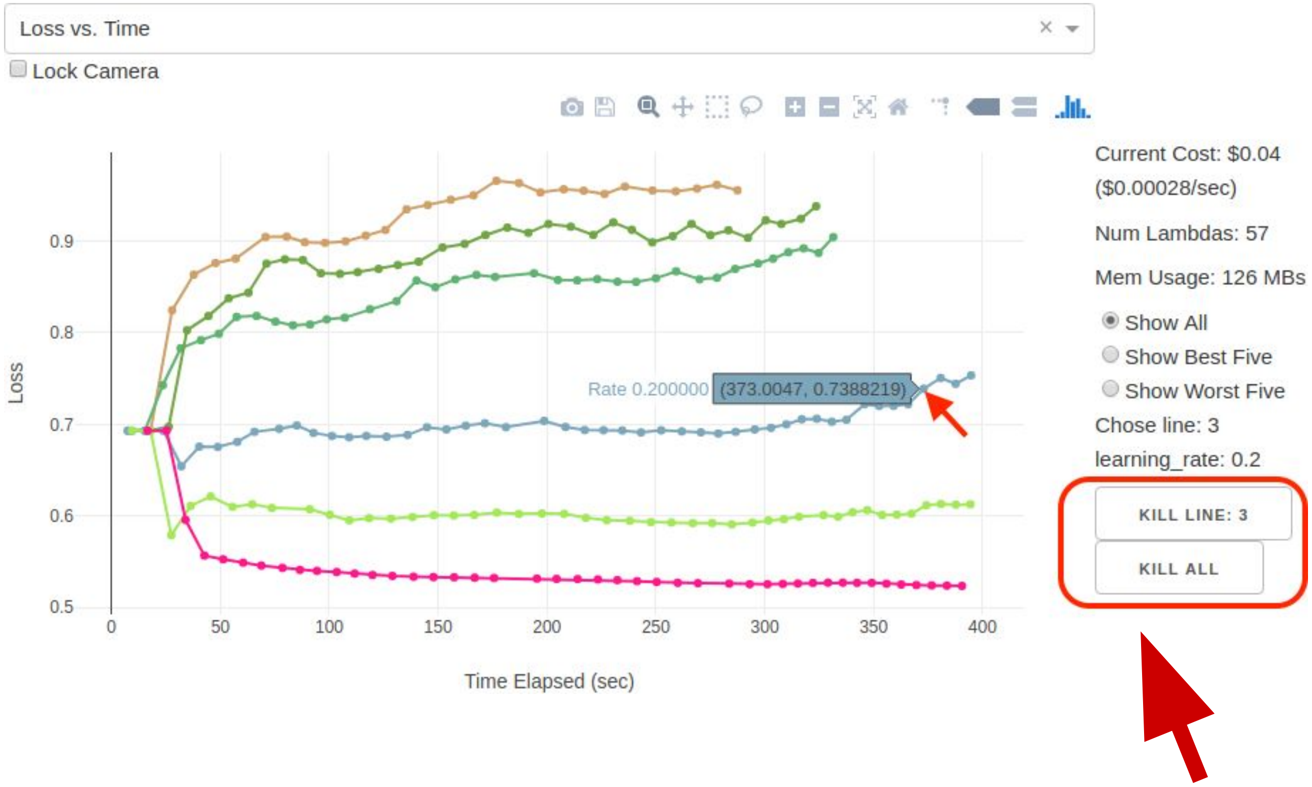
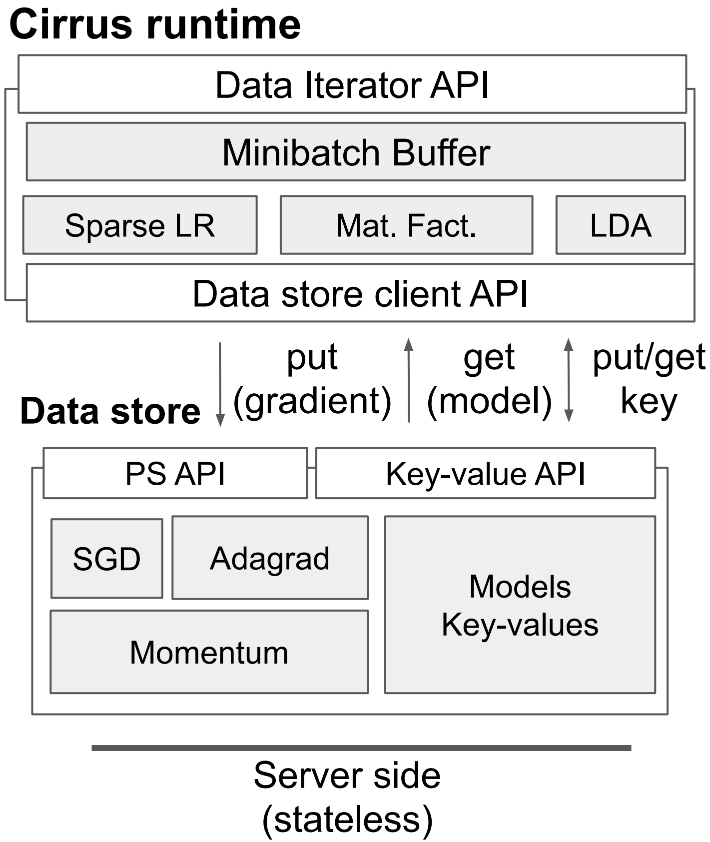


Cirrus architecture (server side)



Cirrus evaluation

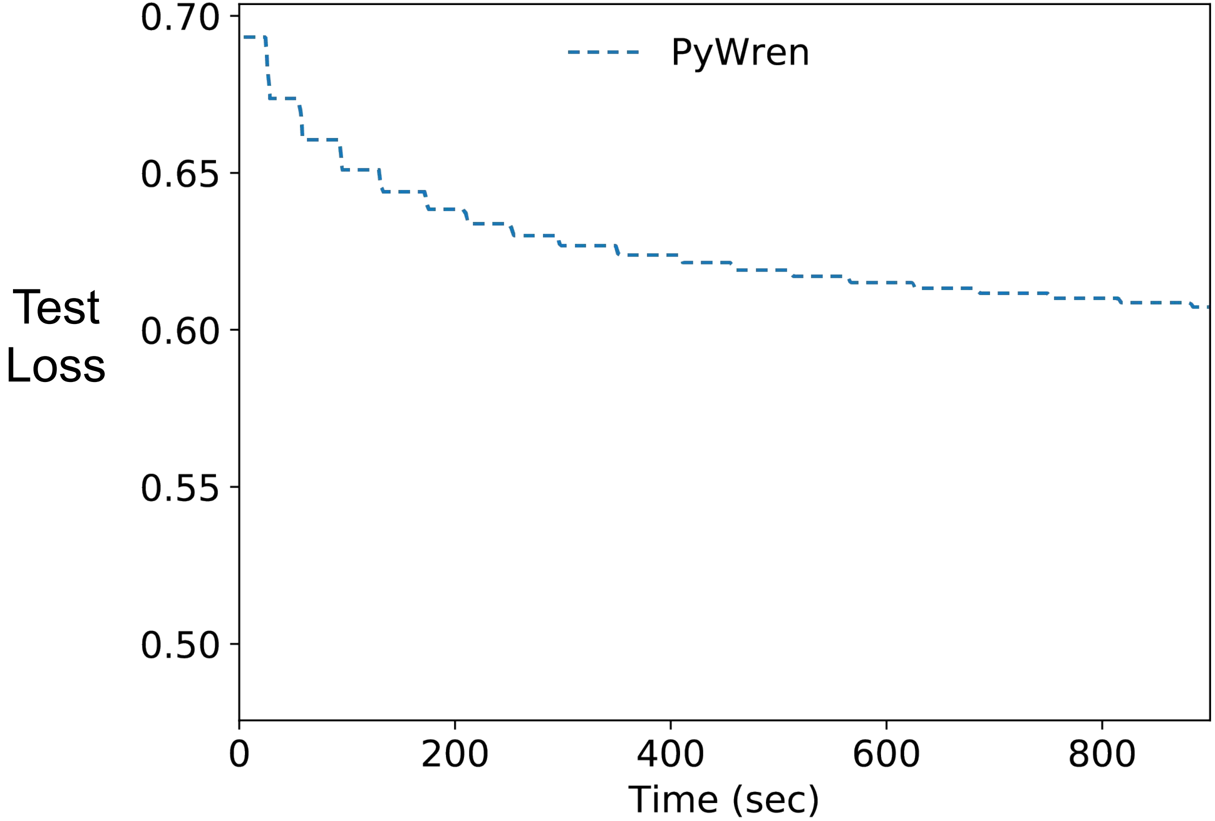
1. Cirrus provides benefits by specializing both for serverless and end-to-end ML

2. We show that Cirrus outperforms a state-of-the-art serverless system: PyWren

Evaluation setup

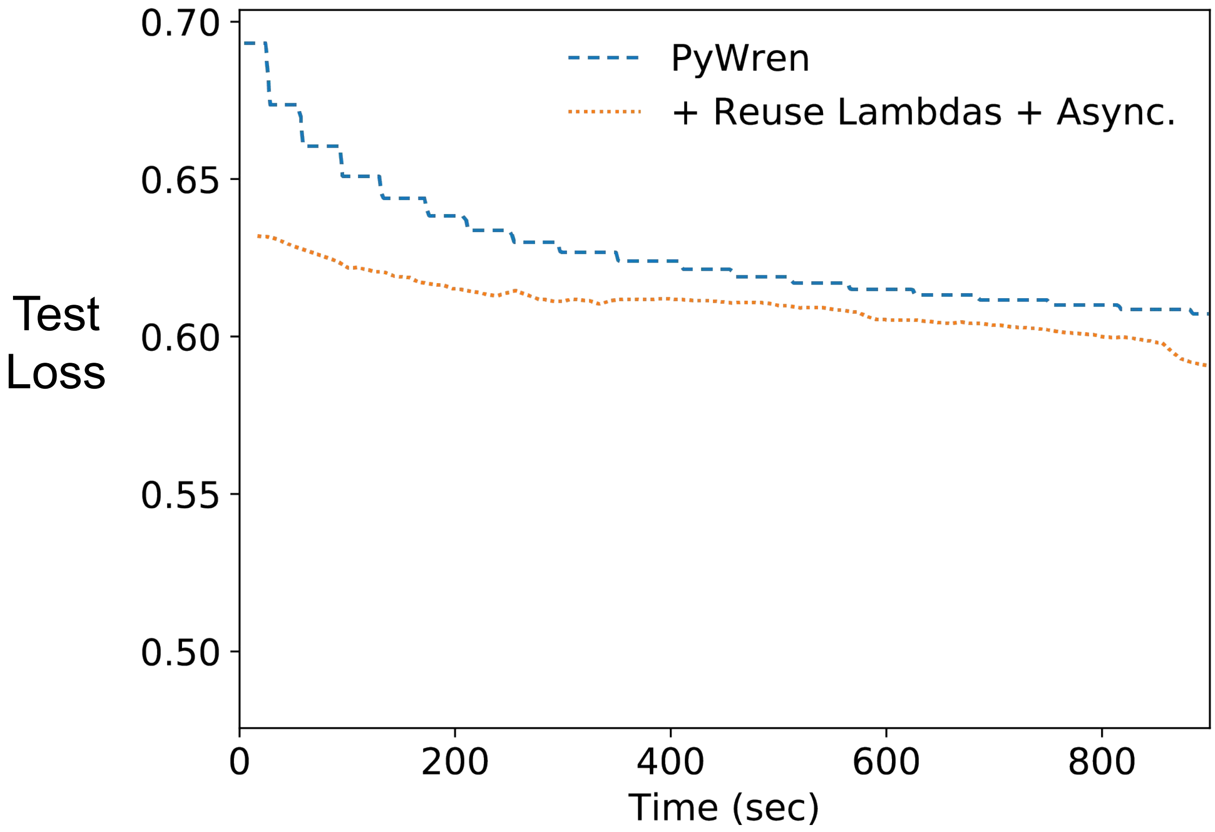
1. Deployment: AWS Lambdas (3GB of mem.)
2. Benchmark: async. distributed SGD Sparse Logistic Regression task
3. Dataset: Criteo Dataset (a dataset of display ads)
4. PyWren:
    a. Baseline: iterative synchronous SGD training using AWS S3 to store gradients and model
    b. + 3 incremental optimizations
5. Cirrus: 2 modes (with/without prefetching)

Cirrus outperforms vanilla serverless



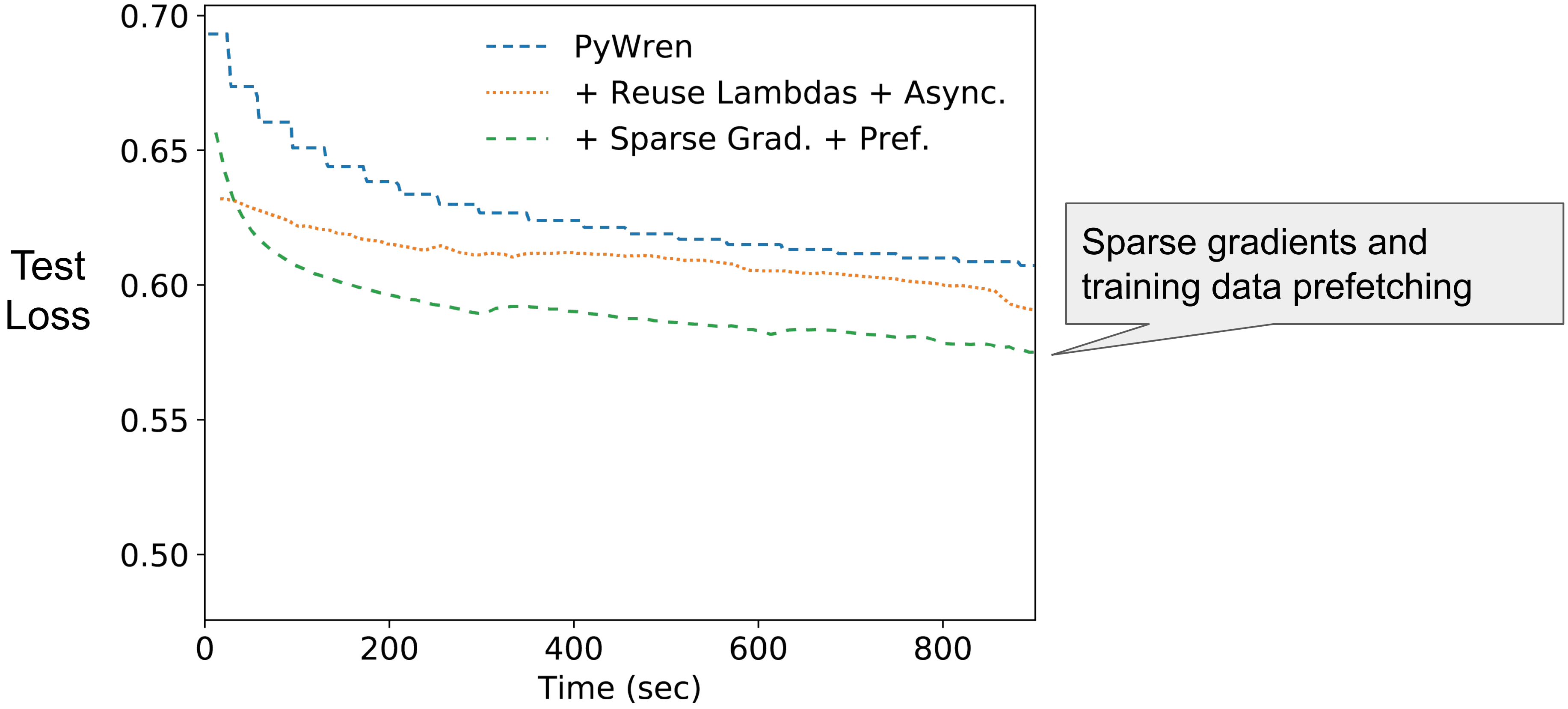
Synchronous SGD training suffers from stragglers

Cirrus outperforms vanilla serverless



- Multiple SGD iterations on each lambda invocation
- Asynchronous SGD

Cirrus outperforms vanilla serverless



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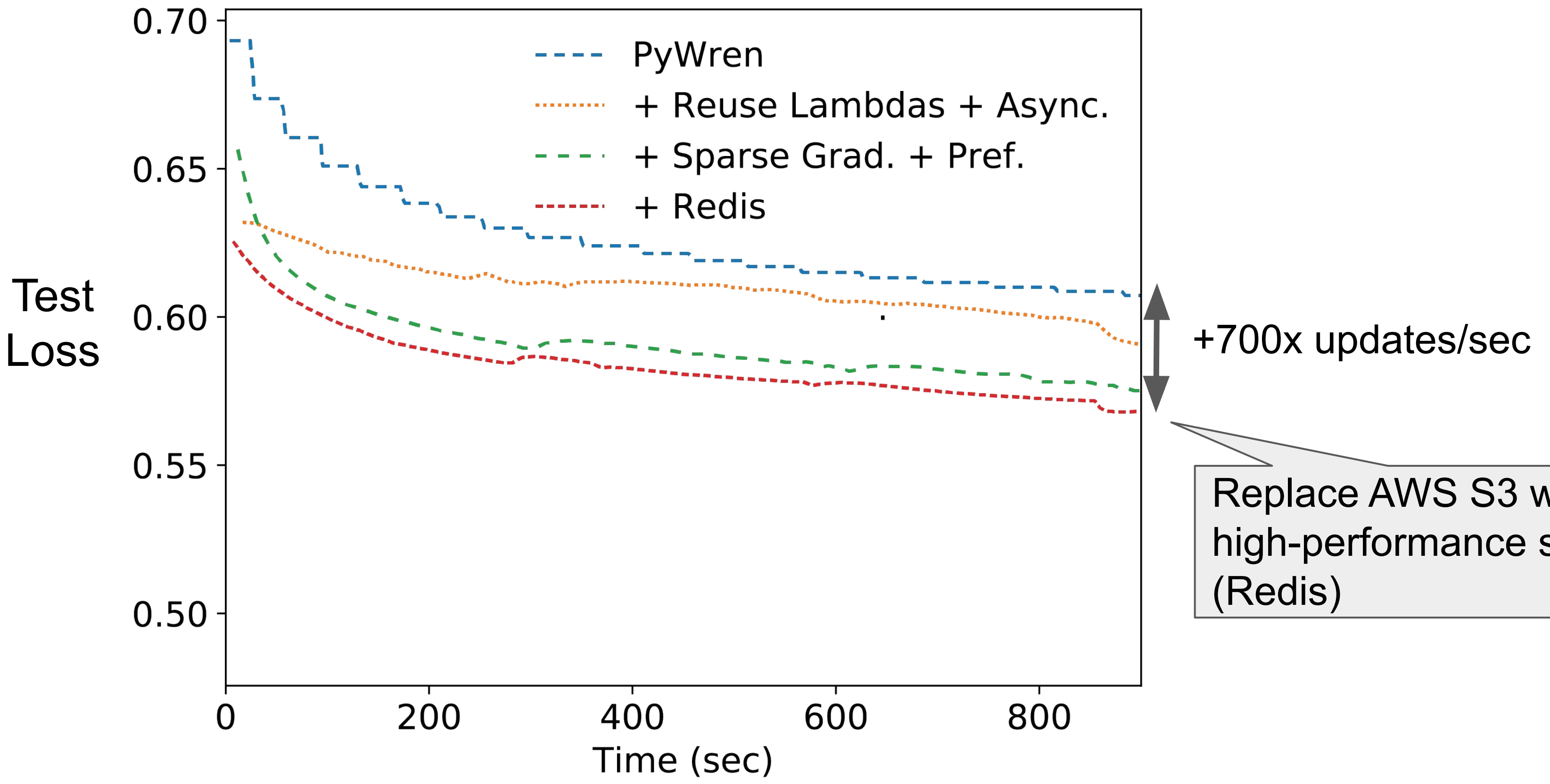
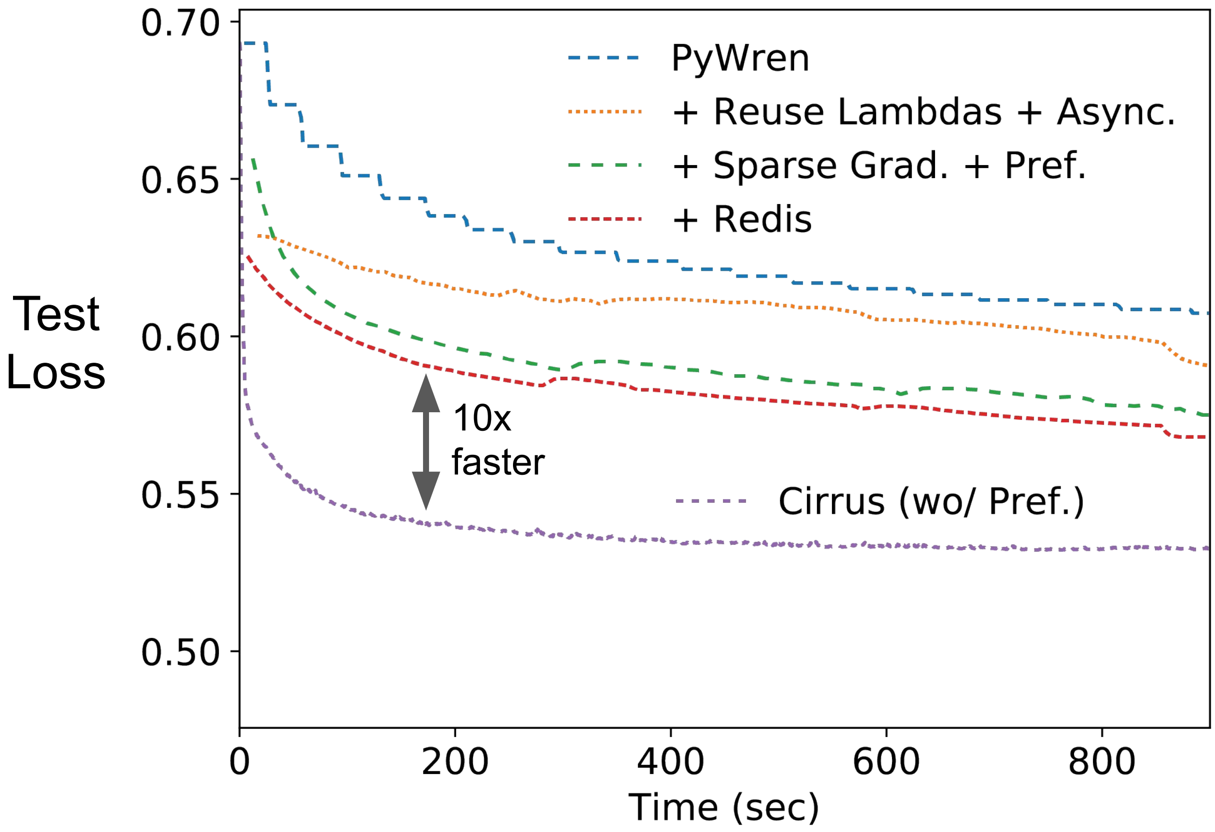


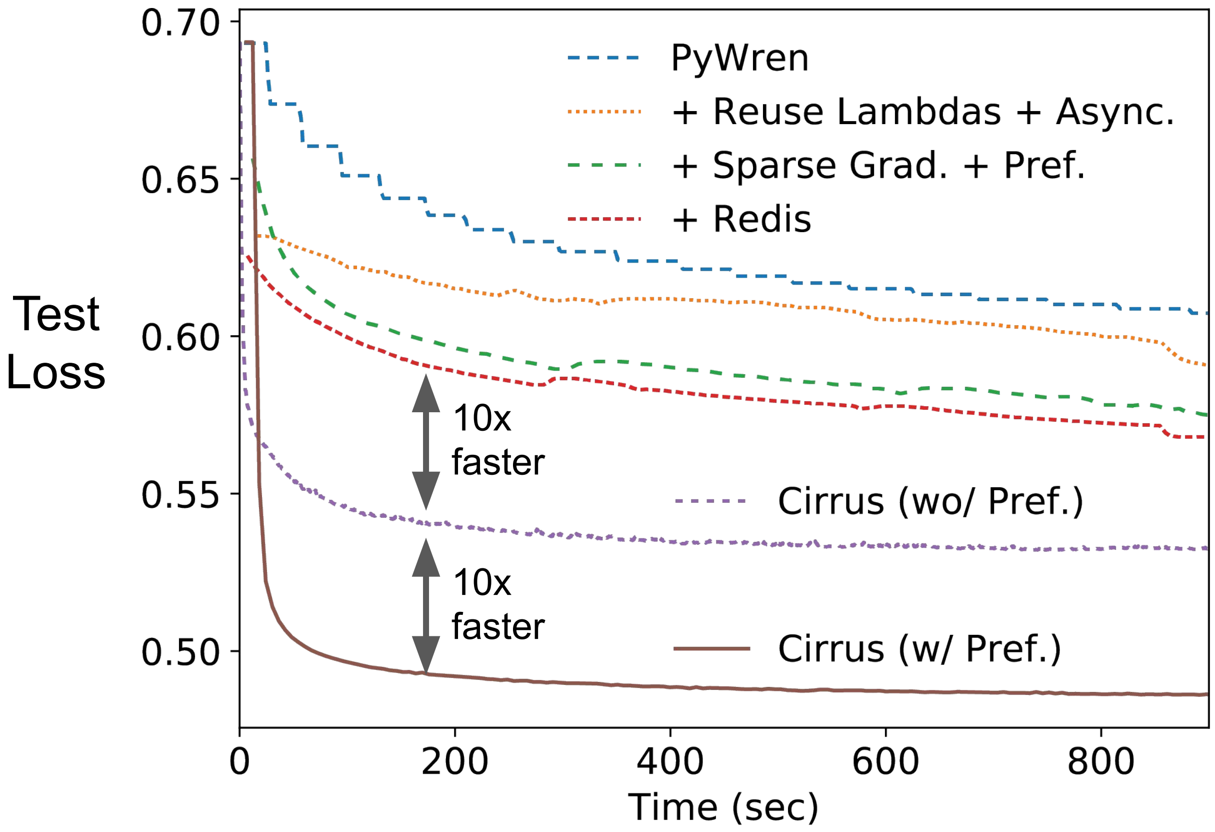
Replace AWS S3 with high-performance store (Redis)

Cirrus outperforms vanilla serverless



Cirrus without training data prefetching

Cirrus outperforms vanilla serverless



Cirrus with training data prefetching

Conclusion

1. End-to-end ML workflows:
   a. time-consuming infrastructure management
   b. resource overprovisioning
2. Cirrus -- serverless end-to-end ML framework:
   a. simplify deployment of ML workflows
   b. per-stage provisioning of resources
3. Cirrus outperforms existing serverless solutions by specializing for <u>serverless</u> and <u>ML</u>

Thank you!

github.com/ucbrise/cirrus

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