BATCH: Machine Learning Inference Serving on Serverless Platforms with Adaptive Batching

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Outline

- Batching workloads in Machine Learning (ML)
- Bursty workloads in ML
- Utilization of Function as a Service (FaaS)
- Lightweight BATCH framework
- Results
- Criticisms and concerns

Understanding the problem

In Machine learning (ML) we train models to infer new instances of data

It is ideal to classify data in batches, not one at a time

Given the burstiness of data inference needs in real life applications, this can be difficult to achieve

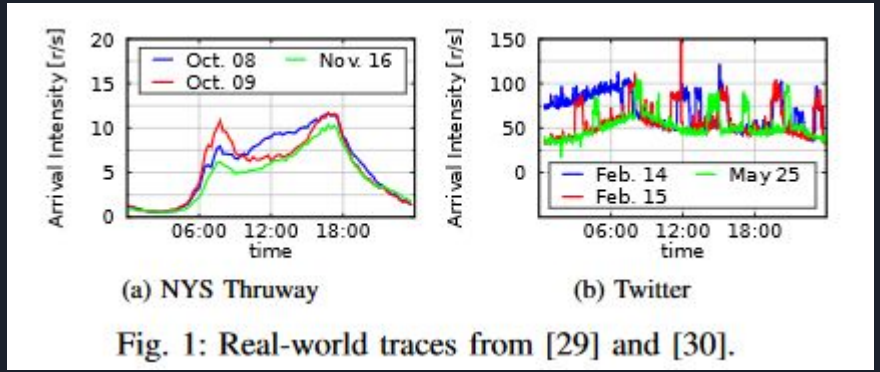
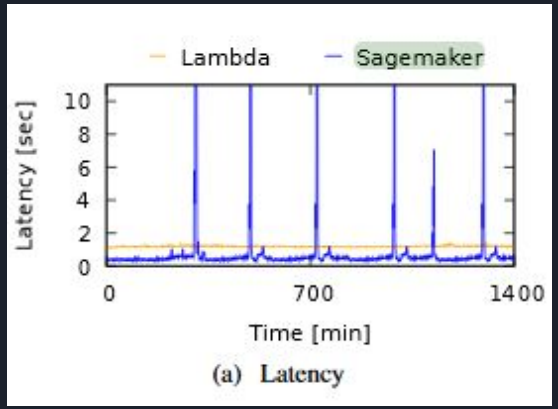


Fig. 1: Real-world traces from [29] and [30].

Previous work

Sagemaker: An industry standard solution which uses an IaaS platform to infer data [1]

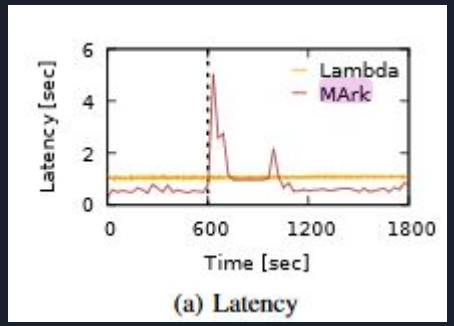
Problem: Strategy does not lend itself to bursty ML workloads.



Previous work

MArk: Creates AWS EC2 instance and creates serverless functions to deal with bursty workloads [2]

Method far outperforms SageMaker in latency, but can still struggle with bursty workloads



Authors Work

Use Functions as a Service (FaaS) to horizontally scale to workloads

Challenges

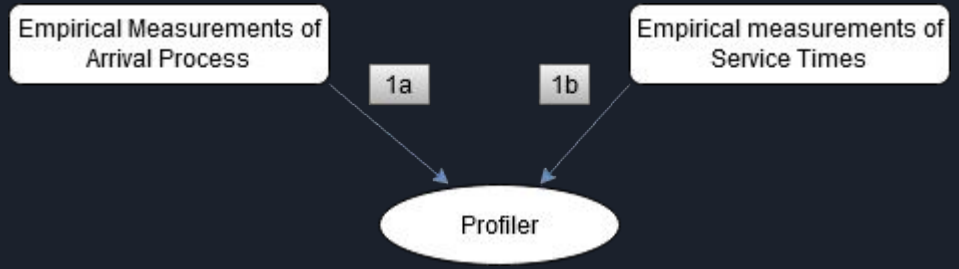
- Given the stateless nature of FaaS, batching is not supported
- Inference needs low latency
- Dynamic tuning of FaaS parameter

Authors introduce their framework, BATCH, to solve these issues

BATCH Framework

Arrival Process: Observes distribution of incoming jobs (1a)

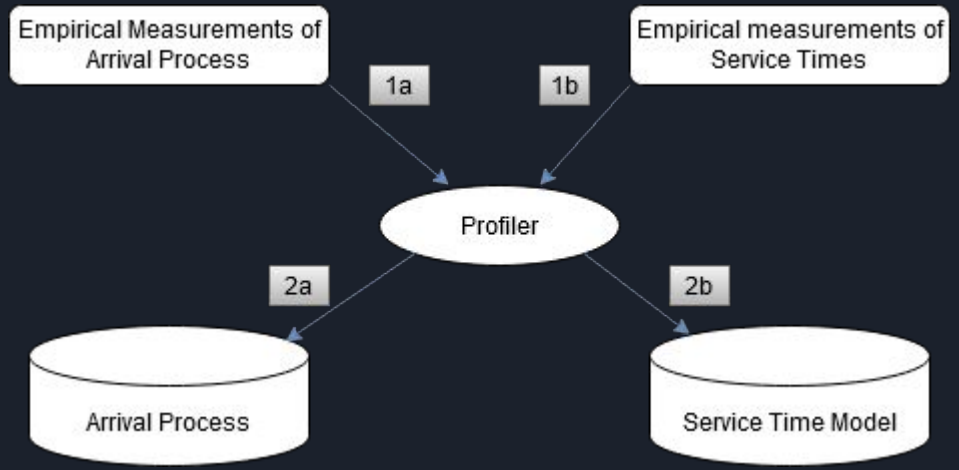
Service Times: How long it takes to infer data (1b)



BATCH Framework

Profiler: Transforms incoming into a stochastic process (2a)

Uses regression analysis to capture the relationship between system configuration and request service times (2b)

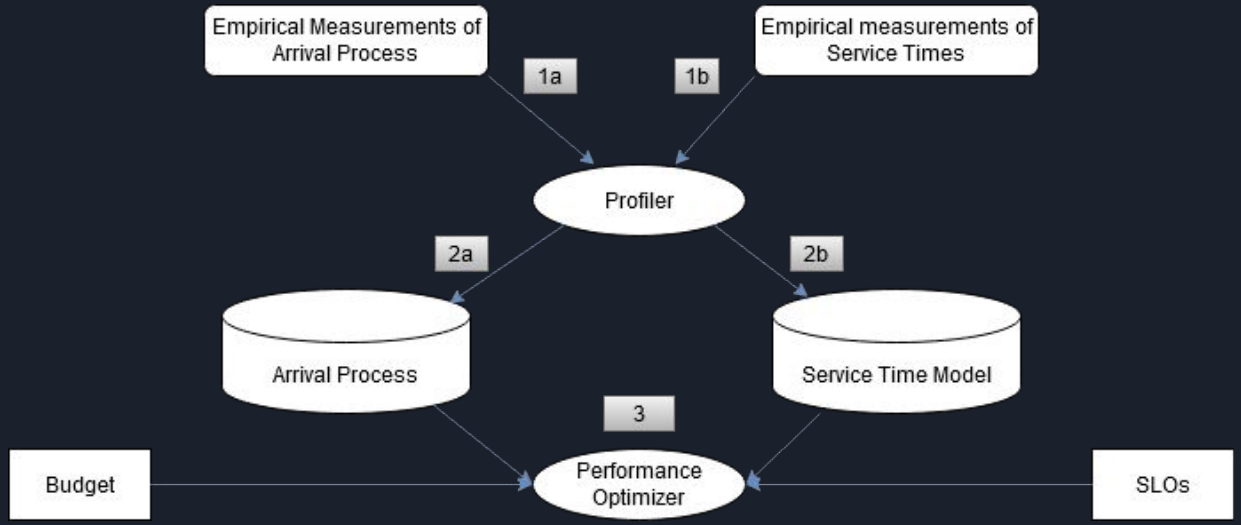


BATCH Framework

Performance Optimizer: Takes multiple inputs and tries to determine optimal batch size/timeout

Budget: How much we are willing to spend

SLO: How much latency we are willing to endure



BATCH Framework

Performance Optimizer: Recommends ideal batch size/timeout (4a)

Memory Size: storage for FaaS (4b)

Workload: Data to infer (5)

Batch Dispatching Buffer: array of data to infer (6)

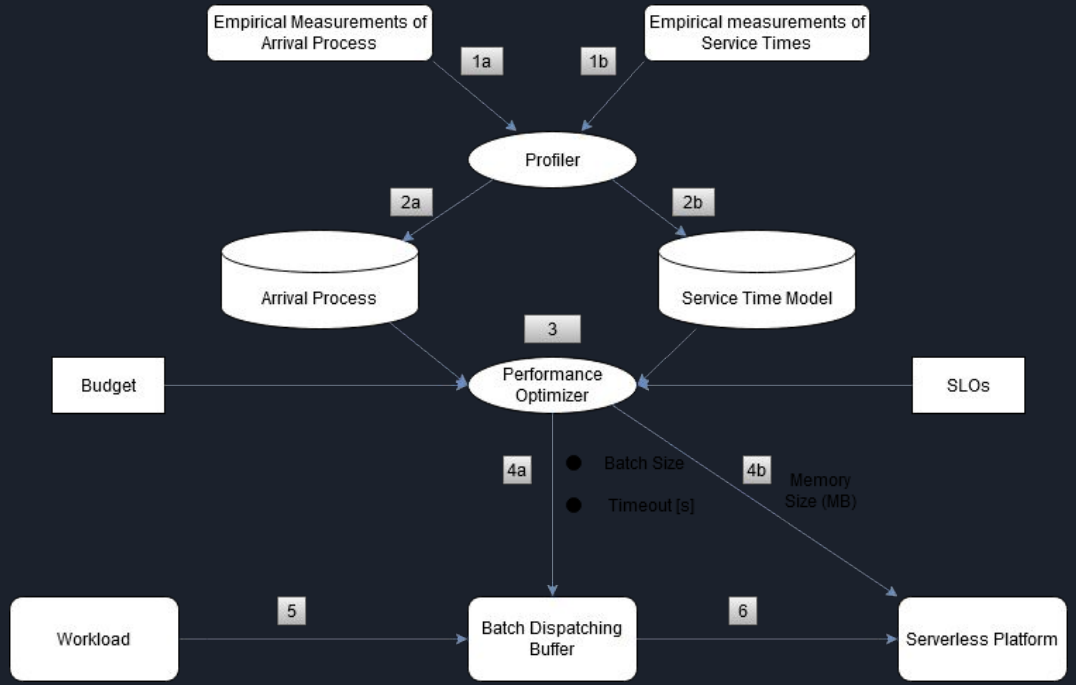


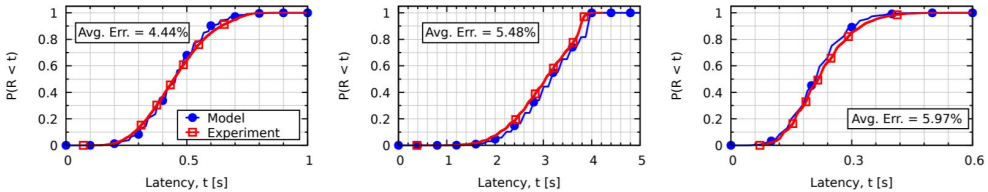
Figure was inspired by Fig. 5 of the paper

The Profiler

Uses an analytical model to predict runtimes and cost for batches on different hardware

No machine learning involved, interpolates based on data for low computational cost and low latency

Runs intermittently, takes 10s in tests (on t2.nano)



(a) MoBiNet, NYS Thruway, 6-7am
Memory=3008 MB, Timeout=100ms
Max Batch Size=20

(b) ResNet-18, NYS Thruway, 7-8am
Memory=2048 MB, Timeout=100ms
Max Batch Size=20

(c) MoBiNet, Twitter, 8-9pm
Memory=2496 MB, Timeout=50ms
Max Batch Size=20

Fig. 13: Request latency distribution with arrivals driven from real workload traces.

BATCH overhead

When compared to AWS SageMaker, cost is only half ($0.14/day)

All components of BATCH run on a single, low cost VM (in the authors' test a t2.nano)

BATCH is itself bursty, lending to cost savings

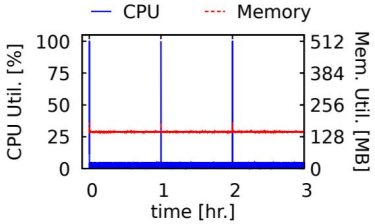
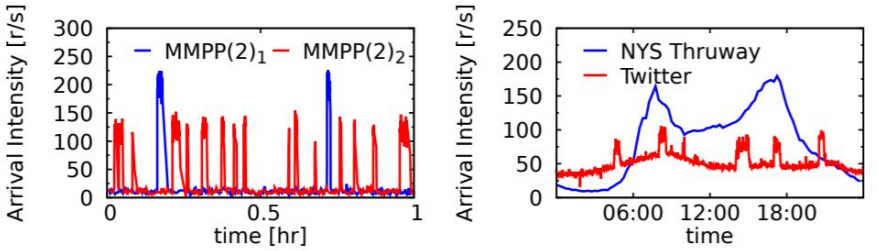


Fig. 9: CPU and memory usage over three hours of an AWS *t2.nano* instance hosting BATCH components. The daily cost of a *t2.nano* instance is less than $0.14.

Testing Distribution

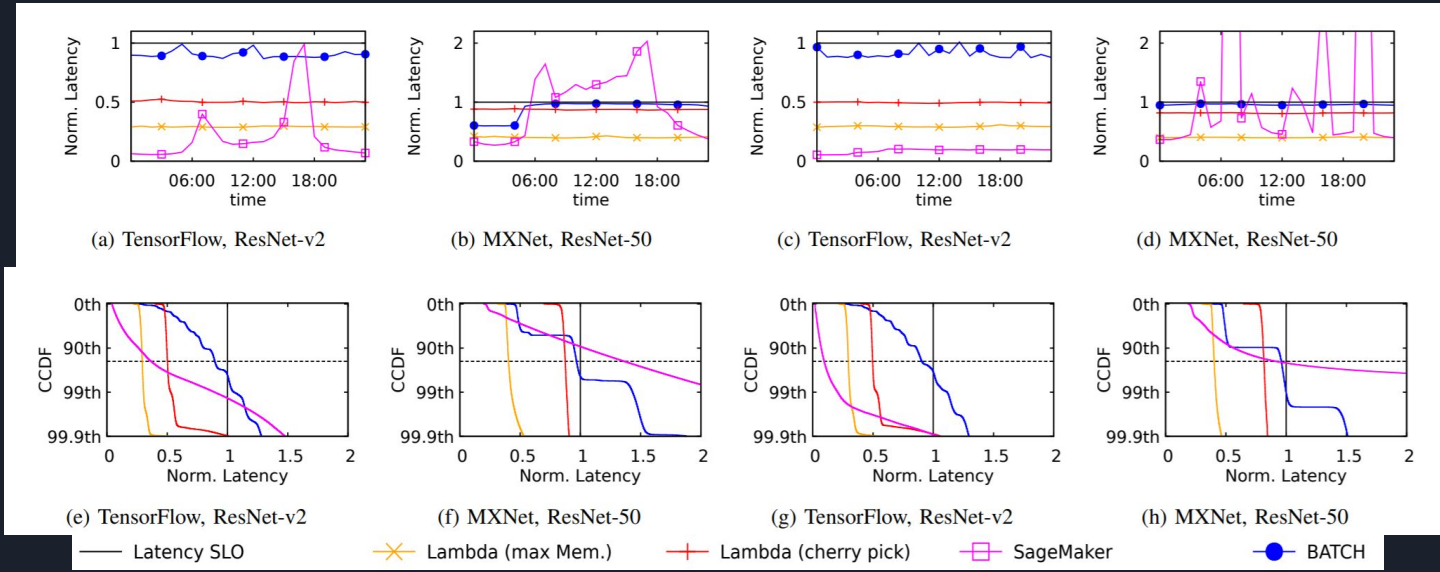


(a) Arrival rate of MMPPs (b) Arrival rate of real traces

Fig. 10: Intensity of arrival processes used to evaluate BATCH.

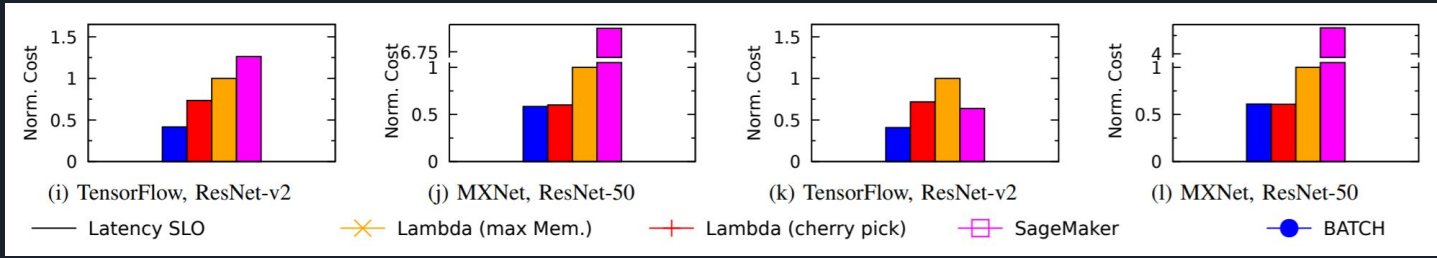
Decently models bursty workloads!

Results: Latency



BATCH generally keeps latency within acceptable bounds, but is significantly higher in general

Results: Cost



At the cost of latency, cost is dramatically reduced

Batch is vastly better than SageMaker in all workloads tested

Batch is even better than optimally configured lambda

CRITIQUE OF RESEARCH PAPER

- Title
- Keywords
- Section I: Introduction
- Section II: Motivation and Challenges
- Section III: BATCH Design
- Section IV: Problem Formulation and Solution
- Section V: Prototype Implementation
- Section VI: Results
- Section VII: Related Work
- Section VIII: Concluding Remarks

STRENGTHS

- Clear and concise
  - “The *Performance Optimizer* is the core component of BATCH”
  - Incorporating “Observation #” boxes within paper
- Numerous and relevant references
- Documentation

WEAKNESSES

- Figure 11
- Optimization
  - Is this the best we can do?
- Assumptions

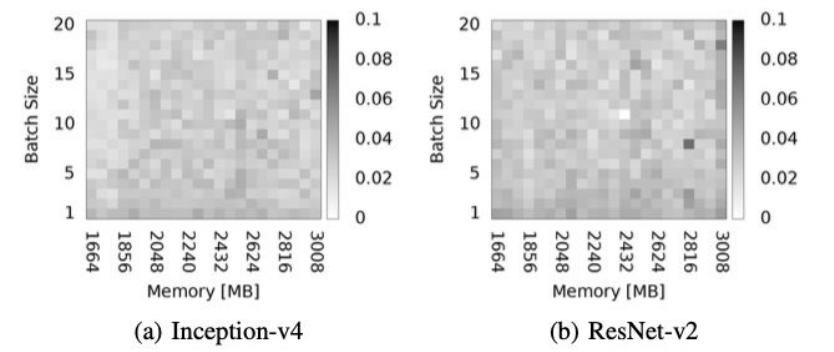


Fig. 11: Coefficient of variation (CV) of service time for various memory/batch size configurations.

GAPS IN RESEARCH

“To the best of our knowledge this is the first analytical model that can capture accurately the shape of the latency distribution in the presence of bursty arrivals and deterministic service times.”

FUTURE WORK

“Future working includes extending BATCH to support different service time distributions and adopting optimization algorithms that are faster than the exhaustive search used here to support co-optimization of latency and cost.”

Citations

[1] “Amazon. Build, train, and deploy machine learning models at scale.” https://docs.aws.amazon.com/lambda/latest/dg/configuration-console.html, [Online; accessed 06-December-2020].

[2] C. Zhang, M. Yu, W. Wang, and F. Yan, “Mark: Exploiting cloud services for cost-effective, slo-aware machine learning inference serving” in 2019 USENIX annual technical Conference (USENIX ATC 19), 2019.