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NoStop: A Novel Configuration Optimization Scheme for Spark Streaming

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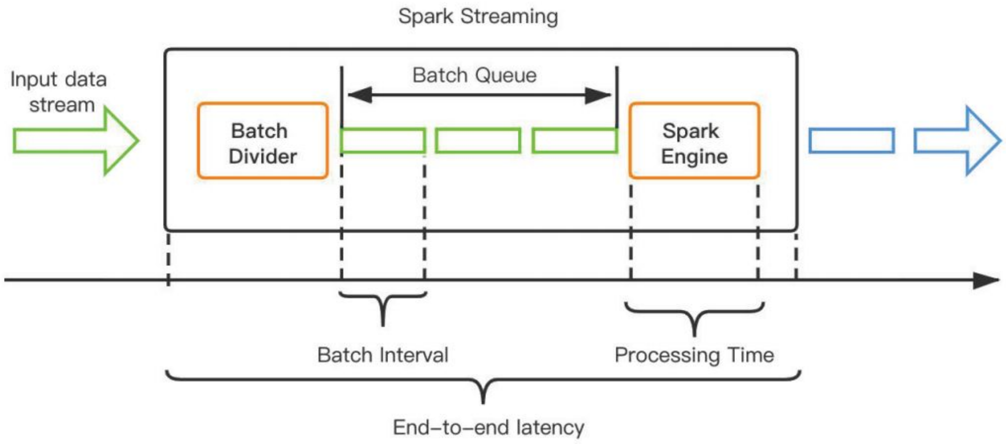
Outline

- Introduction and Motivation
- Related Work
- Problem Statement
- Design of NoStop
- Performance Evaluation

Spark Streaming Model



Spark Streaming receives real-time input data streams and divides the data into multiple batches before passing them to Spark processing engine.

System stability and end-to-end latency are among the utmost important performance metrics for streaming data processing.

The Goal

- For a given Spark Streaming application with a fluctuating input data rate, our goal is to dynamically and adaptively determine the most suitable system configuration to achieve minimum end-to-end delay while maintaining system stability.

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Related Work

- Most of the existing efforts for performance optimization of Spark Streaming consider cases that require a constant input data rate or the ability to scale up cluster resources on demand.

- Some efforts apply machine learning-based approaches, which require a sufficient amount of historical data for training.

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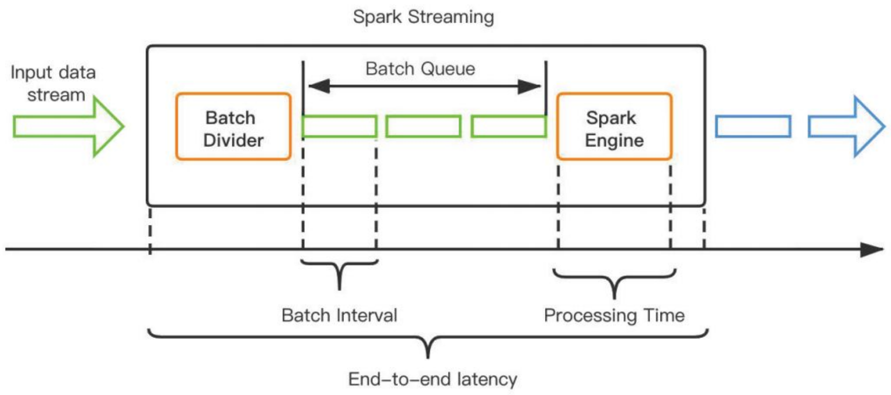
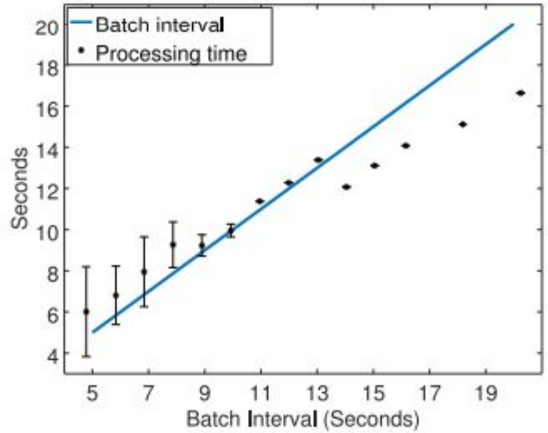
Batch Processing Time and Batch Interval





Batch Interval < Batch Processing Time: Unstable System

Batch Interval > Batch Processing Time: Long end-to-end latency

Batch Interval = Batch Processing Time: Ideal Case

Problem Description

Given a Spark Streaming application executed in a distributed computing environment and an input data stream arriving at a varying speed, we wish to find a proper setting for batch interval and number of executors in real time to achieve minimum end-to-end delay:

$$\underset{\textit{Batch Interval, Number of Executors}}{\operatorname{argmin}} \quad \textit{End-to-end Delay},$$

subject to the following constraint:

$$\textit{Batch Interval} \geq \textit{Batch Processing Time},$$

where the constraint guarantees system stability.

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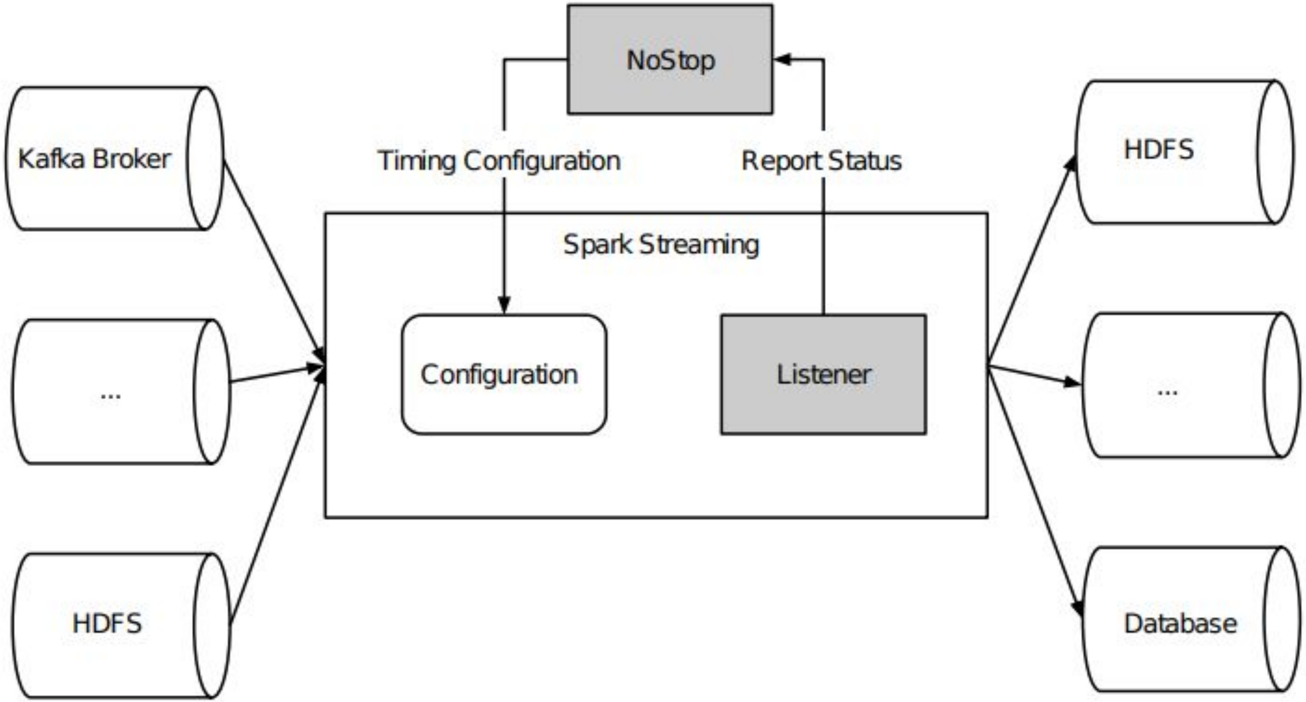
Design Goals

- Noise Tolerance: account for the randomness existing in the dynamics of streaming data processing in distributed environments
- Generality: be applicable to different types of Spark Streaming applications executed in different computing environments
- Efficiency: converge to the minimum end-to-end delay promptly for fluctuating input data with a negligible overhead
- Performance Guarantee: provide a theoretically-proved performance bound

NoStop Architecture



Simultaneous Perturbation Stochastic Approximation (SPSA)-Based Optimization Algorithm

- Rationale on the use of SPSA
  - Does not require an explicit analytical form of end-to-end delay
  - Does not require any additional information about system dynamics, applications and input distribution
  - Low time complexity
  - Does not require a large amount of historical data
  - Performance is theoretically guaranteed

SPSA-Based Optimization Algorithm

Let θ denotes the control parameters, $G(\theta)$ denotes the end-to-end delay.

The standard stochastic approximation form is given by

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \cdot \hat{g}_k(\hat{\theta}_k).$$

where $\hat{\theta}_k$ is the set of control parameter values in the k-th iteration, a_k is a nonnegative gain coefficient.

SPSA-Based Optimization Algorithm

$\hat{g}_k(\hat{\theta}_k)$ is the simultaneous perturbation estimate of $G(\theta)$'s gradient and is calculated as,

$$\hat{g}_k(\hat{\theta}_k) = \frac{y(\hat{\theta}_k + c_k\Delta_k) - y(\hat{\theta}_k - c_k)}{2c_k\Delta_k}\begin{bmatrix}\Delta_{k1}^{-1} \\ \Delta_{k2}^{-1} \\ \vdots \\ \Delta_{kp}^{-1}\end{bmatrix}$$

where $\Delta_k = [\Delta_{k1}^{-1}, \Delta_{k2}^{-1}, \cdots, \Delta_{kp}^{-1}]^T$ is a random perturbation vector and c_k is a positive coefficient.

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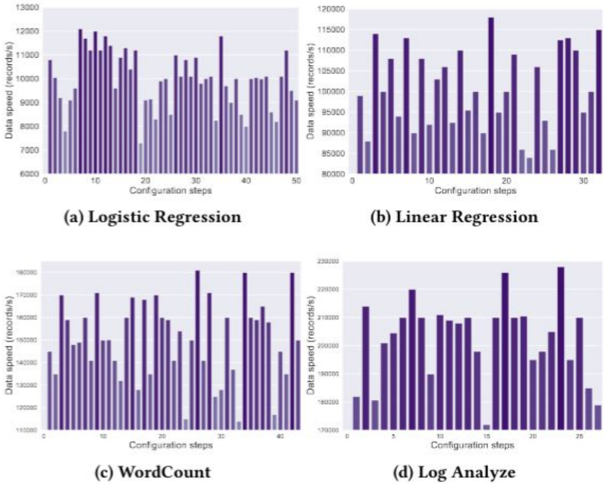
Performance Evaluation

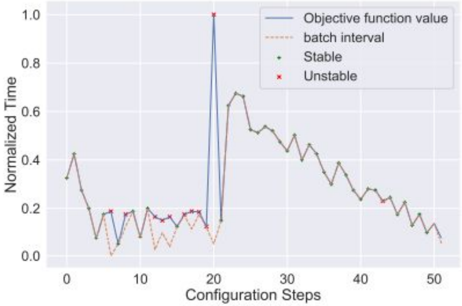
- Experiment Setting
  - A heterogeneous cluster consisting of five compute nodes
  - Apache Hadoop 3.2.1, Apache Spark 3.0.0 and Apache Kafka 2.5.0.
  - Four workloads with varying input data rate.



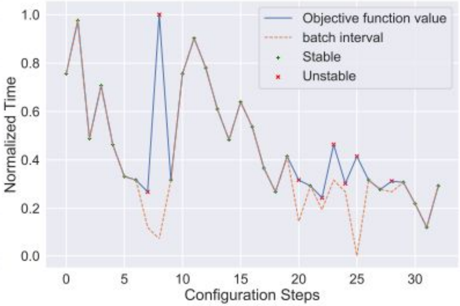
(a) Logistic Regression (b) Linear Regression

(c) WordCount (d) Log Analyze

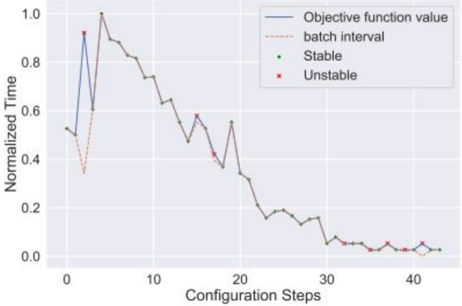
Experimental Results



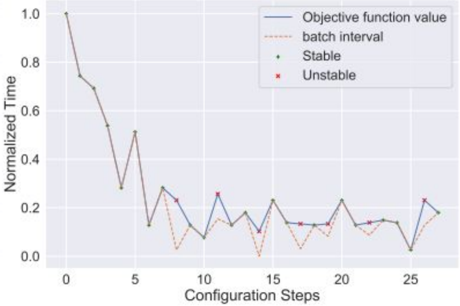
(a) Logistic Regression



(b) Linear Regression



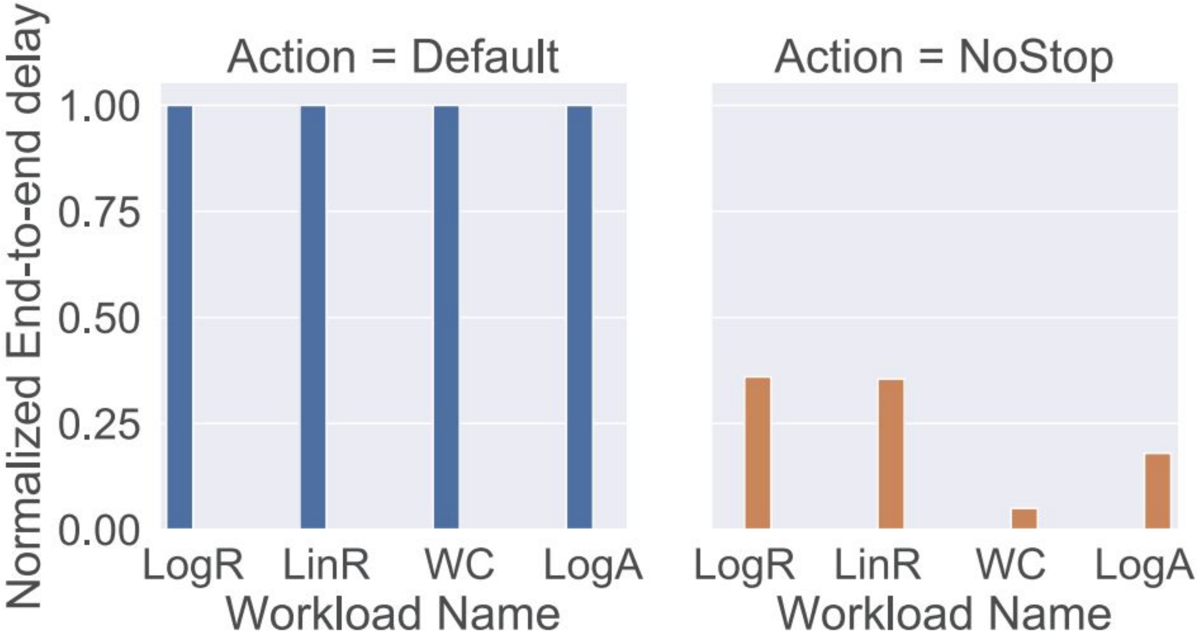
(c) WordCount



(d) Log Analyze

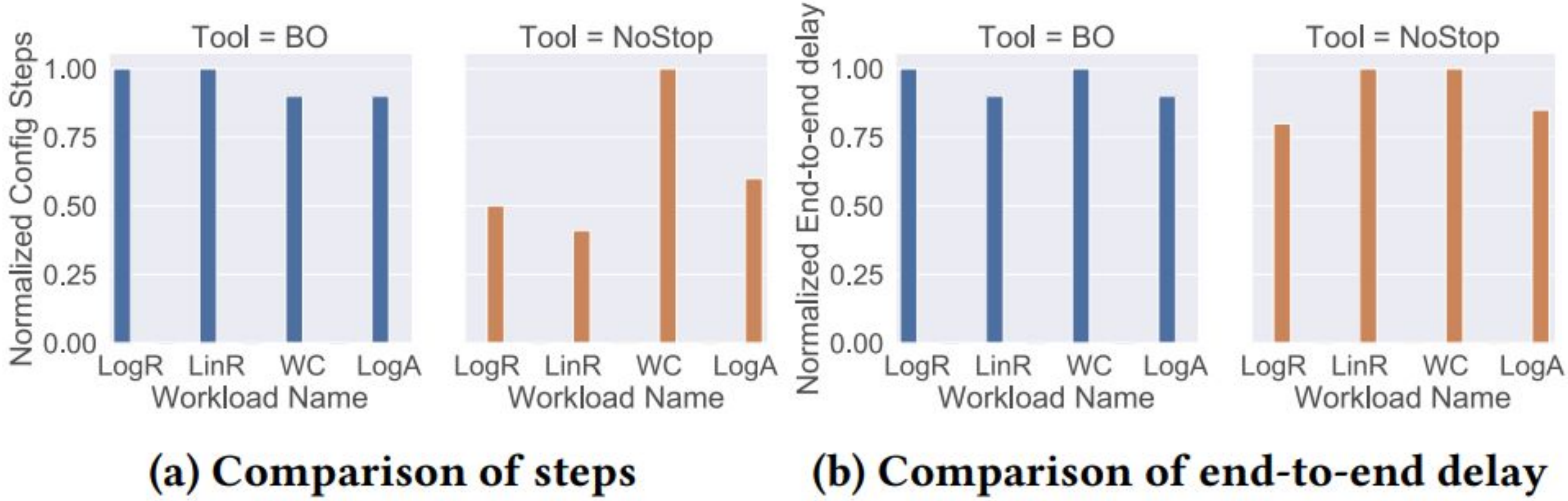
Optimization evolution process

Experimental Results



Performance improvement over initial configurations set by default

Experimental Results



Comparison between SPSA and Bayesian optimization

Thank You!