Splash

User-friendly Programming Interface for Parallelizing Stochastic Algorithms

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Batch Algorithm v.s. Stochastic Algorithm

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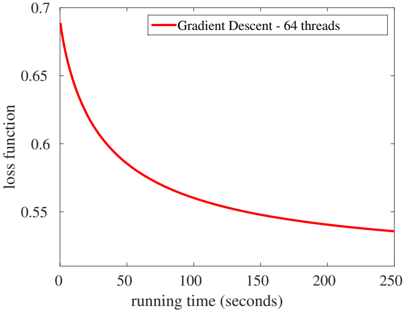
Pros: Easy to parallelize (via Spark).
Cons: May need hundreds of iterations to converge.



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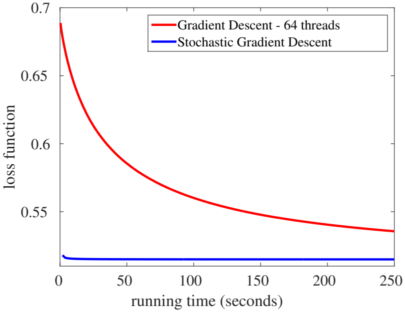
Pros: Much faster convergence.
Cons: Sequential algorithm, difficult to parallelize.



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- Adaptive SGD (Duchi et al.)
- Stochastic Average Gradient Method (Schmidt et al.)
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- Markov chain Monte Carlo and Gibbs sampling
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How to parallelize these algorithms?

First Attempt

After processing a subsequence of random samples...

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Parallel Algorithm:

- Thread 1 (on $1/m$ of samples): $w \leftarrow w + \Delta_1$.
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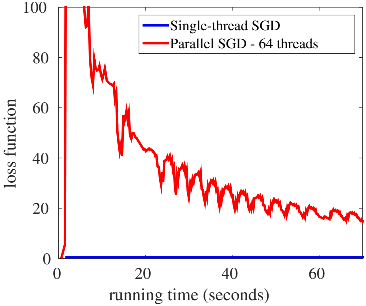

Doesn't work for SGD!

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Reason of failure: $\Delta_1, \ldots, \Delta_m$ simultaneously manipulate the same variable w, causing conflicts in parallel updates.

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How to resolve conflicts

1. Frequent communication between threads:
   - Pros: general approach to resolving conflict.
   - Cons: inter-node (asynchronous) communication is expensive!
2. Carefully partition the data to avoid threads simultaneously manipulating the same variable:
   - Pros: doesn't need frequent communication.
   - Cons: need problem-specific partitioning schemes; only works for a subset of problems.

Splash: A Principle Solution

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- **Fast Performance**: Splash adopts novel strategy for automatic parallelization with infrequent communication. Communication is no longer a performance bottleneck.
- **Integration with Spark**: taking RDD as input and returning RDD as output. Work with KeystoneML, MLlib and other data analysis tools on Spark.

Programming Interface

Programming with **Splash**

Splash users implement the following function:

```
def process(sample: Any, weight: Int, var: VariableSet){
    /*implement stochastic algorithm*/
}
```

where

- sample — a random sample from the dataset.
- weight — observe the sample duplicated by weight times.
- var — set of all shared variables.

Example: SGD for Linear Regression

Goal: find $w^* = \arg\min_w \frac{1}{n} \sum_{i=1}^{n} (wx_i - y_i)^2$.

SGD update: randomly draw (x_i, y_i), then $w \leftarrow w - \eta \nabla_w (wx_i - y_i)^2$.

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Splash implementation:

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def process(sample: Any, weight: Int, var: VariableSet){
    val stepsize = var.get("eta") * weight
    val gradient = sample.x * (var.get("w") * sample.x - sample.y)
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Supported operations: get, add, multiply, delayedAdd.

Get Operations

Get the value of the variable (Double or Array[Double]).

- get(key) returns var[key]
- getArray(key) returns varArray[key]
- getArrayElement(key, index) returns varArray[key][index]
- getArrayElements(key, indices) returns varArray[key][indices]

Array-based operations are more efficient than element-wise operations, because the key-value retrieval is executed only once for operating an array.

Add Operations

Add a quantity δ to the variable.

- add(key, delta): var[key] $+=$ delta
- addArray(key, deltaArray): varArray[key] $+=$ deltaArray
- addArrayElement(key, index, delta): varArray[key][index] $+=$ delta
- addArrayElements(key, indices, deltaArrayElements): varArray[key][indices] $+=$ deltaArrayElements

Multiply Operations

Multiply a quantity γ to the variable v.

- multiply(key, gamma): var[key] *= gamma
- multiplyArray(key, gamma): varArray[key] *= gamma

We have optimized the implementation so that the time complexity of multiplyArray is $\mathcal{O}(1)$, independent of the array dimension.

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Example: SGD with sparse features and ℓ_2-norm regularization.

$$w \leftarrow (1 - \lambda) * w \quad \text{(multiply operation)} \tag{1}$$

$$w \leftarrow w - \eta \nabla f(w) \quad \text{(addArrayElements operation)} \tag{2}$$

Time complexity of (1) = $\mathcal{O}(1)$; Time complexity of (2) = $\text{nnz}(\nabla f(w))$.

Delayed Add Operations

Add a quantity δ to the variable v. The operation is not executed until the next time the same sample is processed by the system.

- delayedAdd(key, delta): var[key] += delta
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Example: Collapsed Gibbs Sampling for LDA – update the word-topic counter n_{wk} when topic k is assigned to word w.

$$n_{wk} \leftarrow n_{wk} + weight \quad \text{(add operation)} \tag{3}$$

$$n_{wk} \leftarrow n_{wk} - weight \quad \text{(delayed add operation)} \tag{4}$$

(3) executed instantly; (4) will be executed at the next time before a new topic is sampled for the same word.

Running Stochastic Algorithm

Three simple steps:

1. Convert RDD dataset to Parametrized RDD:

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3. Start running:

   ```
   paramRdd.run()
   ```

Execution Engine

How does **Splash** work?

In each iteration, the execution engine does:

1. Propose candidate degrees of parallelism $m_1, \ldots, m_k$ such that $\sum_i^k m_i = m :=$ (# of cores). For each $i \in [k]$, collect m_i cores and do:

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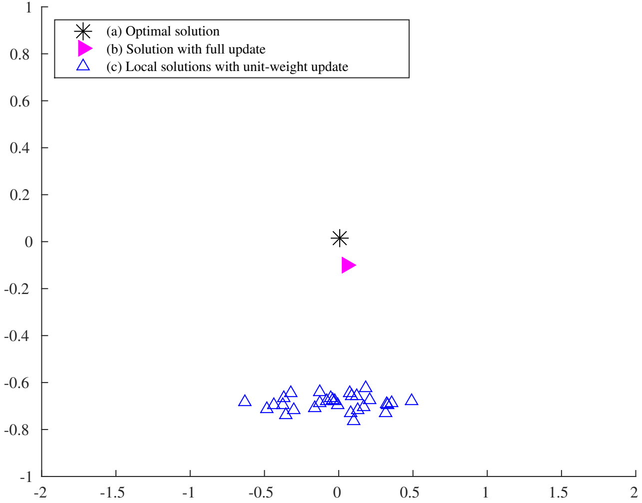
2. If $k > 1$, then select the best m_i by a parallel cross-validation procedure.
3. Broadcast the best update to all machines to apply this update. Then proceed to the next iteration. (degree of parallelism doesn't decrease)

Example: Reweighting for SGD



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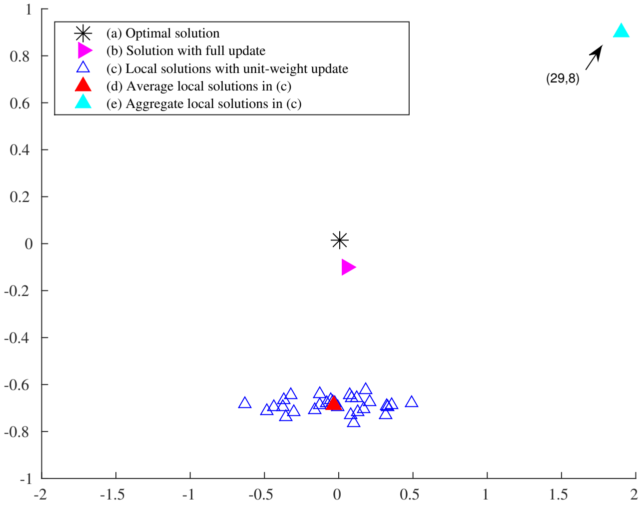

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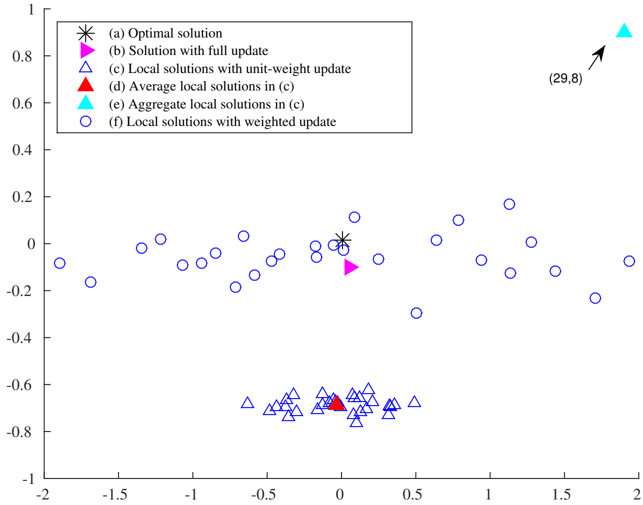

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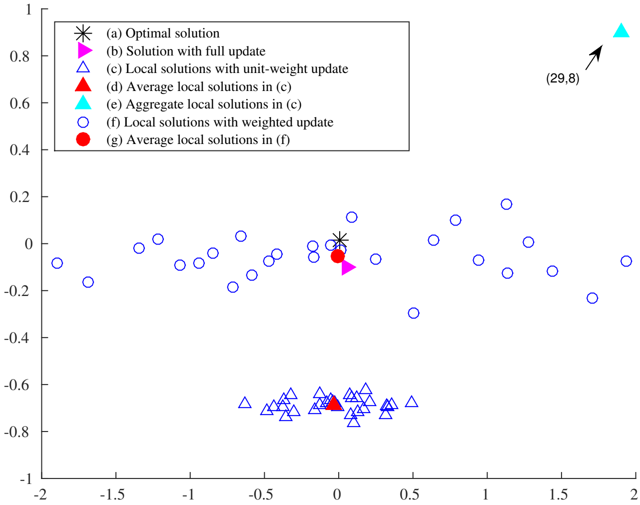
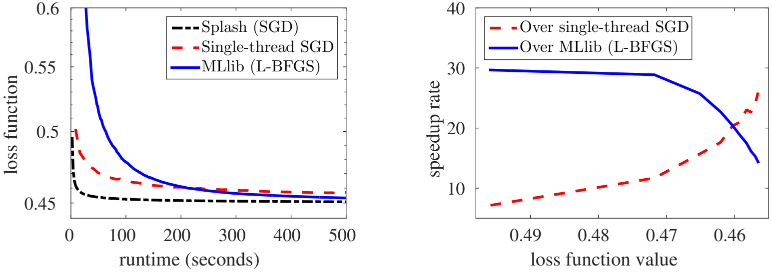


Experiments

Experiment Setups

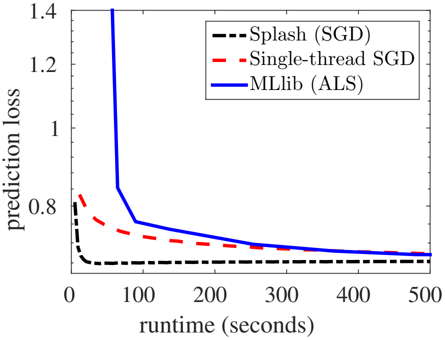
- **System**: Amazon EC2 cluster with 8 workers. Each worker has 8 Intel Xeon E5-2665 cores and 30 GBs of memory and was connected to a commodity 1GB network
- **Algorithms:** SGD for logistic regression; mini-batch SGD for collaborative filtering; Gibbs Sampling for topic modelling;.
- **Datasets:**
  - MNIST 8M (LR): 8 million samples, 7,840 parameters.
  - Netflix (CF): 100 million samples, 65 million parameters.
  - NYTimes (LDA): 100 million samples, 200 million parameters.
- **Baseline methods:** single-thread stochastic algorithm; MLlib (the official machine learning library for Spark).

Logistic Regression on MNIST Digit Recognition



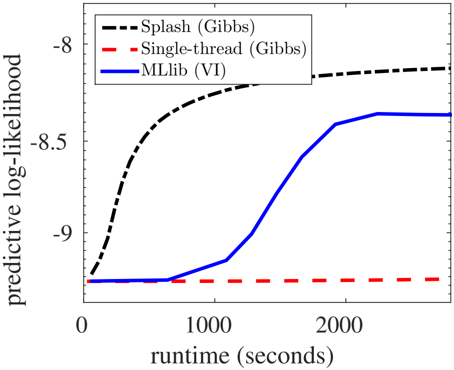
- Splash converges to a good solution in a few seconds, while other methods take hundreds of seconds.
- Splash is 10x - 25x faster than single-thread SGD.
- Splash is 15x - 30x faster than parallelized L-BFGS.

Netflix Movie Recommendation



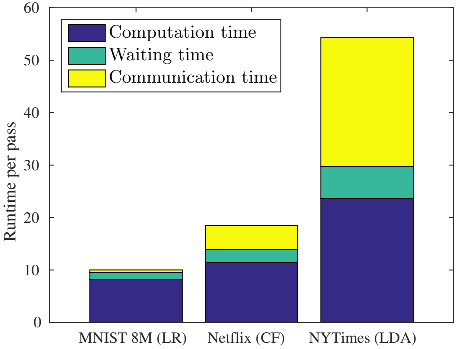
- Splash is 36x faster than parallelized Alternating Least Square (ALS).
- Splash converges to a better solution than ALS (the problem is non-convex).

Topic Modelling on New York Times Articles



- Splash is 3x - 6x faster than parallelized Variational Inference (VI).
- Splash converges to a better solution than VI.

Runtime Analysis



- Waiting time is 16%, 21%, 26% of the computation time.
- Communication time is 6%, 39% and 103% of the computation time.

Machine Learning Package

Stochastic Machine Learning Library on Splash

- **Goal:**
  - Fast performance: order-of-magnitude faster than MLlib.
  - Ease of use: call with one line of code.
  - Integration: easy to build a data analytics pipeline.
- **Algorithms:**
  - Stochastic gradient descent.
  - Stochastic matrix factorization.
  - Gibbs sampling for LDA.
- Will implement more algorithms in the future...

Summary

- **Splash** is a general-purpose programming interface for developing stochastic algorithms.
- **Splash** is also an execution engine for automatic parallelizing stochastic algorithms.
- Reweighting is the key to achieve fast performance without scarifying communication efficiency.
- We observe good empirical performance and we have theoretical guarantees for SGD.
- **Splash** is online at http://zhangyuc.github.io/splash/.