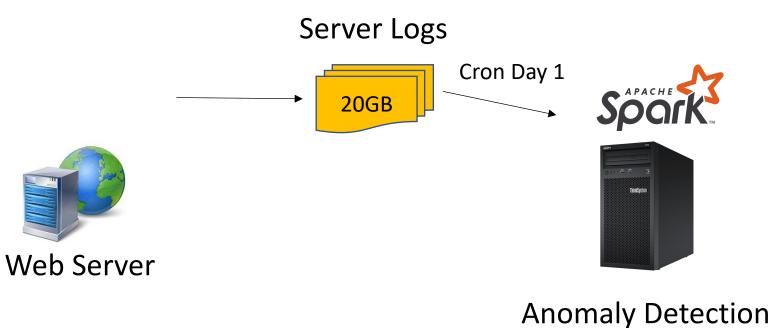
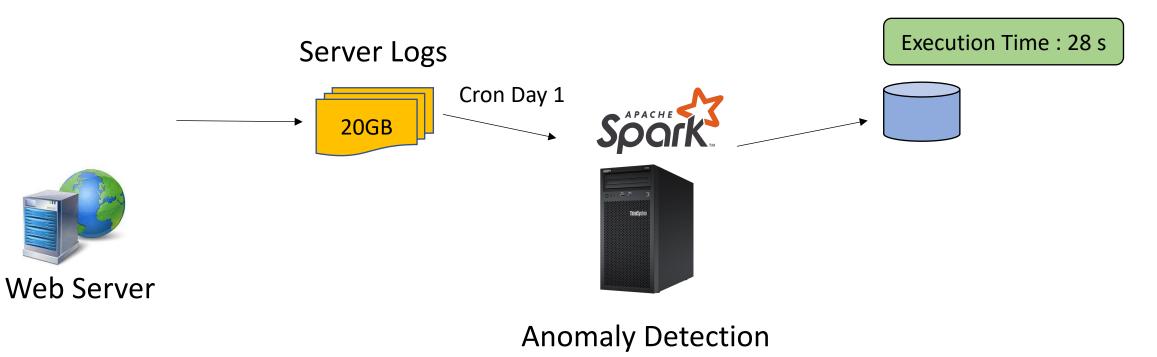
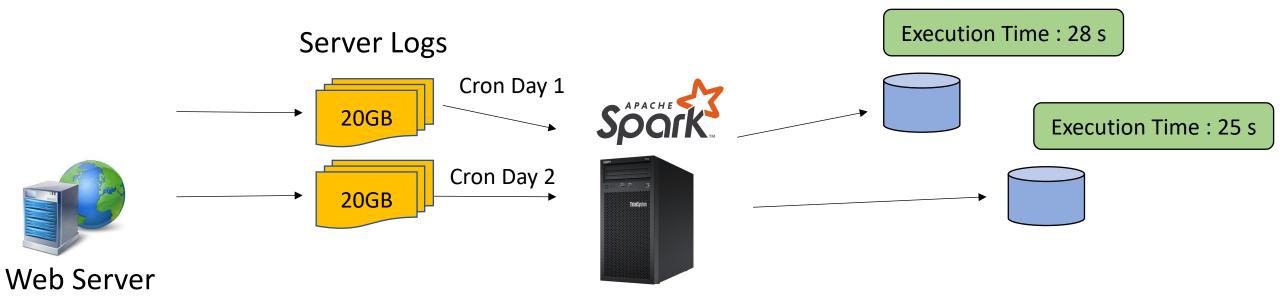
# PerfDebug: Performance Debugging of Computation Skew in Dataflow Systems

Jason Teoh, Muhammad Ali Gulzar, Harry Xu, Miryung Kim
University of California, Los Angeles

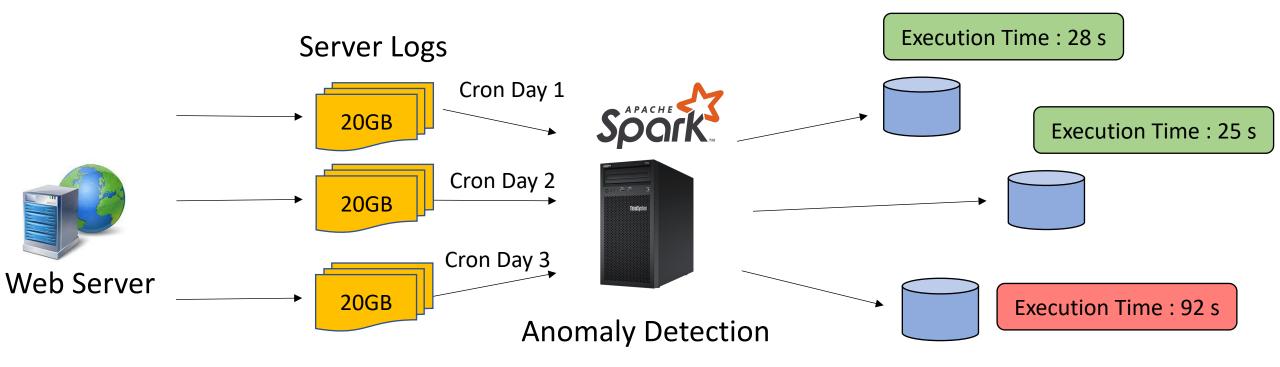


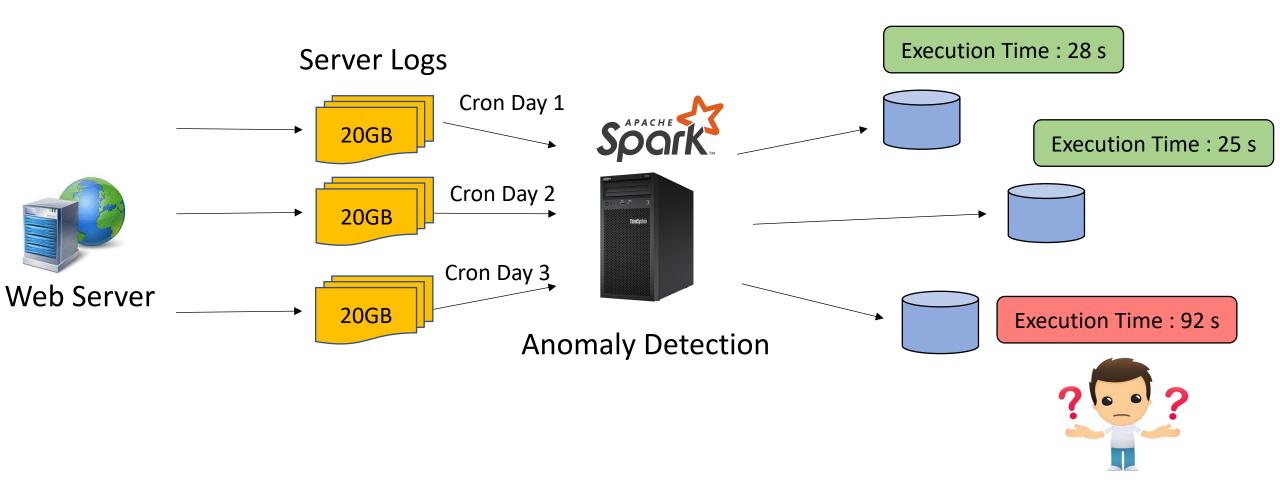


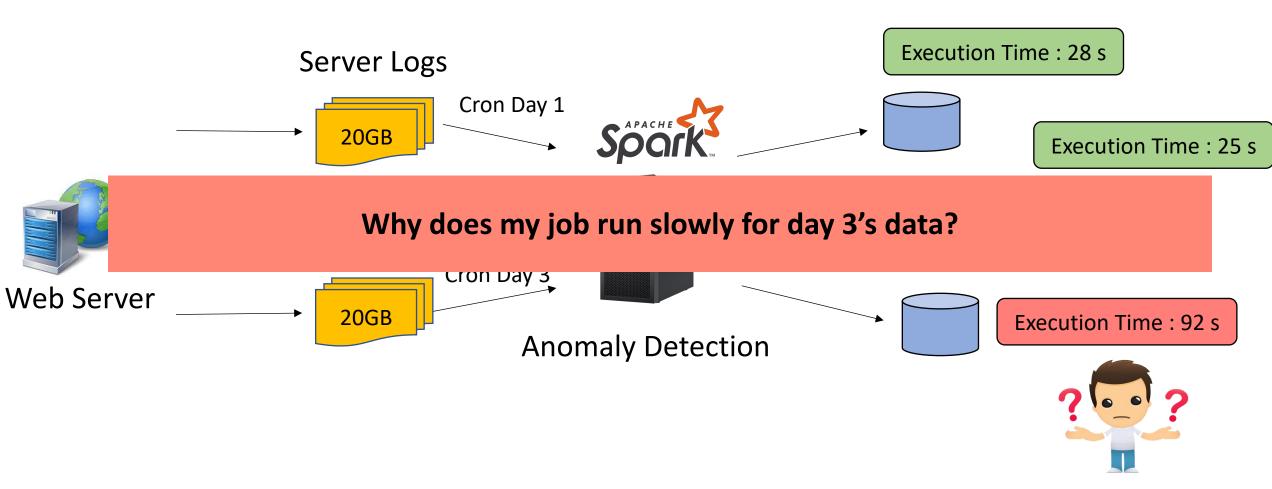




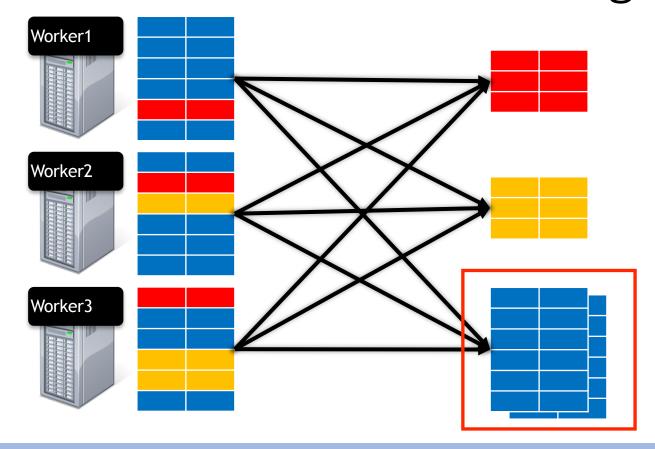
**Anomaly Detection** 







#### Data Skew in Distributed Processing



Uneven distribution of **data** across partitions, tasks, or workers can lead to performance delays.

#### Computation Skew

#### **Term**

Hello World

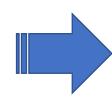
Big Data

Debugging

**PerfDebug** 



#### **User-defined function** commonDefs = { "Hello World": ..,, "Big Data": ..,, "Debugging": ..., if (commonDefs.contains(term)) { return commonDefs.get(term) } else { r = new RedisClient(...) return r.get(term)



Term	Latency
Hello World	2 ms
Big Data	1 ms
Debugging	3 ms
PerfDebug	442 ms

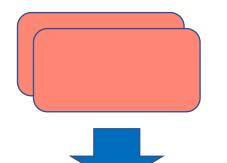
Uneven distribution of **computation** due to interactions between data and application code.

#### Computation Skew

#### Why is it challenging?

- Requires insight on how application code interacts with data.
- Occurs across multiple stages.
- Affected applications are inherently expensive to run.
- Isolating individual records that impact performance is difficult with existing tools.

# Performance Debugging of Computation Skew

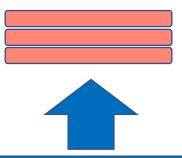


#### Input:

Spark program, input data

#### **Output:**

Individual records responsible for computation skew

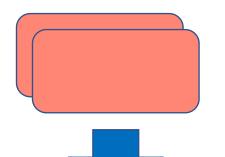


#### PerfDebug

Computation
Skew Detection

Data Provenance+ Record-LevelLatency

## PerfDebug Approach

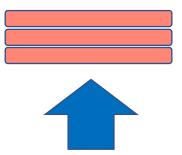


#### Input:

Spark program, input data



Individual records responsible for computation skew



#### PerfDebug

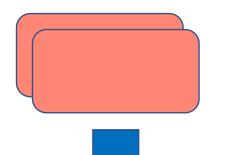
Computation
Skew Detection

Data Provenance+ Record-LevelLatency

- PerfDebug monitors task-level metrics such as latency, garbage collection, and serialization using SparkListener API.
- If potential computation skew is found, rerun the user program in debugging mode to collect additional information.

Spaire. 2.1.1					
<u>Index</u>	<u>ID</u>	Executor ID / Host	<u>Duration</u> ▼	GC Time	Input Size / Records
33	33	8 / 131.179.96.204	1.2 min	7 s	128.0 MB / 17793
34	34	1 / 131.179.96.211	51 s	11 s	128.0 MB / 1
35	35	5/ 131.179.96.212	44s	3 s	128.0 MB / 1
25	25	5 / 131.179.96.212	38 s	2 s	128.0 MB / 33602
36	36	9 / 131.179.96.206	36 s	4 s	128.0 MB / 1
130	130	1 / 131.179.96.211	36 s	9 s	128.0 MB / 33505
37	37	6 / 131.179.96.203	35s	4 s	128.0 MB / 1
22	22	3 / 131.179.96.209	35 s	2 s	128.0 MB / 33564

## PerfDebug Approach

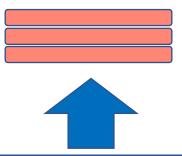


#### Input:

Spark program, input data



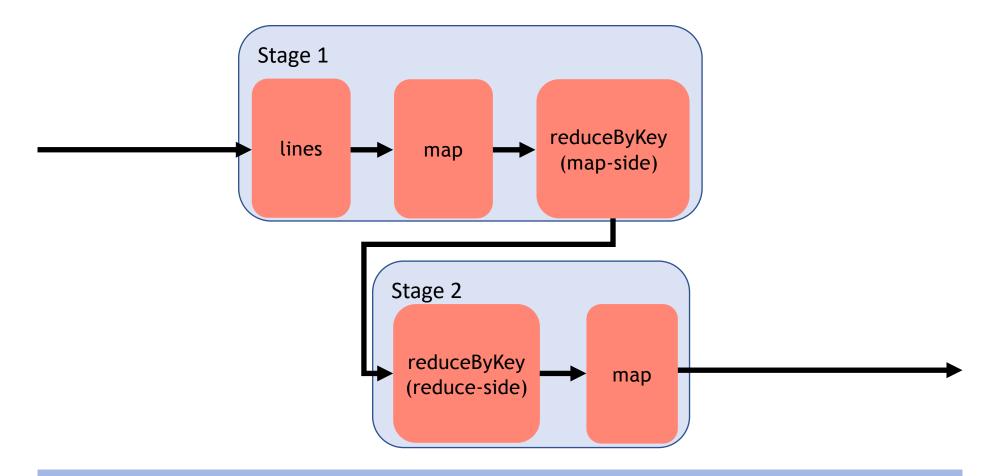
Individual records responsible for computation skew

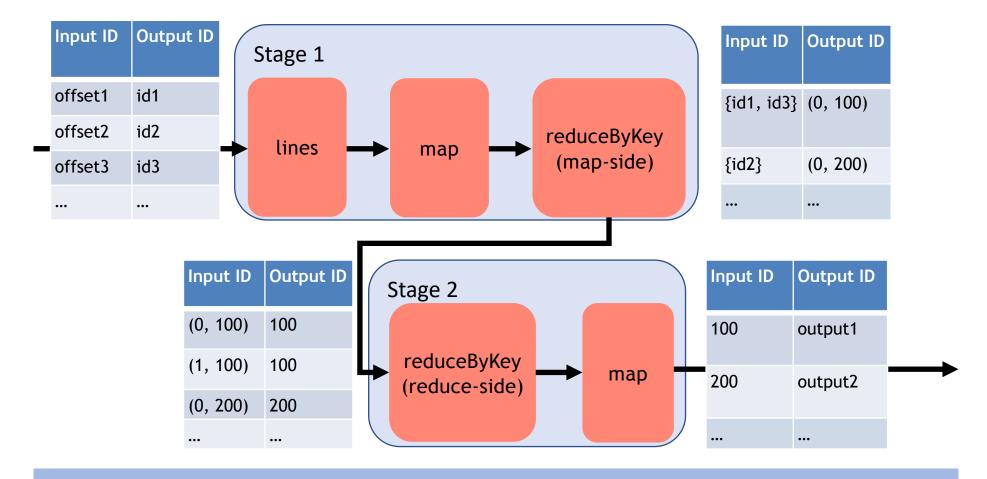


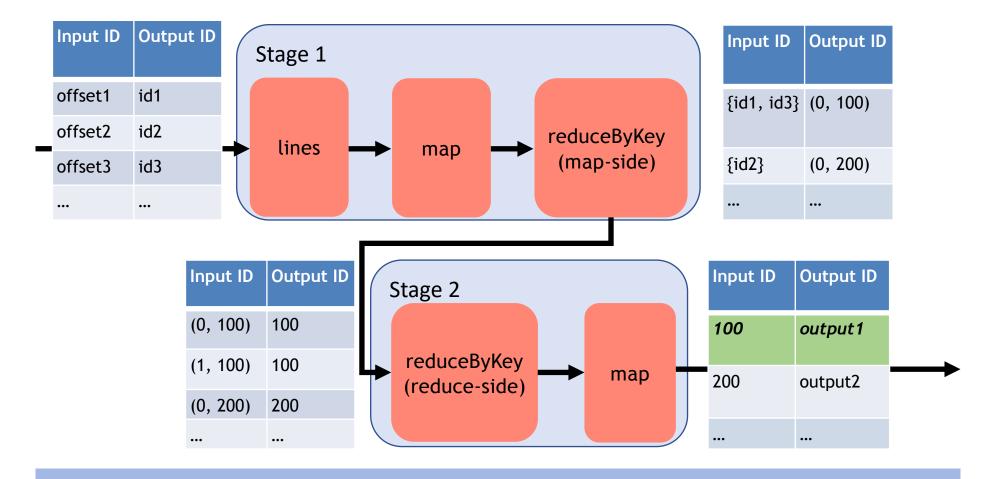
#### PerfDebug

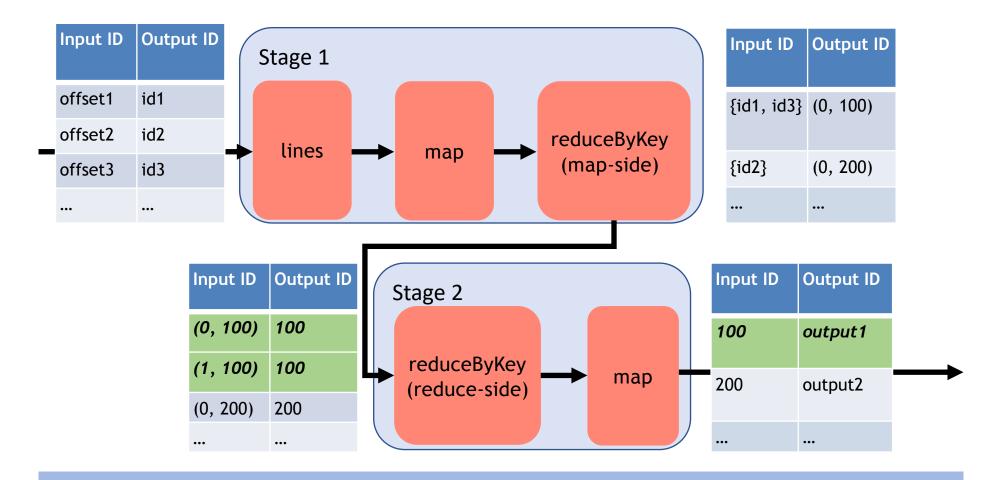
Computation
Skew Detection

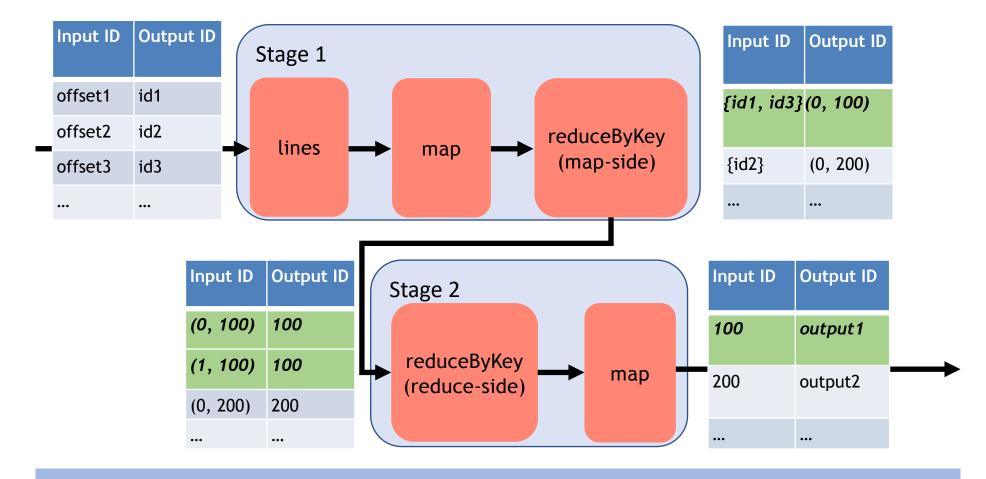
Provenance + Record-Level Latency

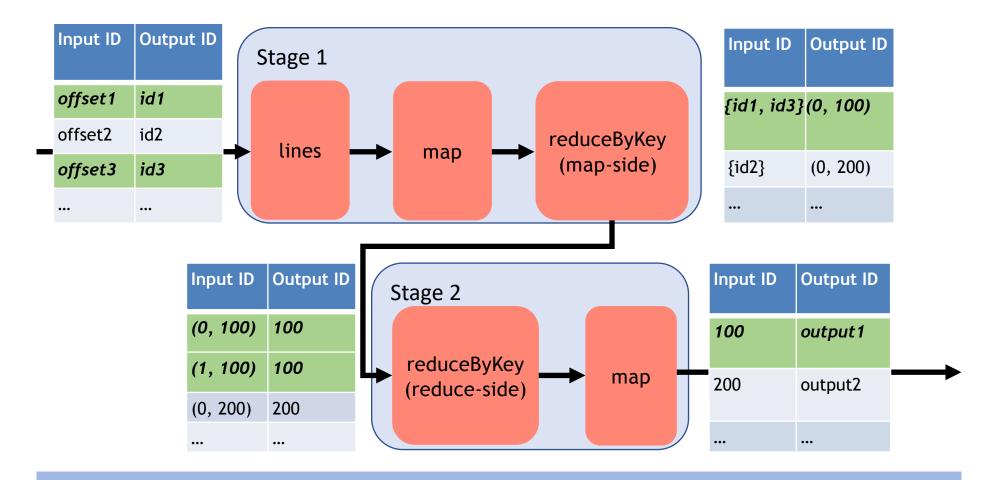








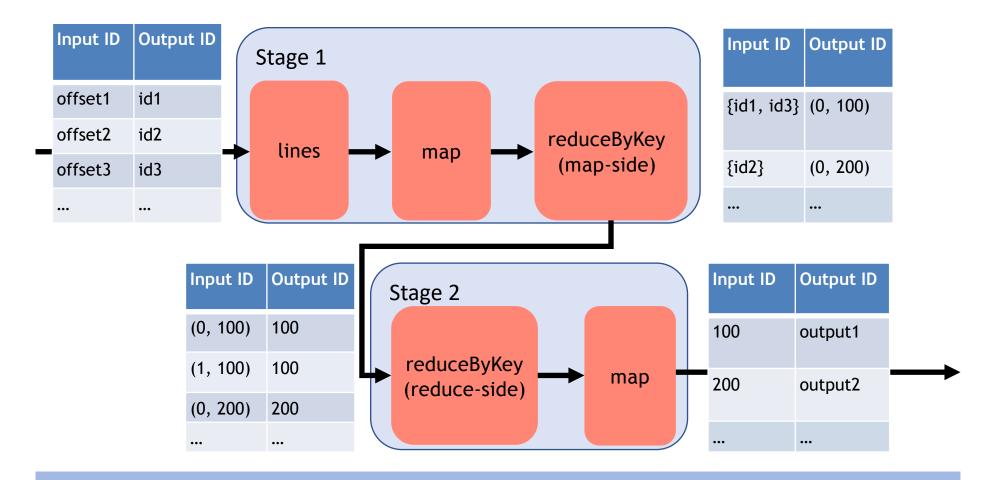




Data
Provenance +
Record-Level
Latency

Expensive Record Identification

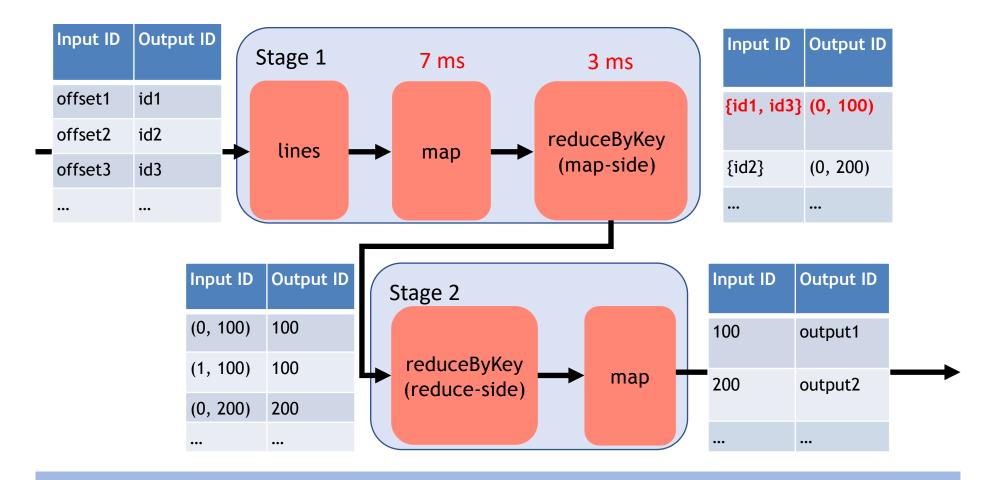
#### Measure UDF Latency



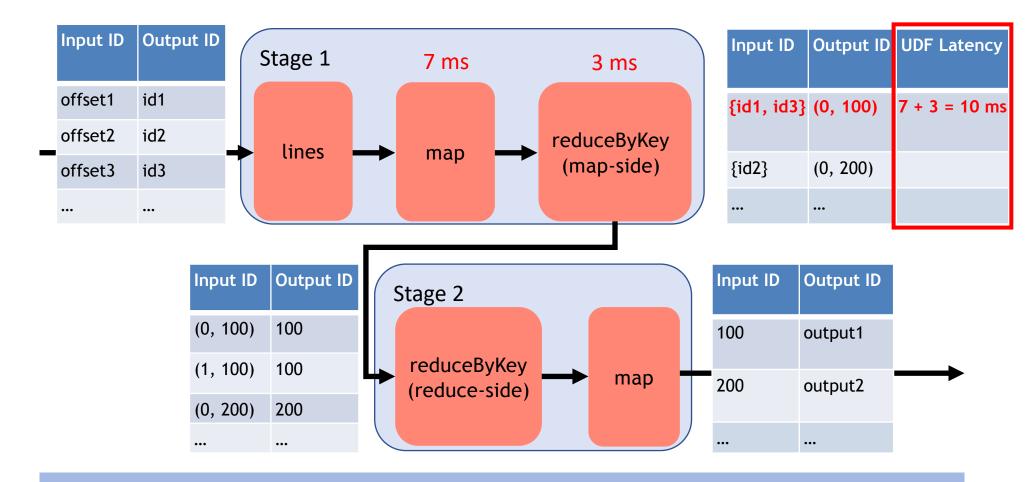
Data
Provenance +
Record-Level
Latency

Expensive Record Identification

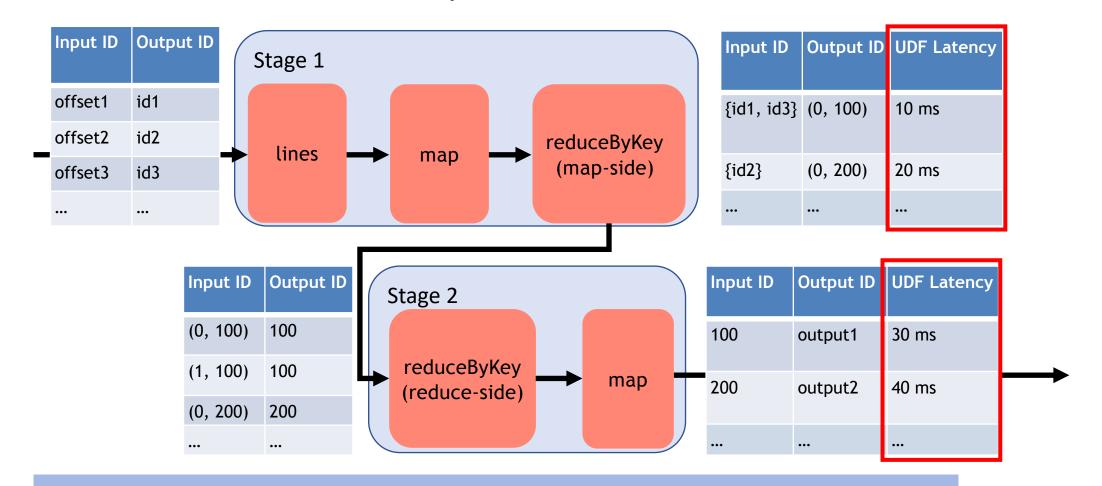
#### Measure UDF Latency



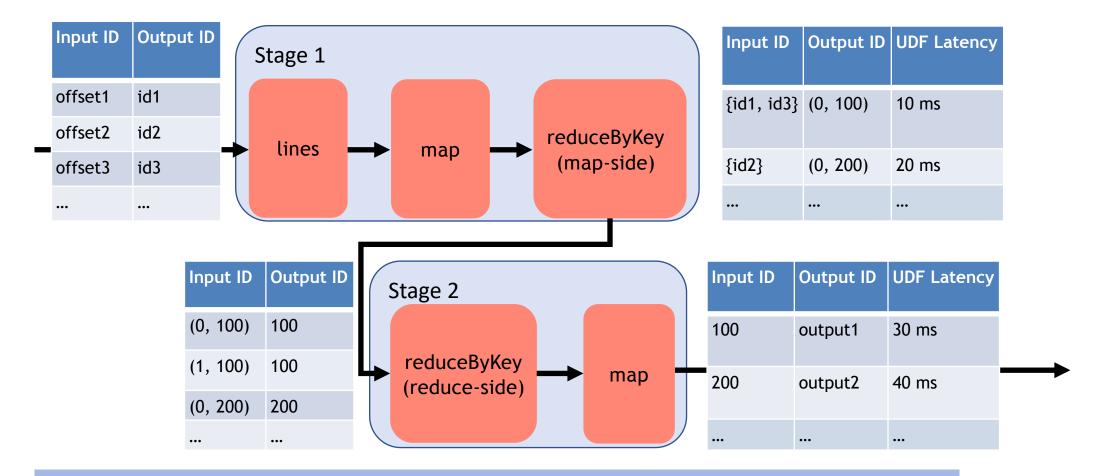
#### Measure UDF Latency



#### Measure UDF Latency

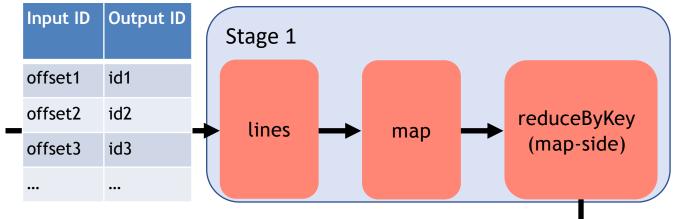


# Measure Shuffle Latency



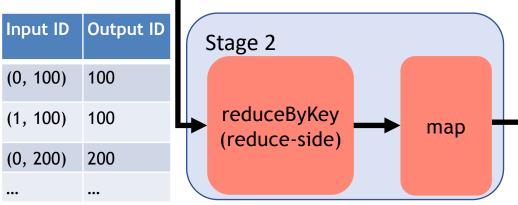
PerfDebug captures data movement costs through partition-level shuffle latencies.

#### Measure Shuffle Latency



Input ID	Output ID	UDF Latency
{id1, id3}	(0, 100)	10 ms
{id2}	(0, 200)	20 ms
•••		***

	Partition	Shuffle Latency
5 2	1	80 ms
Stage 2	2	50 ms
0)	3	100 ms
	•••	•••



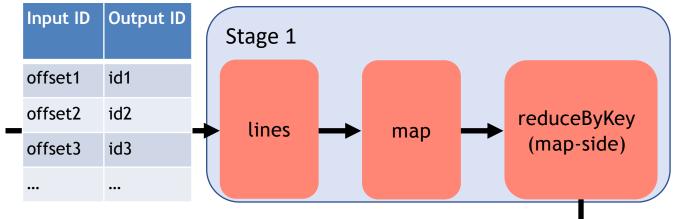
Input ID	Output ID	UDF Latency	
100	output1	30 ms	
200	output2	40 ms	
•••		***	

PerfDebug captures data movement costs through partition-level shuffle latencies.

Data
Provenance +
Record-Level
Latency

Expensive Record Identification

## Calculate Stage Latency



Input ID	Output ID	UDF Latency
{id1, id3}	(0, 100)	10 ms
{id2}	(0, 200)	20 ms
•••	***	***

	Partition	Shuffle Latency
e 2	1	80 ms
Stage 2	2	50 ms
0,	3	100 ms
	•••	•••

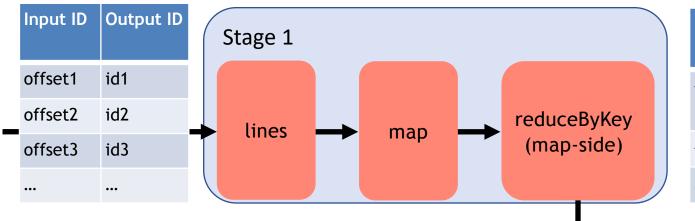
Input ID	Output ID	Stage 2	
(0, 100)	100		
(1, 100)	100	reduceByKey map	
(0, 200)	200	(reduce side)	
•••	•••		

Input ID	Output ID	UDF Latency	
100	output1	30 ms	
200	output2	40 ms	
•••	1000	•••	

Data
Provenance +
Record-Level
Latency

Expensive Record Identification

## Calculate Stage Latency



Input ID	Output ID	UDF Latency	Stg Latency
{id1, id3}	(0, 100)	10 ms	10 + 0 ms
{id2}	(0, 200)	20 ms	20 + 0 ms

	Partition	Shuffle Latency
5 S	1	80 ms
Stage 2	2	50 ms
0,	3	100 ms
	•••	

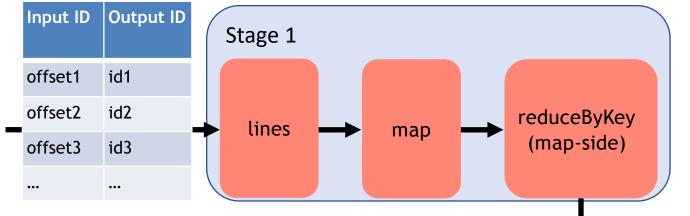
Input ID	Output ID		Stage 2			
(0, 100)	100					
(1, 100)	100	<b>L</b>	reduceByKey (reduce-side)	$\rightarrow$	map	-
(0, 200)	200		(reduce-side)			
						/

1	Input ID	Output ID	UDF Latency	
	100	output1	30 ms	
	200	output2	40 ms	<b>→</b>
1		•••	•••	

Data
Provenance +
Record-Level
Latency

Expensive Record Identification

#### Calculate Stage Latency



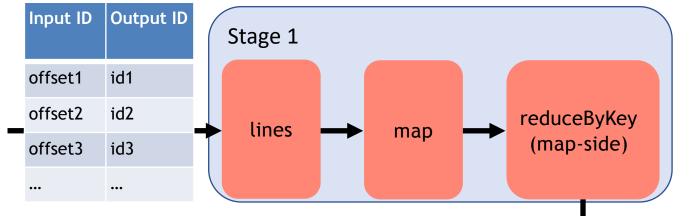
Input ID	Output ID	UDF Latency	Stg Latency
{id1, id3}	(0, 100)	10 ms	10 ms
{id2}	(0, 200)	20 ms	20 ms
•••	•••	•••	•••

	Partition	Shuffle Latency
5 2	1	80 ms
Stage 2	2	50 ms
0,	3	100 ms
	•••	•••

Input ID	Output ID		Stage 2			)
(0, 100)	100					
(1, 100)	100	Ļ	reduceByKey (reduce-side)	<b>→</b>	map	-
(0, 200)	200		(reduce-side)			
						1

Input ID	Output ID	UDF Latency	Stg Latency	
100	output1	30 ms		
200	output2	40 ms		=
	•••	•••	•••	

## Calculate Stage Latency



Input ID	Output ID	UDF Latency	Stg Latency
{id1, id3}	(0, 100)	10 ms	10 ms
{id2}	(0, 200)	20 ms	20 ms
•••	<b>0</b>   <b>0</b>   <b>0</b>	•••	•••

	Partition	Shuffle Latency
5 2	1	80 ms
Stage 2	2	50 ms
<b>(</b> )	3	100 ms
	•••	•••

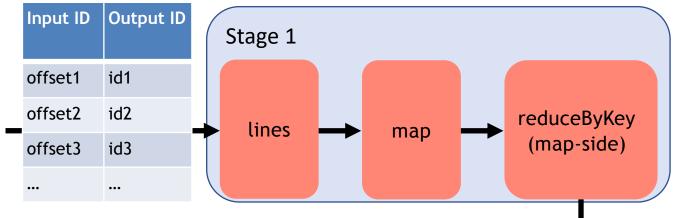
Input ID	Output ID	Stage 2	)
(0, 100)	100		
(1, 100)	100	reduceByKey (reduce-side) map	_
(0, 200)	200	(reduce side)	
			,

Input ID	Output ID	UDF Latency	Stg Latency	
100	output1	30 ms	$30 + \frac{2}{16} * 80$	
200	output2	40 ms		
•••	•••	•••	•••	

Data
Provenance +
Record-Level
Latency

Expensive Record Identification

#### Calculate Stage Latency



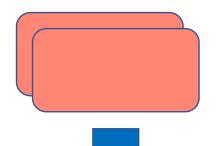
Input ID	Output ID	UDF Latency	Stg Latency
{id1, id3}	(0, 100)	10 ms	10 ms
{id2}	(0, 200)	20 ms	20 ms
•••	•••	•••	•••

	Partition	Shuffle Latency
e 2	1	80 ms
Stage 2	2	50 ms
0,	3	100 ms
	•••	•••

Input ID	Output ID		Stage 2		
(0, 100)	100				
(1, 100)	100	L	reduceByKey (reduce-side)	<b>→</b>	map
(0, 200)	200		(reduce side)		

Input ID	Output ID	UDF Latency	Stg Latency	
100	output1	30 ms	40 ms	
200	output2	40 ms	45 ms	7
•••	•••	•••	•••	

## PerfDebug Approach

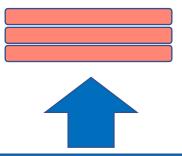


#### Input:

Spark program, input data



Individual records responsible for computation skew



#### PerfDebug

Computation
Skew Detection

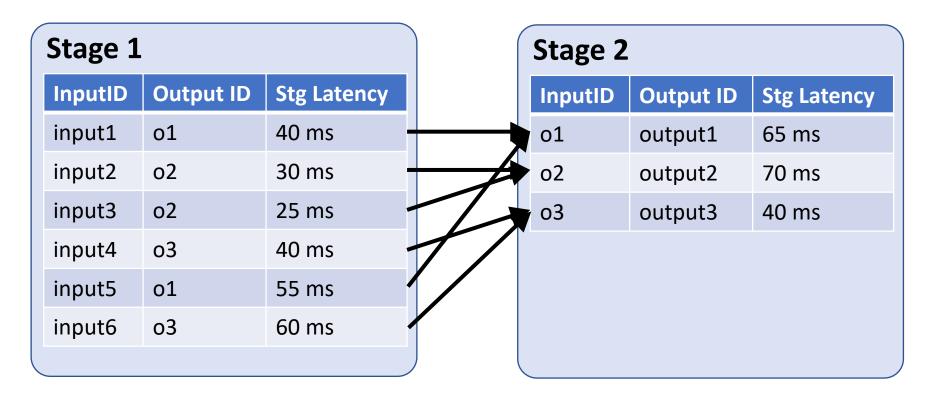
Data Provenance+ Record-LevelLatency

Data
Provenance +
Record-Level
Latency

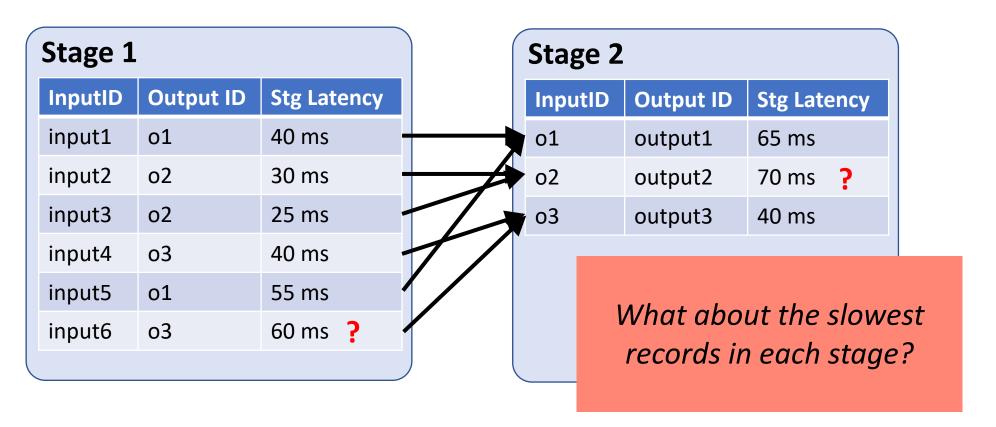
Expensive Record Identification

- Stage Latency is within a given stage and insufficient for debugging.
- Code and data interact across *multiple* stages.

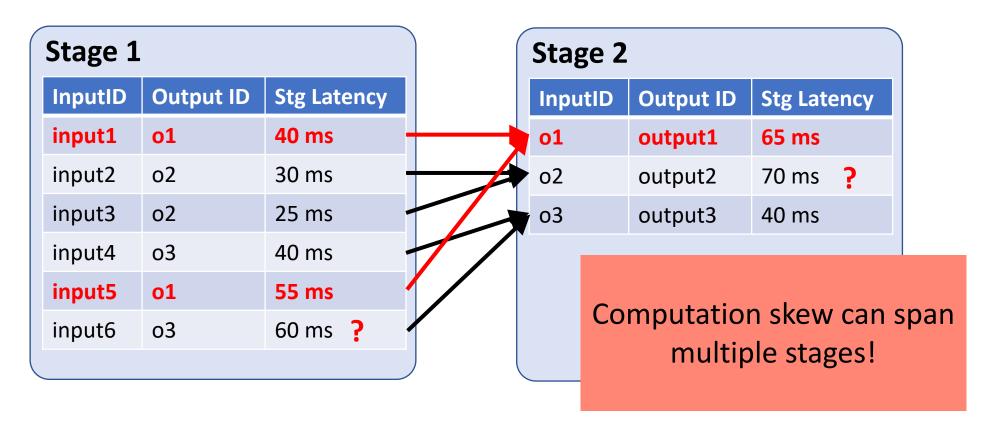
- Stage Latency is within a given stage and insufficient for debugging.
- Code and data interact across multiple stages.



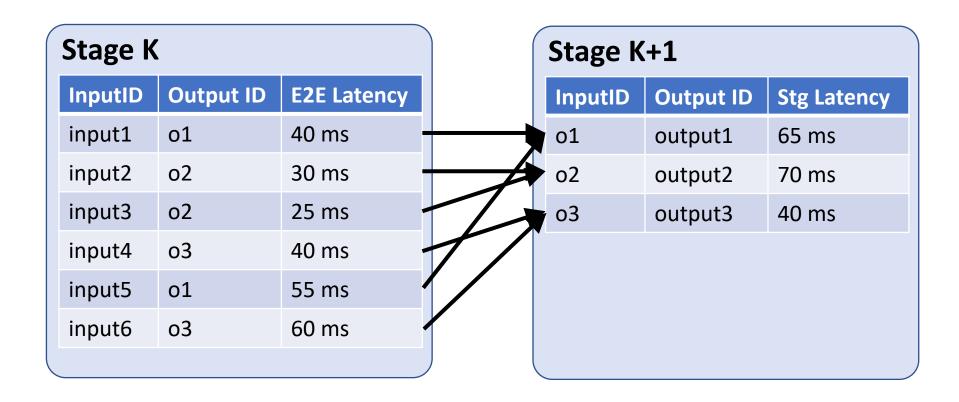
- Stage Latency is within a given stage and insufficient for debugging.
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- Stage Latency is within a given stage and insufficient for debugging.
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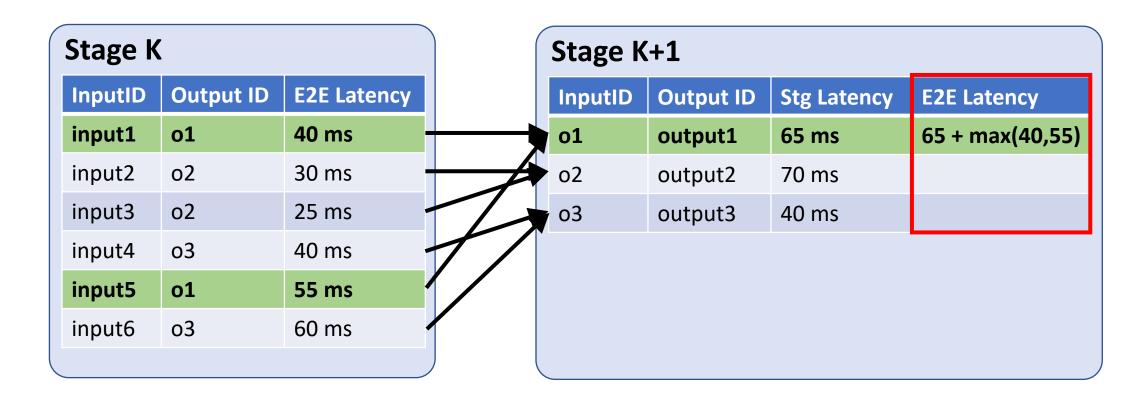
### Propagate End-to-End Latency



Data
Provenance +
Record-Level
Latency

Expensive Record Identification

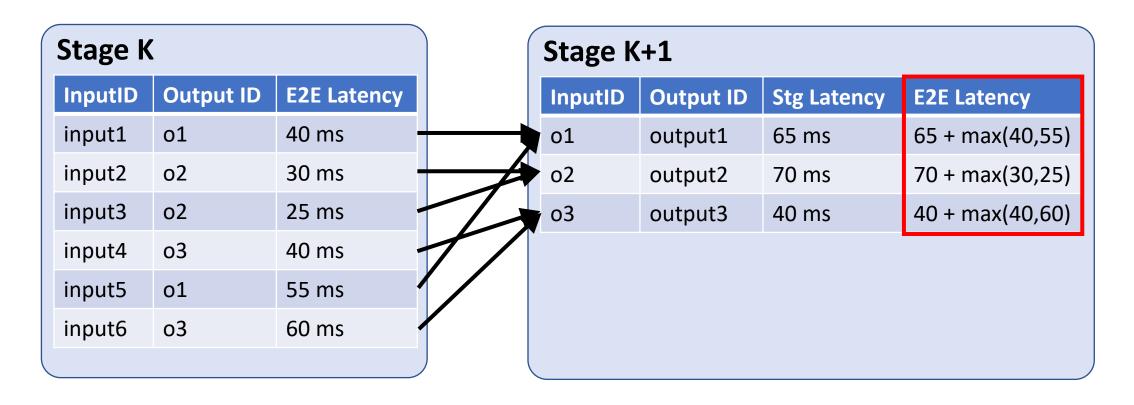
#### Propagate End-to-End Latency



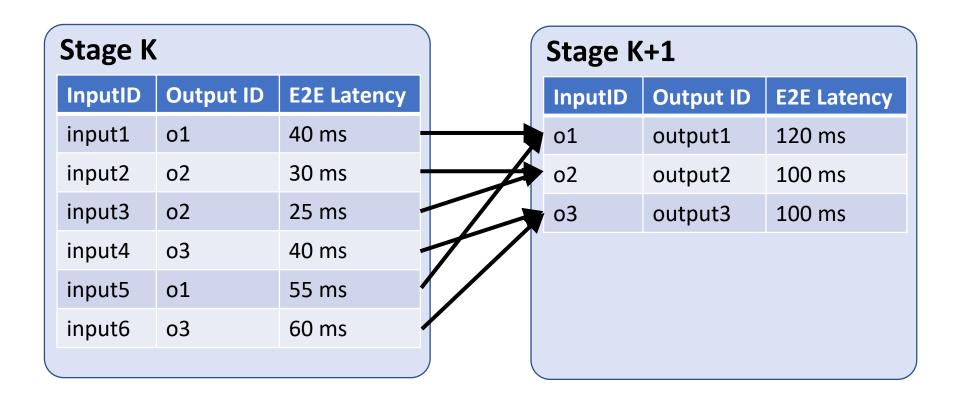
Data
Provenance +
Record-Level
Latency

Expensive Record Identification

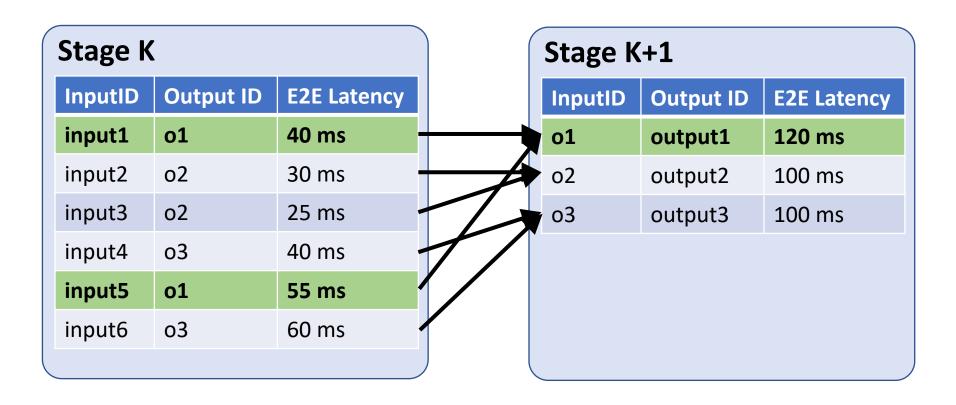
### Propagate End-to-End Latency



### Propagate End-to-End Latency



### Propagate End-to-End Latency

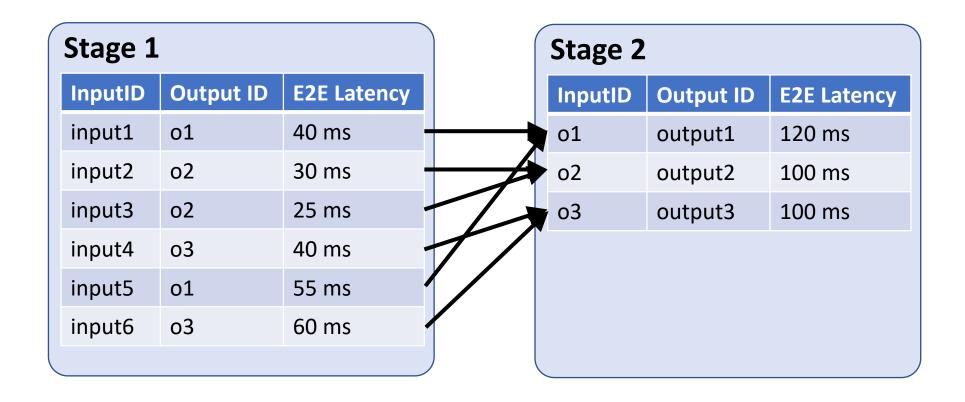


Data
Provenance +
Record-Level
Latency

## Propagate Expensive Inputs

- Not all inputs contribute equally to application performance.
- Data provenance alone cannot differentiate between these inputs if multiple map to the same record.

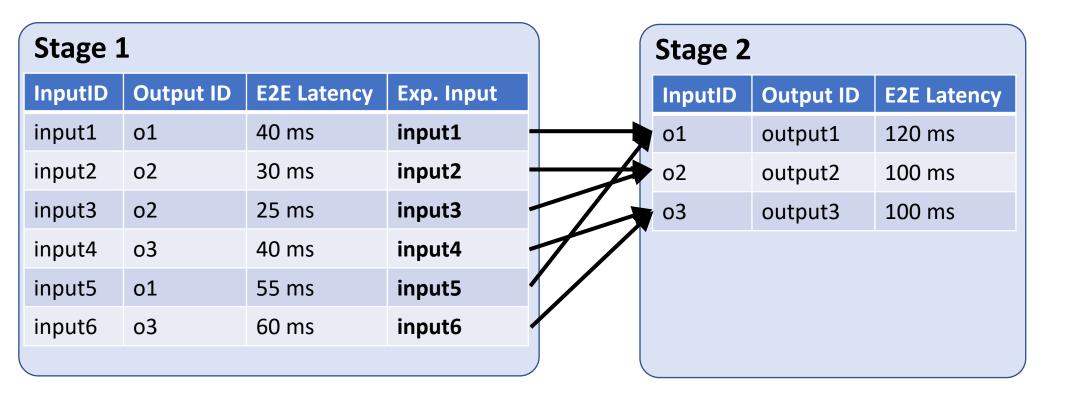
### Propagate Expensive Inputs



Data
Provenance +
Record-Level
Latency

Expensive Record Identification

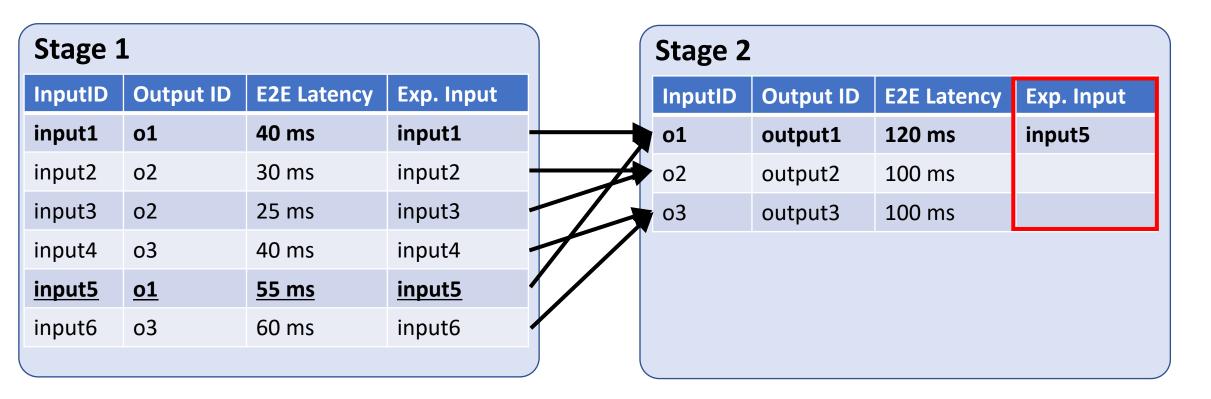
### Propagate Expensive Inputs



Data
Provenance +
Record-Level
Latency

Expensive Record Identification

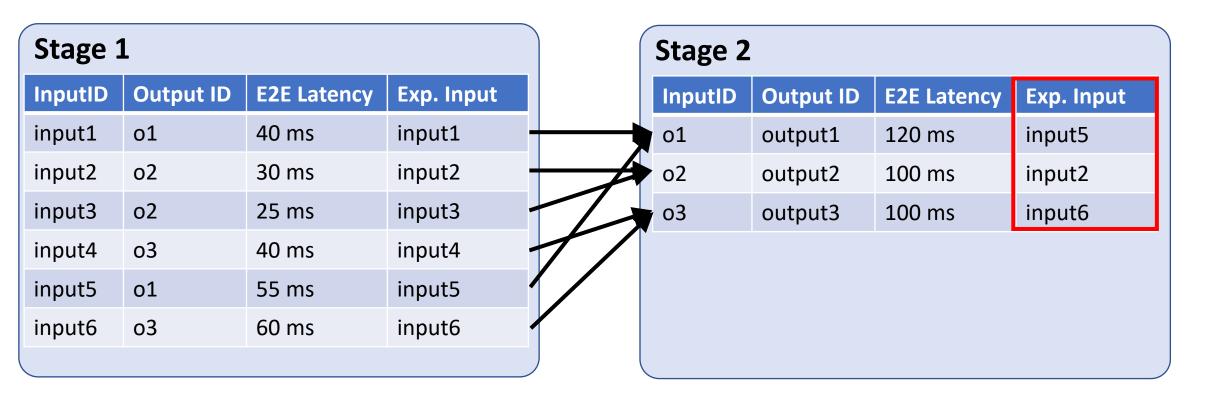
### Propagate Expensive Inputs



Data
Provenance +
Record-Level
Latency

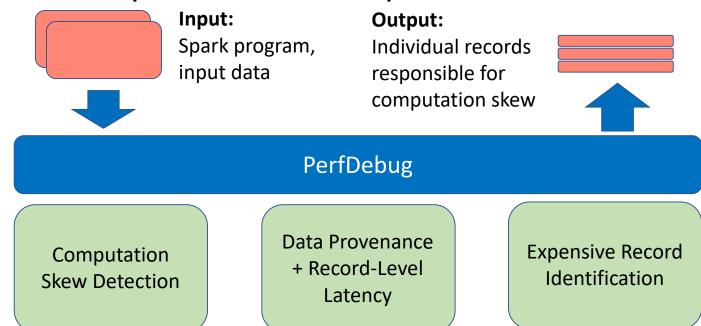
Expensive Record Identification

### Propagate Expensive Inputs



## PerfDebug Approach Recap

- Monitoring to detect presence of computation skew
- Instrumented execution to collect data provenance and latency
- Propagation algorithm to analyze end-to-end record impact and identify records responsible for computation skew



#### Evaluation

**RQ1**: What is the impact of applying appropriate remediations?

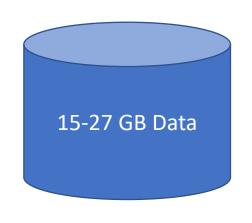
**RQ2**: How much overhead does PerfDebug introduce?

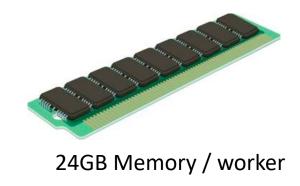
**RQ3**: How accurate is PerfDebug at identifying delay-inducing inputs?

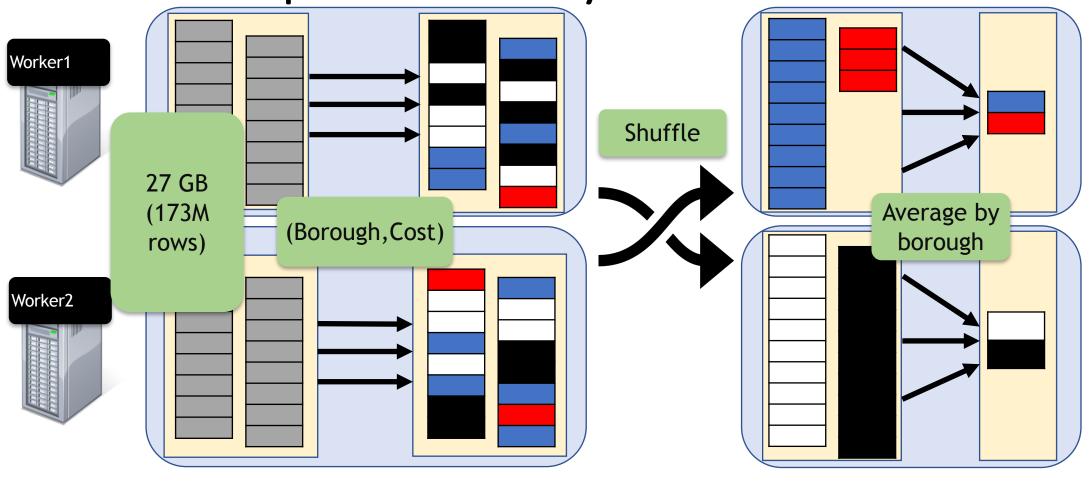
### RQ1: Remediation Impact

- Three case studies with varying computation skew causes: data skew, data quality, and expensive UDF.
- 1.5X to 16X performance improvement with case-specific fixes.



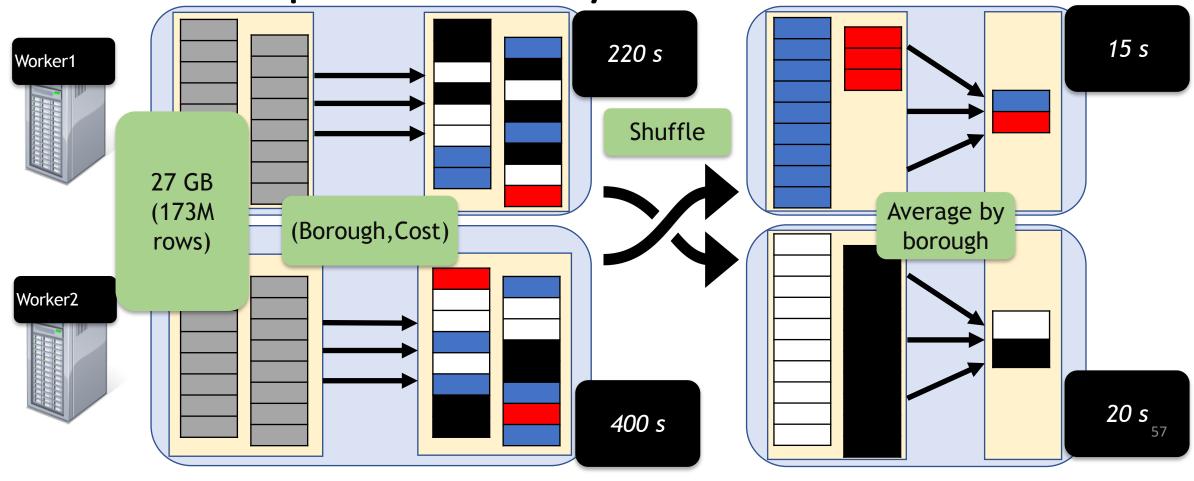




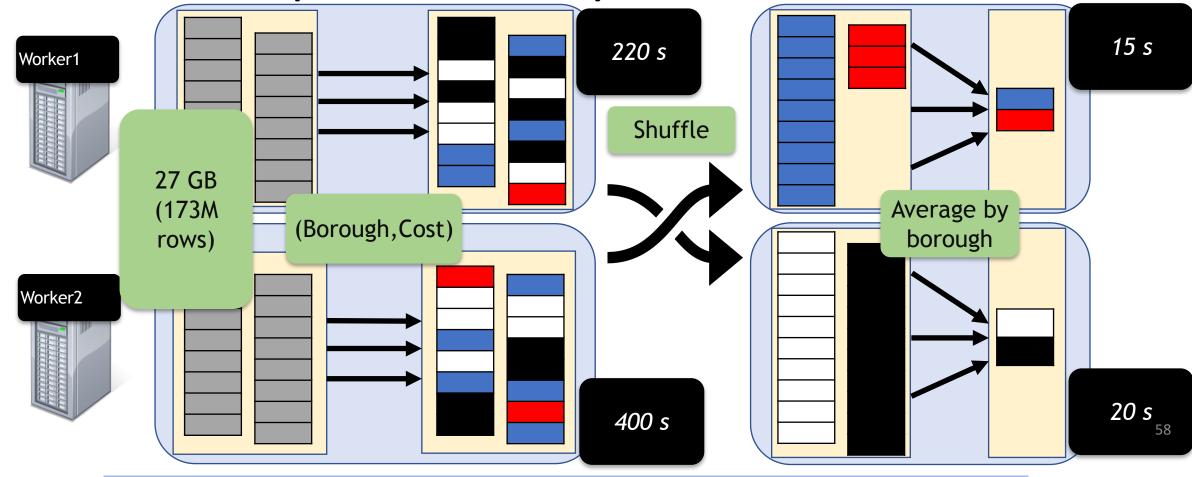


Goal: compute average cost of a taxi ride for each starting borough

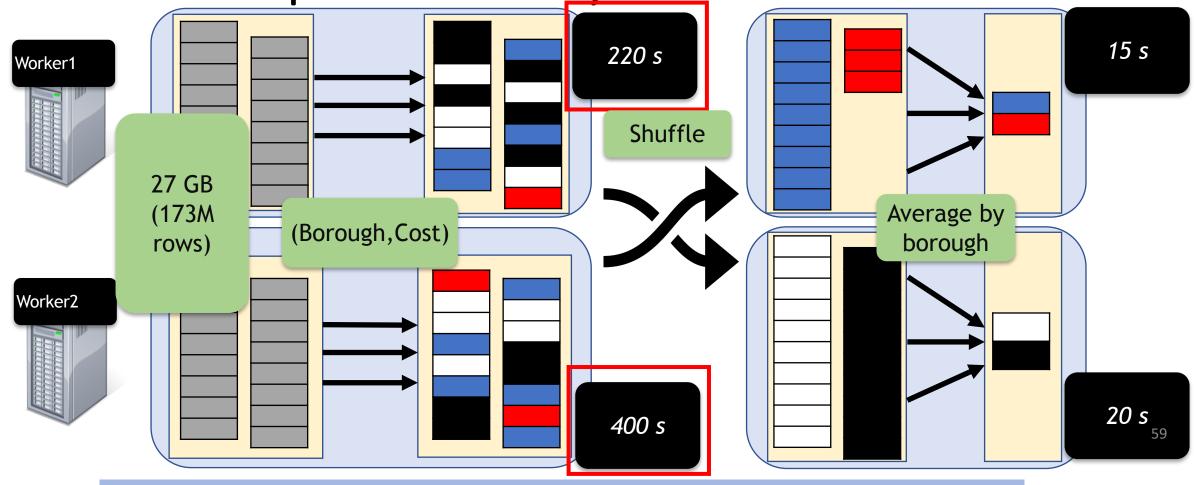
56



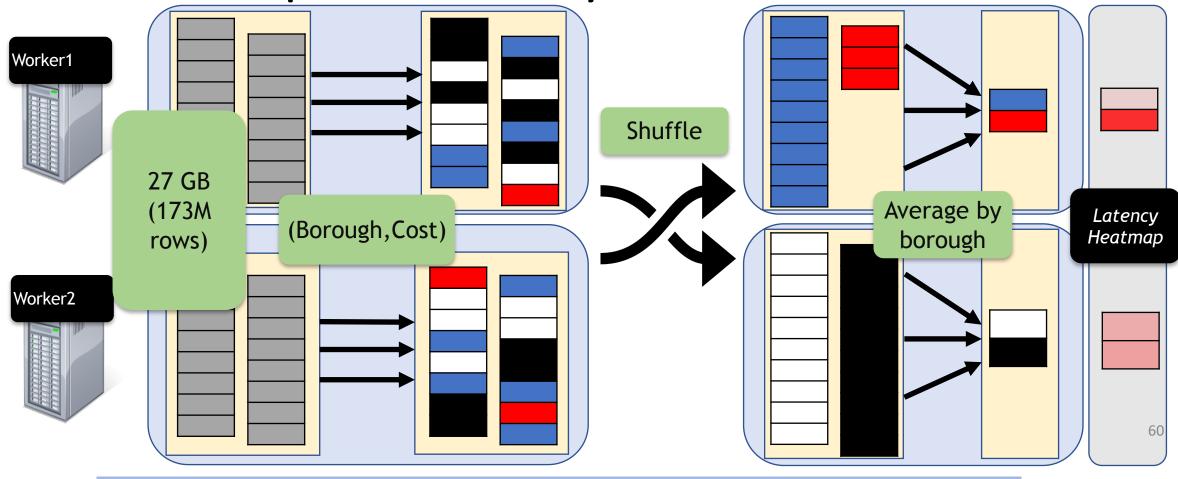
Total runtime: ~7 minutes



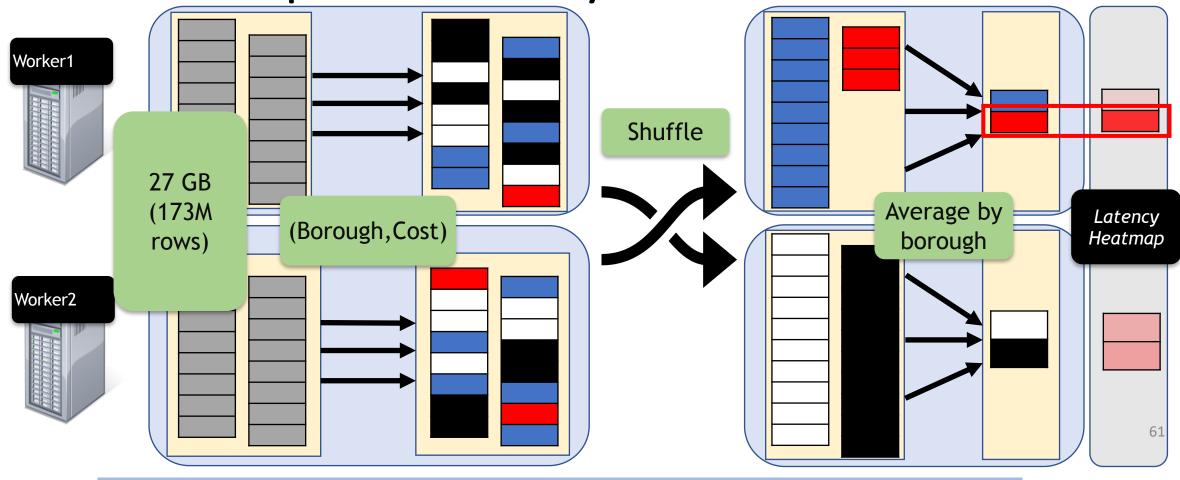
Task times show that data skew is a minor performance factor.



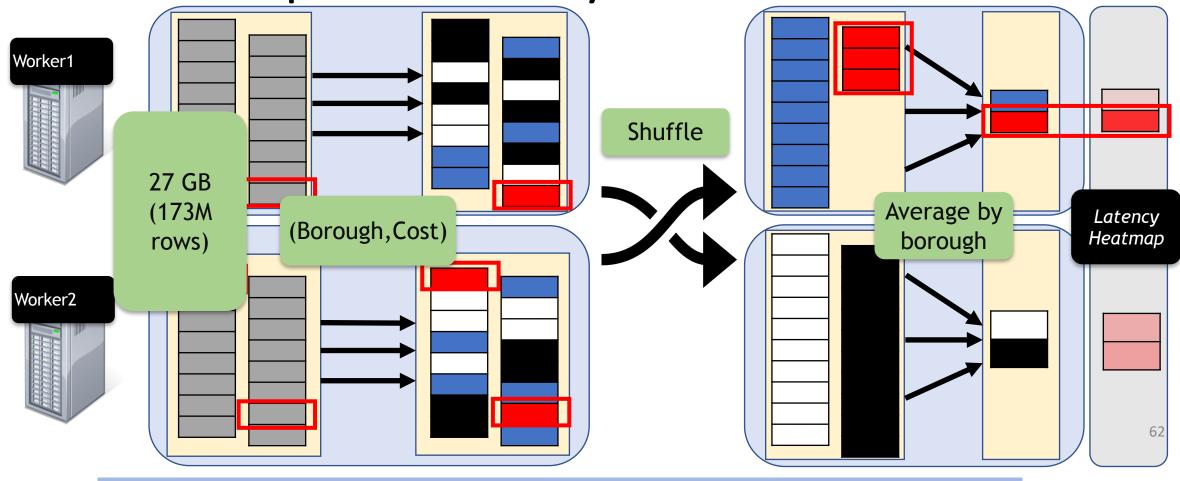
PerfDebug detects potential computation skew in the first stage.



PerfDebug identifies the outputs with the highest latency and uses provenance to trace the corresponding inputs.



PerfDebug identifies the outputs with the highest latency and uses provenance to trace the corresponding inputs.



PerfDebug identifies the outputs with the highest latency and uses provenance to trace the corresponding inputs.

### NYC Taxi Trips Case Study Results

- PerfDebug isolates the source of computation skew to a small subset of inputs: 0.0006%
- Inspection reveals that a *getBorough* UDF consumes majority of task time.

Removal of these records results in ~16X performance improvement.

#### RQ2: Instrumentation Overhead

- Three benchmarks, ten trials each.
- Titian adds ~30% runtime overhead versus Spark [VLDB 2016].
- PerfDebug adds ~30% runtime overhead compared to Titian.
- Majority of additional overhead due to using persistent storage for post-mortem debugging, which was not required in Titian.

#### RQ3: Precision and Recall

- Three benchmarks, ten trials each.
- Use mutation testing to randomly inject an input record with delays.
- PerfDebug consistently identified target: 100% precision and recall.
- 2-6 orders of magnitude better precision compared to provenanceonly input tracing of outputs using Titian.

Benchmark	Accuracy	Precision Improvement	Overhead
Movie Ratings	100%	10 <sup>3</sup> X	1.04X
College Students	100%	10 <sup>6</sup> X	1.39X
Weather Analysis	100%	10 <sup>2</sup> X	1.48X
Average	100%	10 <sup>5</sup> X	1.30X

#### Conclusion

- PerfDebug is a post-mortem performance debugging tool that combines data provenance and record-level latency instrumentation to precisely pinpoint records which cause computation skew.
- Case-specific fixes can yield up to 16X performance improvement.

#### Related Work

- Ernest [NSDI 2016], ARIA [ICAC 2011], Jockey [Eurosys 2012], Starfish [CIDR 2011]: performance modeling for prediction, but not debugging of computation skew
- PerfXplain [VLDB 2012]: job and task comparison for debugging and explanation with respect to collected metrics.
- Titian [VLDB 2016]: data provenance within Apache Spark, used as foundation for PerfDebug implementation.
- Additional works mentioned in paper.