

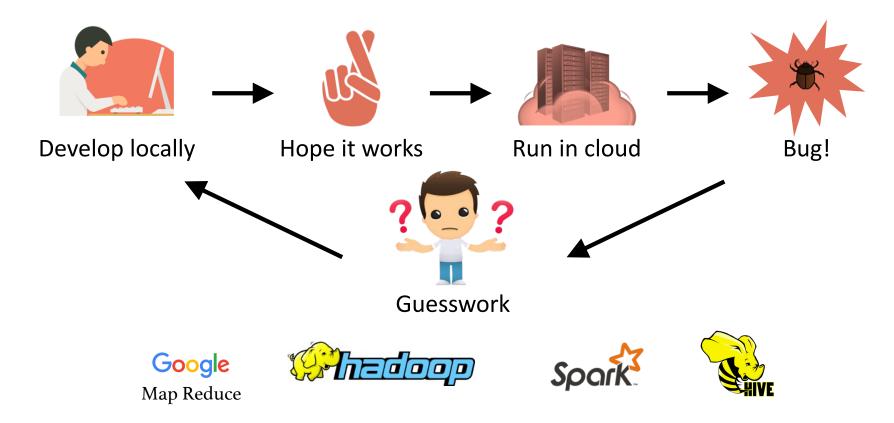
Automated Debugging of Big Data Analytics in Apache Spark Using BigSift

Muhammad Ali Gulzar Miryung Kim University of California, Los Angeles



#Res3SAIS

Big Data Debugging in the Dark





BigDebug: Debugging Primitives for Interactive Big Data Processing

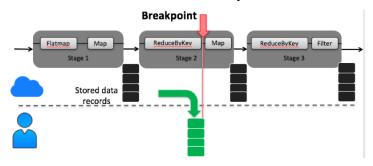
ICSE 2016

Muhammad Ali Gulzar, Matteo Interlandi, Seunghyun Yoo, Sai Deep Tetali Tyson Condie, Todd Millstein, Miryung Kim Presented at <u>Spark Summit 2017</u>

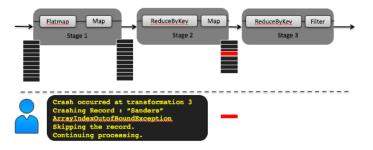


Interactive Debugging with BigDebug

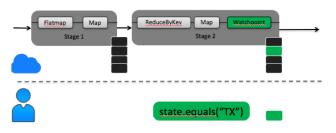
1. Simulated Breakpoint



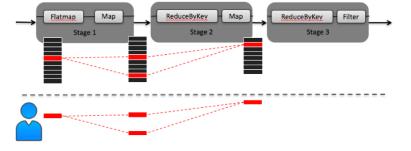
3. Crash Culprit Identification



2. On Demand Guarded Watchpoint



4. Backward and Forward Tracing





Titian: Data Provenance support in Spark

VLDB 2015

Matteo Interlandi, Kshitij Shah, Sai Deep Tetali, Muhammad Ali Gulzar, Seunghyun Yoo, Miryung Kim, Todd Millstein, Tyson Condie



Data Provenance - in SQL

SELECT time, AVG(temp)
FROM sensors
GROUP BY time



Sensors					
Tuple-ID	Time	Sendor-ID	Temperature		
T1	11AM	1	34		
T2	11AM	2	35		
Т3	11AM	3	35		
T4	12PM	1	35		
T5	12PM	2	35		
Т6	12PM	3	100		
T7	1PM	1	35		
T8	1PM	2	35		
T9	1PM	3	80		

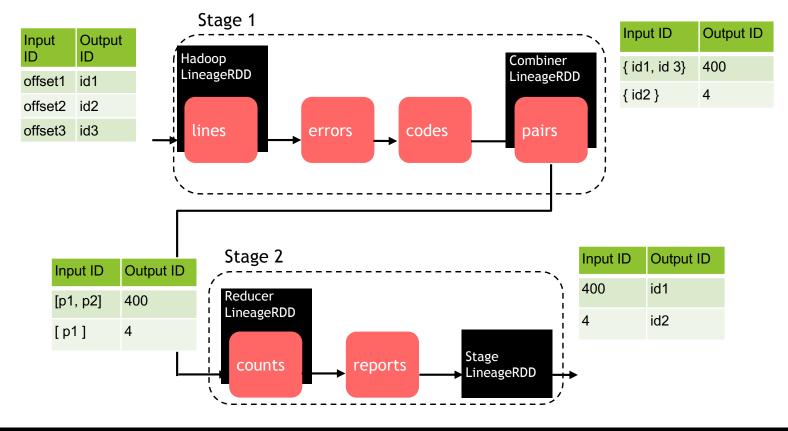
Why ID-2 and ID-3 have those high values?

Result- ID	Time	AVG(temp)
ID-1	11AM	34.6
ID-2	12PM	56.6
ID-3	1PM	50

Outlier Outlier

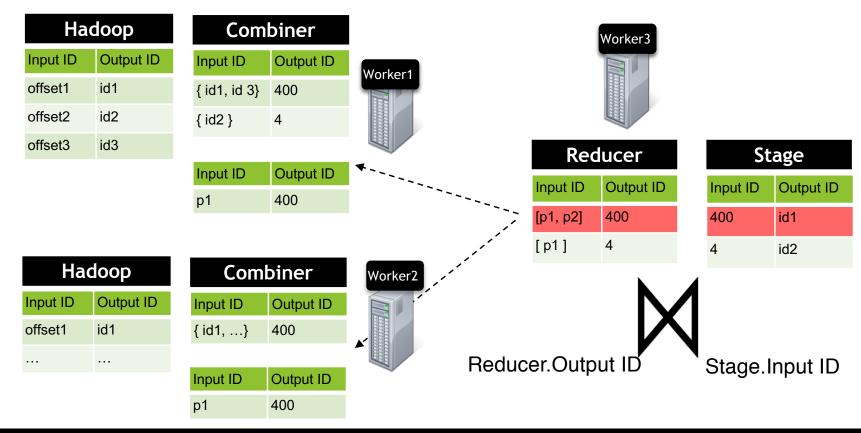


Step 1: Instrument Workflow in Spark





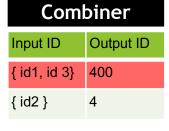
Step 2: Example Backward Tracing





Step 2: Example Backward Tracing

Hadoop Input ID Output ID offset1 id1 offset2 id2 offset3 id3



Input ID	Output ID		
p1	400		



Combiner.Output ID



Hadoop				
Input ID	Output ID			
offset1	id1			

Combiner					
Input ID	Output ID				
{ id1,} 400					
Input ID	Output ID				
p1	400				



Combiner.Output ID

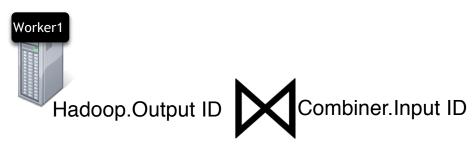




Step 2: Example Backward Tracing

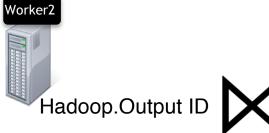
Hadoop				
Input ID	Output ID			
offset1	id1			
offset2	id2			
offset3	id3			

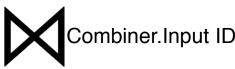
Combiner						
Input ID Output ID						
400						
4						



Hadoop				
Input ID	Output ID			
offset1	id1			

Combiner				
Input ID	Output ID			
{ id1,}	400			







BigSift: Automated Debugging of Big Data Analytics in DISC Applications

SoCC 2017

Muhammad Ali Gulzar, Matteo Interlandi, Xueyuan Han, Tyson Condie, Miryung Kim



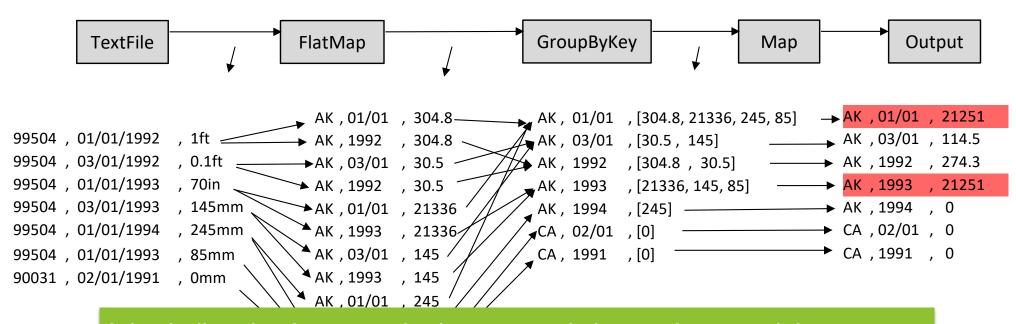
Motivating Example for Automated Debugging with BigSift

- Alice writes a Spark program that identifies, for each state in the US, the delta between the minimum and the maximum snowfall reading for each day of any year and for any particular year.
- An input data record that measures 1 foot of snowfall on January 1st of Year 1992, in the 99504 zip code (Anchorage, AK) area, appears as

99504, 01/01/1992, 1ft



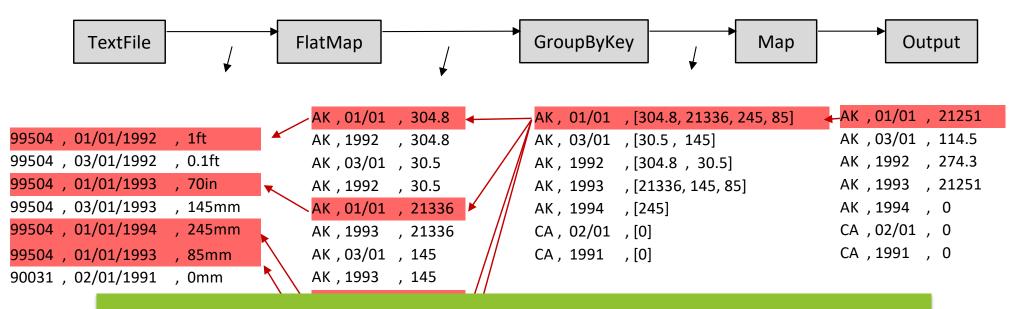
Debugging Incorrect Output



It is challenging because the input records is very large and the program involves computing min and max and a unit conversion



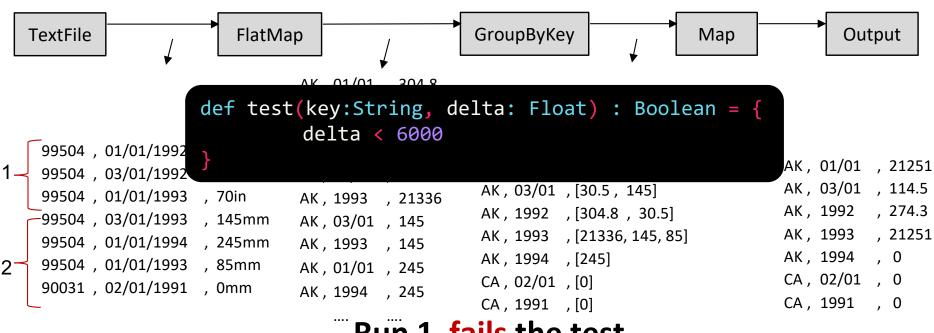
Data Provenance with Titian [VLDB '15]



It over-approximates the scope of failure-inducing inputs *i.e.* records in the faulty key-group are all marked as faulty



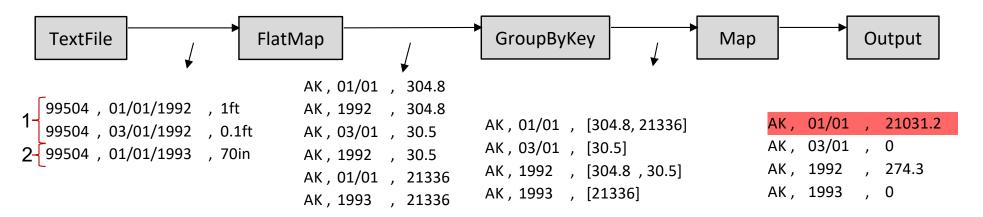
Alice tests the output from different input configurations using a test function



Run 1 fails the test

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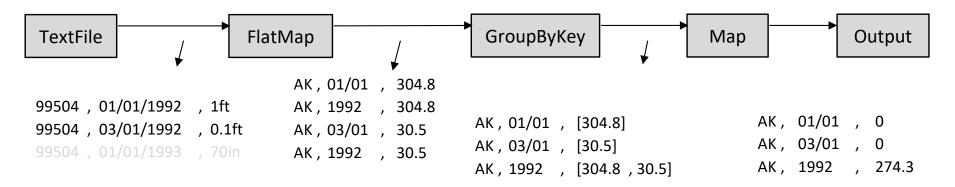
DD is an systematic debugging procedure guided by a test function.
 DD is inefficient because it does not eliminate irrelevant input records upfront.



Run 2 fails the test



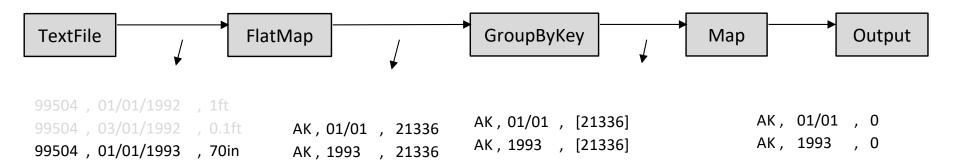
DD is an systematic debugging procedure guided by a test function.
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Run 3 passes the test



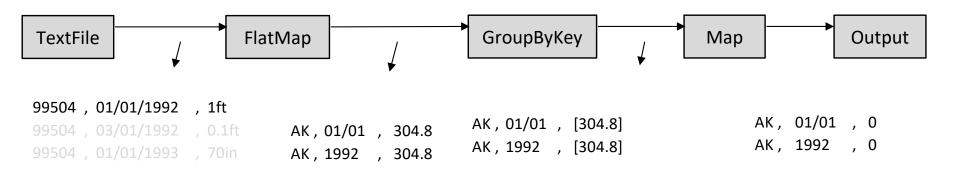
DD is an systematic debugging procedure guided by a test function.
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Run 4 passes the test



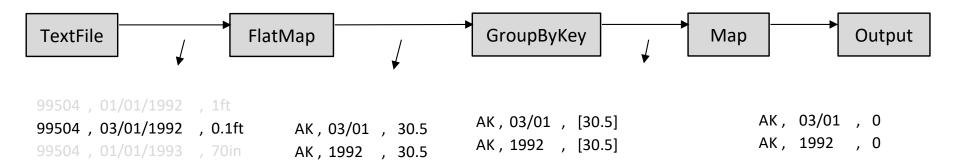
DD is an systematic debugging procedure guided by a test function.
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Run 5 passes the test



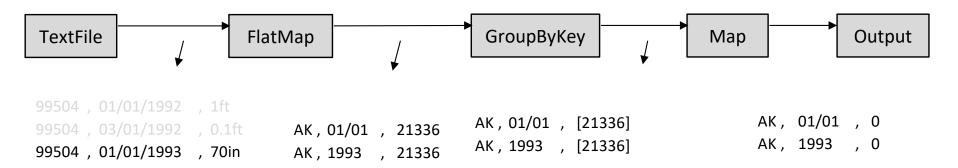
DD is an systematic debugging procedure guided by a test function.
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Run 6 passes the test



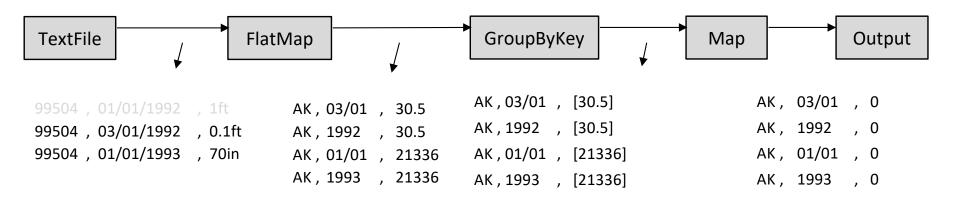
DD is an systematic debugging procedure guided by a test function.
 DD is inefficient because it does not eliminate irrelevant input records upfront.



Run 7 passes the test



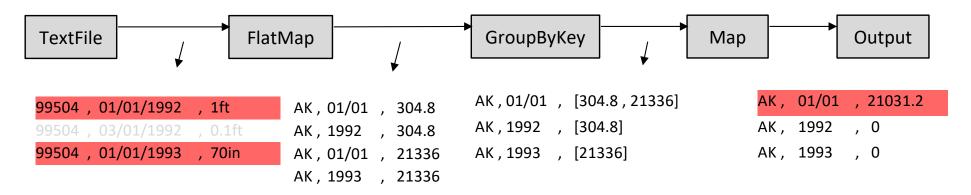
DD is an systematic debugging procedure guided by a test function.
 DD is inefficient because it does not eliminate irrelevant input records upfront.



Run 8 passes the test



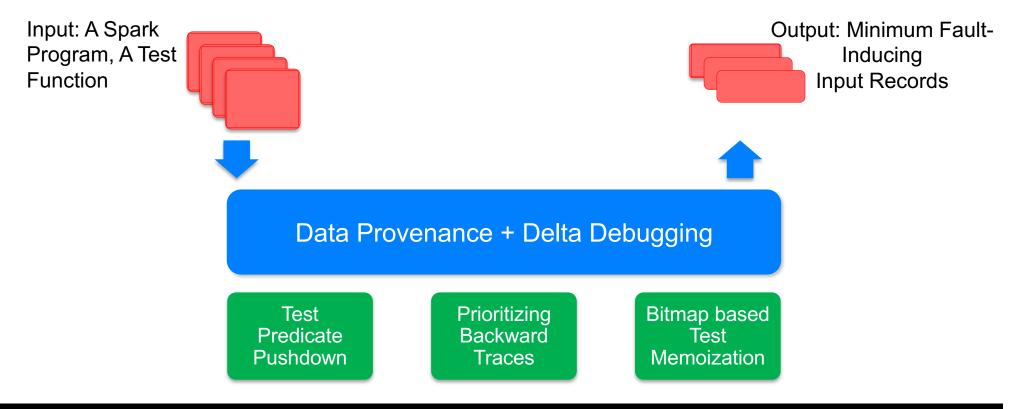
DD is an systematic debugging procedure guided by a test function.
 DD is inefficient because it does not eliminate irrelevant input records upfront.



Run 9 fails the test



Automated Debugging in DISC with BigSift





Optimization 1: Test Predicate Pushdown

 Observation: During backward tracing, data provenance traces through all the partitions even though only a few partitions are faulty

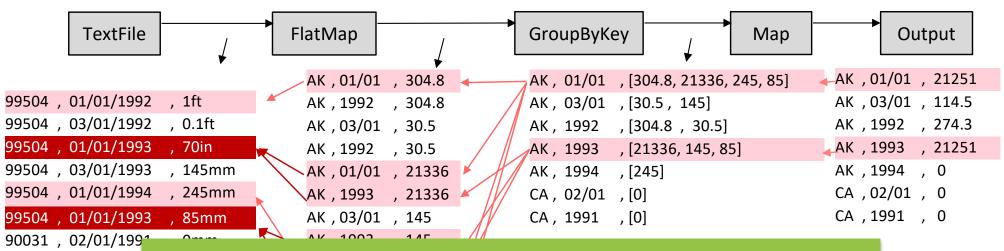


If applicable, BigSift pushes down the test function to test the output of combiners in order to isolate the faulty partitions.



Optimization 2: Prioritizing Backward Traces

 Observation: The same faulty input record may contribute to multiple output records failing the test.

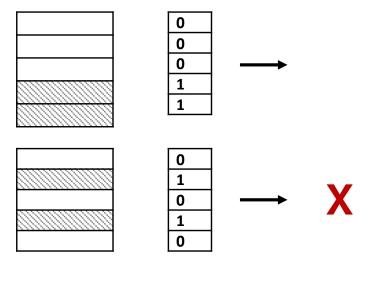


In case of multiple faulty outputs, BigSift overlaps two backward traces to minimize the scope of fault-inducing input records

SPARK+AI SUMMIT 2018

Optimization 3: Bitmap based Test Memoization

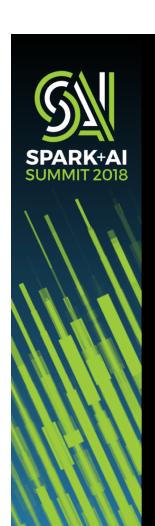
- Observation: Delta debugging may try running a program on the same subset of input redundantly.
- BigSift leverages bitmap to compactly encode the offsets of original input to refer to an input subset



Input Data Bitmap Test Outcome

We use a bitmap based test memoization technique to avoid redundant testing of the same input dataset.





Demo

Debugging Time

Subject Program		Running Time (sec)	Debugging Time (sec)		me (sec)
Subject Program	Fault	Original Job	DD	BigSift	Improvement
Movie Histogram	Code	56.2	232.8	17.3	13.5X
Inverted Index	Code	107.7	584.2	13.4	43.6X
Rating Histogram	Code	40.3	263.4	16.6	15.9X
Sequence Count	Code	356.0	13772.1	208.8	66.0X
Rating Frequency	Code	77.5	437.9	14.9	29.5X
College Student	Data	53.1	235.3	31.8	7.4X
Weather Analysis	Data	238.5	999.1	89.9	11.1X
Transit Analysis	Code	45.5	375.8	20.2	18.6X

BigSift provides up to a 66X speed up in isolating the precise fault-inducing input records, in comparison to the baseline DD



#Res3SAIS 29

Debugging Time

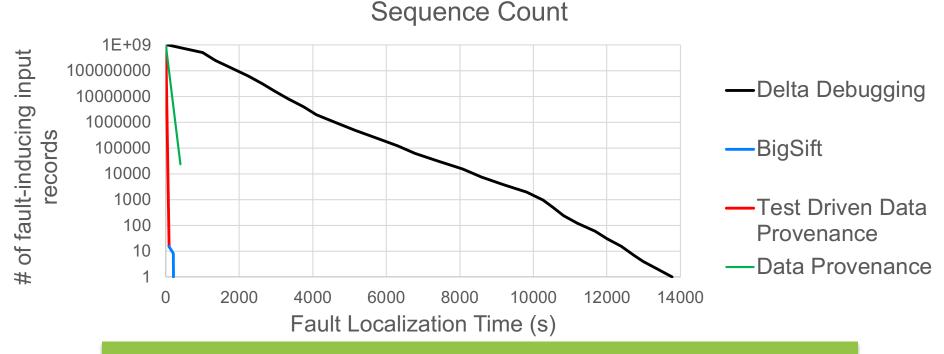
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On average, BigSift takes 62% less time to debug a single faulty output than the time taken for a single run on the entire data.



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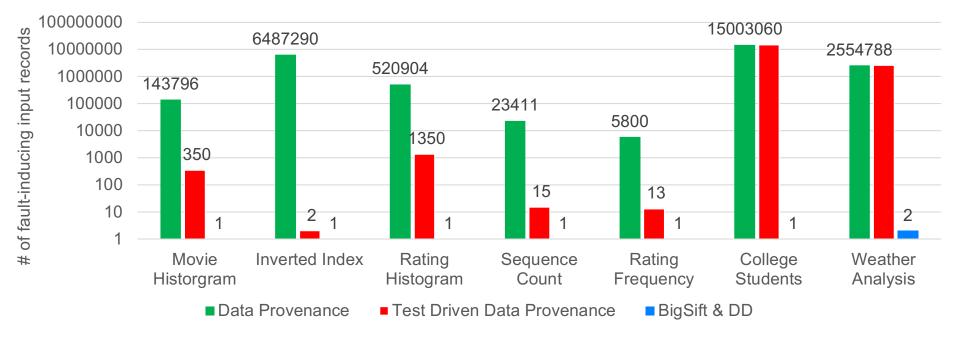
Debugging Time



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Fault Localizability over Data Provenance



BigSift leverages DD after DP to continue fault isolation, achieving several orders of magnitude 103 to 107 better precision.



Summary

- BigSift is the first piece of work in automated debugging of big data analytics in DISC.
- BigSift provides 10³X 10⁷X more precision than data provenance in terms of fault localizability.
- It provides up to 66X speed up in debugging time over baseline Delta Debugging.
- In our evaluation we have observed that, on average, BigSift finds the faulty input in 62% less than the original job execution time.

