A Distributed Timing Analysis Framework for Large Designs

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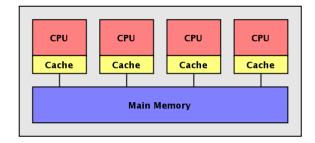




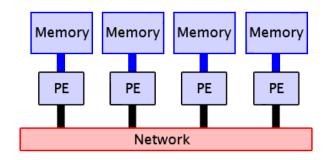


Distributed Timing – Motivation and Goal

- □ Motivation
 - ☐ Ever increasing design complexity
 - Hierarchical partition
 - Abstraction
 - Multi-threading timing analysis
 - ☐ Too costly to afford high-end machines
- ☐ Create a distributed timing engine
 - ☐ Explore a feasible framework
 - ☐ Prototype a distributed timer
 - □ Scalability
 - Performance



Multi-threading in a single machine



Distributed computing on a machine cluster

State-of-the-art Distributed System Packages

□ Open-source cloud computing platforms (https://hadoop.apache.org/) □ Hadoop Reliable, scalable, distributed MapReduce platform on HDFS □ Cassandra A scalable multi-master database with no single points of failure ☐ Chukwa A data collection system for managing large distributed systems ☐ Hbase A scalable, distributed database that supports structured data storage Zookeeper Coordination service for distributed application □ Mesos A high-performance cluster manager with scalable fault tolerance □ Spark

A fast and general computing engine for iterative MapReduce

The Questions Are

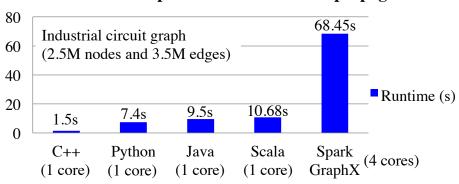
☐ Are these packages really suitable for our applications? ☐ Google/Hadoop MapReduce programming paradigm ■ Spark in-memory iterative batch processing What are the potential hurdles for EDA to use big-data tools? ☐ Big-data tools are majorly written in JVM languages ☐ EDA applications highly rely on high-performance C/C++ ☐ Rewrites of numbers of codes What are the differences between EDA and big data? ☐ Computation intensive vs Data intensive ☐ EDA data is more connected than many of social network

An Empirical Experiment on Arrival Time Propagation

□ Bebchmark

- ☐ Timing graph from ICCAD 2016 CAD contest (*superblue18*)
 - 2.5M nodes
 - 3.5M edges
- □ Implementation
 - ☐ Spark 4 cores
 - ☐ Java, Scala, etc. 1 core
 - ☐ C++ 1 core

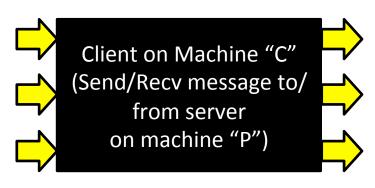
Runtime comparison on arrival time propagation



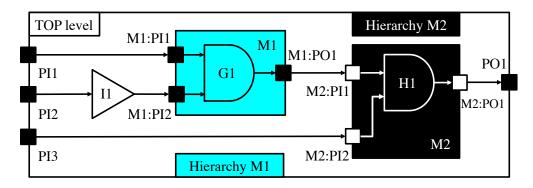
Implementation	Spark 1.4 (RDD + GraphX Pregel)	Scala (Dijkstra)	C++ (Dijkstra)
Runtime (s)	68.45	10.68	1.50
	Overhead of GraphX and messa passing	age Over	thead of JVM

The Proposed Framework for Distributed Timing

- □ Focus on general design partitions
 - ☐ Logical, physical, and hierarchies
 - □ Across multiple machines (DFS)
- ☐ Single-server multiple-client model
 - ☐ Server is the centralized communicator
 - ☐ Client exchange boundary timing with server



Client machine IP: 1.23.456.789



An example design with three partitions



Server machine IP: 140.110.44.32

Key Components in our Framework

Multiple-program multiple-data paradigm ☐ Different programs for clients and server ■ Better scalability and work distribution ■ Non-blocking socket IO ☐ Program returns to users immediately ■ Overlap communication and computation **Event-driven environment** ☐ Callback for message read/write events ☐ Persistent in memory for efficient data processing ☐ Efficient messaging interface ■ Network see bytes only ☐ Serialization and deserialization of timing data

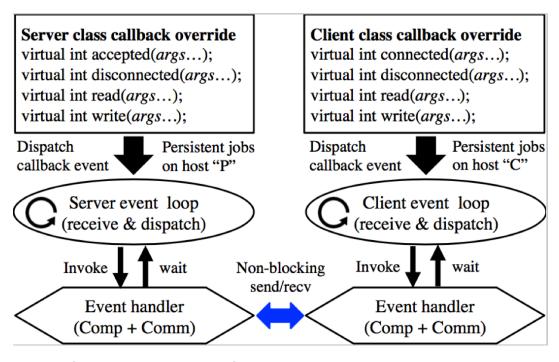
Non-blocking IO and Event-driven Loop with Libevent

- ☐ Libevent (http://libevent.org/)
 - Open-source under BSD license
 - ☐ Actively maintained
 - ☐ C-based library
 - Non-blocking socket
 - □ Reactor model

// Magic inside dispatch call
while (!event_base_empty(base)) {
 // non-block IO by OS kernel
 active_list ← get_active_events
 foreach(event e in active_list) {
 invoke the callback for event e
 }
}

An example event-driven code

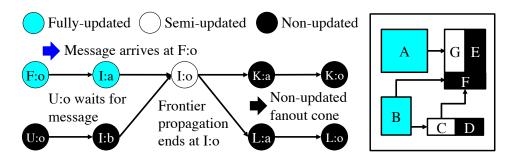




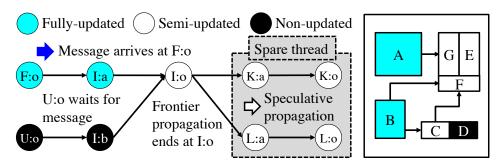
Interface class in our framework (override virtual methods for event callback)

Callback Implementation

- ☐ Client read callback
 - □ Receive boundary timing
 - Propagate timing
 - Send back to the server
- □ Server read callback
 - ☐ Keep boundary mapping
 - □ Receive boundary timing
 - Propagate timing
 - ☐ Send to the client
- ☐ Timing propagation
 - ☐ Frontier vs Speculative



Frontier timing propagation follows the topological order of the timing graph



If multi-threading is available, spare thread performs speculative propagation in order gain advanced saving of frontier work

Efficient Messaging Interface based on Protocol Buffer

Message passing ■ Expensive ☐ TCP byte stream □ Unstructured Data conversion □ Serialization □ Deserialization □ Protocol buffer ☐ Customized protocol ☐ Simple and efficient

☐ Built-in compression

Structured message format (.proto)

```
enum KeyType {PIN_NAME}
enum ValueType {AT, SLACK}
message Key {
  optional KeyType type = 1;
  optional string data = 2;
}
message Value {
  optional ValueType type = 1;
  optional string data = 2;
}
```



C++/Java/Python source code generator



```
.cpp/.h class methods
ParseFromArray(void*, size_t)
SerializeToArray(void*, size_t)
```

Message wrapper

Derived packet struct
header_t header
void* buffer

Integration of Google's open-source protocol buffer into our messaging interface greatly facilitates the data conversion between application-level developments and socket-level TCP byte streams.

Evaluation – Software and Hardware Configuration

□ Written in C++ language on a 64-bit Linux machine □ 3rd-party library ☐ Libevent for event-driven network programming ☐ Google's protocol buffer for efficient messaging □ Benchmarks ☐ 250 design partitions generated by IBM EinsTimer ☐ Millions-scale graphs generated by TAU and ICCAD contests □ Evaluation environment □ UIUC campus cluster (https://campuscluster.illinois.edu/) ☐ Each machine node has 16 Intel 2.6GHz cores and 64GB memory ☐ 384-port Mellanox MSX6518-NR FDR InfiniBand (gigabit Ethernet) ☐ Up to 250 machine nodes

Evaluation – Results and Performance

☐ Overall performance

Circuit	G $ N $	N	N $ V $	E	P	L	W/o speculation			W/ speculation				
		7					cpu	mem	msg	usage	cpu	mem	msg	usage
DesignA	2.2M	1.1M	7.3M	12.4M	250	436	63s	1.6GB	0.7MB	17.3%	76s	1.7GB	1.6MB	64.2%
DesignB	14.5M	9.3M	39.0M	117.0M	37	3216	392s	2.9GB	2.0MB	9.1%	346s	3.1GB	5.7MB	73.1%
DesignC	23.3M	11.3M	76.9M	107.0M	30	2023	478s	4.7GB	2.3MB	19.5%	473s	4.8GB	8.1MB	57.8%
DesignD	42.7M	20.8M	128.1M	178.4M	50	5741	1239s	5.1GB	4.9MB	20.1%	1107s	5.1GB	9.7MB	69.4%

|G|: # of gates. |N|: # of nets. |V|: # of nodes. |E|: # of edges. |P|: # of partitions. L: # of levels. cpu: runtime. mem: peak memory on a program. msg: amount of message passing. usage: avg cpu utilization on a program.

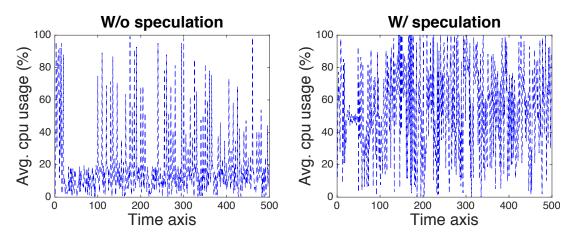
- ☐ Scalability
 - ☐ Scale to 250 machines (DesignA)
- **☐** Runtime efficiency
 - ☐ Less than 1 hour on large designs (DesignC and DesignD)
- ☐ Memory usage
 - ☐ Peak usage is only about 5GB on a machine (DesignD)

Evaluation – A Deeper Look

- □ CPU utilization
 - W/o speculation
 - W speculation

W/ speculation on DesignD

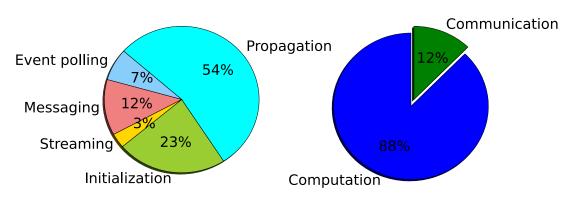
- +49% cpu rate
- +4.8MB on message passing



Average cpu utilization over time across all machines.



- □ 7% event polling
- ☐ 3% streaming
- □ 23% initialization
- ☐ 54% propagation
- ☐ 12% communication



Runtime profile of our framework (12% on communication and 88% on computation)

Conclusion and Future Work

Prototype a distributed timing analysis framework
☐ Server-client model
■ Non-blocking socket IO (overlap communication and computation)
☐ Event-driven loop (autonomous programming)
☐ Efficient messaging interface (serialization and deserialization)
Future work
☐ A system for distributed timing analysis
☐ Fault tolerance
☐ Distributed common path pessimism removal (CPPR)
Acknowledgment
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