End-to-End Tracing Models: Analysis and Unification

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Abstract

Many applications today require distributed systems to store and process massive amounts of data. The complexity of these applications grows as the systems running them become more complex, and as the applications require more systems in order to run. End-to-end tracing is the process of following a request through the network of machines running one or more distributed systems in order to aid in the maintenance, debugging, and optimization of the systems. We will analyze the two primary models used for end-to-end tracing systems, the span model and the event model. We will show that spans are the less powerful model through a formal proof and a practical implementation of the proof, as well as discuss the consequences of using the span model. We will finish by proposing a joint model that incorporates both spans and events.

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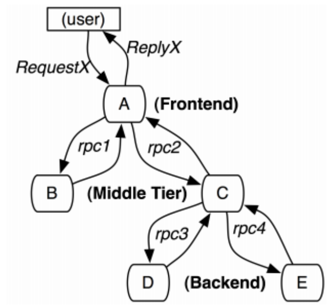


Figure 1: Simple depiction of the path taken through a system to service a request requiring multiple processes' cooperation (each lettered node in the graph represents a process in the system). Taken from [8].

1 Introduction

Many distributed systems have been created in recent years to store and process massive amounts of data. These systems are extremely complex and require the careful coordination of several processes[1] to accomplish even simple tasks. Applications often rely on more than one of these systems, considerably increasing the complexity. End-to-end tracing is the process of following a particular request through this network of processes in order to gain more understanding into how the system works and what may be going wrong, specifically with respect to the causal relationships among different events and processes. The image in Figure 1, taken from Google's Dapper paper [8], provides a high level illustration of the type of information we seek when tracing distributed systems. The trace being displayed is of a simple web request from a user that requires communication to multiple backend systems in order to service the request.

1.1 Uses

End-to-end tracing information is useful for debugging these systems because it provides an important axis of logging information that transcends the standard logging done by each process. In addition to viewing logging information through the standard process and time axes, tracing provides a third axis based on requests. The ability to see exactly which processes were involved in servicing a particular request, as well as the causal relationships among those processes, is invaluable in maintaining, debugging, and improving these systems.

[1]Note that these processes may be on the same machine or span across multiple machines.

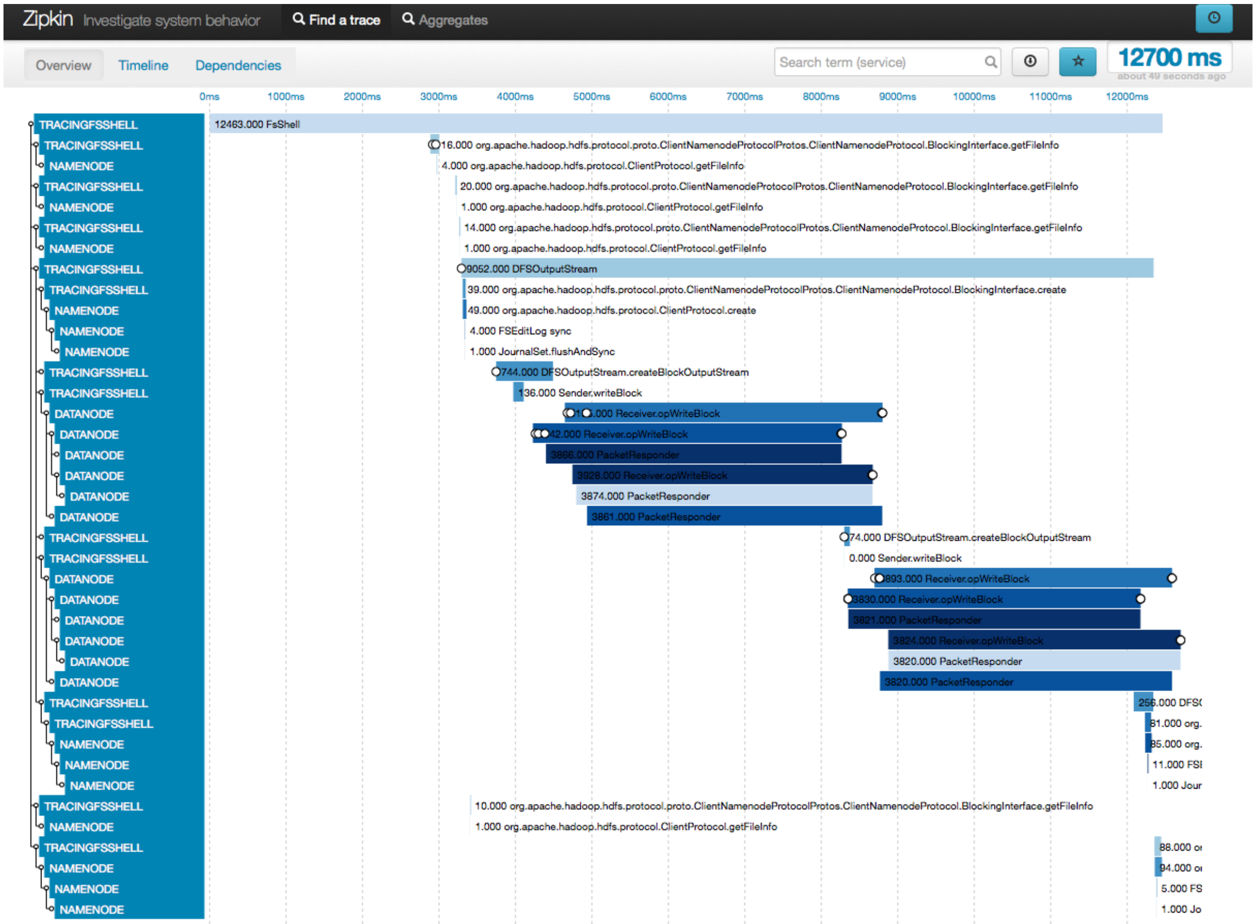


Figure 2: A trace of an HDFS `put` operation created with HTrace (from HDFS-5275 [2]).

Additionally, end-to-end request tracing can be very useful for profiling and improving performance of distributed systems. With a set of trace information for a system, one can see exactly how much time the system is spending on various types of tasks and optimize appropriately. See Figure 2 for a trace of a `put` request in a Hadoop Distributed Filesystem (HDFS) cluster created using HTrace [3] and visualized using Zipkin's [9] visualization tools; the image itself is taken from HDFS-5274 [2].

With end-to-end tracing, damage control and preemptive performance tuning on one's cluster is significantly simplified. In lieu of `GREP`'ing log files in order to find anomalous behavior, one can simply inspect visualizations of traces for faulty executions to find the problem. For example, consider HBase, the column-oriented distributed database built on HDFS. An important part of correctly configuring an HBase cluster is choosing a proper row-key schema. Rows in HBase are sorted by their row-keys. Row-keys that are lexicographically close are kept physically close in the cluster. If the row-key schema is poorly chosen, too many requests might be routed to a particular machine which could become overloaded. While standard machine monitoring would detect an overloaded machine in the cluster, it would only detect it once the machine is already overloaded. With end-to-end tracing in the same situation, automated tools could analyze the tracing data and see that a proportionally high percentage of requests are being routed through one machine and suggest that perhaps the row-key scheme was poorly designed.

A very important feature of any tracing library is the ability to trace both within a system and across systems. The more tracing coverage that exists across systems, the fewer 'black holes' there are in the information collected, and the more useful the information becomes. It would thus be beneficial to create or standardize one primary tracing model and library that would easily allow the coalescence of tracing information collected from many different systems.

2 Tracing Models

There are many tracing implementations, including Dapper [8], HTrace [3], X-Trace [5], Accumulo's Cloudtrace [1], and Zipkin [9]. These libraries represent tracing information with different models, and provide different APIs to the developer trying to instrument a system. HTrace and Zipkin follow the model introduced in Dapper and represent the distributed computation as a tree of *spans*, while X-Trace uses a model of logging a graph of *events*.

2.1 Spans

The span model was first introduced by Google [8], and has since found a fairly good mindshare, with HTrace, Zipkin, and Cloudtrace all using the span model as the basis for their end-to-end tracing systems.

The span model represents a computation as a collection of spans, each of which represents a chunk of work in the computation. Because spans represent an interval of time in the computation, they require a start and an end time. Additionally, each span has information on which other span in the trace started it, representing the causality in the system. If `SpanA` started `SpanB`, `SpanA` is called the parent of `SpanB`. In most systems, each span knows the identity of its parent with a field storing the unique identifier of its parent.

A trace is a collection of spans that were created from the same computation. If we consider each span as a node, and a parent relationship as a directed edge from the parent to the child, a trace can be easily interpreted and understood as a graph. Because the parent relationship represents causality, it is not possible for a cycle to exist in the graph. A cycle would transitively imply that there is some event that caused itself, and also caused the event that caused it – a contradiction. Thus span graphs are just trees with directed edges pointing from the root down toward the leaves.

An important part of the span model is that spans only have a single parent. Tracing systems that use the span model generally keep a stack of the spans that have yet to be 'stopped'. The span at the top of the stack is the current span. When the current span, call it `SpanA`, is stopped, it is delivered (generally to a database), and the next span in the stack, `SpanA's` parent, is the new current span. Such a stack would be impossible if spans could have multiple parents (what span would be current after a span with two parents is popped?).

The stack is kept local to each thread so that parallel computations can be accurately represented. When a remote procedure call (RPC) is sent across the wire, a unique identifier for the span that was current when the RPC was sent and the unique identifier for the entire trace is sent along with the RPC (these identifiers are generally two sixty-four bit unsigned integers). When a new span is started on the machine receiving the RPC, it sets its parent field to the identifier for the span in the RPC and its overall trace identifier (the field for which all spans of the same trace share the same value) to the trace identifier from the RPC. Figure 3 shows a pseudocode example, and Figure 4 depicts the span graph that would be generated by the code in Figure 3.

The span implementation outlined above and used in the example in Figure 3 has a symmetry problem. When several spans are started on the same machine, the stack is maintained and the programmer using the tracing library can 'pop' spans indiscriminately. Once the computation crosses to a new machine, the stack is lost and the programmer can no longer pop spans as he could on one machine. This asymmetry could be solved by sending the entire stack along with each RPC, but this is not feasible because the size of the metadata attached to each RPC would be unbounded. Asymmetry is not necessarily a bad thing, but it can be confusing for the user.

The span model is easy to understand for the programmer using the model in order to instrument a system. The single point of causality provides a call-stack type view of the computation that is conceptually easy for the user of the library to understand. Unfortunately, the span model

```
 // running on machine 1:

// assume doingWhatever has span identifier and trace identifier values
// of 1 and 5 respectively
Span doingWhatever = Trace.startSpan("doing whatever");

// assume 'sendPing' has span identifier and trace identifier values
// of 1 and 2. its parent span field would be 5 because
// the doingWhatever span is its parent.
Span sendPing = Trace.startSpan("sending ping");

// rpcPing would append the information (trace: 2,span: 1)
// along with the RPC information
rpcPing();
// end the spans and deliver them to some source for processing etc.
sendPing.stop();
doingWhatever.stop();


// running on machine 2:
rpcReceivePing(RPC rpc) {
      if (rpc.hasTracingInformation()) {
            // pingSpan's trace id would be 2, its span id would
            // be randomly generated, and its parent id would be 1,
            // signifying that sendPing is its parent because
            // sendPing's span id is 1
            uint64 traceId = rpc.getTraceId(); // 2
            uint64 spanId = rpc.getSpanId(); // 1
            Span pingSpan = Trace.startSpan(traceId=traceId,
                                    parentSpanId=spanId,
                                    description="rcvd ping");
            // do some stuff then stop and deliver the span
            pingSpan.stop();
      }
}
```

Figure 3: Code example of how the span model might be integrated into a system's RPC mechanism.

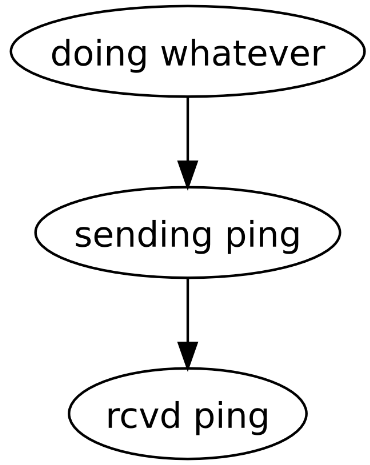


Figure 4: The span graph that would be generated by the code provided in Figure 3

is not powerful enough to represent all aspects of computation. In particular, the span model has trouble representing certain types of computations, particularly those involving events that cannot occur unless more than one other event has already taken place. Many asynchronous computations have such dependencies.

Spans can represent any activation pattern because activation, by definition, is only some action directly causing another action to occur (activating the new action). This activation relationship can be represented by the parent relationship in the span model. Activation patterns do not fully describe the nuances of many computations. For example, some action may only be activated by one other action, but may actually depend on multiple other events occurring before it can be activated. The span model cannot capture this relationship.

2.2 Events

The event model was originally used in the X-Trace end-to-end tracing system [5]. An X-Trace event represents a single point in time in the computation. Causality is represented with *edges* drawn between events. Edges can be drawn arbitrarily between any two events. Specifically, an edge represents the happens-before relationship among arbitrary events, introduced by Leslie Lamport, that signifies that some event could have influenced some other event [6].

Unlike the span model, in which a span can only have a single 'parent' that activated it, events can have multiple incoming edges representing possible dependence on several other events occurring. The ability to have multiple incoming edges for a particular event is beneficial because it allows a more complete representation of some aspects of computations, particularly those involving the joining of multiple threads.

While the relationship among spans is pure activation, the relationship among events is the more general concept of happens-before. All that happens-before represents is that some event happened before some other event, but not necessarily that that ordering is always the case, or is necessary to the computation. For example, `EventA` might happen before `EventB`, but there may be some non-determinism and `EventB` might happen before `EventA` in some executions of the program.

Dependency relationships are a subset of happens-before relationships. A dependency relationship means that some event must happen before some other event in all executions. The differences among activation, dependency and the happens-before relationship are subtle but extremely important.

The downside of the X-Trace model is that it is not necessarily as intuitive for programmers to use as the span model. The call-stack view that the span model provides has a level of simplicity that the event model cannot match.

3 The Span Model Is Less Powerful Than The Event Model

We will show that the span model is strictly less powerful than the event model. We will do this two ways. We will first prove that the event model is fully expressive and can accurately represent any possible computation, and that the span model is not fully expressive. We will then prove that the event model is more powerful than the span model by reducing from the span model to the event model, and providing two examples (one contrived, one from a real system) of computations that spans could not represent and events can represent. After discussing the reduction and examples, we will describe our implementation of the reduction within the X-Trace tracing library.

3.1 Proof That Events Are Fully Expressive And Spans Are Not

Proof. An algorithm, whether it is executed with one or several processes, is fundamentally a series of steps that, when taken, will produce some result. Assume we have an algorithm A we want to carry out that requires n steps, $S = \{s_1, s_2, \ldots, s_n\}$. Assume without loss of generality that s_1 is just some generic start step that does not actually progress the computation. Also assume that executing the steps in order ($s_1 \to s_2 \to \cdots \to s_n$) would yield the desired result.

In the computation A, some of the steps depend on each other and some do not. That is to say that some of the computation can be done in parallel. We could imagine creating a directed graph, G, for which the nodes will be the set $S = \{s_1, s_2, \ldots, s_n\}$, and the set of edges, E, represents dependence. That is to say that there is a directed edge from s_i to s_j if and only if s_j directly depends on the results of s_i. In such a graph, there can be no self-loops because a step cannot depend on itself (we will assume that the computation is deterministic and loops are unrolled). Similarly, there can be no cycles in the graph at all because that would transitively imply that a step depends on itself, which is a contradiction. We use the phrase 'directly depends' so that for some arbitrary step s_i, the set $\{s_j : (s_j, s_i) \in E\}$ represents the smallest possible subset of S such that if all the steps in the subset are computed, it is possible to safely compute s_i. This restriction makes the graph the transitive reduction of the dependency graph. For example, the transitive reduction prevents all events from necessarily depending on s_1 because no event in the computation can occur until the computation has started. The idea for the transitive reduction was taken from [4].

G is both directed and aylic; G is a DAG (directed acyclic graph). To produce a trace representable by the event model given the graph G, log one event for each node in S, and draw the same directed edges between events that exist in G. That is, produce the same graph with events that was made originally with the steps of the computation. This graph fully represents the computation's dependency structure. Thus, every computation's dependency structure can be completely represented by the event model.

$\square$

As a corollary to the above proof, note that the span model could not completely represent any arbitrary computation because the graphs the span model produces can not have multiple incoming edges representing dependency on multiple events that the DAG, G, created in the proof may have. Thus the span model is not fully expressive.

3.2 Proof By Reduction That Events Are More Powerful Than Spans

3.2.1 Proof

Proof. To show that the event model is strictly more powerful than the span model, we will first show a reduction from spans to events. Reproducing the span model with only events shows that the event model is at least as powerful as the span model because it shows that any computation the span model can represent can be represented by the event model via the reduction provided.

Second we will provide an example of a computation that the event model can represent and the span model cannot represent. This example, combined with the reduction, will show that the set of computations that the event model can represent is a strict superset of the set of computations the span model can represent.

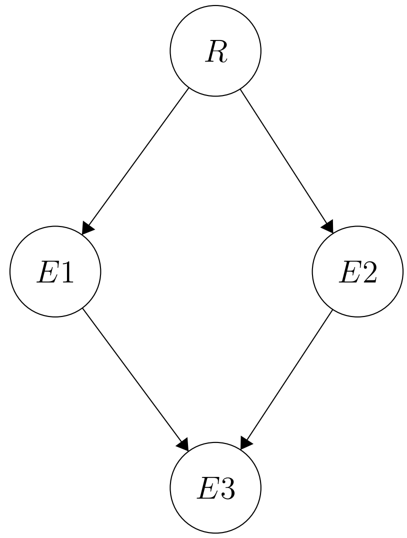
Reduction

The reduction from spans to events is as follows:
Whenever a span is started with `spanID=S`, log a special event that contains some metadata that says this event represents the start of of the span with ID of S. The event must be timestamped, as is generally the case for implementations of the event model. When the span is ended, log a similar event with metadata that describes that the event represents the end of the span with ID of S. The parent relationship critical to the span model can be represented in the event model by drawing causality edges from each event representing the start of a span to the event representing the start of the child span.

More simply, the reduction requires that for each span that is started and stopped, there are two events created: one marking the start of the span, and the other marking the end of the span. The parent relationship of the span model is maintained using the happens-before edges of the event model.

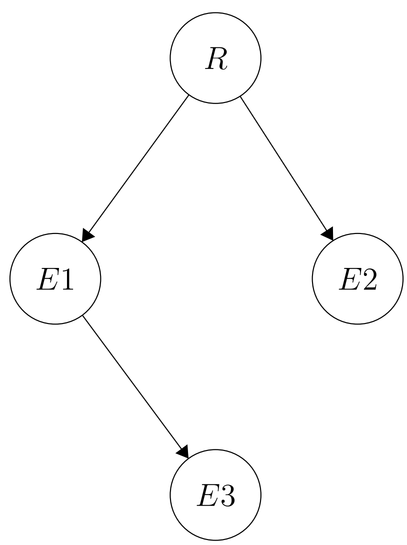
Computation That Events Can Represent And Spans Cannot

As mentioned above, the second part of this proof involves an example of an execution that the event model can represent and the span model cannot represent. This example can trivially be an execution such as the following:

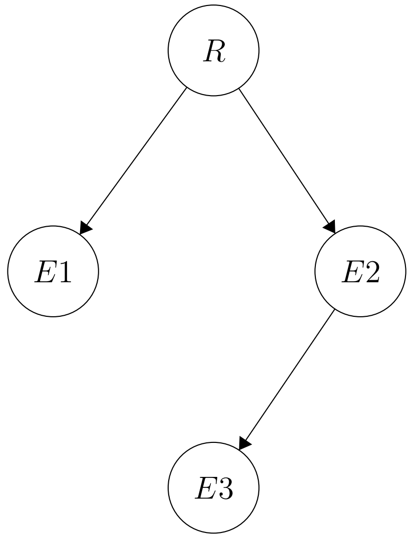


In the image, each node is an event, and the directed edges are the causality edges. If $E3$ could not occur without both $E1$ and $E2$ occurring, the multiple incoming edges to $E3$ are necessary to accurately represent the computation's dependencies. Because the span model represents causality with the singular parent relationship, the execution depicted in the image above could not be accurately represented with the span model.

Instead, the resulting span graph would either look like:



OR



In the images above, each node represents a span, and the directed edges represent the parent relationship (a directed edge from NodeA to NodeB means that NodeA is NodeB's parent). Note that in neither case is the computation accurately represented. These graphs serve as a good example of how the parent relationship is not powerful enough to fully describe all executions. Computations carried out in a multi-process environment require a more powerful construct than just storing which part of the computation started each other part. Such a construct is the edge used in the event model that does not represent pure causality, but instead represents the happens-before relationship.

We modified the X-Trace tracing library to illustrate the reduction described, implementing a span model with the events provided by X-Trace. We will describe the details of this practical reduction later, as well as explain the results.

The contrived example provided above is sufficient for the purposes of our formal proof. On the other hand, the question arises of whether such examples ever occur in real world systems. If they do not, the difference in expressibility of spans and events is less important. Unfortunately for the real world and fortunately for this document, such executions do occur in real world systems.

Such an example can be found in the Hadoop Distributed Filesystem (HDFS). See Figure 5 for an image representing the relevant part of an HDFS `get` operation. Note the `PacketReceiver` node that has two incoming edges from both a `BlockSender` event and a `PacketReceiver` event. This is an example of an event that can only occur if two other events occur before it. A span model of the same computation would not capture this dual dependence. The figure shows the

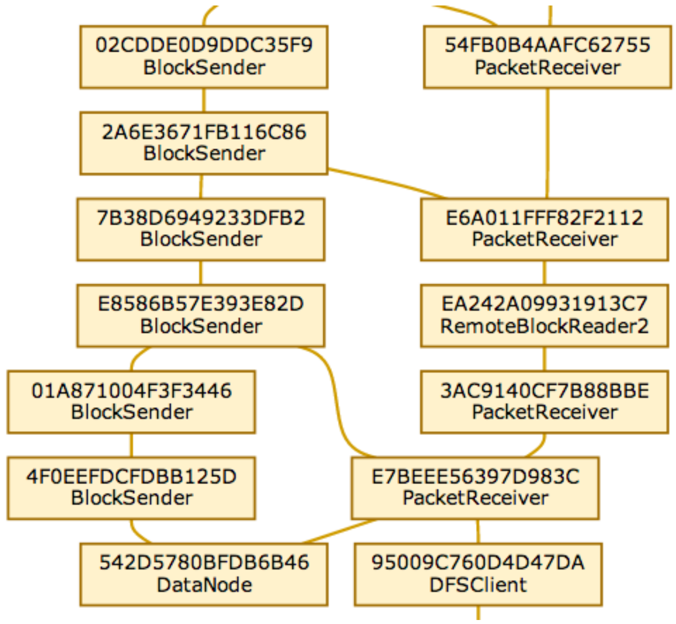


Figure 5: Portion of a trace of an HDFS `get` operation created with X-Trace.

portion of the request during which there is a pipelining of data blocks through a chain of nodes. The dual dependence is showing that the `PacketReceiver` cannot receive an additional block until its ACK has been received and another block is ready to be sent.

Thus we have shown, through a formal reduction and two counterexamples (one practical, one contrived), that the span model is strictly less expressive than the event model. □

3.2.2 Practical Implementation Of The Reduction

The goal of our practical implementation of the reduction described in the proof in the previous section was to produce an API providing the semantics expected from a tracing library implementing the span model using only the events in the X-Trace tracing library. This endeavor was successful.

It is important to note that a non-goal of this practical implementation of the reduction was the ability to use both spans and events together. For the purposes of the reduction it is sufficient to only provide an API giving span model semantics. Thus this implementation does not work properly if spans and events are used in the same trace.

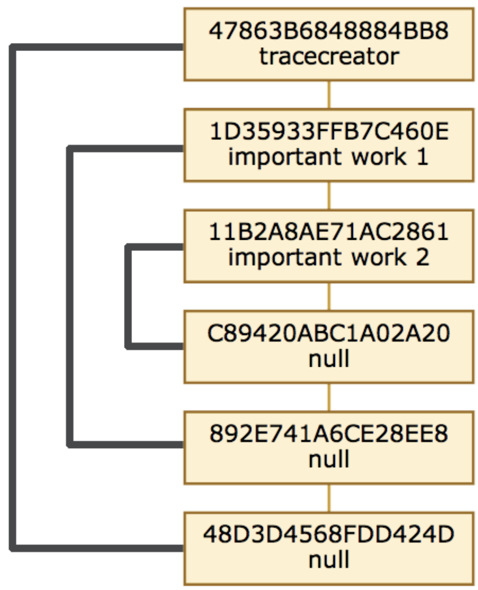
As described in the proof above, the reduction logs a special `startSpan` event when a span is started and a corresponding `stopSpan` event when the span is stopped. Without any type of post-processing, the graph produced with this reduction is very difficult to interpret because there are often edges connecting `endSpan` events to unrelated `startSpan` events. See Figure 6 for the code used to create a trace with the reduction and the resulting event graph. Note that the directions of the edges in the graph shown in Figure 6 are downward. The top three nodes in the chain are the `startSpan` events and the bottom three nodes are the `stopSpan` events. The event with label `C89420ABC1A02A20` has an `END_SPAN` field set to `11B2A8AE71AC2861`, signifying that it is the `stopSpan` event for the event labeled `important work 2`. The event with the label `892E741A6CE28EE8` stops the event labeled `important work 1`, and the event labeled `48D3D4568FDD424D` stops the event labeled `tracecreator`.

Post-processing is required to complete the reduction and convert the graph of events into a graph of spans. A span requires a start time, end time, unique span ID, trace ID, and a parent ID. The ID of the entire trace is taken from the X-Trace ID for the trace. To create the spans given the X-Trace events from the reduction, we find every `startSpan` event and its corresponding `endSpan` event. The start time is the timestamp on the `startSpan` events and the end time is the timestamp on the `stopSpan` event. The spanID is the event ID of the `startSpan` event.

The final remaining field necessary in order to have a complete span is the ID of the span's parent. Simply using the edges drawn between events is incorrect. Instead a traversal of the graph is necessary. The code in Figure 7 illustrates how to find a span's parent given its `startSpan` event, and the event graph of the entire trace.

All the code does is traverse 'up' the edges from the event until an event is found that is neither an `endSpan` event nor a `startSpan` event for which the corresponding `stopSpan` event was already encountered in the traversal. The second part of the conditional prevents a span that was stopped before the span for which we are finding a parent was started from being selected as the span's parent. Figure 8 illustrates a case for which the second part of the conditional is necessary. In Figure 6, we see that for all of the `startSpan` events, the event directly 'above' it is its parent, but that is not necessarily the case. Figure 8 is an example of such a trace.

Note the assumption that events only have one incoming edge. This assumption is only safe because of the reduction, which prevents any event from having more than one incoming edge.




```
startSimpleTrace() {
      Span s = startSpan("tracecreator");
      importantWork1();
      s.stop();
}
importantWork1() {
      Span s = startSpan("important work 1");
      importantWork2();
      s.stop();
}
importantWork2() {
      Span s = startSpan("important work 2");
      sleepForSomeShortInterval();
      s.stop();
}
```

Figure 6: A simple trace created to demonstrate the results of the reduction **(top)** and a shortened version of the code that produced it **(bottom)**. The dark grey lines in the **top** image connect `startSpan` events with their corresponding `stopSpan` events.

```
def getParentId(startSpanEvent, eventGraph):
      if isRootEvent(startSpanEvent, eventGraph):
            startSpanEvent.parentID = ROOT_SPAN_ID
      # edges = list of events this event is dependent on
      cur_event = startSpanEvent.edges[0]
      ends_seen = []

      # Keep traversing 'up' the graph until we find a
      # startSpan event that has not been 'stopped' by an event
      # we have already encountered in the traversal.
      while (cur_event.isStopSpanEvent() or
           cur_event.spanID in
           map(lambda x : x.getIdOfSpanThisEventEnds(), ends_seen)):
            if cur_event.isStopSpanEvent():
                  ends_seen.append(cur_event)
            cur_event = cur_event.edge[0]

      startSpanEvent.parentID = cur_event.spanID
```

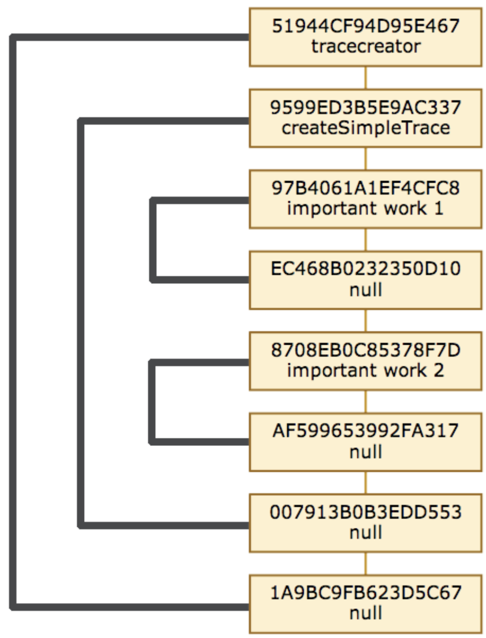
Figure 7: Pseudocode necessary for the reduction from spans to events. The `getParentId` function takes an event representing a `startSpan` and an eventGraph and appropriately sets `startSpanEvent's` parent span.

4 Unification

The span model and the event model both have unique advantages and disadvantages. While spans cannot fully represent all types of computations, they provide a nice call-stack view of the computation that experience has shown to be intuitive for users. Events on the other hand can represent all types of computations (Section 3.1), but it is not always as obvious to users how to best represent their computation with events. Additionally, the span model has a larger mindshare, as evidenced by its use in Google's Dapper (Dapper originally coined the term 'span') [8], Twitter's Zipkin [9], and Cloudera's HTrace [3].

4.1 Motivation

The span model's advantages (ease-of-use and greater mindshare in comparison to the event model) do not outweigh its major disadvantage of not being able to fully express all aspects of a computation. Google's paper titled, 'Modeling the Parallel Execution of Black-Box Services' [7] serves as evidence of such a tradeoff's practical implications. The paper attempts to estimate RPC latencies




```
Span s1 = startSpan("tracecreator");

Span s2 = startSpan("important work 1");

s2.stop();

Span s3 = startSpan("important work 1");

s3.stop();

s1.stop();
```

Figure 8: **Top** is an example of an event graph generated with the reduction for which a span's parent is not always the event directly above it in the chain of causality. **Bottom** is the code generating the graph. The dark grey lines in the **top** image connect `startSpan` events with their corresponding `stopSpan` events.

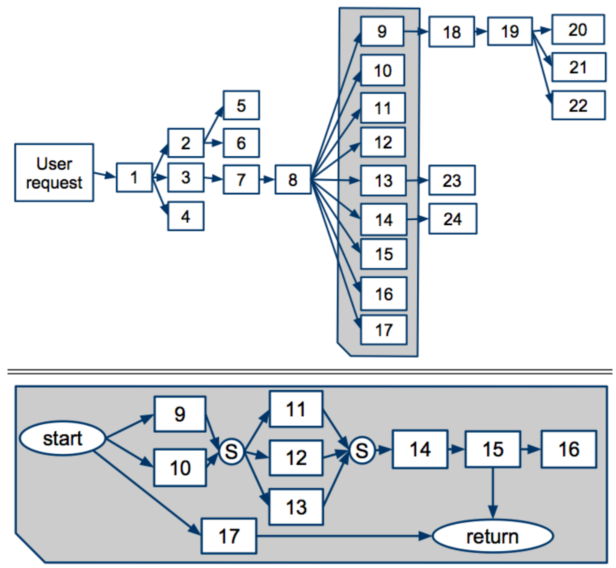


Figure 9: Image from Google's paper, 'Modeling the Parallel Execution of Black-Box Services'[7], showing the information they are working with **(top)**, and the information they are seeking **(bottom)**.

of computations that are "modeled by an 'execution flow', a direct acyclic graph." Their goal is to learn the execution flows by running statistical analysis on many thousands of traces produced using Dapper [8] and its span model.

The graphic in Figure 9 shows the goal of the project behind the paper. Note how the top image is the type of trace created with the span model and the bottom image more closely represents a DAG that could easily be represented with events, and created with X-Trace. The paper describes how using a lot of data can help obtain the necessary information to convert a span graph into an event graph. Had Dapper [8] been built using the event model, the paper would never have been written. The paper shows that the spans Google used in Dapper are not powerful enough to represent the complex interactions that occur in their data centers.

It is possible to have both the simplicity of spans and the power of events. The ideal tracing model would combine the flexibility and power of events, with the call-stack like simplicity of the span model. The simplest solution is to produce a library that allows the user to use both spans and events.

4.2 X-Trace With Spans

Our proposal is that events become the 'assembly language' of end-to-end tracing, and spans a higher level construct built on top of events, similar to the reduction described in Section 3.2.2. That reduction however is unsuitable for actual use because it breaks down if spans and events are mixed.

Ideally the developer would instrument his system with spans whenever possible in order to have the simplest and most understandable tracing information, and with events when the extra expressive power is needed. When viewing traces, the developer should be able to view the trace at a higher span level, and then drill deeper to view the more complex interactions represented with the events. In the next section we describe our attempt to modify the X-Trace [5] tracing library to include such features.

4.2.1 Execution

The X-Trace library has option fields, similar to those in many other networking services, that allow easy extension of the protocol. Option fields are $\langle key, value \rangle$ pairs that are propagated along with the standard X-Trace metadata. Option fields are the perfect place to store the information necessary to properly add spans to the library.

The goal with the extension to the library is to allow the use of both spans and events in the same trace. Unfortunately, the method used in the reduction in Section 3.2.2 is unsuitable because the strategy of walking up the event graph in post-processing to find a span's parent does not work. Without the restriction of the reduction that prevents otherwise, events can be dependent on multiple other events, and when that occurs it is not possible to deterministically walk up the graph to find a parent because there are multiple paths that might lead to different answers for the span's parent.

To solve this problem, we chose to store the ID of the current span (if there is a current span) in the current event's option fields. Because the 'current event' is local to each thread and propagated across machines, the correct span information is also kept thread-local and maintained across machines. The developer can use the existing X-Trace API as normal whenever he pleases, calling the essential functions, such as `logEvent`, `logMerge`, `joinContext`, etc. When he wants to begin a higher level span, he calls the `startSpan` function, which is presented (cleaned up for clarity) in Figure 10. The `startSpan` function returns an `XTraceSpan` object, which stores two ID's: the ID of the span that was just created, and the ID of the span that was current before that span was created (i.e. the newly created span's parent). This object is necessary to stop the span.

Stopping a span is as easy as calling the `stop` function on the `XTraceSpan` object returned from the `startSpan` function. See Figure 11 for the code for the `stopSpan` function. The function takes the `XTraceSpan` object representing the span to be stopped. The function first logs an event with the `END_SPAN` field set to the ID of the span stored in the `XTraceSpan`, which effectively stops the span. Next, the function updates the `current span` option field in the current event's option fields to be the ID of the parent of the span being stopped, which makes it possible to correctly start new spans in the future with the correct parent.

4.3 Results

4.3.1 Differences

There are some differences between the use of the X-Trace library with the span modifications and a tracing library that natively supports spans. Namely, with X-Trace and the spans addition the programmer cannot `pop` spans in the same manner that he can in a library, such as HTrace [3]. In HTrace, the library user can call a generic `pop` function that pops the current span and sets its parent to be the current span, without having to keep a reference to the current span. In X-Trace with spans, such actions are not possible, and the user of the library must maintain the 'stack' of spans himself. Often however, the 'stack' is just the `XTraceSpan` objects that are created in each new function called.

An example from a real world use of the span model provides evidence that developers do not often use the 'pop' functionality mentioned above. Specifically, in the currently proposed patch to integrate HTrace into HDFS, there are no cases in which a span is started but no references are kept to the newly started span [2]. Thus, the requirement of X-Trace with spans that stipulates that programmers must keep references to the spans they create in order to stop them does not constitute a serious disadvantage with the library.

```java
public static XTraceSpan startSpan(String description) {
   // Creates a new event with the description passed in,
   // and sets it as the current event.
   // does not yet send the report that
   // describes the event to the database.
   XTraceEvent event = XTraceContext.createEvent(description);

   // Get the spanID of the current span
   String curSpanString = getCurrentSpanFromOptionFields();
   // X-Trace events support arbitrary key-value pairs.
   // We insert in the event two mappings before we send the report
   // to the database.
   // The first signifies that this event is a special startSpan
   // event.
   // The second stores the spanID of this new span's parent.
   event.put(START_SPAN_FIELDKEY, START_SPAN_STRING);
   event.put(PARENT_SPAN_FIELDKEY, curSpanString);
   event.sendReport();
   // Get the spanID of the span we just created
   String newSpanString =
      getFirstCurrentXTraceMetadata().getOpIdString();
   // and set it in the options for future spans
   // that might be started.
   setCurrentSpanInOptions(newSpanString);
   // Return a container object storing the ID of the
   // span that was just created, and the ID of the
   // span that was current before the new span
   // was created.
   // This object is necessary to properly stop the span.
   return new XTraceSpan(newSpanString, curSpanString);
}
```

Figure 10: The `startSpan` function that uses X-Trace's option fields to store the current span's ID, and allows users to use spans and events in their systems.

```java
public static void stopSpan(XTraceSpan toStop) {
   // Log the event signifying the end of the toStop
   // span.
   XTraceContext.logEvent(SPAN_AGENT,
                          NO_DESC_GIVEN,
                          END_SPAN_FIELDKEY,
                          toStop.getSpan());
    // Set the option field storing the current span,
    // to be toStop's parent (essentially a pop operation).
   setCurrentSpanInOptions(toStop.getSavedSpan());
}
```

Figure 11: The `stopSpan` function that takes an `XTraceSpan`, which stores the ID of the span to be stopped and the ID of the parent span of the span to be stopped.

4.3.2 Example

As an example, we created a simple ‘chat’ program with two threads. The program simulates two RPCs, with one saying ‘hello’ and the other replying back. We instrumented the example program with X-Trace’s events and the spans we added to the X-Trace library to illustrate a trace that contains both spans and events.

In Figure 12 and Figure 13 we can see the X-Trace event graph representing an execution of the chat test program and the span graph created as a result of processing the event graph. Note that in Figure 13, `CR2` and `CR1` stand for `Chat Runnable 2` and `Chat Runnable 1` respectively, which are the two threads simulating the chat clients. `recv1` is the second thread receiving the first message, while `send1` is the first thread sending the first message. The same applies for `resp2` and `recv2`.

Note that while the span representation shows the high level structure of the computation, the specific details of how the greeting and response join together are missing. Figure 14 shows a ‘swim lane’ style representation of the trace that shows both the events and the spans.

5 Conclusion

End-to-end tracing systems are very useful for maintaining and debugging complicated distributed systems and are consequently becoming more widely used among distributed systems developers.

As these tracing systems gain more traction, it is important to ensure the systems are built using the correct models.

The span model is insufficient to represent all aspects of all computations and is thus not a good choice for end-to-end tracing systems. While some developers may find the span model to be sufficient for their current uses, they may encounter problems as their systems grow and produce executions that cannot be modeled with spans. The event model is more powerful than the span model, but is not as simple to use. Distributed systems developers should think carefully when selecting a model for their own end-to-end tracing systems.

As just shown, it is possible to use both spans and events together when representing a complicated computation. The spans can be used to show the activation hierarchy of the execution, and the events can be used to represent the more intricate portions of the execution, as well as serving as the lower level building block on which spans are constructed.

In the future it would be interesting to explore the visualizations and data analysis made possible with systems instrumented with spans and events. The visualization in Figure 14 is a good example of the types of visualizations that could be created with spans and events. A tool that initially shows a trace as only spans and allows the user to zoom in to see the events making up those spans would be very useful in understanding systems' executions.

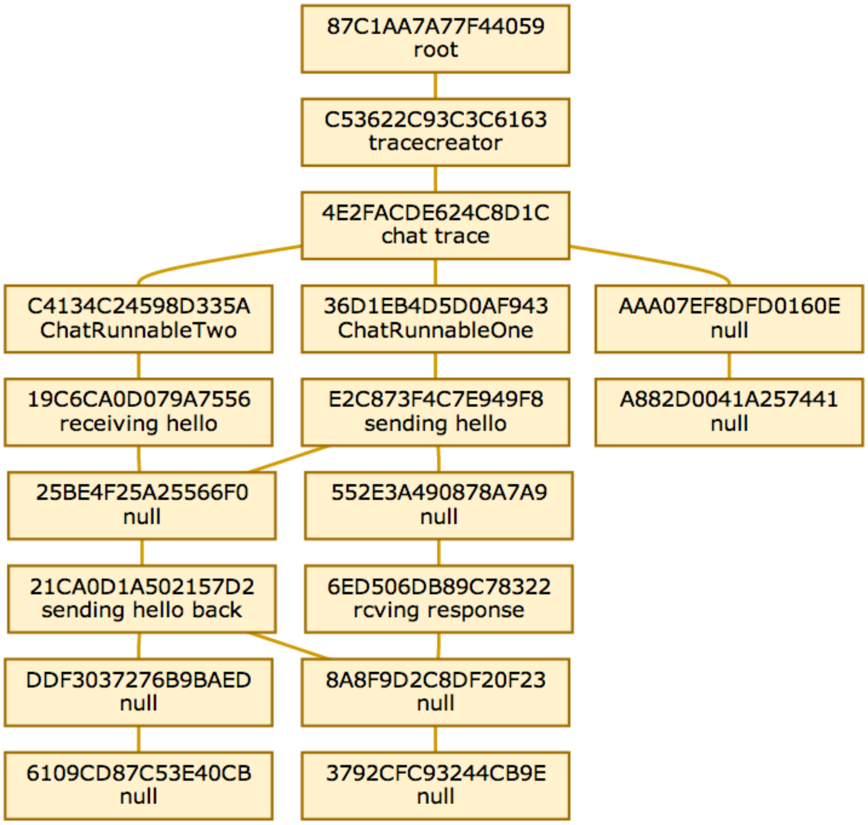


Figure 12: X-Trace event graph for an execution of the test chat program.

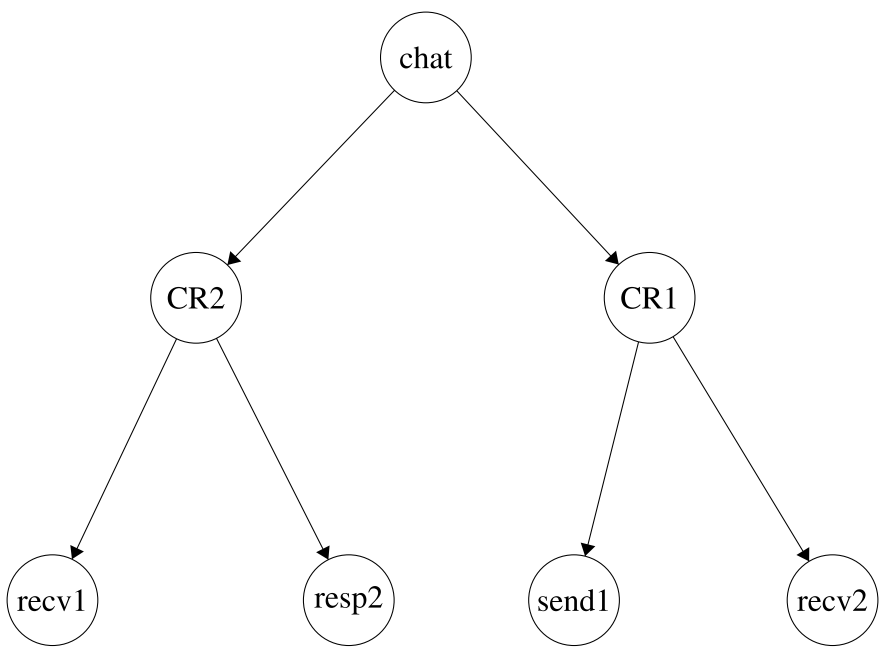


Figure 13: Span graph for an execution of the test chat program.

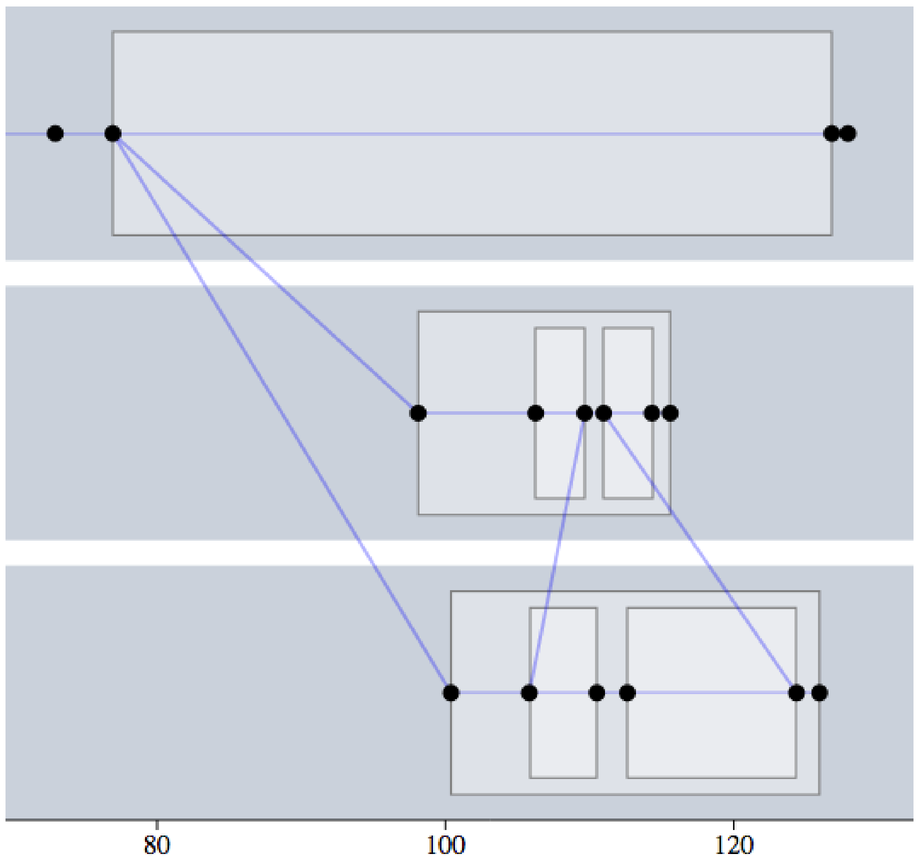


Figure 14: A ‘swimlane’ visualization that shows both the events and spans for an execution of the test chat program. Black dots are events and purple lines are edges between events. The grey rectangles represent spans. Each of the three large horizontal bars in the background represent the three threads in the program. On top is the main thread, in the middle is the thread that receives a message first, and on bottom is the thread that sends the first message. Note how the rectangles representing spans match the span tree in Figure 13. The nested lighter rectangles in the second and third lanes are the spans created for sending and receiving the messages.

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