Sessionizing Video-Player Data

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1 Introduction

Comcast Corporation is a global telecommunications conglomerate and one of the largest and most prominent broadcasting and cable television companies in the world. Comcast is also the largest provider of cable internet access in the United States with over 25 million high-speed internet customers as of 2017.

In their online streaming solution, Xfinity On Demand, consumers can watch movies and TV shows in video players. Each time these players are accessed on an individual device, a new “session” is started. Throughout the session, data is sent back to Comcast regarding the health and lifespan of the player. This includes bit rate changes, frame rate changes, error messages and failures, stream consistency and duration, startup latencies, and geographical location. These *AnalyticsEvents* are analyzed to continually eliminate potential errors, create statistics, and forward billing information on to other carriers and companies.

At any given time, Comcast is receiving *AnalyticsEvents* from tens of thousands of devices across the US. Clearly, this is an immense amount of data which needs to be ordered in some way if it is to be useful. The most relevant way to group the data is by the session from which it was created. This process would effectively give Comcast the ability to “replay” a user session.

The task assigned to the CSM field session team was to develop an application which takes in large amounts of *AnalyticsEvents* and outputs grouped sessions or *PlaybackSessionEvents*. Ideally, Comcast would use this application to more effectively group and analyze sessions in real-time; however, the amount of data received per day is greater than what can currently be processed. In order to prevent data loss, *AnalyticsEvents* are stored in Amazon S3 buckets, which allows data to be processed any time after it has been received. So, our application utilizes this “at rest” data as input and implement a solution to more efficiently “sessionize” player data.

2 Requirements

The definition of done for the project is to produce an Apache Spark application written in Scala that reads *AnalyticsEvents* from an Apache Parquet file, groups the *AnalyticsEvents* by the session from which they were created, transforms the grouped data into *PlaybackSessionEvents*, and writes the *PlaybackSessionEvents* to another Parquet file. The non-functional requirements listed below show the different software tools needed to fulfill the technical design. The functional requirements break down the definition of done into specific tasks necessary for completion of the application.

2.1 Non-Functional Requirements

- Apache Spark application
  - Unified analytics engine for large-scale data processing
- Written in Scala
  - Combined functional and object-oriented language
- Utilizes Apache Parquet for data storage
  - Column-oriented; optimized for compression and scanning efficiency
- Developed using the IntelliJ IDE
- Github for version control and stakeholder accessibility
- Use Trello for backlog and project tracking

2.2 Functional Requirements

- Read in and process large Parquet files containing multiple hours worth of player events, which are called *AnalyticsEvents*.
- Group *AnalyticsEvents* by session information. Sessions are identifiable by the session field in an *AnalyticsEvent*. The *session* field is a struct that contains two values: the *pluginSessionId* (PSI) and the *playbackId* (PBI). A unique combination of these two subfields indicates a single session.
- Gather all other necessary information from the grouped *AnalyticsEvents* to fully populate the *PlaybackSessionEvent* schema. This includes:
  - *header* - contains timestamp and universally unique ID (UUID) of the event
  - *partner* and *partnerId*
  - *startTime*
  - *eventType*
  - *completionStatus*
  - *sessionDuration*
  - *device*
  - *customerAccount*
  - *application*

    - *plugin*
    - *asset*
- Create a map of all the *AnalyticsEvents* of a single session.
    - Key-value-pairs are the event UUID and the event itself
- Order all necessary information such that it fits the *PlaybackSessionEvent* schema
- Write all produced *PlaybackSessionEvents* to an output Parquet file
- Runtime of application must be, at a maximum, half the amount of data processed
    - i.e. two hours worth of *AnalyticsEvents* must be processed in, at most, an hour
- Test cases to validate output data-frame of *PlaybackSessionEvents*, specifically the map of all events from a single session

3 System Architecture

The Figures below illustrate the architecture and system design of the sessionization application. Figure 1 represents the flow of data, beginning with the creation of *AnalyticsEvents* and ending with storage of *PlaybackSessionEvents*.

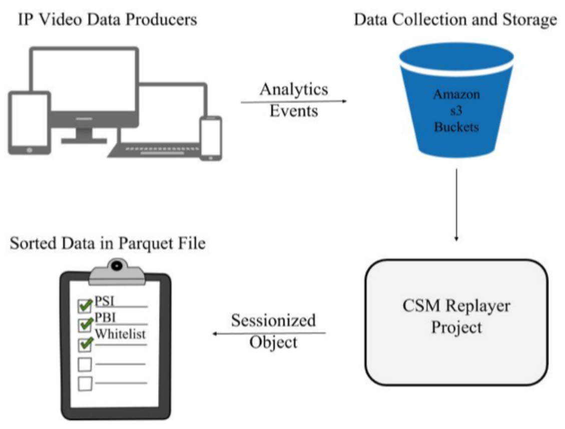


Figure 1: Data Flow

The IP Video Data Producers represent consumers accessing an Xfinity On Demand video player on their phone, laptop, or other portable device. As consumers watch videos, the player continuously creates *AnalyticsEvents* and sends them back to Comcast. Comcast then stores the events in Amazon S3 buckets. Several hours worth of this data was retrieved at the beginning of the project and stored in Parquet files to be used as input for the sessionization application. After processing, the newly created *PlaybackSessionEvents* are again stored in Parquet files to be used by Comcast.

Figure 2 represents the architecture of Apache Spark, as it is the main driver for our application. Because we are working with big data, a single machine cannot provide the necessary processing power to make the application efficient. To account for this, Spark transfers partitioned data to multiple machines or servers, called worker nodes, and executes the same task in parallel. The worker nodes are effectively sent individual tasks by the cluster manager, and, once the task is completed, send them back to the manager. Thus, the cluster manager acts as the interface between the driver and the worker nodes.

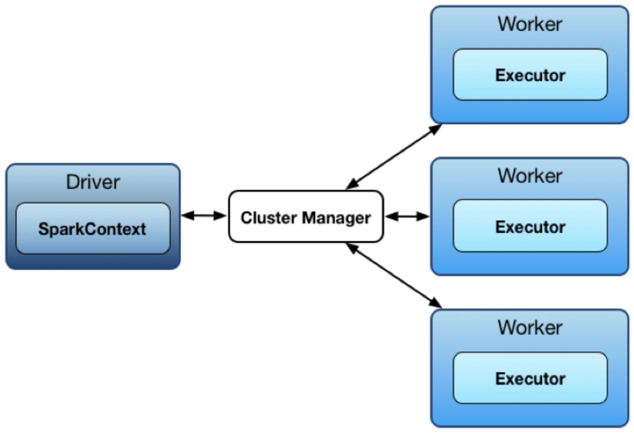


Figure 2: Spark Data Distribution

In the context of our application, Spark is told to partition *AnalyticsEvents* based on their session. This means that each worker node is processing and subsequently returning data from a single session, allowing for an approximately even distribution of work between executors. With roughly the same amount of data being processed on each node, and each node producing a completed output, the application achieves the most efficient runtime possible.

4 Technical Design

The most technically interesting aspect of our application is the function that groups *AnalyticsEvents* by session and gathers all the necessary information to populate *PlaybackSessionEvents*. The full schemas for both events are shown in Figures 3 and 4.

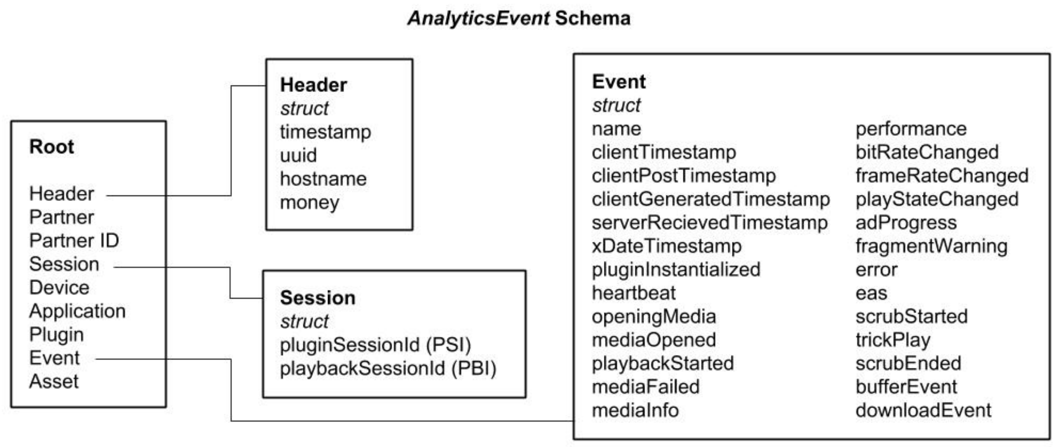


Figure 3: *AnalyticsEvent* Full Schema

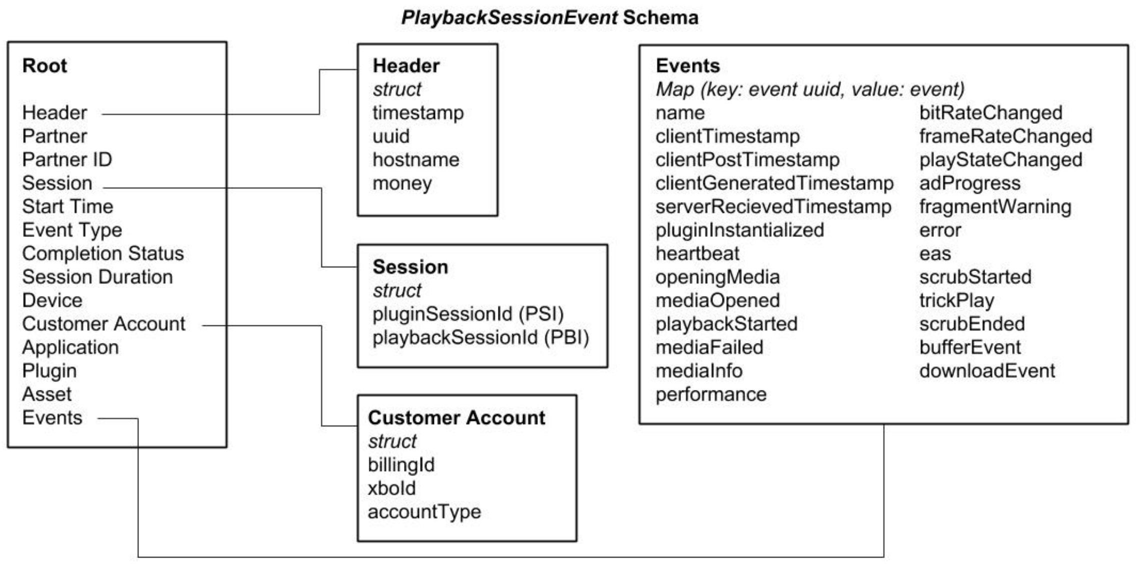


Figure 4: *PlaybackSessionEvent* Full Schema

Much of the information contained in the *AnalyticsEvent* schema is also present in the *PlaybackSessionEvent* schema; however, there are several key fields that need a more in-depth explanation. The most important field is *session*. As previously stated, this is the field on which *AnalyticsEvents* are grouped. A unique combination of both PSI and PBI is what indicates an individual session, so both are taken into account in the grouping function.

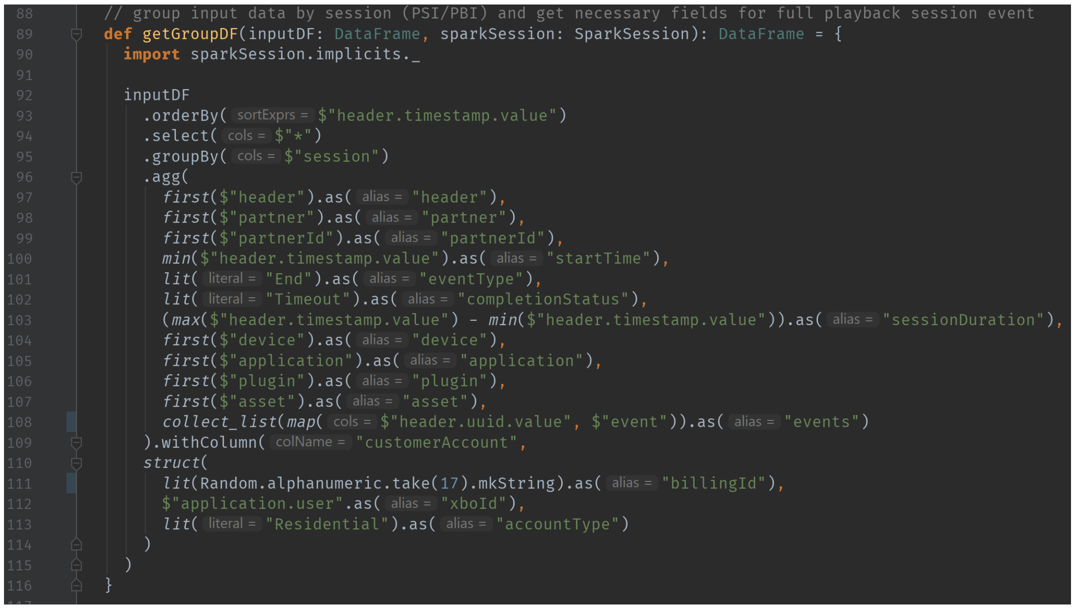
The second most important field is *event*. As seen in the schemas, this field contains all the information regarding the health of the player. Though the *event* field has many subfields, each *AnalyticsEvent* only has one or a few of these subfields populated based on what kind of event it is. If the *AnalyticsEvent* is a heartbeat, it will only have the *heartbeat* subfield populated; if it is a frame rate change, it will only have the *frameRateChanged* subfield populated. When grouped, all the event information from every *AnalyticsEvents* in that session is collected in a map, and this is what populates the *events* field in the *PlaybackSessionEvent*.

Another significant field is the *header*. In an *AnalyticsEvent*, this struct contains the timestamp of the event (when the event was created), the UUID of the event, and a couple other less important subfields. Whenever an *AnalyticsEvent* with a new combination of PSI/PBI is received, this indicates that a new session has been started. So, the timestamp and the rest of the *header* information from the very first *AnalyticsEvent* is used as the *header* for the corresponding *PlaybackSessionEvent*.

Similarly, the startTime and *sessionDuration* fields in the *PlaybackSessionEvent* are populated using the timestamp information from the *AnalyticsEvent* headers. startTime is the timestamp taken from the very first event, and *sessionDuration* is calculated by subtracting the timestamp of the first event from the timestamp of the last event.

Additionally, as deemed necessary by Comcast for our application, the eventType, *completionStatus*, and *customerAccount* fields are created and, for the most part, set as constant values for all *PlaybackSessionEvents*.

Aside from those listed above, all other fields are copied directly from the first *AnalyticsEvent* to its *PlaybackSessionEvent*. The aggregation of all fields in the grouping function can be seen in Figure 5 below.



```
// group input data by session (PSI/PBI) and get necessary fields for full playback session event
def getGroupDF(inputDF: DataFrame, sparkSession: SparkSession): DataFrame = {
  import sparkSession.implicits._

  inputDF
    .orderBy( sortExprs = $"header.timestamp.value")
    .select( cols = $"*")
    .groupBy( cols = $"session")
    .agg(
      first($"header").as( alias = "header"),
      first($"partner").as( alias = "partner"),
      first($"partnerId").as( alias = "partnerId"),
      min($"header.timestamp.value").as( alias = "startTime"),
      lit( literal = "End").as( alias = "eventType"),
      lit( literal = "Timeout").as( alias = "completionStatus"),
      (max($"header.timestamp.value") - min($"header.timestamp.value")).as( alias = "sessionDuration"),
      first($"device").as( alias = "device"),
      first($"application").as( alias = "application"),
      first($"plugin").as( alias = "plugin"),
      first($"asset").as( alias = "asset"),
      collect_list(map( cols = $"header.uuid.value", $"event")).as( alias = "events")
    ).withColumn( colName = "customerAccount",
    struct(
      lit(Random.alphanumeric.take(17).mkString).as( alias = "billingId"),
      $"application.user".as( alias = "xboId"),
      lit( literal = "Residential").as( alias = "accountType")
    )
  )
}
```

Figure 5: Grouping Function Code Snippet

5 Decisions

The following sections describe the main technical design decisions of the application with a rationale for each. In general, the team was focused on finding the best way to implement functional code while matching Comcast's provided event schemas.

5.1 Language and Libraries

To reiterate, the primary language used was Scala, which is a combined functional and object-oriented programming language. Scala was implemented in combination with Apache Spark to create a productive and robust system to analyze and process big data. Spark's ability to partition data, along with its support libraries for SQL and data-frames, allows data to be processed on multiple executor nodes across multiple servers. This functionality is crucial for the large data files we used, as a single system cannot handle the vast amount of data. As aforementioned, each executor processes *AnalyticsEvents* from a single session. This distributes the work as evenly as possible and minimizes the overall runtime. Additionally, Comcast's real-time data processing program is written in Scala and Spark, so our sessionization project followed suit so it can be integrable.

The storage format for the application data is Apache Parquet, which is a column-oriented database management system. This format was chosen for its excellence in compression and scanning efficiency. Additionally, Spark has reliable support for both reading from and writing to Parquet files.

5.2 Software

The Comcast team guiding this project uses IntelliJ as their primary IDE for Scala development, so we decided to use it instead of Eclipse. Though we were all already familiar with Eclipse, we concluded it would be better to learn IntelliJ as we would likely use it in the future, and it allowed us to standardize our development environment with Comcast's.

A private GitHub repository was used for version control. This allowed for seamless code sharing amongst the team and instant delivery to Comcast.

5.3 Driver

As previously stated, Spark's ability to process data on multiple nodes is paramount if the application is to be efficient and viable for Comcast. In accordance with this end, the code could not invoke functions that collect data onto the local machine. As seen (or perhaps not seen) in Figure 5 in Technical Design, the code is very limited in the built-in functionality it uses.

6 Results

6.1 Unimplemented Features

Our team did not leave any required features unimplemented, and we fulfilled Comcast's definition of done. Though all required features were implemented, there are a couple aspects that do not work exactly as intended.

First, our team struggled to accurately generate the map of event UUIDs to events in the *PlaybackSessionEvent* schema. Instead of a single map of key-value-pairs, our code generates an array of maps with a single key-value-pair each. Additionally, one of the subfields in the *customerAccount* field in the *PlaybackSessionEvent* schema needed to be a randomly generated string, different for each session. While our code can generate a random string and populate the subfield for every session, it is not unique for every session. Both of these situations have been communicated with and acknowledged by Comcast.

6.2 Performance Testing

Below is a list of the passing test cases implemented as part of the application to ensure that the data manipulation is accurate.

- Parquet File Test
  - This test reads in a Parquet file and writes to a new one. This verifies that our code for reading and writing data-frames to Parquet files works properly.
- Sessions Created Equals Sessions Expected
  - The purpose of this test is to verify that the number of *PlaybackSessionEvents* in the output data-frame matches the number of unique PSI/PBI combinations from the input data-frame.
- Events Per Map
  - This test ensures that every *AnalyticsEvent* in the input data-frame is uniquely mapped to a *PlaybackSessionEvent* and that no events are lost.
- Processing Factor
  - This test verifies that the data for each session is being processed in a time less than half the duration of the session.

6.3 Summary of Testing

Figure 6 below displays the performance results of processing runtime. The application appears to exhibit an approximately logarithmic complexity; however, after 100,000 events, the run time appears to increase at a linear rate. Though it is difficult to determine the exact complexity of the application without knowing the complexity of specific Spark functions, it is estimated, from Figure 6, to be between O(logn) and O(n). These tests were performed on single machines, so performance would improve if the application was ran on a dedicated cluster of machines. A table with specific runtimes can be found in Appendix A.

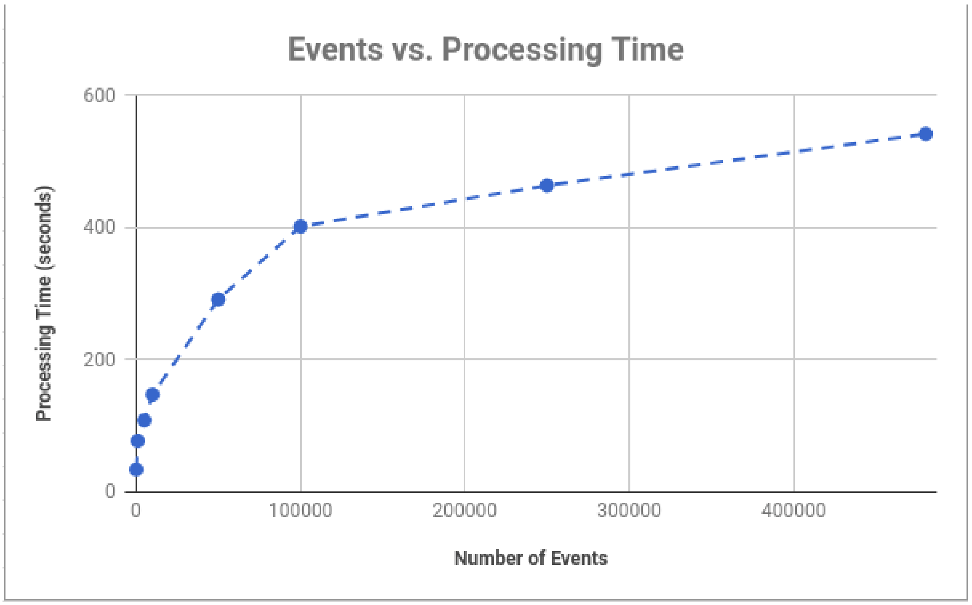


Figure 6: Processing Time

6.4 Future Work/Extensions

One idea for extending the application would be to create an HTML diagnostics page. This would be a document generated per some interval of time during processing, containing a high-level overview of the data for a human to review. This would include information such as the frequency of events, average stream duration, average frame rate, frequency of stream failures, the overall number of events processed, and average number of events per session.

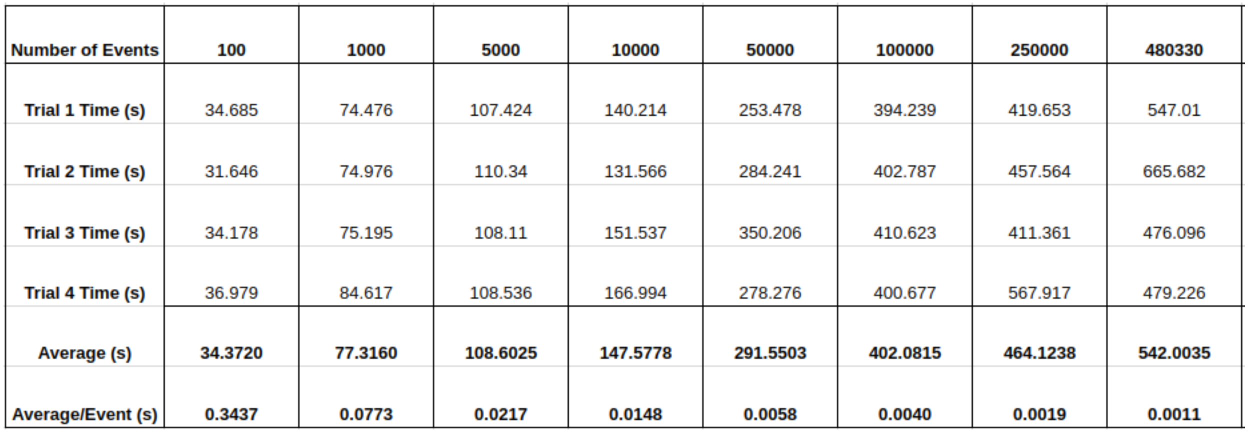
Due to our limited access to Comcast's codebase and Comcast's direction throughout this project, our final application is more functional rather than object-oriented. In context, this means that instead of reading in the input data-frame, creating objects for each *AnalyticsEvent*, and then creating *PlaybackSessionEvent* objects, we simply transform the *AnalyticsEvents* into *PlaybackSessionEvents*. A future extension, if we were given access to certain class definitions, would be a more object-oriented approach, allowing for more direct manipulation of data but possibly a longer runtime.

6.5 Lessons Learned

Scala is similar to Java in that it can be object-oriented, but it is also unique as it is functional language. The object-oriented nature made learning the basic syntax fairly easy, but implementation of Spark functionality was significantly more difficult, taking a lengthy amount of time to Figure out. This will likely be the case in the future when developing with new frameworks, and we will need to allocate a good chunk of time to account for learning curves.

Spark is an extremely powerful tool for processing big data, and since it can be written in multiple languages, it is quite versatile. We wrote our application in Scala to be compatible with Comcast's systems, but writing it in Python, a language with which we have prior experience, may have allowed for faster development and further functionality. On the other hand, having prior experience with SQL made working with data-frames and Spark's version of SQL easier, as we could visualize and more fully understand how we were manipulating data. So, efficient development is best achieved by finding a balance between learning new functionality and drawing from prior experience.

7 Appendix



Number of Events	100	1000	5000	10000	50000	100000	250000	480330
Trial 1 Time (s)	34.685	74.476	107.424	140.214	253.478	394.239	419.653	547.01
Trial 2 Time (s)	31.646	74.976	110.34	131.566	284.241	402.787	457.564	665.682
Trial 3 Time (s)	34.178	75.195	108.11	151.537	350.206	410.623	411.361	476.096
Trial 4 Time (s)	36.979	84.617	108.536	166.994	278.276	400.677	567.917	479.226
Average (s)	**34.3720**	**77.3160**	**108.6025**	**147.5778**	**291.5503**	**402.0815**	**464.1238**	**542.0035**
Average/Event (s)	**0.3437**	**0.0773**	**0.0217**	**0.0148**	**0.0058**	**0.0040**	**0.0019**	**0.0011**

Figure A: Process Performance Data