Analyzing Query Performance and Attributing Blame for Contentions in a Cluster Computing Framework

Prajakta Kalmegh, Shivnath Babu, Sudeepa Roy
Department of Computer Science, Duke University
{pkalmegh,shivnath,sudeepa}@cs.duke.edu

ABSTRACT
Analyzing contention for resources in a cluster computing environment accurately is critical in order to understand the performance interferences faced by a query due to concurrent query executions, and to better manage the workload in the cluster. Today, no tools exist to help an admin perform a deep analysis of resource contentions taking into account the complex interactions among different queries, their stages, and tasks in a shared cluster. In this paper, we present ProtoXplore—a Proto or first system to eXplore the interactions between concurrent queries in a shared cluster. We construct a multi-level directed acyclic graph called ProtoGraph to formally capture different types of explanations that link the performance of concurrent queries. In particular, (a) we designate the components of a query’s lost (wait) time as Immediate Explanations towards its observed performance, (b) represent the rate of contention per machine as Deep Explanations, and (c) assign responsibility to concurrent queries through Blame Explanations. We develop new metrics to accurately quantify the impact and distribute the blame among concurrent queries. We perform an extensive experimental evaluation using ProtoXplore to analyze the query interactions of TPC-DS queries on Apache Spark using microbenchmarks illustrating the effectiveness of our approach, and illustrate how the output from ProtoXplore can be used by alternate scheduling and task placement strategies to help improve the performance of affected queries in recurring executions.

1. INTRODUCTION
Popular data analytics frameworks like Hadoop [19], Spark [37], Teradata [4], Vertica [6], etc. enable organizations to process diverse applications in a cluster shared among multiple tenants. Users submit analytical SQL queries to these systems along with machine learning, graph analytics, and data mining queries. In such systems, long running ETL (Extract-Transform-Load) batch queries often co-exist with short interactive Business Intelligence (BI) queries. Performance variability in a cluster shared among such mixed workloads occurs as a result of inconsistent resource allocations between tenants, and inherently variable characteristics of the workloads and the system [23] (e.g., data skew, change in execution plans, and failure of nodes). Many tools recently have been proposed to monitor the cluster health [12, 7] and diagnose performance problems [24, 35] when a query slows down. These approaches provide methodologies to identify the reason behind performance degradation of an individual query; however, they fail to consider the complex low-level inter-query interference in the cluster. Going beyond, investigating the symptoms of slowdown of a given query due to contention for resources, and appraising the impact due to other concurrently running queries is critical to help the cluster administrator (admin) understand the contention and better manage the workload in the cluster. The admin often controls resource allocations among tenants to reduce conflicts by imposing capped capacities [1] and reserved shares [18] of the cluster. Despite such meticulous measures, providing performance isolation guarantees is still challenging. Consider a multi-tenant database where each tenant submits queries that adhere to a certain business logic or conform to a specific SLA (Service-Level Agreement). Today, resources are either partitioned among these tenants (Capacity Scheduler [1]), or are dynamically allocated based on the configured scheduling policies like FAIR [33] and First-In-First-Out (FIFO). Although each tenant gets a share of the cluster based on such heuristics, today resources are not governed at a fine-granularity leading to a potential interference among concurrent queries. Moreover, the resource allocations are primarily based on only a subset of the resources (only CPU in Spark [37], CPU and Memory in Yarn [32]) leaving the requirements for other shared resources unaccounted for. For instance, two queries that are promised equal shares of resources are allocated equal number of CPU slots in Spark. However, there are no guarantees on the usages of other resources like memory, disk IO, or network bandwidth for these queries. In such a loosely-controlled environment, if a query performs poorly or misses a deadline due to an unexpected heavy contention in the system, diagnosing whether the contention were caused by other queries of the same tenant or by queries belonging to a different tenant can help the admin identify inconsistencies in resource allocations.

Benefits of Analyzing Resource Interferences: Identifying which tenant is responsible for submitting a noisy query, i.e., a source of ‘highest’ contention, can prove useful to revisit the resource shares of these tenants based on

arXiv:1708.08435v1 [cs.DC] 28 Aug 2017
their impact on other queries. Detecting noisy neighbors is a well-defined problem in virtualized environments [5]. Previous attempts like CPI [39], that focus primarily on analyzing CPU contention between processes using hardware counters, are inadequate to help quantify impacts caused by multi-resource contention at an application-level on shared clusters. Today, the admins have no means to analyze this impact apart from looking at individual cluster utilization logs, specific query logs, and manually identifying correlations in both. In particular for recurring queries, analyzing the impact of a change in data distribution, execution plan, and scheduling a query to see if it has caused or reduced any contention in the system is not feasible today. This remains an open and crucial problem that we address in this paper.

Analyzing concurrent query executions can have two additional benefits: First, identifying how much time was spent by the query waiting for individual resources can prove useful for the admin to analyze primary sources of performance bottlenecks in the cluster. A recent study that used blocked time analysis methodology [27] to this end emphasizes the need for using novel metrics for in-depth performance analysis; however, (i) they do not consider contentions faced in a scheduler queue and memory wait times, and (ii) they do not consider the role of concurrent query executions in causing these blocked times for a task - a focus of this paper. Second, analyzing contention on individual machines can help detect those nodes in a well-balanced cluster that are perfectly healthy but are a victim of conflict-driven resource contentions. For example, multiple tasks executing on a node start writing IO data at the same time while holding on to other resources, thus slowing down the node. On cloud-based deployments, since customers are not made aware of the physical nodes where the virtual machines allocated to them are hosted, identifying such slow nodes (the nodes on which they are facing contention) and their corresponding hot resources can be crucial [5]. This will enable them to make better query placement decisions. Even for large ‘on-premise’ clusters, identifying high-contention nodes that are causing applications to run slower can alert the admins to take expedient measures [2]. Tools like [9, 11] have a different focus and pin-point nodes that have heavy utilization for a specific resource in the cluster. However, identifying queries which exhibit high sensitivity towards such slow nodes and a particular hot resource, and ranking them based on the impact on their runtime can help explore optional task placement strategies that will benefit these queries.

Our contributions. We present ProtoXplore, a prototype first system to eXplore the impact of resource interference on the dataflow-based execution of queries on cluster computing systems. ProtoXplore provides a robust, modular, and extensible framework to generate multi-level systematic explanations toward the contentions faced by a target query by unifying the knowledge of high-level dataflow dependencies with the low-level implementation caveats of massively parallel cluster computing frameworks. In particular, we construct a multi-level Directed Acyclic Graph (DAG), called ProtoGraph, of explanations as shown in Figure 5 that captures the conflicts for resources between concurrent queries at different granularity:

- **Immediate Explanations**: identify the times each query spends waiting for a particular resource,
- **Deep Explanations**: inspect the rate of contentions for each resource faced by the query on specific cluster nodes,
- **Blame Explanations**: attribute blame to noisy queries that are the source of these contentions.

We develop a novel metric called Resource Acquire Time Period (RAPT) to capture the resource contentions at each node. We further develop a Degree of Responsibility (DOR) metric to assign blame or responsibility to each node in ProtoGraph for causing contention to a query under consideration. ProtoXplore enables administrators of cluster computing systems to perform three concrete use-cases discussed previously, namely detecting (i) hot resources, (ii) slow nodes, and (iii) noisy queries. The approach developed in ProtoXplore can be applied to any parallel cluster computing framework that summons for an end-to-end performance interference analysis tool for dataflow-based representation of concurrently running queries.

Roadmap. In Section 2 we define preliminary concepts, and describe the key challenges in analyzing dataflows, multi-resource contentions and attributing blame in a shared cluster. We describe our multi-level explanations framework and detail our blame-attribution process in Section 3. We discuss three concrete use-cases in Section 4 and present our experimental results in Section 6. We compare our approach with related work in Section 4 and finally conclude in Section 7.

2. BACKGROUND AND CHALLENGES

In this section, we review some concepts in cluster computing framework, describe the challenges for performing contention analysis on a shared cluster, and introduce concepts to be used in the rest of the paper.

2.1 Stages, Tasks, and Dataflow Dependencies

Users of Hadoop [19] and Spark [37] submit applications through high level data processing engines, e.g., SparkSQL, Dataframes API [15], GraphX [24], D-Streams [38], MLlib [26], Hive [31], and Oozie [22]. These applications are processed as a physical execution plan or a dataflow, which is a DAG of low-level parallelizable units (e.g., map-reduce jobs in Hadoop, stages in Spark). In this paper, for simplicity, we adopt the term stage. Each edge in the DAG represents the dataflow between these stages. A stage is composed of a task set where each task performs the same transformation in parallel on different blocks of the dataset. Each stage starts upon completion of all its parent stages in the dataflow DAG. The root stage of the DAG is the final stage, whereas the leaf stages represent the stages scanning input data. The depth of a stage in the query DAG is counted as the maximum number of stages on a directed path from that stage to the root stage in the DAG. We illustrate these concepts with an example:

**Example 2.1.** Consider the dataflow DAG of a query $Q_0$ in Figure 7 comprising six stages $s_0, s_1, \ldots, s_5$. The stage $s_5$ is the root (output) stage of the DAG, whereas the leaves $s_0, s_1, s_2$ scan input data. The stage $s_3$ can start only when all of $s_0, s_1, s_2$ are completed. The depth of stage $s_5$ is 1, and the depth of stage $s_1$ is 4.

Challenge 1. Analyzing Contentions on Dataflows: Dependencies in the dataflows should be considered when calculating and distributing blame to concurrent queries.

In practice, an application is decomposed into a DAG of jobs; An action of a job, defined by job boundaries, is executed using a DAG of stages. We do not include this additional layer of jobs in our model since it does not affect our approach and algorithms.
To elaborate on this challenge, consider a mixed workload where each query exhibits a varying resource utilization pattern over time. As we illustrate below, even identifying the stages of a query that have faced contentions leading to query delays, as well as identifying other queries and their stages responsible for this contention can be non-trivial in a shared cluster.

**Example 2.2.** Suppose the admin notices a slowdown of the recurring query $Q_0$ shown in Figure 1 in an execution compared to its previous executions, and wants to analyze the contentions that caused this slowdown. The admin can use tools like SparkUI to detect that tasks of stage $s_1$ took much longer than the median task runtime on host (i.e., machine) $X$, and then can use logs from tools like Ganglia to see that host $X$ had a high memory contention in that time-frame. Similarly she notices that $s_5$ was running on host $Y$ that had a high IO contention. Further, the admin sees that stage $s_3$ of another query $Q_1$ was executing concurrently with only stage $s_1$ of $Q_0$, while stages $s_5, s_7, s_9$ of query $Q_2$ were concurrent with $s_1$ and $s_5$. Overall, stages $s_1$ and $s_5$ of $Q_0$ (shown in dark red in Figure 2) took much longer to finish compared to $s_0$ and $s_2$, whereas $s_3$ executed as expected (shown in green) and $s_4$ had a small delay (shown in light red). Today, there is no easy way for the admin to know which stage of $Q_0$ was responsible in the overall slowdown of this query, and whether $Q_1$ or $Q_2$ (and which of their stages) is primarily responsible for creating this contention.

To see the challenges in answering the above questions, note that, although both $s_1$ and $s_5$ incurred high contention for resources, due to the dataflow dependency $s_1 \rightarrow s_3 \rightarrow s_4 \rightarrow s_5$, the resource contention faced by stage $s_5$ could have been different if stage $s_1$ had not faced any resource contention. Since $s_1$ was delayed, $s_5$ started late, and had to run concurrently with other queries competing for resources. Therefore, in this case the queries running concurrently with $s_1$ are more responsible for overall slowdown of $Q_0$. On the other hand, if due to a late start, $s_3$ faced less contention for resources and finished earlier than expected, the effect of delay of $s_1$ would be mitigated. In this situation, if $s_5$ still faced high contention leading to an overall slowdown of $Q_0$, then the queries running concurrently with $s_3$ are more responsible. There are different intricate possibilities even in this toy example, whereas there may be long chains of stages running in parallel in a real production environment. In Section 3, we show how ProtoXplore captures such complex dependencies automatically and correctly attributes blame to concurrently running queries.

### 2.2 Measuring Contentions for Resources

When a physical execution plan of a query in the form of the dataflow DAG of its stages is submitted to the resource allocation module, it assigns available slots to the stages in the scheduling queue based on a resource allocation policy. Figure 2 shows the lifecycle of a task after a stage is ready for execution and is submitted to the resource allocation module. Each task uses multiple resources simultaneously after it is launched (see Figure 3). We use SWT to denote the time it takes for the stage to launch this task while waiting in the scheduling queue. The other components, CWT, MWT, IOWT and NWT (resp. CPU, memory, IO, network) denote the time a task is blocked on a particular resource after it is launched, and contribute to the overall Resource Wait Time as shown in Figure 2. However, they do not necessarily sum up to the total Resource Wait Time, since during its execution a task may be blocked on multiple resources simultaneously. Table 1 summarizes how we capture each of these wait-time components in Apache Spark.

#### Cumulative VS Max Stage-Level Values:

Once we capture the individual task-level values for the wait time components, we compute the cumulative time a stage has spent for $r$, i.e. $\tau'_r = \sum t_r^i$, where $t_r^i$ is the time taken by task $i$ for resource $r$. For example, MWT of a stage refers to the cumulative time spent blocked on network by all tasks in that stage. The other alternative approaches include considering max or average values for the tasks in a stage; however, sum captures the total cluster time (similar to the notion of Database Time in [21]) spent on waiting for resources by each stage and, thus, enables us to analyze the overall contention faced by a stage in the cluster.

**Challenge 2. Capturing Resource Interferences:**

Tasks can use and be also blocked on multiple resources simultaneously resulting in multi-resource interferences between concurrent queries.

Once a stage is selected to launch its tasks in the available slots, the newly launched tasks execute concurrently with other tasks running on the multi-core machine. These concurrently running tasks may belong to (i) the same stage, (ii) a different stage of the same query, or (iii) a different stage of a different query. Therefore, each task can be blocked and compete for resources at different point during its execution either with its own ‘fellow tasks’ (case (i) and (ii)) or with ‘competing tasks’ (case (iii)) as shown in Figure 3. Two tasks can compete for shared resources like fetching data from the network buffer queues, reading or writing data to disk, or even multiplexing between CPU cycles. The contention for CPU cycles is very common in executor-based models like Spark where tasks are launched in long-running threads. Tasks also block each other for accessing execution memory (e.g. sorting, etc.) and for storing input data.

When some tasks get delayed because of a high demand for a particular resource (e.g., CPU), they hold on to other resources (e.g., memory) as well, thus causing contention for other concurrently running queries on the already allocated resource. e.g., cores in Spark and containers in Apache Yarn.
2.3 Measuring Impact from Concurrent Queries

Finally, in order to appropriately attribute blame to another concurrent query for holding resources while the tasks of a stage are waiting, the admin needs to capture the required resources. This cycle, as show in Figure 3, results in a complex cause-effect relationships between resource utilization and runtime of concurrent queries. This also often leads to a cascading effect whereby performing an accurate impact analysis becomes challenging.

Traditional statistical approaches [14, 39] to analyze query interactions are inadequate in this setting as they fail to reason about such intricate multi-resource conflicts among concurrent queries. Today, the admin has to manually traverse through this cycle of query interactions to unravel the underlying performance interferences. This process is brittle and can lead to mis-diagnosed or undetected query conflicts. In order to automate this process, it is important to break this cycle and analyze how the resource usage patterns of one query leads to waiting times on those resources for other concurrent queries, which we address in ProtoXplore.

![Image](image_url)

Figure 3: Example overlap of resource usage between Task$_1$ and Task$_2$. Notice the multiplexing between the tasks for compute time.

To analyze contentions faced by some query, we break the relationship between resource requirements of each task executing on the same machine. The total CPU time that the source stage $s$ caused only CPU contention to the affected target stage $t$, but has been used only in the context of identifying processes that steal CPU time. The stolen time metric cannot be used as is for task executions on cluster computing frameworks as we cannot capture the exact overlap between the multiple resource usage times of two tasks. The need to better capture multi-resource contentions, and to identify queries that steal any resource time from a query requires a more involved metric.

Challenge 3. Computing Blame Attribution: Alternatives like Stolen Time Metric do not capture multi-resource contentions and fail to consider size of input data processed by each task.

In Example 2.2 if we capture that source stage $u_5$ steals the same amount of CPU time from both target stages $s_1$ and $s_5$, it does not imply that both $s_1$ and $s_5$ faced the same amount of contention due to $u_5$. It is possible that $u_5$ affected target stage $s_1$ on more than one resource (memory and other resources) while it caused only CPU contention to target stage $s_5$. In addition, stolen time does not consider the resource requirements of each task executing on the same machines. The total CPU time that the source stage $u_5$ has stolen from target stage $s_5$ will have a higher impact if the amount of input data for $s_5$ was less (since it is a root stage) than that of $s_1$ (since it is a leaf stage).

2.4 Target, Source and Noisy Queries

In this section, we describe some concepts that are used in the rest of the paper.

Critical Path: A dataflow DAG may consist of many sequence of stages running in parallel. We define a critical path in a dataflow as the sequence of stages with maximum overall runtime $i.e.$, the sequence of stages whose total runtime dominates the total runtime of the query. In Figure 1 stages $s_4 \rightarrow s_3 \rightarrow s_4 \rightarrow s_5$ form the critical path of query $Q_6$.

Target query and target stages: Any query in the system can be a potential source or a target of contention.

To analyze contentions faced by some query, we break the resource acquisition and release timelines for every monitored resource for each task. A task may be blocked on multiple resources [27] at the same time (see Figure 3), making it difficult to capture the precise timeline of each resource usage. Previous attempts to capture the timeline of individual resources (CPU) [39] rely on hardware counters, and are not useful to evaluate multi-resource contentions at application level. The concept of stolen time (time stolen by other processes from the CPU cycles of a victim process) [3] evolved with the need to better quantify contentions on a cluster, but has been used only in the context of identifying processes that steal CPU time. The stolen time metric cannot be used as is for task executions on cluster computing frameworks as we cannot capture the exact overlap between the multiple resource usage times of two tasks. The need to better capture multi-resource contentions, and to identify queries that steal any resource time from a query requires a more involved metric.
cycle of interactions (see Figure 1) and refer to this query as a target query, and all its stages as target stages. For instance, in Example 2.2, Q₀ is the target query, and its stages s₀,⋯,s₅ are target stages. A user can choose to select only the stages on the critical path as target stages.

Source query and source stages: We refer to other concurrently running queries, Qₙ that can possibly cause contention to a target query Q₁ as source queries (if the stage(s) of Qₙ are waiting in the scheduler or running concurrently with the stage(s) of Q₁). Each stages of a source query is called a source stage. In Example 2.2 the other queries Q₁, Q₂ concurrently running with the target query Q₀ are source queries, and their stages are source stages.

Noisy Queries and Aggressive Queries: A noisy query is a source query that causes the highest contention for the target query. Noisy queries are not necessarily rogue they might adhere to all resource allocation constraints imposed by the scheduler, and yet hold unaccounted resources that are also needed by another query, thus affecting its performance. A noisy query for one target query may not be necessarily noisy for another query. Some noisy queries cause multi-resource contentions for several concurrent queries with high impact. We refer to them as aggressive queries.

ProtoXplore currently provides the admin with an interface to analyze resource contentions faced by (i) all stages in the critical path, (ii) one single stage in the target query, and (iii) all stages in the target query, and help identify noisy and aggressive queries in the system.

3. PROTOXPLORE FRAMEWORK

ProtoXplore collects three levels of explanations with different granularity to store various levels of contentions during query interactions. These are:

Immediate Explanations (IE) What percent of its total execution time was spent by t-stage waiting for a particular resource?

Deep Explanations (DE) What was the rate of contention (RATP) faced by t-stage for a particular resource r on host h that resulted in the wait time in a child IE node?

Blame Explanations (BE) If t-stage faced contention for a particular resource r on some host h as captured by a child DE node, then how much did a source stage contribute toward this contention?

To represent the cause-effect relationships of Figure 1 through these explanations, we use a multi-layered graph called ProtoGraph as described below.

3.1 Multi-Layered ProtoGraph

Level 0 and Level 1 of ProtoGraph contain the target queries and target stages respectively – these are the queries or stages that the admin wants to analyze. On the other end of ProtoGraph, Level 6 represents all source queries, while Level 5 contains all source stages, which are the queries and stages concurrently running with the target queries. The middle three levels – Levels 2, 3, and 4 – keep track of explanations of different forms and granularity that enable us to connect these two ends of ProtoGraph with appropriate attribution of responsibility to all intermediate nodes and

Users sometimes manipulate queries to consume more resources throughout their execution.
in Section \ref{sec:relatedwork}, which is the cumulative measure of responsibility of $\phi$ toward the contention faced by the target stage \textbf{t-stage}.

Since every explanation $\phi$ explains a particular target stage \textbf{t-stage}, the subgraph formed by the explanation nodes for one target stage at Level 1 is disjoint from the subgraph formed by the nodes for another target stage. They can be connected back at Level 5 if multiple target stages execute concurrently with the same source stage. This property enables us to construct the subgraphs from Level 0 to Level 4 in parallel for each target query to be analyzed, thus reducing the graph construction and analysis time significantly as we see in Section \ref{sec:evaluation}.

Next we give details on these three types of explanations with examples.

### 3.2 Immediate Explanations (IE)

A stage may face delay in its execution by having to wait in the scheduler, or to wait for resources like CPU, Memory, Network, or I/O to be available (resp. SWT, NWT, CWT, MWT, and IOWT, see Section \ref{sec:background}). For each target stage in Level 1, we thus add five nodes in Level 2 corresponding to each of these components of the wait time of a stage.

**Example 3.2. IE\textsubscript{s} in Example 2.2.** Suppose the user selects $Q_0$ as the target query, and wants to analyze the contention of the stages $s_1, s_3, s_4, s_5$ on the critical path. First, we add a node for $Q_0$ in Level 0, and nodes for $s_1, s_3, s_4, s_5$ in Level 1. Then in Level 2, for each of these four stages on the critical path, the admin can see five nodes in Level 2 corresponding to different components of their wait time. Although both $s_1$ and $s_5$ faced high contentsions, using ProtoGraph the admin can understand questions such as whether the MWT of stage $s_1$ was higher than the IOWT of stage $s_5$.

### 3.3 Deep Explanations (DE)

Deep explanations unfold the components of wait time further to keep track of the contention faced by the target stage \textbf{t-stage} on different hosts. First, we find all the hosts that were used to execute the tasks from \textbf{t-stage}. Then, for each IE node in Level 2, we add multiple DE nodes in Level 3 that explain the rate of contention (defined below) faced by \textbf{t-stage} on host $h$ for resource $r$.

The contention faced by a stage depends on the size of input data and the rate at which resources are offered. In order to quantify the latter, we need to consider the amount of resource $r$ requested $R_{T,r,h}$ by a task $t$ on host $h$ and the time for which it had to wait $WT_{T}$ during its execution to get this resource. These metrics are readily available for each resource from logs in the cluster without additional instrumentation.

**Definition 3.3.** We define Resource Acquire Time Period (RATP\textsubscript{$r$}) for a task $t$ to be the time period between getting a unit of the resource $r$ on host $h$.

$$RATP_{T} = \frac{WT_{T,r,h}}{R_{T,r,h}}$$

Intuitively, it is the inverse of the rate of getting the requested amount of resource. For example, consider the metric for remote bytes read over the network in Spark (REMOTE\_BYTES\_READ). We define the corresponding RATP metric as the ‘network bytes read timeperiod’, which equals $\frac{NWT}{REMOTE\_BYTES\_READ}$ for the task, and gives us the wait time between getting one unit (one byte for our analysis) of remote data. As another example, RATP for a task while it waits in the scheduler queue is computed as the time spent waiting (i.e. SWT) per number of slots offered to it in this timeframe (i.e. RATP\_SLOT).

**Example 3.4. DE in Example 2.2.** Since the trailing tasks executing on host $Y$ faced an I/O contention, the cumulative Ratp value for resource $r$ = I/O on host $h$ = $Y$ output by ProtoXplore is likely to be higher than the Ratp values for any other resource and host combination for stage $s_5$, thus explaining the contention faced by $s_5$.

For every IE node in Level 2 corresponding to resource $r$, we add $P_r \times H$ new nodes in Level 3, where $P_r$ is the number of different requests that can lead to a wait time for resource $r$, and $H$ is the number of hosts involved in the execution of \textbf{t-stage}. For instance, the IOWT component of \textbf{t-stage} can be explained by the amount of time spent waiting for IO\_READ and IO\_WRITE. Therefore, for $r = IO$ (i.e., for the IOWT nodes in Level 2), $P_r = 2$, and for each host we add two nodes for IO\_BYTES\_READ\_TIMEPERIOD and IO\_BYTES\_WRITE\_TIMEPERIOD in Level 3. The complete list of metrics considered for DE level can be found in Table \ref{tab:metrics} in Appendix A.

### 3.4 Blame Explanations (BE)

Blame Explanations is a novel concept of ProtoXplore. Using BE, we further investigate contentsions by assigning responsibilities to concurrently running queries and their stages by linking the values of RATP metrics of a target stage and a source stage. To create Levels 4, 5 and 6 of ProtoGraph, first we find all source stages that were concurrent with a target stage \textbf{t-stage} in Level 1; we add these source stages in Level 5 and the source queries they belong to in Level 6. Then, we connect the nodes in Level 5 with the nodes in Level 3 (DE) by creating new Blame Explanations (BE) nodes in Level 4 as follows. For each DE node $u$ in Level 3 corresponding to a target stage \textbf{t-stage}, host $h$, and type of resource request $r_u$, if \textbf{t-stage} was executing concurrently with $P$ source stages on host $h$, we add $P$ nodes in Level 4 and connect them to $u$.

**Example 3.5. BE in Example 2.2.** Since we know that stage $r_3$ of source query $Q_1$ was executing concurrently on machine $X$ with stage $s_1$ of our target query $Q_0$, for each DE vertex corresponding to machine $X$, we add one BE vertex to capture the concurrency from $r_3$. Next, since stages $u_5, u_6, u_7$ of another source query $Q_2$ were running on machine $Y$, for each DE vertex corresponding to machine $Y$ we add three BE vertices in Level 4 to capture this concurrency.

Next, we discuss how we use BEs to address the challenges stated in Section \ref{sec:relatedwork}. If multiple source stages run concurrently with the target stage, then the value of blame attributed to each source stage should depend on (a) the fraction of the overall execution time of target stage on the same host $h$ that it had an overlap with the source stage, and (b) the rate of relative contention faced by the target stage compared to the source stage.

**Definition 3.6.** We thus compute the value of blame $\beta_{s_5 \rightarrow ts}$ for the contention caused by source stage $s_5$ to target stage $ts$ as:

$$\beta_{s_5 \rightarrow ts} = FC_h \times \frac{RATP_{ts}}{RATP_{s_5}}$$

Part(a) i.e., $FC_h$ in Equation \ref{eq:blame_parta} for concurrently waiting stages can be computed from the logs using the time
steps when the stages are submitted to the scheduler and the time steps when the tasks are launched. To capture this fractional concurrency for concurrently running tasks of different queries on the same host, we compute the precise overlap time between each pair of concurrent tasks. We then aggregate these values to get the total overlap between these stages on host $h$. We calculate $F_C = \frac{t}{\tau}$, where $t_\text{r}$ is their overlap time, and $\tau_\text{r}$ is the execution time of the task of target stage. This gives us the fraction of its total execution time that a task of a target stage had an overlap with a task of the source stage.

In Part(b), we normalize the contention faced by the t-stage with the contention faced by the source stage for the same resource on the same host. This approach lets us assign higher blame to queries if their RATP was lower than the RATP of the t-stage, thus resulting in higher resource wait times for tasks of t-stage. Our approach also enables us to avoid the need to compute how much ‘per-resource time’ was stolen by a source stage from a target stage executing on the same machine.

As discussed in Section 2, performing blame attribution in a mixed workload is a highly non-trivial process, which we aim to capture accurately in ProtoXplore by a careful computation of multiple intricate metrics involving different queries, stages, tasks, resources, hosts, data, and wait and run time components. Equation 2 also enables us to avoid attributing blame wrongly to undeserving queries as illustrated in Appendix D.

4. CONTENTION ANALYSIS USING PROTOGRAPH

While the blame value computed using Equation 2 gives the impact a source stage has towards the contention faced by a target stage, we need a more evolved metric to compare the contents at various levels of ProtoGraph. In this section, we discuss how DOR mentioned in Definition 3.1 serves this purpose and describe how it is computed for different explanation nodes by computing two intermediate metrics: Vertex Contributions (VC) for different nodes of ProtoGraph, and Impact Factor (IF) on its edges.

4.1 Three Metrics for Contention Analysis

To measure the impact of any explanation node toward a single target query node in Level 0, we keep track of three metrics: (1) the Vertex Contribution ($VC_u$) is defined on individual nodes $u$ of ProtoGraph, which measures the standalone impact of $u$ toward the slowdown of a target stage t-stage. The VC values of different nodes are carefully computed at different levels by taking into account the semantics of respective explanations nodes. (2) The second metric is the Impact Factor ($IF_{uv}$) defined on edges $(u, v)$ of ProtoGraph, which measures the effect of a parent node $u$ in Level $l$ to a child node $v$ in the level below (Level $l - 1$). (3) The third metric Degree of Responsibility ($DOR_u$) is defined on nodes $u$ like VC. However, in contrast to VC, it measures the cumulative effect of a node $u$ toward a particular target query node $t$, taking into account the VC values of the nodes and the IF values of the edges in the subgraph from $u$ to the node $t$ in Level 0. Next we discuss how we compute these three metrics using the skeleton of ProtoGraph discussed above.

4.1.1 Vertex Contributions (VC)

Vertex Contribution of a node $u$ in ProtoGraph, denoted

$$VC_u = \sum_{w \in \text{IN}(u)} (VC_w)$$

by $VC_u$, measures the standalone impact of $u$ toward the contention faced by a target stage. Since every level of ProtoGraph has different semantics, the computation of $VC_u$, for a node $u$ depends on its level. The details of computing the VC for each level are described in Appendix A and summarized in Table I.

4.1.2 Impact Factor (IF)

Once the Vertex Contributions $VC_u$ of every node $u$ in ProtoGraph is computed to estimate the standalone impact of $u$ on a target stage, we compute the Impact Factor $IF_{uv}$ on the edges $(u, v)$ ProtoGraph, which enables us to distribute the overall impact received by each child node $v$ among its parent nodes $u$s. For instance, $IF_{uv}$ from a DE node $u$ to an IE node $v$ gives what fraction of total impact on an IE node can be attributed to each of its parent DE nodes. We compute $IF_{uv}$ for an edge from node $u$ at Level $l$ to node $v$ at Level $l - 1$ as the Vertex Contribution $VC_u$ of $u$ normalized by the total contribution of all parent nodes of $v$:

$$IF_{uv} = \frac{VC_u}{\sum_{w \in \text{IN}(v)} (VC_w)}$$

Figure 6: Example showing how VC values are used to compute IF of each edge, and how IF values are used to compute DOR values of each node.

Here $IN(v)$ denotes the set of parent nodes $w$ of $v$ with an edge $(w, v)$ in ProtoGraph. Therefore, for any node $v$, the sum of all $IF_{uv}$ values is 1. Figure 6 shows an example of the impact received by node $v_4$ from nodes $v_1, v_2, v_3$. Note that the IF values for the edges $(u, v)$ can be computed by a simple linear time graph traversal algorithm in $O(m + n)$ time starting with the topmost level, where $m, n$ respectively denote the number of edges and nodes of the ProtoGraph.

4.1.3 Degree of Responsibility (DOR)

Once the Vertex Contributions $VC_u$ on the nodes of ProtoGraph and the Impact Factors $IF_{uv}$ on its edges are computed, finally we compute the Degree of Responsibility $DOR_u$ of each node $u$ mentioned in Definition 3.1, which stores the cumulative impact of $u$ on a target query $t$. The value of $DOR_u$ is computed as the sum of the weights of all paths from any node $u$ to the target query node $t$, where the weight of a path is the product of all $IF_{uv}$ values of all the edges $(v, w)$ on this path, which can be efficiently computed as:

$$DOR_u = \begin{cases} VC_u & \text{if the level of } u \text{ is 0} \\ \sum_{v \in \text{OUT}(u)} IF_{uv} \times DOR_v & \text{if the level of } u \text{ is } \geq 1 \end{cases}$$

Here OUT($u$) denotes the set of the child nodes $w$ of $u$ with an edge $(u, w)$ in ProtoGraph. Intuitively, DOR gives the overall responsibility of any node toward the contention faced by the target query taking into account impacts of all its children with appropriate weights. The computation of DOR of node $v_3$ is illustrated in Figure 6. If we choose more than one query at Level 0 for analysis, a mapping of the values of

$$DOR_u = \begin{cases} VC_u & \text{if the level of } u \text{ is 0} \\ \sum_{v \in \text{OUT}(u)} IF_{uv} \times DOR_v & \text{if the level of } u \text{ is } \geq 1 \end{cases}$$

Here OUT($u$) denotes the set of the child nodes $w$ of $u$ with an edge $(u, w)$ in ProtoGraph. Intuitively, DOR gives the overall responsibility of any node toward the contention faced by the target query taking into account impacts of all its children with appropriate weights. The computation of DOR of node $v_3$ is illustrated in Figure 6. If we choose more than one query at Level 0 for analysis, a mapping of the values of
DOR toward each query is stored on nodes at Level 5 and 6. Similar to IF, the values of DOR for the nodes of ProtoGraph can be computed by a linear $O(m + n)$ time algorithm. Now we process the graph in a bottom-up topologically sorted order (in contrast to a top-down traversal for computing IFs), where a node is processed only after all its children are processed.

This completes the discussion on how we construct ProtoGraph, and compute different metrics to measure responsibilities of different explanations. An end-to-end pseudocode for constructing ProtoGraph can be found in Algorithm 1 and the algorithms to update IF and DOR values can be found in Algorithms 2 and 3 respectively in Appendix B.

4.2 Algorithms for Contention Analysis

In this section, we discuss three applications of ProtoXplore that can help the admin understand contention in a shared cluster and manage the workload effectively.

4.2.1 Finding Top-K Contentions for Target Queries

Using ProtoXplore, the admin can ask questions such as (i) What are the top-k components of wait time of a target query for various resources?, (ii) What are the top-k machines on which a given target query is experiencing heavy contention for any or all resources?, (iii) What are the top-k concurrently running queries that are causing these contentions on a particular machine for a specific resource? To answer such questions, ProtoXplore outputs the relevant top-k explanations (IE, DE, BE), or the top-k source stages and queries with a high cumulative impact (DOR) for a given value of k. The admin can choose to halt at particular level of analysis or may unfold all levels of explanations up to the source queries to get a more detailed narrative. An interesting observation is that, even if we are interested only in the top-k nodes at the highest level of ProtoGraph, still we cannot prune the nodes with low DOR values at lower levels, since there may be many paths through lower valued nodes from a lower level to a higher level (see Figure 7).

![Figure 7: Nodes with high weights at a higher level having paths from nodes with low weights at a lower level (assuming high branching and $k = 1$).](image)

Running time. Given the ProtoGraph, the top-k vertices at all levels can be found using the linear time selection algorithm [17] since the nodes at different levels are disjoint. However, since the number of nodes in every level is relatively small for analyzing one target query, we simply sort them to get the top-k nodes at each level.

4.2.2 Detecting Aggressive Source Queries

For $k = 1$ at Level 6, ProtoXplore outputs the most ‘noisy query’ with respect to each target query in Level 0. ProtoXplore also allows the admin to do a top-down analysis on a source query or source stage to explore how it has caused contentions to all concurrent queries. To detect such aggressive queries, we find the (top-k) Level 6 node(s) having the highest value of total DOR toward all affected queries (for each source query, we keep track of the DOR value toward each target query).

4.2.3 Identifying Slow Nodes and Hot Resources

There are three ways an admin can analyze contentions through hosts or resources. First, performing a top-k analysis on IE or DE levels will yield the hot resource (IE) and its corresponding slow node (DE) with respect to a particular target query. Second, to find the instances of top contentions between any source and any target query, the admin can query the top-k paths with maximum weight (product of IF on their edges). Third, in order to get the overall impact of each resource or each host on all target queries, ProtoXplore provides an API to (i) detect slow nodes, i.e., group all nodes in Level 3 (DE) by hosts, and then output the total outgoing impact (sum of all IF values) per host, and (ii) detect hot resources, i.e., output the total outgoing impact per wait-time component nodes in Level 2 (IE). We are able to use this analysis to find meaningful resource bottlenecks as we demonstrate in Section 5.

Running time. Note that the number of paths in the graph is upper-bounded by $n_0 \times \Pi_{\ell = 0}^{\ell_{\text{max}}} \text{indeg}_\ell$, where $n_0$ is the number of nodes in Level 0, $\text{indeg}_\ell$ is the maximum in-degree of nodes at Level $\ell$ from Level $\ell + 1$, and $\ell_{\text{max}} = 6$ is the highest level. As the structure of the explanations graph in Figure 5 shows, three of the levels have $\text{indeg}_\ell = 1$, and even otherwise, the value is relatively small, therefore this algorithm runs efficiently despite looking at all possible paths in our graph.

5. EXPERIMENTAL EVALUATION

We present a series of experiments conducted on Apache Spark 2.1 deployed over a 10-node local cluster. Spark was setup to run using the standalone scheduler in FAIR scheduling mode [30] with other default configurations. Each machine in the cluster has 8 cores, 16GB RAM, and 1 TB storage. A 100 GB TPC-DS [13] dataset was stored in HDFS and accessed through Apache Hive in Parquet [8] format. The SQLs for the TPC-DS queries were taken from the implementations in [20] without any modifications.

Workload: We simulate a real workload from Company ABC (that wishes to remain anonymous) by (i) randomly selecting TPC-DS queries that reflect the cluster utilization and query throughput values of their workload, (ii) matching the submission time of our TPC-DS queries with their query arrival pattern, and (iii) scaling down the total number of queries and maximum concurrency at any time to fit the limitations of our cluster size.

Scale of Experiments: For each experiment, we randomly select a varying number of TPC-DS queries from each of the above categories. The maximum number of jobs handled were 125, with 252 stages and 24k tasks with a maximum concurrency of 10 queries and 21 stages. For more than 8 to 10 concurrent queries we hit cluster resource bottlenecks like exceeding memory, maximum number of open files, etc. Figure 8 shows the timeline execution with maximum concurrency for one sample experiment.

Summary of Experiments: Since there is no known study that analyzes multi-resource contentions in a cluster computing framework to this level of details, we rely on validating the correctness of our methodology and scalability of our framework using the following approaches:

- Experiments by Intervention: These experiments validate that the top-k noisy queries indeed cause contention to a selected target query in a decreasing order of impact.
Experiments by Induction: We cause contention for a particular resource to a specific target query through an induced source query. We then demonstrate how ProtoXplore identifies contention for this hot resource and also the corresponding slow nodes accurately.

The purpose of these experiments is twofold: (a) to validate that ProtoXplore outputs the correct explanations at each level, and (b) to demonstrate how ProtoXplore can be used by an admin to take corrective actions.

5.1 Experiments by Intervention

The steps involved in each experiment are as follows: (i) we generate a BASE run that simulates an hour’s workload from Company ABC. We run each experiment 10 times and the numbers represent an execution with a median runtime for the target query. For simplicity, we present our analysis using a sample BASE consisting of 10 TPC-DS queries\(^4\). (ii) we identify a query that takes the most hit compared to its unconstrained execution time and select it as our target query (for example, TPC-DS query Q39b in our sample run takes a 629% hit in BASE). (iii) we use ProtoXplore to identify top-k noisy queries (for k = 3, we get Q5, Q32, Q12 in-order of decreasing DOR in BASE run.) and an aggressive query (Q4 in our sample run), and finally (iv) we intervene with the schedule or placement of the noisy and aggressive queries to see the impact on (a) the runtime of the target query, and (b) the overall query throughput of BASE.

Contentions in BASE: The dataflow DAG of Q39b consists of 6 jobs and 15 stages with 6 parallel stage chains merging into a stage with depth 2 (second last stage). In BASE, it overlapped with 7 queries during its execution with maximum concurrency faced by its last two stages. Figure 12 shows the fraction of the total contention faced by Q39b in various wait-time components. In this run, SWT constitutes >90% of the contention faced by Q39b. Top-3 analysis on Level-2 (IE) indeed outputs SWT, NWT and CWT as the immediate explanations affecting the last two stages as shown in Table 3. For simplicity, we refer to our target query from the BASE run Q39b as Q1, and the top-3 noisy queries (Q5, Q32, Q12) as Top1, Top2 and Top3.

Reducing Noise from the Noisy Neighbor: To reduce the impact of the noisy queries, we conduct four sub-experiments:

- **INTV0-Eliminate:** To validate that Top1, Top2 and Top3 indeed cause contention to Q1, in a decreasing order, we intervene by eliminating each of them in order from the schedule.

- **INTV1-Delays:** Here, we delay the start time of each noisy query such that it results in lesser overlap with Q1. We demonstrate that lesser overlap with Q1 does not necessarily lead to improvements in runtime as it may lead to different patterns of interferences. However, it results in reduced contention from the noisy query that is being delayed.

- **INTV2-Parallelism:** We increase the parallelism in the system to reduce the primary reason of contention for Q1 (i.e., SWT). We do so by increasing the number of cores per executor (default is 1 core per executor) such that more slots are available to launch new tasks, thus reducing the waiting time for the stage in the scheduler queue.

- **INTV3-Placement:** For this experiment, we now intervene with the most aggressive query, say Qn, in our schedule by placing it in a separate pool. We limit the resource allocation for Qn by configuring the pool weight as \(\frac{1}{n} \) where \(n\) is the number of maximum concurrency in BASE.

5.1.1 INTV0-Eliminate:

Each intervention in INTV0-Top1, INTV0-Top2, and INTV0-Top3 consists of eliminating one of the top-3 queries from the schedule. Figure 9 shows the improvement in the runtime of Q1 and also the overall gain for all queries. Removing each query naturally results in reduced contention for Q1, however, the consequential gain in runtime gradually decreases as we pick a lesser noisy query for our elimination. While this is not a practical solution to handle noisy neighbors, the purpose of this experiment is to show that they cause contention in a decreasing order, as detected by ProtoXplore.

![Figure 9: INTV0-Top1, INTV0-Top2, and INTV0-Top3](image)

5.1.2 INTV1-Delays:

Figure 10b shows the effects of reduced overlap between the noisy queries and Q1 on the DOR values of each noisy query. DOR for both Top1 and Top2 decreases when we delay it by 20 sec and 40 sec. It drops to zero as the overlap becomes insignificant (but non-zero). Even a small delay of 20 sec was substantial to drop the responsibility of Top3.

![Figure 10b: Effects of reduced overlap between the noisy queries and Q1](image)
for causing contention to zero (including any subsequent delays). In our observations as shown in Figure 10a, this decrease in overlap, however, did not necessarily result in improved runtimes for $Q_1$ (e.g. spiked runtime when we delay $Top_1$ by 40 sec) as it led to different interference patterns between $Q_1$ and other concurrent queries. In most other cases, it resulted in gains for $Q_1$, but the benefits did not increase with reduced overlaps. Although determining the exact delays of noisy queries which will result in improvements for $Q_1$ make an interesting discussion, it is beyond the scope of this paper (see Section 7 for future work).

In the previous experiment, we validated the output at Level-6 (Source Queries) by intervening with the top-3 query schedules. Here, we validate Level-2 ($IE$) output by intervening a configuration targeted towards reducing the top $IE$ component. For $Q_1$ in BASE, this was a high amount of time spent by its last two stages in the scheduler queue, i.e. SWT. There are multiple ways to reduce the SWT for a query like increasing its priority, reducing the priority of the noisy queries, placing either of them in a dedicated pool with controlled allocations, or increasing the parallelism in the cluster such that stages spend less time waiting for the tasks to launch. We increase the default 8 cores per executor to 16 cores per executor, a practice commonly seen in production environments to increase cluster utilization. The query

![Figure 10: INTV1:](image)

Figure 10: **INTV1**: (a) Delaying the source stages results in improved runtime over BASE in most cases. However, this reduced overlap between source and target stages does not result in improved runtimes in $Q_1$’s runtimes. (b) DOR of $Top_1$ and $Top_2$ reduces with increasing delay. DOR of $Top_3$ drops to zero even for a small delay.

### 5.1.3 **INTV2-Parallelism**:

In this experiment, we validated the output at Level-6 (Source Queries) by intervening with the top-3 query schedules. Here, we validate Level-2 ($IE$) output by intervening a configuration targeted towards reducing the top $IE$ component. For $Q_1$ in BASE, this was a high amount of time spent by its last two stages in the scheduler queue, i.e. SWT. There are multiple ways to reduce the SWT for a query like increasing its priority, reducing the priority of the noisy queries, placing either of them in a dedicated pool with controlled allocations, or increasing the parallelism in the cluster such that stages spend less time waiting for the tasks to launch. We increase the default 8 cores per executor to 16 cores per executor, a practice commonly seen in production environments to increase cluster utilization. The query

![Figure 11:](image)

**Figure 11: INTV2**: Impact of increasing parallelism on $Q_1$ and total runtime of all queries. SWT reduces significantly as more tasks are launched. ProtoXplore also captures increased CPU contention as a result of this increase in parallelism.

![Figure 12:](image)

**Figure 12: INTV2**: Share of each runtime component in total cumulative runtime of $Q_1$. Fraction of total contention due to SWT reduces as a result of increased parallelism in the cluster.

![Figure 13:](image)

**Figure 13**: IMPU: Improvement in runtime of all queries after our intervention. This, however, risks inflating the impact of other types of contentions, but enables us to validate that SWT was indeed a primary reason for contention for $Q_1$.

In this experiment, we take a different approach to validate the correctness of our blame attribution algorithm. We use ProtoGraph to perform a top-down analysis and find the most aggressive query that causes contention with high cumulative DOR to most other concurrent queries. In BASE, we identify $Q_6$ as our aggressive query, say $Q_a$. We now place $Q_a$ into its own dedicated pool with capped resource allocation equal to the maximum share it was entitled to in a FAIR allocation policy, i.e. $\frac{1}{n}$ where $n$ is the number of maximum concurrency in BASE. We submit all queries with the same schedule as BASE. Figure 14 shows the improved runtime of all queries affected by $Q_a$, which is an improvement of 69% for the top affected query $Q_{22}$ in BASE.

![Figure 14:](image)

**Figure 14**: IMPU: Improvement in runtime of all queries after our intervention. This alternate query placement strategy shows significant improvement (69%) for the top affected query $Q_{22}$ in BASE.

| Top-3 IE | Top-3 DE | Top-3 BE | Top-3 Source Queries |
|---------|----------|----------|-----------------------|
| IE      | DOR      | DE       | DOR                   | Queries | DOR     |
| SWT     | 0.929    | OFFER_TIMEPERIOD | 0.929 | Q2Offers_MASTER     | 0.857   | Q5      | 0.364   |
| NWT     | 0.027    | NETWORK_BYTES_READ_TIMEPERIOD | 0.021 | Q2_NETWORK_HOST-X | 0.045   | Q32     | 0.26    |
| CWT     | 0.009    | CPU_BLOCKED_TIMEPERIOD | 0.003 | Q32_CPU_HOST-Y     | 0.002   | Q12     | 0.169   |

**Table 3: Top-K contentions faced by $Q_1$**
We also succeed in improving the runtimes of most other affected queries, especially the ones with high impact in BASE. Q16 and Q29 did not gain much from this strategy as they both were in their last stages of execution with a few trailing tasks.

Figure 13 shows that the change in DOR of Qa towards each affected query post intervention. Q1 and Q10 who previously were the victims of Qa, did not overlap with the contentious stages of Qa in INTV3. As a result of these reduced DORs, query Qa is no longer the aggressive query in INTV3 run. For some queries, the DOR of Qa increased towards them (particularly Q26), but it still resulted in much gain for Q26. Note that ProtoXplore even captures the contentions caused by a query towards itself as can be seen from both figures (Q6 as one of the affected queries). This is on account of multiple parallel chains of Q6 affecting each other.

5.2 Experiments by Induced Contention

So far we have described how ProtoXplore can be used to detect the performance interference problems. The purpose of our second set of experiments is to verify that ProtoXplore outputs correct results at DE level (list of all hosts that have high-contention for a particular resource). For these experiments, we chose query Q1 from our initial BASE run which suffered the least hit compared to its unconstrained execution (Q7; took only 20% hit). We do so in order to test the effects of a targeted contention on a query that originally remained unaffected by concurrent query interferences. Due to space constraints, we present the results for only INDC-IO (IO contention effect) and INDC-CPU (CPU contention effect) below.

INDC-IO: Q1’s initial stage consists of scanning a large fact table (store_sales). Since many queries in our schedule consume data from the same fact table, when Q1 was executing in BASE it found most blocks in the cache resulting in speedy execution. To create an IO contention for Q1 on a targeted host, we create a few smaller fact tables and load their data only one host Y. This is achieved by shutting down all other HDFS hosts while loading this data. We submit multiple IO-intensive queries where each Qilo scans data from a single fact table and later discards it using an appropriate predicate filter. These queries are submitted at controlled intervals to maximize their impact on IO wait times. We can see in Figure 14 that as the disk utilization peaks during our induced contention, the RATP values for tasks of Q1 on host Y as output at Level-3 closely follow the average IO-wait time observed using the Unix iostat utility.

We now describe how this forced straggler effect on tasks of Q1 can be averted in a recurring execution - another way to validate that in the absence of this induced IO contention, Q1 performs similar to the BASE execution (with minimal resource interference from concurrent queries). In INDC-1, we change the Spark scheduler code to put a constraint on Q1 such that when resources become available on node - X and the tasks of the first stage of Q1 are ready to be launched, Q1 relinquishes the offers. This avoidance resulted in improved performance for Q1 in INDC-1 comparable to its performance in BASE as shown in Figure 14. The total runtime of INDC-1, however, is substantially different than BASE total runtime, as this new query gave rise to a different resource interference for other concurrent queries.

INDC-CPU: This experiment was conducted on similar premise as above, and instead of inducing IO contention, we introduce a CPU-intensive query Qc. In order to isolate a host for inducing CPU contention, we suppress the impact due to IO and network interferences. Our query calculates multiple SHA hash values over parallelized collection of large strings in a loop with configurable number of iterations. The strings are embedded into the code to avoid any disk contention. All SHA hash values are discarded and only a success or failure response is returned. This is to ensure that Qc will have a single stage in its DAG thus avoiding possibility of any network contention. We launch Qc with a dedicated executor (spark.executor.instances parameter in Spark) such that all of its tasks run on a single host X. Figure 14 shows a higher CPU utilization on host X during our experiment using the Ganglia [9] time-series plot. We use DE level output using ProtoXplore to compare the RATP values for slots (our primary reason of bottleneck in BASE) with RAT of CPU on host X in this timeline. These values represent a cumulative RATP for all tasks of Qc executing on host X. A rise in RATPcpu with a corresponding decline in RATPslots during the contention timeline verifies that ProtoXplore indeed identifies this bottleneck accurately.

These examples illustrate how ProtoXplore can be used to accurately identify the slow node and hot resource combination enabling admin to take corrective measures in subsequent executions.

6. RELATED WORK

In this section we compare ProtoXplore with various related research projects: (1) Blocked Time Analysis: A recent study used blocked time metric [27] for analyzing performance of workloads on cluster computing frameworks. Their study considers the time a task spends blocked on CPU, Network and IO. The LE level of ProtoXplore is inspired from their approach, but we extend it to study memory contentions and time spent waiting for slots in the scheduler queue as well. More importantly, ProtoXplore defines a new metric (RATP) that uses the blocked time per resource to analyze contentions due to concurrent queries. (2) Analyzing query interactions: In [13], they show how query interactions can impact database system performance significantly. Unlike [13], we do not require any input on query type models to do performance analysis. Moreover, the focus of our paper is analyzing concurrent executions for symptoms of contentions. (3) Blame Attribution and Causal Monitoring: Causality based monitoring tools like DBSherlock [35] use causal models to perform a root cause analysis. DBSherlock analyzes performance problems in OLTP workloads. Since the motive of ProtoXplore is to focus on contention problems due to concurrent queries, the methodology used in DBSherlock may not be suitable to adopt. Another recent work CPI [59] uses hardware counters for low-level profiling to capture resource usage by antagonist queries while the CPI (CPU Cycles-Per-Instruction) of the victim query takes a hit. Since this approach does not capture multi-resource contentions at application-level, it suffers from finding poor correlations when queries are not compute-intensive. Blame attribution has also been studied in the context of program actions [39]. (4) Performance diagnosis tools: Performance diagnosis has been studied in the database community [21,55], for cluster computing frameworks in PerXP[21], and in cloud based services [28]. PerXPPlain uses a decision-tree approach to
Figure 13: INTV3: Impact of placing $Q_a$ in a dedicated pool. The queries are ordered by the highest impact received in BASE.

Figure 14: (a) INDC-CPU: Shows the dip in the aggregate value of SLOTS_OFFERED.TIMEPERIOD for all tasks launched on host X during our induced CPU contention window. We can see a rise in the aggregate RATP for CPU for all tasks of $Q_t$ too. (b) INDC-IO: Y-axis represents IO ops/sec for Average Disk Throughput (grey line), and it represent number of sec for other two metrics (blue and orange line).

Figure 15: Improvement in Mean Runtime of $TQ_7$ in induced IO-EXP (INDC-1) and CPU-EXP(INDC-2) provide a debugging toolkit to analyze the performance of MapReduce jobs. However, it fails to consider dataflow dependencies and workload interactions. Moreover, low-level job diagnosis predicates may not be useful for a long multi-stage application unless they diagnose each job individually and find correlations in the collected data. ADDM [21] defines a notion of Database Time of a SQL query and they use this metric for performing an impact analysis of any resource or activity in the database. At each level of analysis, they only consider the components of this database runtime and drill-down to lower levels that consumed a significant portion of this database time. ProtoXplore further this approach to provide an end-to-end query contention analysis platform. While these studies help identify some causes for query slowdown, they do not enable an admin to analyze the deep reasons of this slowdown, which is a focus of ProtoXplore. (5) Other work on explanations in databases: In the context of analyzing traditional database query answers, explanation has been studied in many different contexts like data provenance [16], causality and responsibility [25], explaining outliers and unexpected query answers [33, 29], etc. The problem studied and the methods applied in this paper are unrelated to these approaches.

7. FUTURE WORK

We intend to extend this work on offline contention analysis to ProtoXplore-Live, which will provide online performance insights while queries are running. Our on-going research also aims to develop a model for automating dynamic priority levels and delays in stage submissions to devise a contention-aware resource allocation scheme. Another future direction is to investigate impact due to sharing of stages between multiple queries (skipped stages in Spark).

8. REFERENCES

[1] Apache Hadoop Capacity Scheduler. http://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/CapacityScheduler.html.
[2] Collection of small tips in further analyzing your hadoop cluster. https://www.slideshare.net/HadoopSummit/t-325p210-cnoguchi.
[3] Netflix and Stolen Time. https://www.scientlogic.com/blog/netflix-steals-time-in-the-cloud-and-from-users.
[4] Teradata. http://www.teradata.com.
[5] The Noisy Neighbor Problem. https://www.liquidweb.com/blog/why-aws-is-bad-for-small-organizations-and-users/.
[6] Vertica. https://www.vertica.com.
[7] Apache Ambari. http://ambari.apache.org. 2016. [Online; accessed 01-Nov-2016].
[8] Apache Parquet. https://parquet.apache.org. 2016. [Online; accessed 01-Nov-2016].
[9] Ganglia Monitoring System. http://ganglia.info. 2016. [Online; accessed 01-Nov-2016].
[10] jGraphT: Java Graph Library. http://jgrapht.org. 2016. [Online; accessed 01-Nov-2016].
APPENDIX

A. COMPUTING VERTEX CONTRIBUTIONS

Level 0 and Level 1 (Target queries and stages): Level 0 contains the target queries, and therefore, we set \( VC_u = 1 \) for all nodes \( u \) in Level 0. Level 1 contains the target stages, and for a node \( u \) that corresponds to a target stage \( s \) of query \( q \), the \( VC_u \) value is computed as:

\[
VC_u = \text{weight}_u \times \frac{WT_s}{RT}
\]

Here, \( VC_u \) denotes the cumulative value of \( WT_s \) for the tasks of target stage \( s \) on resource \( r \). This value is configurable and options to assign higher weights for some source queries include query priorities, SLA importance, queries from a different pool or tenant, etc.

Level 2 (Immediate Explanations): The \( VC_u \) value for a \( DE \) node \( u \) in Level 2 measures what fraction of the total execution time of \( t\)-stage was spent waiting for resource \( r \), and is computed as:

\[
VC_u = \frac{WT_r}{RT}
\]

Level 3 (Deep Explanations): Once we have the cumulative time spent by a stage waiting for a particular resource, in Level 3 we identify how much of this time was spent on each host per unit of input data processed. That is, the \( VC_u \) value for a \( DE \) node \( u \) is the cumulative value of \( t\)-stage for all tasks of \( t\)-stage that executed on host \( h \), and is calculated as follows:

\[
VC_u = \text{RA}_r \times \frac{WT_r \times h}{RA_h}
\]

Level 4 (Blame Explanations): If multiple stages wait or run concurrently with the target stage then the value of blame attributed to each source stage should depend on (a) the fraction of the overall execution time of \( t\)-stage on the same host \( h \) that it had an overlap with the source stage, and (b) the rate of relative contention faced by \( t\)-stage compared to the source stage. Combining these two aspects, the \( VC_u \) value for a \( BE \) node \( u \) is computed as:

\[
VC_u = \frac{\beta_{s.t} \times \text{FC}_h \times \text{RATP}_{t.s}}{\text{RATP}_{s.s}}
\]

B. ALGORITHMS

Algorithm 1 describes the steps in constructing ProtoGraph. Algorithm 2 lists the steps involved in updating IF values of each edge in ProtoGraph and Algorithm 3 elaborates on how we update the DOR values of each vertex in ProtoGraph and use those to find top-\( k \) explanations for every level. Finally, ProtoXplore enables users to identify a resource contention cause that potentially slows down multiple queries. Algorithm 4 gives the pseudocode for finding high impact paths in ProtoGraph.

C. EXPLANATION CATEGORIES

Table 5 lists the types of explanations captured at each of the IE, DE, BE levels in ProtoXplore.

D. AVOIDING FALSE BLAME ATTRIBUTIONS

Today, admins consider only the percentage overlap between concurrent queries to identify queries to be blamed for resource contention, which may lead to faulty attributions: (a) In Example 2.2, suppose only the trailing tasks of stage \( s_7 \) executing on machine \( Y \) on equal amounts of input data faced IO contention. Since this resulted in a longer runtime of these tasks, it appears that the source queries whose tasks were running concurrently only with the trailing tasks of \( s_7 \) should get high blame. However, if these trailing tasks were reading a much bigger data compared to other tasks, then this attribution is erroneous. Use of RATP for the VC values at Level-3 (DE) helps assign a low responsibility towards this contention, thus mitigating the impact coming from its concurrent queries, and prohibiting assignment of incorrect blame to other queries. (b) Suppose task \( t_s \) of source stage \( u_7 \) had almost 100% overlap with task \( t_c \) of \( t\)-stage \( s_1 \) on machine \( X \). Now, suppose RATP for \( t_s \) is higher than RATP for \( t_c \) for a particular resource \( r \) implying that the time \( t_s \) had to wait to get a unit of resource \( r \) is higher than the time \( t_c \) had to wait to get a unit of the same resource \( r \). Assigning any blame to \( u_7 \) for causing contention in such a scenario is unfair even though \( t_s \) and \( t_c \) had 100% concurrency during execution. The only blame \( u_7 \) deserves is because of the overlap of \( t_s \) and \( t_c \) (which we capture using FC), but it should be minimized as \( t_s \) itself was a victim of resource contention, which we capture by normalizing the RATP value of target stage by the RATP of source stage in Equation 7.

E. PROTOXPLORE VISUALIZATION

We have used the jGraphT library to implement a hierarchical visualization for proGraph. Figure 16 shows a visualization for a simple experiment to see impact of TPCDS Q_3 on Q_7.
Table 4: Summary of Vertex Contribution Values at each Level

| Level | Contribution Values | Description |
|-------|---------------------|-------------|
| \( \ell_0 \) (TQ) | \( VC_{u} = 1 \) | Contribution of Impact towards itself is 1 |
| \( \ell_1 \) (TS) | \( VC_{u} = \text{weight}_u \times \frac{W_{ts}}{W_{tq}} \) | - \( \text{weight} \) = Custom weights for target stages. For example, assign higher weight if the depth of stage in query DAG is high.  
- \( W_{ts} \) denotes the cumulative CPU time (i.e., the work done) by stage \( s \).  
- \( W_{tq} \) denotes the cumulative CPU time (work done) by query \( q \). |
| \( \ell_2 \) (IE) | \( VC_{u} = \frac{W_{tr}}{RT} \) | - \( W_{tr} \) denotes the cumulative time spent waiting for resource \( r \) by the corresponding stage \( t \)-stage at Level 1.  
- \( RT \) denotes the cumulative runtime of stage \( t \)-stage. |
| \( \ell_3 \) (DE) | \( VC_{u} = \text{RATP}_{ts} = \frac{W_{tr,h}}{RA_h} \) | - \( W_{tr,h} \) denotes the total wait time of all tasks of \( t \)-stage for resource \( r \) on host \( h \).  
- \( RA_h \) denotes the amount of data (in bytes) processed by all tasks of \( t \)-stage executing on host \( h \). |
| \( \ell_4 \) (BE) | \( VC_{u} = \beta_{s,s \to t,s} = FC_h \times \frac{\text{RATP}_{ts}}{\text{RATP}_{ss}} \) | - \( FC_h \) denotes the fraction of its execution time that the source stage in \( \ell_5 \) runs concurrently with the target stage in \( \ell_1 \).  
- \( \text{RATP}_{ts} \) denotes the cumulative value of \( \text{RATP} \) for the tasks of target stage executing on host \( h \) for resource \( r \).  
- \( \text{RATP}_{ss} \) is the cumulative value of \( \text{RATP} \) for the tasks of source stage executing on host \( h \) for resource \( r \). |
| \( \ell_5 \) (SS) | \( VC_{u} = \text{weight}_u \) | - \( \text{weight} \) = Custom weights for source stages. |
| \( \ell_6 \) (SQ) | \( VC_{u} = \text{weight}_u \) | - \( \text{weight} \) = Custom weights for source queries. For example, assign higher weight to queries belonging to a particular queue or user. |

Figure 16: Visualization of protoGraph: Approach-1 shows impact of \( Q_3 \) on \( Q_7 \)
Table 5: Explanation Categories

| Immediate Explanations | Deep Explanations | Blame Explanations |
|------------------------|-------------------|--------------------|
| Scheduling Waiting Time (SWT) | RATP = Slots Offered Timeperiod = SWT \(\text{Slots Offered}\) | FC_h = overlap time in the scheduler queue time spent in scheduler queue by target stage RATP_{is} = Slots Offered Timeperiod_{is}, RATP_{ss} = Slots Offered Timeperiod_{ss} |
| CPU Waiting Time (CWT = CBWT + CNWT) | RATP = CPU Blocking Timeperiod = CBWT \(\text{Input Bytes}\) | RATP_{is} = CPU Blocking Timeperiod_{is}, RATP_{ss} = CPU Blocking Timeperiod_{ss} |
| | where CBWT = time a thread is blocked to enter or re-enter monitors | |
| | RATP = CPU Notification Timeperiod = CNWT \(\text{Input Bytes}\) | RATP_{is} = CPU Notification Timeperiod_{is}, RATP_{ss} = CPU Notification Timeperiod_{ss} |
| | where CNWT = time a thread spends waiting for notification | |
| Memory Waiting Time (MWT = SMWT + EMWT) | RATP = Storage Mem Wait Timeperiod = SMWT \(\text{Storage Mem Asked}\) | RATP_{is} = Storage Mem Wait Timeperiod_{is}, RATP_{ss} = Storage Mem Wait Timeperiod_{ss} |
| | where SMWT = time a task waits to get storage memory | |
| | RATP = Execution Mem Wait Timeperiod = EMWT \(\text{Exec Mem Asked}\) | RATP_{is} = Execution Mem Wait Timeperiod_{is}, RATP_{ss} = Execution Mem Wait Timeperiod_{ss} |
| | where EMWT = time a task waits to get execution memory | |
| Network Waiting Time (NWT) | RATP = NWT \(\text{Network Bytes Read Timeperiod}\) = Remote Bytes Read | RATP_{is} = Network Bytes Read Timeperiod_{is}, RATP_{ss} = Network Bytes Read Timeperiod_{ss} |
| IO Waiting time (IOWT = IORWT + IOWWT) | RATP = IO Read Timeperiod = IORWT \(\text{Scanned Bytes}\) | RATP_{is} = IO Read Timeperiod_{is}, RATP_{ss} = IO Read Timeperiod_{ss} |
| | where IORWT = time taken by a task for scanning input data | |
| | RATP = IO Write Timeperiod = IOWWT \(\text{Shuffle Bytes Written}\) | RATP_{is} = IO Write Timeperiod_{is}, RATP_{ss} = IO Write Timeperiod_{ss} |
| | where IOWWT = time taken by a task for writing shuffle data to disk | |
Algorithm 1 Constructing ProtoGraph

1: Input: target_queries; target_stages
2: Output: ProtoGraph(V,E)
3: //Adding vertices at level $\ell_0$
4: for $tq \in target_queries$ do
5: Create node $V_{tq}^{0}$ for $tq$ at Level 0
6: Set $VC_{tq}^{0}$ (formula $tq_0$ in Table 4)
7:
8: //Adding vertices at level $\ell_1$
9: for $ts \in target_stages$ do
10: Create node $V_{ts}^{1}$ in Level 1
11: Set $VC_{ts}^{1}$ (formula $tq_1$ in Table 4)
12: Add edge $V_{ts}^{1} \rightarrow V_{tq}^{0}$
13:
14: //Adding vertices at level $\ell_2$
15: Set WT-comp = \{ SWT, MWT, MWT CWT, IOWT \}
16: for resource $r \in WT-comp$ do
17: Create node $V_{r}^{2}$ at Level 2
18: Set $VC_{r}^{2}$ (formula $tq_2$ in Table 4)
19: Add edge $V_{r}^{2} \rightarrow V_{ts}^{1}$
20:
21: //Adding vertices at level $\ell_3$
22: Find hosts of execution aff-hosts
23: for host $h \in aff-hosts$ do
24: Create node $V_{h,r}^{3}$ at Level 3
25: Set $VC_{h,r}^{3}$ (formula $tq_3$ in Table 4)
26: Add edge $V_{h,r}^{3} \rightarrow V_{r}^{2}$
27:
28: //Adding vertices at level $\ell_4$
29: Get stage sources concurrent with $ts$
30: for $ss \in source_stages$ do
31: Create node $V_{ss,h,r}^{4}$ at Level 4
32: Set $VC_{ss,h,r}^{4}$ (formula $tq_4$ in Table 4)
33: Add edge $V_{ss,h,r}^{4} \rightarrow V_{h,r}^{3}$
34:
35: //Adding vertices at level $\ell_5$
36: if $V_{ss}^{4}$ not found in Level 5 then
37: Create node $V_{ss}^{5}$ in Level 5
38: Set $VC_{ss}^{5}$ (formula $tq_5$ in Table 4)
39: Add edge $V_{ss}^{5} \rightarrow V_{ss,h,r}^{4}$
40: //Adding vertices at level $\ell_6$
41: Get source query sq for $ss$
42: if $V_{sq}^{6}$ not found in Level 6 then
43: Create node $V_{sq}^{6}$ in Level 6
44: Set $VC_{sq}^{6}$ (formula $tq_6$ in Table 4)
45: Add edge $V_{sq}^{6} \rightarrow V_{ss}^{5}$
46: end if
47:
48: end if
49: end for
50: end for
51: end for
52: end for
53: end for

Algorithm 2 Algorithm to update Impact Factors

1: Input: ProtoGraph(V,E)
2: Output: ProtoGraph(V,E) with updated IF
3: Set $\ell = 0$
4: Set $\ell_{max} = 5$
5: while $\ell \leq \ell_{max}$ do
6: curV = Get all nodes at level $\ell$
7: for all $v \in curV$ do
8: $E_{in} = \{ all edges incident on v \}$
9: $V_{in} = \{ all source nodes of each edge in $E_{in}$ \}$
10: Set cumulative_impact = $\sum_{v \in V_{in}} \langle VC_{tq}^{\ell} \rangle$
11: for in_edge $E_{in}$ do
12: in_node = source of in_edge
13: in_node_impact = $VC_{in_node}$
14: $IF_{in_edge} = \frac{in_node_impact}{cumulative_impact}$ ▷ Definition 3
15: end for
16: end for
17: $\ell = \ell + 1$
18: end while

Algorithm 3 Find top-k nodes with highest DOR at a level

1: Input: ProtoGraph(V,E) output from Algorithm 2
2: Output: top-k nodes in all levels $\ell_{in}$
3: // Update Degree of Responsibility values for all nodes
4: Set $\ell = 1$ (for target stages) or $= 0$ (for target queries)
5: while $\ell \leq \ell_{in}$ do
6: curV = Get all nodes at level $\ell$
7: $\forall \ell_{in} = \{ all nodes in level $\ell_{in} + 1$ such that an edge $(u,v)$ exist to some $v \in curV$\}$
8: for $u \in curV$ do
9: Update DOR$_{u}$ using Definition 4
10: end for
11: $\ell = \ell + 1$
12: end while
13: end for
14: Return: $k$ nodes with highest DOR$_{u}$ at level $\ell_{in}$

Algorithm 4 Finding top-k impact paths in ProtoGraph

1: Input: ProtoGraph(V,E) output by Algorithm 2
2: Output: top-k paths with high impact
3: Initialize map_paths_to_impact = Empty
4: source_queries = Get all vertices at Level-6
5: for source $\in source_queries$ do
6: target_queries = Get all vertices at Level-0
7: for target $\in target_queries$ do
8: all_paths = all paths from source to target
9: for path $\in all_paths$ do
10: $u = source vertex of path$, $v = target vertex$ of path
11: path_weight = $\prod_{u} IF_u \rightarrow v$
12: Add path and path_weight to map_paths_to_impact
13: end for
14: end for
15: end for
16: end for
17: sorted_paths = Sort map in map_paths_to_impact in decreasing values (IF)
18: Return top-k values from sorted_paths