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(54) DETERMINING OPTIMAL DATA ACCESS FOR DEEP LEARNING APPLICATIONS ON A CLUSTER

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G06F 9/48	(2006.01)
G06F 18/214	(2023.01)

(52) **U.S. Cl.**

CPC ***G06F 9/5016*** (2013.01); ***G06F 9/4881*** (2013.01); ***G06F 9/5072*** (2013.01); ***G06F 18/214*** (2023.01)

(58) **Field of Classification Search**

None

See application file for complete search history.

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Primary Examiner — Eric C Wai

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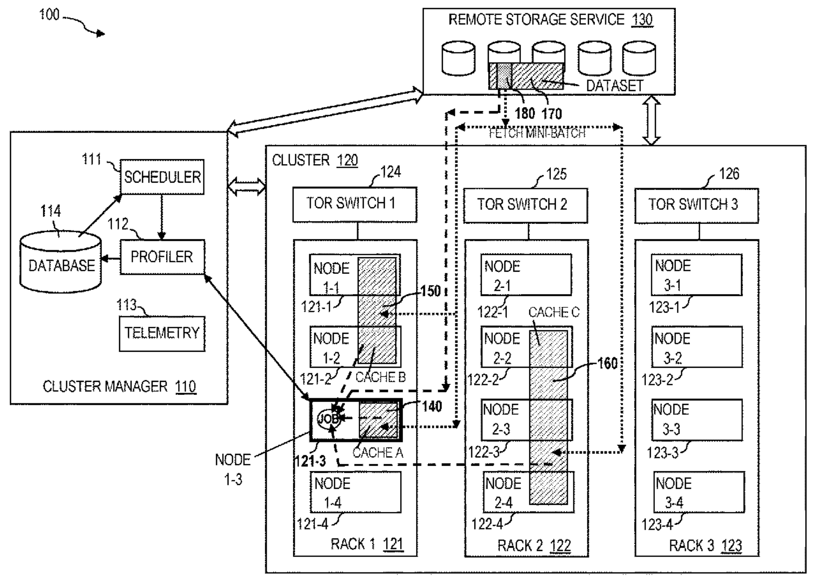
(57) **ABSTRACT**

A computer-implemented method, a computer program product, and a computer system for determining optimal data access for deep learning applications on a cluster. A server determines candidate cache locations for one or more compute nodes in the cluster. The server fetches a mini-batch of a dataset located at a remote storage service into the candidate cache locations. The server collects information about time periods of completing a job on the one or more nodes, where the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location. The server selects, from the candidate cache locations and the remote storage location, a cache location. The server fetches the data of the dataset from the remote storage service to the cache location, and the one or more nodes execute the job against fetched data of the dataset at the cache location.

19 Claims, 8 Drawing Sheets



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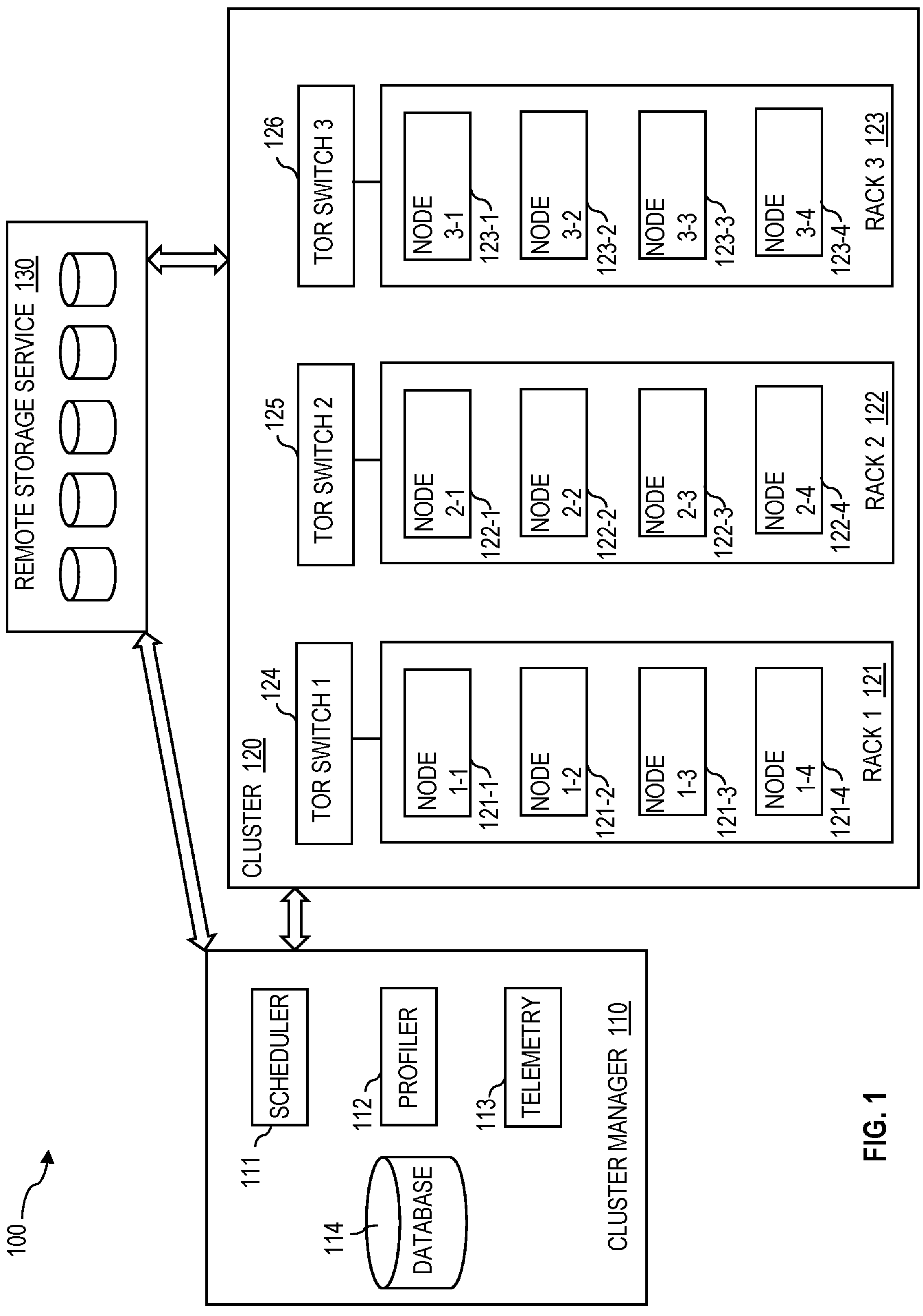
100
REMOTE STORAGE SERVICE 130
CLUSTER 120
TOR SWITCH 1
124
TOR SWITCH 2
125
TOR SWITCH 3
126
NODE 1-1
121-1
NODE 1-2
121-2
NODE 1-3
121-3
NODE 1-4
121-4
RACK 1 121
NODE 2-1
122-1
NODE 2-2
122-2
NODE 2-3
122-3
NODE 2-4
122-4
RACK 2 122
NODE 3-1
123-1
NODE 3-2
123-2
NODE 3-3
123-3
NODE 3-4
123-4
RACK 3 123
SCHEDULER
111
PROFILER
112
TELEMETRY
113
DATABASE
114
CLUSTER MANAGER 110

FIG. 1

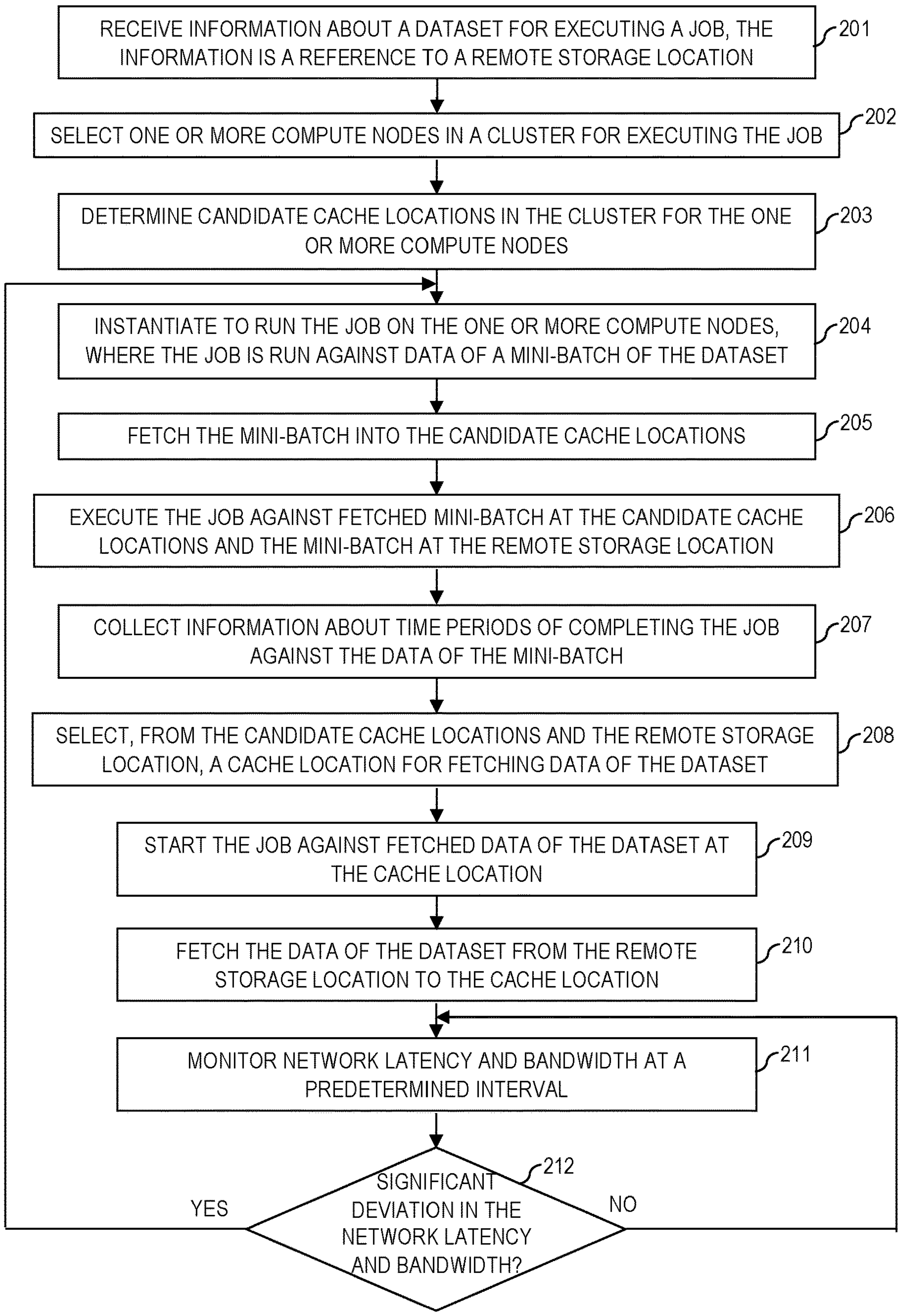
RECEIVE INFORMATION ABOUT A DATASET FOR EXECUTING A JOB, THE INFORMATION IS A REFERENCE TO A REMOTE STORAGE LOCATION
201
SELECT ONE OR MORE COMPUTE NODES IN A CLUSTER FOR EXECUTING THE JOB
202
DETERMINE CANDIDATE CACHE LOCATIONS IN THE CLUSTER FOR THE ONE OR MORE COMPUTE NODES
203
INSTANTIATE TO RUN THE JOB ON THE ONE OR MORE COMPUTE NODES, WHERE THE JOB IS RUN AGAINST DATA OF A MINI-BATCH OF THE DATASET
204
FETCH THE MINI-BATCH INTO THE CANDIDATE CACHE LOCATIONS
205
EXECUTE THE JOB AGAINST FETCHED MINI-BATCH AT THE CANDIDATE CACHE LOCATIONS AND THE MINI-BATCH AT THE REMOTE STORAGE LOCATION
206
COLLECT INFORMATION ABOUT TIME PERIODS OF COMPLETING THE JOB AGAINST THE DATA OF THE MINI-BATCH
207
SELECT, FROM THE CANDIDATE CACHE LOCATIONS AND THE REMOTE STORAGE LOCATION, A CACHE LOCATION FOR FETCHING DATA OF THE DATASET
208
START THE JOB AGAINST FETCHED DATA OF THE DATASET AT THE CACHE LOCATION
209
FETCH THE DATA OF THE DATASET FROM THE REMOTE STORAGE LOCATION TO THE CACHE LOCATION
210
MONITOR NETWORK LATENCY AND BANDWIDTH AT A PREDETERMINED INTERVAL
211
SIGNIFICANT DEVIATION IN THE NETWORK LATENCY AND BANDWIDTH?
212
YES
NO

FIG. 2

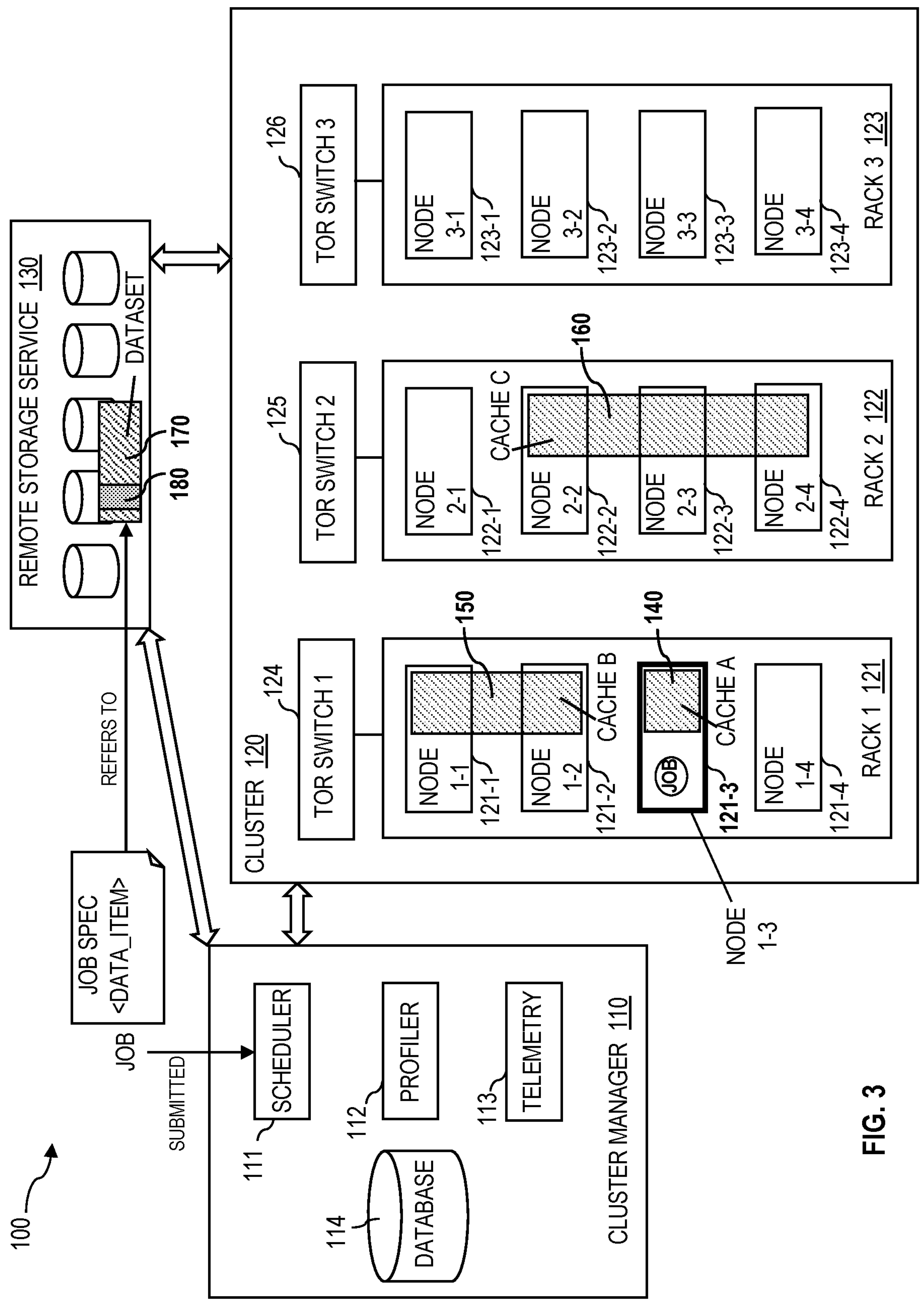
100
REMOTE STORAGE SERVICE 130
DATASET
170
180
REFERS TO
JOB SPEC <DATA_ITEM>
JOB
SUBMITTED
SCHEDULER
111
PROFILER
112
TELEMETRY
113
DATABASE
114
CLUSTER MANAGER 110
CLUSTER 120
TOR SWITCH 1
124
TOR SWITCH 2
125
TOR SWITCH 3
126
NODE 1-1
121-1
NODE 1-2
121-2
JOB
121-3
NODE 1-4
121-4
CACHE A
140
CACHE B
150
RACK 1 121
NODE 2-1
122-1
NODE 2-2
122-2
NODE 2-3
122-3
NODE 2-4
122-4
CACHE C
160
RACK 2 122
NODE 3-1
123-1
NODE 3-2
123-2
NODE 3-3
123-3
NODE 3-4
123-4
RACK 3 123
NODE 1-3

FIG. 3

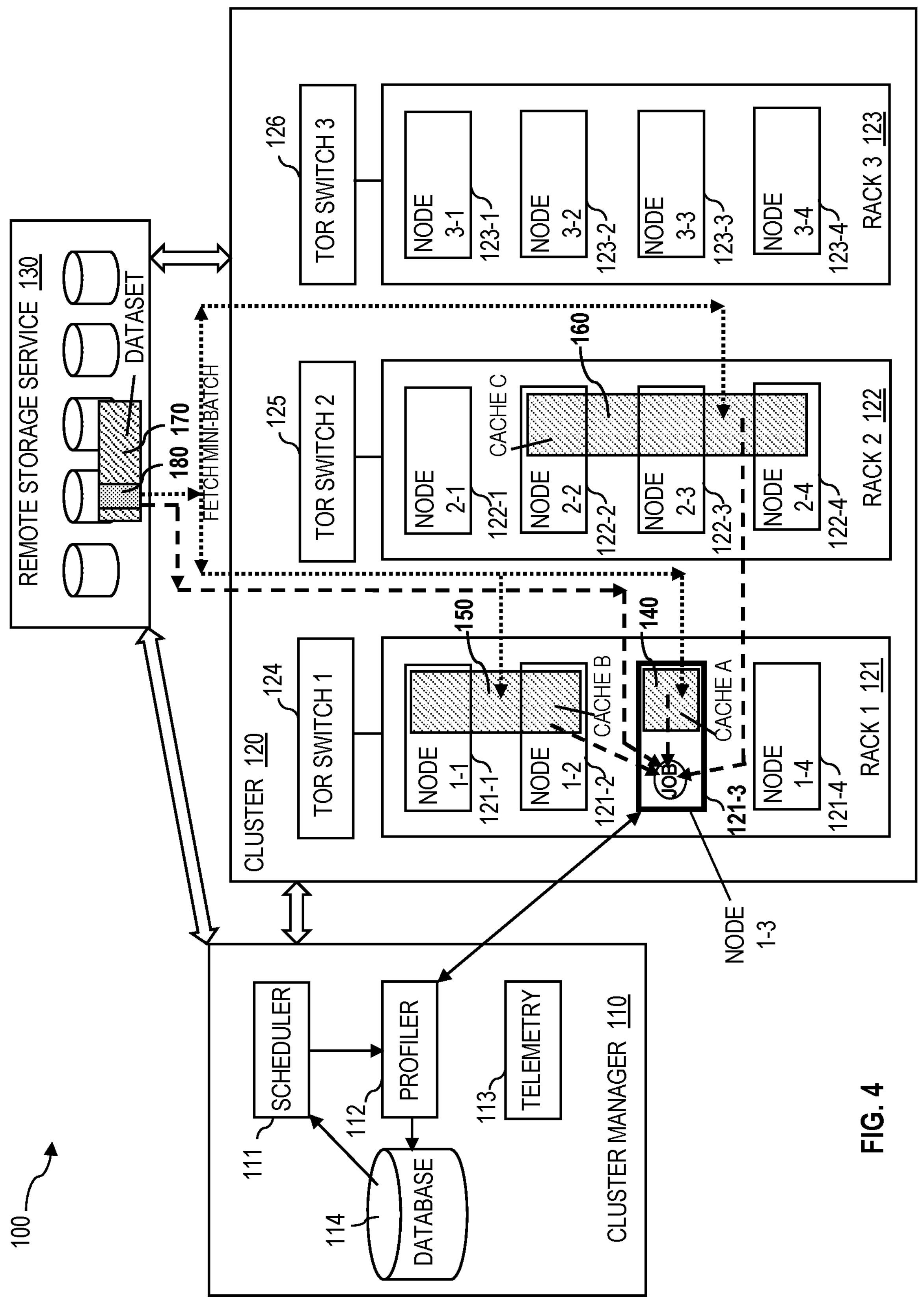
100
REMOTE STORAGE SERVICE 130
DATASET
180 170
FETCH MINI-BATCH
CLUSTER 120
TOR SWITCH 1
124
TOR SWITCH 2
125
TOR SWITCH 3
126
NODE 1-1
121-1
NODE 1-2
121-2
JOB
121-3
NODE 1-4
121-4
RACK 1 121
CACHE A
140
CACHE B
150
NODE 2-1
122-1
NODE 2-2
122-2
NODE 2-3
122-3
NODE 2-4
122-4
RACK 2 122
CACHE C
160
NODE 3-1
123-1
NODE 3-2
123-2
NODE 3-3
123-3
NODE 3-4
123-4
RACK 3 123
NODE 1-3
SCHEDULER
111
PROFILER
112
TELEMETRY
113
DATABASE
114
CLUSTER MANAGER 110

FIG. 4

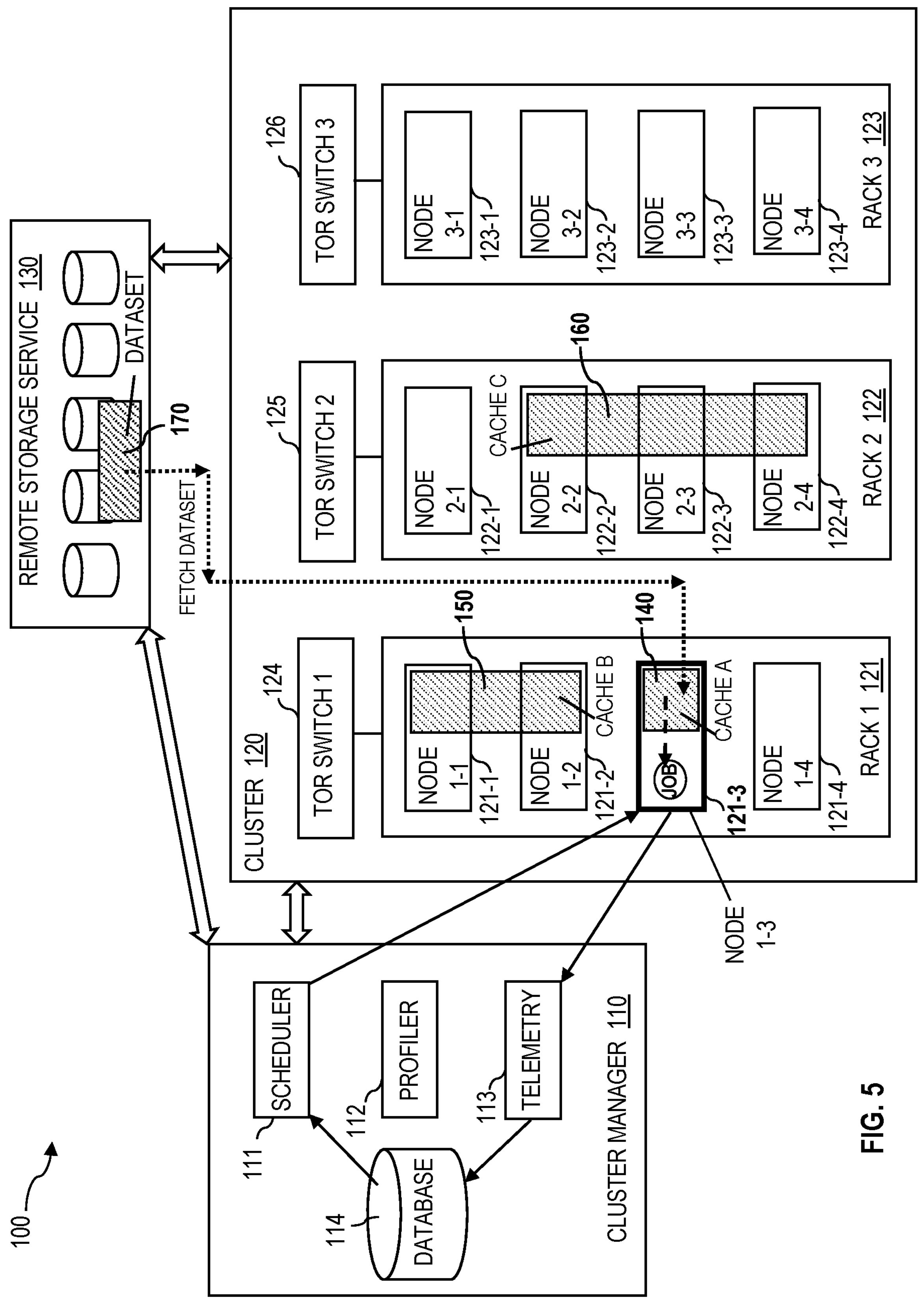
100
REMOTE STORAGE SERVICE 130
DATASET
170
FETCH DATASET
CLUSTER 120
TOR SWITCH 1
124
TOR SWITCH 2
125
TOR SWITCH 3
126
NODE 1-1
121-1
NODE 1-2
121-2
CACHE B
150
140
CACHE A
JOB
121-3
NODE 1-4
121-4
RACK 1 121
NODE 2-1
122-1
NODE 2-2
122-2
CACHE C
160
NODE 2-3
122-3
NODE 2-4
122-4
RACK 2 122
NODE 3-1
123-1
NODE 3-2
123-2
NODE 3-3
123-3
NODE 3-4
123-4
RACK 3 123
NODE 1-3
SCHEDULER
111
PROFILER
112
TELEMETRY
113
DATABASE
114
CLUSTER MANAGER 110

FIG. 5

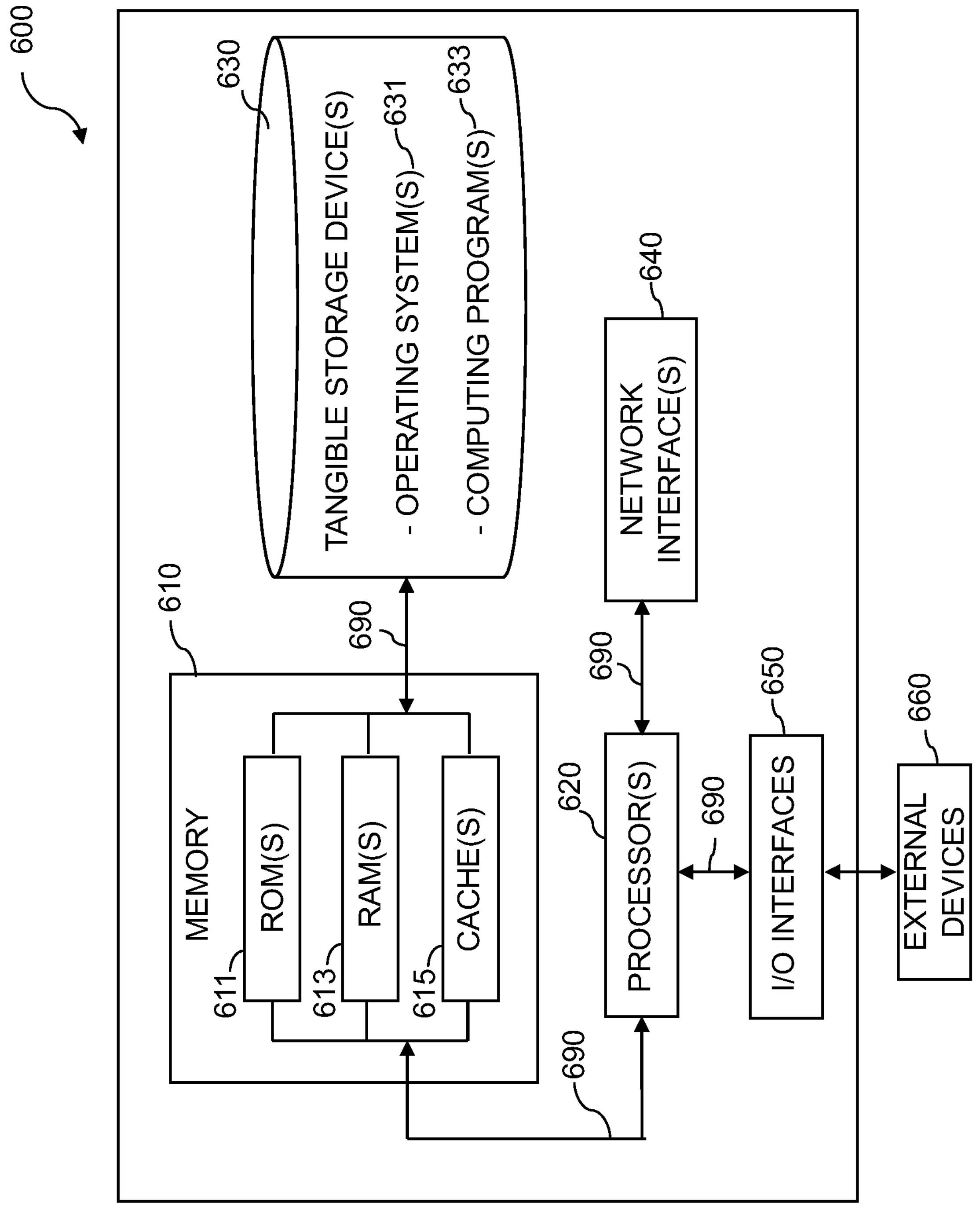
600
630
TANGIBLE STORAGE DEVICE(S)
- OPERATING SYSTEM(S)
631
- COMPUTING PROGRAM(S)
633
610
MEMORY
ROM(S)
611
RAM(S)
613
CACHE(S)
615
690
640
NETWORK INTERFACE(S)
620
PROCESSOR(S)
650
I/O INTERFACES
660
EXTERNAL DEVICES

FIG. 6

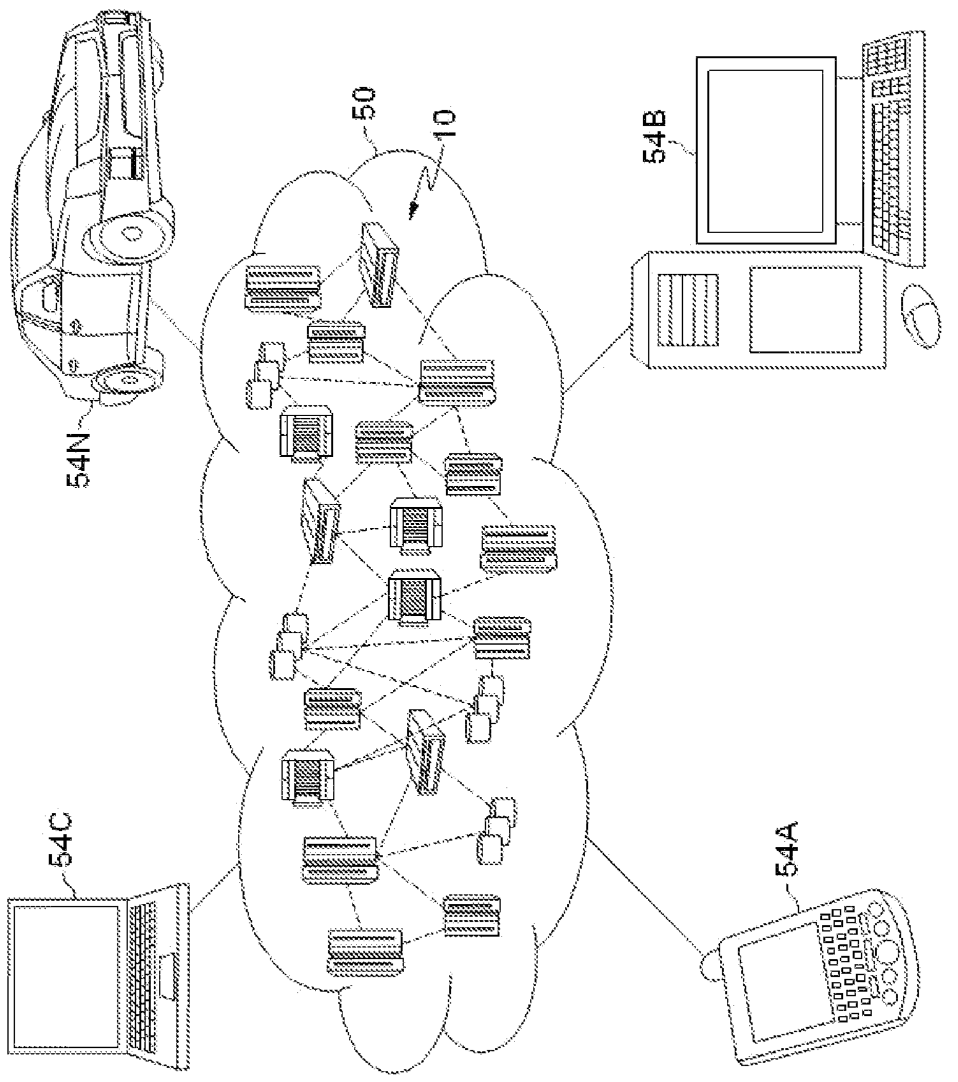

FIG. 7

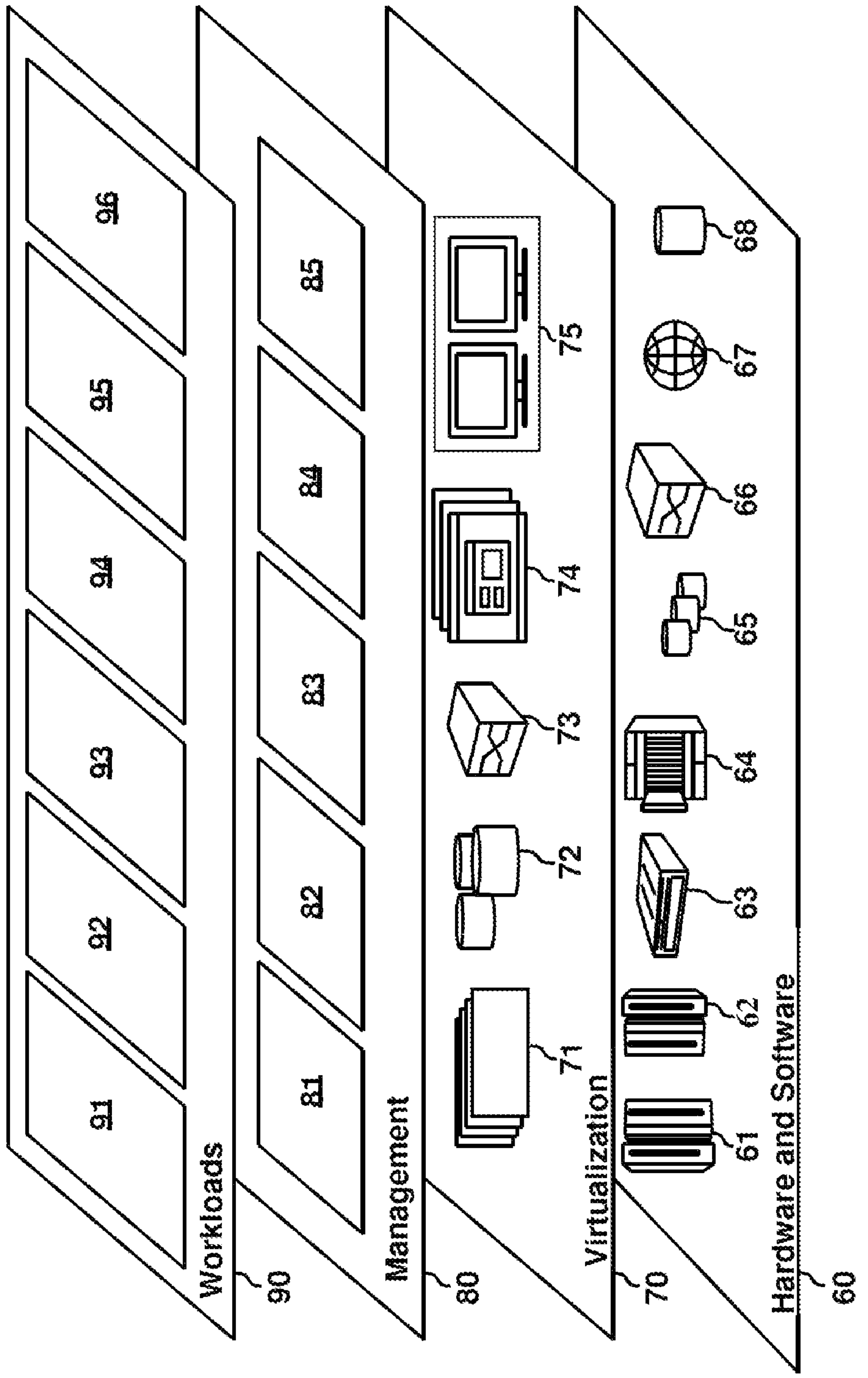
Workloads
90
91
92
93
94
95
96
Management
80
81
82
83
84
85
Virtualization
70
71
72
73
74
75
Hardware and Software
60
61
62
63
64
65
66
67
68

FIG. 8

DETERMINING OPTIMAL DATA ACCESS FOR DEEP LEARNING APPLICATIONS ON A CLUSTER

BACKGROUND

The present invention relates generally to accelerating performance of training deep learning models, and more particularly to determining optimal data access for deep learning applications on a cluster.

Training large neural networks or so-called deep neural networks is performed on compute clusters endowed with central processing units (CPUs) and graphics processing units (GPUs), and it requires an enormous amount of data as input. Current sizes of input datasets start from 100 gigabytes and go up to terabytes. In many systems, data is kept offsite in a storage area network (SAN) or in remote cloud object storage and is fetched when required for training jobs. Recent advances have attempted to cache this training data to avoid wastage of compute resources while waiting for the data to arrive.

Deep learning is a technological breakthrough in machine learning that enables features to be extracted at higher efficiency from large volumes of data. Deep learning has applications in domains such as image classification, speech translation, object detection, and document extraction. However, training deep learning networks requires massive datasets, and it involves heavy use of compute, storage, and network resources. This has significant impact on data centers that are shared infrastructures between multiple users.

Currently, users store large volumes of data in object storage services that are offered by all major cloud providers. The object storage services offer inexpensive storage that is accessible through web interface and application programming interfaces. In other cases, such as in high performance computing (HPC) installations, data may be stored on storage area networks (SANs), external to compute infrastructures. In either case, there is a performance overhead as well as expense associated with accessing such remote storage services.

Recent research has focused on caching this data, either partially or completely, in compute infrastructures. However, storage space in compute clusters are limited. Therefore, it is not possible to cache the data for every training job.

SUMMARY

In one aspect, a computer-implemented method for determining optimal data access for deep learning applications on a cluster is provided. The computer-implemented method includes determining candidate cache locations for one or more compute nodes in the cluster. The computer-implemented method further includes fetching a mini-batch of a dataset located at a remote storage service into the candidate cache locations. The computer-implemented method further includes collecting information about time periods of completing a job on the one or more compute nodes, where the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location. The computer-implemented method further includes selecting, from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job. The computer-implemented method further includes fetching the data of the dataset from the remote storage service to the cache location, where the one or more compute nodes execute the job against fetched data of the dataset at the cache location.

In another aspect, a computer program product for determining optimal data access for deep learning applications on a cluster is provided. The computer program product comprises a computer readable storage medium having program instructions embodied therewith, and the program instructions are executable by one or more processors. The program instructions are executable to: determine candidate cache locations for one or more compute nodes in the cluster; fetch a mini-batch of a dataset located at a remote storage service into the candidate cache locations; collect information about time periods of completing a job on the one or more compute nodes, where the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location; select, from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job; fetch the data of the dataset from the remote storage service to the cache location, wherein the one or more compute nodes execute the job against fetched data of the dataset at the cache location.

In yet another aspect, a computer system for determining optimal data access for deep learning applications on a cluster is provided. The computer system comprises one or more processors, one or more computer readable tangible storage devices, and program instructions stored on at least one of the one or more computer readable tangible storage devices for execution by at least one of the one or more processors. The program instructions are executable to determine candidate cache locations for one or more compute nodes in the cluster. The program instructions are further executable to fetch a mini-batch of a dataset located at a remote storage service into the candidate cache locations. The program instructions are further executable to collect information about time periods of completing a job on the one or more compute nodes, the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location. The program instructions are further executable to select, from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job. The program instructions are further executable to fetch the data of the dataset from the remote storage service to the cache location. In the computer system, the one or more compute nodes execute the job against fetched data of the dataset at the cache location.

BRIEF DESCRIPTION OF THE SEVERAL VIEWS OF THE DRAWINGS

FIG. **1** is a systematic diagram illustrating a system of data access for deep learning applications on a cluster, in accordance with one embodiment of the present invention.

FIG. **2** presents a flowchart showing operational steps of determining optimal data access for deep learning applications on a cluster, in accordance with one embodiment of the present invention.

FIG. **3**, FIG. **4**, and FIG. **5** illustrate the operational steps shown in FIG. **2**, in accordance with one embodiment of the present invention.

FIG. **6** is a diagram illustrating components of a computing device or server, in accordance with one embodiment of the present invention.

FIG. **7** depicts a cloud computing environment, in accordance with one embodiment of the present invention.

FIG. **8** depicts abstraction model layers in a cloud computing environment, in accordance with one embodiment of the present invention.

DETAILED DESCRIPTION

FIG. **1** is a systematic diagram illustrating system **100** of data access for deep learning applications on a cluster, in accordance with one embodiment of the present invention. System **100** includes cluster **120**. Cluster **120** is a networked system of individual machines. Each machine has at least a processor, memory, and attached storage. Such a machine is described in more detail in later paragraphs with reference to FIG. **6**. Some machines may have additional components such as GPUs (graphics processing units) and accelerators. Machines are organized into racks; in an example shown in FIG. **1**, machines in cluster **120** are organized into rack **1 121**, rack **2 122**, and rack **3 123**. Each rack includes multiple machines as nodes in the networked system. For example, rack **1 121** includes node **1-1 121-1**, node **1-2 121-2**, node **1-3 121-3**, and node **1-4 121-4**; rack **2 122** includes node **2-1 122-1**, node **2-2 122-2**, node **2-3 122-3**, and node **2-4 122-4**; rack **3 123** includes node **3-1 123-1**, node **3-2 123-2**, node **3-3 123-3**, and node **3-4 123-4**. All the machines in a rack are connected to a top of rack (ToR) switch. For example, the machines (nodes) in rack **1 121** are connected to ToR switch **1 124**, the machines (nodes) in rack **2 122** are connected to ToR switch **2 125**, and the machines (nodes) in rack **3 123** are connected to ToR switch **3 126**. Racks (such as rack **1 121**, rack **2 122**, and rack **3 123**) are connected to each other in various topologies or network architectures.

System **100** further includes cluster manager **110**. Cluster manager **110** may be implemented on a server. A server is described in more detail in later paragraphs with reference to FIG. **6**. Cluster manager **110** includes scheduler **111**. Scheduler **111** assigns jobs to compute and storage resources. In embodiments of the present invention, the jobs are training of deep learning neural networks. In some embodiments, there can be multiple schedulers in a cluster manager. Cluster manager **110** further includes profiler **112**. Profiler **112** probes the cache and storage locations to determine the effect of data transfer on job performance. Cluster manager **110** further includes telemetry **113**. Telemetry **113** monitors resource and network performance. Intra-cluster network monitoring is setup to measure bandwidth (via link utilization) and latency (via pings) between compute nodes. Inter-cluster network monitoring is also setup to measure bandwidth and latency to the remote cloud object store. Cluster manager **110** further includes database **114** which keeps track of the history of various scheduling decisions and also keeps track of cluster node and network performance data.

System **100** further includes remote storage service **130** which is a service outside of cluster **120**. Remote storage service **130** stores data and serves cluster **120** through a network. In some embodiments, remote storage service **130** may be an object storage service that stores data as objects instead of files. The nature of the storage service permits large amounts of data to be stored.

Cluster manager **110**, cluster **120** (including compute nodes), and remote storage service **130** are connected by a network. The network can be any combination of connections and protocols which support communications among one or more computing devices or servers. For example, the network may be the Internet which represents a worldwide collection of networks and gateways to support communications between devices connected to the Internet; the network may be implemented as an intranet, a local area network (LAN), a wide area network (WAN), and a wireless network. System **100** may be implemented in a cloud computing environment. The cloud computing environment is described in more detail in later paragraphs with reference to FIG. **7** and FIG. **8**.

FIG. **2** presents a flowchart showing operational steps of determining optimal data access for deep learning applications on a cluster, in accordance with one embodiment of the present invention. At step **201**, a cluster manager receives information about a dataset for executing a job. The job is a unit of work to be executed in a cluster. In this disclosure, jobs are specifically, but not limited to, training of deep learning neural networks. The job definition includes the executable, its parameters, and the input data. Generally, neural network training requires datasets sized more than hundreds of gigabytes, and the datasets are generally stored outside of the cluster in an object storage service. The information about the dataset is a reference to its canonical storage location, i.e., the remote storage service. As shown in FIG. **3**, a job specification including the information of the dataset is submitted to scheduler **111** in cluster manager **110**. The dataset information is a reference to dataset **170** at remote storage service **130**.

At step **202**, the cluster manager selects one or more compute nodes in the cluster for executing the job. Selecting the one or more compute nodes is based on certain constraints such as availability of CPUs or other accelerators. As shown in FIG. **3**, scheduler **111** in cluster manager **110** selects node **1-3 121-3** in rack **1 121** of cluster **120** to execute the job.

At step **203**, the cluster manager determines candidate cache locations in the cluster for the one or more compute nodes. The candidate cache locations with respect to the selected one or more compute nodes are node-local, rack-local, cluster-local, and remote storage. A cache is a storage area in the cluster that retains data obtained from the remote storage service. The node-local cache is a cache situated on the same node where the job is executed. The rack-local cache is a cache located in the same rack but not the same node where the job is executed. The cluster-local cache is a cache located in the same cluster but not in the same rack where the job is executed. Remote storage is remote cloud object storage (remote storage service) located outside the cluster. If any of these cache locations is not already present, the cluster manager will create one. The mini-batch is a sample of the dataset located at the remote storage service.

As shown in FIG. **3**, scheduler **111** in cluster manager **110** determines following candidate cache locations: cache A **140** as a node-local cache located at node **1-3 121-3** where the job is executed, cache B **150** as a rack-local cache located at node **1-1 121-1** and node **1-2 121-2** in rack **1 121** (the same rack), cache C **160** as a cluster-local cache located in rack **2 122** of cluster **120** (the same cluster), and remote storage service **130**. FIG. **3** also shows mini-batch **180** which is a sample of dataset **170** located in remote storage service **130**.

At step **204**, the cluster manager instantiates to run the job on the one or more compute nodes, where the job is run against data of a mini-batch of the dataset. Shown in FIG. **4**, scheduler **111** in cluster manager **110** instantiates profiler **112** which runs the job on node **1-3 121-3**, where the job accesses mini-batch **180** as input data. At step **205**, the cluster manager fetches the mini-batch into the candidate cache locations. As shown by dotted lines in FIG. **4**, mini-batch **180** is fetched into cache A **140**, cache B **150**, and cache C **160**.

At step **206**, the one or more compute nodes execute the job against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location. The fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location are used in turn by the job. As shown by dashed lines in FIG. **4**, the fetched mini-batch at cache A **140**, cache B **150**, cache C **160** is accessed by the job; mini-batch **180** at remote storage service **130** is also accessed by the job.

At step **207**, the cluster manager collects information about time periods of completing the job against the data of the mini-batch. For using the different candidate cache locations and the remote storage location, the execution of the job may take different time periods to complete, and the execution of the job may also take the same time period (i.e., the execution of the job may be indifferent to locations of the data). The information about the time periods of completing the job may be used to evaluate which one of the candidate cache locations and the remote storage location provides optimal data access for executing the job. In the embodiment shown in FIG. **4**, the information about the time periods is collected by profiler **112** of cluster manager **110**; the profiler **112** enters the information about the time periods into database **114**. The information stored in database **114** will be used by scheduler **111** to evaluate optimal data access for executing the job.

At step **208**, the cluster manager selects, from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset. Selecting the cache location for fetching the dataset is based on the information about the time periods of completing the job. Intuitively, it may seem that the best decision is to cache the data on a compute node where the job is allocated to execute; however, this ignores many factors such as the job being distributed over multiple machines, storage limitations of the target compute machine, resources shared between multiple jobs (for a virtualized environment), variations in network traffic, etc. In the embodiment shown in FIG. **5**, scheduler **111** reads the job execution data (the time periods of completing the job) from database **114** and selects cache A **140** as the cache location for fetching the data of the dataset. In response to determining that the execution of the job takes the same time period, the cluster manager (for example, scheduler **111**) determines not to cache the data.

At step **209**, the cluster manager starts the job on the one or more computer nodes, where the job is executed against fetched data of the dataset at the cache location selected at step **208**. The cluster manager may instruct the one or more compute nodes to execute the job against the fetched data the dataset at the cache location selected. While the one or more compute nodes execute the job, the cluster manager at step **210** fetches the data of the dataset from the remote storage service to the cache location. In the embodiment shown in FIG. **5**, cluster manager **110** fetches the data of dataset **170** from remote storage service **130** to cache A **140**. In FIG. **5**, the dotted line indicates fetching the data of dataset **170** from remote storage service **130** to cache A **140**; the dashed line indicates that node **1-3 121-3** executes the job against the data fetched to cache A **140**.

At step **211**, the cluster manager monitors network latency and bandwidth, at a predetermined interval. While the one or more compute nodes execute the job, the cluster manager monitors the latency and bandwidth in a network linking the one or more compute nodes, the cache location, and the remote storage service. The cluster manager stores the measurement data of the network latency and bandwidth on a database. In the embodiment shown in FIG. **5**, telemetry **113** of cluster manager **110** monitors the latency and bandwidth in a network linking node **1-3 121-3** and remote storage service **130**, and telemetry **113** stores the measurement data of the network latency and bandwidth on database **114**.

At step **212**, the cluster manager determines whether significant deviation in the network latency and bandwidth occurs. In determining whether the significant deviation occurs, the cluster manager determines whether the deviation in the network latency and bandwidth exceeds a predetermined threshold. In the embodiment shown in FIG. **5**, scheduler **111** of cluster manager **110** determines whether significant deviation in the network latency and bandwidth occurs, based on the measurement data of the network latency and bandwidth stored on database **114**.

In response to determining that the significant deviation in the network latency and bandwidth occurs (YES branch of decision block **212**), the cluster manager iterates step **204**. In the embodiment shown in FIG. **4** and FIG. **5**, scheduler **111** in cluster manager **110** re-instantiates profiler **112** which runs the job on node **1-3 121-3** using data of mini-batch **180** as input data. After the job is run with the mini-batch, the cluster manager may make a new selection from the candidate cache locations and the remote storage location. In response to determining that the significant deviation in the network latency and bandwidth does not occur (NO branch of decision block **212**), the cluster manager iterates step **211**, continuing to monitor the network latency and bandwidth.

The selected cache location at step **208** may be used for subsequent executions of other submitted jobs that required the same dataset. When a new job is submitted, the cluster manager (for example, scheduler **111** of cluster manager **110** shown in FIG. **1**) may refer to a database (for example, database **114** of cluster manager **110** shown in FIG. **1**) for a combination of compute nodes and cache locations. In this case, the cluster manager may choose to not run a profiling job in the interest of conserving resources.

FIG. **6** is a diagram illustrating components of computing device or server **600**, in accordance with one embodiment of the present invention. It should be appreciated that FIG. **6** provides only an illustration of one implementation and does not imply any limitations with regard to the environment in which different embodiments may be implemented.

Referring to FIG. **6**, computing device or server **600** includes processor(s) **620**, memory **610**, and tangible storage device(s) **630**. In FIG. **6**, communications among the above-mentioned components of computing device or server **600** are denoted by numeral **690**. Memory **610** includes ROM(s) (Read Only Memory) **611**, RAM(s) (Random Access Memory) **613**, and cache(s) **615**. One or more operating systems **631** and one or more computer programs **633** reside on one or more computer readable tangible storage device(s) **630**.

Computing device or server **600** further includes I/O interface(s) **650**. I/O interface(s) **650** allows for input and output of data with external device(s) **660** that may be connected to computing device or server **600**. Computing device or server **600** further includes network interface(s) **640** for communications between computing device or server **600** and a computer network.

The present invention may be a system, a method, and/or a computer program product at any possible technical detail level of integration. The computer program product may include a computer readable storage medium (or media) having computer readable program instructions thereon for causing a processor to carry out aspects of the present invention.

The computer readable storage medium can be a tangible device that can retain and store instructions for use by an instruction execution device. The computer readable storage medium may be, for example, but is not limited to, an electronic storage device, a magnetic storage device, an optical storage device, an electromagnetic storage device, a semiconductor storage device, or any suitable combination of the foregoing. A non-exhaustive list of more specific examples of the computer readable storage medium includes the following: a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), a static random access memory (SRAM), a portable compact disc read-only memory (CD-ROM), a digital versatile disk (DVD), a memory stick, a floppy disk, a mechanically encoded device such as punch-cards or raised structures in a groove having instructions recorded thereon, and any suitable combination of the foregoing. A computer readable storage medium, as used herein, is not to be construed as being transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a wave-guide or other transmission media (e.g., light pulses passing through a fiber-optic cable), or electrical signals transmitted through a wire.

Computer readable program instructions described herein can be downloaded to respective computing/processing devices from a computer readable storage medium or to an external computer or external storage device via a network, for example, the Internet, a local area network, a wide area network and/or a wireless network. The network may comprise copper transmission cables, optical transmission fibers, wireless transmission, routers, firewalls, switches, gateway computers and/or edge servers. A network adapter card or network interface in each computing/processing device receives computer readable program instructions from the network and forwards the computer readable program instructions for storage in a computer readable storage medium within the respective computing/processing device.

Computer readable program instructions for carrying out operations of the present invention may be assembler instructions, instruction-set-architecture (ISA) instructions, machine instructions, machine dependent instructions, microcode, firmware instructions, state-setting data, configuration data for integrated circuitry, or either source code or object code written in any combination of one or more programming languages, including an object oriented programming language such as Smalltalk, C++, or the like, and procedural programming languages, such as the C programming language or similar programming languages. The computer readable program instructions may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection may be made to an external computer (for example, through the Internet using an Internet Service Provider). In some embodiments, electronic circuitry including, for example, programmable logic circuitry, field-programmable gate arrays (FPGA), or programmable logic arrays (PLA) may execute the computer readable program instructions by utilizing state information of the computer readable program instructions to personalize the electronic circuitry, in order to perform aspects of the present invention.

Aspects of the present invention are described herein with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems), and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer readable program instructions.

These computer readable program instructions may be provided to a processor of a computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks. These computer readable program instructions may also be stored in a computer readable storage medium that can direct a computer, a programmable data processing apparatus, and/or other devices to function in a particular manner, such that the computer readable storage medium having instructions stored therein comprises an article of manufacture including instructions which implement aspects of the function/act specified in the flowchart and/or block diagram block or blocks.

The computer readable program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other device to cause a series of operational steps to be performed on the computer, other programmable apparatus or other device to produce a computer implemented process, such that the instructions which execute on the computer, other programmable apparatus, or other device implement the functions/acts specified in the flowchart and/or block diagram block or blocks.

The flowchart and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods, and computer program products according to various embodiments of the present invention. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of instructions, which comprises one or more executable instructions for implementing the specified logical function(s). In some alternative implementations, the functions noted in the blocks may occur out of the order noted in the Figures. For example, two blocks shown in succession may, in fact, be accomplished as one step, executed concurrently, substantially concurrently, in a partially or wholly temporally overlapping manner, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts or carry out combinations of special purpose hardware and computer instructions.

It is to be understood that although this disclosure includes a detailed description on cloud computing, implementation of the teachings recited herein are not limited to a cloud computing environment. Rather, embodiments of the present invention are capable of being implemented in conjunction with any other type of computing environment now known or later developed.

Cloud computing is a model of service delivery for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, network bandwidth, servers, processing, memory, storage, applications, virtual machines, and services) that can be rapidly provisioned and released with minimal management effort or interaction with a provider of the service. This cloud model may include at least five characteristics, at least three service models, and at least four deployment models.

Characteristics are as Follows:

On-demand self-service: a cloud consumer can unilaterally provision computing capabilities, such as server time and network storage, as needed automatically without requiring human interaction with the service's provider.

Broad network access: capabilities are available over a network and accessed through standard mechanisms that promote use by heterogeneous thin or thick client platforms (e.g., mobile phones, laptops, and PDAs).

Resource pooling: the provider's computing resources are pooled to serve multiple consumers using a multi-tenant model, with different physical and virtual resources dynamically assigned and reassigned according to demand. There is a sense of location independence in that the consumer generally has no control or knowledge over the exact location of the provided resources but may be able to specify location at a higher level of abstraction (e.g., country, state, or datacenter).

Rapid elasticity: capabilities can be rapidly and elastically provisioned, in some cases automatically, to quickly scale out and rapidly released to quickly scale in. To the consumer, the capabilities available for provisioning often appear to be unlimited and can be purchased in any quantity at any time.

Measured service: cloud systems automatically control and optimize resource use by leveraging a metering capability at some level of abstraction appropriate to the type of service (e.g., storage, processing, bandwidth, and active user accounts). Resource usage can be monitored, controlled, and reported, providing transparency for both the provider and consumer of the utilized service.

Service Models are as Follows:

Software as a Service (SaaS): the capability provided to the consumer is to use the provider's applications running on a cloud infrastructure. The applications are accessible from various client devices through a thin client interface such as a web browser (e.g., web-based e-mail). The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user-specific application configuration settings.

Platform as a Service (PaaS): the capability provided to the consumer is to deploy onto the cloud infrastructure consumer-created or acquired applications created using programming languages and tools supported by the provider. The consumer does not manage or control the underlying cloud infrastructure including networks, servers, operating systems, or storage, but has control over the deployed applications and possibly application hosting environment configurations.

Infrastructure as a Service (IaaS): the capability provided to the consumer is to provision processing, storage, networks, and other fundamental computing resources where the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, deployed applications, and possibly limited control of select networking components (e.g., host firewalls).

Deployment Models are as Follows:

Private cloud: the cloud infrastructure is operated solely for an organization. It may be managed by the organization or a third party and may exist on-premises or off-premises.

Community cloud: the cloud infrastructure is shared by several organizations and supports a specific community that has shared concerns (e.g., mission, security requirements, policy, and compliance considerations). It may be managed by the organizations or a third party and may exist on-premises or off-premises.

Public cloud: the cloud infrastructure is made available to the general public or a large industry group and is owned by an organization selling cloud services.

Hybrid cloud: the cloud infrastructure is a composition of two or more clouds (private, community, or public) that remain unique entities but are bound together by standardized or proprietary technology that enables data and application portability (e.g., cloud bursting for load-balancing between clouds).

A cloud computing environment is service oriented with a focus on statelessness, low coupling, modularity, and semantic interoperability. At the heart of cloud computing is an infrastructure that includes a network of interconnected nodes.

Referring now to FIG. **7**, illustrative cloud computing environment **50** is depicted. As shown, cloud computing environment **50** includes one or more cloud computing nodes **10** with which local computing devices are used by cloud consumers, such as mobile device **54**A, desktop computer **54**B, laptop computer **54**C, and/or automobile computer system **54**N may communicate. Nodes **10** may communicate with one another. They may be grouped (not shown) physically or virtually, in one or more networks, such as Private, Community, Public, or Hybrid clouds as described hereinabove, or a combination thereof. This allows cloud computing environment **50** to offer infrastructure, platforms and/or software as services for which a cloud consumer does not need to maintain resources on a local computing device. It is understood that the types of computing devices **54**A-N are intended to be illustrative only and that computing nodes **10** and cloud computing environment **50** can communicate with any type of computerized device over any type of network and/or network addressable connection (e.g., using a web browser).

Referring now to FIG. **8**, a set of functional abstraction layers provided by cloud computing environment **50** (FIG. **7**) is shown. It should be understood in advance that the components, layers, and functions shown in FIG. **8** are intended to be illustrative only and embodiments of the invention are not limited thereto. As depicted, the following layers and corresponding functions are provided:

Hardware and software layer **60** includes hardware and software components. Examples of hardware components include: mainframes **61**; RISC (Reduced Instruction Set Computer) architecture based servers **62**; servers **63**; blade servers **64**; storage devices **65**; and networks and networking components **66**. In some embodiments, software components include network application server software **67** and database software **68**.

Virtualization layer **70** provides an abstraction layer from which the following examples of virtual entities may be provided: virtual servers **71**; virtual storage **72**; virtual networks **73**, including virtual private networks; virtual applications and operating systems **74**; and virtual clients **75**.

In one example, management layer **80** may provide the functions described below. Resource provisioning **81** provides dynamic procurement of computing resources and other resources that are utilized to perform tasks within the cloud computing environment. Metering and Pricing **82** provide cost tracking as resources are utilized within the cloud computing environment, and billing or invoicing for consumption of these resources. In one example, these resources may include application software licenses. Security provides identity verification for cloud consumers and tasks, as well as protection for data and other resources. User portal **83** provides access to the cloud computing environment for consumers and system administrators. Service level management **84** provides cloud computing resource allocation and management such that required service levels are met. Service Level Agreement (SLA) planning and fulfillment **85** provide pre-arrangement for, and procurement of, cloud computing resources for which a future requirement is anticipated in accordance with an SLA.

Workloads layer **90** provides examples of functionality for which the cloud computing environment may be utilized. Examples of workloads and functions which may be provided from this layer include: mapping and navigation **91**; software development and lifecycle management **92**; virtual classroom education delivery **93**; data analytics processing **94**; transaction processing **95**; and function **96**. Function **96** in the present invention is the functionality of determining optimal data access for deep learning applications on a cluster.

What is claimed is:

1. A computer-implemented method for determining optimal data access for deep learning applications on a cluster, the computer-implemented method comprising:

determining candidate cache locations for two or more compute nodes in the cluster;

fetching a mini-batch of a dataset located at a remote storage service into the candidate cache locations, wherein the mini-batch is a sample of the dataset;

collecting information about time periods of completing a job on the two or more compute nodes, where the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location;

selecting, based on the collecting information and from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job;

fetching the data of the dataset from the remote storage service to the cache location; and

wherein the two or more compute nodes execute the job against fetched data of the dataset at the cache location.

2. The computer-implemented method of claim **1**, further comprising:

receiving information about the dataset for executing the job, the information about the dataset being a reference to the remote storage location; and

selecting the compute node in the cluster for executing the job.

3. The computer-implemented method of claim **1**, further comprising:

instantiating to run the job on the two or more compute nodes, wherein the job is run against data of the mini-batch.

4. The computer-implemented method of claim **1**, further comprising:

instructing the two or more compute nodes to execute the job against the fetched data of the dataset at the cache location.

5. The computer-implemented method of claim **1**, further comprising:

monitoring network latency and bandwidth, at a predetermined interval, while the two or more compute nodes executing the job against the fetched data of the dataset at the cache location; and

determining whether significant deviation in the network latency and bandwidth occurs;

in response to determining that the significant deviation in the network latency and bandwidth occurs, re-instantiating to run the job against data of the mini-batch, and making a new selection from the candidate cache locations and the remote storage location.

6. The computer-implemented method of claim **1**, wherein the candidate cache locations include one or more node-local locations that are situated on the two or more compute nodes, wherein the candidate cache locations further include one or more rack-local locations that are situated in a rack of the two or more compute nodes but not on the two or more compute nodes, wherein the candidate cache locations further include two or more cluster-local locations that are situated in the cluster but not in the rack of the two or more compute nodes.

7. The computer-implemented method of claim **1**, wherein the job is training a deep learning model.

8. A computer program product for determining optimal data access for deep learning applications on a cluster, the computer program product comprising a computer readable storage medium having program instructions embodied therewith, the program instructions executable by one or more processors, the program instructions executable to:

determine candidate cache locations for two or more compute nodes in the cluster;

fetch a mini-batch of a dataset located at a remote storage service into the candidate cache locations, wherein the mini-batch is a sample of the dataset;

collect information about time periods of completing a job on the two or more compute nodes, wherein the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location;

select, based on the collecting of information and from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job;

fetch the data of the dataset from the remote storage service to the cache location; and

wherein the two or more compute nodes execute the job against fetched data of the dataset at the cache location.

9. The computer program product of claim **8**, further comprising the program instructions executable to:

receive information about the dataset for executing the job, the information about the dataset being a reference to the remote storage location; and

select the two or more compute nodes in the cluster for executing the job.

10. The computer program product of claim **8**, further comprising the program instructions executable to:

instantiate to run the job on the two or more compute nodes, wherein the job is run against data of the mini-batch.

11. The computer program product of claim **8**, further comprising the program instructions executable to:

instruct the two or more compute nodes to execute the job against the fetched data of the dataset at the cache location.

12. The computer program product of claim **8**, further comprising the program instructions executable to:

monitor network latency and bandwidth, at a predetermined interval, while the two or more compute nodes executing the job against the fetched data of the dataset at the cache location; and

determine whether significant deviation in the network latency and bandwidth occurs;

in response to determining that the significant deviation in the network latency and bandwidth occurs, re-instantiate to run the job against data of the mini-batch, and make a new selection from the candidate cache locations and the remote storage location.

13. The computer program product of claim **8**, wherein the candidate cache locations include one or more node-local locations that are situated on the two or more compute nodes, wherein the candidate cache locations further include one or more rack-local locations that are situated in a rack of the two or more compute nodes but not on the two or more compute nodes, wherein the candidate cache locations further include one or more cluster-local locations that are situated in the cluster but not in the rack of the two or more compute nodes.

14. The computer program product of claim **8**, wherein the job is training a deep learning model.

15. A computer system for determining optimal data access for deep learning applications on a cluster, the computer system comprising one or more processors, one or more computer readable tangible storage devices, and program instructions stored on at least one of the one or more computer readable tangible storage devices for execution by at least one of the one or more processors, the program instructions executable to:

determine candidate cache locations for one or more compute nodes in the cluster, wherein the candidate cache locations include one or more node-local locations that are situated on the one or more compute nodes, wherein the candidate cache locations further include one or more rack-local locations that are situated in a rack of the one or more compute nodes but not on the one or more compute nodes, wherein the candidate cache locations further include one or more cluster-local locations that are situated in the cluster but not in the rack of the one or more compute nodes;

fetch a mini-batch of a dataset located at a remote storage service into the candidate cache locations, wherein the mini-batch is a sample of the dataset;

collect information about time periods of completing a job on the one or more compute nodes, wherein the job is executed against fetched mini-batch at the candidate cache locations and the mini-batch at the remote storage location;

select, from the candidate cache locations and the remote storage location, a cache location for fetching data of the dataset, based on the information about the time periods of completing the job;

fetch the data of the dataset from the remote storage service to the cache location; and

wherein the one or more compute nodes execute the job against fetched data of the dataset at the cache location.

16. The computer system of claim **15**, further comprising the program instructions executable to:

receive information about the dataset for executing the job, the information about the dataset being a reference to the remote storage location; and

select the one or more compute nodes in the cluster for executing the job.

17. The computer system of claim **15**, further comprising the program instructions executable to:

instantiate to run the job on the one or more compute nodes, wherein the job is run against data of the mini-batch.

18. The computer system of claim **15**, further comprising the program instructions executable to:

instruct the one or more compute nodes to execute the job against the fetched data of the dataset at the cache location.

19. The computer system of claim **15**, further comprising the program instructions executable to:

monitor network latency and bandwidth, at a predetermined interval, while the one or more compute nodes executing the job against the fetched data of the dataset at the cache location; and

determine whether significant deviation in the network latency and bandwidth occurs;

in response to determining that the significant deviation in the network latency and bandwidth occurs, re-instantiate to run the job against data of the mini-batch, and make a new selection from the candidate cache locations and the remote storage location.

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