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Real Time Big Data Analytics Dependence on Network Monitoring Solutions using Tensor Networks and its Decomposition

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Abstract
Organizations dealing with huge volumes of data must have a big data infrastructure in place that can accommodate the load of storing, analysing and transporting the data. Suboptimal network performance represents a potential point of failure. Therefore, it is essential to implement redundancy and/or a fail over strategy in order to minimize downtime. With network monitoring, we come to know the status of everything on the network without having to watch it personally and be able to take the timely action to correct problems. But to the extent that companies increase their reliance on real-time streams of marketing and performance big data, the network will become a central part of big data application performance. This is why incorporating network monitoring should be on the company's big data road map if we anticipate using live streaming and analytics of big data in business applications.
Keywords: Big Data analytics, suboptimal network performance, network monitoring, live streaming, WAN Management, Network Application Performance Management, Tensor Networks

1. Big Data-An Introduction

The term Big Data is used to describe a massive amount of structured and unstructured data that is so large that it would be difficult to process using traditional database and software techniques. Processing and storage of this data is posing a tough challenge. In majority of the enterprise scenarios, the data is ether too big or the data transfer speeds are too fast that they exceed the current processing capacity. Therefore, big data has the potential to help companies make faster and intelligent decisions, and hence improve their operations.

Big data can be defined by its three characteristics volume, variety and velocity [1]. Together they define what is called Big Data. Through these characteristics, it is now possible to look into the insights of data as never before. It is important to study big data analytics because it enables organizations to gather, store, manage, and manipulate vast amounts data at the right speed, at the right time, and to gain the right insights. While the potential benefits of big data are real and significant, and some initial successes have already been achieved.

The real importance of big data lies not just in having it, but in harvesting it for quick, fact-based decisions that lead to real business value. For example, disasters such as the recent financial meltdown and mortgage crisis might have been prevented with risk computation on historical data at a massive scale. Financial institutions were essentially taking bundles of thousands of loans and looking at them as one. The general rule is that the larger the data sample, the more accurate may the statistics and other products of the analysis.

If we define big data as the data volume, variety, velocity that exceed an organization's ability to manage and analyze it in a timely fashion, then there are candidates in any industry. It doesn't matter if the breaking point is reached at hundreds of gigabytes or tens or hundreds of terabytes. The principles that apply to big data and big data analytics are similar and can help the smaller organization extract more value from its data assets and IT resources.

Here are three key technologies that can help you get a handle on big data – and even more importantly, extract meaningful business value from it.

- *Information management for big data.* Manage data as a strategic, core asset, with ongoing process control for big data analytics.
- *High-performance analytics for big data*. Gain rapid insights from big data and the ability to solve increasingly complex problems using more data.
- *Flexible deployment options for big data.* Choose between options for on- premises or hosted, software-as-a service (SaaS) approaches for big data and big data analytics.

As with other waves in data management, big data is built on top of the evolution of data management practices over the past five decades. What is new is that for the first time, the cost of computing cycles and storage has reached a tipping point. Why is this important? Only a few years ago, organizations typically would compromise by storing snapshots or subsets of important information because the cost of storage and processing limitations prohibited them from storing everything they wanted to analyze [2].

Big Data also allows for geographic opportunities to anticipate customer needs. Whether they're on the highway, visiting a shopping center or out to dinner, we have an opportunity to communicate with customers at virtually any time using a mobile device. No, it's not rocket science. In fact, some companies are already using analytics to anticipate their customers' next moves.

Google Now's Google Cards are a great example of how data is already being used to understand customers' needs before they search. Google Cards works on Android phones to search existing user content, in addition to other data patterns including geographic location, to anticipate what the user will need.

1.1 Need for Big data

A typical architecture for large-scale data analysis includes a data source, a data warehouse, and business intelligence and analytics systems – all of which are usually centered on relational databases. However, relational database is a specialty and not a foundation. Moreover, the abstractions provided by them are no longer useful on their own for analytical data management. Over the past few years, there has been an explosion in data volume primarily originating from machine generated logs. By simply tweaking an Apache log, you can grow your data volume and complexity by several orders of magnitude. As we see in the Facebook's case, their relational database approach simply didn't scale and they soon needed new tools to handle the load. Also, the percentage of data that actually gets stored in a relational database is shrinking [4]**.**

In many cases, enterprise software does not service developers well. Many relational data warehouses simply just expose SQL; but to get real traction/adoption from developers, there is a need for more than that. Open applications for analysis are required, not just a SQL interface. In addition, these data stores often expose a proprietary interface for application programming (e.g. PL/SQL or TSQL), but not the full power of procedural programming. More programmer friendly parallel data-flow languages await discovery,

A great example of this is the data contained in the black box, which contains a vast amount of data related to the airplane's flight. The black box contains data from the flight's take –off till its crash. The basic use of this black box is in investigating the flight crash, in case it happens. Managing the data contained in black-box is very difficult using the traditional technique since a large amount of this data is unstructured and very complex too.

2. Challenges in Big Data Analysis

Some of the commonly faced changes in big data and its analysis are**:**

- *Heterogeneity and Incompleteness* We consume information, a great deal of heterogeneity is comfortably tolerated. In fact, the nuance and richness of natural language can provide valuable depth. However, machine analysis algorithms expect homogeneous data, and cannot understand nuance. In consequence, data must be carefully structured as a first step in (or prior to) data analysis.
- *Scale:* The first thing anyone thinks of with Big Data is its size. After all, the word "big" is there in the very name. Managing large and rapidly increasing volumes of data has been a challenging issue for many decades. In the past, this challenge was mitigated by processors getting faster, following Moore's law, to provide us with the resources needed to cope with increasing volumes of data. But, there is a fundamental shift underway now: data volume is scaling faster than compute resources, and CPU speeds are static. In the past, large data processing systems had to worry about parallelism across nodes in a cluster; now, one has to deal with parallelism within a single node. Unfortunately, parallel data processing techniques that were applied in the past for processing data across nodes don't directly apply for intra-node parallelism, since the architecture looks very different; for example, there are many more hardware resources such as processor caches and processor memory channels that are shared across cores in a single node.
- *Timeliness***:** The flip side of size is speed. The larger the data set to be processed, the longer it will take to analyze. The design of a system that effectively deals with size is likely also to result in a system that can process a given size of data set faster. However, it is not just this speed that is usually meant when one speaks of. Velocity in the context of Big Data. Rather, there is an acquisition rate challenge. There are many situations in which the result of the analysis is required immediately. For example, if a fraudulent credit card transaction is suspected, it should ideally be flagged before the transaction is completed – potentially preventing the transaction from taking place at all. Obviously, a full analysis of a user's purchase history is not likely to be feasible in real time. Rather, we need to develop partial results in advance so that a small amount of incremental computation with new data can be used to arrive at a quick determination.
- *Privacy***:** The privacy of data is another huge concern, and one that increases in the context of Big Data. For electronic health records, there are strict laws governing what can and cannot be done. For other data, regulations, particularly in the US, are less forceful. However, there is great public fear regarding the inappropriate use of personal data, particularly through linking of data from multiple sources. Managing privacy is effectively both a technical and a sociological problem, which must be addressed

jointly from both perspectives to realize the promise of big data.

- *Human Collaboration:* In spite of the tremendous advances made in computational analysis, there remain many patterns that humans can easily detect but computer algorithms have a hard time finding. Indeed, CAPTCHAs exploit precisely this fact to tell human web users apart from computer programs. Ideally, analytics for Big Data will not be all computational – rather it will be designed explicitly to have a human in the loop. The new sub-field of visual analytics is attempting to do this, at least with respect to the modeling and analysis phase in the pipeline. There is similar value to human input at all stages of the analysis pipeline [5].

3. Need for Network Monitoring

A network typically has both internal and external users, including employees, customers, partners, and other stakeholders. Suboptimal network performance affects companies in different ways, depending on the type of user. For example, if employees can't access the applications and information they need to do their jobs, it means lost productivity and missed deadlines. When customers can't complete transactions online, it means lost revenues and damaged reputation. And when strategic partners can't collaborate or communicate with the company, it harms the relationship and affects their bottom line. Even stakeholders such as investors and analysts who can't get the information they need when they need it will also look unfavorably at your company, leading to lower stock prices and loss of shareholder value. The fact is, though, that networks are so complex that something will go wrong. Every component in the network represents a potential point of failure. That's why it's essential to implement redundancy and/or a failover strategy in order to minimize downtime. This way, if a server or router fails, another one waiting idly until needed can automatically come online to mitigate the impact of the failed equipment. Of course, not every problem can be addressed quite so proactively before any warning signs are apparent. However, if you can monitor network performance proactively in real time, you can identify problems before they become emergencies. An overloaded server, for example, can be replaced before it crashes – but only if you know that its utilization rate is increasing to such an extent that a crash is all but imminent. With network monitoring, you should know the status of everything on your network without having to watch it personally, and be able to take the timely action needed to minimize and, when necessary, quickly correct problems.

3.1 Reasons to use Network Monitoring:

- *Know what is happening.* Network monitoring solutions keeps us informed about the operation and connectivity of the devices and resources on the network. Without these features, we have to wait until someone tells us something is down before it can be fixed.
- *Plan for upgrades or changes.* If a device is constantly down, or the bandwidth to a specific subnet is constantly running near the limit, it may be time to make a change. Network monitoring applications allows us to track this type of data and make appropriate changes with ease. C. *Diagnose problems quickly.* One of the servers is unreachable from the intranet. Unfortunately, without network monitoring, we may not be able to tell if the problem is the server, the switch the server is connected to, or the router. Knowing exactly where the problem is saves time.
- *Show others what is going on.* Graphical reports go a long way in explaining the health of and activity on your network. They're great tools in showing that a troublesome device needs replacing.
- *Know when to apply the disaster-recovery solutions.* With enough warning, we can transfer the operation of important servers to a backup system until the primary system can be repaired and brought back online. Without network monitoring, we may not know there is a problem until it is too late.
- *Make sure the security systems are operating properly.* Companies spend a lot of money on security software and hardware. Without a network monitoring solution, how can a person be sure that the security devices are up and running as configured?
- *Keep track of our customer-facing resources.*
- Many devices on our network are really just applications running on a server (HTTP, FTP, mail, and so on). Network monitoring can watch these applications and make sure that our customers can connect to the servers and are seeing what they need to see.
- *Be informed of our network status from anywhere.* Many network monitoring applications provide remote viewing and management from anywhere with an Internet connection. That way, if a person is on vacation and problem crops up, he can log into your Web interface and see what's wrong.
- *Ensure customer uptime.* If the customers are depending on the network for their business, we have to be sure they're up and running at all times. It is better to know the problem when it occurs and fix it before the customer finds out.
- *Save money* Above all, network monitoring helps to cut down on the total amount of downtime and

time it takes to investigate problems. This translates to fewer man-hours and less money when problems occur [6].

4. Network Monitoring as an Important Tool for Big Data Analysis

Network-related problems will increasingly come to bear on big data. Network professionals prefer not to hear this, because they already have their hands full taking care of network service levels for big data applications. But to the extent that companies increase their reliance on real-time streams of marketing and performance big data, the network will become a central part of big data application performance. This is already having a major impact on IT and its service level guarantees. Organizationally, more CIOs are taking a serious look at reorganizing their departments so that a combined application performance management (APM) group that consists of applications and network professionals works together to support the applications of big data. The move is not a comfortable one for IT professionals who are used to having their own silos of expertise, and are not used to working on a departmental team with employees who have different IT specialties .In addition to the impact of reorganization on IT culture and workflows, CIOs also have to think about a new set of forces that can affect network performance and, ultimately, the ability to acquire and to act on real-time or near real-time big data [7].

4.1 Importance of Network Monitoring in Big Data

A large retailer measures consumer response to an online promotion in real-time and gauges which items are generating the most sales. The retailer has the option of immediately pushing out a new promotion for either the most popular items or less popular merchandise that will further generate sales. This is revenue capture that never would have been possible in the days of static promotions, where there was no way to respond to revenue stream activity while the stream was in process.

A pharmaceutical company ships environmentally sensitive drugs via air freight and continuously monitors sensors within the packages containing the drugs to ensure that temperature and humidity remain steady. If there is a breakage in the package seal, or if the environments begin to fail, the sensor immediately issues an alert, and the situation can be remedied before the valuable cargo spoils. A failure in any of these circumstances not only cuts off revenue, but can also mean the difference between life and death. And while sensors can be failed over and internal systems can be fail-proofed, while the same cannot be done if the wide area network (WAN) that flows over public internet and is beyond the control fails.

This is why incorporating network monitoring should be on the company's big data road map if we anticipate using live streaming and analytics of big data and Internet of Things (IoT) data in mission-critical business applications.

5. Network Monitoring Solutions for Big Data Analytics

5.1. Big data infrastructure depends on good WAN management

Organizations dealing with huge volumes of data must have a big data infrastructure in place that can accommodate the load of storing, analyzing and transporting the data. IT teams must be proactive to ensure their network and WAN management is properly mapped out when big data is on the roadmap. Depending on the kind of data management software in use and the kinds of data analyzed, big data can affect the size and frequency of data movements among servers and between servers and storage. To meet that kind of demand, IT needs to make sure that storage systems and the storage area network (SAN) have sufficient throughput to handle big data traffic in addition to normal operation traffic. Where they don't, it's time to either beef things up or spread things out: Increase I/O on storage controllers or the amount of bandwidth supporting the SAN, or sidestep that by distributing data across more controllers [8].

- *On the WAN:* If the data to be analyzed are being gathered from locations across the WAN -- retail outlets, factories, regional offices -- and the data represents brand-new traffic, IT must make sure the WAN can handle the new load. This will be more of a challenge if the data objects are large, such as video content. Prioritization and traffic shaping can be remedies if problems crop up. WAN optimizers can help as well; many kinds of data that are fundamental in big data analyses are highly compressible, such as security logs or office documents.
- *On the Internet:* Sometimes, the data may be coming from an Internet source. Moreover, the internal site from which data is being pulled may be one without a dedicated WAN link, so data has to move over a VPN across the Internet. In either case, the Internet link on the data center end has to be sized to handle the new load in addition to existing normal traffic. IT may need to use prioritization on the connection to keep the big data transfers from interfering with higher priority traffic streams, such as those for telephony, conferencing or more mission critical applications. Compression can be an effective approach to minimizing the impact on bandwidth, where it can be implemented either via an appliance (virtual or physical) or via a soft client. When the data is coming from a third-party source,

though, compression is not usually an option. To be ready for big data, any organization needs to assess its infrastructure's readiness -- and not just the storage and computer portions. By scoping the types and sizes of data objects moving across the various network tiers, IT can properly prepare the network where needed, applying traffic shaping and other optimization tools in place to keep the data flowing without making any other services suffer.

5.2 Intelligent Network Monitoring:

Intelligent network monitoring switches can gather, collate, filter, process and distribute packets to analysis tools, assuring data visibility, stability, security and optimization of our tool investment. The features of state-of-the-art intelligent network monitoring switches that make it possible to manage Big Data are:

a) *Packet duplication* calls the stream of duplicate information that can make up 40% of network monitoring system traffic. We need to eliminate duplication to get a good look at the real data. Filtering out duplicate packets also saves money because we're not buying multiple tools or incremental tool licenses to analyze the same data over and over again.

b) *Packet slicing* strips data packets of bits that are unnecessary for certain tools. Packet payloads can be removed for IDS tools that do not need payload information to perform their work. Credit card numbers and social security numbers can be sliced away when packets are sent to traffic analysis tools. This lightens the load while serving the dual purpose of increasing throughput efficiency and maintaining security regulatory compliance.

c) *Time stamping* allows you to know the exact moment – within fewer than 10 nanoseconds – when some event happened on the network, in precise relation to the last event and the next event. With Big Data, when something happened can be as important as what happened. By stamping each packet with its exact time of entry, we create a new level of metadata that allows the analysis tools to precisely reconstruct a sequence of events.

d) *Multi Stage Filtering* techniques simplify the process of sorting unstructured data. To be used effectively, each analysis tool needs to receive a complete set of accurate traffic; nothing more and definitely nothing less. Multi Stage Filtering takes a Big Data input stream and directs it through a series of filters that you design, carefully sorting the individual data packets and directing them to tools or to additional filters for pinpoint accuracy. When we eliminate irrelevant packets from a tool's input stream, we get the full value of our data without wasting resources [9].

5.3 Network Application Performance Measurement

Monitoring the performance of big data repositories is just as important as monitoring the performance of any other type of database. It is important to monitor not only the big data repository, but to also monitor the applications that are querying the repository.

- *Big data repositories*. We do that by tracking all of the application transactions across all of the application tiers and analyzing their response times. Given this information it's easy to identify exactly which components are experiencing problems at any given time.
- *Code level details* – When we've identified that there is a performance problem in the big data application we need to understand what portion of the code is responsible for the problems. The only way to do this is by using a tool that provides deep code diagnostics and is capable of showing the call stack of our problematic transactions [10]**.** *Back end processing* – Tracing transactions from the end user, through the application tier, and into the backend repository is required to properly identify and isolate performance problems. Identification of poor performing backend tiers (big data repositories, relational databases, etc…) is easy if we have the proper tools in place to provide the view of our transactions.
- *Big data metrics* – Each big data technology has its own set of relevant KPIs just like any other technology used in the enterprise. The important part is to understand what normal behavior for each metric is while performance is good and then identify when KPIs are deviating from normal. This combined with the end to end transaction tracking will tell you if there is a problem, where the problem is, and possibly the root cause.
- *Big data deep dive* – Sometimes KPIs aren't enough to help solve your big data performance issues. That's when you need to pull out the big guns and use a deep dive tool to assist with troubleshooting. Deep dive tools will be very detailed and very specific to the big data repository type that you are using/monitoring.

Tensors are abstract objects describable by arrays of functions. Each function of such an array is called a component. Components are functions of the selected co-ordinate system. As such the component can change with the change of reference system. However, the value of the property they serve to represent do not. Let's try to visualize a the components of a tensor and their relation to real physical values they represent:

"Picture relating reference system, components and invariant values via a tensor"

A tensor is called an n^{th} order tensor when it comprises an array of r^n components, where r is the number of the dimension is use. We will be mainly seeing second or third-order tensors in three or four dimensions, so that our arrays can have from 32 to 43 components. Arrays with nine components can be written in the form of a 3x3 matrix. Arrays with 81 components are more difficult to visualize because they are described by a three-dimensional lattice array 3 x 3 x 3. In the case of more than two dimensions indicial notation becomes a very convenient way to deal with tensors.

Stress on a surface can be treated as a "stress vector" and is also called a traction vector ($\vec{T}$) Traction is defined as:

$$\vec{T} = \lim \Delta A \rightarrow 0 \frac{\Delta \vec{F}}{\Delta A}$$

Using indicial notation, $\Delta\vec{F}$ can be written as $F_i = \Delta F_i x_i$

In other words, stress is the force per unit area. We convene that the surface stress acts on the outer surfaces of the cube upon the inner surface.

Each face of the cube can experience three tractions. We use the following convention to denote stress:

$$\sigma_{ij},$$

where i is the index of the axis to which the face is normal and j is the index of the direction in which the component of the traction vector is applied. When the component of the traction vector is applied in the direction of the basis vector, our convention is to use a positive value and negative when the component is applied opposite to the sense of the basis vector. Sometimes

$\sigma_{ij} = \sigma_{(i)i}$ and each component is called normal traction component. Often when $i \neq j$, , , $\sigma_{ij} = \tau_{ij}$ and , τ_{ij} being used to denote the shear traction component.

If the cube does not rotate then the shear tractions must cancel each other out, so that for each case,

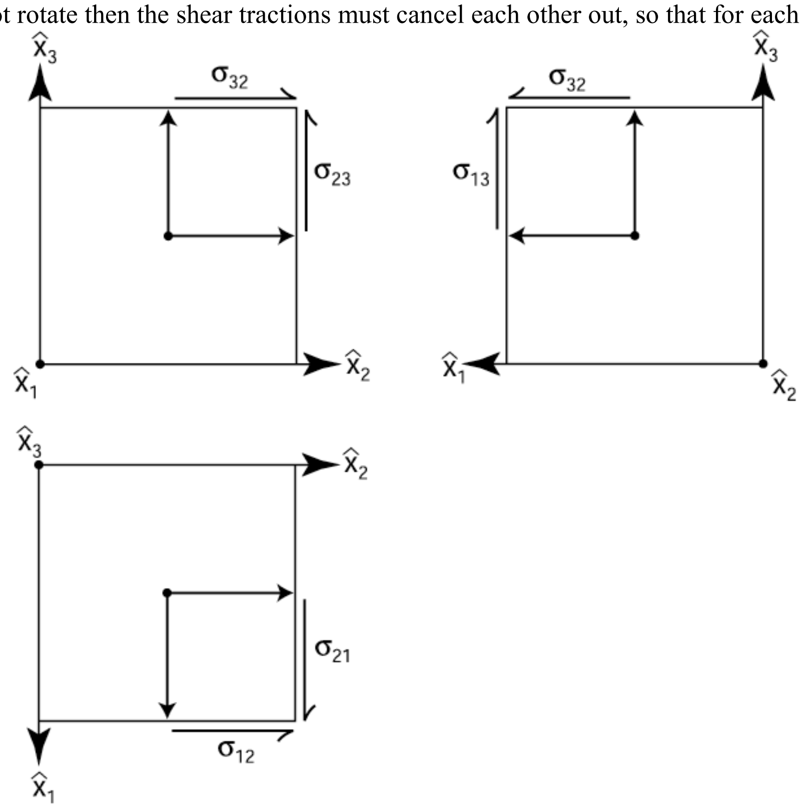

Figure 1: Representation of tensors

For the three cases we get:

$$\hat{x}_1(\sigma_{21}dx_2)\times r\hat{x}_2 = -\hat{x}_2(\sigma_{12}dx_1)r\hat{x}_1$$
$$\hat{x}_3(\sigma_{23}dx_2)\times r\hat{x}_2 = -\hat{x}_2(\sigma_{32}dx_3)r\hat{x}_3$$
$$\hat{x}_3(\sigma_{13}dx_1)\times r\hat{x}_1 = -\hat{x}_1(\sigma_{31}dx_3)r\hat{x}_3$$

In indicial notation these three cases can be written as:

$$\varepsilon_{kij} x_i(\sigma_{ij}dx_j)rx_j = -x_j(\sigma_{ij}dx_i)rx_i\varepsilon_{kij}$$

If the equation is true then $\sigma_{ji} = \sigma_{ij}$, which is the description of a symmetric tensor. A tensor is symmetric iff $\varepsilon_{ijk}t_{jk} = 0$

This research idea may be simulated for the proposed hypothesis over the computer networks. Much of the technology required for big-data computing is developing at a satisfactory rate due to market forces and technological evolution. For example, disk drive capacity is increasing and prices are dropping due to the ongoing progress of magnetic storage technology and the large economies of scale provided by both personal computers and large data centers.

6. Conclusion

Network monitoring solutions keeps us informed about the operation and connectivity of the resources. Without network monitoring, we may not be able to tell if the problem is the server, the switch the server is connected to, or the router. Knowing exactly where the problem is saves time. Big data and network monitoring help an organization to pinpoint exactly where the problem is. This saves a lot of time, less time means more efficiency. Most importantly, using big data to monitor the network can help in diagnosing the problem at a very initial stage. The earlier a problem is diagnosed, the earlier it will be considered for an action. So there are a multitude of reasons, why and how big data with network monitoring is must in IT organizations.

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