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REVIEW THE DYNAMIC REPRESENTATION AND VISUALIZATION TECHINUQUE IN NETWORKING FOR BIG DATA

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Abstract- Recent developments in the Internet of Things (IoT)—a term that encompasses people, sensors, and mobile devices—have led to vastly improved network size, intelligence, and responsiveness. A primary reason for this is the proliferation of internet-enabled mobile devices. The network is dynamic in space and time if and when its topology shifts and the properties of its components evolve over time. Keeping up with the construction and evolution of dynamic networks is becoming increasingly crucial. The statistical features of networks can be examined via data mining methods. While effective, these methods are prohibitively expensive to implement on big, dynamic networks. People can only take in so much information at once, therefore traditional methods of displaying data like as animations and sequences of snapshot graphs aren't very helpful. We offer a dynamic representation and visualization in networking for big data(DRVN-BD) system that allows users to examine a graph's components in terms of their physical location and chronological progression. Networks are examined and analysed in real time by this technology. we apply topological dynamics in conjunction with attribute dynamics to increase the spatial and temporal isolation of nodes and edges (e.g., time and locations of connectivity). DRVN-BD is designed to facilitate scalable network analysis of large, dynamic networks. It accomplishes this via built-in data filtering modules, graph views, and statistical dynamic overviews. we demonstrate how DRVN-BD may be used to detect and rank anomalies in real-world dynamic networks, such as those used in computer communication. it is best to combine analytical and visualisation processes. In this research work, we demonstrate both time-honored methods of displaying information and modifications to those methods suitable for Big Data analysis. The difficulties of deciphering Big Data are discussed. Recent developments in the methods, tools, and understanding of Big Data visualisation are discussed.

Keywords: Data visualization , Big Data , Dynamic Representation.

1. INTRODUCTION

The term "data visualisation" refers to a method of displaying data that makes use of attributes and variables to define the data's "unit of information" [1]. Users in the business world can combine data from multiple sources to get new insights by using visualization-based data discovery techniques. Methods for creating dynamic and animated images for use on desktops, laptops, and mobile devices like tablets and smartphones can be bolstered by advanced analytics. Communication networks have grown not just in size and complexity but also in responsiveness as a result of recent technological developments related to the Internet of

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Things. That's why it's so challenging to make sense of the massive volumes of network traffic logs generated whenever people and mobile devices are in motion. In order to address these issues, researchers are making strides in the area of dynamic network analysis. This area will significantly affect numerous existing practises. A network operator, for instance, may need to monitor their system for any unusual activity in order to detect and fix fundamental issues and potential security flaws. It's feasible that a commander needs to learn to be situationally aware and familiar with how terrorist groups function as a whole in order to lead an army effectively. To identify potentially influential[2] people in social networks, it is necessary to track their movements and actions over time. On the other hand, finding aberrant tumour cells might need researchers to understand how networks of proteins collaborate. It is more difficult to analyse dynamic networks due to the inherent complexity of spatial-temporal networks, which arises from the fact that their structure and attributes are always evolving. Since nodes in dynamic networks are permanently linked to one another, the topology of these networks is always evolving. Communication networks are illustrative of this idea since they are dynamic systems in which links can be established and severed at any time. This complicates the ability to perform a static examination of the network.

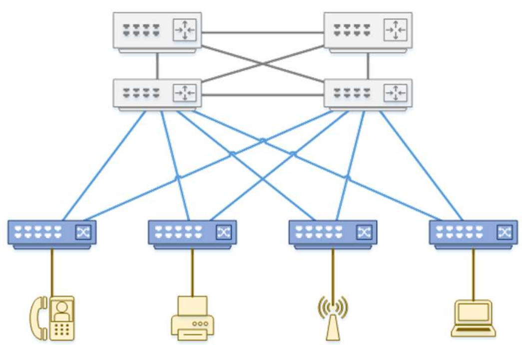

Figure 1: Basic Hierarchical Network Model[4]

It is common practise to employ higher-dimensional spaces for encoding dynamic networks. One facet of an edge may be the locations where connections were established and the associated link quality metrics (such as the loss rate, latency, or capacity). Nodes can also store data like user profiles and the current system status (e.g., CPU, memory, or disc utilizations). It's challenging to determine how best to investigate these intricate interconnections, especially given the dynamic nature of their nature. Traditional methods like statistics and graph theory are useful for studying static networks, but they may not be enough for analysing dynamic ones, such as the Internet. There is a corpus of literature [3] that examines the utility of clustering [4] and link prediction for gaining insight into dynamic networks and locating anomalies within them. Due to the ever-increasing number, dimensions, and complexity of dynamic networks, traditional data mining techniques are no longer adequate. This is due to the fact that attempting to forecast every possible event is statistically impossible. It has also been proposed to use visualisation techniques to spot trends and anomalies in dynamic networks. Research on dynamic networks typically makes use of small multiples and animation as two visualisation approaches. However, due to the inherent limitations of the human mind, keeping up with the pace of historical change will always be a formidable challenge. Some alternative proposals for representing dynamic networks have looked into 3D space or used superimposition and layer juxtaposition but these have all suffered from problems with visual clutter, readability, and mental map preservation . Alternative methods of illustrating the inner workings of a dynamic network have been proposed. As a result, we developed a straightforward web application for monitoring and analysing networks called dynamic representation and visualization in networking for big data(DRVN-BD) system. An integral feature of this technology is the dynamic representation and visualization in networking for big data(DRVN-BD) system dynamic graph visualisation. Since most people have some familiarity with more conventional graphs, we find that a node-link diagram works best for our customers. However, our dynamic graphs are distinct from traditional graphs in that they include both temporal and spatial data directly into their design. This distinguishes them from standard graphs in a significant way. dynamic representation and visualization in networking for big data(DRVN-BD) system was developed so that users may draw on a network to examine its structure and operation, rather than relying on animation or a more complex spatial representation. Therefore, our dynamic networks' nodes and edges are divided into subsets according to the time dimensions and user-selected properties of the nodes and edges. It is possible to further subdivide the data if there is more than one status value for a specific time period. Changes in the characteristics of the network's nodes and edges are graphically represented using a spectrum of colours. To display a dynamic network in a single, static view without requiring users to memorise changes, as is the case with animation schemes, we partition the graph's primary components. We can use this to go to our destination more quickly. When conducting in-depth analysis, dynamic graphics prove invaluable. dynamic representation and visualization in networking for big data(DRVN-BD) system also heavily utilises the macro-level insights obtained through data mining and statistical processing. Over the entire time frame, networks can be understood by looking at temporal trends in connection sizes, network entropies, and property value distributions, for example. These trends can also indicate which periods are out of the ordinary and warrant closer inspection. To perform massive-scale dynamic graph analysis, DRVN-BD might be employed. Graphs can be viewed in both high-level and granular detail. Numerous improvements have been made to the user interface. As a first step, researchers can narrow their emphasis on dynamic graphs by using a time selection box. Next, analysts have the ability to limit the maximum distance between two nodes. Small enough subgraphs are created, so even extremely huge networks are easily discernible. The ability to filter nodes and edges based on their weights is the last feature, although it's not necessarily the least significant. We evaluated DRVN-BD using two publicly available datasets [16, 17] that detail the dynamics between users and networks in terms of traffic patterns over time and across geographies. By analysing DRVN-BD, anomalies in network traffic can be localised to a specific time and location. Following this structure, the rest of the paper will be written: Through the presentation of traditional visualisation techniques and the extension of some of them to the handling of big data, the discussion of the challenges of big data visualisation, and the analysis of the technological progress in big data visualisation, this paper aims to present new methods and advances of Big Data visualisation. The authors of this study began by doing a search of academic libraries seeking recently published articles on the topic of data visualisation. The authors have thus far essentially summarised both established and cutting-edge approaches to data visualisation. The next step was a search for relevant articles on the topic of large data visualisation. In light of the relative novelty of the field of big data, the vast majority of these publications have appeared within the past three years. At now, authors have discovered that traditional data visualisation techniques do not work for huge data. Some traditional visualisation methods have not been functionally extended nearly enough to handle huge data. The authors examined the difficulties associated with big data visualisation and discussed solutions, including novel approaches, technological advancements, and newly created tools.

2. RELATED WORK

In general, there have been either data mining or visualization approaches in order to understand the dynamics of large complex networks. Data mining of network graphs (graph mining) is historically performed on static graphs. In recent Scalability and the complexity of data that changes over time are two of the biggest problems in visual analysis. Having a lot of different kinds of data makes it much harder to see a big picture of a lot of data (whether structured or unstructured). To analyse[5] a lot of data correctly, you need a time variable with a size that has never been seen before. Big data could be a problem when trying to make a new tool for visualising data that has good indexing. Big Data, cloud computing, and a sophisticated graphical user interface can be used together to make it easier to control scalability, which can change how information is shown. Methods for visualising unstructured data need to be able to work with a wide range of data types and formats. Most of the time, big data is shown in forms that are not organized[6]. Even though bandwidth and power consumption are limits, the visualisation should get much closer to the data so that useful information can be gathered as quickly and easily as possible. It is best to run the visualisation software on your own computer. Due to the sheer amount of data being processed, there needs to be a lot of parallelization of the data for data visualisation to work well. Separating a problem into separate tasks that can be done at the same time is a major problem for algorithms that allow for simultaneous viewing. When trying to see a lot of data at once, you might run into problems[7] like the ones below: Visual clutter: most of the parts of the dataset are connected in too many ways. When looking at a lot of data, there are often other problems to deal with, like the ones below. They can't be looked at separately because they can't be taken apart. There is a chance that some useful information will be lost when the size of publicly available datasets is cut down. In addition to the aspect ratio and device resolution, the way a person sees things also limits the ways that data can be shown. The speed at which the picture is coming together[8]: customers look at data, but they can't respond to the volume or intensity of how quickly the data changes. Performance needs are high, but in static visualisation, they are less obvious because the speed of the display doesn't need to be as fast. Things to think about before picking a visualization To reach your goal of effectively communicating with your target audience, you need to change how the information is delivered. Users of fitness software who want to keep track of their progress will like how easy the app is to use. But it's fine — and often encouraged — to use more complicated visual aids than simple diagrams when explaining ideas to scientists or experienced decision-makers. This is because scientists and people with a lot of experience making decisions have more knowledge and experience. We're happy to tell you that the strategies used were the best ones for the types of data that were in question. Line graphs, for example, are often used to show how metrics change[9] over time and how they interact with each other. You will use something called a "dispersion plot" to show the relationship between two variables. Because of the way they are made, bar graphs are especially good for comparing things. Depending on how they are presented, your graphs can be understood in a number of different ways. for example, use a shimmering colour to draw attention to the most important part of the graph, such as a big increase in profits compared to the previous years. Instead, we use colours that are different from each other to do this. Just a few words about dynamics. Every piece of information represents a different rate of change. For example, financial results might be measured once a month or once a year, while time series and data tracking are always changing. Depending on the nature of the shift, a static representation might be more acceptable. However, a dynamic (steaming) representation would be more accurate. How the data is looked at depends a lot on what the people looking at it plan to do with it. Dashboards can include visualisations, checks, and filters to make it easier to look at a system as a whole or combine different types of data to get a more in-depth view. You don't need a dashboard, though, if all you want to do with your data presentation is show off a single piece of information here and there.

3. PROPOSED METHODOLOGY

The vast majority of the objects in the dataset are too close to each other, making it impossible to tell them apart. There is no way to tell the difference between the two with your eyes[10], and the user can't either. It is possible to make a set of data easier to work with by hiding data that is less important, but doing so could cost you important insights.

Data visualisation methods are limited by both the size of the display and the ability of the human visual system to understand information at a certain scale.

People might find it hard to keep up with the fast changes in the way things look on the screen[11].

In contrast to dynamic visualisation, which has strict requirements for speed, static visualisation often makes it hard to see how well it works.

There are a lot of problems with visualising huge amounts of data, including problems with scalability, how the data is shown, and how useful it is. When too many data points are plotted at once, it may be hard to understand and think about the information. When data are deleted, either by sampling or filtering, it is possible that interesting patterns or outliers will be hidden. People's conversations can be thrown off by how long it takes to get answers from very large data sources [12]. Eventually, in some way... [Note: Needs a citation]

In the context of Big Data applications, data visualisation is a big problem because Big Data is so big and has so many different dimensions. Most of the methods we have now for visualising large amounts of data are either too slow or don't work well enough, or both. When doing visual analytics, it can be hard to make good visualisations when there is a lot of uncertainty [13].

The problems and worries that come up when you try to visualise a lot of data, as well as possible solutions, were looked at [14]:

At first, hardware might be used to satisfy the need for action right away that the situation creates. This used to be impossible, but changes in RAM size and parallel computing have made it possible now. Grid computing uses a network of different computers to store data in RAM in a different way than traditional methods.

Data analysis can be made easier with the help of people who know a lot about a certain subject.

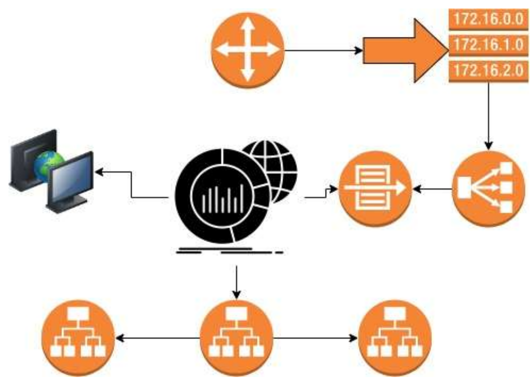

Figure 2: proposed dynamic representation and visualization in networking for big data(DRVN-BD)

Third, the data's quality needs to be looked at. Data governance and information management give us the tools we need to check the accuracy of the data.

The fourth step in telling people about big discoveries is to break down the related information into smaller pieces that are easier to understand and can be seen clearly.

When working with data that has outliers, you either have to get rid of the outliers or show them in a way that is different from the norm. The main goal of this study is to come up with effective and inexpensive data structures for cluster indexing. Because of this, it will be easier to run queries across very large networks. In other words, this can be done at the same time as step. During step, the most important characteristics will be used to form clusters, and duplicates will be removed automatically. Right now, a low-cost cluster[15] is being worked on to make it better and ready to use. On the other hand, if this strategy is used, it could cut the number of redundant network nodes by a large amount. A lot of research has been done on how networked systems work and how they change over time. A run-through of the most common ways to do dynamic network analysis. Because of this, it can be hard to do a snapshot analysis and a streaming evolution analysis at the same time on a dynamic graph.

First, give users an overview of the data. Then, let users zoom in on the data and filter it. Finally, give users access to more detailed information as needed [16]. When trying to make sense of the huge amounts of data we have today, it helps to zoom out first. By using big data and visualisation tools, businesses might be able to find out everything there is to know about their customers. Relationships are a key part of many different ways that huge amounts of data can be used. Most people know that text and tables make it hard to understand social networks, which are the most well-known type of system like this. This is because social networks are made to make it easy for users to talk to each other. On the other hand, it is easy to spot new trends and patterns in networks when you use visualisation [17]. The goal of making a cloud-based visualisation method was to help users better understand the natural relationships that exist in social networks. This method has the potential to show how users get along with each other in a way that makes sense for the situation. It does this by using a correlation matrix to show the hierarchical relationship between user nodes in a social network. One other way of looking at this is as a hierarchy. This method uses a cloud that is built on Hadoop for distributed parallel processing of visualisations [18]. This is helpful for quickly processing the huge amounts of data that are usually associated with social networks.

Multiple representation displays, dynamic factor changes, filtering (dynamic query filters, star-field display, and tight coupling), and other methods can be used to show a lot of data . Some other ways are: Displays with tight coupling, star fields, and many different representations are also easy to use. The different ways of visualising data were put into groups and rated based on the characteristics of the data, such as (1) the amount of big data, (2) the different kinds of data, and (3) the rate at which the data changes [12]. A space-filling tree diagram is used by the Treemap method to show data that is based on a hierarchy. In addition to treemap, there is also circular packing, which is very closely related to treemap. In addition, its basic shape is a circle, and more complex hierarchies can be used to nest other shapes inside circles. Sunburst shows the information as a treemap that is set up by polar coordinates. One of the most important differences is that the dimensions that can be changed are not the horizontal and vertical ones, but rather the arc's length and radius. This is the one and only thing that really sets them apart from everyone else. When looking at a larger set of data, using parallel coordinates lets you look at the data visually in a more thorough and complete way. Because of this, we can now look into a wider range of topics. Streamgraphs turn the stacking so it is in the middle of an axis. The graph now has a shape that looks more organic and natural. Streamgraphs are a type of stacked area graph that can change the order in which its stacking elements are arranged. In a circular network diagram, the data points are grouped together and linked by arcs of different lengths. The length of each arc shows how far apart the data points are. Comparing the lengths of the lines or the saturation of the colours of two things is a common way to figure out how big one thing is compared to the other.

Still, when there is a lot of data, the usual ways of visualising data are likely to get clogged up very quickly. Several different ways were used to show how data changed over time. First, a design area for scalable visual summaries was talked about. Every summary gives a different kind of information by making good use of the information that is available (such binned aggregation or sampling). After multivariate data tiles were added to concurrent query processing, interactive querying strategies for binned displays like brushing and joining were made possible. Because of this, people reached out to each other. imMens is a visual analysis system that can be accessed through a web browser and uses tried and true methods. [13] It processes data and shows images by using WebGL on the graphics processing unit (GPU). The Hadoop architecture makes it possible to make many different tools for studying large amounts of data in depth. Some of the most important parts of Hadoop are Hadoop Common, Hadoop Distributed File System (HDFS), Hadoop Resource and Job Scheduler (YARN), and Hadoop MapReduce. Their strength is in analysing data, but they have a lot of room to improve when it comes to graphing. To make data visualisations easier to understand and use, a lot of software packages that focus on interaction and visualisation have been made [3]. Pentaho is a business intelligence (BI) platform that offers many tools, such as data mining, enterprise-level reporting, interactive dashboards, and in-depth company data analysis. Flare is a data-visualization library. It was made with ActionScript, and you'll need Adobe Flash Player for it to work. This place sells flair, and that's where you can buy it. There is also a layer of cutting-edge software called JasperReports that is built in. Its main job is to make reports by digging through huge data warehouses to find information that is relevant to the problem at hand. Dygraphs is a toolbox for making graphs that has everything you need. JavaScript was used to make it. It's not hard to adjust, and it moves very quickly. One of the things it is used for is to find patterns in large datasets that might be hard to understand otherwise. Datameer Analytics Solution with Cloudera: Datameer and Cloudera have joined forces to give users a solution that will help them get the most out of the Hadoop architecture while reducing the time and effort needed to put it into production. With the help of the Platfora tool, Hadoop's huge amount of unprocessed data can be turned into an interesting engine for processing data. Users can choose from a lot of different configuration settings for the in-memory data engine.

IBM uses a tool called ManyEyes to help them see what they are doing. Many Eyes is a public website where anyone can put in their own data and build their own interactive visualisation. Many Eyes is the name of this site. Tableau is a type of business intelligence (BI) software that lets you look at data in a graphical and interactive way. Tableau is part of some packages of BI software. When using a data engine that runs entirely in memory, the time it takes to visualise data can be cut down, which is a good thing. The Tableau Desktop edition, the Tableau Server edition, and the Tableau Public edition are the three most important pieces of software to have if you want to use Tableau to manage large datasets. Tableau supports Hadoop, and it also has its own help for the data storage system built in. It uses the Hive architecture, which means that analytical processes can be done in memory instead of on the disc. This takes away the need to access the disc. By caching, Hadoop clusters can work faster. This means that it might make it easier for end users and applications that use Big Data to talk to each other. The technology used to handle huge amounts of data can easily handle ZB (zettabyte) and PB (petabyte) amounts of data, but it's not always easy to see what this data looks like. Hadoop, HPCC, Storm, Apache Drill, RapidMiner, and Pentaho BI are just some of the technologies that are now used to process large amounts of data. Some data visualisation tools that are available right now are NodeBox, R, Weka, Gephi, the Google Chart API, Flot, and Visual.ly. Visual.ly is another example. It was proposed that RHadoop be used as the core of a unified model to analyse and display huge amounts of data, and this is what was done. The integrated model can be used to study data from both ZB and PB, and the results of these studies can be useful. Due to the fact that the model can be changed, it is possible to make parallel methods for both ZB and PB data .

The most natural and straightforward way to find patterns of clustering is to use an interactive visual cluster analysis tool. [Clustering] The hardest part of this approach will be coming up with a way to show multidimensional data in a way that lets people explore the data in an interactive way and find hidden grouping structures. Models of star-coordinate visualisation optimization have been made so that cluster exploration of large datasets can be done in an effective and interactive way. Star-coordinate models are probably the most scalable way to show large datasets, compared to parallel coordinates and scatter-plot matrices: Even though star coordinates can have tens of dimensions, they are usually not used when there are fewer than ten dimensions. Instead, parallel coordinates and the scatter plot matrix are used. The number of different dimensions that can be shown with star coordinates is literally out of this world. Once a certain number of points in the star-coordinate representation have been reached, a density-based representation is used. Cluster displays that use star coordinates don't try to measure the distance between each individual data point. Instead, it uses a part of the mapping model that is being used in the background to keep part of the link between the distances. This function will make sure that the space between each record is always the same. With this great tool, it has never been easier to work with huge data sets.
Software for Making Visualizations from Huge Amounts of Datasets Power BI is a good tool for business analysis because it lets you view and share your data, as well as add it to applications and blogs. Your information will come to life when you connect it to a wide range of user accounts and real-time dashboards. By using Microsoft Power BI, a person can learn new things about their company's data. Power BI can share, convert, and clean the data before it is shown visually as a chart or diagram. All of this information can be shared with other people in the organisation who use Power BI. The data models that come with Power BI can be used in a business in a number of different ways, such as to do "what-if" analyses and see patterns in data. A Power BI account can also help predict how different parts of an organisation will follow the company's standards and deal with problems as they come up in real time. With Power BI's corporate dashboards, executives can learn more about their organisation. Power BI has two different dashboards. Kibana is an open-source log analysis and time series analysis information visualisation and exploring tool that can be used to keep an eye on apps and operational intelligence instances. Kibana can also search for information. There are many features available, such as histograms, graphs, pie charts, thermal maps, and built-in support for geographic information. The Kibana data visualisation tool is currently the most popular way to access data that is stored in Elasticsearch. This is because it works well with Elasticsearch, a widely used analytics and search engine. Elasticsearch was made

to work with Kibana, which made it possible to see and understand complicated streams of data in real time. Elasticsearch and Kibana were made to work together. Elasticsearch's analytics not only give new ideas, but they also make mathematical improvements that make the process of gathering information more efficient. The software makes an interactive dashboard that is colourful and includes PDF reports when the user wants it to or at set intervals. The papers that are made can show search results in bar, row, scatter plot, and paste graph sizes, and the colour schemes can be changed to suit your needs. The Kibana system also lets you share and visualise data.

Grafana is a set of open-source tools for measuring and displaying data. It comes in at number three. But many people also use it for infrastructure and implementation analysis, as well as agricultural and home automation, climate and process control, and so on. It is also used in a lot of other situations.

Tabulation Tableau has been widely used in the business intelligence industry because it is a powerful and quickly growing tool for visualising information. Simplifying the raw data can make it easier to understand. Tableau's data analysis is very fast, and the dashboards and tablets that come out of it show you what the data looks like. Using Tableau, any knowledgeable person in any department in an organisation can make sense of the organization's data. Even if you don't know much about technology, you can use this software to make your own dashboard. Some of Tableau's finest qualities are Combining data analysis done in person with analysis done in real time Sharing information is one of Tableau's best features because anyone can use it without needing technical or programming skills. People from different walks of life, including business professionals, academics, and workers from a wide range of fields, have shown interest in the instrument.

4. DISCUSSION

The goal of this paper is to give a broad overview of network theory, which is the basis for big data. Specific topics covered include the capacity, management, and data processing needs of big data; the architecture of big data, which includes the MapReduce paradigm and the Hadoop distributed architecture; fabric network infrastructure; and software defined networks (SDN). Managing large amounts of data is becoming more and more important, so there is a pressing need for more research to find effective solutions. When trying to use this technology, it is important to keep in mind the specific needs that big data has for its networking infrastructure. Some of these abilities are the ability to scale, keep performance consistent, handle huge amounts of traffic, and split data into multiple parts. Big data is very demanding, and it is clear that this is putting a strain on the different network infrastructures that are already in place. MapReduce and Hadoop are both examples of frameworks for processing large amounts of data. These frameworks make it easier to manage and process data by splitting up the work so that it can be done at the same time all over the network. Scientists who study data have found that a topology based on a fabric is the best way to send large amounts of data over a network. It has many advantages over a hierarchical one, such as better load balancing and scalability, less latency, and fewer bottlenecks. Other benefits include faster and more efficient work. After finding that many Big Data networking theories talked about eventually integrating with SDN, we show how software-defined networking (SDN) can be used to solve Big Data problems that can be solved through programming with the right topology, scheduling, and optimization techniques. In particular, we show how SDN can be used to solve problems with Big Data that can be solved by using optimization techniques. This study comes to a close by giving an overview of how big data works, comparing and contrasting different network topologies, going over ways to process, store, and manage huge amounts of data, and looking at possible solutions.

5. CONCLUSION

Visualizations can be static or they can move around. Unlike with static information tools, when you look at content in an interactive format, you often find out new things. One way to quickly get a feel for the size of the big data project you are working on is to use an interactive view. Using tools like interactive brushes and linking visualisation techniques to web resources can speed up the scientific method. Using a web-based interface, it is possible to keep an eye on live data and make changes in response to any changes. Some ways of visualising data can't be changed to handle large amounts of data. It is important to come up with new ways to look at big data and to develop technologies that can be used in a wide range of big data applications. More research needs to be done to find more effective ways to scale up to larger networks.

Reference

[1]. Zaidi, F., Muelder, C., Sallaberry, A. (2014). Analysis and Visualization of Dynamic Networks. In: Alhajj, R., Rokne, J. (eds) Encyclopedia of Social Network Analysis and Mining. Springer, New York, NY. https://doi.org/10.1007/978-1-4614-6170-8_382

[2]. Li, W., Wu, S., Song, M. et al. A scalable cyberinfrastructure solution to support big data management and multivariate visualization of time-series sensor observation data. Earth Sci Inform 9, 449–464 (2016). https://doi.org/10.1007/s12145-016-0267-1

[3]. Torre-Bastida, A.I., Díaz-de-Arcaya, J., Osaba, E. et al. Bio-Inspired computation for big data fusion, storage, processing, learning and visualization: state of the art and future directions. Neural Comput & Applic (2021). https://doi.org/10.1007/s00521-021-06332-9.

[4]. Marwan Al-shawi and Andre Laurent – Designing for Cisco Network Service Architectures (ARCH) Foundation Learning Guide: CCDP ARCH 300-320 (ISBN 158714462X)

[5]. Saleem, M., Valle, H.E., Brown, S. et al. The Hiperwall tiled-display wall system for Big-Data research. J Big Data 5, 41 (2018). https://doi.org/10.1186/s40537-018-0150-7

[6]. Qi, E., Yang, X. & Wang, Z. Data mining and visualization of data-driven news in the era of big data. Cluster Comput 22 (Suppl 4), 10333–10346 (2019). https://doi.org/10.1007/s10586-017-1348-8

[7]. Olshannikova, E., Ometov, A., Koucheryavy, Y. et al. Visualizing Big Data with augmented and virtual reality: challenges and research agenda. Journal of Big Data 2, 22 (2015). https://doi.org/10.1186/s40537-015-0031-2

[8]. Mohamed, A., Najafabadi, M.K., Wah, Y.B. et al. The state of the art and taxonomy of big data analytics: view from new big data framework. Artif Intell Rev 53, 989–1037 (2020). https://doi.org/10.1007/s10462-019-09685-9.
[9]. Bibri, S.E., Krogstie, J. The core enabling technologies of big data analytics and context-aware computing for smart sustainable cities: a review and synthesis. J Big Data 4, 38 (2017). https://doi.org/10.1186/s40537-017-0091-6
[10]. Mishra, P., Kumar, S. & Chaube, M.K. Graph Interpretation, Summarization and Visualization Techniques: A Review and Open Research Issues. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-021-11582-9.
[11]. Zenkert, J., Klahold, A. & Fathi, M. Knowledge discovery in multidimensional knowledge representation framework. Iran J Comput Sci 1, 199–216 (2018). https://doi.org/10.1007/s42044-018-0019-0
[12]. Katsurai, M., Ono, S. TrendNets: mapping emerging research trends from dynamic co-word networks via sparse representation. Scientometrics 121, 1583–1598 (2019). https://doi.org/10.1007/s11192-019-03241-6
[13]. Pathak, A.R., Pandey, M. & Rautaray, S. Construing the big data based on taxonomy, analytics and approaches. Iran J Comput Sci 1, 237–259 (2018). https://doi.org/10.1007/s42044-018-0024-3
[14]. Mohan, A., Pramod, K.V. Network representation learning: models, methods and applications. SN Appl. Sci. 1, 1014 (2019). https://doi.org/10.1007/s42452-019-1044-9
[15]. Zhuang, Yt., Wu, F., Chen, C. et al. Challenges and opportunities: from big data to knowledge in AI 2.0. Frontiers Inf Technol Electronic Eng 18, 3–14 (2017). https://doi.org/10.1631/FITEE.1601883.
[16]. S. F. Boubrahimi, B. Aydin, D. Kempton, S. S. Mahajan and R. Angryk, "Filling the Gaps in Solar Big Data: Interpolation of Solar Filament Event Instances," 2016 IEEE International Conferences on Big Data and Cloud Computing (BDCloud), Social Computing and Networking (SocialCom), Sustainable Computing and Communications (SustainCom) (BDCloud-SocialCom-SustainCom), 2016, pp. 97-104, doi: 10.1109/BDCloud-SocialCom-SustainCom.2016.25.
[17]. M. Glenski et al., "Learning Global Proliferation Expertise Evolution Using AI-Driven Analytics and Public Information," in IEEE Transactions on Nuclear Science, vol. 69, no. 6, pp. 1375-1384, June 2022, doi: 10.1109/TNS.2022.3162216.
[18]. Z. Peng, L. Wu, J. Ren, R. Zhang and P. Luo, "CUImage: A Neverending Learning Platform on a Convolutional Knowledge Graph of Billion Web Images," 2018 IEEE International Conference on Big Data (Big Data), 2018, pp. 1787-1796, doi: 10.1109/BigData.2018.8622090.
[19]. Y. Zhou, H. Chen, Y. Wu, J. Wu, J. Li and L. Chen, "A Method for Analyzing Pick-Up/Drop-Off Distribution of Taxi Passengers' in Urban Areas Based on Dynamical Network View," 2019 IEEE International Conference on Big Data and Smart Computing (BigComp), 2019, pp. 1-8, doi: 10.1109/BIGCOMP.2019.8679396.

[20]. S. Zhang, J. Li, H. Zhou, Q. Zhu, S. Zhang and D. Wang, "MERITS: Medication Recommendation for Chronic Disease with Irregular Time-Series," 2021 IEEE International Conference on Data Mining (ICDM), 2021, pp. 1481-1486, doi: 10.1109/ICDM51629.2021.00192.
[21]. Ram Kumar, Sarvesh Kumar, Kolte V. S.," A Model for Intrusion Detection Based on Undefined Distance", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-1 Issue-5, November 2011