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# Big Data: Opportunities and Challenges in Asset Management

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16. Abstract

State Departments of Transportation and other transportation agencies collect vast quantities of data but managing, accessing and sharing data has been problematic and well documented. This project reviewed the similar challenges faced by other industries and investigated what approaches have been taken by these industries to address those challenges. In the project, we also explored what kinds of data sets in the transportation industry are posing big data challenges, and reviewed relevant studies on emerging applications of these data sets. It is reasonable to conclude that the rise of big data demands more efficient and effective and scalable data analysis methods that must transcend traditional analysis methods in the field of statistics, data mining and machine learning. Therefore, a detailed literature survey was also conducted on what kind of tools and data analytics have been proposed and used for big data analytics. Many use cases are highlighted in the report to demonstrate the opportunities with big data. At the end of the project, a half-day workshop was conducted to disseminate the findings of this research and solicity inputs from leading industry and academic researcher in the field of engineering informatics, cloud computing, and big data analytics. Many presentations in the workshop have echoed the findings of this project.

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# INTRODUCTION

## Description of the Problem

Asset management is largely a data driven process as one of the key elements of asset management is using data to support decisions. However, the databases representing inventory and historical records of road, bridge, and roadside assets collected using video logging, automated pavement distress survey, regular inspections, structural health monitoring, and other methods can rapidly explode. Such data is key to maintaining physical assets in a state of good repair and addressing safety issues. Simple tasks such as capture, curation, storage, search, sharing, and analysis are challenging as our ability to collect data expands. Ideally “better” data will be understandable, transparent, interoperable, automated, and visual. Some of the experiences with "big data" in other fields may help to manage, more pro-actively, our data assets to support the management of our physical assets. “Big Data” refers to data sets that are so large and complex they are not easily manipulated using the commonly available database tools. These challenges are characterized by the three “V’s” – velocity, volume and variety. This project identifies areas where big data may be an issue for asset management in DOTs and develops strategies for dealing with big data.

## Relevance to Strategic Goals

Each of the USDOT Strategic Goals is supported by data and "big data" plays a role. Data from diverse and diffuse sources can be used to support and inform decisions and develop models. This project focuses on data to support decisions related to state of good repair. In turn, these decisions are strongly influenced by the impact on safety and economic competitiveness. Many of the tools and techniques to be explored are broadly applicable to all the strategic goals.

## Background

"Big Data" promises to provide insights into behavior, performance and interactions. At the same time, the nature of the data sets poses challenges as not all data have the same quality. Boyd and Crawford (2011) identify six issues: 1) Automating the analysis changes the definition of knowledge; 2) Objectivity and accuracy; 3) Better data; 4) Data quality and consistency; 5) Ethics; and 6) Limited access. While some of these issues are more relevant to the social sciences, all have some relevance to the data needed to support asset management and the opportunities arising from access to users' preferences and behavior, and sharing of data across jurisdictions.

State Departments of Transportation have frequently been characterized as "data rich but information poor." The departments collect vast quantities of data but managing, accessing and sharing data has been problematic and well documented. National Cooperative Highway Research Program Report 706 (Cambridge Systematics Inc, 2011) recognized nine categories of data processes that offer potential for addressing these issues:

- Collection,
- Archiving/storage,
- Processing,
- Analysis,
- Reporting/dissemination,
- Sharing,
- Access,
- Institutional issues, and
- New technology.

"Big Data" offers solutions in many of these areas, particularly data processing and analysis in terms of data quality and metadata. However, the challenges associated with governments using big data are all too familiar – the need to break down silos, the control tower approach to security and privacy and the enormous variety of data. (Kim et al, 2014).

## Research Goals and Objectives

The goal of this project is to identify the types of "big data" that can be used for asset management, and the appropriate tools for the analysis of this data, as well as other alternatives such as data mining and meta data.

Specific objectives are:

(1) Defining what constitutes "big data" for asset management

(2) Understanding when to use tools such as Hadoop and Mapreduce and their strengths and limitations (Lin, 2013)

(3) Identifying opportunities for data integration, data mining, visualization, meta data and other techniques for data aggregation and summarization (techniques such as PDA (DeCoster, 2004)

(4) Identifying ways to share data.

The products of this research will be a catalog of tools and techniques including where they should be applied and their limitations for analyzing data to support asset management.

## Overview of the Report

This report documents the research approach, methodology, findings, conclusions and recommendations of this collaborative research project. The following sections outline the approach and methodology. The next section presents the findings, followed by sections documenting the conclusions and making recommendations for future work and application in state Departments of Transportation.

# APPROACH

This collaborative research project was conducted by researchers at Rutgers University, Utah State University[1], and University of Delaware. The project builds on the research

[1] Professor Kevin Heaslip, formerly at Utah State University is now at Virginia Tech.

team’s experience and expertise in computing methods and asset inventory data collection. Three key areas were addressed:

- Data collection, data query and information retrieval, and data visualization.
- The role of data from traffic operations and ITS.
- Techniques for metadata analysis, data aggregation and summarization.

Key elements of the project are the documentation of examples of "big data" in asset management. The documentation not only includes the type of data (graphics, text, numerical data), but also include information on data quantity and quality, access, rate of change (frequency of data collection), access and longevity. Examples of data include condition data, traffic data, related data such as census, weather and environmental data and descriptive data. Data of special interest includes research data and its management. To facilitate the exploration of "big data" we pose questions that require the use of "big data" techniques to obtain answers.  This was accomplished in consultation with our partners in state DOTs.

The project also explored techniques for analyzing big data based on literature reviews of applications in other fields such as marketing, biology, and sociology.  This served as the foundation for a catalog of "big data" tools and techniques. As a complement to the catalog, we also identified environments to support data sharing include applications such as Mathematica's Alpha and cloud based options.

Finally we will evaluate the tools and techniques in terms of their strengths and weaknesses for answering "big data" questions related to asset management.  Our team developed criteria that are broadly applicable and helped us to benchmark the techniques.

## METHODOLOGY

The project relied largely on literature review, discussion and expert input. The original proposal involved eight tasks that are summarized here for completeness.

Task 1: Identify "big data" relevant to asset management.

This task required exploration of a wide variety of data sets and the relationships between different types of data that may be used for operations and real-time management but are rich sources of information on user preferences and behavior related to usage of physical infrastructure. Other data sets include environmental and census data and research data particularly in areas like structural health monitoring. This task will make use of various databases, our research partners, and the literature in the field.

Task 2: Develop questions related to "big data" and asset management.

These questions are used to guide our search for and evaluation of tools and techniques. They help us to understand how we can use "big data" to support asset management. For example, much of the discussion about identifying adaptation techniques for transportation infrastructure to respond to climate change suggest using asset management as the decision making strategy. However these decisions require understanding land use, environmental data, climate models, and infrastructure deterioration in the context of topography, hydrology and other natural features. We conferred with our research partners to help with this task.

Task 3: Identify environments to support data sharing.

Much of the relevant data is not widely accessible. Security concerns are often largely unfounded. Nevertheless security is an issue but the assembling data from multiple jurisdictions offers opportunities for new insights and adequate data to support model development. Over the past five years, new technologies including social networking and ubiquitous and cloud-based computing provide new environments to support the gathering and sharing of data that has not been fully recognized in asset management.

Task 4: Identify tools and techniques to support "big data" for asset management.

Drawing on the literature, and popular press accounts of big data applications in other fields we identify tools and techniques, in particular those related to big data analytic.

Task 5: Catalog and evaluate the tools and techniques.

We develop a catalog of tools and techniques including an assessment of their strengths and weakness in the context of the questions identified in Task 2.

Task 6. Develop and conduct a Workshop for practitioners.

Task 7: Develop a graduate course module on "Big Data" and Asset Management

Task 8: Develop the final report.

## FINDINGS

Our findings are organized around the key questions and concepts:

- What is big data?
- Characteristics of big data
- Tools for working with big data
- Examples of big data
- Examples of big data and big data questions in transportation
- Big data and asset management
- Tools for big data and asset management

### What is Big Data?

Big data is characterized as a collection of data that is very large in size as determined by the number of bytes of data. “Big” is considered to be of the order of petabytes, where:

1Pb = 1,000,000,000,000,000 b = 10^15 bytes

Big data is also loosely structured in terms of the format. **Error! Reference source not found.** is a representation of the size and scale of big data. More formally, big data is a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications. The challenges include capture, curation, storage, search, sharing, transfer, analysis, and visualization.

What is considered "big data" varies depending on the capabilities of the organization managing the set, and on the capabilities of the applications that are traditionally used to process and analyze the data set in its domain. "For some organizations, facing hundreds of gigabytes of data for the first time may trigger a need to reconsider data management options. For others, it may take tens or hundreds of terabytes before data size becomes a significant consideration.

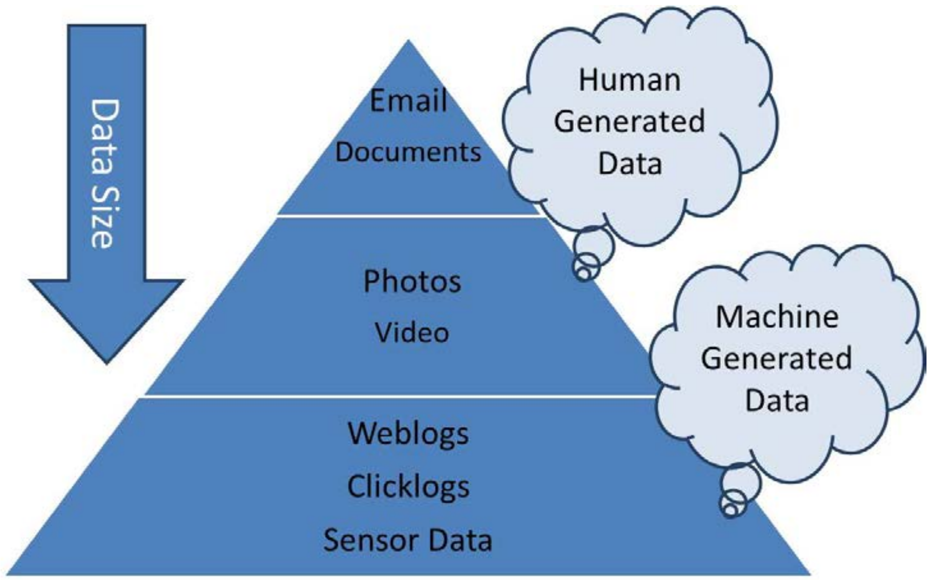


**Figure 1 A Representation of CThe Scale of Big Data**

Elements of "Big Data" include:

- The degree of complexity within the data set
- The amount of value that can be derived from innovative vs. non-innovative analysis techniques
- The use of longitudinal information supplementing the analysis

While size provides the primary definition of big data, a more refined definition also recognizes the number of independent data sources, each with the potential to interact. Big data does not lend itself well to being tamed by standard data management techniques simply because of its inconsistent and unpredictable combinations.

Although size is the primary distinguish characteristic, data variety and data structure must also be considered. Small data sets from a variety of sensors can be very big due to their data structure complexity. A well-known example is that a plane on a regular one hour flight can have a hundred thousand individual sensors monitoring the operating condition of the airplane. An hour of data collection in this situation would yield less than 3GB of data, a data volume that is not big at all. However, with so many sensors, the combinations are incredibly complex and vary with the error tolerance and characteristics of individual devices. Therefore, the data streaming from a hundred thousand sensors on an aircraft is big data. In contrast, there are an increasing number of systems that generate very large quantities of very simple data. Although these data sets are very large, such as media streaming data sets, they are not big in the same way as the data coming from arrays of different sensors deployed in advance machinery systems.

### Characteristics of big data

There are many recent efforts to characterize big data. A recent research report (Douglas, 2001) defined data growth challenges and opportunities as being three-dimensional, i.e. increasing volume (amount of data), velocity (speed of data in and out), and variety (range of data types and sources). Since then, Gartner (Beyer, 2011), and now much of the industry, continue to use this "3Vs" model for characterizing big data. In 2012, Gartner refined its definition as “Big data are high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization (Douglas, 2012)." Some organizations also added a new V “veracity” as a dimension to characterize big data. This is due to the fact that the trustworthy of big data becomes a growing concern as the variety and number of sources grows.

Thinking context-based may add more Vs to definition. For instance, in the context of travel and transportation “Value” is another V. The notion of value is twofold. It is the value from improving internal operational capabilities, but it is also about improving the customer/consumer experience and generating incremental revenue. Berman (2013) lists some additional characteristics of big data:

- Big data is often housed in multiple locations because of the size and computational demands of big data.

- Big data often has very flexible goals and isn't designed to answer a specific question,
- Big data needs to be stored in perpetuity, and
- Big data needs to be queried even to understand what it inside the database.

In summary, the existing literature characterizes big data based on 3Vs, flexible goals, location, structure, longevity, reproducibility, introspection, condition, and population. Table 1 provides a quick summary of these attributes.

**Table 1 Big Data Characteristics**

| Attributes | Characteristics |
|---|---|
| 3 V's | Volume: a lot of data<br>Variety: different formats<br>Velocity: content is constantly changing through addition of new data |
| Flexible goals | data isn't designed to answer a specific question |
| Location | Stored in multiple locations |
| Structure | Includes many types of data including unstructured |
| Longevity | Data often stored in perpetuity |
| Reproducibility | Changes in data make analysis unrepeatable |
| Introspection | Need to query data for even an understanding of what the data contains |
| Condition | Big data is "dirty" because of multiple sources and after merging can be fuzzy |
| Population | Merge of multiple non-random samples of unknown populations |

## Examples of Big Data

As our world becomes more connected and large numbers of distributed sensors collect data in every shrinking time steps, big data is ubiquitous and continues to grow and expand. Companies have been using big data to help us make selections, provide us with current and relevant information, and make our environments more comfortable and functional. Table 2 lists some of these typical applications.

**Table 2 Applications of Big Data**

| Area | Actions | Organizations |
|---|---|---|
| Consumer behavior and preferences | Movie selection | Netflix |
| | Social network connections | Facebook |
| | Purchases | Amazon |
| Finance | Credit card fraud | |

| | | |
|---|---|---|
| | Stock trends | |
| Infrastructure | Dynamic analysis of electric power consumption (smart meters | |

The following sections provide more specific examples of applications in some pioneering industries such as healthcare, the automotive industry, supply chains and logistics, retail and entertainment.

**Healthcare**

According to McKinsey (Groves et al, 2013), companies who miss big data opportunities of today will miss the next frontier of innovation, competition, and productivity. This opportunity is emerging with the conversion to Electronic Medical Records (EMR). Among other things, EMR allow data to be exchanged more easily. To prevent privacy concerns, the new programs remove names and other personal information from records being transported into large databases, complying with all health insurance portability and accountability act (HIPAA) patient-confidentiality standards. Companies that have already commercialized big data privilege include, but are not limited to:

- Premier, a group purchasing organization and information aggregator. Premier provides data driven informatics derived from integrated data sets.
- OptumInsight for United Health, Active Health for Aetna, and Healthcore for Wellpoint. These companies provide services related to data driven issues like cost and performance benchmarking, as well as opportunities for data integration using different data sets.
- Italian Medicines Agency. They collect and analyze clinical data on expensive new drugs as part of national cost-effectiveness program.  Based on the results, it may re-evaluate prices and market access conditions

Examples of the impacts of big data on the healthcare system include:

- The use of pathways - right living, right care, right provider (always treat by high performing professionals), right value (cost effectiveness of care), right innovation (identification of new therapies) – to customize healthcare. These value pathways are always evolving as new information becomes available to inform what is right and most effective, fostering an ecosystem feedback loop. **Error! Reference source not found.** shows an assessment of the impact on healthcare costs.

- Kaiser Permanente has fully implemented its health connect system to ensure information exchange across all medical facilities and incorporate electronic health records into clinical practice. The integrated system reduced total office visits by 26.2% and scheduled telephone visits increased more than eightfold (Chen et al, 2009).

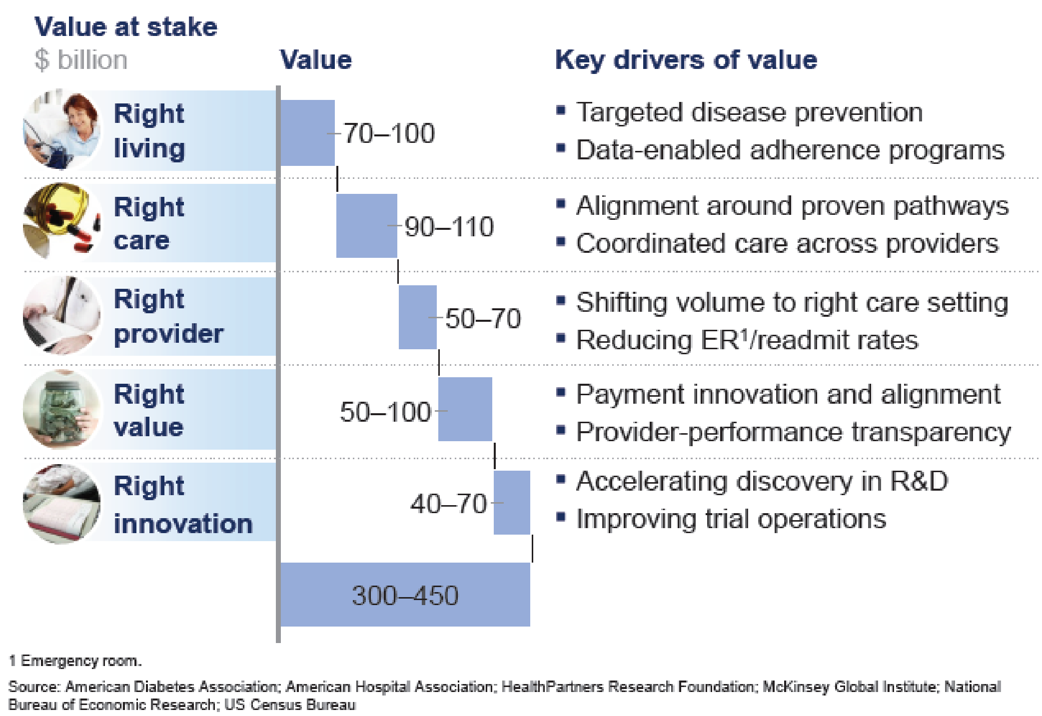


**Figure 2 The Impact of Pathways on Reduction in Healthcase Costs (Source: Groves et al, 2013)**

  - Example: prevention actions in right living pathways, aspirin use by those at risk for coronary heart disease, early cholesterol screening for patients with associated family histories, hypertension screening for adults could reduce the total healthcare costs by $38 billion.
  - Long-term benefits of big data is clear, what about short to medium-term impacts?

    - Some companies currently benefit from the inefficiencies that a lack of liquid data provides, and they could lose business as more information becomes public.
- Asthmapholis has created a GPS-enabled tracker that monitors inhaler usage by asthmatics. Information ported to central database, identify population trends, and developing personalized treatment plans and spot prevention opportunities.
- Ginger.io. Smartphone application for diabetes patients.
    - Making core definitions by evidence and value – make it less subjective
    - Changing mindset to share instead of protect
    - Investment on: Data analysis, data management, and system management

**The Automotive Industry**

Increasing digitization and connectivity of modern vehicles provides access to unprecedented amounts of data. A white paper by T-Systems International GmbH provides some insights into the variety of applications of big data (T-Systems International GmbH, 2013).

The industry is facing an array of challenges that cannot be tackled with design, development, and production excellence alone. Manufacturer-customer communication can help to tackle these issues. One example of these issues could be “Recalls”.

Recalls are one of the most hotly debated topics on the world’s top automobile forums is product recalls – a carmaker’s worst nightmare. In addition to the enormous cost of ordering thousands of vehicles back to dealerships, a recall nearly always damages a company’s carefully choreographed and cultivated image. According to industry figures, Japanese automaker Toyota recalled about 10 million vehicles between 2009 and 2010 – for relatively trivial errors such as loose floor mats and sticky gas pedals. Though the majority of the recalls took place in North America, more than 200,000 vehicles were affected in Germany. This incident is a clear example of missed opportunities. Long before the recall, reports from drivers had flooded diverse web forums and social media platforms, not to mention direct customer contact, as evidenced by actual complaints at dealerships.  However, they were apparently unable to read the all-too-clear warning signs, much less react. Before the floor mat debacle, Toyota did not have an active social media strategy. On the other hand, applications of social media at various car dealerships are soaring.

In another example, Ford has a massive, distributed and varied data environment to begin with—and is creating new data wells with a slew of new connected machines, including the end product, vehicles. For example, Ford's modern hybrid Fusion model generates up to 25 gigabytes per hour—all data that is a potential goldmine for Ford, as long as it can find the right pickaxes for the job.

Another rising application of big data in the field of automotive industry is car sharing. For example, Uber is a smartphone-app based taxi booking service which connects users who need to get somewhere with drivers willing to give them a ride. Uber's entire business model is based on the very Big Data principle of crowd sourcing: anyone with a car who is willing to help someone get to where they want to go can offer to help get them there. Because Uber holds a vast database of drivers in all of the cities it covers, they can instantly match customers who ask for a ride with the most suitable drivers.

Other applications of big data within the industry are: 1) User-based insurance services such as "Pay As You Drive (PAYD); 2) Location-based services (local weather information, traffic warnings, parking space locators, and 3) autonomous driving.

**Supply Chain, Logistics, and Industrial Engineering**

Railroad and trucking industries have begun leveraging big data in operations. For example, the Union Pacific Railroad, the nation's largest railroad company, mounts infrared thermometers, microphones and ultrasound scanners alongside its tracks. These sensors scan every train as it passes and send readings to the railroad's data centers, where pattern-matching software identifies equipment at risk of failure. Data is sent via fiber-optic cables that run alongside UP's tracks back to its Omaha-area data centers. There, complex pattern-matching algorithms flag the outliers, letting experts decide within five minutes of taking a reading whether a driver should pull a train off the track for inspection, or perhaps just slow it from 70 to 35 mph until it can be repaired at the next station. Using all of these technologies, UP has cut bearing-related derailments by 75%. Union Pacific is a choice place to assess the gap between the dream and the reality of what's commonly called the "Internet of things." Like a lot of technology movements, the Internet of things is easy to describe but hard to execute. It means putting sensors on all manner of machines to collect data, linking them over wired and wireless networks, and then applying data analytics to assess when a train's wheel needs replacing, a power plant needs fixing, a soybean field needs watering, or a patient needs reviving. In the trucking industry, companies are using telematics and big data to streamline trucking fleets and how they can improve fuel usage and routes. It is estimated that these types of new capabilities can contribute $15 trillion to the global GDP by 2030 by using systematic, data-driven analysis to trim costs (Ullekh 2012).

**Retail**

The large amounts of data collected by retailers and financial institutions made it possible to extract consumer behaviors with business intelligence and analytics. Some of these applications also drive the need of real-time data processing. For example, Walmart is using big data from 10 different websites to feed shopper and transaction data into an analytical system. More specifically, Walmart uses The Inkiru Predictive Intelligence™ platform, which provides an enhanced view of customers and makes predictions about their current and future transaction behavior. The Inkiru Predictive Intelligence Platform includes:

- Predictive algorithms, customized to address your specific business challenges. The predictive analysis can be implemented to address many challenges on areas such as revenue enhancement, customer satisfaction, inventory, and loss management.
- Mapping of information and its interrelationships to better understand each customer interaction.
- Scoring of customers and their information throughout each transaction, enabling progressive analysis of each transaction.
- Just-in-time recommendations provided by the system and customized through the Decision Logic engine. These recommendations help drive behavior within

your organization on how to work with each customer while they interact on your site.

- Decision Logic engine to enable customization of the actions taken as a result of the platform's recommendations.
- Online and Offline Champion/Challenger testing to allow businesses to test new predictive algorithms against actual transaction information with a graduation cycle to implement the algorithms in a production environment.
- Machine learning techniques that automatically renew algorithms, keeping the analysis up-to-date and minimizing maintenance and refreshes.
- Integration with data from a variety of external sources to augment your transactional information, providing a much greater degree of insight about each customer interaction as it happens.
- Customer Portal providing innovative dashboards that expose the decision logic, the analysis, and the results of the predictive algorithms, enabling analysts and business owners to see their results in real time.

The other examples include:

- **Sears and Kmart** are also trying to improve the personalization of marketing campaigns, coupons, and offers with big data to compete better with Wal-Mart, Target, and Amazon.
- **Amazon** is using Hadoop to support its associates program, in which affiliates post links to Amazon-based products on their websites and get a percentage of related revenue. Second, Amazon uses Hadoop to classify high-risk, high-value items that must be stored in highly secured areas of its fulfillment center.
- **Airbnb** is an online marketplace that allows anybody to advertise and rent out spare room to travellers. If you're living in San Francisco, for example, and have a free couch, you could make a few bucks if you let a backpacker from France crash in your living room for a couple nights. Like Amazon, Airbnb uses Hadoop to store all of its user data – that's 10 million http requests per day – to support multiple use cases.

- **S&P CapitalIQ** provides its users with comprehensive information around particular companies or organizations they may want to invest in. It does this by allowing users to build personalized, online dashboards that detail the "key developments" of the companies they're interested in. They leveraged Hadoop to suggest to users which companies to keep an eye on by analyzing both user behavior and tracking and scoring news stories related to the companies it watches. For example, it analyzes news stories and press releases to determine which events to highlight in a company's history. The system learns as it processes more and more data, so it now knows for example that a company announcing a "dividend increase" is more noteworthy than a "dividend affirmation," which is nothing more than company confirming a previous announcement (Zeralli and Strenberg, 2012).

**Entertainment**

There are abundant big data applications in the entertainment industry. Aggregate data analysis and predictive analytics are helping cable firms redistribute bandwidth, retain Netflix-centric customers, suggest decent advertisements, and provide custom packages. Companies such as Time Warner Cable have been using big data to determine the course of both their marketing efforts and their network infrastructure. Big Data is also a part of everyday life in the advertising department. According to Time Warner Cable Media president Joan Gillman, the company uses sophisticated correlation solutions that meld publicly available data such as voter registration records and real estate records with local viewing habits. This helps Time Warner's clients launch custom campaigns tailored to geographic or demographic microsegments of users. In the video gaming industry, the industry has grown from 200M active users to 1.5B players worldwide. Many games, such as Battlefield and Call of Duty, serve millions of players a day and numbers close to that concurrently. As they play, they leave behind traces of themselves, behaviors, activity, and even their own personalization–all of these digitally recordable as data that tells video game companies how consumers play their games. Add together the potential 1.5B players, indicates that so much of data is difficult to sift through it without a plan–or an analytics suite. EA CTO

Rajat Taneja has mentioned that EA has turned to the ever-popular Hadoop for collating and processing all that information, which is then distilled down using map reduce in order to allow distinct elements of the gameplay to be visualized. A process that used to take EA days to boil down and recondense now can occur in a matter of minutes; allowing the game company to mix historical data and current models of player behavior to see what's going on.

**Electric power**

Power systems function near high risk operating points leading to a high risk of cascading outages which can cover a large geographic area.  However, a lot of data is available from synchrophasors and residential smart meters.  This data can be used to measure critical slowing down to estimate proximity to unstable operating points. Technology can warn operators when they are approaching critical points and this can be used to prevent large scale outages (Sánchez and Eduardo, 2012).

**Public sector**

A significant amount of the current use of big data is within the private sector. However, there are a lot of opportunities to apply big data in the public sector. For example, one report out of the UK suggests that potential public sector applications of big data include real time management information, countering non-compliance, fraud and error, transforming and personalizing the citizen experience, improving healthcare and patient outcomes and delivering more timely population estimates as lower cost (Yiu, 2012).

## Tools for Working with Big Data

The opportunities enabled by big data are always followed by challenges. On the one hand, Big data bring many attractive opportunities. On the other hand, lots of challenges lie for handling big data problem. Difficulties arise in processes such as data capturing, storage, searching, sharing, analysis, and visualization (Ozsu and Valduriez 2011). One major challenge which exists in computer architecture is the system imbalancement (heavy CPU but poor I/O) (Ahn 2012). Analysis of Big data also deals with challenges including data inconsistence and incompleteness, scalability, timeliness and data security. As the prior step to data analysis, data must be well-constructed. However, considering the variety of data sets in Big Data problems, it is still a big challenge to purpose efficient representation, access, and analysis of unstructured or semi-structured data.

Big data techniques involve a number of disciplines, including statistics, data mining, machine learning, neural networks, optimization methods and visualization approaches. Here we briefly review some categories of applicable techniques:

**Table 3 Example Big Data Techniques**

| Techniques | Definition | Examples |
|---|---|---|
| Statistics | The science of the collection, organization, and interpretation of data, including the design of surveys and experiments. | A/B testing, spatial analysis, predictive modeling |
| Data mining | A set of techniques to extract patterns from large datasets by combining methods from statistics and machine learning with database management. | Association rule learning, cluster analysis, classification, regression |
| Machine learning | A subspecialty of computer science concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data. | Natural language processing, sentiment analysis |
| Data fusion and integration | A set of techniques that integrate and analyze data from multiple sources in order to develop insights in ways that are more efficient and potentially more accurate than if they were developed by analyzing a single source of data. | Kalman filter |
| Network analysis | A set of techniques used to characterize relationships among discrete nodes in a graph or a network. | Crowdsourcing, centrality analysis |
| Simulation | Modeling the behavior of complex systems, often used for forecasting, predicting and scenario planning. | Agent-based simulation |

In order to utilize Big data, new tools were developed (platforms). Current tools concentrate on three classes, namely, batch processing tools, stream processing tools, and interactive analysis tools (Chen and Zhang 2014). Batch processing is the execution of a series of programs on a computer without manual intervention. Most batch processing tools are based on the Apache Hadoop infrastructure. Apache

Hadoop is one of the most well-established software platforms that support data-intensive distributed applications. It implements the computational paradigm named Map/Reduce (Deam and Ghemawat 2008). Apache Hadoop platform consists of the Hadoop kernel, Map/Reduce and Hadoop distributed file system (HDFS), as well as a number of related projects, including Apache Hive, Apache HBase, and so on. In a nutshell, the Hadoop framework provides both reliability and data motion to applications. It implements a computational paradigm – MapReduce, where the application is divided into many small fragments of work, each of which may be executed or re-executed on any node in the cluster. The architecture of the Hadoop platform is designed to be tolerable to node failures. The entire Apache platform now includes a family of tools including the Hadoop kernel, MapReduce, HDFS, Apache Hive, Apach HBase, and others.

In summary, MapReduce and Hadoop are the standard methods for computation and other software and hardware options are limited (Courtney, 2012; Lin, 2012). Some of the main difficulties with processing big data are the huge variation in batch processing jobs and the need to minimize data trafficking (Ingersoll 2009). There are many other big data platforms that have been developed on top of MapReduce and Hadoop. For example, Mahout and Dryad are two examples of batch processing tools based on Apache Hadoop infrastructure. The latter is more like necessary for real-time analytic for stream data applications. Stream processing is a computer programming paradigm, related to SIMD (single instruction, multiple data), that allows some applications to more easily exploit a limited form of parallel processing. Storm and S4 are good examples for large scale streaming data analytic platforms. The last class of tools is often referred as interactive analysis tools. The interactive analysis processes the data in an interactive environment, allowing users to undertake their own analysis of information. The user is directly connected to the computer and hence can interact with it in real time. The data can be reviewed, compared and analyzed in tabular or graphic format or both at the same time. Google's Dremel (Melnik et al. 2010) and Apache Drill (Kelly, J. 2013) are Big Data platforms based on interactive analysis.

There are a growing number of technologies used to aggregate, manipulate, manage, and analyze big data including granular computing, cloud computing, biological computing systems and quantum computing. These technologies are invented in order to manage, analyze, visualize, and exploit informative knowledge from large, diverse, distributed and heterogeneous data sets. Granular computing (GrC) may refer to a general computation theory for effectively using granules such as classes, clusters, subsets, groups and intervals to build an efficient computational model for complex applications with huge amounts of data, information and knowledge. Cloud computing refers to usage of virtual computers (Bell et al. 2009). The development of virtualization technologies have made supercomputing more accessible and affordable. Powerful computing infrastructures hidden in virtualization software make systems to be like a true physical computer, but with the flexible specification of details such as number of processors, memory and disk size, and operating system. Biological computing models are better appropriate for Big Data because they have mechanisms to organize, access and process data in ways that are more practical for the ranging and nearly infinite inputs we deal with every day. This class of computation technique is inspired by human brain where processing for information is executed in highly distributed and parallel ways. The multi-located storage schema and synchronous parallel processing approaches make computation so fast and efficiently. Biologically inspired Computing (Bongard 2009) shall provide tools to solve Big Data problems from hardware design to software design.

### Critiques on Big Data Technology

One of the very controversial aspects of big data is that it is a reversal of traditional research methods. In traditional data analysis, research question(s) are posed before analysis, and then data is collected to seek answers for those pre-designed questions. A sample is taken from a known population to conduct the analysis in a relational database environment. Big data analytics, however, works with a framework such as Hadoop that performs data analysis of entire known or unknown populations. This has been heralded as the “End of Theory” where we no longer need hypotheses and models; we can simply query a database to understand the correlations (Anderson, 2008). In addition, we can do research and prove ideas that we could never have hypothesized (Sánchez and Eduardo, 2012). This concept is not entirely new as exploratory data analysis (analysis is guided by the data itself) was created by Tukey (1977). Statisticians accept data mining if it follows the EDA paradigm looking for unexpected information rather than trying to confirm something expected (Ratner, 2012).

However, with the increase in big data, the concerns have become quite common. Some issues are that this new methodology could change the definition of knowledge, have errors and create new digital divides (Boyd and Crawford, 2011). Also, large measurement errors in big data can make it impossible to find subtle associations (Ioannidis, 2013). The other barrier is the continuous flow of big data as opposed to traditional "stock-data-in-warehouse" situation . This represents a substantial change from the past, when data analysts performed multiple analyses to find meaning in a fixed supply data.

Last but not least, leveraging datasets generated by various sources and agencies brings up new challenges on data ownership, interoperability, security and privacy which is beyond the definitions of traditional data managements (Al-Khouri 2012). For example, in traditional analytics there is usually one central governance team focused on governing the way data is used and distributed in the enterprise, while big data analytics need multiple governance in play simultaneously, each geared toward answering a specific business question.

### Summary

Big data present great opportunities and challenges. The issues of scale, heterogeneity, lack of structure, error-handling, privacy, timeliness, provenance, and visualization make it challenging to effectively utilize big data in various applications. These challenges exist at all stages of the analysis pipeline from data acquisition to result interpretation. Given these challenges, there is a need for methods that are different from traditional methods. This is due to several limitations associated with traditional methods.

Traditional architectures struggle to provide fast results to queries on such large data sets because they rely on monolithic architectures designed in an era of smaller data sets and slower data growth. They are typically expensive and cumbersome to scale as data grows due to inflexible systems, requirements that force "super-size" upgrades, required downtime, and error-prone upgrade processes.

Traditional architectures for data management and analytics are not designed to move terabytes to petabytes of data through the data pipeline to the analytic application for processing. The larger the data volume, the larger the time and effort needed to move it from one location to another. The resulting performance and latency problems are so severe that application developers and analysts commonly compromise the quality of their analysis by avoiding big data computations. Thus, the traditional extract-transform-load (ETL) data approach should be altered with one that minimizes data movement and improves processing power (SAS 2012). It is not an overstatement that standard relational databases and SQL reach fundamental capacity and scaling limits when dealing with big data.

Traditional structured data is always used after it has been collected and organized neatly, but big data takes any form of data structure. The difference is better described this way: Unlike relation-based data, big data manages data in any format and does not require the time and effort to create a model first to capture, process, and analyze the data (Intel 2012).Since big data analytics handle non-stop streams, it offers opportunities to seek answers for questions either already posed or newly raised during the process - questions we may otherwise not be able to ask.

Traditional data management and analytics, such as SQL-based platforms, use a powerful but fixed syntax. Big data generally needs procedural languages and the ability to program arbitrary new logic. This is due to that much of the processing requires iterative logic, complex branching, and special analytic algorithms.

Yan (2013) provided a concise summary of the major differences between traditional and big data analytics along the dimensions of data features and technologies. In terms of data features, traditional data analytics only provide environment suitable for structured data only and the usual unit of volume is megabyte or gigabyte, while the big data analytics need a data handling environment for any kind of data from multiple sources and the usual unit of volume is terabyte or petabyte. In terms of technology, traditional data analytics often rely on SQL-based approaches, relational databases, and batch or offline processing. Big data analytics often rely on massively parallel processing and NoSQL capabilities, Hadoop framework, streaming processing, live data, and near real-time processing.

All these characteristics also cause new fundamental challenges to big data research and industries. Because big data can change constantly, research on it can be unrepeatable (Berman, 2013). The combination of different sources can make big data "dirty" and fuzzy and it can consist of unknown combinations of nonrandom populations (Ratner, 2012). It can also be expensive and politically difficult to collect, store, process and analyze data (Goldston, 2008). Because of the various sources of the data, working with big data creates new questions about informed consent (Ioannidis, 2013). Also, there is a shortage of labor for this work as research on big data requires both knowledge in big data analysis and domain specific knowledge (Waller and Fawcett, 2014).

### Big Data for Transportation Applications

The transportation sector is on the edge of a paradigm shift thanks to big data. Discovering novel ways to manage and analyze big data to create value will increase the accuracy of predictions, improve management, enhance road use safety, and transportation infrastructure security. Transportation agencies collect vast quantities of data to support infrastructure planning, condition monitoring, and operation. At the same time, an increasing number of transportation system users are generating new types of data through self-reporting. The notable ones are social media and geolocation data. Collectively, large data sets related to transportation include, but are not limited to, the following categories.

- Sensor data
    - Structural Health Monitoring data
    - Traffic data

- WIM
- Video logs

- Demographics
  - Trends
  - Household
  - Survey data
- Infrastructure
  - Inventory
  - Repair history and costs
- Natural Environment
  - Weather data
  - Tides
  - Air quality
  - Flow rates
  - Remote sensing data set - Terrain/LIDAR
- Safety performance data
- Social media data
- Geolocation data

There are abundant use cases for big data applications in the transportation industry. In the following, we provide a detailed analysis on some example large data sets which likely present a big data problem to transportation agencies. In the meantime, we discuss application scenarios and use cases of these data sets.

**Safety Performance Data**

In January of 2014, the Federal Highway Administration issued a broad agency announcement on requesting proposals on adapting suitable methodologies for handling, processing, and analyzing massive data sets. This RFP clearly indicated that ongoing safety programs such as "Second Strategic Highway Research Program (SHRP2)" are generating petabyte of data. These data promise better understanding of the causes of vehicle crashes and unsafe behavior. However, traditional data and analysis methods no longer provide dramatic new findings about crash causation and potential effective countermeasures. Further, traditional methods are limited in assessing the value of new data, integrating new data, and automating quality control and quality assurance.

While there are many different types of transportation safety data, two data sets that have posted significant challenges to traditional data analysis methods are HSIS data and Naturalistic driving study dataset.

**HSIS data** - HSIS is a roadway-based system that provides quality data on a large number of accident, roadway, and traffic variables. It uses data already being collected by States for managing the highway system and studying highway safety. The data are acquired annually from a select group of States, processed into a common computer format, documented, and prepared for analysis. HSIS is used in support of the FHWA safety research program and provides input for program policy decisions. HSIS is also available to professionals conducting research under the National Cooperative Highway Research Program, universities, and others studying highway safety. HSIS data are stored in a relational database that contains basic crash files, roadway inventory files, and traffic volume files from these nine States. The database also includes information about highway intersections, interchanges, and curves/grades from some States. Table 4 details the information available from each of the currently participating States.

**Table 4 Data Types in the HSIS Data Set**

| Data Files | States | | | | | | |
|---|---|---|---|---|---|---|---|
| | California | Illinois | Maine | Minnesota | North Carolina | Ohio | Washington |
| Crash | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Roadway | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Traffic Volume | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Curve/Grade | × | ✓ | × | × | × | ✓ | ✓ |
| Intersection | ✓ | × | ✓ | ✓ | × | × | × |
| Interchange | ✓ | ✓ | ✓ | ✓ | × | × | ✓ |
| Supplementry | × | × | × | × | × | × | ✓ |

**Naturalistic driving study dataset** – Naturalistic driving study data are the result of the largest, most comprehensive naturalistic driving study (NDS) ever conducted by SHRP2 to monitor how drivers interact with their vehicles and the highway environment. The study collects real-time data on more than 5.8 million trips from more than 3,100 participants, ages 16-80 in 6 study sites across the country. The data will include 33 million travel miles, more than 1.4 million driving hours, and will exceed more than 4 petabytes in size. The NDS database contains continuous data from all trips taken by volunteers over one to two years. Volunteers' vehicles are heavily instrumented and record vehicle location, forward radar, vehicle control positions, and many other data elements, including video of the forward roadway and of the driver's face and hands. Crash investigations are conducted after certain crashes to gather more detailed data. There are six NDS site states: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. The types of data collected in this study are summarized in Table 5.

**Table 5 Data Types in the NDS data set**

| **NDS Data** |
|---|
| MultipleVideos; front, rear, driver face and hands |
| Accelerometer data; 3 axis |
| GPS location – latitude, longitude, elevation, time, velocity |
| Forward radar – positions and velocities |
| Vehicle network data – speed, accelerator, brake, gear position, steering wheel angle, turn signals, horn, seat belt use, air bag deployment, etc. |
| Illuminance sensor |
| Infrared illumination |
| Incident push button |
| Turn signals |
| Cell phone calls – beginning and end times |
| Passive alcohol sensor |
| Driver assessment data – vision, cognition, health, medication, driving knowledge and history |
| **Roadway Information Data** |
| Number of lanes |
| ane type and width |
| Grade |
| Cross slope |
| Horizontal curvature: curve start, end, direction, length, and radius |
| Lighting |

## Remote Sensing Data Sets

Remote sensing technologies, such as static and mobile LiDAR have been increasingly used by state DOTs to collect highway inventory data (Figure 3). A general trend of these technologies is their capability to collect very high resolution spatial data sets, leading to an exploding amount of data (Figure 4). Remote sensing data sets collected by other government agencies, such as airborne LiDAR and imagery, are also rapidly growing in volume and type. Many of these data sets can be leveraged by transportation agencies for infrastructure planning, road inventory, and disaster response applications. These emerging data collection methods have produced large and heterogeneous geospatial temporal data sets spanning multiple spatial and temporal scales and with varying levels of confidence. One particular challenge is that these data sets are in very low-level data format – three dimensional point data; feature, pattern, and knowledge extraction from these data sets require significant computation efforts. The other type of large-size data sets that are routinely collected by state DOTs are pavement databases. Transportation agencies often use mobile data collection services such as those provided by Pathway services for annual pavement data collection. Since each state transportation agency often need to manage thousands of miles of roadways, these data collection efforts often generate tremendous volumes of data sets (Figure 5). In summary, effective utilization of the above growing volumes of remotely sensed data sets poses significant challenges to state transportation agencies. Processing of these data sets often require sophisticated and scalable machine learning methods.

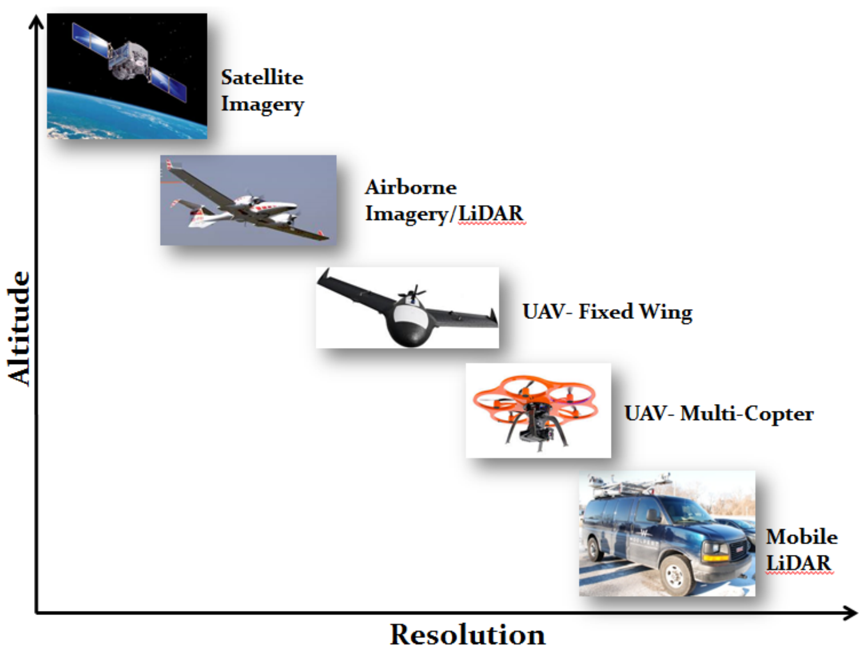


**Figure 3 Remote Sensing Technologies for Transportation Infrastructure Data Collection**

**Figure 4 Highway Mobile LiDAR Data**

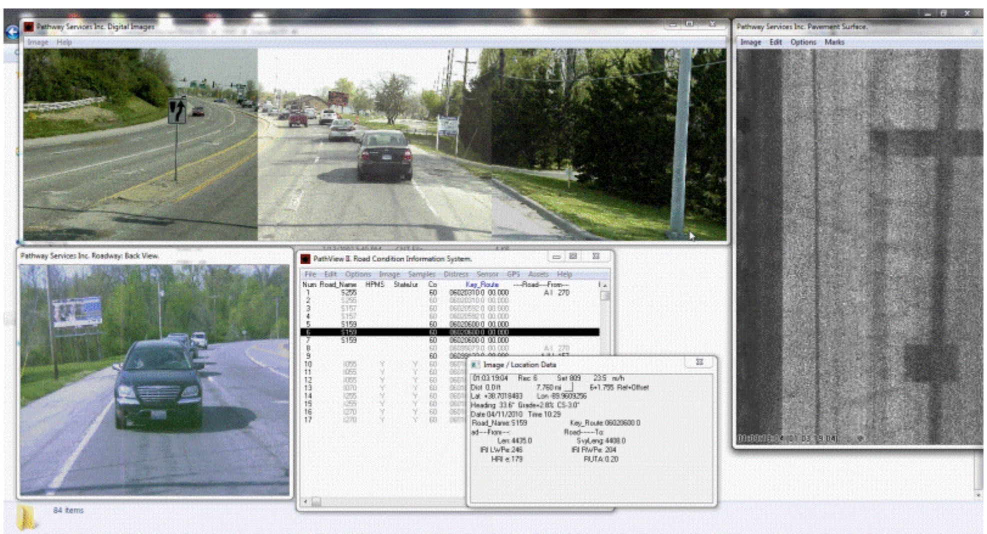

**Figure 5 Pavement Condition Assessment**

### Social Media Data

Social networks, like Twitter, and Facebook, are now widely used in our society. A total of 4 out of 5 active internet users visit social networks and blogs. Social Networks and Blogs account for 23% of the total time users spend on the internet (Nielsen 2009). The rise of social media has the potential to improve existing transportation service user satisfaction measurement practices. Many transit agencies are already sophisticated users of Facebook and Twitter. Typically transit agencies use social media to announce service changes, provide instant notification to users about problems, and to build a relationship with customers (Harnack 2011). Recently, social network tools have been used to analyze sustainable transportation organizations (Watts and Witham 2012). However, no transit agency is analyzing the text input of system users on a real time basis to identify problems as they are occurring in real-time.

In recent years, Big Data has become a vibrant research field in transportation. Social media data is widely considered as one important type of Big Data in transportation research. Sentiment analysis is one emerging data analytics that can be used for mining the vast quantity of social media data generated by transportation service users. Thus, combining social media data with sentiment analysis methods provides a new lens that transportation agencies can potentially use to observe their service performances. This has encouraged research effort in understanding the potential role of social media and sentiment analysis in transportation related operations. These efforts include, but are not limited to, use of social media data and sentiment analysis for vehicle defect detection (Abrahams et al. 2012), sentiment analysis for roadway traffic safety enhancement (Chen and Krishman 2013), use of social media to predict traffic flow under special event conditions (Ni et al. 2013), use of social media as a novel transit rider satisfaction metric (Collins et al. 2013), international surveys to gauge the level of acceptance and utilization in using social media for improving transit operations (Pender et al. 2013), use of social media as a new intelligent transportation tool (Cao et al. 2014), and integrating social media data for road traffic prediction (He et al. 2011).

In parallel with academic research studies, industry giants such as IBM have also invested heavily in developing social media data analytics for business intelligence, such as Social Media Analytics (IBM 2013). One obvious use of these analytics can be in the transportation field such as forecasting travel demands. Another similar online social media analytic platform is Sentiment 140 (Sentiment 140 2014), which allows users to discover the Twitter sentiment for a product or brand. While these platforms can provide off-the-shelf analytics capabilities that transportation agencies can use to start reap the benefits of social media data, the methodologies used in these platforms are a complete black box to transportation agencies. Studies that have benchmarked the performance of these systems or have evaluated transportation agencies' experience in using these systems are scarce. It is suffice to say that compared to the rapid development and implementation of sentiment analysis in other fields, the potential of opinion mining and sentiment analysis has not been fully realized by transit agencies. Opinion mining and sentiment analysis of transit social media data also requires new methods and new models as vocabularies and language patterns are often sensitive to context and tend to be domain specific.

### Applications and Use Cases

The travel & transportation industry is an asset intensive business. In order to drive results, organizations must continually get yield from those assets. Big data provides an opportunity to connect user preferences and agency decisions. The types of problems that can be addressed by transportation related big data include:

- Predictions version actual experience
    - Transit ridership
    - Costs/bids
    - Usage
- Incident management and response from crowd sourcing
- Emergency management
- Determining the right action at the right time

The following provides a comprehensive review of existing industry applications and academic studies that have already tapped into the potential of big data in the transportation domain.

Smart City - In collaboration with IBM, the Dublin City Council (DCC), which provides housing, water and transportation services to 1.2 million people, is using big data strategies to help the area's bus traffic move smoothly. The road and traffic management at the Dublin City leverages real-time data streams from a variety of sources including road sensors, video cameras, and GPS updates from the city's 1,000 buses. Traffic controllers use these data to overlay real-time locations of Dublin's buses on a digital map of the city. The advantage of this approach is that it allows Dublin's traffic managers to quickly visualize potential problems in the city's bus network. For instance, areas experiencing delays can be quickly pinpointed and the source of the problem can be quickly identified before it spreads to other routes (Bertolucci 2013). In addition, instruments include smartphones, sensors, and onboard vehicle hardware are deployed in the city to enable continuous collection, communication, and processing of mobility data—anything from traffic and weather conditions to parking spots and rideshares. There are also novel analytics applications built on top of these large data sets. For example, transportation planners use Clockwork to design and optimize transportation systems to improve availability of the fleet, lower costs, and improve customer good will. It should be noted that transportation systems are made up of a variety of systems (rail, bus, and subway) as well as their enabling infrastructure (i.e. power, control, signaling etc.).

London Olympic - During London Olympic, big data has been used to manage traffic. For example, traffic lights respond to traffic flows in realtime, with the red light being prolonged at some junctions if the dedicated lanes become too congested. The free Inrix Traffic app uses multiple data sources to help drivers determine the fastest route and avoid delays with up-to-the-second traffic information. The app provides traffic forecasts that help travellers know what to expect on the roads before they take a trip.

Controlling Driving Offenses (Fatemi and Karimi 2013) – This study proposed an efficient and intelligence model for control driving offenses by using three main technologies namely, Image Processing, Artificial Intelligence, and Cloud Computing. In the proposed model, Vertical-Edge Detection Algorithm (VEDA) was used for car license plate detection process in highways to provide an efficient image processing process with low quality images that were taken from installed cameras. Furthermore, two intelligence cloud based Software-as-a-Service applications were used for car license plate detection, matching violations detected numbers with entrance detected numbers, and identification of possible exit routes for further processes. The suggested model contains a cloud server for storing databases and violation records which make them always accessible according to cloud computing concepts.

Traffic Incident Detection (Kinane et al. 2014) – This study presented a system for heterogeneous stream processing and crowdsourcing supporting intelligent urban traffic management. Complex events related to traffic congestions are detected from heterogeneous sources involving fixed sensors mounted at traffic intersections and mobile sensors mounted on public transport vehicles. To deal with the inherent data veracity, a crowdsourcing component handles and resolves source disagreement.
Communication between traffic authority, staff and the public (Xian et al. 2013) – This study attempted to design a traffic safety information platform based on cloud computing technology, data warehousing and data mining which serves as an excellent channel for communication between traffic authority, staff and the public. The goal is quick access to updated road traffic information for city travelers. It aims to take full advantage of road safety information database in attempt to generalize, judge and predict various safety information such as traffic accident black-spots, vehicle types liable to serious accidents and weather based on already occurred accidents on one hand and gather, tackle and share detailed traffic conditions without delay such as road condition, potential risks, accidents, disasters and weather on the other hand
Parallelized fusion on multi-sensor transportation data – Xia et al. (2013) proposed an approach using parallelized fusion on multi-sensor transportation data. The framework may resolve two main challenges namely processing heterogeneous transportation data collected from different types of traffic sensors and reducing the high computation intensity for processing massive transportation data.  Parallelized fusion is an embodied case of CyberITS framework, which is developed for the synthesis of cyber infrastructure and ITS.
Big data storage and processing solutions for intelligent transportation system – Dai et al. (2012) presented the new paradigm (the Hadoop stack) that is required for big data storage and processing using a case study of ITS application. They described how to optimize the Hadoop deployment through proven methodologies and tools provided by Intel (such as HiBench and HiTune). Challenges and possible solutions for real-world big data applications using a case study of an ITS application are demonstrated.

Congestion Prediction – Ma et al. (2012) proposed a user-driven Cloud Transportation system (CTS) which employs a scheme of user-driven crowdsourcing to collect user data for traffic model construction and congestion prediction including data collection, filtering, modeling, and intelligent computation. In the study, application scenario, system architecture, and core CTS services models are described in detail.

Traffic Surveillance in Cloud – Li et al. (2011) investigated the processing of massive floating car data (FCD) for traffic surveillance in cloud-computing environments, with the goal of exploring the use of emerging cloud-computing technologies to solve data-intensive geospatial problems in urban traffic systems. The experimental results indicated that cloud computing technologies (e.g. Bigtable and MapReduce) can provide substantial utility for data-intensive geospatial computing, as both scalability and near real-time computational performance can be adequately enhanced through proposed data storage, management, and parallel processing models.

GPS Data Processing – Huang and Qiao (2013) presented a novel parallel map matching algorithm to realize high-performance processing of GPS data. The main idea is to adapt the serial map matching algorithm for cloud computing environment by reforming its' data intensive or I/O-intensive computing stages using MapReduce paradigm.

Clockwork – Clockwork is a predictive analytic solution that computes the best options for maintaining and increasing utilization levels at the lowest possible cost for asset management. Compared to traditional methods that are often based on small subsets of historical data or past experience, Clockwork can leverage data growing at exponential scales and turns them into savings and profitability. Asset managers in the transportation industry can use Clockworks to predict maintenance issues and schedule appropriate repairs to ensure the fleet is operational and system uptime is maximized.

GIS-T - Geographic Information Systems for Transportation (GIS-T) refers to the principles and applications of applying geographic information technologies to transportation problems.

GSM - The most interesting new data source, however, is GSM (Global System for Mobile Communications) location data, which is location based information retrieved from mobile phones. Each mobile phone is at all moments connected to a certain GSM cell site antenna. Such a cell, provided by a mobile provider, knows what mobile phones are present in that cell. The basic version only knows that a particular mobile phone is present, the more advanced cells know from what direction (angle) the phone is connecting to the cell antenna. The most advanced cells also return an indication of the distance from to mobile phone to the cell antenna. This results in fairly accurate positioning of a phone. When the phone moves, for example during a car ride, the mobile phone switches over from one cell to another cell. Monitoring the movement of an anonymized mobile phone through the provider’s network gives the desired data on mobility.

### Big Data Use Cases and Requirements

While there appears to be many use cases for big data in the transportation domain, it is not clear that whether these use cases can be stated and compared at a high level for the purposes of extracting requirements or comparing usages across fields. It is necessary to develop a consensus list of Big Data requirements across all stakeholders in transportation applications. Recently, NIST has organized a systematic effort to examine big data use cases in diverse fields and to develop a standard procedure for defining and comparing requirements across these different use cases (NIST, 2015). A collection of 51 use cases in the field of Government Operation, Commercial, Defense, Healthcare and Life Sciences, Deep Learning and Social Media, The Ecosystem for Research, Astronomy and Physics, Earth, Environmental, and Polar Science, and Energy was examined in this effort. Surprisingly, transportation use cases were only marginally included as the only use case related to transportation is cargo shipping. Nevertheless, the NIST framework for eliciting big data application requirements is a valuable outcome for use in benchmarking the big data challenges and opportunities in the transportation sector. The following table provides detailed procedures or steps used in the NIST case study research.

## Table 6 NIST Big Data Case Study Template

| | | |
|---|---|---|
| Use Case Title | | |
| Vertical (area) | | |
| Author/Company/Email | | |
| Actors/ Stakeholders and their roles and responsibilities | | |
| Goals | | |
| Use Case Description | | |
| Current Solutions | Compute(System) | |
| | Storage | |
| | Networking | |
| | Software | |
| Big Data Characteristics | Data Source (distributed/centralized) | |
| | Volume (size) | |
| | Velocity (e.g. real time) | |
| | Variety (multiple datasets, mashup) | |
| | Variability (rate of change) | |
| Big Data Science (collection, curation, analysis, action) | Veracity (Robustness Issues, semantics) | |
| | Visualization | |
| | Data Quality (syntax) | |
| | Data Types | |
| | Data Analytics | |
| Big Data Specific Challenges (Gaps) | | |
| Big Data Specific Challenges in Mobility | | |
| Security and Privacy Requirements | | |
| Highlight issues for generalizing this use case (e.g. for ref. architecture) | | |
| More Information (URLs) | | |
| Note: <additional comments> | | |

## Table 7 Detailed explanations of fields

| Terminology | Explanation |
|---|---|
| Goals | Objectives of the use case |
| Use Case Description | Brief description of the use case |
| Current Solutions | Describes current approach to processing Big Data at the hardware and software infrastructure level |
| Compute (System): | Computing component of the data analysis system |
| Storage | Storage component of the data analysis system |

| | |
|---|---|
| Networking | Networking component of the data analysis system |
| Software | Software component of the data analysis system |
| Big Data Characteristics | Describes the properties of the (raw) data including the four major 'V's' of Big Data |
| Data Source | The origin of data, which could be from instruments, Internet of Things, Web, Surveys, Commercial activity, or from simulations. The source(s) can be distributed, centralized, local, or remote. |
| Volume | The characteristic of data at rest that is most associated with Big Data. The size of data varied drastically between use cases from terabytes to petabytes for science research, or up to exabytes in a commercial use case. |
| Velocity | Refers to the rate of flow at which the data is created, stored, analyzed, and visualized. For example, big velocity means that a large quantity of data is being processed in a short amount of time. |
| Variety | Refers to data from multiple repositories, domains, or types. |
| Variability | Refers to changes in rate and nature of data gathered by use case |
| Big Data Science | Describes the high level aspects of the data analysis process |
| Veracity | Refers to the completeness and accuracy of the data with respect to semantic content |
| Visualization | Refers to the way data is viewed by an analyst making decisions based on the data. Typically visualization is the final stage of a technical data analysis pipeline and follows the data analytics stage. |
| Data Quality | This refers to syntactical quality of data. In retrospect, this template field could have been included in the Veracity field |
| Data Types | Refers to the style of data such as structured, unstructured, images (e.g., pixels), text (e.g., characters), gene sequences, and numerical |
| Data Analytics | analytics refers broadly to tools and algorithms used in processing the data at any stage |

## Summary

The field of big data is rapidly evolving, with new frameworks and tools emerging at an unprecedented rate. This research project provides a snapshot of this research field from the perspective of transportation infrastructure management. Applications of relevant tools and methods for the transportation sector can be examined from the perspectives of data type, data storage and management, and data analytics.

To determine which platform and tools are best for different transportation applications, it is necessary to characterize data types and analysis requirement. For data types, it is important to differentiate the following categories:

- Data collected locally and stored in widely distributed repositories (i.e. health care)
- Data collected with advanced sensing systems and stored in large data centers (i.e. earth observation systems)
- Data collected through social networking and internet (i.e. social media)
- Data generated during simulation and experimental processes (i.e. astro-physical simulations)

A common denominator of these data is their sheer volume. Nevertheless, they often require fundamentally different data management and analysis strategies. For example, for data collected with advanced sensing systems and stored in large data centers, it is difficult to migrate; consequently, distributed analyses are being deployed for such applications. Data generated from social media often require advanced graph-based analytics that can scale up to very large data sets. Data generated during simulation and experimental processes require interactive analysis capabilities.

Therefore, it is important to categorize datasets used in transportation applications. It appears that transportation datasets are multi-modal, spanning multiple categories as described above. A majority of transportation datasets including traffic data from ITS infrastructures, asset condition data, and safety performance data are mainly collected at the point of events but stored in centralized databases. Nevertheless, to tap into some emerging data sources such as social media data, it is also necessary for transportation agencies to look into ways to handle social media data which are massively distributed. Transportation agencies also have the need to access and utilize data hosted by other agencies such as demographic data, weather forecast data, and so on. Collectively, these considerations are strong influencing factors on which big data platform to use as different data platforms excel at different applications. Table 6 shows a summary of common big data databases from different vendors.

**Table 8 Types of Databases for Storing Big Data**

| Type | Description | Example Tools |
|---|---|---|
| Document-oriented | Document-oriented data stores are mainly designed to store and retrieve collections of documents or information and support complex data forms in several standard formats, such as XML. | MongoDB; SimpleDB; CouchDB |
| Column-oriented | A database stores its content in columns aside from rows, with attribute values belonging to the same column stored contiguously | Google BigTable; |
| Graph database | A graph database is designed to store and represent data that utilize a graph model with nodes, edges, and properties related to one another through relations | Neo4j |
| Key-value | Key-value is an alternative relational database system that stores and accesses data designed to scale to a very large size | Apache HBase; Apache Cassandra; Voldemort; |

Another critical consideration in choosing big data platforms and tools is the requirement on how these data should be analyzed. There are three dominant paradigms in big data analytics: (1) batch processing; (2) stream processing; and (3) interactive analysis. Batch processing explores parallelism in data processing either through vertical and horizontal scaling. The vertical scaling leverages investment in adding more CPUs and GPUs into a single computer to scale up processing capabilities. The horizontal scaling leverages investment in adding more commodity-grade computers to form clusters of computers to realize distributed processing. Both approaches enable users to deal with ever increasing volumes of data and prevent data analysis from degrading into crawls. Nevertheless, batch processing is not designed for real-time analytics, but stream processing is. Stream processing is a critical need for transportation agencies as in various scenarios transportation agencies need to analyze and act on real-time streaming data such as traffic congestion data and incident event data. In a traditional database model, data is first stored and indexed and then subsequently processed by queries. In contrast, stream processing takes the inbound data while it is in flight, as it streams through the server. The interactive analysis processes the data in an interactive environment, allowing users to undertake their own analysis of information. This class of analytics has strong applications in large-scale simulation studies such as traffic simulation and simulating behavior of large infrastructure systems. Many existing tools can be used to support these big data analytics needs. Table 7 provides a summary of these common tools. Depending on specific needs, transportation agencies are suggested to choose the most appropriate tools that can best support the envisioned applications.

**Table 9 A Catalog of Big Data Analytic Tools**

| Category | Tools | Application Area |
|---|---|---|
| Batch processing tools | Apache Hadoop & MapReduce | Data-intensive distributed applications |
| | Dryad | Parallel and distributed processing of large data sets using a very small cluster or a large cluster |
| | Apache Mahout | Large-scale data analysis applications with scalable and commercial machine learning techniques |
| | Apache Spark | Batch and stream processing of large data sets |
| | Jaspersoft BI Suite | Report generation from columnar databases |
| | Pentaho Business Analytics | Report generation from both structured and unstructured large volume of data |
| | Talend Open Studio | Visual analysis of big data sets |
| Real-time stream processing tools | Storm | A distributed and fault-tolerant real-time computation system for processing limitless streaming data |
| | S4 | A general-purpose, distributed, scalable, fault-tolerant, pluggable computing platform for processing continuously unbounded streams of data |
| | SQLstream s-Server | Processing of large-scale streaming data in real-time |
| | Splunk | A real-time and intelligent big data platform for exploiting information from machine-generated big data |
| | Apache Kafka | A high-throughput messaging system for managing streaming and operational data via in-memory analytical techniques for obtaining real-time decision making. |
| | SAP Hana | An in-memory analytics platform aimed for real-time analysis on business processes, predictive analysis, and sentiment data. |
| Interactive analysis tool | Google's Dremel | A system for processing nested data and capable of running aggregation queries over trillion-row tables in seconds |
| | Apache drill | A distributed interactive big data analysis tool capable of supporting different query languages, data formats, and data sources. |

## CONCLUSIONS

Over the past decade, transportation infrastructure management has become a largely data driven process in an increasingly networked, digitized, sensor-laden, information-driven world. Transportation departments collect vast quantities of data sets taking on varied properties such as volume, velocity, variety, variability and veracity, but managing, analyzing, accessing and sharing data has been problematic and well documented. "Big Data" is the broad term given to address these emerging challenges. This project reviewed the similar challenges faced by other industries and investigated what approaches have been taken by these industries to address those challenges. The review results suggest that there is a broad agreement among industry, academic, and government stakeholders about the remarkable potential of Big Data to spark innovation, fuel commerce, and drive progress in various sectors.

In this project, we also explored what kinds of data sets in the transportation industry are posing big data challenges. Our literature review suggests that big data challenges are ubiquitous in the transportation industry. Infrastructure condition data, traffic data, safety performance data, driver behavior data, and social media data are very examples of big data. As these types of data continue to grow in size, they open up a wealth of applications and ability to answer questions previously out of reach, including the following:

- How can bridge conditions be rapidly synthesized and further predicted from a corpus of terabytes of data including design records, construction reports, inspection reports, photos, structure health monitoring data, non-destructive testing results, traffic volume, and climate conditions?
- Can new construction materials with advanced properties be predicted before these materials have even been synthesized?
- How can potential cascading or escalating failures in the transportation systems and beyond in the face of extreme events reliably be detected early enough to intervene?

Nevertheless, addressing these questions with big data would require more efficient and effective and scalable data analysis methods that must transcend traditional analysis methods in the field of statistics, data mining, and machine learning. Therefore, a detailed literature survey was also conducted in this study on what kind of tools and data analytics have been developed and used for big data analytics. To this end, we characterized common big data storage and big data analytic platforms. While there are many platforms available to use, choices of platforms should be made based on detailed evaluation on the nature of data problems faced by particular agencies. A short education module focused on introduction of big data to civil engineers was developed (see Appendix A). At the end of the project, a half-day workshop was conducted to disseminate the findings of this research and solicit inputs from leading industry and academic researchers in the field of engineering informatics, cloud computing, and big data analytics (see Appendix B). An important message from this workshop is that many attendees believe the big data challenge faced by state transportation agencies would be best addressed by a public private partnership approach given the fact that private industries have been leading the big data R&D activities and have demonstrated many successful applications in domains including city management, financial investment, and e-commerce.

## RECOMMENDATIONS

This exploratory study suggests that the field of Big Data is rapidly maturing in capabilities, applications, and utility. With the rise of big data, applications of big data in the transportation industry are rapidly emerging. Given the critical role and the vast reach of transportation services in our everyday life, leveraging big data to improve transportation services presents a huge opportunity to transportation agencies although the transition from the traditional database based approach to a big data based enterprise approach won't be an easy journey. The following recommendations to transportation agencies are made based on this study:

- There is a need for DOT agencies to establish task forces to systematically evaluate what kind of big data challenges they are facing and they will face. We highly suggest transportation agencies to use the widely used NIST big data framework to characterize their big data challenges.

- A general observation derived from this study is that the private sectors are driving the innovations in big data. State DOTs do not have to find solutions by their own. Public private partnership is the best pathway that can lead to rapid development in this area.
- While transportation agencies collect a large variety and volume of data, much of these data are not open data, meaning they are not available to the public. Data sharing will certainly provide opportunities to developers and researchers, who will in turn drive the innovations in this field.
- There is a need to educate transportation workforces and students on the fundamentals of big data and develop dedicated education modules.
- It appears that there is no systematic cataloging of latest development of big data applications in the transportation industry. Resources related to big data development in the transportation sector are scattered and difficult to find. Therefore, this is a need to establish a repository that shows the continuously updated cutting edge development in this field.
- While there are big data-related funding opportunities available at the federal level, these opportunities are scarce at the state DOT level. Given the differences between states in demography, economy, climate, traffic condition, and transportation assets, state funding for examining big data issues will be critical in training state DoT employees and students, therefore forging a big data savvy workforce.

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# APPENDIX A – Introduction to Big Data – A first lesson to Civil Engineers

## APPENDIX B – Big Data Workshop Agenda

# Big Data for Transportation Infrastructure Management Workshop

December 1, 2014

State Departments of Transportation and other transportation agencies collect vast quantities of data but managing, accessing and sharing data has been problematic and well documented. At the same time, asset management is described as a data driven process and a key element of asset management is using data to support decisions. Big data – data sets that are so large and complex that they are not easily manipulated with conventional database tools -- offers new opportunities to use data never previously considered to support asset management. The field of Big Data is rapidly maturing in capabilities, applications, and utility. This workshop will examine the role of big data and analytics in transportation infrastructure management. It will bring leaders from the R+D, practitioner, and end-user communities to examine and propose solutions to economic, legal, and technical barriers which currently hinder big data and analytics to be effectively used by transportation agencies. It will also look at the future of the big data technology and potential future applications.

1. ***Objective:*** A look to current and future role of big data and analytics in transportation infrastructure management. One shapes the other.
2. ***When:*** 8:30AM-3:15PM, Friday, 5 December, 2014
3. ***Where:*** CAIT, Rutgers
4. ***Organizer:***
    a. Jie Gong, Assistant Professor, Department of Civil and Environmental Engineering, Rutgers
    b. Sue McNeil, Professor, Department of Civil and Environmental Engineering, University of Delaware
    c. Kevin P. Heaslip, Associate Professor, Department of Civil and Environmental Engineering, Virginia Tech
5. ***Outcome:***
    a. Position paper on the emerging role of big data in transportation applications and barriers to effective use of big data for transportation infrastructure management.
    b. Decision on whether an ongoing workgroup should pursue a specific theme.
    c. Decision on whether a second workshop should be held: objectives, theme, attendees, and timing.
6. ***Attendees:*** a mélange of three communities: R+D, practitioners and end-users.
    a. R+D community (those building next-gen hardware, software, apps):
        i. Academics
        ii. Industry
    b. Practitioners (those generating/manipulating/using data):
        i. Government
        ii. Academics
        iii. Data collectors
    c. End-users (those who make decisions based on underlying data, but do not know, nor need to know a thing about Big Data)

| Big Data for Transportation Infrastructure Management<br>Friday, December 5, 2014 | |
|---|---|
| 8:30 AM – 9:00 AM | **Coffee and Registration** |
| 9:00 AM - 9:15 AM | **Welcome and Introduction**<br>Presenter: Ali Maher/Sue McNeil |
| 9:15AM – 9:45 AM | **Keynote – Capture and Management of Transportation related Data Sets**<br>Presenter: Robert Sheehan, USDOT ITS JPO Multimodal Program Manager |
| 9:45AM – 10:45AM | **Session 1: Overview of Big Data Technology and applications** |
| 9:45AM – 10:00AM | **Role of Big Data in Inspection, Maintenance, and Management of Transportation Assets**<br>Presenter: Lee Tanase, Director Business Development, GeoStuct and Bridge, Bentley Systems, Incorporated |
| 10:00AM – 10:15AM | **Building Computing Infrastructure for Big Data Applications**<br>Presenter: Manish Parashar, Director of Rutgers Discovery Informatics Institute, Co-Director NSF Cloud & Autonomic Computing Center |
| 10:15 AM – 10:30AM | **Discussion – What is big data?**<br>Moderator: Sue McNeil |
| 10:30 AM – 10:45AM | Break |
| 10:45AM – 12:00PM | **Session 2: Transportation Infrastructure Data Collection, Management, and Analysis** |
| 10:45AM – 11:00AM | **Traffic Data/ITS Data**<br>Presenter: Kevin P. Heaslip, Associate Professor, Department of Civil and Environmental Engineering, Virginia Tech |
| 11:00AM – 11:15AM | **Map 21-Performance Management: An Analytical Performance Measurement Approach**<br>**Presenter:** Konstantinos P Triantis, John Lawrence Professor, Department of Industrial and Systems Engineering, Virginia Tech |
| 11:15AM – 11:30AM | **RABIT-A Robotic Bridge Deck Evaluation Tool**<br>Presenter: Nenad Gucunski, Professor and Chair, Department of Civil and Environmental Engineering, Rutgers University |
| 11:30AM – 11:45AM | **Asset Data Collection and Management – An data collection update on Long Term Bridge Performance Program**<br>Presenter: Hooman Parvardeh, LTBP, Center for Advanced Infrastructure and Transportation |
| 11:45AM – 12:00PM | **Discussion – Do we have a big data problem in transportation?**<br>Moderator: Jie Gong |
| 12:00 PM – 1:00 PM | Lunch at the Busch Dining Hall in the Busch Student Center |
| 1:00PM – 2:30PM | **Session 3: Big Data Applications in Transportation** |
| 1:00PM – 1:15PM | **Big Data and Bridge Health Modeling**<br>**Zheng Yi Wu, Bentley Fellow,** Bentley Systems, Incorporated |
| 1:15PM – 1:30PM | **Geospatial Big Data for Transportation Infrastructure Management during Normal and Extreme Events**<br>Presenter: Jie Gong, Department of Civil and Environmental Engineering, Rutgers |
| 1:30PM – 1:45PM | **Social Media Data/Geolocation Data for Improving Transportation Planning and Operation**<br>Presenter: Peter Jin, Department of Civil and Environmental Engineering, Rutgers |

| | |
|---|---|
| 1:45PM – 2:00PM | **Discussion – What are the potentials and barriers for applying big data in transportation infrastructure management?**<br>Moderator: Kevin Heaslip |
| 2:00PM – 2:30PM | **Panel discussion** |
| 2:30PM – 2:45PM | **Closing remarks** |

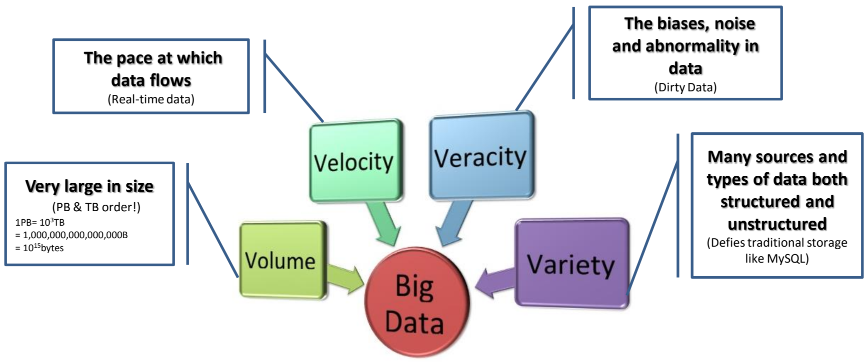
# An Introduction to Big Data

Jie Gong
Rutgers University
Department of civil & Environmental Engineering

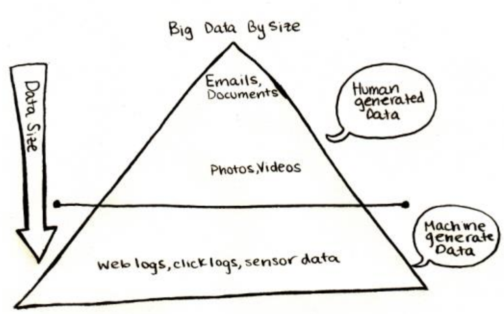
## Outline

- Introduction to Big Data
- Hadoop
- Big Data Examples

# What is Big Data?

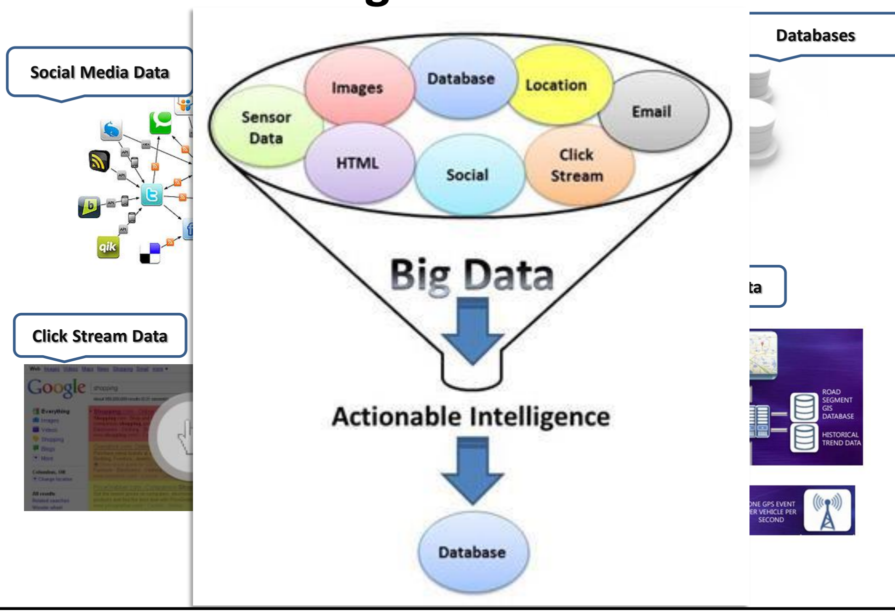



# Big Data: Human Generated Data and Machine Generated Data

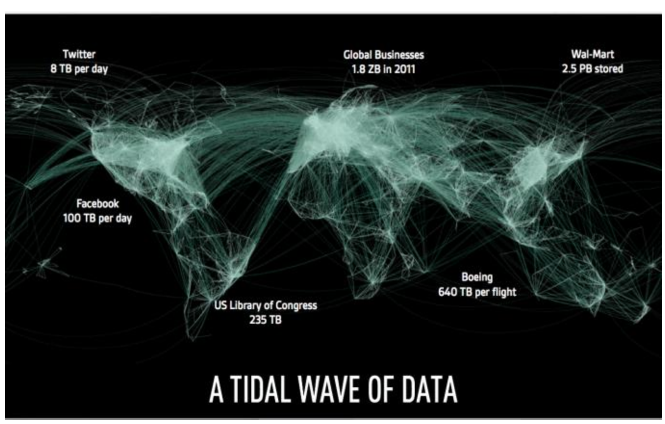



- Before hadoop was in the scene, the machine generated data was mostly ignored and not captured. **It is because dealing with the volume was NOT possible, or NOT cost effective.**

# Where does Big Data come from?




# Examples of Big Data in the Real world



# Examples of Big Data in the Real world

**Quora**
www.quora.com/Data/Where-can-I-find-large-datasets-open-to-the-public

**Research Pipeline**
http://www.researchpipeline.com/mediawiki/index.php?title=Main_Page

**Google Public Data Directory**
http://www.google.com/publicdata/directory

**InfoChimps**
InfoChimps market place

**Stanford network data collection**
http://snap.stanford.edu/data/index.html

**Open Flights**
http://openflights.org/

**Flight arrival data**
http://stat-computing.org/dataexpo/2009/the-data.html

**Natural Earth Data**
http://www.naturalearthdata.com/downloads/

**National Institute of Health**
http://projectreporter.nih.gov/reporter.cfm

**Aid information**
http://www.aidinfo.org/data

**UN Data**
http://data.un.org/Explorer.aspx

**Genomes data**
http://www.geonames.org/

**US GIS Data**
http://libremap.org/

**Google N-gram data**
google ngram

**Stack Overflow data**
http://blog.stackoverflow.com/category/cc-wiki-dump/

**US government data**
data.gov

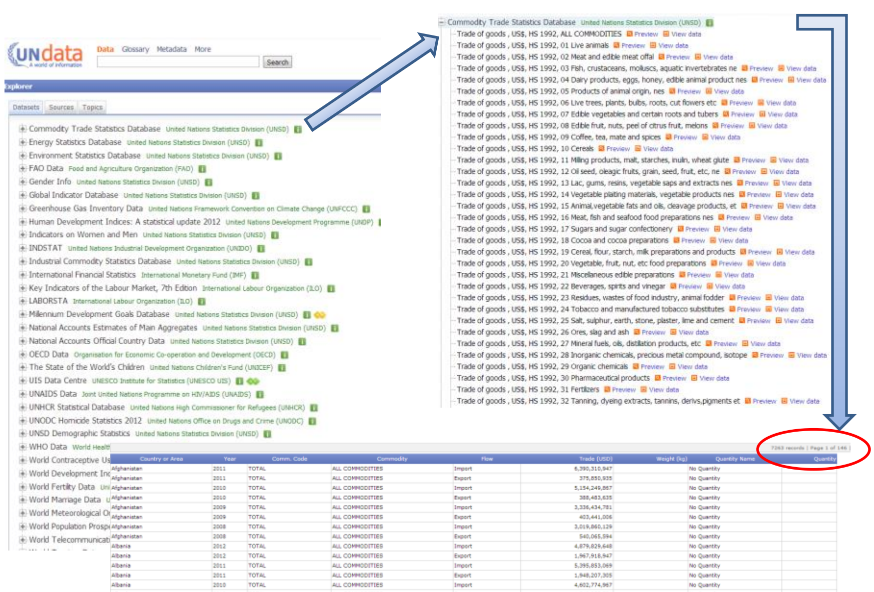
**UK government data**
data.gov.uk

**US Patent and Trademark Office Filings**
www.google.com/googlebooks/uspto.html

**World Bank Data**
http://datacatalog.worldbank.org/

**Public Health Datasets**
http://phpartners.org/health_stats.html

# Examples of Big Data in the Real world



# Example Big Data in Transportation

- Sensor data
  - Structural Health Monitoring data
  - Traffic data
  - WIM
  - Video logs
- Demographics
  - Trends
  - Household
  - Survey data
- Infrastructure
  - Inventory
  - Repair history and costs
- Natural Environment
  - Weather data
  - Tides
  - Air quality
  - Flow rates
  - Remote sensing data set - Terrain/LIDAR
- Safety performance data
- Social media data
- Geolocation data

# Naturalistic Driving Study Dataset

- The result of the largest, most comprehensive naturalistic driving study (NDS) ever conducted by SHRP2 to monitor how drivers interact with their vehicles and the highway environment
- Statistics
  - 5.8 million trips from more than 3,100 participants in 6 study sites in U.S.
  - 33 million travel miles
  - 1.4 million driving hours
  - 4 petabytes in size

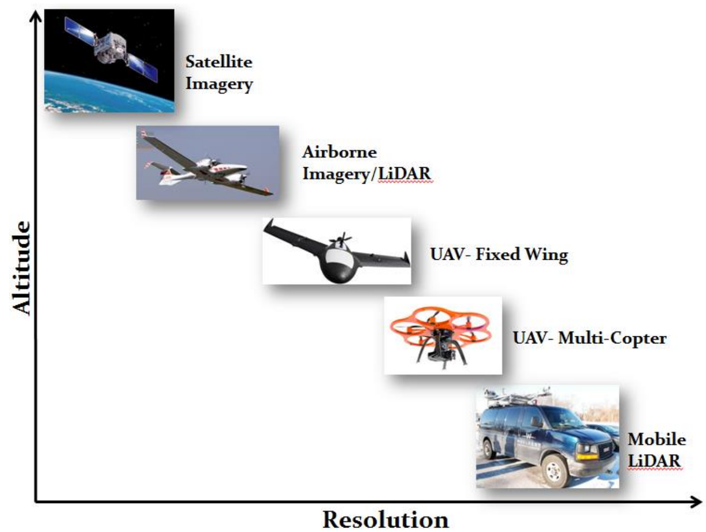
# Naturalistic Driving Study Dataset

- Volunteers' vehicles are heavily instrumented and record:
  - vehicle location, forward radar, vehicle control positions, and many other data elements, including video of the forward roadway and of the driver's face and hands.

# Naturalistic Driving Study Dataset

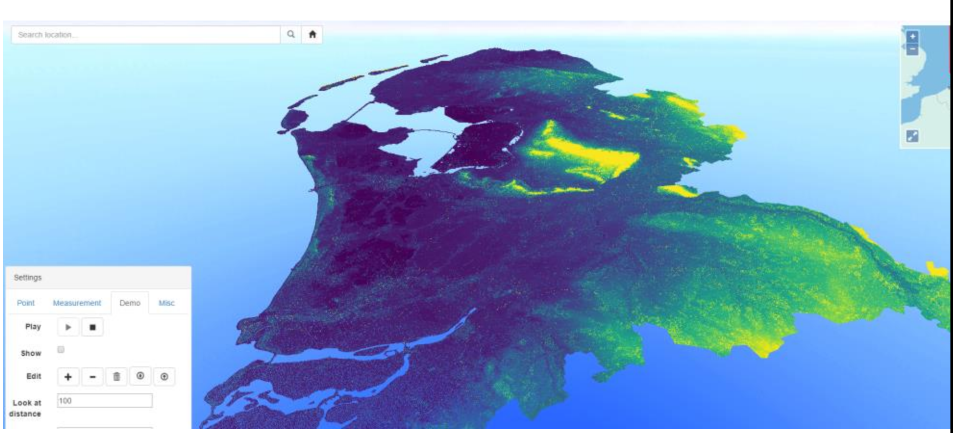
| NDS Data |
|---|
| MultipleVideos; front, rear, driver face and hands |
| Accelerometer data; 3 axis |
| GPS location – latitude, longitude, elevation, time, velocity |
| Forward radar – positions and velocities |
| Vehicle network data – speed, accelerator, brake, gear position, steering wheel angle, turn signals, horn, seat belt use, air bag deployment, etc. |
| Illuminance sensor |
| Infrared illumination |
| Incident push button |
| Turn signals |
| Cell phone calls – beginning and end times |
| Passive alcohol sensor |
| Driver assessment data – vision, cognition, health, medication, driving knowledge and history |
| **Roadway Information Data** |
| Number of lanes |
| ane type and width |
| Grade |
| Cross slope |
| Horizontal curvature: curve start, end, direction, length, and radius |
| Lighting |

# Remote Sensing Data Sets



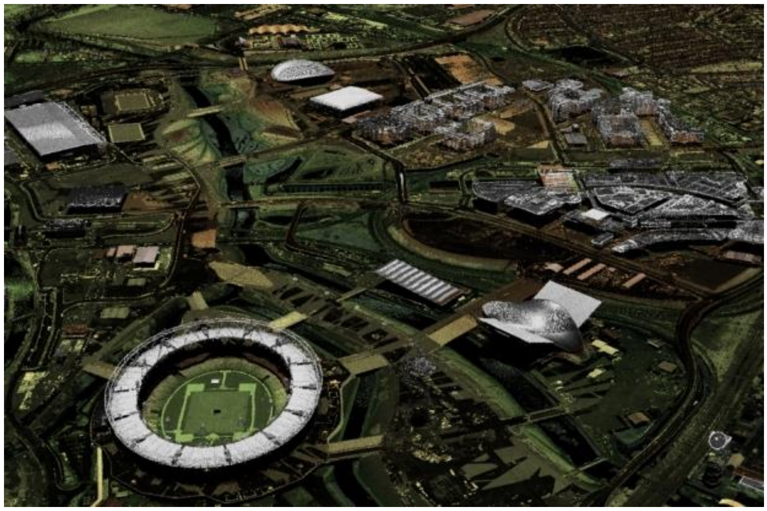

# Remote Sensing Data Sets

- Open Lidar Data in Dutch (http://ahn2.pointclouds.nl/)



# Remote Sensing Data Sets

Open Lidar Data in UK



# Real World Examples (continue)

Social Media for Smart and Resilient City

Pulse of Toyko

https://www.youtube.com/watch?v=jtwzADysoMQ

Pulse of New York City

https://www.youtube.com/watch?v=wrInToGwiZQ

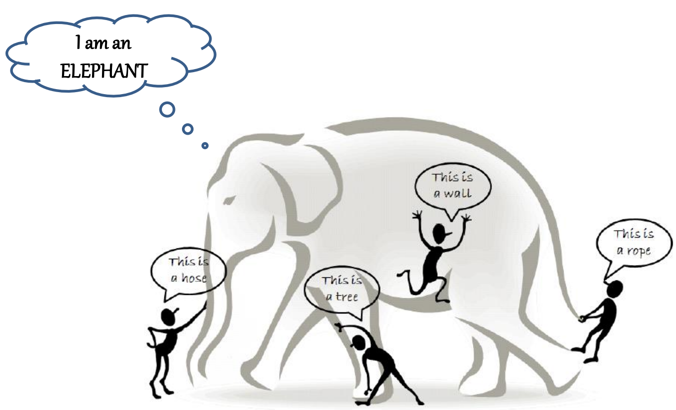
Hurricane Sandy Impacts

https://www.youtube.com/watch?v=3FYeuQQa4tQ&feature=youtu.be

# Social Media Checking-In


# Big Data

**The bigger the picture, The less biased conclusion**



# Challenges of Big Data

- **Sheer size of Big Data**

For a small company that is used to dealing with data in gigabytes, 10TB of data would be BIG. However for companies like Facebook and Yahoo, petabytes is big.

Just the size of big data, makes it impossible (or at least cost prohibitive) to store in traditional storage like databases or conventional filers.

Using traditional storage filers can cost a lot of money to store Big Data.

- **Big Data is unstructured or semi structured**

A lot of Big Data is unstructured. For example clickstream log data might look like

`<timestamp,user_id,page,referer_page>`

**Lack of structure makes relational databases not well suited to store Big Data**

+

**Not many databases can cope with storing billions of rows of data**

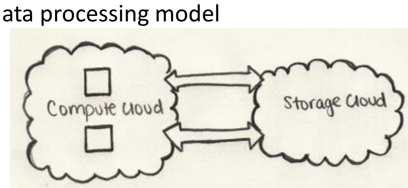
# Challenges of Big Data

- **No point in just storing big data, if we can't process it**

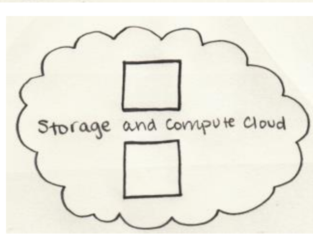
Storing Big Data is part of the game. We have to process it to **mine intelligence out of it**. Traditional storage systems are pretty 'dumb' as in they just store bits

**They don't offer any processing power**

- The traditional data processing model




**Solution**



## What is Hadoop?

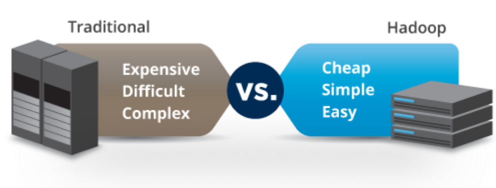
- hadoop is an open source software stack that runs on a cluster of machines
- hadoop provides distributed storage and distributed processing for very large data sets

***1. Hadoop Distributed File System (HDFS)***

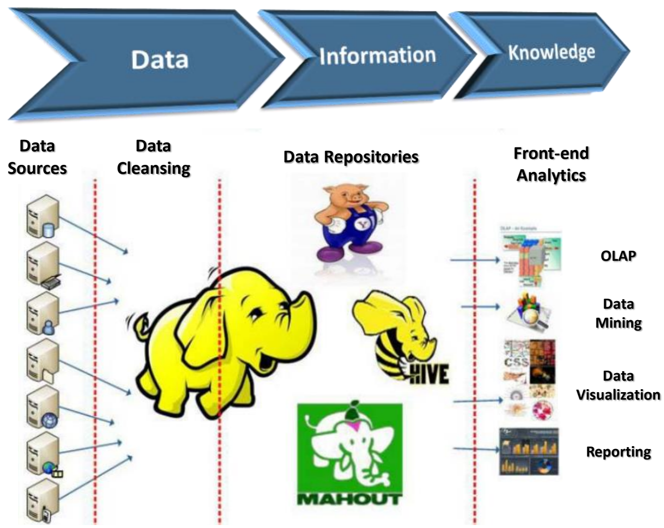
***2. Hadoop MapReduce***

## Why Hadoop?

- The short answer is that it simplifies dealing with Big Data
- The hadoop framework has built-in power and flexibility to do ***what you could not do before***



# Why Hadoop?




# How Hadoop solves the Big Data problem

- hadoop clusters scale horizontally
- hadoop can handle unstructured / semi-structured data
- hadoop clusters provides storage & computing

# What is HDFS?

- Today's big data is 'too big' to store in ONE single computer
- No matter how powerful it is and how much storage it has.

- This eliminates lot of storage system and databases that were built for single machines.

**Hadoop solution : Data is stored on multiple computers (NODES!)**

- The file system will look like a unified single file system to the 'outside' world

# What is HDFS?

- We want our system to be cost-effective, so we are not going to use 'expensive' machines.

- **hadoop solution : Run on commodity hardware**

- Server class machines

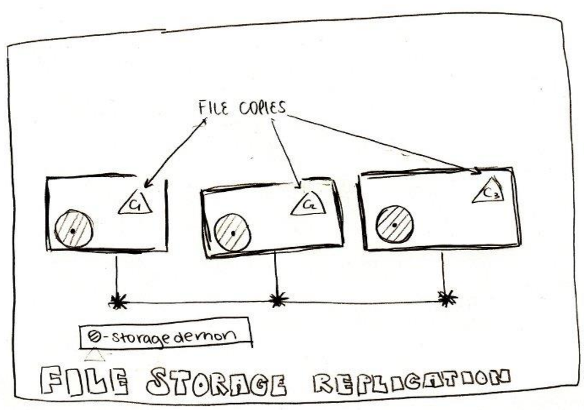
✓ These will be commodity servers that you can order from any of the vendors (Dell, HP, etc)

# What is HDFS?

- **Problem : Commodity hardware will fail**
- The approach we will take is we build the 'intelligence' into the software.
- **hadoop solution : Software is intelligent enough to deal with hardware failure**
- The software detects hardware failures and takes corrective actions automatically -- without human intervention. Our software will be smarter!

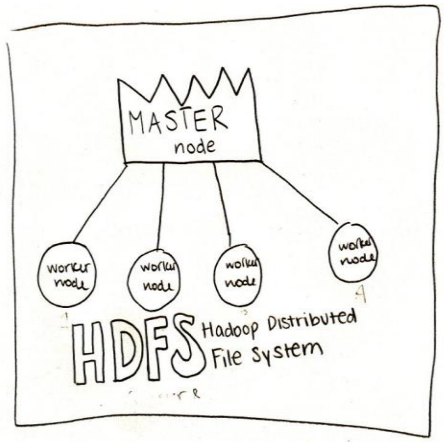
# What is HDFS?

- **Hardware failure may lead to data loss**
- **hadoop Solution : Replicate data**



# What is HDFS?

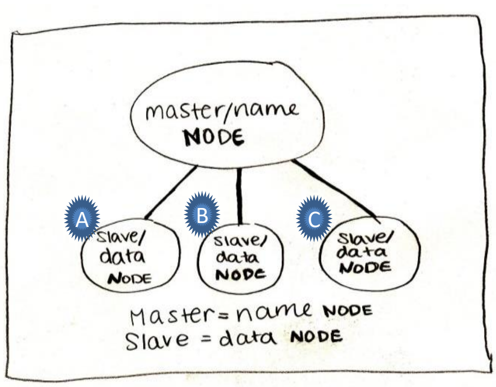
- **HDFS master / worker design**




✓ **Master node co-ordinates all the worker nodes**

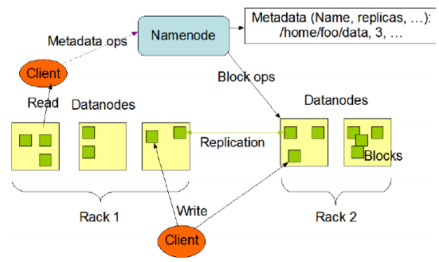
# What is HDFS?

- In an HDFS cluster, there is ONE master node [**Name Node (NN)** ]and many worker nodes [**Data Nodes (DN)** ].



# What is HDFS?

- Immutable File System – Read, Write, Sync/Flush – No Random writes
- Storage Server used for Computation – Move Computation to Data
- Fault Tolerant & Easy Management – Built in Redundancy, Tolerates Disk & Node Failure, Auto-Managing
- Not a SAN but high bandwidth network access to data via Ethernet
- Used typically to Solve problems not feasible with traditional systems

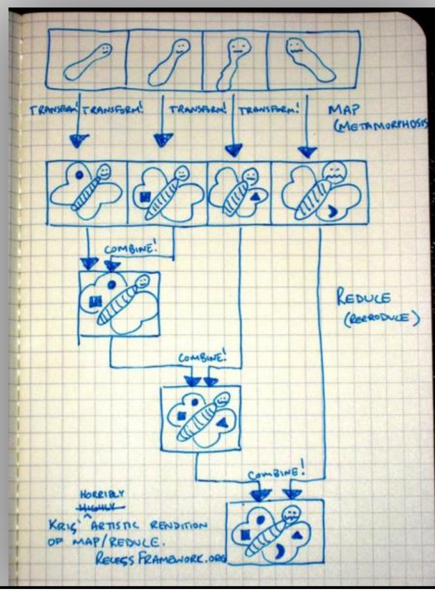



# What Map Reduce does for you?

- Organizes your multiple computers in a cluster in order to perform the calculations you need.
- Takes care of distributing the work between computers and of putting together the results of each computer's computation.
- Takes care of hardware and network failures, so that they do not affect the flow of your computation.

You, in turn…
Have to break your problem into separate pieces which can be processed in parallel by multiple machines

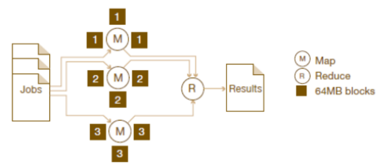
## What Map Reduce does for you?




## What Map Reduce does for you?

# What Map Reduce does for you?

- A Distributed Computing Model
- Typical Pipeline
  (Input>Map>Shuffle/Sort>Reduce>Output)
- Easy to Use
- Schedules work on HDFS node with data
- Scan through data, reducing seeks
- Automatic Reliability and re-execution on failure




# I am not sure my company has a big data problem

- No 'Big Data Problem'? then hadoop probably isn't the best fit for your company

- How much data is considered Big Data?

It differs from company to company. For some companies, 10 TB of data would be considered Big Data; for others 1 PB would be Big Data

***Now that Hadoop can help with Big Data, it may be possible to start capturing data that wasn't captured before.***

**If you don't have a 'Big Data problem' now …**

**Is that because you are not capturing some data?**

Companies choose to **NOT** capturing data, because **there wasn't a feasible way to store and process it.**

# How much does it cost to adopt Hadoop?


$3.3 million IBM Blue Gene/P supercomputer with two racks

capable of providing processing power measured in teraflops

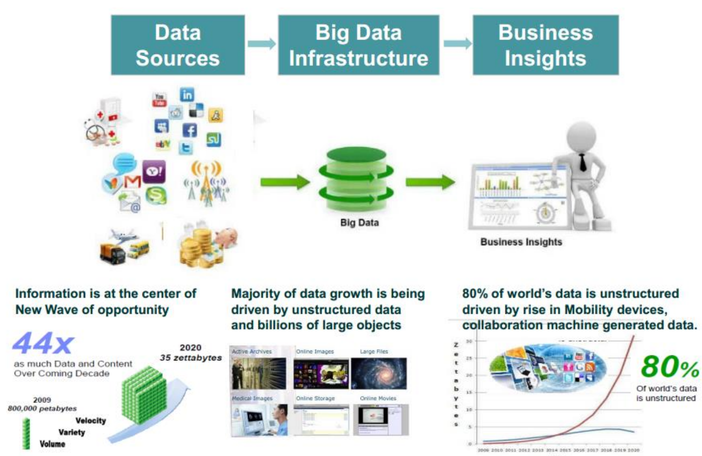
One teraflop is the equivalent of one trillion floating-point operations per second

Blue Gene/P runs on IBM PowerPC 450 processors in a quad-core architecture

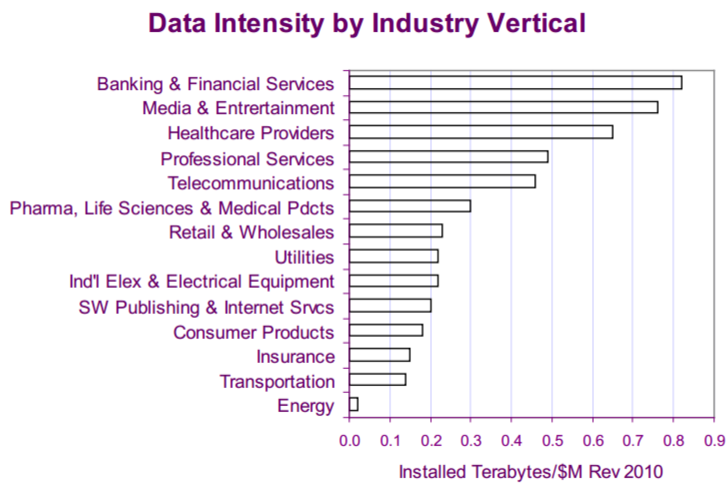
00

One ne… erational costs like Da… oling, electricity,…

# Harnessing Big Data for Business Insights

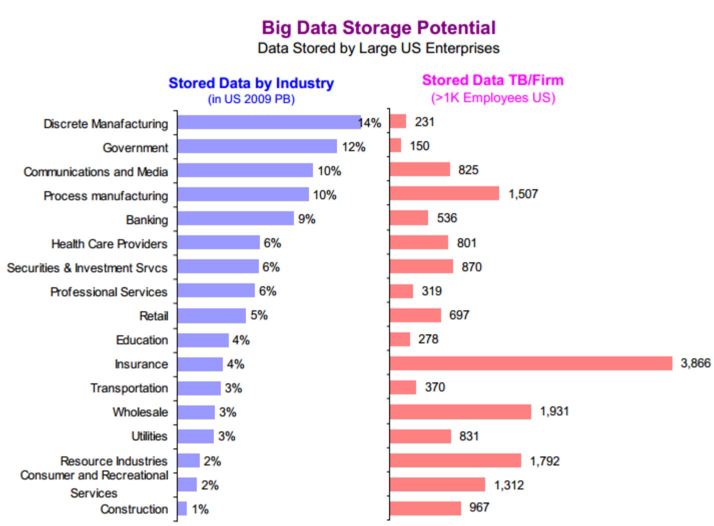


# Big Data Targets – Storage Infrastructure

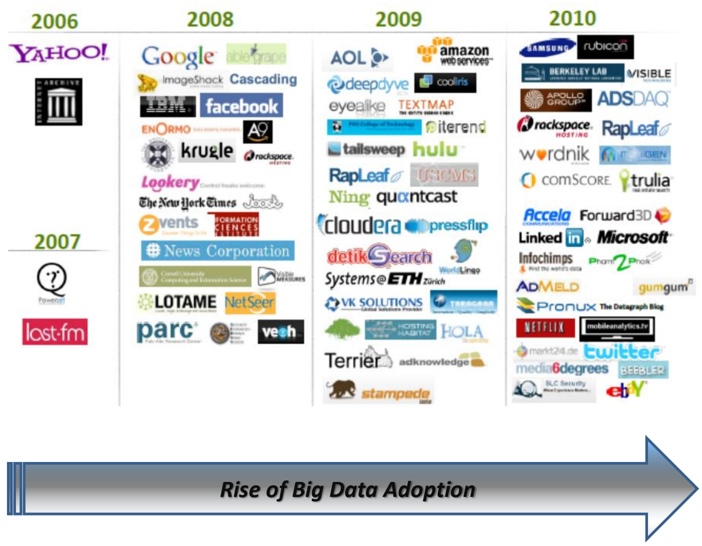



- ✓ Relationship between IT spending and revenue

# Big Data Targets – Storage Infrastructure



# Real World Examples




# Real World Examples

## ***Data Storage***

- NetApp collects diagnostic data from its storage systems deployed at customer sites. This data is used to analyze the health of NetApp systems.
- **Problem:** NetApp collects over 600,000 data transactions weekly, consisting of unstructured logs and system diagnostic information. Tradional data storage systems proved inadequate to capture and process this data.
- **Solution:** A Cloudera Hadoop system captures the data and allows parallel processing of data.
- **Vendor:** Cloudera
- **Cluster/Data size:** 30+ nodes; 7TB of data / month

NetApp

# Real World Examples (continue)

## ***Financial Services***

- A leading retail bank is using Cloudera and Datameer to validate data accuracy and quality to comply with regulations like Dodd-Frank
- **Problem:** The previous solution using Teradata and IBM Netezza was time consuming and complex, and the data mart approach didn't provide the data completeness required for determining overall data quality.
- **Solution:** A Cloudera + Datameer platform allows analyzing trillions of records which currently result in approximately one terabyte per month of reports.
- hadoop **Vendor:** Cloudera + Datameer
- **Cluster/Data size:** 20+ nodes; 1TB of data / month


# Real World Examples (continue)

## ***Health Care***

- **Storing and processing Medical Records**
- **Problem:** A health IT company instituted a policy of saving seven years of historical claims and remit data, but its in-house database systems had trouble meeting the data retention requirement while processing millions of claims every day
- **Solution:** A Hadoop system allows archiving seven years' claims and remit data, which requires complex processing to get into a normalized format, logging terabytes of data generated from transactional systems daily, and storing them in CDH for analytical purposes
- hadoop **Vendor:** Cloudera
- **Cluster/Data size:** 10+ nodes pilot; 1TB of data / day

# Real World Examples (continue)

## ***Health Care***

- **Monitoring patient vitals at Los Angeles Childrens Hospital**
- Researchers at LA Childrens Hospital is using Hadoop to capture and analyze medical sensor data.
- **Problem:** Collecting lots (billions) of data points from sensors / machines attached to the patients. This data was periodically purged before because storing this large volume of data on expensive storage was cost-prohibitive.
- **Solution:** Continuously streaming data from sensors/machines is collected and stored in HDFS. HDFS provides scalable data storage at reasonable cost.
- **Vendor:** Unknown
- **Cluster/Data size:** ???

# Real World Examples (continue)

## ***Human Sciences***

- NextBio is using Hadoop MapReduce and HBase to process massive amounts of human genome data.
- **Problem:** Processing multi-terabyte data sets wasn't feasible using traditional databases like mysql.
- **Solution:** NextBio uses Hadoop map reduce to process genome data in batches and it uses HBase as a scalable data store
- **Vendor:** Intel

# Real World Examples (continue)

## ***Telecom***

- **China Telecom Guangdong**
- **Problem:** Storing billions of mobile call records and providing real time access to the call records and billing information to customers. Traditional storage/database systems couldn't scale to the loads and provide a cost effective solution
- **Solution:** Hbase is used to store billions of rows of call record details. 30TB of data is added monthly
- **Vendor:** Intel
- **Hadoop cluster size:** 100+ nodes

# Real World Examples (continue)

## ***Telecom***

- **Nokia**
- Nokia collects and analyzes vast amounts of data from mobile phones
- **Problem:**
  (1) Dealing with 100TB of structured data and 500TB+ of semi-structured data
  (2) 10s of PB across Nokia, 1TB / day
- **Solution:** HDFS data warehouse allows storing all the semi/multi structured data and offers processing data at petabyte scale
- **Vendor:** Cloudera
- **Cluster/Data size:**
  (1) 500TB of data
  (2) 10s of PB across Nokia, 1TB / day

# Real World Examples (continue)

## ***Travel***

- **Orbitz**
- **Problem:** Orbitz generates tremendous amounts of log data. The raw logs are only stored for a few days because of costly data warehousing. Orbitz needed an effective way to store and process this data, plus they needed to improve their hotel rankings.
- **Solution:** A Hadoop cluster provided a very cost effective way to store vast amounts of raw logs. Data is cleaned and analyzed and machine learning algorithms are run.
- hadoop **Vendor:** ?
- **Cluster/Data size:** ?

# Real World Examples (continue)

## ***Energy***

- **Seismic Data at Chevron**
- **Problem:** Chevron analyzes vast amounts of seismic data to find potential oil reserves.
- **Solution:** Hadoop offers the storage capacity and processing power to analyze this data.
- hadoop **Vendor:** IBM Big Insights
- **Cluster/Data size:** ?

# Real World Examples (continue)

## ***Energy***

- **OPower**
- Opower works with utility companies to provide engaging, relevant, and personalized content about home energy use to millions of households.
- **Problem:** Collecting and analyzing massive amounts of data and deriving insights into customers' energy usage.
- **Solution:** Hadoop provides a single storage for all the massive data and machine learning algorithms are run on the data.
- hadoop **Vendor:** ?
- **Cluster/Data size:** ?

OPOWER

# Real World Examples (continue)

## ***Logistics***

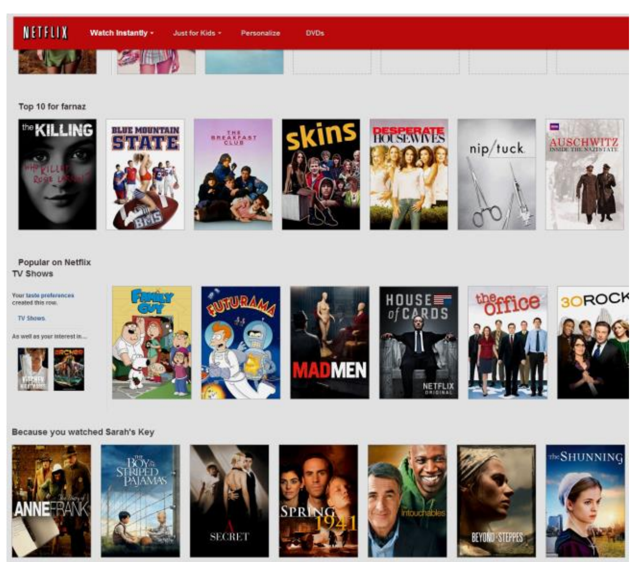
- **Trucking data @ US Xpress**
- US Xpress - one of the largest trucking companies in US - is using Hadoop to store sensor data from their trucks. The intelligence they mine out of this, saves them $6 million / year in fuel cost alone.
- **Problem:** Collecting and and storing 100s of data points from thousands of trucks, plus lots of geodata.
- **Solution:** Hadoop allows storing enormous amount of sensor data. Also Hadoop allows querying / joining this data with other datasets.
- hadoop **Vendor:** ?
- **Cluster/Data size:** ?

U.S. XPRESS COMING THROUGH

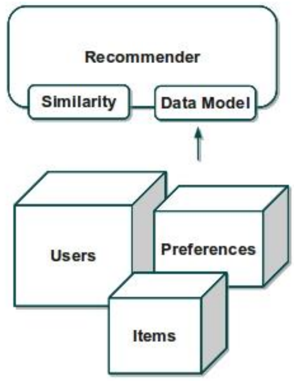
***Get more detailed…***
***Movie Recommendation Engine Example***

## Movie Recommendation Engine

- Predicting list of new items a user would like based on preferences of previous items



# Movie Recommendation Flowchart




$$S \times U = R$$

**Similarity Matrix**

$e_{jk}$ value:

Frequency of their co-ocurance
(j-th item is seen, the k-th item is seen as well)

**User's Preference Vector**

Each cell represents the user's preference for j-th item

**Recommendation Vector**

Prediction of recommendation of the j-th item for the user

k →, j ↓

| | Item1 | Item2 | Item3 | Item4 | Item5 | Item6 |
|---|---|---|---|---|---|---|
| Item1 | 1 | 4 | 2 | 0 | 1 | 2 |
| Item2 | 4 | 1 | 1 | 3 | 1 | 6 |
| Item3 | 2 | 1 | 1 | 5 | 3 | 0 |
| Item4 | 0 | 3 | 5 | 1 | 2 | 7 |
| Item5 | 1 | 1 | 3 | 2 | 1 | 1 |
| Item6 | 2 | 6 | 0 | 7 | 1 | 1 |

×

| | |
|---|---|
| Item1 | 2 |
| Item2 | 1 |
| Item3 | 0 |
| Item4 | 0 |
| Item5 | 4.5 |
| Item6 | 0 |

=

| | |
|---|---|
| Item1 | 11 |
| Item2 | 14 |
| Item3 | 19 |
| Item4 | 12 |
| Item5 | 8 |
| Item6 | 15 |

**Recommendations**

- Item3
- Item6
- Item4

# Why Map Reduce

- Large DATASET
- Problem can be easily split into independent subtasks that can be processed in parallel.
- We are dealing with UNSTRUCTURED data
- It is attractive because it allows a programmer to write software for execution on a computing cluster with little knowledge of parallel or distributed computing.

# Map Reduce Phases

Parallel Computing

1. Generating List of ItemIDs
2. Create Preference Vector
3. Count Unique Users
4. Transpose Preferences Vectors
5. Create Similarity Matrix
6. Pre-partial multiply, Similarity Matrix
7. Pre-partial multiply, Preferences
8. Partial Multiply
9. Filter Items
10. Aggregate and Recommend

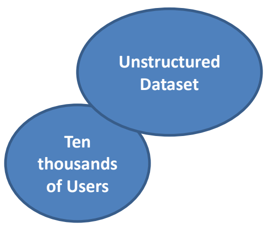
The Apache Mahout™ machine learning is built on top of HADOOP

(It includes: classification, regression, evolutionary algorithms, and recommenders)

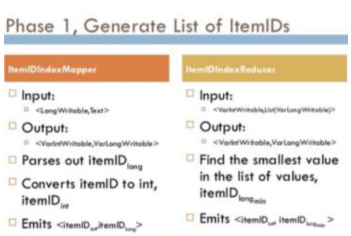
Mahout's recommender engine transforms an expected input format into predicted recommendations

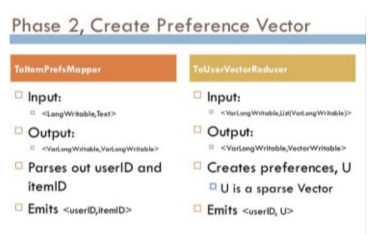
- ✓ Series of Map Reduce phases are used to accomplish predicting recommendations

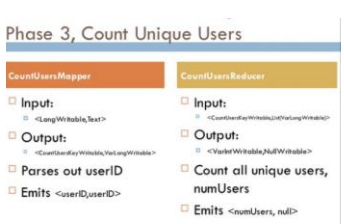
```
userID,itemID[,preference[,timestamp]]
.
.
.
.
.
.
.
.
.
```

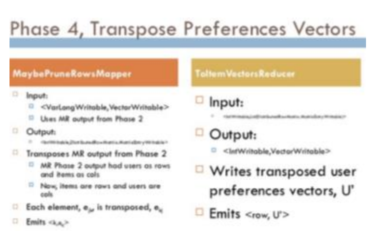



```
1 [845:5.0,550:5.0,546:5.0,25:5.0,531:5.0]
2 [546:5.0,288:5.0,11:5.0,25:5.0,531:5.0]
3 [137:5.0,284:5.0,508:4.8,248:4.8,285:4.8]
4 [748:5.0,1296:5.0,546:5.0,568:5.0,538:5.0]
5 [732:5.0,550:5.0,9:5.0,546:5.0,11:5.0]
6 [739:5.0,9:5.0,546:5.0,11:5.0,25:5.0]
```



## Phase 5.1, RowSimilarityJob, Compute Weights

**RowWeightMapper**
- Input:
  - <IntWritable,VectorWritable>
  - Uses MR output from Phase 4
- Output:
  - <VarIntWritable,WeightedOccurrence>
- For each element, $e_{jk}$, compute its weighted occurrence, $w_{jk}$
- Emits <k,$w_{jk}$>

**WeightedOccurrencesPerColumnReducer**
- Input:
  - <VarIntWritable,List(WeightedOccurrence)>
- Output:
  - <VarIntWritable,WeightedOccurrenceArray>
- Transfers weighted occurrences to array and writes results
- Emits <k, $w_{jk}$>

## Phase 5.2, RowSimilarityJob, Compute Similarities

**CooccurrencesMapper**
- Input:
  - <VarIntWritable,WeightedOccurrenceArray>
  - Uses MR output from Phase 5.1
- Output:
  - <WeightedRowPair,Cooccurrence>
- For pair of rows, p, write its column coocurrences, c
- Emits < p, c>

**SimilarityReducer**
- Input:
  - <WeightedRowPair,List(Cooccurrence)>
- Output:
  - <SimilarityMatrixEntryKey,MatrixEntryWritable>
- Compute the row similarities between $row_a$ and $row_b$, and write corresponding position in the matrix
- Emits <row, matrix entry>

## Phase 5.3, RowSimilarityJob, Similarity Matrix

**Mapper**
- Input:
  - <SimilarityMatrixEntryKey,MatrixEntryWritable>
  - Uses MR output from Phase 5.2
- Output:
  - <SimilarityMatrixEntryKey,MatrixEntryWritable>
- Writes similarity matrix entry key, sme, and matrix entry, me, as is
- sme is basically each row
- me is basically each row-col entry of the similarity matrix
- Emits <sme,me>

**EntriesToVectorsReducer**
- Input:
  - <SimilarityMatrixEntryKey,List(MatrixEntryWritable)>
- Output:
  - <IntWritable,VectorWritable>
- Write the row and its associated vector out
- Emits <row, vector>

## Phase 6, Pre-partial multiply, Similarity Matrix

**SimilarityMatrixRowWrapperMapper**
- Input:
  - < IntWritable,VectorWritable>
  - Uses MR output from Phase 5.3
- Output:
  - <IntWritable,VectorOrPrefWritable>
- Wraps the similarity vector, $v_1$, into a different vector format, $v_2$
- Emits <row,$v_2$>

**Reducer**
- Input:
  - <IntWritable,List(VectorOrPrefWritable)>
- Output:
  - <IntWritable,VectorOrPrefWritable>
- Write the row and each of its associated vector out
- Emits <row, vector>

## Phase 7, Pre-partial multiply, Preferences

**UserVectorSplitterMapper**
- Input:
  - < VarLongWritable,VectorWritable>
  - Uses MR output from Phase 2
- Output:
  - < VarIntWritable,VectorOrPrefWritable>
- Maps userID and preference vector, U
- Emits <userID,U>

**Reducer**
- Input:
  - <IntWritable,List(VectorOrPrefWritable)>
- Output:
  - <IntWritable,VectorOrPrefWritable>
- Write the row and each of its associated vector out
- Emits <row, vector>

## Phase 8, Partial Multiply

**Mapper**
- Input:
  - < VarLongWritable,VectorWritable>
  - Uses MR outputs from Phases 6 and 7
- Output:
  - < VarIntWritable,VectorOrPrefWritable>
- Maps row and vector, v
- Emits <row,v>

**ToVectorAndPrefReducer**
- Input:
  - <VarIntWritable,List(VectorOrPrefWritable)>
- Output:
  - <IntWritable,VectorOrPrefWritable>
- Write the row and each of its associated vector similarity, userIDs, and preference values
- Emits <row, vector>

## Phase 9, Filters Items

**ItemFilterMapper**
- Input:
  - <LongWritable,Text>
- Output:
  - <VarLongWritable,VectorLongWritable>
- Parses userID and itemID
- Emits <itemID,userID>

**ItemFilterAsVectorAndPrefReducer**
- Input:
  - <VarLongWritable,List(VarLongWritable)>
- Output:
  - <VarIntWritable,VectorOrPrefWritable>
- Writes itemID and vector of userIDs and preferences
- Emits <itemID, vector>

## Phase 10, Aggregate and Recommend

**PartialMultiplyMapper**
- Input:
  - <VarIntWritable,VectorAndPrefsWritable>
  - Uses MR outputs from phases 8 and 9
- Output:
  - <VarLongWritable,PrefAndSimilarityColumnWritable>
- Writes userID and recommendations
- Emits <userID,recommendation>

**AggregateAndRecommendReducer**
- Input:
  - <VarLongWritable,List(PrefAndSimilarityColumnWritable)>
- Output:
  - <VarLongWritable,RecommendedItemsWritable>
- Writes userID and vector of recommendations
- Emits <userID, vector>

# Type of Databases for Storing Big Data

| Type | Description | Example Tools |
|---|---|---|
| **Document-oriented** | Document-oriented data stores are mainly designed to store and retrieve collections of documents or information and support complex data forms in several standard formats, such as JSON, XML, and binary forms (e.g., PDF and MS Word). A document-oriented data store is similar to a record or row in a relational database but is more flexible and can retrieve documents based on their contents (e.g., MongoDB, SimpleDB, and CouchDB) | MongoDB; SimpleDB; CouchDB |
| **Column-oriented** | A column-oriented database stores its content in columns aside from rows, with attribute values belonging to the same column stored contiguously. Column-oriented is different from classical database systems that store entire rows one after the other | Google BigTable; |
| **Graph database** | A graph database is designed to store and represent data that utilize a graph model with nodes, edges, and properties related to one another through relations | Neo4j |
| **Key-value** | Key-value is an alternative relational database system that stores and accesses data designed to scale to a very large size. | Apache HBase; Apache Cassandra; Voldemort; |

# Big Data Analytic Tools

| Category | Tools |
|---|---|
| **Batch processing tools** | Apache Hadoop and MapReduce |
| | Dryad |
| | Apache Mahout |
| | Apache Spark |
| | Jaspersoft BI Suite |
| | Pentaho Business Analytics |
| | Talend Open Studio |
| **Real-time stream processing tools** | Storm |
| | S4 |
| | SQLstream s-Server |
| | Splunk |
| | Apache Kafka |
| | SAP Hana |
| **Interactive analysis tool** | Google’s Dremel |
| | Apache drill |

**_Thank you_**