Networking in the Big Data Era

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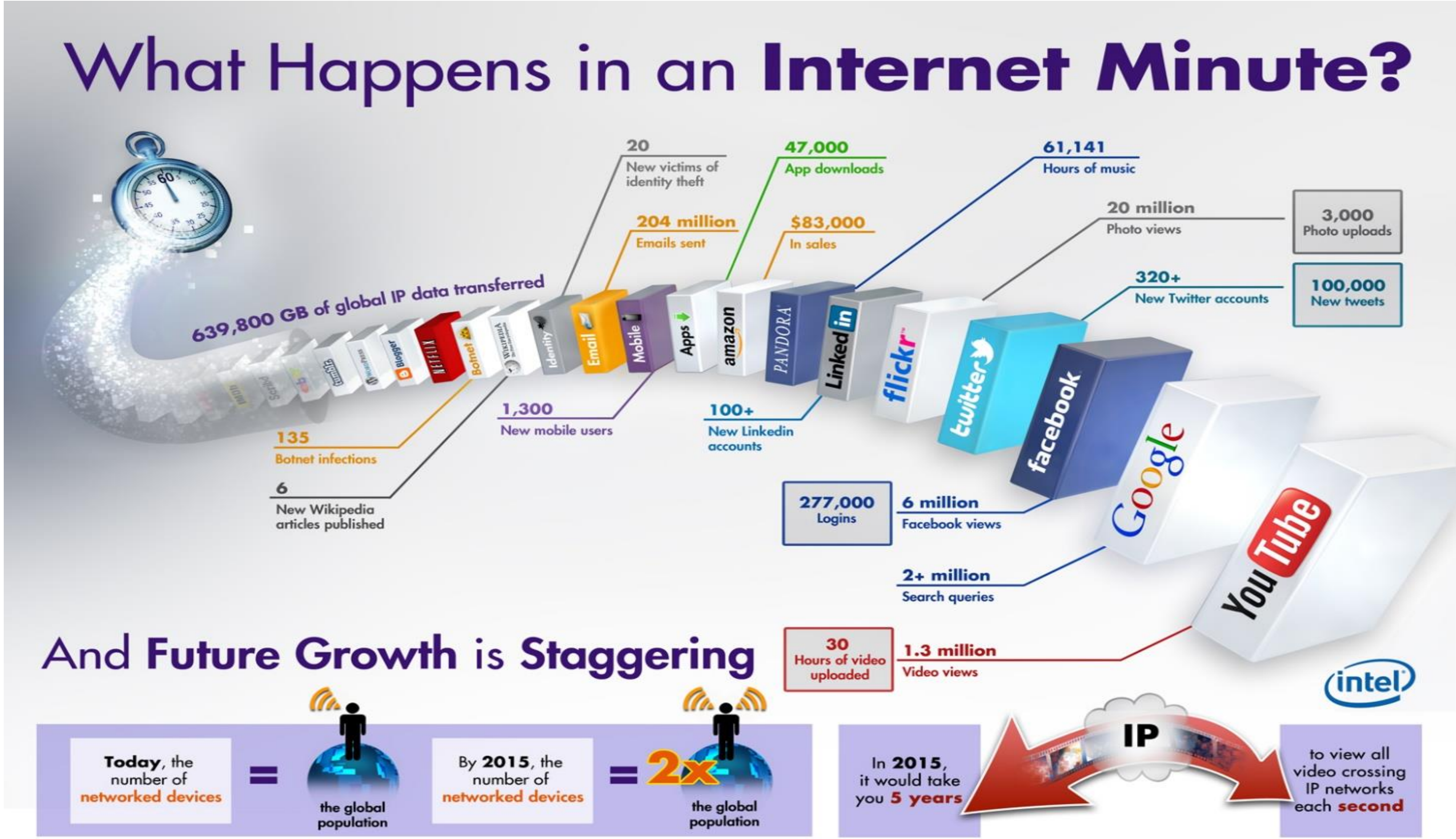
International Teletraffic Congress 27
Ghent, Belgium
Sep 10th, 2015

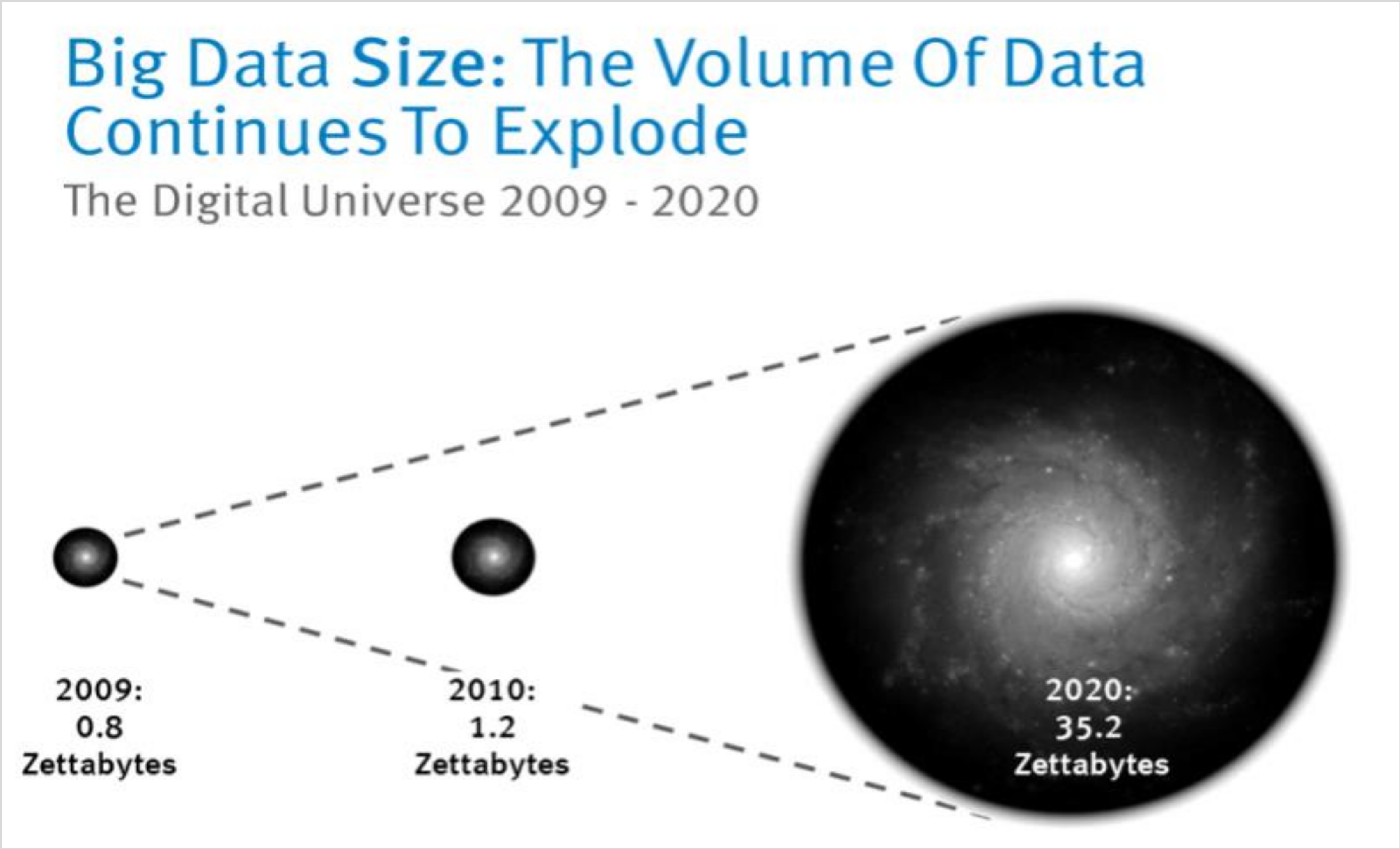
Outline

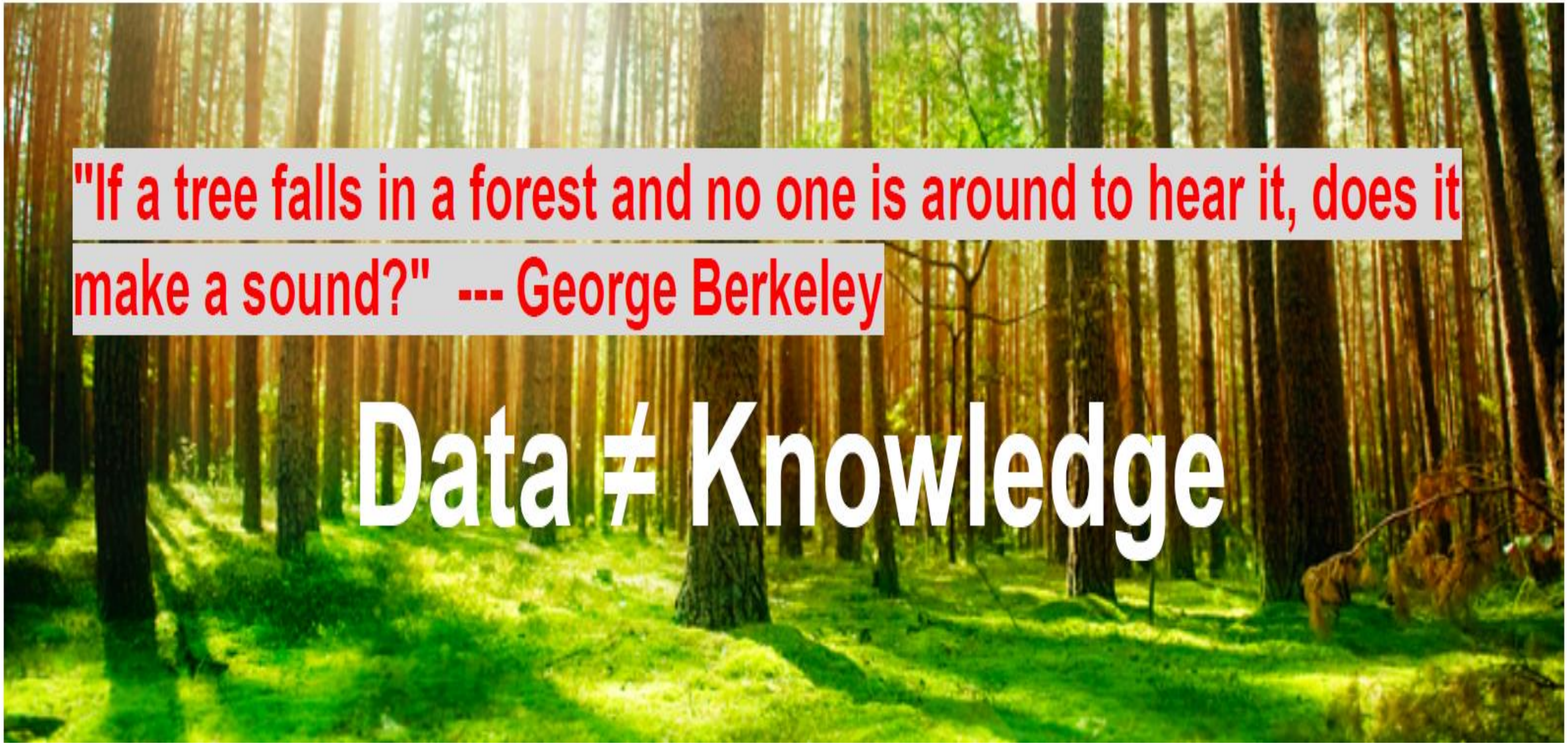
- Big Data
- Networking for Big data
- Big Data for Networking
- Some Research Problems

What are big data?



What Happens in an Internet Minute?
639,800 GB of global IP data transferred
20
New victims of identity theft
47,000
App downloads
61,141
Hours of music
204 million
Emails sent
$83,000
In sales
20 million
Photo views
3,000
Photo uploads
320+
New Twitter accounts
100,000
New tweets
1,300
New mobile users
100+
New Linkedin accounts
135
Botnet infections
6
New Wikipedia articles published
277,000
Logins
6 million
Facebook views
2+ million
Search queries
30
Hours of video uploaded
1.3 million
Video views
And Future Growth is Staggering
Today, the number of networked devices
=
the global population
By 2015, the number of networked devices
= 2x
the global population
In 2015, it would take you 5 years
IP
to view all video crossing IP networks each second

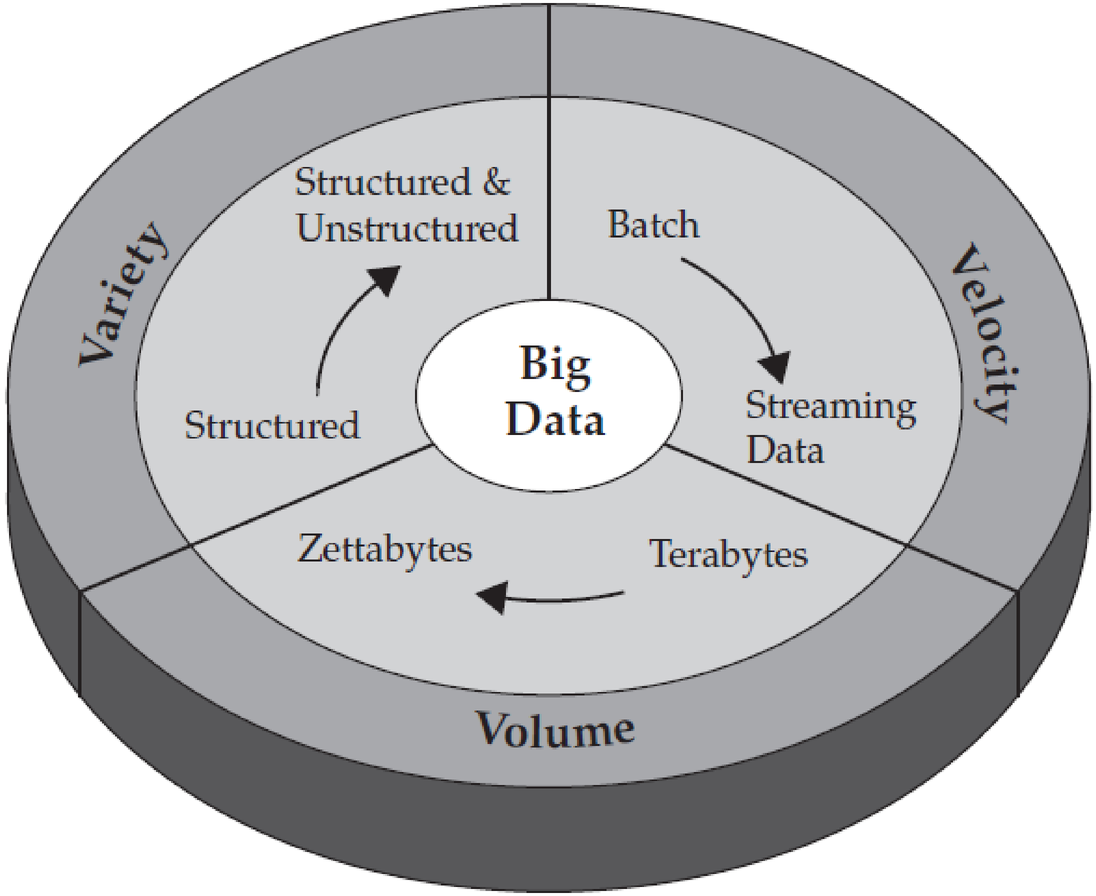

Big Data Size: The Volume Of Data Continues To Explode
The Digital Universe 2009 - 2020
2009: 0.8 Zettabytes
2010: 1.2 Zettabytes
2020: 35.2 Zettabytes


"If a tree falls in a forest and no one is around to hear it, does it make a sound?" --- George Berkeley
Data ≠ Knowledge

Processing Big Data


1%
of the world's data is analyzed
today

Big Data



Siewert, S. B. "Biga data in the cloud", IBM Developerworks, Tech. Rep., http://www.ibm.com/developerworks/library/bd-bigdatacloud/#what-is-big-data, July 9, 2013.

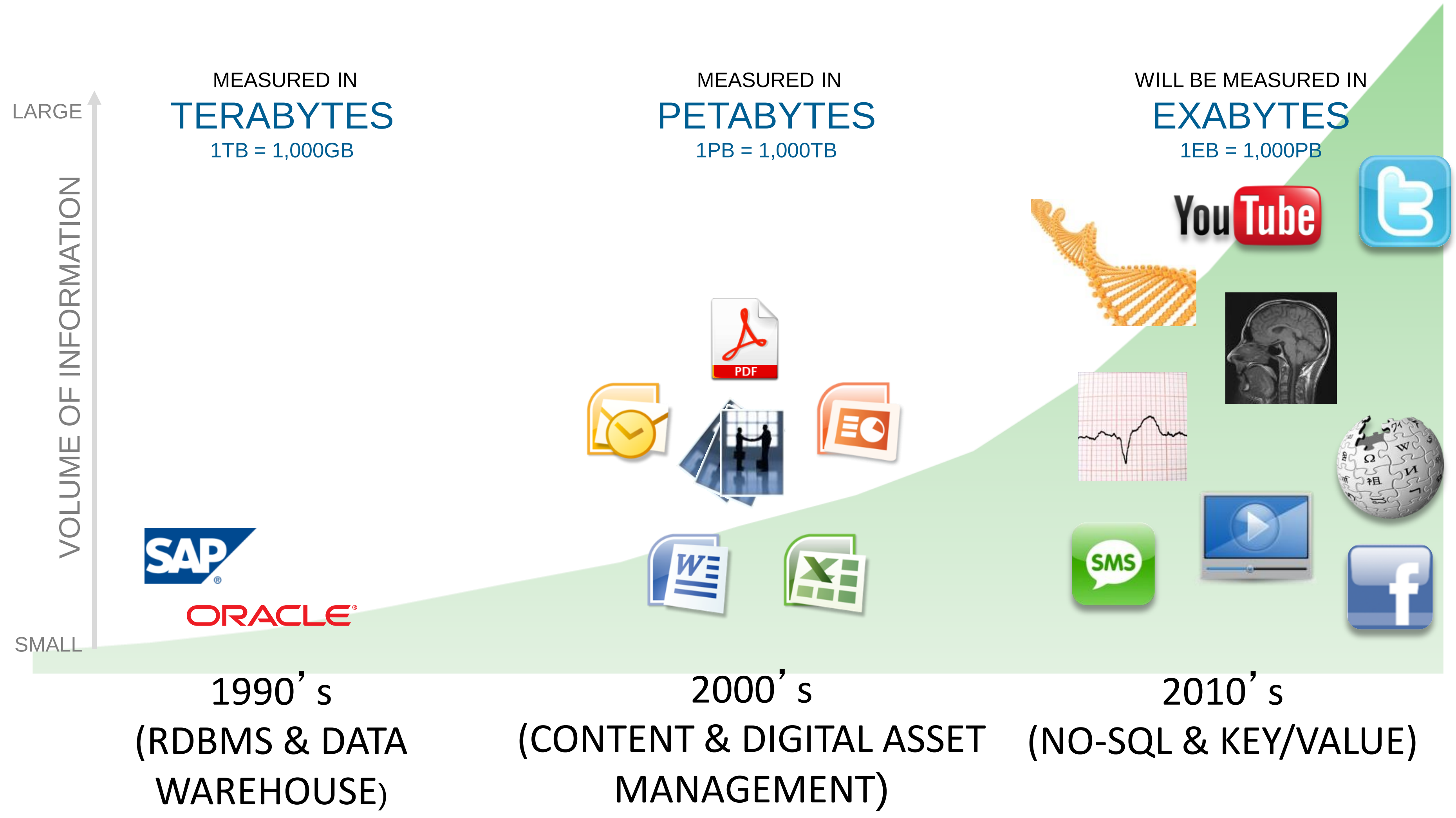
Volume

- Data set to be processed at a time is too large
- Data set is not too large but the collection of data set is large
- Volume of data set too large per se, but processing is time consuming perhaps due to too many IO operations

Present of Big Data

Too big to handle

New Applications Driving Data Volume



Velocity

- Data arrive is faster than the processing capacity
- Results must be produced with certain delay bound, processing is limited by disk I/O throughput

Future of Big Data

Drinking from a firehose

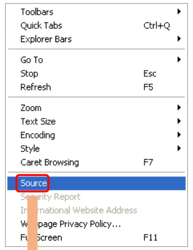
Variety

Structured Data

SUMMER FOOD SERVICE PROGRAM 1] (Data as of August 01, 2011)				
Fiscal Year	Number of Sites	Peak (July) Participation	Meals Served	Total Federal Expenditures 2]
	-----------Thousands-----------		--Mil.--	---Million $---
1969	1.2	99	2.2	0.3
1970	1.9	227	8.2	1.8
1971	3.2	569	29.0	8.2
1972	6.5	1,080	73.5	21.9
1973	11.2	1,437	65.4	26.6
1974	10.6	1,403	63.6	33.6
1975	12.0	1,785	84.3	50.3
1976	16.0	2,453	104.8	73.4
TQ 3]	22.4	3,455	198.0	88.9
1977	23.7	2,791	170.4	114.4
1978	22.4	2,333	120.3	100.3
1979	23.0	2,126	121.8	108.6
1980	21.6	1,922	108.2	110.1

Semi-Structured Data

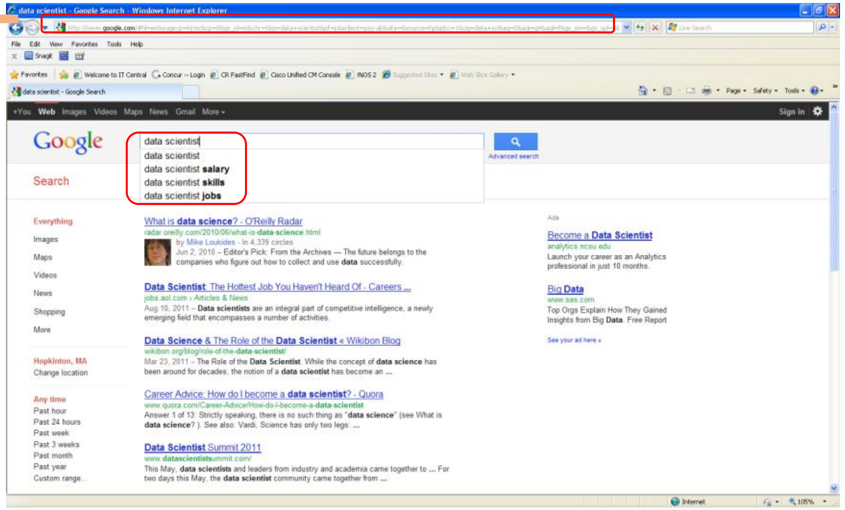
View → Source




```
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN" "http://www.w3.org/TR/xhtml1/DTD/xhtml1-trans
<html xmlns="http://www.w3.org/1999/xhtml">

        <head>
                <meta http-equiv="Content-Type" content="text/html; charset=UTF-8" />
                <META name="y_key" content="859b4020e1c9acec">
                        <link rel="canonical" href="http://www.emc.com/index.htm" />
                                <META NAME="verify-v1" CONTENT="yiZt9V0P4eV0jFdIPeVVIfRP32g4qtwFE0I2UvTMfSU
                <title>EMC - Data Recovery, Cloud Computing, and Storage Hardware</title>
                <META NAME="description" CONTENT="EMC is a leading provider of storage hardware solutions th
 data recovery and improve cloud computing." />
                        <META NAME="keywords" CONTENT="emc,network storage,data recovery,information manager
 software,nas storage,information protection,information management" />
                <!-- Start :stylehseet incldues -->
<link rel="stylesheet" href="/_admin/css/styles.css" />
<link rel="stylesheet" href="/_admin/css/styles_nav.css" />
<!--[if IE]>
```

Quasi-Structured Data



http://www.google.com/#hl=en&sugexp=kjrmc&cp=8&gs_id=2m&xhr=t&q=data+scientist&pq=big+data&pf=p&sclient=psyb&source=hp&pbx=1&oq=data+sci&aq=0&aqi=g4&aql=f&gs_sm=&gs_upl=&bav=on.2,or.r_gc.r_pw.,cf.osb&fp=d566e0fbd09c8604&biw=1382&bih=651

Unstructured Data

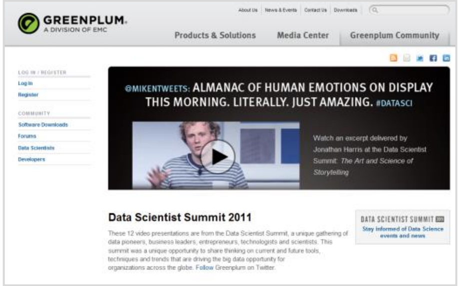
The Red Wheelbarrow, by William Carlos Williams

so much depends
upon

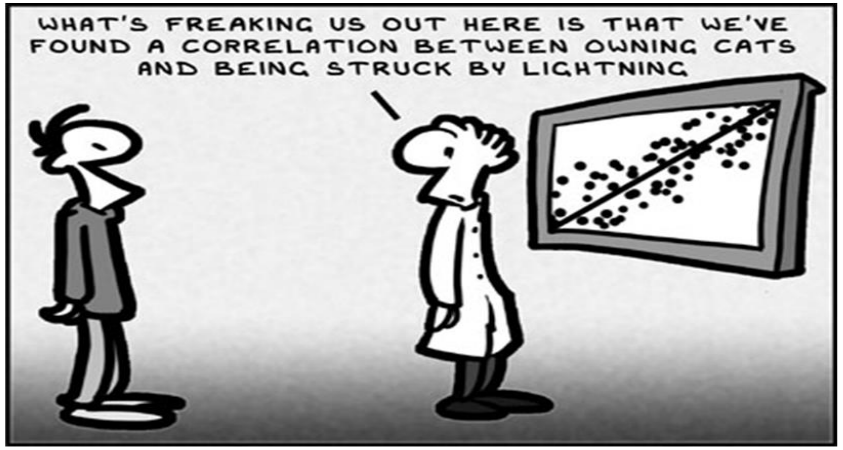
a red wheel
barrow

glazed with rain
water

beside the white
chickens.



Other V´s



- Valence: Non-trivial inter-relatedness of data
- Veracity: The degree of certainty in data
- Variability: variable interpretations

Why Big Data?

Revolutions needs Innovation…

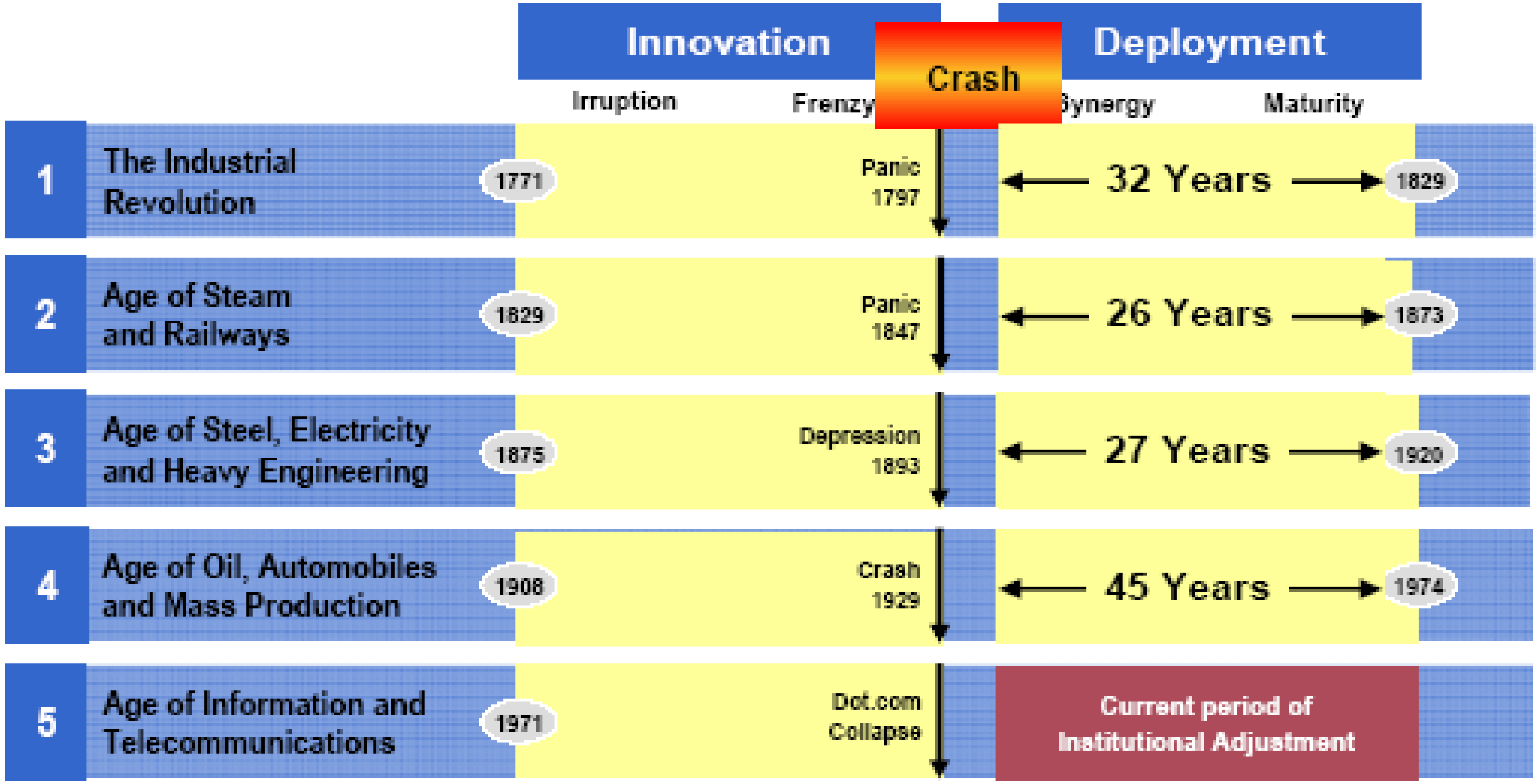
Five historical cycles …

		Innovation: Irruption	Innovation: Frenzy	Crash	Deployment: Synergy / Maturity	
1	The Industrial Revolution	1771	Panic 1797		• Formation of Mfg. industry • Repeal of Corn Laws opening trade	1829
2	Age of Steam and Railways	1829	Panic 1847		• Joint stock companies • Industry exploits economies of scale	1873
3	Age of Steel, Electricity and Heavy Engineering	1875	Depression 1893		• Separation of savings, investment banks • FDIC, SEC	1920
4	Age of Oil, Automobiles and Mass Production	1908	Crash 1929		• Build-out of Interstate highways • IMF, World Bank, BIS	1974
5	Age of Information and Telecommunications	1971	Dot.com Collapse		Current period of Institutional Adjustment	

Source: "Technological Revolutions and Financial Capital, Carlota Perez, 2002

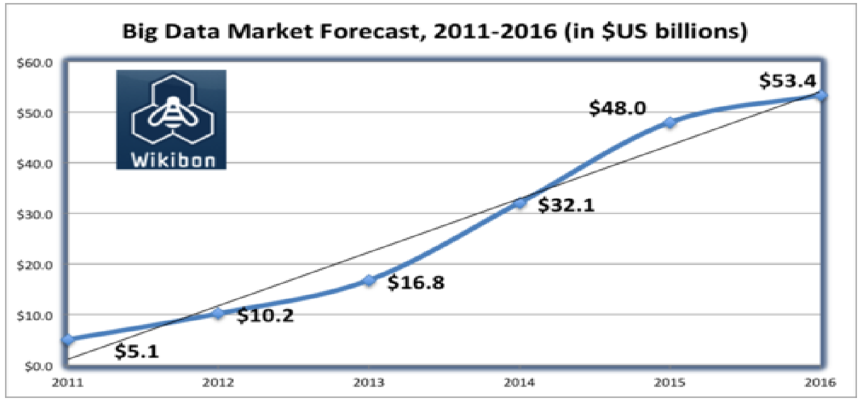
Takes time to deploy…

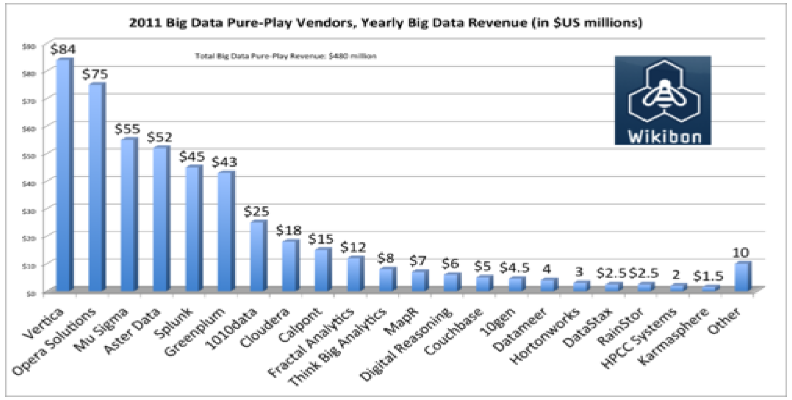
The deployment phase lasts 26 to 45 years …

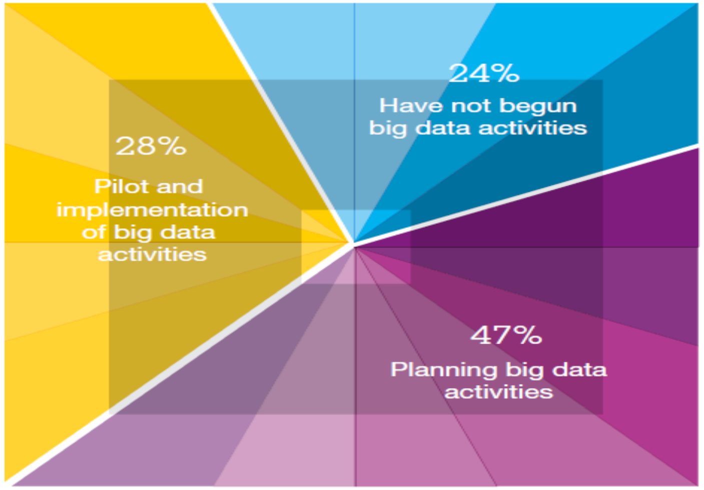


Source: "Technological Revolutions and Financial Capital, Carlota Perez, 2002

Big Data and Enterprise

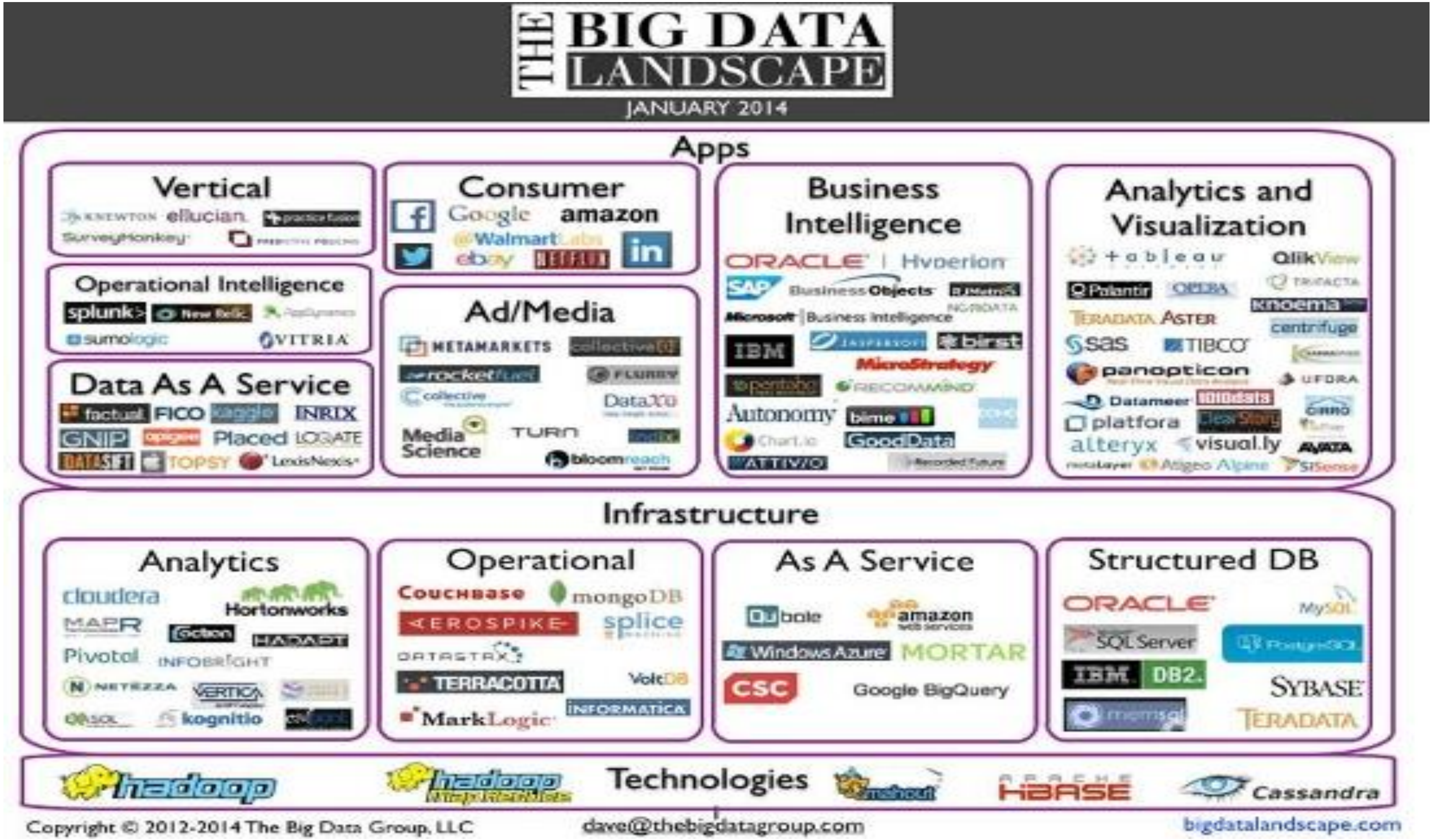






http://wikibon.org/wiki/v/Big_Data_Market_Size_and_Vendor_Revenues

Analytics: The real-world use of big data: How innovative enterprises extract value from uncertain data, Executive REport, IBM Institute for Business Value


THE BIG DATA LANDSCAPE
JANUARY 2014
Apps
Vertical
Consumer
Business Intelligence
Analytics and Visualization
Operational Intelligence
Ad/Media
Data As A Service
Infrastructure
Analytics
Operational
As A Service
Structured DB
Technologies
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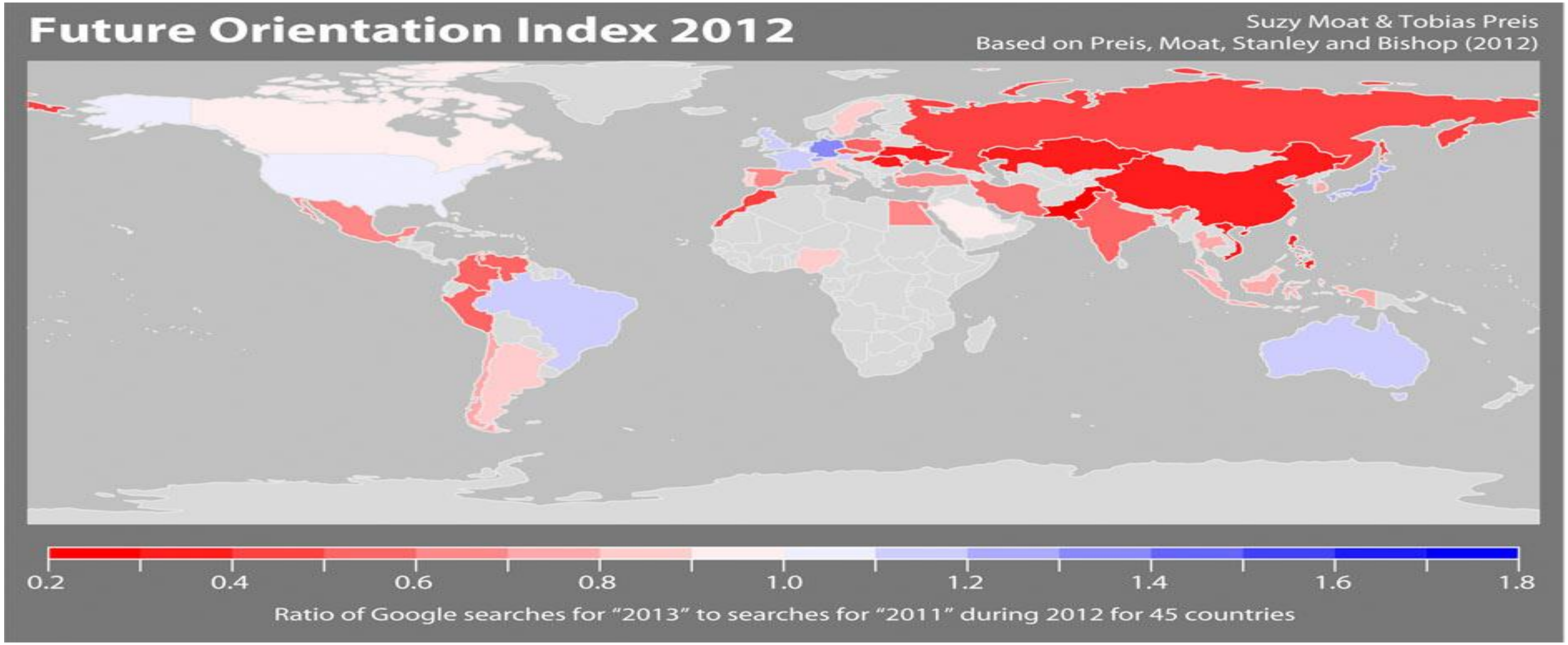
dave@thebigdatagroup.com
bigdatalandscape.com

Big Data and the Goverment

Big Data and the Goverment

"Can you explain all the emails you've received from Russia and Iran?"

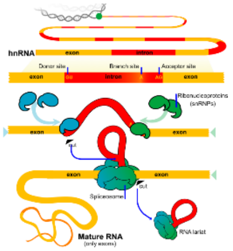
Big Data and Economy

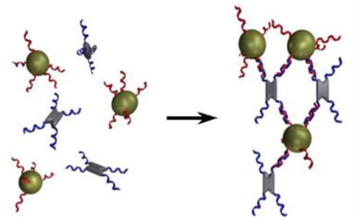


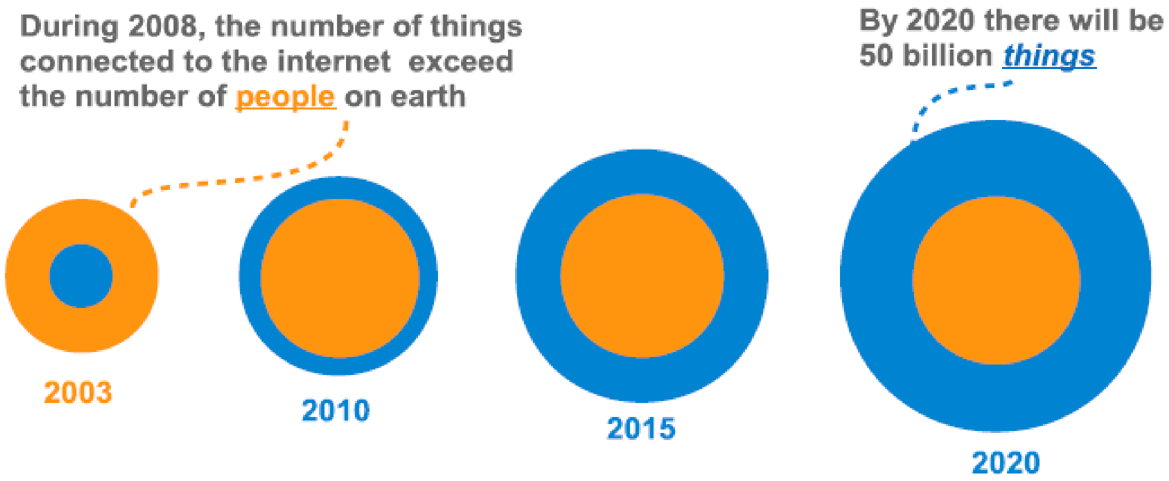
"We see two leading explanations for this relationship between search activity and GDP. Firstly, these findings may reflect international differences in attention to the future and the past, where a focus on the future supports economic success. Secondly, these findings may reflect international differences in the type of information sought online, perhaps due to economic influences on available Internet infrastructure."

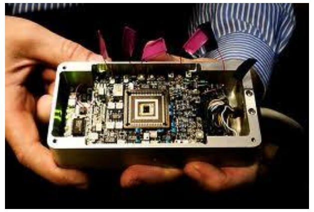
What are the sources of data ?

Sensors

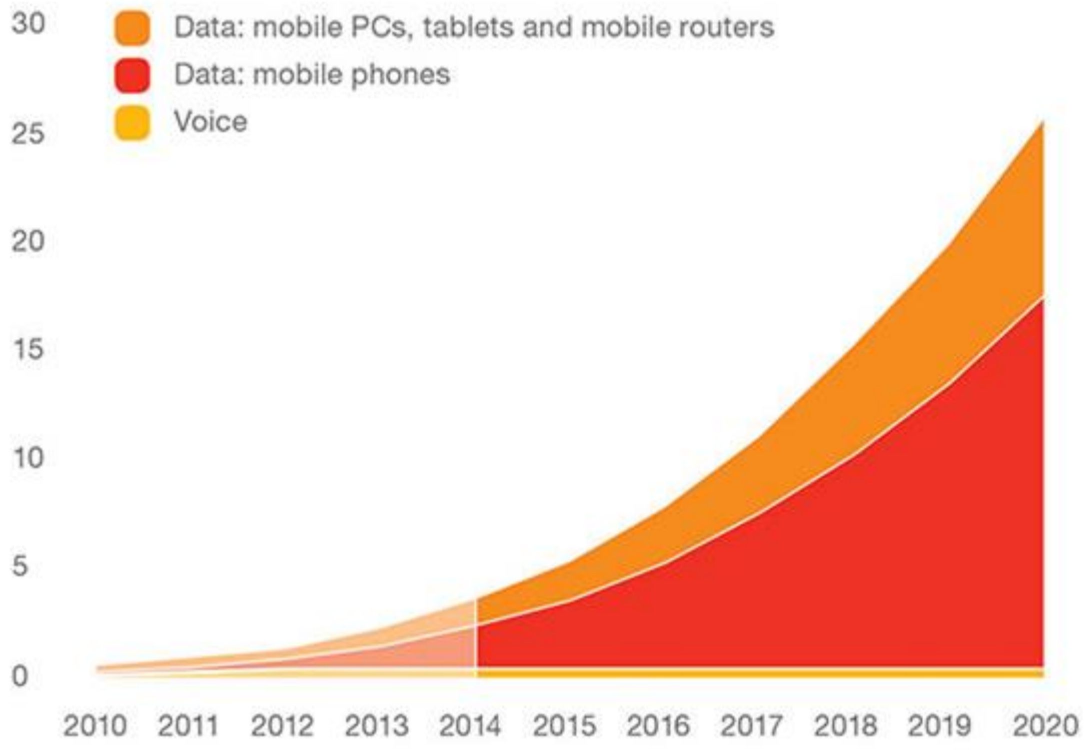




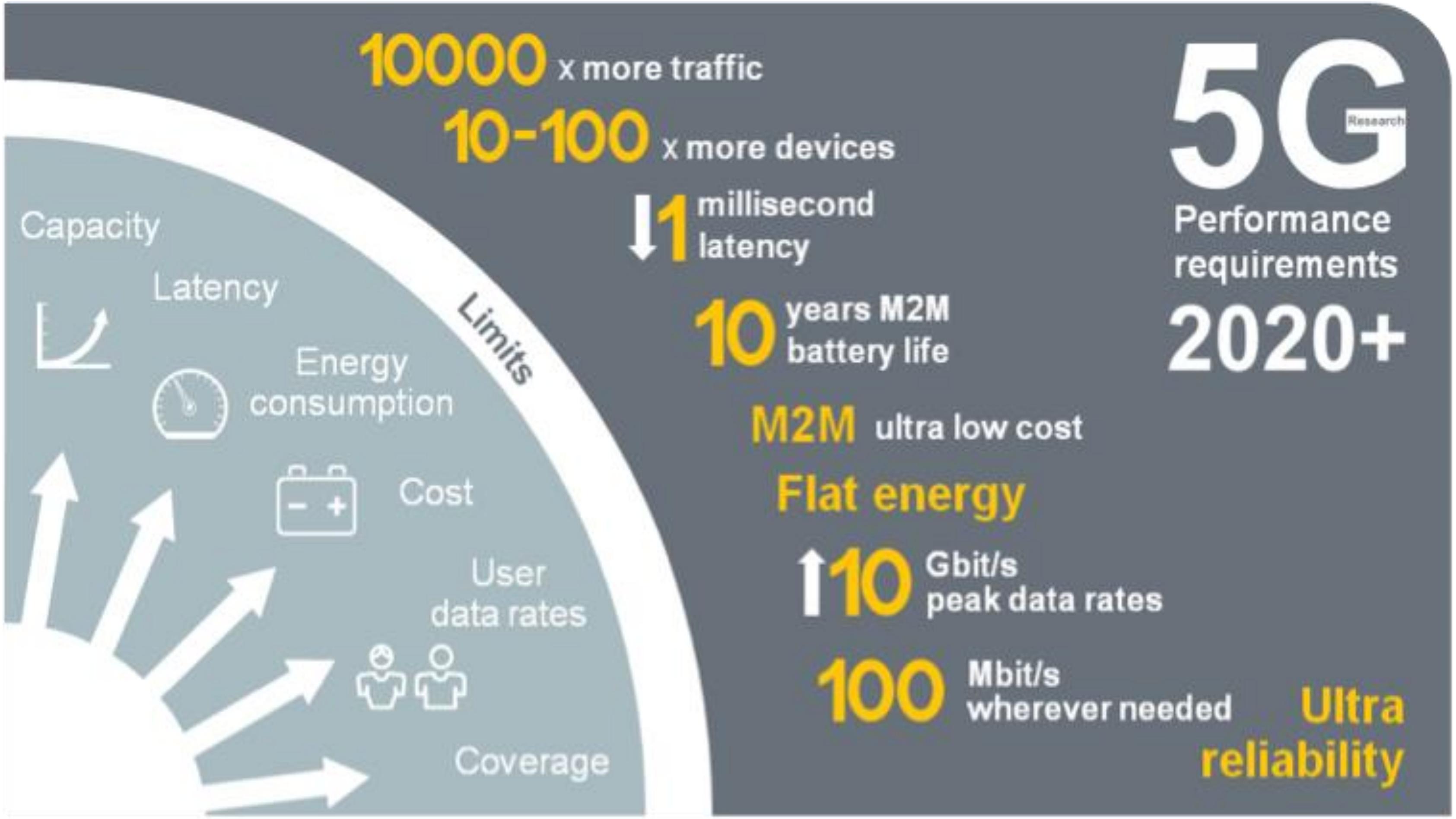

During 2008, the number of things connected to the internet exceed the number of people on earth
By 2020 there will be 50 billion things
2003
2010
2015
2020



Mobile Traffic Growth (in ExaBytes)



5G Requirements



You are What you Eat and Drink

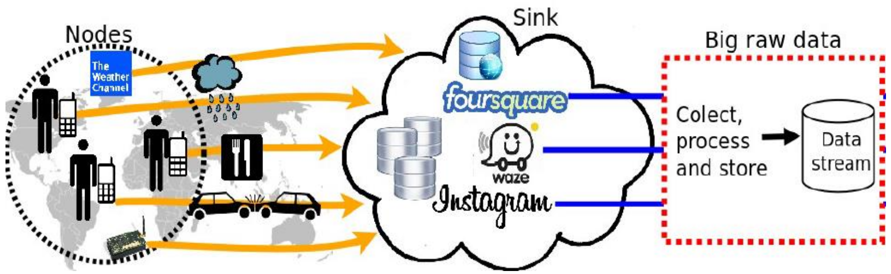
- Food and drink became also a strong cultural aspect, being able to describe strong differences

- Foursquare, created in 2009, registered 5 million users in December 2010 and 45 million users in January 2014

- Possiblity to sense human activities related to food and drink practices in large geographical areas
- Delineate and describe regions that have common cultural elements, defining signatures that represent cultural differences between distinct areas around the planet

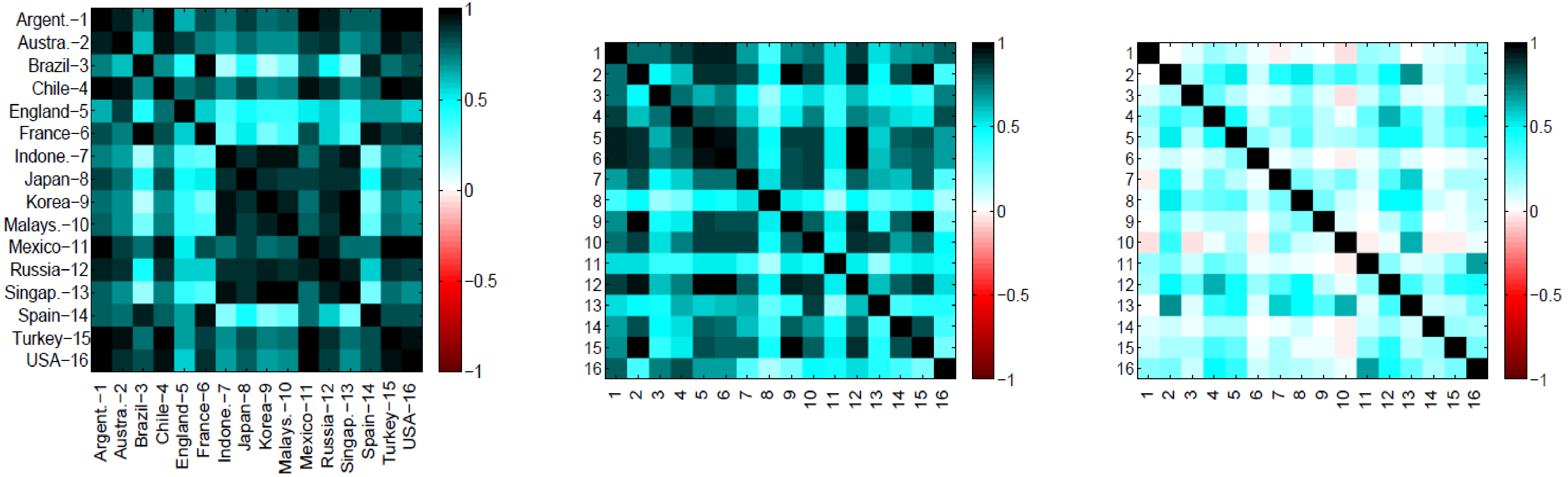
Thiago H Silva, Pedro O. S. Vaz de Melo, Jussara M. Almeida, Mirco Musolesi, Antonio A. F. Loureiro, You are What you Eat (and Drink): Identifying Cultural Boundaries by Analyzing Food & Drink Habits in Foursquar , ICWSM 2014

You are What you Eat and Drink



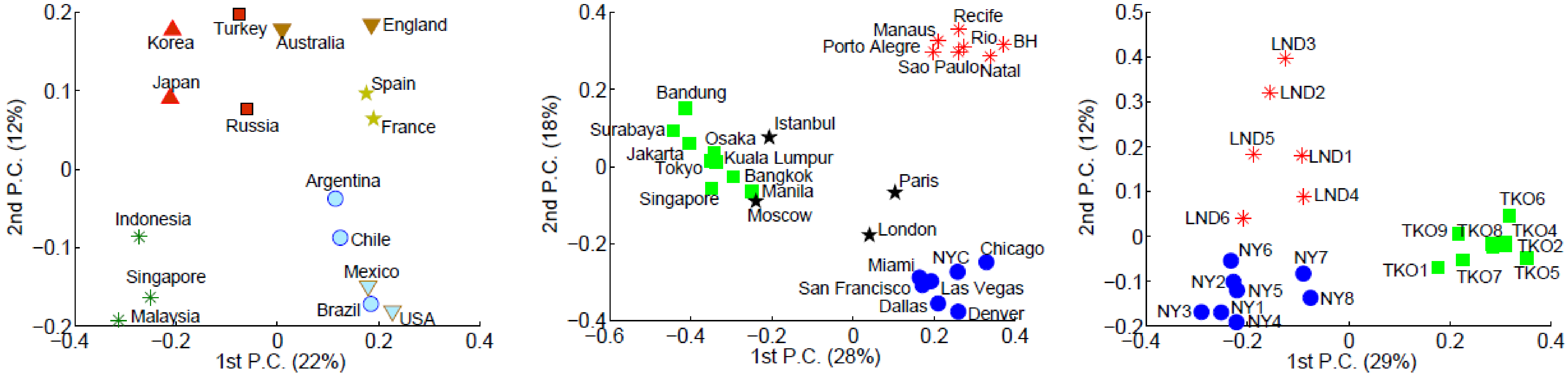
- 4.7 million tweets containing check-ins were gathered, each one providing a URL to the Foursquare website (one-week dataset same order of magnitude of the number of interviews performed in World Values Survey in almost three decades)
- Locationbased social networks (LBSNs)
- Location identified by free reverse geocoding API offered by Yahoo (http://developer.yahoo.com)

You are What you Eat and Drink

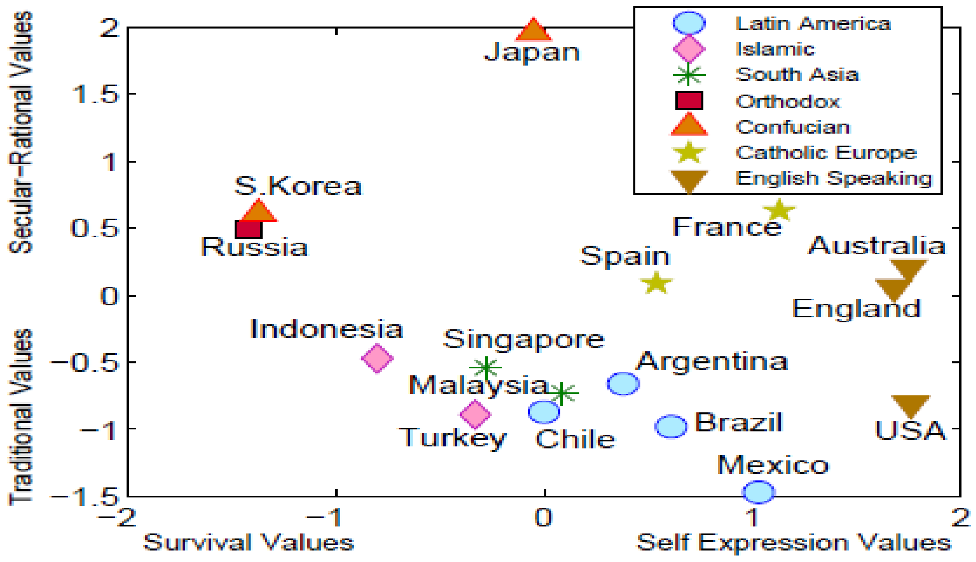


(a) Drink (b) Fast Food (c) Slow Food

Figure 3: Correlation of preferences between countries.



(a) Countries (b) Cities (c) Regions



What is the role of networking in Big Data?

Big Data ...
and the Next Wave of *InfraStress*

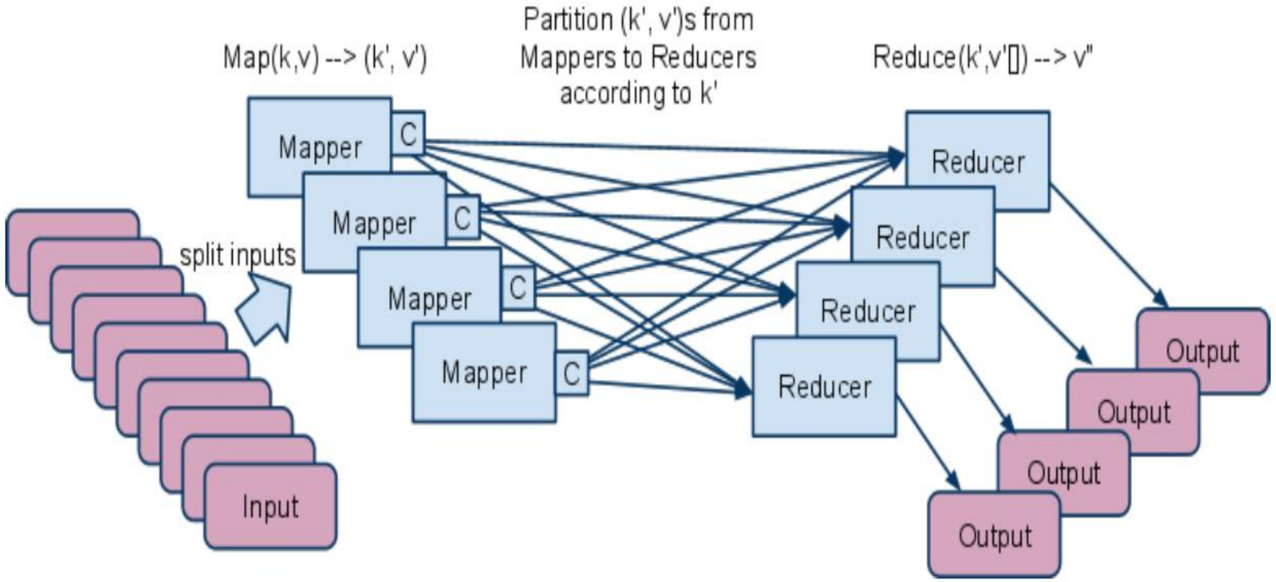
John R. Mashey
Chief Scientist, SGI

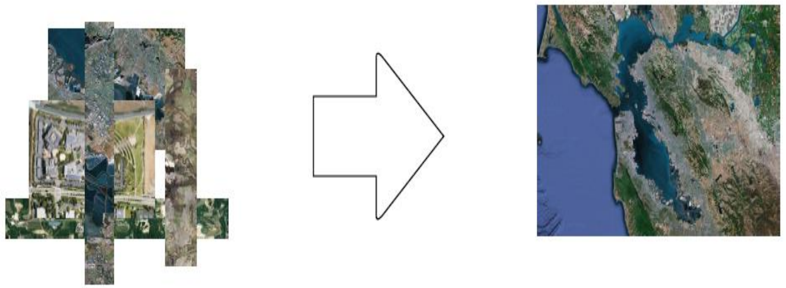
Technology Waves:
NOT technology for technology's sake
IT'S WHAT YOU DO WITH IT
But if you don't understand the trends
IT'S WHAT IT WILL DO TO YOU

"Infrastress"

Alibaba Mall processes in a single day (Nov 11th, 2013) 105.8 million online transactions from 213 million users and 4.1 billion transactions

Map-Reduce





Facebook Trace analysis: 30% to 50% of running time took up by communication phase

Machine Learning Algorithms

	Supervised	Unsupervised
Categorical	(Classification) *k* Nearest Neighbors Support Vector Machine Neural Networks	Hidden Markov Model
Continuous	Decision Trees Random Forests Regression	(Clustering and Dimensionality Reduction) Principal Component Analysis Singular Value Decomposition Gaussian Mixture Model

Machine Learning Algorithms

- The use of Latent Dirichlet Allocation algorithm for text mining requires all sampled topics to be multicasted interactively, which can exceed 1GB per interaction and over 1,000 interactions, leading to terabytes of data to be multicasted
- Logistic Regression algorithm for Twitter and the Alternating least Square algorithm for Netflix movie rating prediction take hundred of interactions. In each interaction roughly 300MB are distributed, leading to tens of gigabytes multicasted
- Multicast communication accounts for 30% to 45% of job completition time

Networking for Big Data

Networking Requirements for Big Data

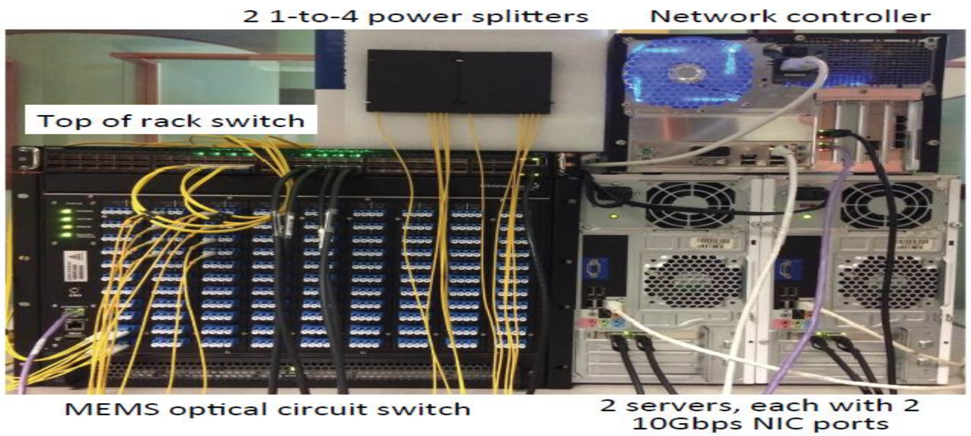
- Elastic bandwidth: to match the variability of volume
- High Speed data transfer
- Security: Access control privacy, threat detection, all in real-time in a highly scalable manner
- Network partitioning to handle big data
- Network congestion control for big data applications
- Network service consistency

Optical Multicast

- Data analytics applications routinely need to distribute terabytes of data from a central data source to hundreds of servers for processing
- In Hadoop Distributed File System(HDFS), multicast sender stores the data in HDFS and a multitude of receivers retrieve the data from a few data replicas, creating very high fan-out on the replicas. Bottleneck for over 40 recipients
- In Spark, a BitTorrent style P2P overlay among the recipient nodes, but BitTorrent suffers from suboptimal multicast trees that render high link stress, performs worse than HDFS

Y Xia, TSE Ng, XS Sun, Blast: Accelerating High-Performance Data Analytics Applications by Optical Multicast, IEEE INFOCOM 2015

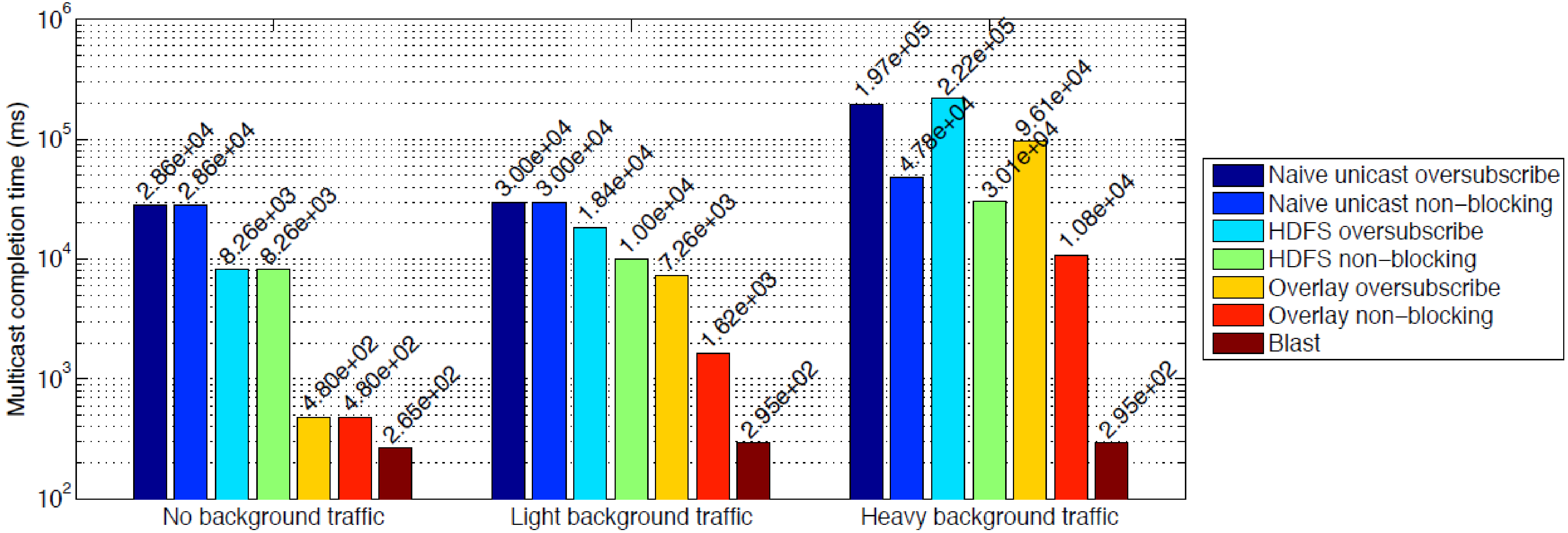
Optical Multicast



- Inherent performance limitations of application-layer overlays
- Difficult to performTCP-friendly congestion control in network multicast traffic.
- Blast uses optical transmission to realize a physical-layer broadcast medium, via passive optical power splitting, to connect a data source to its receivers
- tailor-made control plane, capable of collaborating with data analytics applications interactively, making resource allocation decisions nearly optimally, and directing the data flows in optical and electrical components in the network

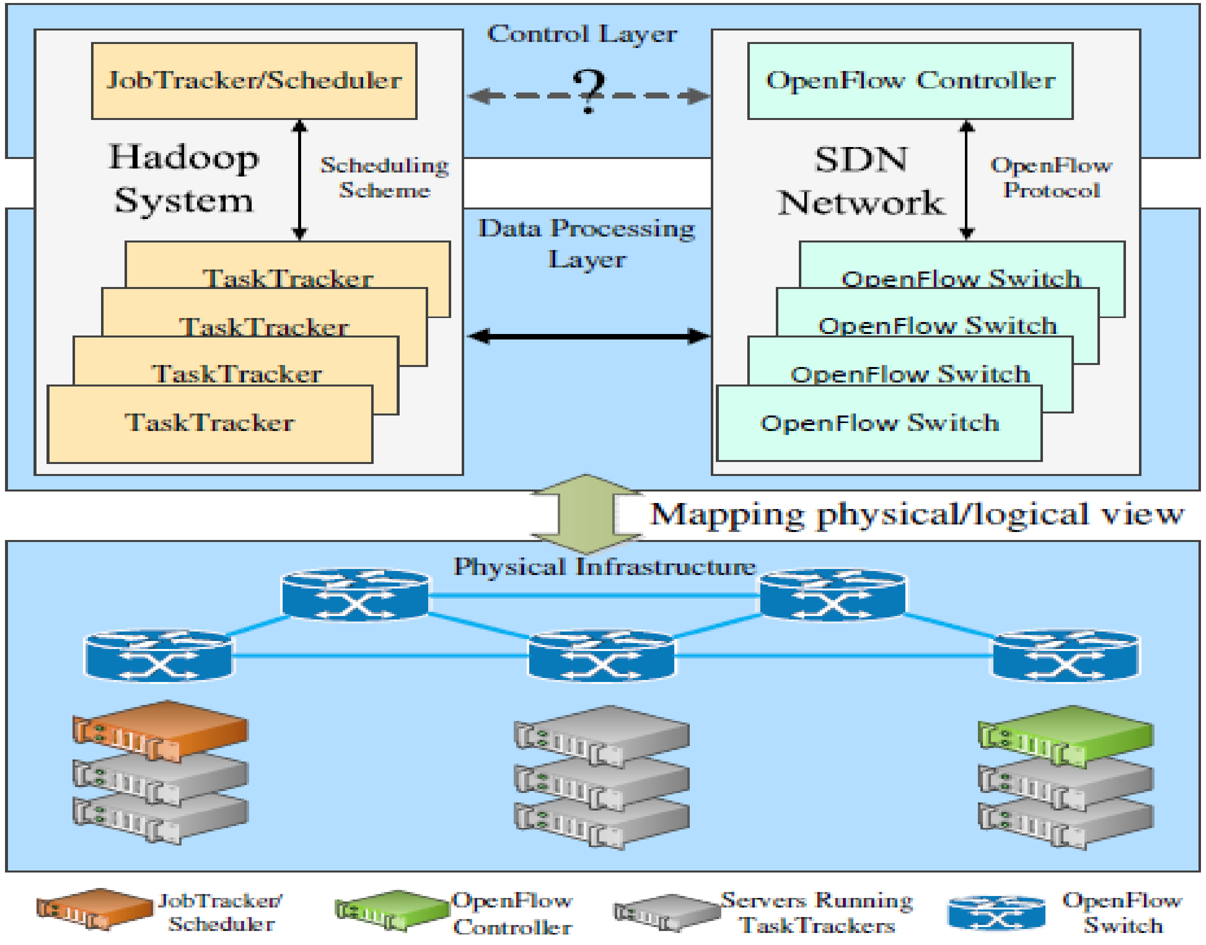
Y Xia, TSE Ng, XS Sun, [Blast: Accelerating High-Performance Data Analytics Applications by Optical Multicast](), IEEE INFOCOM 2015

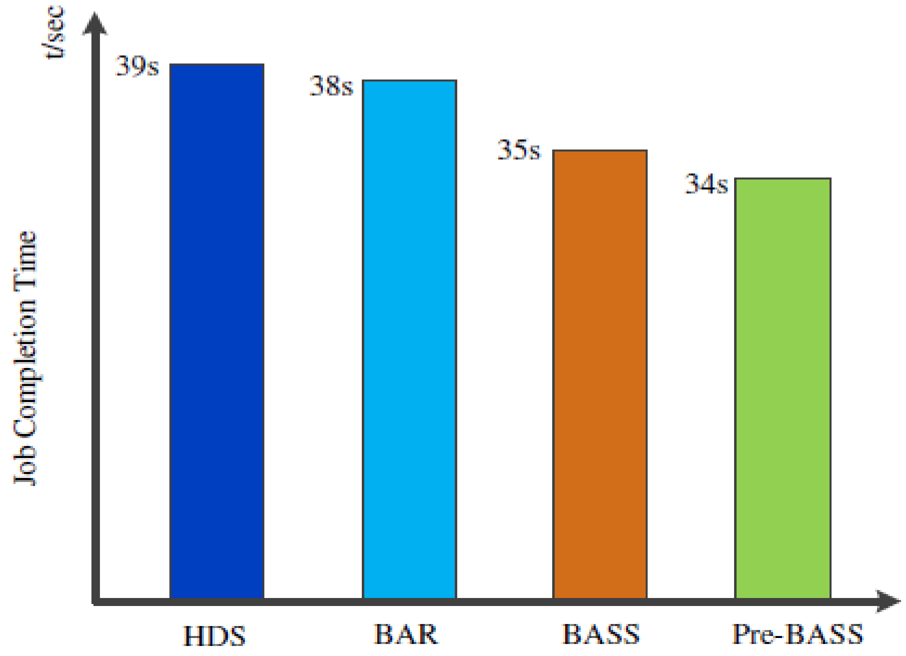
Optical Multicast



Y Xia, TSE Ng, XS Sun, Blast: Accelerating High-Performance Data Analytics Applications by Optical Multicast, IEEE INFOCOM 2015

SDN & Hadoop





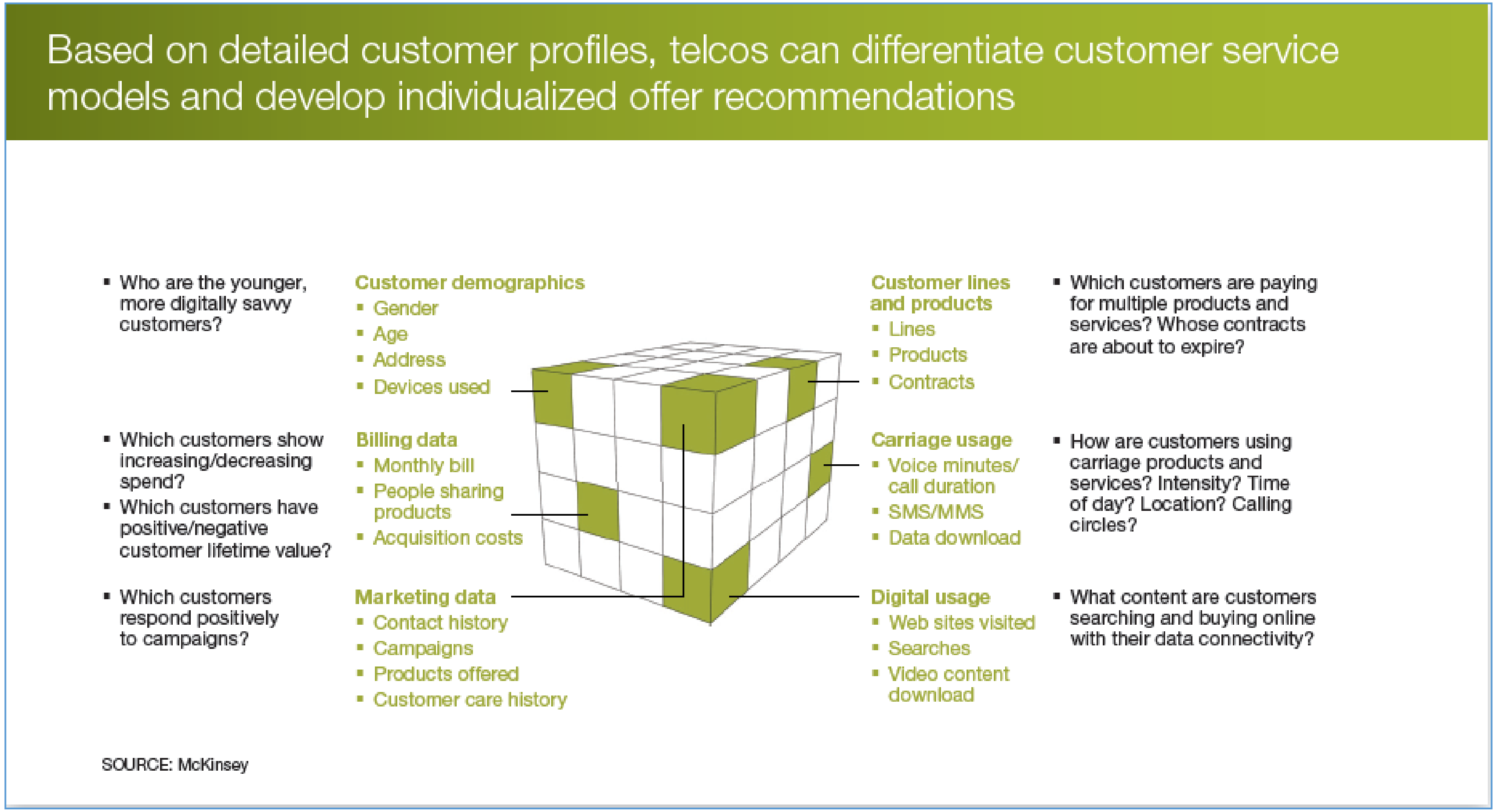
P. Qin, B. Dai, B,. Huang and G. Xu, "Bandwidth-Aware Scheduling with SDN in Hadoop: A New Trend for Big Data", arXiv:1403.2800, 2014

Big Data for Networking

Big data for Networking

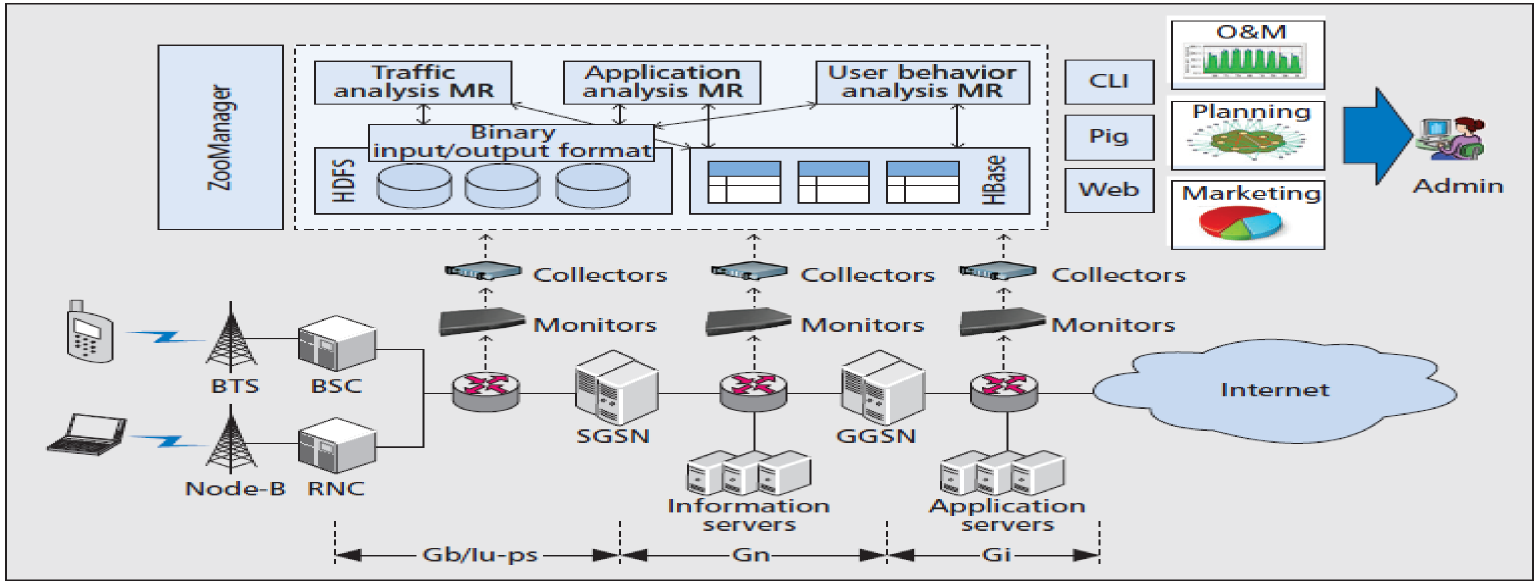
- Traffic Classification
- Intrusion Detection
- Definition of new services and class of services
- Anomaly detection
- Fault detection
- Cognitive networks
- Network configuration
- Sevice level prediction

Definition of new Services and Class of Services



Identifying Communities of Website users

- Mobile operator in China
- Objective: to find website communities of users and identify their usage behavior



Jun Liu, Feng Li, Ansari, N." Monitoring and analyzing big traffic data of a large-scale cellular network with Hadoop", IEEE Networks, vol 28, n4, p 32-39, 2014

Identifying Communities of Website users

- Traffic Monitor:
  - Line-speed packet parsing (PPPoE, GRE at various interface Gb, Gn, Gi)
  - Real-time traffic classification (19 sub-service classes)
  - Multi-level traffic statistics (packet, flow and aggregate level)
- Hbase in HDFS Hadoop, key/value stored in a columnar manner
- Mining logs of HTTP:
  - Affinity graphs models website usage
  - Sparsified affinity graph constructed by employing a scale free fitting index (node in-degree larger than a threshold)
  - Nodes are ranked by an influence score

Identifying Communities of Website users

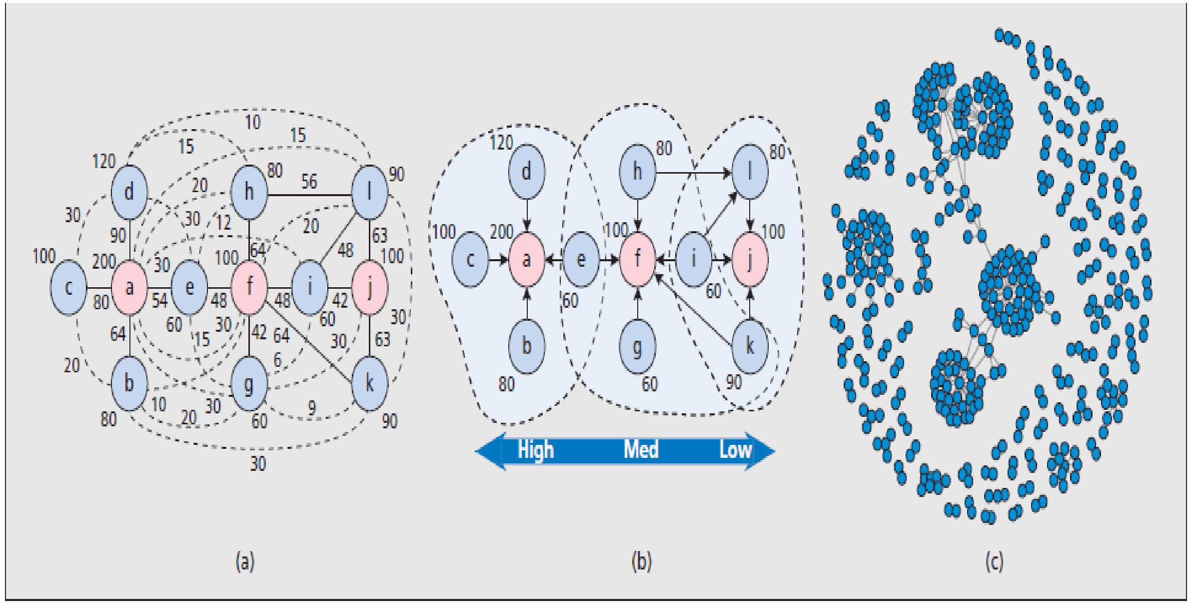
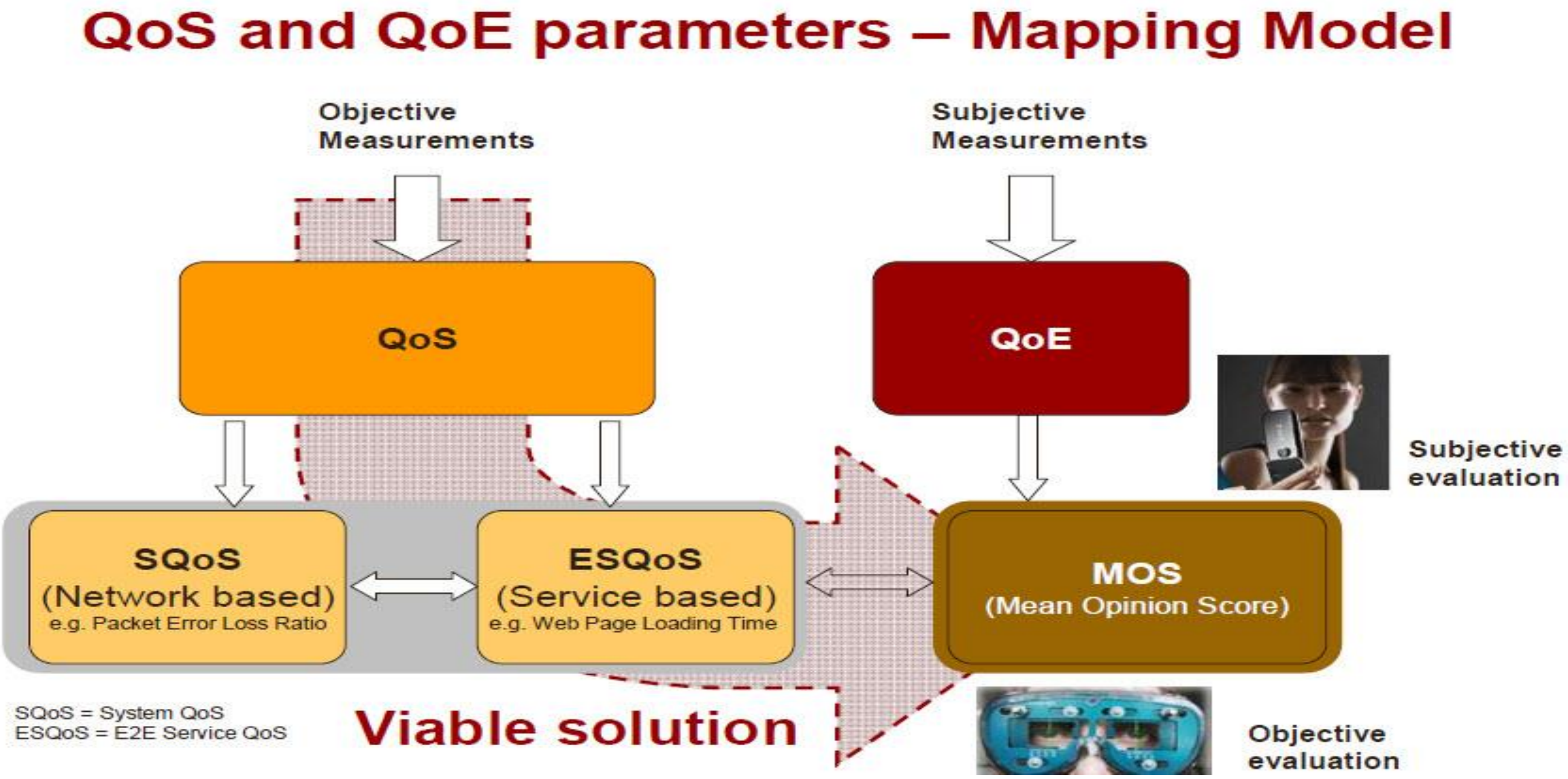


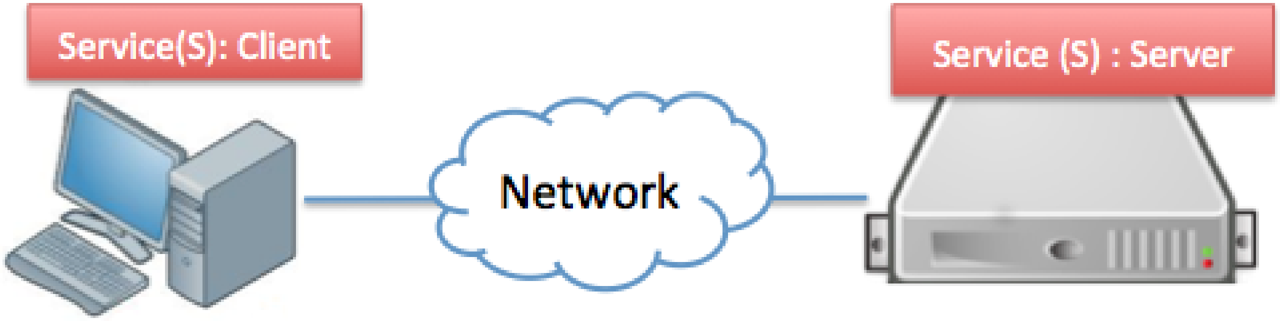
Figure 3. Website community identficiation: a) example of user distribution among websites; b) example sparsified affinity graph; c) identified website communities.

Figure 4. Mobile client model identification and user behavior analysis: a) example of identification results; b) accuracy of identification; c) density of network access time.

Service Level Prediction



Service Level Prediction - VoD



Y: service-level metrics

X: device statistics

- **Video streaming**: video frame rate, audio buffer rate, RTP packet rate

- CPU load, memory load, #network active sockets, #context switching, #processes, etc..
- raw data from /proc provided by Linux kernel

• Building block for real-time service assurance for a telecom cloud

R. Yanggratoke, J. Ahmed, J. Ardelius, C. Flinta, A. Johnsson, D. Gillblad, and R. Stadler, "Predicting Real-time Service-level Metrics from Device Statistics, IM

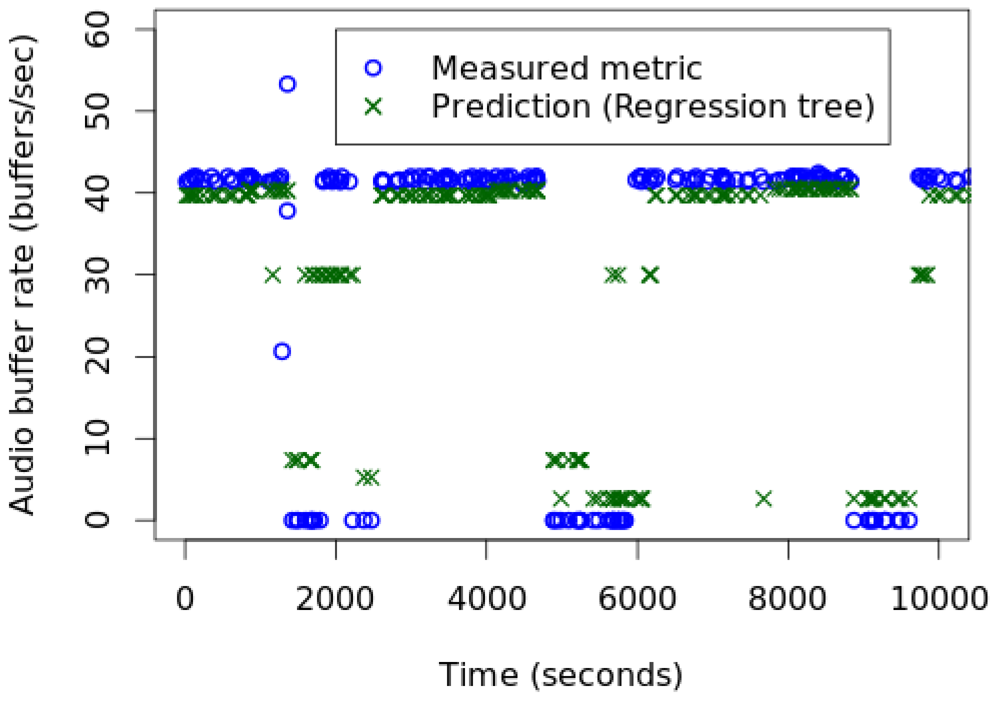
Service Level Prediction - VoD

- Statistical learning on low-level (OS-level) metrics, taking a large number of features (> 4000) rather than few service-specific features (<= 10)
- Measured metrics
  - Video frame rate (frames/sec)
  - Audio buffer rate (buffers/sec)
  - RTP packet rate (packets/sec)
- Linear regression, Regression tree, Random forest, Lasso regression
- Network statistics and client low-level metrics not considered
- Network and client machine are lightly loaded

R. Yanggratoke, J. Ahmed, J. Ardelius, C. Flinta, A. Johnsson, D. Gillblad, and R. Stadler, "Predicting Real-time Service-level Metrics from Device Statistics, IM

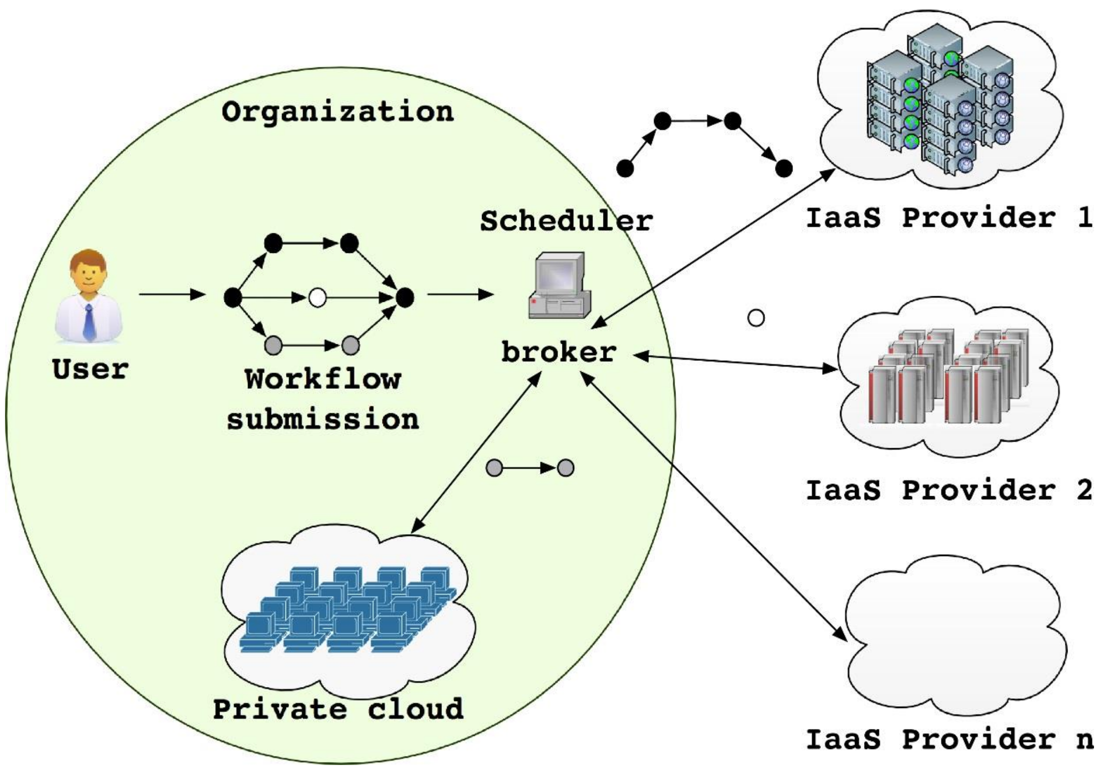
Service Level Prediction-VoD

- It is feasible to accurately predict client-side metrics based on low-level device statistics
  - Normalized Mean Absolute Error below 15% across service-level metrics and traces
- Preprocessing of X is critical
- Trade-off between computational resources vs. prediction accuracy
- No time dependence considered



Service Level Prediction- hybrid cloud

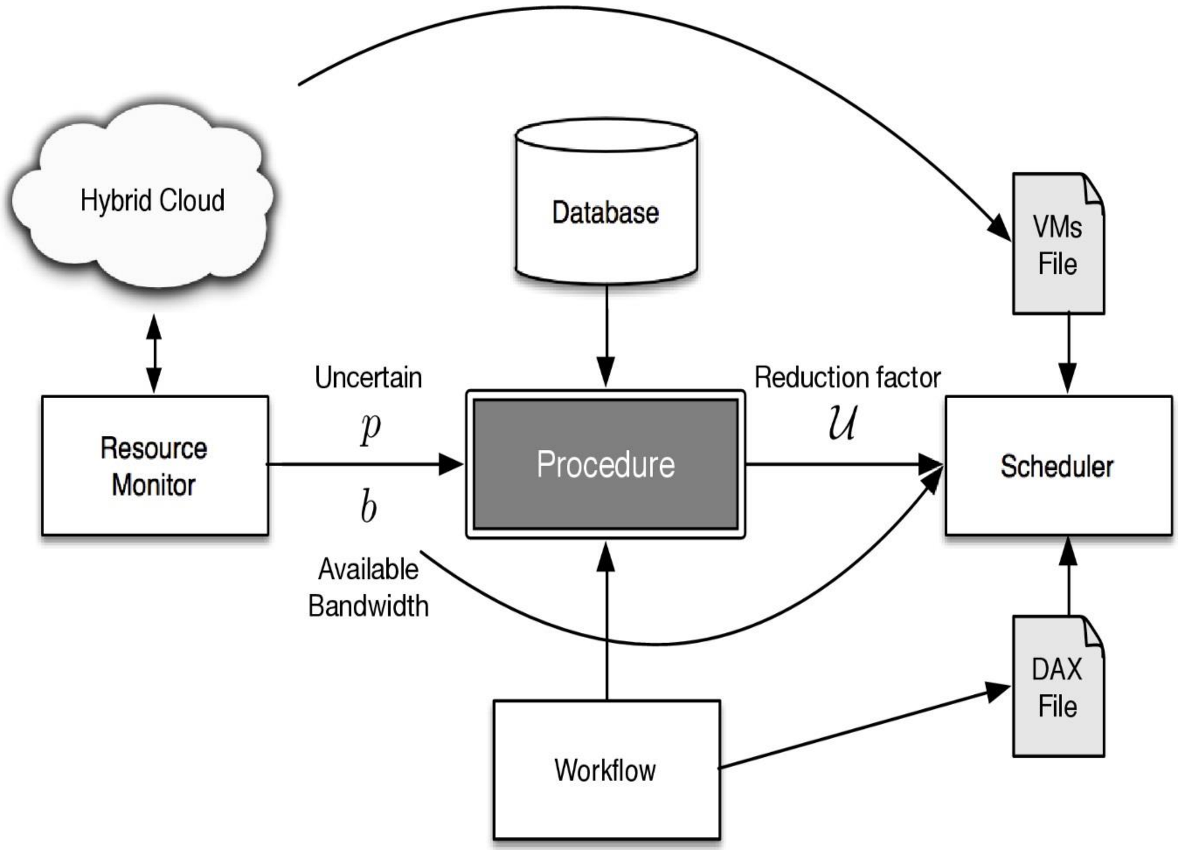
- Impact of intercloud link bandwidth on makespan of workflow execution
- Overestimation of available bandwidth can lead to increased makespan and higher cost
- Understimation of the bandwidth leads to uncesseary leasing of resources
- Available bandwidth varies during execution of workflow



GENEZ, T. ; Luiz F. Bittencourt ; da Fonseca, Nelson L. S. ; MADEIRA, E. R. M. . Refining the Estimation of the Available Bandwidth in Inter-Cloud Links for Task Scheduling. IEEE Transactions on Cloud Computing, 2015

Service Level Prediction- hybrid cloud

- Deflating fator to measured available bandwidth
- Database with historical data on performance relating avaliable bandwidth, type of workflow, deflating fator, quality of information and estimation erros
- Multiple linear regression
- Reduced the number of disqualified solutions and reduced costs



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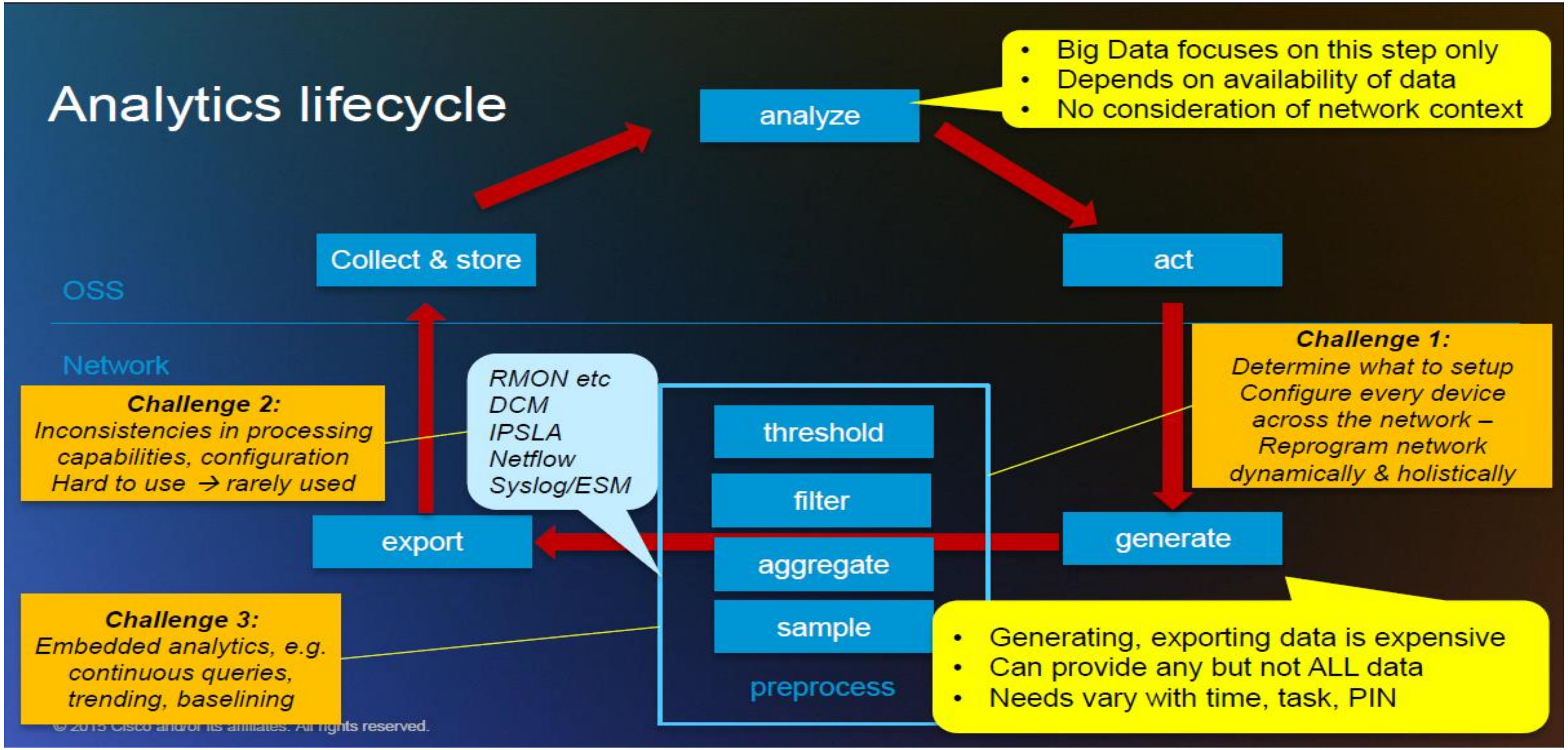
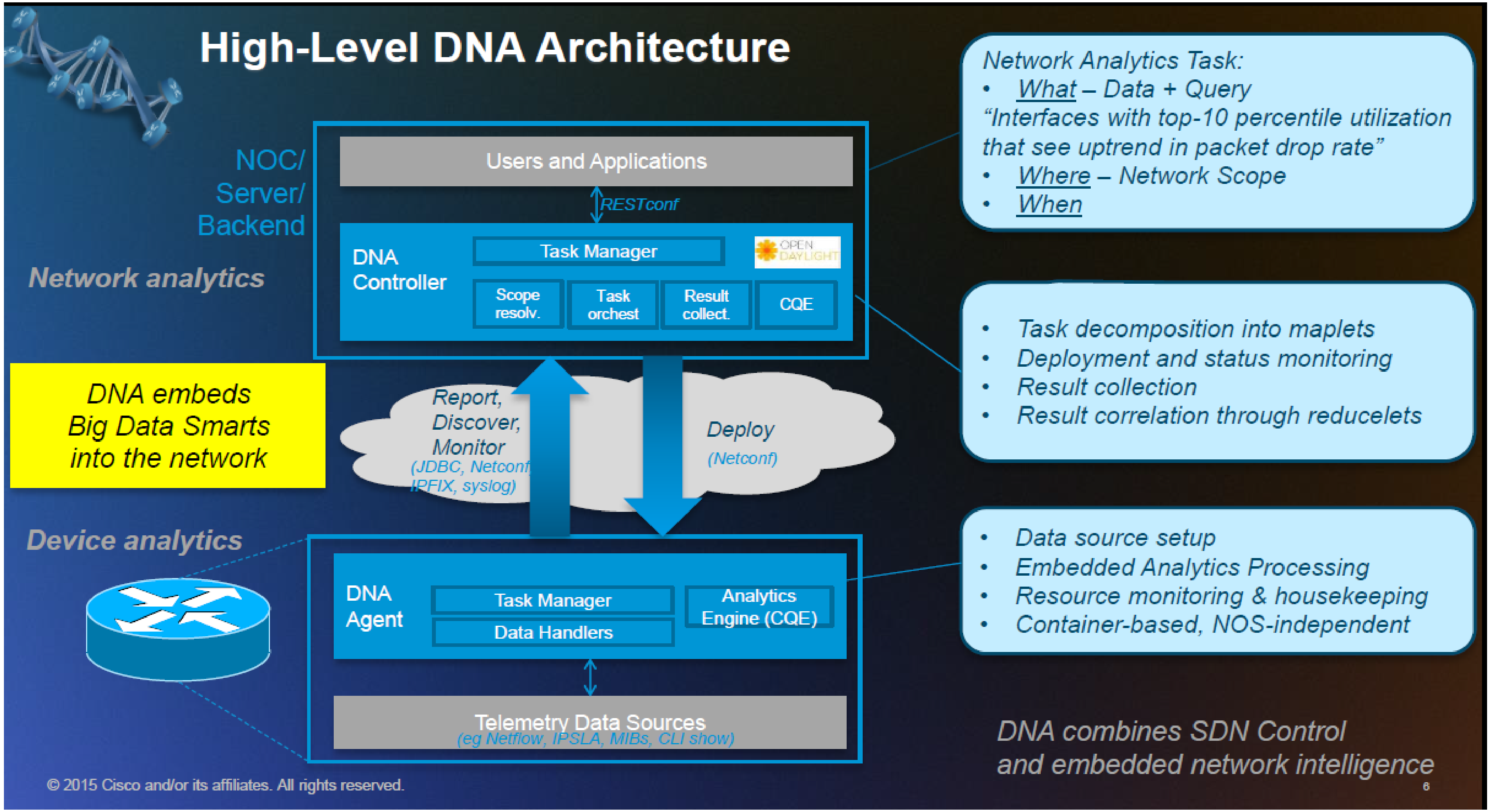
Big Data for Network Management and Operation



A. Clemm, M. Chandramouli and S. Krishnamurthy, DNA: An SDN Framework for Distributed Network Analytics, IEEE/IFIP IM 2015

Big Data for Network Management and Operation



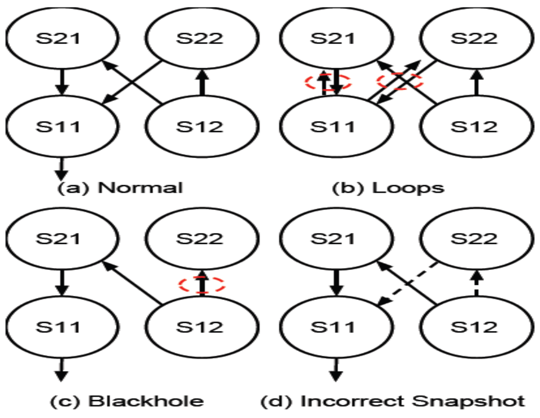
A. Clemm, M. Chandramouli and S. Krishnamurthy, DNA: An SDN Framework for Distributed Network Analytics, IEEE/IFIP IM 2015

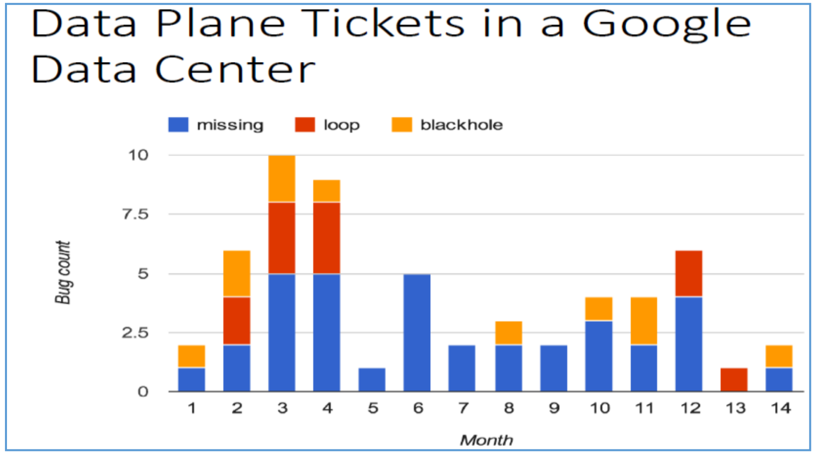
Verification of Forwarding Tables

- 10,000s switches in modern data centers
- Traditional approach of scaling-out and redundant design assumes correct reaction to erros
- Dormant bugs in routing systems triggers rare boundary counditions, some times perceived when benign event happens
- Two major deficiencies of available tools:
  - Assumption of consistente snapshot of forwarding tables
  - Not sufficiently fast to meet requirements of modern datacenters

H. Zeng, S. Zhang, F. Ye, V. Jeyakumar, M. Ju, J. Liu, N. McKeown, Amin Vahdat, Libra: Divide and Conquer to Verify Forwarding Tables in Huge Networks. NSDI 2014: 87-99

Verificationof Forwarding Tables



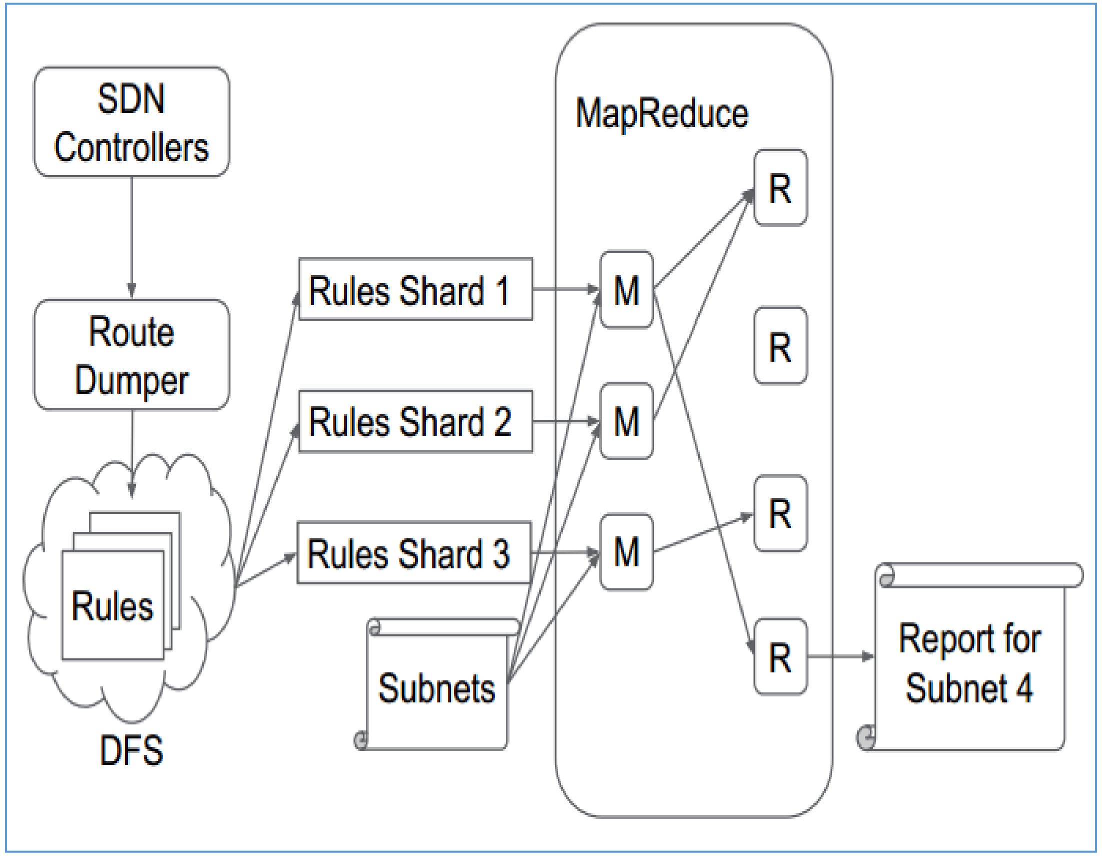


- Loops – usually caused by prefix aggregation
- Black-holes - lost BGP updating information
- Inconsistent snapshot – in an event of failure, changes to forwarding table may conflict with previous forwarding information

H. Zeng, S. Zhang, F. Ye, V. Jeyakumar, M. Ju, J. Liu, N. McKeown, Amin Vahdat, Libra: Divide and Conquer to Verify Forwarding Tables in Huge Networks. NSDI 2014: 87-99

Verification of Forwarding Tables

- Reachability – subnet can be reached from any switch; depth-first-serach from the subnet switch, verify if all other switches are reachable
- Loop detection – strongly connected component
- Black-role – if a switch does not have a matching entry for the subnet



Verification of Forwarding Tables

- Libra: Dive-and-Conquer approach

Data set	Switches	Rules	Subnets
DCN	11,260	2,657,422	11,136
DCN-G	1,126,001	265,742,626	1,113,600
INET	316	151,649,486	482,966

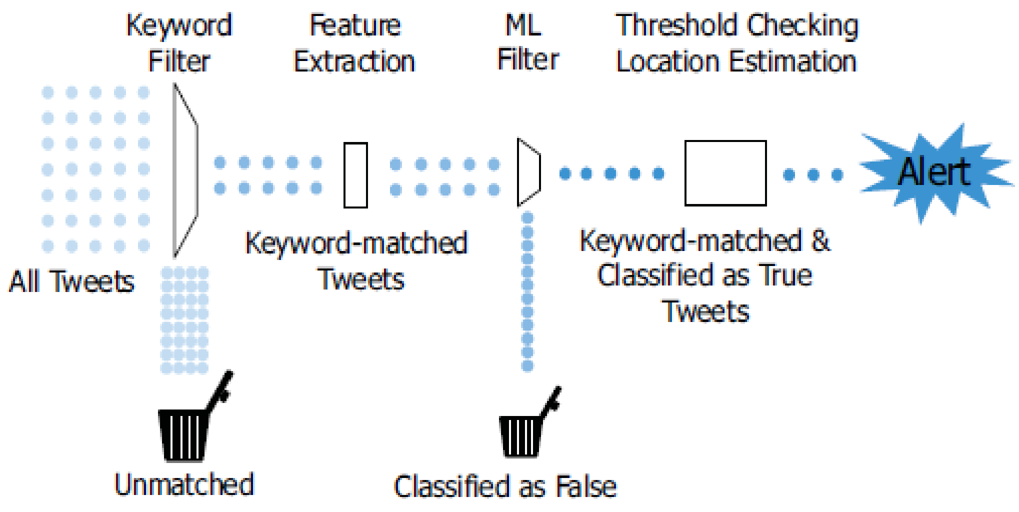
	DCN	DCN-G	INET
Machines	50	20,000	50
Map Input/Byte	844M	52.41G	12.04G
Shuffle Input/Byte	1.61G	16.95T	5.72G
Reduce Input/Byte	15.65G	132T	15.71G
Map Time/s	31	258	76.8
Shuffle Time/s	32	768	76.2
Reduce Time/s	25	672	16
Total Time/s	**57**	**906**	**93**

Fault Identification and Location

- Some network failures become silente failures to mobile operators; difficult to establish rules for failure detection
- Most failures are not reported to call centers
- Monitoring Tweeter to detect failure in mobile services
  - ✓ "Why can´t I text messages ?"
- Most tweets are not related to network failure
  - ✓I dropped my phone in toilet when I called my friend

Takeshita, K., Yokota, M. and Nishimatsu, K. Early network failure detection system by analyzing Twitter data, IEEE/IFIP IM 2015

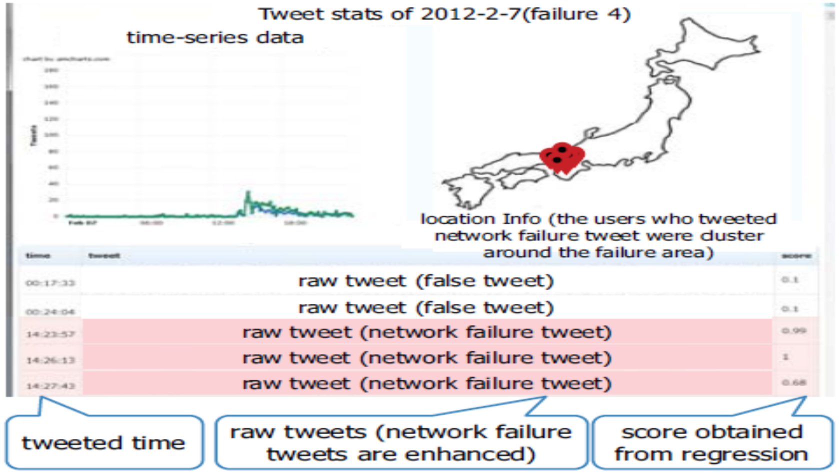
Fault Identification and Location



- Two requirements:
  - ✓reduction of false positives and
  - ✓location and when incidente happened
- Imbalance between network failure teweets and others
- Closeness of network failure tweets and false positives
- Three stages: keyword filtering, machine learn filter and alert system

Takeshita, K., Yokota, M. and Nishimatsu, K. Early network failure detection system by analyzing Twitter data, IEEE/IFIP IM 2015

Fault Identification and Location



- Keyword filtering: selection of features related to network failure
  - ✓ 4398 network failure and 6924 false positives
  - ✓ 10K tweets/sec for 40 keywords
- Four diferente techniques in machine learning filtering: SVM with and without Guassian Kernel, Naive Bayes and Adaptative Regularization of weights
  - ✓ 1% of raw tweets,
  - ✓ Capacity of 1 K tweets per second
  - ✓ 1 hour to construct a model
- Location: name of city, station or landmark; use of gazetteer and kernel density estimation to estimate location of fault; known GPS location of tweets
  - ✓ Heavy processing load; 0.2 users/second

Radio Environment Maps

- Spatial maps of received signal strengths can be used in dynamic spectrum access to, for example, discover coverage holes in cellular networks
- Perfrom drive test to collect data and perform spactial interpolation
- Methods from Spatial statistics, such as Kriging, are accurate and robust. However, its complexity is $\mathcal{O}(n^3)$ where n is the number of measurement points
- Current used approaches can only give a rough estimation since propagation simulations have inherent innacuracies due to limited information on landscape date. Moreover, drive tests are too expensive

Radio Environment Maps

- Minimization of drive tests developed by 3GPP makes every mobile phone a spectrum measurement device, making available a large number of path loss or received signal strength and GPS location information
- Operators can harvest unprecedented amount of data
- Employment of fixed rank kriging techniques with linear computational complexity to process hundreds of thousands of measurements, spatial estimate
- Model fitting takes 20 seconds of computation in a desktop and individual predictions less than miliseconds

Radio Environment Maps

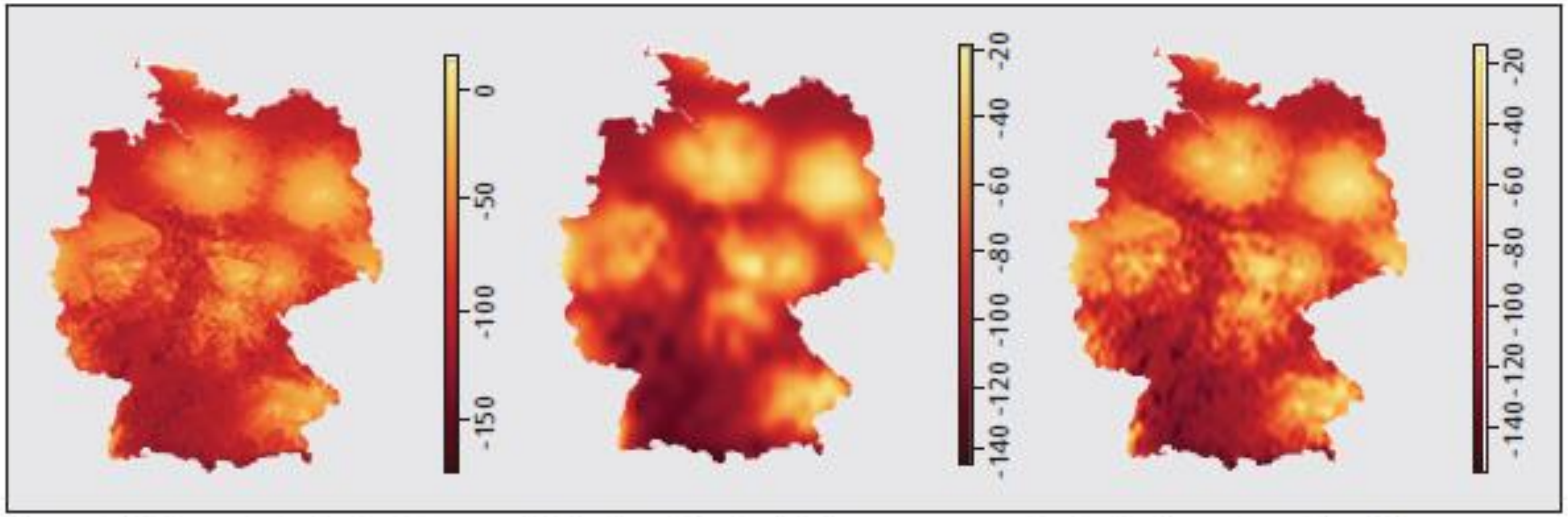
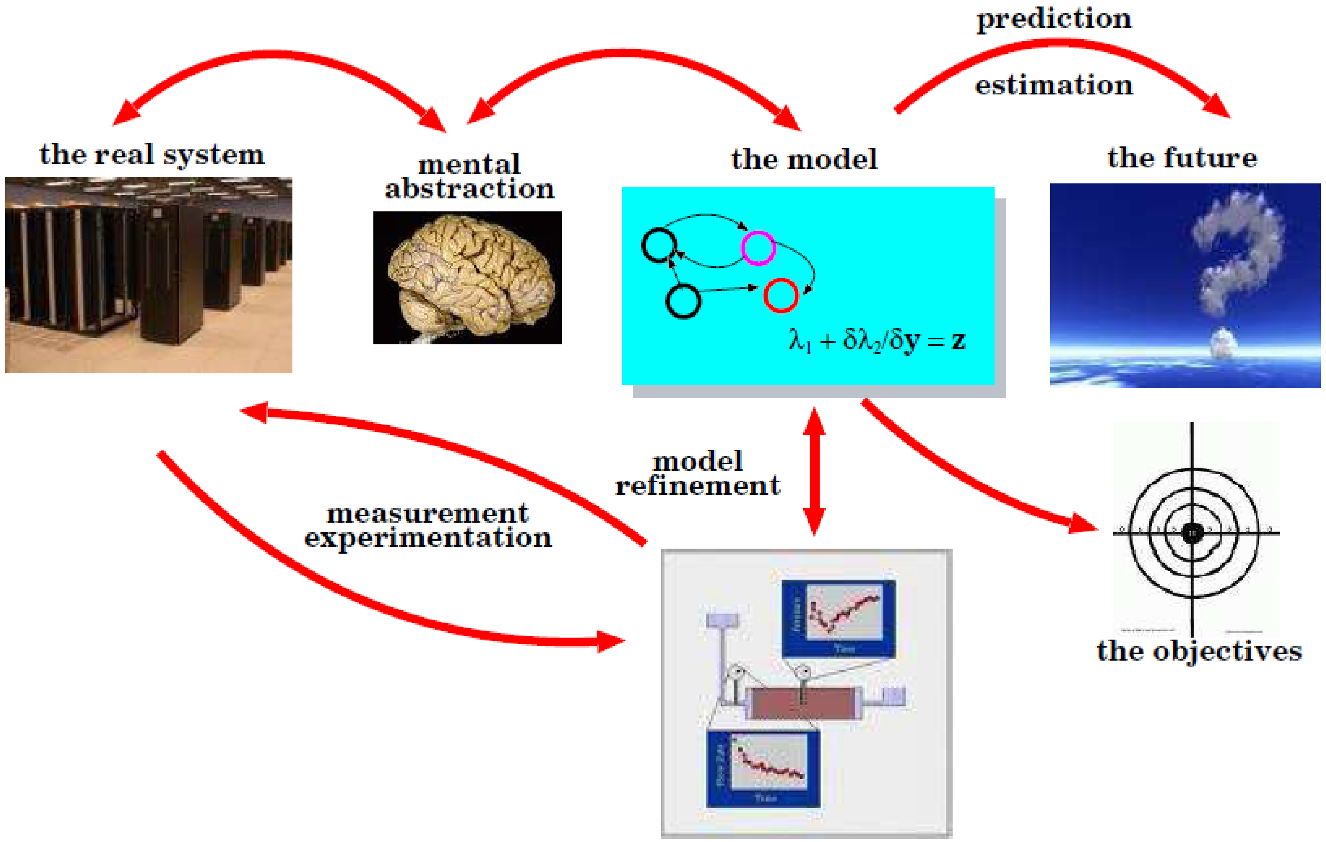


Figure 1. Example of a typical spatial estimation task in management of wireless networks. The map on the left shows the actual coverage of a digital TV network over Germany (total area of approximately 350,000 km^2), whereas the middle and right figures show spatial estimates based on 10,000 and 27,000 distributed measurements, respectively.

Christine Jardak, Petri Mähönen, and Janne Riihijärvi, Spatial Big Data and Wireless Networks: Experiences, Applications, and Research Challenges, IEEE Networks, pp 26-31, vol 28, n 4, 2014

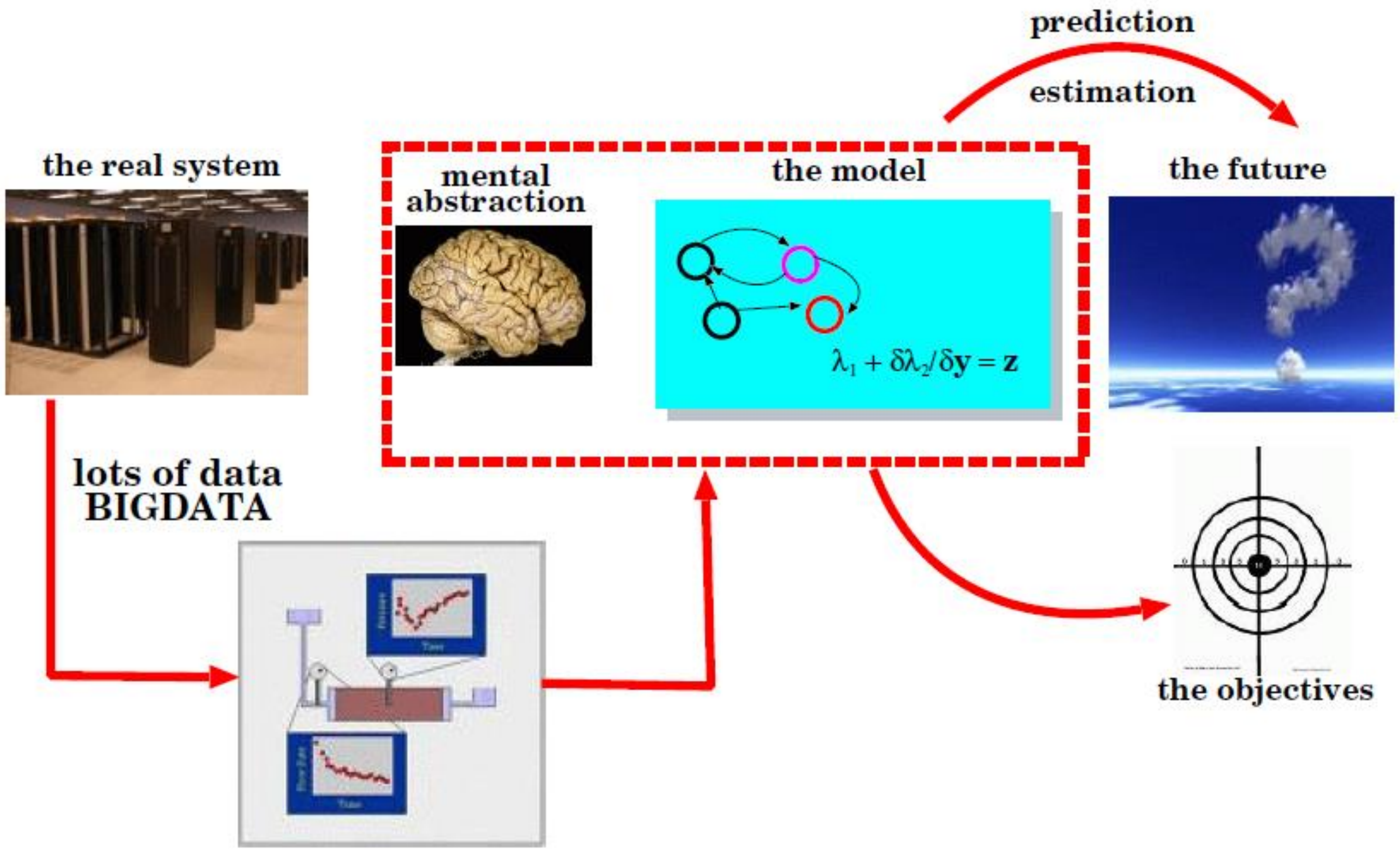
Performance Evaluation

“Traditional” Analytical Modeling



Edmundo Sousa e Silva, Avaliação de Desempenho e Aprendizado de Máquina: uma Dupla Dinâmica, Wperformance 2015

Analytics


prediction
estimation
the real system
mental
abstraction
the model
$\lambda_1 + \delta\lambda_2/\delta y = z$
the future
lots of data
BIGDATA
the objectives

Some Research Problems

- Understand the traffic generated by Big Data processing to evaluate the need for novel congestion control mechanisms
- Process data at the edge of the network and transport partial results – use of distributed machine learning algorithms
- Investigate how software defined network and network function virtualization can be explored for application-aware networking, specially for congestion control
- Lavarage the integration of “traditional” analytical modelling and machine learning techniques for performance evaluation

- My hearthy thank you for ITC27 organisers, especially to Michela Meo, Sabine Wittevrongel and Peter von Daele

- Alexander Clemm, Edmundo Sousa e Silva and Rolf Stadler for providing some slides

- ITC atendees for their attention and sincere aplogies for not being able to make it to Ghent