Fisher CIO Leadership Program: "Big Data **Analytics: Making Big Data Work"**

Bill Ruh Vice President, Global Software Center, GE November 1, 2012





Software is Eating the World*



Disruption in Industrial Market

Digital industry transformation trends

		INDUSTRY	TRANSFORMATION	ANALOG INDUSTRY	DIGITAL INDUSTRY
2000	2	Communications: Telco's and Cable	Data Transmission	Landline POTS & MCI	Mobile Internet
2005		Consumer: Retail Media Gaming, Advertising	Transactions & Interactions	Stores – Music, Book, DVD & Tower Records, Borders, Blockbusters	iTunes Kindle Online Media
NOW		Industrials: Energy Healthcare Aviation Mining Transportation	Sensing Analytics Control & collaboration	Analog products Manual processes Limited use of sensors & software	HC – telemedicine, digital health records, medical devices Aviation – integrated modular avionics Energy – smart grid, smart buildings

First movers & fast followers win

New opportunities emerging...enabled by technology, and driven by mega trends Rising customer expectations in both cost & complexity reductions Accelerating pace of Software innovation...real-time capabilities New competitive threats and challenges...and new business models



imagination at work

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Forces Shaping the Future

GE is a company that builds the machines that make the world work and has access to and deep understanding of the information that can make them work better

1 Internet

Hyper-connectivity: a living network of machines data and people

Internet of things: more devices tap into the Internet than people on Earth to use them

2Intelligent Machines

Increasing system intelligence through embedded software

Rise of machines: networked devices overtook the global population in 2011

3.Big Data

Democratization of data

Data overload: 2.5 quintillion bytes of data created every day

4_Analytics

Generating data-driven insights

Enhancing asset performance by detecting & predicting forecasts

Algorithms on installed base

Scale of Industrial Internet

Social media versus electric generating power source

2012 Twitter Usage

Gas Turbine Compressor Blade Monitoring potential*

VS.

80 Gigabytes per day

enabling social connections

588 Gigabytes per day

enabling capital asset productivity

Data volume potential is 7x greater from a gas turbine than current Twitter usage



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Value of Data & Analytics

Monitor fleet of ~25,000* engines ... 3.6MM flight records/month



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DATA

90,000 flight records analyzed

~200 parameters per flight record

~18MM parameters per month

System & Optimization

✓ Time & space management

✓ Fuel efficiency

Airspace capacity

Integrated systems = increased airline productivity value-added services

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Drives strong alignment with customers

Creates productivity in long-term service agreements

Value-added services fuels growth

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The Industrial Internet

Intelligent Machines

Intelligent Information

Intelligent Collaboration



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GE Analytics Cloud

Ecosystem for collaborative analytics development



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Software & Analytics Strategy

Core technologies to drive productivity...

	Real Time	Physics	Historical Data	Data Analytics	
Remote monitoring & diagnostics	-	•	•••	•	
Controls/sensors	•	••	•	•	
Performance optimization	••	•••	••	••	
Usage based	-	•••	•••	•••	
Note: dots represent level of importance & difficulty	When to inspect, when to repair, how to operate.				
	GE expertise				

Build solid foundations in every business

GE's advantage...

Customer productivity & operational flexibility



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Big Challenges Are Our Future

5 multi-disciplinary R&D centers 40k engineers worldwide 3k research team 8k software developers 500 Industrial Internet experts 150 Data Scientists Over \$5B in R&D spend

Niskayuna: New York



Over 1,200 engineers R&D Headquarters Software Sciences & Analytics "I find out what the world needs... Then I proceed to invent it." - Thomas Edison

Global Research Europe: Munich

China Technology Park: Shanghai



Over 1150 engineers Leading ICFC efforts Connected to innovation centers

John F. Welch Technology Center: Bangalore



Over 4,200 engineers First global site...1999 Growing emerging markets



Over 170 engineers Located on tech campus (TUM) Clean, distributed energy focus

Brazil Technology Center: Rio de Janeiro (2013)



Over 400 engineers O&G, transportation focus Customer & university relations



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The Next Chapter: Software COEs

Tapping the world's most important information is the science of work

Building a Silicon Valley presence

Focused on software & analytics 190 employees hired in 12 months Targeting 1000 staff

Award winning facility Gold LEED Open architecture: consolidation opportunity

Shared services

GE digital architecture for industrial solutions Expertise: user experience, cloud, analytics





What this means?

- Disruption is occurring in every industry <u>Analog to Digital</u> Industries
- <u>Software</u> coupled with <u>new processing architectures</u> are the enabler for these digital industry architectures
- Future of software is in <u>analytics</u> that drive <u>meaningful & real-</u> <u>time insight</u>
- R&D is critical to lead the change: not just new products but <u>new</u> solutions, systems & industry architectures



Uncovering Hidden Business Potential Through Big Data And Analytics

Kim Stevenson Vice President Chief Information Officer Intel Corp.



IN A NEW ERA OF COMPUTING

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From Era of IT Productivity...



... To Era of Business Productivity

The "I" in IT

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The "I" in IT

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Making Sense of Data to UNLOCK THE POTENTIAL

THE RECIPE for Insights

Identify The Info Synthesize It Ask The Right Questions

Results in a Valuable Outcome

Sales and Marketing



Manufacturing



Examples Can Be Found Across Multiple Functions



Channel Reseller



Intel Inside Fraud prevention

Post-silicon Validation

Spare Parts Forecasting

Challenges and Opportunities

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External Data Data Visualization Skills Development



Follow the Recipe Focus on Key Business Problems Get Started

Data & Predictive Analytics are the key to Unlocking the Potential





Smarter Decision Making Leverage Big Data to Gain New Actionable Insights

Anjul Bhambhri VP, Big Data, Information Management, IBM





Where is big data coming from?







Big Data (4Vs): This is just the beginning



Benchmark of Global Big Data Activities (Oct 2012)

Realizing a competitive advantage



Nearly two out of three respondents reports realizing a **competitive advantage** from information and analytics



Three out of four organizations have **big data activities** underway; and one in four are either in **pilot or production**



Improving *customer experience* by better understanding behaviors drives almost half of all active big data efforts followed by *Operational Optimization*

IBM Institute for Business Value and the University of Oxford Saïd Business School

www.ibm.com/2012bigdatastudy



More Mission-Critical Apps Ride on Big Data Platforms



- Integrate and manage the full variety, velocity and volume of data
- Apply advanced analytics to information in its native form
- Visualize all available data for ad-hoc analysis and discovery
- Development environment for building new analytic applications
- Integration and deploy applications with enterprise grade *availability*, *manageability*, *security*, and *performance*

The new era of analytics delivers value across the enterprise

Network Operations

...identify network bottlenecks in realtime for faster resolution **Customer Service Representatives** ... offer personalized price promotions to **Executive Leaders** different customer segments in real-time ... get real-time reports and analysis based on data inside as well as outside the enterprise (web, social media etc.) Big Data Finance analyze all Call Detail Records. Business Development (CDRs) to identify and reduce revenue leakage due to unbilled mechanisms to monetize / underbilled CDRs Marketing network traffic and partner with upstream content

.. analyze subscriber usage pattern in real-time and combine that with the profile for delivering promotional or retention offers

Google

facebook. You Tube

Business Analysts

analyze social media buzz

for the new services/offerings to gauge initial success and any course correction needed

twitter

External Data

providers

Vestas optimizes capital investments based on **2.5 Petabytes** of information.

- Model the weather to optimize placement of turbines, maximizing power generation and longevity.
- Reduce time required to identify placement of turbine from weeks to hours.
- Incorporate 2.5 PB of structured and semi-structured information flows. Data volume expected to grow to 6 PB.

Vestas

Cisco turns to IBM big data for intelligent infrastructure management

Optimize building energy consumption with centralized monitoring Automate preventive and corrective maintenance

Capabilities Utilized:

- Streaming Analytics
- Hadoop System
- Business Intelligence

Applications:

- Log Analytics
- Energy Bill Forecasting
- Energy consumption optimization
- Detection of anomalous usage
- Presence-aware energy mgt.
- Policy enforcement


Dublin City Centre Increases Bus Transportation Performance

Capabilities Utilized:

Stream Computing

- Public transportation awareness solution improves on-time performance and provides real-time bus arrival info to riders
- Continuously analyzes bus location data to infer traffic conditions and predict arrivals
- Collects, processes, and visualizes location data of all bus vehicles
- Automatically generates transportation routes and stop locations

Results:

- Monitoring 600 buses across 150 routes
- Analyzing 50 bus locations per second
- Anticipated to Increase bus ridership



Asian telco reduces billing costs and improves customer satisfaction.

Capabilities:

Stream Computing Analytic Accelerators

Real-time mediation and analysis of 6B CDRs per day

Data processing time reduced from 12 hrs to 1 sec

Hardware cost reduced to 1/8th

Proactively address issues (e.g. dropped calls) impacting customer satisfaction.



To-the-minute and historical product insight

NC, 81 OH, 82

FL 105

TX. 185

-300

-200

-100

100

200

300

Studen



Male, 2074

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Big Data Platform and Application Framework







Big Data Platform – Internet Scale Analytics



Platform Capabilities

- Built-in analytics
 - Text analytics engine, annotators, Eclipse tooling
 - Interface to project R (statistical platform)
- Deep integration with enterprise software stack
- Analytical tool for analysts
- Ready-made business process accelerators
- Integrated installation of supported open source and other components
- Web Console for admin and application access
- Platform enrichment: additional security, performance features, . . .
- World-class support
- Full open source compatibility

Business benefits

- Quicker time-to-value due to IBM technology and support
- Reduced operational risk
- Enhanced business knowledge with flexible analytical platform
- Leverages and complements existing software





Massively Scalable Stream Analytics

Sources

Linear Scalability

 Clustered deployments – unlimited scalability

Automated Deployment

 Automatically optimize operator deployment across clusters

Performance Optimization

- JVM Sharing minimize memory use
- Fuse operators on same cluster
- Telco client 25 Million messages per second

Analytics on Streaming Data

- Analytic accelerators for a variety of data types
- Optimized for real-time performance



Deep Analytics Appliance – Revolutionizing Analytics



- **Speed**: 10-100x faster than traditional systems
- Simplicity: Minimal administration and tuning
- Scalability: Peta-scale user data capacity
- Smart: High-performance advanced analytics



New classes of applications for end-users





Emerging Pattern of Big Data Implementation





IBM's Big Data Business Partner Ecosystem





Thank You!





A Bright Idea – Analytics on Small and Big Data

It works for:

- Old companies (GE, P&G, Marriott, American Express)
- Middle-aged companies (Capital One, Google, Ebay, Netflix, etc.)
- New companies (Quid, Recorded Future, Kyruus, GNS Healthcare, and a host of Silicon Valley and Boston companies you don't know)
- Technology companies (SAP, HP, Teradata, EMC, IBM, etc.)

The Analytical DELTA (Small Data, but Relevant to Big)

Data breadth, integration, quality, novelty Enterprise approach to managing analytics Leadership passion and commitment Targets first deep, then broad Analysts professionals and amateurs

The Rise of Big Data

What is it?	 Data that's too big (petabytes), too unstructured (not in rows and columns), or too diverse (mashups) to be stored and analyzed by conventional means (also relative) 	
Where does it come from?	 Internet/social media 	10101010101000 1011010101010 1010101010
	 Genomic analysis 	010100101001010 010100101010101 101010101010010
	 Voice and video 	0101010101010100 01001010101010010 0100101010010010 01001010100101010 0110101010
	 Sensors everywhere 	101010101010101010 10101011010101010 10101010
What is to be done with it?	• Structure, classify, and count it	10101000000000000000000000000000000000
	 Then analyze it (just as you would 	uld small data)

What's Different About Big Data?

The need for continuous flows of data, not stocks	 Stocks may be useful to develop models, but big data eventually requires a continuous process of analysis on moving data
Data scientists, not analysts	 IT "hacking" abilities in addition to the usual analyst attributes
	 Scientific and exploration focus
	 Closer to the product or process
New ways of deciding and acting on it	 It just keeps on coming, so have to establish ongoing processes to manage or decide on it

What's Different About Big Data? (cont.)

- Filtering, structuring, and classification tools MapReduce, Hadoop, etc.
- Content analytics tools--NLP
- Data redundancy management
- Cloud analytics
- Machine learning
- Open source everything, including R (it's capable, it's free, and that's what everybody coming out of school wants to use)



New technologies to manage it

The Rise of the Data Scientist

Hybrids	 Half analytical, with modeling, statistics, and experimentation skills Half focused on data management – extraction, filtering, sampling, structuring Lots of programming skills – Python, Ruby, Hadoop, Pig, Hive
Scientific	 Experimental physicists Computational biologists Statisticians with dirty hands Ecologists, anthropologists, psychologists, etc.
Impatient	 Try something and iterate Don't wait for a data person to get your data "We're a pain in the ass" Job tenure is short
Ground- breaking	 "Nobody's ever done this before" "If we wanted to deal with structured data, we'd be on Wall Street" "Being a consultant is the dead zone – too hard to get things implemented" "The output should be a product or a demo – not a report"

The Rise of Data Scientists and Analysts



Courtesy LinkedIn Corp.

Some Use Cases for Big Data

- Social media analytics "People You May Know" at LinkedIn
- Voice analytics Call center triage
- Text analytics Voice of customer, sentiment analysis, warranty analysis
- Video analytics Intelligence, policing, retail applications
- at
- Genome data what genetic profiles are associated with certain cancers?

Big Data at eBay



"Analytics platform," with heavy focus on testing

40 petabytes of storage in Teradata EDW, with hundreds of "virtual data marts"—and much more in Hadoop clusters 50 new terabytes per day

Platform includes:

Hadoop and MapReduce for image similarity networks

R for statistical analysis

User-developed apps described in "Data Hub"

Big Data at GE



New \$2B corporate center for software and analytics

Hiring 400 data scientists—200 already on board

Includes financial and marketing applications, but with special focus on industrial uses of big data

When will this gas turbine need maintenance?

How can we optimize the performance of a locomotive?

What is the best way to make decisions about energy finance?





Bought Greenplum, a big data appliance vendor, in 2010

Realized that data scientist availability would be gating factor in big data capabilities

Developed a big data analytics course for employee and customer consumption

Using early graduates to examine probability that product innovation ideas will succeed

Big Data at Quid



Small startup, but working with big organizations

Works to map the structure of technology ideas, funding, and product breakthroughs using primarily Internet data

e.g., opportunities at intersection of biopharma, social media, gaming, and ad targeting

Works with major IT vendors and governments; beginning to work with strategy consulting firms

Big Data and Small Data Analytics – How Do They Compare?

Focus

- Big data is often external, small data often internal
- Big data is often part of a product or service, small data is used to manage

Relationships

- Big data and small data analysts require good relationships
- But relationships are different: product managers and customers for big data analysts; internal managers for small data analysts

Technologies

- Big data requires data management (Hadoop, Pig, Hive, Python)
 Analysis in visual (Tableau, Spotfire), open-source (R) tools
- Small data requires less data management SQL is sufficient
 - Analysis in BI (BO, Cognos, Qlikview) or statistical (SAS, SPSS) tools

Flies in the Big Data Ointment

- Labor intensive, and labor expensive
- "Not much abstraction going on here"
- Big data = small math
 - Step 1 is just getting the data counted
 - Step 2 is providing nice visualizations of it
 - Step 3 will be doing real analytics on it
- Lots of interfaces and integration necessary
- Technologies and people will be easier if you can wait



Elements in Common: Leadership



"Our CEO is a real data dog" Sara Lee executive

Gary Loveman at Caesars

- "Do we think, or do we know?"
- "Three ways to get fired"

Jeff Bezos at Amazon

"We never throw away data"

Reid Hoffman at LinkedIn

"Web 3.0 is about data"

Elements in Common: Getting Much Faster!

In-memory analytics

HANA from SAP

High-performance analytics

 From 19 hours to 19 minutes to optimize prices for all categories at Macy's

In-database processing

 Propensity scoring for all customers in seconds, not weeks, at Cabela's



Elements in Common: New Analyst Skills



"Tell a story with data"



"Be courageous"





"Build a rapid prototype"

Turn It On!

- Make sure your leaders are on board
- Figure out your targets
- Build, buy, or borrow the people you need
- Assess your technology
- Improve some decisions or some products and services!





BIG DATA AT EBAY

Hugh E. Williams Vice President, Experience, Search, and Platforms eBay Marketplaces <u>hugh.williams@ebay.com</u> @hughewilliams

Auction Web

[Menu] [Listings] [Buyers] [Sellers] [Search] [Contact/Help] [Site Map]

Welcome to today's online marketplace...

...the market that brings buyers and sellers together in an honest and open environment... Welcome to our community. I'm glad you found us. AuctionWeb is dedicated to bringing together buyers and sellers in an honest and open marketplace. Here, thanks to our <u>auction format</u>, merchandise will always fetch its market value. And there are plenty of great deals to be found!

<u>Take a look at the listings</u>. There are always several hundred auctions underway, so you're bound to find something interesting.

If you don't find what you like, take a look at our **Personal Shopper**. It can help you search all the listings. Or, it can keep an eye on new items as they are posted and let you know when something you want appears. If you want to let everyone know what you want, post something on our wanted page.

If you have something to sell, start your auction instantly.

Join our community. Become a registered user. Registered users receive <u>additional benefits</u> such as daily updates and the right to participate in our user feedback forum and the bulletin board.

Welcome to eBay's AuctionWeb.



every 49 minutes a Ford Mustang is sold

every **5 seconds** a cell phone is sold

every 6 seconds a pair of shoes is sold













108+ million	Active buyers and sellers worldwide
250+ million	Queries every day to the eBay search engine
350+ million	Live global listings



20+ petabytes	Of data in our Hadoop and Teradata clusters
2 billion	Page views each day

75 billion Database calls each day


EVEN OUR QUALITATIVE DATA IS BIG

- Inline and other surveys to capture ratings and verbatims
- •Touch point NPS to capture promoter and detractor effects
- Customer service data
- •User experience research studies to watch and learn from customers
- •Meeting, listening, and recording customer experiences



WHY IS BIG DATA TRANSFORMATIONAL?



BIG DATA IS TRANSFORMATIONAL

- •Big data informs on:
 - -Patterns
 - -Anomalies and outliers
 - -Generalizations
 - -Predictions
 - -Relative performance
 - -An holistic customer picture
- •Vast array of applications at eBay:
 - -*Product development, A/B testing,* system performance, fraud and risk detection, *purchase prediction,* customer support, buyer demand, seller intelligence, financial performance, ...



PATTERNS: QUERY REWRITES

- In 2010, our search engine was very literal: it matched exactly what you typed
- •We're on a journey to make it more intuitive, so it does a great job of understanding user intent and finding all of the relevant results
- Idea: Mine our extreme data, look for patterns, and use these to map words in user queries to synonyms and structured data associated with items for sale at eBay



PATTERNS: QUERY REWRITES ...





HOW DO BUYERS PURCHASE THE PILZLAMPE?

- •It turns out, they try one (or more) of a few things:
 - -Type pilzlampe, and purchase
 - -Type pilzlampe, ..., pilz lampe, and purchase
 - -Type pilzlampe, ..., pilzlampen, and purchase
 - -Type pilz lampen, ..., pilzlampe, and purchase



—...

PATTERNS: QUERY REWRITES ...

- •From our big data mining:
 - -We automatically discover that *pilz lampe* and *pilzlampe* are the same
 - -We also discover that *pilz* and *pilze* are the same, and *lampe* and *lampen* are the same
- •From these patterns, we rewrite the user's query pilzlampe as: pilzlampe OR "pilz lampe" OR "pilz lampen" OR pilzlampen OR "pilze lampe" OR pilzelampe OR "pilze lampen" OR pilzelampen



ARE QUERY REWRITES EASY?

- •Nothing is easy at scale
 - -Incorrect strong signals:
 - •CMU is not Central Michigan University
 - -Colliding signals
 - Mariners is not the same as Marines
 - -Context matters
 - •Correcting Seattle Marines to Seattle Mariners is (generally) right
 - Jacksonville Jaguars is not Jacksonville in the Motors category



PREDICTION: ITEM QUALITY IN BEST MATCH

- •Our goal in search is to show the best matching items for each user's query
- •We use tens of *ranking factors* to rank
 - -Factors are drawn from item text, item images, seller information, buyer information, and *behavioral big data*
- •Factors are combined into a *ranking function* using a machine-learned ranking model



PREDICTION: ITEM QUALITY IN BEST MATCH

•One ranking factor we compute is *item quality*

- The likelihood that an item will sell, and its likely selling price
- Predictions are based on our vast data sets of item and seller performance
- •At listing time, we compute *predicted* item quality
- •As users interact with the item, we observe and learn its *true* quality 100%





EVERY BIG DATA IDEA IS CHALLENGING TO BUILD AT SCALE

•We often have more than six million item updates per hour

- -Log events flow from individual machines when the events occur
- -A listener cluster accumulates events
- -Events are sorted by their unique identifier
- -A queue of events is created by likely impact of the changes
- -We process queues and update the Best Match factors

•Rinse, repeat frequently



TEST VS CONTROL EXPERIMENTATION

- Divide customers into populations
- •One population is the *control*
- •One or more populations are the *tests*
- •Collect data from each population
- •Compute metrics from the data, including confidence intervals
- •Understand the results
- Make decisions



A FLEXIBLE APPROACH



ONE SIZE DOESN'T FIT ALL

- •There isn't one solution for driving an organization with big data:
 - -Hadoop is for:
 - •Engineers, batch (asynchronous), map reduce (divide and conquer), unstructured, flexible problems
 - -HBase is for:
 - •Engineers, real-time, large data blob, unstructured, key lookup, flexible problems
 - -Teradata (or another data warehousing solution) is for:
 - •Analysts, real-time or batch, structured, flexible problems
 - -Cassandra (or MongoDB or ...) is for:
 - •Engineers, real-time, smaller data blob, unstructured, key lookup, flexible problems
 - -Some problems warrant specialized solutions



THE BIG DATA OUTLOOK



SHOPPING IS CHANGING

We are at an inflection point!



TRADITIONAL BOUNDARIES HAVE BLURRED:

Technology is fundamentally changing the way people shop





IT'S JUST COMMERCE

There's no longer online and offline





THE PLAYING FIELD IS BEING LEVELED



Cost of entry is lower than ever, consumers are in the driver's seat



THE BIG DATA OUTLOOK

- Vastly more data, from:
 - -New customers
 - -New applications
 - -Noisier applications
 - -A widening landscape
 - -Engineers and analysts creating derivatives
- •A new set of challenges:
 - -Curation
 - -Cleaning up
 - -Documentation
 - -Managing the user population
 - -Stability and scalability of big data systems





Psstt... We're hiring. Email: hugh.williams@ebay.com











Big Data Where Are We?

Fisher CIO Leadership Hadoop Conference November 1, 2012

Category Maturity Life Cycle Where is Big Data Today?





Digital Disruptors













Digital Disrupters vs. Digital Disruptees







Technology Disruptions How Technology Enters the Mainstream





Impact of Category State on Company Power Business Model Adapts to Life Cycle Dynamics





- Project orientation
 Sell, Design, Build
- Focus on *performance*
- Solution orientation
- Design, Sell, Build
- Focus on *performance/price*



- **Product orientation**
- Design, Build, Sell
- Focus on *price/performance*



- Systems orientation
- Build, Sell, Design
- Focus on *price/TCO*



Genomics











Digital Advertising: Real-Time Bidding





Digital Advertising: Real-Time Bidding





Digital Marketing





Digital Marketing




Algo Trading

Lab49 WPF Equities Trading Application	Ticking stock list	Trade entry
File Launch Feeds Window About	🗇 Disable All 🔘 Enable Zoom 🔘 Enable Lens 🔘 Enable Meta	MSFT
: Launch: 👔 🏪 🛄 💁 🖓 🚆	Symbol Open Low Bid Ask High Change	Price: £16.9449
Stocks list Stocks graph Stock 3D Chart Trade entry Trade history Blotter	MSFT £18,4561 £1,2133 £16,9449 £16,9449 £22,1473 -8,19%	High: £22.1473 Low: £1.2133 Issued Shares: 2363900000
Coral8 Alerts Coral8 Summary Short v Long	LAB49 13.3421 11.2572 113.0433 113.0433 124.7402 171.43%	
vs 1.0.459 anks on big prints and sizes	YHOO £14,6152 £3,0375 £24,5394 £24,5394 £30,5675 67,90%	
Stock 3D Chart	GM £1.5193 £1.2154 £20.7949 £20.7949 £23.0061 1268.73%	H:£22.1473 O:£18.4561
2Q: 1624.14%	F £6.5678 £3.2161 £16.9131 £16.9131 £31.9034 157.52%	
	Stock price graph	L-£1.2133
1 286.44%	Stock symbol: MSFT Company name: Bid: 16.9449 ×0	Buy Quantity 100 Execute Sell Bought 100 MSFT @ £12.1196
1984 DD 45.37%	B B B B B B B B B B B B B B B B B B B	Blotter
MC 2 4 33% 888 79 5% HHL 9.37% MS: 95,89% T 2.07% NNN: 183% UUU: 65,35% YHOO: 34,02% AAPL-47.90% GOOG: 1,26,58% SUNW: 77,67%	B B B B B B B B C <thc< th=""> <thc< th=""> <thc< th=""> <thc< th=""></thc<></thc<></thc<></thc<>	Symbol Quantity CurrentValue YHOO 100 £2,453,9381 MSFT 100 £1,694.4862
Short v Long	al8 Summary [connected]	Trade history
Symbol: DELL Apply Sy	bol Price High Low Number 📥 Time Action Symbol 🔺	Symbol Qty PPS Buy/Sell
Long CCI Short CCI DJU	O.X £0.0000 £0.0000 0 16/03/2007 10:43:36 Buy DGAS	MSFT 100 £12.1196 Buy 16/03/2
	ET.X £0.0000 £0.0000 0 16/03/2007 10:43:35 Sell DGX	MSFT 100 £12.0304 Buy 16/03/2
	£13.8900 £14.0100 £13.8900 27 16/03/2007 10:43:20 Sell DUK	MSFI 100 ±11.9/22 Sell 16/03/2
	£14.2900 £14.3400 £14.2300 12 16/03/2007 10:43:20 Buy DDS	VHOO 170 £20.7013 Sell 10/03/2 VHOO 170 £23.5122 Bury 16/03/2
8 7 7 7	10/03/2007 10/43:05 Sell DGX	YHOO 100 £21.0871 Buy 16/03/2
	£10,5400 £0,0000 £0,0000 0 16/03/2007 10/43/05 Buy DIA	
DIU	PR.X £0.0000 £0.0000 0 16/03/2007 10:42:50 Buy DRI	
8 DM	£7.5300 £7.5300 £7.5300 4 - 16/03/2007 10:42:35 Buy DYAX	
0 36 72	16/03/2007 10:42:35 Sell DNDN	4 ¥









Fraud Detection





Fraud Detection





Loyalty Programs









Brand Management





Brand Management





Smart Grid











Internet of Things









Key Takeaways

- Project orientation
- Sell, Design, Build
- Focus on *performance*
 - Solution orientation
 - Design, Sell, Build
- Focus on *performance/price*
 - **Product orientation**
- Design, Build, Sell
- Focus on price/performance
- Systems orientation
- Build, Sell, Design
- Focus on price/TCO

- Four business models
- Each fit for purpose
- Match to market maturity
- Match to your own crown jewels



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charles SCHWAB

Big Data At Schwab

- Nicholas Grabowski, Charles Schwab & Co.
- Stephen Sorkin, Splunk Inc.



About Us

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splunk

- Founded in 1973 as a discount brokerage.
- Grown to a full service financial services company: Brokerage, Banking, Investment Advisor Services, Retirement Planning, etc.
- 13,700 employees.
- Founded 2004, first software release in 2006
- April 2012 IPO
- 4,400 customers in 80+ countries, Over half of the Fortune 100
- Major use cases: Application Management, Operations Management, Developers, Security, Business and Web Analytics

Why Big Data at Schwab?... To better serve our clients

- Serving our clients means understanding what is happening to their transactions and assets at all times.
- Our clients trust Schwab with:
 - Over 1.8 trillion in total assets.
 - Over 9 million accounts.

The Schwab ecosystem:

- Terabytes of log data per day.
- Log collection and storage for multiple lines of business
- Troubleshooting and cross system data mining abilities are critical.



Key Requirements



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World's Digital Data Growing Exponentially



October 2012

Splunk Turns Machine Data into Real-time Insights

Optimized for real-time, low latency and interactivity



New Approach to Analyzing Heterogeneous Data

Universal	Late Structure	Analysis and
Indexing	Binding	Visualization
 No data normalization Automatically handles timestamps Parsers not required Index every term and pattern "blindly" No attempt to "understand" up front 	 Knowledge applied at search-time No brittle schema to work around Multiple views into the same data Find transactions, patterns and trends 	 Normalization as it's needed Faster implementation Easy search language Multiple views into the same data

Rapid time-to-deploy: hours or days



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Splunk's Search: Ask Any Question

"What is the average price of Pad Thai in Berkeley over the last 6 months as a chart broken out by zip code?"

"pad thai" "Berkeley" | timechart avg(price) by zipcode

"pad thai" "Berkeley" sourcetype=menu | timechart avg(price) by zipcode

"pad thai" earliest=-3m | stats max(price) by restaurant



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Splunk's Search Processing Language

Lots of random "hypothetical examples" from our Mugs

Find happiness happiness Find true love "true love" Down and dirty, or fast and furious (down dirty) OR (fast furious)
Where's Waldo? name="waldo" fields latitude longitude altitude Friend, friendly, friends, friendlier friend*
What were you doing at sourcetype=actions person="you" [search action=murder eval earliest=_time-600 eval the time of the murders ? latest=_time+600 fields earliest latest format "(" "(" "" ")" "OR" ")"]
Zombie infestation trends, daily simple sourcetype=zombies timechart span=1day dc(id) as Where the streets source=streets and exponential moving averages z_count trendline sma10(z_count) ema10(z_count) have no name NOT name=*
Hosts that have not metadata type=hosts where Is San Francisco really source=weather city=sf-ca timechart span=1d reported in lately lastTime < now()-3600 colder in the summer? avg(temp) max(temp) min(temp)
How much have you had earliest=@d+17h+15m latest=now item=beer OR item=wine OR item=liquor lookup nutritioninfo to drink tonight, sir? item OUTPUT alcohol_pct stats sum(eval((alcohol_pct/100)*qty)) as oz_alcohol
How long is this source=history stats stdev(dur) as stdev, avg(dur) as avg All the king's source=hm_stables top going to take? eval soonest=avg-(3*stdev) eval latest=avg+(3*stdev) horses limit=0 horse
splunk How about a nice hot cup of search and analytics?

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Solution: Enterprise Logging Initiative (ELI) and Splunk

Key Requirements : Correlation, Normalization, Visibility, and Centralization

- Real time collection of data
- Centralized collection and storage
- Democratizes logs searching <u>all</u> machine data via a single web interface
- Stores large volumes of data (10s of Terabytes for Schwab)
- Format agnostic

splunk>

- Provides long term storage via Hadoop
- Specifies log events, format, fields, and format
- Provides Splunk to Hadoop integration



Enterprise Logging Initiative & Splunk in Action

Mobile



Feature Launch Analysis & Behavior Tracking A Big Data demo at Schwab.

Mobile Check Deposit

- Tracking success.
- Not all deposit attempts succeed. Why not?
- How do clients learn over time?
- What can we do to help clients?



Enterprise Logging Initiative & Splunk in Action



What did we learn from Splunk?

Tracking success of the Mobile Check Deposit.

- About 85% of clients succeed on first attempt.
- Within first 10 days 98+% of clients succeed.

Not all deposit attempts succeed. Why not?

- Image reading is the most common mishap.
 - blurry image, check not in image, etc.

How do clients learn over time?

 With the help of customer service or through trial and error, they figure it out. 98+%

What can we do to help our clients?

- Reach out to them directly.
- Note their account incase they call us.

How Schwab Uses Splunk

Behavior tracking

"How do reps behave during market storm events?"

KPI reporting

"Are trades increasing or decreasing? Is site performance improving?"

Feature analysis

"How did mobile check deposit do?"

Operational monitoring

"There is a production outage!"

Application debugging

"What caused the production outage?"



Splunk at Schwab by the Numbers



250GB+ Data Archived to Hadoop per Day for Long-term Storage

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Linked in .

Big Data Ecosystem @ LinkedIn

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Outline

- LinkedIn Overview
- Why Data is important
- Big-Data Ecosystem

in

 LinkedIn is the world's largest professional network at 175M members and growing, with a vision of connecting talent with opportunity at massive scale for the world's 640M professionals.

- We have a selection of data driven products.
 - Recruiter (Hiring Solutions)
 - Premium Subscriptions
 - Marketing Solutions

in

Some Data Stats.....

On-Line systems (Oracle)

Data Size: 150 TB Growth month-over-month (approx): 10TB Queries Per Sec : 150K qps

Offline (TD + Hadoop)

Teradata Data Size approx: 300TB Daily Data Load: 2.5 TB Growth month-over-month (approx): 30TB

Hadoop

Total Size approx : 15 PB of raw storage, 5 PB of usable storage Total # of (grids) clusters: 9 Total # machines : 5000 Total Jobs per day: 20K Internal Users: 550 Dedicated Dev & Ops team

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What does this translate to

 1TB of compressed data written to local 'Kafka' clusters per day. Compression ratio is about 3x. This data is replicated to out of the local colo to create global feeds for Data Warehouse and live consumers

.....so what is actually sent over the wire is $\sim 2x$

• We ETL around 1.5 TB (similar compression ratio) into Hadoop and less than that into Teradata. This is the above Kafka data plus database dumps.

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Mission: Connect the world's professionals to make them more productive and successful.

Vision: Create economic opportunity for every Professional in the world

We must leverage this mountain of data to fulfill the mission & vision of the company....

Outline

- LinkedIn Overview
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Data and Infrastructure Drivers

- 1. Building Enterprise and User-facing Products
 - 1. Business analytics (e.g., growth, forecasting)
 - 2. Sales analytics (e.g., customer segmentation, targeting)
 - 3. Marketing (e.g., campaigns)
 - 4. Talent Connect (Best candidate for job and vice versa)
 - 5. Data insights for Customers (e.g., Career site analytics)
- 2. Measuring and Iterating on Products
 - On-line: Experimentation (we run ~1000 experiments on the site daily, based on data/analytics)
 - 2. Off-line: Product analytics (e.g., what is working, what is not)
- 3. Running the Site
 - 1. Engineering/Operations/Security metrics (real-time monitoring/alerting for site failures, fraud/abuse)
- 4. Data Discovery (given the aggregation and the ability to slice/dice in many ways, we can answer questions no one can)

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Our members come first – they are the most important asset for LinkedIn!

They provide profile data, professional graph/connection data and activity stream data.

With this data, we can answer questions that no one else can answer

A Sampling of Our Data Driven Products

Jobs You May Be Interested In

in





Companies

Recommendations, similar companies search, peer companies, and company browse maps, company products and services browse maps

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Talent Match



Related search

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product of Autor

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Performance Metrics & Tracking Framework

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Behind the Scenes

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Jobs browse maps



Ad matching engine

pCTR = f(member, creative, advertiser, context, inventory, OCTR)

Referral Engine

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Pandora Search for People

Similar Profiles Adrian Silvesou (50)

May Be Interested In



Groups browse maps



Students + Colleges + Companies + Linkedin: A win-win-win based on data & network



What does Big-Data mean at LinkedIn

- Platform and solutions that
 - Enable scaling with data complexity
 - Simplify the data continuum across online, near-line and offline

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Big Data at LinkedIn



* Chart from Philip Russom- Research Director: TDWI



LinkedIn Data Infrastructure: Three-Phase Abstraction



Infrastructure	Latency & Freshness Requirements	Products
Online	Activity that should be reflected immediately	 Member Profiles Company Profiles Connections Skills
Near-Line	Activity that should be reflected soon	 Activity Streams Profile Standardization News Messages
Offline	Activity that can be reflected later	 People You May Know Recommendations Connection Strength News

LinkedIn Data Infrastructure: Sample Stack



Infra challenges in 3-phase ecosystem are diverse, complex and specific



Some off-the-shelf. Significant investment in home-grown, deep and interesting platforms



LinkedIn Data Infrastructure: Data Stores





LinkedIn Data Infrastructure: Specialized Indexes





LinkedIn Data Infrastructure: Pipelines



Systems	Capabilities
Kafka	Messaging for site events, monitoringHigh throughput
Databus	 Change data capture stream Reliable, consistent, low latency pipe



LinkedIn Data Infrastructure: Off-line Analysis





LinkedIn Data Infrastructure: Cluster Management





- Generic framework for building distributed systems
- Declarative model of cluster management Primitives
- Encapsulates multiple shard-management logic (Assignment of Master-Slave, Elasticity and Rebalancing, Fault Tolerance and Recovery)
- Leverage: Used in Search, Databus, Espresso



Open Source Contributions



Kamikaze Utility package for compressed arrays



Voldemort Distributed key-value storage system. LinkedIn created



Sensei A distributed, elastic, real-time, searchable database. LinkedIn created



Zoie Real-time search and indexing system built on top of Apache Lucene



Azkaban Simple hadoop workflow. LinkedIn created



Kafka Data pipeline and messaging. LinkedIn created



Bobo Fast faceted search with Lucene



Helix Generic Cluster Manager



Simpleton History of Data and Computing

- First there was horizontal distribution of the data (e.g., sharding in Oracle)
- Next there was horizontal distribution of the computation (e.g., GFS, Hadoop, Map-reduce)
- What is next? Data1, Data2,Data n fed into computation engineA, computation engineB, ... Computation engine n in realtime (holy grail)
- Why is this important: the nature of the data has changed with use models on the Internet, including social/professional media, mobile computing, cloud computing
- More than ever we need to derive useful signals from the noise and clutter of information at speed and scale ("Hyper-cube")

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Web 3.0 – It's all about data!!

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