Supply Chain Analytics: End to End, Data Driven Decision Making

Presented by:
Steven Carnovale, Ph.D.

Pandion
OPTIMIZATION ALLIANCE

2019 Healthcare Innovations Conference

November 13, 2019

Agenda

Three Parts:

- Part 1: Develop an Understanding of Analytics
  - What is analytics?
- Part 2: Identify the business goal & match the analytical capability
  - Descriptive
  - Predictive
  - Prescriptive
- Part 3: Select areas of application for SC Analytics to HC
  - Opportunities to make the business case

Steven Carnovale, Ph.D.

- Education:
  - BS Management and Global Business from Rutgers University
  - Ph.D. in Supply Chain Management, Minor in Marketing Science (Applied Econometrics) from Rutgers University

- Professional Background
  - 3 Years in IT Analytics, Sales and Sales Operations (purchasing and vendor management) from 2006-2009
  - 2 Years in Marketing/Strategy Consulting (co-founded a B2B firm) from 2009-2011
  - 7 years in Operations/Marketing Research consulting from 2011-Present
    - Econometric modeling
  - 4 Years as Assistant Professor of SCM at Portland State U., 2014-2018
  - 1+ year as Assistant Professor of SCM at RIT, Saunders COB 2018-Present

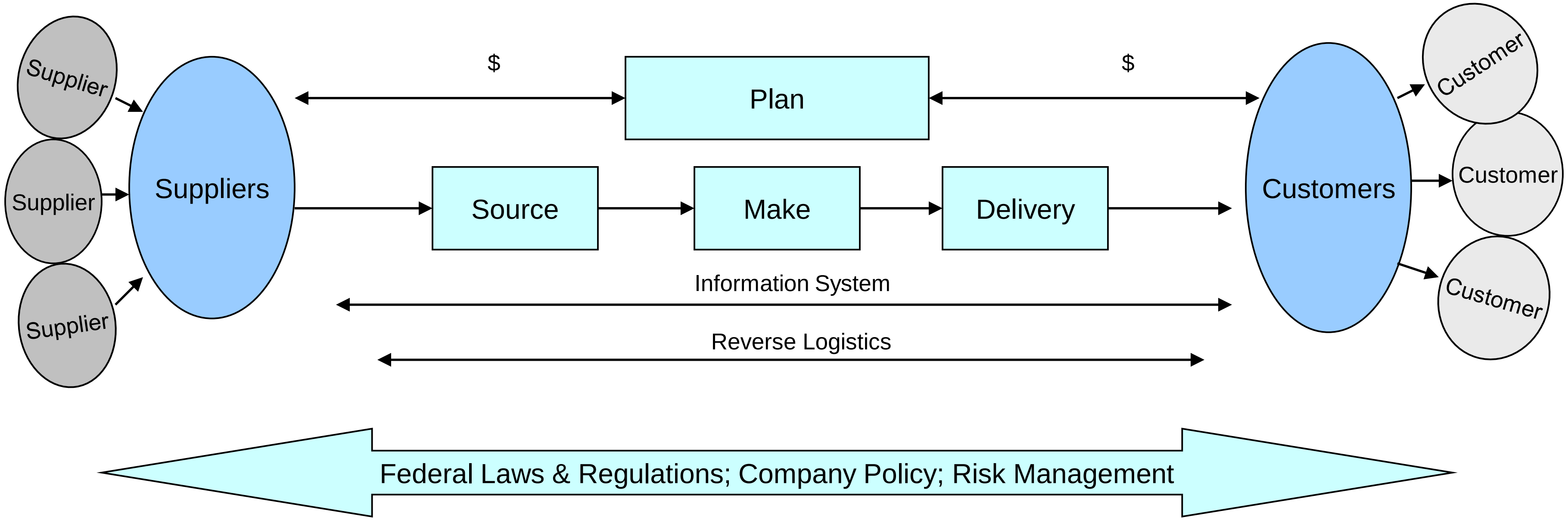
- Academic Background
  - Research in SC network design, SC risk management, econometric modeling, buyer supplier relationships, supply chain fraud.
  - Teaching in Operations Management, Supply Chain Management and Reverse Logistics and Closed Loop Supply Chains

Part 0: My SCM outlook/orientation

Supply Chain Management

It is about delivering the **right** product/service at the **right** time, **right** quantity, **right** price to the **right** customer

- Managing the plan and operating the flow of materials sourcing, production process, distribution, delivery, reverse logistics, information system and financial supply chain while optimizing the costs and risks and meeting federal laws, regulations and company policy



Part 1: Develop an Understanding of Analytics

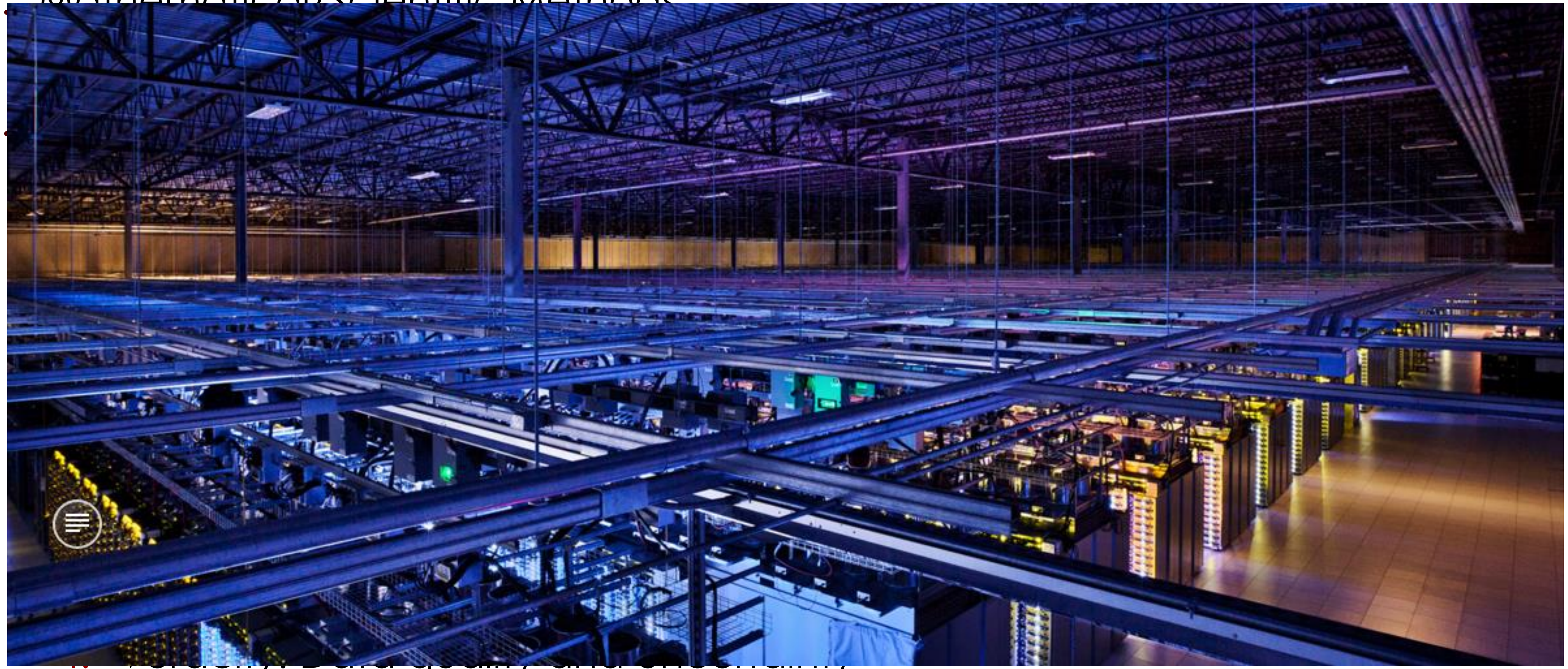
What’s all the hype about?

- “Recent Accenture research reveals that … **97 percent of executives report having an understanding of how big data analytics can benefit their supply chain, but only 17 percent report** having already implemented analytics in one or more supply chain functions“ [1]
- Why?
- “Top-performing organizations use analytics five times more than lower performers” [2].
- Collections Treatment Optimization (CTO) program at Toyota Financial Services [3]
  - Micro-segmentation of delinquent customer records
  - Action-effect modeling
  - 6,000 customers avoided repossession
  - TFS grew by 9% w/o head count additions.

Analytics: What is it?

- "Analytics in general, involves the use of mathematical or scientific methods to generate insight from data" [4]

- Key components of that definition:
  1. Mathematical/Scientific Methods
  2.

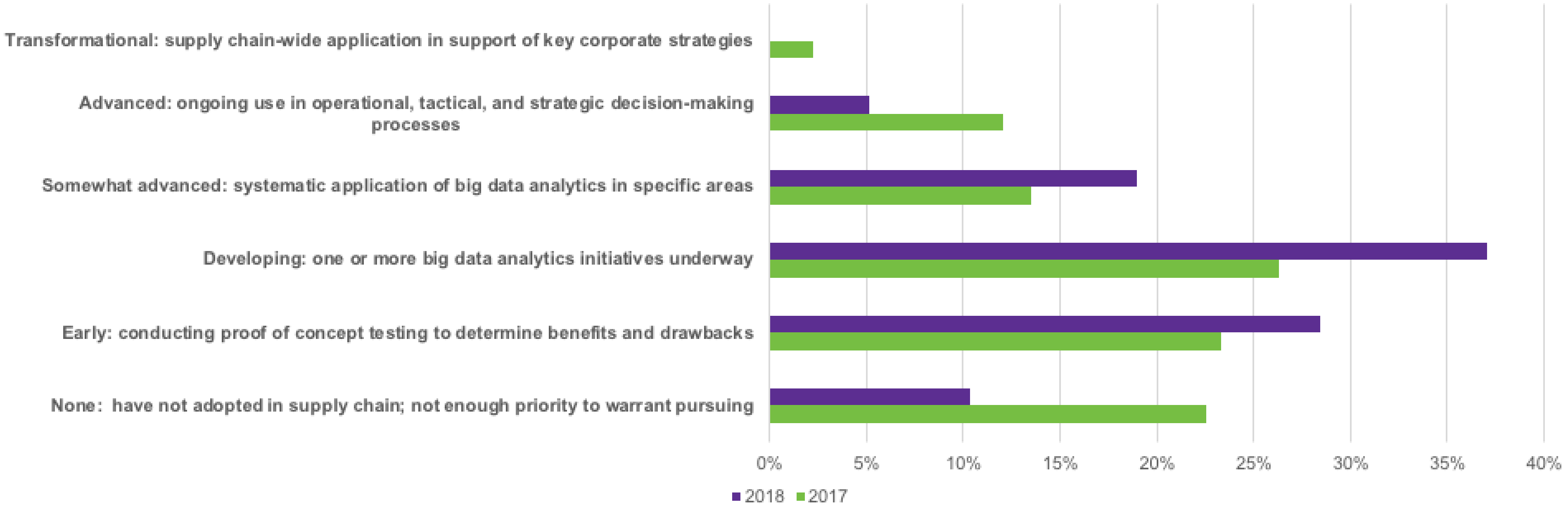


Google's Data Center in Council Bluffs, Iowa

Why analytics?

- "Supply Chain Analytics aims to improve operational efficiency and effectiveness by enabling data-driven decisions at ***strategic***, ***operational*** and ***tactical*** levels" [6]
- Think about the supply chain and its stakeholders
- SC Integration through MRP/MRPII/EDI/ERP
  - Gradual transition to fully integrated systems
- Increases in tech capabilities → better/larger data collection
- What do we do with all the data?
- Key Deliverables of a good analytics programs:
  - Reduce inventory holding costs
  - Free up cash on hand
  - Increase forecast accuracy
  - Optimize freight utilization and loading

Characterizing Maturity in Analytics



Source (with permission): Rogers, Z. et al. (2018). 2nd annual big data analytics survey

Realized Benefits of Analytics Use

Source (with permission): Rogers, Z. et al. (2018). 2nd annual big data analytics survey

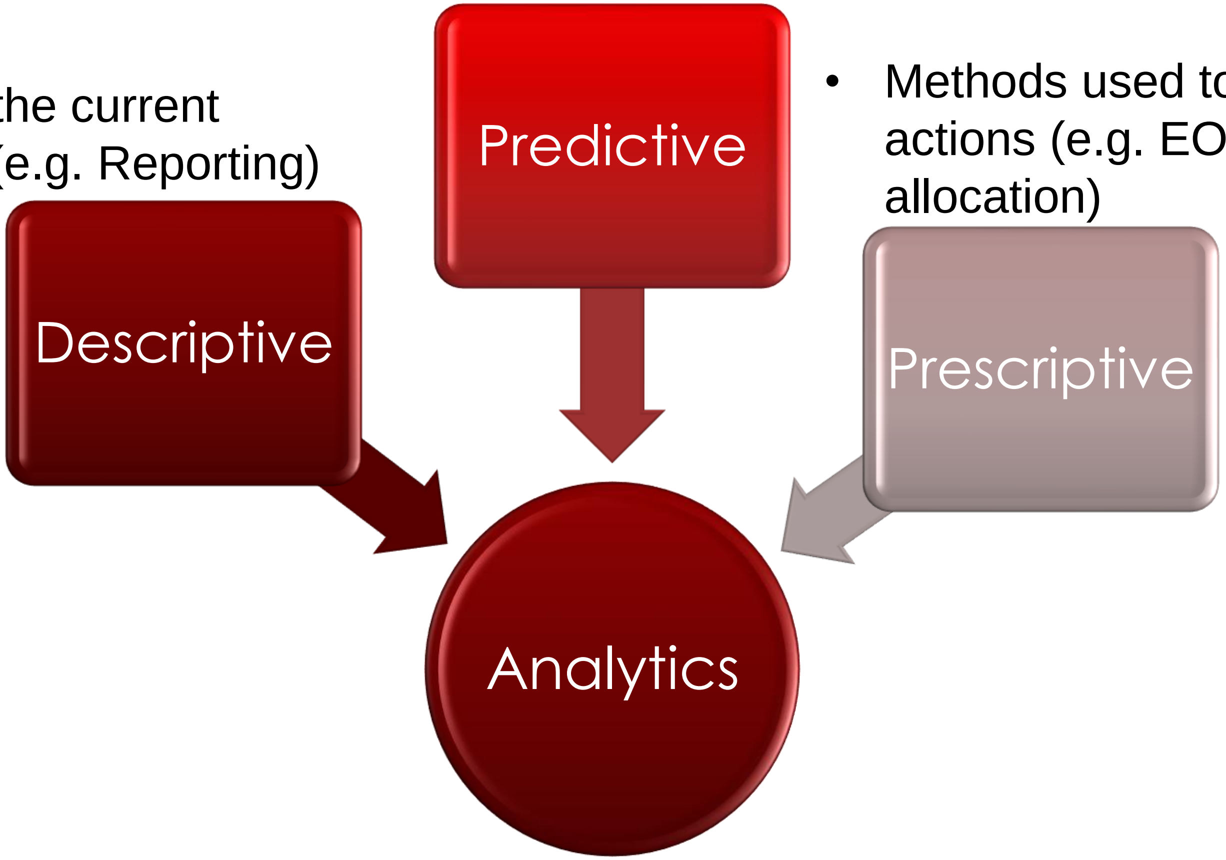
Part 2: Identify the business goal & match the analytical capability

Three Large Components

- Analyze current and historical information to make predictions
- What will happen, with a likelihood associated

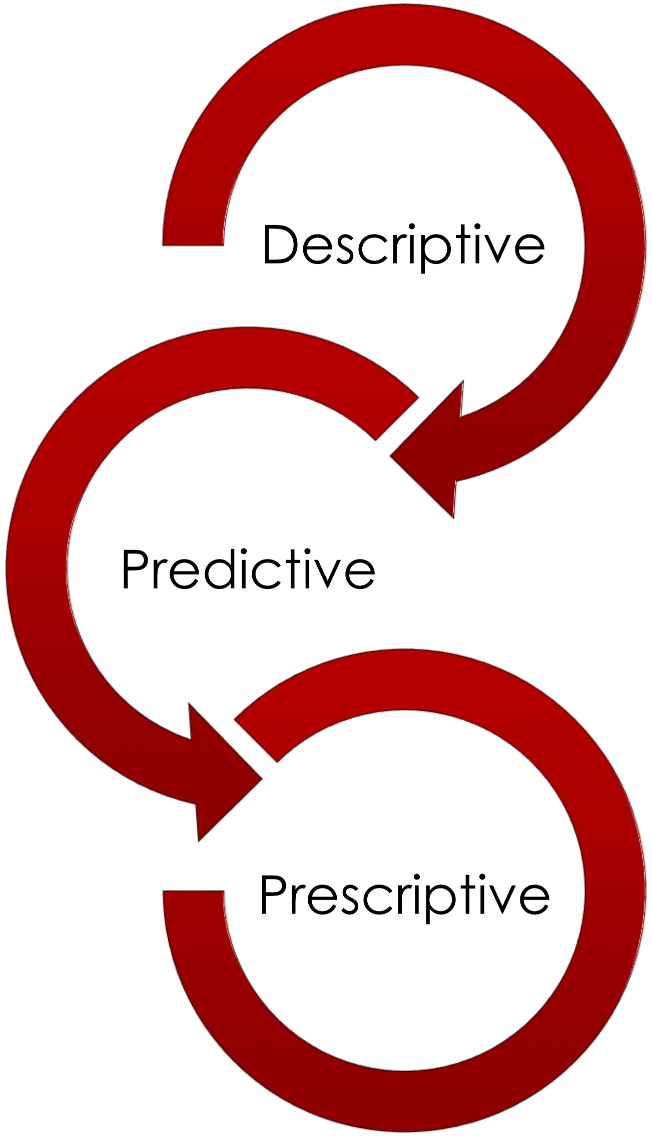
- Explains the current situation (e.g. Reporting)

- Methods used to recommend actions (e.g. EOQ, resource allocation)



Three Large Components

Really, It's a mutually reinforcing system:



Historical demand information used to inform…

Forecasting and other predictive decision making processes which …

Helps to make sound, scientifically driven managerially relevant decisions.

Type 1: Descriptive Analytics

- What is it [7]?
  - Prepares and analyzes historical data
  - Identifies patterns from samples and reporting of trends

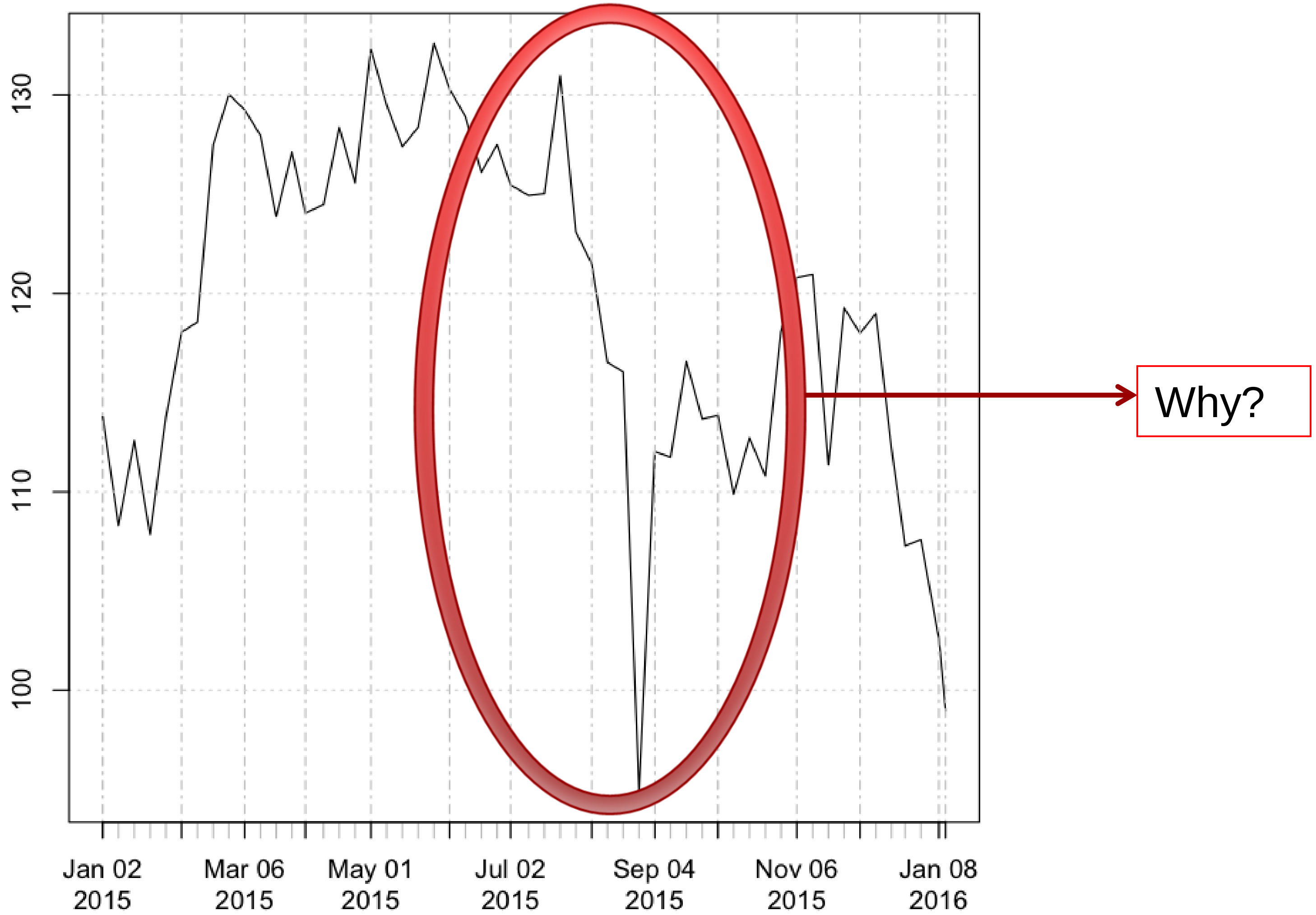
- Some estimates suggest that over 80% of analytics are descriptive in nature [8].

- Data Counters

- Tools-Simple and explanatory
  - Descriptive statistics
  - Correlations
  - Graphical Representations of Data

Type 1: Descriptive Analytics

- Examples:
  - Historical Stock Prices (AAPL for 2015)



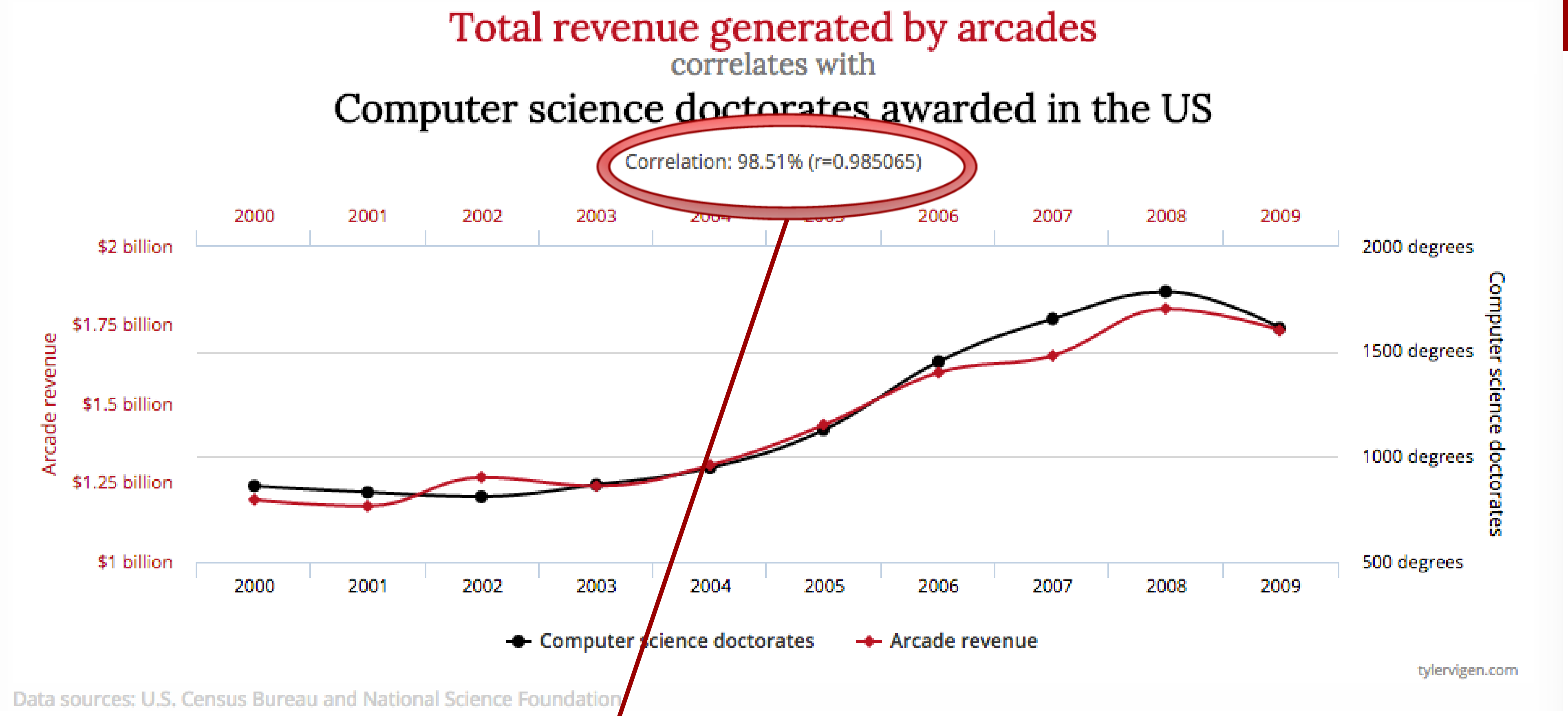
Type 1: Descriptive Analytics

- Examples:
  - Facebook Statistics [9]:
    - 1.01 billion daily active users on average for September 2015
    - 894 million mobile daily active users on average for September 2015
    - 1.55 billion monthly active users as of September 30, 2015
    - 1.39 billion mobile monthly active users as of September 30, 2015
    - Approximately 83.5% of our daily active users are outside the US and Canada

Implications for advertising?

Type 1: Descriptive Analytics

- Examples:
  - Spurious Correlations [10]:



Just because its correlated, can we scientifically make any decisions based on it?

Type 1: Descriptive Analytics

- Essentially tells us *WHAT* is happening
- Allows for insight into *WHY*, but does not tell the whole story
- Predictive analytics, however, beings to reveal the relationships at play
  - i.e. gets us to the *WHY*

Type 2: Predictive Analytics

- What is it [7]?
  - Predicts future probabilities and trends
  - Finds relationships in data that may not be readily apparent with descriptive analysis
- Transition from simply examining extant data to making predictions with/from it
- Leverages statistics/probability theory to ascertain individual likelihoods
- Tools:
  - Predictive Modeling-Parametric & non-parametric models (e.g. multiple linear or Poisson regression vs. Kernel regression)
  - Machine learning (e.g. artificial neural networks, Bayesian Networks)
  - Data Mining (Intersection of CS/AI & statistics)

Type 2: Predictive Analytics

- Example: Multiple Linear Regression to Attribute Causality/Forecast Returns
  - Causal modeling: what's the relationship between product characteristics and return rates?

$$General\ Form: y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \varepsilon$$

Tells us, given a 1-unit change in the x, how much the y will go up or down

$$\#\ of\ Returns = b_0 + b_1 \#\ of\ Colors + b_2 Price$$
$$+ b_3 Quantity\ Sold + b_4 \#\ of\ Sizes$$

So, after we calculate these, we know to what degree each impacts returns to predict their frequency

Type 2: Predictive Analytics

- Example: Data Mining for Intelligent couponing/Product Recommendations [12]:

- Organize:

$I = \{i_1, i_2, \ldots, i_n\}$ *is a set of n binary attributes called items*

$D = \{t_1, t_2, \ldots, t_n\}$ *is a set of transactions called the database*

Each transaction in D has a unique ID and contains a subset of the items in I

Define a rule as:

$X \Rightarrow Y, \text{where } X, Y \subseteq I \text{ and } X \cap Y = \varnothing$

Antecedent

Consequent

Cust. ID	Trans. ID	Milk	Bread	Butter	Beer	Diapers
0001	1	1	1	0	0	0
0002	2	0	0	1	0	0
0003	3	0	0	0	1	1
0004	4	1	1	1	0	0
0005	5	0	1	0	0	0

Type 2: Predictive Analytics

- Example: Data Mining for Intelligent couponing/Product Recommendations [12]

- Create association rules derived from data:

$$
\begin{aligned}
&if\ \ D_{0004,4} = \{milk, bread, butter\}\\
&the\ rule\ might\ be:\\
&X_{0004,4} = \{milk, bread\} \Rightarrow\ Y_{0004,4} = \{butter\}
\end{aligned}
$$

- Usefulness:
  - Intelligent couponing at the individual level
  - Amazon's "Customer's also bought…"
  - **Target's controversial (and accurate) "Pregnancy Predictions"**

- Data heavy process
  - Key for determining statistical significance

Type 2: Predictive Analytics

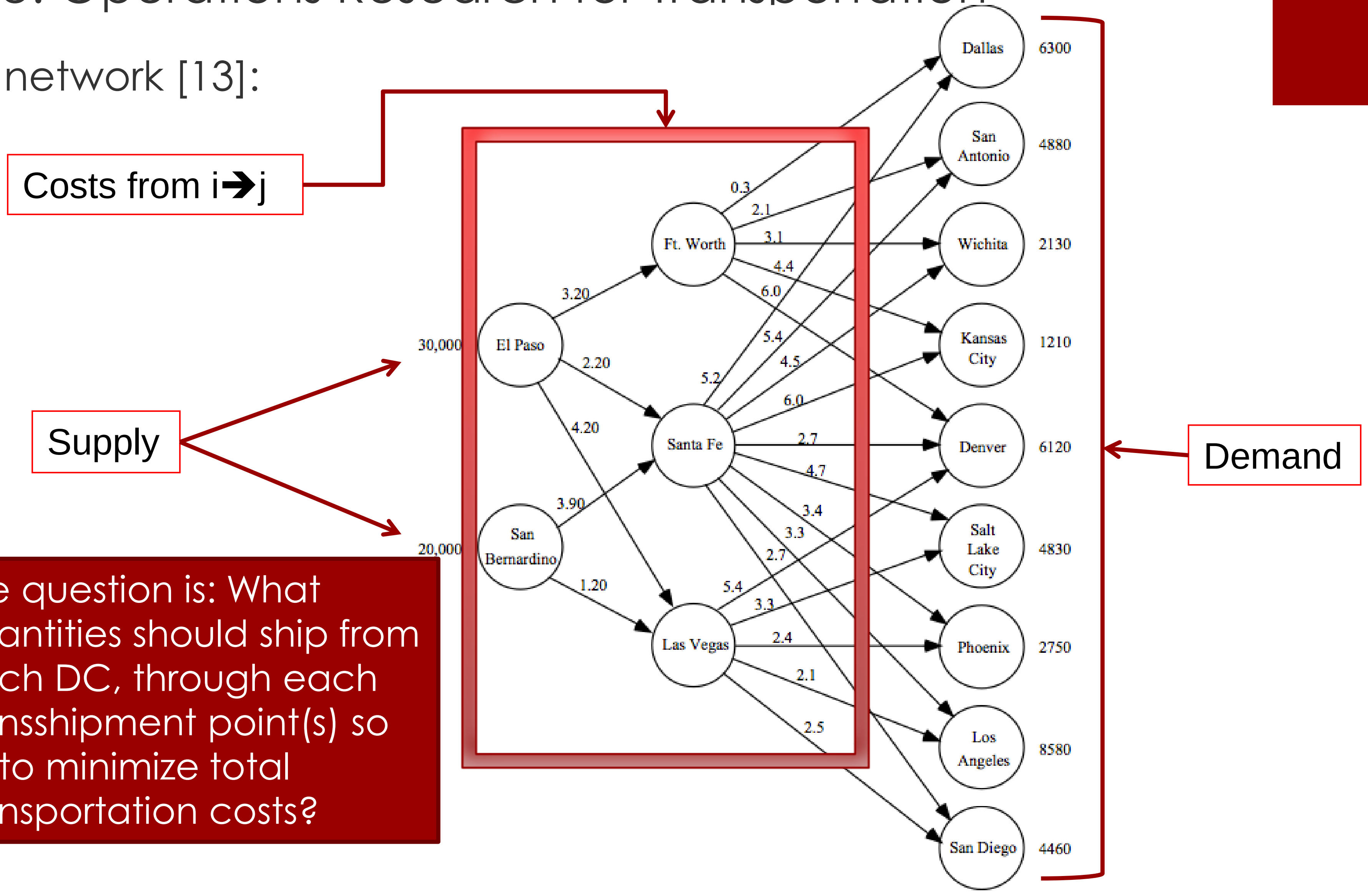
- Now we know:
  - What has happened (Descriptive)
  - Why it has been happening (Predictive)
  - What might happen next (Predictive)
- But, we do NOT know what to do!
- In comes prescriptive analytics . . .

Type 3: Prescriptive Analytics

- What is it [7]?
  - Evaluates and determines **new** ways to operate
  - Targets business objectives
  - Balances all constraints
- Creates a plan given extant operating conditions (Strategic)
- Several Scientific areas:
  - Employs techniques from mathematical sciences
  - Used in IE, economics, industrial organization
  - Key for SCM: cost minimization, transportation models, SC network design

Type 3: Prescriptive Analytics

- Example: Operations Research for Transportation
- Take this network [13]:



The question is: What quantities should ship from each DC, through each transshipment point(s) so as to minimize total transportation costs?

Type 3: Prescriptive Analytics

- Example: Operations Research for Transportation
  - Problem is a network optimization problem
  - Solved using linear programming
  - Simplex Method➔ensures global optimality

Cost of shipping from location i to location j

General Form:

Cost minimizing objective function

$$\text{Min } Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

Minimize the transportation cost

Quantity shipping from location i to location j
This is our so called “decision variable”

Supply constraint

$$\text{s.t.} \quad \sum_{j=1}^{n} x_{ij} = s_i \quad \text{for } i = 1, 2, \ldots, m,$$

Cannot ship more than supply/production

Demand constraint

$$\sum_{i=1}^{m} x_{ij} = d_j \quad \text{for } j = 1, 2, \ldots, n,$$

Each location MUST receive at least its demand

$$x_{ij} \geq 0 \quad \forall i, j.$$

No negative products!

Non-negativity constraint

Type 3: Prescriptive Analytics

- Example: Operations Research for Transportation
- Results:

I to j	Xij
EP_to_FW	14520
EP_to_SF	6740
EP_to_LV	0
SB_to_SF	0
SB_to_LV	20000
FW_to_DA	6300
FW_to_SA	4880
FW_to_WI	2130
FW_to_KC	1210
FW_to_DE	0
SF_to_DA	0
SF_to_SA	0
SF_to_WI	0
SF_to_KC	0
SF_to_DE	6120
SF_to_SL	0
SF_to_PH	0
SF_to_LA	0
SF_to_SD	620
LV_to_DE	0
LV_to_SL	4830
LV_to_PH	2750
LV_to_LA	8580
LV_to_SD	3840

Total shipped to demand points: 41,260

Recall that we had the constraint that supply cannot exceed demand

Which necessitates that we meet the demand at DA, SA, WI, KS, DE, SL, PH. LA and SD

The total demand here is 41,260

So, we have satisfied this important constraint at the minimum cost!

Part 3: Select areas of application for SCM Analytics in Healthcare

Opportunities in HC

- Medical Devices
- Analytics' Usefulness:
  - Descriptive: Empirical representation of demand patterns and costing components
    - HUGE in should costing/competitive bidding
  - Predictive: forecasts of:
    - Return rates
    - Sales
    - Seasonality/cyclicality
    - Supply Risk
  - Prescriptive:
    - Cost/network optimization
    - Optimal production planning
    - Traveling salesperson problem

Opportunities in HC

- Hospital/ER Service Operations
- Analytics' Usefulness:
  - Descriptive:
    - Describing demand patterns and demand concentration
    - Good for capacity analysis
  - Predictive:
    - Predicting (to the best degree possible) when/where/what people will enter the ER for
  - Prescriptive:
    - Scheduling of physicians
    - Capacity expansions
    - Detection of tumors

Opportunities in SC Analytics

- Supply Chain Risk Management
  - "90 percent of firms do not quantify risk when outsourcing production" [15]
  - Those firms who experienced SC disruptions saw [15]:
    - Operating income declined by 107 percent, and Return On Assets (ROA) declined by 114 percent.
- Descriptive Analytics Potential:
  - Understand current SC structure/infrastructure
  - Diagnose potential areas of vulnerability
- Predictive Analytics Potential:
  - Incorporate predictive modeling for Weather/natural disaster and economic downturns
- Prescriptive Analytics Potential:
  - Analytic techniques for SC design (facility location)
  - Design of sourcing arrangements

So, what is it?

The anti SWAG approach to SCM!

Questions?

Thank you!

- Contact information:

Steven Carnovale, Ph.D.

Assistant Professor of Supply Chain Management

Associate Editor-Journal of Supply Chain Management

Associate Editor- Journal of Purchasing and Supply Management

Saunders College of Business

Rochester Institute of Technology

Email: scarnovale@saunders.rit.edu-OR- steven.carnovale.jr@gmail.com

References

- [1] Accenture, https://www.accenture.com/us-en/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Global/PDF/Industries_14/Accenture-Big-Data-POV.pdf
- [2] Hopkins, Michael S. MIT Sloan Management Review. Winter2011, Vol. 52 Issue 2, p21-22. 2p
- [3] Woodie, Alex. (2016). How Toyota Revamped Its Collections Biz with Big Data Analytics. http://www.datanami.com/2016/01/11/how-toyota-revamped-its-collections-biz-with-big-data-analytics/
- [4] Brenda L. Dietrich, Emily C. Plachy, Maureen F. Norton. (2014). Analytics Across the Enterprise: How IBM Realizes Business Value from Big Data and Analytics. IBM Press. ISBN-13: 978-0133833034
- [5] IBM, 2014: http://www.ibmbigdatahub.com/infographic/four-vs-big-data
- [6] Capgemini, https://www.capgemini.com/resource-file-access/resource/pdf/supply_chain_analytics_0.pdf
- [7] INFORMS, https://www.informs.org/Community/Analytics
- [8] Information Week http://www.informationweek.com/big-data/big-data-analytics/big-data-analytics-descriptive-vs-predictive-vs-prescriptive/d/d-id/1113279
- [9] Facebook, http://newsroom.fb.com/company-info/
- [10] Tyler Vigen http://www.tylervigen.com/spurious-correlations
- [11] Carnovale, S. and Yeniyurt, S. (2015). “The Role of Ego Networks in Facilitating Supply Network Innovations”. Journal of Supply Chain Management, Vol. 51 No. 2, pp. 22-46.
- [12] Agrawal, R.; Imieliński, T.; Swami, A. (1993). "Mining association rules between sets of items in large databases". Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD '93. p. 207. doi:10.1145/170035.170072. ISBN 0897915925.
- [13] Hillier and Lieberman. (2001). Introduction to Operations Research. McGraw Hill
- [14] Ernst & Young. http://www.ey.com/Publication/vwLUAssets/EY-re-engineering-the-supply-chain-for-the-omni-channel-of-tomorrow/$FILE/EY-re-engineering-the-supply-chain-for-the-omni-channel-of-tomorrow.pdf
- [15] J. Paul Ditman. http://globalsupplychaininstitute.utk.edu/publications/documents/Risk.pdf
- [16] https://www.theretailequation.com/Retailers/images/public/pdfs/industry_reports/ir_2014_nrf_retail_returns_survey.pdf