



TECH | 2/16/2012 @ 11:02AM | 1,549,799 view

### How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

Every time you go shopping, you share intimate details about your consumption patterns with retailers. And many of those retailers are studying those details to figure out what you like, what you need, and which coupons are most likely to make you happy. Target, for example, has figured out how to data-mine its way into your womb, to figure out whether you have a baby on the way long before you need to start buying diapers.

Charles Duhigg outlines in the  $\underline{\text{New York}}$   $\underline{\text{Times}}$  how Target tries to hook parents-to-be at that crucial moment before they turn into rampant — and loyal — buyers of all things



Target has got you in its aim



Guest Editorial:

The Shape of Marketing Research in 2021

ANCA CRISTINA MICU NIM DEDEKER, UAN LEWIS, ROBERT MORAN, GOED NETZER, JOSEPH PLUMMER,

INTRODUCTION
It is year 2011. A chief marketing officer (CMC) sits at his desk very early one meeming. His consumer insights team's deck from a presentation the previous night still is in front of him. The CMC leans hack in his chair, take his glasses off, starts wiging.

communics and led by China.

I also know that all of this is only the tip of the inference function of see the eight-ninths beneath the surface yet.

The basis of marketing dairs' change; I still need to disorily, derelay, and market products and arration falseting, described, and market products and arration that satisfy customer medic over an ethy lop in averaged of the competition. I must do a batter lop in average to sungs. I need to be better at articipating the foliace, and at atoming consumer and customers, and market, at bringing the transmission of the constraints of the constraints of the with crossmers and customers, at authorizationly and and deferring against commerce needs around the world, and it approximately preserved in operations protected world, and at recogniting protection of plections prosets.

I wonder what the "new normal" will be

ECOLOGY OR STRATEGY? Induced or Autonomous Ada

If nothing else, the "new normal" will ofter constant change and adaptation. Focusing on strategic change in companies, some scholars have documented major epochs—periods of quantum change, and recrimations in strategy making whereas others have documented the engoing process of strategy making in organizations.

From an organizational strategy perspective, stribuling changes to sweeping environmental riggers or long-term strategic planning means taking either an ecological or strategic view-point. The ecological-versus-strategic debate centers on the same of environmental determinism versus stratetic choice.

Whether knowd by the environment or as the result of strategic planeing, adaptation to change ringgens who delivities width as company coupsed in an adaptation process. Adapting comparies able to either induced or autoremous processes to adapt. The induced process concerns initiatives that are width the expect of the organization's cumust strategy and build on existing organizational barrings whereas the autoremous process corcerns initiatives that energie custoide of it and provide the potential for new organizational learning whereas the control of the company control of the state of the control of the control of the state of the control of the control of the state of the control of Columbia
Business
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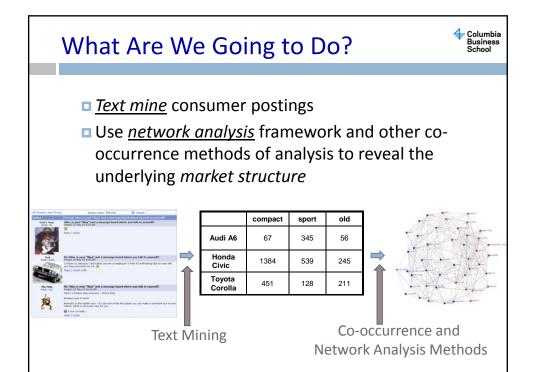
Mine Your Own Business: Market Structure Surveillance (Netzer, Feldman, Goldenberg, and Fresko 2012)



- Can we use the Web as a marketing research playground?
- Can we quantify the rich, yet unstructured, information consumers post on the web?



Uncovering market structure from information consumers are posting on the Web



### **Text Mining Background**



- A rapid flow (river) of information available in digital format
- Managers have less time to absorb more information



### **Mining Consumer Forums**



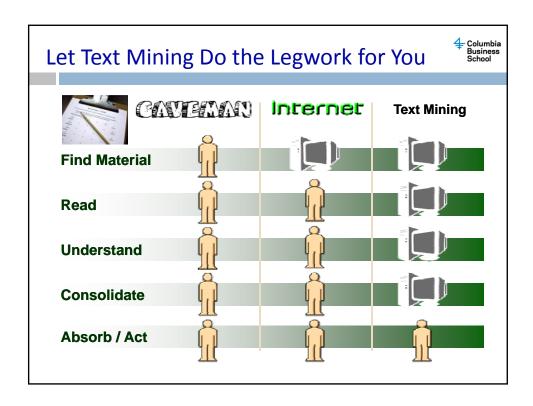
### **Opportunities**

- A combination of observational and descriptive marketing research
- Permits both qualitative and quantitative information
- Non-invasive (no demand effect)
- Minimizes recall error
- Very rich data
- Sample size is not an issue
- Real time data

### **Difficulties**

- Massive amount of data
- Data is all over the Web
- Data is unstructured
- Population may not be representative
- Topic of discussion may not be representative

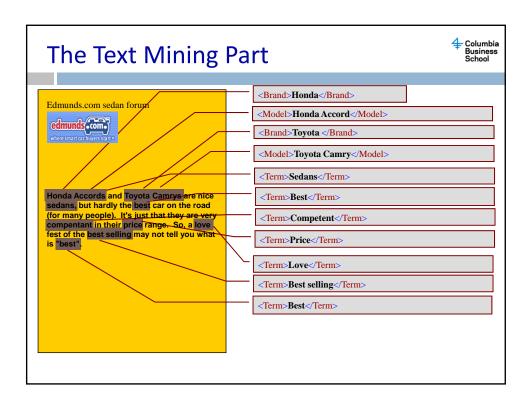




### The Text Mining Process



- Downloading: html-pages are downloaded from a given forum site
- Cleaning: html-like tags and non-textual information like images, commercials, etc. are cleaned from the downloaded pages
- **Chunking:** the textual parts are divided into informative units like threads, messages, and sentences
- Information Extraction: products and product attributes are extracted from the messages
- Comparisons between products are extracted: either by using co-occurrence analysis or by utilizing learned comparison patterns



### **Major Issues**



- Handling Negation
  - Prevent bone loss
- Deciding if a phrase is positive or negative, verbs alone are not enough, and nouns alone are not enough.
  - Reducing losses vs. Reducing forecasts
- Anaphora Resolution
  - The company
  - The 3<sup>rd</sup> biggest US oil producer (COP)
- Catching Meaningful Phrases





### **Information Extraction Approach** · Rules are written by inspecting the text Hand- Requires linguistic and domain experts Crafted · Can't manually list all patterns **Rules** · Can take a lot of time · Skilled programmer is need **Hybrid** Approach · Training data is tagged manually Conditional Random Fields are applied Supervised on training data Machine • The trained system is applied on the full Learning • The system is language independent · Large training data is sometimes needed

### Some Text Mining Difficulties



- We are interested in:
  - Brand names (e.g., car companies)
  - Model names (e.g., car models)
  - Some common terms (mostly noun-phrases and adjectives)
- Brand names are relatively easy
  - Need to deal with abbreviations and spelling mistakes
- Models are more complex
  - Variations in writing styles
    - Honda Civic could be written as "Honda Civic"; "Civic"; "Honda Civic LS"; "Honda Civic LE"; "LE"; "H. Civic"; "Hondah Sivik"
    - Model numbers can be written as: 5, V, Five "The Audi A6 is great! the 6 is better than the 4"
    - Model can be referred to as numbers but numbers do not always refer to models (e.g., "1010 for New Balance 1010", but \$1010)

## How Accurate Are We?



Information Type	Recall	Precision	Overall Accuracy
Car Brands	98%	98%	98%
Car Models	88%	95%	91%
Drugs	89%	100%	94%
Side Effects	74%	90%	82%
DrugSide Effect	60%	96%	74%



# **Empirical Applications**





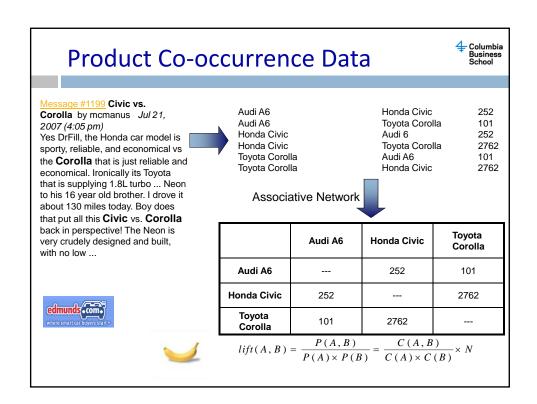


### Sedan Cars Application: Edmunds.com

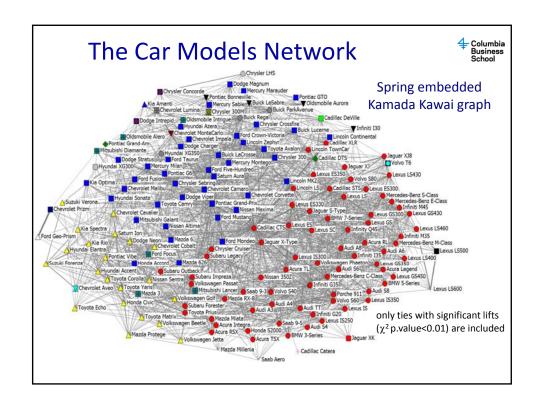


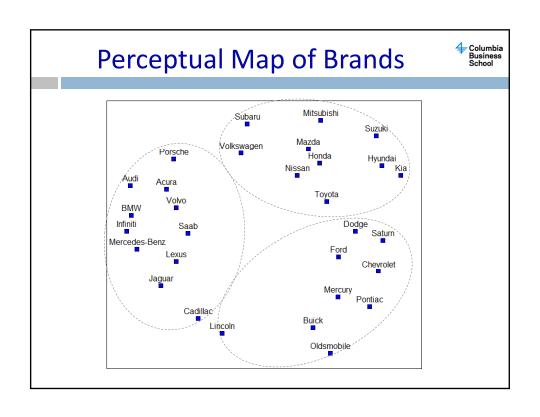


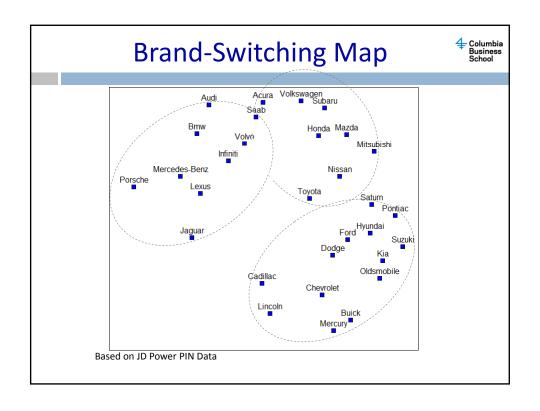
"Honda Accords and Toyota Camrys are nice sedans, but hardly the best car on the road (for many people). It's just that they are very compentant in their price range. So, a love fest of the best selling may not tell you what is "best". That depends very much on what is important to you. A car could have a quirk, that you would just love, but not be popular to many people. Thus, the best car for you might not sell many. If you are looking for resale value, then it might be a factor."

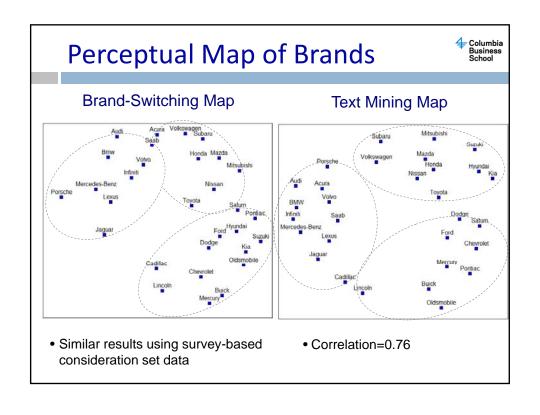


### Columbia Business School Cars That Are Most Central to the Discussion No. of Car model Degree Betweenness Eigenvector occurrences Honda Accord 100.00 0.954 13.56 60,546 36,038 99.41 0.891 Toyota Camry 13.54 Volkswagen Passat 99.41 0.861 17,151 13.53 BMW 3-Series 98.81 0.710 13.48 34,595 Lexus ES 98.81 0.794 13.45 10,630 Nissan Altima 0.441 13.49 13,191 11,501 Nissan Maxima 98.81 0.385 13 51 Toyota Avalon 98.81 13.48 13,153 0.412 Honda Civic 98.21 0.402 13.39 25,037 10 Infiniti G35 98.21 0.417 13.47 24,131 11 Mazda 6 97.02 0.372 13.29 10,664 Acura TL 96.43 0.363 13.36 27,262 13 BMW 5-Series 96.43 0.402 13.32 27,075 5,658 14 Chrysler 300 95.83 0.411 13.28 Toyota Corolla 95.83 0.342 13.21 7,256 Cadillac CTS 16 95.24 0.352 13.24 6,582 17 Lexus GS 95.24 0.284 13.12 8.843 Audi A4 94.64 0.298 13.18 11,974 18 Audi A6 19 94.64 0.278 13.13 13,848 Mercedes-Benz E-Class 0.325 13.12 9,220

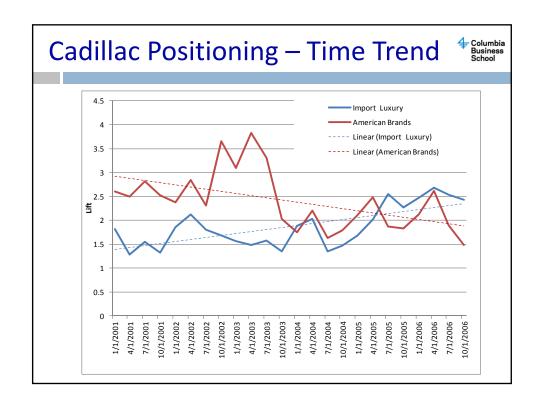


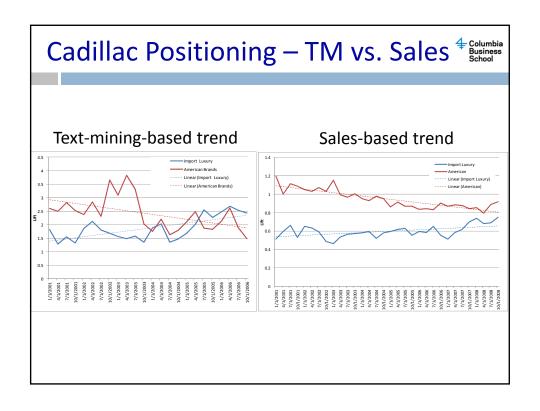


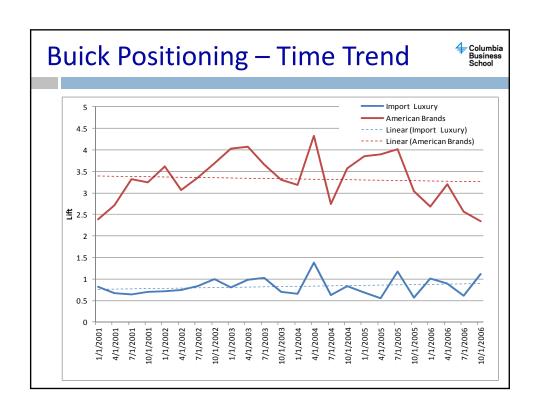


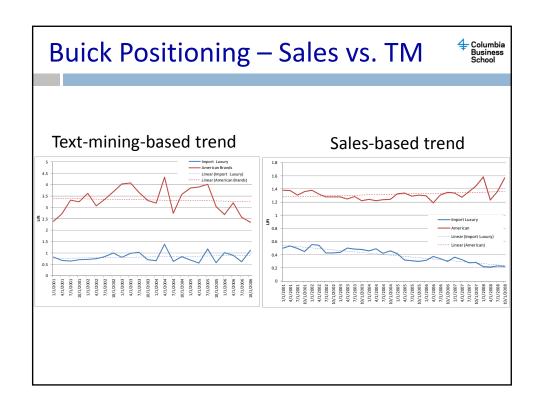


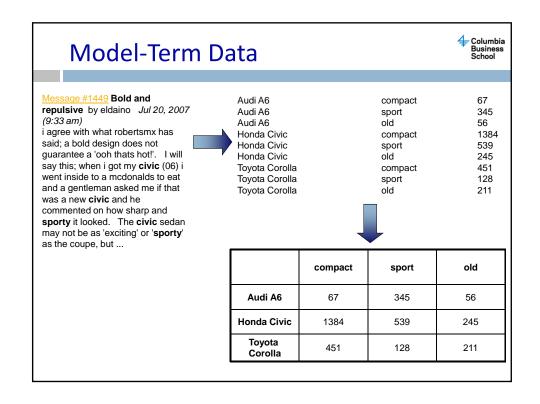


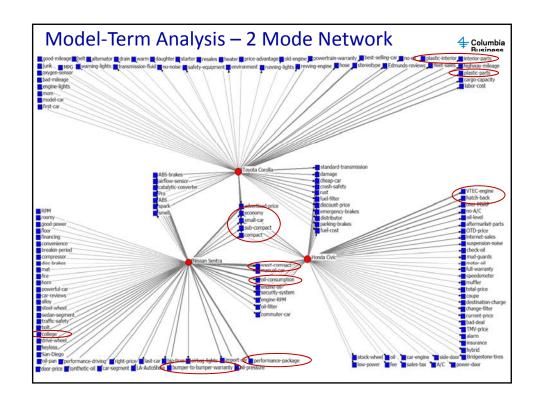


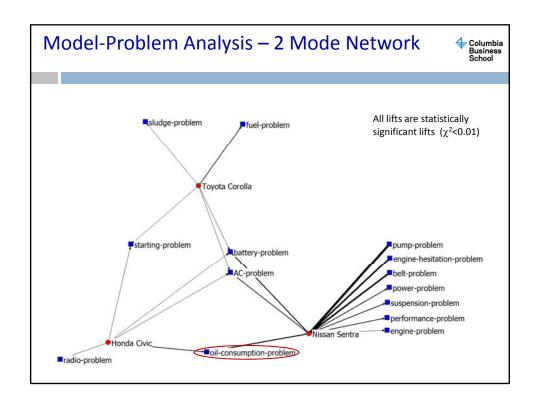












## **Explaining the Car Models Discussion**



 $Lift(Y_i, Y_i) = f(same\_brand, same\_manuf, country\_of\_origin, car\_size, used)$ 

- Observations are correlated cannot use simple regression
- Converted  $Lift(Y_i, Y_j)$  to  $log(1 + Lift(Y_i, Y_j))$
- Used Dekker Semi-Partialling QAP Regression

	Coefficient	Standardized Coefficient	Pseudo P. value
Intercept	0.2204	1	0.000
Same brand	0.3423	0.2031	0.000
Same manufacturer	0.1732	0.1708	0.000
Same country of origin	0.0903	0.1259	0.000
Same size class	0.1325	0.1826	0.100
Price Difference	-0.0054	-0.1629	0.000

## **Explaining the Car Models Discussion**



 $log(1 + Lift(Y_i, Y_j)) = f$  (terms used to describe the cars)

- Use factor analysis to reduce the dimensionality of the terms
- Six main factors found

Upscale	Looks	Driving Experience	Customer Value	Forum Sentiment	Comfortable Ride
MSRP	Styling	Fun	Value	Fuel (neg.)	Ride
Premium	Interior	Handle/handling	Quality	Power (neg.)	Room
Bad (neg.)	Nice	Drive	Consumer	Engine (neg.)	Suspension
Luxury	Looks	Manual	Reliability	Love	Back-Seats
Navigation		Speed		Great	Leather
Sports		Automatic		Board	Seats
				Comment	

# Explaining the Car Models Discussion



 $log(1 + Lift(Y_i, Y_i)) = f$  (terms used to describe the cars)

	Coefficient	Standardized Coefficient	Pseudo P. value
Intercept	0.5104		0.000
Occurrence	0.0003	0.0176	0.161
Factors			
Upscale	-0.0904	-0.2374	0.000
Looks	-0.0302	-0.0829	0.000
Driving experience	-0.0216	-0.0598	0.004
Consumer value	-0.0530	-0.1490	0.000
Forum sentiment	-0.0312	-0.0899	0.000
Comfortable ride	0.0022	0.0057	0.358

# Explaining the Car Models Discussion Columbia Business School



	Coefficient	Standardized Coefficient	Significance
Intercept	0.3952		0.000
Same brand	0.3197	0.1897	0.000
Same manufacturer	0.1778	0.1754	0.000
Same country of origin	0.0765	0.1067	0.000
Same size class	0.1332	0.1836	0.000
Price Difference	-0.0029	-0.0866	0.000
Occurrence	-0.0003	-0.0609	0.000
Factors			
Upscale	-0.0708	-0.1860	0.000
Looks	-0.0326	-0.0897	0.000
Driving experience	-0.0096	-0.0267	0.1259
Consumer value	-0.0396	-0.1114	0.000
Forum sentiment	-0.0287	-0.0827	0.000
Comfortable ride	0.0061	0.0163	0.2324

# Robustness Check 1 How Much Data is Needed?



	# of messages	Correlation with the Full Dataset	
1/16 of the messages	54,261	0.983	
1/8 of the messages	108,52	0.989	
1/4 of the messages	217,044	0.995	
1/2 of the messages	434,088	0.997	

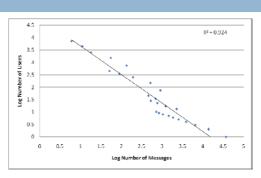
# Robustness Check 2 How Much Training Data is Needed?



	Recall	Precision	Overall Accuracy (F)
276 messages	91%	90%	90%
138 messages	86%	90%	87%
69 messages	84%	87%	86%
34 messages	81%	86%	83%
17 messages	73%	86%	79%

# Robustness Check 3 Are all Forum Participants Equal?





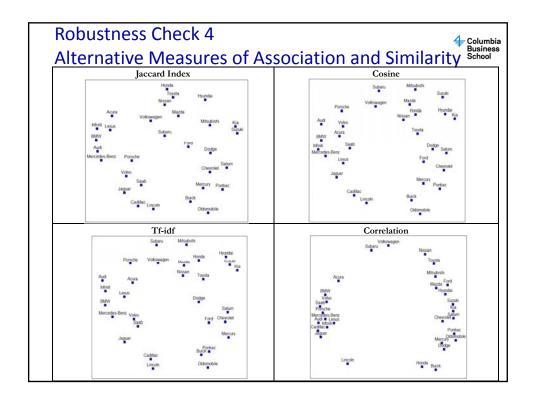
- 10% of the users post over 80% of the content
- Participation in the forum follows the power law
- The correlation between "heavy" users and "light" users is r=0.79
- The correlation between short and long messages is r=0.96

# Robustness Check 4 Alternative Measures of Association and Similarity

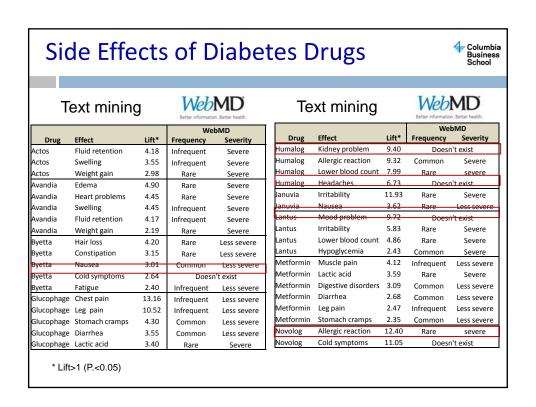
### Other association and similarity measures

- Cosine Similarity  $Cosine_{ij} = \frac{X_{ij}}{\sqrt{X_j X_i}}$
- $\begin{array}{ccc} \textbf{TF-IDF} & & CO(tf-idf)_{ij} = \sum_{m \in D} \left(tf_{jm} idf_{j} \times tf_{im} idf_{i}\right) \\ \\ & & tf_{jm} = X_{jm} \, / \, N_{m} & idf_{j} = \log(D \, / \, M_{j}) \end{array}$

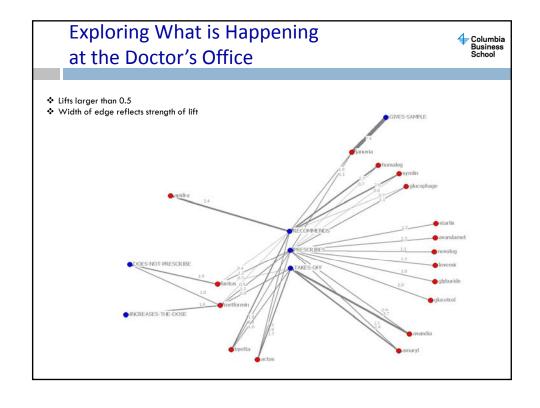
### Robustness Check 4 Alternative Measures of Association and Similarity Correlations among similarity measures and with trade-ins Lift Jaccard Cosine tf-idf Correlation **Cars Trade-ins** Lift 0.753 0.970 0.708 **Jaccard Index** 1.000 0.970 0.753 Cosine tf-idf 0.961 0.919 0.961 0.714 Correlation 0.623 0.623 0.578 0.575 0.473

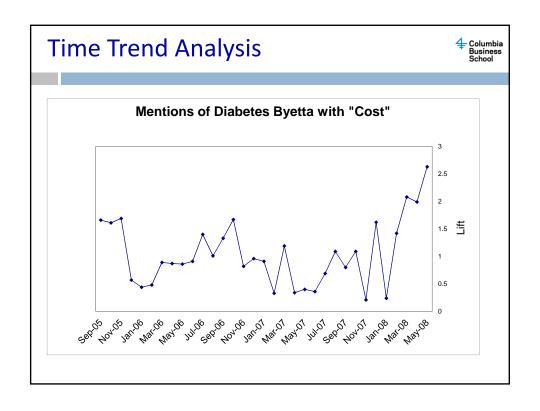


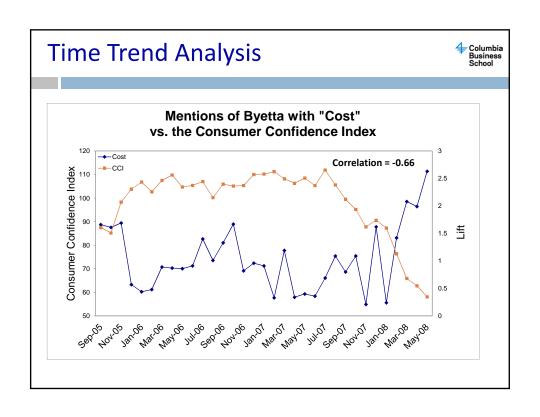
# Pharmaceutical Application: Diabetes Drugs Five diabetes forums diabetesforums.com of Diabetesforums on healthboards.com healthboards.com forum.lowcarber.org diabetes.blog.com diabetesdaily.com Over 670K messages



Drug Co-tak	ing with Byett	a	
Drug	Co-Occurrence	Lift	Byetta is mentioned as "taken
Januvia	67	2.96	together" more frequently than
Symlin	48	1.90	chance (lift>1): with
Glucovance	13	1.55	• Januvia
Metformin	448	1.51	Symlin
Amaryl	42	1.11	<ul><li>Metformin (generic name)</li></ul>
Starlix	12	1.02	• Amaryl
Glipizide	23	0.92	• Starlix
Actos	46	0.82	
Glyburide	24	0.76	
Glucophage	24	0.53	
Avandia	20	0.47	
Lantus	86	0.26	
Humalog	28	0.15	







# Deriving Insights...





- Competitive landscape
- Building brand association maps
- Competitive intelligence
- Identifying customers (opinion leaders, potentially profitable, at risk)
- Brand monitoring
- "structured" exploratory research
- Tracking marketing campaign effectiveness
- Utilizing other textual information (e.g., call center)



# What's Next? Columbia Business School The Columbia Business Scho

