

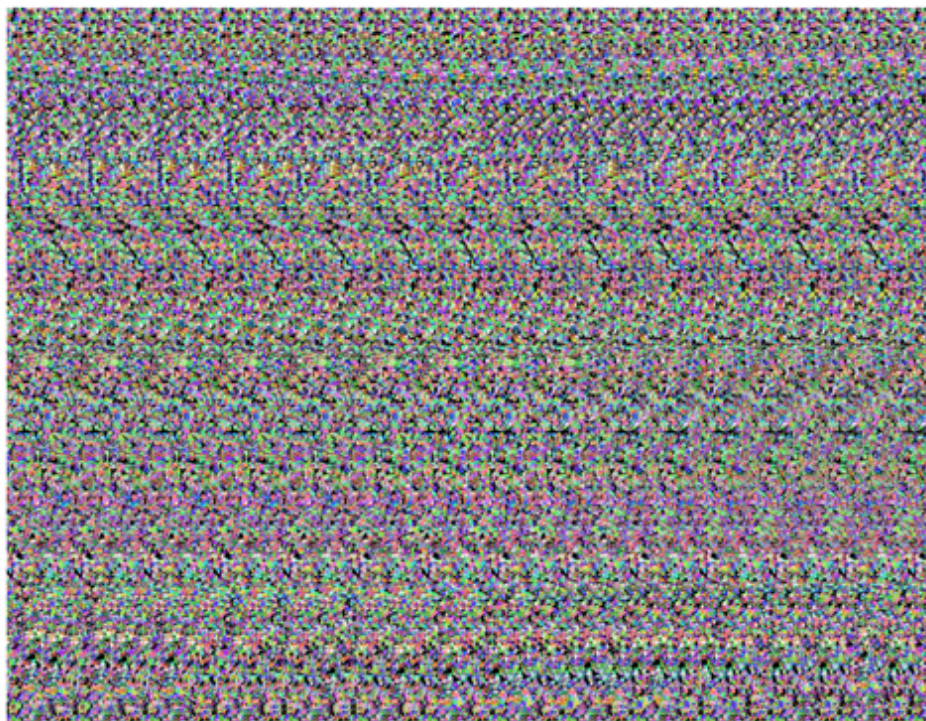


FROM DATA TO SOLUTIONS

MINE YOUR OWN BUSINESS

Oded Netzer

Columbia Business School



FOLLOW THESE INSTRUCTIONS TO UNLOCK A HIDDEN MESSAGE!

- ① STARE AT
YOUR
COMPUTER
FOR
UNHEALTHY
AMOUNTS OF
TIME (IT'S
CALLED
"RESEARCH")



- ② ALLOW YOUR
EYES TO
GLAZE
OVER AND
YOUR MIND
TO START
QUESTIONING
REALITY



- ③ START
SEEING
THINGS
THAT ARE
NOT REALLY
THERE!



JORGE CHAM © 2012

WWW.PHDCOMICS.COM

“Leadership is to see what everybody else has seen, and to think what nobody else has thought.”

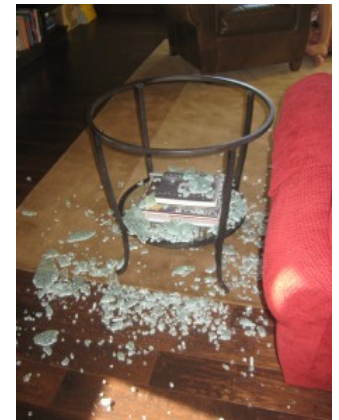


Where Do We Stand on Using Social Media for Business Decisions?

- Lots of counting, not enough evaluating
 - “If you can’t measure it you can’t manage it” ≠ “if you can measure it you should manage it”
- Too much ‘data’, not enough ‘insights’
- Thinking Big Data is primarily an IT challenge
- Some success stories...



P O T T E R Y B A R N





MINE YOUR OWN BUSINESS

Netzer, Feldman, Goldenberg, Fresko 2012

The Business Problem

- 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

What Are We Going to Do?

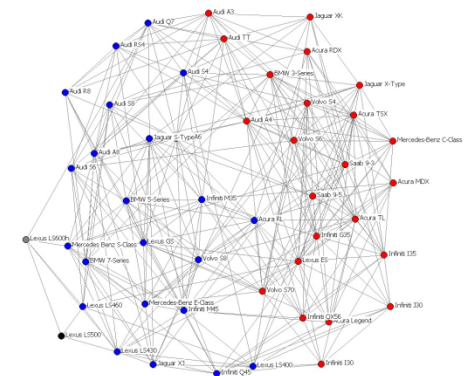
- ▣ Text mine consumer postings
- ▣ Use network analysis framework and other co-occurrence methods of analysis to reveal the underlying *market structure*



Text Mining

	compact	sport	old
Audi A6	67	345	56
Honda Civic	1384	539	245
Toyota Corolla	451	128	211

Co-occurrence and
Network Analysis Methods



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

radian⁶ nielsen
.....online



VISIBLE
TECHNOLOGIES



Let Text Mining Do the Legwork for You



CAVEMAN

Internet

Text Mining

Find Material



Read



Understand



Consolidate



Absorb / Act



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



The Text Mining Part

Edmunds.com sedan forum



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 competent in their price range. So, a love fest of the best selling may not tell you what is "best".

<Brand>Honda</Brand>

<Model>Honda Accord</Model>

<Brand>Toyota </Brand>

<Model>Toyota Camry</Model>

<Term>Sedans</Term>

<Term>Best</Term>

<Term>Competent</Term>

<Term>Price</Term>

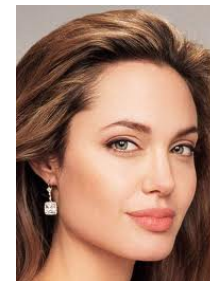
<Term>Love</Term>

<Term>Best selling</Term>

<Term>Best</Term>

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 3rd biggest US oil producer (COP)
- ▣ Catching Meaningful Phrases



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%
Drug--Side Effect	60%	96%	74%

Empirical Applications



Sedan Cars Application: Edmunds.com



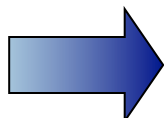
“ Honda Accords and Toyota Camrys are nice sedans, but hardly the best car on the road (for many people). It's just that they are very compentant in their price range. So, a love fest of the best selling may not tell you what is "best". That depends very much on what is important to you. A car could 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.”

Product Co-occurrence Data

Message #1199 Civic vs. Corolla

by mcmanus Jul 21, 2007 (4:05 pm)

Yes DrFill, the Honda car model is sporty, reliable, and economical vs the **Corolla** that is just reliable and economical. Ironically its Toyota that is supplying 1.8L turbo ... Neon to his 16 year old brother. I drove it about 130 miles today. Boy does that put all this **Civic** vs. **Corolla** back in perspective! The Neon is very crudely designed and built, with no low ...



Audi A6
Audi A6
Honda Civic
Honda Civic
Toyota Corolla
Toyota Corolla

Honda Civic 252
Toyota Corolla 101
Audi 6 252
Toyota Corolla 2762
Audi A6 101
Honda Civic 2762

Associative Network

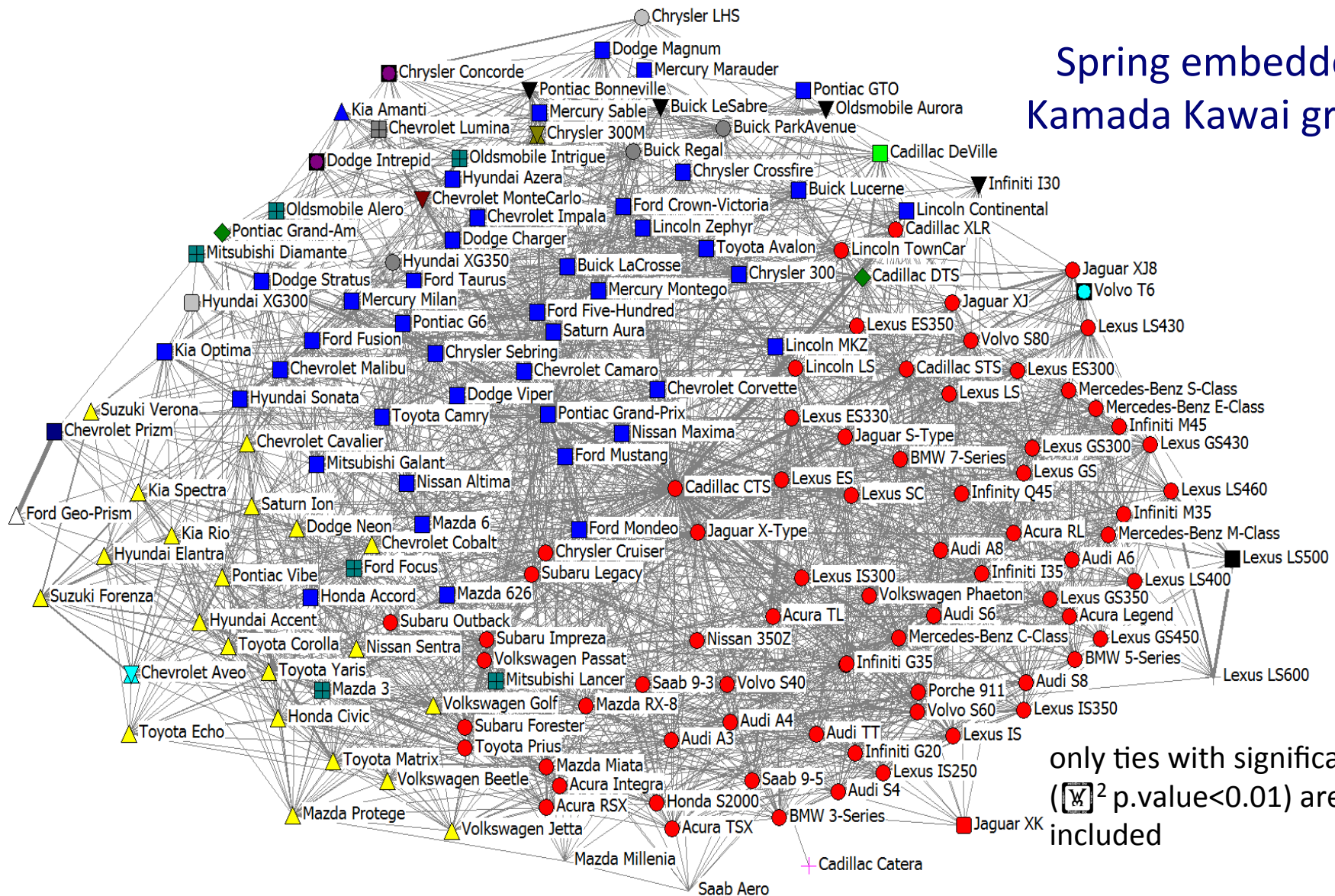


	Audi A6	Honda Civic	Toyota Corolla
Audi A6	---	252	101
Honda Civic	252	---	2762
Toyota Corolla	101	2762	---

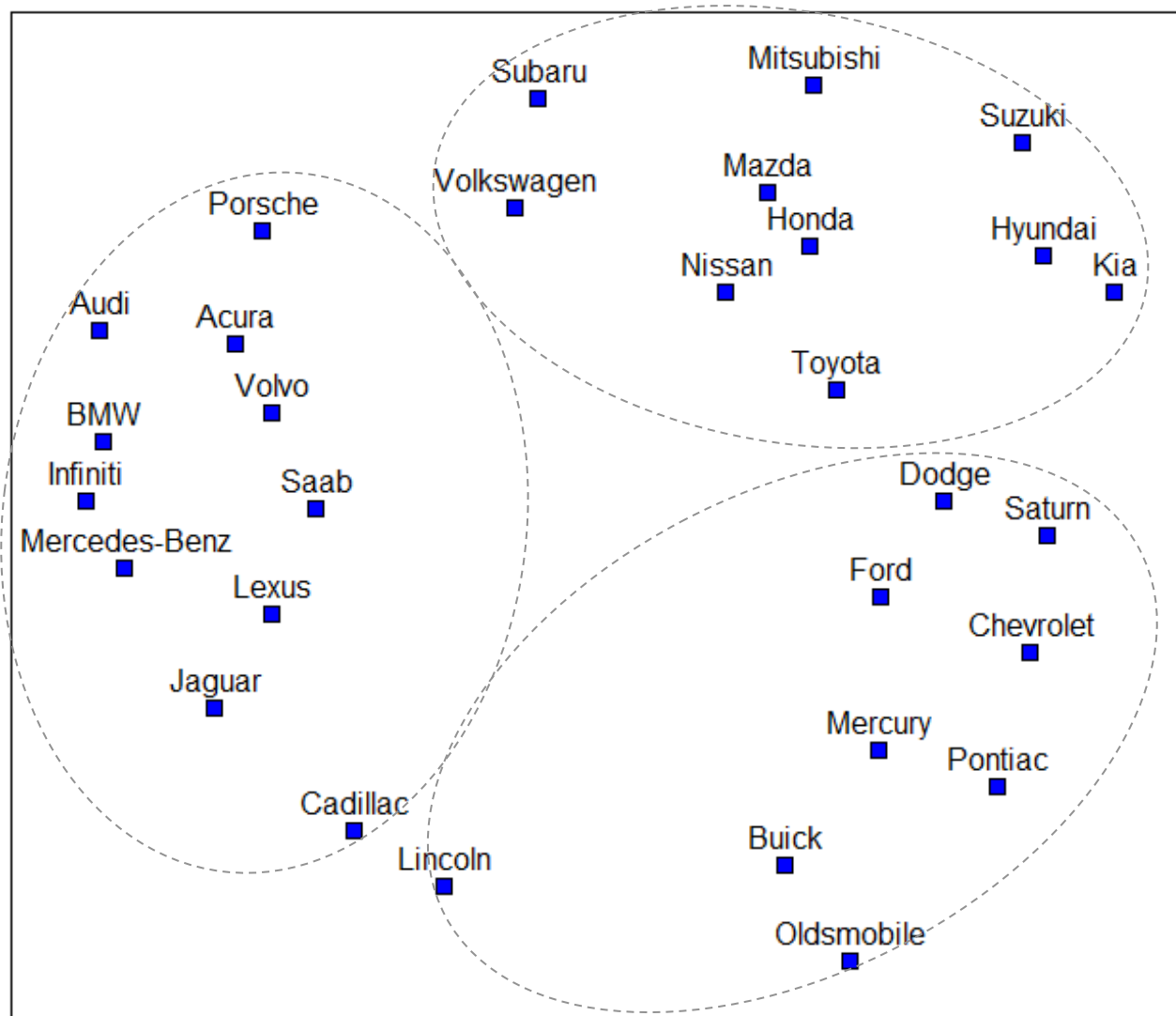
$$lift(A, B) = \frac{P(A, B)}{P(A) \times P(B)} = \frac{C(A, B)}{C(A) \times C(B)} \times N$$

The Car Models Network

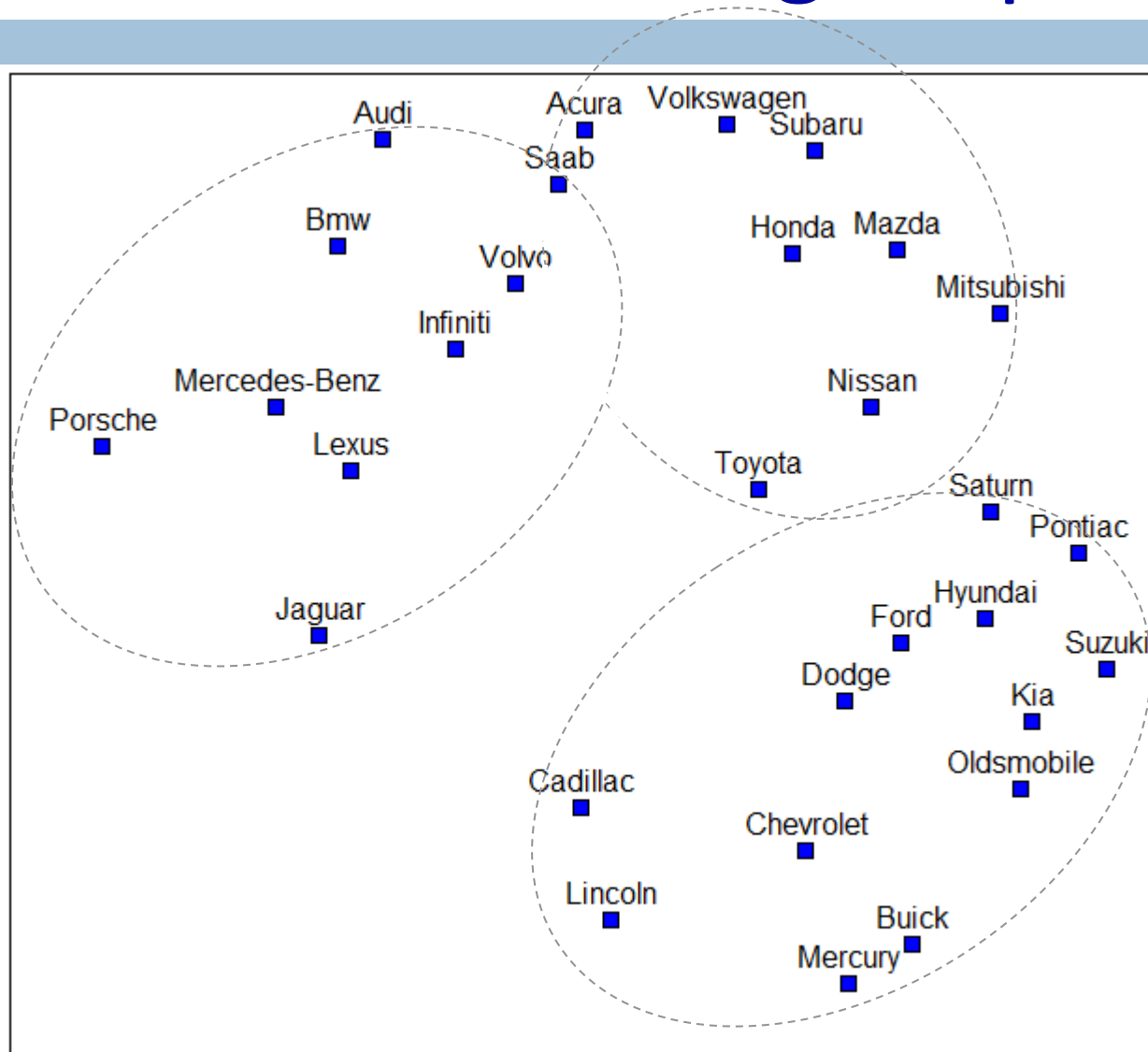
Spring embedded
Kamada Kawai graph



Perceptual Map of Brands



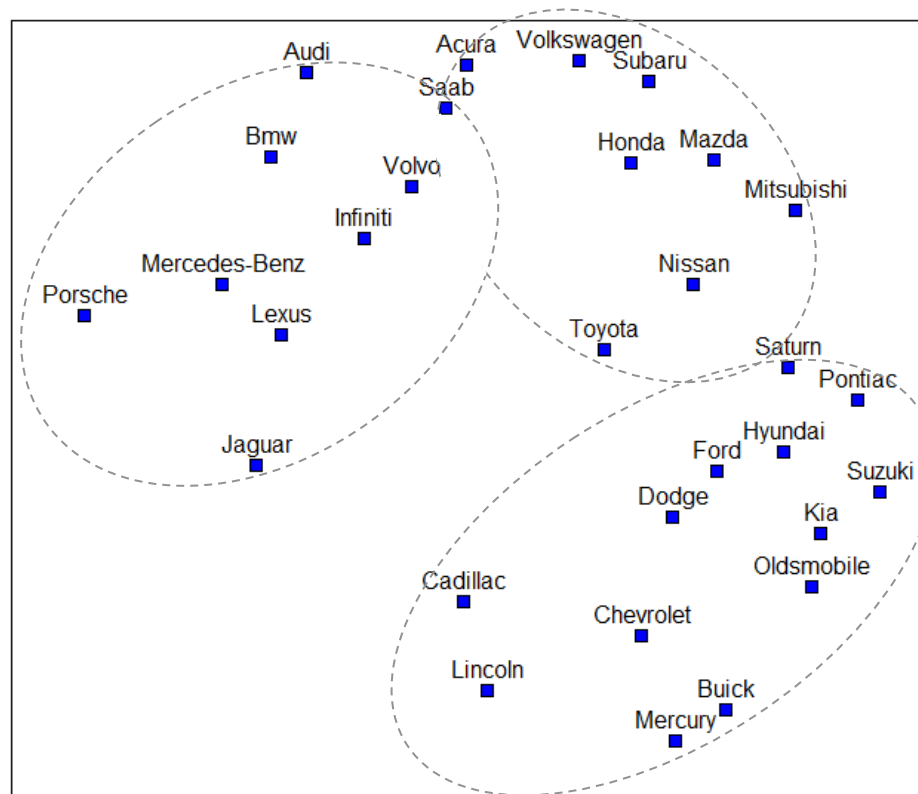
Brand-Switching Map



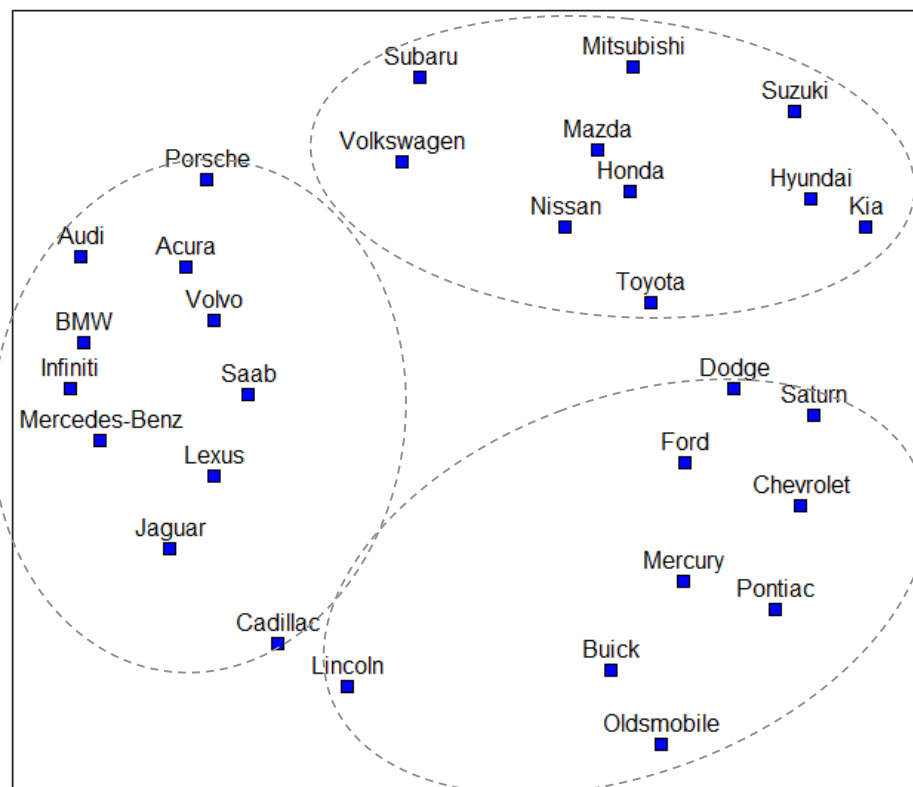
Based on JD Power PIN Data

Perceptual Map of Brands

Brand-Switching Map



Text Mining Map



- Similar results using survey-based consideration set data

- Correlation=0.76

Robustness Check 1

Alternative Measures of Association and Similarity

Other association and similarity measures

- ▣ *Jaccard Index*
$$Jaccard_{ij} = \frac{X_{ij}}{X_j + X_i - X_{ij}}$$

- ▣ *Cosine Similarity*
$$Cosine_{ij} = \frac{X_{ij}}{\sqrt{X_j X_i}}$$

- ▣ *TF-IDF*
$$CO(tf-idf)_{ij} = \sum_{m \in D} (tf_{jm} - idf_j \times tf_{im} - idf_i)$$
$$tf_{jm} = X_{jm} / N_m \quad idf_j = \log(D / M_j)$$

- ▣ *Pearson Correlation*
$$\rho_{ij} = correl(\mathbf{X}_i, \mathbf{X}_j)$$

Robustness Check 1

Alternative Measures of Association and Similarity

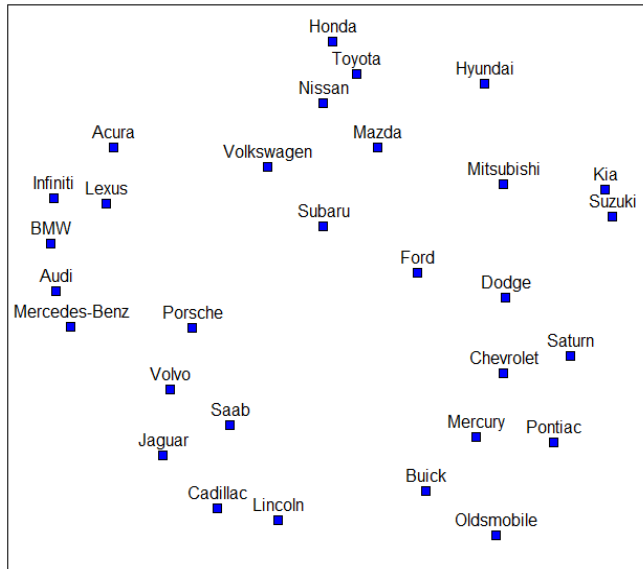
Correlations among similarity measures and with trade-ins

	Lift	Jaccard	Cosine	tf-idf	Correlation	Cars Trade-ins
Lift	--					0.753
Jaccard Index	0.970	--				0.708
Cosine	1.000	0.970	--			0.753
tf-idf	0.961	0.919	0.961	--		0.714
Correlation	0.623	0.575	0.623	0.473	--	0.578

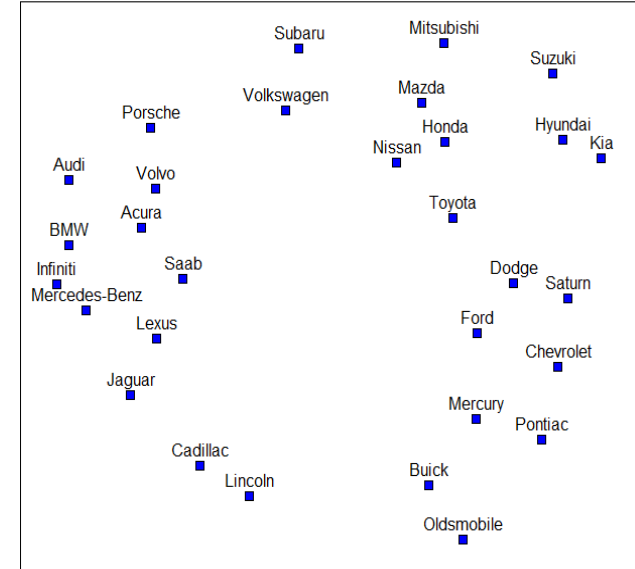
Robustness Check 1

Alternative Measures of Association and Similarity

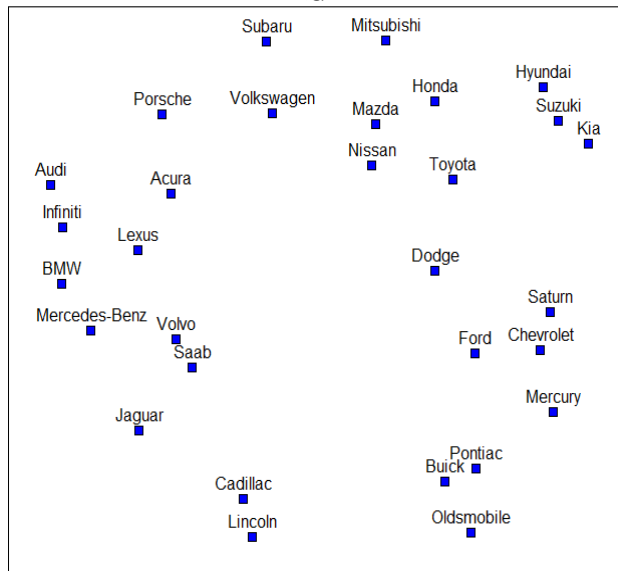
Jaccard Index



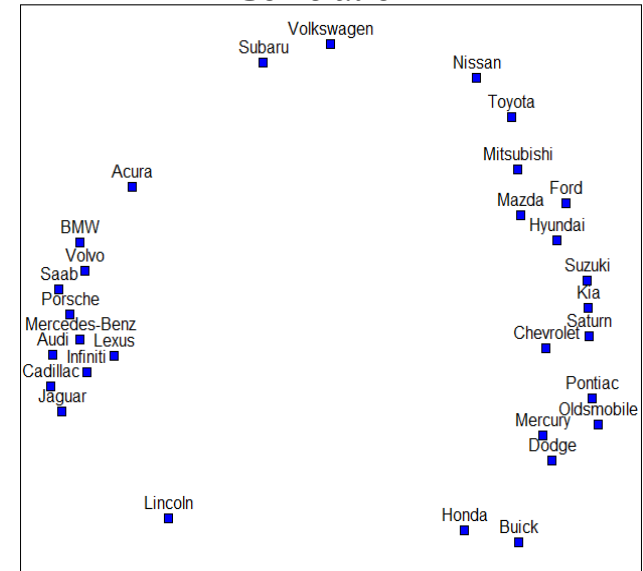
Cosine



Tf-idf



Correlation



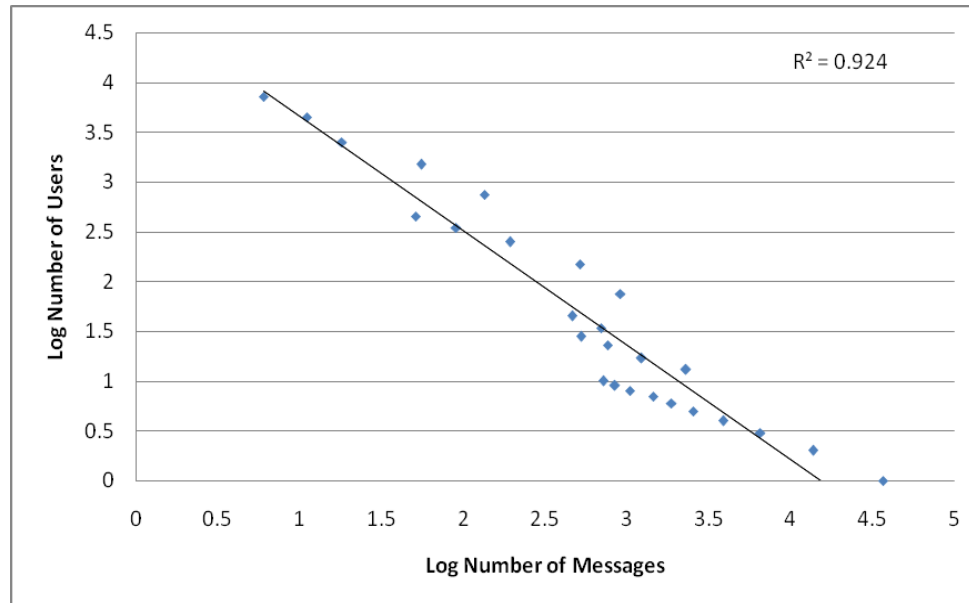
Robustness Check 2

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 $r=0.96$

The Second Coming Of Cadillac

Nov. 4, 2003

By David Welch

PUTTING A NEW SPIN ON CADDY

GM has taken significant strides toward making Cadillac a stronger rival to luxury import cars:

- 1 IMAGE** Ads featuring Led Zeppelin's rock music seized boomers' attention. Now Caddy will begin focusing more on its improved sporty ride and handling. It's also putting its cars front and center at glitzy events like the Oscars and Wimbledon.
- 2 QUALITY** GM's highly automated \$540 million Cadillac plant in Lansing, Mich., is one of the most efficient auto factories in the U.S. More important, the cars have earned consistently high marks in the J.D. Power & Associates quality survey.
- 3 PERFORMANCE** Beating BMW and Mercedes requires an upgrade under the hood. In January, Cadillac will start selling the CTS-V, a 400-horsepower version of the CTS that will hit the racing circuit.
- 4 PRESENTATION** A new incentive plan doubles bonuses for dealers who upgrade showrooms to a more cutting-edge look that includes black porcelain tile floors and black leather furniture.



2004 CADILLAC XLR

Cadillac stakes a claim in the luxury-roadster arena.

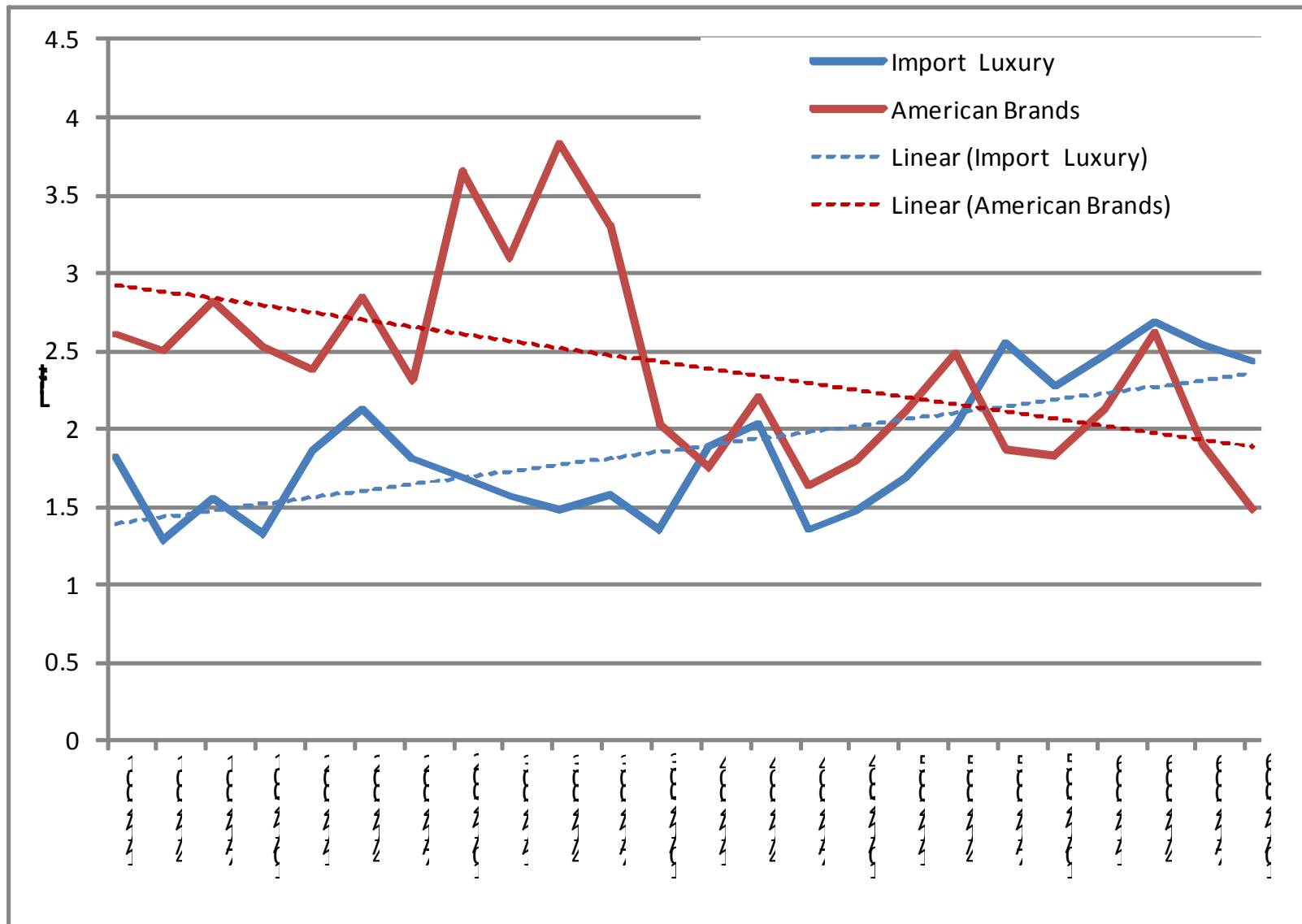
June 2003

BY CSABA CSERE

“Looks like Cadillac intends to become a full-service luxury carmaker again.”

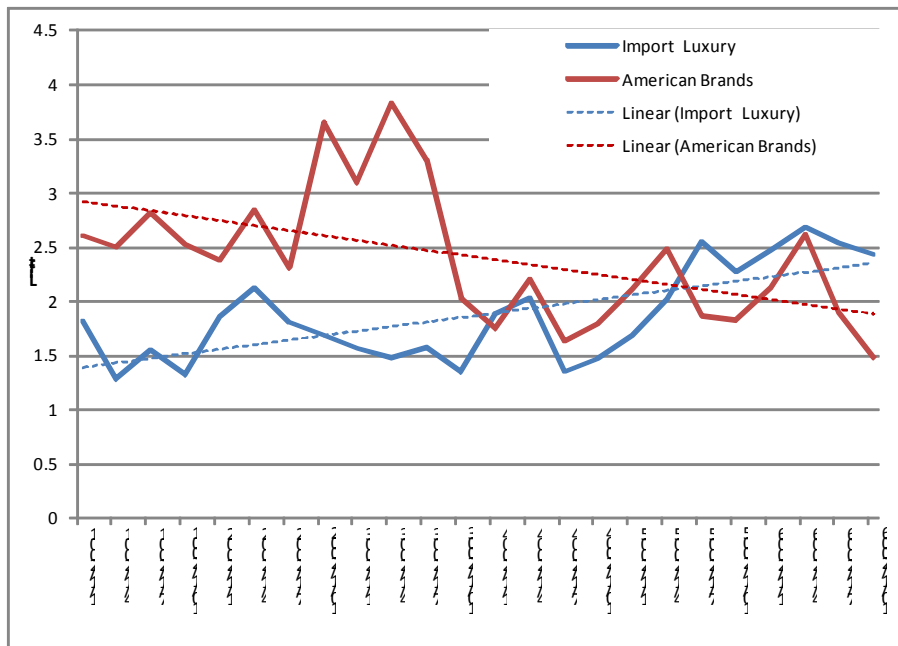


Cadillac Positioning – Time Trend

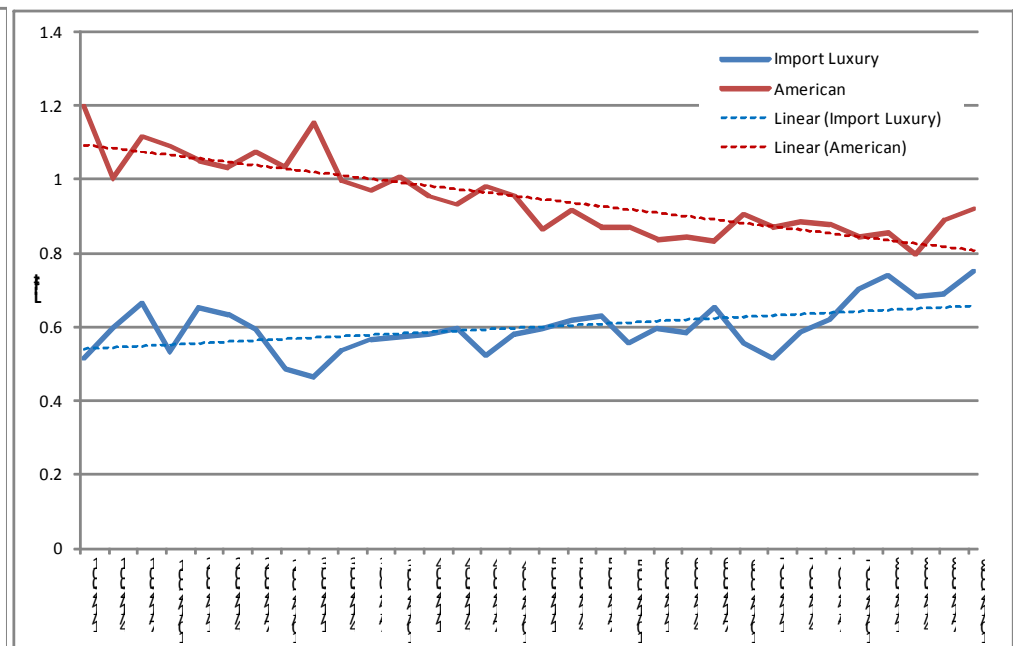


Cadillac Positioning – TM vs. Sales

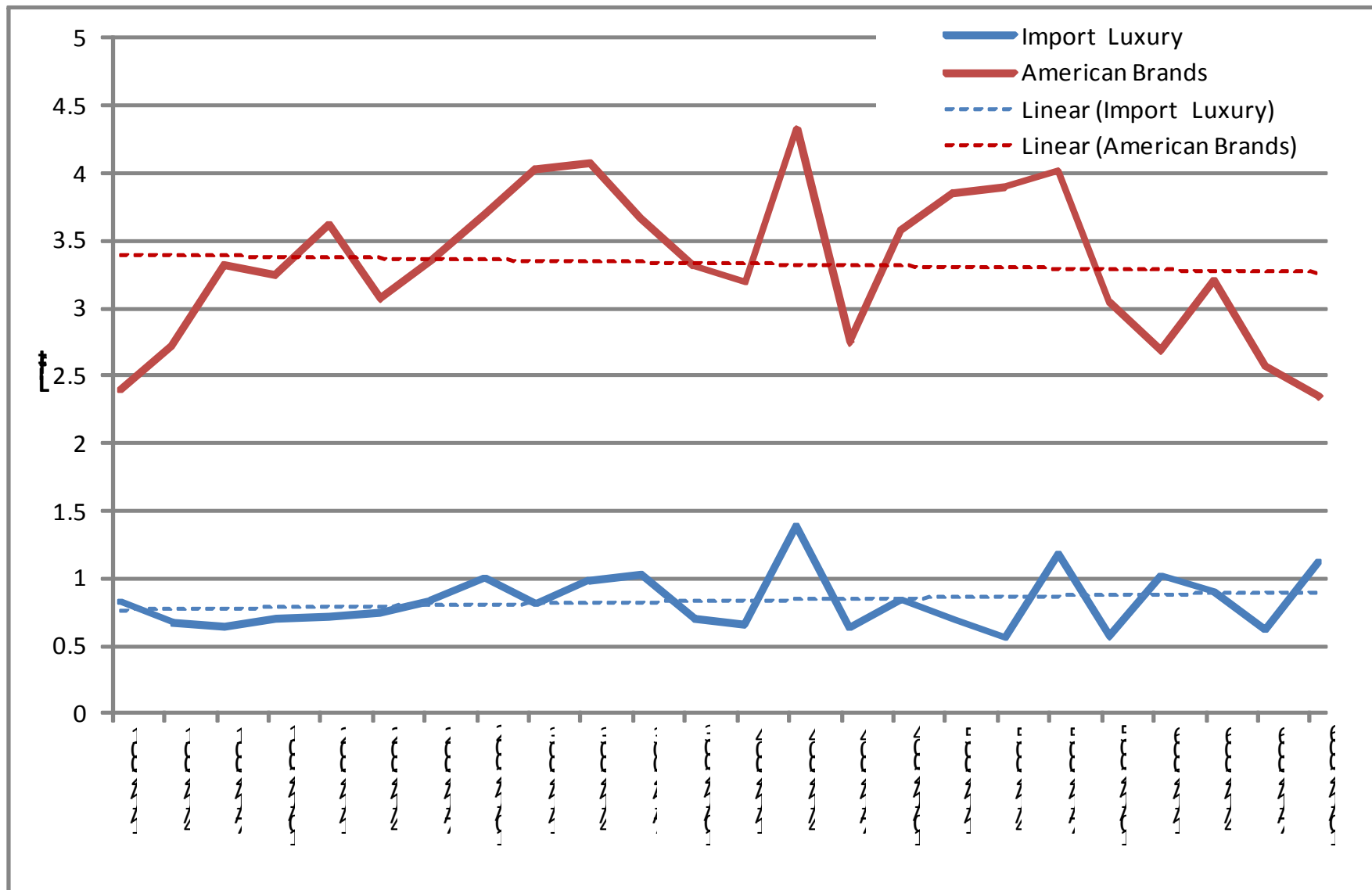
Text-mining-based trend



Sales-based trend

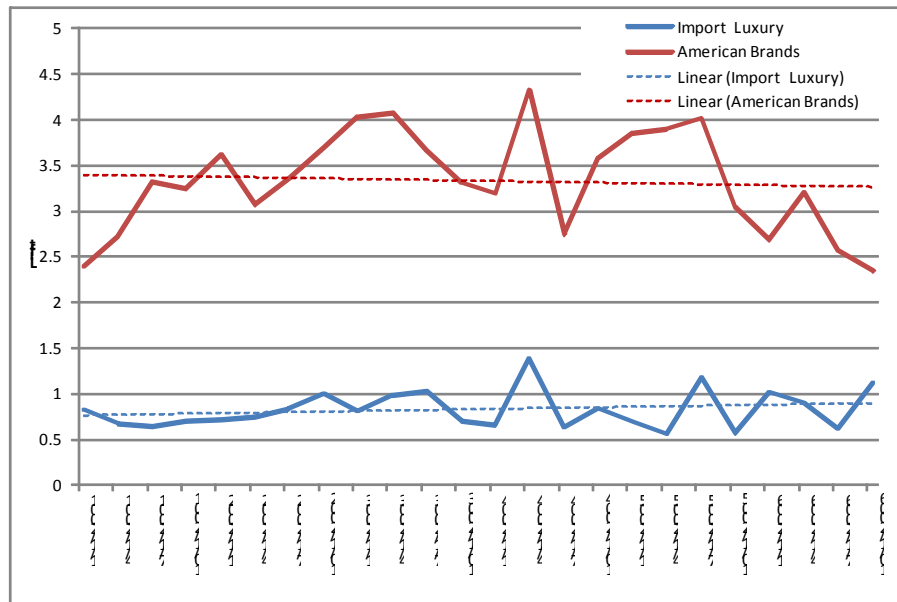


Buick Positioning – Time Trend

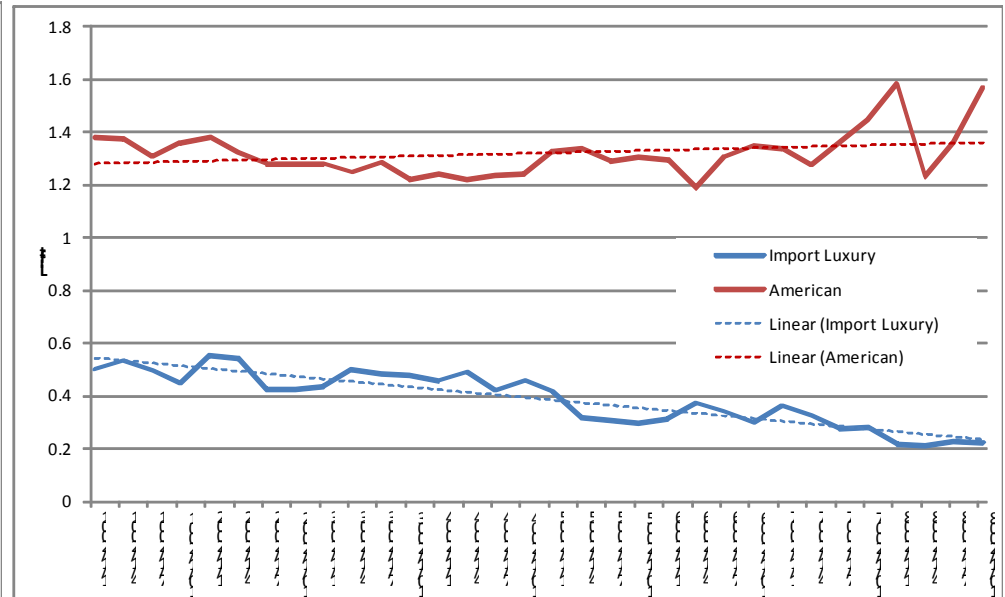


Buick Positioning – Sales vs. TM

Text-mining-based trend



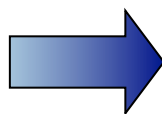
Sales-based trend



Model-Term Data

Message #1449 **Bold and repulsive** by eldaino Jul 20, 2007 (9:33 am)

i agree with what robertsmx has said; a bold design does not guarantee a 'ooh thats hot!'. I will say this; when i got my **civic** (06) i went inside to a mcdonalds to eat and a gentleman asked me if that was a new **civic** and he commented on how sharp and **sporty** it looked. The **civic** sedan may not be as 'exciting' or '**sporty**' as the coupe, but ...

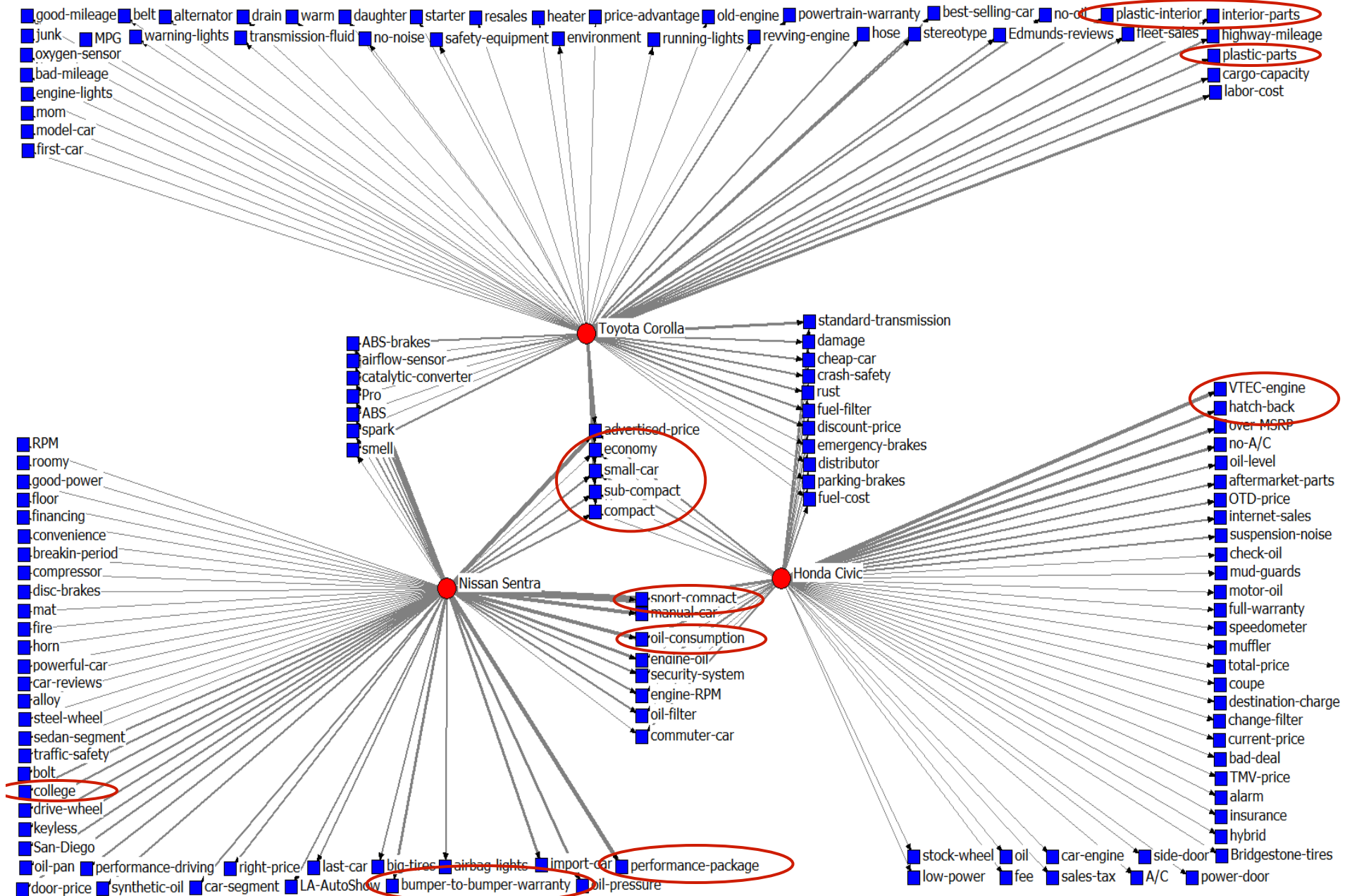


Audi A6	compact	67
Audi A6	sport	345
Audi A6	old	56
Honda Civic	compact	1384
Honda Civic	sport	539
Honda Civic	old	245
Toyota Corolla	compact	451
Toyota Corolla	sport	128
Toyota Corolla	old	211

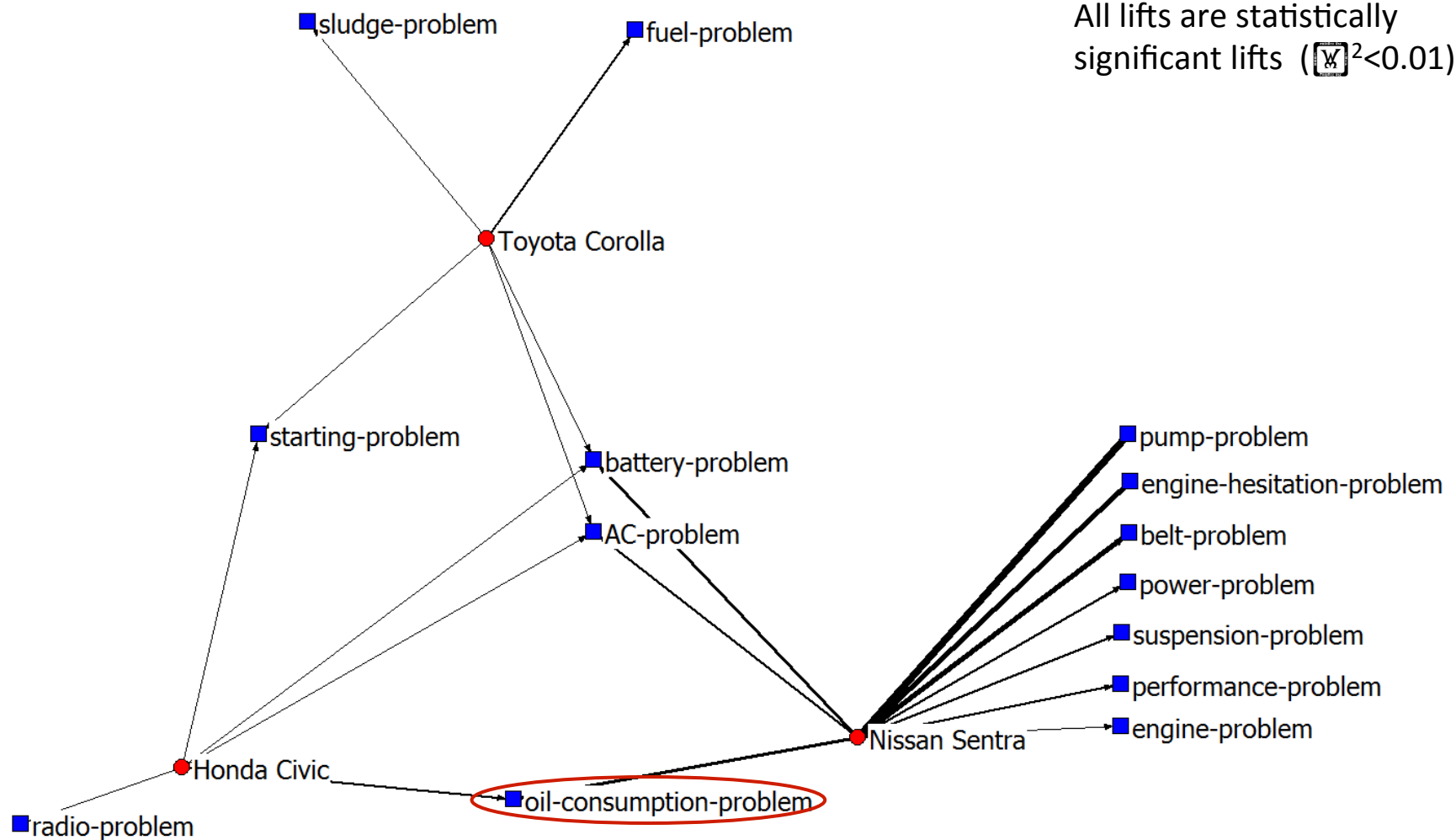


	compact	sport	old
Audi A6	67	345	56
Honda Civic	1384	539	245
Toyota Corolla	451	128	211

Model-Term Analysis – 2 Mode Network



Model-Problem Analysis – 2 Mode Network





UTILIZING TEXT MINING ON ONLINE MEDICAL FORUMS TO PREDICT LABEL CHANGE DUE TO ADVERSE DRUG REACTIONS

Feldman, Netzer, Peretz, Rosenfled 2015

Adverse Drug Reactions

- Adverse drug events comprise the 4th leading cause of death in the US.
- Clinical trials are often limited in terms of the number of participants and scope. Accordingly, these trials sometimes fail to indicate adverse drug reactions (ADRs) associated with a particular drug.
- ADRs that were not found in the clinical trials are often reported (years) later on as FDA label changes

Objective

Present a text mining methodology that will allow rather unlaborious, yet reliable, detection of unreported ADRs that are likely to be identified in the future.

Put our approach to a predictive test: Empirically demonstrate the ability of our proposed methodology to credibly predict ADRs prior to their reporting by the FDA.

Methodology

- ▣ Processing
- ▣ Relation Pattern Acquisition
- ▣ Extraction
- ▣ Post-processing

Methodology

- ▣ Processing
- ▣ Relation Pattern Acquisition
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Relation Pattern Acquisition

- Run Unsupervised Relationship Extraction (URE) in order to learn **Drug-ADR relation** patterns between the following entity types: **Person**, **Drug**, **Symptom** and, when relevant, **Disease**
- Manually remove irrelevant relations

Methodology

- ▣ Processing
- ▣ Relation Pattern Acquisition
- ▣ Extraction
- ▣ Post-processing

Extraction

- The output of this process includes all extracted relevant entities and relations in the form of HPSG semantic structures

Methodology

- ▣ Processing
- ▣ Relation Pattern Acquisition
- ▣ Extraction
- ▣ Post-processing

Post Processing

- Many valuable relations that are mentioned in more indirect, elusive ways are missed.
- Try and catch those undetected relations
- For example, merging the two partial relations Person_take_Drug and Person_suffer_Symptom:
“I took Lipitor and suffered muscle weakness and memory loss”

Case Study 1 - Statins and Cognitive Impairment

- February 2012: FDA approves safety label changes for **statins**. Among others, addition of label information with regard to the potential for **non-serious and reversible cognitive side effects**.
- Memory loss, forgetfulness, amnesia, memory impairment, confusion, etc.

Case Study 1 - Statins and Cognitive Impairment

Co-mentions up to 2011

Top Extracted ADRs	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total
pain	12	4	12	20	11	453	512
muscle pain	9	0	14	37	9	374	443
flushing	2	0	0	2	180	16	200
heart attack	1	0	4	4	13	172	194
muscle damage	1	2	6	24	7	141	181
feeling weak	1	0	7	20	4	147	179
allergic reaction	3	2	2	8	21	101	137
liver failure	4	0	10	0	42	63	119
diabetes	6	2	2	5	17	78	110
cognitive impairment	1	0	4	2	2	95	104
leg pain	5	0	5	7	7	77	101
muscle problems	2	1	2	8	2	57	72
infection	1	0	2	1	9	59	72
leg cramps	3	2	2	4	2	56	69
muscle weakness	0	2	6	3	0	56	67
cancer	2	0	0	4	4	54	64
head pain	5	2	4	4	10	30	55
heart problems	0	0	1	0	2	51	54
stroke	2	0	2	3	1	42	50
burning sensation	1	0	0	0	4	38	43
Total	61	17	85	156	347	2,160	2,826

Case Study 1 - Statins and Cognitive Impairment

Lift up to 2011

Relation-Driven Lift	1	2	3	4	5	6	1	2	3	4	5	6
pain	1.1	1.3	0.8	0.7	0.2	1.2	0.1	0.3	0.0	0.0	0.0	50.3
muscle pain	0.9	0.0	1.1	1.5	0.2	1.1	0.0	0.0	0.0	8.1	0.0	18.6
flushing	0.5	0.0	0.0	0.2	7.3	0.1	0.0	0.0	0.0	0.0	1207.0	0.0
heart attack	0.2	0.0	0.7	0.4	0.5	1.2	0.0	0.0	0.0	0.0	0.0	17.3
muscle damage	0.3	1.8	1.1	2.4	0.3	1.0	0.0	0.8	0.1	22.2	0.0	0.2
feeling weak	0.3	0.0	1.3	2.0	0.2	1.1	0.0	0.0	0.5	11.7	0.0	3.4
allergic reaction	1.0	2.4	0.5	1.1	1.2	1.0	0.0	1.8	0.0	0.0	1.2	0.0
liver failure	1.6	0.0	2.8	0.0	2.9	0.7	0.9	0.0	12.4	0.0	61.1	0.0
diabetes	2.5	3.0	0.6	0.8	1.3	0.9	5.9	2.8	0.0	0.0	1.1	0.0
cognitive impairment	0.4	0.0	1.3	0.3	0.2	1.2	0.0	0.0	0.3	0.0	0.0	13.3
leg pain	2.3	0.0	1.6	1.3	0.6	1.0	3.9	0.0	1.4	0.4	0.0	0.0
muscle problems	1.3	2.3	0.9	2.0	0.2	1.0	0.1	0.8	0.0	4.4	0.0	0.3
infection	0.6	0.0	0.9	0.3	1.0	1.1	0.0	0.0	0.0	0.0	0.0	1.2
leg cramps	2.0	4.8	1.0	1.1	0.2	1.1	1.6	6.2	0.0	0.0	0.0	0.9
muscle weakness	0.0	5.0	3.0	0.8	0.0	1.1	0.0	6.5	8.3	0.0	0.0	1.9

Critical Values		
lift	chi-square value	p-value
1.00	3.84	0.05
	6.64	0.01

Case Study 1 - Statins and Cognitive Impairment

- How early could have detected?

Year	Relation-driven lift	Chi-square value	Classic-induced lift	Chi-square value
2011	1.20	13.33	1.99	49.28
2010	1.21	13.24	1.94	42.21
2009	1.22	13.35	1.97	40.03
2008	1.21	10.70	1.89	31.42
2007	1.20	9.95	2.00	36.46
2006	1.21	10.30	1.89	28.20
2005	1.20	6.63	2.04	25.12
2004	1.25	3.46	2.18	12.93
2003	1.27	1.55	2.16	5.79

- All values in bold are chi-square values ≥ 3.85 or ≥ 6.64 , corresponding p-value ≤ 0.05 or ≤ 0.01 .

Case Study 2 - Wellbutrin and Agitation

- July 2009: FDA alert informing that manufacturers of **Wellbutrin** were required to add new boxed warnings highlighting the risk of **serious neuropsychiatric symptoms** in patients using the drug.
- Among those symptoms were **agitation** and **hostility**.

Case Study 2 - Wellbutrin and Agitation

Co-mentions 1999-2008

Top Extracted ADRs	celexa	effexor	pristiq	wellbutrin	xanax	zoloft	Total
anxiety	217	359	3	343	423	492	1,837
weight gain	71	144	1	130	11	169	526
head pain	56	127	1	100	21	102	407
panic state	44	70	0	19	133	96	362
sleep disorder	43	78	1	86	49	104	361
allergic reaction	46	69	0	67	23	98	303
feeling weak	40	74	3	48	15	60	240
pain	21	74	0	38	30	60	223
tremors	29	59	0	30	43	57	218
agitation	24	46	0	77	11	54	212
nausea	22	89	2	33	7	51	204
sweating	22	103	1	21	5	42	194
seizure	5	16	0	113	40	16	190
dizziness	18	66	1	25	9	50	169
suicidality	15	67	0	18	9	36	145
sexual dysfunction	21	37	0	46	2	28	134
cognitive impairment	10	41	1	17	23	21	113
weight loss	5	23	0	61	2	18	109
mood swings	18	36	0	21	3	27	105
sleepiness	26	32	0	17	5	17	97
Total	753	1,610	14	1,310	864	1,598	6,149

Case Study 2 - Wellbutrin and Agitation

Lift up to 2011

Relation-Driven Lift	C	E	P	W	X	Z	C	E	P	W	X	Z
anxiety	1.0	0.7	0.7	0.9	1.6	1.0	0.0	0.0	0.0	0.0	174.7	0.9
weight gain	1.1	1.0	0.8	1.2	0.1	1.2	0.8	0.4	0.0	4.0	0.0	11.3
head pain	1.1	1.2	1.1	1.2	0.4	1.0	0.9	5.7	0.0	2.8	0.0	0.0
panic state	1.0	0.7	0.0	0.2	2.6	1.0	0.0	0.0	0.0	0.0	164.0	0.1
sleep disorder	1.0	0.8	1.2	1.1	1.0	1.1	0.0	0.0	0.0	1.5	0.0	1.6
allergic reaction	1.2	0.9	0.0	1.0	0.5	1.2	2.6	0.0	0.0	0.1	0.0	6.7
feeling weak	1.4	1.2	5.5	0.9	0.4	1.0	4.5	2.8	11.5	0.0	0.0	0.0
pain	0.8	1.3	0.0	0.8	1.0	1.0	0.0	5.9	0.0	0.0	0.0	0.1
tremors	1.1	1.0	0.0	0.6	1.4	1.0	0.2	0.1	0.0	0.0	6.0	0.0
agitation	0.9	0.8	0.0	1.7	0.4	1.0	0.0	0.0	0.0	29.5	0.0	0.0
nausea	0.9	1.7	4.3	0.8	0.2	1.0	0.0	33.2	5.3	0.0	0.0	0.0
sweating	0.9	2.0	2.3	0.5	0.2	0.8	0.0	75.1	0.7	0.0	0.0	0.0
seizure	0.2	0.3	0.0	2.8	1.5	0.3	0.0	0.0	0.0	170.4	8.0	0.0
dizziness	0.9	1.5	2.6	0.7	0.4	1.1	0.0	14.9	1.0	0.0	0.0	1.2
suicidality	0.8	1.8	0.0	0.6	0.4	1.0	0.0	30.8	0.0	0.0	0.0	0.0

Critical Values		
lift	chi-square value	p-value
1.00	3.84	0.05
	6.64	0.01

Case Study 2 - Wellbutrin and Agitation

- How early could have detected?

Year	Relation-driven lift	Chi-square value	Classic-induced lift	Chi-square value
2008	1.70	29.53	1.81	28.79
2007	1.75	28.70	1.83	26.97
2006	1.72	21.13	1.61	12.91
2005	1.69	16.54	1.78	15.90
2004	1.46	5.13	1.51	5.13
2003	1.64	8.03	2.05	13.99
2002	1.78	6.41	2.36	12.25

- All values in bold are chi-square values ≥ 3.85 or ≥ 6.64 , corresponding p-value ≤ 0.05 or ≤ 0.01 .

Summary

- ▣ We are facing a river flow of information
- ▣ We need to develop fishing rods to fish the river for insights
- ▣ Text mining tools are constantly advancing
- ▣ Complex textual relationships require more advanced text mining skills/tools
- ▣ Social media and other sources of textual data:
 - ▣ are VERY large and messy
 - ▣ keep coming in real time
 - ▣ can be extremely useful if we learn how to listen...

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?



Contact information: Oded Netzer
Columbia Business School
onetzer@gsb.columbia.edu

