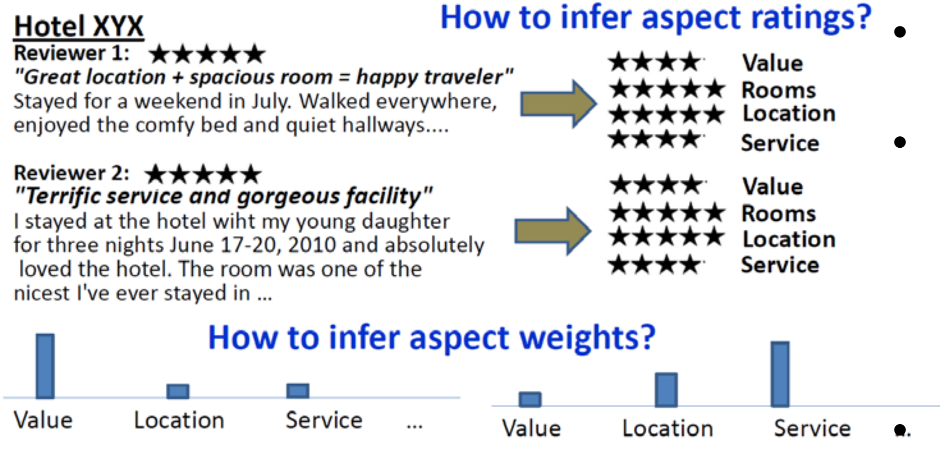
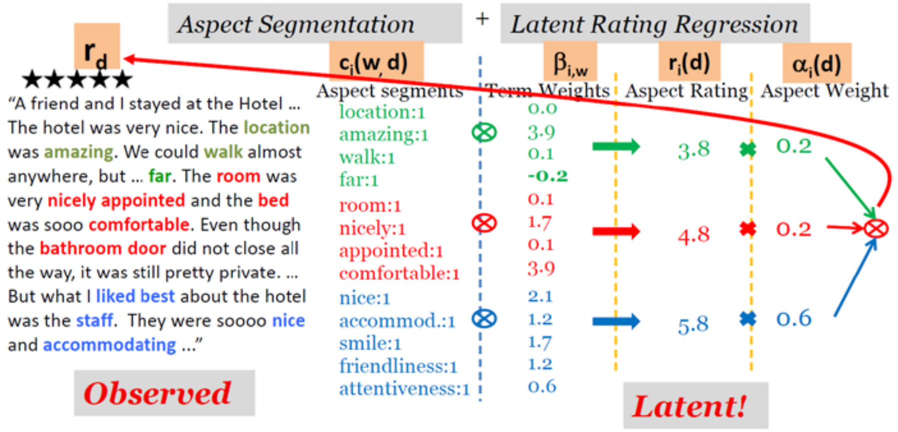
Opinion Mining and Sentiment Analysis: Latent Aspect Rating Analysis (Part 1)

Motivation



Solving LARA in Two Stages



Latent Aspect Rating Analysis [Wang et al. 10]

- Given a set of review articles about a topic with overall ratings
- Output
  - **Major aspects** commented on in the reviews
  - **Ratings** on each aspect
  - **Relative weights** placed on different aspects **by reviewers**
- Many applications
  - Opinion-based **entity ranking**
  - Aspect-level **opinion summarization**
  - Reviewer **preference analysis**
  - **Personalized recommendation** of products
  - …

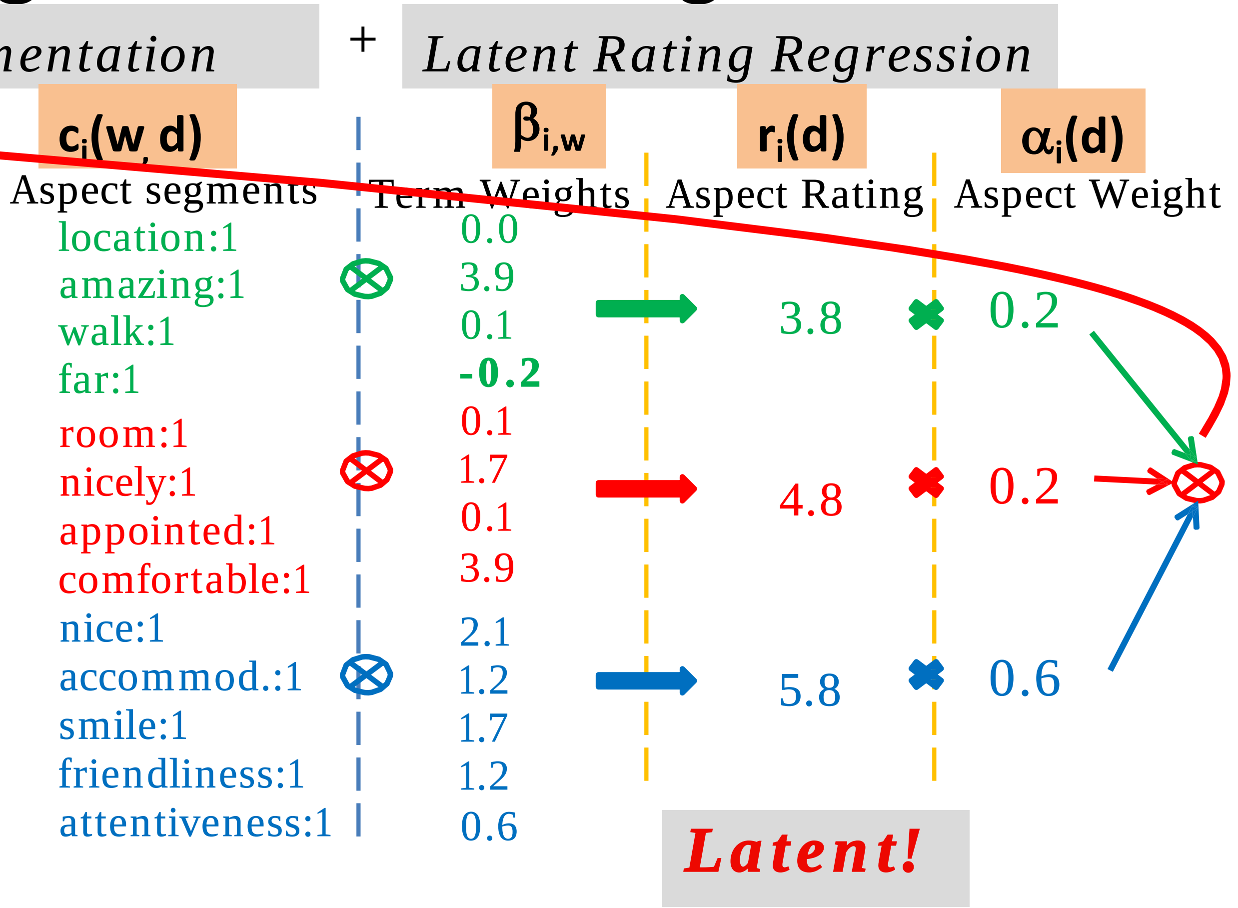
Solving LARA in Two Stages

r_d

★★★★★

"A friend and I stayed at the Hotel … The hotel was very nice. The **location** was **amazing**. We could **walk** almost anywhere, but … **far**. The **room** was very **nicely appointed** and the **bed** was sooo **comfortable**. Even though the **bathroom door** did not close all the way, it was still pretty private. … But what I **liked best** about the hotel was the **staff**. They were soooo **nice** and **accommodating** …"

Observed



Latent Rating Regression [Wang et al. 10]

- Data: a **set of review docs w/overall ratings**: $C=\{(d, r_d)\}$
  - **d** is pre-segmented into **k aspect segments**
  - **$c_i(w,d)$ =** count of word w **in aspect segment i** (zero if w didn't occur)

- Model: predict rating based on d: $p(r_d \mid d)$

Overall Rating = Weighted Average of Aspect Ratings

Multivariate Gaussian Prior

$$r_d \sim N\left(\sum_{i=1}^{k} \alpha_i(d) r_i(d), \delta^2\right), \qquad \vec{\alpha}(d) \sim N(\vec{\mu}, \Sigma)$$

$$r_i(d) = \sum_{w \in V} c_i(w,d)\beta_{i,w} \qquad \beta_{i,w} \in \Re$$

Aspect-Specific Sentiment of w

Aspect Rating = Sum of sentiment weights of words in the aspect

Latent Rating Regression (cont.)

- Maximum Likelihood Estimate
  - Parameters: $\Lambda = (\{\beta_{i,w}\}, \vec{\mu}, \Sigma, \delta^2)$
  - ML estimate: $\Lambda^* = \arg\max_\Lambda \prod_{d \in C} p(r_d \mid d, \Lambda)$
- Aspect Rating for aspect i

$$r_i(d) = \sum_{w \in V} c_i(w,d)\beta_{i,w}$$

c_i(w,d)=0 for words not occurring in aspect segment i

- Aspect Weights: $\alpha_i(d)$ =weight on aspect i

$$\vec{\alpha}(d)^* = \arg\max_{\vec{\alpha}(d)} p(\vec{\alpha}(d) \mid \mu, \Sigma) p(r_d \mid d, \{\beta_{i,w}\}, \delta^2, \vec{\alpha}(d))$$

Maximum a Posteriori **Prior** **Likelihood**

Opinion Mining and Sentiment Analysis: Latent Aspect Rating Analysis (Part 2)

A Unified Generative Model for LARA [Wang et al. 11]

Any Entity

Sample Result 1: Rating Decomposition [Wang et al. 10]

- Hotels with the same overall rating but different aspect ratings

(All 5 Stars hotels, ground-truth in parenthesis)

Hotel	*Value*	*Room*	*Location*	*Cleanliness*
HOTEL 1	4.2(4.7)	3.8(3.1)	4.0(4.2)	4.1(4.2)
HOTEL 2	4.3(4.0)	3.9(3.3)	3.7(3.1)	4.2(4.7)
HOTEL 3	3.7(3.8)	4.4(3.8)	4.1(4.9)	4.5(4.8)

- Reveal detailed opinions at the aspect level

Sample Result 2: Comparison of Reviewers [Wang et al. 10]

- Per-Reviewer Analysis
  – Different reviewers' ratings on the same hotel

Reviewer	*Value*	*Room*	*Location*	*Cleanliness*
Reviewer 1	3.7(4.0)	3.5(4.0)	3.7(4.0)	5.8(5.0)
Reviewer 2	5.0(5.0)	3.0(3.0)	5.0(4.0)	3.5(4.0)

  – Reveal differences in opinions of different reviewers

Sample Result 3: Aspect-Specific Sentiment Lexicon [Wang et al. 10]

Value	*Rooms*	*Location*	*Cleanliness*
resort 22.80	view 28.05	restaurant 24.47	clean 55.35
value 19.64	comfortable 23.15	walk 18.89	smell 14.38
excellent 19.54	modern 15.82	bus 14.32	linen 14.25
worth 19.20	quiet 15.37	beach 14.11	maintain 13.51
bad -24.09	*carpet -9.88*	*wall -11.70*	*smelly -0.53*
money -11.02	*smell -8.83*	*bad -5.40*	*urine -0.43*
terrible -10.01	*dirty -7.85*	*road -2.90*	*filthy -0.42*
overprice -9.06	*stain -5.85*	*website -1.67*	*dingy -0.38*

Learn sentimental information directly from the data.

Sample Result 4: Validating Preference Weights [Wang et al. 10]

Top-10: Reviewers with the highest Val/X ratio (emphasize "value")

Bot-10: Reviewers with the lowest Val/X ratio (emphasize a non-value aspect)

City	Avg. Price	Group	Val/Loc	Val/Rm	Val/Ser
Amsterdam	241.6	top-10	190.7	214.9	221.1
		bot-10	**270.8**	**333.9**	**236.2**
San Francisco	261.3	top-10	214.5	249.0	225.3
		bot-10	**321.1**	**311.1**	**311.4**
Florence	272.1	top-10	269.4	248.9	220.3
		bot-10	**298.9**	**293.4**	**292.6**

Higher!

Application 1: Rated Aspect Summarization

Aspect	Summary	Rating
Value	Truly unique character and a great location at a reasonable price Hotel Max was an excellent choice for our recent three night stay in Seattle.	**3.1**
	Overall not a negative experience; however, considering that the hotel industry is very much in the impressing business, there was a lot of room for improvement.	**1.7**
Location	The location, a short walk to downtown and Pike Place market, made the hotel a good choice.	**3.7**
	When you visit a big metropolitan city, be prepared to hear a little traffic outside!	**1.2**
Business Service	You can pay for wireless by the day or use the complimentary Internet in the business center behind the lobby, though.	**2.7**
	My only complaint is the daily charge for Internet access when you can pretty much connect to wireless on the streets anymore.	**0.9**

Application 2: Discover Consumer Preferences [Wang et al. 2011]

- Amazon reviews: No guidance

Table 2: Topical Aspects Learned on MP3 Reviews

Low Overall Ratings			High Overall Ratings		
unit	jack	service	files	player	vision
usb	headphone	charge	format	music	video
battery	warranty	problem	included	download	player
charger	replacement	support	easy	headphones	quality
reset	problem	hours	convert	button	great
time	player	months	mp3	set	product
hours	back	weeks	videos	hours	sound
work	months	back	file	buds	radio
thing	buy	customer	wall	volume	accessory
wall	amazon	time	hours	ear	fm

battery life accessory service file format volume video

Application 3: User Rating Behavior Analysis [Wang et al. 10]

	Expensive Hotel		*Cheap Hotel*	
	5 Stars	*3 Stars*	*5 Stars*	*1 Star*
Value	0.134	0.148	**0.171**	0.093
Room	0.098	0.162	0.126	0.121
Location	0.171	0.074	0.161	0.082
Cleanliness	0.081	**0.163**	0.116	**0.294**
Service	**0.251**	0.101	0.101	0.049

People like expensive hotels because of good service.

People like cheap hotels because of good value.

Application 4: Personalized Ranking of Entities [Wang et al. 10]

Query: 0.9 value
0.1 others

Non-personalized → Approach 1

Personalized (Query-specific) → Approach 2

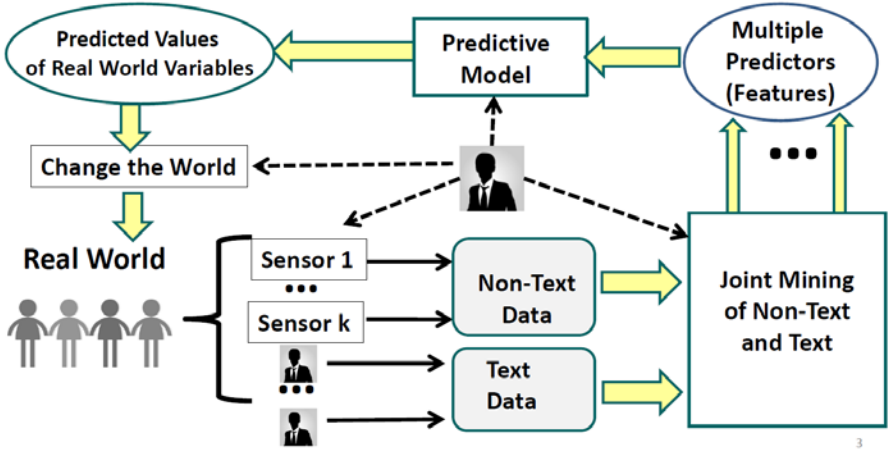
	Hotel	Overall Rating	Price	Location
Approach 1	Majestic Colonial	5.0	339	Punta Cana
	Agua Resort	5.0	753	Punta Cana
	Majestic Elegance	5.0	537	Punta Cana
	Grand Palladium	5.0	277	Punta Cana
	Iberostar	5.0	157	Punta Cana
Approach 2	Elan Hotel Modern	5.0	216	Los Angeles
	Marriott San Juan Resort	4.0	354	San Juan
	Punta Cana Club	5.0	409	Punta Cana
	Comfort Inn	5.0	155	Boston
	Hotel Commonwealth	4.5	313	Boston

Summary of Opinion Mining

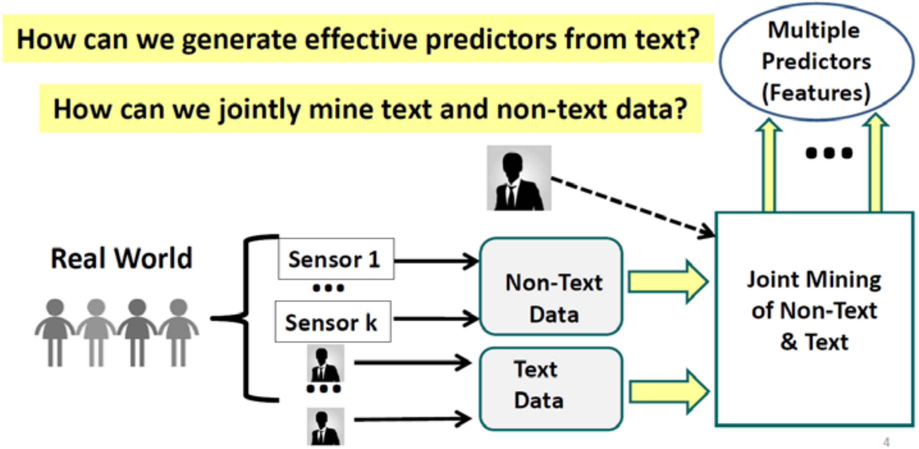
- Very important with **a lot of applications**!
- Sentiment analysis can be done using **text categorization techniques**
  - With enriched feature representation
  - With consideration of ordering of the categories
- **Generative models** are powerful for mining **latent user preferences**
- **Most** approaches were proposed for **product reviews**
- Opinion mining from **news and social media** remains **challenging**

Text-Based Prediction

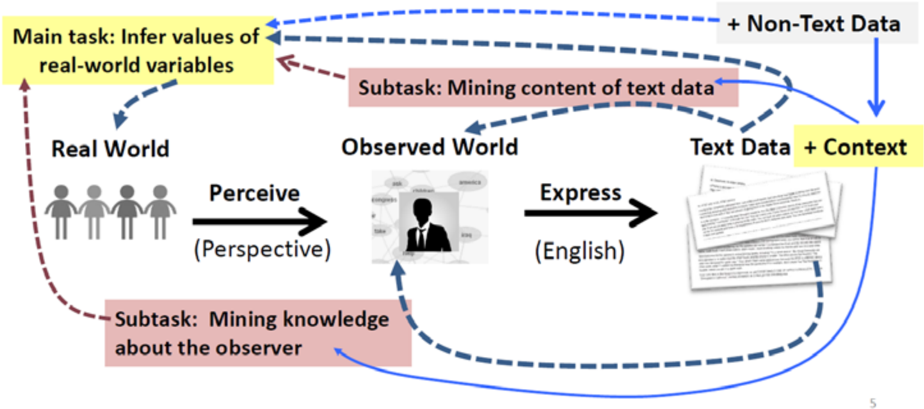
The Big Picture of Prediction: Data Mining Loop



Text-Based Prediction



Text-Based Prediction = a Unified View of Text Mining and Analysis



Joint Mining and Analysis of Text and Non-Text Data

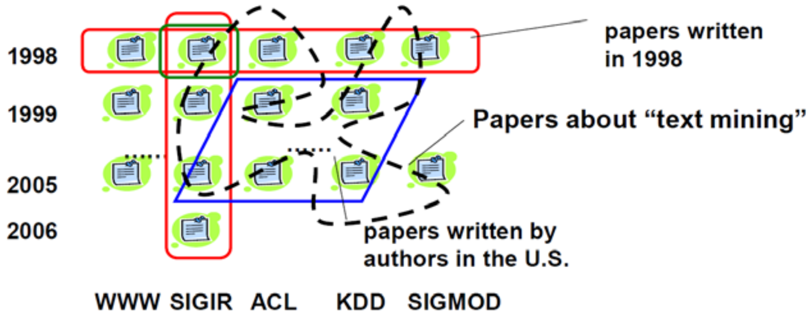
- Non-text data help text mining
  - **Non-text data** provide **context** for mining text data
  - **Contextual Text Mining**: Mining text in the context defined by non-text data (see [Mei 2009] for a large body of work)
- Text data help non-text data mining
  - **Text data** help **interpret patterns** discovered from non-text data
  - **Pattern Annotation**: Using text data to interpret patterns found in non-text data (see [Mei et al. 2006] for detail)

Contextual Text Mining: Motivation

Contextual Text Mining: Motivation

- **Text** often has **rich context** information
  - **Direct context** (**Meta-Data**): time, location, authors, source, …
  - **Indirect context** (additional data **related to meta-data**): social network of the author, author's age, other text from the same source, etc.
  - **Any related data** can be regarded as context
- **Context** can be **used to**
  - **Partition text** data for **comparative** analysis
  - Provide **meaning** to the **discovered topics**

Context = Partitioning of Text



Enables discovery of knowledge associated with different context as needed

Many Interesting Questions Require Contextual Text Mining

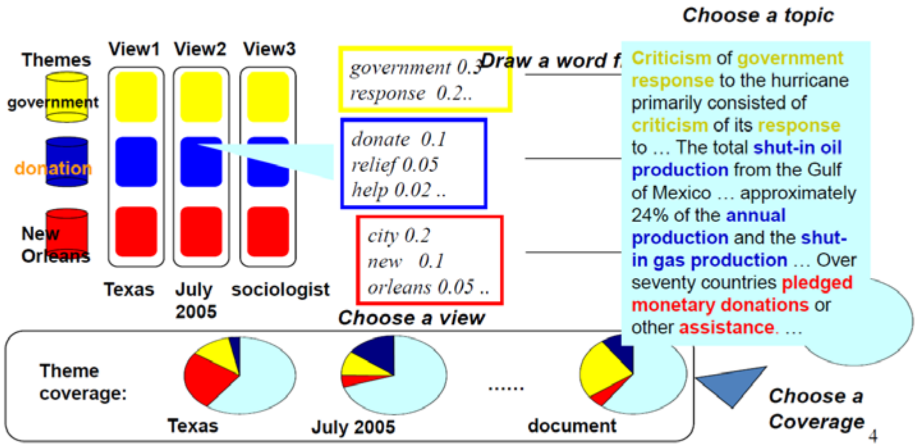
- What **topics** have been gaining **increasing attention** recently in data mining research? (time as context)
- Is there any difference in the **responses** of people **in different regions to the event**? (location as context)
- What are the **common research interests** of two researchers? (authors as context)
- Is there any **difference in the research** topics published by authors **in the USA and those outside**? (author's affiliation and location as context)
- Is there any **difference** in the **opinions** about a topic expressed **on one social network and another**? (social network of authors and topic as context)
- Are there topics in **news** data that are **correlated** with sudden **changes in stock prices**? (time series as context)
- What **issues "mattered"** in the **2012 presidential election**? (time series as context)

Contextual Text Mining:
Contextual Probabilistic Latent Semantic Analysis

Contextual Probabilistic Latent Semantic Analysis (CPLSA) [Mei & Zhai 06]

- General idea:
  - Explicitly **add interesting context variables** into a **generative model** (➔ enable discovery contextualized topics)
  - **Context influences** both coverage and content variation of **topics**
- As an **extension of PLSA**
  - Model the conditional likelihood of text given context
  - Assume context-dependent views of a topic
  - Assume context-dependent topic coverage
  - EM algorithm can still be used for parameter estimation
  - Estimated parameters naturally contain context variables, enabling contextual text mining

Generation Process of CPLSA



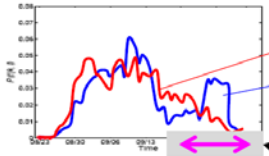
Comparing News Articles [Zhai et al. 04]
Iraq War (30 articles) vs. Afghan War (26 articles)

The common theme indicates that "United Nations" is involved in both wars

	Cluster 1	Cluster 2	Cluster 3
Common Theme	united 0.042 nations 0.04 …	killed 0.035 month 0.032 deaths 0.023 …	…
Iraq Theme	n 0.03 Weapons 0.024 Inspections 0.023 …	troops 0.016 hoon 0.015 sanches 0.012 …	…
Afghan Theme	Northern 0.04 alliance 0.04 kabul 0.03 taleban 0.025 aid 0.02 …	taleban 0.026 rumsfeld 0.02 hotel 0.012 front 0.011 …	…

Collection-specific themes indicate different roles of "United Nations" in the two wars

Theme Life Cycles in Blog Articles About "Hurricane Katrina" [Mei et al. 06]



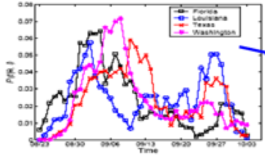
(a) Theme life cycles in Texas (Hurricane Katrina)

Oil Price

price 0.0772
oil 0.0643
gas 0.0454
increase 0.0210
product 0.0203
fuel 0.0188
company 0.0182
…

New Orleans

Hurricane Rita



(b) Theme "New Orleans" over states (Hurricane Katrina)

city 0.0634
orleans 0.0541
new 0.0342
louisiana 0.0235
flood 0.0227
evacuate 0.0211
storm 0.0177
…

6

Spatial Distribution of the Topic "Government Response" in Blog Articles About Hurricane Katrina [Mei et al. 06]

(a) Week1: 08/23-08/29

(b) Week Two: 08/30-09/05

(c) Week Three:09/06-09/12

Theme 1
Government Response
bush 0.0716374
president 0.0610942
federal 0.0514114
govern 0.0476977
fema 0.0474692
administrate 0.0233903
response 0.0208351
brown 0.0199573
blame 0.0170033
governor 0.0142153

(d) Week Four: 09/13-09/19

(e) Week Five: 09/20-09/26

7

Event Impact Analysis: IR Research [Mei & Zhai 06]

Topic: retrieval models

SIGIR papers

term 0.1599
relevance 0.0752
weight 0.0660
feedback 0.0372
independence 0.0311
model 0.0310
frequent 0.0233
probabilistic 0.0188
document 0.0173
…

vector 0.0514
concept 0.0298
extend 0.0297
model 0.0291
space 0.0236
boolean 0.0151
function 0.0123
feedback 0.0077
…

xml 0.0678
email 0.0197
model 0.0191
collect 0.0187
judgment 0.0102
rank 0.0097
subtopic 0.0079
…

A seminal paper [Croft & Ponte 98]

1992

year

Star

1998

probabilist 0.0778
model 0.0432
logic 0.0404
ir 0.0338
boolean 0.0281
algebra 0.0200
estimate 0.0119
weight 0.0111
…

model 0.1687
language 0.0753
estimate 0.0520
parameter 0.0281
distribution 0.0268
probable 0.0205
smooth 0.0198
markov 0.0137
likelihood 0.0059
…

Contextual Text Mining:
Mining Topics with Social Network Context

Topic Analysis with Network Context

- The **context** of a text article can form a **network**, e.g.,
  - Authors of research articles may form **collaboration networks**
  - Authors of social media content form **social networks**
  - Locations associated with text can be connected to form a **geographic network**
- **Benefit** of **joint analysis** of text and its network context
  - Network imposes **constraints** on topics in text (**authors** connected **in a network** tend to write about **similar topics**)
  - Text **characterizes** the content associated with **each subnetwork** (e.g., <u>difference in opinions</u> in <u>two subnetworks</u>?)

Network Supervised Topic Modeling: General Idea [Mei et al. 08]

- **Probabilistic topic modeling** as optimization: **maximize likelihood**

$$\Lambda^* = \arg\max_{\Lambda} p(\text{TextData} \mid \Lambda)$$

- <u>Main idea</u>: network imposes **constraints on model** parameters Λ
  - The text at **two adjacent nodes** of the network tends to cover **similar topics**
  - **Topic distributions** are **smoothed** over <u>adjacent nodes</u>
  - Add **network-induced regularizers** to the <u>likelihood objective function</u>

Any generative model

Any network

$$\Lambda^* = \arg\max_{\Lambda} f(p(\text{TextData} \mid \Lambda), r(\Lambda, \text{Network}))$$

Any way to combine

Any regularizer

Instantiation: NetPLSA [Mei et al. 08]

Network-induced prior: Neighbors have similar topic distribution

Modified objective function

Text collection

PLSA log-likelihood

$$O(C,G) = (1-\lambda)\cdot\left(\boxed{\sum_{d}\sum_{w} c(w,d)\log\sum_{j=1}^{k} p(\theta_j \mid d)\,p(w \mid \theta_j)}\right)$$

$$+\boxed{\lambda}\cdot\left(-\frac{1}{2}\sum_{\langle u,v\rangle\in E} \underline{w(u,v)}\,\underline{\sum_{j=1}^{k}\left(p(\theta_j \mid u)-p(\theta_j \mid v)\right)^2}\right)$$

Network graph

Influence of network constraint

Weight of edge (u,v)

Quantify the difference in the topic coverage at node u and v

Mining 4 Topical Communities: Results of PLSA

Can't uncover the 4 communities (IR, DM, ML, Web)

Topic 1		Topic 2		Topic 3		Topic 4	
term	0.02	peer	0.02	visual	0.02	interface	0.02
question	0.02	patterns	0.01	analog	0.02	towards	0.02
protein	0.01	mining	0.01	neurons	0.02	browsing	0.02
training	0.01	clusters	0.01	vlsi	0.01	xml	0.01
weighting	0.01	stream	0.01	motion	0.01	generation	0.01
multiple	0.01	frequent	0.01	chip	0.01	design	0.01
recognition	0.01	e	0.01	natural	0.01	engine	0.01
relations	0.01	page	0.01	cortex	0.01	service	0.01
library	0.01	gene	0.01	spike	0.01	social	0.01

Mining 4 Topical Communities: Results of NetPLSA

Uncovers the 4 communities well

Information Retrieval		Data Mining		Machine Learning		Web	
retrieval	0.13	mining	0.11	neural	0.06	web	0.05
information	0.05	data	0.06	learning	0.02	services	0.03
document	0.03	discovery	0.03	networks	0.02	semantic	0.03
query	0.03	databases	0.02	recognition	0.02	services	0.03
text	0.03	rules	0.02	analog	0.01	peer	0.02
search	0.03	association	0.02	vlsi	0.01	ontologies	0.02
evaluation	0.02	patterns	0.02	neurons	0.01	rdf	0.02
user	0.02	frequent	0.01	gaussian	0.01	management	0.01
relevance	0.02	streams	0.01	network	0.01	ontology	0.01

Text Information Network

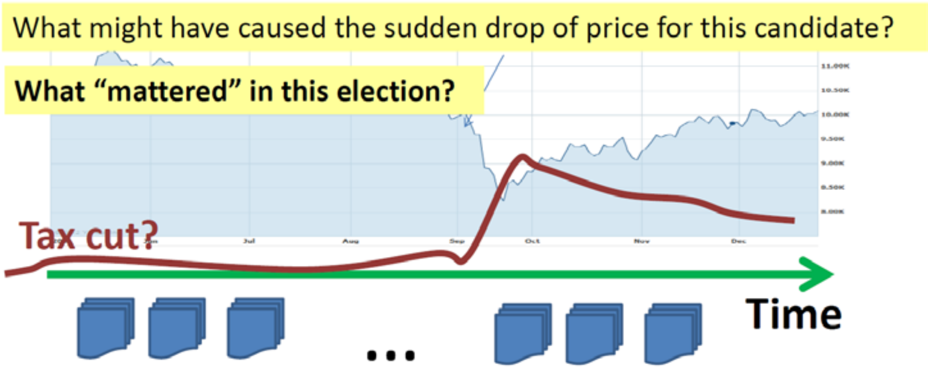
- In general, we can view text data that naturally "lives" in a rich information network with all other related data
- **Text data** can be **associated with**
  - Nodes of the network
  - Edges of the network
  - Paths of the network
  - Subnetworks
  - …
- Text analysis - **using the entire network**!

Contextual Text Mining:
Mining Causal Topics with Time Series Supervision

Text Mining for Understanding Time Series

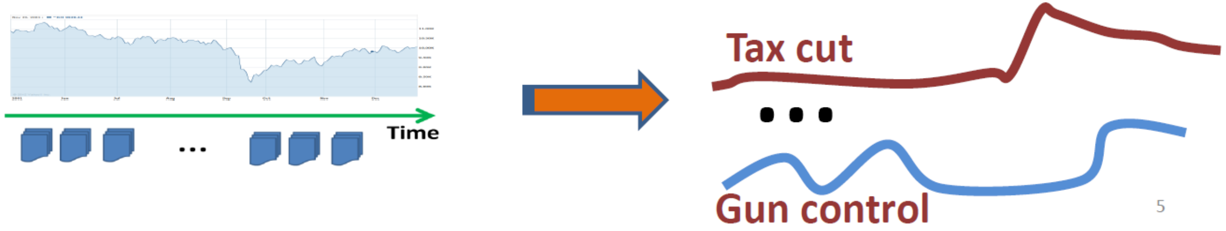
Dow Jones Industrial Average [Source: Yahoo Finance]

Analysis of Presidential Prediction Markets

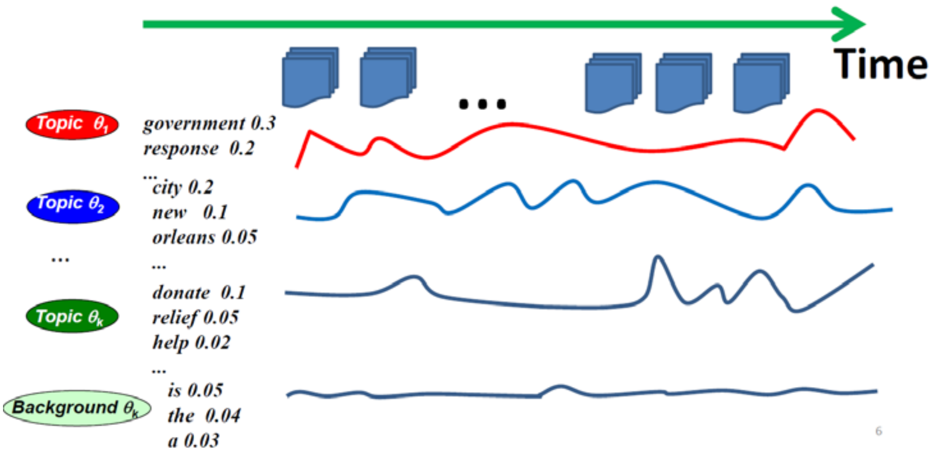


Joint Analysis of Text and Time Series to Discover "Causal Topics"

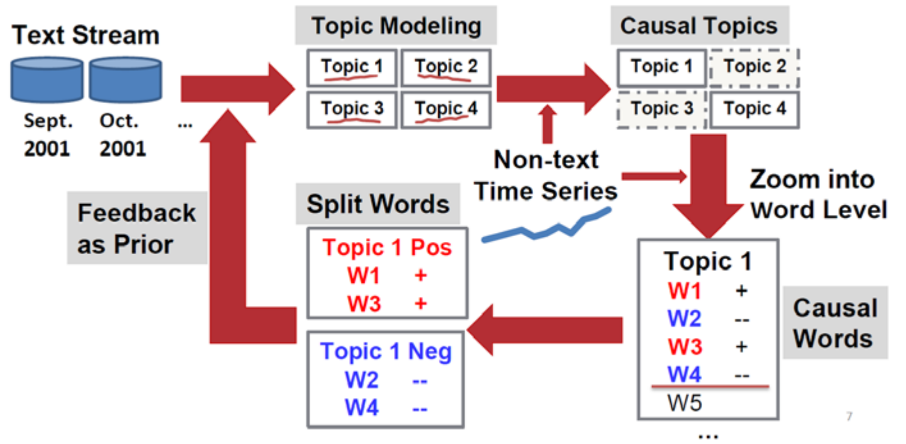
- **Input**:
  - <u>Time series</u>
  - <u>Text data</u> produced in a similar time period (text stream)
- **Output**
  - **Topics** whose coverage in the text stream has **strong correlations** with the **time series** (<u>"causal" topics</u>)



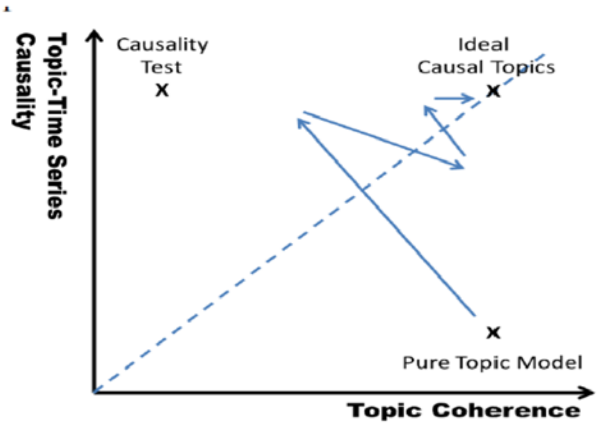
When a Topic Model Applied to Text Stream



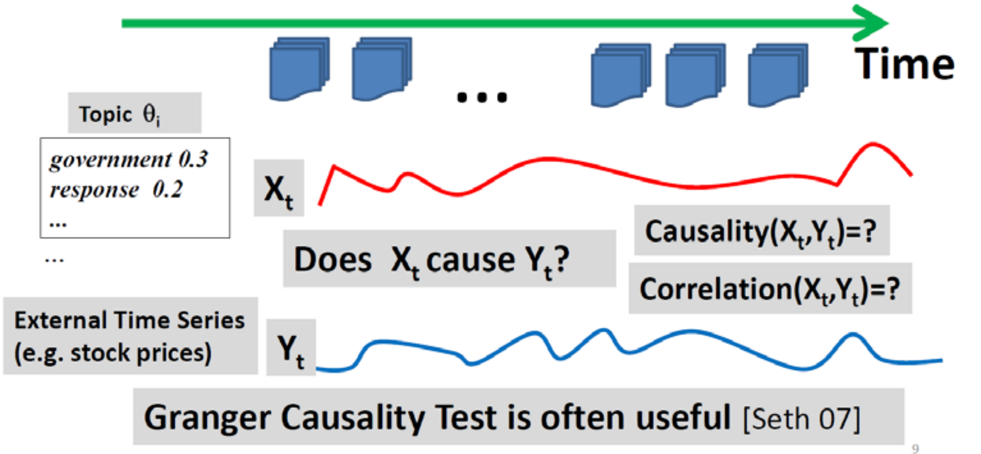
Iterative Causal Topic Modeling [Kim et al. 13]



Heuristic Optimization of Causality + Coherence



Measuring Causality (Correlation)



Topics in NY Times Correlated with Stocks [Kim et al. 13]: June 2000 ~ Dec. 2011

AAMRQ (American Airlines)	AAPL (Apple)
russia russian putin	paid notice st
europe european	russia russian europe
germany	olympic games olympics
bush gore presidential	she her ms
police court judge	oil ford prices
airlines airport air	black fashion blacks
united trade terrorism	**computer technology software**
food foods cheese	**internet com web**
nets scott basketball	football giants jets
tennis williams open	japan japanese plane
awards gay boy	
moss minnesota chechnya	

Topics are biased toward each time series

Major Topics in 2000 Presidential Election [Kim et al. 13]

Top Three Words in Significant Topics from NY Times
tax cut 1
screen pataki guiliani
enthusiasm door symbolic
oil energy prices
news w top
pres al vice
love tucker presented
partial **abortion** privatization
court supreme **abortion**
gun control nra

Text: NY Times (May 2000 - Oct. 2000)
Time Series: Iowa Electronic Market
http://tippie.uiowa.edu/iem/

Issues known to be important in the 2000 presidential election

Summary of Text-Based Prediction

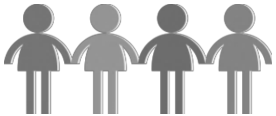
- **Text-based prediction** is very useful for "**big data" applications**:
  - Inferring **new knowledge** about the world
  - **Optimizing decision making**
- Text data is often **combined with non-text data** for prediction
  - **Joint analysis** of text and non-text is necessary and useful
  - Non-text data provide **context for text mining** (**contextual text mining**)
  - Text data help **interpret patterns discovered** from **non-text data** (**pattern annotation**)
- An **active research topic** with many open challenges

Course Summary

Key High-Level Take-Away Messages

13. Joint mining of text and non-text
14. Contextual PLSA
15. NetPLSA
16. Causal topic mining

6. Probabilistic Topic Model (PLSA, LDA)
7. Generative model; ML estimate; EM
8. Text clustering: model vs. similarity-based
9. Text categorization: generative vs. discriminative
10. Evaluation of clustering and categorization



Perceive

(Perspective)

1. NLP → Text representation → Knowledge discovery
2. Robust TM = Word-based rep + Statistical analysis

representation

(English)

11. Sentiment classification: ordinal regression
12. Latent Aspect Rating Analysis

3. Paradigmatic and syntagmatic relations
4. Text similarity: Vector space, BM25
5. Co-occurrence analysis: Entropy, MI

What to Learn Next

- **Natural Language Processing**
  - Foundation for all text-based applications
  - More NLP ➔ Deeper knowledge discovery
- **Statistical Machine Learning**
  - Backbone techniques for NLP and text analysis
  - Key to predictive modeling and "big data" applications
- **Data Mining**
  - **General data mining algorithms** can always be applied to text
- **Text/Information Retrieval**
  - Essential system component in any text-based application (human in the loop)
  - Some techniques useful for text data mining

Main Techniques for Harnessing Big Text Data: Text Retrieval + Text Mining