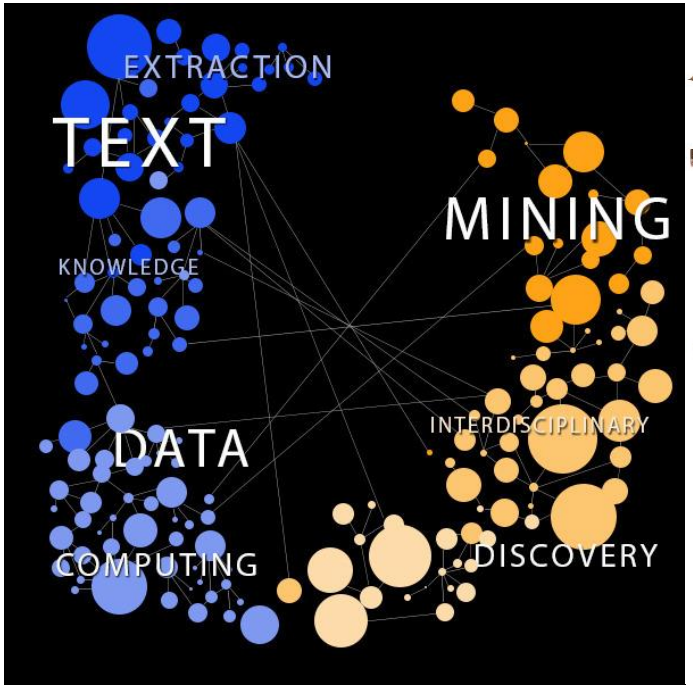
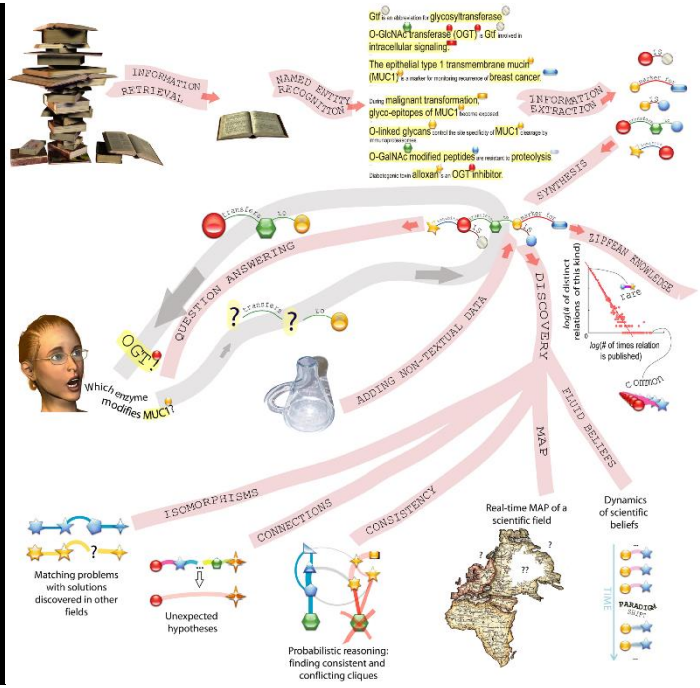




Lecture 1: Introduction to Text Analytics

Pilsung Kang

School of Industrial Management Engineering

Korea University

AGENDA

Text Analytics: Background

- Motivation
  - ✓ Approximately 80% of the world's data is help in unstructured formats
  - ✓ Simple document retrieval is not enough, but knowledge discovery is required!

Topic: Storage *Follow via:*

Within two years, 80% of all medical data will be unstructured

Summary: *The data storage load for medical organizations is going to skyrocket.*

By Denise Amrich for ZDNet Health | April 9, 2013 -- 01:09 GMT (18:09 PDT)

Follow @deniseamrich

We are all aware of the growth in medical health records because of changes in regulation. You would think, then, that most of the storage requirements would be for managing and storing those health records.

But the following IBM video states that 80 percent of health data stored in 2015 will be unstructured data, data that doesn't fit into nice rows and columns. Since nearly all medical records subject to the Affordable Care Act are, essentially, form data, that means that a huge amount of the storage required by the medical world isn't a result of that particular set of regulations.

In fact, IBM says that the body of medical knowledge doubles every five years. As imaging improves and M2M grows, more mobile data is captured. More intelligent sensors are deployed, both to home and hospital-bound patients. The data storage load for medical organizations is simply going to skyrocket.

This, of course, leads to another huge problem: Confidentiality and security. The Health Insurance Portability and Accountability Act (HIPAA) and the Health Information Technology for Economic and Clinical Health Act (HITECH) both require record-keeping safeguards. As medical data explodes in volume, that data protection challenge gets greater and greater.

The following video from IBM explores some of the scope of the problem. It's a marketing video, so keep that in mind, but it gives you a good understanding of the sorts of challenges and solutions that we'll be looking at for medical data storage.

http://www.zdnet.com/within-two-years-80-percent-of-medical-data-will-be-unstructured-7000013707/

How to manage unstructured data for business benefit

Stephen Pritchard, Contributor

Share 16 +1 0 Tweet 56

Businesses across all industries are gathering and storing more and more data on a daily basis. But when it comes to assessing the benefits and challenges of big data, sometimes it is easy to overlook one key point: Most of the business information in use today does not reside in a standard relational database.

An often-cited statistic is that 80% of business data is unstructured, be it in word processor, spreadsheet and PowerPoint files, audio, video, sensor and log data, or external data such as social media feeds.

Exploiting unstructured data

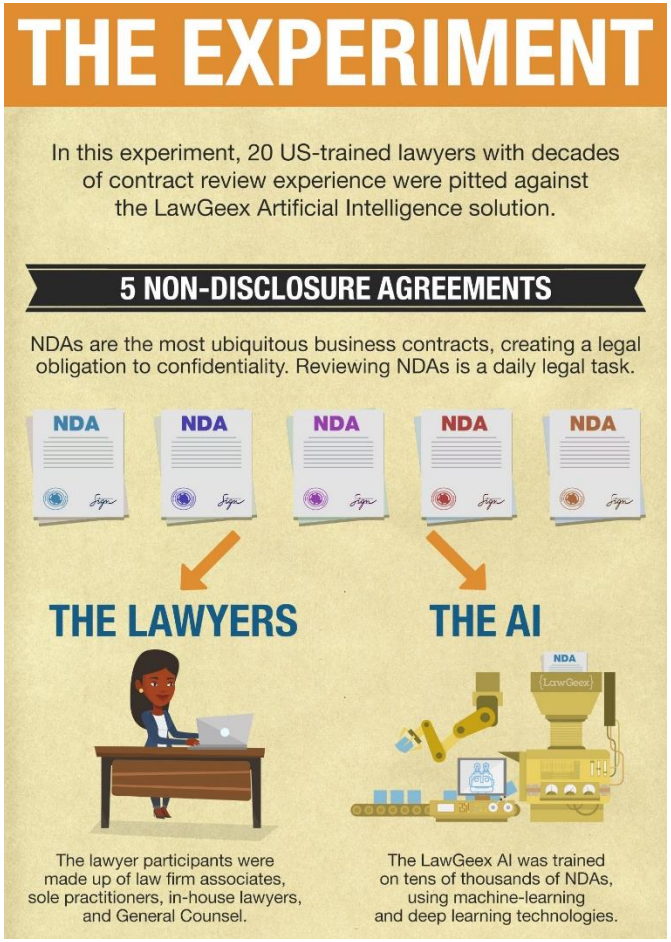
This raises some issues for organisations that need to process and exploit unstructured data. Some big data tools, primarily those based on Hadoop, are designed from the ground up to manage and analyse unstructured information. Other, more conventional business intelligence (BI) and data warehousing technologies may not be.

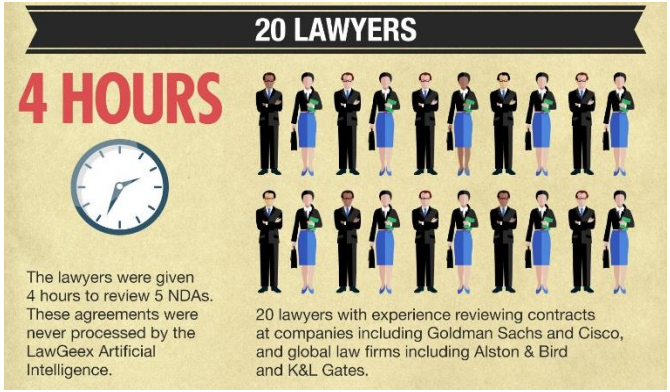
Business intelligence (BI) and data warehousing suppliers have been adding support for unstructured data management to their tool sets, and some IT organisations have built their own platforms for converting unstructured data into structured records, for example, through knowledge management systems. But that can be a time-consuming and expensive process.

http://www.computerweekly.com/feature/How-to-manage-unstructured-data-for-business-benefit

Text Analytics: Background

- AI vs. Lawyers: The ultimate showdown
  - ✓ Task: to spot issues in five Non-Disclosure Agreements (NDAs)

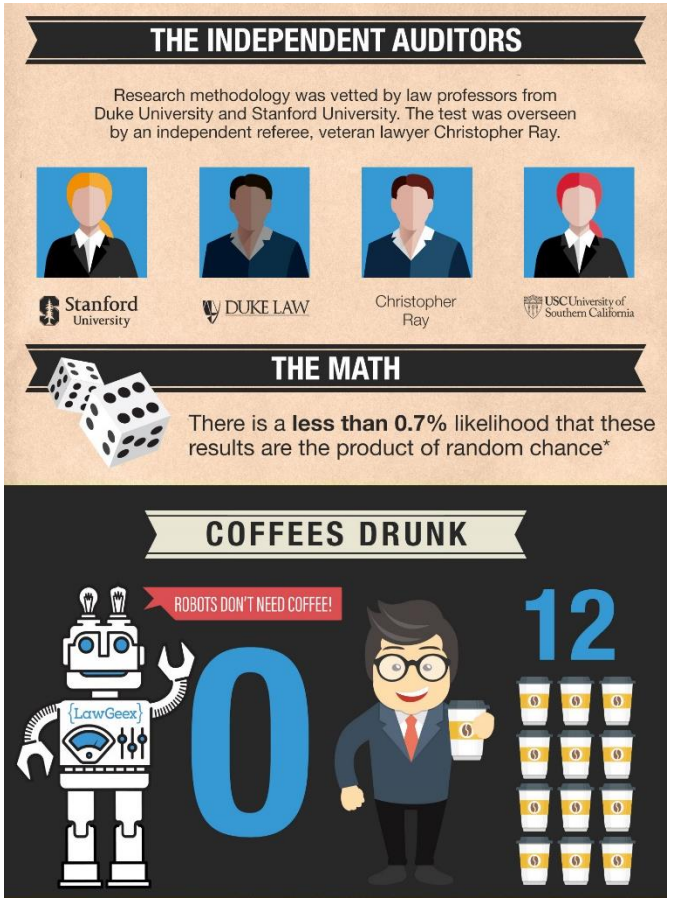




https://www.lawgeex.com/resources/AIvsLawyer/

Text Analytics: Background

- AI vs. Lawyers: The ultimate showdown



https://www.lawgeex.com/resources/AIvsLawyer/

Example: AI papers in arXiv

- The number of papers in the "artificial intelligence" section
  - ✓ Can you read them all?

적독 積讀

발음 [적똑]

표준국어대사전 | 고려대한국어대사전 N

적독 [2]

명사

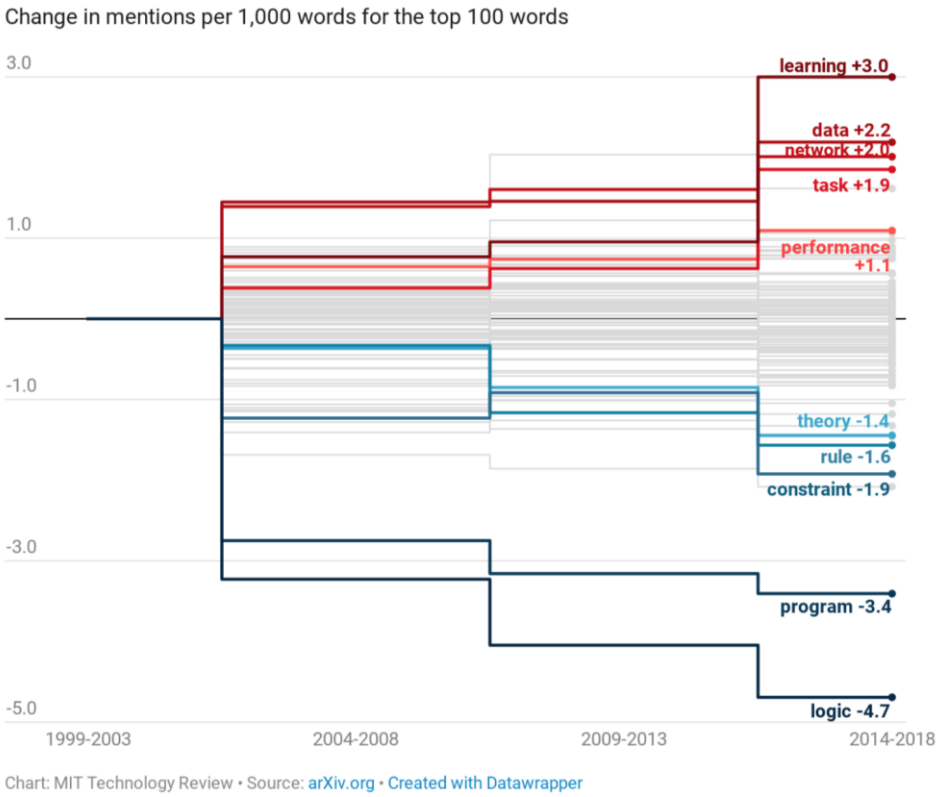
책을 읽지 아니하고 쌓아 두기만 함을 놀림조로 이르는 말.

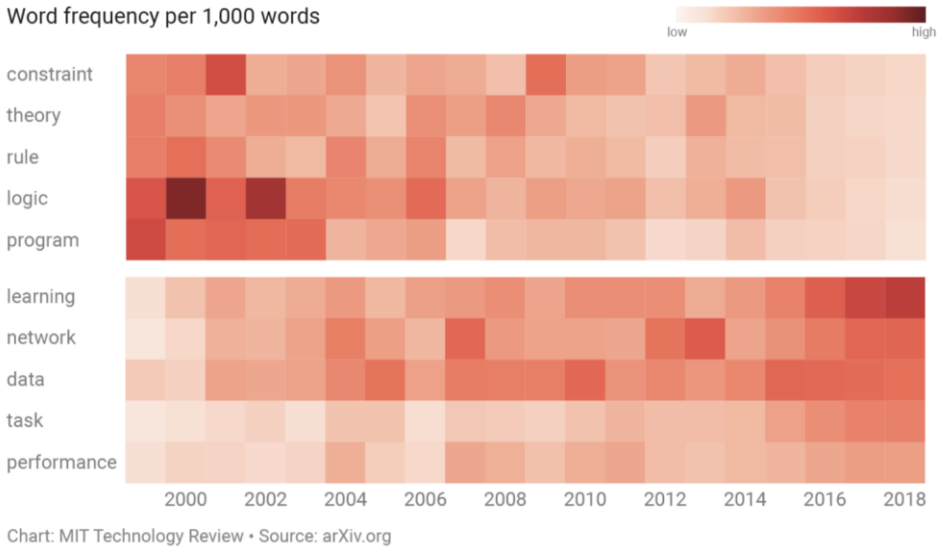
- **적독만** 해도 그렇게 지식이 풍부하시니 그 책을 다 읽는다면 어떻게 되겠소.

https://www.technologyreview.com/s/612768/we-analyzed-16625-papers-to-figure-out-where-ai-is-headed-next/?utm_source=facebook&utm_campaign=site_visitor.unpaid.engagement&utm_medium=tr_social

Example: AI papers in arXiv

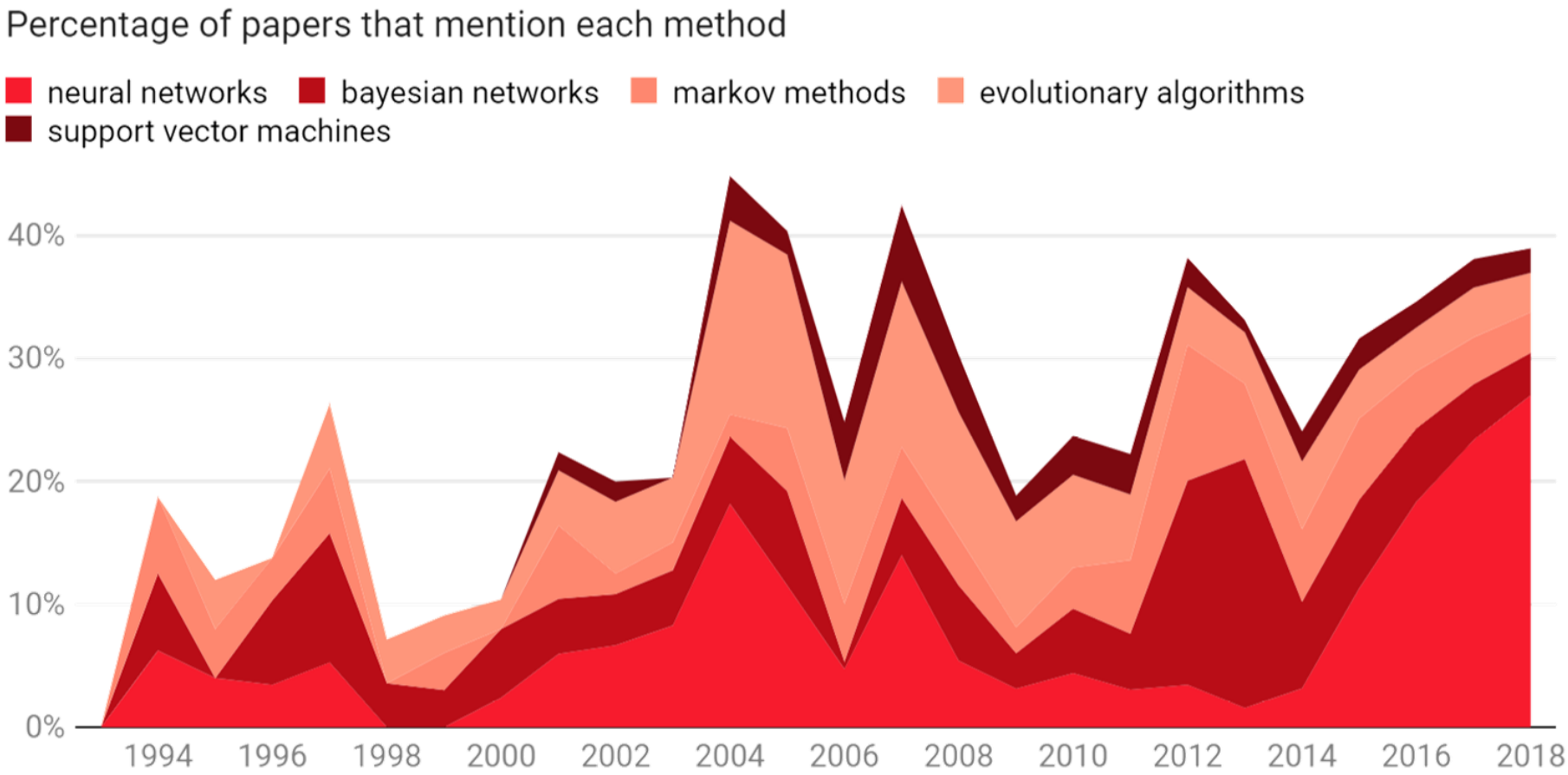
- Let's do some text mining!
  - ✓ Actually, it was just a simple word frequency analysis
- Discovery 1: Machine learning eclipses knowledge-based reasoning





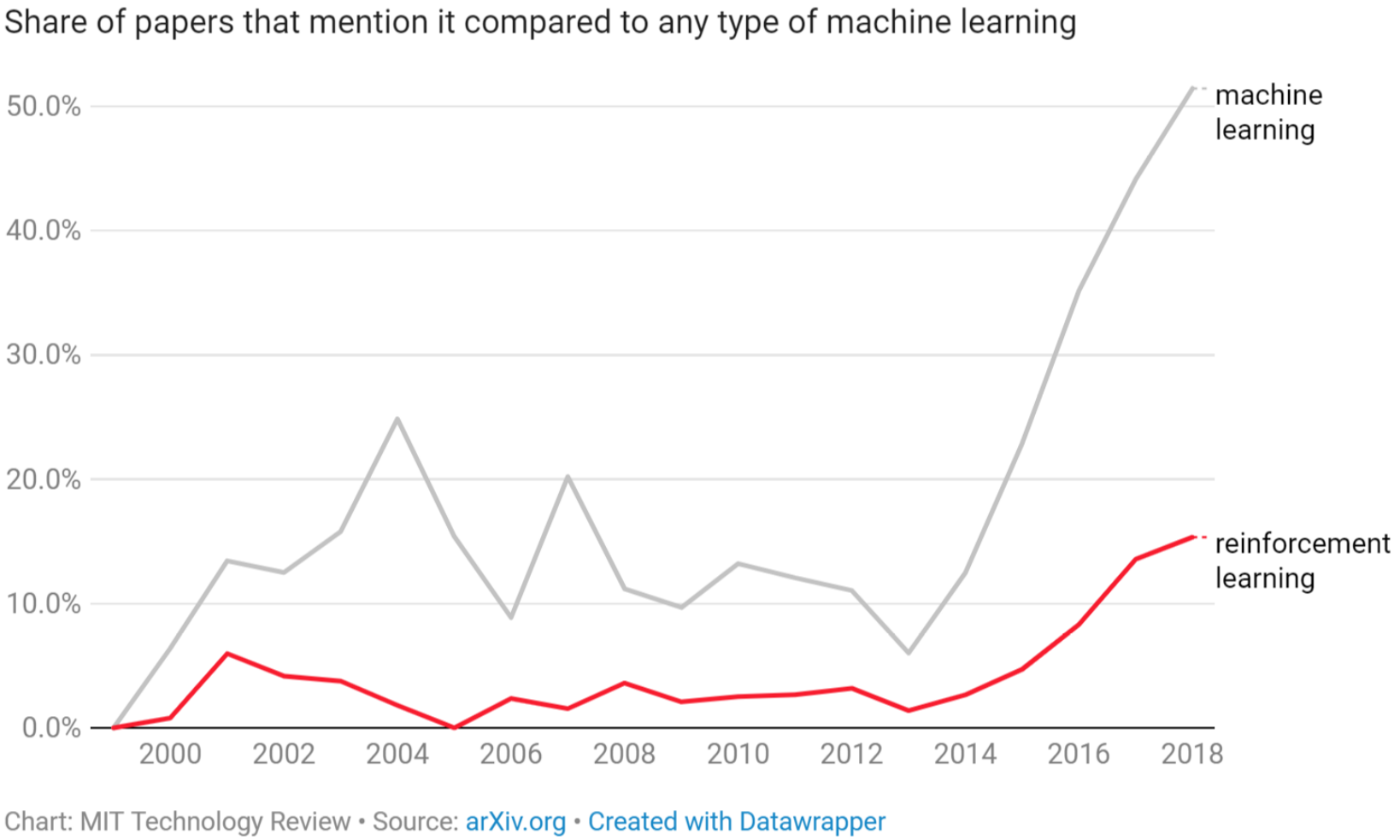
Example: AI papers in arXiv

- Discovery 2: The Neural-Network Boom



Example: AI papers in arXiv

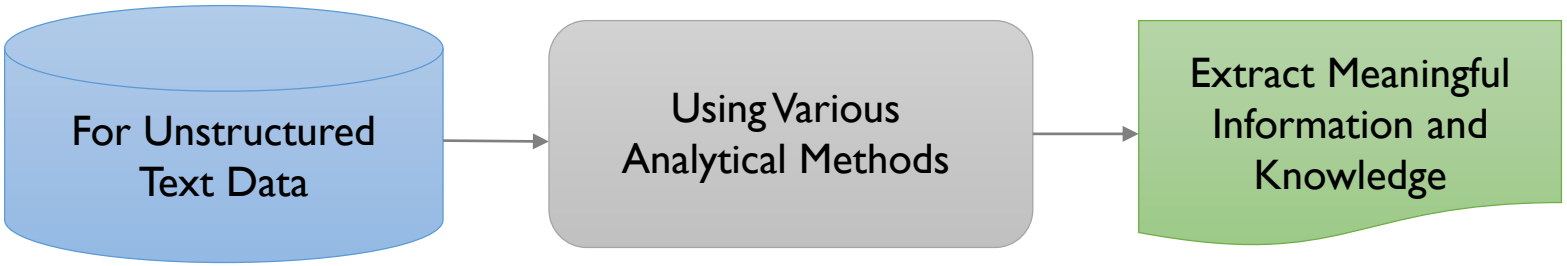
- Discovery 3: The rise of reinforcement learning



Text Analytics: Definition

Text Mining (Def. *Wikipedia*)

Text mining, also known as intelligent text analysis, text data mining or knowledge-discovery in text (KDT), refers generally to the process of extracting interesting and non-trivial information and knowledge from unstructured text. Text mining is a young interdisciplinary field which draws on information retrieval, data mining, machine learning, statistics and computational linguistics. As most information (over 80%) is stored as text, text mining is believed to have a high commercial potential value.

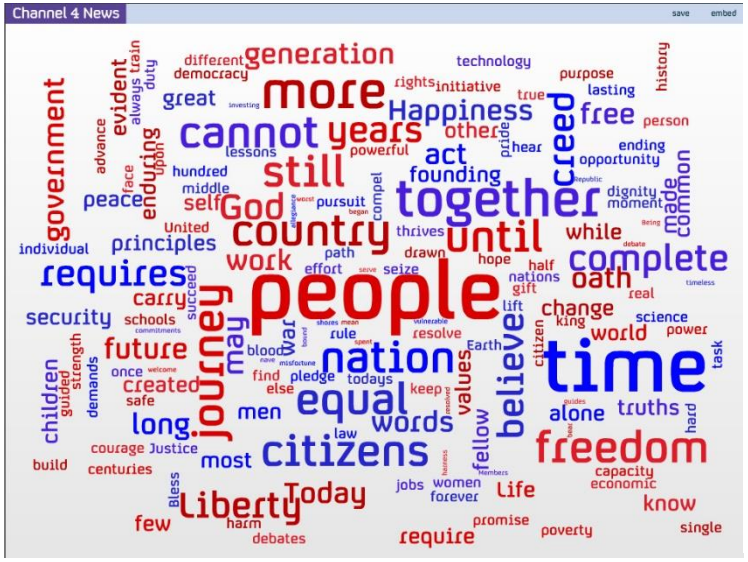


Text Analytics: Applications

- Information Abstraction/Summarization/Visualization

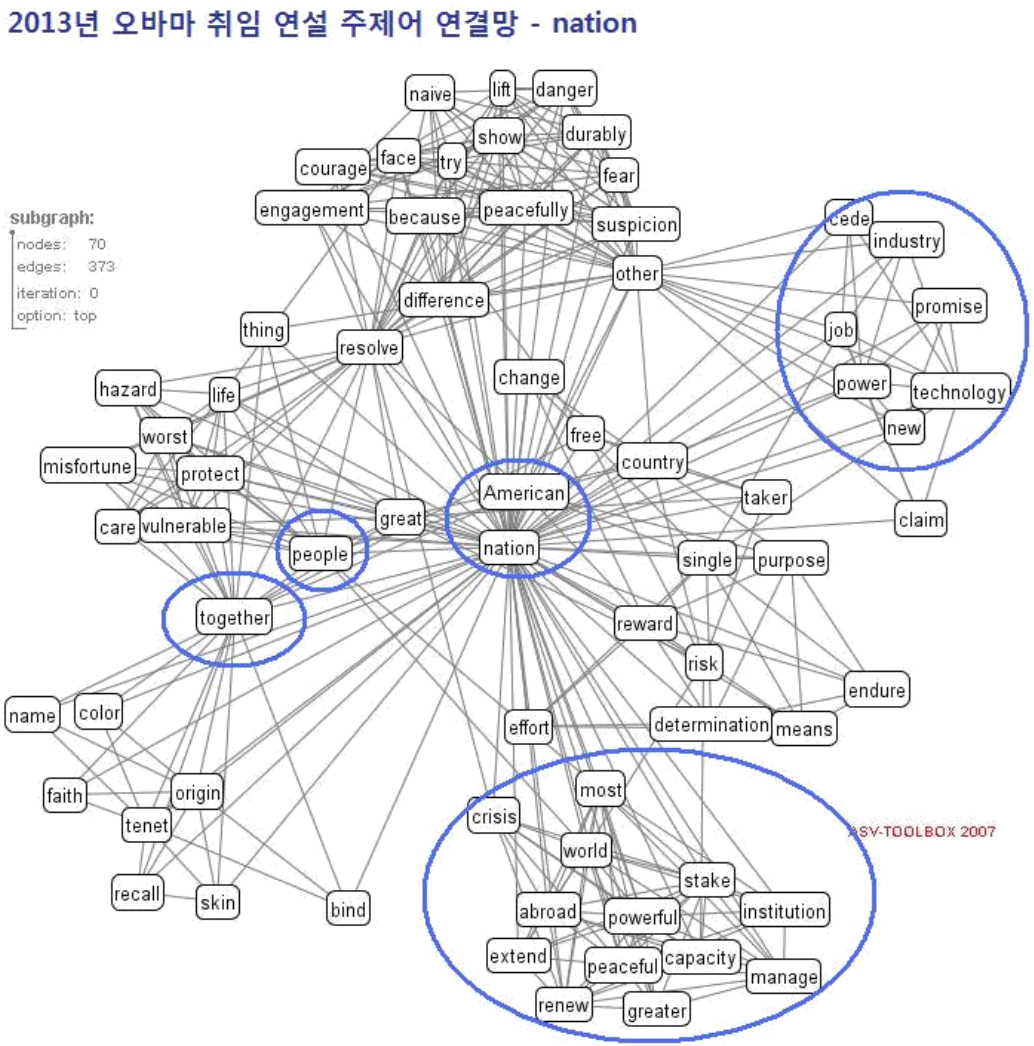
Text Analytics: Applications

- Information Abstraction/Summarization/Visualization



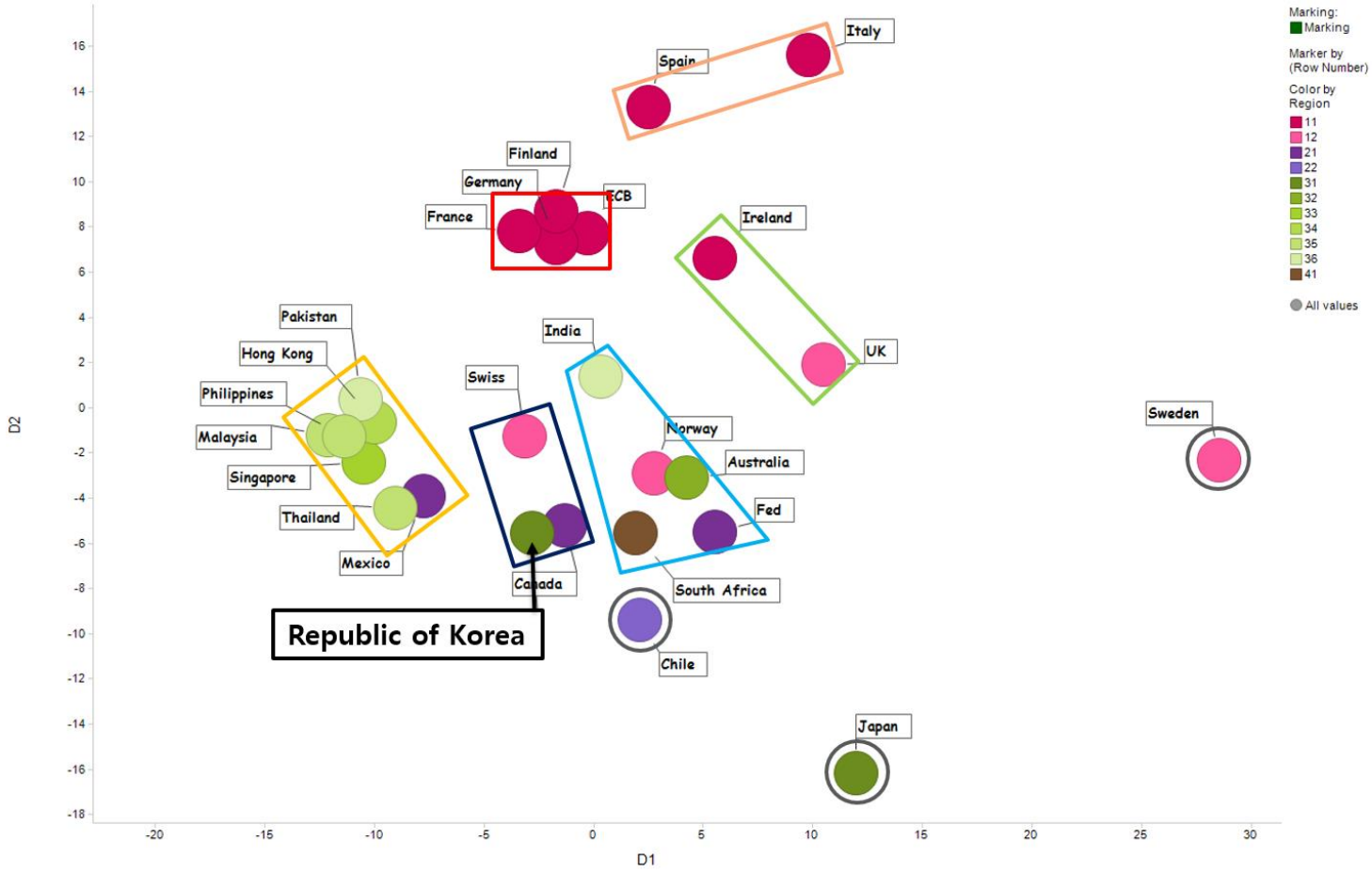
Text Analytics: Applications

- Information Abstraction/Summarization/Visualization



Text Analytics: Applications

- Information Abstraction/Summarization/Visualization
  - ✓ Central Bank speech analysis: Similarities between the central banks in the world



Text Analytics: Applications

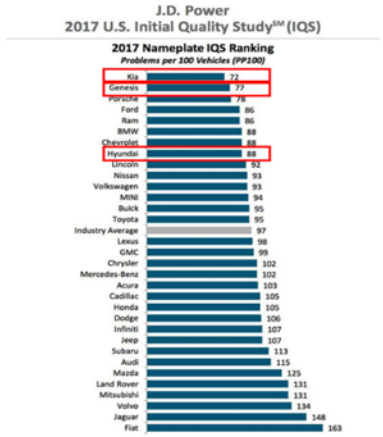
- Information Abstraction/Summarization/Visualization
  - ✓ Central Bank speech analysis: Similarities between the central banks in the world

Year	Common Concern	Federal Reserve System	European Central Bank	Deutsche Bundesbank	Bank of England	Bank of Japan
2004	Sustainability Credibility	Expansion Imports	Parliaments Cooperation	Retirement Ages Working Hours	Household-Spending	QE Deflation
2005	China Inflation	Deficits Competitive	Financial Integration	Global Imbalance	Households Future Inflation	QE Recession
2006	Competitive Global Imbalance	Incentives Risk Taking	Administered Price Indirect Taxes	Inflation	China / India Commodities	Domestic and-External Demand
2007	Subprime-Mortgage	Subprime-Mortgage	Price Stability Turmoil	Banking Supervision Disclosure	Credit	Subprime-Mortgage
2008	Financial Turmoil Commodity Prices	Financial Turmoil Funding Markets	Financial Turmoil Liquidity	Financial Turmoil Subprime	Commodity Prices Housing Market	Securitized Product
2009	Financial Crisis Lehman Brothers	Financial Crisis ABS	Non-standard-Measure	Financial Crisis Rescue	Asset Purchase Recovery	Credit Bubble Financial Crisis
2010	Recovery Reform	Recovery Recession	ESRB/ FSB Deficits	Microprudential Macroprudential	Recovery/ QE VAT/ TAX	Deflation
2011	Sovereign Debt Basel III	Dodd-Franc Act Recovery	Sovereign Debt EFSF	Debt Crisis Basel III	Commodity Prices Basel III	Asset Purchase ETFs / REITs
2012	Europe Deleveraging	Recovery (has been) Labor Market	OMT/ ESM/ SSM Fragmentation	Banking Union Taxpayer	Investment-Banking	European Debt Deleveraging
2013	Real Economy Price Stability	(At least as long as) Unemployment	SRM/ SSM/ OMT	SRM / SSM Banking Union	Prudential-Regulation	Price Stability QE

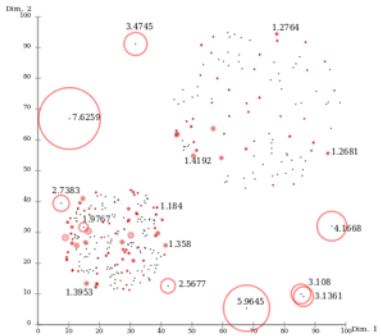
Text Analytics: Applications

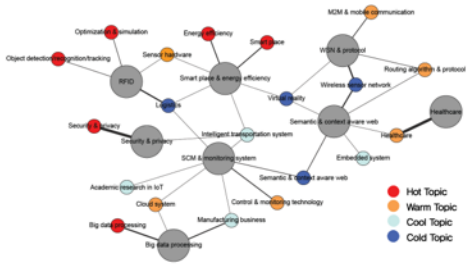
Seo et al. (2019+)

- Information Abstraction/Summarization/Visualization
  - ✓ Unusual customer response identification and visualization



Doc	Comment
Doc 1	Commen1
Doc 2	Comment2
Doc 3	Comment3





VDS 주관식 문항 추출

데이터 마이닝 기법 적용

효율적인 소비자 의견 파악

Text Analytics: Applications

Seo et al. (2019+)

- Information Abstraction/Summarization/Visualization
  - ✓Unusual customer response identification and visualization

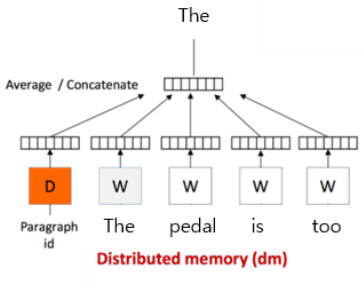
1. 데이터 전처리 및 벡터화

데이터 전처리

- 속어, 구어체 등은 고려하지 않음
- Space →Apostrophe로 변환
- Na, 중복 문서 제거
- 이상 단어 탐지 및 검출

문서 벡터화

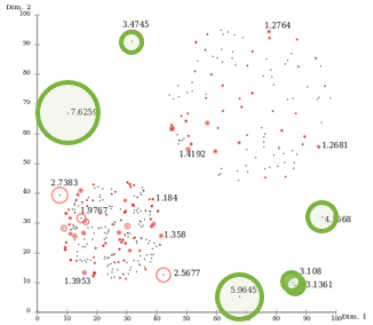
- Tokenization
- Doc2Vec



2. 특이 소비자 의견 탐지

Novelty Detection

- Doc2vec으로 벡터화 된 문서를 바탕으로 Local Outlier Factor(LOF) 기법 적용



키워드 추출

- TF-IDF 방법에 기반하여 일반적인 문서와 중복되지 않는 특이 응답 문서의 중요 단어를 추출

TF-IDF
Term x within document y

$\mathbf{tf}_{x,y}$ = frequency of x in y
$\mathbf{df}_x$ = number of documents containing x
$\mathbf{N}$ = total number of documents

$$\mathbf{W}_{x,y} = \mathbf{tf}_{x,y} \times \log\left(\frac{\mathbf{N}}{\mathbf{df}_x}\right)$$

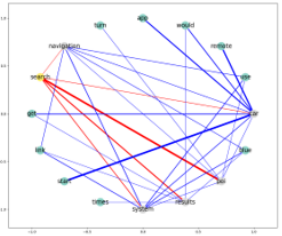
3. 키워드 및 관계도 분석

연관 규칙 관계 분석

- 키워드와 통계적 연관성이 높은 단어 분석

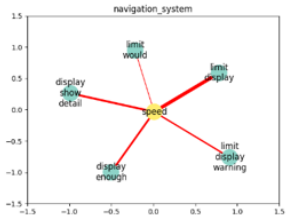
빈도 기반 관계 분석

- 키워드와 함께 등장한 단어 빈도 분석
- 키워드와 관련성이 높은 단어를 모두 포함하고 있는 문서 자동 추출



거리 기반 관계 분석

- 키워드의 단어 벡터와 N-gram의 벡터 사이에 거리 분석



Text Analytics: Applications

Seo et al. (2019+)

- Information Abstraction/Summarization/Visualization
  - ✓ Unusual customer response identification and visualization

Response comments	Ranking
had to be reprogrammed to give expressway routes....stopped doing this w/o my making changes.	1/17,430
This problem has persisted the entire length I have owned the vehicle; however, it only happens on 1 out of 10 start ups so it is not something that causes much grief.	1/17,430
Also, bell comes at a specific place near my home which address is deleted.	1/17,430

(a) Responses with the highest LOF scores for Navigation System

Response comments	Ranking
I drove a Lexus for many years. The seats were soft cushioning and soft leather covered.	1/8,687
THIS IS MY SECOND HYUNDAI. SAME PROBLEM. ON 2012 VERA CRUZ.	1/8,687
I have not had any trouble with the seat covers but I do think that they should be treated with something before they are sold, that would make them easier to keep clean.	1/8,687

(b) Responses with the highest LOF scores for Seat Material

Text Analytics: Applications

Seo et al. (2019+)

- Information Abstraction/Summarization/Visualization

Response comments	Ranking
The app takes forever to load up, forever to send signal, and more often than not it's useless because my car is far from warmed up. Perhaps if I could set it to warm for longer than 10 min.	1/20,575
I ABSOLUTELY hate the fact that the hazards flash the entire time when remote starting the car. We live in NH, have had over 4 feet of snow this past month, temperatures haven't been above freezing in weeks and I still won't use the auto start because of the flashing lights. We will definitely be canceling the service because of this. And judging by all of the comments from other owners I read online, we are in the majority on this.	1/20,575
Whether connected to wiFi or mobile data, the app takes forever to log in (application to database coding flaws I'm sure) then, when in the app, when I press "lock" or "unlock" it takes a good 30 seconds to say "request sent" then, once the request is sent, it takes almost 3-5 minutes for the door to unlock! The app, by concept is brilliant, however the team working on the coding clearly is inexperience and doesn't know how to write scripts to compile and run efficiently!	1/20,575

(c) Responses with the highest LOF scores for Bluetooth

Text Analytics: Applications

Seo et al. (2019+)

- Information Abstraction/Summarization/Visualization
  - ✓ Unusual customer response identification and visualization

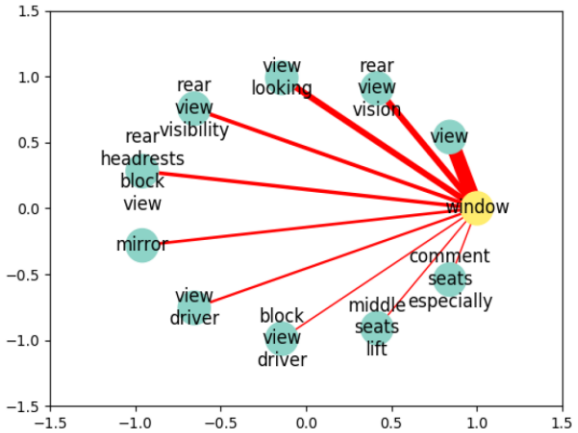
Table 4: Keywords that are more frequently used in unusual customer response comments for each category

Category	Keywords
Adjustments and Controls	air, leather, window, cars, belt, setting, cooling, door, view
BlueLink Telematic System	money, information, area, month, right, auto, miles, oil, driving, user
Bluetooth	update, names, help
Navigation System	entering, iphone, dealership, locations, speed, manual
Ride Quality	engine, firm, genesis, body, driver, seats
Seat Belt	leg, extenders, thing, plastic, road, wheel, leather, arm, care, miles end, frame, years
Seat material	warranty, type, seating
Wind noise	bumper, seat, paint, water, trunk, mirror, rain, mileage

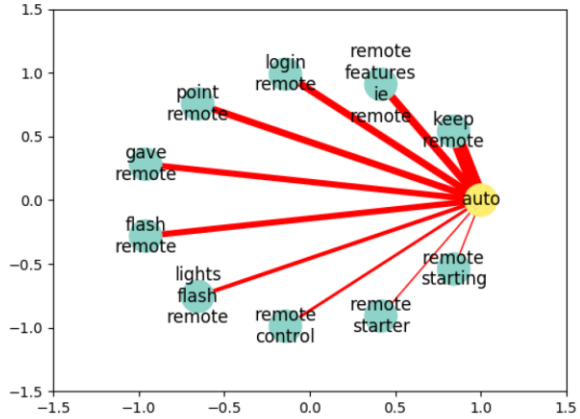
Text Analytics: Applications

Seo et al. (2019+)

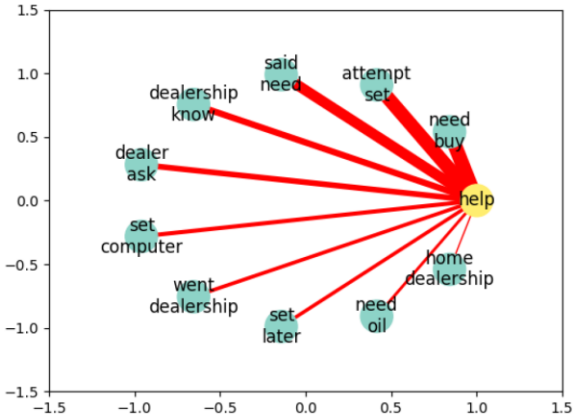
- Information Abstraction/Summarization/Visualization
  - ✓ Unusual customer response identification and visualization



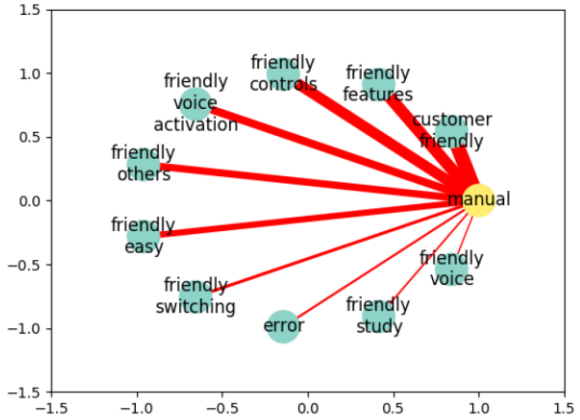
(a) Adjustments and controls



(b) BlueLink Telematic System



(c) Bluetooth

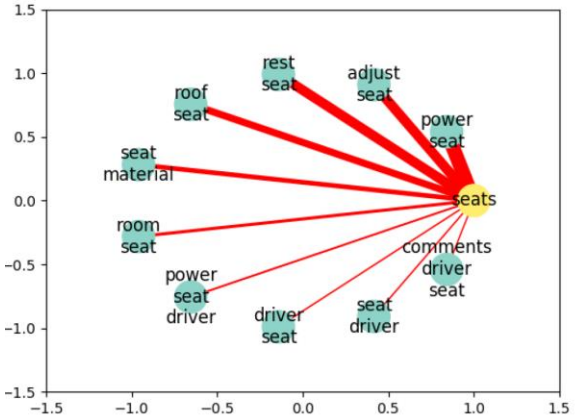


(d) Navigation system

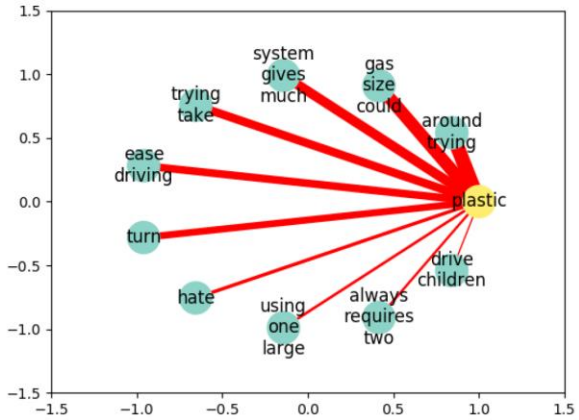
Text Analytics: Applications

Seo et al. (2019+)

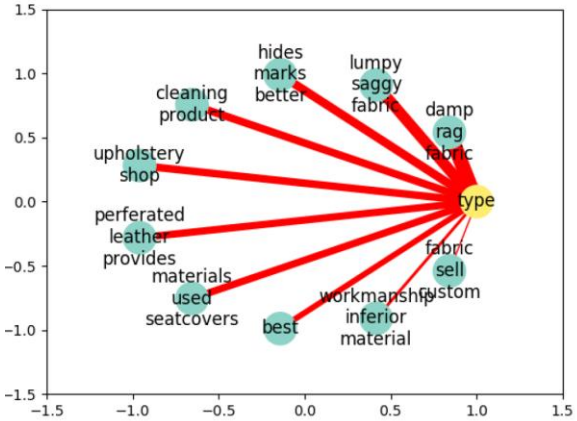
- Information Abstraction/Summarization/Visualization
  - ✓ Unusual customer response identification and visualization



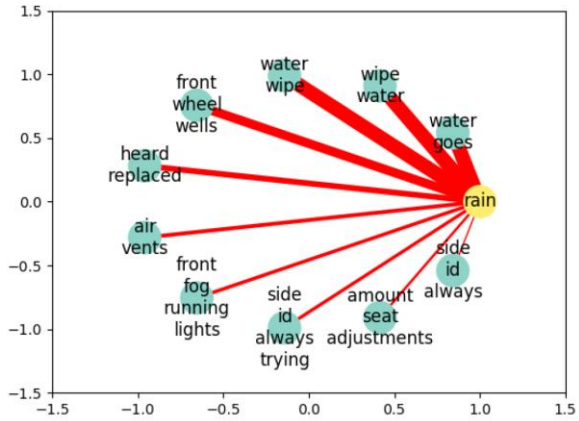
(e) Ride quality



(f) Seat belt



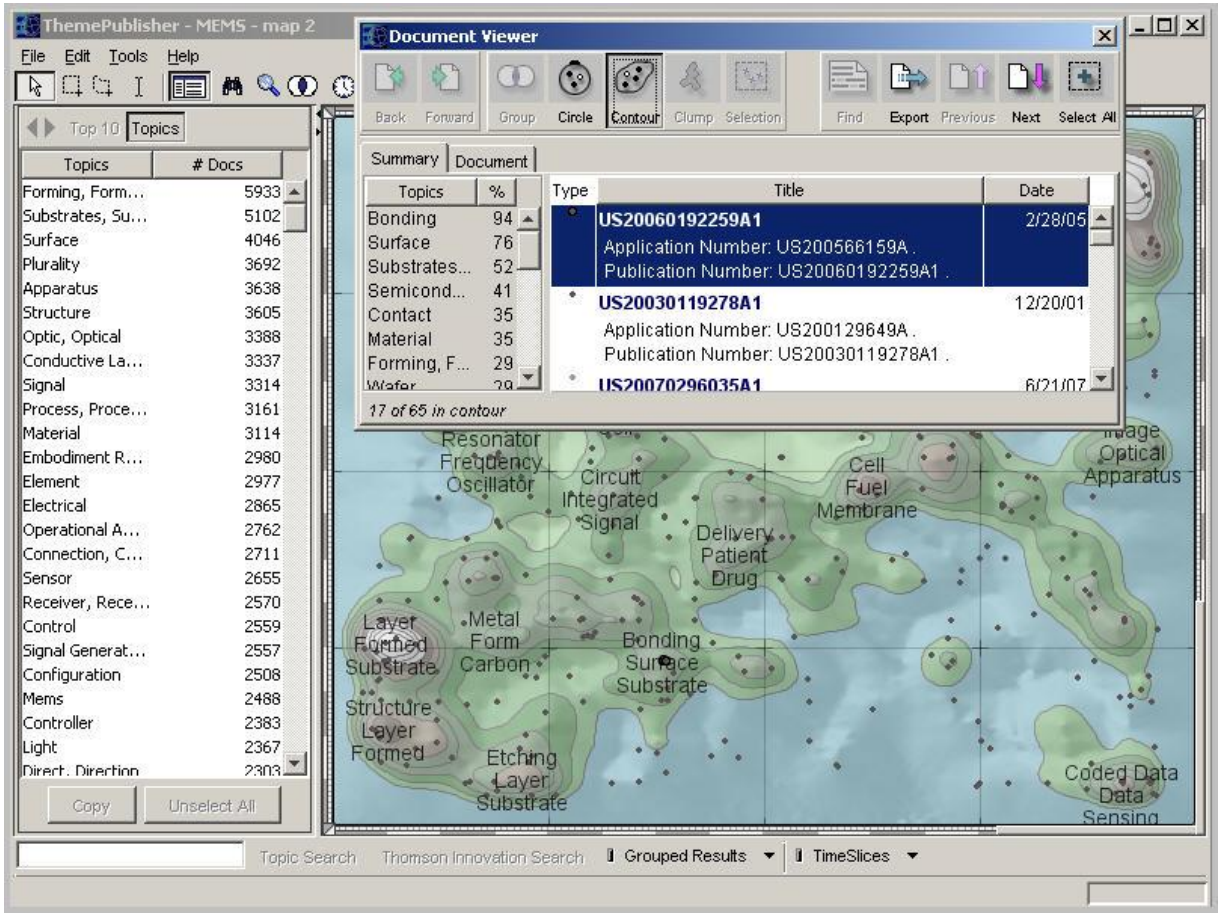
(g) Seat material



(h) Wind noise

Text Analytics: Applications

- Document Clustering
  - ✓ Cluster documents and extract representative keywords for each cluster



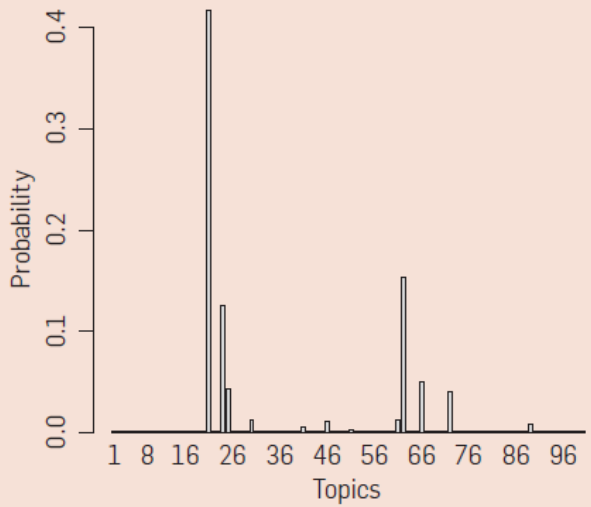
Text Analytics: Applications

- Document Clustering

Text Analytics: Applications

- Topic Extraction
  - ✓ Analyze documents and extract latent topics in the corpus

Figure 2. Real inference with LDA. We fit a 100-topic LDA model to 17,000 articles from the journal *Science*. At left are the inferred topic proportions for the example article in Figure 1. At right are the top 15 most frequent words from the most frequent topics found in this article.



"Genetics"	"Evolution"	"Disease"	"Computers"
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

Text Analytics: Applications

Kim et al. (2016)

- Topic Extraction
  - ✓ 30 Topics discovered by LDA

Fault detection with DBN	Convolutional neural network	Network Learning	Representation learning	Face Recognition	Speech Recognition	Acoustic Modeling	Extreme Learning	Deep learning architecture	Image Segmentation
deep	neural	layer	feature	face	speaker	speech	deep	deep	image
belief	convolutional	input	level	recognition	speech	recognition	learn	architecture	scene
network	pool	output	extract	estimation	noise	acoustic	algorithm	neural	scale
dbn	convolution	unit	learn	facial	adaptation	hmm	structure	standard	segmentation
fault	convnet	hide	extraction	shape	source	neural	extreme	explore	pixel
		function							

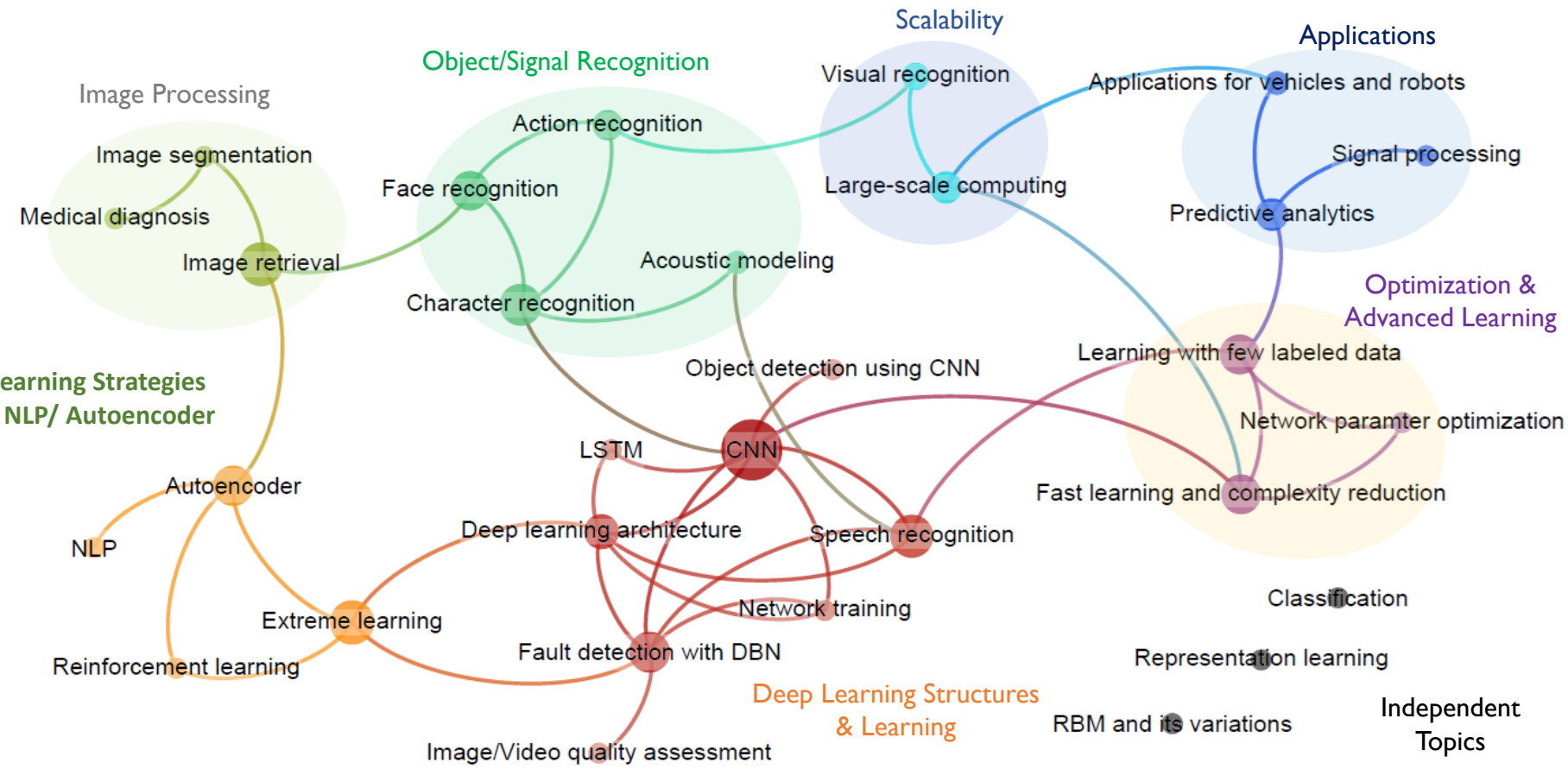
Long-short term memory	Predictive analytics	Signal processing	Classification models	Large-scale computing	Image quality assessment	Visual recognition	NLP	Detection using CNN	Action recognition
term	data	analysis	classification	application	domain	pattern	word	cnn	video
recurrent	prediction	filter	classifier	implementation	state	process	text	detection	human
long	technique	signal	class	efficient	quality	compute	language	convolutional	temporal
lstm	information	component	vector	process	resolution	visual	representation	neural	action
network	research	audio	support	power	relationship	field	semantic	detect	track

Image retrieval	Medical image di agnosis	Reinforcement learning	Parameter optimization	Auto encoder	RBM and variations	Learning with few labeled data	Fast learning complexity reduction	Applications for vehicles & robots	Character recognition
image	image	learn	train	representation	machine	train	fast	time	recognition
visual	segmentation	question	algorithm	learn	boltzmann	data	reduce	real	system
retrieval	disease	state	gradient	sparse	rbm	label	parameter	application	character
descriptor	cell	answer	sample	encode	restrict	few	weight	drive	network
attribute	medical	reinforcement	optimization	stack	distribution	transfer	complexity	Vehicle	neural

Text Analytics: Applications

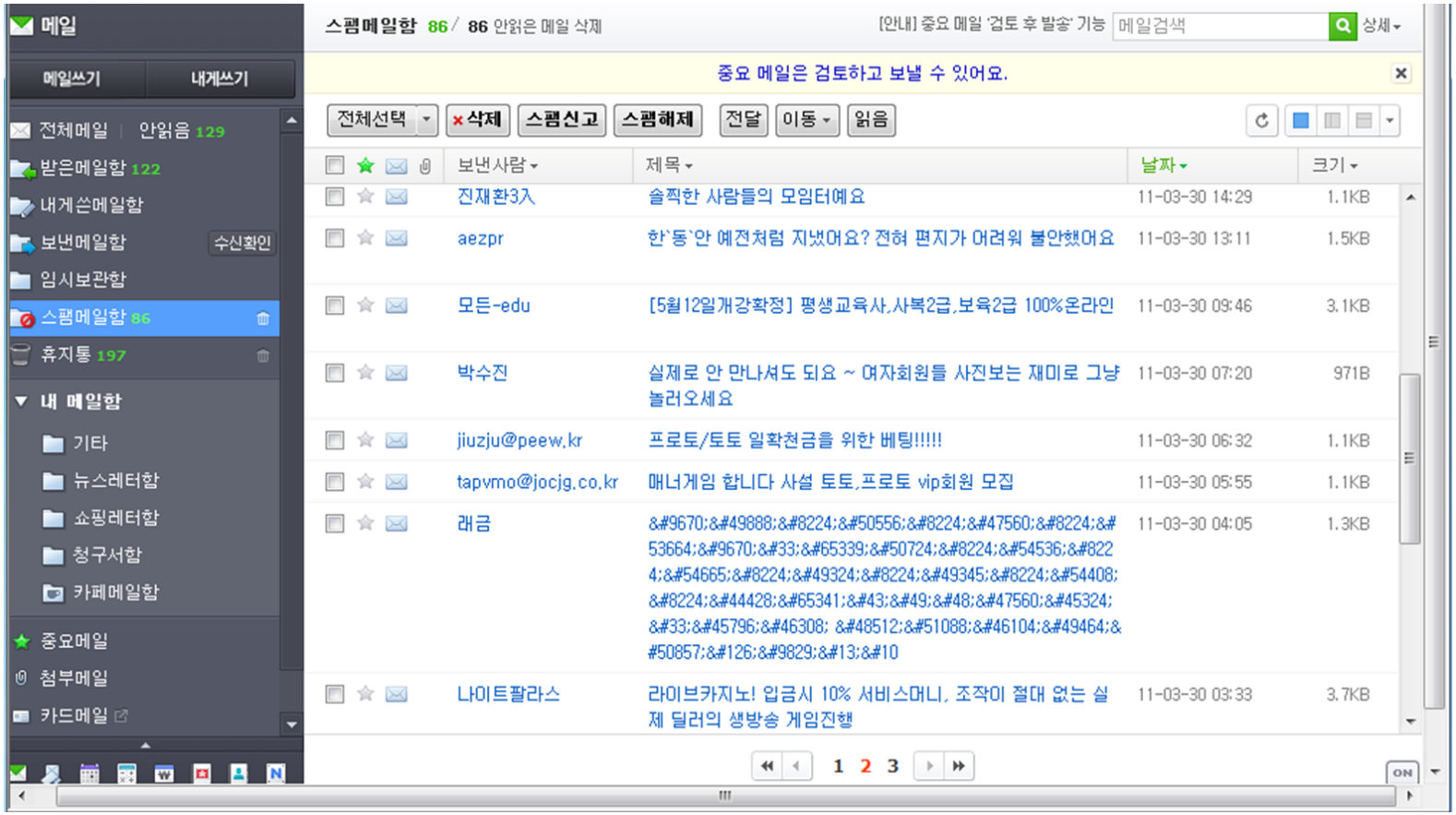
Kim et al. (2016)

- Topic Extraction
  - ✓ Relations between topics



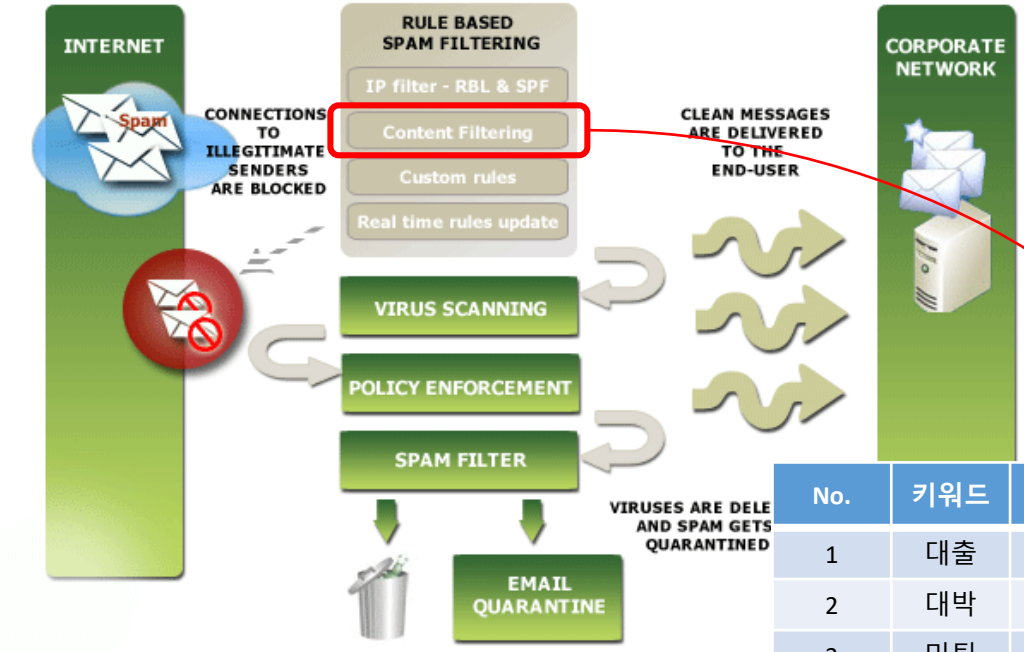
Text Analytics: Applications

- Document Categorization/Classification
  - ✓ Spam mail filtering



Text Analytics: Applications

- Document Categorization/Classification
  - ✓ Spam mail filtering

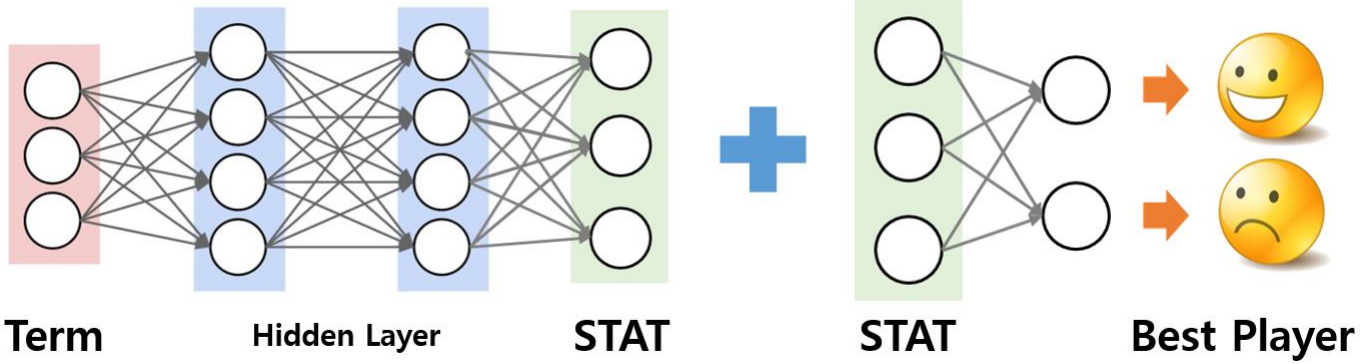


No.	키워드	Mail 1	Mail 2	Mail 3	...	Mail N
1	대출	0	2	0	...	0
2	대박	0	0	0	...	0
3	미팅	0	0	2	...	0
4	이상형	0	0	2	...	0
5	머니	0	2	0	...	0
6	외로	0	0	3	...	1
스팸 여부		N	Y	Y	...	N

Text Analytics: Applications

Kim et al. (2016)

- Document Categorization/Classification
  - ✓ Sport player evaluation



Text Analytics: Applications

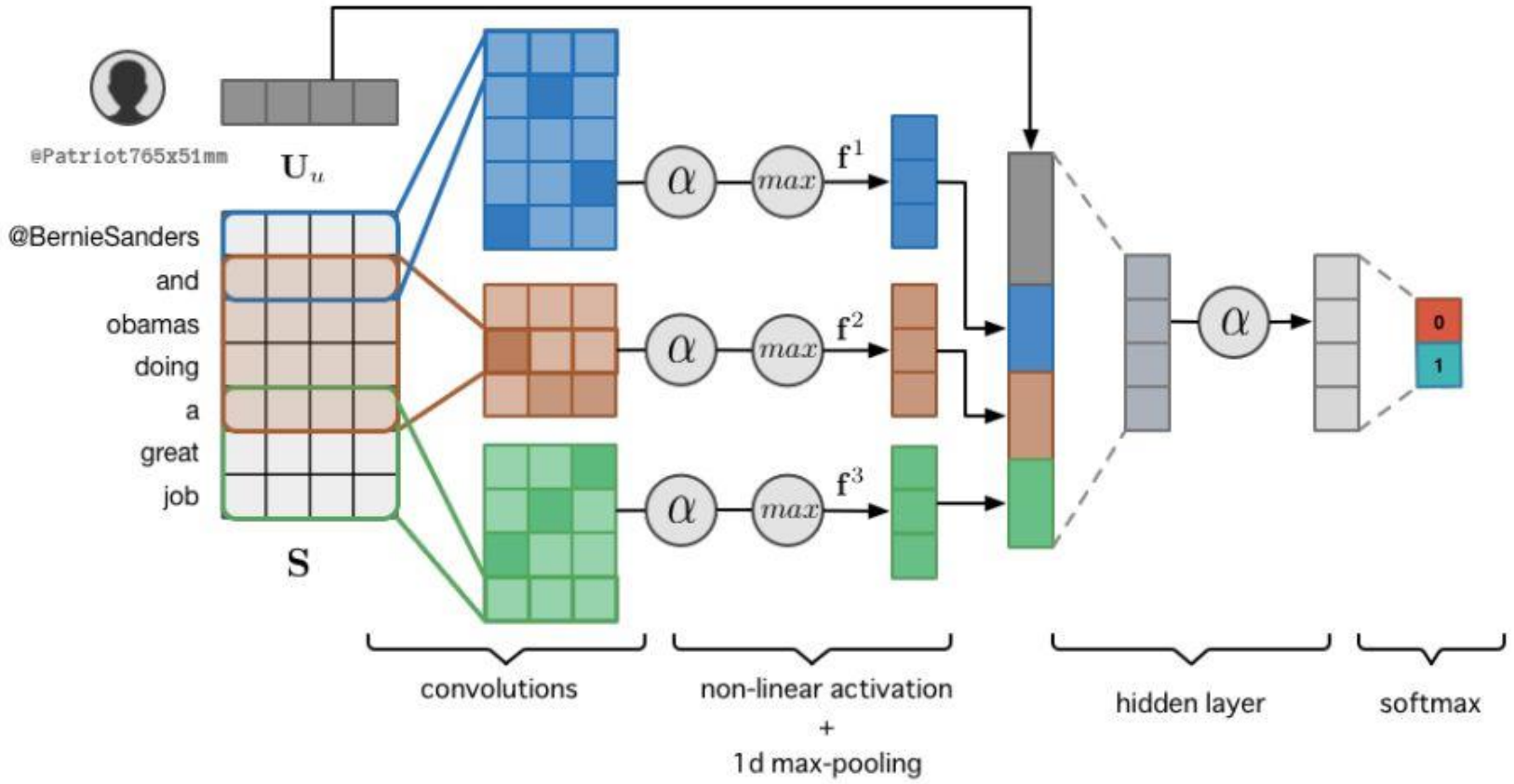
Lee et al. (2017)

- Document Categorization/Classification
  - ✓ Sentiment Analysis

Player	Line	Score	승	패배	피안타	피홈런	볼넷	실점	평균 자책점	이닝당 삼진	이닝당 볼넷	삼진 /볼넷	방어율
웨버	NC웨버는 7이닝 동안 1안타 3볼넷 10탈삼진으로 무실점 호투했다.	0.991	1	0	0	0	1	0	0	1	1	1	0
이재학	이재학 '10승', 3년만에 달라진 위상 증명하다	0.986	1	0	0	1	0	1	0	0	0	1	0
이태양	'이태양 완벽투' NC, LG 상대로 창단 첫 스윕	0.966	1	0	0	0	0	0	0	0	0	1	0
에릭	한편, 이날 7이닝 3실점으로 잘 던지며 7경기 만에 국내 첫 승을 거둔 에릭은 "굉장히 흥분된다.	0.803	1	0	1	0	0	0	0	0	0	0	0
찰리	어이없는 실책 2개가 나오자 찰리는 흔들리기 시작했다.	0.506	0	1	1	1	0	1	0	1	0	1	1
찰리	찰리가 대량 실점을 했지만 그 과정에서 3루수 모창민과 1루수 테임즈의 실책이 동반되면서 자책은 1점 밖에 되지 않았다.	0.506	0	1	1	1	0	1	0	1	0	1	1
원종현	NC 원종현이 패전투수가 됐다.	0.293	0	1	0	0	0	1	1	1	0	1	1
원종현	세 번째 투수로 등판한 원종현 역시 1사 후 8번 김성현에게 솔로포를 맞았다.	0.102	0	0	0	1	1	0	1	1	1	0	0
이재학	NC 선발 이재학은 8이닝 8피안타(2홈런) 5탈삼진 3볼넷 2실점을 기록했다.	0.079	0	0	1	1	0	1	1	0	0	0	1
이혜천	이혜천이 올라온 뒤 한꺼번에 5점을 내주면서 맥빠진 경기가 되고 말았다.	0.066	0	0	1	1	0	1	0	0	1	0	0

Text Analytics: Applications

- Document Categorization/Classification
  - ✓ Sentiment Analysis

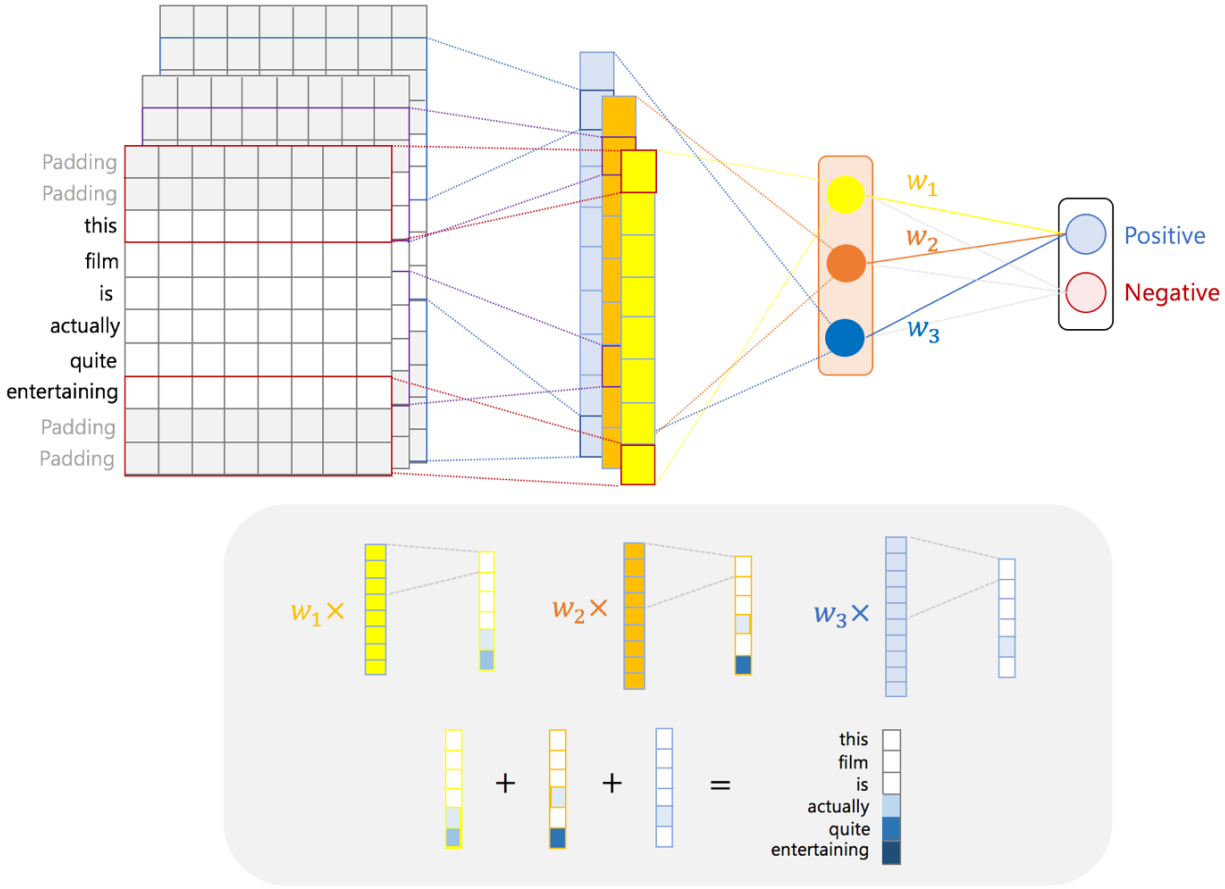


https://techxplore.com/news/2016-08-deep-neural-network-approach-sarcasm.html

Text Analytics: Applications

Lee et al. (2017)

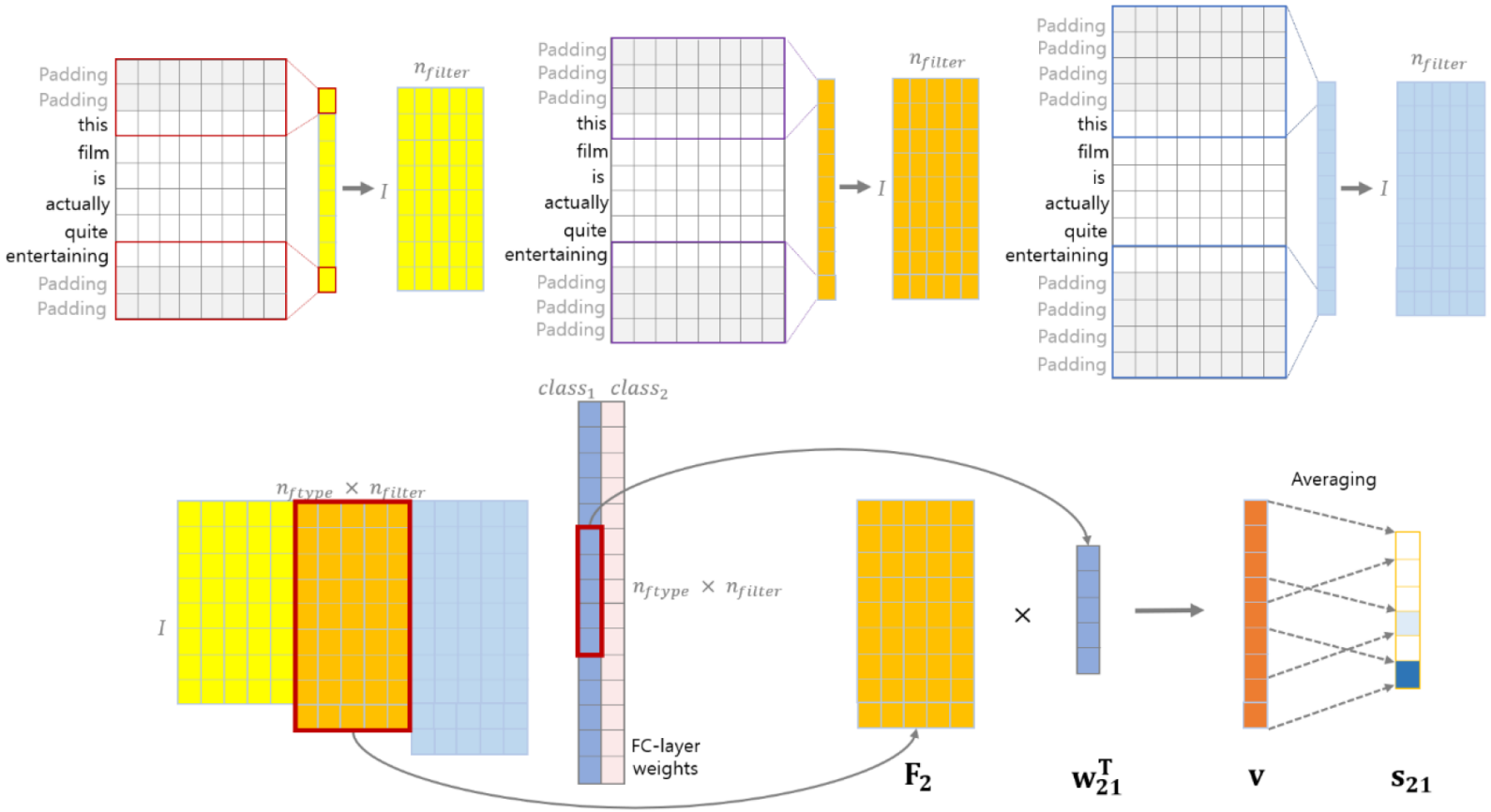
- Document Categorization/Classification
  - ✓ Sentiment Analysis



Text Analytics: Applications

Lee et al. (2017)

- Document Categorization/Classification
  - ✓ Sentiment Analysis



Text Analytics: Applications

Lee et al. (2017)

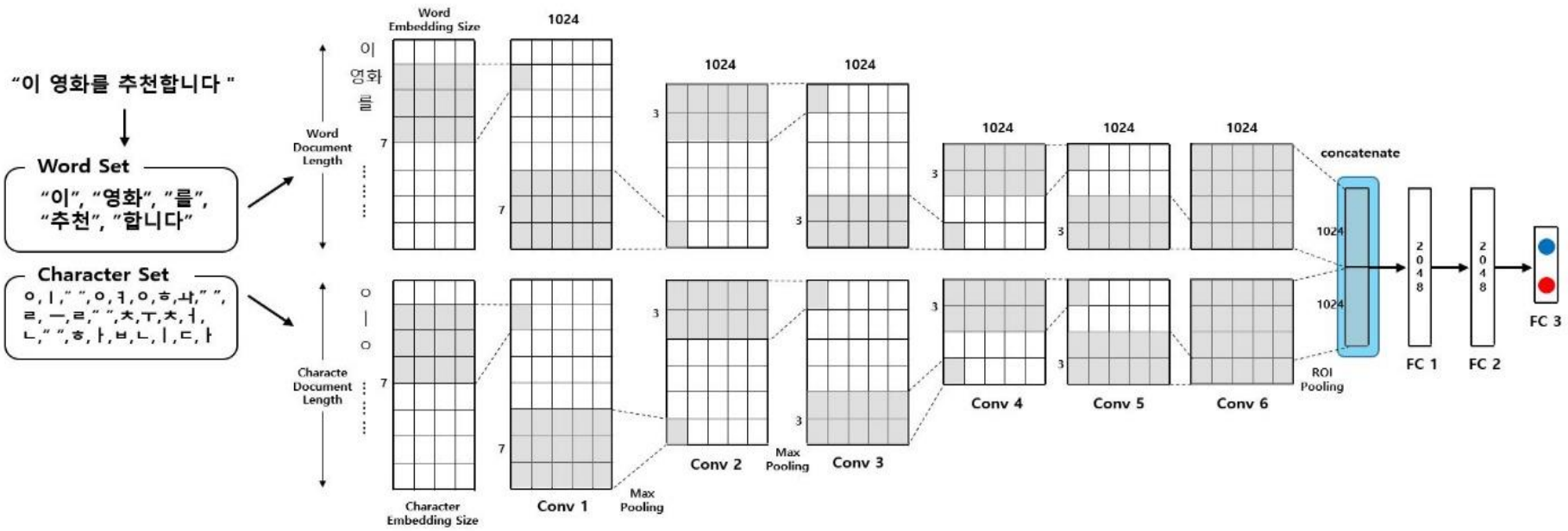
- Document Categorization/Classification
  - ✓ Sentiment Analysis

Methodology	Sentence
Raw text	I hate this movie. It is a horrid movie. Sean Young's character is completely unsympathetic. Her performance is wooden at best. The storyline is completely predictable and completely uninteresting. I would never recommend this film to anyone. It is one of the worst movies I have ever had the misfortune to see. *(1 / 10 points)*
CAM²-Rand	I hate this movie It is a horrid movie Sean Young s character is completely unsympathetic He r performance is wooden atbest The storyline is completely **predictable and completely uni nteresting** I would never recommend this film to anyone It is one of the **worst** movies I have ever had the misfortune to see **Negative**
CAM²-Static	I hate this movie It is a horrid movie Sean Young s character is completely unsympathetic He r performance is wooden atbest The storyline is **completely predictable and completely uni nteresting** I would never recommend this film to anyone It is one of the worst movies I have ever had the misfortune to see **Negative**
CAM²-Non-Static	I hate this movie It is a horrid movie Sean Young s character is completely unsympathetic He r performance is wooden atbest The storyline is completely **predictable and completely uni nteresting** I would never recommend this film to anyone It is one of the **worst** movies I have ever had the misfortune to see **Negative**
CAM²-2channel	I hate this movie It is a horrid movie Sean Young s character is completely unsympathetic He r performance is woodenat best The storyline is completely **predictable and completely uni nteresting** I would never recommend this film to anyone It is one of the **worst** movies I have ever had the misfortune to see **Negative**
CAM²-4channel	I hate this movie It is a horrid movie Sean Young s character is completely unsympathetic He r performance is woodenat best The storyline is completely **predictable and completely uni nteresting** I would never recommend this film to anyone It is one of the **worst** movies I have ever had the misfortune to see **Negative**
HAN	I **hate** this movie It is a **horrid** movie Sean Youngs character **is** completely unsympathetic He rperformance **is** wooden at best The storyline is completely predictable and completely **unin teresting** I would never recommend **this** film to anyone It is one of the **worst** movies I have e ver had the misfortune to see **Negative**

Text Analytics: Applications

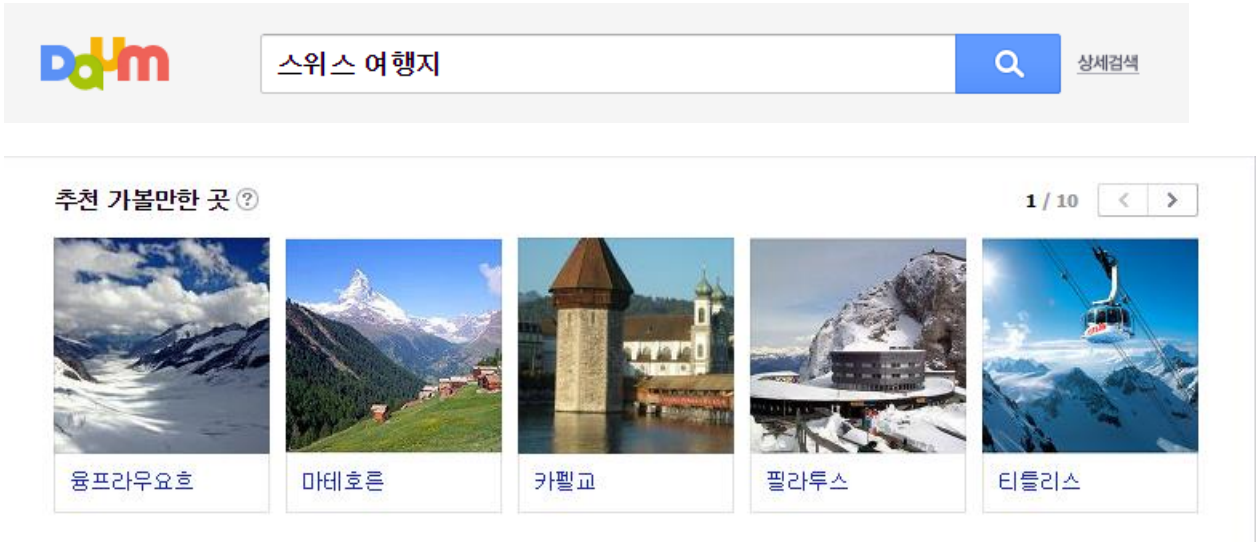
Mo et al. (2017)

- Document Categorization/Classification
  - ✓ Sentiment Analysis



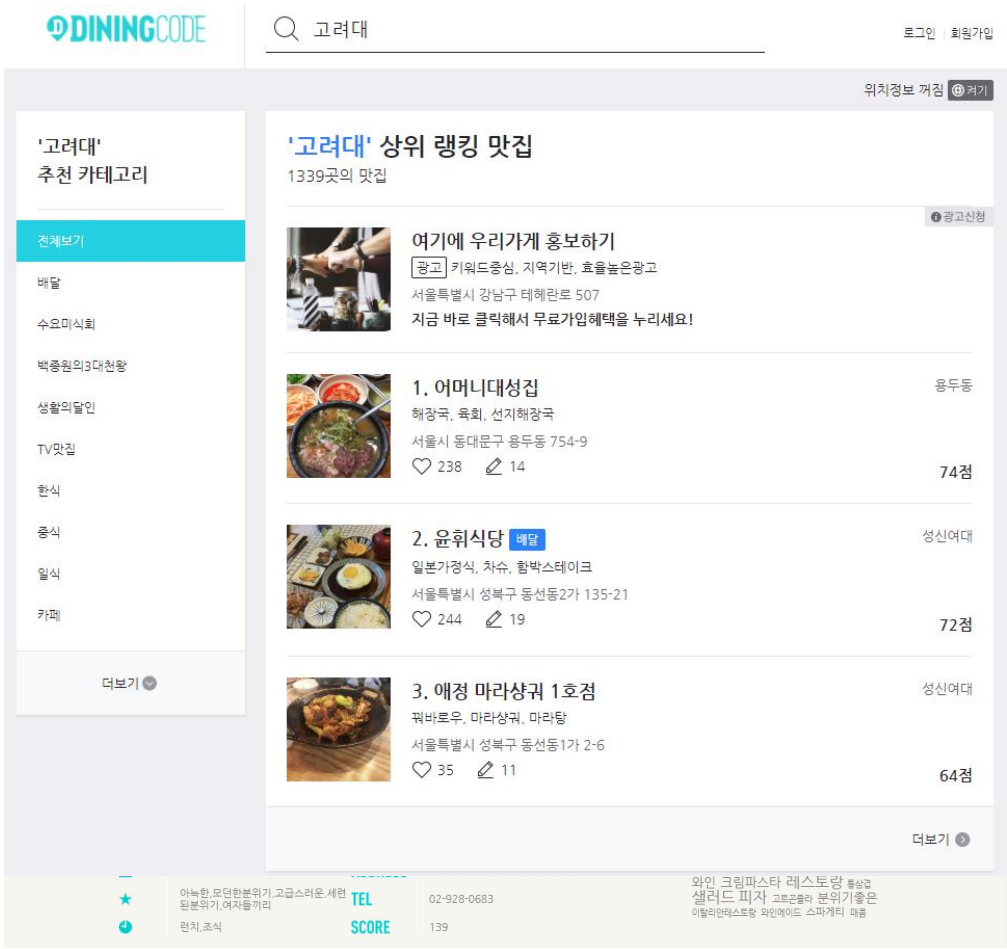
Text Analytics: Applications

- Recommendation
  - ✓ Analyze texts in daum café, blogs, and SNS contents
  - ✓ Named entity recognition/extraction (NEE/NER) technique in natural language processing is used
  - ✓ For 60,000 keywords



Text Analytics: Applications

- Recommendation
  - ✓ Dining code: restaurant recommendation service
    - Analyze restaurant review from top 3 blog services (naver, daum, tistory)
    - Assign higher weights to opinion leaders' posts
    - Filter advertising blog posts by analyzing the comments on a post



Developed by HS Shin, KKU http://www.diningcode.com/

Text Analytics: Applications

Kim et al. (2015)

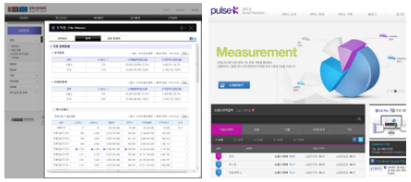
- Improve forecasting accuracy combined with structured data
  - ✓ Forecasting the box office scores based on the polarity of SNS posts

1 Movie Selection & Data Collection

Filtering rules
- Not too general title (ex: Mother)
- Total number of audiences ≥ 100,000

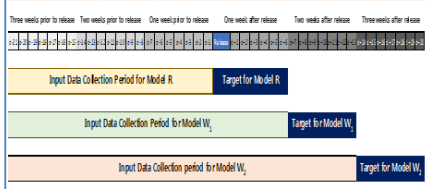
Screening data
- KOFIC
- www.kobis.or.kr

SNS data
- pulseK
- www.pulsek.com



2 Model Configuration & Variable Definition

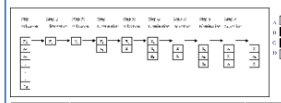
Model configuration
- Three forecasting models at different forecasting time and data collection periods



Variable definition
- Model **R** : 25 variables (1 screening, 24 SNS)
- Model $\mathbf{W_1}$: 32 variables (4 screening, 28 SNS)
- Model $\mathbf{W_2}$: 38 variables (6 screening, 32 SNS)

3 Variable Selection

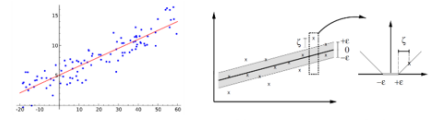
Variable selection
- Perform stepwise selection for forecasting models with screening data only
- Perform genetic algorithm for forecasting models with screening & SNS data



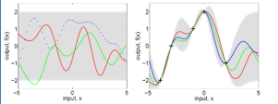
		w/o SNS	with SNS			
		Baseline	MLR	SVR	GPR	k-NN
Model R	Screening	1	1	1	1	1
	SNS		7	7	3	5
Model W_1	Screening	2	2	2	4	2
	SNS		2	6	0	8
Model W_2	Screening	4	3	6	5	6
	SNS		7	6	10	9

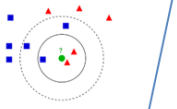
4 Single Forecasting Model Development & Evaluation

Single forecasting models
- 1 linear algorithm
- 3 machine learning-based algorithms


(a) Multivariate linear regression (MLR)

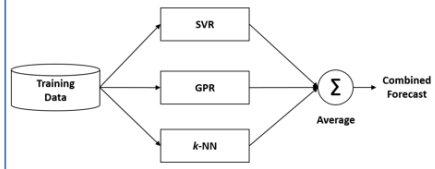
(b) Support vector regression (SVR)


(c) Gaussian process regression (GPR)


(d) k-Nearest Neighbor Regression (k-NN)

5 Combining Forecasts & Evaluation

Forecasting Combination
- Individual models: machine learning-based algorithms
- Combining rule: Equally weighted average



Text Analytics: Applications

Kim et al. (2015)

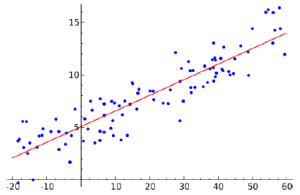
- Improve forecasting accuracy combined with structured data
  - ✓ Forecasting the box office scores based on the polarity of SNS posts

Category	Attribute	Model R	Model W_1	Model W_2
Target 1		Log_{10}(Box_office^1)	Log_{10}(Box_office^2)	Log_{10}(Box_office^3)
Target 2		Log_{10}(Box_office^1)	$Log_{10}(\sum_{i=1}^{2}$ Box_office$^i)$	$Log_{10}(\sum_{i=1}^{3}$ Box_office$^i)$
Screening	Original	N_seat_1	Box_office^1 N_seat_2 N_seat^1	Box_office^1+Box_office^2 N_seat_3 N_seat^2
	Derived		Weekly_seat_increase	N_seat^1+N_seat^2 Weekly_seat_increase Weekly_cumulative_seat_increase
SNS	Original	N_mention^p N_emotional^p N_positive^p N_negative^p $p \in \{-3, -2, -1\}$	N_mention^p N_emotional^p N_positive^p N_negative^p $p \in \{-3, -2, -1, 1\}$	N_mention^p N_emotional^p N_positive^p N_negative^p $p \in \{-3, -2, -1, 1, 2\}$
	Derived	Cumulative_mention Cumulative_emotional Cumulative_positive Cumulative_negative Avg_mention_increase Weekly_mention_increase Avg_emotional_increase Weekly_emotional_increase Avg_positive_increase Weekly_positive_increase Avg_negative_increase Weekly_negative_increase	Cumulative_mention Cumulative_emotional Cumulative_positive Cumulative_negative Avg_mention_increase Weekly_mention_increase Avg_emotional_increase Weekly_emotional_increase Avg_positive_increase Weekly_positive_increase Avg_negative_increase Weekly_negative_increase	Cumulative_mention Cumulative_emotional Cumulative_positive Cumulative_negative Avg_mention_increase Weekly_mention_increase Avg_emotional_increase Weekly_emotional_increase Avg_positive_increase Weekly_positive_increase Avg_negative_increase Weekly_negative_increase

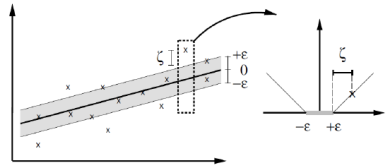
Text Analytics: Applications

Kim et al. (2015)

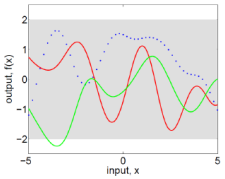
- Improve forecasting accuracy combined with structured data
  - ✓ Forecasting the box office scores based on the polarity of SNS posts

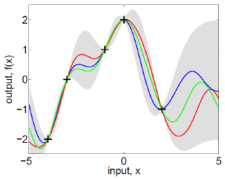


(a) Multivariate linear regression (MLR)

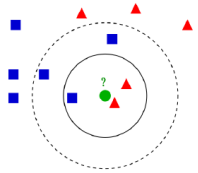


(b) Support vector regression (SVR)





(c) Gaussian process regression (GPR)



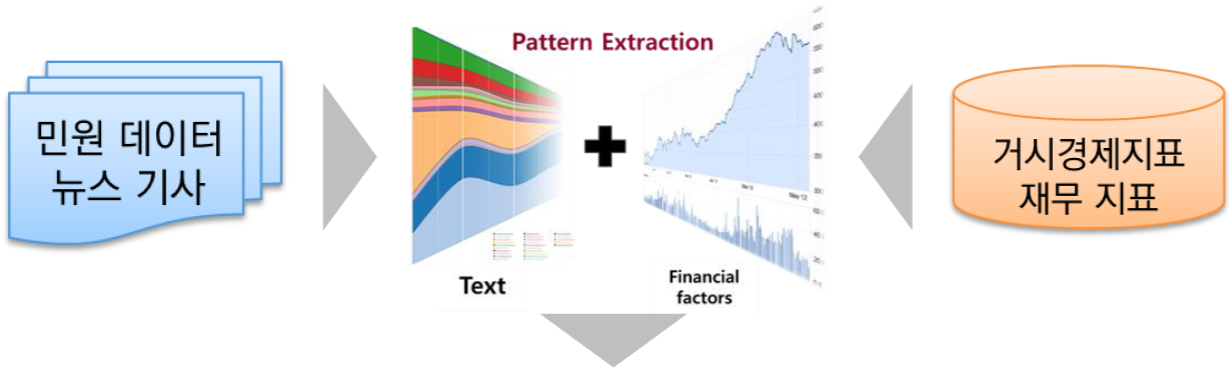
(d) k-nearest neighbor regression (k-NN)

Model	Linear Algorithm		Machine Learning				Combination
	Baseline	MLR	SVR	GPR	k-NN	Average	
Model R	0.8626	0.5958 (30.93%)	0.4278 (50.40%)* (28.19%)+	0.5087 (41.02%)* (14.62%)+	0.4605 (46.61%)* (22.71%)++	0.4657 (46.01%) (21.84%)	0.4496 (47.88%)* (24.54%)++ (3.45%)
Model W_1	0.1664	0.1535 (7.76%)	0.1251 (24.83%) (18.51%)	0.1206 (27.52%) (21.43%)	0.1288 (22.62%) (16.11%)	0.1248 (24.99%) (18.68%)	0.1216 (26.93%) (20.78%) (2.58%)
Model W_2	0.0624	0.0587 (5.90%)	0.0473 (24.16%)* (19.41%)+	0.0541 (13.29%) (7.86%)	0.0486 (22.15%) (17.27%)	0.0500 (19.87%) (14.84%)	0.0453 (27.38%)* (22.83%)+ (9.38%)

Text Analytics: Applications

송서하 외 (2019)

- Improve forecasting accuracy combined with structured data
  - ✓ Early warning model for financial firms



27 차원 재무 데이터	기사 Doc2Vec 50차원	기사 LDA 30차원	기사 개수	민원 개수	민원 LDA 30차원	민원 Doc2Vec 50차원

(27+50+30+1+1+30+50)
인스턴스 마다
총 189 차원 변수

+ 2 Scala
그룹화 되기 전 분기별 기사의 수
그룹화 되기 전 분기별 민원의 수

Text Analytics: Applications

송서하 외 (2019)

- Improve forecasting accuracy combined with structured data
  - ✓ Early warning model for financial firms

27개 재무 변수	
BIS자기자본비율	총자산경비율
BIS기본자본비율	자기자본이익률
총여신대비외화대출비율	수지비율
순이자마진율	원화예대금리차
단순자기자본비율	외화예대금리차
고정이하여신비율	총자산순이익율_1
연체대출채권비율	총자산순이익률_2
대손충당금적립비율	단기대출비율
커버리지비율	예대율
순요주의이하여신비율	부채총계
부채총계대비외화부채비율	자산총계
총여신대비고객예수금	자본총계
고정이하여신비율	순이자마진율
대손충당금비율	

실제 로지스틱 회귀

조기 경보 모형에서 사용중인 재무 변수

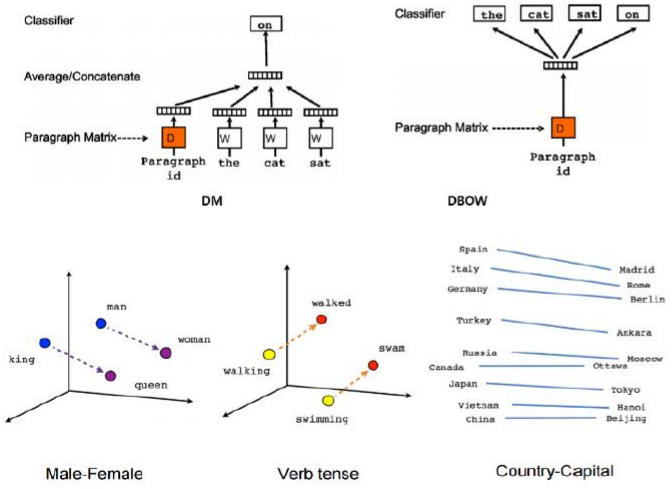
사.코드	회사명	날짜	C001.BIS자	C002.BIS기	A011.총여	E012.순이	C003.단순
10001	우리	200212	11.5927	6.580368	9.567668	3.136833	4.736041
10001	우리	200303	11.25434	6.543492	9.626936	3.149197	4.804393
10001	우리	200306	11.93472	7.269505	8.343038	3.306897	4.925109
10001	우리	200309	11.83714	7.351041	7.785889	3.2216	6.153432
10001	우리	200312	11.22903	6.821693	8.040745	3.19587	5.533509
10001	우리	200403	11.39602	6.975554	7.571517	3.170896	5.818036
10001	우리	200406	12.06747	7.559141	7.553917	3.000672	6.220084
10001	우리	200409	12.08542	7.152281	7.333561	3.041082	5.867916
10001	우리	200412	12.20036	7.814226	7.264898	2.987705	7.257877
10001	우리	200503	12.27278	8.625104	7.760409	2.915894	7.155567
10001	우리	200506	12.49602	8.935698	7.881458	2.90306	7.530039
10001	우리	200509	12.32116	9.035741	8.025136	2.820672	7.546571
10001	우리	200512	11.64708	8.085056	7.725328	2.967578	7.742147
10001	우리	200603	11.20014	7.847749	7.518282	2.904957	7.951988
10001	우리	200606	11.47836	7.582419	7.224173	2.776941	7.116087
10001	우리	200609	12.11703	7.700332	7.255265	2.666571	6.956471

Text Analytics: Applications

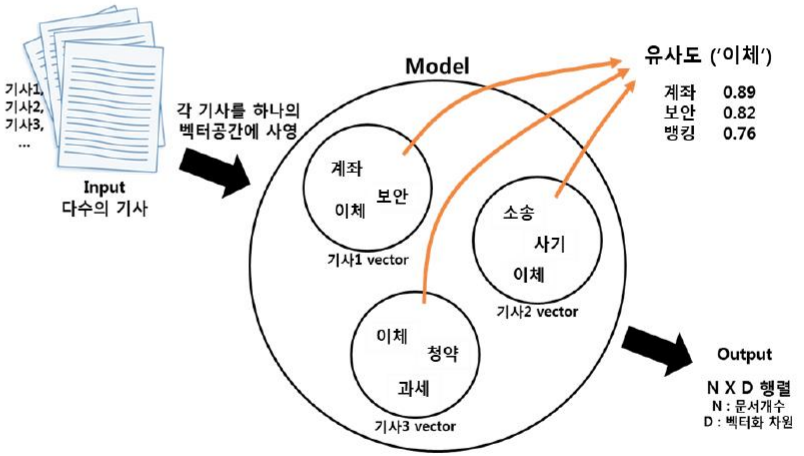
송서하 외 (2019)

- Improve forecasting accuracy combined with structured data
  - ✓ Early warning model for financial firms

Doc2Vec(paragraph vector)



〈 단어들사이의 의미론적 관계의 보존 〉



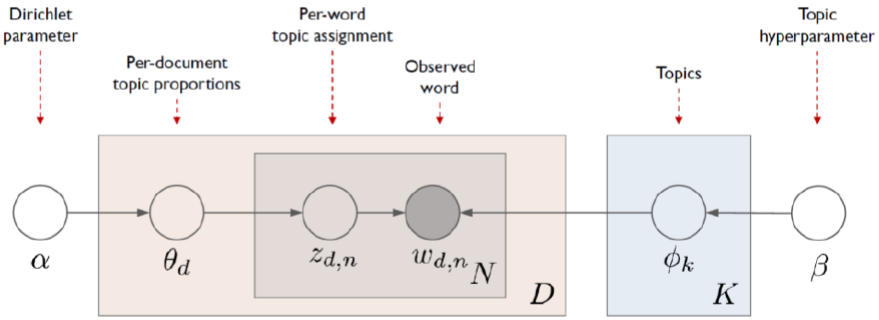
〈 Doc2Vec을 통한 뉴스기사 및 민원 데이터 표현 〉

Text Analytics: Applications

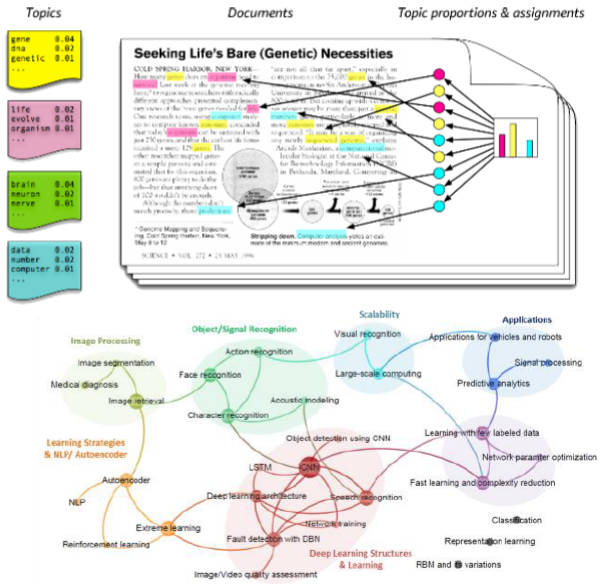
송서하 외 (2019)

- Improve forecasting accuracy combined with structured data
  - ✓ Early warning model for financial firms

Topic Modeling(Latent Dirichlet Allocation;LDA)



〈 Topic Modeling(LDA) 프로세스 〉



〈 토픽 모델링 수행 결과 예시 〉

Text Analytics: Applications

송서하 외 (2019)

- Improve forecasting accuracy combined with structured data
  - ✓ Early warning model for financial firms

Table 4. Model performance evaluation

		without text data			with text data		
		Precision	Recall	F1	Precision	Recall	F1
recent 1 quarter	logistic regression	0.5557 (0.2117)	0.90 (0.2)	0.6636 (0.1837)	0.6162 (0.2239)	0.950 (0.15)	0.722 (0.1703)
	random forest	0.8889 (0.2733)	0.7667 (0.3091)	0.8044 (0.2758)	0.9556 (0.1133)	1.0 (0)	**0.9733 (0.0680)**
	recurrent neural net	/	/	/	/	/	/
recent 2 quarters	logistic regression	0.8544 (0.1871)	1.0 (0)	0.9070 (0.1340)	0.6289 (0.232)	1.0 (0)	0.7483 (0.1692)
	random forest	0.8833 (0.2693)	0.80 (0.3055)	0.8189 (0.2686)	0.9556 (0.1133)	1.0 (0)	**0.9733 (0.0680)**
	recurrent neural net	0.8733 (0.1868)	0.8111 (0.1863)	0.8252 (0.1539)	0.9228 (0.1462)	0.8667 (0.1846)	0.8775 (0.1426)
recent 3 quarters	logistic regression	0.8633 (0.1871)	1.0 (0)	0.9146 (0.1206)	0.5967 (0.2466)	0.950 (0.150)	0.7083 (0.1955)
	random forest	0.9278 (0.2094)	0.90 (0.2380)	0.9033 (0.2147)	0.9556 (0.1133)	1.0 (0)	**0.9733 (0.0680)**
	recurrent neural net	0.9444 (0.1242)	0.9833 (0.0898)	0.9556 (0.0916)	0.9167 (0.1537)	0.9833 (0.0898)	0.9488 (0.1074)
recent 4 quarters	logistic regression	0.6911 (0.2016)	1.0 (0)	0.8013 (0.1354)	0.6144 (0.1979)	0.9833 (0.0898)	0.7384 (0.1475)
	random forest	0.9444 (0.1449)	0.8833 (0.2115)	0.8978 (0.1655)	0.950 (0.1302)	0.9833 (0.0898)	**0.9633 (0.1048)**
	recurrent neural net	0.9222 (0.1595)	0.9833 (0.0898)	0.940 (0.1133)	0.9111 (0.1652)	0.9667 (0.1247)	0.9222 (0.1242)

Text Analytics: Challenges

- Challenges
  - ✓ High number of possible "dimensions" (word, phrases, etc.)

List of dictionaries by number of words

From Wikipedia, the free encyclopedia

This list is incomplete; you can help by expanding it.

This is a list of dictionaries considered authoritative or complete by approximate number of total words, or headwords, included. These figures do not take account of entries with senses for different word classes (such as noun and adjective) and homographs. Although it is possible to count the number of entries in a dictionary, it is not possible to count the number of words in a language.[1][2] In compiling a dictionary, a lexicographer decides whether the evidence of use is sufficient to justify an entry in the dictionary. This decision is not the same as determining whether the word exists.[*citation needed*]

Language	Approx. no. of words	Dictionary	Notes
Korean	1,100,373	우리말샘 (Woori Mal Saem, 2017)	Online open dictionary including dialects of South and North Korea.[3]
Turkish	616,767	Büyük Türkçe Sözlük	Online dictionary of the Turkish Language Association[4]
Swedish	600,000	Svenska Akademiens ordbok, Swedish Academy	After having completed letters ***A*** through ***T*** SAOB included 470,000 words, but 600,000 words when the alphabet was completed in 2017. Svenska Akademiens ordlista, which includes only commonly used words, currently includes ~126,000 words after having added 13,500 and removed 9,000 in its latest edition, SAOL 14, plus an additional 200,000 still encountered words in earlier editions.[5][6]
Icelandic	560,000	Orðabók Háskólans	43,000 basic words and 519,000 compound words of which more than half are attested only once or don't get into print ("instant combinations")[7]
Japanese	500,000	Nihon Kokugo Daijiten	[8]
Lithuanian	500,000	Lietuvių kalbos žodynas (Academic Dictionary of Lithuanian)	22,000 pages in 20 volumes with quotations from all kinds of writing and dialect records between 1547 and 2001. Accessible online at www.lkz.lt.[9]
Norwegian	500,000	Norsk Ordbok	[10]
English	470,000	Merriam-Webster, Third Edition and Addenda Section	[11]
Dutch	400,000	Woordenboek der Nederlandsche Taal	The 43 volumes of the WNT (including three supplements) consist of 49,255 pages, describing Dutch words from 1500 to 1976.[12]
English	350,000	The American Heritage Dictionary of the English Language, Third Edition	In in the introduction to the 4th and 5th editions, it is mentioned that more than 10,000 words have been added, thus the total for the 5th edition will be more than 370,000 words.[13]
German	330,000	Deutsches Wörterbuch	330,000 words in use since the mid-fifteenth century. — Duden's *Großes Wörterbuch der deutschen Sprache* contains over 200,000 contemporary words.[14][15]
Gujarati	281,377	Bhagavadgomandal	2.81 lakh words and their meanings in 9 volumes. Also serves as an encyclopedia with almost 8.22 lakh words.[16]
Italian	260,000	Grande dizionario italiano dell'uso	The number of "sayable and writable" word forms is estimated at over 2 million[17]
Czech	250,000	cs:Příruční slovník jazyka českého	Nine volumes of this dictionary were printed in years 1935-1957. They contain about 250,000 words, their meanings and example usage from literature. The dictionary is available online. [18]
Belarusian	223,000	Большой словарь белорусского языка	[19]
English	207,016	WordNet, 3.1	As of November 2012 WordNet's latest Online-version is 3.1. The database contains 155,327 words organized in 175,979 synsets for a total of 207,016 word-sense pairs.[20]
Danish	200,000	Ordbog over det danske sprog, Dansk Sprognævn	Dansk Sprognævn grows with 5,000 to 7,000 words a year[21]
English	171,476	Oxford English Dictionary, Second Edition	Oxford Dictionary has 273,000 headwords; 171,476 of them being in current use, 47,156 being obsolete words and around 9,500 derivative words included as subentries. The dictionary contains 157,000 combinations and derivatives in bold type, and 169,000 phrases and combinations in bold italic type, making a total of over 600,000 word-forms.[22][23] There is one count that puts the English vocabulary at about 1 million words — but that count presumably includes words such as Latin species names, prefixed and suffixed words, scientific terminology, jargon, foreign words of extremely limited English use and technical acronyms.[24] [25][26]

Text Analytics: Challenges

- Challenges
  - ✓ Complex and subtle relationship between concepts in texts

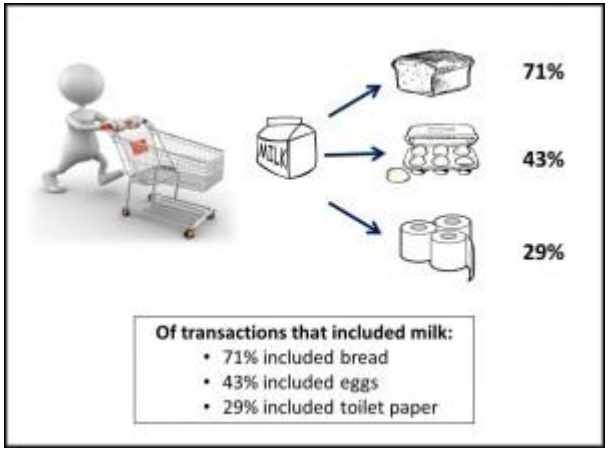
"장명준은 즐겁게 오버워치를 하다가 지도교수에게 들켰다 "

"강필성 교수는 우연히 들른 신공학관 220호에서 게임을 하는 한 학생을 목격했다 "

Text Analytics: Challenges

- Challenges
  - ✓ Ambiguity and context sensitivity
    - automobile = car = vehicle = Hyundai

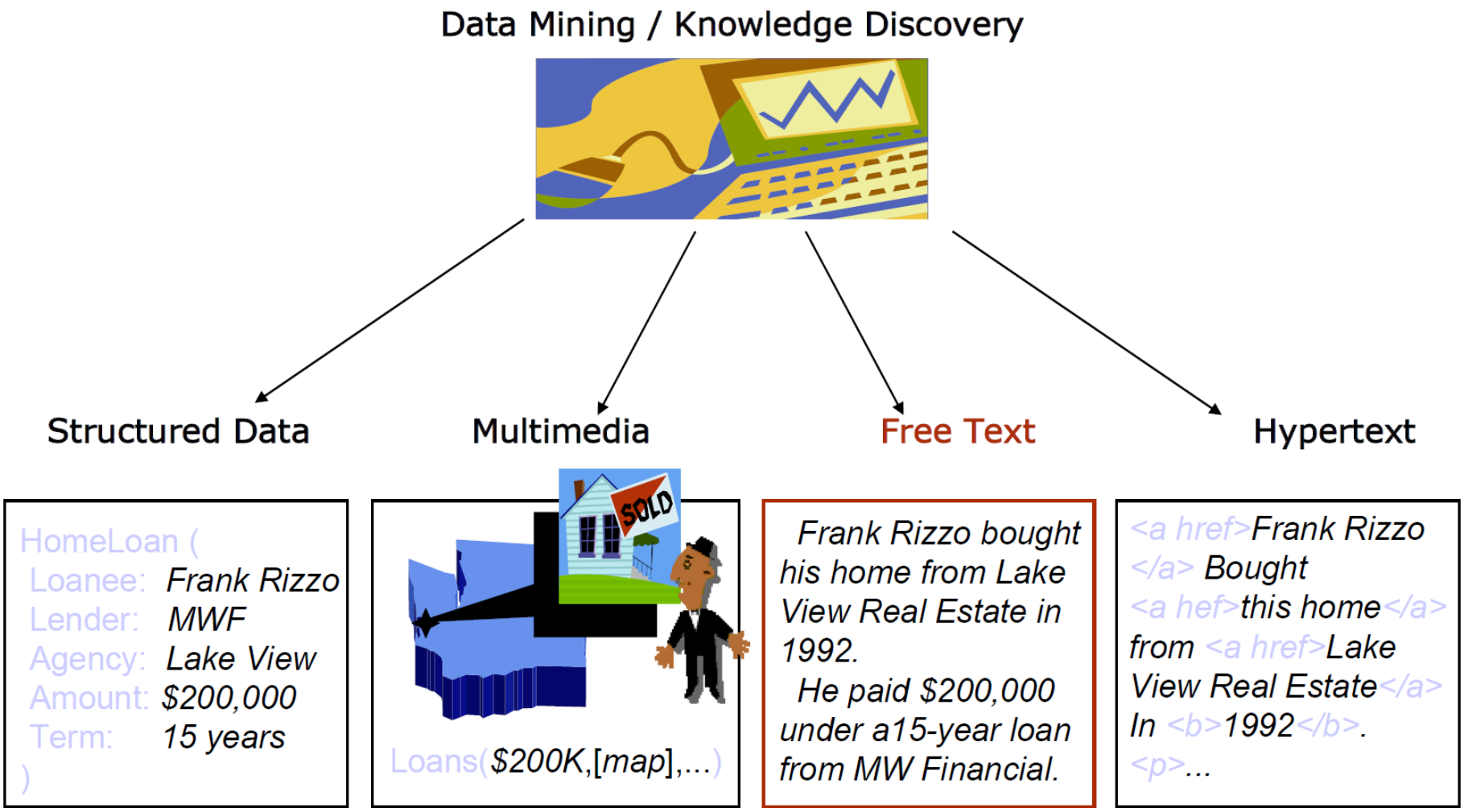
vs.



vs.

Text Analytics: Text Structures

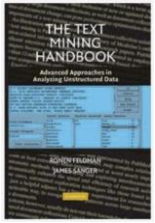
- Structure of text data



http://www.slideshare.net/pierluca.lanzi/machine-learning-and-data-mining-19-mining-text-and-web-data

Text Analytics: Text Structures

Abbott (2013)

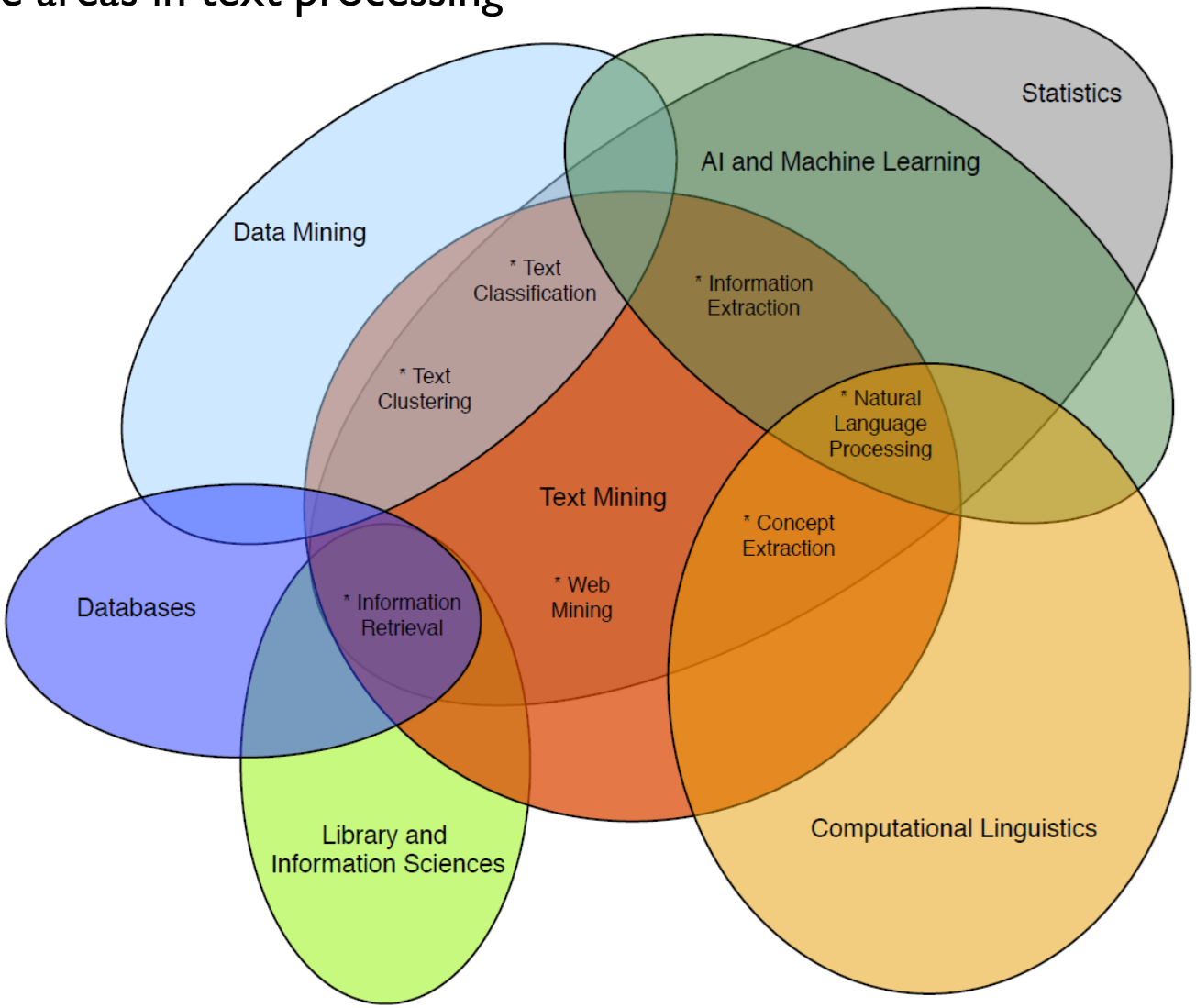


- How Unstructured is "Unstructured"? (by Feldman and Sanger)
  - ✓ Weakly structured
    - Few structural cues to text based layout or markups: research papers, legal memoranda, news stories, etc.
  - ✓ Semi-structured
    - Extensive format elements, metadata, field labels: E-mail, HTML/XML web pages, pdf files, etc.
- Why is Text Mining Hard?
  - ✓ Language itself is ambiguous
    - Contexts is needed to clarify
    - Same word with different meanings, different words with same meaning
    - Misspellings, abbreviations, etc.

Text Analytics: Areas

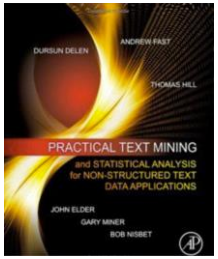
Abbott (2013)

- Active areas in text processing



Types of Text Analytics

Abbott (2013)



- Seven Types of Text Mining (by Elder et al.)
  - ✓ Document Classification
    - Grouping and categorizing snippets, paragraphs, or document using data mining classification methods, based on models trained on labeled examples
  - ✓ Document Clustering
    - Grouping and categorizing terms, snippets, paragraphs or documents using data mining clustering methods
  - ✓ Concept Extraction
    - Grouping or words and phrases into semantically similar groups

Mining Text Data

Abbott (2013)

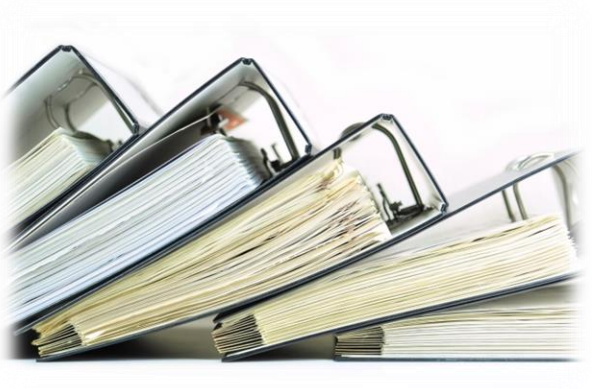
- Seven Types of Text Mining (by Elder et al.)
  - ✓ Search and Information Retrieval (IR)
    - Storage and retrieval of text documents, including search engines and keyword search
  - ✓ Information Extraction (IE)
    - Identification and extraction of relevant facts and relationships from unstructured texts, the process of making structured data from unstructured and semi-structured texts
  - ✓ Web Mining
    - Data and text mining on the internet with a specific focus on the scale and interconnectedness of the web
  - ✓ Natural Language Processing (NLP)
    - Low-level language processing and understanding tasks (e.g., tagging part of speech)
    - Often used synonymously with computational linguistics

A Simplified Process of Text Analytics

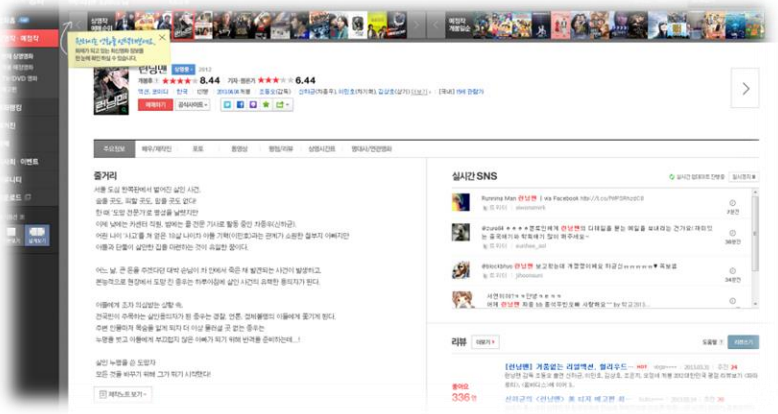
Source of text data

Digital library

Corporate document archive



Word Wide Web (WWW)



SNS

Step 1:
Decide what to mine
& Collect text data

A Simplified Process of Text Analytics

From unstructured to structured!

S1: Jon likes to watch movies. Mary likes too.

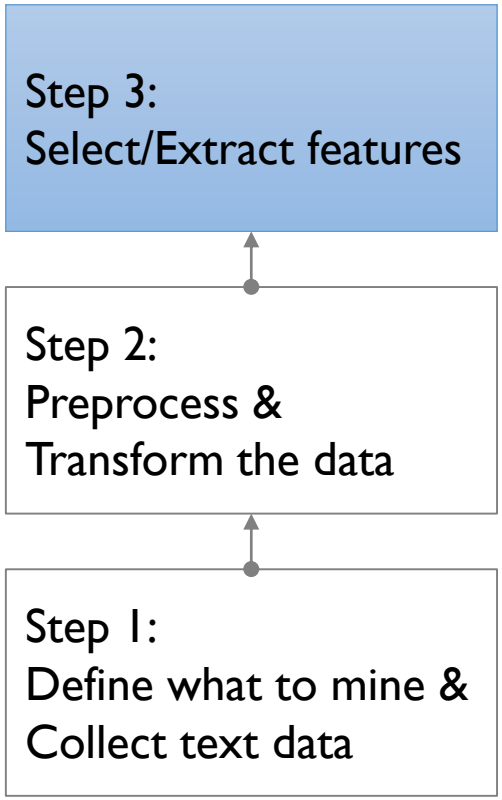
S2: John also likes to watch football game.

Word	S1	S2
John	1	1
Likes	2	1
To	1	1
Watch	1	1
Movies	1	0
Also	0	1
Football	0	1
Games	0	1
Mary	1	0
too	1	0

Step 2:
Preprocess &
Transform the data

Step 1:
Define what to mine &
Collect text data

A Simplified Process of Text Analytics



Reduce the number of features

Word	S1	S2
John	1	1
Likes	2	1
To	1	1
Watch	1	1
Movies	1	0
Also	0	1
Football	0	1
Games	0	1
Mary	1	0
too	1	0

Word	S1	S2
Likes	2	1
Watch	1	1
Movies	1	0
Football	0	1
Games	0	1

A Simplified Process of Text Analytics

Step 4:
Algorithm Learning & Evaluation

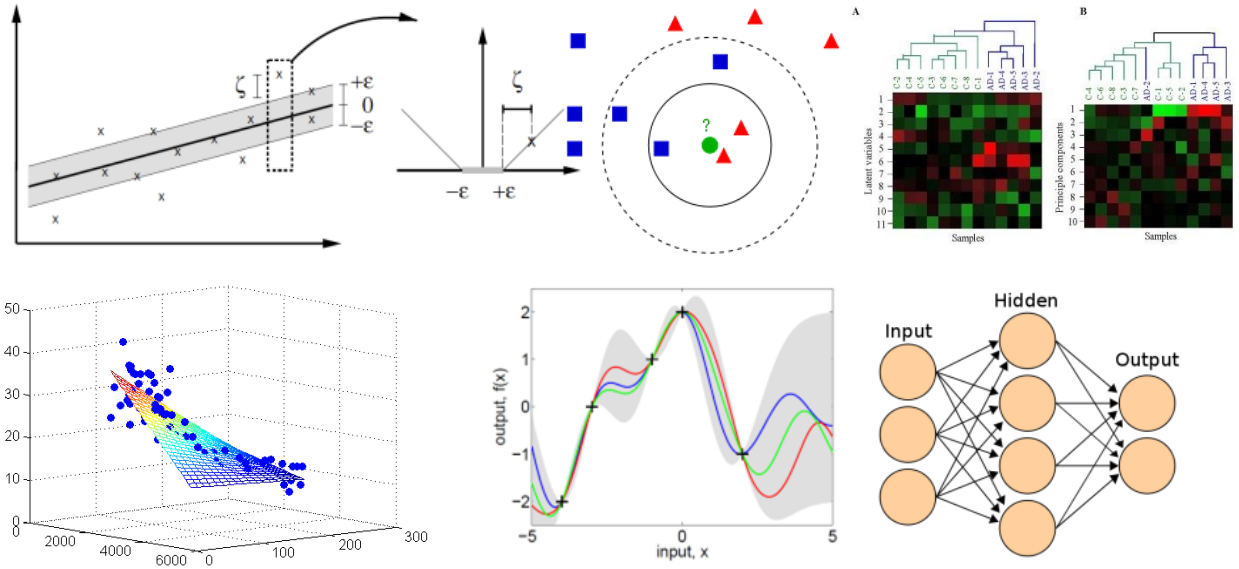
Step 3:
Select/Extract features

Step 2:
Preprocess & Transform the data

Step 1:
Define what to mine & Collect text data

Select appropriate algorithm

- Vector space model vs. Probabilistic model
- Classification vs. Clustering vs. Association



AGENDA

01 Text Analytics: Overview

02 TA Process 1: Collection & Preprocessing

03 TA Process 2: Transformation

04 TA Process 3: Dimensionality Reduction

05 TA Process 4: Learning & Evaluation

Decide What to Mine

Witte (2006)

- From a wide range of text sources…

Emails, Instant Messages, Blogs, . . .

Look for:

- Entities (Persons, Companies, Organizations, . . .)
- Events (Inventions, Offers, Attacks, . . .)

Biggest existing system: ECHELON (UKUSA)

News: Newspaper articles, Newswires, . . .

Similar to last, but additionally:

- collections of articles (e.g., from different agencies, describing the same event)
- contrastive summaries (e.g., event described by U.S. newspaper vs. Arabic newspaper)
- also needs temporal analysis
- main problems: cross-language and cross-document analysis

Many publicly accessible systems, e.g. *Google News* or *Newsblaster*.

Decide What to Mine

Witte (2006)

- From a wide range of text sources…

(Scientific) Books, Papers, . . .

- detect new trends in research
- automatic curation of research results in Bioinformatics

need to deal with highly specific language

Software Requirement Specifications, Documentation, . . .

- extract requirements from software specification
- detect conflicts between source code and its documentation

Web Mining

extract and analyse information from web sites

- mine companies' web pages (detect new products & trends)
- mine Intranets (gather knowledge, find "illegal" content, . . .)

problems: not simply plain text, also hyperlinks and hidden information ("deep web")

Decide What to Mine

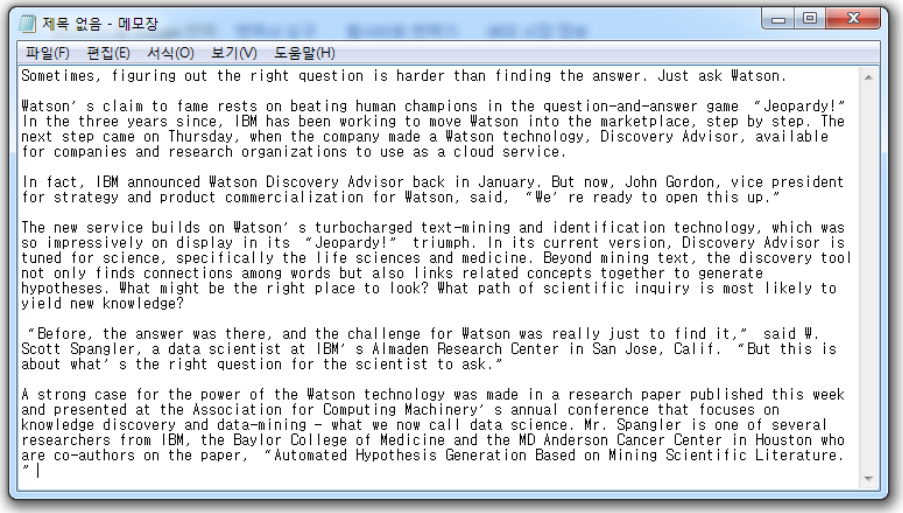
Witte (2006)

- Open datasets/repositories
  - ✓ The best 25 datasets for NLP (2018.06.07)
    - https://gengo.ai/datasets/the-best-25-datasets-for-natural-language-processing/
  - ✓ Alphabetical list of free/public domain datasets with text data for use in Natural Language Processing (NLP)
    - https://github.com/niderhoff/nlp-datasets
  - ✓ 50 Free Machine Learning Datasets: Natural Language Processing
    - https://blog.cambridgespark.com/50-free-machine-learning-datasets-natural-language-processing-d88fb9c5c8da
  - ✓ 25 Open Datasets for Deep Learning Every Data Scientist Must Work With
    - https://www.analyticsvidhya.com/blog/2018/03/comprehensive-collection-deep-learning-datasets/

Text Preprocessing Level 0: Text

- Remove unnecessary information from the collected data

- Remove figures, advertisements, html syntax, hyperlinks, etc.



Text Preprocessing Level 0: Text

- Do not remove meta-data, which contains significant information on the text
  - ✓ Ex) Newspaper article: author, date, category, language, newspaper, etc.
- Meta-data can be used for further analysis
  - ✓ Target class of a document
  - ✓ Time series analysis

New York City Public Schools Should Be Evaluated Based on Diversity, Not Just Tests, Panel Says

Mayor Bill de Blasio, flanked by New York City Schools Chancellor Richard Carranza, right, delivers remarks about a diversity plan in Brooklyn. Dave Sanders for The New York Times

By Eliza Shapiro

Feb. 12, 2019

[What you need to know to start the day: Get New York Today in your inbox.]

A high-level panel commissioned by Mayor Bill de Blasio called on the city to adopt a sweeping measure to address entrenched segregation in education: create diversity targets for all 1,800 schools so that their population reflects the racial and economic makeup of the surrounding areas.

Over the next five years, the panel recommended, elementary and middle schools should reflect the racial makeup of their local school district, and high schools should look as much like their local borough as possible, in terms of race, income level, disability and proficiency in English.

New York's schools have become increasingly divided along racial lines over the last two decades, and the city is currently home to one of the most segregated urban public school systems in America.

Mr. de. Blasio, now in his second term, ran on a promise to reduce inequality in all aspects of city life. But, when it comes to school segregation, he has been stymied by the same quandary that previous mayors faced: How to redistribute resources so that black and Hispanic students have more access to high-quality schools without alienating middle class, white families.

Text Preprocessing Level 1: Token

- Extracting meaningful (worth being analyzed) tokens (word, number, space, etc.) from a text is not an easy task.
  - ✓ Is John's sick one token or two?
    - If one → problems in parsing (where is the verb?)
    - If two → what do we do with John's house?
  - ✓ What to do with hyphens?
    - database vs. data-base vs. data base
  - ✓ What to do with "C++", "A/C", ":-)", "…", "ㅋㅋㅋㅋㅋㅋㅋㅋㅋ"?
  - ✓ Some languages do not use whitespace (e.g., Chinese)

2013年5月，习主席在视察成都战区时，郑重提出在适当时候召开全军政治工作会议，并明确提出到古田召开这次会议，以更好弘扬我党我军的光荣传统和优良作风。6月，总政治部向中央军委提交《关于筹备召开全军政治工作会议的请示》，提出要通过召开会议形成一个指导性文件。习主席随即批示同意，明确要求这个文件要充分体现深厚的历史积淀和政治意蕴，能够管一个时期，起到历史性作用。

- Consistent tokenization is important for all later processing steps.

Text Preprocessing Level 1: Token

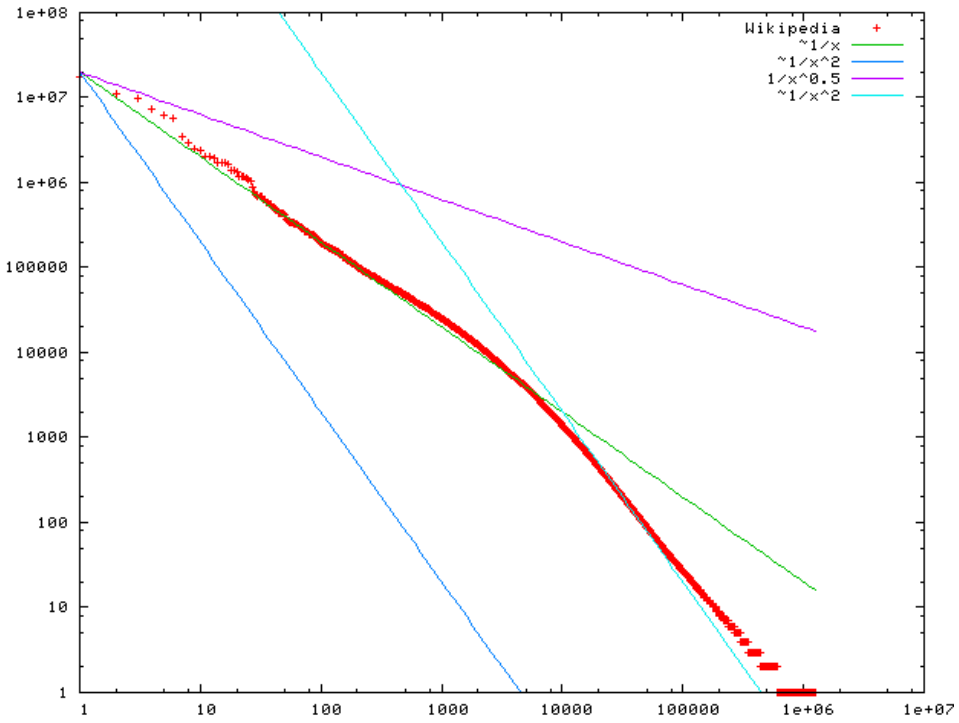
- Power distribution in word frequencies
  - ✓ It is not true that more frequently appeared words (tokens) are more important for text mining tasks.

100 common words in the Oxford English Corpus

Rank	Word	Rank	Word	Rank	Word	Rank	Word	Rank	Word
1	the	21	this	41	so	61	people	81	back
2	be	22	but	42	up	62	into	82	after
3	to	23	his	43	out	63	year	83	use
4	of	24	by	44	if	64	your	84	two
5	and	25	from	45	about	65	good	85	how
6	a	26	they	46	who	66	some	86	our
7	in	27	we	47	get	67	could	87	work
8	that	28	say	48	which	68	them	88	first
9	have	29	her	49	go	69	see	89	well
10	I	30	she	50	me	70	other	90	way
11	it	31	or	51	when	71	than	91	even
12	for	32	an	52	make	72	then	92	new
13	not	33	will	53	can	73	now	93	want
14	on	34	my	54	like	74	look	94	because
15	with	35	one	55	time	75	only	95	any
16	he	36	all	56	no	76	come	96	these
17	as	37	would	57	just	77	its	97	give
18	you	38	there	58	him	78	over	98	day
19	do	39	their	59	know	79	think	99	most
20	at	40	what	60	take	80	also	100	us

http://en.wikipedia.org/wiki/Most_common_words_in_English

Word frequency distribution in Wikipedia



http://upload.wikimedia.org/wikipedia/commons/b/b9/Wikipedia-n-zipf.png

Text Preprocessing Level 1: Word

- Stop-words
  - ✓ Words that do not carry any information
    - Mainly functional role
    - Usually remove them to help the machine learning algorithms to perform better
  - ✓ Natural language dependent
    - English: a, about, above, across, after, again, against, all, also, etc.
    - 한국어: …습니다, …로서(써), …를 등

[Original text]

Information Systems Asia Web - provides research, IS-related commercial materials, interaction, and even research sponsorship by interested corporations with a focus on Asia Pacific region.

[After removing stop words]

Information Systems Asia Web provides research IS-related commercial materials interaction research sponsorship interested corporations focus Asia Pacific region

http://eprints.pascal-network.org/archive/00000017/01/Tutorial_Marko.pdf

Text Preprocessing Level 1: Word

- Stemming
  - ✓ Different forms of the same word are usually problematic for text data analysis, because they have different spelling and similar meaning
    - Learns, learned, learning, …
  - ✓ Stemming is a process of transforming a word into its stem (normalized form)
    - In English: Porter2 stemmer (http://snowball.tartarus.org/algorithms/english/stemmer.html)
    - In Korean, 꼬꼬마 형태소 분석기 (http://kkma.snu.ac.kr/documents/)

word	stem	word	stem
consign	consign	knack	knack
consigned	consign	knackeries	knackeri
consigning	consign	knacks	knack
consignment	consign	knag	knag
consist	consist	knave	knave
consisted	consist	knaves	knave
consistency	consist	knavish	knavish
consistent	consist	kneaded	knead
consistently	consist	kneading	knead
consisting	consist	knee	knee
consists	consist	kneel	kneel
consolation	consol	kneeled	kneel
consolations	consol	kneeling	kneel
consolatory	consolatori	kneels	kneel
console	consol	knees	knee
consoled	consol	knell	knell
consoles	consol	knelt	knelt
consolidate	consolid	knew	knew
consolidated	consolid	knick	knick
consolidating	consolid	knif	knif

Text Preprocessing Level 1: Word

- Lemmatization
  - ✓ Although stemming just finds any base form, which does not even need to be a word in the language, but lemmatization finds the actual root of a word

Word	Stemming	Lemmatization
Love	Lov	Love
Loves	Lov	Love
Loved	Lov	Love
Loving	Lov	Love
Innovation	Innovat	Innovation
Innovations	Innovat	Innovation
Innovate	Innovat	Innovate
Innovates	Innovat	Innovate
Innovative	Innovat	Innovative

Text Preprocessing Level 2: Sentence

- Correct sentence boundary is also important
  - ✓ For many downstream analysis tasks
    - POS-Tagger maximize probabilities of tags within a sentence
    - Summarization systems rely on correct detection of sentence

Mark Sentence Boundaries

Detects sentence units. Easy case:

- often, sentences end with ".", "!", or "?"

Hard (or annoying) cases:

- difficult when a "." do not indicate an EOS:
  "MR. X", "3.14", "Y Corp.", ...
- we can detect common abbreviations ("U.S."), but what if a sentence ends with one?
  "...announced today by the U.S. The..
- Sentences can be *nested* (e.g., within quotes)

AGENDA

Text Transformation

- Document representation
  - ✓ Bag-of-words: simplifying representation method for documents where a text is represented in a vector of an unordered collection of words

S1: Jon likes to watch movies. Mary likes too.

S2: John also likes to watch football game.

Word	S1	S2
John	1	1
Likes	2	1
To	1	1
Watch	1	1
Movies	1	0
Also	0	1
Football	0	1
Games	0	1
Mary	1	0
too	1	0

aardvark	0
about	2
all	2
Africa	1
apple	0
anxious	0
...	
gas	1
...	
oil	1
…	
Zaire	0

Text Transformation

- Word Weighting
  - ✓ Each word is represented as a separate variable with a numeric weight
  - ✓ Term frequency and inverse document frequency (**TF-IDF**)
    - $tf(w)$: term frequency (number of word occurrences in a document)
    - $df(w)$: number of documents containing the word (number of documents containing the word)

$$TF - IDF(w) = tf(w) \times \log\left(\frac{N}{df(w)}\right)$$

The word is more important if it appears several times in a target document

The word is more important if it appears in less documents

Text Transformation

- Word weighting (cont'): example

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	5.25	3.18	0	0	0	0
Brutus	1.21	6.1	0	1	0	0
Caesar	8.59	2.54	0	1.51	0.25	0.35
Calpurnia	0	1.54	0	0	0	0
Cleopatra	2.85	0	0	0	0	0
mercy	1.51	0	1.9	0.12	5.25	0.88
worser	1.37	0	0.11	4.15	0.25	1.95

Text Transformation

- One-hot-vector representation
  - ✓ The most simple & intuitive representation

$$w^{aardvark} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, w^{a} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, w^{at} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \ldots w^{zebra} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$$

  - ✓ Can make a vector representation, but similarities between words cannot be preserved.

$$(w^{hotel})^{\top} w^{motel} = (w^{hotel})^{\top} w^{cat} = 0$$

Text Transformation

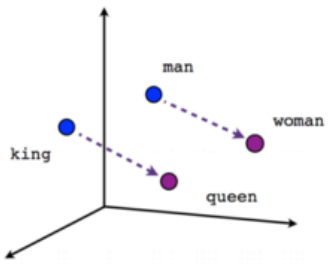
- Word vectors: distributed representation
  - ✓ A parameterized function mapping words in some language to a certain dimensional vectors

$$W : \text{words} \rightarrow \mathbb{R}^n$$

$$W(\text{“cat”}) = (0.2,\ \text{-}0.4,\ 0.7,\ \ldots)$$

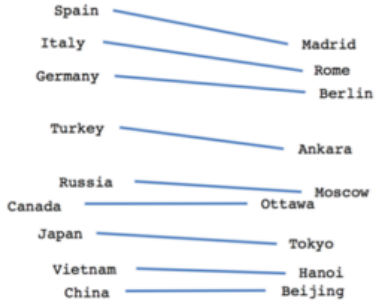
$$W(\text{“mat”}) = (0.0,\ 0.6,\ \text{-}0.1,\ \ldots)$$

- Interesting feature of word embedding
  - ✓ Semantic relationship between words can be preserved



Male-Female

Verb tense



Country-Capital

Text Transformation

- Word vectors: distributed representation

http://nlp.stanford.edu/projects/glove/

AGENDA

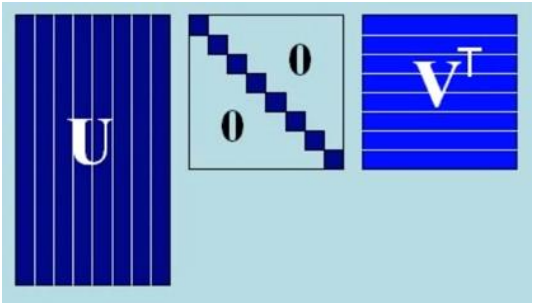
Feature Selection/Extraction

- Feature subset selection
  - ✓ Select only the best features for further analysis
    - The most frequent
    - The most informative relative to the all class values, …
  - ✓ Scoring methods for individual feature (for supervised learning tasks)
    - Information gain: $\sum_{F=W,\overline{W}} P(F) \sum_{C=pos,neg} P(C|F) \log \frac{P(C|F)}{P(C)}$
    - Cross-entropy: $P(W) \sum_{C=pos,neg} P(C|W) \log \frac{P(C|W)}{P(C)}$
    - Mutual information: $\sum_{C=pos,neg} P(C) \log \frac{P(W|C)}{P(W)}$
    - Weight of evidence: $\sum_{C=pos,neg} P(C)P(W) \left| \log \frac{P(C|W)(1-P(C))}{P(C)(1-P(C|W))} \right|$
    - Odds ratio: $\log \frac{P(W|pos) \times (1-P(W|neg))}{(1-P(W|pos)) \times P(W|neg)}$
    - Frequency: $Freq(W)$

Feature Selection/Extraction

- Feature subset extraction
  - ✓ Feature extraction: construct a set of variables that preserve the information of the original data by combining them in a linear/non-linear form
  - ✓ Latent Semantic Analysis (LSA) that is based on singular value decomposition is commonly used

m x r r x r r x n

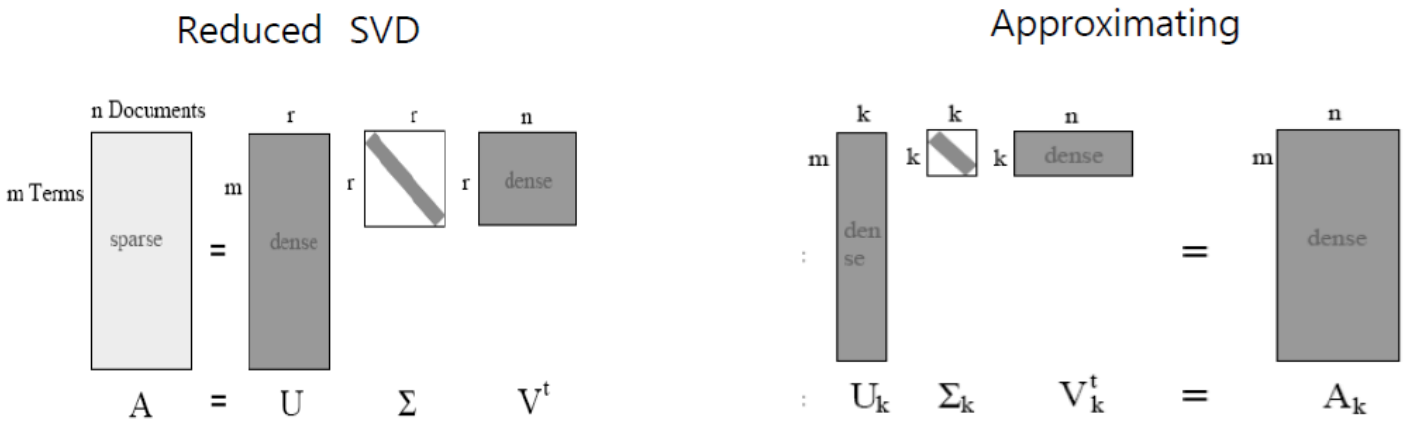


- Rectangular matrix A(m x n) can be decomposed as $\mathbf{A} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathbf{T}}$
- All singular vectors of the matrices U and V are orthogonal $\mathbf{U}^{\mathbf{T}}\mathbf{U} = \mathbf{V}^{\mathbf{T}}\mathbf{V} = \mathbf{I}$
- Eigenvalues of the matrix ∑ is positive and sorted in a descending order

Feature Selection/Extraction

Lee (2010)

- SVD in Text Mining (Latent Semantic Analysis/Indexing)



✓ Step 1) Using SVD, a term-document matrix D is reduced to D_k

$$\mathbf{D} \approx \mathbf{D}_k = \mathbf{U}_k \mathbf{\Sigma}_k \mathbf{V}_k^{\mathrm{T}}$$

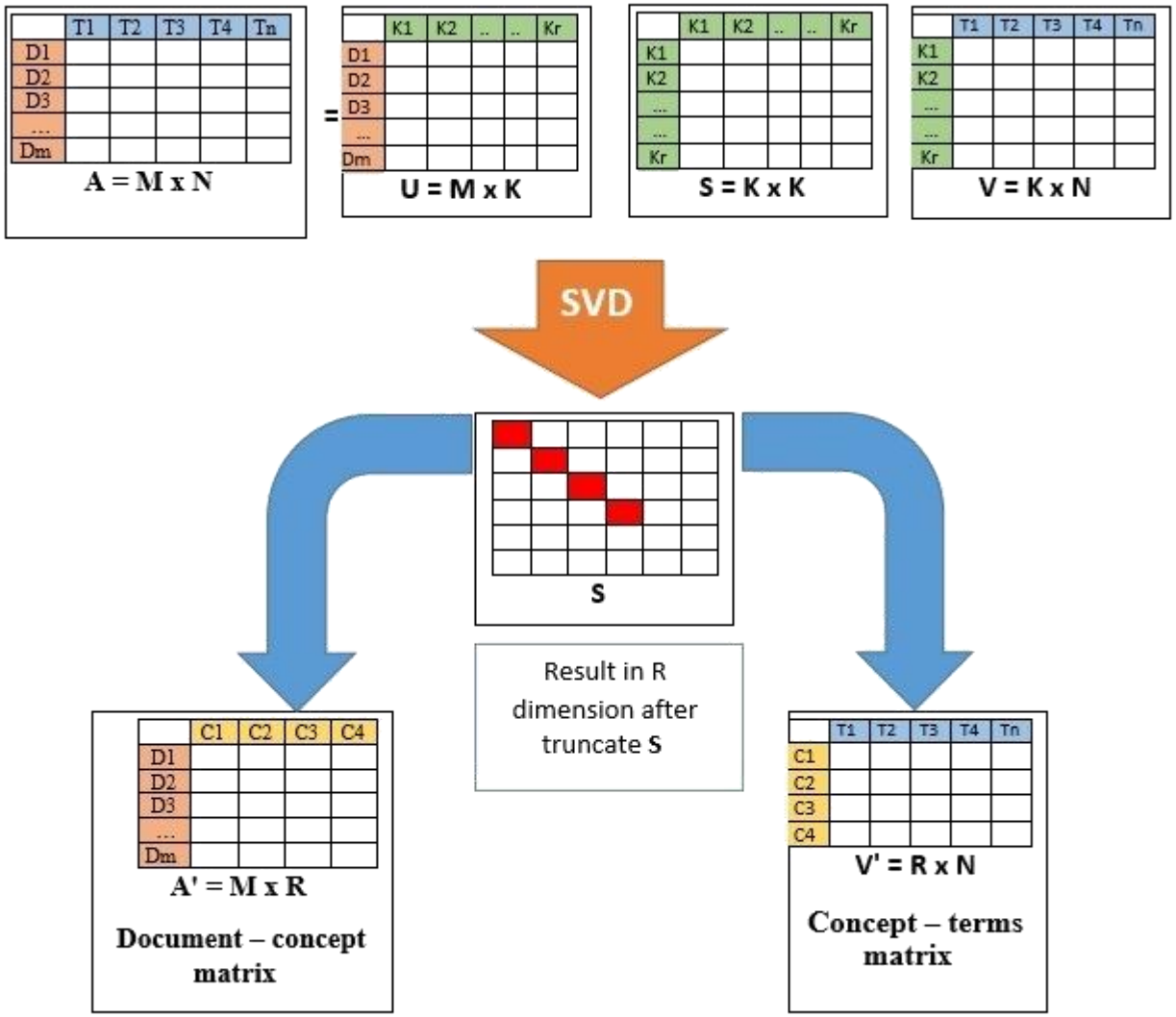
✓ Step 2) Multiply the transpose of the matrix U_k

$$\mathbf{U}_k^{\mathrm{T}} \mathbf{D}_k = \mathbf{\Sigma}_k \mathbf{V}_k^{\mathrm{T}}$$

✓ Apply data mining algorithms to the matrix obtained in the Step 2)

Feature Selection/Extraction

- LSA



https://www.quora.com/How-is-LSA-used-for-a-text-document-clustering

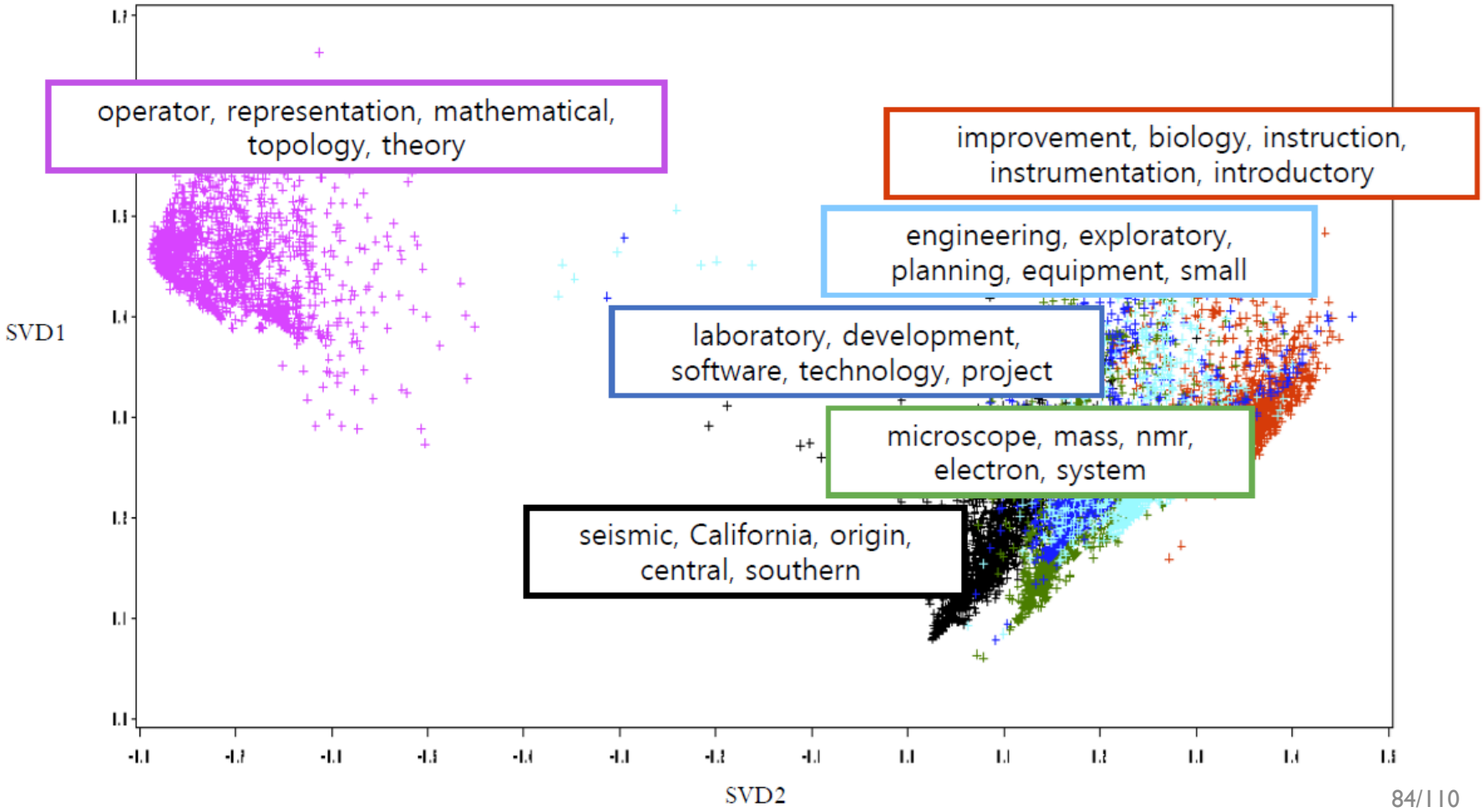
Feature Selection/Extraction

- LSA example
  - ✓ Data: 41,717 abstracts of the research projects that were funded by National Science Foundation (NSF) between 1990 and 2003
  - ✓ Top 10 positive and negative keywords for each SVD

(−) SVD1	(+)	(−) SVD2	(+)	(−) SVD3	(+)
sister−chromatid	real	sum	electronics	revised	evaporation
plastids	other	diophantine	enhanced	major	agglomerate
segregation	reduction	mathematical	video	introductory	mobility
pneumoniae	dimensional	yang−mills	computer−based	miniority	transient
males	complex	noetherian	improved	computer−based	multicomponent
candida	multiple	differential equations	major	micro computer	lateral
trait	expansion	equations	support	laboratory	distribution
decline	domain	invariant	instructional	unix−based	copolymer
factorial	vector	asymtotic	theme	ample	compacted
gmp	stability	non−commutative	capability	inquiry	long

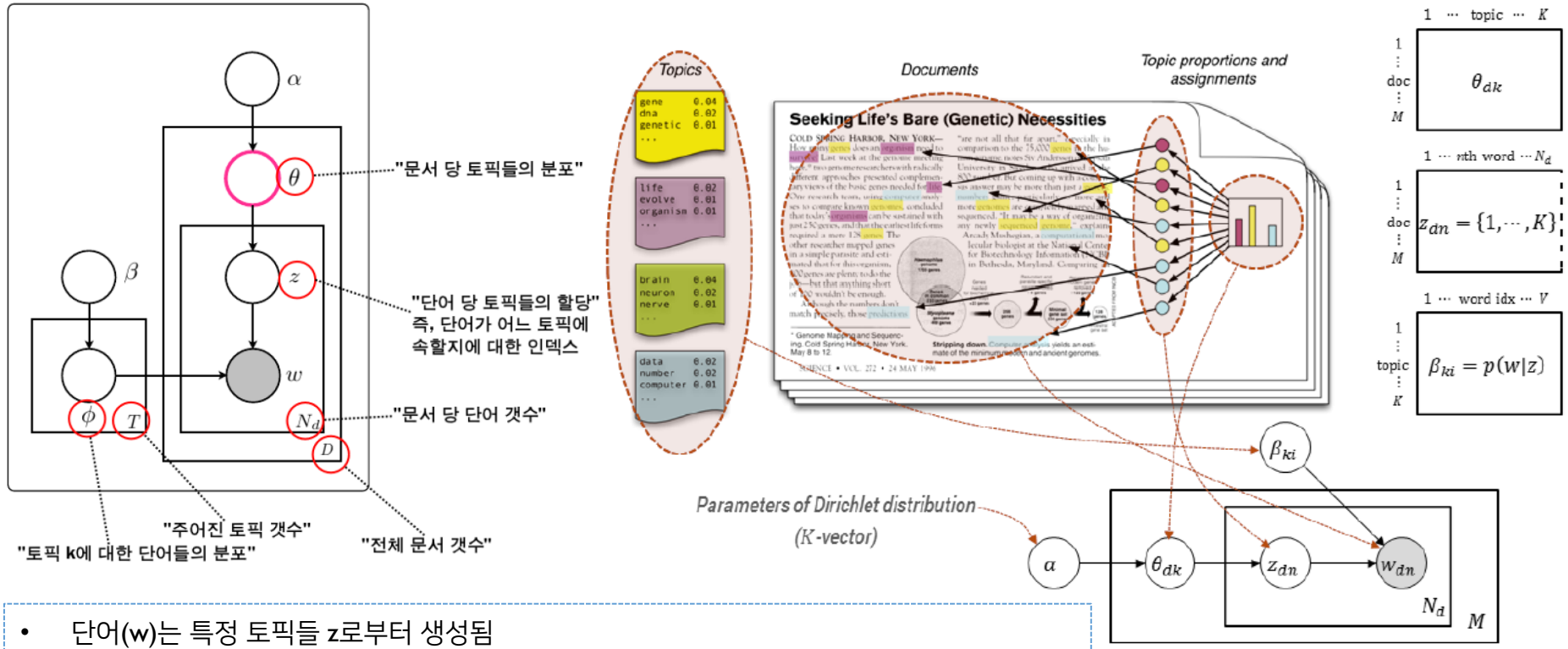
Feature Selection/Extraction

- LSA example
  - ✓ Visualize the project in the reduced 2-D space



Feature Selection/Extraction

- Topic Modeling as a Feature Extractor
  - ✓ Latent Dirichlet Allocation (LDA)



- 단어(w)는 특정 토픽들 z로부터 생성됨
- 해당 문서가 어떤 토픽 비율(topic proportion, θ)을 가질 것인지는 파라미터가 α인 Dirichlet distribution에 의해 결정됨
- w만 실제로 관찰할 수 있는 값이고 θ, z, Φ는 숨겨진 값임
- 문서 생성 프로세스는 먼저 다항분포 θ로부터 토픽이 나타날 확률 θ를 추출하고 이를 바탕으로 단어가 나타날 확률인 w를 산출함

Feature Selection/Extraction

- Topic Modeling as a Feature Extractor
  - ✓ Two outputs of topic modeling
    - Per-document topic proportion
    - Per-topic word distribution

(a) Per-document topic proportions (θ_d)

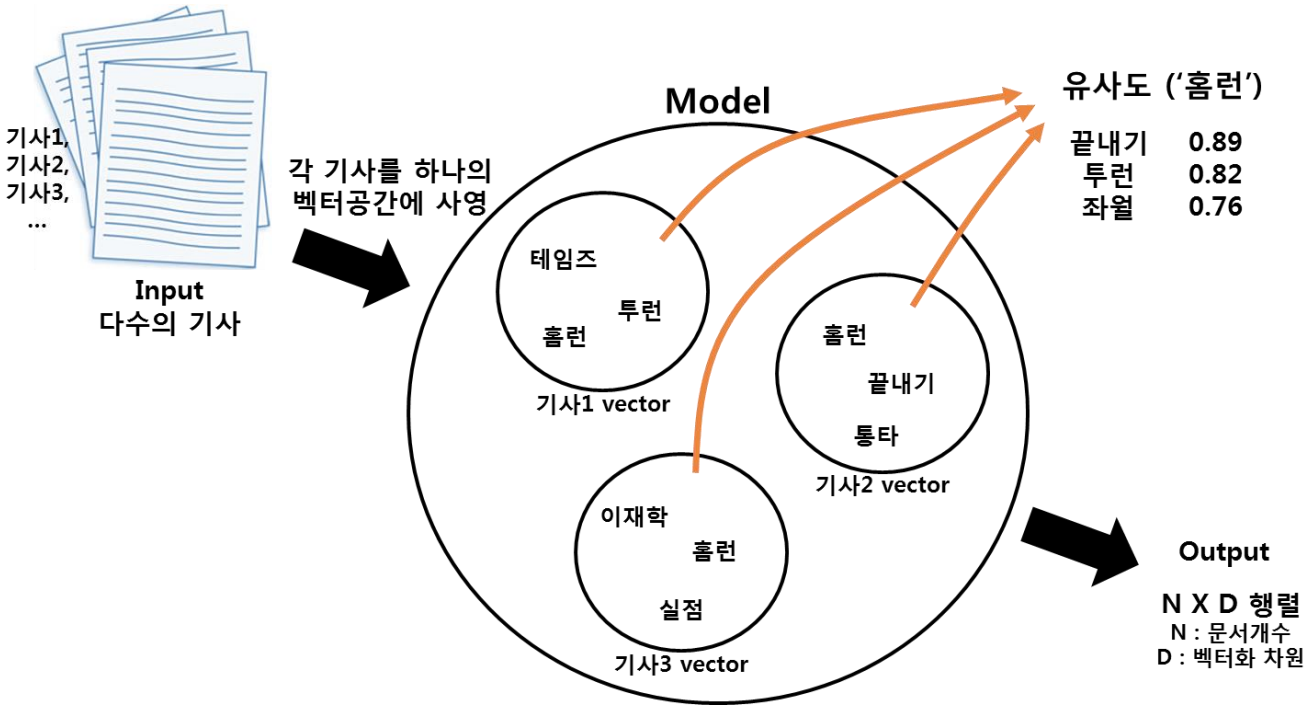
	Topic 1	Topic 2	Topic 3	…	Topic K	Sum
Doc 1	0.20	0.50	0.10	…	0.10	1
Doc 2	0.50	0.02	0.01	…	0.40	1
Doc 3	0.05	0.12	0.48	…	0.15	1
…	…	…	…	…	…	1
Doc N	0.14	0.25	0.33	…	0.14	1

(b) Per-topic word distributions (ϕ_k)

	Topic 1	Topic 2	Topic 3	…	Topic K
word 1	0.01	0.05	0.05	…	0.10
word 2	0.02	0.02	0.01	…	0.03
word 3	0.05	0.12	0.08	…	0.02
…	…	…	…	…	…
word V	0.04	0.01	0.03	…	0.07
Sum	1	1	1	1	1

Feature Selection/Extraction

- Document to vector (Doc2Vec)
  - ✓ A natural extension of word2vec
  - ✓ Use a distributed representation for each document



Feature Selection/Extraction

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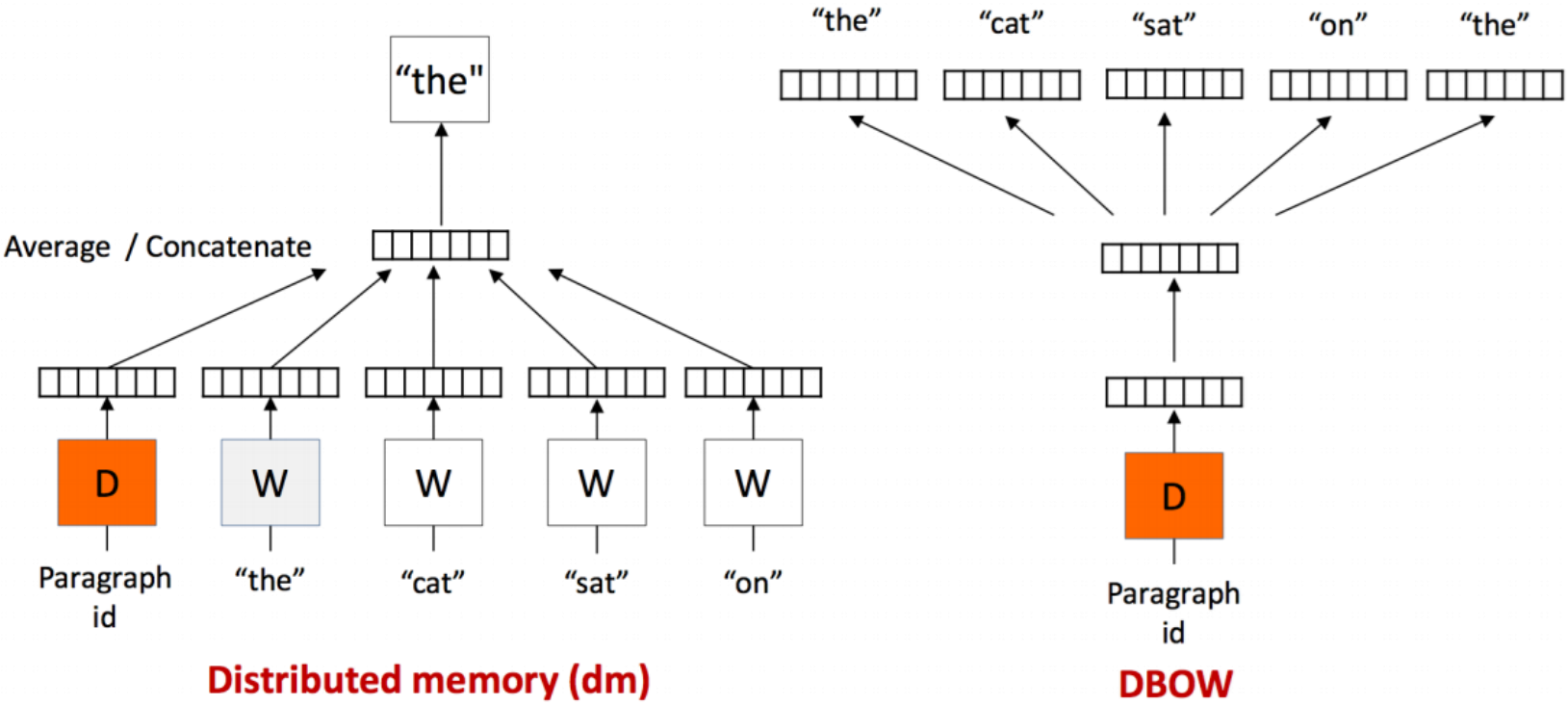


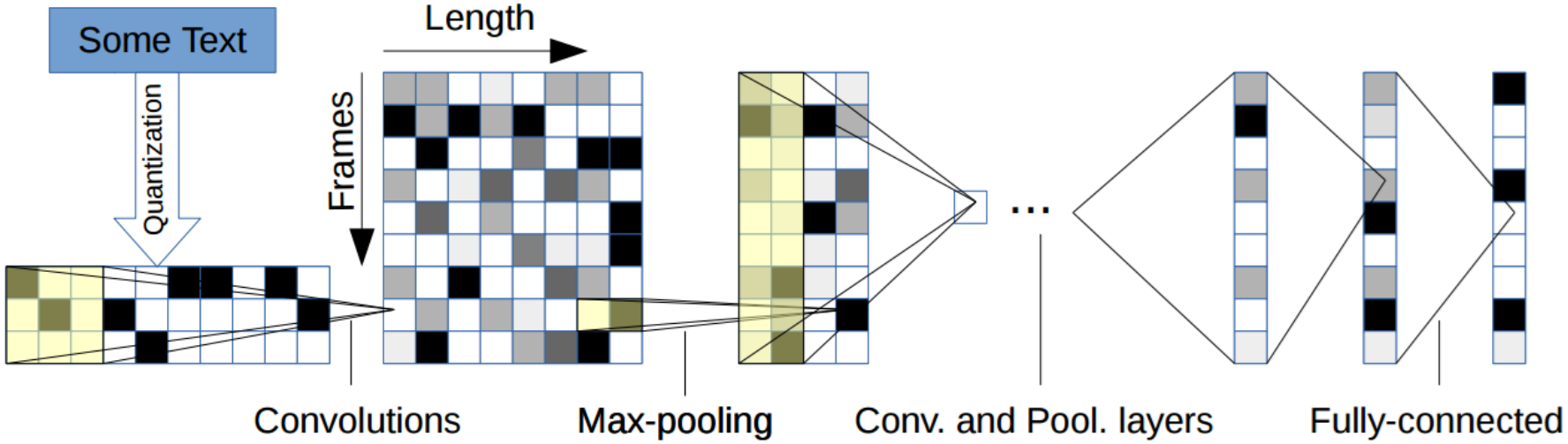
Feature Selection/Extraction

Zhang and LeCun (2015)

- No needs for feature engineering
  - ✓ 1-of-M encoding
    - 70 characters are encoded

```
abcdefghijklmnopqrstuvwxyz0123456789
-,;.!?:'''/\|_@#$%^&*~`+-=<>()[]{}
```

  - ✓ ConvNet Structure



Feature Selection/Extraction

Zhang and LeCun (2015)

- No needs for feature engineering
  - ✓ Performances for various TM tasks
    - Amazon review sentiment analysis

	Total	Full	Polarity
1	2,746,559	730,000	1,275,000
2	1,791,219	730,000	725,000
3	2,892,566	730,000	0
4	6,551,166	730,000	725,000
5	20,705,260	730,000	1,275,000

Full score

Model	Thesaurus	Train	Test
Large ConvNet	No	62.96%	58.69%
Large ConvNet	Yes	68.90%	59.55%
Small ConvNet	No	**69.24%**	59.47%
Small ConvNet	Yes	62.11%	**59.57%**
Bag of Words	No	54.45%	54.17%
word2vec	No	36.56%	36.50%

Polarity

Model	Thesaurus	Train	Test
Large ConvNet	No	**97.57%**	94.49%
Large ConvNet	Yes	96.82%	**95.07%**
Small ConvNet	No	96.03%	94.50%
Small ConvNet	Yes	95.44%	94.33%
Bag of Words	No	89.96%	89.86%
word2vec	No	72.95%	72.86%

Feature Selection/Extraction

Zhang and LeCun (2015)

- No needs for feature engineering
  - ✓ Performances for various TM tasks
    - Yahoo! Answers topic classification dataset

Category	Total	Train	Test
Society & Culture	295,340	140,000	6,000
Science & Mathematics	169,586	140,000	6,000
Health	278,942	140,000	6,000
Education & Reference	206,440	140,000	6,000
Computers & Internet	281,696	140,000	6,000
Sports	146,396	140,000	6,000
Business & Finance	265,182	140,000	6,000
Entertainment & Music	440,548	140,000	6,000
Family & Relationships	517,849	140,000	6,000
Politics & Government	152,564	140,000	6,000

Model	Thesaurus	Train	Test
Large ConvNet	No	73.42%	70.45%
Large ConvNet	Yes	**75.55%**	**71.10%**
Small ConvNet	No	72.84%	70.16%
Small ConvNet	Yes	72.51%	70.16%
Bag of Words	No	66.83%	66.62%
word2vec	No	56.37%	56.47%

Feature Selection/Extraction

Zhang and LeCun (2015)

- No needs for feature engineering
  - ✓ Performances for various TM tasks
    - News categorization

Category	Total	Train	Test
World	81,456	30,000	1,900
Sports	62,163	30,000	1,900
Business	56,656	30,000	1,900
Sci/Tech	41,194	30,000	1,900

Model	Thesaurus	Train	Test
Large ConvNet	No	99.44%	**87.18%**
Large ConvNet	Yes	**99.49%**	86.61%
Small ConvNet	No	99.20%	84.35%
Small ConvNet	Yes	96.81%	85.20%
Bag of Words	No	88.02%	86.69%
word2vec	No	78.20%	76.73%

Category	Total	Train	Test
Sports	645,931	90,000	12,000
Finance	315,551	90,000	12,000
Entertainment	160,409	90,000	12,000
Automobile	167,647	90,000	12,000
Technology	188,111	90,000	12,000

Model	Thesaurus	Train	Test
Large ConvNet	No	**99.14%**	**95.12%**
Small ConvNet	No	93.05%	91.35%
Bag of Words	No	92.97%	92.78%

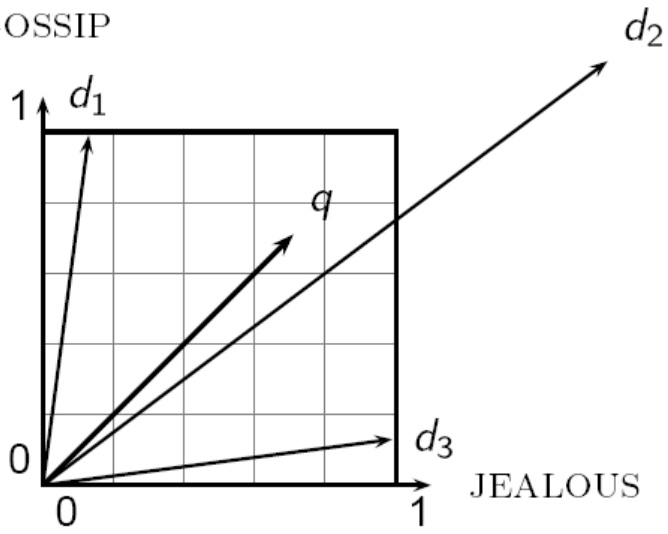
AGENDA

Similarity Between Documents

- Document similarity
  - ✓ Use the cosine similarity rather than Euclidean distance
    - Which two documents are more similar?

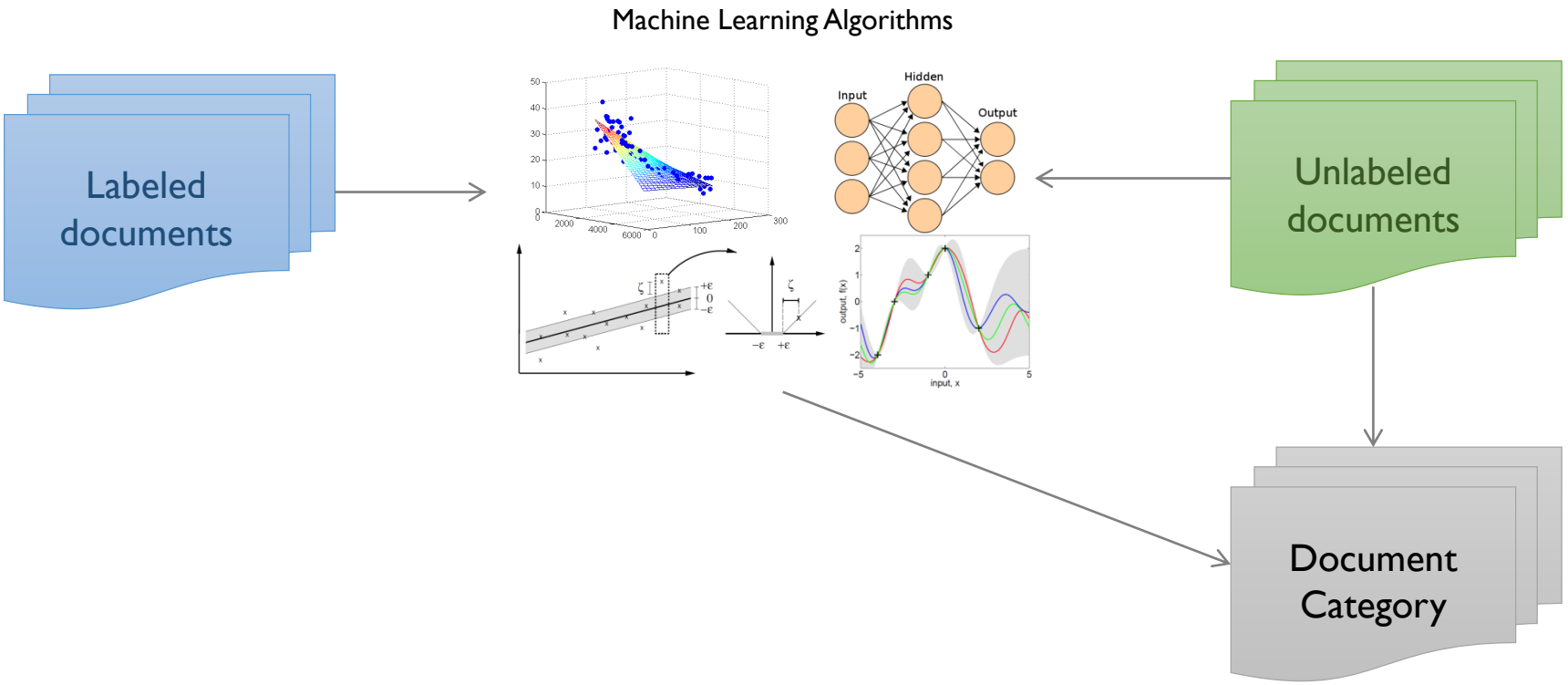
Doc.	Word 1	Word 2	Word 3
Document 1	1	1	1
Document 2	3	3	3
Document 3	0	2	0

$$Sim(D_1, D_2) = \frac{\sum_i x_{1i} x_{2i}}{\sqrt{\sum_j x_j^2}\sqrt{\sum_k x_k^2}}$$



Learning Task 1: Classification

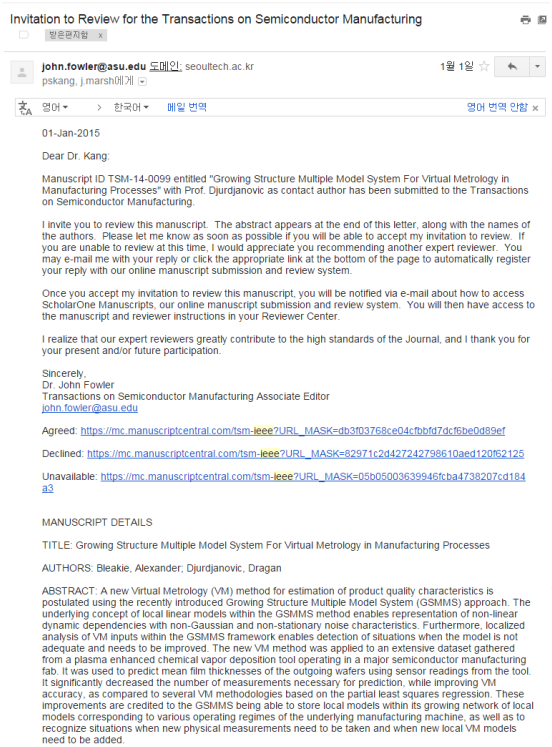
- Document categorization (classification)
  - ✓ Automatically classify a document into one of the pre-defined categories



Learning Task 1: Classification

- Spam filtering

Raw Data


Invitation to Review for the Transactions on Semiconductor Manufacturing

john.fowler@asu.edu 도메인: seoultech.ac.kr 1월 1일

pskang, j.marsh에게

영어 › 한국어 메일 번역 영어 번역 안함

01-Jan-2015

Dear Dr. Kang:

Manuscript ID TSM-14-0099 entitled "Growing Structure Multiple Model System For Virtual Metrology in Manufacturing Processes" with Prof. Djurdjanovic as contact author has been submitted to the Transactions on Semiconductor Manufacturing.

I invite you to review this manuscript. The abstract appears at the end of this letter, along with the names of the authors. Please let me know as soon as possible if you will be able to accept my invitation to review. If you are unable to review at this time, I would appreciate you recommending another expert reviewer. You may e-mail me with your reply or click the appropriate link at the bottom of the page to automatically register your reply with our online manuscript submission and review system.

Once you accept my invitation to review this manuscript, you will be notified via e-mail about how to access ScholarOne Manuscripts, our online manuscript submission and review system. You will then have access to the manuscript and reviewer instructions in your Reviewer Center.

I realize that our expert reviewers greatly contribute to the high standards of the Journal, and I thank you for your present and/or future participation.

Sincerely,
Dr. John Fowler
Transactions on Semiconductor Manufacturing Associate Editor
john.fowler@asu.edu

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MANUSCRIPT DETAILS

TITLE: Growing Structure Multiple Model System For Virtual Metrology in Manufacturing Processes

AUTHORS: Bleakie, Alexander; Djurdjanovic, Dragan

ABSTRACT: A new Virtual Metrology (VM) method for estimation of product quality characteristics is postulated using the recently introduced Growing Structure Multiple Model System (GSMMS) approach. The underlying concept of local linear models within the GSMMS method enables representation of non-linear dynamic dependencies with non-Gaussian and non-stationary noise characteristics. Furthermore, localized analysis of VM inputs within the GSMMS framework enables detection of situations when the model is not adequate and needs to be improved. The new VM method was applied to an extensive dataset gathered from a plasma enhanced chemical vapor deposition tool operating in a major semiconductor manufacturing fab. It was used to predict mean film thicknesses of the outgoing wafers using sensor readings from the tool. It significantly decreased the number of measurements necessary for prediction, while improving VM accuracy, as compared to several VM methodologies based on the partial least squares regression. These improvements are credited to the GSMMS being able to store local models within its growing network of local models corresponding to various operating regimes of the underlying manufacturing machine, as well as to recognize situations when new physical measurements need to be taken and when new local VM models need to be added.

Features

Vector space model (Bag of words)

Domain knowledge-based phrases ("Free money", "!!!")

Meta-data (sender, mailing list, etc.)

Model

Likelihood

Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

Posterior Probability

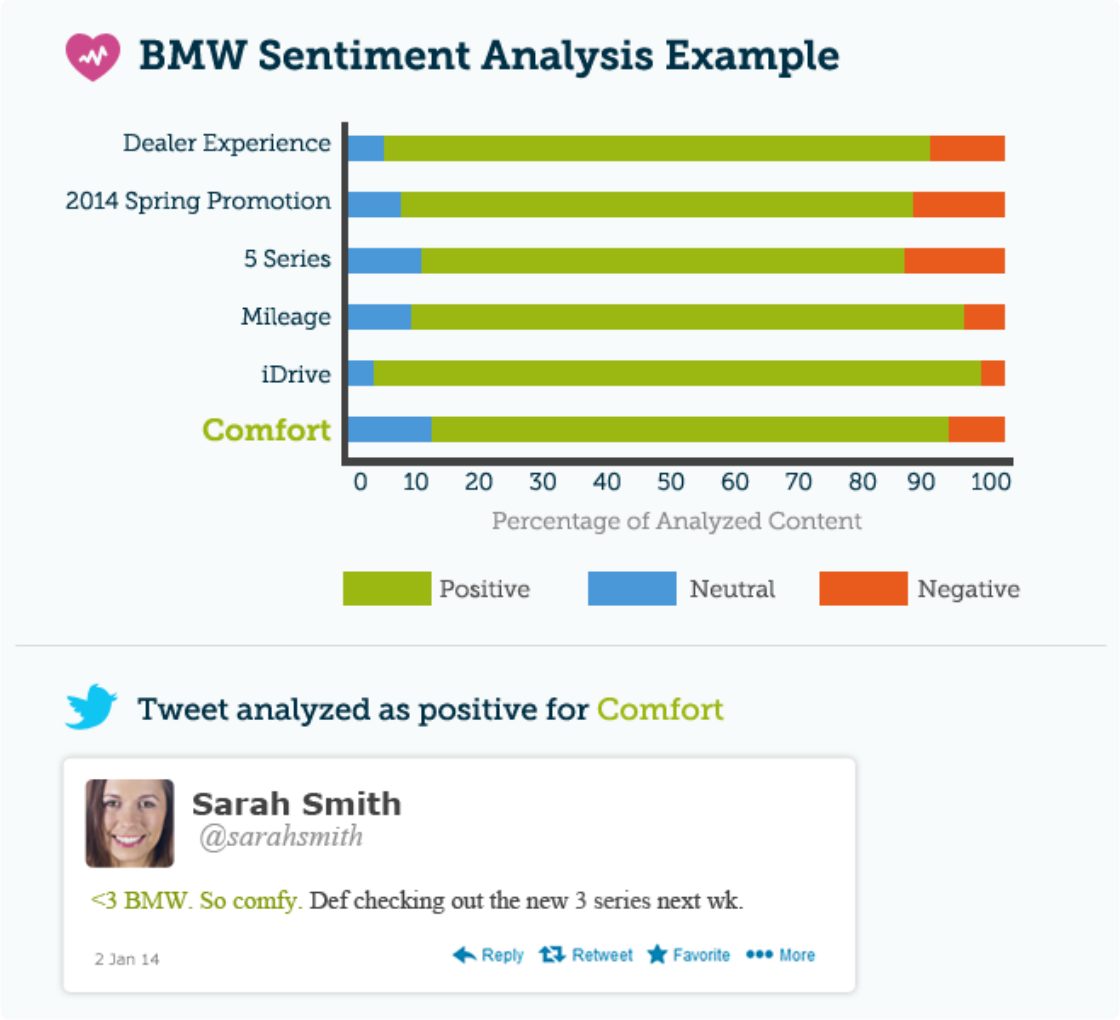
Predictor Prior Probability

$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Feature Regime	Junk		Legitimate	
	Precision	Recall	Precision	Recall
Words only	97.1%	94.3%	87.7%	93.4%
Words + Phrases	97.6%	94.3%	87.8%	94.7%
Words + Phrases + Domain-Specific	100.0%	98.3%	96.2%	100.0%

Learning Task 1: Classification

- Sentiment Analysis

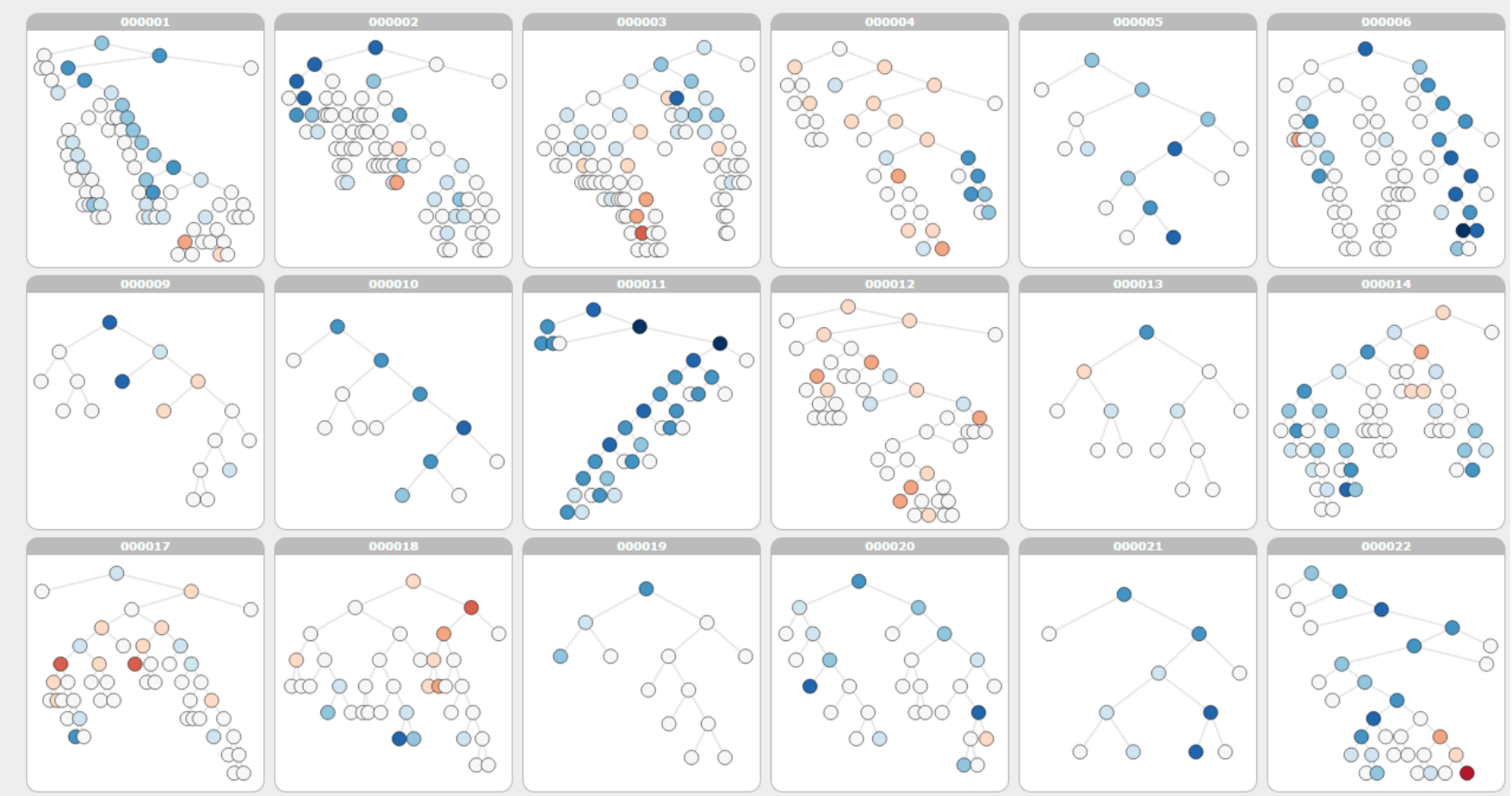


http://www.crowdsource.com/solutions/content-moderation/sentiment-analysis/

Learning Task 1: Classification

Socher et al. (2013)

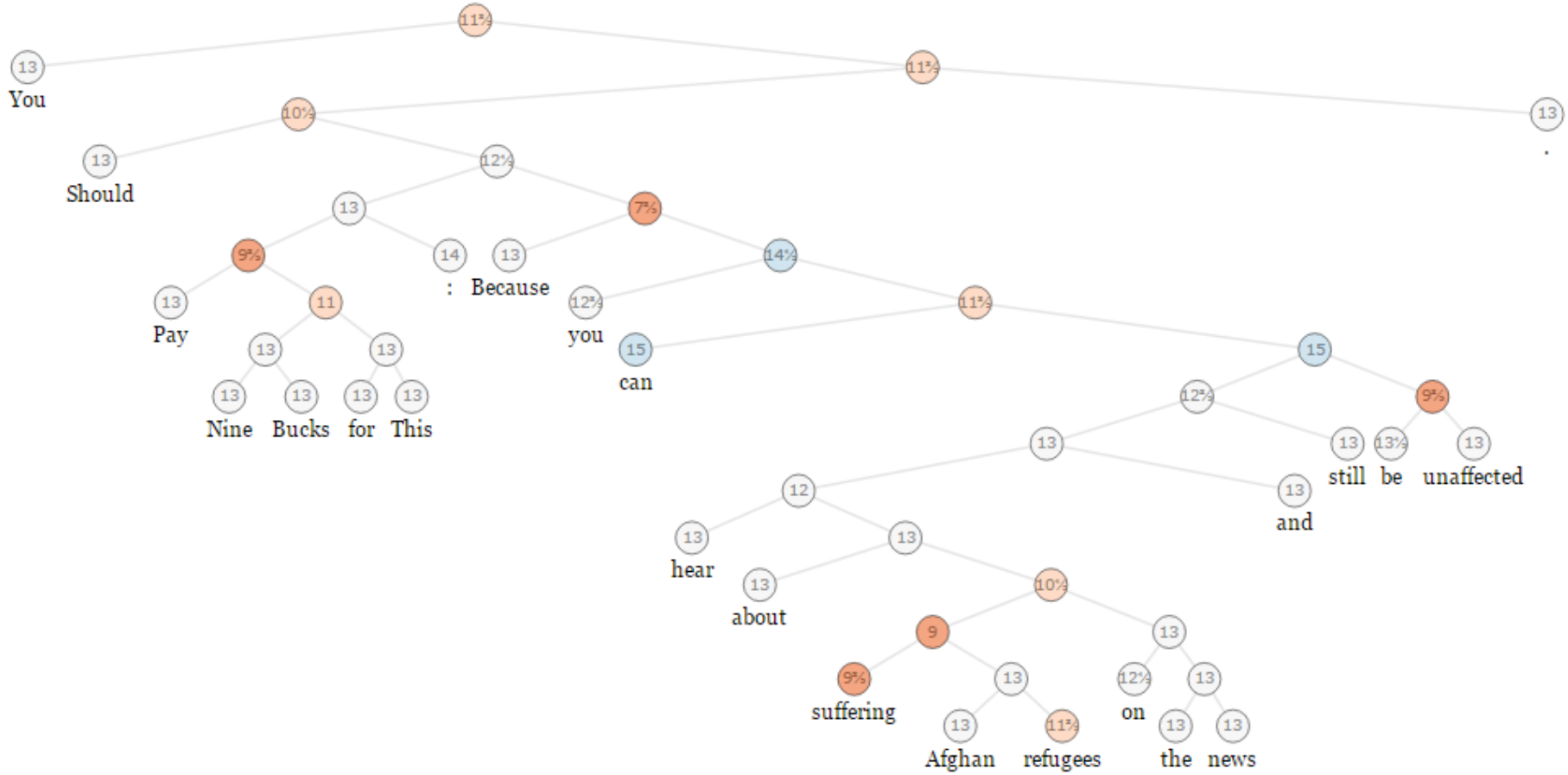
- Sentiment Analysis
  - ✓ Sentiment tree bank @Stanford NLP Lab



Learning Task 1: Classification

Socher et al. (2013)

- Sentiment Analysis
  - ✓ Sentiment tree bank @Stanford NLP Lab



Learning Task 2: Clustering

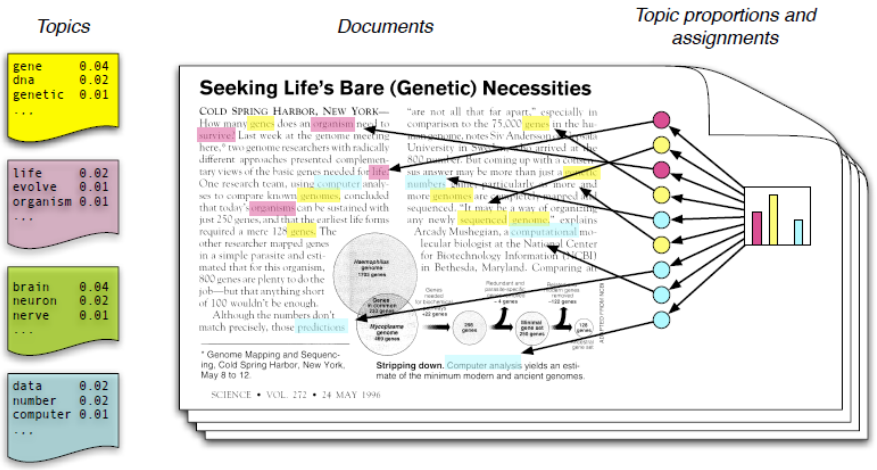
- Document Clustering & Visualization
  - ✓ Have a top level view of the topics in the corpora
  - ✓ See relationships between topics
  - ✓ Understand better what's going on

Raw Data

Source.title	Year	Title	Abstract
IEEE Transactions on Enginee	2014	Impact of interorganizational relationshi	Interorganizational relationships are an integral part of an organization's decision-
IEEE Transactions on Enginee	2014	Exploring the boundary conditions of dis	We explore the boundary conditions of Christensen's theory of disruption. Using te
IEEE Transactions on Enginee	2014	Two stage procurement processes with c	This paper considers a sourcing problem faced by a manufacturer who outsources
IEEE Transactions on Enginee	2014	Identifying emerging customer requirem	Rapid changes of new technologies, market dynamics, and swift fluctuation of cus
IEEE Transactions on Enginee	2014	Supply chain quality integration: Antece	This study extends quality management from an individual company perspective to
IEEE Transactions on Enginee	2014	Achieving IT-enabled enterprise agility ir	An ongoing challenge that enterprises currently face is that of fostering agile minc
IEEE Transactions on Enginee	2014	Accessing external technological knowle	This study elucidates how a firm accesses external technological knowledge (TK) a
IEEE Transactions on Enginee	2014	An investigation on centralized and dece	Design for supply chain has become an essential consideration while designing a
IEEE Transactions on Enginee	2014	ISO 9000 internalization and organizatio	This study presents an investigation of the relationship between internalization of
IEEE Transactions on Enginee	2014	Knowledge specialization in ph.D. Studer	Researchers have argued that specialization within groups yields productivity gains
IEEE Transactions on Enginee	2014	An overlapping-based design structure r	To gain competitive leverage, firms that design and develop complex products see
IEEE Transactions on Enginee	2014	The TOC-based algorithm for solving mu	In a previous paper in this journal named The TOC-Based Algorithm for Solving M
IEEE Transactions on Enginee	2014	Toward environmental and quality sustai	In the last decade, industrial research for sustainable development and environmer
IEEE Transactions on Enginee	2014	Balancing exploration and exploitation ir	This study investigates the influence of supply chain portfolios on the paradox of
IEEE Transactions on Enginee	2014	Managing nuclear spare parts inventorie	This paper presents a methodology for developing a spare parts inventory manage
IEEE Transactions on Enginee	2014	Scenario-based modeling of interdepenc	This paper develops a scenario generation framework for modeling demand and s
IEEE Transactions on Enginee	2014	Governing the portfolio management pr	Past strategy and innovation research has basically ignored potential effects of po
IEEE Transactions on Enginee	2014	Is an efficacious operation a safe operat	One of the most fundamental indicators of a facility's social sustainability is the he
IEEE Transactions on Enginee	2014	Managing highly innovative projects: Th	The climate change debate and economic recovery strategies in various industries
IEEE Transactions on Enginee	2014	Improved mean and variance estimating	The program evaluation and review technique (PERT) is a popular method for mea
IEEE Transactions on Enginee	2014	Openness and appropriation: Empirical e	The adoption of open innovation creates a dilemma for firms. On one hand, a com
IEEE Transactions on Enginee	2014	The redundancy queuing-location-alloca	Redundancy queuing-location-allocation problems (RQLAPs) involve the economic
IEEE Transactions on Enginee	2014	Response to buyout options in internet a	A buyout option allows a bidder to acquire an auctioned product immediately at a
IEEE Transactions on Enginee	2014	Contracting a development supplier in th	The development of important components for a new product is frequently outsou
IEEE Transactions on Enginee	2014	Exploration, exploitation, and growth thr	This study investigates how firm age and environmental adversity influence explora
IEEE Transactions on Enginee	2014	Innovation and performance: The role of	Innovation has become the cornerstone for achieving competitive advantage and i
IEEE Transactions on Enginee	2014	Spotting lemons in platform markets: A	This study addresses the understudied question of how content integrity for digita
IEEE Transactions on Enginee	2014	Business models and tactics in new proc	Effectuation and causation are two contrasting approaches to new business develc
IEEE Transactions on Enginee	2014	Energy technological change and capaci	This paper explores the role of learning in managing the capacities of existing and

- 8,850 articles from 11 Journals for the recent 10 years
- 21,434 terms after preprocessing

Features

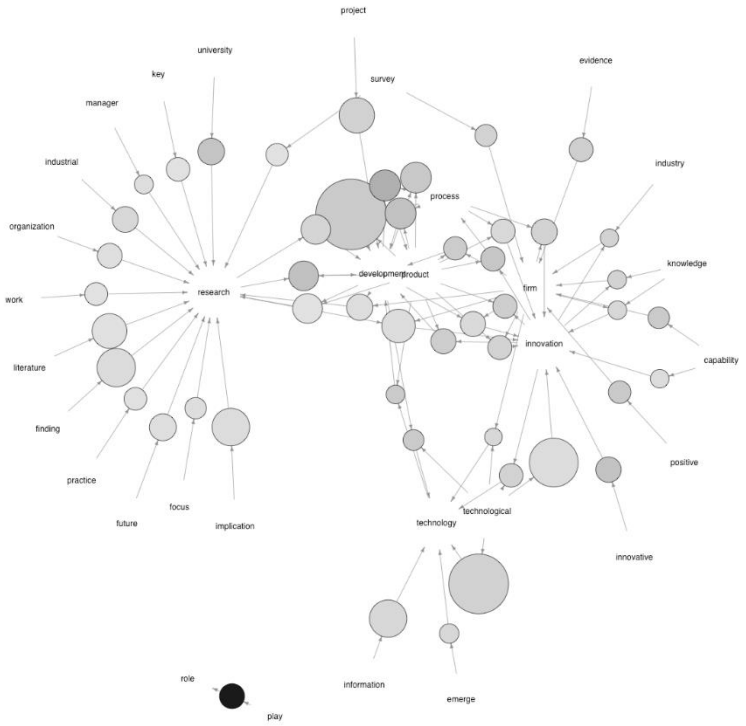


- 50 topics from Latent Dirichlet Allocation (LDA)

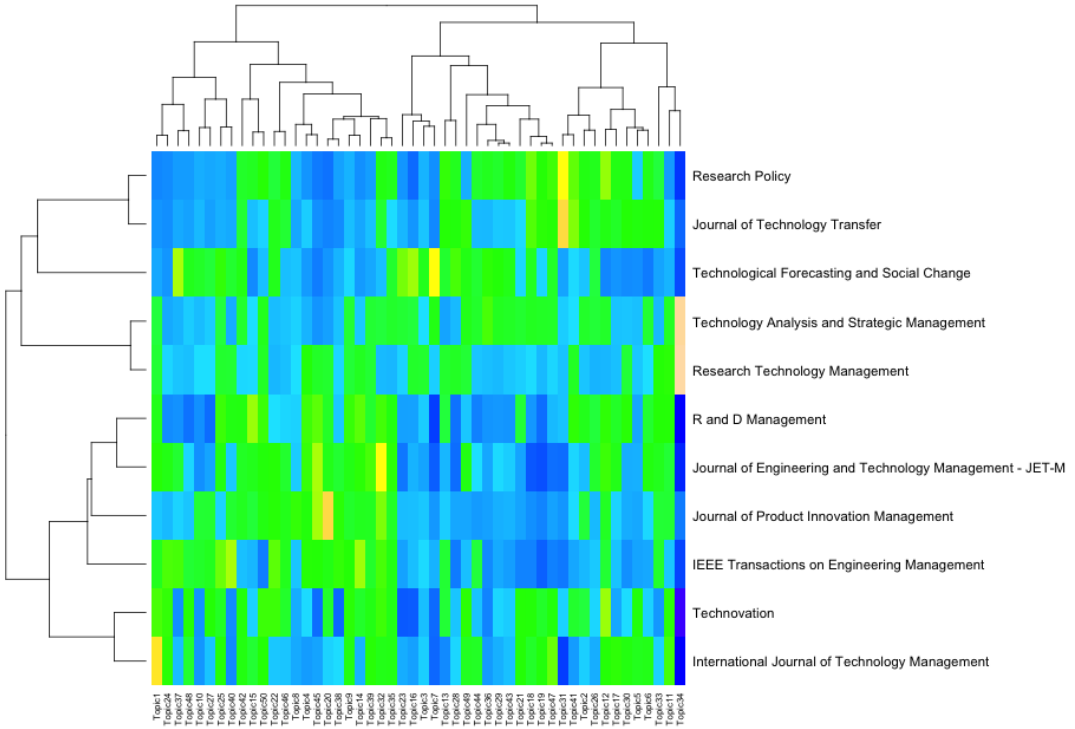
Learning Task 2: Clustering

- Document Clustering & Visualization

Keywords association

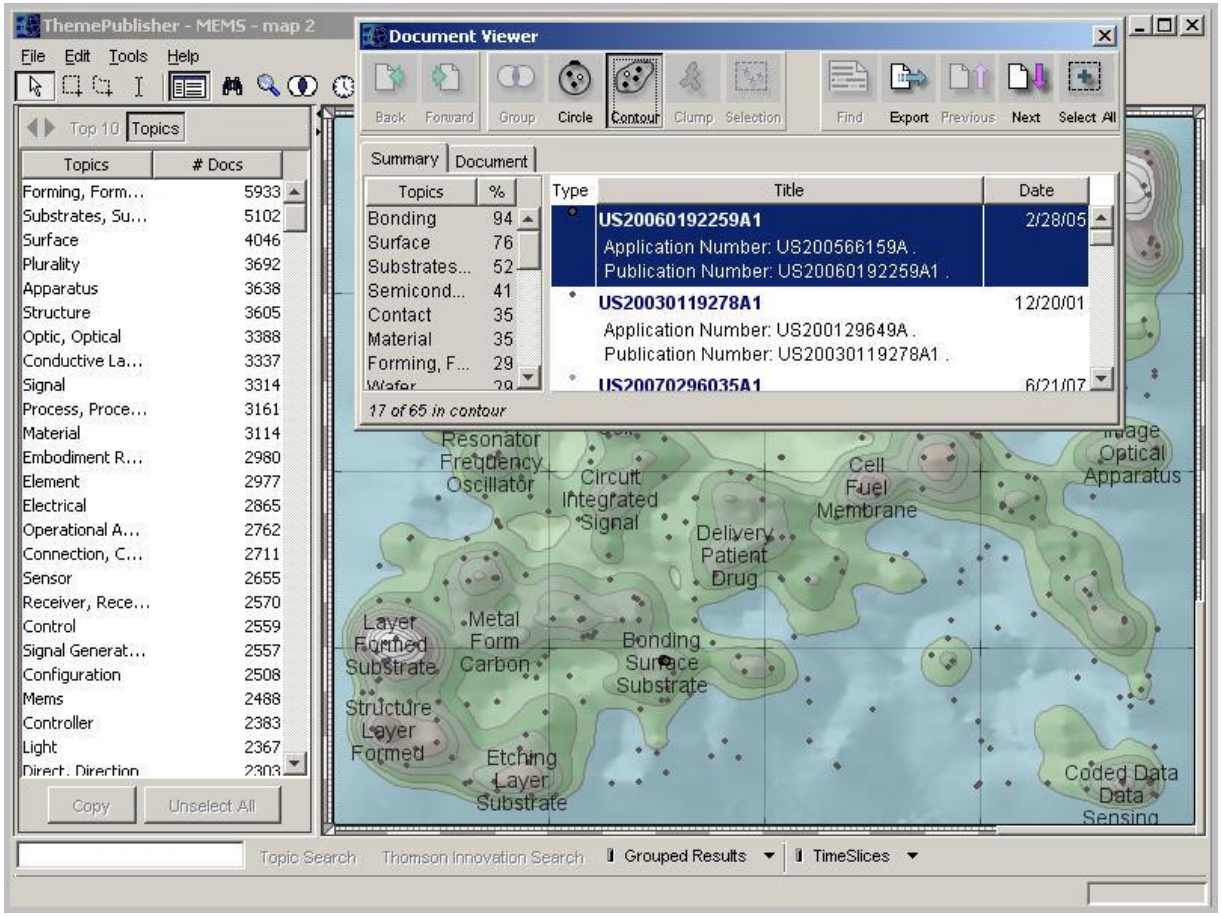


Journal/Topic Clustering



Learning Task 2: Clustering

- Document Clustering & Visualization
  - ✓ Themescape: contents maps from Thomson innovation full text patent data



Learning Task 3: Information Extraction/Retrieval

Yang et al. (2013)

- Information extraction/retrieval
  - ✓ Find useful information from text databases
  - ✓ Examples: identify the relationships between the symptoms and medicines (Yang et al., 2013)

연구대상 : 방약합편 (方藥合編)

- 한의학의 경험과 지식 축적은 주로 서적의 형태로 정리
- 방약합편 : 동의보감이 발간된 이후, 병증을 중점으로 두고 각 병증의 말미에 처방을 제시한 서적
- 병증에 따라 유용한 처방을 한눈에 제시
- 처방에 필요한 약재(본초)들을 명시

Learning Task 3: Information Extraction/Retrieval

- Information retrieval (cont')
  - ✓ Construct keyword database

Materia medica/prescription	Ginseng Radix	Citri Pericarpium	Pinelliae Rhizoma	Poria(red)	...	...
Prescription 1	1	0	0	0		
Prescription 2	1	1	0	1		
Prescription 3	0	0	0	1		
Prescription 4	0	0	1	1		
...						
Prescription 521	1	1	0	0		

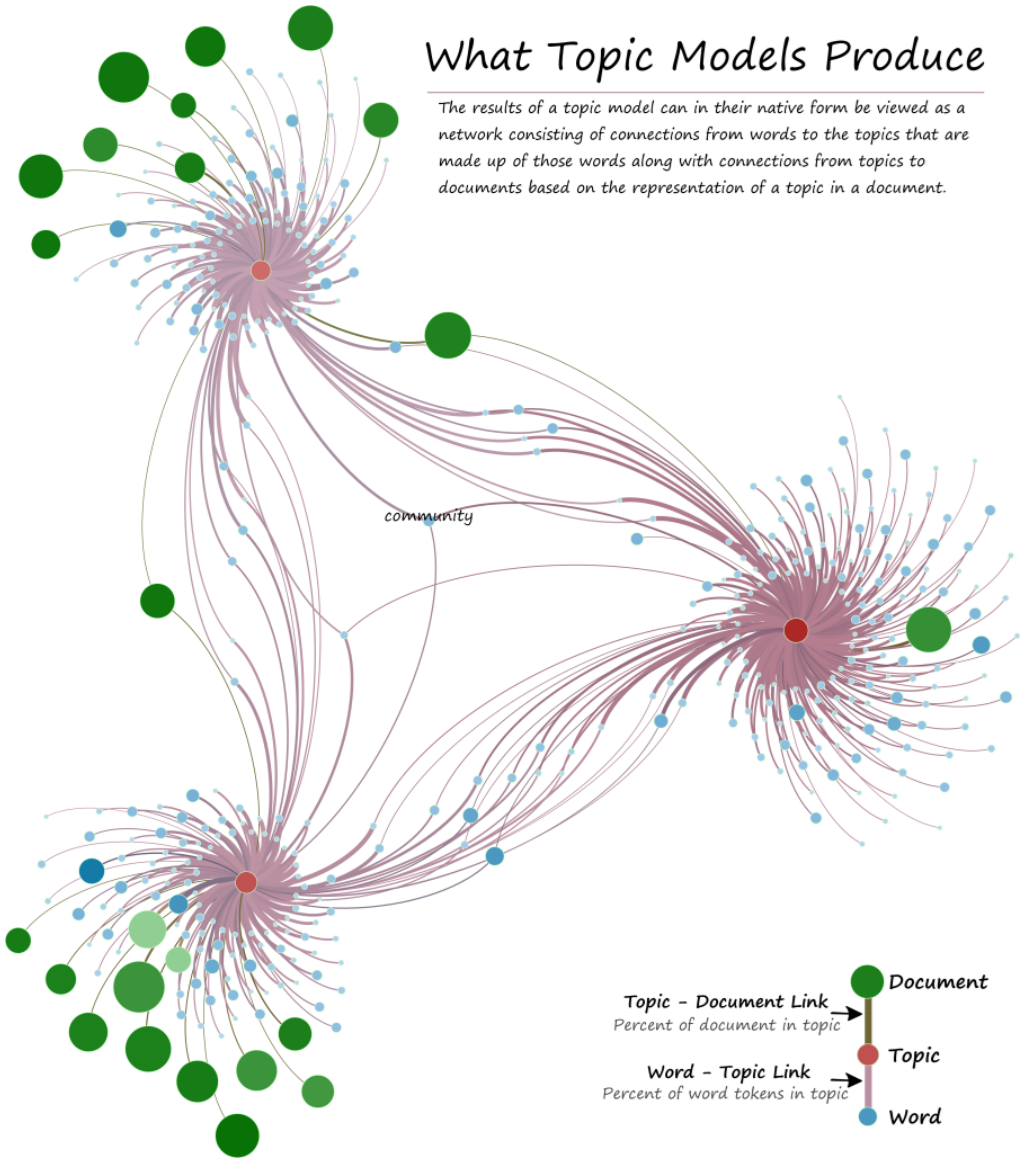
Learning Task 3: Information Extraction/Retrieval

- Information retrieval (cont')
  - ✓ Perform association rule to extract symptom-medicine relationships

Antecedent (symptom)	Consequent (herbal materials)	Support (%)	Confidence (%)	Lift
Coughs	Pinelliae Rhizoma	4.2	46.0	2.2
	Citri Pericarpium	3.9	42.9	1.3
	Rehmanniae Radix Preparat	2.2	23.8	1.8
	Poria(red)	2.0	22.2	1.3
	Poria(white)	2.0	22.2	1.1
	Armeniacae Semen	1.9	20.6	3.0
Overexertion/Fatigue	Rehmanniae Radix Preparat	3.5	70.5	4.5
	Angelicae Gigantis Radix	3.3	67.6	1.9
	Ginseng Radix	2.0	41.1	1.4
	Poria(white)	1.9	38.2	1.9
	Dioscoreae Rhizoma	1.7	35.3	5.0
	Paeoniae Radix Alba	1.7	35.3	1.8
	Atractylodis Rhizoma Alba	1.6	32.3	1.2
	Corni Fructus	1.4	29.4	5.8
	Capreoli Cornu	1.3	26.5	8.2
	Astragali Radix	1.3	26.5	2.4
	Achyranthis Radix	1.2	23.5	5.0
	Pulvis Aconiti Tuberis Purificatum	1.2	23.5	2.8
	Cinnamomi Cortex Spissus	1.2	23.5	1.8
	Moutan Cortex	1.0	20.6	3.6
	Schizandrae Fructus	1.0	20.6	3.4

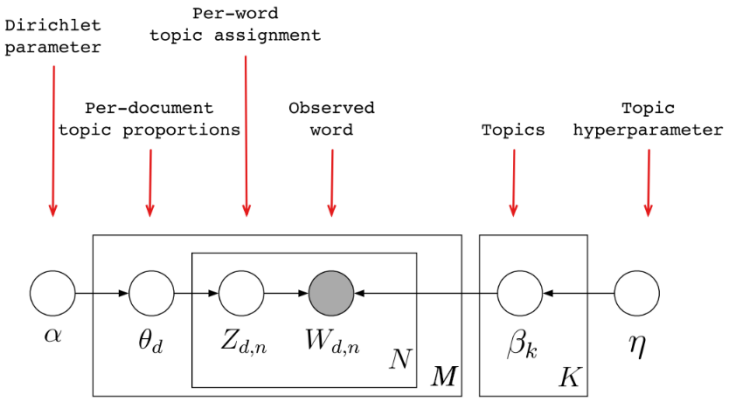
Learning Task 3: Information Extraction/Retrieval

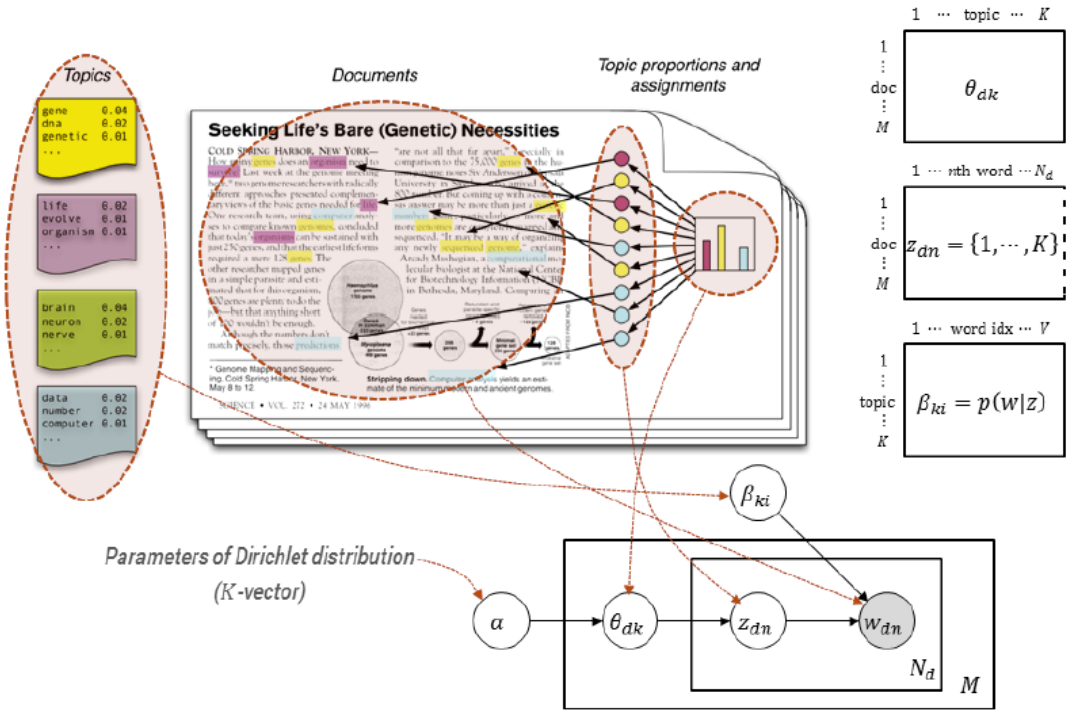
- Topic Modeling
  - ✓ A suite of algorithms that aim to discover and annotate large archives of documents with thematic information
  - ✓ Statistical methods that analyze the words of the original texts to discover
    - the themes that run through them
    - how themes are connected to each other
    - how they change over time



Learning Task 3: Information Extraction/Retrieval

- Latent Dirichlet Allocation (LDA)





- Words (w) are statistically generated from the topics Z
- Topic proportion for a document (θ_d) is determined by the Dirichlet distribution with the parameter α
- We can only observe W; θ, z, Φ are latent variables (hidden, cannot be observed)
- Document generation process: (1) Estimate the topic proportions θ, (2) estimate the word probability w from θ


ANY
questions?

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